(Summer School) 딥러닝 기반 Neuroimaging 데이터 분석

텐서플로우(TensorFlow) 기초 및 실습

*본 실습은 TensorFlow v1.9 기준으로 진행됩니다.

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강사: 석흥일

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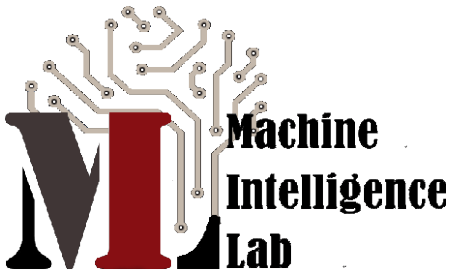
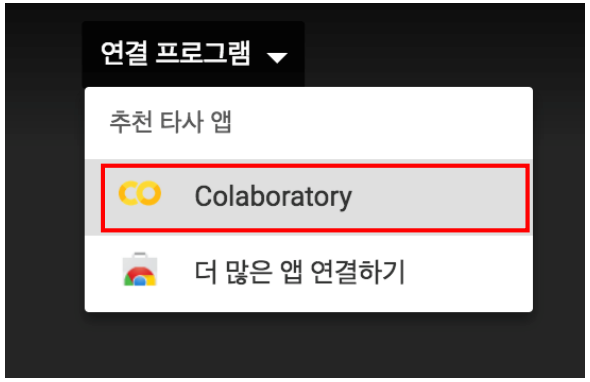


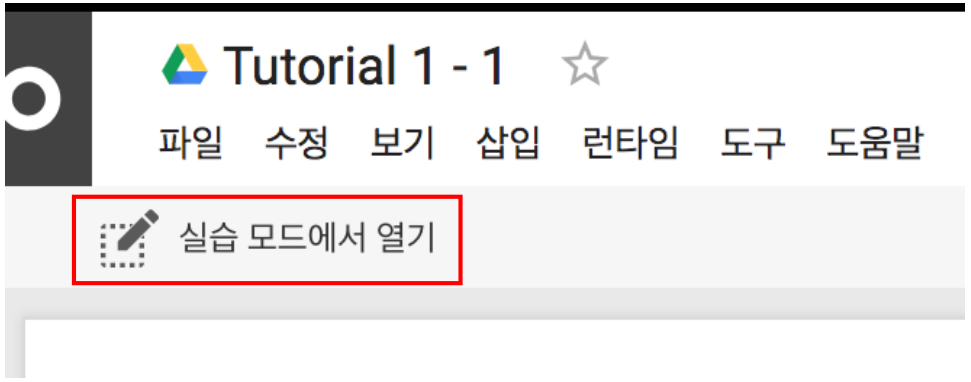
고려대학교 뇌공학과
기계지능연구실

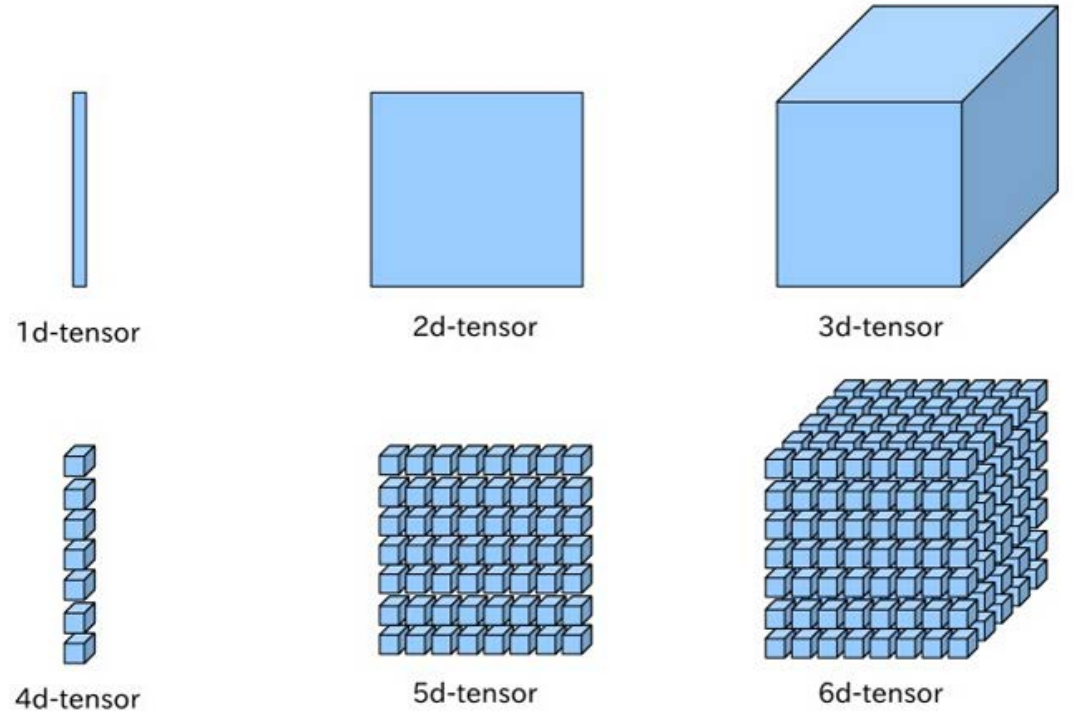
2018년 8월 18일

Google Colaboratory 실습 환경 준비

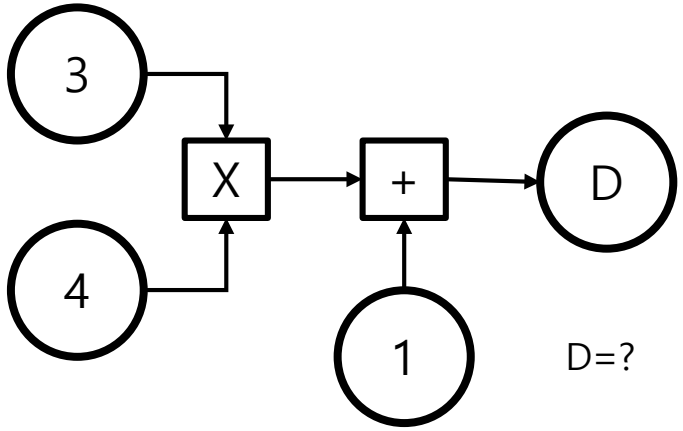
1. drive.google.com 로그인
2. https://goo.gl/RCJQeg 접속
3. Tutorial 1-1 더블 클릭 (연결 프로그램 – Colaboratory 클릭)
4. 왼쪽 상단 “실습 모드에서 열기” 클릭
5. 셀 실행 (각 셀의 재생 버튼 또는 단축키 사용)







계산식을
Tensor: 텐서로 형성된 그래프로
Flow: 흘려 보내
풀어주는 딥러닝 라이브러리



Tensorflow 구성

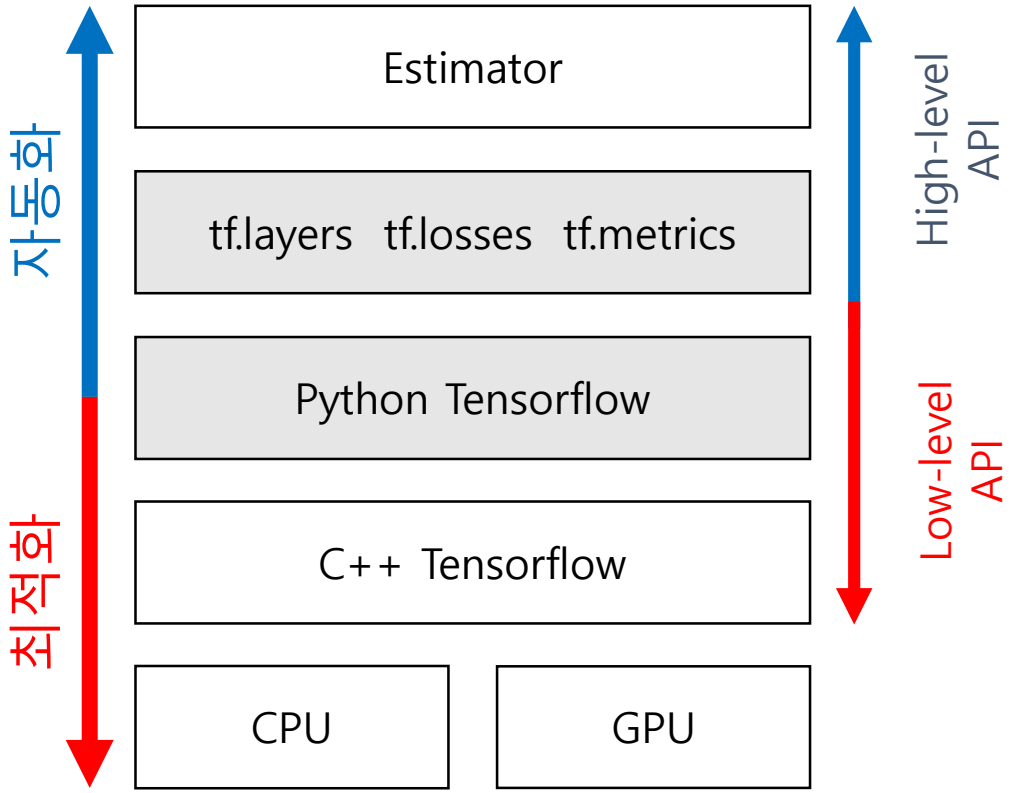
API (Application Programming Interface)

CPU 및 GPU에서 사용될 미리 정의된 **명령어**

Tensorflow API: tf.add(A, B)

↓

CPU / GPU: A+B

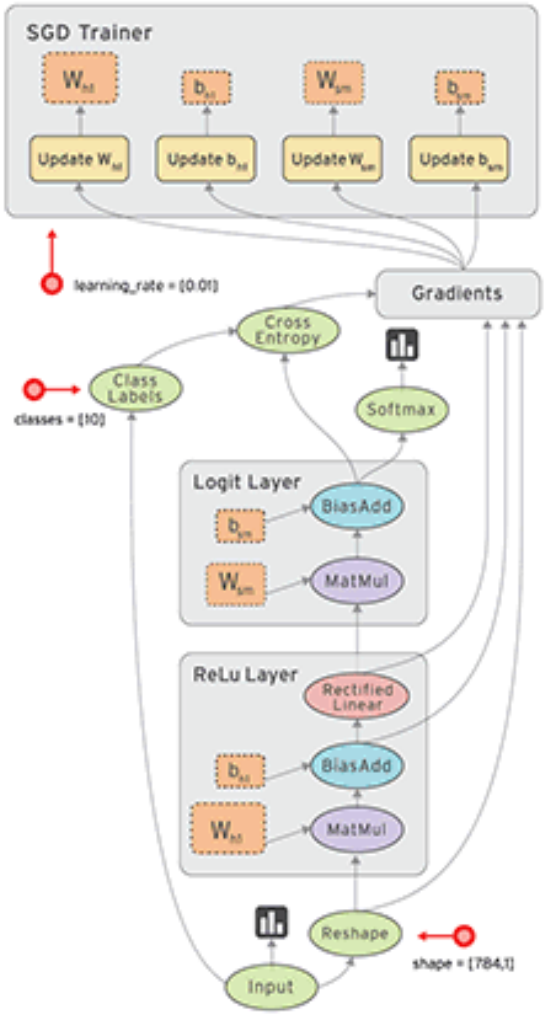


TensorFlow의 프로그래밍 구조

Graph
계산식 구축
예: Logit, ReLu Layer

Session
계산 실행
예: Tensor의 입력 및 출력

Trainer
가중치 갱신
예: SGD (Stochastic Gradient Descent)

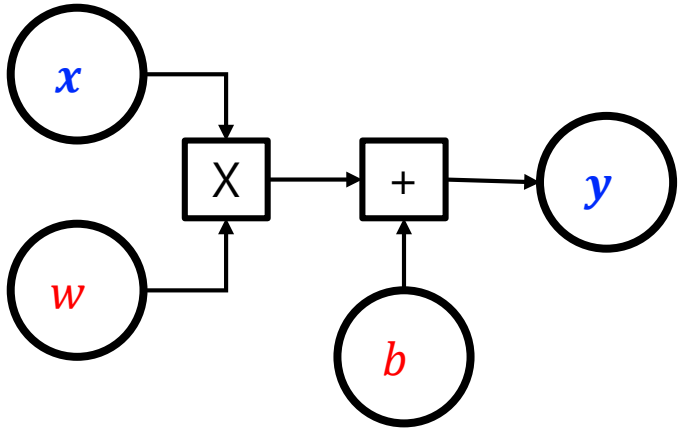


Step 1. Tensor and Variable

변수 Tensor – tf.**Variable**

입력 Tensor – tf.**Placeholder**

$$y = Wx + b$$



Step 2. Loss, Optimizer

Error / Loss 함수

L1: |target-prediction|

L2: $(target - prediction)^2$

학습 알고리즘

SGD, Adam, Adagrad...

tf.train.Optimizer(learning_rate).minimize(loss)

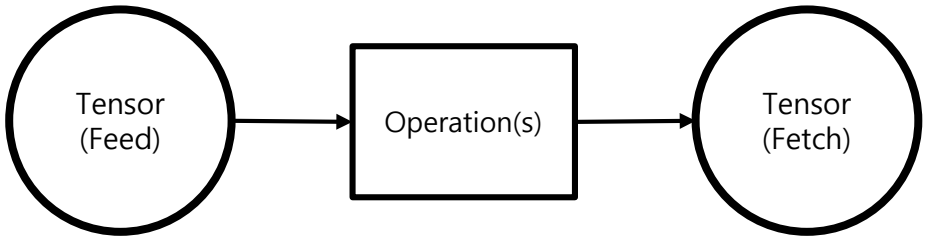
Step 3. Session 정의 및 학습 실행

Session – Tensor에 대한 계산 실행

Feed tensor를 입력으로 받고, **fetch tensor**를 출력

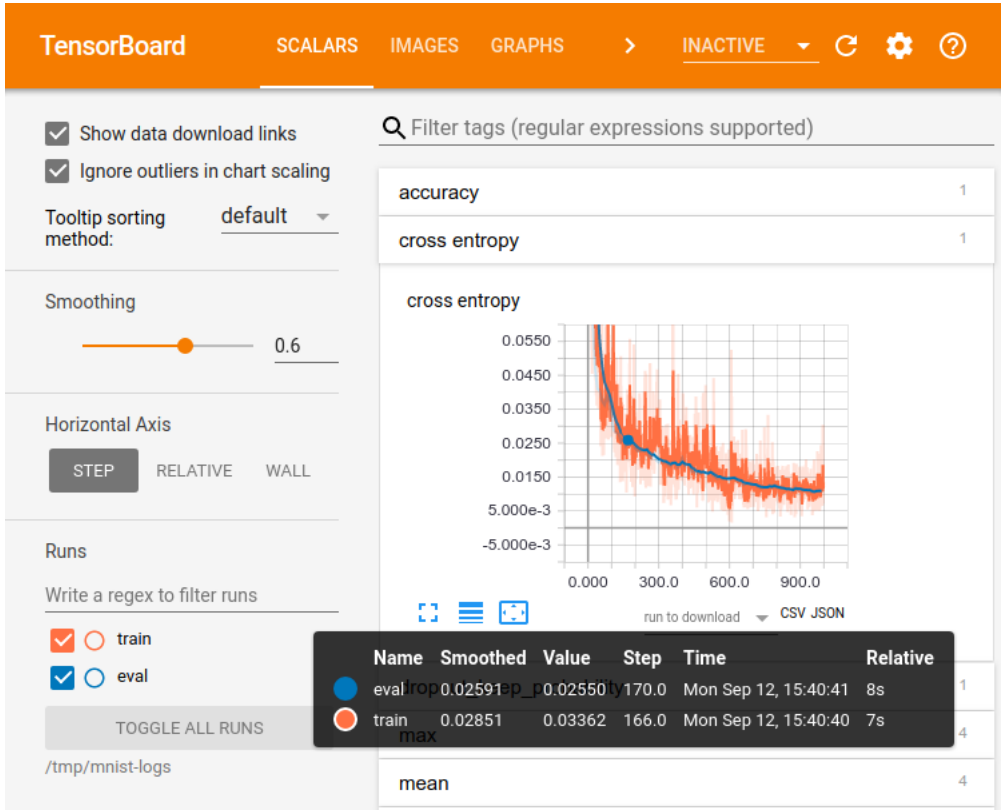
Session.run(fetch, feed)

Optimizer을 fetch 하면 학습 실행!



Step 4. Tensorboard

딥러닝 학습 시 유용한 시각화 툴



요약

Graph

그래프 구축 – $y = ax + b$

Trainer

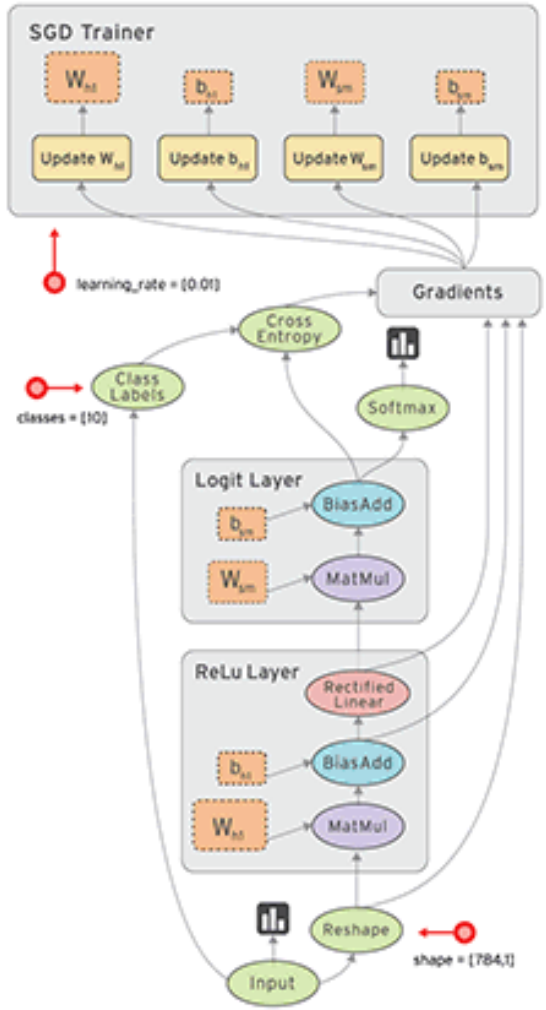
Loss 함수 정의

Optimizer – 미분, 갱신

Session

입력 – Feeding

출력 및 실행 – sess.run(Fetching)



Thank You

Q & A

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(Summer School) 딥러닝 기반 Neuroimaging 데이터 분석

딥 뉴럴 네트워크 기반 Resting-State fMRI 분석 및 실습

*본 실습은 TensorFlow v1.9 기준으로 진행됩니다.

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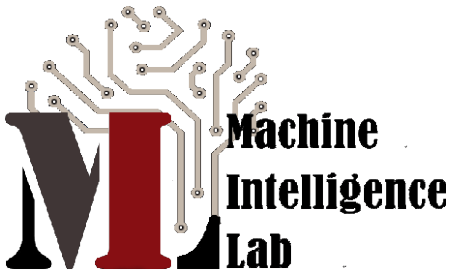


2018년 8월 18일

개요

목표 Matrix factorization 관점에서의 Deep neural network 기반 Resting-state fMRI 분석

Data

ADNI2
Resting-state fMRI
http://adni.loni.usc.edu/

61 subjects (MCI 31/ CN 30)
(Mild Cognitive Impairment/ Cognitive Normal)
130 time scans
116 ROIs

Computation 문제로
voxel을 AAL116 atlas 이용하여
ROIs 단위로 변경

Matrix Factorization

Independent
Component Analysis

(ICA)

vs.

Deep Neural Networks

(DNN)

Deep Neural Network

Auto-encoder

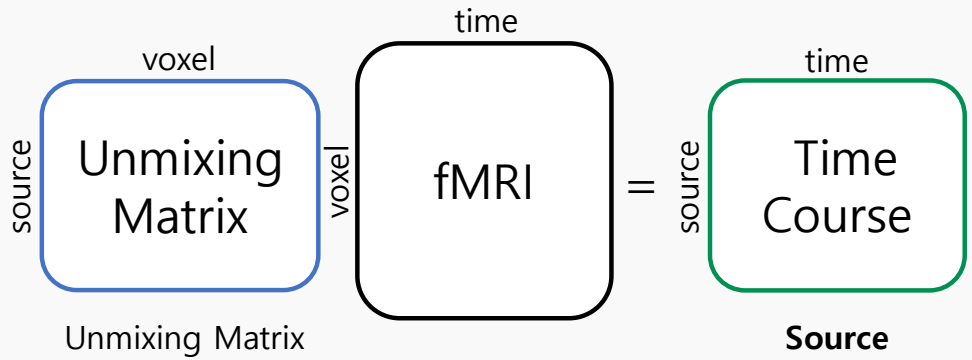
Stacked Auto-encoder

Sparse Auto-encoder

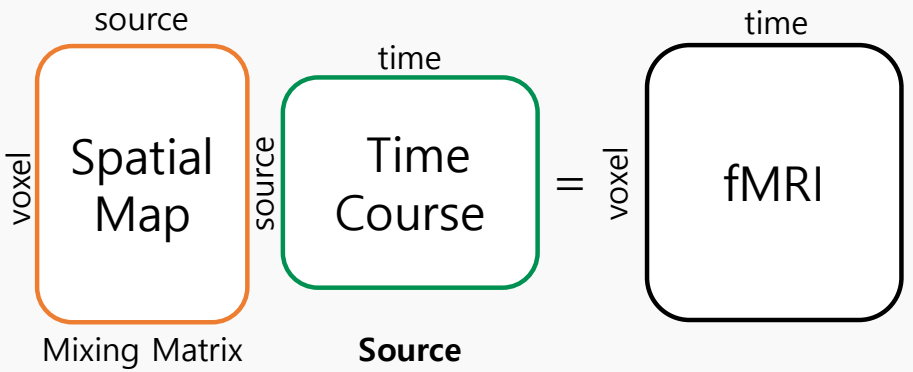
Matrix Factorization

ICA

$$A^T X = S$$

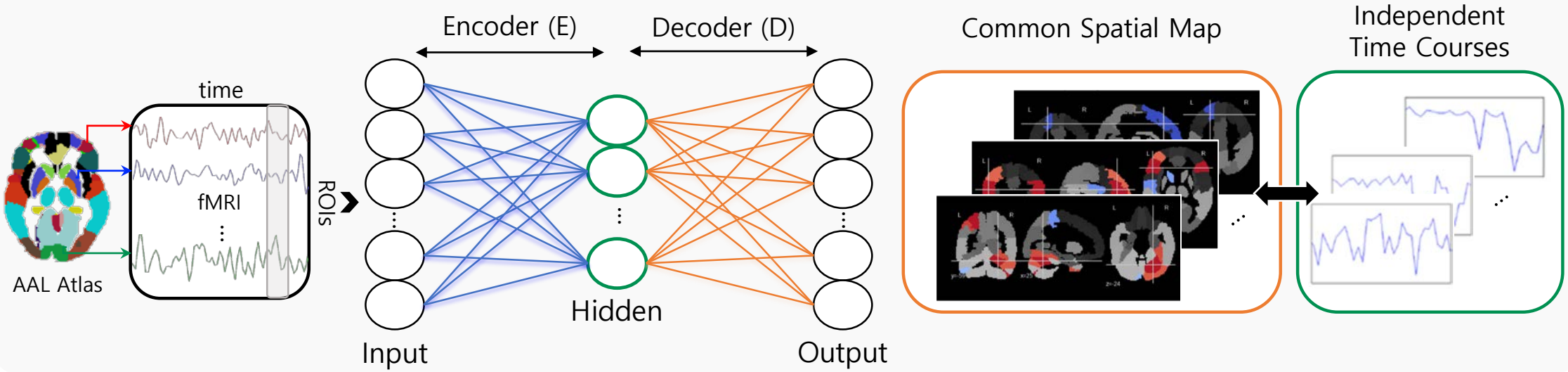


$$AS = \hat{X}$$



DNN

$$W_E X = H \quad W_D H = X$$



Auto-encoder & Stacked Auto-encoder

Encoder: $\mathbf{h} = f_E(\mathbf{W}_E\mathbf{x} + \mathbf{b}_E)$

Decoder: $\hat{\mathbf{x}} = f_D(\mathbf{W}_D\mathbf{h} + \mathbf{b}_D) \approx \mathbf{x}$

Loss: $J(\mathbf{W}, \mathbf{b}) = \frac{1}{N}\sum_{n=1}^{N} \| \mathrm{x} - \hat{\mathrm{x}} \|_2^2$

$\mathbf{x} \in \mathbb{R}^{D_I}$, $\mathbf{h} \in \mathbb{R}^{D_H}$

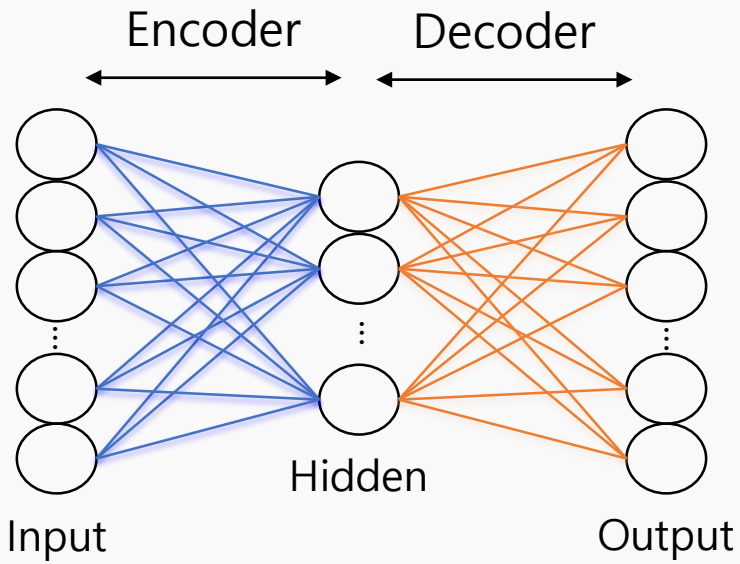
D_I: # of ROIs,
D_H: # of hidden layer units

$\mathbf{W}_E \in \mathbb{R}^{D_I \times D_H}$, $\mathbf{W}_D \in \mathbb{R}^{D_H \times D_I}$

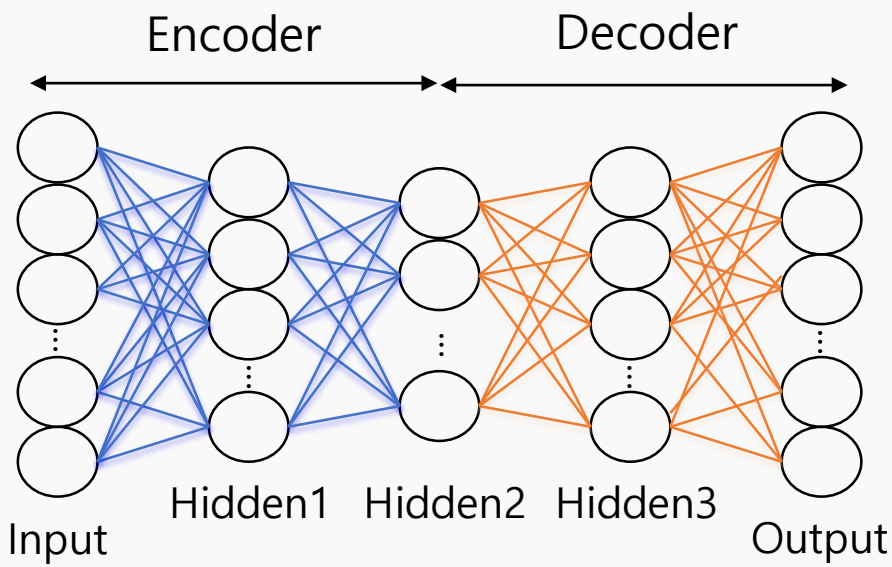
N: # of data samples

f_E: non-linear activation function

f_D: linear activation function



Auto-encoder



Stacked auto-encoder

Sparse Auto-encoder

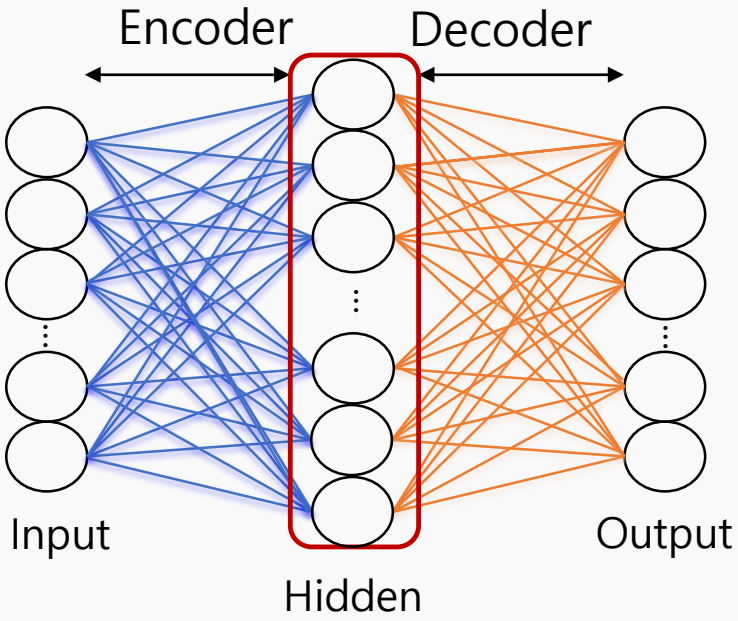
Constraint: $\widehat{\rho_j} = \rho$

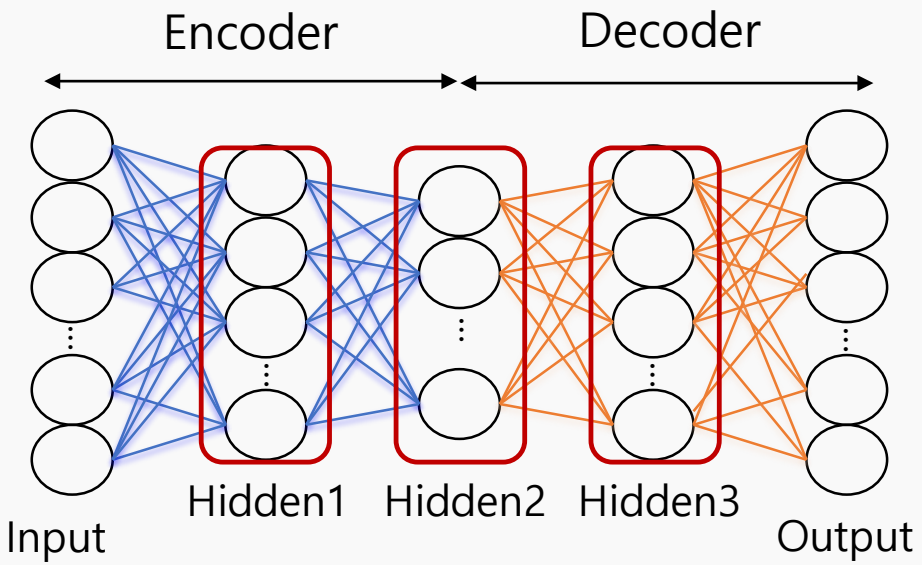
Loss: $J(\mathbf{W}, \mathbf{b}) + \beta \sum_{j=1}^{D_H} KL(\rho || \widehat{\rho_j})$

Mean Squared Error (MSE) + Sparsity

ρ: sparsity parameter
β: sparsity parameter

N : # of data samples
D_H: # of hidden layer units
$\widehat{\rho_j} = \frac{1}{N} \sum_{n=1}^{N} \mathbf{h_j}$





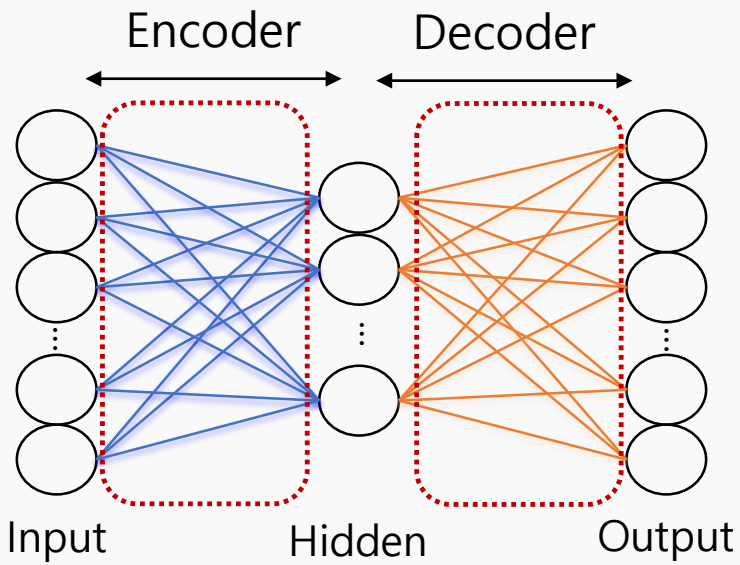
L2 Regularization

Loss: $J(\mathbf{W}, \mathbf{b}) + \lambda \| \mathbf{W} \|_2^2$

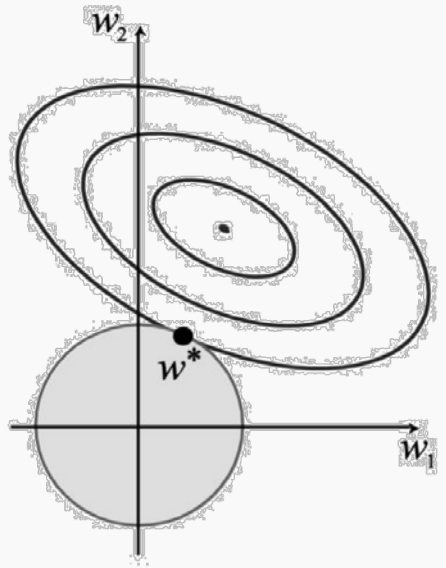
Mean Squared Error (MSE) + L2 regularization

λ: L2 regularization parameter

W: Encoder or decoder weight



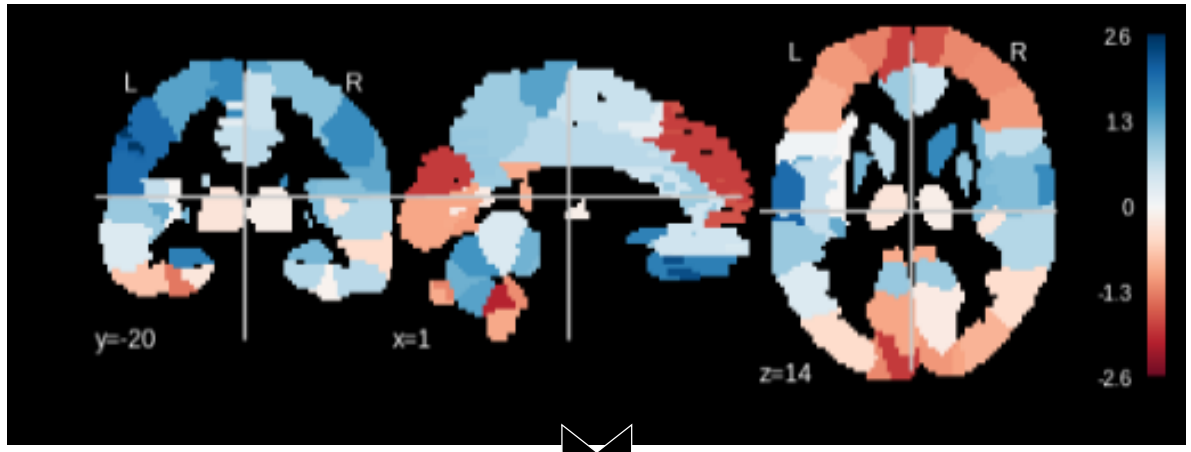
Auto-encoder



L2 regularization

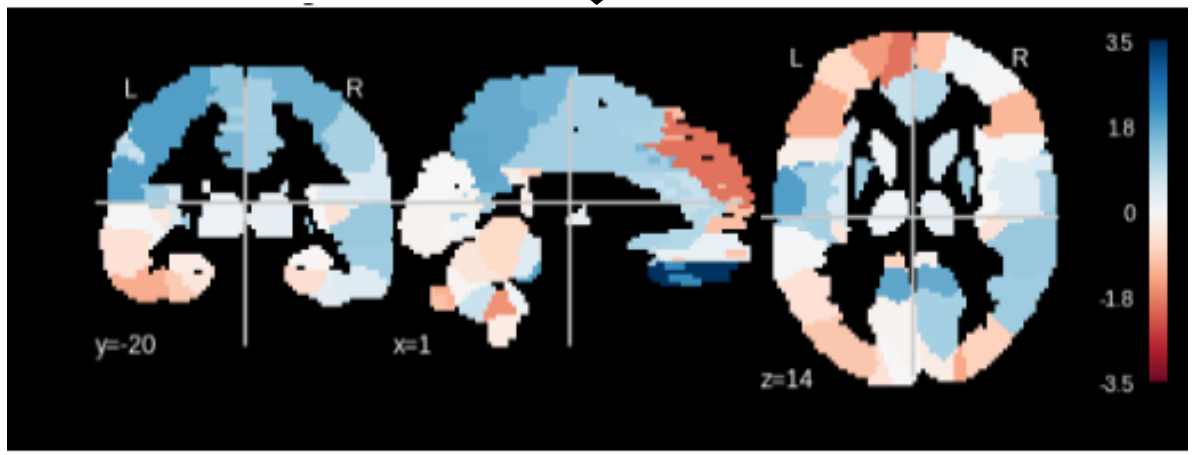
Visualization : Auto-encoder Input & Output

Input fMRI (subject1)



Auto-Encoder

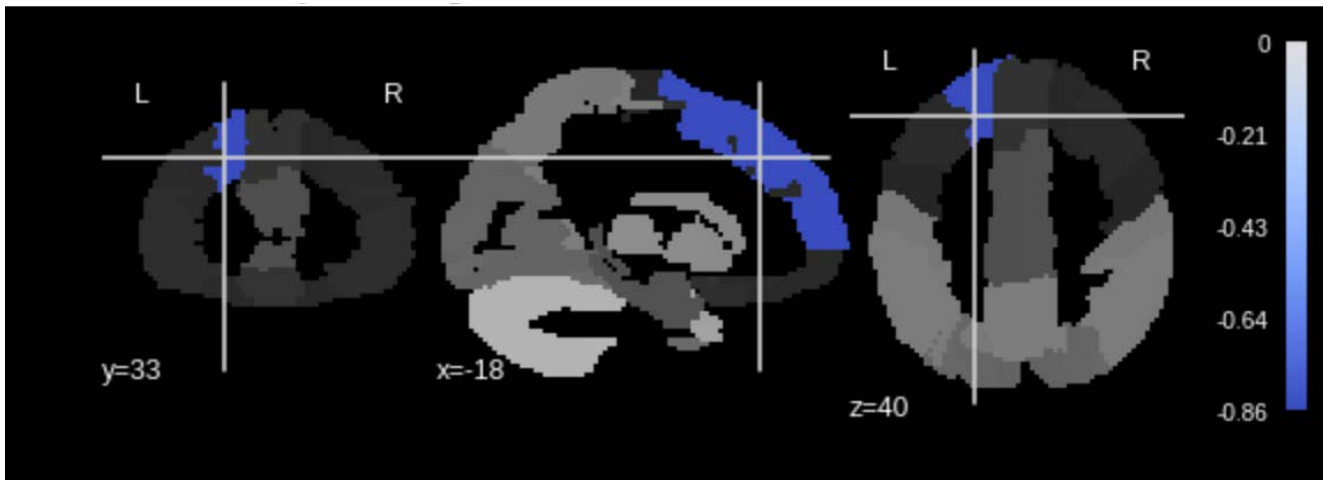
Output fMRI (subject1)



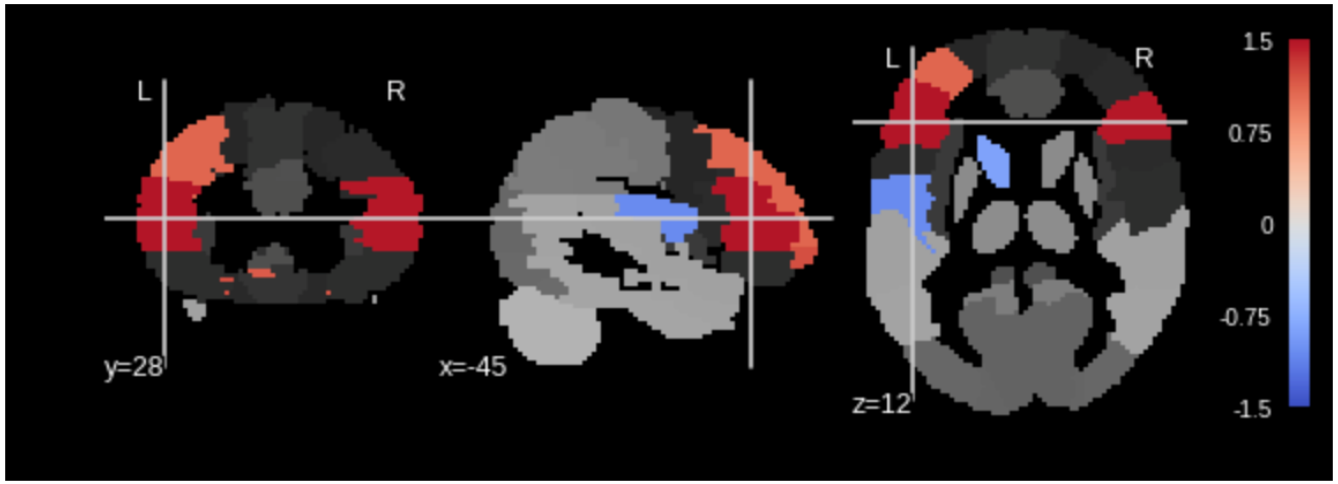
Visualization : Auto-encoder Decoder Weight

- Thresholded image

Weight Component 16



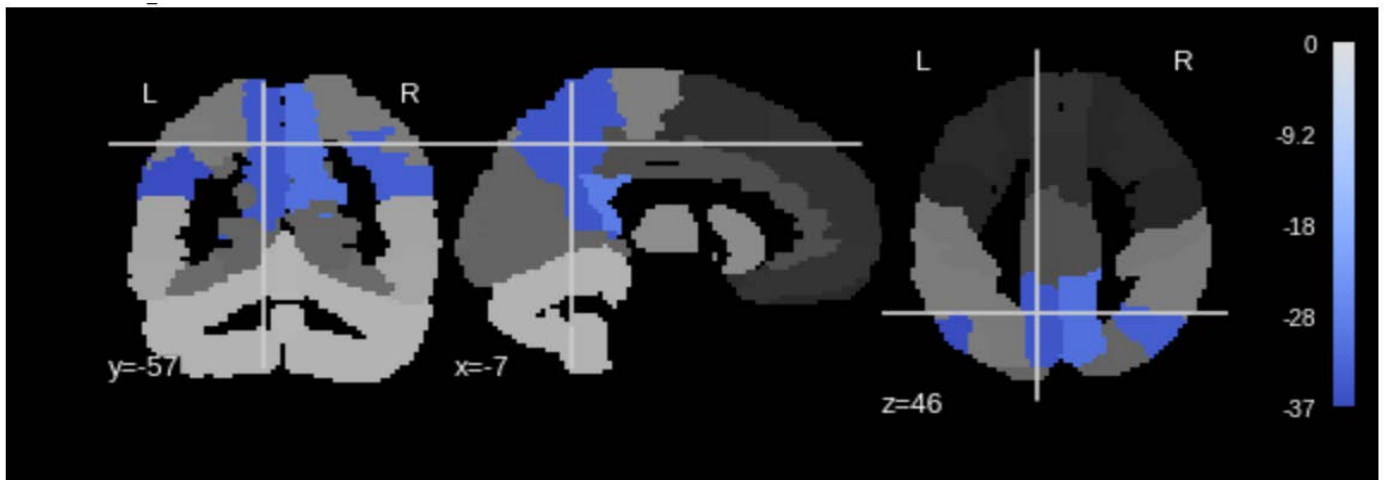
Weight Component 20



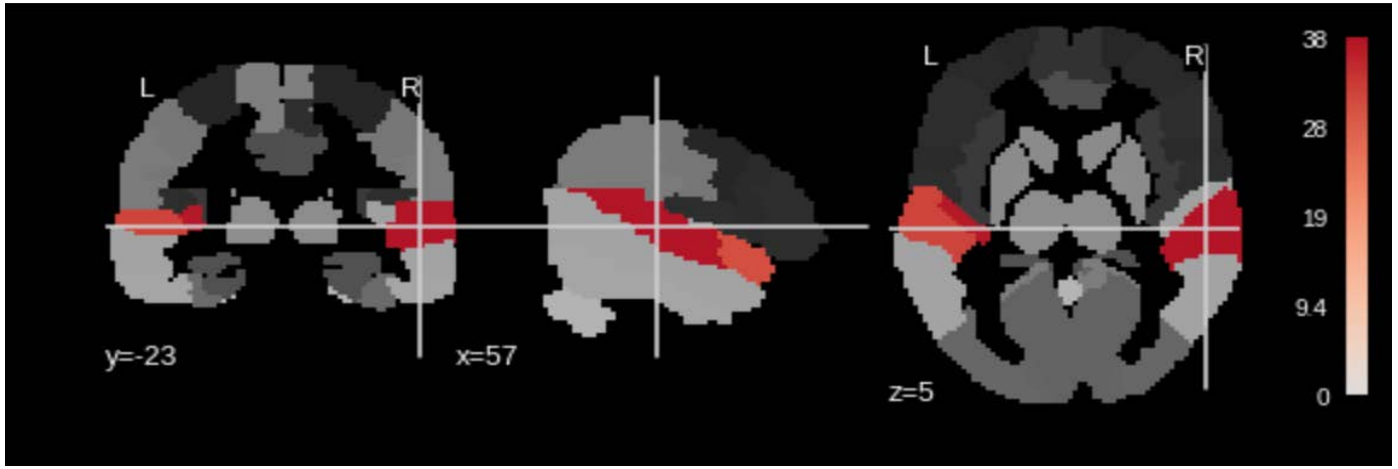
Visualization : ICA Spatial Map

- Thresholded image

ICA Component 20

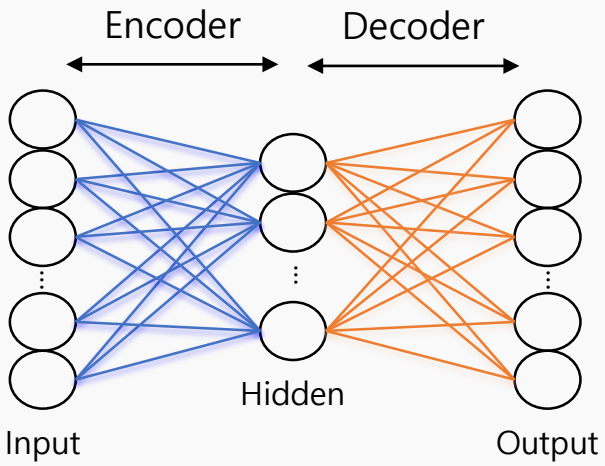


ICA Component 24

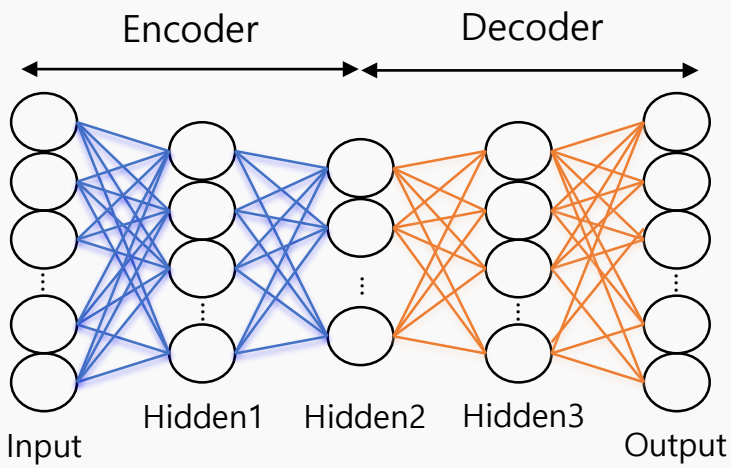


요약

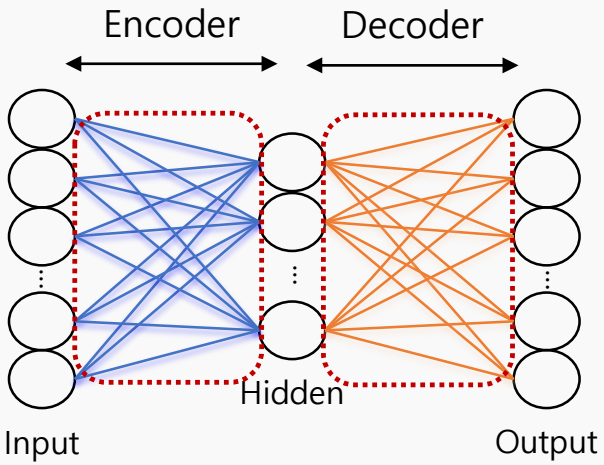
Auto-encoder



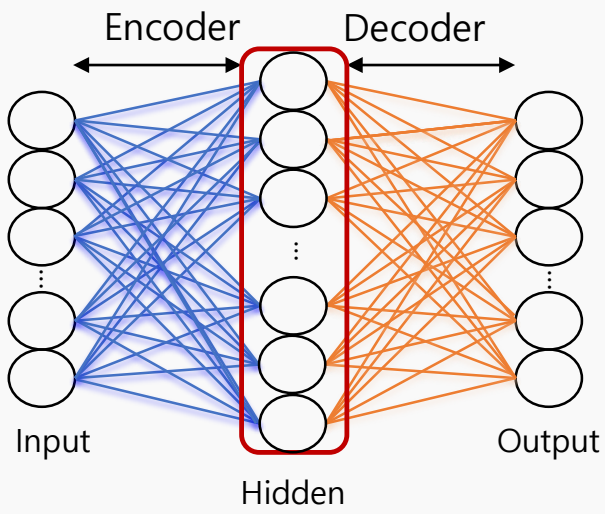
Stacked auto-encoder



L2 regularization



Sparse auto-encoder



Thank You

Q & A

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컨볼루션 네트워크 기반 EEG 신호 분석 및 실습

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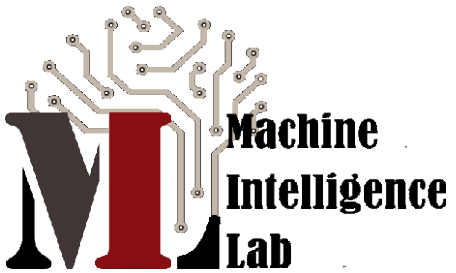

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기계지능연구실

2018년 8월 18일

개요

목표 컨볼루션 네트워크를 이용한 EEG 신호 분석 및 공간축 컨볼루션층 해석

데이터

BCI Competition IV

BCI Competition IV-IIa
Motor Imagery EEG
http://www.bbci.de/competition/iv/

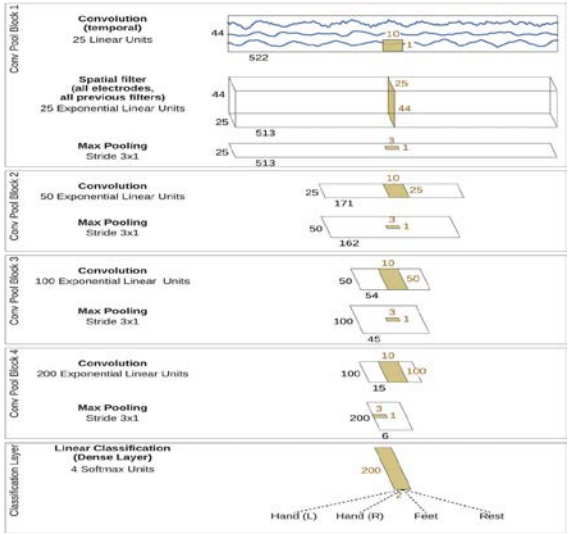
9 subjects
22 channels
4 classes

실습을 위해 subject 1의 왼손,
오른손 motor imagery EEG를 사용

컨볼루션 네트워크

Deep ConvNet

[Schirrmeister *et al., HBM*, 2017**]**

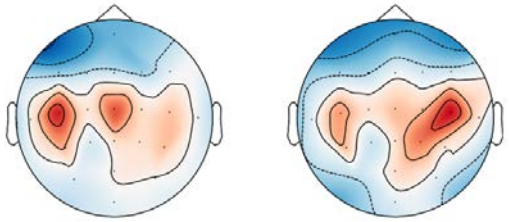


컨볼루션층 해석

Activation Pattern

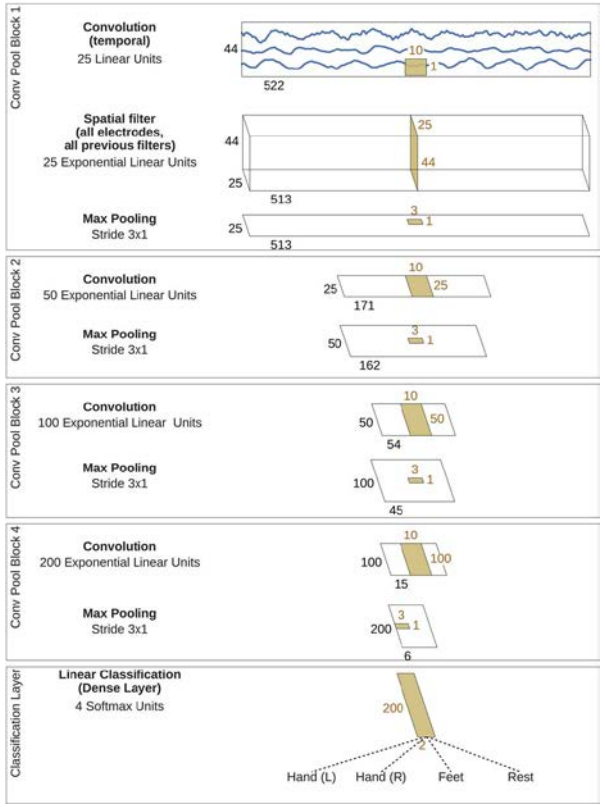
[Haufe et al., NeuroImage, 2014]

$$\mathbf{A} = \Sigma_{\mathbf{x}} \mathbf{W} \Sigma_{\hat{\mathbf{s}}}^{-1}$$

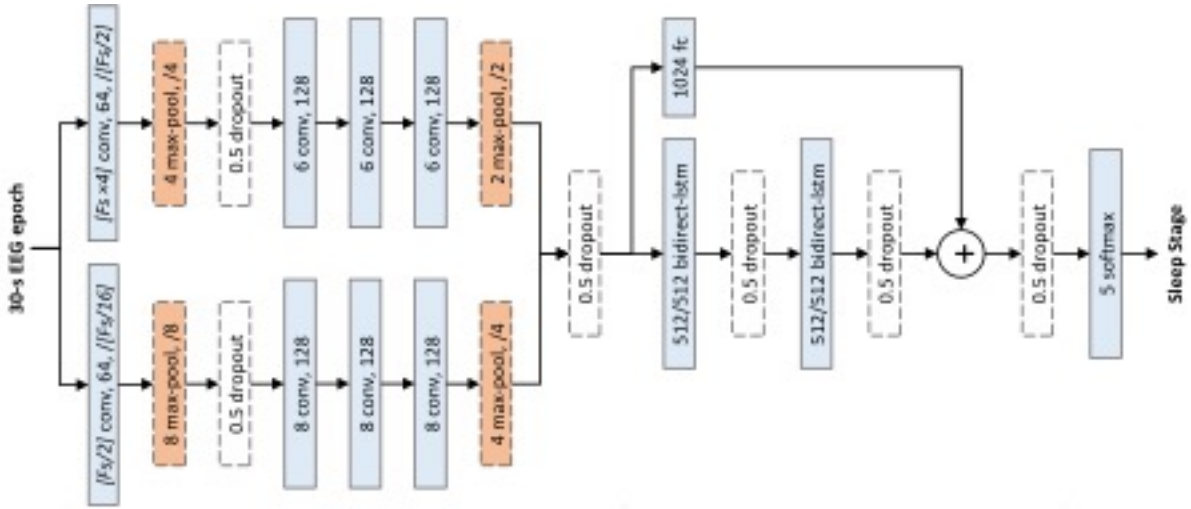


오른손, 왼손 motor imagery EEG에
활성화된 컨볼루션층의 지형도

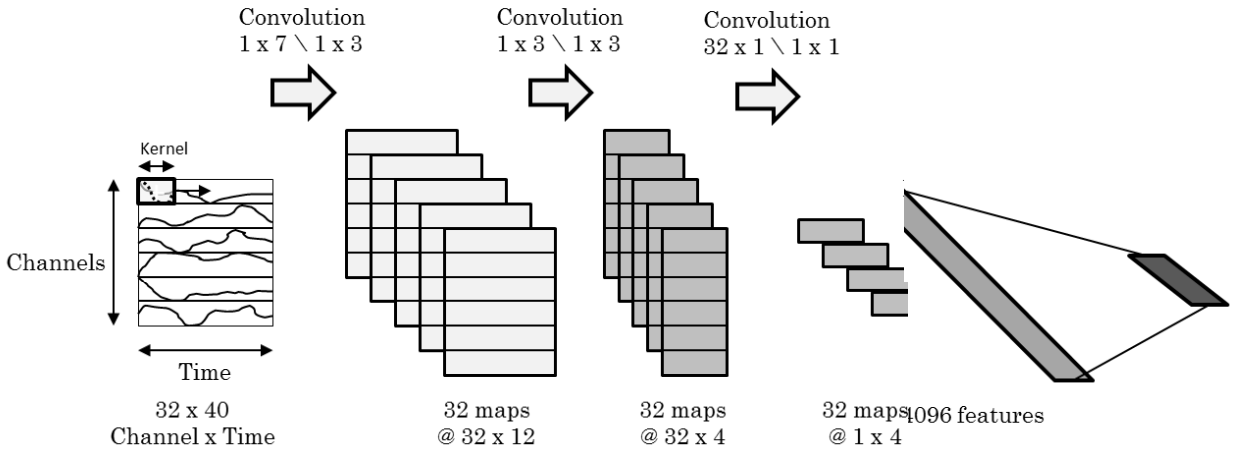
컨볼루션 네트워크를 이용한 EEG 분석 예시



[Schirrmeister *et al.*, *HBM*, 2017]



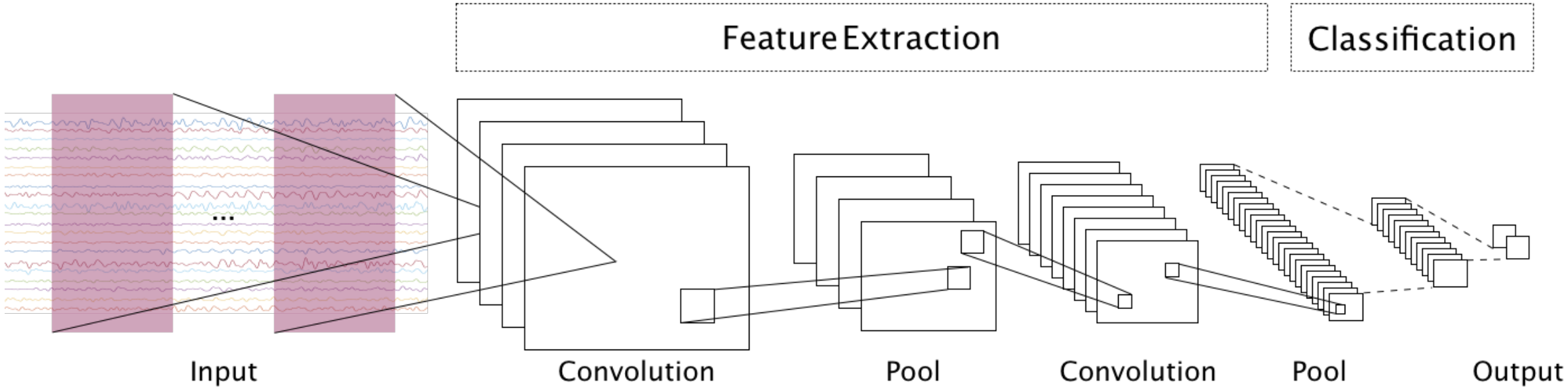
[Supratak *et al.*, *IEEE-TNSRE*, 2017]



[Sakhavi *et al.*, *IEEE-TNNLS*, 2018]

Fully Connected Layer vs. Convolutional Neural Network

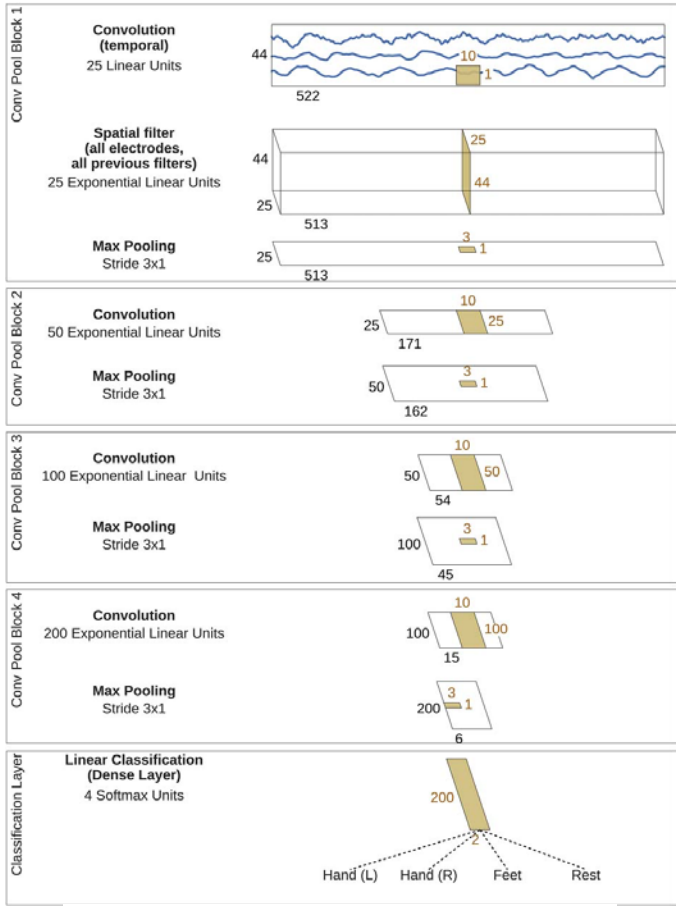
- Fully Connected Layer는 1차원의 입력 데이터를 다루는 데에 최적화되어 있음
  - 컨볼루션 네트워크(CNN)는 다차원의 정보를 다루기에 용이

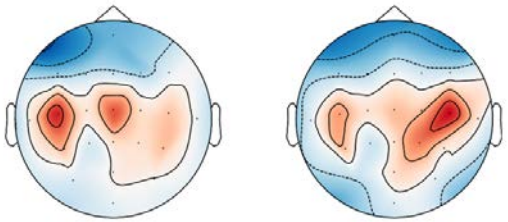


- 컨볼루션 네트워크는 EEG 신호의 반복되는 패턴들을 parameter sharing을 통해 효율적으로 찾아낼 수 있음

- EEG 신호에 함축되어 있는 공간축, 시간축 정보를 추출하기가 용이함

개요





시간축, 공간축 컨볼루션을 이용하여 정보 추출 후 pooling을 이용하여 downsampling
(해석을 위한 공간축 컨볼루션 필터 추출)

시간축 정보 추출 후 downsampling

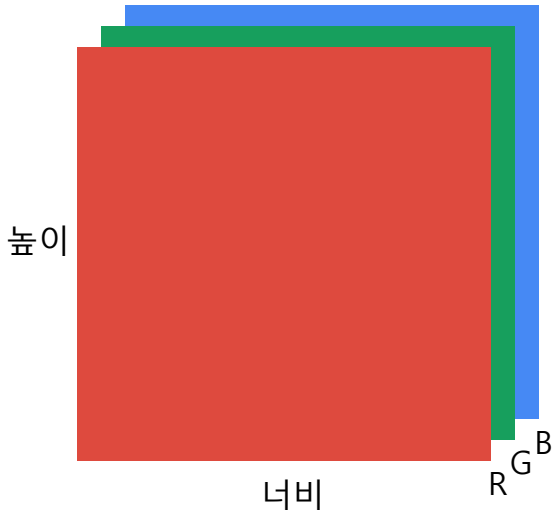
시간축 정보 추출 후 downsampling

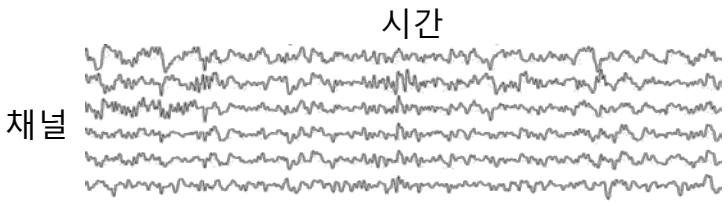
시간축 정보 추출 후 downsampling
(여러 층에 걸친 컨볼루션으로 데이터의 hierarchical한 정보 추출)

Dense layer로 분류

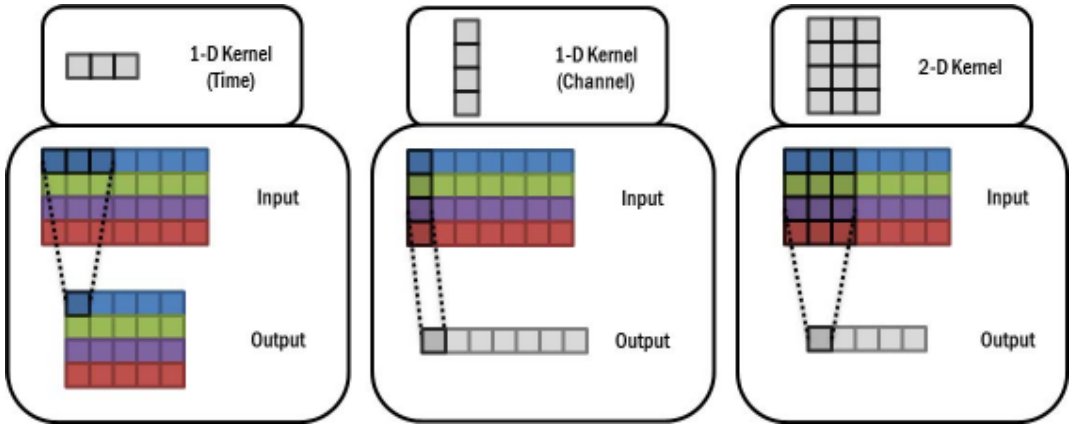
Activation pattern을 이용한 해석

컨볼루션 네트워크를 위한 EEG 표현법





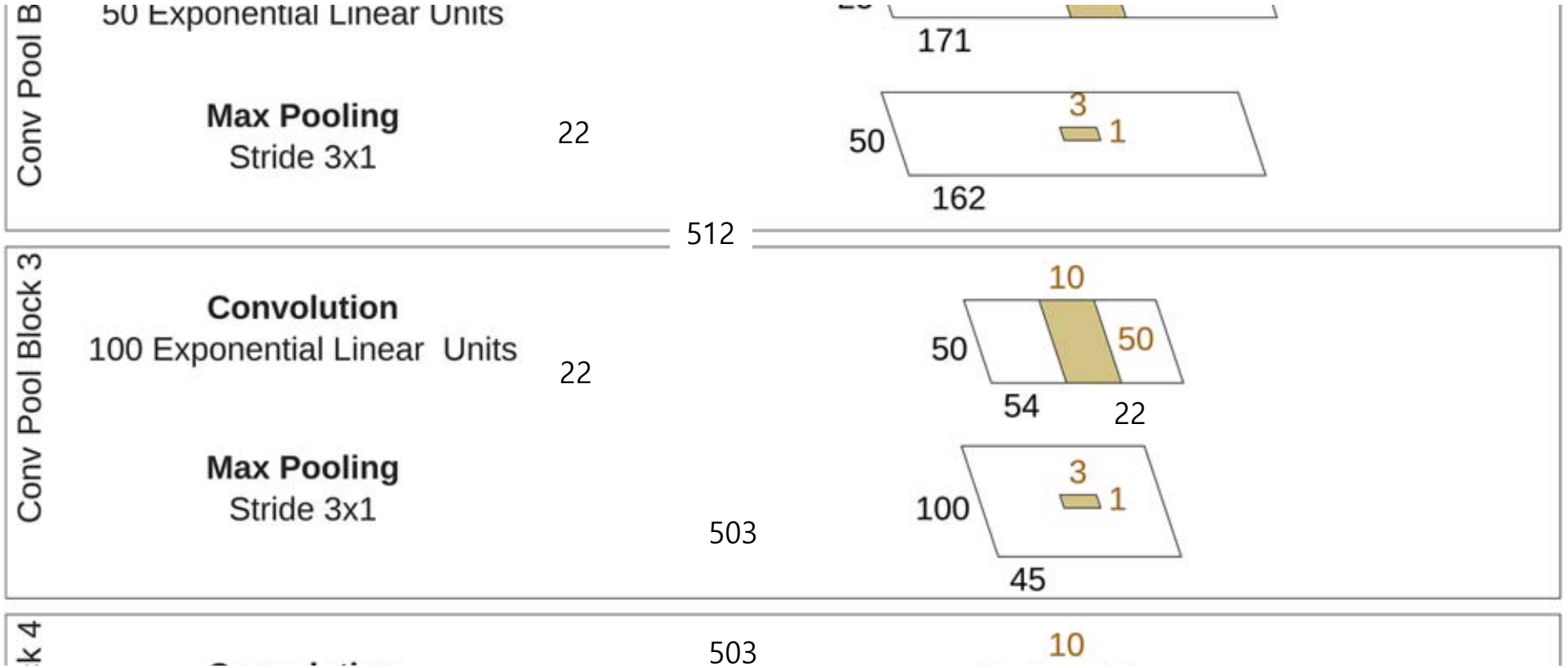
[높이×너비×RGB] → [채널×시간×1(Feature map)]



[Sakhavi *et al.*, *IEEE-TNNLS*, 2018]

컨볼루션 커널 모양에 따라
시간축(temporal),
공간축(spatial),
2차원 컨볼루션으로 나뉨

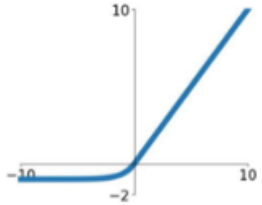
DeepConvNet [Schirrmeister *et al.*, 2017]

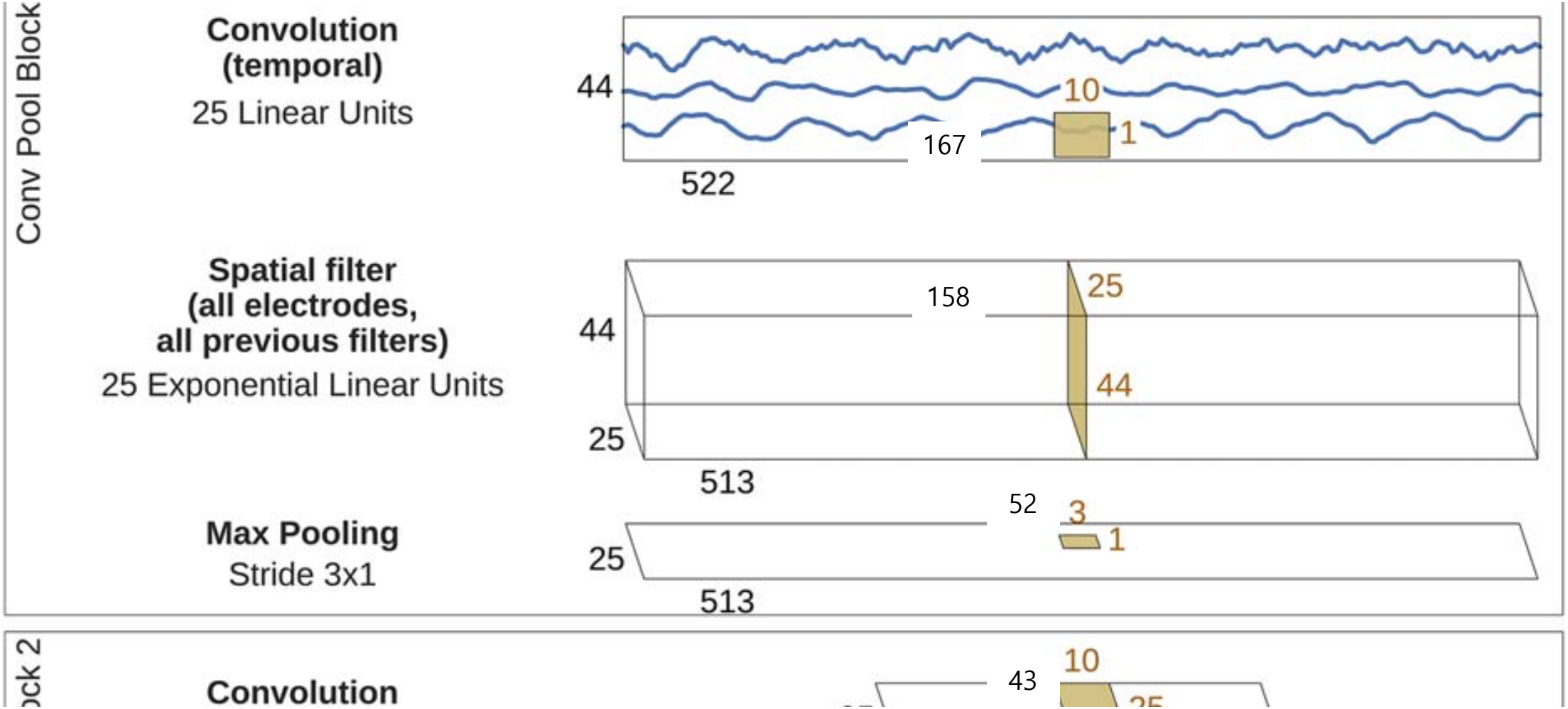


1. 시간축 정보 추출(1×10 커널), Feature Map의 개수 증대(1 → 25)
2. 공간축 정보 추출(22×1 커널), Batch normalization, ELU 활성화
3. Max Pooling을 통한 downsampling, Dropout

ELU

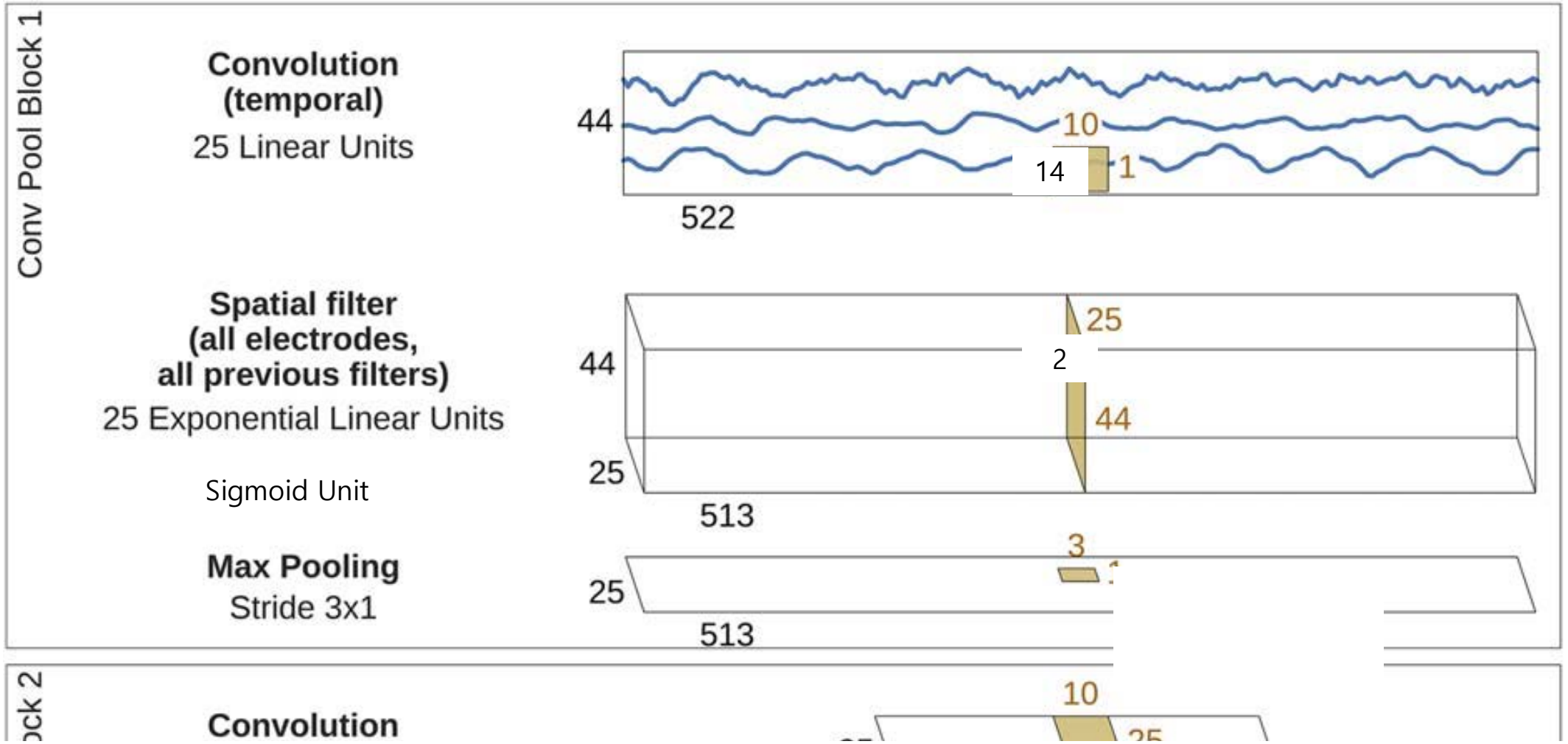
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$





4. 시간축 정보 추출(1×10 커널), Batch normalization, ELU 활성화, Feature Map의 개수 증대(25→50)
5. Max Pooling을 통한 downsampling, Dropout

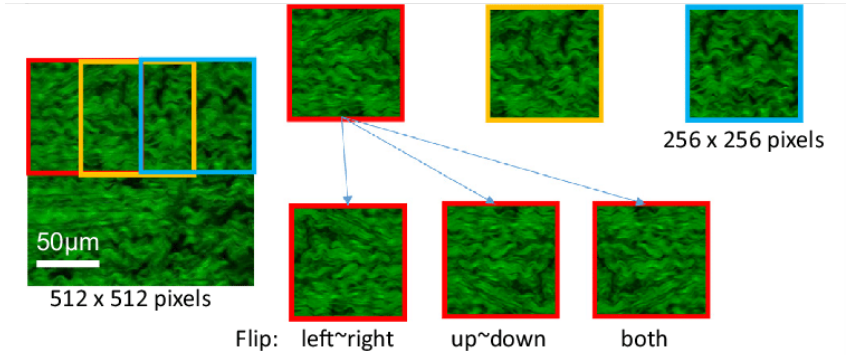
6. 시간축 정보 추출(1×10 커널), Batch normalization, ELU 활성화, Feature Map의 개수 증대(50→100)
7. Max Pooling을 통한 downsampling, Dropout



8. 시간축 정보 추출(1×10커널), Batch normalization, ELU 활성화, Feature Map의 개수 증대(100→200)
9. Max Pooling을 통한 downsampling, Dropout

10. Dense layer(sigmoid 활성화)로 Classifier 구성

분류 실험



슬라이딩 윈도우(sliding window)를 통한 데이터 증대(data augmentation)

$$CE = -\sum_{x} p(x) \log q(x)$$

Sigmoid 함수를 거쳐 나온 예측값과 실제 레이블 값과의 cross-entropy 값을 목적함수로 사용

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta = \theta - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t$$

Adam optimizer를 이용하여 loss의 기울기값을 통해 최적화된 parameter를 찾음

- 학습 시, 매 epoch마다 training 데이터를 무작위로 뒤섞어서, 알고리즘이 데이터의 순서를 외우지 않도록 조정

- 매 epoch마다 loss를 출력하여, 학습이 잘 진행되는지 확인

네트워크 해석

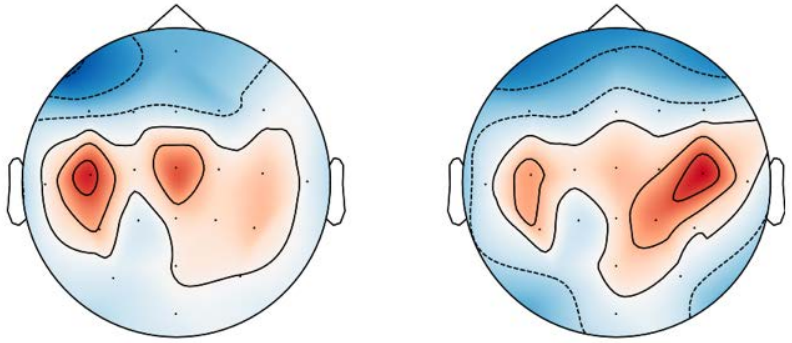
추출한 공간축 컨볼루션 필터는 신경생리학적으로 무의미함, 즉 해석의 의미가 없음

$$\mathbf{A} = \Sigma_{\mathbf{x}}\mathbf{W}\Sigma_{\hat{\mathbf{s}}}^{-1}.$$

[Haufe *et al.*, *NeuroImage*, 2014]

Haufe *et al.* 은 필터에 입력의 공분산, 추측 레이블의 공분산의 역을 곱해서 activation pattern을 계산하는 방법을 제안함

Blind source의 source들이 활성화 되는 정도를 계산



계산한 activation pattern 값을 이용하여 뇌 지형도(topography)를 그려 오른손, 왼손 동작 상상 뇌신호에 따른 활성화 정도를 관찰할 수 있음

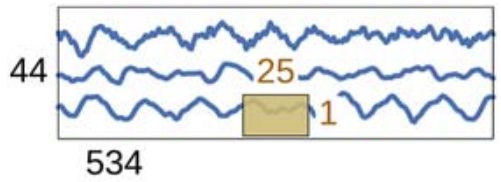
Thank You

Q & A

wjko@korea.ac.kr
https://ku-milab.org

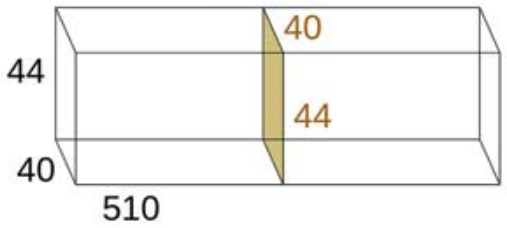
(Backup) ShallowConvNet [Schirrmeister *et al.*]

Convolution (temporal)
40 Units



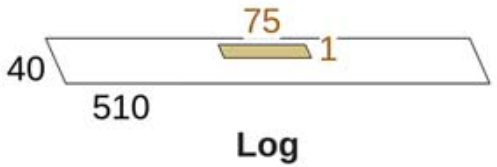

```
w1, b1 = get_params(name="conv1", shape=(1, 25, 1, 40), n_filter=40)
conv1 = conv(input=input, w=w1, b=b1)
```

Spatial filter (all electrodes, all previous filters)
40 Units



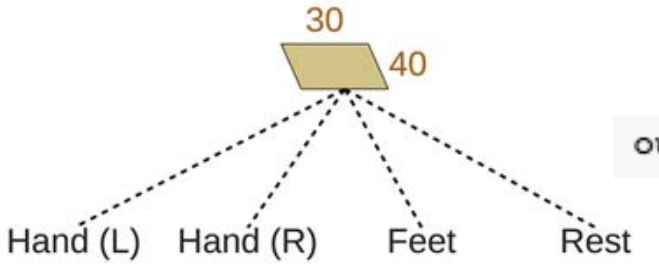

```
w2, b2 = get_params(name="conv1", shape=(22, 1, 40, 40), n_filter=40)
conv2 = conv(input=conv1, w=w2, b=b2)
conv2 = tf.square(conv2)
```

Mean Pooling
Stride 15x1




```
conv2 = tf.nn.avg_pool(value=conv2, ksize=(1, 1, 75, 1),
                       strides=(1, 15), padding= "VALID")
conv2 = tf.log(conv2)
```

Linear Classification (Dense Layer+Softmax)
4 Units




```
output = fclayer(input=conv2, name="output", num_output=4)
```