

DL4j学习率衰减策略

```
1. package org.deeplearning4j.nn.conf;
2.
3. /**
4.  * Learning Rate Policy
5.  *
6.  * How to decay learning rate during training.
7.  *
8.  * <p><b>None</b> = do not apply decay policy aka fixed in Caffe <br>
9.  * <p><b>Exponential</b> = applies decay rate to the power of the # batches <br>
10.  * <p><b>Inverse</b> = divide learning rate by negative (1 + decay rate
11.  * # batches)^power <br>
12.  * <p><b>Poly</b> = polynomial decay that hits 0 when iterations are complete <br>
13.  * <p><b>Sigmoid</b> = sigmoid decay rate <br>
14.  * <p><b>Step</b> = decay rate to the power of the floor (nearest integer) of # of batches by # of steps <br>
15.  * <p><b>Schedule</b> = rate to use at a specific iteration <br>
16.  * <p><b>Score</b> = apply decay when score stops improving <br>
17.  */
18. // TODO provide options using epochs in addition to iterations
19.
20. public enum LearningRatePolicy {
21.     None, Exponential, Inverse, Poly, Sigmoid, Step, TorchStep, Schedule,
22.     Score
23. }
```

dl4j的学习率衰减策略应用部分是在反向传播计算完地图之后，调用Updater.update()方法对梯度进行更新并且进行梯度的衰减。

调用学习率衰减的为 `package org.deeplearning4j.optimize.solvers` 包下

的 `BaseOptimizer` 抽象类中

的 `updateGradientAccordingToParams(Gradient gradient, Model model, int batchSize)` 方法中的 `updater.update(layer, gradient, getIterationCount(model), batchSize);` 语句。

- 后面衰减策略所使用的iteration为Model的总迭代次数
- 衰减率由 `NeuralNetConfiguration.Builder()` 的 `lrPolicyDecayRate()` 方法进行配置，衰减率通常为0~1中间的一个值。

Exponential

```
1. newLr = lr * Math.pow(decayRate, iteration);
```

$$newLr = lr \times decayRate^{iteration}$$

Inverse

```
1. newLr = lr / Math.pow((1 + decayRate * iteration), conf.getLrPolicyPower());
```

$$newLr = \frac{lr}{1 + (decayRate \times iteration)^{conf.getLrPolicyPower()}}$$

注：LrPolicyPower由用户自定义设置。默认值为0。

Step

```
1. newLr = lr * Math.pow(decayRate, Math.floor(iteration / conf.getLrPolicySteps()));
```

$$newLr = lr \times decayRate^{\lfloor \frac{iteration}{conf.getLrPolicySteps()} \rfloor}$$

注：LrPolicySteps 由用户自定义，默认值为0。

TorchStep

```
1. //当模型的总迭代次数>1次且设置的lrPolicySteps 正好是当前总迭代次数的倍数的时候调用
2. if (iteration > 1 && conf.getLrPolicySteps() % iteration == 0) {
```

```

3.     newLr = lr * decayRate;
4. } else {
5.     newLr = lr;
6. }

```

$$newLr = lr \times decayRate$$

Poly

```

1. newLr = lr * Math.pow((1 - ((double) iteration) / conf.getNumIterations()
), conf.getLrPolicyPower());

```

$$newLr = lr * \left(1 - \frac{iteration}{conf.getNumIterations()}\right)^{conf.getLrPolicyPower()}$$

注：conf.getNumIterations()，是对于每一个miniBatch的数据中的迭代次数。

Sigmoid

```

1. newLr = lr / (1 + Math.exp(-decayRate * (iteration -
conf.getLrPolicySteps())));

```

$$newLr = \frac{lr}{1 + e^{-decayRate \times (iteration - conf.getLrPolicySteps())}}$$

Schedule

```

1. if (baseLayer.getLearningRateSchedule().containsKey(iteration)) {
2.     newLr = baseLayer.getLearningRateSchedule().get(iteration);
3. } else {
4.     newLr = lr;
5. }

```

根据前面设置的Schedule来更改对应的学习率，例如设置的Schedule为：

```

1. // Map为<iterations, learningRate>的key-value对

```

```

2.  Map<Integer, Double> schedule = new HashMap<>();
3.  schedule.put(200, 0.01);
4.  schedule.put(60000, 0.001);
5.  schedule.put(80000, 0.0001);

```

就是在模型迭代第200次的时候，学习率变更为0.01；在第60000次的时候变更为0.001...依次类推

Score

Score的触发条件和前面几个都不一样，触发的代码为：

```

1.  @Override
2.  public boolean checkTerminalConditions(INDArray gradient, double
   oldScore, double score, int i) {
3.      for (TerminationCondition condition : terminationConditions) {
4.          //log.info("terminations: {}", condition);
5.          if (condition.terminate(score, oldScore, new Object[] {gradient})
   ) {
6.              log.debug("Hit termination condition on iteration {}: score={
   }, oldScore={}, condition={}", i, score,
7.                  oldScore, condition);
8.
9.              //触发EpsTermination, 且当前网络层不为空且衰减策略为Score的时候调用
10.             if (condition instanceof EpsTermination && conf.getLayer() !=
   null
11.                 && conf.getLearningRatePolicy() == LearningRateP
   olicy.Score) {
12.                 model.applyLearningRateScoreDecay();
13.             }
14.             return true;
15.         }
16.     }
17.     return false;
18. }

```

其中策略的实现方式基本为：

```

1.  @Override
2.  public void applyLearningRateScoreDecay() {
3.      for (Map.Entry<String, Double> lrPair : conf.getLearningRateByParam())

```

```
        .entrySet())
4.         conf.setLearningRateByParam(lrPair.getKey(),
5.                                     lrPair.getValue() * (conf.getLrPolicyDecayRate() +
Nd4j.EPS_THRESHOLD));
6.     }
```

$newLr = lr \times (conf.getLrPolicyDecayRate() + Nd4j.EPS_THRESHOLD)$

注：

1. Nd4j.EPS_THRESHOLD的默认值为 $1e^{-5}$
2. 使用这个策略的时候，网络模型损失函数得分容易进入 `ZeroDirectionTermination` 使得模型学习率不再衰减，使得模型停止更新。

更多文档可以查看 <https://github.com/sjsdfg/deeplearning4j-issues>。

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