### LeNet-5

### 实验思路

根据LeNet的论文,构造网络(见conv.py),使用NMIST数据集,直接用torchvision提高的函数下载导入(见utils.py),最后在main.py中实现训练的过程以及测试的步骤(见main.py)。

## 实验环境

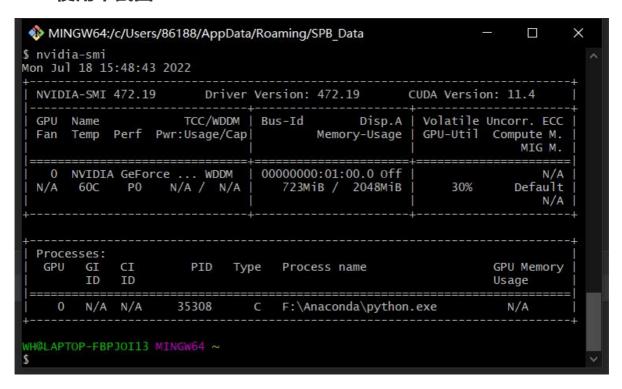
硬件环境:

GPU: Nvidia GeForce MX350

CPU: intel core i5 10th Gen

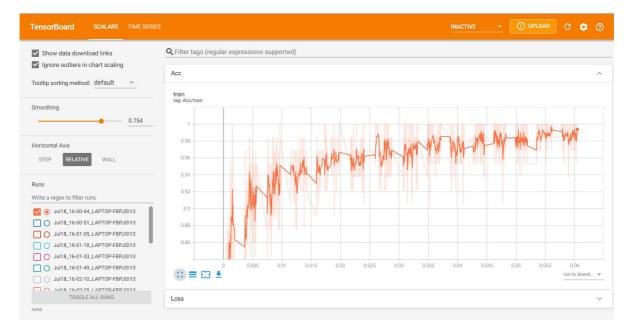
### 实验截图

#### GPU使用率截图

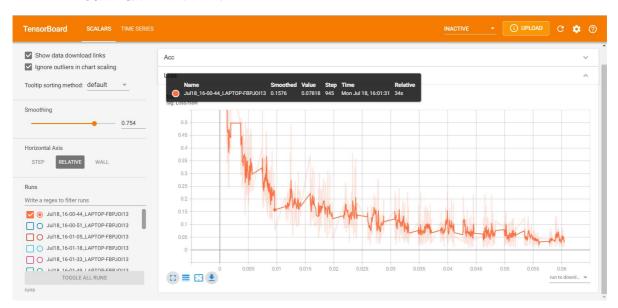


#### LeNet损失函数、精确度截图

LeNet训练阶段精确度曲线



#### LeNet训练阶段损失函数曲线



LeNet测试集准确度

```
F:\Anaconda\python.exe "E:/Grade Three/ShortSemester/HPC101/lab5/LeNet-5/main.py"
Now start training
Already load the data
size of training set is: 938 | size of test set is: 157
Training Time: Epoch[1/15], Total loss 802.4512
Training Time: Epoch[2/15], Total loss 312.9650
Training Time: Epoch[3/15], Total loss 230.6375
Training Time: Epoch[4/15], Total loss 181.9661
Training Time: Epoch[5/15], Total loss 149.4177
Training Time: Epoch[6/15], Total loss 125.9481
Training Time: Epoch[7/15], Total loss 108.0310
Training Time: Epoch[8/15], Total loss 93.9804
Training Time: Epoch[9/15], Total loss 82.6292
Training Time: Epoch[10/15], Total loss 73.3027
Training Time: Epoch[11/15], Total loss 66.4058
Training Time: Epoch[12/15], Total loss 60.2132
Training Time: Epoch[13/15], Total loss 54.6760
Training Time: Epoch[14/15], Total loss 50.3322
Training Time: Epoch[15/15], Total loss 46.2792
Save model successfully and start to test the model
Test accuracy: 0.9845
Process finished with exit code 0
```

经过15个epoch的训练, lenet在测试集上准确度达到了98.45%

### GPT2

本实验模型基于minGPT (https://github.com/karpathy/minGPT) 改写而来

### 实验思路

通过对transformer和gpt2的论文学习以及对minGPT开源代码的学习,改写了模型代码;其中 trainer.py的作用为提供开始训练及测试的函数,model.py为构造模型的代码,utils.py为一些调用的工 具类型函数,train.py为启动代码;训练时,直接调用shrun\_\*.sh即可

### 实验理解

tokenizer选择了hugging face提供的API,直接导入了训练完成的BPE tokenizer,然后自己构建了数据集,每次取原始数据集的1025长度的tokens,使用bpe将前1024个tokens和后1024个tokens分别分词,输入模型;gpt2的实验目的是通过观察前面的tokens,预测出下一个token;Trainer类提供了初始化的接口和训练的接口,同时也有实现数据并行的DDP,数据转到gpu上面实验的代码等。

model.py是gpt2的模型代码,从GPT类进入后,根据config中gpt2的类型确定超参数的数值,之后根据参数构建网络组件,初始化网络参数等部分均在\_\_init\_\_中实现;forward是模型的主要代码,wte是token embedding,wpe是position embedding,两个相加之后得到同时包含位置信息和token信息的embedding信息,将其输入到层层堆叠的block当中,最后再通过全连接层映射到vocab维度,和target进行cross entropy得到loss

Block类是实现每个block的代码,其中self.atten使用的是CausalSelfAttention的代码,另外transformer中采用了residual network。

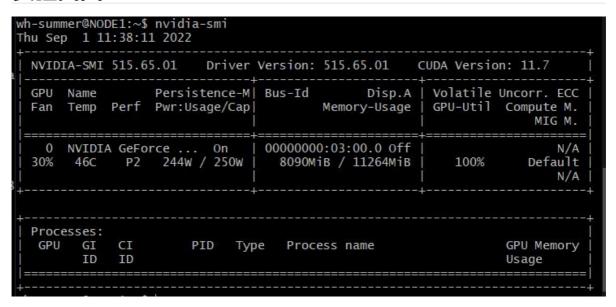
最后,若干个模块拼接在一起,组成了gpt2模型全部的代码。

### 实验环境

## 并行策略

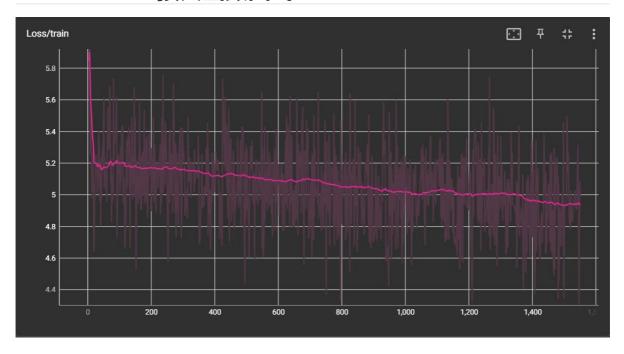
采用了数据并行的方式,使用pytorch提供的DistributedDataParallel函数将数据集平分给不同的节点,因为模型本身参数量较大,所以设置batch\_size为1,因此不同节点每次并行计算一个batch的数据后独立计算梯度,每个进程将梯度依次传给下一个进程,直到所有的进程得到全部的梯度,最后整体做梯度下降,之后再各自计算分配到的batch的数据,周而复始

### 实验截图



### 实验结果

# tensorboard损失函数曲线



### 2节点

使用了2节点,每个节点1块GPU的数据并行,因测试发现中等大小的X.txt的token数量在3.15M左右, 所以总共设定的4个epoch完成12M的token训练任务;batch\_size设为1;训练全部时长为46.45min, 训练完12M个token时长为44.24min,损失也成功收敛,低于7;

#### 1节点

```
The device is
                 cuda
    == TRAIN TIME
       TRAINING LEN IS 3081
       EPOCH: [0/4], STEP: [0/3081], TRAIN LOSS 10.98853
     = EPOCH:
                [0/4], STEP: [500/3081], TRAIN LOSS 6.72221
       EPOCH:
                [0/4], STEP: [1000/3081], TRAIN LOSS 6.41928
                [0/4], STEP:
                              [1500/3081], TRAIN LOSS 6.09135
[2000/3081], TRAIN LOSS 5.87746
       EPOCH:
                [0/4], STEP:
       EPOCH:
                [0/4], STEP:
                              [2500/3081], TRAIN LOSS 5.95929
       EPOCH:
                [0/4], STEP:
                               [3000/3081], TRAIN LOSS 5.76737
       EPOCH:
                [1/4], STEP:
                               [0/3081], TRAIN LOSS 5.91194
       EPOCH:
                [1/4], STEP:
                               [500/3081], TRAIN LOSS 5.93509
     = EPOCH:
       EPOCH:
                [1/4], STEP:
                               [1000/3081], TRAIN LOSS 5.77170
                              [1500/3081], TRAIN LOSS 5.47760
[2000/3081], TRAIN LOSS 5.53770
                [1/4], STEP:
       EPOCH:
                [1/4], STEP:
       EPOCH:
                              [2500/3081], TRAIN LOSS 5.53647
                [1/4], STEP:
      = EPOCH:
      = EPOCH:
                [1/4], STEP:
                               [3000/3081], TRAIN LOSS 5.19615
                              [0/3081], TRAIN LOSS 5.52452
[500/3081], TRAIN LOSS 5.48708
                [2/4], STEP:
       EPOCH:
                [2/4], STEP:
     = EPOCH:
                [2/4], STEP: [1000/3081], TRAIN LOSS 5.44500
     = EPOCH:
                [2/4], STEP:
                              [1500/3081], TRAIN LOSS 5.16286
      = EPOCH:
               [2/4], STEP: [2000/3081], TRAIN LOSS 5.24477
       EPOCH:
                [2/4], STEP: [2500/3081], TRAIN LOSS 5.15223
     == EPOCH:
                              [3000/3081], TRAIN LOSS 4.80683
      = EPOCH:
                [2/4], STEP:
                              [0/3081], TRAIN LOSS 5.24304
[500/3081], TRAIN LOSS 5.16729
                [3/4], STEP:
     = EPOCH:
                [3/4], STEP:
      = EPOCH:
                [3/4], STEP:
                              [1000/3081], TRAIN LOSS 5.17569
     = EPOCH:
                [3/4], STEP:
                              [1500/3081], TRAIN LOSS 4.87085
       EPOCH:
               [3/4], STEP: [2000/3081], TRAIN LOSS 5.07560 [3/4], STEP: [2500/3081], TRAIN LOSS 4.87081
       EPOCH:
     == EPOCH:
     == EPOCH: [3/4], STEP: [3000/3081], TRAIN LOSS 4.54390
Time is: 35.7539 min
save the model
```

使用1节点,避免了节点通讯的时间成本,训练全部时长为35.75min,训练完12Mtokens时长为34.05min,损失也成功收敛,低于7;

### 复现

#如果使用2节点的话需要修改master\_addr和world\_size,将master\_addr改成主节点的地址,端口随便 选一个,world\_size设置为2,sh脚本中也要将--nnodes改成2 # 主节点 sh run\_0.sh # 子节点 sh run\_1.sh

#如果使用1节点,则修改 $master\_addr$ ,其他不变

sh run\_0.sh