



Progress and Challenges in Large-Scale and Translational Neuroimaging Projects

Eugene Duff, FMRIB Analysis Group
University of Oxford



Overview

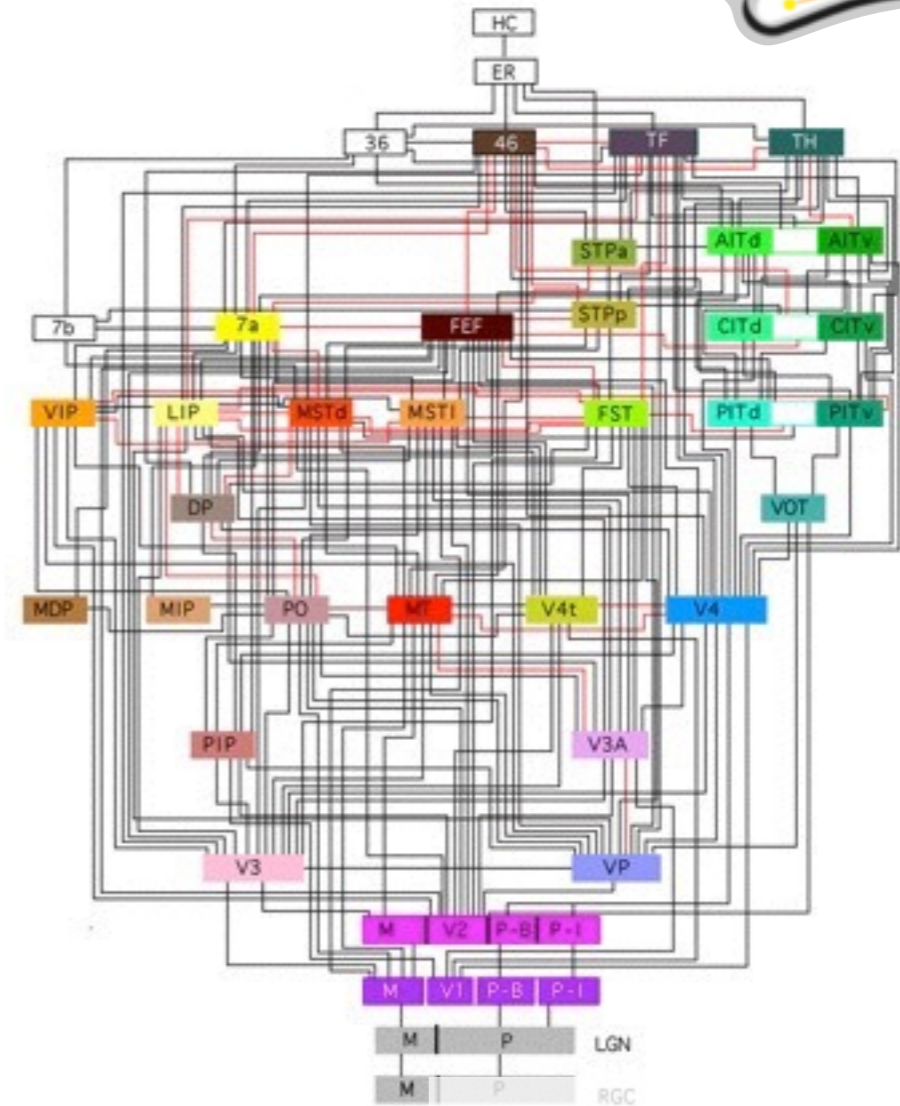
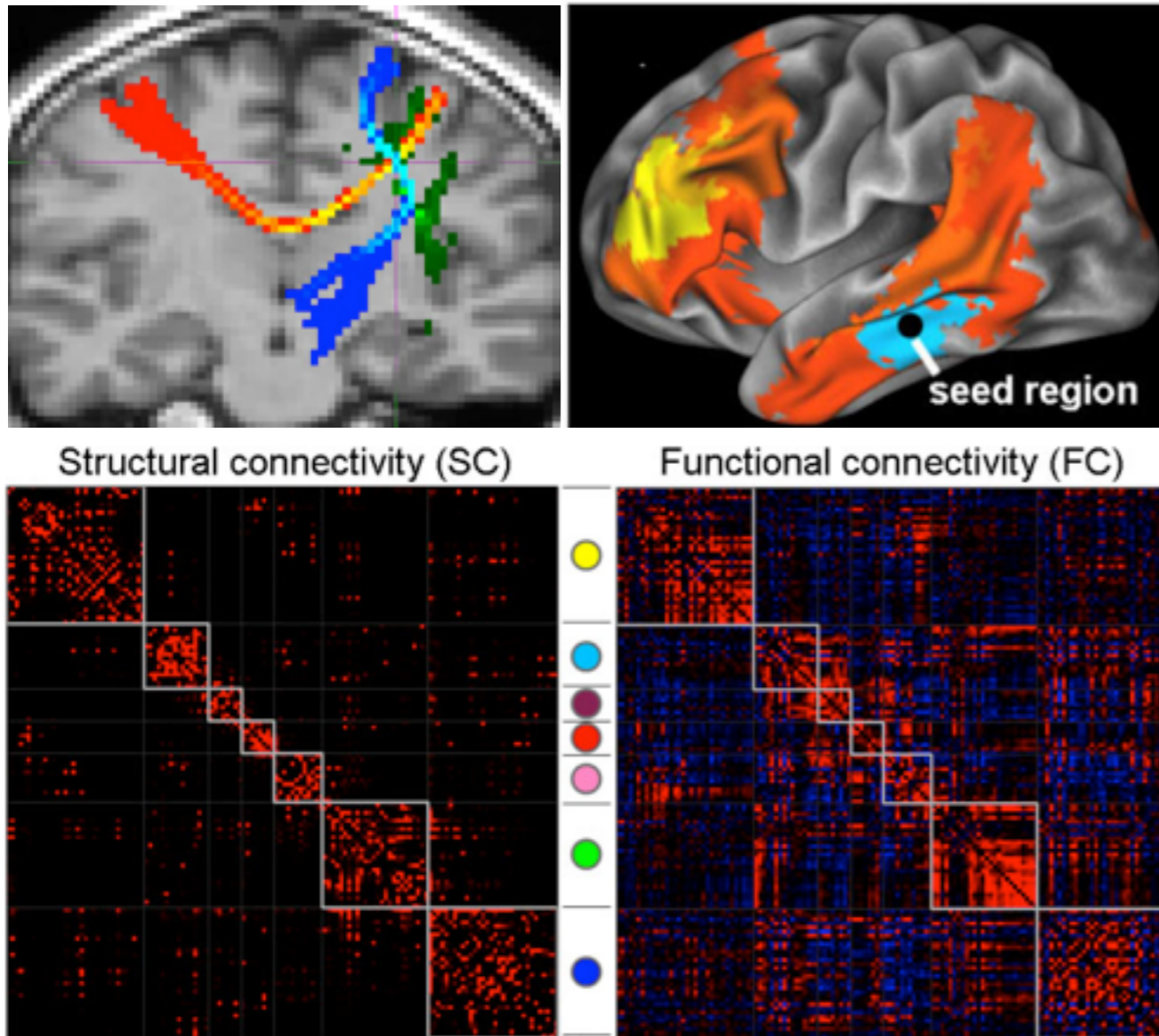
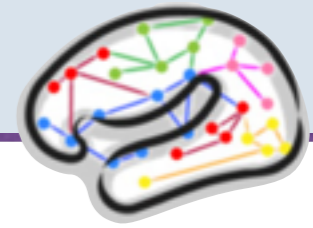
Review of the large-scale studies we are working on at FMRI

- Human Connectome Project
- Developing Human Connectome Project
- UK Biobank Imaging extension
- Multi-study identification of pharmacological biomarkers

Themes

- Pipeline development and applications
- Multi-modal analysis methods
- Automated QA
- Sparse methods
- Meta-analysis and multi-study inference

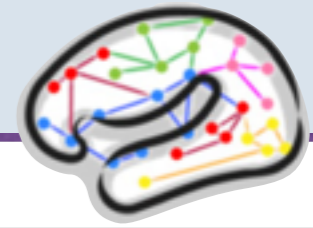
Human Connectome Project



Felleman & Van Essen, 1991

- \$30m project: the best *in vivo* human macro-connectome mapping
- Main groups: WashU (Van Essen), UMinn (Ugurbil) & FMRIIB
- Diffusion-MRI ↔ Resting-FMRI ↔ behavioural measures ↔ genetics
- 1200 subjects
- Data and network models freely available

Human Connectome Project



Acquisition



Pushing spatial and temporal resolution for functional and diffusion MRI in the Human Connectome Project

Kamil Ugurbil^{a,*}, Junqian Xu^{a,b}, Edward J. Auerbach^a, Steen Moeller^a, An T. Vu^a, Julio M. Duarte-Carvajalino^a, Christophe Lenglet^a, Xiaoping Wu^a, Sebastian Schmitter^a, Pierre Francois Van de Moortele^a, John Strupp^a, Guillermo Sapiro^{a,c}, Federico De Martino^{a,d}, Dingxin Wang^{a,c}, Noam Harel^a, Michael Garwood^a, Liyong Chen^{e,g}, David A. Feinberg^{e,g}, Stephen M. Smith^h, Karla L. Miller^h, Stamatios N. Sotiropoulos^h, Saad Jbabdi^h, Jesper L.R. Andersson^h, Timothy E.J. Behrens^{h,i}, Matthew F. Glasser^j, David C. Van Essen^j, Essa Yacoub^a
for the WU-Minn HCP Consortium

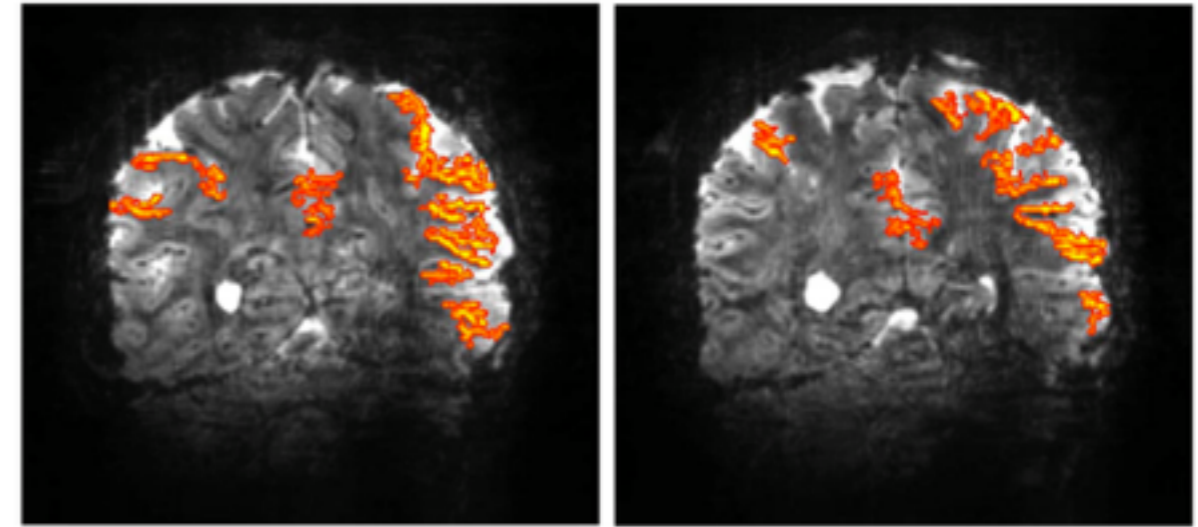
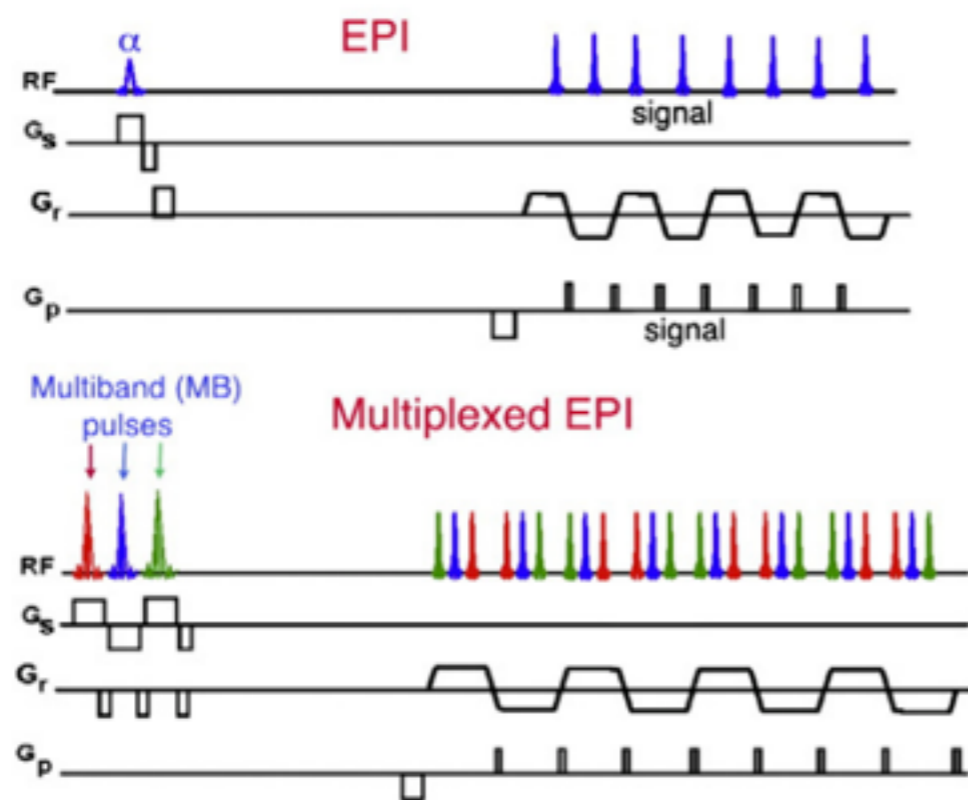


Fig. 3. Functional maps at 7 T obtained with slice and phase-encode acceleration. Two representative coronal slices showing functional activation maps obtained with 16 fold two dimensional acceleration (4 fold slice (i.e. MB = 4) and 4 fold in-plane phase encode accelerations) for a complex visuo-motor dissociation task; 90 slices were acquired in 1.5 s with $1 \times 1 \text{ mm}^2$ in plane resolution 2 mm slice thickness. A total of 252 images were obtained with the subjects performing the task during three blocks of on-off periods. Maximal aliasing in these data was 16 fold. Adapted from Moeller et al. (2008, 2010).



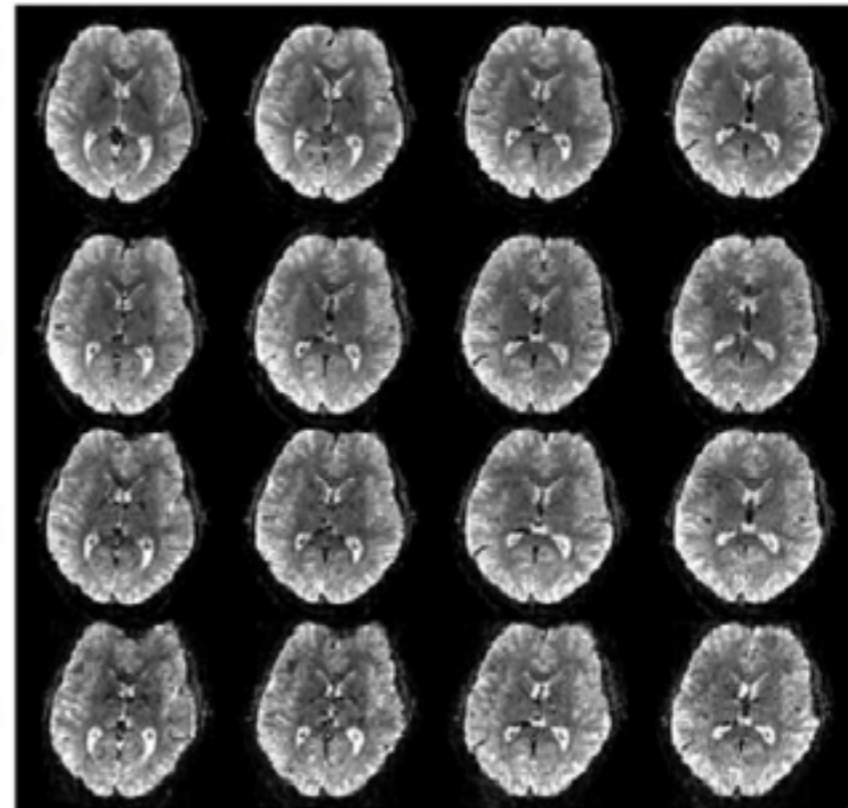
(s x m)

