

# Normative modelling: the what, when and why

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Post Doctoral Researchers  
Predictive Clinical Neuroscience Lab



Predictive Clinical Neuroscience Lab

Slides by: @DrHannahSavage Dr. Charlotte Fraza @CharFraza Dr. Barbora Rehák Bučková @BarboraRehak Dr. Johanna Bayer@likeajumprope

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## OUTLINE

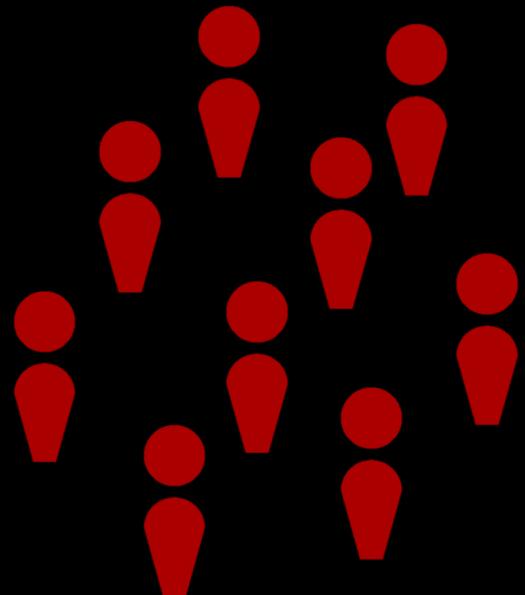
1. Short and conceptual introduction to normative modelling
2. How to train your own normative models
3. How to use our pretrained models
4. Methodological developments
5. Tutorial (Jupyter notebooks)

### Resources:

- PCN Toolkit: <https://pcn toolkit.readthedocs.io/en/latest/>
- PCN Portal: <https://pcn portal.dccn.nl/>
- Tutorials and Repository for this talk:  
[https://github.com/likeajumpope/Tutorial\\_normative\\_modelling/blob/master/README.md](https://github.com/likeajumpope/Tutorial_normative_modelling/blob/master/README.md)
- Pre-fitted models: <https://github.com/predictive-clinical-neuroscience/braincharts>
- More tutorials: <https://github.com/predictive-clinical-neuroscience/PCN toolkit-demo>

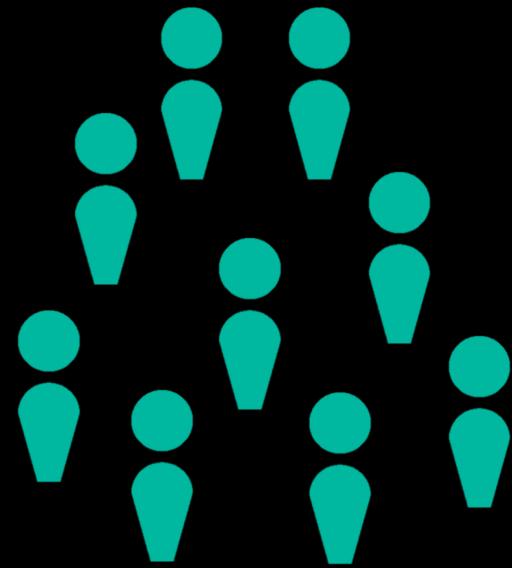
## THE SHORTCOMINGS OF CLASSICAL STATISTICS

CASE



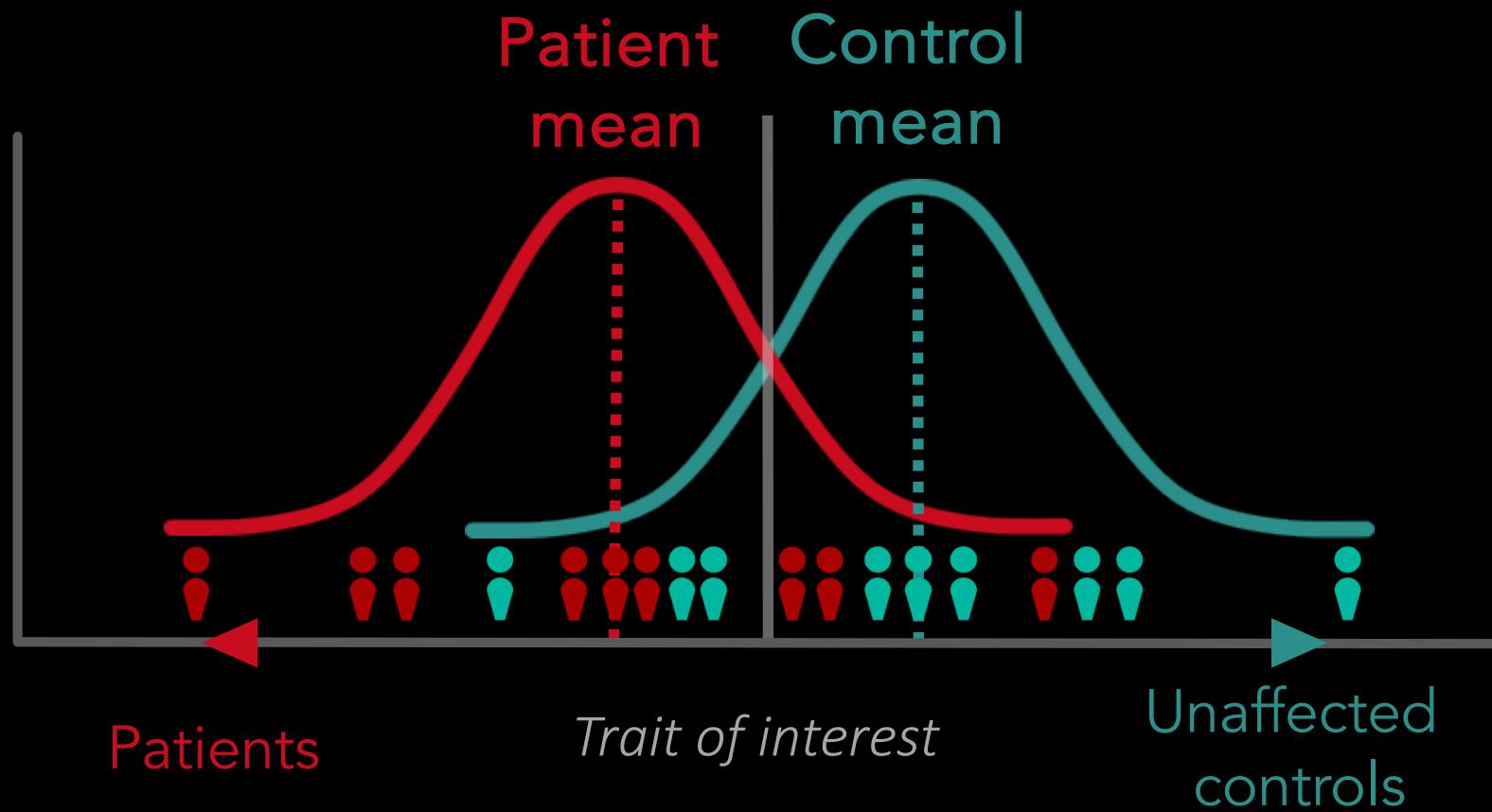
Patients

CONTROL

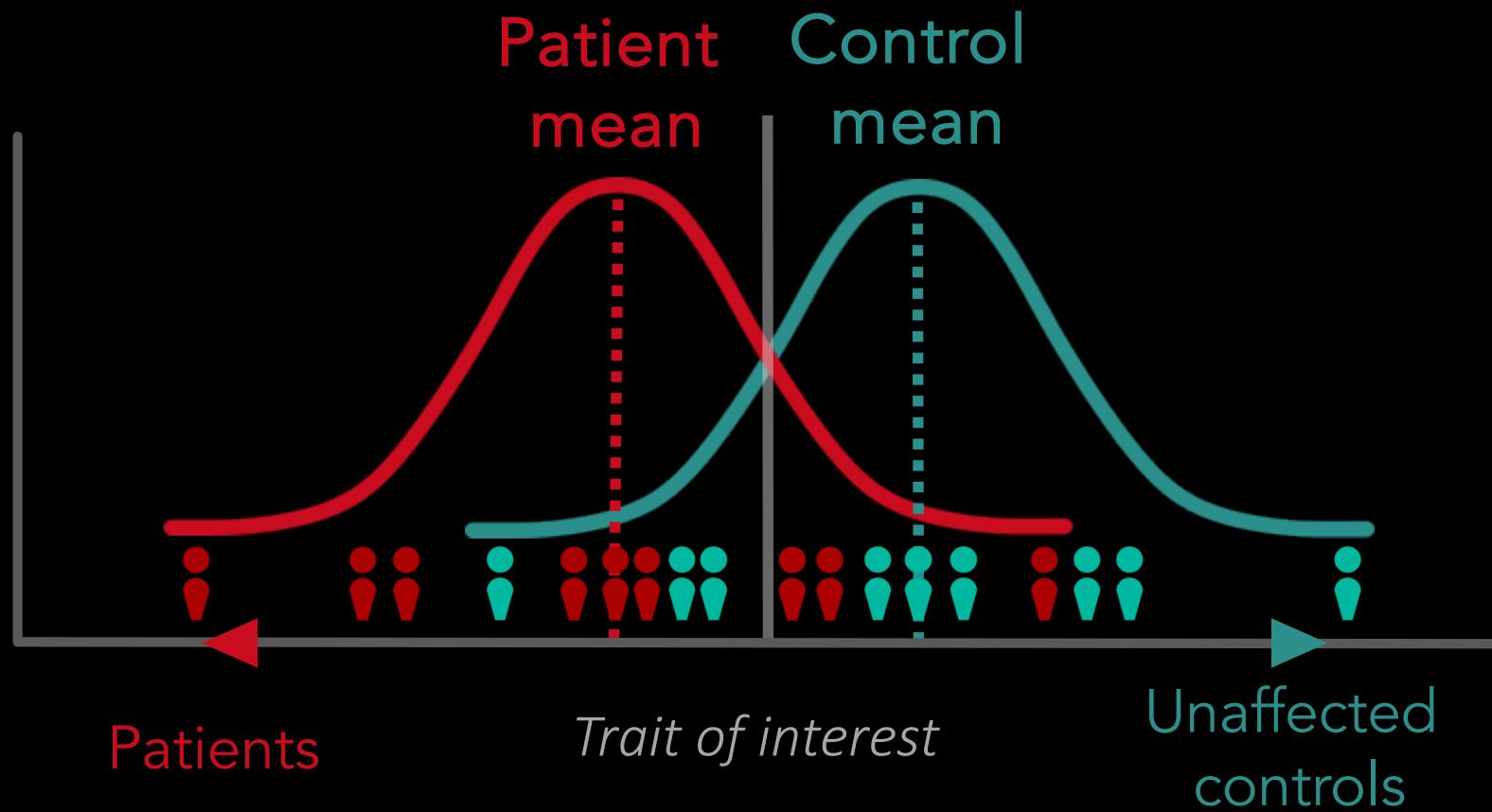


Unaffected  
controls

## THE SHORTCOMINGS OF CLASSICAL STATISTICS

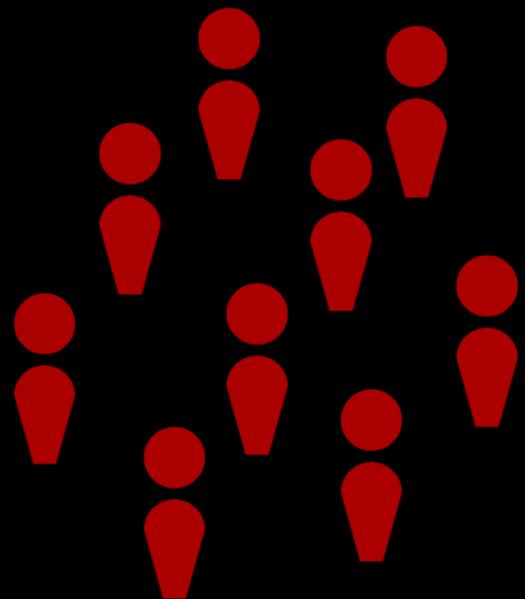


## THE SHORTCOMINGS OF CLASSICAL STATISTICS

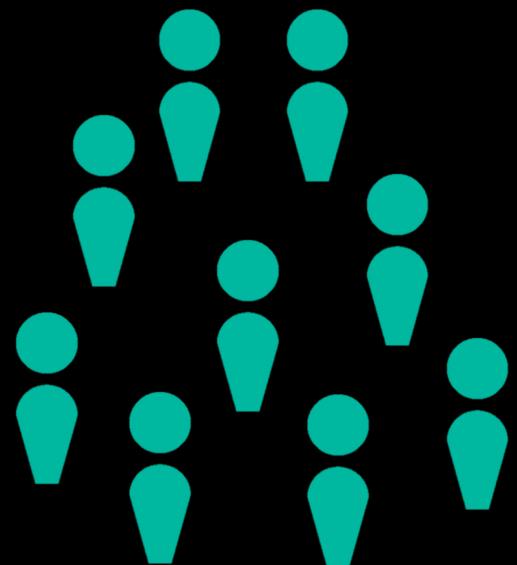


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## ON HETEROGENEITY



Patients



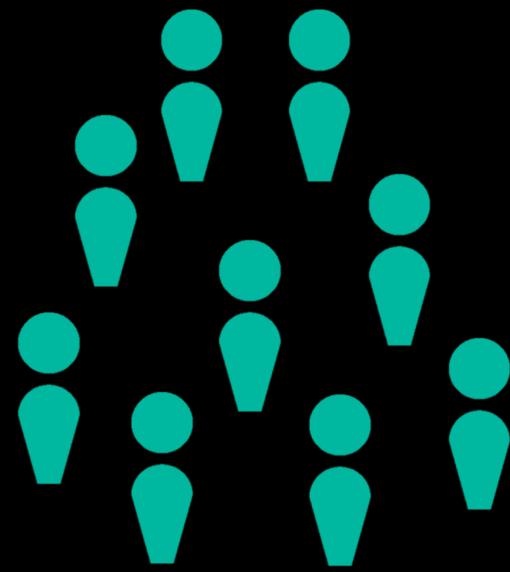
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controls

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## ON HETEROGENEITY



Patients



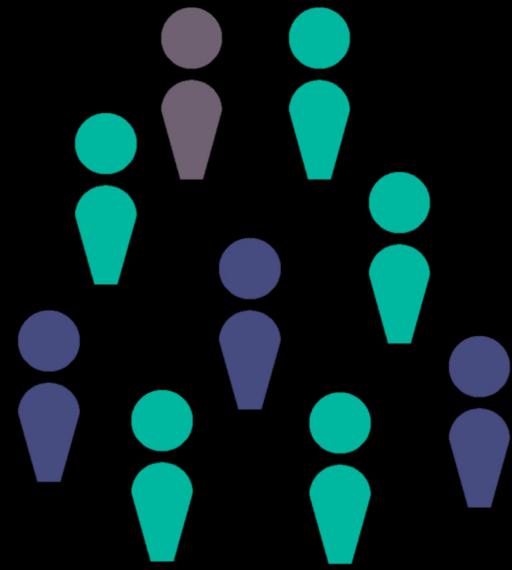
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controls

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## ON HETEROGENEITY



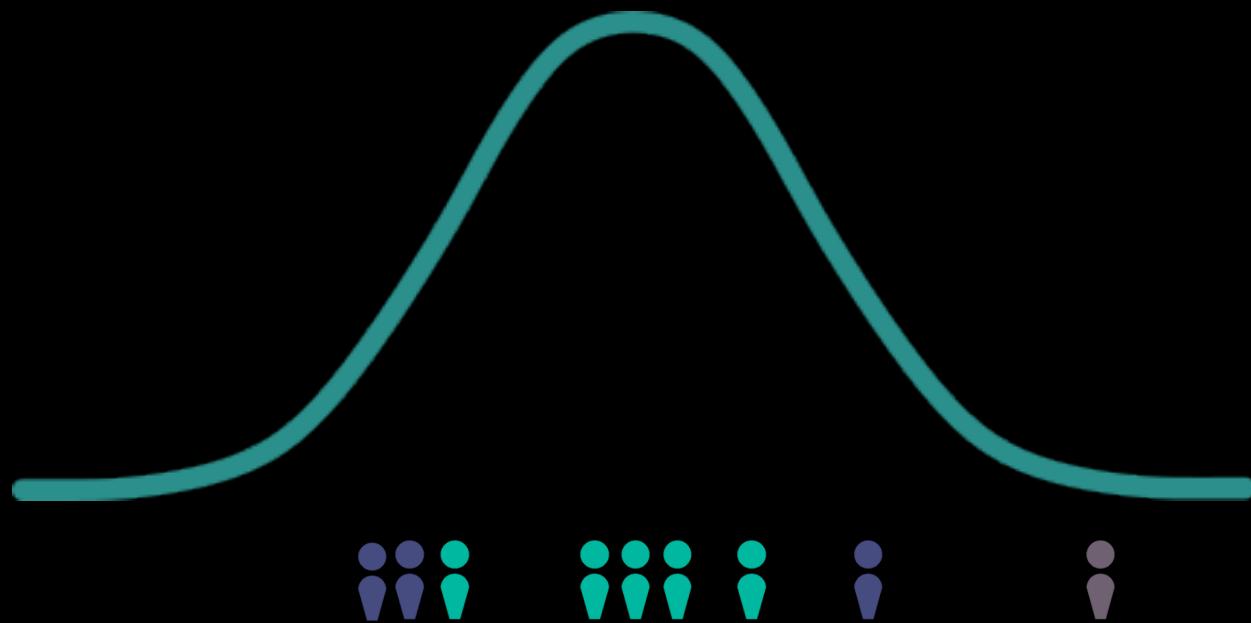
Patients



Unaffected  
controls

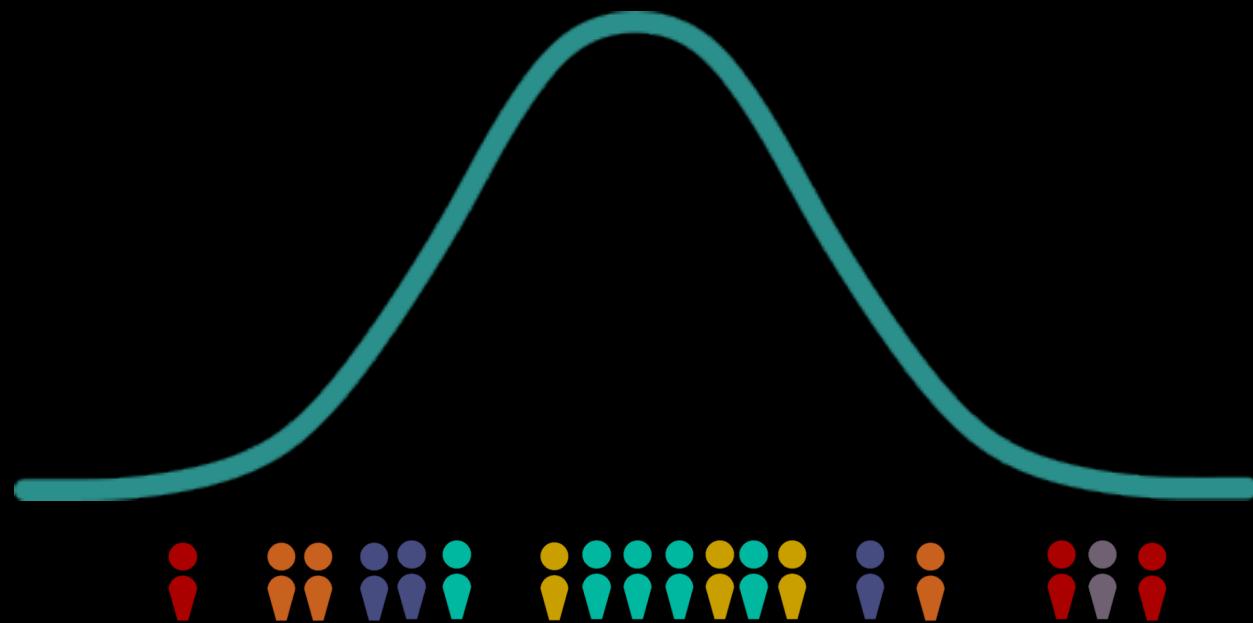
HETEROGENEITY

NORMATIVE MODELLING



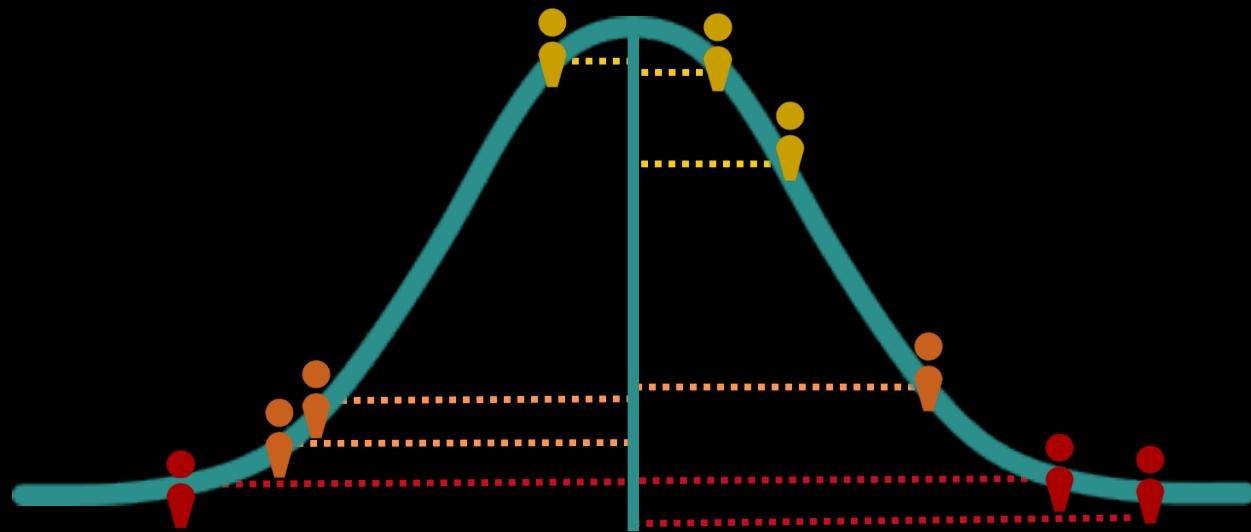
HETEROGENEITY

NORMATIVE MODELLING



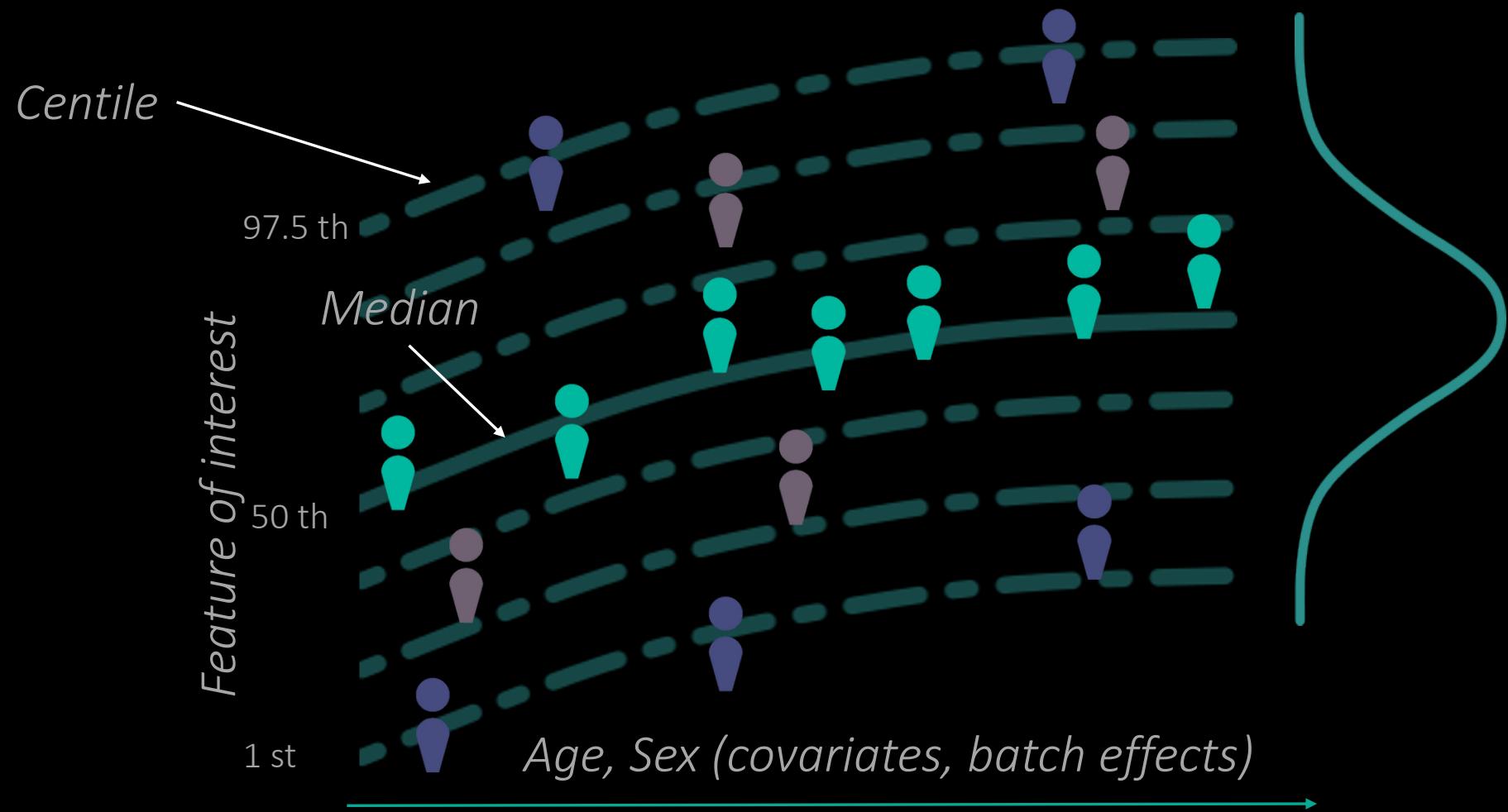
## HETEROGENEITY

### NORMATIVE MODELLING



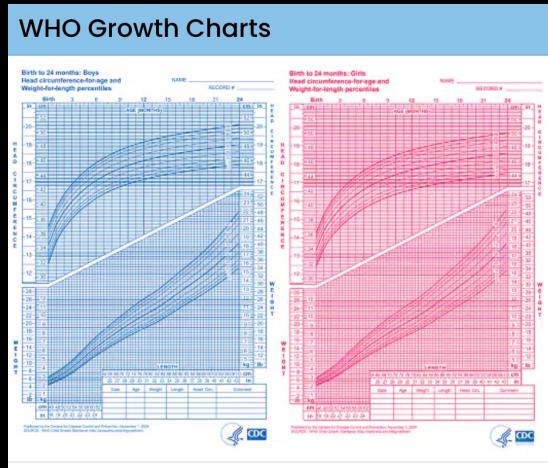
## HETEROGENEITY

### NORMATIVE MODELLING



# HETEROGENEITY

## NORMATIVE MODELLING



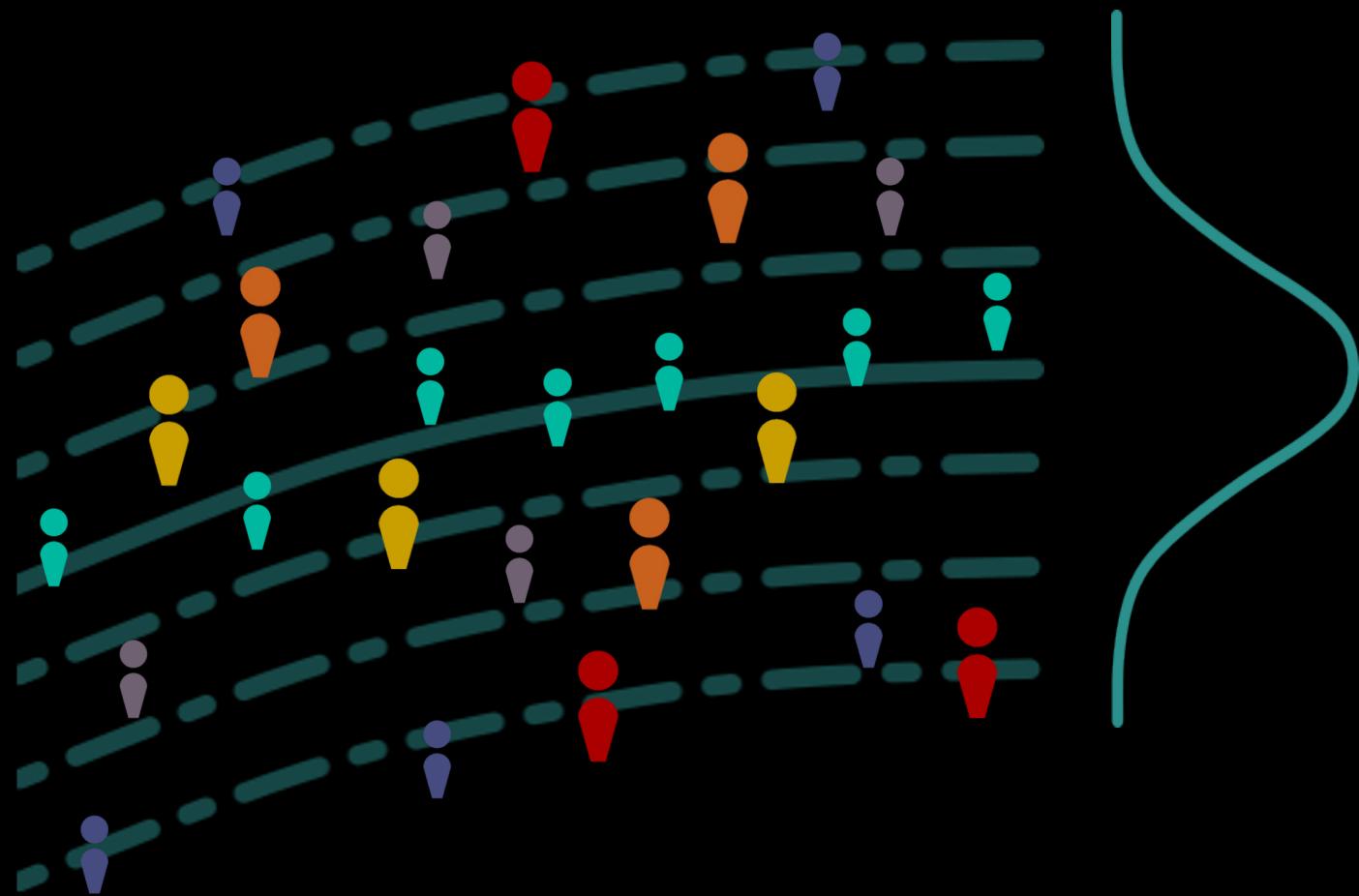
Feature of interest



## HETEROGENEITY

### NORMATIVE MODELLING

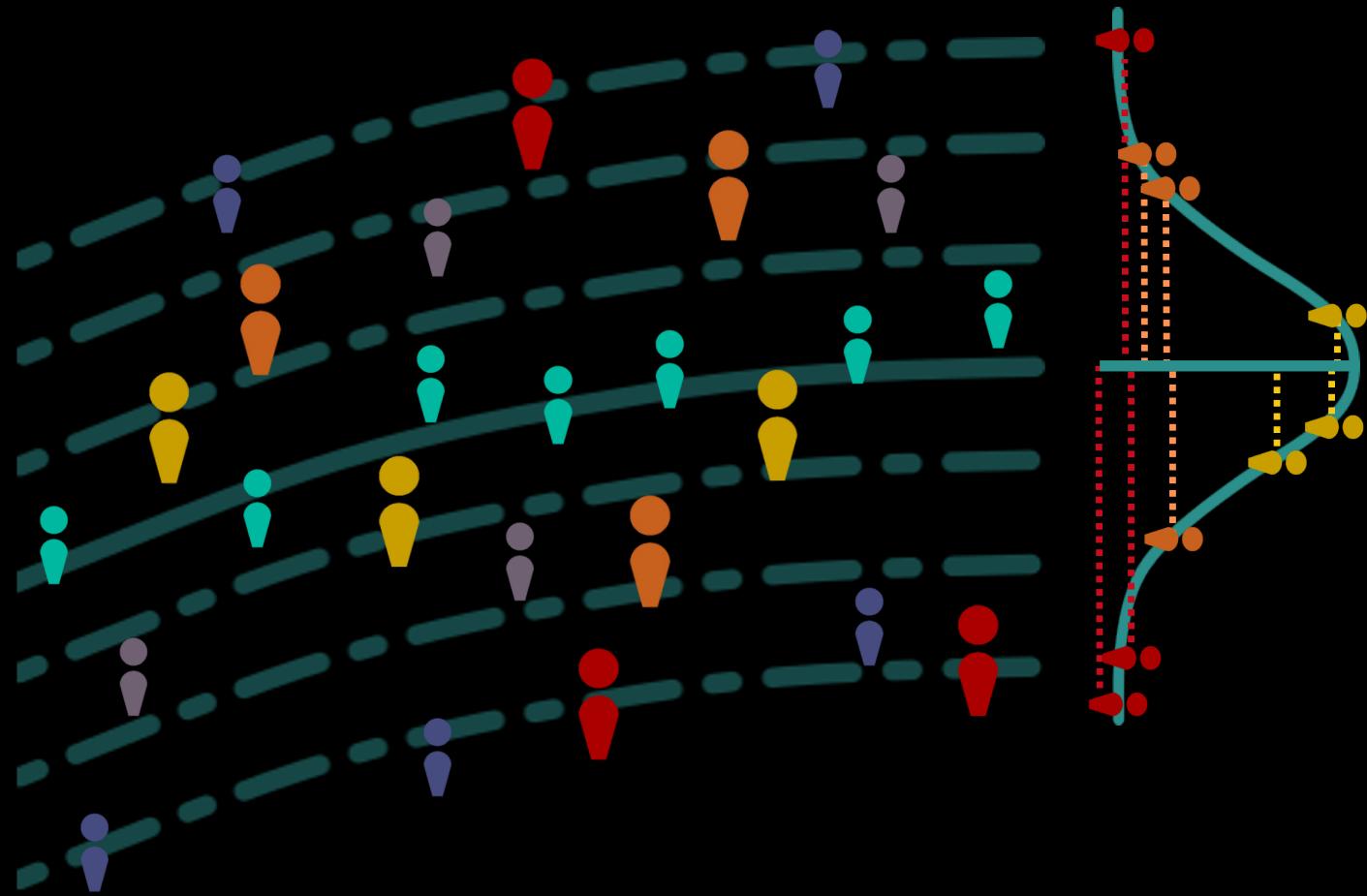
*Feature of interest*



# HETEROGENEITY

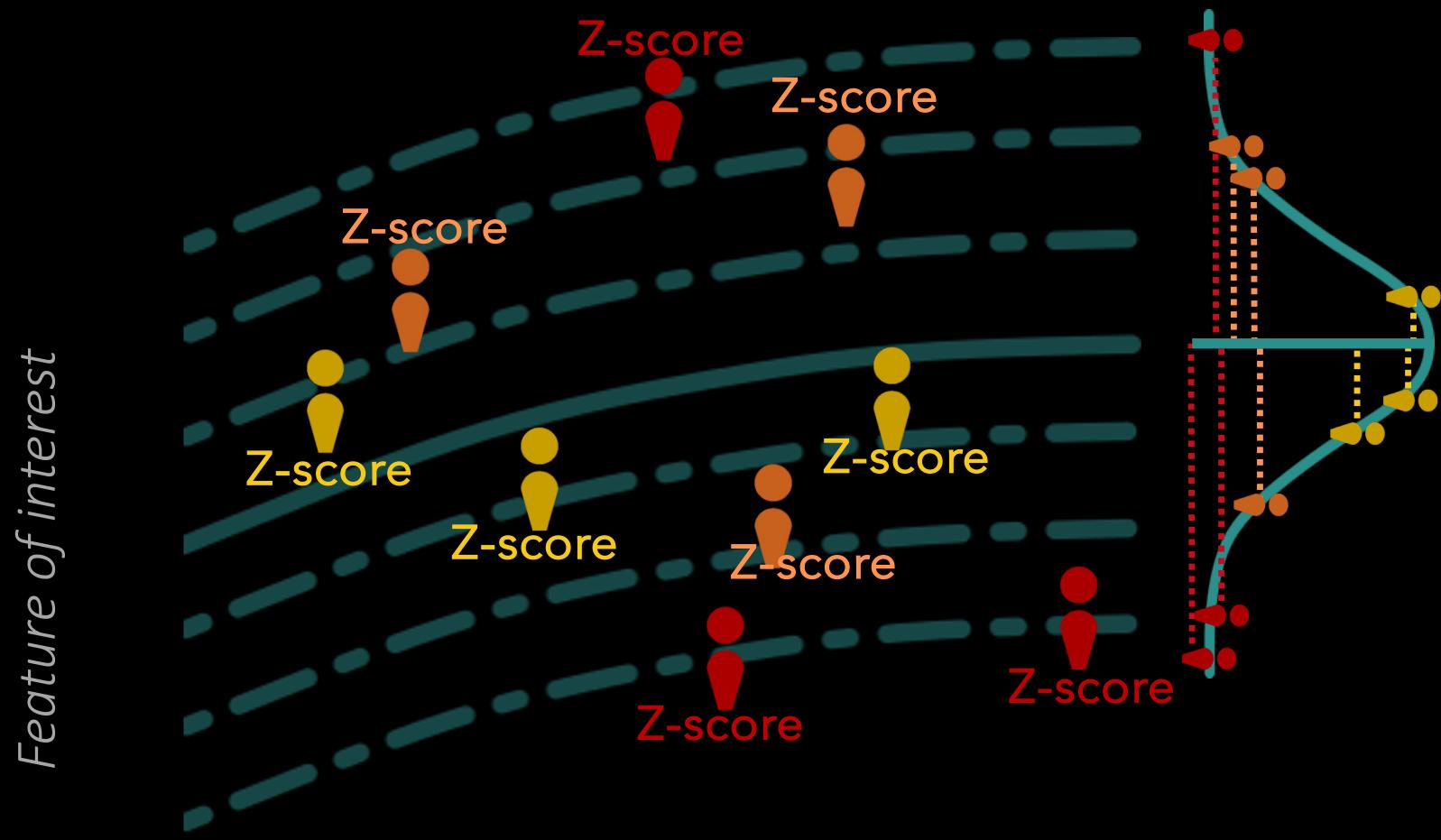
## NORMATIVE MODELLING

*Feature of interest*



## HETEROGENEITY

### NORMATIVE MODELLING



HETEROGENEITY   NORMATIVE MODELLING

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APPLICATIONS & DEVELOPMENT

Training your  
own models

Applying pre-  
trained models

Methodology

Training your  
own models

Applying pre-  
trained models

Methodology

HETEROGENEITY NORMATIVE MODELLING

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APPLICATIONS & DEVELOPMENT

Y

Brain  
(BOLD signal in  
voxel, ROI)

$$Y = f(X, \theta) + \varepsilon$$

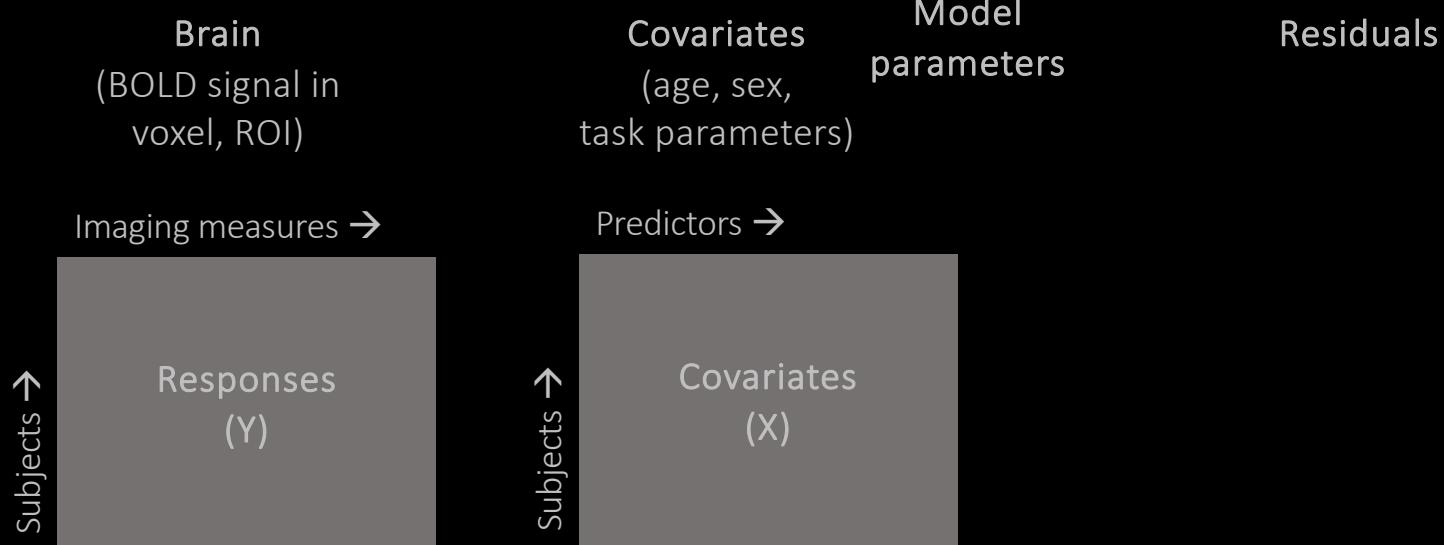
Brain  
(BOLD signal in  
voxel, ROI)

Covariates  
(age, sex,  
task parameters)

Model  
parameters

Residuals

$$Y = f(X, \theta) + \epsilon$$

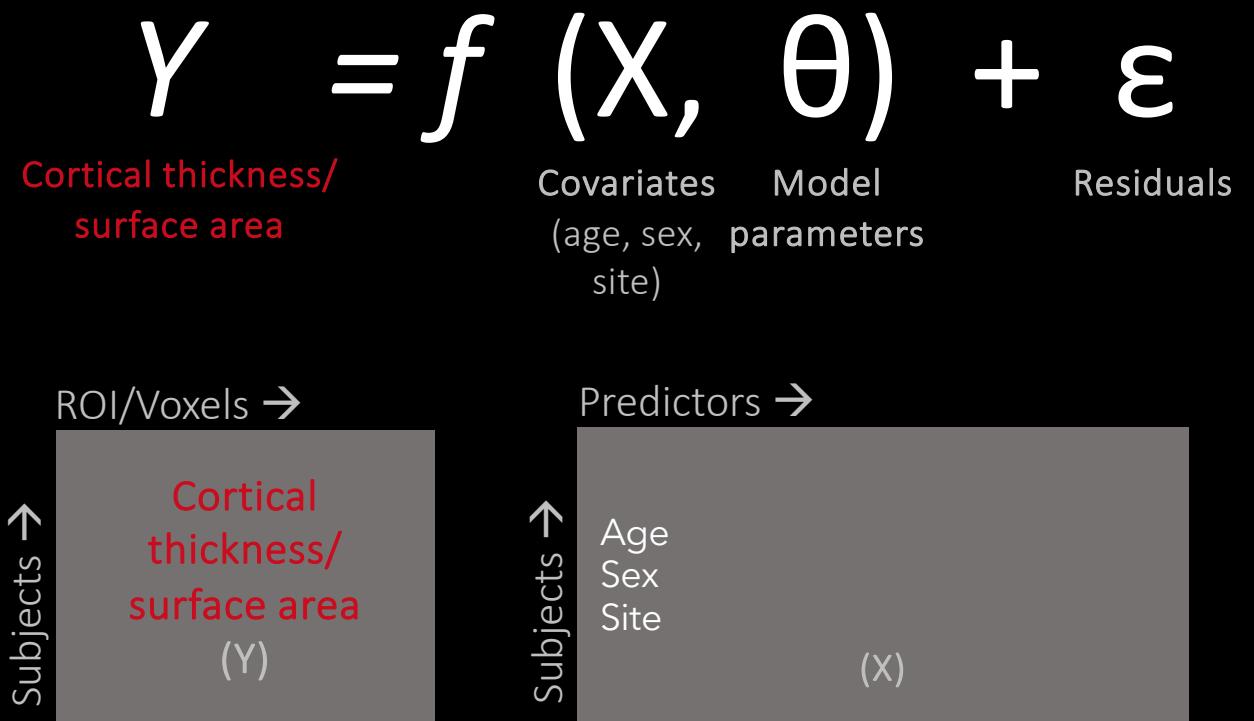


## HETEROGENEITY NORMATIVE MODELLING

### TRAINING YOUR OWN MODELS

### APPLICATIONS & DEVELOPMENT

- Training and evaluating the normative model on local dataset



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$$Y = f(X, \theta) + \epsilon$$

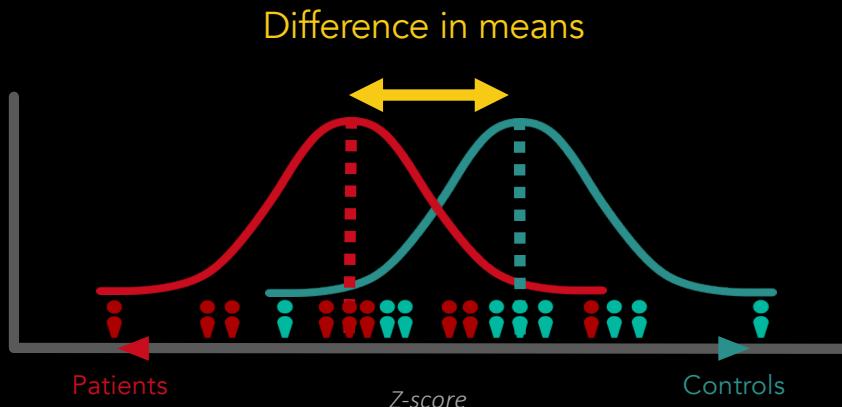
Cortical thickness/ surface area	Covariates (age, sex, parameters site)	Model	Residuals
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$$\hat{Y}, \sigma_s, \sigma_\epsilon = f(X, \theta) + \epsilon$$

$$Z = \frac{\hat{Y} - Y}{\sqrt{\sigma_s + \sigma_\epsilon}}$$

## HETEROGENEITY NORMATIVE MODELLING

### APPLICATIONS: Structural Imaging



*Reminiscent of case-control design, but controlling  
for individual variation*

? Do patients show overlapping deviation  
scores in brain regions significantly different  
from control group ?



Charlotte Fraza et al., (2024) Reconceptualizing  
psychopathology as extreme deviations from a  
normative reference model. BioRxiv

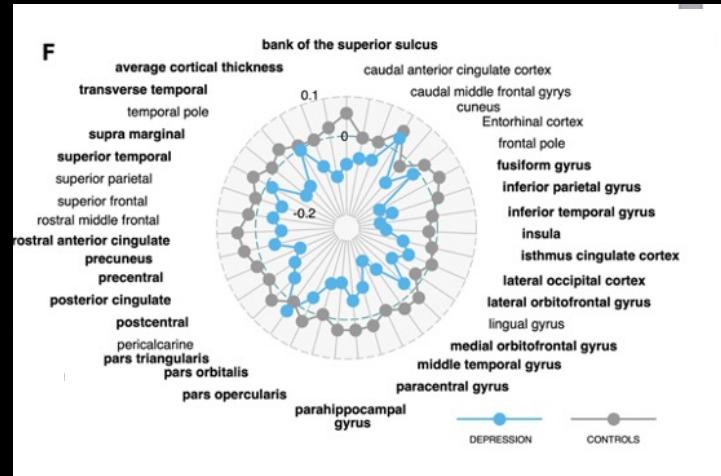
? Are patients more likely to lie in the tails  
of distribution of (cortical thickness) ?

## HETEROGENEITY NORMATIVE MODELLING

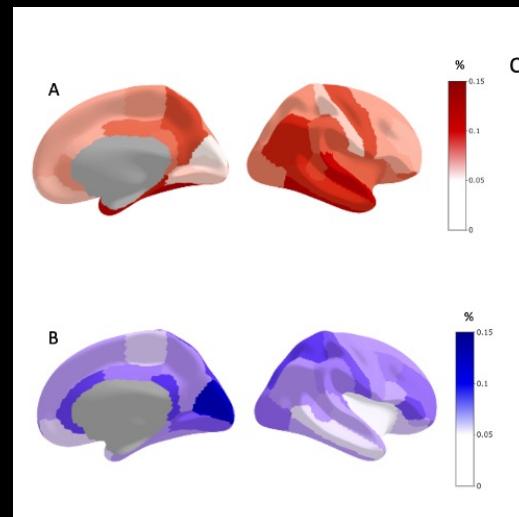
### APPLICATIONS: Structural Imaging

I.

#### Parse heterogeneity



#### Extreme negative deviations



#### Extreme positive deviations

2.

#### Brain-behavior mappings

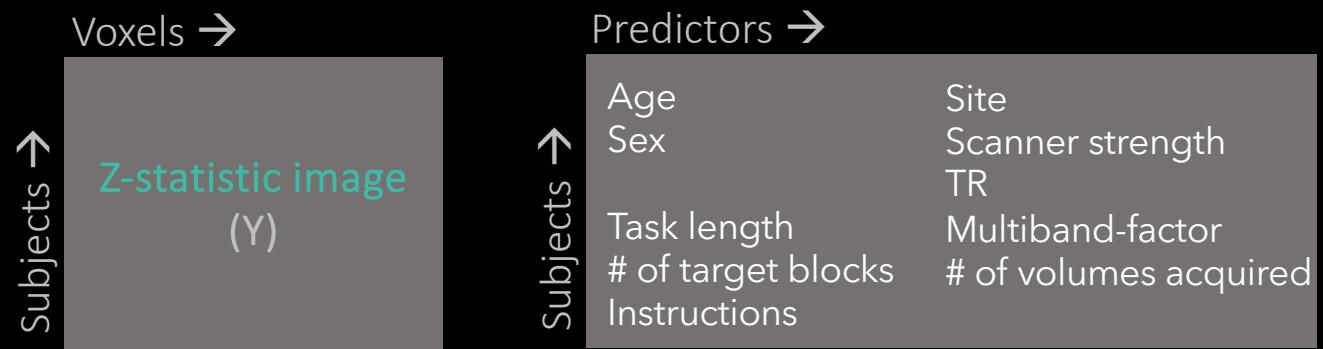
- earlier onset of depression
  - more severe depressive symptoms
  - higher BMI
- 
- being remitted
  - not taking antidepressants
  - less severe symptoms

- Training and evaluating the normative model on local dataset

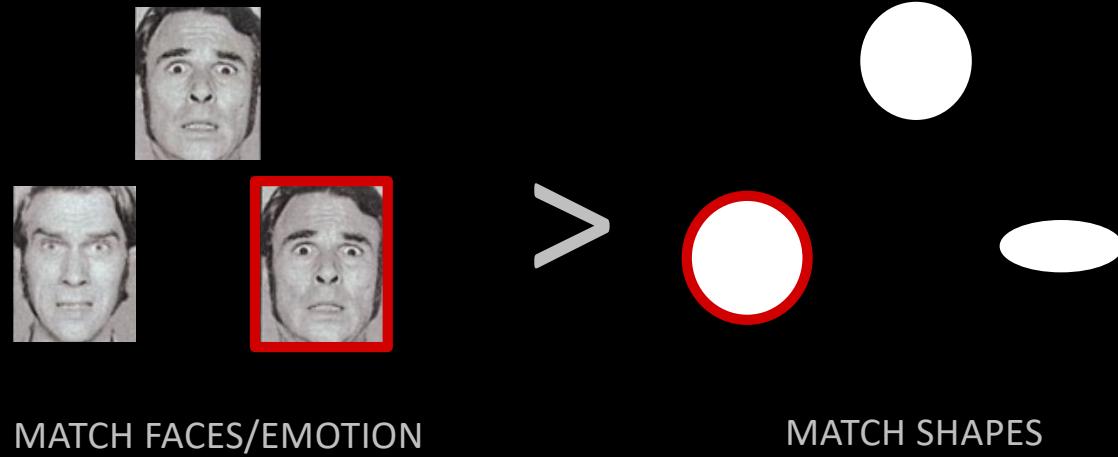
$$Y = f(X, \theta) + \epsilon$$

Legend:

- Bold Signal**: Covariates (age, sex, Task parameters)
- Covariates**: Model parameters
- Model**: Residuals
- Residuals**



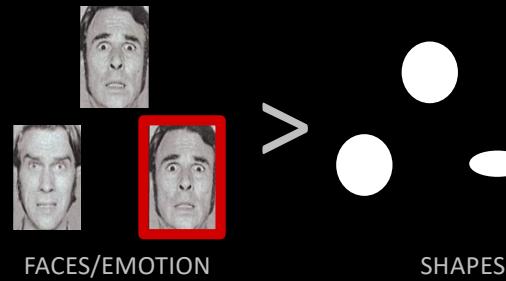
- Training and evaluating the normative model on local dataset



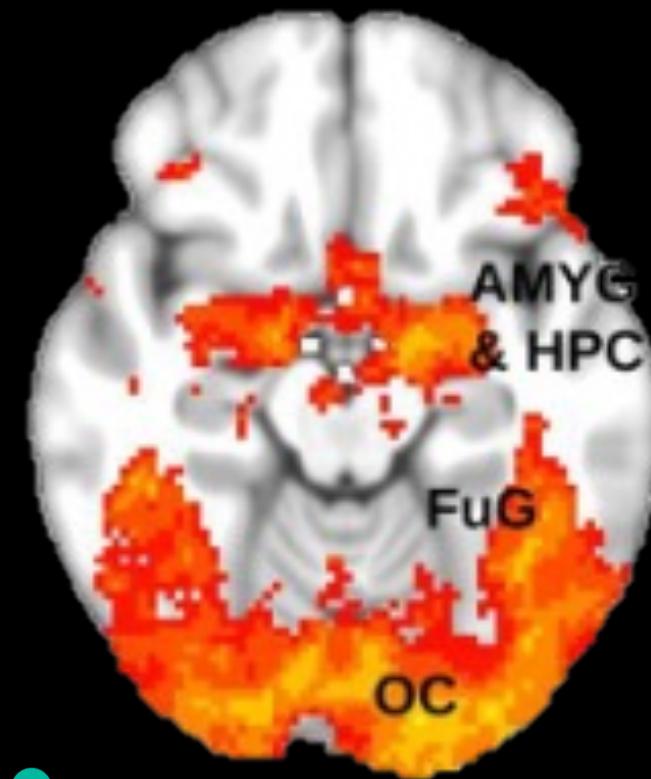
## HETEROGENEITY NORMATIVE MODELLING

### APPLICATIONS: Functional Imaging

- Training and evaluating the normative model on local dataset



FACES/EMOTION

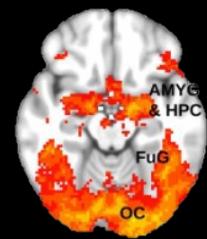


 Unaffected controls

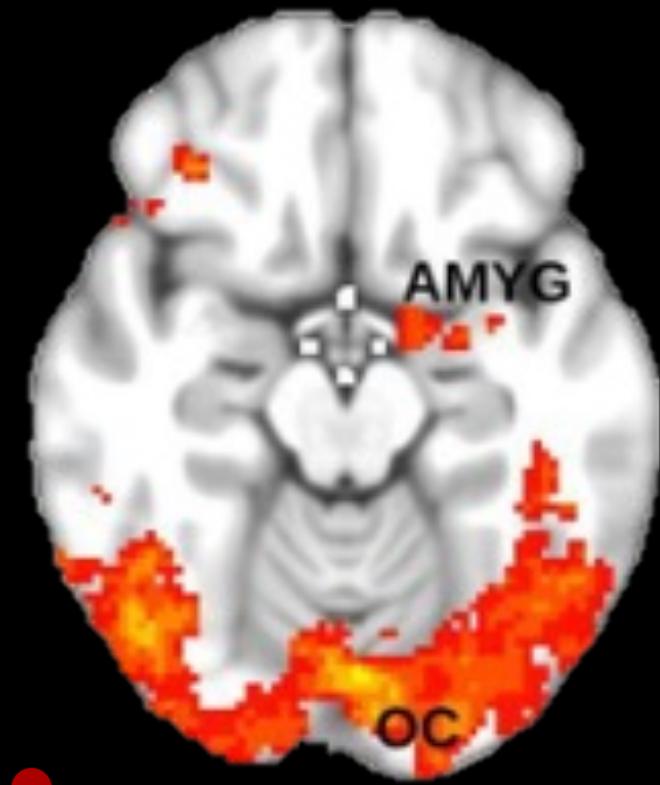
## HETEROGENEITY NORMATIVE MODELLING

### APPLICATIONS: Functional Imaging

- Training and evaluating the normative model on local dataset



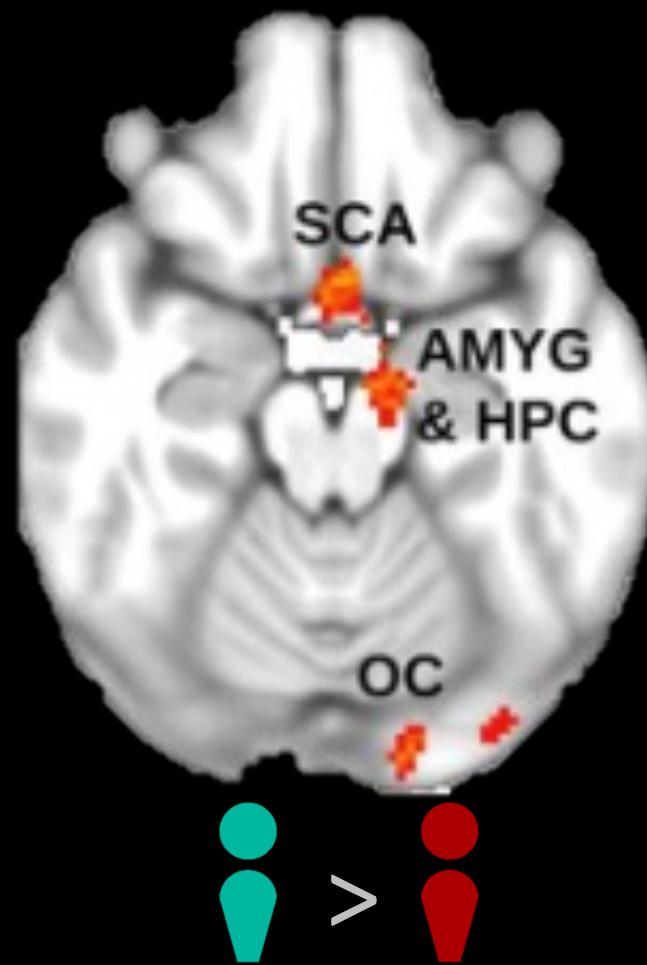
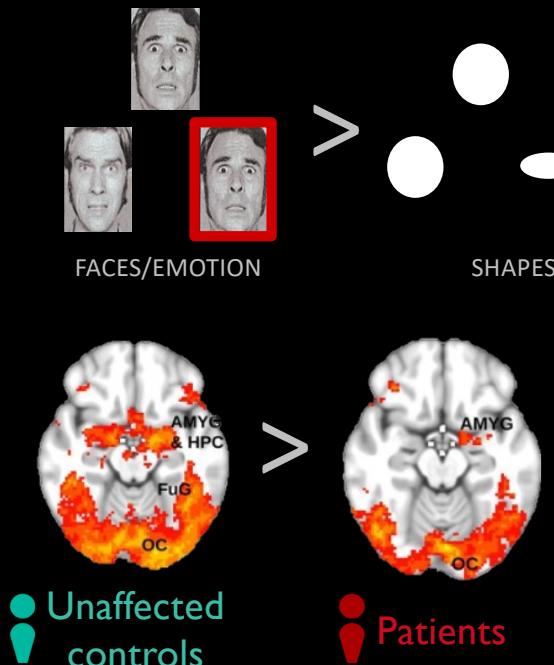
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controls



## HETEROGENEITY NORMATIVE MODELLING

### APPLICATIONS: Functional Imaging

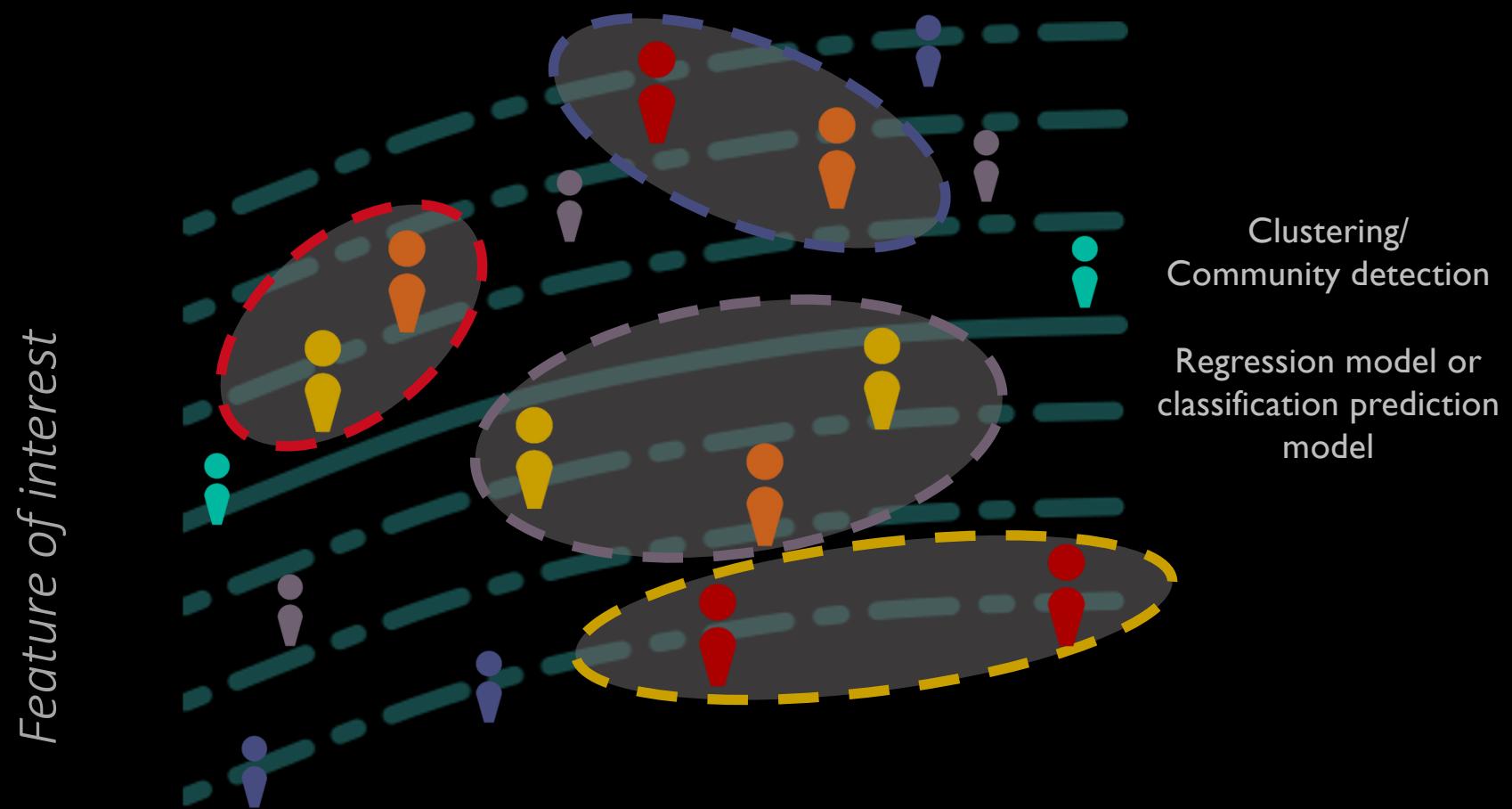
- Training and evaluating the normative model on local dataset



## HETEROGENEITY NORMATIVE MODELLING

### NEUROBIOLOGICAL SUBTYPING

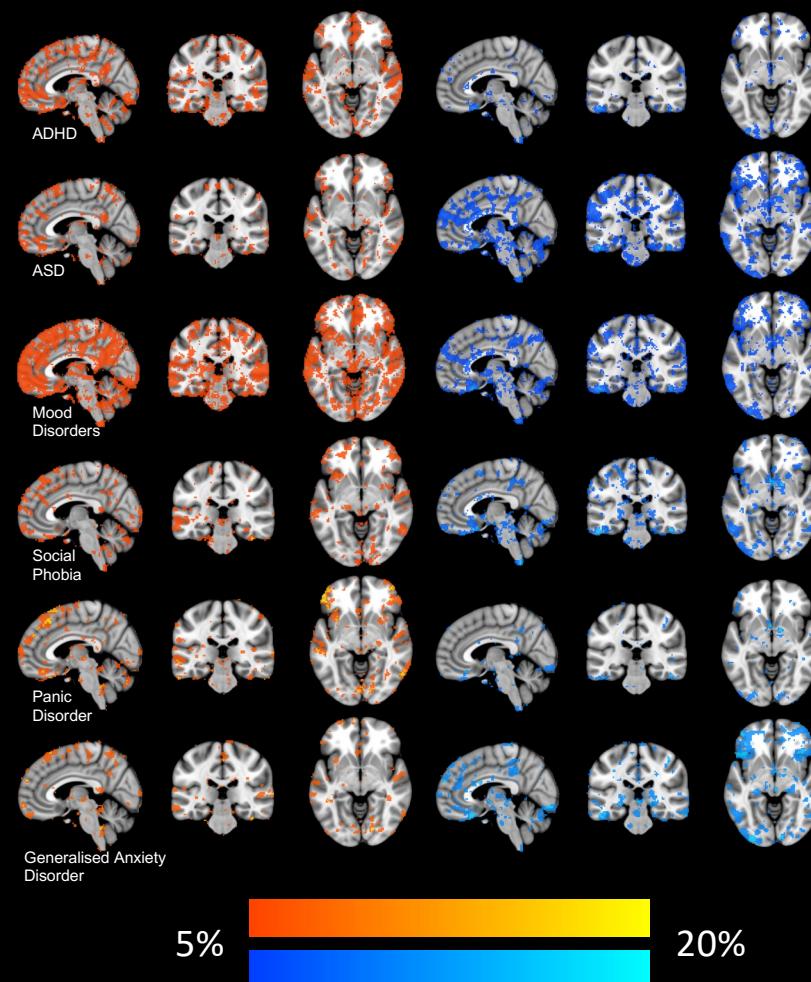
### APPLICATIONS



## HETEROGENEITY NORMATIVE MODELLING

### APPLICATIONS: Functional Imaging

- Training and evaluating the normative model on local dataset



Hannah Savage et al., (2024) Dissecting task-based fMRI activity using normative modelling: an application to the Emotional Face Matching Task. *Communications Biology* 7.1: 888.

HETEROGENEITY   NORMATIVE MODELLING

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APPLICATIONS & DEVELOPMENT

Training your  
own models

Applying pre-  
trained models

Methodology

Training your  
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Methodology

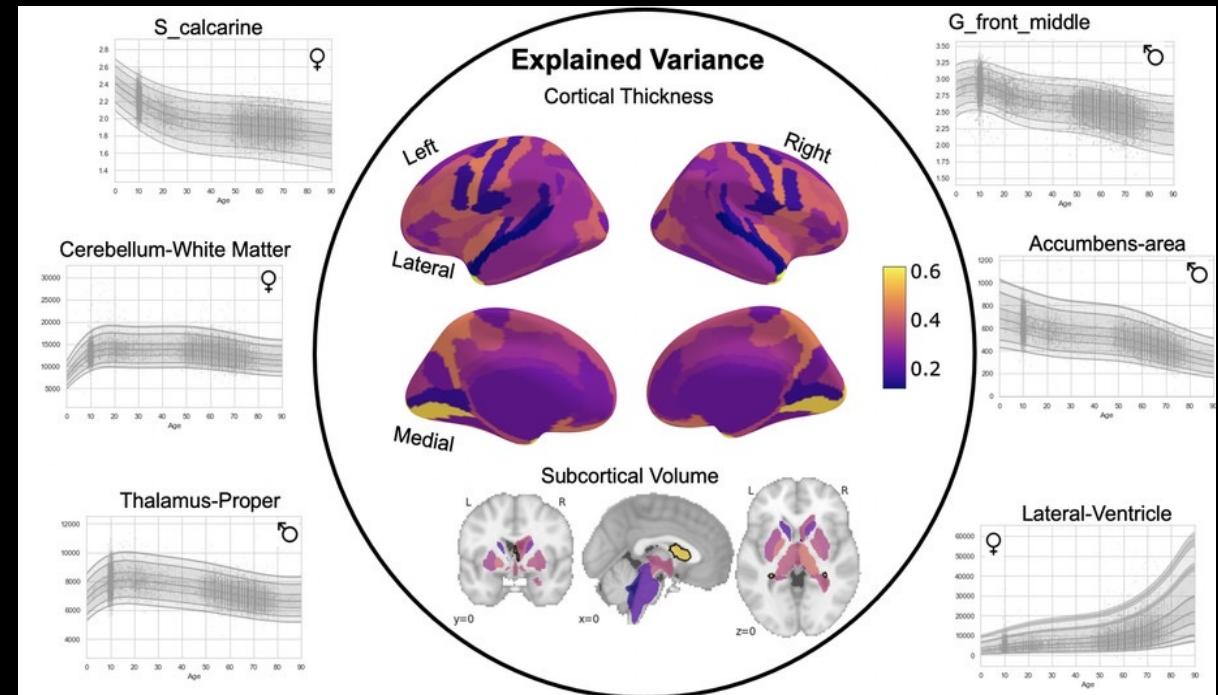
## HETEROGENEITY NORMATIVE MODELLING

### USE PRETRAINED MODELS

- Using pre-trained models, evaluating on local datasets

- 58,836 individuals
- 82 scan sites
- aged 2–100

Normative models for cortical thickness and subcortical volumes derived from Freesurfer



Saige Rutherford et al.,  
(2022) Charting brain growth  
and aging at high spatial  
precision. *eLife* 11:e72904.

$$\hat{Y}, \sigma_S, \sigma_\epsilon = f(X, \theta) + \epsilon$$

USE PRETRAINED MODELS

- Using pre-trained models, evaluating on local datasets

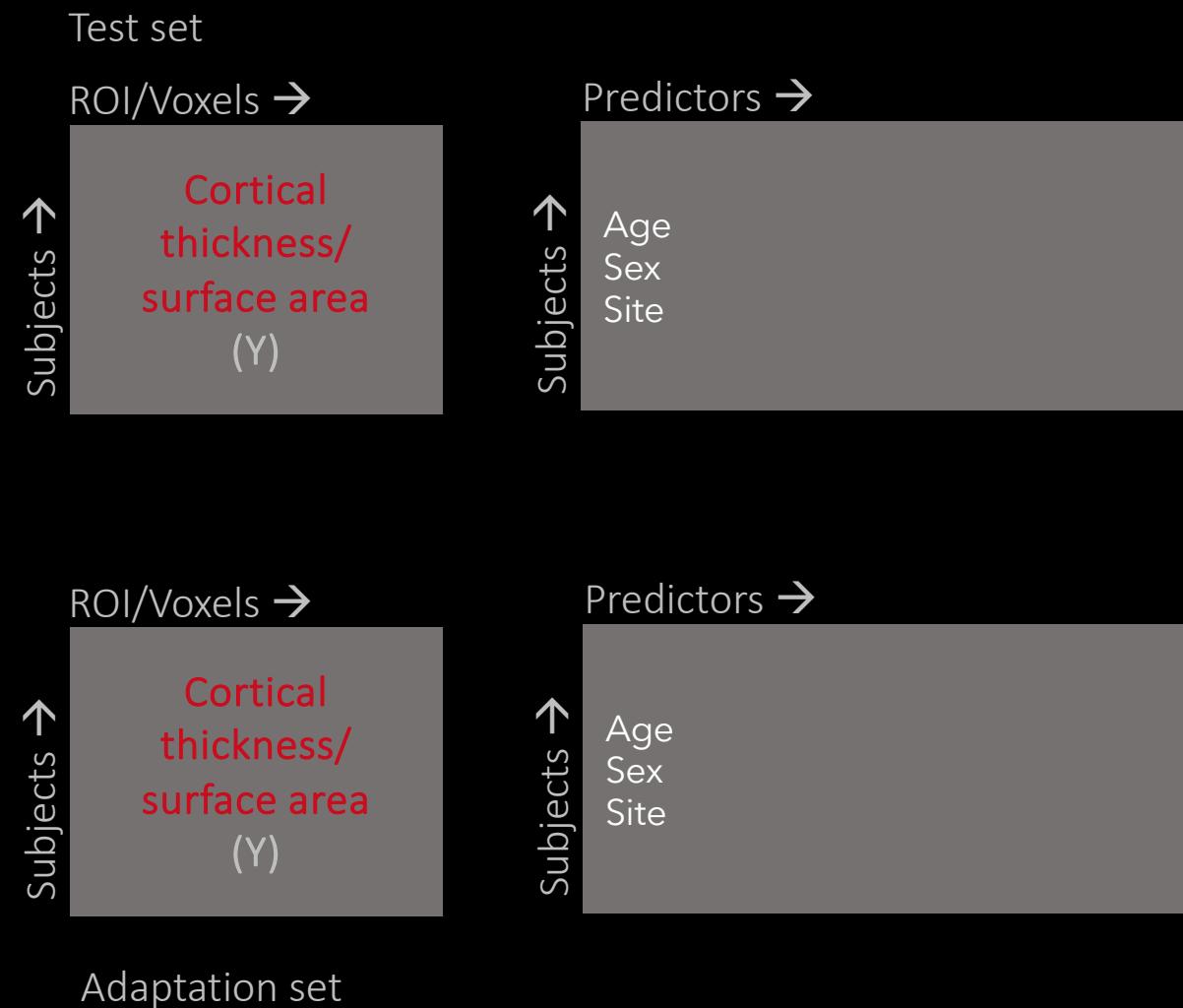
$$Z = \frac{\hat{Y} - Y}{\sqrt{\sigma_s + \sigma_\epsilon}}$$

## HETEROGENEITY NORMATIVE MODELLING

### USE PRETRAINED MODELS

- Using pre-trained models, evaluating on local datasets

$$\hat{Y} - Y$$



Training your  
own models

Applying pre-  
trained models

Methodology

Training your  
own models

Applying pre-  
trained models

Methodology

## METHODOLOGICAL ADVANCES

$$Y = f(X, \theta) + \epsilon$$

Brain  
(BOLD signal in  
voxel, ROI)

Covariates  
(age, sex,  
task parameters)

Model  
parameters

Residuals

Gaussian  
process  
regression



Warped  
Bayesian  
linear  
regression



Generalized  
additive models  
of location scale  
and shape

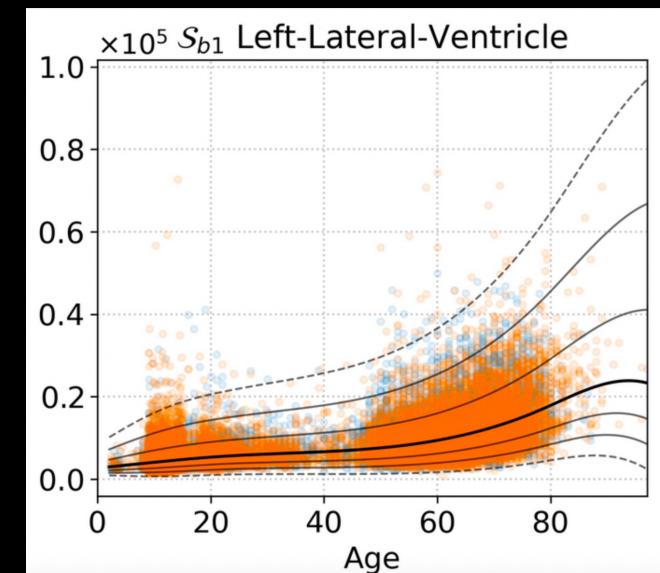
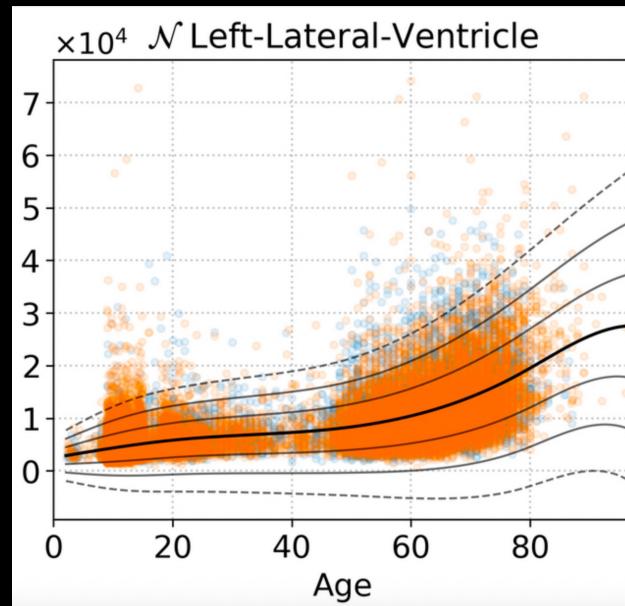


Hierarchical  
Bayesian  
regression



## COMPLEX PHENOTYPES

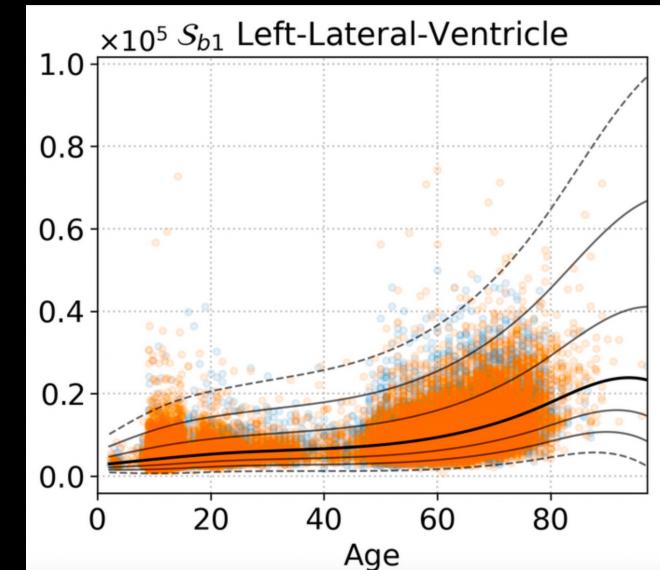
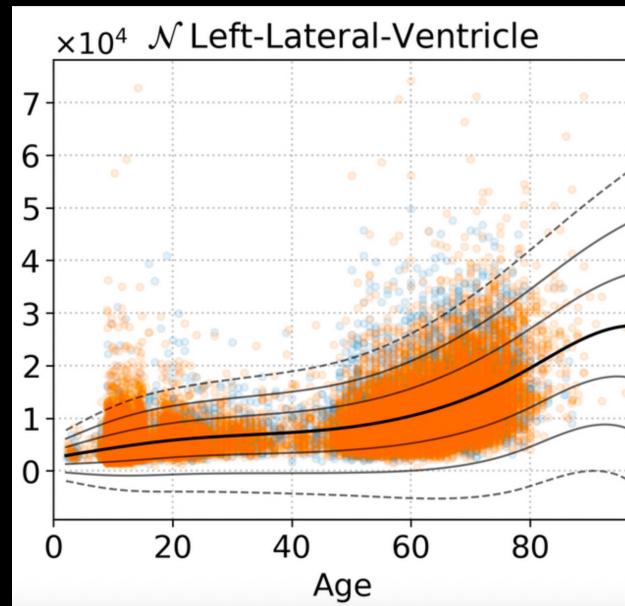
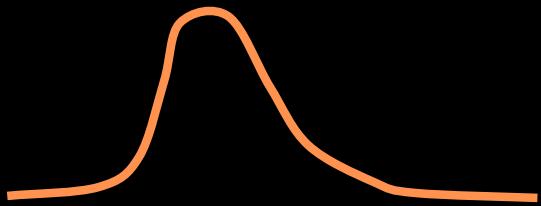
- Hierarchical Bayesian Regression with non-gaussian SHASH likelihood allows to model skewed and heteroscedastic distributions



de Boer, A. A. A. Bayer, J. M. M. et al. (2024) Non-Gaussian normative modelling with hierarchical Bayesian regression. *Imaging Neuroscience* 2, 1–36.

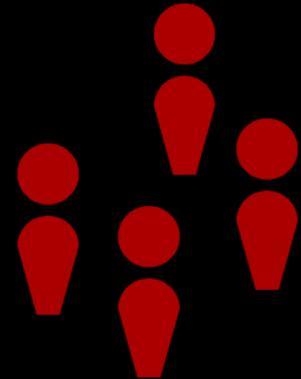
## COMPLEX PHENOTYPES

- Hierarchical Bayesian Regression with non-gaussian SHASH likelihood allows to model skewed and heteroscedastic distributions

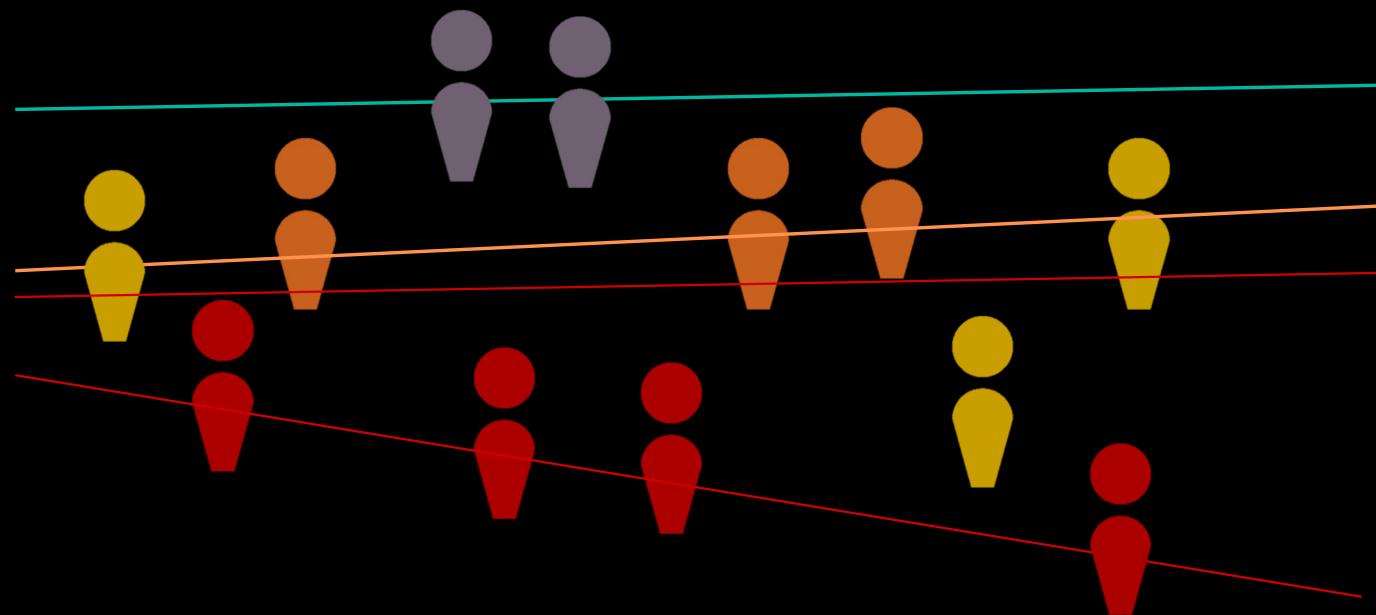


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## SITE EFFECTS



## SITE EFFECTS

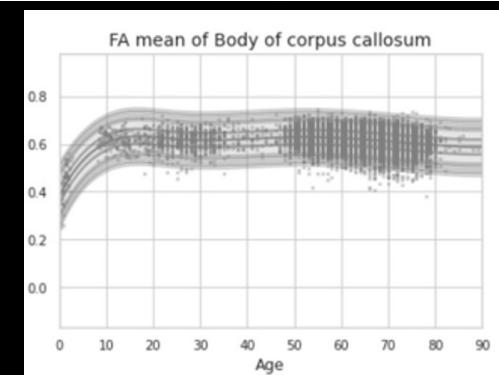
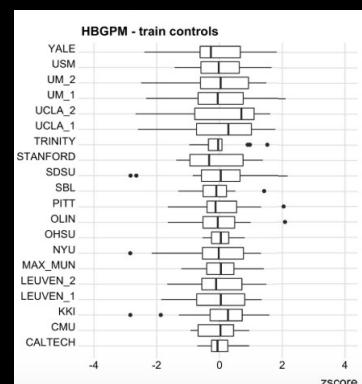
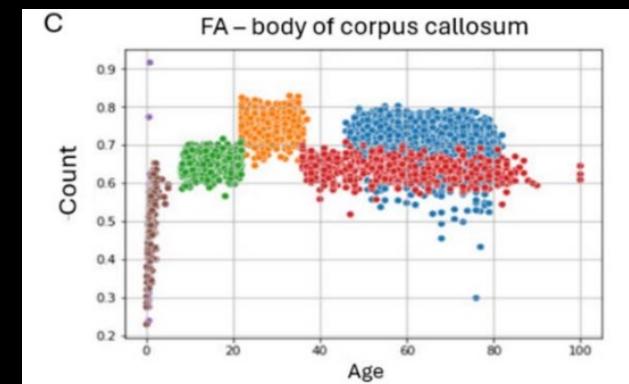
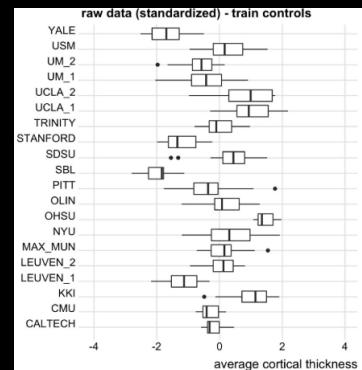


## SITE EFFECTS



## SITE EFFECTS

- Including site as batch effect into normative model
- Inverting z-scores between sites

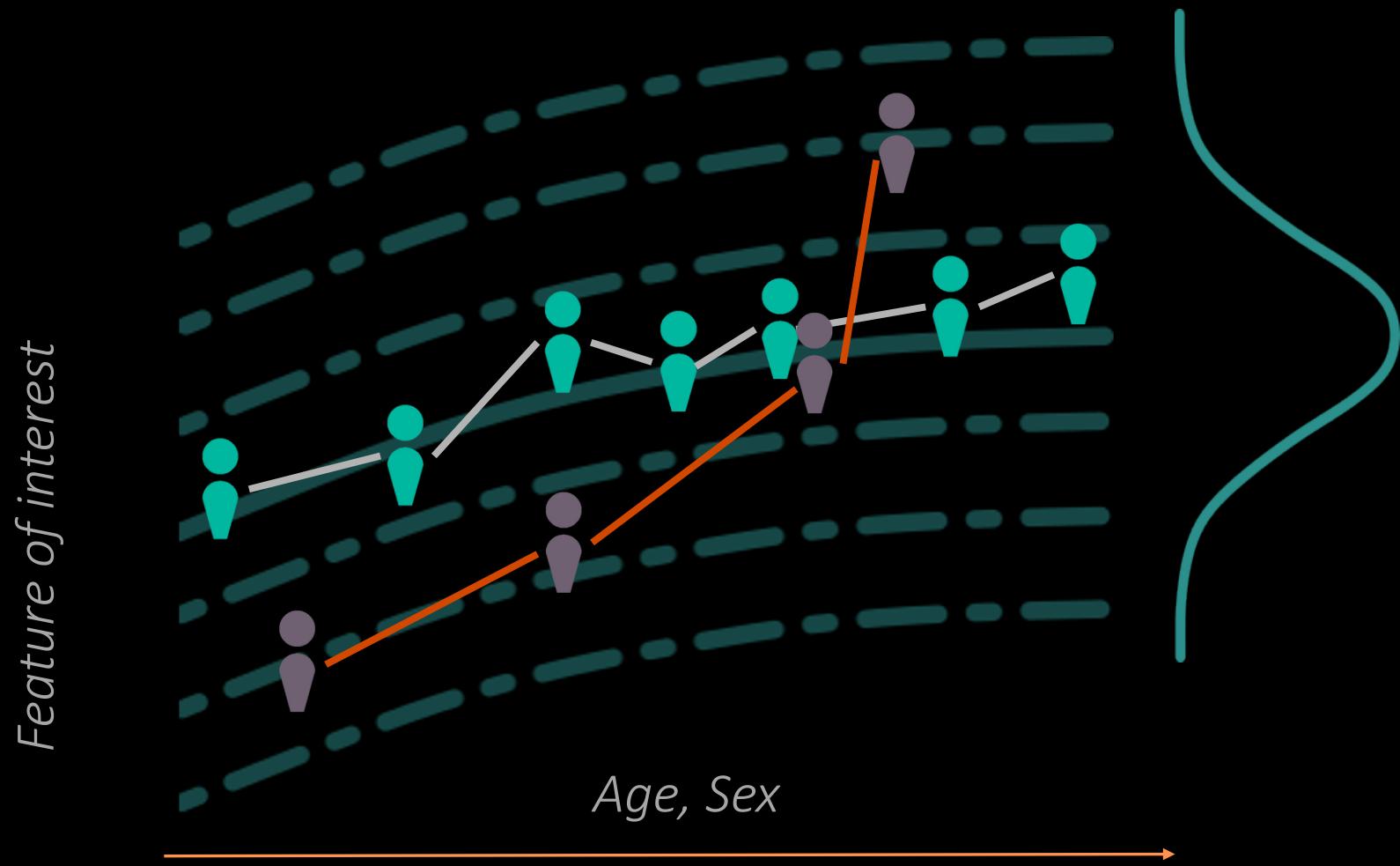


Bayer, J. M. M. *et al.* Accommodating site variation in neuroimaging data using normative and hierarchical Bayesian models. *Neuroimage* **264**, 119699 (2022).

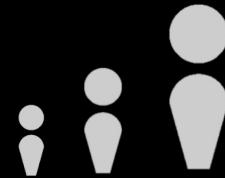


Cirstian, R. *et al.* Lifespan normative models of white matter fractional anisotropy: Applications to Early Psychosis. *bioRxiv.org* 2024.12.11.627897 (2024) doi:10.1101/2024.12.11.627897.

## LONGITUDINAL NORMATIVE MODELLING

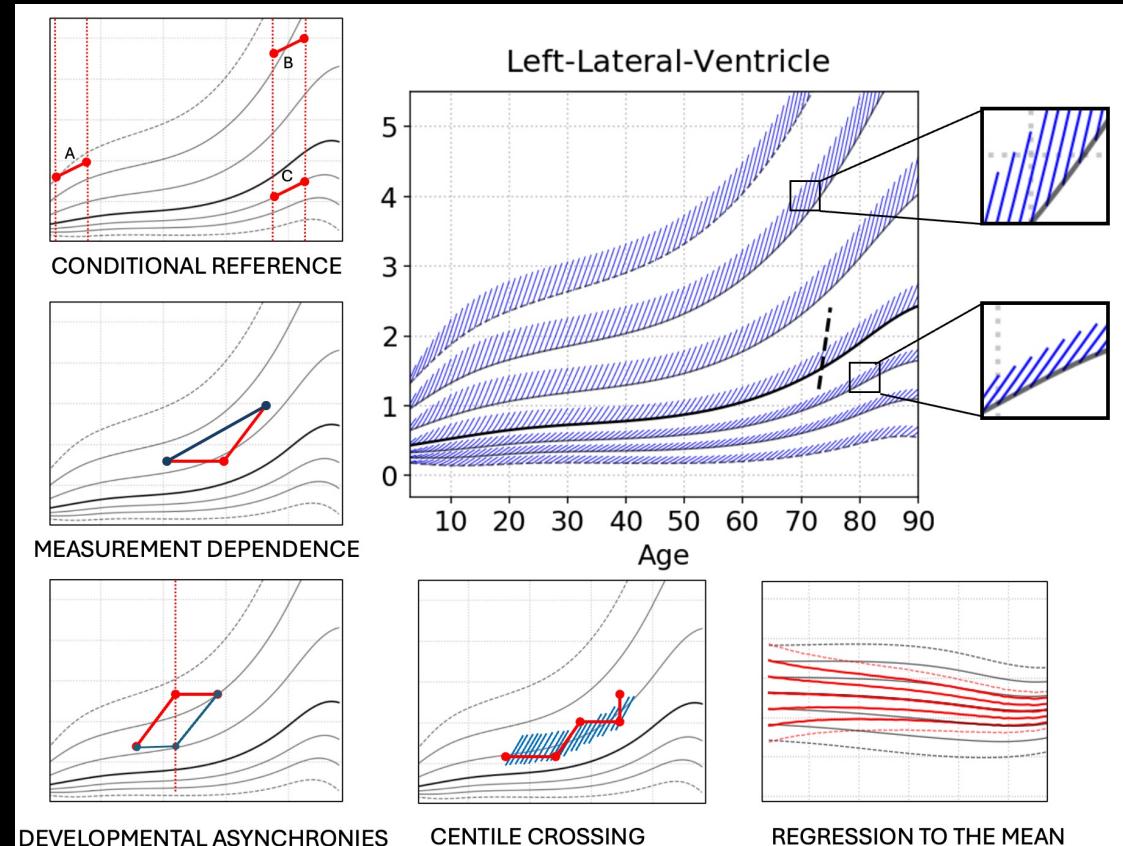


## LONGITUDINAL NORMATIVE MODELLING



**Longitudinal models –  
From longitudinal data  
Thrive lines**

- 22000 longitudinal data points
- Age range: 7 days – 97 years
- Thrive lines: estimate the point of failure to thrive
- Allow for true longitudinal predictions and an estimate of centile crossing
- Normal rate of change varies with age



Bayer 2024, in prep.

[https://github.com/likeajumprope/Tutorial\\_normative\\_modelling](https://github.com/likeajumprope/Tutorial_normative_modelling)

## Tasks

Task 1: Fitting normative models from scratch  [Open in Colab](#)

Task 2: Applying pre-trained normative models  [Open in Colab](#)

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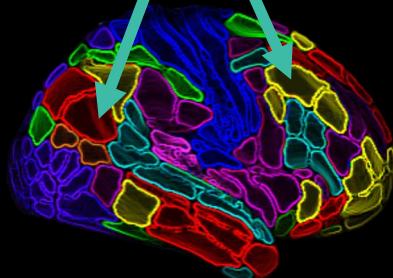
TUTORIAL I.

ESTIMATING LIFESPAN NORMATIVE MODELS

- 
- Install and load the packages
  - Clone the Github directory
  - Split data into train/test

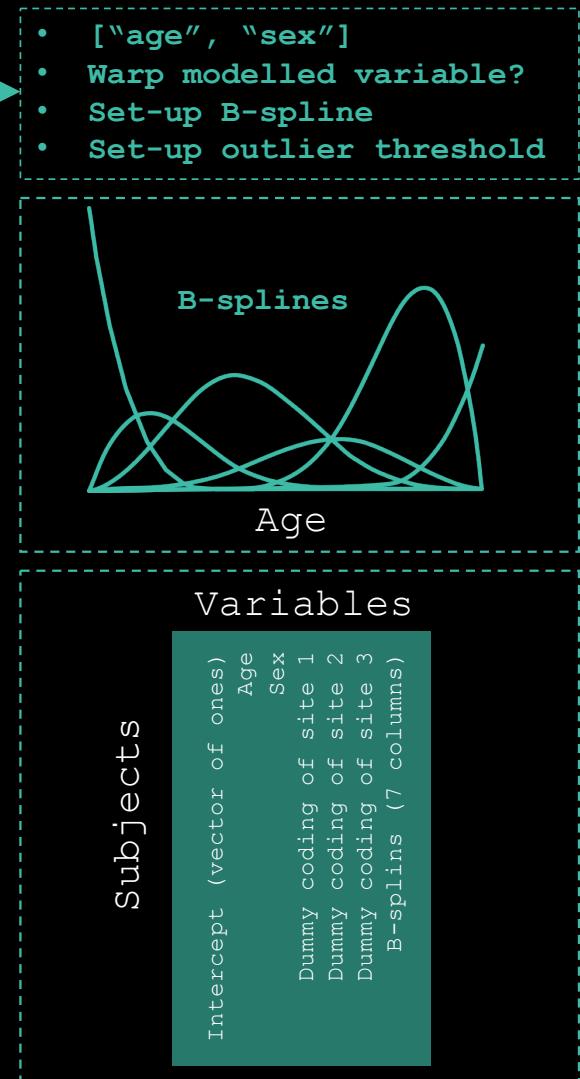
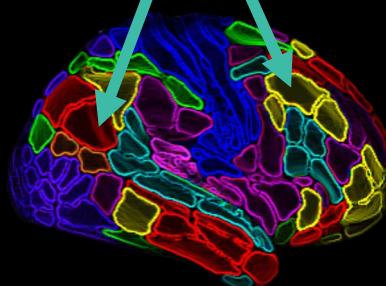
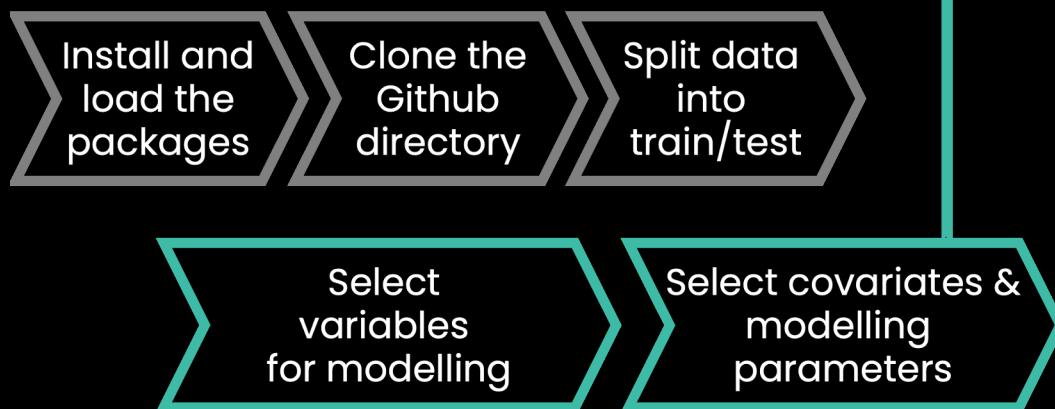
## TUTORIAL I.

## ESTIMATING LIFESPAN NORMATIVE MODELS



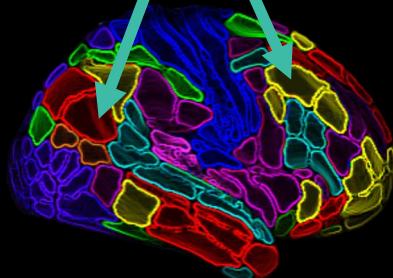
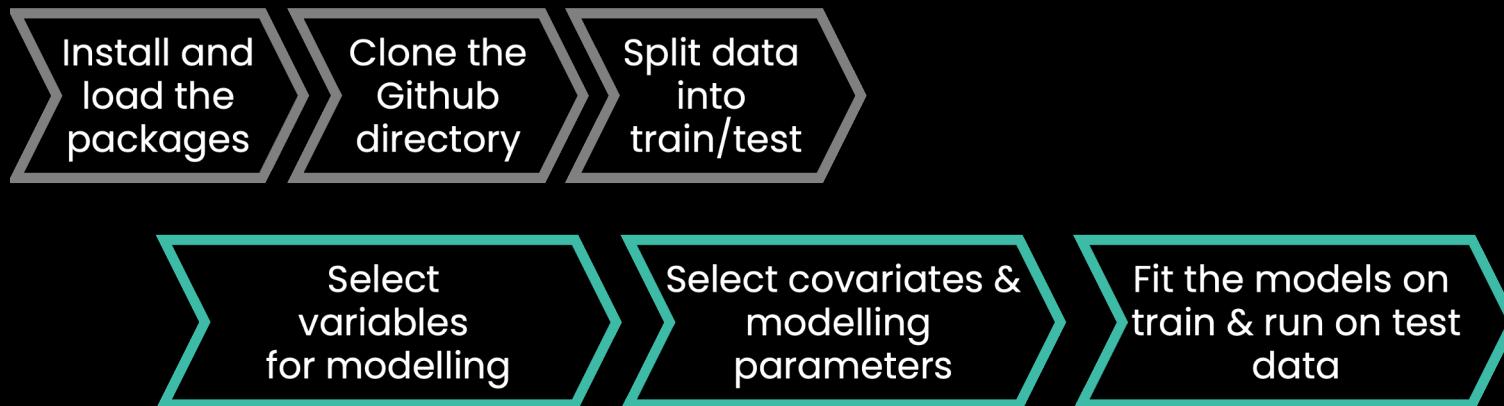
## TUTORIAL I.

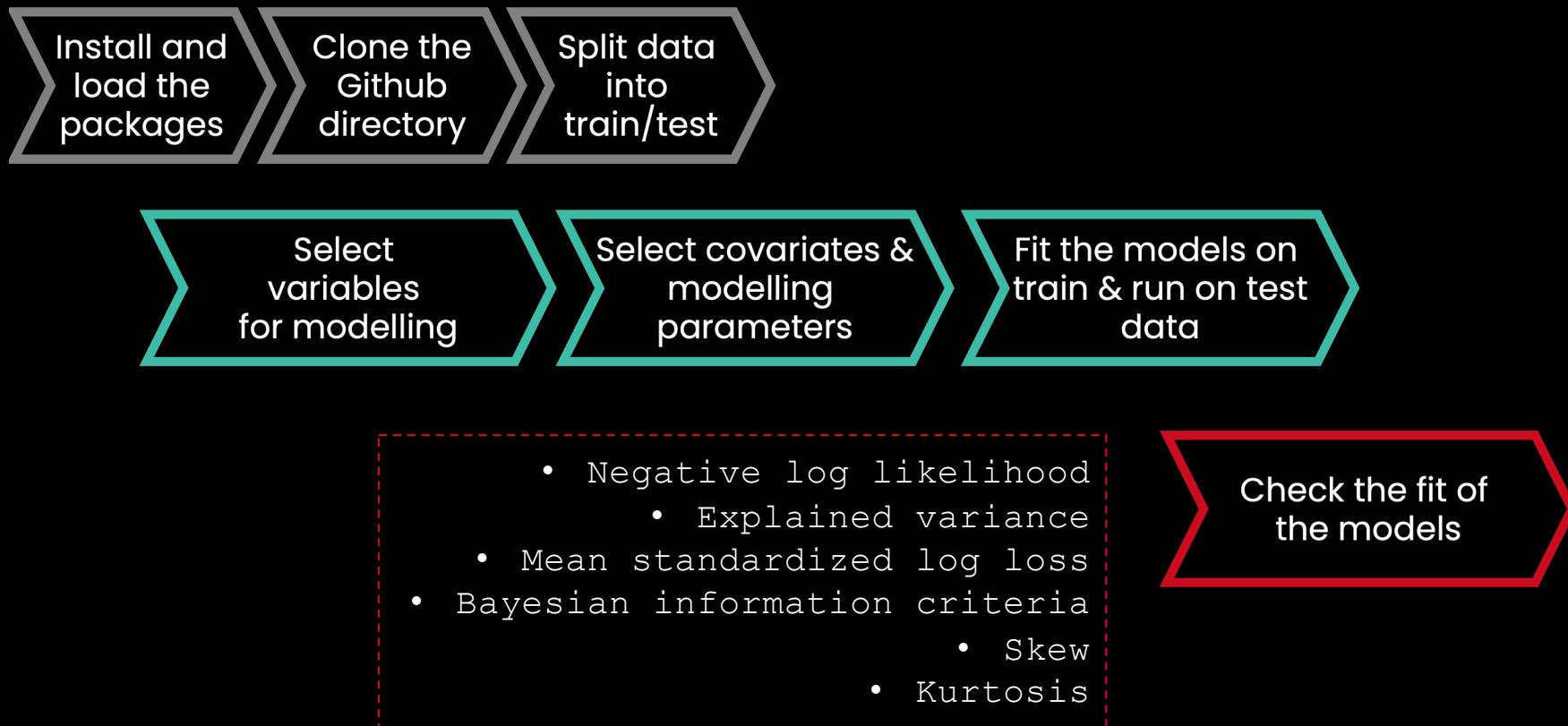
## ESTIMATING LIFESPAN NORMATIVE MODELS

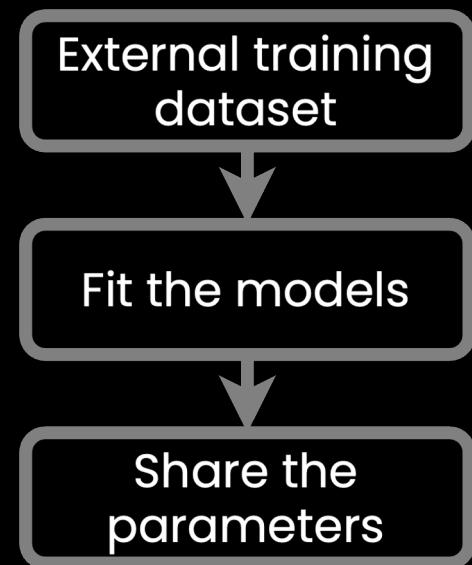


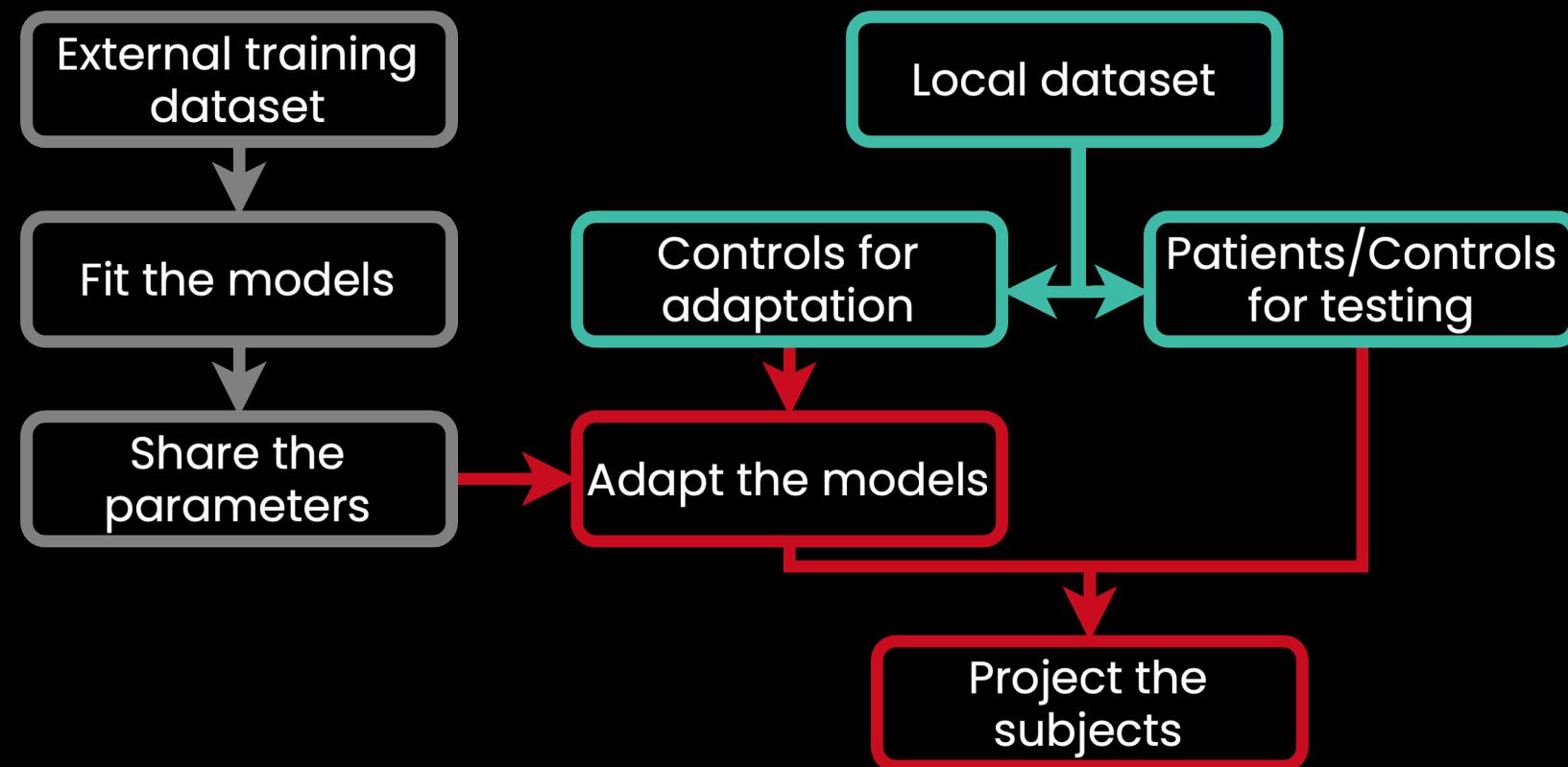
## TUTORIAL I.

## ESTIMATING LIFESPAN NORMATIVE MODELS









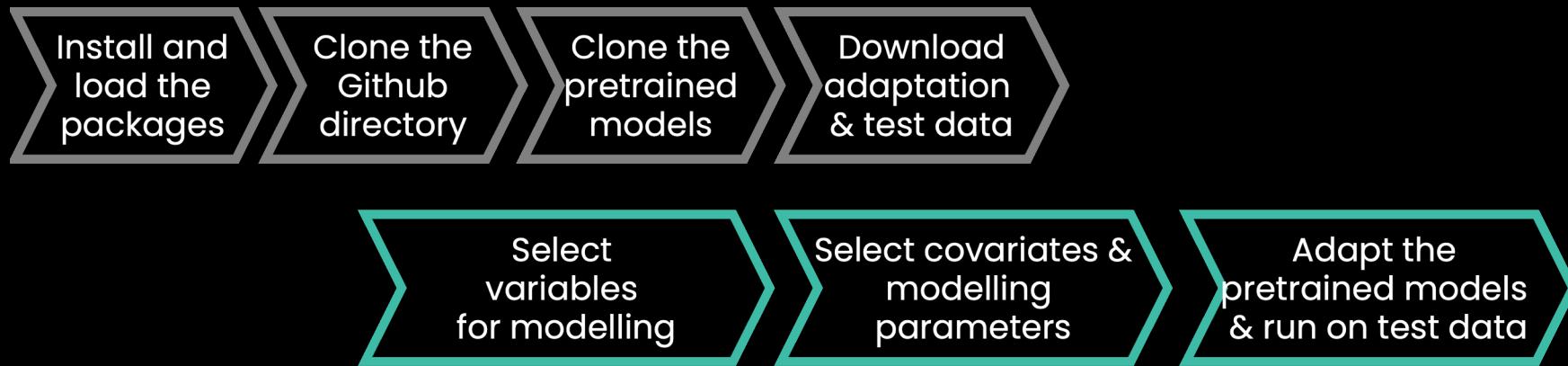
TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS



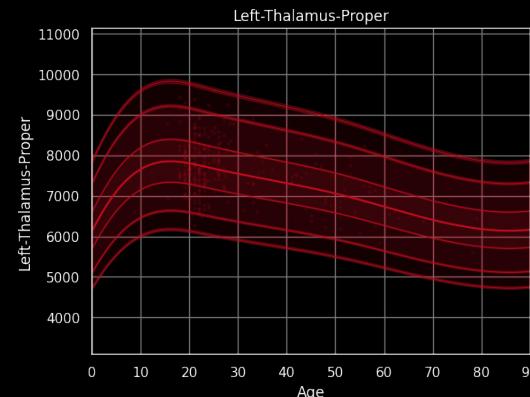
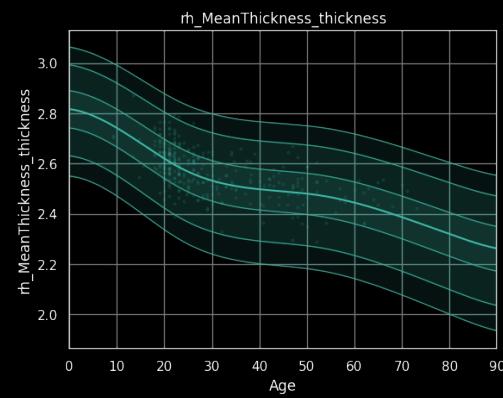
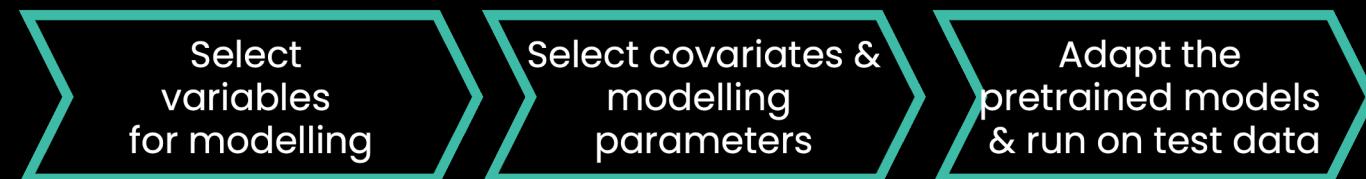
## TUTORIAL II.

## APPLYING PRE-TRAINED NORMATIVE MODELS



## TUTORIAL II.

## APPLYING PRE-TRAINED NORMATIVE MODELS





Download the toolbox  
here:  
[github.com/amarquand](https://github.com/amarquand)



[pcnportal.dccn.nl](https://pcnportal.dccn.nl)



<https://pcntoolkit.readthedocs.io>

## Predictive Clinical Neuroscience Lab

Professor Andre Marquand



THANK YOU!

[https://github.com/likeajumprope/Tutorial\\_normative\\_modelling](https://github.com/likeajumprope/Tutorial_normative_modelling)

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