final-ml4sci-task-2

March 8, 2023

1 ML4SCI TASK 2

2 Quark-Gluon Classification

ACTUALLY THE ARRAY IS OF SIZE 3 IN WHICH EACH ELEMENT IS ITSELF AN ARRAY OF 125 ELEMENTS AND THAT 125 ELEMENTS IS AN ARRAY OF 125 ELEMENTS

THIS NOTEBOOK SHOWS THE CONVERSION OF THIS TYPE OF MATRIX INTO 3,125,125

THE KAGGLE NOTEBOOK LINK IS HERE-https://www.kaggle.com/code/vishakkbhat/ml4sci-task-2

[31]:
```
# importing basic modules"
import pandas as pd
import numpy as np
```

Lets import the data……

We find that the data is toooo huge and normal pd.read_parquet(”) causes cpu overload and hence doesnt get read

SO WHAT IS MY APPRACH??

- 1) **I ran a for loop from 0 to total rows with step size of chunk_size variable**
- 2) **Then reading the ith elementand converting it into pandas**
- 3) **Lastly appending them all to form the dataFrame**

TO SET THE NUMBER OF EXAMPLES TO EXTRACT

If u set the value of chunk size as n , then u will get total rows//n number of examples

[32]:
```
import pyarrow.parquet as pq
# Set the size of each chunk in rows
chunk_size = 25

# Create a Parquet file reader object
parquet_file = pq.ParquetFile('/kaggle/input/ml4sci/
↪QCDToGGQQ_IMGjet_RH1all_jet0_run0_n36272.test.snappy.parquet')
```

```python
# Determine the total number of rows in the file
total_rows = parquet_file.metadata.num_rows

# Loop over the file in chunks
dfs = []
for i in range(0, total_rows, chunk_size):
    # Read a chunk of rows from the file
    chunk = parquet_file.read_row_group(i)
    df = chunk.to_pandas()
#     print(i)
    dfs.append(df)

# Concatenate all the DataFrames into a single DataFrame
final_df = pd.concat(dfs, ignore_index=True)
```

[33]:
```python
parquet_file.metadata    #Shows us what is there inside the parquet file
```

[33]:
```
<pyarrow._parquet.FileMetaData object at 0x7f161d0b46b0>
  created_by: parquet-cpp version 1.3.1-SNAPSHOT
  num_columns: 4
  num_rows: 36272
  num_row_groups: 36272
  format_version: 1.0
  serialized_size: 14143781
```

[34]:
```python
parquet_file.read_row_group(0).to_pandas()
```

[34]:
```
                                              X_jets          pt         m0  \
0  [[[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0…  112.411095  21.098248

     y
0  0.0
```

[35]:
```python
final_df['X_jets'][0].shape
```

[35]:
```
(3,)
```

Above we see that the each element under the X__jets is just an array of 3 elements… but that 3 elements is it self an array of 125 elements where that 125 elements is an array of 125 elements

I created a function that stacks this and creates a 3,125,125 matrix

[36]:
```python
def to_3d(arr):
    vishak=[]
    for i in range (0,3):
        vis=np.stack(np.stack(arr)[i],axis=-1)
        vishak.append(vis)
```

```
    vishak=np.array(vishak)
    return vishak
```

calling the above created function

[37]:
```
rr=final_df['X_jets'].shape[0]
```

[38]:
```
for i in range (0,rr):
    final_df['X_jets'][i]=to_3d(final_df['X_jets'][i])
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[39]:
```
final_df['X_jets'][0],final_df['X_jets'][0].shape
```

[39]:
```
(array([[[0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         …,
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.]],

        [[0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         …,
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.]],

