Predicting task-evoked activity from resting-state data

Elvis Dohmatob
(with B. Thirion and G. Varoquaux)

Parietal Team, INRIA

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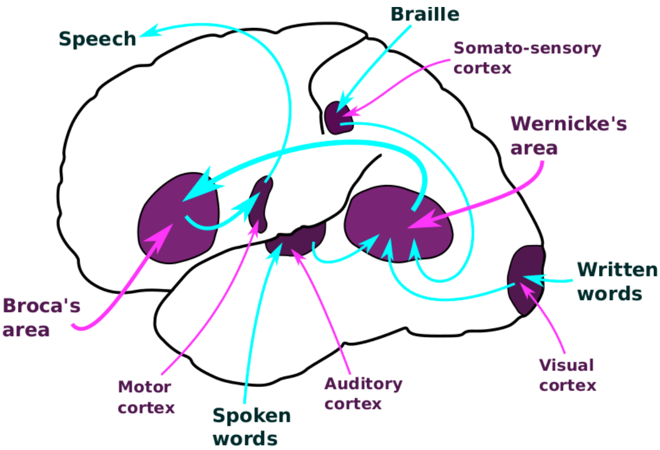
Introduction

Brain function regions and networks

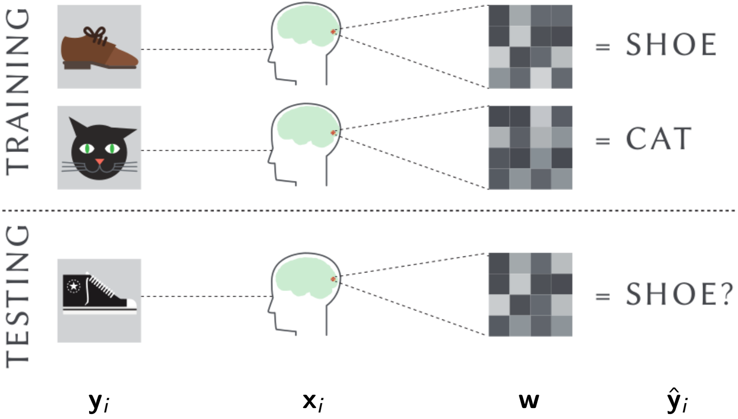
Part of the language network



(Picture is courtesy of Gael Varoquaux)

A zoom on brain-decoding

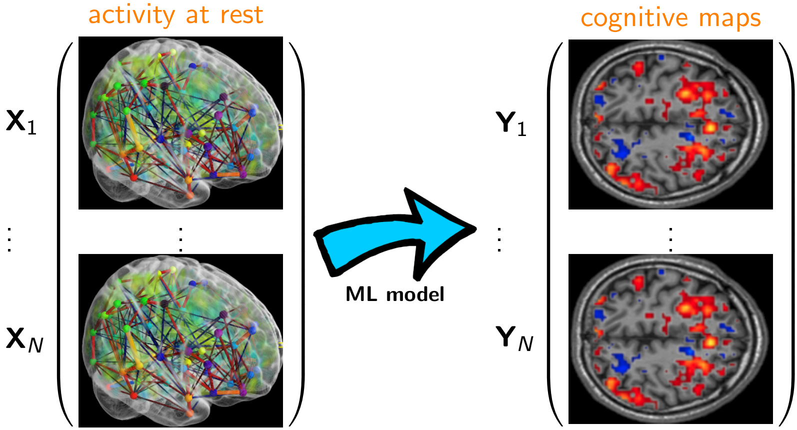
(Picture is courtesy of F. Pedregosa)



Spontaneous / resting-state brain activity

- Can we predict task-evoked activity from this ?

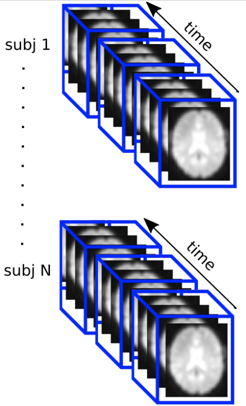
Can we predict task maps from resting-state data ?



- $\mathbf{X}_s$: resting-state functional connectivity graph for subject s
- $\mathbf{Y}_s$: task-specific activation maps for subject s

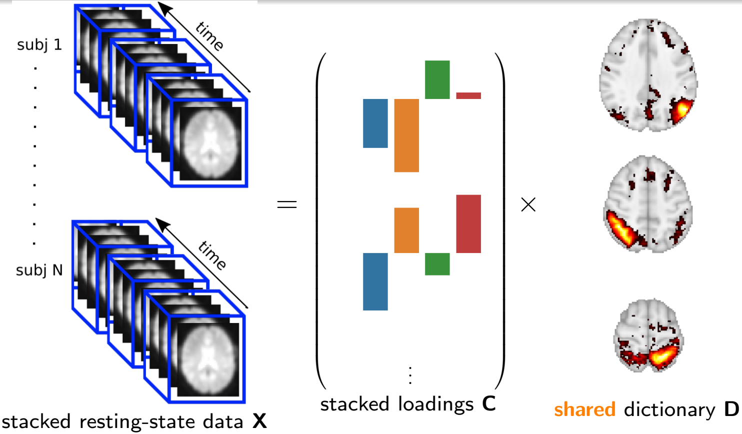
Methods

Shared dictionary



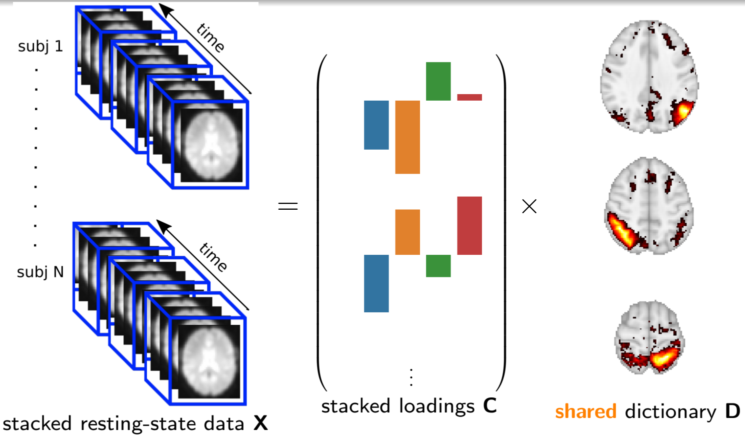
stacked resting-state data **X**

Shared dictionary



- $\mathbf{X}_s \in \mathbb{R}^{n_s \times p}$: resting-state data for subject s.
- $p = \#$ voxels; n_s = number of 3D scans (i.e time points)

Shared dictionary



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- $p = \#$ voxels; $n_s =$ number of 3D scans (i.e time points)
- $k \ll \min(p, \min_s n_s)$. E.g $p = 2 \times 10^5$, $\min_s n_s = 1200$, $k = 100$

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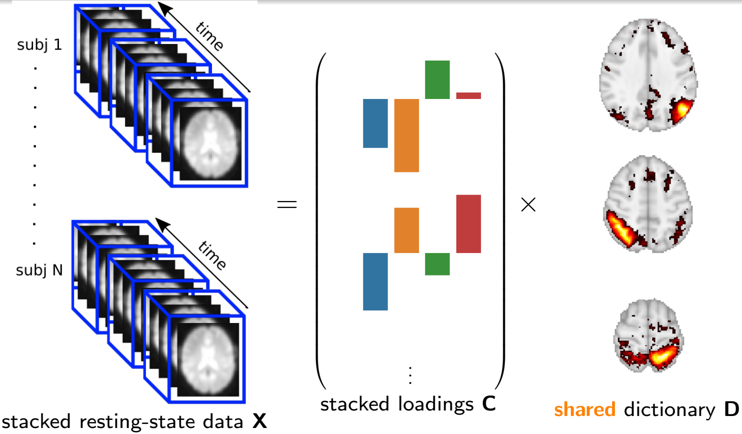