1x1

2x2

3x2

4x3

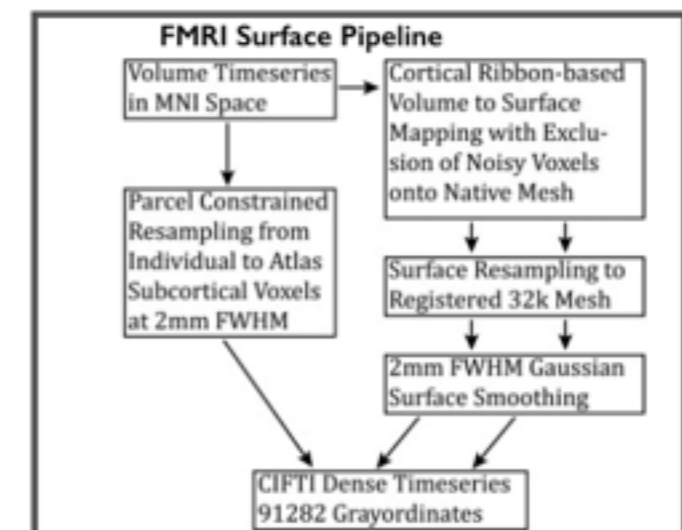
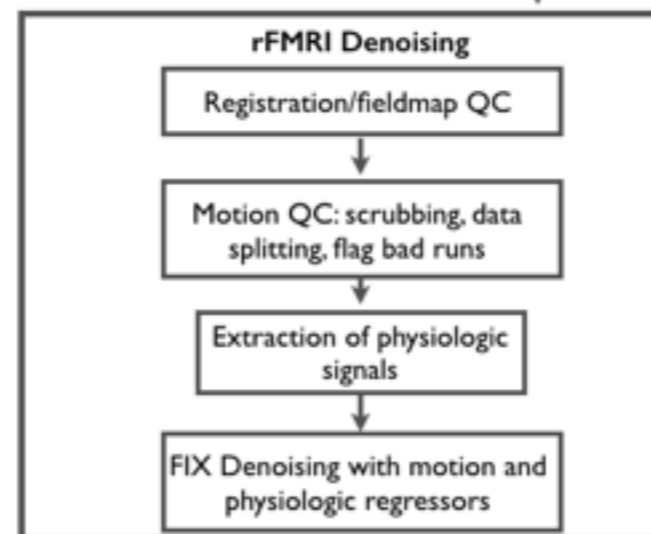
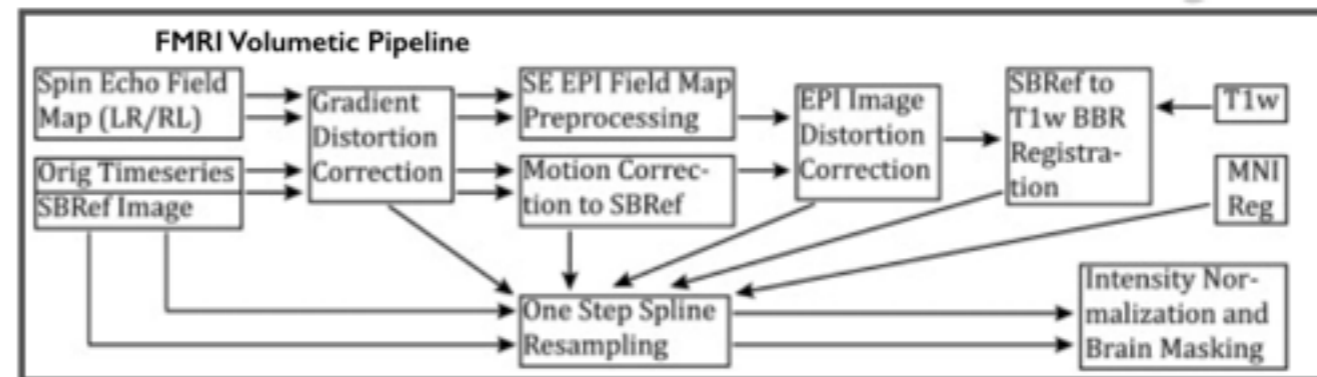
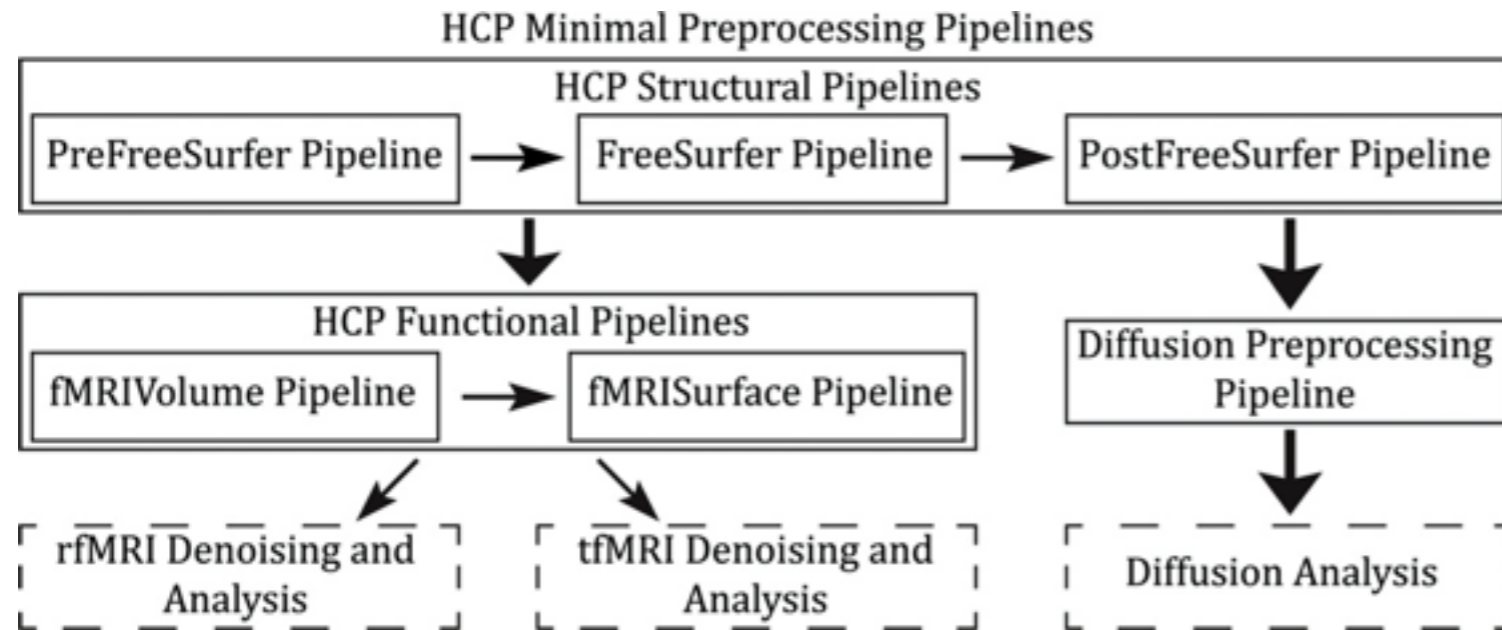


- Parallel Imaging: Multiband Acquisitions

Human Connectome Project

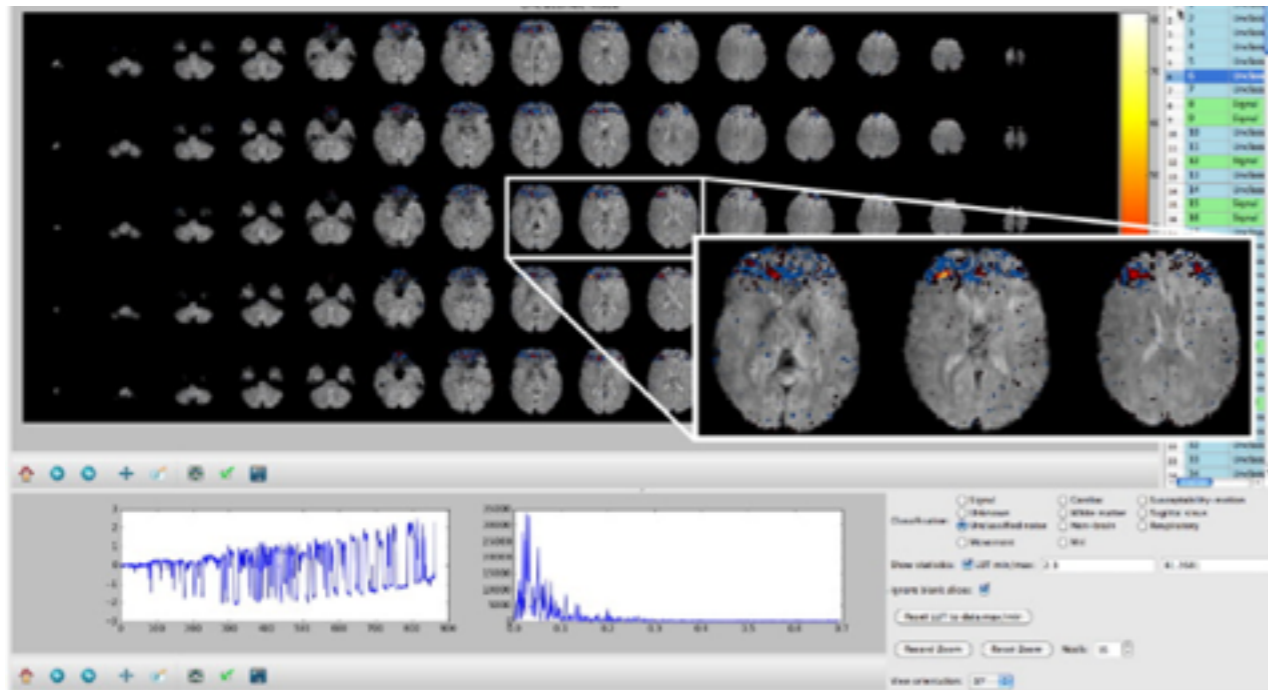


Analysis Pipelines





FSL FIX



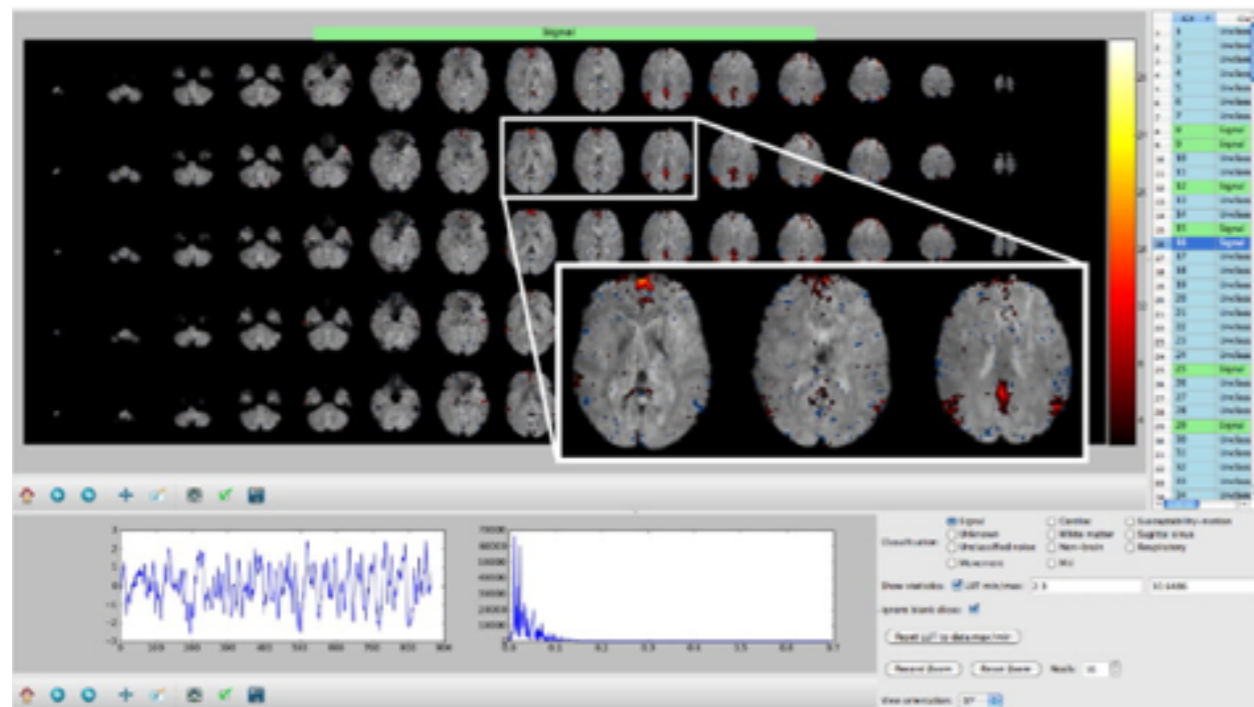
Identifies and removes artifactual components from FMRI time series.

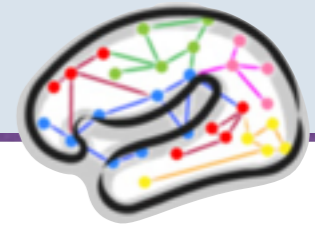
- Utilises spatial and temporal signatures identified from large, human generated training dataset (multiband and standard EPI – can train your self)

Workflow:

- 1) preprocess
- 2) run ICA
- 3) run FIX
- 4) run analysis (Feat, Melodic)

- Currently available as download (need MATLAB, R).



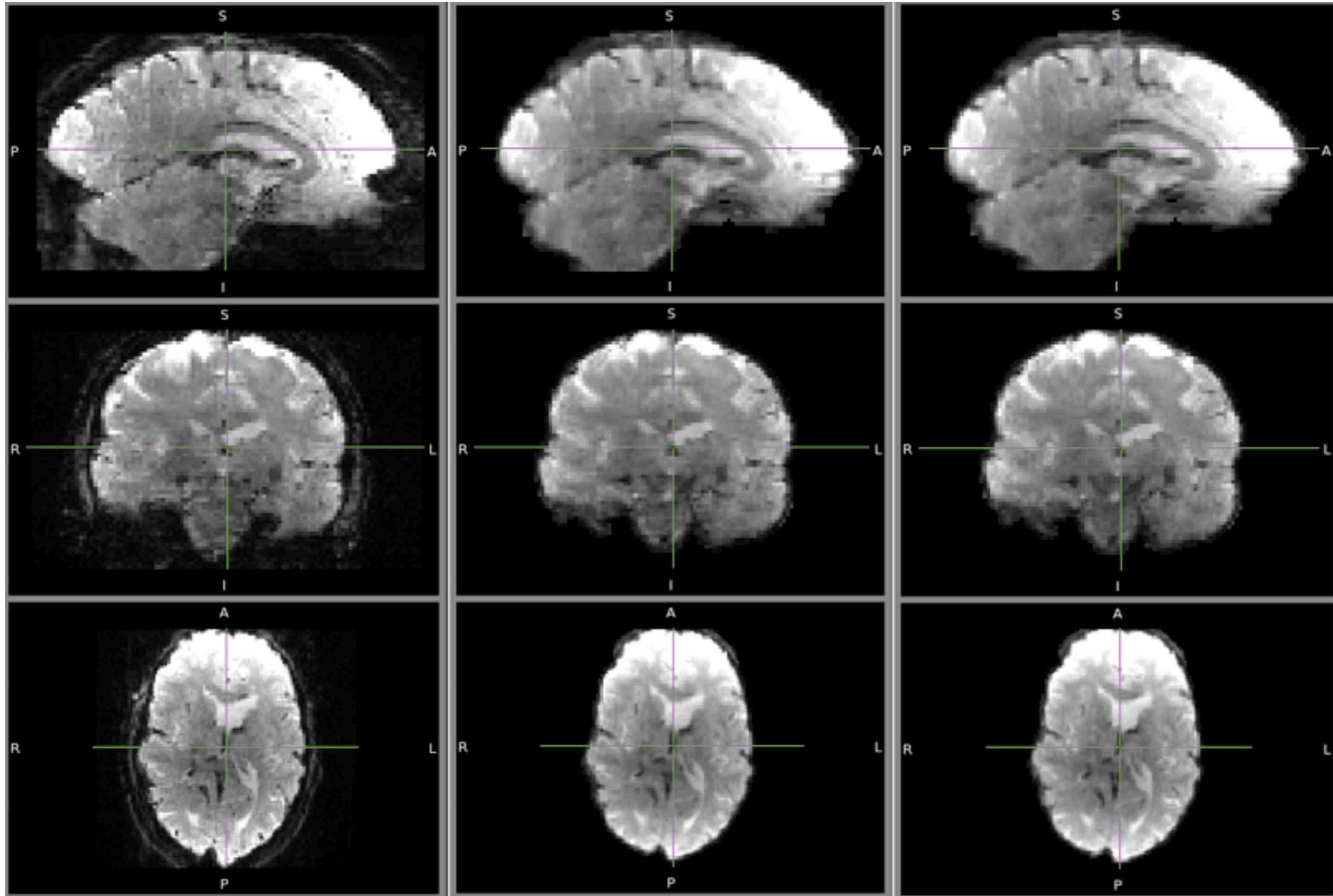


FSL FIX

raw data (multiband 6)

