

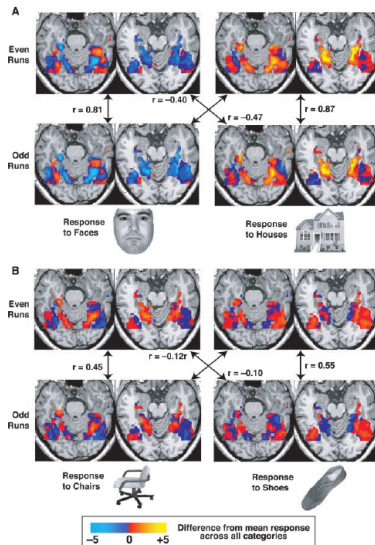
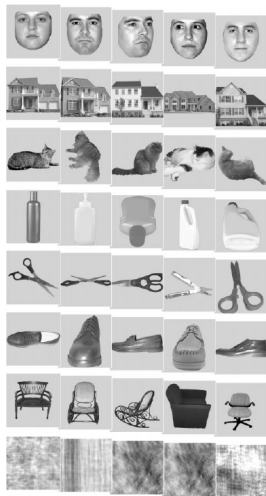
Basic MVPA strategies

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University of Magdeburg, Germany
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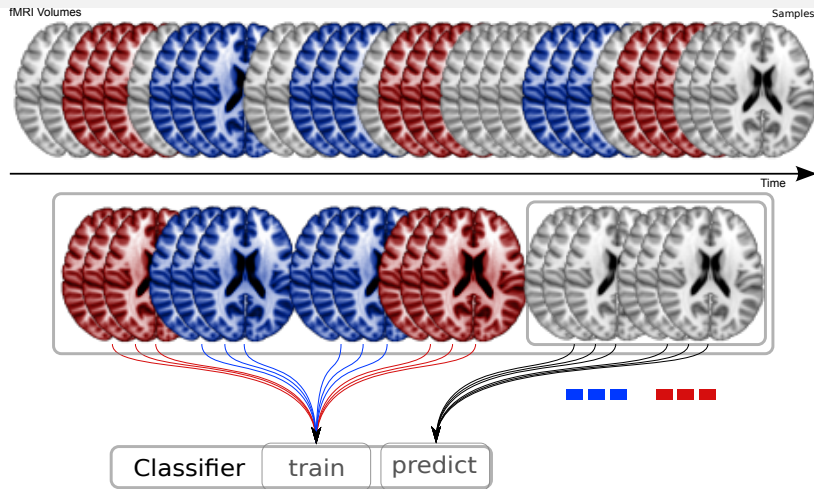
Delmenhorst 2014

How it all began: VT ROI, Haxby *et al.* 2001

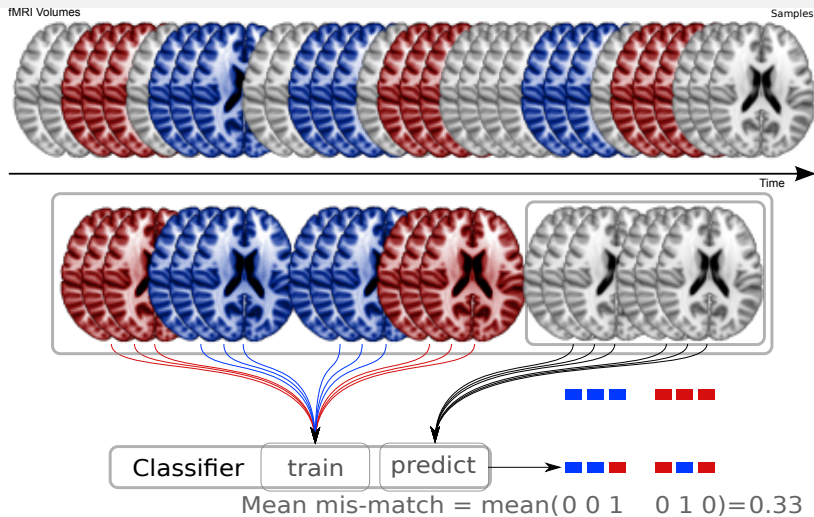


Haxby, J. V., Gobbini, M. I., Furey, M. L., Ishai, A., Schouten, J. L., and Pietrini, P. (2001). Distributed and overlapping representations of faces and objects in ventral temporal cortex. *Science*, 293, 2433-2439.

