学习率

选择合适的学习率对于神经网络训练的成功至关重要,包括对于训练卷积神经网络(CNN)分类MNIST数据集。学习率决定了模型在每次迭代中参数更新的幅度。如果学习率过高,模型可能会在最优解附近震荡而无法收敛;如果学习率过低,训练过程可能会过于缓慢,需要更多时间才能达到满意的结果。

对于MNIST这类相对简单的数据集,初始学习率通常可以设置在0.01到0.001之间。然而,最佳学习率往往需要根据具体的模型架构,优化器选择,及其它训练参数等进行微调。

在实践中,一种常见的方法是使用学习率衰减策略,比如步长衰减、指数衰减或余弦退火等。这意味着 开始时可以设定一个较大的学习率,如0.01,然后随着训练的进行逐步降低学习率。这样可以帮助模型 在初始阶段快速收敛,而在后期更精细地调整权重。

总的来说,选择最佳学习率通常需要一些实验和调整。

• LEARNING_RATE=0.1 :

o 在复杂的网络结构中: 学习率高, 大幅震荡明显 (err与acc都在震荡), 难收敛, 效果差

```
//三层卷积层的神经网络结构
M.add_conv( 1, 5, 8, {28, 28, 1} );
M.add_relu( M.output_size() );
M.add_pool( 2, 2, M.output_size() );
M.add_conv( 1, 2, 10, M.output_size() );
M.add_relu( M.output_size() );
M.add_pool( 2, 2, M.output_size() );
M.add_conv( 1, 2, 12, M.output_size() );
M.add_relu( M.output_size() );
M.add_relu( M.output_size() );
M.add_relu( M.output_size() );
```

```
root@730aa3418e90:/ws/CNN_yxy/cnn_yxy# ./main
 start training...
 cases: 1000 err=192.172 acc=0.149
 cases: 2000 err=191.347 acc=0.204
 cases: 3000 err=191.525 acc=0.159
 cases: 4000 err=191.533 acc=0.157
 cases: 5000 err=191.389 acc=0.19
 cases: 6000 err=191.231 acc=0.19
 cases: 7000 err=193.729 acc=0.107
 cases: 8000 err=195.16 acc=0.129
 cases: 9000 err=194.792 acc=0.165
 cases: 10000 err=194.454 acc=0.21
 cases: 11000 err=194.173 acc=0.183
 cases: 12000 err=195.051 acc=0.143
 cases: 13000 err=196.271 acc=0.102
 cases: 14000 err=196.65 acc=0.112
 cases: 15000 err=196.322 acc=0.16
 cases: 16000 err=195.987 acc=0.198
 cases: 17000 err=195.731 acc=0.21
 cases: 18000 err=196.684 acc=0.086
 cases: 19000 err=197.052 acc=0.103
 cases: 20000 err=196.796 acc=0.175
 cases: 21000 err=196.54 acc=0.178
 cases: 22000 err=196.271 acc=0.223
 cases: 23000 err=196.237 acc=0.167
 cases: 24000 err=196.158 acc=0.169
 cases: 25000 err=195.913 acc=0.247
 cases: 26000 err=195.702 acc=0.305
 cases: 27000 err=195.289 acc=0.333
 cases: 28000 err=194.561 acc=0.464
 cases: 29000 err=193.611 acc=0.542
 cases: 30000 err=192.649 acc=0.576
cases: 31000 err=191.741 acc=0.578
cases: 103000 err=171.903 acc=0.583
cases: 104000 err=171.724 acc=0.688
cases: 105000 err=171.627 acc=0.59
cases: 106000 err=171.744 acc=0.397
cases: 107000 err=171.732 acc=0.504
cases: 108000 err=171.697 acc=0.522
cases: 109000 err=171.796 acc=0.382
cases: 110000 err=171.907 acc=0.341
cases: 111000 err=171.781 acc=0.632
cases: 112000 err=171.947 acc=0.281
cases: 113000 err=171.949 acc=0.503
cases: 114000 err=171.826 acc=0.629
cases: 115000 err=171.713 acc=0.632
cases: 116000 err=171.557 acc=0.67
cases: 117000 err=171.407 acc=0.68
cases: 118000 err=171.276 acc=0.629
cases: 119000 err=171.081 acc=0.714
cases: 120000 err=170.914 acc=0.683
start testing ...
testing results: acc=0.5303
```

• **在简单的网络结构中**: 学习率高,收敛速度快,训练后期出现震荡(轻度),测试集上的表现较好

```
//一层卷积层的神经网络结构
M.add_conv( 1, 5, 10, {28, 28, 1} );
M.add_relu( M.output_size() );
M.add_pool( 2, 2, M.output_size() );
M.add_fc( M.output_size(), 10 );
```

```
root@730aa3418e90:/ws/CNN yxy/cnn yxy# ./main
 start training...
 cases: 1000 err=161.118 acc=0.575
 cases: 2000 err=145.983 acc=0.85
 cases: 3000 err=137.856 acc=0.895
 cases: 4000 err=132.893 acc=0.918
 cases: 5000 err=130.062 acc=0.912
 cases: 6000 err=127.932 acc=0.919
 cases: 7000 err=126.289 acc=0.931
 cases: 8000 err=125.337 acc=0.916
 cases: 9000 err=124.711 acc=0.906
 cases: 10000 err=123.596 acc=0.95
 cases: 11000 err=122.692 acc=0.949
 cases: 12000 err=122.211 acc=0.93
 cases: 13000 err=121.724 acc=0.932
 cases: 14000 err=121.278 acc=0.938
 cases: 15000 err=120.997 acc=0.931
 cases: 16000 err=120.604 acc=0.94
 cases: 17000 err=120.107 acc=0.957
 cases: 18000 err=119.861 acc=0.93
 cases: 19000 err=119.425 acc=0.96
 cases: 20000 err=119.077 acc=0.954
cases: 21000 err=118.828 acc=0.952
cases: 109000 err=114.275 acc=0.953
cases: 110000 err=114.29 acc=0.941
cases: 111000 err=114.282 acc=0.955
cases: 112000 err=114.25 acc=0.959
cases: 113000 err=114.25 acc=0.959
cases: 114000 err=114.236 acc=0.948
cases: 115000 err=114.215 acc=0.961
cases: 116000 err=114.194 acc=0.968
cases: 117000 err=114.165 acc=0.962
cases: 118000 err=114.148 acc=0.963
cases: 119000 err=114.085 acc=0.984
cases: 120000 err=114.039 acc=0.966
start testing ...
testing results: acc=0.9516
```

• LEARNING_RATE=0.01:

。 **复杂网络 (三层卷积层)** : 没有大幅震荡, err稳步下降, 逐步收敛, 拟合效果较好, 测试集

```
root@730aa3418e90:/ws/CNN_yxy/cnn_yxy# ./main
              start training...
              cases: 1000 err=195.464 acc=0.124
              cases: 2000 err=194.228 acc=0.175
              cases: 3000 err=193.547 acc=0.188
              cases: 4000 err=193.16 acc=0.191
              cases: 5000 err=192.755 acc=0.227
              cases: 6000 err=192.516 acc=0.234
             cases: 7000 err=192.231 acc=0.263
              cases: 8000 err=191.976 acc=0.285
             cases: 9000 err=191.653 acc=0.307
             cases: 10000 err=191.199 acc=0.377
上表现更优
             cases: 11000 err=190.712 acc=0.368
              cases: 12000 err=190.065 acc=0.447
              cases: 13000 err=189.423 acc=0.424
              cases: 14000 err=188.708 acc=0.459
              cases: 15000 err=187.985 acc=0.444
              cases: 16000 err=187.144 acc=0.539
              cases: 17000 err=186.381 acc=0.516
              cases: 18000 err=185.641 acc=0.53
              cases: 19000 err=184.82 acc=0.587
              cases: 20000 err=183.962 acc=0.588
              cases: 21000 err=183.243 acc=0.578
              cases: 22000 err=182.417 acc=0.614
cases: 106000 err=156.66 acc=0.847
cases: 107000 err=156.445 acc=0.836
cases: 108000 err=156.233 acc=0.835
cases: 109000 err=155.994 acc=0.852
cases: 110000 err=155.812 acc=0.823
cases: 111000 err=155.59 acc=0.848
cases: 112000 err=155.363 acc=0.844
cases: 113000 err=155.173 acc=0.822
cases: 114000 err=154.958 acc=0.848
cases: 115000 err=154.748 acc=0.842
cases: 116000 err=154.518 acc=0.868
cases: 117000 err=154.291 acc=0.871
cases: 118000 err=154.084 acc=0.856
cases: 119000 err=153.784 acc=0.944
cases: 120000 err=153.516 acc=0.905
start testing ...
testing results: acc=0.8191
```

。 **简单网络(单层卷积层)**: 收敛速度比高学习率更慢, 拟合效果好。

```
root@730aa3418e90:/ws/CNN yxy/cnn yxy# ./main
 start training...
cases: 1000 err=180.569 acc=0.39
cases: 2000 err=168.054 acc=0.666
cases: 3000 err=159.376 acc=0.768
cases: 4000 err=153.912 acc=0.821
cases: 5000 err=150.244 acc=0.83
cases: 6000 err=147.443 acc=0.85
cases: 7000 err=145.025 acc=0.85
cases: 8000 err=143.591 acc=0.832
cases: 9000 err=142.492 acc=0.835
cases: 10000 err=140.839 acc=0.899
cases: 11000 err=139.529 acc=0.895
cases: 12000 err=138.533 acc=0.878
cases: 13000 err=137.891 acc=0.847
cases: 14000 err=137.273 acc=0.862
cases: 15000 err=136.977 acc=0.836
cases: 16000 err=136.417 acc=0.868
cases: 17000 err=135.791 acc=0.894
cases: 18000 err=135.276 acc=0.883
 cases: 19000 err=134.45 acc=0.928
cases: 20000 err=133.822 acc=0.909
cases: 110000 err=117.188 acc=0.958
cases: 111000 err=117.133 acc=0.966
cases: 112000 err=117.059 acc=0.972
cases: 113000 err=117.014 acc=0.966
cases: 114000 err=116.949 acc=0.972
cases: 115000 err=116.881 acc=0.986
cases: 116000 err=116.812 acc=0.973
cases: 117000 err=116.747 acc=0.971
cases: 118000 err=116.684 acc=0.98
cases: 119000 err=116.59 acc=0.989
cases: 120000 err=116.514 acc=0.981
 start testing ...
 testing results: acc=0.9706
```

○ 简单网络中收敛速度略慢,在几种网络中都未出现震荡,在测试集上表现都优于高学习率。

• LEARNING_RATE=0.001:

在不同网络结构种都表现为:收敛速度慢,拟合不充分。

```
root@730aa3418e90:/ws/CNN_yxy/cnn_yxy# ./main
  start training...
  cases: 1000 err=192.699 acc=0.223
  cases: 2000 err=191.819 acc=0.303
  cases: 3000 err=190.251 acc=0.402
  cases: 4000 err=188.361 acc=0.446
  cases: 5000 err=185.535 acc=0.573
  cases: 6000 err=182.621 acc=0.651
  cases: 7000 err=179.389 acc=0.715
  cases: 8000 err=176.881 acc=0.696
  cases: 9000 err=174.295 acc=0.724
  cases: 10000 err=171.564 acc=0.787
  cases: 11000 err=169.258 acc=0.782
  cases: 12000 err=167.335 acc=0.77
  cases: 13000 err=165.764 acc=0.736
  cases: 14000 err=164.332 acc=0.737
  cases: 15000 err=163.218 acc=0.725
  cases: 16000 err=161.885 acc=0.785
  cases: 17000 err=160.776 acc=0.818
  cases: 18000 err=159.729 acc=0.831
  cases: 19000 err=158.481 acc=0.882
  cases: 20000 err=157.368 acc=0.852
  cases: 21000 err=156.384 acc=0.843
  cases: 22000 err=155.332 acc=0.873
  cases: 23000 err=154.55 acc=0.838
  cases: 24000 err=153.728 acc=0.851
  cases: 25000 err=153.06 acc=0.836
  cases: 26000 err=152.271 acc=0.873
  cases: 27000 err=151.606 acc=0.861
  cases: 28000 err=150.942 acc=0.875 משפשר בני. בני. בני. שששששר מכב. שני. שני מכבים 
cases: 101000 err=134.446 acc=0.895
cases: 102000 err=134.393 acc=0.866
cases: 103000 err=134.349 acc=0.855
cases: 104000 err=134.239 acc=0.911
cases: 105000 err=134.156 acc=0.886
cases: 106000 err=134.093 acc=0.861
cases: 107000 err=134.023 acc=0.872
cases: 108000 err=133.958 acc=0.867
cases: 109000 err=133.863 acc=0.905
cases: 110000 err=133.829 acc=0.856
cases: 111000 err=133.755 acc=0.883
cases: 112000 err=133.659 acc=0.902
cases: 113000 err=133.609 acc=0.854
cases: 114000 err=133.522 acc=0.893
cases: 115000 err=133.449 acc=0.879
cases: 116000 err=133.346 acc=0.912
cases: 117000 err=133.255 acc=0.909
cases: 118000 err=133.171 acc=0.902
cases: 119000 err=133.031 acc=0.942
cases: 120000 err=132.909 acc=0.929
start testing ...
testing results: acc=0.8822
```

权重初值

在神经网络训练中,权重的初始化非常重要。合适的初始化可以帮助网络更快地收敛,并可能避免 梯度消失或爆炸的问题。

以下是一些常见的权重初始化方法:

- 1. **零初始化**:最简单的一种方法是将所有权重初始化为零。但这并不是一个好的选择,因为这会导致 所有神经元在反向传播过程中学习到相同的更新,这样的网络等同于一个单一神经元的网络。
- 2. **随机初始化**:将权重初始化为很小的随机数是常见的做法。这可以打破神经元的对称性,每个神经元可以学习到不同的特征。常见的随机初始化方法有均匀分布和正态分布,通常数值范围设定在-0.01到0.01之间。
- 3. **Glorot/Xavier 初始化**: 这种方法由 Xavier Glorot 和 Yoshua Bengio 提出,它的基本思想是保持输入和输出的方差一致。对于tanh等饱和型激活函数,这种初始化方法效果较好。

4. **He 初始化**: He初始化由Kaiming He等人提出,适用于ReLU及其变种的激活函数。与Xavier初始化不同,He初始化在计算权重初始值时考虑了ReLU的非线性特性。

这些初始化策略在许多深度学习框架中,如TensorFlow和PyTorch,都有内置实现。最终选择哪种初始化方法,取决于具体模型和激活函数的选择。

最后,偏置通常可以初始化为零,这并不会带来和权重全零初始化相同的问题,因为偏置并不会参与到层间的相互作用中。

```
//卷积核的初始化
for ( int i = 0; i < extend_filter; i++ )
    for ( int j = 0; j < extend_filter; j++ )
        for ( int z = 0; z < in_size.z; z++ )
            neww( i, j, z ) = 1.0f / N * rand() / 2147483647.0;
```

N 为上一层的神经元数量, 2147483647.0 是能 rand() 出来的最大值。

这个初始化方法的基本思路是为每个权重分配一个在0到 1.0 f / N 之间的随机数,其中 N 是输入神经元的数量。这是一个简单的标准化或者说缩放策略,让初始权重的大小与输入神经元的数量成反比。

rand() / 2147483647.0 产生了一个在[0,1]范围内的均匀分布的随机数,然后将这个随机数乘以 1.0f / N 得到最终的初始权重。这个方法的目标是使所有权重的初始值都较小,且均匀分布。

这种初始化策略与Xavier/Glorot初始化有一些相似之处,Xavier/Glorot初始化也是根据输入神经元的数量调整权重的初始值。但在Xavier/Glorot初始化中,权重的初始值是从一个更复杂的分布中抽取的,目的是使得每个神经元的输出都具有相同的方差。