

NeuroMark PET: Towards a fully automated PET ICA pipeline

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Outline

- Motivation
- Preprocessing
- Blind ICA
- The NeuroMark framework
- NeuroMark PET (FBP and FBB)
- Multimodal comparison

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ROIs and brain networks

- Anatomy based atlases or fixed ROIs are often used to summarize positron emission tomography (PET) data.
- Fixed binary atlases do not capture variation among individuals and may average together voxels which are functionally distinct
- Functional boundaries do not correspond 1-1 with anatomic boundaries, and brain networks (and tissue types, e.g., white matter) can overlap

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A data-driven approach

- Independent component analysis (ICA) is one of the most widely used data-driven approaches in fMRI
- ICA allows extraction of maximally independent covarying sources which can overlap with one another
- ICA has been used successful in dozens of PET studies, but it can be challenging to compare as each study results in different components

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Independent Component Analysis (ICA)

One PET scan

Voxels →

Data(X)

Subjects ↓

=

Mixing matrix

A

×

Spatially Independent Components

Components (S)

Spatial ICA estimates maximally spatially independent component maps

Subject loadings/ expression

spatial maps

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Loading Coefficients

Voxels →

Data(X)

Subjects ↓

=

Mixing matrix

A

×

Spatially Independent Components

Components (S)

Loading coefficients (i.e., the mixing matrix): represent the relative degree each ICA component is 'expressed' in a given subject's PET data

PET FNC (functional network covariation): covariation among the columns of A.

Subjects ↓

Mixing Matrix

ICA Weights

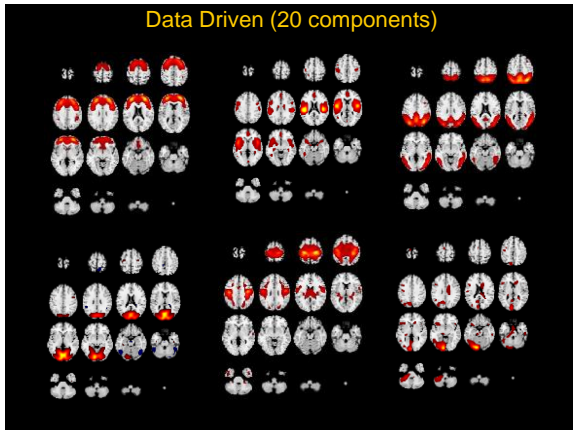
Columns: Patients

Sources →

Statistical tests (e.g., two sample test) can be applied to each column of the mixing matrix to test differences between two groups.

The columns of the mixing matrix can also be regressed against other variable (e.g. age, site, etc.

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PET Data and Preprocessing

Data:

- FBP: N = 250, 76+/-8.2 yrs
- FBB: N = 175, ages: 70.8+/-7.47 yrs
- FDG: N = 220, ages 74+/- 6.4 yrs
- Each w/ four 5-minute frames/scans for each subject

Preprocessing:

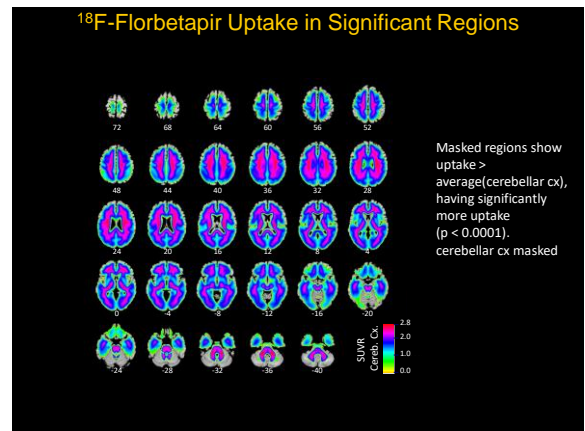
- PET data converted to BIDS structure
- Motion correction (4 frames)
- FreeSurfer applied to T1 (create reference)
- PETSURfer: combine frames, transform the images into MNI space and extract cerebellar cortex size and intensities
- SUVR relative to cerebellum applied as below
- Data masked via a one-sample t-test to include the voxels that have significantly ($p < 0.0001$) more uptake than the reference (e.g., cerebellar cortex)

