Multi-State Health Transition Modelling Using Neural Networks

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Introduction

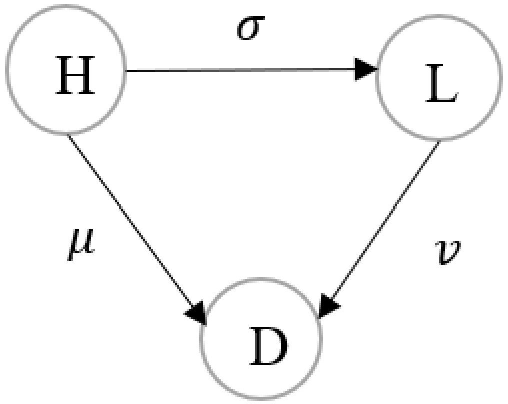
We develop a **new model** that **combines a neural network with a generalized linear model (GLM)** to **estimate and predict age-specific health transition intensities**

- Includes age effects, time trends, socioeconomic and lifestyle factors
- Detects and incorporates linear and nonlinear relationships among variables
- Takes expert opinion into account
- Uses transfer learning to link the models for different health transition processes

New model has **broad applications** in insurance, actuarial and health research.

- Focus: long-term care transitions for older individuals
  - To predict LTC needs → LTC services and LTC insurance
- Discuss other applications: health claim data modeling, mortality predictions, …

Introduction



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

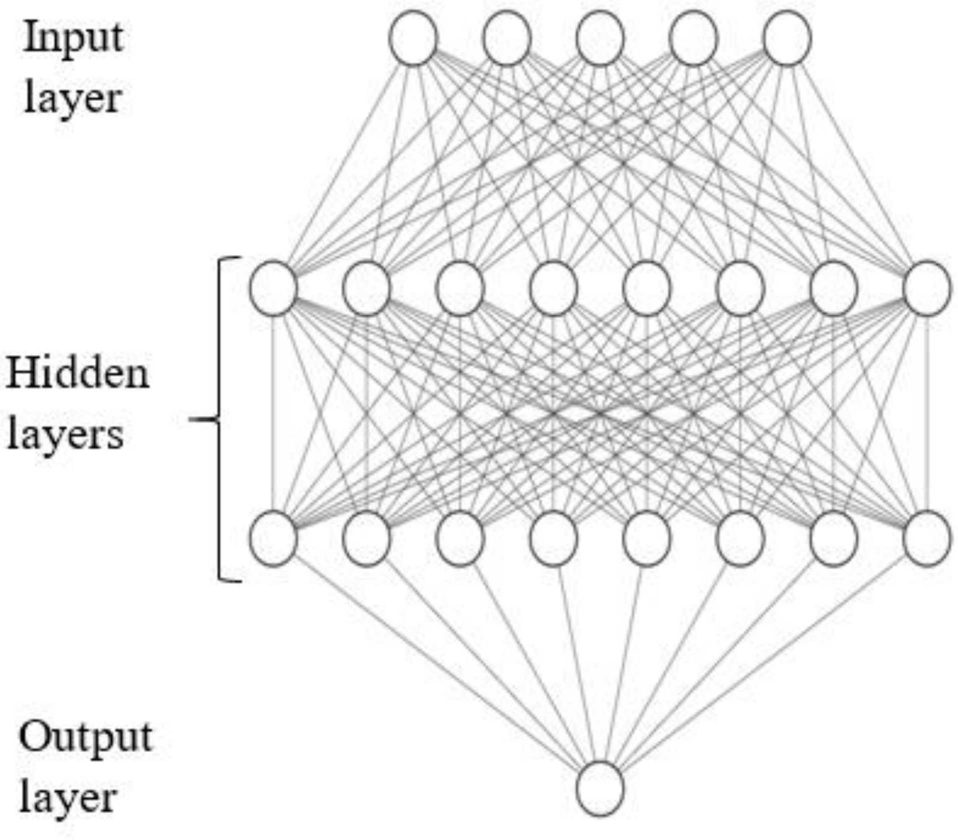
$$\eta_x = \sum_{s=0}^{k} \beta_s x^s = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_k x^k.$$