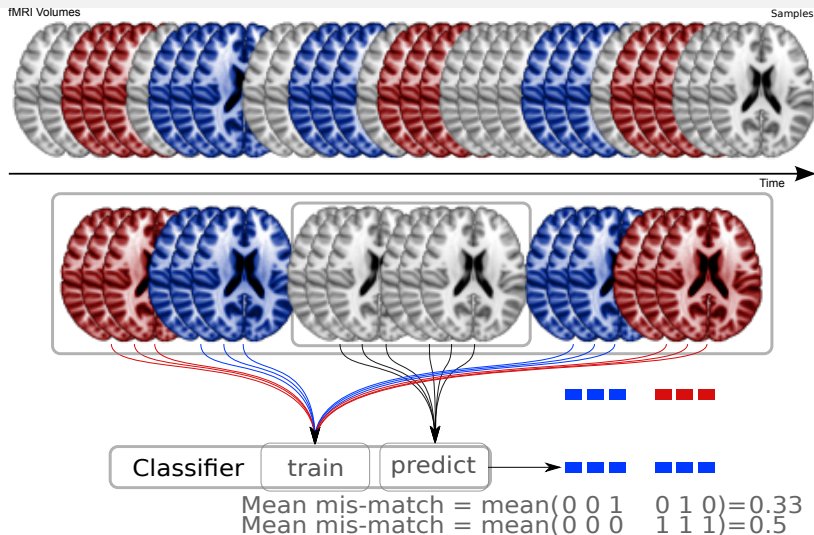
Cross-validation



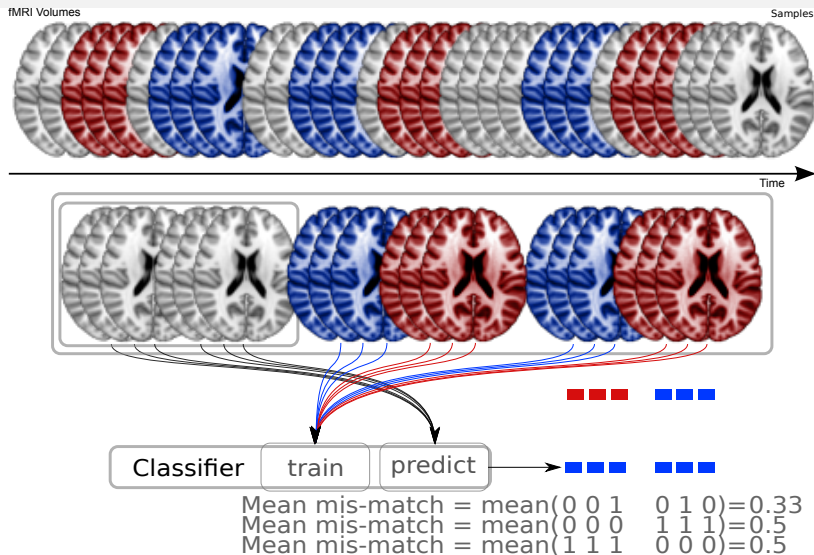
Cross-validation



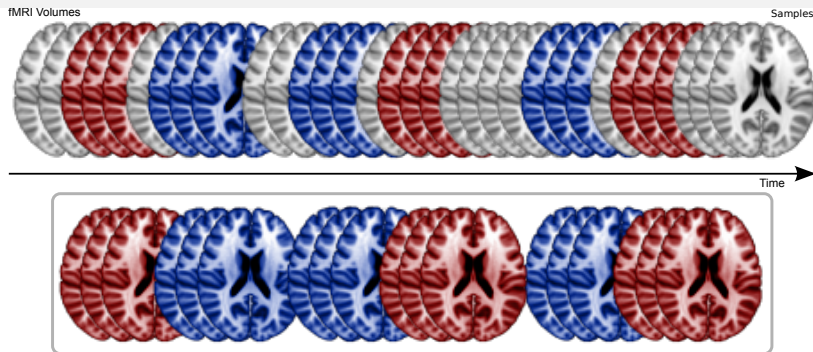
N-fold Cross-validation



N-fold Cross-validation



N-fold Cross-validation



$$\text{Total mean mis-match} = \text{mean}(0.33 \ 0.5 \ 0.5) = 0.44$$

N-fold Cross-validation

fMRI Volumes

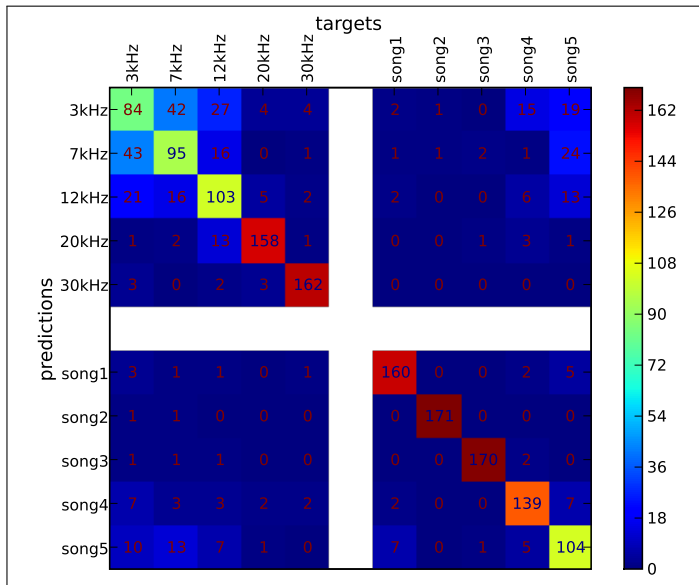
Samples



-----.	3kHz	7kHz	12kHz	20kHz	30kHz	song1	song2	song3	song4	song5							
predict.\targets	38	39	40	41	42	43	44	45	46	47							
3kHz / 38	84	42	27	4	4	2	1	0	15	19	P'	N'	FP	FN	PPV	NPV	TPR
7kHz / 39	43	94	16	0	1	1	1	2	1	24	198	1351	114	90	0.42	0.93	0.48
12kHz / 40	21	16	103	5	2	2	0	0	6	13	168	1312	65	70	0.61	0.95	0.6
20kHz / 41	1	2	13	158	1	0	0	1	3	1	180	1202	22	15	0.88	0.99	0.91
30kHz / 42	3	0	2	3	162	0	0	0	0	0	170	1194	8	11	0.95	0.99	0.94
song1 / 43	3	1	1	0	1	160	0	0	2	5	173	1199	13	14	0.92	0.99	0.92
