MNIST-Pytorch

January 24, 2021

0.0.1 Convolutional Neural Network

[1]:
```
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

import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
plt.style.use('seaborn-white')
import warnings
warnings.filterwarnings('ignore','DeprecatedWarnings')
```

[2]:
```
torch.__version__
```

[2]:
```
'1.7.1'
```

0.0.2 Loading Datasets

[3]:
```
# MNIST Is considered to be the Hello World of CNN's and Deep Learning in␣
↪General, so it is
# generally provided from as the inbuild go-to project for beginners
transforms = transforms.ToTensor()
train_data = datasets.MNIST(root='../Data', train=True, download=True,␣
↪transform=transforms)
test_data = datasets.MNIST(root='../Data', train=False, download=True,␣
↪transform=transforms)
```

[4]:
```
train_data
```

[4]:
```
Dataset MNIST
    Number of datapoints: 60000
    Root location: ../Data
    Split: Train
    StandardTransform
```

```
Transform: ToTensor()
```

[5]:
```
test_data
```

[5]:
```
Dataset MNIST
    Number of datapoints: 10000
    Root location: ../Data
    Split: Test
    StandardTransform
Transform: ToTensor()
```

0.0.3 Data Loader Object

[6]:
```
# Pytorch's convention to create dataloader objects, to be used in the models␣
 ↪train cycle
batch_s = 10
train_loader = DataLoader(train_data,batch_size=batch_s,shuffle=True)
test_loader = DataLoader(test_data,batch_size=batch_s,shuffle=False)
```

0.0.4 What is the Data about?

[7]:
```
# pipeline obj=1/
desc = '''
The MNIST database of handwritten digits, available from this page, has a␣
 ↪training set of 60,000 examples, and a test set of 10,000 examples. It is a␣
 ↪subset of a larger set available from NIST. The digits have been␣
 ↪size-normalized and centered in a fixed-size image.
'''
print(desc)
```

```
The MNIST database of handwritten digits, available from this page, has a
training set of 60,000 examples, and a test set of 10,000 examples. It is a
subset of a larger set available from NIST. The digits have been size-normalized
and centered in a fixed-size image.
```

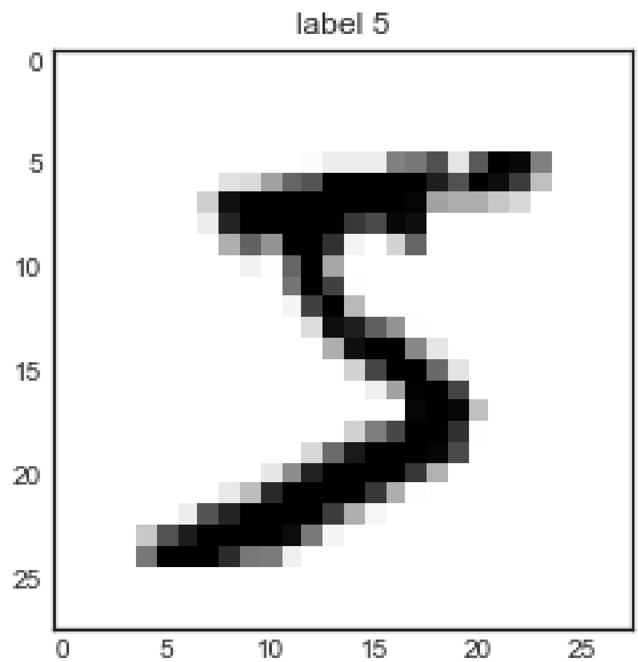
[8]:
```
(x_train, y_train) = train_data[0] # one sample
```

[9]:
```
y_train # label
```

[9]:
```
5
```

[10]:
```
plt.imshow(x_train[0],cmap='binary')
plt.title('label {}'.format(y_train))
```

[10]: Text(0.5, 1.0, 'label 5')



0.0.5 Convolutional Neural Network Class

0.0.6 Buidling Model

[11]:
```
class convolutional(nn.Module):

    def __init__(self,in_channel=1,output=10):
        super().__init__() # inheriting nn.Module
        # defining Layer Functions
        # input dimension = (b,28,28,1)
        self.conv1 = nn.Conv2d(in_channels=in_channel, out_channels=6,␣
 ↪kernel_size=(3,3), stride=1 )
        # (b,26,26,6)
        self.pool = nn.MaxPool2d(kernel_size=(2,2), stride=(2,2)) # f=2, s=2
        #  dimension (b,12,12,6)
        self.conv2 = nn.
 ↪Conv2d(in_channels=6,out_channels=16,kernel_size=(3,3),stride=1)
        # dimension (b,10,10,16)
        # we apply one more pool after this dimension so (b,5,5,16)
        self.fc1 = nn.Linear(5*5*16,120)
        self.fc2 = nn.Linear(120, 64)
        self.fc3 = nn.Linear(in_features=64,out_features=output)
```

```
    def forward(self,X):
        # Construction of the Architecture
        X = F.relu(self.conv1(X))
        X = self.pool(X)
        X = F.relu(self.conv2(X))
        X = self.pool(X)
        X = X.view(-1, 5*5*16) # Flatten
        X = F.relu(self.fc1(X))
        X = F.relu(self.fc2(X))
        X = self.fc3(X)
        return F.log_softmax(X, dim=1)
```

[12]:

```
net = convolutional()
```

[13]:

```
net
```

[13]:

```
convolutional(
  (conv1): Conv2d(1, 6, kernel_size=(3, 3), stride=(1, 1))
  (pool): MaxPool2d(kernel_size=(2, 2), stride=(2, 2), padding=0, dilation=1,
ceil_mode=False)
  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=400, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=64, bias=True)
  (fc3): Linear(in_features=64, out_features=10, bias=True)
)
```

[14]:

```
print('Total Learnable Params :')
params = [p.numel() for p in net.parameters() if p.requires_grad]
for item in params:
    print(f'{item:>10}')
print(f'___________\n{sum(params):>10}')
```

```
Total Learnable Params :
        54
         6
       864
        16
     48000
       120
      7680
        64
       640
        10
```

```
-----------
     57454
```

[15]:
```
# defining the loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(net.parameters(),lr=0.001)
```

[17]:
```
# The TRAIN CYCLE
import time
start = time.perf_counter()
# trackers, for post evaluation
epochs = 5
train_losses = []
test_losses = []
train_correct = []
test_correct = []
accuracy = []

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

    # Run the training batches
    for b, (X_train, y_train) in enumerate(train_loader):
        b+=1

        # Apply the model
        y_pred = net(X_train)   # we don't flatten X-train here
        loss = criterion(y_pred, y_train)

        # Tally the number of correct predictions
        _, predicted = y_pred.max(1)
        batch_corr = (predicted == y_train).sum()
        trn_corr += batch_corr

        # Update parameters
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # Print interim results
        if b%600 == 0:
            print(f'epoch: {i:2}  batch: {b:4} [{10*b:6}/60000]  loss: {loss.
 ↪item():10.8f}  \
accuracy: {trn_corr.item()*100/(10*b):7.3f}%')
            accuracy.append(trn_corr.item()*100/(10*b))
```

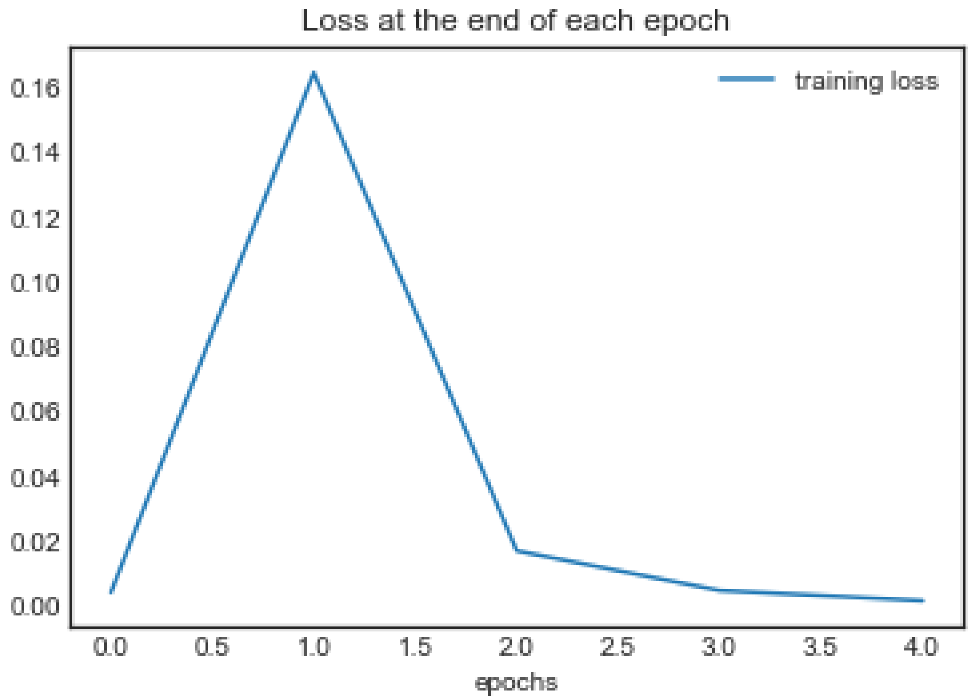
```
    train_losses.append(loss)
    train_correct.append(trn_corr)

    # Run the testing batches
    with torch.no_grad():
        for b, (X_test, y_test) in enumerate(test_loader):

            # Apply the model
            y_val = net(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_losses.append(loss)
    test_correct.append(tst_corr)

elapsed = (time.perf_counter() - start)/60
print('ELAPSED {:.2f}'.format(elapsed))
```

```
epoch:  0  batch:  600 [  6000/60000]  loss: 0.11924569  accuracy:  75.550%
epoch:  0  batch: 1200 [ 12000/60000]  loss: 0.12763628  accuracy:  84.292%
epoch:  0  batch: 1800 [ 18000/60000]  loss: 0.04454534  accuracy:  87.811%
epoch:  0  batch: 2400 [ 24000/60000]  loss: 0.00629141  accuracy:  89.662%
epoch:  0  batch: 3000 [ 30000/60000]  loss: 0.05193086  accuracy:  90.840%
epoch:  0  batch: 3600 [ 36000/60000]  loss: 0.02835705  accuracy:  91.792%
epoch:  0  batch: 4200 [ 42000/60000]  loss: 0.56388974  accuracy:  92.493%
epoch:  0  batch: 4800 [ 48000/60000]  loss: 0.00274723  accuracy:  93.071%
epoch:  0  batch: 5400 [ 54000/60000]  loss: 0.08888493  accuracy:  93.496%
epoch:  0  batch: 6000 [ 60000/60000]  loss: 0.00419691  accuracy:  93.852%
epoch:  1  batch:  600 [  6000/60000]  loss: 0.00491270  accuracy:  97.450%
epoch:  1  batch: 1200 [ 12000/60000]  loss: 0.00427231  accuracy:  97.458%
epoch:  1  batch: 1800 [ 18000/60000]  loss: 0.04439243  accuracy:  97.544%
epoch:  1  batch: 2400 [ 24000/60000]  loss: 0.01586340  accuracy:  97.588%
epoch:  1  batch: 3000 [ 30000/60000]  loss: 0.02111457  accuracy:  97.633%
epoch:  1  batch: 3600 [ 36000/60000]  loss: 0.00026605  accuracy:  97.717%
epoch:  1  batch: 4200 [ 42000/60000]  loss: 0.26243860  accuracy:  97.743%
epoch:  1  batch: 4800 [ 48000/60000]  loss: 0.29612529  accuracy:  97.783%
epoch:  1  batch: 5400 [ 54000/60000]  loss: 0.13613828  accuracy:  97.850%
epoch:  1  batch: 6000 [ 60000/60000]  loss: 0.16438568  accuracy:  97.848%
epoch:  2  batch:  600 [  6000/60000]  loss: 0.00097367  accuracy:  98.367%
epoch:  2  batch: 1200 [ 12000/60000]  loss: 0.00730920  accuracy:  98.342%
epoch:  2  batch: 1800 [ 18000/60000]  loss: 0.44688016  accuracy:  98.356%
epoch:  2  batch: 2400 [ 24000/60000]  loss: 0.02830379  accuracy:  98.350%
epoch:  2  batch: 3000 [ 30000/60000]  loss: 0.16491416  accuracy:  98.333%
```

```
epoch:  2  batch: 3600 [ 36000/60000]  loss: 0.31121570  accuracy:  98.328%
epoch:  2  batch: 4200 [ 42000/60000]  loss: 0.83973742  accuracy:  98.360%
epoch:  2  batch: 4800 [ 48000/60000]  loss: 0.02205916  accuracy:  98.369%
epoch:  2  batch: 5400 [ 54000/60000]  loss: 0.01329469  accuracy:  98.387%
epoch:  2  batch: 6000 [ 60000/60000]  loss: 0.01703760  accuracy:  98.410%
epoch:  3  batch:  600 [  6000/60000]  loss: 0.00008939  accuracy:  98.950%
epoch:  3  batch: 1200 [ 12000/60000]  loss: 0.00989255  accuracy:  98.833%
epoch:  3  batch: 1800 [ 18000/60000]  loss: 0.01814078  accuracy:  98.850%
epoch:  3  batch: 2400 [ 24000/60000]  loss: 0.00006347  accuracy:  98.867%
epoch:  3  batch: 3000 [ 30000/60000]  loss: 0.08430563  accuracy:  98.833%
epoch:  3  batch: 3600 [ 36000/60000]  loss: 0.00083146  accuracy:  98.814%
epoch:  3  batch: 4200 [ 42000/60000]  loss: 0.00024983  accuracy:  98.790%
epoch:  3  batch: 4800 [ 48000/60000]  loss: 0.04406525  accuracy:  98.785%
epoch:  3  batch: 5400 [ 54000/60000]  loss: 0.00120888  accuracy:  98.794%
epoch:  3  batch: 6000 [ 60000/60000]  loss: 0.00479843  accuracy:  98.792%
epoch:  4  batch:  600 [  6000/60000]  loss: 0.03544014  accuracy:  98.967%
epoch:  4  batch: 1200 [ 12000/60000]  loss: 0.00299220  accuracy:  99.017%
epoch:  4  batch: 1800 [ 18000/60000]  loss: 0.02138555  accuracy:  99.000%
epoch:  4  batch: 2400 [ 24000/60000]  loss: 0.00595939  accuracy:  98.971%
epoch:  4  batch: 3000 [ 30000/60000]  loss: 0.00030641  accuracy:  98.980%
epoch:  4  batch: 3600 [ 36000/60000]  loss: 0.00556433  accuracy:  99.000%
epoch:  4  batch: 4200 [ 42000/60000]  loss: 0.07285134  accuracy:  98.936%
epoch:  4  batch: 4800 [ 48000/60000]  loss: 0.00090826  accuracy:  98.973%
epoch:  4  batch: 5400 [ 54000/60000]  loss: 0.00183687  accuracy:  98.954%
epoch:  4  batch: 6000 [ 60000/60000]  loss: 0.00166669  accuracy:  98.988%
ELAPSED 2.48
```

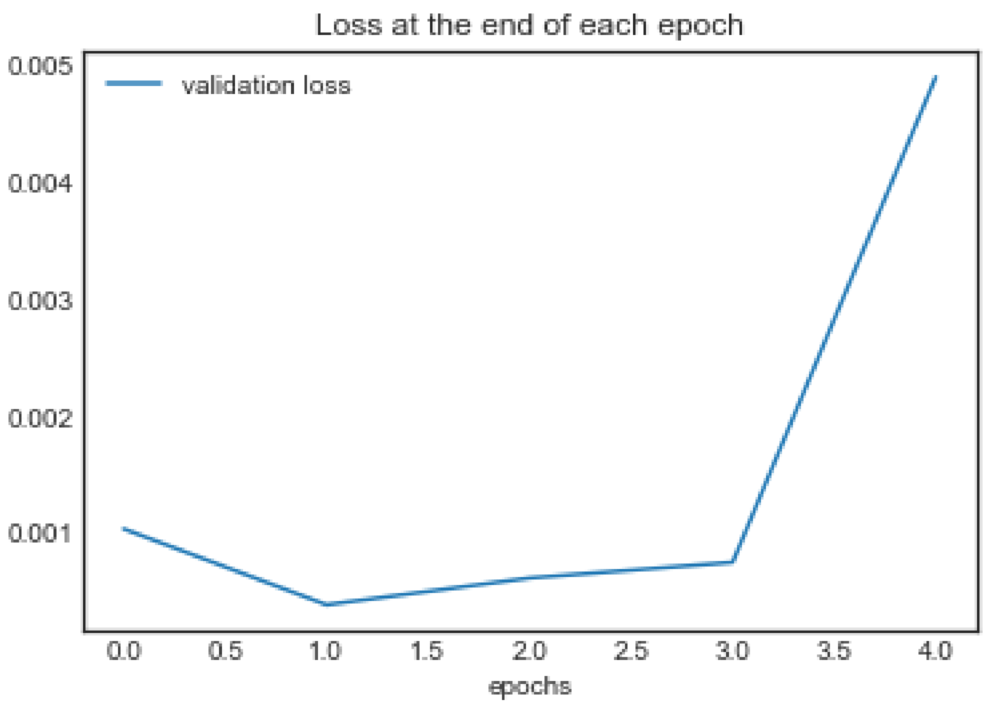
[18]:

```
plt.plot(train_losses, label='training loss')
plt.title('Loss at the end of each epoch')
plt.xlabel('epochs')
plt.legend();
```

