Machine learning as signal processing

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AARHUS UNIVERSITY

INTERACTING MINDS CENTRE

CFIN

Contents

Signal and noise

What is signal?

What is signal?

- Why care about signal?

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  - variance is what we test

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What is signal?

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  - task irrelevant variance is the experiment killer
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  - signal = data - noise
  - noise = data - signal

Global field power

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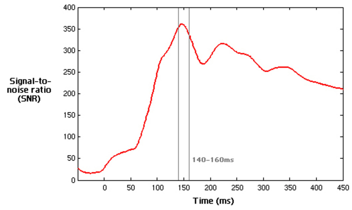


(Figure from Moseley et al., 2013)

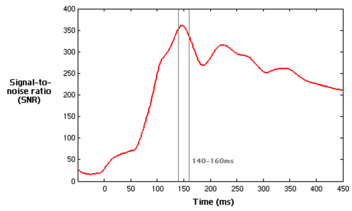
Global field power

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

$$\text{global } snr_i = \frac{amplitude_i}{std\_dev(baseline)}$$

root mean square:

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

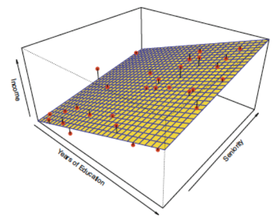


(Figure from Moseley et al., 2013)

Principle component analysis

Dimensionality reduction

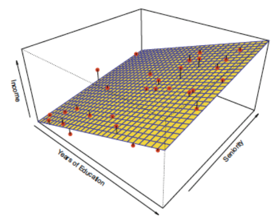
- data dimensions

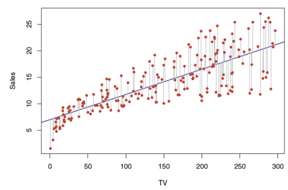


(Figure from James et al., 2013)

Dimensionality reduction

- data dimensions

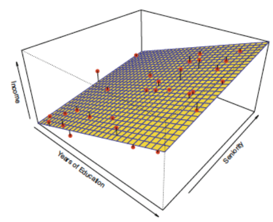


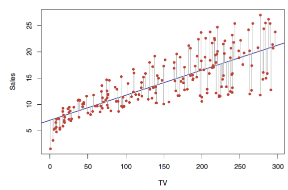


(Figure from James et al., 2013)

Dimensionality reduction

- data dimensions
- computation time

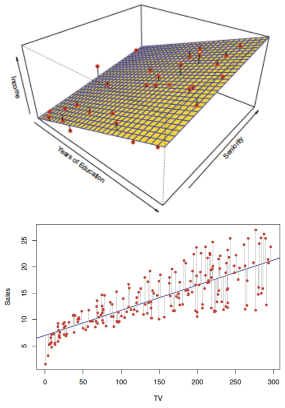




(Figure from James et al., 2013)

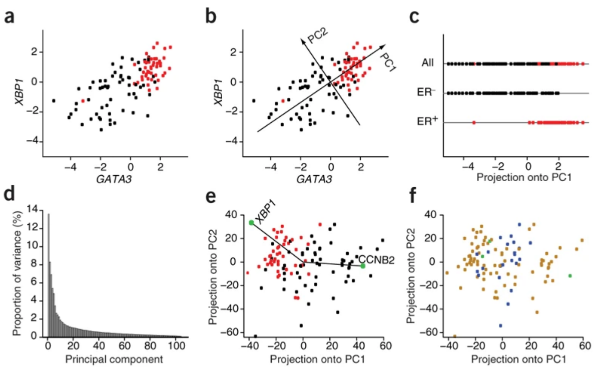
Dimensionality reduction

- 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:

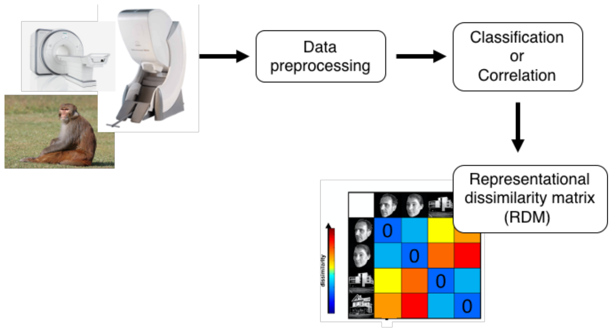
- components are non-interpretable

Representational similarity analysis

Representational similarity analysis

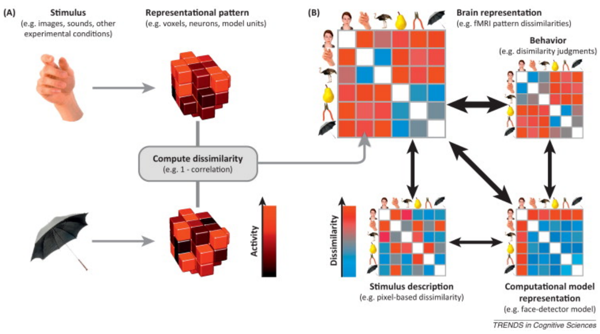
> *"Representational Similarity Analysis (RSA) is used to perform summary statistics on supervised classifications where the number of classes is relatively high."*
>
> *(MNE-python RSA example)*

RSA workflow



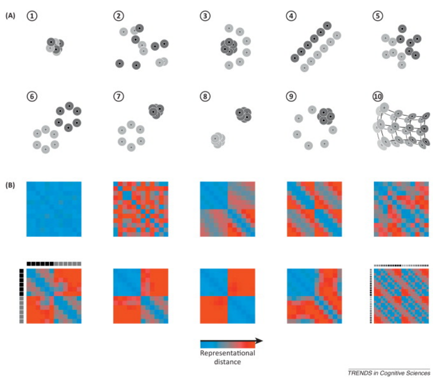
Kriegeskorte, (2008).
doi:10.3389/neuro.06.004.2008

RSA workflow



(Figure from Kriegeskorte & Kievit, 2013)

RSA workflow



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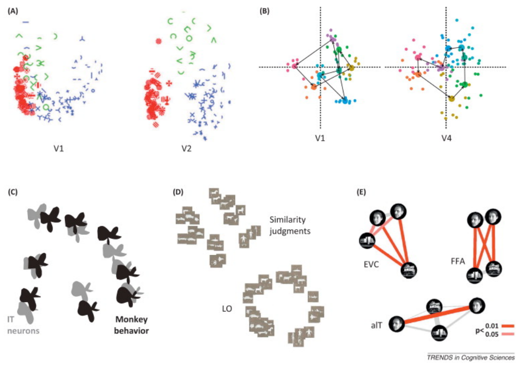
RSA workflow



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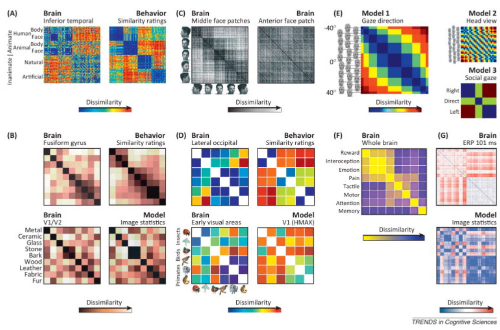
RSA workflow



(Figure from Kriegeskorte & Kievit, 2013)

Cichy et al. 2014

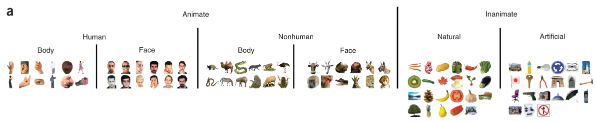
nature neuroscience

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



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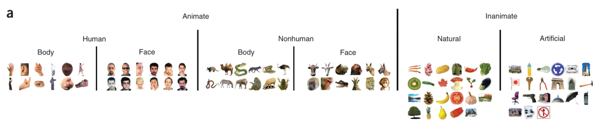

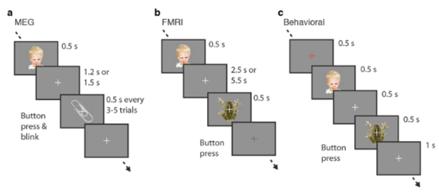

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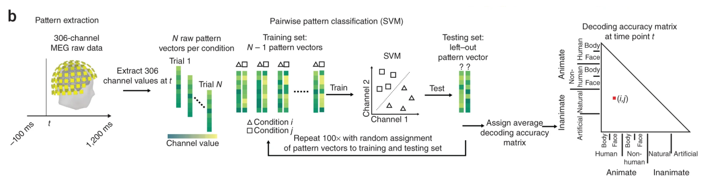

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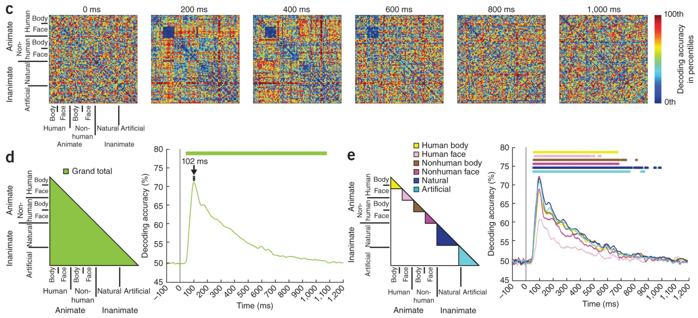

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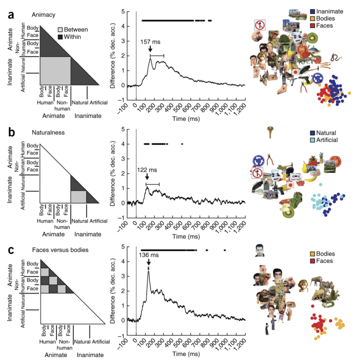

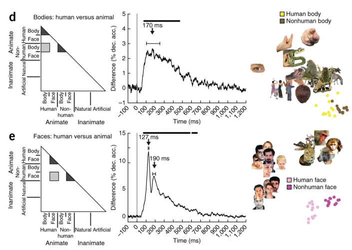

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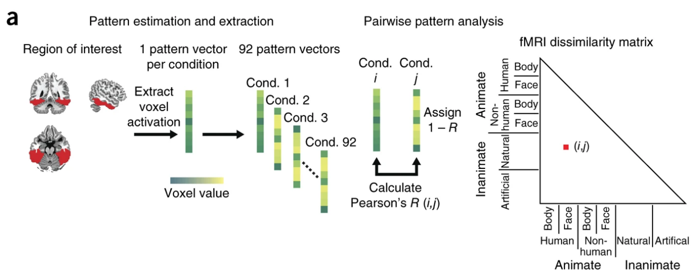

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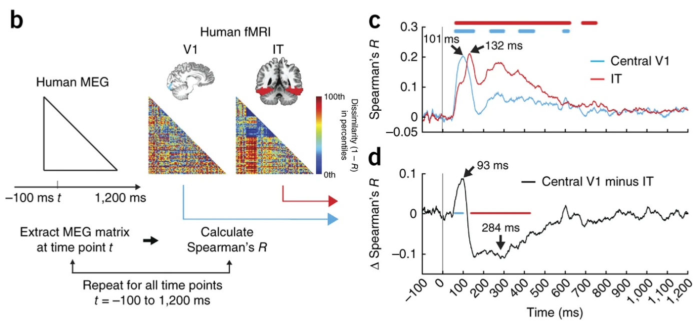

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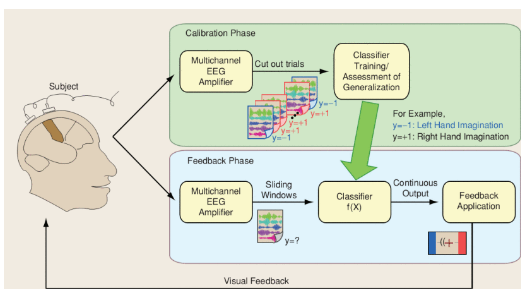
Common spatial patterns

Brain-computer interface



(Figure from Blankertz et al., 2008)

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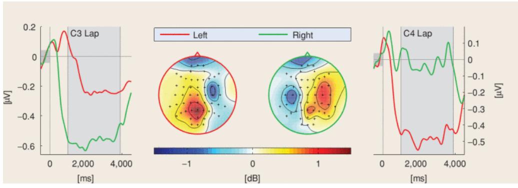

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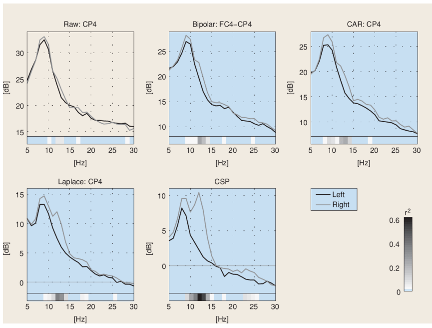

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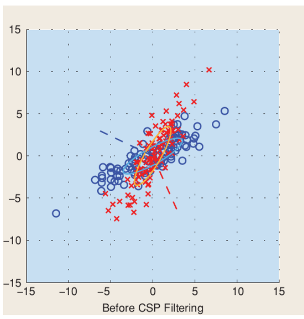

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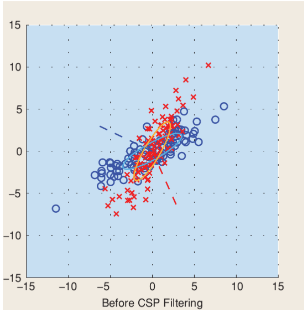

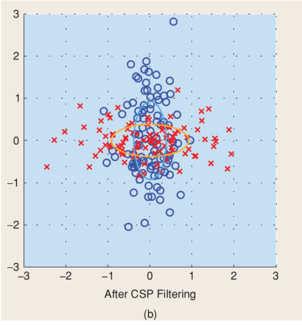

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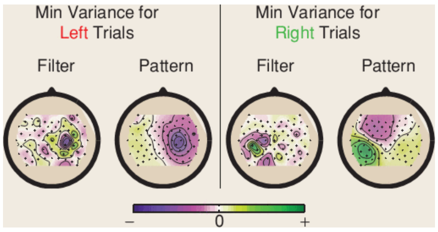

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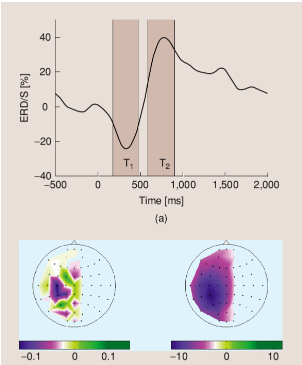

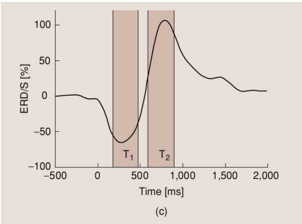

(Figure from Blankertz et al., 2008)

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 30$^{\text{th}}$ of November
- no extentions
- feedback will be given on December 7$^{\text{th}}$ & 9$^{\text{th}}$

References I

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