06_Source_Reconstruction

Mittwoch, 27. Juni 2018 10:13

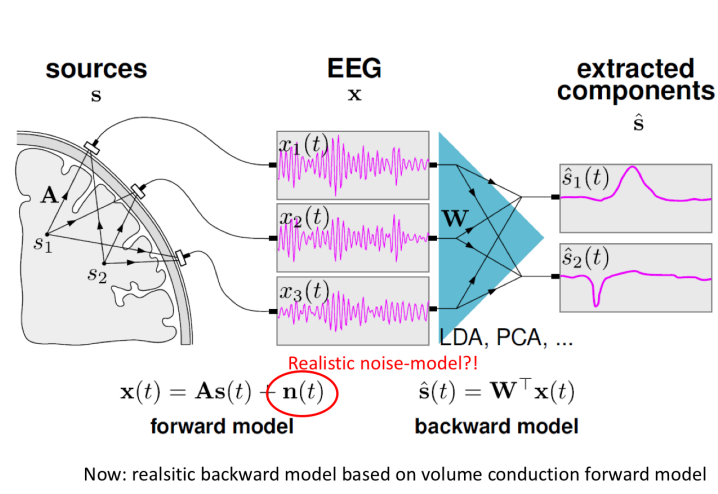
06_Source_Reconstr...

last lecture
Part 3 tasks: project

Brain Computer Interfacing

From Neurons To Data
Session 6: Source Reconstruction & Connectivity

Forward vs. Backward model



Realistic noise-model?!

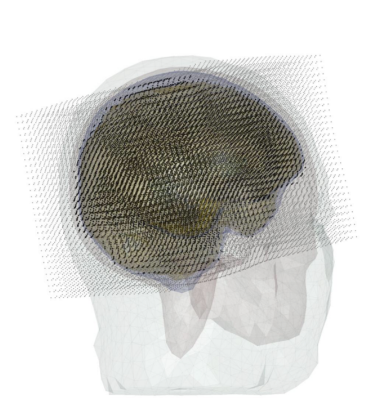
$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t)$ forward model

$\hat{\mathbf{s}}(t) = \mathbf{W}^\top \mathbf{x}(t)$ backward model

Now: realsitic backward model based on volume conduction forward model

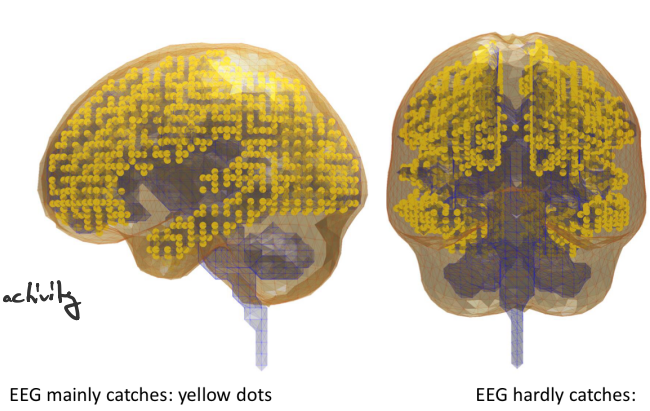
SOURCE RECONSTRUCTION

Where are sources?



Every location in the brain?

Where are neuronal sources?

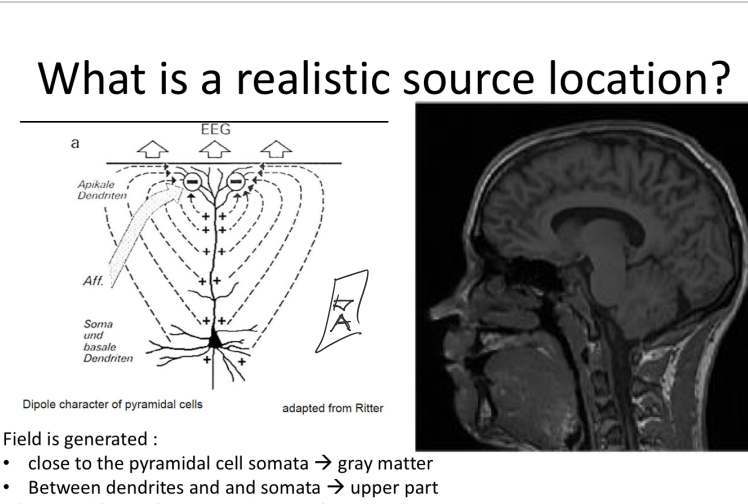


mainly cortex activity

EEG mainly catches: yellow dots
- E/IPSPs from the neocortex
- Synchronized activity from cell assemblies (resolution mm to cm)

EEG hardly catches:
- Subcortical structures
- Cerebellum
- Medulla

What is a realistic source location?



Dipole character of pyramidal cells

adapted from Ritter

Field is generated :
- close to the pyramidal cell somata → gray matter
- Between dendrites and and somata → upper part

Often used (some for practical reasons):
- gray/white matter boundary (easy extraction & stability in BEM due to distance to surface)
- 2/3 in the distance between gray/white boundary and cortex surface (harder to extract but more precise)

EEG also catches

- Eye artefacts:
  - Eyeball as an electric dipole
  - Eye blinks
  - Retinal activity
- Muscle artefacts
  - Jaw muscles
  - Neck muscles
- Biological "background noise" (1/f)
- Measurement & other external noise sources

=> make it harder to estimate

Source separation/reconstruction

- Blind Source Separation (BSS):
  - ICA
  - PCA => don't take head model
  - TDSEP -> statistic
  - ...
- Source reconstruction
  - Minimum-Norm estimate
  - Beamforming -> uses the physical headmodel
  - ...

L> this is harder to do

which choose: depends on what you want to do ...

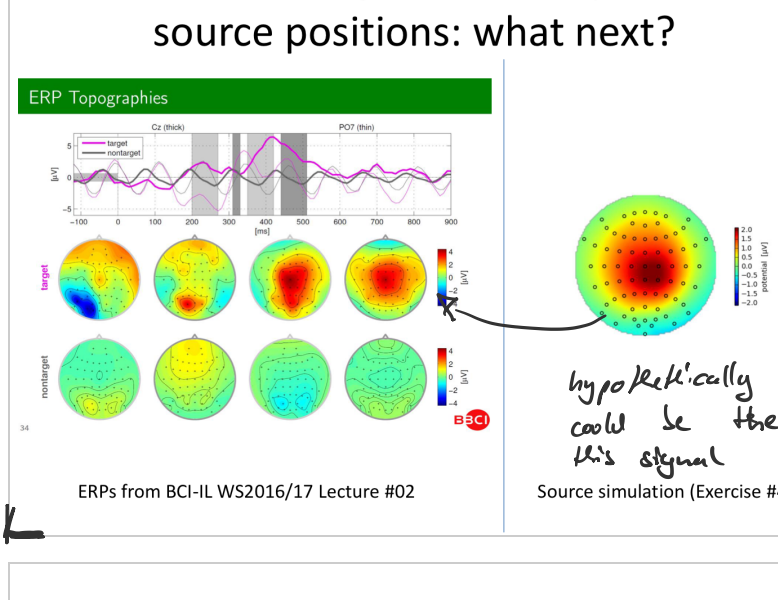
Blind-Source Separation

- PCA, ICA etc. try to reconstruct independent/uncorrelated sources
- Separation based on signal statistics (unsupervised)
- No physical head model involved

How can we involve a head model?

- Ideas?

We know the signal and the potential source positions: what next?



hypothetically this source could be the source for this signal

ERPs from BCI-IL WS2016/17 Lecture #02

Source simulation (Exercise #4)

Ways to reconstruct the sources

(Most known algorithms)

- Estimation: Minimal norm estimate (MNE), Low-Resolution Tomography (LORETA) etc.
- Filtering/Beamforming : Linearly Constrained Minimum Variance (LMCV), Multiple Signal Classification Approach (MUSIC) (?), repeated MUSIC (rapMUSIC)
- Distributed Source imaging: e.g. Bayesian

Smoothness vs. Sparsity

- Event-related cortical activity is expected to be sparse in space (brain)
- Time course of sources is expected to be smooth/stationary

→can be included as constraints

Most straight-forward approach

Example: Minimum-Norm Estimate

(nxQ) leadfield matrix

(1xQ) source dipole vector

- Forward model: $v(t) = Ls^T(t)$
- Measured scalp potential $\hat{v}(t)$
- Find source with most similar scalp pattern:

$$E = \|Ls^T - \hat{v}\|_2$$

Amplitude and orientation (=dipole moment) have to be estimated

Usually L_2norm e.g. L_1 constrain for sparsity

Music-Algorithm

(nxQ) leadfield matrix

(TxQ) source dipole matrix

Spatio-temporal noise matrix

- Singular value decomposition of $M = LS^T + \epsilon$:

$$M = U\Sigma V^T$$

- $U_s$first p left singular vectors spanning the signal subspace
- $P_{s\perp} = I - U_s U_s^T$ projection onto noise subspace
- Cost function $J(r,\theta) = \frac{\|P_{s\perp} l(r,\theta)\|_2^2}{\|l(r,\theta)\|_2^2}$

$l(r,\theta)$ lies in the subspace of the leadfield L

Beamforming: LCMCV

- Linearly Constrained Minimum Variance (LCMCV)
- Spatial filter $y(t) = W^T v(t)$

Output of beamforming

Spatial filter

signal

- Maximizing distance between sources of interest (at location r_q) and others

$$\min_{W^T}\{C_y\} = \min_{W^T}\{W^T C_v W\} \text{ subject to } W^T L(r_q) = I$$

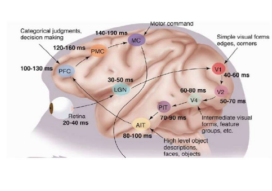
Covariance of filered signal

L(r) ... (Nx3) forward matrix/leadfield for location r

BRAIN CONNECTIVITY

Brain Connectivity

- Functional connectivity: brain activation based



e.g. visual pathways

- Structural connectivity: physically/anatomically

e.g. white mater fiber architecture (from http://www.humanconnectomeproject.org)

THEY ARE NOT INDEPENDENT!

Connectivity in EEG

- EEG measures the effects of neural activations

→Functional connectivity (between brain areas)

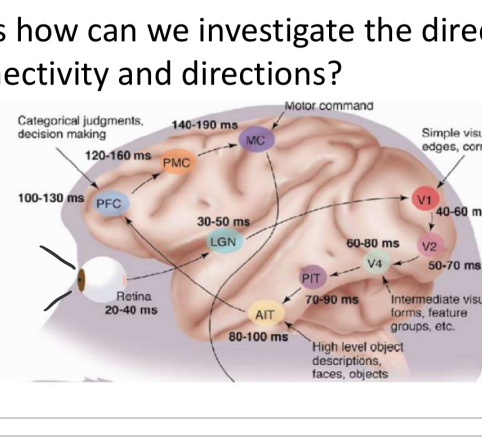
- Say we have succesfully reconstructed the time course of different sources in the cortex: How can we investigate their connectivity?

