Classification of ROI-based fMRI data in short-term memory tasks using discriminant analysis and neural networks

Marcin Tutajewski
PhD Candidate in Technical Computer Science @ Jagiellonian University

People – cognitive, biodata, machine learning

T Marek
M Fąfrowicz
H Ogińska
B
Sikora-Wachowic
z
K Lewandowska
A Ceglarek

P Oświęcimka
M Wątorek
JK Ochab
T Stanisz
M Tutajewski

I Podolak
I Sieradzki

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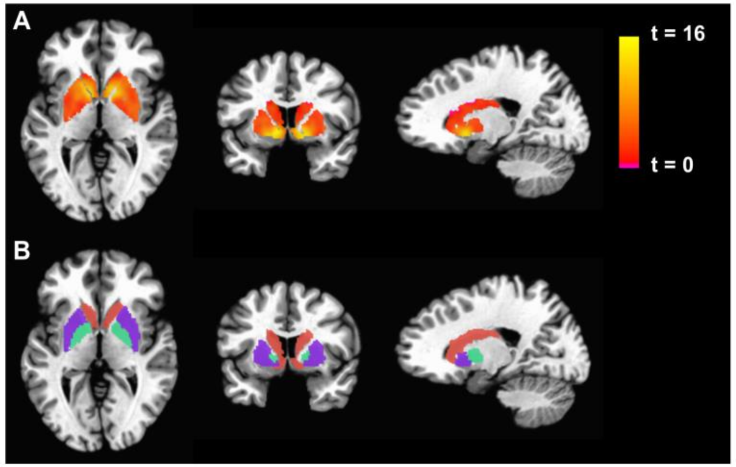
1. fMRI

Functional magnetic resonance imaging (fMRI) is a method of studying brain activity based on the blood-oxygen level-dependent (BOLD) imaging.

Unlike EEG, fMRI does not directly measure brain activity, but instead it relies on fluctuations in the oxyganation level, blood volume, and flow.

fMRI scanner and fMRI scan
https://www.flickr.com/photos/jannem/6278833383
https://upload.wikimedia.org/wikipedia/commons/1/10/CFS-brain-scan-basal-ganglia-fMRI.png



1.1 fMRI vs Electroencephalography (EEG)

Feature	EEG	fMRI
Temporal resolution (TR)	High – in ms	Low – between 1 and 4 seconds on average (1.8s in our case)
Spatial resolution (SR)	Low – in cm ^3 (cubed)	High – mm ^3 voxel sizes

1.2. How can we extract time-series from fMRI data?

Each of the voxels conveys a numeric value. While there are millions of such data points, we can average them based on a specific schema.

The schema that was used for the study was the Automated Anatomical Labelling Atlas (AAL).

AAL divides brain into 116 anatomical regions of interest (ROIs), where each ROI represents a certain brain area.

AAL ROIs (prefrontal.org/blog/2008/05/brain-art-aal-patchwork)

1.2. How can we extract time-series from fMRI data?

Having such split, we obtain a matrix of n_steps * n_ROIs.

For instance, if we took measurements every 1.8s for 15 minutes, that would result in roughly 500 ((15 * 60s) / 1.8s) steps and 116 ROIs for each of the steps.

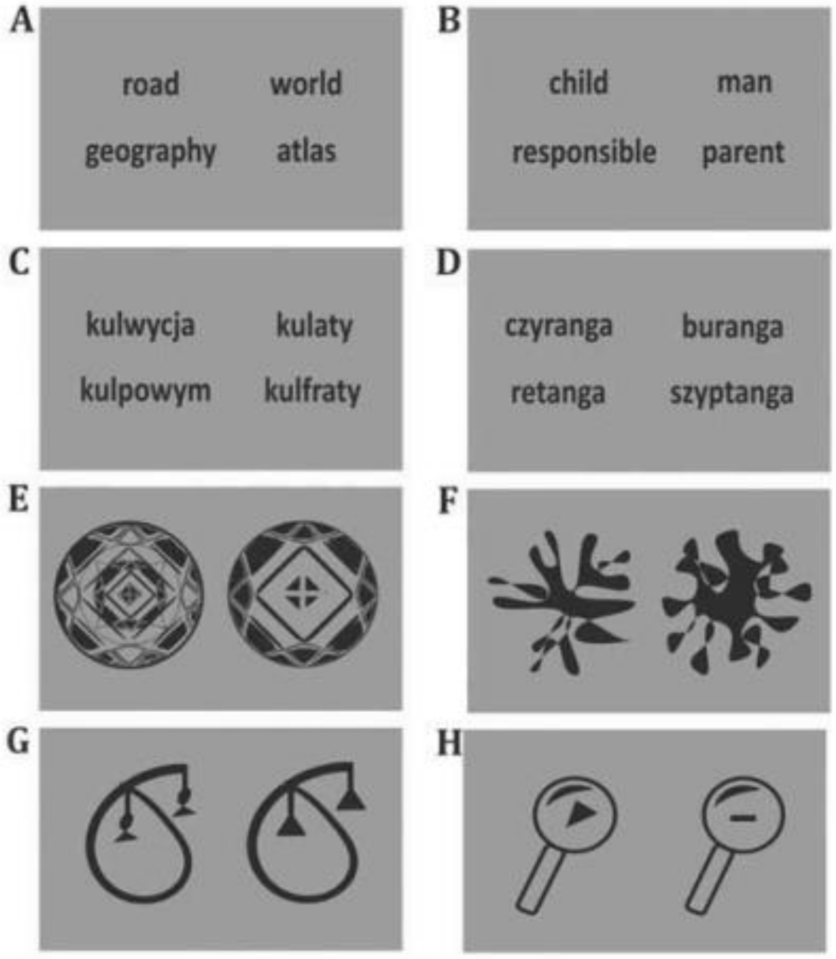
We can track and compare changes for both time, and the ROIs.

2. Short-term (working) memory experiment

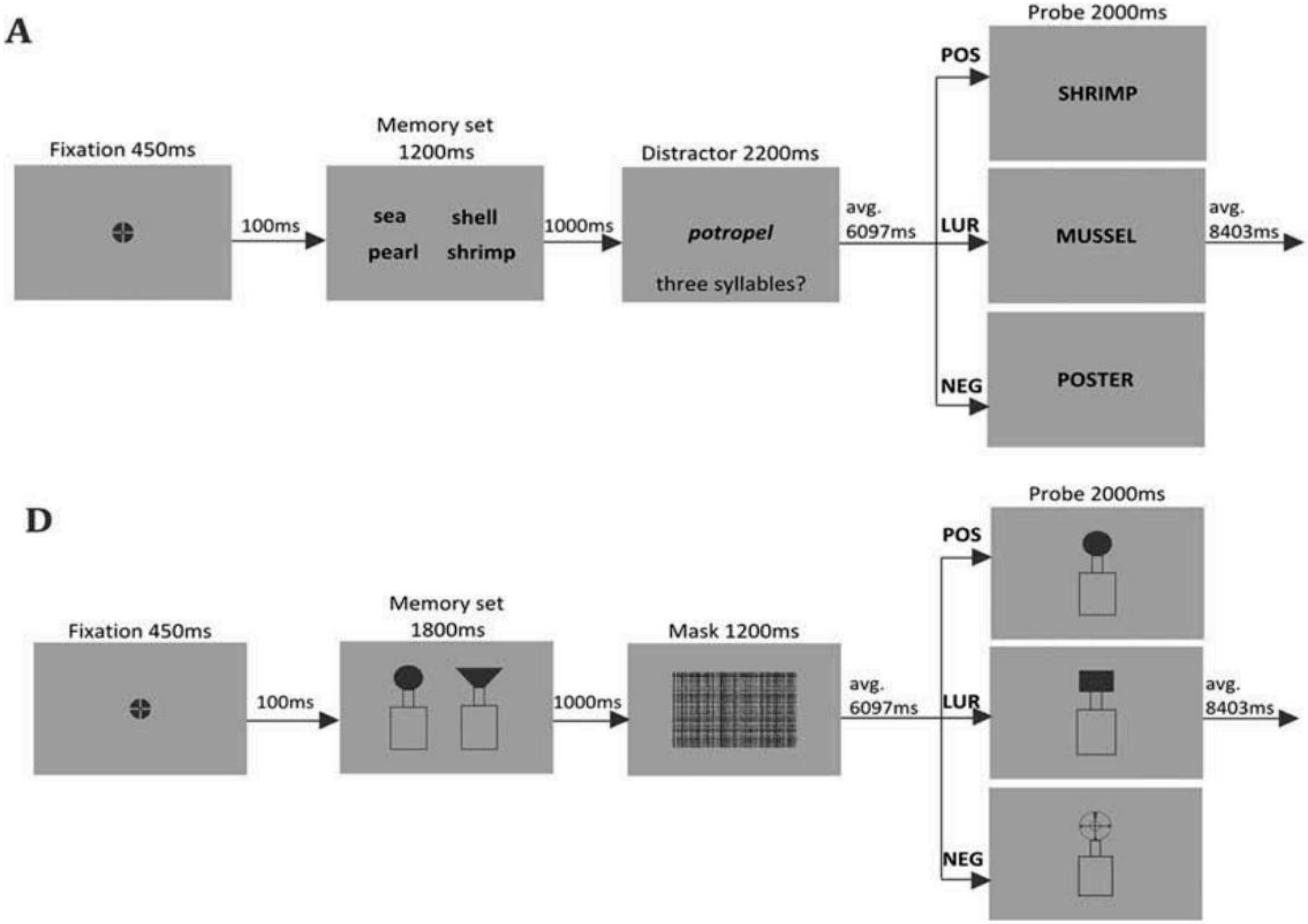
Koryna Lewandowska et al. conducted a working memory experiment in which participants performed four experimental tasks twice - in the morning and in the evening.

They were asked to memorize sets of stimuli and to respond after a while if they had seen a particular set or not.

The researchers however, not only showed sets that could be easily told apart, but also sets that were very similar, but not the same to the previously shown (Lewandowska et al. 2017).



Examples of memory sets in semantic (A,B), phonological (C,D), global (E,F), and local (G,H) tasks (Lewandowska et al., 2017)



SEMantic and LOCal processing experiments (Lewandowska et al., 2017)

2.1 Purpose of the experiment

1. Can time of the day affect someone's response?
2. How will the brain react to the "lures"? (Lewandowska, 2017)

2.2 Participants

Fifty-two paid volunteers participated in the study (38 females, age range: 20–35; mean ± SD: 23.96 ± 3.14 years). They were all non-smokers and drug-free, with no physical or psychiatric disorders.

Their sleep quality was controlled using the Pittsburgh Sleep Quality Index.

The group consisted of 18 morning-oriented and 34 evening-oriented participants, based on the morningness-eveningness questionnaire.

2.2 Results of the experiment

1. Time of the day (TOD) strongly affects individual decision bias. Responses tend to be more liberal in the evening than in the morning.

2. The phenomenon is observable for all of the tasks (Lewandowska et al., 2017).

3. fMRI signal classification study

1. What can we find in such fMRI data?
2. Can we tell those signals apart?
3. Which ROIs are the most significant?

3.1 Data split

Temporal resolution of 1.8s, 116 ROIs

1 x 116 array used with classical ML methods

6 x 116 matrix used with Neural Networks

Encoding – stage of learning

Retrieval – stage of retrieving the information

Resting state (REST) - subjects instructed to keep their eyes open, think of nothing, and not to fall asleep

Classification tests for both encoding and retrieval, with 2 to 5 classes (8 in total)

Random split into 90% used for training and 10% for testing

3.2 Methods Used

Classifiers

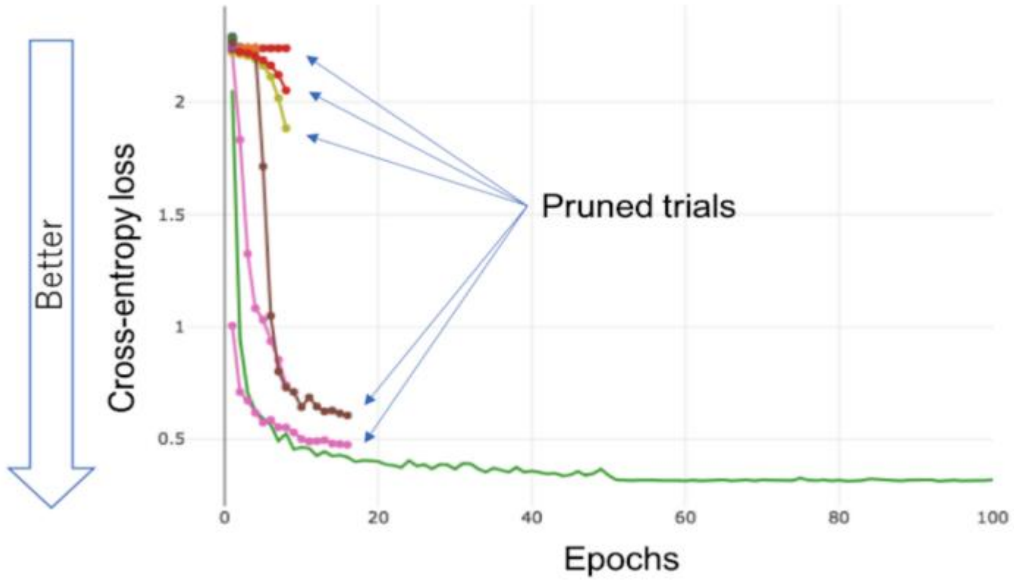
Quadratic Discriminant Analysis (QDA) – a model which focuses on data distributions rather than creating conditional boundaries between the classes. It aims to find class which minimizes the quadratic discriminant function. It differs from LDA in that the covariance matrix need to be estimated separately for each class.

Light Gradient Boosting Machine (LGBM) – boosting algorithm which creates and combines multiple "weak" learners to form a "strong" one. The algorithm works by inspecting the results of one training phase to reduce errors in the following one. It does that by assigning more weight to spaces which are difficult to separate.

3.2 Methods Used

Fine-tuning

Optuna – hyperparameter optimisation framework. It can automatically construct search spaces, to improve the algoritm fit.



Optuna hyperparameter tuning example https://optuna.readthedocs.io/en/v1.1.0/tutorial/pruning.html

3.3 Metrics

Precision – true positives / (true positives + false positives)

Recall – true positives / (true positives + false negatives)

F1 – 2 * (precision * recall) / precision + recall

Classifier fit time – time for the algorithm to run the hyperparameter optimization and converge

3.4 Results

Experiment name	Component 1	Component 2	Component 3	Component 4	Component 5
ENC2	GLO, LOC	SEM, PHO			
ENC3	GLO, LOC	SEM, PHO	REST		
ENC4	GLO	LOC	SEM	PHO	
ENC5	GLO	LOC	SEM	PHO	REST
RET2	GLO, LOC	SEM, PHO			
RET3	GLO, LOC	SEM, PHO	REST		
RET4	GLO	LOC	SEM	PHO	
RET5	GLO	LOC	SEM	PHO	REST

Model	Classifier Type	ENC2	ENC3	ENC4	ENC5	RET2	RET3	RET4	RET5
Ridge	Linear	0.541	0.433	0.312	0.458	0.532	0.425	0.292	0.263
Logistic Regression	Linear	0.542	0.433	0.319	0.461	0.532	0.424	0.292	0.266
SGD Classifier	Linear	0.521	0.440	0.242	0.428	0.504	0.394	0.288	0.249
Gaussian NB	Linear	0.543	0.374	0.296	0.443	0.535	0.366	0.298	0.282
Decision Tree	Nonlinear	0.375	0.338	0.252	0.416	0.365	0.325	0.247	0.254
Random Forest	Nonlinear	0.447	0.436	0.368	0.506	0.444	0.428	0.373	0.409
LDA	Linear	0.541	0.432	0.317	0.460	0.532	0.425	0.293	0.266
QDA	Nonlinear	0.608	0.498	0.404	0.531	0.594	0.480	0.394	0.405
LGBM	Nonlinear	0.580	0.520	0.368	0.498	0.580	0.514	0.354	0.387

F1 scores for each of the tasks and algorithms tested

3.5 Conclusions

1. It is possible to automatically differentiate between tasks using machine learning. Among the algorithms we have tested, best results were achieved with non-linear methods.

2. Some ROIs seem to be more important than others.

3. The accuracy does not necessarily decrease with classes.

3.6 Future work

1. Predicting responders’ response errors before they occur

2. Interpreting features that were distinguished as „important” by machine learning algorithms

3. Exploring correlations between such features and types of tasks / responses

4. Citations

Anna Ceglarek, Magdalena Hubalewska-Mazgaj, Koryna Lewandowska, Barbara Sikora-Wachowicz, Tadeusz Marek, Magdalena Fafrowicz. (2021) Time-of-day effects on objective and subjective short-term memory task performance. Chronobiology International 38:9, pages 1330-1343.

http://dx.doi.org/10.1080/07420528.2017.1386666