大数据管理技术 第五次上机

林汇平 1800013104

项目链接：https://github.com/phoenixrain-pku/BigDataSummer

- 实习要求：根据Spark安装指导安装Spark。完成如下任务：
  1. Spark RDD：对给出的莎士比亚文集Shakespere.txt进行wordcount（注：文件中包含特殊字符，请先进行过滤操作仅留下英文字符）
  2. Spark SQL： 在tmdb数据上实现的两个实用的查询功能。
  3. Spark MLlib: 使用TitanicTrainTest.zip中的训练集训练一个分类模型(比如决策树)，并且给出在测试集上的正确率。
  4. 用GraphX再次实现PageRank。
- 报告内容：请在报告中写明技术方法及实验结果，必要时附上相应的代码段或截图。
- 实习环境：

  Linux环境：

  虚拟机：Ubuntu 15.1.0 build-13591040

  主机操作系统：Windows 10, 64-bit (Build 17134) 10.0.17134

  内存：4GB

  硬盘：20GB

  CPU：Intel(R) Core(TM) i7-8550U CPU @ 1.80GHz(1992 MHz)

---

1. Spark RDD：对给出的莎士比亚文集Shakespere.txt进行wordcount。

   实习成果展示：

   - 下载并安装Spark：

```
wget https://mirrors.tuna.tsinghua.edu.cn/apache/spark/spark-2.3.3/spark-2.3.3-bin-hadoop2.7.tgz
sudo mkdir /usr/local/spark
sudo tar zxf spark-2.3.3-bin-hadoop2.7.tgz -C /usr/local/spark
sudo chmod -R 755 /usr/local/spark/spark-2.3.3-bin-hadoop2.7
sudo chown -R phoenix /usr/local/spark/spark-2.3.3-bin-hadoop2.7
```

   - 配置Spark：

```
cd /usr/local/spark/spark-2.3.3-bin-hadoop2.7
cp ./conf/spark-env.sh.template ./conf/spark-env.sh
gedit ./conf/spark-env.sh
```

   - 安装、配置成功，开启交互模式：

```
./bin/spark-shell
```

   运行成功可以看到下图，进入了Scala交互界面。

```
mmon/lib/slf4j-log4j12-1.7.10.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
20/07/31 10:44:59 WARN util.NativeCodeLoader: Unable to load native-hadoop libra
ry for your platform... using builtin-java classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLeve
l(newLevel).
Spark context Web UI available at http://Master:4040
Spark context available as 'sc' (master = local[*], app id = local-1596163507435
).
Spark session available as 'spark'.
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 3.0.0
      /_/

Using Scala version 2.12.10 (OpenJDK 64-Bit Server VM, Java 1.8.0_252)
Type in expressions to have them evaluated.
Type :help for more information.

scala> 
```

- 导入数据集，可以在hdfs中导入、再导入Spark，也可以直接从本地导入Spark，具体如下：
  - 从hdfs中导入：

```
phoenix@Master:~/桌面/home/spark-3.0.0-bin-hadoop2.7$ hdfs dfs -mkdir -p /
spark/datasrc/
phoenix@Master:~/桌面/home/spark-3.0.0-bin-hadoop2.7$ hdfs dfs -put /home/
phoenix/桌面/Shakespeare /spark/datasrc
20/07/31 10:49:34 WARN hdfs.DFSClient: DataStreamer Exception
org.apache.hadoop.ipc.RemoteException(java.io.IOException): File /spark/da
tasrc/Shakespeare._COPYING_ could only be replicated to 0 nodes instead of
 minReplication (=1).  There are 0 datanode(s) running and no node(s) are
excluded in this operation.
        at org.apache.hadoop.hdfs.server.blockmanagement.BlockManager.choo
seTarget4NewBlock(BlockManager.java:1620)
        at org.apache.hadoop.hdfs.server.namenode.FSNamesystem.getNewBlock
Targets(FSNamesystem.java:3135)
        at org.apache.hadoop.hdfs.server.namenode.FSNamesystem.getAddition
alBlock(FSNamesystem.java:3059)
        at org.apache.hadoop.hdfs.server.namenode.NameNodeRpcServer.addBlo
ck(NameNodeRpcServer.java:725)
        at org.apache.hadoop.hdfs.protocolPB.ClientNamenodeProtocolServerS
ideTranslatorPB.addBlock(ClientNamenodeProtocolServerSideTranslatorPB.java
:493)
        at org.apache.hadoop.hdfs.protocol.proto.ClientNamenodeProtocolPro
tos$ClientNamenodeProtocol$2.callBlockingMethod(ClientNamenodeProtocolProt
os.java)
        at org.apache.hadoop.ipc.ProtobufRpcEngine$Server$ProtoBufRpcInvok
er.call(ProtobufRpcEngine.java:616)
        at org.apache.hadoop.ipc.RPC$Server.call(RPC.java:982)
        at org.apache.hadoop.ipc.Server$Handler$1.run(Server.java:2217)
        at org.apache.hadoop.ipc.Server$Handler$1.run(Server.java:2213)
```

  通过hdfs的-ls命令可以看到数据集成功导入：

```
phoenix@Master:~/桌面/home/spark-3.0.0-bin-hadoop2.7$ hdfs dfs -ls /spark
Found 1 items
drwxr-xr-x   - phoenix supergroup          0 2020-07-31 10:49 /spark/datasrc
```

  - 从本地导入：

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 3.0.0
      /_/

Using Scala version 2.12.10 (OpenJDK 64-Bit Server VM, Java 1.8.0_252)
Type in expressions to have them evaluated.
Type :help for more information.

scala> val lines = sc.textFile("file:///home/phoenix/桌面/Shakespeare")
lines: org.apache.spark.rdd.RDD[String] = file:///home/phoenix/桌面/Shakespeare
MapPartitionsRDD[1] at textFile at <console>:24

scala> lines.first()
res0: String = "The Complete Works of William Shakespeare "

scala>
```

可以通过scala交互中的lines.first()语句取出文件的第一行，看到我们已经正确读取了文件内容。

- 完成wordcount：

  实习要求我们不但完成wordcount，且要先进行过滤操作仅留下英文字符。因此这个wordcount的任务实际上是需要两步来完成：1. 实现拆分（split） 2. 实现过滤（filter）。拆分可以使用split函数，非常方便；而过滤掉所有非英文字符可以通过正则表达式来实现。

  因此这里我使用的命令为：

```scala
val lines = sc.textFile("file:///home/phoenix/桌面/Shakespeare")
val wordCount = lines
    .flatMap(line => line.split(" "))
    .map(word => (word.replaceAll("[^a-zA-Z]", ""),1))
    .reduceByKey((a, b) => a + b)
wordCount.collect()
wordCount.foreach(println)
```

  其中，`line.split`函数是为了按照空格拆分单词，`word.replaceAll`是为了过滤掉非英文字符，即使用正则表达式对特殊字符进行替换。`reduceByKey`的作用对像是(key, value)形式的rdd，其作用是对相同key的数据进行处理，最终每个key只保留一条记录。

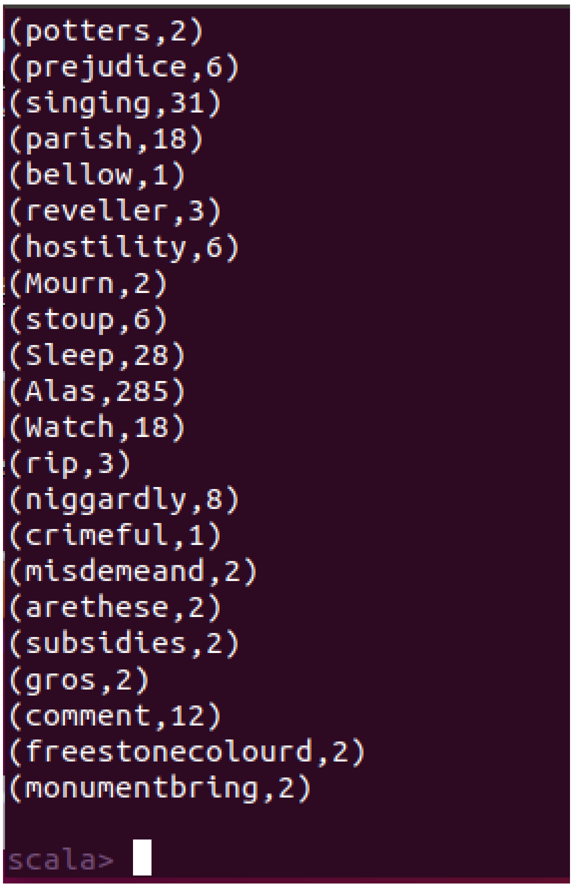
  最终输出wordCount结果。

  运行结果如下：

```
scala> val wordCount = lines .flatMap(line => line.split(" ")) .map(word => (wor
d.replaceAll("[^a-zA-Z]", ""),1)) .reduceByKey((a, b) => a + b)
wordCount: org.apache.spark.rdd.RDD[(String, Int)] = ShuffledRDD[4] at reduceByK
ey at <console>:25

scala> wordCount.collect()
res1: Array[(String, Int)] = Array((pinnace,6), (bone,20), (lug,2), (vailing,2),
 (bombast,5), (Thrive,1), (Mantua,36), (halfchequed,2), (gaping,17), (Rancour,2)
, (hellkite,1), (eer,147), (ravencolourd,1), (hem,12), (suppd,6), (stinks,2), (f
orsooth,79), (been,1241), (demiparadise,2), (fuller,2), (Friend,18), (pig,13), (
countervail,3), (crying,47), (Sought,3), (Corivalld,2), (breath,352), (dumbdisco
ursive,2), (battering,4), (continuantly,2), (contemptible,4), (swain,44), (clien
ts,4), (OLIVIA,254), (fowl,23), (jade,19), (afterward,16), (andirons,2), (accomp
lished,12), (Theyll,28), (unfelt,5), (supporter,4), (Herefords,14), (overkind,2)
, (inquisition,4), (stern,48), (lightens,9), (Abates,2), (espoused,5), (sheepwhi
stling,2), (tush,11), (manwhateer,2), (burghers,4),...
```

  使用`wordCount.foreach(println)`将词频统计结果输出到屏幕，以下为部分结果展示：



2. Spark SQL： 在tmdb数据上实现的两个实用的查询功能。

实习成果展示:

- 对数据预处理：由于`tmdb_5000_movies.csv`文件中有大量数据与多余字段，如homepage、overview等，只是对电影本身的描述，和我们做数据分析无关。因此在统计前，我们删去部分字段。这项操作在excel里就可以完成，非常方便。在本次任务中，我们只保留了original_title, revenue, vote_average, production_companies 这四列。
- 利用 Spark SQL 可以快速实现在电影数据集上的过滤、筛选、分组求和：此处我继续使用python撰写脚本对数据进行处理。

  我想完成的查询任务为：1. 统计6.5分以上的高分电影 2. 统计收入排名前10的电影制作公司。因此我首先需要对数据做以下处理:

  - `df_filter=df.filter(df['production_companies']!='[]')`语句将出品公司为空的电影过滤掉；
  - `explode(split("production_companies", ","))`语句针对一个电影有多个出品公司的情况，将出品公司按逗号拆分成多行；
  - `df_res=df_where.groupBy('production_companies_tmp').agg({"revenue":"sum"}).withColumnRenamed("sum(revenue)","sum_revenue").orderBy(F.desc('sum_revenue'))`语句按照出品公司分组求和并降序排列。

  最终的python代码如下:

```
import org.apache.spark.sql.SparkSession
import spark.implicits._

import sys
sys.path.append("/home/phoenix/桌面/home/spark-3.0.0-bin-hadoop2.7/python")

import pyspark
spark = pyspark.sql.SparkSession.builder.appName("SimpleApp").getOrCreate()
sc = spark.sparkContext

```

```python
df = spark.read.csv('tmdb_5000_movies.csv', inferSchema = True, header = True)
df.printSchema()

df_filter = df.filter(df['production_companies']!='[]')
#出版公司为空的电影

df_whith=df_filter.withColumn('production_companies_tmp', explode(split("production_companies", ",")))
df_whith.select('production_companies_tmp').show(10)
#将出版公司拆为逗号分隔

df_where = df_whith.where(F.col("vote_average")>'6.5')
df_where.printSchema()
#筛选出6.5分以上电影

df_res = df_where.groupBy('production_companies_tmp').agg({"revenue":"sum"}).withColumnRenamed("sum(revenue)","sum_revenue").orderBy(F.desc('sum_revenue'))


df_res.show(10)
```

- 在Spark上运行python脚本：

```
phoenix@Master:~/task$ python3 edit.py
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/phoenix/%e6%a1%8c%e9%9d%a2/home/spark-3.0.0-bin-hadoop2.7/jars/slf4j-log4j12-1.7.30.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/local/hadoop/hadoop-2.7.7/share/hadoop/common/lib/slf4j-log4j12-1.7.10.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
20/07/31 15:01:05 WARN util.NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
```

- 运行结果：
  - 6.5分以上的高分电影展示：

```
+--------------------+----------+------------+
|      original_title|   revenue|vote_average|
+--------------------+----------+------------+
|              Avatar|2787965087|         7.2|
|Pirates of the Ca...| 961000000|         6.9|
|The Dark Knight R...|1084939099|         7.6|
|             Tangled| 591794936|         7.4|
|Avengers: Age of ...|1405403694|         7.3|
|Harry Potter and ...| 933959197|         7.4|
|Pirates of the Ca...|1065659812|           7|
|        The Avengers|1519557910|         7.4|
|The Hobbit: The B...| 956019788|         7.1|
|The Hobbit: The D...| 958400000|         7.6|
|           King Kong| 550000000|         6.6|
|             Titanic|1845034188|         7.5|
|Captain America: ...|1153304495|         7.1|
|             Skyfall|1108561013|         6.9|
|        Spider-Man 2| 783766341|         6.7|
|          Iron Man 3|1215439994|         6.8|
| Monsters University| 743559607|           7|
|         Toy Story 3|1066969703|         7.6|
|           Furious 7|1506249360|         7.3|
|         World War Z| 531865000|         6.7|
|X-Men: Days of Fu...| 747862775|         7.5|
|Star Trek Into Da...| 467365246|         7.4|
|    The Great Gatsby| 351040419|         7.3|
|         Pacific Rim| 407602906|         6.7|
|   The Good Dinosaur| 331926147|         6.6|
```

- 计算所有公司高分电影收入总和，展示收入前十的公司：

```
+-----------------------+------------+
|production_companies_tmp|sum(revenue)|
+-----------------------+------------+
|            Warner Bros.| 28916590255|
|     Twentieth Century...| 22744461916|
|      Paramount Pictures| 20523892859|
|    Walt Disney Pictures| 18222166395|
|      Universal Pictures| 18039225745|
|          Marvel Studios|  9974688606|
|         New Line Cinema|  9615893827|
|    Pixar Animation S...|  9249940392|
|          DreamWorks SKG|  8653805106|
|       Columbia Pictures|  8492534916|
+-----------------------+------------+
only showing top 10 rows
```

3. 使用TitanicTrainTest.zip中的训练集训练一个分类模型(比如决策树)，并且给出在测试集上的正确率。

实习成果展示：

本任务工作量较大，因此需要分段展示。我们逐一进行展示。

- 数据预处理阶段：

  由于原始数据包含很多维度，但各个字段与我们要进行的生存预测的相关度差别较大，因此先进行数据预处理，筛选出 Pclass, Sex, Age, SibSp, Parch, Fare, Embarked。因此我们筛选出相关的维度，并将数据调整为Spark MLlib读取的格式。

- 编写 python 脚本：

  利用Spark MLlib提供的决策树分类器SVM算法，在已经进行预处理的Train数据集上运行模型，并在 Test数据集上进行测试，最终输出 Test 数据集上的accuracy。

```python
from pyspark.mllib.util import MLUtils
from pyspark.mllib.classification import SVMWithSGD

import sys
sys.path.append("/home/phoenix/桌面/home/spark-3.0.0-bin-hadoop2.7/python")

import pyspark
spark = pyspark.sql.SparkSession.builder.appName("SimpleAPP").getOrcreate()
sc = spark.sparkContext

train_data = MLUtils.loadLibSVMFile(sc = sc, path = '/home/phoenix/Desktop/trainwithlabels.csv'')
test_data = MLUtils.loadLibSVMFile(sc = sc, path = '/home/phoenix/Desktop/testwithlabels.csv')

#使用SVM算法

model = SVMWithSGD.train(train_data, iterations = 100, step = 1, miniBatchFraction = 1.0)

prediction = model.predict(test_data.map(lambda x: x.features)).collect()
true_label = test_data.map(lambda x :x.label).collect()

account = 0
for index in range(len(true_label)):
    if true_label[index] == prediction[index]:
        account += 1

print("accuracy: " + 100*account/len(true_label) + "%")
```

- 在Spark 环境中运行脚本，结果如下：

```
20/06/02 15:15:54 WARN Utils: Your hostname, adela-virtual-machine resolves to a
 loopback address: 127.0.0.1; using 192.168.228.128 instead (on interface ens33)
20/06/02 15:15:54 WARN Utils: Set SPARK_LOCAL_IP if you need to bind to another
address
20/06/02 15:15:55 WARN NativeCodeLoader: Unable to load native-hadoop library fo
r your platform... using builtin-java classes where applicable
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLeve
l(newLevel).
accuracy : 81%
```

可以看到：利用Spark MLlib提供的 SVM 模型，在Titanic数据集上的accuracy能够达到81%。

- 还可以使用随机森林： （此部分内容与信科的吴钰晗同学讨论）

```python
train_path='/home/phoenix/Desktop/trainwithlabels.csv'
test_path='/home/phoenix/Desktop/testwithlabels.csv'
# 加载csv文件
train_rdd = sc.textFile(train_path)
test_rdd = sc.textFile(test_path)
def parseTrain(rdd):
    # 提取第一行的header
    header = rdd.first()
    # 除去header
    body = rdd.filter(lambda r: r!=header)
    def parseRow(row):
        # 删去双引号，根据逗号分隔
        row_list = row.replace('"','').split(",")
        # 转换成tuple
        row_tuple = tuple(row_list)
        return row_tuple
```

```python
    rdd_parsed = body.map(parseRow)
    colnames = header.split(",")
    colnames.insert(3,'FirstName')

    return rdd_parsed.toDF(colnames)

## Parse Test RDD to DF
def parseTest(rdd):
    header = rdd.first()
    body = rdd.filter(lambda r: r!=header)
    def parseRow(row):
        row_list = row.replace('"','').split(",")
        row_tuple = tuple(row_list)
        return row_tuple

    rdd_parsed = body.map(parseRow)
    colnames = header.split(",")
    colnames.insert(2,'FirstName')

    return rdd_parsed.toDF(colnames)

train_df = parseTrain(train_rdd)
test_df = parseTest(test_rdd)
```

合并数据，转为数值类型并填充:

```python
from pyspark.sql.functions import lit, col
train_df = train_df.withColumn('Mark',lit('train'))
test_df = (test_df.withColumn('Survived',lit(0))
                  .withColumn('Mark',lit('test')))
test_df = test_df[train_df.columns]
df = train_df.unionAll(test_df)

df = (df.withColumn('Age',df['Age'].cast("double"))
            .withColumn('SibSp',df['SibSp'].cast("double"))
            .withColumn('Parch',df['Parch'].cast("double"))
            .withColumn('Fare',df['Fare'].cast("double"))
            .withColumn('Survived',df['Survived'].cast("double"))
            )

numVars = ['Survived','Age','SibSp','Parch','Fare']
def countNull(df,var):
    return df.where(df[var].isNull()).count()

missing = {var: countNull(df,var) for var in numVars}
age_mean = df.groupBy().mean('Age').first()[0]
fare_mean = df.groupBy().mean('Fare').first()[0]
df = df.na.fill({'Age':age_mean,'Fare':fare_mean})
```

```
>>> df.printSchema()
root
 |-- PassengerId: string (nullable = true)
 |-- Survived: double (nullable = true)
 |-- Pclass: string (nullable = true)
 |-- FirstName: string (nullable = true)
 |-- Name: string (nullable = true)
 |-- Sex: string (nullable = true)
 |-- Age: double (nullable = true)
 |-- SibSp: double (nullable = true)
 |-- Parch: double (nullable = true)
 |-- Ticket: string (nullable = true)
 |-- Fare: double (nullable = true)
 |-- Cabin: string (nullable = true)
 |-- Embarked: string (nullable = true)
 |-- Mark: string (nullable = false)
```

提取尊称:

```
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType

gettitle = udf(lambda name: name.split('.')[0].strip(),StringType())
df = df.withColumn('Title', gettitle(df['Name']))
```

```
>>> from pyspark.sql.functions import udf
>>> from pyspark.sql.types import StringType
>>>
>>> gettitle = udf(lambda name: name.split('.')[0].strip(),StringType())
>>> df = df.withColumn('Title', gettitle(df['Name']))
>>> df.select('Name','Title').show(3)
+-----------------+-----+
|             Name|Title|
+-----------------+-----+
|    Mrs. (Hedwig)|  Mrs|
| Mr. Johan Birger|   Mr|
|        Mr. Ivan|   Mr|
+-----------------+-----+
only showing top 3 rows
```

特征值标签转换，并把特征转为向量:

```
from pyspark.ml.feature import StringIndexer

catVars = ['Pclass','Sex','Embarked','Title']

def indexer(df,col):
    si = StringIndexer(inputCol = col, outputCol = col+'_indexed').fit(df)
    return si

indexers = [indexer(df,col) for col in catVars]

from pyspark.ml import Pipeline
pipeline = Pipeline(stages = indexers)
df_indexed = pipeline.fit(df).transform(df)

catVarsIndexed = [i+'_indexed' for i in catVars]
featuresCol = numVars+catVarsIndexed
featuresCol.remove('Survived')
labelCol = ['Mark','Survived']

```

```python
from pyspark.sql import Row
from pyspark.ml.linalg import DenseVector
row = Row('mark','label','features')

df_indexed = df_indexed[labelCol+featuresCol]
lf = (df_indexed.rdd.map(lambda r: (row(r[0],r[1],DenseVector(r[2:]))))
                .toDF())
lf = (StringIndexer(inputCol = 'label',outputCol='index')
                .fit(lf)
                .transform(lf))
```

分割，并使用随机森林:

```python
train = lf.where(lf.mark =='train')
test = lf.where(lf.mark =='test')

train,validate = train.randomSplit([0.7,0.3],seed =111)

print('Train Data Number of Row: '+ str(train.count()))
print('Validate Data Number of Row: '+ str(validate.count()))
print('Test Data Number of Row: '+ str(test.count()))

from pyspark.ml.classification import RandomForestClassifier,DecisionTreeClassifier,LogisticRegression

lr = LogisticRegression(maxIter = 100, regParam = 0.05, labelCol='index').fit(train)
rf = RandomForestClassifier(numTrees = 100, labelCol = 'index').fit(train)
dt = DecisionTreeClassifier(maxDepth = 3, labelCol ='index').fit(train)

from pyspark.ml.evaluation import BinaryClassificationEvaluator
def testModel(model, validate = validate):
    pred = model.transform(validate)
    evaluator = BinaryClassificationEvaluator(labelCol = 'index')
    return evaluator.evaluate(pred)

print('LogisticRegression'+str(testModel(lr)))
print('DecistionTree'+str(testModel(dt)))
print('RandomForest'+str(testModel(rf)))
```

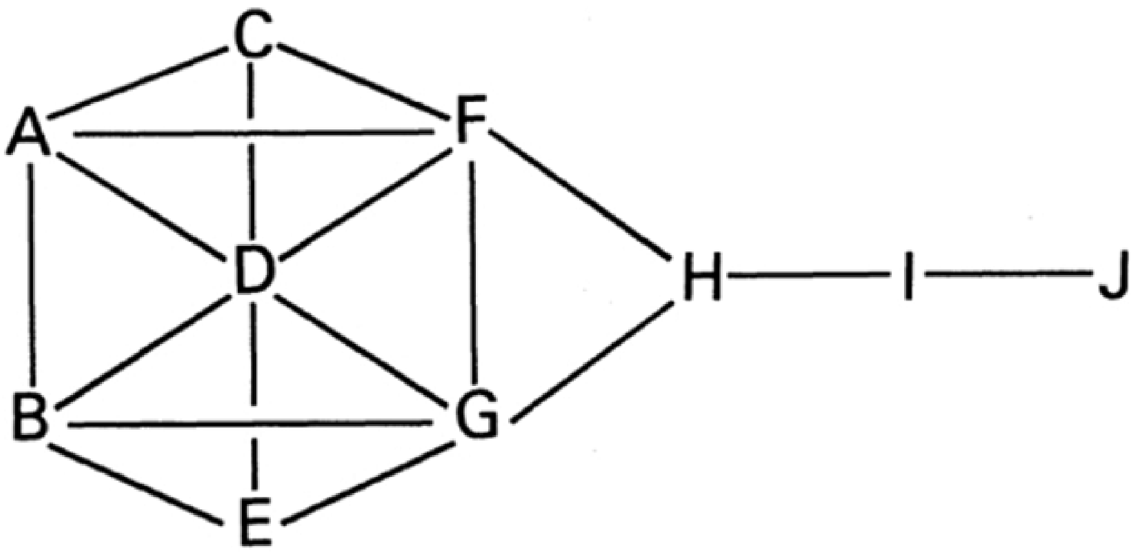
最终训练结果：正确率达到了86%。

```
>>> from pyspark.ml.classification import RandomForestClassifier,DecisionTreeClassifier,LogisticRegression
>>>
>>> lr = LogisticRegression(maxIter = 100, regParam = 0.05, labelCol='index').fit(train)
>>> rf = RandomForestClassifier(numTrees = 100, labelCol = 'index').fit(train)
>>> dt = DecisionTreeClassifier(maxDepth = 3, labelCol ='index').fit(train)
>>>
>>> from pyspark.ml.evaluation import BinaryClassificationEvaluator
>>> def testModel(model, validate = validate):
...     pred = model.transform(validate)
...     evaluator = BinaryClassificationEvaluator(labelCol = 'index')
...     return evaluator.evaluate(pred)
...
>>> print('LogisticRegression'+str(testModel(lr)))
LogisticRegression0.8505685856432124
>>> print('DecistionTree'+str(testModel(dt)))
DecistionTree0.8267590618336886
>>> print('RandomForest'+str(testModel(rf)))
RandomForest0.8671375266524525
```

4. 用GraphX再次实现PageRank。

实习成果展示：

如图是实习要求中给出的network图片。要在这张图上实现PageRank：



- 将 network 转换成edge list的形式并上传至HDFS。

```
network.txt
~/Downloads
1 2
1 3
1 4
1 6
2 1
2 4
2 5
2 7
3 1
3 4
3 6
4 1
4 2
4 3
4 5
4 6
4 7
5 2
5 4
5 7
6 1
6 3
6 4
6 7
6 8
7 2
7 4
7 5
7 6
7 8
8 6
8 7
8 9
9 8
9 10
10 9
```

使用`hdfs dfs -mkdir -p /spark/datasrc/`与`hdfs dfs -put network.txt /spark/datasrc/`语句，将network的edge list文件上传。

- 启动Spark Shell，进入python环境，导入对应的包：

```
scala> import org.apache.spark.SparkConf
import org.apache.spark.SparkConf

scala> import org.apache.spark.SparkContext
import org.apache.spark.SparkContext

scala> val sparkConf = new SparkConf().setAppName("GraphFromFile")
sparkConf: org.apache.spark.SparkConf = org.apache.spark.SparkConf@5981b51

scala> val sc = new SparkContext(sparkConf)
```

- 导入edge list文件，并对其调用PageRank算法函数：

在调用之前，我们首先要将network.txt导入到graph中。使用`GraphLoader`即可将之前上传至HDFS的network.txt导入graph。导入后使用命令`graph.vertices.take(10)`检查是否导入成功。若成功，即会输出如图所示的边集。

```
scala> val graph = GraphLoader.edgeListFile(sc,"hdfs://localhost:9000/spark/data
src/network.txt")
graph: org.apache.spark.graphx.Graph[Int,Int] = org.apache.spark.graphx.impl.Gra
phImpl@60729135

scala> graph.vertices.take(10)
res7: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,1), (1,1), (6,1)
, (3,1), (7,1), (9,1), (8,1), (10,1), (5,1), (2,1))
```

再进行PageRank初始化操作并调用，将每个网页的初始权重设置为0.1。

```
scala> val pr = graph.pageRank(0.1).vertices
pr: org.apache.spark.graphx.VertexRDD[Double] = VertexRDDImpl[119] at RDD at Ver
texRDD.scala:57
```

- 输出结果:

  使用命令`pr.take(10)`即可输出运行结果:

```
scala> pr.take(10)
res8: Array[(org.apache.spark.graphx.VertexId, Double)] = Array((4,1.21952505966
7058), (1,0.9534763230544803), (6,1.2271394760036767), (3,0.8489269723451542), (
7,1.2271394760036767), (9,0.9563089134630316), (8,1.0615248534075887), (10,0.703
5556306557004), (5,0.8489269723451542), (2,0.9534763230544803))
```

- 结果分析:

  该表格展示了实习二中的计算结果:

网页\迭代次数	1	10	20	30
A	0.9597	0.09600	0.09600	0.09600
B	0.9597	0.09600	0.09600	0.09600
C	0.6933	0.06933	0.06933	0.06933
D	0.14528	0.14533	0.14533	0.14533
E	0.06933	0.06933	0.06933	0.06933
F	0.12261	0.12267	0.12267	0.12267
G	0.12261	0.12267	0.12267	0.12267
H	0.09200	0.09200	0.09200	0.09200
I	0.12664	0.12667	0.12667	0.12667
J	0.06000	0.06000	0.06000	0.06000

  与实习二中的计算结果进行对比，发现两次计算结果基本一致，产生的细微偏差可能是由于我们在实习二中设置的跳跃因子$\beta = 0.2$，而GraphX自带的PageRank函数源码中的默认跳跃因子被设置成了$\beta = 0.15$。

心得与体会:

- 在任务1中，我们使用Spark RDD实现了wordcount。这里我们通过简单的几行命令就完成了wordcount，且能很好地实现切分和特殊词替换。这比用java实现wordcount要便捷得多。
- 在任务2中，我们使用Spark SQL实现了对电影数据的统计。这一部分我使用python写脚本，感觉比起直接在Spark Shell里面交互具有一定难度，但也比较方便，直接运行就可以看到想要的结果。统计结果的展示也是很清晰的。

- 在任务3中，我们使用Spark MLlib训练了分类模型。我先使用了Spark MLlib自带的决策树分类器SVM算法。这部分通过撰写python脚本可以很方便地实现，正确率达到了81%。我又尝试了随机森林，这部分是通过直接在Spark Shell的命令行中交互，过程比较繁琐，不过正确率到了86%，效果很好。

- 在任务4中，我们使用了GraphX自带的PageRank函数。由于GraphX的PageRank函数调用比较简单，这个实习实现起来很方便。与之前实习二中利用MapReduce编写PageRank代码相比，GraphX的函数调用方式与接口都非常简洁，参数也很好设置。考虑到实际应用在实际应用中的网络拓扑会更加庞大（节点个数更多，边也更多），在真实情况下突出 GraphX 在分布式图处理中的强大优势。

这次实习的内容很多，但是让我系统性地了解到Spark的功能，也感受到了Spark功能的丰富性。在本次实习中我们实现了wordcount、SQL、机器学习、PageRank，这些似乎完全不同的任务都可以集中在Spark上完成，正是体现了Spark的功能丰富。