https://github.com/CharFraza/CPC_ML_tutorial

Tasks

Task 1: Fitting normative models from scratch Open in Colab

Task 2: Applying pre-trained normative models Open in Colab

Task 3: Interpreting and visualizing the outputs of normative models Open in Colab

Task 4: Using the outputs (Z-scores) as features in predictive model Open in Colab

Normative Modeling

Quantifying Individual Risk for Brain Disorders

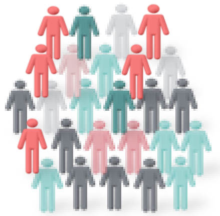
Charlotte Fraza

The Promise of Quantifying Individual Risk for Brain Disorders through Normative Modeling, a Narrative Review

*Material by: @DrHannahSavage, @CharFraza, @BarboraRehak and PCNlab

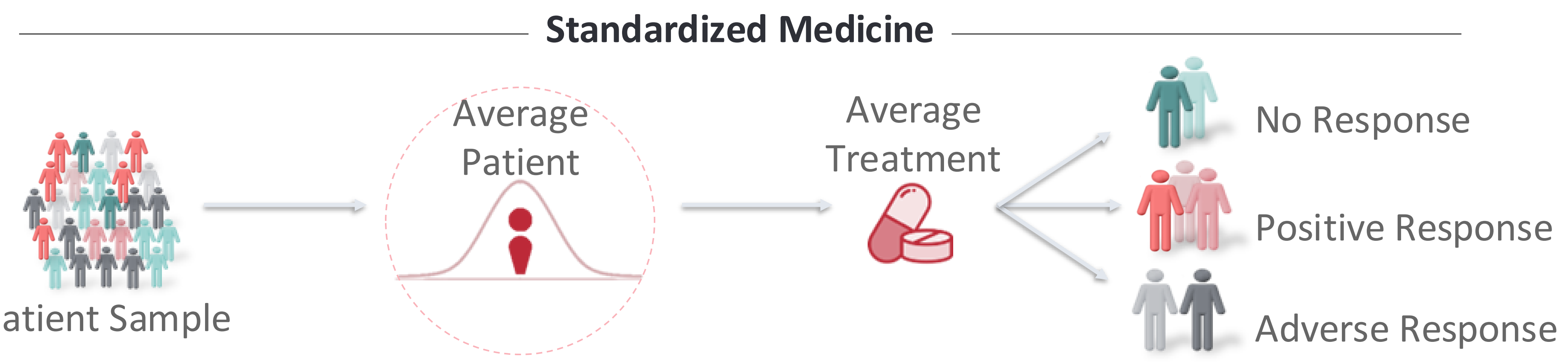
THE GOAL OF COMPUTATIONAL PSYCHIATRY

Standardized Medicine



Patient Sample

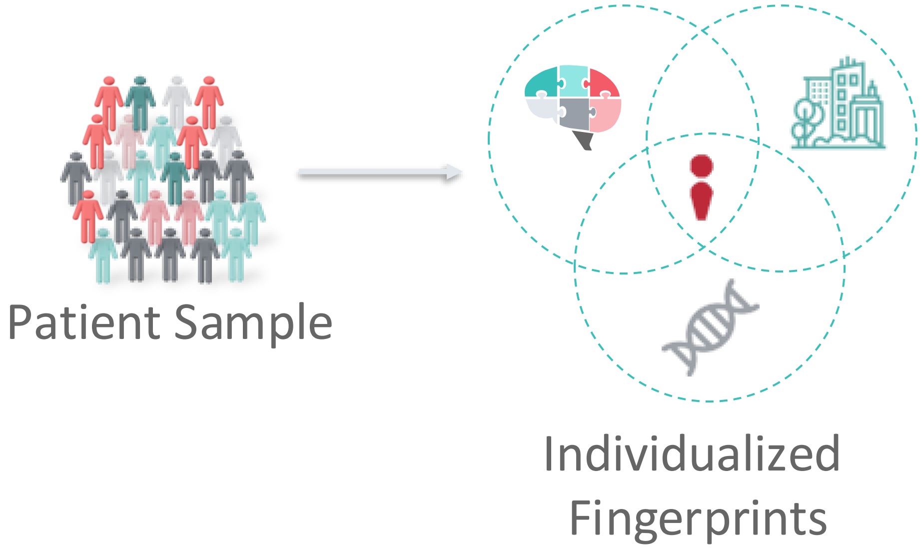
THE GOAL OF COMPUTATIONAL PSYCHIATRY



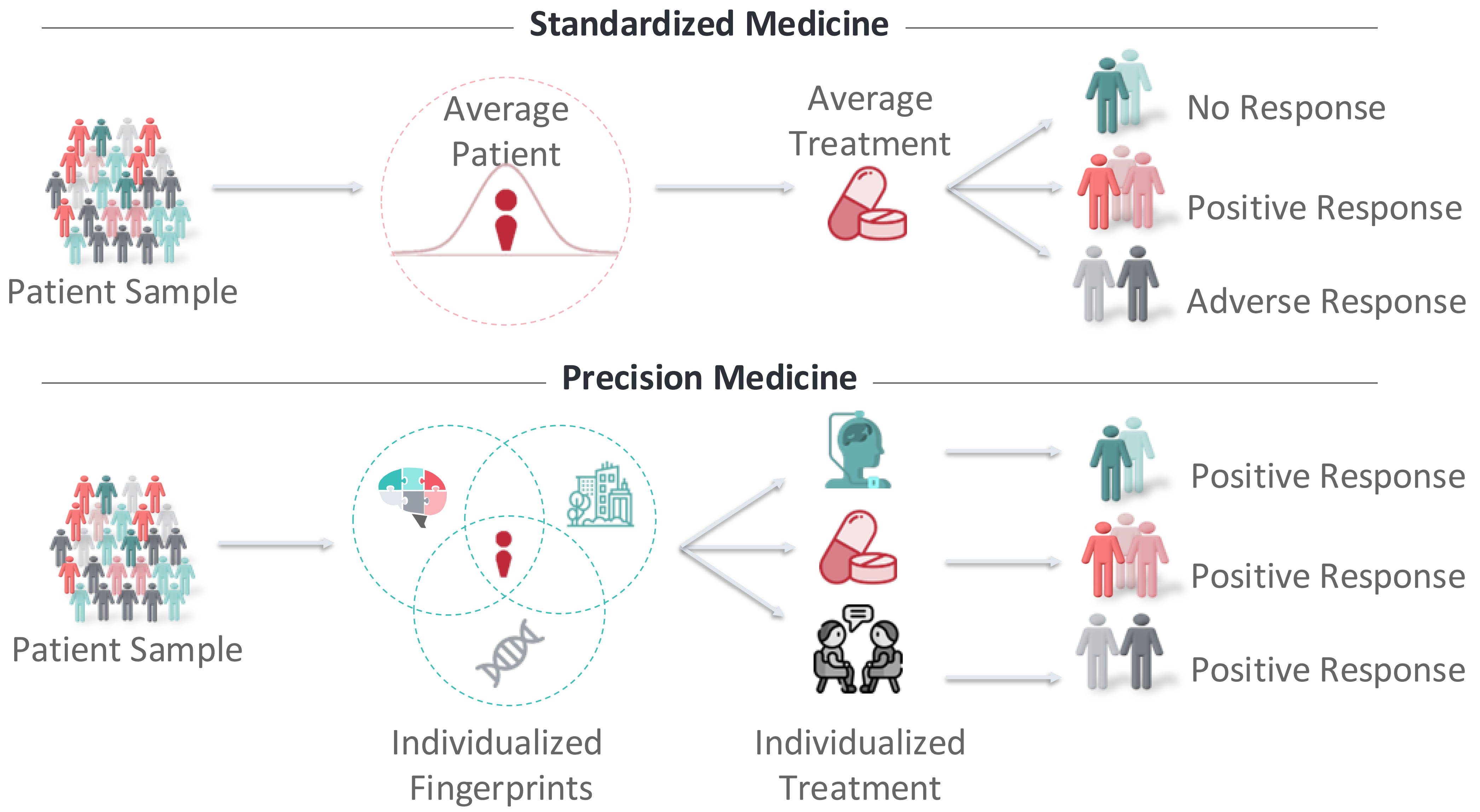
THE GOAL OF COMPUTATIONAL PSYCHIATRY

Standardized Medicine

Precision Medicine



THE GOAL OF COMPUTATIONAL PSYCHIATRY

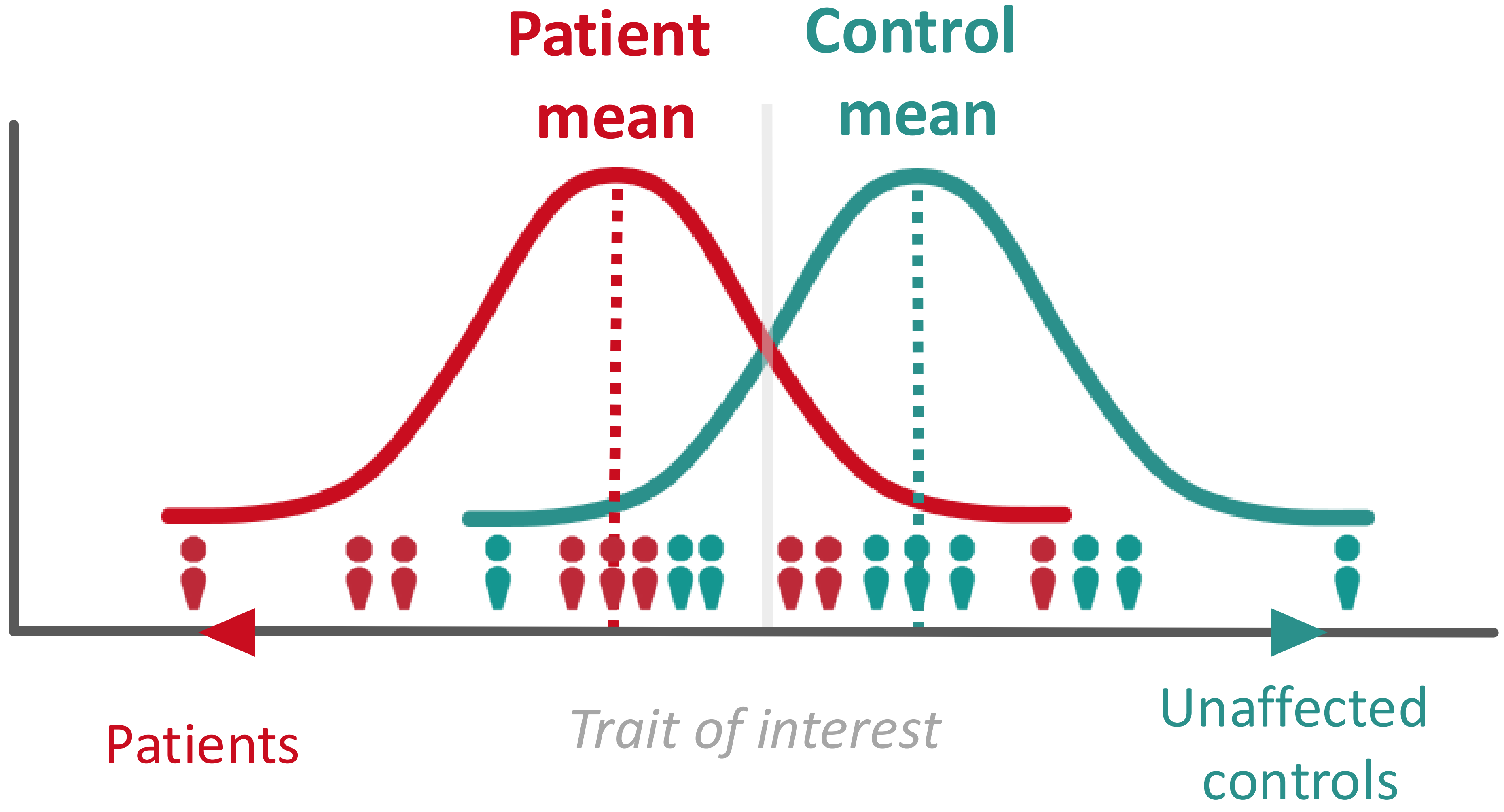


CASE **CONTROL**

Patients

Unaffected controls

THE SHORTCOMINGS OF CLASSICAL STATISTICS



ON HETEROGENEITY

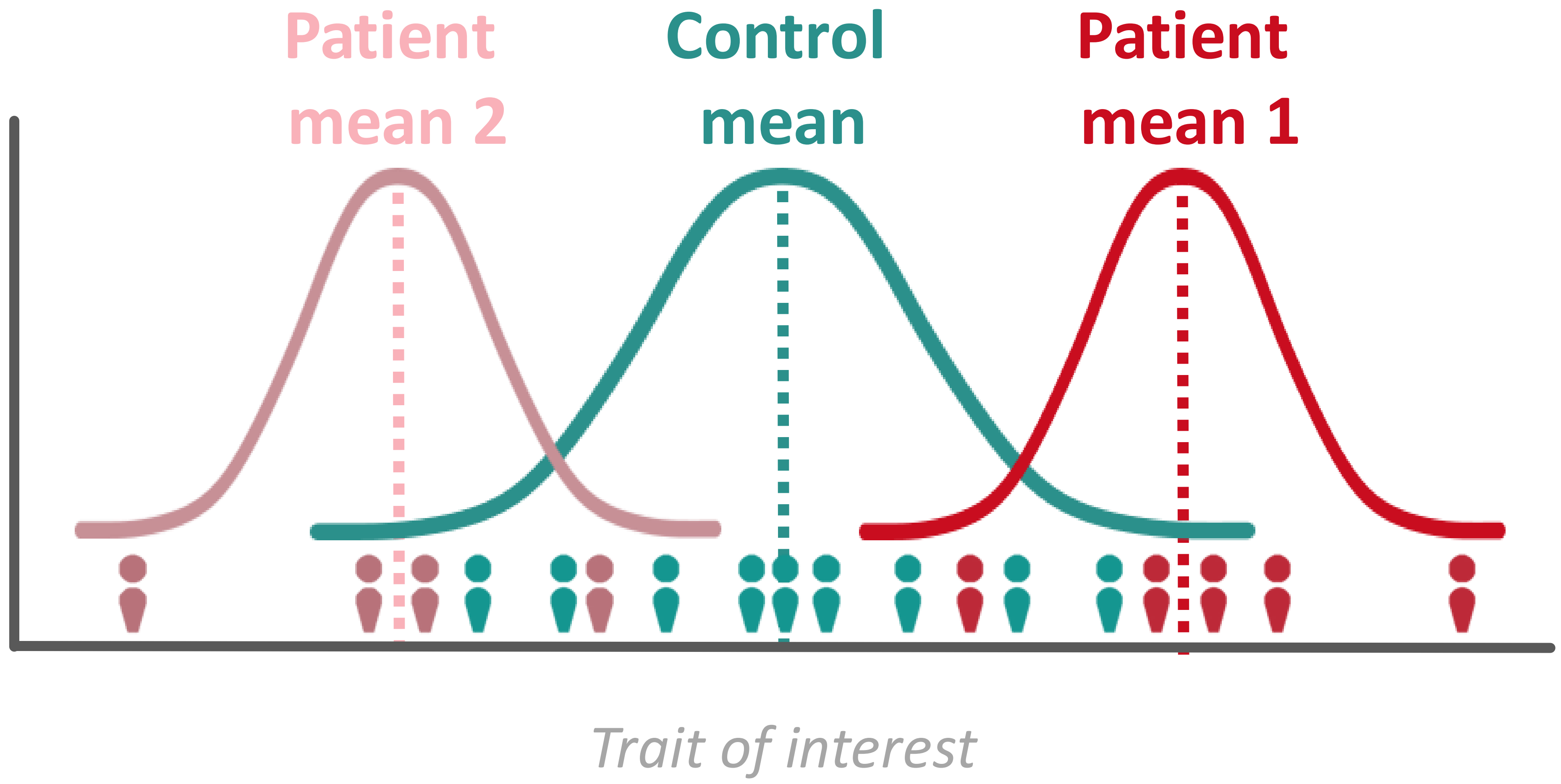
Patients

Unaffected controls

ON HETEROGENEITY

ON HETEROGENEITY

ON HETEROGENEITY



ON HETEROGENEITY

Patients

Unaffected controls

Patients

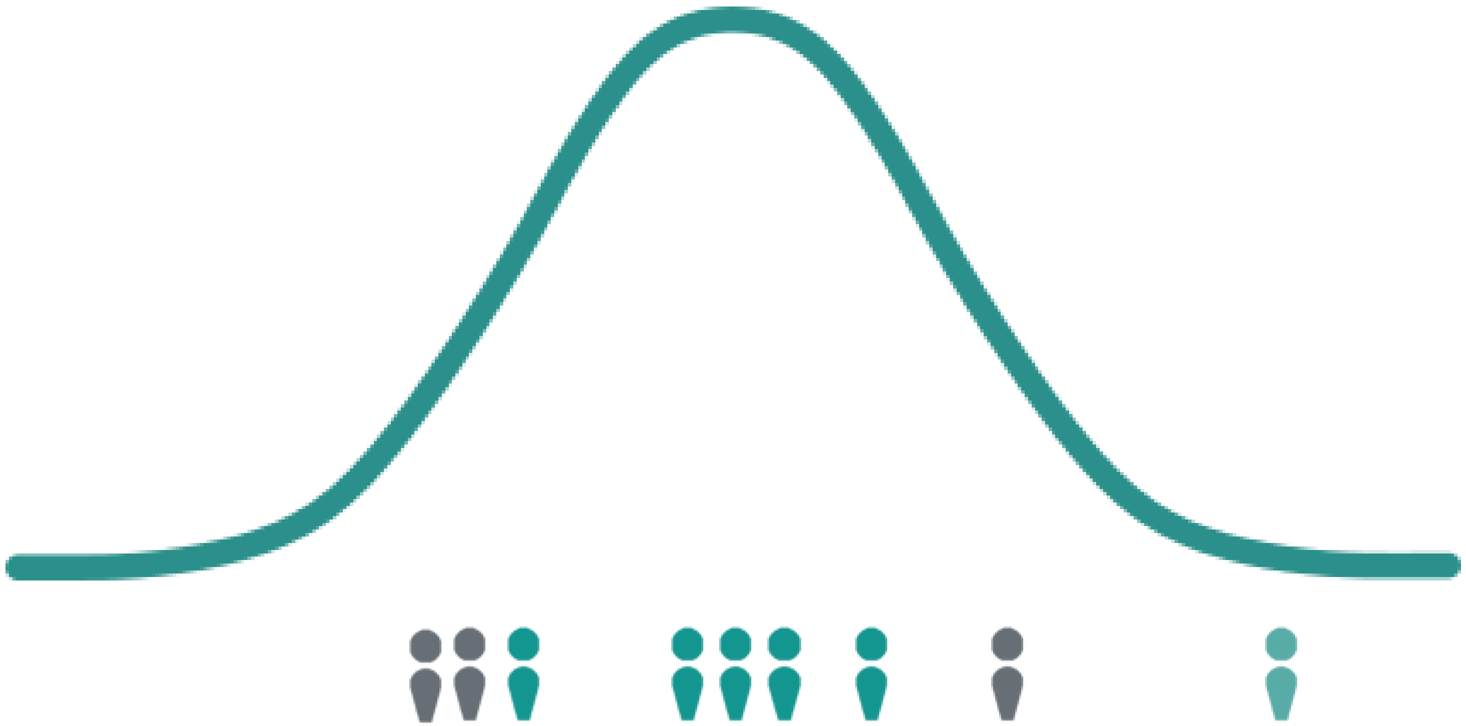
Unaffected controls

ON HETEROGENEITY

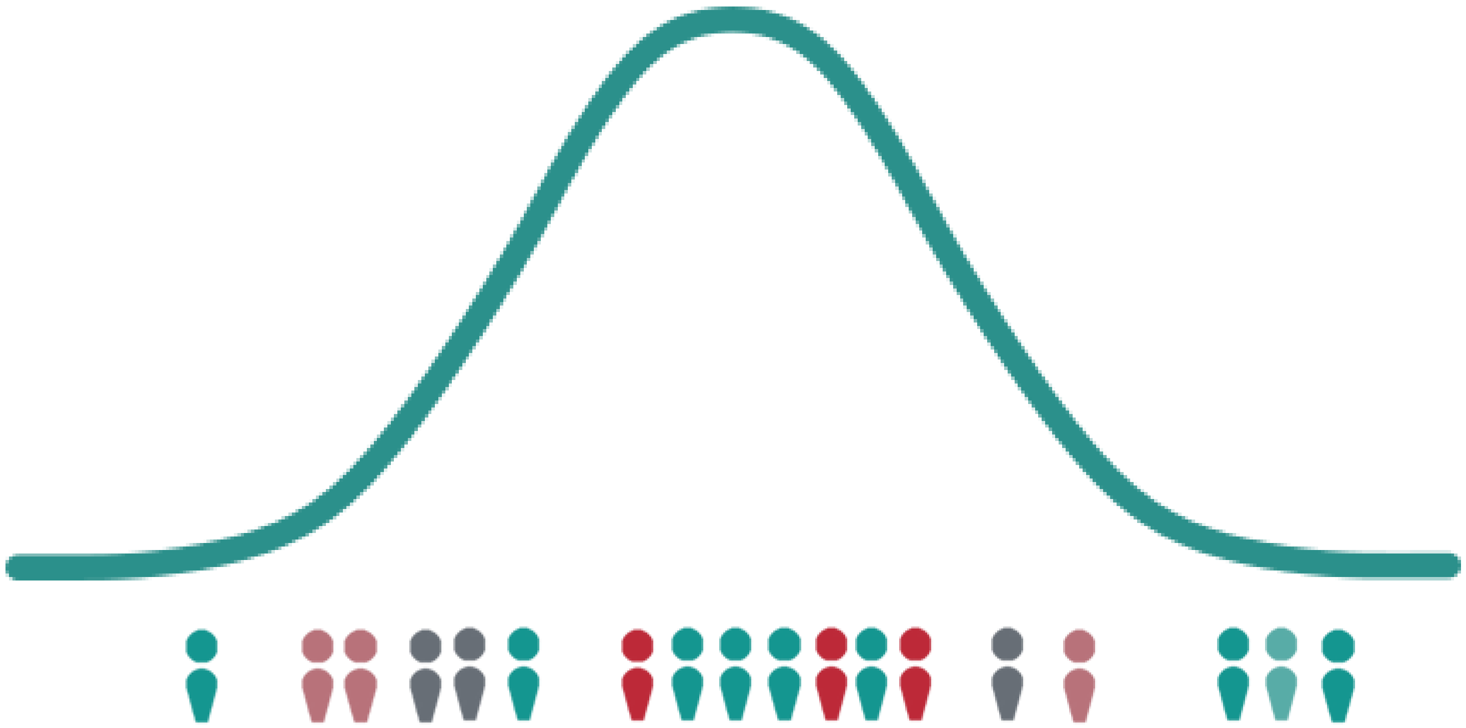
Patients

Unaffected controls

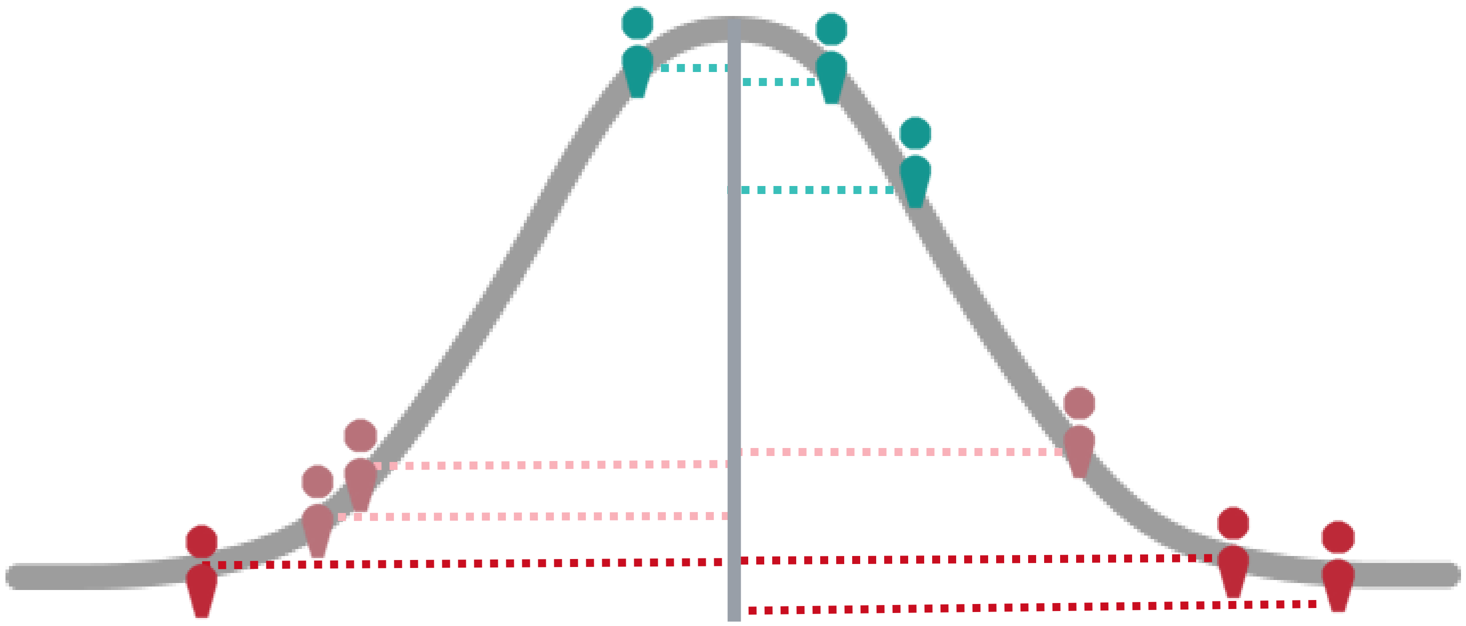
NORMATIVE MODELLING



NORMATIVE MODELLING



NORMATIVE MODELLING



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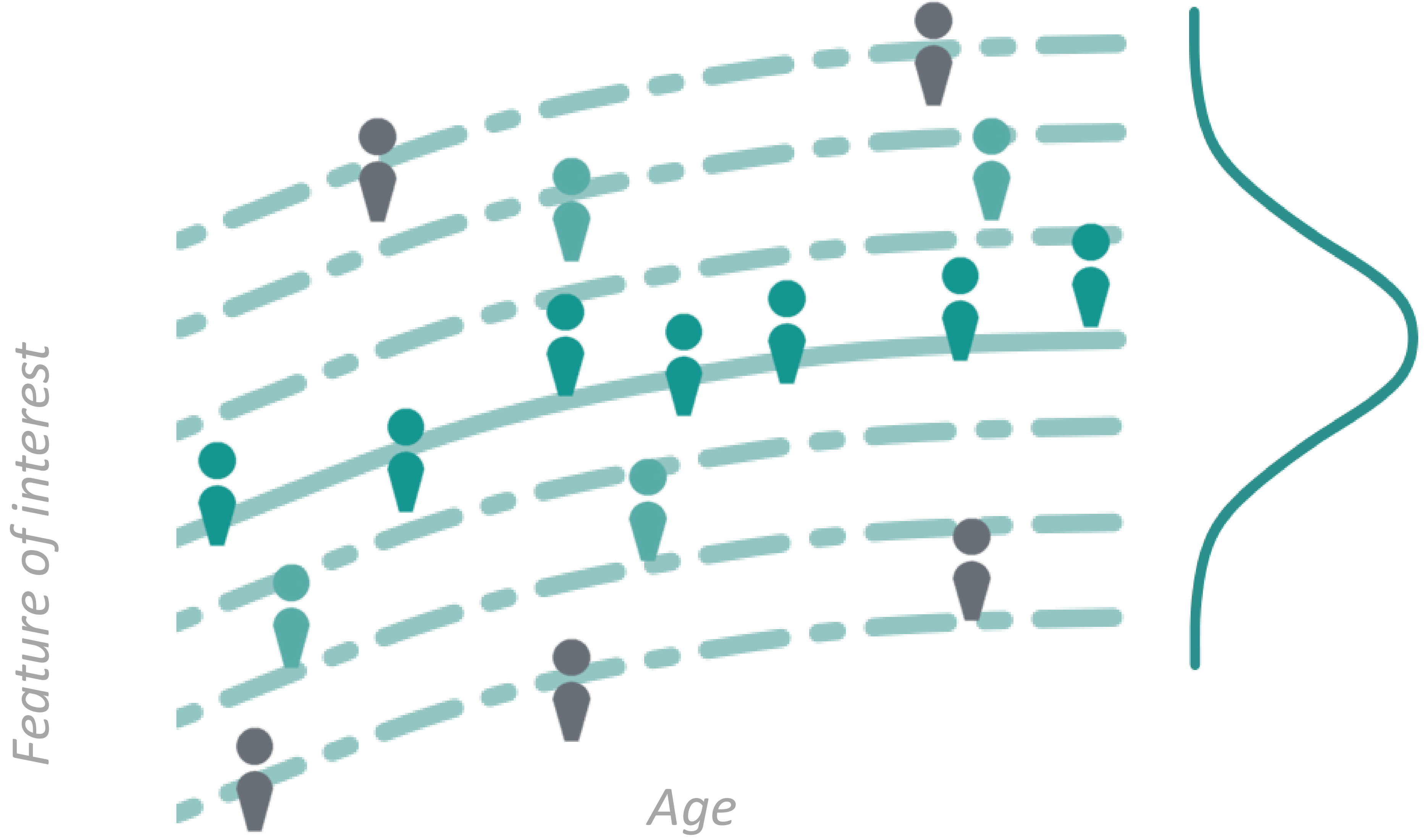

