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A Self-Supervised voxel shuffling framework for Kernel-Based fMRI activation detection

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Statement

- We declare that there is no conflict of interest.
- The data used in this paper comes from Human Connectome Project projects (HCP) [1] and our in-house scans [2].
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[1] Barch, D., et al. Neuroimage, 80, 169-189. (2013)
[2] Jin, M., et al. Magnetic Resonance Imaging, 30(4), pp.459-470. (2012)

Background

Complexity

Size	Linear	Nonlinear	Deep learning
Voxel	General linear model with Gaussian smoothing [3], Local CCA [4, 5]	Local CCA + Constraints [6],	Deep CCA [7]
Whole Brain	Linear KCCA [8, 9]	Nonlinear KCCA [10]	

[3] Friman, O., et al., NeuroImage 19.3 837-845. (2003)
[4] Friman, O., et al., Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 45(2), pp.323-330. (2001)
[5] Cordes, D., et al., Human brain mapping, 33(11), pp.2611-2626. (2012)
[6] Zhuang, X., et al., NeuroImage, 149, pp.63-84. (2017)
[7] Zhengshi, Y., et al., (Accepted)
[8] Hardoon, D.R., et al., Neural computation, 16(12), pp.2639-2664. (2004)
[9] Yang, Z., et al., NeuroImage, 169, pp.240-255. (2018)
[10] Chendi, H., et al., ISMRM (2024)

Nonlinear KCCA

➢ Data processing pipeline

$$\mathbf{Y} \in \Re^{T\times Q} \rightarrow \tilde{\mathbf{Y}} = \mathbf{YA} \rightarrow K_{\mathbf{Y}}$$

fMRI data

$$\max_{\mathbf{v_Y},\mathbf{v_X}} \frac{\mathbf{v}_{\mathbf{Y}}^T K_{\mathbf{Y}} K_{\mathbf{X}} \mathbf{v_X}}{\sqrt{\mathbf{v}_{\mathbf{Y}}^T (K_{\mathbf{Y}}^2 + \gamma K_{\mathbf{Y}}) \mathbf{v_Y}} \sqrt{\mathbf{v}_{\mathbf{X}}^T (K_{\mathbf{X}}^2 + \gamma K_{\mathbf{X}}) \mathbf{v_X}}}$$

$$s = \mathrm{sign}\left[\mathrm{corr}(\mathbf{X}_{\mathrm{eff}}, K_{\mathbf{Y}} \mathbf{v_Y})\right]$$

$$\mathbf{X} \in \Re^{T\times D} \rightarrow \mathbf{X}_{\mathrm{eff}} \rightarrow K_{\mathbf{X}} = \mathbf{X}_{\mathrm{eff}} \mathbf{X}_{\mathrm{eff}}^T$$

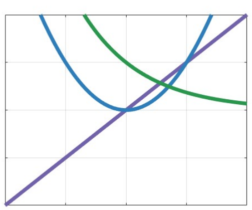
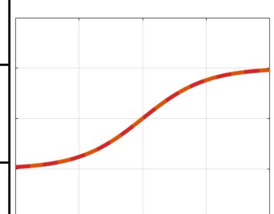
Design signal

$$\rightarrow \boldsymbol{\alpha} = s \mathbf{A} \tilde{\mathbf{Y}}^T \left(\tilde{\mathbf{Y}} \tilde{\mathbf{Y}}^T\right)^{\dagger} K_{\mathbf{Y}} \mathbf{v_Y}$$

$$\boldsymbol{\alpha} = s \sum_t \frac{\partial \left(K_{\mathbf{Y}} \mathbf{v_Y}\right)_t}{\partial \mathbf{Y}_t}$$

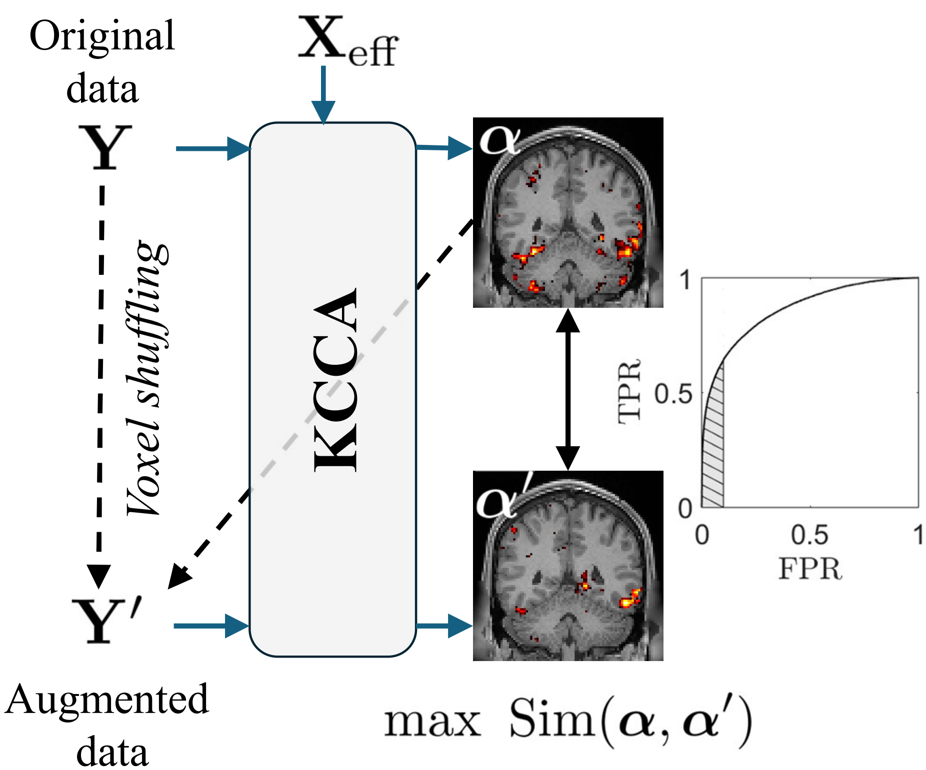
Activation pattern

➢ Kernel selection

	Kernel name	**Expression**		**Kernel name**	**Expression**
	Linear	$K_{\mathbf{Y}} = \mathbf{YY}^T$		Tanh	$K_{\mathbf{Y}} = \tanh(b\mathbf{YY}^T + c)$
	Parabolic	$K_{\mathbf{Y}} = (\mathbf{YY}^T + b^2)^2$		Mixed Tanh	$K_{\mathbf{Y}} = \tanh(b_1 \mathbf{YY}^T + b_2 \lVert \mathbf{Y} - \mathbf{Y}^T \rVert^2 + c)$
	Gaussian	$K_{\mathbf{Y}} = \exp\left(-\lVert \mathbf{Y} - \mathbf{Y}^T \rVert^2 / \sigma^2\right)$			

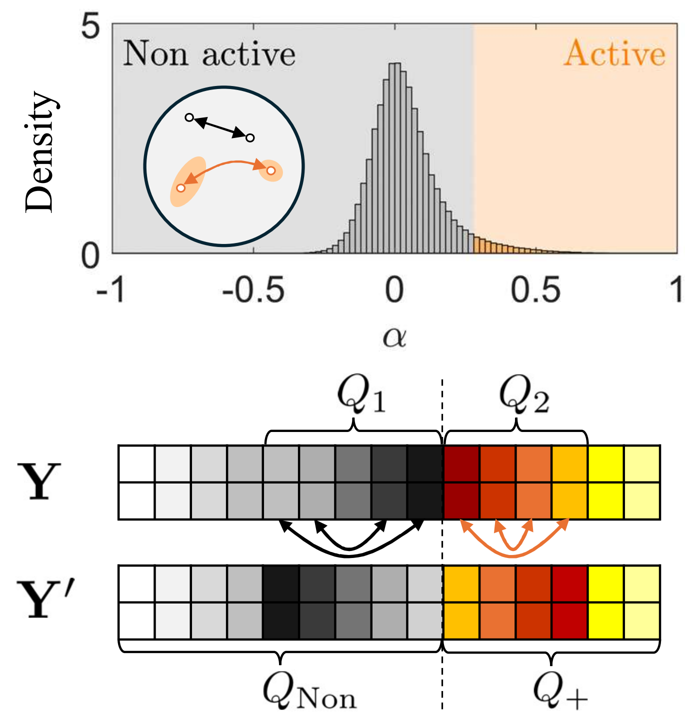
Self-supervised learning

- Similarity comparison [11]



[11] Chen, T., et al., International conference on machine learning (pp. 1597-1607). PmLR. (2020)

- Voxel shuffling



Shuffling 1	$Q_1 = Q_2 = 0.5Q_+$
Shuffling 2	$Q_1 = Q_{\text{Non}},\ Q_2 = Q_+$

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Self-supervised learning

- Objective function

$$\max_{\text{Unkonwn parameters}} \text{Robustness} = \text{AUC}_{\text{FPR}<0.1}(\text{Shuffling 1}) + \text{AUC}_{\text{FPR}<0.1}(\text{Shuffling 2})$$

- Testing (Simulated fMRI)

FPR: Activated voxel not on ground truth
TPR: Activated voxel on ground truth

- Testing (Task fMRI)

FPR: Activated voxel not on gray matter
TPR: Activated voxel on gray matter

- Assumption

High shuffling robustness $\longleftrightarrow$ **Accurate activation pattern**

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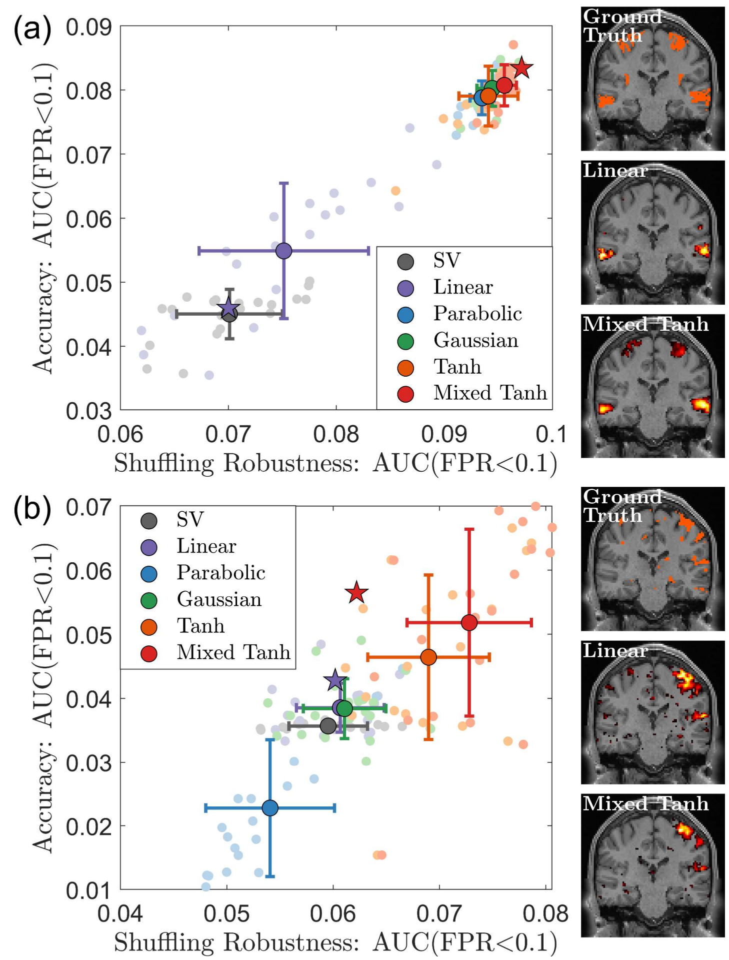
Results (simulated-fMRI)

Simulation (a):
Number of subjects: 20
Activated regions: Anterior cingulate, precentral gyrus, inferior frontal, insula, mid frontal and mid temporal

Simulation (b):
Number of subjects: 20
Activated regions: voxels with the top 10% highest correlations to the design signal



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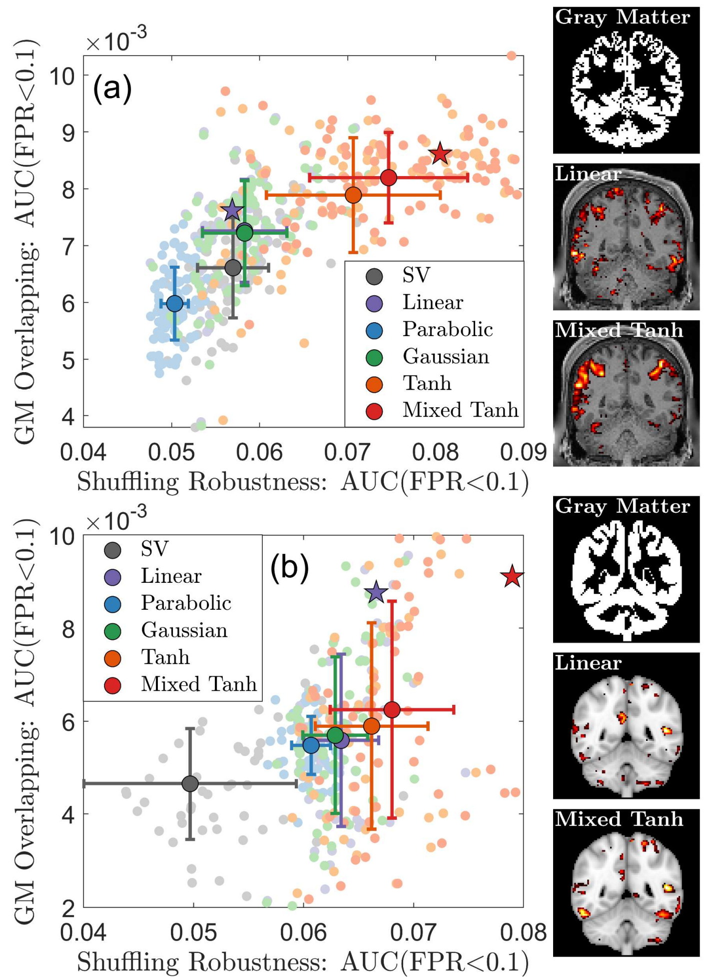
Results (task-fMRI)

Task fMRI (a):
Name: HCP
Number of subjects: 87
Contrasts: Targets minus non-targets

Task fMRI (b):
Name: In-house scans
Number of subjects: 64
Contrasts: Encoding minus control/
Recognition minus control



Summary

Previously hyperparameter optimization algorithm

- Resting state (Linear KCCA)
- Activation overlays on gray matter (Deep CCA)

Our results

- Self-supervised learning framework to optimize hyperparameters in nonlinear KCCA

Thanks for your attention !