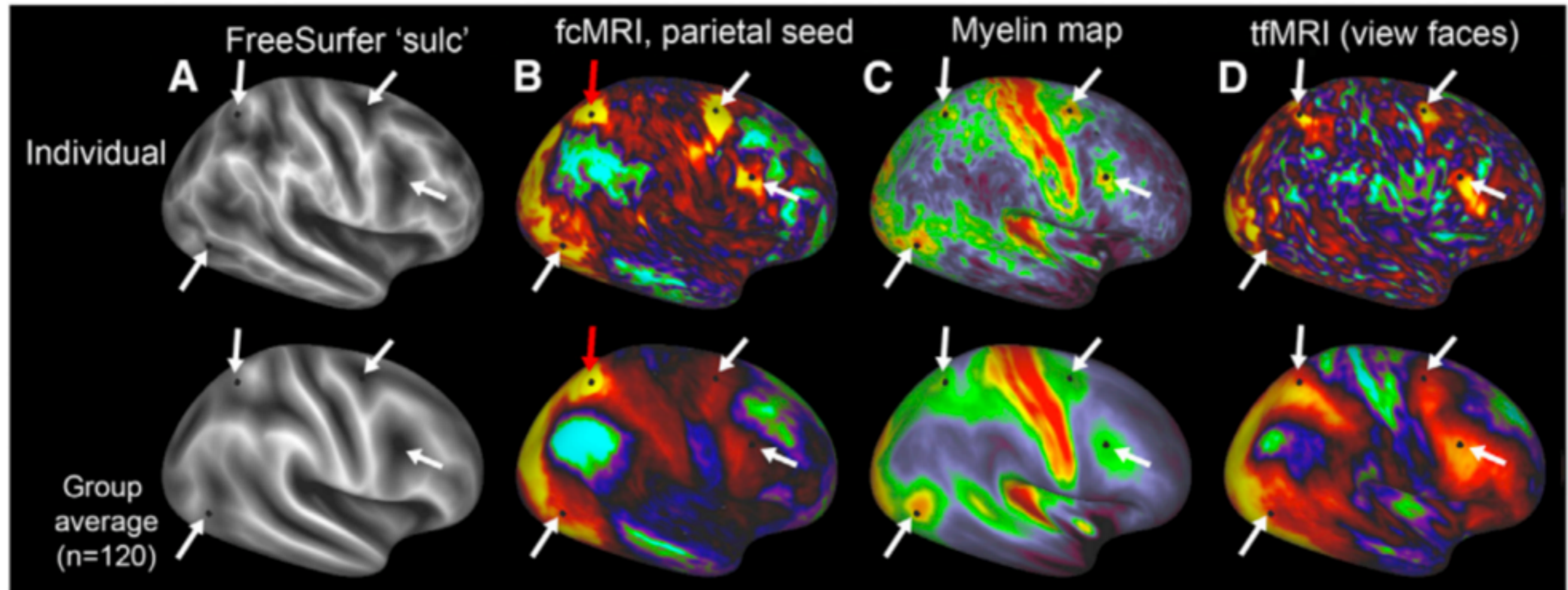
+ preprocessing

+ ICA+FIX

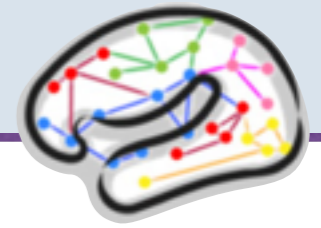




Multimodal parcellation

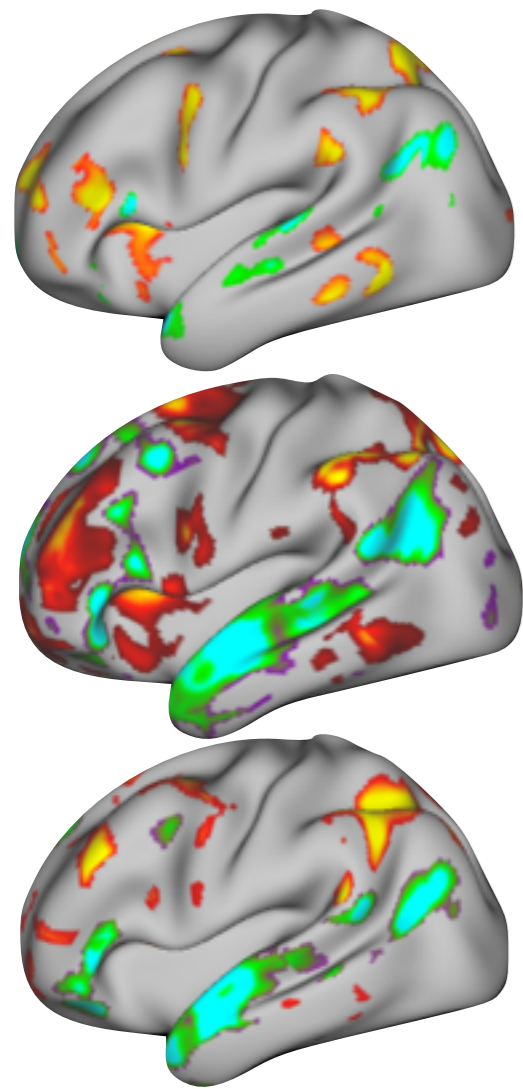


Human Connectome Project



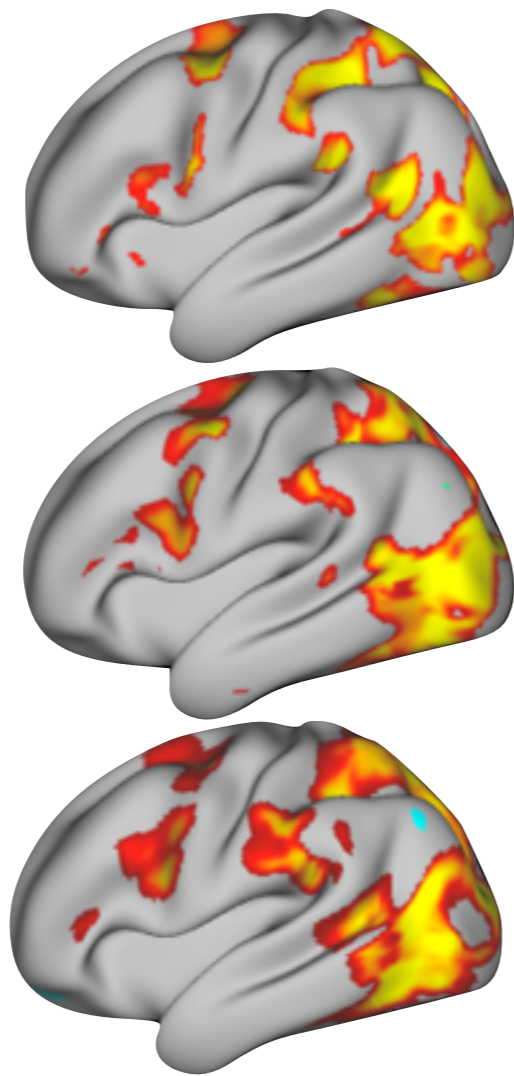
Individual differences

Language



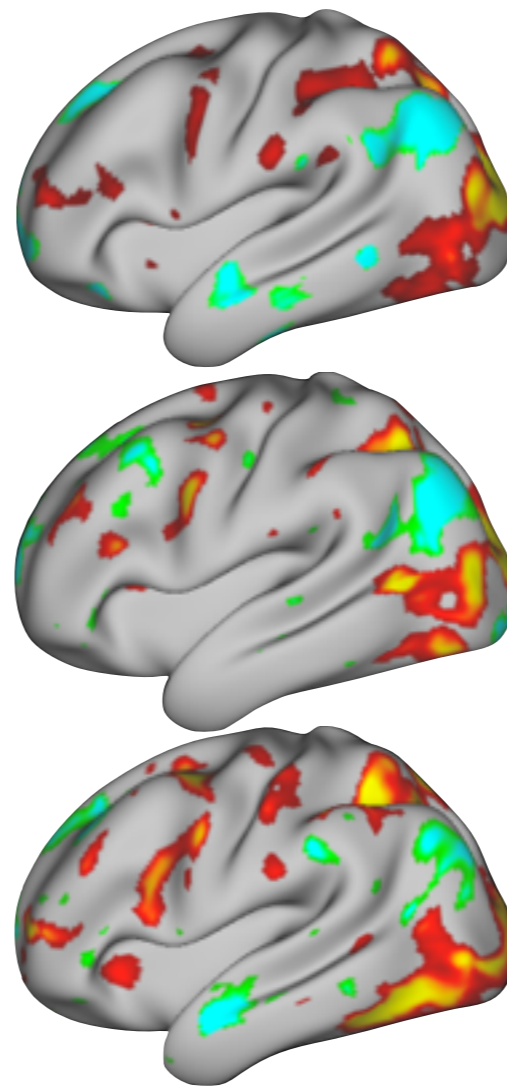
⋮

Theory of mind



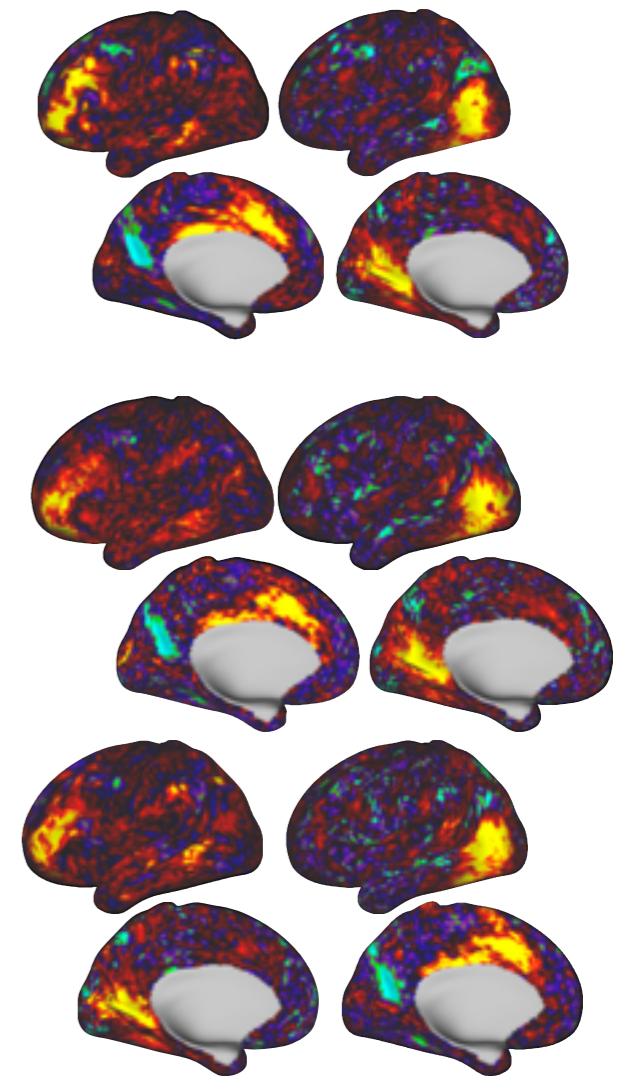
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Gambling



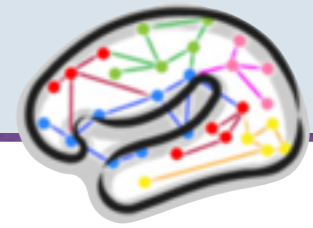
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RSNs

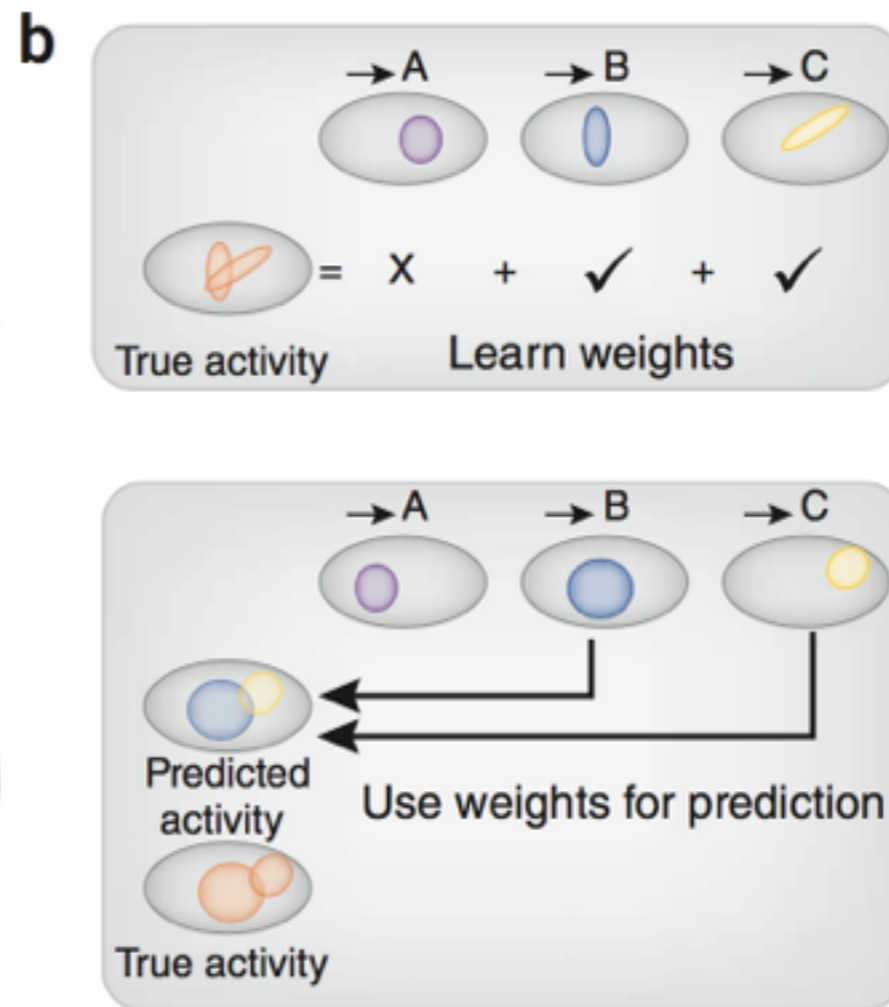
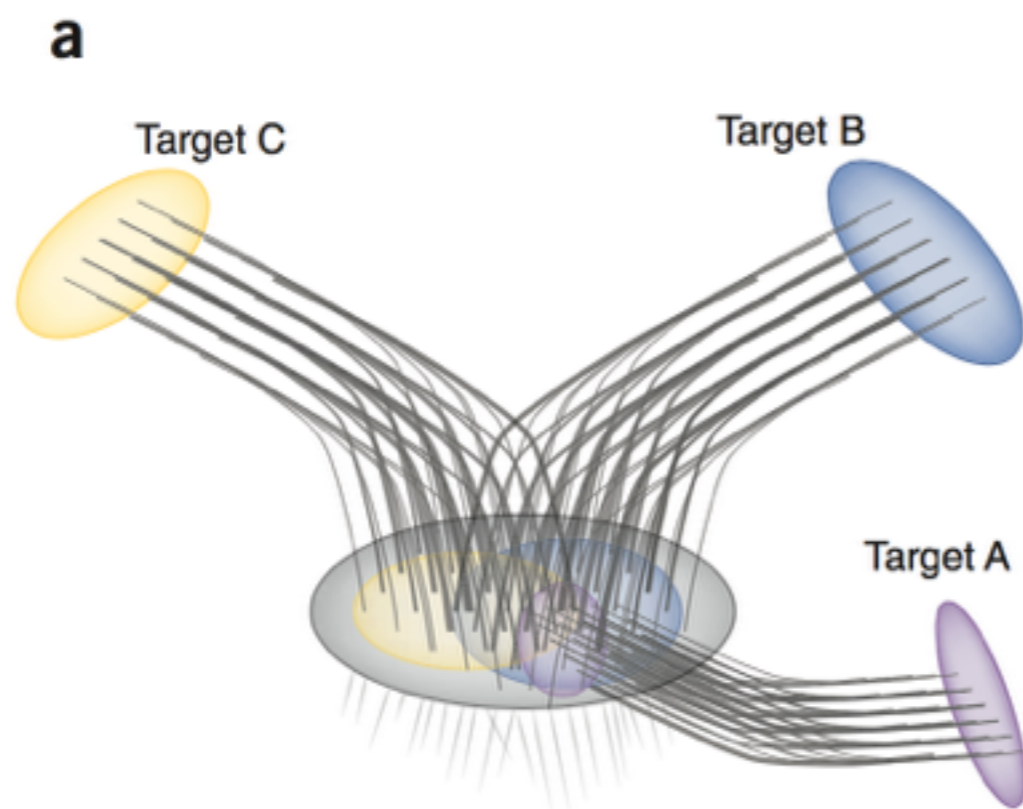


