



Can we extract individual differences with fMRI? Can we go on to create “biomarkers”?

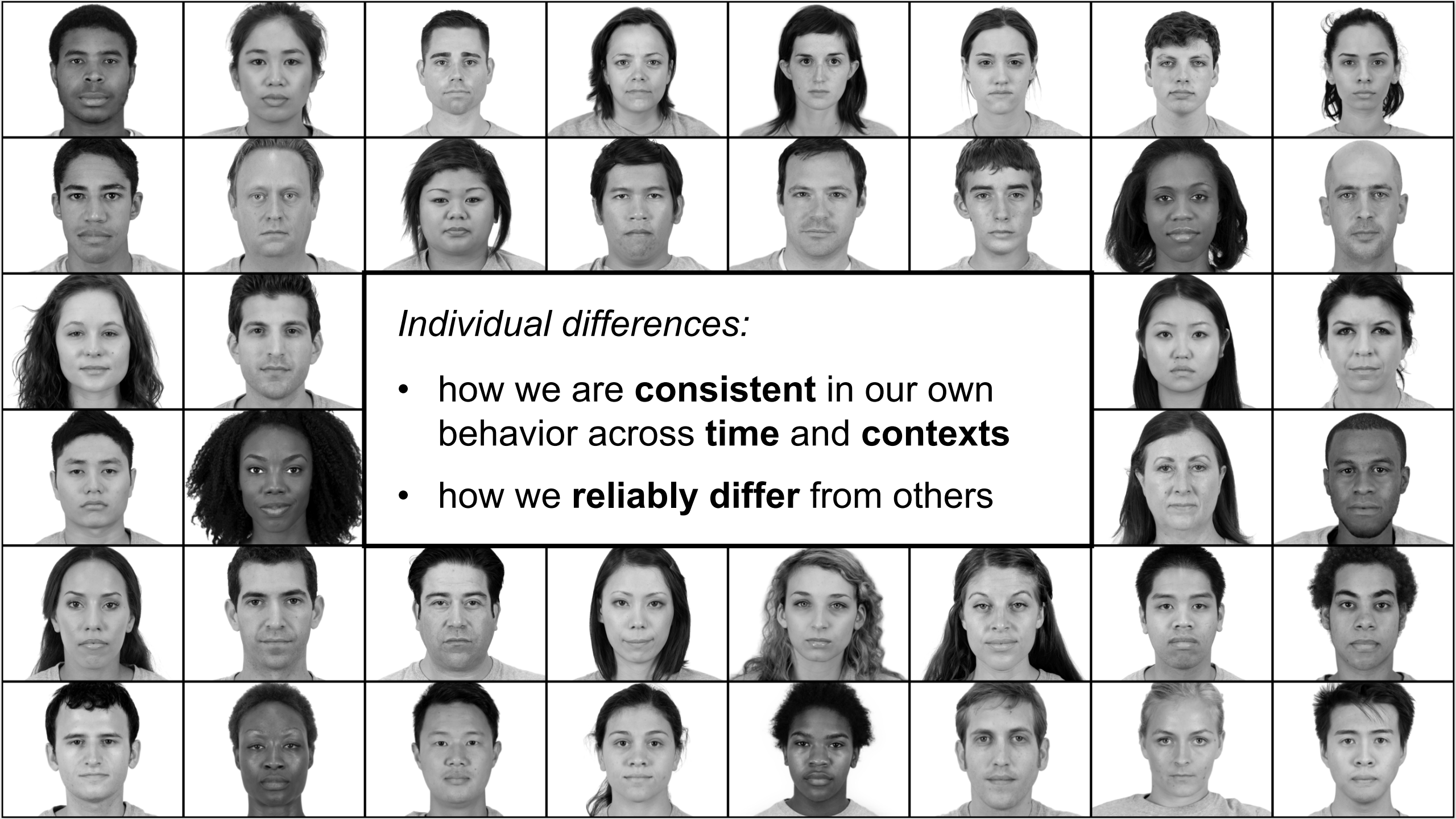
Emily S. Finn, PhD

Postdoctoral Fellow, Section on Functional Imaging Methods
National Institute of Mental Health

NIH Summer Neuroimaging Course
August 6, 2019

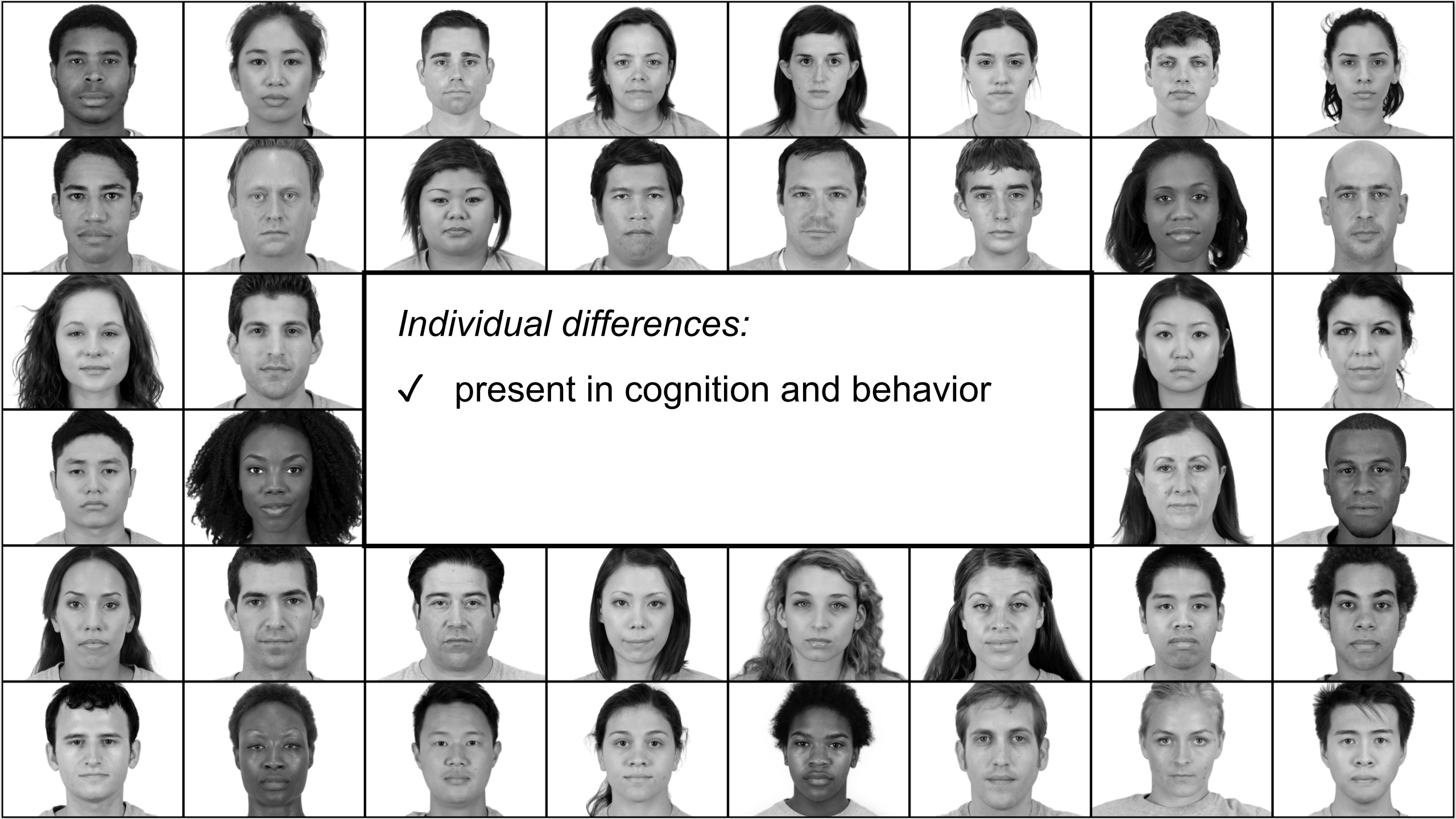


@esfinn

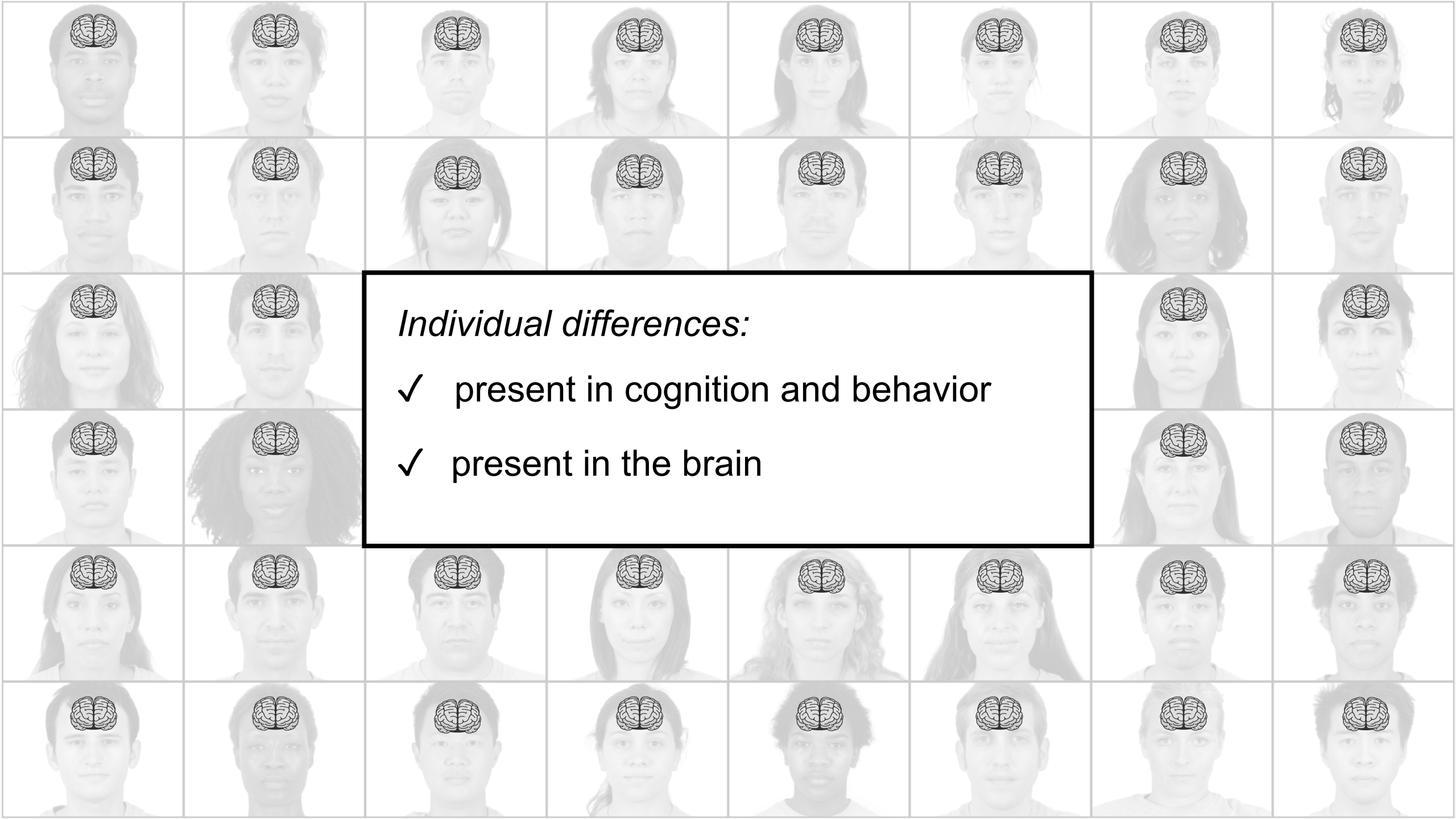


Individual differences:

- how we are **consistent** in our own behavior across **time** and **contexts**
- how we **reliably differ** from others

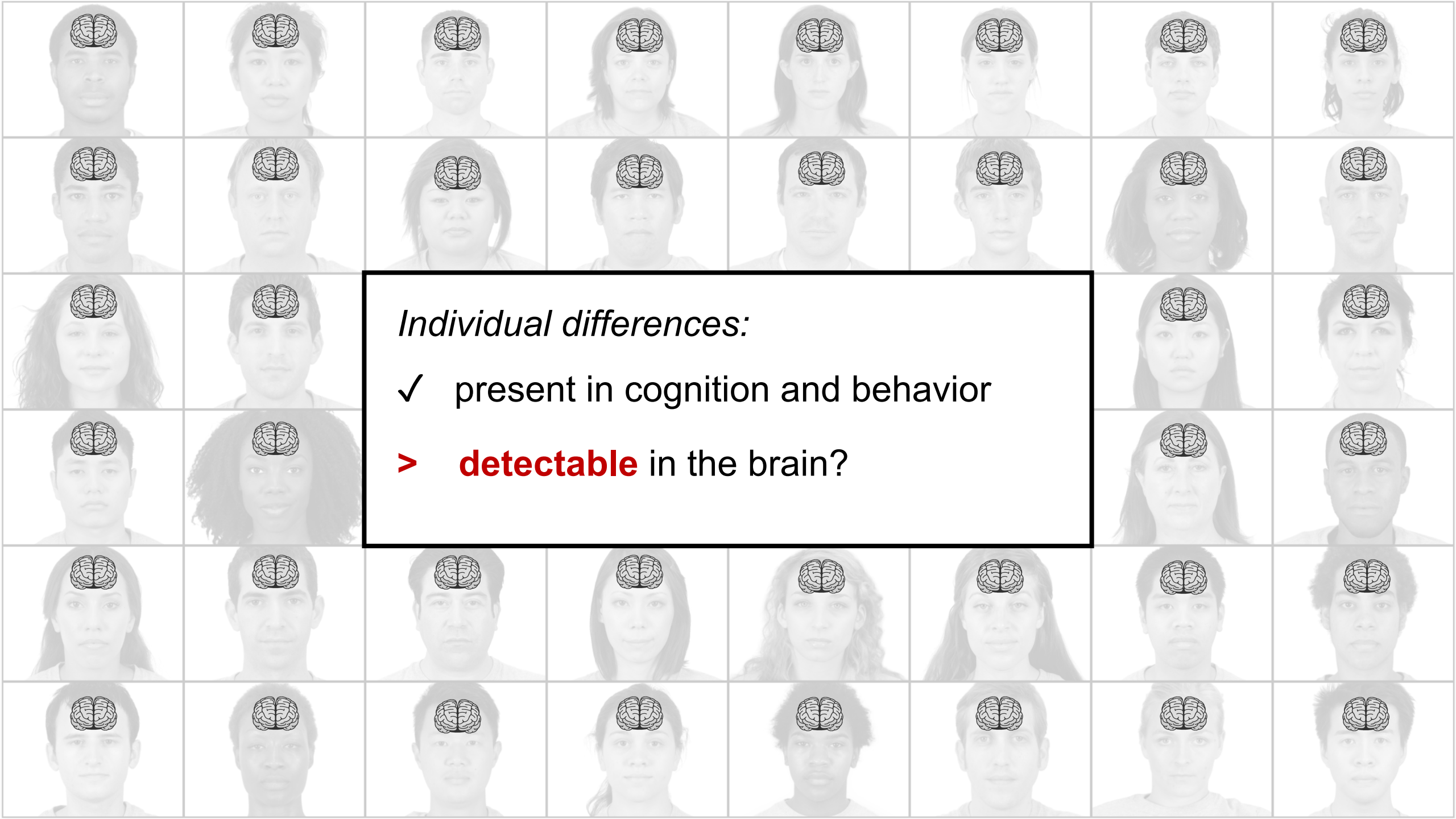


Individual differences:
✓ present in cognition and behavior



Individual differences:

- ✓ present in cognition and behavior
- ✓ present in the brain



Individual differences:

✓ present in cognition and behavior

> **detectable** in the brain?

Outline

1. **Why** should we care about individual differences?
2. **What** do we know about individual differences?
3. **Where** are the open questions & controversies?



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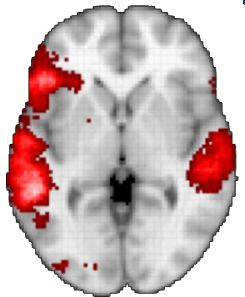
Toward a deeper understanding of cognition

Group average

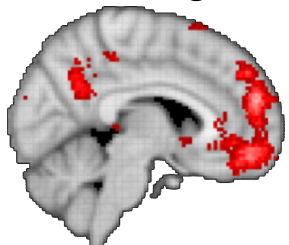
Working memory



Language

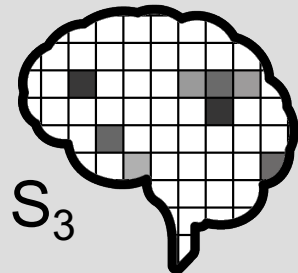
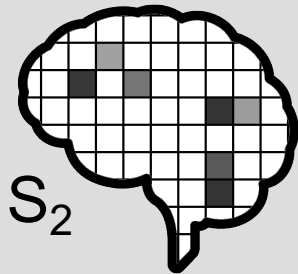
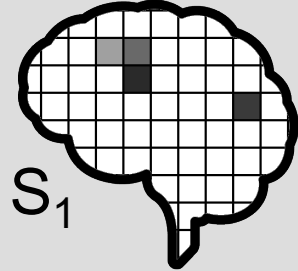


Social cognition



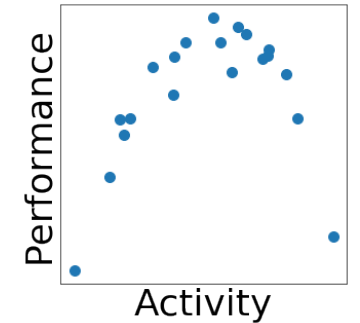
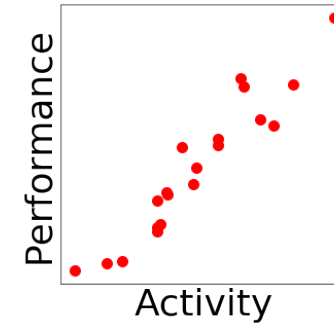
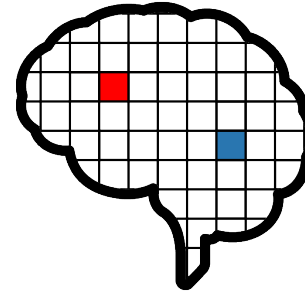
neurosynth.org

Individual maps



Degeneracy:

- Task performance?



- Cognitive strategies, styles?
- Within-subject changes (i.e., learning)?

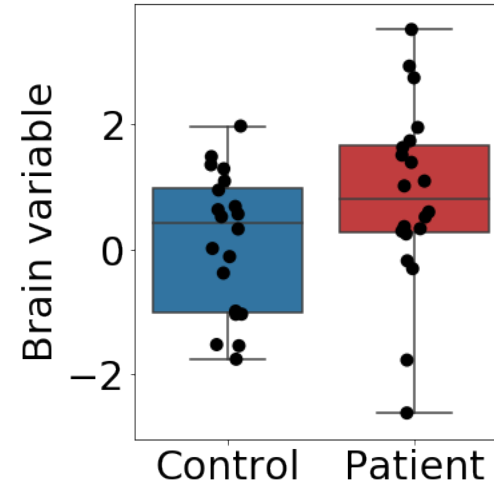
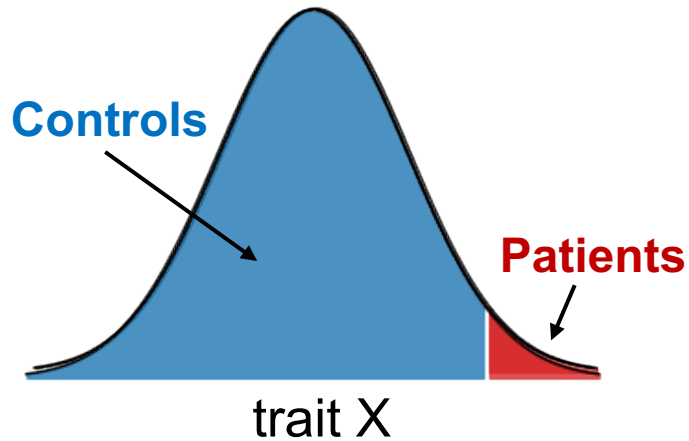


Univariate or multivariate relationships

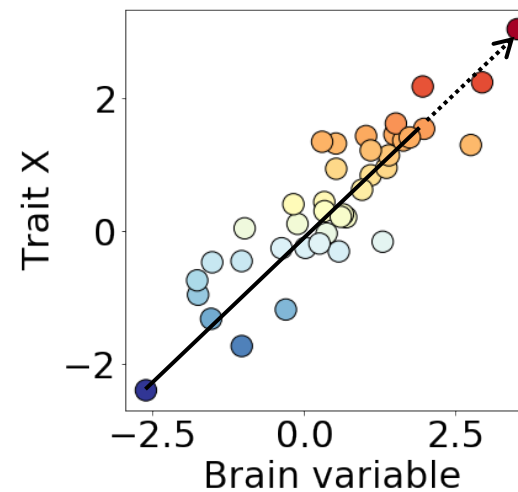
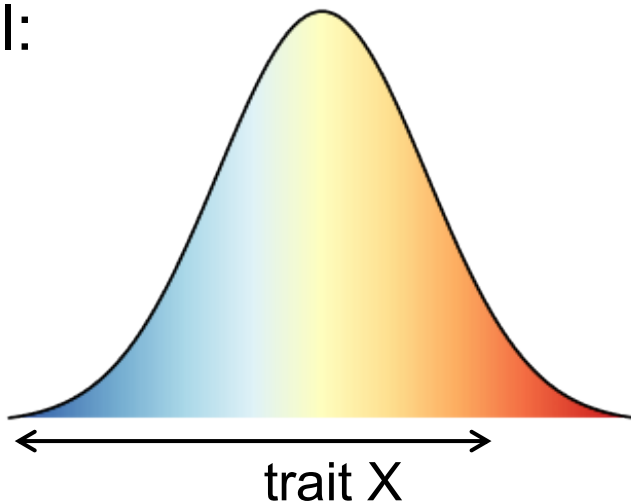
Activity, connectivity, other features

Insight into mental illness

Categorical:



Dimensional:



Translational tools?

Insel et al., *Am J Psychiat* (2010)
Gabrieli et al., *Neuron* (2015)
Finn & Constable, *Dial Clin Neurosci* (2016)
Woo et al., *Nat Neurosci* (2017)

Outline

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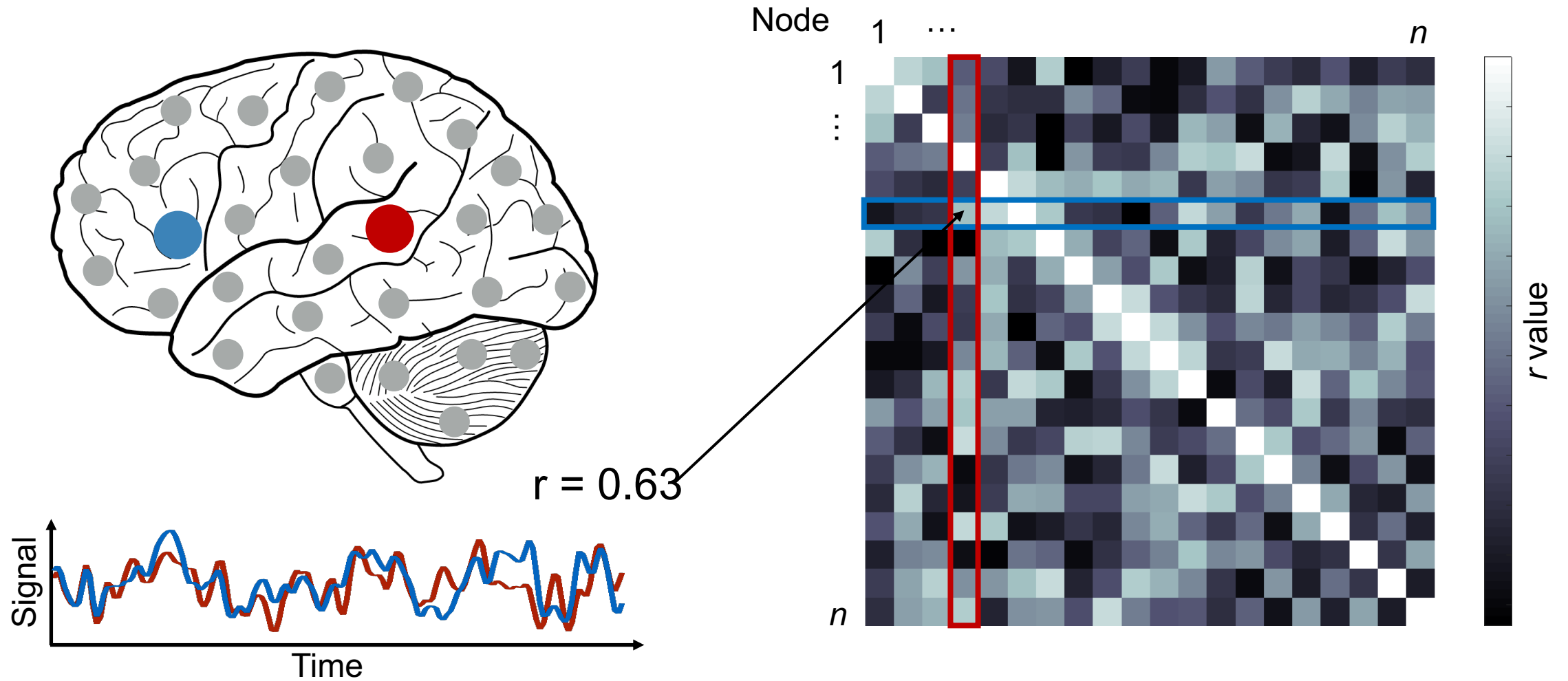


Outline

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Functional connectivity



Functional connectome “fingerprints”

- n = 126 healthy adults
- 22-35 years old
- 50 sets of twins

Day 1

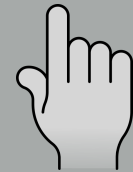
Resting (**R1**)



Working memory
(**WM**)



Motor (**Mt**)



Day 2

Resting (**R2**)



Language (**Lg**)

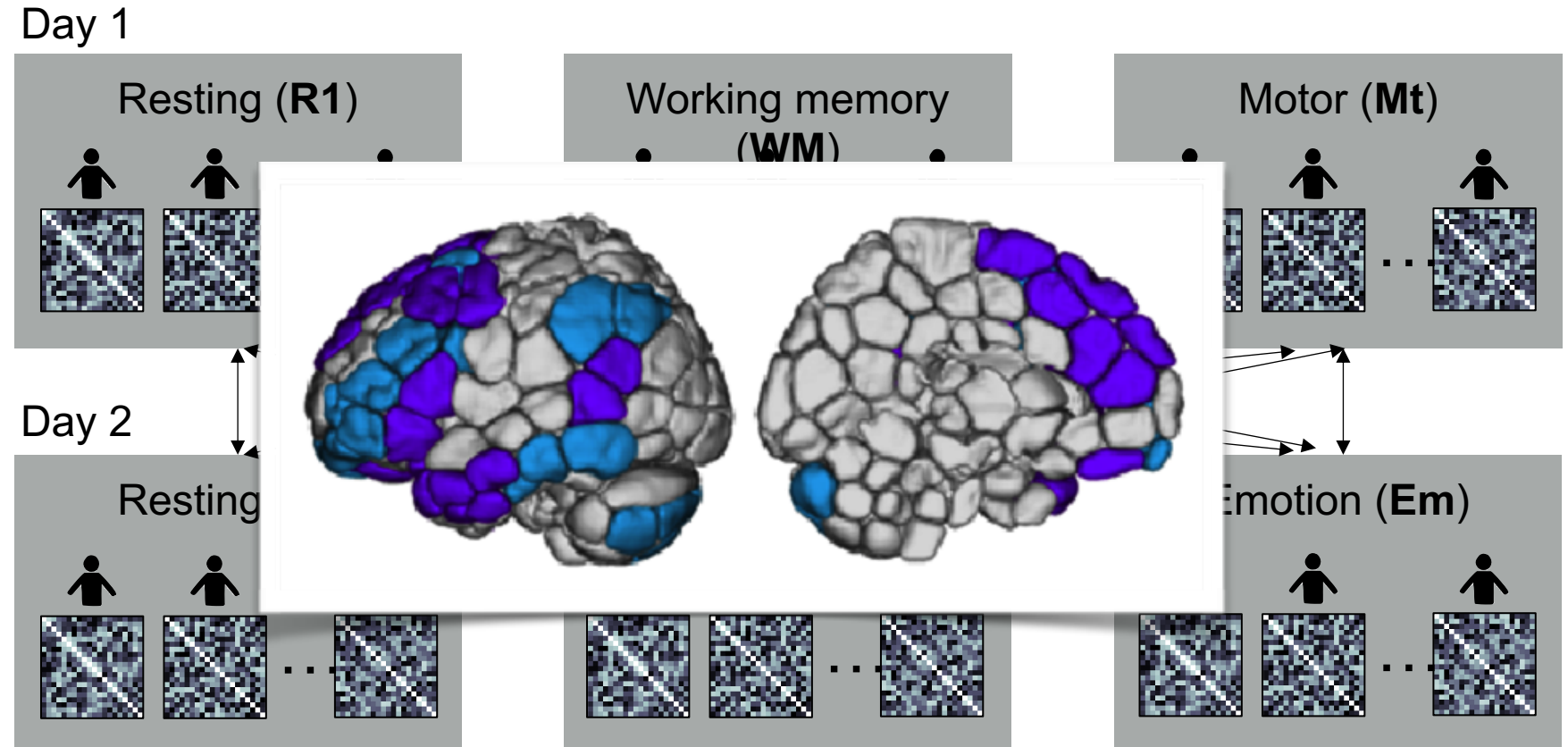


Emotion (**Em**)



Functional connectome “fingerprints”

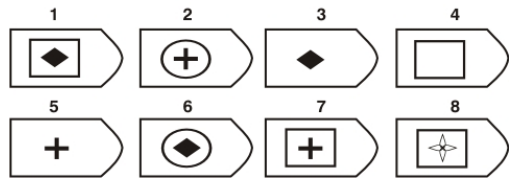
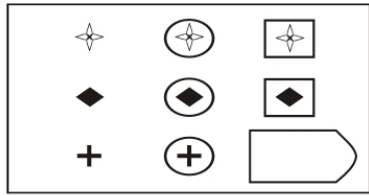
- n = 126 healthy adults
- 22-35 years old
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Accuracy: 54 – 94% (mean: 76%)

chance < 1%

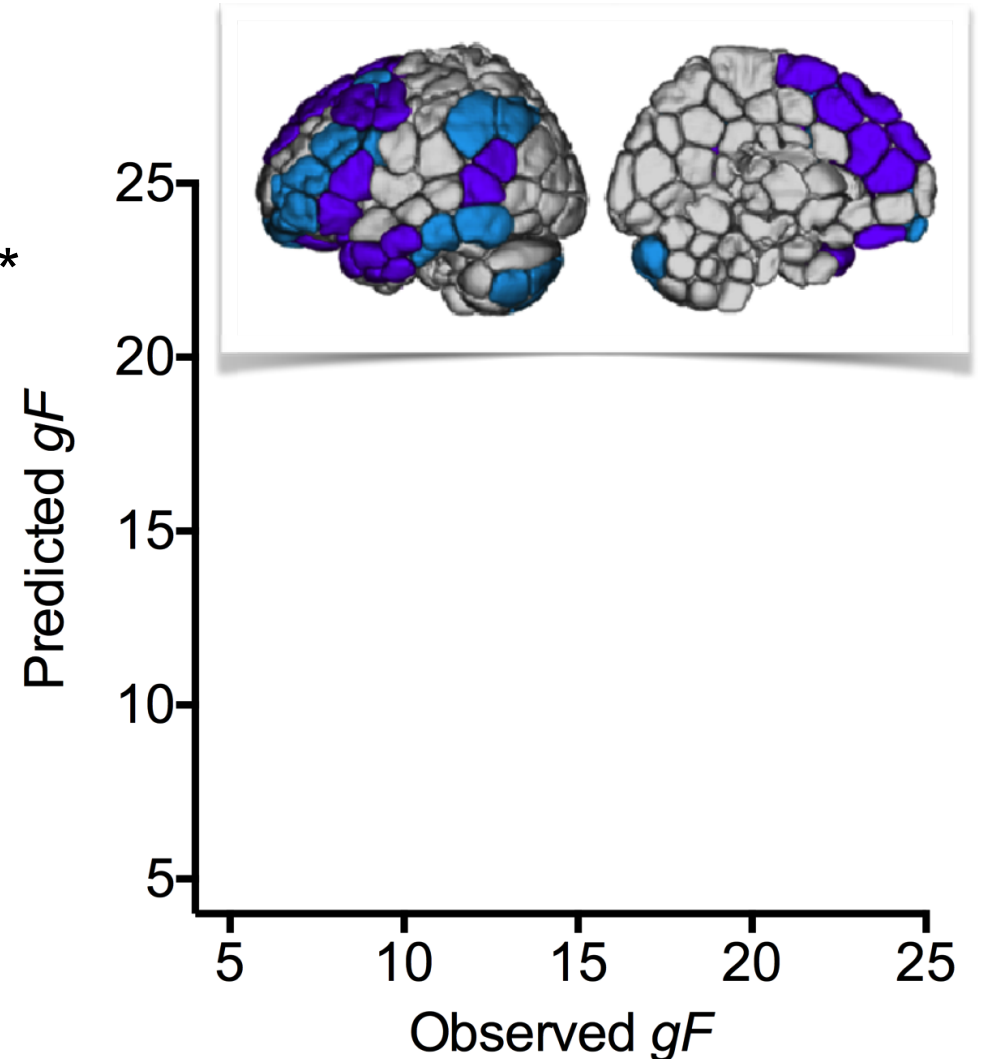
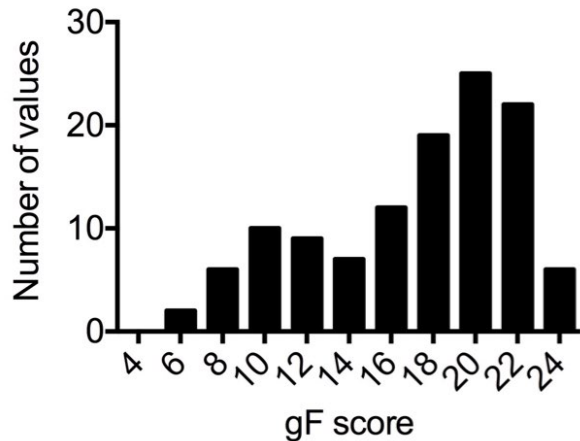
Functional connectomes predict fluid intelligence



Connectome-based Predictive Modeling (CPM)*



Subj	Matrix	Score
		17
		9
		24

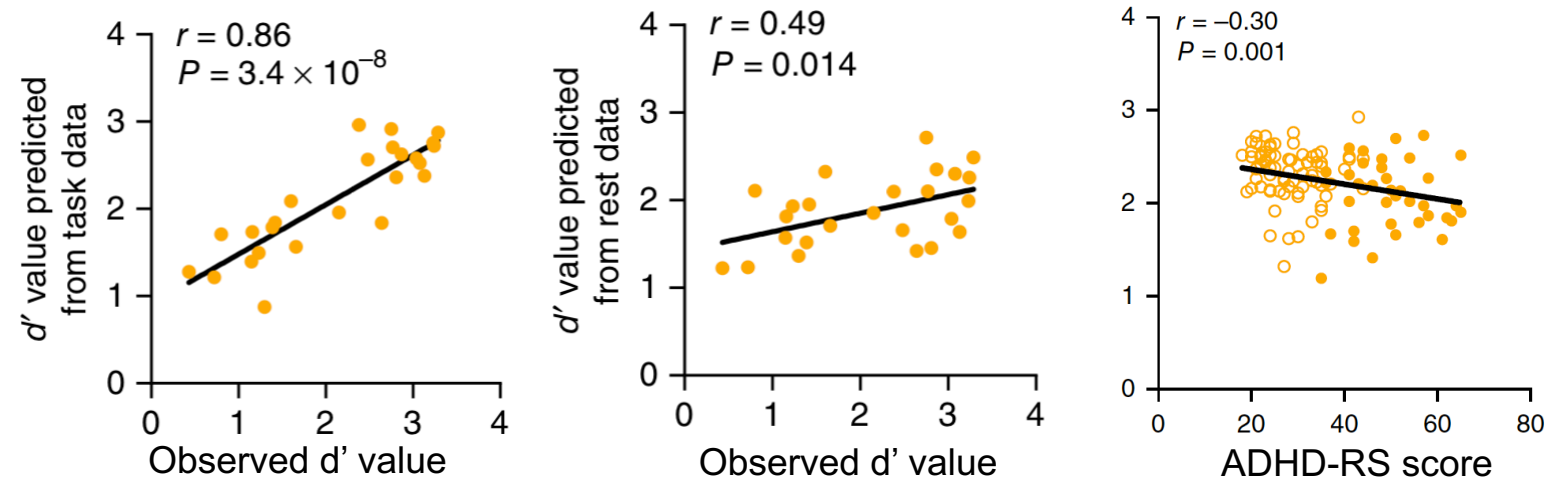


*Shen, Finn et al. *Nat Protoc* (2017)

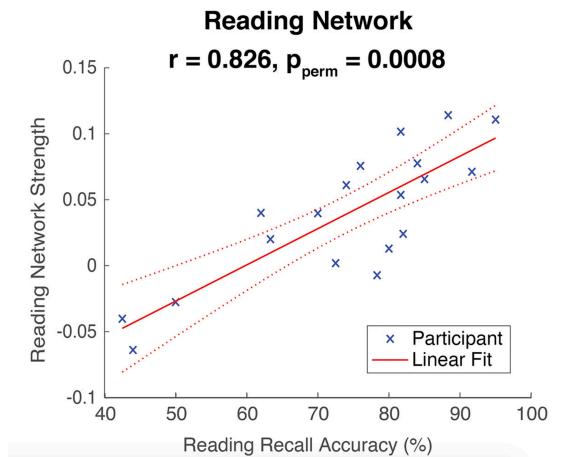
Finn, Shen et al., *Nat Neurosci* (2015)

Predicting behavior from functional connectomes

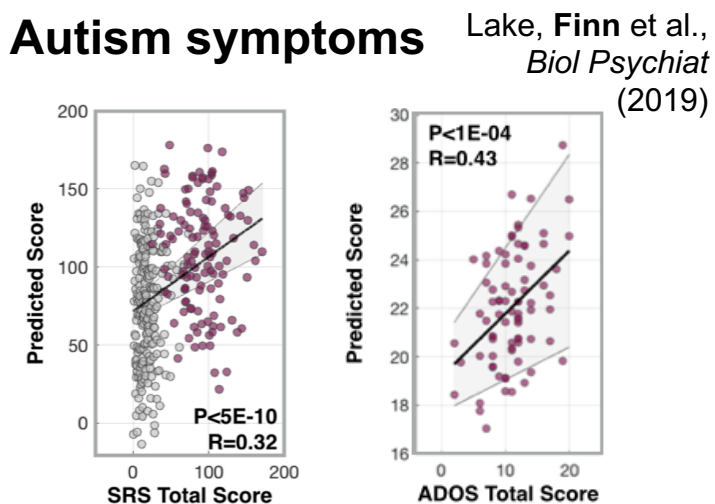
Sustained attention & ADHD symptoms



Reading ability

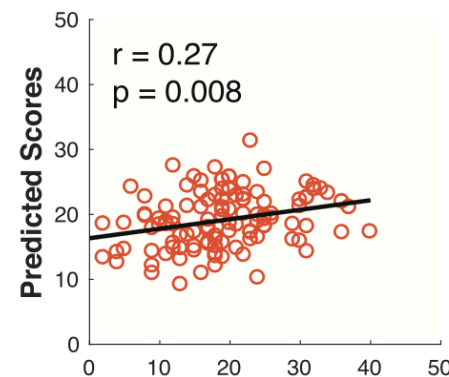


Autism symptoms

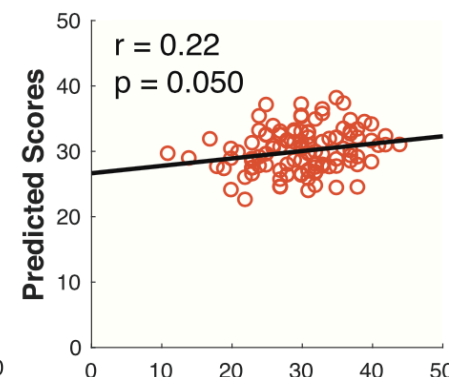


Personality traits

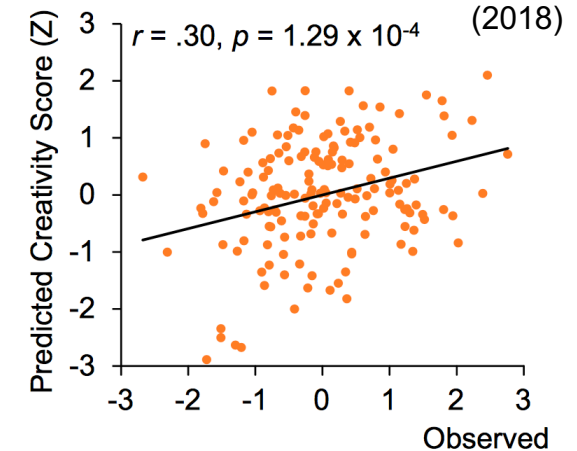
Neuroticism



Extraversion



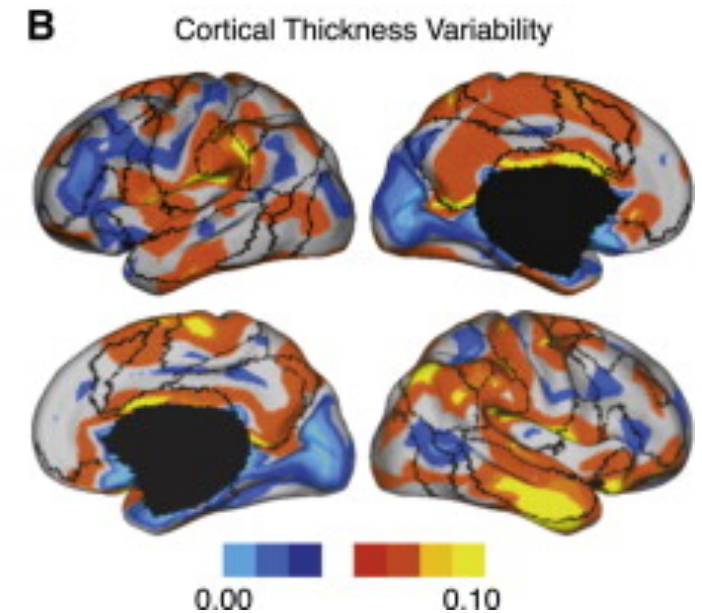
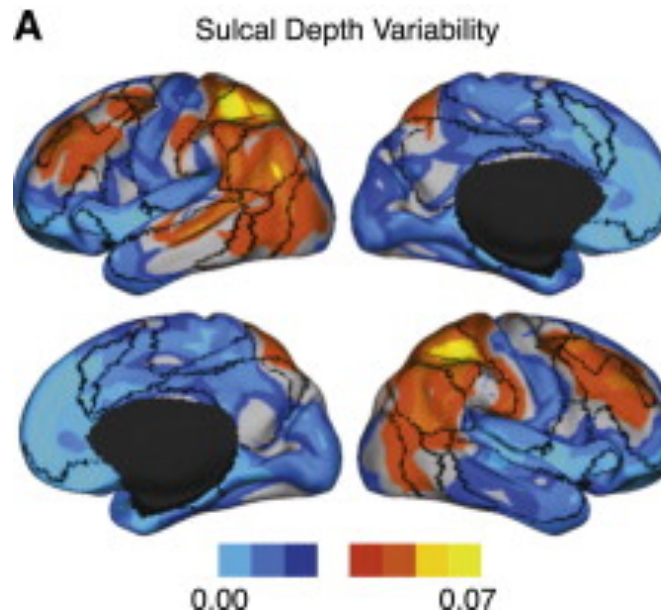
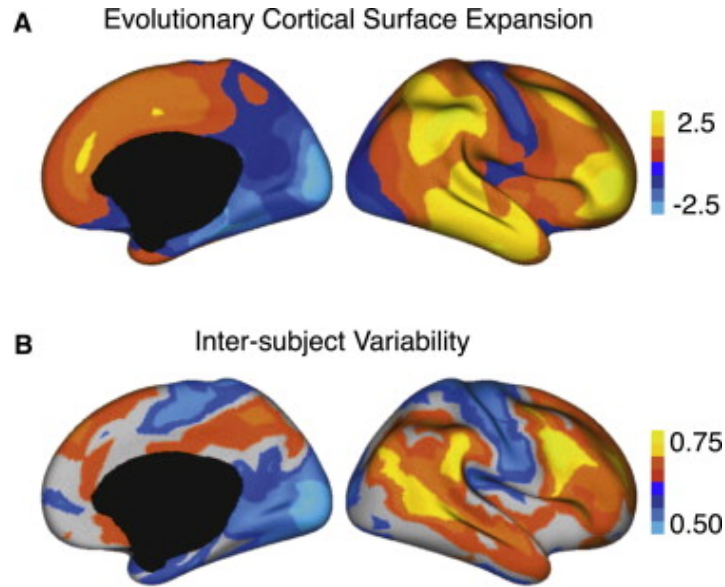
Creativity



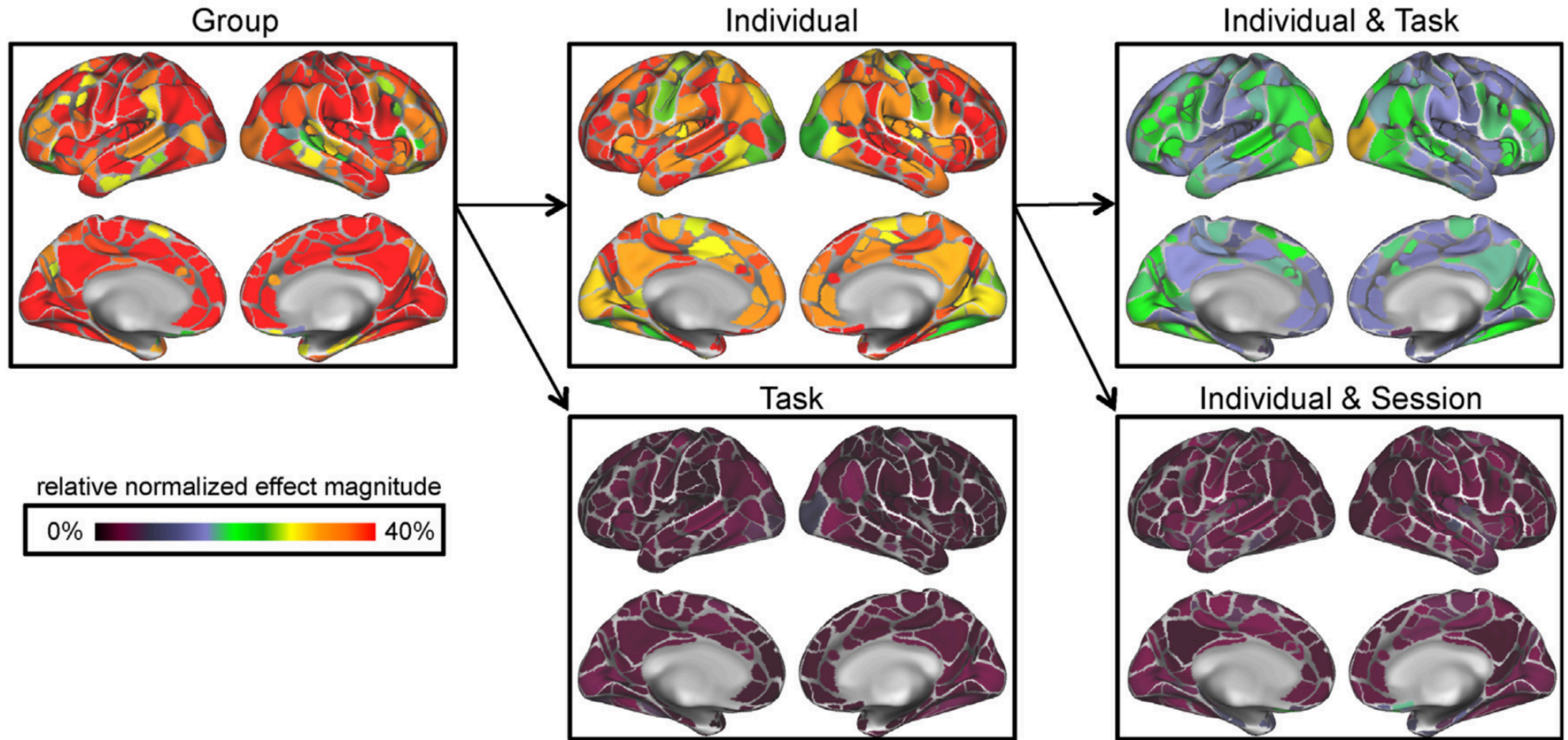
Localizing individual differences

Biggest differences found in most evolutionarily recent regions:

Anatomical differences also play a (large) role:



Individuals account for the most variance!



Gratton et al., *Neuron* (2018)

Outline

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Questions & controversies

Data acquisition



Subjects

- High n , sparsely sampled or low n , densely sampled?
- Which populations?

Data analysis



Applications

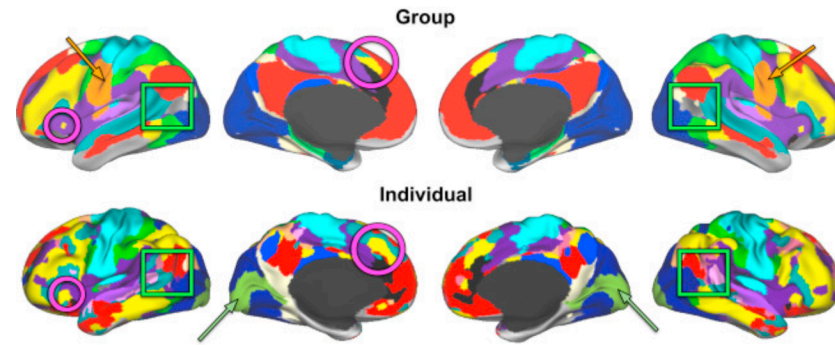


High n , sparsely sampled? Or low n , densely sampled?

Dense sampling helps characterize:

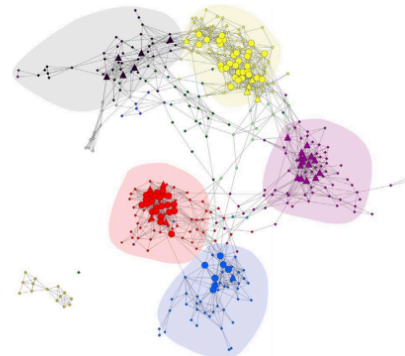
- Within-subject variability
→ *understand fluctuations in psychiatric illness*
- Between-subject variability

“MyConnectome”

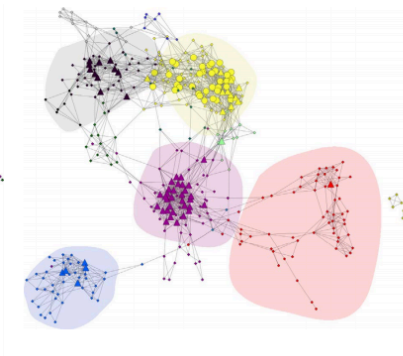


Laumann et al., *Neuron* (2015)

Tuesday (fasted/no caffeine)

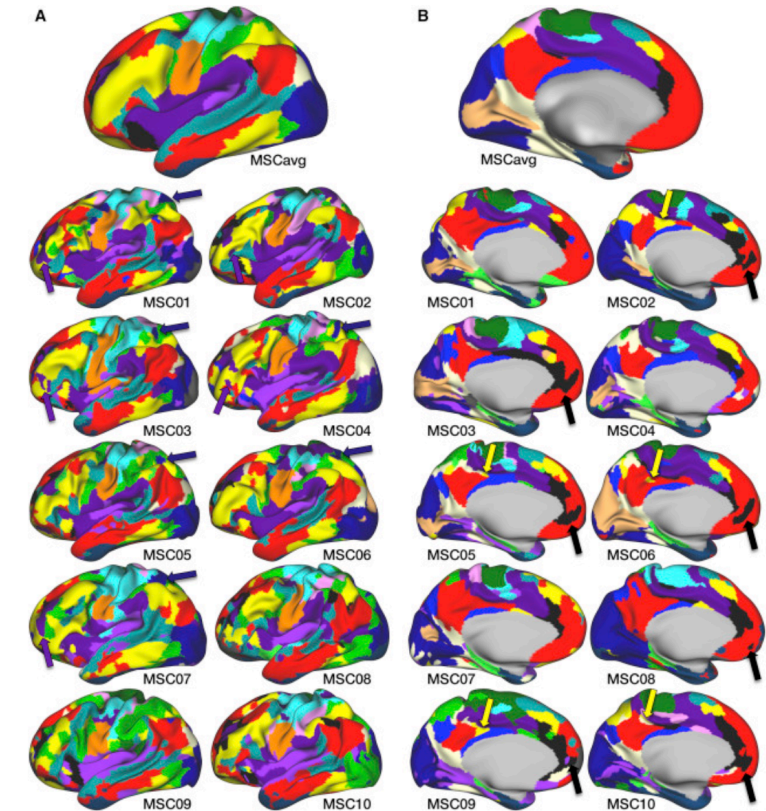


Thursday (fed/cafeinated)



Poldrack et al., *Neuron* (2015)

Midnight Scan Club



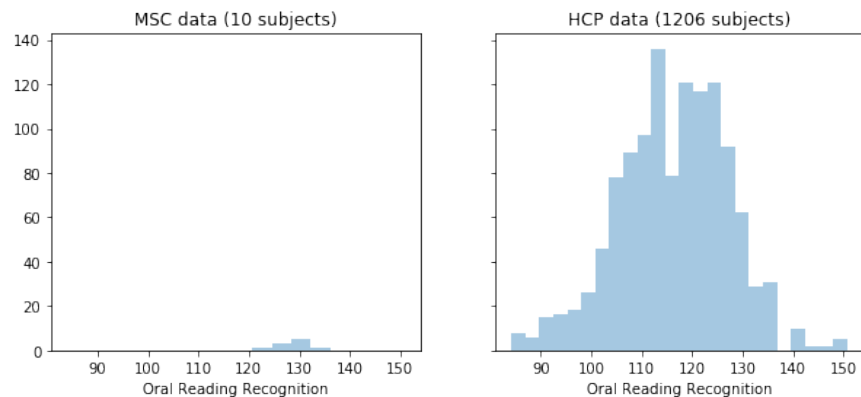
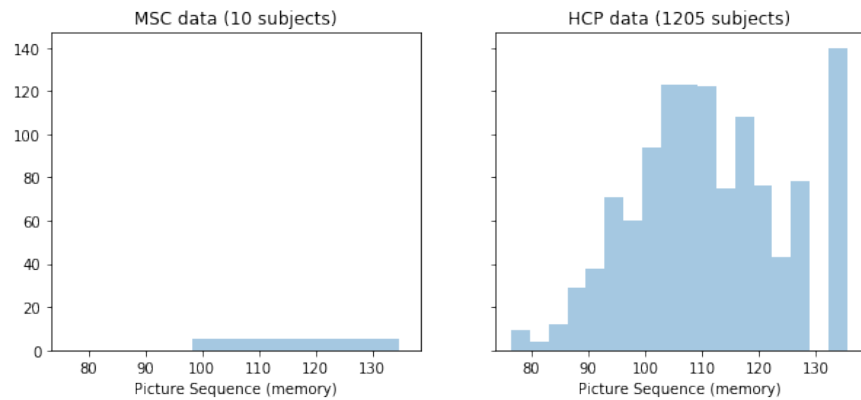
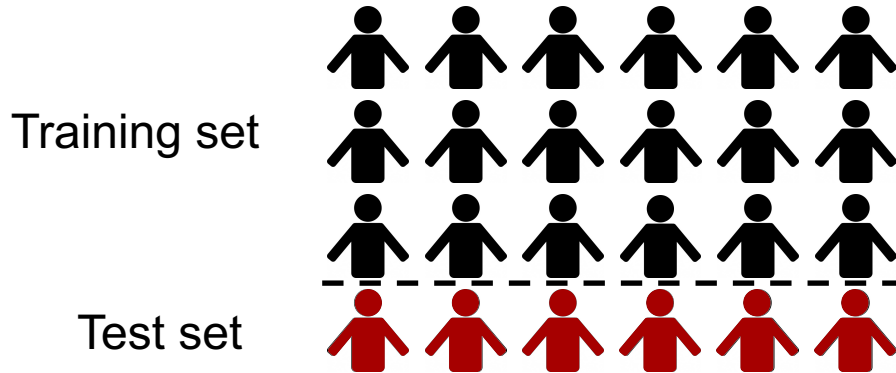
■ Default ■ Med Vis ■ Lat Vis ■ Cing-Operc ■ Salience ■ Fronto-Par ■ Dors Attn ■ Ant MTL ■ Context
■ Vent Attn ■ Auditory ■ Hand SM ■ Face SM ■ Foot SM ■ Premotor ■ Par Memory ■ Post MTL

Gordon et al., *Neuron* (2017)

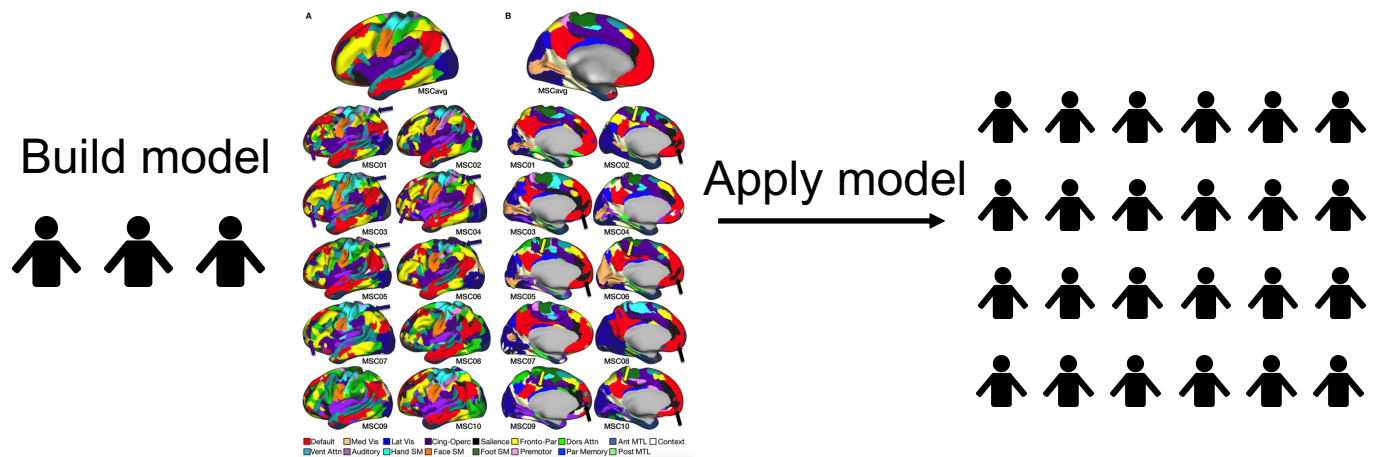
High n , sparsely sampled? Or low n , densely sampled?

Advantages of high n sampling:

- Wider distribution of behavior/phenotypes
- Allows for cross-validated model building
- More realistic for real-world applications



Combination approach?



Who should we recruit?

- Patients or controls? Ideally both
- Which diagnosi(e)s to target? Ideally several
- A “help-seeking” model can enrich samples for pathology
- Longitudinal studies are key (recruit patients while they’re still controls!)

Symptom-based categories

Major depressive disorder



Mild depression (dysthymia)



Bipolar depression



Integrated data

Genetic risk

polygenic risk score

Brain activity

insula cortex

Physiology

inflammatory markers

Behavioral process

affective bias

Life experience

social, cultural, and environmental factors

Data-driven categories

Cluster 1



Cluster 2



Cluster 3



Cluster 4



Insel & Cuthbert, *Science* (2015)

Are you worried about your child?

Our mental health study can help.

Your child will receive:

- A no-cost diagnostic consultation
- Referrals for follow-up care
- Compensation for your time

Contact us

347.934.2880
healthybrainnetwork.org



CHILD MIND[®]
INSTITUTE
healthy brain network



Questions & controversies

Data acquisition



Subjects

- High n , sparsely sampled or low n , densely sampled?
- Which populations?

Imaging

- Data quality?
- Brain state (“stress test”)?
- Multisite studies?

Data analysis



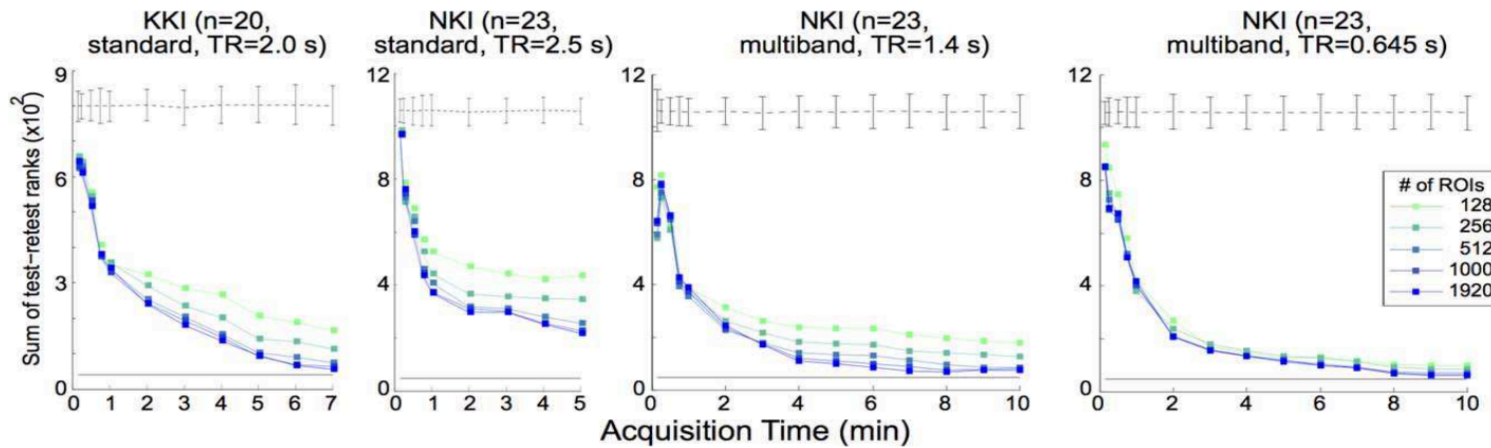
Applications



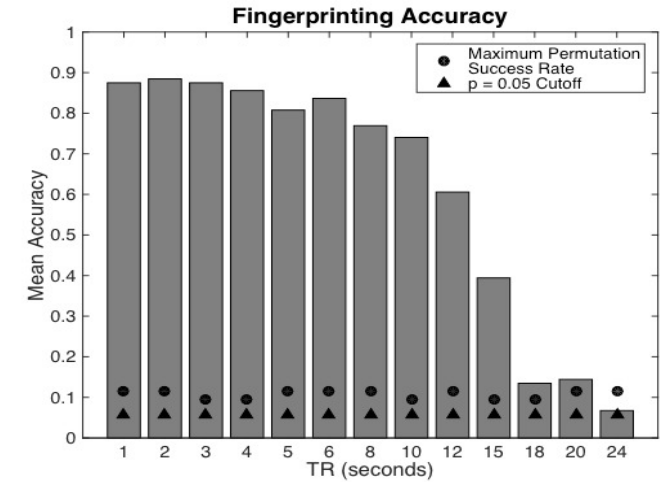
Q. Do you need HCP-quality data?

A. Not really

ID is fairly robust even at more standard spatial & temporal resolutions:



Airan et al., Hum Brain Mapp (2016)



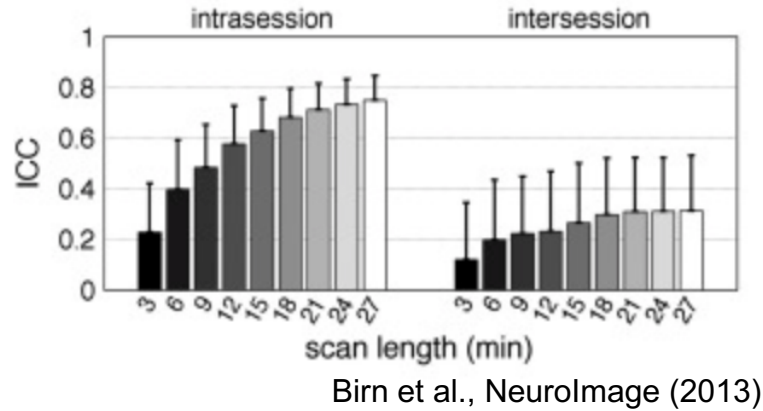
Courtesy of Jason Druzgal

Q. What about amount of data?

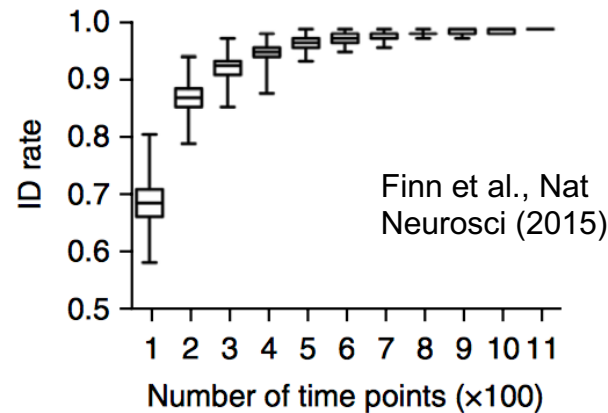
A. Scan duration matters!

Longer acquisitions are better:

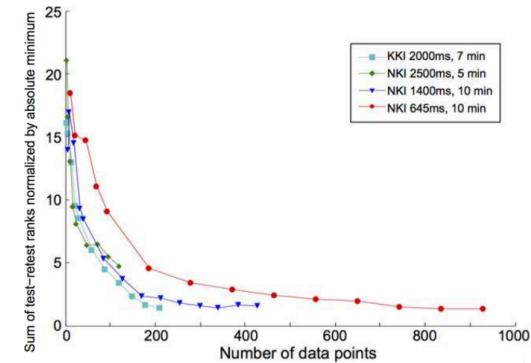
- higher reliability within subjects



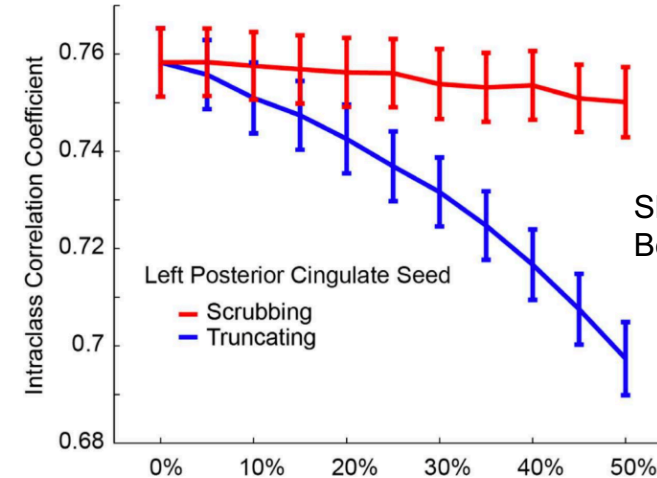
- higher identifiability across subjects



- ▶ higher sampling rate (shorter TR) cannot make up for shorter scan duration



Airan et al., Hum Brain Mapp (2016)



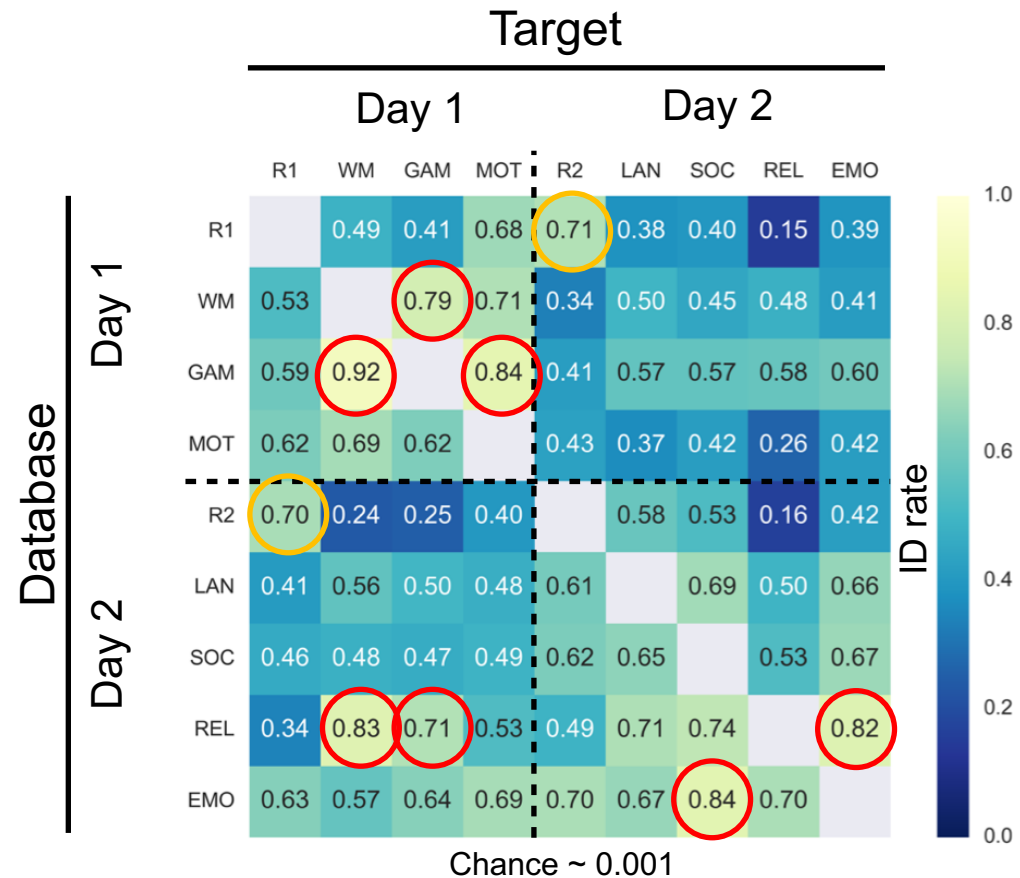
Shah et al., Brain & Behav (2016)

Q. Does scan condition matter?

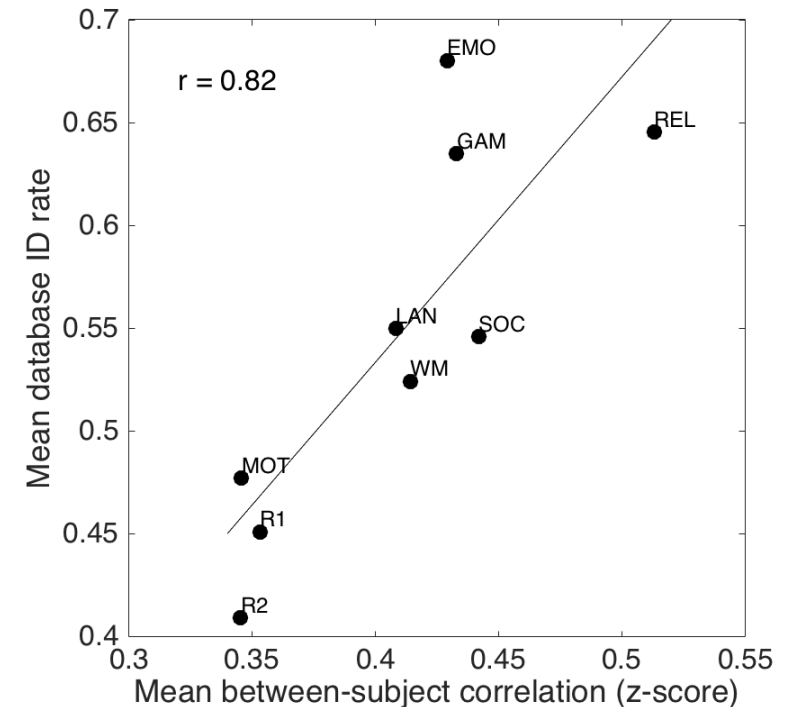
A. Yes!

Rest has become the default condition for FC & individual differences, but tasks may increase signal-to-noise

Replicating identification experiments:

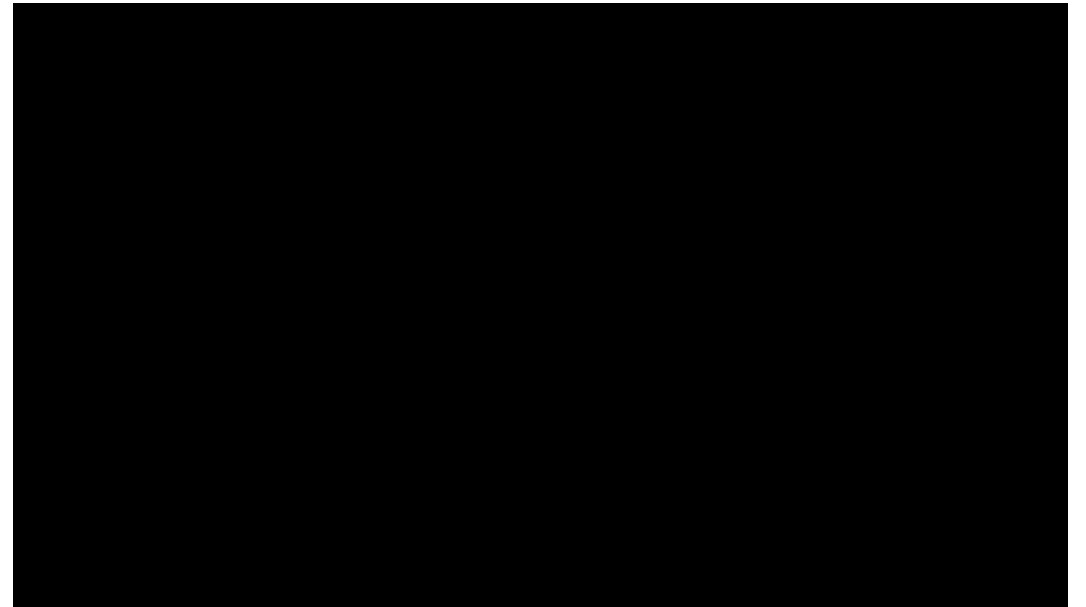
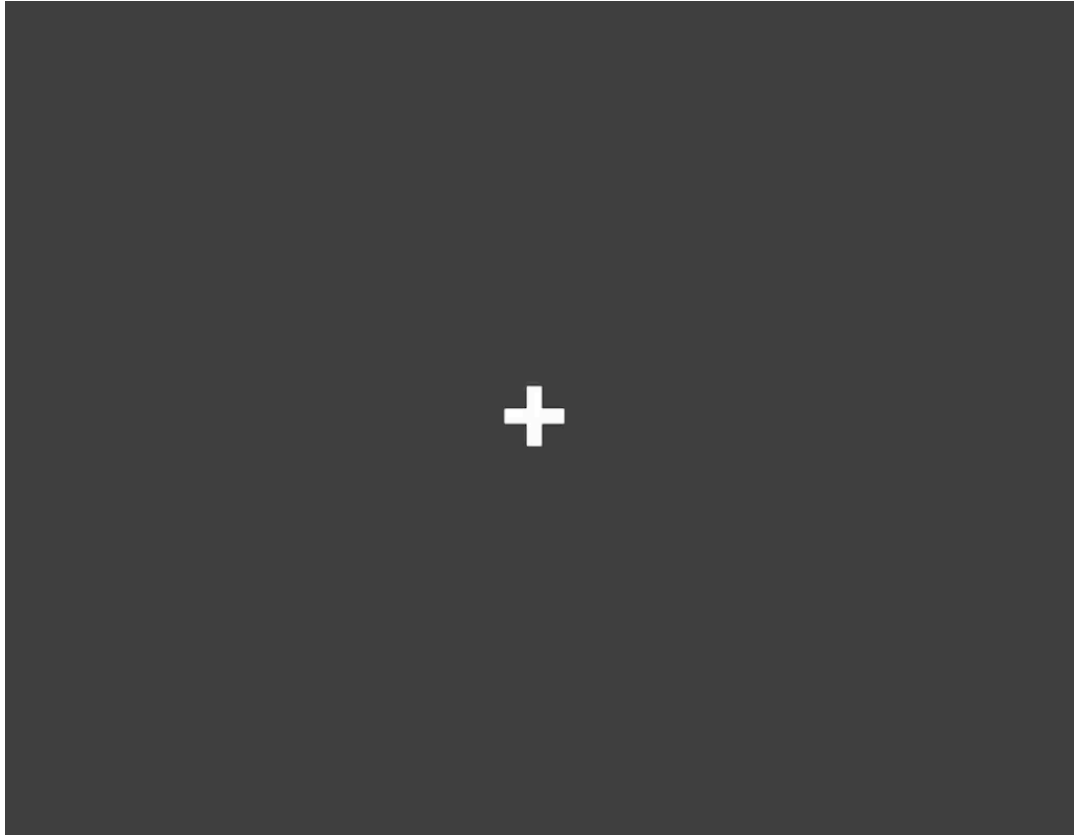


Conditions that make subjects look **more similar** to one another actually make **better databases** for identification:



Q. *Is rest best?*
A. Probably not

Consider naturalistic tasks:



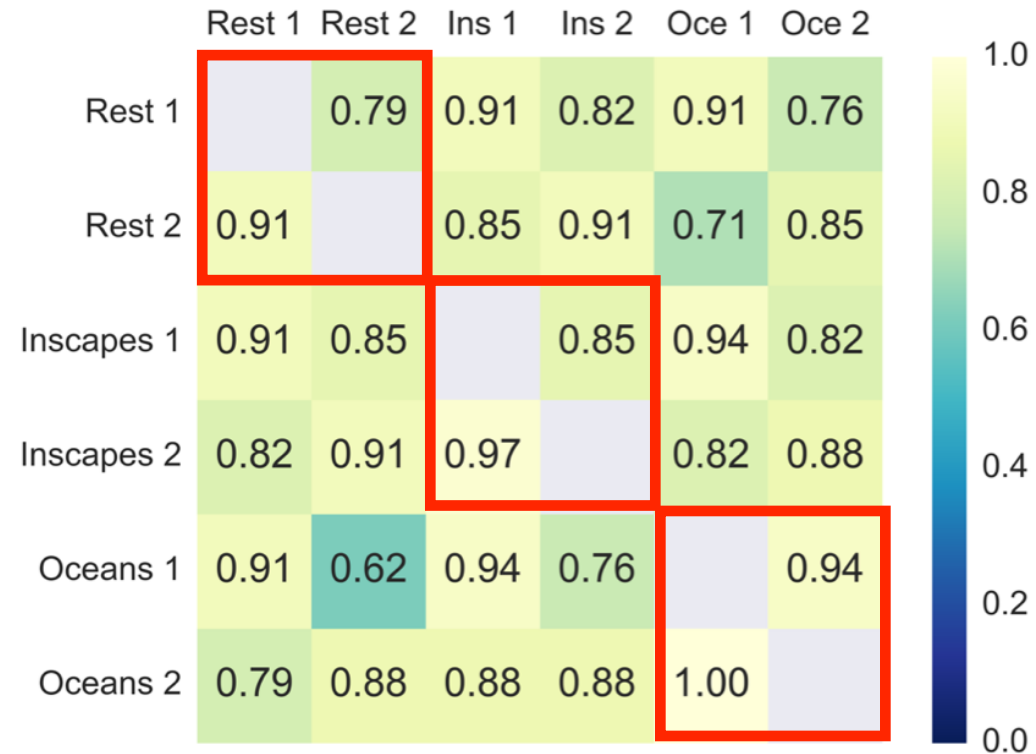
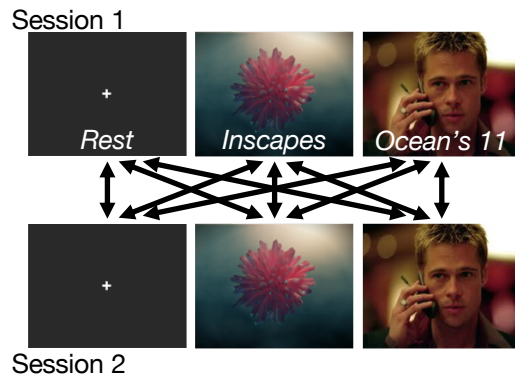
Inscapes: Vanderwal et al., *NeuroImage* 2015
headspacestudios.org

Q. Is rest best?

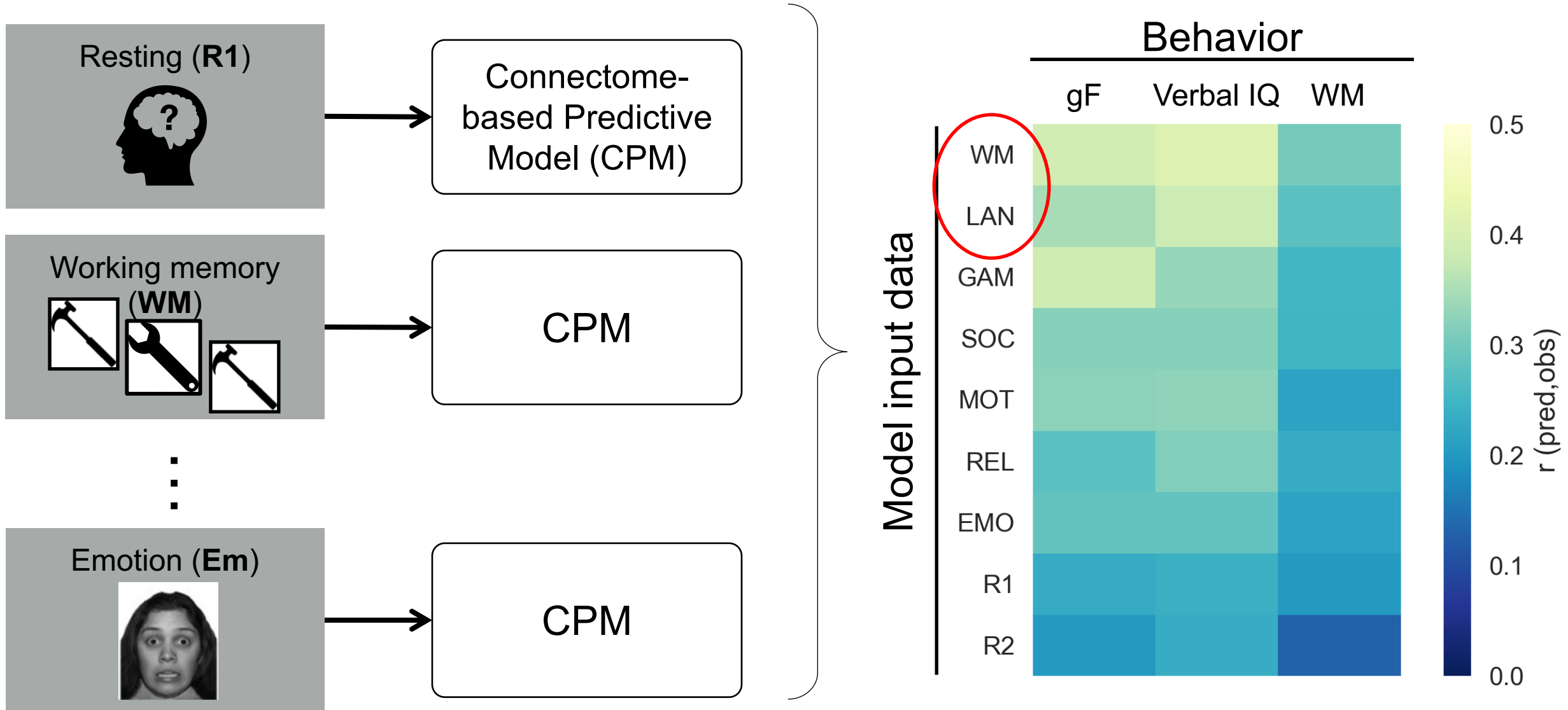
A. Probably not

Consider naturalistic tasks:

- ID rate is just as good as (if not better than) rest



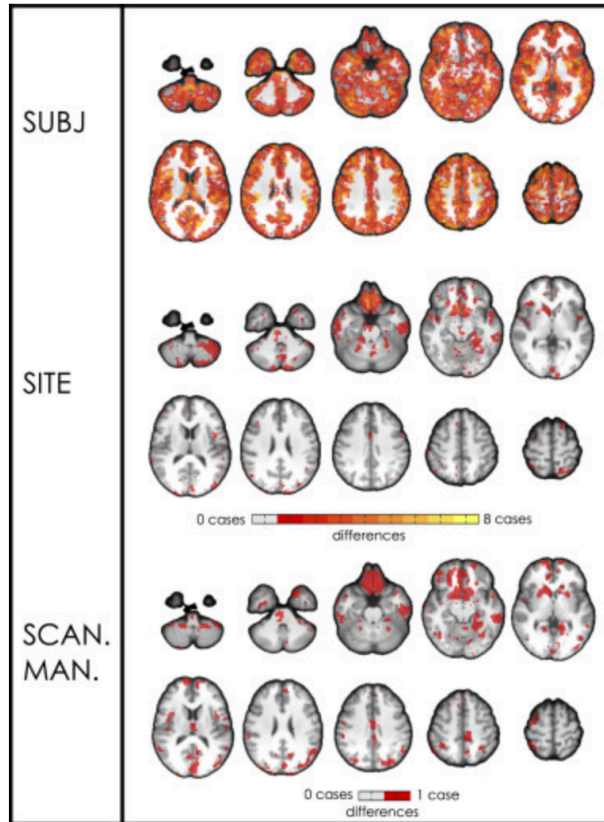
Cognitive brain states best predict cognitive ability



n = 716; 10-fold CV

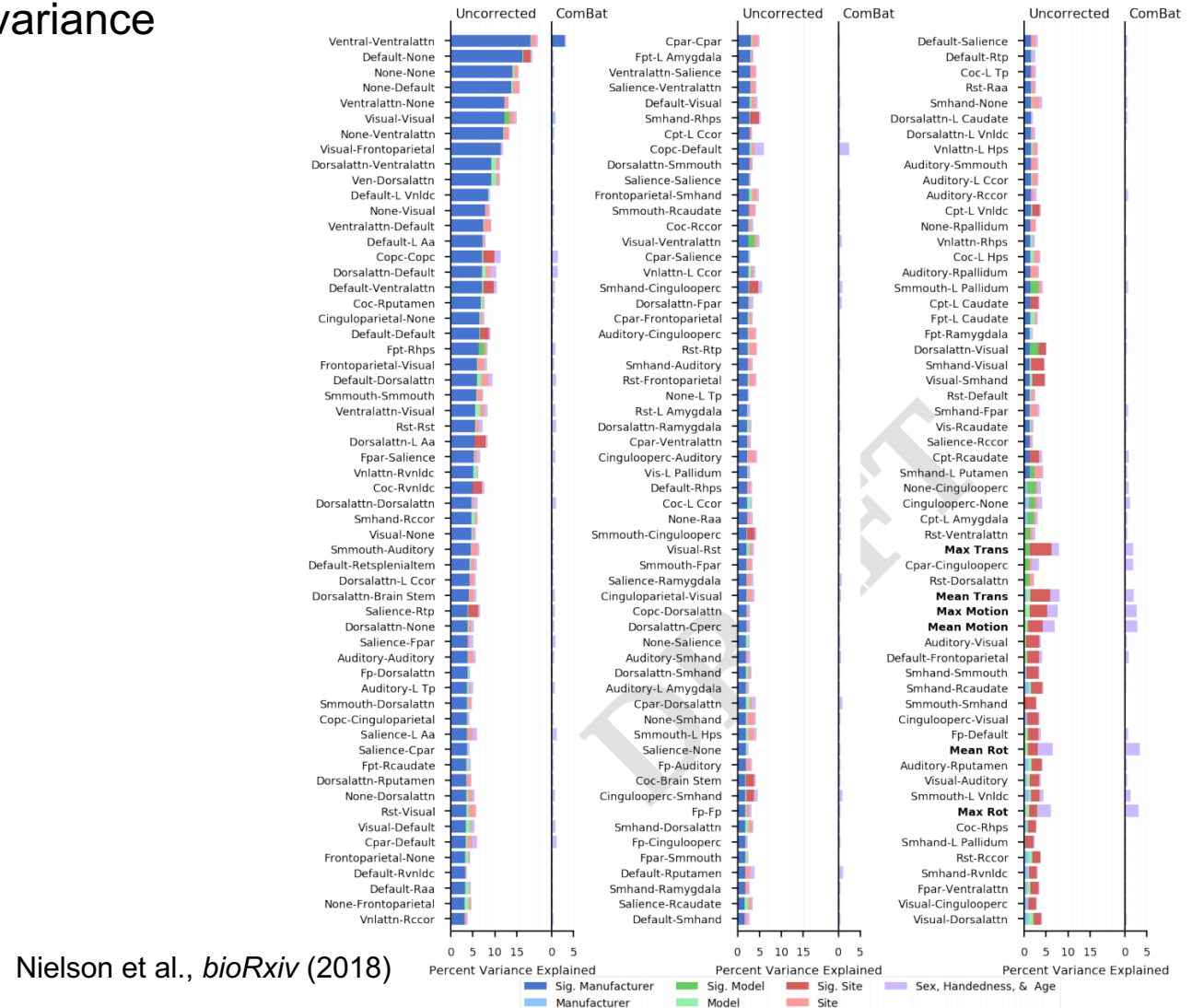
Multisite studies?

- Multisite studies help increase n
- But site and scanner effects can introduce added variance
- Ultimately, biomarkers need to be robust to site



Noble et al., *NeuroImage* (2017)

- Harmonization techniques are promising:



Nielson et al., *bioRxiv* (2018)

Questions & controversies

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Imaging

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Behavior

- Self-report or task-based?
- *Inter-* vs *intra*-subject variability?

Data analysis

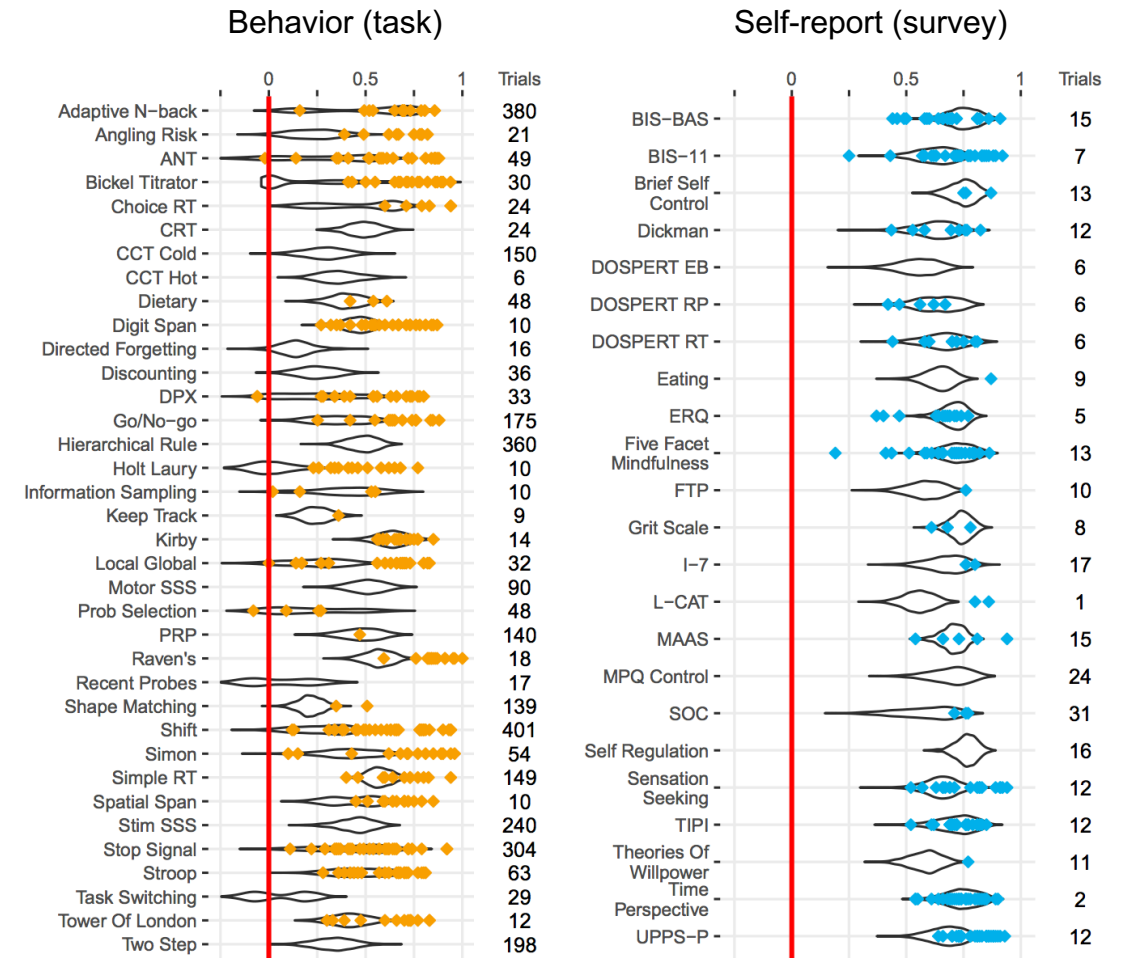
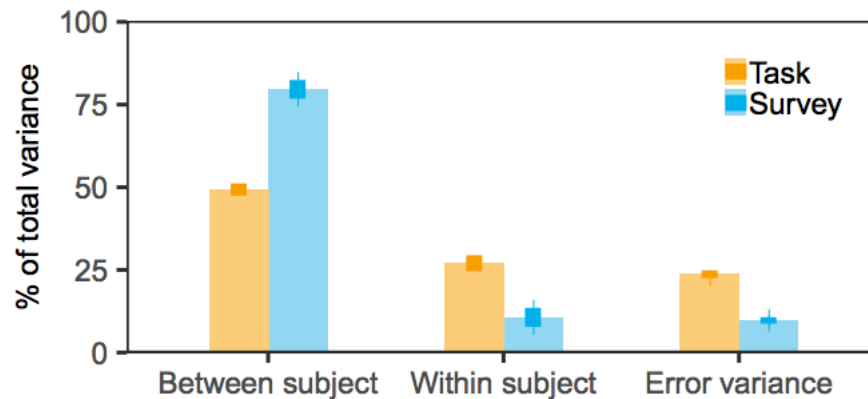


Applications



Self-report or behavior?

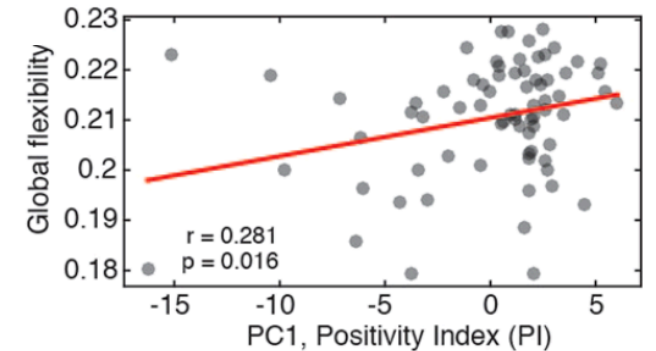
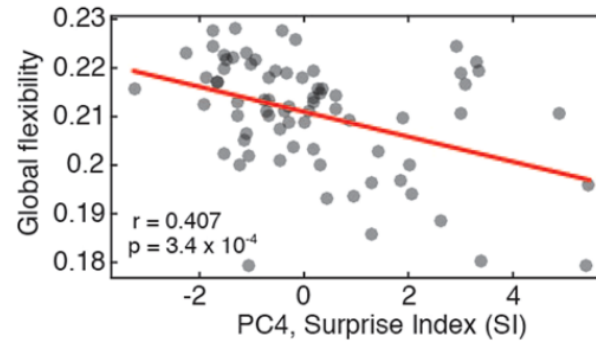
- Self-report is subject to demand characteristics, limited by people's ability to introspect accurately
- Behavior may be less biased
- But self-report may be more stable within individuals (and more variable across individuals)
- Predicting "real-world" behavior (e.g., outcomes) will be gold standard



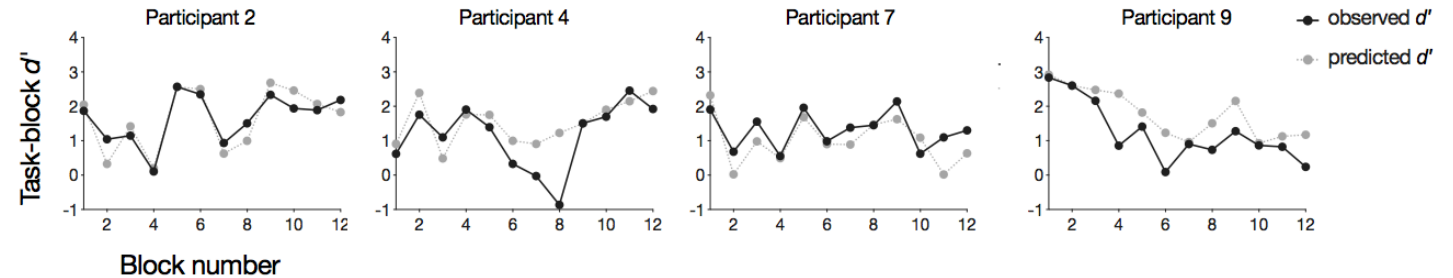
Inter- versus intra-subject variability

Is your behavior stable?

- Trait vs. state
- State variables may be better suited to within-subject analysis

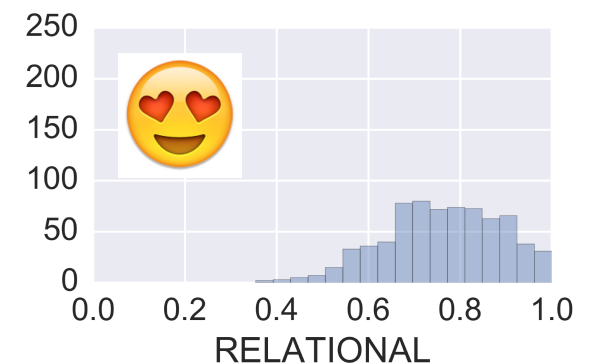
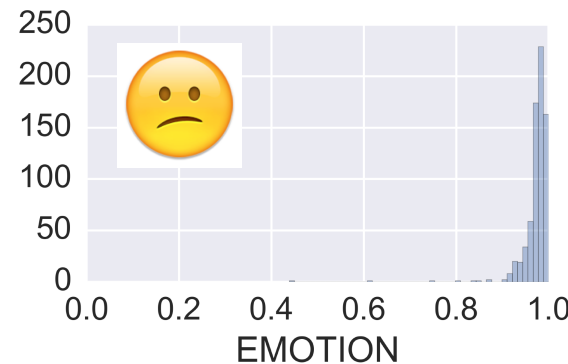


Betzel et al., Sci Rep (2017)



Rosenberg et al., bioRxiv (2019)

Does it show a good distribution in your population?



Questions & controversies

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Data analysis



Features / level of analysis

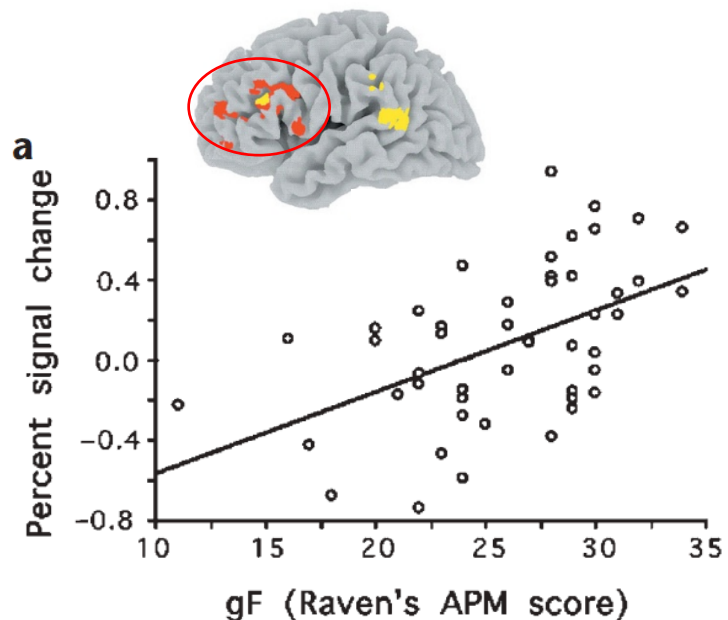
- Functional connectivity?
Activation? Combo?
- Parcel boundaries?
Connections between parcels? Both?

Applications



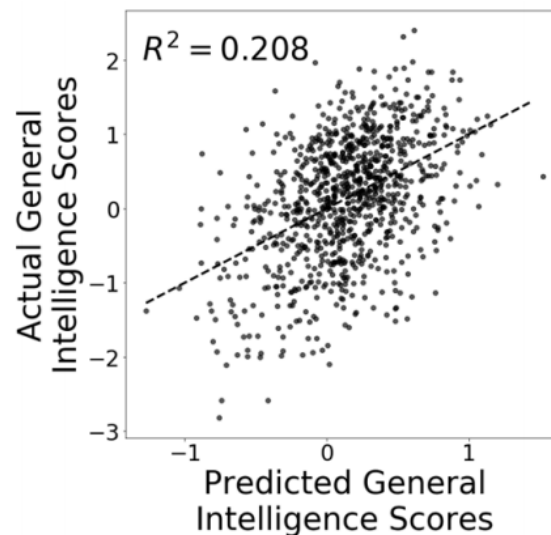
Connectivity? Activation? Both? Something else?

- Current focus on functional connectivity stems from explosion of resting-state & large-scale datasets
- But many task-based studies have shown parametric relationships between activity and behavior
- Combining the two may be most powerful
- Other non-traditional approaches such as inter-subject correlation (ISC) have potential

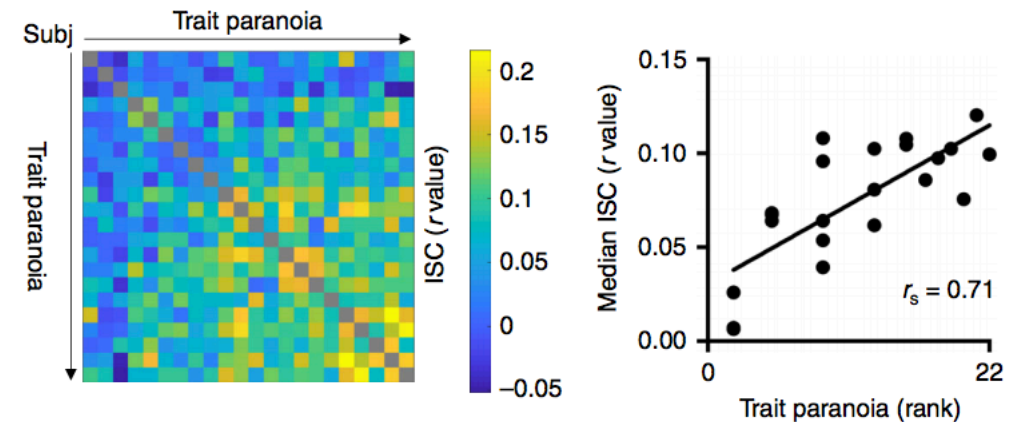


Gray et al., *Nat Neuro* (2003)

Model based on
[FPN activity – DMN activity]
during n-back task



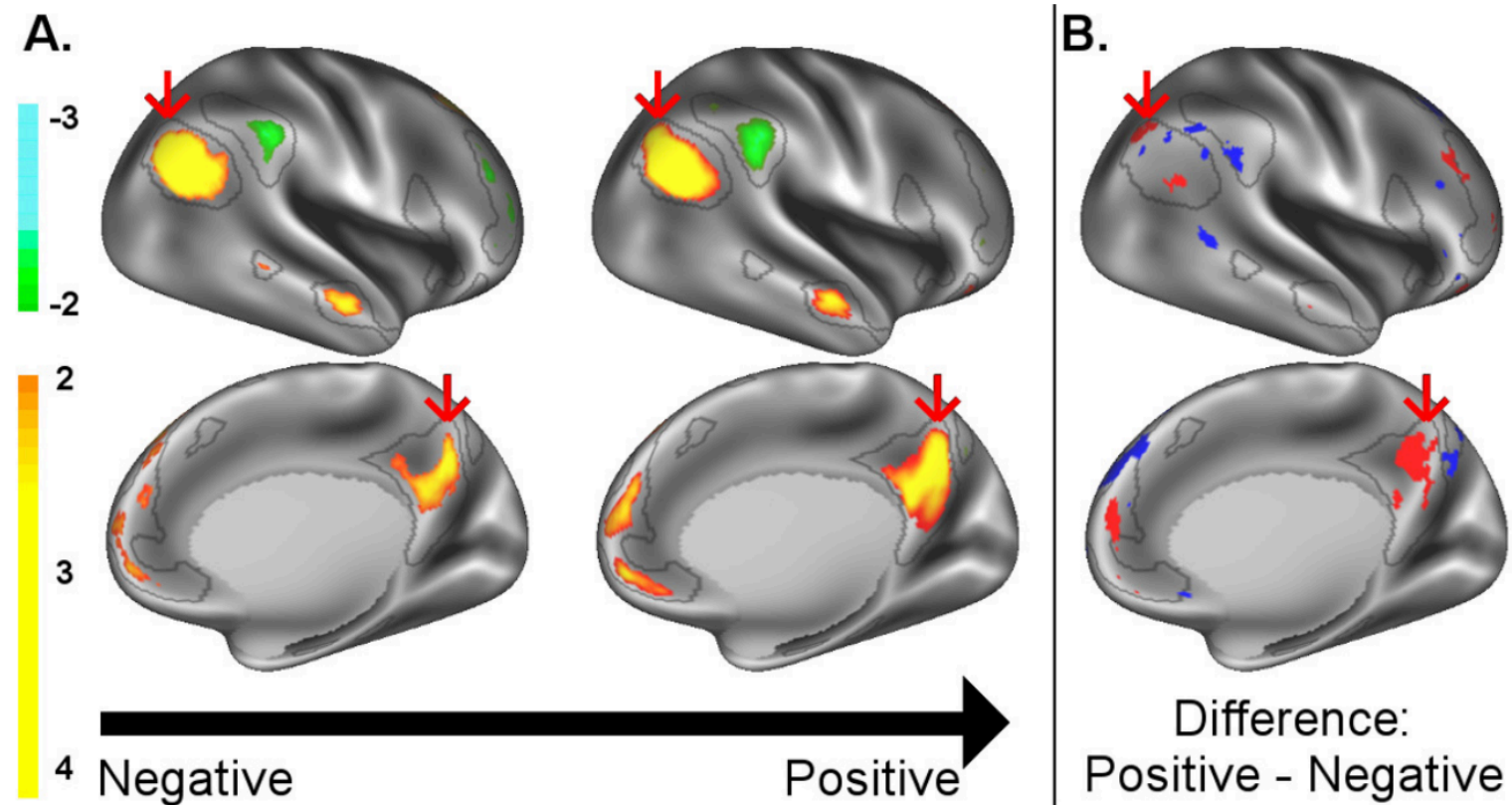
Sripada et al., *bioRxiv* (2019)



Finn et al., *Nat Commun* (2018)

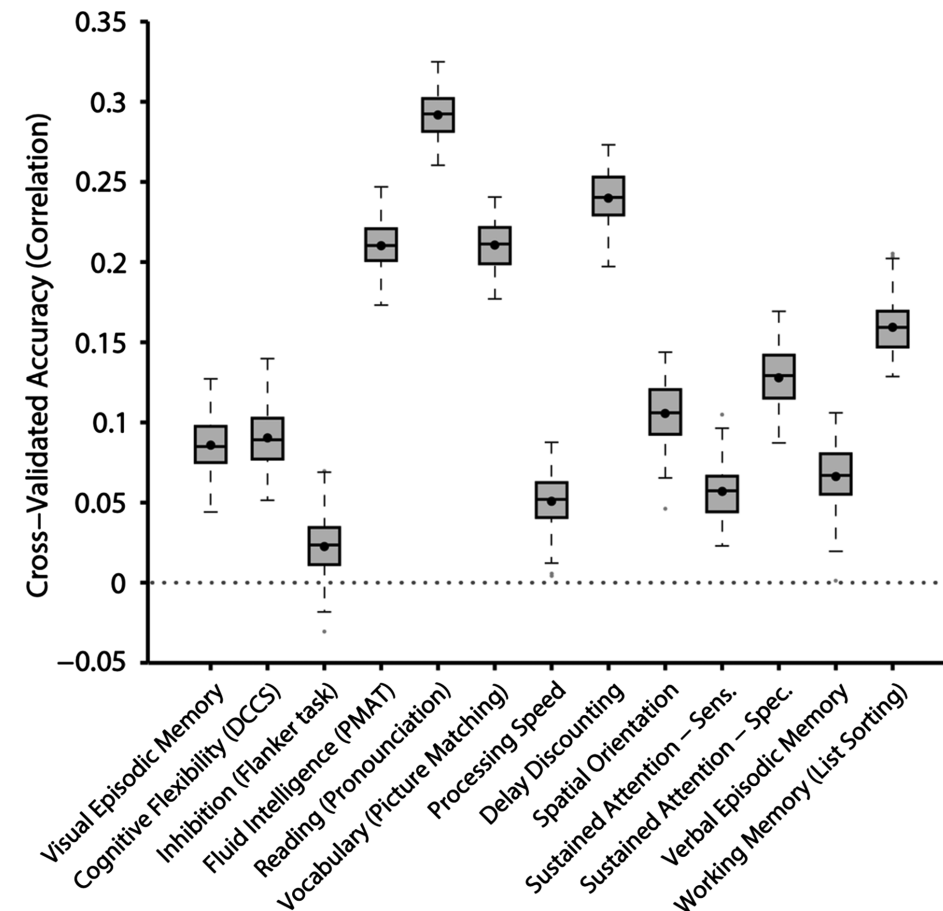
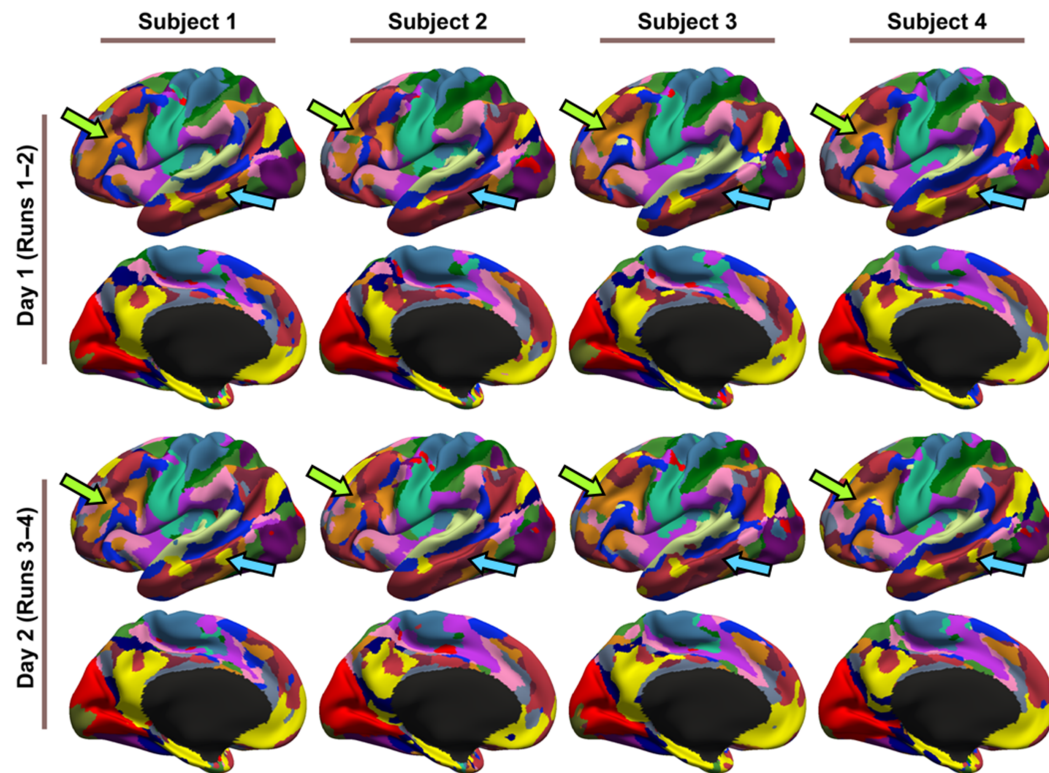
Node boundaries or functional connections?

- Imposing a group atlas can obscure individual differences in node boundaries
- Node boundaries themselves may contain meaningful information



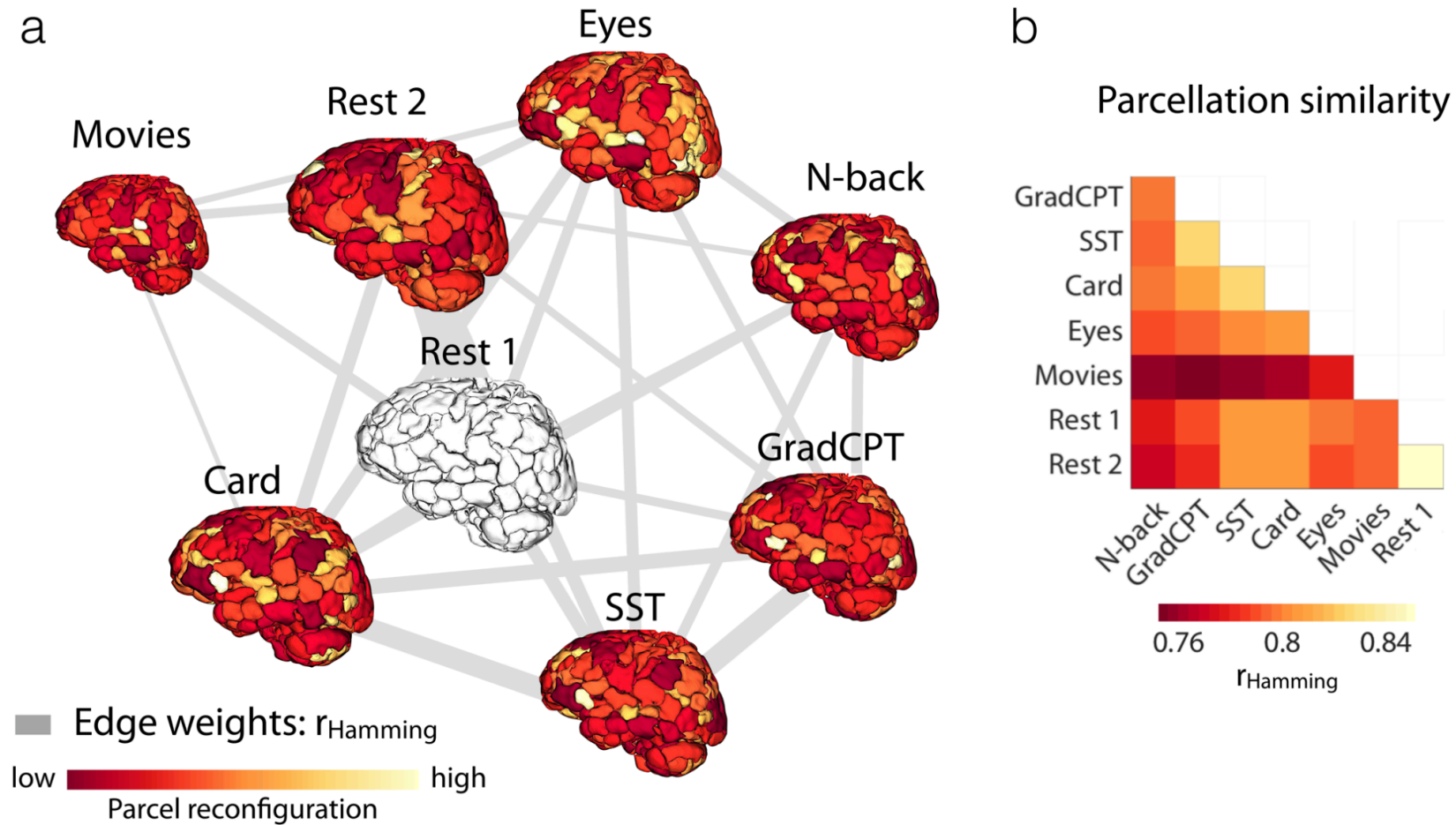
Node boundaries or functional connections?

- Imposing a group atlas can obscure individual differences in node boundaries
- Node boundaries themselves may contain meaningful information



Node boundaries or functional connections?

Even individual-specific parcellations may be task-dependent:



Questions & controversies

Data acquisition



Subjects

- High n , sparsely sampled or low n , densely sampled?
- Which populations?

Imaging

- Data quality?
- Brain state (“stress test”)?
- Multisite studies?

Behavior

- Self-report or task-based?
- *Inter-* vs *intra*-subject variability?

Data analysis



Features / level of analysis

- Functional connectivity?
Activation? Combo?
- Parcel boundaries?
Connections between parcels? Both?

Confounds

- Head motion, others

Applications



Behavior: Mitigating confounds

Many behaviors/phenotypes are correlated with head motion!

- Patients of any kind move more
- Children & older adults move more

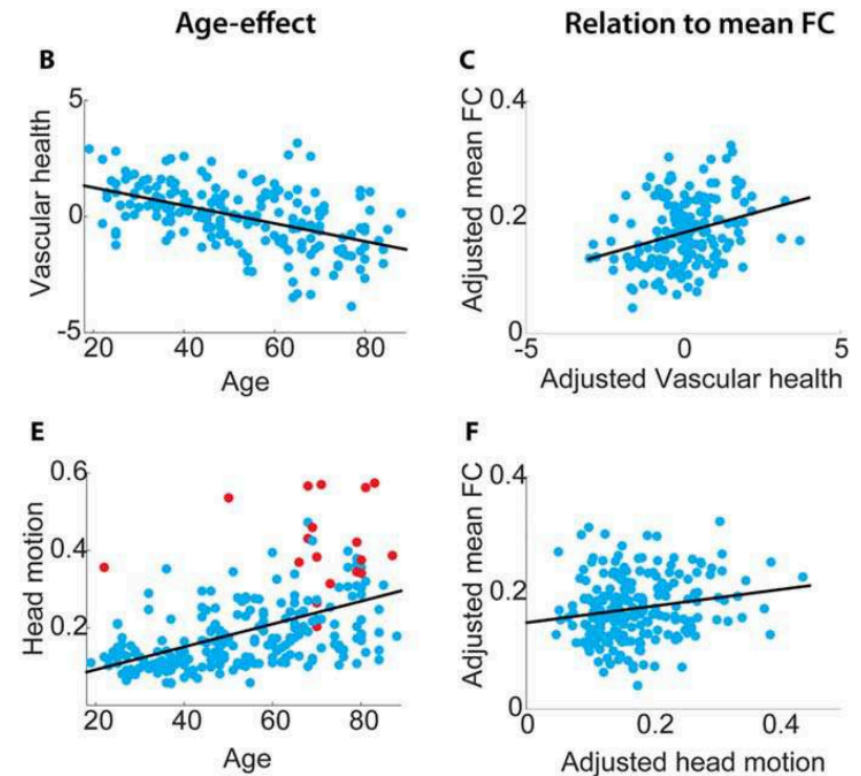
Negatively:

Positively:

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

Siegel et al., *Cerebral Cortex* (2016)

Age, vascular health:

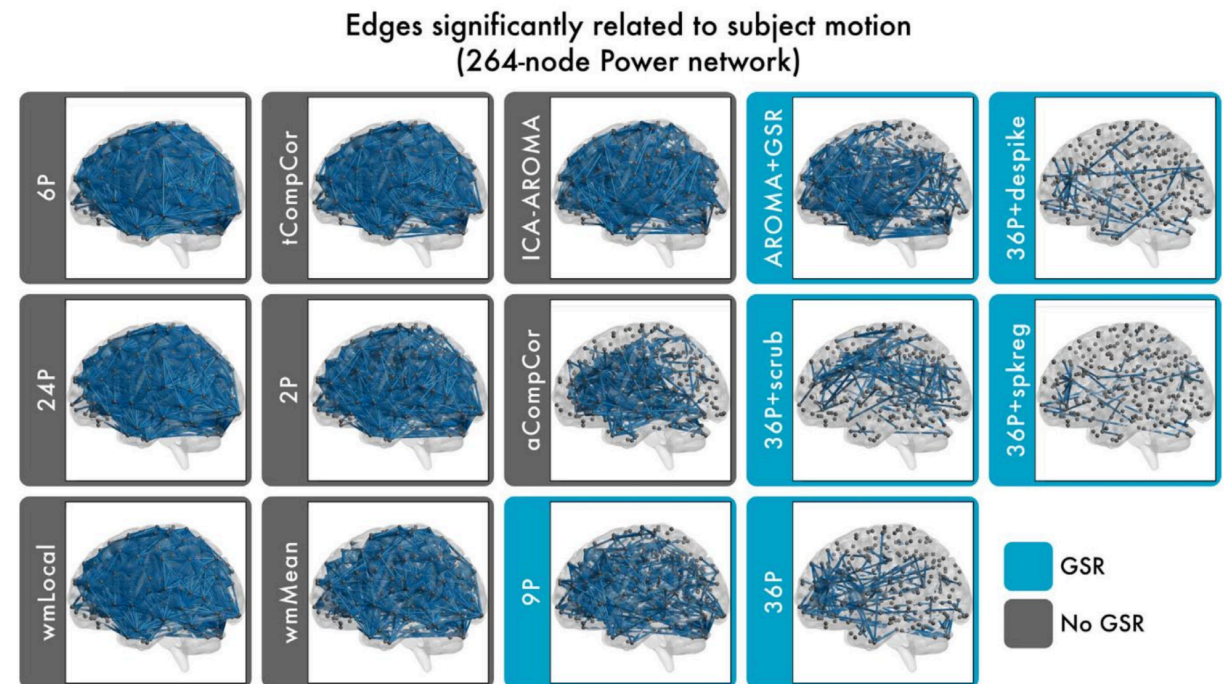


Geerligs et al., *Hum Brain Mapp* (2017)

Behavior: Mitigating confounds

Many behaviors/phenotypes are correlated with head motion!

- ▶ Check correlation in your sample
- ▶ Consider excluding very high-motion subjects
- ▶ Choose appropriate preprocessing techniques
- ▶ Use motion as an explicit covariate



Ciric et al., NeuroImage (2017)

Questions & controversies

Data acquisition



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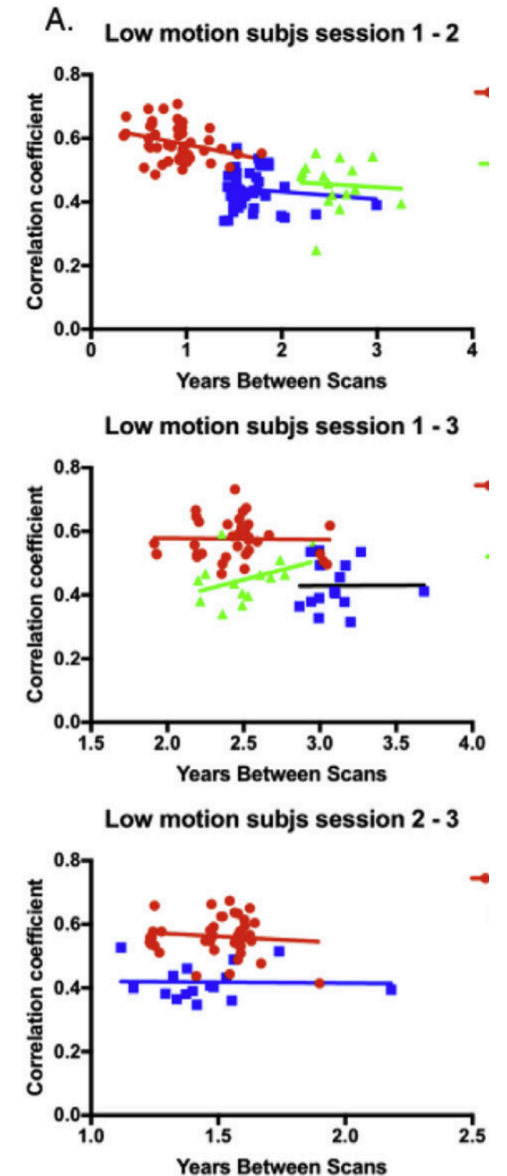
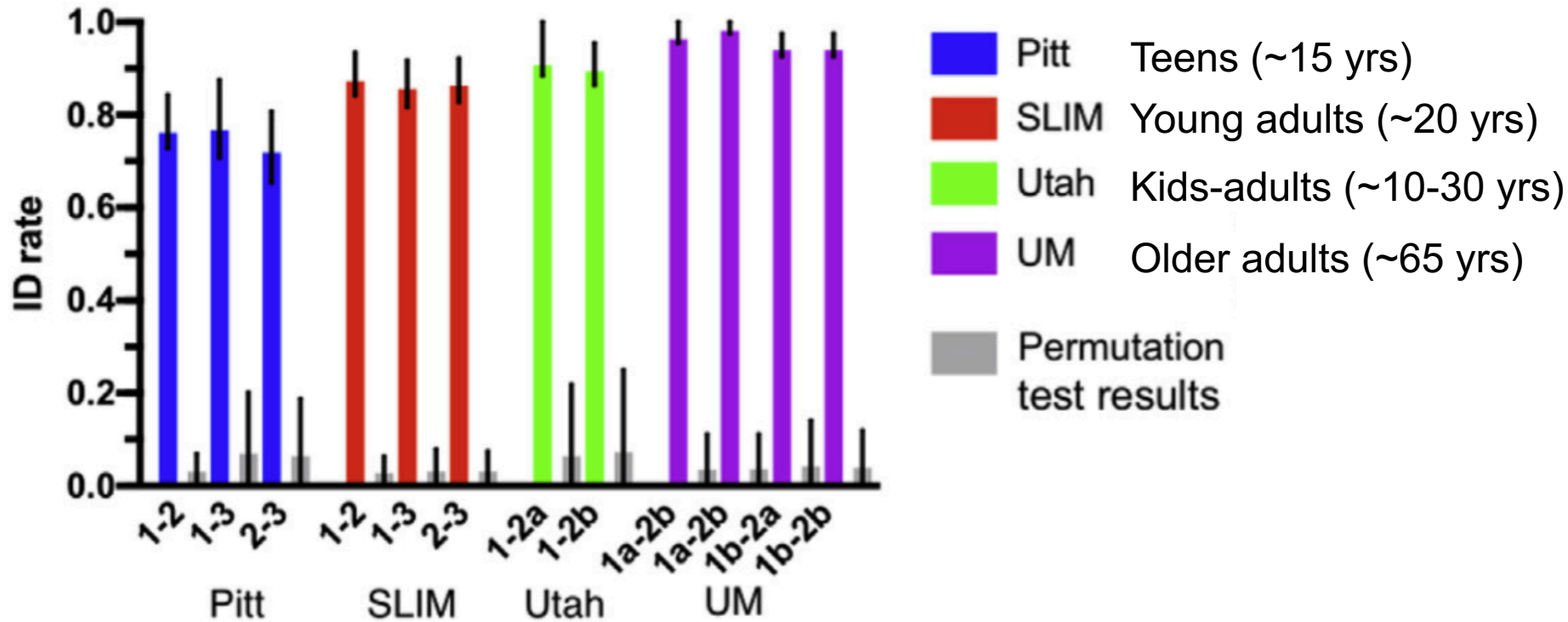


Mutability

- Development? Disease?
Plasticity/training?

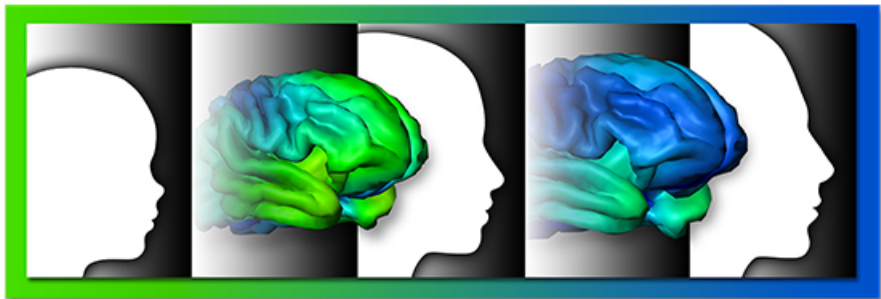
“Fingerprinting” across development, aging

- Identification is possible across sessions separated by a period of years:

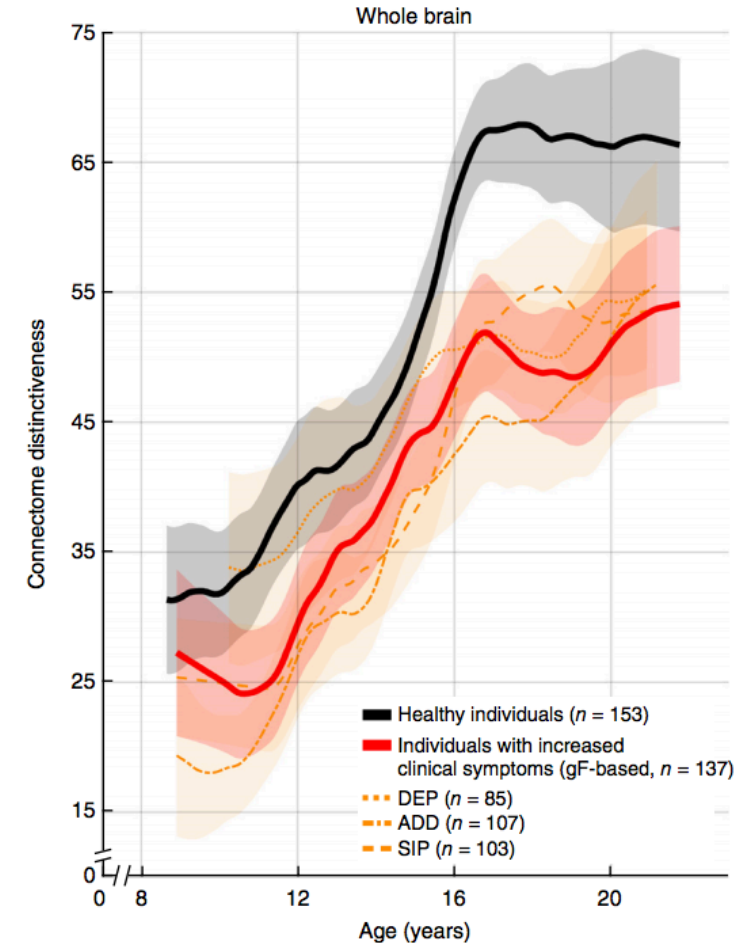
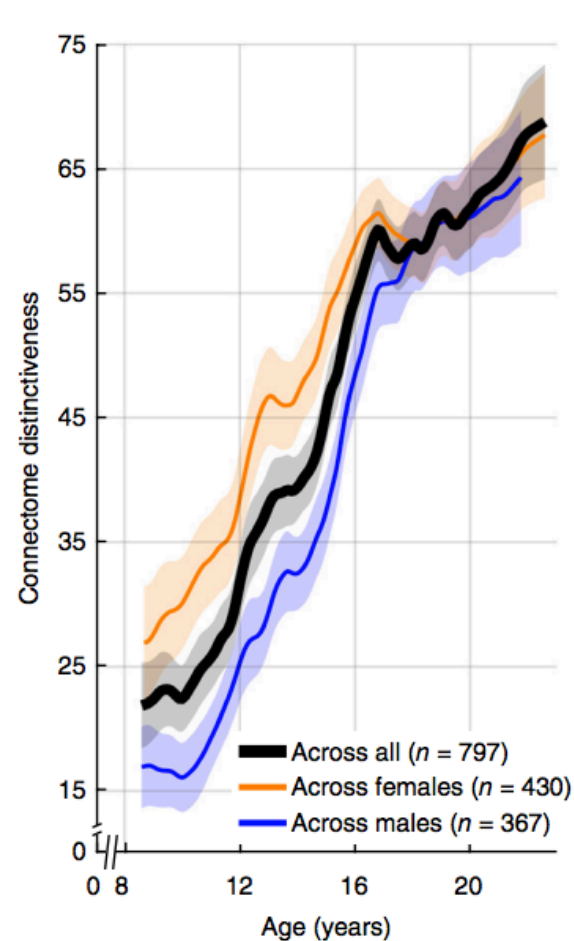


“Fingerprinting” across development, disease

- Connectomes grow more distinct with age
- This process is delayed in mental illness
- Need longitudinal data!



Adolescent Brain Cognitive Development[®]
Teen Brains. Today's Science. Brighter Future.



Questions & controversies

Data acquisition



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Mutability

- Development? Disease?
Plasticity/training?

Looking ahead

- Translational utility?
- Ethics?

Questions & controversies

Data acquisition



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Data analysis



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- Head motion, others

Applications



Mutability

- Development? Disease? Plasticity/training?

Looking ahead

- Translational utility?
- Ethics?

Further reading & open data sets

Selected reviews:

Prediction as a humanitarian and pragmatic contribution from human cognitive neuroscience

Gabrieli, Ghosh & Gabrieli, *Neuron* (2015)

Building a science of individual differences from fMRI

Dubois & Adolphs, *Trends in Cognitive Sciences* (2016)

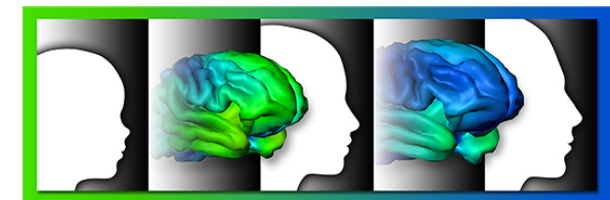
From regions to connections and networks: new bridges between brain and behavior

Misic & Sporns, *Current Opinion in Neurobiology* (2016)

Can brain state be manipulated to emphasize individual differences in functional connectivity?

Finn et al., *NeuroImage* (2017)

Open data sets with brain and behavior:



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Marvin Chun

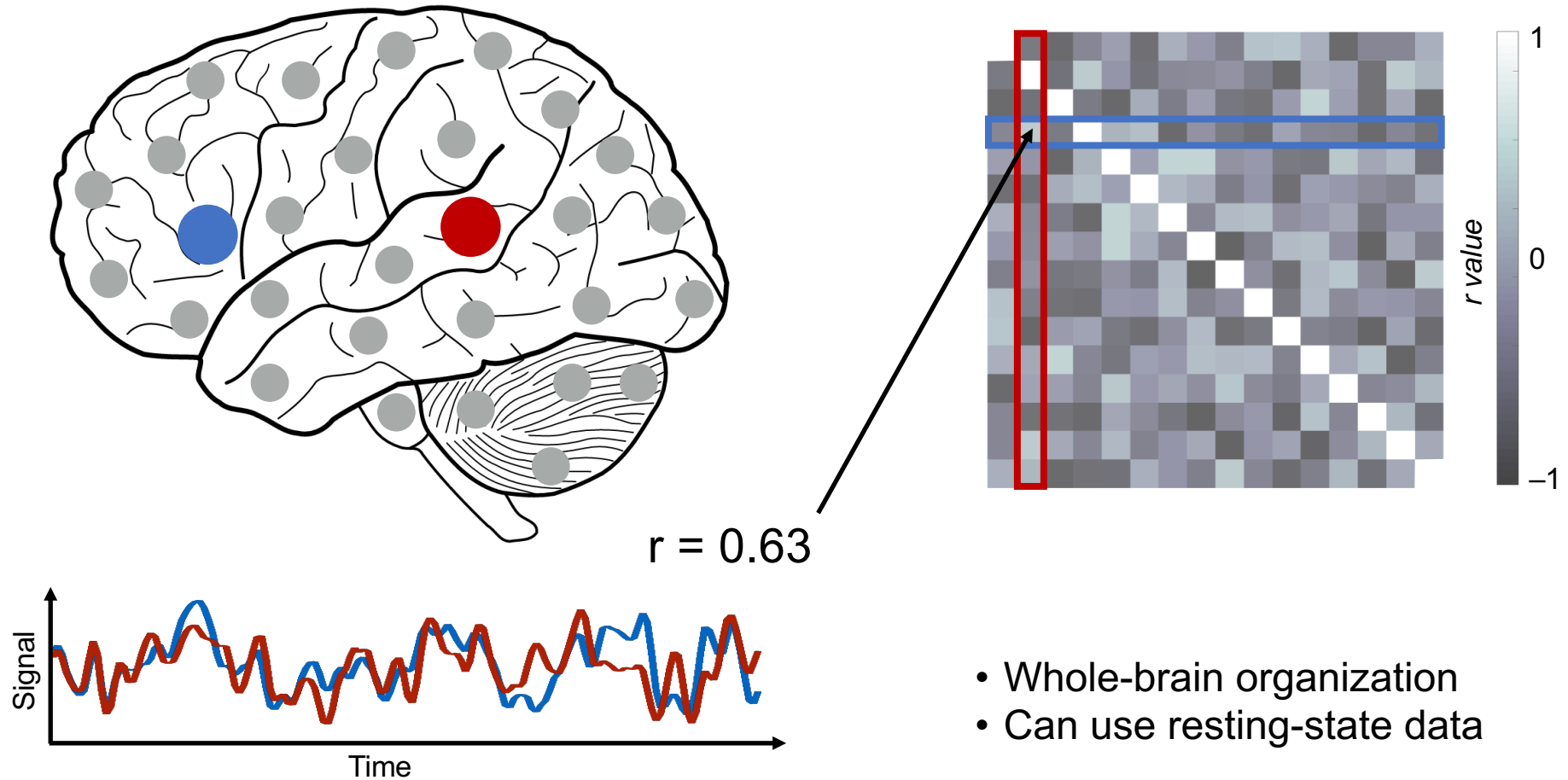
Monica Rosenberg

Tamara Vanderwal

emily.finn@nih.gov



Functional connectivity



Identification experiments

Human Connectome Project

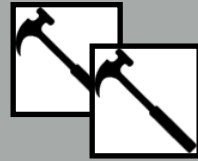
- 126 healthy subjects (50 sets of twins)
- Age 22-35 years old

Day 1

Resting
R1



Working memory
WM

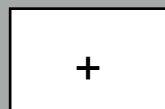


Motor
Mt



Day 2

Resting
R2



Language
Lg



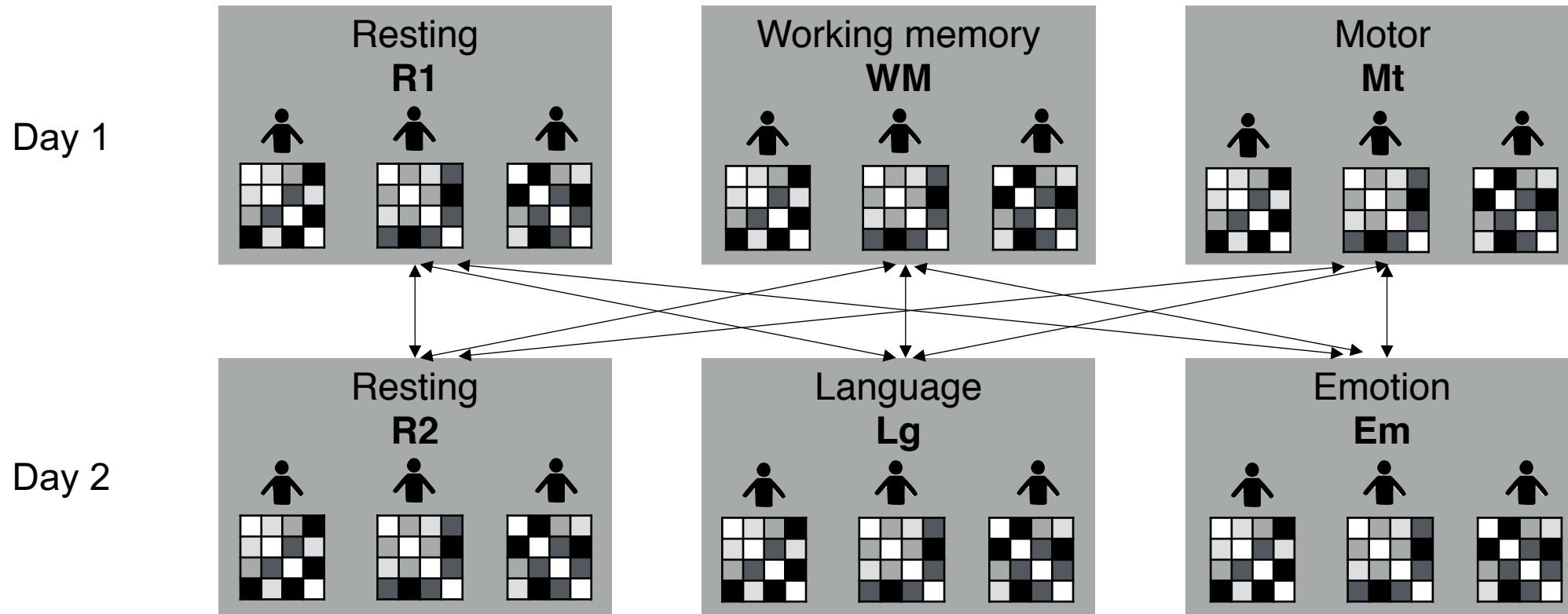
Emotion
Em



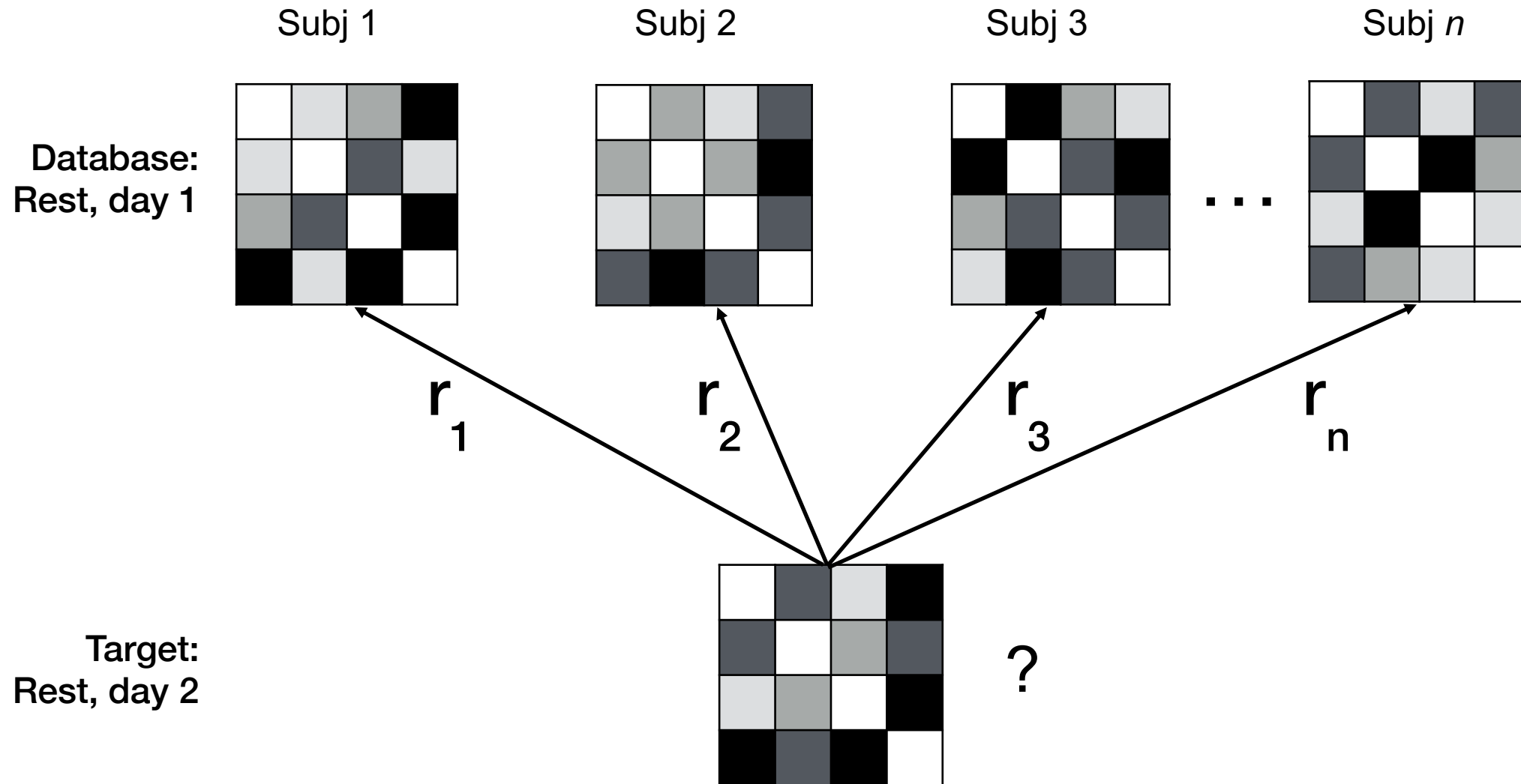
Identification experiments

Human Connectome Project

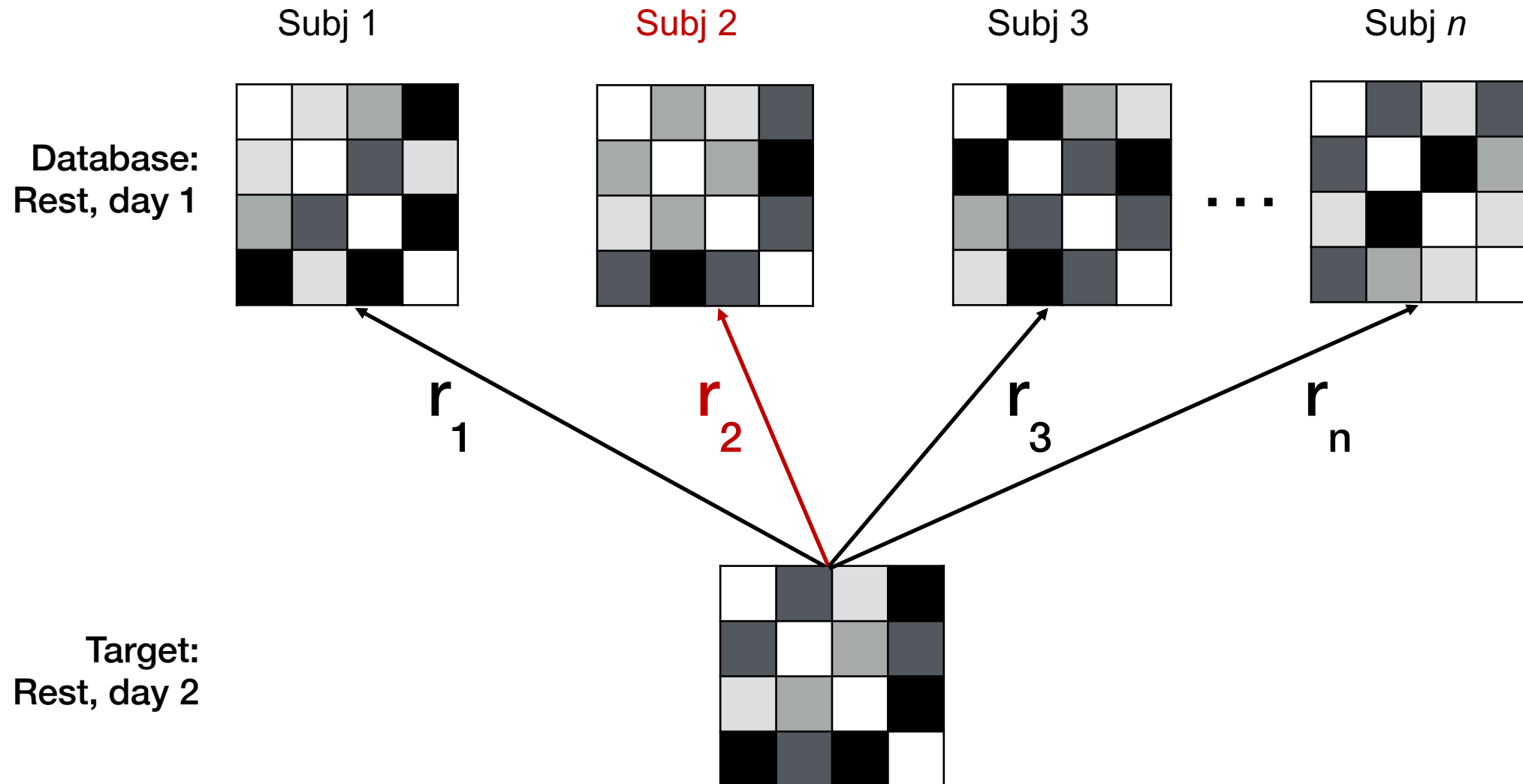
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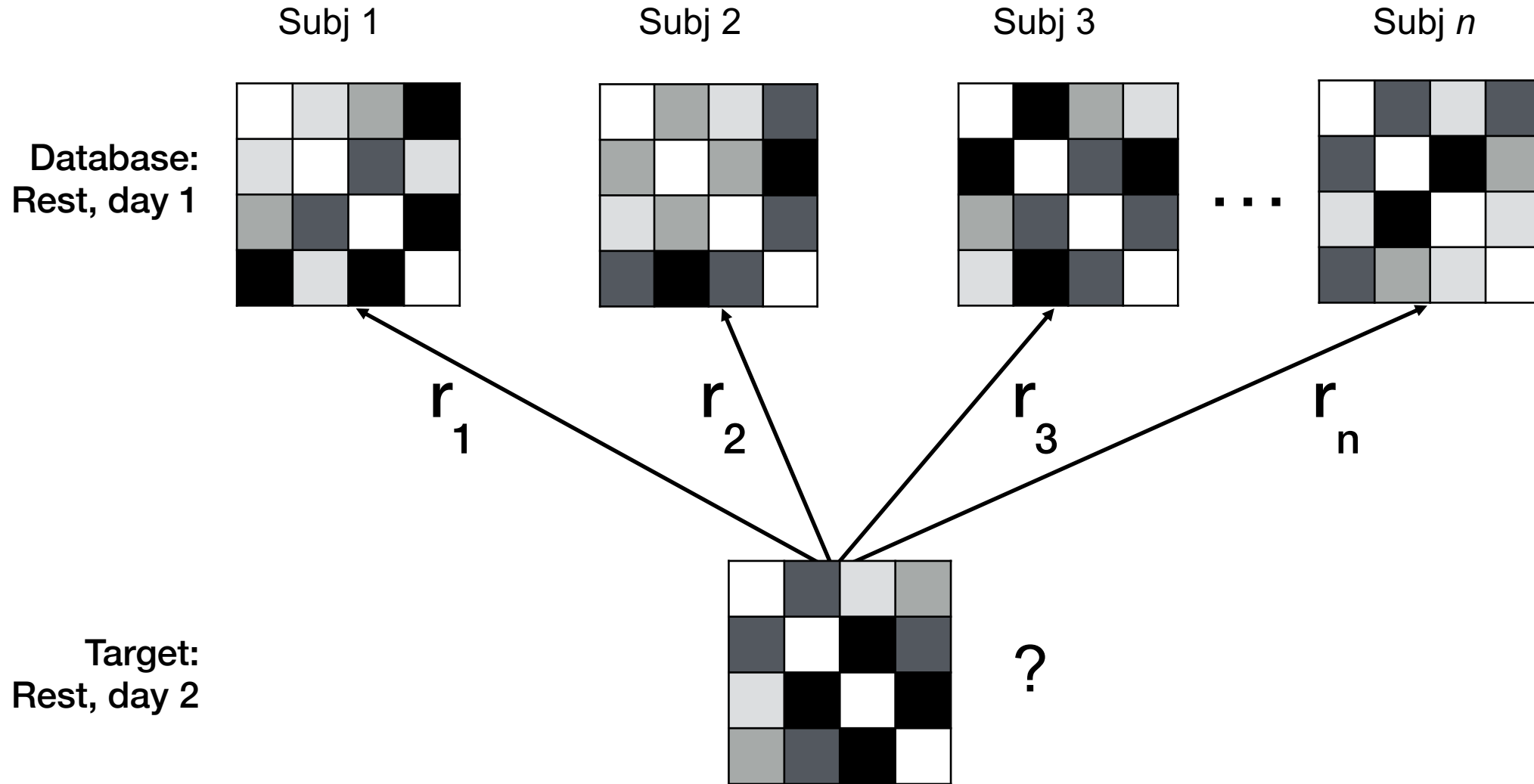
Identification experiments



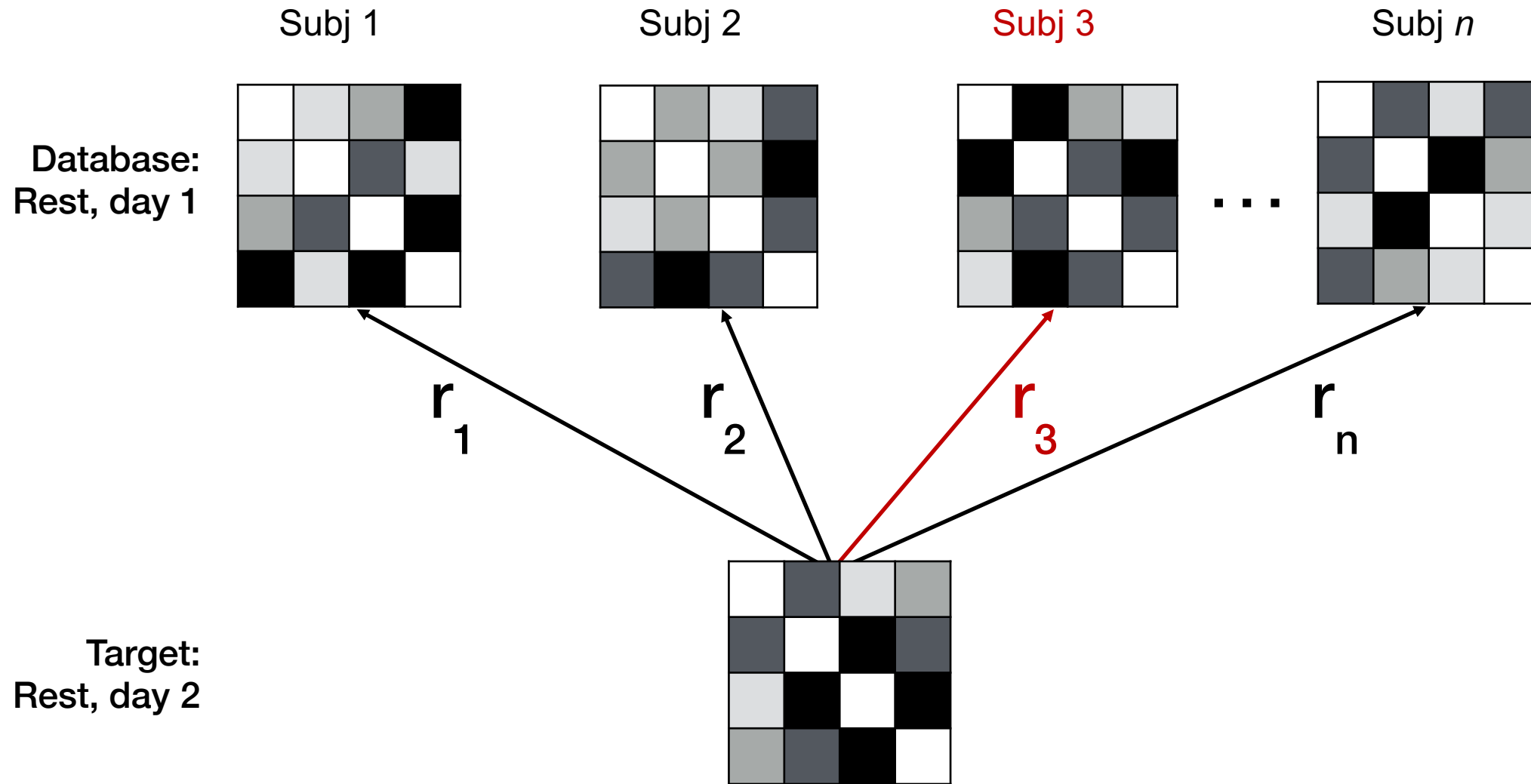
Identification experiments



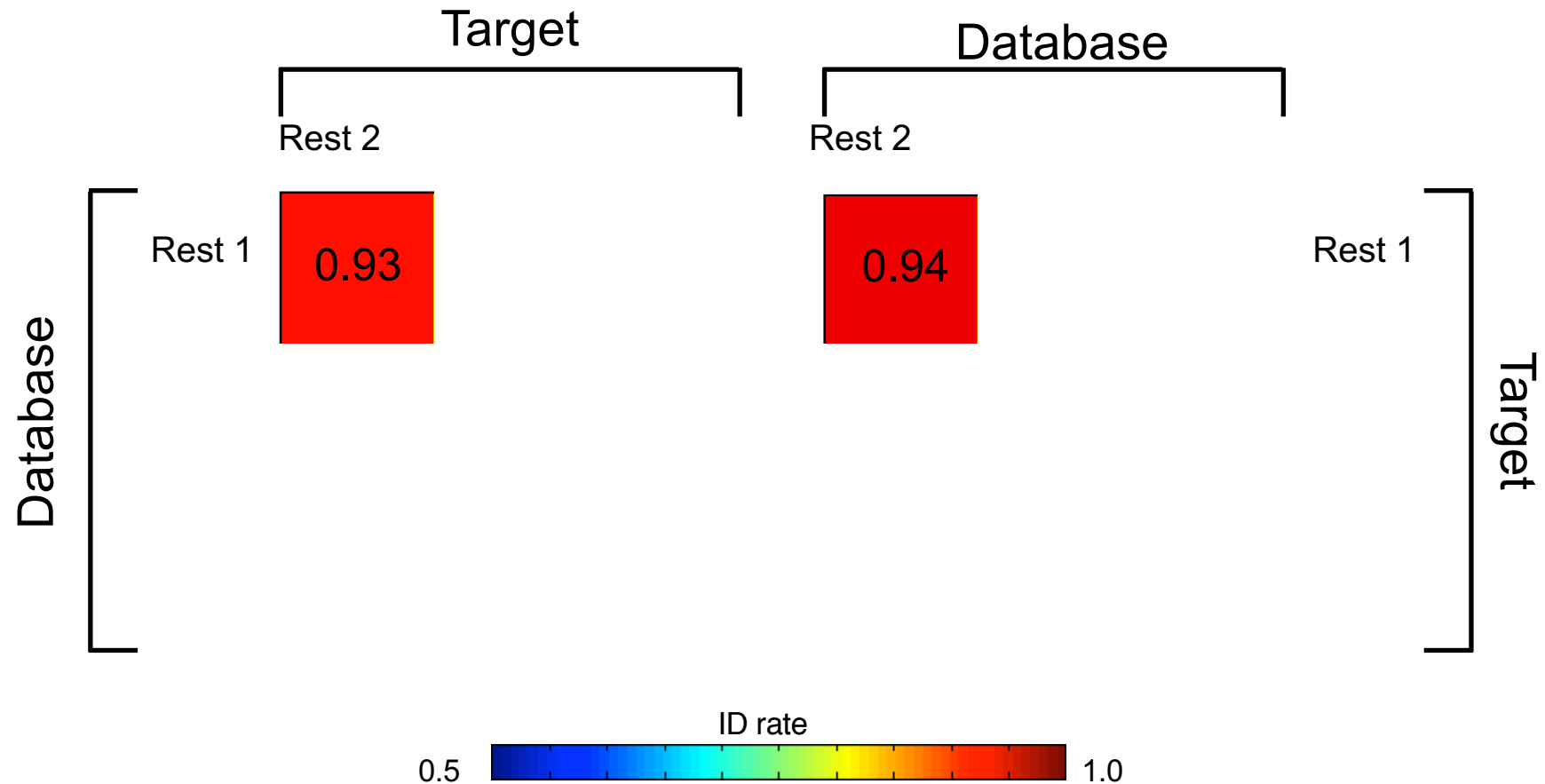
Identification experiments



Identification experiments



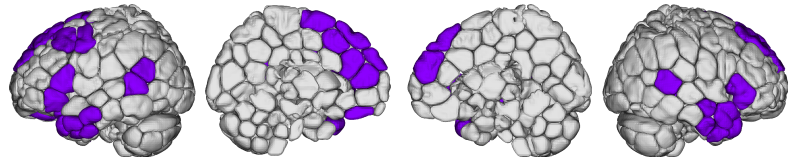
Identification results



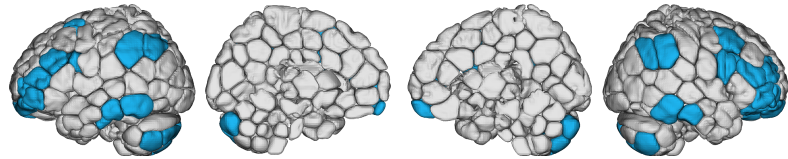
Chance: ~0.008

Network-based identification

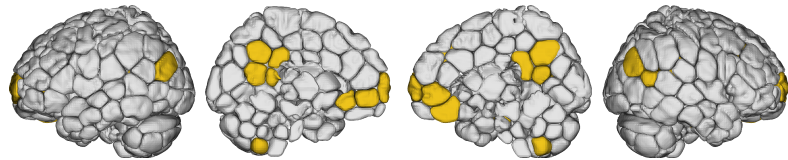
1. Medial frontal



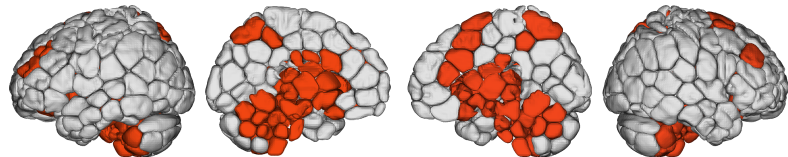
2. Frontoparietal



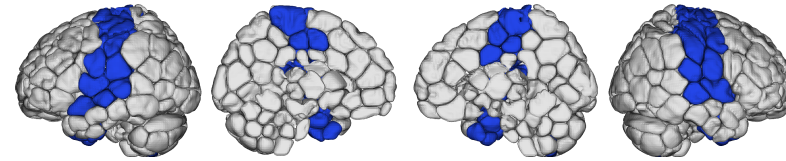
3. Default mode



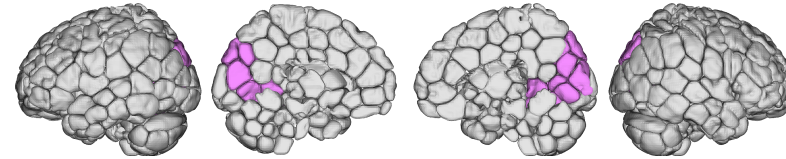
4. Subcortical/cerebellum



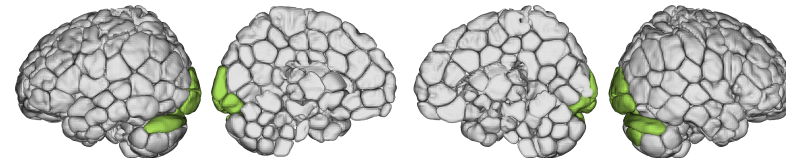
5. Somato-motor



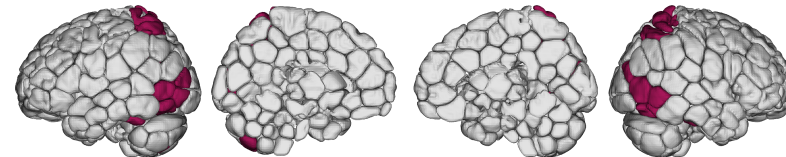
6. Visual I



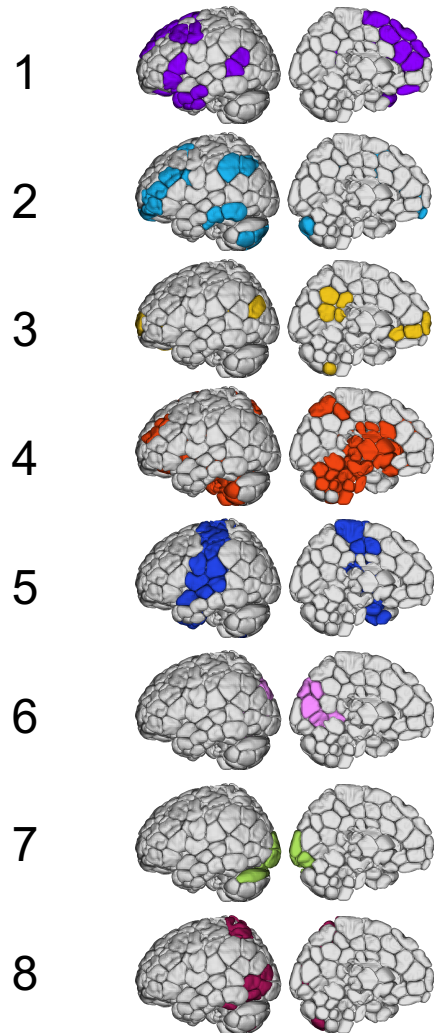
7. Visual II



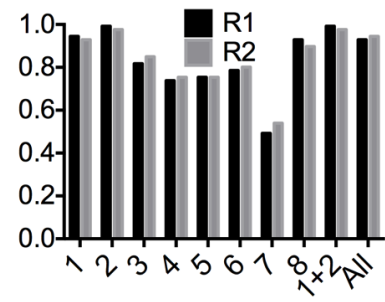
8. Visual association



Network-based identification



Identification rate



Network