Studying Brain-Behavior Correlations with fMRI

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Section on Functional Imaging Methods, NIMH

FMRIF Summer Neuroimaging Course

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Outline

- What are brain-behavior correlations?
- Why study brain-behavior correlations?
- **How** to study brain-behavior correlations?

What are brain-behavior correlations?

Brain

- Activation (in an ROI, a network)
- Functional connectivity (at rest, during task)
- Structural measures (cortical thickness, DWI)
- Other modalities (EEG, MEG, etc)

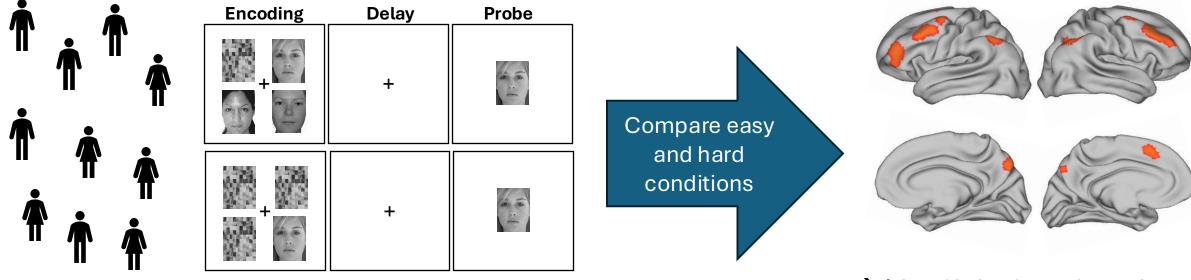
- Performance on a task (accuracy, RT)
 - Could be in or outside the scanner
- Self-report measures (personality traits, psychiatric symptoms)

Behavior Correlations

Some sort of statistical connection/association between the two

Why study brain-behavior correlations?

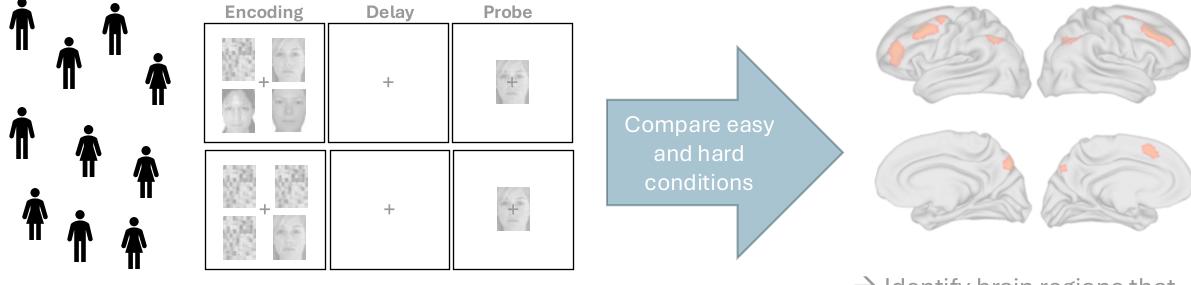
Traditional fMRI (group-level) analyses



→ Identify brain regions that care about the difficulty of visual working memory task



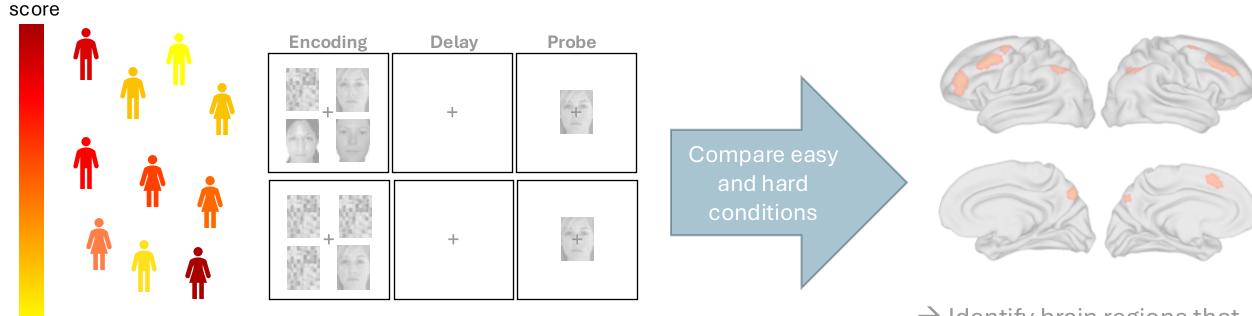
Traditional fMRI (group-level) analyses



→ Identify brain regions that care about the difficulty of visual working memory load



But wait, there's more (information!)



