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Nonparametric Bayesian Multi-facet Clustering for Longitudinal Data

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Biomedical AI
UKRI CENTRE FOR DOCTORAL TRAINING

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AI MULTIPLY

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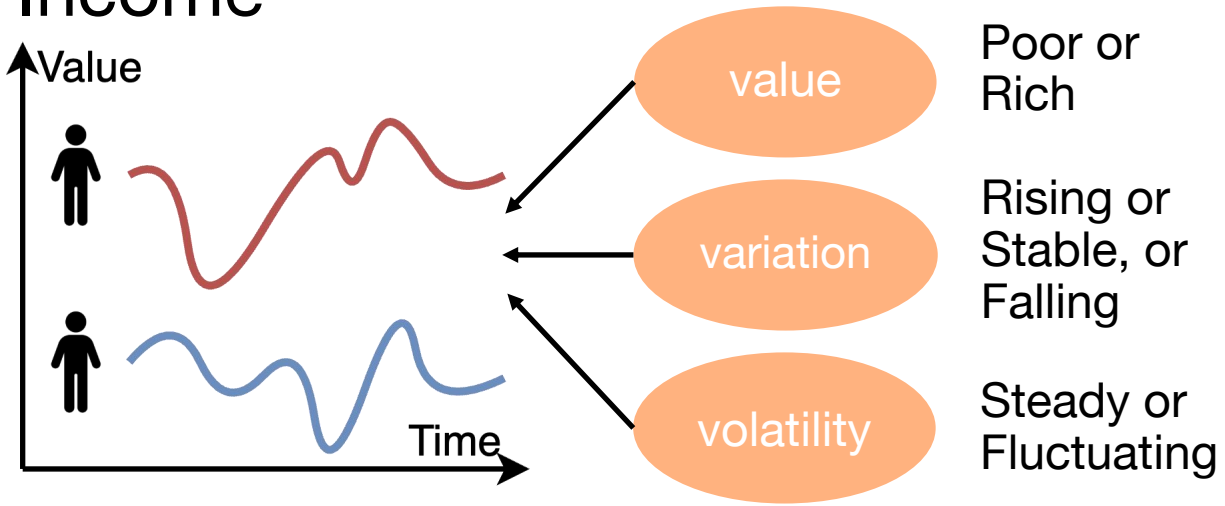
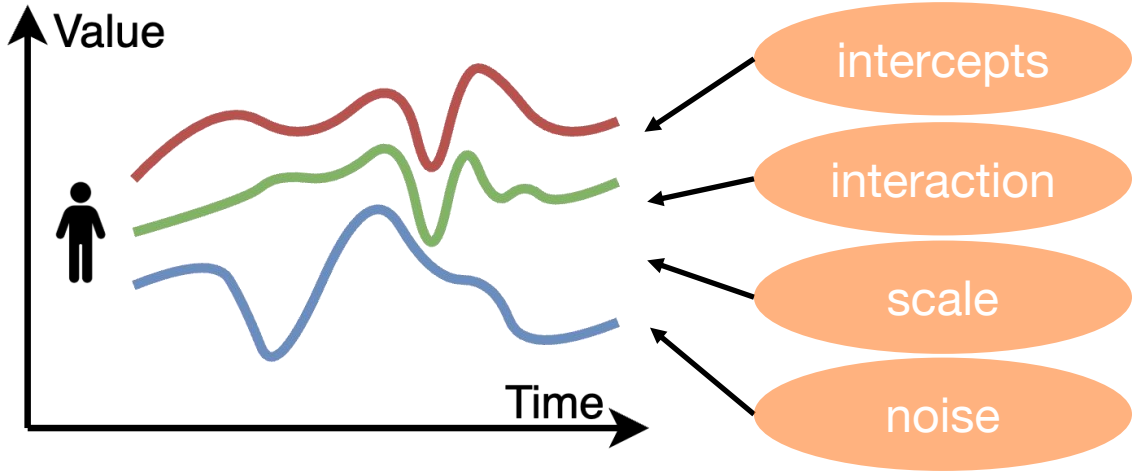
Multiple facets of longitudinal data

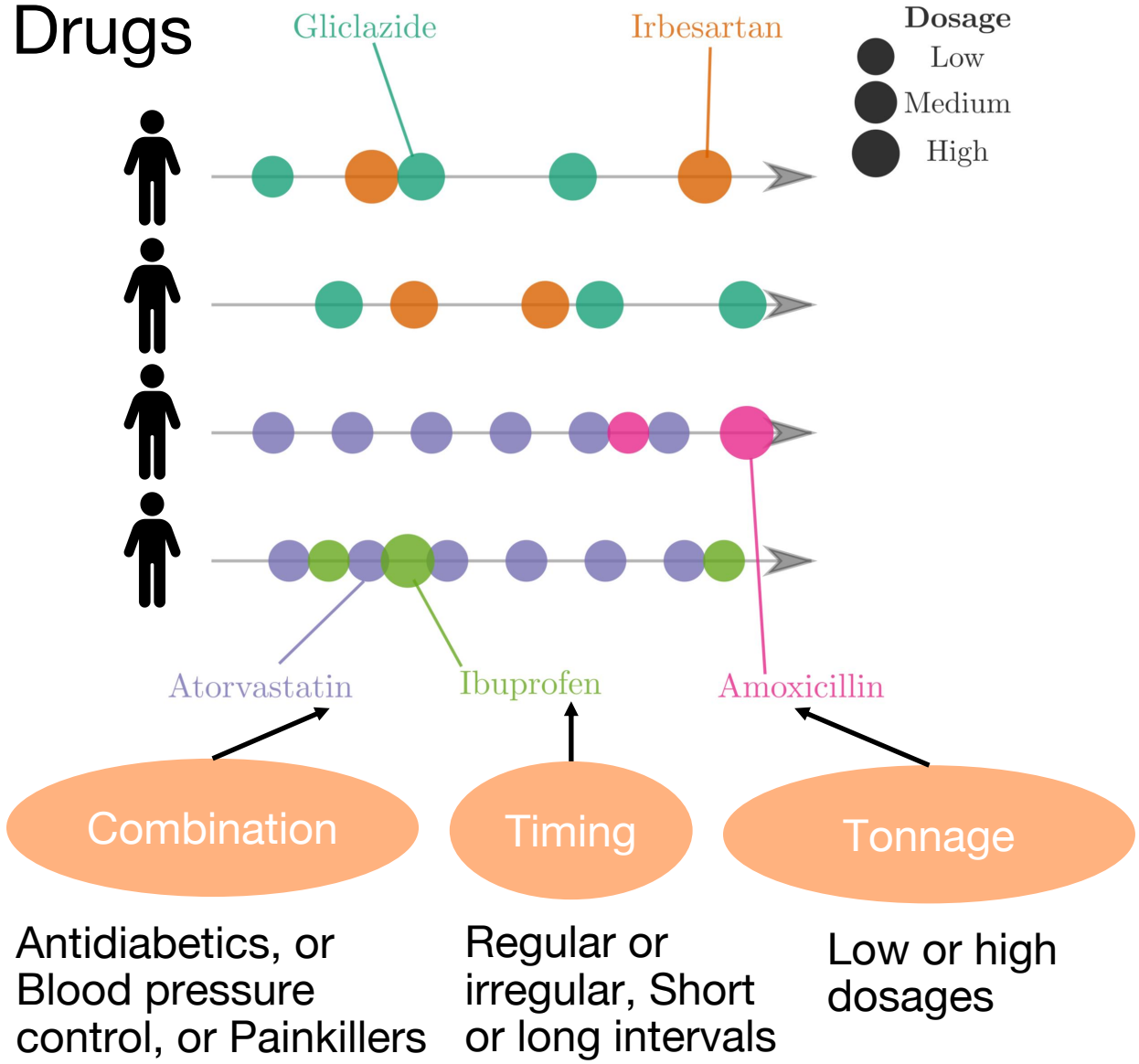
Income



Frailty, wellbeing & social isolation

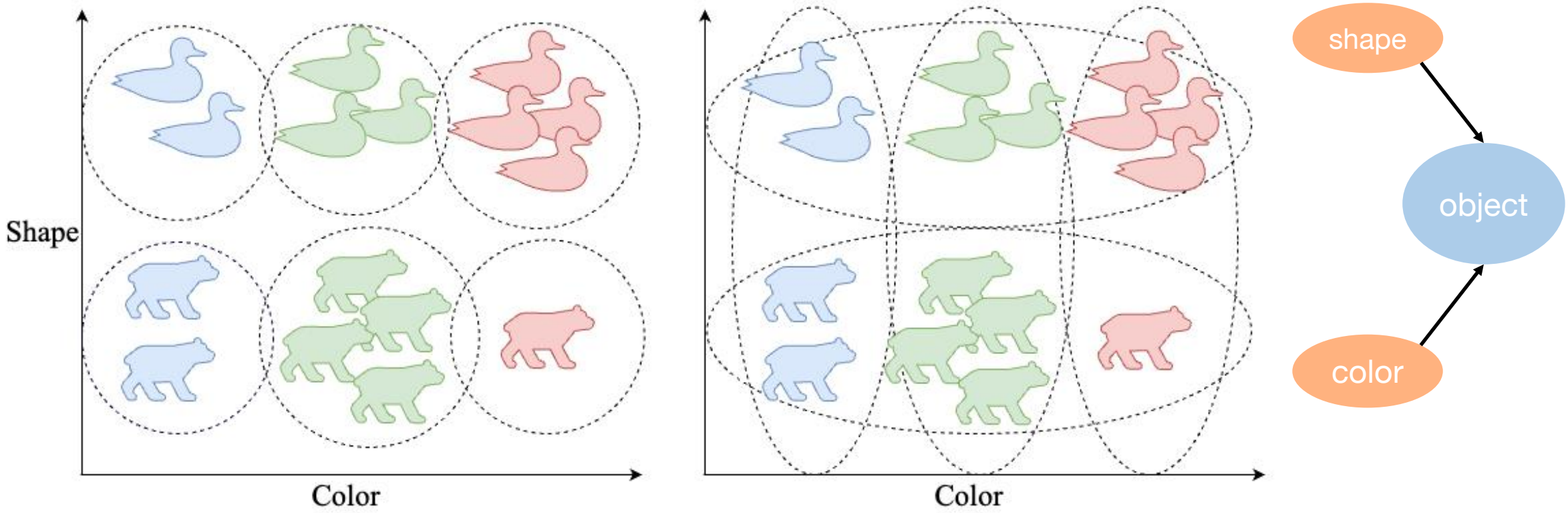


Drugs



Disentangle facets for interpretability

- **Traditional clustering** aggregates all facets/characteristics
  → poor interpretability
- **Multi-facet clustering:** along different facets/characteristics



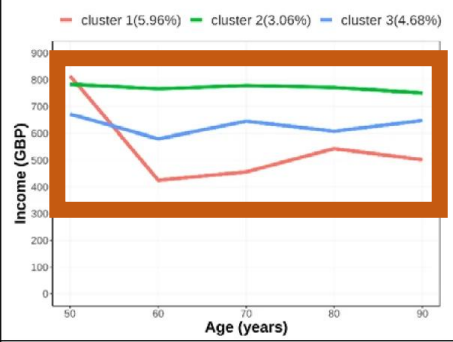
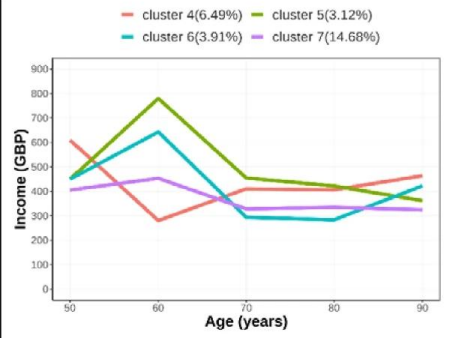
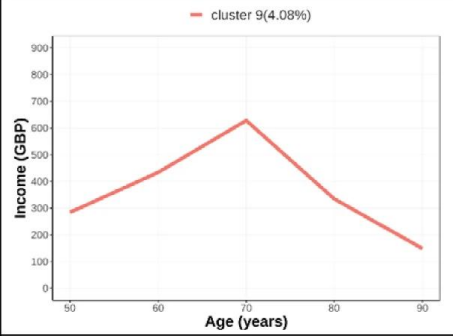
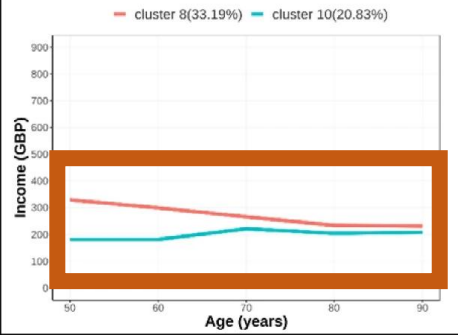
Single-facet versus multi-facet clustering.

Method

- **Multi-Facet Mixture Model (MMM):** separate clustering per facet

$$\sum_{k_1=1}^{K_1} \cdots \sum_{k_F=1}^{K_F} \pi_{k_1}^{(1)} \cdots \pi_{k_F}^{(F)} p(\mathbf{y} \mid \boldsymbol{\theta}_{k_1}^{(1)}, \ldots, \boldsymbol{\theta}_{k_F}^{(F)})$$

- Independent facets apriori
- Time series data i.e. y(t)
- Facets defined by users
- *Dirichlet Process prior* for automatic cluster discovery
- *Variational Bayesian inference* for scalability vs MCMC
- Implemented for two time series models
  - Nonlinear Growth Model (NLG) & Vector Autoregressive Model (VAR)
  - More being added!

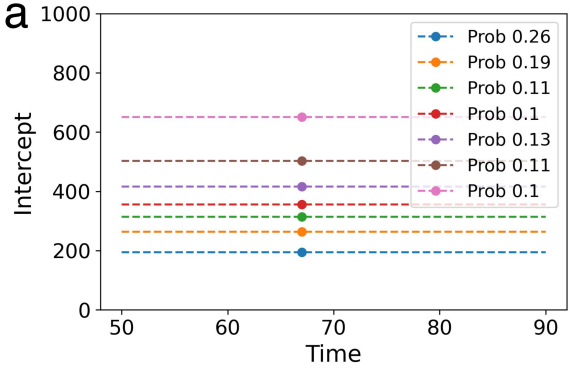
Income trajectory clusters	Income trajectory group (combines clusters)
	**Luxury:** These trajectories comprise 13.7% of the sample and share a high income that is at or above £500 per week for most of retirement. Cluster 1 (Luxury – pre-retirement income drop) – 5.7% (N=775) Clusters 2 (Luxury, highest stable income) - 3.1% (N=398) Cluster 3 (Luxury – medium stable income) – 4.7% (N=609)
	**Comfortable:** These clusters comprise 28% of the population and share a mid-level income from age 65 that is between £300-£500 per week. Cluster 4 (Comfortable: pre-retirement drop in income) – 6.5% (N=844) Cluster 5 (Comfortable: spike in pre-retirement income) – 3.1% (N=406) Cluster 6 (Comfortable: spike in pre-retirement income) – 3.9% (N=508) Cluster 7 (Comfortable – stable income trajectory) – 14.7% (N=1,909)
	**Boom-to-Bust** This group comprises 4.1% (N=530) of the sample and one cluster (9) with a spike of very high income at age 70 of £600 per week falling below £300 per week at the oldest ages (80+).
	**Always Poor:** These trajectories share an income that is typically below £300 per week from age 65 and to around £230 from age 80. Clusters 8 (Always Poor: higher within-group income) – 33% (N=4,317) Cluster 10 (Always Poor: lower within group income) 21% (N=2,709)

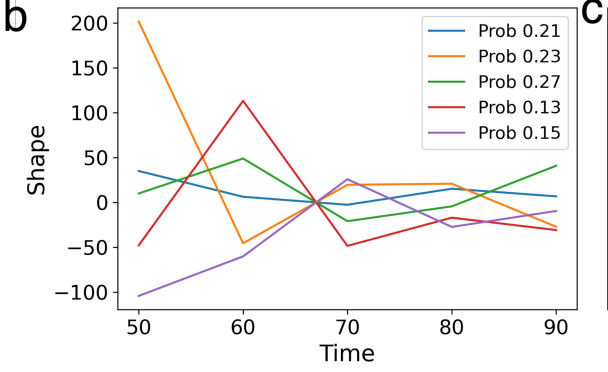
Single-facet clustering

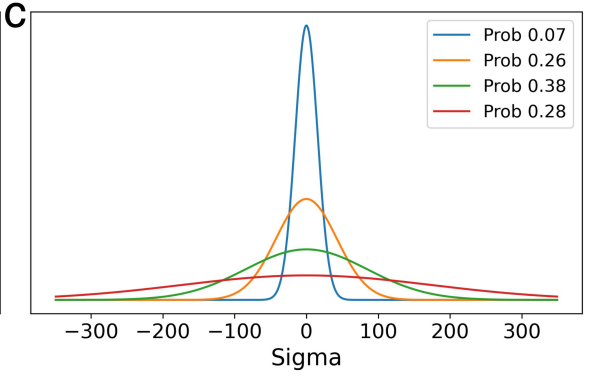
- **English Longitudinal Study of Ageing (ELSA)**
  - N = 13,002
  - Age: 50-90
  - Missingness: 86.8%
- **10** income trajectory clusters
- Manually grouped to **4 super-clusters** based on income at retirement
  - Luxury
  - Comfortable
  - Boom-to-bust
  - Always Poor
- **Similar variations** of trajectory
- **No volatility**

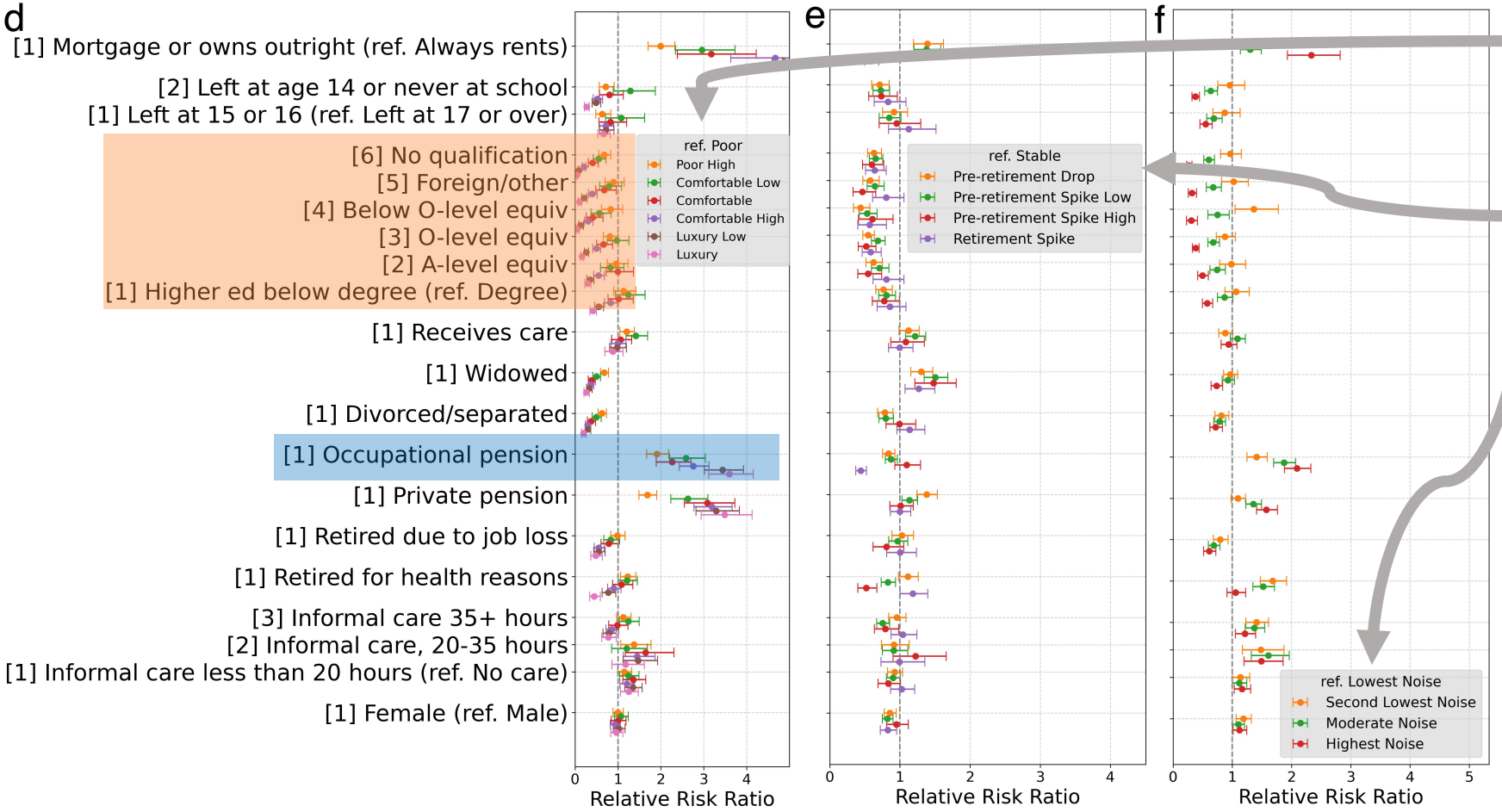
Marshall, A., Eke, C., Guthrie, B. et al. Income Trajectories and Precarity in Later life. Population Ageing 17, 335–363 (2024). https://doi.org/10.1007/s12062-023-09437-2

Income clusters & their drivers









7 value clusters

(Poor → Luxury)

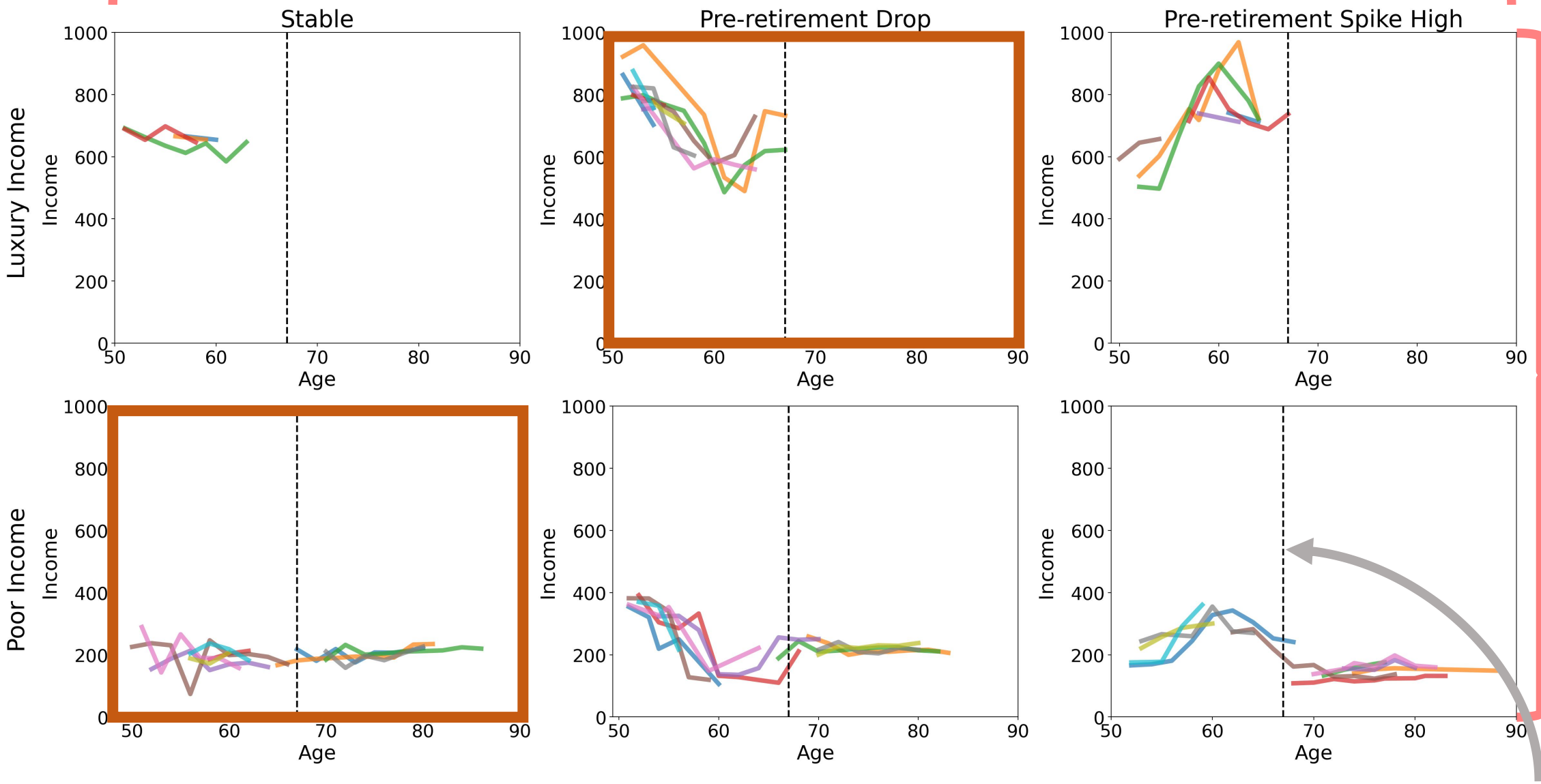
5 variation clusters

4 volatility clusters

Low education ↓ luxury

Pensions ↑ luxury

Facet 2: Income variation



Facet 1: Income value

retirement age at 67

Summary

Real-world data are multi-faceted

1. **Interpretable** by disentangling multiple facets
2. Current implementation supports
   a) Large datasets
   b) Automatic number of clusters
3. Broader **applicability** to various trajectories
   a) Socioeconomics
   b) Health
   c) and many more!

Thank you and get in touch!

Full Paper

MMM Code