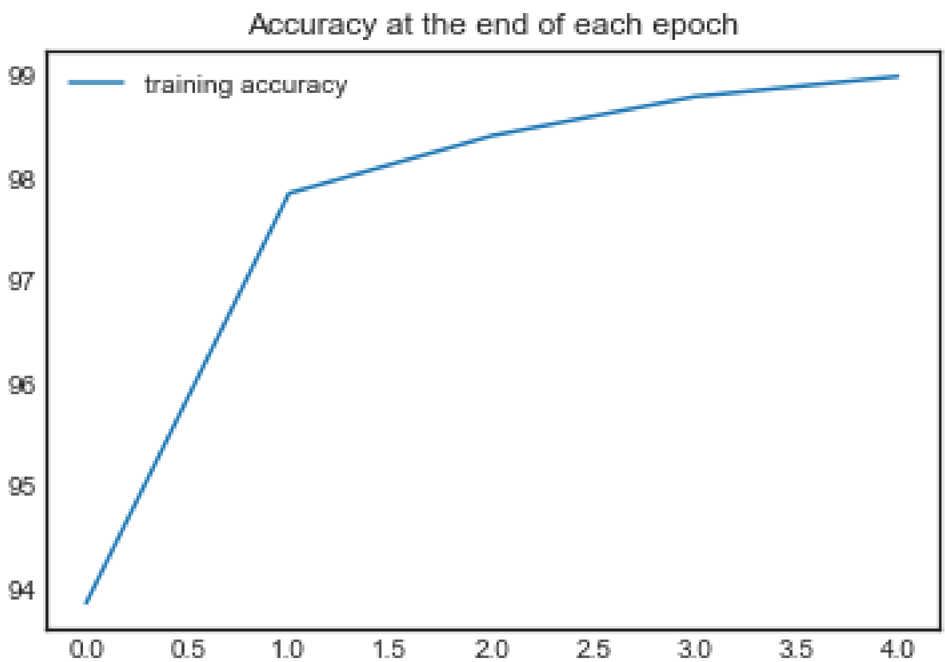


[19]:

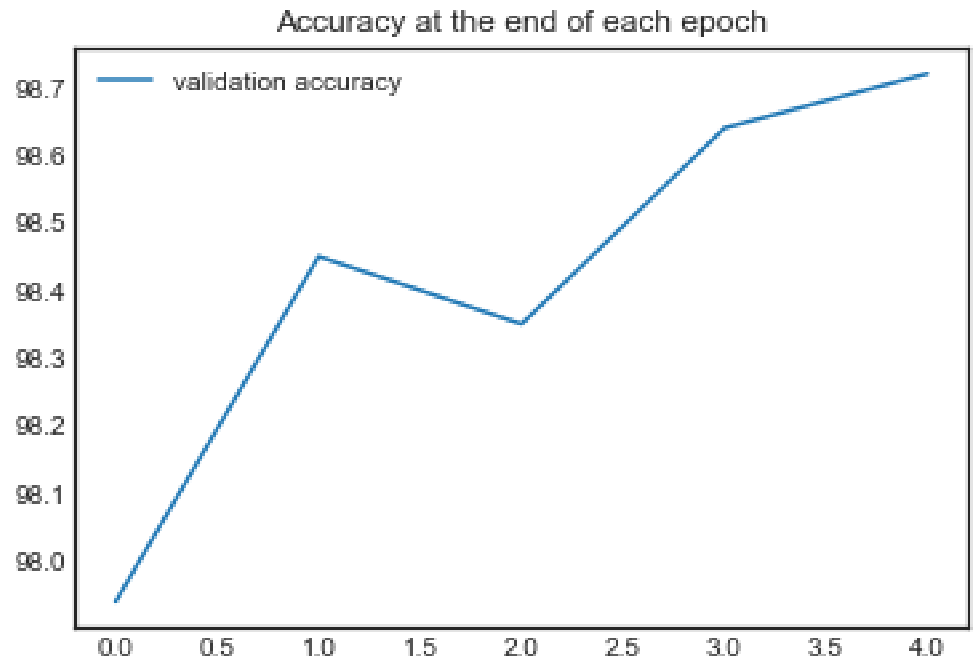
```
plt.plot(test_losses, label='validation loss')
plt.title('Loss at the end of each epoch')
plt.xlabel('epochs')
plt.legend();
```



[20]:
```
plt.plot([t/600 for t in train_correct], label='training accuracy')

plt.title('Accuracy at the end of each epoch')
plt.legend();
```



[21]:
```
plt.plot([t/100 for t in test_correct], label='validation accuracy')
plt.title('Accuracy at the end of each epoch')
plt.legend();
```



0.0.7 Overall Evaluation

[22]:
```
test_load = DataLoader(test_data,batch_size=10000, shuffle=False)
```

[23]:
```
with torch.no_grad():
    correct = 0
    for x_test, y_test in test_load:
        y_val = net(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)):7.3f}%')
```

```
Test accuracy: 9872/10000 =  98.720%
```

[24]:
```
predicted
```

[24]: tensor([7, 2, 1, …, 4, 5, 6])

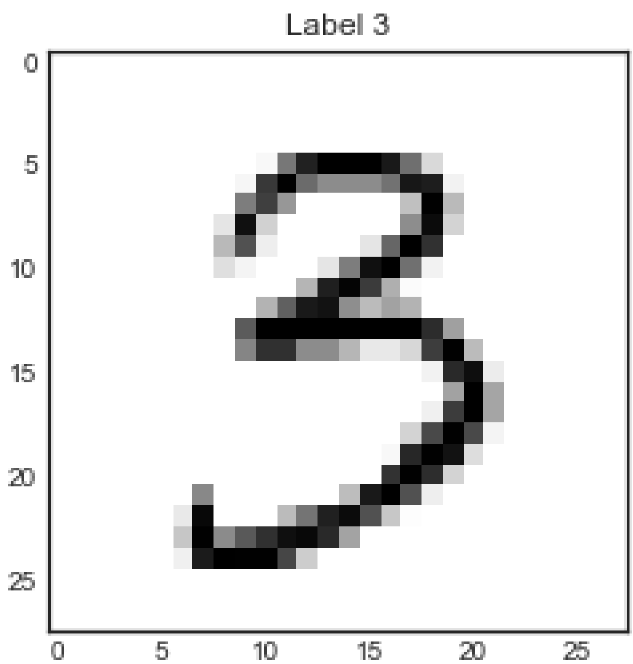
[25]:
```
# Missed Pictures and their indexes
misses = np.array([])

for i in range(len(predicted.view(-1))):

    if predicted[i] != y_test[i]:
        misses = np.append(misses,i).astype('int64')

misses
```

[25]:
```
array([  18,   62,  115,  158,  340,  359,  551,  582,  619,  629,  659,
        684,  716,  720,  740,  924,  947, 1014, 1039, 1112, 1226, 1242,
       1247, 1299, 1328, 1393, 1500, 1522, 1621, 1709, 1721, 1737, 1782,
       1790, 1878, 1901, 1909, 2018, 2024, 2035, 2070, 2090, 2130, 2135,
       2293, 2343, 2447, 2488, 2496, 2582, 2597, 2648, 2654, 2743, 2771,
       2927, 2939, 2953, 2959, 2970, 3030, 3225, 3289, 3448, 3520, 3702,
       3726, 3756, 3762, 3767, 3778, 3806, 3808, 3902, 3906, 3941, 4163,
       4176, 4194, 4201, 4284, 4360, 4497, 4504, 4536, 4571, 4740, 4783,
       4838, 4860, 4880, 4911, 5127, 5457, 5634, 5642, 5937, 5955, 5973,
       5981, 5997, 6101, 6560, 6571, 6576, 6597, 6625, 6651, 6783, 6883,
       7216, 7574, 7899, 7928, 7990, 8279, 8325, 8469, 8509, 8520, 9009,
       9540, 9669, 9729, 9839, 9891, 9904, 9905])
```

0.0.8 Single Image Test

[26]:
```
index = 2020
plt.figure(figsize=(4,4))
plt.imshow(x_test[index].reshape(28,28),cmap='binary')
plt.title('Label {}'.format(y_test[2020]))
```

[26]: Text(0.5, 1.0, 'Label 3')



[27]:
```
net.eval()
with torch.no_grad():
    yhat = net(x_test[index][0].view(1,1,28,28))
    print('Prediction ~ {}'.format(yhat.argmax()))
    print('Reality - {}'.format(y_test[index]))
```

```
Prediction ~ 3
Reality - 3
```

0.0.9 Miscellaneous

[28]:
```
# PipeLine Script Data
```

[89]:
```
project_name = 'MNIST'
framework = 'Pytorch'
prediction_type = 'Classification'
network_type = 'Convolutional Neural Network'
Architecture = str(net)
layers = 6
hidden_units = None
Activations = "['relu','softmax']"
epochs = 5
metrics = 'Accuracy'
Train_Accuracy = np.mean(accuracy)
Test_Accuracy = 98.720
```

```
elapsed = '2.48 Min'
Desc = desc.strip()
```

[90]:
```
param = dict()
var = ['project_name', 'framework','prediction_type','network_type',
       'Architecture','layers','hidden_units','Activations','epochs',
       'metrics','Train_Accuracy','Test_Accuracy','elapsed','Desc']
```

[91]:
```
for val in var:
    param[val] = eval(val)
```

[92]:
```
import pickle
file = open("state_dict.txt", "wb")

dictionary = param

pickle.dump(dictionary, file)
file.close()
```

[95]:
```
param
```

[95]:
```
{'project_name': 'MNIST',
 'framework': 'Pytorch',
 'prediction_type': 'Classification',
 'network_type': 'Convolutional Neural Network',
 'Architecture': 'convolutional(\n  (conv1): Conv2d(1, 6, kernel_size=(3, 3),
stride=(1, 1))\n  (pool): MaxPool2d(kernel_size=(2, 2), stride=(2, 2),
padding=0, dilation=1, ceil_mode=False)\n  (conv2): Conv2d(6, 16,
kernel_size=(3, 3), stride=(1, 1))\n  (fc1): Linear(in_features=400,
out_features=120, bias=True)\n  (fc2): Linear(in_features=120, out_features=64,
bias=True)\n  (fc3): Linear(in_features=64, out_features=10, bias=True)\n)',
 'layers': 6,
 'hidden_units': None,
 'Activations': "['relu','softmax']",
 'epochs': 5,
 'metrics': 'Accuracy',
 'Train_Accuracy': 96.62335542328043,
 'Test_Accuracy': 98.72,
 'elapsed': '2.48 Min',
 'Desc': 'The MNIST database of handwritten digits, available from this page,
has a training set of 60,000 examples, and a test set of 10,000 examples. It is
a subset of a larger set available from NIST. The digits have been size-
normalized and centered in a fixed-size image.'}
```

[99]:
```
import pandas as pd
pd.DataFrame(pd.Series(param)).T
```

[99]:
```
  project_name framework prediction_type                  network_type  \
0        MNIST   Pytorch  Classification  Convolutional Neural Network

                                       Architecture layers hidden_units  \
0  convolutional(\n  (conv1): Conv2d(1, 6, kernel…      6         None

          Activations epochs   metrics Train_Accuracy Test_Accuracy   elapsed  \
0  ['relu','softmax']      5  Accuracy        96.6234         98.72  2.48 Min

                                                Desc
0  The MNIST database of handwritten digits, avai…
```

[ ]: