Explaining the Human Visual Brain 2019 competition and workshop

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Kraków

RJ 1907.00950 [q-bio.NC]

Outline

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The Algonauts Project

algonauts.csail.mit.edu

The quest to understand the nature of human intelligence and engineer more advanced forms of artificial intelligence are increasingly intertwined. The Algonauts Project brings biological and artificial intelligence researchers together on a common platform to exchange ideas and advance both fields...

Researchers at MIT, Freie Univ. Berlin, Singapore University of Technology and Design

Idea: Organize a competition on the borderline of neuroscience/ML and a subsequent workshop@MIT...

Another edition is planned for 2020...

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- The object is to explain/compare the coding of the human visual system in terms of Deep Neural Network (DNN) features...
- ... apparently a very active research field...
- ... also slightly controversial – however for higher levels of human visual processing, DNN features seem to be better than anything else

Ties in exactly with our Research Goal #11:

Porównanie percepcji obrazów w mózgu i w sztucznej sieci neuronowej na podstawie danych fMRI (np. BOLD5000)

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The competition

The competition formulated the problem in terms of **Representational Similarity Analysis**.

- The idea is to show a set of images to a human/DNN
- See how **dissimilar** are each pair of images $\longrightarrow$ this forms an **RDM** (Representational Dissimilarity Matrix)
- Try to find a set of DNN features whose RDM is **closest** to the human RDM...

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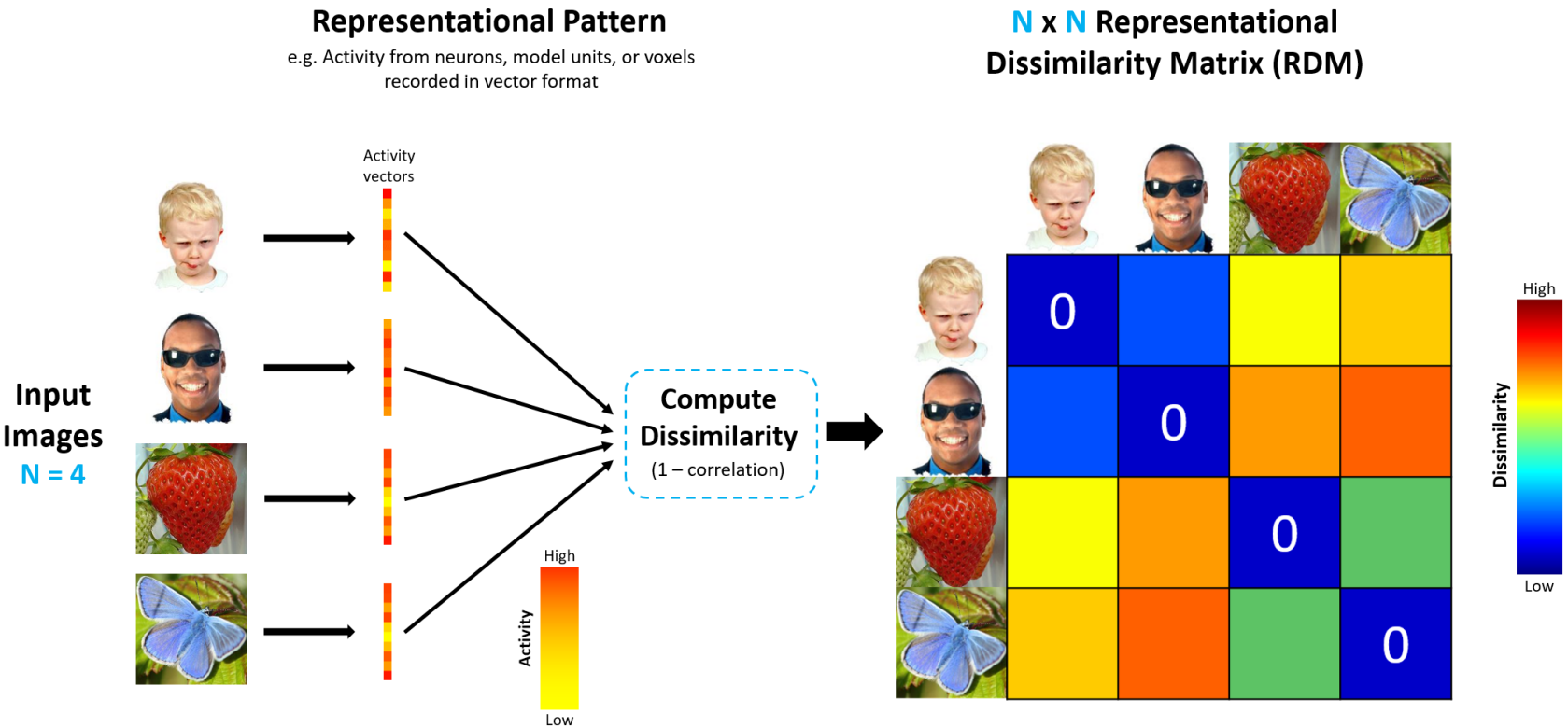
RDM


Representational Pattern
e.g. Activity from neurons, model units, or voxels recorded in vector format
N x N Representational Dissimilarity Matrix (RDM)
Input Images
N = 4
Activity vectors
High
Activity
Low
Compute Dissimilarity
(1 – correlation)
0
0
0
0
High
Dissimilarity
Low

How to compare different RDM's?

- Use **Spearman's correlation coefficient**
- Take the off-diagonal components of each RDM and flatten them into a vector...
- Substitute the values by their **ranks** in each vector
- Compute an ordinary correlation coefficient of the rank vectors...
- Take the square... $\longrightarrow R^2$
- In the competition we have 15 human subjects, so 15 human RDM's

$$score(RDM_{DNN}) = \frac{1}{15}\sum_{i=1}^{15} R^2(RDM_{DNN}, RDM_i)$$

- The human RDM's differ between themselves so one cannot hope to get a perfect score...
- Normalize by a noise threshold