- We use the following simplified SUVR equation (CB=cerebellum)
- $ratio = \frac{Left_CB_cx_vol}{left_CB_cx_vol+right_CB_cx_vol}$
- $SUVR = \frac{mean(frames_voxel_raw)}{left_CB_cx_intensity \times ratio + right_CB_cx_intensity \times (1-ratio)}$

where cerebellar_cx_intensity is the average intensity of all the voxels inside the cerebellar cortex

https://github.com/trendscenter/gif-bids/tree/main/misc/pet/pipe/onp/example_fbb

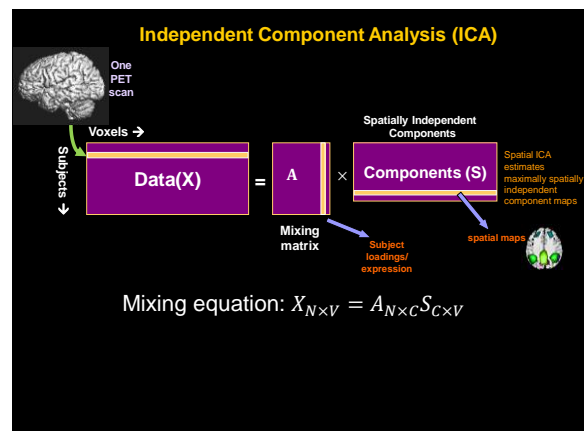
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Scaling (SUVR) does not impact ICA sources

Mixing equation: $X_{N \times V} = A_{N \times V} S_{C \times V}$

Subject specific (SUVR) scaling: $B_{N \times N} = \begin{bmatrix} b_1 & \dots & b_N \\ b_1 & \dots & b_N \\ \dots & \dots & \dots \\ b_1 & \dots & b_N \end{bmatrix}$

Apply (SUVR) scaling to the data: $B_{N \times N} X_{N \times V} = B_{N \times N} A_{N \times V} S_{C \times V} = (B_{N \times N} A_{N \times V}) S_{C \times V}$

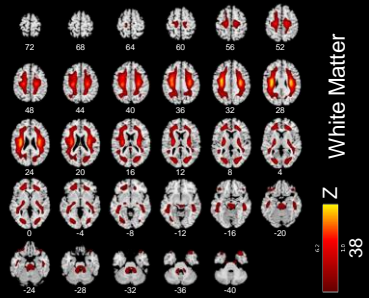
$$(B_{T \times T}^T A_{T \times V}) = \begin{bmatrix} b_1 & \dots & b_N \\ b_1 & \dots & b_N \\ \dots & \dots & \dots \\ b_1 & \dots & b_N \end{bmatrix} \begin{bmatrix} A_{11} & \dots & A_{1V} \\ A_{21} & \dots & A_{2V} \\ \dots & \dots & \dots \\ A_{N1} & \dots & A_{NV} \end{bmatrix} = \begin{bmatrix} b_1 A_{11} & \dots & b_1 A_{1V} \\ b_2 A_{21} & \dots & b_2 A_{2V} \\ \dots & \dots & \dots \\ b_N A_{N1} & \dots & b_N A_{NV} \end{bmatrix} = \begin{bmatrix} b_1 A_1 \\ b_2 A_2 \\ \dots & \dots \\ b_N A_N \end{bmatrix}$$

$$B_{N \times N} X_{N \times V} = B_{N \times N} A_{N \times V} S_{C \times V} = (B_{N \times N} A_{N \times V}) S_{C \times V} = \begin{bmatrix} b_1 A_1 \\ b_2 A_2 \\ \dots & \dots \\ b_N A_N \end{bmatrix} S_{C \times V}$$

This tells us that the source maps are invariant to the scaling. It allows us to scale the loading parameters post ICA.

