A Self-Supervised Voxel Shuffling Framework for Kernel-Based fMRI activation detection

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Introduction

Kernel-based methods are powerful for dimension reduction in fMRI analysis. Previous methods used supervised optimization [1] or an additional dataset serving as negative pairs [2] to determine the unknown kernel mapping, which is less efficient and hard to expand to real datasets when there is no ground truth. Inspired by self-supervised learning in image processing [3], we propose a data augmentation method that could generate supervisory examples by voxel shuffling. By maximizing the similarity before and after augmentation, we show our method could reduce overfitting and increase accuracy even for complicated kernels. The results are validated using real fMRI datasets from two different sources for the activation detection problem.

Nonlinear Kernel Canonical Correlation Analysis (KCCA)

➢ Processing [4]

Voxel specific activation

$$\mathbf{Y}\in\Re^{T\times Q} \longrightarrow \tilde{\mathbf{Y}}=\mathbf{YA} \longrightarrow K_{\mathbf{Y}} \longrightarrow K_{\mathbf{Y}}\mathbf{v}_{\mathbf{Y}} \longrightarrow \boldsymbol{\alpha}=s\mathbf{A}\tilde{\mathbf{Y}}^T\left(\tilde{\mathbf{Y}}\tilde{\mathbf{Y}}^T\right)^{\dagger}K_{\mathbf{Y}}\mathbf{v}_{\mathbf{Y}}$$

fMRI data

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

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

A: spatial filter
Q: number of voxels
T: number of time points
D: number of design signals

$$\mathbf{X}\in\Re^{T\times D}\xrightarrow{[5]}\mathbf{X}_{\text{eff}}\longrightarrow K_{\mathbf{X}}=\mathbf{X}_{\text{eff}}\mathbf{X}_{\text{eff}}^T$$

Design signal

➢ Nonlinear kernels

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

Self-supervised voxel shuffling framework

➢ Assumption

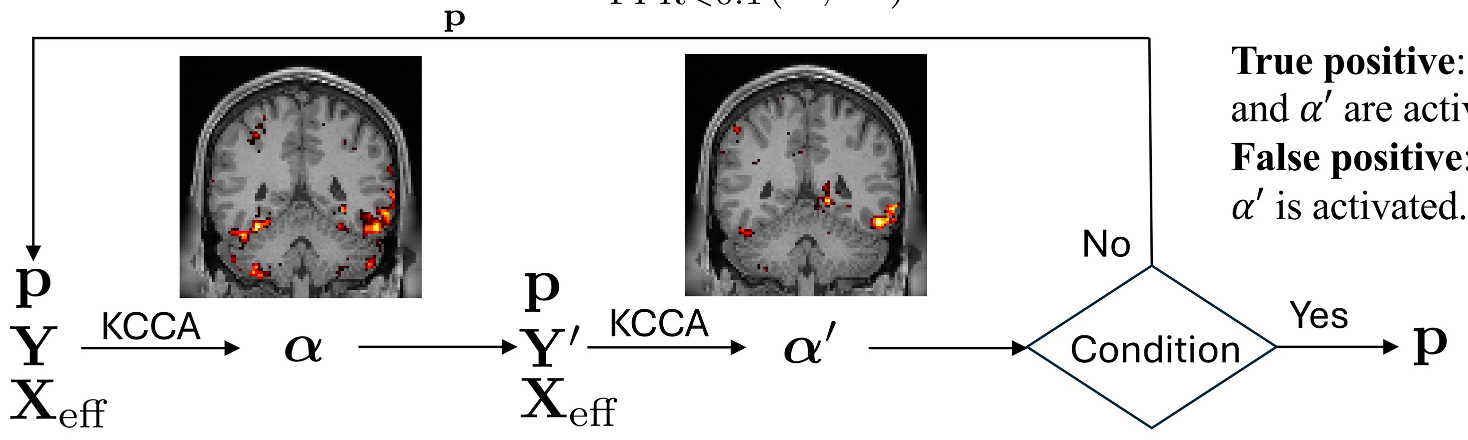
Isolated activated voxels are rare. A good method will try to maintain the prediction results even after the voxel location has changed