Our methodological contributions:

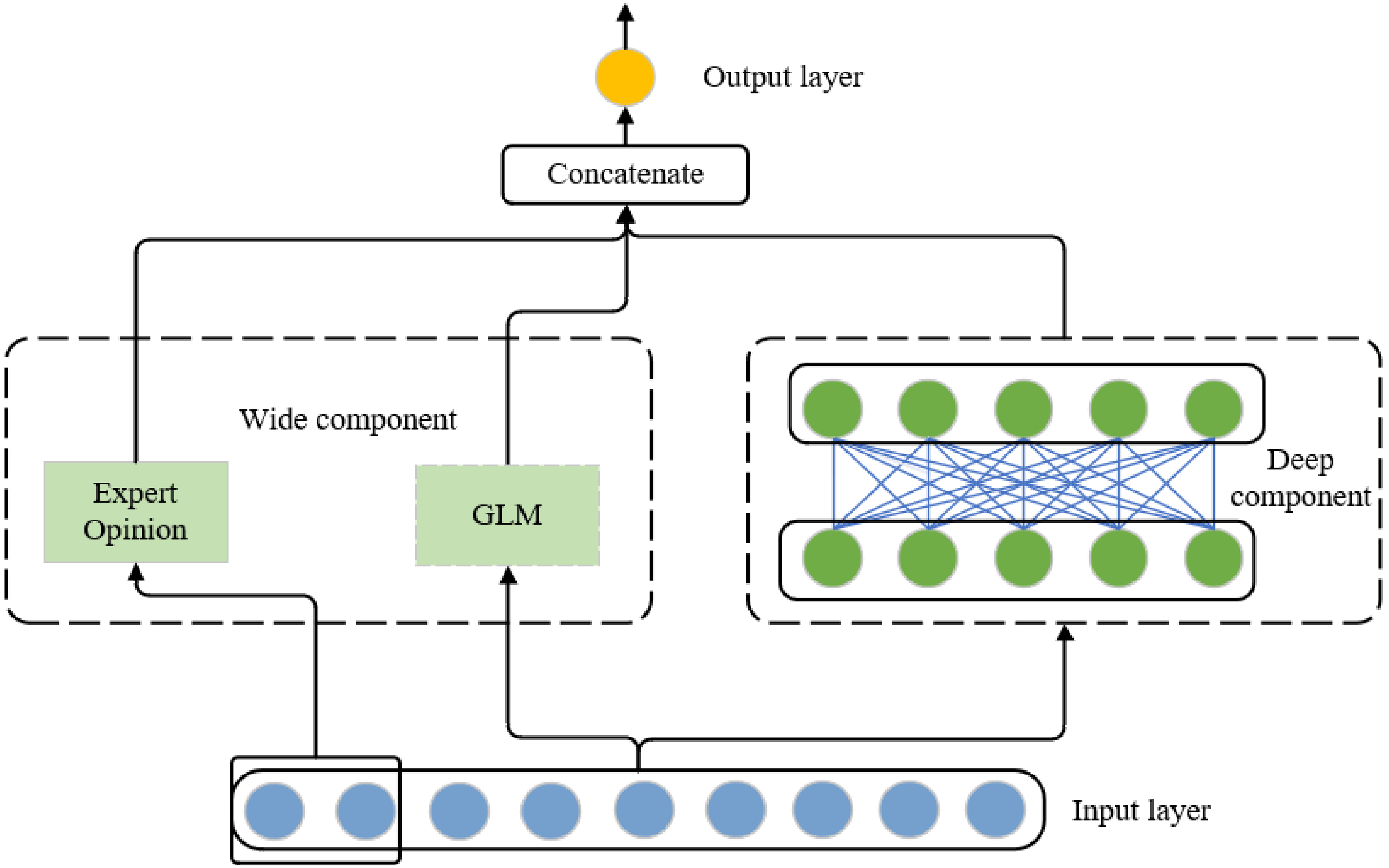
1. Introduce socioeconomic and lifestyle factors in the modeling of health transitions
2. Introduce neural networks to health transition modeling to …
   - Incorporate additional factors
   - Find and incorporate linear and nonlinear relationships among variables
   - Emphasize expert opinion
3. Use transfer learning to link the models for different health transitions