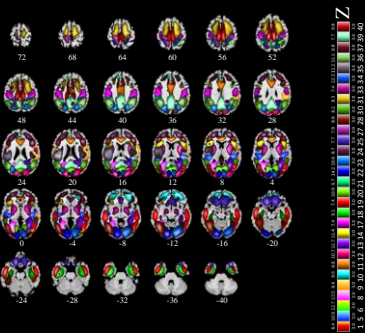
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Example nuisance component



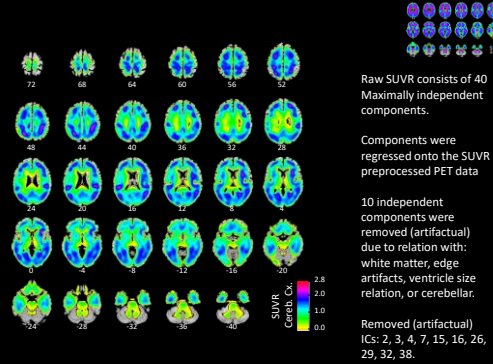
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Non-Artifactual Components (30)



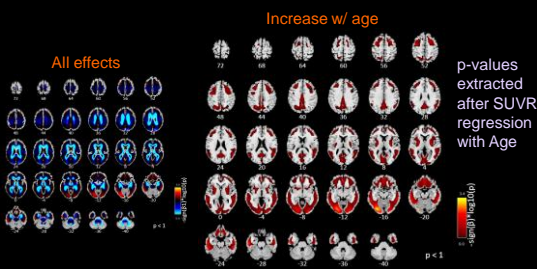
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FBP SUVR minus artifactual ICs



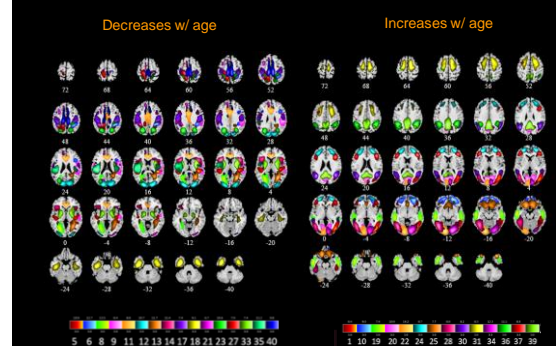
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Non-ICA: FBP Age Regression p-values (+)



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Age effects on (non-artifactual) components



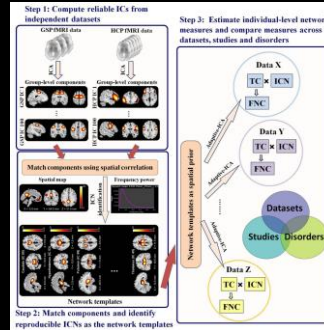
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NeuroMark: A fully automated ICA pipeline



Source independence

$$\max_{\{S_i^k\}} \left\{ \begin{aligned} &F(S_i^k) = \{E[G(S_i^k)] - E[G(w)]\}^2 \\ &F(S_i^k) = E[S_i^k S_i^{k*}] \end{aligned} \right.$$

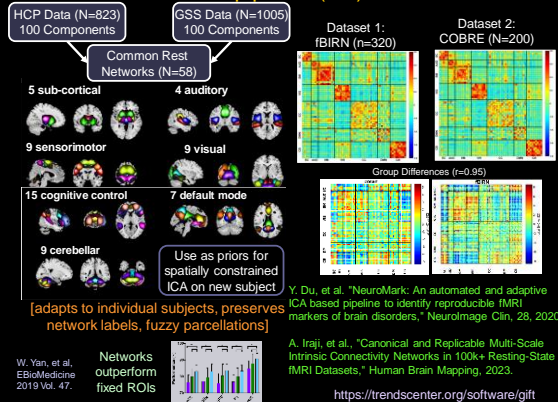
s. t. $\|w_i^k\| = 1$
 $S_i^k = (w_i^k)^T \cdot X^k$

Similarity to template

Y. Du, et al., "NeuroMark: An automated and adaptive ICA based pipeline to identify reproducible fMRI markers of brain disorders," Neuroimage Clin, vol. 28, p. 102375, 2020, PMC7509081.

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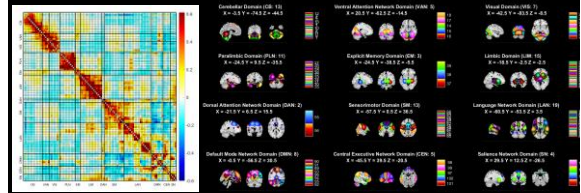
NeuroMark pipeline (1.0) rsfMRI



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NeuroMark Multi-scale fMRI template

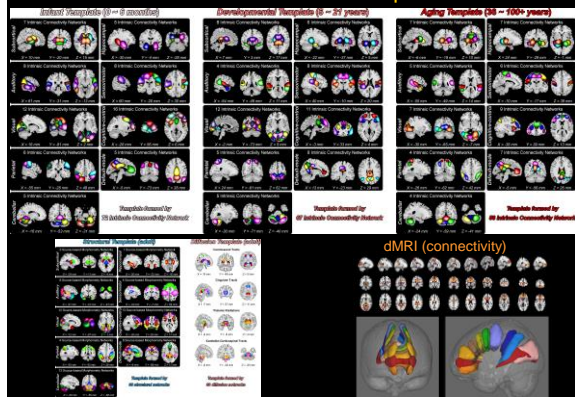
100K subjects, very broadly defined....
 ICA model orders: 25, 50, 75, 100, 125, 150, 175, 200
 Final template: 105 components across model orders



A. Irajli, et al., "Identifying canonical and replicable multi-scale intrinsic connectivity networks in 100k+ resting-state fMRI datasets," Hum Brain Mapp, vol. 44, pp. 5729-5748, 2023.

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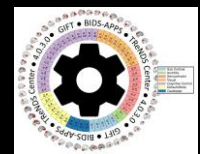
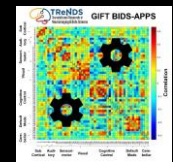
NeuroMark 3.0: Other templates



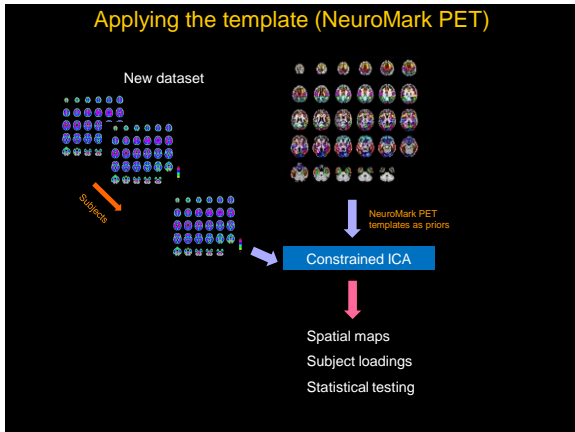
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TRENDS GIFT BIDS-App

