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Equitable Thresholding and Clustering

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June 11th, 2018

NKI



Neural correlates of interspecies perspective taking in the post-mortem Atlantic Salmon: An argument for multiple comparisons correction

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INTRODUCTION

With the extreme dimensionality of functional neuroimaging data comes extreme risk for false positives. Across the 130,000 voxels in a typical fMRI volume the probability of a false positive is almost certain. Correction for multiple comparisons should be completed with these datasets, but is often ignored by investigators. To illustrate the magnitude of the problem we carried out a real experiment that demonstrates the danger of not correcting for chance properly.

METHODS

Subject. One mature Atlantic Salmon (*Salmo salar*) participated in the fMRI study. The salmon was approximately 18 inches long, weighed 3.8 lbs, and was not alive at the time of scanning.

Task. The task administered to the salmon involved completing an open-ended mentalizing task. The salmon was shown a series of photographs depicting human individuals in social situations with a specified emotional valence. The salmon was asked to determine what emotion the individual in the photo must have been experiencing.

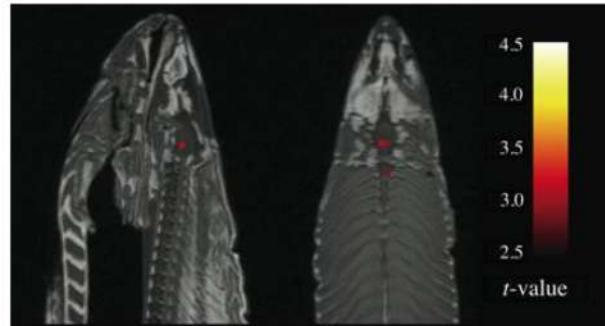
Design. Stimuli were presented in a block design with each photo presented for 10 seconds followed by 12 seconds of rest. A total of 15 photos were displayed. Total scan time was 5.5 minutes.

Preprocessing. Image processing was completed using SPM2. Preprocessing steps for the functional imaging data included a 6-parameter rigid-body affine realignment of the fMRI timeseries, coregistration of the data to a T_1 -weighted anatomical image, and 8 mm full-width at half-maximum (FWHM) Gaussian smoothing.

Analysis. Voxelwise statistics on the salmon data were calculated through an ordinary least-squares estimation of the general linear model (GLM). Predictors of the hemodynamic response were modeled by a boxcar function convolved with a canonical hemodynamic response. A temporal high pass filter of 128 seconds was included to account for low frequency drift. No autocorrelation correction was applied.

Voxel Selection. Two methods were used for the correction of multiple comparisons in the fMRI results. The first method controlled the overall false discovery rate (FDR) and was based on a method defined by Benjamini and Hochberg (1995). The second method controlled the overall familywise error rate (FWER) through the use of Gaussian random field theory. This was done using algorithms originally devised by Friston et al. (1994).

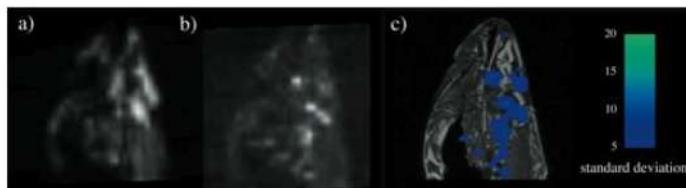
GLM RESULTS



A t -contrast was used to test for regions with significant BOLD signal change during the photo condition compared to rest. The parameters for this comparison were set to a cluster-forming threshold of $p < 0.05$.

Task. The task administered to the salmon involved completing an open-ended mentalizing task. The salmon was shown a series of photographs depicting human individuals in social situations with a specified emotional valence. The salmon was asked to determine what emotion the individual in the photo must have been experiencing.

VOXELWISE VARIABILITY



OHBM 2010

Ig Nobel Neuroscience
2012

And then in 2016, this paper came out...

PNAS



Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates

Anders Eklund^{a,b,c,1}, Thomas E. Nichols^{d,e}, and Hans Knutsson^{a,c}

^aDivision of Medical Informatics, Department of Biomedical Engineering, Linköping University, S-581 85 Linköping, Sweden; ^bDivision of Statistics and Machine Learning, Department of Computer and Information Science, Linköping University, S-581 83 Linköping, Sweden; ^cCenter for Medical Image Science and Visualization, Linköping University, S-581 83 Linköping, Sweden; ^dDepartment of Statistics, University of Warwick, Coventry CV4 7AL, United Kingdom; and ^eWMG, University of Warwick, Coventry CV4 7AL, United Kingdom

Edited by Emery N. Brown, Massachusetts General Hospital, Boston, MA, and approved May 17, 2016 (received for review February 12, 2016)

Which had the following statement in the Highlights section of the paper ...

“These results question the validity of some **40,000** fMRI studies
and may have a large impact on the interpretation of
neuroimaging results”

Which generated ...

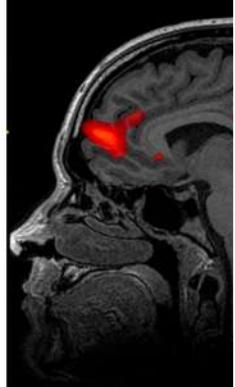


Technology

15 years of brain imaging studies invalidated by a bug found in fMRI software
Swedish scientists

Up to 70% of fMRI analyses may be invalidating the validity of

By Mary-Ann Russon
Updated July 13, 2016



Scientists claim to have found serious bugs in fMRI software



Yoshi Sodeoka

NEWS ANALYSIS

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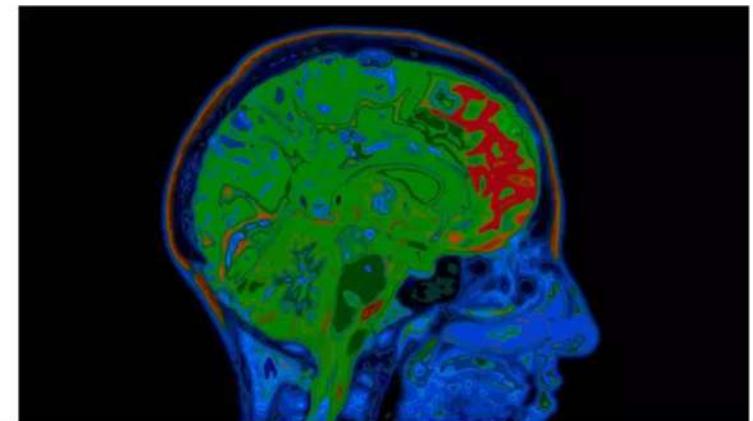
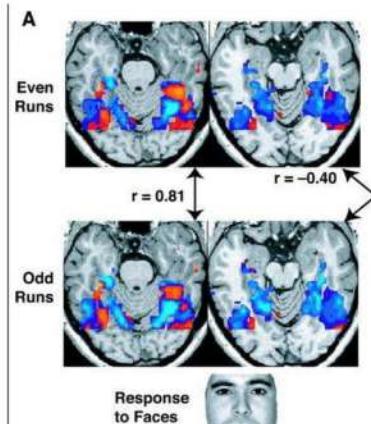
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Bug in fMRI software years of research in question

Popular pieces of software for fMRI were found to contain a bug that could affect up to 70%



By EMILY REYNOLDS



And in the Scientific community...

Reevaluating “cluster inference” in nonparametric contrast

Daniel Kessler, Mike Angstadt, and Charles E. Nelson
PNAS April 25, 2017; 114 (17) E3372-E3373; published ahead of print April 10, 2017.
<https://doi.org/10.1073/pnas.1614502114>

This article has letters. Please see:
[Relationship between Letter and Replicability](#)
[Relationship between Research Article and Replicability](#)

Article

Figures & SI

In a substantial contribution to the field, we demonstrate that random field theory does not control error rates well, and that cluster inference does not control error rates well. This is particularly pronounced for lenient cluster-defining thresholds. We argue that RFT assumptions are the culprit for this behavior.

Article Author

To test the validity of statistical inference in fMRI studies for the first time, large-scale experiments were conducted using fMRI measurements to replicate previous results. The authors compare familywise error rates and type I error rates across different methods.

Controversy in functional mapping

Emery N. Brown and Marlene Fischl
PNAS April 25, 2017; 114 (17) E3368-E3369; published ahead of print April 10, 2017.
<https://doi.org/10.1073/pnas.1705515114>

This article has letters. Please see:
[Relationship between Letter and Replicability](#)
[Relationship between Research Article and Replicability](#)

Article Author

To test the validity of statistical inference in fMRI studies for the first time, large-scale experiments were conducted using fMRI measurements to replicate previous results. The authors compare familywise error rates and type I error rates across different methods.

fMRI clustering

Robert W. Cox, Gang Chen, Eklund et al.
PNAS April 25, 2017; 114 (17) E3370-E3371; published ahead of print April 10, 2017.
<https://doi.org/10.1073/pnas.161496>

This article has letters. Please see:
[Relationship between Letter and Replicability](#)
[Relationship between Research Article and Replicability](#)

Article Figure

Recently, Eklund et al. (1) argue that “the current state of fMRI analysis is unacceptable” (which we maintain), FSL, and SPM “are not appropriate for fMRI studies”; (ii) nonparametric methods are “not appropriate for fMRI studies”; (iii) a common flaw in fMRI studies is that the noise is Gaussian-shaped; and (iv) the use of parametric procedures contributed to producing “false positives” in fMRI studies.

HUMAN BRAIN MAPPING

Technical Report | Open Access 

Analysis of family-wise error rates in statistical parametric mapping using random field theory

Guillaume Flandin , Karl J. Friston

First published: 01 November 2017 | <https://doi.org/10.1002/hbm.23839> | Cited by: 2

[Read the full text >](#)

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Abstract

This technical report revisits the analysis of family-wise error rates in statistical parametric mapping—using random field theory—reported in (Eklund et al. [2015]: arXiv 1511.01863). Contrary to the understandable spin that these sorts of analyses attract, a review of their results suggests that they endorse the use of parametric assumptions—such as Gaussian noise—and random field theory—in the analysis of functional neuroimaging data. We briefly rehearse the advantages parametric analyses offer over nonparametric alternatives and then unpack the implications of (Eklund et al. [2015]: arXiv 1511.01863) for parametric procedures. *Hum Brain Mapp*, 2017. © 2017 The Authors Human Brain Mapping Published by Wiley Periodicals, Inc.

Later the Highlights where changed...

From:

“These results question the validity of some 40,000 fMRI studies and may have a large impact on the interpretation of neuroimaging results”

To:

“These results question the validity of a number of fMRI studies and may have a large impact on the interpretation of weakly significant neuroimaging results.”

FMRI Clustering in AFNI: False-Positive Rates Redux

Cox Robert W., Chen Gang, Glen Daniel R., Reynolds Richard C., and Taylor Paul A.

Published Online: 1 Apr 2017 | <https://doi.org/10.1089/brain.2016.0475>

Tools Share

Abstract

Abstract Recent reports of inflated false-positive rates (FPRs) in FMRI group analysis tools by Eklund and associates in 2016 have become a large topic within (and outside) neuroimaging. They concluded that existing parametric methods “allow clusters to form in up to 70%,” mainly due to the fact that they are “unconstrained by a spatially shaped and stationary,” contrast. In response, we argue that nonparametric methods, such as permutation tests, can control FPRs at the cluster level. We show that AFNI showed “particular care” in controlling FPRs, and that AFNI’s results were consistent with those from other software packages. We conclude that the reported inflated FPRs are likely artifacts of the statistical models used in the analysis.

[arXiv.org > stat > arXiv:1709.07471](https://arxiv.org/abs/1709.07471)

Statistics > Applications

Stability of Spatial Smoothness and Cluster-Size Threshold Estimates in FMRI using AFNI

Robert W Cox, Paul A Taylor

(Submitted on 21 Sep 2017)

In a recent analysis of FMRI datasets [K Mueller et al, *Front Hum Neurosci* 11:345], the estimated spatial smoothness parameters and the statistical significance of clusters were found to depend strongly on the resampled voxel size (for the same data, over a range of 1 to 3 mm) in one popular FMRI analysis software package (SPM12). High sensitivity of thresholding results on such an arbitrary parameter as final spatial grid size is an undesirable feature in a processing pipeline. Here, we examine the stability of spatial smoothness and cluster-volume threshold estimates with respect to voxel resampling size in the AFNI software package's pipeline. A publicly available collection of resting-state and task FMRI datasets from 78 subjects was analyzed using standard processing steps in AFNI. We found that the spatial smoothness and cluster-volume thresholds are fairly stable over the voxel resampling size range of 1 to 3 mm, in contradistinction to the reported results from SPM12.

Comments: 4 figures, 20 pages

Subjects: Applications (stat.AP)

Cite as: [arXiv:1709.07471](https://arxiv.org/abs/1709.07471) [stat.AP]

(or [arXiv:1709.07471v1](https://arxiv.org/abs/1709.07471v1) [stat.AP] for this version)

GENERAL COMMENTARY ARTICLE

Front. Hum. Neurosci., 28 June 2017 | <https://doi.org/10.3389/fnhum.2017.00345>



Commentary: Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates

Karsten Mueller^{1*}, Jörn Lepsien¹, Harald E. Möller¹ and Gabriele Lohmann^{2,3}

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²Department of Biomedical Magnetic Resonance, University Hospital Tuebingen, Tuebingen, Germany

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extent have inflated false-positive rates

16). *Proc. Natl. Acad. Sci. U.S.A.* 113, 7900–7905.

d inflated false positive rates in functional MRI
ere we would like to draw attention to an important
specifically, we would like to note that statistical
epend heavily on a preprocessing parameter not
resolution to which the data sets are resampled

Eklund is still at it...

arXiv.org > stat > arXiv:1804.03185

Search or Article

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Statistics > Applications

Cluster Failure Revisited: Impact of First Level Design and Data Quality on Cluster False Positive Rates

Anders Eklund, Hans Knutsson, Thomas E Nichols

(Submitted on 9 Apr 2018)

Methodological research rarely generates a broad interest, yet our work on the validity of cluster inference methods for functional magnetic resonance imaging (fMRI) created intense discussion on both the minutia of our approach and its implications for the discipline. In the present work, we take on various critiques of our work and further explore the limitations of our original work. We address issues about the particular event-related designs we used, considering multiple event types and randomisation of events between subjects. We consider the lack of validity found with one-sample permutation (sign flipping) tests, investigating a number of approaches to improve the false positive control of this widely used procedure. We also discuss the implications of our work on the fMRI literature as a whole, estimating that at least 10% of the fMRI studies have used the most problematic cluster inference method ($P = 0.01$ cluster defining threshold), and how individual studies can be interpreted in light of our findings. These additional results underscore our original conclusions, on the importance of data sharing and thorough evaluation of statistical methods on realistic null data.

How do you solve the Multiple Comparison problem?

Family-wise error rate (FWER): defined as the probability of obtaining at least one false positive in a family of tests

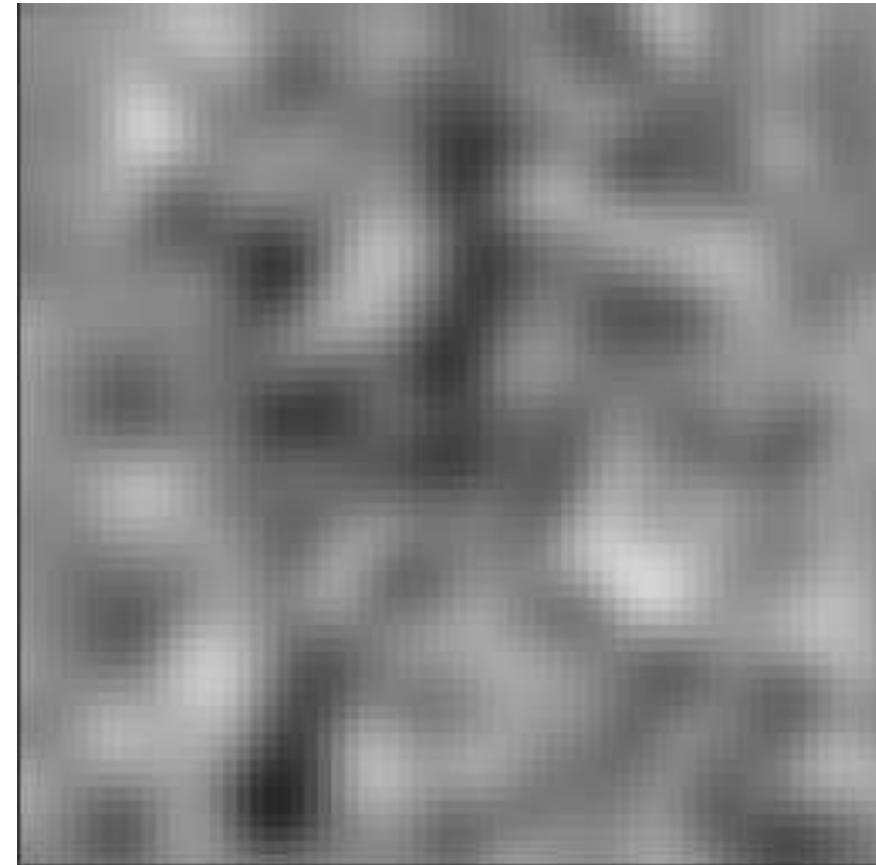
Bonferroni

Random Field Theory

False discovery rate (FDR): defined as the proportion of false positives among all rejected tests.

Random Field Theory (RFT)

- Random field theory provides a method to determine statistical threshold while controlling FWE rate
- t-maps (or Z, F and χ^2) modeled as realizations of a random process
- Takes into account **smoothness AND number of activated voxels**



How to measure smoothness

- AFNI – 3dFWHMx

2.1 Purpose

Program 3dFWHM provides a means of estimating the spatial correlation of voxels in an *AFNI* 3D dataset. In order to use program *AlphaSim*, it is necessary to know the degree of voxel spatial correlation, so that this can be accounted for in the simulation. Spatial correlation is modeled by applying a Gaussian filter to the random image data. The extent of spatial correlation is specified by entering the width of the Gaussian filter corresponding to each axis. The numbers $FWHM_x$, $FWHM_y$, and $FWHM_z$ (FWHM, for "Full Width Half Maximum") are estimated by program 3dFWHM for a user specified input dataset.

2.2 Theory

Forman *et al.* [1] derive the following equation for estimating the Gaussian filter width s :

$$s = \sqrt{-\frac{1}{4 \times \ln \left(1 - \frac{S_\delta^2}{2S^2}\right)}}$$

where

s = width (standard deviation) of Gaussian filter in voxels;

S_δ^2 = variance of the difference between each voxel and its nearest neighbors over the entire image;

S^2 = variance of voxel intensities over the entire image.

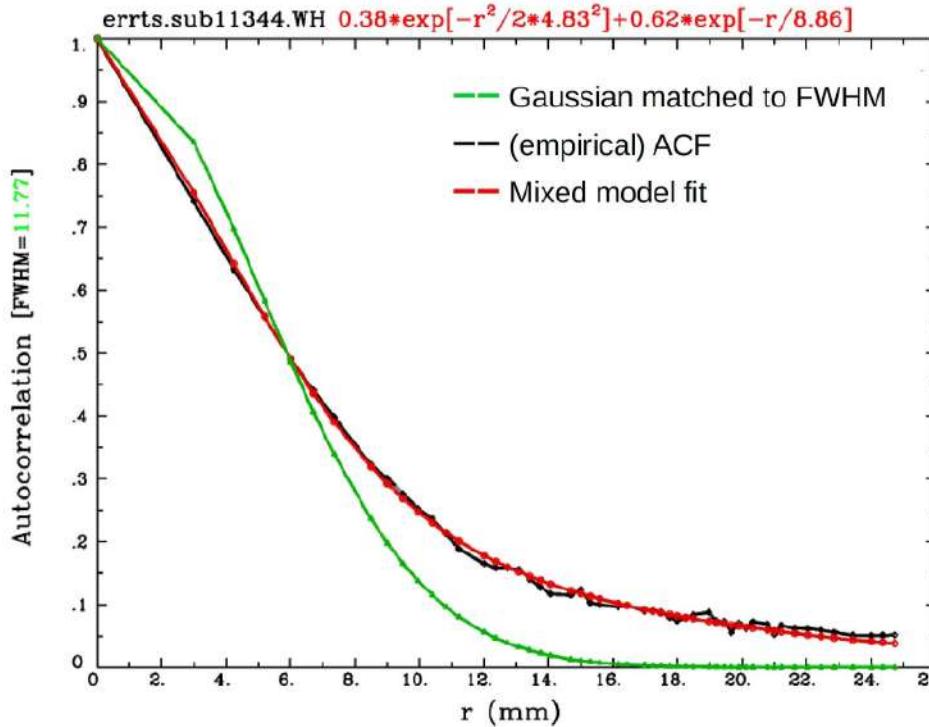


Figure 3. An example comparison of the original Gaussian fit (green) and the globally estimated empirical ACF values (black) from a single subject, which have large differences (importantly, in the tail drop-off above $r \sim 8$ mm). The proposed mixed model (red) after fitting parameters as described in Eq. (3) provides a much better fit of the data in this case (and in all cases in the datasets used herein). This plot is automatically generated in program 3dFWHMx.

Source: Cox et al. FMRI Clustering in AFNI: False-Positive Rates Redux, Brian Connectivity (2017)

Usage: 3dFWHMx [options] dataset

***** NOTICE *****

You should use the '**-acf**' option (which is what [afni proc.py](#) uses now).
The 'Classic' method giving just a Gaussian FWHM can no longer be
considered reliable for FMRI statistical analyses!

>>>> **20 July 2017: Results from the 'Classic' method are no longer output!**

>>>> If you want to see these values, you must give the
>>>> command line option '**-ShowMeClassicFWHM**'.
>>>> You no longer need to give the '**-acf**' option, as it
>>>> is now the default method of calculation (and
>>>> cannot be turned off). Note that if you need the
>>>> FWHM estimate, the '**-acf**' method gives a value
>>>> for that as its fourth output.
>>>> Options and comments that only apply to the 'Classic' FWHM estimation
>>>> method are now marked below with this '**>>>>**' marker, to indicate that
>>>> they are obsolete, archaic, and endangered (as well as fattening).

>>>> Unlike the older [3dFWHM](#), this program computes FWHMs for all sub-bricks
>>>> in the input dataset, each one separately. The output for each one is
>>>> written to the file specified by '**-out**'. The mean (arithmetic or geometric)
>>>> of all the FWHMs along each axis is written to stdout. (A non-positive
>>>> output value indicates something bad happened; e.g., FWHM in z is meaningless
>>>> for a 2D dataset; the estimation method computed incoherent intermediate results.)

(Classic) METHOD: <<<< NO LONGER OUTPUT -- SEE ABOVE >>>>

- Calculate ratio of variance of first differences to data variance.
- Should be the same as 3dFWHM for a 1-brick dataset.
(But the output format is simpler to use in a script.

```
*****  
***** IMPORTANT NOTE [Dec 2015] *****  
*****
```

A completely new method for estimating and using noise smoothness values is now available in 3dFWHMx and 3dClustSim. This method is implemented in the '**-acf**' options to both programs. **'ACF' stands for (spatial) AutoCorrelation Function**, and it is estimated by calculating moments of differences out to a larger radius than before.

Notably, **real FMRI data does not actually have a Gaussian-shaped ACF**, so the estimated ACF is then fit (in 3dFWHMx) to a mixed model (**Gaussian plus mono-exponential**) of the form

$$\text{ACF}(r) = a * \exp(-r*r/(2*b*b)) + (1-a)*\exp(-r/c)$$

where 'r' is the radius, and 'a', 'b', 'c' are the fitted parameters.

The apparent FWHM from this model is usually somewhat larger in real data than the FWHM estimated from just the nearest-neighbor differences used in the 'classic' analysis.

The longer tails provided by the mono-exponential are also significant.
3dClustSim has also been modified to use the ACF model given above to generate noise random fields.

```
*****  
** The take-away (TL;DR or summary) message is that the 'classic' 3dFWHMx and **  
** 3dClustSim analysis, using a pure Gaussian ACF, is not very correct for **  
** FMRI data -- I cannot speak for PET or MEG data. **  
*****
```

Code:

```
# -- estimate blur for each run in errts --
touch blur.errts.1D

# restrict to uncensored TRs, per run
foreach run ( $runs )
    set trs = `1d_tool.py -infile X.xmat.1D -show_trs_uncensored encoded \
                -show_trs_run $run`
    if ( $trs == "" ) continue
    3dFWHMx -detrend -mask full_mask.$subj+tlrc \
              -ACF files_ACF/out.3dFWHMx.ACF.errts.r$run.1D \
              errts.${subj}+tlrc"[$trs]" >> blur.errts.1D
end

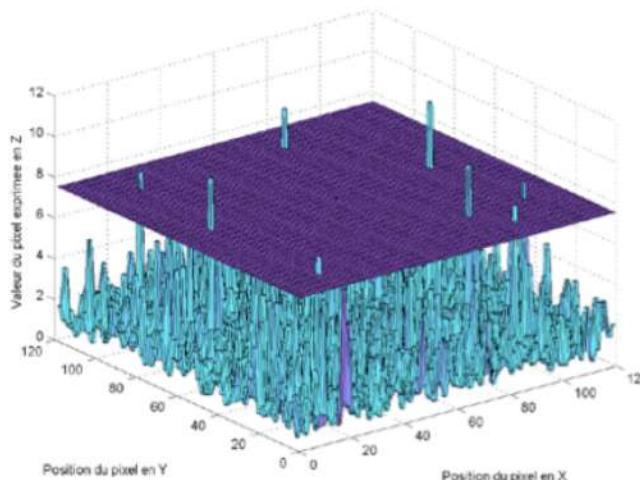
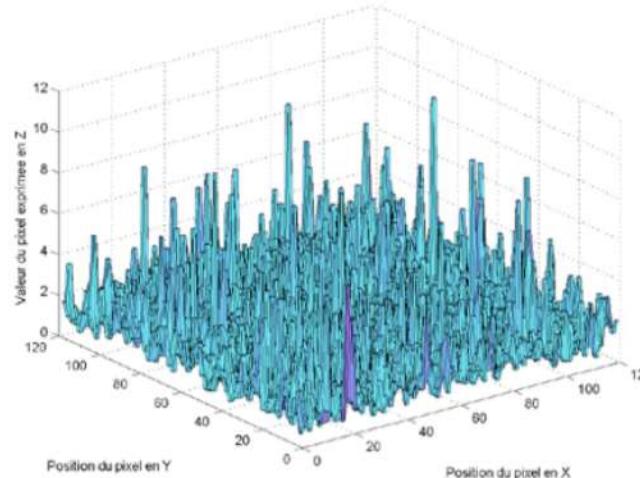
# compute average ACF blur (from every other row) and append
set blurs = ( `3dTstat -mean -prefix - blur.errts.1D'{1..$(2)}'` )
echo average errts ACF blurs: $blurs
echo "$blurs # errts ACF blur estimates" >> blur_est.$subj.1D
```

Output:

```
afranco@inser:~/DATA/VIVA/VIVA023/visit1/PROC.RMET$ more blur_est.VIVA023.1D
10.4453 10.364 9.00825 9.91638 # epits FWHM blur estimates
0.437901 5.89822 13.1252 15.3785 # epits ACF blur estimates
10.3545 10.2873 8.93106 9.83491 # errts FWHM blur estimates
0.452279 5.90349 12.7922 15.195 # errts ACF blur estimates
```

Topology of Random Fields

- Euler Characteristic (EC) is a measure of the ‘roughness’ of a random field
- In neuroimaging number of blobs (aka clusters) that remain after thresholding at a particular p-value defines EC (minus holes/hollows)



3dClustSim

Usage: 3dClustSim [options]

Program to estimate the probability of false positive (noise-only) clusters.
An adaptation of Doug Ward's **AlphaSim**, streamlined for various purposes.

This program has several different modes of operation, each one involving simulating noise-only random volumes, thresholding and clustering them, and counting statistics of how often data 'survives' these processes at various threshold combinations (per-voxel and cluster-size).

OLDEST method = simulate noise volume assuming the spatial auto-correlation function (ACF) is given by a **Gaussian-shaped function**, where this shape is specified using the FWHM parameter. The FWHM parameter can be estimated by program [3dFWHMx](#).

** THIS METHOD IS NO LONGER RECOMMENDED **

NEWER method = simulate noise volume assuming the ACF is given by a mixed-model of the form $a * \exp(-r*r/(2*b*b)) + (1-a) * \exp(-r/c)$, where a,b,c are 3 parameters giving the shape, and can also be estimated by program 3dFWHMx.

** THIS METHOD IS ACCEPTABLE **

NEWEST method = program [3dttest++](#) simulates the noise volumes by randomizing and permuting input datasets, and sending those volumes into 3dClustSim directly. There is no built-in math model for the spatial ACF.

** THIS METHOD IS **MOST ACCURATE** AT CONTROLLING FALSE POSITIVE RATE **

** You invoke this method with the '-Clustsim' option in 3dttest++ **

ClustSim: Table of Sizes Found

<u>size</u>	<u>count</u>			<i>Out of 10000 simulations</i>	
1	1830	11	82	21	2
2	2106	12	45	22	3
3	1572	13	44	23	0
4	1204	14	32	24	3
5	792	15	12	25	0
6	595	16	13	26	1
7	405	17	11	27	0
8	302	18	9	28	0
9	177	19	6	29	1
10	127	20	5		

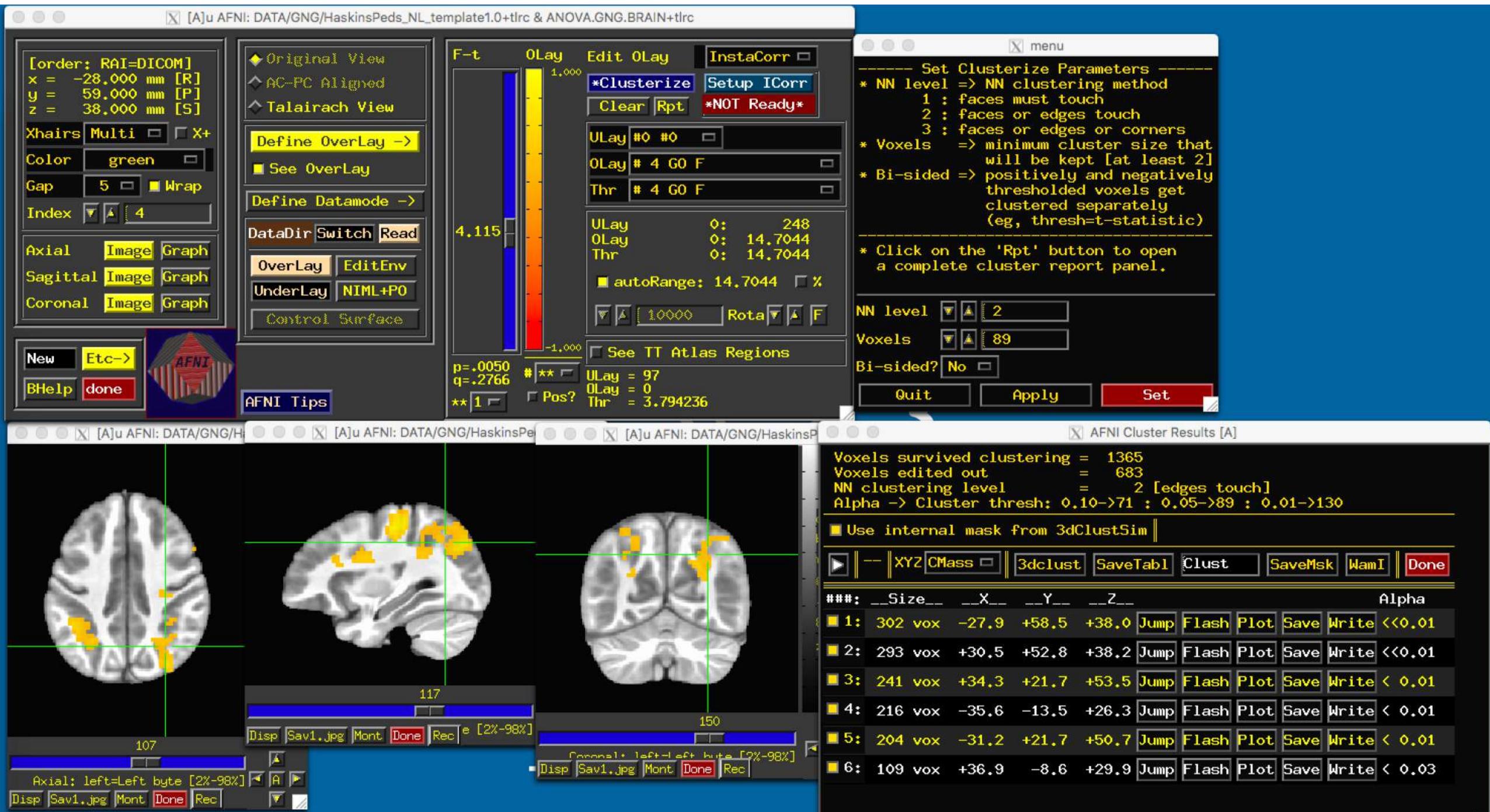
Add up
until total
just less
than 500

Smallest cluster size with < 500 false positives (5% FPR) above

Output from ClustSim

2. bash

# -NN 2 alpha = Prob(Cluster >= given size)	.10000 .09000 .08000 .07000 .06000 .05000 .04000 .03000 .02000 .01000
0.100000 1561.3 1606.5 1650.3 1708.3 1778.5 1852.7 1942.0 2064.0 2252.0 2515.0	
0.090000 1305.7 1350.0 1400.0 1442.3 1500.2 1568.2 1657.0 1740.0 1897.5 2156.0	
0.080000 1082.0 1115.5 1161.0 1202.7 1249.0 1304.0 1374.0 1460.0 1579.0 1821.0	
0.070000 887.7 914.0 944.7 989.0 1028.2 1079.0 1135.0 1211.0 1300.0 1477.0	
0.060000 708.5 736.5 764.7 792.0 829.7 870.3 919.5 977.0 1065.0 1214.0	
0.050000 556.5 574.3 593.6 620.5 652.2 683.3 723.0 776.2 846.0 972.0	
0.040000 425.5 437.9 450.5 467.7 488.4 515.0 553.0 593.0 654.0 754.0	
0.030000 307.2 317.8 327.9 341.2 355.2 372.0 392.0 426.0 473.9 539.3	
0.020000 208.7 214.8 222.2 230.6 240.7 252.6 265.0 285.3 311.0 369.2	
0.015000 161.2 166.7 172.3 179.1 185.9 195.3 206.7 222.0 243.7 294.7	
0.010000 116.1 120.6 124.9 129.5 135.2 142.8 151.8 164.3 179.7 212.3	
0.007000 88.7 92.1 95.2 99.4 104.6 110.6 117.8 126.5 140.9 162.5	
0.005000 70.6 72.8 75.5 78.8 82.9 88.4 94.0 102.2 113.2 130.4	
0.003000 50.6 52.5 54.6 57.0 59.8 63.6 67.4 74.1 81.7 96.4	
0.002000 39.4 40.7 42.2 44.1 46.1 48.8 52.8 57.9 65.5 78.0	
0.001500 33.1 34.3 35.7 37.3 39.2 41.5 44.5 49.1 55.0 66.6	
0.001000 26.4 27.4 28.5 29.9 31.7 33.6 36.2 39.4 44.0 54.2	
0.000700 21.7 22.6 23.7 24.8 26.0 27.7 29.7 32.6 36.9 44.8	
0.000500 18.0 18.8 19.8 20.8 21.8 23.2 25.0 27.3 31.0 37.1	
0.000300 13.6 14.2 15.0 15.8 16.9 17.9 19.2 21.1 23.8 29.2	
0.000200 10.8 11.4 12.0 12.7 13.5 14.4 15.5 17.1 19.4 23.4	
0.000150 9.2 9.6 10.1 10.7 11.4 12.2 13.3 14.6 17.0 20.7	
0.000100 7.3 7.7 8.1 8.6 9.2 9.8 10.6 12.0 13.8 17.5	
7.000e-5 5.9 6.2 6.6 7.0 7.5 8.0 8.7 9.7 11.4 14.9	
5.000e-5 4.8 5.1 5.4 5.8 6.2 6.7 7.4 8.2 9.7 12.8	
3.000e-5 3.6 3.8 4.0 4.3 4.7 5.1 5.6 6.3 7.5 10.2	
2.000e-5 2.8 3.0 3.2 3.5 3.7 4.1 4.6 5.2 6.2 8.4	
1.500e-5 2.4 2.5 2.7 2.9 3.2 3.5 3.9 4.5 5.4 7.2	
1.000e-5 1.9 2.0 2.1 2.3 2.5 2.8 3.1 3.6 4.4 6.0	



3dttest++

* The new-ish options '-Clustsim' and '-ETAC' will use randomization and permutation simulation to produce cluster-level threshold values that can be used to control the false positive rate (FPR) globally. These options are slow, since they will run 1000s of simulated 3D t-tests in order to get cluster-level statistics about the 1 actual test.

-Clustsim = With this option, after the commanded t-tests are done, then:

- (a) the residuals from '-resid' are used with '-randomsign' to simulate about 10000 null 3D results, and then
- (b) 3dClustSim is run with those to generate cluster-threshold tables, and then
- (c) [3drefit](#) is used to pack those tables into the main output dataset, and then
- (d) the temporary files created in this process are deleted.

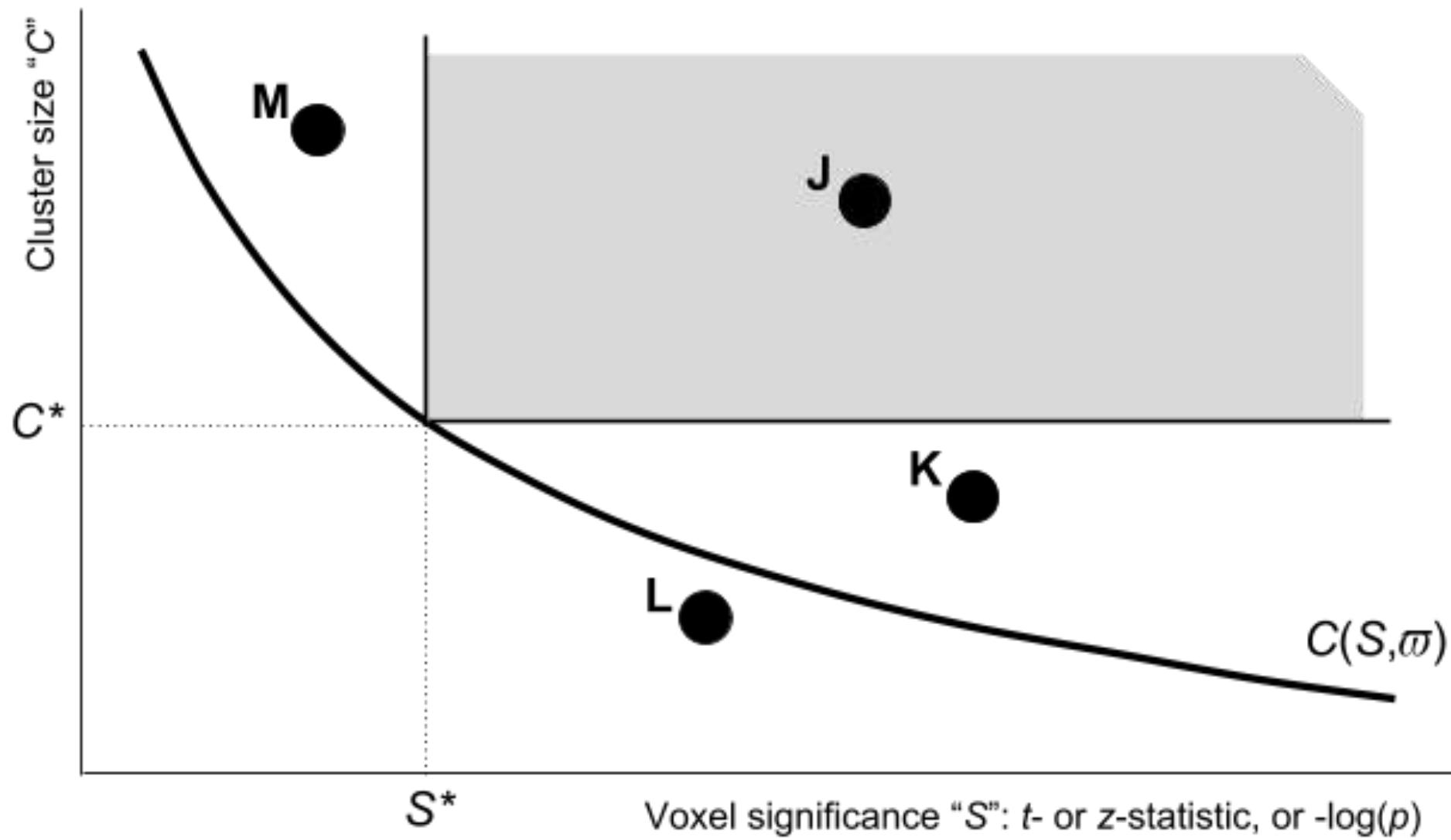
-resid q = Output the residuals into a dataset with prefix 'q'.

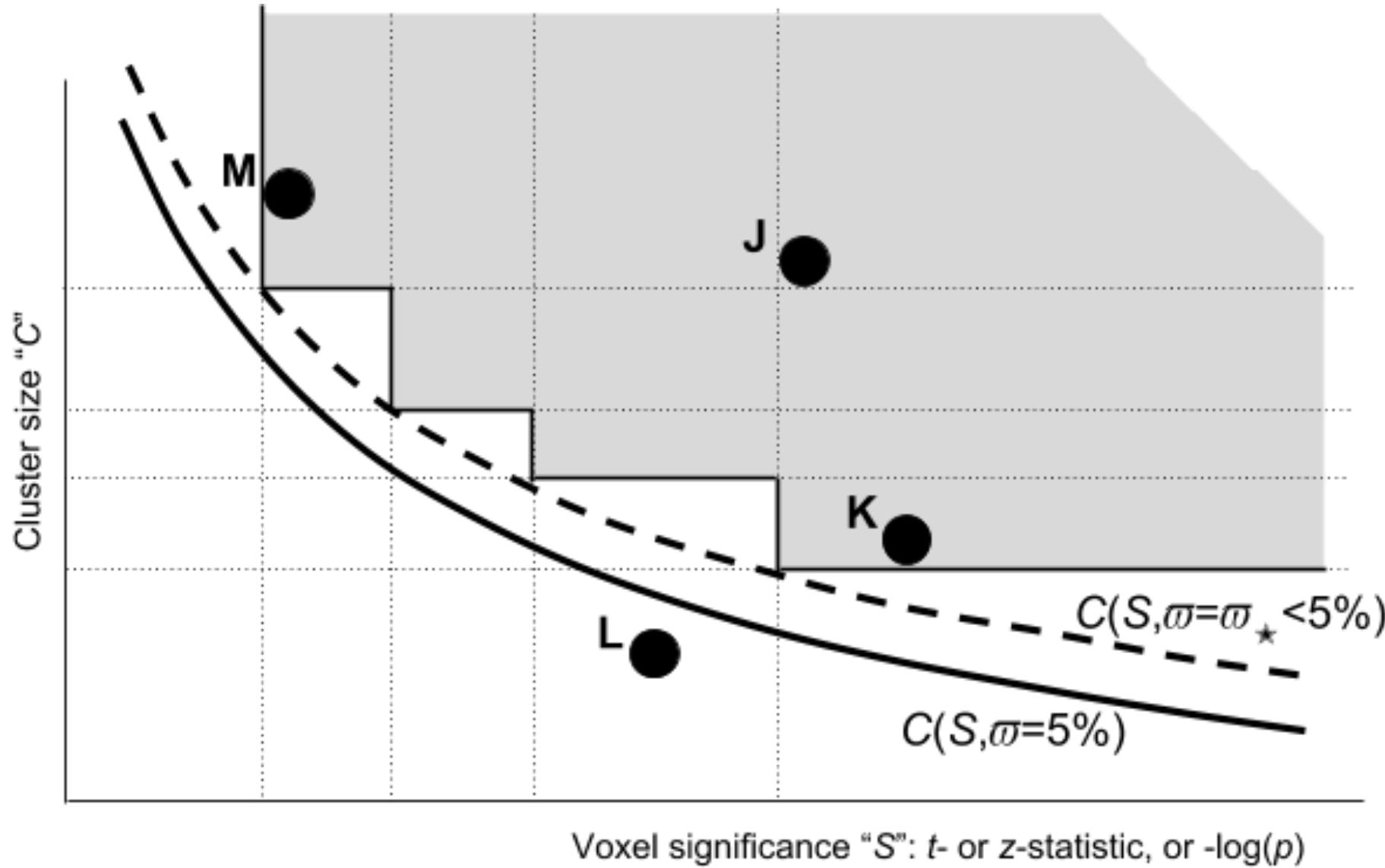
++ The residuals are the difference between the data values and their prediction from the set mean (and set covariates).

Equitable Thresholding and Clustering - ETAC

ETAC approach is grounded in two ideas:

- (i) reducing the dependence of clustering results on **arbitrary parameter values** by using multiple sub-tests—each equivalent to a “standard” FMRI clustering analysis—to make decisions about which groups of voxels are potentially “significant”, then combining the results of each sub-test to decide which voxels are “accepted” ;
- (ii) **adjusting the cluster-thresholding parameters** of each sub-test from (i) in an equitable way—so that the individual false positive rates (FPRs) are balanced across sub-tests and voxels—to achieve a desired global FPR (e.g., 5%).





Simulation

Paired t-test

Go x NoGo

N = 36

Average ate = 12

ADHD

Script for simulations

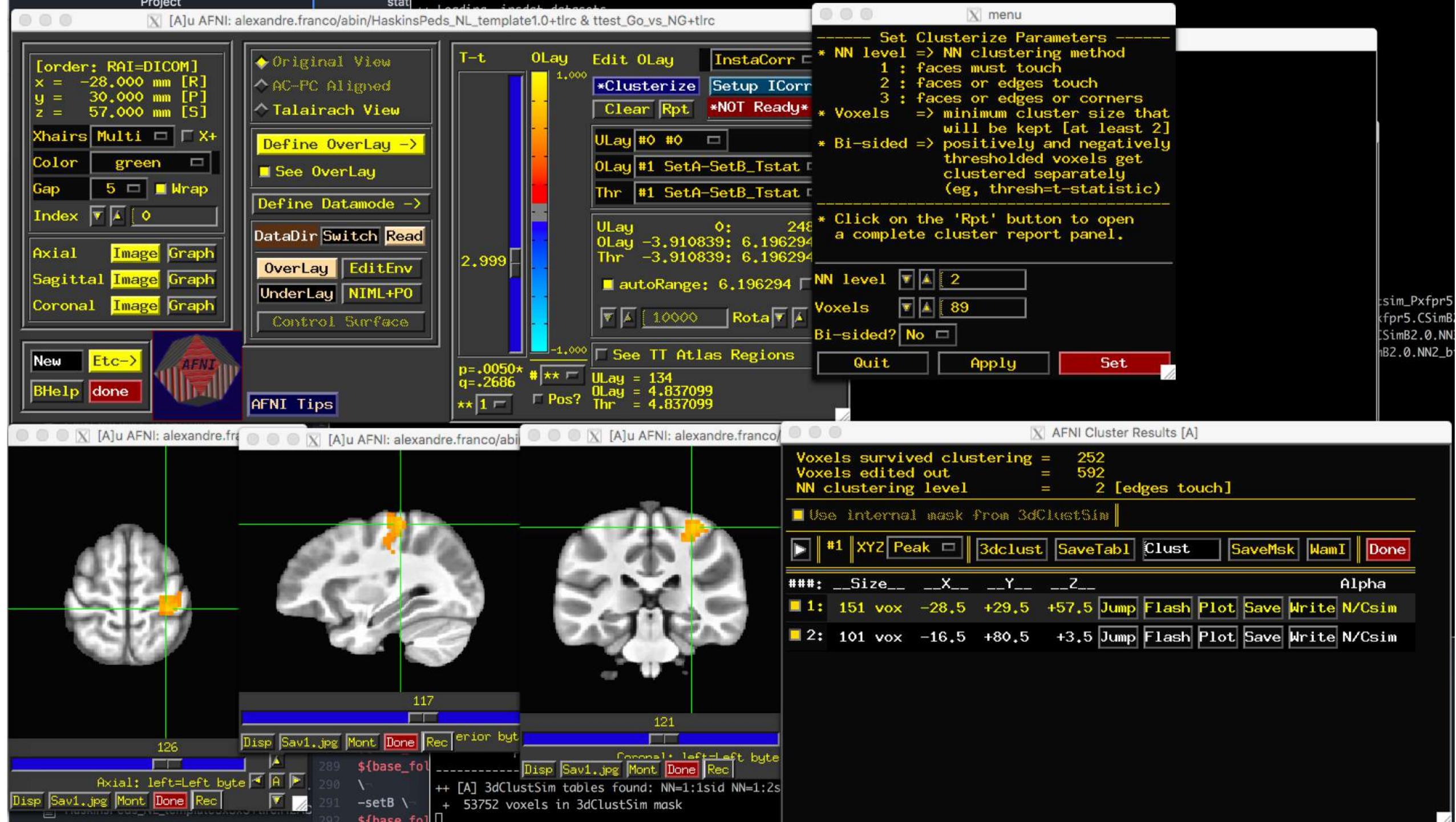
```
244 3dttest++ -paired \
245 -mask $mask \
246 -Clustsim \
247 -ETAC \
248 -ETAC_blur 2 4 \
249 -ETAC_opt sid=2:pthr=0.01,0.005,0.002,0.01:fpr=5:name=FPR5 \
250 -prefix ttest_Go_vs_NG_ClustSim \
251 -prefix_clustsim Clustsim_Pxfpr5 \
252 -setA \
253 ${base_folder}/visit1/stats.RWM002.G0+tlrc \
254 ${base_folder}/visit1/stats.RWM003.G0+tlrc \
255 ${base_folder}/visit1/stats.RWM005.G0+tlrc \
256 ${base_folder}/visit1/stats.RWM008.G0+tlrc \
257 ${base_folder}/visit1/stats.RWM012.G0+tlrc \
258 ${base_folder}/visit1/stats.RWM013.G0+tlrc
```

Generated 8.1 GB of data in the process

Took 2 hours to process on this laptop: 2.3GHz i5, 8GB ram

3dClustSim – output

```
afranco@edias-pc:~/TEMP/VIRGINIA/GNG$ more ClustSim.NN2_2sided.1D
# 3dClustSim -acf 0.479023889 5.571080278 12.30551389 -LOTS -iter 10000 -NN 123 -both -mask /home/afranco/DATA/ROHDE_WM/RWM002/vis
it1/PROC.GNG/mask_group+tlrc.BRIK.gz -prefix ClustSim
# 2-sided thresholding
# Grid: 60x73x61 3.00x3.00x3.00 mm^3 (53752 voxels in mask)
#
# CLUSTER SIZE THRESHOLD(pthr,alpha) in Voxels
# -NN 2 | alpha = Prob(Cluster >= given size)
# pthr | .10000 .09000 .08000 .07000 .06000 .05000 .04000 .03000 .02000 .01000
# ----- | -----
0.10000 1561.3 1606.5 1650.3 1708.3 1778.5 1852.7 1942.0 2064.0 2252.0 2515.0
0.09000 1305.7 1350.0 1400.0 1442.3 1500.2 1568.2 1557.0 1740.0 1897.5 2156.0
0.08000 1082.0 1115.5 1161.0 1202.7 1249.0 1304.0 1374.0 1460.0 1579.0 1821.0
0.07000 887.7 914.0 944.7 989.0 1028.2 1079.0 1135.0 1211.0 1300.0 1477.0
0.06000 708.5 736.5 764.7 792.0 829.7 870.3 919.5 977.0 1065.0 1214.0
0.05000 556.5 574.3 593.6 620.5 652.2 683.3 723.0 776.2 846.0 972.0
0.04000 425.5 437.9 450.5 467.7 488.4 515.0 553.0 593.0 654.0 754.0
0.03000 307.2 317.8 327.9 341.2 355.2 372.0 392.0 426.0 473.9 539.3
0.02000 208.7 214.8 222.2 230.6 240.7 252.6 265.0 285.3 311.0 369.2
0.01500 161.2 166.7 172.3 179.1 185.9 195.3 206.7 222.0 243.7 294.7
0.01000 116.1 120.6 124.9 129.5 135.2 142.8 151.8 164.3 179.7 212.3
0.00700 88.7 92.1 95.2 99.4 104.6 110.6 117.8 126.5 140.9 162.5
0.00500 70.6 72.8 75.5 78.8 82.9 88.4 94.0 102.2 113.2 130.4
0.00300 50.6 52.5 54.6 57.0 59.8 63.6 67.4 74.1 81.7 96.4
0.00200 39.4 40.7 42.2 44.1 46.1 48.8 52.8 57.9 65.5 78.0
0.001500 33.1 34.3 35.7 37.3 39.2 41.5 44.5 49.1 55.0 66.6
0.001000 26.4 27.4 28.5 29.9 31.7 33.6 36.2 39.4 44.0 54.2
0.000700 21.7 22.6 23.7 24.8 26.0 27.7 29.7 32.6 36.9 44.8
0.000500 18.0 18.8 19.8 20.8 21.8 23.2 25.0 27.3 31.0 37.1
0.000300 13.6 14.2 15.0 15.8 16.9 17.9 19.2 21.1 23.8 29.2
0.000200 10.8 11.4 12.0 12.7 13.5 14.4 15.5 17.1 19.4 23.4
0.000150 9.2 9.6 10.1 10.7 11.4 12.2 13.3 14.6 17.0 20.7
0.000100 7.3 7.7 8.1 8.6 9.2 9.8 10.6 12.0 13.8 17.5
7.000e-5 5.9 6.2 6.6 7.0 7.5 8.0 8.7 9.7 11.4 14.9
5.000e-5 4.8 5.1 5.4 5.8 6.2 6.7 7.4 8.2 9.7 12.8
3.000e-5 3.6 3.8 4.0 4.3 4.7 5.1 5.6 6.3 7.5 10.2
2.000e-5 2.8 3.0 3.2 3.5 3.7 4.1 4.6 5.2 6.2 8.4
1.500e-5 2.4 2.5 2.7 2.9 3.2 3.5 3.9 4.5 5.4 7.2
1.000e-5 1.9 2.0 2.1 2.3 2.5 2.8 3.1 3.6 4.4 6.0
afranco@edias-pc:~/TEMP/VIRGINIA/GNG$
```



ClustSim from 3dttest++

```
alexandre.franco@CMI-RSCH-MBP031:~/TEMP/ETAC/DATA/GNG/ETAC$ more Clustsim_Pxfpr5_noBlur.CSimA.NN2_2sided.1D
# 3dClustSim -prefix Clustsim_Pxfpr5_noBlur.CSimA -LOTS -both -nodec -cmd Clustsim_Pxfpr5_noBlur.CSimA.cmd -
insdat /Users/alexandre.franco/TEMP/ETAC/DATA/GNG/HaskinsPeds_NL_template.MASK+tlrc.HEAD ./Clustsim_Pxfpr5_n
oBlur.0000.sdat ./Clustsim_Pxfpr5_noBlur.0001.sdat ./Clustsim_Pxfpr5_noBlur.0002.sdat ./Clustsim_Pxfpr5_noBl
ur.0003.sdat
# 2-sided thresholding
# Grid: 60x73x61 3.00x3.00x3.00 mm^3 (52603 voxels in mask)
#
# CLUSTER SIZE THRESHOLD(pthr,alpha) in Voxels
# -NN 2 | alpha = Prob(Cluster >= given size)
# pthr | .10000 .09000 .08000 .07000 .06000 .05000 .04000 .03000 .02000 .01000
# ----- | -----
0.100000 7581 8133 8706 9276 9946 10727 11696 12830 14374 16876
0.090000 6511 7040 7622 8240 8891 9623 10587 11699 13223 15651
0.080000 5444 5920 6413 7053 7750 8465 9360 10462 11971 14433
0.070000 4384 4780 5251 5797 6487 7204 8090 9175 10685 13083
0.060000 3304 3671 4077 4547 5128 5854 6675 7757 9256 11590
0.050000 2397 2680 3017 3375 3776 4358 5117 6208 7610 9906
0.040000 1606 1790 2016 2305 2614 3044 3597 4442 5749 8030
0.030000 972 1083 1218 1392 1615 1883 2274 2819 3743 5720
0.020000 503 556 629 709 820 959 1167 1453 1964 3141
0.015000 333 367 406 457 530 615 740 935 1252 2067
0.010000 192 211 234 261 297 344 414 512 697 1119
0.007000 120 132 146 163 186 215 253 315 417 667
0.005000 81 88 96 108 122 143 168 206 265 423
0.003000 45 49 54 60 68 78 91 113 148 232
0.002000 30 32 35 39 44 50 59 72 95 147
0.001500 22 24 26 29 33 37 43 53 68 108
0.001000 15 16 18 20 22 25 29 35 46 71
0.000700 11 12 13 14 16 18 21 25 33 50
0.000500 8 9 10 10 12 13 15 18 24 35
0.000300 5 6 6 7 7 8 10 12 15 22
0.000200 4 4 4 5 5 6 7 8 10 15
0.000150 3 3 3 4 4 5 5 7 8 12
0.000100 2 2 3 3 3 3 4 5 6 9
7.000e-5 2 2 2 2 2 3 3 4 5 7
5.000e-5 1 2 2 2 2 2 2 3 4 5
3.000e-5 1 1 1 1 1 2 2 2 2 4
2.000e-5 1 1 1 1 1 1 1 2 2 3
1.500e-5 1 1 1 1 1 1 1 1 2 2
1.000e-5 1 1 1 1 1 1 1 1 1 2
```

ETAC Output





Acknowledgments

Cox:

“The ideas for equitable application of multiple sub-tests came to RWC while hiking in Grand Canyon National Park and in Gunnison National Forest; thanks go to the US National Park Service and US Forest Service for maintaining these inspirational public treasures.”