ML4SCI TASK 1

ELECTRON VS PHOTONS

Have trained the model in kaggle and then downloaded notebook and have paster here

Used the GPU of the kaggle to train the model

The link of the kaggle notebook ---https://www.kaggle.com/code/vishakkbhat/ml4sci-task-1

```
# importing basic modules
import pandas as pd
import numpy as np
```

To read the file of type hdf5 we need to import h5py

```
import h5py
```

This code below separates the X and y for the training from both the directories inside the root/input directory

```
vishak =
h5py.File('/kaggle/input/electron-vs-photons-ml4sci/SingleElectronPt50
_IMGCROPS_n249k_RHv1.hdf5')
```

```
vishak.keys()
```

```
<KeysViewHDF5 ['X', 'y']>
```

WE SEE THAT IT CONTAINS X AND y INSINDE IT SO THAT WE CAN SPLIT IT LATER ON

```
vishak['/X']  # code to open the X values inside the File

#Same way can be used for y
```

```
<HDF5 dataset "X": shape (249000, 32, 32, 2), type "<f4">
```

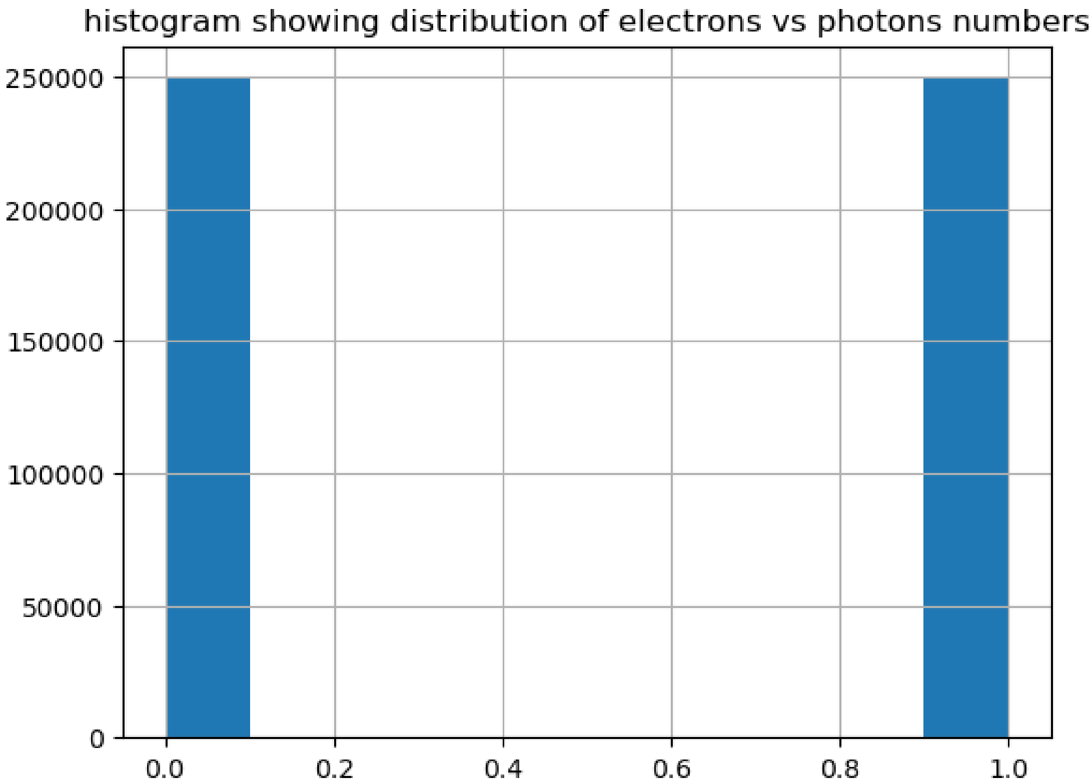
****LETS CREATE A FUNCTION THAT CONCATENATES THE IMAGES OF TWO DIRECTORIES ie ELECTRONS AND PHOTONS****

```
img_rows, img_cols, nb_channels=32, 32, 2 #   channels=2(hit energy
and time)  image dimension is 32*32
input_dir = '/kaggle/input/electron-vs-photons-ml4sci'

decays=['SinglePhotonPt50_IMGCROPS_n249k_RHv1','SingleElectronPt50_IMG
CROPS_n249k_RHv1']
```

```
def load_data(decays):
    global input_dir

    dsets = [h5py.File(input_dir+'/'+decay+'.hdf5') for decay in
decays]

    X = np.concatenate([dset['/X'][0:300000] for dset in dsets])
    y = np.concatenate([dset['/y'][0:300000] for dset in dsets])
    assert len(X) == len(y)

    return X, y


X,y=load_data(decays)

y=pd.DataFrame(y)

y.value_counts(normalize=False)
```

```
0.0    249000
1.0    249000
dtype: int64
```

```
import matplotlib.pyplot as plt

y.hist()
plt.title("histogram showing distribution of electrons vs photons
numbers");
```



WE SEE THAT BOTH THE ELECTRONS AND PHOTONS HAVE EQUAL NUMBER OF IMAGES

LETS TRY PRINTING THE IMAGE

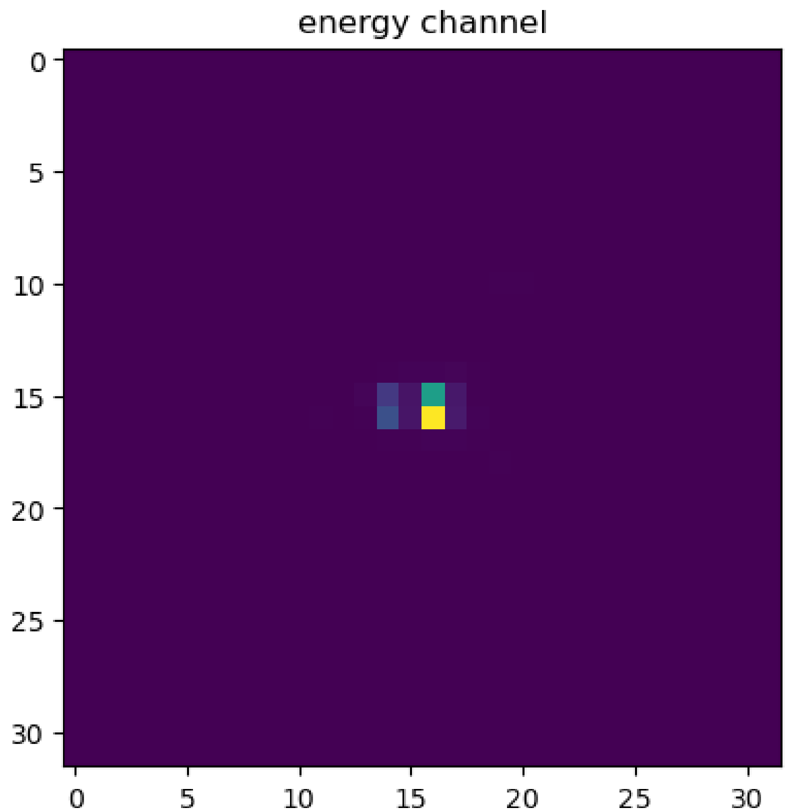
```
X.shape
```

```
(498000, 32, 32, 2)
```

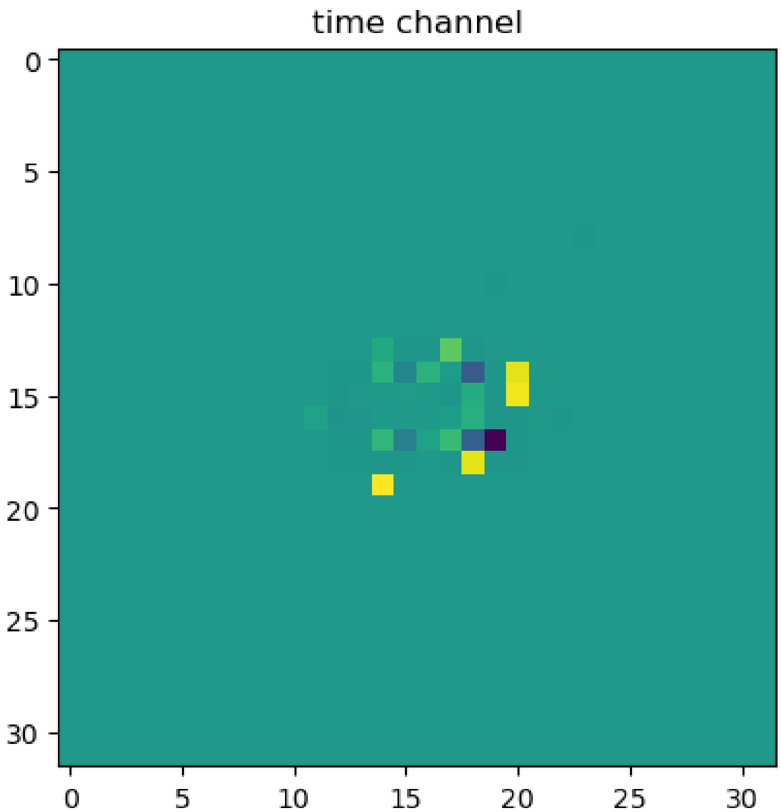
```
X[0].shape
```

```
(32, 32, 2)
```

```
plt.imshow(X[0,:,:,0])   #shows us the first channel out of the two channels
plt.title("energy channel");
```




```
plt.imshow(X[0,:,:,1])   #shows us the second channel out of the two
channels
plt.title("time channel");
```



REFERENCE

- DATASETS TAKEN FROM ML4SCI -- https://cernbox.cern.ch/index.php/s/AtBT8y4MiQYFcgc (photons) https://cernbox.cern.ch/index.php/s/FbXw3V4XNyYB3oA (electrons)

PIPELINE OF THE PROJECT

- LETS SPLIT THE DATA INTO TRAIN AND TEST
- LETS CREATE THE DATASET AND DATA LOADER FIRST
- CREATE THE ARCHITECTURE OF THE MODEL

```
X=X/(X.max())

from sklearn.model_selection import train_test_split

X=X.transpose(0,3,1,2)

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.1,shuff
le=True,random_state=17)

import torch
import torch.nn as nn
from torch.utils.data import Dataset,DataLoader
import torch.nn.functional as F
```

```
device=torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

```
device
```

```
device(type='cuda')
```

```
y_train=np.array(y_train)
y_test=np.array(y_test)
```

```
X_train=(torch.tensor(X_train,dtype=torch.float32)).to(device)
X_test=torch.tensor(X_test,dtype=torch.float32)
y_train=torch.tensor(y_train,dtype=torch.float32).to(device)
y_test=torch.tensor(y_test,dtype=torch.float32)
```

Creating A dataset class which returns the training example for the given index under the getindex function

```
class train_dset(Dataset):

    def __init__(self,X,y):

        self.X=X
        self.y=y

    def __len__(self):
        return len(self.X)

    def __getitem__(self,idx):

        return self.X[idx],self.y[idx]


traindset= train_dset(X_train,y_train)
```

Setting up the train loader so that we can use the dataloader to feed to the training loop

```
train_loader= DataLoader(traindset,batch_size=32,shuffle=True)
```

```
next(iter(train_loader))[0].shape
```

```
torch.Size([32, 2, 32, 32])
```

Created a class for the architecture of the CNN network with 2 conv layers followed by fully conncected layers. Have used ReLU activation

```
class EPArchi(nn.Module):
    def __init__(self):
        super(EPArchi, self).__init__()
        # define convolutional layers
        self.conv1 = nn.Conv2d(in_channels=2, out_channels=16,
```

```
kernel_size=3, stride=1, padding=1)
        self.conv2 = nn.Conv2d(in_channels=16, out_channels=32,
kernel_size=3, stride=1, padding=1)
        # define fully connected layers
        self.fc1 = nn.Linear(in_features=32*8*8, out_features=64)
        self.fc2 = nn.Linear(in_features=64, out_features=1)
        # define activation function
        self.relu = nn.ReLU()
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        # pass input through convolutional layers
        x = self.conv1(x)
        x = self.relu(x)
        x = nn.functional.max_pool2d(x, 2)
        x = self.conv2(x)
        x = self.relu(x)
        x = nn.functional.max_pool2d(x, 2)
        # flatten the output of convolutional layers
        x = torch.flatten(x, 1)
        # pass the flattened output through fully connected layers
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        # apply sigmoid activation function to output
        x = self.sigmoid(x)
        return x

model = EPArchi().to(device)
```

TRAINING LOOP

Have used BCE loss function

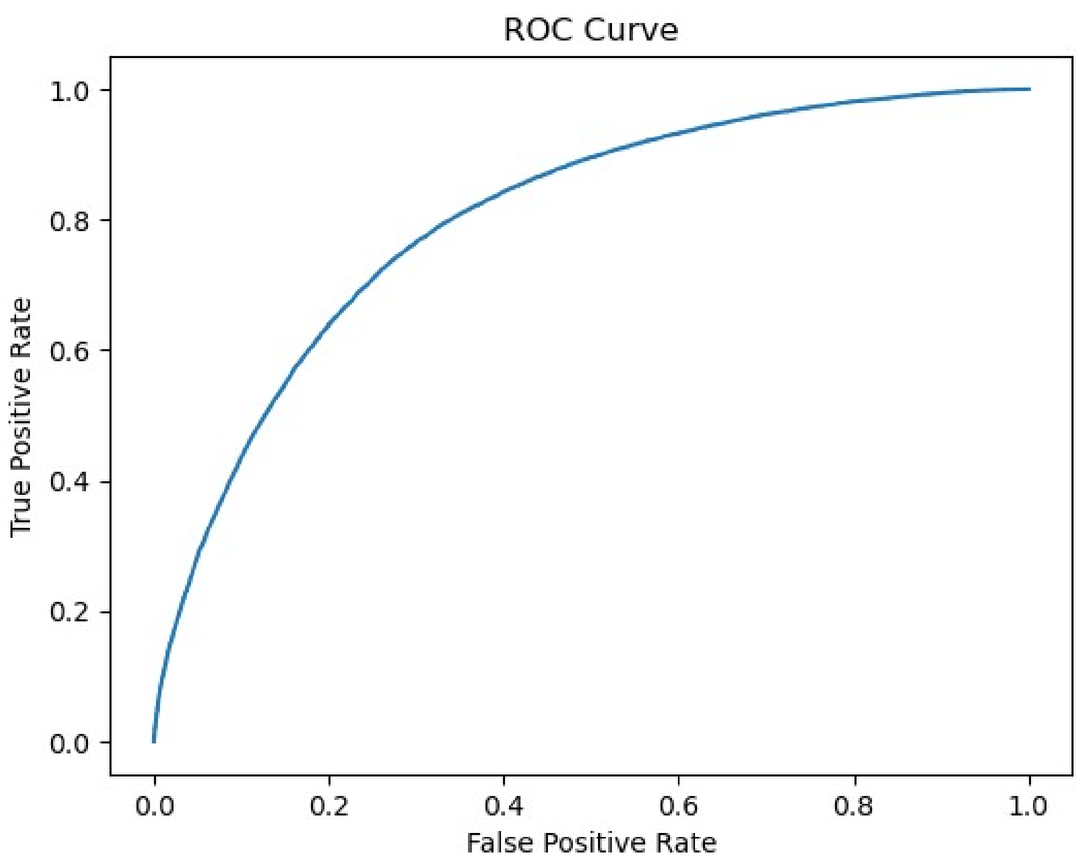
** ADAM optimization **

```
import torch
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt

# define hyperparameters
batch_size = 32
learning_rate = 1e-3
num_epochs = 80

model=model.to(device)
```

```python
# define loss function and optimizer
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)

# initialize variables for storing loss and epoch count
train_loss = []
epoch_count = []

# train model
for epoch in range(num_epochs):
    running_loss = 0.0
    for i, data in enumerate(train_loader, 0):
        # get the inputs and labels from the dataloader
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()

    # store the epoch loss and epoch count
    train_loss.append(running_loss / len(train_loader))
    epoch_count.append(epoch + 1)

    # print epoch statistics
    print('Epoch %d loss: %.3f' % (epoch+1, running_loss /
len(train_loader)))

# plot the loss graph
plt.plot(epoch_count, train_loss)
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()

print('Finished training')

from sklearn.metrics import roc_auc_score, roc_curve
# set model to evaluation mode
model.eval()
mdoel=model.to('cpu')
```

```
# evaluate test data
with torch.no_grad():
    y_pred = (model(X_test))
#     test_loss = nn.BCELoss()(y_pred, y_test.float())
    test_roc_auc = roc_auc_score(y_test, y_pred)

# print('Test Loss: %.3f' % test_loss)
print('Test ROC AUC: %.3f' % test_roc_auc)

# plot ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()
```

```
Test ROC AUC: 0.801
```



After a lot of time in tuning the hyper parameters managed to get the ROC AUC above 80 and the above graph shows it