Lab 8

January 14, 2022

Machine Learning Lab

Lab 08

0.0.1 Exercise 1: Optical Character Recognition via Neural Networks

Importing Packages

[1]:
```
import pandas as pd                                          #Importing Pandas
import numpy as np                                           #Importing Numpy
from sklearn.datasets import load_digits                     #Importing MNIST␣
 ↪Dataset from Sklearn
import matplotlib.pyplot as plt                              #Importing Matplotlib
from sklearn.model_selection import train_test_split         #Importing Train test␣
 ↪Split
from sklearn.neural_network import MLPClassifier             #Importing MLP␣
 ↪Classifier
from sklearn.model_selection import RandomizedSearchCV       #Importing Randomized␣
 ↪Search
from sklearn.metrics import accuracy_score                   #Importing Accuracy␣
 ↪Score
```

Initializing Random Seed

[2]:
```
random_seed = 3116
```

Loading the MNIST digits dataset via sklearn provided built-in utility function(s).

[3]:
```
mnist_digits = load_digits()
```

Plotting the Initial 10 Handwritten Digits from the Dataset

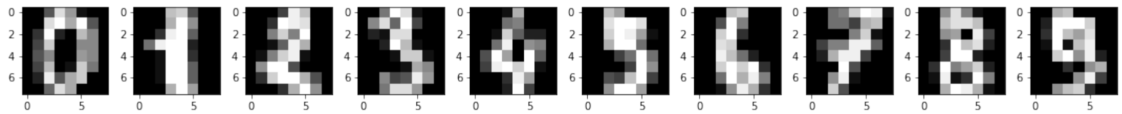
[4]:
```
#Creating a Figure
fig = plt.figure(figsize=(15, 10))

#Iterating through the first 10 handwritten digits from the dataset
for i in range(1, 11):
    #Adding a subplot
    plt.subplot(1, 10, i)

    #Plotting the Image in Grayscale
```

```
    plt.imshow(mnist_digits.images[i - 1], cmap = 'gray')

#Adjusting Spacing and Showing the plots
plt.tight_layout()
plt.show()
```



K-cross Fold Validation and Train Test Split

Initializing the value of k for K-cross fold validation

[5]:
```
k = 5
```

Splitting the Dataset into Train and Test with 20% Testing set

[6]:
```
X_train, X_test, y_train, y_test = train_test_split(mnist_digits.data,␣
↪mnist_digits.target, test_size = 0.2, random_state = random_seed)
```

Defining a hyperparameter grid for the MLP Classifier

[7]:
```
hyperparameter_grid = {
    'hidden_layer_sizes': [(10,), (10,20), (10,20,10)],             #The number␣
↪of neurons in each hidden layer
    'activation': ['identity', 'logistic', 'tanh', 'relu'],         #Activation␣
↪function for the hidden layer
    'solver': ['lbfgs', 'sgd', 'adam'],                             #Weight␣
↪Optimization techniques
    'alpha': [0.5, 0.01, 0.001, 0.0001,],                           #L2␣
↪Regularization term
    'learning_rate': ['constant', 'invscaling', 'adaptive']         #Learning␣
↪rate schedule for weight updates
}
```

Defining a Random Search procedure over the ranges of Hyperparameters above

[8]:
```
#Creating the object of MLP(Multi Layer Perceptron) Classifier with maximum␣
↪iteration of 100
mlp = MLPClassifier(max_iter = 100, random_state = random_seed)

#Creating and Initializing the object for Randomized Search with the MLP␣
↪Classifier and the hyperparameter grid
rand_mlp = RandomizedSearchCV(mlp, hyperparameter_grid, random_state =␣
↪random_seed, n_jobs = -1,n_iter = 20, cv = k, scoring = 'accuracy')
```

```
#Fitting the training dataset on the MLP Classifier using Randomized Search for␣
↪finding the best hyperparameters
rand_mlp.fit(X_train, y_train)
```

[8]:
```
RandomizedSearchCV(cv=5,
                   estimator=MLPClassifier(max_iter=100, random_state=3116),
                   n_iter=20, n_jobs=-1,
                   param_distributions={'activation': ['identity', 'logistic',
                                                       'tanh', 'relu'],
                                        'alpha': [0.5, 0.01, 0.001, 0.0001],
                                        'hidden_layer_sizes': [(10,), (10, 20),
                                                               (10, 20, 10)],
                                        'learning_rate': ['constant',
                                                          'invscaling',
                                                          'adaptive'],
                                        'solver': ['lbfgs', 'sgd', 'adam']},
                   random_state=3116, scoring='accuracy')
```

Reporting the test accuracy and the best hyperparameters found

Best Hyperparameters Found

[9]:
```
print('The Best Hyperparameter Combination is:')
rand_mlp.best_params_
```

```
The Best Hyperparameter Combination is:
```

[9]:
```
{'solver': 'lbfgs',
 'learning_rate': 'constant',
 'hidden_layer_sizes': (10, 20, 10),
 'alpha': 0.0001,
 'activation': 'identity'}
```

Test Accuracy

[10]:
```
print('The Test Accuracy of MLP Classifier with best Hyperparameters is: {:.
↪2f}'.format(accuracy_score(y_test, rand_mlp.predict(X_test))))
```

```
The Test Accuracy of MLP Classifier with best Hyperparameters is: 0.96
```

0.0.2 Exercise 2: End-to-End Self-Driving via Convolutional Neural Networks

Importing Packages

[11]:
```
import torch                                                #Importing torch
from torch.utils.data import DataLoader , Dataset           #Importing Dataloader␣
↪and Dataset from pytorch
import torchvision                                          #Importing Torchvision
from torch.utils.data import random_split                   #Importing Random␣
↪Split from pytorch
```

```
import torch.nn.functional as F                                   #Importing Activation␣
↪Functions from pytorch
from torch import nn                                              #Importing Neural␣
↪Network helper functions from nn package of pytorch
import cv2                                                        #Importing Opencv
import numpy as np                                                #Importing Numpy
import matplotlib.pyplot as plt                                   #Importing Matplotlib
```

```
C:\Users\dell\anaconda3\envs\ml_lab\lib\site-
packages\torchvision\io\image.py:11: UserWarning: Failed to load image Python
extension: Could not find module 'C:\Users\dell\anaconda3\envs\ml_lab\Lib\site-
packages\torchvision\image.pyd' (or one of its dependencies). Try using the full
path with constructor syntax.
  warn(f"Failed to load image Python extension: {e}")
```

Class to load Dataset containing data and its labels

[12]:
```
class Dataset(Dataset):#Inherits from torch.utils.data.Dataset

    #Constructor Function which read image names and its label from the␣
↪directory
    def __init__(self):
        #default directory where data is loaded
        self.filepath = 'archive/driving_dataset/'

        #default directory where labels for each image is saved
        self.filepath_angles = 'archive/driving_dataset/angles.txt'

        #Creating lists for storing filenames and its label(steering angle)
        self.filenames = []
        self.steering_angle = []

        #Opening the angles file and saving the filenames and angles in the␣
↪created lists
        with open(self.filepath_angles) as angles:
            line = angles.readline()
            while line:
                tokens = line.split()
                self.filenames.append(tokens[0])
                self.steering_angle.append(tokens[1])
                line = angles.readline()

    #Function to return the total datapoints in the dataset
    def __len__(self):
        return len(self.filenames)

    #Function to get the image and its label at specified index
    def __getitem__(self, index):
```

```
        #Extracting filename and angle from the list
        filename = self.filenames[index]
        angle = self.steering_angle[index]

        #Reading the image using opencv
        img = cv2.imread(self.filepath + filename)

        #Resizing images to(32,32)
        resized = cv2.resize(img, (200, 66),interpolation = cv2.INTER_AREA)

        #return the image converted to a numpy array its corresponding steering␣
↪angle
        return torch.from_numpy(resized.transpose()).float(), torch.tensor(np.
↪float32(angle))
```

Class which Implements the Convolutional Neural Network Architecture proposed in the paper

[13]:
```
class ConvNet(torch.nn.Module):

    #Constructor function which list all the layers in CNN model
    def __init__(self):
        super().__init__()
        self.norm1 = nn.LayerNorm([200,66])
        self.conv1 = nn.Conv2d(in_channels = 3, out_channels = 24, kernel_size␣
↪= 5, stride = 2)
        self.conv2 = nn.Conv2d(in_channels = 24, out_channels = 36, kernel_size␣
↪= 5, stride = 2)
        self.conv3 = nn.Conv2d(in_channels = 36, out_channels = 48, kernel_size␣
↪= 5, stride = 2)
        self.conv4 = nn.Conv2d(in_channels = 48, out_channels = 64, kernel_size␣
↪= 3, stride = 1)
        self.conv5 = nn.Conv2d(in_channels = 64, out_channels = 64, kernel_size␣
↪= 3, stride = 1)
        self.fc1 = nn.Linear(in_features = 64 * 1 * 18, out_features = 100)
        self.fc2 = nn.Linear(in_features = 100, out_features = 50)
        self.fc3 = nn.Linear(in_features = 50, out_features = 10)
        self.fc4 = nn.Linear(in_features = 10, out_features = 1)

    #Function to link all the layers in the sequence
    def forward(self, x):
        x = self.norm1(x)
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = F.relu(self.conv3(x))
        x = F.relu(self.conv4(x))
        x = F.relu(self.conv5(x))
```

```
        x = x.view(x.shape[0], -1)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        x = self.fc4(x)
        return x
```

Dividing the dataset into corresponding train/validation/test splits. Leaving the last 10k images for testing.

[14]:
```
#Creating the Dataset object
car_dataset = Dataset()

#Total rows to be included in Test set
test_rows = 10000

#Total rows to be included in Validation set
train_rows = car_dataset.__len__() - test_rows
val_rows = int(train_rows * 0.2)

#Total rows to be included in training set
train_rows -= val_rows

#Splitting the dataset into Train/Validation/Test sets using Pytorch Random␣
↪Split function
train_dataset, val_dataset, test_dataset = random_split(car_dataset,␣
↪[train_rows, val_rows, test_rows],
                                                        generator=torch.
↪Generator().manual_seed(random_seed))
```

Converting the Datasets into Dataloaders for Iterations

[15]:
```
#Train Dataloader
train_dataloader = DataLoader(train_dataset, batch_size = 64, shuffle = True)

#Validation Dataloader
val_dataloader = DataLoader(val_dataset, batch_size = 64, shuffle = True)

#Test Dataloader
test_dataloader = DataLoader(test_dataset, batch_size = 64, shuffle = True)
```

Training and Evaluating the CNN on the dataset Sets

Checking for GPU, if present then changing device to Cuda

[16]:
```
device = 'cpu'
if torch.cuda.is_available():
    device = 'cuda'
torch.device(device)
```

[16]: device(type='cuda')

Creating the Object of our CNN model and transferring it to the Device

[17]:
```
model = ConvNet().to(device)
model
```

[17]:
```
ConvNet(
  (norm1): LayerNorm((200, 66), eps=1e-05, elementwise_affine=True)
  (conv1): Conv2d(3, 24, kernel_size=(5, 5), stride=(2, 2))
  (conv2): Conv2d(24, 36, kernel_size=(5, 5), stride=(2, 2))
  (conv3): Conv2d(36, 48, kernel_size=(5, 5), stride=(2, 2))
  (conv4): Conv2d(48, 64, kernel_size=(3, 3), stride=(1, 1))
  (conv5): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=1152, out_features=100, bias=True)
  (fc2): Linear(in_features=100, out_features=50, bias=True)
  (fc3): Linear(in_features=50, out_features=10, bias=True)
  (fc4): Linear(in_features=10, out_features=1, bias=True)
)
```

Initiating the RMSE Loss function and the ADAM optimizer

[18]:
```
#Creating the RMSE loss function object provided in Pytorch
criterion = nn.MSELoss()

#Creating the Adam Optimizer object with model parameters and learning rate
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
```

[19]:
```
#Initializing the number of Epochs
epochs = 30

#Creating list to store the RMSE of Training and Validation dataset in each␣
 ↪Epochs
training_rmse = []
validation_rmse = []
```

Training the model and Evaluating it on the Validation dataset

[20]:
```
#Iterating over all Epochs
for e in range(epochs):

    #Initiating the training and validation loss to 0
    running_loss = 0.0
    val_running_loss = 0.0

    #Iterating over all Training datapoints
    for inputs, labels in train_dataloader:
```

```
        #Extracting Input image and label and doing a forward pass on our CNN␣
↪model
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model(inputs)

        #Calculating the RMSE loss
        loss = criterion(outputs, labels)

        #Setting the gradient to Zero for next Iteration
        optimizer.zero_grad()

        #Computing the Back propogation on CNN
        loss.backward()
        optimizer.step()

        #Adding the RMSE loss to the total loss
        running_loss += loss.item()

    #Evaluating the model on the Validation set
    with torch.no_grad():

        #Iterating over the validation dataset
        for val_inputs, val_labels in val_dataloader:

            #Extracting Input image and label and doing a forward pass on our␣
↪CNN model
            val_inputs = val_inputs.to(device)
            val_labels = val_labels.to(device)
            val_outputs = model(val_inputs)

            #Calculating the RMSE loss
            val_loss = criterion(val_outputs, val_labels)

            #Adding the RMSE loss to the total validation loss
            val_running_loss += val_loss.item()

    #Calculating the current Epoch average RMSE loss on training and Validation␣
↪dataset
    epoch_loss = np.sqrt(running_loss/len(train_dataloader))
    val_epoch_loss = np.sqrt(val_running_loss/len(val_dataloader))

    #Apending the loss in the final list
    training_rmse.append(epoch_loss)
    validation_rmse.append(val_epoch_loss)

    #Printing the Results
```

```python
    print('epoch :', (e+1))
    print('training loss: {:.4f}'.format(epoch_loss))
    print('validation loss: {:.4f}'.format(val_epoch_loss))
```

```
C:\Users\dell\anaconda3\envs\ml_lab\lib\site-
packages\torch\nn\modules\loss.py:520: UserWarning: Using a target size
(torch.Size([64])) that is different to the input size (torch.Size([64, 1])).
This will likely lead to incorrect results due to broadcasting. Please ensure
they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
C:\Users\dell\anaconda3\envs\ml_lab\lib\site-
packages\torch\nn\modules\loss.py:520: UserWarning: Using a target size
(torch.Size([37])) that is different to the input size (torch.Size([37, 1])).
This will likely lead to incorrect results due to broadcasting. Please ensure
they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
C:\Users\dell\anaconda3\envs\ml_lab\lib\site-
packages\torch\nn\modules\loss.py:520: UserWarning: Using a target size
(torch.Size([41])) that is different to the input size (torch.Size([41, 1])).
This will likely lead to incorrect results due to broadcasting. Please ensure
they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
```

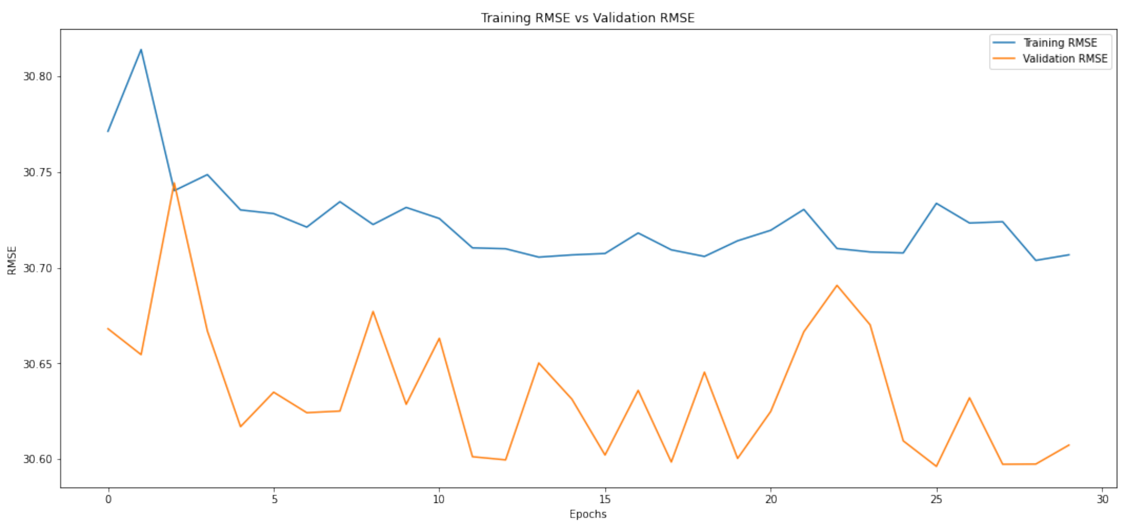
```
epoch : 1
training loss: 30.7713
validation loss: 30.6681
epoch : 2
training loss: 30.8140
validation loss: 30.6546
epoch : 3
training loss: 30.7403
validation loss: 30.7443
epoch : 4
training loss: 30.7487
validation loss: 30.6669
epoch : 5
training loss: 30.7302
validation loss: 30.6170
epoch : 6
training loss: 30.7283
validation loss: 30.6350
epoch : 7
training loss: 30.7212
validation loss: 30.6243
epoch : 8
training loss: 30.7345
validation loss: 30.6251
epoch : 9
```

```
training loss: 30.7226
validation loss: 30.6772
epoch : 10
training loss: 30.7315
validation loss: 30.6287
epoch : 11
training loss: 30.7257
validation loss: 30.6631
epoch : 12
training loss: 30.7104
validation loss: 30.6013
epoch : 13
training loss: 30.7099
validation loss: 30.5996
epoch : 14
training loss: 30.7055
validation loss: 30.6503
epoch : 15
training loss: 30.7067
validation loss: 30.6314
epoch : 16
training loss: 30.7075
validation loss: 30.6021
epoch : 17
training loss: 30.7182
validation loss: 30.6359
epoch : 18
training loss: 30.7094
validation loss: 30.5985
epoch : 19
training loss: 30.7059
validation loss: 30.6455
epoch : 20
training loss: 30.7141
validation loss: 30.6004
epoch : 21
training loss: 30.7196
validation loss: 30.6249
epoch : 22
training loss: 30.7305
validation loss: 30.6666
epoch : 23
training loss: 30.7101
validation loss: 30.6908
epoch : 24
training loss: 30.7082
validation loss: 30.6702
epoch : 25
```

```
training loss: 30.7077
validation loss: 30.6096
epoch : 26
training loss: 30.7337
validation loss: 30.5962
epoch : 27
training loss: 30.7234
validation loss: 30.6321
epoch : 28
training loss: 30.7240
validation loss: 30.5973
epoch : 29
training loss: 30.7038
validation loss: 30.5974
epoch : 30
training loss: 30.7068
validation loss: 30.6074
```

Plotting Training RMSE vs Validation RMSE in each Epoch

[21]:
```
fig = plt.figure(figsize=(18,8))
plt.plot(training_rmse, label = 'Training RMSE')
plt.plot(validation_rmse, label = 'Validation RMSE')
plt.title('Training RMSE vs Validation RMSE')
plt.xlabel('Epochs')
plt.ylabel('RMSE')
plt.legend()
plt.show()
```



From the above graph we can see that both Train RMSE and Test RMSE are decreasing but fluctuation very abruptly, to smooth this curve we can basically use the regularization term to add some weight on negative examples.

Evaluating the Trained CNN Model with the Test Dataset

[22]:
```
#Initializing the loss to 0
running_loss = 0.0

#Evaluating the model on the Test set
with torch.no_grad():

    #Iterating over the Test dataset
    for inputs, labels in test_dataloader:

        #Extracting Input image and label and doing a forward pass on our CNN␣
 ↪model
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model(inputs)

        #Calculating the RMSE loss
        loss = criterion(outputs, labels)

        #Adding the RMSE loss to the total Test loss
        running_loss += loss.item()

#Calculating the current Epoch average RMSE loss on Test dataset
epoch_loss = np.sqrt(running_loss/len(test_dataloader))
```

```
C:\Users\dell\anaconda3\envs\ml_lab\lib\site-
packages\torch\nn\modules\loss.py:520: UserWarning: Using a target size
(torch.Size([16])) that is different to the input size (torch.Size([16, 1])).
This will likely lead to incorrect results due to broadcasting. Please ensure
they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
```

[23]:
```
print('Test RMSE: {:.4f}'.format(epoch_loss))
```

```
Test RMSE: 31.6328
```