

Handgrip strength prediction using behavioural and anthropometric features in 179K individuals from the UK Biobank

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Introduction

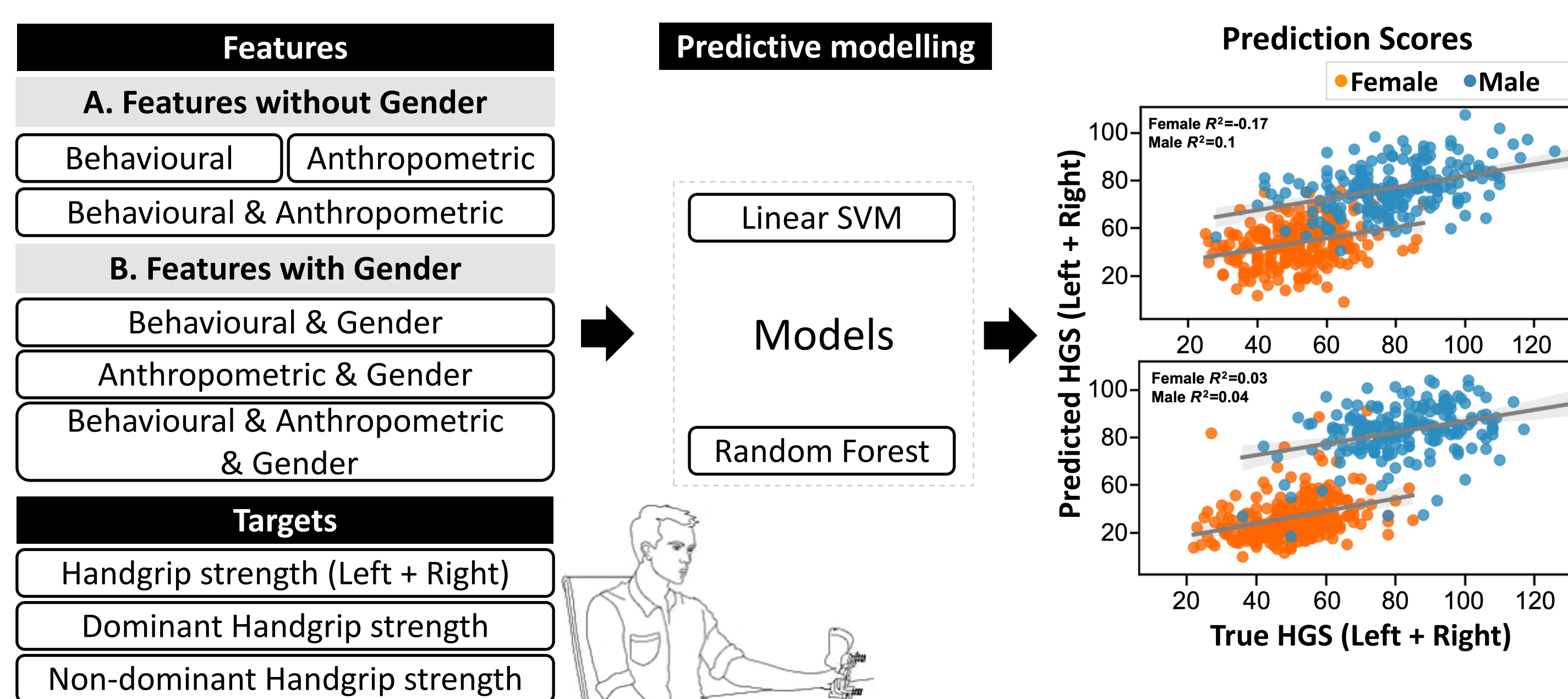
- Handgrip strength (HGS) is a valid biomarker for motor performance [1].
 - is an inexpensive, non-invasive, and commonly available measure in clinics.
 - is a powerful health condition predictor [2].
 - can diagnose and prognosticate acute stroke patients [2].
- Normative models can identify abnormality and in turn brain changes that affect HGS and other motor functions
 - Using a wide range of behavioural phenotypes and anthropometric measures.

Aim: Use anthropometric and behavioural features to build machine learning-based models to predict HGS.

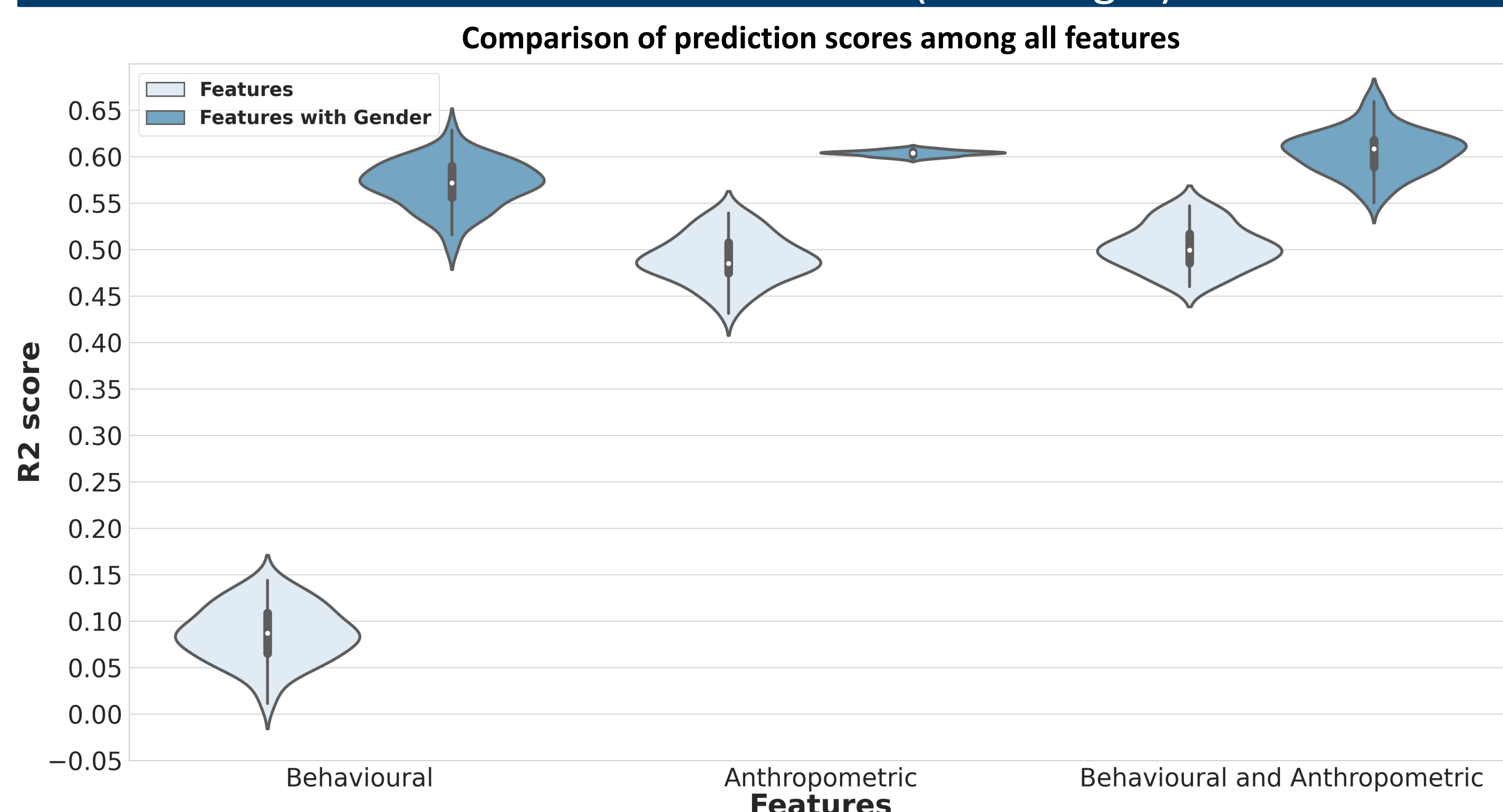
Data and Methods

- Data from non-MRI healthy controls in the UK Biobank
- Participants with dominant handgrip strength < 4 kg excluded [2]
- 30 behavioural phenotypes, e.g. cognitive functions, anxiety, depression, neuroticism [2-5]
- Anthropometric measures; BMI, Height and waist-to-hip circumference ratio [2]
- Features with or without the inclusion of gender (which confounds HGS)
- Models were also built for the genders separately
- Predictive models: **Linear Support Vector Machine (SVM)** and **Random Forest**
 - CV scheme with 10 repeats and 5 folds
 - R² score (coefficient of determination) for evaluation
 - Sample size effects were analysed

Block Diagram of Study



Results: Prediction of HGS (Left + Right)

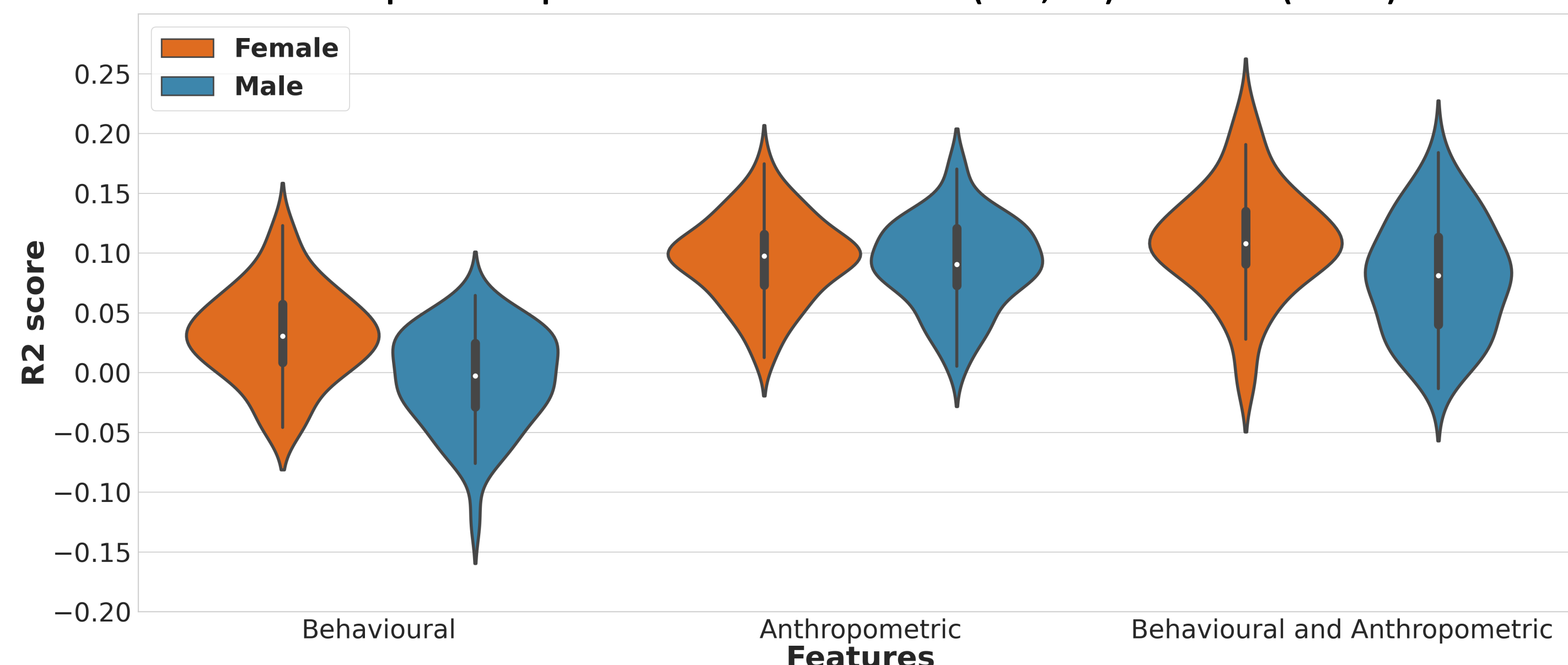


- Figure 1:**
- 2,143 subjects with completed assessments of all behavioural phenotypes
 - Behavioural features have the lowest R² (median=.087)
 - Anthropometric features showed high R² (median=.485)
 - Adding gender as a feature significantly increased the prediction scores.

References

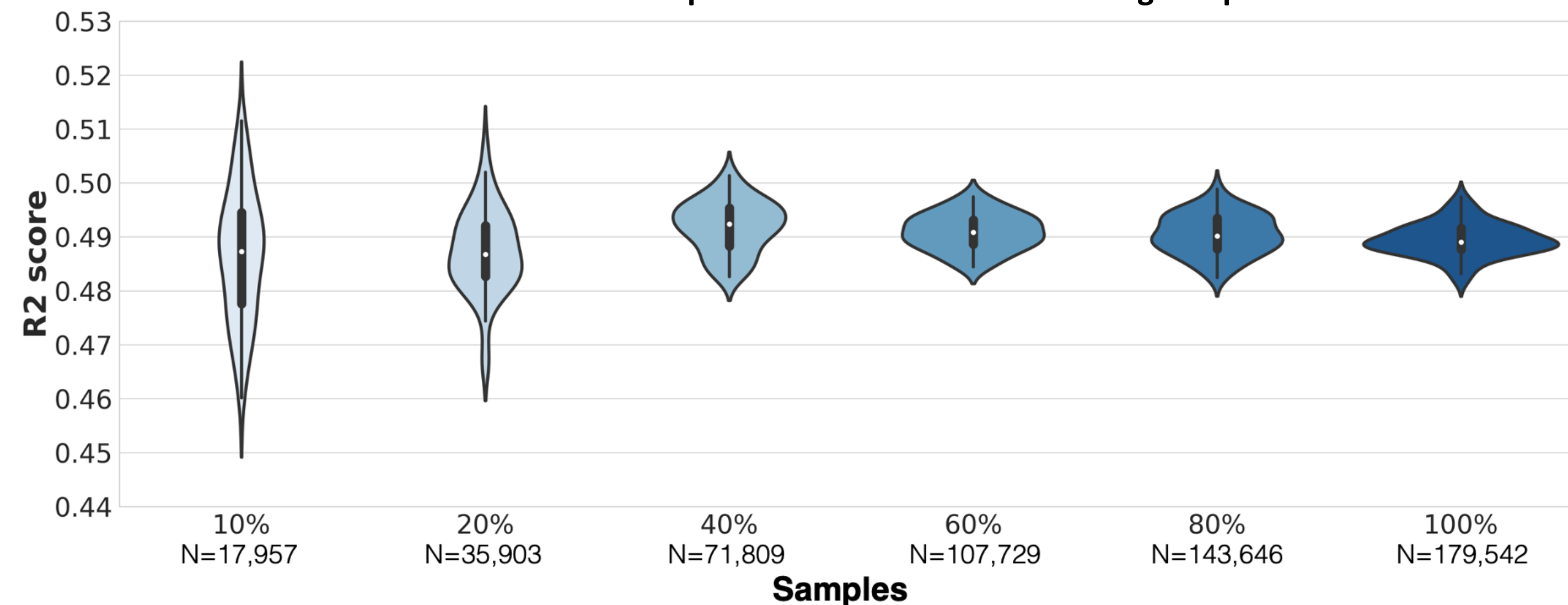
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- Acknowledgements: "This research has been conducted using data from UK Biobank, a major biomedical database". www.ukbiobank.ac.uk

Comparison of prediction scores for females (N=1,167) and males (N=976)



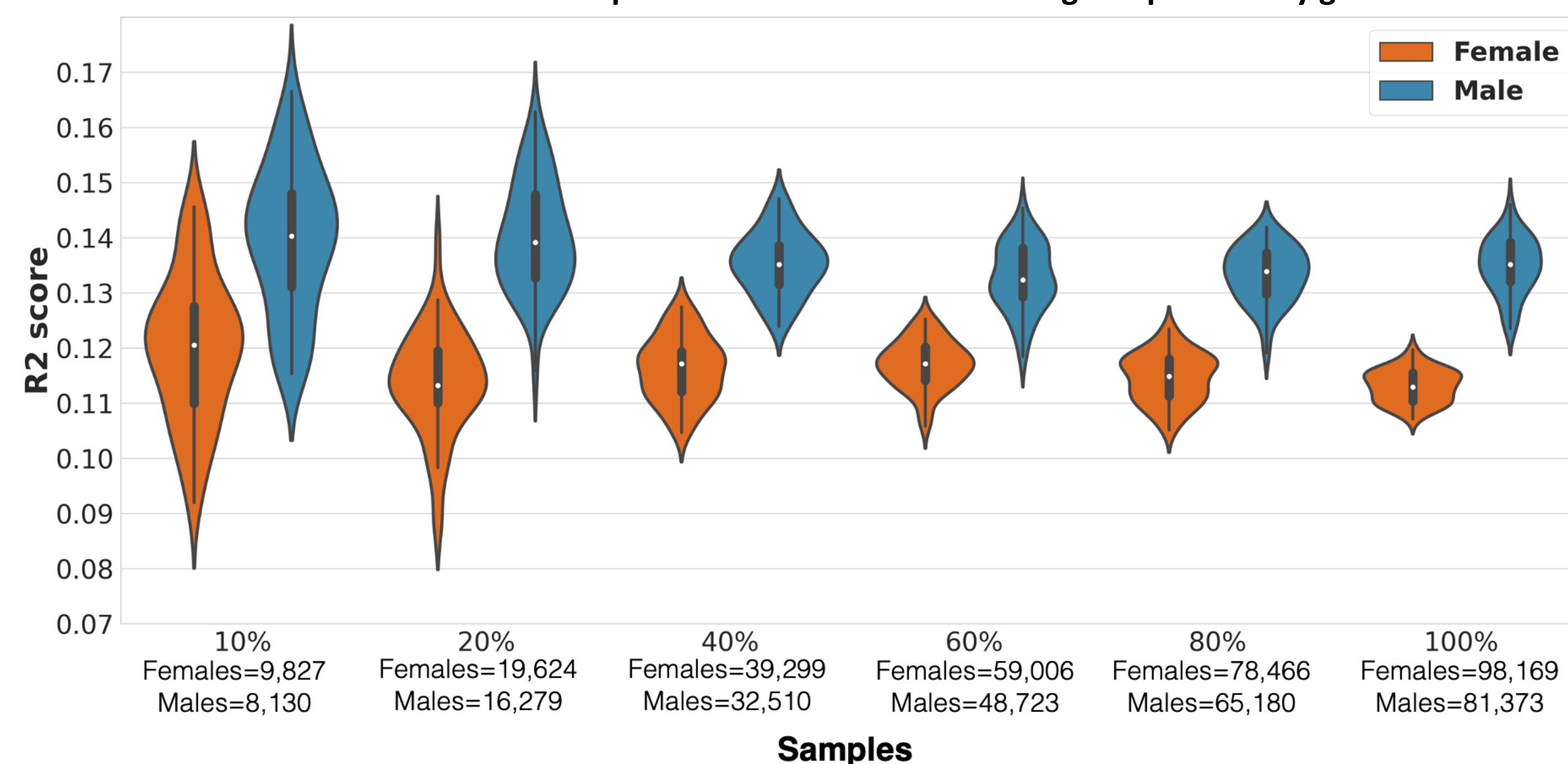
- Figure 2:**
- Building the model separately decreased accuracy significantly
 - The difference between females and males was not pronounced within each feature type.
 - Anthropometric features were still better than behavioural features
 - The drop in accuracy (Fig. 1) indicates HGS information encoded in gender

Performance of anthropometric features for increasing sample sizes



- Figure 3:**
- The lower sample size of anthropometric features shows a high variance [6].
 - Median accuracy first increased and then slightly decreased.
 - The performance saturates around N=71k

Performance of anthropometric features for increasing sample sizes by gender



- Figure 4:**
- The prediction accuracy dropped when males and females were analysed separately
 - Predictions in males were better than in females at all sample sizes.
 - The difference became pronounced and more significant with increasing sample size.

Conclusion

- Linear SVM outperformed Random Forest.
- Using gender as an additional feature considerably increased prediction accuracy.
 - Gender is a strong confound when modelling HGS.
- Males predicted HGS better than females with anthropometric features.
- (Non-)dominant HGS could be predicted but the HGS (Left + Right) predictions were more accurate.

Next steps

- Deploy the models to predict individuals with MRI data
- Identify brain correlates (e.g. WM intensity)
- Apply the pipeline to stroke patients

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