PSYCH 5621 Intro to the ERP

Week 15: EEG Data Analysis based on Python

Guest Lecturer:
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PSYCH 5621

11/28/2023 TUESDAY

Python Pipeline of EEG Data Analysis

(preprocess -> ERP analysis -> time-frequency analysis;
single-subject analysis -> multiple-subject analysis)

11/30/2023 THURSDAY

Advanced EEG Data Analyses

(MVPA: classification-based decoding, representational similarity analysis;
Link between EEG and Deep Learning in cognitive neuroscience)

Multi-Variate Pattern Analysis (MVPA)

Classification-based decoding
Representational Similarity Analysis

- We will walk through the hands-on tutorial

Link between EEG and Deep Learning

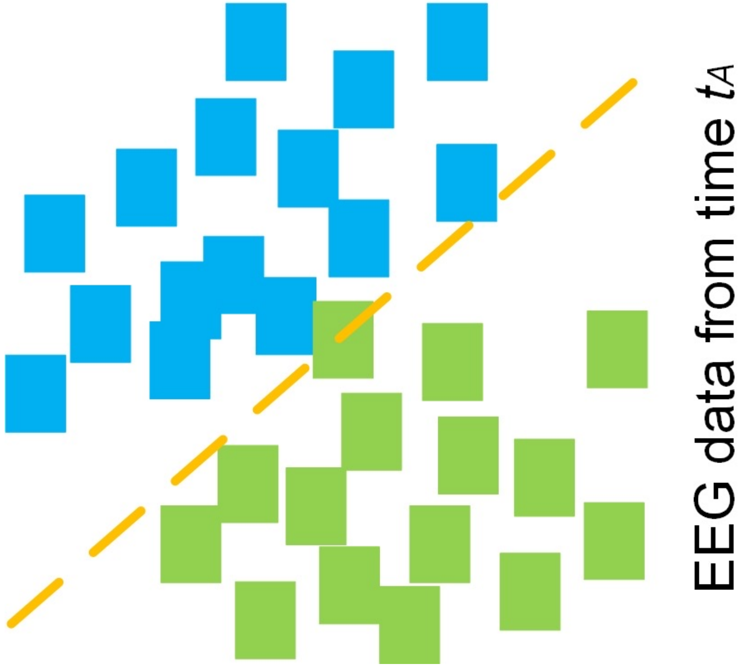
Comparisons between EEG signals and DL models
EEG decoding models
    category-classification; EEG-to-Image reconstruction
EEG encoding models
    Image-to-EEG generation

- I will give a brief introduction of the research progress

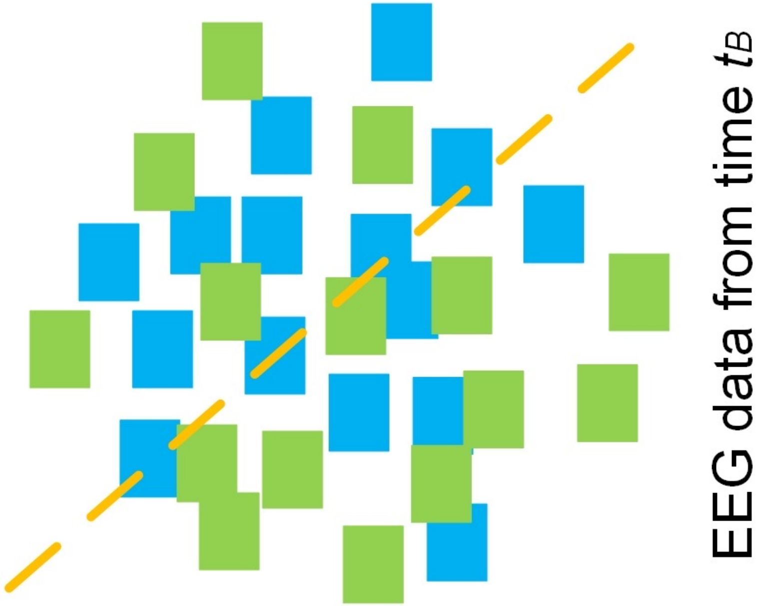
MVPA – Classification-based Decoding

For EEG

Classification-based decoding
birthday cake vs. ***boat***



Higher classification accuracy



Lower classification accuracy

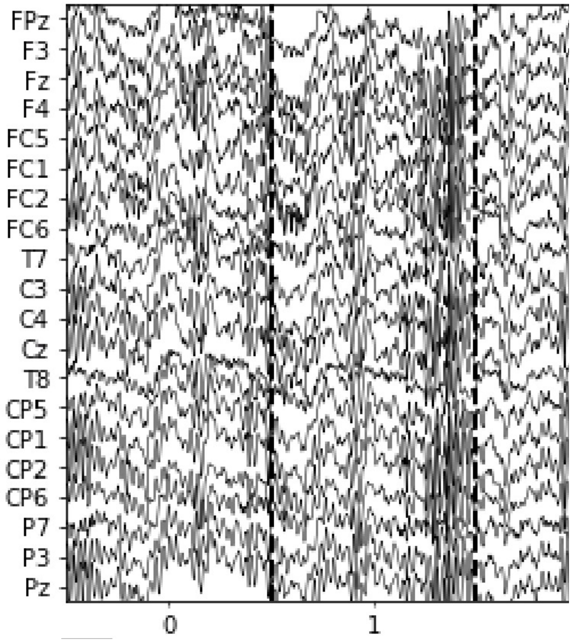
The representational differences between birthday cake and boat were more strongly encoded at t_A

MVPA – Classification-based Decoding

For EEG

Time-by-time decoding:
to conduct independent classification for each subject and each timepoint using linear classifiers

birthday cake vs. ***boat***



EEG signals for one trial

MVPA – Classification-based Decoding

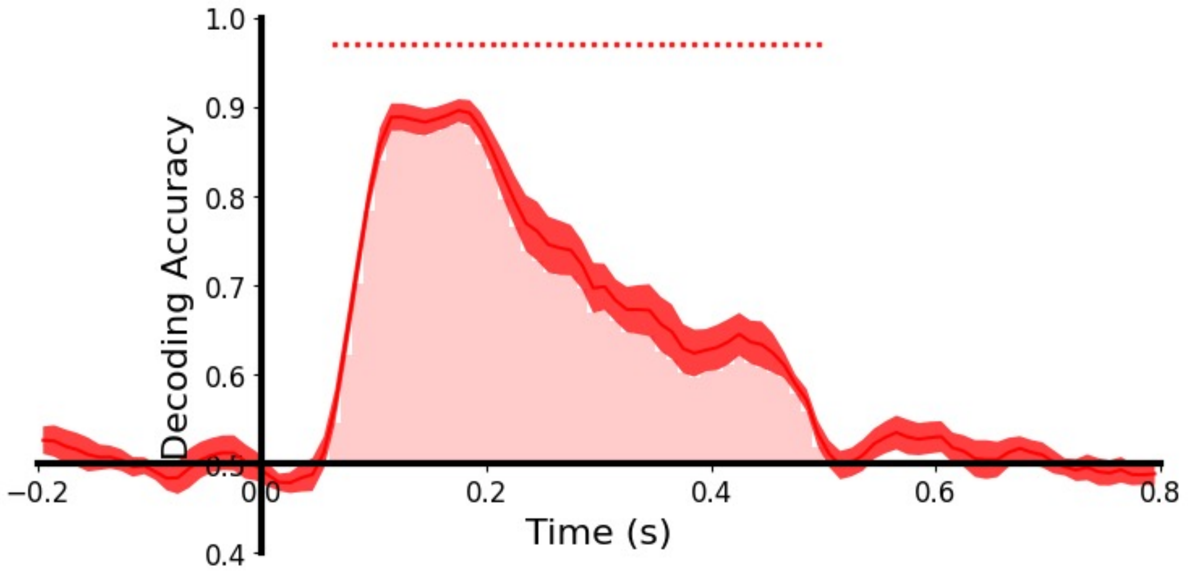
Framework

Data we have:
EEG data:
N_subjects * N_trials * N_channels * N_timepoints
Label data:
N_trials

What should we do:
Classify birthday cake vs. boat for each subject and each timepoint
Use channels as features
Cross-validation for each step

What we want:
Decoding results:
N_subjects * N_timepoints

birthday cake vs. **boat**



MVPA – Classification-based Decoding

Inputs:

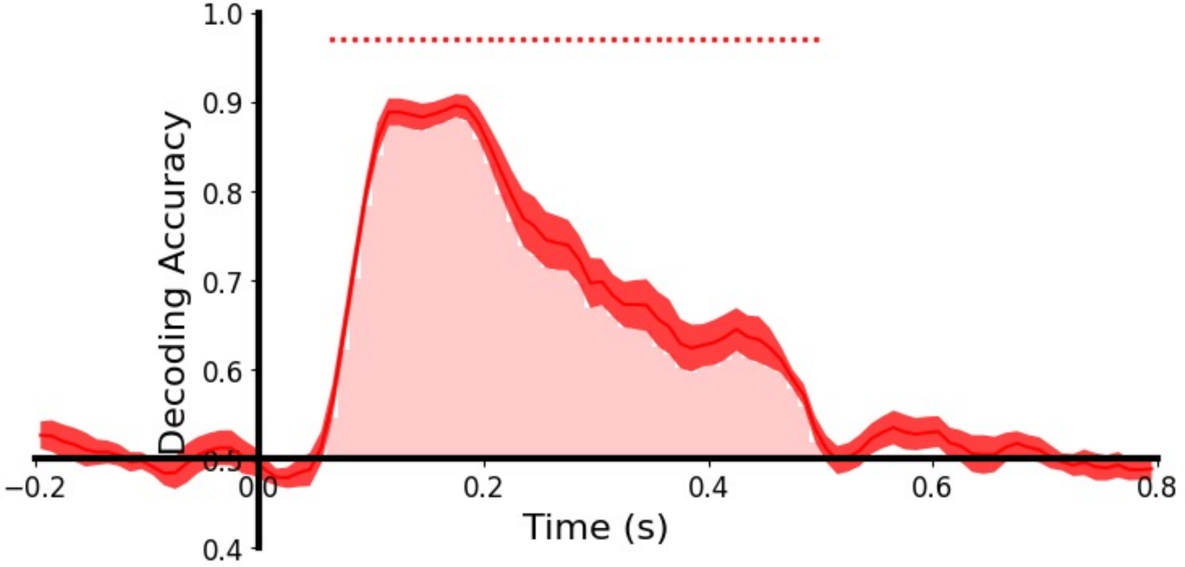
EEG data
– [n_subjects, n_trials, n_channels, n_timepoints]

Label data
– [n_subjects, n_trials]

Outputs:

Decoding accuracies
– [n_subjects, n_timepoints]

birthday cake vs. *boat*



MVPA – Classification-based Decoding

Coding time:
Let’s learn to decode image representations based on Python

https://github.com/ZitongLu1996/Python-EEG-Handbook

MVPA – Classification-based Decoding

2-class classification -> decode the brain representations of two images

Some experimental designs:

To investigate size representations -> set small and large objects, and classify small vs. large

To investigate depth representations -> set font and back objects, and classify font vs. back

To investigate facial expression representations ->
set face images with different expressions, and classify happy vs. neutral vs. sad vs. angry …

To investigate color representations ->
set squares with different colors, and classify red vs. yellow vs. green vs. …

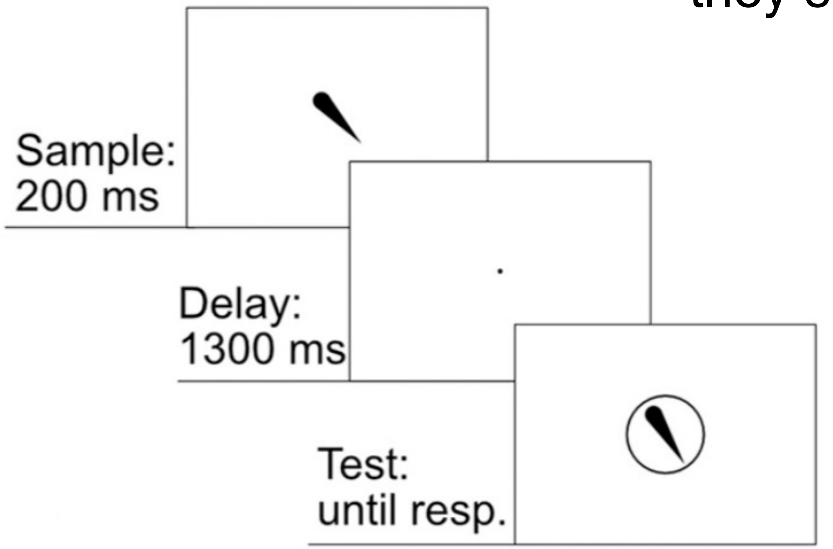
Sometimes, there are more than 2 classes

MVPA – Classification-based Decoding

Sometimes, there are more than 2 classes

To investigate orientation representation,

they set 16 different orientations (0°, 22.5°, 45°, …, 315°, 337.5°).



(Bae and Luck, JNeuro, 2018)

The only difference between 2-class and 16-class decoding:

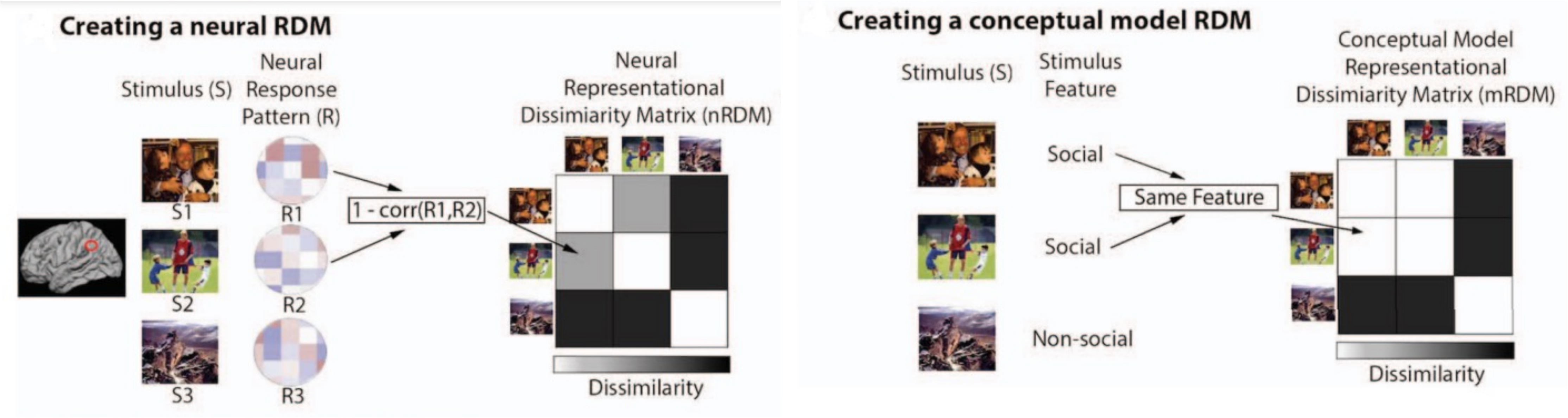
Chance level = 50% (1/2) vs. 6.25% (1/16)

MVPA – Classification-based Decoding

Coding time:
Let's learn to decode orientation representations based on Python

https://github.com/ZitongLu1996/Python-EEG-Handbook

MVPA – Representational Similarity Analysis

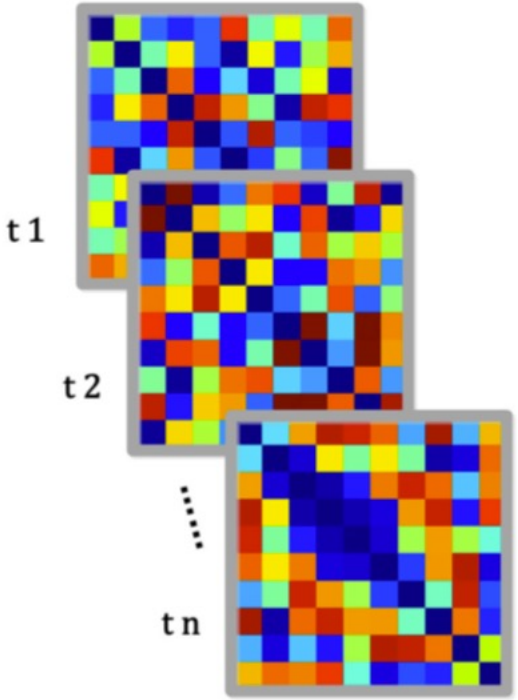


(Popal et al. , 2020, SCAN)

MVPA – Representational Similarity Analysis

Hypothesis-based RDM

Time-by-time EEG RDMs



Framework

Make hypothesis-based RDM

N_conditions * N_conditions

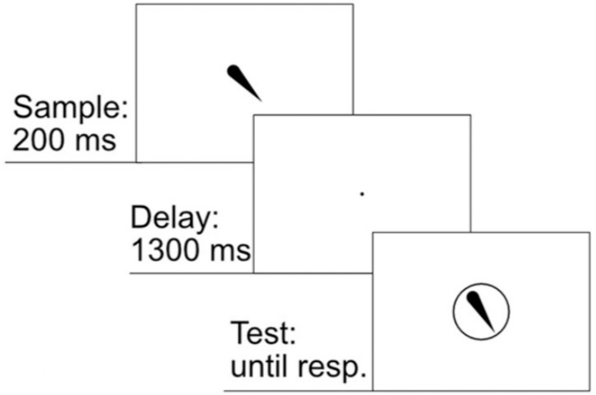
Make neural RDMs

N_subjects * N_timepoints * N_conditions * N_conditions

Compare between hypothesis-based RDM and neural RDMs

N_subjects * N_timepoints

MVPA – Representational Similarity Analysis



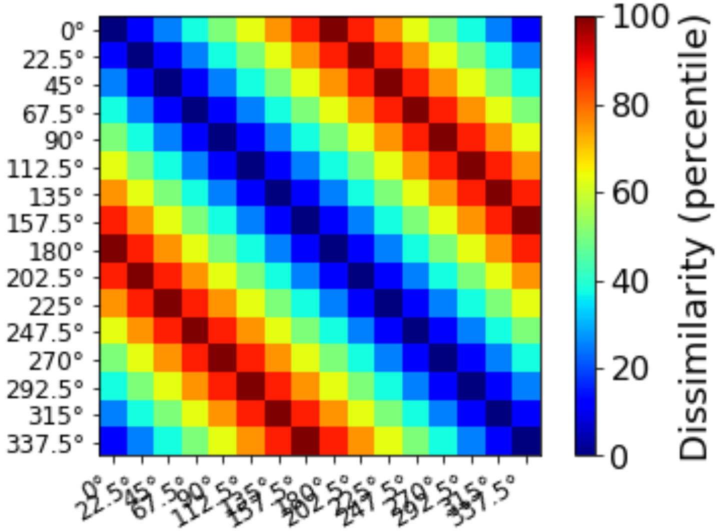
(Bae and Luck, JNeuro, 2018)

To investigate orientation representations:

Method 1: decoding 16 orientations.

Method 2: How about making a hypothesis-based orientation RDM?
Then compare with EEG RDMs?

A hypothesis-based orientation RDM:



Three steps:
1. Make hypothesis-based RDM
2. Make neural RDMs
3. Compare between hypothesis-based RDM and neural RDMs

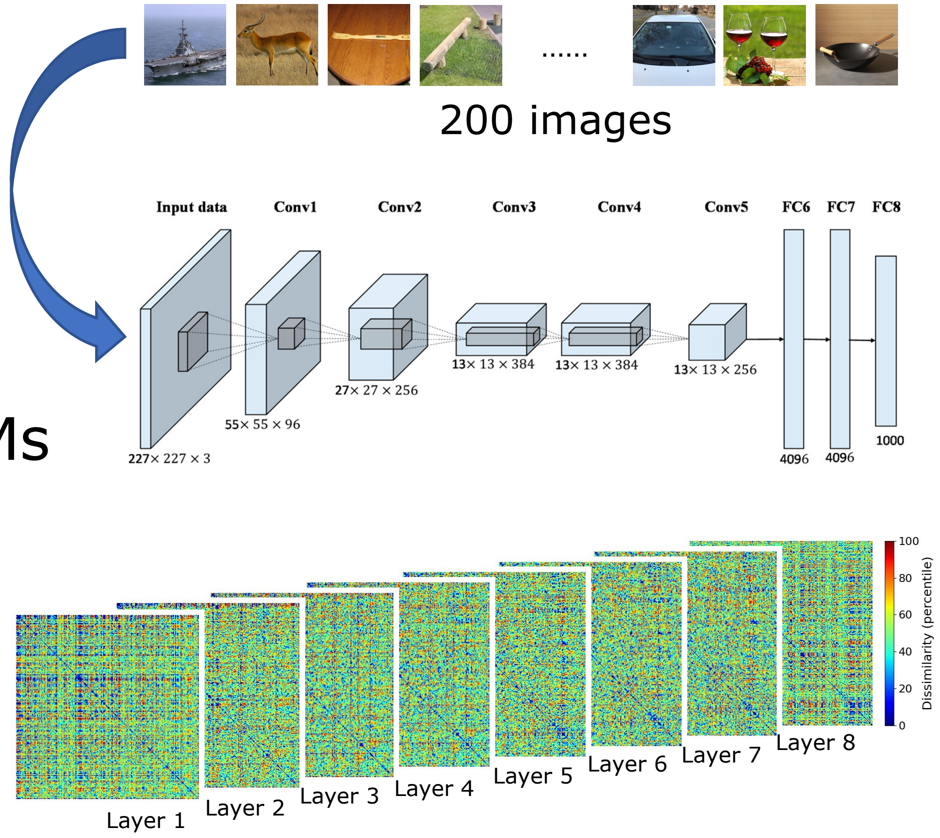
MVPA – Representational Similarity Analysis

Coding time:
Let's learn to decode orientation representations using RSA based on Python

https://github.com/ZitongLu1996/Python-EEG-Handbook

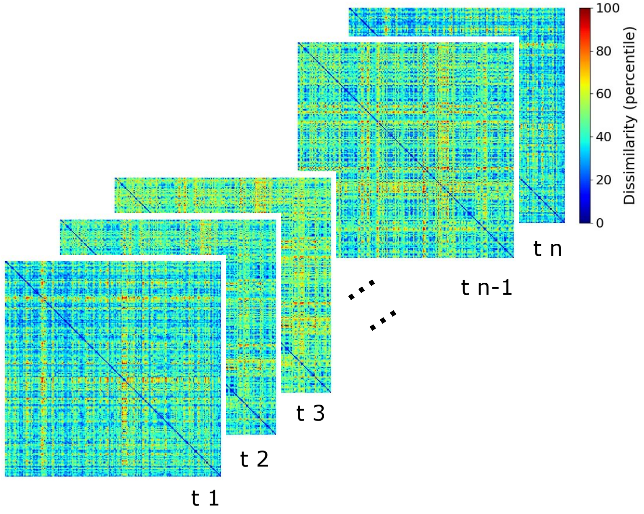
Link between EEG and Deep Learning
- Comparisons between EEG signals and DL models

To explore the temporal representation in visual perception



DCNN RDMs

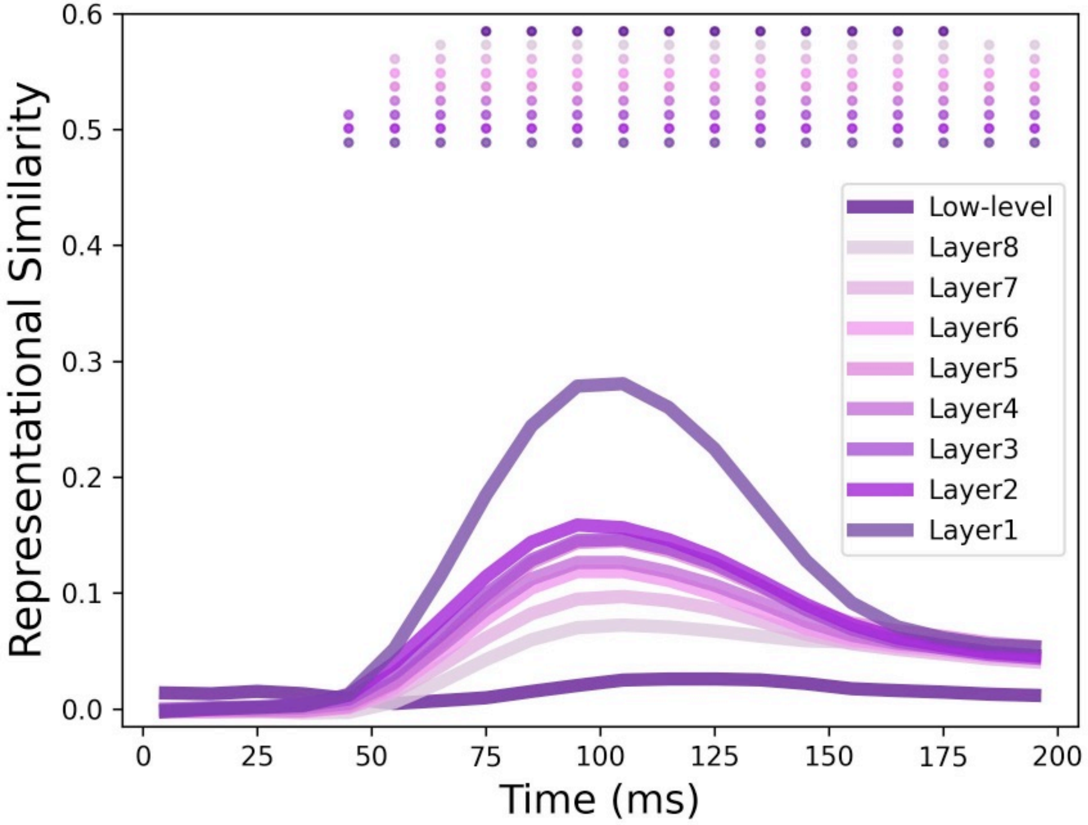
EEG RDMs



(Lu & Golomb, 2023, CogSci23')

Link between EEG and Deep Learning
- Comparisons between EEG signals and DL models

To explore the temporal representation in visual perception



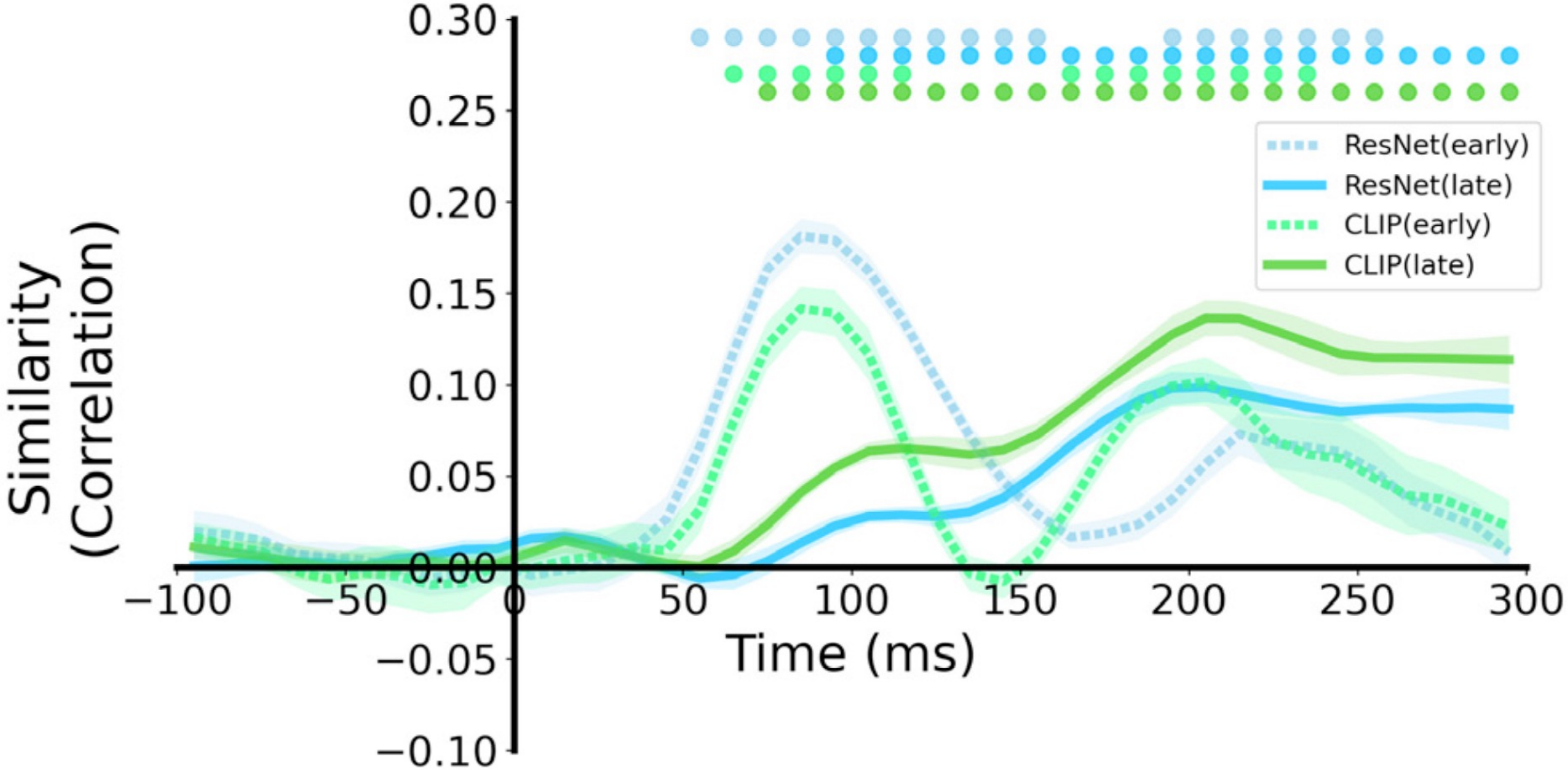
(Lu & Golomb, 2023, CogSci23')

Link between EEG and Deep Learning
- Comparisons between EEG signals and DL models

To assess the similarity of DL models to human brains

ResNet:
a pure visual DL model

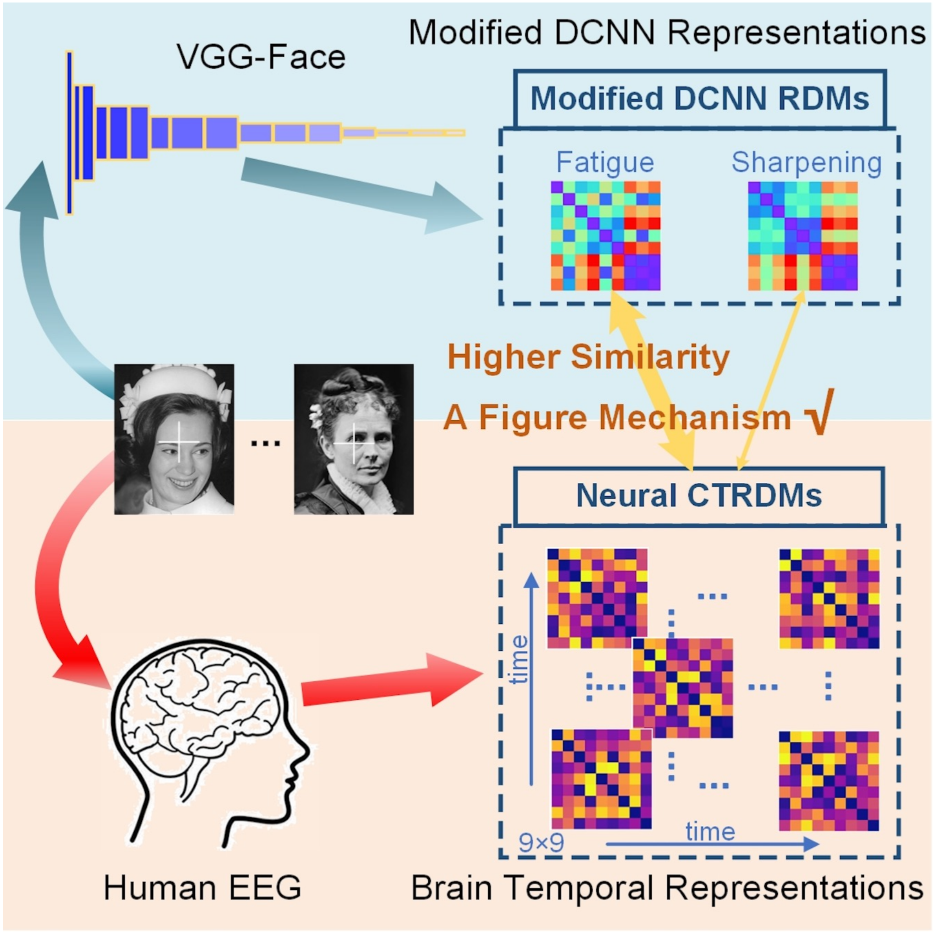
CLIP:
a DL model combining both
visual and semantic information

