ML_challenge

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1 ML challenge: sleep stage detection

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2 Challenge description

This challenge is provided by Dreem which aims to develop an algorithm of sleep staging that can differentiate between Wake, N1, N2, N3 and REM on windows of 30 seconds of raw data. The raw data includes 7 EEG channels in frontal and occipital position, 1 pulse oximeter infrared channel, and 3 accelerometer channels (x, y and z).

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[1]:
```
import h5py
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from scipy.interpolate import interp1d
from scipy.signal import butter, lfilter
from sklearn.metrics import f1_score, classification_report
from sklearn.model_selection import train_test_split
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision.transforms import Normalize
import warnings
warnings.filterwarnings("ignore", category=UserWarning)

PATH = ""
```

3 Data description

The data is separated between in different channels recorded by the Dreem headband. Windows of 30 seconds of data are extracted from 61 subject records.

EEG signals are measured at 7 different locations around the head (eeg_1 -> eeg_7). The sampling frequency is 50 Hz. Pulse oximeter (pulse_oximeter_infrared) and acceleromter (accelerometer_[x/y/z]) channels are sampled at 10Hz ### Main data - eeg_1 - EEG in frontal position sampled at 50 Hz -> 1500 values
- eeg_2 - EEG in frontal position sampled at 50 Hz -> 1500 values
- eeg_3 - EEG in frontal position sampled at 50 Hz -> 1500 values
- eeg_4 - EEG in frontal-occipital position sampled at 50 Hz -> 1500 values
- eeg_5 - EEG in frontal-occipital position sampled at 50 Hz -> 1500 values
- eeg_6 - EEG in frontal-occipital position sampled at 50 Hz -> 1500 values
- eeg_7 - EEG in frontal-occipital position sampled at 50 Hz -> 1500 values
- x - Accelerometer along x axis sampled at 10 Hz -> 300 values
- y - Accelerometer along y axis sampled at 10 Hz -> 300 values
- z - Accelerometer along z axis sampled at 10 Hz -> 300 values
- pulse - Pulse oximeter infrared channel sampled at 10 Hz -> 300 values

3.0.1 Additionnal meta-data

- index - Subject ID
- index_absolute - correspondance index with y_train, and y_test
- index_window - Index starting at 0 for the first 30-seconds window of a subject then 1 for the following window etc. until the end of the subject's record

3.0.2 Output Description

The output is a label between 0 and 4 - 0 Wake - 1 NREM1 Sleep (light sleep 1) - 2 NREM2 Sleep (light sleep 2) - 3 NREM3 sleep (deep sleep) - 4 REM sleep (paradoxical sleep)

3.0.3 Dataset Dimension

In the train dataset, each signal has a dimension of 24688 x (sampling frequency * 30). E.g: eeg_1 has a dimension of 24688 x 1500 and accelerometer 24688 x 300

In the test dataset, each signal has a dimension of 24980 x (sampling frequency * 30). E.g: eeg_1 has a dimension of 24980 x 1500 and accelerometer 24980 x 300

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4 Data preprocessing

Since the data come from different sensors, there exist two main drawbacks : * The existence of noise containing useless information which can disturb our prediction * Different length of data resulting in heterogeneousness

The preprocessing of data becomes important to get a better prediction. Hence we first create three functions: smooth_filter, upsample and normalize to solve these problems above. * smooth_filter is based on butter function, butter is used to design an Nth-order digital or analog Butterworth filter and return the filter coefficients. Here we use a low-pass filter and return a digital filter. * upsample is based on interp1d which is a method that creates a function based on fixed data points, which can be evaluated anywhere within the domain defined by the given data using linear interpolation. We have extended the data of length 300 to the data of length 1500 without changing the shape of signal.

[2]:
```
#This function aims to reduce noise. X is the data with size(24688,1500), for␣
↪example: egg1
def smooth_filter(X, cutoff, fs, order=5):
    def butter_lowpass(cutoff, fs, order=5):
        nyq = 0.5 * fs
        normal_cutoff = cutoff / nyq
        b, a = butter(order, normal_cutoff, btype='low', analog=False)
        return b, a
    b, a = butter_lowpass(cutoff, fs, order=order)
    X_filtered = lfilter(b, a, X)
    return X_filtered

#This function aims to upstream data. X is the data with size(24688,300), for␣
↪example: pulse
#And it will return an array with size(24688,1500)
def upsample(X):
    cX = np.zeros((X.shape[0], 5*X.shape[1]))
    x = np.linspace(0, 5*X.shape[1],X.shape[1])
    xnew = np.linspace(0, 5*X.shape[1],5*X.shape[1])
    for i in range(X.shape[0]):
        y = X[i].copy()
        f = interp1d(x,y,kind='linear')
        cX[i] = f(xnew)
    return cX

def normalize(X):
    return (X-X.mean(axis=-1, keepdims=True))/(X.std(axis=-1, keepdims=True))

def preprocess_channel(X, upsampling=False, filtering=True):
    """
    X is a channel of size (N,300) or (N,1500)
    """
    if upsampling:
        if filtering:
            X_prep = smooth_filter(upsample(X), cutoff=1.5, fs=10, order=5)
        else:
            X_prep = upsample(X)
    else:
        if filtering:
            X_prep = smooth_filter(X, cutoff=5, fs=50, order=5)
```

```
        else:
            X_prep = X.copy()
    return normalize(X_prep)

KEYS_FIL = ['eeg_1', 'eeg_2', 'eeg_3', 'eeg_4', 'eeg_5', 'eeg_6', 'eeg_7']
KEYS_UP_FIL = ['pulse']
KEYS_UP = ['x', 'y', 'z']
KEYS = KEYS_FIL + KEYS_UP_FIL + KEYS_UP
def preprocess_dataset(dataset):
    return torch.Tensor([
        preprocess_channel(dataset[key], upsampling=False, filtering=True) if␣
 ↪key in KEYS_FIL else
        preprocess_channel(dataset[key], upsampling=True, filtering=True) if␣
 ↪key in KEYS_UP_FIL else
        preprocess_channel(dataset[key], upsampling=True, filtering=False) for␣
 ↪key in KEYS]).transpose(0,1)
```

[3]:
```
X_train_h5 = h5py.File(PATH + "X_train.h5", "r")
X_test_h5 = h5py.File(PATH + "X_test.h5", "r")
y_train_pd = pd.read_csv(PATH + "y_train.csv")
X_train_h5_prep = preprocess_dataset(X_train_h5)
y_train_h5_prep = torch.LongTensor(y_train_pd["sleep_stage"])
X_train, X_valid, y_train, y_valid = train_test_split(
    X_train_h5_prep, y_train_h5_prep, test_size=0.1, random_state=0)
X_test = preprocess_dataset(X_test_h5)
submission = pd.read_csv(PATH + "sample_submission.csv")
```

4.0.1 Save datasets

[4]:
```
torch.save(X_train_h5_prep, PATH + "data/X_train_h5_prep.pt")
torch.save(y_train_h5_prep, PATH + "data/y_train_h5_prep.pt")
torch.save(X_train, PATH + "data/X_train.pt")
torch.save(X_valid, PATH + "data/X_valid.pt")
torch.save(y_train, PATH + "data/y_train.pt")
torch.save(y_valid, PATH + "data/y_valid.pt")
torch.save(X_test, PATH + "data/X_test.pt")
```

4.1 Directly load data

[5]:
```
X_train_h5 = h5py.File(PATH + "X_train.h5", "r")
X_test_h5 = h5py.File(PATH + "X_test.h5", "r")
y_train_pd = pd.read_csv(PATH + "y_train.csv")
X_train_h5_prep = torch.load(PATH + "data/X_train_h5_prep.pt")
y_train_h5_prep = torch.load(PATH + "data/y_train_h5_prep.pt")
X_train = torch.load(PATH + "data/X_train.pt")
X_valid = torch.load(PATH + "data/X_valid.pt")
y_train = torch.load(PATH + "data/y_train.pt")
```

```
y_valid = torch.load(PATH + "data/y_valid.pt")
X_test = torch.load(PATH + "data/X_test.pt")
submission = pd.read_csv(PATH + "sample_submission.csv")
```

[7]:
```
BATCH_SIZE = 64
train_dataset = torch.utils.data.TensorDataset(X_train, y_train)
train_loader = torch.utils.data.DataLoader(train_dataset,␣
↪batch_size=BATCH_SIZE, shuffle=False)
valid_dataset = torch.utils.data.TensorDataset(X_valid, y_valid)
test_dataset = torch.utils.data.TensorDataset(X_test)
full_train_dataset = torch.utils.data.TensorDataset(torch.cat((X_train,␣
↪X_valid)), torch.cat((y_train, y_valid)))
full_train_loader = torch.utils.data.DataLoader(full_train_dataset,␣
↪batch_size=BATCH_SIZE, shuffle=True)
```

---

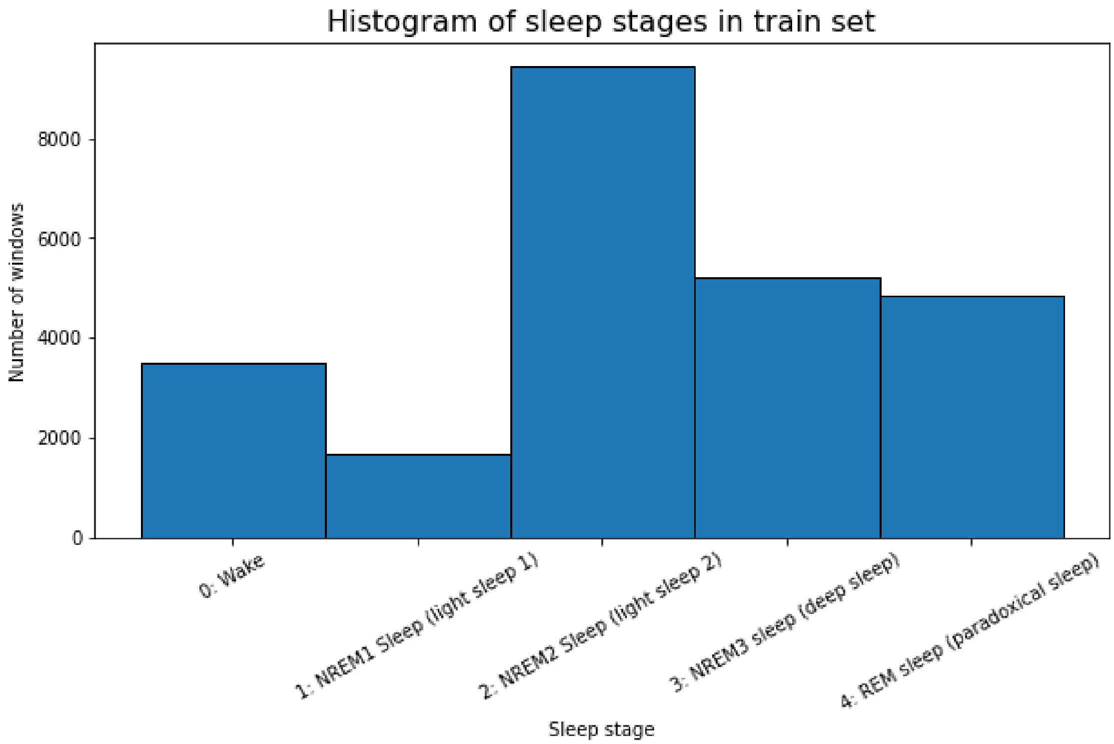
5 Data visualization

[8]:
```
print("Shapes          |    Train set      |    Test set")
print("---------------|------------------|---------------")
for key in X_train_h5.keys():
    print("{:15s}|  {:14s}  |  {:14s}".format(key, str(X_train_h5.get(key).
↪shape), str(X_test_h5.get(key).shape)))
```

```
Shapes          |    Train set      |    Test set
---------------|------------------|---------------
eeg_1          |  (24688, 1500)    |  (24980, 1500)
eeg_2          |  (24688, 1500)    |  (24980, 1500)
eeg_3          |  (24688, 1500)    |  (24980, 1500)
eeg_4          |  (24688, 1500)    |  (24980, 1500)
eeg_5          |  (24688, 1500)    |  (24980, 1500)
eeg_6          |  (24688, 1500)    |  (24980, 1500)
eeg_7          |  (24688, 1500)    |  (24980, 1500)
index          |  (24688,)         |  (24980,)
index_absolute |  (24688,)         |  (24980,)
index_window   |  (24688,)         |  (24980,)
pulse          |  (24688, 300)     |  (24980, 300)
x              |  (24688, 300)     |  (24980, 300)
y              |  (24688, 300)     |  (24980, 300)
z              |  (24688, 300)     |  (24980, 300)
```

[9]:
```
SLEEP_STAGES = {
    0: "Wake",
    1: "NREM1 Sleep (light sleep 1)",
    2: "NREM2 Sleep (light sleep 2)",
    3: "NREM3 sleep (deep sleep)",
```

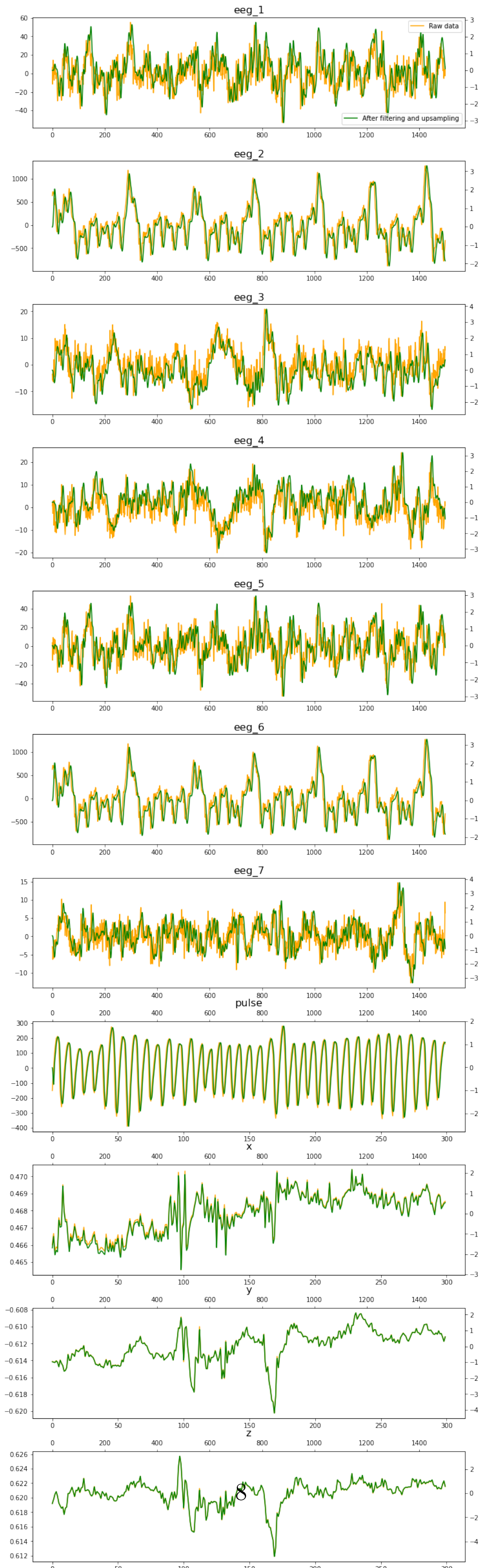
```
    4: "REM sleep (paradoxical sleep)"
}
plt.figure(figsize=(10,5));
plt.hist(y_train_pd["sleep_stage"], bins=np.arange(6)-0.5, edgecolor='black');
plt.xticks(list(SLEEP_STAGES.keys()), [str(i)+": "+sleep_stage for i,␣
 ↪sleep_stage in SLEEP_STAGES.items()], rotation=30);
plt.xlabel("Sleep stage");
plt.ylabel("Number of windows");
plt.title("Histogram of sleep stages in train set", fontsize=16);
```



[24]:
```
np.random.seed(0)
window_id = np.random.randint(0, X_train_h5_prep.shape[0]-1)
print("Subject ID:", X_train_h5["index"][window_id])
print("Subject's window number:", X_train_h5["index_window"][window_id])
print("Window ID:", X_train_h5["index_absolute"][window_id])
print("Sleep stage:", y_train_pd.loc[window_id, "sleep_stage"])
plt.figure(figsize=(12, 4*len(KEYS)));
for i, key in enumerate(KEYS):
    plt.subplot(len(KEYS), 1, i+1);
    plt.subplots_adjust(hspace=0.3);
    plt.plot(X_train_h5[key][window_id], c="orange", label="Raw data");
    if i==0: plt.legend(loc="upper right");
    plt.twinx();
```

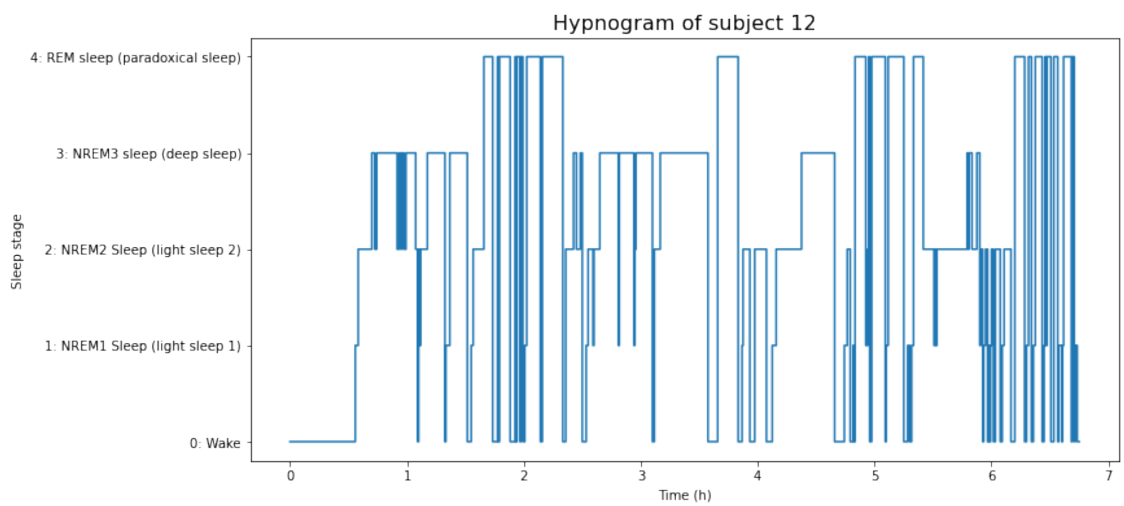
```
    if key in KEYS_UP_FIL + KEYS_UP:
        plt.twiny();
    plt.plot(X_train_h5_prep[window_id][i], c="green", label="After filtering␣
↪and upsampling");
    if i==0: plt.legend(loc="lower right");
    plt.title(key, fontsize=16);
```

```
Subject ID: 2
Subject's window number: 944
Window ID: 2732
Sleep stage: 2
```


eeg_1
Raw data
After filtering and upsampling
eeg_2
eeg_3
eeg_4
eeg_5
eeg_6
eeg_7
pulse
x
y
z

We can see from the result that the noise has been significantly reduced, therefore it can improve our future predictions for different stages by cleaning the useless information.

[11]:
```
np.random.seed(0)
subject_id = np.random.randint(max(X_train_h5["index"]))

hypnogram = [y_train_pd.loc[window_id, "sleep_stage"]
             for window_id, subject_index in enumerate(X_train_h5["index"])
             if subject_index == subject_id]

plt.figure(figsize=(12,6));
plt.step(30/3600 * np.arange(len(hypnogram)), hypnogram);
plt.xlabel("Time (h)");
plt.ylabel("Sleep stage");
plt.yticks(list(SLEEP_STAGES.keys()), [str(i)+": "+sleep_stage for i,␣
↪sleep_stage in SLEEP_STAGES.items()]);
plt.title("Hypnogram of subject {}".format(subject_id), fontsize=16);
```



One can see that sleep stages can highly vary within a night.

---

6 Models

[12]:
```
class StagerNet2(nn.Module):
    def __init__(self, C=11):
        super(StagerNet2, self).__init__()
```

```
        self.conv_1 = nn.Conv2d(in_channels=1, out_channels=C,␣
↪kernel_size=(C,1))
        self.conv_2 = nn.Conv2d(in_channels=1, out_channels=64,␣
↪kernel_size=(1,20))
        self.batch_norm_1 = nn.BatchNorm2d(64)
        self.max_pool_1 = nn.MaxPool2d(kernel_size=(1,4))
        self.conv_3 = nn.Conv2d(in_channels=64, out_channels=128,␣
↪kernel_size=(1,20))
        self.batch_norm_2 = nn.BatchNorm2d(128)
        self.max_pool_2 = nn.MaxPool2d(kernel_size=(1,4))
        self.flatten = nn.Flatten()
        self.linear_1 = nn.Linear(in_features=C*128*87, out_features=100)
        self.dropout = nn.Dropout(p=0.4)
        self.linear_2 = nn.Linear(in_features=100, out_features=5)
        self.softmax = nn.Softmax(dim=-1)
        self.relu = nn.ReLU()

    def forward(self, x):
        x = x.unsqueeze(1)
        x = self.conv_1(x).transpose(2,1)
        x = self.conv_2(x)
        x = self.batch_norm_1(x)
        x = self.max_pool_1(x)
        x = self.relu(x)
        x = self.conv_3(x)
        x = self.batch_norm_2(x)
        x = self.max_pool_2(x)
        x = self.relu(x)
        x = self.flatten(x)
        x = self.linear_1(x)
        x = self.dropout(x)
        x = self.relu(x)
        x = self.linear_2(x)
        x = self.softmax(x)
        return x

    def classify(self, x):
        x = self(x)
        return torch.argmax(x, 1)
```

[13]:

```
class OneDCNN(nn.Module):
    """https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6406978/table/
↪ijerph-16-00599-t002/"""
    def __init__(self, C=11):
        super(OneDCNN, self).__init__()
        self.relu = nn.ReLU()
        self.flatten = nn.Flatten()
```

```python
        self.conv_1 = nn.Conv1d(
            in_channels=C, out_channels=64, kernel_size=5, stride=3)
        self.conv_2 = nn.Conv1d(
            in_channels=64, out_channels=128, kernel_size=5, stride=1)
        self.max_pool_3 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.dropout_4 = nn.Dropout(p=0.2)
        self.conv_5 = nn.Conv1d(
            in_channels=128, out_channels=128, kernel_size=13, stride=1)
        self.conv_6 = nn.Conv1d(
            in_channels=128, out_channels=256, kernel_size=7, stride=1)
        self.max_pool_7 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv_8 = nn.Conv1d(
            in_channels=256, out_channels=256, kernel_size=7, stride=1)
        self.conv_9 = nn.Conv1d(
            in_channels=256, out_channels=64, kernel_size=7, stride=1)
        self.max_pool_10 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv_11 = nn.Conv1d(
            in_channels=64, out_channels=32, kernel_size=3, stride=1)
        self.conv_12 = nn.Conv1d(
            in_channels=32, out_channels=64, kernel_size=6, stride=1)
        self.max_pool_13 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv_14 = nn.Conv1d(
            in_channels=64, out_channels=8, kernel_size=5, stride=1)
        self.conv_15 = nn.Conv1d(
            in_channels=8, out_channels=8, kernel_size=2, stride=1)
        self.max_pool_16 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.dense_18 = nn.Linear(in_features=64, out_features=64)
        self.dropout_18 = nn.Dropout(p=0.2)
        self.dense_19 = nn.Linear(in_features=64, out_features=5)
        self.softmax = nn.Softmax(dim=-1)

    def forward(self, x):
        x = self.relu(self.conv_1(x))
        x = self.relu(self.conv_2(x))
        x = self.max_pool_3(x)
        x = self.dropout_4(x)
        x = self.relu(self.conv_5(x))
        x = self.relu(self.conv_6(x))
        x = self.max_pool_7(x)
        x = self.relu(self.conv_8(x))
        x = self.relu(self.conv_9(x))
        x = self.max_pool_10(x)
        x = self.relu(self.conv_11(x))
        x = self.relu(self.conv_12(x))
        x = self.max_pool_13(x)
        x = self.relu(self.conv_14(x))
        x = self.relu(self.conv_15(x))
```

```
        x = self.max_pool_16(x)
        x = self.flatten(x)
        x = self.dropout_18(self.relu(self.dense_18(x)))
        x = self.dense_19(x)
        x = self.softmax(x)
        return x

    def classify(self, x):
        x = self(x)
        return torch.argmax(x, 1)
```

[14]:
```
class OneDCNN2(nn.Module):
    """https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6406978/table/
 ↪ijerph-16-00599-t002/"""
    def __init__(self, C=11):
        super(OneDCNN2, self).__init__()
        self.relu = nn.ReLU()
        self.conv_1 = nn.Conv1d(
            in_channels=C, out_channels=64, kernel_size=5, stride=3)
        self.conv_2 = nn.Conv1d(
            in_channels=64, out_channels=128, kernel_size=5, stride=1)
        self.max_pool_3 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.dropout_4 = nn.Dropout(p=0.2)
        self.conv_5 = nn.Conv1d(
            in_channels=128, out_channels=128, kernel_size=13, stride=1)
        self.conv_6 = nn.Conv1d(
            in_channels=128, out_channels=256, kernel_size=7, stride=1)
        self.max_pool_7 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv_8 = nn.Conv1d(
            in_channels=256, out_channels=256, kernel_size=7, stride=1)
        self.conv_9 = nn.Conv1d(
            in_channels=256, out_channels=64, kernel_size=7, stride=1)
        self.max_pool_10 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv_11 = nn.Conv1d(
            in_channels=64, out_channels=32, kernel_size=3, stride=1)
        self.conv_12 = nn.Conv1d(
            in_channels=32, out_channels=64, kernel_size=6, stride=1)
        self.max_pool_13 = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv_14 = nn.Conv1d(
            in_channels=64, out_channels=16, kernel_size=5, stride=1)
        self.conv_15 = nn.Conv1d(
            in_channels=16, out_channels=16, kernel_size=2, stride=1)
        self.flatten_17 = nn.Flatten()
        self.dense_18 = nn.Linear(in_features=272, out_features=256)
        self.dropout_18 = nn.Dropout(p=0.2)
        self.dense_19 = nn.Linear(in_features=256, out_features=5)
        self.softmax = nn.Softmax(dim=-1)
```

```
    def forward(self, x):
        x = self.relu(self.conv_1(x))
        x = self.relu(self.conv_2(x))
        x = self.max_pool_3(x)
        x = self.dropout_4(x)
        x = self.relu(self.conv_5(x))
        x = self.relu(self.conv_6(x))
        x = self.max_pool_7(x)
        x = self.relu(self.conv_8(x))
        x = self.relu(self.conv_9(x))
        x = self.max_pool_10(x)
        x = self.relu(self.conv_11(x))
        x = self.relu(self.conv_12(x))
        x = self.max_pool_13(x)
        x = self.relu(self.conv_14(x))
        x = self.relu(self.conv_15(x))
        x = self.flatten_17(x)
        x = self.dropout_18(self.relu(self.dense_18(x)))
        x = self.dense_19(x)
        x = self.softmax(x)
        return x

    def classify(self, x):
        x = self(x)
        return torch.argmax(x, 1)
```

[15]:
```
for parameter in OneDCNN2().parameters():
    print(parameter.numel())
```

```
3520
64
40960
128
212992
128
229376
256
458752
256
114688
64
6144
32
12288
64
5120
16
```

```
512
16
69632
256
1280
5
```

[16]:
```
print("Number of parameters StagerNet2: {:,}".format(sum([parameter.numel() for␣
 ↪parameter in StagerNet2().parameters()])))
print("Number of parameters OneDCNN:    {:,}".format(sum([parameter.numel() for␣
 ↪parameter in OneDCNN().parameters()])))
print("Number of parameters OneDCNN2:    {:,}".format(sum([parameter.numel()␣
 ↪for parameter in OneDCNN2().parameters()])))
```

```
Number of parameters StagerNet2: 12,416,033
Number of parameters OneDCNN:    1,086,901
Number of parameters OneDCNN2:    1,156,549
```

---

7 Training

[ ]:
```
device = "cuda" if torch.cuda.is_available() else "cpu"
print("Device:", device)
```

```
Device: cuda
```

[17]:
```
def plot_curves(train_loss, valid_loss, train_f1_score, valid_f1_score,␣
 ↪print_epochs=1, N=10):
    # N: running mean, print_epochs: number of epochs in between each point
    plt.plot(
        np.arange(print_epochs, print_epochs*(len(train_loss)+1), print_epochs),
        train_loss, c="blue", alpha=1, label="Training loss");
    plt.plot(
        np.arange(print_epochs, print_epochs*(len(valid_loss)+1), print_epochs),
        valid_loss, c="brown", alpha=1, label="Validation loss");
    plt.ylabel("Loss");
    plt.xlabel("Epochs");
    plt.legend();
    plt.twinx();
    plt.plot(
        np.arange(print_epochs, print_epochs*(len(valid_f1_score)+1),␣
 ↪print_epochs),
        valid_f1_score, c="orange", alpha=1, label="Validation f1 score");
    plt.plot(
        np.arange(print_epochs, print_epochs*(len(train_f1_score)+1),␣
 ↪print_epochs),
        train_f1_score, c="green", alpha=1, label="Training f1 score");
```

```
    plt.legend();
    plt.ylabel("F1 score");
    plt.tight_layout();
```

[ ]:
```
torch.manual_seed(0)
cla = OneDCNN().to(device)
loss_fn = nn.CrossEntropyLoss()
optimizer = optim.Adam(cla.parameters(), lr=0.00001)
EPOCHS = 400
PRINT_EPOCHS = 10
```

