## machine learning for (f)MRI

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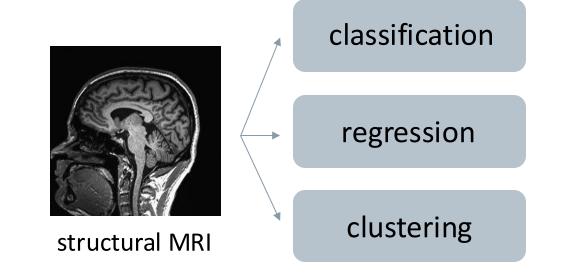
## what is machine learning?

- study of computer programs that learn to predict something
- learn from data, without being told how to do it explicitly

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[Arthur Samuel, 1959]
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- "statistics, reinvented poorly from first principles"
- "statistics, but it works for real problems"

[assorted trash talking heard over the years]



"is this structural image of a patient or a control? why?"

"can we predict participant characteristics from the image?"

"are there subgroups of patients with similar images?"

#### science is about questions, not methods

#### description

"Are observations explainable in terms of a few (latent) variables?"

#### prediction

"Is the evolution of an outcome variable predictable from observations (or latent variables estimated from them)? How?"

#### causality and control

"How would intervening on some variables affect others?"

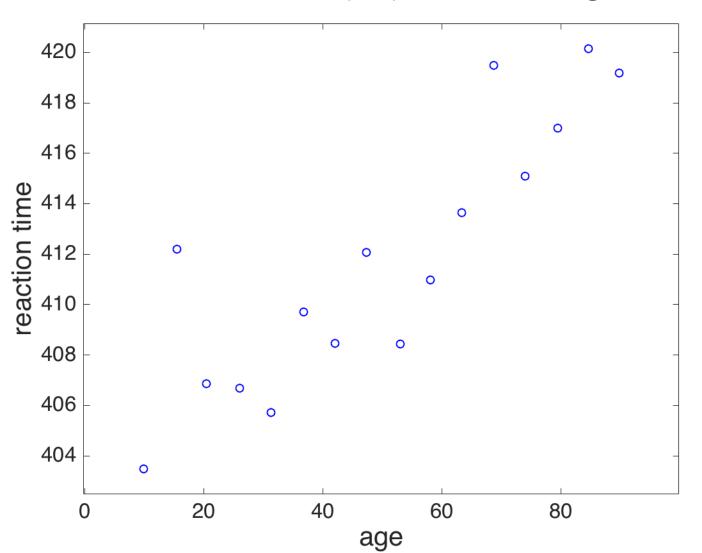
#### mechanism or computation

"How does an input get transformed to produce the observations?"

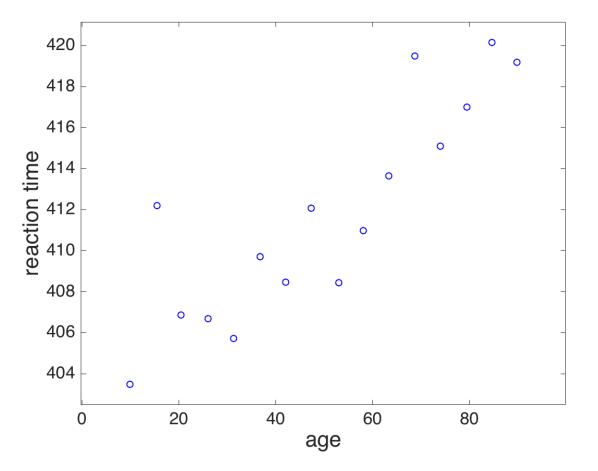
# linear regression from a machine learning viewpoint

[adapted from slides by Russ Poldrack]

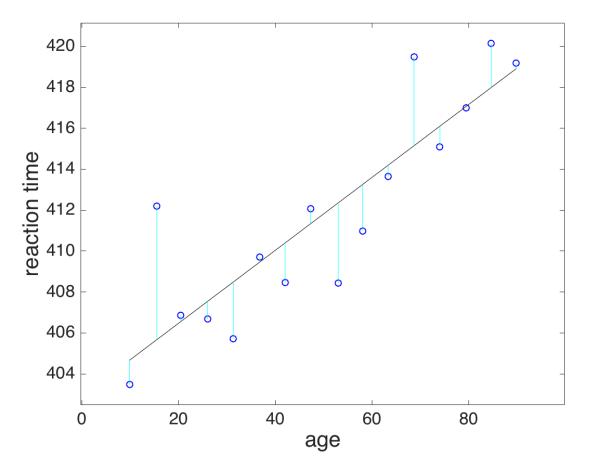
#### once upon a time there was a sample...



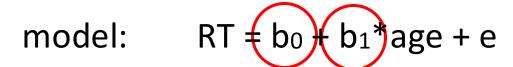
is reaction time (RT) related to age?

