# CIFAR10_Pytorch

February 9, 2021

#### 0.0.1 CIFAR-10 Using Pytorch

[92]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
from torchvision.utils import make_grid
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

import numpy as np
```

[2]:
```
transform = transforms.ToTensor()

train_data = datasets.CIFAR10(root='../Data', train=True, download=True,␣
 ↪transform=transform)
test_data = datasets.CIFAR10(root='../Data', train=False, download=True,␣
 ↪transform=transform)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

[3]:
```
train_data
```

[3]:
```
Dataset CIFAR10
    Number of datapoints: 50000
    Root location: ../Data
    Split: Train
    StandardTransform
Transform: ToTensor()
```

[4]:
```
test_data
```

[4]:
```
Dataset CIFAR10
    Number of datapoints: 10000
```

```
    Root location: ../Data
    Split: Test
    StandardTransform
Transform: ToTensor()
```

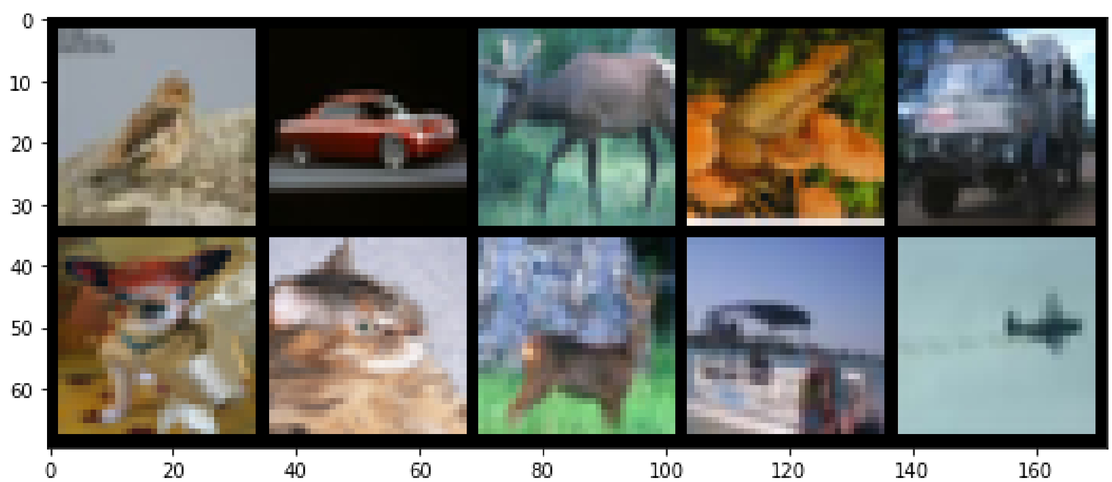
[5]:
```
# torch.manual_seed(101)
train_loader = DataLoader(train_data, batch_size=10, shuffle=True)
test_loader = DataLoader(test_data, batch_size=10, shuffle=False)
```

[6]:
```
for images,labels in train_loader:
    break
```

[7]:
```
class_names = ['plane', '  car', ' bird', '  cat', ' deer', '  dog', ' frog',␣
↪'horse', ' ship', 'truck']
```

[8]:
```
for images,labels in train_loader:
    break

# Print the labels
print('Label:', labels.numpy())
print('Class:', *np.array([class_names[i] for i in labels]))

# Print the images
im = make_grid(images, nrow=5)
plt.figure(figsize=(10,10))
plt.imshow(np.transpose(im.numpy(), (1, 2, 0)));
```

```
Label: [2 1 4 6 9 5 3 4 8 0]
Class:  bird   car  deer  frog truck   dog   cat  deer  ship plane
```



[9]:
```
class convnet(nn.Module):

    def __init__(self):
        super().__init__()
        # input dims - (b,32,32,3)
        self.conv3_32 = nn.Conv2d(3, 32, 3, 1) # channels_in =3, # filters = 32␣
↪(3,3) stride =1
        self.conv32_32 = nn.Conv2d(32,32, 3, 1) # channels_in =16, # filters =␣
↪32 (3,3) stride =1
        self.pool = nn.MaxPool2d(kernel_size=(2,2), stride=(2,2))
        self.drop_4 = nn.Dropout2d(p=0.4)
        self.conv32_64 = nn.Conv2d(32,64,3,1)
        self.conv64_64 = nn.Conv2d(64,64,3,1)
        self.fc1 = nn.Linear(5*5*64,512)
        self.drop_5 = nn.Dropout2d(p=0.5)
        self.fc2 = nn.Linear(512,10)


    def forward(self,X):

        X = F.relu(self.conv3_32(X)) # dims 32,32,3 c-> 30,30,32
        X = F.relu(self.conv32_32(X)) # 30,30,32 c-> 28,28,32
        X = self.pool(X) # 15,15,32
        X = self.drop_4(X)

        X = F.relu(self.conv32_64(X)) # 13,13,64
        X = F.relu(self.conv64_64(X)) # 11,11,64
        X = self.pool(X) # 5,5,64
        X = self.drop_4(X)

        X = X.view(-1,5*5*64)

        X = F.relu(self.fc1(X))
        X = self.drop_5(X)
        X = F.relu(self.fc2(X))

        return F.log_softmax(X, dim=1)
```

[11]:
```
class ConvolutionalNetwork(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 6, 3, 1)  # changed from (1, 6, 5, 1)
        self.conv2 = nn.Conv2d(6, 16, 3, 1)
        self.fc1 = nn.Linear(6*6*16, 120)   # changed from (4*4*16) to fit␣
↪32x32 images with 3x3 filters
        self.fc2 = nn.Linear(120,84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, X):
        X = F.relu(self.conv1(X))
        X = F.max_pool2d(X, 2, 2)
        X = F.relu(self.conv2(X))
        X = F.max_pool2d(X, 2, 2)
        X = X.view(-1, 6*6*16)
        X = F.relu(self.fc1(X))
        X = F.relu(self.fc2(X))
        X = self.fc3(X)
        return F.log_softmax(X, dim=1)
```

[12]:
```
model = ConvolutionalNetwork()
model
```

[12]:
```
ConvolutionalNetwork(
  (conv1): Conv2d(3, 6, kernel_size=(3, 3), stride=(1, 1))
  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=576, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
```

[13]:
```
def count_parameters(model):
    params = [p.numel() for p in model.parameters() if p.requires_grad]
    for item in params:
        print(f'{item:>6}')
    print(f'______\n{sum(params):>6}')
```

[14]:
```
count_parameters(model)
```

```
   162
     6
   864
    16
 69120
   120
 10080
```

```
    84
   840
    10
------
 81302
```

[15]:

```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

[21]:

```
import time
start = time.perf_counter() # starts a counter

epochs = 12
train_correct = []
test_correct = []
train_losses = []
test_losses = []

for i in range(epochs):
    trn_corr = 0
    tst_corr = 0

    for b, (x_train,y_train) in enumerate(train_loader):
        b += 1

        # forward pass
        y_pred = model(x_train)
        loss = criterion(y_pred,y_train)

        # tally
        predictions = torch.max(y_pred.data,1)[1]
        batch_corr = (predictions == y_train).sum()
        trn_corr += batch_corr

        # back propagation
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # printing the interim status
        if b%1000 == 0:
            print(f'epoch {i:2} batch: {b:4} [{10*b:6}/50000] loss: {loss.
↪item():10.2f}  accuracy: {trn_corr.item()*100/(10*b):7.3f}% ')

    # record losses
    train_losses.append(loss)
    train_correct.append(trn_corr)
```

```python
    with torch.no_grad():
        for b, (x_test,y_test) in enumerate(test_loader):

            #on test set
            y_val = model(x_test)

            # Tally the number of correct predictions
            predicted = torch.max(y_val.data, 1)[1]
            tst_corr += (predicted == y_test).sum()

    loss = criterion(y_val, y_test) # test loss
    test_losses.append(loss)
    test_correct.append(tst_corr)


elapsed = time.perf_counter() - start # elapsed time calculation
```

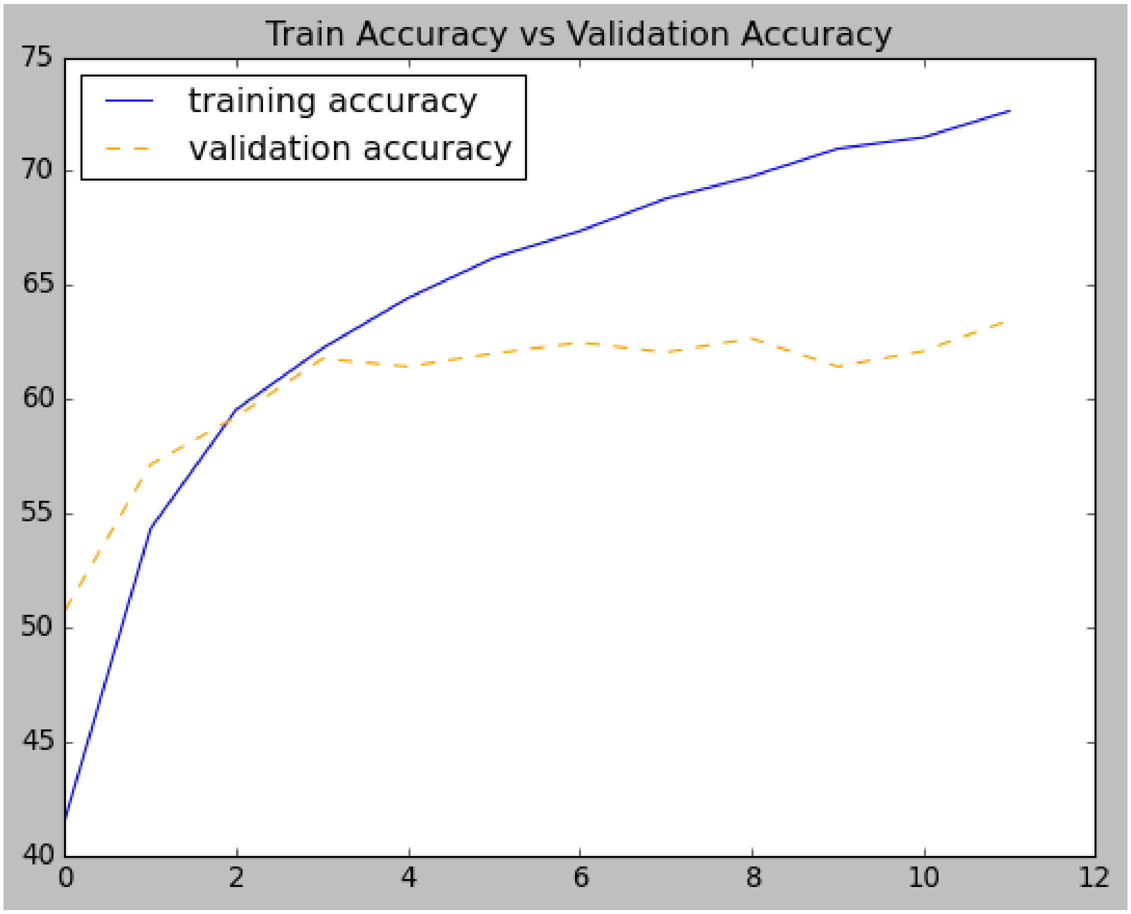
```
epoch  0 batch: 1000 [ 10000/50000] loss:       1.81  accuracy:  27.990%
epoch  0 batch: 2000 [ 20000/50000] loss:       1.88  accuracy:  34.205%
epoch  0 batch: 3000 [ 30000/50000] loss:       0.82  accuracy:  37.403%
epoch  0 batch: 4000 [ 40000/50000] loss:       1.73  accuracy:  39.675%
epoch  0 batch: 5000 [ 50000/50000] loss:       1.33  accuracy:  41.522%
epoch  1 batch: 1000 [ 10000/50000] loss:       1.18  accuracy:  52.070%
epoch  1 batch: 2000 [ 20000/50000] loss:       0.70  accuracy:  52.110%
epoch  1 batch: 3000 [ 30000/50000] loss:       1.59  accuracy:  52.963%
epoch  1 batch: 4000 [ 40000/50000] loss:       0.85  accuracy:  53.572%
epoch  1 batch: 5000 [ 50000/50000] loss:       1.36  accuracy:  54.314%
epoch  2 batch: 1000 [ 10000/50000] loss:       1.31  accuracy:  58.840%
epoch  2 batch: 2000 [ 20000/50000] loss:       1.55  accuracy:  59.115%
epoch  2 batch: 3000 [ 30000/50000] loss:       0.71  accuracy:  59.213%
epoch  2 batch: 4000 [ 40000/50000] loss:       1.67  accuracy:  59.362%
epoch  2 batch: 5000 [ 50000/50000] loss:       0.90  accuracy:  59.550%
epoch  3 batch: 1000 [ 10000/50000] loss:       0.85  accuracy:  63.160%
epoch  3 batch: 2000 [ 20000/50000] loss:       0.67  accuracy:  62.395%
epoch  3 batch: 3000 [ 30000/50000] loss:       1.02  accuracy:  62.130%
epoch  3 batch: 4000 [ 40000/50000] loss:       1.07  accuracy:  62.060%
epoch  3 batch: 5000 [ 50000/50000] loss:       1.31  accuracy:  62.224%
epoch  4 batch: 1000 [ 10000/50000] loss:       0.69  accuracy:  64.310%
epoch  4 batch: 2000 [ 20000/50000] loss:       0.75  accuracy:  64.700%
epoch  4 batch: 3000 [ 30000/50000] loss:       1.20  accuracy:  64.643%
epoch  4 batch: 4000 [ 40000/50000] loss:       1.28  accuracy:  64.550%
epoch  4 batch: 5000 [ 50000/50000] loss:       1.23  accuracy:  64.438%
epoch  5 batch: 1000 [ 10000/50000] loss:       0.86  accuracy:  67.210%
epoch  5 batch: 2000 [ 20000/50000] loss:       0.56  accuracy:  66.605%
epoch  5 batch: 3000 [ 30000/50000] loss:       0.56  accuracy:  66.343%
epoch  5 batch: 4000 [ 40000/50000] loss:       0.83  accuracy:  66.055%
```

```
epoch  5 batch: 5000 [ 50000/50000] loss:      0.42 accuracy:  66.200%
epoch  6 batch: 1000 [ 10000/50000] loss:      0.64 accuracy:  67.810%
epoch  6 batch: 2000 [ 20000/50000] loss:      0.87 accuracy:  67.555%
epoch  6 batch: 3000 [ 30000/50000] loss:      1.00 accuracy:  67.747%
epoch  6 batch: 4000 [ 40000/50000] loss:      0.72 accuracy:  67.480%
epoch  6 batch: 5000 [ 50000/50000] loss:      1.49 accuracy:  67.372%
epoch  7 batch: 1000 [ 10000/50000] loss:      0.91 accuracy:  69.870%
epoch  7 batch: 2000 [ 20000/50000] loss:      0.80 accuracy:  69.690%
epoch  7 batch: 3000 [ 30000/50000] loss:      0.09 accuracy:  69.310%
epoch  7 batch: 4000 [ 40000/50000] loss:      0.98 accuracy:  69.080%
epoch  7 batch: 5000 [ 50000/50000] loss:      0.76 accuracy:  68.792%
epoch  8 batch: 1000 [ 10000/50000] loss:      0.68 accuracy:  70.430%
epoch  8 batch: 2000 [ 20000/50000] loss:      0.87 accuracy:  70.385%
epoch  8 batch: 3000 [ 30000/50000] loss:      0.88 accuracy:  70.030%
epoch  8 batch: 4000 [ 40000/50000] loss:      1.04 accuracy:  70.058%
epoch  8 batch: 5000 [ 50000/50000] loss:      0.92 accuracy:  69.766%
epoch  9 batch: 1000 [ 10000/50000] loss:      0.49 accuracy:  71.750%
epoch  9 batch: 2000 [ 20000/50000] loss:      0.56 accuracy:  71.380%
epoch  9 batch: 3000 [ 30000/50000] loss:      0.77 accuracy:  71.040%
epoch  9 batch: 4000 [ 40000/50000] loss:      1.15 accuracy:  71.028%
epoch  9 batch: 5000 [ 50000/50000] loss:      0.44 accuracy:  70.984%
epoch 10 batch: 1000 [ 10000/50000] loss:      0.47 accuracy:  72.010%
epoch 10 batch: 2000 [ 20000/50000] loss:      1.83 accuracy:  71.860%
epoch 10 batch: 3000 [ 30000/50000] loss:      0.81 accuracy:  71.897%
epoch 10 batch: 4000 [ 40000/50000] loss:      0.72 accuracy:  71.552%
epoch 10 batch: 5000 [ 50000/50000] loss:      0.33 accuracy:  71.482%
epoch 11 batch: 1000 [ 10000/50000] loss:      0.60 accuracy:  73.540%
epoch 11 batch: 2000 [ 20000/50000] loss:      0.61 accuracy:  73.310%
epoch 11 batch: 3000 [ 30000/50000] loss:      0.41 accuracy:  73.173%
epoch 11 batch: 4000 [ 40000/50000] loss:      1.12 accuracy:  72.805%
epoch 11 batch: 5000 [ 50000/50000] loss:      0.73 accuracy:  72.634%
```

[107]:
```
plt.style.use('classic')
plt.figure(figsize=(7,5))
plt.plot(train_losses, label='training loss')
plt.plot(test_losses, label='validation loss',color='orange',ls='--')
plt.title('Loss at the end of each epoch')
plt.legend(loc='upper left');
```


[48]:
```
plt.title('Train Accuracy vs Validation Accuracy')
plt.plot([t/500 for t in train_correct], label='training accuracy')
plt.plot([t/100 for t in test_correct], label='validation␣
 ↪accuracy',ls='--',color='orange')
plt.legend(loc='upper left')
```

[48]: <matplotlib.legend.Legend at 0x7f8618f8ceb0>




[53]:
```
from sklearn.metrics import classification_report, confusion_matrix
```

[70]:
```
```

[70]: 10000

[71]:
```
test_load = DataLoader(test_data,batch_size=test_data.data.shape[0],)
```

[81]:
```
with torch.no_grad():
    correct = 0
    for x_test,y_test in test_load:

        y_val = model(x_test)
        _, predicted = y_val.max(1)

        correct += (predicted == y_test ).sum()

print(f"Test Accuracy {correct.item()}/{len(test_data)} : {correct.item()*100/
 ↪(len(test_data))}%")
```

```
accuracy = correct.item()*100/ (len(test_data))
```

```
Test Accuracy 6346/10000 : 63.46%
```

[83]:
```
print(class_names)
print(classification_report(predicted,y_test))
```

```
['plane', '  car', ' bird', '  cat', ' deer', '  dog', ' frog', 'horse', '
ship', 'truck']
              precision    recall  f1-score   support

           0       0.69      0.66      0.68      1050
           1       0.73      0.74      0.74       987
           2       0.50      0.57      0.53       890
           3       0.49      0.45      0.47      1095
           4       0.53      0.61      0.57       868
           5       0.53      0.54      0.54       980
           6       0.71      0.72      0.72       985
           7       0.68      0.70      0.69       962
           8       0.80      0.66      0.72      1205
           9       0.68      0.70      0.69       978

    accuracy                           0.63     10000
   macro avg       0.63      0.64      0.63     10000
weighted avg       0.64      0.63      0.64     10000
```

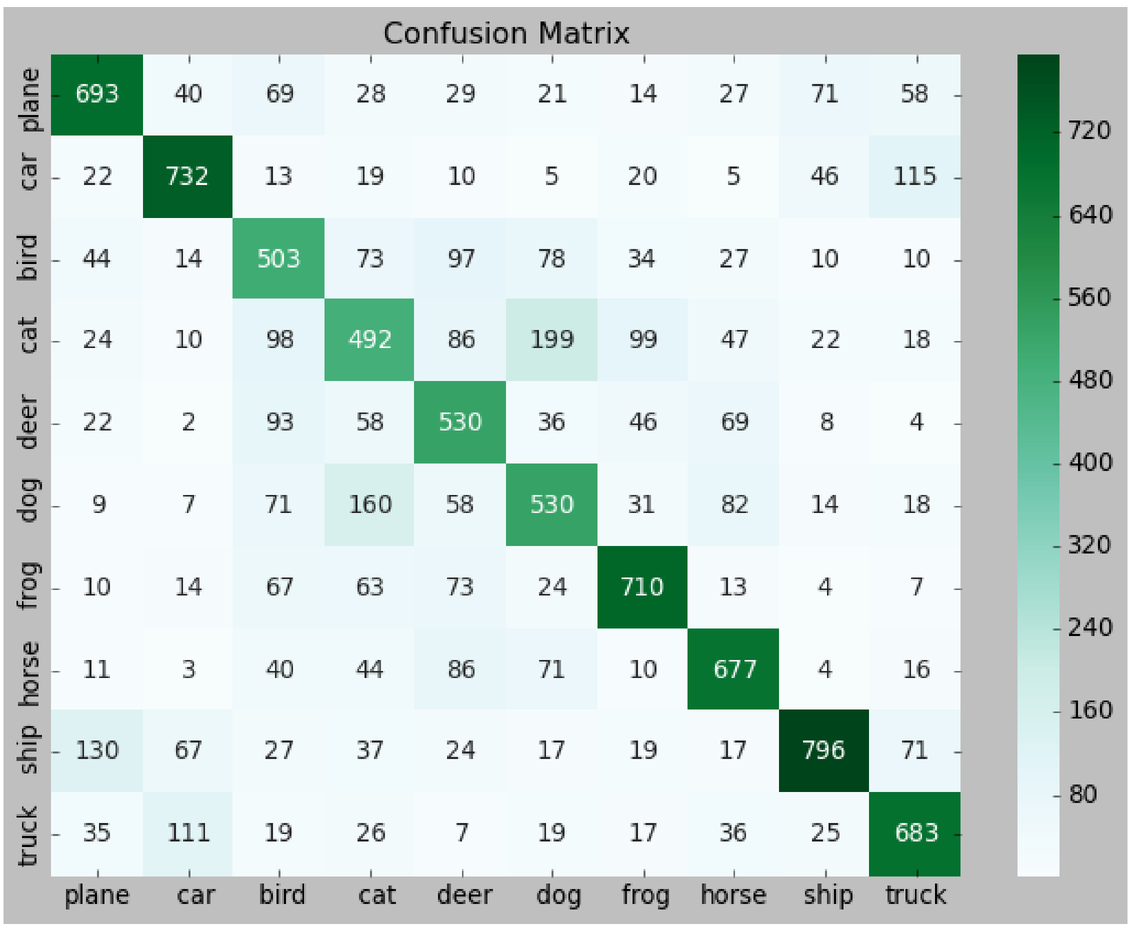
[84]:
```
report = '''
['plane', '  car', ' bird', '  cat', ' deer', '  dog', ' frog', 'horse', '␣
 ↪ship', 'truck']
              precision    recall  f1-score   support

           0       0.69      0.66      0.68      1050
           1       0.73      0.74      0.74       987
           2       0.50      0.57      0.53       890
           3       0.49      0.45      0.47      1095
           4       0.53      0.61      0.57       868
           5       0.53      0.54      0.54       980
           6       0.71      0.72      0.72       985
           7       0.68      0.70      0.69       962
           8       0.80      0.66      0.72      1205
           9       0.68      0.70      0.69       978

    accuracy                           0.63     10000
   macro avg       0.63      0.64      0.63     10000
weighted avg       0.64      0.63      0.64     10000
```

```
'''
```

[94]:
```
confmat = pd.DataFrame(confusion_matrix(predicted,y_test))
confmat.index = class_names
confmat.columns = class_names
```

[104]:
```
plt.figure(figsize=(10,7))
sns.heatmap(confmat,annot=True,fmt='d',cmap='BuGn')
plt.title('Confusion Matrix')
```

[104]: Text(0.5, 1.0, 'Confusion Matrix')



### 0.0.2 Miscellaneous

[108]:
```
import os
path = '../samples/'
overview_path = '../samples/overview.txt'
eval_path  = '../samples/evaluate.txt'

if os.path.exists(path):

    print('samples dir, exists..checking for dictionaries existence..')

    if os.path.exists(overview_path) and os.path.exists(eval_path):
        print('Data exists. no need of overwritting.')
    else:
        print("overview and eval doesn't exist, proceed to step-2")

else:
    print("samples/ dir is non-existent, Establishing one..")
    os.mkdir(path) # samples directory
```

```
samples dir, exists..checking for dictionaries existence..
Data exists. no need of overwritting.
```

[110]:
```
# desc-----string
# project_name-----string
# framework-----string
# prediction_type-----string
# network_type-----string
# architecture-----model()
# layers-----int
# hidden_units-----int
# activations-----string(list)
# epochs-----int
# metrics-----string(list)
# loss-----string
# optimiser-----string
# learning_rate-----float
# batch_size-----int/string
# train_performance-----float
# test_performance-----float
# classification_report-----string
# elapsed-----float
# summary-----string
# ipynb-----path
# plots-----path
```

[113]:
```
model
```

[113]:
```
ConvolutionalNetwork(
  (conv1): Conv2d(3, 6, kernel_size=(3, 3), stride=(1, 1))
  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=576, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
```

[125]:
```
synopsis = '''My Analogy behind the worse performance of pytorch compared to␣
↪keras is the change in network architecture because, as a novice learner of␣
↪pytorch I'm still figuring out how to implement 'SAME' padding in Pytorch␣
↪without which the dimensions of the image decreases ridiculously with each␣
↪convolutions and pooling, so it sort of forced me to use complex␣
↪architechtures as I did with keras'''
```

[127]:
```
synopsis
```

[127]:
```
"My Analogy behind the worse performance of pytorch compared to keras is the
change in network architecture because, as a novice learner of pytorch I'm still
figuring out how to implement 'SAME' padding in Pytorch without which the
dimensions of the image decreases ridiculously with each convolution, so it sort
of forced me to use complex architechtures as I did with keras"
```

[140]:
```
desc = '''The CIFAR-10 dataset consists of 60000 32x32 colour images in 10␣
↪classes, with 6000 images per class. There are 50000 training images and␣
↪10000 test images. The classes include various cars, ships, deers, dogs and␣
↪cats, trucks etc.'''
project_name = 'CIFAR-10'
framework = 'Pytorch'
prediction_type = 'Multi-Class Classification of 10 Classes'
network_type = 'Convolutional Neural Network'
architecture = str(model)
layers = 5
hidden_units = 'None'
activations = "['relu','softmax']"
epochs = 12
metrics = 'Accuracy'
loss = 'Categorical Cross-Entropy'
optimiser = 'Adam'
learning_rate = '0.001'
batch_size = 10
train_performance = '72.63%'
test_performance = '63.46%'
classification_report = report
elapsed = '5.3 Mins, runtime: local'
summary = synopsis
ipynb = './Projects/CIFAR10/Pytorch/CIFAR10-Pytorch.pdf'
```

```
plots = './Projects/CIFAR10/Pytorch/Plots'
```

[141]:
```
var = ['desc','project_name', 'framework','prediction_type','network_type',
    'architecture','layers','hidden_units','activations','epochs',
   ␣
 ↪'metrics','loss','optimiser','learning_rate','batch_size','train_performance','test_perform
    ,'ipynb','plots']
param = {}
for val in var:

    try:
        param[val] = eval(val)

    except:
        param[val] = val
```

[142]:
```
param
```

[142]:
```
{'desc': 'The CIFAR-10 dataset consists of 60000 32x32 colour images in 10
classes, with 6000 images per class. There are 50000 training images and 10000
test images. The classes include various cars, ships, deers, dogs and cats,
trucks etc.',
 'project_name': 'CIFAR-10',
 'framework': 'Pytorch',
 'prediction_type': 'Multi-Class Classification of 10 Classes',
 'network_type': 'Convolutional Neural Network',
 'architecture': 'ConvolutionalNetwork(\n  (conv1): Conv2d(3, 6, kernel_size=(3,
3), stride=(1, 1))\n  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1,
1))\n  (fc1): Linear(in_features=576, out_features=120, bias=True)\n  (fc2):
Linear(in_features=120, out_features=84, bias=True)\n  (fc3):
Linear(in_features=84, out_features=10, bias=True)\n)',
 'layers': 5,
 'hidden_units': 'None',
 'activations': "['relu','softmax']",
 'epochs': 12,
 'metrics': 'Accuracy',
 'loss': 'Categorical Cross-Entropy',
 'optimiser': 'Adam',
 'learning_rate': '0.001',
 'batch_size': 10,
 'train_performance': '72.63%',
 'test_performance': '63.46%',
 'classification_report': "\n['plane', '  car', ' bird', '  cat', ' deer', '
dog', ' frog', 'horse', ' ship', 'truck']\n              precision    recall
f1-score   support\n\n           0       0.69      0.66      0.68      1050\n
1       0.73      0.74      0.74       987\n           2       0.50      0.57
0.53       890\n           3       0.49      0.45      0.47      1095\n
```

```
4        0.53      0.61      0.57       868\n           5        0.53      0.54
0.54       980\n           6        0.71      0.72      0.72       985\n
7        0.68      0.70      0.69       962\n           8        0.80      0.66
0.72      1205\n           9        0.68      0.70      0.69       978\n\n
accuracy                           0.63     10000\n   macro avg       0.63
0.64      0.63     10000\nweighted avg       0.64      0.63      0.64
10000\n\n\n\n\n",
 'elapsed': '5.3 Mins, runtime: local',
 'summary': "My Analogy behind the worse performance of pytorch compared to
keras is the change in network architecture because, as a novice learner of
pytorch I'm still figuring out how to implement 'SAME' padding in Pytorch
without which the dimensions of the image decreases ridiculously with each
convolution, so it sort of forced me to use complex architechtures as I did with
keras",
 'ipynb': './Projects/CIFAR10/Pytorch/CIFAR10-Pytorch.pdf',
 'plots': './Projects/CIFAR10/Pytorch/Plots'}
```

[143]:

```python
import pickle
file = open("artefacts.txt", "wb")
dictionary = param
pickle.dump(dictionary, file)
file.close()
```

[ ]:

```

```