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Human Connectome Project



Using connectivity as a signature of functional areas



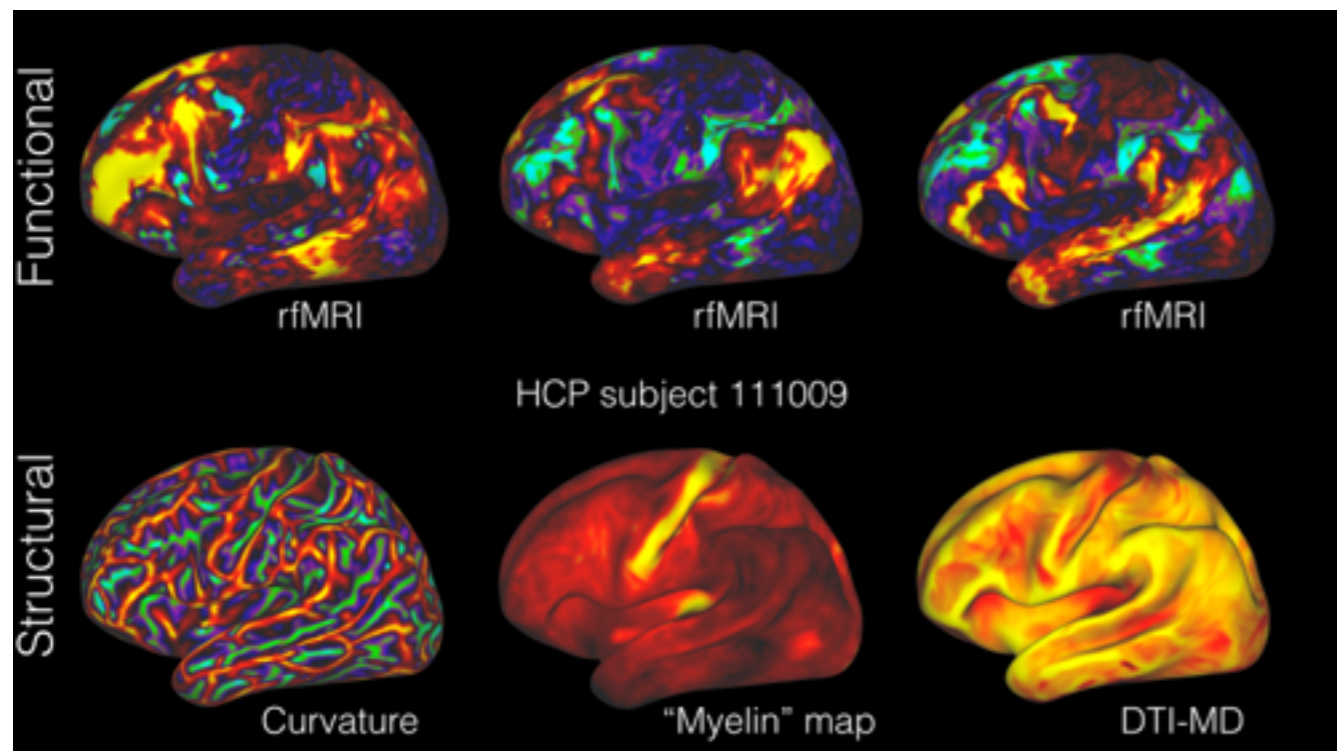
Train

Test

Human Connectome Project

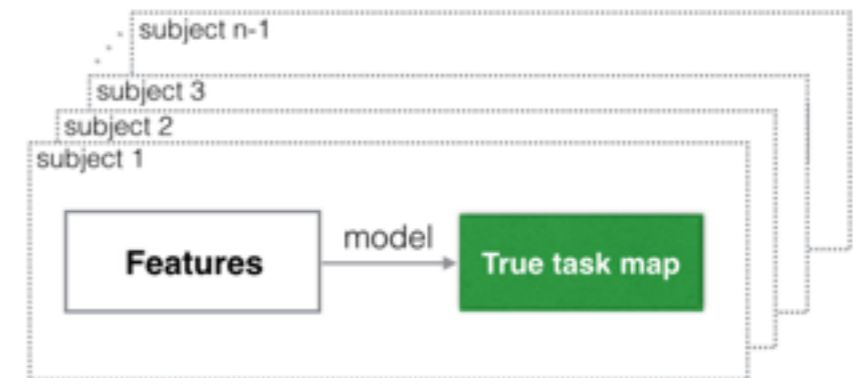


Using connectivity as a signature of functional areas

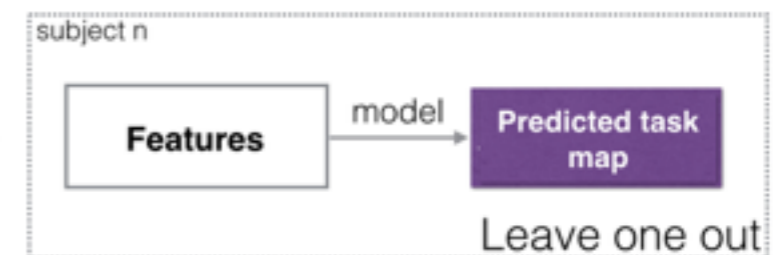


Features

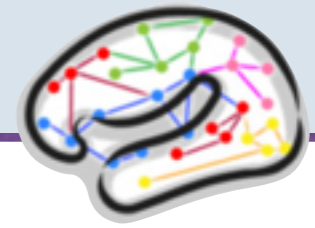
Training



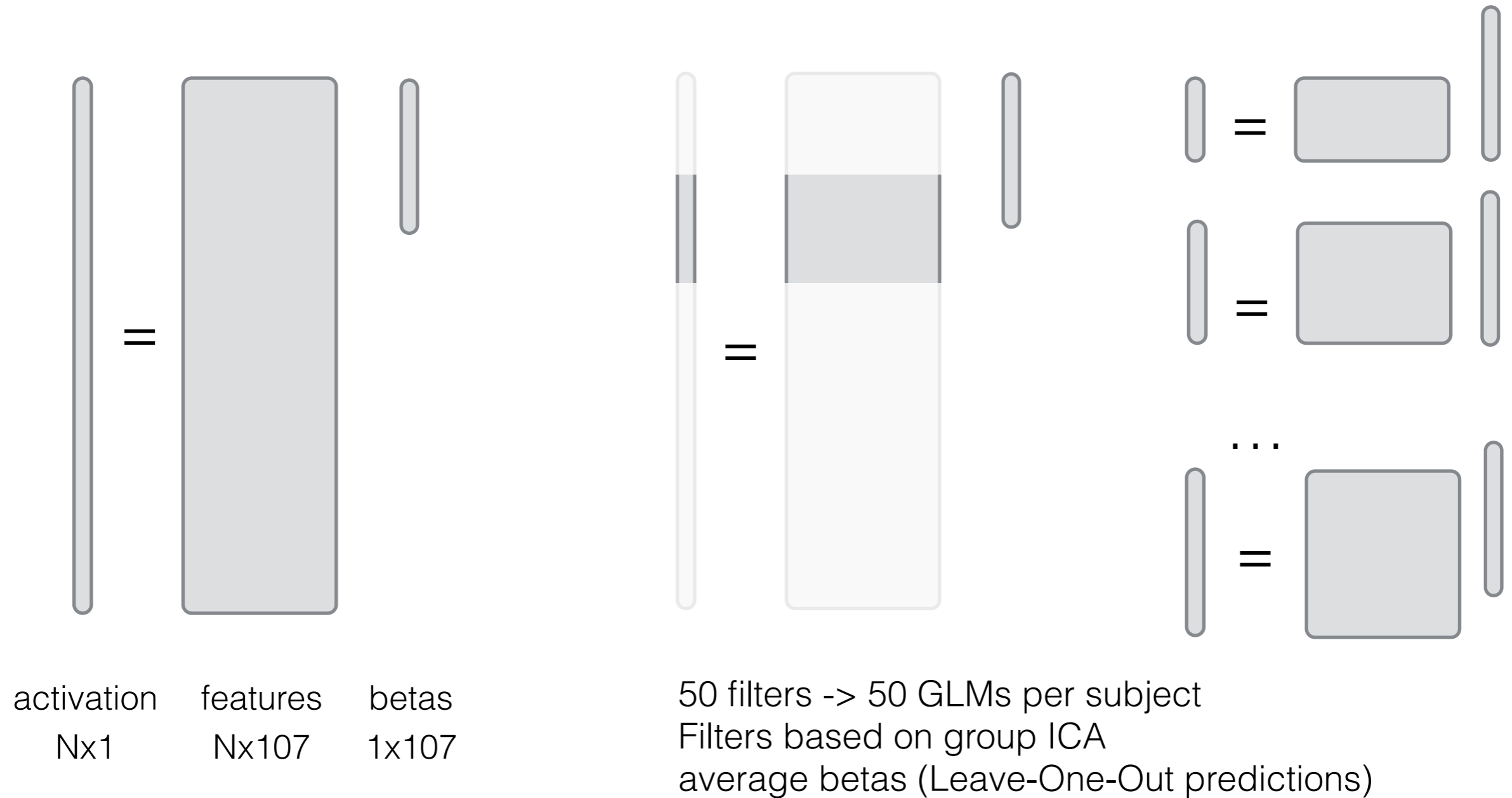
Prediction



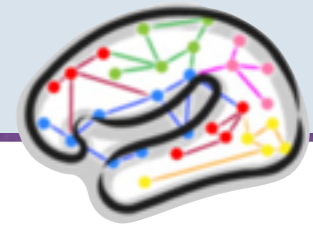
Human Connectome Project



Using connectivity as a signature of functional areas

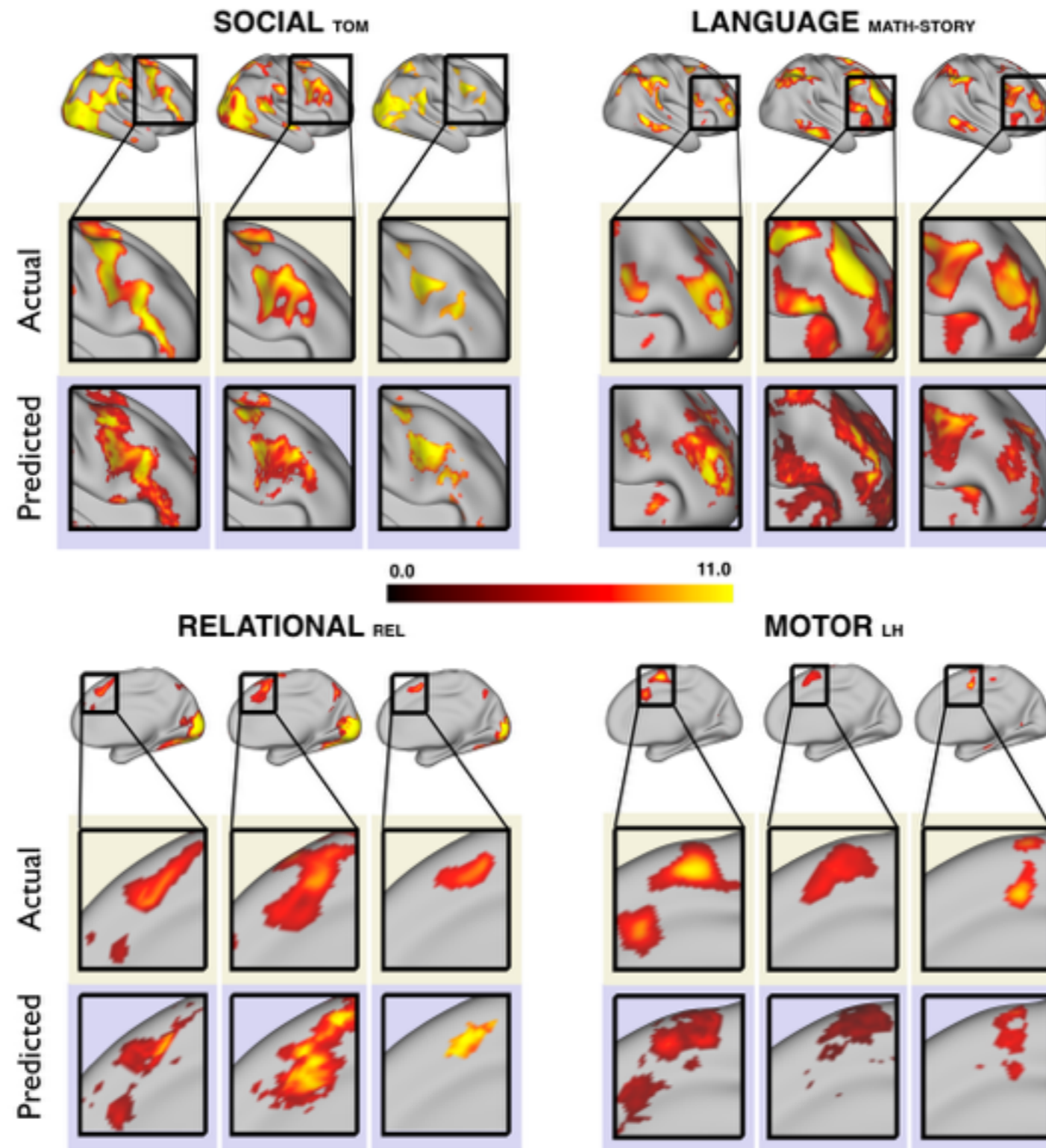


Human Connectome Project

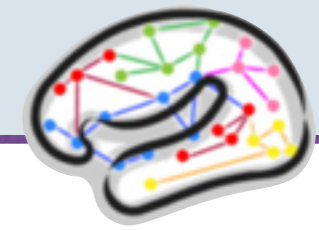


Using connectivity as a signature of functional areas

Results



Human Connectome Project

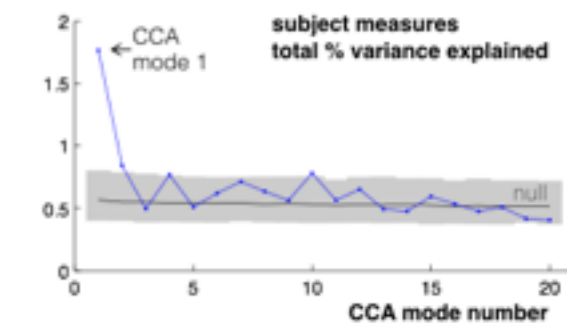
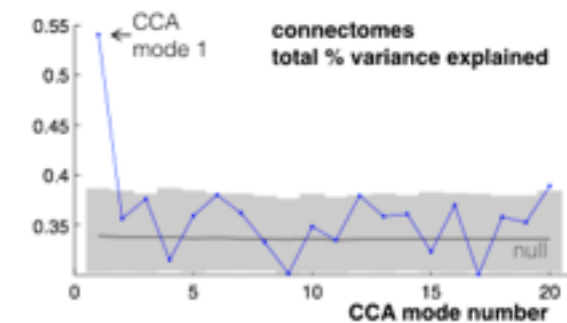
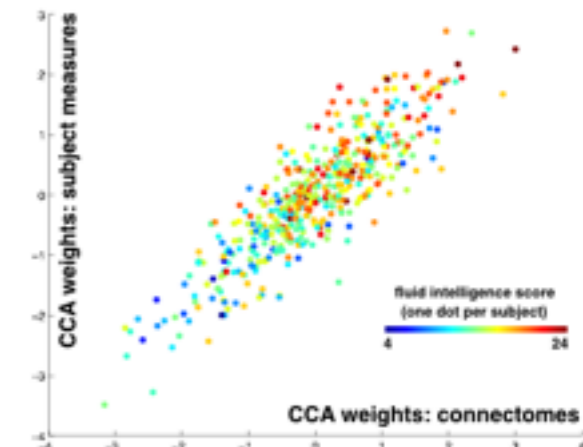
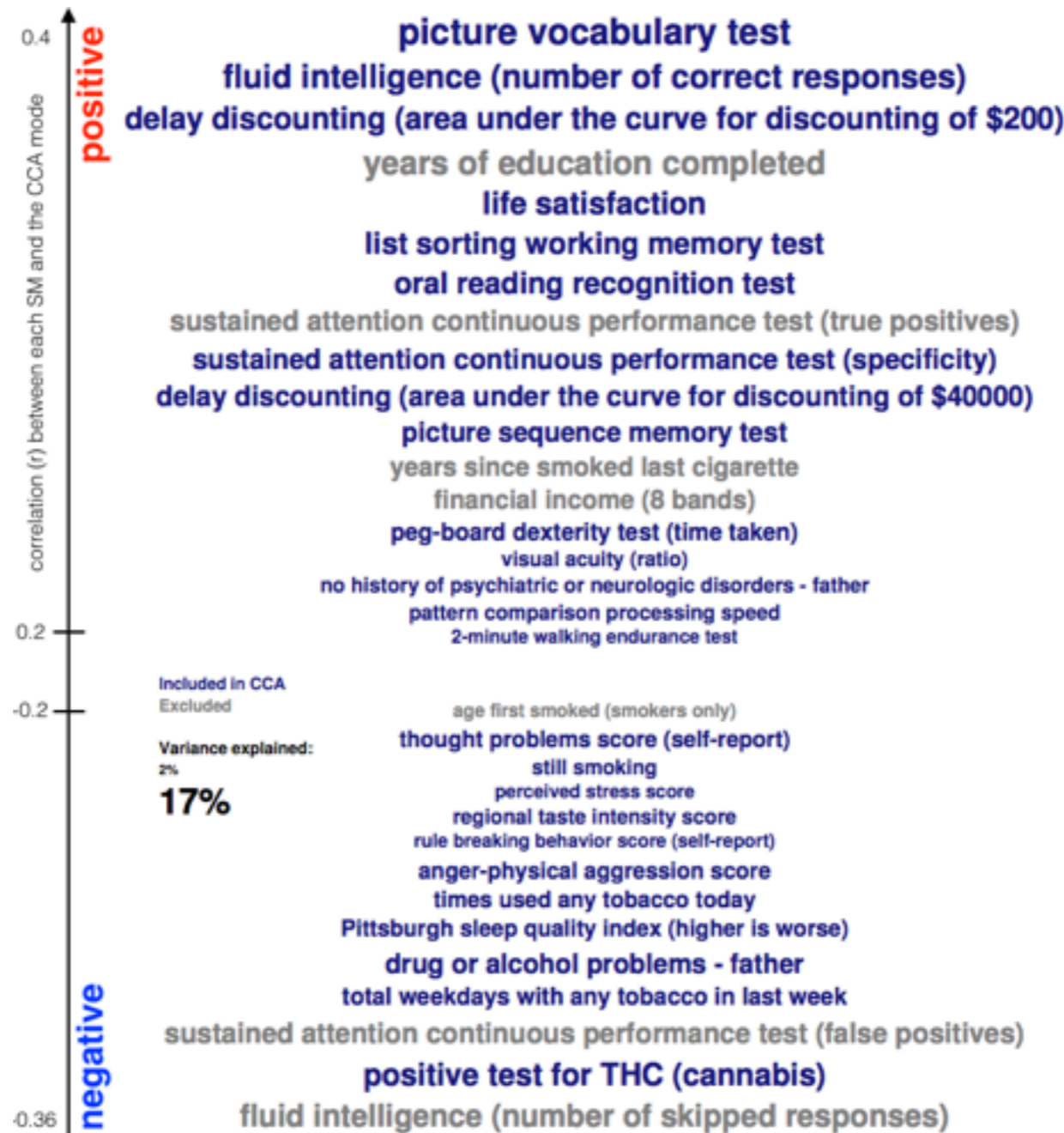


nature
neuroscience

A positive-negative mode of population covariation links brain connectivity, demographics and behavior

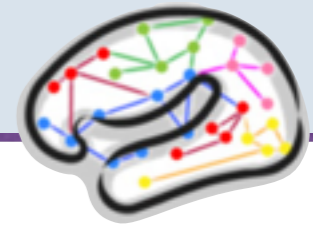
Stephen M Smith¹, Thomas E Nichols², Diego Vidaurre³, Anderson M Winkler¹, Timothy E J Behrens¹, Matthew F Glasser⁴, Kamil Ugurbil⁵, Deanna M Barch⁴, David C Van Essen⁴ & Karla L Miller¹

We investigated the relationship between individual subjects' functional connectomes and 280 behavioral and demographic measures in a single holistic multivariate analysis relating imaging to non-imaging data from 461 subjects in the Human Connectome Project. We identified one strong mode of population co-variation: subjects were predominantly spread along a single 'positive-negative' axis linking lifestyle, demographic and psychometric measures to each other and to a specific pattern of brain connectivity.



Smith, Nichols, Vidaurre, Winkler, Behrens, Glasser, Ugurbil, Barch, Van Essen, Miller
Nature Neuroscience 2015