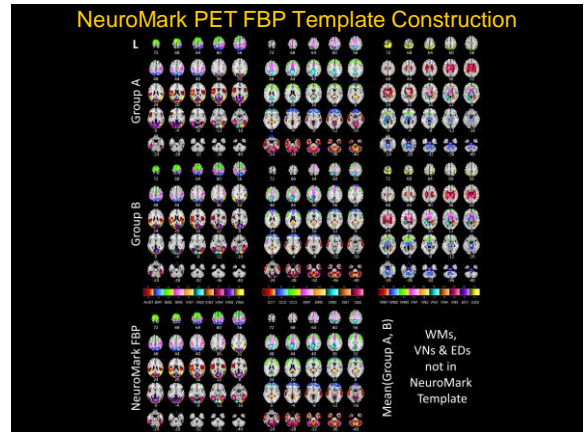
- GIFT BIDS-App includes a full suite of ICA tools
 - <https://github.com/trendscenter/gift-bids>
- Implements fully automated spatially constrained ICA
 - NeuroMark <https://ncbi.nlm.nih.gov/pubmed/32961402>
 - Enables single subject ICA, preserving component correspondence
 - Suppresses artifacts



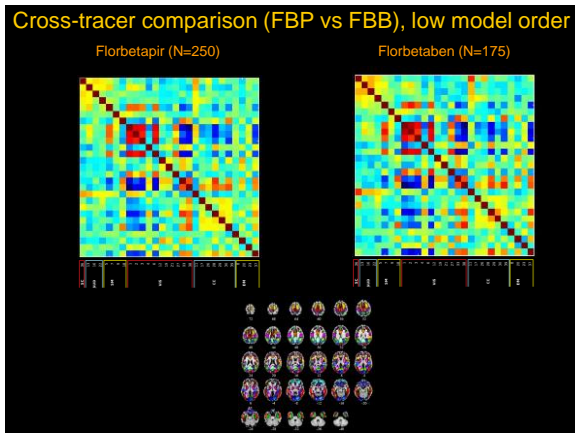
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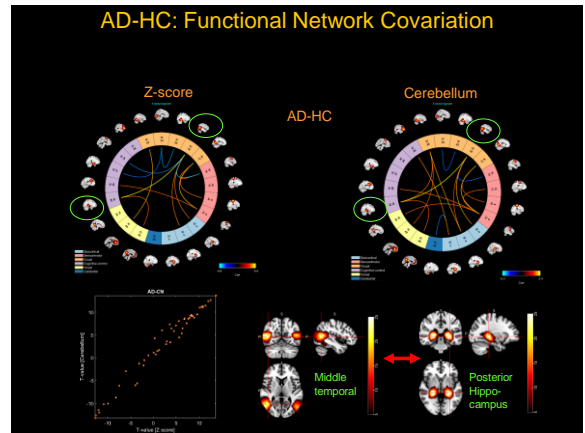
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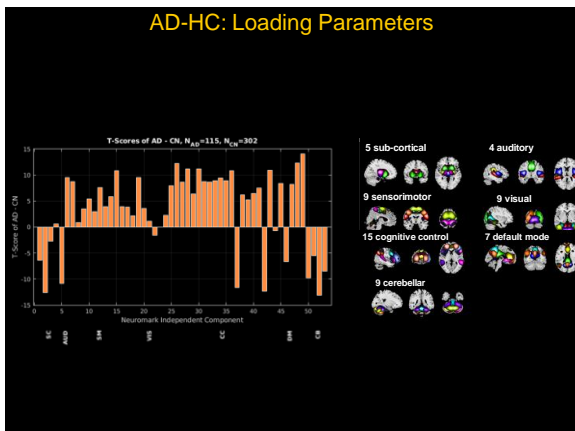
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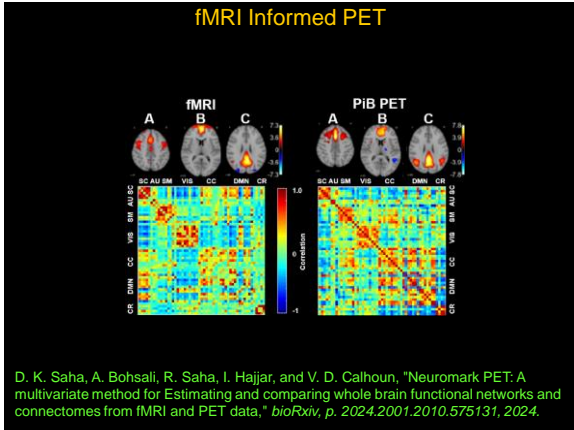
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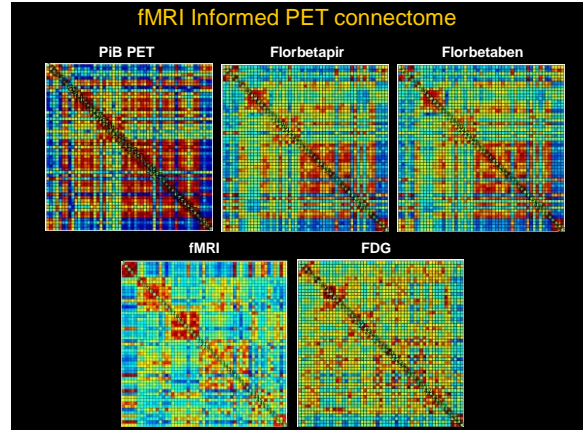
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Software

- <http://trendscenter.org/software>
- freeware, written in MATLAB (also offering compiled versions), python, etc: over 25,000 unique downloads
- **GIFT (Group ICA of fMRI Toolbox)**
 - Single subject/Group ICA
 - MANCOVA testing framework
 - Source based morphometry
 - ICASSO (clustering/stability)
 - Dynamic FNC/Coherence
- **FIT (Fusion ICA Toolbox)**
 - Parallel ICA, jICA
 - mCCA+jICA & much more!
- **Simulation Toolbox (SimTB)**
 - Flexible generation of fMRI-like data
- **COINS (data management/capture/sharing)**
 - <http://coins.trendscenter.org>
- **COINSTAC (decentralized analysis, privacy)**
 - <https://coinstac.org>
- **CORTEX (deep learning)**
 - <https://github.com/rdevon/cortex>

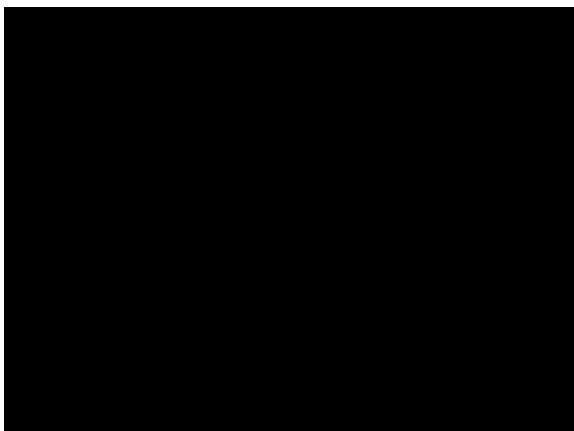
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OpenNeuroPET team (+ more)

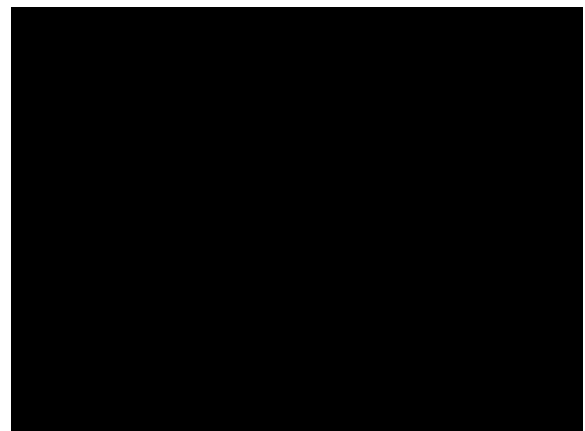
<http://trendscenter.org>

R01EB005846, R01EB006841, P20GM103472, 1U01NS062074, 5R41MH100070, R01MH094524, 1R01MH104680

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