Computer Vision Assignment 01: Introduction to PyTorch Report

2 Simple 2D Classifier

2.3 Training loop

Question: Once this is done, you should be able to run the `train.py` script. What accuracy do you achieve with the linear classifier? Is this an expected result? Justify your answer.

```
>>> python train.py
[Epoch 01] Acc.: 43.0556%
[Epoch 02] Loss: 0.7339
[Epoch 02] Acc.: 40.6746%
[Epoch 03] Loss: 0.7000
[Epoch 03] Acc.: 49.8016%
[Epoch 04] Loss: 0.6960
[Epoch 04] Acc.: 32.9365%
[Epoch 05] Loss: 0.6942
[Epoch 05] Acc.: 40.6746%
[Epoch 06] Loss: 0.6934
[Epoch 06] Acc.: 41.8651%
[Epoch 07] Loss: 0.6933
[Epoch 07] Acc.: 44.6429%
[Epoch 08] Loss: 0.6933
[Epoch 08] Acc.: 47.0238%
[Epoch 09] Loss: 0.6932
[Epoch 09] Acc.: 46.6270%
[Epoch 10] Loss: 0.6933
[Epoch 10] Acc.: 48.6111%
```

- The accuracy is `48.6111%` which is lower than expected (`50%` for random guess). However, the data shown below is not linearly separable, so the accuracy closed to `50%` becomes **reasonable**.

2.4 Multi-layer perceptron

Question: Switch to the new network by uncommenting `L83` in `train.py`. What accuracy does this network obtain? Why are the results better compared to the previous classifier?

```
>>> python train.py
[Epoch 01] Loss: 0.6409
[Epoch 01] Acc.: 51.3889%
[Epoch 02] Loss: 0.5039
[Epoch 02] Acc.: 95.2381%
[Epoch 03] Loss: 0.2507
[Epoch 03] Acc.: 99.4048%
[Epoch 04] Loss: 0.0961
[Epoch 04] Acc.: 99.6032%
[Epoch 05] Loss: 0.0484
[Epoch 05] Acc.: 99.6032%
[Epoch 06] Loss: 0.0299
[Epoch 06] Acc.: 99.6032%
[Epoch 07] Loss: 0.0210
[Epoch 07] Acc.: 99.6032%
[Epoch 08] Loss: 0.0160
[Epoch 08] Acc.: 99.6032%
[Epoch 09] Loss: 0.0128
[Epoch 09] Acc.: 99.8016%
[Epoch 10] Loss: 0.0111
[Epoch 10] Acc.: 99.8016%
```

- The final accuracy is `99.8016%`, which is better than the linear classifier.

2.5 Feature transform

Question: Think of a coordinate system that renders the two classes linearly separable and justify your choice.

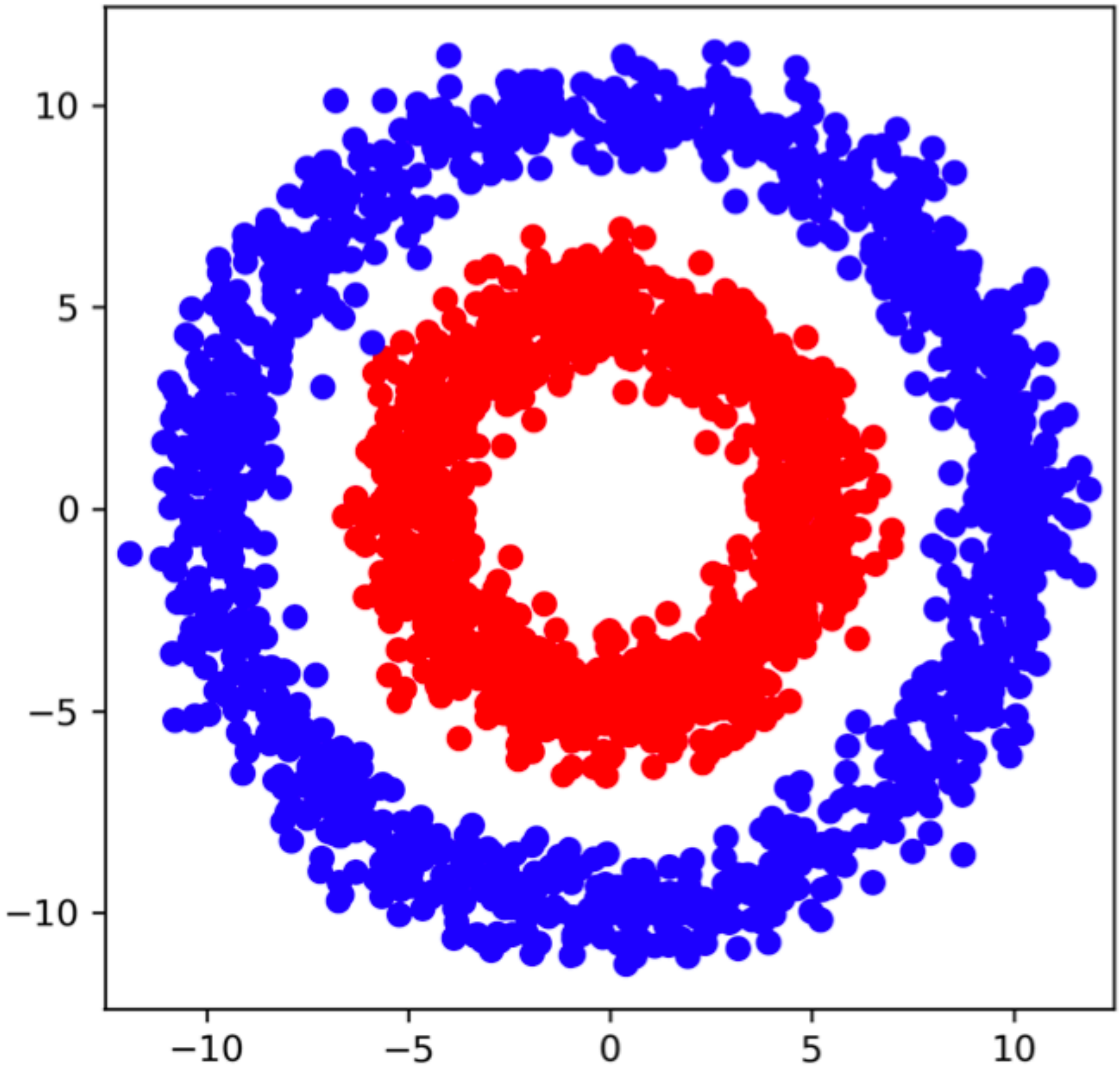


Figure 1: **Training data for 2D classifier.**

- By observation, the data is not linearly separable since it is a circle. However, by changing the coordinate system to polar system or simply use $(x, y) \mapsto (x^2, y^2)$. Then the data will distribute on two lines:

$$\begin{aligned} x^2 + y^2 = r_1 \\ x^2 + y^2 = r_2 \end{aligned} \tag{1}$$

  Therefore, the classes become linearly separable.

Question: Verify the hypothesis by training a linear classifier on the new representation.

```
>>> python train.py
```

```
[Epoch 01] Loss: 0.7104
[Epoch 01] Acc.: 50.0000%
[Epoch 02] Loss: 0.6177
[Epoch 02] Acc.: 50.0000%
[Epoch 03] Loss: 0.5581
[Epoch 03] Acc.: 50.1984%
[Epoch 04] Loss: 0.5060
[Epoch 04] Acc.: 53.3730%
[Epoch 05] Loss: 0.4578
[Epoch 05] Acc.: 71.4286%
[Epoch 06] Loss: 0.4140
[Epoch 06] Acc.: 76.9841%
[Epoch 07] Loss: 0.3766
[Epoch 07] Acc.: 91.0714%
[Epoch 08] Loss: 0.3412
[Epoch 08] Acc.: 93.6508%
[Epoch 09] Loss: 0.3106
[Epoch 09] Acc.: 97.8175%
[Epoch 10] Loss: 0.2824
[Epoch 10] Acc.: 99.6032%
```

- Although it does not converge as fast as the MLP model, the accuracy is significantly improved.

3 Digit classifier

3.3 Multi-layer perceptron

Question: Implement a linear classifier by filling in the `MLPClassifier` class from `lib/networks.py`. What performance do you obtain?

```
self.layers = nn.Sequential(
    nn.Linear(784, 10)
)
```

```
>>> python train.py
100%|██████████████████████████████| 3750/3750 [00:30<00:00, 122.82it/s]
[Epoch 01] Loss: 0.4088
[Epoch 01] Acc.: 90.8600%
100%|██████████████████████████████| 3750/3750 [00:30<00:00, 121.56it/s]
[Epoch 02] Loss: 0.3350
[Epoch 02] Acc.: 89.1800%
100%|██████████████████████████████| 3750/3750 [00:30<00:00, 121.43it/s]
[Epoch 03] Loss: 0.3208
[Epoch 03] Acc.: 90.8300%
100%|██████████████████████████████| 3750/3750 [00:33<00:00, 112.44it/s]
[Epoch 04] Loss: 0.3146
[Epoch 04] Acc.: 91.8800%
100%|██████████████████████████████| 3750/3750 [00:32<00:00, 113.81it/s]
```

```
[Epoch 05] Loss: 0.3092
[Epoch 05] Acc.: 91.2600%
```

Question: Next, use an MLP with one hidden layer of dimension 32 followed by ReLU and then the final linear prediction layer. What is the new testing accuracy?

```python
self.layers = nn.Sequential(
    nn.Linear(784, 32),
    nn.ReLU(),
    nn.Linear(32,10)
)
```

```
>>> python train.py
100%|██████████████████████████████| 3750/3750 [00:32<00:00, 114.94it/s]
[Epoch 01] Loss: 0.4166
[Epoch 01] Acc.: 91.4300%
100%|██████████████████████████████| 3750/3750 [00:32<00:00, 117.09it/s]
[Epoch 02] Loss: 0.2859
[Epoch 02] Acc.: 92.6200%
100%|██████████████████████████████| 3750/3750 [00:33<00:00, 113.34it/s]
[Epoch 03] Loss: 0.2429
[Epoch 03] Acc.: 93.5000%
100%|██████████████████████████████| 3750/3750 [00:31<00:00, 117.46it/s]
[Epoch 04] Loss: 0.2165
[Epoch 04] Acc.: 94.3700%
100%|██████████████████████████████| 3750/3750 [00:32<00:00, 115.52it/s]
[Epoch 05] Loss: 0.1986
[Epoch 05] Acc.: 93.6400%
```

3.4 Convolutional network

Question: What testing accuracy do you obtain with this architecture?

```
100%|██████████████████████████████| 3750/3750 [00:42<00:00, 88.20it/s]
[Epoch 01] Loss: 0.2677
[Epoch 01] Acc.: 97.3400%
100%|██████████████████████████████| 3750/3750 [00:41<00:00, 89.81it/s]
[Epoch 02] Loss: 0.0810
[Epoch 02] Acc.: 97.7400%
100%|██████████████████████████████| 3750/3750 [00:49<00:00, 76.11it/s]
[Epoch 03] Loss: 0.0614
[Epoch 03] Acc.: 98.4200%
100%|██████████████████████████████| 3750/3750 [00:41<00:00, 89.31it/s]
[Epoch 04] Loss: 0.0495
[Epoch 04] Acc.: 98.3700%
100%|██████████████████████████████| 3750/3750 [00:41<00:00, 89.70it/s]
[Epoch 05] Loss: 0.0440
[Epoch 05] Acc.: 98.4500%
```

3.5 Comparison of number of parameters

Question: Compute the number of parameters of the MLP with one hidden layer. Compute the number of parameters of the convolutional network. **You should count both the weights and biases**. Provide detailed explanations and computations.

- MLP: For each layer, number of weight is the number of input dimension times the number of output dimension, number of bias is the output dimension, therefore:

$$Parameter\_Num = \sum_{i}^{layers} (in\_channel_i + 1)(out\_channel_i) \tag{2}$$

- Convolution: For each layer, number of weight equals to the number of kernel times the number of weight in each kernel. Number of bias is the output channel number:

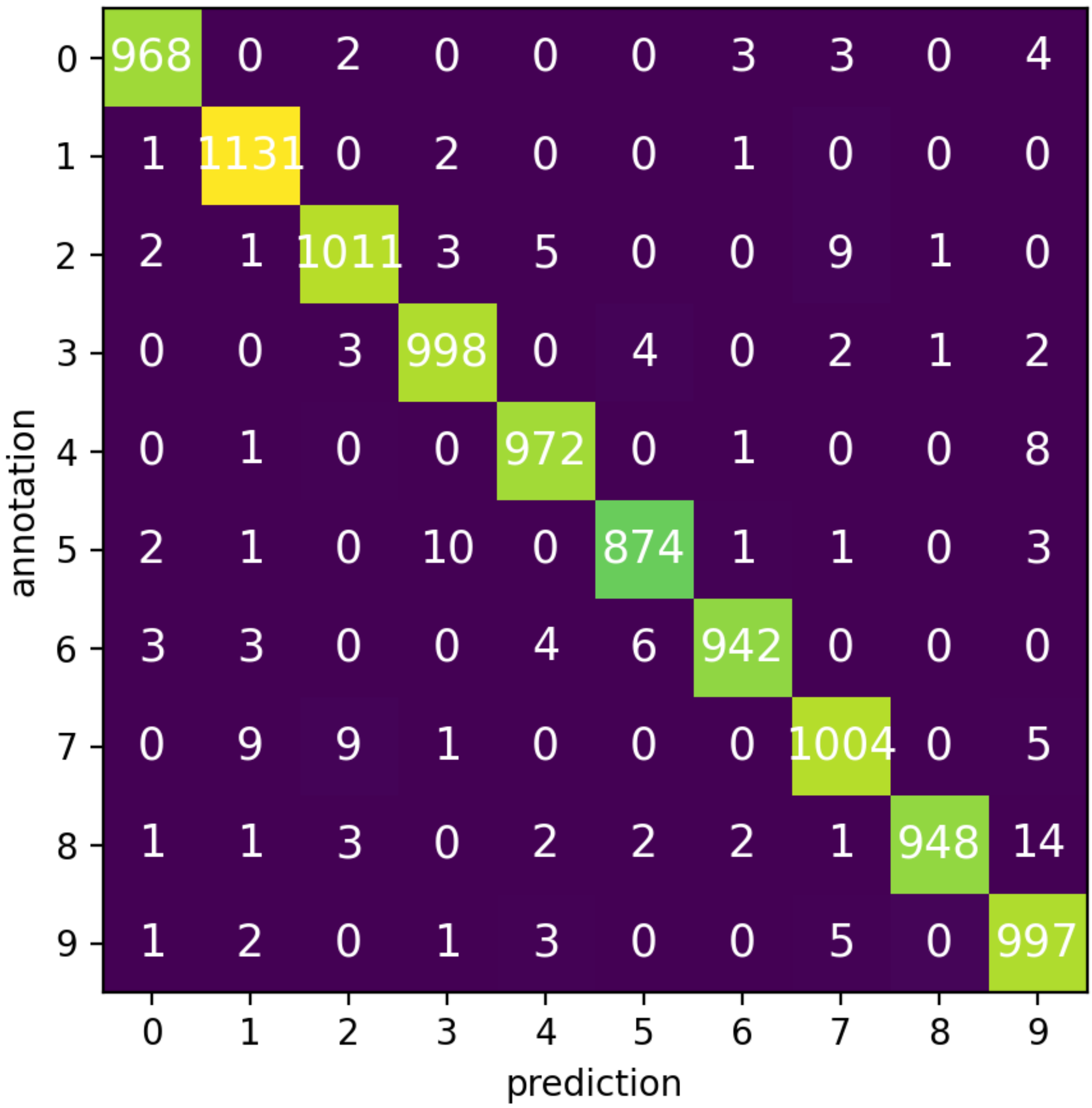
$$Parameter\_Num = \sum_{i}^{layers} (in\_channel_i \times width_i \times height_i + 1)(out\_channel_i) \tag{3}$$

- The result is shown as below:

$$\begin{aligned} Parameter\_Num_{MLP} &= (784 + 1) \times 32 + (32 + 1) \times 10 = 25450 \\ Parameter\_Num_{convolution} &= 8 \times (1 + 3 \times 3 \times 1) + 16 \times (1 + 3 \times 3 \times 8) \\ &+32 \times (1 + 3 \times 3 \times 16) = 5888 \end{aligned} \tag{4}$$

3.6 Confusion matrix

Question: The confusion matrix $M_{i,j}$ is a useful tool for understanding the performance of a classifier. It is defined as follows: $M_{i,j}$ is the number of test samples for which the network predicted i, but the ground-truth label was j. Ideally, in the case of `100%` accuracy, this will be a diagonal matrix. Based on the run validation epoch function from `train.py`, update `plot_confusion_matrix.py` to compute the confusion matrix. Provide the plot in the report and comment the results.



- The summation of the matrix equals to the size of the dataset. The performance of the model is good because the matrix is very closed to a diagonal matrix.