Human Connectome Project

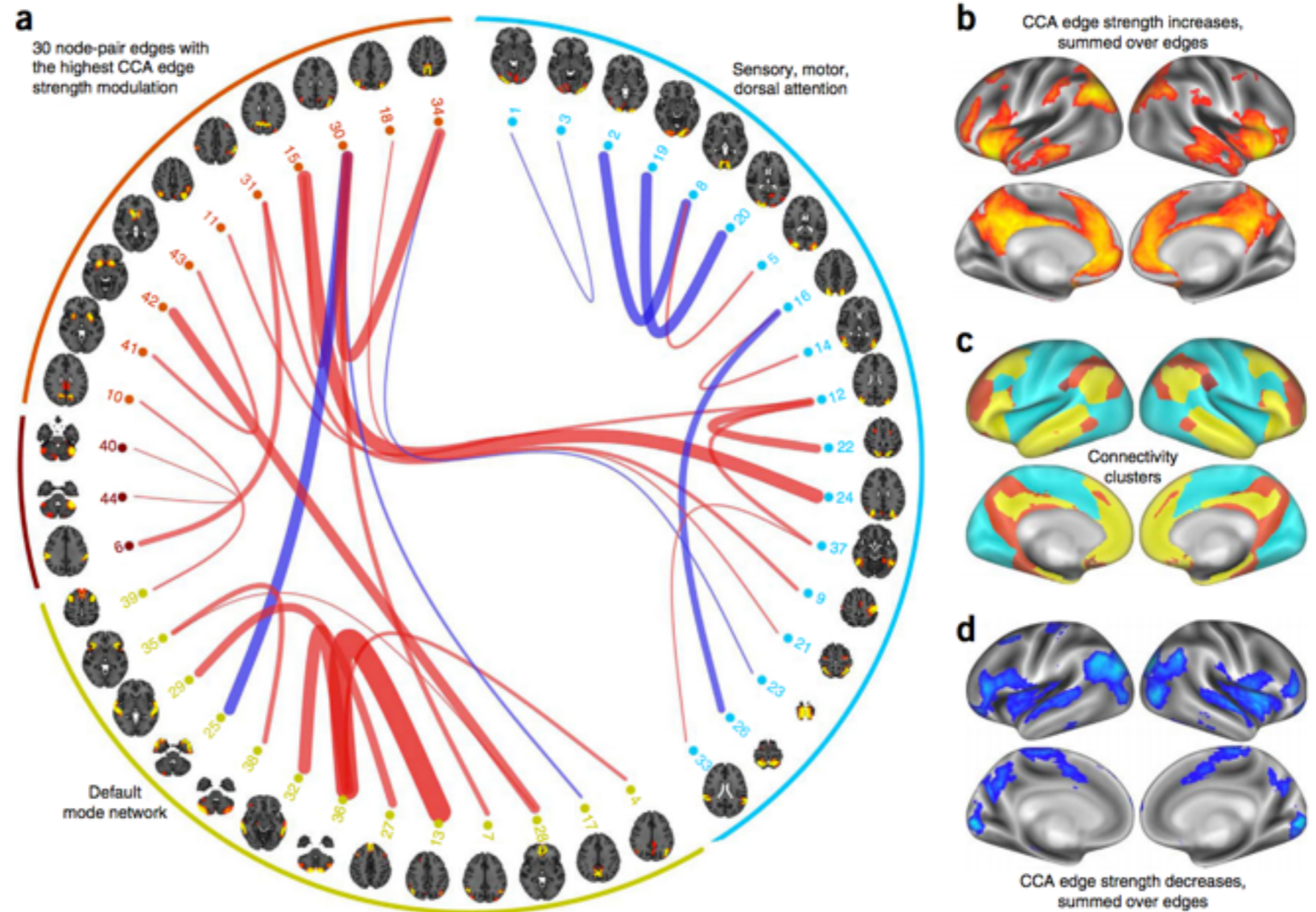


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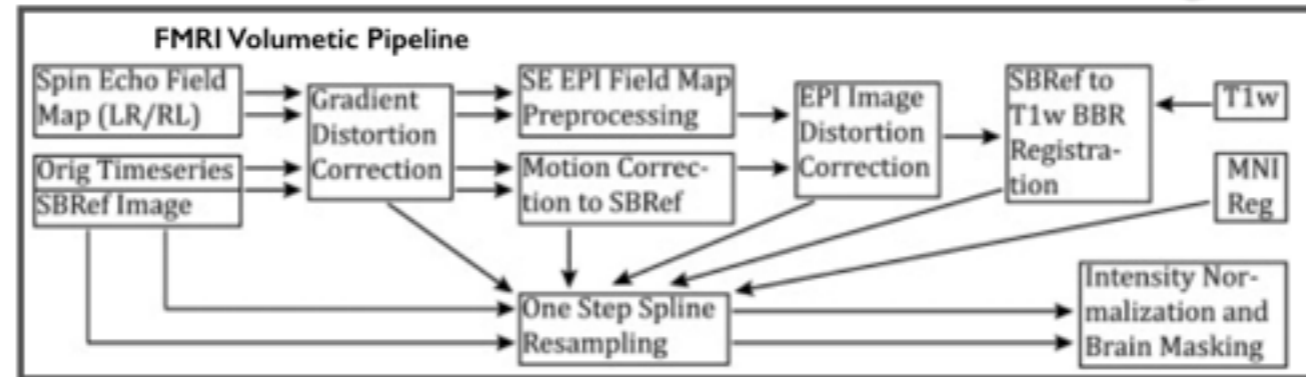
- Now extend brain connectivity mapping to understand brain ***development...***
- ... imaging babies before and after birth (>1000 babies)
- ... and modelling the effects of genes and environment
- *Collaboration between FMRIB Oxford, Kings and Imperial*

Developing Human Connectome Project

Updates to pipelines

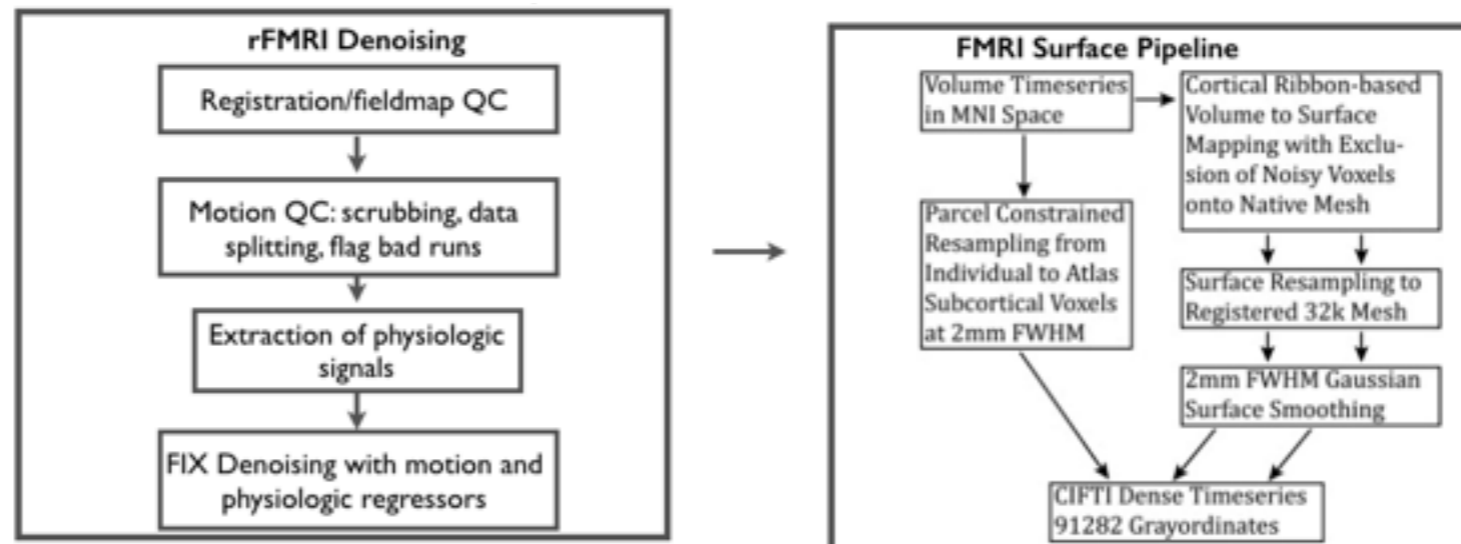
Automated selection of fieldmaps, templates

Rewritten EPI2Struct



New age-dependent templates

Updated Resampling



Adjusted surface projection

MB pre-MC cleanup

Slice to volume reg

Robustified Motion Corr

Upgraded FIX automatic artefact cleanup

MSM Surface registration

Developing Human Connectome Project



Initial surface projections and ICA

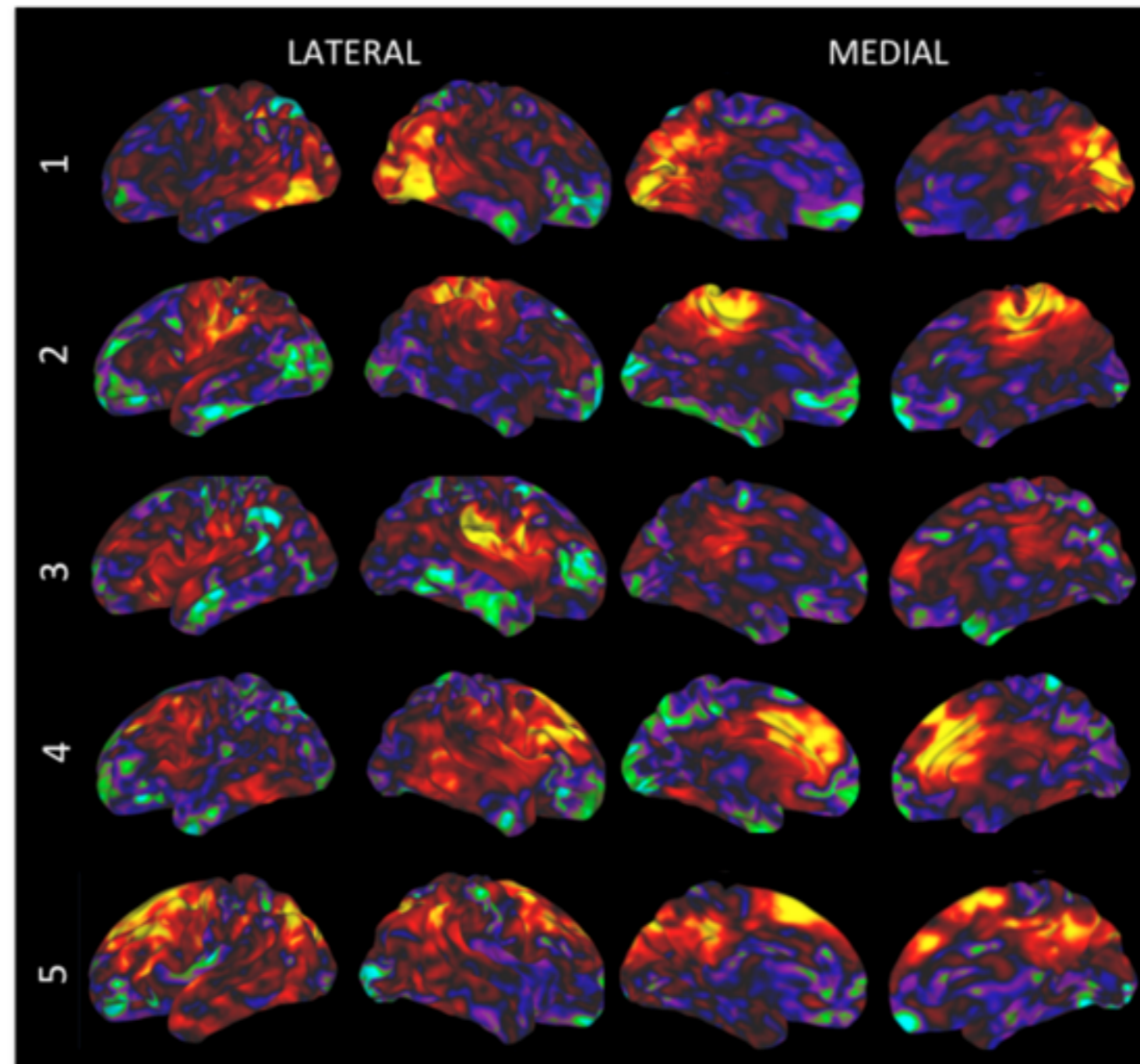
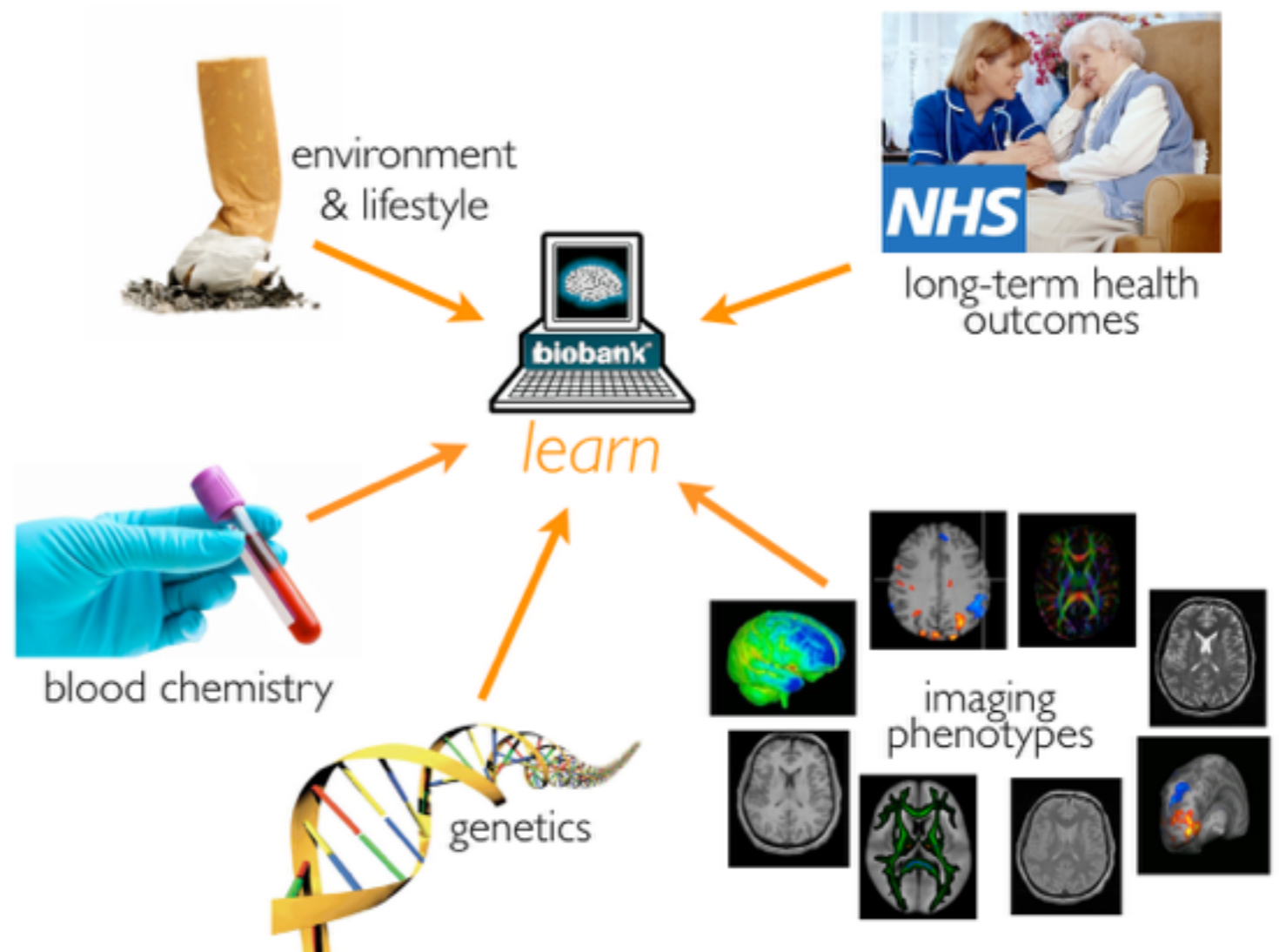


Figure 1. Resting state networks resulting from a group ICA performed on 8 subjects spanning 35-42 weeks PMA. These show some correlation with the following adult networks: 1=Visual; 2=Somatomotor; 3=Auditory; 4=Executive control; 5=Frontal parietal

- Brain imaging scientific direction: Stephen Smith, Karla Miller (Oxford), Paul Matthews (Imperial)
- Brain imaging analysis pipeline: Fidel Alfaro Almagro, Stephen Smith (Oxford) and many others

- Original prospective epidemiological study: 500,000, 45-70y
- Imaging Extension: bring back **100,000** for brain, heart, body imaging
- Discover multi-modal early imaging markers of disease



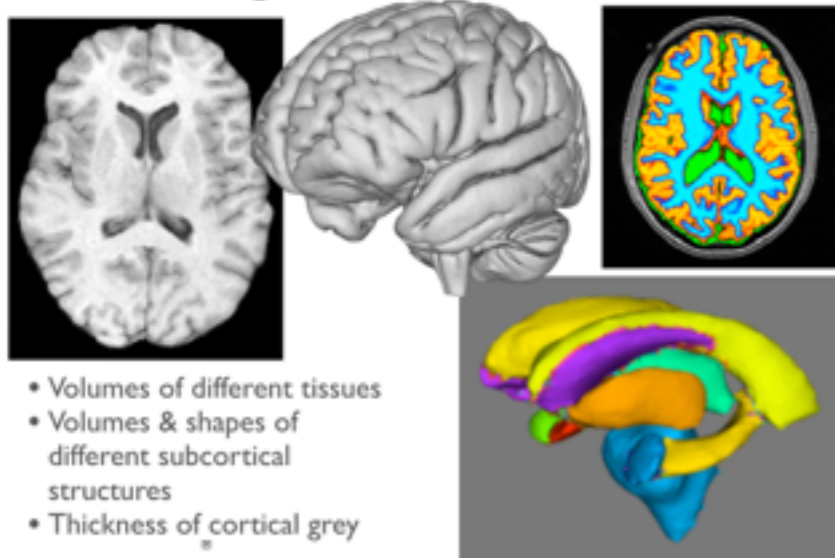
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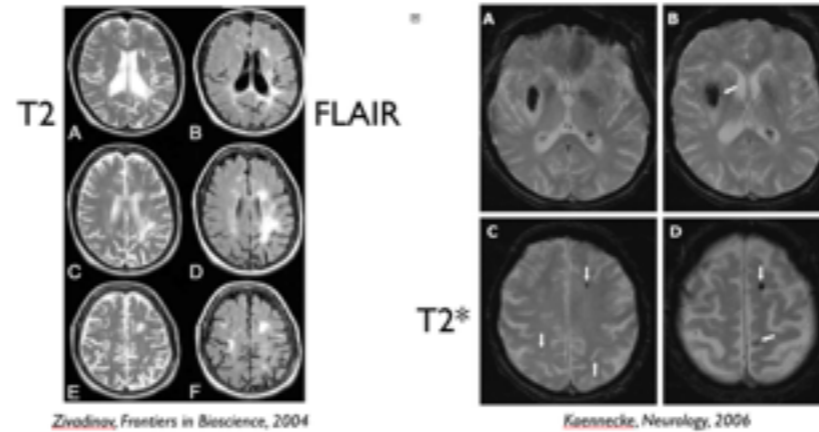
- How do you scan 100,000 subjects?
 - 3 dedicated centres, 54 subjects/day, 7 days/week, 5 years!
- What imaging data can you get in 100,000 subjects?
 - 35 mins each: brain MRI, cardiac+body MRI, bone density, carotid US
- **Brain imaging** (3T Siemens Skyra, 32ch, multiband fMRI/dMRI)
 - **T1 anatomical (5 mins)**
 - **T2 FLAIR (6 mins)**
 - **Multi-shell diffusion (7.5 mins)**
 - **Resting FMRI (6 mins)**
 - **Task FMRI (4 mins)**
 - **Susceptibility-weighted (2.5 mins)**

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T1-weighted Structural Data

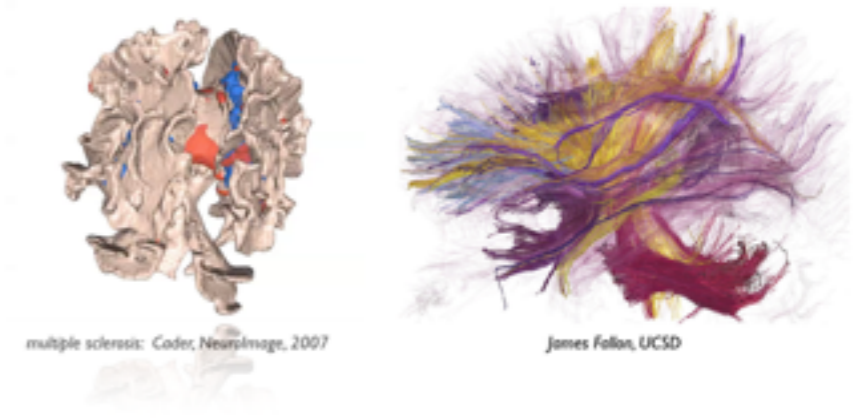


T2, PD, FLAIR, T2* Structural



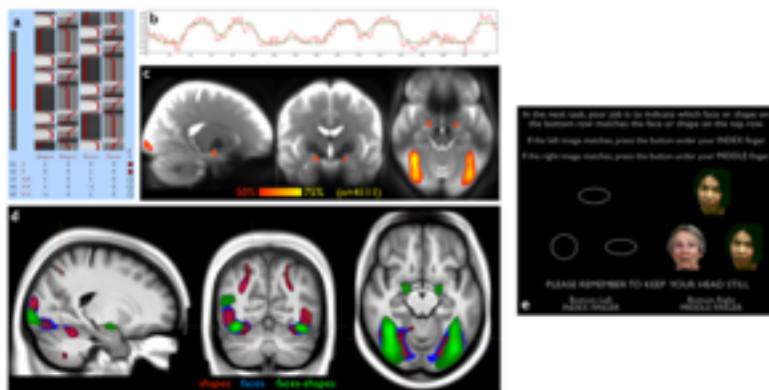
- Lesion volumes (& spatial distribution) Multiple sclerosis...
- Microbleed volumes Stroke...
- CSF volume Alzheimer's...