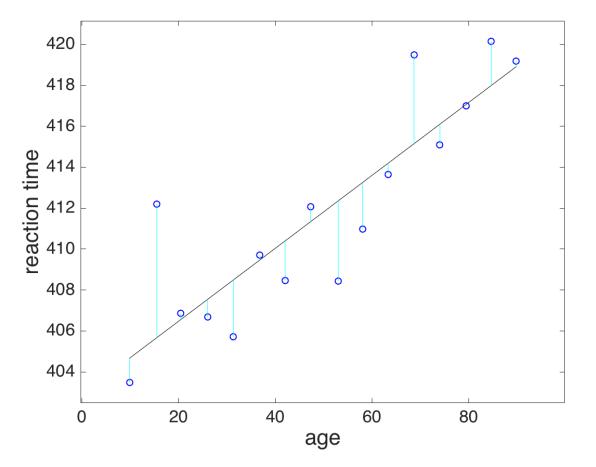


model:  $RT = b_0 + b_1^*age + e$ 



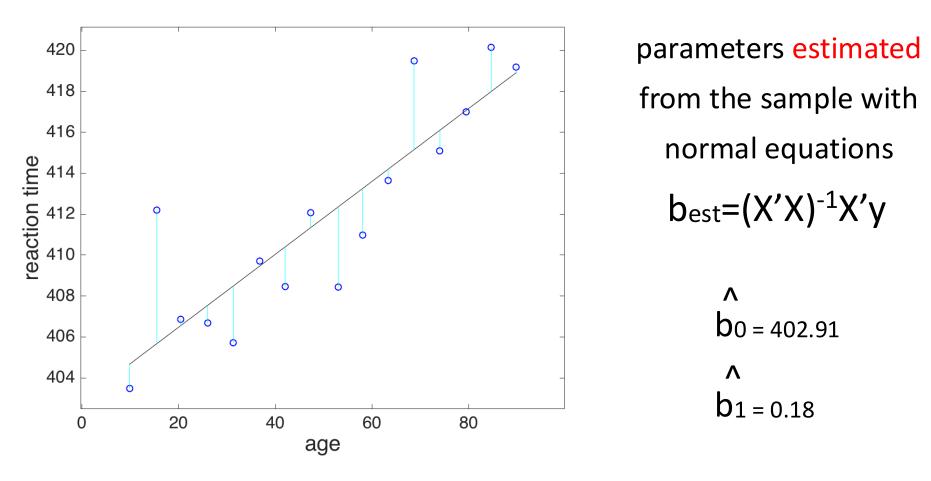
#### parameters in the population



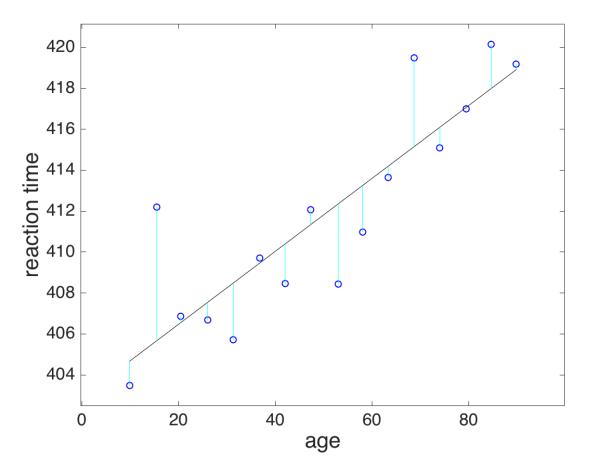


#### parameters in the population

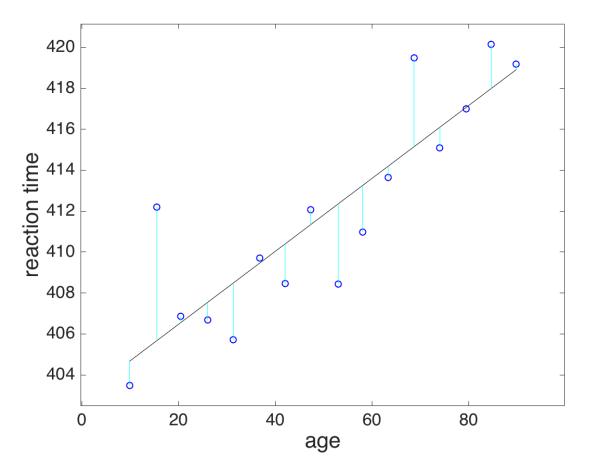
model:  $RT \neq b_0 + b_1^*age + e$ 



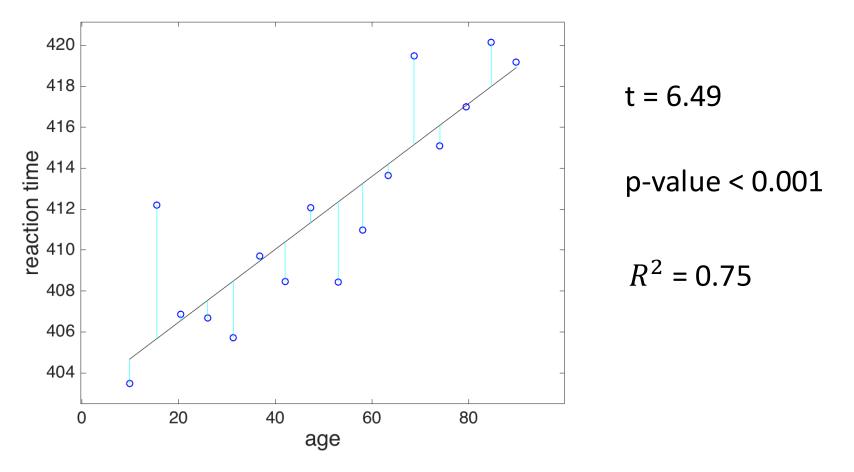
null hypothesis: $b_1 = 0$ alternative: $b_1 \neq 0$ 



 how likely is the parameter estimate ( $b_1 = 0.18$ ) if the null hypothesis is true?



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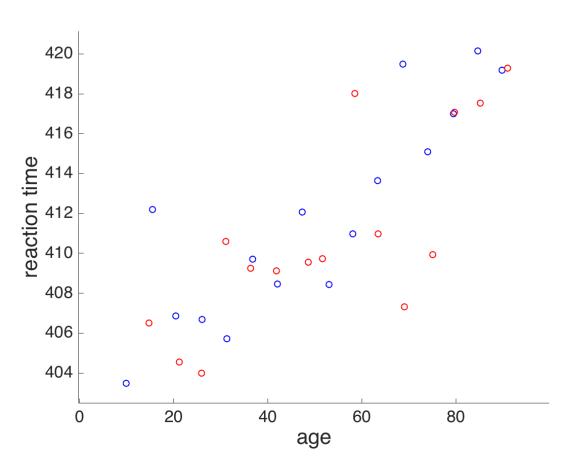


#### what can we conclude?

- from this sample
  - p < 0.001 reject null hypothesis that "RT is unrelated to age"</p>
  - $R^2$  age accounts for 75% of variance in RT
  - 95% confidence interval b1 = 0.18
    0.1193 0.2370

- the test does not tell us
  - how well we can predict RT from age in the population
  - whether this is the right model (or at least better than others)
  - whether or how age causes reaction time (or vice versa)

## what happens with a new sample?



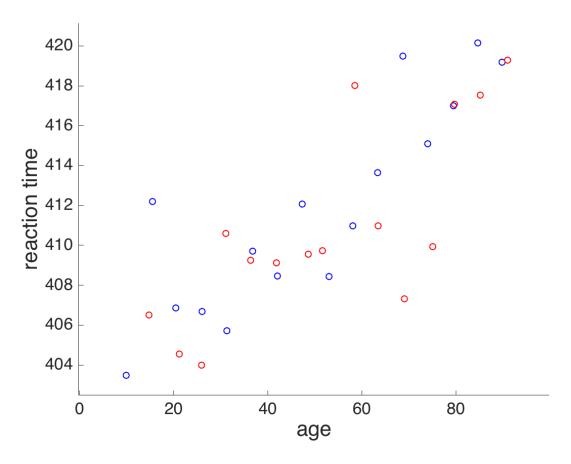
draw a new sample from the same population

compute the  $R^2$  using parameters estimated in the original sample

 $R^2 = 0.65$  (new sample)  $R^2 = 0.75$  (original sample)

## what happens with a new sample?

draw 100 new samples



using model parameters estimated from the original sample, average  $R^2 = 0.71$ 

an estimate of how good the original model would be on any new sample

## description vs prediction perspectives

#### estimating model parameters:

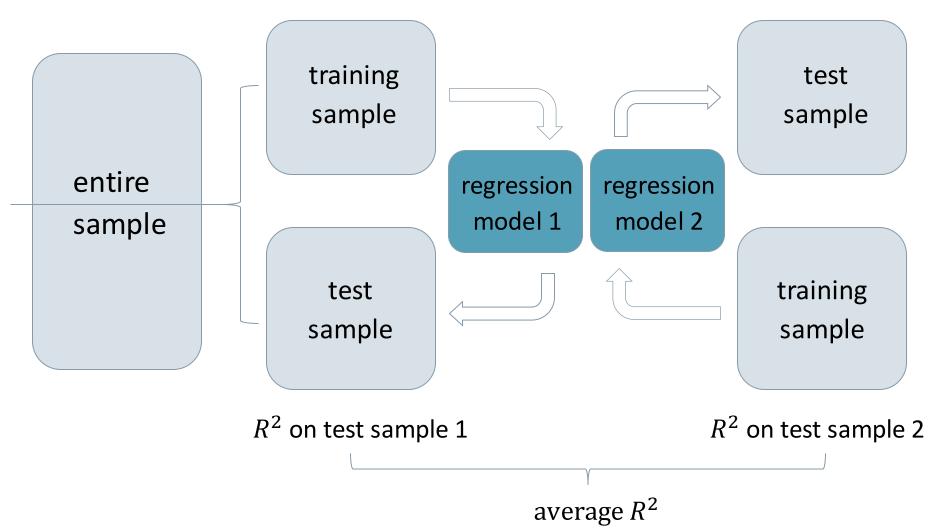
- description: describe variable relations in terms of few parameters
- prediction: learn about to model variable relation from training sample

#### evaluating the model

- description: goodness of fit, for limited model complexirty
- prediction: apply the model to a test sample not used in learning the model

## but what if you cannot get more data?

there are two samples inside your sample...

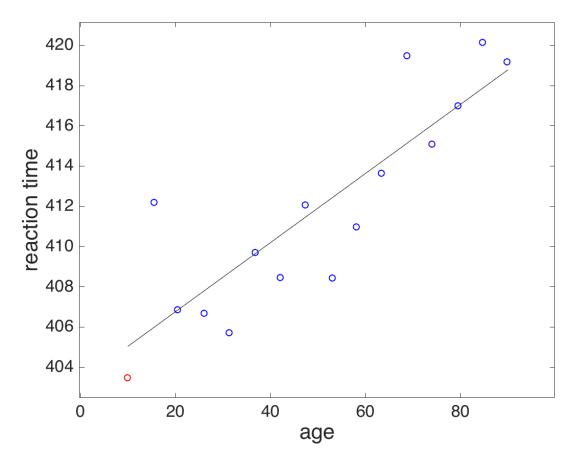


#### cross-validation

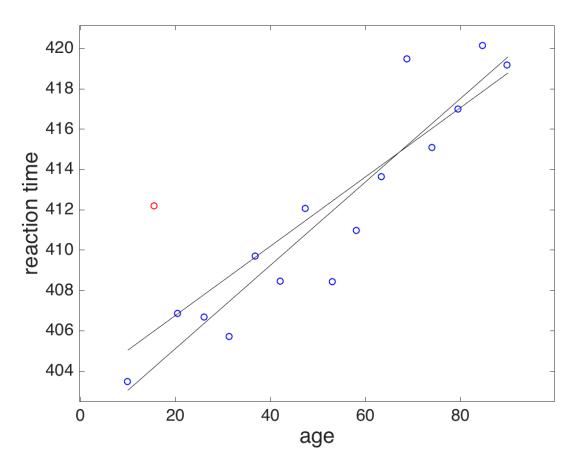
#### k-fold cross-validation:

- split into k folds
- train on k-1, test on the left out, iterate
- calculate average prediction measure across all k folds

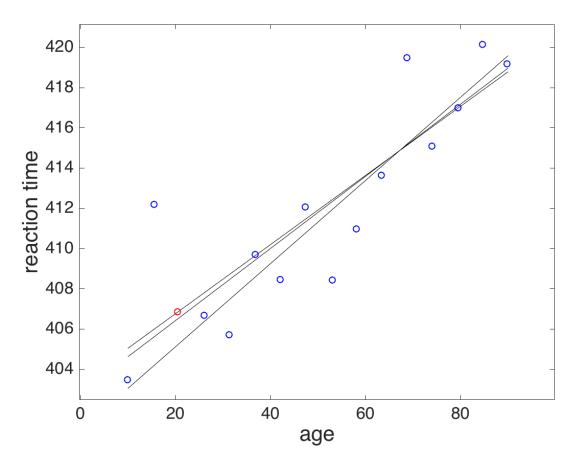
leave out the first data point, fit model to the others



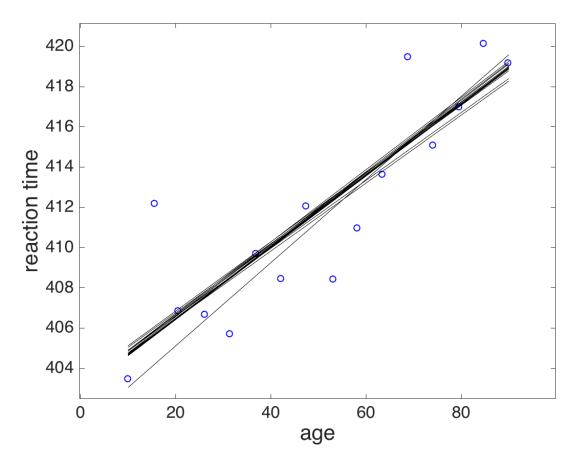
leave out the second data point, fit model to the others



leave out the third data point, fit model to the others



#### all leave-one-out regression lines



leave-one-out  $R^2 = 0.67$ 

original sample  $R^2 = 0.75$ 

mean of 100 new samples  $R^2 = 0.71$ 

#### cross-validation

#### k-fold cross-validation:

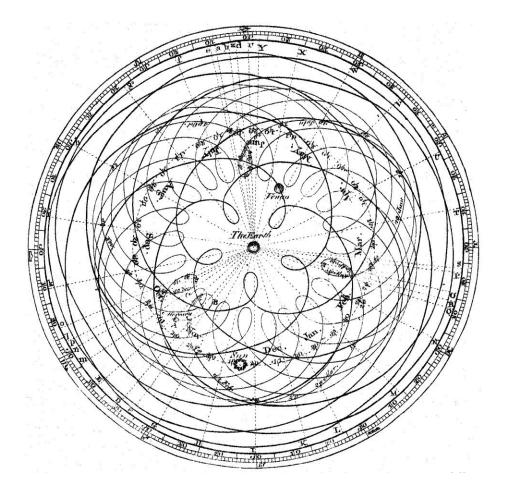
- split into k folds
- train on k-1, test on the left out, iterate
- calculate average prediction measure across all k folds

considerations:

- key assumption: models in different folds are very similar
- typical schemes are 10-fold or leave-one-out (more expensive, other issues)
- can be conservative and high variance, especially for small samples
- mistakes are easier to make than with separate train/test samples
- recommended reading:

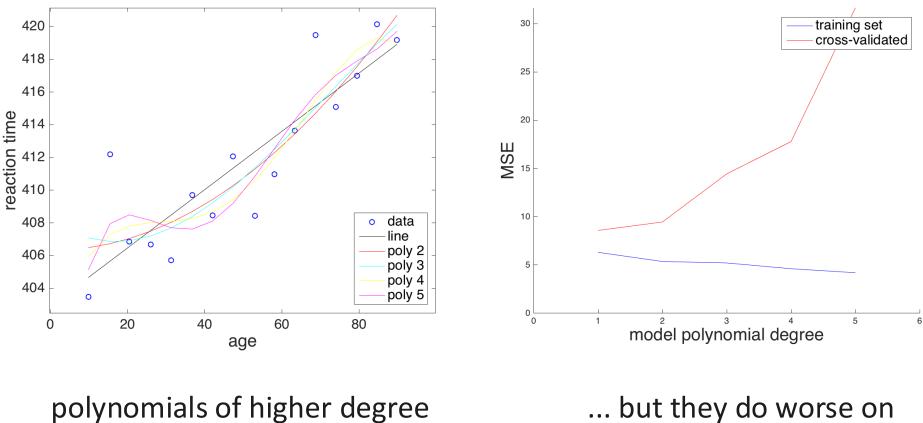
"Assessing and tuning brain decoders: cross-validation, caveats, and guidelines" Varoquaux et al. 2017

## model complexity



as model complexity goes up, we can always fit the training data better

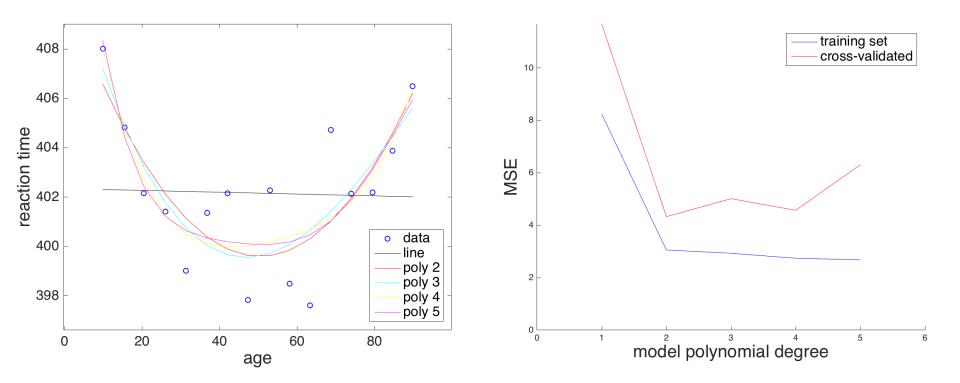
## model complexity



fit the training data better...

test data (overfitting)

## model complexity



if the relationship in the population were more complicated, a line would be too simple (underfitting)...

... but cross-validation can show us a reasonable model complexity!

## "All models are wrong, but some are useful."

George Box

## what is machine learning, redux

- generalization: ability to make predictions about new data
- a model that generalizes well
  - shows that there is information in the data about a prediction target
  - can be dissected to understand how the prediction can be made

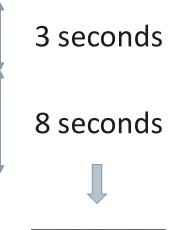
but what does this have to do with brains?

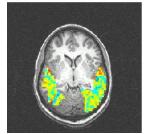
[data from Rob Mason and Marcel Just, CCBI, CMU]

- subjects read concrete nouns in 2 categories
  - words name either tool or building types
  - trial:

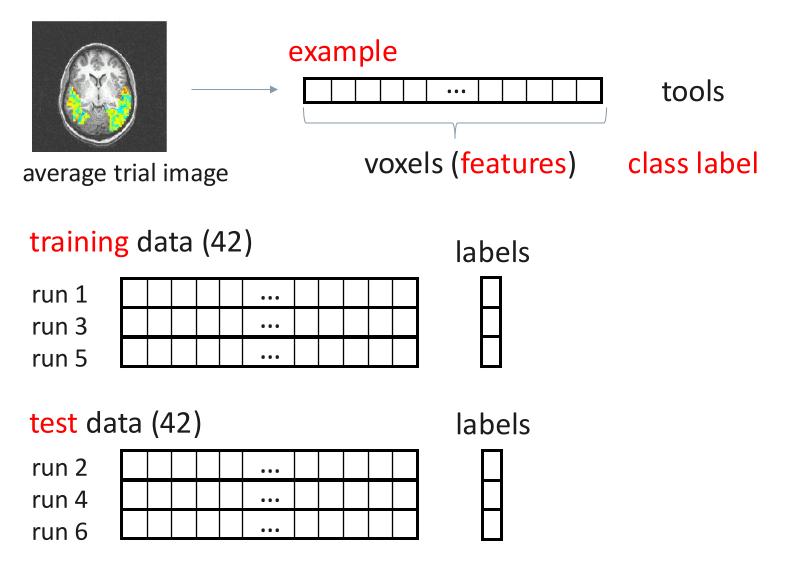
see a word think about properties, use, visualize blank

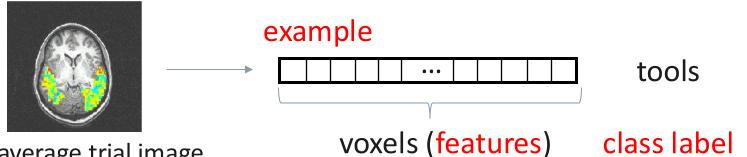
 average images around response peak to get one labelled image per trial (84 trials in 6 runs)





tools





average trial image

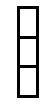
#### training data (42)

run 1			•••			
run 3			•••			
run 5						

test data (42)

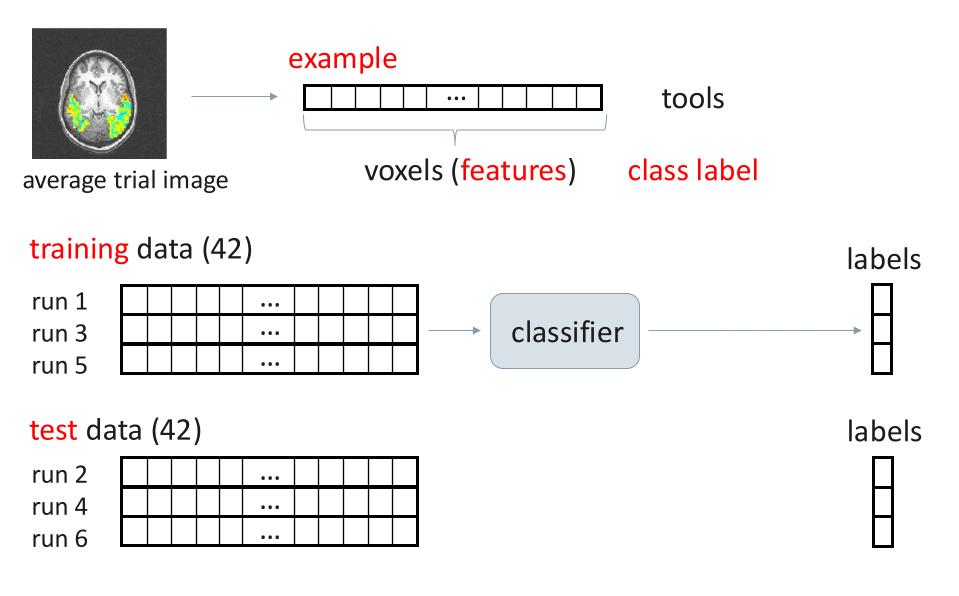
run 2						
run 4						
run 6			•••			

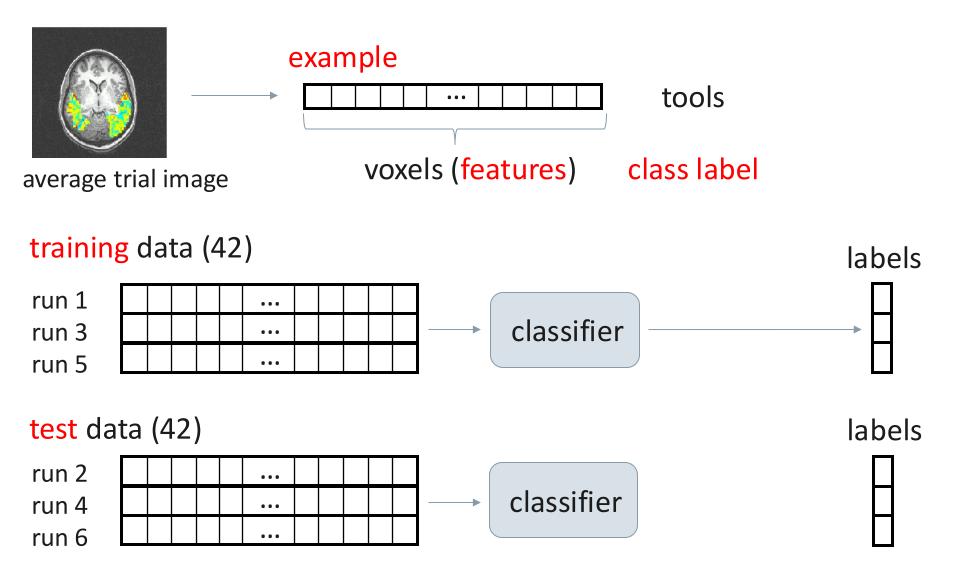
labels

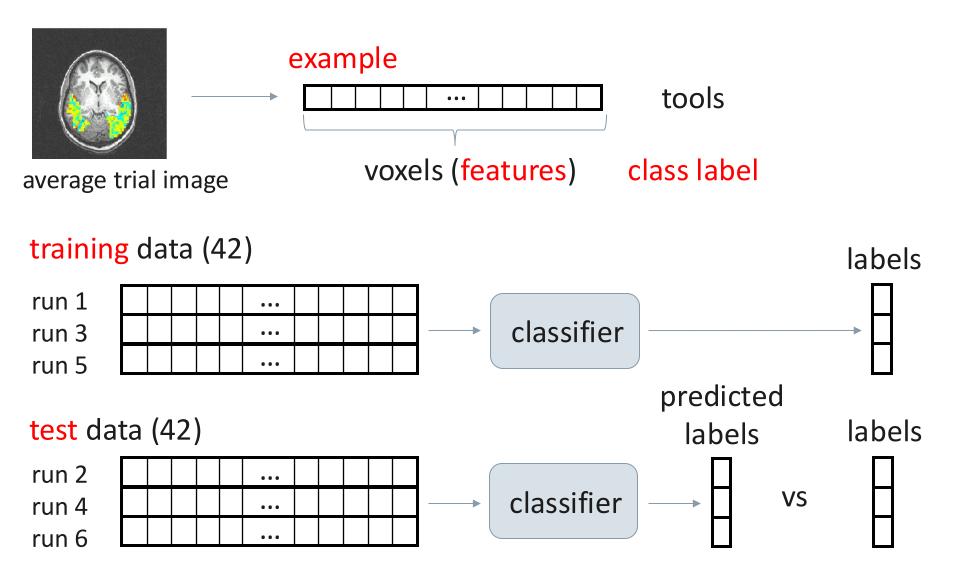


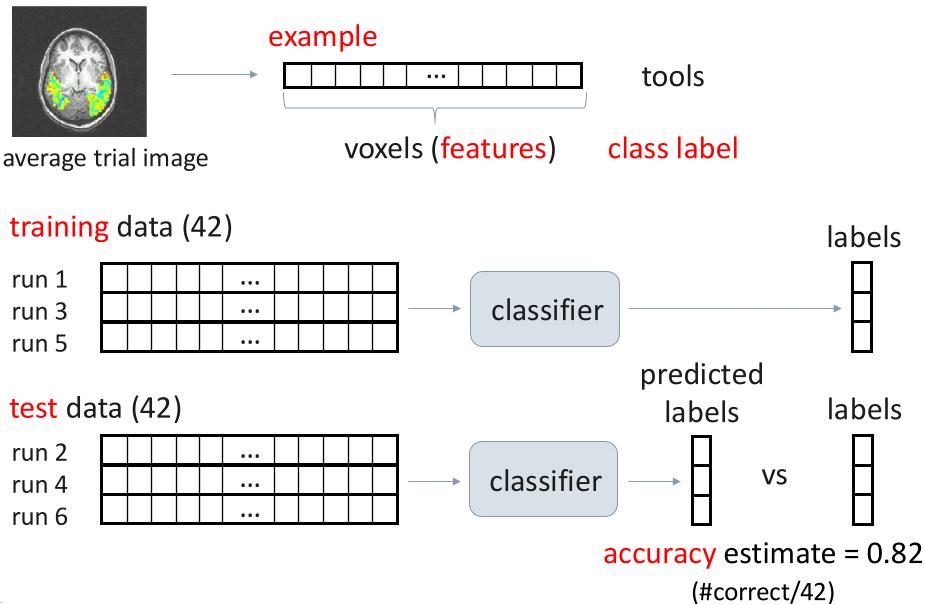




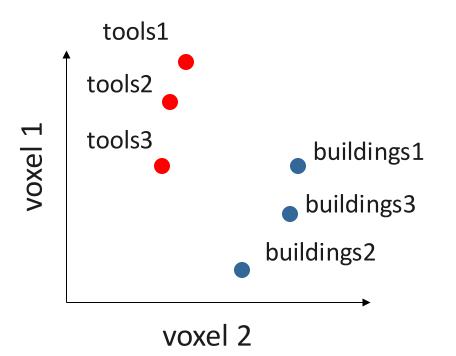


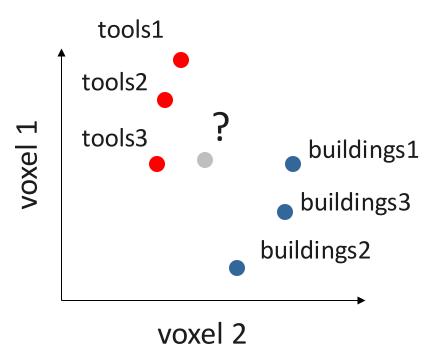


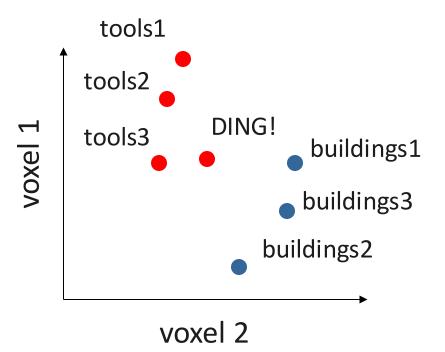


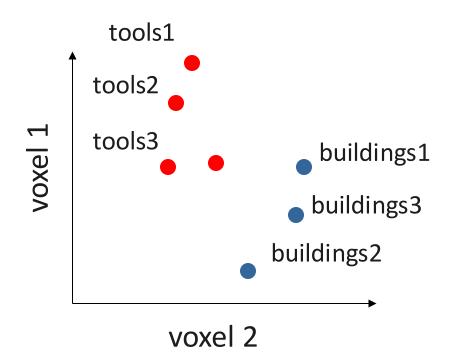


what is inside the grey box?



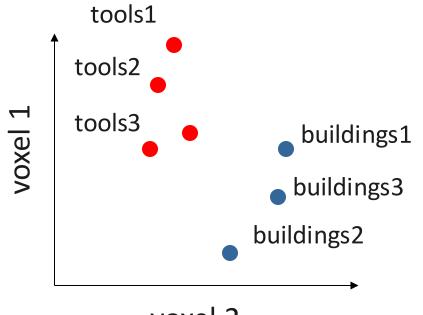




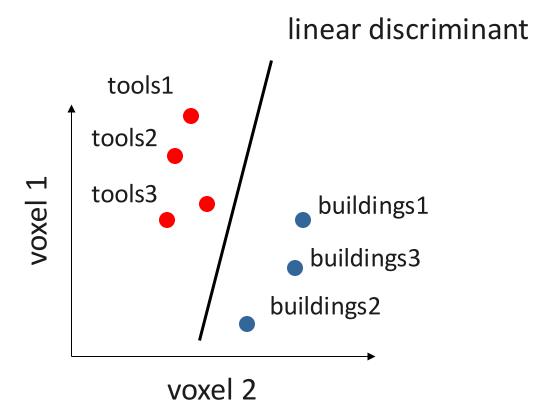


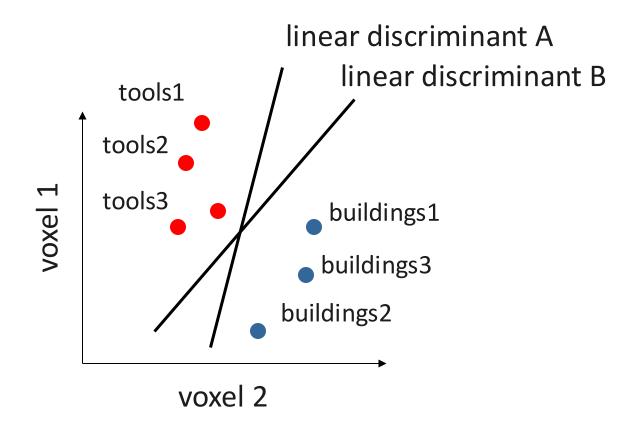
simplest function is no function at all: "nearest neighbour"

- implicit example similarity/distance measure
- can use more points in decision (k-nearest ...)

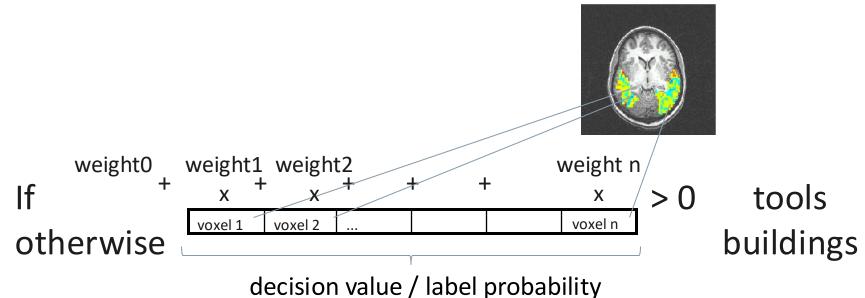


voxel 2

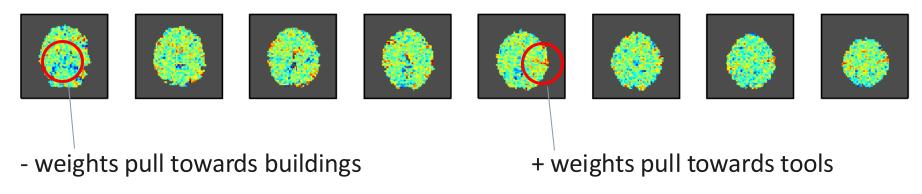




- there are many possible linear discriminants
- LDA, logistic regression, linear SVM, ...

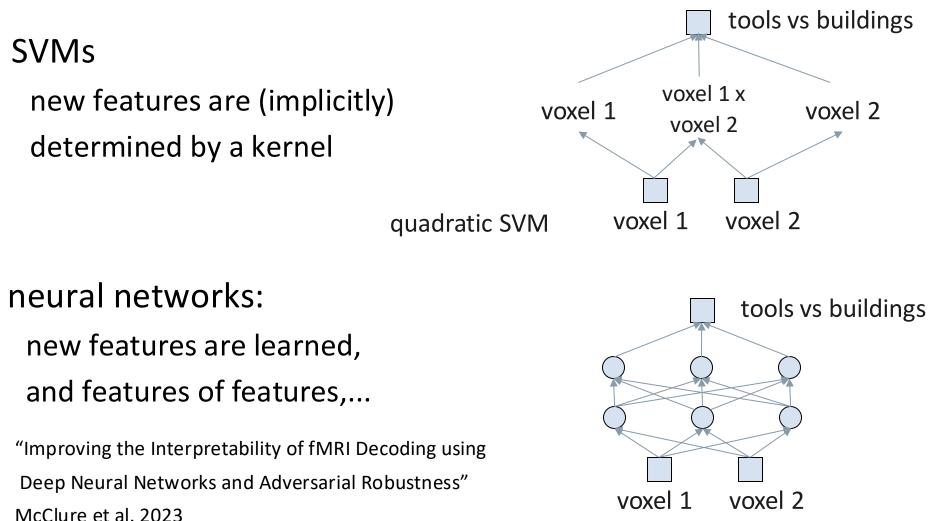


#### classifier weights (linear Support Vector Machine)



## inside the grey box – nonlinear classifiers

linear on a transformed feature space!



# how do we test a classification result?

## how do we test predictions?



null hypothesis:

"classifier learnt nothing" — "predicts randomly"

## how do we test predictions?

null hypothesis: classifier learned nothing

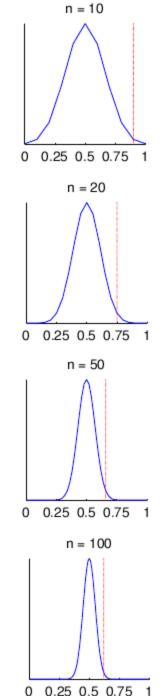
- X = #correct
- P(X|null is true) is binomial(#test,0.5)
- p-value is P(X >= result to test|null is true)

#### many caveats:

- accuracy is an estimate

- must correct for multiple comparisons

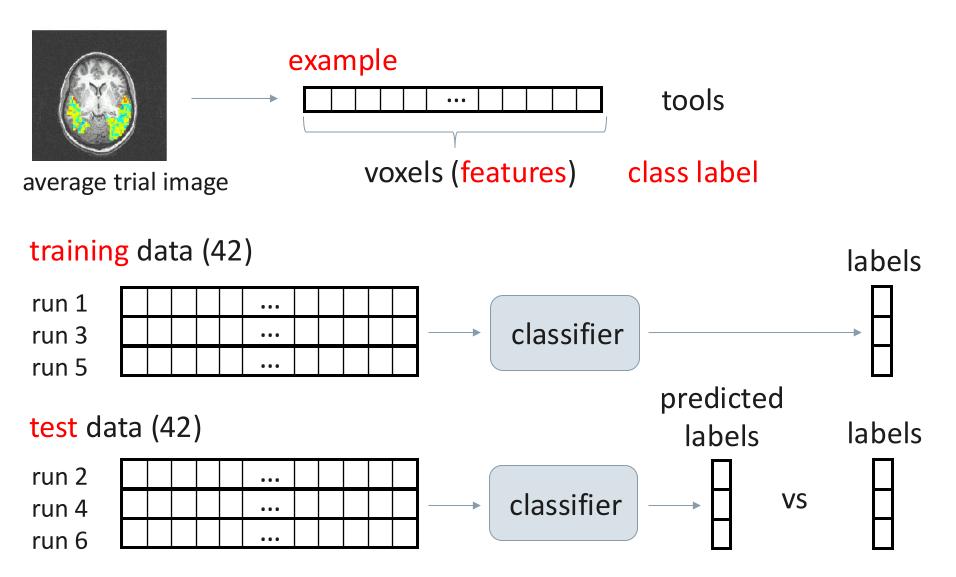
## distribution under null (0.05 p-value cut-off)



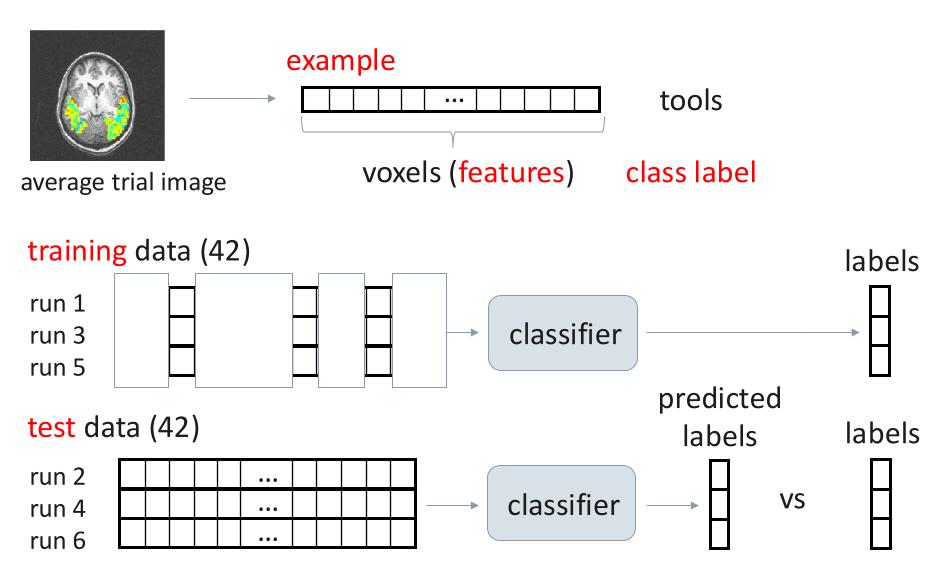
#### feature and example selection

- a classifier answers one question, but often needs help...
- restrict voxels by
  - space (e.g. anatomical ROI, a priori ROI, etc)
  - time (e.g. different points in a trial)
  - behaviour (e.g. selective for a condition, consistent across them)

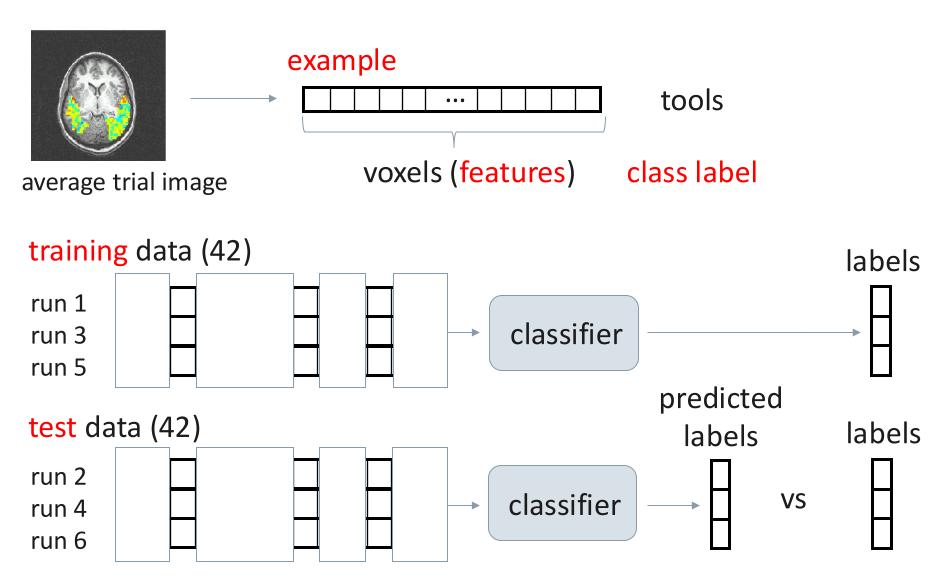
#### feature selection



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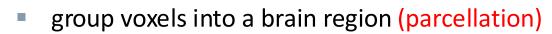


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  - behaviour (e.g. selective for a condition, consistent across them)
- restrict examples by
  - experiment phase (e.g. study versus free recall blocks)
  - trials (e.g. successful or not)

## what about other modalities?

#### structural MRI



create a surface model (triangle mesh) 

#### diffusion MRI

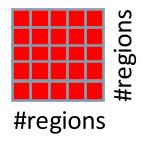
- count tracts passing through each region
- derive structural connectivity matrix

#### resting state fMRI

- - create average time series per region
  - calculate correlation between them
  - derive functional connectivity matrix







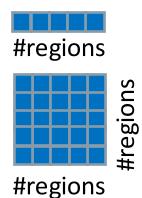


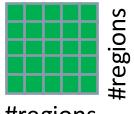
## what about other modalities?



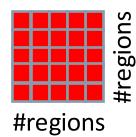


- cortical thickness
- surface area
- covariance of measures between regions









- reduce connectivity to region pairs or networks
- matrices => graphs => graph-theory measures
- dynamic versions (over time windows)



## what about other modalities?

- problems to solve
  - classification: patients vs controls, treatment or disease outcome, ...
  - regression: symptom intensity, time to symptoms, subject characteristics
  - clustering: patient groups
- feature selection
  - region-of-interest or network restriction
  - t-test for individual matrix entries (within training set)
- other issues
  - interpreting classifier weights (aggregate by ROI is typical)
  - combining modalities (all together, meta-classifier, ...)

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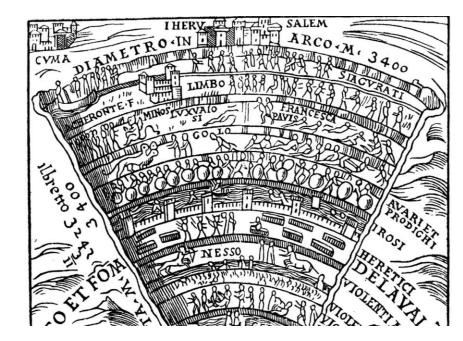
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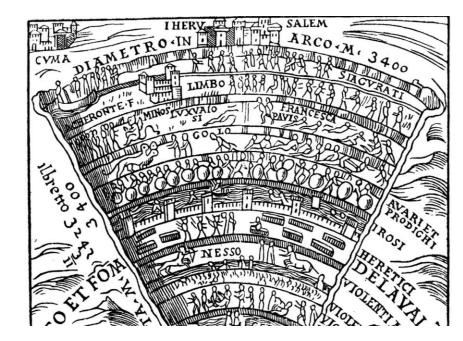
(or email francisco.pereira@nih.gov later)

- small sample sizes
- significant but small effect
- class imbalance
- p-hacking
- circularity / double-dipping
- reporting training set results



- small sample sizes
  - Iow power is still an issue, even with a separate test set
  - suggestion: require power analysis (past effect sizes may be optimistic...)
- significant but small effect
  - what does 60% accuracy mean?
  - suggestion: error analysis (is there a pattern to errors?)
- class imbalance
  - if one class is more frequent than other, null model is not valid
  - suggestions: (under | over)sample class, nonparametric null

- small sample sizes
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#### p-hacking

- try many things, report a single one -> optimistic bias
- suggestion:
  - make method decisions on sample 1, test on sample 2
  - consider doing a pre-registration before sample 2

#### circularity / double-dipping

- using train+test data to make decisions (e.g. feature selection)
- in the limit, can give you a result where there is none at all
- suggestion:

always redo the analysis with permuted labels, a few times (if results are better than random, there is something wrong)

#### reporting training set results

- vastly optimistic bias (especially for small datasets)
- suggestion: be wary of very high accuracy claims...

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