Machine learning as signal processing

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AARHUS UNIVERSITY

IMC
INTERACTING MINDS CENTRE

CFIN

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   - Example: resolving human object recognition in space and time
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Signal and noise

What is signal?

What is signal?

- Why care about signal?

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What is signal?

- Why care about signal?
  - variance is what we test
  - task irrelevant variance is the experiment killer
- what is signal?
  - data = signal + noise
  - signal = data - noise
  - noise = data - signal

Global field power

$$\text{global } snr_i = \sqrt{\left(\frac{amplitude_i}{std\_dev(baseline)}\right)^2}$$

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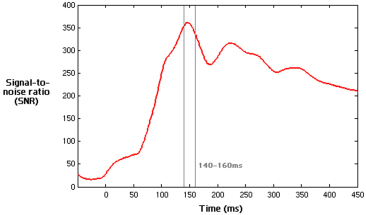

(Figure from Moseley et al., 2013)

Global field power

$$\text{global } snr_i = \sqrt{\left(\frac{amplitude_i}{std\_dev(baseline)}\right)^2}$$

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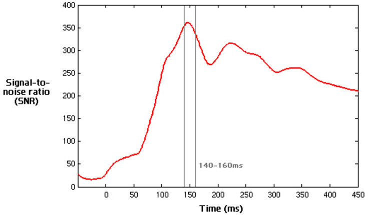
root mean square:

$$rms = \frac{1}{N}\sum_{i=1}^{N} x_i^2 = \sqrt{\frac{x_1^2 + x_2^2 + \ldots + x_N^2}{N}}$$

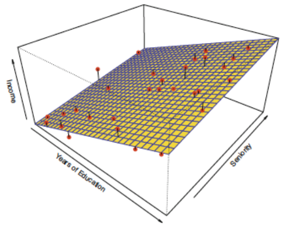


(Figure from Moseley et al., 2013)

Principle component analysis

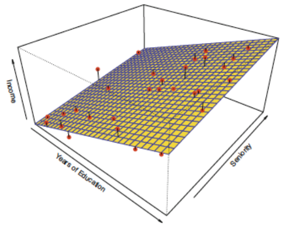
Dimensionality reduction

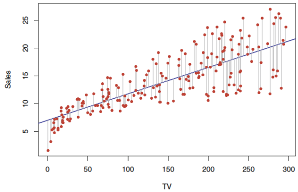
- data dimensions



(Figure from James et al., 2013)

- data dimensions

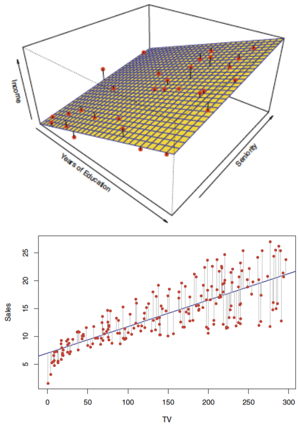




(Figure from James et al., 2013)

Dimensionality reduction

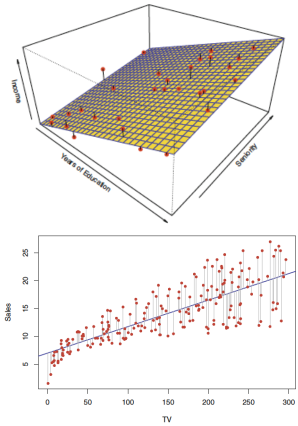
- data dimensions
- computation time



(Figure from James et al., 2013)

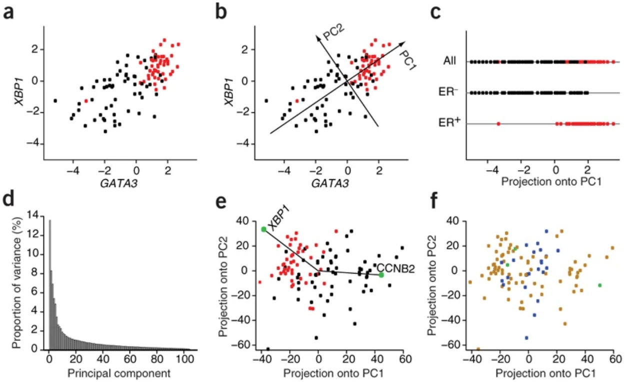
Dimensionality reduction

- data dimensions
- computation time
- increase SNR



(Figure from James et al., 2013)

Principal component analysis



(Figure from Ringnér, 2008)

Principal component analysis

Pros:

- reduced dimensions in data
- components are ordered

Principal component analysis

Pros:

- reduced dimensions in data
- components are ordered

Cons:

- components are non-interpretable

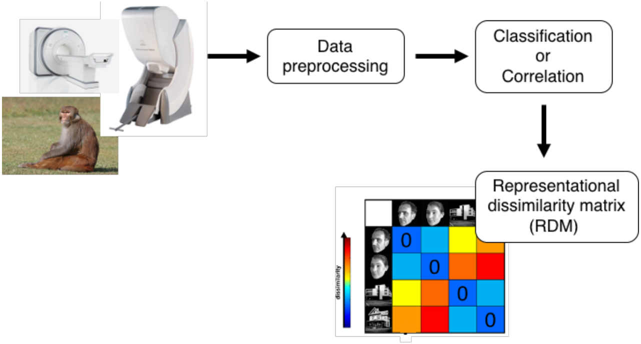
Representational similarity analysis

Representational similarity analysis

"Representational Similarity Analysis (RSA) is used to perform summary statistics on supervised classifications where the number of classes is relatively high."

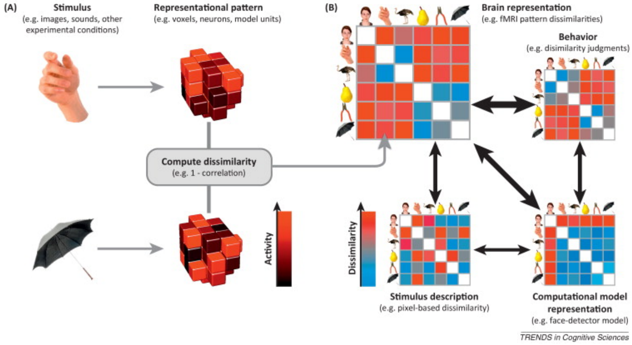
(MNE-python RSA example)

RSA workflow



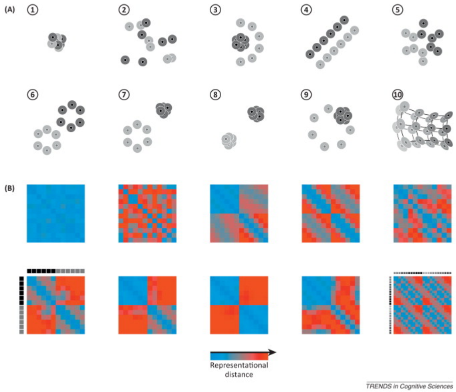
Kriegeskorte, (2008).
doi:10.3389/neuro.06.004.2008

RSA workflow



(Figure from Kriegeskorte & Kievit, 2013)

RSA workflow



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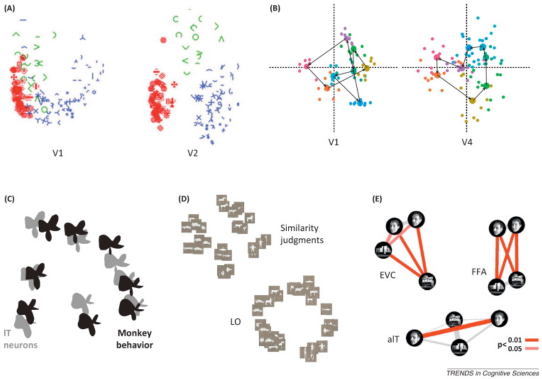
RSA workflow



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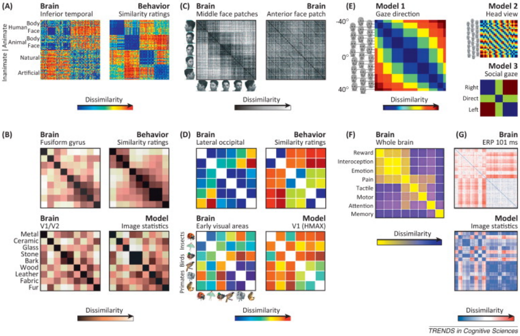
RSA workflow



(Figure from Kriegeskorte & Kievit, 2013)

Cichy et al. 2014

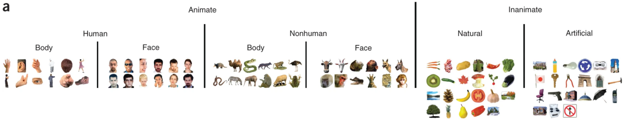
nature neuroscience

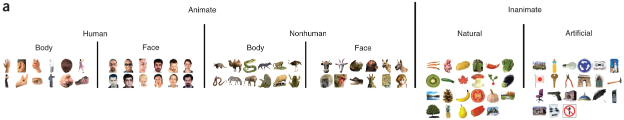
Resolving human object recognition in space and time

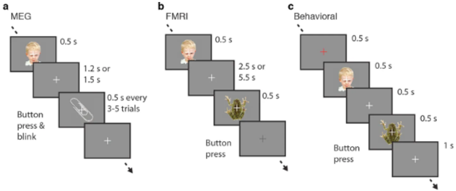
Radoslaw Martin Cichy[1], Dimitrios Pantazis[2] & Aude Oliva[1]

(Figure from Cichy et al., 2014)

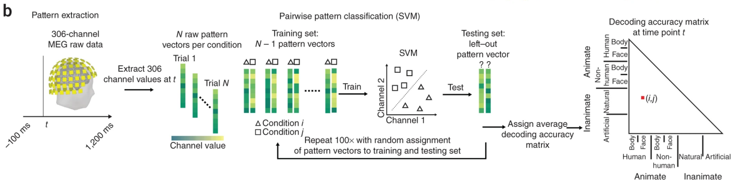
Resolving human object recognition in space and time







(Figure from Cichy et al., 2014)



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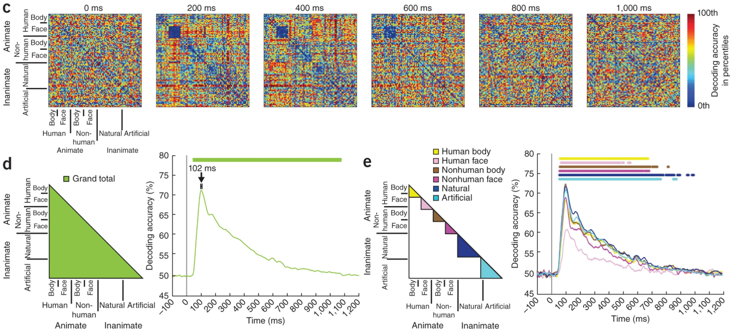

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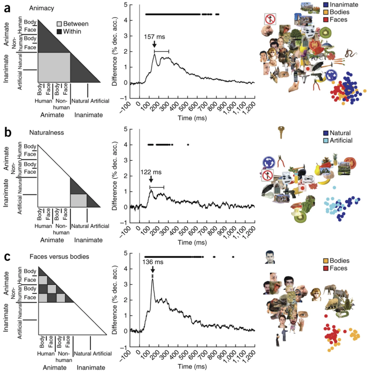

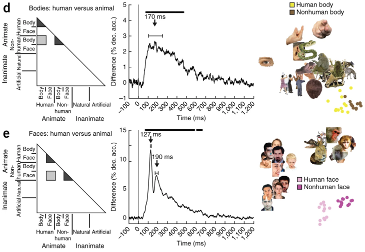

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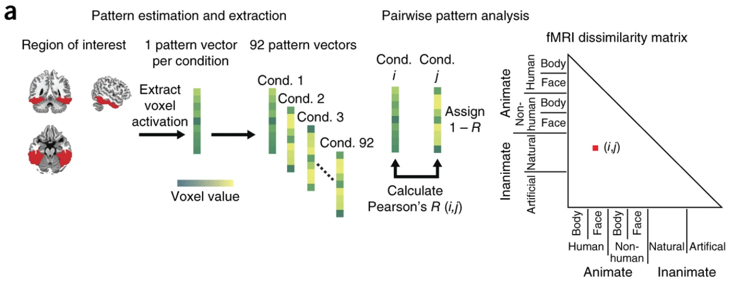

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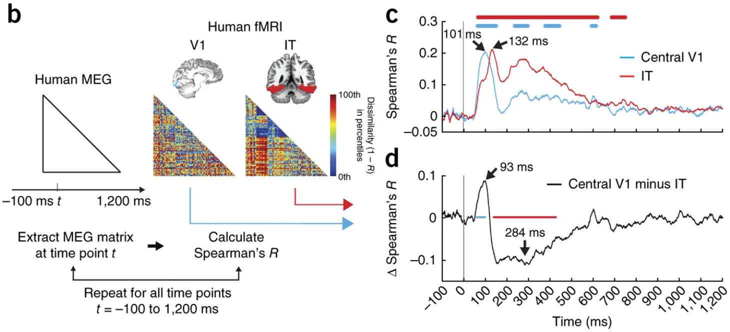
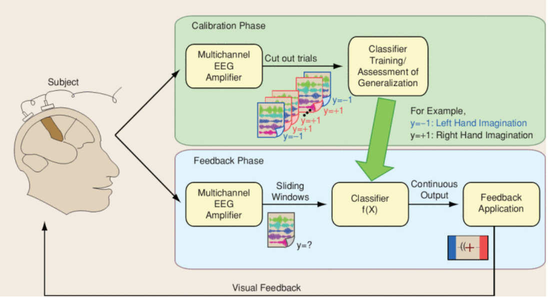
Resolving human object recognition in space and time



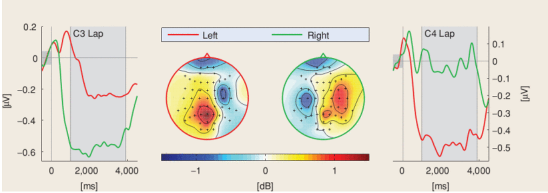
(Figure from Cichy et al., 2014)

Common spatial patterns



(Figure from Blankertz et al., 2008)

Brain-computer interface



(Figure from Blankertz et al., 2008)

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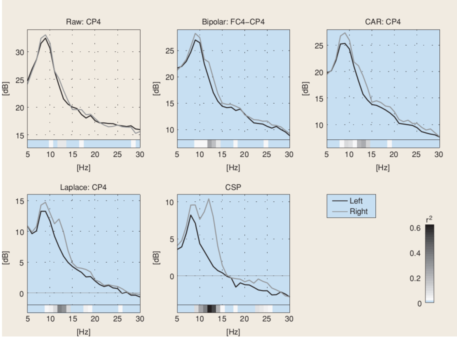
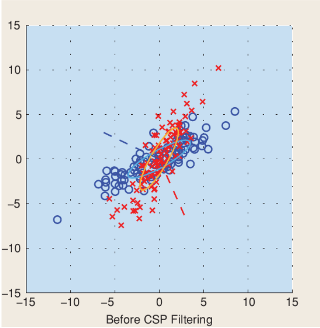


(Figure from Blankertz et al., 2008)

Common spatial patterns



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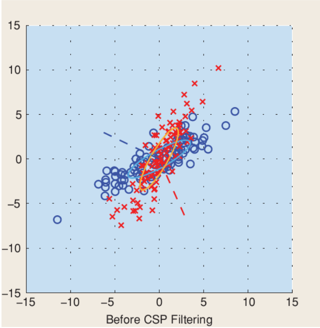

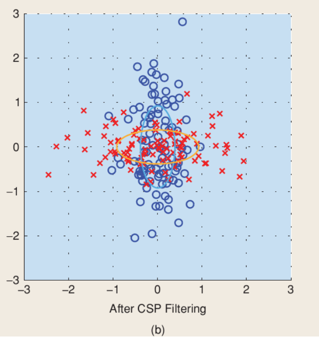

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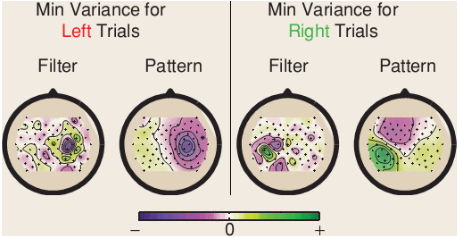

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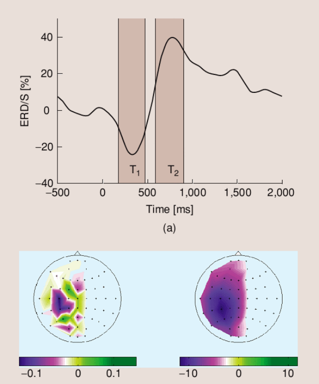

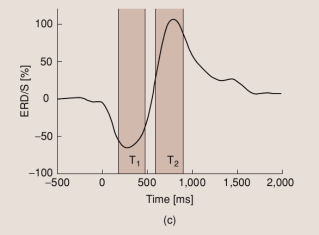

(Figure from Blankertz et al., 2008)

Practical class on Wednesday

- Create your own RSA analysis
- a large file is needed ($\sim$6 GB), make sure to have it downloaded before class
- description of the task is available on BlackBoard and in *practical_classes* folder on GitHub

Feedback on papers

- submit one paper for feedback
- deadline for paper submission: Monday 30th of November
- no extentions
- feedback will be given on December 7th & 9th

References I

Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., & Muller, K.-R. (2008). Optimizing spatial filters for robust EEG single-trial analysis. *IEEE Signal processing magazine*, *25*(1), 41–56.

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