Improved motion correction for functional MRI using an omnibus regression model

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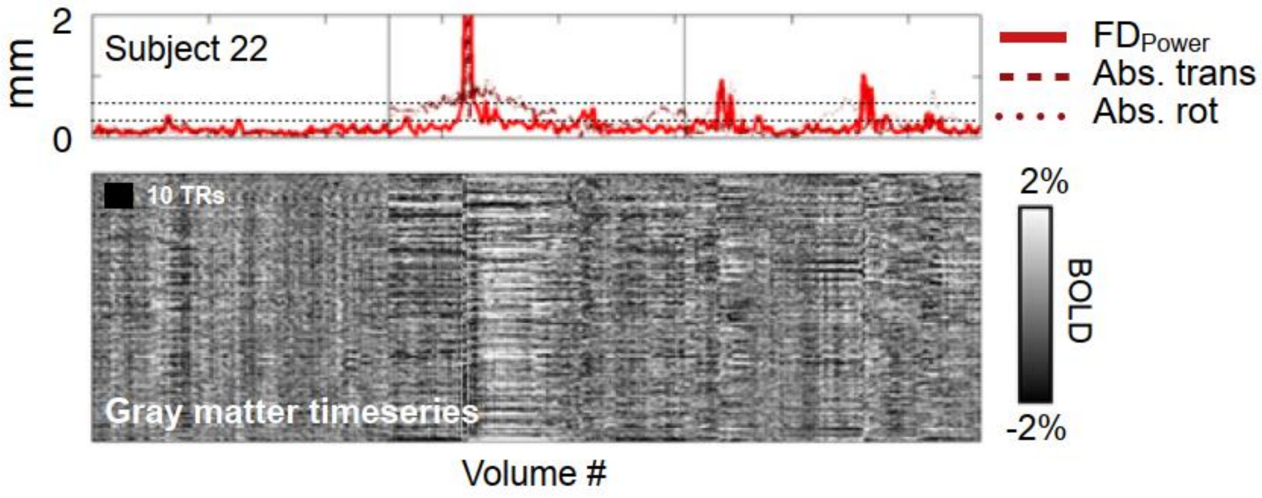
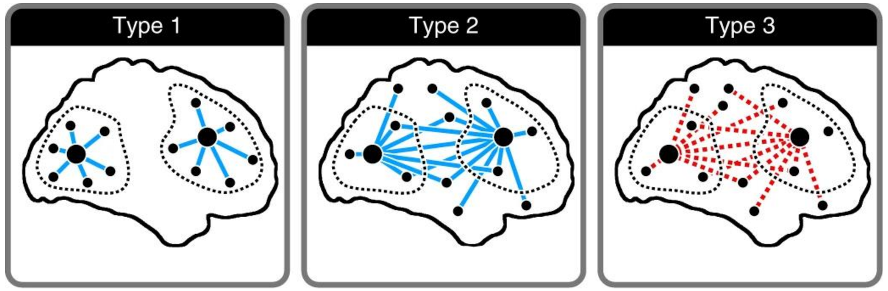
Background: Head motion in fMRI



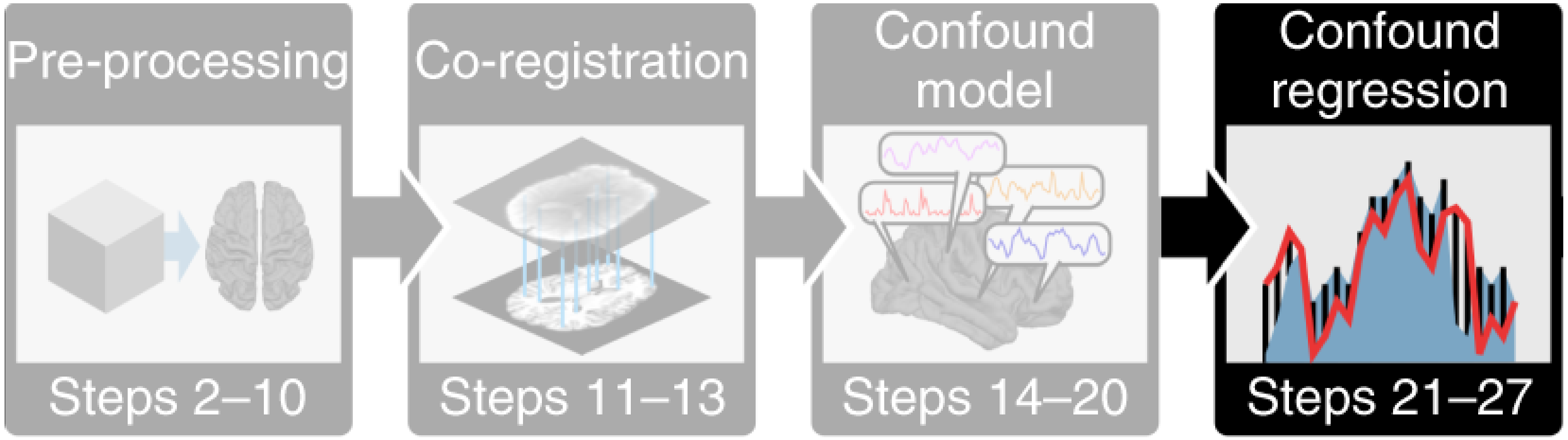


- **Head motion is a significant source of noise in fMRI. It can:**
  - **Account for over 30-90% of the fMRI signal**
  - **Cause distance-dependent artifacts in functional connectivity**
  - **Act as a major confounder. Systematically affect data from:**
    - **Children**
    - **Elderly**
    - **Diseases that cause increased head movement**

Power et al. (2015)
Ciric et al. (2018)

Background: Previous approaches

- Removing motion artifact is highly nontrivial
  - More pipelines than papers!
  - Motion correction involve a sequence of regression steps
  - Artifact removed by a linear regression of data on nuisance covariates



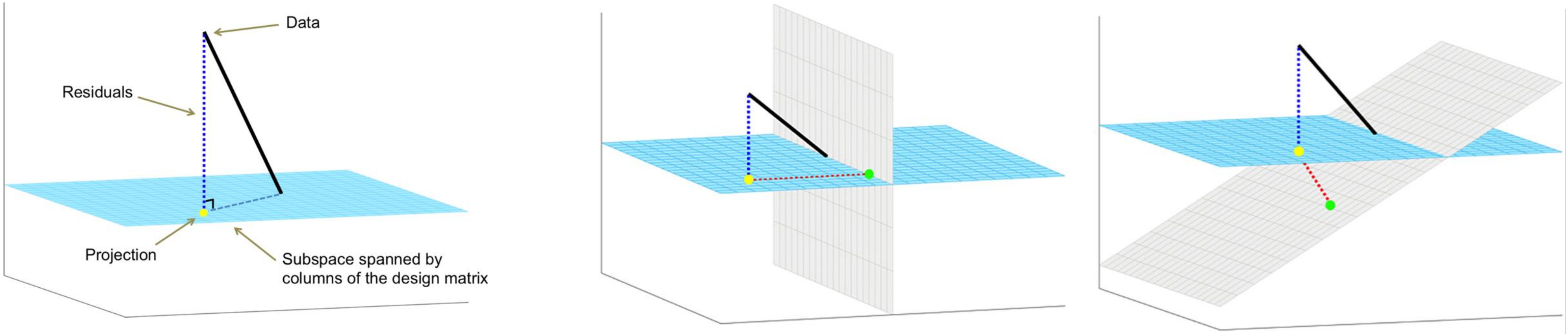
Ciric et al. (2018)

Background: The problem with previous approaches

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{e}$$

$$\begin{pmatrix} Y_1 \\ Y_2 \\ Y_N \end{pmatrix} = \begin{pmatrix} X^1_{(t1)} & X^2_{(t1)} \ldots & X^L_{(t1)} \\ X^1_{(t2)} & X^2_{(t2)} \ldots & X^L_{(tS)} \\ X^1_{(tN)} & X^2_{(tN)} \ldots & X^L_{(tN)} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_L \end{pmatrix} + \begin{pmatrix} \varepsilon_{(t1)} \\ \varepsilon_{(t2)} \\ \varepsilon_{(tN)} \end{pmatrix}$$

- **A sequence of linear filtering operations can reintroduce artifacts**
  - **Regression = Projection onto subspace**
  - **Sequential projections = Orthogonality lost**



$$\boldsymbol{e_1} = \boldsymbol{y_1} - \boldsymbol{X_1\beta_1}$$

$$\boldsymbol{e_2} = \boldsymbol{e_1} - \boldsymbol{X_2\beta_2}$$

Lindquist et al. (2019)

Goal of this work

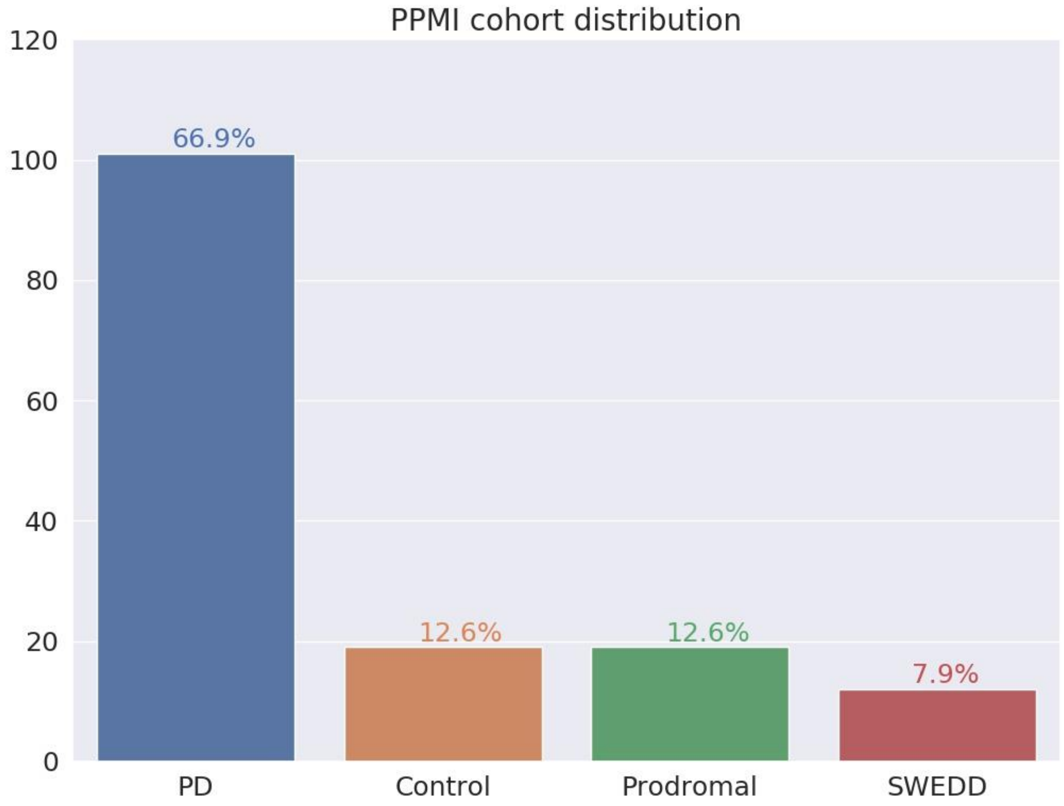
- Create an **omnibus regression model** that
  - combines state-of-the-art artifact suppression algorithms
  - avoids reintroduction of artifacts from sequential regression

- Quantitatively **evaluate** this model **against other commonly used pipelines** on a large clinically relevant dataset (*n* = 151)

Data: Subjects

- **151 subjects from the Parkinson's Progression Markers Initiative (PPMI) database**
  - **3T Siemens scanner**
  - **GE-EPI pulse sequence**
  - **TE=25 ms**
  - **TR=2400 ms,**
  - **resolution 68 x 66 x 40 voxels**
  - **voxel size 3.294 x 3.294 x 3.3 mm**
  - **scan duration 504 s**

- **Diseased and non-diseased subjects considered to capture diversity of motion artifact**



Methods: Preprocessing

- Standard steps for fMRI analysis

Affine realignment
- FMRIB's Linear Image Registration Tool (MCFLIRT)

Skull stripping
- FSL Brain Extraction Tool (BET)
- Analysis of Functional NeuroImages (AFNI) 3dAutomask

Spatial normalization
- Coregistration with EPI template in MNI space
- Symmetric Normalization in Advanced Normalization Tools (ANTs)

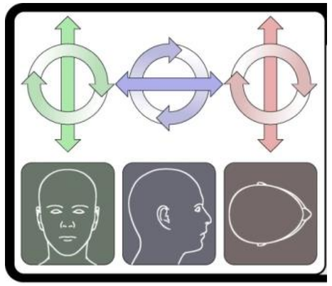
Smoothing
- 6 mm FWHM Gaussian kernel

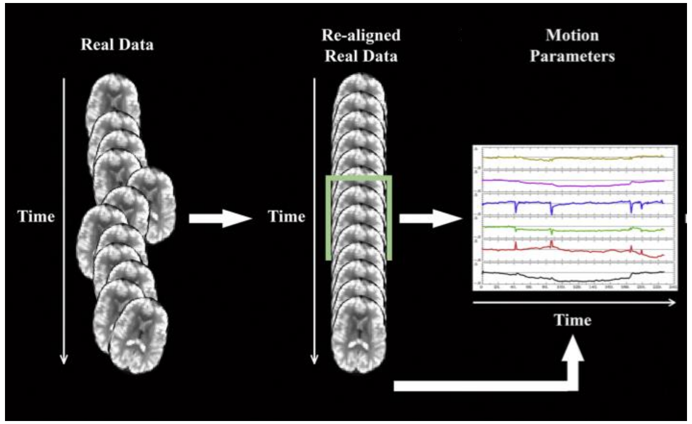
<Motion Correction model>

Functional Connectivity
- Gordon 333 ROI atlas

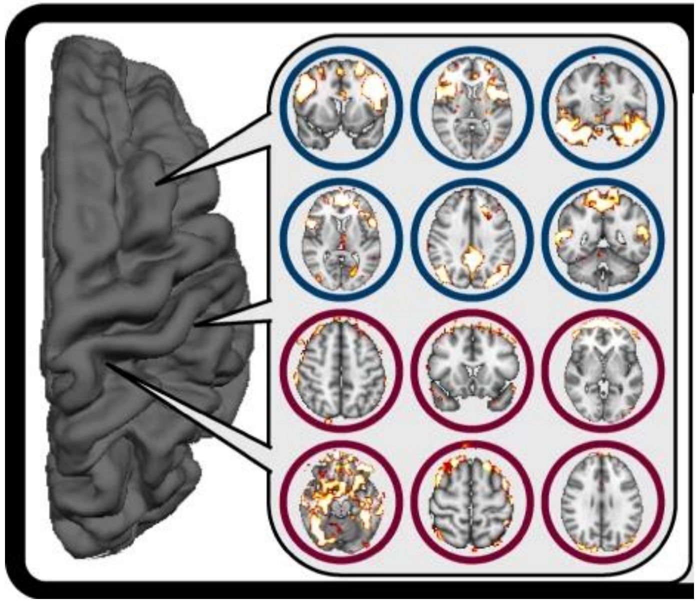
Methods: Nuisance regressors

- Three sets of nuisance regressors:
  - Head motion parameters (HMP)
  - ICA motion components (AROMA)
  - Physiological regressors (PHYSIO)

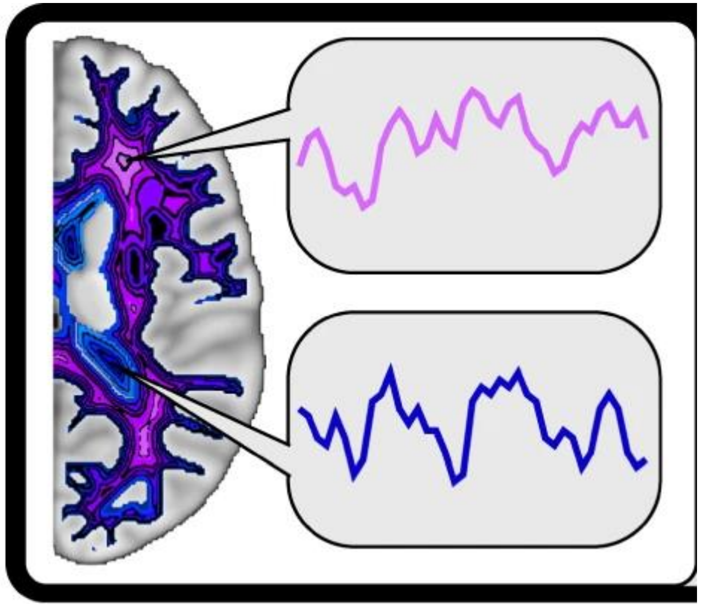




X_{HMP}



X_{AROMA}



X_{Physio}

Ciric et al. (2018)
Patriat et al. (2017)
Pruim et al. (2015)

Methods: Motion correction pipelines

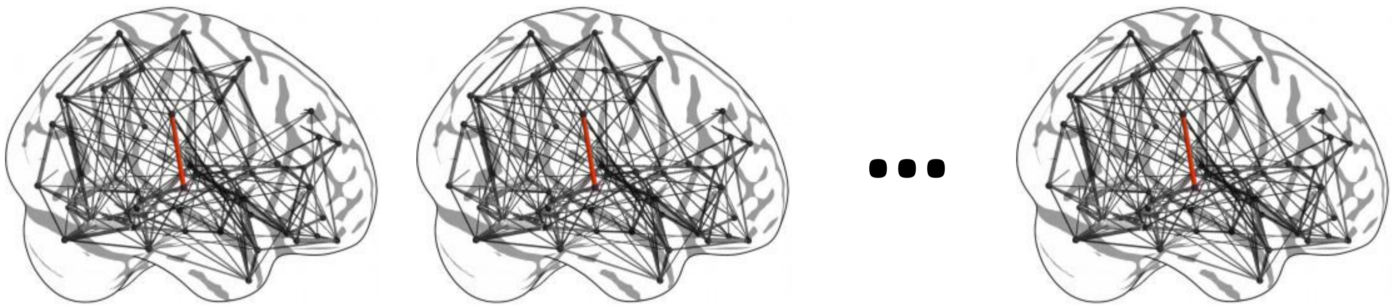
- 4 Pipelines compared
  - Baseline
    - No motion correction
  - HMP > AROMA > Physio
    - $e = ((y - X_{HMP}\beta_1) - X_{AROMA}\beta_2) - X_{Physio}\beta_3$
  - AROMA > HMP > Physio
    - $e = ((y - X_{AROMA}\beta_4) - X_{HMP}\beta_5) - X_{Physio}\beta_6$
  - [AROMA, HMP, Physio]
    - $e = y - [X_{HMP} X_{AROMA} X_{Physio}]\beta_7$

Methods: Quality assessment

- **Framewise Displacement (FD)**
  - **To quantify subject's head motion**

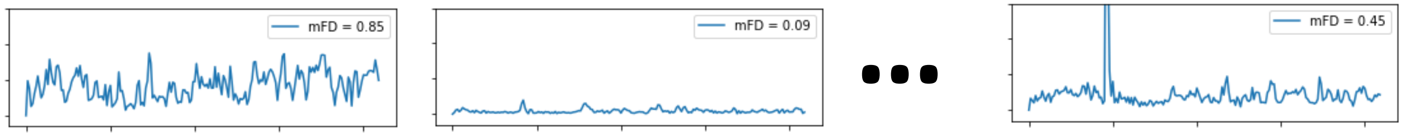
$$FD(t) = |d_x(t) - d_x(t-1)| + |d_y(t) - d_y(t-1)| + |d_z(t) - d_z(t-1)| + |\theta_x(t) - \theta_x(t-1)| + |\theta_y(t) - \theta_y(t-1)| + |\theta_z(t) - \theta_z(t-1)|$$

- **QC-FC correlation *(FC-edge wise)***
  - **Pearson's correlation between mean FD and FC edges**



Subject 1 **Subject 2** ... **Subject *n***

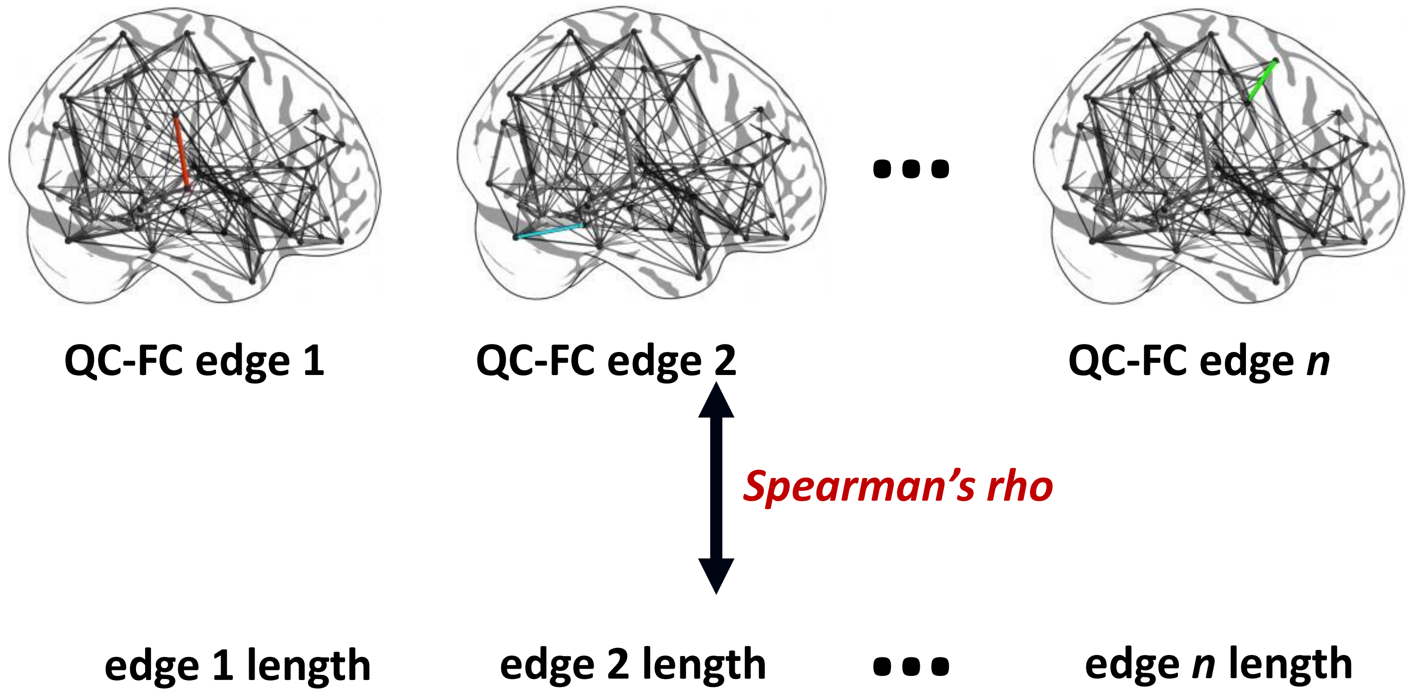
Pearson's r



Subject 1 FD **Subject 2 FD** ... **Subject *n* FD**

Methods: Quality assessment

- **QC-FC distance dependence *(QC-FC-edge wise)***
  - **Spearman's rank correlation between QC-FC correlation of each edge and the Euclidean length of the edge in the brain**

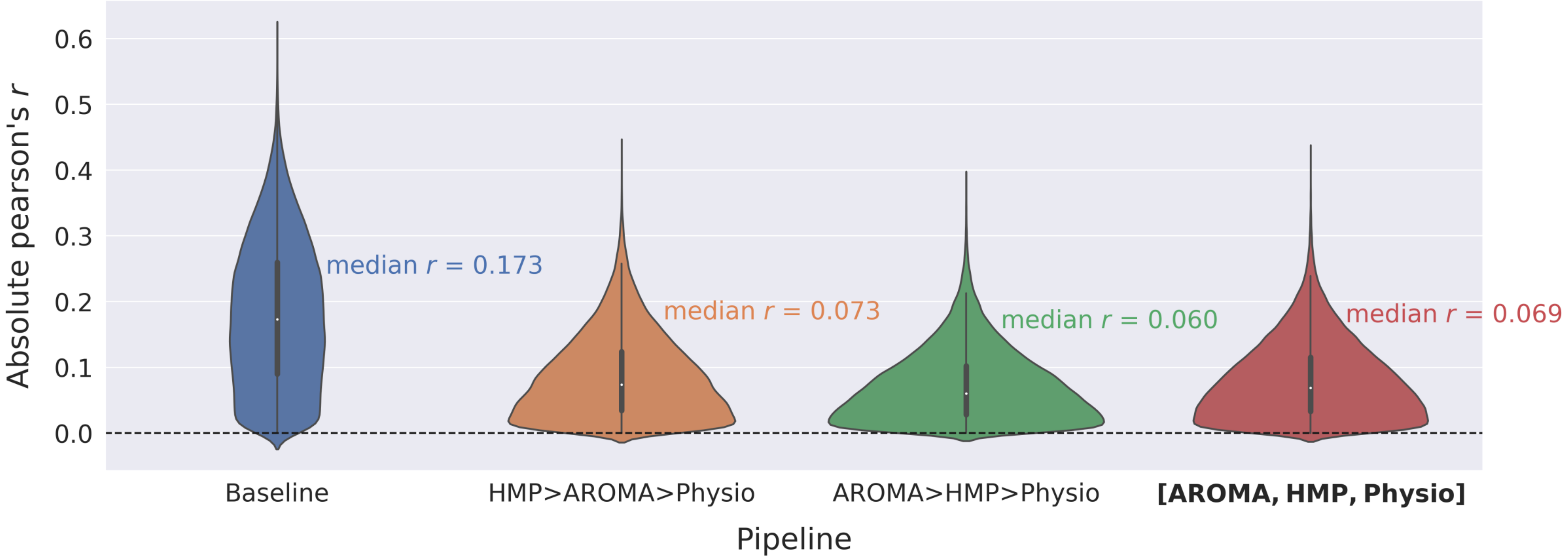


- **QC-FC and QC-FC distance dependence metrics extensively used previously**

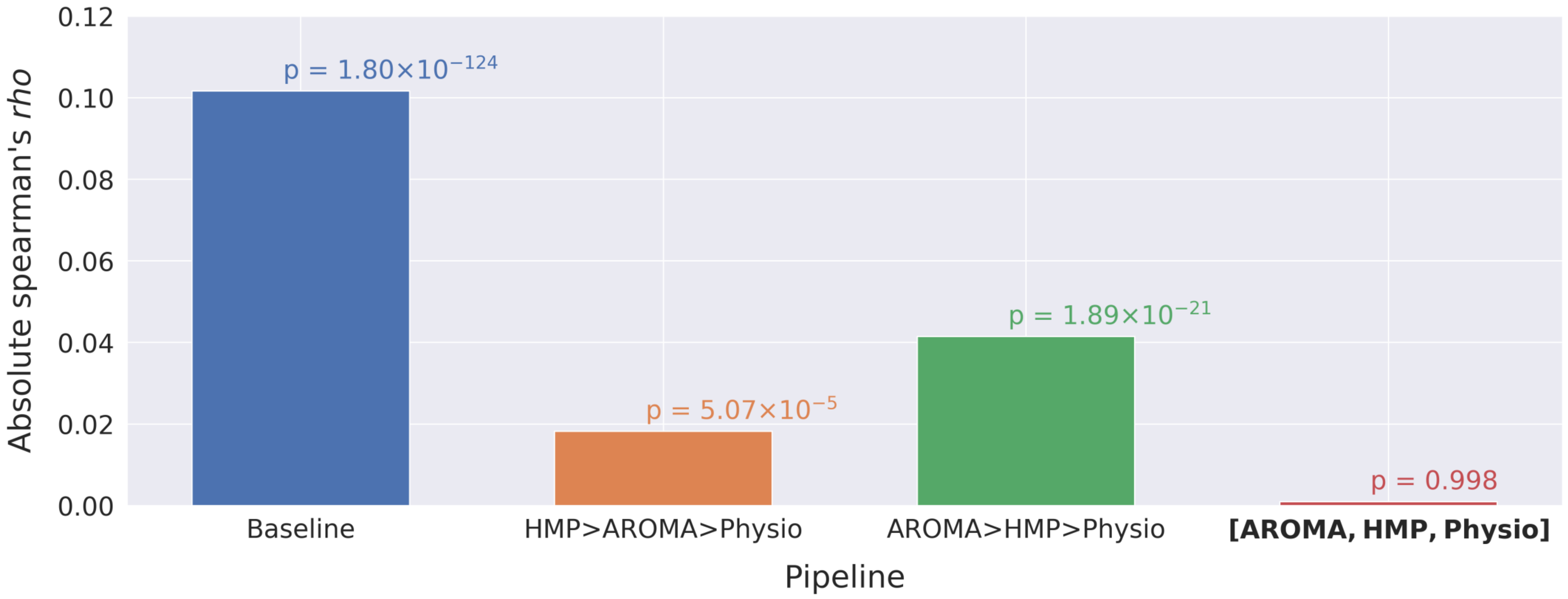
Parkes et al. (2018)
Power et al. (2015)

Results: QC-FC

- **All methods performed similarly at reducing motion noise from functional connectivity**



Results: QC-FC distance dependence

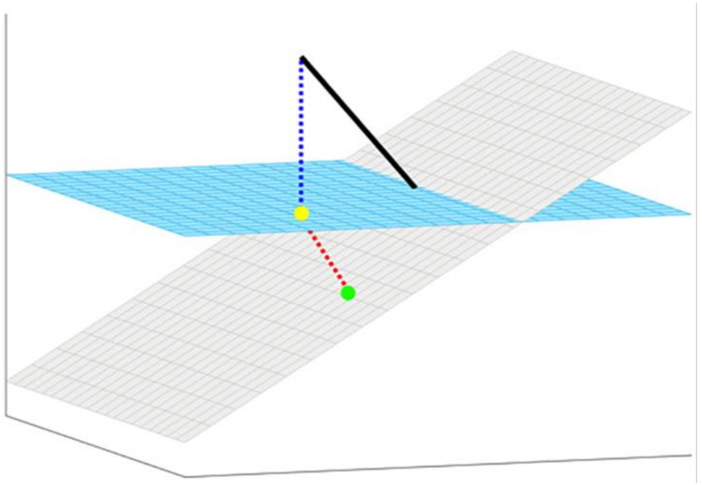


- **Omnibus model alone eliminates all significant distance-dependent noise**

Discussion: Omnibus regression model empirically robust

- **Motion correction is essential**
  - Without it, baseline images and derived functional connectivity measures are heavily contaminated

- **Omnibus model removed distance-dependent artifact**
  - The only model in the comparison to do so successfully
  - Sequential regression pipelines were significantly contaminated



- **No pipeline could completely remove motion artifact**
  - Sequential and omnibus pipelines had similar median QC-FC
  - There is no ground truth

Limitations

- **Single dataset**:
  - Fairly large (151 subjects) and diverse
  - Replication on independent dataset would further confirm findings
- **No ground truth**:
  - Simulation experiments could address this

Conclusions

- **Benefits of omnibus regression model:**
  - **Significantly reduces distance-dependent artifact compared to standard sequential pipelines**
  - **Can be used to reduce confounds in fMRI analyses**