RDM peculiarities, effective receptive fields and surrogate features

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The competition was especially interesting for me in view of

Bio-inspired Artificial Neural Networks

a 4-year research project at the Jagiellonian University, starting in Fall 2019

involving groups in

- **Machine Learning**
- **Cognitive science**
- **Physics**

we will be hiring **group leaders** for three new groups:

- **(low-level) Neuroscience**
- **Bio Data Science**
- **InfoTech**

some post-doc positions will be available...

any questions: ask me or e-mail me (`romuald.janik@gmail.com`) or see the website bionn.matinf.uj.edu.pl

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Main ingredients of the Algonauts Challenge submissions...

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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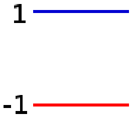

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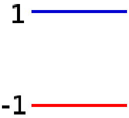

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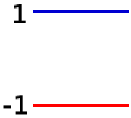

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This behavior (insensitivity to the global signal) can be countered by adding uninformative features...

- 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...
- The above suggests another (apart from cosine) possible modification of RDM definition:

$$\langle x \rangle \longrightarrow \text{featurewise average over the dataset}$$

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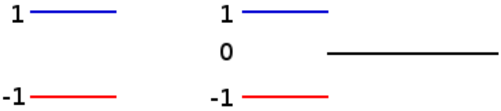

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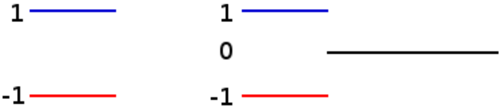

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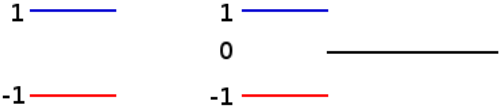

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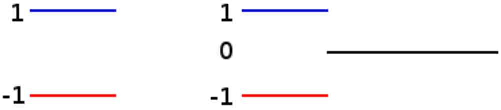

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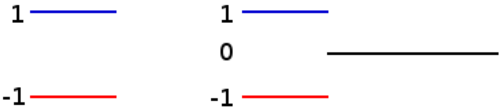

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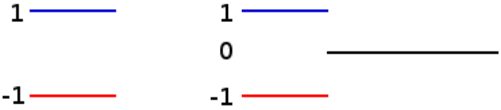

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Effective receptive field

`resnet50`

`block1` $256 \times 56 \times 56$
`block2` $512 \times 28 \times 28$
`block3` $1024 \times 14 \times 14$
`block4` $2048 \times 7 \times 7$

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
- At the same time, features become more higher level...

Question: What is the natural resolution characteristic of brain RDMs?

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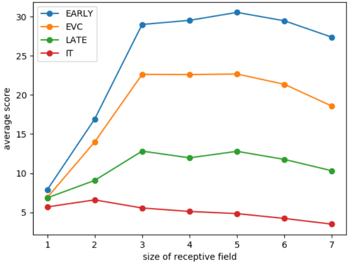

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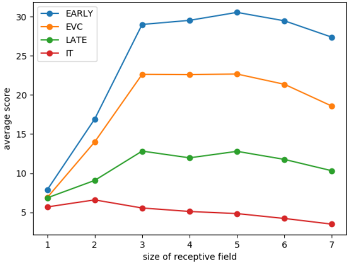

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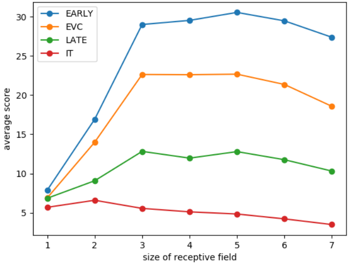

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- Try to avoid overfitting...

  (choosing feature weights to maximize score on training dataset does not generalize...)

A For each of the 15 subjects *individually* evaluate the reference score and the modified score (with an added or erased feature). Then take the mean/z-score of the 15 differences.

B Randomly choose 30 subsets of 1/4 images and use these for the reference and modified scores. Take the mean/z-score of the 30 differences.

- For feature pruning use option A on CV test folds as well as on predictions on other dataset...
- For adding features, we used also a modification of B, with 10 different splits into 5 parts, and requiring positivity on both 118 and 92 datasets...

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We erase corners in EARLY and EVC...

The score increases also on the test dataset...

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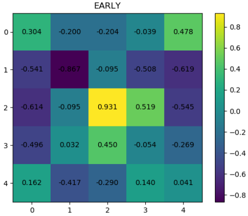

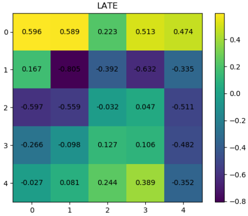

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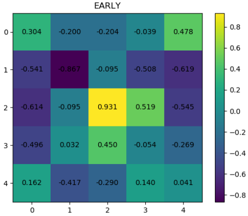

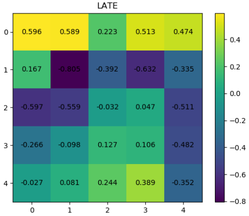

We erase corners in EARLY and EVC...

The score increases also on the test dataset...

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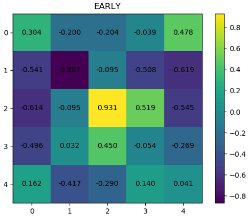

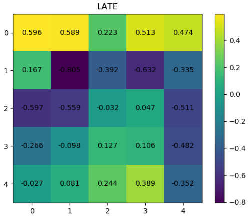

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Solutions for EVC and EARLY MEG are very simple...

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Score: 28.40

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

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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)**:

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

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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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
   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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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
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Summary and outlook

- 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...
- Max-pooling much better than average-pooling...

- Perhaps it would be better to modify the definition of RDM to eliminate the peculiarities mentioned here...
- Instead of MDS, one can generate features (embedding) to approximate RDM minimizing the mean squared error...
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