

# pARI PACKAGE: VALID DOUBLE-DIPPING VIA PERMUTATION-BASED ALL RESOLUTIONS INFERENCE

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fMRI measures brain activation as changes in blood flow (BOLD) under a sequence of stimuli.

### Cluster-wise method:

- Analyze set of contiguous voxels ( $S$ );
- $H_S$  rejected means that  $S$  contains at least one active voxel  
→ We don't know which ones and how many!!
- **Spatial specificity paradox;**
- **Double-dipping.**

**Solution:** All-resolutions inference (ARI) <sup>1</sup> → Inference on the number of truly active voxels.

- **pARI** is the Permutation-based version of **ARI**. The permutation structure permits to account for the correlation structure between tests unlike **ARI**;
- Both methods are based on the **closed testing procedure** for controlling the familywise error rate.

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<sup>1</sup>Resenblatt, J. et al. (2018).

Every time that we want to infer inside a **data-driven (and not) cluster** (features set), we can use **ARI/pARI**:

- **Cluster fMRI data analysis** <sup>2</sup>;
- **Gene expression cluster analysis** <sup>3</sup>;
- **Cluster EEG data analysis** <sup>4</sup>.

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<sup>2</sup>Woo, C. et al. (2014).

<sup>3</sup>Berge, K. et al. (2017).

<sup>4</sup>Maris, E. et al. (2007).

```
devtools::install_github(angeella/pARI)
library(pARI)
```

- fMRI framework:

```
pARIbrain(copes, thr, mask, alpha, ...)
```

where `copes` is a list of **contrast** parameter estimates involving brain activation differences for each subject in NIfTI format.

- General framework:

```
pARI(data, ix, alpha, test.type, ...)
```

where `ix` is the **features set** of interest. It can be a vector of indices or a vector with length equals the number of features where different values indicate the different sets.

We analyzed the **Auditory data** collected by Pernet et al. (2015), i.e, people listening vocal and non-vocal sounds.

Group analysis on 140 subjects of the Vocal > Non-vocal **contrast** by the one sample t-test flipping the sign of 140 voxel-wise contrasts maps.

First, let download the data from the fMRIdata package:

```
devtools::install_github(angeella/fMRIdata)
library(fMRIdata)
data(Auditory_clusterTH3_2)
data(Auditory_copes)
data(Auditory_mask)
```

```
pARIbrain(copes = Auditory_copes,  
          cluster = Auditory_clusterTH3_2,  
          mask = Auditory_mask,  
          alpha = 0.05)
```

Cluster $S$	Threshold $t$	Size $ S $	% active $\bar{\pi}(S)$		P-Values $p_{FWER}$
			pARI	ARI	
Right STG/PT HG/IFG/T	3.2	11683	92.36%	84.98%	< 0.0001
Right STG/PT HG/IFG/T	4	8875	99.54%	98.5%	—
Right IFG	4	422	91.47%	83.18%	—
Right T	4	292	85.96%	64.04%	—
Right T	4	15	13.33%	0%	—




map\_TDP: Create **true discovery proportion map** in nifti format.




Thanks to the amazing group that worked on the paper  
*Permutation-based true discovery proportions for fMRI cluster analysis!* (in arXiv)

- Livio Finos University of Padua;
- Jelle Goeman Leiden University Medical Centre;
- Jesse Hemerik Wageningen University;
- Wouter Weeda Leiden University;

and thanks for your attention!

 [https://github.com/angeella/useR\\_2021](https://github.com/angeella/useR_2021)

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