

Modelling the Neuroanatomical Progression of Alzheimers Disease and Posterior Cortical Atrophy

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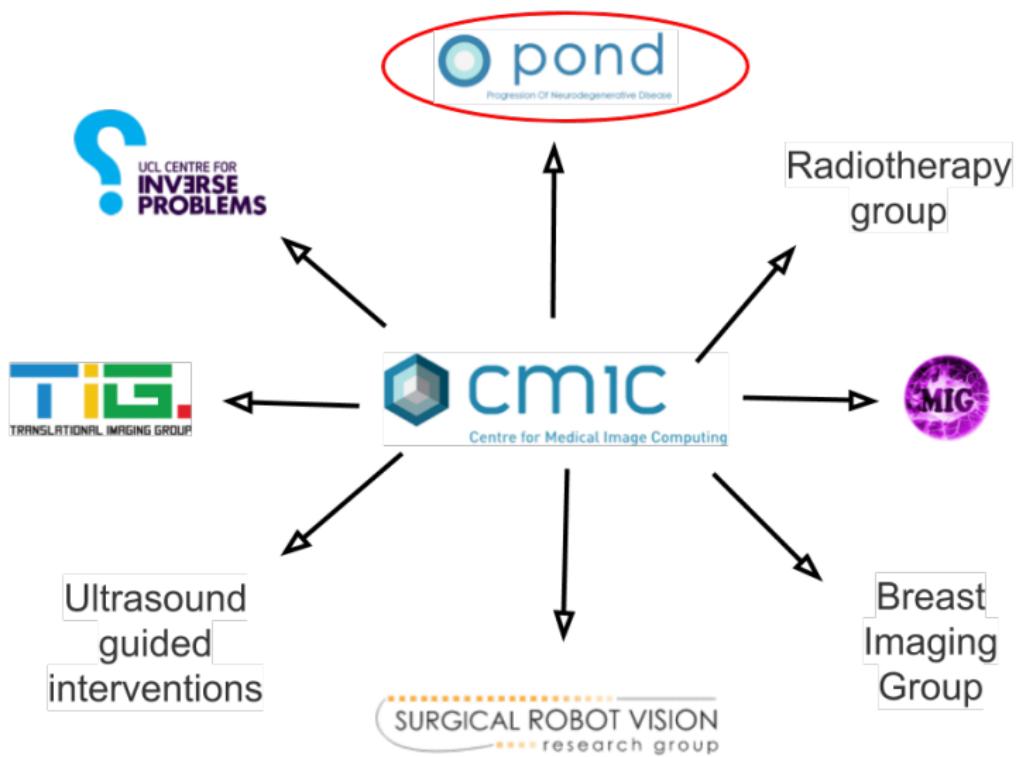


About me

- ▶ Grew up in Pitesti, Romania
- ▶ 2010-2014: Studied a 4-year MEng in Computer Science at Imperial College London
- ▶ 2014-2019: PhD in Medical Imaging at UCL (with Daniel Alexander)
- ▶ 2019: Postdoc at MIT with Pollina Golland (working on image analysis of stroke)

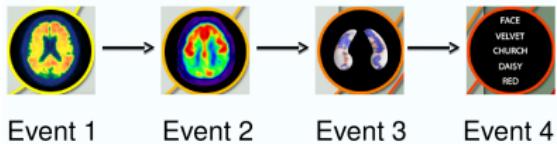


Progression of Neurodegenerative Diseases (POND)

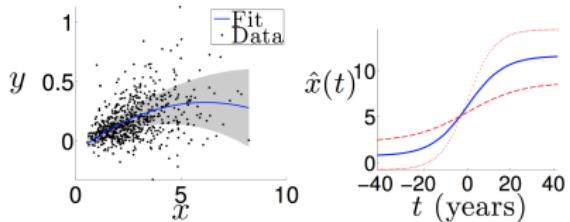


POND Aim: Develop Computational Models for Disease Progression

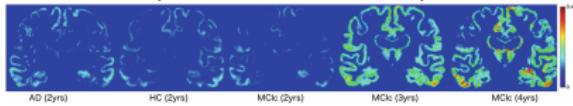
Event-Based Model
(Fontejin et al., Neuroimage, 2012)



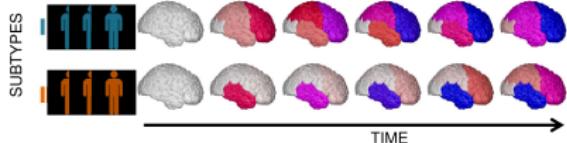
Differential Equation Model
(Oxtoby et al., submitted, 2017)



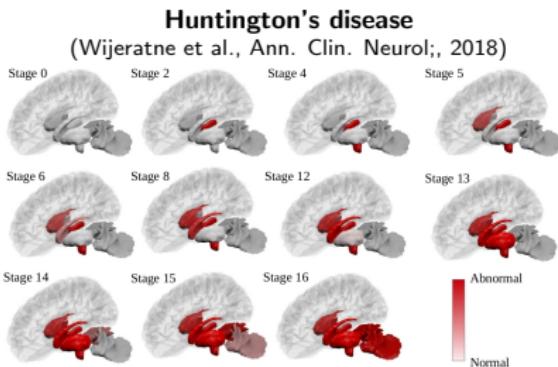
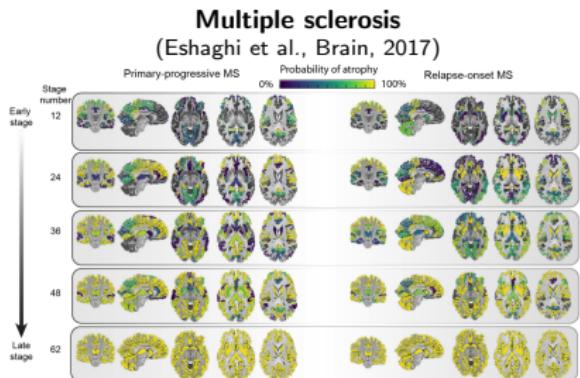
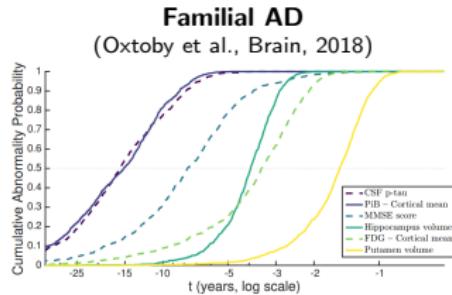
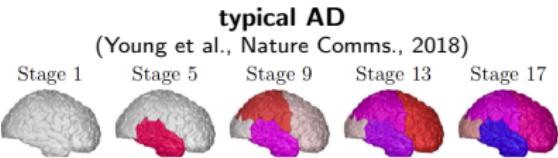
Gaussian-Process Regression
(Lorenzi et al., IPMI, 2015)



