```
import torch, torchvision
from torch import nn
from torch import optim
import torchvision.transforms as TT
import torch.nn.functional as F
import matplotlib.pyplot as plt
```

```
from sklearn.metrics import confusion_matrix
import pandas as pd
import numpy as np
from PIL import Image
```

```
T = torchvision.transforms.Compose([
    TT.ToTensor(), TT.Normalize((0.5,),(0.5,))
])
no_of_batch = 64
train_data = torchvision.datasets.MNIST('mnist_data', train=True, download=True
val_data = torchvision.datasets.MNIST('mnist_data', train=False, download=True,
train_dl = torch.utils.data.DataLoader(train_data, batch_size = no_of_batch)
val_dl = torch.utils.data.DataLoader(val_data, batch_size = no_of_batch)
```

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

100% 9912422/9912422 [00:00<00:00, 130235441.74it/s]

```
Extracting mnist_data/MNIST/raw/train-images-idx3-ubyte.gz to mnist_data/MN

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to
```

100% 28881/28881 [00:00<00:00, 549959.34it/s]

```
Extracting mnist_data/MNIST/raw/train-labels-idx1-ubyte.gz to mnist_data/MN

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
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```

100% 1648877/1648877 [00:00<00:00, 45074928.77it/s]

```
Extracting mnist_data/MNIST/raw/t10k-images-idx3-ubyte.gz to mnist_data/MNI

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to m
```

```
print(type(train_data[0][0]))
```

```
<class 'torch.Tensor'>
```

```
len(train_data)
```

```
60000
```

```
len(val_data)
```

```
10000
```

```
# for i in range(10):
#  t = train_data[i][0]    # t is object containing both image and its label
#  img = np.array(t)
#  im = plt.imshow(img)
#  plt.show()
```

```
# Creating a model
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
class Net(nn.Module):
    """order of build model:- ConvNet -> Max_Pool -> RELU -> ConvNet -> Max_Poo
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 20, 5, 1)
        self.conv2 = nn.Conv2d(20, 50, 5, 1)
        self.fc1 = nn.Linear(4*4*50, 500)
        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*50)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return F.log_softmax(x, dim=1)
```

```
n_epochs = 4
batch_size_train = 64
batch_size_test = 1000
learning_rate = 0.01
# momentum = 0.5
log_interval = 10
```

```
model = Net().to(device)
optimizer = optim.Adam(model.parameters(),lr=learning_rate)
```

```
criterion = nn.CrossEntropyLoss()
if torch.cuda.is_available():
    model = model.cuda()
    criterion = criterion.cuda()
```

```
print(model)
```

```
Net(
```

```
  (conv1): Conv2d(1, 20, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(20, 50, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=800, out_features=500, bias=True)
  (fc2): Linear(in_features=500, out_features=10, bias=True)
)
```

```
# Model Summary
from torchsummary import summary
summary(model, input_size=(1,28,28))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 20, 24, 24]             520
            Conv2d-2             [-1, 50, 8, 8]          25,050
            Linear-3                  [-1, 500]         400,500
            Linear-4                   [-1, 10]           5,010
================================================================
Total params: 431,080
Trainable params: 431,080
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.12
Params size (MB): 1.64
Estimated Total Size (MB): 1.76
----------------------------------------------------------------
```

```
train_losses = []
train_counter = []
val_loss1 = []
val_losses = []
val_counter = []
```

```
def train(epoch):
  model.train()
  for batch_idx, (data, target) in enumerate(train_dl):
    data = data.cuda()
    target = target.cuda()
    optimizer.zero_grad()
    output = model(data)
    loss = criterion(output, target)
    loss.backward()
    optimizer.step()
    if batch_idx % log_interval == 0:
      print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
        epoch, batch_idx * len(data), len(train_dl.dataset),
        100. * batch_idx / len(train_dl), loss.item()))
      train_losses.append(loss.item())
      train_counter.append((batch_idx*64) + ((epoch-1)*len(train_dl.dataset)))
```

```
def val_loss(epoch):
    model.eval()
    for batch_idx, (data, target) in enumerate(val_dl):
```

```
      data = data.cuda()
      target = target.cuda()
      optimizer.zero_grad()
      output = model(data)
      loss = criterion(output, target)
      loss.backward()
      optimizer.step()
      if batch_idx % log_interval == 0:
        print('Val Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
          epoch, batch_idx * len(data), len(val_dl.dataset),
          100. * batch_idx / len(val_dl), loss.item()))
        val_loss1.append(loss.item())
        val_counter.append((batch_idx*64) + ((epoch-1)*len(val_dl.dataset)))
```

```
def val_accu():
  model.eval()
  val_loss = 0
  correct = 0
  with torch.no_grad():
    for data,target in val_dl:
      data = data.cuda()
      target = target.cuda()
      output = model(data)
      val_loss += criterion(output, target).item()
      pred = output.data.max(1, keepdim=True)[1]
      correct += pred.eq(target.data.view_as(pred)).sum()
  val_loss /= len(val_dl.dataset)
  val_losses.append(val_loss)
  print('\nTest set: Avg. loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
    val_loss, correct, len(val_dl.dataset),
    100. * correct / len(val_dl.dataset)))
```

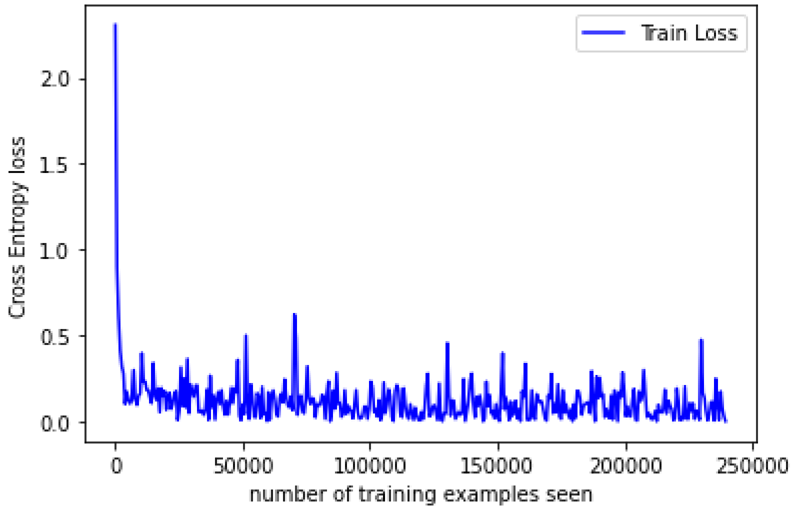
```
for epoch in range(1, n_epochs + 1):
  train(epoch)
  val_loss(epoch)
  val_accu()
```

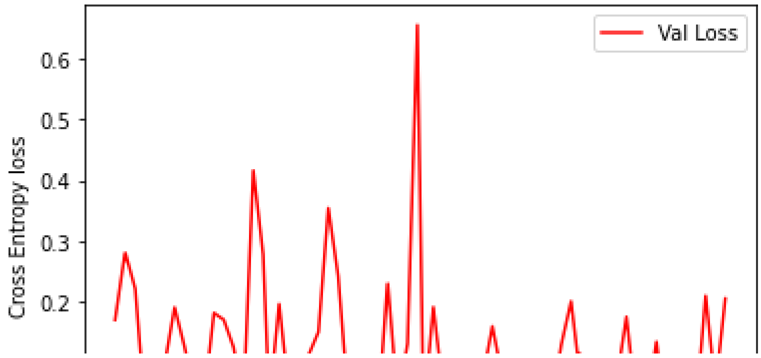
```
Val Epoch: 3 [3200/10000 (32%)] Loss: 0.034198
Val Epoch: 3 [3840/10000 (38%)] Loss: 0.071830
Val Epoch: 3 [4480/10000 (45%)] Loss: 0.157967
Val Epoch: 3 [5120/10000 (51%)] Loss: 0.075607
Val Epoch: 3 [5760/10000 (57%)] Loss: 0.038551
Val Epoch: 3 [6400/10000 (64%)] Loss: 0.028009
Val Epoch: 3 [7040/10000 (70%)] Loss: 0.011252
Val Epoch: 3 [7680/10000 (76%)] Loss: 0.004285
Val Epoch: 3 [8320/10000 (83%)] Loss: 0.024648
Val Epoch: 3 [8960/10000 (89%)] Loss: 0.127178
Val Epoch: 3 [9600/10000 (96%)] Loss: 0.199457

Test set: Avg. loss: 0.0013, Accuracy: 9807/10000 (98%)

Train Epoch: 4 [0/60000 (0%)]   Loss: 0.099846
Train Epoch: 4 [640/60000 (1%)] Loss: 0.020276
Train Epoch: 4 [1280/60000 (2%)]        Loss: 0.178354
Train Epoch: 4 [1920/60000 (3%)]        Loss: 0.175131
```

```
Train Epoch: 4 [2560/60000 (4%)]	Loss: 0.126930
Train Epoch: 4 [3200/60000 (5%)]	Loss: 0.038620
Train Epoch: 4 [3840/60000 (6%)]	Loss: 0.091242
Train Epoch: 4 [4480/60000 (7%)]	Loss: 0.099996
Train Epoch: 4 [5120/60000 (9%)]	Loss: 0.109382
Train Epoch: 4 [5760/60000 (10%)]	Loss: 0.109759
Train Epoch: 4 [6400/60000 (11%)]	Loss: 0.047011
Train Epoch: 4 [7040/60000 (12%)]	Loss: 0.290384
Train Epoch: 4 [7680/60000 (13%)]	Loss: 0.118871
Train Epoch: 4 [8320/60000 (14%)]	Loss: 0.000545
Train Epoch: 4 [8960/60000 (15%)]	Loss: 0.258911
Train Epoch: 4 [9600/60000 (16%)]	Loss: 0.135672
Train Epoch: 4 [10240/60000 (17%)]	Loss: 0.251775
Train Epoch: 4 [10880/60000 (18%)]	Loss: 0.143522
Train Epoch: 4 [11520/60000 (19%)]	Loss: 0.157935
Train Epoch: 4 [12160/60000 (20%)]	Loss: 0.024100
Train Epoch: 4 [12800/60000 (21%)]	Loss: 0.072212
Train Epoch: 4 [13440/60000 (22%)]	Loss: 0.038258
Train Epoch: 4 [14080/60000 (23%)]	Loss: 0.018026
Train Epoch: 4 [14720/60000 (25%)]	Loss: 0.151196
Train Epoch: 4 [15360/60000 (26%)]	Loss: 0.010569
Train Epoch: 4 [16000/60000 (27%)]	Loss: 0.180696
Train Epoch: 4 [16640/60000 (28%)]	Loss: 0.145909
Train Epoch: 4 [17280/60000 (29%)]	Loss: 0.000164
Train Epoch: 4 [17920/60000 (30%)]	Loss: 0.171249
Train Epoch: 4 [18560/60000 (31%)]	Loss: 0.141871
Train Epoch: 4 [19200/60000 (32%)]	Loss: 0.282870
Train Epoch: 4 [19840/60000 (33%)]	Loss: 0.182656
Train Epoch: 4 [20480/60000 (34%)]	Loss: 0.029370
Train Epoch: 4 [21120/60000 (35%)]	Loss: 0.087558
Train Epoch: 4 [21760/60000 (36%)]	Loss: 0.033027
Train Epoch: 4 [22400/60000 (37%)]	Loss: 0.028485
Train Epoch: 4 [23040/60000 (38%)]	Loss: 0.121118
Train Epoch: 4 [23680/60000 (39%)]	Loss: 0.188900
Train Epoch: 4 [24320/60000 (41%)]	Loss: 0.009253
Train Epoch: 4 [24960/60000 (42%)]	Loss: 0.004044
Train Epoch: 4 [25600/60000 (43%)]	Loss: 0.174736
Train Epoch: 4 [26240/60000 (44%)]	Loss: 0.117377
Train Epoch: 4 [26880/60000 (45%)]	Loss: 0.141804
Train Epoch: 4 [27520/60000 (46%)]	Loss: 0.297068
```

```
fig = plt.figure()
plt.plot(train_counter, train_losses, color='blue')
plt.legend(['Train Loss'], loc='upper right')
plt.xlabel('number of training examples seen')
plt.ylabel('Cross Entropy loss')

fig = plt.figure()
plt.plot(val_counter, val_loss1, color='red')
plt.legend(['Val Loss'], loc='upper right')
plt.xlabel('number of training examples seen')
plt.ylabel('Cross Entropy loss')
```

```
Text(0, 0.5, 'Cross Entropy loss')
```






```
def predict_dl(model, data):
    y_pred = []
    y_true = []
    for i, (images, labels) in enumerate(data):
        images = images.cuda()
        x = model(images)
        value, pred = torch.max(x, 1)
        pred = pred.data.cpu()
        y_pred.extend(list(pred.numpy()))
        y_true.extend(list(labels.numpy()))
    return np.array(y_pred), np.array(y_true)
```

```
y_pred, y_true = predict_dl(model,val_dl)
```

```
pd.DataFrame(confusion_matrix(y_true, y_pred, labels=np.arange(0,10)))
```

	0	1	2	3	4	5	6	7	8	9
0	980	0	0	0	0	0	0	0	0	0
1	0	1130	2	1	0	0	0	2	0	0
2	6	2	1013	4	0	0	4	3	0	0
3	0	0	3	1005	0	1	0	1	0	0
4	1	0	0	0	976	0	1	0	0	4
5	3	0	0	13	0	875	0	0	0	1
6	13	3	0	0	3	1	936	0	2	0
7	3	3	4	2	2	1	0	1003	1	9
8	12	3	10	4	2	4	0	4	922	13
9	11	2	0	3	10	0	0	1	0	982