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Generalizability in sex classification models

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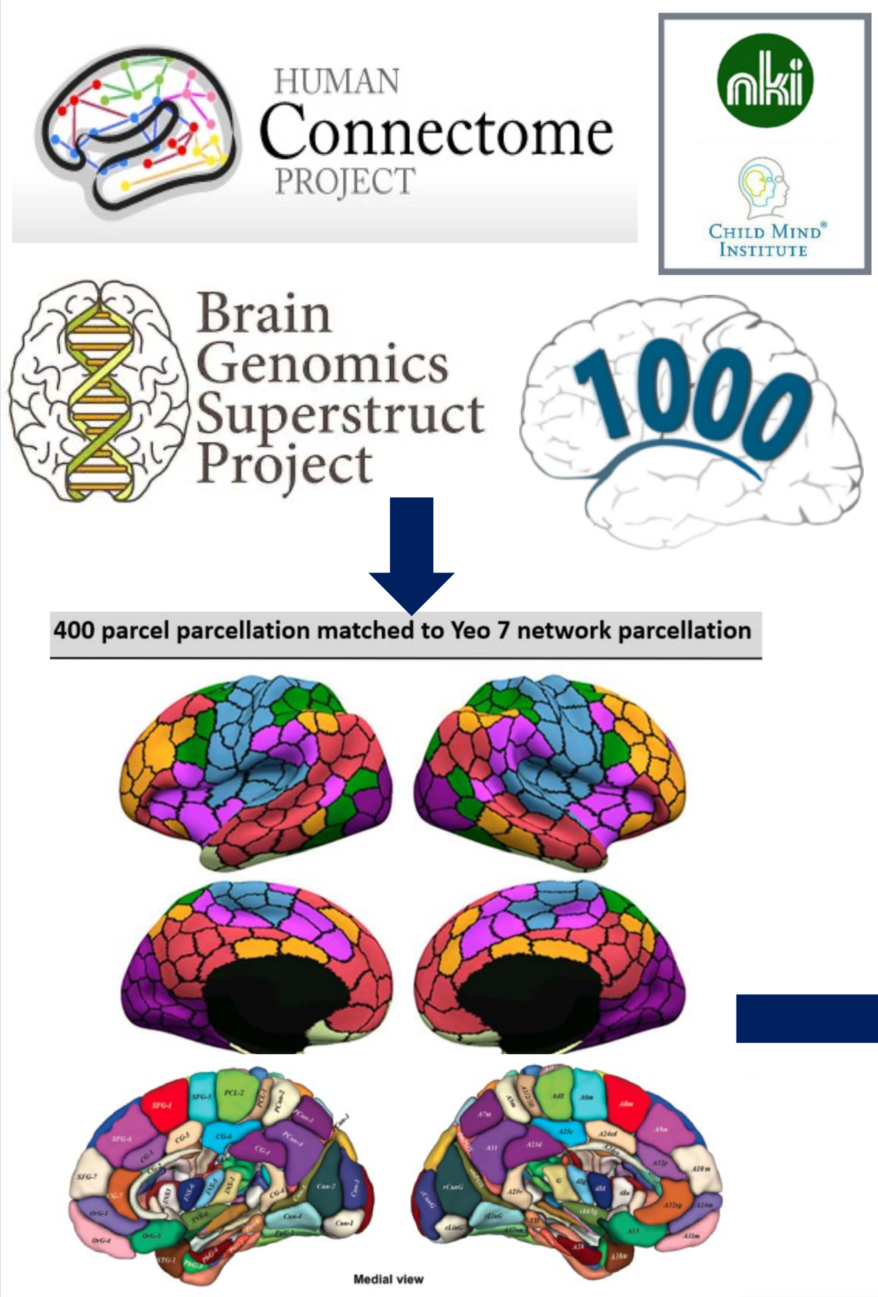
Introduction

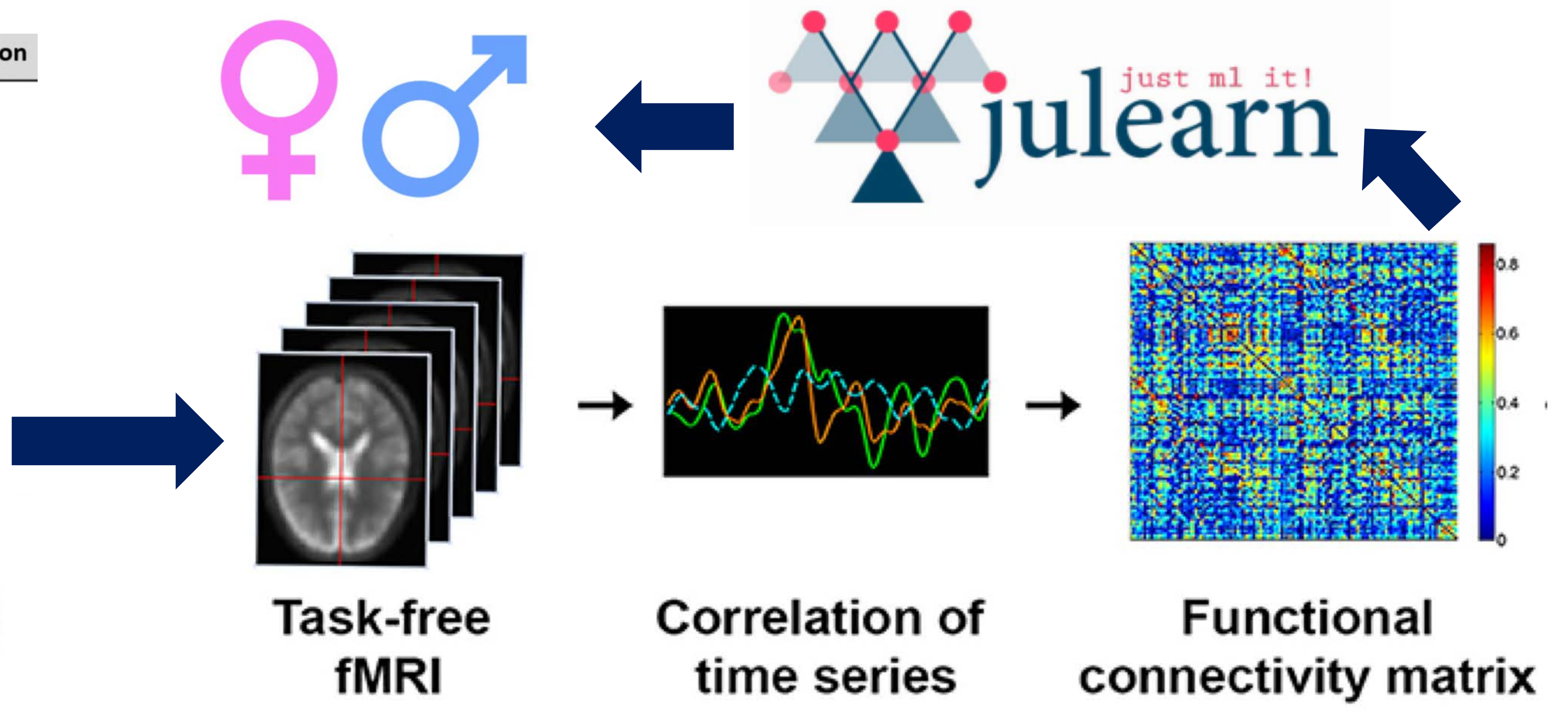
- Machine-learning analyses allow for the prediction of phenotypes from neuroimaging data (e.g. sex)
- Which sample characteristics provide highest model performance for within- and between-sample predictions?
- The present study adresses this question for sex classification analyses based on the resting-state functional connectivity (RSFC)
- RSFC of four cohorts differing in sample size, age range and image quality (HCP [1], GSP [2], eNKI [3] and 1000Brains [4])
- Data of the four cohorts were combined in various ways to examine which model provides highest classification accuracies and high generalizability

Methods



- HCP: N = 878, age range 22-37 (M = 28.49)
- GSP: N = 854, age range: 21-35 (M = 22.92)
- eNKI: N = 190, age range: 20-83 (M = 46.02)
- 1000Brains: N = 1000, age range: 21-85 (M = 61.18)

- Parcelwise approach (Weis et al. (2020, [5]): 400 parcels from the Schaefer Atlas [6]; 36 parcels from the Brainnetome Atlas [7]
- Support vector machine (SVM) classifier with 5 repetitions of a 10-fold cross-validation (Julearn)



Results

Table 1. Sex classification accuracies for within- and between sample predictions for model 1-5

	Model trained on	Within – predictions	Model applications
Model 1	75% of 1000Brains, eNKI, GSP and HCP (N = 2190)	62.9 (53.7 - 70.1)	HCP (25%): 65.3 (45.9 - 74.6) GSP (25%): 60.6 (49.1 - 70.1) eNKI (25%): 64.8 (47.9 - 83.3) 1000Brains (25%): 62.9 (52.4 - 75.2)
Model 2	eNKI, GSP, HCP (N = 1922)	64.9 (53.0 - 71.3)	1000Brains: 58.0 (49.5 - 68.0)
Model 3	1000Brains, GSP, HCP (N = 2732)	63.8 (53.0 - 70.5)	eNKI: 61.4 (50.0 - 72.6)
Model 4	1000Brains, eNKI, HCP (N = 2068)	63.9 (52.8 - 71.7)	GSP: 57.3 (48.7 - 68.6)
Model 5	1000Brains, eNKI, GSP (N = 2044)	61.5 (54.1 - 68.4)	HCP: 59.4 (48.8 - 69.9)

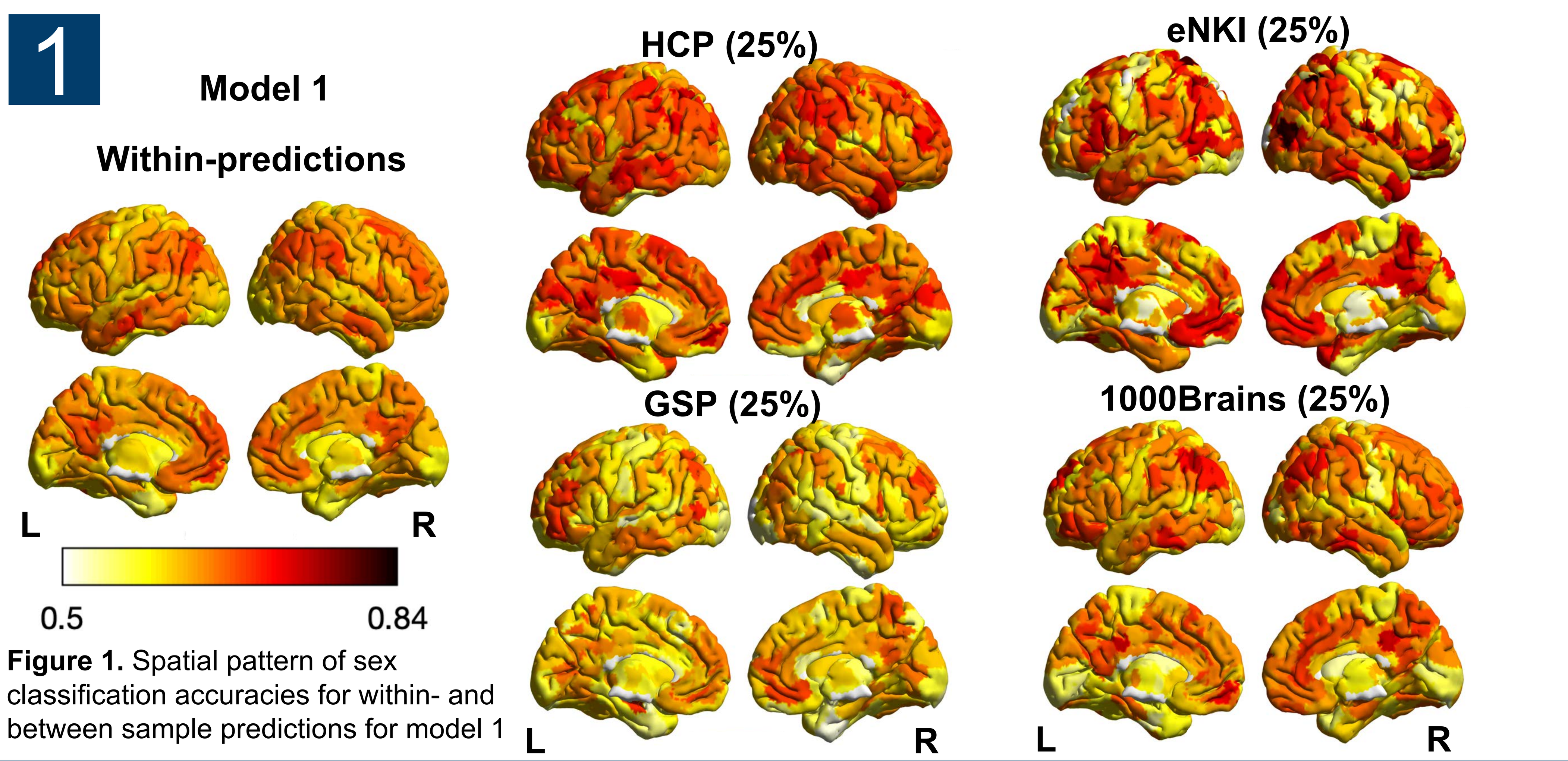


Figure 1. Spatial pattern of sex classification accuracies for within- and between sample predictions for model 1

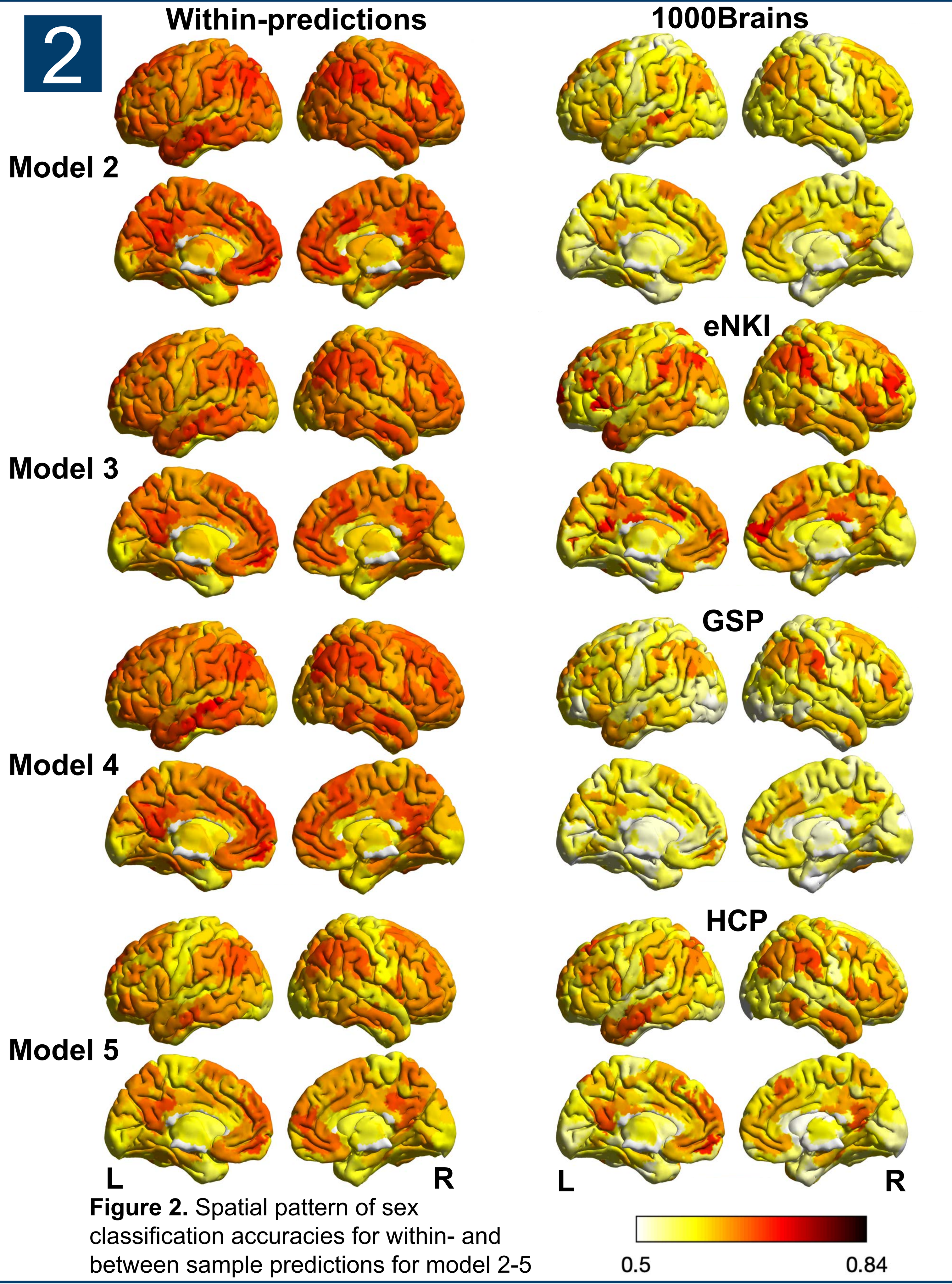


Figure 2. Spatial pattern of sex classification accuracies for within- and between sample predictions for model 2-5

Discussion

- Model 2 was trained on smallest sample size but outperformed all other models the in within-predictions
- Model 3 displayed higher between-prediction accuracy compared to model 2, 4 and 5
- Despite similar sample sizes, model 4 and 5 differed in classification accuracies:
  → model 4 achieved higher within-predictions, model 5 achieved higher between-predictions
- Model 2,3 and 4 were trained on samples of different size but exhibited similar ranges of classification accuracies for within-predictions
  → including HCP in training sample results in similar accuracies for within-predictions (63-64% mean prediction accuracy)
- Model 1 achieved highest accuracies for the eNKI-dataset with up to 83%, exceeding also the within-predictions for that model
  → Model 1 generalized best

→ Consistent spatial pattern of highly classifying parcels despite differently trained models

→ Higher sample size in training does not necessarily lead to higher accuracies

→ Best generalization performance for model 1 with heterogenous training sample, including parts of the test-dataset to adapt the model accordingly

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https://juaml.github.io/julearn/main/index.html
https://www.nitrc.org/projects/bnv/

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