在 Tiny-ImageNet 数据集上训练 Resnet 模型

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2022/5/17

摘要

Tiny-ImageNet 是一个小型的、常用于教学的数据集,包括 200 个类型,10 万张训练图片和 1 万张验证图片。在本次实验中,以 PyTorch 官网基于 ImageNet 的示例代码为基础,在其上修改以适配 Tiny-ImageNet,并且限定模型为 resnet18。

本次实验的代码地址参见https://github.com/JONATHONCHOW/tiny-imagenet_resnet18

前言

本次实验主要完成了 resnet18.py、update_val.py、main.py、compare.py,分别实现了分析 resnet18 模型结构、修改训练数据集 val、改动示例代码使适配 Tiny-ImageNet、比较两个 checkpoint 差异。

任务 1: 分析 resnet18 模型结构

利用 PyTorch 的模型解析的包,再根据 Tiny-ImageNet 图片大小(3*64*64)编写代码。

- 1 model = models.___dict___['resnet18']()
- 2 input_num = model.fc.in_features

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```
3 model.fc = nn.Linear(input_num, 200)
4 # gpu to cpu
5 summary(model, (3, 64, 64), device = "cpu")
```

运行文件 resnet18.py,得到各层的名称及图片经过各层处理后的中间结果的大小。

1	Layer (type)	Output Shape	Param #
2 === 3	Conv2d-1	[-1, 64, 32, 32]	9,408
4	BatchNorm2d-2	[-1, 64, 32, 32]	128
5	ReLU-3	[-1, 64, 32, 32]	0
6	MaxPool2d-4	[-1, 64, 16, 16]	0
7	Conv2d-5	[-1, 64, 16, 16]	36,864
8	BatchNorm2d-6	[-1, 64, 16, 16]	128
9	ReLU-7	[-1, 64, 16, 16]	0
10	Conv2d-8	[-1, 64, 16, 16]	36,864
11	BatchNorm2d-9	[-1, 64, 16, 16]	128
12	ReLU-10	[-1, 64, 16, 16]	0
13	BasicBlock-11	[-1, 64, 16, 16]	0
14	Conv2d-12	[-1, 64, 16, 16]	36,864
15	BatchNorm2d-13	[-1, 64, 16, 16]	128
16	ReLU-14	[-1, 64, 16, 16]	0
17	Conv2d-15	[-1, 64, 16, 16]	36,864
18	BatchNorm2d-16	[-1, 64, 16, 16]	128
19	ReLU-17	[-1, 64, 16, 16]	0
20	BasicBlock-18	[-1, 64, 16, 16]	0
21	Conv2d-19	[-1, 128, 8, 8]	73,728
22	BatchNorm2d-20	[-1, 128, 8, 8]	256
23	ReLU-21	[-1, 128, 8, 8]	0
24	Conv2d-22	[-1, 128, 8, 8]	$147,\!456$
25	BatchNorm2d-23	[-1, 128, 8, 8]	256
26	Conv2d-24	[-1, 128, 8, 8]	8,192
27	BatchNorm2d-25	[-1, 128, 8, 8]	256
28	ReLU-26	[-1, 128, 8, 8]	0
29	BasicBlock-27	[-1, 128, 8, 8]	0
30	Conv2d-28	[-1, 128, 8, 8]	$147,\!456$
31	BatchNorm2d-29	[-1, 128, 8, 8]	256
32	ReLU-30	[-1, 128, 8, 8]	0
33	Conv2d-31	[-1, 128, 8, 8]	147,456
34	BatchNorm2d-32	[-1, 128, 8, 8]	256
35	ReLU-33	[-1, 128, 8, 8]	0
36	BasicBlock-34	[-1, 128, 8, 8]	0
37	Conv2d-35	[-1, 256, 4, 4]	294,912
38	BatchNorm2d-36	[-1, 256, 4, 4]	512
39	ReLU-37	[-1, 256, 4, 4]	0
40	Conv2d-38	[-1, 256, 4, 4]	589,824
41	BatchNorm2d-39	[-1, 256, 4, 4]	512
42	Conv2d-40	[-1, 256, 4, 4]	32,768
43	BatchNorm2d-41	[-1, 256, 4, 4]	512

	ReLU-42	[-1, 256, 4, 4]	0
45	BasicBlock-43	[-1, 256, 4, 4]	0
46	Conv2d-44	[-1, 256, 4, 4]	589,824
47	BatchNorm2d-45	[-1, 256, 4, 4]	512
48	ReLU-46	[-1, 256, 4, 4]	0
49	Conv2d-47	[-1, 256, 4, 4]	589,824
50	BatchNorm2d-48	[-1, 256, 4, 4]	512
51	ReLU-49	[-1, 256, 4, 4]	0
52	BasicBlock-50	[-1, 256, 4, 4]	0
53	Conv2d-51	[-1, 512, 2, 2]	$1,\!179,\!648$
54	BatchNorm2d-52	[-1, 512, 2, 2]	1,024
55	ReLU-53	[-1, 512, 2, 2]	0
56	Conv2d-54	[-1, 512, 2, 2]	$2,\!359,\!296$
57	BatchNorm2d-55	[-1, 512, 2, 2]	1,024
58	Conv2d-56	[-1, 512, 2, 2]	131,072
59	BatchNorm2d-57	[-1, 512, 2, 2]	1,024
60	ReLU-58	[-1, 512, 2, 2]	0
61	BasicBlock-59	[-1, 512, 2, 2]	0
62	Conv2d-60	[-1, 512, 2, 2]	$2,\!359,\!296$
63	BatchNorm2d-61	[-1, 512, 2, 2]	1,024
64	ReLU-62	[-1, 512, 2, 2]	0
65	Conv2d-63	[-1, 512, 2, 2]	$2,\!359,\!296$
66	BatchNorm2d-64	[-1, 512, 2, 2]	1,024
67	ReLU-65	[-1, 512, 2, 2]	0
68	BasicBlock-66	[-1, 512, 2, 2]	0
69	Adaptive Avg Pool 2d-67	[-1, 512, 1, 1]	0
70	Linear-68	[-1, 200]	102,600
71			

任务 2: 改动示例代码使适配 Tiny-ImageNet

以 PyTorch 官网基于 ImageNet 的示例代码 main.py 为基础,在其上修改以适配 Tiny-ImageNet。 1

2.1 修改训练数据集 val

利用 os 库先将 val 文件夹重命名为 originval 文件夹, 再重新创建 val 文件夹。

```
os.rename("./tiny-imagenet-200/val", "./tiny-imagenet-200/originval")
os.mkdir("./tiny-imagenet-200/val")
```

利用 train 文件夹的结构,构造 val 文件夹,使得更新后的 val 文件夹结构与 ImageNet 的相同。

¹main.py 的改动说明参见附录。

```
1 for filename in os.listdir("./tiny-imagenet-200/train"):
2 if filename in os.listdir("./tiny-imagenet-200/originval"):
3 pass
4 else:
5 os.mkdir(os.path.join("./tiny-imagenet-200/val", filename))
```

利用 val_annotations.txt 文件重新修订标签。

```
with open("./tiny-imagenet-200/originval/val_annotations.txt") as f:
labels = f.readlines()
for i, label in enumerate(labels):
    filename = label.split("\t")[1]
    src = "./tiny-imagenet-200/originval/images/val_" + str(i) + ".JPEG"
    dst = "./tiny-imagenet-200/val/" + filename + "/val_" + str(i) +".JPEG"
    shutil.copyfile(src, dst)
```

在运行 main.py 之前需要先运行文件 update_val.py。

2.2 其他修改

在 main.py 中修改 output 维数、删除对图片进行伸缩和裁剪的代码。

```
1 # change output dimension from 1000 to 200
2 input_num = model.fc.in_features
3 model.fc = nn.Linear(input_num, 200)
```

```
1 # transforms.RandomResizedCrop(224),
2 # transforms.RandomHorizontalFlip(),
3 # transforms.Resize(256),
4 # transforms.CenterCrop(224),
```

任务 3: 在 TensorBoard 中观察训练参数

在代码中增加 torch.utils.tensorboard 的代码,利用函数传参,使得能在 TensorBoard 中观察训练集 Loss、训练集精度、验证集 Loss、验证集精度的变化。

```
writer.add_scalar('Train/Loss', losses_train, epoch)
writer.add_scalar('Train/Top5', acc5_train, epoch)
writer.add_scalar('Train/Top1', acc1_train, epoch)
```

```
writer.add_scalar('Validate/Loss', losses, epoch)
writer.add_scalar('Validate/Top5', acc5, epoch)
writer.add_scalar('Validate/Top1', acc1, epoch)
```

任务 4: 运行程序并分析曲线变化

4.1 运行程序

运行 main.py,为将 resnet18 在训练集上的精度(Top5)训练到 95% 以上,batch_size 为默认值 256,设置 epochs=25,事实上大约 12 个 epochs 就可以达到精度要求。

在任务端²的 Command Prompt 中输入命令³。

```
python main.py --epochs 25 tiny-imagenet-200
```

4.2 利用 TensorBoard 分析曲线变化

在任务端的 Command Prompt 中输入命令打开 TensorBoard。

```
1 tensorboard --logdir=runs
```

得到训练集 Loss、训练集精度(Top1、Top5)、验证集 Loss、验证集精度(Top1、Top5)的变化曲线图,参见图 1、图 2。

Train

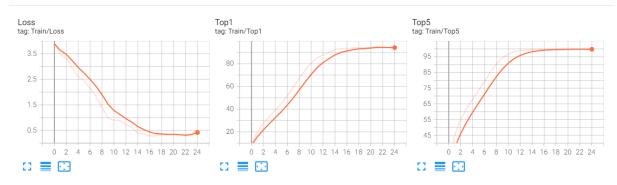


图 1: TensorBoard_Train

²注意不能是本地端的 Command Prompt。

³也可以在 IDE 的运行配置中设置形参。

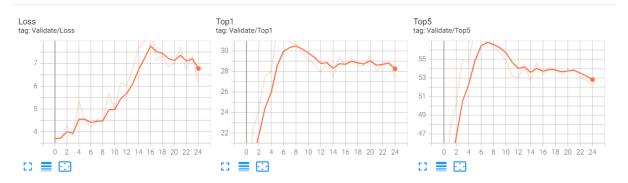


图 2: TensorBoard_Validate

训练集: Loss 曲线单调下降,这是利用梯度下降法的原因。Top1 和 Top5 曲线单调上升,模型在大约 15 个 epochs 处就趋于稳定,精度分别达到了 90% 和 95% 以上。

验证集:模型存在轻微的过拟合现象,这是训练时间过长的原因。Loss 曲线在大约 15个 epochs 处达到峰值,然后轻微下降趋于平稳。Top1 和 Top5 曲线在大约 8个 epochs 处达到峰值,然后轻微下降趋于平稳,精度分别在 30% 和 55% 左右。

任务 5: 保存 checkpoint 并评估差异

5.1 保存 checkpoint

保存每个 epoch 的 checkpoint 总共 25 个,以及验证集 Top1 曲线峰值时的 checkpoint。

```
1 save_checkpoint({
2    'epoch': epoch + 1,
3    'arch': args.arch,
4    'state_dict': model.state_dict(),
5    'best_accl': best_accl,
6    'optimizer': optimizer.state_dict(),
7    'scheduler': scheduler.state_dict()
8    }, is_best, "checkpoint{}.pth.tar".format(epoch + 1))
```

利用 checkpoint 可以方便地进行断点重启⁴,比如从第 10 个 epoch 开始继续运行(需要恢复第 10 个 epoch⁵运行结束后的断点 checkpoint10.pth.tar),在任务端的 Command Prompt 中输入如下命令。

 $^{^4}$ 注意并不需要手工赋予参数 start_epoch 的值,这是由于 checkpoint 中已经有 start_epoch 的值。

⁵注意第 i 个 epoch 相当于 epoch i 也相当于 Epoch: [i-1]。

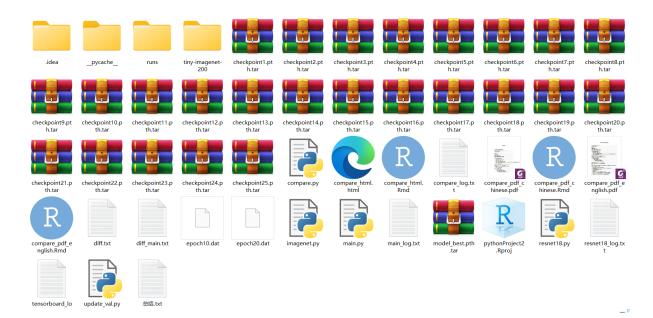


图 3: checkpoint

```
python main.py --epochs 25 --resume checkpoint10.pth.tar tiny-imagenet-200
```

5.2 评估不同 checkpoint 的差异

使用代码中的 –evaluate 选项,编写代码以保存指定 epoch (相当于指定 checkpoint) 处的训练结果。

```
1 if args.evaluate:
2   torch.save(save, "epoch" + str(args.start_epoch) + ".dat")
3   return
```

在任务端的 Command Prompt 中输入如下命令以保存第 10 个和第 20 个 epoch 处的训练结果,存储为文件 epoch10.dat 和 epoch20.dat。

```
python main.py --resume checkpoint10.pth.tar -e tiny-imagenet-200
python main.py --resume checkpoint20.pth.tar -e tiny-imagenet-200
```

对比两次评估的差异:由于验证集存在轻微的过拟合现象,第 10 个 epoch 处的准确率比第 20 个 epoch 处的准确率略高一些。

```
1 Epoch: [9]
2 Test: [ 0/40]
                Time 5.740 ( 5.740)
                                         Loss 3.0113e+00 (3.0113e+00)
                                                                        Acc@1 38.67 ( ...
              Acc@5 62.89 ( 62.89)
      38.67)
3 Test: [10/40] Time 0.023 ( 0.562)
                                         Loss 3.7513e+00 (3.5626e+00)
                                                                        Acc@1 26.56 ( ...
              Acc@5 55.47 ( 58.03)
      31.36)
4 Test: [20/40] Time 0.054 ( 0.313)
                                         Loss 3.4789e+00 (3.7384e+00)
                                                                              32.03 ( ...
                                                                        Acc@1
              Acc@5 56.25 ( 55.77)
      29.32)
  Test: [30/40] Time 0.053 (0.226)
                                         Loss 3.9178e+00 (3.7831e+00)
                                                                        Acc@1 29.30 ( ...
      29.07)
              Acc@5 56.25 ( 55.12)
       Acc@1 29.790 Acc@5 55.760
```

```
1 Epoch: [19]
2 Test: [ 0/40]
                 Time 5.696 ( 5.696)
                                         Loss 4.1153e+00 (4.1153e+00)
                                                                        Acc@1 35.16 ( ...
              Acc@5 61.72 ( 61.72)
      35.16)
                 Time 0.023 ( 0.557)
 Test: [10/40]
                                         Loss 4.6135e+00 (4.6518e+00)
                                                                        Acc@1 31.25 ( ...
      30.01) Acc@5 56.25 ( 56.89)
 Test: [20/40] Time 0.039 ( 0.310)
                                         Loss 4.7686e+00 (4.8993e+00)
                                                                        Acc@1 25.78 ( ...
      27.79) Acc@5 53.91 ( 53.39)
  Test: [30/40] Time 0.029 (0.224)
                                         Loss 5.8639e+00 (4.9703e+00)
                                                                        Acc@1 19.14 ( ...
      27.70)
              Acc@5 45.31 ( 52.19)
       Acc@1 28.590 Acc@5 53.350
```

利用 os 库对文件地址操作、利用 numpy 库将 tensor 转化成易于处理的数据类型、利用 matplotlib 库显示图像,编写程序得到 compare.py。

```
1 for i in range(n):
2    figure = mpimg.imread(files[i])
3    plt.imshow(figure)
4    plt.axis("off")
5    plt.show()
6    print("answer:", index_word[index[i] // 50])
7    print("epoch10:", [index_word[j] for j in pred1[:,index[i]]])
8    print("epoch20:", [index_word[j] for j in pred2[:,index[i]]])
```

运行 compare.py, 找出其中 10 张评判结果不同的图片如下。









```
3 epoch20: ['triumphal arch', 'dam, dike, dyke', 'butcher shop, meat market', 'bullet ...
train, bullet', 'suspension bridge']
```









```
1 answer: wooden spoon
2 epoch10: ['wooden spoon', 'espresso', 'slug', 'bathtub, bathing tub, bath, tub', ...
        'drumstick']
3 epoch20: ['espresso', 'mashed potato', 'plate', 'wooden spoon', 'Chihuahua']
```



1 answer: cauliflower



参考文献

- [1] 郑歆慰: Python 与深度学习基础课件
- [2] https://github.com/pytorch/examples/blob/main/imagenet/main.py
- [3] https://pytorch.org/docs/stable/tensorboard.html

附录

main.py 的改动说明如下。6

```
1 diff - -git
2 a / main.py
3 b / main.py
4 index
5 44e06
6 d8.
7 .297
```

```
8 baf7
9 100644
   --- a / main.py
11 +++ b / main.py
12
13
14
   @ @-19
15
   , 12 + 19, 16 @ @
   import torchvision.transforms as transforms
17
   import torchvision.datasets as datasets
   import torchvision.models as models
20
21
   from torch.utils.tensorboard import SummaryWriter
22
23
   +
24
   +writer = SummaryWriter()
^{25}
26
   model_names = sorted(name for name in models.___dict___
27
                          if name.islower() and not name.startswith("___")
28
29
                         and callable (models.__dict__[name]))
30
   parser = argparse.ArgumentParser(description='PyTorch ImageNet Training')
   + # enter parameters in "Run" or "Command Line"
   parser.add_argument('data', metavar='DIR', default='imagenet',
                        help='path to dataset (default: imagenet)')
34
   parser.add_argument('-a', '--arch', metavar='ARCH', default='resnet18',
   @ @ -138, 6 + 142, 10 @ @
36
37
38
   def main_worker(gpu, ngpus_per_node, args):
40
        print("=> creating model '{}'.".format(args.arch))
        model = models.\_\_dict\_\_[\,args.arch\,]\,(\,)
41
42
43
   + # change output dimension from 1000 to 200
44
        input\_num = model.fc.in\_features
         model.fc = nn.Linear(input_num, 200)
46
   +
   +
47
   if not torch.cuda.is_available():
48
        print('using CPU, this will be slow')
49
    elif args.distributed:
52
       @ @-213
53
54
55
   , 8 + 221, 8 @ @
56
57
```

```
def main_worker(gpu, ngpus_per_node, args):
         train_dataset = datasets.ImageFolder(
60
             traindir,
             transforms.Compose ([
61
                               transforms.RandomResizedCrop(224),
62
                               transforms.RandomHorizontalFlip(),
63
 64
                 + # transforms.RandomResizedCrop(224),
 65
                 + # transforms.RandomHorizontalFlip(),
 66
                 transforms. To Tensor(),
                 normalize,
 67
             ]))
 68
 69
 70
71
    @ @-230
72
73
    , 8 + 238, 8 @ @
74
 75
76
    def main_worker(gpu, ngpus_per_node, args):
         val_loader = torch.utils.data.DataLoader(
 77
             datasets.ImageFolder(valdir, transforms.Compose([
 78
                               transforms. Resize (256),
 79
                               transforms.CenterCrop(224),
 80
 81
                 + # transforms.Resize(256),
 82
                 + # transforms.CenterCrop(224),
                 transforms. To Tensor(),
                 normalize,
 84
             ])),
 85
                      @ @ -247, 13 + 255, 20 @ @
 86
 87
         def main_worker(gpu, ngpus_per_node, args):
             train_sampler.set_epoch(epoch)
 90
 91
 92
    \# train for one epoch
 93
              train(train_loader, model, criterion, optimizer, epoch, args)
 94
    +
              losses\_train\;,\;acc5\_train\;,\;acc1\_train\;=\;train(train\_loader\;,\;model\;,\;criterion\;,\;\dots
95
         optimizer, epoch, args)
 96
    # evaluate on validation set
97
              acc1 = validate(val_loader, model, criterion, args)
98
99
              losses, acc5, acc1 = validate(val_loader, model, criterion, args)
    scheduler.step()
101
102
              writer.add_scalar('Train/Loss', losses_train, epoch)
103
104
   +
              writer.add_scalar('Train/Top5', acc5_train, epoch)
105
              writer.add_scalar('Train/Top1', acc1_train, epoch)
106
              writer.add_scalar('Validate/Loss', losses, epoch)
```

```
writer.add_scalar('Validate/Top5', acc5, epoch)
107 +
              writer.add_scalar('Validate/Top1', acc1, epoch)
108
109 +
# remember best acc@1 and save checkpoint
    is\_best = acc1 > best\_acc1
111
    best\_acc1 = max(acc1, best\_acc1)
112
113
114
115
    @ @-267
116
    , 7 + 282, 7 @ @
117
118
119
    def main_worker(gpu, ngpus_per_node, args):
         'best_acc1': best_acc1,
121
         'optimizer': optimizer.state_dict(),
122
123
         'scheduler': scheduler.state_dict()
124
125
    -}, is_best)
    +}, is_best, "checkpoint{}.pth.tar".format(epoch + 1))
127
128
    def train(train_loader, model, criterion, optimizer, epoch, args):
129
        @ @-315
130
131
132
         , 6 + 330, 7 @ @
133
134
         def train(train_loader, model, criterion, optimizer, epoch, args):
135
         if i % args.print_freq = 0:
136
             progress.display(i)
137
138
139
140
141
    return loss, top5.avg, top1.avg
142
143
    def validate(val_loader, model, criterion, args):
145
146
147
        @ @-342
148
    , 6 + 358, 17 @ @
149
150
151
    def validate(val_loader, model, criterion, args):
152
         output = model(images)
153
154
         loss \, = \, criterion \, (\, output \, , \, \, target \, )
155
156
```

```
157 + # compute output in evaluation
158 +
    if args.evaluate:
159
        + # find max
160
                      \_, pred = output.topk(5, 1, True, True)
161 +
162
                      pred = pred.t()
163
164
    if i == 0:
165
                              save = pred
166 + else:
                          save = torch.cat((save, pred), 1)
167 +
168 +
169 continue
171 # measure accuracy and record loss
   acc1, acc5 = accuracy(output, target, topk=(1, 5))
173
    losses.update(loss.item(), images.size(0))
174
175
176
   @ @-355
    , 9 + 382, 13 @ @
178
179
180
    def validate(val_loader, model, criterion, args):
        if i % args.print_freq == 0:
183
            progress.display(i)
184
185
186
187
    if args.evaluate:
                    torch.save(save, "epoch" + str(args.start_epoch) + ".dat")
188
189
   return
190
191 +
    progress.display_summary()
192
193
194
    return top1.avg
195
196 +
    return loss, top5.avg, top1.avg
197
198
199
    def save_checkpoint(state, is_best, filename='checkpoint.pth.tar'):
201
202
        @ @-454
203
204
205
    , 4 + 485, 4 @ @
206
```