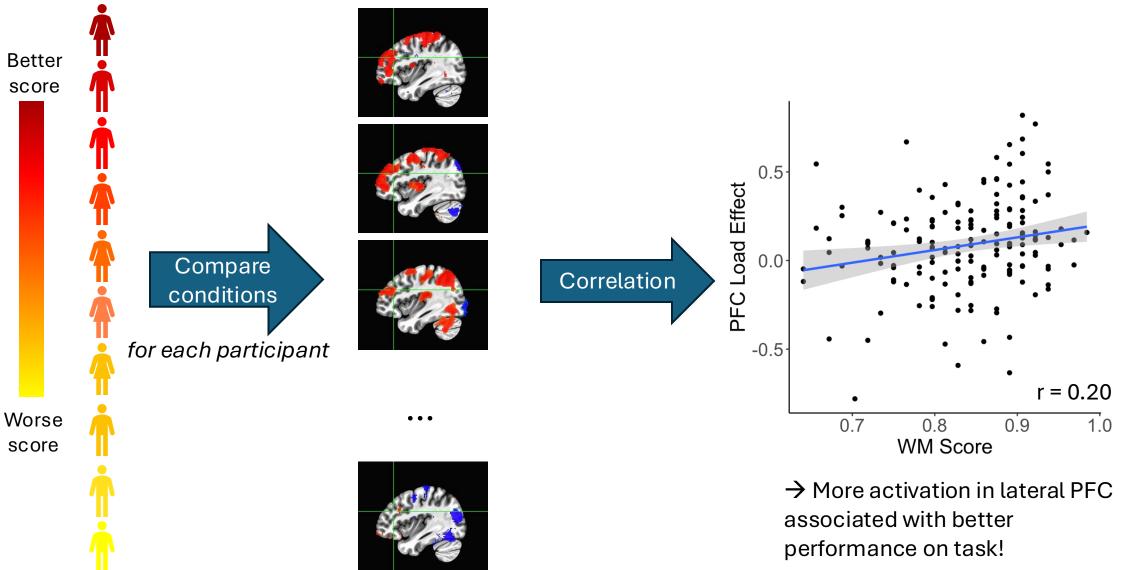
Worse score

Better



→ Identify brain regions that care about the difficulty of visual working memory load

But wait, there's more (information!)



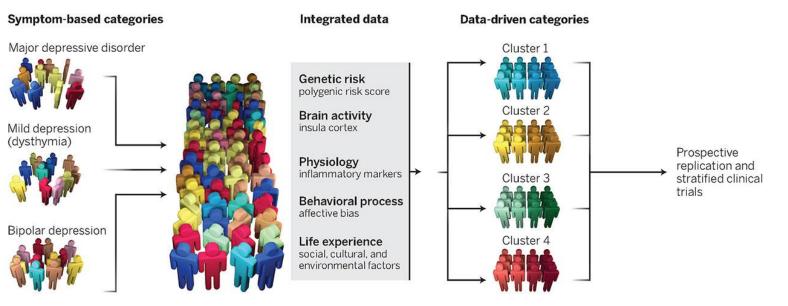
Psychiatric symptoms as dimensional, not categorical

Research Domains Criteria (RDoC)

Goal: "to develop, for research purposes, new ways of classifying mental disorders based on dimensions of observable behavior and neurobiological measures"

Deconstructed, parsed, and diagnosed.

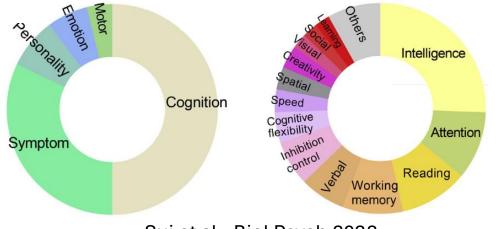
A hypothetical example illustrates how precision medicine might deconstruct traditional symptom-based categories. Patients with a range of mood disorders are studied across several analytical platforms to parse current heterogeneous syndromes into homogeneous clusters.



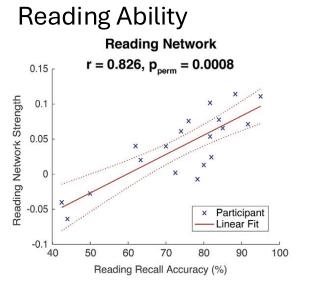
So what?

- Better understanding of disease pathophysiology
- Track disease progression
- Develop new (more effective) treatments
- Understand who will respond to which treatments

Predicting cognition

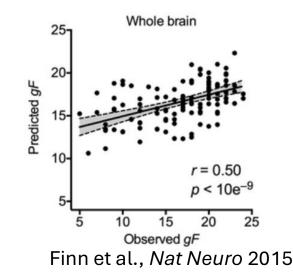


Sui et al., Biol Psych 2022

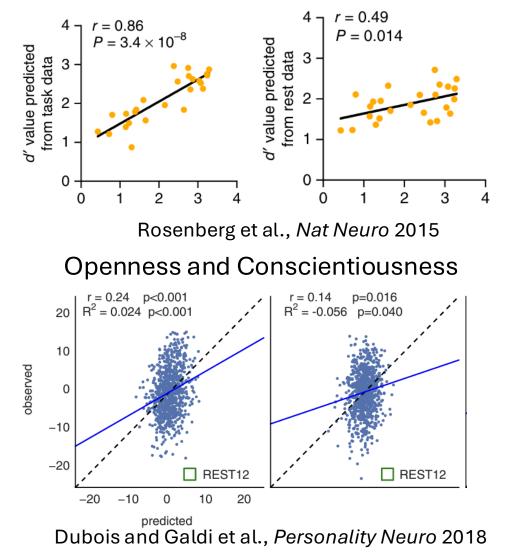


Jangraw et al., NeuroImage 2018

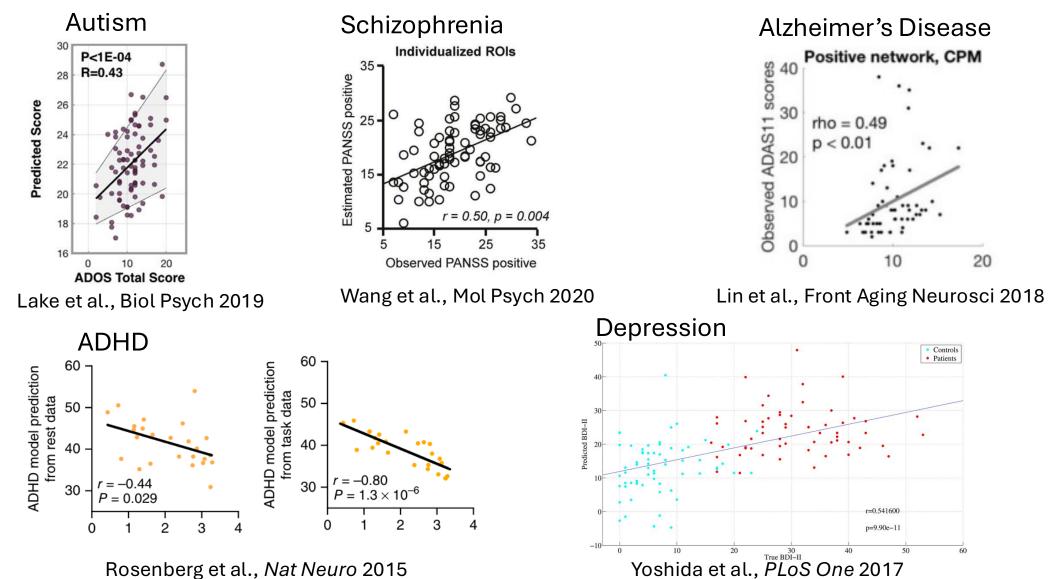
Fluid Intelligence



Sustained Attention



Predicting psychiatric symptoms



Why study brain-behavior correlations?

- Basic science!
 - New insights into neural processes
- Move towards brain-based psychiatry
 - Better understanding of how diseases work and how they progress
 - More personalized, targeted interventions: drugs, therapies, etc

But wait!

Are most brain-behavior correlations even meaningful?!? NEWS | 17 March 2022

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Reproducible brain-wide association studies requ thousands of individuals

By Ewen Callaway

Scott Marek [™], Brenden Tervo-Clemmens [™], Finnegan J. Calabro, David F. Montez, Benjamin P. Kay, Alexander S. Hatoum, Meghan Rose Donohue, William Foran, Ryland L. Miller, Timothy J. Hendrickson, Stephen M. Malone, Sridhar Kandala, Eric Feczko, Oscar Miranda-Dominguez, Alice M. Graham, Eric A. Earl, Anders J. Perrone, Michaela Cordova, Olivia Doyle, Lucille A. Moore,

Uriarte, Kathy Snider, Benjamin J. Lynch, ... Nico U. F. Dosenbach

Nature **603**, 654–660 (2022) Cite this article

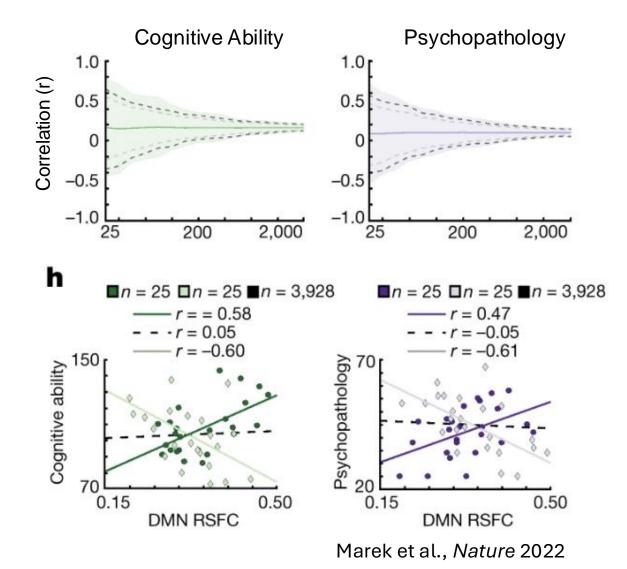
Scanning the Brain to Pre 'Task' for MRI

June 3, 2020 TAGS: BRAIN IMAGING FMRI NEWS TASK PERFORMANCE

Can brain scans reveal behaviour? Bombshell study says r

Most studies linking features in brain imagi small to be reliable, argues a controvers

We need thousands of individuals?!?

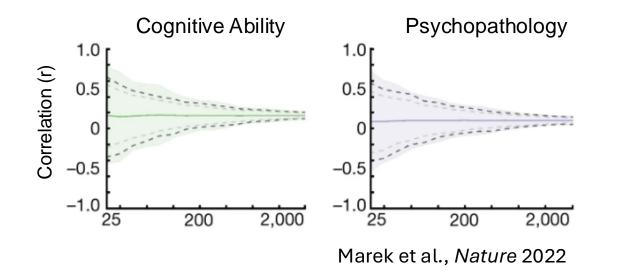


→ Widely varying effect sizes at small sample sizes – even producing completely opposite results!

How to study* brain-behavior correlations?

*robustly

Sample size



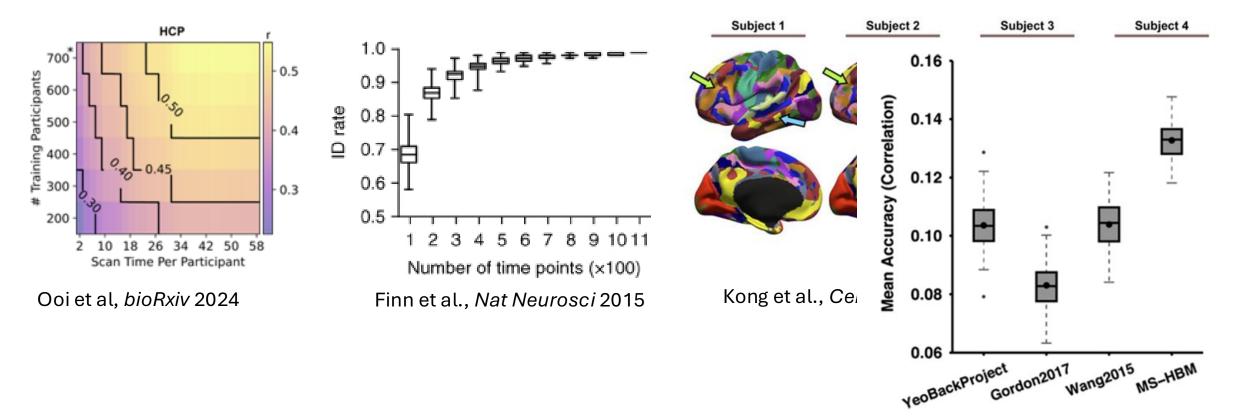
Benefits of a larger sample size:

- Correlations get more reliable!
- Wider distribution of phenotypes
- Allows us to use more robust statistical/machine learning methods like cross validation

Problems with using a larger sample size:

- Expensive
- Time consuming
- Hard to recruit patients

 \rightarrow Get more scan time with fewer subjects

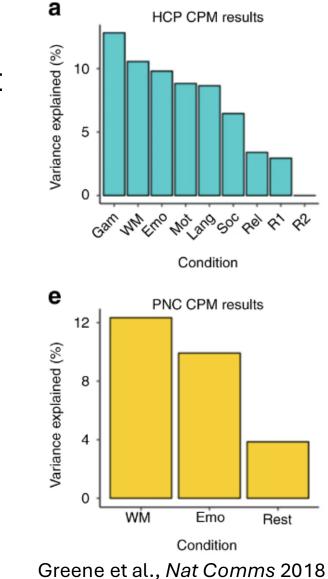


→ Consider the measures you use: task vs rest

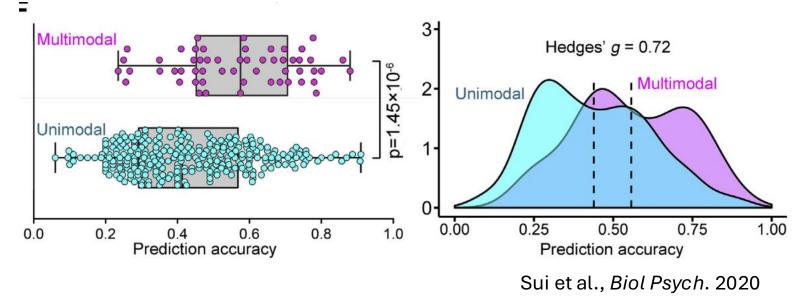
Many studies use resting state fMRI to predict behavior

- Relatively reliable across session ("traitlike")
- Reflects functional networks that are a "backdrop" to anything that happens during task
- Easy to measure no task to learn, requires relatively little scan time (~15 minutes)
- Many big, open datasets include it!

BUT: is rest the best for prediction? Maybe not.



→ Consider the measures you use: task vs rest (or both!?)



→ Integrating across neuroimaging features can improve prediction performance and leverage unique aspects of brain structure and function to better characterize behavioral traits

→ Consider the measures you use: self-report vs cognitive task Take for example: face blindness (prosopagnosia)

Option 1: Self-report measures

20 item prosopagnosia index (PI20)

1	My face recognition ability is worse than most people
2	I have always had a bad memory for faces
3	l find it notably easier to recognize people who have distinctive facial features
4	l often mistake people I have met before for strangers
5	When I was at school I struggled to recognize my classmates

Shah et al., R. Soc. Open sci, 2015

Option 2: Data from cognitive tasks

Cambridge Face Memory Test



Examples



Introduction: Test item with identical images



Test item with novel images

Duchaine et al., Neuropsychologia 2006

→ Consider the measures you use: self-report vs cognitive task

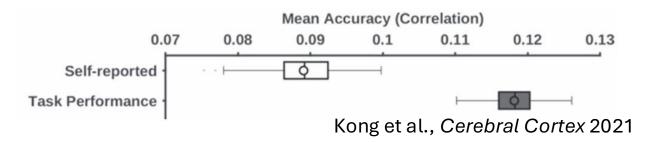
Take for example: face blindness (prosopagnosia)

Option 1: Self-report measures

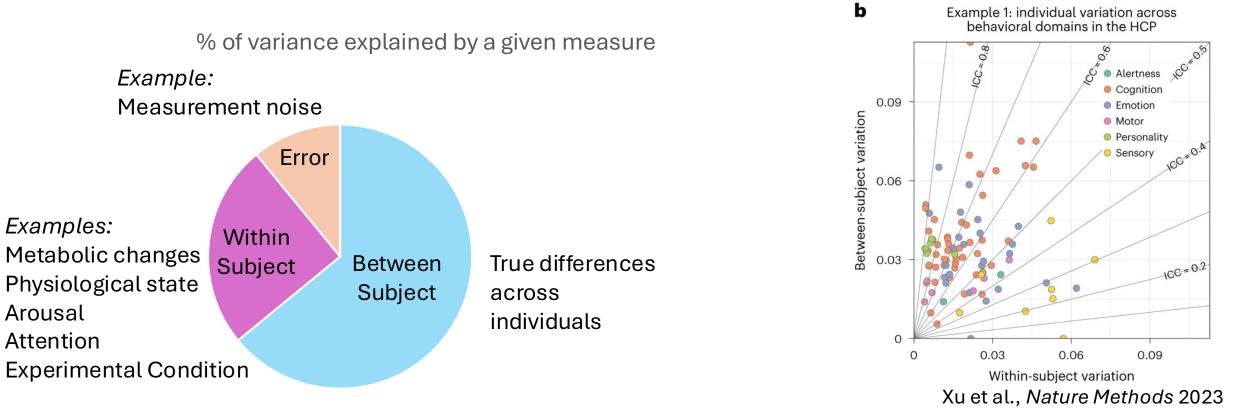
- Pros:
 - Easy to administer
 - Might be more relevant for psychiatric conditions
 - Potentially more stable within an individual
- Cons:
 - Potential for bias
 - Relies on participant's ability to introspect

Option 2: Data from cognitive tasks

- Pros:
 - Less potential for bias
 - Able to do in scanner
 - Easier to predict?
- Cons:
 - Might have less relevance for "biomarkers"
 - Potentially less generalizable



→ Consider the measures you use: optimize sources of variance



Between and within subject variance can both be interesting targets of prediction, they just are asking different questions!

 \rightarrow Consider the measures you use: optimize sources of variance

Between and within subject variance can both be interesting targets of prediction, they just are asking different questions!

 \rightarrow Different questions necessitate different tasks

Within Subject Effects (Group/Condition Differences)

 $t = \frac{Difference in conditions}{Error}$

→ Consider the measures you use: optimize sources of variance

Between and within subject variance can both be interesting targets of prediction, they just are asking different questions!

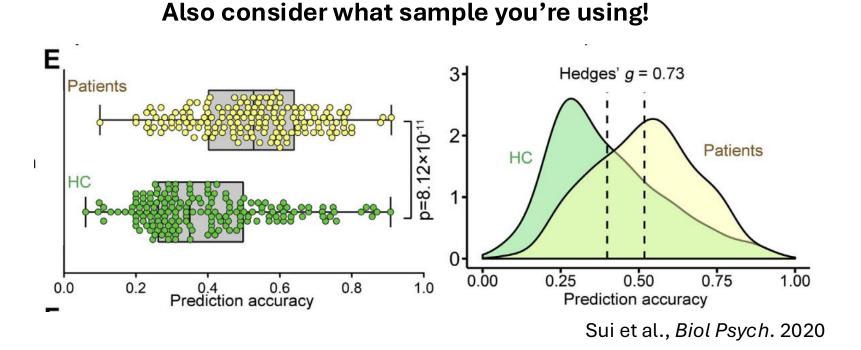
 \rightarrow Different questions necessitate different tasks

Within Subject Effects
(Group/Condition Differences)Between Subject Effects
(Brain-behavior Correlations) $t = \frac{Difference in conditions}{Variance between individual. + Error}$ Uariance between individual. + Error

→ Tasks that are optimized for within-subjects effects may be poorly optimized for between-subjects effects

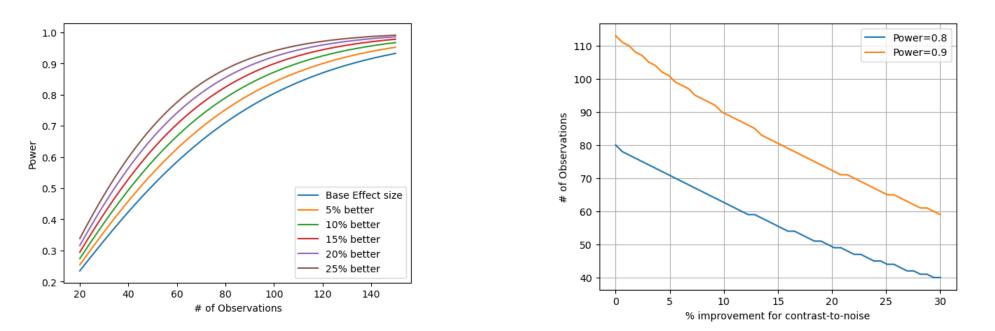
See Hedge et al., Beh. Res. Methods 2017 for more info/math

 \rightarrow Consider the measures you use: optimize sources of variance



Consider: if you're trying to find a biomarker for a specific psychiatric phenotype in a sample of healthy volunteers, there might not be enough between-subject psychiatric variance for a model to pick up on

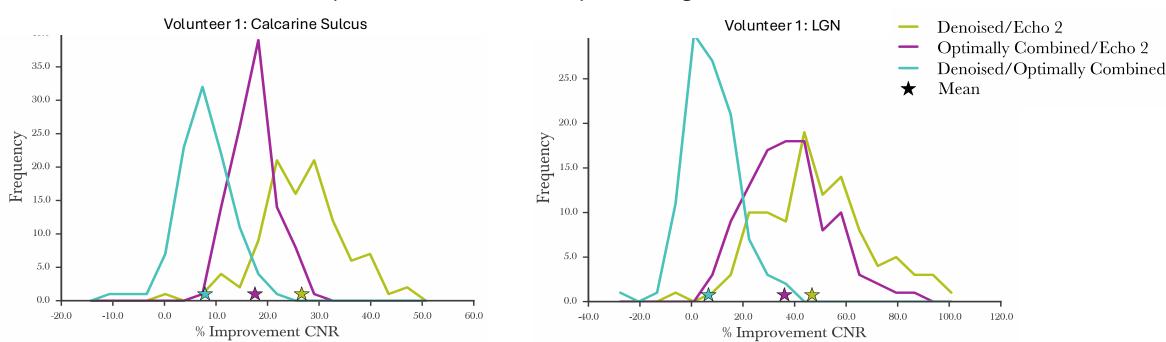
 \rightarrow Improve your data quality



A 10% improvement in contrast-to-noise could mean a statistical power of 0.8 is possible with 63 vs 80 subjects

Slide from Dan Handwerker

→ Improve your data quality: acquisition parameters (use multi-echo!)



CNR % Improvement Between Preprocessing Methods

Slide from Dan Handwerker

\rightarrow Improve your data quality: decrease head motion

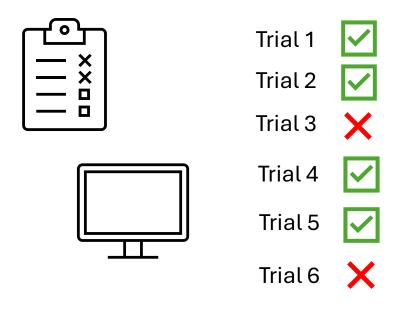
Subject measures	Pearson
ReadEng (AgeAdj)	-0.23
ReadEng (Unadj)	-0.23
Vocabulary (AgeAdj)	-0.19
Dexterity (Unadj)	-0.18
CardSort (Unadj)	-0.18
Dexterity (AgeAdj)	-0.18
CardSort (AgeAdj)	-0.18
Education	-0.17
Fluid intelligence	-0.17
Spatial orientation	-0.17
Vocabulary (unadjj)	-0.17
Emotion recognition	-0.16
DSM somatic problems (pct)	0.16
DSM antisocial (raw)	0.16
ASR externalizing (raw)	0.16
DSM somatic problems (raw)	0.16
Tobacco use 7 day	0.18
Diastolic blood pressure	0.18
ASR externalizing	0.18
Tobacco use today	0.2
Systolic blood pressure	0.23
Weight	0.52
Body mass index (BMI)	0.66

- Head motion significantly correlated with subject measures from HCP
- →Also see greater head motion in certain populations: kids, older adults, psychiatric patient populations

Siegel et al., Cerebral Cortex 2017

→ Improve your data quality: maximize reliability

Key assumption of brain-behavior correlations: we are measuring stable, trait-like things Put another way: the things we are measuring are **RELIABLE**



Overall accuracy: 0.66

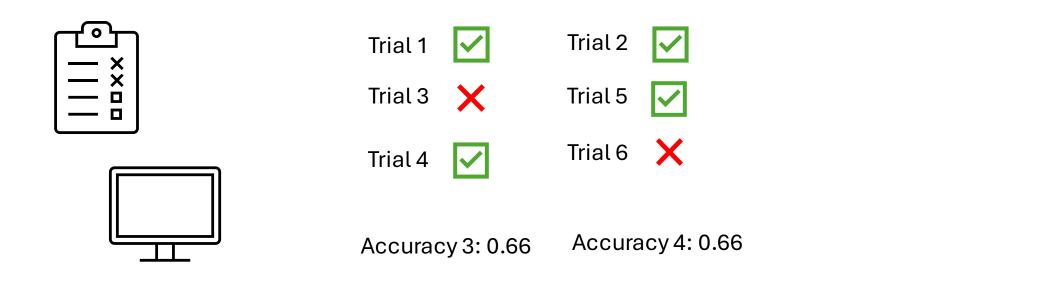
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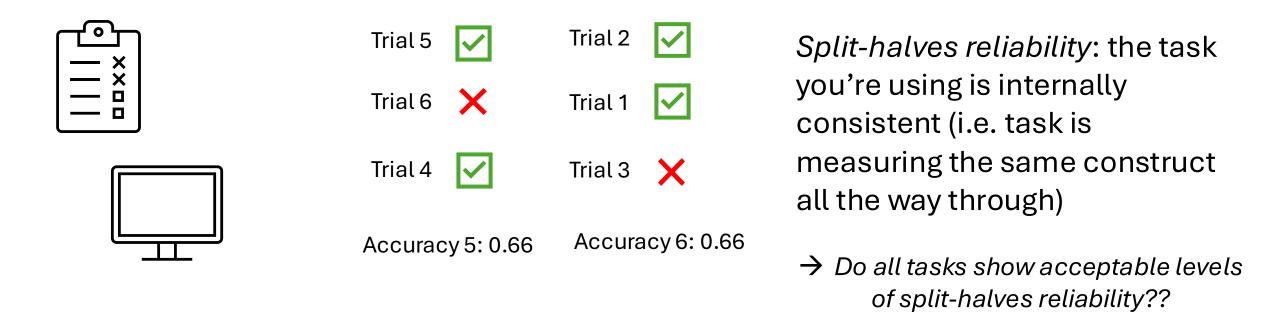
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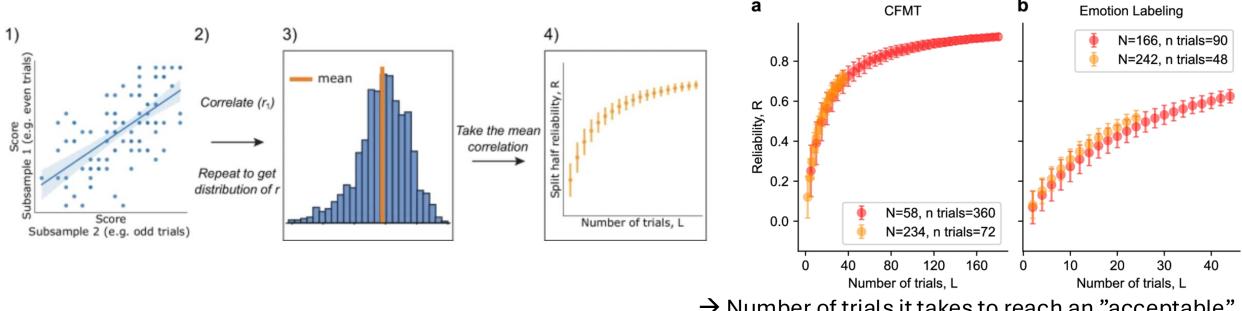
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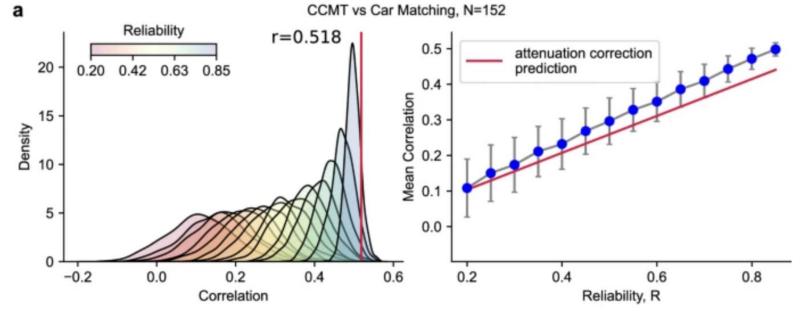


→ Number of trials it takes to reach an "acceptable" level of reliability varies across task

Kadlec, Walsh et al., Comms Psych 2024

→ Improve your data quality: maximize reliability

Key assumption of brain-behavior correlations: we are measuring stable, trait-like things Put another way: the things we are measuring are **RELIABLE**



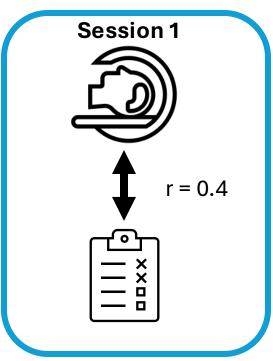
→Less reliable tasks show attenuated correlations, even when they are truly related

** Mathematically the same for brain-behavior, behavior-behavior, brain-brain, etc **

Kadlec, Walsh et al., Comms Psych 2024

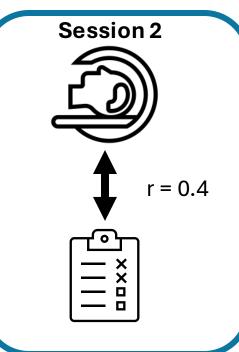
 \rightarrow Improve your data quality: maximize reliability

Key assumption of brain-behavior correlations: we are measuring stable, trait-like things Put another way: the things we are measuring are **RELIABLE**





Time passes! Days, weeks, months, years...



→ Test-retest reliability: If we measure you at two different time points, you will score similarly

 \rightarrow Improve your data quality: maximize reliability

3 batches of (non-overlapping) participants completed 2 а versions of CFMT: Same day 0.8 A few days apart 7-8 months apart 0.7 Reliability 9.0 If sessions are equivalent (i.e. time doesn't matter), test-retest = split halves Light colors: test-retest reliability (forms are kept separate) 0.4 Dark colors: split-halves reliability (forms are pooled) 0.3 \rightarrow Pooling data across sessions increases reliability of

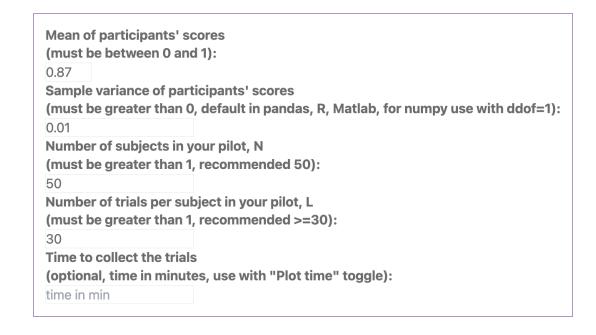
N=42 Same day Same day pooled Separate days Separate days pooled Months apart Months apart pooled 20 40 60 Number of trials, L

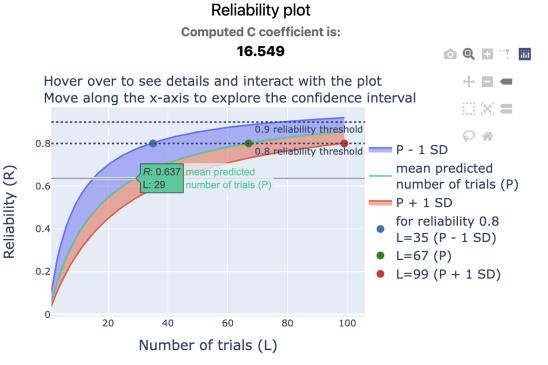
Reliability CFMT

Kadlec, Walsh et al., Comms Psych 2024

measures

\rightarrow Improve your data quality: maximize reliability





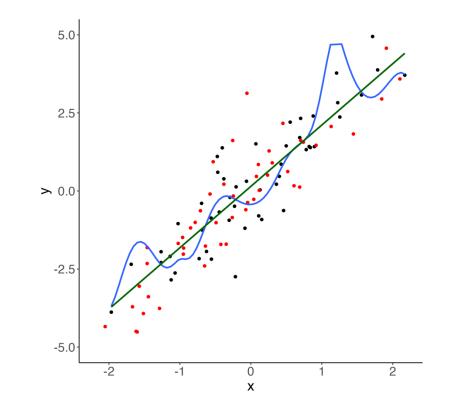
 \rightarrow Web app to help explore reliability of tasks from a pilot sample (N ~ 50)

Kadlec, Walsh et al., Comms Psych 2024

https://jankawis.github.io/reliability-web-app/

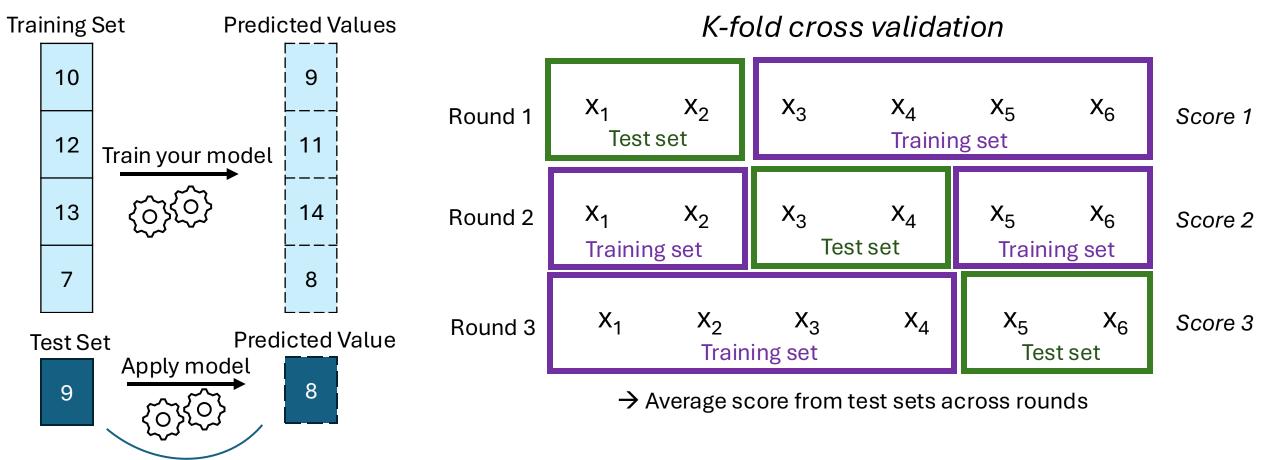
 \rightarrow Use better statistical methods: Cross-Validation

x = randomly drawn from normal distribution y = 2*x + noise



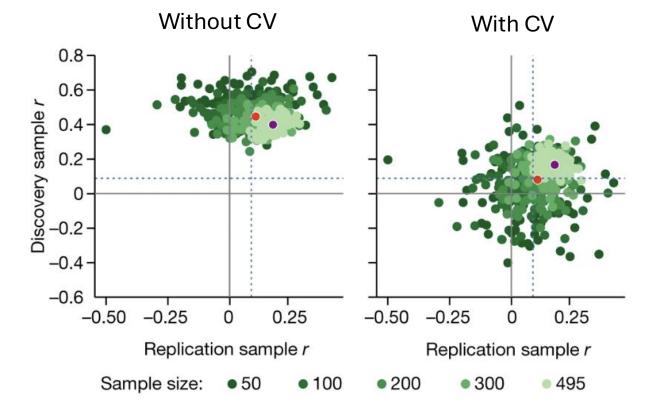
→ Creating your model in your entire sample can lead to fitting to sample specific characteristics (i.e. noise) and lead you to think you're doing better than you actually are

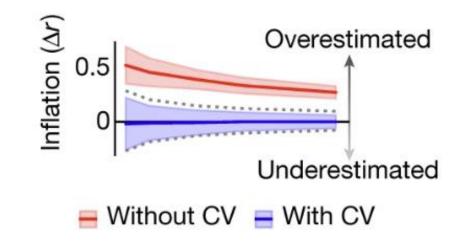
 \rightarrow Use better statistical methods: Cross-Validation



Compare actual to predicted value

 \rightarrow Use better statistical methods: Cross-Validation

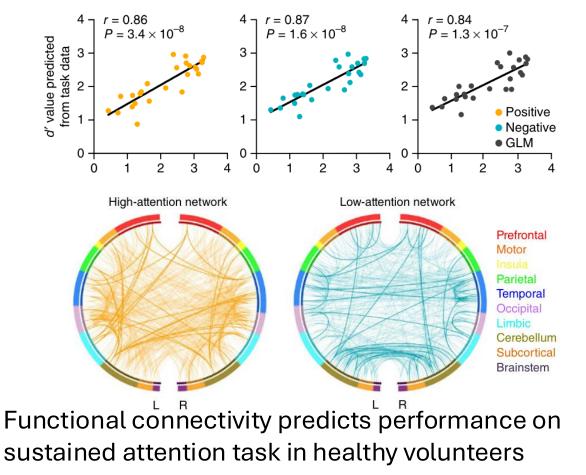


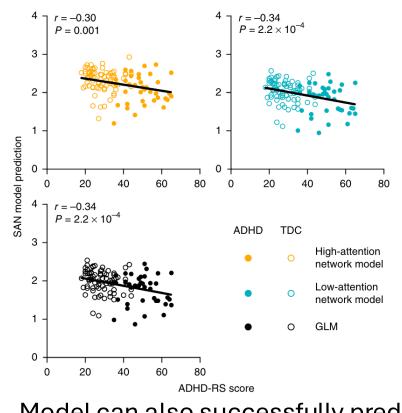


→ Without CV, effects are overestimated in discovery sample
→ Cross validation un-biases effect estimates

Spisak et al., Nature 2023

→ Use better statistical methods: Generalize to independent sample





Model can also successfully predict ADHD scores in an independent sample Rosenberg et al., *Nat Neuro* 2015

Wrapping it all up

- What are brain-behavior correlations?
 - Statistical association between some sort of brain measure and some sort of behavioral measure
- Why should we care about brain-behavior correlations?
 - They give us new insights into nuances behind neural processes and support the move towards brain-based psychiatry
- How can we robustly study brain-behavior correlations?
 - Increase your sample size and/or scan duration
 - Think critically about which measures you're going to collect
 - Improve data quality of both the brain and behavior
 - Use appropriate statistical/machine learning methods like cross validation and generalization in an independent sample

Acknowledgements



Section on Functional Imaging Methods

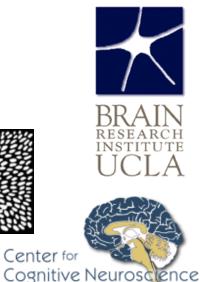
- Peter Bandettini
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