Disease Knowledge Transfer across Neurodegenerative Diseases

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Introduction

- Recently disease progression models work well on large, multimodal datasets
- Datasets on rare neurodegenerative diseases (e.g., Posterior Cortical Atrophy) are limited and cross-sectional.

Aim

Develop a transfer learning model to transfer knowledge between diseases

Method

- We propose Disease Knowledge Transfer:
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$$\gamma_{ij}^{l} = f(\beta_i + m_{ij}; \lambda_{d_i}^{l}) \tag{1}$$

$$p(y_{ijk}|\theta_k, \lambda_{d_i}^{\psi(k)}, \beta_i, \epsilon_k) = N(y_{ijk}|g(\gamma_{ij}^{\psi(k)}; \theta_k), \epsilon_k) \tag{2}$$

$$p(y|\theta, \lambda, \beta, \epsilon) = \prod_{(i,j,k) \in \Omega} p(y_{ijk}|\theta_k, \lambda_{d_i}^{\psi(k)}, \beta_i) \tag{3}$$

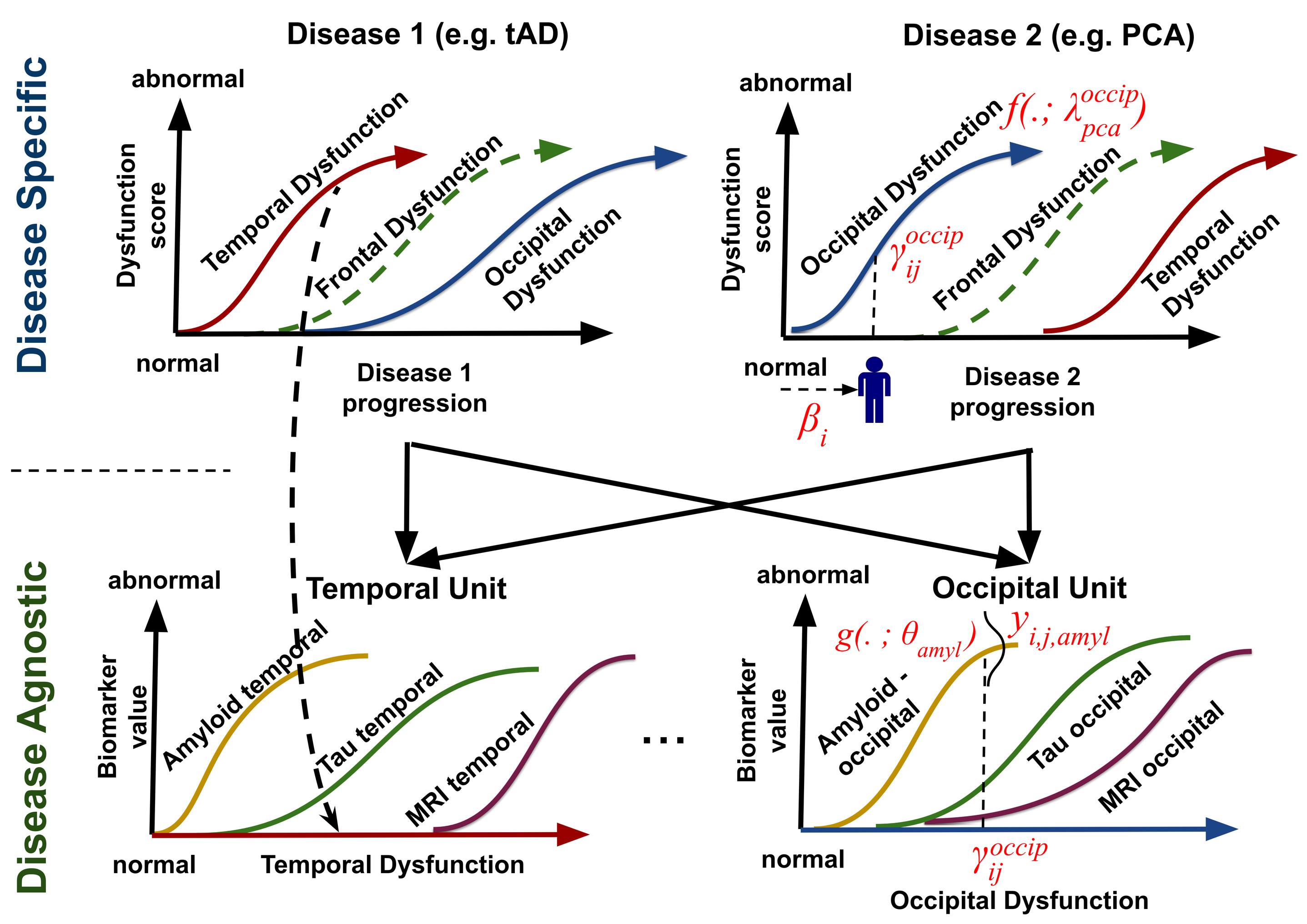

Figure 1

Results

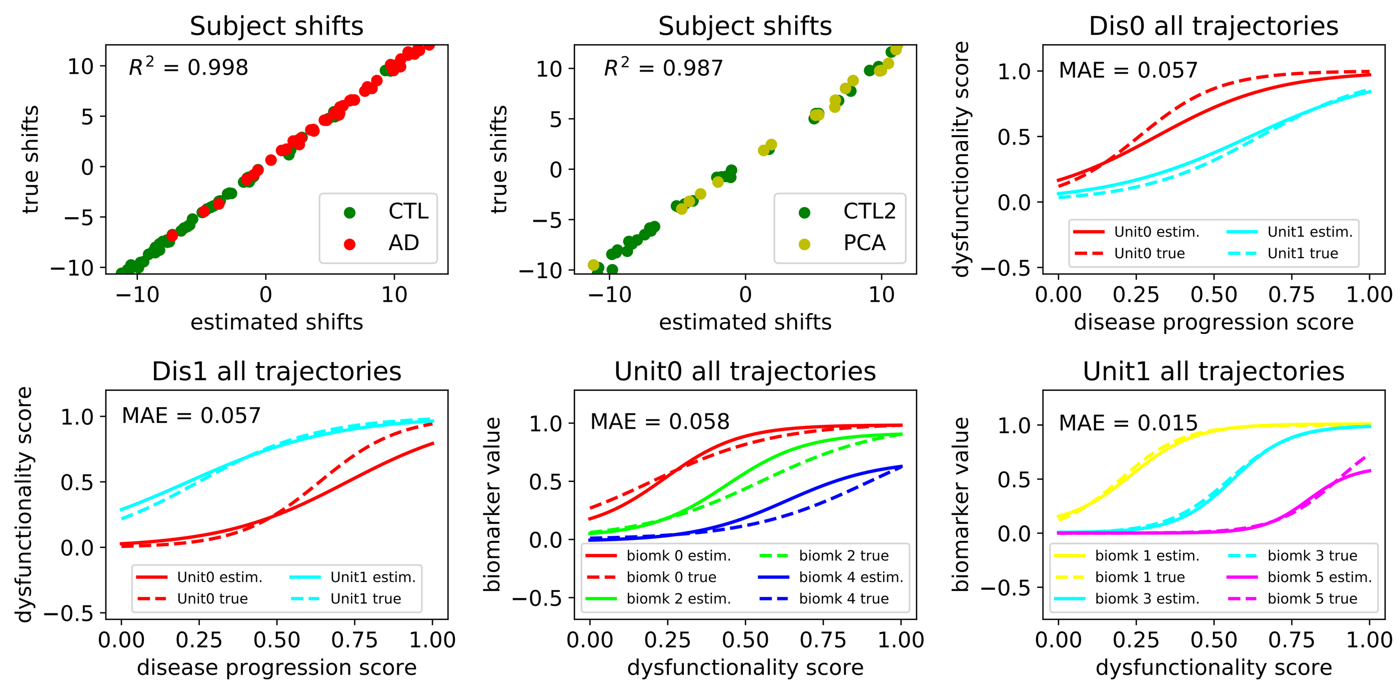

Figure 2: Comparison between true and DKT-estimated subject time-shifts and biomarker trajectories.