Subtype and Stage Inference
(Young et al., submitted, 2017)

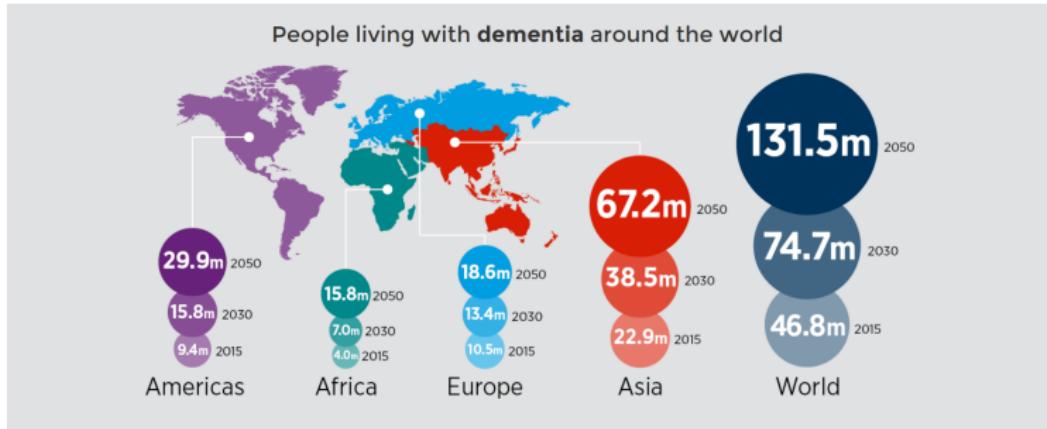


POND Aim 2: Apply the Models to Distinct Neurodegenerative Diseases



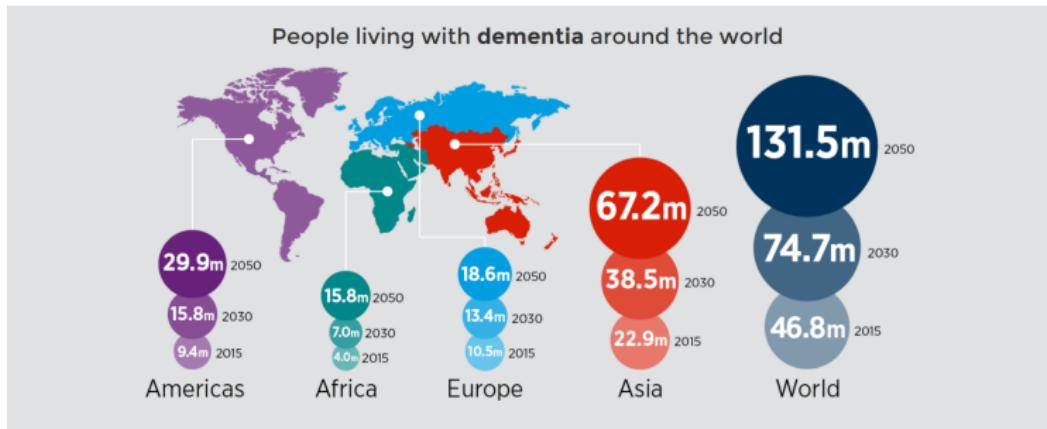
Alzheimer's Disease is a Devastating Disease

- ▶ 46 million people affected worldwide



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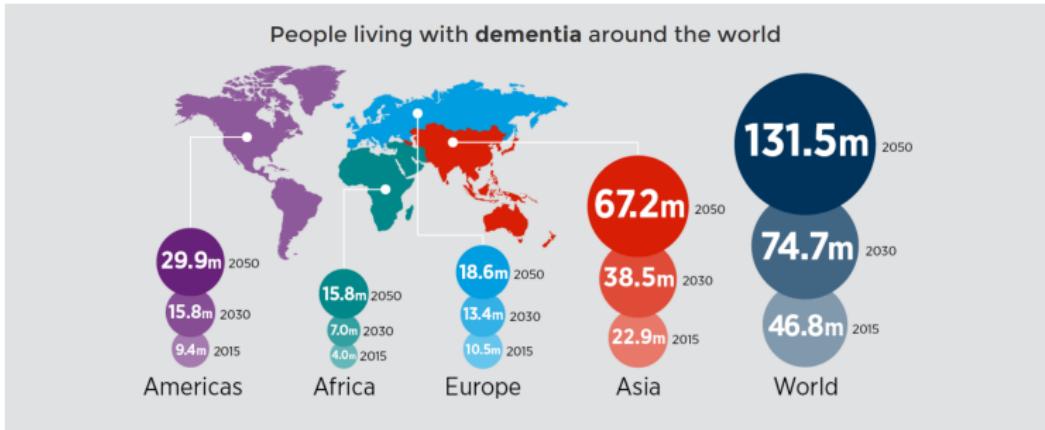
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- ▶ No treatments available that stop or slow down cognitive decline
- ▶ Q: Why did clinical trials fail? A: Treatments were not administered early enough

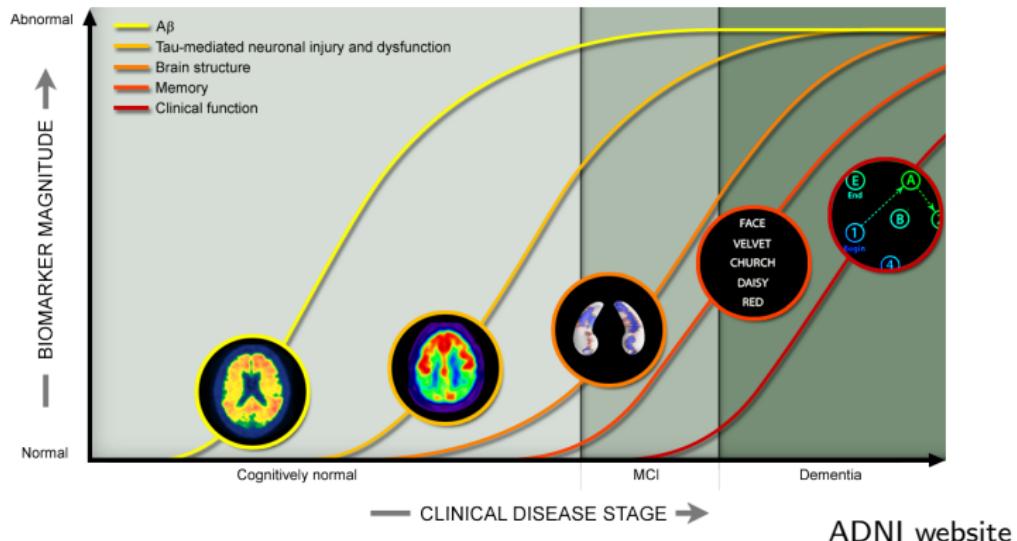
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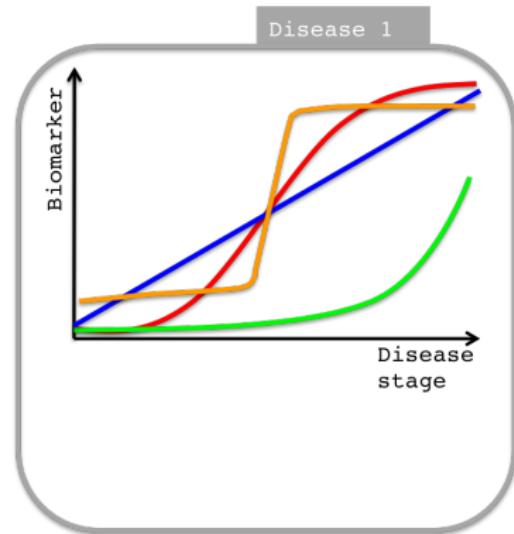
- ▶ No treatments available that stop or slow down cognitive decline
- ▶ Q: Why did clinical trials fail? A: Treatments were not administered early enough
- ▶ Q: How can we then identify subjects **early** in order to administer treatments?
- ▶ A: Biomarkers ...

Biomarker Evolution creates a Unique Disease Signature that can be used for Staging Individuals in Clinical Trials



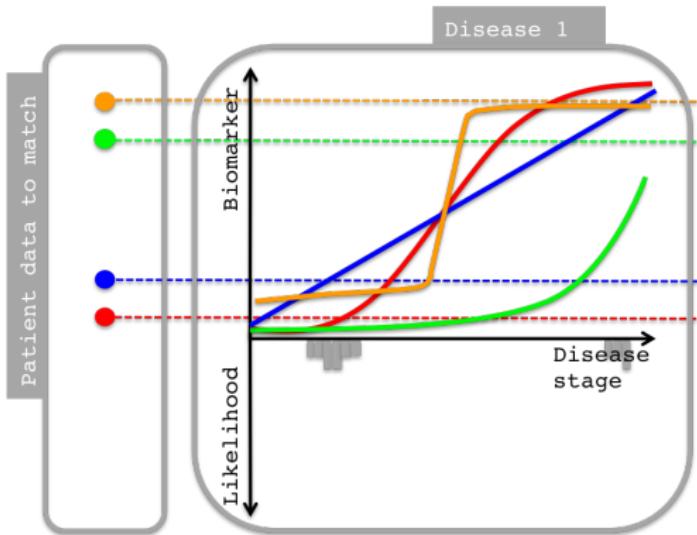
- ▶ Accurate disease staging → better patient stratification
- ▶ Problem: This is a "hypothetical" (i.e. qualitative) disease progression model
- ▶ Why construct a quantitative model?

Benefits of Quantitative Disease Progression Models



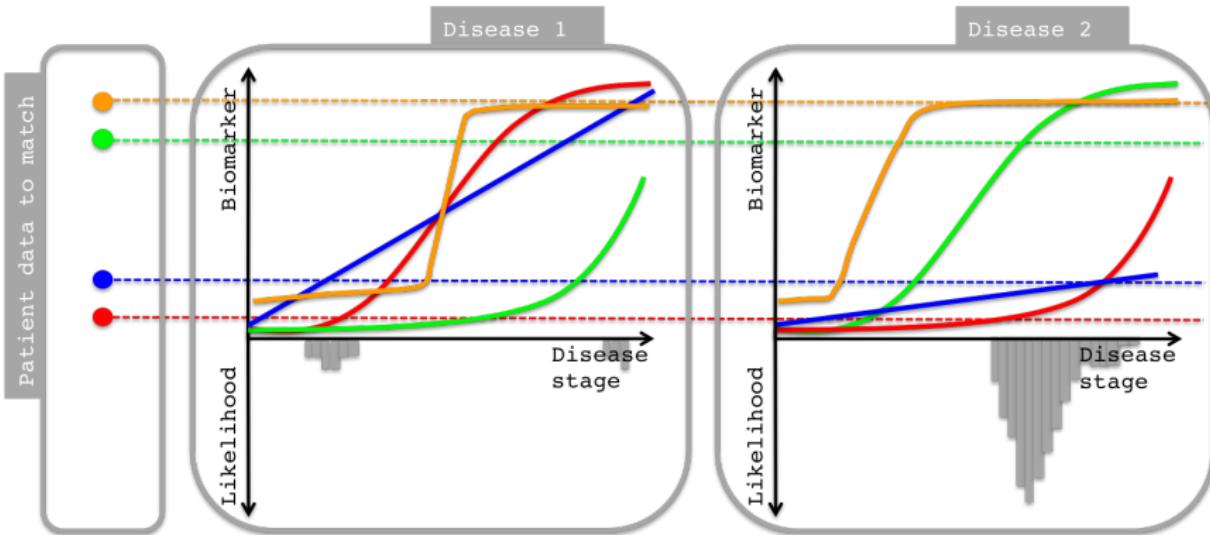
- Basic biological insight

Benefits of Quantitative Disease Progression Models



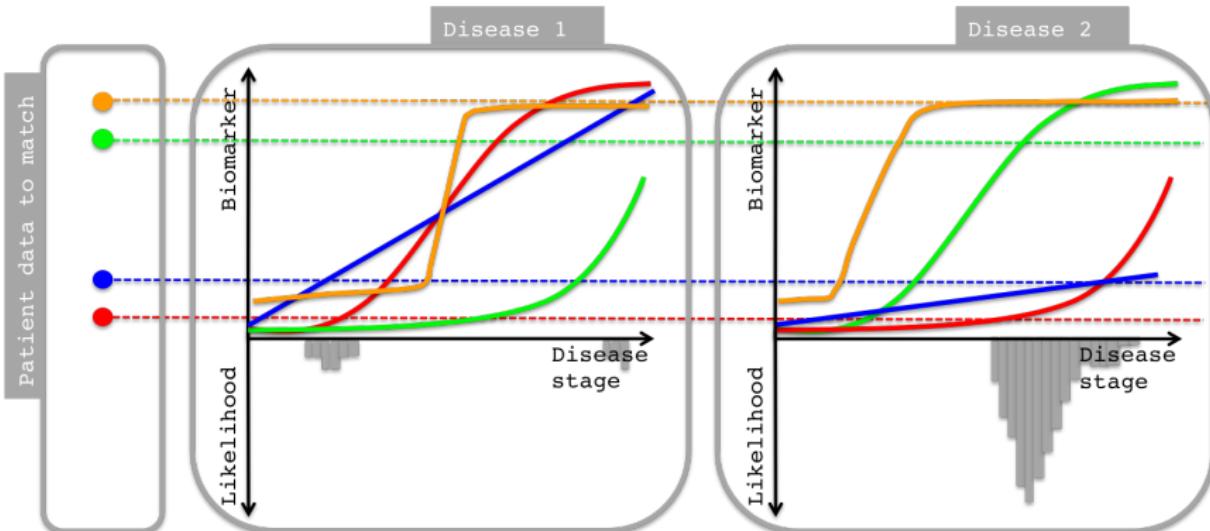
- ▶ Basic biological insight
- ▶ Staging can help stratification in clinical trials

Benefits of Quantitative Disease Progression Models



- ▶ Basic biological insight
- ▶ Staging can help stratification in clinical trials
- ▶ Differential diagnosis and prognosis

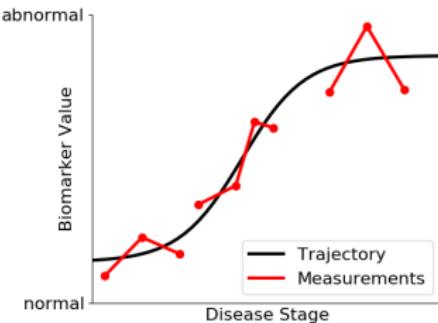
Benefits of Quantitative Disease Progression Models



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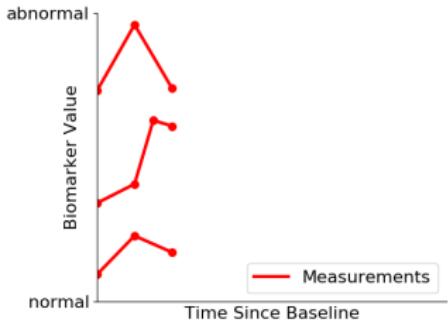
How can we build such a disease progression model?

Building a Quantitative Disease Progression Model is difficult

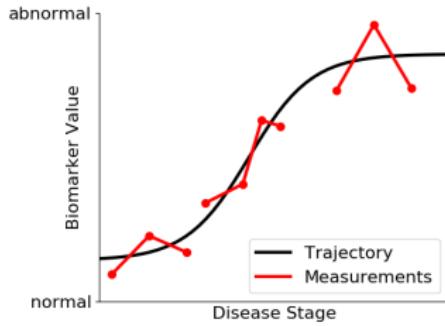


Building a Quantitative Disease Progression Model is difficult

what we have



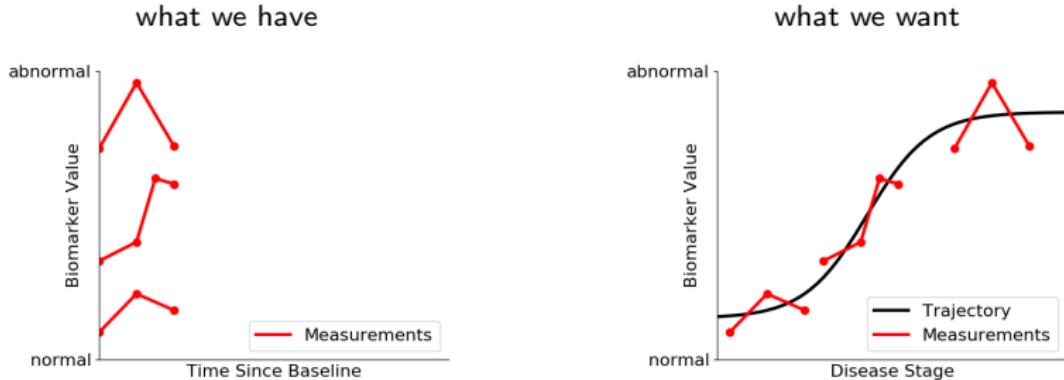
what we want



Challenges:

- ▶ Patients are at unknown disease stages

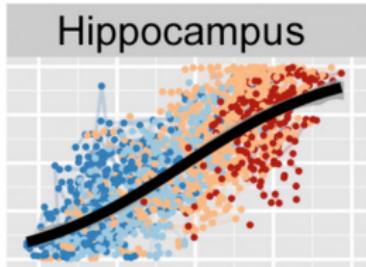
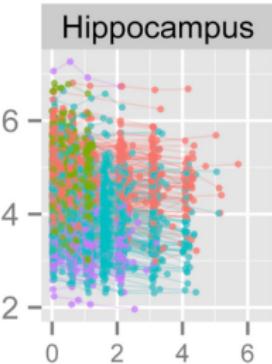
Building a Quantitative Disease Progression Model is difficult



Challenges:

- ▶ Patients are at unknown disease stages
- ▶ X-axis are not the same (need to construct the disease stage axis)

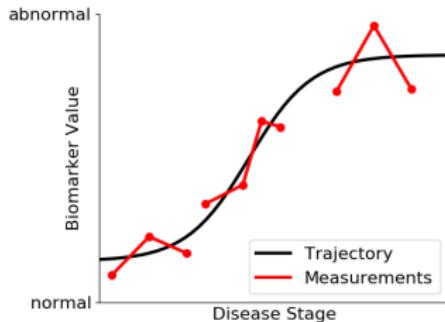
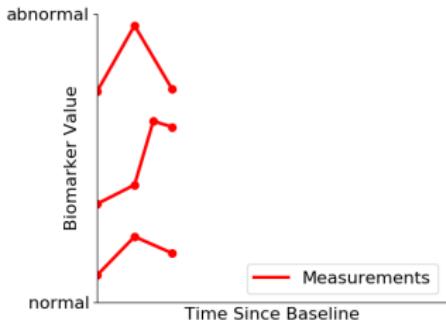
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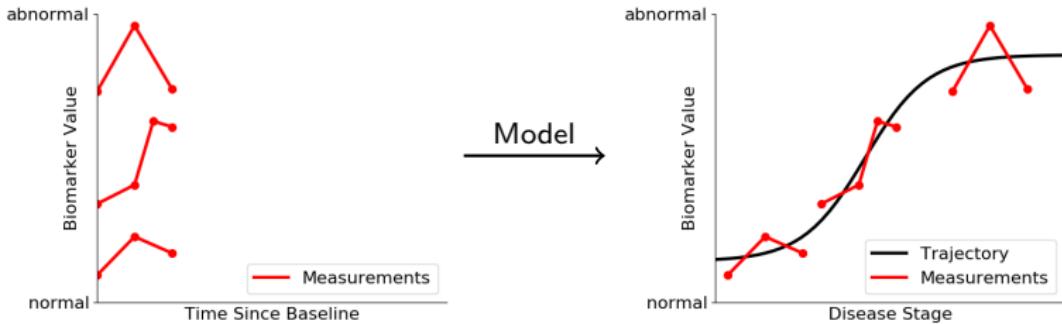
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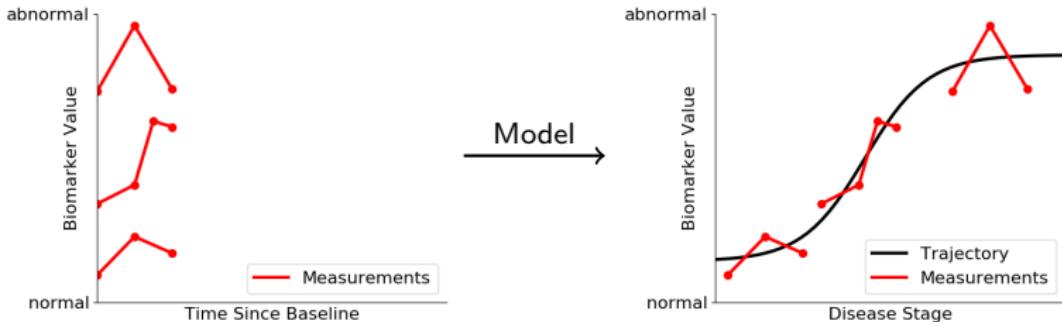
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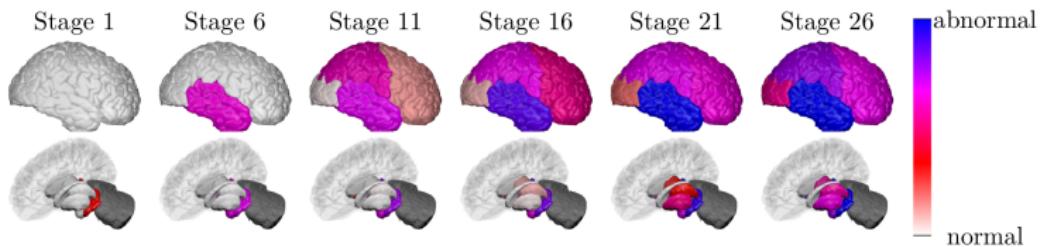


Challenges:

- ▶ Patients are at unknown disease stages
- ▶ X-axis are not the same (need to construct the disease stage axis)
- ▶ Biomarkers have different trajectory shapes
- ▶ Cohort is heterogenous
- ▶ Control population not well defined

1. Study the progression of atrophy in two diseases (using existing models):

- ▶ typical Alzheimer's Disease (tAD)
- ▶ Posterior Cortical Atrophy (PCA)

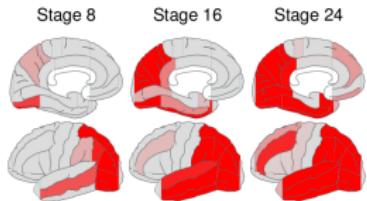


2. Develop novel disease progression models (DPMs)

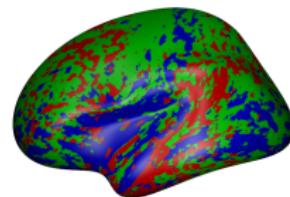
$$p(X|S) = \prod_{j=1}^J \left[\sum_{k=0}^N p(k) \left(\prod_{i=1}^k p(x_{s(i),j} | E_{s(i)}) \prod_{i=k+1}^N p(x_{s(i),j} | \neg E_{s(i)}) \right) \right] \quad (1)$$

My PhD Contributions

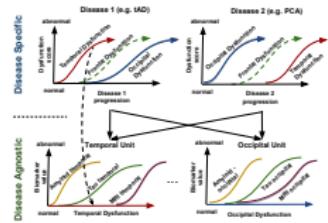
1. Modelled progression of PCA and tAD



2. Spatio-temporal Progression Modelling



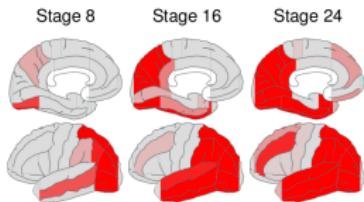
3. Disease Knowledge Transfer across Neurodegenerative Diseases



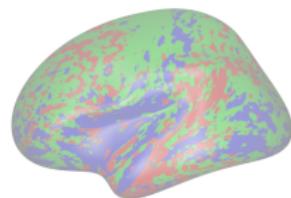
4. TADPOLE Competition



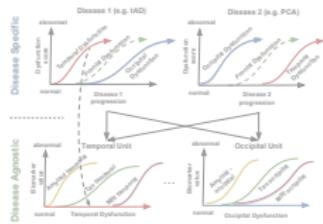
1. Modelled progression of PCA and tAD



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3. Disease Knowledge Transfer across Neurodegenerative Diseases



4. TADPOLE Competition



Clinical question: Find the order in which GM regions become atrophied

- ▶ in PCA
- ▶ in tAD

Why? No previous studies modelled disease progression in PCA

Demographics:

- ▶ cohort from the Dementia Research Centre with uniquely large PCA population (70)

	# Subjects	Gender M/F	Age at baseline (years)	Years from onset (years)
Controls	89	33/56	60.5 ± 11	-
PCA	70	27/43	63.0 ± 7	4.4 ± 2.8
AD	65	34/31	66.3 ± 8	4.8 ± 2.6

Data: Structural MRI scans

Impact: the first major investigation of PCA disease progression

How? The Event-Based Model ...

Key Idea: The Event-Based Model Estimates an Atrophy Sequence from Informative Patient Snapshots

- ▶ Event-Based Model (EBM): Fontejin et al., Neroimage, 2012.
- ▶ Aim: Region 1 → Region 2 vs Region 2 → Region 1

	Patient 1	Patient 2	Patient 3
Region 1	1.1	0.9	0.1
Region 2	0.95	0.0	0.05

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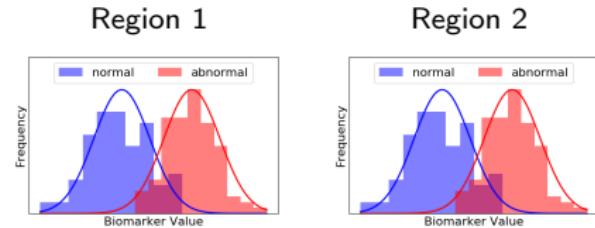
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	Patient 1	Patient 2	Patient 3		Patient 1	Patient 2	Patient 3
Region 1	1.1	0.9	0.1	Region 1	normal	normal	abnormal
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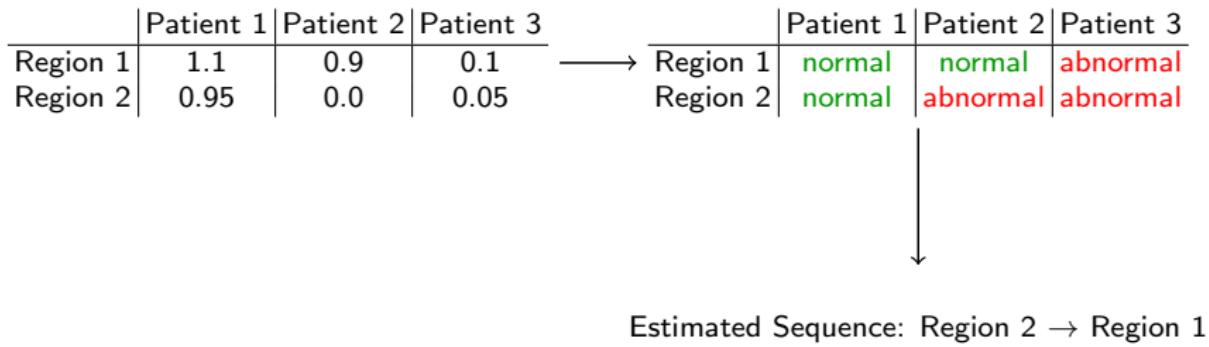
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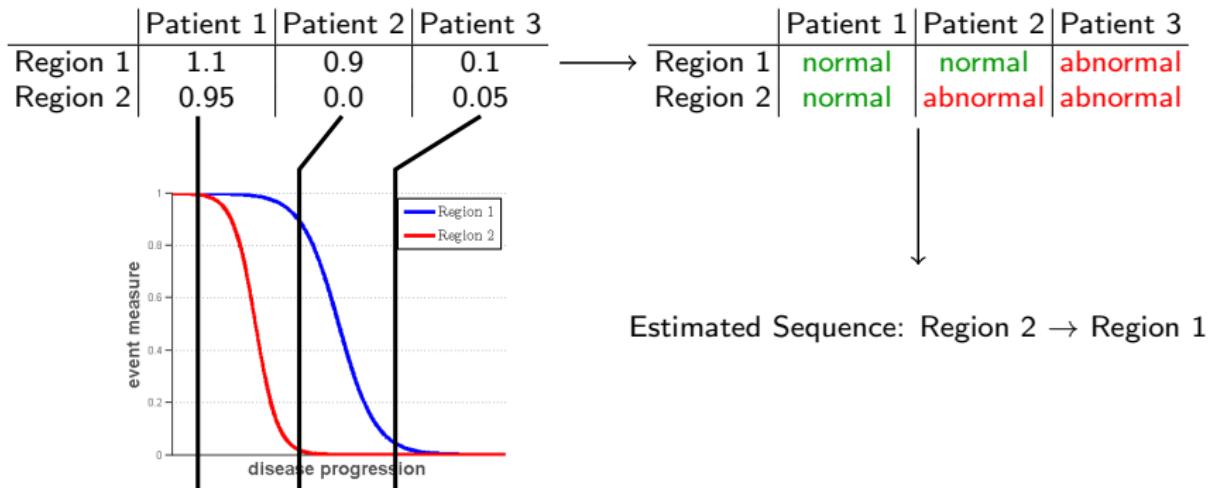
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- ▶ Aim: Region 1 → Region 2 vs Region 2 → Region 1



The EBM assumes a subject at stage k has first k biomarkers "**abnormal**" and the last $N - k$ biomarkers "**normal**"

- ▶ Evaluate data likelihood under normal and abnormal distributions:

- ▶ normal - $p(x_{s(i),j} | \neg E_{s(i)})$
- ▶ abnormal - $p(x_{s(i),j} | E_{s(i)})$

- ▶ Compute likelihood of one subject j being at stage k given sequence S :

$$p(X_j|S, k) = \prod_{i=1}^k p(x_{s(i),j} | E_{s(i)}) \prod_{i=k+1}^N p(x_{s(i),j} | \neg E_{s(i)})$$

- ▶ Marginalise stage k :

$$p(X_j|S) = \sum_{k=0}^N p(k) \left(\prod_{i=1}^k p(x_{s(i),j} | E_{s(i)}) \prod_{i=k+1}^N p(x_{s(i),j} | \neg E_{s(i)}) \right)$$

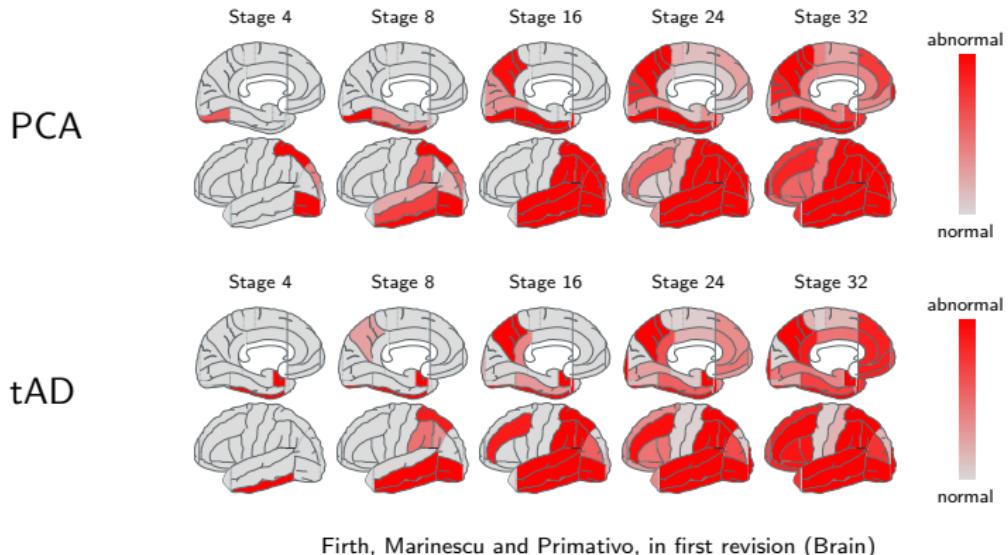
- ▶ Extend to all subjects:

$$p(X|S) = \prod_{j=1}^J \left[\sum_{k=0}^N p(k) \left(\prod_{i=1}^k p(x_{s(i),j} | E_{s(i)}) \prod_{i=k+1}^N p(x_{s(i),j} | \neg E_{s(i)}) \right) \right]$$

- ▶ Sequence and uncertainty estimated with MCMC sampling

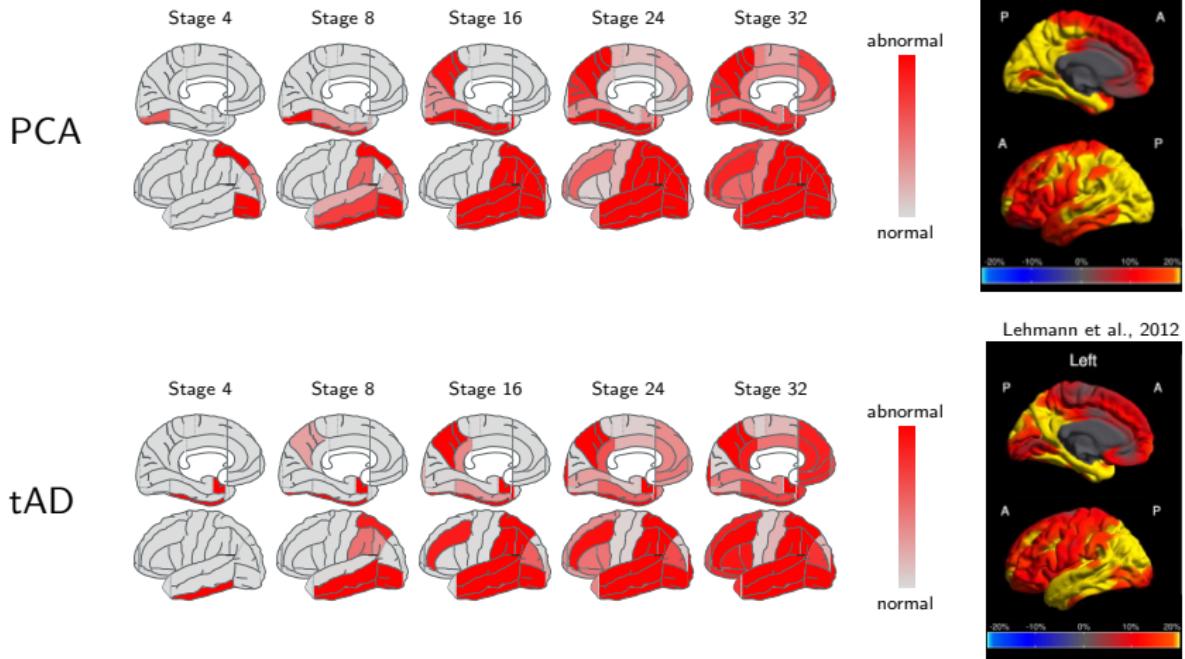
The EBM finds a Distinct Atrophy Sequence in PCA compared to tAD

- ▶ PCA → early occipital and superior parietal atrophy
- ▶ tAD → early hippocampal and inferior temporal atrophy



Atrophy Patterns Resemble Previous Studies from the Literature

- ▶ PCA → early occipital and superior parietal atrophy
- ▶ tAD → early hippocampal and inferior temporal atrophy



Firth, Marinescu and Primativo, in first revision (Brain)

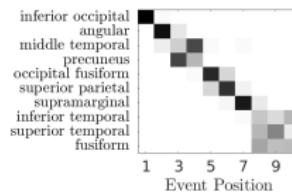
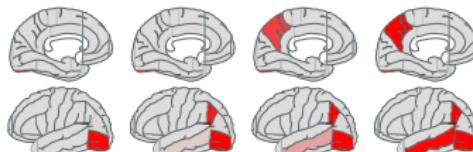
PCA Subtypes show Different Atrophy Progressions, providing Evidence for Heterogeneity within PCA

1. Basic visual impairment → early atrophy in occipital lobe

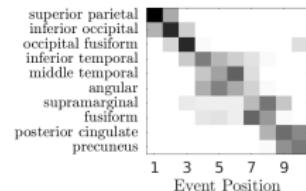
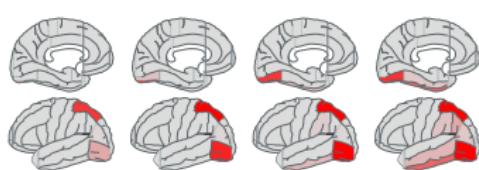
Initial hypotheses

- Space perception impairment → early atrophy in superior parietal lobe
- Visuoperceptual impairment → early atrophy in inferior temporal lobe

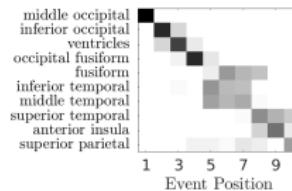
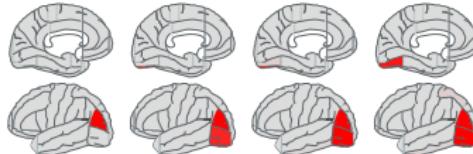
1. Basic visual impairment (n=21)



2. Space perception impairment (n=21)

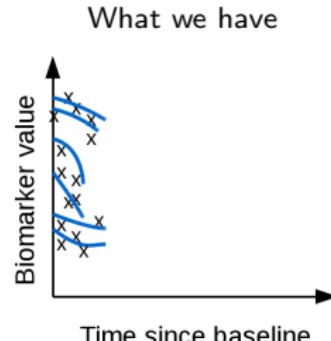
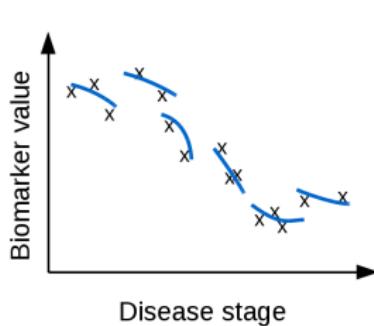
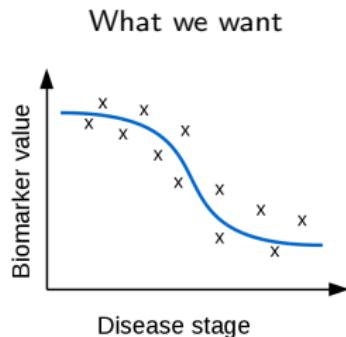


3. Visuo-perceptual impairment (n=22)



Firth, Marinescu and Primaitivo, in first revision (Brain)

The Differential Equation Model reconstructs Biomarker Trajectories from Short-term Longitudinal Measurements

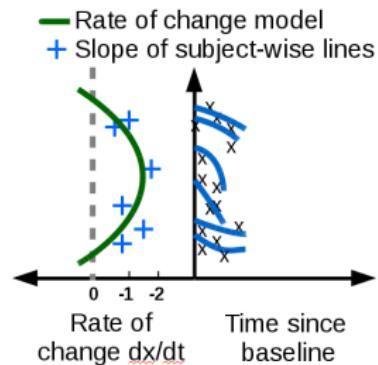
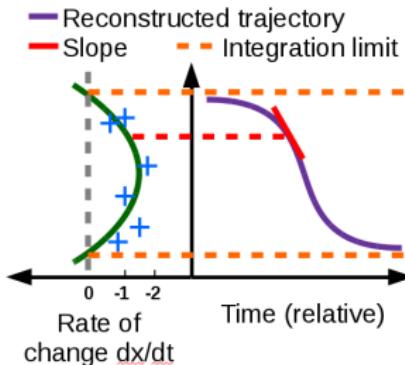


$$\lim_{\Delta t \rightarrow 0} \frac{\Delta x}{\Delta t} = \frac{\delta x}{\delta t} = f(x)$$

Solve for x using the Euler method:

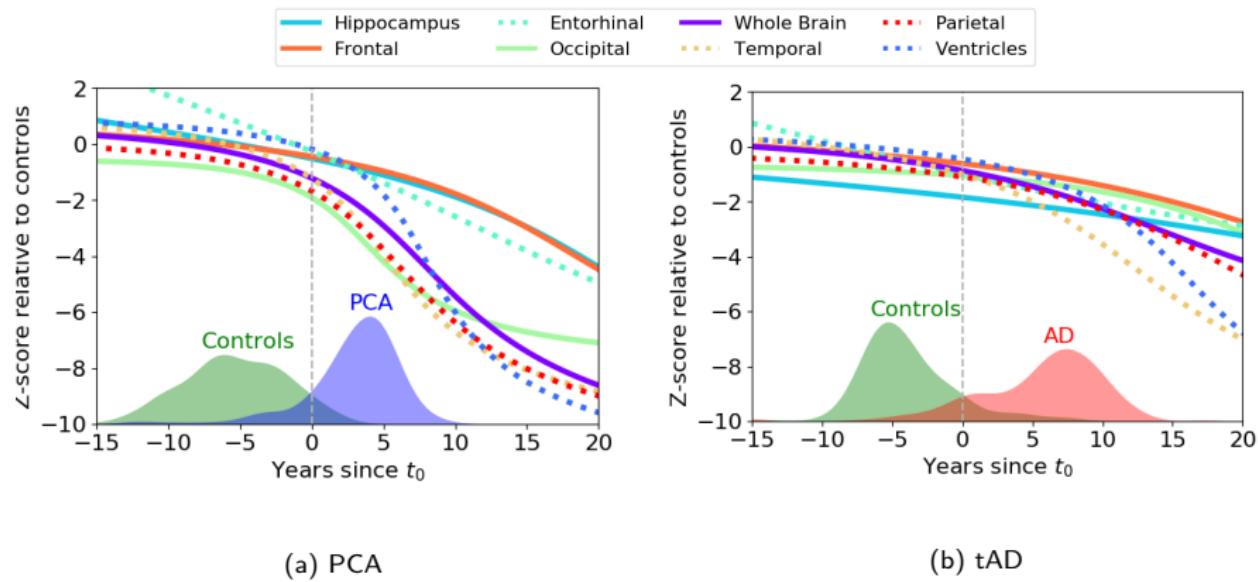
$$t_1 = t_0 + \delta t$$

$$x_1 = x_0 + f(x_0)\delta t$$



Model Recapitulates Differences in PCA vs tAD Atrophy Progression

- ▶ PCA: rapid and extensive atrophy in occipital and parietal regions
- ▶ tAD: global atrophy pattern, with early hippocampal involvement



(a) PCA

(b) tAD

Firth, Marinescu and Primativo, in first revision (Brain)