Diffusion Data



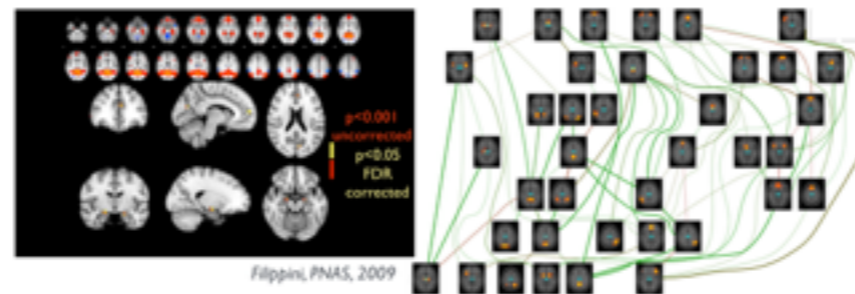
- Structural connectivity (white-matter tracts) psychiatric diseases...
- White matter biological properties white matter pathologies...

Task FMRI



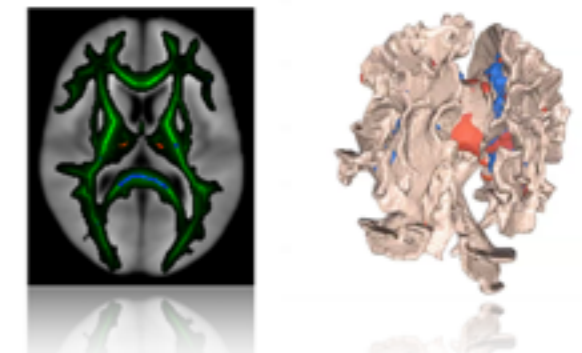
- Localise brain function & networks psychiatric diseases...

Resting FMRI



- Measure all functional networks potentially all pathologies....

TBSS : Tract-Based Spatial Statistics



- Need: robust "voxelwise" cross-subject stats on DTI
- Problem: alignment issues confound valid local stats
- TBSS: solve alignment using alignment-invariant features:
- Compare FA taken from tract centres (via skeletonisation)

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T1-weighted Structural Data

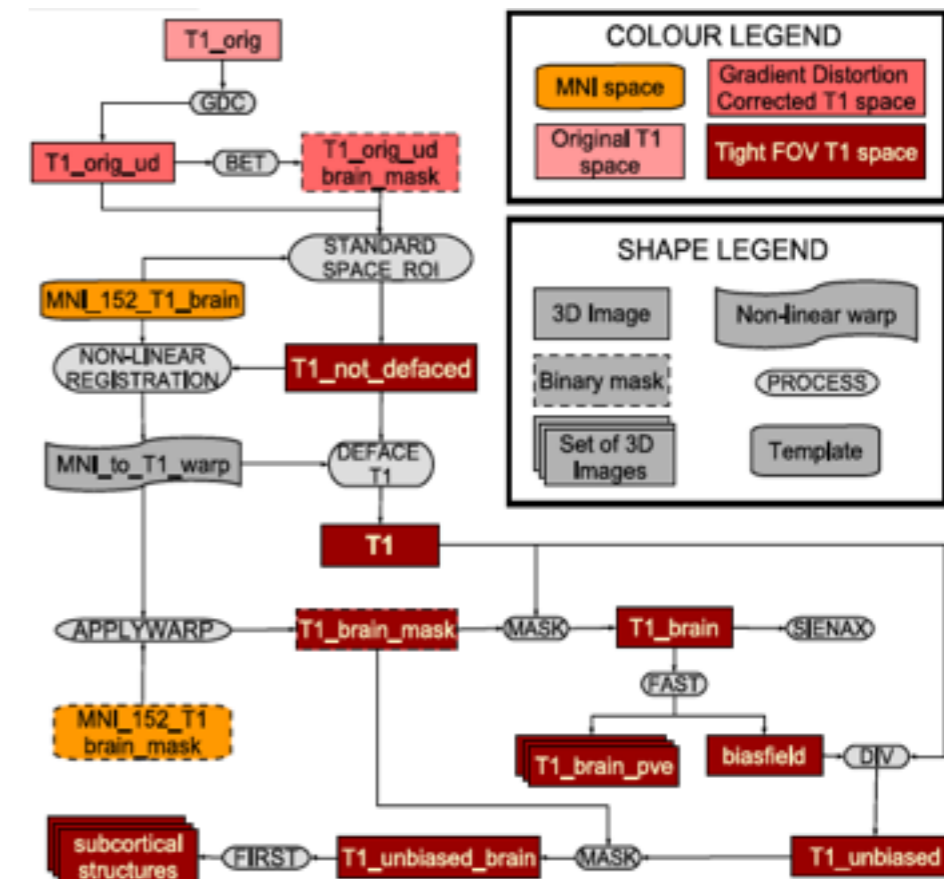
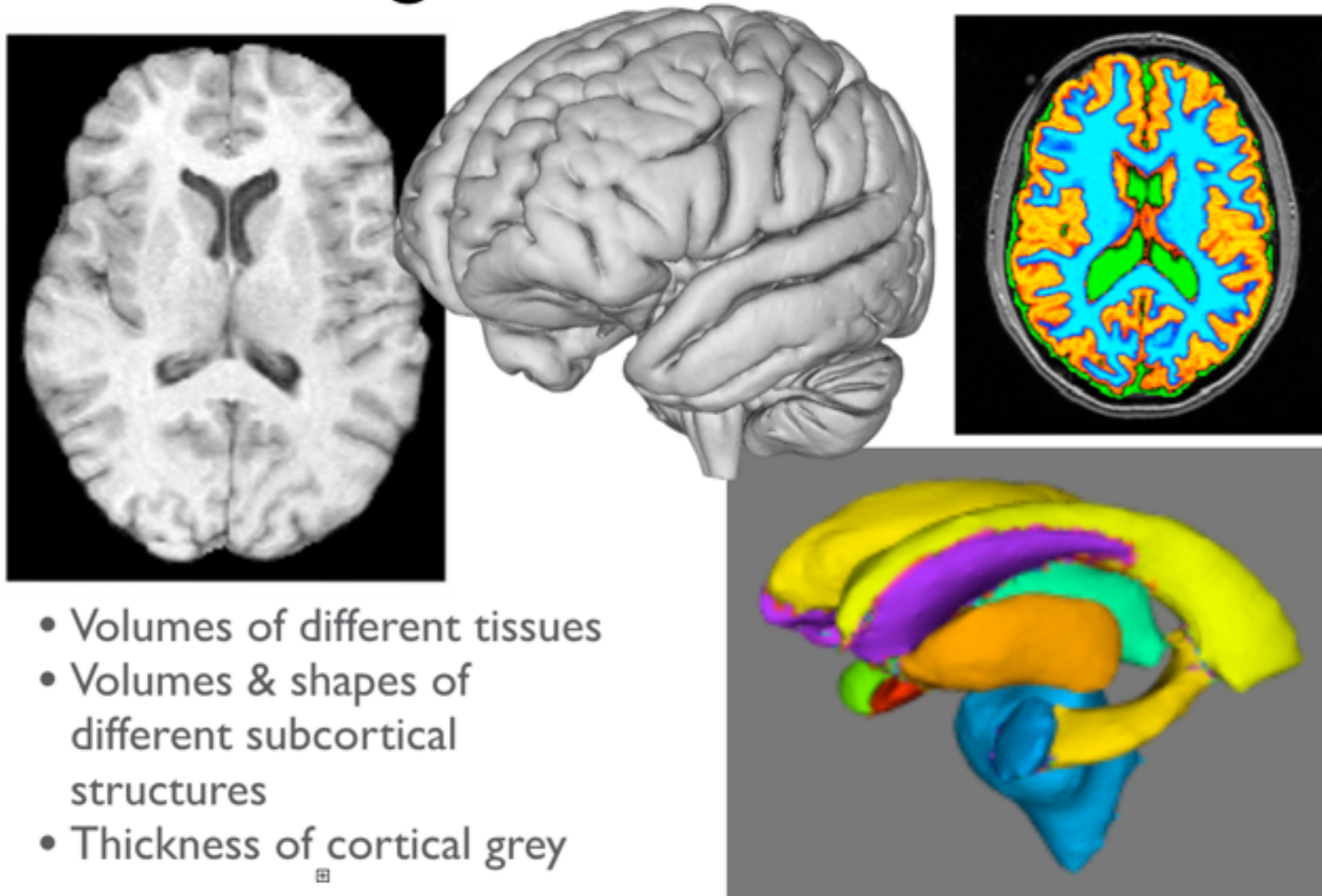
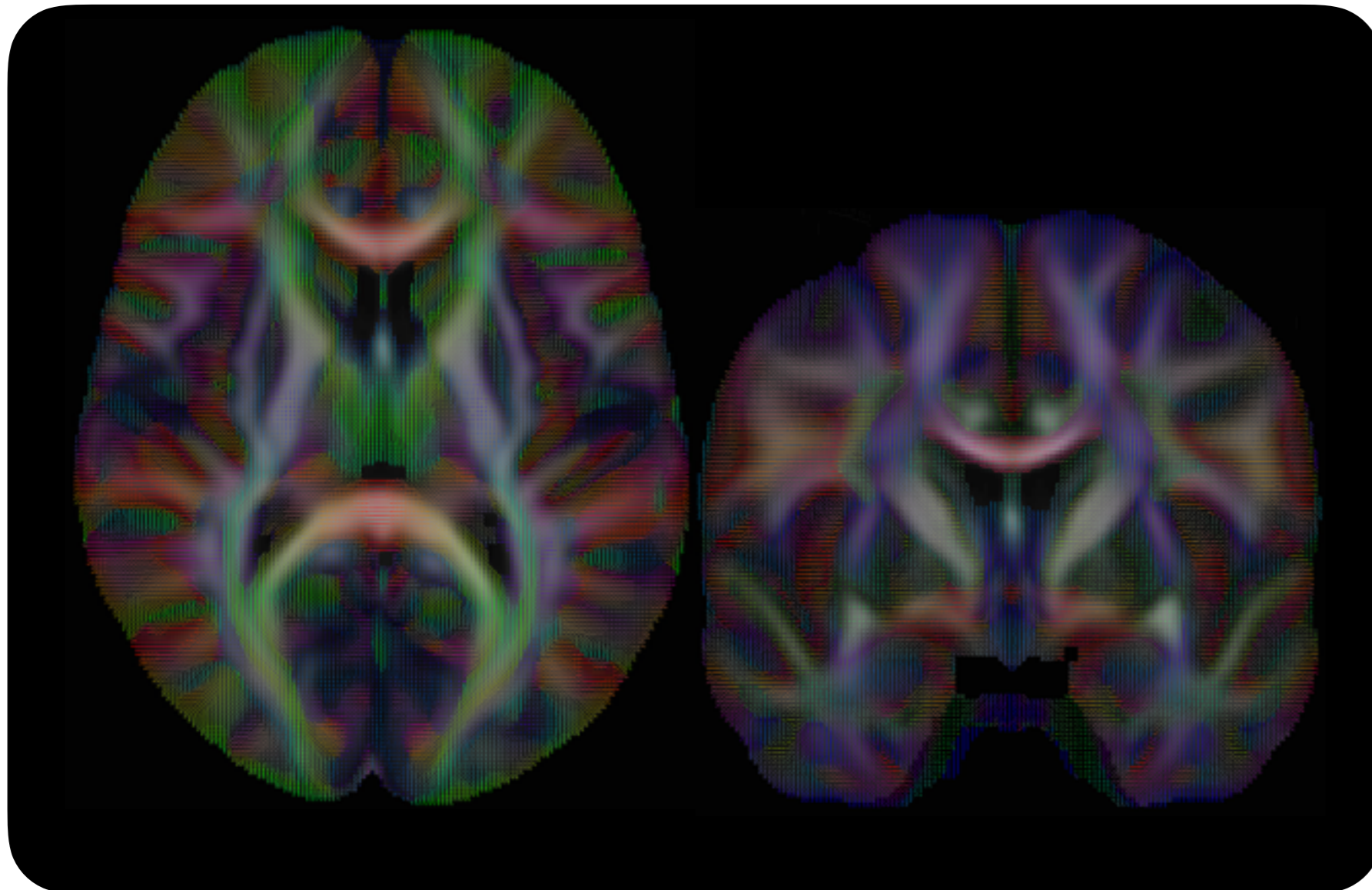


Fig 1: Structural T1 pipeline

- Brain imaging scientific direction:
Stephen Smith, Karla Miller (Oxford), Paul Matthews (Imperial)
- Brain imaging analysis pipeline:
Fidel Alfaro Almagro, Stephen Smith (Oxford) and many others



probabilistic dMRI
modelling:
dominant fibre
direction
**averaged over
4000 subjects**

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probabilistic dMRI
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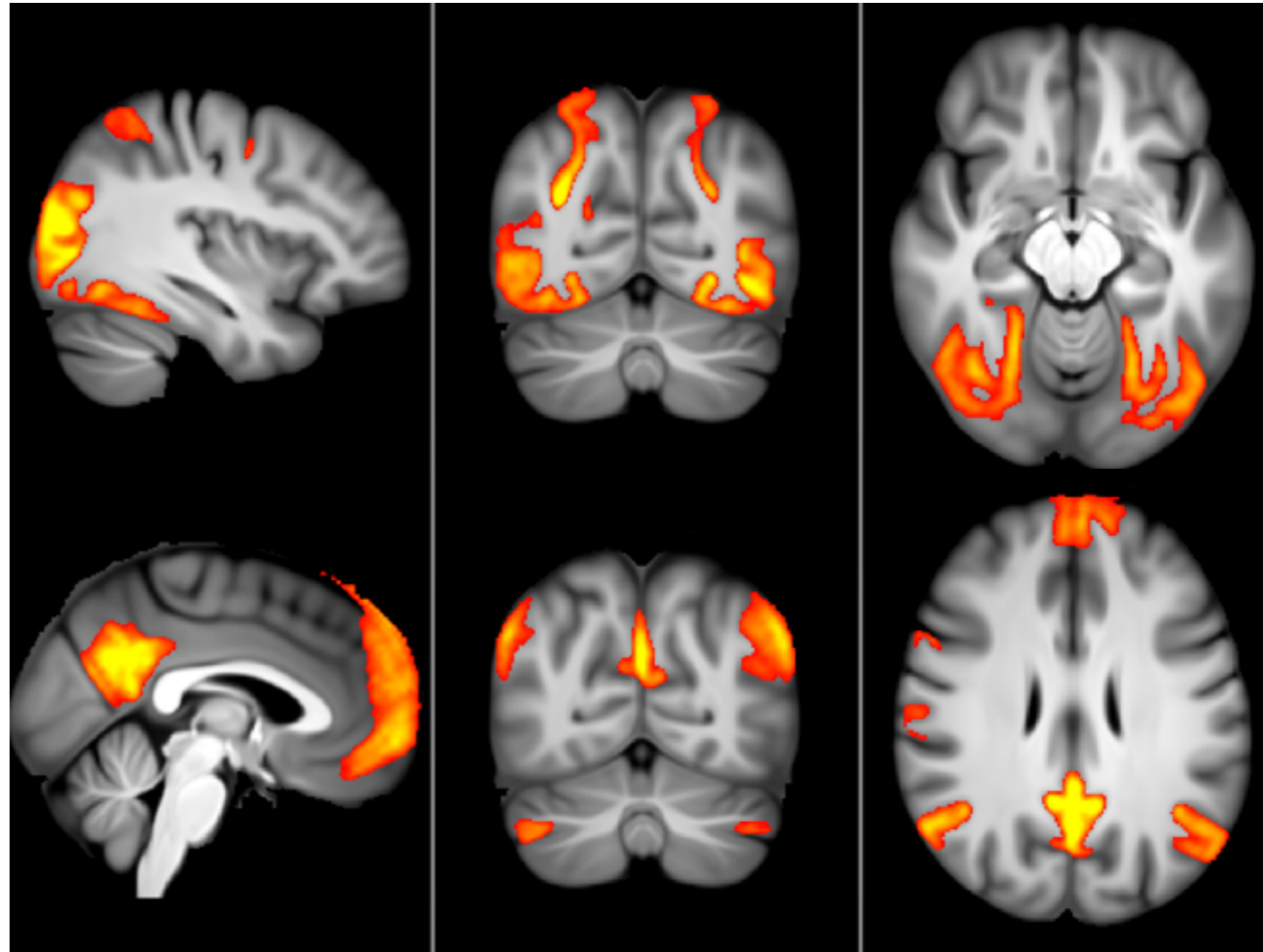
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Resting-state networks:
4000-subject
group-ICA