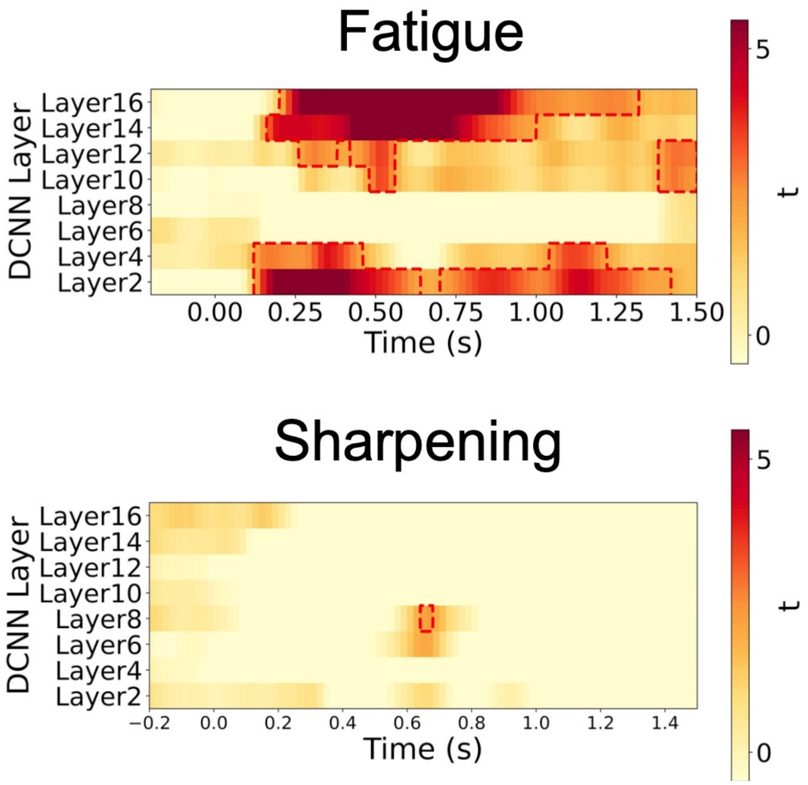


(Lu & Golomb, 2023, preprint)

Link between EEG and Deep Learning
- Comparisons between EEG signals and DL models

To apply reverse engineering methods to explore neural mechanisms

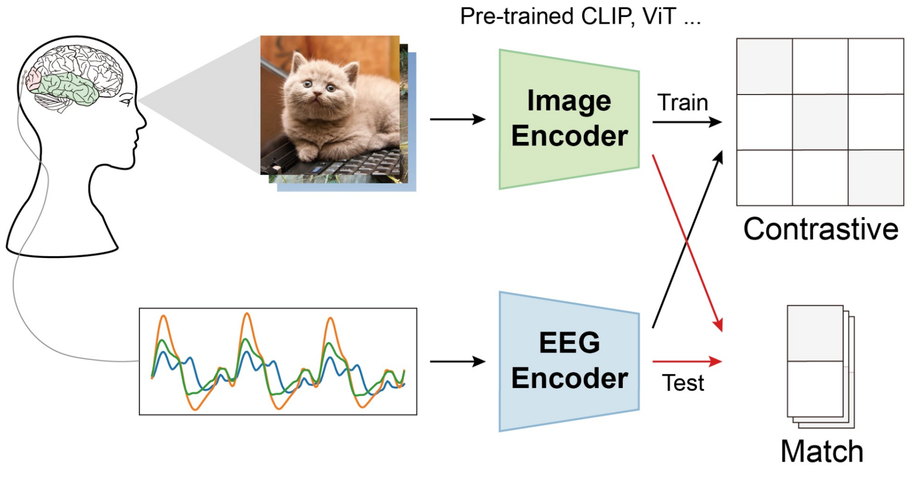




(Lu & Ku, 2023, iScience)

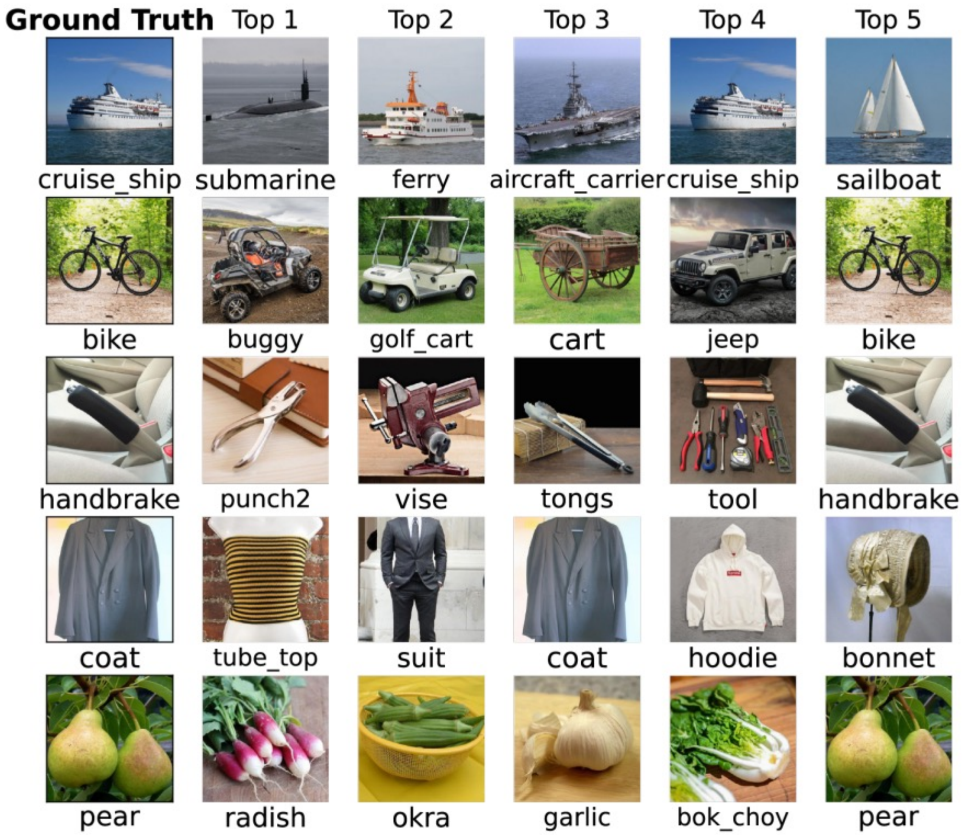
Link between EEG and Deep Learning
- EEG decoding models

To classify the image category based on EEG



Overall accuracy (%) of 200-way zero-shot classification: top-1 and top-5

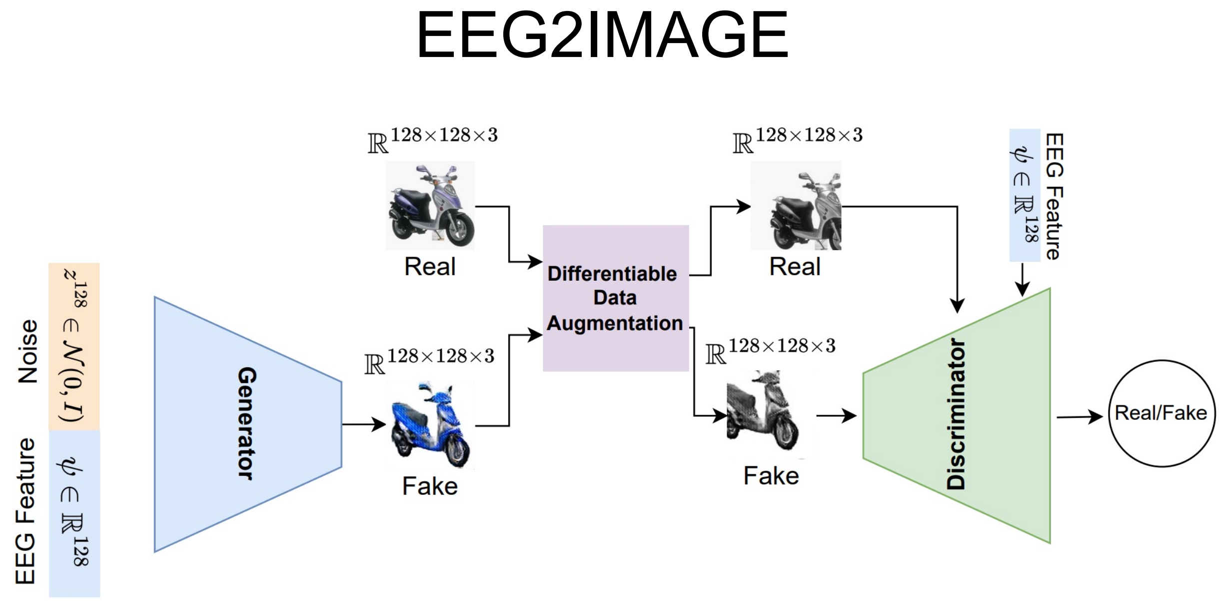
	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5		Subject 6		Subject 7		Subject 8		Subject 9		Subject 10		Ave	
Method	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5
Subject dependent - train and test on one subject																						
BraVL	6.1	17.9	4.9	14.9	5.6	17.4	5.0	15.1	4.0	13.4	6.0	18.2	6.5	20.4	8.8	23.7	4.3	14.0	7.0	19.7	5.8	17.5
NICE	12.3	36.6	10.4	33.9	13.1	39.0	16.4	47.0	8.0	26.9	14.1	40.6	15.2	42.1	20.0	49.9	13.3	37.1	14.9	41.9	**13.8**	**39.5**
NICE - SA	13.3	40.2	12.1	36.1	15.3	39.6	15.9	49.0	9.8	34.4	14.2	42.4	17.9	43.6	18.2	50.2	14.4	38.7	16.0	42.8	14.7	41.7
NICE - GA	15.2	40.1	13.9	40.1	14.7	42.7	17.6	48.9	9.0	29.7	16.4	44.4	14.9	43.1	20.3	52.1	14.1	39.7	19.6	46.7	15.6	42.8
Subject independent - leave one subject out for test																						
BraVL	2.3	8.0	1.5	6.3	1.4	5.9	1.7	6.7	1.5	5.6	1.8	7.2	2.1	8.1	2.2	7.6	1.6	6.4	2.3	8.5	1.8	7.0
NICE	7.6	22.8	5.9	20.5	6.0	22.3	6.3	20.7	4.4	18.3	5.6	22.2	5.6	19.7	6.3	22.0	5.7	17.6	8.4	28.3	**6.2**	**21.4**
NICE - SA	7.0	22.6	6.6	23.2	7.5	23.7	5.4	21.4	6.4	22.2	7.5	22.5	3.8	19.1	8.5	24.4	7.4	22.3	9.8	29.6	7.0	23.1
NICE - GA	5.9	21.4	6.4	22.7	5.5	20.1	6.1	21.0	4.7	19.5	6.2	22.5	5.9	19.1	7.3	25.3	4.8	18.3	6.2	26.3	5.9	21.6



(Song et al., 2023, preprint)

Link between EEG and Deep Learning
- EEG decoding models

To reconstruct the image from EEG signals



(Singh et al., 2023, ICASSP23')

Link between EEG and Deep Learning
- EEG decoding models

To reconstruct the image from EEG signals

Why it is important to visualize our mind's eye?

OXFORD

Psychoradiology, 2023, **0**, 1–4
DOI: 10.1093/psyrad/kkad022
Advance access publication date: 11 October 2023
Commentary

Visualizing the mind's eye: a future perspective on applications of image reconstruction from brain signals to psychiatry