$$\frac{score(RDM_{DNN})}{score\left(\frac{1}{15}\sum_{i=1}^{15} RDM_i\right)}$$

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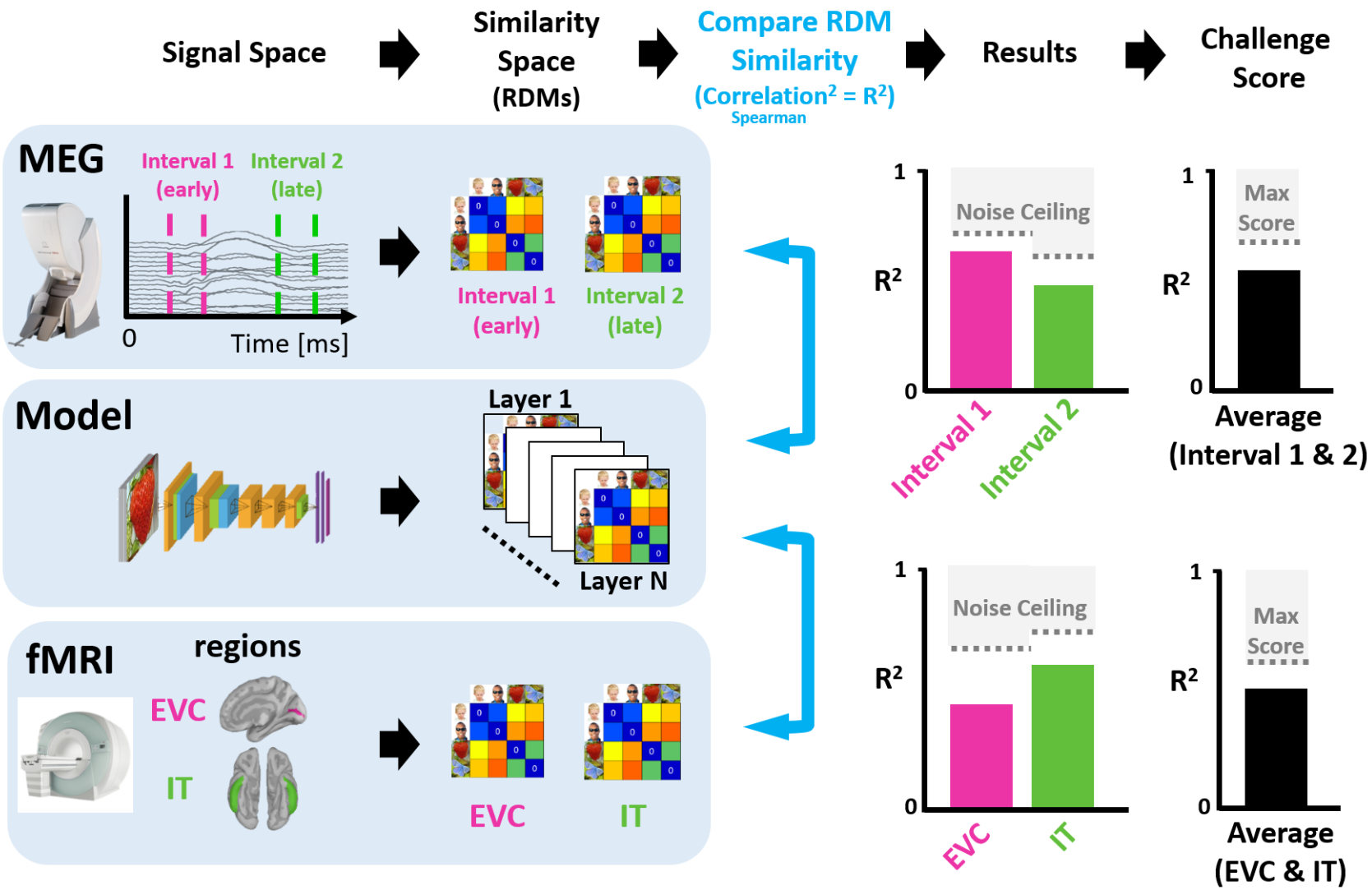
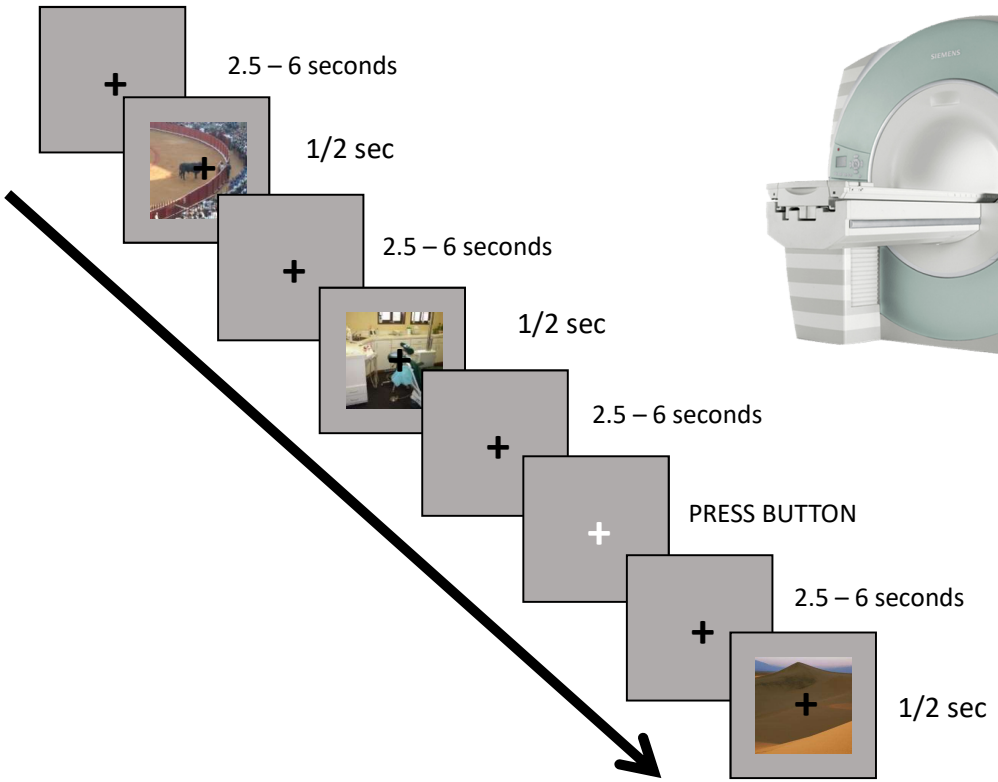
fMRI and MEG tracks of the competition



fMRI details

N=15



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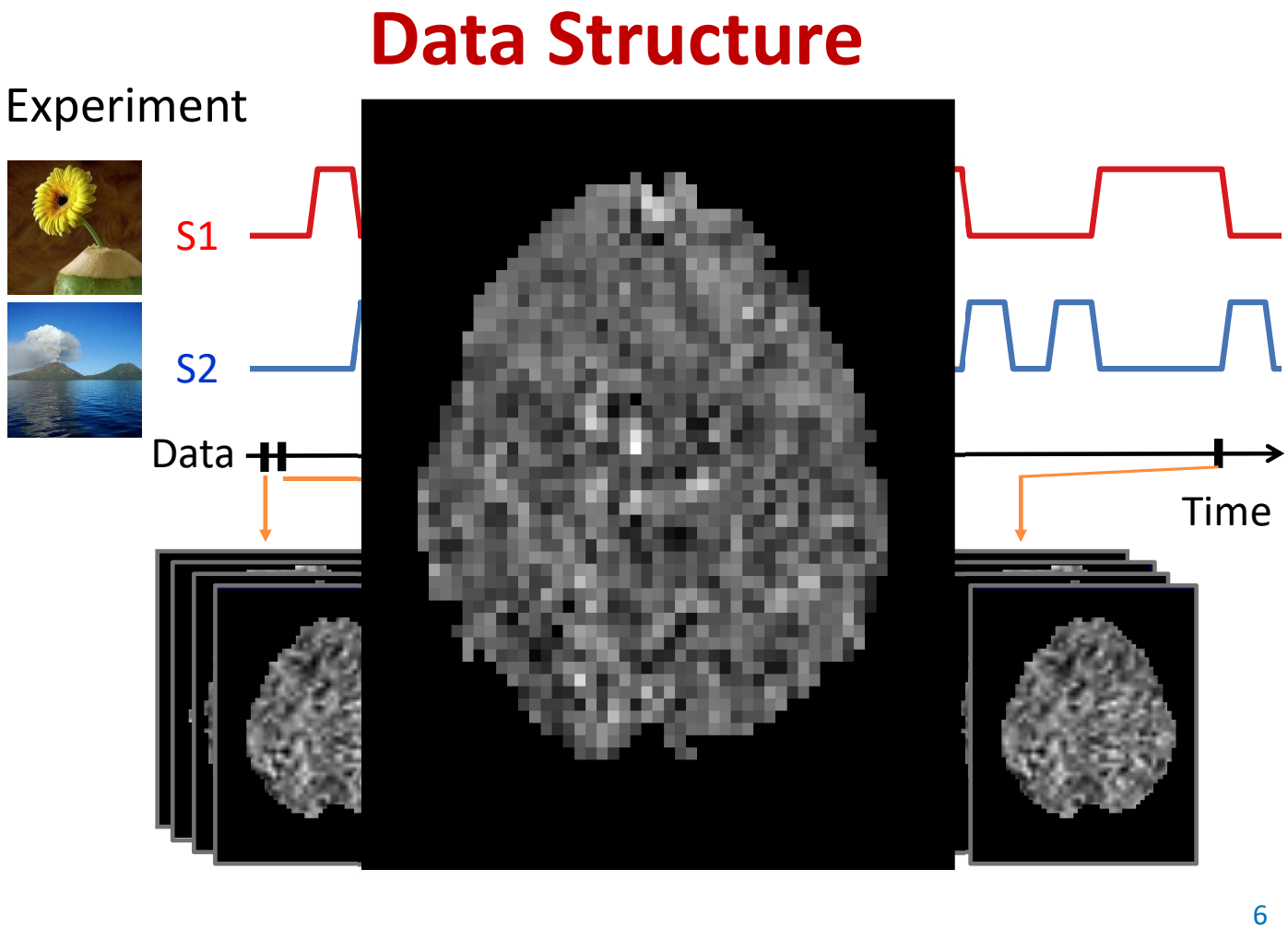
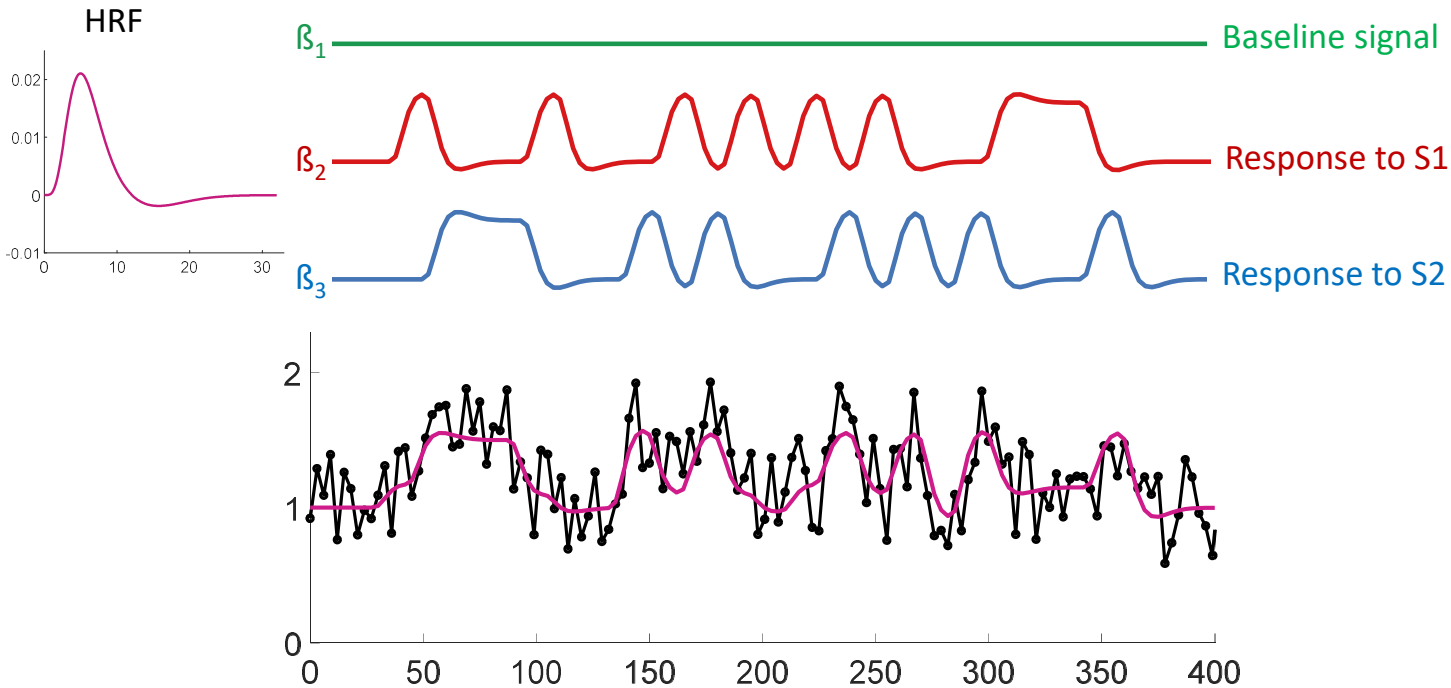
from Yalda Mohsenzadeh lecture