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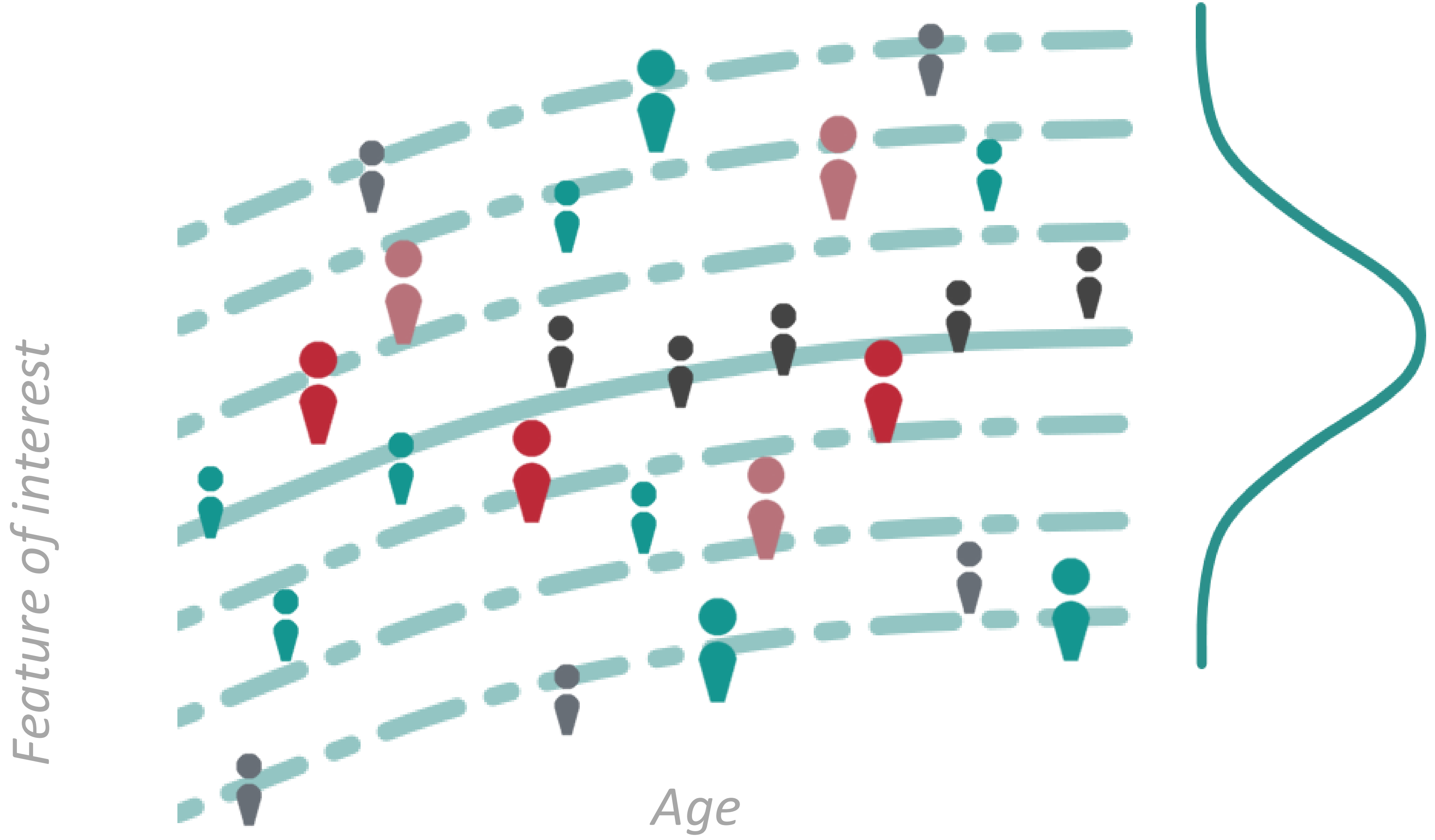

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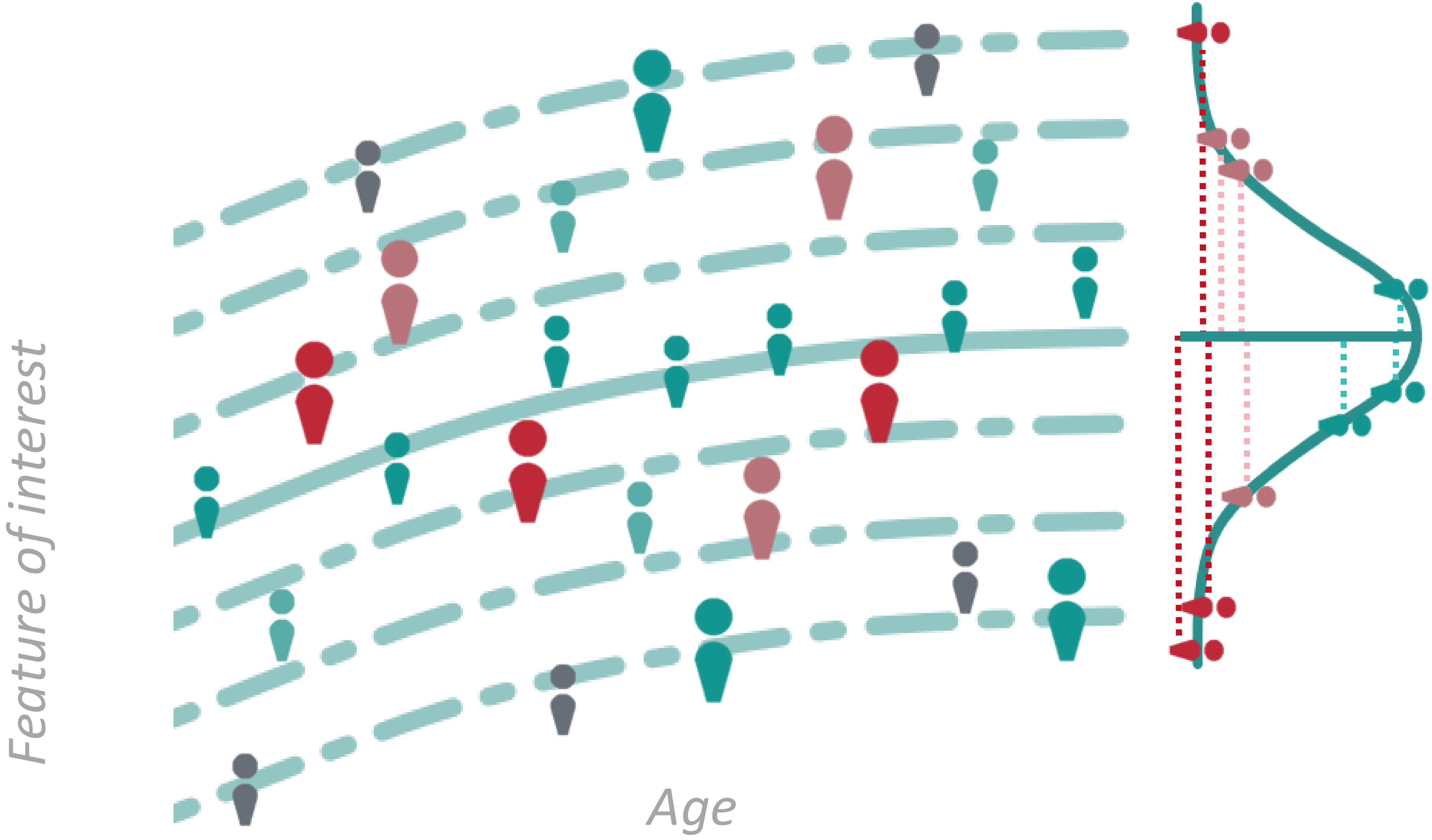

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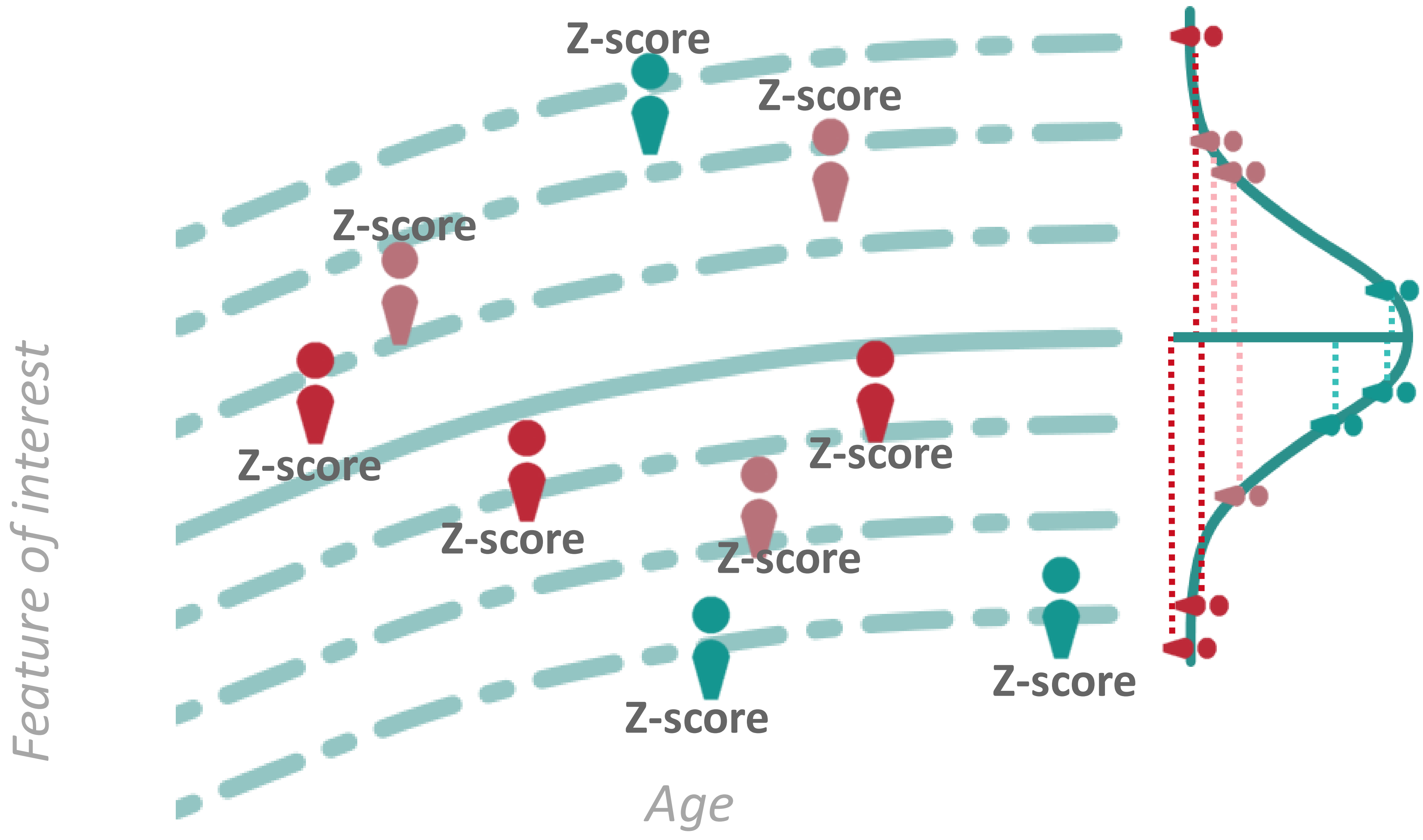
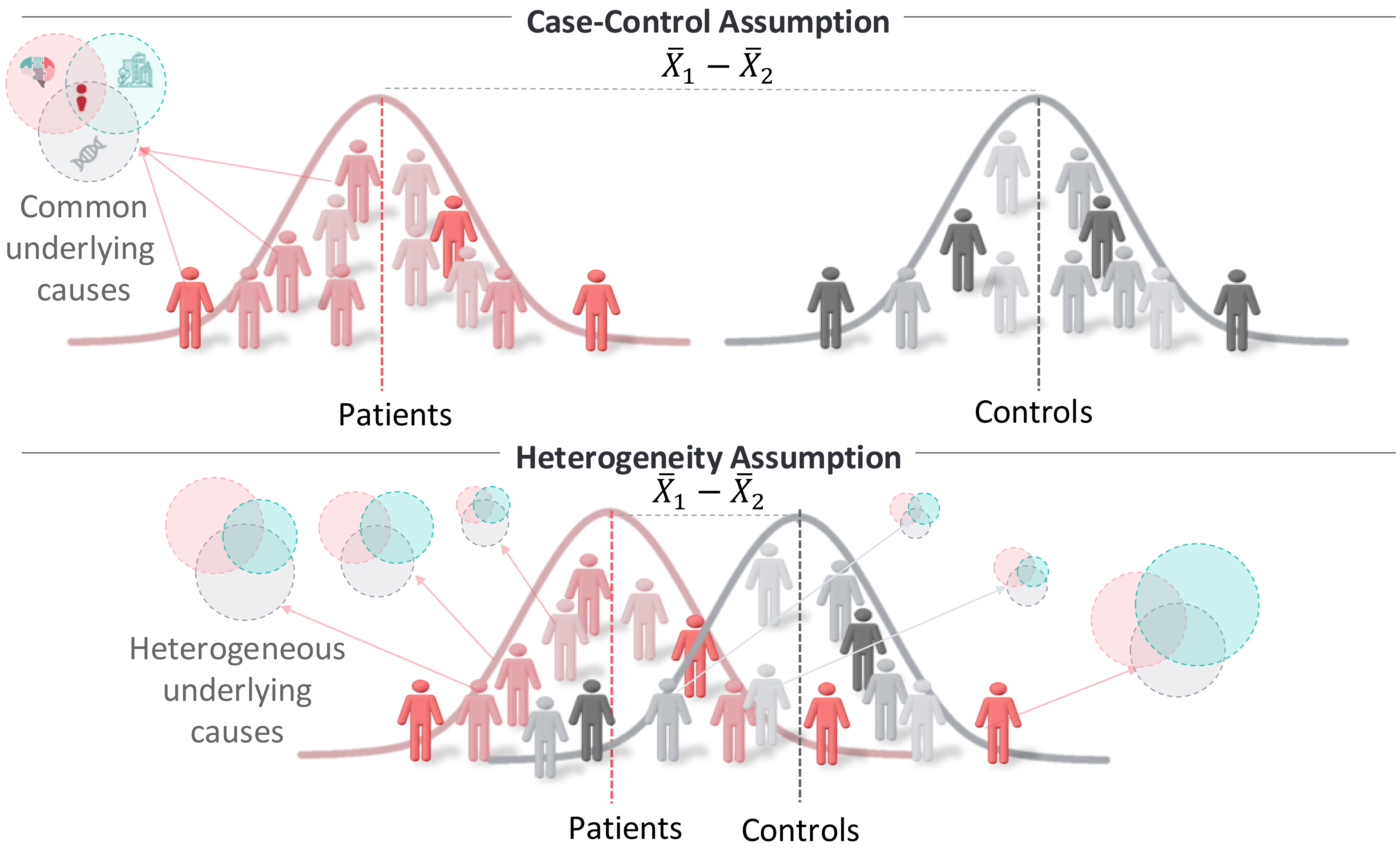
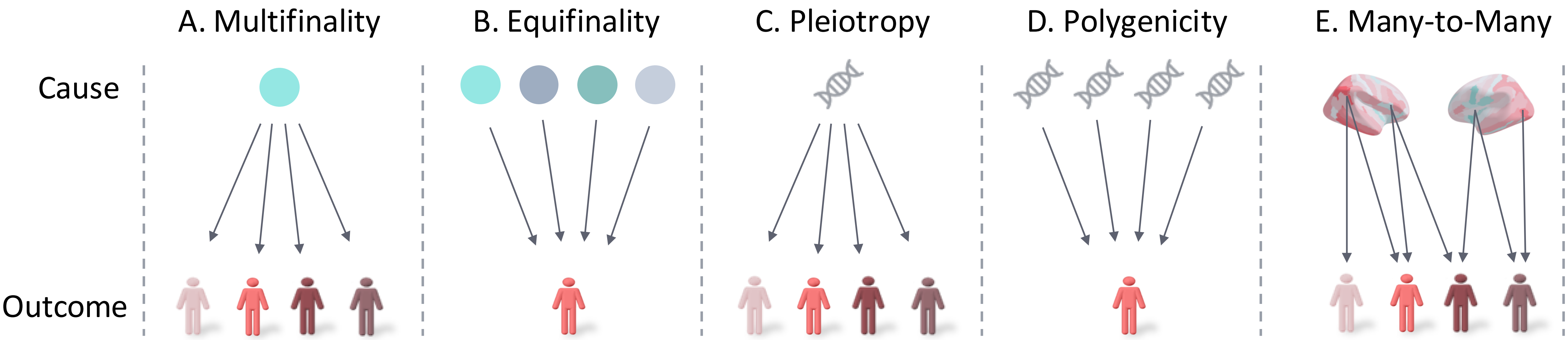



Case-Control Assumption
$\bar{X}_1 - \bar{X}_2$
Common underlying causes
Patients
Controls
Heterogeneity Assumption
$\bar{X}_1 - \bar{X}_2$
Heterogeneous underlying causes
Patients
Controls

NORMATIVE MODELLING

Factors of Heterogeneity



NORMATIVE MODELLING

Y

Brain
(BOLD signal in voxel, ROI)

NORMATIVE MODELLING

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

Brain
(BOLD signal in voxel, ROI)

Covariates
(age, sex, task parameters)

Model parameters

Residuals

NORMATIVE MODELLING

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

Brain
(BOLD signal in voxel, ROI)

Covariates
(age, sex, task parameters)

Model parameters

Residuals

Imaging measures →

Subjects →

Responses (Y)

Predictors →

Subjects →

Covariates (X)

NORMATIVE MODELLING

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

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

NORMATIVE MODELLING

Normative modelling of brain morphometry across the lifespan with CentileBrain: algorithm benchmarking and model optimisation

*Ruiyang Ge, Yuetong Yu, Yi Xuan Qi, Yu-nan Fan, Shiyu Chen, Chuntong Gao, Shalaila S Haas, Faye New, Dorret I Boomsma, Henry Brodaty, Rachel M Brouwer, Randy Buckner, Xavier Caseras, Fabrice Crivello, Eveline A Crone, Susanne Erk, Simon E Fisher, Barbara Franke, David C Glahn, Udo Dannlowski, Dominik Grotegerd, Oliver Gruber, Hilleke E Hulshoff Pol, Gunter Schumann, Christian K Tamnes, Henrik Walter, Lara M Wierenga, Neda Jahanshad, Paul M Thompson, Sophia Frangou, ENIGMA Lifespan Working Group**

The value of normative models in research and clinical practice relies on their robustness and a systematic comparison of different modelling algorithms and parameters; however, this has not been done to date. We aimed to identify the optimal approach for normative modelling of brain morphometric data through systematic empirical benchmarking, by quantifying the accuracy of different algorithms and identifying parameters that optimised model performance. We developed this framework with regional morphometric data from 37 407 healthy individuals (53% female and 47% male; aged 3–90 years) from 87 datasets from Europe, Australia, the USA, South Africa, and east Asia following a comparative evaluation of eight algorithms and multiple covariate combinations pertaining to image acquisition and quality, parcellation software versions, global neuroimaging measures, and longitudinal stability. The multivariate fractional polynomial regression (MFPR) emerged as the preferred algorithm, optimised with non-linear polynomials for age and linear effects of global measures as covariates. The MFPR models showed excellent accuracy across the lifespan and within distinct age-bins and longitudinal stability over a 2-year period. The performance of all MFPR models plateaued at sample sizes exceeding 3000 study participants. This model can inform about the biological and behavioural implications of deviations from typical age-related neuroanatomical changes and support future study designs. The model and scripts described here are freely available through CentileBrain.

NORMATIVE MODELLING

Normative modelling of brain morphometry across the lifespan
model c

Ruiyang Ge, Yueto
Rachel M Brouwer,
Udo Dannlowski, I
Lara M Wierenga, I

The value of nc
of different mc
optimal approa
by quantifying
We developed
47% male; age
a comparative
and quality, pa
fractional poly
for age and lin
lifespan and w
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behavioural in
designs. The n

Correspondence

Fairly evaluating the performance of normative models

We write in response to the recent article in *The Lancet Digital Health* by Ruiyang Ge and colleagues.[1] We would first like to commend the authors on assembling a large multisite dataset, having harmonised protocols, and for their evaluation of many different algorithms for normative modelling in their experiments. However, we would like to express our concern about several aspects of the evaluation of the different algorithms presented in the paper and we believe the evidence presented in the manuscript does not support the conclusions derived.

First, the evaluation metrics used, namely the root mean squared error (RMSE), the mean absolute error (MAE) and the explained variance, are not sufficient to assess the fit of normative models.[2,3] These metrics only measure the accuracy of the estimated centre of the issue arises because the Z-statistics are computed by dividing the residual errors by the RMSE (which can be seen as an estimate of the error variance) rather than fully accounting for the estimated error distribution as proposed elsewhere,[3–5] which can invalidate inference based on Z-scores if the errors have heteroskedastic or non-Gaussian distributions.[2,3,5]

In order to address these issues, we recommend that the authors: (1) comprehensively evaluate the relative performance using metrics that are sensitive to the shape (eg, in terms of skew and kurtosis)[2] of the distribution used to model the data;[3] (2) evaluate the fit of resulting Z-statistics to the centiles of a standard normal distribution including for image-derived phenotypes having non-Gaussian distributions; and (3) share the analysis code and preferably also preprocessed publicly available data, to allow other researchers independently validate the results of the study.

AM received fees for lecturing from Wiegerink BV

5 De Boer AAA, Bayer JMM, Kia SM, et al. Non-Gaussian normative modelling with hierarchical Bayesian regression. *Imaging Neurosci (Camb)* 2024; **2:** 1–36.

oa

NORMATIVE MODELLING

Normative modelling of brain morphometry across the lifespan … model c…

Ruiyang Ge, Yueto…
Rachel M Brouwer, …
Udo Dannlowski, …
Lara M Wierenga, …

The value of no… of different mo… optimal approa… by quantifying… We developed… 47% male; age… a comparative… and quality, pa… fractional poly… for age and lin… lifespan and w… models plateau… behavioural in… designs. The n…

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NORMATIVE MODELLING

Normative modelling of brain morphometry across the lifespan with CentileBrain: algorithm benchmarking and model optimisation

Ruiyang Ge, Yı
Rachel M Brou
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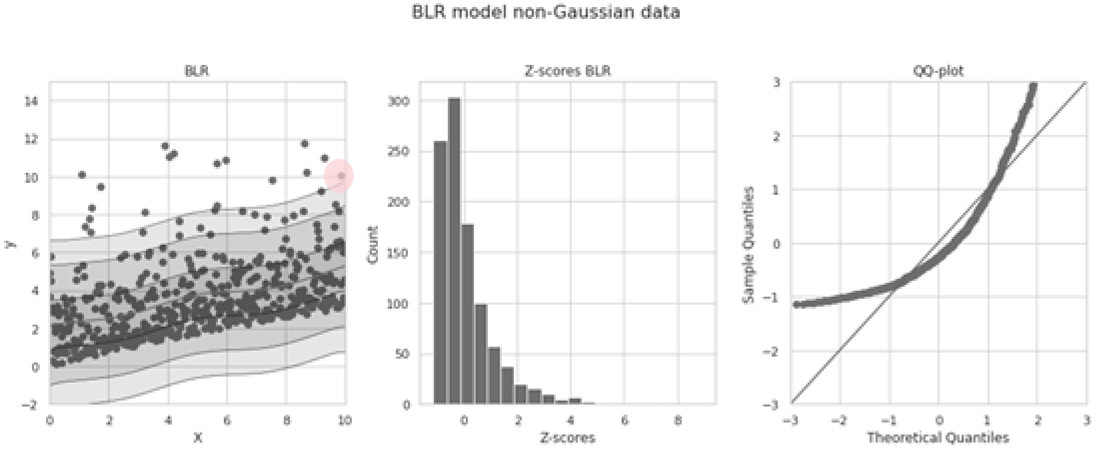
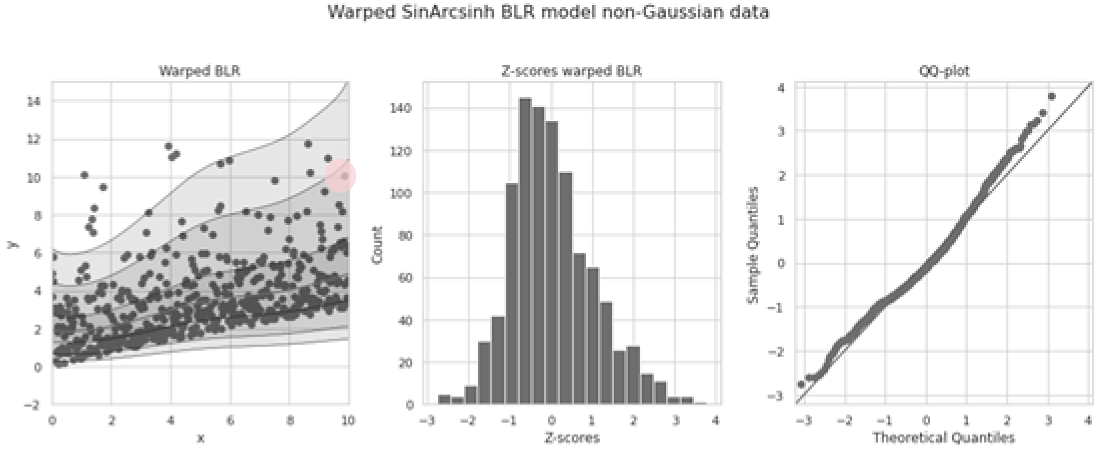
Marquand, Andre, Saige Rutherford, and Richard Dinga. "Fairly evaluating the performance of normative models." *The Lancet Digital Health* 6.11 (2024): e775.

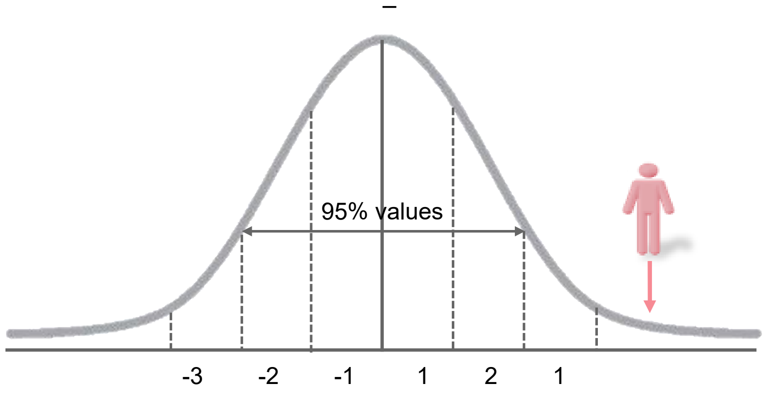
Normative Model Evaluation Steps

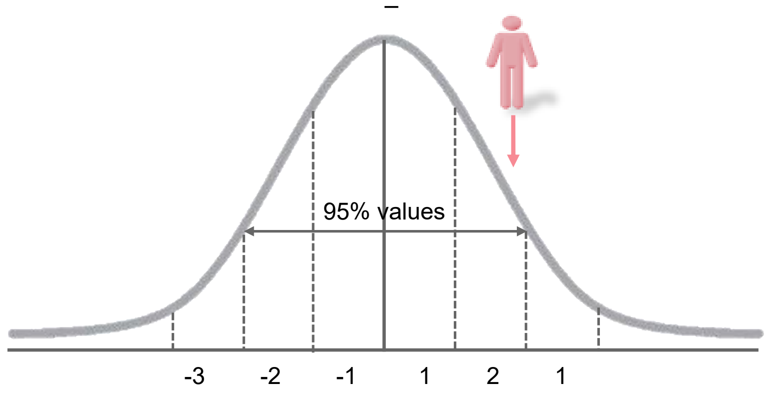
1. **Use Shape-Sensitive Metrics**
   - Go beyond RMSE, MAE, and explained variance
   - Include metrics that assess distribution shape (e.g. skewness, kurtosis, QQ-plots)
   - Focus especially on outer centiles, which are clinically significant
2. **Validate Z-Statistic Calibration**
   - Ensure Z-scores reflect proper standard normal quantiles
   - Account for heteroskedasticity and non-Gaussianity
3. **Reproducibility**
   - Share analysis code and ideally preprocessed public data
   - Enable independent validation of findings by other researchers

NORMATIVE MODELLING









Fraza, Charlotte J., et al. "Warped Bayesian linear regression for normative modelling of big data." NeuroImage 245 (2021): 118715.

$$\varphi_{SinhArcsinh}(\boldsymbol{y};\boldsymbol{\gamma}) = \sinh(b * \operatorname{arcsinh}(\boldsymbol{y}) - a)$$

https://github.com/CharFraza/CPC_ML_tutorial

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TUTORIAL I.

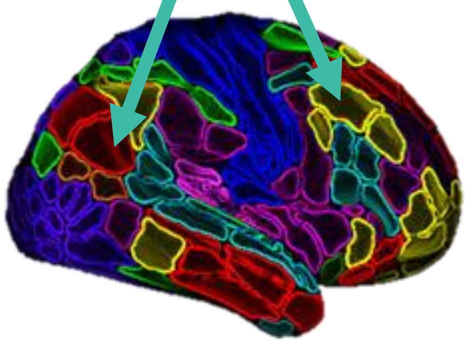
ESTIMATING LIFESPAN NORMATIVE MODELS

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

TUTORIAL I. ESTIMATING LIFESPAN NORMATIVE MODELS

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

Select variables for modelling → Select covariates & modelling parameters



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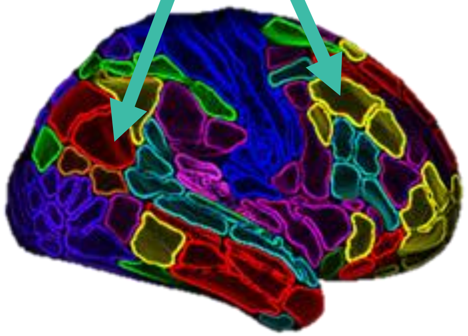
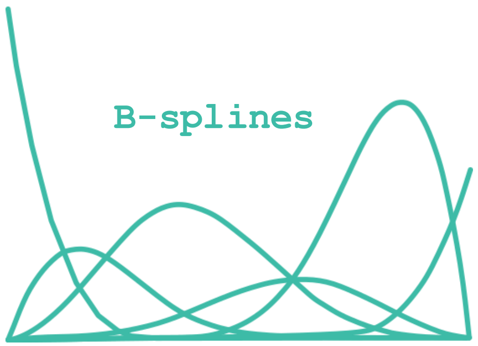


- ["age", "sex"]
- Warp modelled variable?
- Set-up B-spline
- Set-up outlier threshold



Intercept (vector of ones)
Age
Sex
Dummy coding of site 1
Dummy coding of site 2
Dummy coding of site 3
B-splins (7 columns)

TUTORIAL I.

ESTIMATING LIFESPAN NORMATIVE MODELS

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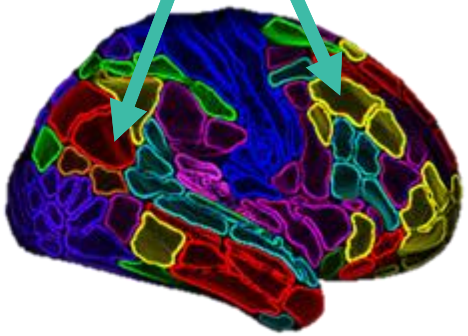
Select variables for modelling

Select covariates & modelling parameters

Fit the models on train & run on test data



TUTORIAL I.

ESTIMATING LIFESPAN NORMATIVE MODELS

Install and load the packages

Clone the Github directory

Split data into train/test

Select variables for modelling

Select covariates & modelling parameters

Fit the models on train & run on test data

- Negative log likelihood
- Explained variance
- Mean standardized log loss
- Bayesian information criteria
- Skew
- Kurtosis

Check the fit of the models

Part 2 Normative Modeling

Applications

The Promise of Quantifying Individual Risk
for Brain Disorders through Normative
Modeling, a Narrative Review

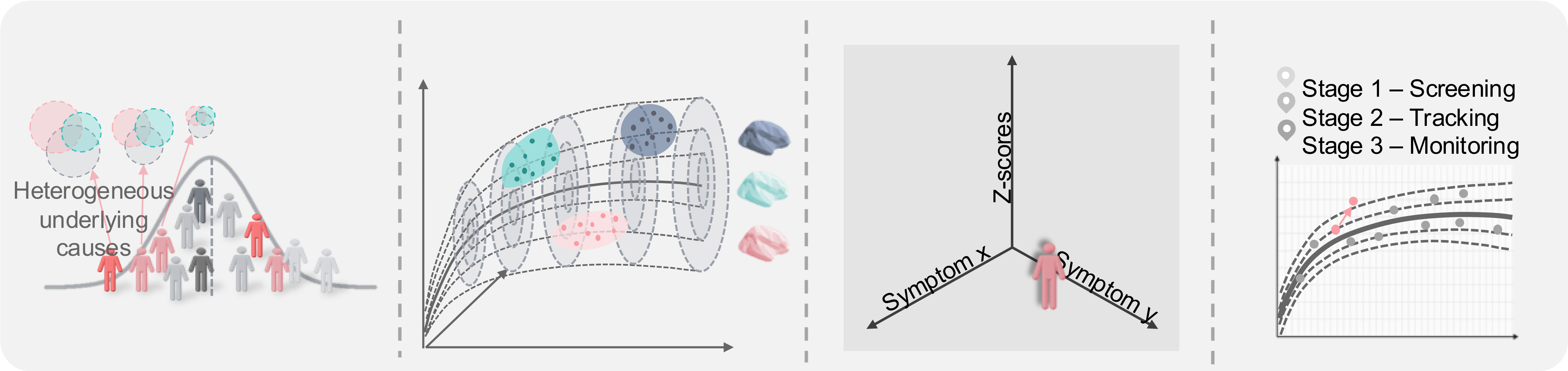
APPLICATIONS

Parsing heterogeneity

Neurobiological subtyping

Brain-behavior mappings

Other



APPLICATIONS

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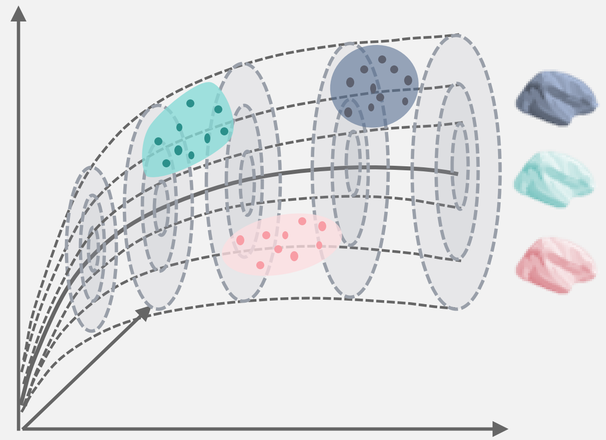
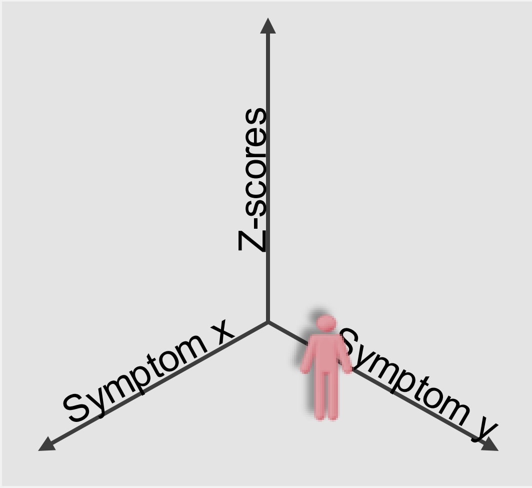
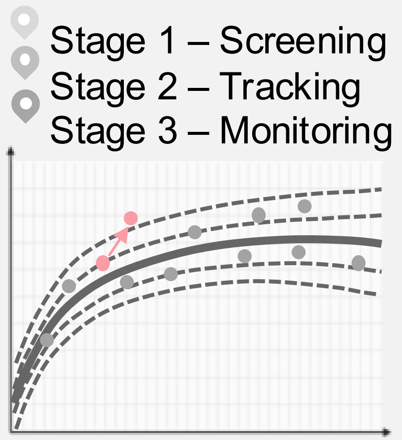
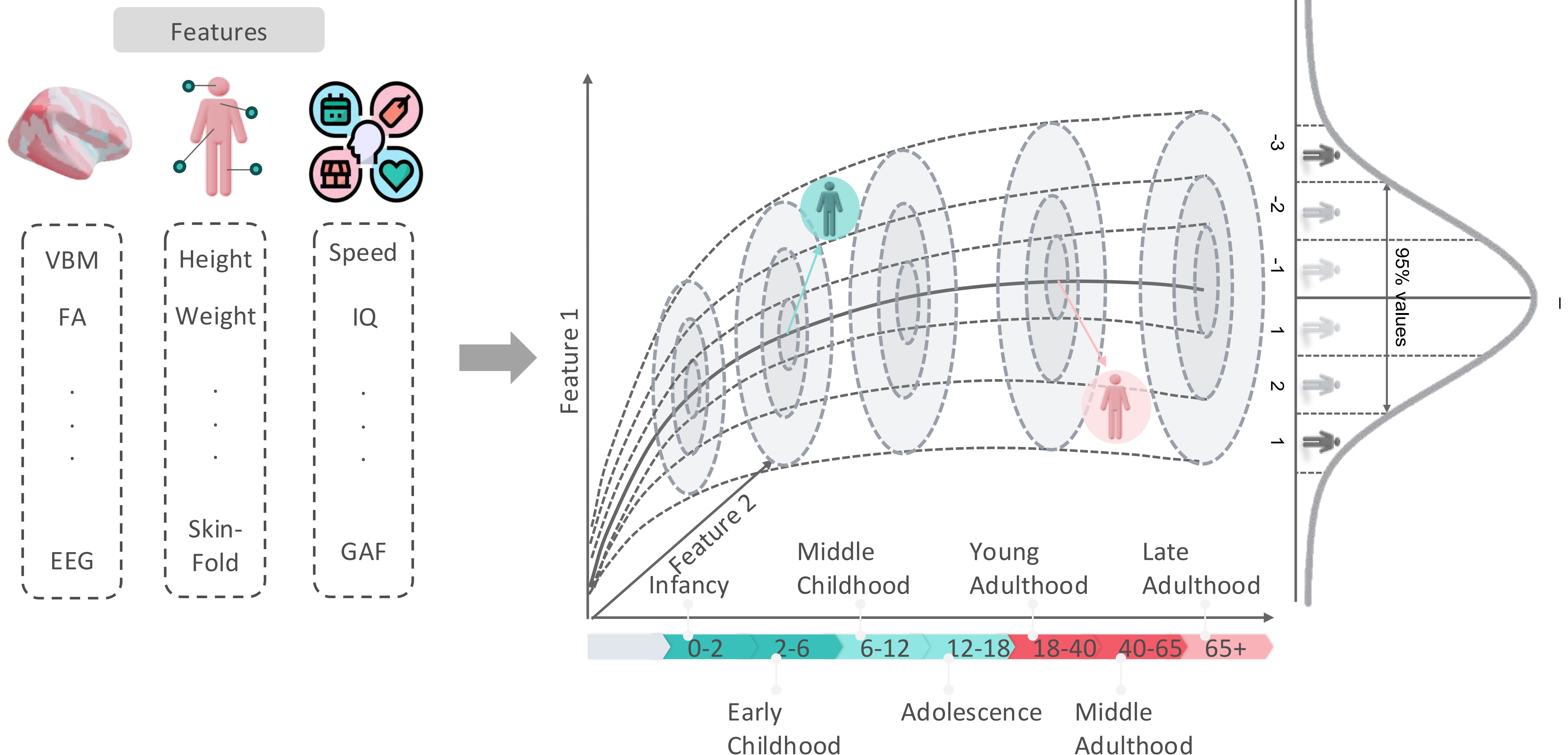






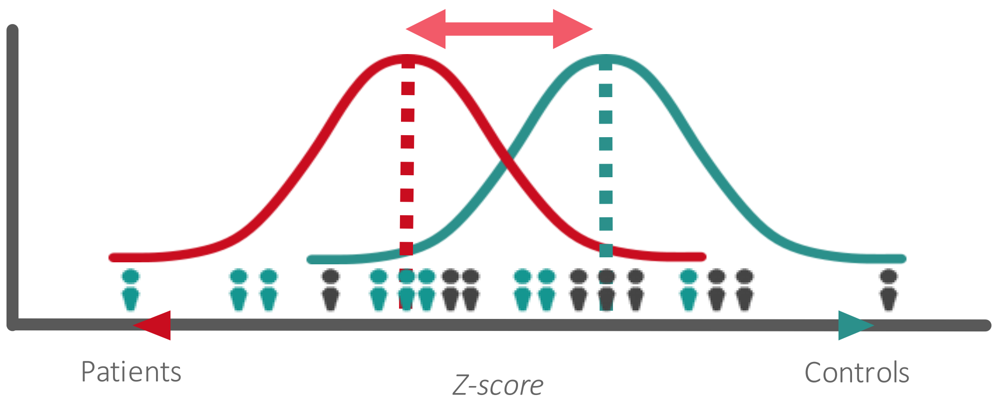
APPLICATIONS

Multimodal Normative Modeling



PARSING HETEROGENEITY

Difference in means

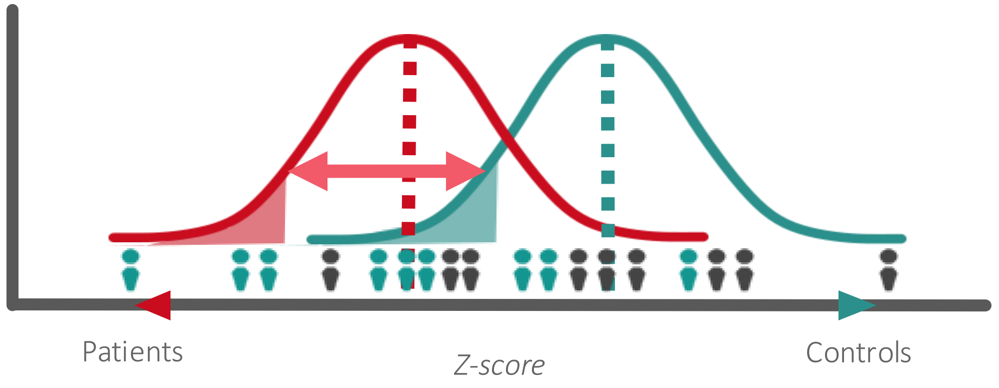


Reminiscent of case-control design, but controlling for individual variation

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

APPLICATIONS

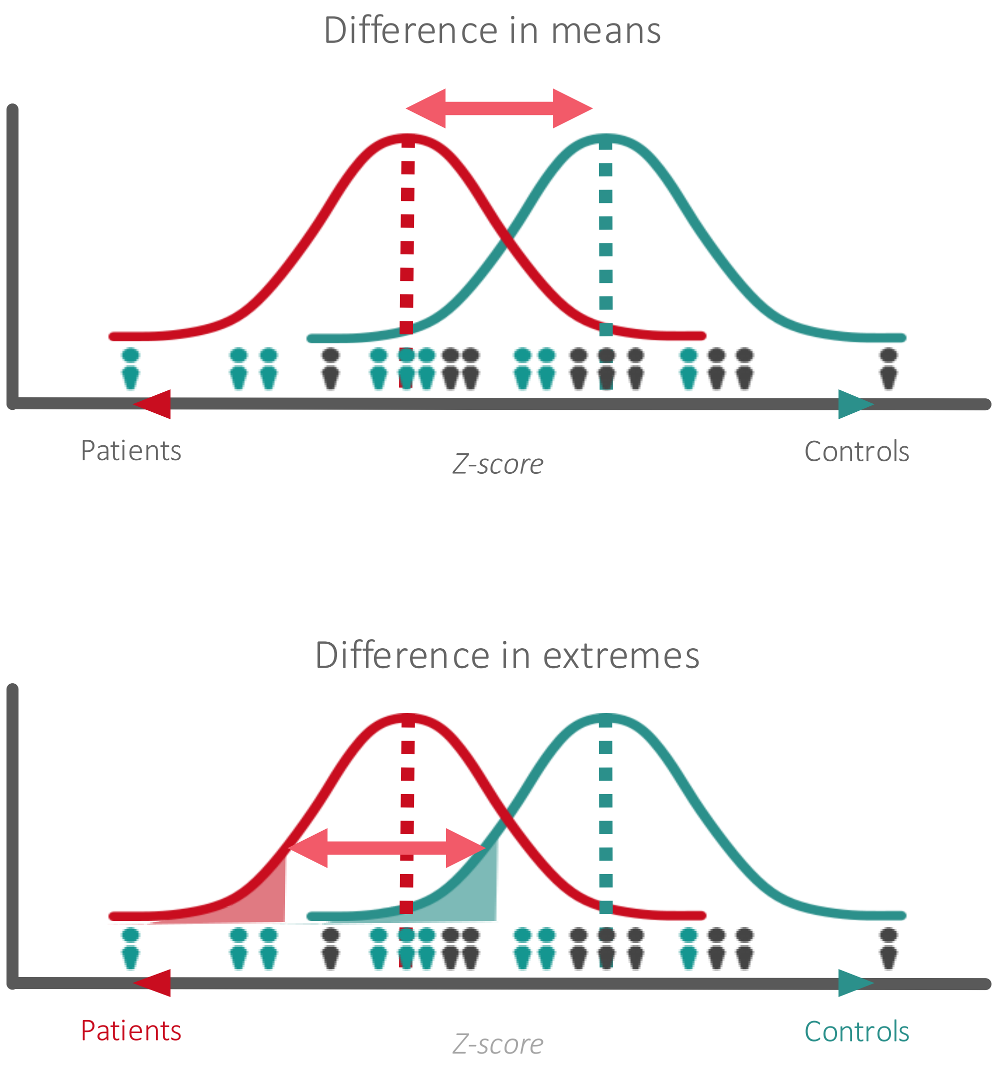
Difference in extremes



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 the distribution of (cortical thickness)?

PARSING HETEROGENEITY



APPLICATIONS

- Training and evaluating the normative model on local dataset
- Using pre-trained models, evaluating on local datasets

- Training and evaluating the normative model on local dataset

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

Cortical thickness/ surface area

Covariates (age, sex, site)

Model parameters

Residuals

Gaussian process regression

ROI/Voxels →

Subjects →

Cortical thickness/ surface area (Y)

Predictors →

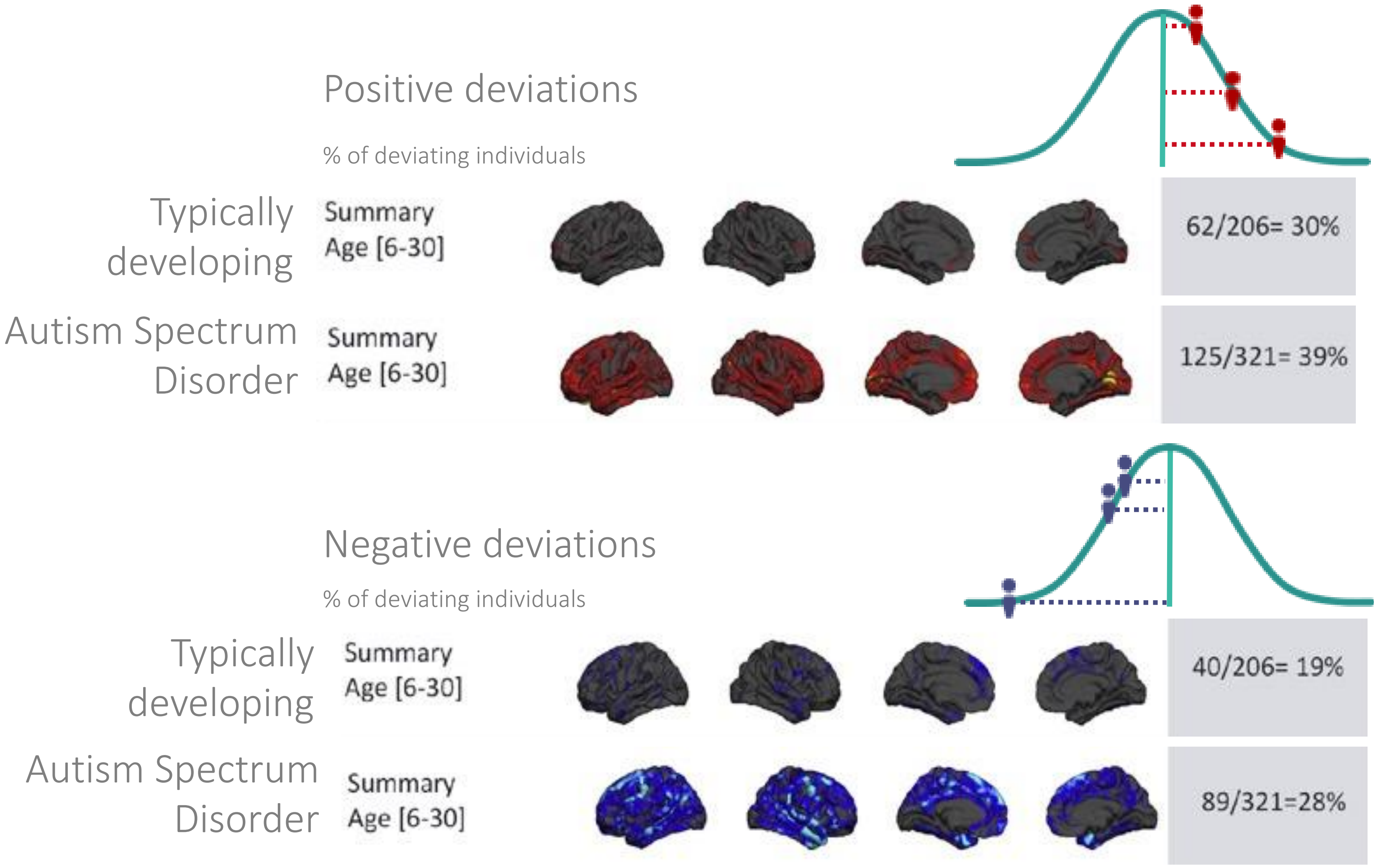
Subjects →

Age
Sex
Site

(X)

PARSING HETEROGENEITY APPLICATIONS: Structural Imaging

- Training and evaluating the normative model on local dataset



Zabihi, M., et al., (2019) Dissecting the Heterogeneous Cortical Anatomy of Autism Spectrum Disorder Using Normative Models. Biol Psychiatry Cogn Neurosci Neuroimaging, 4(6): 567-578.

- Training and evaluating the normative model on local dataset
- Frequency of Extreme Deviations: Patients vs. Reference Cohort

Warped Bayesian linear regression

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

Bold Signal

Covariates (age, sex, Task parameters)

Model parameters

Residuals

Voxels →

Subjects →

Z-statistic image (Y)

Predictors →

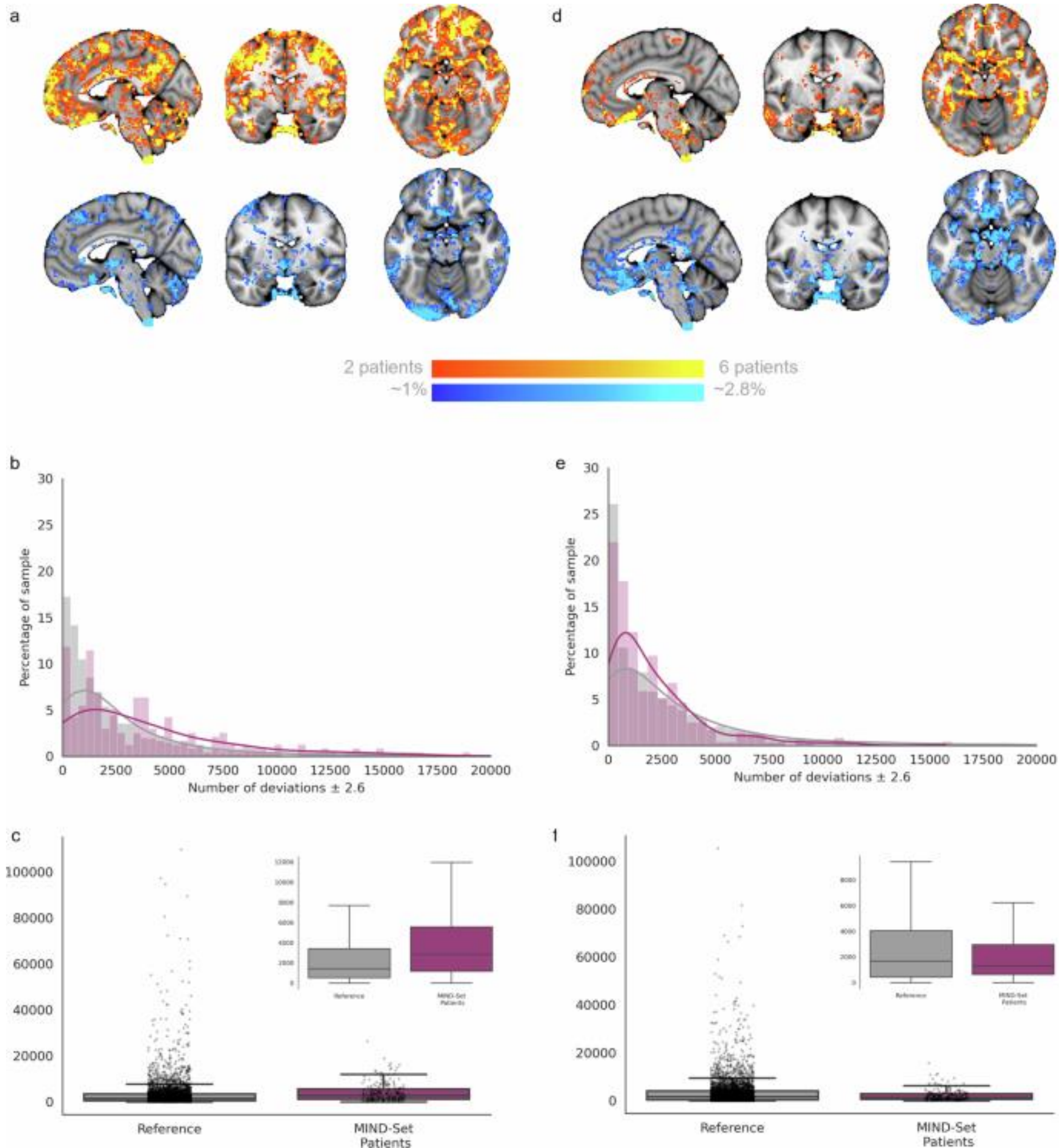
Subjects →

Age
Sex
Task length
# of target blocks
Instructions

Site
Scanner strength
TR
Multiband-factor
# of volumes acquired

- Frequency of Extreme Deviations: Patients vs. Reference Cohort

- Patients (MIND-Set cohort) showed significantly more extreme deviations (z > ±2.6) than the reference test cohort.



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.

- Using pre-trained models, evaluating on local datasets

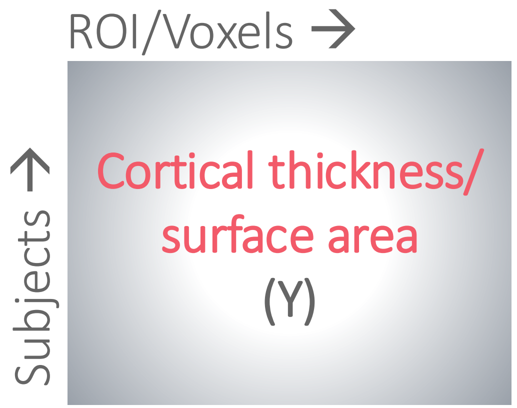
$$Y = f\,(X,\ \theta) + \varepsilon$$

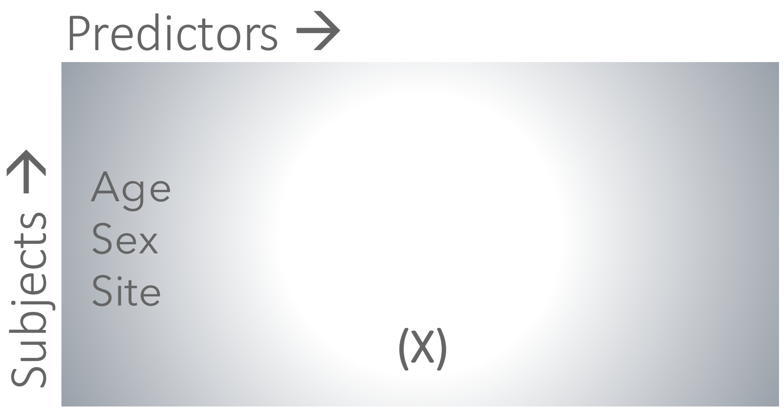
Y: Cortical thickness/ surface area

X: Covariates (age, sex, site)

θ: Model parameters

ε: Residuals



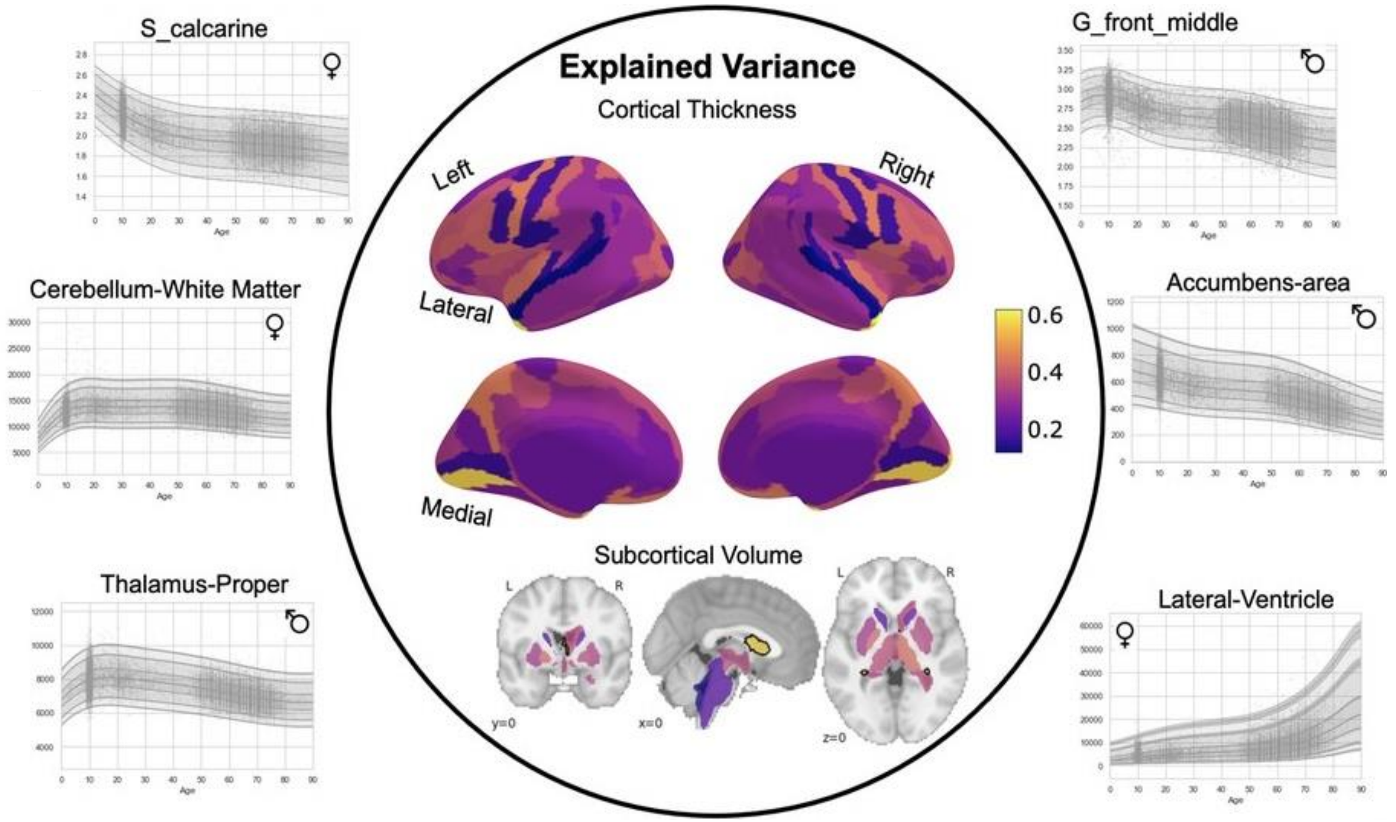


Warped Bayesian linear regression

- 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.

PARSING HETEROGENEITY

APPLICATIONS: Structural Imaging

- 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

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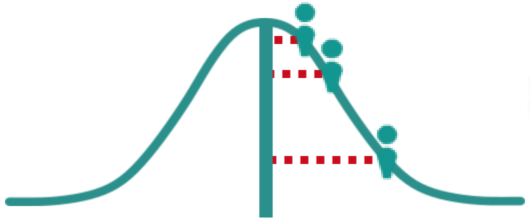
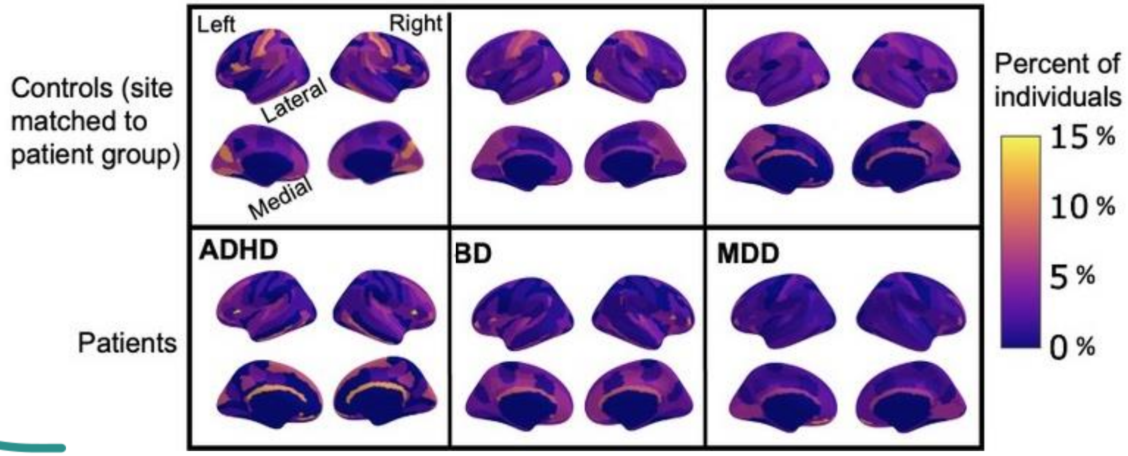
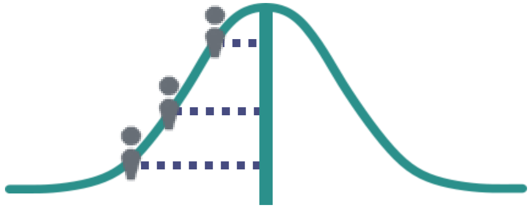
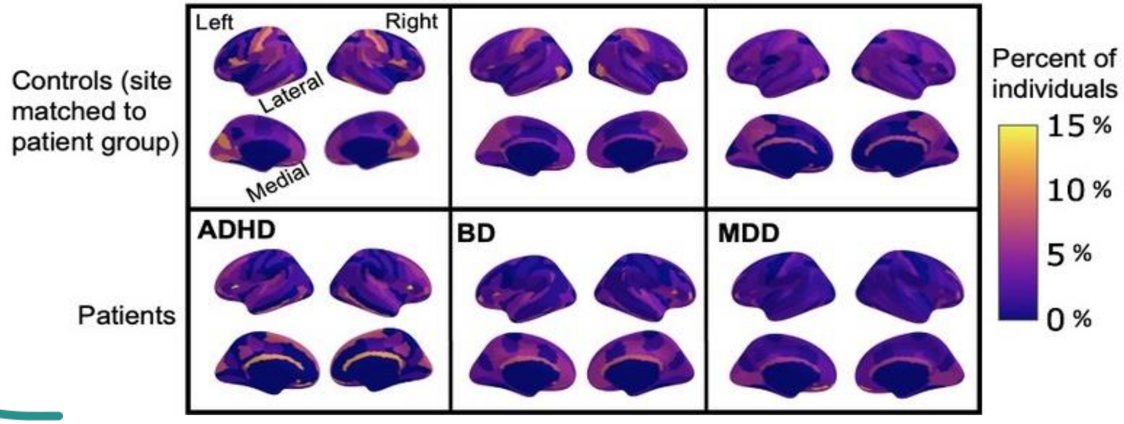
Positive deviations





Negative deviations





https://github.com/CharFraza/CPC_ML_tutorial

Tasks

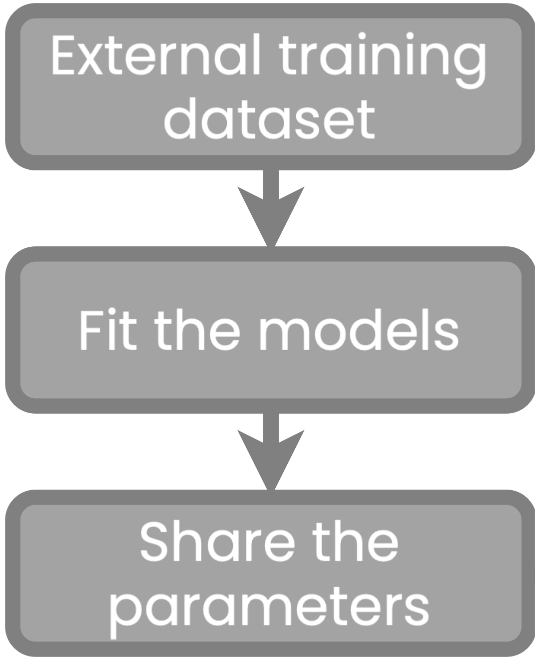
Task 1: Fitting normative models from scratch Open in Colab

Task 2: Applying pre-trained normative models Open in Colab

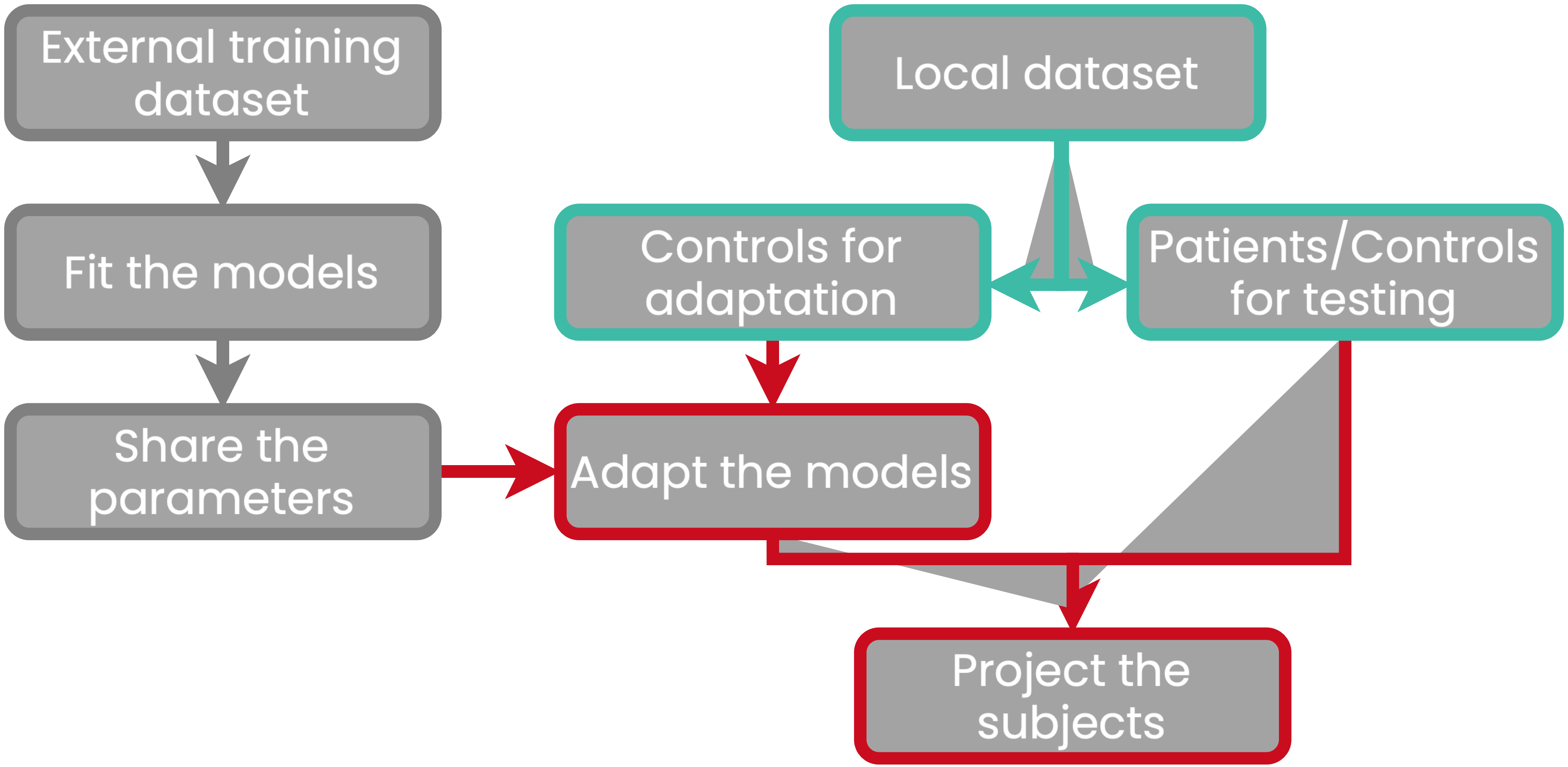
Task 3: Interpreting and visualizing the outputs of normative models Open in Colab

Task 4: Using the outputs (Z-scores) as features in predictive model Open in Colab

TUTORIAL II. APPLYING PRE-TRAINED NORMATIVE MODELS



TUTORIAL II. APPLYING PRE-TRAINED NORMATIVE MODELS



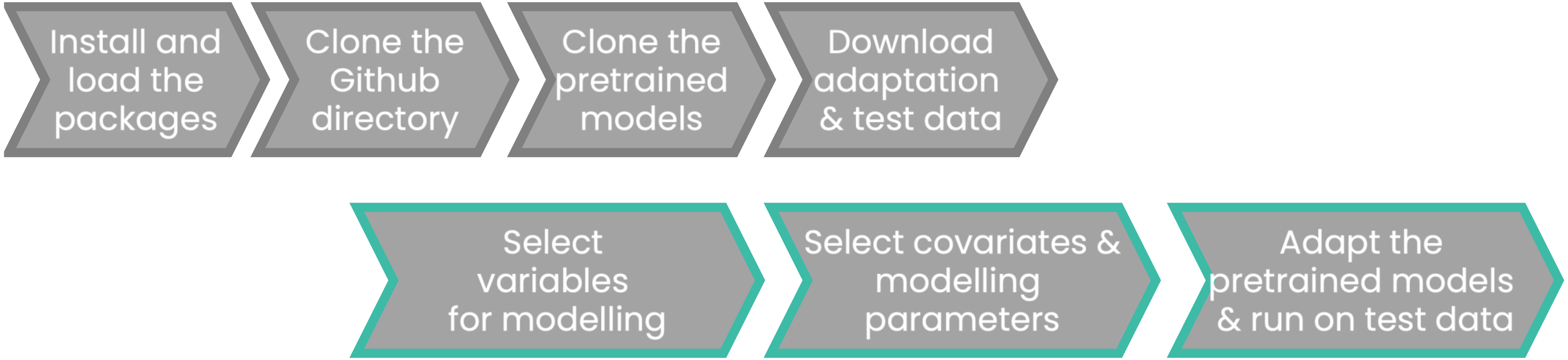
TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS

Install and load the packages → Clone the Github directory → Clone the pretrained models → Download adaptation & test data

TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS



TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS

Install and load the packages

Clone the Github directory

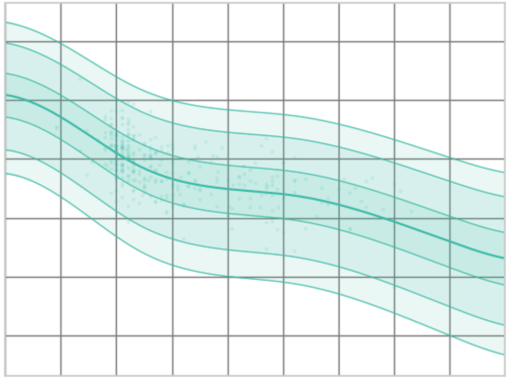
Clone the pretrained models

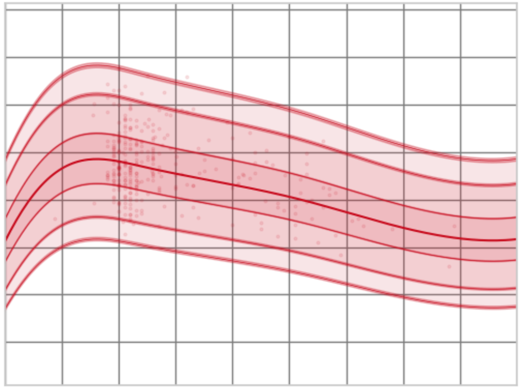
Download adaptation & test data

Select variables for modelling

Select covariates & modelling parameters

Adapt the pretrained models & run on test data





Visualize

https://github.com/CharFraza/CPC_ML_tutorial

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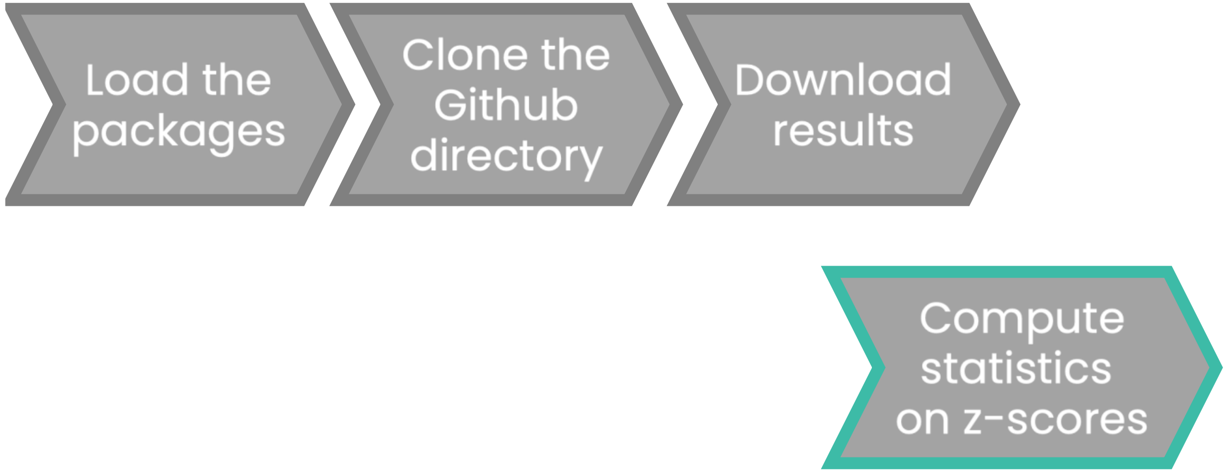
TUTORIAL III.

INTERPRETING AND VISUALIZING THE OUTPUTS OF NORMATIVE MODELS



TUTORIAL III.

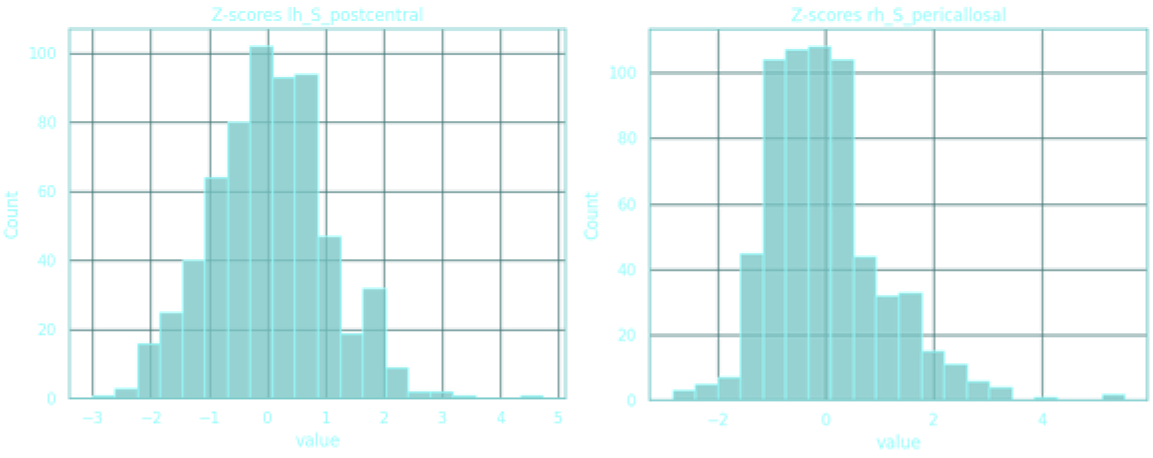
INTERPRETING AND VISUALIZING THE OUTPUTS OF NORMATIVE MODELS

Load the packages

Clone the Github directory

Download results

Compute statistics on z-scores



Visualize individual ROI histograms

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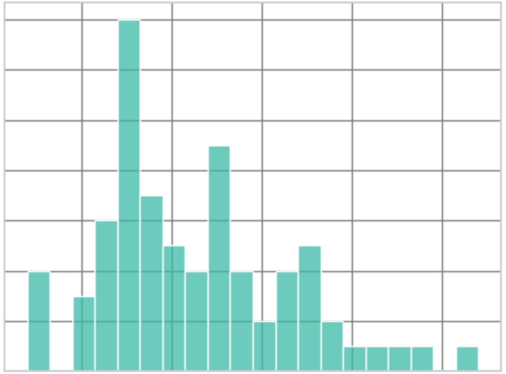

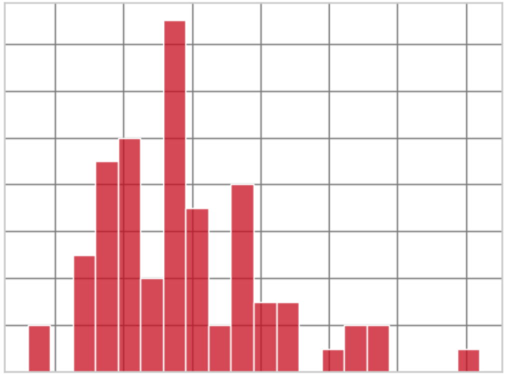

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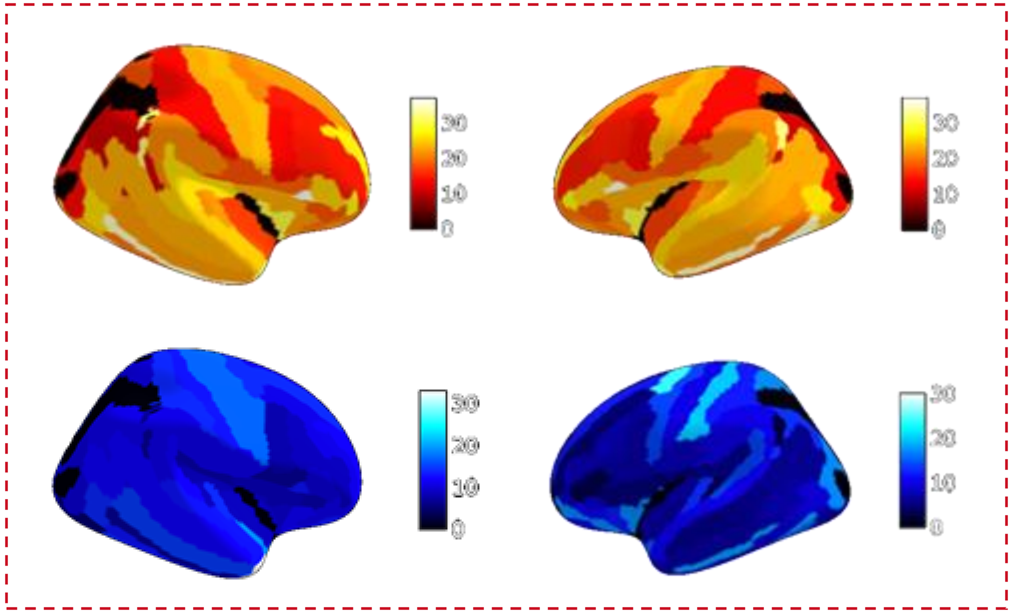


Visualize individual ROI histograms

Project results on cortical surface

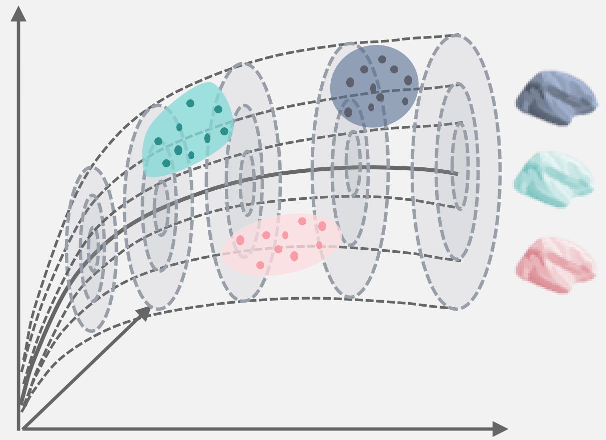
APPLICATIONS

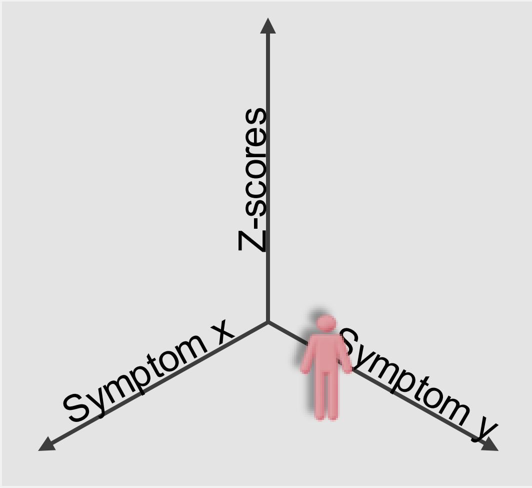
Parsing heterogeneity

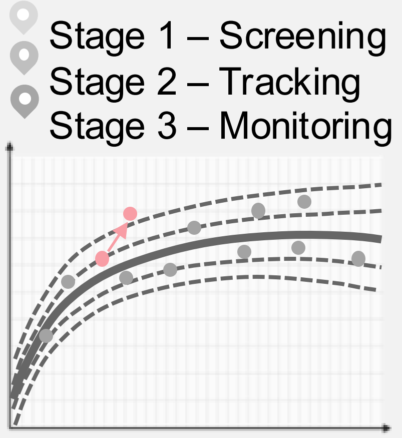
Neurobiological subtyping

Brain-behavior mappings

Other







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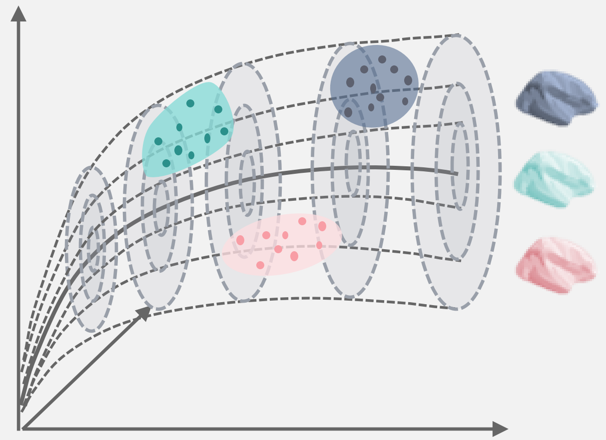
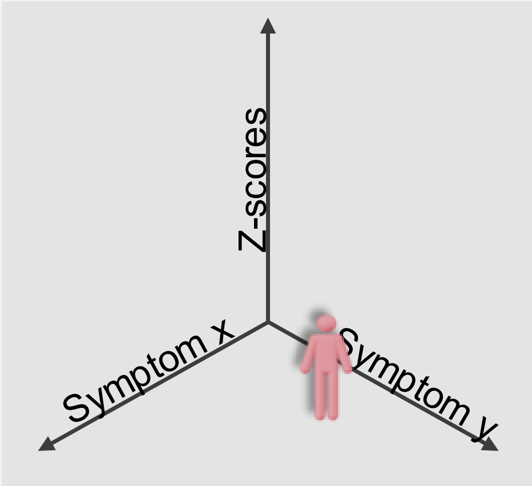
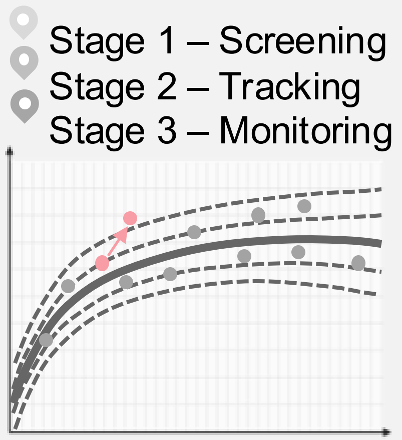
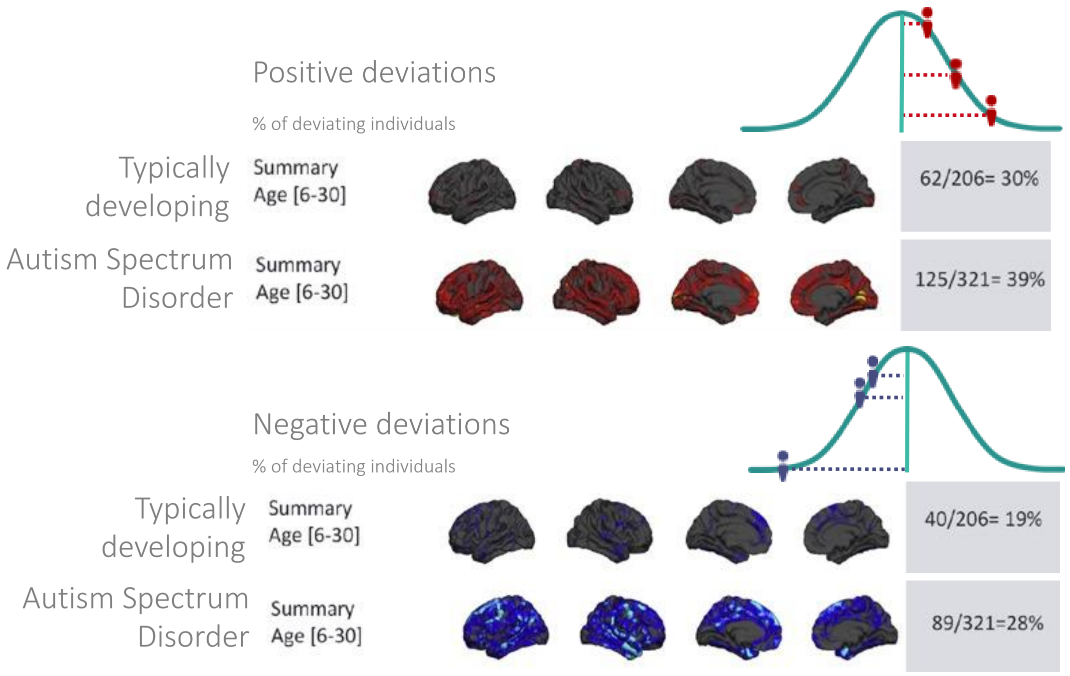




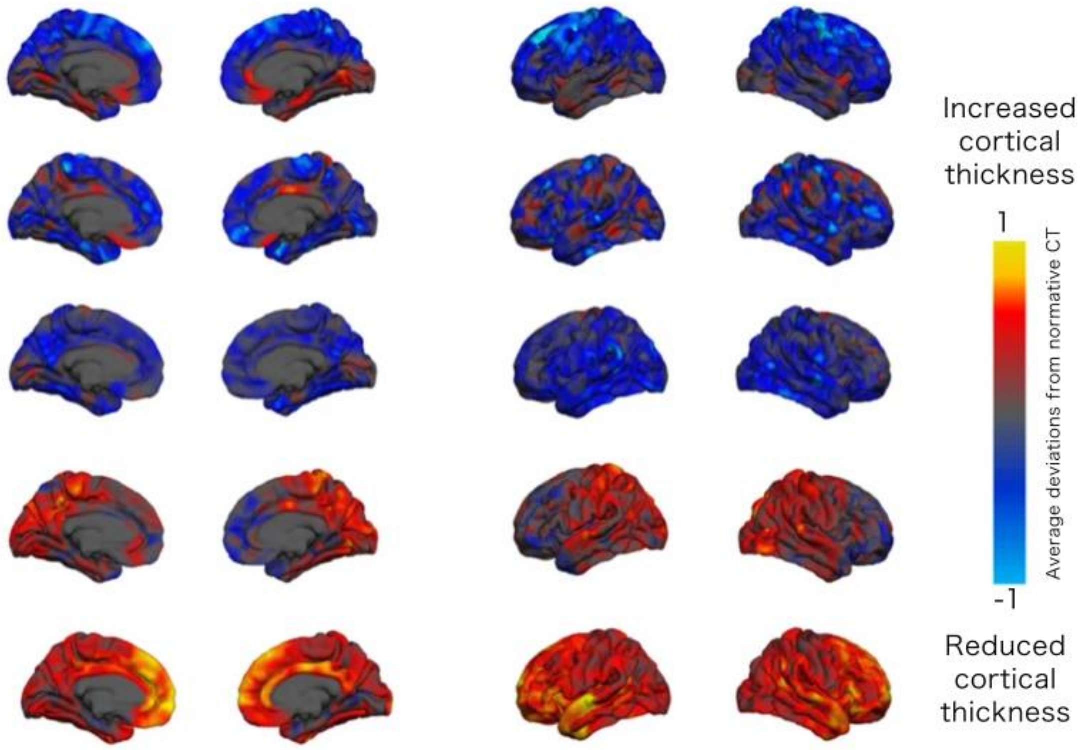


NEUROBIOLOGICAL SUBTYPING

APPLICATIONS



5 CLUSTERS



Zabihi, M., et al., (2020) **Fractionating autism based on neuroanatomical normative modeling.** Translational Psychiatry, 10.1: 384.

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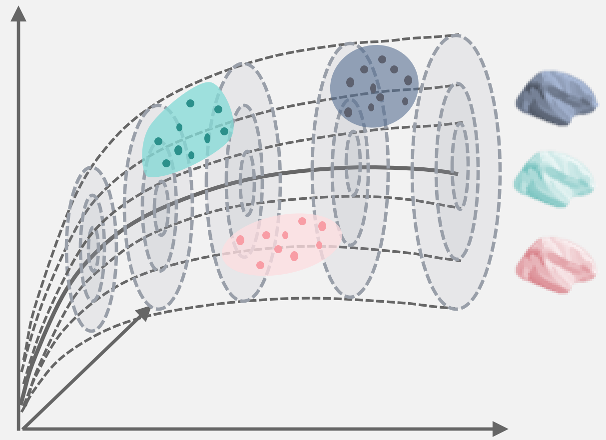

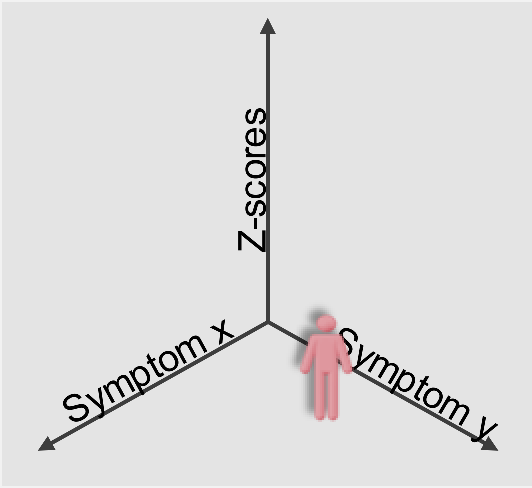

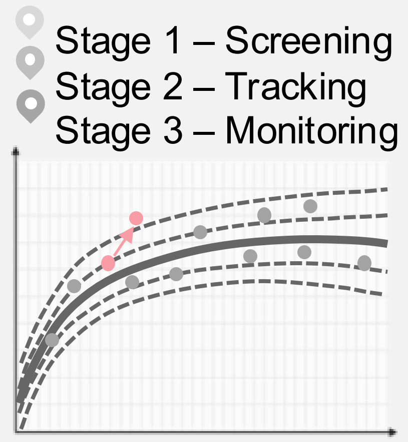

APPLICATIONS

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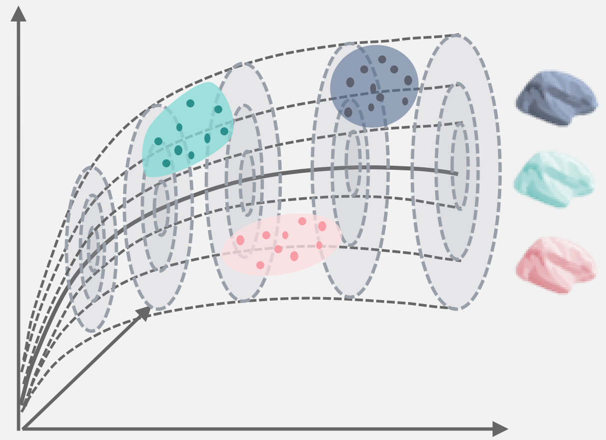
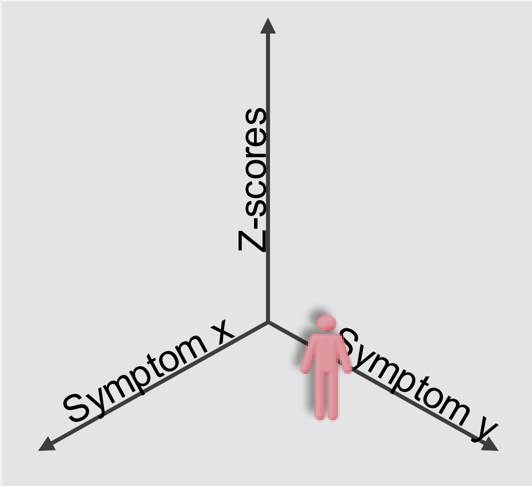
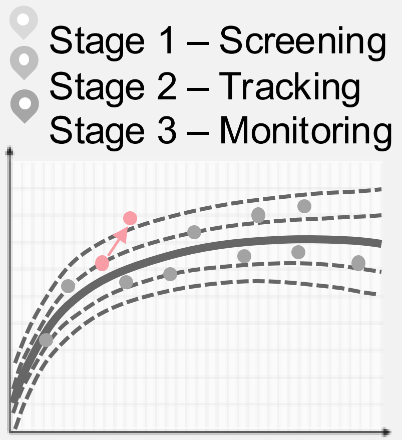
Neurobiological subtyping



Brain-behavior mappings



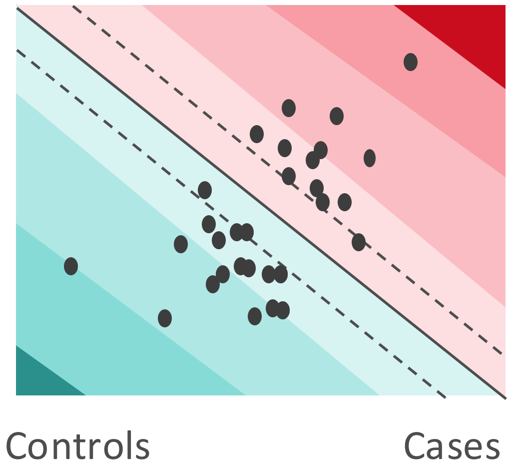
Other



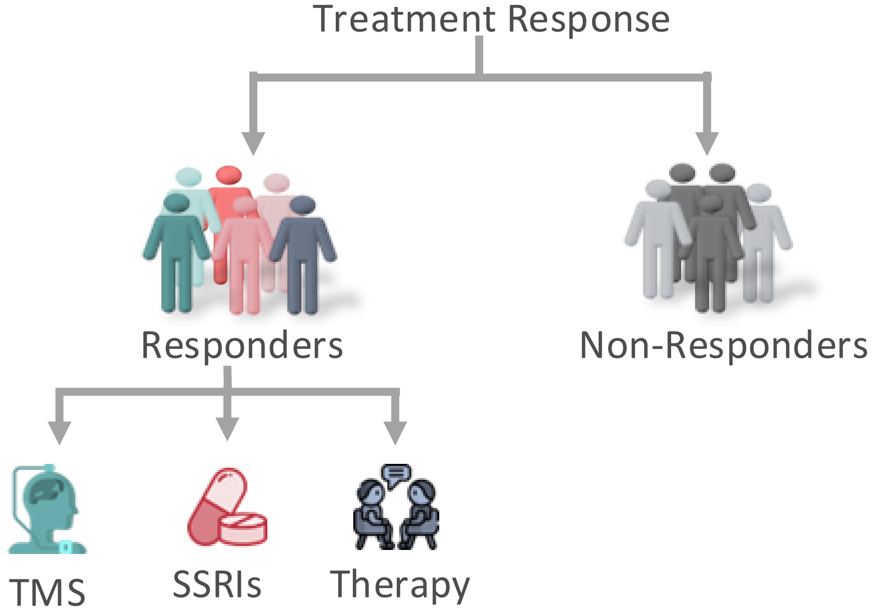
APPLICATIONS

Group Level Inference Out-of-Sample

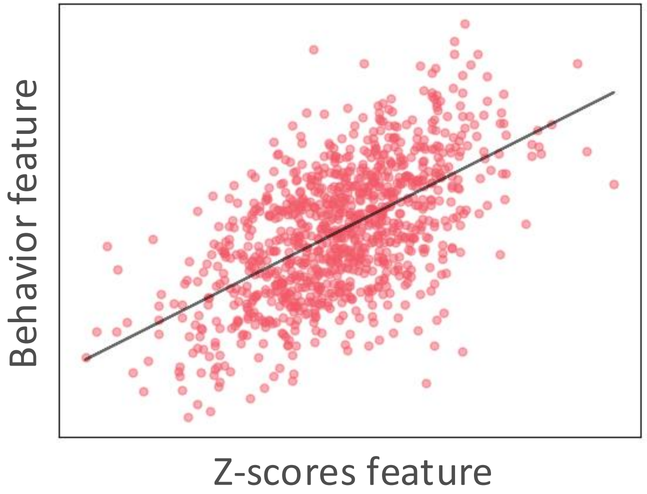
Classification



Prediction Treatment



Prediction Behavior



BRAIN-BEHAVIOR MAPPINGS

APPLICATIONS

Parse heterogeneity

Neurobiological subtyping

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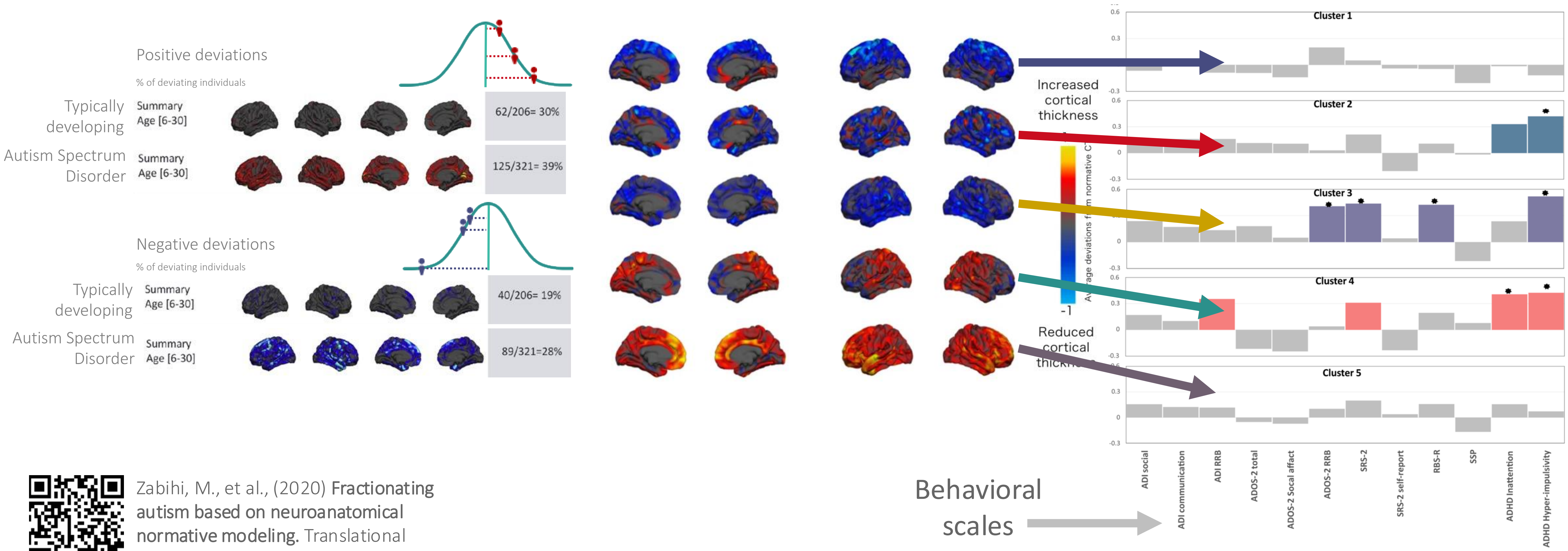

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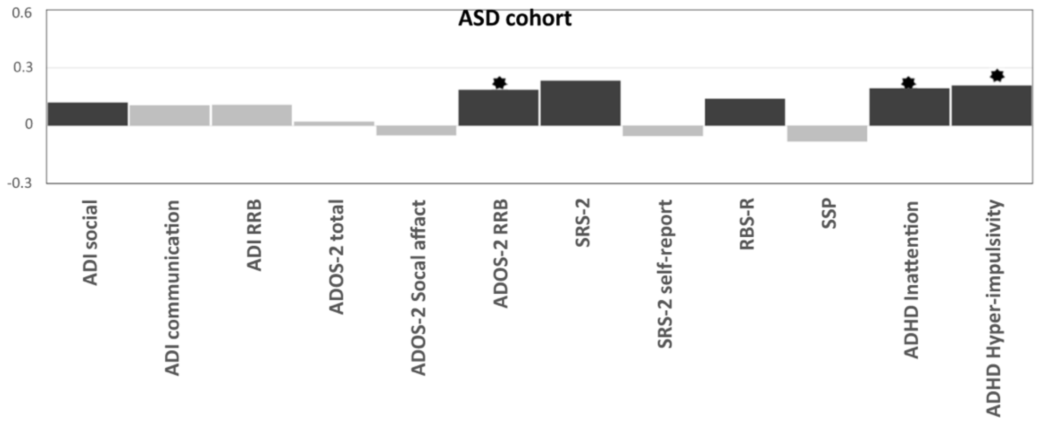
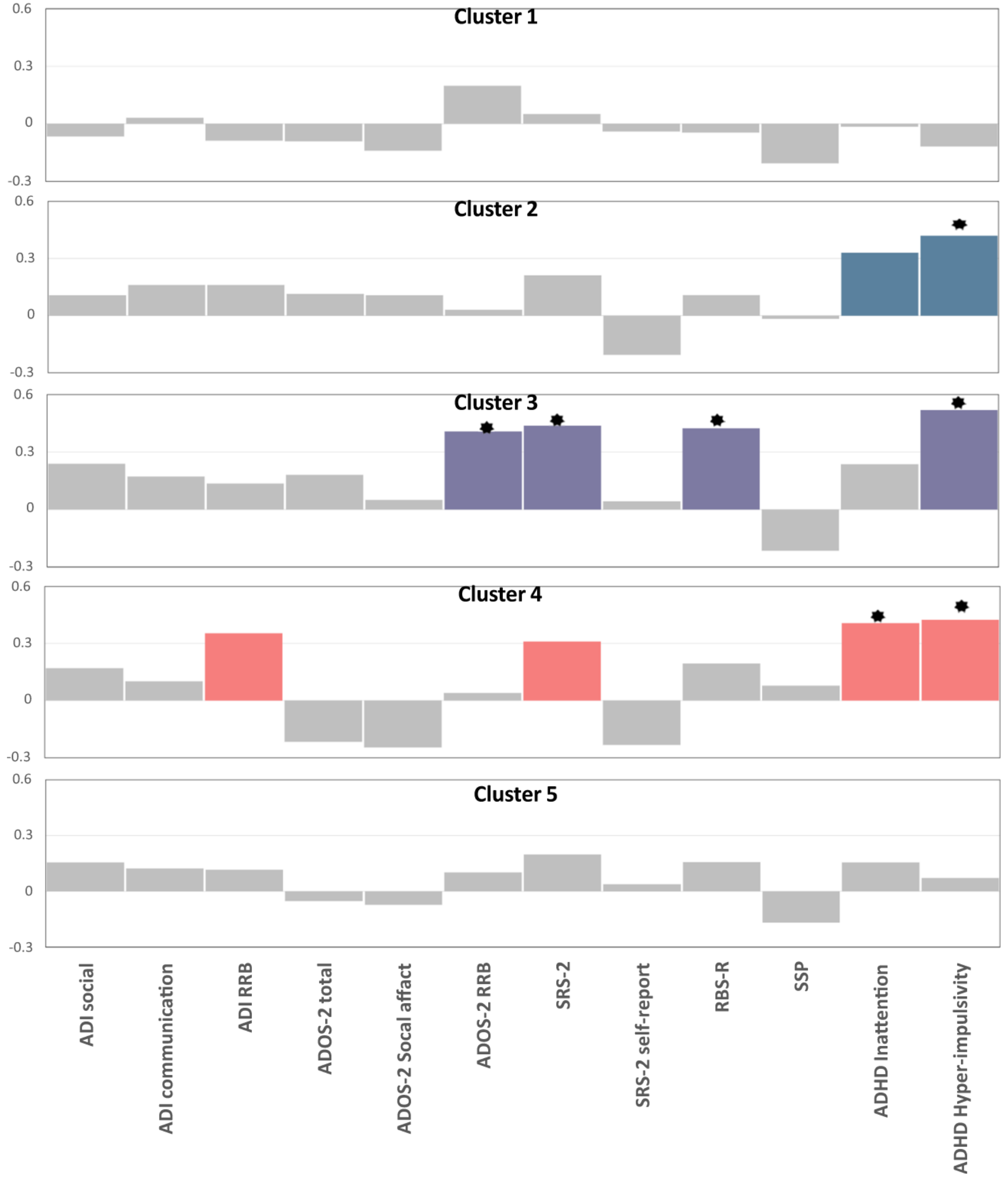
BRAIN-BEHAVIOR MAPPINGS

APPLICATIONS

- Relate identified deviation scores to behavioral measures related to psychopathology or disease severity



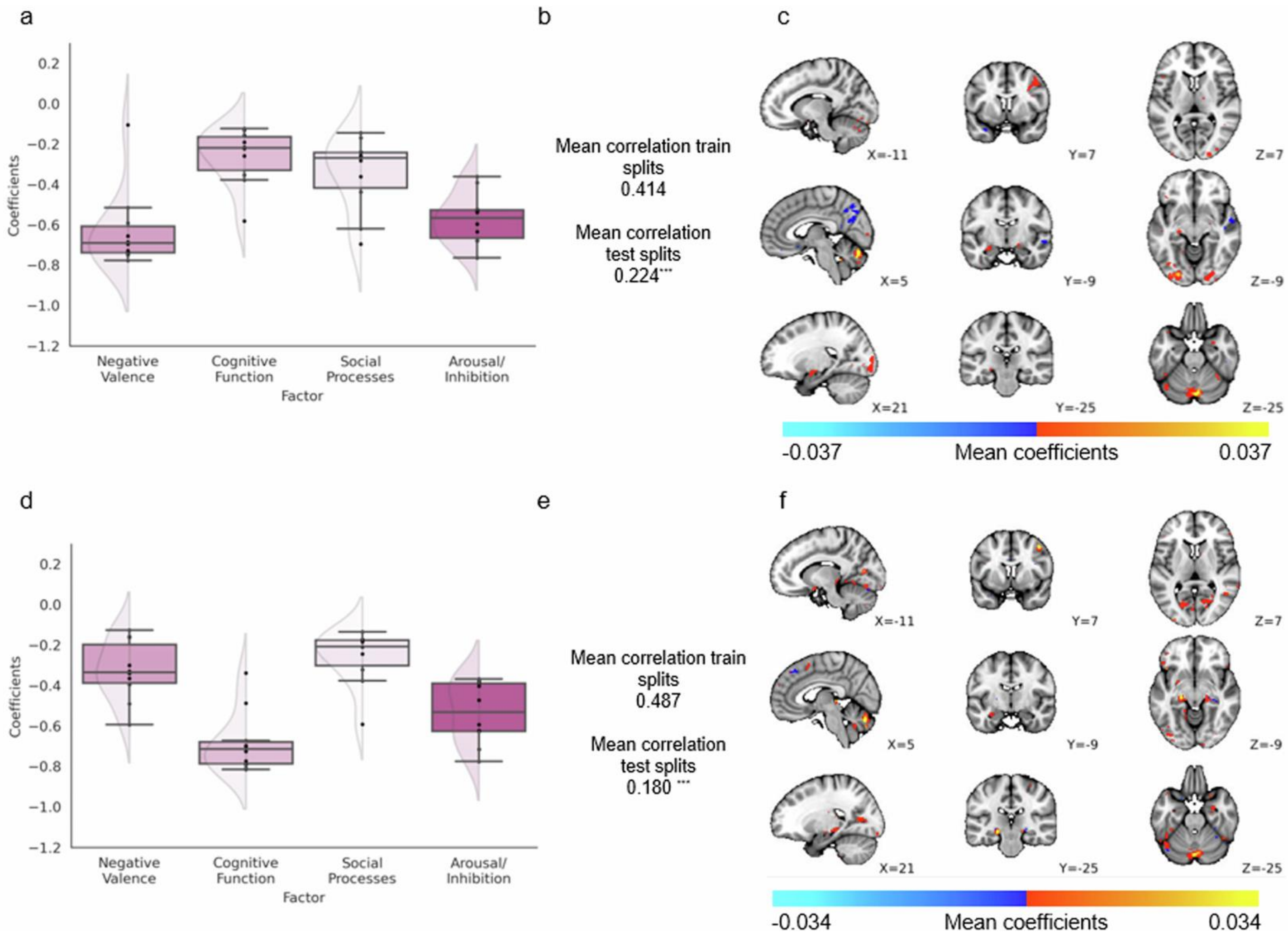


Zabihi, M., et al., (2020) Fractionating autism based on neuroanatomical normative modeling. Translational Psychiatry, 10.1: 384.

BRAIN-BEHAVIOR MAPPINGS

APPLICATIONS

- Relate identified deviation scores to behavioral measures related to psychopathology or disease severity
- Sparse CCA:
  - Negative Valence
  - Cognitive Function
  - Social Processes
  - Arousal/Inhibition



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.

APPLICATIONS

Parsing heterogeneity

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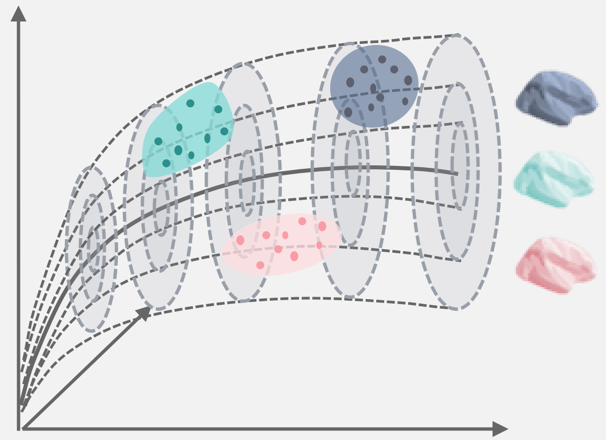

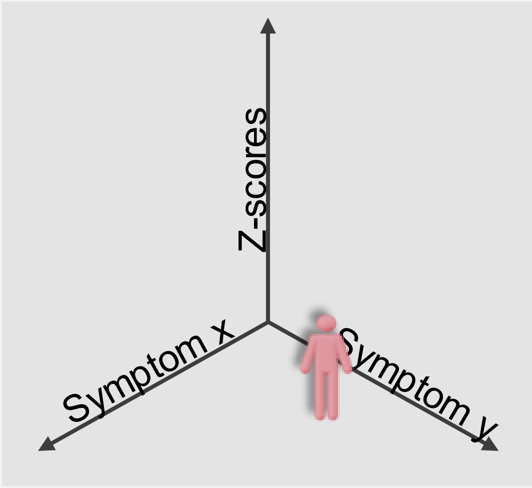

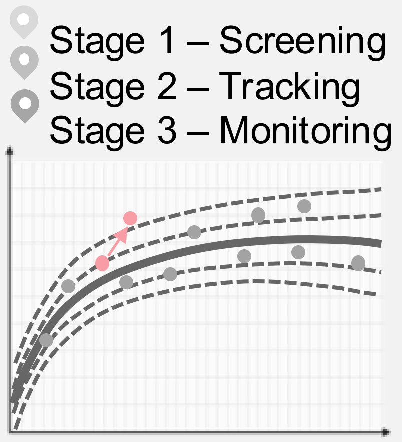

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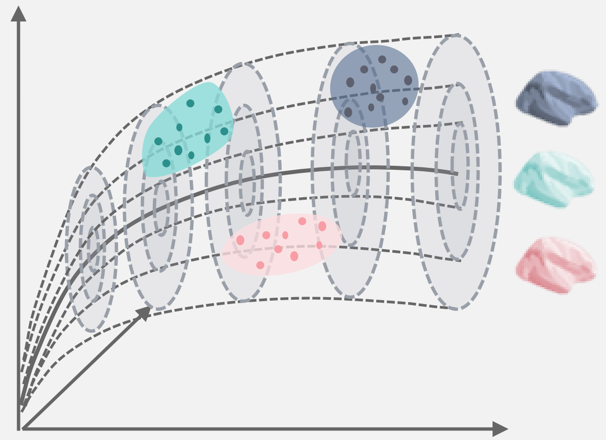

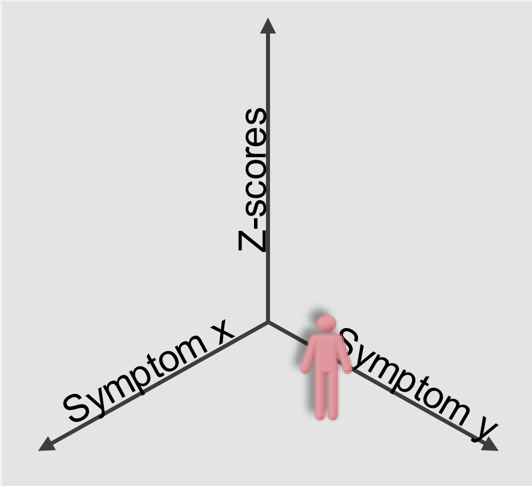

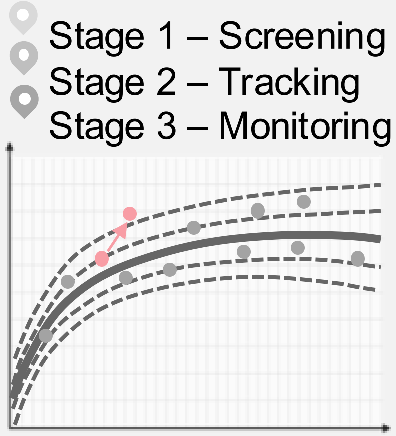

OTHER APPLICATIONS

DTI

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OTHER

APPLICATIONS

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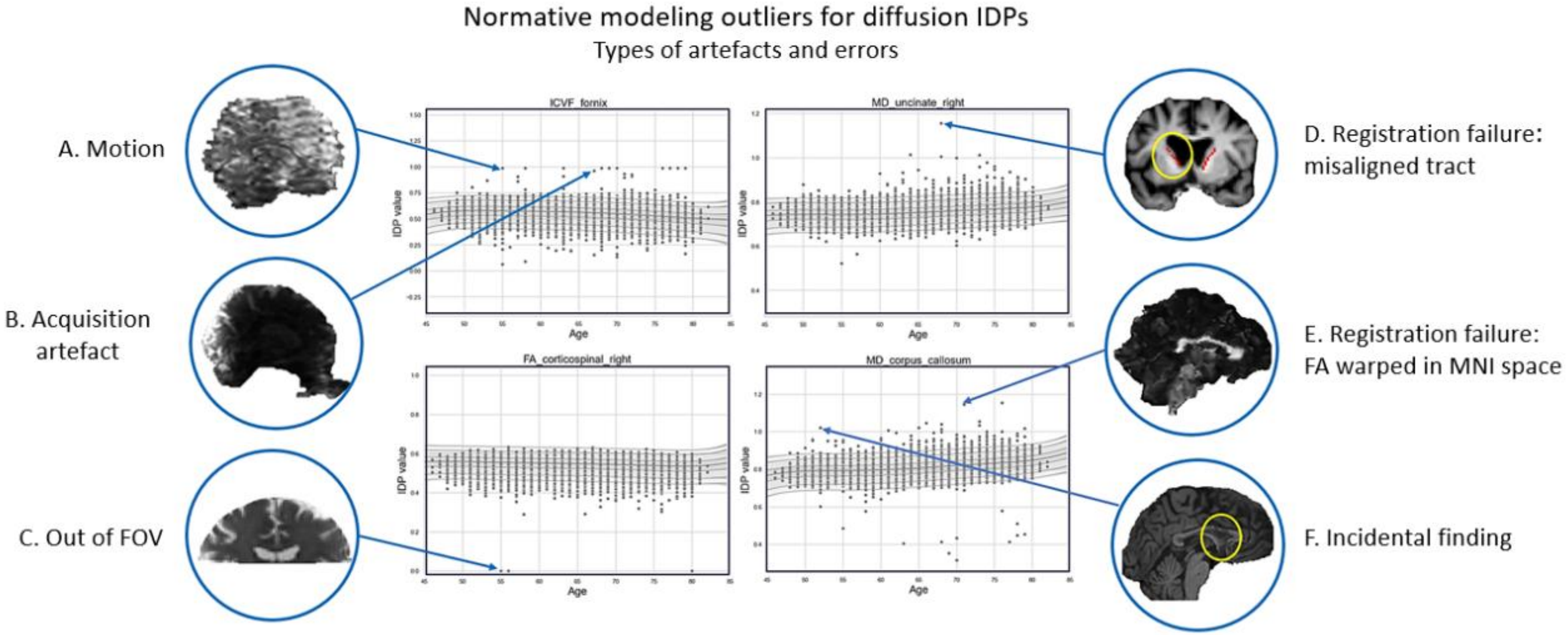
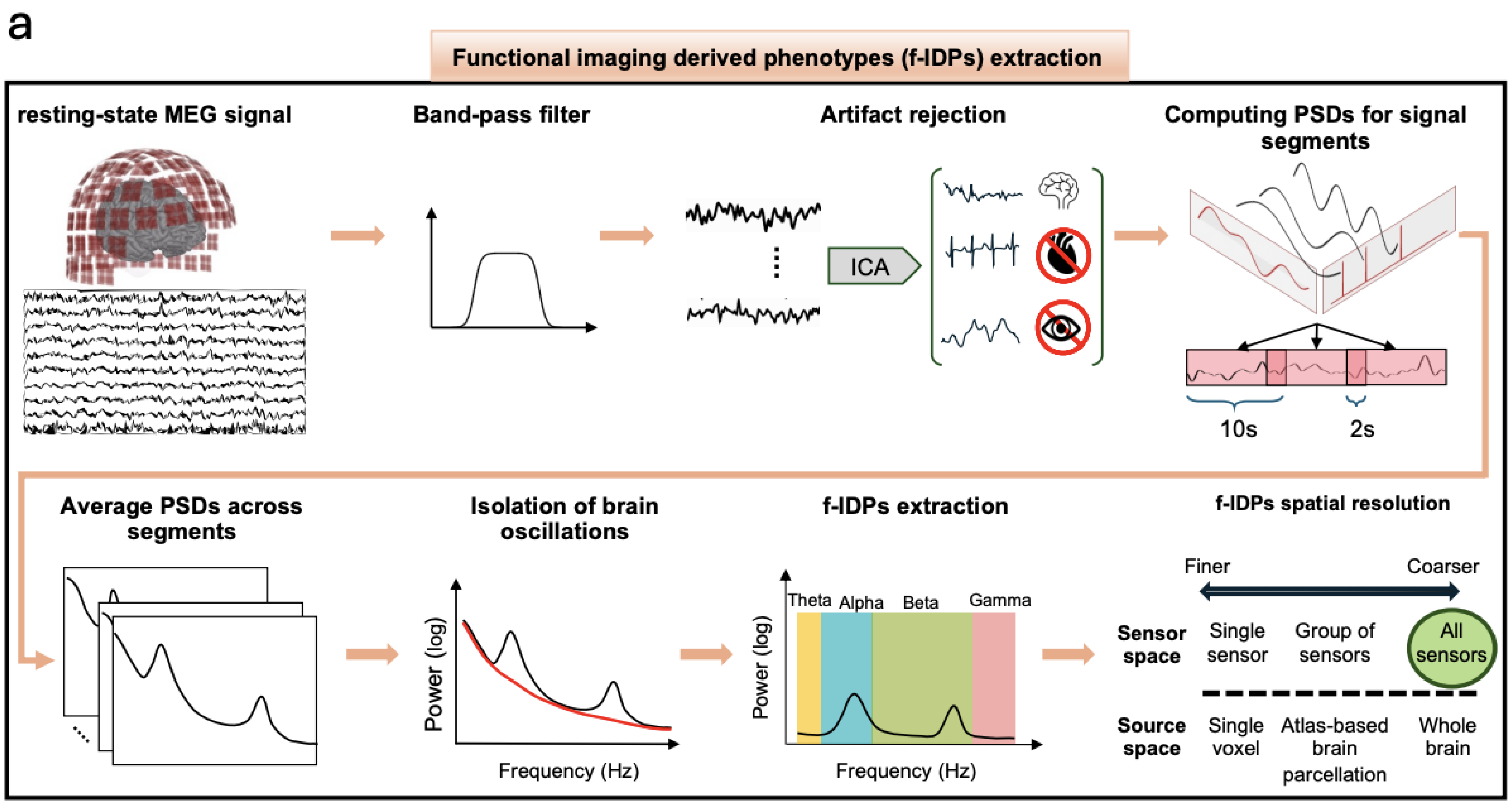


Ramona Cirstian et al., (2024) **Objective QC for diffusion MRI data: artefact detection using normative modelling**. *Imaging Neuroscience* 2: 1-14.

EEG/MEG

Dr. Seyed Mostafa Kia
S.M.Kia@tilburguniversity.edu



Zamanzadeh, Mohammad, et al. "**MEGaNorm: Normative Modeling of MEG Brain Oscillations Across the Human Lifespan.**" *bioRxiv* (2025): 2025-06.

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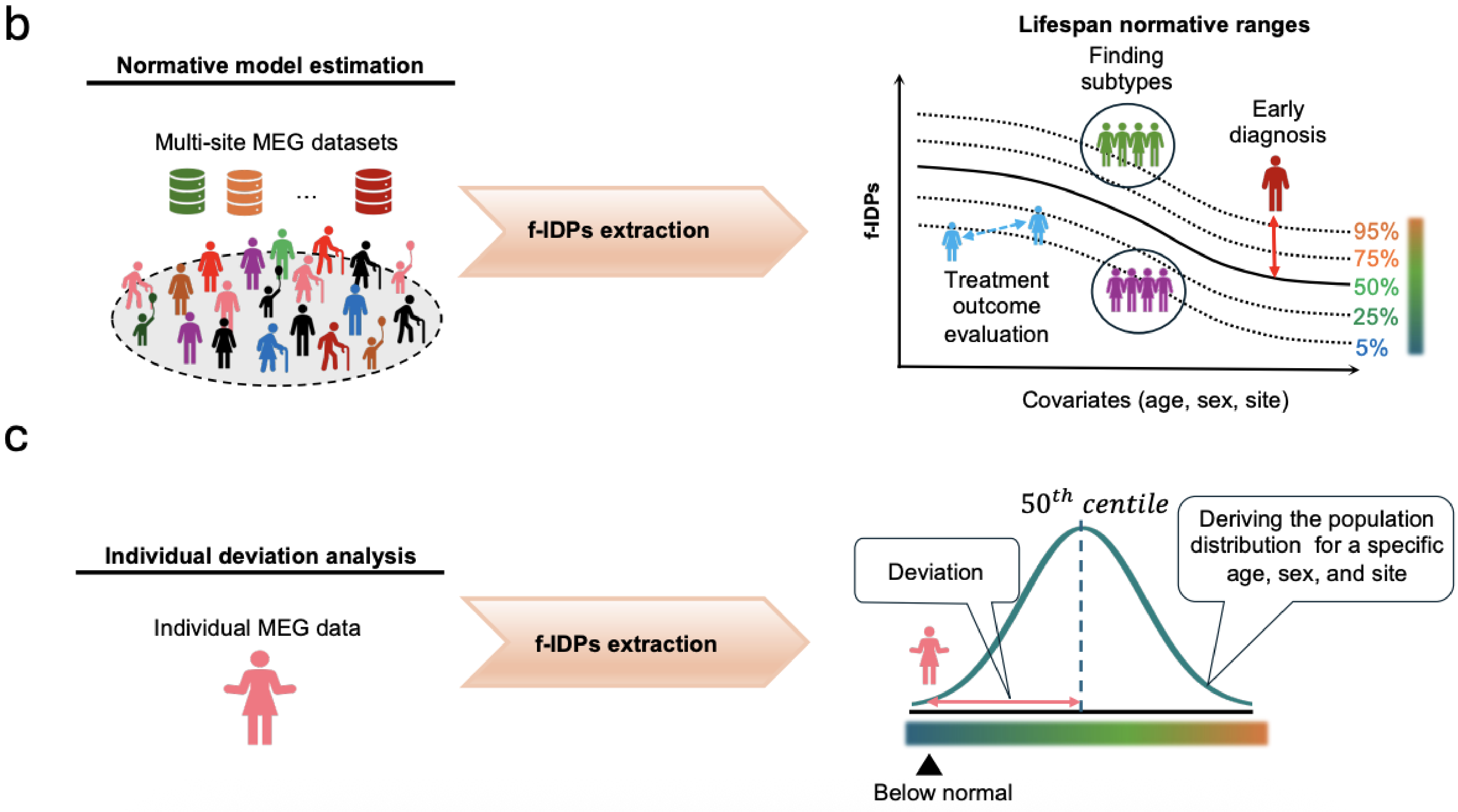

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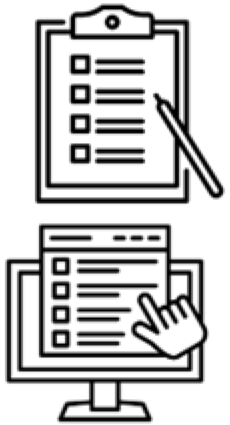
Psychometrics

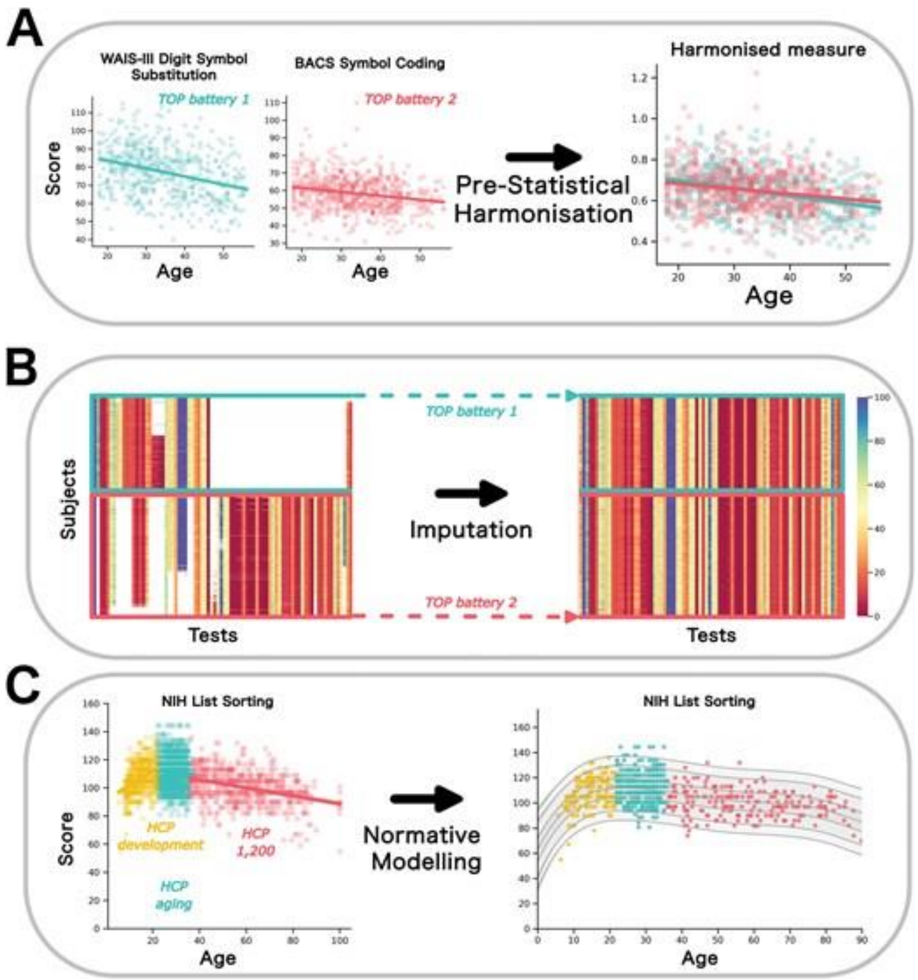
Dr. Barbora Rehák Bučková
barbora.rehak-buckova@radboudumc.nl

OTHER



Psychometrics

APPLICATIONS



Marquand, Andre F., et al. "**Learning latent profiles via cognitive growth charting in psychosis: design and rationale for the PRECOGNITION project.**" Schizophrenia Bulletin Open 6.1 (2025): sgaf007.

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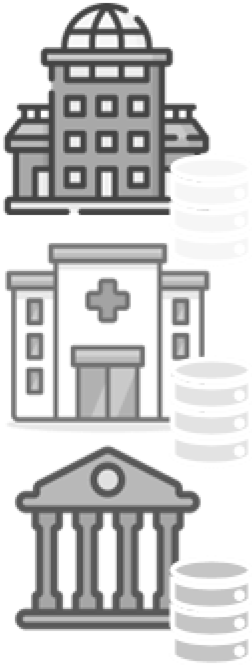

Federated

Stijn de Boer
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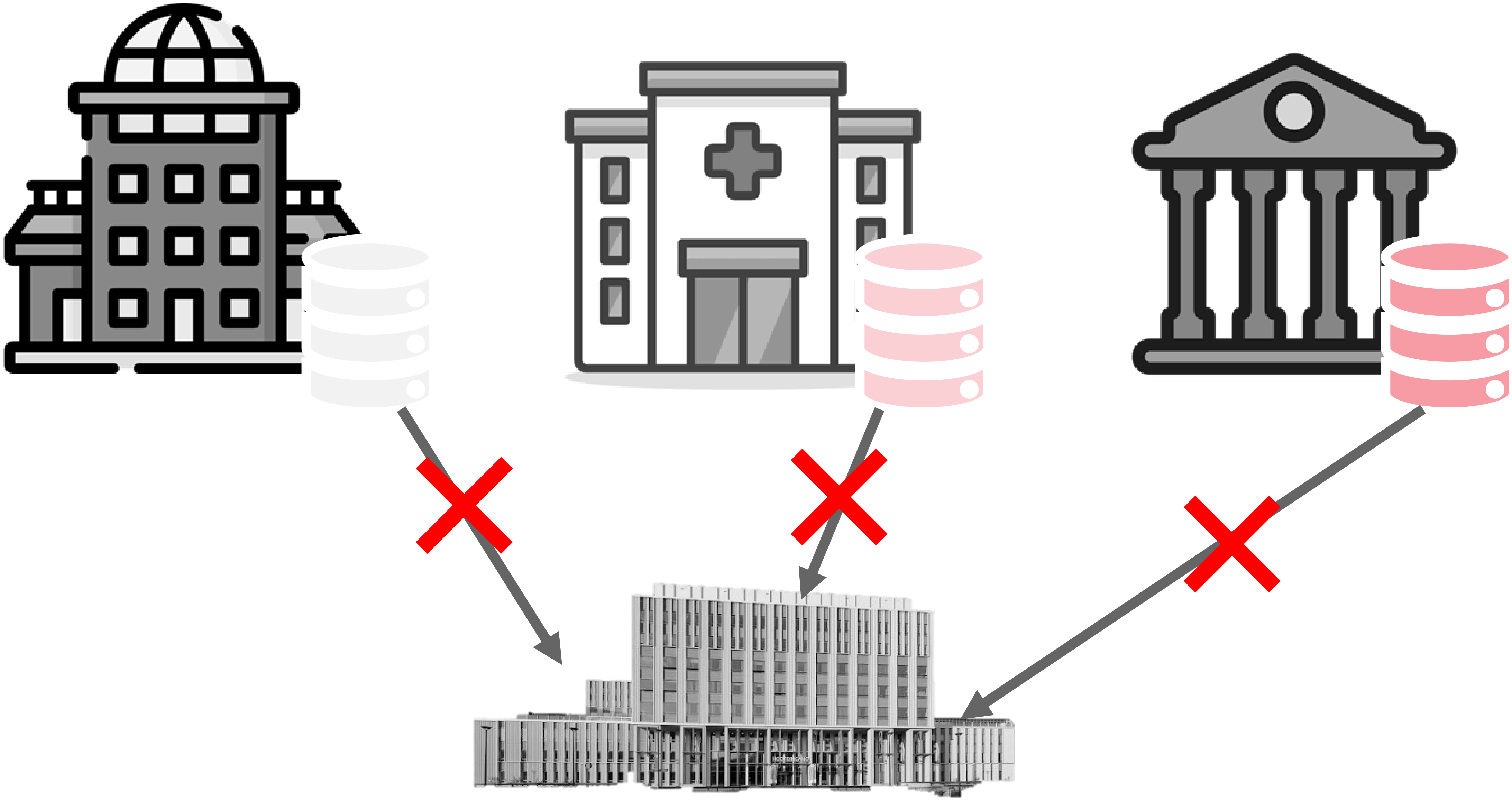
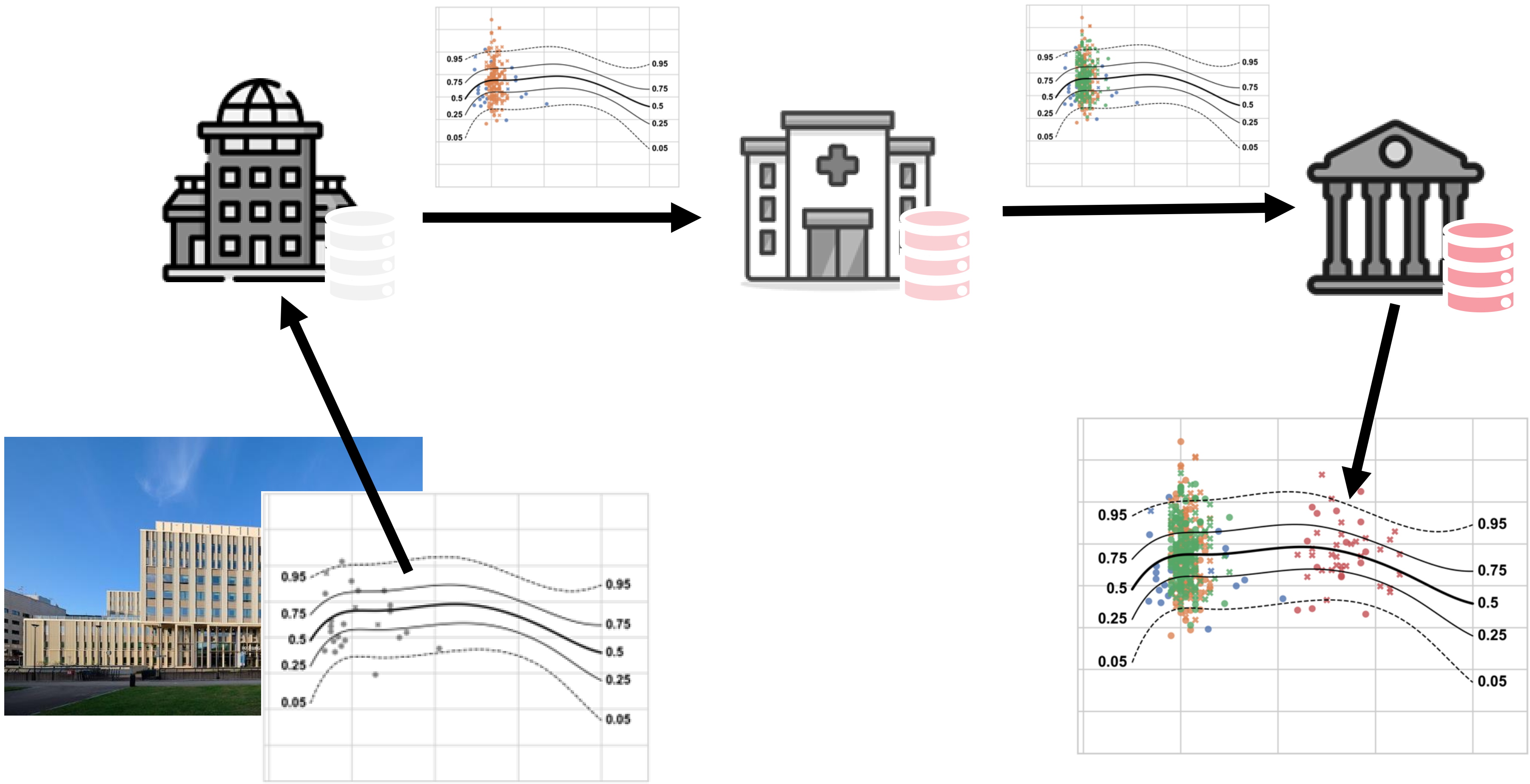
OTHER APPLICATIONS



OTHER

APPLICATIONS



De Boer, A. A., Bayer, J. M., Kia, S. M., Rutherford, S., Zabihi, M., Fraza, C., ... & Marquand, A. (2024). Non-Gaussian normative modelling with hierarchical Bayesian regression. Imaging Neuroscience, 2, 1-36

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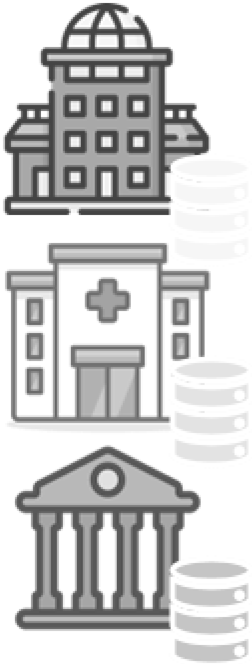

Federated

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Longitudinal

Dr. Barbora Rehák Bučková and Dr. Johanna Bayer
Johanna.bayer@donders.ru.nl

Cross-sectional

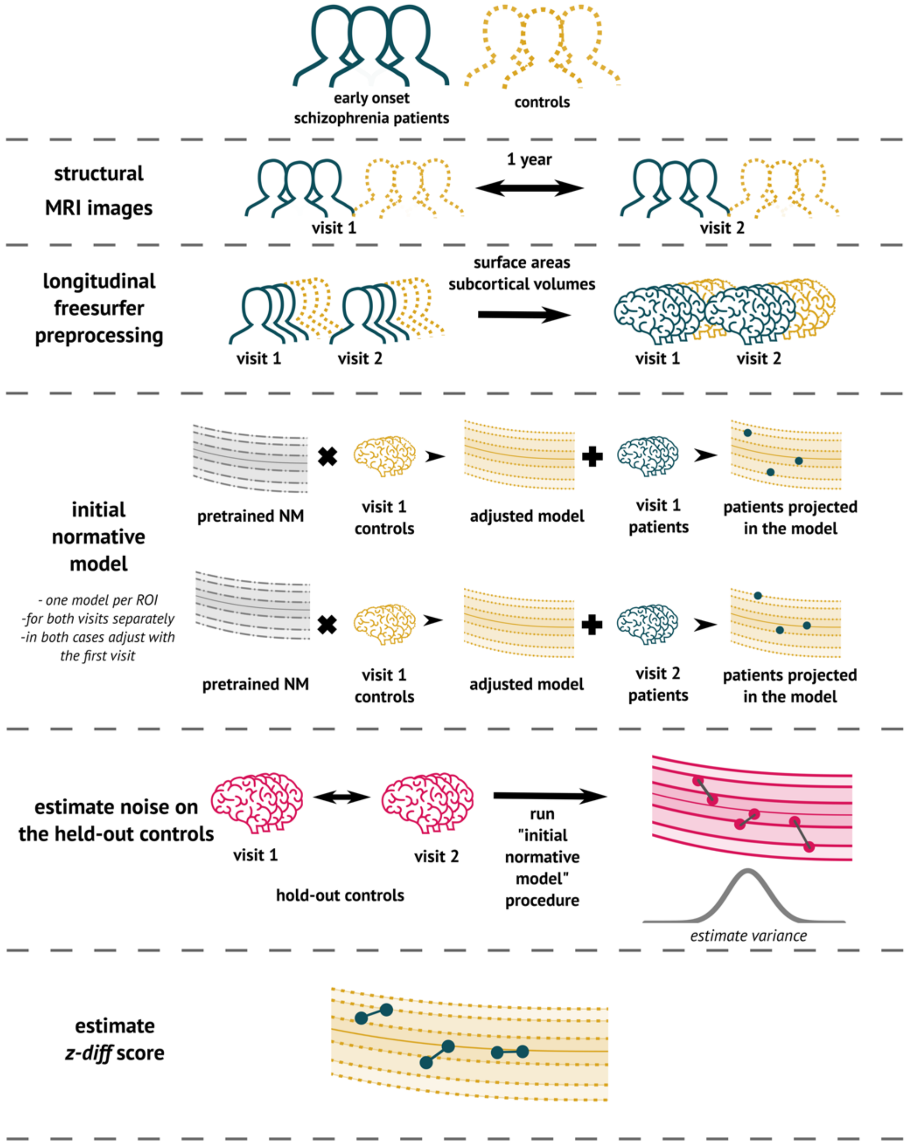
- Do not capture individual developmental trajectories.
- Can over- or underestimate future outcomes.
- Cannot distinguish typical vs. atypical changes over time.
- Don’t account for natural centile crossing, which can be normal (e.g., due to puberty or growth spurts).

OTHER

APPLICATIONS

Longitudinal

- Lack of methods for evaluating longitudinal changes
- Lack of resources to construct a fully longitudinal model
- Use pre-trained models and longitudinal controls to estimate a "healthy change"



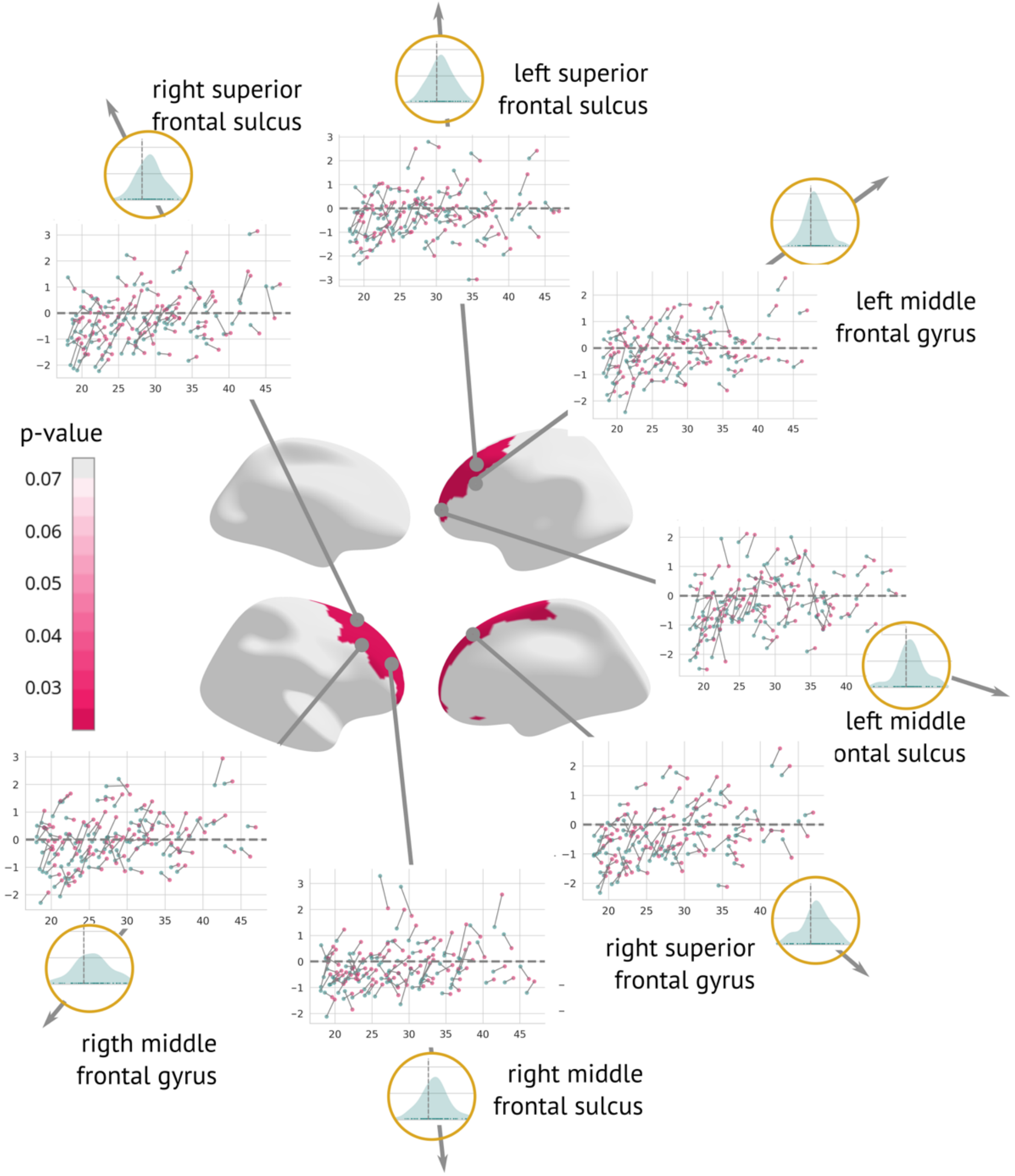
Barbora Rehák Bučková et al., (2024) Using normative models pre-trained on cross-sectional data to evaluate longitudinal changes in neuroimaging data *BioArxiv.*

OTHER

APPLICATIONS

Longitudinal

- New Metric – "z-diff" Score
- Quantifies whether observed changes are statistically meaningful based on model uncertainty and measurement noise.



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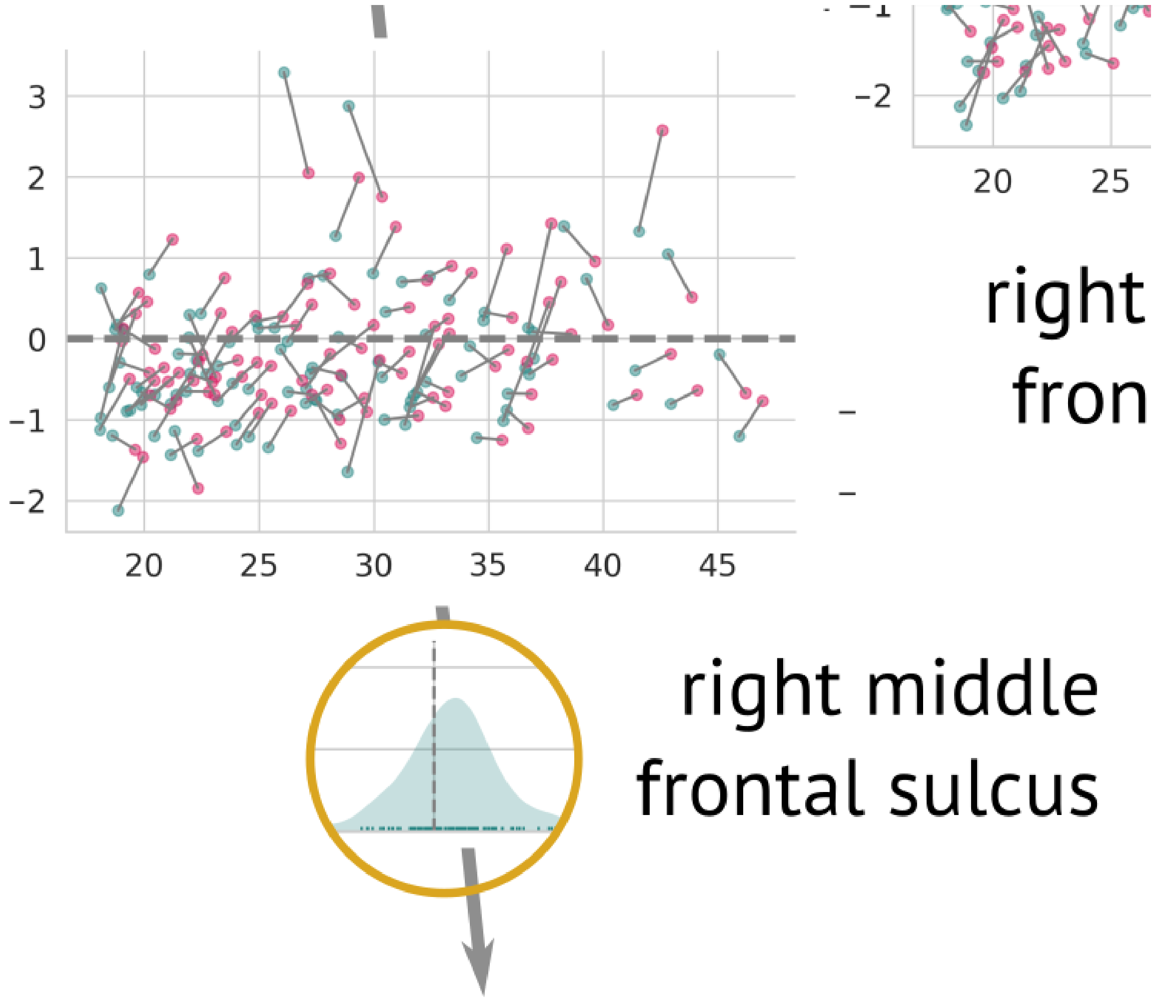
APPLICATIONS

Longitudinal

- Lack of methods for evaluating longitudinal changes
- Lack of resources to construct a fully longitudinal model
- Use pre-trained models and longitudinal controls to estimate a “healthy change”



Barbora Rehák Bučková et al., (2024) Using normative models pre-trained on cross-sectional data to evaluate longitudinal changes in neuroimaging data *BioArxiv.*

OTHER

APPLICATIONS

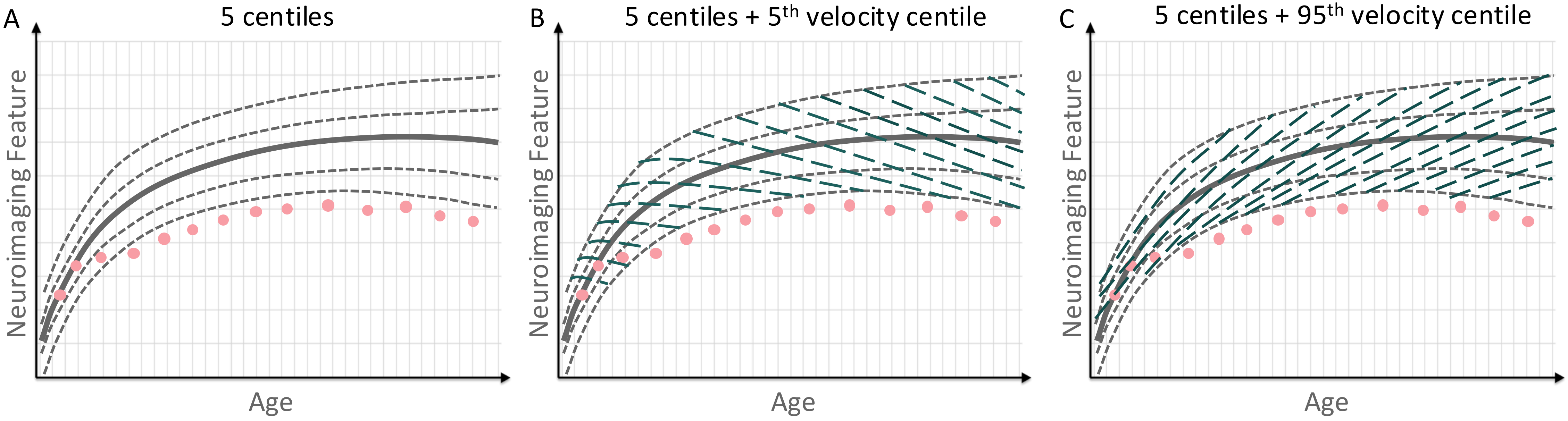
Velocity charts

Velocity = rate of change between two measurements $v = \frac{f_2 - f_1}{t_2 - t_1}$,

Standardized Velocity $z^v = \frac{z_2 - z_1}{\sigma(\Delta z)}$, with $\sigma(\Delta z) = \sqrt{2(1-r)}$

Conditional Velocity (Conditional SD Gain Score) (Adjusts for regression to the mean)

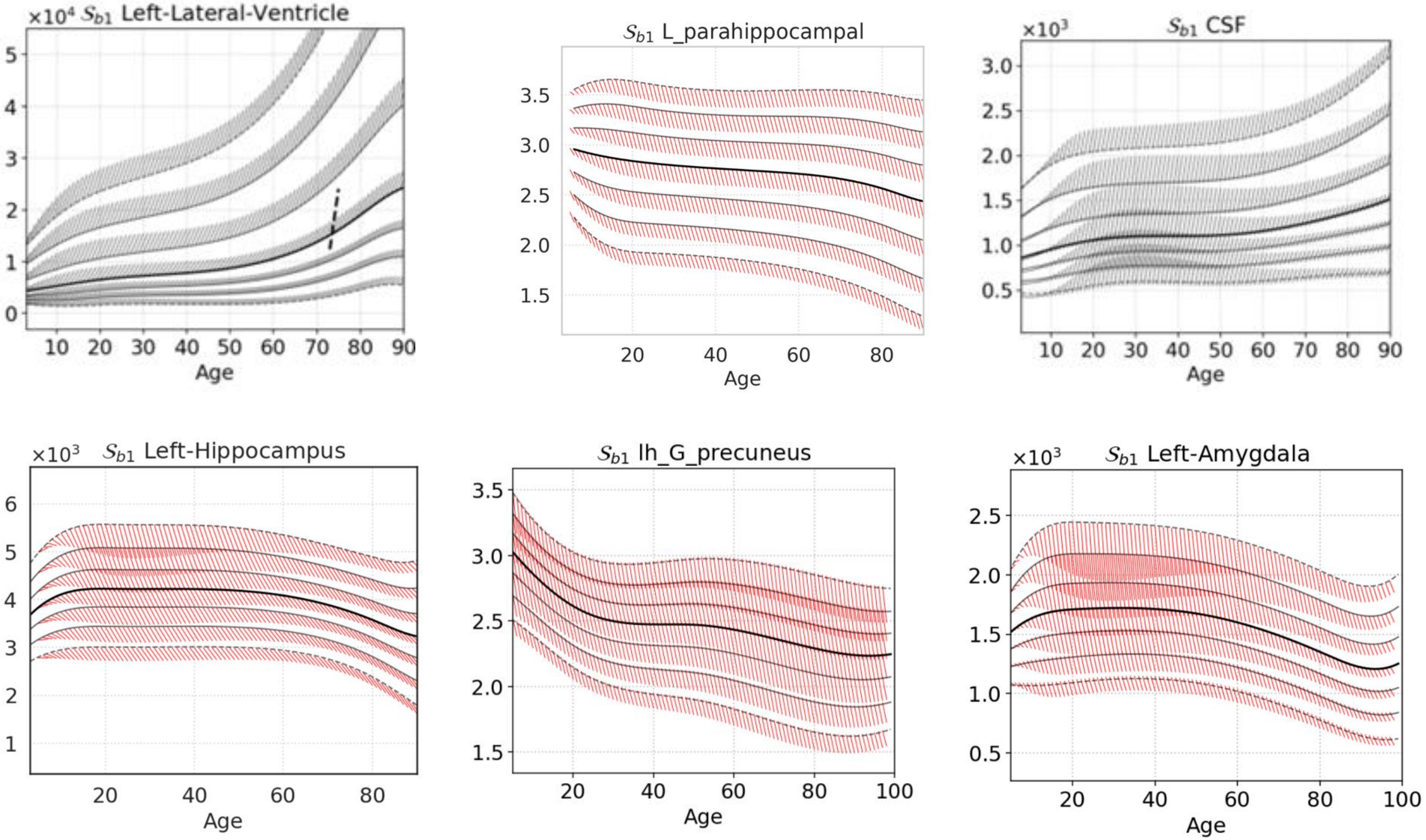
Failure to Thrive



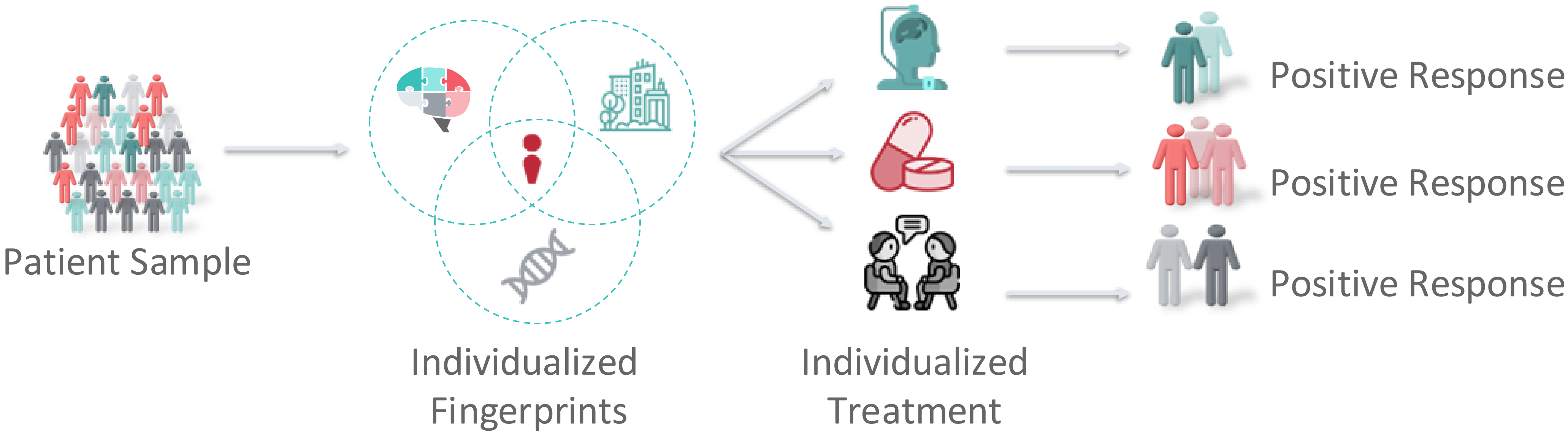
The promise of quantifying individual risk for brain disorders through normative modeling: A narrative review. *Neuroscience and Biobehavioral Reviews*.

Longitudinal

Thrive lines, examples:



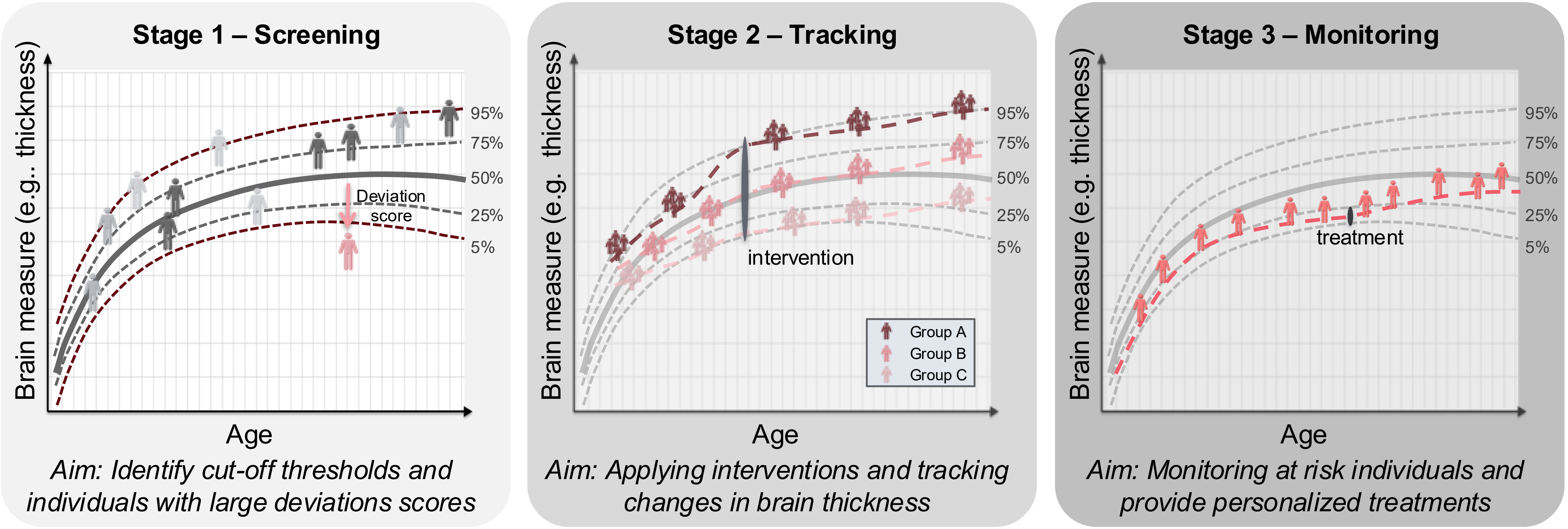
Precision Medicine

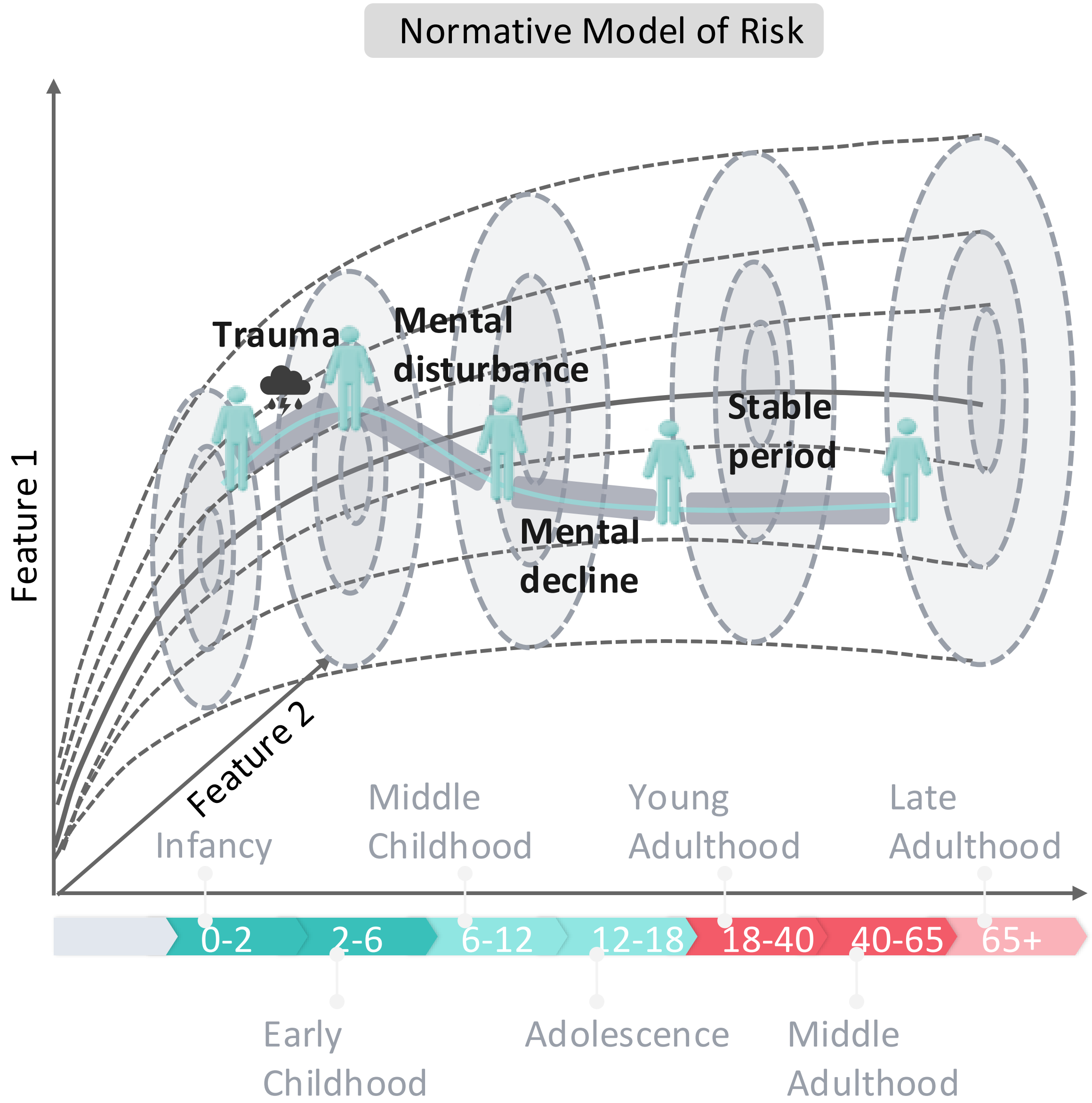


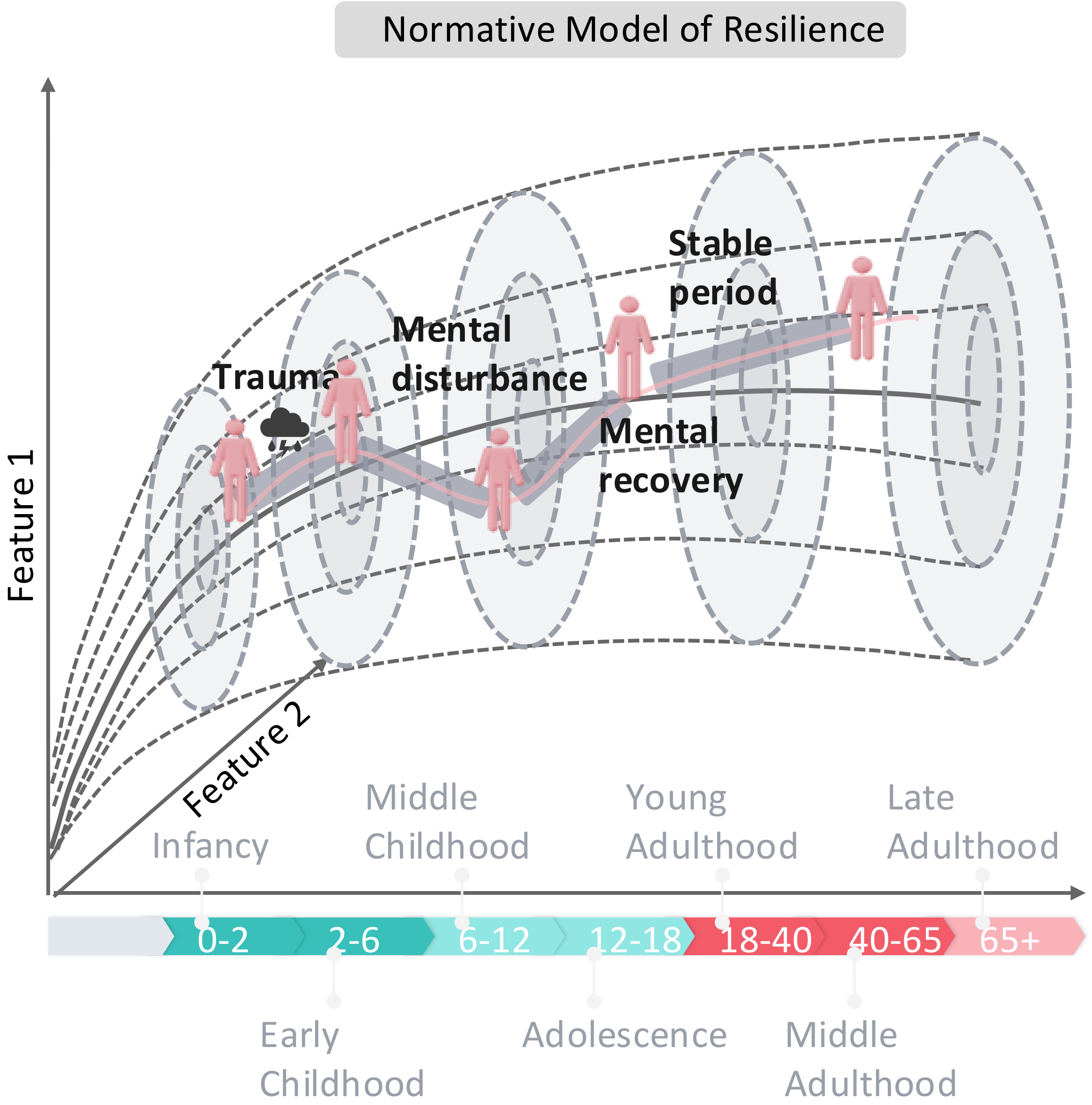
OTHER

APPLICATIONS

Precision Medicine




Normative Model of Risk
Feature 1
Feature 2
Trauma
Mental disturbance
Mental decline
Stable period
Infancy
Early Childhood
Middle Childhood
Adolescence
Young Adulthood
Middle Adulthood
Late Adulthood
0-2
2-6
6-12
12-18
18-40
40-65
65+


Normative Model of Resilience
Feature 1
Feature 2
Trauma
Mental disturbance
Mental recovery
Stable period
Infancy
Early Childhood
Middle Childhood
Adolescence
Young Adulthood
Middle Adulthood
Late Adulthood
0-2
2-6
6-12
12-18
18-40
40-65
65+

https://github.com/CharFraza/CPC_ML_tutorial

Tasks

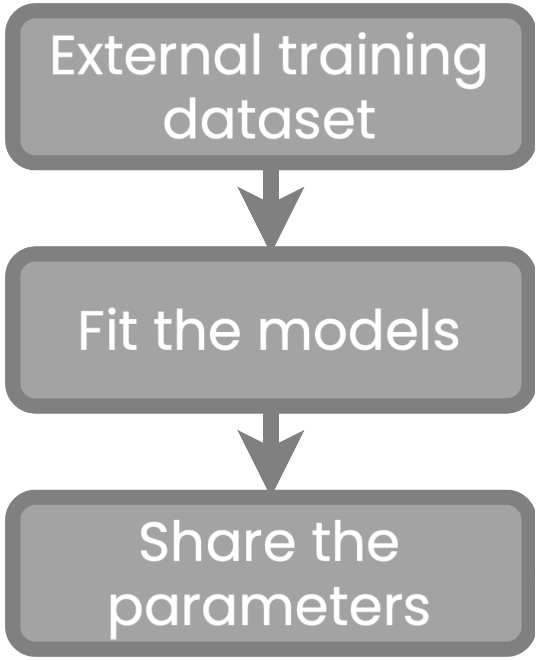
Task 1: Fitting normative models from scratch Open in Colab

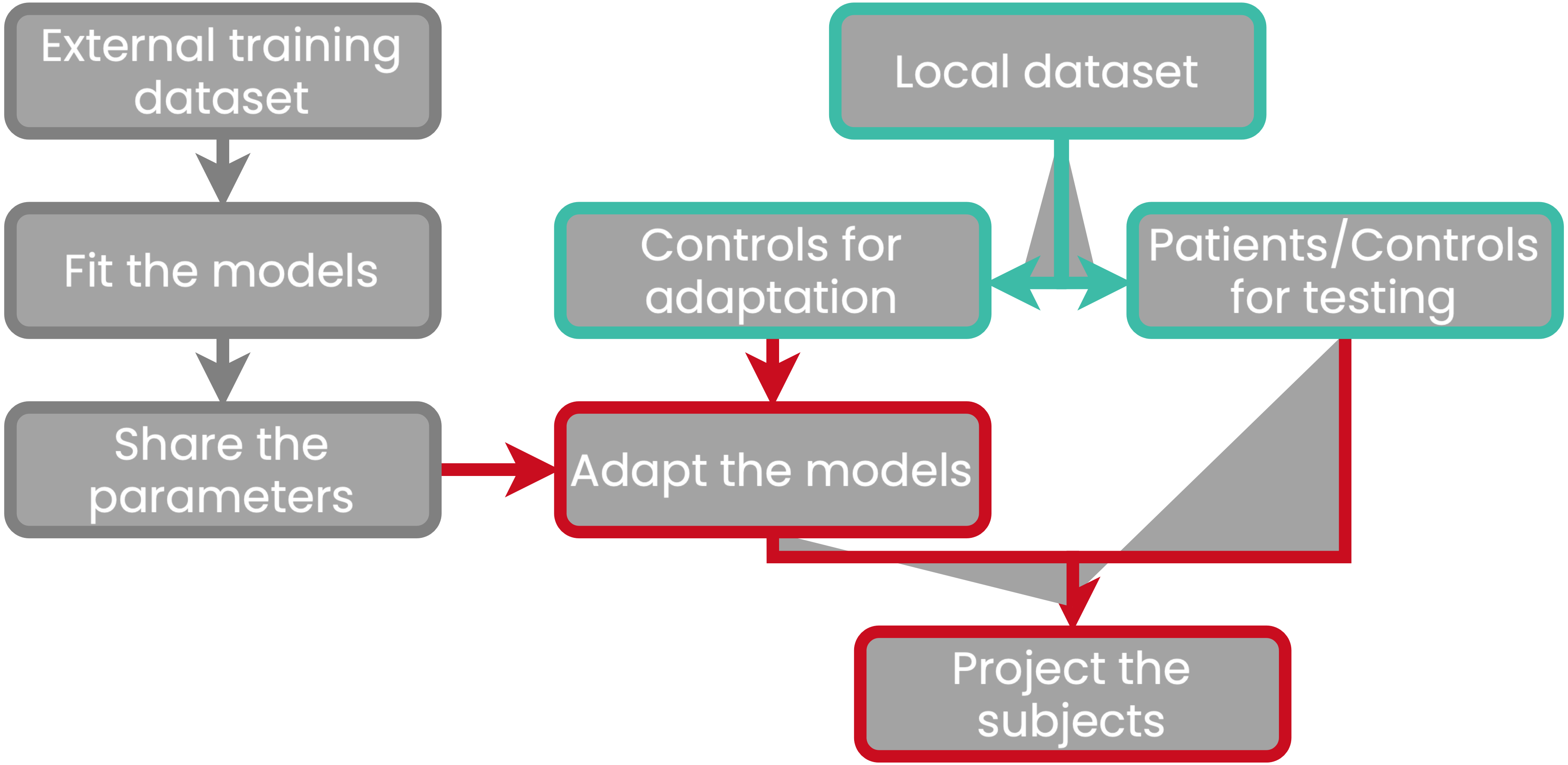
Task 2: Applying pre-trained normative models Open in Colab

Task 3: Interpreting and visualizing the outputs of normative models Open in Colab

Task 4: Using the outputs (Z-scores) as features in predictive model Open in Colab

APPLYING PRE-TRAINED NORMATIVE MODELS




External training dataset
Fit the models
Share the parameters
Local dataset
Controls for adaptation
Patients/Controls for testing
Adapt the models
Project the subjects

TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS

Install and load the packages → Clone the Github directory → Clone the pretrained models → Download adaptation & test data

TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS

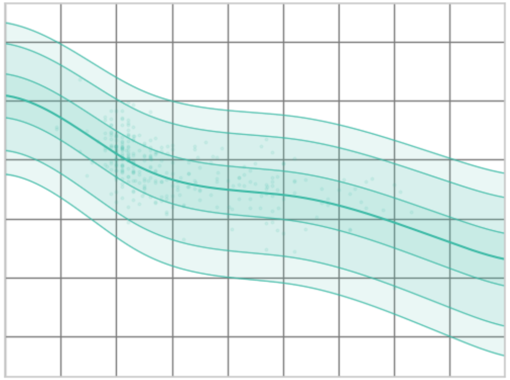
1. Install and load the packages
2. Clone the Github directory
3. Clone the pretrained models
4. Download adaptation & test data
5. Select variables for modelling
6. Select covariates & modelling parameters
7. Adapt the pretrained models & run on test data

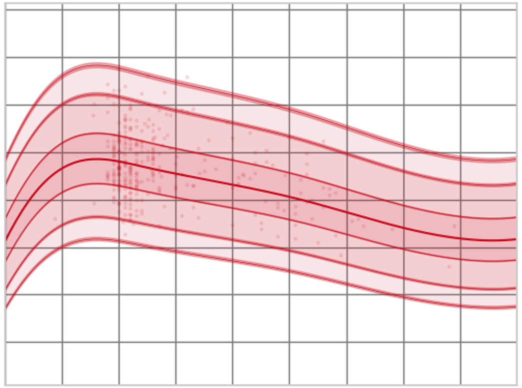
TUTORIAL II.

APPLYING PRE-TRAINED NORMATIVE MODELS

Install and load the packages → Clone the Github directory → Clone the pretrained models → Download adaptation & test data

Select variables for modelling → Select covariates & modelling parameters → Adapt the pretrained models & run on test data





Visualize

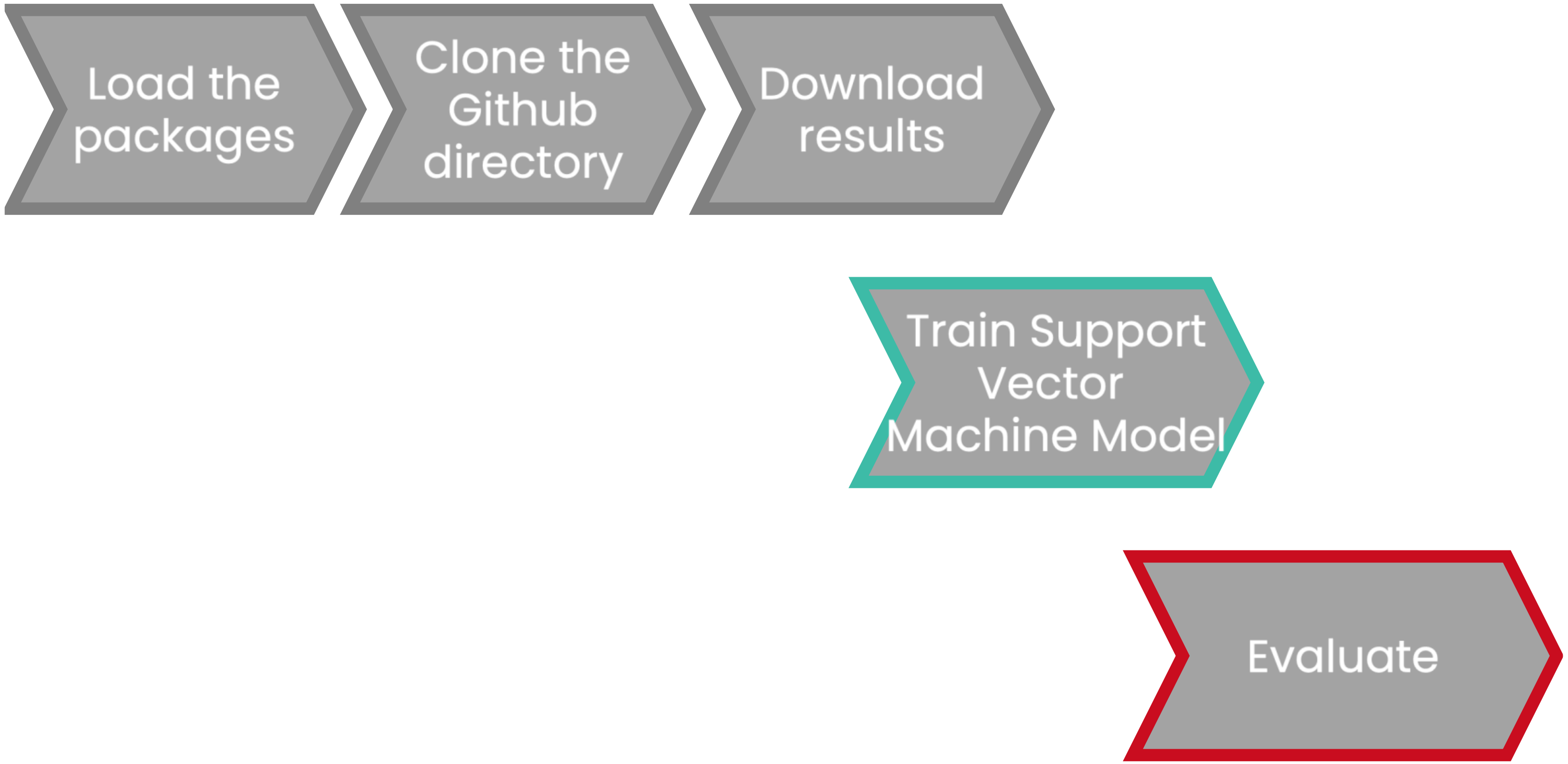
TUTORIAL III.

INTERPRETING AND VISUALIZING THE OUTPUTS OF NORMATIVE MODELS

Load the packages → Clone the Github directory → Download results

TUTORIAL IV.

USING THE OUTPUTS AS FEATURES IN PREDICTIVE MODEL



Predictive utility of structural MRI data and normative modeling in Spinocerebellar Ataxia Type 1
Alice Chavanne

Charting the velocity of brain growth and development
Johanna Bayer

Structured Missingness in Psychiatry
Barbora Rehák Bučková

Empirical Comparison of Brain Age and Normative Modeling Derived Biomarkers of Healthy Brain Aging
Richard Dinga

Longitudinal normative modelling of cortical thickness in the ABCD dataset
Philipp Seidel

Normative Modelling of Large-Scale Electroencephalographic Data
Francesco Mallus

Using normative models to predict EEG features based on structural brain imaging data
Jonathan Möller

Ensemble Clustering of Internalizing Disorder Patients Using Multimodal Clinical and Neuroimaging Data
Marija Tochadse

Predictive Clinical Neuroscience Lab

The Promise of Quantifying Individual Risk for Brain Disorders through Normative Modeling, a Narrative Review

THANK YOU!

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