Prithvi_Poddar_17191_report_2_CNN

June 23, 2020

1 Report 2

1.1 Prithvi Poddar 17191

1.1.1 In this report, we'll implement a simple Convolutional Neural Network and train it on the entire MNIST dataset so see the results.

P.S. This notebook was created entirely in google colab as it provides GPU facility, so that the training can be faster. Thus, I had to mention all the classes wwithin the notebook itself as I cannot import classes from my local machine. We will be using PyTorch for this notebook

Run the next line if your computer doen't have pytorch installed. Otherwise you can skip it.

[ ]:
```
!pip3 install torch torchvision
```

[1]:
```
import torch
import numpy as np
from torch import nn
import torch.nn.functional as F
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
```

[2]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

[3]:
```
device
```

[3]:
```
device(type='cuda', index=0)
```

Creating the transform function to convert the images into tensors that are readable by pytorch

[4]:
```
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
↪5,),(0.5))])
```

Downloading the MNIST dataset from torchvision

[5]:
```
training_dataset = datasets.MNIST(root='./data', train=True, download=True,␣
↪transform=transform)
validation_dataset = datasets.MNIST(root='./data', train=False, download=True,␣
↪transform=transform)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to
./data/MNIST/raw/train-images-idx3-ubyte.gz
```

```
HBox(children=(FloatProgress(value=1.0, bar_style='info', max=1.0), HTML(value='')))
```

```
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to
./data/MNIST/raw/train-labels-idx1-ubyte.gz
```

```
HBox(children=(FloatProgress(value=1.0, bar_style='info', max=1.0), HTML(value='')))
```

```
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to
./data/MNIST/raw/t10k-images-idx3-ubyte.gz
```

```
HBox(children=(FloatProgress(value=1.0, bar_style='info', max=1.0), HTML(value='')))
```

```
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to
./data/MNIST/raw/t10k-labels-idx1-ubyte.gz
```

```
HBox(children=(FloatProgress(value=1.0, bar_style='info', max=1.0), HTML(value='')))
```

```
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
Processing...
Done!
```

```
/pytorch/torch/csrc/utils/tensor_numpy.cpp:141: UserWarning: The given NumPy
array is not writeable, and PyTorch does not support non-writeable tensors. This
means you can write to the underlying (supposedly non-writeable) NumPy array
using the tensor. You may want to copy the array to protect its data or make it
writeable before converting it to a tensor. This type of warning will be
suppressed for the rest of this program.
```

[6]:
```
training_loader = torch.utils.data.DataLoader(training_dataset, batch_size=100,␣
 ↪shuffle=True)
validation_loader = torch.utils.data.DataLoader(validation_dataset, batch_size␣
 ↪= 100, shuffle=False)
```

Now we define the training function. We'll be using the Cross Entropy loss and the Adam optimizer.

[7]:
```
def train(model, epochs, learning_rate):
  criterion = nn.CrossEntropyLoss()
  optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

  training_losses=[]
  training_accuracies=[]
  test_losses=[]
```

```
test_accuracies=[]

for e in range(epochs):
  training_loss = 0.0
  training_accuracy = 0.0
  test_loss = 0.0
  test_accuracy = 0.0

  for inputs, labels in training_loader:
    inputs = inputs.to(device)
    labels = labels.to(device)
    outputs = model.forward(inputs)
    loss = criterion(outputs, labels)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    _, preds = torch.max(outputs, 1) #returns the max value along axis 1␣
↪along with its index
    training_loss += loss.item()
    training_accuracy += torch.sum(preds==labels.data)

  else:
    with torch.no_grad():
      for val_inputs, val_labels in validation_loader:
        val_inputs = val_inputs.to(device)
        val_labels = val_labels.to(device)
        val_outputs = model.forward(val_inputs)
        val_loss = criterion(val_outputs, val_labels)

        _, val_preds = torch.max(val_outputs, 1)
        test_loss += val_loss.item()
        test_accuracy += torch.sum(val_preds == val_labels.data)

    epoch_loss = training_loss/len(training_loader)
    epoch_acc = training_accuracy.float()/ len(training_loader)
    training_losses.append(epoch_loss)
    training_accuracies.append(epoch_acc)

    val_epoch_loss = test_loss/len(validation_loader)
    val_epoch_acc = test_accuracy.float()/ len(validation_loader)
    test_losses.append(val_epoch_loss)
    test_accuracies.append(val_epoch_acc)
    print('epoch :', (e+1))
    print('training loss: {:.4f}, acc {:.4f} '.format(epoch_loss, epoch_acc.
↪item()))
```

```
        print('validation loss: {:.4f}, validation acc {:.4f} '.
↪format(val_epoch_loss, val_epoch_acc.item()))

    return training_losses, training_accuracies, test_losses ,test_accuracies
```