from Yalda Mohsenzadeh lecture

General Linear Model: Constructing BOLD signals



error(t) = signal (t) – prediction (t)

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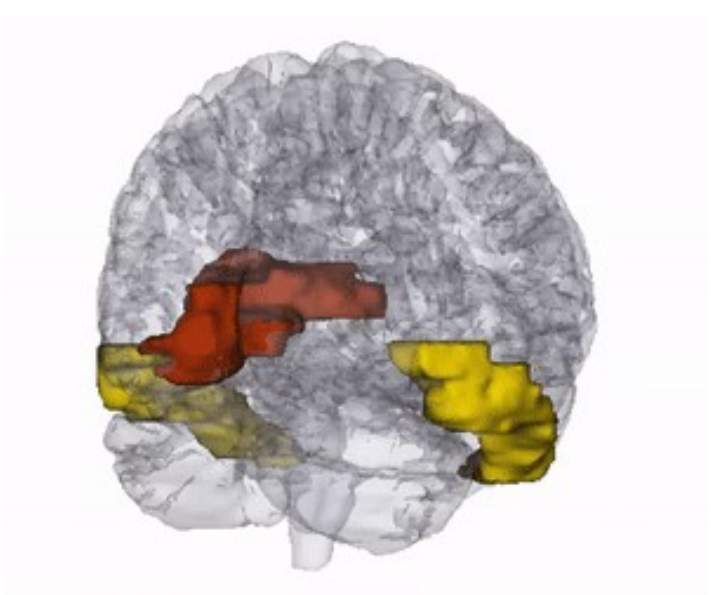
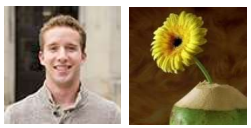
from Yalda Mohsenzadeh lecture

Visual Recognition in the Brain



EVC

IT



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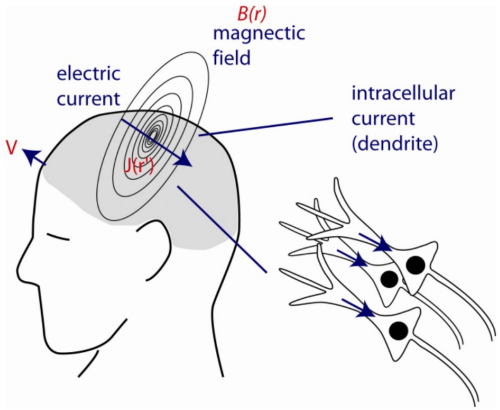
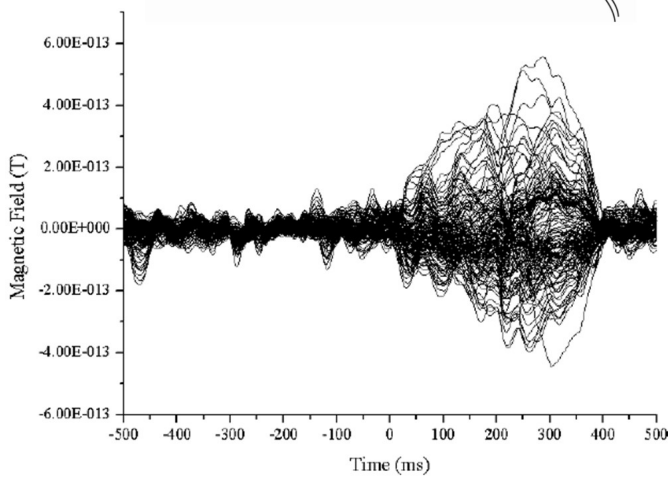
from Yalda Mohsenzadeh lecture

Magnetoencephalography (MEG) / Electroencephalography (EEG)

306 Channel
SQUID sensor array

EEG





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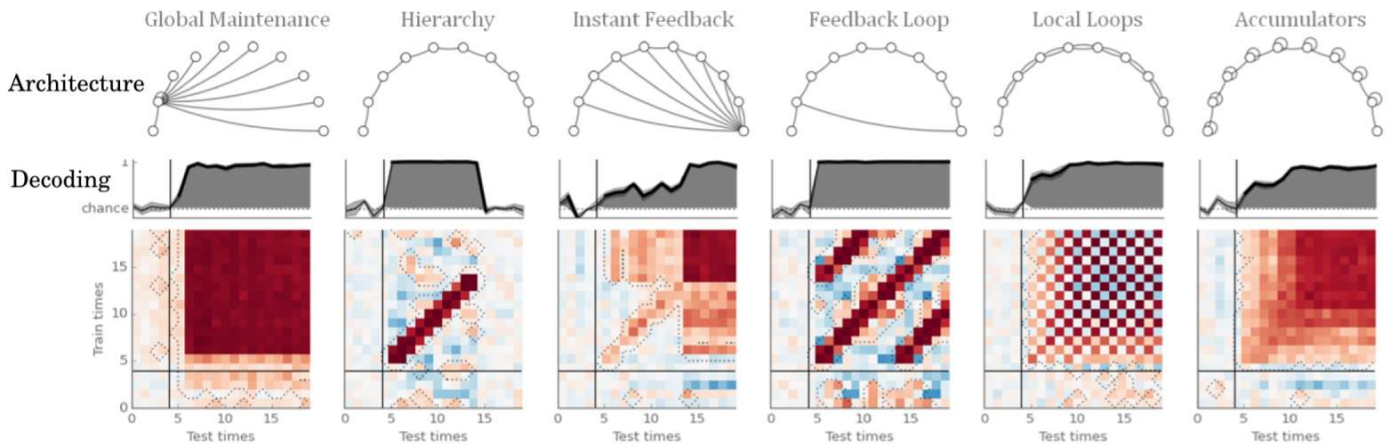
from Yalda Mohsenzadeh lecture

MEG – digression: an interesting application

Possible Neural Architectures



(King et al., 2016)

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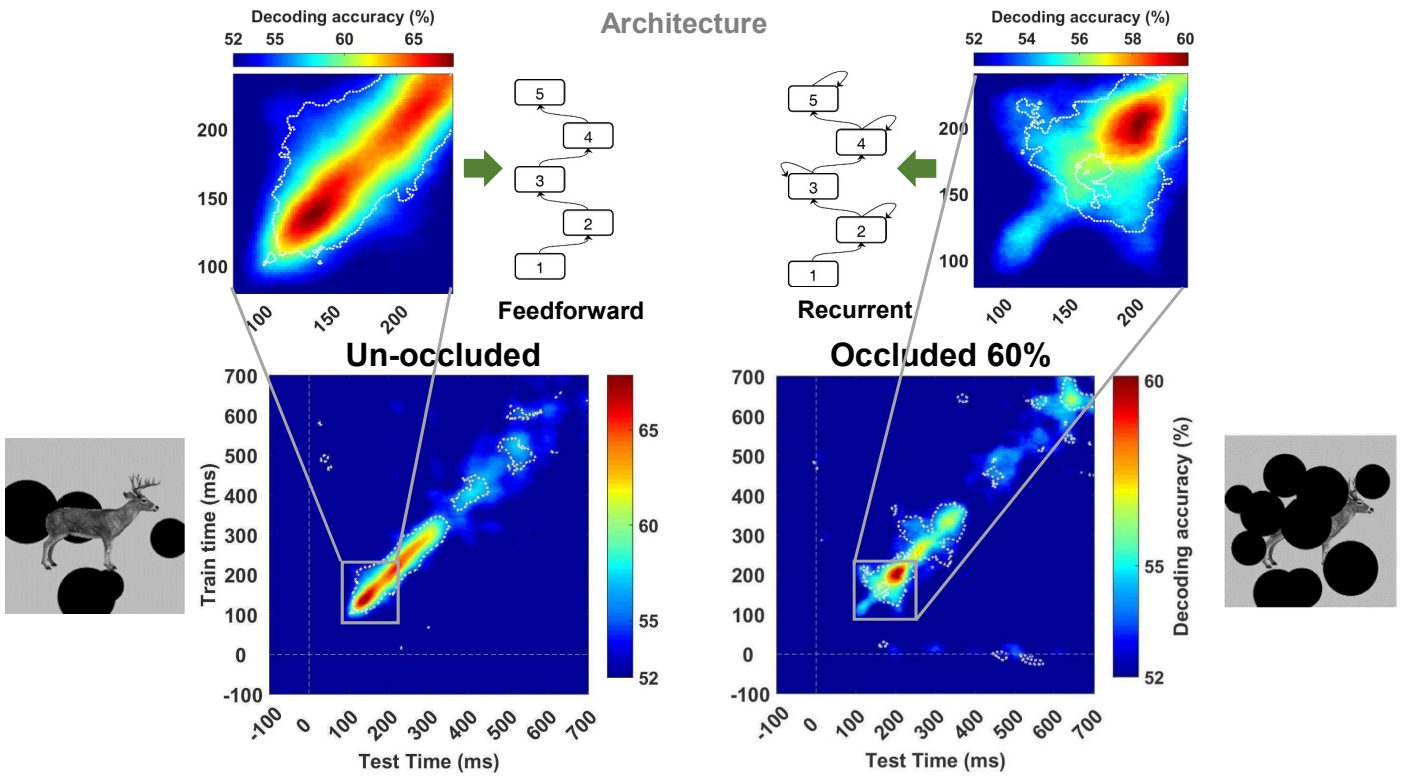
(see also King, Dehaene 2014)

from Yalda Mohsenzadeh lecture

A Neural Architecture with Recurrent Interactions



(Rajaei, Mohsenzadeh, Ebrahimpour, Khaligh-Razavi, 2019)

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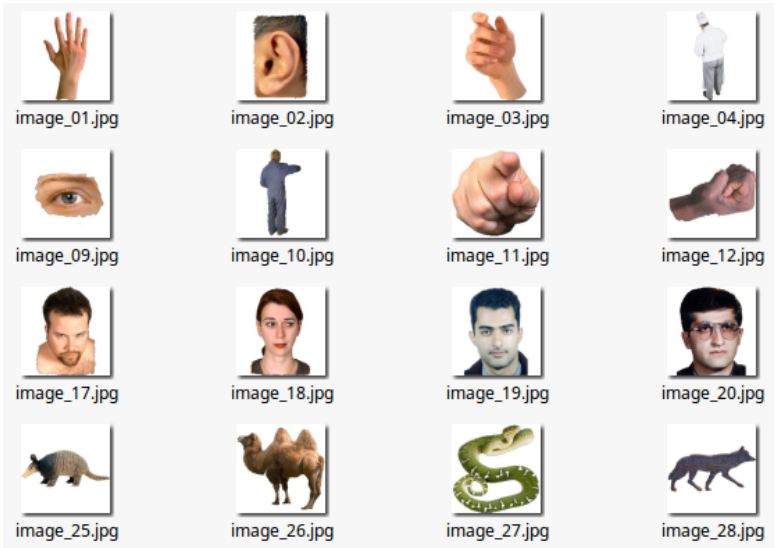
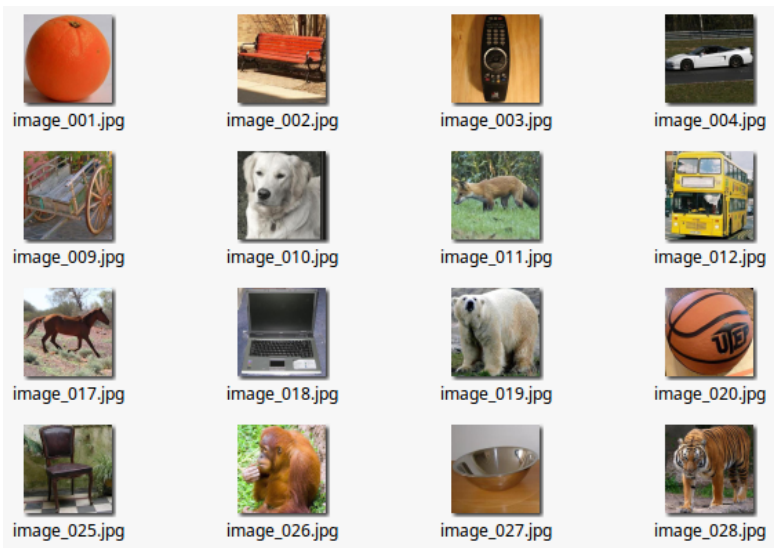
from Yalda Mohsenzadeh lecture

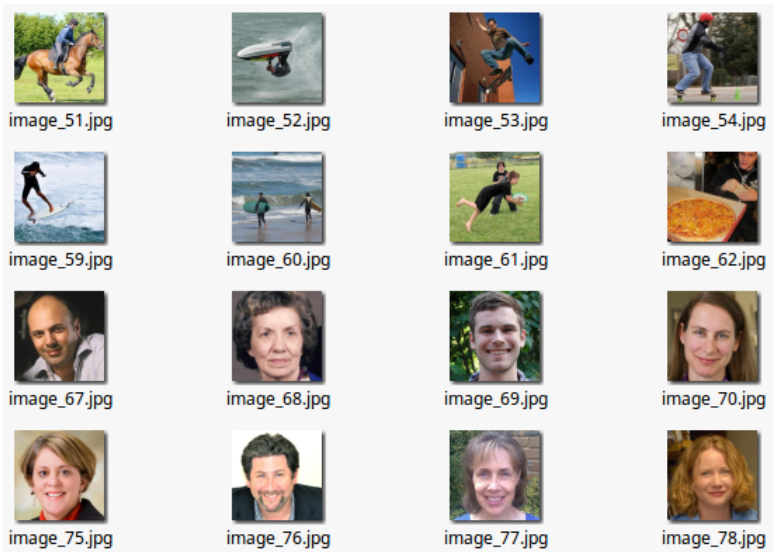
The competition – datasets

Training datasets





Test dataset



- All 3 datasets are distinct
- The competition results were based on the test dataset
- After the end of the competition the participants had to give predictions on a hidden test set (very similar to the test dataset) to check for overfitting...

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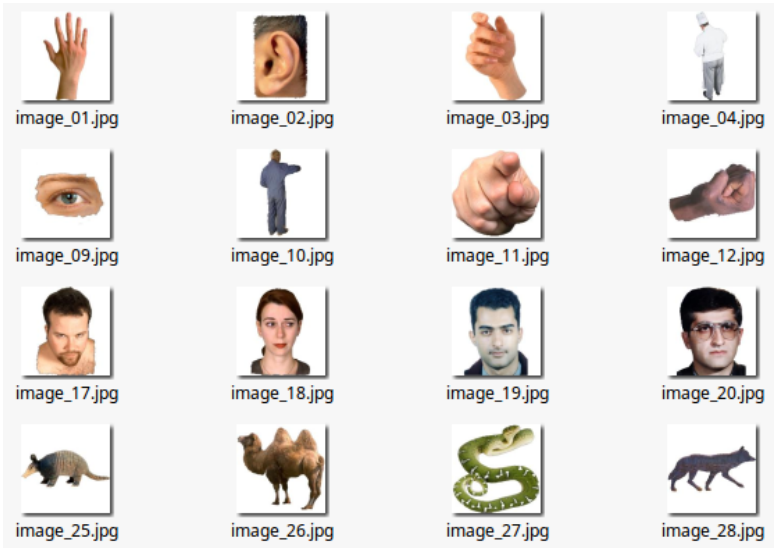

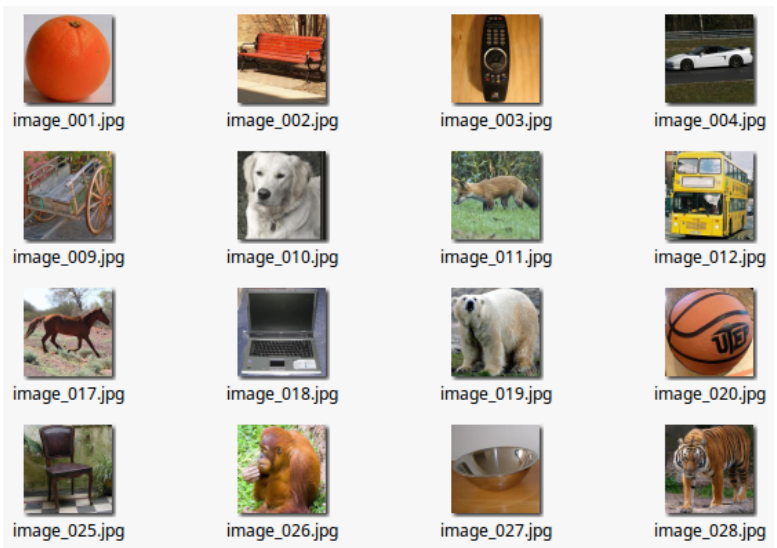

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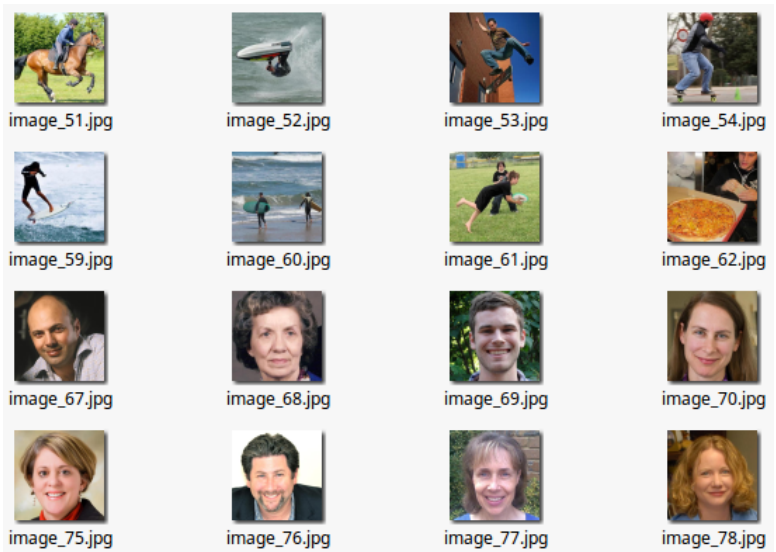

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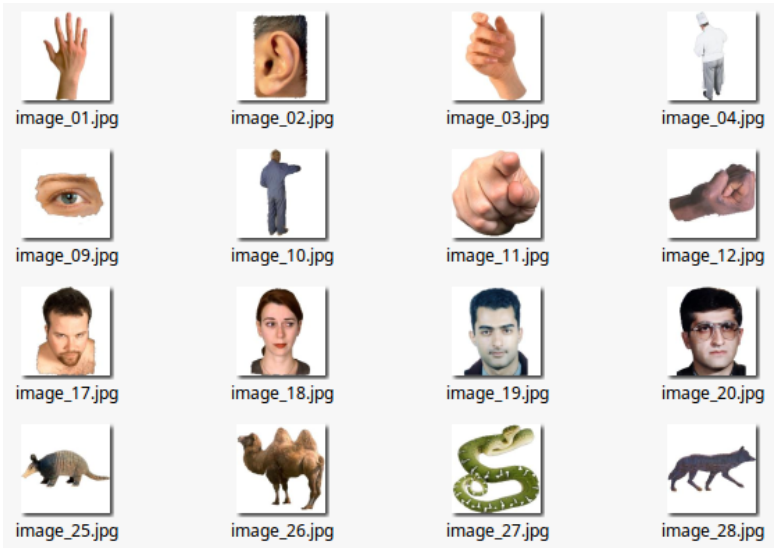

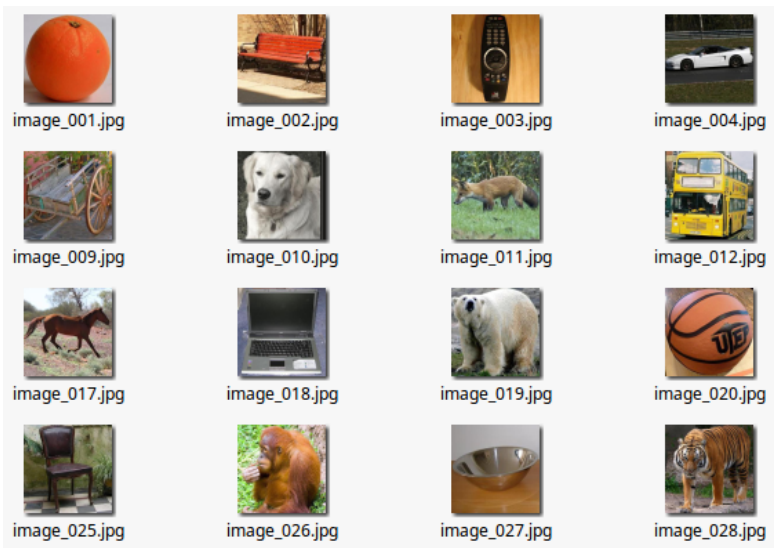

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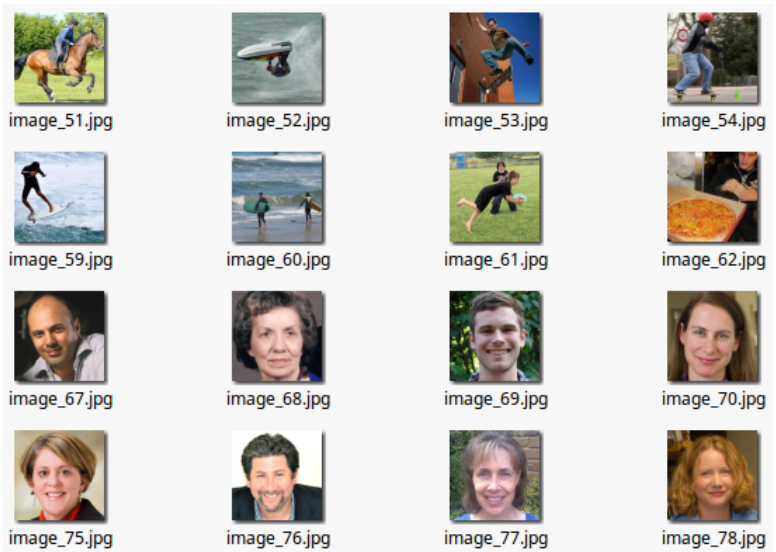

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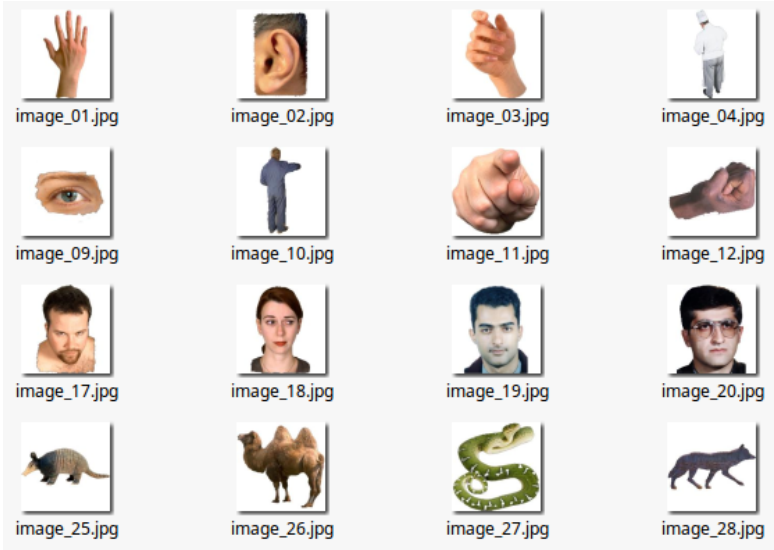

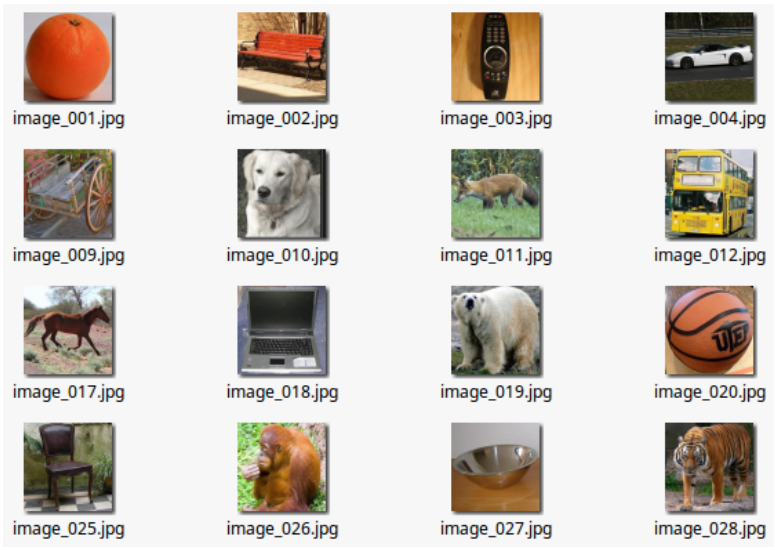

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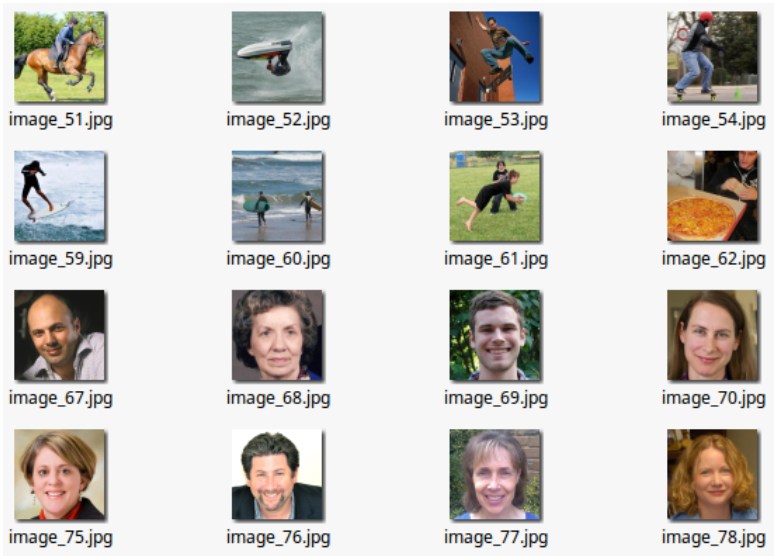

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- On the hidden test dataset, I got 2^{nd} place in the MEG track and 1^{st} in the fMRI track
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RDM peculiarities

Representational Dissimilarity Matrices (RDM) by construction have two rather unexpected and somewhat unwelcome features:

- They can miss a very strong discriminative signal (if correlated)
- They are influenced by irrelevant uninformative features...

$$1 - R(x, y) = 1 - \frac{(x - \langle x \rangle)(y - \langle y \rangle)}{\sigma_x \sigma_y}$$

$$x_i = +1 \qquad y_i = -1$$

RDM will measure only correlation of noise...

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Representational Dissimilarity Matrices (RDM) by construction have two rather unexpected and somewhat unwelcome features:

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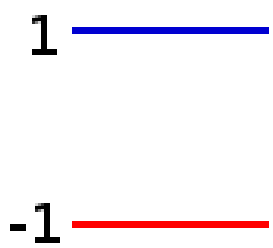

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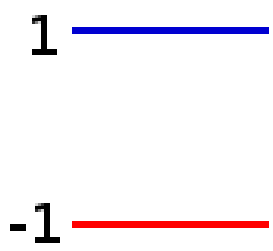

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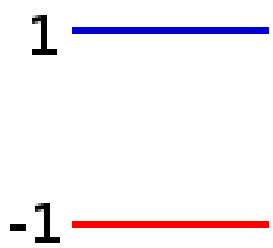

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- This effectively transforms Pearson RDM into *cosine dissimilarity*

$$1 - \frac{x \cdot y}{|x||y|}$$

- This modification significantly increases the scores...
  (average of NN activations is relevant for describing brain RDM's)
- To some extent, the constant level matters...
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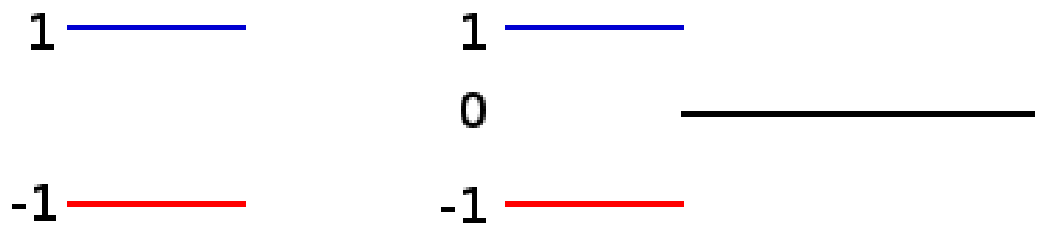

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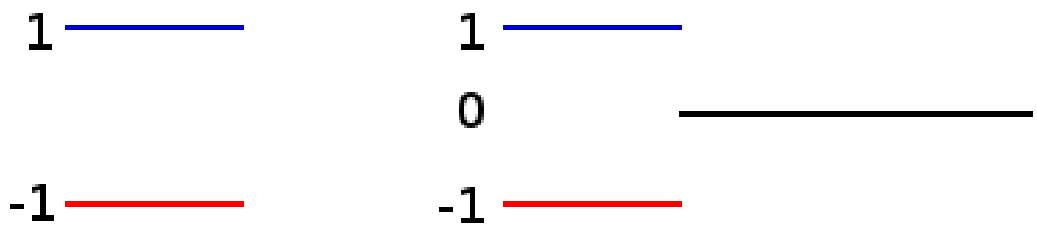

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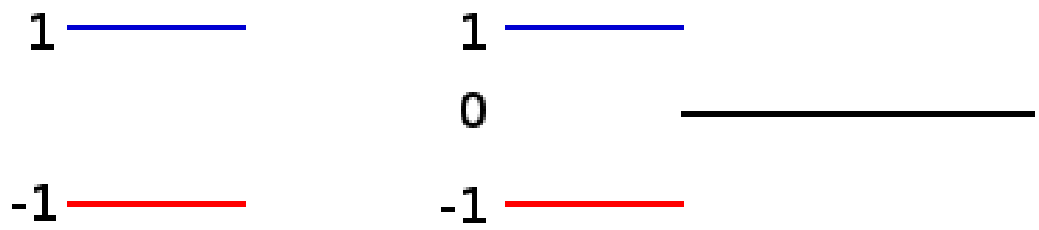

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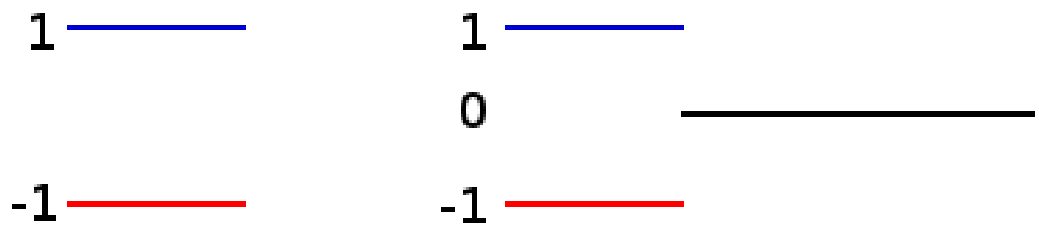

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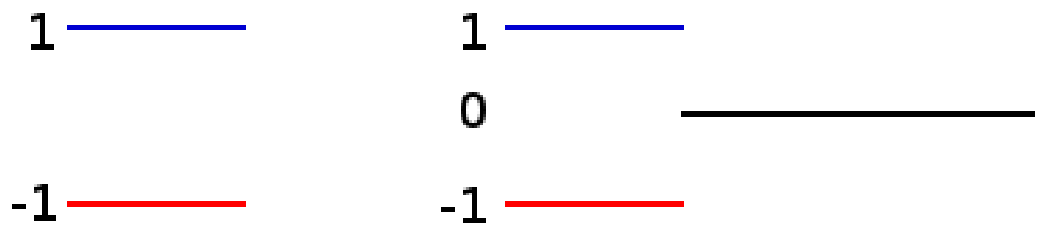

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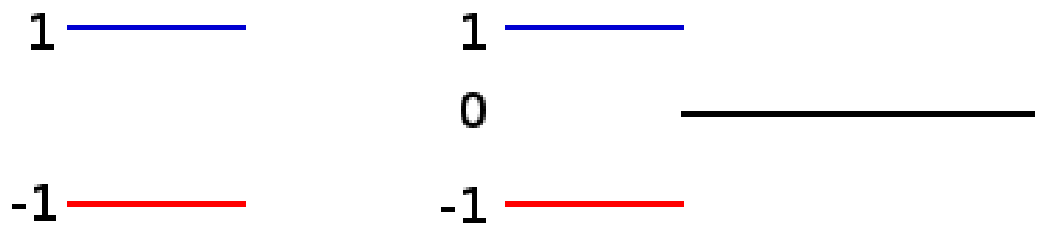

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`resnet50`

`block1` $256 \times 56 \times 56$
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Use `adaptive_max_pool2d` to reduce each layer to $k \times k$

IT: use 2×2
EVC, EARLY, LATE: 5×5

Results **much worse** with average pooling

- NN convolutional features partition the image into various resolutions
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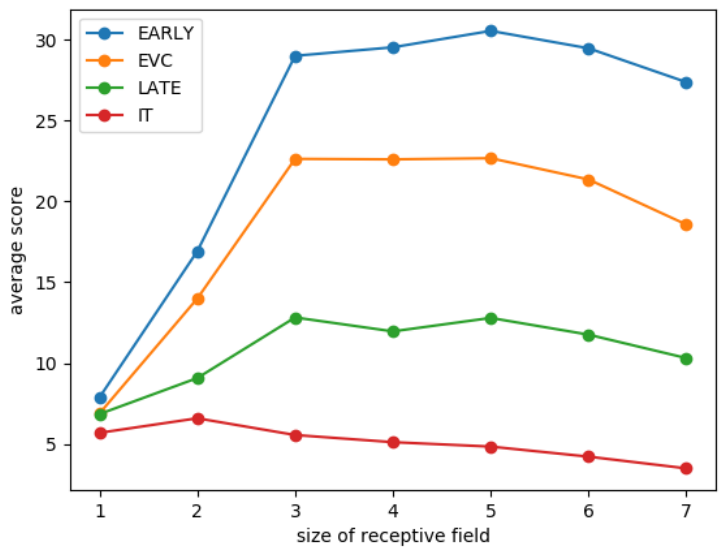

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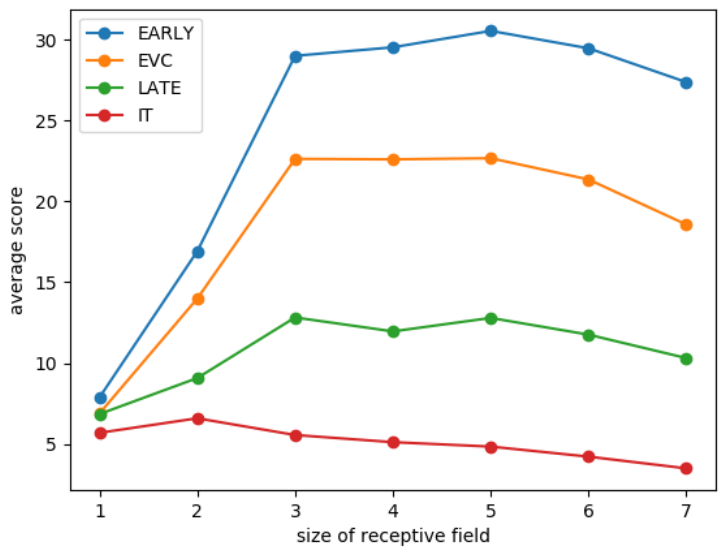

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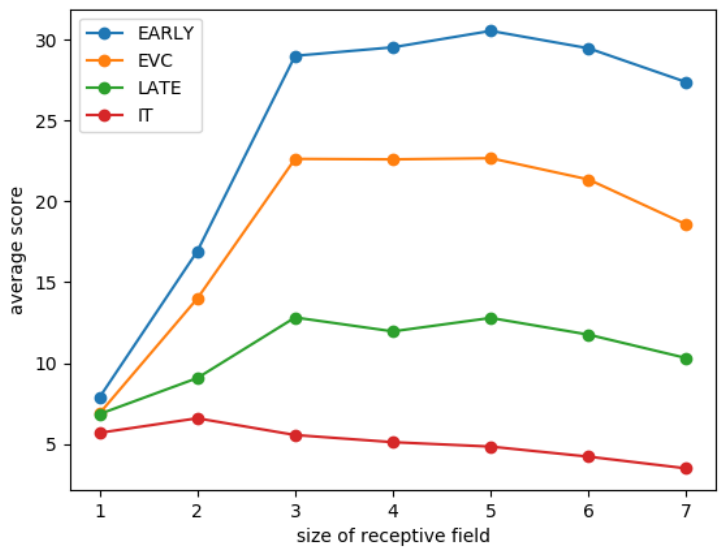

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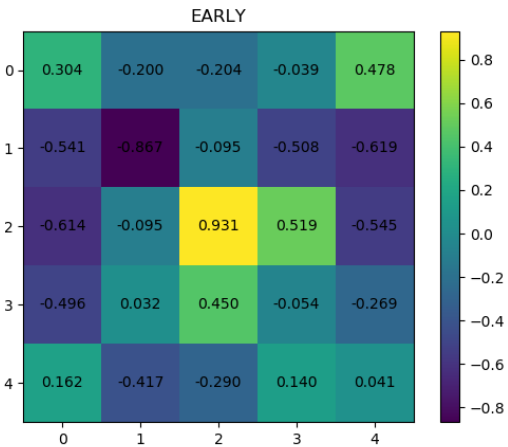

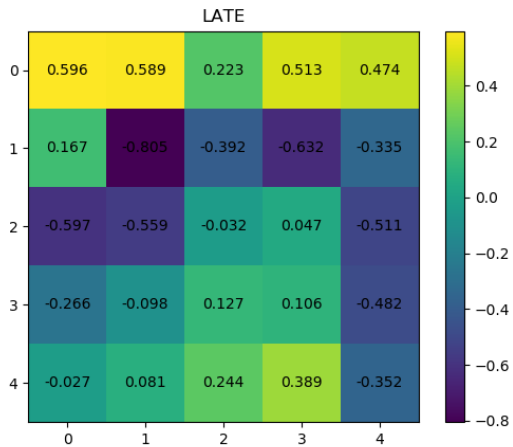

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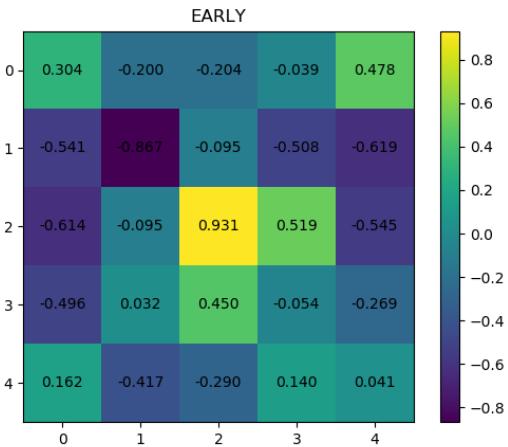

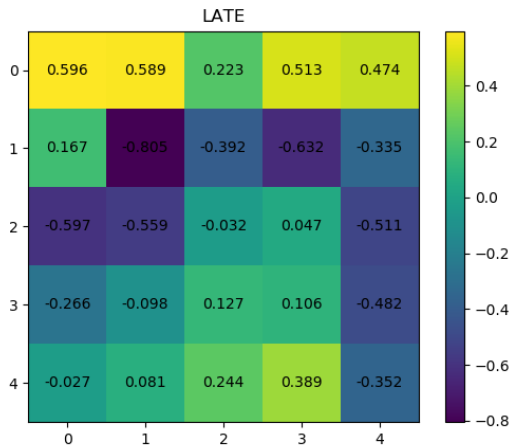

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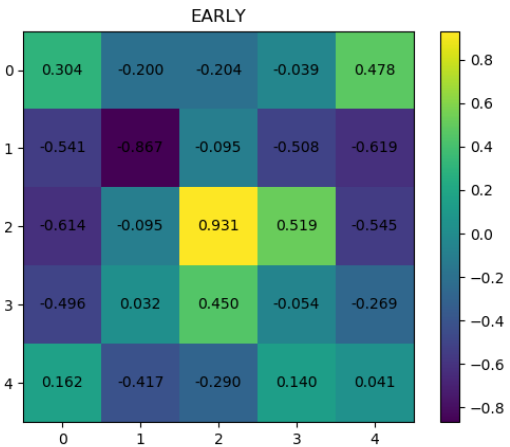
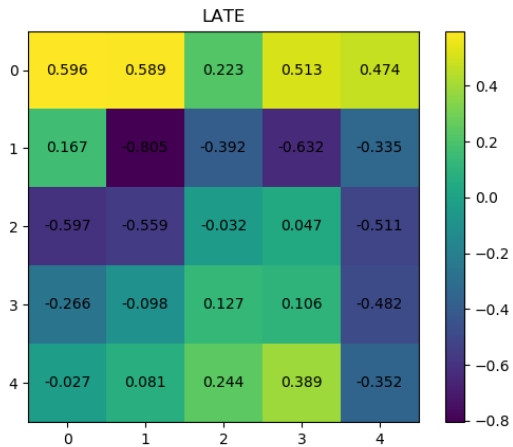
This feature selection procedure (option A) can also be used to study the importance of parts of receptive fields (`maxpool2` of `vgg19` on the 118 image dataset) (positive values bad)





We erase corners in EARLY and EVC...

The score increases also on the test dataset...

Solutions for EVC and EARLY

Solutions for EVC and EARLY MEG are very simple...

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6. add best features from `maxpool2` of `vgg19` (shrunk $0.5\times$)

Score: 28.40

Erronously adding worst features from other layers instead of **5.** + **6.** gave the best score: 32.68

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2. reduce to 5×5, extend by 0.5
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Solutions for IT and LATE – surrogate features

Question: What (abstract) features would reproduce the given brain RDM (averaged across subjects)? (as measured by Spearman's...)

Use **Multidimensional Scaling (MDS)**:

$$\overline{MDS}^{4}_{118\times118} \longrightarrow \mathbb{R}^{118\times10}$$ repeat with 10 random seeds

using the constructed 100 features gives a score around 77% for the same dataset

General procedure:

1. Fit the resulting 100 features with NN features
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IT

1. Use `resnet50`, convolutional features reduced to 2×2
2. For 118 dataset MDS features: ridge regression; OMP(6)
   For 92 dataset MDS features: OMP(7)
3. Concatenate to get 300 features
4. Prune bad features imposing positivity on 118 dataset
5. Extend with a constant of 1.0

   19.42
6. Add in 75+75 ICA from `block1`, `block3` of `resnet34`

Score: 20.77

LATE

1. Use `resnet50`, convolutional features reduced to 5×5
2. For 118 dataset MDS features: GBR(5) with Huber loss
   For 92 dataset MDS features: GBR(5) with Huber loss
3. Concatenate to get 200 features
4. Prune bad features which are bad (> 0.05) on both datasets
5. Extend with a constant of 1.0

Score: 57.38

Solutions for IT and LATE – surrogate features

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4. Prune bad features which are bad (> 0.05) on both datasets
5. Extend with a constant of 1.0

Score: 57.38

Solutions for IT and LATE – surrogate features

IT

1. Use `resnet50`, convolutional features reduced to 2×2
2. For 118 dataset MDS features: ridge regression; OMP(6)
   For 92 dataset MDS features: OMP(7)
3. Concatenate to get 300 features
4. Prune bad features imposing positivity on 118 dataset
5. Extend with a constant of 1.0

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6. Add in 75+75 ICA from `block1`, `block3` of `resnet34`

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- Key difficulty: overfitting
  - lots of NN features versus small number of images
  - The three datasets were quite distinct...
- Sometimes CV, as well as assessment of feature importance, was not reliable
- Try to stick to simple models...
- The receptive field reductions to 5×5 (or 2×2 for IT) seemed to be quite robust for all datasets.
- "second level" (`block2` or `maxpool2`) NN features seem to be a good staring point...
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- Perhaps it would be better to modify the definition of RDM to eliminate the peculiarities mentioned here...
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