```
In [1]: import os
        import io
        import numpy as np
        import torch
        import torch.nn as nn
        import torch.optim as optim
        from torch.utils.data import Dataset, DataLoader
        import torchvision.transforms as transforms
        from PIL import Image
        import matplotlib.pyplot as plt
        import seaborn as sns
        import torch.nn.functional as F
        import data
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        print("Using device:", device)
        class MNIST(Dataset):
            def init (self, dataframe, transform=None):
                self.dataframe = dataframe
                self.transform = transform
            def len (self):
                return len(self.dataframe)
            def __getitem__(self, index):
                try:
                    row = self.dataframe.iloc[index]
                    imgBytes = row['image']['bytes']
                    image = Image.open(io.BytesIO(imgBytes)).convert('L')
                    imageNp = np.array(image, dtype=np.float32).reshape(28, 28)
                    paddedImage = np.zeros((32, 32), dtype=np.float32)
                    paddedImage[2:30, 2:30] = imageNp
                    normalizedImage = (paddedImage / 127.5) - 1.0
                    inputTensor = torch.from numpy(normalizedImage).unsqueeze(0)
                    label = int(row['label'])
```

```
if self.transform:
                # Convert numpy array to PIL Image to apply transforms
                imgPil = Image.fromarray(normalizedImage)
               inputTensor = self.transform(imgPil)
            return inputTensor, label
       except Exception as exception:
            print(f"Error at index {index}: {exception}")
            raise exception
transform = transforms.Compose([
    transforms.RandomApply([transforms.RandomRotation(15)], p=0.5),
   transforms.RandomAffine(0, translate=(0.1, 0.1)),
   transforms.RandomHorizontalFlip(p=0.5),
   transforms.ToTensor(),
   transforms.Normalize((0.5,),(0.5,)),
])
def generateDigitBitmaps():
    baseTemplates = {
        0: [
       ],
       1: [
       ],
       2: [
```

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7: [
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       9: [
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           " ###
   def pad_row(row):
       return row.ljust(12)
   bitmaps = []
   for digit in range(10):
       template = [pad_row(row) for row in baseTemplates[digit]]
       bitmap = [[1 if char == "#" else -1 for char in row] for row in template]
       bitmaps.append(torch.tensor(bitmap, dtype=torch.float32).flatten())
   return torch.stack(bitmaps)
class LeNet5Model(nn.Module):
   def __init__(self):
```

```
super(LeNet5Model, self). init ()
       self.conv1 = nn.Conv2d(1, 6, kernel_size=5, stride=1, padding=0, bias=True)
       self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
       self.conv2 = nn.Conv2d(6, 16, kernel_size=5, stride=1, padding=0, bias=True)
       self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
       self.conv3 = nn.Conv2d(16, 120, kernel_size=5, stride=1, padding=0, bias=True)
       self.fc1 = nn.Linear(120, 84, bias=True)
       self.fc2 = nn.Linear(84, 10, bias=True)
       #self.fc2 = nn.Linear(84, 84, bias=True)
       self.act = nn.ReLU()
       self.dropout = nn.Dropout(0.6)
   def forward(self, x):
       x = self.conv1(x)
       x = self.act(x)
       x = self.pool1(x)
       x = self.conv2(x)
       x = self.act(x)
       x = self.pool2(x)
       x = self.conv3(x)
       x = self.act(x)
       x = x.view(x.size(0), -1)
       x = self.fc1(x)
       x = self.dropout(x)
       x = self.fc2(x)
       return x
class StochasticDiagonalLevenbergMarquardt(optim.Optimizer):
   def init (self, parameters, lr=0.01, mu=1e-3, eta=1e-2):
       defaults = {'lr': lr, 'mu': mu, 'eta': eta}
       super(StochasticDiagonalLevenbergMarquardt, self). init (parameters, defaults)
   def step(self, closure=None):
       loss = None
       if closure is not None:
           loss = closure()
       for group in self.param_groups:
           lr = group['lr']
           mu = group['mu']
```

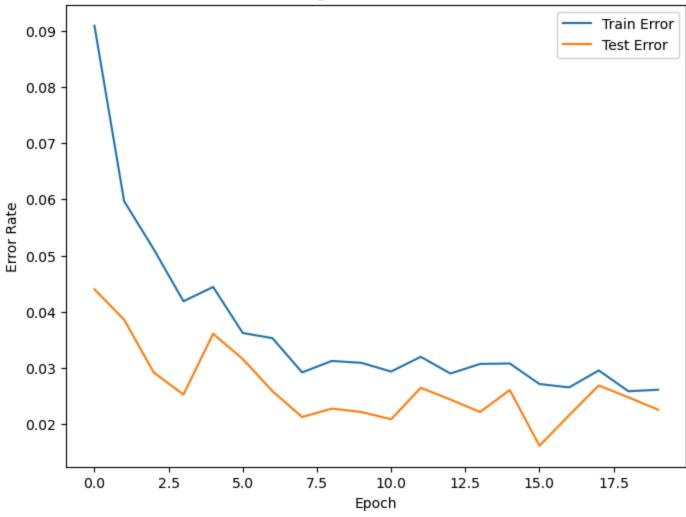
```
for param in group['params']:
                if param.grad is None:
                    continue
                grad = param.grad.data
                state = self.state[param]
               if 'hessianDiag' not in state:
                    state['hessianDiag'] = torch.zeros_like(param.data)
               hessianDiag = state['hessianDiag']
               hessianDiag.add_(grad ** 2)
               adaptiveLr = lr / (mu + hessianDiag.sqrt())
               param.data -= adaptiveLr * grad
       return loss
class MAPLossFunction(nn.Module):
   def __init__(self, j: float = 0.1):
       super(MAPLossFunction, self).__init__()
       self.j = j
   def forward(self, outputs, targets):
        penalties = F.log softmax(-outputs, dim=1)
       correctClassPenalty = penalties[range(len(targets)), targets]
       expOtherClasses = torch.exp(-penalties).sum(dim=1)
       jTensor = torch.tensor(self.j, device=outputs.device)
       competitivePenalty = torch.log(torch.exp(-jTensor) + exp0therClasses)
       mapLoss = correctClassPenalty + competitivePenalty
       return mapLoss.mean()
def evaluateRbf(model, loader, targetVectors):
   model.eval()
   total = 0
   correct = 0
   predictions, targets = [], []
   with torch.no_grad():
       for inputs, labels in loader:
           inputs, labels = inputs.to(device), labels.to(device)
           outputs = model(inputs)
           probs = F.softmax(outputs, dim=1)
           preds = probs.argmax(dim=1)
```

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correct += (preds == labels).sum().item()
           total += labels.size(0)
            predictions.append(preds.cpu())
           targets.append(labels.cpu())
   return correct / total, torch.cat(predictions), torch.cat(targets)
def train(model, trainLoader, testLoader, targetVectors, epochs, optimizer, lossFunction):
   trainErrors, testErrors = [], []
   for epoch in range(1, epochs + 1):
       model.train()
       runningLoss = 0.0
       for inputs, labels in trainLoader:
            inputs, labels = inputs.to(device), labels.to(device)
           optimizer.zero_grad()
           predictions = model(inputs)
           loss = lossFunction(predictions, labels)
           loss.backward()
           optimizer.step()
           runningLoss += loss.item() * inputs.size(0)
       trainAcc, _, _ = evaluateRbf(model, trainLoader, targetVectors)
       testAcc, testPredictions, testTargets = evaluateRbf(model, testLoader, targetVectors)
       trainErrors.append(1 - trainAcc)
       testErrors.append(1 - testAcc)
        print(f"Epoch {epoch}, Loss: {runningLoss / len(trainLoader.dataset):.4f}, Train Accuracy: {trainAcc:.4f}, Telegraphic
   print("Training completed.")
   return trainErrors, testErrors, testPredictions, testTargets
def confusionMatrix(predictions, targets):
   matrix = torch.zeros(10, 10, dtype=torch.int64)
   for prediction, target in zip(predictions, targets):
       matrix[target, prediction] += 1
   return matrix
```

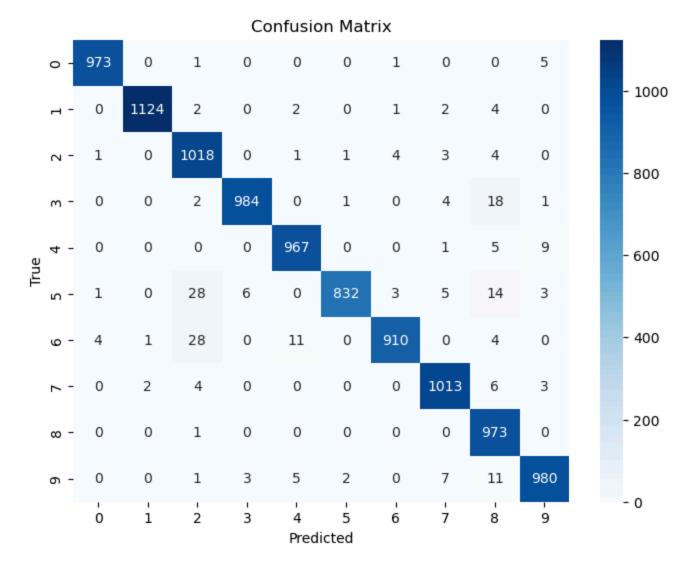
```
if __name__ == "__main__":
    dfTrain = data.df_train
    dfTest = data.df_test
    trainDataset = MNIST(dfTrain, transform=transform)
    testDataset = MNIST(dfTest, transform=None)
    trainLoader = DataLoader(trainDataset, batch size=64, shuffle=True, num workers=0)
    testLoader = DataLoader(testDataset, batch_size=64, shuffle=False, num_workers=0)
    print("Initializing model...")
    digitBitmaps = generateDigitBitmaps().to(device)
    model = LeNet5Model().to(device)
    #optimizer = StochasticDiagonalLevenbergMarquardt(model.parameters(), lr=0.01, mu=1e-3, eta=1e-2)
    optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)
    #lossFunction = MAPLossFunction(j=0.1)
    lossFunction = nn.CrossEntropyLoss()
    trainErrors, testErrors, testPredictions, testTargets = train(
        model, trainLoader, testLoader, digitBitmaps, epochs=20, optimizer=optimizer, lossFunction=lossFunction
    print(f"Final Train Error at epoch {len(trainErrors)}: {trainErrors[-1] * 100:.2f}%")
    print(f"Final Test Error at epoch {len(testErrors)}: {testErrors[-1] * 100:.2f}%")
```

```
Using device: cuda
       Initializing model...
       Epoch 1, Loss: 0.6697, Train Accuracy: 0.9092, Test Accuracy: 0.9560
       Epoch 2, Loss: 0.2697, Train Accuracy: 0.9403, Test Accuracy: 0.9614
       Epoch 3, Loss: 0.2068, Train Accuracy: 0.9489, Test Accuracy: 0.9708
       Epoch 4, Loss: 0.1782, Train Accuracy: 0.9581, Test Accuracy: 0.9747
       Epoch 5, Loss: 0.1637, Train Accuracy: 0.9556, Test Accuracy: 0.9639
       Epoch 6, Loss: 0.1508, Train Accuracy: 0.9638, Test Accuracy: 0.9684
       Epoch 7, Loss: 0.1410, Train Accuracy: 0.9647, Test Accuracy: 0.9741
       Epoch 8, Loss: 0.1380, Train Accuracy: 0.9708, Test Accuracy: 0.9787
       Epoch 9, Loss: 0.1289, Train Accuracy: 0.9687, Test Accuracy: 0.9772
       Epoch 10, Loss: 0.1250, Train Accuracy: 0.9691, Test Accuracy: 0.9778
       Epoch 11, Loss: 0.1172, Train Accuracy: 0.9706, Test Accuracy: 0.9791
       Epoch 12, Loss: 0.1173, Train Accuracy: 0.9680, Test Accuracy: 0.9735
       Epoch 13, Loss: 0.1150, Train Accuracy: 0.9710, Test Accuracy: 0.9756
       Epoch 14, Loss: 0.1107, Train Accuracy: 0.9693, Test Accuracy: 0.9778
       Epoch 15, Loss: 0.1106, Train Accuracy: 0.9692, Test Accuracy: 0.9739
       Epoch 16, Loss: 0.1091, Train Accuracy: 0.9728, Test Accuracy: 0.9838
       Epoch 17, Loss: 0.1029, Train Accuracy: 0.9734, Test Accuracy: 0.9784
       Epoch 18, Loss: 0.1034, Train Accuracy: 0.9704, Test Accuracy: 0.9731
       Epoch 19, Loss: 0.1036, Train Accuracy: 0.9741, Test Accuracy: 0.9752
       Epoch 20, Loss: 0.1043, Train Accuracy: 0.9738, Test Accuracy: 0.9774
       Training completed.
       Final Train Error at epoch 20: 2.62%
       Final Test Error at epoch 20: 2.26%
In [2]: plt.figure(figsize=(8, 6))
        plt.plot(trainErrors, label="Train Error")
        plt.plot(testErrors, label="Test Error")
        plt.xlabel("Epoch")
        plt.ylabel("Error Rate")
        plt.title("Training and Test Error Rate")
        plt.legend()
        plt.show()
```

## Training and Test Error Rate



```
In [3]: confusionMat = confusionMatrix(testPredictions, testTargets)
    plt.figure(figsize=(8, 6))
    sns.heatmap(confusionMat.numpy(), annot=True, fmt='d', cmap='Blues')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()
```



```
In [4]: misclassifiedCounts = {i: {j: 0 for j in range(10)} for i in range(10)}
examples = {i: {j: None for j in range(10)} for i in range(10)}

with torch.no_grad():
    for i in range(len(testDataset)):
        inputTensor, label = testDataset[i]
        inputTensor = inputTensor.unsqueeze(0).to(device)

        outputTensor = model(inputTensor)
```

```
prediction = outputTensor.argmax(dim=1).item()

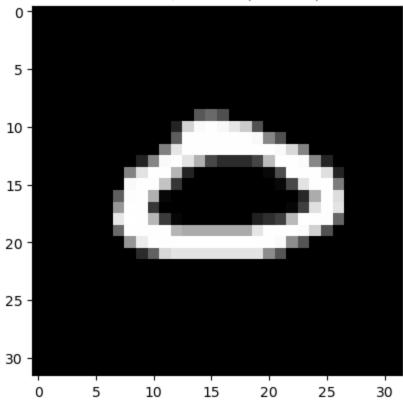
if prediction != label:
    misclassifiedCounts[label][prediction] += 1
    if examples[label][prediction] is None:
        examples[label][prediction] = inputTensor.cpu()

for trueLabel in range(10):
    maxMisclassified = max(misclassifiedCounts[trueLabel], key=misclassifiedCounts[trueLabel].get)
    count = misclassifiedCounts[trueLabel][maxMisclassified]

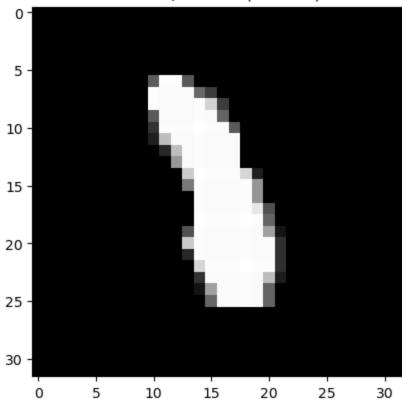
if count == 0:
    print(f"No misclassifications for digit {trueLabel}")

else:
    example = examples[trueLabel][maxMisclassified]
    plt.imshow(example.squeeze().numpy(), cmap="gray")
    plt.title(f"True: {trueLabel}, Pred: {maxMisclassified} ({count} times)")
    plt.show()
```

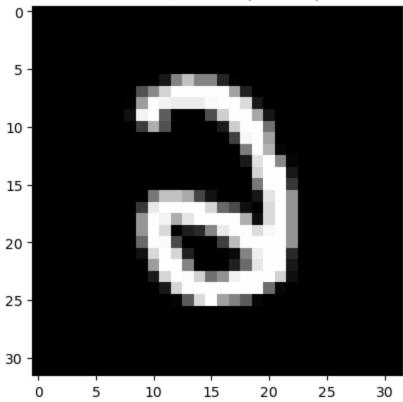
True: 0, Pred: 9 (5 times)



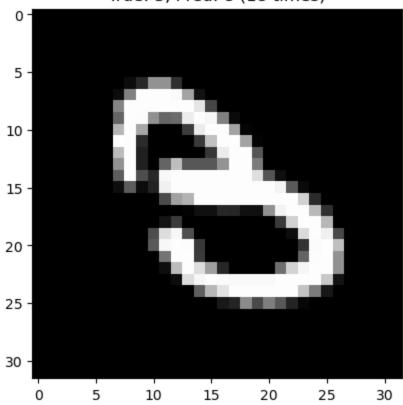
True: 1, Pred: 8 (4 times)



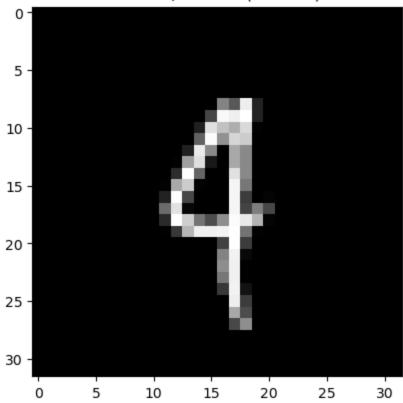
True: 2, Pred: 6 (4 times)



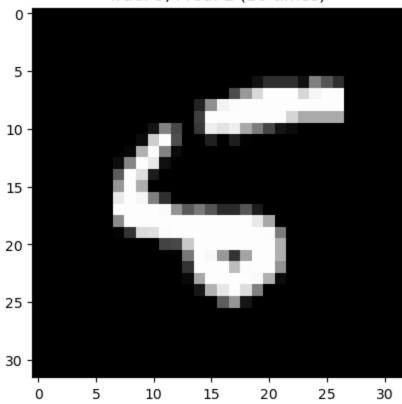
True: 3, Pred: 8 (18 times)



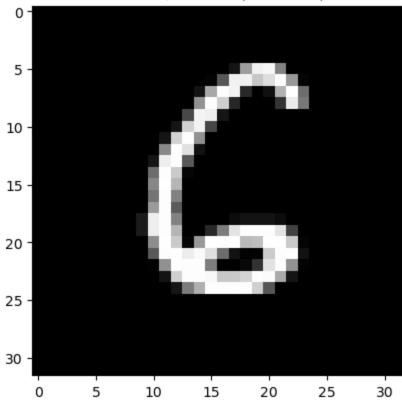
True: 4, Pred: 9 (9 times)



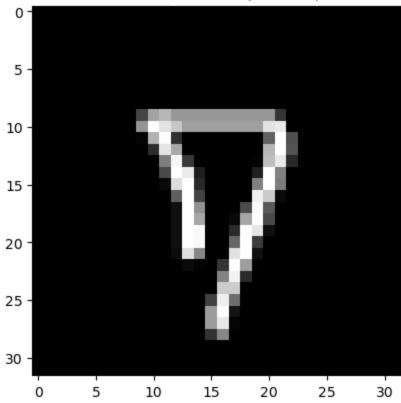
True: 5, Pred: 2 (28 times)



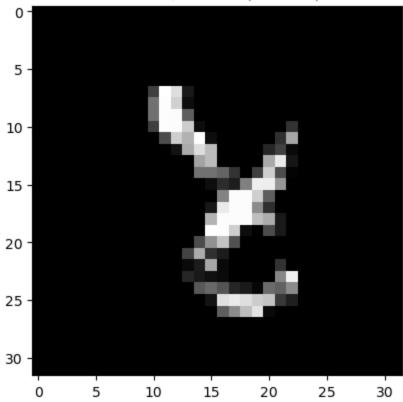
True: 6, Pred: 2 (28 times)

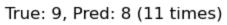


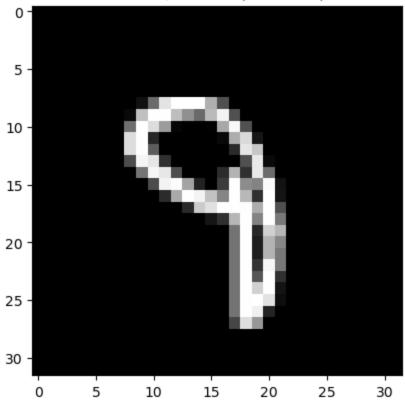
True: 7, Pred: 8 (6 times)



True: 8, Pred: 2 (1 times)







In [ ]: