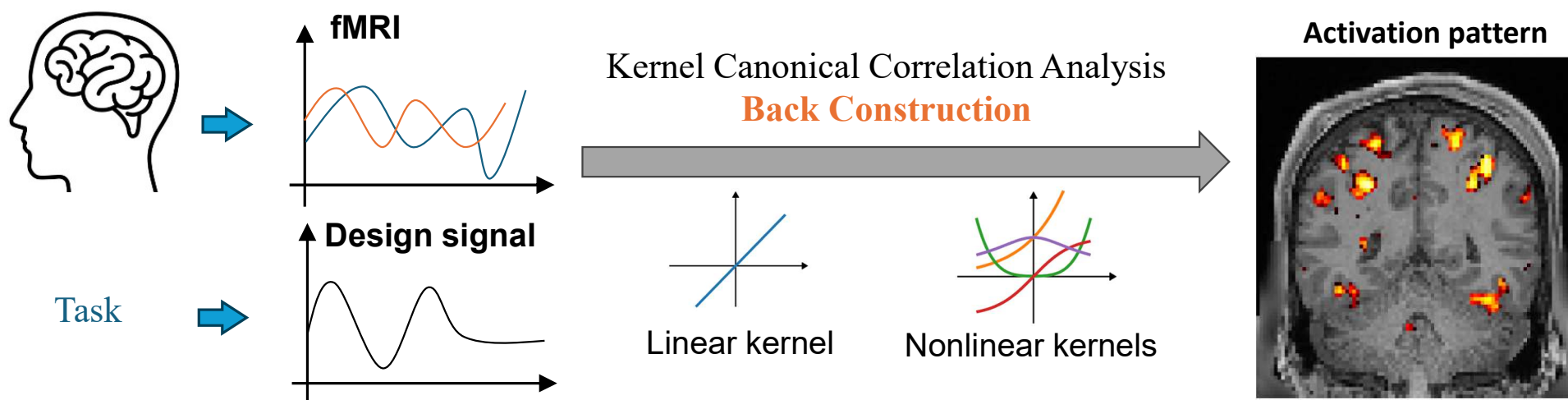


Nonlinear kernel-based fMRI activation detection

Chendi Han

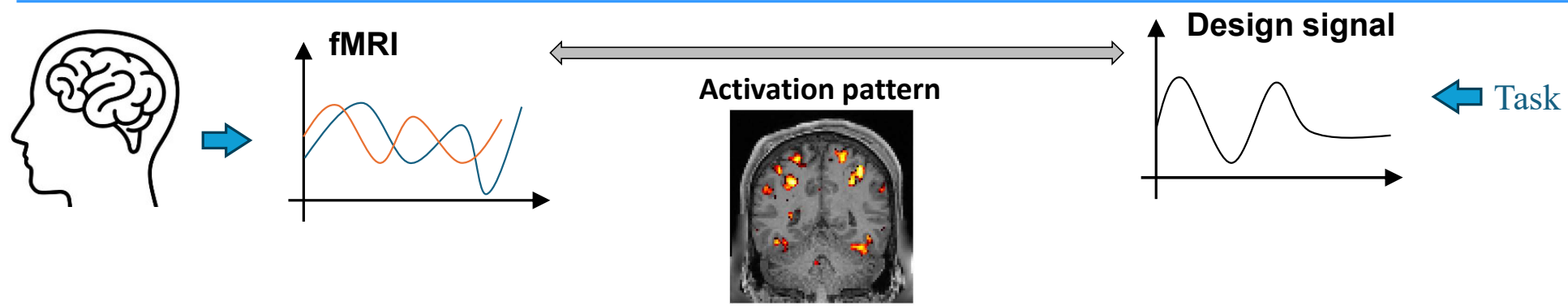
Cleveland Clinic Lou Ruvo Center for Brain Health,
Las Vegas, Nevada, USA



- We declare that there is no conflict of interest.
- The data used in this paper comes from Human Connectome Project projects (HCP) [1]. All the data are publicly accessible, and patients' information is protected.
- This work was funded by NIH-R01AG071566-02 and NIH-P20GM109025-08

