

Stacking Learning of Multimodal Neuroimaging data enhances cognitive prediction

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GOAL

Assess and quantify how unique variability in multimodal neuroimaging data contributes and aids to enhance predictive accuracies of individual cognitive performance.

DATASET

Observations:

-1050 subjects from the Human Connectome Project.

Independent Variables:

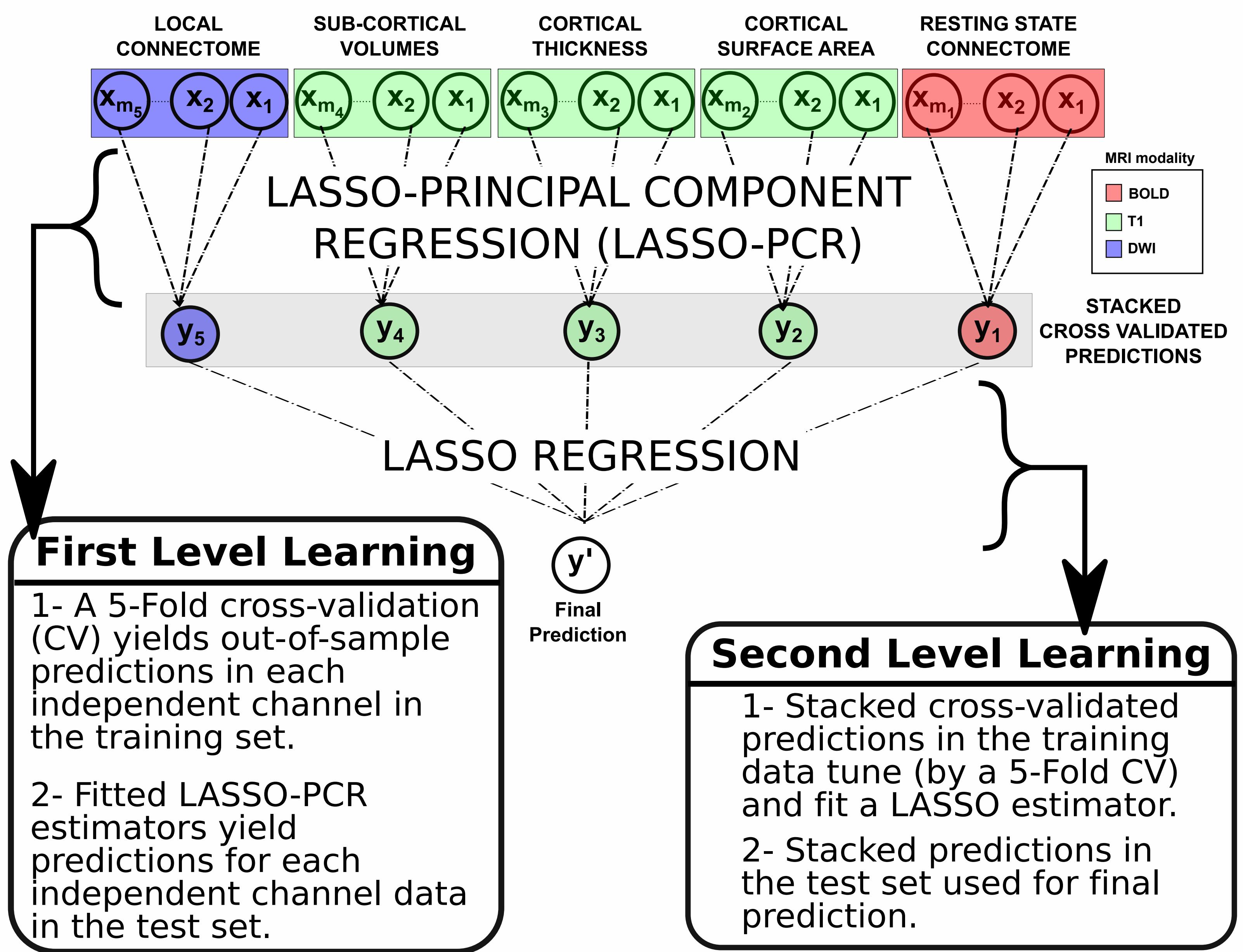
- Functional data (Resting-state connectivity)
- Structural data (Cortical Surface Areas, Cortical Thickness, Global and Sub-cortical volumes)
- Diffusion data (Local Connectome fingerprints)

Dependent Variables:

- NIH Toolbox Cognition Total Composite Score (*Global cognition*)
- NIH Toolbox Cognition Fluid Composite test score (*Fluid intelligence*)
- NIH Toolbox Cognition Crystallized Composite test (*Crystallized intelligence*)
- Short Penn Continuous Performance Test (*Sustained attention*)
- Area Under the Curve for Discounting of \$200 (*Self-regulation*)
- Total Number of Correct Responses in a Penn Word Memory test (*Verbal episodic memory*)
- Total number of correct responses in a Variable Short Penn Line Orientation test (*Spatial orientation*)

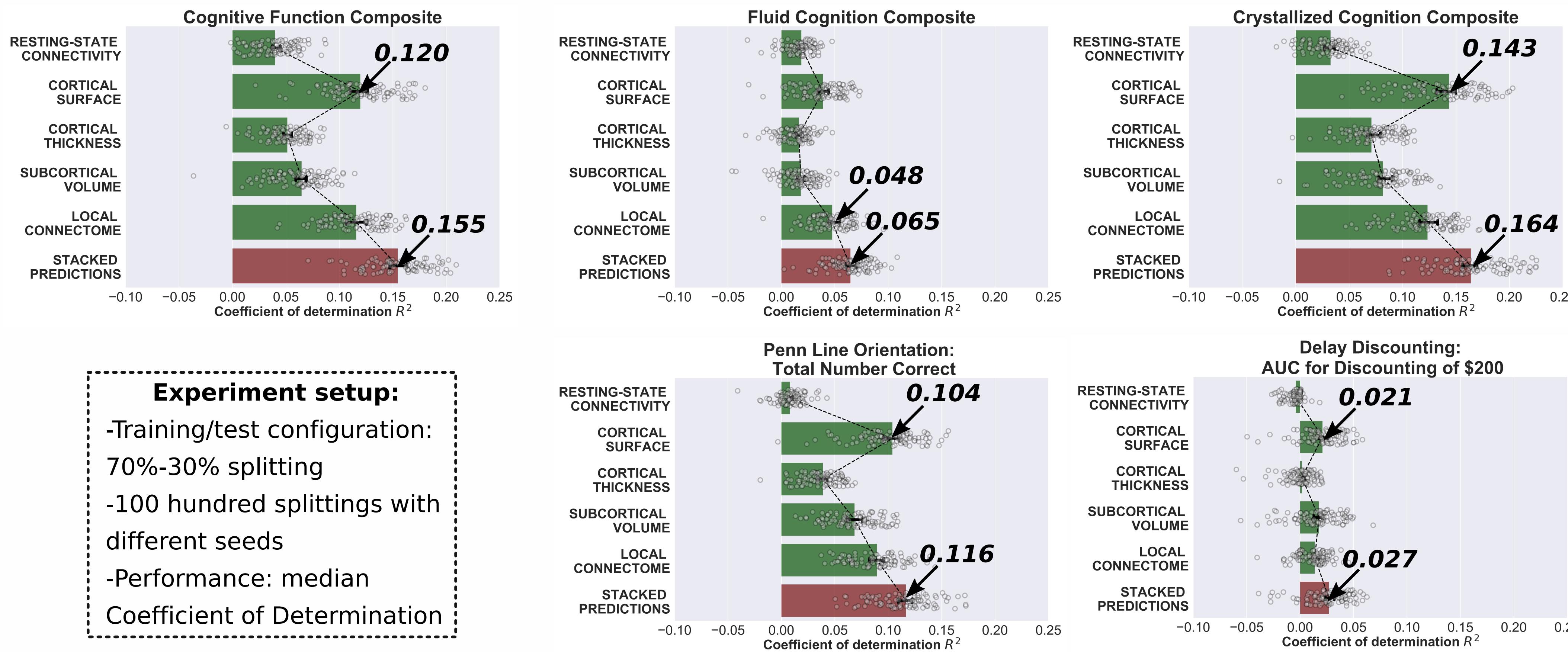
METHODOLOGY

Two-level stacking learning approach where each group of features (channels) is trained individually and then these predictions stacked to feed a second classifier that allows to account for redundant effects

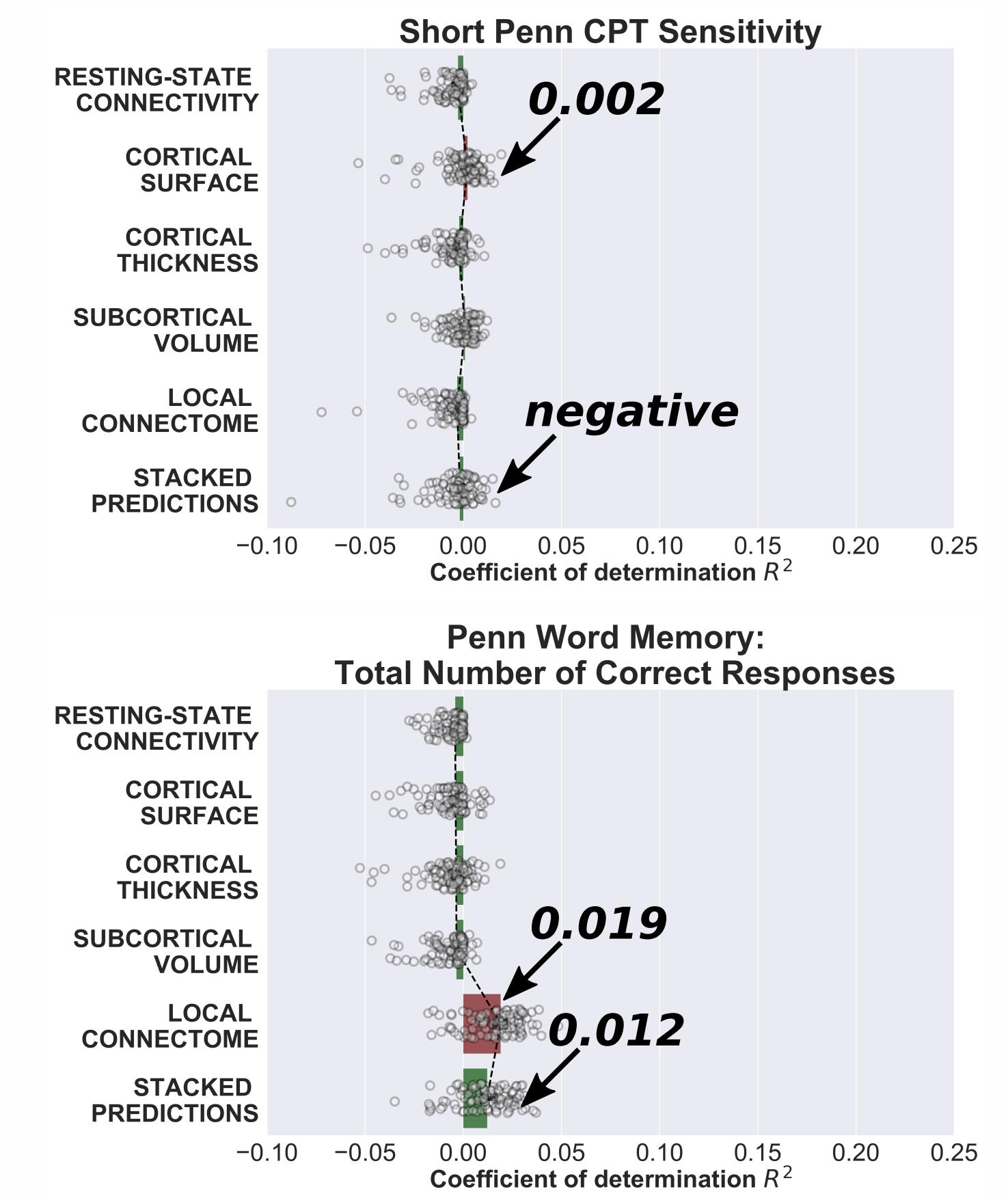


SINGLE CHANNEL AND STACKING PREDICTIVE SCORES

Cognitive areas where stacking improves accuracies with respect to best single channel:
Global cognition, Fluid intelligence, Crystallized intelligence, Spatial orientation and Self-regulation



Cognitive areas where stacking does not enhance performance:
Sustained attention, Verbal memory



CHANNEL CONTRIBUTION TO STACKING LEARNING

Measurement	Resting-state connectivity	Cortical Surface Areas	Cortical Thickness	Global and sub-cortical Volumes	Local Connectome
NIH Cognition Total Composite Score	0.360 95% CI [0.337, 0.386]	0.508 95% CI [0.483, 0.526]	0.193 95% CI [0.154, 0.223]	n.s.	0.560 95% CI [0.531, 0.584]
NIH Fluid Composite score	0.514 95% CI [0.474, 0.559]	0.462 95% CI [0.397, 0.517]	0.247 95% CI [0.163, 0.297]	n.s.	0.571 95% CI [0.535, 0.609]
NIH Crystallized Composite score	0.224 95% CI [0.148, 0.285]	0.535 95% CI [0.510, 0.566]	0.290 95% CI [0.260, 0.334]	n.s.	0.469 95% CI [0.431, 0.497]
AUC for Discounting of \$200	n.s. 95% CI [0.429, 0.534]	0.452 95% CI [0.429, 0.534]	n.s. 95% CI [0.332, 0.477]	0.442 95% CI [0.294, 0.419]	0.344 95% CI [0.294, 0.419]
Variable Short Penn Line Orientation test	n.s. 95% CI [0.482, 0.545]	0.512 95% CI [0.482, 0.545]	0.175 95% CI [0.100, 0.224]	n.s.	0.504 95% CI [0.478, 0.527]

- Local Connectome and Cortical Surface Areas are the most powerful channels, consistently contributing across all cognitive scores.
- Resting-state connectivity contributes particularly during Fluid Intelligence cognitive assessment.
- Cortical Thickness factors are a sub-leading contributing channel.
- Global and Sub-cortical volume Information only contributes non-redundantly to prediction in Impulsivity/self-regulation domain.

*Median Lasso weights from the second level learning. Only shown those scores where stacking enhanced accuracies.

CONCLUSIONS

Stacking Learning shows that each neuroimaging modality provides unique and complementary information about cognitive functioning.

These results establish a solid and reliable lower bound for cognitive prediction in different domains using multimodal neuroimaging data.

Prospect: Decompose input channels into a larger number of orthogonal representations for a better cognitive prediction.

REFERENCES

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- [3] Liem, Franziskus et al. "Predicting brain-age from multimodal imaging data captures cognitive impairment." NeuroImage vol. 148 (2017): 179-188.