

Dynamic modeling of disease progression using joint modeling of latent processes and times-to-events: the example of Multiple-System Atrophy

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joint work with Tiphaine Saulnier, Viviane Philipps, Alexandra Foubert-Samier

and MSA cohort board W G Meissner, A Pavy-Le Traon, O Rascol, M Fabbri, D Bendetowicz, F Sirna

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Workshop - Designing Synthetic Benchmarks for Real-World Cohort Data - Freiburg, June 2025

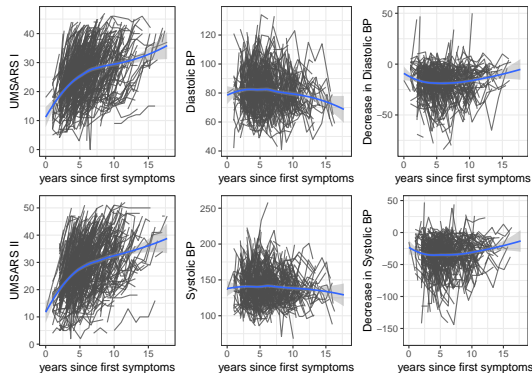


Biostatistics

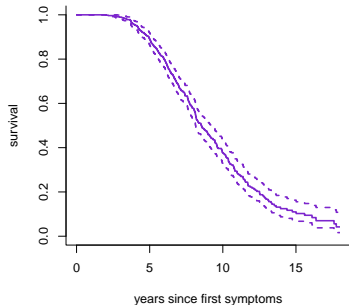


Progression of health phenomena in epidemiological studies

- repeated measures of markers (e.g., blood biomarker, MRI features, PRO / QoL scales) or exposure (e.g., blood pressure, BMI)



- times to health outcome (e.g., death, diagnosis, progression, dropout)

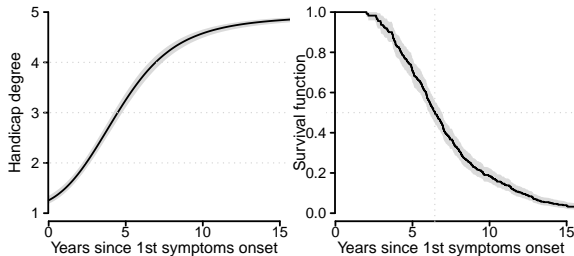


Provide complementary and interrelated information to be simultaneously studied

Multiple System Atrophy (MSA)

- Type of neuro-degenerative disease:

- ▶ rare (annual incidence 3/100,000 individuals)
- ▶ abnormal accumulation of α -synuclein in the brain
- ▶ poor prognosis (median survival time 4 years since diagnosis)
- ▶ little knowledge on etiology, natural history & progression
- ▶ no treatment



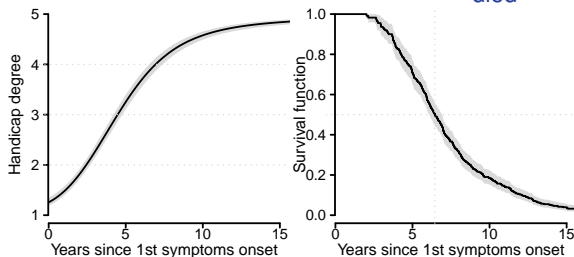
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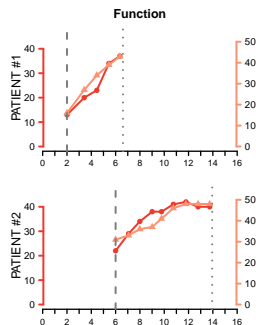
- French MSA cohort:

- ▶ Patients recruited from 2007 and 2019
- ▶ in two French Hospitals (Bordeaux and Toulouse)
- ▶ Follow-up every year (mean=0.96, sd=0.37 years between visits)
- ▶ $N > 750$ patients including ~450 who died



Multiple analytical challenges in neurodegenerative diseases

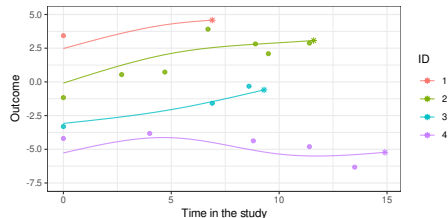
- Multiple processes evolving over time
 - ▶ in MSA: functional and motor impairments, orthostatic hypotension, brain atrophy, Hr-QoL impairments
- Some processes measured by measurement scales
 - ▶ in MSA: **26 5-level items** for clinical evaluation (Unified MSA Rating Scale (UMSARS))
+ **40 5-level items** for Quality-of-Life evaluation (MSA-QoL)
- Highly suspected heterogeneity:
 - ▶ in MSA: subphenotypes with varying speeds of progression
- Delayed entry in cohorts
 - ▶ in MSA: lag of several years since disease onset
- Truncation by death
 - ▶ in MSA: fatal disease



Definition of processes in continuous time

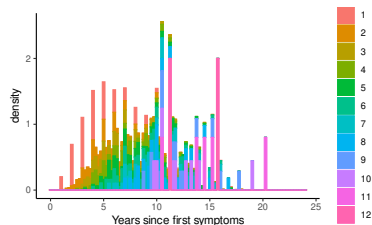
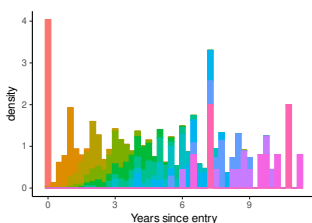
- Marker/Exposure data are **measures of an underlying process**:

- ▶ measured with error
- ▶ measured at sparse and irregular timings
- ▶ observation truncated by event occurrence



- Discrete framework almost impossible

- ▶ according to years since entry
- ▶ according to years since first symptoms



Latent process mixed model/ Continuous-time latent variable model

- **Underlying process of interest** $\Lambda(t)$ defined at any time $t \in \mathbb{R}$

- ▶ modeling its trajectory over time t
- ▶ structural mixed model / random-effect model:

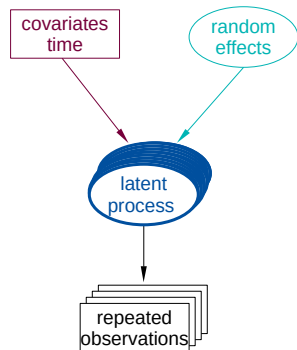
$$\Lambda_i(t) = \mathbf{X}_i(t)^\top \boldsymbol{\beta} + \mathbf{Z}_i(t)^\top \mathbf{b}_i$$

- ▶ with individual random effects $\mathbf{b}_i \sim \mathcal{N}(0, \mathbf{B})$

- **Observations** Y_{ij} at sparse times t_{ij}

- ▶ with most often truncation at an event time: $\max(t_{ij}) < T_i$
- ▶ measurement model defined according to Y:

$$Y_{ij} = \Lambda_i(t_{ij}) + \varepsilon_{ij} \quad \text{with } \varepsilon_{ij} \underset{iid}{\sim} \mathcal{N}(0, \sigma^2)$$



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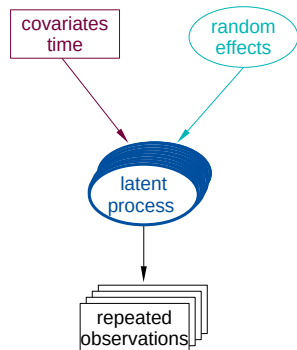
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- **Observations** Y_{ij} at sparse times t_{ij}

- ▶ with most often truncation at an event time: $\max(t_{ij}) < T_i$
- ▶ measurement model defined according to Y:
⚠ different natures (Gaussian, Non-Gaussian, ordinal,...)

$$Y_{ij} = H(\Lambda_i(t_{ij}) + \varepsilon_{ij} \ ; \ \boldsymbol{\eta}) \quad \text{with} \quad \varepsilon_{ij} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$$

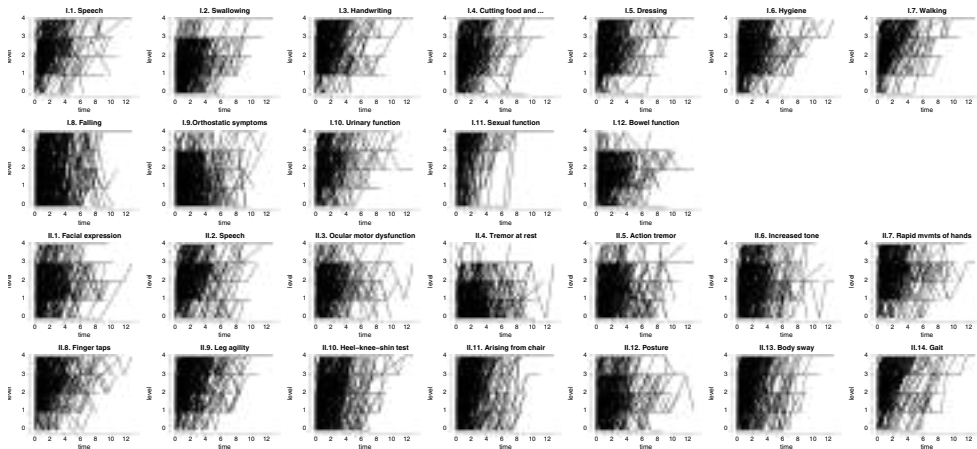
- ▶ with H a parameterized link function (e.g., H^{-1} = linear, inverse splines, H = thresholds)



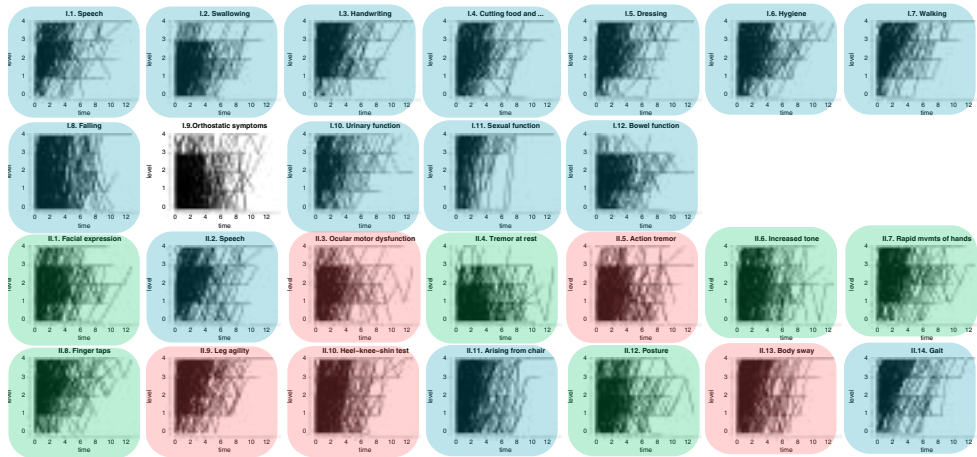
Two examples of continuous-time latent variable modeling in MSA

- 1 Trajectories of manifestations from repeated measurement scales along with disease progression in health studies
- 2 Heterogeneity of progressions in health studies using a latent class approach

Description of 26 items of UMSARS



Description of 26 items of UMSARS



3 dimensions identified from PROMIS procedure adapted to repeated data (CFA, conditional independence, monotonicity (4S method, Saulnier 2024))

Continuous-time Item Response Theory modeling (Proust-Lima 2022)

- **Underlying process of interest** $\Lambda(t)$ defined at any time $t \in \mathbb{R}$

- ▶ modeling its trajectory over time t
- ▶ structural mixed model / random-effect model:

$$\Lambda_i(t) = \mathbf{X}_i(t)^\top \boldsymbol{\beta} + \mathbf{Z}_i(t)^\top \mathbf{b}_i$$

- ▶ with individual random effects $\mathbf{b}_i \sim \mathcal{N}(0, \mathbf{B})$

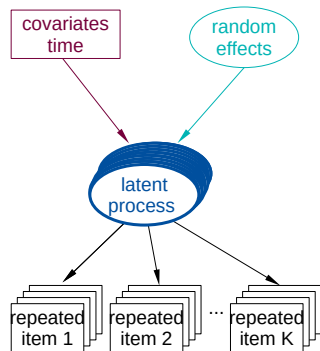
- **Observations** of multiple ordinal items Y_{ij}^k at sparse times t_{ijk}

- ▶ cumulative logit or cumulative probit link:

$$Y_{ij}^k = m \Leftrightarrow \delta_{k,m} < \Lambda_i(t_{ijk}) + \epsilon_{ij}^k \leq \delta_{k,m+1}$$

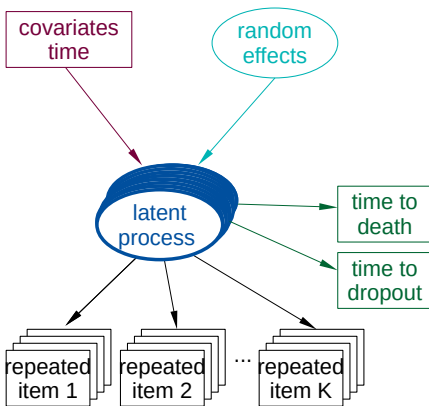
- ▶ ϵ_{ij}^k with the logistic or normal errors

⚠ **Assumptions:** unidimensionality, conditional independence, monotonicity



Progression over time, accounting for informative dropout and death

(Saulnier 2022)



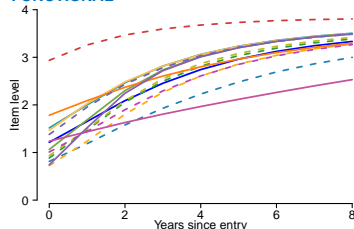
- **joint modeling approach** =
continuous-time IRT model
+ associated instantaneous risks of dropout
and death before dropout (cause p):

$$\lambda_{ip}(t) = \lambda_{0p}(t) \exp(X_{Ti} \delta_p + \Lambda_i(t) \eta_p)$$

- Estimation by Maximum Likelihood
in JLPM R package
⚠ left-truncation to be accounted for

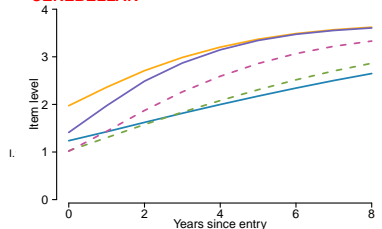
Predicted trajectories in the three underlying dimensions of UMSARS (Saulnier arxiv 2024)

FUNCTIONAL



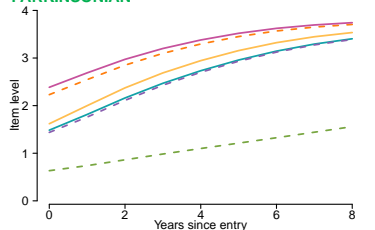
- I.1. Speech
- I.2. Swallowing
- I.3. Handwriting
- I.4. Cutting food and ...
- I.5. Dressing
- I.6. Hygiene
- I.7. Walking
- I.8. Falling
- I.10. Urinary function
- I.11. Sexual function
- I.12. Bowel function
- I.2. Speech
- I.11. Arising from chair
- I.14. Gait

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- II.3. Ocular motor dysfunction
- II.5. Action tremor
- II.9. Leg agility
- II.10. Heel-knee-shin test
- II.13. Body sway

PARKINSONIAN

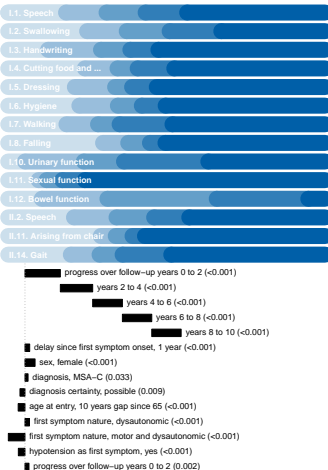


- II.1. Facial expression
- II.4. Tremor at rest
- II.6. Increased tone
- II.7. Rapid alter
- II.8. Finger tap
- II.12. Posture

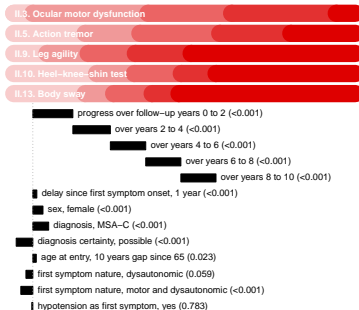
Three dimensions identified from PROMIS procedure adapted to repeated data (CFA, conditional independence, monotonicity (4S method, Saulnier 2024))

Translation into a sequence of impairments with modulators ...

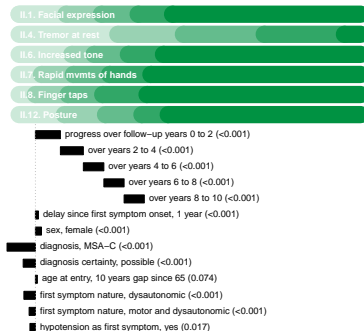
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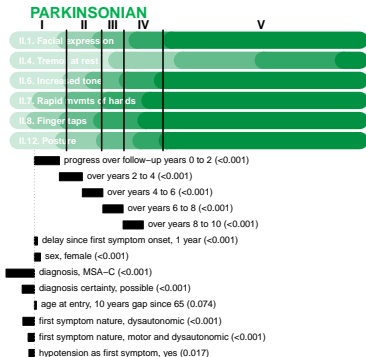
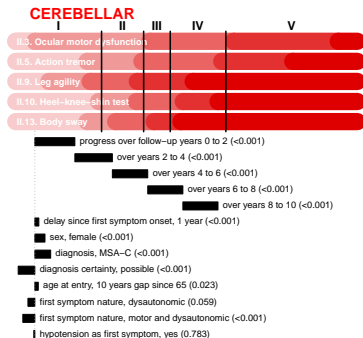
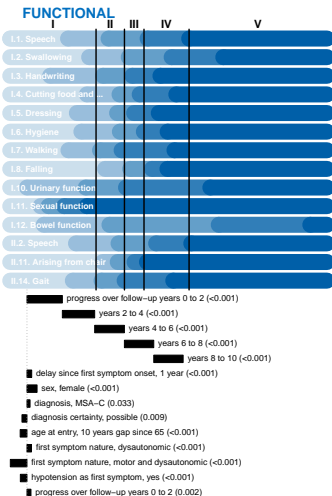
CEREBELLAR



PARKINSONIAN



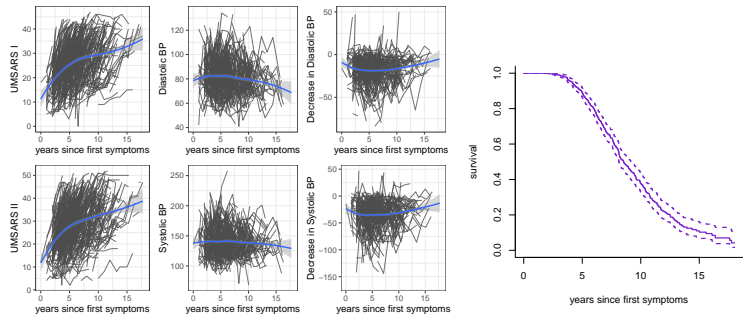
... and an anchoring on the disease progression stages (Saulnier 2024)



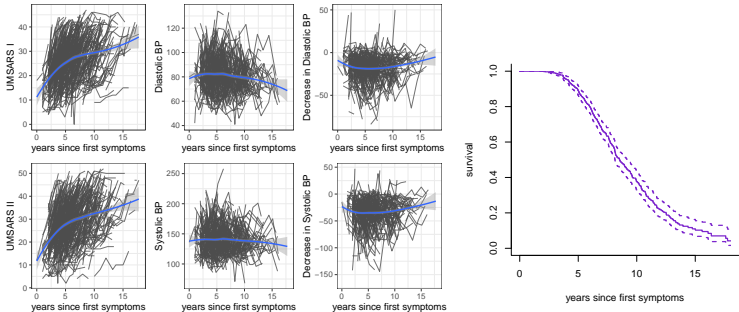
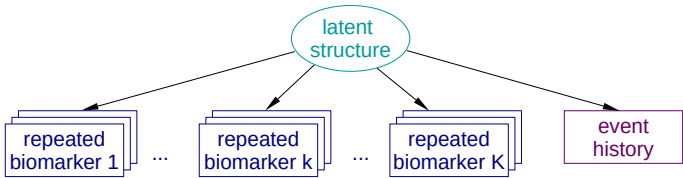
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Joint modeling of multivariate dimensions over time

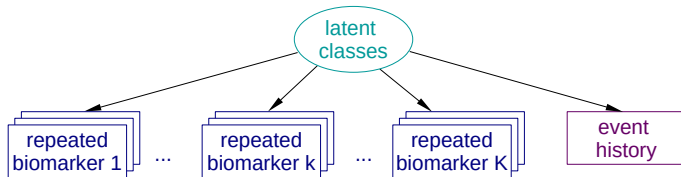


Joint modeling of multivariate dimensions over time



multivariate Joint Latent Class Models (multJLCM) (Proust-Lima 2023)

Latent class $c_i = g$ if individual i belongs to class g



Marker-specific trajectory:

Class-specific latent process model for each marker

$$\Lambda_i^k(t) |_{c_i=g} = X_{Lik}(t)^\top \beta_{kg} + Z_{ik}(t)^\top b_{ikg}$$

$$Y_{ij}^k |_{c_i=g} = \Lambda_i^k(t) |_{c_i=g} + \epsilon_{ijk}$$

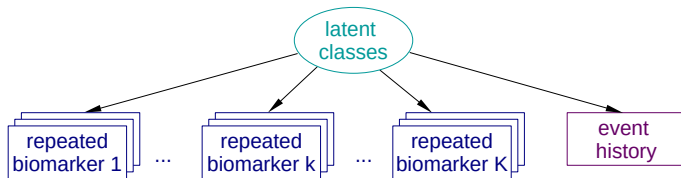
Risk of each cause of event:

Class-specific cause-specific hazard model

$$\lambda_{ip}(t |_{c_i=g}) = \lambda_{0pg}(t) \exp(X_{Ti}^\top \delta_{pg})$$

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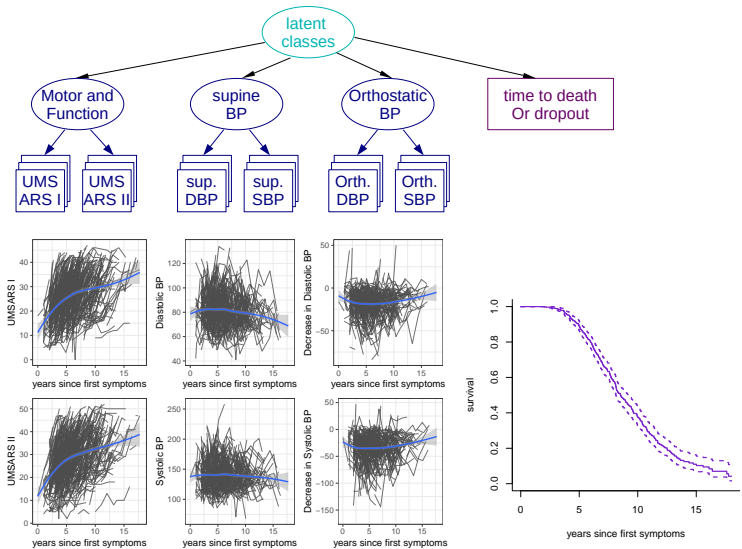
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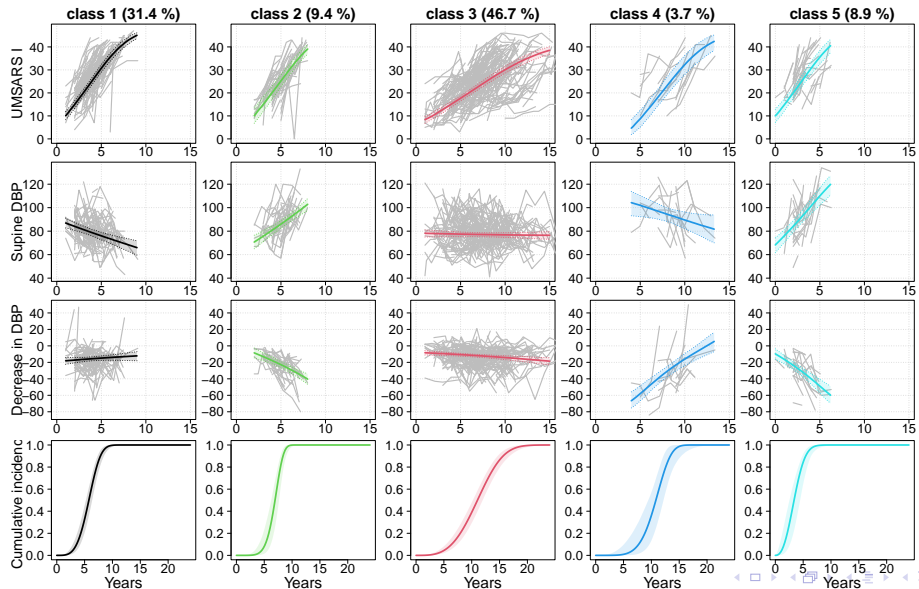
$$\lambda_{ip}(t |_{c_i=g}) = \lambda_{0pg}(t) \exp(X_{Ti} \delta_{pg})$$

- describes the processes as made of homogenous subgroups
- descriptive approach appropriate for *a priori* heterogeneous populations
- **lcmm** R package (**mpjlcm**, **externVar** functions)

Joint modeling of multivariate dimensions over time in MSA

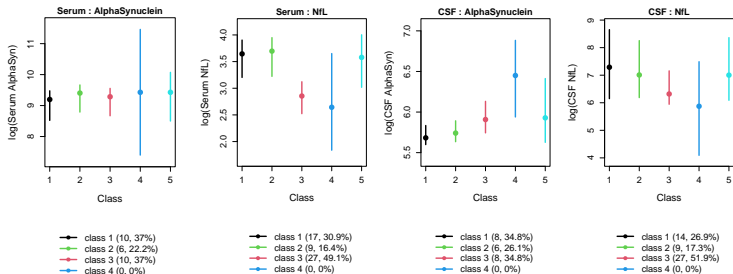
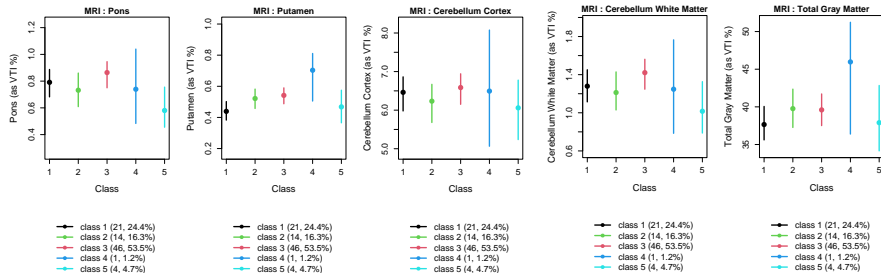


5 latent classes of clinical progression identified (using BIC, entropy & ICL)



Association with biomarkers from MRI, CSF & serum

- Linear regression adjusted for measurement time + assignment uncertainty (Δ) N ≤ 86



Concluding remarks

- Dynamic models, parametric approach based on latent variables:
 - ▶ random effects for intra-individual correlation
 - ▶ latent classes for heterogeneity
 - ▶ latent processes for underlying latent traits
- Additional characteristics to capture in synthetic data
 - ▶ irregularity of timings
 - ▶ missing data / dropout
 - ▶ nature of the outcomes under study
 - ▶ association across processes
 - ▶ interval-censored events and semi-competing risks
 - ▶ ...
- Dynamic models and derived synthetic data useful for
 - ▶ subphenotyping/staging (Proust-Lima SiM 2023)
 - ▶ describing progression & assessing risk factors
 - ▶ predicting progression and future events (Ferrer SMMR 2019)
 - ▶ understanding of the mechanisms with differential equations (Taddé Bcs 2020)
 - ▶ mediation analysis for continuous processes (Le Bourdonnec Bcs 2025)
 - ▶ ...

● Software



- ▶ **lcmmm**: <https://cecileproust-lima.github.io/lcmmm/>
- ▶ **JLPM**: <https://cran.r-project.org/web/packages/JLPM/>

● References

- ▶ **Latent process mixed models**: Proust-Lima et al - *Br J Math Stat Psychol* 2013;66(3):470-87.
Proust-Lima et al. - *Methods* 2022;204:386-95.
- ▶ **joint models with JLPM**: Saulnier et al. - *Methods* 2022;203:142-51.
- ▶ **Network of latent processes**: Taddé et al. - *Biometrics* 2020; 76(3):886-99
Le Bourdonnec et al. - *Biometrics* 2025 in press
- ▶ **IRT-based 4S method**: Saulnier et al. - *arXiv* 2024 - 2407.08278
- ▶ **Joint Latent Class Model**: Proust-Lima et al. - *Statistics in Medicine* 2023;42:3996-4014
- ▶ **lcmmm R package**: Proust-Lima et al. - *Journal of Statistical Software* 2017;78(2):1-56.

● Fundings

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