Shuffling robustness ⇔ **Accurate activation pattern**

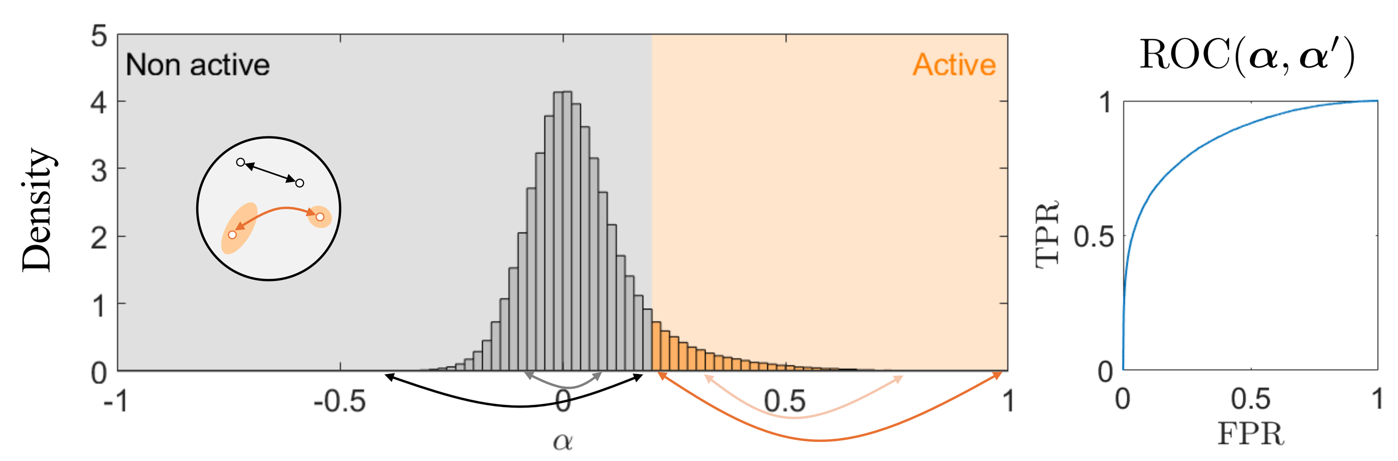
➢ Voxel shuffling

p: unknown hyperparameters for KCCA
$\boldsymbol{\alpha}$: Activation before shuffling
$\boldsymbol{\alpha}'$: Activation after shuffling

$$\max_{\mathbf{p}}\text{AUC}_{\text{FPR}<0.1}(\boldsymbol{\alpha},\boldsymbol{\alpha}')$$



True positive: Both α and α' are activated.
False positive: Only α' is activated.



Shuffling rule

- 10% of voxels with higher α values are activated, others are nonactivated
- Select Q1 voxels in the nonactivated cluster, and Q2 voxels in the activated cluster
- Within Q1/Q2, we exchange the location between voxels with the **highest** α and **lowest** α, then between voxels with the second highest and second lowest α, and so on

➢ Shuffling robustness

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

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

Q_+: Total number of activated voxels
Q_{Non}: Total number of non-activated voxels

Dataset

➢ Simulation

Ground truth available

	Number of subjects	Noise	Activation regions	Metrics
Simulation 1	20	Resting state fMRI	6 AAL regions [6]	AUC with FPR<0.1
Simulation 2	20	Resting state fMRI	10% voxels with high correlation to design signal [5]	AUC with FPR<0.1

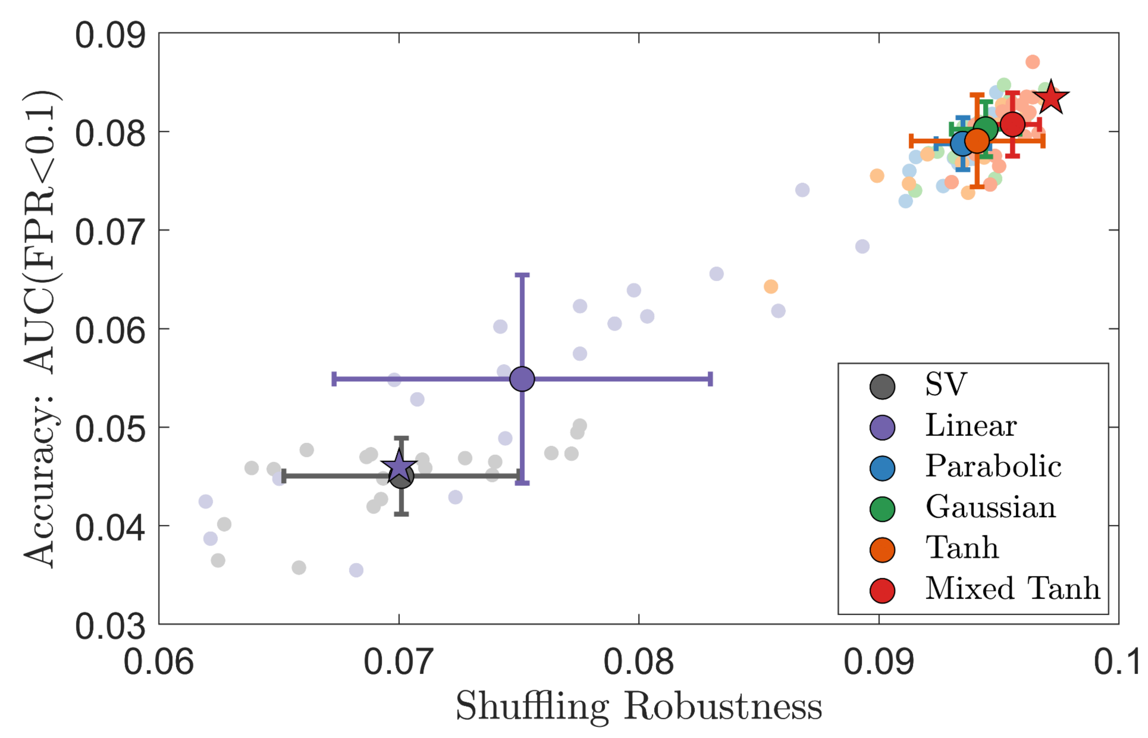
➢ Real fMRI

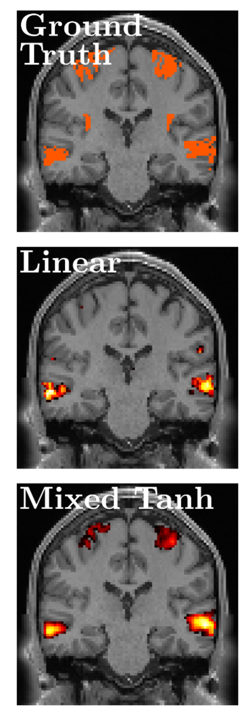
True positive: Activation appears in the Gray matter (GM).
False positive: Activation not in the Gray matter.

	Number of subjects	Task	Contrast	Metrics
HCP [7]	87	Working memory	Targets minus non-targets	AUC with FPR<0.1
In-house scan [8]	16	Episodic memory	Encoding minus control/ Recognition minus control	AUC with FPR<0.1

