

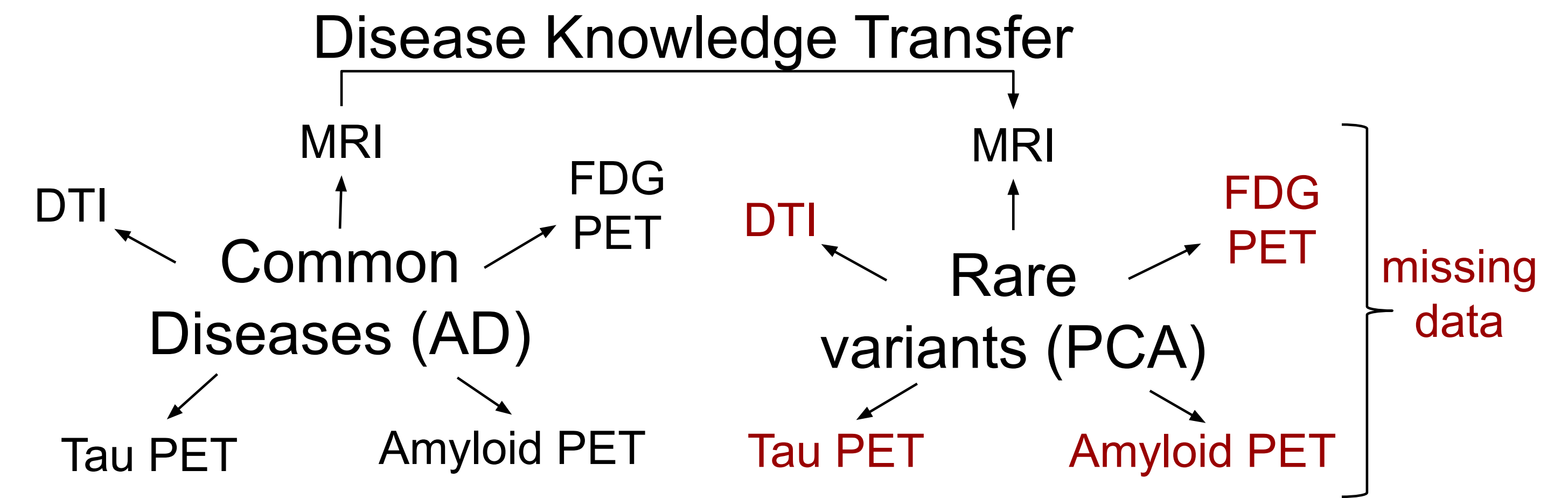
Disease Knowledge Transfer across Neurodegenerative Diseases



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Aim Infer progression of multimodal biomarkers in rare neurodegenerative diseases (NDs) by leveraging larger datasets of common, related variants.

Why Posterior Cortical Atrophy (PCA): progression of multimodal biomarkers not known → Identify outcome measures and suitable subjects for PCA clinical trials.

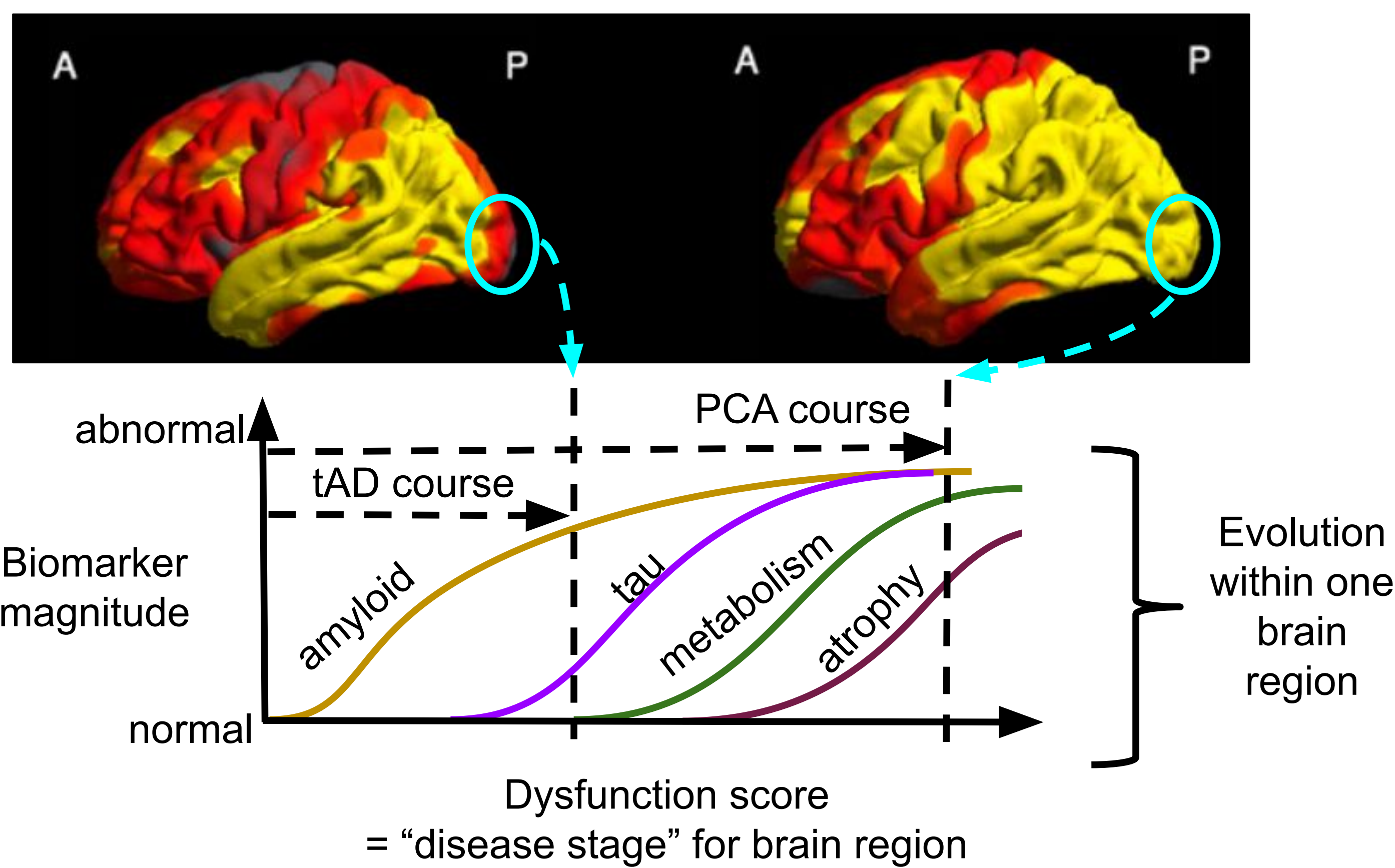


1. Intuition

- Diseases affect different brain regions un-equally, but underlying mechanisms are the same (amyloid cascade).
- **Idea:** a brain region follows “the same pathology course” for both diseases, but to different extents and with different speed.

Typical Alzheimer’s disease

Posterior Cortical Atrophy



2. Method

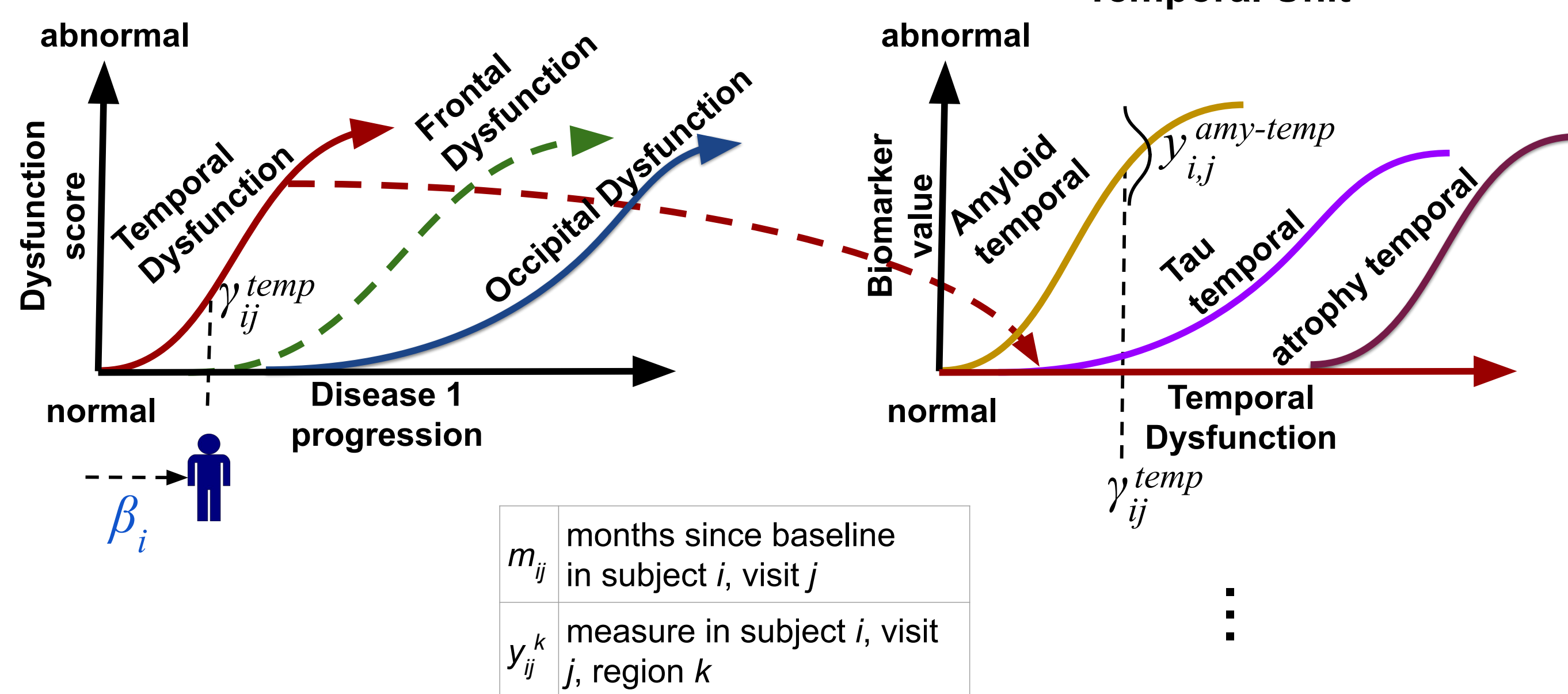
1. Each disease characterised by region-specific **dysfunction trajectories**
2. Dysfunction trajectory modelled using region-specific **biomarker trajectories**

$$\gamma_{ij}^l = f(\beta_i + m_{ij}; \lambda_{d_i}^l)$$

Disease 1 (e.g. tAD)

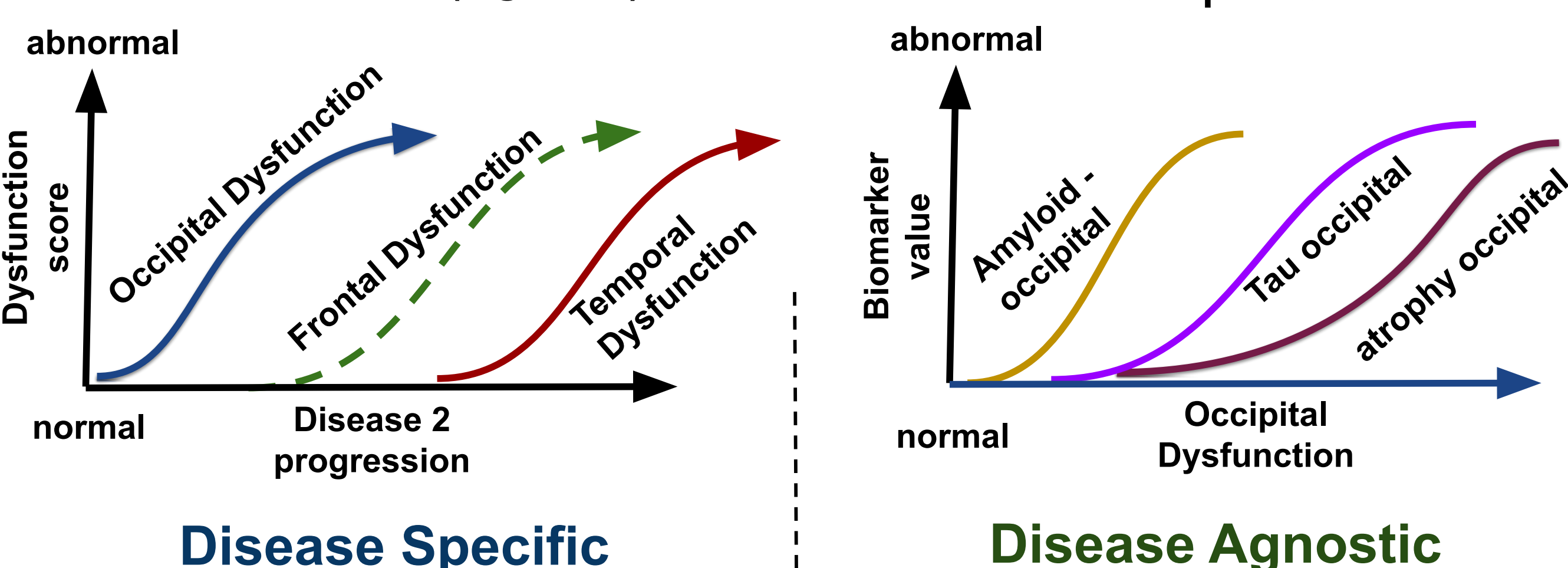
$$y_{ij}^k = g(\gamma_{ij}^{\psi(k)}; \theta_k) + N(0, \epsilon_k)$$

Temporal Unit



Disease 2 (e.g. PCA)

Occipital Unit



Disease Specific

Disease Agnostic

3. Inference with belief propagation

while θ, λ, β not converged do

; // Estimate **biomarker trajectories** (disease agnostic)

$$\theta_k^{(u)} = \arg \min_{\theta_k} \sum_{(i,j) \in \Omega_k} \left[y_{ij}^k - g \left(f(\beta_i^{(u-1)} + m_{ij}; \lambda_{d_i}^{\psi(k),(u-1)}); \theta_k \right) \right]^2$$

; // Estimate **dysfunction trajectories** (disease specific)

$$\lambda_d^{l,(u)} = \arg \min_{\lambda_d^l} \sum_{(i,j,k) \in \Omega_{d,l}} \left[y_{ij}^k - g \left(f(\beta_i^{(u-1)} + m_{ij}; \lambda_d^l); \theta_k^{(u)} \right) \right]^2$$

; // Estimate **subject-specific time shifts**

$$\beta_i^{(u)} = \arg \min_{\beta_i} \sum_{(j,k) \in \Omega_i} \left[y_{ij}^k - g \left(f(\beta_i + m_{ij}; \lambda_{d_i}^{\psi(k),(u)}); \theta_k^{(u)} \right) \right]^2$$

4. Datasets

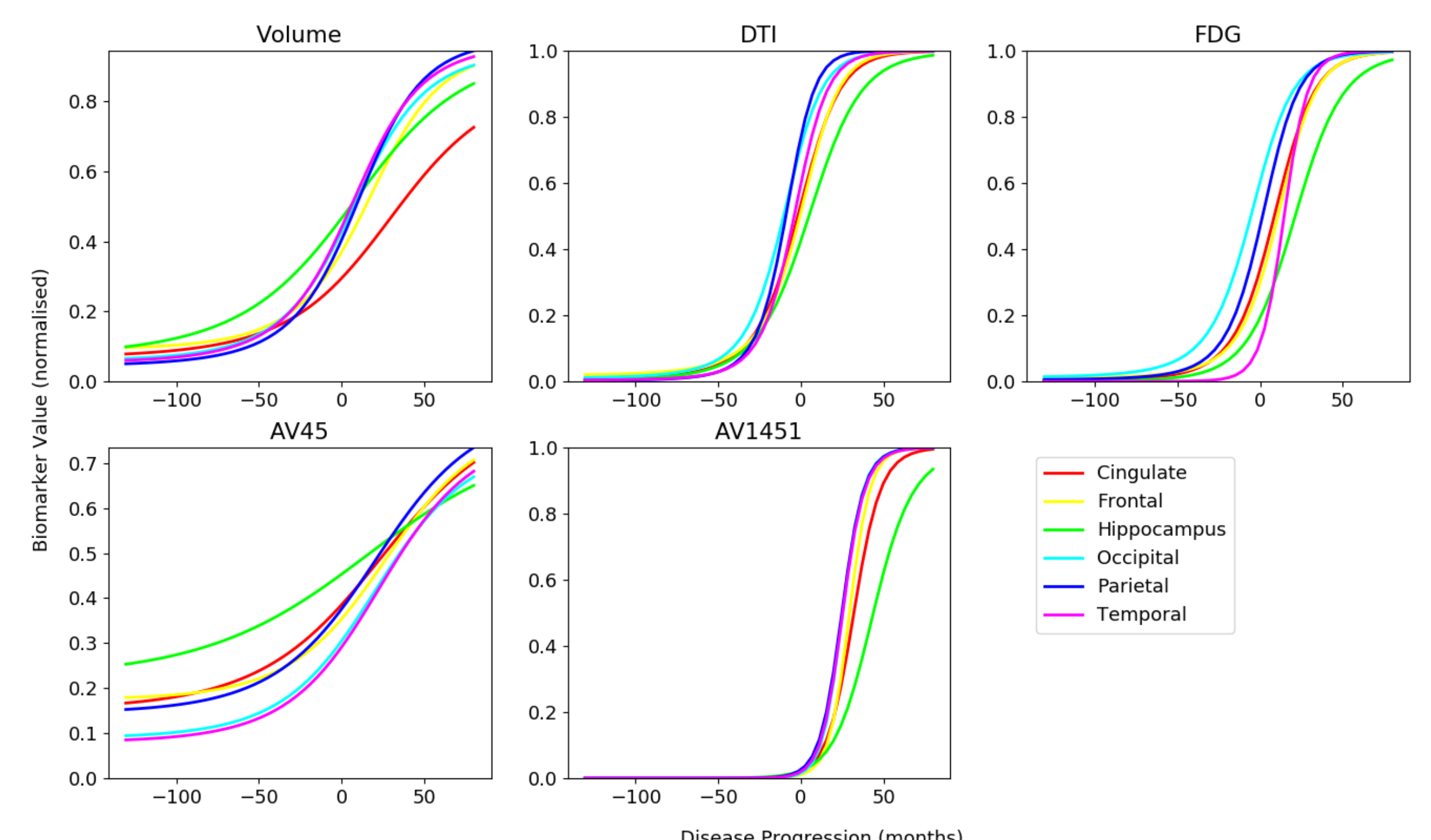
- TADPOLE dataset (ADNI) split into three subgroups with different progressions: 21 hippocampal, 35 cortical, 27 subcortical.
- Dementia Research Center cohort: MRI scans from 76 PCA, 67 tAD, 87 controls for training, 10 PCA with DTI for validation.

5. Results

- Our model has favourable performance compared to other models, on two different datasets.

Model	Cingulate	Frontal	Hippocam.	Occipital	Parietal	Temporal
TADPOLE: Hippocampal subgroup to Cortical subgroup						
DKT (ours)	0.56 ± 0.23	0.35 ± 0.17	0.58 ± 0.14	-0.10 ± 0.29	0.71 ± 0.11	0.34 ± 0.26
AD model	0.44 ± 0.25	0.34 ± 0.21	0.34 ± 0.24*	-0.07 ± 0.22	0.64 ± 0.16	0.08 ± 0.24*
Multivariate	0.60 ± 0.18	0.11 ± 0.22*	0.12 ± 0.29*	-0.22 ± 0.22	-0.44 ± 0.14*	-0.32 ± 0.29*
Spline	-0.24 ± 0.25*	-0.06 ± 0.27*	0.58 ± 0.17	-0.16 ± 0.27	0.23 ± 0.25*	0.10 ± 0.25*
Linear	-0.24 ± 0.25*	0.20 ± 0.25*	0.58 ± 0.17	-0.16 ± 0.27	0.23 ± 0.25*	0.13 ± 0.23*
typical Alzheimer’s to Posterior Cortical Atrophy						
DKT (ours)	0.77 ± 0.11	0.39 ± 0.26	0.75 ± 0.09	0.60 ± 0.14	0.55 ± 0.24	0.35 ± 0.22
AD model	0.80 ± 0.09	0.53 ± 0.17	0.80 ± 0.12	0.56 ± 0.18	0.50 ± 0.21	0.32 ± 0.24
Multivariate	0.73 ± 0.09	0.45 ± 0.22	0.71 ± 0.08	-0.28 ± 0.21*	0.53 ± 0.22	0.25 ± 0.23*
Spline	0.52 ± 0.20*	-0.03 ± 0.35*	0.66 ± 0.11*	0.09 ± 0.25*	0.53 ± 0.20	0.30 ± 0.21*
Linear	0.52 ± 0.20*	0.34 ± 0.27	0.66 ± 0.11*	0.64 ± 0.17	0.54 ± 0.22	0.30 ± 0.21*

- Inferred multimodal trajectories for PCA in lack of such data.
- Results are plausible, suggesting late-stage posterior damage.



6. Conclusion

- Developed a novel methodology and model for transfer learning across different diseases
- Inferred multimodal trajectories for Posterior Cortical Atrophy

Weblinks

- Source code: <https://github.com/mrazvan22/dkt>
- Website: <https://people.csail.mit.edu/razvan/>

Funders