Defining the plotting function to plot the accuracies and losses later on

[8]:
```
def plot_loss(training_losses, testing_losses):
  plt.plot(training_losses, label='training loss')
  plt.plot(testing_losses, label='testing loss')
  plt.legend()
```

[9]:
```
def plot_accuracy(training_accuracies, testing_accuracies):
  plt.plot(training_accuracies, label='training accuracy')
  plt.plot(testing_accuracies, label='testing accuracy')
  plt.legend()
```

1.1.2 Having defined the helping functions, we can now start forming our CNN module.

Since, training takes substantial time, even when using a gpu, I'll be referring to the results from https://www.kaggle.com/cdeotte/how-to-choose-cnn-architecture-mnist

In the above mentioned link, experiments have already been done to determine the optimum parameters for training on the MNIST data set For our model ,we'll have **2 convolutional layers**. The **first one with 32 filetrs and second one with 64 filters. Filter size will be 5 with stride=1** There will be **2 fully connected layers with 128 neurons in the first layer and 10 in the second layer** which will be the output layer. Activation function will be **RELU with softmax applied to the last layer**. Intermediate **max pooling will be done with kernel size=2 and strides=2. Dropout in the fully connected layer will be 0.4**

Important formulae that we'll need are:

Output height = ((height-kernel_size+2*padding)/stride)+1

Output width = ((width-kernel_size+2*padding)/stride)+1

We'll use max_pooling of size 2 and stride 2. This will simply half the size of the feature map, hence making our manual calculations easier

[10]:
```
class Network_CNN(nn.Module):
    def __init__(self):
      super().__init__()
      self.conv1 = nn.Conv2d(1, 32, 5, 1)
      self.conv2 = nn.Conv2d(32, 64, 5, 1)
      self.fc1 = nn.Linear(4*4*64, 500)
      self.dropout1 = nn.Dropout(0.4)
      self.fc2 = nn.Linear(500, 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, 4*4*64)
```

```python
        x = F.relu(self.fc1(x))
        x = self.dropout1(x)
        x = F.softmax(self.fc2(x), dim=1)
        return x

    def visualize(self, x):
        a = F.relu(self.conv1(x))
        b = F.max_pool2d(a, 2, 2)
        c = F.relu(self.conv2(b))
        d = F.max_pool2d(c, 2, 2)
        return a, b, c, d
```

[11]:
```python
model = Network_CNN().to(device)
model
```

[11]:
```
Network_CNN(
  (conv1): Conv2d(1, 32, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=1024, out_features=500, bias=True)
  (dropout1): Dropout(p=0.4, inplace=False)
  (fc2): Linear(in_features=500, out_features=10, bias=True)
)
```

[12]:
```python
training_losses, training_accuracies, test_losses, test_accuracies =␣
 ↪train(model, 50, 0.0001)
```

```
epoch : 1
training loss: 1.6740, acc 82.4383
validation loss: 1.5233, validation acc 94.5700
epoch : 2
training loss: 1.5132, acc 95.5450
validation loss: 1.4992, validation acc 96.7700
epoch : 3
training loss: 1.4975, acc 96.8550
validation loss: 1.4892, validation acc 97.6100
epoch : 4
training loss: 1.4887, acc 97.5900
validation loss: 1.4865, validation acc 97.7100
epoch : 5
training loss: 1.4851, acc 97.8933
validation loss: 1.4812, validation acc 98.3000
epoch : 6
training loss: 1.4818, acc 98.1717
validation loss: 1.4789, validation acc 98.4100
epoch : 7
training loss: 1.4793, acc 98.3817
validation loss: 1.4776, validation acc 98.5000
epoch : 8
training loss: 1.4776, acc 98.5467
```

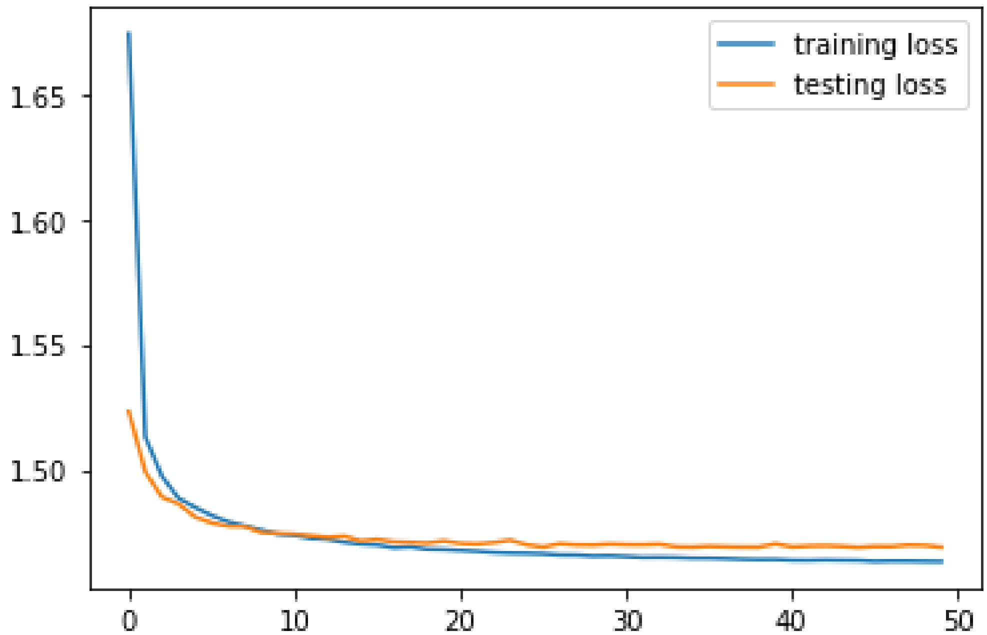
```
validation loss: 1.4775, validation acc 98.4700
epoch : 9
training loss: 1.4760, acc 98.6900
validation loss: 1.4750, validation acc 98.8600
epoch : 10
training loss: 1.4743, acc 98.8600
validation loss: 1.4747, validation acc 98.7600
epoch : 11
training loss: 1.4739, acc 98.8900
validation loss: 1.4744, validation acc 98.8800
epoch : 12
training loss: 1.4727, acc 98.9783
validation loss: 1.4738, validation acc 98.8300
epoch : 13
training loss: 1.4723, acc 98.9950
validation loss: 1.4731, validation acc 98.9000
epoch : 14
training loss: 1.4711, acc 99.1150
validation loss: 1.4736, validation acc 98.8700
epoch : 15
training loss: 1.4704, acc 99.1850
validation loss: 1.4717, validation acc 99.0200
epoch : 16
training loss: 1.4700, acc 99.2300
validation loss: 1.4723, validation acc 98.9800
epoch : 17
training loss: 1.4689, acc 99.3133
validation loss: 1.4713, validation acc 99.0600
epoch : 18
training loss: 1.4693, acc 99.2733
validation loss: 1.4711, validation acc 99.1000
epoch : 19
training loss: 1.4683, acc 99.3767
validation loss: 1.4708, validation acc 99.0500
epoch : 20
training loss: 1.4682, acc 99.3850
validation loss: 1.4717, validation acc 99.0200
epoch : 21
training loss: 1.4679, acc 99.4067
validation loss: 1.4707, validation acc 99.1100
epoch : 22
training loss: 1.4675, acc 99.4367
validation loss: 1.4705, validation acc 99.1300
epoch : 23
training loss: 1.4671, acc 99.4983
validation loss: 1.4710, validation acc 99.0800
epoch : 24
training loss: 1.4668, acc 99.5150
```

```
validation loss: 1.4720, validation acc 99.0000
epoch : 25
training loss: 1.4667, acc 99.5133
validation loss: 1.4701, validation acc 99.1800
epoch : 26
training loss: 1.4665, acc 99.5233
validation loss: 1.4692, validation acc 99.2800
epoch : 27
training loss: 1.4660, acc 99.5817
validation loss: 1.4706, validation acc 99.0500
epoch : 28
training loss: 1.4660, acc 99.5717
validation loss: 1.4701, validation acc 99.1400
epoch : 29
training loss: 1.4656, acc 99.6117
validation loss: 1.4700, validation acc 99.1600
epoch : 30
training loss: 1.4657, acc 99.6067
validation loss: 1.4705, validation acc 99.1000
epoch : 31
training loss: 1.4654, acc 99.6317
validation loss: 1.4702, validation acc 99.1200
epoch : 32
training loss: 1.4651, acc 99.6567
validation loss: 1.4702, validation acc 99.1500
epoch : 33
training loss: 1.4651, acc 99.6633
validation loss: 1.4704, validation acc 99.1200
epoch : 34
training loss: 1.4650, acc 99.6583
validation loss: 1.4693, validation acc 99.2600
epoch : 35
training loss: 1.4648, acc 99.6883
validation loss: 1.4692, validation acc 99.2200
epoch : 36
training loss: 1.4648, acc 99.6833
validation loss: 1.4696, validation acc 99.1900
epoch : 37
training loss: 1.4646, acc 99.7050
validation loss: 1.4693, validation acc 99.2000
epoch : 38
training loss: 1.4644, acc 99.7200
validation loss: 1.4692, validation acc 99.2300
epoch : 39
training loss: 1.4642, acc 99.7433
validation loss: 1.4692, validation acc 99.2300
epoch : 40
training loss: 1.4642, acc 99.7217
```

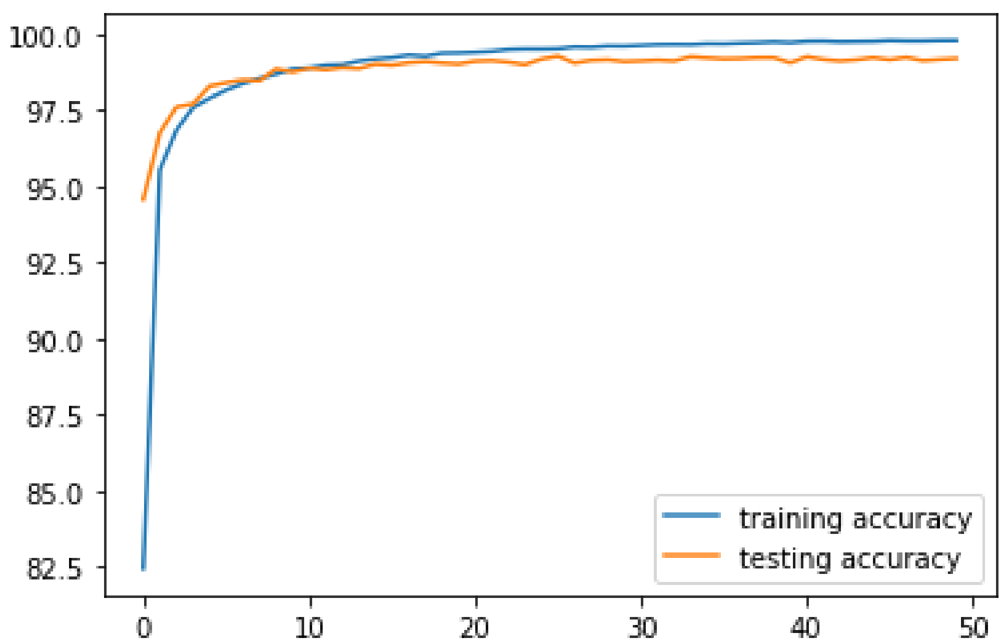
```
validation loss: 1.4706, validation acc 99.0600
epoch : 41
training loss: 1.4639, acc 99.7650
validation loss: 1.4693, validation acc 99.2600
epoch : 42
training loss: 1.4639, acc 99.7700
validation loss: 1.4696, validation acc 99.1700
epoch : 43
training loss: 1.4640, acc 99.7483
validation loss: 1.4698, validation acc 99.1200
epoch : 44
training loss: 1.4639, acc 99.7567
validation loss: 1.4695, validation acc 99.1600
epoch : 45
training loss: 1.4639, acc 99.7633
validation loss: 1.4691, validation acc 99.2300
epoch : 46
training loss: 1.4635, acc 99.7917
validation loss: 1.4695, validation acc 99.1600
epoch : 47
training loss: 1.4636, acc 99.7800
validation loss: 1.4695, validation acc 99.2400
epoch : 48
training loss: 1.4636, acc 99.7800
validation loss: 1.4700, validation acc 99.1300
epoch : 49
training loss: 1.4635, acc 99.7933
validation loss: 1.4699, validation acc 99.1700
epoch : 50
training loss: 1.4634, acc 99.7967
validation loss: 1.4692, validation acc 99.2000
```

We get an accuracy of 99%, much more than what we achieved earlier using just fully connected linear neural networks

[13]:
```
plot_loss(training_losses, test_losses)
```



[14]:
```
plot_accuracy(training_accuracies, test_accuracies)
```



I had already done some pre-testing with the learning rate and it turned out that a slow learning rate provides a smoother accuracy curve as this network is quite complex in terms of the parameters to be learned

1.1.3 Now lets take a look at the indivisual concolutional layer outputs to try to visualize what the model is learning

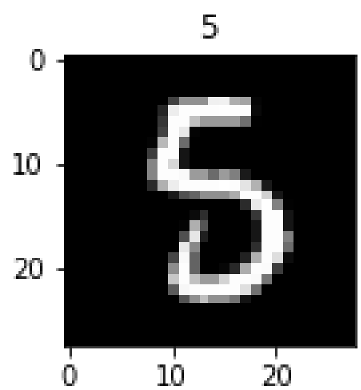
[15]:
```
data = iter(training_loader)
images, labels = data.next()
```

[16]:
```
def im_convert(tensor):
  image = tensor.cpu().clone().detach().numpy()
  image = image.transpose(1, 2, 0)
  image = image * np.array((0.5, 0.5, 0.5)) + np.array((0.5, 0.5, 0.5))
  image = image.clip(0, 1)
  return image
```

[31]:
```
def filter_convert(tensor):
  image = tensor.cpu().clone().detach().numpy()
  image = image.clip(0, 1)
  return image
```

[23]:
```
fig = plt.figure(figsize=(2, 2))
plt.imshow(im_convert(images[3]))
plt.title(str(labels[3].item()))
```

[23]: Text(0.5, 1.0, '5')

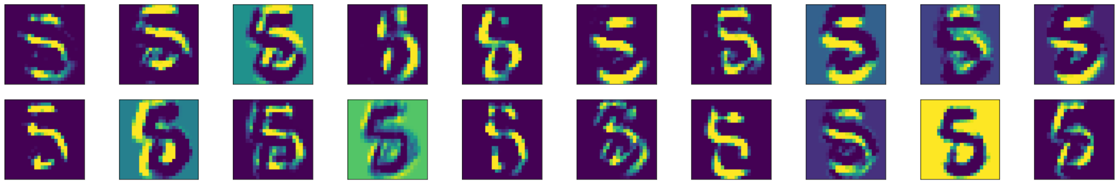


So this will be the input to our network i.e. the image of '5'

[19]:
```
a, b, c, d = model.visualize(images.to(device))
```

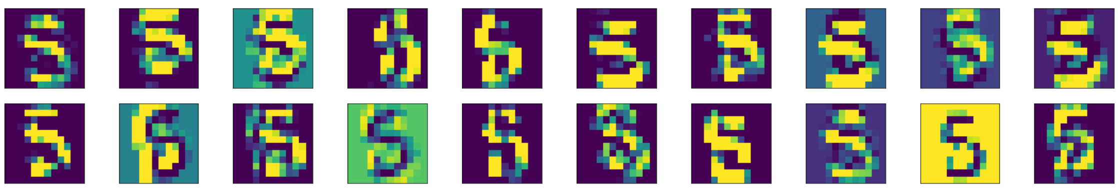
1.1.4 Looking at the output of Conv. Layer 1

[32]:
```
fig = plt.figure(figsize=(25, 4))
for idx in np.arange(20):
  ax = fig.add_subplot(2, 10, idx+1, xticks=[], yticks=[])
  plt.imshow(filter_convert(a[3][idx]))
```



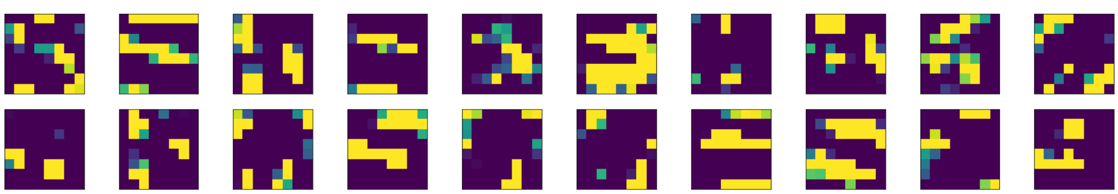
1.1.5 Output of the max pool of Conv Layer 1

[26]:
```
fig = plt.figure(figsize=(25, 4))
for idx in np.arange(20):
  ax = fig.add_subplot(2, 10, idx+1, xticks=[], yticks=[])
  plt.imshow(filter_convert(b[3][idx]))
```



1.1.6 Output of Conv Layer 2

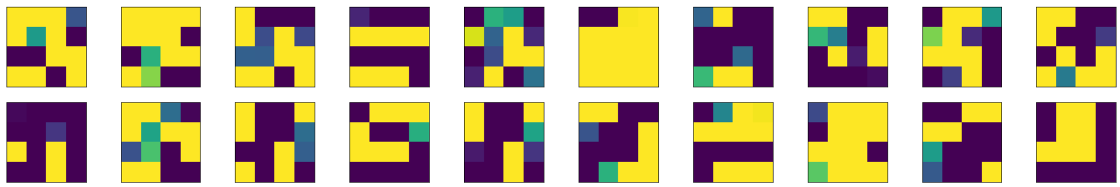
[27]:
```
fig = plt.figure(figsize=(25, 4))
for idx in np.arange(20):
  ax = fig.add_subplot(2, 10, idx+1, xticks=[], yticks=[])
  plt.imshow(filter_convert(c[3][idx]))
```



1.1.7 Output of max pool of Conv Layer 2

[28]:
```
fig = plt.figure(figsize=(25, 4))
for idx in np.arange(20):
  ax = fig.add_subplot(2, 10, idx+1, xticks=[], yticks=[])
```

```
plt.imshow(filter_convert(d[3][idx]))
```



1.2 Analysis of the above filter images

1.2.1 We can see that the 1st Conv Layer grabs the entire image of 5 as a whole along with the major curves and dashes

1.2.2 The second Conv Layer grabs the smaller curves and bends that are specific to only the number 5

1.2.3 At the end, the number 5 is just a superposition of these curves and dashes and hence the network is able to recognize it!!

[ ]:

```

```