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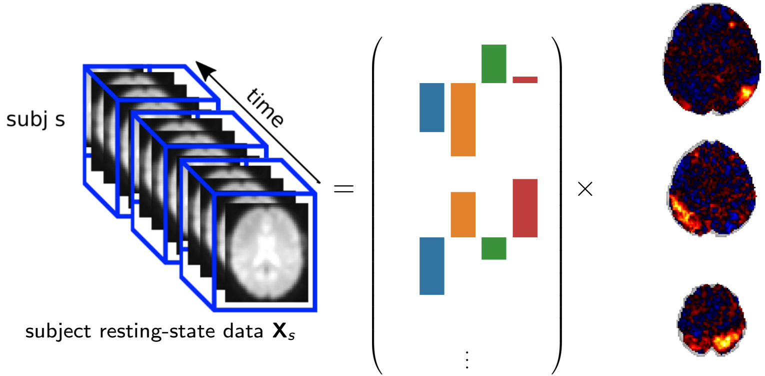
Subject-specific dictionary



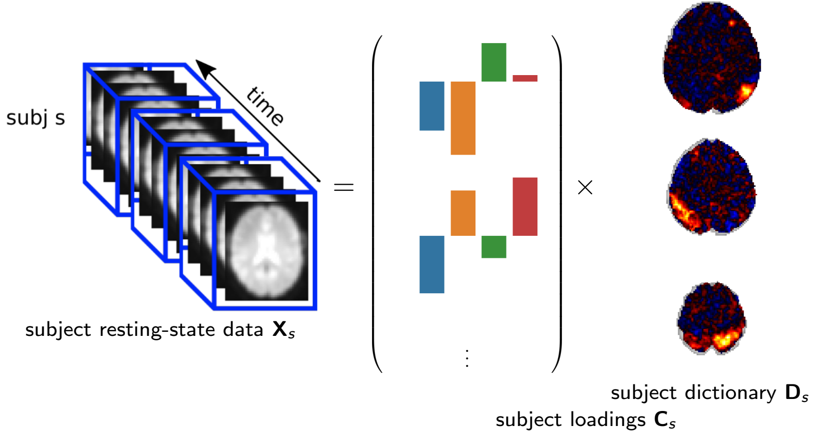
subject resting-state data $\mathbf{X}_s$

subject dictionary $\mathbf{D}_s$

subject loadings $\mathbf{C}_s$

- $\mathbf{C}_s \in \text{argmin}_{\mathbf{C}_s \in \mathbb{R}^{n_s \times k}} \|\mathbf{X}_s - \mathbf{C}_s\mathbf{D}\|^2_{\text{Fro}}$ ($\mathbf{D}$ = shared dictionary)

Subject-specific dictionary



- $\mathbf{C}_s \in \mathrm{argmin}_{\mathbf{C}_s \in \mathbb{R}^{n_s \times k}} \|\mathbf{X}_s - \mathbf{C}_s \mathbf{D}\|^2_{\mathrm{Fro}}$ ($\mathbf{D}$ = **shared** dictionary)
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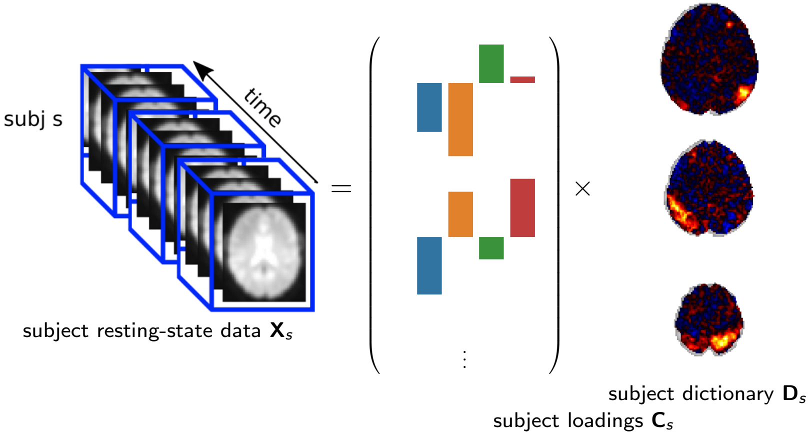
Subject-specific dictionary



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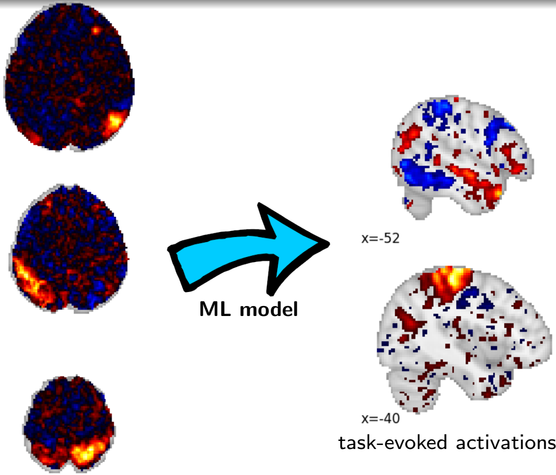
- $\mathbf{D}_s \in \operatorname{argmin}_{\mathbf{D}_s \in \mathbb{R}^{k \times p}} \|\mathbf{X}_s - \mathbf{C}_s \mathbf{D}_s\|^2_{\text{Fro}}$

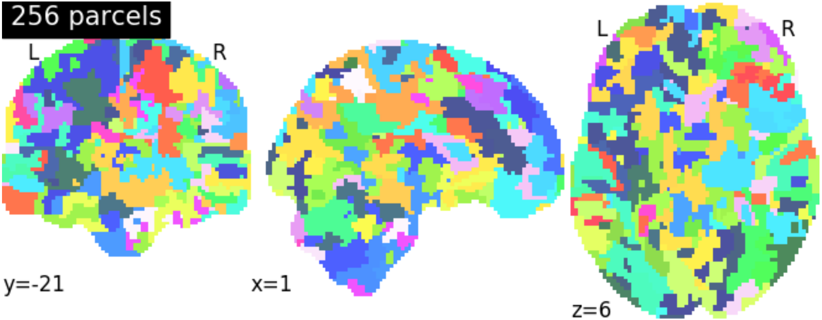
Subject-level model



task-evoked activations $\mathbf{Y}_s$

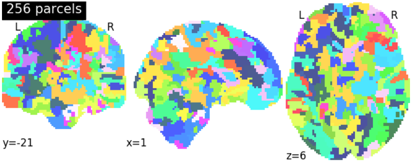
subject dictionary $\mathbf{D}_s$

Parcellations



- Fit a "small" linear model per parcel per subject
- Imposes spatial locality
- Piece-linear model

Learning algorithm



parallel for each parcellation $\mathcal{P}$ **do**
    parallel for each parcel $\mathcal{M} \in \mathcal{P}$ **do**
        parallel for each subjects s **do**
            Fit a model $\hat{f}_s$ for predicting $\mathbf{Y}_s$ from $\mathbf{D}_s$ restricted on the parcel $\mathcal{M}$
        end pararell for
    end pararell for
end pararell for

Prediction algorithm

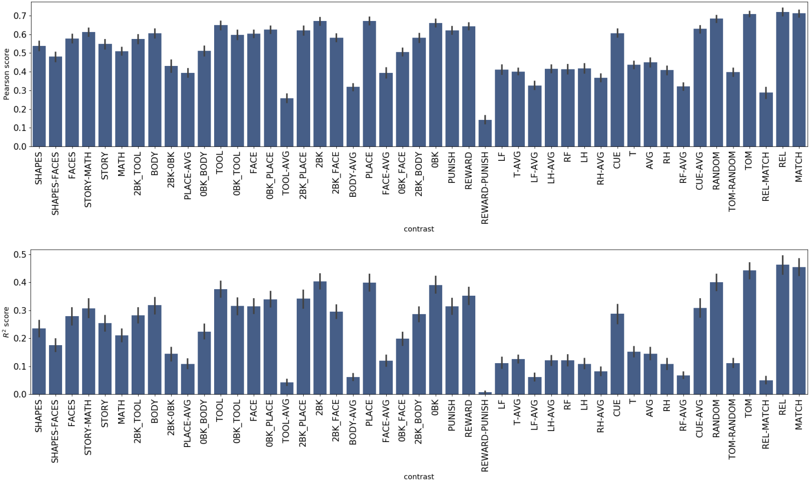
```
parallel for each parcellation 𝒫 do
    parallel for each parcel ℳ ∈ 𝒫 do
        f̂ ← bagged linear model for this parcel
        parallel for each test subject s do
            Predict Y_s via f̂_s:
```

$$\hat{\mathbf{Y}}_s|_{\mathcal{M}} \leftarrow \hat{\mathbf{Y}}_s|_{\mathcal{M}} + \underbrace{\hat{f}(\mathbf{D}_s|_{\mathcal{M}})}_{\text{contribution of parcellation } \mathcal{P}}$$

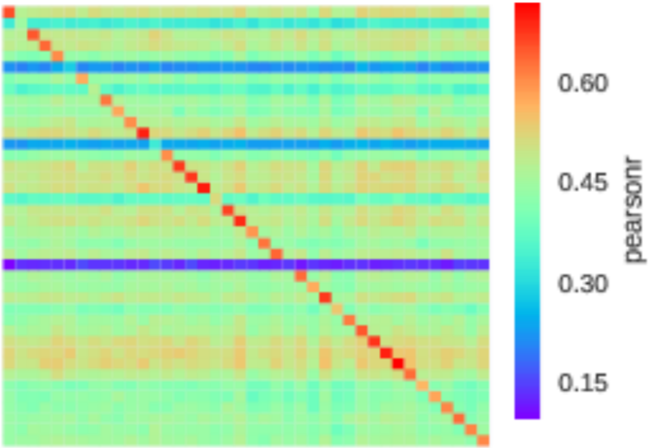
```
        end pararell for
    end pararell for
end pararell for
```

Results

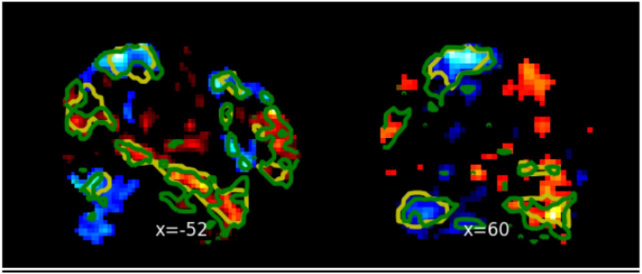
Prediction accuracy



Prediction accuracy: confusion matrices

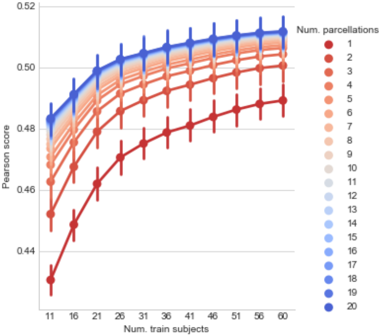


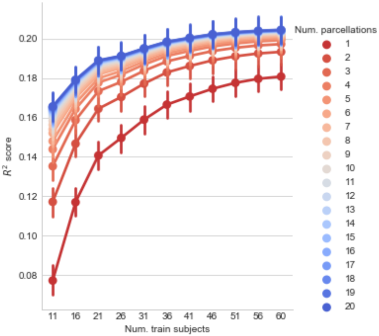
Predicted typographies



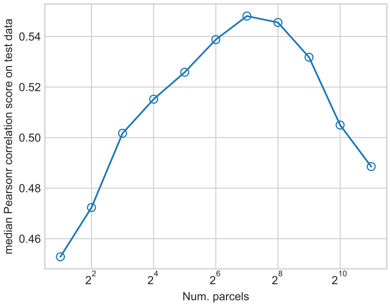
- predicted
- group mean

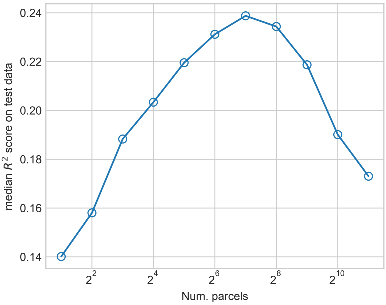
Using multiple parcellations improves sample-complexity





Number of parcels transparently controls model complexity



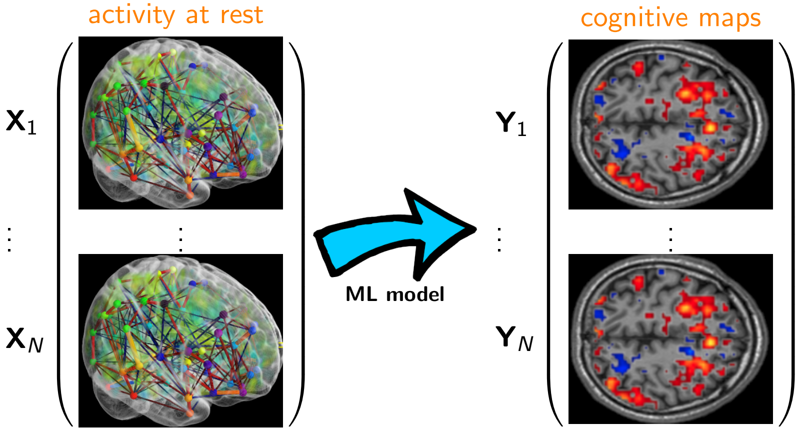


Concluding remarks

Perspective: using deep-learning

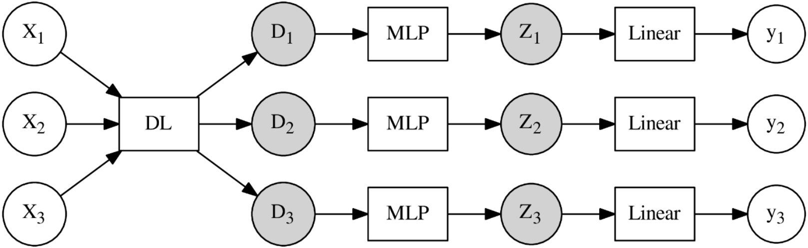
- rsfmri predicts task-evoked activity

Can we predict task maps from resting-state data ?



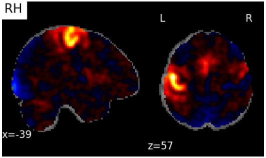
- $\mathbf{X}_s$: resting-state functional connectivity graph for subject s

Proposal: Deep semi-supervised voxel encoding

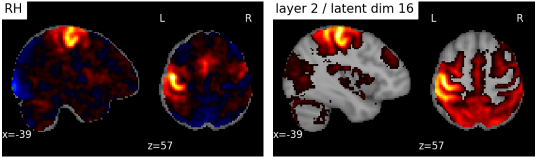


- $\mathbf{Y} \in \mathbb{R}^{p \times C}$: subject-specific GLM maps of brain activity
- $\mathbf{X} \in \mathbb{R}^{p \times T}$: resting-state fMRI data

Preliminary results: learned features



Preliminary results: learned features



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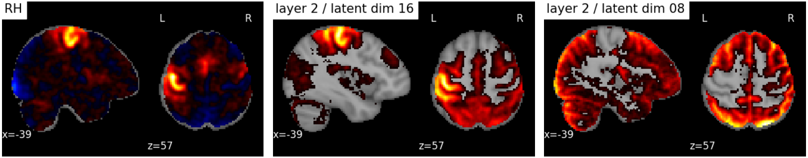

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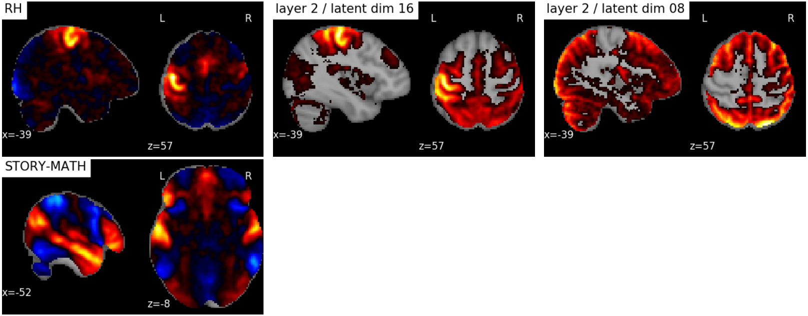

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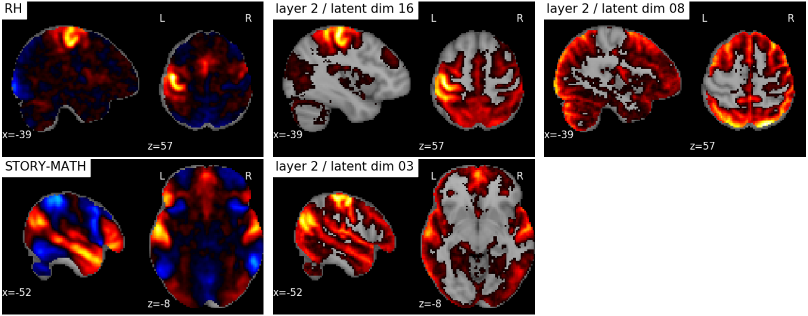

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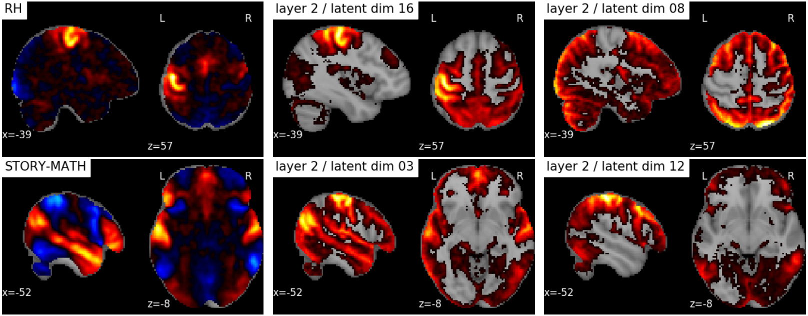

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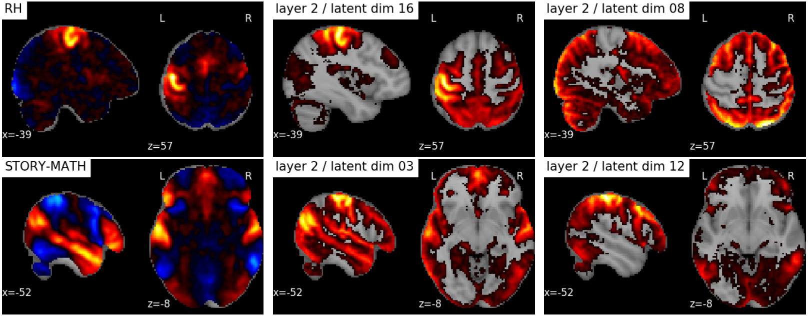
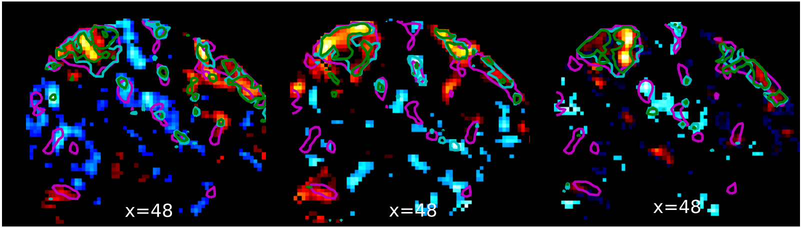


- Learned the a presentation of task activity in resting-state space!
- This is ongoing application of models developed in previous sections!

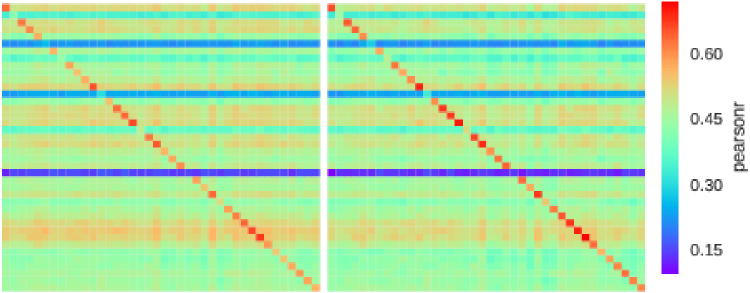
Preliminary results: predicted individual maps



2BK vs 0BK contrast of the Working Memory task
[van Essen '12]

- magenta = population mean
- reference method [Tavor '16]
- proposed method
  - Prediction agrees with subject's topography more faithfully

Preliminary results: quantitative



Confusion matrix for predicted versus true activation maps

Relevant contributions I