        [[0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         …,
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.],
         [0., 0., 0., …, 0., 0., 0.]]]),
 (3, 125, 125))
```

So we see that our dataframe final_df now has a column called X_jets which contains 3,125,125 sized matrix

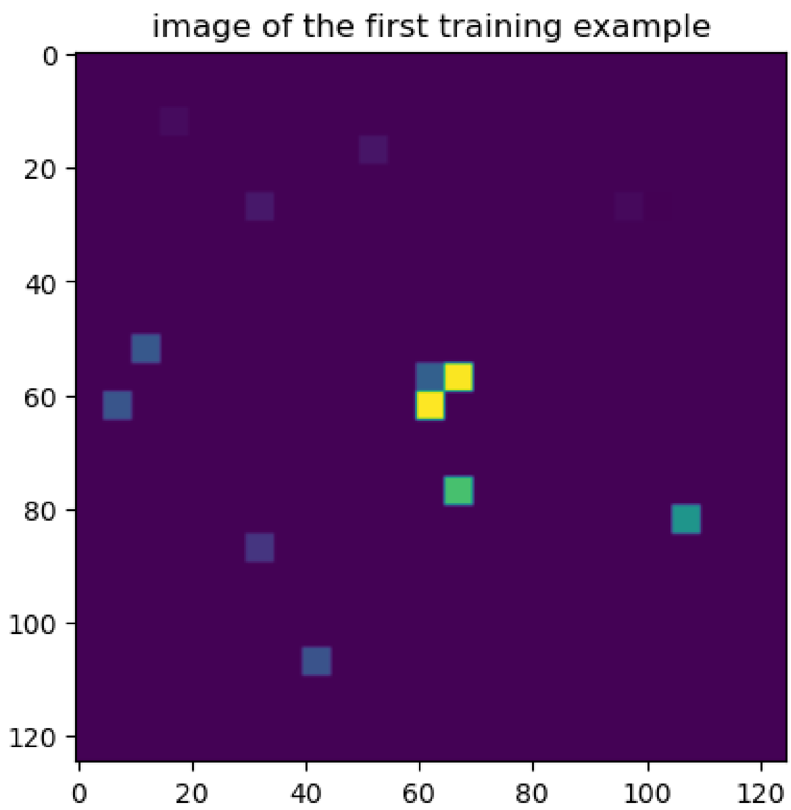
[40]:
```python
import matplotlib.pyplot as plt
```

Lets plot and see how the image looks like

[41]:
```python
plt.imshow(final_df['X_jets'][0][0,:,:])
plt.imshow(final_df['X_jets'][0][1,:,:])
plt.imshow(final_df['X_jets'][0][2,:,:])

plt.title("image of the first training example");
label=final_df['y'][0]
print(f"Label is ={label}")
```

```
Label is =0.0
```



Plotting multiple images and seeing

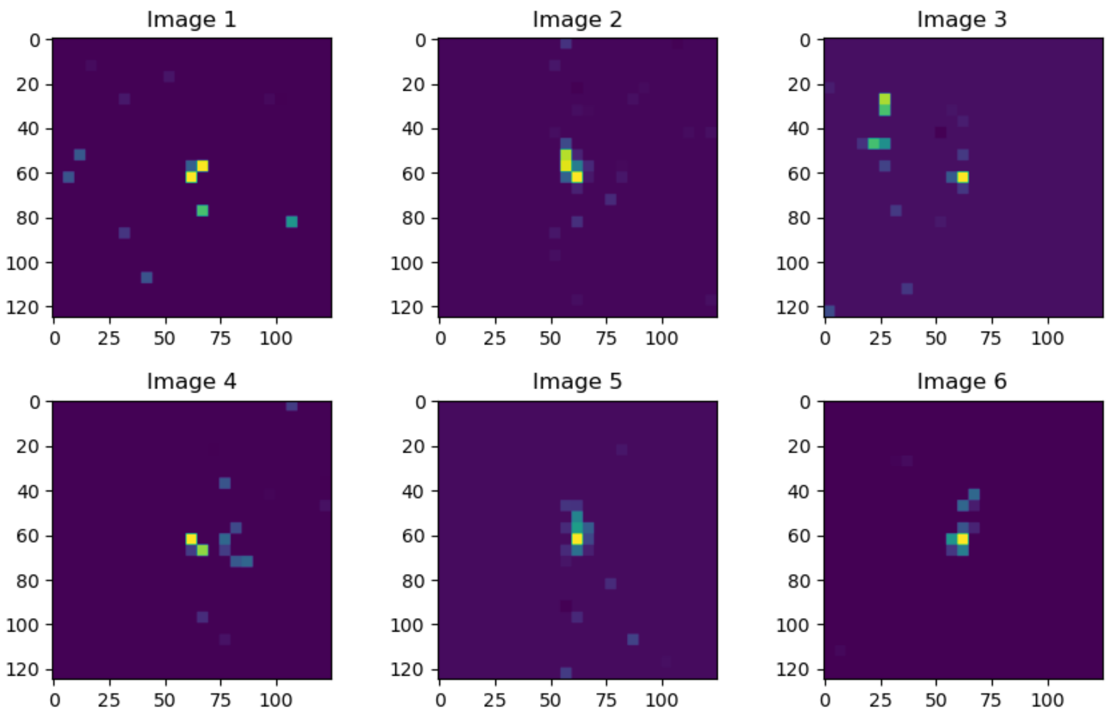
[42]:
```python
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(10, 6))

# Loop over the axes and image ids, and plot each image on a separate subplot
for i, ax in enumerate(axes.flatten()):
    image = final_df['X_jets'][i][2,:,:]
    ax.imshow(image)
```

```python
    ax.set_title(f'Image {i+1}')

# Adjust spacing between subplots
plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.3,␣
 ↪hspace=0.3)

# Show the plot
plt.show()
```



3 TASKS PERFORMED

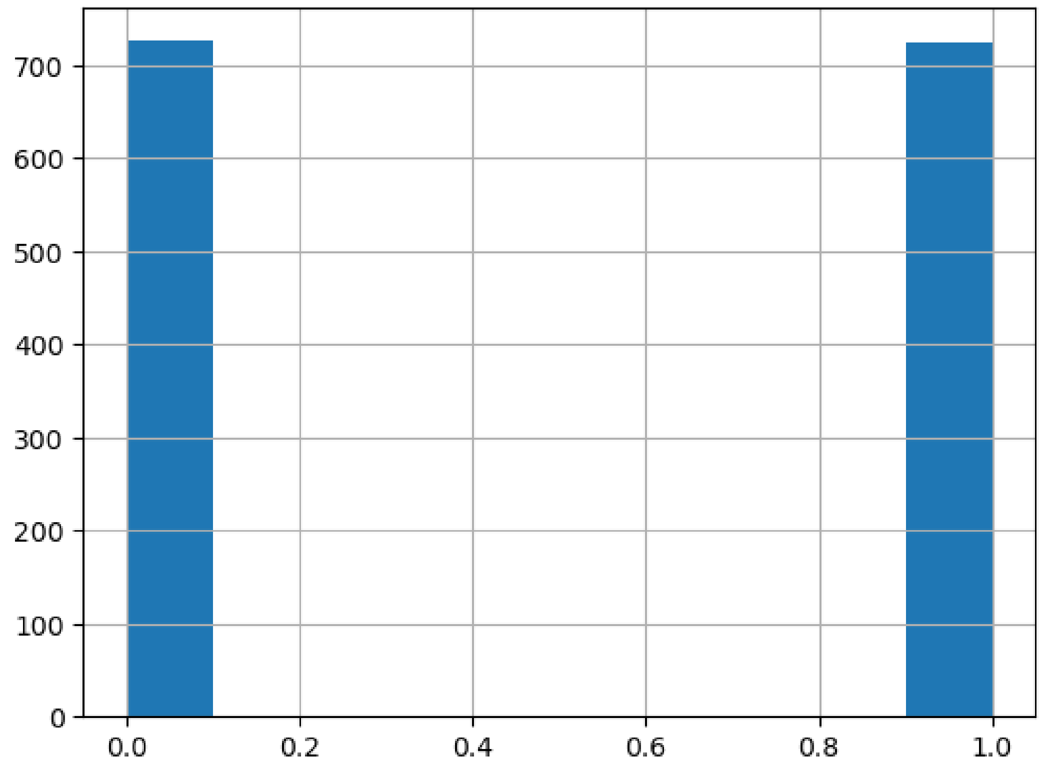
1. **Created a dataframe now which has the matrix of 3,125,125 and pt m0 and label y**
2. **Now lets create the class dataset and dataloader and then split the data into training and testing set**
3. **Lets now create the class of architecture which contains the architecture from nn.module**
4. **Setting the optimizer and the scheduler and the criterion**
5. **Validating our model with the help of metrics like accuracy and roc auc etc**

[43]:
```python
import torch
import torch.nn as nn
from torch.utils.data import DataLoader,Dataset, random_split
```

```
import torch.optim as optim
```

[44]:
```
final_df['y'].hist()
```

[44]: <AxesSubplot:>



Almost equal examples for both the classes… NO DATA IMBALANCE

This class below converts returns us the value of X and y which is the matrix for image and the respected targer in tensor float 32

[45]:
```
class QGdset(Dataset):

    def __init__(self,ddf):

        self.data=ddf
        self.X= ddf['X_jets']
        self.y= ddf['y']
        self.pt= ddf['pt']
        self.m0= ddf['m0']

    def __len__(self):
        return (self.data.shape[0])
```

```
    def __getitem__(self,idx):


        return torch.tensor(self.X[idx]/12,dtype=torch.float32), torch.
 ↪tensor(self.y[idx],dtype=torch.float32)
```

[46]:
```
train_data= QGdset(final_df)
```

LETS SPLIT THE train_data INTO TRAIN AND TEST SO THAT WE CAN VALIDATE OUR MODEL

[47]:
```
train_size = int(0.8 * len(train_data))  # use 80% of data for training
test_size = len(train_data) - train_size  # use remaining 20% for testing
train_dataset, test_dataset = random_split(train_data, [train_size, test_size])␣
 ↪ # split dataset into train and test
```

[48]:
```
len(train_dataset),len(test_dataset)
```

[48]:
```
(1160, 291)
```

Setting up the dataLoaders so that we can feed it to the loops further

[49]:
```
train_loader= DataLoader(train_dataset,batch_size=32,shuffle=True)
test_loader=DataLoader(test_dataset,batch_size=32,shuffle=True)
```

Creating architure as below

QGArchi(* (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) * (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) * (relu1): ReLU() * (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False) * (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) * (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) * (relu2): ReLU() * (pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False) * (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) * (bn3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) * (relu3): ReLU() * (pool3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False) * (fc1): Linear(in_features=14400, out_features=128, bias=True) * (fc2): Linear(in_features=128, out_features=1, bias=True))**

[50]:
```
import torch.nn as nn

class QGArchi(nn.Module):
    def __init__(self):
        super(QGArchi, self).__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, stride=1, padding=1)
        self.bn1 = nn.BatchNorm2d(16)
        self.relu1 = nn.ReLU()
```

```
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=3, stride=1, padding=1)
        self.bn2 = nn.BatchNorm2d(32)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv3 = nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1)
        self.bn3 = nn.BatchNorm2d(64)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.fc1 = nn.Linear(64 * 15 * 15, 128)
        self.fc2 = nn.Linear(128, 1)

    def forward(self, x):
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu1(out)
        out = self.pool1(out)
        out = self.conv2(out)
        out = self.bn2(out)
        out = self.relu2(out)
        out = self.pool2(out)
        out = self.conv3(out)
        out = self.bn3(out)
        out = self.relu3(out)
        out = self.pool3(out)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.fc2(out)
        return nn.Sigmoid()(out.squeeze())
```

[51]:
```
model=QGArchi()
```

[52]:
```
# Define the loss function
criterion = nn.CrossEntropyLoss()

# Define the learning rate and optimizer
lr = 0.001
optimizer = optim.Adam(QGArchi().parameters(), lr=lr)

# Define the scheduler
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, factor=0.1,
 ↪patience=2)
```

Lets write the code to set the device that is the GPU

[53]:
```
device=torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

[54]:
```
device    #checking if the device is on cuda...
```

[54]:
```
device(type='cuda')
```

[55]:
```
from sklearn.metrics import roc_auc_score, confusion_matrix␣
↪,plot_confusion_matrix,roc_curve
import matplotlib.pyplot as plt
import seaborn as sns


#we need to import these stuffs to validate our model and see the losses and␣
↪accuracy
```

[56]:
```
# Set the number of epochs
epochs = 150

# Initialize the optimizer and the learning rate scheduler
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, patience=3,␣
↪factor=0.1, verbose=True)

# Initialize the loss function
criterion = nn.BCELoss()

# Move the model and the loss function to the device
model.to(device)
criterion.to(device)

# Initialize the lists to store the loss and accuracy values
train_losses = []
test_losses = []
train_accs = []
test_accs = []

# Iterate over the epochs
for epoch in range(epochs):
    # Set the model to training mode
    model.train()
    running_loss = 0
    correct_train = 0
    total_train = 0

    # Iterate over the training set
    for X, y in train_loader:
        # Move the input and target tensors to the device
        X, y = X.to(device), y.to(device)
```

```
        # Zero the gradients
        optimizer.zero_grad()

        # Forward
        outputs = model(X)

        # Compute the loss
        loss = criterion(outputs, y.float())

        # Backward and optimize
        loss.backward()
        optimizer.step()

        # Update the running loss
        running_loss += loss.item()

        # Compute the number of correct predictions
        predicted_train = torch.round(outputs)
        correct_train += (predicted_train == y).sum().item()
        total_train += y.size(0)

    # Compute the training loss and accuracy
    train_loss = running_loss / len(train_loader)
    train_acc = 100 * correct_train / total_train
    train_losses.append(train_loss)
    train_accs.append(train_acc)

    # Set the model to evaluation mode
    model.eval()
    running_loss = 0
    correct_test = 0
    total_test = 0
    y_true = []
    y_scores = []

    # Disable gradient computation to save memory
    with torch.no_grad():
        # Iterate over the test set
        for X, y in test_loader:
            # Move the input and target tensors to the device
            X, y = X.to(device), y.to(device)

            # Forward
            outputs = model(X)

            # Compute the loss
            loss = criterion(outputs, y.float())
```

```
            # Update the running loss
            running_loss += loss.item()

            # Compute the number of correct predictions
            predicted_test = torch.round(outputs)
            correct_test += (predicted_test == y).sum().item()
            total_test += y.size(0)

            # Append the true and predicted target values
            y_true += y.cpu().numpy().tolist()
            y_scores += outputs.cpu().numpy().tolist()

    # Compute the test loss, accuracy, and ROC-AUC score
    test_loss = running_loss / len(test_loader)
    test_acc = 100 * correct_test / total_test
    test_losses.append(test_loss)
    test_accs.append(test_acc)
    roc_auc = roc_auc_score(y_true, y_scores)

    # Print the loss and accuracy values
    if(epoch%30==0):print(f"Epoch {epoch + 1}/{epochs}, Train Loss: {train_loss:
↪.4f}, Train Acc: {train_acc:.2f}%, Test Loss: {test_loss:.4f}, Test Acc:␣
↪{test_acc:.2f}%, ROC-AUC: {roc_auc:.4f}")

    # Update the learning

    scheduler.step(test_loss)
```

```
Epoch 1/150, Train Loss: 2.4838, Train Acc: 55.60%, Test Loss: 0.7914, Test Acc:
49.83%, ROC-AUC: 0.6149
Epoch 00008: reducing learning rate of group 0 to 1.0000e-04.
Epoch 00012: reducing learning rate of group 0 to 1.0000e-05.
Epoch 00016: reducing learning rate of group 0 to 1.0000e-06.
Epoch 00020: reducing learning rate of group 0 to 1.0000e-07.
Epoch 00024: reducing learning rate of group 0 to 1.0000e-08.
Epoch 31/150, Train Loss: 0.2793, Train Acc: 91.55%, Test Loss: 1.0932, Test
Acc: 68.04%, ROC-AUC: 0.6929
Epoch 61/150, Train Loss: 0.2783, Train Acc: 91.81%, Test Loss: 1.0568, Test
Acc: 67.70%, ROC-AUC: 0.6925
Epoch 91/150, Train Loss: 0.2778, Train Acc: 91.55%, Test Loss: 1.0672, Test
Acc: 68.04%, ROC-AUC: 0.6930
Epoch 121/150, Train Loss: 0.2748, Train Acc: 91.90%, Test Loss: 1.0541, Test
Acc: 68.04%, ROC-AUC: 0.6927
```

[ ]: