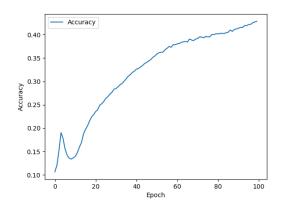
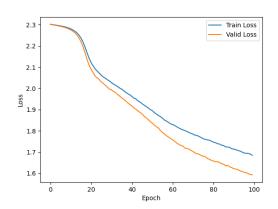
视听信息系统导论编程 1

高艺轩 毕嘉仪

第1题

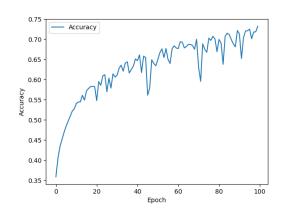
在 SGD 优化器下,输出的结果如下:

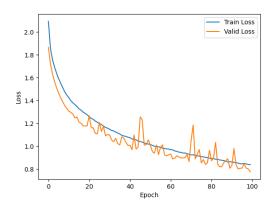




第2题

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

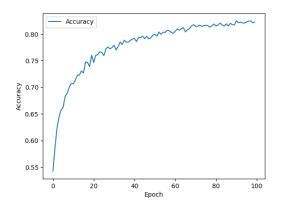


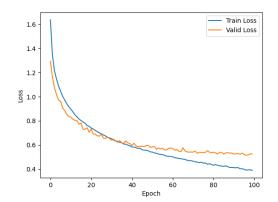


第3题

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

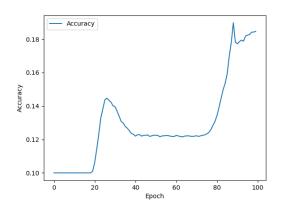


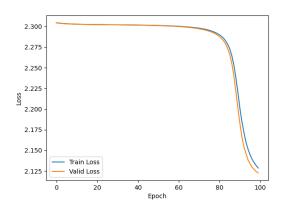


第 4 题

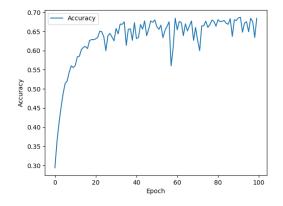
4.1

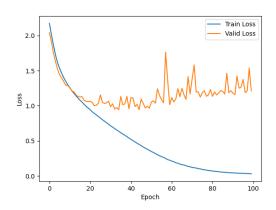
仍旧使用 tanh 作为激活函数, SGD 优化器:





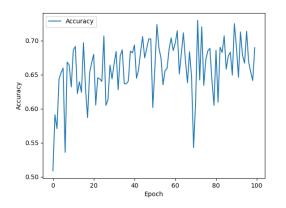
4.2 将激活函数更改为 ReLU 函数,并使用 BatchNorm,使用 SGD:

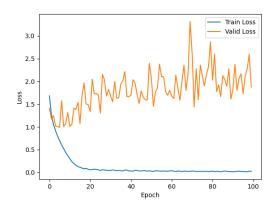




4.3

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 2,3 部分均出现了过拟合现象,分别发生在 epoch 35 附近以及 epoch 5 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
   import torch
2
   import torchvision
4 import numpy as np
5 from tqdm import tqdm
6 import torch.nn as nn
7
   import torch.nn.functional as F
   import torch.optim as optim
8
   import torchvision.transforms as transforms
9
   import matplotlib.pyplot as plt
10
11
   from PIL import Image
12
  from typing import *
13
14
   device = 'cuda' if torch.cuda.is available() else 'cpu'
15
16
17
   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
24
   class CustomCIFAR10(torchvision.datasets.CIFAR10):
      def __init_ (
25
         self,
26
27
         root.
         train,
28
29
         transform = None,
30
         target_transform = None,
         download = False,
31
      ):
32
         super().__init__(root, train, transform, target_transform, download)
33
         new data = []
34
         new_target = []
35
         for i in tqdm(range(len(self.data))):
36
```

```
37
           img, target = self.data[i], self.targets[i]
           # print(self.data.shape)
38
           # print(img.shape)
39
           img = Image.fromarray(img)
40
41
           if self.transform is not None:
42
43
              img = self.transform(img)
44
           if self.target_transform is not None:
45
              target = self.target_transform(target)
46
47
           new_data.append(img)
48
           new_target.append(target)
49
50
51
         self.data = torch.Tensor(np.stack(new_data, axis=0)).to(device)
         self.targets = torch.Tensor(new_target).to(torch.int64).to(device)
52
53
      def __getitem__(self, index):
54
         return self.data[index], self.targets[index]
55
56
57
   # train_dset = torchvision.datasets.CIFAR10(root='./CIFAR10',train=True,
      download=False,transform=train_transform)
   # test_dset = torchvision.datasets.CIFAR10(root='./CIFAR10',train=False,
58
      download=False,transform=transforms.ToTensor())
   train_dset = CustomCIFAR10(root='./CIFAR10',train=True,download=False,
59
      transform=train_transform)
   test dset = CustomCIFAR10(root='./CIFAR10',train=False,download=False,
60
      transform=transforms.ToTensor())
   train_loader = torch.utils.data.DataLoader(train_dset, batch_size=128,
61
      shuffle=True, num_workers=0)
   test_loader = torch.utils.data.DataLoader(test_dset, batch_size=128, shuffle=
62
      False, num_workers=0)
63
   64
65
   66
   class Net(nn.Module):
67
      def __init__(self,act):
68
         super(Net, self).__init__()
69
         # 卷积层 (32x32×3的图像)
70
         self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
71
72
         # 卷积层(16x16×16)
         self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
73
```

```
74
         # 卷积层(8x8×32)
75
         self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
76
         # 最大池化层
         self.pool = nn.MaxPool2d(2, 2)
77
         # linear layer (64 * 4 * 4 -> 500)
78
         self.fc1 = nn.Linear(64 * 4 * 4, 500)
79
80
         # linear layer (500 -> 10)
81
         self.fc2 = nn.Linear(500, 10)
         if act = 'relu':
82
            self.act = F.relu
83
         elif act = 'tanh':
84
            self.act = F.tanh
85
         elif act = 'sigmoid':
86
87
            self.act = F.sigmoid
88
       def forward(self, x):
89
         # add sequence of convolutional and max pooling layers
90
         x = self.pool(self.act(self.conv1(x)))
91
92
         x = self.pool(self.act(self.conv2(x)))
         x = self.pool(self.act(self.conv3(x)))
93
94
         # flatten image input
95
         x = x.view(-1, 64 * 4 * 4)
96
         x = self.act(self.fc1(x))
97
98
99
         x = self.fc2(x)
100
         return x
101
    102
class BnNet(nn.Module):
104
       def __init__(self, act):
105
         super(BnNet, self).__init__()
106
         # 卷积层 (32x32×3的图像)
107
         self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
108
109
         self.bn1 = nn.BatchNorm2d(16)
110
         # 卷积层(16x16×16)
111
         self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
112
         self.bn2 = nn.BatchNorm2d(32)
113
114
         # 卷积层(8x8×32)
115
         self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
116
```

```
117
         self.bn3 = nn.BatchNorm2d(64)
118
         # 最大池化层
119
         self.pool = nn.MaxPool2d(2, 2)
120
121
         # linear layer (64 * 4 * 4 -> 500)
122
123
         self.fc1 = nn.Linear(64 * 4 * 4, 500)
124
         self.bn4 = nn.BatchNorm1d(500)
125
         # linear layer (500 -> 10)
126
127
         self.fc2 = nn.Linear(500, 10)
128
129
         if act = 'relu':
130
            self.act = F.relu
         elif act = 'tanh':
131
            self.act = F.tanh
132
         elif act = 'sigmoid':
133
134
            self.act = F.sigmoid
135
       def forward(self, x):
136
137
         # add sequence of convolutional and max pooling layers
138
         x = self.pool(self.act(self.bn1(self.conv1(x))))
         x = self.pool(self.act(self.bn2(self.conv2(x))))
139
         x = self.pool(self.act(self.bn3(self.conv3(x))))
140
141
142
         # flatten image input
         x = x.view(-1, 64 * 4 * 4)
143
144
145
         x = self.act(self.bn4(self.fc1(x)))
         x = self.fc2(x)
146
147
         return x
148
    149
150
151
152
    class DeepNet(nn.Module):
       def __init__(self):
153
154
         super(DeepNet, self).__init__()
         155
         self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
156
157
         self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
         self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
158
159
         self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
```

```
160
         self.conv5 = nn.Conv2d(128, 256, 3, padding=1)
         self.conv6 = nn.Conv2d(256, 512, 1, padding=0)
161
         self.fc1 = nn.Linear(512, 256)
162
163
         self.fc2 = nn.Linear(256, 128)
         self.fc3 = nn.Linear(128, 10)
164
165
         self.act = F.tanh
166
         self.pool = nn.MaxPool2d(2, 2)
167
         self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
168
         169
170
      def forward(self, x):
         # convolutional layers
171
172
         x = self.act(self.conv1(x))
173
         x = self.pool(self.act(self.conv2(x)))
174
         x = self.act(self.conv3(x))
175
         x = self.pool(self.act(self.conv4(x)))
176
         x = self.act(self.conv5(x))
177
         x = self.avgpool(self.act(self.conv6(x)))
178
         x = x.view(-1, 512)
179
180
181
         x = self.act(self.fc1(x))
         x = self.act(self.fc2(x))
182
         x = self.act(self.fc3(x))
183
         184
185
         return x
186
187
    class BnDeepNet(nn.Module):
188
      def init (self,act):
         super(BnDeepNet, self).__init__()
189
         190
191
         self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
         self.bn1 = nn.BatchNorm2d(16)
192
         self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
193
194
         self.bn2 = nn.BatchNorm2d(32)
195
         self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
196
         self.bn3 = nn.BatchNorm2d(64)
         self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
197
         self.bn4 = nn.BatchNorm2d(128)
198
         self.conv5 = nn.Conv2d(128, 256, 3, padding=1)
199
         self.bn5 = nn.BatchNorm2d(256)
200
201
         self.conv6 = nn.Conv2d(256, 512, 1, padding=0)
202
         self.bn6 = nn.BatchNorm2d(512)
```

```
203
         self.fc1 = nn.Linear(512, 256)
204
         self.bnfc1 = nn.BatchNorm1d(256)
         self.fc2 = nn.Linear(256, 128)
205
         self.bnfc2 = nn.BatchNorm1d(128)
206
         self.fc3 = nn.Linear(128, 10)
207
         if act = 'relu':
208
209
           self.act = F.relu
210
         elif act = 'tanh':
211
           self.act = F.tanh
        elif act = 'sigmoid':
212
213
           self.act = F.sigmoid
214
         self.pool = nn.MaxPool2d(2, 2)
215
         self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
         216
217
      def forward(self, x):
218
219
        # convolutional layers
220
        221
        x = self.act(self.bn1(self.conv1(x)))
        x = self.pool(self.act(self.bn2(self.conv2(x))))
222
        x = self.act(self.bn3(self.conv3(x)))
223
224
        x = self.pool(self.act(self.bn4(self.conv4(x))))
        x = self.act(self.bn5(self.conv5(x)))
225
        x = self.avgpool(self.act(self.bn6(self.conv6(x))))
226
        x = x.view(-1, 512)
227
228
        x = self.act(self.bnfc1(self.fc1(x)))
229
230
        x = self.act(self.bnfc2(self.fc2(x)))
231
        x = self.act(self.fc3(x))
232
        return x
233
         234
235
236
    237
238
239
    model = BnDeepNet('relu').to(device)
240
    criterion = nn.CrossEntropyLoss().to(device)
241
242 | optimizer_type = "AdamW" #或者换成AdamW
243 | if optimizer type = "SGD":
244
      optimizer = optim.SGD(model.parameters(), lr=0.001)
245 elif optimizer_type = "AdamW":
```

```
246
      ######### 代码填空: 请在此填补Adam优化器计算代码, lr=0.0001 ###########
247
      optimizer = optim.AdamW(model.parameters(), lr=0.0001)
      248
249
      pass
250
251 | n_{epochs} = 100
252
    train_losses = []
253
    valid losses = []
    accuracies = []
254
255
    256
257
258
    259
    for epoch in range(n_epochs):
260
      train loss = 0.0
      valid loss = 0.0
261
      model.train()
262
      for idx,(img,label) in tqdm(enumerate(train_loader)):
263
264
         # img, label = img.to(device), label.to(device)
         optimizer.zero grad()
265
266
         output = model(img)
267
         loss = criterion(output, label)
         loss.backward()
268
         optimizer.step()
269
270
         train_loss += loss.item() * img.shape[0]
271
      model.eval()
272
273
      correct = 0
274
      total = 0
      for idx,(img,label) in tqdm(enumerate(test_loader)):
275
         # img, label = img.to(device), label.to(device)
276
         output = model(img)
277
         loss = criterion(output, label)
278
         valid loss += loss.item() * img.shape[0]
279
280
         _, predicted = torch.max(output.data, 1)
281
         total += label.size(0)
         correct += (predicted = label).sum().item()
282
283
284
      train_loss = train_loss / len(train_dset)
      valid_loss = valid_loss / len(test_dset)
285
286
287
      train losses.append(train loss)
288
      valid_losses.append(valid_loss)
```

```
289
      accuracy = correct / total
290
      accuracies.append(accuracy)
291
      print(f"Epoch:{epoch}, Acc:{correct/total}, Train Loss:{train_loss}, Test
292
        Loss:{valid loss}")
293
   294
   295
   print("MAX ACC: ",np.max(accuracies))
296
297
   plt.plot(range(n_epochs), train_losses, label='Train Loss')
   plt.plot(range(n_epochs), valid_losses, label='Valid Loss')
298
   plt.xlabel('Epoch')
299
300 plt.ylabel('Loss')
301 plt.legend()
302 plt.savefig("Loss.png")
   plt.clf()
303
304 # 绘制验证集准确率随epoch的变化曲线
305 | plt.plot(range(n_epochs), accuracies, label='Accuracy')
306
   plt.xlabel('Epoch')
   plt.ylabel('Accuracy')
307
308 plt.legend()
309 plt.savefig("Acc.png")
```