2.4x2.4x2.4mm³
MB=8, TR=0.73s

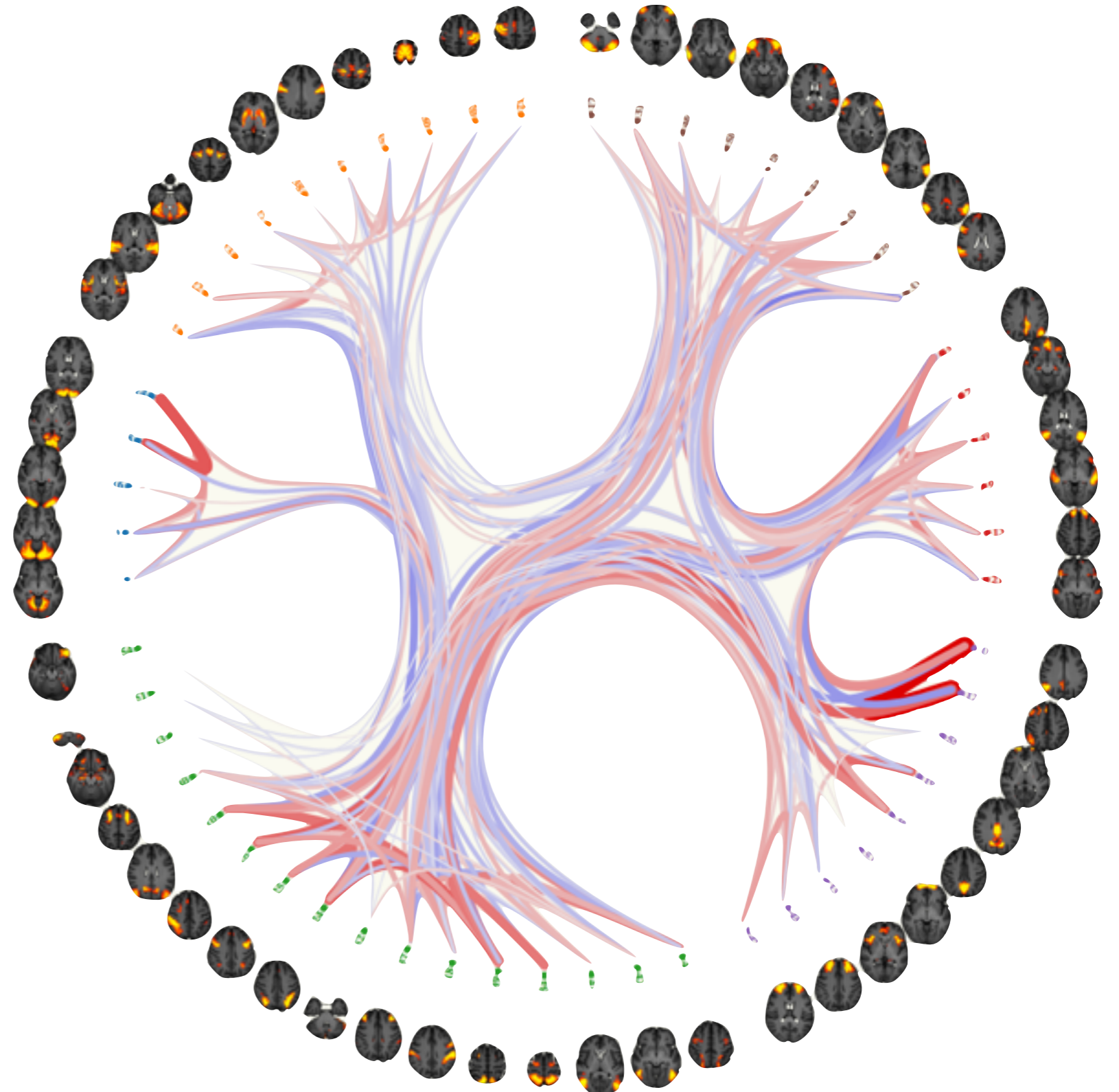
tinyurl.com/ukbbrain

Default mode Dorsal attention



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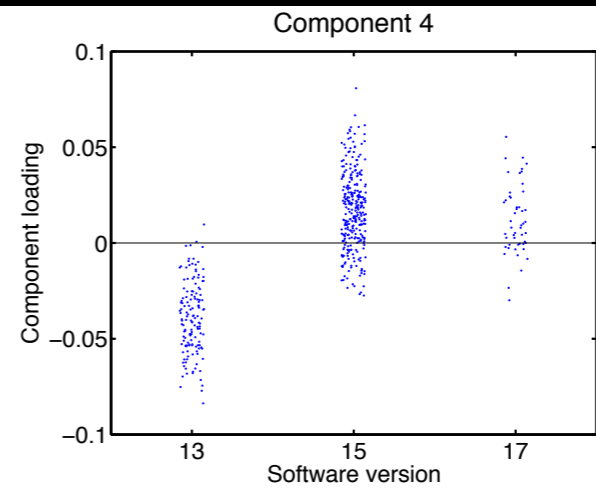
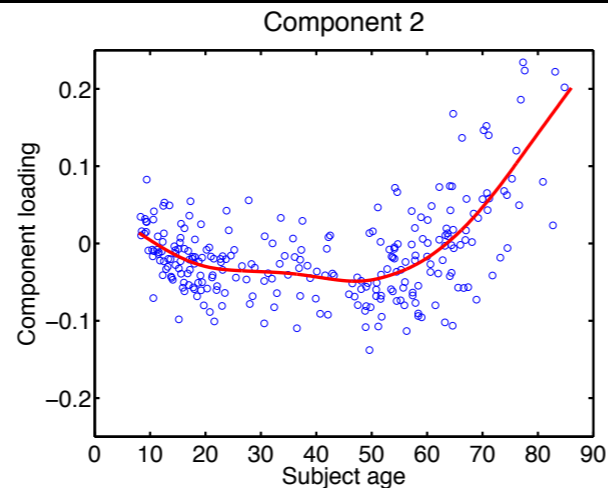
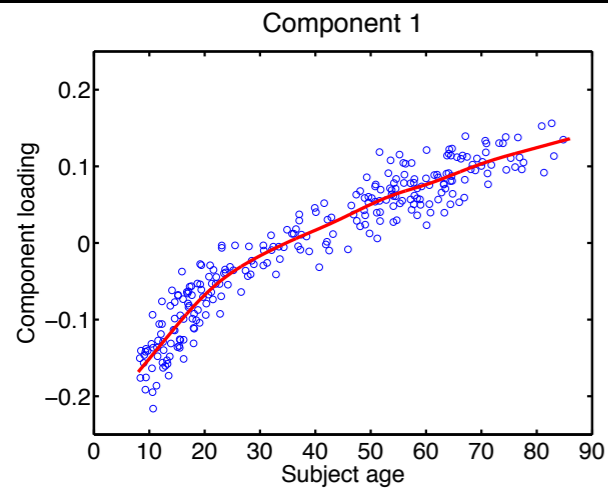
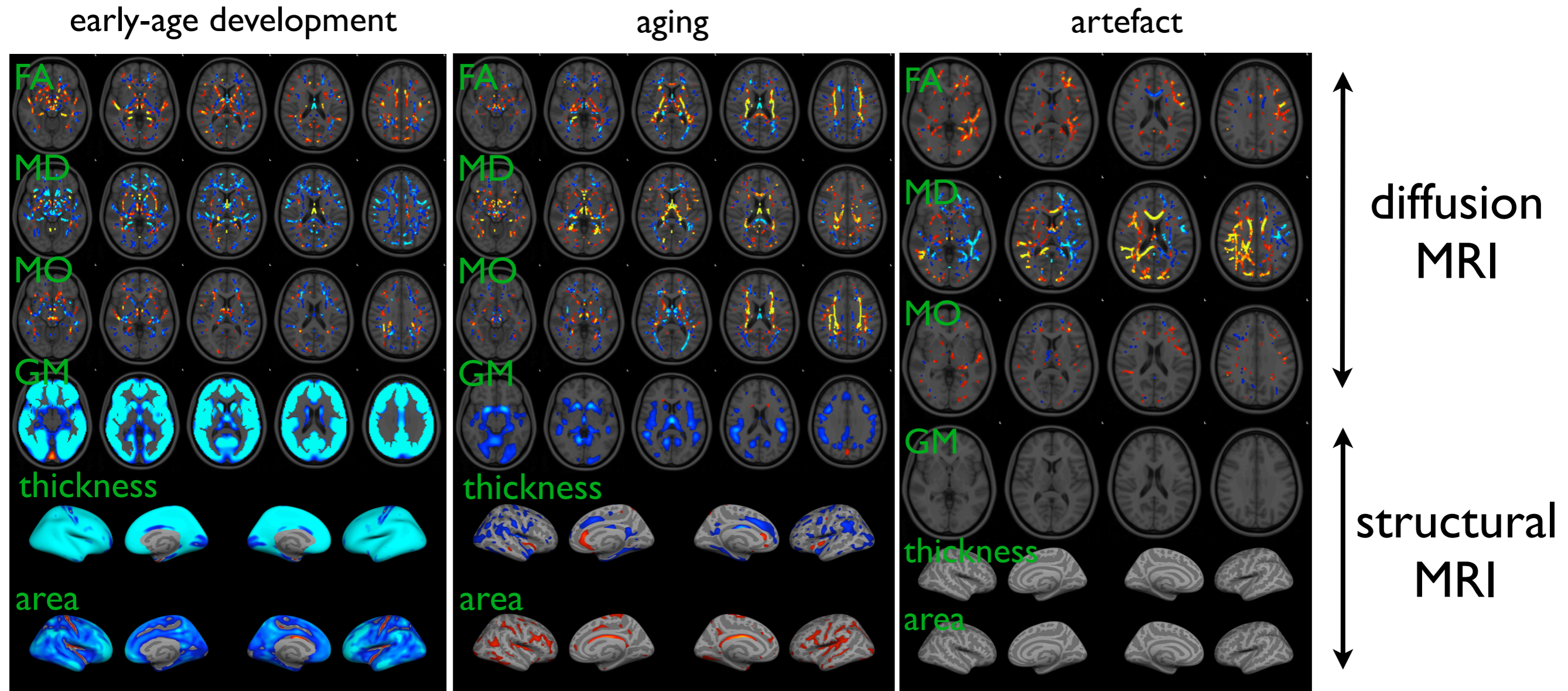
Resting-state
networks:
4000-subject
group-ICA



$2.4 \times 2.4 \times 2.4 \text{mm}^3$
MB=8, TR=0.73s

tinyurl.com/ukbbrain

Multivariate population modelling: multimodal Bayesian ICA



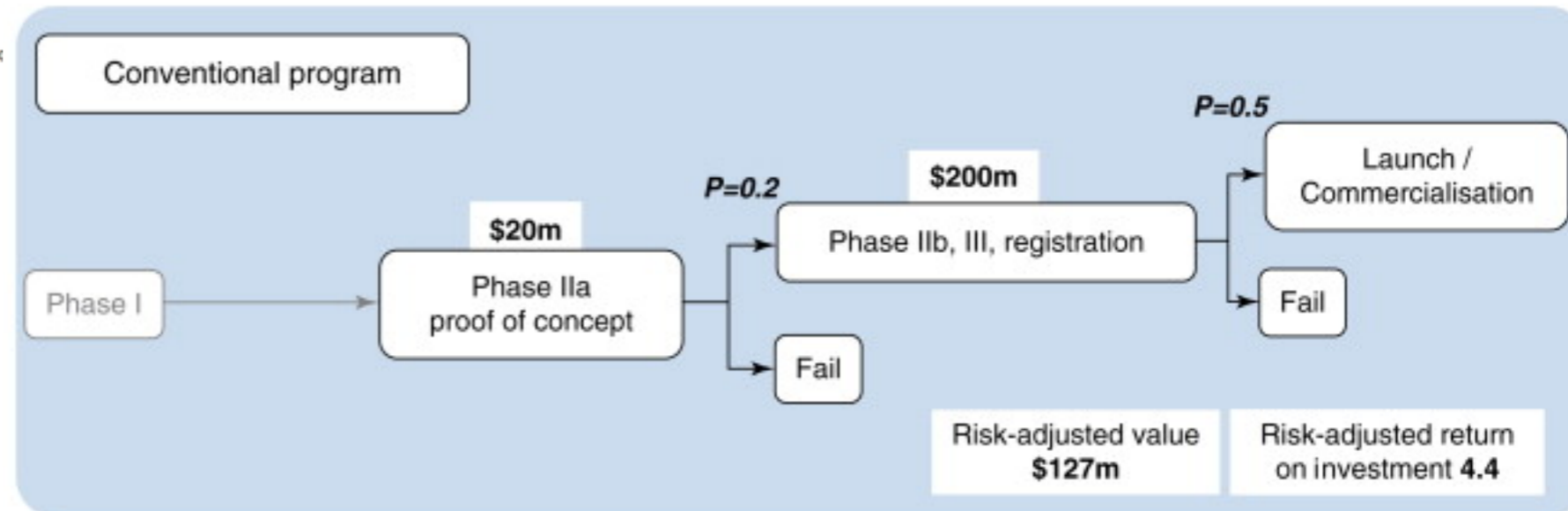
484 healthy subjects, ages 8-85y, from collaborators in Oslo (Fjell et al.)

FMRI Biomarker Identification



Richard G. Wise¹ and Cliff Preston²

¹Cardiff University Brain Research Imaging Centre, School of Psychology, Cardiff University, Park Place, Cardiff CF11
²Portfolio & Decision Analysis Group, Pfizer Ltd, Ramsgate Road, Sandwich CT13 9NJ, UK



FMRI Biomarker Identification

Drug Discovery Today • Volume 15, Numbers 21/22 • November 2010

REVIEWS

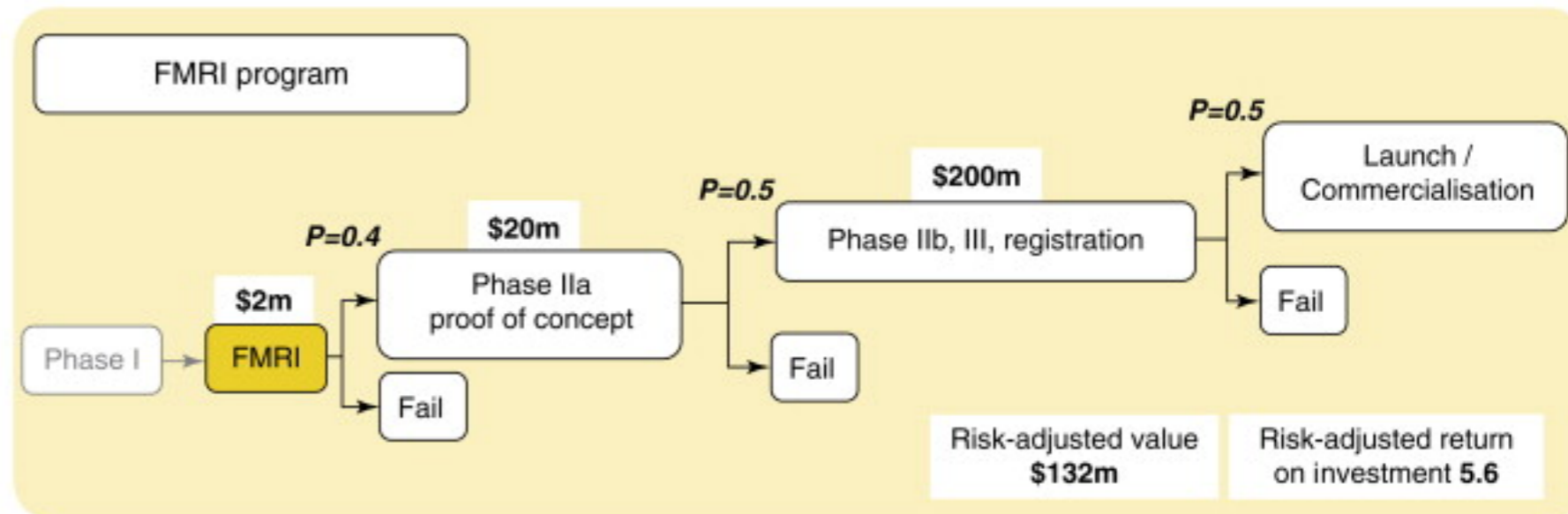
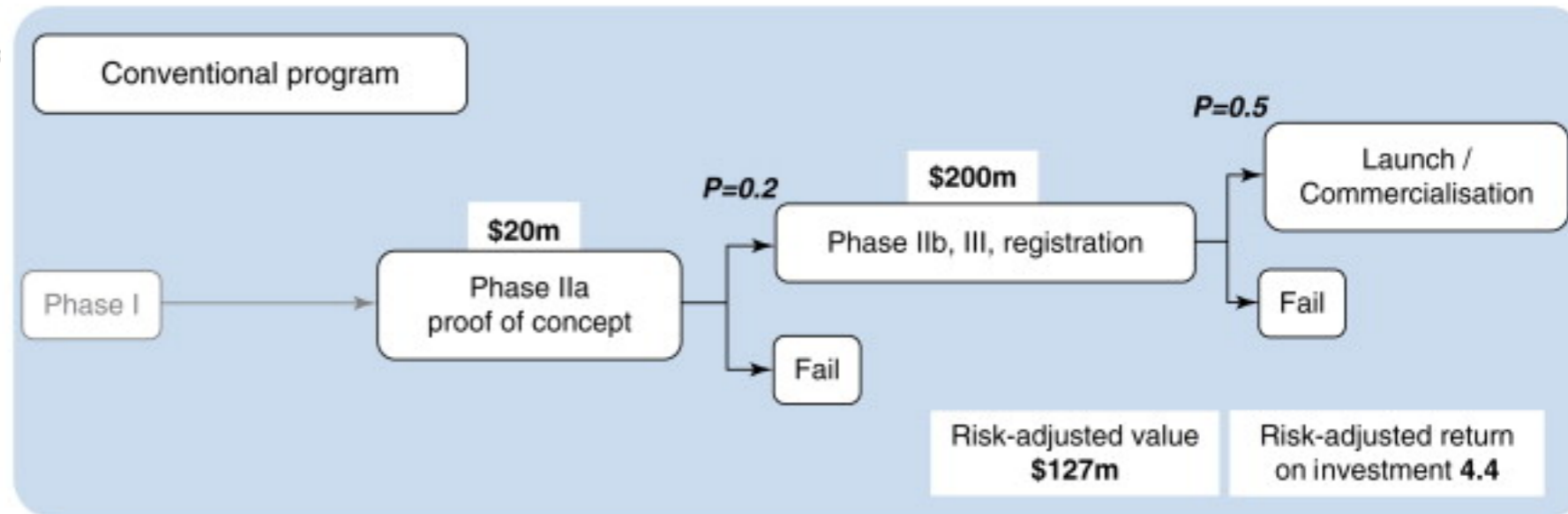


What is the value of human FMRI in CNS drug development?

Richard G. Wise¹ and Cliff Preston²

¹Cardiff University Brain Research Imaging Centre, School of Psychology, Cardiff University, Park Place, Cardiff CF11

²Portfolio & Decision Analysis Group, Pfizer Ltd, Ramsgate Road, Sandwich CT13 9NJ, UK



FMRI Biomarker Identification

a. Quality Assurance

Pause.
Reassess experimental protocol and analysis strategy. Result is not informative of drug effects.

No.
Problem with protocol or analysis pipeline

Can basic responses be detected and do they match past studies?

Yes.
Baseline responses and modeling appear OK

b. Pharmacodynamic Effect

Stop.
Negative result. Indicates problem with drug, drug dosage, or the imaging protocol lacks sensitivity.

No.
Little indication that drug has an identifiable effect on responses

Can drug effect be reliably identified based on other subjects in study?

Yes.
Drug has a reliable effect on brain responses.

c. Clinical Efficacy

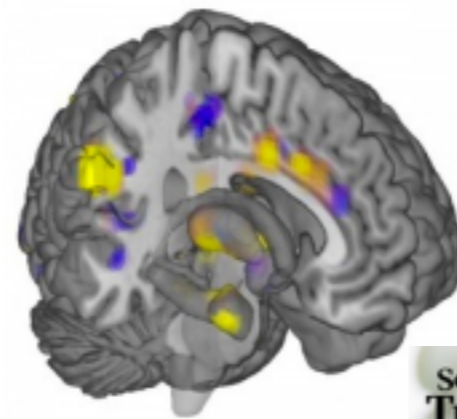
Qualified Go.
Drug has an effect on brain, but does not match past studies. Assess spatial effects, other evidence

Go.
Proceed with clinical trials. Accelerate programme if evidence is particularly strong.

No.
Baseline responses and modeling appear appropriate.

Can the drug modulation be identified based on a validated signature of clinical efficacy?

Yes.
Imaging suggests that drug is a promising candidate.



RESEARCH ARTICLE

NEUROIMAGING

Learning to identify CNS drug action and efficacy using multistudy fMRI data

Eugene P. Duff,^{1*} William Vennart,² Richard G. Wise,³ Matthew A. Howard,⁴ Richard E. Harris,⁵ Michael Lee,¹ Karolina Wartolowska,¹ Vishvarani Wanigasekera,¹ Frederick J. Wilson,² Mark Whitlock,² Irene Tracey,¹ Mark W. Woolrich,^{1,6} Stephen M. Smith¹

FMRI Biomarker Identification

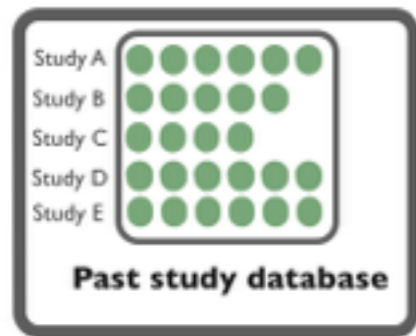
a. Quality Assurance

Pause.
Reassess experimental protocol and analysis strategy. Result is not informative of drug effects.

No.
Problem with protocol or analysis pipeline

Can basic responses be detected and do they match past studies?

Yes.
Baseline responses and modeling appear OK



Stimulus validity assessment. Test for differences between responses of test study and responses elicited in validated existing studies.

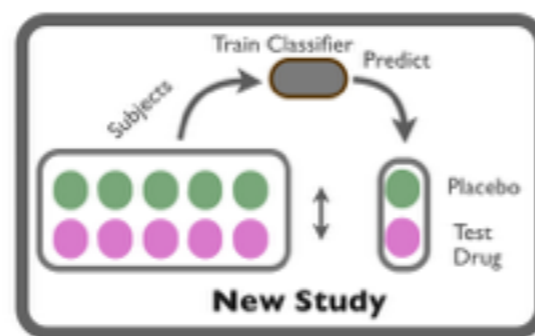
b. Pharmacodynamic Effect

Stop.
Negative result. Indicates problem with drug, drug dosage, or the imaging protocol lacks sensitivity.

No.
Little indication that drug has an identifiable effect on responses

Can drug effect be reliably identified based on other subjects in study?

Yes.
Drug has a reliable effect on brain responses.



Cross-validated signature of pharmacodynamic effect. Train MVPA algorithm to discriminate drug from control session maps. Test on held-out subjects (i.e. leave-one-subject-out cross validation).

c. Clinical Efficacy

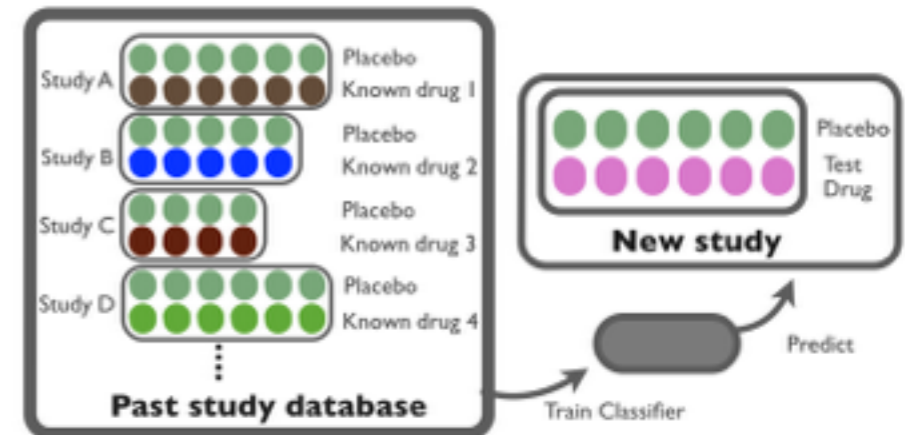
Qualified Go.
Drug has an effect on brain, but does not match past studies. Assess spatial effects, other evidence

Go.
Proceed with clinical trials. Accelerate programme if evidence is particularly strong.

No.
Baseline responses and modeling appear appropriate.

Can the drug modulation be identified based on a validated signature of clinical efficacy?

Yes.
Imaging suggests that drug is a promising candidate.



Multi-study signature of efficacy. Train MVPA algorithm to identify brain responses associated with established efficacious drugs, using a set of existing studies. Determine whether algorithm successfully identifies the presence of the test compound.

FMRI Biomarker Identification

Assessments of analgesic studies

	Quality Control Significant changes within ROI derived from past studies	Drug effect Ability to identify drug session in new subjects	Drug efficacy Ability to identify drug using efficacy signature	Decision
A. Gabapentin 12 Healthy controls Punctate stimulus to allodynic area	Pass	75%	88%	GO
B. Pregabalin (I) 23 Fibromyalgia Patients Squeeze stimulus	Pass After optimisation following initial fail	70%	65%	GO
C. Pregabalin (II) 16 PTNP Patients Punctate stimulus	Pass	78%	66%	GO
D. Tramadol 16 PTNP Patients Punctate stimulus	Pass	47%	58%	Stop Little evidence. Check protocol behaviour, dose.
E. Remifentanyl (I) 22 Healthy controls Punctate/thermal stimuli	Pass	89%	84%	GO
F. Remifentanyl (II) 12 Healthy controls Laser stimulus	Pass	83%	58%	GO Strong effect of drug may have affected efficacy detection
G. THC 14 Healthy controls Punctate stimulus	Pass	64%	64%	GO
H. Naproxen 19 Healthy controls Punctate stimulus	Pass	58%	71%	GO

Assessments of control studies

	Quality Control Significant differences from past pain responses	Drug effect Ability to identify drug in new subjects	Drug efficacy Ability to identify drug using efficacy signature	Decision
A. Pregabalin mismodelled pain stimulus Healthy controls Punctate stimulus	Fail	56%	52%	Pause Assess protocol and analysis
B. Visual Stimulus Remifentanyl	Fail	75%	25%	Pause Assess protocol and analysis
C. Auditory Stimulus Remifentanyl	Fail	83%	50%	Pause Assess protocol and analysis
D. Baseline scans Fibromyalgia Laser stimulus	Pass	43%	39%	Stop Little evidence of drug effect on brain.
E. Inverse effect (switch Drug w/ Placebo) Gabapentin: Healthy controls Punctate stimulus to allodynic area	Pass	75%	12%	Stop Brain effect, but opposite to efficacious drug



RESEARCH ARTICLE

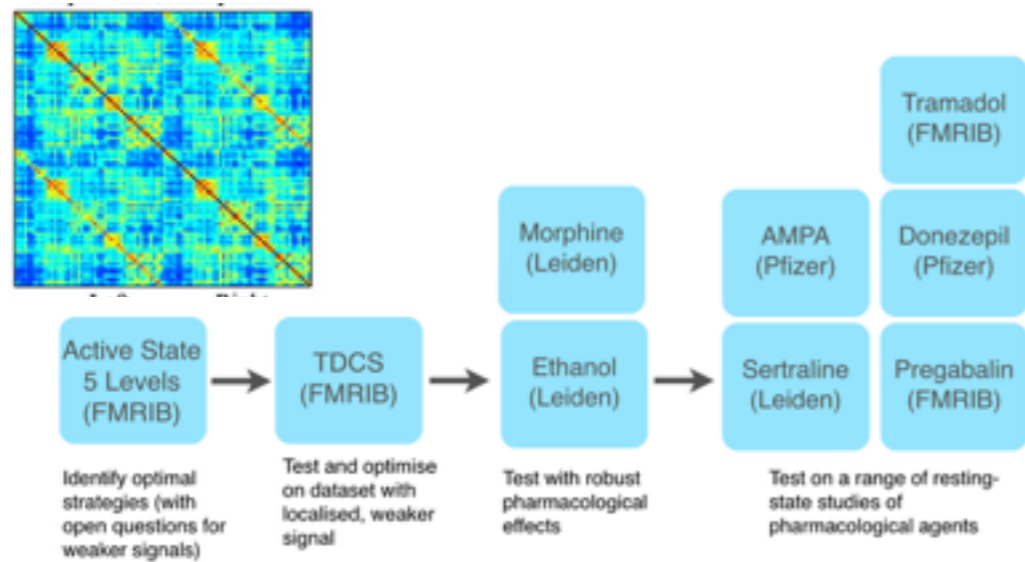
NEUROIMAGING

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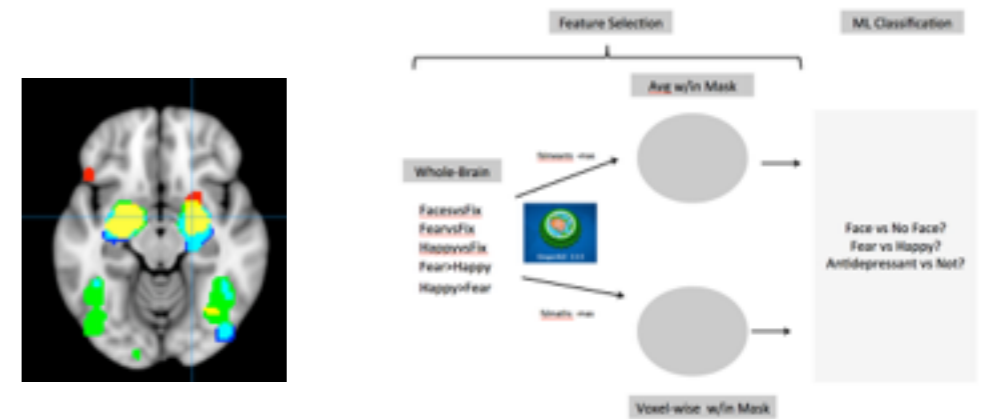
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FMRI Biomarker Identification

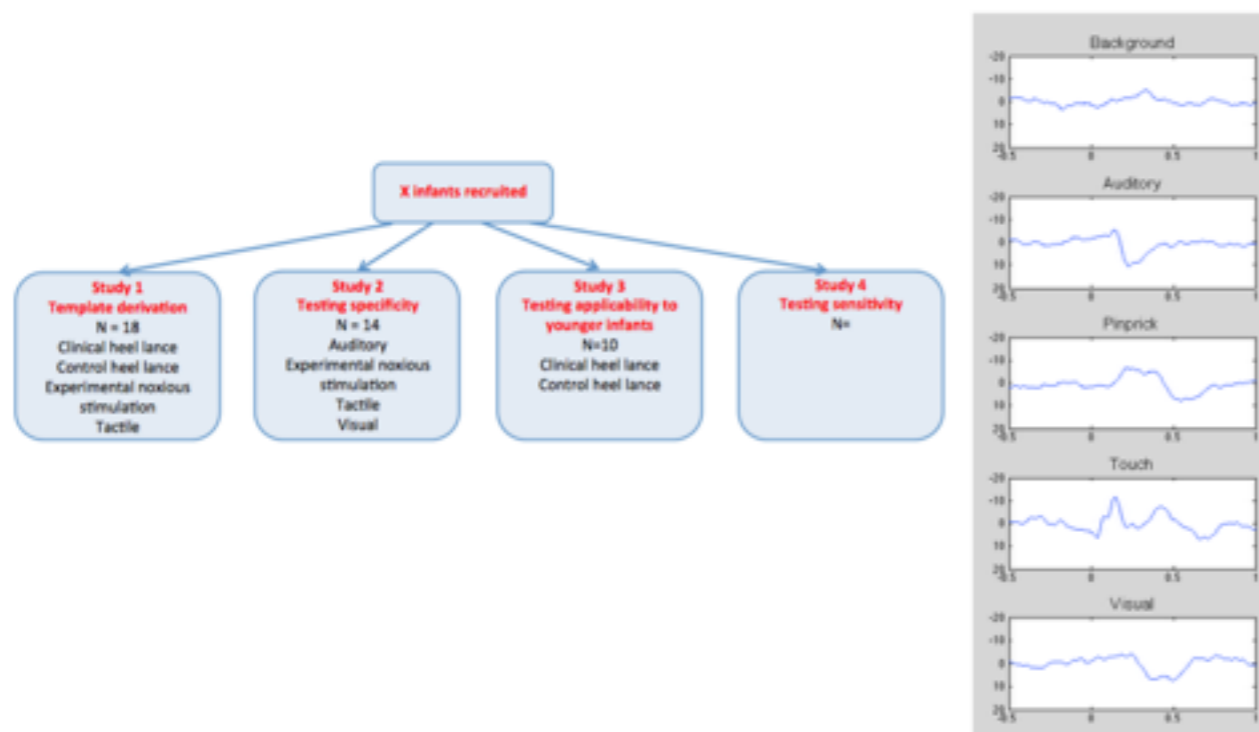
Resting-state pharmacologic studies



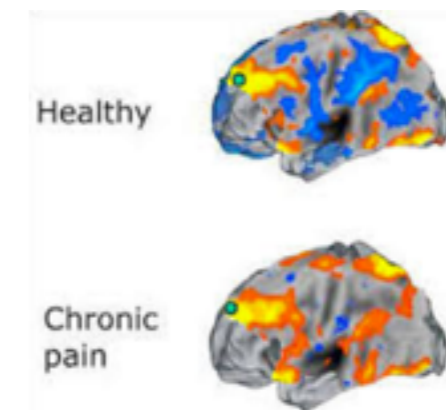
Biomarker for Antidepressant Action



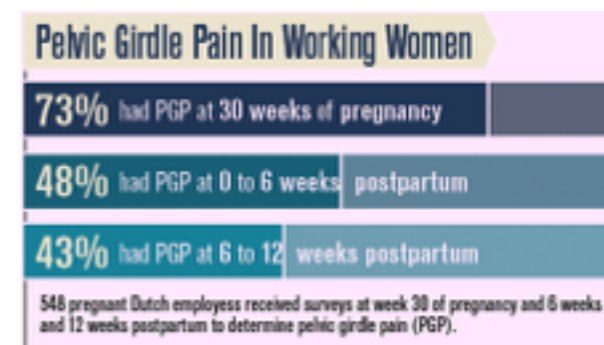
Pain Biomarker for Newborn babies (FMRI & EEG)



Biomarker for Chronic Pain



Predictors of postpartum pain



Summary

Brain imaging is moving to the realm of big data, multimodal data, and multi-study data.

Work at FMRI is grappling with the increasing complexity of analysis pipelines, data exploration, and identification of structure.

Challenges of integration of modalities remain.

- We have been cautious about implementing complex biophysical models
- Sparse methods are crucial

Automated QC is under development

There is still a central role for traditional, smaller studies.

- Analyses need to be integrated into large-scale and multi-scale frameworks.

FMRIB Analysis Group

GROUP HEADS

- Head of Analysis & Functional MRI, **Steve Smith**, steve@fmrib.ox.ac.uk
- Head of Structural & Physics Modelling, **Mark Jenkinson**, mark@fmrib.ox.ac.uk
- Head of Computational Neuroscience, **Tim Behrens**, behrens@fmrib.ox.ac.uk
- Head of Bayesian Neuroimaging & MEG, **Mark Woolrich**, woolrich@fmrib.ox.ac.uk
- Head of Multivariate Modelling, **Christian Beckmann**, c.beckmann@donders.ru.nl

RESEARCH FELLOWS

- **Jesper Andersson**, jesper@fmrib.ox.ac.uk
- **Michael Chappell**, chappell@fmrib.ox.ac.uk
- **Gwenaëlle Douaud**, douaud@fmrib.ox.ac.uk
- **Eugene Duff**, eduff@fmrib.ox.ac.uk
- **Saad Jbabdi**, saad@fmrib.ox.ac.uk
- **Tom Nichols**, t.e.nichols@warwick.ac.uk
- **Stamatios Sotiropoulos**, stam@fmrib.ox.ac.uk



POSTDOCS / RESEARCH ASSOCIATES

- **Fidel Alfaro Almagro**, fidel.alfaro.almagro@gmail.com
- **Matteo Bastiani**, matteo.bastiani@ndcn.ox.ac.uk
- **Michiel Cottaar**, michiel.cottaar@ndcn.ox.ac.uk
- **Sean Fitzgibbon**, sean.fitzgibbon@ndcn.ox.ac.uk
- **Ludovica Griffanti**, ludovica.griffanti@ndcn.ox.ac.uk
- **Oiwi Parker Jones**, oiwi.parkerjones@ndcn.ox.ac.uk
- **Evangelos Roussos**, eroussos7@yahoo.co.uk
- **Eelke Visser**, evisser@fmrib.ox.ac.uk

STUDENTS

- **Zobair Arya**, zobair.arya@jesus.ox.ac.uk
- **Giles Colclough**, giles.colclough@gmail.com
- **Jonathan Hadida**, jonathan.hadida@univ.ox.ac.uk
- **Sam Harrison**, samuel.harrison@balliol.ox.ac.uk
- **Moises Hernandez Fernandez**, moises.hernandez@um.es
- **Emmanuel Vallee**, emmanuel.vallee@wadh.ox.ac.uk
- **Anderson Winkler**, winkler@fmrib.ox.ac.uk