1. Barch, D., et al. Neuroimage, 80, 169-189. (2013)

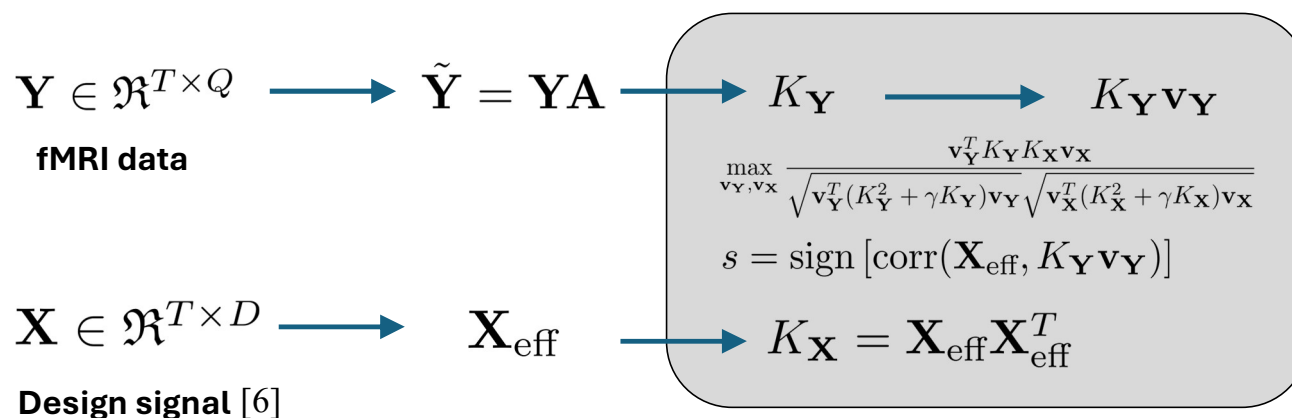
Background



	Multi variable	Global method	Nonlinear relationship
Single voxel smoothing [2]	No	No	No
Canonical Correlation Analysis (CCA) [3]	Yes	No	Nonlinear constraints [4]
Linear Kernel Canonical Correlation Analysis (KCCA) [5]	Yes	Yes	No
Nonlinear KCCA	Yes	Yes	Nonlinear kernels

2. Friman, O., et al. NeuroImage, 19(3), 837-845. (2003)
3. Friman, O., et al. Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 45(2) 323-330. (2001)
4. Xiaowei, Z., et al. NeuroImage, 149, 63-84. (2017)
5. Hardoon, D., et al. Neural computation, 16(12), 2639-2664. (2004)

Step 1: Back construction Algorithm



Voxel specific activation

$$\alpha \in \mathbb{R}^{Q \times 1}$$

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

➤ Assumption

$$\mathbf{Y}\alpha \equiv K_{\mathbf{Y}}\mathbf{v}_{\mathbf{Y}}$$

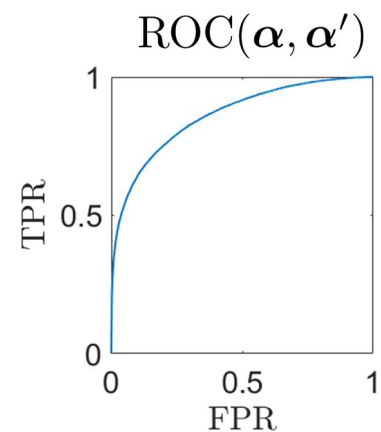
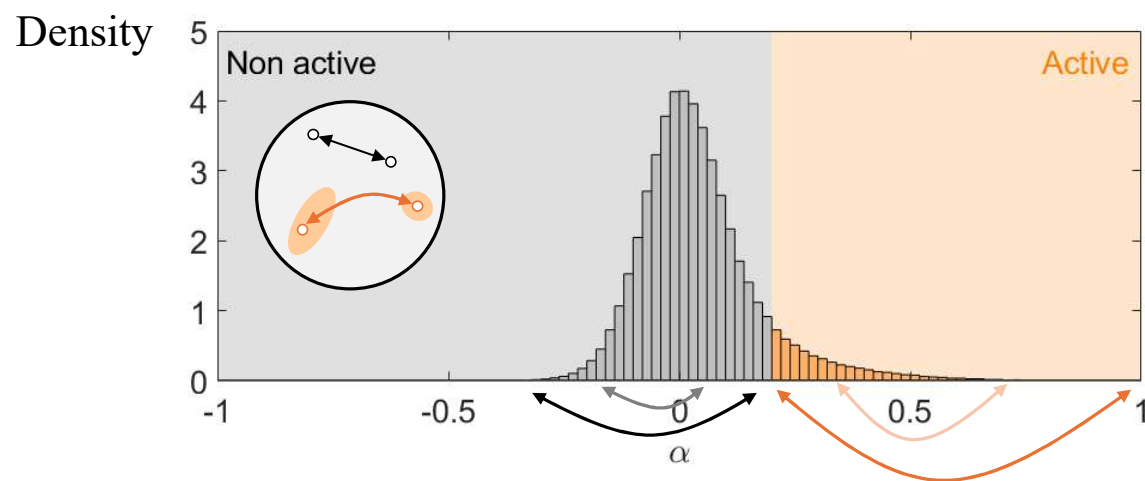
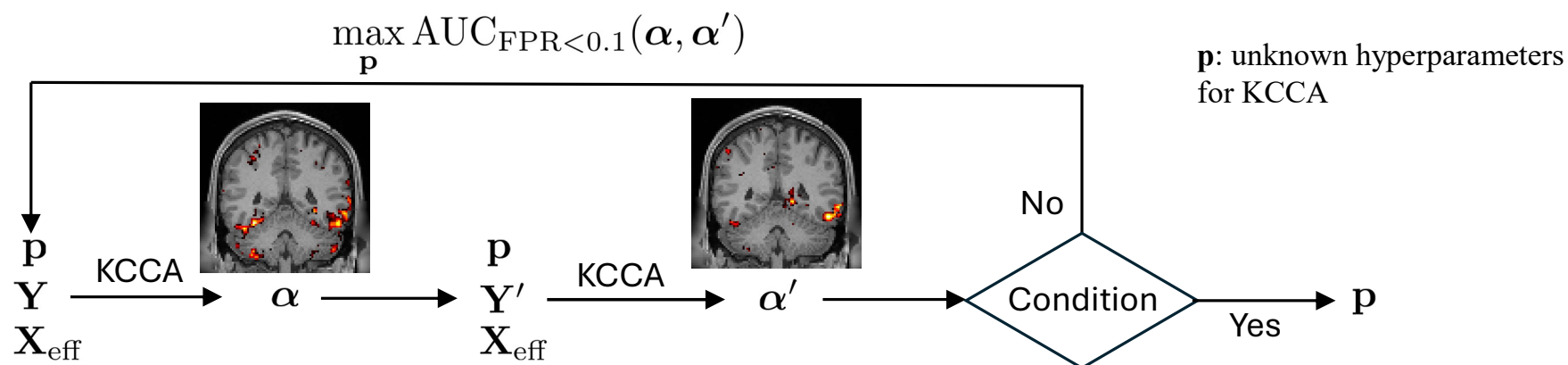
Back construction 1:
$$\alpha = s \sum_t \frac{\partial (K_{\mathbf{Y}}\mathbf{v}_{\mathbf{Y}})_t}{\partial \mathbf{Y}_t}$$

Back construction 2:
$$\alpha = s \mathbf{A} \tilde{\mathbf{Y}}^T \left(\tilde{\mathbf{Y}} \tilde{\mathbf{Y}}^T \right)^\dagger K_{\mathbf{Y}}\mathbf{v}_{\mathbf{Y}}$$

6. Cordes, D., et al. **33**: p. 2611-2626. (2012)

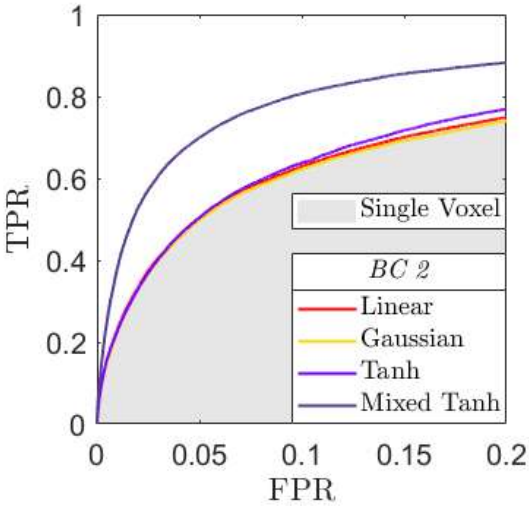
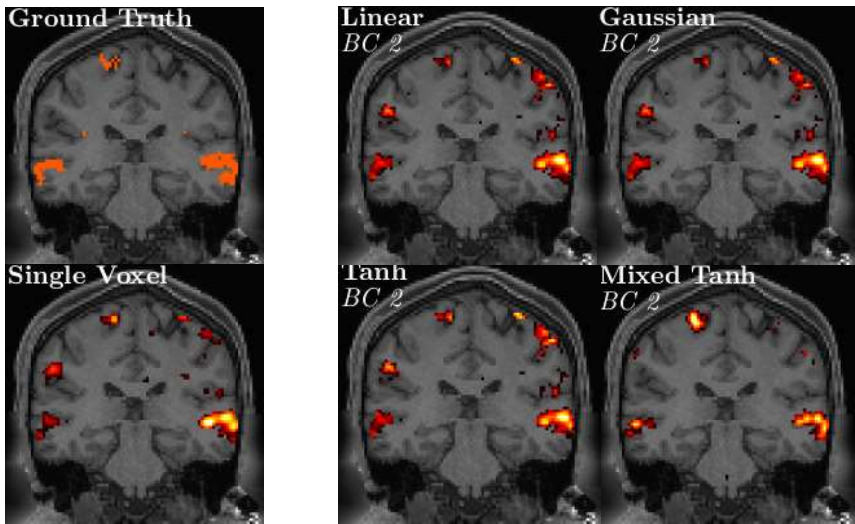
Name	Expression	Number of hyperparameters
Linear	$K_{\mathbf{Y}} = \tilde{\mathbf{Y}}\tilde{\mathbf{Y}}^T$	1
Parabolic	$K_{\mathbf{Y}} = (\tilde{\mathbf{Y}}\tilde{\mathbf{Y}}^T + b^2)^2$	2
Gaussian	$K_{\mathbf{Y}} = \exp\left(-\ \tilde{\mathbf{Y}} - \tilde{\mathbf{Y}}^T\ /\sigma^2\right)$	2
Inverse square	$K_{\mathbf{Y}} = 1/\sqrt{\ \tilde{\mathbf{Y}} - \tilde{\mathbf{Y}}^T\ + b^2}$	2
Bounded Linear	$K_{\mathbf{Y}} = \min\left(C, \tilde{\mathbf{Y}}\tilde{\mathbf{Y}}^T\right)$	2
Square	$K_{\mathbf{Y}} = \ \tilde{\mathbf{Y}} - \tilde{\mathbf{Y}}^T\ $	1
Tanh	$K_{\mathbf{Y}} = \tanh\left(b\tilde{\mathbf{Y}}\tilde{\mathbf{Y}}^T + c\right)$	3
Mixed Tanh	$K_{\mathbf{Y}} = \tanh\left(b_1\tilde{\mathbf{Y}}\tilde{\mathbf{Y}}^T + b_2\ \tilde{\mathbf{Y}} - \tilde{\mathbf{Y}}^T\ + c\right)$	4

Step 3: Hyperparameters optimization



True positive: Both α and α' are activated.

False positive: Only α' is activated.



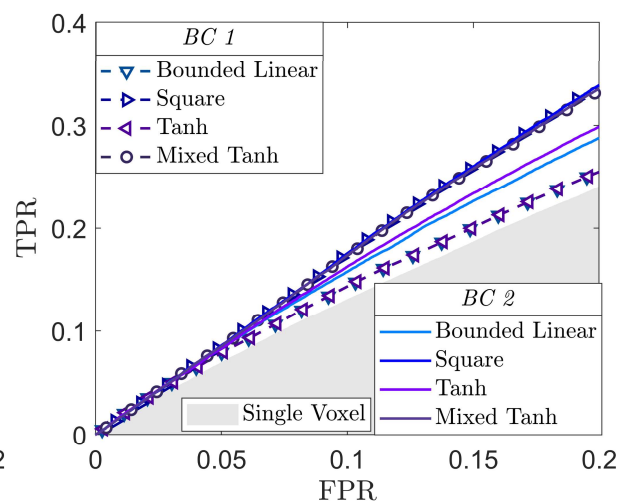
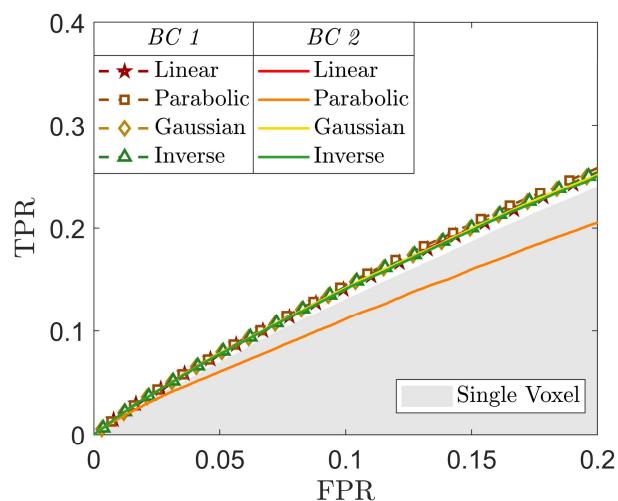
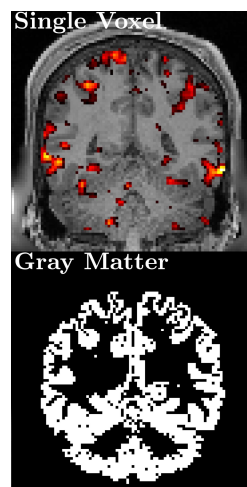
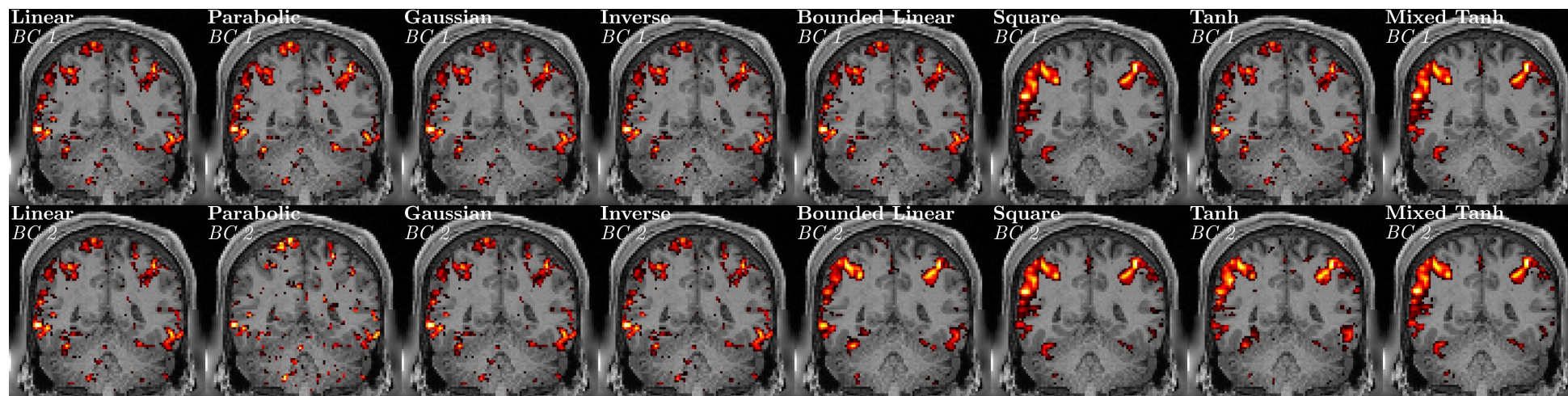
➤ Group level study for *BC2*

$$r = \frac{\text{AUC}_{\text{FPR} < 0.1}(\text{KCCA})}{\text{AUC}_{\text{FPR} < 0.1}(\text{Single Voxel Smoothing})}$$

Mean and standard deviation for 87 subjects

Linear	1.12 ± 0.27	Bounded Linear	1.39 ± 0.37
Parabolic	1.09 ± 0.31	Square	0.99 ± 0.40
Gaussian	1.21 ± 0.27	Tanh	1.39 ± 0.37
Inverse	1.14 ± 0.30	Mixed Tanh	1.42 ± 0.36

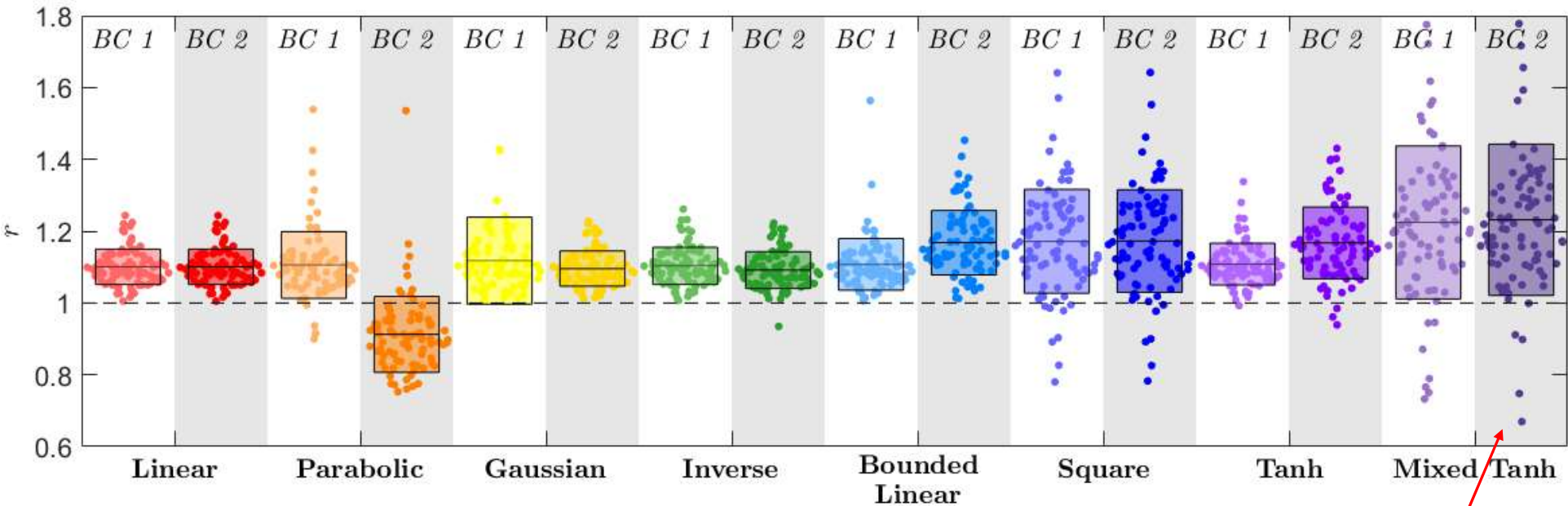
[7] Yang, Z., et al. Medical Image Analysis, **60**, 101622. (2020)



True positive: Activation appears on the Gray matter.
False positive: Activation not on the Gray matter.

$$r = \frac{\text{AUC}_{\text{FPR} < 0.1}(\text{KCCA})}{\text{AUC}_{\text{FPR} < 0.1}(\text{Single Voxel Smoothing})}$$

Mean and standard deviation for 87 subjects



23% improvement

Previously results

- Linear kernel based KCCA for fMRI activation detection.

Our results

- New proposed back construction algorithm work for general type of nonlinear kernels.
- Mixed Tanh under BC2 gives the best performance.

Thanks for your attention !