# T-720 Custom Transformer Multiclass Classification

November 7, 2022

# 1 Initialisation

## 1.1 Imports and General Functions

[1]:
```
def IsNotebook():
    """Indicate the shell name, whether code is running on a notebook, and if␣
 ↪so whether it's hosted on googlecolab."""
    isnotebook, isgooglecolab, shell = None, None, None
    try:
        shell = get_ipython().__class__.__name__
        if shell == 'ZMQInteractiveShell':
            isnotebook, isgooglecolab = True, False   # Jupyter notebook or␣
 ↪qtconsole
        elif shell == "Shell":
            isnotebook, isgooglecolab = True, True    # Google Colab
        elif shell == 'TerminalInteractiveShell':
            isnotebook, isgooglecolab = False, False  # Terminal running IPython
        else:
            isnotebook, isgooglecolab = False, False  # Other type (?)
    except NameError:
        isnotebook, isgooglecolab = False, False      # Probably standard␣
 ↪Python interpreter
    return shell, isnotebook, isgooglecolab
shell, isnotebook, isgooglecolab = IsNotebook()
if isnotebook and not isgooglecolab: #If we are in a notebook but not on google␣
 ↪colab, let's use all the available screen
    from IPython.display import display, HTML
    display(HTML("<style>.container { width:99% !important; }</style>"))
    if not isgooglecolab:
        try: #Using the jedi completer takes too long to complete words
            %config Completer.use_jedi = False
        except:
            pass
if isgooglecolab: #If we are in a google colab environment, we probably need to␣
 ↪mount our google drive
    try:
        from google.colab import drive
```

```
        drive.mount('/content/drive')
    except Exception as e:
        print(e)
```

```
<IPython.core.display.HTML object>
```

[2]:

```
#######################
### General Imports ###
import os #Making sure we're using all CPU cores for faster calculations
IsWindows = os.name == 'nt'
os.environ["OMP_NUM_THREADS"] = str(os.cpu_count())
os.environ["OPENBLAS_NUM_THREADS"] = str(os.cpu_count())
os.environ["MKL_NUM_THREADS"] = str(os.cpu_count())
os.environ["VECLIB_MAXIMUM_THREADS"] = str(os.cpu_count())
os.environ["NUMEXPR_NUM_THREADS"] = str(os.cpu_count())

import sys #Printing version for posterity
print("Python version:", sys.version)

try: #Allows saving and loading of variables
    import pickle5 as pickle
except:
    import pickle
try: #Printing version for posterity
    print("Pickle version:", pickle.__version__)
except:
    print("Pickle version:", pickle.format_version)

import dill as dill #Allows even deeper saving (associated classes, etc., as␣
 ↪well)
print("Dill version:", dill.__version__)

import warnings #Ability to create custom warnings, like warnings.
 ↪warn("deprecated", DeprecationWarning)
import itertools #Needed for Confusion Matrix

if IsWindows:
    import winsound #Uses the computer's speakers to alert you (e.g. when␣
 ↪training is done)
from tqdm import tqdm #Iterations can show a progress bar (like in Training)
from collections import Counter #Allows for frequency counting similar with R's␣
 ↪"table"
from collections import OrderedDict
#######################


#####################
```

```python
### Date and Time ###
import time #Gets the current time
from pytz import timezone #Allows for timezones to be set. #pytz.all_timezones
from datetime import datetime #Allows for Datetime objects like current␣
↪Datetime. #datetime.fromisoformat('2021-05-24')
#There's also: np.datetime64('2021-08-01')
#####################


###################
### Mathematics ###
import numpy as np #Working with numeric arrays
print("Numpy version:", np.__version__)
from numpy.lib.stride_tricks import as_strided
###################


#######################################
### Statistics and Machine Learning ###
#Utility
from sklearn.preprocessing import OrdinalEncoder, StandardScaler, MinMaxScaler␣
↪#Various ways of scaling the data
from sklearn.model_selection import train_test_split

#Metrics
from sklearn.metrics import f1_score, precision_score, recall_score,␣
↪RocCurveDisplay, PrecisionRecallDisplay
from sklearn.metrics import roc_auc_score
from sklearn.metrics import confusion_matrix
#######################################


##################
### Dataframes ###
import pandas as pd
##################


#############
### Plots ###
import matplotlib.pyplot as plt #Allows use of Pyplot plots

import seaborn as sns #Allows use of Seaborn plots
sns.set() #Sets default plot theme

from matplotlib.ticker import AutoMinorLocator, MultipleLocator
#############
```

```
#########################
### Images / Pictures ###
from PIL import Image
#########################


######################
### String or Text ###
import json #Can encode or decode JSON string objects
import string #Provides functions for strings
######################


###################################
### Files, Directories, Folders ###
from pathlib import Path
###################################


################################
### Neural Network Libraries ###
#General
import torch
import torch.nn as nn
# from torchsummary import summary
if isgooglecolab:
    !pip install torchinfo
from torchinfo import summary

#Data
from torch.utils.data import Dataset, TensorDataset

#Images
from torchvision import datasets, transforms, models

#Info and configuration
print()
print(f"PyTorch v{torch.__version__}")
IS_GPU_AVAILABLE = torch.cuda.is_available()
print(f"CUDA device available: {IS_GPU_AVAILABLE}")
if (torch.cuda.is_available()):
    print(f"{torch.cuda.device_count()} devices available")
    for n in range(torch.cuda.device_count()):
        print("\t" + torch.cuda.get_device_name(n))
```

```python
    print(f"cuda: {torch.cuda.current_device()}") #It can give you information␣
 ↪like the GPU is not supported
print("Num threads set to:", os.cpu_count())
torch.set_num_threads(os.cpu_count())
################################


########################
### Useful functions ###
if "OrigFigSize" not in locals() and "OrigFigSize" not in globals(): #Just in␣
 ↪case Initialisation is re-run after any of these have chaned
    OrigFigSize   = plt.rcParams["figure.figsize"]

NonNans = lambda List: List[np.logical_not(np.isnan(List))]
LastNonNan = lambda List: NonNans(List)[-1] if np.sum(np.isnan(List)) <␣
 ↪len(List) else np.array([]) if type(List) == np.ndarray else []

def NpShift(arr, num, fill_value = np.nan):
    """Shift numpy array arr by num and fill shifted values with fill_value."""
    result = np.empty_like(arr)
    if num > 0:
        result[:num] = fill_value
        result[num:] = arr[:-num]
    elif num < 0:
        result[num:] = fill_value
        result[:num] = arr[-num:]
    else:
        result[:] = arr
    return result

def ZeroANumber(Number, MaxLength, ForceMaxLength = False):
    """Take a single Number and prepend '0's to it until it meets MaxLength, or␣
 ↪if ForceMaxLength then also clip digits from the end until it meets␣
 ↪MaxLength."""
    res = str(Number).zfill(MaxLength)
    if ForceMaxLength: res = res[:MaxLength]
    return res

def SpaceAString(CurString, MaxLength, SpaceTheFront = True, ForceMaxLength =␣
 ↪False, ForceRemoveFromFront = False):
    """Prepend/Append (SpaceTheFront) spaces to CurString until it meets␣
 ↪ForceMaxLength or if ForceMaxLength also Clip characters from the beginning/
 ↪end (ForceRemoveFromFront) until it meets ForceMaxLength."""
    CurLen = len(CurString)
    Result = CurString
```

```python
    if CurLen < MaxLength:
        if SpaceTheFront:
            Result = (" " * (MaxLength-CurLen)) + CurString
        else:
            Result = CurString + (" " * (MaxLength-CurLen))
    elif CurLen > MaxLength and ForceMaxLength:
        if ForceRemoveFromFront:
            Result = CurString[(CurLen - MaxLength):]
        else:
            Result = CurString[:-(CurLen - MaxLength)]
    return Result

def WriteText(TextParsableVar, FullFilePath):
    """Take a string (or string-parsable variable) and save it as text file on␣
↪the directory and with a name indicated by FullFilePath."""
    try:
        DirName = Path(FullFilePath).parent.absolute()
        os.makedirs(DirName, exist_ok = True)

        FileOptions = open(FullFilePath, "w")
        FileOptions.writelines(
            f"{TextParsableVar}"
        )
    except Exception as e:
        print(f"Exception:\n{e}")
    finally:
        try:
            FileOptions.close()
        except Exception:
            pass
SaveText = lambda TextParsableVar, FullFilePath: WriteText(TextParsableVar,␣
↪FullFilePath) #Alias for WriteText to be the same as Save/Load Variable

def ReadText(FullFilePath):
    """Read the string content of a text file given by FullFilePath and return␣
↪it as a string."""
    with open(FullFilePath, "r+", encoding = "utf8") as io:
        TextString = io.read()
    return TextString
LoadText = lambda FullFilePath: ReadText(FullFilePath) #Alias for ReadText to␣
↪be the same as Save/Load Variable

def SaveVariable(Variable, FileName):
    """Create the directory path for and pickle Variable under FileName."""
    DirName = Path(FileName).parent.absolute()
    os.makedirs(DirName, exist_ok = True)
    with open(FileName, 'wb') as io:
```

```python
        pickle.dump(Variable, io)

def SaveVariableDill(Variable, FileName):
    """Create the directory path for and deep-save Variable under FileName␣
 ↪using dill."""
    DirName = Path(FileName).parent.absolute()
    os.makedirs(DirName, exist_ok = True)
    with open(FileName, 'wb') as io:
        dill.dump(Variable, io)

def LoadVariable(FileName):
    """Un-pickle a binary file saved under FileName and return it as a variable.
 ↪"""
    with open(FileName, "rb") as io:
        Res = pickle.load(io)
    return Res

def LoadVariableDill(FileName):
    """Read the content of a binary file saved under FileName and return it as␣
 ↪a variable."""
    with open(FileName, 'rb') as io:
        Res = dill.load(io)
    return Res

def RemLastLine(s):
    """Remove the last line in the string s."""
    return s[:s.rfind('\n')]
########################

device = "cuda" if torch.cuda.is_available() else "cpu"
# device = "cpu" #To FORCE CPU
print("device=", device)
```

```
Python version: 3.10.6 | packaged by conda-forge | (main, Oct 24 2022, 16:02:16)
[MSC v.1916 64 bit (AMD64)]
Pickle version: 4.0
Dill version: 0.3.6
Numpy version: 1.23.4

PyTorch v1.13.0+cu117
CUDA device available: True
1 devices available
        NVIDIA GeForce RTX 2080 SUPER
cuda: 0
Num threads set to: 48
device= cuda
```

## 1.2 Architecture

[3]:
```
#Custom Transformer Encoder
class Custom_Tranformer_Encoder(nn.Module):
    """A custom PyTorch implementation of a Transformer Encoding layer."""
    def __init__(self, seq_size, input_size, num_heads, ff_dim, epsilon = 1e-6,␣
 ↪dropout = 0, activation = "relu"):
        super(Custom_Tranformer_Encoder, self).__init__()
        self.seq_size = seq_size
        self.input_size = input_size
        self.num_heads = num_heads
        self.ff_dim = ff_dim
        self.epsilon = epsilon
        self.dropout = dropout
        self.activation = activation

        self.layers = nn.ModuleList([
            nn.LayerNorm(self.input_size, eps = self.epsilon,␣
 ↪elementwise_affine = True),
            torch.nn.MultiheadAttention(self.input_size, self.num_heads,␣
 ↪dropout = self.dropout, bias = True, add_bias_kv = False, add_zero_attn =␣
 ↪False, kdim = None, vdim = None, batch_first = True),
            nn.Dropout(self.dropout),
            nn.LayerNorm(self.input_size, eps = self.epsilon,␣
 ↪elementwise_affine = True),
            nn.Conv1d(in_channels = self.seq_size, out_channels = self.ff_dim,␣
 ↪kernel_size = 1, stride = 1, padding = 0, dilation = 1, bias = True),
            self.GetActivationLayer(),
            nn.Dropout(self.dropout),
            nn.Conv1d(in_channels = self.ff_dim, out_channels = self.seq_size,␣
 ↪kernel_size = 1, stride = 1, padding = 0, dilation = 1, bias = True)
        ])

    def forward(self, inputs):
        """Take a PyTorch Tensor input and use the forward direction of the␣
 ↪Transformer to get an output of the same shape."""
        x_out = self.layers[0](inputs)
        x_out = self.layers[1](x_out, x_out, x_out)[0]
        x_out = self.layers[2](x_out)
        res = torch.add(x_out, inputs)
        x_out = self.layers[3](res)
        x_out = self.layers[4](x_out)
        x_out = self.layers[5](x_out)
        x_out = self.layers[6](x_out)
        x_out = self.layers[7](x_out)
        result = torch.add(x_out, res)
        return(result)
```

```python
    def GetActivationLayer(self):
        Result = None
        if (self.activation == "relu"): #Not differentiable at 0. Doesn't need␣
↪Greedy layer-wise pretraining (Hinton) because it doesn't suffer from␣
↪vanishing gradient
            Result = nn.ReLU()
        elif (self.activation == "relu6"):
            Result = nn.ReLU6()
        elif (self.activation == "elu"): #Like ReLu but allows values to be␣
↪negative, so they can be centred around 0, also potential vanishing gradient␣
↪on the left side but doesn't matter
            Result = nn.ELU(alpha = 0.1) #alpha: Slope on the left side
        elif (self.activation == "tanh"): #Suffers from Vanishing Gradient
            Result = nn.Tanh()
        elif (self.activation == "sigmoid"): #Suffers from Vanishing Gradient
            Result = nn.Sigmoid() #Result isn't centred around 0. Maximum␣
↪derivative: 0.25
        return Result

class Net(nn.Module):
    def __init__(self, T, K, num_units, activation, usebias, dropout, EluAlpha,␣
↪ReluAlpha, transf_nhead, transf_ff_dim, transf_l_norm, transf_drp = 0.1,␣
↪transf_actv = "relu"):
        super(Net, self).__init__()
        self.T = T
        self.K = K
        self.num_units = num_units
        self.activation = activation
        self.usebias = usebias
        self.dropout = dropout
        self.EluAlpha = EluAlpha
        self.ReluAlpha = ReluAlpha
        self.transf_nhead = transf_nhead
        self.transf_ff_dim = transf_ff_dim
        self.transf_l_norm = transf_l_norm
        self.transf_drp = transf_drp
        self.transf_actv = transf_actv

        self.layers = nn.ModuleList([
            Custom_Tranformer_Encoder(
                seq_size = self.T,
                input_size = self.num_units[0],
                num_heads = self.transf_nhead[0],
                ff_dim = self.transf_ff_dim[0],
                epsilon = self.transf_l_norm[0],
                dropout = self.transf_drp[0],
```

```
                activation = self.transf_actv[0]
            ),
            self.GetActivationLayer(0),
            nn.Dropout(p = self.dropout[0], inplace = False),
            nn.Linear(in_features = (self.T * self.num_units[1]), out_features = self.num_units[2], bias = self.usebias[1]),
            self.GetActivationLayer(1),
            nn.Dropout(p = self.dropout[1], inplace = False),
            nn.Linear(in_features = self.num_units[2], out_features = self.num_units[3], bias = self.usebias[2]),
            self.GetActivationLayer(2),
            nn.Dropout(p = self.dropout[2], inplace = False),
            nn.Linear(in_features = self.num_units[3], out_features = self.K, bias = self.usebias[3])
        ])

    def forward(self, x):
        out = self.layers[0](x)
        out = out.view(out.shape[0], -1)
        out = self.layers[1](out)
        out = self.layers[2](out)
        out = self.layers[3](out)
        out = self.layers[4](out)
        out = self.layers[5](out)
        out = self.layers[6](out)
        out = self.layers[7](out)
        out = self.layers[8](out)
        out = self.layers[9](out)
        return out

    def GetActivationLayer(self, layer):
        Result = None
        if (self.activation[layer] == "relu"): #Not differentiable at 0. Doesn't need Greedy layer-wise pretraining (Hinton) because it doesn't suffer from vanishing gradient
            Result = nn.LeakyReLU(self.ReluAlpha) if self.ReluAlpha != 0 else nn.ReLU() #alpha: Controls the angle of the negative slope
        elif (self.activation[layer] == "relu6"):
            Result = nn.ReLU6()
        elif (self.activation[layer] == "elu"): #Like ReLu but allows values to be negative, so they can be centred around 0, also potential vanishing gradient on the left side but doesn't matter
            Result = nn.ELU(alpha = self.EluAlpha) #alpha: Slope on the left side
        elif (self.activation[layer] == "tanh"): #Suffers from Vanishing Gradient
```

```
            Result = nn.Tanh()
        elif (self.activation[layer] == "sigmoid"): #Suffers from Vanishing␣
 ↪Gradient
            Result = nn.Sigmoid() #Result isn't centred around 0. Maximum␣
 ↪derivative: 0.25
        return Result
print("Done")
```

```
Done
```

