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

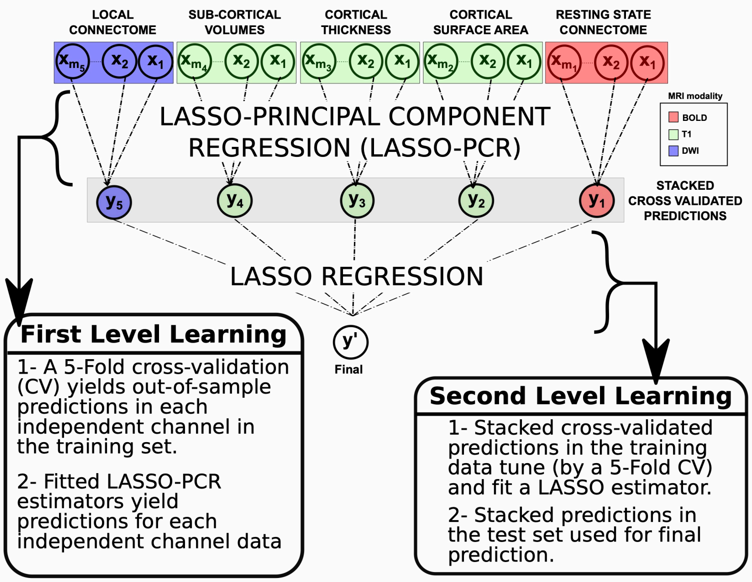
Observations:
-1050 subjects from the Human Connectome Project.

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*)

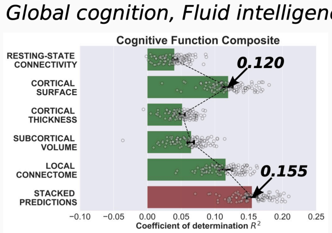
METHODOLOGY

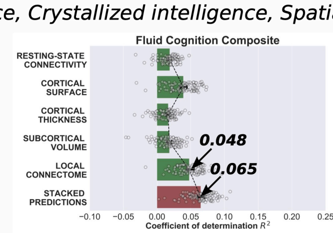
Two-level stacking learning approach where each group of features (channels) is trained individually and then these predictions stacked to feed a second classifier that allows to account for redundant effects

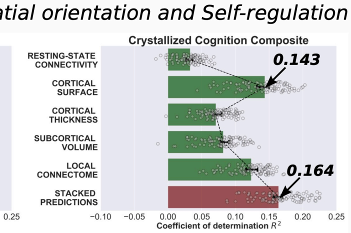


SINGLE CHANNEL AND STACKING PREDICTIVE SCORES

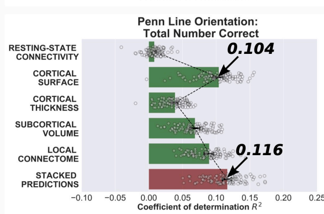
Cognitive areas where stacking improves accuracies with respect to best single channel:
Global cognition, Fluid intelligence, Crystallized intelligence, Spatial orientation and Self-regulation

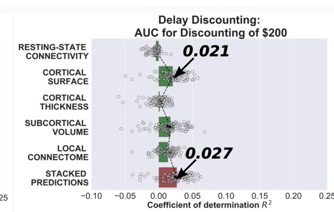




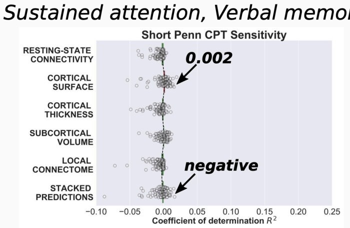


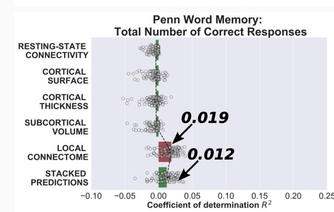
Experiment setup:
-Training/test configuration: 70%-30% splitting
-100 hundred splittings with different seeds
-Performance: median





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





CHANNEL CONTRIBUTION TO STACKING LEARNING

Cognitive score \ 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.	0.452 95% CI [0.429, 0.534]	n.s.	0.442 95% CI [0.332, 0.477]	0.344 95% CI [0.294, 0.419]
Variable Short Penn Line Orientation test	n.s.	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]

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

- 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.

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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