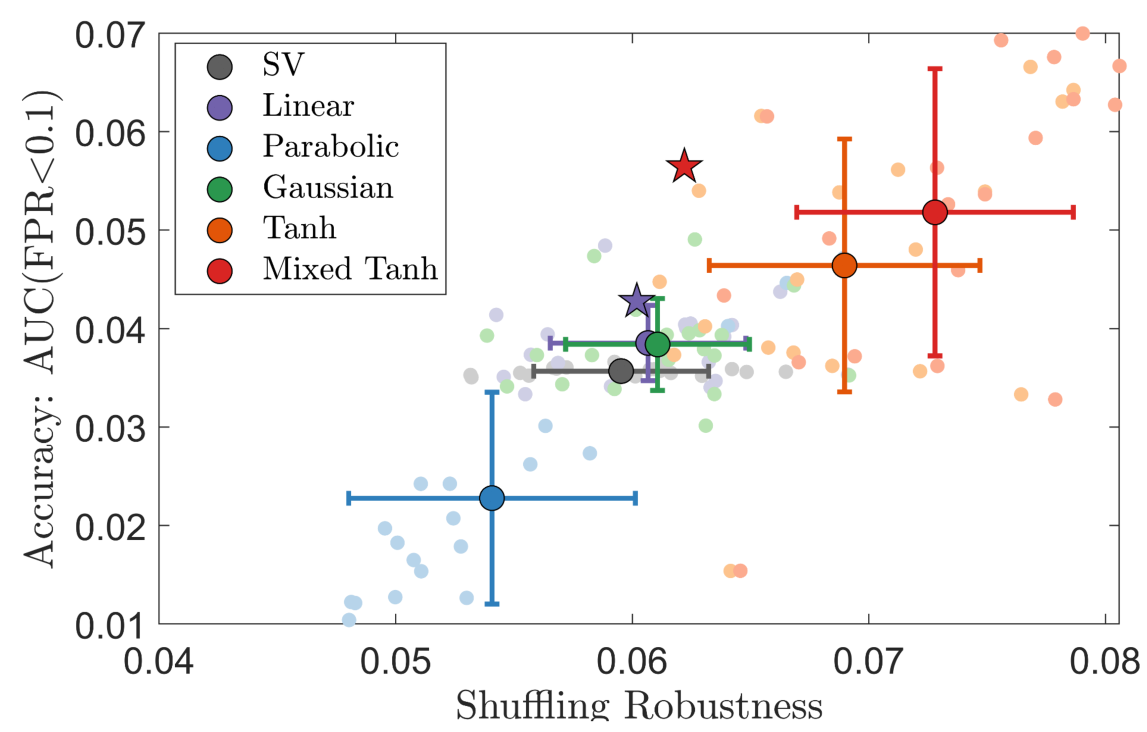
Result

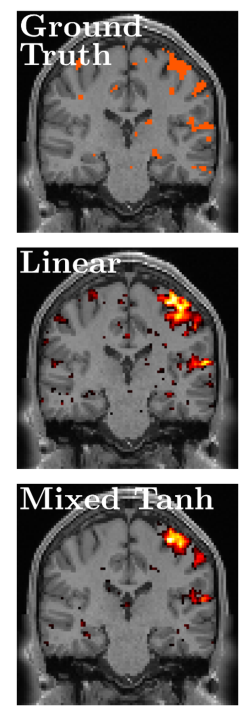
➢ Simulation 1



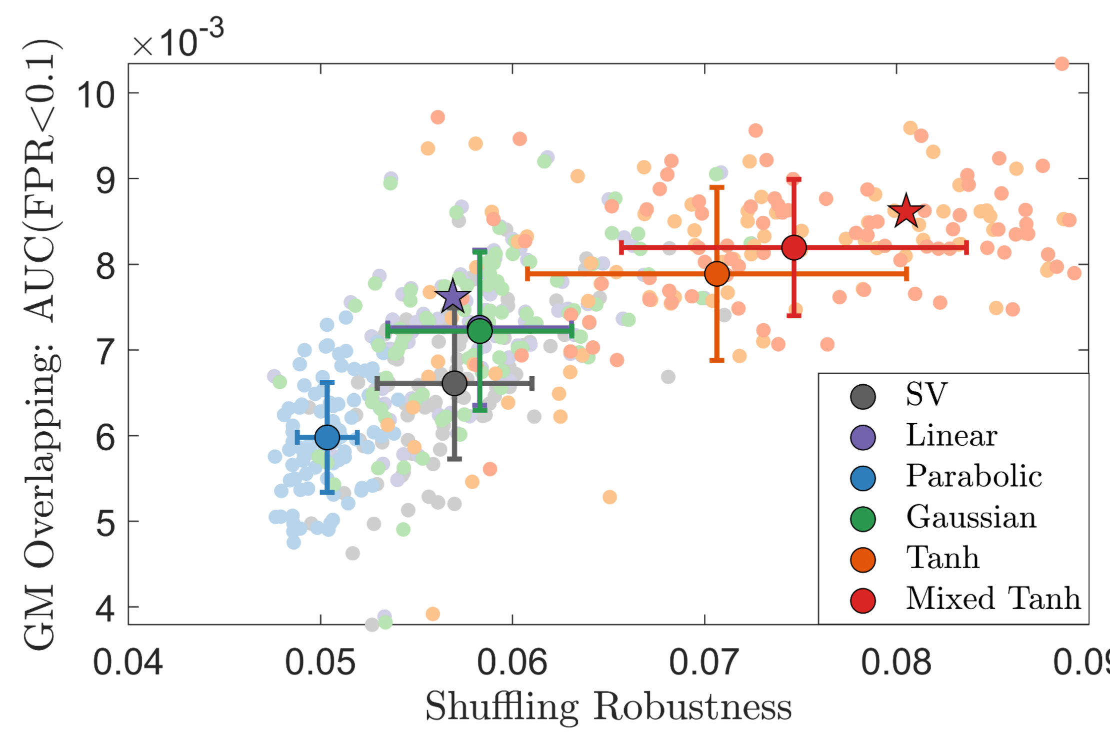


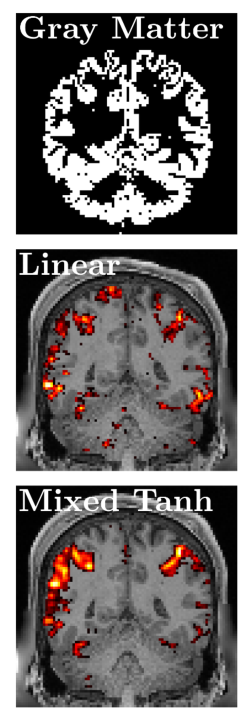
➢ Simulation 2



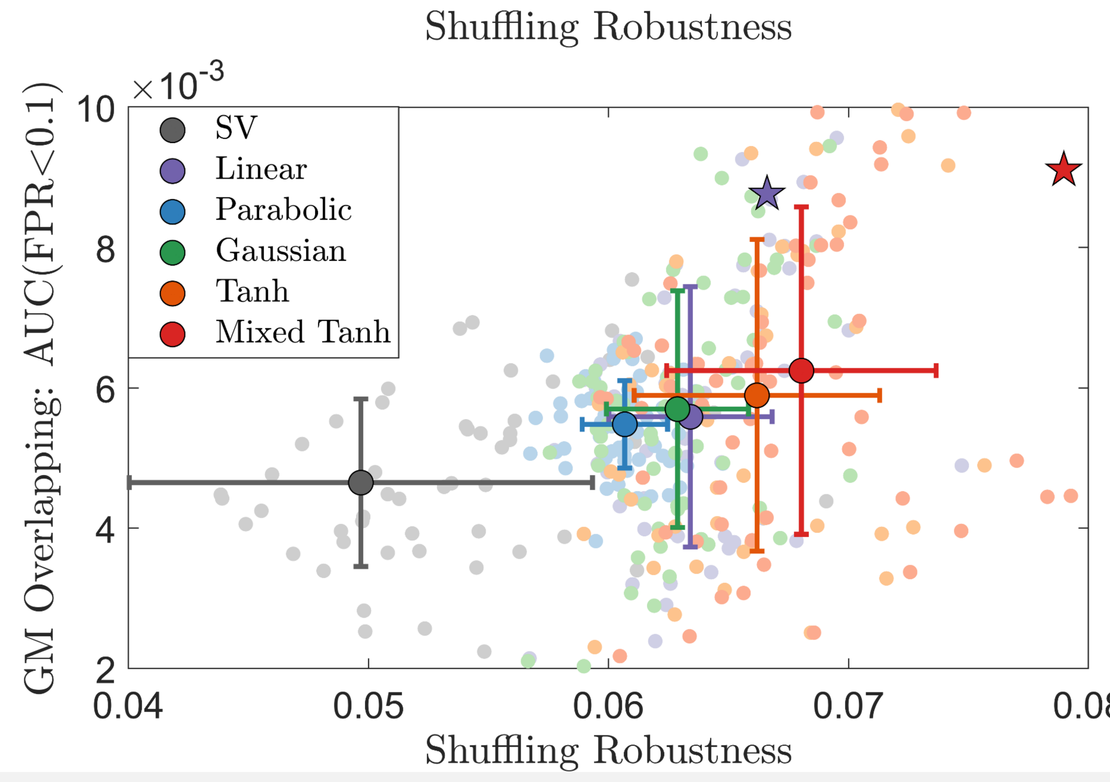


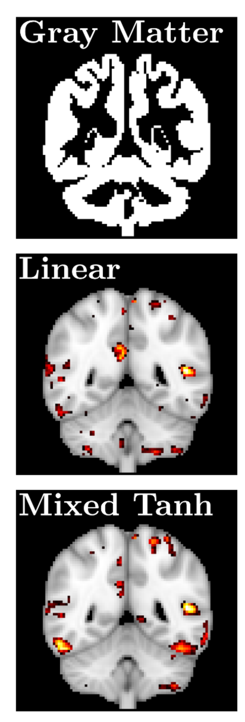
➢ HCP





➢ In-house scan





Acknowledge

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Reference

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