### 1.3 Dataset Functions

[4]:
```
def train_valid_test_split(X_Data, train_size, valid_size, Y_Data = None,␣
 ↪random_state = None, shuffle = True, stratify = None):
    """Split the dataset, optionally in a stratified manner, into a Train,␣
 ↪Validation and Test set"""

    if (type(train_size) == int and sum([train_size, valid_size]) >=␣
 ↪len(X_Data)) or (type(train_size) != int and sum([train_size, valid_size])␣
 ↪>= 1):
        raise ValueError(f"The train_size [{train_size}] + the valid_size␣
 ↪[{valid_size}] should sum up to less than 100% so that there's some␣
 ↪percentage left for the test set")

    TrainIdx, ValidTestIdx = train_test_split(np.arange(len(X_Data)),␣
 ↪train_size = train_size, shuffle = shuffle, stratify = stratify,␣
 ↪random_state = random_state)
    TrainX     = X_Data[TrainIdx]
    ValidTestX = X_Data[ValidTestIdx]
    if Y_Data is not None:
        TrainY     = Y_Data[TrainIdx]
        ValidTestY = Y_Data[ValidTestIdx]

    if type(train_size) != int: #For the 2nd split we need the validation␣
 ↪percent relative to the Valid/Test portion of the dataset alone
        test_size  = 1 - train_size - valid_size #Actual test size
        valid_size = 1 - (test_size / (valid_size + test_size)) #Relative (to␣
 ↪ValidTest) valid size
        test_size  = 1 - valid_size #Relative (to ValidTest) test size

    if Y_Data is not None:
        ValidX, TestX, ValidY, TestY = train_test_split(ValidTestX, ValidTestY,␣
 ↪train_size = valid_size, shuffle = shuffle, stratify =␣
 ↪stratify[ValidTestIdx] if stratify is not None else None, random_state =␣
 ↪random_state)
        return TrainX, ValidX, TestX, TrainY, ValidY, TestY
    else:
```

```python
        ValidX, TestX = train_test_split(ValidTestX, train_size = valid_size, shuffle = shuffle, stratify = stratify[ValidTestIdx] if stratify is not None else None, random_state = random_state)
        return TrainX, ValidX, TestX
```

[5]:

```python
def Scale(x_data, scaler_mean, scaler_sd, verbose = True):
    """Scale a Torch Tensor or Numpy Array to have zero mean and unit variance."""
    if isinstance(x_data, torch.Tensor):
        if (isinstance(scaler_mean, np.number) or isinstance(scaler_sd, np.number)) and x_data.shape[1] != 1:
            if verbose:
                print("Info: Scaler is a scalar but X's observations are not. Safely ignore this if you intended to normalise with scalar parameters.")
            return ((x_data - scaler_mean) / scaler_sd).float()
        else:
            return ((x_data - torch.from_numpy(scaler_mean)) / torch.from_numpy(scaler_sd)).float()
    elif isinstance(x_data, np.ndarray):
        if verbose and (isinstance(scaler_mean, np.number) or isinstance(scaler_sd, np.number)) and x_data.shape[1] != 1:
            print("Info: Scaler is a scalar but X's observations are not. Safely ignore this if you intended to normalise with scalar parameters.")
        return ((x_data - scaler_mean) / scaler_sd).astype(np.float32)
    else:
        raise Exception("Cannot scale the variable because it is neither a Torch Tensor nor a Numpy Array")
        return None

def UnScale(x_data, scaler_mean, scaler_sd, verbose = True):
    """Inverse the scaling of a Torch Tensor or Numpy Array that currently have zero mean and unit variance."""
    if isinstance(x_data, torch.Tensor):
        if (isinstance(scaler_mean, np.number) or isinstance(scaler_sd, np.number)) and x_data.shape[1] != 1:
            if verbose:
                print("Info: Scaler is a scalar but X's observations are not. Safely ignore this if you intended to normalise with scalar parameters.")
            return ((x_data * scaler_sd) + scaler_mean).float()
        else:
            return ((x_data * torch.from_numpy(scaler_sd)) + torch.from_numpy(scaler_mean)).float()
    elif isinstance(x_data, np.ndarray):
        if verbose and (isinstance(scaler_mean, np.number) or isinstance(scaler_sd, np.number)) and x_data.shape[1] != 1:
```

```
            print("Info: Scaler is a scalar but X's observations are not.␣
↪Safely ignore this if you intended to normalise with scalar parameters.")
        return ((x_data * scaler_sd) + scaler_mean).astype(np.float32)
    else:
        raise Exception("Cannot unscale the variable because it is neither a␣
↪Torch Tensor nor a Numpy Array")
        return None
```

[6]:
```
def GetConvPaddingAndOutputSizes(T_Length, conv_input_size, input_size,␣
↪layer_type, conv_mode, conv_filter_size, conv_stride, conv_dilation,␣
↪conv_pool_padding, conv_pool_dilation, conv_pool_size, conv_pool_stride,␣
↪conv_global_maxpool_instead_of_flatten, H1, W1, num_units, bidir_rnns):
    """Calculate the padding and output size each convolutional layer in the␣
↪network.

    In tensorflow or so, the output size of each consecutive layer is␣
↪automatically calculated and passed as an input the the next layer in line.
    The same applies for the padding size needed on X to achieve "full", "same"␣
↪or "valid" size, however we need to calculate them in PyTorch.
    """
    conv_padding = []
    try:
        conv_output_size = [conv_input_size[0]] #If T_Length is not None then␣
↪conv_input_size=TxD and we need D to get lower with mode=="valid"
    except:
        conv_output_size = [input_size]

    if (any([x in ["conv", "stridedconv", "convpool"] for x in layer_type])):
        for i in range(len(layer_type)):
            if (layer_type[i] in ["conv", "stridedconv", "convpool"]):
                if (conv_mode[i] == "same"):
                    conv_padding.append((conv_filter_size - 1) // 2)
                elif (conv_mode[i] == "valid"):
                    conv_padding.append(0)
                elif (layer_type[i] not in ["convpool"] and conv_mode[i] is␣
↪None):
                    conv_padding.append((conv_filter_size - 1) // 2) #If it's␣
↪not convpool then this isn't used and the size remains the same like in␣
↪"same"
                else:
                    conv_padding.append("UnknownPadding")
                    conv_output_size.append("UnknownPadding")

                tmpStride = 1 if layer_type[i] != "stridedconv" else conv_stride
                conv_output_size.append(int(np.floor((
```

```
                    (conv_output_size[len(conv_output_size)-1] +␣
↪2*conv_padding[len(conv_padding)-1] - conv_dilation*(conv_filter_size-1) -␣
↪1) / tmpStride
                ) + 1
                )))

                if (layer_type[i] == "convpool"):
                    conv_output_size[len(conv_output_size)-1] = int(np.
↪floor(((conv_output_size[len(conv_output_size)-1] + 2*conv_pool_padding -␣
↪conv_pool_dilation*(conv_pool_size-1) - 1) / conv_pool_stride) + 1))

                if (i == len(layer_type) - 1) or (layer_type[i+1] == "dense"):
                    if conv_global_maxpool_instead_of_flatten:
                        conv_output_size.
↪append(conv_output_size[len(conv_output_size)-1] ** (2 if T_Length is None␣
↪and H1>0 and W1>0 else 1)) # " **2 " as in: once for the Width and once for␣
↪Height #If we globalmaxpool, then num_units[i+1] disappear
                    elif (i != 0) and (layer_type[i-1] in ["gru", "rnn",␣
↪"lstm"]):
                        conv_output_size.
↪append(conv_output_size[len(conv_output_size)-1] * num_units[i+1])
                    else:
                        conv_output_size.
↪append((conv_output_size[len(conv_output_size)-1] ** (2 if T_Length is None␣
↪and H1>0 and W1>0 else 1)) * num_units[i+1]) # " **2 " as in: once for the␣
↪Width and once for Height

            elif (layer_type[i] in ["transfenc", "customtransfenc"]):
                conv_padding.append(None)
                conv_output_size.append(conv_output_size[-1]) # D dimension␣
↪will remain the same on a Transformer Encoding Layer

            elif (layer_type[i] in ["gru", "rnn", "lstm"]):
                conv_padding.append(None)
                conv_output_size.append(num_units[i+1] * 2 if bidir_rnns[i]␣
↪else num_units[i+1])

            else:
                conv_padding.append(None)
                conv_output_size.append(num_units[i+1])
        conv_output_size = conv_output_size[1:]
    return(conv_padding, conv_output_size)
```

### 1.4 Optimisation Functions

[7]:
```python
def ClassAccMulti(Targets, Preds, K):
    """Calculate the Class-Wise accuracy for a multi-class task"""
    return(np.mean([(Targets == k) == (Preds == k) for k in range(K)]))
```

[8]:
```python
def AccCalculation(Y_Hat, Targets):
    """Calculate the Accuracy given the Actual values and Predictions for␣
 ↪Binary and Multiclass Classification."""
    if isinstance(Targets, torch.Tensor):
        Targets = Targets.cpu().numpy()

    if isinstance(Y_Hat, torch.Tensor):
        Y_Hat = Y_Hat.cpu().numpy()

    return np.mean(Y_Hat.squeeze() == Targets.squeeze())
```

[9]:
```python
def AUCCalculation(Targets, Y_Prob, Y_Hat, Verbose = True):
    """Calculate the Area Under the Receiver Operating Characteristic Curve␣
 ↪given the Actual values and Predictions for Binary and Multiclass␣
 ↪Classification using sklearn's roc_auc_score()."""
    if isinstance(Targets, torch.Tensor):
        Targets = Targets.cpu().numpy()

    if isinstance(Y_Prob, torch.Tensor):
        Y_Prob = Y_Prob.cpu().numpy()

    if isinstance(Y_Hat, torch.Tensor):
        Y_Hat = Y_Hat.cpu().numpy()

    try:
        CurMetric2 = roc_auc_score(Targets, Y_Prob, multi_class = "ovr",␣
 ↪average = 'weighted') #Calculating Weighted AUC #Cares for performance both␣
 ↪in Positives and Negatives (but may not fare well with heavy class imbalance)
    except Exception as exc:
        CurMetric2 = np.nan
        if Verbose:
            warnings.warn(f"\nAn error occurred in AUC calculation (probably␣
 ↪because of missing classes in the random batch of data?).\nThe error reads:␣
 ↪{exc}")
            print("AUC Warning. set(Targets):", list(set(Targets.reshape(-1))),␣
 ↪"set(Outputs): ", list(set(Y_Hat.reshape(-1))))

    return CurMetric2
```

[10]:
```python
def F1ScoreCalculation(Targets, Y_Hat):
```

```python
    """Calculate the F1 score given the Actual values and Predictions for␣
↪Binary and Multiclass Classification using sklearn's f1_score()."""
    if isinstance(Targets, torch.Tensor):
        Targets = Targets.cpu().numpy()

    if isinstance(Y_Hat, torch.Tensor):
        Y_Hat = Y_Hat.cpu().numpy()

    try:
        CurMetric3 = f1_score(Targets, Y_Hat, average = 'weighted')␣
↪#Calculating Weighted F1 #Cares about balance between Precision and Recall␣
↪(Sensitivity)
    except Exception as exc:
        CurMetric3 = np.nan
        warnings.warn(f"\nAn error occurred in F1 score calculation (probably␣
↪because of missing classes in the random batch of data?).\nThe error reads:␣
↪{exc}")

    return CurMetric3
```

[11]:
```python
def PrintIterationMetrics(it, epochs, t0, train_loss, test_loss, first_metric,␣
↪first_metric_Name, second_metric, second_metric_Name, third_metric,␣
↪third_metric_Name, MaxTrainLossLen, MaxTestLossLen, MaxMetric1Len,␣
↪MaxMetric2Len, MaxMetric3Len):
    """Print information about the Current Epoch, Train/Test losses as well as␣
↪metrics and duration, and return the Max length of each metric viewed as a␣
↪string in order to keep a consistent text alignment amongst consecutive␣
↪epochs."""
    dt = datetime.now() - t0

    strTrainLoss = f"{train_loss:.4f}"
    strTestLoss = f"{test_loss:.4f}"
    strMetric1 = f'{first_metric:.3f}'
    strMetric2 = f'{second_metric:.3f}'
    strMetric3 = f'{third_metric:.3f}'
    if it == 0:
        MaxTrainLossLen = len(strTrainLoss)
        MaxTestLossLen = len(strTestLoss)
        MaxMetric1Len = len(strMetric1)
        MaxMetric2Len = len(strMetric2)
        MaxMetric3Len = len(strMetric3)
    print(f'Epoch {ZeroANumber(it+1, len(str(epochs)))}/{epochs}, Train Loss:␣
↪{SpaceAString(strTrainLoss, MaxTrainLossLen)}, Test Loss:␣
↪{SpaceAString(strTestLoss, MaxTestLossLen)} | {first_metric_Name}:␣
↪{SpaceAString(strMetric1, MaxMetric1Len)}, {second_metric_Name}:␣
↪{SpaceAString(strMetric2, MaxMetric1Len)}, {third_metric_Name}:␣
↪{SpaceAString(strMetric3, MaxMetric1Len)}, Duration: {dt}')
```

```
    return MaxTrainLossLen, MaxTestLossLen, MaxMetric1Len, MaxMetric2Len,␣
↪MaxMetric3Len
```

[12]:
```
def UpdateMetricsAndSaveModel(model, train_loss, test_loss, train_best_loss,␣
↪test_best_loss, CurMetric1, Metric1, CurMetric2, Metric2, CurMetric3,␣
↪Metric3):
    """if current model outperform's best model, save current model's state and␣
↪update best performance metrics to reflect this model's."""
    if (test_loss < test_best_loss): #Saving the model if it outperforms␣
↪previous iteration's model
        test_best_loss = test_loss
        train_best_loss = train_loss
        torch.save(model.state_dict(), f"model_dict.pt") #Saving Model's␣
↪Dictionary

        if np.isfinite(CurMetric1) and CurMetric1 >= Metric1:
            Metric1 = CurMetric1
            Metric2 = CurMetric2
            Metric3 = CurMetric3
            torch.save(model.state_dict(), f"acc_model_dict.pt") #Saving␣
↪Model's Dictionary
    return train_best_loss, test_best_loss, Metric1, Metric2, Metric3
```

[13]:
```
def PrintFinishingInformation(start_time, JustCalculateElapsedTime = False):
    """Calculate and print (and return) the elapsed time over all the training␣
↪epochs."""
    elapsed_time = time.time() - start_time
    if not JustCalculateElapsedTime:
        FinishedOn = datetime.now(timezone('Europe/Athens')).strftime("%a,␣
↪%Y-%m-%d %H:%M %Z %z")
        print("Done (" + FinishedOn + ") Elapsed time: " +␣
↪str(round(elapsed_time, 1)) + " seconds")

    return elapsed_time
```

[14]:
```
def TrainModel(model, optimiser, criterion, X_Train, Y_Train):
    """Train by calculating the gradients and taking one step."""
    model.train() #Putting model in training mode so that things like dropout()␣
↪are activated again

    optimiser.zero_grad() #Initialisation of the gradient of
    outputs = model(X_Train) #Getting the prediction using the forward␣
↪direction of the Neural Net

    loss = criterion(outputs.squeeze(), Y_Train.squeeze()) #Calculating the␣
↪loss according to the loss function
```

```
    loss.backward() #Calculating the Gradient Δ of the loss function with␣
↪respect to the parameters

    optimiser.step() #Calculates and updates the parameters   using gradient␣
↪descent, as   =   - *Δ

    return optimiser, outputs, loss
```

[15]:
```
def EvaluateModelFromPreds(criterion, Y_Prob, Targets, Verbose):
    """Use the forward direction of the model following with a␣
↪sigmoid+threshold or softmax+argmax for binary or multiclass classification␣
↪respectively, and calculate and return the predictions and evaluation␣
↪metrics."""
    with torch.no_grad(): #Making sure that we don't update the gradient␣
↪outside the training part
        loss_scalar = criterion(Y_Prob.squeeze(), Targets.squeeze()).item()␣
↪#Calculating the loss according to the loss function

        Y_Prob = nn.Softmax(dim = 1)(Y_Prob) #dim: every slice along dim will␣
↪sum to 1
        _, Y_Hat = torch.max(Y_Prob, 1) #Prediction. torch.max returns both max␣
↪(value) and argmax (index)

        CurMetric1, CurMetric2, CurMetric3 = GetCategoricalMetrics(Y_Prob.
↪squeeze(), Y_Hat.squeeze(), Targets, Verbose = Verbose)
        return loss_scalar, CurMetric1, CurMetric2, CurMetric3
```

[16]:
```
def EvalForwardPass(model, inputs, criterion = None, Targets = None): #This is␣
↪used at the very end on "Evaluation" Section. Unifies the forward pass, but␣
↪doesn't calculate loss/metrics like EvaluateModel() does as we need greater␣
↪granularity.
    """Use the forward direction of the model, potentially following with a␣
↪sigmoid+threshold or softmax+argmax for binary or multiclass classification␣
↪respectively."""

    if Targets is not None and criterion is None:
        warnings.warn(f"\nTargets are present but loss cannot be calculated␣
↪because criterion is None.")

    model.eval() #Putting model in evaluation mode so that things like␣
↪dropout() are deactivated
    with torch.no_grad(): #Making sure that we don't update the gradient␣
↪outside the training part
        Y_Prob = model(inputs) #Getting the prediction using the forward␣
↪direction of the Neural Net
```

```
        if Targets is not None:
            loss_scalar = criterion(Y_Prob.squeeze(), Targets.squeeze()).item()␣
↪#Calculating the loss according to the loss function

        Y_Prob = nn.Softmax(dim = 1)(Y_Prob) #dim: every slice along dim will␣
↪sum to 1
        _, Y_Hat = torch.max(Y_Prob, 1) #Prediction. torch.max returns both max␣
↪(value) and argmax (index)

    if Targets is not None:
        return Y_Prob, Y_Hat, loss_scalar
    else:
        return Y_Prob, Y_Hat
```

[17]:
```
def FixFormatAndDTypes(device, Inputs, Targets):
    """Ensure that the Inputs and Targets are Torch Tensors and of the correct␣
↪shape and dtype before returning them."""
    if isinstance(Inputs, np.ndarray):
        Inputs = torch.from_numpy(Inputs)
    if isinstance(Targets, np.ndarray):
        Targets = torch.from_numpy(Targets)

    Inputs = Inputs.to(device)
    Targets = Targets.squeeze().to(device).long()

    return Inputs, Targets
```

### 1.5 Evaluation Functions

[18]:
```
def plot_confusion_matrix(cm, classes, normalise = False, title = 'Confusion␣
↪matrix', colourmap = plt.cm.Blues):
    """Plot the Confusion Matrix object returned by sklearn's␣
↪confusion_matrix() and normalise it if normalise==True."""
    plt.grid(False)
    if normalise:
        print('Confusion matrix')
        print(cm)
        cm = cm.astype('float') / cm.sum(axis = 1)[:, np.newaxis]
        plt.imshow(cm, interpolation = 'nearest', cmap = colourmap)
        plt.clim(0.0, 1.0)
    else:
        plt.imshow(cm, interpolation = 'nearest', cmap = colourmap)
    plt.title(title)
    with warnings.catch_warnings():
        warnings.simplefilter("ignore")
        plt.colorbar()
    tick_marks = np.arange(len(classes))
```

```
    plt.xticks(tick_marks, classes, rotation = 45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalise else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment = "center",
                 color = "white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()

def PlotHistory(Train_History, Test_History = None, Key = "Loss", figsize = (12, 8), MajorLineStyle = "--", MinorLineStyle = ":", MajorLines = 10, MinorInbetweenLinesEvery = 4, test_alpha = 1.0):
    """Plot a juxtaposition of a Train and Test metric (parametrised by Key), usually 'Loss'"""
    fig, ax = plt.subplots(figsize = figsize)
    plt.plot(Train_History, label = f"Train {Key}")
    if (Test_History is not None):
        plt.plot(Test_History, label = f"Test {Key}", alpha = test_alpha)
    xfrom, xto = ax.get_xlim()
    yfrom, yto = ax.get_ylim()
    ax.xaxis.set_major_locator(MultipleLocator(int(np.ceil((xto-xfrom)/MajorLines))))
    ax.yaxis.set_major_locator(MultipleLocator((yto-yfrom)/MajorLines))
    ax.xaxis.set_minor_locator(AutoMinorLocator(MinorInbetweenLinesEvery))
    ax.yaxis.set_minor_locator(AutoMinorLocator(MinorInbetweenLinesEvery))
    ax.grid(which = 'major', color='#FFFFFF', linestyle = MajorLineStyle)
    ax.grid(which = 'minor', color='#CCCCCC', linestyle = MinorLineStyle)
    plt.legend()
    plt.show()
    return None

def PlotAllMetrics(Titles, TrainMetrics, TestMetrics = None, figsize = [19, 13], test_alpha = 1.0):
    fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize = figsize)
    ax1.set_title(Titles[0])
    ax1.plot(TrainMetrics[0], label = f"Train")
    if TestMetrics is not None:
        ax1.plot(TestMetrics[0], label = f"Test", alpha = test_alpha)
    ax1.legend()
    ax2.set_title(Titles[1])
    ax2.plot(TrainMetrics[1], label = f"Train")
```

```
    if TestMetrics is not None:
        ax2.plot(TestMetrics[1], label = f"Test", alpha = test_alpha)
    ax2.legend()
    ax3.set_title(Titles[2])
    ax3.plot(TrainMetrics[2], label = f"Train")
    if TestMetrics is not None:
        ax3.plot(TestMetrics[2], label = f"Test", alpha = test_alpha)
    ax3.legend()
    ax4.set_title(Titles[3])
    ax4.plot(TrainMetrics[3], label = f"Train")
    if TestMetrics is not None:
        ax4.plot(TestMetrics[3], label = f"Test", alpha = test_alpha)
    ax4.legend()
    plt.show()
    return None
```

[19]:
```
def GetCategoricalMetrics(Y_Prob, Y_Hat, Targets, Verbose = True):
    """Calculate Categorical variable metrics (Accuracy, Area Under the Curve,␣
 ↪F1 score) given the class Probability vector (binary) / matrix (multiclass),␣
 ↪the class index (0 to K-1), and the Actual values."""
    test_Acc = AccCalculation(Y_Hat, Targets)
    test_AUC = AUCCalculation(Targets, Y_Prob, Y_Hat, Verbose = Verbose)
    test_F1 = F1ScoreCalculation(Targets, Y_Hat)

    return test_Acc, test_AUC, test_F1
```

[20]:
```
def PlotCategoricalMetrics(Y_Hat, Targets, ClassNames, normalise, figsize =␣
 ↪None):
    """Plots the Confusion matrix given the class index (0 to K-1), and the␣
 ↪Actual values."""
    PrevFigSize = plt.rcParams['figure.figsize']
    plt.rcParams['figure.figsize'] = figsize if figsize is not None else␣
 ↪PrevFigSize

    cm = confusion_matrix(Targets, Y_Hat)
    plot_confusion_matrix(cm, ClassNames, normalise = normalise)

    plt.rcParams['figure.figsize'] = PrevFigSize
```

[21]:
```
# def EvalPredict(model, device, test_loader_or_X_Test):
#     """Use EvalForwardPass() to use the forward direction of the model and␣
 ↪return the Y_probability, Y_Hat, and respective Y given X."""
#     Preds_prob = []
#     Preds = []
#     Targets = []
```

```
#     for inputs, targets in tqdm(test_loader_or_X_Test, total =
↪len(test_loader_or_X_Test), leave = False):
#         inputs, targets = FixFormatAndDTypes(device, inputs, targets)
#         outputs_prob, outputs = EvalForwardPass(model, inputs, criterion =
↪None, Targets = None)

#         Preds_prob.append(outputs_prob)
#         Preds.append(outputs)
#         Targets.append(targets)

#     Preds_prob = torch.cat(Preds_prob).cpu().numpy()
#     Preds = torch.cat(Preds).cpu().numpy()
#     Targets = torch.cat(Targets).cpu().numpy()

#     del inputs
#     del outputs_prob
#     del outputs
#     del targets
#     if IS_GPU_AVAILABLE:
#         torch.cuda.empty_cache()

#     return Preds_prob, Preds, Targets

def EvalPredict(model, test_batch_size, device, X_Test, Y_Test, print_batch_num
↪= True):
    """Use EvalForwardPass() to use the forward direction of the model and
↪return the Y_probability, Y_Hat, and respective Y given X."""
    Preds_prob = []
    Preds = []
    Targets = []

    test_inputs = X_Test
    test_targets = Y_Test

    test_batches_per_epoch = int(np.ceil(test_targets.shape[0] /
↪test_batch_size))
    print(f"#batches: {test_batches_per_epoch}.") if print_batch_num else None

    #for j in range(test_batches_per_epoch):
    for j in tqdm(range(test_batches_per_epoch), total =
↪test_batches_per_epoch, leave = False):
        inputs  = test_inputs[ j*test_batch_size : (j+1)*test_batch_size].copy()
        targets = test_targets[j*test_batch_size : (j+1)*test_batch_size].copy()

        inputs, targets = FixFormatAndDTypes(device, inputs, targets)
```

```
        Y_Prob, Y_Hat = EvalForwardPass(model, inputs, criterion = None,␣
↪Targets = None)

        Preds_prob.append(Y_Prob)
        Preds.append(Y_Hat)
        Targets.append(targets)

    Preds_prob = torch.cat(Preds_prob).cpu().numpy()
    Preds = torch.cat(Preds).cpu().numpy()
    Targets = torch.cat(Targets).cpu().numpy()

    del inputs
    del Y_Prob
    del Y_Hat
    del targets
    if IS_GPU_AVAILABLE:
        torch.cuda.empty_cache()

    return Preds_prob, Preds, Targets
```

[22]:
```
def PlotPerClassMetrics(K_Length, PerClassAccuracy, PerClassAUC, PerClassF1,␣
↪Labels = None):
    fig, ((ax1), (ax2), (ax3)) = plt.subplots(1, 3, figsize = [min(1.2 *␣
↪K_Length, 13.3) * 3, 4], sharey = True)
    if Labels is not None:
        sn1 = sns.barplot(ax = ax1, x = Labels, y = np.round(PerClassAccuracy,␣
↪3)) #Names might not fit if names or along or too many
    else:
        sn1 = sns.barplot(ax = ax1, x = list(range(K_Length)), y =␣
↪PerClassAccuracy)
    for i in sn1.containers:
        sn1.bar_label(i,)
    ax1.set_title("Classes' Accuracies")
    ax1.set_xlabel("Class")
    ax1.set_ylabel("Accuracy")

    if Labels is not None:
        sn2 = sns.barplot(ax = ax2, x = Labels, y = np.round(PerClassAUC, 3))␣
↪#Names might not fit if names or along or too many
    else:
        sn2 = sns.barplot(ax = ax2, x = list(range(K_Length)), y = PerClassAUC)
    for i in sn2.containers:
        sn2.bar_label(i,)
    ax2.set_title("Classes' AUCs")
    ax2.set_xlabel("Class")
    ax2.set_ylabel("AUC")
```

```
    if Labels is not None:
        sn3 = sns.barplot(ax = ax3, x = Labels, y = np.round(PerClassF1, 3))␣
↪#Names might not fit if names or along or too many
    else:
        sn3 = sns.barplot(ax = ax3, x = list(range(K_Length)), y = PerClassF1)
    for i in sn3.containers:
        sn3.bar_label(i,)
    ax3.set_title("Classes' F1s")
    ax3.set_xlabel("Class")
    ax3.set_ylabel("F1")

    plt.show()

def PlotPerClassROCCurve(K_Length, TrueClasses, Preds_prob, Labels = None):
    Width  = int(np.ceil(np.sqrt(K_Length))) + 1
    Height = int(np.floor(np.sqrt(K_Length))) - (1 if K_Length % Width == 0␣
↪else 0)
    fig, ax = plt.subplots(Height, Width, figsize = [min(5 * Width, 40), min(5␣
↪* Height, 40)])
    if Height == 1:
        ax = [ax]
    k = -1
    for HeightIdx in range(Height):
        for WidthIdx in range(Width):
            k += 1
            if (k + 1) > K_Length:
                ax[HeightIdx][WidthIdx].grid(False)
                ax[HeightIdx][WidthIdx].set_axis_off()
                continue
            cur_ax = RocCurveDisplay.from_predictions(TrueClasses[k],␣
↪Preds_prob[:, k], ax = ax[HeightIdx][WidthIdx])
            ax[HeightIdx][WidthIdx].set_title(f"{Labels[k] if Labels is not␣
↪None else k}")
            ax[HeightIdx][WidthIdx].plot(np.linspace(0, 1, num = 20), np.
↪linspace(0, 1, num = 20), 'b--')
    plt.show()

def PlotPerClassPRCurve(K_Length, TrueClasses, Preds_prob, Labels = None):
    Width  = int(np.ceil(np.sqrt(K_Length))) + 1
    Height = int(np.floor(np.sqrt(K_Length))) - (1 if K_Length % Width == 0␣
↪else 0)
    fig, ax = plt.subplots(Height, Width, figsize = [min(5 * Width, 40), min(5␣
↪* Height, 40)])
    if Height == 1:
        ax = [ax]
    k = -1
```

```
    for HeightIdx in range(Height):
        for WidthIdx in range(Width):
            k += 1
            if (k + 1) > K_Length:
                ax[HeightIdx][WidthIdx].grid(False)
                ax[HeightIdx][WidthIdx].set_axis_off()
                continue
            cur_ax = PrecisionRecallDisplay.from_predictions(TrueClasses[k],␣
↪Preds_prob[:, k], ax = ax[HeightIdx][WidthIdx])
            ax[HeightIdx][WidthIdx].set_title(f"{Labels[k] if Labels is not␣
↪None else k}")
            ax[HeightIdx][WidthIdx].plot(1 - np.linspace(0, 1, num = 20), np.
↪linspace(0, 1, num = 20), 'b--')
    plt.show()
```

### 1.6 Gradient Descent Functions

[23]:
```
def minibatch_gd(model, device, criterion, optimiser, scheduler, D_Length,␣
↪X_Train, Y_Train, X_Test, Y_Test, epochs, batch_size, ShufflePerIteration,␣
↪PrintInfoEverynEpochs, train_best_loss, test_best_loss, BestMetric1,␣
↪BestMetric2, BestMetric3, print_batch_num,\
                 Verbose = True, test_batch_size = None):
    """Use the Train, Evaluation, Metrics calculation and printing functions to␣
↪train a model over certain epochs taking steps in every batch and keeping␣
↪track of the metrics on each epoch as well as the overall best metrics"""
    MaxTrainLossLen, MaxTestLossLen, MaxMetric1Len, MaxMetric2Len,␣
↪MaxMetric3Len = None, None, None, None, None #For output text formatting
    test_batch_size = batch_size if test_batch_size is None else test_batch_size

    start_time = time.time() #To calculate the duration of the whole learning␣
↪procedure
    model.to(device) #If there is a GPU, let's ensure model is sent to the GPU ␣
↪

    #Initialising the Metrics
    train_losses, test_losses, train_metric1s, train_metric2s, train_metric3s,␣
↪test_metric1s, test_metric2s, test_metric3s = np.repeat(np.nan, epochs), np.
↪repeat(np.nan, epochs), np.repeat(np.nan, epochs), np.repeat(np.nan,␣
↪epochs), np.repeat(np.nan, epochs), np.repeat(np.nan, epochs), np.repeat(np.
↪nan, epochs), np.repeat(np.nan, epochs)

    batches_per_epoch = int(np.ceil(Y_Train.shape[0] / batch_size))
    print("batch_size:", batch_size, "batches_per_epoch:", batches_per_epoch)␣
↪if print_batch_num else None

    for it in range(epochs):
```

```
        t0 = datetime.now() #To calculate the duration of the current epoch

        #Initialising the loss for current epoch
        train_loss, train_metric1, train_metric2, train_metric3, train_weights,␣
↪test_loss, CurMetric1, CurMetric2, CurMetric3, test_weights = [], [], [],␣
↪[], [], [], [], [], [], []

        #Shuffling
        if (ShufflePerIteration):
            RandIndx = np.arange(Y_Train.shape[0])
            np.random.shuffle(RandIndx) #inplace function

            X_Train = X_Train[RandIndx]
            Y_Train = Y_Train[RandIndx]

        OutputsTrain, TargetsTrain, OutputsTest, TargetsTest = [], [], [], []

        #== Training ==#
        for j in range(batches_per_epoch):
        #for j in tqdm(range(batches_per_epoch), initial = 0, total =␣
↪batches_per_epoch, leave = False):
            inputs = X_Train[j*batch_size:(j+1)*batch_size]
            targets = Y_Train[j*batch_size:(j+1)*batch_size]

            inputs, targets = FixFormatAndDTypes(device, inputs, targets)␣
↪#Making sure we have Tensors of the correct Format and Data Type
            optimiser, outputs, loss = TrainModel(model, optimiser, criterion,␣
↪inputs, targets) #Training the model on Train set
            #This loss includes dropout() and stuff as it was not done under␣
↪model.eval()
            OutputsTrain.append(outputs.cpu())
            TargetsTrain.append(targets.cpu())
            del inputs, targets, outputs

        OutputsTrain = torch.cat(OutputsTrain)
        TargetsTrain = torch.cat(TargetsTrain)

        train_loss, CurTrainMetric1, CurTrainMetric2, CurTrainMetric3 =\
            EvaluateModelFromPreds(criterion, OutputsTrain, TargetsTrain,␣
↪Verbose) #Evaluating the model on Train set

        #== Evaluation ==#
        test_batches_per_epoch = int(np.ceil(Y_Test.shape[0] / test_batch_size))
        for j in range(test_batches_per_epoch):
        #for j in tqdm(range(test_batches_per_epoch), total =␣
↪test_batches_per_epoch, leave = False):
```

```
            inputs = X_Test[j*test_batch_size:(j+1)*test_batch_size]
            targets = Y_Test[j*test_batch_size:(j+1)*test_batch_size]

            inputs, targets = FixFormatAndDTypes(device, inputs, targets)␣
↪#Making sure we have Tensors of the correct Format and Data Type
            model.eval()
            with torch.no_grad():
                outputs = model(inputs)
                OutputsTest.append(outputs.cpu())
                TargetsTest.append(targets.cpu())
                del inputs, targets, outputs

        OutputsTest = torch.cat(OutputsTest)
        TargetsTest = torch.cat(TargetsTest)

        test_loss, CurMetric1, CurMetric2, CurMetric3 =\
            EvaluateModelFromPreds(criterion, OutputsTest, TargetsTest,␣
↪Verbose) #Evaluating the model on Evaluation set

        if np.logical_or(np.isinf(test_loss), np.isnan(test_loss)):
            print("!Loss is Infinite; Stopping!")
            break

        if scheduler is not None:
            if list(scheduler.keys())[0].lower() == "Plateau".lower():
                scheduler[list(scheduler.keys())[0]].step(test_loss)
            elif list(scheduler.keys())[0].lower() == "StepLR".lower():
                scheduler[list(scheduler.keys())[0]].step()

        #Saving the metrics
        train_losses[it], train_metric1s[it], train_metric2s[it],␣
↪train_metric3s[it], test_losses[it], test_metric1s[it], test_metric2s[it],␣
↪test_metric3s[it] = train_loss, CurTrainMetric1, CurTrainMetric2,␣
↪CurTrainMetric3, test_loss, CurMetric1, CurMetric2, CurMetric3

        if (it + 1) % PrintInfoEverynEpochs == 0 or it == 0 or it == epochs - 1:
            MaxTrainLossLen, MaxTestLossLen, MaxMetric1Len, MaxMetric2Len,␣
↪MaxMetric3Len = PrintIterationMetrics( #Prints Iteration Metrics
                it, epochs, t0, train_loss, test_loss,
                CurMetric1, "Acc",
                CurMetric2, "AUC",
                CurMetric3, "F1" ,
                MaxTrainLossLen, MaxTestLossLen,
                MaxMetric1Len, MaxMetric2Len, MaxMetric3Len
            )
```

```
        train_best_loss, test_best_loss, BestMetric1, BestMetric2, BestMetric3␣
↪= UpdateMetricsAndSaveModel(model, train_loss, test_loss, train_best_loss,␣
↪test_best_loss, CurMetric1, BestMetric1, CurMetric2, BestMetric2,␣
↪CurMetric3, BestMetric3) #Updating Metrics and Saving the model if it␣
↪outperforms previous iteration's model

    elapsed_time = PrintFinishingInformation(start_time,␣
↪JustCalculateElapsedTime = False) #Prints finishing information
    return train_losses, test_losses, train_best_loss, test_best_loss,␣
↪train_metric1s, train_metric2s, train_metric3s, test_metric1s,␣
↪test_metric2s, test_metric3s, CurMetric1, CurMetric2, CurMetric3,␣
↪BestMetric1, BestMetric2, BestMetric3, elapsed_time
```

