

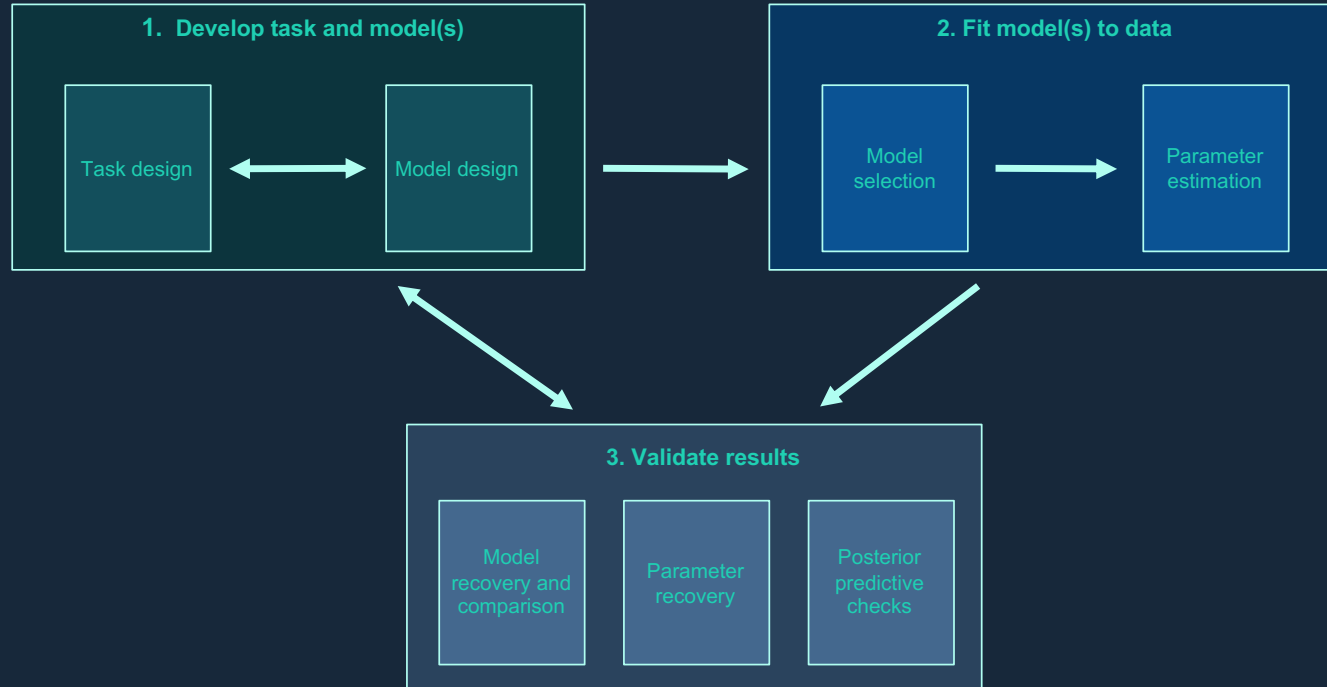
What is Computational Model(1)ing?

"All models are wrong, but some are useful"
George E. P. Box

What we will cover:

- Brief *introduction* to computational modelling
- *Development* of a computational model
- Principles of *model fitting*
- *Model comparison, selection and validation*

Framework:



What we will cover:

- Brief *introduction* to computational models
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Session No. I | Introduction

Brief Introduction

Alisa Loosen | Nadescha Trudel

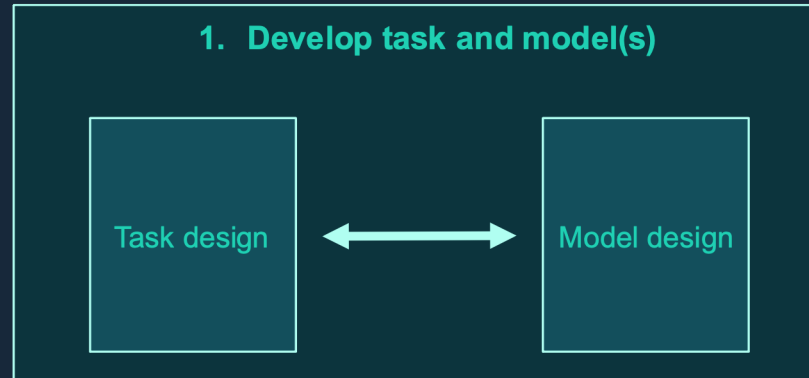
What we will cover:

- Why and for what data do we use computational models?
- Principles of computational modelling introduced by General Linear Models (GLMs)
 - Model fitting
 - Model complexity
 - Model comparison

Computational models help us make sense of
Behavioural data (e.g., decision-making, learning)
Eye-tracking data
Neuroimaging data ...

e.g., Hong et al., 2008;
Hartley & Somerville, 2015;
Hauser et al., 2019; Nour et
al., 2021

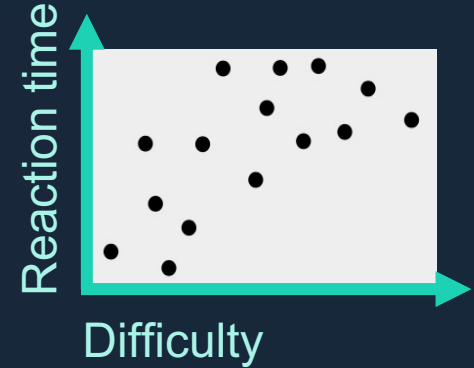
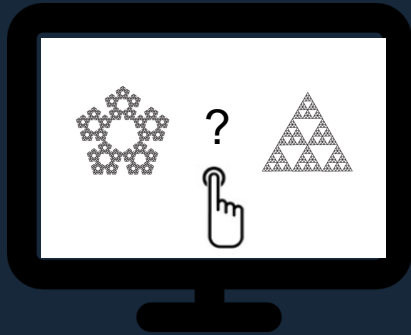
They help us capture differences linked to
Psychiatric conditions
Developmental stages ...



Input

Cognitive processes

Output



“hidden computations”



“hidden computations”

Observed data =

intercept + (slope * predictor) + residuals

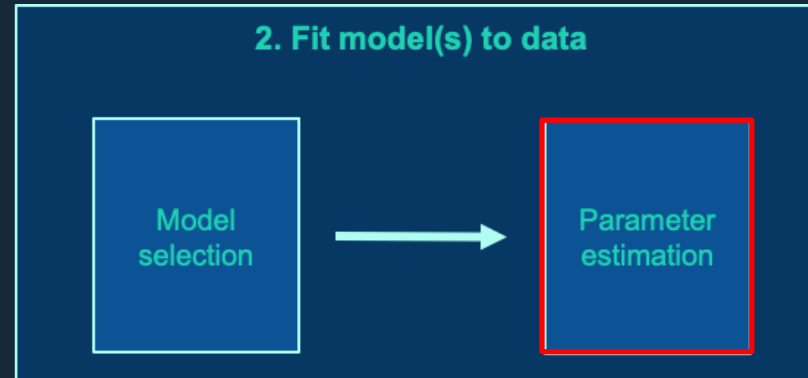
$$y = b_0 + b_1x + e$$

Some math happens

$$y = f(x)$$

reaction time difficulty







Model fit: parameter estimation

Observed data =
 $\text{intercept} + (\text{slope} * \text{predictor}) + \text{residuals}$

Reaction time =
 $b_0 + b_1 \text{difficulty} + e$

Free parameters

Model fit:

try to estimate the values of (free) parameters that best describe data

Techniques:

Least Square Approach: find parameter estimate that minimizes the sum of square of residuals (i.e., unexplained variance)

Model fit: parameter estimation

Example:

Observed data =
intercept + (slope * predictor) + residuals

$$\text{Reaction time} = b_0 + b_1 \text{difficulty} + e$$

Free parameters



$$y = b_0 + b_1 \text{difficulty} + e$$

Model fit: parameter estimation

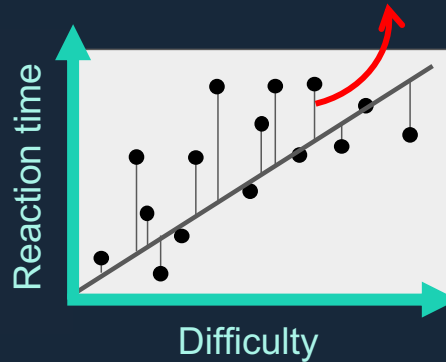
Observed data =
intercept + (slope * predictor) + residuals

$$\text{Reaction time} = b_0 + b_1 \text{ difficulty} + e$$

Free parameters

Example:

LQM: minimize distance



$$y = b_0 + b_1 \text{ difficulty} + e$$

Least Square Method:
minimizes sum of square
residuals: vertical lines between
data points and fitted line.

Regression coefficient:
reflects the steepness
and sign of the fitted slope



Model fit: parameter estimation

Example:

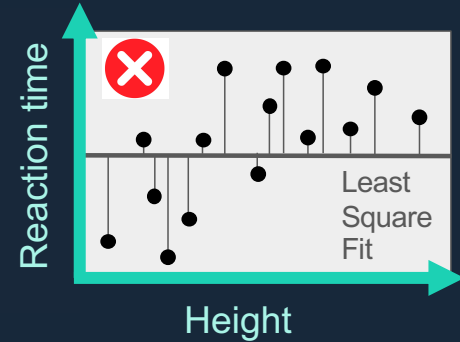
Observed data =
intercept + (slope * predictor) + residuals

$$\text{Reaction time} = b_0 + b_1 \text{difficulty} + e$$

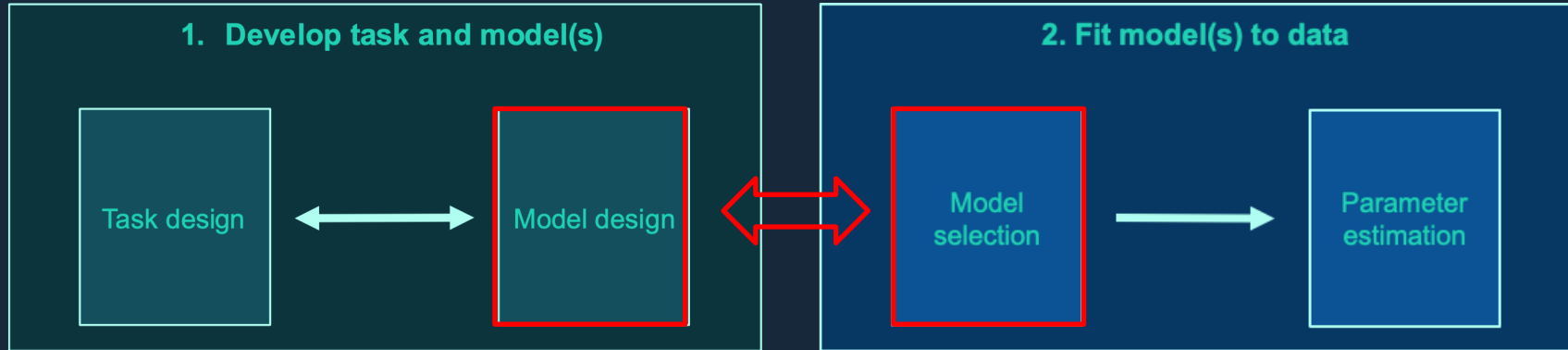
Free parameters



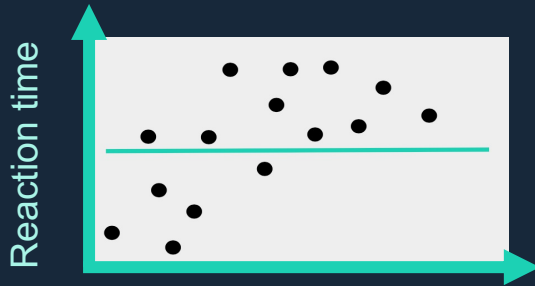
$$y = b_0 + 1.5x\text{difficulty} + e$$



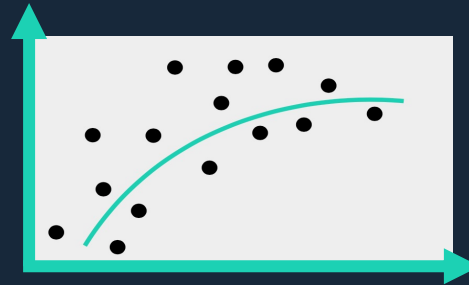
$$y = b_0 + 0x\text{height} + e$$



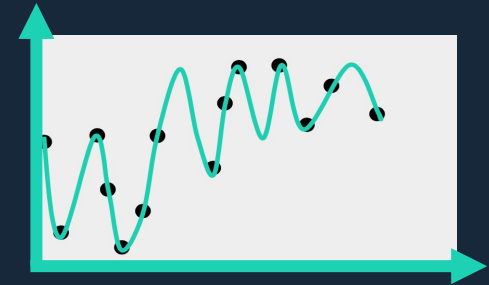
Model complexity



$$y = b_0 + e$$



$$y = b_0 + b_1 * \text{difficulty} + b_2 * \text{time pressure} + e$$

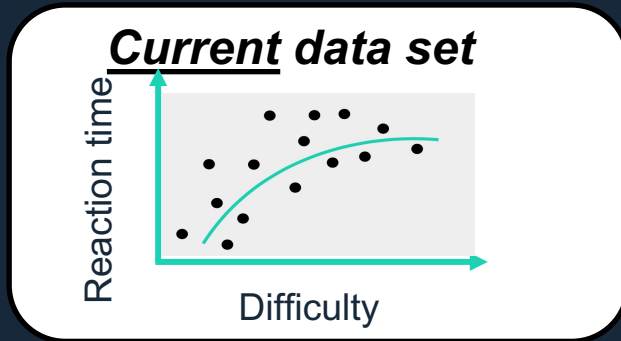


$$y = b_0 + b_1 x^1 + b_2 x^2 + \dots + b_6 x^6 + e$$

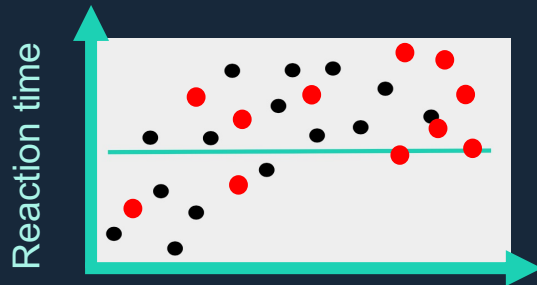
- Temperature
- Daytime
- ...

Adapted from Bonifay (2021)

Model complexity

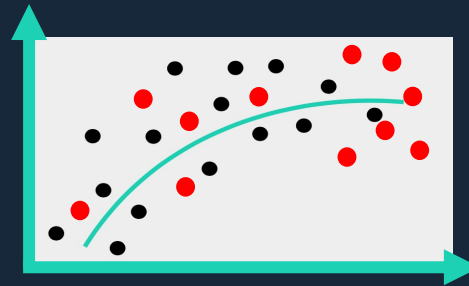


Model complexity



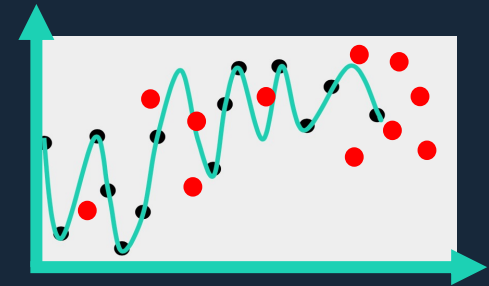
Underfitting

$$y = b_0 + e$$



Robust

$$y = b_0 + b_1 * \text{difficulty} + b_2 * \text{time pressure} + e$$



Overfitting

$$y = b_0 + b_1 x^1 + b_2 x^2 + \dots + b_6 x^6 + e$$

- Temperature
- Daytime
- ...

Adapted from Bonifay (2021)



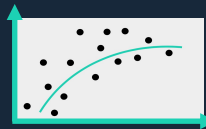
Model complexity



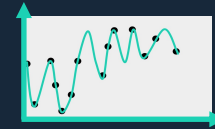
Underfitting



Robust



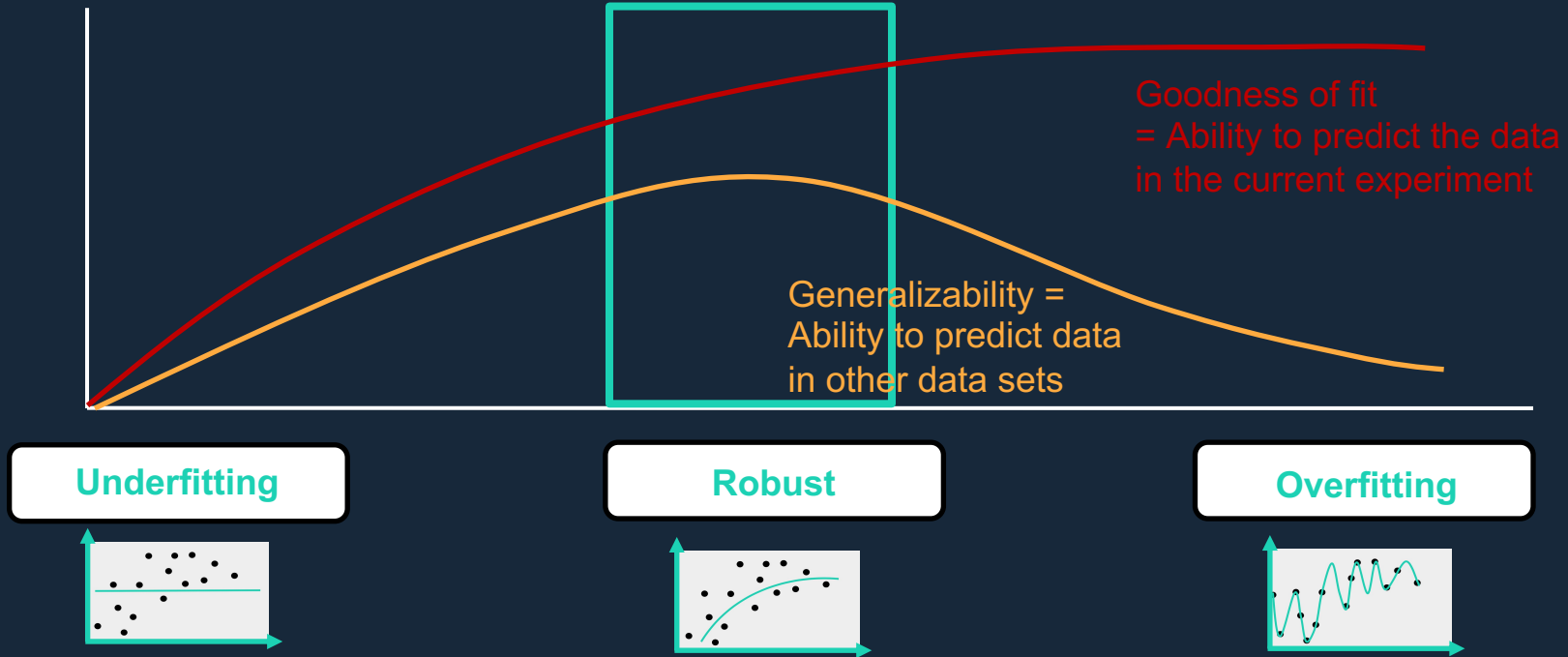
Overfitting



Adapted from Bonifay (2021)



Model complexity



Adapted from Bonifay (2021)

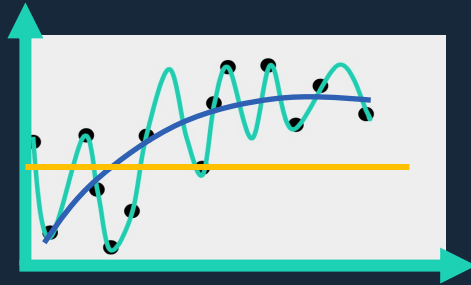
3. Validate results

Model
recovery and
comparison

Parameter
recovery

Posterior
predictive
checks

Model comparison

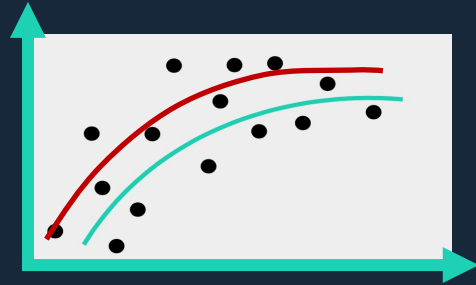


Underfitted model
Robust model
Overfitted model

Model comparison:

Which model, out of a set of possible models, is most likely to have generated the data.

Model comparison



$$y = b_0 + b_1 \text{difficulty} + e$$

$$y = b_0 + b_1 \text{time pressure} + e$$

Model comparison:

Which model, out of a set of possible models, is most likely to have generated the data.

Techniques:

Bayesian Information Criterion (BIC)

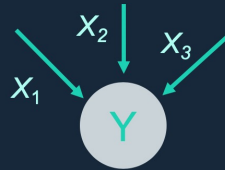
Akaike Information Criterion (AIC)

GLM vs. computational models

GLMs

→ requires explicit formulation of task variables

→ receives one or more parallel direct inputs

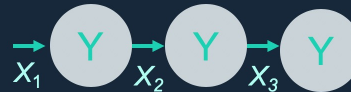


Parallel input

Computational model

→ Can infer latent (hidden) processes (e.g., beliefs,...)

→ Predict data of nonlinear systems, that involve series pathways, feedback processes etc.



Serial input

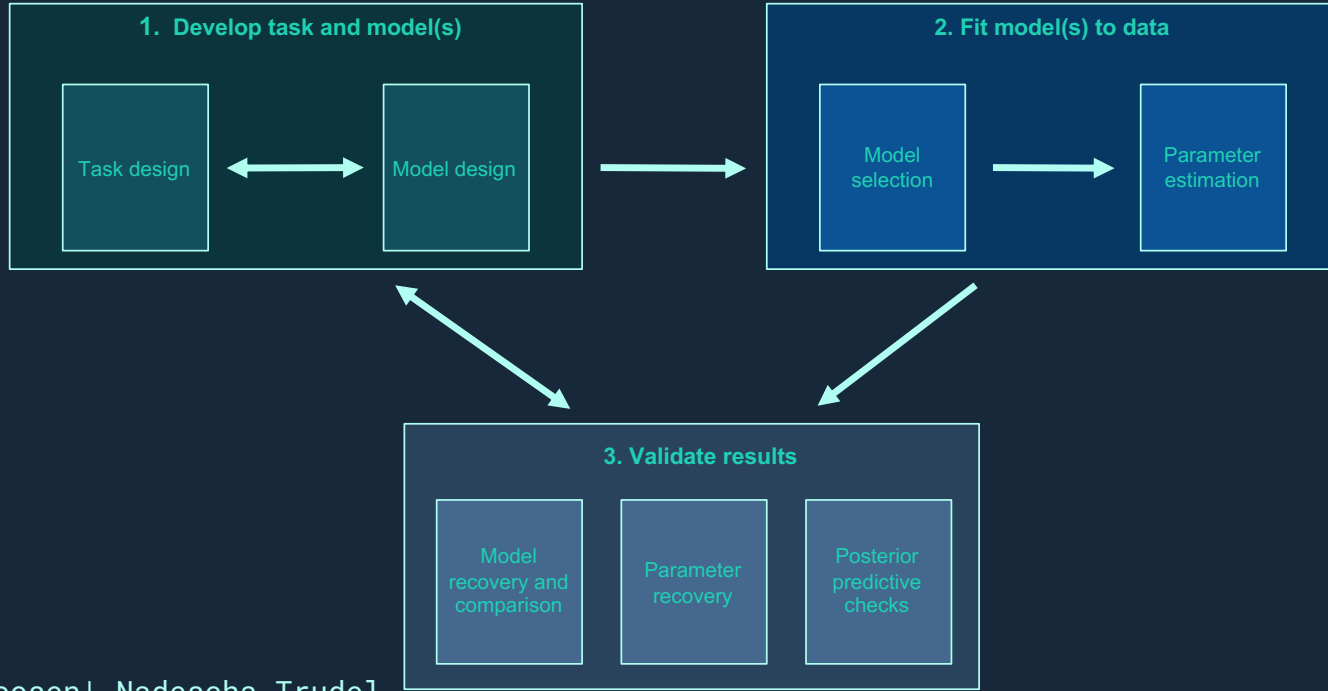


Feedback

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Adapted from Mujica-Parodi & Strey (2020)

Overview



References

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