MVPA: Principles, pitfalls and perspectives

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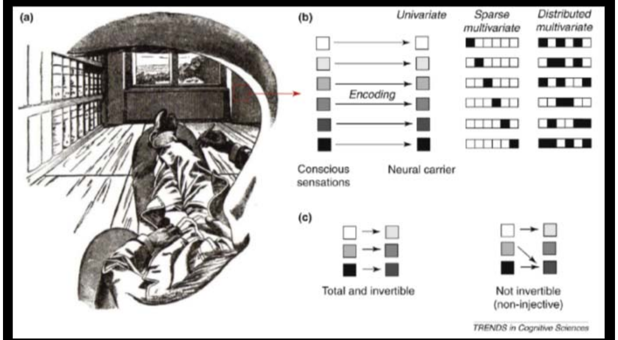
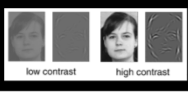
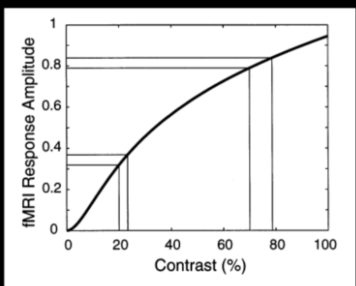
Representations



Haynes TICS 2009

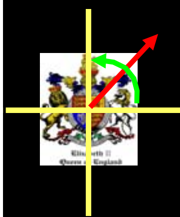
Univariate codes?





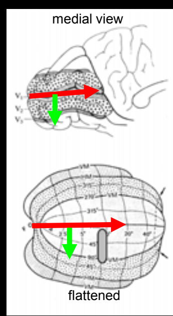
Boynton & Heeger 1999

Sparse multivariate codes?

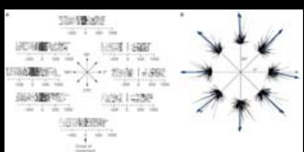


Eccentricity

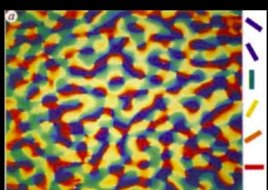
Polar angle



Distributed population codes

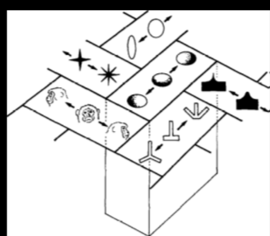


Georgopoulos et al. 1982

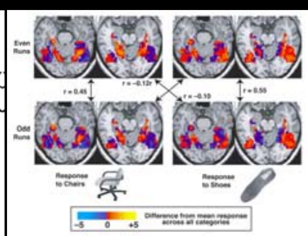


Blasdel & Salama 1986

Distributed population codes

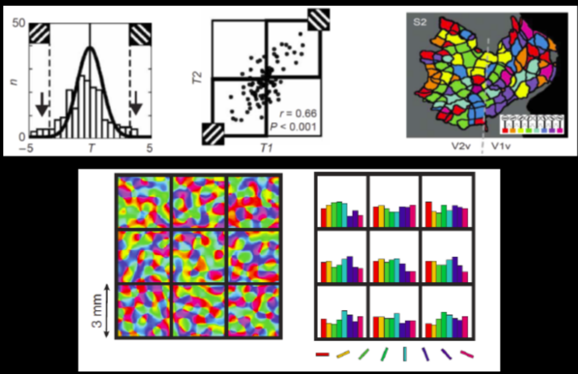


Tanaka 1997



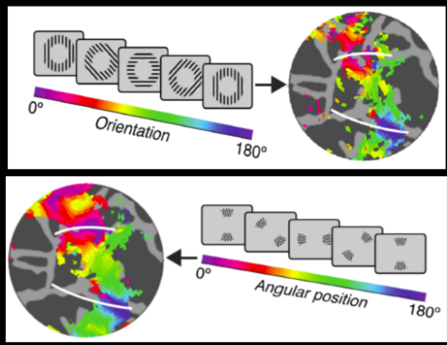
Haxby et al. 2001

Origin of single voxel response patterns?



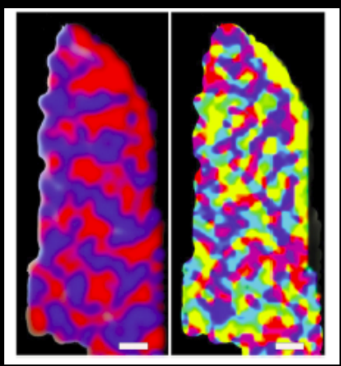
Haynes & Rees 2005; Kamitani & Tong 2005; Boynton 2005

Origin of single voxel response patterns?



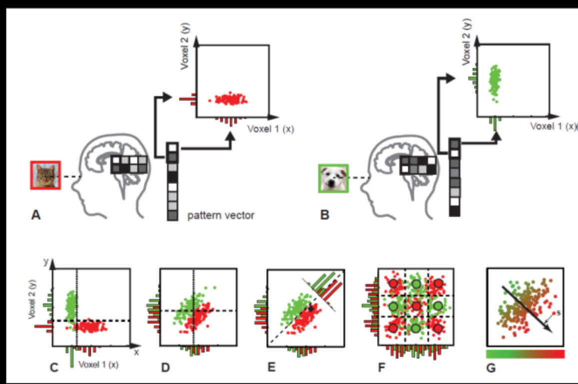
Freeman et al. 2011

The future?



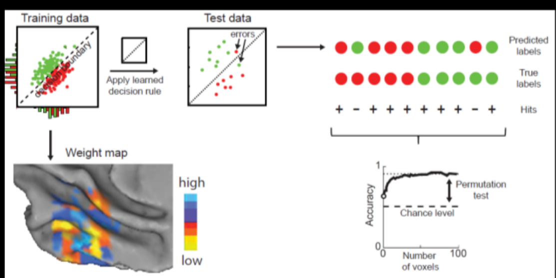
Jacoub et al. 2008

Classifiers



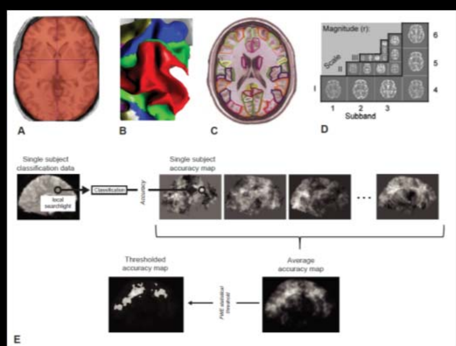
Haynes, Neuron 2015

Cross-validation



Haynes, Neuron 2015

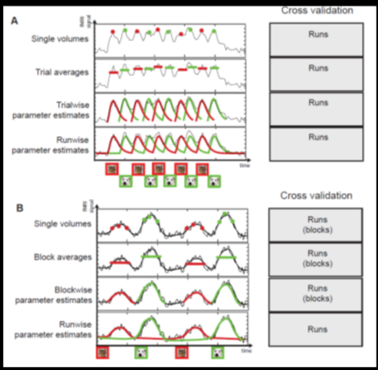
Spatial selection



Alternatives: Information-based feature selection

Haynes, Neuron 2015

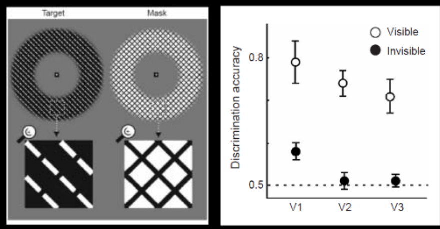
Temporal selection



Temporal selection is also linked to cross-validation and statistical options

Haynes, Neuron 2015

Pitfalls: Accuracies



What does the classification accuracy „mean"?

Haynes & Rees NN 2005; Haynes, Neuron 2015

Pitfalls: Accuracies

Underestimating information
Classification accuracies reflect the result of a complex sampling of single cell populations. Because a voxel might sample more than a million neurons the information might be underestimated at the level of voxels.

Overestimating information
The hemodynamic delay might integrate information across longer timescales than neuronal integration time windows. Thus, the single-cell population information might be overestimated.

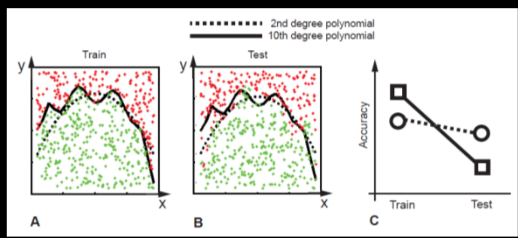
Comparison across areas
Different regions might have different sampling patterns, different numbers of neurons and voxels, different SNRs, different hemodynamic response efficiencies, etc. Thus, a direct comparison of information across regions is not possible.

Processing options
Levels of accuracy depend on partitioning of data into training and test.

Haynes, Neuron 2015

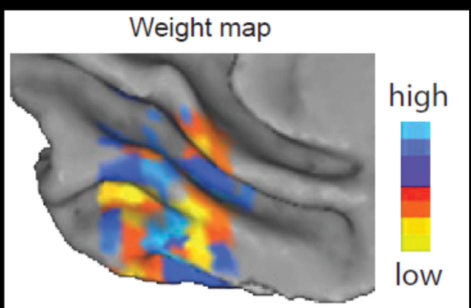
Pitfalls: Circularity and overfitting

Proper cross-validation
If different classifiers and parameters are used (linear, nonlinear, parametric, nonparametric, etc.) this needs to be done in a nested cross-validation, otherwise accuracies can be biased.



Haynes, Neuron 2015

Pitfalls: Weight maps



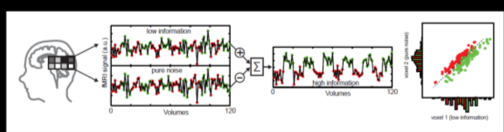
What does the weight map „mean"?

Haynes, Neuron 2015

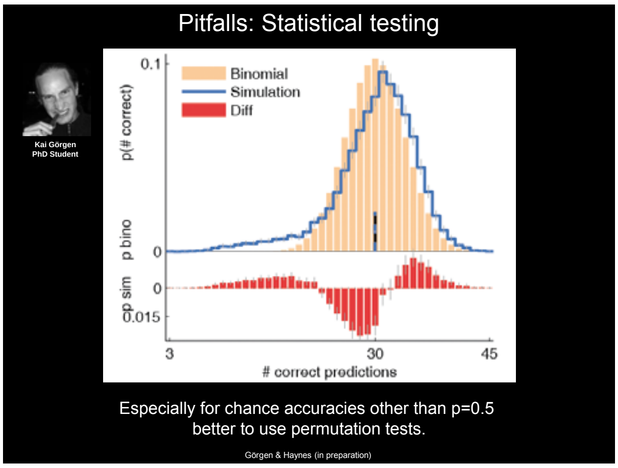
Pitfalls

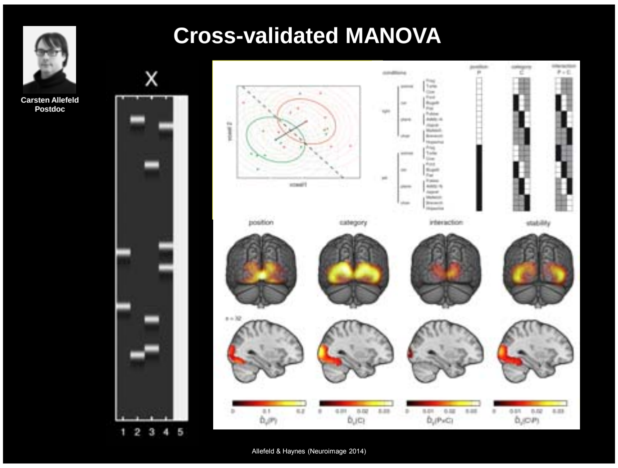
A weight map pertains to a classifier as a whole and does not (directly) allow to interpret the involvement of individual voxels
→ presurgical mapping

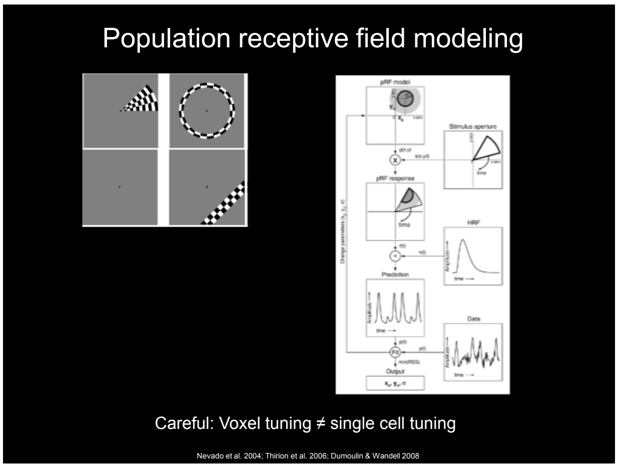
If a voxel has a positive weight this does not imply that this voxel has „information" about the labels.

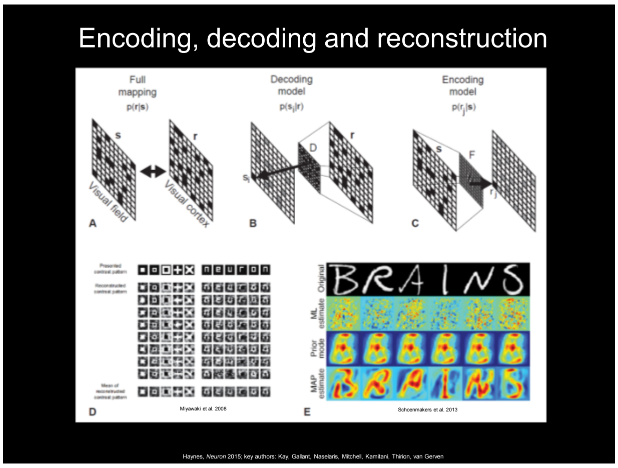


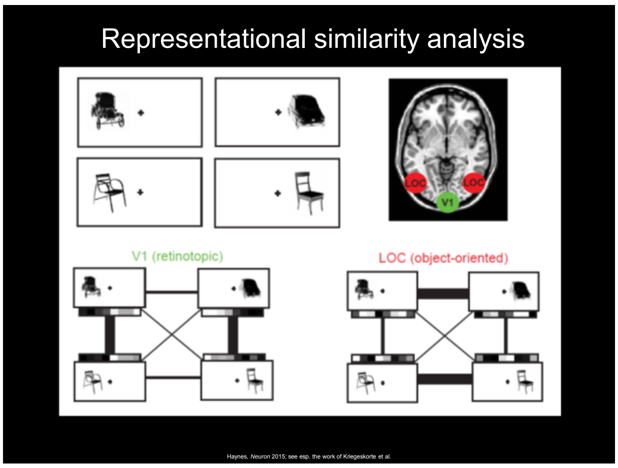
Haynes, Neuron 2015; Haufe et al. 2014

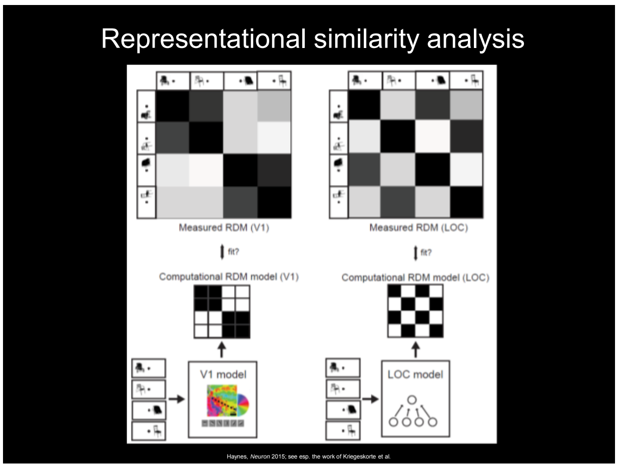

Pitfalls: Statistical testing
Kai Görgen
PhD Student
0.1
p(# correct)
p bino
0
Δp sim
0
0.015
Binomial
Simulation
Diff
3
30
45
correct predictions
Especially for chance accuracies other than p=0.5
better to use permutation tests.
Görgen & Haynes (in preparation)


Cross-validated MANOVA
Carsten Allefeld
Postdoc
X
1 2 3 4 5
position
category
interaction
stability
Allefeld & Haynes (Neuroimage 2014)


Population receptive field modeling
Careful: Voxel tuning ≠ single cell tuning
Nevado et al. 2004; Thirion et al. 2006; Dumoulin & Wandell 2008


Encoding, decoding and reconstruction
Full
mapping
p(r|s)
Decoding
model
Encoding
model
Visual field
Visual cortex
A
B
C
D
E
Original
ML estimate
Prior mode
MAP estimate
Miyawaki et al. 2008
Schoenmakers et al. 2013
Haynes, Neuron 2015; key authors: Kay, Gallant, Naselaris, Mitchell, Kamitani, Thirion, van Gerven


Representational similarity analysis
LOC
V1
V1 (retinotopic)
LOC (object-oriented)
Haynes, Neuron 2015; see esp. the work of Kriegeskorte et al.


Representational similarity analysis
Measured RDM (V1)
Measured RDM (LOC)
fit?
fit?
Computational RDM model (V1)
Computational RDM model (LOC)
V1 model
LOC model
Haynes, Neuron 2015; see esp. the work of Kriegeskorte et al.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