[24]:
```
def batch_gd(model, device, criterion, optimiser, scheduler, train_loader,␣
↪test_loader, epochs, PrintInfoEverynEpochs, train_best_loss, test_best_loss,␣
↪BestMetric1, BestMetric2, BestMetric3, Verbose = True):
    """Use the Train, Evaluation, Metrics calculation and printing functions to␣
↪train a model over certain epochs taking steps in every batch and keeping␣
↪track of the metrics on each epoch as well as the overall best metrics"""
    MaxTrainLossLen, MaxTestLossLen, MaxMetric1Len, MaxMetric2Len,␣
↪MaxMetric3Len = None, None, None, None, None #For output text formatting

    start_time = time.time() #To calculate the duration of the whole learning␣
↪procedure
    model.to(device) #If there is a GPU, let's ensure model is sent to the GPU ␣
↪

    #Initialising the Metrics
    train_losses, test_losses, train_metric1s, train_metric2s, train_metric3s,␣
↪test_metric1s, test_metric2s, test_metric3s = np.repeat(np.nan, epochs), np.
↪repeat(np.nan, epochs), np.repeat(np.nan, epochs), np.repeat(np.nan,␣
↪epochs), np.repeat(np.nan, epochs), np.repeat(np.nan, epochs), np.repeat(np.
↪nan, epochs), np.repeat(np.nan, epochs)

    for it in range(epochs):
        t0 = datetime.now() #To calculate the duration of the current epoch
        ProbsTrain = []
        TargetsTrain = []
        Probs = []
        Targets = []

        #== Training ==#
        for inputs, targets in train_loader:
#         for inputs, targets in tqdm(train_loader, total = len(train_loader),␣
↪leave = False):
```

```
            inputs, targets = FixFormatAndDTypes(device, inputs, targets)␣
 ↪#Making sure we have Tensors of the correct Format and Data Type
            optimiser, outputs, loss = TrainModel(model, optimiser, criterion,␣
 ↪inputs, targets) #Training the model on Train set
            #This loss includes dropout() and stuff as it was not done under␣
 ↪model.eval()
            ProbsTrain.append(outputs.cpu())
            TargetsTrain.append(targets.cpu())
            del inputs, targets, outputs

        ProbsTrain   = torch.cat(ProbsTrain)
        TargetsTrain = torch.cat(TargetsTrain)

        train_loss, CurTrainMetric1, CurTrainMetric2, CurTrainMetric3 =␣
 ↪EvaluateModelFromPreds(criterion, ProbsTrain, TargetsTrain, Verbose =␣
 ↪Verbose) #Evaluating the model on Train set

        #== Evaluation ==#
        for inputs, targets in test_loader:
#          for inputs, targets in tqdm(test_loader, total = len(test_loader),␣
 ↪leave = False):
            inputs, targets = FixFormatAndDTypes(device, inputs, targets)␣
 ↪#Making sure we have Tensors of the correct Format and Data Type
            Y_Prob, _ = EvalForwardPass(model, inputs)
            Probs.append(Y_Prob.cpu())
            Targets.append(targets.cpu())

            del inputs, targets, Y_Prob#, Y_Hat

        Probs   = torch.cat(Probs)
        Targets = torch.cat(Targets)

        test_loss, CurMetric1, CurMetric2, CurMetric3 =␣
 ↪EvaluateModelFromPreds(criterion, Probs, Targets, Verbose = Verbose)␣
 ↪#Evaluating the model on Evaluation set

        if np.any(np.logical_or(torch.isinf(Probs).cpu().numpy(), torch.
 ↪isnan(Probs).cpu().numpy())):
            print(f"!Predictions contain infinities ({np.mean(np.logical_or(np.
 ↪isinf(Probs), np.isnan(Probs))) * 100:.2f}%); Stopping!")
            break

        if np.logical_or(np.isinf(test_loss), np.isnan(test_loss)):
            print("!Loss is Infinite; Stopping!")
            break
```

```
        if scheduler is not None:
            if list(scheduler.keys())[0].lower() == "Plateau".lower():
                scheduler[list(scheduler.keys())[0]].step(test_loss)
            elif list(scheduler.keys())[0].lower() == "StepLR".lower():
                scheduler[list(scheduler.keys())[0]].step()

        #Saving the metrics
        train_losses[it], train_metric1s[it], train_metric2s[it],␣
↪train_metric3s[it], test_losses[it], test_metric1s[it], test_metric2s[it],␣
↪test_metric3s[it] = train_loss, CurTrainMetric1, CurTrainMetric2,␣
↪CurTrainMetric3, test_loss, CurMetric1, CurMetric2, CurMetric3

        if (it + 1) % PrintInfoEverynEpochs == 0 or it == 0 or it == epochs - 1:
            MaxTrainLossLen, MaxTestLossLen, MaxMetric1Len, MaxMetric2Len,␣
↪MaxMetric3Len = PrintIterationMetrics( #Prints Iteration Metrics
                it, epochs, t0, train_loss, test_loss,
                CurMetric1, "Acc",
                CurMetric2, "AUC",
                CurMetric3, "F1" ,
                MaxTrainLossLen, MaxTestLossLen,
                MaxMetric1Len, MaxMetric2Len, MaxMetric3Len
            )

        train_best_loss, test_best_loss, BestMetric1, BestMetric2, BestMetric3␣
↪= UpdateMetricsAndSaveModel(model, train_loss, test_loss, train_best_loss,␣
↪test_best_loss, CurMetric1, BestMetric1, CurMetric2, BestMetric2,␣
↪CurMetric3, BestMetric3) #Updating Metrics and Saving the model if it␣
↪outperforms previous iteration's model

    elapsed_time = PrintFinishingInformation(start_time,␣
↪JustCalculateElapsedTime = False) #Prints finishing information
    return train_losses, test_losses, train_best_loss, test_best_loss,␣
↪train_metric1s, train_metric2s, train_metric3s, test_metric1s,␣
↪test_metric2s, test_metric3s, CurMetric1, CurMetric2, CurMetric3,␣
↪BestMetric1, BestMetric2, BestMetric3, elapsed_time
```

### 1.7 Dataloader

[25]:
```
def NxD_to_N2xTxD(X_Data, OtherVar, T, Y_Data = None, TrainingMode = True,␣
↪OffsetT = 0, OffsetY = 0, KeepUntilOffsetY = False):
    """Transform a Numpy Array (X_Data) of shape NxD to one of shape NxTxD as␣
↪per the specifications of layers such as RNNs.

    Parameters:
        X_Data (2D-Numpy Array)         : The Input data X
        OtherVar (dD-Numpy Array)       : Some other variable such that␣
↪X_Data[i] corresponds to OtherVar[i] and len(X_Data) == len(OtherVar)
```

```
        T (int)                         : The time parameter for the NxTxD␣
↪transformation, i.e. the sequence length we want to impose
        Y_Data (None or dD-Numpy Array): The Actual target Y
        TrainingMode (Boolean)          : True when evaluating so for every row␣
↪in X we get a corresponding Y (and the last rows never become part of X␣
↪because we use them as Future values for Y, or False when we want the whole␣
↪dataset to be transformed into X for blind mode/Forecast)
        OffsetT                         : How many additional timesteps into the␣
↪future we want our Y (which comes naturally as the next row of X) to be␣
↪[OffsetT = 0 means X[i, -1, :] is at timestep t and its corresponding Y[i]␣
↪is the (t+1)+0]
        OffsetY                         : How many additional timesteps into the␣
↪future we want our Y (which is given as an argument) to be [OffsetY = 0␣
↪means X[i, -1, :] is at timestep t and its corresponding Y[i] is the (t+1)+0]
        KeepUntilOffsetY                : When Y_Data is given as an argument,␣
↪the transformed (output) Y[i] has the elements of original Y's: [Y[i],␣
↪Y[i+1], Y[i+2], ..., Y[i+OffsetY]], instead of just Y[i+OffsetY],
                                          and when Y_Data is not given so that Y␣
↪comes from X, the transformed (output) Y[i] has the elements of the original␣
↪X's: [X[i+1+1], X[i+1+2], ..., X[i+1+OffsetT]], instead of just␣
↪X[i+1+OffsetT]]

    Returns:
        X_Data (3D-Numpy Array)         : The transformed dataset of shape NxTxD␣
↪where this N (let's call it N2) is a function of the original input's N␣
↪(call it N1): N2 = N1-T-(OffsetT|OffsetY) if TrainingMode else N1-(T-1)
        OtherVar (dD-Numpy Array)       : The subsampled OtherVar of shape Nx(...
↪) where this N (let's call it N2) is a function of the original OtherVar's N␣
↪(call it N1): N2 = N1-T-(OffsetT|OffsetY) if TrainingMode else N1-(T-1)
        [Optionally] Y_Data             : Returned only if TrainingMode. The␣
↪newly created (in case Y_Data == None) or subsampled Y_Data of shape Nx(...)␣
↪where this N (let's call it N2) is a function of the original Y_Data's N␣
↪(call it N1): N2 = N1-T-(OffsetT|OffsetY)
    """
    if T != 0:
        if Y_Data is not None and TrainingMode == False:
            warnings.warn(f"{inspect.stack()[0][3]}: On prediction mode␣
↪(TrainingMode==False), 'Y_Data' is not considered as it's supposed to be␣
↪unknown!")

        if OffsetY != 0 and (TrainingMode == False or Y_Data is None):
            OffsetY = 0
            warnings.warn(f"{inspect.stack()[0][3]}: On prediction mode␣
↪(TrainingMode==False) or When YisX (Y_Data==None), There is no 'Y_Data' to␣
↪offset!")
```

```
        if OffsetT != 0 and ((Y_Data is not None and OffsetT is not None) or␣
↪(TrainingMode == False)):
            OffsetT = 0
            if (Y_Data is not None and OffsetT is not None):
                warnings.warn(f"{inspect.stack()[0][3]}: When not YisX (Y_Data!
↪=None), 'OffsetT' is not considered as Y can't be adjusted to an offset␣
↪since Y is its own entity!")
            else:
                warnings.warn(f"{inspect.stack()[0][3]}: On prediction mode␣
↪(TrainingMode==False), 'OffsetT' is not considered as there is no Y output␣
↪to be adjusted to an offset!")

        if Y_Data is None and KeepUntilOffsetY and OffsetT == 0:
            warnings.warn(f"{inspect.stack()[0][3]}: When YisX (Y_Data is None)␣
↪and KeepUntilOffsetY == True, 'OffsetT' needs to be something other than 0␣
↪so we can keep everything until that value!")

        X_Data_Orig = X_Data
        X_Strides = X_Data.strides
        X_Data  = as_strided(
            X_Data,
            shape = (X_Data.shape[0] - T + 1, T, X_Data.shape[1]),
            strides = (X_Strides[0], X_Strides[0], X_Strides[1]),
            writeable = False
        )

        if TrainingMode:       #TRAINING (Getting Y)
            if Y_Data is None: #* Y comes from X
                if T > 0:
                    if OtherVar is not None:
                        OtherVar = OtherVar[T+np.abs(OffsetT):]
                    if KeepUntilOffsetY and OffsetT != 0:
                        Y_Data = as_strided(
                            X_Data_Orig,
                            shape = (X_Data_Orig.shape[0], X_Data_Orig.
↪shape[0], X_Data_Orig.shape[1]),
                            strides = (X_Strides[0], X_Strides[0],␣
↪X_Strides[1]),
                            writeable = False
                        )[T:-OffsetT, :(OffsetT+1), :]
                    else:
                        Y_Data = X_Data_Orig[T+np.abs(OffsetT):, :]
                    X_Data = X_Data[:(len(X_Data) - OffsetT) - 1, :, :]
                else:
                    if OtherVar is not None:
                        OtherVar = OtherVar[:T-np.abs(OffsetT)]
```

```
                    Y_Data = X_Data_Orig[:T-np.abs(OffsetT), :]         #T is␣
↪already negative
                    X_Data = X_Data[:(len(X_Data) - OffsetT) - 1, :, :] #T is␣
↪already negative

            else:              #* Y is its own entity
                if not KeepUntilOffsetY:
                    Y_Data = NpShift(Y_Data, -np.abs(OffsetY) if T > 0 else np.
↪abs(OffsetY))
                else:
                    tmp2 = Y_Data
                    Y_Data = NpShift(Y_Data, -1 if T > 0 else 1)
                    Y_Data = Y_Data.reshape(-1, 1)
                    for i_y in range(np.abs(OffsetY) - 1):
                        Y_Data = np.concatenate((Y_Data, NpShift(tmp2, -i_y-2␣
↪if T > 0 else +i_y+2).reshape(-1, 1)), axis = 1)

                if T > 0:
                    if OtherVar is not None:
                        OtherVar = OtherVar[T-1:(None if OffsetY == 0 else -np.
↪abs(OffsetY))]
                    Y_Data = Y_Data[T-1:(None if OffsetY == 0 else -np.
↪abs(OffsetY))]
                    X_Data = X_Data[:(len(X_Data) - OffsetT), :, :]
                else:
                    if OtherVar is not None:
                        OtherVar = OtherVar[(None if OffsetY == 0 else np.
↪abs(OffsetY)):T+1]
                    Y_Data = Y_Data[(None if OffsetY == 0 else np.abs(OffsetY)):
↪T+1] #T is already negative
                    X_Data = X_Data[:(len(X_Data) - OffsetT), :, :]            ␣
↪     #T is already negative
            return (X_Data, Y_Data, OtherVar) if OtherVar is not None else␣
↪(X_Data, Y_Data)

        else:                  #TESTING (No Y available)
            if T > 0:
                if OtherVar is not None:
                    OtherVar = OtherVar[T-1:]
                X_Data = X_Data
            else:
                if OtherVar is not None:
                    OtherVar = OtherVar[:T+1]
                X_Data = X_Data[:T+1, 1:, :]      #T is already negative
            return (X_Data, OtherVar) if OtherVar is not None else X_Data
```

```
    else:
        print("NxD_to_N2xTxD:", "T [{T}] can't be zero")
        if Y_Data is None:
            if OtherVar is not None:
                return X_Data, OtherVar
            else:
                return X_Data
        else:
            if OtherVar is not None:
                return X_Data, Y_Data, OtherVar
            else:
                return X_Data, Y_Data
```

