在我的上一篇里我写的那个只是个人对KMeans聚类在这个项目中的一部分,今天花了很长时间写完和完整的运行测试完这个代码,篇幅很长,都是结合写的加上自己完善的异常检测部分,废话不多说,直接代码实战:

```
package internet
import org.apache.spark.mllib.clustering.{KMeansModel, KMeans}
import org.apache.spark.mllib.linalg.{Vectors, Vector}
import org.apache.spark.rdd.RDD
import org.apache.spark.{SparkContext, SparkConf}
/**
  * Created by 汪本成 on 2016/7/24.
object CheckAll {
 def main(args: Array[String]) {
   //创建入口对象
   val conf = new SparkConf().setAppName("CheckAll").setMaster("local")
   val sc= new SparkContext(conf)
   val HDFS DATA PATH = "hdfs://node1:9000/user/spark/sparkLearning/cluster/kddcup.data"
   val rawData = sc.textFile(HDFS_DATA_PATH)
   /** 分类统计样本, 降序排序 **/
     clusteringTake1(rawData)
   /** 评价k值 **/
     clusteringTake2(rawData)
//
     clusteringTake3(rawData)
    clusteringTake4(rawData)
//
//
    clusteringTake5(rawData)
   /** R数据可视化 **/
   /** 异常检测 **/
   var beg = System.currentTimeMillis()
   anomalies(rawData)
   var end = System.currentTimeMillis()
   println("用时: " + (end - beg) / 1000 + "s")
  }
  //Clustering, Task1
 def clusteringTake1(rawData: RDD[String]) = {
   //分类统计样本个数,降序排序
   rawData.map(_.split(",").last).countByValue().toSeq.sortBy(_._2).reverse.foreach(println)
   val labelsAndData = rawData.map {
     line =>
       //将csv格式的行拆分成列,创建一个buffer,是一个可变列表
      val buffer = line.split(",").toBuffer
       //删除下标从1开始的三个类别型列
      buffer.remove(1, 3)
       //删除下标最后的标号列
       val label = buffer.remove(buffer.length - 1)
       //保留其他值并将其转换成一个数值型(Double型对象)数组
       val vector = Vectors.dense(buffer.map( .toDouble).toArray)
       //将数组和标号组成一个元祖
       (label, vector)
    }
```

```
* 为啥要进行LabeLsAndData => data转化?
   * 1、k均值在运行过程中只用到特征向量(即没有用到数据集的目标标号列)
   * 2、使data这个RDD只包含元祖的只包含元组的第二个元素
   * 3、实现2可以通过元组类型RDD的values属性得到,在放入缓存中,减少落地
   */
 //提取出元组的特征向量
 val data = labelsAndData.values.cache()
 //实例化Kmeans类对象
 val kmeans = new KMeans()
 //建立KMeansModel
 val model = kmeans.run(data)
 //输出每个簇的质心
 model.clusterCenters.foreach(println)
 val clusterLabelCount = labelsAndData.map {
   case (label, datum) =>
     //预测样本datum的分类cluster
     val cluster = model.predict(datum)
     //返回类别-簇的元组
    (cluster, label)
 }.countByValue()
 //对簇-类别对分别进行计数,并以可读方式输出
 clusterLabelCount.toSeq.sorted.foreach {
   case ((cluster, label), count) =>
     println(f"$cluster%1s$label%18s$count%8s")
 data.unpersist()
}
/**
  * 欧氏距离公式
 * a.toArray.zip(b.toArray)对应 "两个向量相应元素"
  * map(p => p._1 - p._2)对应 "差"
  * map(d => d*d).sum对应 "平方和"
  * math.sqrt()对应 "平方根"
  * @param a
  * @param b
  * @return
def distance(a: Vector, b: Vector) =
 math.sqrt(a.toArray.zip(b.toArray).map(p => p._1 - p._2).map(d => d * d).sum)
  * 欧氏距离公式应用到model中
 * KMeansModeL.predict方法中调用了KMeans对象的findCloest方法
 * @param datum
  * @param model
  * @return
def distToCenter(datum: Vector, model: KMeansModel) = {
 //预测样本datum的分类cluster
 val cluster = model.predict(datum)
 //计算质心
 val center = model.clusterCenters(cluster)
  //应用距离公式
```

```
distance(center, datum)
}
  * 平均质心距离
 * @param data
  * @param k
  * @return
def clusteringScore(data: RDD[Vector], k: Int): Double = {
 val kmeans = new KMeans()
 //设置k值
 kmeans.setK(k)
 //建立KMeansModel
 val model = kmeans.run(data)
 //计算k值model平均质心距离, mean()是平均函数
 data.map(datum => distToCenter(datum, model)).mean()
}
  * 平均质心距离优化
 * @param data
  * @param k
  * @param run 运行次数
 * @param epsilon 阈值
 * @return
def clusteringScore2(data: RDD[Vector], k: Int, run: Int, epsilon: Double): Double = {
 val kmeans = new KMeans()
  kmeans.setK(k)
 //设置k的运行次数
 kmeans.setRuns(run)
 //设置阈值
 kmeans.setEpsilon(epsilon)
 val model = kmeans.run(data)
 data.map(datum => distToCenter(datum, model)).mean()
}
//Clustering, Take2
def clusteringTake2(rawData: RDD[String]): Unit ={
 val data = rawData.map {
   line =>
     val buffer = line.split(",").toBuffer
     buffer.remove(1, 3)
     buffer.remove(buffer.length - 1)
     Vectors.dense(buffer.map( .toDouble).toArray)
  }.cache()
 val run = 10
 val epsilon = 1.0e-4
  //在(5,30)区间内以5为等差数列数值不同k值对其评分
 (5 to 30 by 5).map(k => (k, clusteringScore(data, k))).foreach(println)
 //在(20,120)区间内以10为等差数列数值不同k值对其评分
 (30 to 100 by 10).par.map(k => (k, clusteringScore2(data, k, run, epsilon))).foreach(println)
  data.unpersist()
}
```

```
* 加工出R可视化数据存入HDFS中
  * @param rawData
  * @param k
  * @param run
  * @param epsilon
def visualizationInR(rawData: RDD[String], k: Int, run: Int, epsilon: Double): Unit ={
  val data = rawData.map {
     val buffer = line.split(",").toBuffer
     buffer.remove(1, 3)
     buffer.remove(buffer.length - 1)
     Vectors.dense(buffer.map(_.toDouble).toArray)
  }.cache()
  val kmeans = new KMeans()
  kmeans.setK(k)
  kmeans.setRuns(run)
  kmeans.setEpsilon(epsilon)
  val model = kmeans.run(data)
  val sample = data.map(
    datum =>
      model.predict(datum) + "," + datum.toArray.mkString(",")
  ).sample(false, 0.05) //选择了5%行
 sample.saveAsTextFile("hdfs://nodel:9000/user/spark/R/sample")
  data.unpersist()
}
/**
  * @param data
  * @return
def buildNormalizationFunction(data: RDD[Vector]): (Vector => Vector) = {
  //将数组缓冲为Array
  val dataAsArray = data.map(_.toArray)
  //数据集第一个元素的长度
 val numCols = dataAsArray.first().length
  //返回数据集的元素个数
 val n = dataAsArray.count()
  //两个数组对应元素相加求和
 val sums = dataAsArray.reduce((a, b) \Rightarrow a.zip(b).map(t \Rightarrow t. 1 + t. 2))
  //将RDD聚合后进行求平方和操作
 val sumSquares = dataAsArray.aggregate(new Array[Double](numCols))(
    (a, b) \Rightarrow a.zip(b).map(t \Rightarrow t._1 + t._2 * t._2),
   (a, b) \Rightarrow a.zip(b).map(t \Rightarrow t._1 + t._2)
  /** zip函数将传进来的两个参数中相应位置上的元素组成一个pair数组。
   * 如果其中一个参数元素比较长,那么多余的参数会被删掉。
   * 个人理解就是让两个数组里面的元素——对应进行某些操作
   */
  val stdevs = sumSquares.zip(sums).map {
    case (sumSq, sum) => math.sqrt(n * sumSq - sum * sum) / n
```

```
}
 val means = sums.map( / n)
  (datum : Vector) => {
    val normalizedArray = (datum.toArray, means, stdevs).zipped.map(
      (value, mean, stdev) =>
        if(stdev <= 0) (value- mean) else (value - mean) /stdev</pre>
   Vectors.dense(normalizedArray)
 }
}
//clustering, Task3
def clusteringTake3(rawData: RDD[String]): Unit ={
 val data = rawData.map { line =>
    val buffer = line.split(',').toBuffer
   buffer.remove(1, 3)
   buffer.remove(buffer.length - 1)
   Vectors.dense(buffer.map( .toDouble).toArray)
 val run = 10
 val epsilon = 1.0e-4
 val normalizedData = data.map(buildNormalizationFunction(data)).cache()
  (60 to 120 by 10).par.map(
   k => (k, clusteringScore2(normalizedData, k, run, epsilon))
  ).toList.foreach(println)
 normalizedData.unpersist()
}
/**
  * 基于one-hot编码实现类别型变量替换逻辑
 * @param rawData
  * @return
def buildCategoricalAndLabelFunction(rawData: RDD[String]): (String => (String, Vector)) = {
 val splitData = rawData.map(_.split(","))
 //建立三个特征
 val protocols = splitData.map(_(1)).distinct().collect().zipWithIndex.toMap //特征值是1,0,0
 val services = splitData.map(_(2)).distinct().collect().zipWithIndex.toMap
