Lab1 : EEG classification

Lab Objective:

In this lab, you will need to implement simple EEG classification models which are EEGNet, DeepConvNet [1] with BCI competition dataset. Additionally, you need to try different kinds of activation function including ReLU, Leaky ReLU, ELU.

Important Date:

1. Experiment Report Submission Deadline: 11/3 (Wed) 12:00 a.m.
2. Demo date: 11/3 (Wed)

Turn in:

1. Experiment Report (.pdf)
2. Source code (.py)

Notice: zip all files in one file and name it like
「DLP_LAB1_yourID_name.zip」

Requirements:

1. Implement the EEGNet, DeepConvNet with three kinds of activation function including ReLU, Leaky ReLU, ELU
2. In the experiment results, you have to show the highest accuracy (not loss) of two architectures with three kinds of activation functions.
3. To visualize the accuracy trend, you need to plot each epoch accuracy (not loss) during training phase and testing phase.

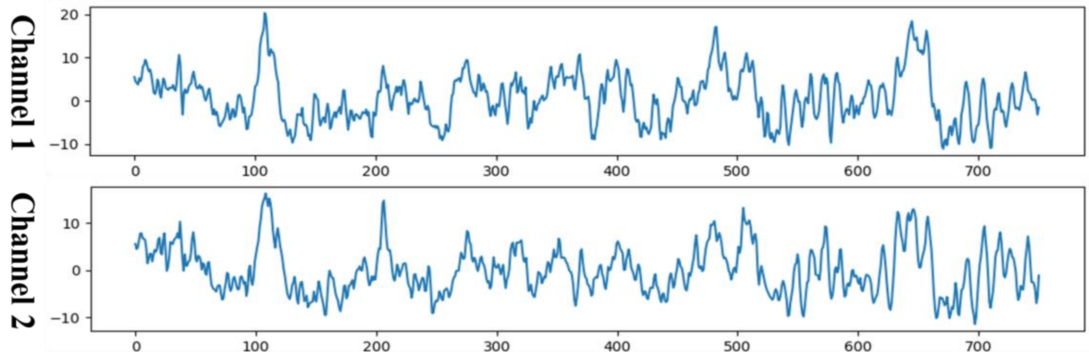
Dataset:

BCI Competition III - IIIb Cued motor imagery with online feedback (non-stationary classifier) with 2 classes (left hand, right hand) from 3 subjects
[2 classes, 2 bipolar EEG channels]
Reference: http://www.bbci.de/competition/iii/desc_IIIb.pdf

Implementation Details:

- ## Prepare Data

The training data and testing data have been preprocessed and named [S4b_train.npz, X11b_train.npz] and [S4b_test.npz, X11b_test.npz] respectively. Please download the preprocessed data and put it in the same folder. To read the preprocessed data, refer to the "dataloader.py".

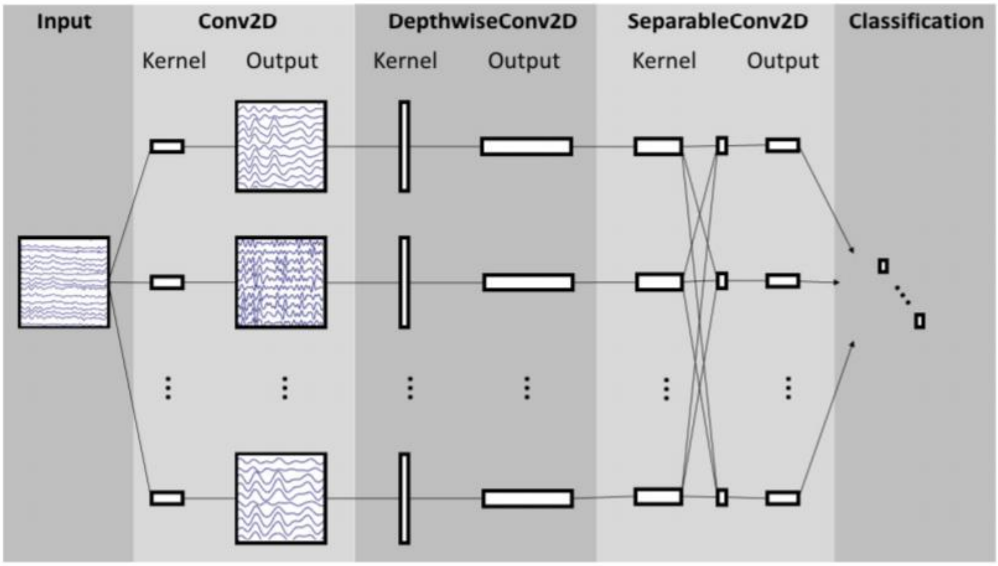


- ## Model Architecture

You need to implement simple EEG classification models which are EEGNet and DeepConvNet.

EEGNet:

Overall visualization of the EEGNet architecture



Reference: Depthwise Separable Convolution
https://towardsdatascience.com/a-basic-introduction-to-separable-convolutionsb99ec3102728

EEGNet implementation details:

```
EEGNet(
  (firstconv): Sequential(
    (0): Conv2d(1, 16, kernel_size=(1, 51), stride=(1, 1), padding=(0, 25), bias=False)
    (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (depthwiseConv): Sequential(
    (0): Conv2d(16, 32, kernel_size=(2, 1), stride=(1, 1), groups=16, bias=False)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ELU(alpha=1.0)
    (3): AvgPool2d(kernel_size=(1, 4), stride=(1, 4), padding=0)
    (4): Dropout(p=0.25)
  )
  (separableConv): Sequential(
    (0): Conv2d(32, 32, kernel_size=(1, 15), stride=(1, 1), padding=(0, 7), bias=False)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ELU(alpha=1.0)
    (3): AvgPool2d(kernel_size=(1, 8), stride=(1, 8), padding=0)
    (4): Dropout(p=0.25)
  )
  (classify): Sequential(
    (0): Linear(in_features=736, out_features=2, bias=True)
  )
)
```

DeepConvNet:

You need to implement the DeepConvNet architecture by using the following table, where C =2, T = 750 and N = 2. **The max norm term is ignorable.**

Layer	# filters	size	# params	Activation	Options
Input		(C, T)			
Reshape		(1, C, T)			
Conv2D	25	(1, 5)	150	Linear	mode = valid, max norm = 2
Conv2D	25	(C, 1)	25 * 25 * C + 25	Linear	mode = valid, max norm = 2
BatchNorm			2 * 25		epsilon = 1e-05, momentum = 0.1
Activation				ELU	
MaxPool2D		(1, 2)			
Dropout					p = 0.5
Conv2D	50	(1, 5)	25 * 50 * 5 + 50	Linear	mode = valid, max norm = 2
BatchNorm			2 * 50		epsilon = 1e-05, momentum = 0.1
Activation				ELU	
MaxPool2D		(1, 2)			
Dropout					p = 0.5
Conv2D	100	(1, 5)	50 * 100 * 5 + 100	Linear	mode = valid, max norm = 2
BatchNorm			2 * 100		epsilon = 1e-05, momentum = 0.1
Activation				ELU	
MaxPool2D		(1, 2)			
Dropout					p = 0.5
Conv2D	200	(1, 5)	100 * 200 * 5 + 200	Linear	mode = valid, max norm = 2
BatchNorm			2 * 200		epsilon = 1e-05, momentum = 0.1
Activation				ELU	
MaxPool2D		(1, 2)			
Dropout					p = 0.5
Flatten					
Dense	N			softmax	max norm = 0.5

- ## Activation Functions

$$\mathrm{ReLU}(x) = \max(0, x)$$

$$\mathrm{LeakyRELU}(x) = \begin{cases} x, & \text{if } x \geq 0 \\ \text{negative\_slope} \times x, & \text{otherwise} \end{cases}$$

By default, the negative slope = 0.01

$$\mathrm{ELU}(x) = \max(0, x) + \min(0, \alpha * (\exp(x) - 1))$$

The α value for the ELU formulation.Default: 1.0

Reference:

https://medium.com/tinymind/a-practical-guide-to-relu-b83ca804f1f7

https://pytorch.org/docs/stable/nn.html

In the PyTorch framework, it is easy to implement the activation function. Just typing the following code!

```
nn.LeakyReLU(),
nn.ReLU(),
nn.ELU(),
```

- ## Hyper Parameters

Batch size= 64 Learning rate = 1e-2 Epochs = 300

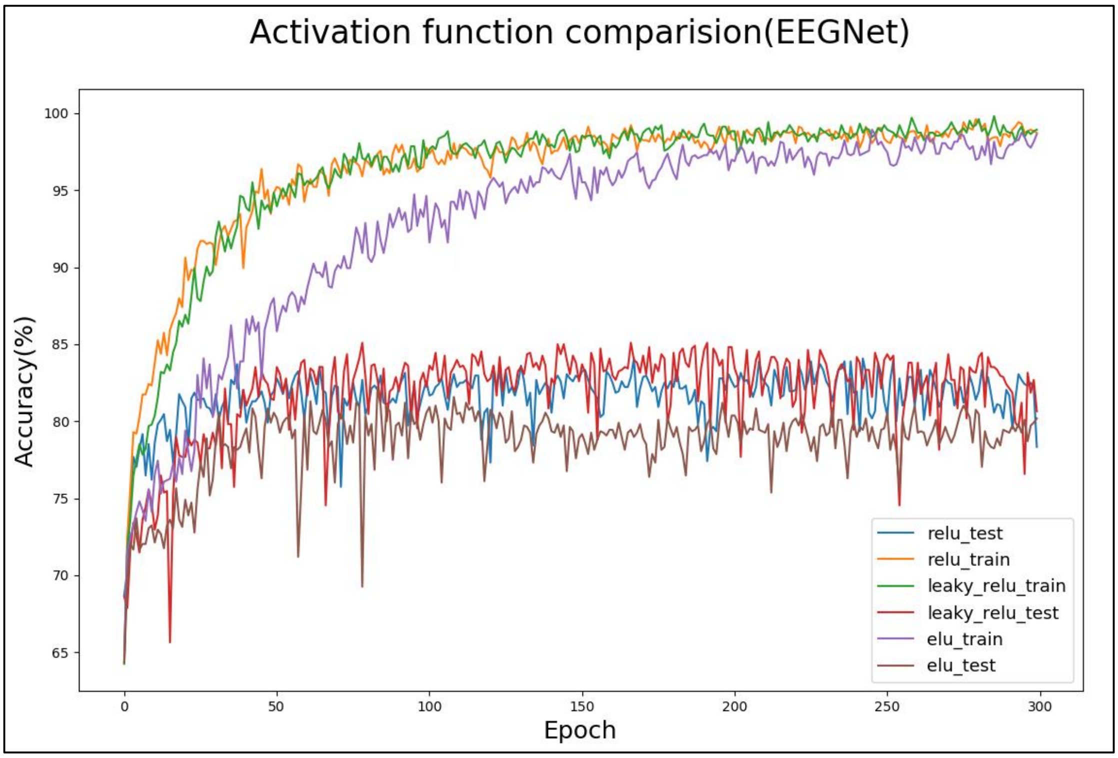
Optimizer: Adam Loss function: torch.nn.CrossEntropyLoss()

You can adjust the hyper-parameters according to your own ideas.

● Result comparison

In this part, you can use the matplotlib library to draw the graph.
Reference : https://matplotlib.org/

The comparison figure should like the example as below. (EEGNet)



- ## Report Spec

1. Introduction (20%)
2. Experiment set up (30%)
    A. The detail of your model
    - EEGNet
    - DeepConvNet

    B. Explain the activation function (ReLU, Leaky ReLU, ELU)
3. Experimental results (30%)
    A. The highest testing accuracy
    - Screenshot with two models
    - anything you want to present

    B. Comparison figures
    - EEGNet
    - DeepConvNet
4. Discussion (20%)
    A. Anything you want to share

- ## Experimental results

---- Criterion of result (40%) ----

Accuracy > = 87% = 100 pts

Accuracy 85~87% = 90 pts

Accuracy 80~85% = 80 pts

Accuracy 75~80% = 70 pts

Accuracy < 75% = 60 pts

Score: 40% experimental results + 60% (report+ demo score)

Reference:

[1] EEGNet: A Compact Convolutional Neural Network for EEG-based Brain-Computer Interfaces