[ ]:
```
train_loss, valid_loss, valid_f1_score, train_f1_score = [], [], [], []
cla.train()
epoch_train_loss = 0
for epoch in range(EPOCHS):
    for i, data in enumerate(train_loader):
        inputs = data[0].to(device)
        labels = data[1].to(device)
        optimizer.zero_grad()
        outputs = cla(inputs)
        loss = loss_fn(outputs, labels)
        loss.backward()
        optimizer.step()
        epoch_train_loss += loss.item()
    if epoch%PRINT_EPOCHS == PRINT_EPOCHS-1:
        cla.eval()
        epoch_valid_loss = loss_fn(cla(X_valid.to(device)), y_valid.to(device)).
 ↪item()
        valid_predict = cla.classify(X_valid.to(device))
        train_indices = np.random.choice(range(len(X_train)),␣
 ↪size=20*BATCH_SIZE, replace=False)
        train_predict = cla.classify(X_train[train_indices].to(device))
        valid_f1 = f1_score(y_valid, valid_predict.cpu(), average="micro")
        train_f1 = f1_score(y_train[train_indices], train_predict.cpu(),␣
 ↪average="micro")
        epoch_train_loss = epoch_train_loss/(len(train_loader)*PRINT_EPOCHS)
        print("[epoch {:2d}]  train_loss: {:.3f}  valid_loss: {:.3f} ␣
 ↪train_f1_score: {:.3f}  valid_f1_score: {:.3f}".format(
            epoch+1, epoch_train_loss, epoch_valid_loss, train_f1, valid_f1))
        train_loss.append(epoch_train_loss)
        valid_loss.append(epoch_valid_loss)
        valid_f1_score.append(valid_f1)
        train_f1_score.append(train_f1)
        epoch_train_loss = 0
        cla.train()
```

```
cla = cla.eval()
```

```
[epoch 10]  train_loss: 1.523  valid_loss: 1.519  train_f1_score: 0.404
valid_f1_score: 0.379
[epoch 20]  train_loss: 1.497  valid_loss: 1.503  train_f1_score: 0.412
valid_f1_score: 0.387
[epoch 30]  train_loss: 1.470  valid_loss: 1.472  train_f1_score: 0.442
valid_f1_score: 0.418
[epoch 40]  train_loss: 1.452  valid_loss: 1.459  train_f1_score: 0.424
valid_f1_score: 0.424
[epoch 50]  train_loss: 1.429  valid_loss: 1.426  train_f1_score: 0.484
valid_f1_score: 0.470
[epoch 60]  train_loss: 1.399  valid_loss: 1.397  train_f1_score: 0.532
valid_f1_score: 0.501
[epoch 70]  train_loss: 1.383  valid_loss: 1.386  train_f1_score: 0.531
valid_f1_score: 0.513
[epoch 80]  train_loss: 1.372  valid_loss: 1.378  train_f1_score: 0.527
valid_f1_score: 0.520
[epoch 90]  train_loss: 1.364  valid_loss: 1.372  train_f1_score: 0.553
valid_f1_score: 0.528
[epoch 100]  train_loss: 1.359  valid_loss: 1.367  train_f1_score: 0.545
valid_f1_score: 0.533
[epoch 110]  train_loss: 1.354  valid_loss: 1.365  train_f1_score: 0.562
valid_f1_score: 0.533
[epoch 120]  train_loss: 1.351  valid_loss: 1.364  train_f1_score: 0.553
valid_f1_score: 0.534
[epoch 130]  train_loss: 1.347  valid_loss: 1.358  train_f1_score: 0.573
valid_f1_score: 0.542
[epoch 140]  train_loss: 1.343  valid_loss: 1.371  train_f1_score: 0.559
valid_f1_score: 0.530
[epoch 150]  train_loss: 1.340  valid_loss: 1.356  train_f1_score: 0.557
valid_f1_score: 0.549
[epoch 160]  train_loss: 1.337  valid_loss: 1.354  train_f1_score: 0.572
valid_f1_score: 0.545
[epoch 170]  train_loss: 1.334  valid_loss: 1.352  train_f1_score: 0.584
valid_f1_score: 0.548
[epoch 180]  train_loss: 1.331  valid_loss: 1.350  train_f1_score: 0.571
valid_f1_score: 0.551
[epoch 190]  train_loss: 1.328  valid_loss: 1.346  train_f1_score: 0.577
valid_f1_score: 0.557
[epoch 200]  train_loss: 1.326  valid_loss: 1.347  train_f1_score: 0.555
valid_f1_score: 0.557
[epoch 210]  train_loss: 1.323  valid_loss: 1.342  train_f1_score: 0.582
valid_f1_score: 0.559
[epoch 220]  train_loss: 1.321  valid_loss: 1.339  train_f1_score: 0.592
valid_f1_score: 0.563
[epoch 230]  train_loss: 1.318  valid_loss: 1.336  train_f1_score: 0.605
valid_f1_score: 0.566
```

```
[epoch 240]  train_loss: 1.314  valid_loss: 1.334  train_f1_score: 0.598
valid_f1_score: 0.568
[epoch 250]  train_loss: 1.306  valid_loss: 1.322  train_f1_score: 0.628
valid_f1_score: 0.574
[epoch 260]  train_loss: 1.296  valid_loss: 1.315  train_f1_score: 0.616
valid_f1_score: 0.585
[epoch 270]  train_loss: 1.287  valid_loss: 1.304  train_f1_score: 0.617
valid_f1_score: 0.590
[epoch 280]  train_loss: 1.277  valid_loss: 1.289  train_f1_score: 0.637
valid_f1_score: 0.608
[epoch 290]  train_loss: 1.270  valid_loss: 1.280  train_f1_score: 0.639
valid_f1_score: 0.620
[epoch 300]  train_loss: 1.261  valid_loss: 1.275  train_f1_score: 0.663
valid_f1_score: 0.626
[epoch 310]  train_loss: 1.254  valid_loss: 1.268  train_f1_score: 0.657
valid_f1_score: 0.633
[epoch 320]  train_loss: 1.248  valid_loss: 1.272  train_f1_score: 0.652
valid_f1_score: 0.627
[epoch 330]  train_loss: 1.242  valid_loss: 1.260  train_f1_score: 0.698
valid_f1_score: 0.642
[epoch 340]  train_loss: 1.238  valid_loss: 1.259  train_f1_score: 0.690
valid_f1_score: 0.643
[epoch 350]  train_loss: 1.233  valid_loss: 1.256  train_f1_score: 0.682
valid_f1_score: 0.645
[epoch 360]  train_loss: 1.229  valid_loss: 1.259  train_f1_score: 0.673
valid_f1_score: 0.644
[epoch 370]  train_loss: 1.224  valid_loss: 1.256  train_f1_score: 0.689
valid_f1_score: 0.643
[epoch 380]  train_loss: 1.222  valid_loss: 1.249  train_f1_score: 0.703
valid_f1_score: 0.650
[epoch 390]  train_loss: 1.218  valid_loss: 1.250  train_f1_score: 0.695
valid_f1_score: 0.650
[epoch 400]  train_loss: 1.216  valid_loss: 1.247  train_f1_score: 0.700
valid_f1_score: 0.653
```

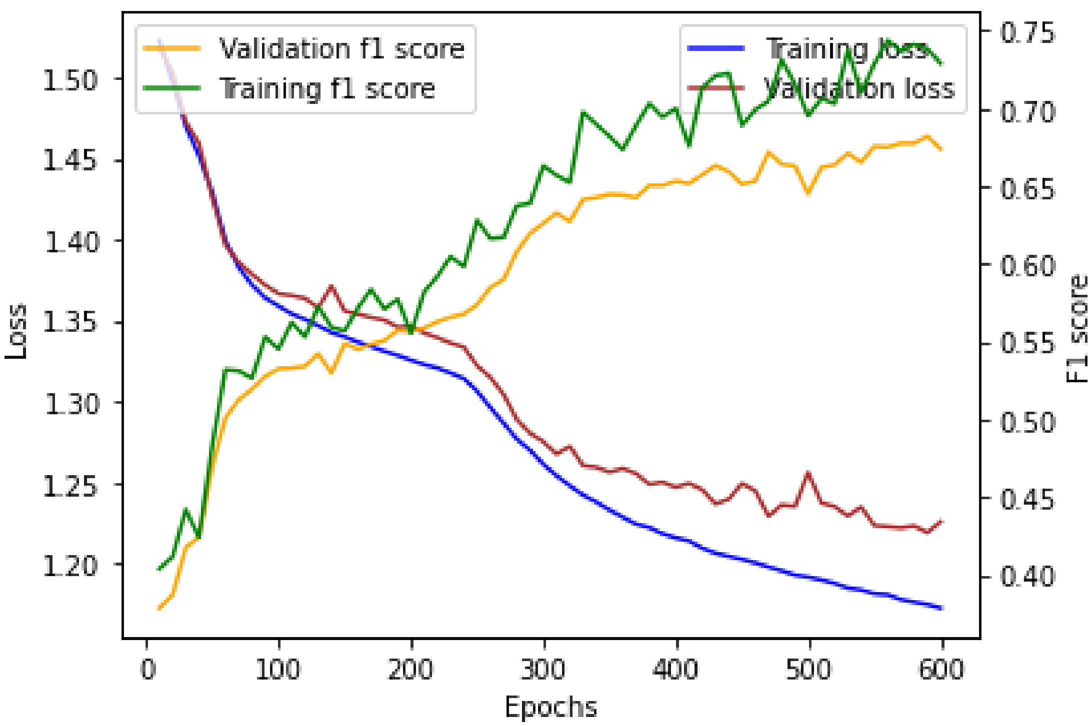
[ ]:
```python
cla.train()
epoch_train_loss = 0
for epoch in range(400, 400 + 200):
    for i, data in enumerate(train_loader):
        inputs = data[0].to(device)
        labels = data[1].to(device)
        optimizer.zero_grad()
        outputs = cla(inputs)
        loss = loss_fn(outputs, labels)
        loss.backward()
        optimizer.step()
        epoch_train_loss += loss.item()
```

```
    if epoch%PRINT_EPOCHS == PRINT_EPOCHS-1:
        cla.eval()
        epoch_valid_loss = loss_fn(cla(X_valid.to(device)), y_valid.to(device)).
↪item()
        valid_predict = cla.classify(X_valid.to(device))
        train_indices = np.random.choice(range(len(X_train)),␣
↪size=20*BATCH_SIZE, replace=False)
        train_predict = cla.classify(X_train[train_indices].to(device))
        valid_f1 = f1_score(y_valid, valid_predict.cpu(), average="micro")
        train_f1 = f1_score(y_train[train_indices], train_predict.cpu(),␣
↪average="micro")
        epoch_train_loss = epoch_train_loss/(len(train_loader)*PRINT_EPOCHS)
        print("[epoch {:2d}]  train_loss: {:.3f}  valid_loss: {:.3f} ␣
↪train_f1_score: {:.3f}  valid_f1_score: {:.3f}".format(
            epoch+1, epoch_train_loss, epoch_valid_loss, train_f1, valid_f1))
        train_loss.append(epoch_train_loss)
        valid_loss.append(epoch_valid_loss)
        valid_f1_score.append(valid_f1)
        train_f1_score.append(train_f1)
        epoch_train_loss = 0
        cla.train()
cla = cla.eval()
```

```
[epoch 410]  train_loss: 1.214  valid_loss: 1.249  train_f1_score: 0.676
valid_f1_score: 0.652
[epoch 420]  train_loss: 1.210  valid_loss: 1.246  train_f1_score: 0.713
valid_f1_score: 0.657
[epoch 430]  train_loss: 1.206  valid_loss: 1.237  train_f1_score: 0.721
valid_f1_score: 0.663
[epoch 440]  train_loss: 1.204  valid_loss: 1.240  train_f1_score: 0.723
valid_f1_score: 0.659
[epoch 450]  train_loss: 1.203  valid_loss: 1.249  train_f1_score: 0.689
valid_f1_score: 0.651
[epoch 460]  train_loss: 1.200  valid_loss: 1.245  train_f1_score: 0.699
valid_f1_score: 0.653
[epoch 470]  train_loss: 1.198  valid_loss: 1.229  train_f1_score: 0.705
valid_f1_score: 0.672
[epoch 480]  train_loss: 1.195  valid_loss: 1.236  train_f1_score: 0.731
valid_f1_score: 0.664
[epoch 490]  train_loss: 1.193  valid_loss: 1.235  train_f1_score: 0.716
valid_f1_score: 0.663
[epoch 500]  train_loss: 1.192  valid_loss: 1.256  train_f1_score: 0.695
valid_f1_score: 0.645
[epoch 510]  train_loss: 1.190  valid_loss: 1.237  train_f1_score: 0.706
valid_f1_score: 0.662
[epoch 520]  train_loss: 1.188  valid_loss: 1.235  train_f1_score: 0.703
valid_f1_score: 0.664
```

```
[epoch 530]  train_loss: 1.185  valid_loss: 1.229  train_f1_score: 0.738
valid_f1_score: 0.671
[epoch 540]  train_loss: 1.184  valid_loss: 1.235  train_f1_score: 0.710
valid_f1_score: 0.665
[epoch 550]  train_loss: 1.181  valid_loss: 1.223  train_f1_score: 0.729
valid_f1_score: 0.676
[epoch 560]  train_loss: 1.181  valid_loss: 1.223  train_f1_score: 0.744
valid_f1_score: 0.675
[epoch 570]  train_loss: 1.178  valid_loss: 1.222  train_f1_score: 0.737
valid_f1_score: 0.678
[epoch 580]  train_loss: 1.176  valid_loss: 1.223  train_f1_score: 0.741
valid_f1_score: 0.678
[epoch 590]  train_loss: 1.175  valid_loss: 1.219  train_f1_score: 0.738
valid_f1_score: 0.682
[epoch 600]  train_loss: 1.172  valid_loss: 1.226  train_f1_score: 0.729
valid_f1_score: 0.674
```

[ ]:
```
plot_curves(train_loss, valid_loss, train_f1_score, valid_f1_score,␣
↪print_epochs=PRINT_EPOCHS)
```



We draw the validation score, validation loss, training score and training loss together to observe our model's performance. Apparently, both score continu growning and both loss are declining. Finaly, the validation f1 score reachs around 67%, it won't augment anymore even with more epochs.

Besides, the training f1 score reachs around 73% which is higher than validation score indicating there may be the overfitting.

```
[ ]: torch.manual_seed(0)
cla = cla.train().to(device)
optimizer = optim.Adam(cla.parameters(), lr=0.00001)
epoch_train_loss = 0
for epoch in range(600, 600 + 200):
    for i, data in enumerate(train_loader):
        inputs = data[0].to(device)
        labels = data[1].to(device)
        optimizer.zero_grad()
        outputs = cla(inputs)
        loss = loss_fn(outputs, labels)
        loss.backward()
        optimizer.step()
        epoch_train_loss += loss.item()
    if epoch%PRINT_EPOCHS == PRINT_EPOCHS-1:
        cla.eval()
        epoch_valid_loss = loss_fn(cla(X_valid.to(device)), y_valid.to(device)).
 ↪item()
        valid_predict = cla.classify(X_valid.to(device))
        train_indices = np.random.choice(range(len(X_train)),␣
 ↪size=20*BATCH_SIZE, replace=False)
        train_predict = cla.classify(X_train[train_indices].to(device))
        valid_f1 = f1_score(y_valid, valid_predict.cpu(), average="micro")
        train_f1 = f1_score(y_train[train_indices], train_predict.cpu(),␣
 ↪average="micro")
        epoch_train_loss = epoch_train_loss/(len(train_loader)*PRINT_EPOCHS)
        print("[epoch {:2d}]  train_loss: {:.3f}  valid_loss: {:.3f} ␣
 ↪train_f1_score: {:.3f}  valid_f1_score: {:.3f}".format(
            epoch+1, epoch_train_loss, epoch_valid_loss, train_f1, valid_f1))
        train_loss.append(epoch_train_loss)
        valid_loss.append(epoch_valid_loss)
        valid_f1_score.append(valid_f1)
        train_f1_score.append(train_f1)
        epoch_train_loss = 0
        cla.train()
cla = cla.eval()
```

```
[epoch 610]  train_loss: 1.170  valid_loss: 1.222  train_f1_score: 0.749
valid_f1_score: 0.680
[epoch 620]  train_loss: 1.169  valid_loss: 1.218  train_f1_score: 0.747
valid_f1_score: 0.684
[epoch 630]  train_loss: 1.166  valid_loss: 1.220  train_f1_score: 0.750
valid_f1_score: 0.682
[epoch 640]  train_loss: 1.165  valid_loss: 1.224  train_f1_score: 0.733
valid_f1_score: 0.677
[epoch 650]  train_loss: 1.164  valid_loss: 1.220  train_f1_score: 0.772
```

```
valid_f1_score: 0.680
[epoch 660]  train_loss: 1.161  valid_loss: 1.214  train_f1_score: 0.761
valid_f1_score: 0.686
[epoch 670]  train_loss: 1.160  valid_loss: 1.215  train_f1_score: 0.759
valid_f1_score: 0.686
[epoch 680]  train_loss: 1.157  valid_loss: 1.216  train_f1_score: 0.761
valid_f1_score: 0.684
[epoch 690]  train_loss: 1.155  valid_loss: 1.216  train_f1_score: 0.752
valid_f1_score: 0.684
[epoch 700]  train_loss: 1.153  valid_loss: 1.216  train_f1_score: 0.765
valid_f1_score: 0.682
[epoch 710]  train_loss: 1.152  valid_loss: 1.215  train_f1_score: 0.775
valid_f1_score: 0.685
[epoch 720]  train_loss: 1.151  valid_loss: 1.214  train_f1_score: 0.770
valid_f1_score: 0.687
[epoch 730]  train_loss: 1.149  valid_loss: 1.216  train_f1_score: 0.748
valid_f1_score: 0.684
[epoch 740]  train_loss: 1.147  valid_loss: 1.213  train_f1_score: 0.779
valid_f1_score: 0.689
[epoch 750]  train_loss: 1.145  valid_loss: 1.215  train_f1_score: 0.773
valid_f1_score: 0.687
[epoch 760]  train_loss: 1.143  valid_loss: 1.216  train_f1_score: 0.777
valid_f1_score: 0.685
[epoch 770]  train_loss: 1.143  valid_loss: 1.221  train_f1_score: 0.752
valid_f1_score: 0.682
[epoch 780]  train_loss: 1.140  valid_loss: 1.212  train_f1_score: 0.771
valid_f1_score: 0.688
[epoch 790]  train_loss: 1.139  valid_loss: 1.214  train_f1_score: 0.769
valid_f1_score: 0.687
[epoch 800]  train_loss: 1.137  valid_loss: 1.220  train_f1_score: 0.767
valid_f1_score: 0.680
```

We see clearly that training f1 score climbs a little bit but validation f1 score does not augment anymore.

[ ]:
```
torch.manual_seed(0)
cla = OneDCNN2().to(device)
loss_fn = nn.CrossEntropyLoss()
optimizer = optim.Adam(cla.parameters(), lr=0.00005)
EPOCHS = 500
PRINT_EPOCHS = 10
```

[ ]:
```
train_loss, valid_loss, valid_f1_score, train_f1_score = [], [], [], []
cla.train()
epoch_train_loss = 0
for epoch in range(EPOCHS):
```

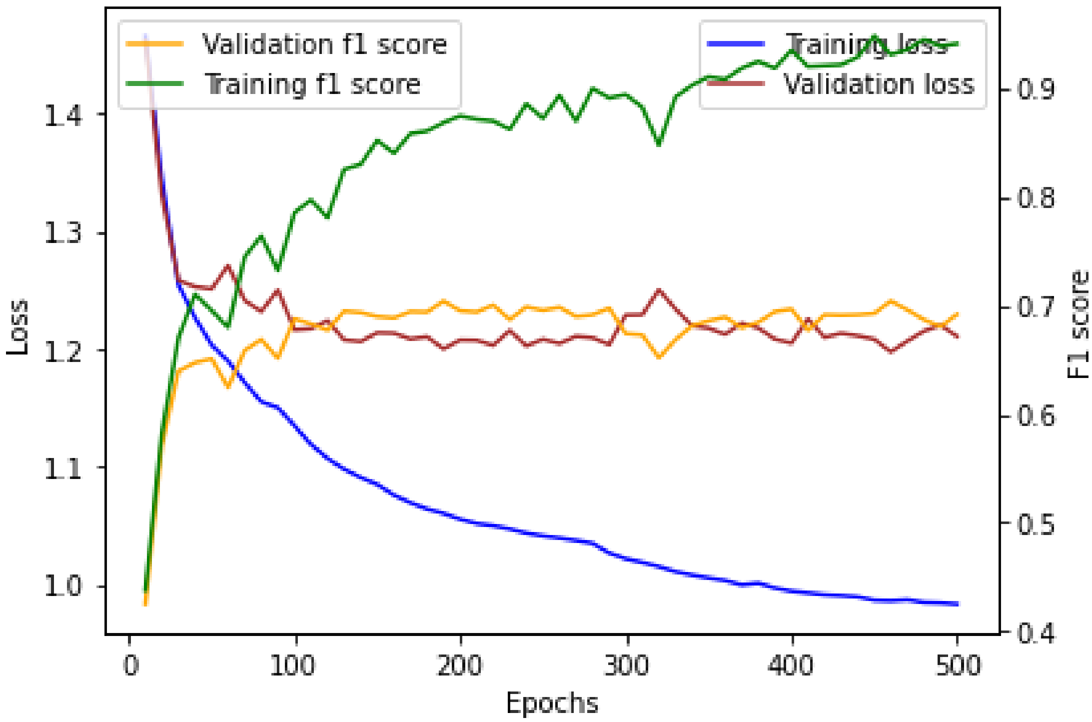
```
    for i, data in enumerate(train_loader):
        inputs = data[0].to(device)
        labels = data[1].to(device)
        optimizer.zero_grad()
        outputs = cla(inputs)
        loss = loss_fn(outputs, labels)
        loss.backward()
        optimizer.step()
        epoch_train_loss += loss.item()
    if epoch%PRINT_EPOCHS == PRINT_EPOCHS-1:
        cla.eval()
        epoch_valid_loss = loss_fn(cla(X_valid.to(device)), y_valid.to(device)).
↪item()
        valid_predict = cla.classify(X_valid.to(device))
        train_indices = np.random.choice(range(len(X_train)),␣
↪size=20*BATCH_SIZE, replace=False)
        train_predict = cla.classify(X_train[train_indices].to(device))
        valid_f1 = f1_score(y_valid, valid_predict.cpu(), average="micro")
        train_f1 = f1_score(y_train[train_indices], train_predict.cpu(),␣
↪average="micro")
        epoch_train_loss = epoch_train_loss/(len(train_loader)*PRINT_EPOCHS)
        print("[epoch {:2d}]  train_loss: {:.3f}  valid_loss: {:.3f} ␣
↪train_f1_score: {:.3f}  valid_f1_score: {:.3f}".format(
            epoch+1, epoch_train_loss, epoch_valid_loss, train_f1, valid_f1))
        train_loss.append(epoch_train_loss)
        valid_loss.append(epoch_valid_loss)
        valid_f1_score.append(valid_f1)
        train_f1_score.append(train_f1)
        epoch_train_loss = 0
        cla.train()
cla = cla.eval()
```

```
[epoch 10]  train_loss: 1.466  valid_loss: 1.462  train_f1_score: 0.438
valid_f1_score: 0.425
[epoch 20]  train_loss: 1.344  valid_loss: 1.330  train_f1_score: 0.583
valid_f1_score: 0.571
[epoch 30]  train_loss: 1.254  valid_loss: 1.258  train_f1_score: 0.670
valid_f1_score: 0.640
[epoch 40]  train_loss: 1.226  valid_loss: 1.253  train_f1_score: 0.710
valid_f1_score: 0.647
[epoch 50]  train_loss: 1.203  valid_loss: 1.251  train_f1_score: 0.695
valid_f1_score: 0.651
[epoch 60]  train_loss: 1.189  valid_loss: 1.271  train_f1_score: 0.680
valid_f1_score: 0.625
[epoch 70]  train_loss: 1.171  valid_loss: 1.241  train_f1_score: 0.745
valid_f1_score: 0.659
[epoch 80]  train_loss: 1.155  valid_loss: 1.232  train_f1_score: 0.764
```

```
valid_f1_score: 0.669
[epoch 90]  train_loss: 1.150  valid_loss: 1.250  train_f1_score: 0.732
valid_f1_score: 0.651
[epoch 100]  train_loss: 1.135  valid_loss: 1.216  train_f1_score: 0.785
valid_f1_score: 0.688
[epoch 110]  train_loss: 1.119  valid_loss: 1.217  train_f1_score: 0.797
valid_f1_score: 0.683
[epoch 120]  train_loss: 1.107  valid_loss: 1.224  train_f1_score: 0.780
valid_f1_score: 0.677
[epoch 130]  train_loss: 1.098  valid_loss: 1.207  train_f1_score: 0.825
valid_f1_score: 0.695
[epoch 140]  train_loss: 1.090  valid_loss: 1.206  train_f1_score: 0.830
valid_f1_score: 0.693
[epoch 150]  train_loss: 1.085  valid_loss: 1.214  train_f1_score: 0.852
valid_f1_score: 0.690
[epoch 160]  train_loss: 1.076  valid_loss: 1.213  train_f1_score: 0.840
valid_f1_score: 0.689
[epoch 170]  train_loss: 1.069  valid_loss: 1.208  train_f1_score: 0.858
valid_f1_score: 0.694
[epoch 180]  train_loss: 1.064  valid_loss: 1.210  train_f1_score: 0.860
valid_f1_score: 0.694
[epoch 190]  train_loss: 1.060  valid_loss: 1.200  train_f1_score: 0.868
valid_f1_score: 0.704
[epoch 200]  train_loss: 1.055  valid_loss: 1.207  train_f1_score: 0.874
valid_f1_score: 0.695
[epoch 210]  train_loss: 1.051  valid_loss: 1.207  train_f1_score: 0.871
valid_f1_score: 0.694
[epoch 220]  train_loss: 1.050  valid_loss: 1.203  train_f1_score: 0.870
valid_f1_score: 0.700
[epoch 230]  train_loss: 1.047  valid_loss: 1.215  train_f1_score: 0.862
valid_f1_score: 0.687
[epoch 240]  train_loss: 1.043  valid_loss: 1.202  train_f1_score: 0.885
valid_f1_score: 0.699
[epoch 250]  train_loss: 1.041  valid_loss: 1.208  train_f1_score: 0.872
valid_f1_score: 0.695
[epoch 260]  train_loss: 1.039  valid_loss: 1.204  train_f1_score: 0.893
valid_f1_score: 0.698
[epoch 270]  train_loss: 1.037  valid_loss: 1.211  train_f1_score: 0.870
valid_f1_score: 0.690
[epoch 280]  train_loss: 1.035  valid_loss: 1.209  train_f1_score: 0.899
valid_f1_score: 0.691
[epoch 290]  train_loss: 1.026  valid_loss: 1.204  train_f1_score: 0.891
valid_f1_score: 0.697
[epoch 300]  train_loss: 1.021  valid_loss: 1.229  train_f1_score: 0.894
valid_f1_score: 0.674
[epoch 310]  train_loss: 1.018  valid_loss: 1.229  train_f1_score: 0.882
valid_f1_score: 0.673
[epoch 320]  train_loss: 1.015  valid_loss: 1.250  train_f1_score: 0.847
```

```
valid_f1_score: 0.652
[epoch 330]  train_loss: 1.010  valid_loss: 1.234  train_f1_score: 0.891
valid_f1_score: 0.668
[epoch 340]  train_loss: 1.008  valid_loss: 1.219  train_f1_score: 0.902
valid_f1_score: 0.681
[epoch 350]  train_loss: 1.005  valid_loss: 1.217  train_f1_score: 0.910
valid_f1_score: 0.686
[epoch 360]  train_loss: 1.003  valid_loss: 1.212  train_f1_score: 0.908
valid_f1_score: 0.689
[epoch 370]  train_loss: 0.999  valid_loss: 1.222  train_f1_score: 0.918
valid_f1_score: 0.679
[epoch 380]  train_loss: 1.001  valid_loss: 1.217  train_f1_score: 0.924
valid_f1_score: 0.684
[epoch 390]  train_loss: 0.997  valid_loss: 1.208  train_f1_score: 0.918
valid_f1_score: 0.694
[epoch 400]  train_loss: 0.994  valid_loss: 1.205  train_f1_score: 0.934
valid_f1_score: 0.697
[epoch 410]  train_loss: 0.992  valid_loss: 1.225  train_f1_score: 0.920
valid_f1_score: 0.677
[epoch 420]  train_loss: 0.991  valid_loss: 1.210  train_f1_score: 0.920
valid_f1_score: 0.691
[epoch 430]  train_loss: 0.990  valid_loss: 1.213  train_f1_score: 0.921
valid_f1_score: 0.691
[epoch 440]  train_loss: 0.989  valid_loss: 1.211  train_f1_score: 0.928
valid_f1_score: 0.691
[epoch 450]  train_loss: 0.986  valid_loss: 1.208  train_f1_score: 0.948
valid_f1_score: 0.693
[epoch 460]  train_loss: 0.986  valid_loss: 1.197  train_f1_score: 0.930
valid_f1_score: 0.704
[epoch 470]  train_loss: 0.987  valid_loss: 1.206  train_f1_score: 0.935
valid_f1_score: 0.696
[epoch 480]  train_loss: 0.984  valid_loss: 1.215  train_f1_score: 0.945
valid_f1_score: 0.687
[epoch 490]  train_loss: 0.984  valid_loss: 1.220  train_f1_score: 0.938
valid_f1_score: 0.680
[epoch 500]  train_loss: 0.983  valid_loss: 1.210  train_f1_score: 0.941
valid_f1_score: 0.692
```

[ ]:
```
plot_curves(train_loss, valid_loss, train_f1_score, valid_f1_score,
 ↪print_epochs=PRINT_EPOCHS)
```



Compared to OneDCNN model, OneDCNN2 get a much better score around 95% for training data which is quite accurate.

On the contrary, the validation score stay around 70%. There is no significant improvement compared with OneDCNN model for the final score and may also have the problem of overfitting.

However, OneDCNN2 converge much faster than OneDCNN. Within 200 epochs, OneDCNN2 already reach 70% but it takes OneDCNN 600 epochs to get the same score.

7.1 Save model

[ ]:
```
torch.save(cla.state_dict(), PATH + "OneDCNN2_500.pt")
```

[ ]:
```
print(classification_report(cla.to("cuda").classify(X_valid.to("cuda")).cpu().
↪numpy(), y_valid.numpy()))
```

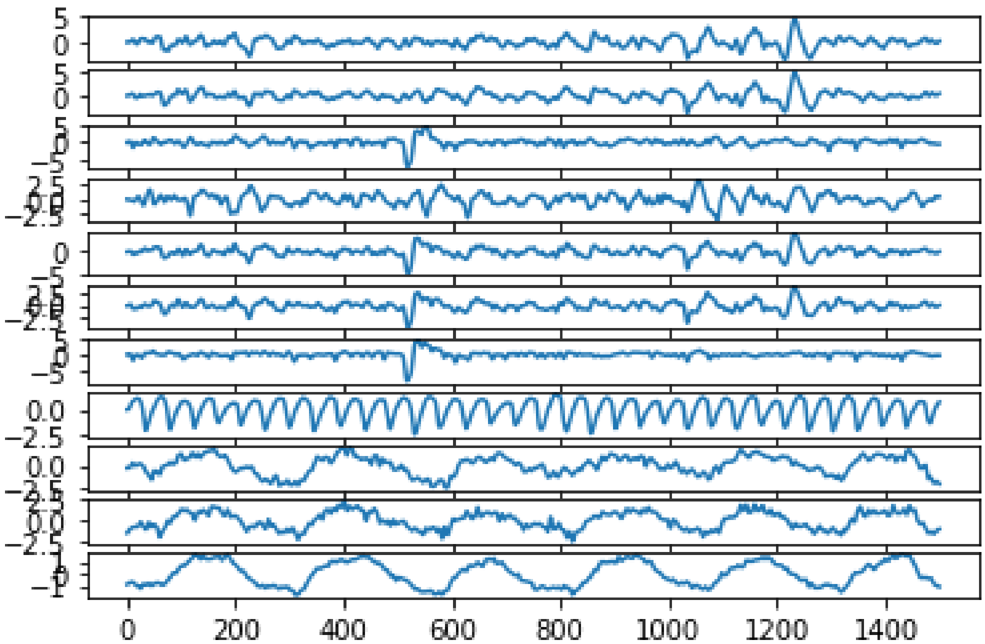
```
              precision    recall  f1-score   support

           0       0.70      0.68      0.69       378
           1       0.19      0.19      0.19       183
           2       0.72      0.76      0.74       853
           3       0.83      0.82      0.82       526
           4       0.68      0.64      0.66       529
```

```
    accuracy                           0.69      2469
   macro avg       0.62      0.62      0.62      2469
weighted avg       0.69      0.69      0.69      2469
```

8 Submission

Test set visualization

[ ]:
```
for i in range(11):
    plt.subplot(11,1,i+1);
    plt.plot(X_test[100][i]);
```



Load trained model

[ ]:
```
cla = OneDCNN2()
cla.load_state_dict(torch.load(PATH + "OneDCNN2_500.pt"))
cla.eval()
```

[ ]:
```
OneDCNN(
  (relu): ReLU()
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (conv_1): Conv1d(11, 64, kernel_size=(5,), stride=(3,))
  (conv_2): Conv1d(64, 128, kernel_size=(5,), stride=(1,))
  (max_pool_3): MaxPool1d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (dropout_4): Dropout(p=0.2, inplace=False)
```

```
  (conv_5): Conv1d(128, 128, kernel_size=(13,), stride=(1,))
  (conv_6): Conv1d(128, 256, kernel_size=(7,), stride=(1,))
  (max_pool_7): MaxPool1d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (conv_8): Conv1d(256, 256, kernel_size=(7,), stride=(1,))
  (conv_9): Conv1d(256, 64, kernel_size=(7,), stride=(1,))
  (max_pool_10): MaxPool1d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (conv_11): Conv1d(64, 32, kernel_size=(3,), stride=(1,))
  (conv_12): Conv1d(32, 64, kernel_size=(6,), stride=(1,))
  (max_pool_13): MaxPool1d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (conv_14): Conv1d(64, 8, kernel_size=(5,), stride=(1,))
  (conv_15): Conv1d(8, 8, kernel_size=(2,), stride=(1,))
  (max_pool_16): MaxPool1d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (dense_18): Linear(in_features=64, out_features=64, bias=True)
  (dropout_18): Dropout(p=0.2, inplace=False)
  (dense_19): Linear(in_features=64, out_features=5, bias=True)
  (softmax): Softmax(dim=-1)
)
```

[ ]:
```
submission
```

[ ]:

	index	sleep_stage
0	24688	0
1	24689	0
2	24690	0
3	24691	0
4	24692	0
…	…	…
24975	49663	2
24976	49664	4
24977	49665	4
24978	49666	4
24979	49667	0

[24980 rows x 2 columns]

Model predictions on test set

[ ]:
```
submission["sleep_stage"] = -1
for i in range(249):
    submission.loc[100*i:100*(i+1)-1, "sleep_stage"] = cla.
 ↪classify(X_test[100*i:100*(i+1)]).numpy()
submission.loc[24900:, "sleep_stage"] = cla.classify(X_test[24900:]).numpy()
```

[ ]:
```
submission
```

[ ]:

```
       index  sleep_stage
0      24688            0
1      24689            0
2      24690            0
3      24691            0
4      24692            0
…      …              …
24975  49663            4
24976  49664            1
24977  49665            4
24978  49666            4
24979  49667            0

[24980 rows x 2 columns]
```

[ ]:

```
submission.to_csv(PATH + "to_submit.csv", index=False)
```