[26]:
```
def ListOf_NxD_to_N2xTxD(ListOfXYs, ListOfOtherVar, YisX, T, ListOfY_Data =␣
↪None, scaler = None, TrainingMode = True, OffsetT = 0, OffsetY = 0,␣
↪KeepUntilOffsetY = False): #N2 = N-T (applies to each N of the ListOfXYs)
    """Iteratively use NxD_to_N2xTxD() on each NxD numpy array inside ListOfXYs␣
↪which represent independent samples/datasets and after each dataset is␣
↪transformed into NxTxD, concatenate everything together into 1 big NxTxD␣
↪dataset"""
    X = []
    X_Other = []
    if TrainingMode:
        Y = []

    for i in range(len(ListOfXYs)):
        if TrainingMode and not YisX:
            if ListOfY_Data is None:
                CurXDF, CurYDF = ListOfXYs[i]
            else:
                CurXDF = ListOfXYs[i]
                CurYDF = ListOfY_Data[i]
        else:
            CurXDF = ListOfXYs[i]
            CurYDF = None

        CurOtherVar = ListOfOtherVar[i]

        if scaler is not None:
            if isinstance(scaler, tuple):
                CurXDF = Scale(CurXDF, *scaler)
            elif isinstance(scaler, StandardScaler):
                CurXDF = scaler.transform(CurXDF)
            else:
                raise Exception("scaler is neither a tuple nor an sklearn␣
↪scaler")
```

```
                return None

        if TrainingMode:
            X_Data, Y_Data, CurOtherVar = NxD_to_N2xTxD(CurXDF, CurOtherVar, T,␣
↪CurYDF if not YisX else None, TrainingMode, OffsetT = OffsetT, OffsetY =␣
↪OffsetY, KeepUntilOffsetY = KeepUntilOffsetY) #CurYDF is None in the case of␣
↪YisX
            Y.append(Y_Data)
        else:
            X_Data, CurOtherVar = NxD_to_N2xTxD(CurXDF, CurOtherVar, T, None,␣
↪TrainingMode, OffsetT = OffsetT, OffsetY = OffsetY, KeepUntilOffsetY =␣
↪KeepUntilOffsetY)

        X.append(X_Data)
        X_Other.append(CurOtherVar)

    X = np.concatenate(X)
    X_Other = np.concatenate(X_Other)
    if TrainingMode:
        Y = np.concatenate(Y)

    if TrainingMode:
        if YisX:
            return X.astype(np.float32), Y.astype(np.float32), X_Other #If YisX␣
↪then they should be the same dtype
        else:
            return X.astype(np.float32), Y, X_Other                    #Else Y␣
↪can be whatever it is
    else:
        return X.astype(np.float32), X_Other
```

# 2 Data

[27]:
```
#Configuring the basic structure of our current directory
path_root = f"{os.getcwd()}"
path_data = f"{Path(path_root).absolute()}/Data"
path_models = f"{path_root}/Models"
print(path_root)
print(path_data)
print(path_models)
```

```
D:\GiannisM\Downloads\Exercises\Fiver\100. frotribe FFNN Multiclass
Classification
D:\GiannisM\Downloads\Exercises\Fiver\100. frotribe FFNN Multiclass
Classification/Data
D:\GiannisM\Downloads\Exercises\Fiver\100. frotribe FFNN Multiclass
Classification/Models
```

[28]:
```
############################
## Data Hyperparameters ####
Seed           = 42
T_Length       = 720
OffsetT        = 0
OffsetY        = 0
batch_size     = 500
TrainPerc      = 0.8
ValidPerc      = 0.1
TestPerc       = 1 - TrainPerc - ValidPerc
CustomNAString = None
#############################

########################
### Reading the Data ###
Classes = ['drinking water', 'smoking', 'standing up', 'sit down', 'mopping the␣
↪floor', 'sweeping the floor', 'walking', 'unknown']
XY_DF = pd.read_csv(f"{path_data}/11-16 (1).csv", header = None).rename({0:␣
↪"Target"}, axis = 1)
display(XY_DF) if isnotebook else print(XY_DF)
########################

####################
### Handling NAs ###
NBeforeCustomNADrop = None
DroppedCustomNARows = None
NBeforeNADrop = len(XY_DF)
XY_DF = XY_DF.dropna()
DroppedNARows = NBeforeNADrop - len(XY_DF)
if DroppedNARows > 0:
    print(f"Dropped NA rows count: {DroppedNARows} (out of {NBeforeNADrop})")

if CustomNAString is not None:
    NBeforeCustomNADrop = len(XY_DF)
    XY_DF = XY_DF.replace(CustomNAString, np.nan, regex = False).dropna()
    DroppedCustomNARows = NBeforeCustomNADrop - len(XY_DF)
    if DroppedCustomNARows > 0:
        print(f"Dropped custom NA rows count: {DroppedCustomNARows} (out of␣
↪{NBeforeCustomNADrop})", )
if DroppedNARows > 0 or (DroppedCustomNARows is not None and␣
↪DroppedCustomNARows > 0):
    print()
####################

##########################
### Melting the Dataset ###
```

```python
#Getting a proper NxD matrix where N are the observations and D is the number␣
↪of variables
#Melted_XY_DF = pd.melt(XY_DF, id_vars=["Target"], value_vars=np.arange(1200) +␣
↪1, var_name = "Timestamp", value_name = "Accelerometer")
Melted_XY_DF = []
for i in range(len(XY_DF)):
    tmpDF = pd.DataFrame({"Accelerometer": np.trim_zeros(XY_DF.iloc[i, np.
↪arange(1200) + 1].values)})
    tmpDF["Target"] = XY_DF.iloc[i, 0]
    Melted_XY_DF.append(tmpDF[["Target", "Accelerometer"]])
Melted_XY_DF = pd.concat(Melted_XY_DF).reset_index(drop = True)
Melted_XY_DF
###########################

########################
### Scaling the Data ###
# scaler = LoadVariable(f"{SaveFolder}/scaler") #After loading a model with a␣
↪different scaler we need to re-run this using the newly loaded scaler.
# print("\n\n\n!!!!!!!!!!!!\nDEBUGGING:\nScaling with SaveFolder scaler!!!\n!!!!
↪!!!!!!!!\n\n\n")

# if os.path.exists(f"{path_models}/scaler"):
#     print("!!\n!! Using saved scaler.\n!!\n")
#     scaler = LoadVariable(f"{path_models}/scaler")
# else:
scaler = StandardScaler(with_mean = True, with_std = True).fit(Melted_XY_DF.
↪iloc[:, 1:].values)
SaveVariable(scaler, f"{path_models}/scaler")

scaler_mean = scaler.mean_
scaler_sd = scaler.scale_
scaler_mean_sd = (scaler_mean, scaler_sd)

#Numpy takes care of the broadcasting automatically
Melted_XY_DF.iloc[:, 1:] = Scale(Melted_XY_DF.iloc[:, 1:].values,␣
↪*scaler_mean_sd)
########################

############################
### Getting an X and a Y ###
XY_DFs = [y for x, y in Melted_XY_DF.groupby(["Target"])]
Xs_Data = [DF.iloc[:, 1: ].values.astype(np.float32) for DF in XY_DFs]
Ys_Data = [DF.iloc[:, 0:1].values.astype(int) - 1    for DF in XY_DFs]

Ls_Data  = [np.array([Classes[y] for y in CurYData.squeeze()]) for CurYData in␣
↪Ys_Data]
```

```
############################

###########################################
# ### Transforming the data into NxTxD  ###
X_Data, Y_Data, L_Data = ListOf_NxD_to_N2xTxD(Xs_Data, Ls_Data, False,␣
 ↪T_Length, ListOfY_Data = Ys_Data, TrainingMode = True, OffsetT = OffsetT,␣
 ↪OffsetY = OffsetY, KeepUntilOffsetY = False)
###########################################

######################################
### Creating Train/Valid/Test sets ###
#==Stratified Split
TrainIndx, ValidIndx, TestIndx = train_valid_test_split(np.arange(X_Data.
 ↪shape[0]), train_size = TrainPerc, valid_size = ValidPerc, Y_Data = None,␣
 ↪random_state = Seed, shuffle = True, stratify = Y_Data)
X_Train      = X_Data[TrainIndx]
Y_Train      = Y_Data[TrainIndx]
Labels_Train = L_Data[TrainIndx]
X_Valid      = X_Data[ValidIndx]
Y_Valid      = Y_Data[ValidIndx]
Labels_Valid = L_Data[ValidIndx]
X_Test       = X_Data[TestIndx ]
Y_Test       = Y_Data[TestIndx ]
Labels_Test  = L_Data[TestIndx ]
######################################

###################################
### Creating Dataset/Dataloader ###
Dataset_Train = TensorDataset(torch.from_numpy(X_Train), torch.
 ↪from_numpy(Y_Train))
Dataset_Valid = TensorDataset(torch.from_numpy(X_Valid), torch.
 ↪from_numpy(Y_Valid))
Dataset_Test  = TensorDataset(torch.from_numpy(X_Test ), torch.
 ↪from_numpy(Y_Test ))

Loader_Train = torch.utils.data.DataLoader(
    dataset = Dataset_Train,
    batch_size = batch_size,
    shuffle = True,
    pin_memory = True

)
Loader_Valid = torch.utils.data.DataLoader(
    dataset = Dataset_Valid,
    batch_size = batch_size,
    shuffle = False,
    pin_memory = True
```

```
)
Loader_Test = torch.utils.data.DataLoader(
    dataset = Dataset_Test,
    batch_size = batch_size,
    shuffle = False,
    pin_memory = True
)
###################################

##############################
### Extracting Information ###
O_Length, K_Length, N_Length, D_Length = Y_Train.shape[1], len(set(Y_Train.squeeze())) if len(Y_Train.squeeze().shape) == 1 else [len(set(Y_Train[:, i])) for i in range(Y_Train.shape[-1])], X_Train.shape[0], X_Train.shape[-1]
H1, W1 = T_Length, D_Length
print(f"X_Train.shape { X_Train.shape} {X_Train.dtype} | Y_Train.shape {Y_Train.shape} {Y_Train.dtype}")
print(f"X_Valid.shape { X_Valid.shape} {X_Valid.dtype} | Y_Valid.shape {Y_Valid.shape} {Y_Valid.dtype}")
print(f"X_Test .shape {  X_Test.shape} { X_Test.dtype} | Y_Test.shape  { Y_Test.shape} { Y_Test.dtype}")
print(f"X_Train: min = {X_Train.min():.4f}, max = {X_Train.max():.4f}")
print(f"X_Valid: min = {X_Valid.min():.4f}, max = {X_Valid.max():.4f}")
print(f"X_Test : min = { X_Test.min():.4f}, max = { X_Test.max():.4f}")
print(f"O_Length: {O_Length} K_Length: {K_Length}")
print(f"N_Length: {N_Length} H1: {H1} W1: {W1} D_Length: {D_Length}")

plt.rcParams['figure.figsize'] = [9, 3]
print(f"\nClasses:")
sns.countplot(x = [Classes[int(y)] for y in sorted(Y_Data.squeeze())])
plt.show()

CountData = sorted(Counter(Y_Data.squeeze()).items())
FreqKeys = [kv[0] for kv in CountData]
FreqData = np.array([kv[1] for kv in CountData]) / len(Y_Data) * 100
for i in range(len(FreqData)):
    print(f"{FreqKeys[i]}: {SpaceAString(f'{FreqData[i]:.2f}', MaxLength = 5)}% [{SpaceAString(f'{CountData[i][1]}', MaxLength = 5)}]")

print(f"\nClasses [TRAIN]:")
sns.countplot(x = [Classes[int(y)] for y in sorted(Y_Train.squeeze())])
plt.show()

print(f"\nClasses [Valid]:")
sns.countplot(x = [Classes[int(y)] for y in sorted(Y_Valid.squeeze())])
plt.show()
```

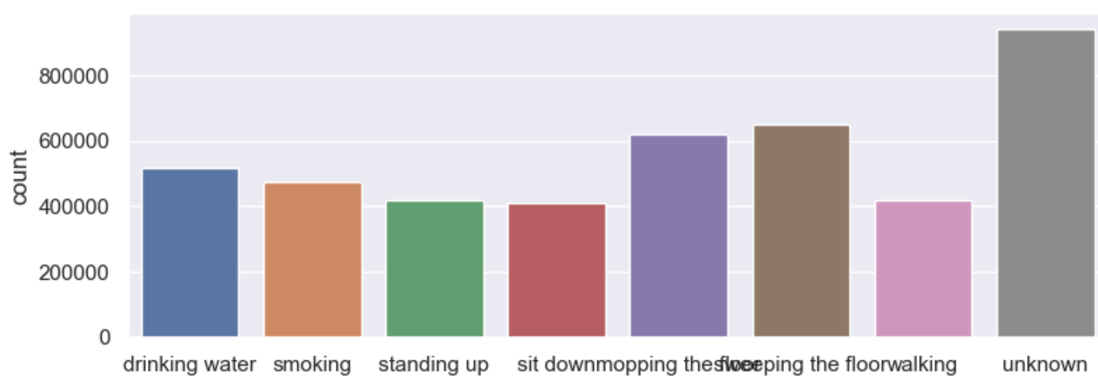
```python
print(f"\nClasses [Test ]:")
sns.countplot(x = [Classes[int(y)] for y in sorted(Y_Test.squeeze() )])
plt.show()
plt.rcParams['figure.figsize'] = OrigFigSize

CountTrain = sorted(Counter(Y_Train.squeeze()).items())
FreqTrain  = np.array([kv[1] for kv in CountTrain]) / len(Y_Train) * 100
CountValid = sorted(Counter(Y_Valid.squeeze()).items())
FreqValid  = np.array([kv[1] for kv in CountValid]) / len(Y_Valid) * 100
CountTest  = sorted(Counter(Y_Test.squeeze()).items())
FreqTest   = np.array([kv[1] for kv in CountTest ]) / len(Y_Test ) * 100

for i in range(len(FreqKeys)):
    print(f"{FreqKeys[i]}: Train {SpaceAString(f'{FreqTrain[i]:.2f}', MaxLength = 5)}% [{SpaceAString(f'{CountTrain[i][1]}', MaxLength = 5)}], Valid {SpaceAString(f'{FreqValid[i]:.2f}', MaxLength = 5)}% [{SpaceAString(f'{CountValid[i][1]}', MaxLength = 5)}], Test {SpaceAString(f'{FreqTest[i]:.2f}', MaxLength = 5)}% [{SpaceAString(f'{CountTest[i][1]}', MaxLength = 5)}]")
##############################

print("\nDone")
```

```
      Target         1         2         3         4         5         6  \
0          1  0.147911  0.133120  0.025052 -0.070056 -0.060896 -0.121567
1          1  0.096198 -0.066323 -0.180289 -0.175182 -0.108132 -0.080090
2          1 -0.500452 -0.502092 -0.475572 -0.425861 -0.389736 -0.402447
3          1 -0.307718 -0.320017 -0.344007 -0.309607 -0.289414 -0.333693
4          1 -0.103104 -0.148786 -0.189899 -0.093382  0.025787  0.158881
…        …       …       …       …       …       …       …
4830       8 -0.064396 -0.178618 -0.246944 -0.049874  0.179200  0.079402
4831       8  0.117115  0.049382  0.134941  0.065425  0.011479  0.212872
4832       8  0.213987  0.145185  0.117739  0.140440  0.290152  0.308540
4833       8  0.088052  0.105103 -0.000214  0.090305  0.115749  0.151577
4834       8  0.115733  0.043828  0.224749  0.098849  0.132058  0.092996

             7         8         9  …  1191  1192  1193  1194  1195  1196  \
0    -0.098642 -0.011251 -0.005818  …   0.0   0.0   0.0   0.0   0.0   0.0
1     0.250950 -0.125172  0.287903  …   0.0   0.0   0.0   0.0   0.0   0.0
2    -0.495722 -0.568901 -0.576617  …   0.0   0.0   0.0   0.0   0.0   0.0
3    -0.414461 -0.556066 -0.711506  …   0.0   0.0   0.0   0.0   0.0   0.0
4     0.220521  0.142476  0.063623  …   0.0   0.0   0.0   0.0   0.0   0.0
…        …       …       …  …   …  …   …   …   …
4830  0.045606  0.273751  0.224829  …   0.0   0.0   0.0   0.0   0.0   0.0
4831  0.394126  0.320238  0.258048  …   0.0   0.0   0.0   0.0   0.0   0.0
4832  0.079455  0.088747  0.010922  …   0.0   0.0   0.0   0.0   0.0   0.0
4833  0.101945  0.152081 -0.005337  …   0.0   0.0   0.0   0.0   0.0   0.0
4834  0.096625  0.142984  0.051117  …   0.0   0.0   0.0   0.0   0.0   0.0
```

```
      1197  1198  1199  1200
0      0.0   0.0   0.0   0.0
1      0.0   0.0   0.0   0.0
2      0.0   0.0   0.0   0.0
3      0.0   0.0   0.0   0.0
4      0.0   0.0   0.0   0.0
…    …    …    …    …
4830   0.0   0.0   0.0   0.0
4831   0.0   0.0   0.0   0.0
4832   0.0   0.0   0.0   0.0
4833   0.0   0.0   0.0   0.0
4834   0.0   0.0   0.0   0.0

[4835 rows x 1201 columns]
```

```
C:\Users\GiannisM\AppData\Local\Temp\ipykernel_38048\4257472009.py:76:
FutureWarning: In a future version of pandas, a length 1 tuple will be returned
when iterating over a groupby with a grouper equal to a list of length 1. Don't
supply a list with a single grouper to avoid this warning.
  XY_DFs = [y for x, y in Melted_XY_DF.groupby(["Target"])]
```

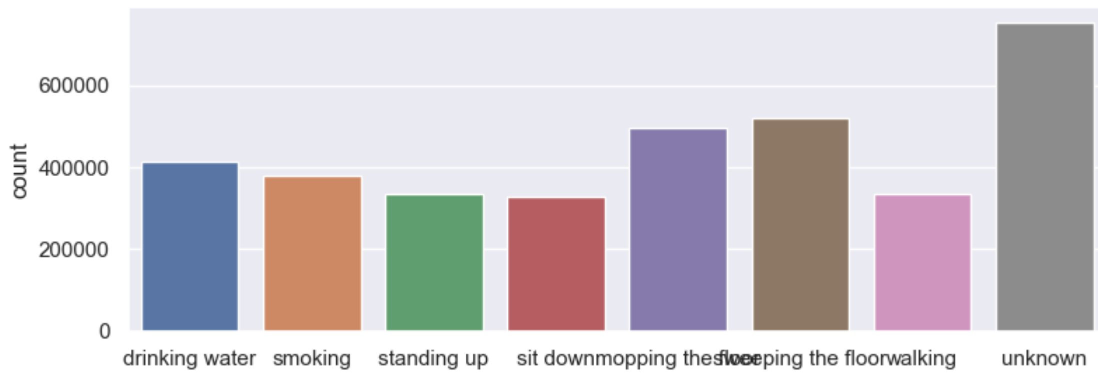
```
X_Train.shape (3562118, 720, 1) float32 | Y_Train.shape (3562118, 1) int32
X_Valid.shape (445265, 720, 1) float32 | Y_Valid.shape (445265, 1) int32
X_Test .shape (445265, 720, 1) float32 | Y_Test.shape  (445265, 1) int32
X_Train: min = -40.7155, max = 49.0740
X_Valid: min = -40.7155, max = 49.0740
X_Test : min = -40.7155, max = 49.0740
O_Length: 1 K_Length: 8
N_Length: 3562118 H1: 720 W1: 1 D_Length: 1

Classes:
```



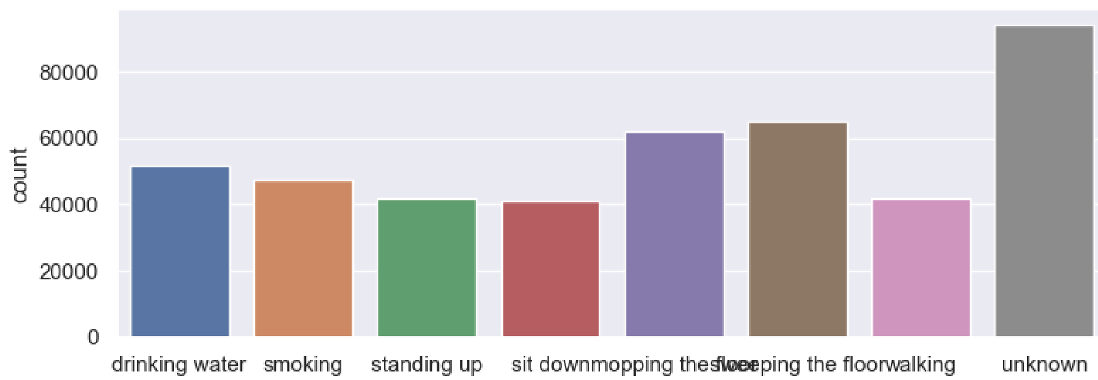

```
0: 11.57% [515051]
1: 10.69% [476091]
```

```
2:  9.42% [419251]
3:  9.24% [411211]
4: 13.88% [618131]
5: 14.62% [651131]
6:  9.44% [420311]
7: 21.14% [941471]
```

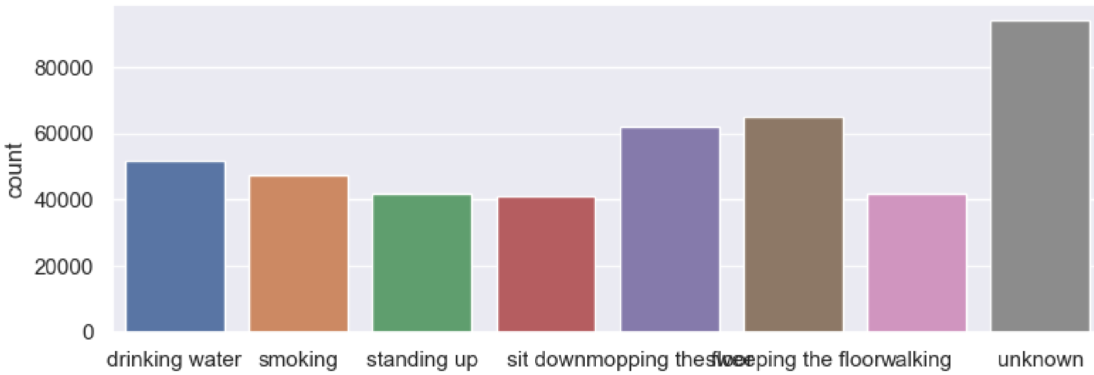
```
Classes [TRAIN]:
```




```
Classes [Valid]:
```




```
Classes [Test ]:
```




```
0: Train 11.57% [412041], Valid 11.57% [51505], Test 11.57% [51505]
1: Train 10.69% [380873], Valid 10.69% [47609], Test 10.69% [47609]
2: Train  9.42% [335401], Valid  9.42% [41925], Test  9.42% [41925]
3: Train  9.24% [328969], Valid  9.24% [41121], Test  9.24% [41121]
4: Train 13.88% [494505], Valid 13.88% [61813], Test 13.88% [61813]
5: Train 14.62% [520904], Valid 14.62% [65114], Test 14.62% [65113]
6: Train  9.44% [336249], Valid  9.44% [42031], Test  9.44% [42031]
7: Train 21.14% [753176], Valid 21.14% [94147], Test 21.14% [94148]

Done
```

# 3 Neural Network

## 3.1 Hyper Parameters

[29]:
```
conv_input_size = (T_Length, D_Length)
input_size = np.prod(conv_input_size)
output_size = np.prod(O_Length)
print("conv_input_size: " + str(conv_input_size) + ", input_size: " +
 ↪str(input_size) + ", D_Length: " + str(D_Length) + ", output_size: " +
 ↪str(output_size))
hn1 = D_Length

ReluAlpha = 0
EluAlpha = 0

layer_type     = ['transfenc', 'dense', 'dense'] #Last layer is the output
 ↪layer and always exists, no need to specify it here
transf_nhead   = [1      ]
transf_ff_dim  = [2048   ] #Transform D -> Hidden -> D
transf_l_norm  = [1e-5   ]
transf_drp     = [0.1    ]
transf_actv    = ["relu"]
```

```python
###
NUM = 1
num_units  = [hn1, hn1, 256, 512]
num_units  = [num_units[0]] + [n_unit * NUM for n_unit in num_units[1:]]
activation = ["relu"] + ["relu"] * (len(layer_type)-1) #None, "relu6" "relu", "elu", "softplus", "tanh", "sigmoid"
dropout    = [0.1] * 1 + [0.1] * (len(layer_type)-1)
###
usebias = [True] * len(layer_type) + [True] #Length +1 because of the Output layer
###
l2_lamda = 0.05
mu = 0.99 #Momentum
###
conv_padding, conv_output_size = GetConvPaddingAndOutputSizes(T_Length, conv_input_size, input_size, layer_type, None, None, None, None, None, None, None, None, False, T_Length, D_Length, num_units, None)
print()
print("nPadding:", conv_padding)
print("X's Dims:", conv_output_size)
print("num_units", num_units)
print(f"\nbatch_size: {batch_size}")

assert len(num_units) == (len(layer_type) + 1), f"num_units should have a length of len(layer_type)+1"
lt = 0
if layer_type[lt] in ['transfenc', "customtransfenc"]:
    assert (num_units[lt] == num_units[lt + 1] if lt == 0 or (lt > 0 and bidir_rnns is None) or (lt > 0 and not bidir_rnns[lt-1]) else num_units[lt] * 2 == num_units[lt + 1]), f"lt: {lt}. Transformer encoder layer output shape must be the same as its input"
    assert num_units[lt] % transf_nhead[lt] == 0, f"lt: {lt}. embed_dim [{num_units[lt]}] must be divisible by num_heads [{transf_nhead[lt]}]"
for lt in range(len(layer_type) - 1):
    if layer_type[lt] in ['transfenc', "customtransfenc"]:
        assert (num_units[lt] == num_units[lt + 1] if lt == 0 or (lt > 0 and bidir_rnns is None) or (lt > 0 and not bidir_rnns[lt-1]) else num_units[lt] * 2 == num_units[lt + 1]), f"lt: {lt}. Transformer encoder layer output shape must be the same as its input"
        assert num_units[lt] % transf_nhead[lt] == 0, f"lt: {lt}. embed_dim [{num_units[lt]}] must be divisible by num_heads [{transf_nhead[lt]}]"
```

```
conv_input_size: (720, 1), input_size: 720, D_Length: 1, output_size: 1

nPadding: []
X's Dims: [720]
num_units [1, 1, 256, 512]
```

```
batch_size: 500
```

## 3.2 Optimisation

### 3.2.1 Structure

[30]:
```python
print(device)
Debug = False

model = Net(T_Length, K_Length, num_units, activation, usebias, dropout,␣
↪EluAlpha, ReluAlpha, transf_nhead, transf_ff_dim, transf_l_norm, transf_drp,␣
↪transf_actv)
# if device != "cpu":
#     model = nn.DataParallel(model)
print(model)

#Initialising the Metrics
train_losses, train_metric1s, train_metric2s, train_metric3s, valid_losses,␣
↪valid_metric1s, valid_metric2s, valid_metric3s = np.array([]), np.array([]),␣
↪np.array([]), np.array([]), np.array([]), np.array([]), np.array([]), np.
↪array([])
train_best_loss, valid_best_loss, valid_best_metric1, valid_best_metric2,␣
↪valid_best_metric3 = np.Inf, np.Inf, 0, np.nan, np.nan
```

```
cuda
Net(
  (layers): ModuleList(
    (0): Custom_Tranformer_Encoder(
      (layers): ModuleList(
        (0): LayerNorm((1,), eps=1e-05, elementwise_affine=True)
        (1): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=1,
out_features=1, bias=True)
        )
        (2): Dropout(p=0.1, inplace=False)
        (3): LayerNorm((1,), eps=1e-05, elementwise_affine=True)
        (4): Conv1d(720, 2048, kernel_size=(1,), stride=(1,))
        (5): ReLU()
        (6): Dropout(p=0.1, inplace=False)
        (7): Conv1d(2048, 720, kernel_size=(1,), stride=(1,))
      )
    )
    (1): ReLU()
    (2): Dropout(p=0.1, inplace=False)
    (3): Linear(in_features=720, out_features=256, bias=True)
    (4): ReLU()
    (5): Dropout(p=0.1, inplace=False)
```

```
      (6): Linear(in_features=256, out_features=512, bias=True)
      (7): ReLU()
      (8): Dropout(p=0.1, inplace=False)
      (9): Linear(in_features=512, out_features=8, bias=True)
    )
  )
```

[31]:
```
print("conv_input_size:", conv_input_size, "\n")
summary(model, input_size = [1, *conv_input_size], device = device, verbose =␣
 ↪1, col_names = ["kernel_size", "input_size", "output_size", "num_params",␣
 ↪"mult_adds"], depth = 3)

if IS_GPU_AVAILABLE:
    torch.cuda.empty_cache()
```

```
conv_input_size: (720, 1)

================================================================================
================================================================================
==============================
Layer (type:depth-idx)                                               Kernel Shape
Input Shape                Output Shape               Param #
Mult-Adds
================================================================================
================================================================================
==============================
Net                                                                  --
--                         --                         --                         --
 ModuleList: 1-1                                                    --
--                         --                         --                         --
      Custom_Tranformer_Encoder: 2-1                               --
--                         --                         (recursive)                --
           ModuleList: 3-1                                        --
--                         --                         2,951,900                  --
      Custom_Tranformer_Encoder: 2-2                               --
[1, 720, 1]                [1, 720, 1]                --                         --
      ReLU: 2-3                                                    --
[1, 720]                   [1, 720]                   --                         --
      Dropout: 2-4                                                 --
[1, 720]                   [1, 720]                   --                         --
      Linear: 2-5                                                  [720, 256]
[1, 720]                   [1, 256]                   184,576
184,576
      ReLU: 2-6                                                    --
[1, 256]                   [1, 256]                   --                         --
      Dropout: 2-7                                                 --
[1, 256]                   [1, 256]                   --                         --
      Linear: 2-8                                                  [256, 512]
```

```
[1, 256]                  [1, 512]                  131,584
131,584
     ReLU: 2-9                                                   --
[1, 512]                  [1, 512]                  --                         --
     Dropout: 2-10                                               --
[1, 512]                  [1, 512]                  --                         --
     Linear: 2-11                                                [512, 8]
[1, 512]                  [1, 8]                    4,104
4,104
================================================================================
================================================================================
==============================
Total params: 3,272,158
Trainable params: 3,272,158
Non-trainable params: 0
Total mult-adds (M): 3.27
================================================================================
================================================================================
==============================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.04
Params size (MB): 13.09
Estimated Total Size (MB): 13.13
================================================================================
================================================================================
==============================
```

[32]:

```
#Setting the Loss Function and Optimisation technique
criterion = nn.CrossEntropyLoss() #Using Categorical Cross Entropy loss function
print(criterion.__class__.__name__)
print("Multiclass Classification")

learning_rate = 1e-3
optimiser = torch.optim.AdamW(model.parameters(), lr = learning_rate, betas =␣
 ↪(mu, 0.999), weight_decay = l2_lamda, amsgrad = False)
```

```
CrossEntropyLoss
Multiclass Classification
```

[33]:

```
# for prm_grp in optimiser.param_groups:
#     prm_grp['lr'] = 1e-4
# #     prm_grp['weight_decay'] = 0.1
```

### 3.2.2 Minibatch Gradient Descent (Numpy)

[ ]:
```
Epochs = int(2)
PrintInfoEverynEpochs = 1
ShufflePerIteration = True
scheduler = None
# scheduler = torch.optim.lr_scheduler.StepLR(optimiser, step_size = Epochs //␣
 ↪10 if Epochs > 10 else 3, gamma = 0.8)

valid_batch_size = None #None Y_Valid.shape[0]
#Each consecutive run returns its losses/Metrics and those get concatenated to␣
 ↪the overall losses/metrics
new_train_losses, new_valid_losses, train_best_loss, valid_best_loss,␣
 ↪new_train_metric1s, new_train_metric2s, new_train_metric3s,␣
 ↪new_valid_metric1s, new_valid_metric2s, new_valid_metric3s,\
Metric1, Metric2, Metric3, valid_best_metric1, valid_best_metric2,␣
 ↪valid_best_metric3, elapsed_time = \
    minibatch_gd(model, device, criterion, optimiser, scheduler, D_Length,␣
 ↪X_Train, Y_Train, X_Valid, Y_Valid, epochs = Epochs, batch_size = batch_size,
                 ShufflePerIteration = ShufflePerIteration,␣
 ↪PrintInfoEverynEpochs = PrintInfoEverynEpochs, train_best_loss =␣
 ↪train_best_loss, test_best_loss = valid_best_loss,
                 BestMetric1 = valid_best_metric1, BestMetric2 =␣
 ↪valid_best_metric2, BestMetric3 = valid_best_metric3, print_batch_num =␣
 ↪True, Verbose = False,
                 test_batch_size = valid_batch_size)

train_losses, valid_losses = np.append(train_losses, new_train_losses), np.
 ↪append(valid_losses, new_valid_losses)
train_metric1s, train_metric2s, train_metric3s = np.append(train_metric1s,␣
 ↪new_train_metric1s), np.append(train_metric2s, new_train_metric2s), np.
 ↪append(train_metric3s, new_train_metric3s)
valid_metric1s, valid_metric2s, valid_metric3s = np.append(valid_metric1s,␣
 ↪new_valid_metric1s), np.append(valid_metric2s, new_valid_metric2s), np.
 ↪append(valid_metric3s, new_valid_metric3s)
train_loss, valid_loss, valid_metric1, valid_metric2, valid_metric3 =␣
 ↪LastNonNan(new_train_losses), LastNonNan(new_valid_losses), Metric1,␣
 ↪Metric2, Metric3

print(f'\ntrain_best_loss: {train_best_loss:.5f}, valid_best_loss:␣
 ↪{valid_best_loss:.5f}, "Acc": {valid_metric1:.5f}, "AUC": {valid_metric2:.
 ↪5f}, "F1": {valid_metric3:.5f}')

if IS_GPU_AVAILABLE:
    torch.cuda.empty_cache()
if IsWindows:
```

```
    winsound.PlaySound('SystemExit', winsound.SND_NOSTOP)
```

#### 3.2.3 Stochastic Gradient Descent (Dataset)

[ ]:
```
# Epochs = int(50)
# PrintInfoEverynEpochs = 1
# scheduler = None
# # scheduler = torch.optim.lr_scheduler.StepLR(optimiser, step_size = Epochs //
 ↪ 10 if Epochs > 10 else 3, gamma = 0.8)

# new_train_losses, new_valid_losses, train_best_loss, valid_best_loss,␣
 ↪new_train_metric1s, new_train_metric2s, new_train_metric3s,␣
 ↪new_valid_metric1s, new_valid_metric2s, new_valid_metric3s,\
# Metric1, Metric2, Metric3, valid_best_metric1, valid_best_metric2,␣
 ↪valid_best_metric3, elapsed_time = \
#     batch_gd(model, device, criterion, optimiser, scheduler, Loader_Train,␣
 ↪Loader_Valid, epochs = Epochs, PrintInfoEverynEpochs = PrintInfoEverynEpochs,
#               train_best_loss = train_best_loss, test_best_loss =␣
 ↪valid_best_loss, BestMetric1 = valid_best_metric1, BestMetric2 =␣
 ↪valid_best_metric2, BestMetric3 = valid_best_metric3,
#               Verbose = False
#     )

# train_losses, valid_losses = np.append(train_losses, new_train_losses), np.
 ↪append(valid_losses, new_valid_losses)
# train_metric1s, train_metric2s, train_metric3s = np.append(train_metric1s,␣
 ↪new_train_metric1s), np.append(train_metric2s, new_train_metric2s), np.
 ↪append(train_metric3s, new_train_metric3s)
# valid_metric1s, valid_metric2s, valid_metric3s = np.append(valid_metric1s,␣
 ↪new_valid_metric1s), np.append(valid_metric2s, new_valid_metric2s), np.
 ↪append(valid_metric3s, new_valid_metric3s)
# train_loss, valid_loss, valid_metric1, valid_metric2, valid_metric3 =␣
 ↪LastNonNan(new_train_losses), LastNonNan(new_valid_losses), Metric1,␣
 ↪Metric2, Metric3

# print(f'\ntrain_best_loss: {train_best_loss:.5f}, valid_best_loss:␣
 ↪{valid_best_loss:.5f}, Acc: {valid_metric1:.5f}, AUC: {valid_metric2:.5f},␣
 ↪F1: {valid_metric3:.5f}')

# if IS_GPU_AVAILABLE:
#     torch.cuda.empty_cache()
# if IsWindows:
#     winsound.PlaySound('SystemExit', winsound.SND_NOSTOP)
```

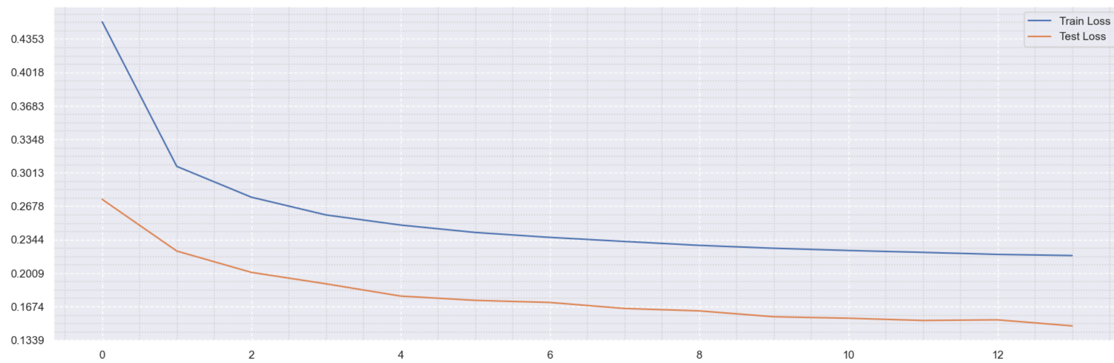
[150]:
```
# #Loading the best trained model (in case the last one was overfitted)
# model.load_state_dict(torch.load("model_dict.pt"))
```

```
# model.eval()
# train_loss = train_best_loss
# valid_loss = valid_best_loss
# valid_metric1 = valid_best_metric1
# valid_metric2 = valid_best_metric2
# valid_metric3 = valid_best_metric3
```

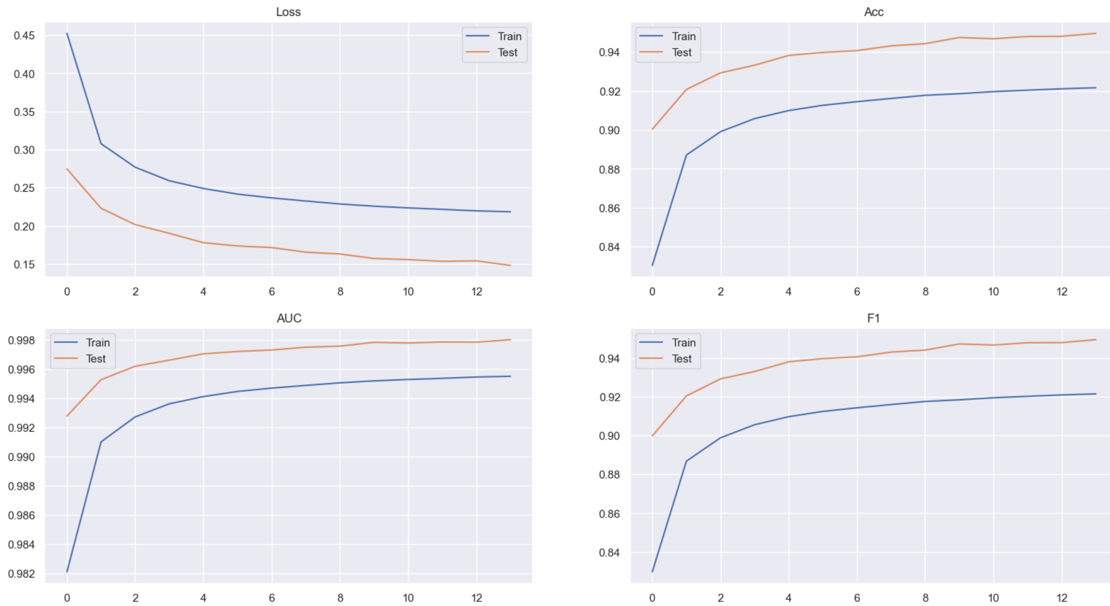
# 4 Evaluation

## 4.1 Training Metrics

[44]:
```
PlotHistory(train_losses[-(50):], valid_losses[-(50):], figsize=(19, 6),␣
↪test_alpha = 1)
```




[36]:
```
PlotAllMetrics(["Loss", "Acc", "AUC", "F1"],
               [train_losses, train_metric1s, train_metric2s, train_metric3s],
               TestMetrics = [valid_losses, valid_metric1s, valid_metric2s,␣
↪valid_metric3s],
               figsize = [19, 10], test_alpha = 0.90)
```



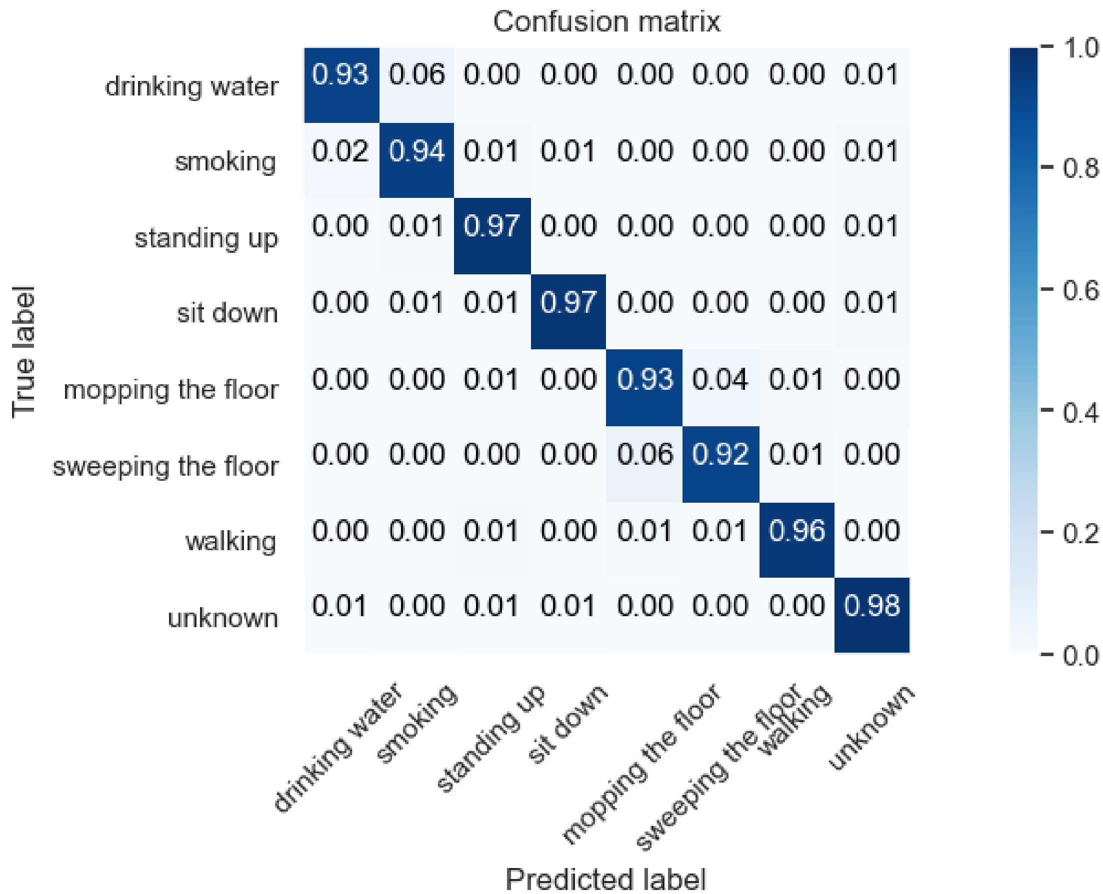

## 4.2 Multiclass Classification

[41]:
```
Labels = Classes
MaxLabelsLen = max([len(lbl) for lbl in Labels])
with torch.no_grad(): #Making sure that we don't update the gradient outside the training part
        model.eval() #Putting model in evaluation mode so that things like dropout() are deactivated
        model.to(device) #Moving the model to the appropriate device (CPU/CUDA/etc.)

        #Using the Forward direction of the model to get the Predictions (also returning the corresponding Targets in case there's suffling and X_Test isn't indexed the same)
        Preds_prob, Preds, Targets = EvalPredict(model, batch_size, device, X_Test, Y_Test)

test_Acc, test_AUC, test_F1 = GetCategoricalMetrics(Preds_prob, Preds, Targets)
print(f'Sample-wise Acc: {test_Acc * 100:.2f}%, AUC: {test_AUC:.2f}, F1: {test_F1:.2f}')
print(f"Class-wise  Acc: {ClassAccMulti(Targets, Preds, K_Length) * 100:.2f}%, Recall: {recall_score(Targets, Preds, average = 'weighted'):.3f}, Precision: {precision_score(Targets, Preds, average = 'weighted'):.3f}\n") #'micro', 'macro', 'weighted', 'samples'

#Viewing the overall Categorical metrics and Plotting the Confusion Matrix
```

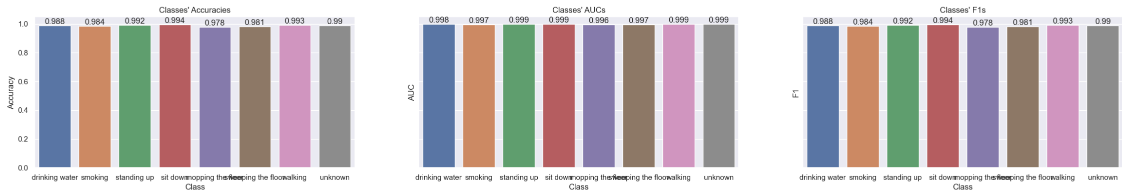
```python
PlotCategoricalMetrics(Preds, Targets, Labels, normalise = True, figsize = [11,␣
↪5])
print("")

plt.rcParams['figure.figsize'] = [5, 5]
TrueClasses, PerClassAccuracy, PerClassAUC, PerClassF1 = [], [], [], []
for k in range(K_Length):
    PredClass = Preds.squeeze()   == k
    TrueClass = Targets.squeeze() == k
    TrueClasses.append(TrueClass)
    cur_test_Acc, cur_test_AUC, cur_test_F1 = GetCategoricalMetrics(Preds_prob[:
↪, k], PredClass, TrueClass)
    PerClassAccuracy.append(cur_test_Acc)
    PerClassAUC.append(cur_test_AUC)
    PerClassF1.append(cur_test_F1)
    print(f"Class {SpaceAString(Labels[k], MaxLabelsLen)}. Acc: {np.
↪mean(TrueClass == PredClass):.3f}, Recall: {recall_score(TrueClass,␣
↪PredClass):.3f}, Precision: {precision_score(TrueClass, PredClass):.3f}, F1:␣
↪{f1_score(TrueClass, PredClass):.3f}")
PerClassAccuracy, PerClassAUC, PerClassF1 = np.array(PerClassAccuracy), np.
↪array(PerClassAUC), np.array(PerClassF1)

print("\nPer Class Metrics:")
PlotPerClassMetrics(K_Length, PerClassAccuracy, PerClassAUC, PerClassF1, Labels␣
↪= Labels)

print("\nPer Class ROC:")
PlotPerClassROCCurve(K_Length, TrueClasses, Preds_prob, Labels = Labels)

print("\nPer Class Precision-Recall Curve:")
PlotPerClassPRCurve(K_Length, TrueClasses, Preds_prob, Labels = Labels)

plt.rcParams['figure.figsize'] = OrigFigSize
```

```
#batches: 870.


Sample-wise Acc: 95.01%, AUC: 1.00, F1: 0.95
Class-wise  Acc: 98.75%, Recall: 0.950, Precision: 0.950

Confusion matrix
[[48067  2863    79    70    70    32    36   288]
 [ 1168 44751   514   310    57    16   111   682]
 [   35   334 40688   185   115    23   128   417]
 [   53   282   262 39894    67    15    49   499]
 [   30   187   396   209 57259  2668   782   282]
 [   36    72   166    98  4096 59826   570   249]
```

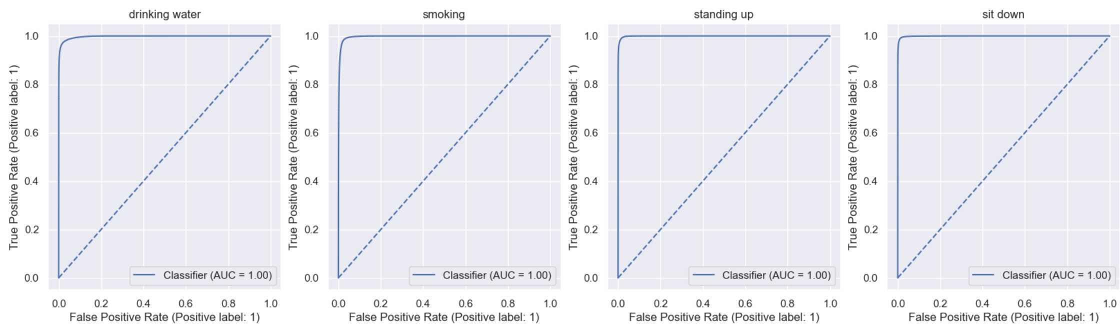
```
[    3   184   396    72   562   295 40435    84]
[  539   215   527   608    79    22    41 92117]]
```



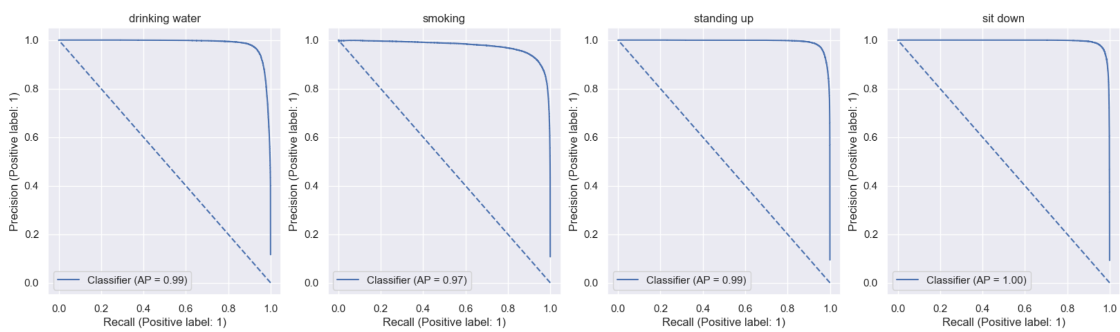

```
Class     drinking water. Acc: 0.988, Recall: 0.933, Precision: 0.963, F1: 0.948
Class            smoking. Acc: 0.984, Recall: 0.940, Precision: 0.915, F1: 0.928
Class        standing up. Acc: 0.992, Recall: 0.970, Precision: 0.946, F1: 0.958
Class           sit down. Acc: 0.994, Recall: 0.970, Precision: 0.963, F1: 0.966
Class  mopping the floor. Acc: 0.978, Recall: 0.926, Precision: 0.919, F1: 0.923
Class sweeping the floor. Acc: 0.981, Recall: 0.919, Precision: 0.951, F1: 0.935
Class            walking. Acc: 0.993, Recall: 0.962, Precision: 0.959, F1: 0.961
Class            unknown. Acc: 0.990, Recall: 0.978, Precision: 0.974, F1: 0.976

Per Class Metrics:
```




Per Class ROC:




Per Class Precision-Recall Curve:




[ ]:
```
# Labels = Classes
# with torch.no_grad(): #Making sure that we don't update the gradient outside
↪the training part
#         model.eval() #Putting model in evaluation mode so that things like
↪dropout() are deactivated
#         model.to(device) #Moving the model to the appropriate device (CPU/
↪CUDA/etc.)
```

```
#         #Using the Forward direction of the model to get the Predictions␣
↪(also returning the corresponding Targets in case there's suffling and␣
↪X_Test isn't indexed the same)
#         Preds_prob, Preds, Targets = EvalPredict(model, device, Loader_Test)

# test_Acc, test_AUC, test_F1 = GetCategoricalMetrics(Preds_prob, Preds,␣
↪Targets)
# print(f'Sample-wise Acc: {test_Acc * 100:.2f}%, AUC: {test_AUC:.2f}, F1:␣
↪{test_F1:.2f}')
# print(f"Class-wise  Acc: {ClassAccMulti(Targets, Preds, K_Length) * 100:.
↪2f}%, Recall: {recall_score(Targets, Preds, average = 'weighted'):.3f},␣
↪Precision: {precision_score(Targets, Preds, average = 'weighted'):.3f}\n")␣
↪#'micro', 'macro', 'weighted', 'samples'

# #Viewing the overall Categorical metrics and Plotting the Confusion Matrix
# PlotCategoricalMetrics(Preds, Targets, Labels, normalise = True, figsize =␣
↪[11, 5])
# print("")

# plt.rcParams['figure.figsize'] = [5, 5]
# TrueClasses, PerClassAccuracy, PerClassAUC, PerClassF1 = [], [], [], []
# for k in range(K_Length):
#     PredClass = Preds.squeeze()   == k
#     TrueClass = Targets.squeeze() == k
#     TrueClasses.append(TrueClass)
#     cur_test_Acc, cur_test_AUC, cur_test_F1 =␣
↪GetCategoricalMetrics(Preds_prob[:, k], PredClass, TrueClass)
#     PerClassAccuracy.append(cur_test_Acc)
#     PerClassAUC.append(cur_test_AUC)
#     PerClassF1.append(cur_test_F1)
#     print(f"Class {SpaceAString(Labels[k], MaxLabelsLen)}. Acc: {np.
↪mean(TrueClass == PredClass):.3f}, Recall: {recall_score(TrueClass,␣
↪PredClass):.3f}, Precision: {precision_score(TrueClass, PredClass):.3f}, F1:␣
↪{f1_score(TrueClass, PredClass):.3f}")
# PerClassAccuracy, PerClassAUC, PerClassF1 = np.array(PerClassAccuracy), np.
↪array(PerClassAUC), np.array(PerClassF1)

# print("\nPer Class Metrics:")
# PlotPerClassMetrics(K_Length, PerClassAccuracy, PerClassAUC, PerClassF1,␣
↪Labels = Labels)

# print("\nPer Class ROC:")
# PlotPerClassROCCurve(K_Length, TrueClasses, Preds_prob, Labels = Labels)

# print("\nPer Class Precision-Recall Curve:")
# PlotPerClassPRCurve(K_Length, TrueClasses, Preds_prob, Labels = Labels)
```

```
# plt.rcParams['figure.figsize'] = OrigFigSize
```

## 5 Saving the Model

[48]:
```
print("path_root:", path_root, "\n")

SaveFolder = (f'{path_root}/Models/' +
              f'{datetime.now(timezone("Europe/Athens")).strftime("%Y-%m-%d␣
 ↪%H-%M")}' +
              f", T-{T_Length} Valid Loss {valid_loss:.2f}" +
              f' Acc {valid_metric1:.2f}' +
              f', Test Acc {test_Acc:.2f}' +
              f' AUC {test_AUC:.2f}' +
              f' F1 {test_F1:.2f}'
)
print(SaveFolder)
os.makedirs(SaveFolder, exist_ok = True)
```

```
path_root: D:\GiannisM\Downloads\Exercises\Fiver\100. frotribe FFNN Multiclass
Classification

D:\GiannisM\Downloads\Exercises\Fiver\100. frotribe FFNN Multiclass
Classification/Models/2022-11-02 22-59, T-720 Valid Loss 0.15 Acc 0.95, Test Acc
0.95 AUC 1.00 F1 0.95
```

[34]:
```
if isnotebook:
    i = 2
```

[ ]:
```
if isnotebook:
    i += 1
    print(i)
    display(_ih[i])
```

[36]:
```
if isnotebook:
    PossibleNetClass = _ih[i]
```

[37]:
```
### Saving the Model ###
QuoteIfNone = lambda x: f"'{x}'" if x is not None else "None"

#Saving the Parameters
WriteText(
    f"#PyTorch v{torch.__version__}\n#CUDA device available:␣
 ↪{IS_GPU_AVAILABLE}\n{f'#{torch.cuda.device_count()} devices available' if␣
 ↪torch.cuda.is_available() else ''}\n#device = {device}\n" +
    f"#isnotebook = {isnotebook}\n#isgooglecolab = {isgooglecolab}\n#shell =␣
 ↪{shell}\n\n" +
```

```
    f"layer_type = {json.dumps(layer_type)}\nSeed = {Seed}\nnum_units = {json.
  ↪dumps(num_units)}\nactivation = {json.dumps(activation)}\ndropout = {json.
  ↪dumps(dropout)}\nusebias = {usebias}\n" +
    f"batch_size = {batch_size}\n" +
    f"T_Length = {T_Length}\nK_Length = {K_Length}\nD_Length = {D_Length}\nH1 =␣
  ↪{H1}\nW1 = {W1}\nconv_input_size = {conv_input_size}\ninput_size =␣
  ↪{input_size}\noutput_size = {output_size}\nhn1 = {hn1}\n\n" +
    f"transf_nhead = {transf_nhead}\ntransf_ff_dim =␣
  ↪{transf_ff_dim}\ntransf_l_norm = {transf_l_norm}\ntransf_drp =␣
  ↪{transf_drp}\ntransf_actv = {transf_actv}\n" +
    f"l2_lamda = {l2_lamda}\nmu = {mu}\n" +
    f"\nPrintInfoEverynEpochs = {PrintInfoEverynEpochs}\n" +
    f"\ntrain_best_loss = {train_best_loss}\nvalid_best_loss =␣
  ↪{valid_best_loss}\nReluAlpha = {ReluAlpha}\nEluAlpha = {EluAlpha}\n" +
    f"valid_metric1 = {valid_metric1}\nvalid_metric2 =␣
  ↪{valid_metric2}\nvalid_metric3 = {valid_metric3}\n"
    f"valid_best_metric1 = {valid_best_metric1}\nvalid_best_metric2 =␣
  ↪{valid_best_metric2}\nvalid_best_metric3 = {valid_best_metric3}\n",
f"{SaveFolder}/Parameters.py")

#Saving the Losses so we can plot them in the future
WriteText(json.dumps(train_losses.tolist())  , f"{SaveFolder}/Metrics/
  ↪train_losses.json"  )
WriteText(json.dumps(valid_losses.tolist())  , f"{SaveFolder}/Metrics/
  ↪valid_losses.json"  )
WriteText(json.dumps(train_metric1s.tolist()), f"{SaveFolder}/Metrics/
  ↪train_metric1s.json")
WriteText(json.dumps(train_metric2s.tolist()), f"{SaveFolder}/Metrics/
  ↪train_metric2s.json")
WriteText(json.dumps(train_metric3s.tolist()), f"{SaveFolder}/Metrics/
  ↪train_metric3s.json")
WriteText(json.dumps(valid_metric1s.tolist()), f"{SaveFolder}/Metrics/
  ↪valid_metric1s.json")
WriteText(json.dumps(valid_metric2s.tolist()), f"{SaveFolder}/Metrics/
  ↪valid_metric2s.json")
WriteText(json.dumps(valid_metric3s.tolist()), f"{SaveFolder}/Metrics/
  ↪valid_metric3s.json")

#Saving the Optimiser
WriteText(optimiser, f"{SaveFolder}/Optimiser.txt")
#Saving the optimiser's parameters
torch.save(optimiser.state_dict(), f"{SaveFolder}/optimiser_dict.pt")

#Saving the Criterion
SaveVariable(criterion, f"{SaveFolder}/criterion.pt")
#Saving the Criterion's name (easier to see by looking at the file)
```

```
WriteText(criterion, f"{SaveFolder}/criterion.txt")

#Saving the Net() Class
if isnotebook:
    print(PossibleNetClass.partition('\n')[0])
    WriteText(PossibleNetClass, f"{SaveFolder}/Net.py")
else:
    WriteText(f"#Net() not found.\n#Probably not a notebook?\n", f"{SaveFolder}/
↪Net.py")

#Saving the Scaler Variable
SaveVariable(scaler, f"{SaveFolder}/scaler")
#Saving the Scaler's parameters as text
WriteText(scaler_mean.tolist(), f"{SaveFolder}/scaler_mean.json")
WriteText(scaler_sd.tolist(), f"{SaveFolder}/scaler_std.json")

#Saving Model itself
torch.save(model.state_dict(), f"{SaveFolder}/model_dict.pt")
#Saving Model itself
SaveVariableDill(model, f"{SaveFolder}/model.pt")

#Saving the Scheduler
SaveVariableDill(scheduler, f"{SaveFolder}/scheduler.pt")
print("Done!")
```

```
#Custom Transformer Encoder
Done!
```

## 6 Loading the Model

[28]:

```
SaveFolder = f"{path_root}/Models/T-720 Valid Loss 0.15 Acc 0.95, Test Acc 0.95␣
↪AUC 1.00 F1 0.95"
```

[29]:

```
# PrevT_Length = T_Length
# PrevTrainPerc = TrainPerc
# PrevValidPerc = ValidPerc
#Loading the Parameters
exec(ReadText(f"{SaveFolder}/Parameters.py"))
# if PrevT_Length != T_Length:
#     warnings.warn(f"PrevT_Length: {PrevT_Length}, whilst now after loading,␣
↪T_Length: {T_Length}. Re-run the DATA section!")
# if PrevTrainPerc != TrainPerc:
#     warnings.warn(f"PrevTrainPerc: {PrevTrainPerc}, whilst now after loading,␣
↪TrainPerc: {TrainPerc}. Re-run the DATA section!")
# if PrevValidPerc != ValidPerc:
```

```
#     warnings.warn(f"PrevValidPerc: {PrevValidPerc}, whilst now after loading,␣
↪ValidPerc: {ValidPerc}. Re-run the DATA section!")

#Loading the Criterion
criterion = LoadVariable(f"{SaveFolder}/criterion.pt")

#Loading Model itself
model = LoadVariableDill(f"{SaveFolder}/model.pt").to(device)
model.eval() #Putting model in evaluation mode so that things like dropout()␣
↪are deactivated

#Loading the Optimiser
optimiser = torch.optim.AdamW(model.parameters(), lr = 0.1, betas = (0.9, 0.9),␣
↪weight_decay = 0, amsgrad = False)
optimiser.load_state_dict(torch.load(f"{SaveFolder}/optimiser_dict.pt"))

#Loading the Scheduler
scheduler = LoadVariableDill(f"{SaveFolder}/scheduler.pt")

#Loading the Scaler
print("!!! Be EXTRA careful when loading a scaler as it might be different to␣
↪the one used in the beginning under 'Data' to scale current X_Test, and if␣
↪so, re-run 'Data' with its scaler loading commented off !!!")
scaler = LoadVariable(f"{SaveFolder}/scaler")
scaler_mean = np.array(json.loads(ReadText(f"{SaveFolder}/scaler_mean.json")))␣
↪if os.path.exists(f"{SaveFolder}/scaler_mean.json") else scaler.mean_
scaler_sd = np.array(json.loads(ReadText(f"{SaveFolder}/scaler_std.json"))) if␣
↪os.path.exists(f"{SaveFolder}/scaler_std.json") else scaler.scale_
scaler_mean_sd = (scaler_mean, scaler_sd)

print("Done!")
```

```
!!! Be EXTRA careful when loading a scaler as it might be different to the one
used in the beginning under 'Data' to scale current X_Test, and if so, re-run
'Data' with its scaler loading commented off !!!
Done!
```

[30]:
```
train_losses   = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪train_losses.json")))
valid_losses   = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪valid_losses.json")))
train_metric1s = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪train_metric1s.json")))
train_metric2s = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪train_metric2s.json")))
train_metric3s = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪train_metric3s.json")))
```

```
valid_metric1s = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪valid_metric1s.json")))
valid_metric2s = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪valid_metric2s.json")))
valid_metric3s = np.array(json.loads(ReadText(f"{SaveFolder}/Metrics/
↪valid_metric3s.json")))
print("Done!")
```

```
Done!
```

[31]:
```
model = Net(T_Length, K_Length, num_units, activation, usebias, dropout,␣
↪EluAlpha, ReluAlpha, transf_nhead, transf_ff_dim, transf_l_norm, transf_drp,␣
↪transf_actv)

if device != "cpu":
    model.load_state_dict(torch.load(f"{SaveFolder}/model_dict.pt"))
#     model = nn.DataParallel(model)
else:
    model.load_state_dict(torch.load(f"{SaveFolder}/model_dict.pt",␣
↪map_location = torch.device("cpu")))

#model.load_state_dict(OrderedDict((k.replace("module.", ""), v) for k, v in␣
↪torch.load(f"{SaveFolder}/model_dict.pt", map_location = "cpu").items()))␣
↪#De-DataParallel the model
model.eval()
print("Done!")
```

```
Done!
```

# 7 Predicting on External Data

[33]:
```
External_DF = pd.read_csv(f"{path_data}/11-16 (1).csv", header = None).iloc[:,␣
↪1:]
Melted_External_DF = []
for i in range(len(External_DF)):
    tmpDF = pd.DataFrame({"Accelerometer": np.trim_zeros(External_DF.iloc[i, :].
↪values)})
    Melted_External_DF.append(tmpDF[["Accelerometer"]])
Melted_External_DF = pd.concat(Melted_External_DF).reset_index(drop = True)
Melted_External_DF
X_External = Scale(Melted_External_DF.values, *scaler_mean_sd)
X_External = NxD_to_N2xTxD(X_External, None, T_Length, Y_Data = None,␣
↪TrainingMode = False, OffsetT = 0, OffsetY = 0, KeepUntilOffsetY = False)

MYDataset = TensorDataset(torch.from_numpy(X_External.copy()))
MYDataLoader = torch.utils.data.DataLoader(
    MYDataset,
```

```
    batch_size = batch_size,
    pin_memory = True
)

model.to(device)
model.eval()
with torch.no_grad():
    TestPredictions = []
    for inputs in tqdm(MYDataLoader, initial = 0, total = len(MYDataLoader),␣
 ↪leave = False):
        TestPredictions.append(model(inputs[0].to(device)))
    _, TestPredictions = torch.max(nn.Softmax(dim = 1)(torch.
 ↪cat(TestPredictions)), 1)
    TestPredictions += 1
    TestResults = pd.DataFrame(TestPredictions.cpu().numpy()).reset_index()
    TestResults.columns = ["Id", "Class"]

FileExportPath = f"{path_root}/Exports/Results.csv"
TestResults.to_csv(FileExportPath, sep = ',', header = True, index = False)
print(f"Results saved on: {FileExportPath}")

TestResults
```

```
Results saved on: D:\GiannisM\Downloads\Exercises\Fiver\100. frotribe FFNN
Multiclass Classification/Exports/Results.csv
```

[33]:

| | Id | Class |
|---|---|---|
| 0 | 0 | 1 |
| 1 | 1 | 1 |
| 2 | 2 | 1 |
| 3 | 3 | 1 |
| 4 | 4 | 5 |
| … | … | … |
| 4457676 | 4457676 | 8 |
| 4457677 | 4457677 | 8 |
| 4457678 | 4457678 | 8 |
| 4457679 | 4457679 | 8 |
| 4457680 | 4457680 | 8 |

[4457681 rows x 2 columns]

[ ]: