Statistical inference and multiple testing correction in MVPA

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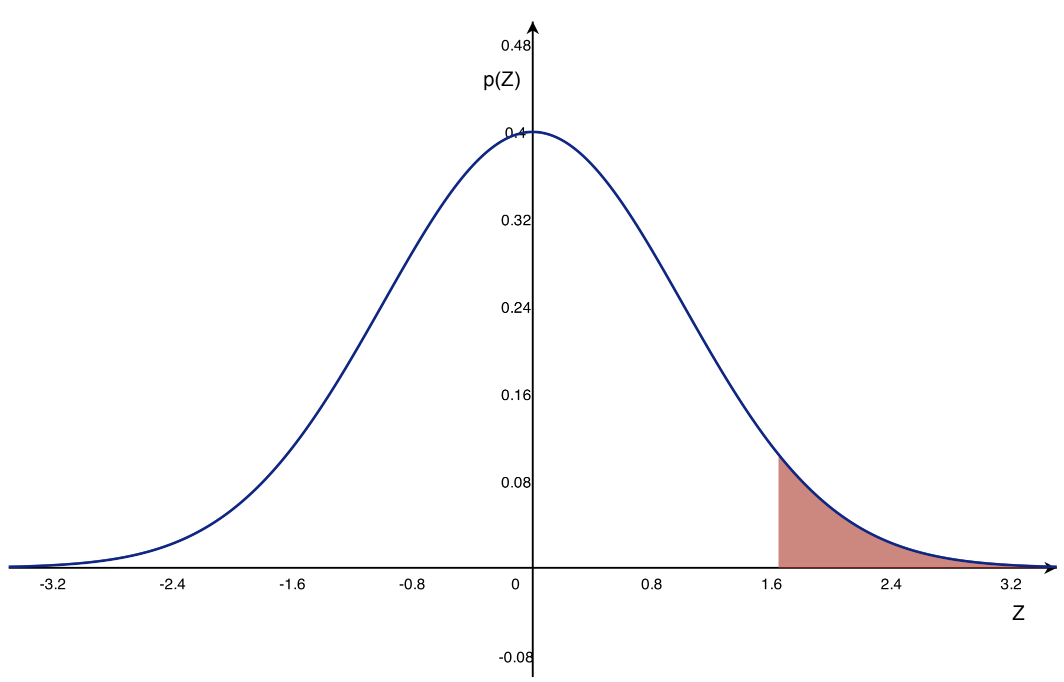
whole-brain map of classifier's estimates (e.g. decoding accuracies)

→

thresholded map indicating statistical significance

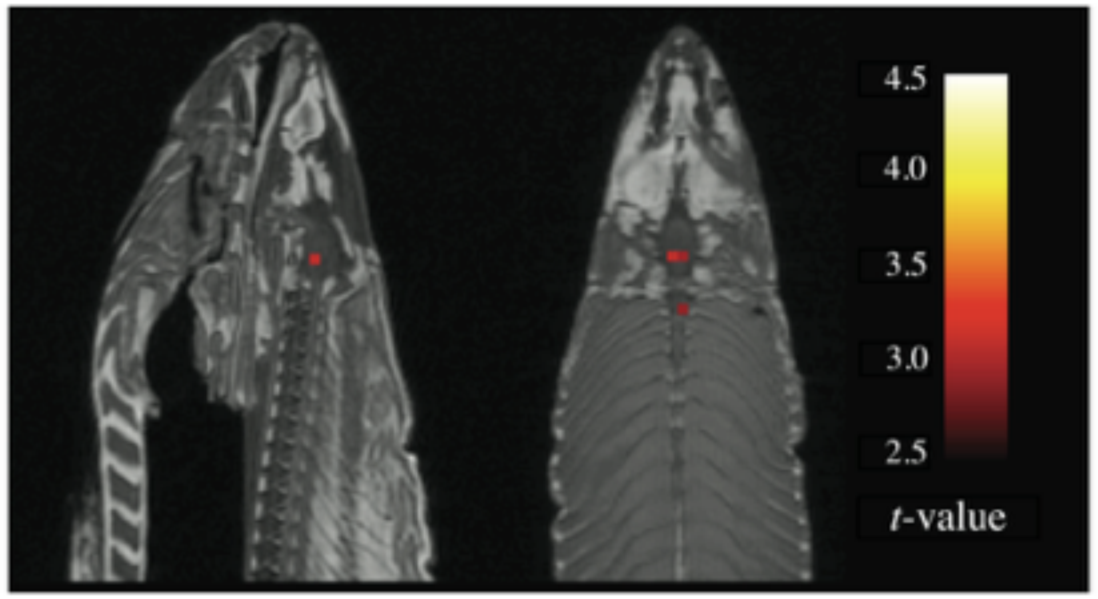
Assuming the classifier "guesses":
what is the likelihood to observe
a given decoding accuracy (or larger)?

how to get
null **distribution**



$$Pr\{Z \geq Z_0\} = \int_{Z_0}^{\infty} f(Z)dZ$$

how to correct
for **multiple** testing



how to get null distribution *parametrically* (common approaches in mvpa):

- binomial models
- t-based stats

real label	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b
classifier’s estimate	b	a	a	b	b	a	a	b	a	a	b	b	a	b	a	b	a	b	b	a

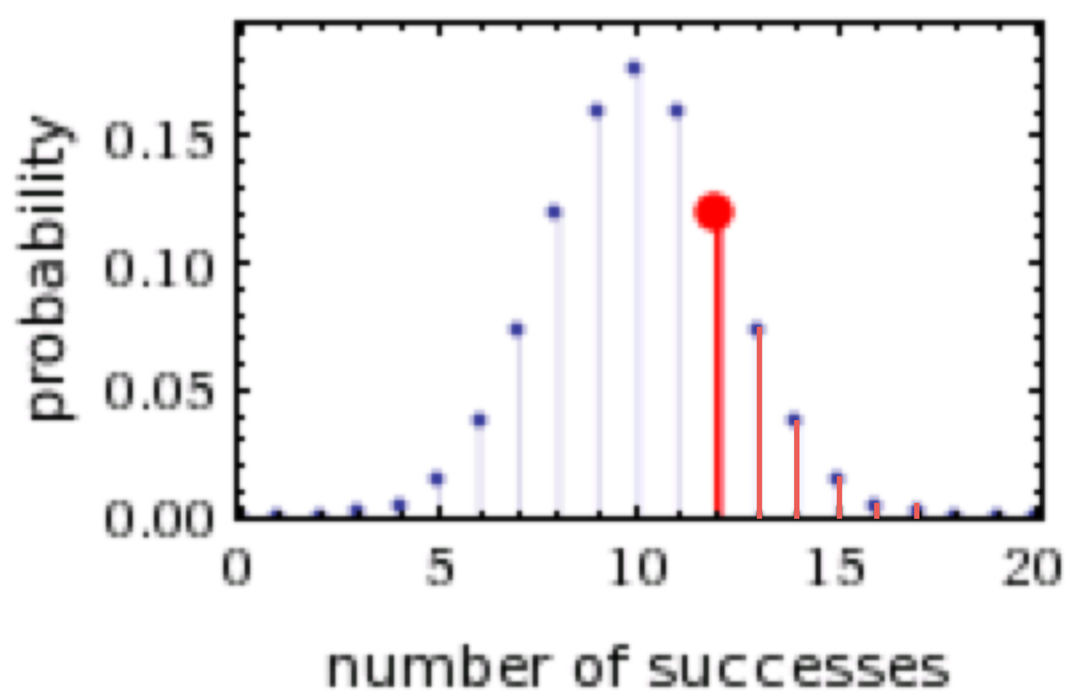
number of samples **N** = 20

correct samples **c** = 12

accuracy = 0.6

binomial model:

$$p_X(c) = \binom{N}{c} p^c (1-p)^{N-c}$$



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
real label	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b
classifier’s estimate	b	a	a	b	b	a	a	b	a	a	b	b	a	b	a	b	a	b	b	a

test set T

2x CV											T	T	T	T	T	T	T	T	T	T
4x CV																T	T	T	T	T
5x CV																	T	T	T	T
10x CV																			T	T
20x CV																				T

single model (no CV): $$p_X(c) = \binom{N}{c} p^c (1-p)^{N-c} \qquad c = 0, 1, ..., N$$

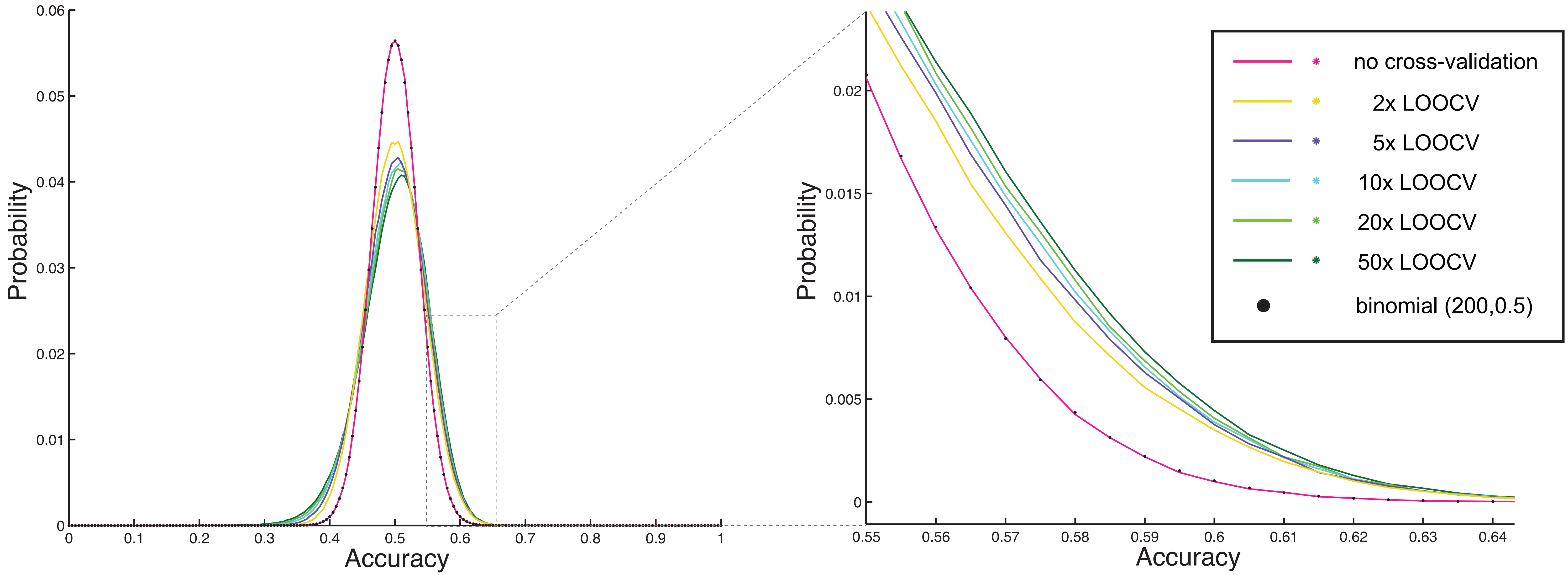
with **t** CV-folds:
(N trials per fold) $$p_X(c) = \binom{N \cdot t}{c} p^c (1-p)^{N \cdot t - c} \qquad c = 0, 1, ..., N \cdot t$$

Stelzer, J., Chen, Y., & Turner, R. (2013). Statistical inference and multiple testing correction in classification-based multi-voxel pattern analysis (MVPA): random permutations and cluster size control. Neuroimage, 65, 69–82. doi:10.1016/j.neuroimage.2012.09.063

real label	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b	a	b
classifier's estimate	b	a	a	b	b	a	a	b	a	a	b	b	a	b	a	b	a	b	b	a

test set T

2x CV											T	T	T	T	T	T	T	T	T	T
4x CV																T	T	T	T	T
5x CV																	T	T	T	T
10x CV																			T	T
20x CV																				T



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problems regarding binomial model

- dependency between cross-validation folds undermines assumption of independency between trials
- (ignoring above problem): solution for one single voxel - multiple testing solution needed!

t-based methods and random fields procedure

- get voxel-wise accuracy map for each subject
- one sample t-test against 0.5 (2 classes)
- apply gaussian random-fields cluster level correction

problems regarding t-based framework

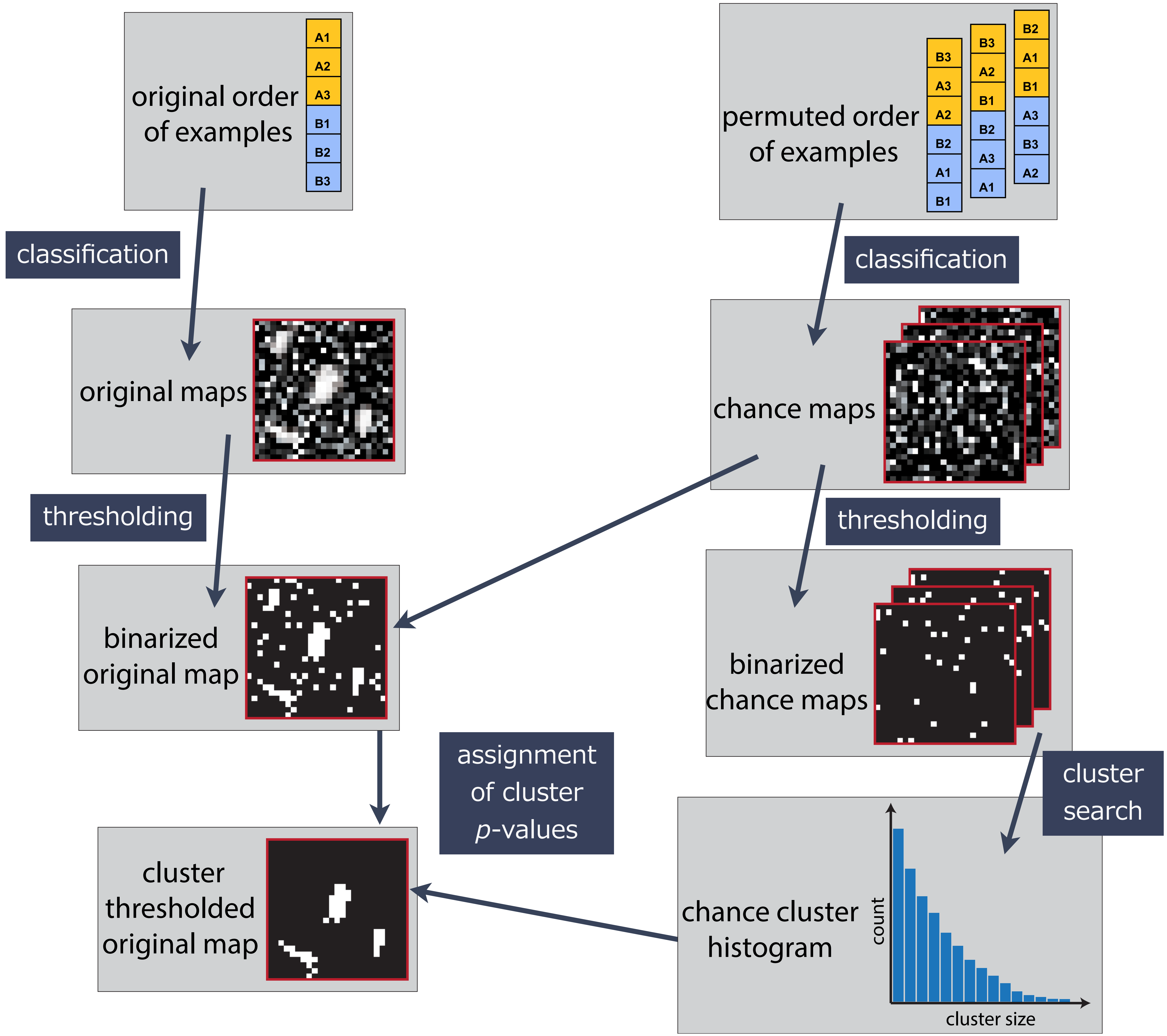
- decoding accuracies discrete (t-test assumes continuous)
- accuracies don’t follow normal distribution
- assumptions regarding random field theory & estimation of spatial smoothness not met

advantages of permutation testing

- (practically) assumption free
- yields voxel-wise null distribution
- spatial “chance maps” for free!
  - this provides a null distribution of cluster sizes!

Golland, P., Liang, F., Mukherjee, S., and Panchenko, D. (2005). Permutation Tests for Classification. 3559, 501–515. doi: 10.1007/11503415_34.

Hayasaka, S., and Nichols, T. E. (2003). Validating cluster size inference: random field and permutation methods. 20, 2343–2356. doi: 10.1016/j.neuroimage.2003.08.003.



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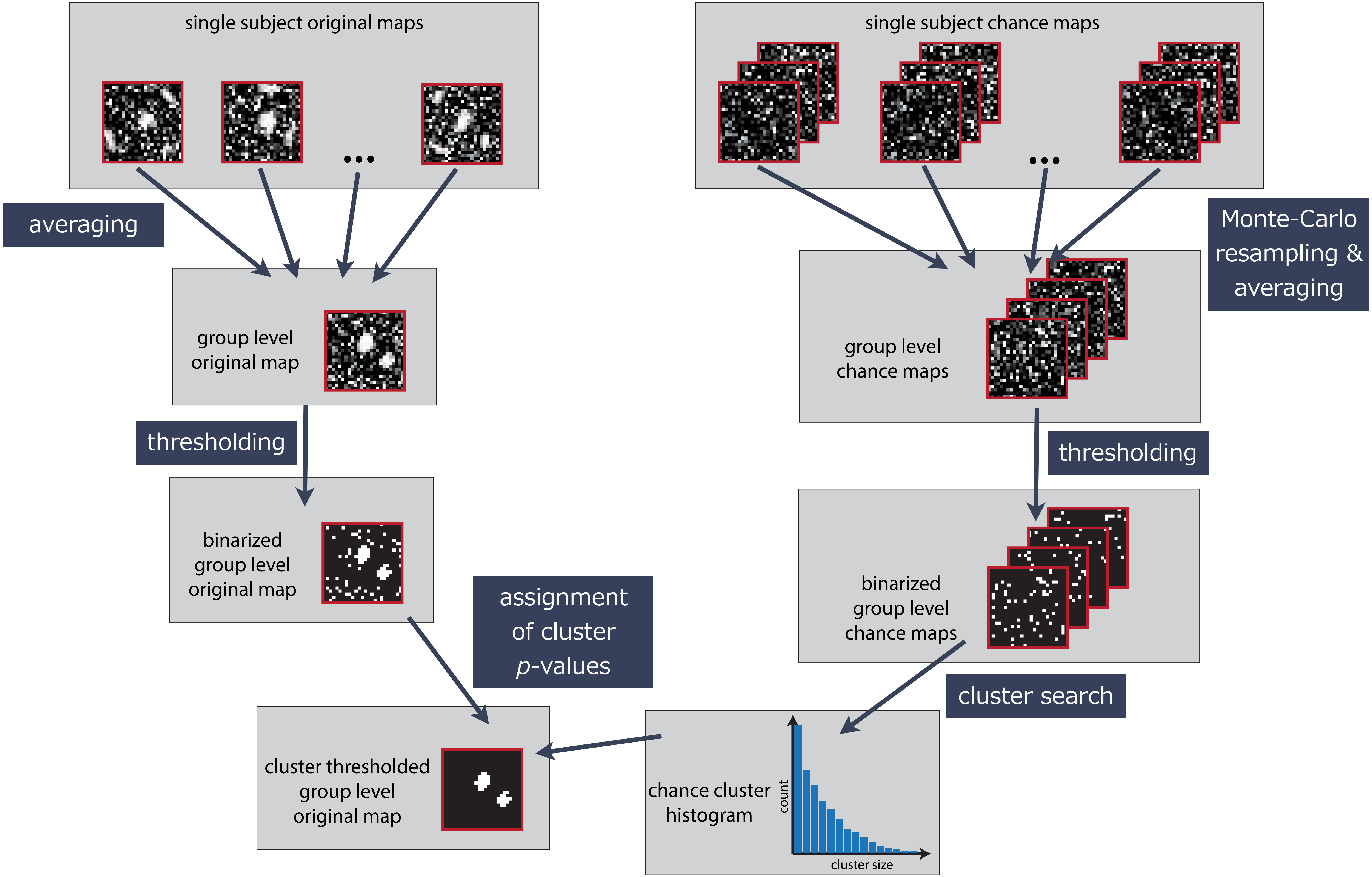

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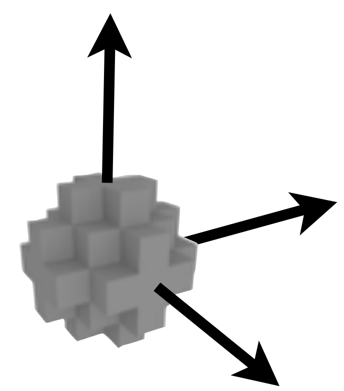
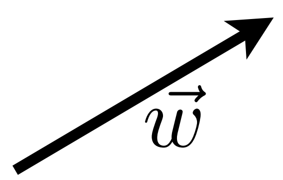
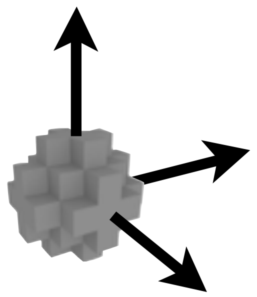
Two common MVPA mapping methods



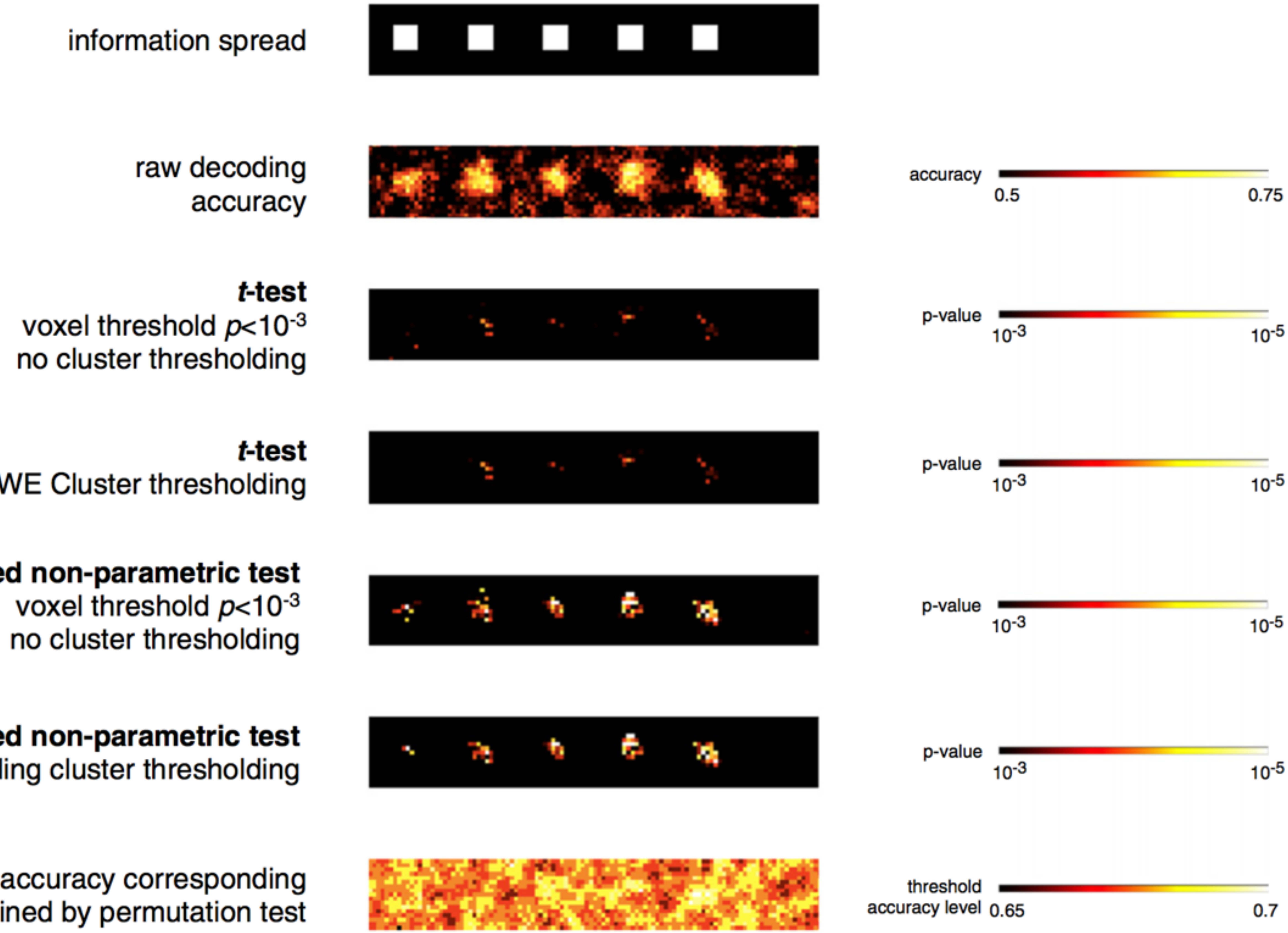
searchlight decoding

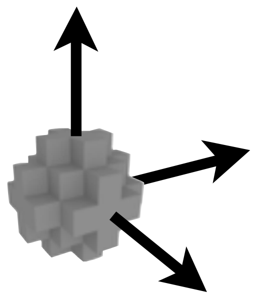


mapping classifier
weights



searchlight





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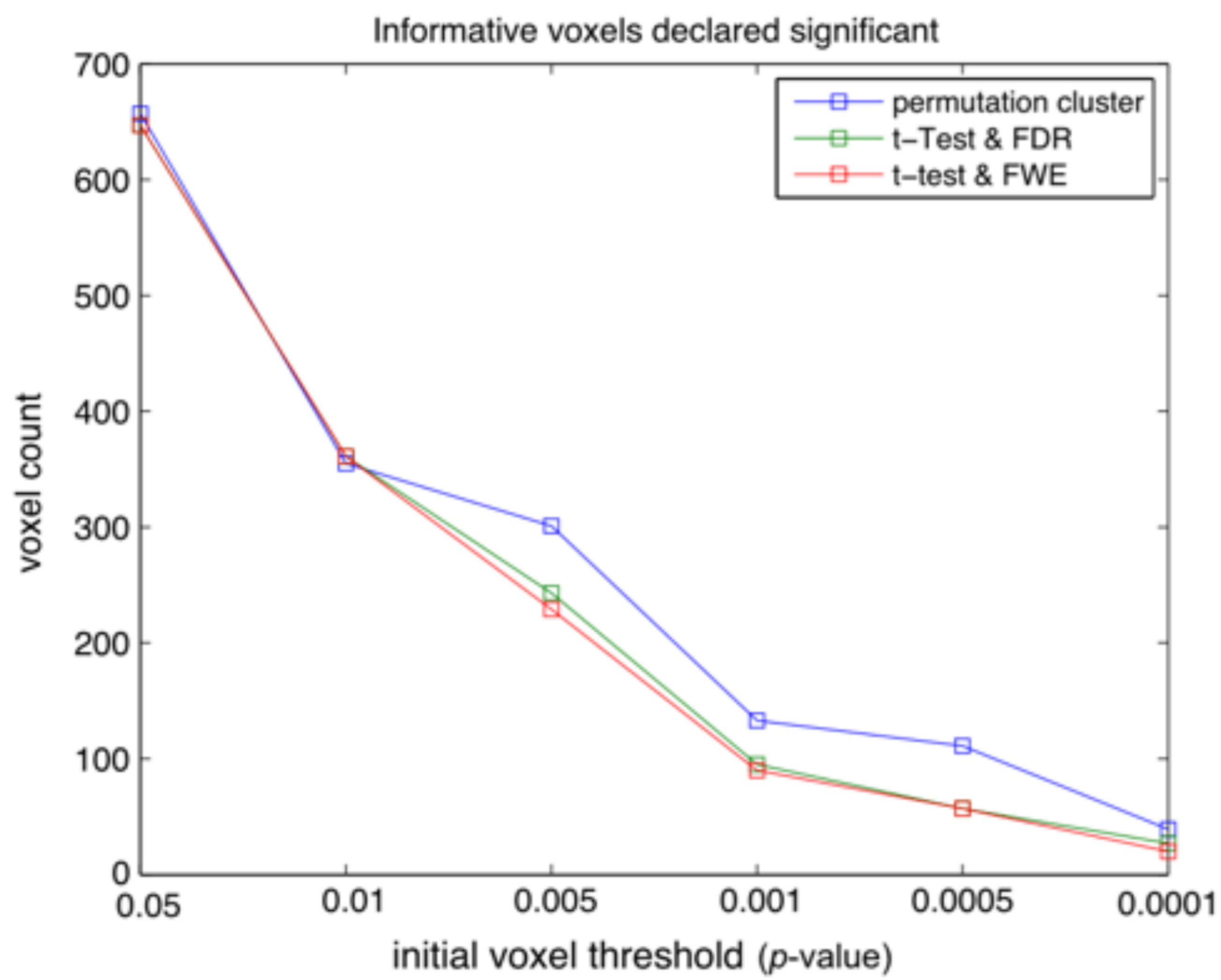
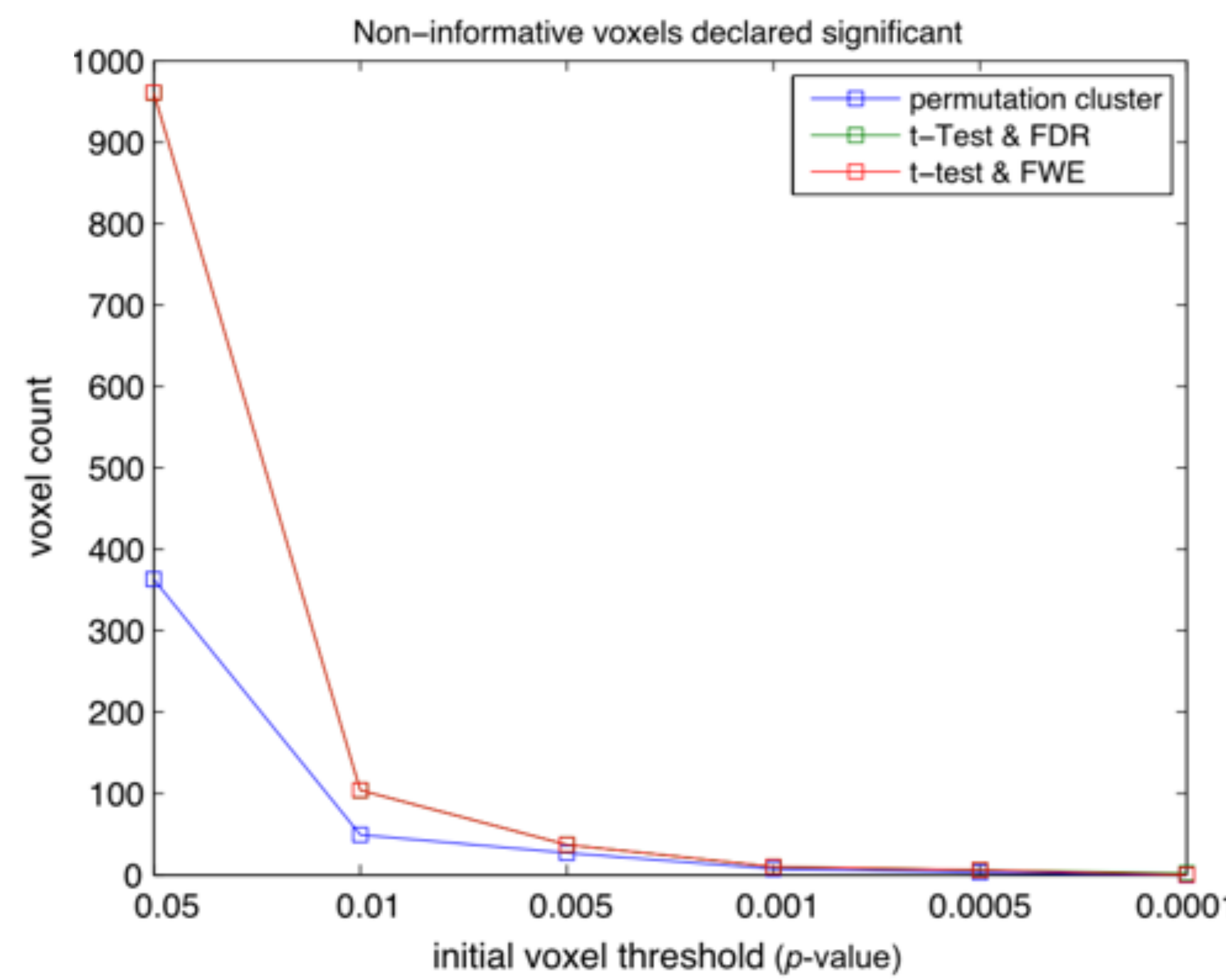
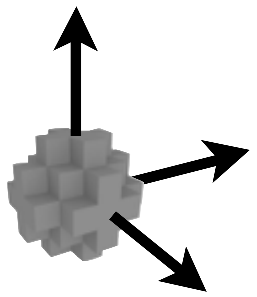
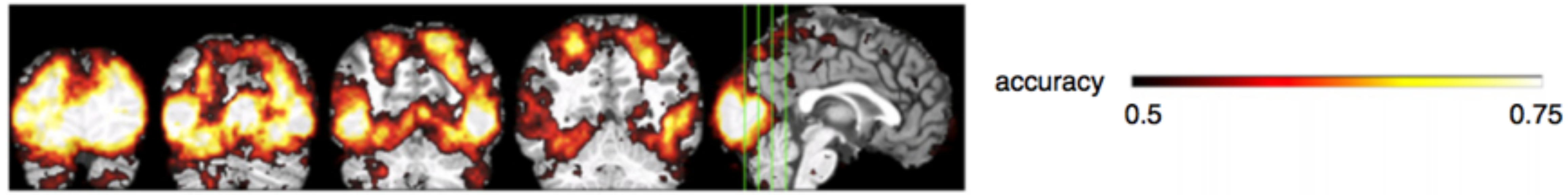




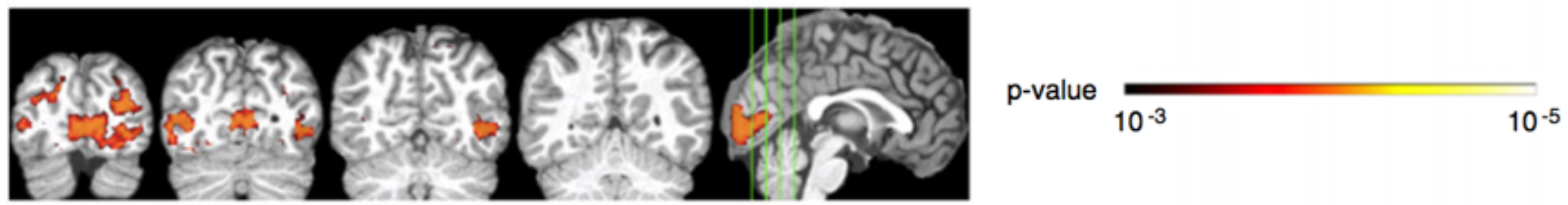


searchlight

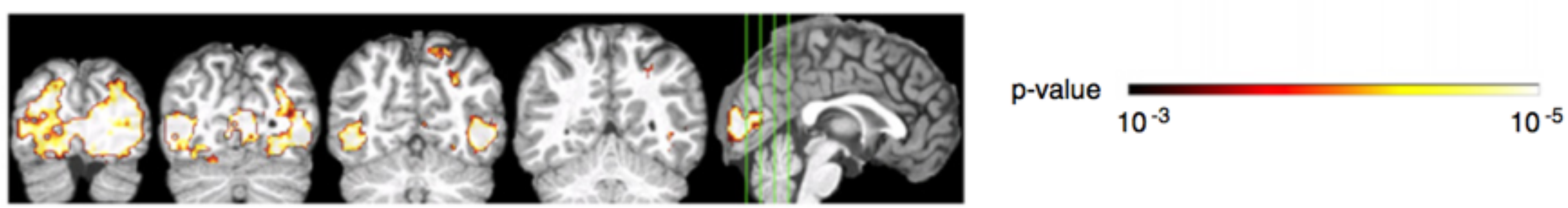
raw decoding accuracy
no cluster size thresholding

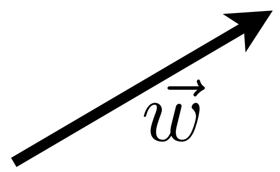


***t*-test**
FWE cluster thresholding

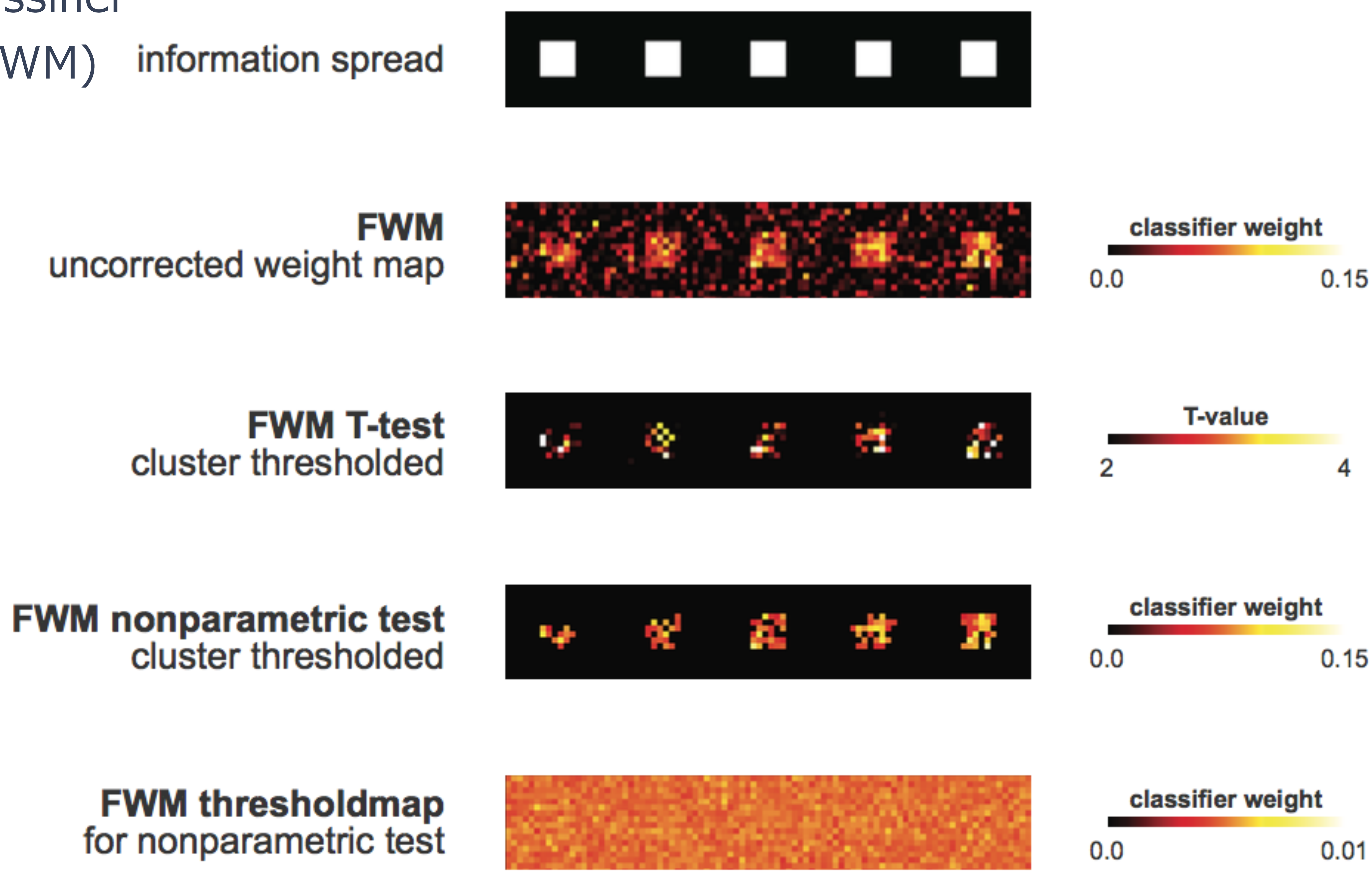


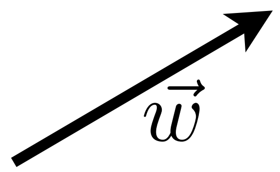
proposed non-parametric test
including cluster thresholding





mapping classifier weights (FWM)





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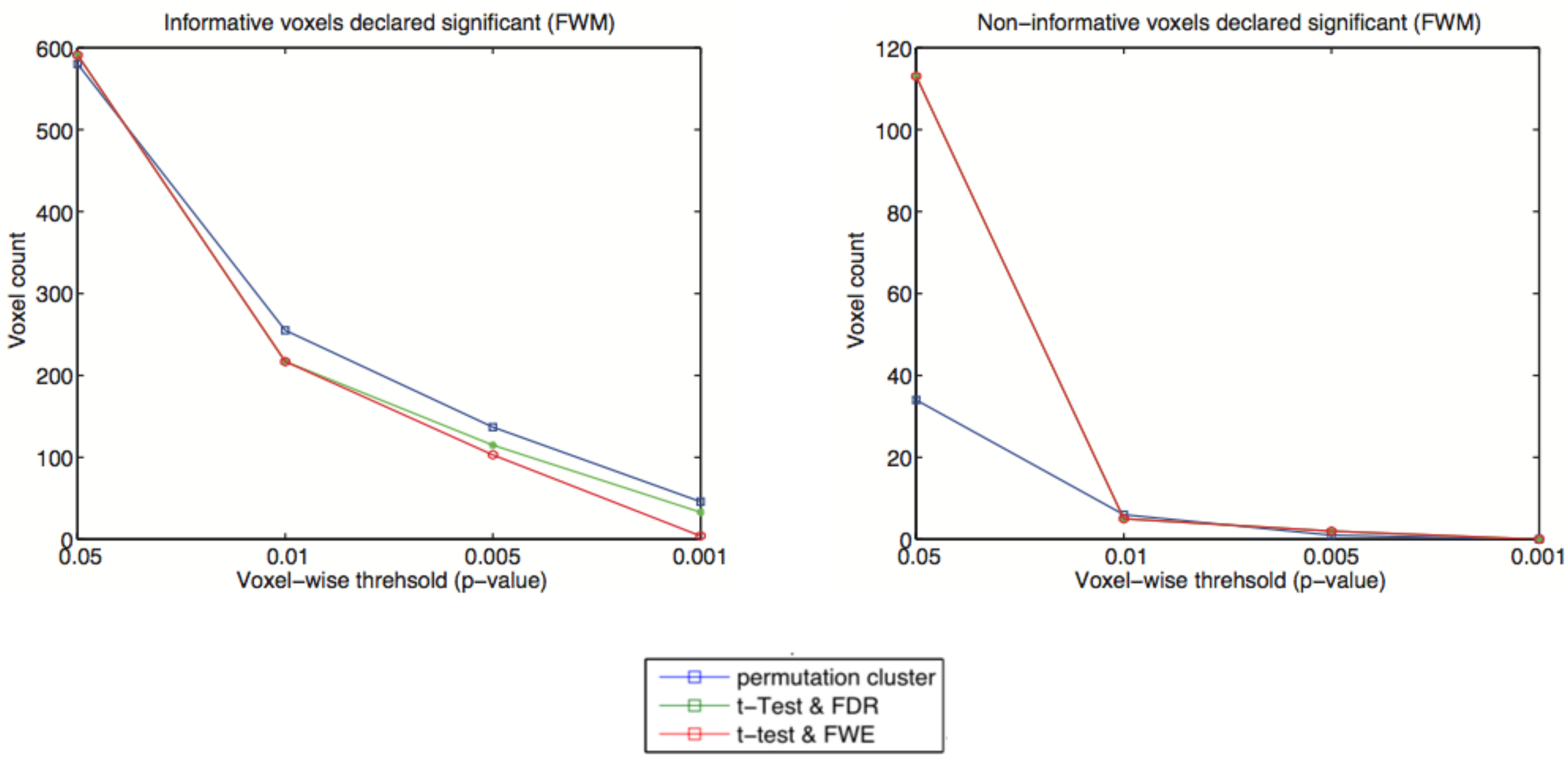
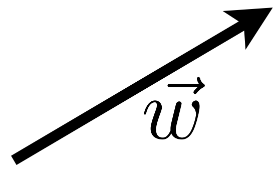
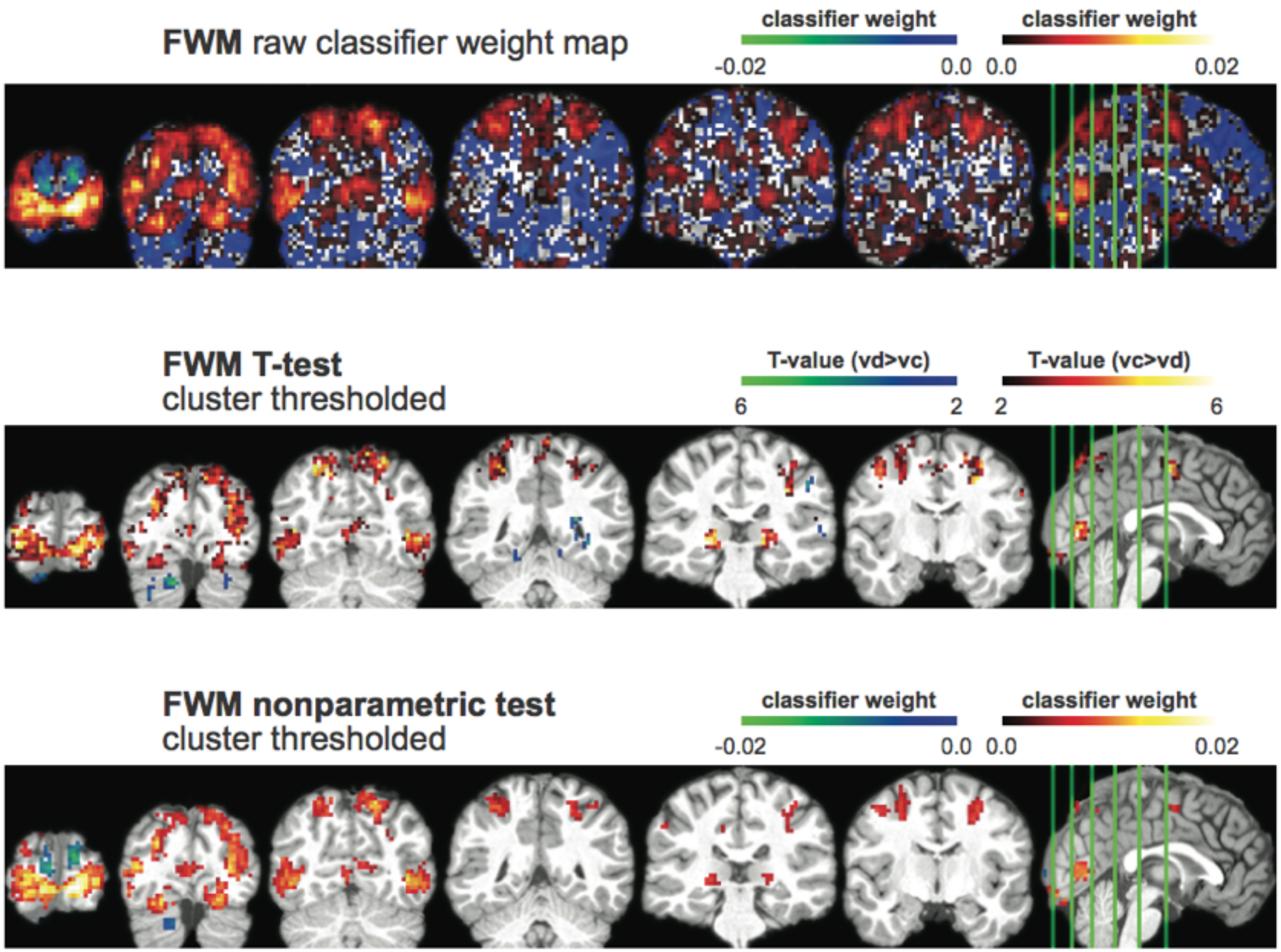
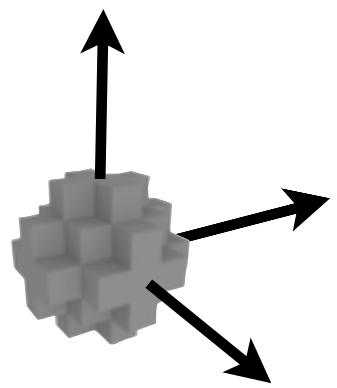




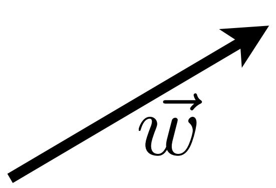
mapping classifier weights (FWM)



group level null simulations
100 simulations carried out



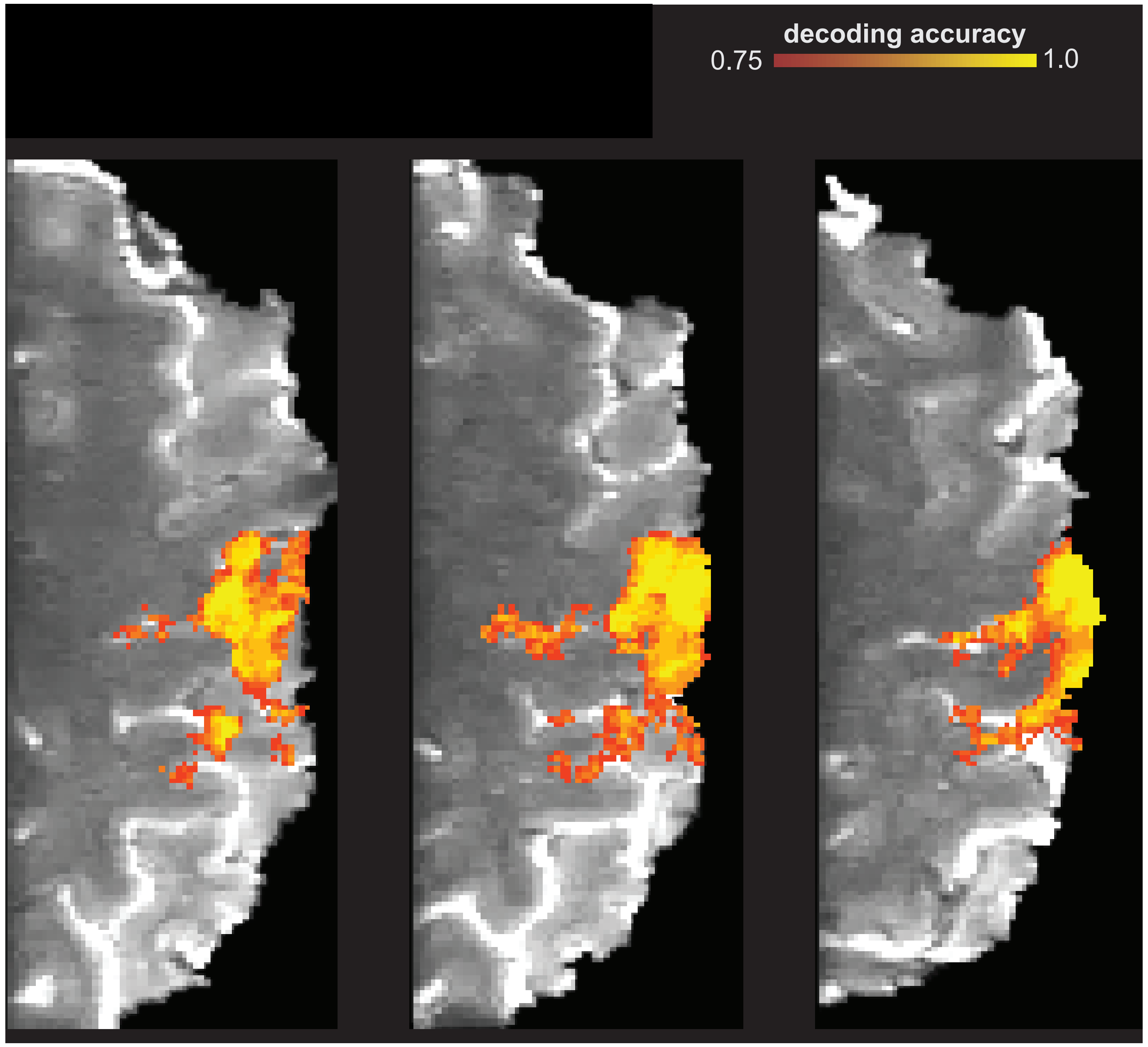
cluster threshold (p)	0,01	0,02	0,03	0,04	0,05
E(clusters)	1	2	3	4	5
nonparametric: clusters	0	1	1	1	1
T-based: clusters	4	7	11	13	17



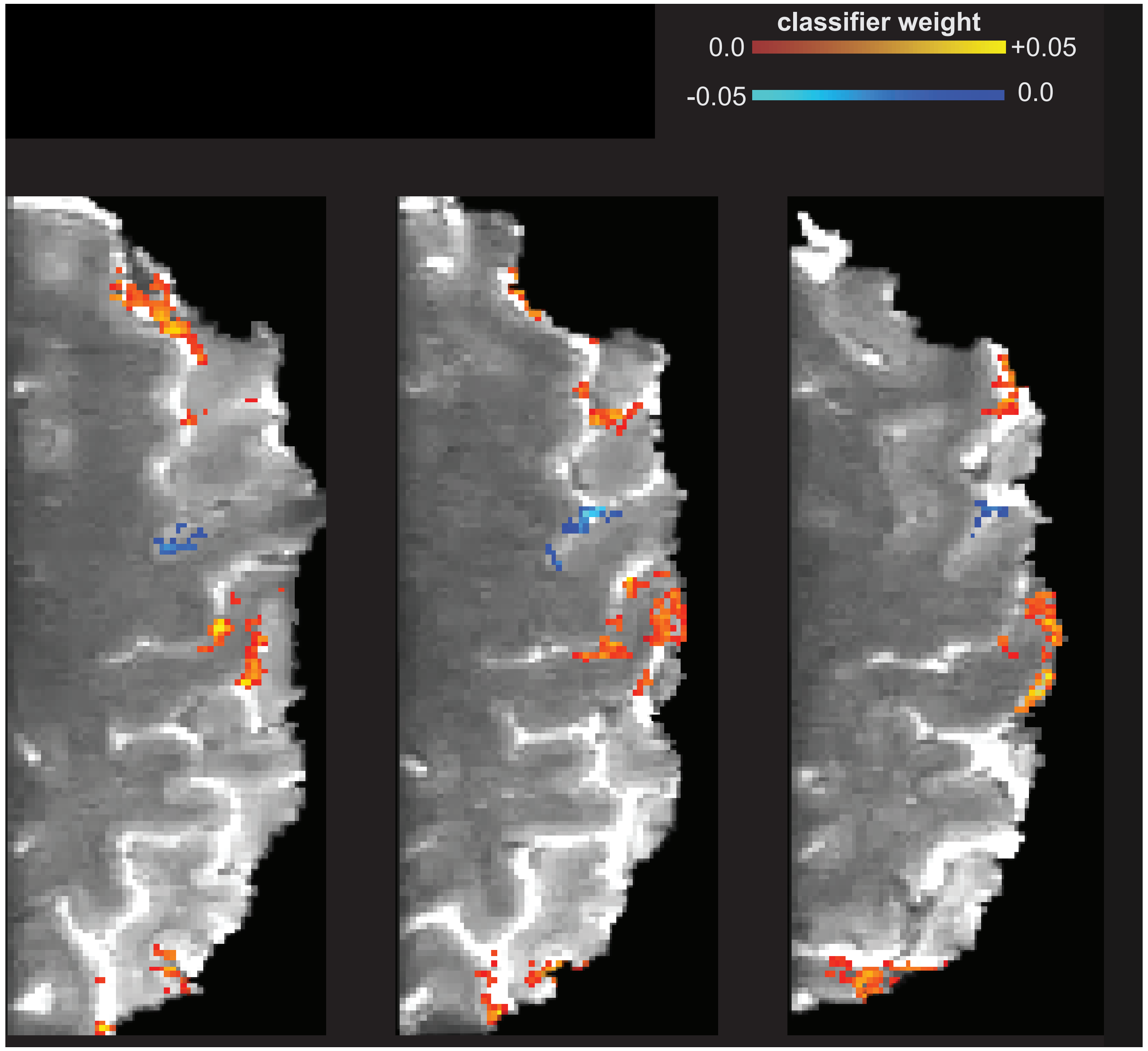
cluster threshold (p)	0,01	0,02	0,03	0,04	0,05
E(clusters)	1	2	3	4	5
nonparametric: (+)clusters	0	1	1	1	1
nonparametric: (-)clusters	0	2	2	2	2
T-based: (+)clusters	1	2670	2670	2670	2670
T-based: (-)clusters	0	2548	2548	2548	2548

MVPA @ 7T

searchlight decoding



feature weight mapping



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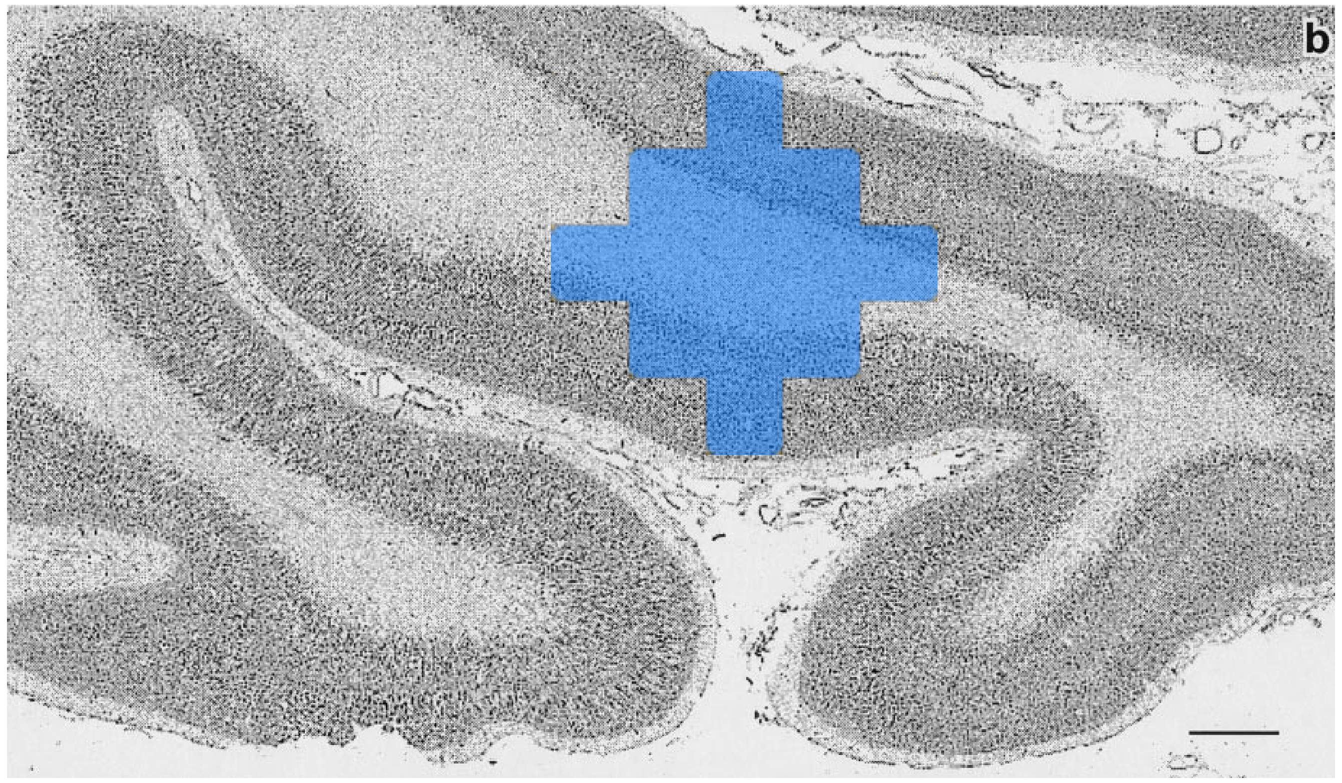
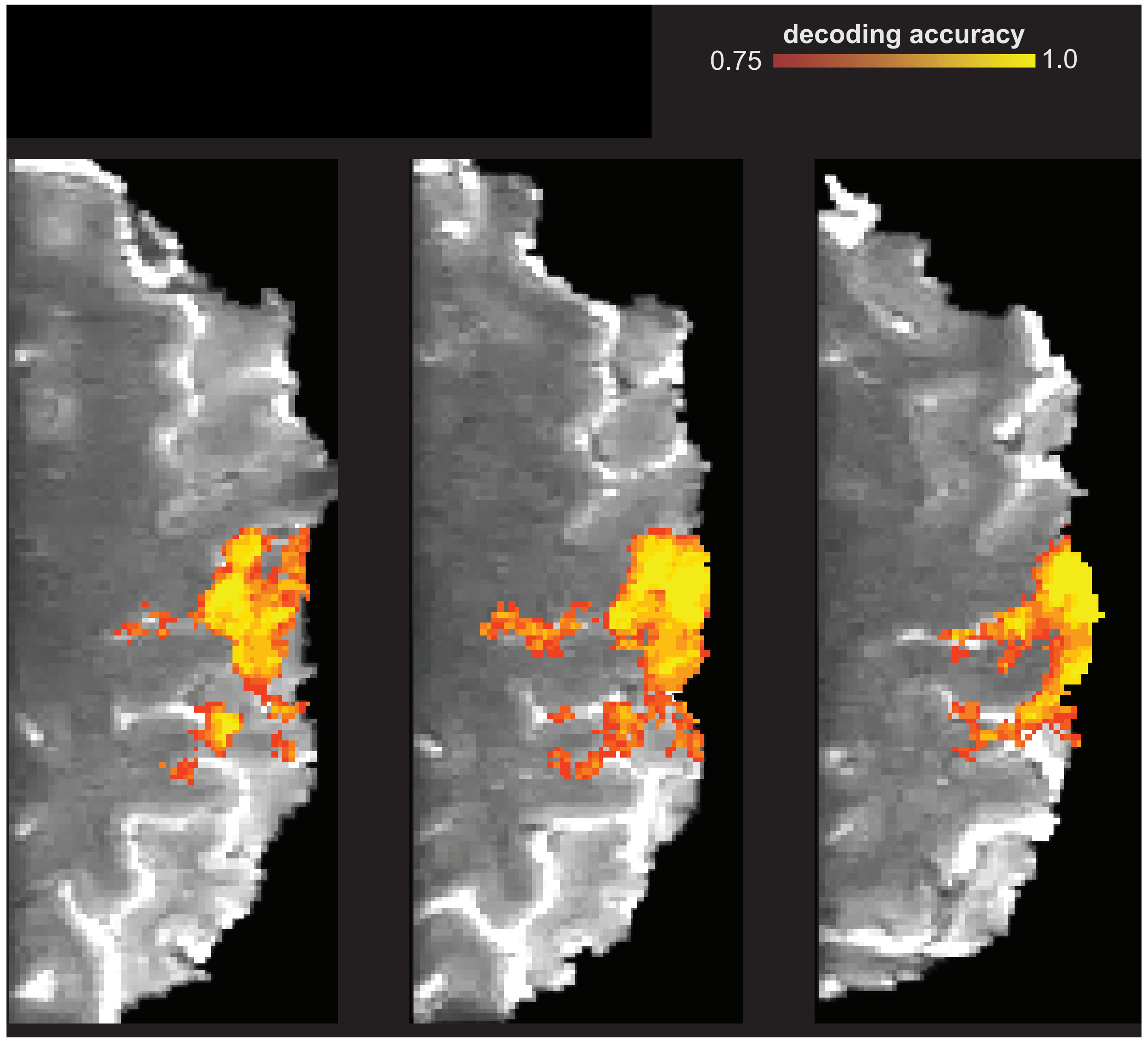
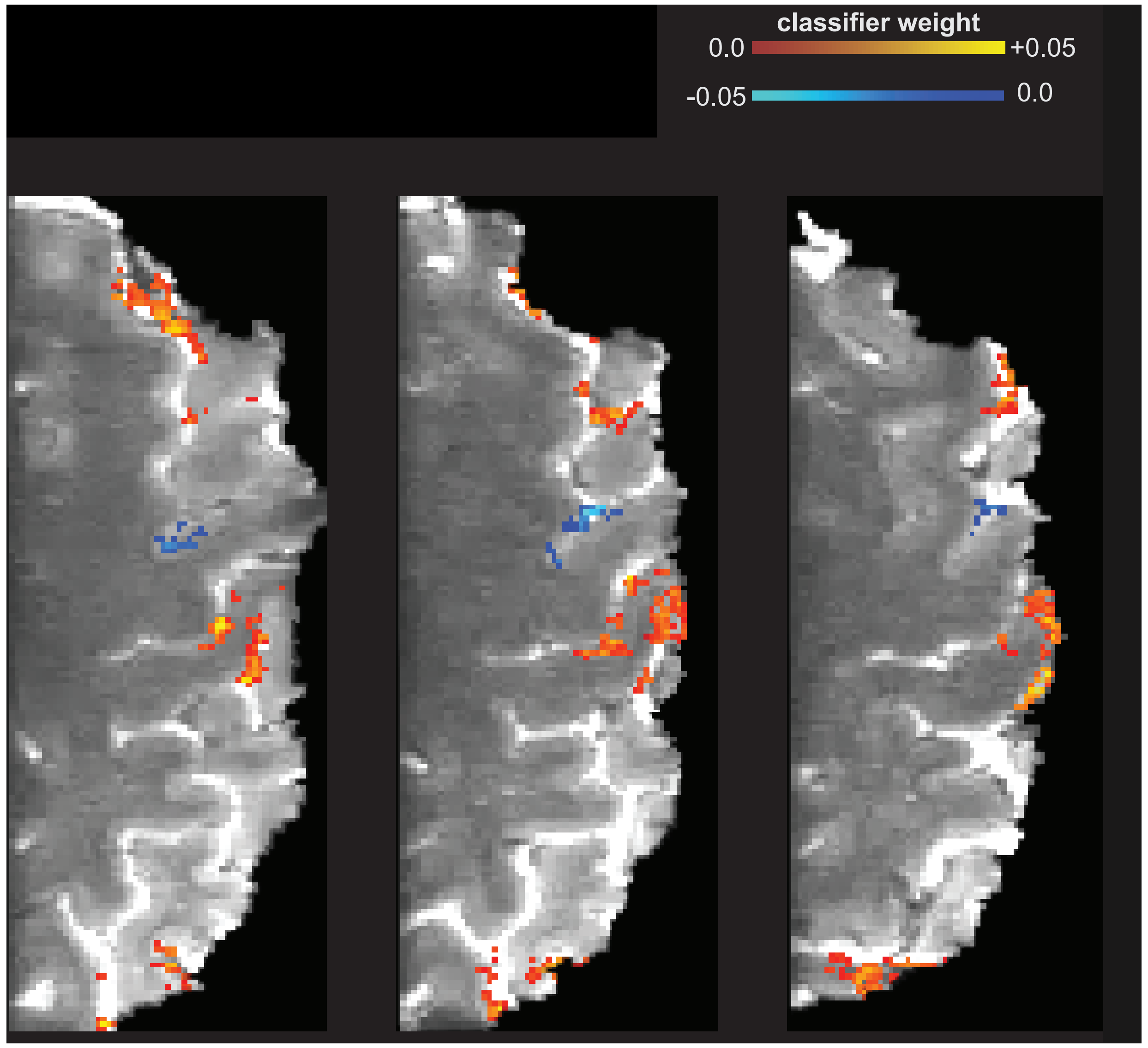
MVPA @ 7T







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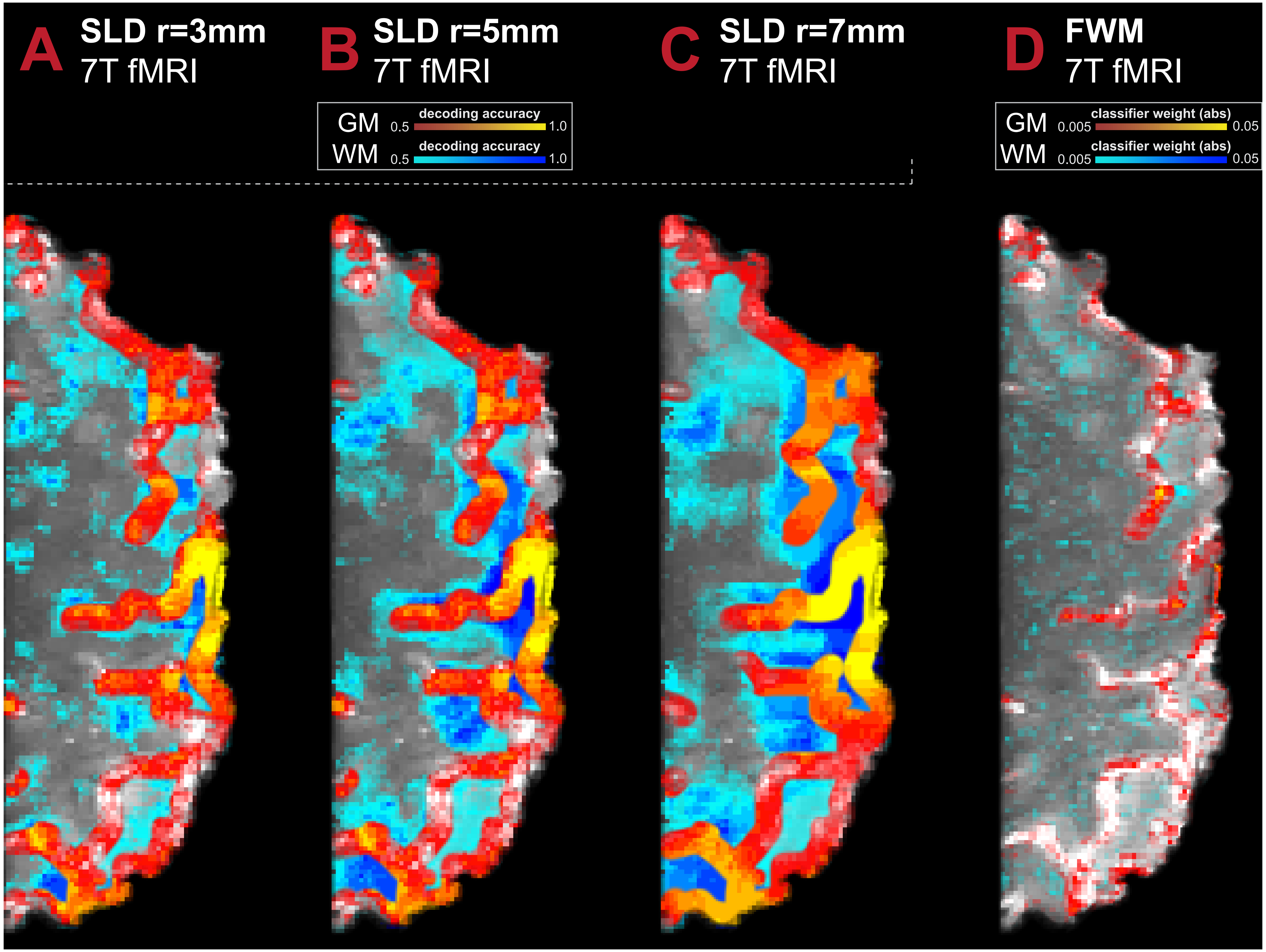

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issues

- computational burden
- spatial smoothness homogeneous
- small-scale patterns invisible (cluster stats)
- group stat issues

Eklund, A., Dufort, P., Villani, M., and LaConte, S. (2014). BROCCOLI: Software for Fast fMRI Analysis on Many-Core CPUs and GPUs. Front Neuroinform 8. doi:10.3389/fninf.2014.00024.

Stelzer, J., Lohmann, G., Mueller, K., Buschmann, T., and Turner, R. (2014). Deficient approaches to human neuroimaging. Front. Hum. Neurosci. 8. doi:10.3389/fnhum.2014.00462.

implementations

- PyMVPA (http://www.pymvpa.org/)
- CoSMoMVPA (http://cosmomvpa.org/)
- Lipsia 3.0 (to be released soon)

thanks for your attention!

& thanks to

Robert Turner

Yi Chen

Gabriele Lohmann

Tilo Buschmann

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