Scientific Causal Investigations

- General scientific causal approach:
  - Manipulate variable
  - Measure effect
- How manipulate complex network which you can only measure partly and decide what drives what?
  - Manipulate brain structure directly: internal stimulation (tCS, tMS,DBS,...)
  - External stimulation: through senses (visual, auditory, sensory, etc.) -> BCI Research does mainly this part
  - Resting-state investigations for inherent functional connections

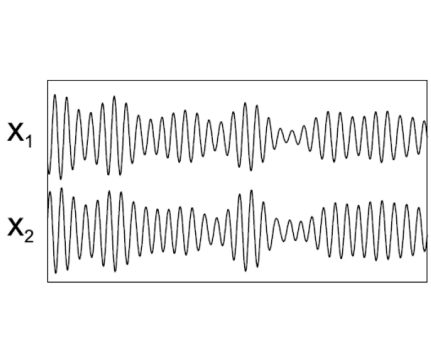
Sensory Stimulation → Connectivity

- Do we recover all sources?
- If yes how can we investigate the direct connectivity and directions?

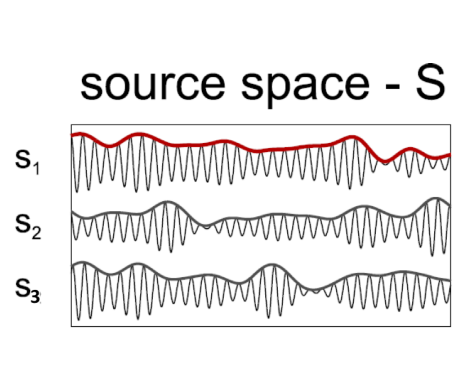

Categorical judgments, decision making
140-190 ms
Motor command
MC
120-160 ms
PMC
Simple visual forms edges, corners
100-130 ms
PFC
V1
40-60 ms
30-50 ms
LGN
60-80 ms
V2
V4
50-70 ms
PIT
Retina 20-40 ms
70-90 ms
Intermediate visual forms, feature groups, etc.
AIT
80-100 ms
High level object descriptions, faces, objects

EEG channels – How do they interact?

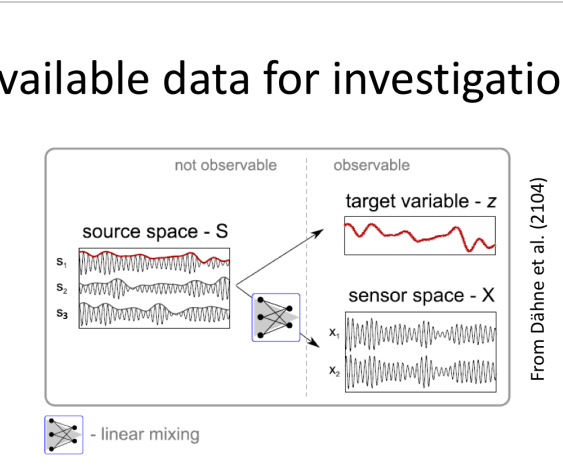
L> mixture of activities



sources - How do they interact?



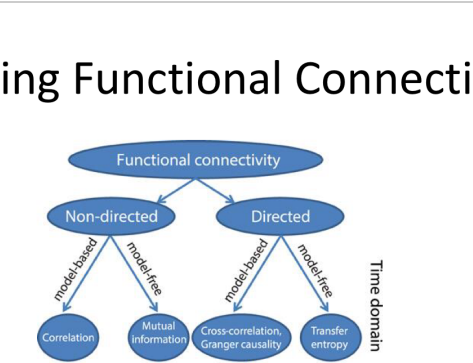
Available data for investigation



From Dähne et al. (2104)

Fig. 3. Illustration of the problem setting. The unobservable source space signals (e.g. oscillatory brain sources) are mixed to constitute the sensor space signals (e.g. EEG/MEG). The time course of the observed target variable z (e.g. stimulus intensity, reaction times) corresponds to the power (or envelope) modulation of one of the sources.

Estimating Functional Connectivity



From Bastos 2016

Estimating Functional Connectivity

- Cross-Correlation: $\rho_{xy}(\tau) = \frac{E[(x_t-\mu_x)(y_{t+\tau}-\mu_y)]}{\sigma_x \sigma_y}$
  - "How is the correlation at time lag τ?"
  - Interpretation: cause preceeds action
- Coherence: $C_{xy}(f) = \frac{|G_{xy}(f)|^2}{G_{xx}(f)G_{yy}(f)}$
  - $G_{xy}(f)$ ... cross-spectral density (fourier transform of cross-correlation)
  - "Which frequencies are behaving similarly?"

Coherence vs. Coherency

- Coherency: $C_{xy}(f) = \frac{G_{xy}(f)^2}{G_{xx}(f)G_{yy}(f)}$
  - $G_{xy}(f)$ ... cross-spectral density (fourier transform of cross-correlation)
  - Can be used to interpret phase differences:
    - Differences in phase can relate to causal interactions
    - Several related measures:
      - Phase-Slope Index
      - Phase-Locking Value
      - ...

Theory from mathematical economy

Granger Causality

has been used widely for a long time, but has to be treated carefully

correlation does not mean causality . . .

- Variables x,y
- Parametric: based on two regressive models:
  1. autoregressive: $y(t) = a_0 + a_1 y(t-1) + a_2 y(t-2) + \cdots + \varepsilon$
  2. autoregressive with additional lagged x $y(t) = a_0 + a_1 y(t-1) + a_2 y(t-2) + \cdots + b_1 x(t-1) + b_2 x(t-2) + \cdots + \varepsilon$
  - If adding time-lagged x improves the reconstruction of $y(t)$, x Granger causes y
- Non-Parametric

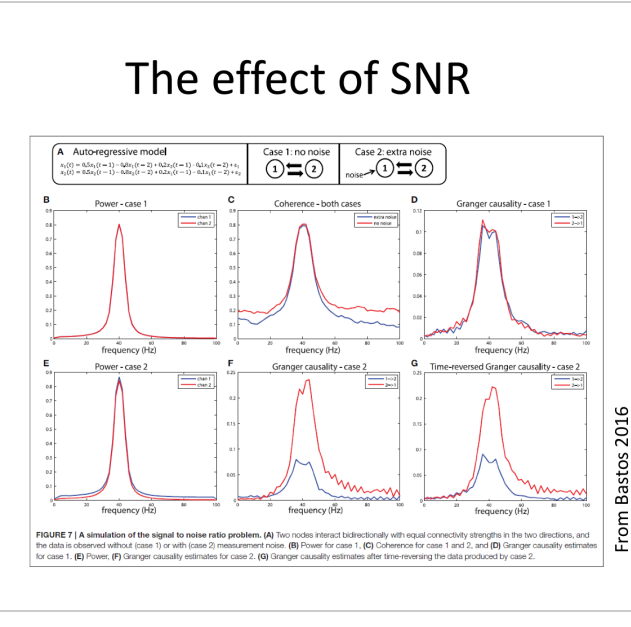
Granger Causality

- There are also Frequency Domain Formulations
- Closely related to Cross-Correlations of signals

Caution

- Correlation vs. Causality
- Limited number of sources could exclude actual source driving the others
- Noise level (SNR) (is a problem)
- Electrode Referencing has an effect (e.g bipolar vs unipolar/common reference)

The effect of SNR



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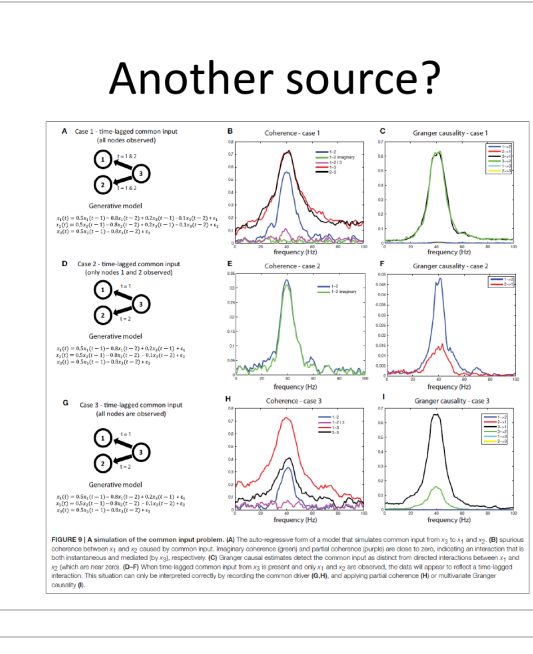
Another source?



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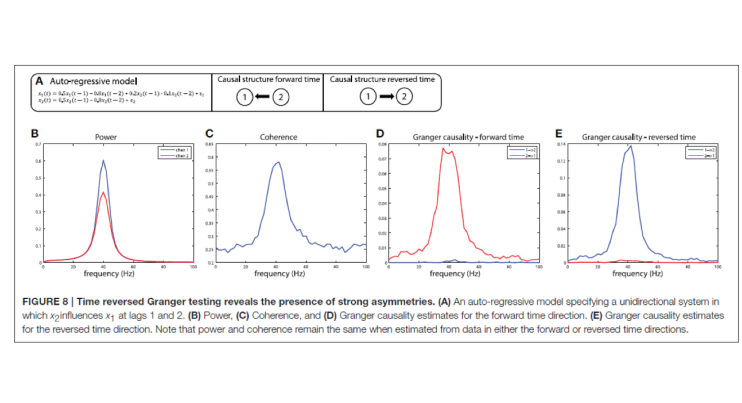
CORTEX

Time-reverse testing



From Bastos 2016

PROJECT: TOPICS AND GROUPS

Overview over course topics

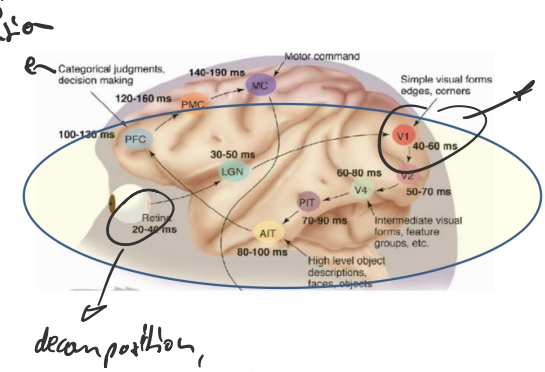
Session 2: Neural Networks 1
Session 1: Neurons
Session 3: Neural Networks 2
Session 6: Source Reconstruction
Session 4: Head modeling
Session 5: Electrodes & Electronics

Project goal: replicate visual stream

object recognition

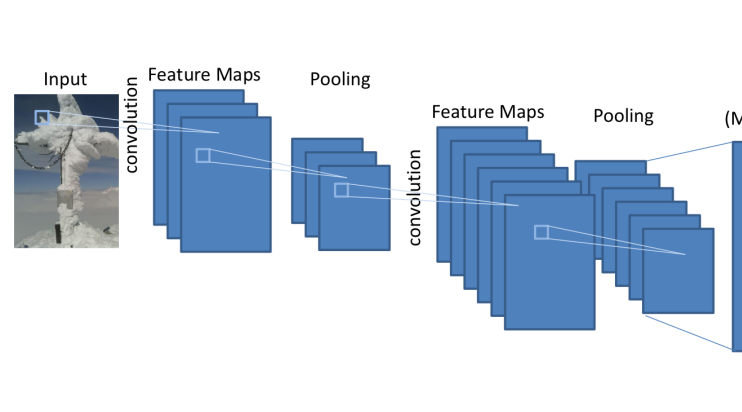
object recognition/ classification

Gabor-like-filter



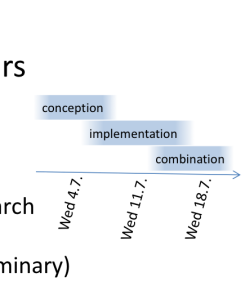
decomposition, RGB-color separation

CNN – typical architecture



Project groups

- 30 students: 5 groups @ 6 members
- 3 dates – rough timeline:
  - 4.7.2018: Conception Phase
    - Create concept from your knowledge
    - Define topics for further (internal) research
    - Start basic implementation
    - Define Interfaces to other groups (perliminary)
  - 11.7.2018: Implementation Phase
    - Re-evaluate and refine concept
    - Define Interfaces to other groups (final)
  - 18.7.2018: Final Phase
    - Bringing it all together!



Project topics

- Visual input creation & Retina
- Neural Network: recurrent MLP (involving CNN layers)
  - Architecture & Implementation
    - V1-V4: CNN
    - Object recognition: MLP
- Source mapping
  - Volume conduction
- EEG simulation
  - Spectra
- Visualization & Analysis:
  - brain activity on cortex
  - EEG

Group 1: Visual Input & Retina

Tasks:
- Collect/Design visual input
- Simulate retinal processing:
  - saliency detection
  - ~~Maybe:~~ color decomposition (RGB->CMYK)
- Construct training labels
  - AIM: Object recognition categories
  - Vector of class labels

Dependencies:
- Group 2/5: define datastructure together

Group 2: Neural Network

Tasks:
- Design multilayer perceptron (MLP)
- Including convolutional/maxpool layers
- Train Network on labels
- You can use the code in Git or frameworks like Pytorch/tensorflow

Dependencies:
- Group 1/5: define datastructure together
- Group 3: define source positions together
- Group 4: define tranfer from MLP to time together
- Group 5: define data structure for network acitivity together

Group 3: Source Mapping

Tasks:
- Define anatomical locations for different layers
- Find corresponding source locations in the head model
- Model the source to sensors volume conduction

Dependencies:
- Group 2: define source positions together
- Group 4: define data structure for EEG simulation

Group 4: EEG simulation

Tasks:
- Translate network activity to source activity
- Introduce timing/time delays
- Simulate source activity as oscillations
- Simulate noise (1/f in sources)
- Generate an EEG signal

Dependencies:
- Group 2: define tranfer from MLP to time together
- Group 3: define data structure for EEG simulation
- Group 5: define data structure for output together

Group 5: Visualisation & Analysis

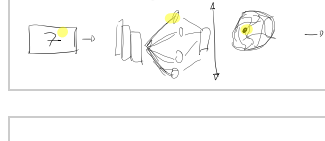
Tasks:
- Visualize in a GUI:
  - input (image) and output (label)
  - network activity
  - electrical activity (cortex & electrodes)

· Brain Pic
· EEG

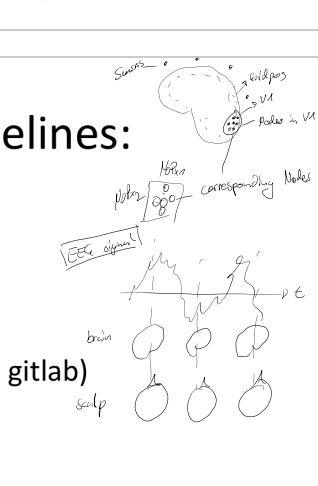
Dependencies
- Group 1/2: define data structure -> Picture
- Group 2: define data structure for network acitivity together -> Network architecture -> time points active layer
- Group 3: get soruce locations -> time points //source
- Group 4: define data structure for output together

vis L S

-> 7 layers / neural network



Grading guidelines:



- 80% Exercises (past)
- 20% Project:
  - 20% concepts (written)
  - 30% coding style (upload to gitlab)
  - 30% achieved functionality
  - 20% (live) engagement

General Guidelines

- Be creative: implement several ideas and investigate the differences
- Be communicative: work together also over group boundaries
- Share and divide work
- Document well: Code & Wiki
- Use GitHub repository

https://gitlab.tubit.tu-berlin.de/roydick1.0/Neurons-To-Data-Project

Milestones

- 9.7. (Mon): Hand in concepts (text)
- 18.7. (Wed): Finish implementation (code)