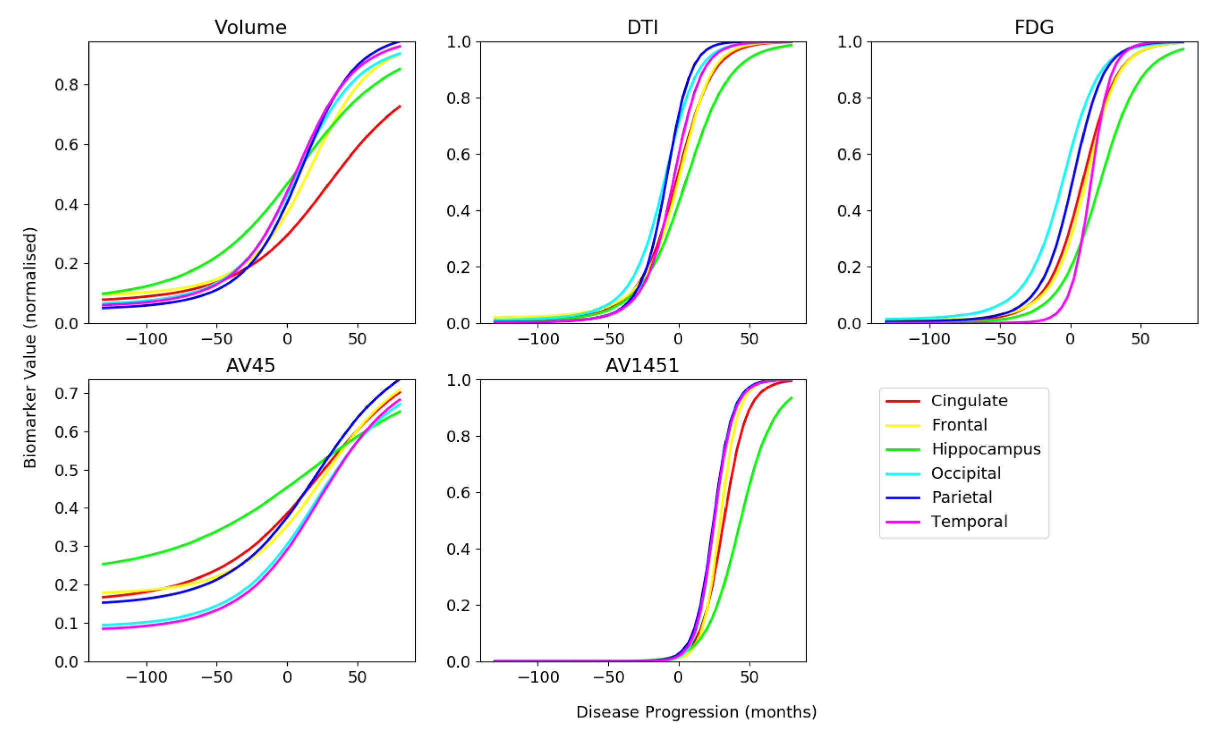

Figure 3: Estimated trajectories for the PCA cohort. The only data that were available were the MRI volumetric data. The dynamics of the other biomarkers has been inferred by the model using data from typical AD, and taking into account the different spatial distribution of pathology in PCA vs tAD.

Conclusion

References

1. Fontejin et al., Neuroimg., 2012
2. Young et al., Nat. Comms., 2018
3. Villemagne et al., Lancet Neurol., 2013
4. Marinescu et al., IPMI, 2017

Weblinks

- UCL Progression of Neurodegenerative Disease (POND): cmic.cs.ucl.ac.uk/pond/
- UCL Centre for Medical Image Computing: www.ucl.ac.uk/cmic/

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