DAT565/DIT407 Assignment 6

Connell Hagen connellh@student.chalmers.se

Måns Redin mansre@student.chalmers.se

2024-10-16

1 Problem 1: Pre-processing the Dataset

The dataset used in this project was a MNIST dataset. This pre-defined Py-Torch dataset consists of 70 000 images of handwritten digits, with their respective labels. The dataset was split into two parts: a training set of size 60 000, and a test set of the remainder. Different neural network models will be discussed and were implemented with their test accuracy showing which were most effective. The images size was verified to be 28x28, with all pixels in the normalized greyscale.

2 Problem 2: Single Hidden Layer

We constructed a fully-connected, one layer neural network using ReLU as the activation function, Stochastic Gradient Descent as the optimization function, and Cross Entropy Loss as the loss function. We did not use any special parameters for this model beyond the default. Our single layer was 200 neurons large. The total accuracy came out to be 87.17%. The accuracy after each epoch can be viewed in table 1.

Table 1: The Single-Layer Model's Validation Accuracy with Respect to the Test Set for $10~{\rm Epochs}$

Epoch	Accuracy
1	36.12
2	39.82
3	43.81
4	44.45
5	45.17
6	45.99
7	47.54
8	49.32
9	50.76
10	51.88

3 Problem 3: Two Hidden Layers

We expanded our network by using a second hidden layer, next. For these layers, the first was 500 neurons large, and the second was 300 neurons large. We used ReLU, SGD, and Cross Entropy Loss, like the previous model. We also enabled L2 regularization by using the weight decay parameter with a value of 0.0001. We also set the learning rate to 0.01. The total The results can be viewed in table 2.

Table 2: The Dual-Layer Model's Validation Accuracy with Respect to the Test Set for 60 Epochs

Epoch	Accuracy	Epoch	Accuracy	Epoch	Accuracy
1	71.89	21	96.31	41	97.49
2	88.39	22	96.30	42	97.53
3	90.02	23	96.37	43	97.62
4	91.14	24	96.45	44	97.65
5	92.09	25	96.61	45	97.62
6	92.38	26	96.57	46	97.70
7	93.16	27	96.66	47	97.72
8	93.50	28	96.89	48	97.74
9	93.79	29	97.03	49	97.72
10	97.04	30	97.05	50	97.81
11	94.26	31	97.09	51	97.71
12	94.55	32	97.25	52	97.74
13	94.87	33	97.31	53	97.79
14	95.05	34	97.34	54	97.75
15	95.24	35	97.30	55	97.72
16	95.26	36	97.38	56	97.90
17	95.65	37	97.37	57	97.87
18	95.85	38	97.33	58	97.94
19	96.06	39	97.49	59	97.93
20	96.18	40	97.57	60	97.82

As can be seen in table 2, the accuracy increased vastly from the neural network with one hidden layer.

4 Problem 4: Convolutional Neural Network

In this part of the project, a Convolutional Neural Network (CNN) was implemented. CNNs are designed to detect essential features in early layers, and analyze each feature further in the deeper layers. The architecture was made of two convolutional layers, a pooling layer, and 2 fully-connected layers, making it fairly computationally heavy, certainly heavier than the recent trained models. It comes, however, with an increased accuracy for image recognition. We used a weight decay value of 0.00001, and a learning rate of 0.01 for this model. We reached an accuracy of 98.9% at best, but for the last 40 epochs the accuracy oscillated around 98.5-99%.

Table 3: The Convolutional Model's Validation Accuracy with Respect to the Test Set for $60~{\rm Epochs}$

Epoch	Accuracy	Epoch	Accuracy	Epoch	Accuracy
1	85.68	21	98.35	41	98.67
2	91.70	22	98.48	42	98.87
3	94.88	23	98.02	43	98.63
4	94.80	24	98.47	44	98.64
5	96.45	25	98.12	45	98.78
6	97.32	26	98.04	46	98.30
7	97.21	27	98.61	47	98.77
8	97.82	28	98.66	48	98.55
9	97.77	29	98.63	49	98.76
10	97.85	30	98.63	50	98.78
11	98.17	31	98.70	51	98.75
12	98.11	32	98.53	52	98.88
13	97.85	33	98.66	53	98.69
14	98.27	34	98.64	54	98.85
15	98.27	35	98.51	55	98.85
16	98.24	36	98.75	56	98.82
17	98.40	37	98.75	57	98.89
18	98.39	38	98.84	58	98.89
19	97.92	39	98.55	59	98.80
20	98.38	40	98.64	60	98.85

A Code

```
2 import numpy as np
3 import pandas as pd
4 import matplotlib.pyplot as plt
5 import torch
6 import torch.nn.functional as F
7 from PIL import Image
8 from torch import nn
9 from torch.utils.data import DataLoader
10 \quad {\tt from} \quad {\tt torch.nn} \quad {\tt import} \quad {\tt CrossEntropyLoss}
11 from torch.optim import SGD
12 from torchvision import datasets
13 from torchvision.transforms import ToTensor
14 from tqdm import tqdm
15
16 training_data = datasets.MNIST(
17
       root="./data",
18
       train=True,
19
       download=True,
20
       transform=ToTensor()
21 )
22
23 test_data = datasets.MNIST(
      root="./data",
25
       train=False,
26
       download=True,
27
       transform=ToTensor()
28 )
29
30 train_dataloader = DataLoader(training_data,
      batch_size=64, shuffle=True)
31 test_dataloader = DataLoader(test_data, batch_size=64,
        shuffle=True)
32
33
34 train_features, train_labels = next(iter(
      train_dataloader))
35 img = train_features[0].squeeze()
36 label = train_labels[0]
37 plt.imshow(img, cmap="gray")
38 \, \text{plt.show()}
39
40 test_features, test_labels = next(iter(test_dataloader
      ))
41 img = test_features[0].squeeze()
42 label = test_labels[0]
43 plt.imshow(img, cmap="gray")
```

```
44 plt.show()
45
46
47 \text{ L1_NEURONS} = 200
48
49 class OneLayer(nn.Module):
50
       def __init__(self):
51
            super(OneLayer, self).__init__()
52
            self.fc1 = nn.Linear(28 * 28, L1_NEURONS)
53
            self.fc2 = nn.Linear(L1_NEURONS, 10)
54
55
56
       def forward(self, x):
57
            x = F.relu(self.fc1(x));
58
            x = F.relu(self.fc2(x))
59
60
            return x
61
62 model = OneLayer()
63 loss_fn = CrossEntropyLoss()
64 optimizer = SGD(model.parameters())
65
66
67 epochs = 10
68 \text{ running\_loss} = 0
69
70 for e in range (epochs):
71
        for i, data in tqdm(enumerate(train_dataloader)):
72
            model.train()
73
74
            inputs, labels = data
75
76
            optimizer.zero_grad()
77
            flattened_inputs = inputs.view(inputs.size(0),
78
79
            outputs = model(flattened_inputs)
80
81
            loss = loss_fn(outputs, labels)
82
            loss.backward()
83
84
            optimizer.step()
85
86
            running_loss += loss.item()
87
88
        print(f"Epochu{e}: \_Average\_loss\_of\_{\text{running_loss}\_/
           ⊔64}⊔per⊔batch")
89
        running_loss = 0
90
91
       # test benchmark
```

```
92
        model.eval()
93
94
        total_correct = 0
        total_samples = 0
96
        for i, (inputs, labels) in tqdm(enumerate(
97
           test_dataloader)):
98
            flattened_inputs = inputs.view(inputs.size(0),
                 -1)
99
100
            outputs = model(flattened_inputs)
101
            _, predicted = torch.max(outputs, 1)
102
103
            total_correct += (predicted == labels).sum().
                item()
104
            total_samples += labels.size(0)
105
106
        accuracy = 100 * total_correct / total_samples
107
        print(f"Epochu{e}, _Accuracy: _{accuracy}")
108
109
    torch.save(model.state_dict(), "model/one_layer_model.
       pth")
110
111
112 L1_NEURONS = 500
113 L2_NEURONS = 300
114
115 class TwoLayers(nn.Module):
116
        def __init__(self):
117
            super(TwoLayers, self).__init__()
118
119
            self.fc1 = nn.Linear(28 * 28, L1_NEURONS)
120
            self.fc2 = nn.Linear(L1_NEURONS, L2_NEURONS)
121
            self.fc3 = nn.Linear(L2_NEURONS, 10)
122
123
        def forward(self, x):
124
            x = F.relu(self.fc1(x))
125
            x = F.relu(self.fc2(x))
126
            x = F.relu(self.fc3(x))
127
128
            return x
129
130 model = TwoLayers()
   loss_fn = CrossEntropyLoss()
131
132
    optimizer = SGD(model.parameters(), weight_decay=1e-4,
        lr=0.01) # weight decay for L2 regularization
133
134 epochs = 60
135 running_loss = 0
136
```

```
137 for e in range (epochs):
138
         for i, data in tqdm(enumerate(train_dataloader)):
139
             model.train()
140
141
             inputs, labels = data
142
143
             optimizer.zero_grad()
144
145
             flattened_inputs = inputs.view(inputs.size(0),
146
             outputs = model(flattened_inputs)
147
148
             loss = loss_fn(outputs, labels)
149
             loss.backward()
150
151
             optimizer.step()
152
153
             running_loss += loss.item()
154
         print(f"Epoch_{\sqcup}\{e\}:_{\sqcup}Average_{\sqcup}loss_{\sqcup}of_{\sqcup}\{running\_loss_{\sqcup}/
155
            _{\sqcup}64\}_{\sqcup}per_{\sqcup}batch")
156
         running_loss = 0
157
         # test benchmark
158
159
         model.eval()
160
161
         total_correct = 0
162
         total_samples = 0
163
164
         for i, (inputs, labels) in tqdm(enumerate(
            test_dataloader)):
165
             flattened_inputs = inputs.view(inputs.size(0),
                  -1)
166
167
             outputs = model(flattened_inputs)
168
             _, predicted = torch.max(outputs, 1)
169
170
             total_correct += (predicted == labels).sum().
                 item()
171
             total_samples += labels.size(0)
172
173
         accuracy = 100 * total_correct / total_samples
174
         print(f"Epoch (e), Accuracy: (accuracy)")
175
176
    torch.save(model.state_dict(), "model/2-layer-0-01-
        learning-rate.pth")
177
178
179 L1_OUTPUT_CHANNELS = 16
180 L2_OUTPUT_CHANNELS = 32
```

```
181
182 class ConvNetwork(nn.Module):
183
        def __init__(self):
            super(ConvNetwork, self).__init__()
184
185
186
            # convolutional layers
187
            self.conv1 = nn.Conv2d(in_channels=1,
                out_channels=L1_OUTPUT_CHANNELS,
                kernel_size=3, padding=1)
188
            self.conv2 = nn.Conv2d(in_channels=
                L1_OUTPUT_CHANNELS, out_channels=
                L2_OUTPUT_CHANNELS, kernel_size=3, padding
                =1)
189
190
            # pooling layer
191
            self.pool = nn.MaxPool2d(kernel_size=2, stride
                =2)
192
193
            # fully-connected layers
            self.fc1 = nn.Linear(L2_OUTPUT_CHANNELS * 7 *
194
               7, 128)
195
            self.fc2 = nn.Linear(128, 10)
196
197
198
        def forward(self, x):
            x = self.pool(F.relu(self.conv1(x)))
199
200
            x = self.pool(F.relu(self.conv2(x)))
201
            x = x.view(-1, L2_OUTPUT_CHANNELS * 7 * 7) #
               flatten images
202
            x = F.relu(self.fc1(x))
203
            x = self.fc2(x)
204
205
            return x
206
207 model = ConvNetwork()
208 loss_fn = CrossEntropyLoss()
    optimizer = SGD(model.parameters(), weight_decay=1e-5,
        lr=0.01) # weight decay for L2 regularization
210
211
212 epochs = 60
213 running_loss = 0
214
215 for e in range (epochs):
216
        for i, data in tqdm(enumerate(train_dataloader)):
217
            model.train()
218
219
            inputs, labels = data
220
221
            optimizer.zero_grad()
```

```
222
223
             outputs = model(inputs)
224
225
             loss = loss_fn(outputs, labels)
226
             loss.backward()
227
228
             optimizer.step()
229
230
             running_loss += loss.item()
231
232
        print(f"Epochu{e}: \_Average\_loss\_of\_{\text{running_loss}\_/
            ⊔64}⊔per⊔batch")
233
        running_loss = 0
234
235
        # test benchmark
236
        model.eval()
237
238
        total_correct = 0
239
        total_samples = 0
240
241
        for i, (inputs, labels) in tqdm(enumerate(
            test_dataloader)):
242
             outputs = model(inputs)
             _, predicted = torch.max(outputs, 1)
243
244
245
             total_correct += (predicted == labels).sum().
246
             total_samples += labels.size(0)
247
248
        accuracy = 100 * total_correct / total_samples
249
        print(f"Epoch (e), Accuracy: (accuracy)")
250
251 \quad {\tt torch.save (model.state\_dict(), \ "model/conv-network.pth")}
       ")
```