                                                                              //特征值是0,1,0
 val tcpStates = splitData.map(_(3)).distinct().collect().zipWithIndex.toMap
                                                                              //特征值是0,0,1
 //
  (line: String) => {
   val buffer = line.split(",").toBuffer
   val protocol = buffer.remove(1)
   val service = buffer.remove(1)
   val tcpState = buffer.remove(1)
   val label = buffer.remove(buffer.length - 1)
   val vector = buffer.map( .toDouble)
   val newProtocolFeatures = new Array[Double](protocols.size)
    newProtocolFeatures(protocols(protocol)) = 1.0
    val newServiceFeatures = new Array[Double](services.size)
    newServiceFeatures(services(service)) = 1.0
```

```
val newTcpStateFeatures = new Array[Double](tcpStates.size)
    newTcpStateFeatures(tcpStates(tcpState)) = 1.0
   vector.insertAll(1, newTcpStateFeatures)
   vector.insertAll(1, newServiceFeatures)
   vector.insertAll(1, newProtocolFeatures)
    (label, Vectors.dense(vector.toArray))
 }
}
//Clustering, Task4
def clusteringTake4(rawData: RDD[String]): Unit ={
 val paraseFunction = buildCategoricalAndLabelFunction(rawData)
 val data = rawData.map(paraseFunction).values
 val normalizedData = data.map(buildNormalizationFunction(data)).cache()
 val run = 10
 val epsilon = 1.0e-4
  (80 to 160 by 10).map(
   k=> (k, clusteringScore2(normalizedData, k, run, epsilon))
  ).toList.foreach(println)
 normalizedData.unpersist()
}
//Clustering, Task5
  * 对各个簇的熵加权平均,将结果作为聚类得分
 * @param counts
  * @return
def entropy(counts: Iterable[Int]) = {
 val values = counts.filter( > 0)
 val n: Double = values.sum
  values.map {
   v =>
     val p = v / n
     -p * math.log(p)
  }.sum
}
  * 计算熵的加权平均
 * @param normalizedLabelsAndData
  * @param k
  * @param run
  * @param epsilon
  * @return
def clusteringScore3(normalizedLabelsAndData: RDD[(String, Vector)], k: Int, run: Int, epsilon: Double) =
 val kmeans = new KMeans()
  kmeans.setK(k)
  kmeans.setRuns(run)
  kmeans.setEpsilon(epsilon)
```

```
//建立KMeansModel
   val model = kmeans.run(normalizedLabelsAndData.values)
   //对每个数据集预测簇类别
   val labelAndClusters = normalizedLabelsAndData.mapValues(model.predict)
   //将RDD[(String, Vector)] => RDD[(String, Vector)],即swap Keys / Values,对换键和值
   val clustersAndLabels = labelAndClusters.map(_.swap)
   //按簇提取标号集合
   val labelsInCluster = clustersAndLabels.groupByKey().values
   //计算所有集合中有多少标签(label),即标号的出现次数
   val labelCounts = labelsInCluster.map(_.groupBy(1 => 1).map(_._2.size))
   //通过类别大小来反映平均信息量,即熵
   val n = normalizedLabelsAndData.count()
   //根据簇大小计算熵的加权平均
   labelCounts.map(m => m.sum * entropy(m)).sum() / n
 }
 def clusteringTake5(rawData: RDD[String]): Unit ={
   val parseFunction = buildCategoricalAndLabelFunction(rawData)
   val labelAndData = rawData.map(parseFunction)
   val normalizedLabelsAndData = labelAndData.mapValues(buildNormalizationFunction(labelAndData.values)).ca
()
   val run = 10
   val epsilon = 1.0e-4
   (80 to 160 by 10).map(
     k => (k, clusteringScore3(normalizedLabelsAndData, k, run, epsilon))
   ).toList.foreach(println)
   normalizedLabelsAndData.unpersist()
 }
 //Detect anomalies(发现异常)
 def bulidAnomalyDetector(data: RDD[Vector], normalizeFunction: (Vector => Vector)): (Vector => Boolean) =
   val normalizedData = data.map(normalizeFunction)
   normalizedData.cache()
   val kmeans = new KMeans()
   kmeans.setK(150)
   kmeans.setRuns(10)
   kmeans.setEpsilon(1.0e-6)
   val model = kmeans.run(normalizedData)
   normalizedData.unpersist()
   //度量新数据点到最近簇质心的距离
   val distances = normalizedData.map(datum => distToCenter(datum, model))
   //设置阀值为已知数据中离中心点最远的第100个点到中心的距离
   val threshold = distances.top(100).last
   //检测, 若超过该阀值就为异常点
   (datum: Vector) => distToCenter(normalizeFunction(datum), model) > threshold
```

```
* 异常检测
        * @param rawData
    def anomalies(rawData: RDD[String]) = {
        val parseFunction = buildCategoricalAndLabelFunction(rawData)
        val originalAndData = rawData.map(line => (line, parseFunction(line). 2))
        val data = originalAndData.values
        val normalizeFunction = buildNormalizationFunction(data)
        val anomalyDetector = bulidAnomalyDetector(data, normalizeFunction)
        val anomalies = originalAndData.filter {
            case (original, datum) => anomalyDetector(datum)
        }.keys
        //取10个异常点打印出来
        anomalies.take(10).foreach(println)
    }
写的有点杂,但是全部自己封装好了。运行起来也没问题,仅供大家参考学习,多多关注下我写的注释就好。
累死我了,或许是我电脑不行缘故,计算这1G数据花了这么长时间,现在我把异常检测部分运行结果给大家看看好了
16/07/24 22:48:18 INFO Executor: Running task 0.0 in stage 65.0 (TID 385)
16/07/24 22:48:18 INFO HadoopRDD: Input split: hdfs://node1:9000/user/spark/sparkLearning/cluster/kddcup.data:0+134217728
16/07/24 22:48:30 INFO Executor: Finished task 0.0 in stage 65.0 (TID 385). 3611 bytes result sent to driver
16/07/24 22:48:30 INFO TaskSetManager: Finished task 0.0 in stage 65.0 (TID 385) in 11049 ms on localhost (1/1)
16/07/24 22:48:30 INFO TaskSchedulerImpl: Removed TaskSet 65.0, whose tasks have all completed, from pool
16/07/24 22:48:30 INFO DAGScheduler: ResultStage 65 (take at CheckAll.scala:413) finished in 11.049 s
16/07/24 22:48:30 INFO DAGScheduler: Job 41 finished: take at CheckAll.scala:413, took 11.052917 s
0, tcp, http, S1, 299, 26280, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 15, 16, 0.07, 0.06, 0.00, 0.00, 1.00, 0.00, 0.01, 2.231, 255, 1.00, 0.00, 0.00, 0.01, 0.01, 0.01, 0.00, 0.00, nor 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1
13, tcp, telnet, SF, 246, 11938, 0, 0, 0, 0, 4, 1, 0, 0, 0, 0, 2, 0, 0, 0, 0, 1, 1, 0.00, 0.00, 0.00, 0.00, 1.00, 0.00, 0.00, 89, 2, 0.02, 0.04, 0.01, 0.00, 0.00, 0.00, 0.00, 0.00, normal and the second 
12249,tcp,telnet,SF,3043,44466,0,0,0,1,0,1,13,1,0,0,12,0,0,0,0,0,1,1,0.00,0.00,0.00,1.00,0.00,0.00,0.00,61,8,0.13,0.05,0.02,0.00,0.00,0.00,0.00
用时: 4602s
16/07/24 22:48:30 INFO SparkContext: Invoking stop() from shutdown hook
16/07/24 22:48:30 INFO SparkUI: Stopped Spark web UI at http://192.168.1.102:4040
16/07/24 22:48:30 INFO MapOutputTrackerMasterEndpoint: MapOutputTrackerMasterEndpoint stopped!
16/07/24 22:48:30 INFO MemoryStore: MemoryStore cleared
16/07/24 22:48:30 INFO BlockManager: BlockManager stopped
16/07/24 22:48:30 INFO BlockManagerMaster: BlockManagerMaster stopped
16/07/24 22:48:30 INFO OutputCommitCoordinator$OutputCommitCoordinatorEndpoint: OutputCommitCoordinator stopped!
16/07/24 22:48:30 INFO SparkContext: Successfully stopped SparkContext
16/07/24 22:48:30 INFO ShutdownHookManager: Shutdown hook called
16/07/24 22:48:30 INFO ShutdownHookManager: Deleting directory C:\Users\Administrator\AppData\Local\Temp\spark-1ab0ec11-672d-47
9ae8-2050f44a5f91
16/07/24 22:48:30 INFO RemoteActorRefProvider$RemotingTerminator: Shutting down remote daemon.
16/07/24 22:48:30 INFO RemoteActorRefProvider$RemotingTerminator: Remote daemon shut down; proceeding with flushing remote trans
```

Process finished with exit code 0