song2 / 44	1	1	0	0	0	0	171	0	0	0	173	1176	2	2	0.99	1	0.99
song3 / 45	1	1	1	0	0	0	0	170	2	0	175	1179	5	4	0.97	1	0.98
song4 / 46	7	3	3	2	2	2	0	0	139	7	165	1240	26	34	0.84	0.97	0.8
song5 / 47	10	14	7	1	0	7	0	1	5	104	149	1310	45	69	0.7	0.95	0.6
Per target:																	
P	174	174	173	173	173	174	173	174	173	173							
N	1560	1560	1561	1561	1561	1560	1561	1560	1561	1561							
TP	84	94	103	158	162	160	171	170	139	104							
TN	1261	1251	1242	1187	1183	1185	1174	1175	1206	1241							
Summary \ Means:																	
ACC	0.78										173	1249	38	39	0.78	0.97	0.78
ACC%	77.57																
# of sets	8																

Hanke, M., Halchenko, Y. O., Sederberg, P. B., Olivetti, E., Fründ, I., Rieger, J. W., Herrmann, C. S., Haxby, J. V., Hanson, S. J., and Pollmann, S. (2009b). PyMVPA: A unifying approach to the analysis of neuroscientific data. *Frontiers in Neuroinformatics*, 3(3). PMC2638552

N-fold Cross-validation

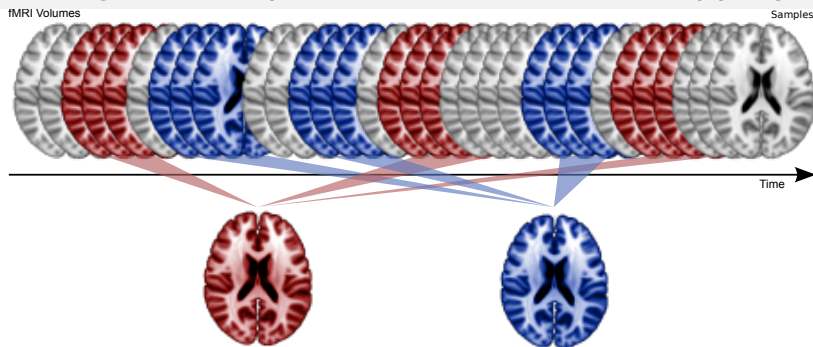


Hanke et al., Frontiers in Neuroinformatics, 2009

Classification analysis

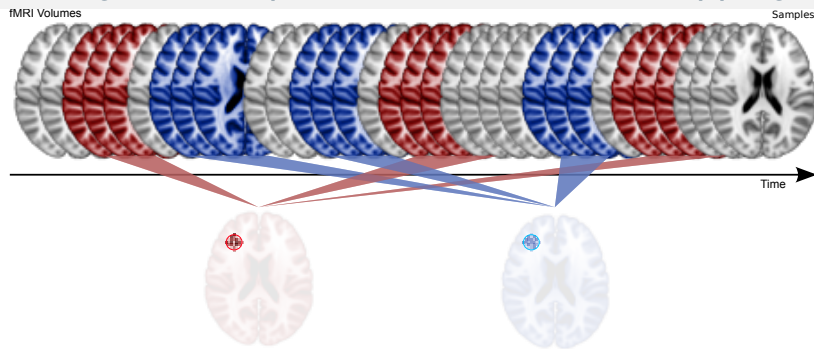
- Pros
 - fancy: “brain reading”
 - easy to grasp
 - multivariate (uses information from multiple voxels)
 - subject to significance estimation (via permutation)
 - base for additional strategies (e.g., voxel, ROI, or components *sensitivity*)
- Cons
 - there is no *best* classifier
 - spatially non-specific (depends on choice of ROI)
 - *curse of dimensionality*

Searchlight Concept: Information-based mapping



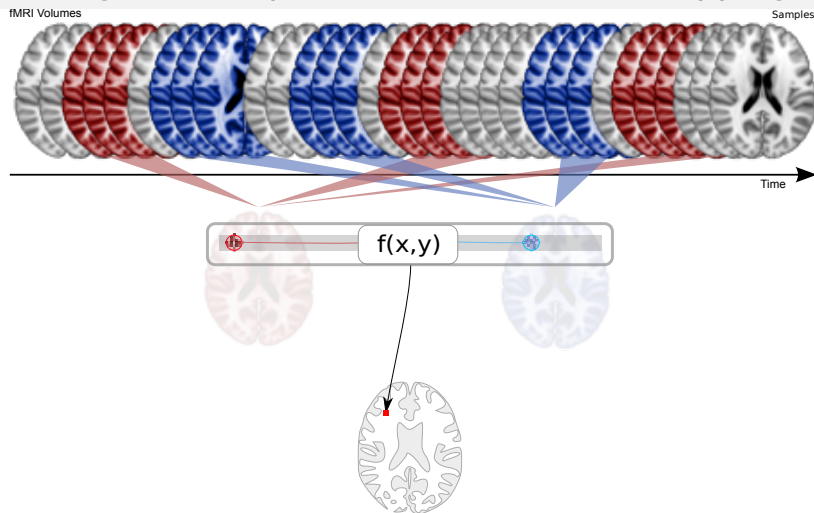
Kriegeskorte, N., Goebel, R., and Bandettini, P. (2006). Information-based functional brain mapping. *Proceedings of the National Academy of Sciences of the USA*, 103:3863–3868

Searchlight Concept: Information-based mapping



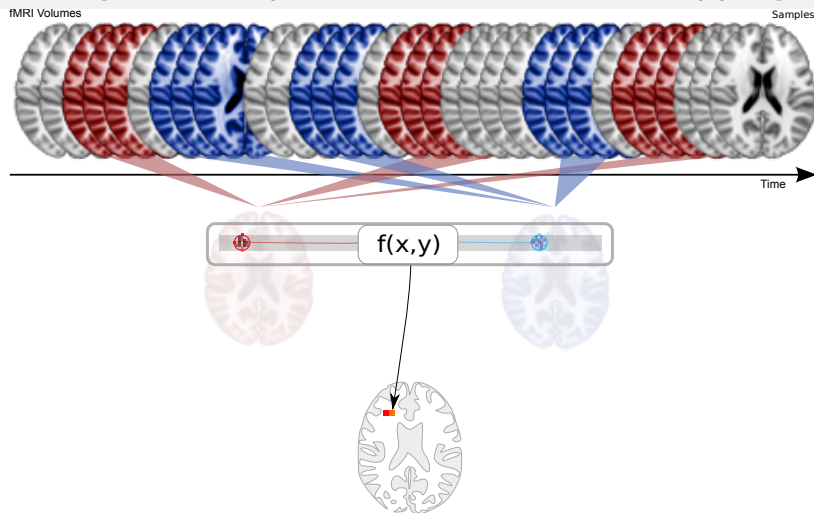
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Searchlight Concept: Information-based mapping



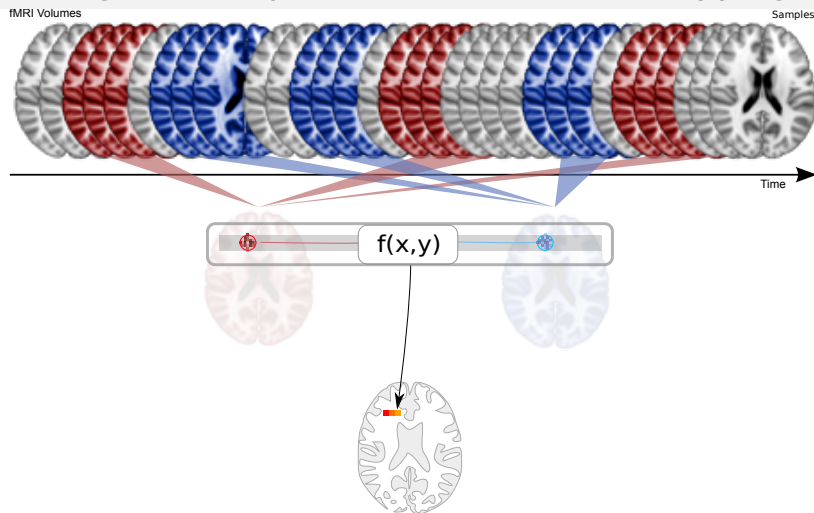
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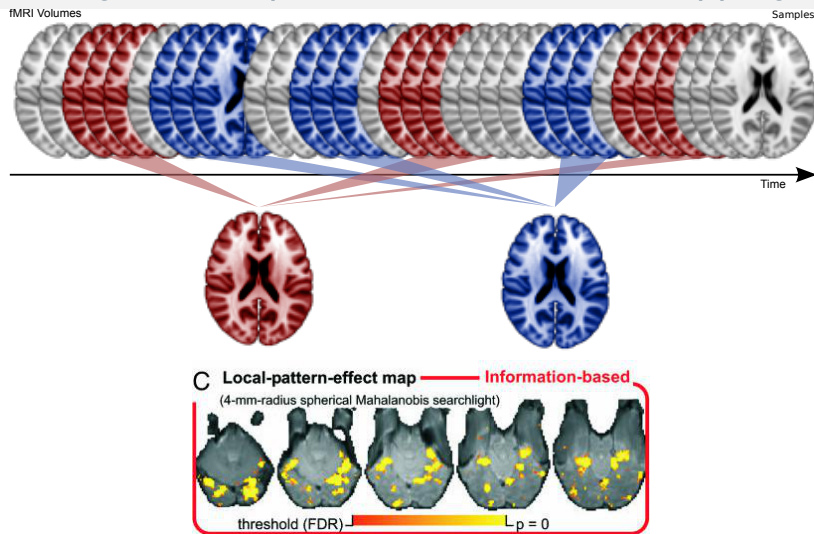
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Searchlight Concept: Information-based mapping

Assumptions replicable spatio-temporal response model

Goals benefit from high spatial resolution through

- multivariate measure
- eliminating need for smoothing

Input predictor amplitudes, 1 sample per category

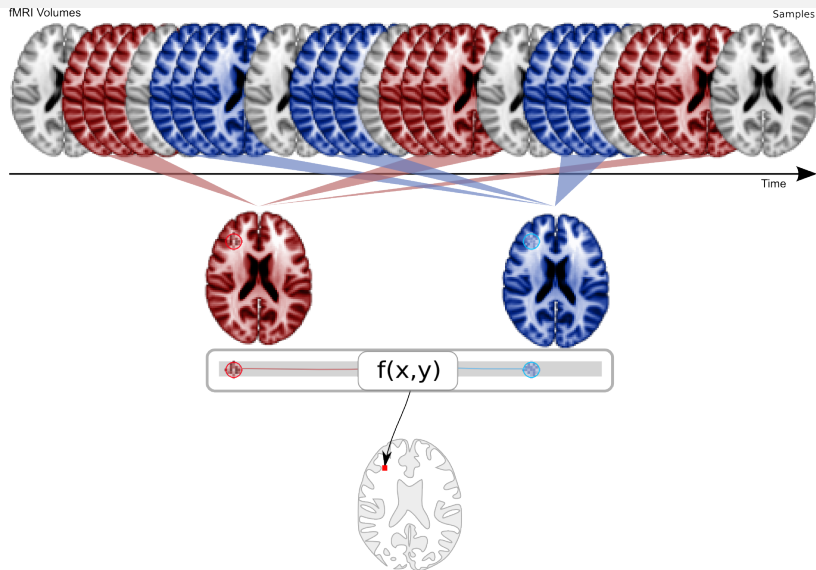
Measure Mahalanobis distance

$$\Delta = (a_2 - a_1) \hat{\Sigma}^{-1} (a_2 - a_1)^T$$

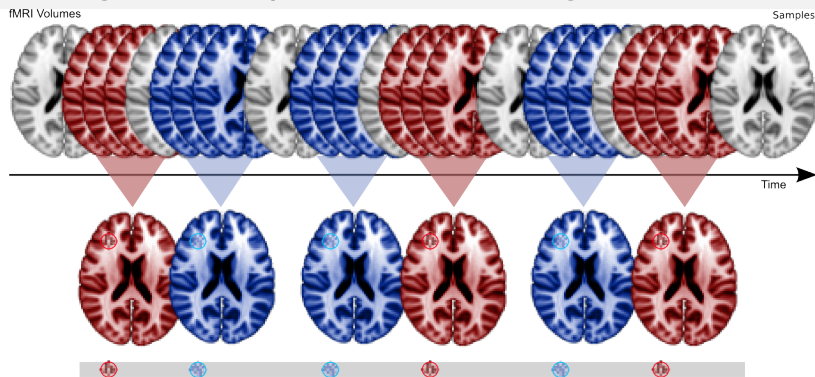
Statistic p-value (FDR correction) against results on 1000 random design sequences

Kriegeskorte, N., Goebel, R., and Bandettini, P. (2006). Information-based functional brain mapping. *Proceedings of the National Academy of Sciences of the USA*, 103:3863–3868

Searchlight Concept

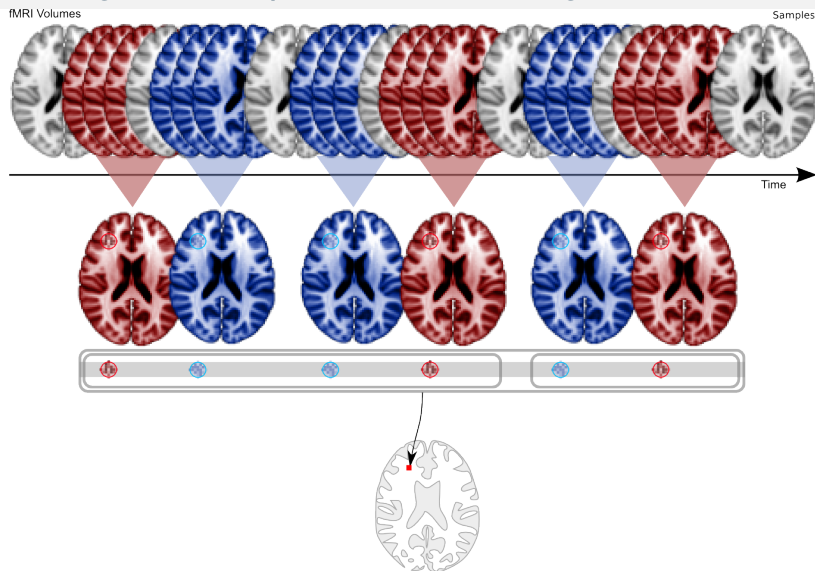


Searchlight Concept: Classification generalization



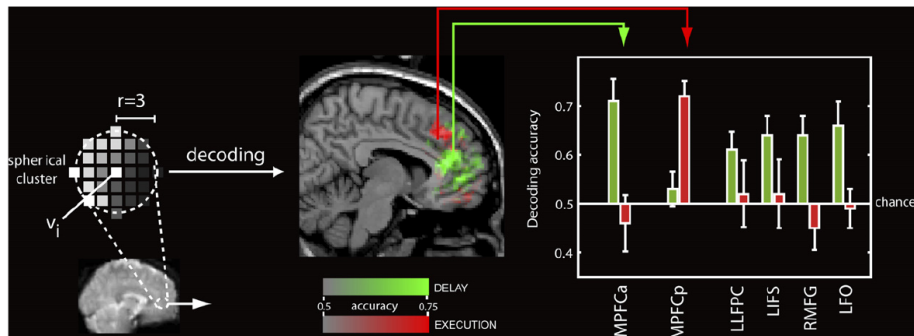
Haynes, J.-D., Sakai, K., Rees, G., Gilbert, S., Frith, C., and Passingham, R. E. (2007). Reading hidden intentions in the human brain. *Current Biology*, 17:323–328

Searchlight Concept: Classification generalization



Haynes, J.-D., Sakai, K., Rees, G., Gilbert, S., Frith, C., and Passingham, R. E. (2007). Reading hidden intentions in the human brain. *Current Biology*, 17:323–328

Searchlight Concept: Classification generalization



- Classify hidden intentions
- Smoothed with a Gaussian kernel of 6 mm FWHM
- Classifier input: GLM-parameter estimates per each of 8 runs
- Sphere radius approx 7.5 mm

Haynes, J.-D., Sakai, K., Rees, G., Gilbert, S., Frith, C., and Passingham, R. E. (2007). Reading hidden intentions in the human brain. *Current Biology*, 17:323–328

Classification Searchlight

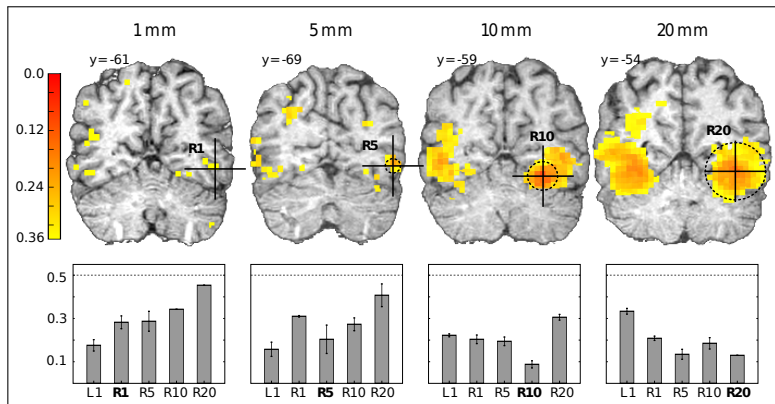
Pros

- easier to grasp
- investigates local patterns
- does (fancy) “brain reading”
- is not limited to classification (RSA, consistency, *etc.*)

Cons

- compromised spatial specificity (Etzel et al., 2013)
- difficult to do permutation-based significance testing (but see Pereira and Botvinick, 2011; Stelzer et al., 2013)

Classification Searchlight: Spatial specificity



Hanke, M., Halchenko, Y. O., Sederberg, P. B., Hanson, S. J., Haxby, J. V., and Pollmann, S. (2009a). PyMVPA: A Python toolbox for multivariate pattern analysis of fMRI data. *Neuroinformatics*, 7(1):37–53. PMC2664559

References

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- Haynes, J.-D., Sakai, K., Rees, G., Gilbert, S., Frith, C., and Passingham, R. E. (2007). Reading hidden intentions in the human brain. *Current Biology*, 17:323–328.
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