Neural networks

- Inspired by biological neural networks
- Find linear/nonlinear underlying relationships
- Improve model performance
  - Classification: accuracy
  - Approximation: loss



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 models for health transition processes

Data

Chinese Longitudinal Healthy Longevity Survey (CLHLS)

- One of the largest samples of the oldest-old in the world
- 8 waves (1998, 2000, 2002, 2005, 2008, 2011, 2014, 2018)
- Ages 65-105
- Self-reported difficulties with 6 Activities of Daily Living (ADLs)
- 31,660 transitions/ 69,063 observations
- Publicly available: https://opendata.pku.edu.cn/dataset.xhtml?persistentId=doi:10.18170/DVN/WBO7LK

Table 2. Transition Counts for Different Variables.

Variables		Transition counts			Exposure years	
		σ: H→L	μ: H→D	ν: L→D	H	L
Gender	Male	1,758	8,457	2,453	61,876	7,446
	Female	3,145	10,118	5,729	70,499	17,053
Marital status	With spouse	1,011	3,426	875	47,913	3,922
	Without spouse	3,892	15,149	7,307	84,463	20,578
Residency	Rural	2,540	11,103	4,431	75,867	12,917
	Urban	2,363	7,472	3,751	56,509	11,583
Smoke	Yes	730	3,385	638	27,781	2,466
	No	4,173	15,190	7,544	104,594	22,033
Drink	Yes	834	3,761	940	28,872	3,226
	No	4,069	14,814	7,242	103,504	21,273
Total		4,903	18,575	8,182	132,376	24,500

Model comparison

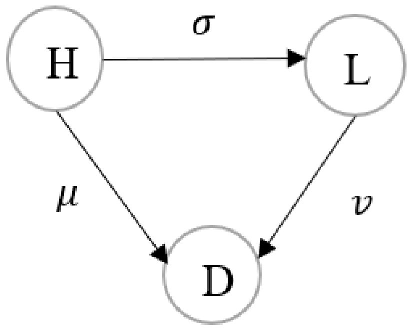
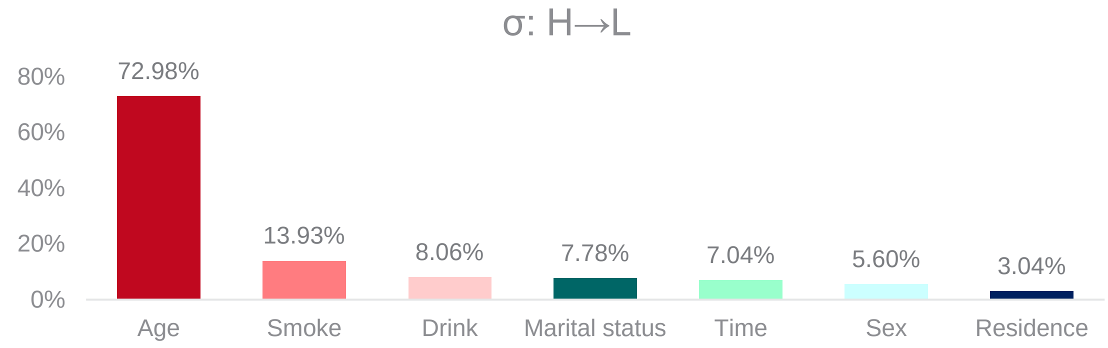
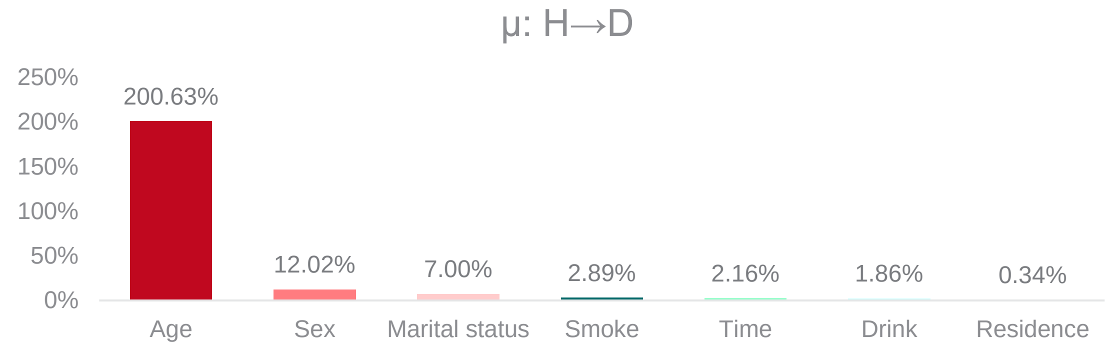


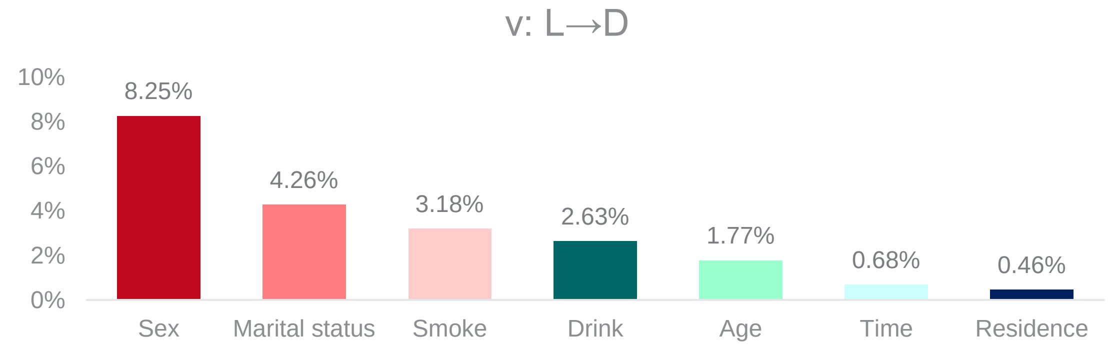
Table. MSE Loss Comparison and Computing Time for Different Models.

Models	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
GLM	80.69	86.42	56.08	95.22	96.80	55.78	0.04	0.06	0.04
NN0	129.11	59.27	30.11	145.65	18.98	53.31	2.55	2.57	2.23
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

Results







Life expectancies for 75-year-old healthy people.

			male		female	
75			rural	urban	rural	urban
1998	Smoke	Yes	7.03	7.45	7.32	7.27
		No	7.59	8.02	9.54	9.47
	Drink	Yes	7.31	7.44	8.33	7.96
		No	7.38	8.01	9.48	9.40
	Marital	Yes	7.57	8.26	9.58	8.37
		No	7.14	7.35	9.33	8.36
2018	Smoke	Yes	7.68	8.45	9.02	9.02
		No	9.55	10.20	11.06	11.69
	Drink	Yes	8.28	8.62	9.96	9.34
		No	8.94	10.06	11.00	11.66
	Marital	Yes	9.28	10.56	12.58	13.63
		No	8.14	8.64	10.54	11.07
2038	Smoke	Yes	9.09	9.69	9.68	9.55
		No	11.44	11.36	11.86	12.54
	Drink	Yes	9.99	9.99	10.87	10.58
		No	10.61	11.16	11.78	12.43
	Marital	Yes	10.98	11.67	14.54	15.25
		No	9.90	9.89	11.13	11.68

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 transition models via transfer learning

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

Additional analyses: importance of variables, survival curves, proportional hazards model, NN hyperparameters testing → see: https://www.cepar.edu.au/publications/working-papers/multi-state-health-transition-modeling-using-neural-networks

Conclusion

Our new model has **broad applications and provides a starting point for future research**:

- **Other health datasets** and **different health-related applications**
  - Mortality modeling using individual-level data
- **Classification problems**
  - Risk classification for insurance claims
- **Microsimulation health models**
  - FEM (Future Elderly Model) and COMPAS model
- **Multi-population mortality models**
- **LTCI pricing**
- Determine the **causality** between socioeconomic variables and health transitions

Thank you!

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