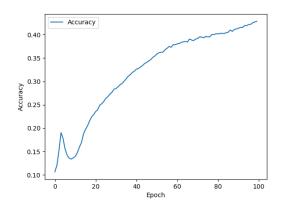
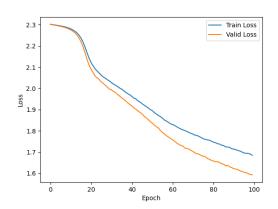
视听信息系统导论编程 1

高艺轩 毕嘉仪

第1题

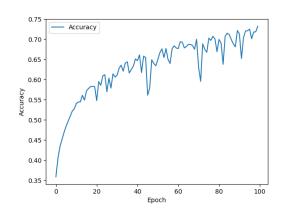
在 SGD 优化器下,输出的结果如下:

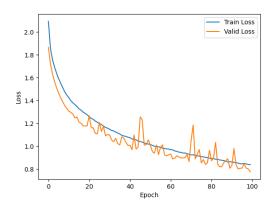




第2题

在 SGD 优化器下,使用 ReLU 激活函数与 Batch Normalization,输出的结果如下:

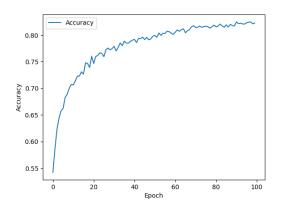


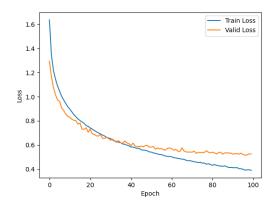


第3题

在 AdamW 优化器下,使用 ReLU 激活函数与 Batch Normalization,输出的结果如下:

第 4 题 2

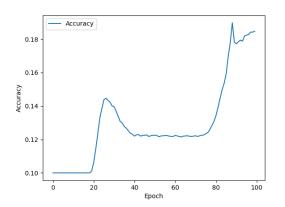


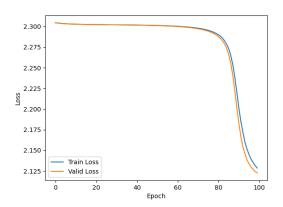


第 4 题

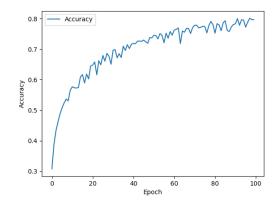
4.1

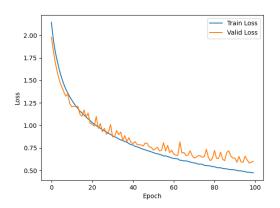
仍旧使用 tanh 作为激活函数, SGD 优化器:





4.2 将激活函数更改为 ReLU 函数,并使用 BatchNorm,使用 SGD:

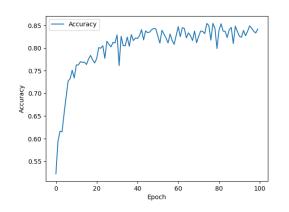


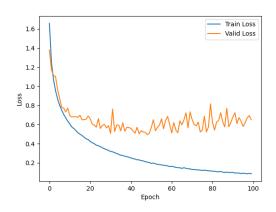


第5题

4.3

在 AdamW 优化器下,使用 ReLU 激活函数与 Batch Normalization,输出的结果如下:





3

第5题

1. 请根据结果分析 ReLU 和 tanh 激活函数的表现.

由于实验 1 与实验 2 同时更改了激活函数与是否增加 Batch Normalization,我们无法直接从实验结果中通过对比得出 ReLU 与 tanh 到底哪个表现更好。不过从理论上进行分析,ReLU 激活函数在当前任务中的表现应当会优于 tanh 激活函数。这是由于 ReLU 激活函数不存在梯度消失问题,能够使网络快速收敛,无论网络深浅;而 tanh 函数容易陷入饱和区、导致梯度消失,使得网络收敛速度大幅降低,特别是在深层次网络中这一现象更加明显;因此,在 CNN 架构中,ReLU 激活函数表现应该会优于 tanh。

2. 请根据结果分析 BatchNorm 的作用.

由于实验 1 与实验 2 同时更改了激活函数与是否增加 Batch Normalization, 我们无法直接从实验结果中通过对比看出 BatchNorm 的作用。不过从理论上进行分析, BatchNorm 可以使网络中每一层的数据分布均值为 0、方差为 1, 这样神经元输出值不会太大,加强了网络稳定性,同时防止出现梯度爆炸(或梯度消失),使网络能够较快收敛;此外, Batch Normalization 可以使相同 batch 中的所有样本相互关联,加强了泛化性,避免过拟合。

3. 请根据结果分析更换优化器的效果.

从实验 2、3 的结果对比中可以看出,使用 SGD 优化器会导致测试准确率与训练、测试损失出现明显震荡,而更换了 AdamW 优化器以后准确率曲线与损失曲线都更加平滑。SGD 优化器容易出现振荡是由于它会导致梯度值相差较大的方向上优化步长差异也大,致使梯度值大的方向上产生振荡;而 Adam 优化器可以根据不同参数梯度值自适应地调整各个方向的优化步长大小,以使各个方向都能同时得到有效且合理的优化。

4. 请根据你的结果分析模型是否出现了过拟合,如有,请在图像中指出在哪里出现了过拟合。如 无,请给出你判断的原因.

通过训练/测试损失曲线以及测试准确率曲线可知,实验 4 的第 3 部分出现了过拟合现象,发生在 epoch 35 附近。判断依据:训练损失持续降低,而测试损失不再降低甚至开始升高且出现巨幅振荡,测试准确率也不再增加。

程序源代码

```
import os
2
   import torch
   import torchvision
4 import numpy as np
5 from tqdm import tqdm
6 import torch.nn as nn
   import torch.nn.functional as F
7
8
  import torch.optim as optim
9
   import torchvision.transforms as transforms
10
   import matplotlib.pyplot as plt
11
   from PIL import Image
12
13 | from typing import *
14
   device = 'cuda' if torch.cuda.is_available() else 'cpu'
15
16
train_transform = transforms.Compose([
18
     transforms.RandomHorizontalFlip(),
19
     transforms.RandomCrop(32, padding=4),
20
     transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2),
21
     transforms.ToTensor()
22
23
  1)
24
   train_dset = torchvision.datasets.CIFAR10(root='./CIFAR10',train=True,download=
25
      False, transform=train_transform)
   test_dset = torchvision.datasets.CIFAR10(root='./CIFAR10',train=False,download=
26
      False,transform=transforms.ToTensor())
   train_loader = torch.utils.data.DataLoader(train_dset, batch_size=128, shuffle=
27
      True, num_workers=0)
   test_loader = torch.utils.data.DataLoader(test_dset, batch_size=128, shuffle=
28
      False, num_workers=0)
   29
30
31
  32
```

```
class Net(nn.Module):
33
      def __init__(self,act):
34
         super(Net, self).__init__()
35
         # 卷积层 (32x32x3的图像)
36
         self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
37
         # 卷积层(16x16x16)
38
         self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
39
40
         # 卷积层(8x8x32)
         self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
41
         # 最大池化层
42
         self.pool = nn.MaxPool2d(2, 2)
43
         # linear layer (64 * 4 * 4 -> 500)
44
         self.fc1 = nn.Linear(64 + 4 + 4, 500)
45
46
         # linear layer (500 -> 10)
47
         self.fc2 = nn.Linear(500, 10)
         if act == 'relu':
48
49
            self.act = F.relu
         elif act == 'tanh':
50
            self.act = F.tanh
51
         elif act == 'sigmoid':
52
            self.act = F.sigmoid
53
54
      def forward(self, x):
55
         # add sequence of convolutional and max pooling layers
56
         x = self.pool(self.act(self.conv1(x)))
57
58
         x = self.pool(self.act(self.conv2(x)))
         x = self.pool(self.act(self.conv3(x)))
59
         # flatten image input
60
         x = x.view(-1, 64 + 4 + 4)
61
62
         x = self.act(self.fc1(x))
63
64
65
         x = self.fc2(x)
66
         return x
   67
68
   69
70
   class BnNet(nn.Module):
71
      def __init__(self, act):
         super(BnNet, self).__init__()
72
         # 卷积层 (32x32x3的图像)
73
74
         self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
         self.bn1 = nn.BatchNorm2d(16)
75
```

```
76
 77
          # 卷积层(16x16x16)
          self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
 78
          self.bn2 = nn.BatchNorm2d(32)
 79
80
          # 卷积层(8x8x32)
81
82
          self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
83
          self.bn3 = nn.BatchNorm2d(64)
84
          # 最大池化层
85
          self.pool = nn.MaxPool2d(2, 2)
86
87
          # linear layer (64 * 4 * 4 -> 500)
88
89
          self.fc1 = nn.Linear(64 * 4 * 4, 500)
90
          self.bn4 = nn.BatchNorm1d(500)
91
          # linear layer (500 -> 10)
92
          self.fc2 = nn.Linear(500, 10)
93
94
          if act == 'relu':
95
             self.act = F.relu
96
97
          elif act == 'tanh':
             self.act = F.tanh
98
99
          elif act == 'sigmoid':
             self.act = F.sigmoid
100
101
       def forward(self, x):
102
103
          # add sequence of convolutional and max pooling layers
104
          x = self.pool(self.act(self.bn1(self.conv1(x))))
          x = self.pool(self.act(self.bn2(self.conv2(x))))
105
          x = self.pool(self.act(self.bn3(self.conv3(x))))
106
107
108
          # flatten image input
          x = x.view(-1, 64 + 4 + 4)
109
110
          x = self.act(self.bn4(self.fc1(x)))
111
          x = self.fc2(x)
112
113
          return x
    114
115
116
117
118 class DeepNet(nn.Module):
```

```
119
      def __init__(self):
        super(DeepNet, self).__init__()
120
        121
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
122
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
123
124
        self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
125
        self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
126
        self.conv5 = nn.Conv2d(128, 256, 3, padding=1)
127
        self.conv6 = nn.Conv2d(256, 512, 1, padding=0)
        self.fc1 = nn.Linear(512, 256)
128
        self.fc2 = nn.Linear(256, 128)
129
        self.fc3 = nn.Linear(128, 10)
130
        self.act = F.tanh
131
        self.pool = nn.MaxPool2d(2, 2)
132
133
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        134
135
      def forward(self, x):
136
137
        # convolutional layers
138
        139
        x = self.act(self.conv1(x))
140
        x = self.pool(self.act(self.conv2(x)))
        x = self.act(self.conv3(x))
141
142
        x = self.pool(self.act(self.conv4(x)))
        x = self.act(self.conv5(x))
143
144
        x = self.avgpool(self.act(self.conv6(x)))
        x = x.view(-1, 512)
145
146
147
        x = self.act(self.fc1(x))
        x = self.act(self.fc2(x))
148
        x = self.act(self.fc3(x))
149
150
        151
        return x
152
153
   class BnDeepNet(nn.Module):
154
      def __init__(self,act):
        super(BnDeepNet, self).__init__()
155
        156
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
157
        self.bn1 = nn.BatchNorm2d(16)
158
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
159
        self.bn2 = nn.BatchNorm2d(32)
160
161
        self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
```

```
162
         self.bn3 = nn.BatchNorm2d(64)
         self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
163
164
         self.bn4 = nn.BatchNorm2d(128)
165
         self.conv5 = nn.Conv2d(128, 256, 3, padding=1)
         self.bn5 = nn.BatchNorm2d(256)
166
167
         self.conv6 = nn.Conv2d(256, 512, 1, padding=0)
168
         self.bn6 = nn.BatchNorm2d(512)
169
         self.fc1 = nn.Linear(512, 256)
170
         self.bnfc1 = nn.BatchNorm1d(256)
         self.fc2 = nn.Linear(256, 128)
171
         self.bnfc2 = nn.BatchNorm1d(128)
172
         self.fc3 = nn.Linear(128, 10)
173
174
         if act == 'relu':
175
            self.act = F.relu
176
         elif act == 'tanh':
            self.act = F.tanh
177
         elif act == 'sigmoid':
178
            self.act = F.sigmoid
179
180
         self.pool = nn.MaxPool2d(2, 2)
181
         self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
182
         183
      def forward(self, x):
184
185
         # convolutional layers
         186
187
         x = self.act(self.bn1(self.conv1(x)))
         x = self.pool(self.act(self.bn2(self.conv2(x))))
188
189
         x = self.act(self.bn3(self.conv3(x)))
         x = self.pool(self.act(self.bn4(self.conv4(x))))
190
         x = self.act(self.bn5(self.conv5(x)))
191
         x = self.avgpool(self.act(self.bn6(self.conv6(x))))
192
193
         x = x.view(-1, 512)
194
195
         x = self.act(self.bnfc1(self.fc1(x)))
196
         x = self.act(self.bnfc2(self.fc2(x)))
197
         x = self.act(self.fc3(x))
198
         return x
         199
200
201
202
    203
204
```

```
205 | model = BnDeepNet('relu').to(device)
    criterion = nn.CrossEntropyLoss().to(device)
206
207
208 optimizer_type = "AdamW" #或者换成AdamW
    if optimizer_type == "SGD":
209
210
      optimizer = optim.SGD(model.parameters(), lr=0.001)
211 elif optimizer_type == "AdamW":
212
      213
      optimizer = optim.AdamW(model.parameters(), lr=0.0001)
214
      215
      pass
216
217 | n_epochs = 100
218 | train_losses = []
219
    valid_losses = []
    accuracies = []
220
    221
222
223
    224
225
   for epoch in range(n_epochs):
226
      train_loss = 0.0
227
      valid_loss = 0.0
228
      model.train()
229
      for idx,(img,label) in tqdm(enumerate(train_loader)):
230
         img, label = img.to(device), label.to(device)
         optimizer.zero_grad()
231
232
         output = model(img)
         loss = criterion(output, label)
233
         loss.backward()
234
         optimizer.step()
235
236
         train_loss += loss.item() * img.shape[0]
237
238
      model.eval()
239
      correct = 0
240
      total = 0
241
      for idx,(img,label) in tqdm(enumerate(test_loader)):
242
         img, label = img.to(device), label.to(device)
243
         output = model(img)
         loss = criterion(output, label)
244
245
         valid_loss += loss.item() * img.shape[0]
246
         _, predicted = torch.max(output.data, 1)
247
         total += label.size(0)
```

```
248
         correct += (predicted == label).sum().item()
249
      train_loss = train_loss / len(train_dset)
250
251
      valid_loss = valid_loss / len(test_dset)
252
      train_losses.append(train_loss)
253
254
      valid_losses.append(valid_loss)
255
      accuracy = correct / total
256
      accuracies.append(accuracy)
257
258
      print(f"Epoch:{epoch}, Acc:{correct/total}, Train Loss:{train_loss}, Test Loss
         :{valid_loss}")
    259
260
261
    print("MAX ACC: ",np.max(accuracies))
262
263 plt.plot(range(n_epochs), train_losses, label='Train Loss')
   plt.plot(range(n_epochs), valid_losses, label='Valid Loss')
264
265
    plt.xlabel('Epoch')
266 plt.ylabel('Loss')
267 plt.legend()
268 plt.savefig("Loss.png")
269 plt.clf()
270 # 绘制验证集准确率随epoch的变化曲线
271 plt.plot(range(n_epochs), accuracies, label='Accuracy')
272 | plt.xlabel('Epoch')
273 plt.ylabel('Accuracy')
274 plt.legend()
275
   plt.savefig("Acc.png")
```