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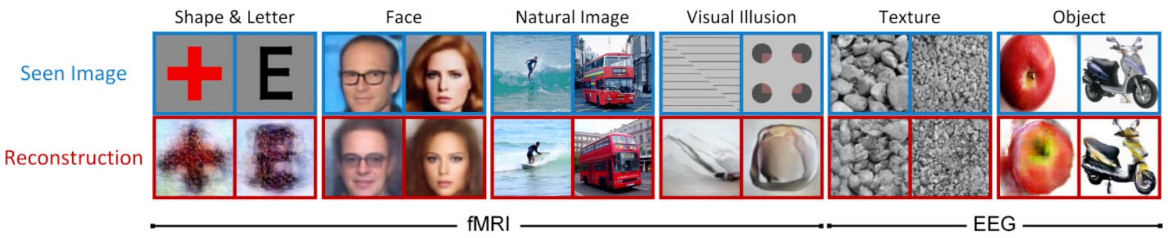
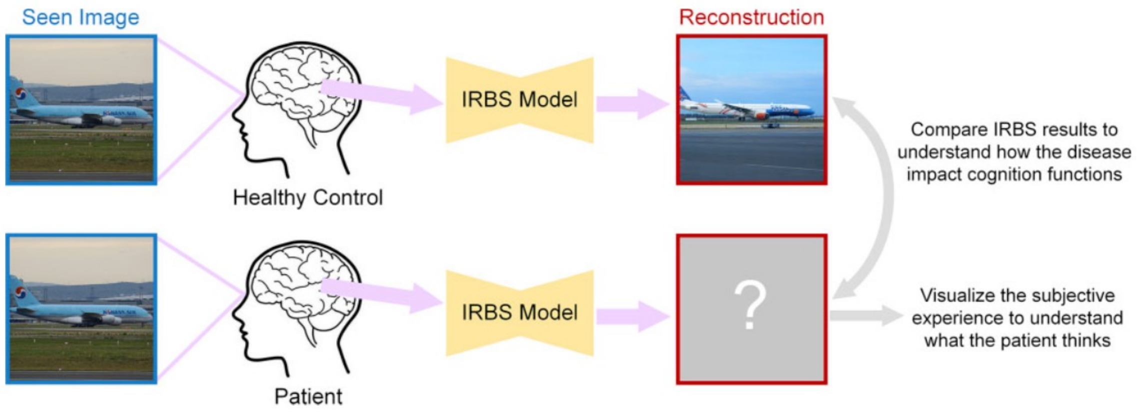
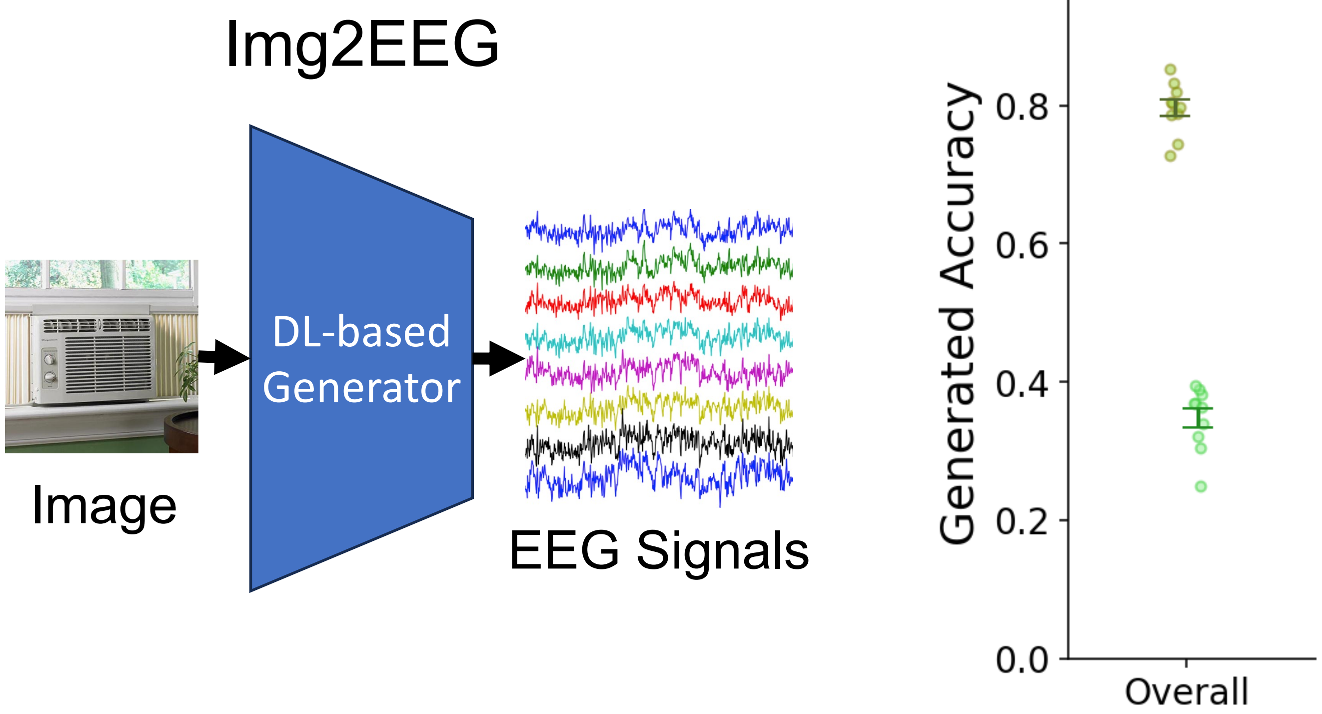


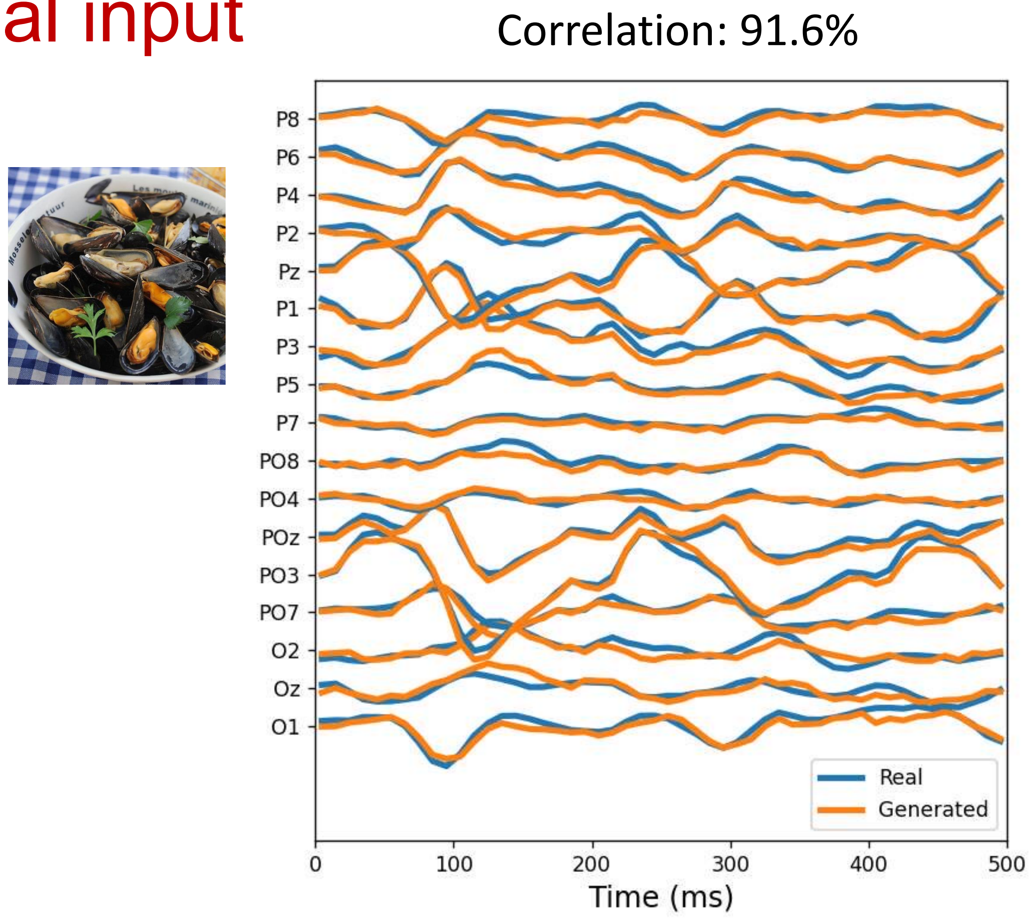


(Lu, 2023, Psyrad)

Link between EEG and Deep Learning
- EEG encoding models

To generate EEG signals from the visual input





(Lu & Golomb, ongoing)

Q&A

Any question about the final project?