# 实验四基于Spark的银行贷款违约预测

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#### 1. 问题背景

在借贷交易中,银行和其他金融机构通常提供资金给借款人,期望借款人能够按时还款本金 和利

息。然而,由于各种原因,有时借款人可能无法按照合同规定的方式履行还款义务,从而导致贷

款违约。本次实验以银行贷款违约为背景,选取了约30万条贷款信息,包含在 application\_data.csv文件中,数据描述包含在columns\_description.csv文件夹中。

数据来源: https://www.kaggle.com/datasets/mishra5001/credit-card/data

#### 2. 环境配置

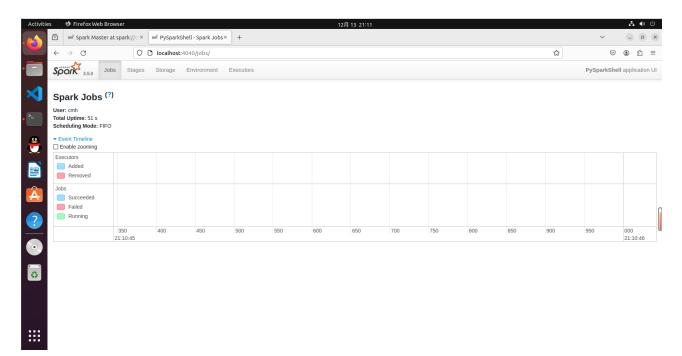
## 2.1 版本信息

- 操作系统: LINUX (ubuntu-22.04.3)
- JAVA: java-8-openjdk-amd64 (1.8.0\_382)
- Hadoop: 3.3.6
- Spark:

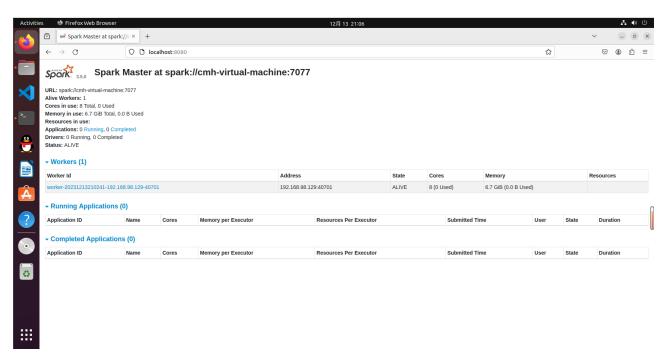
#### 2.2 Spark安装及配置

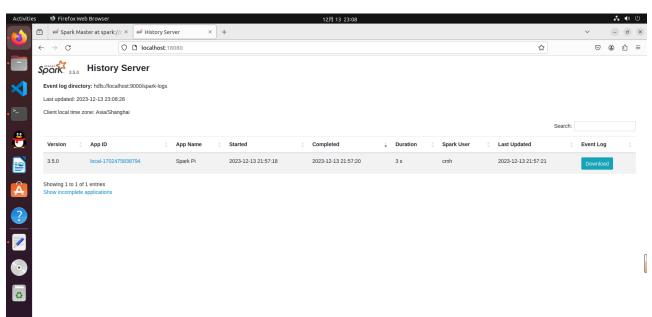
- 1 1. 安装并配置Anaconda环境
- 2 wget https://mirror.nju.edu.cn/anaconda/archive/Anaconda3-2021.11-Linux-x86\_64.sh
- 3 sh ./Anaconda3-2021.11-Linux-x86\_64.sh

- 4 conda create -n pyspark python=3.6 # 基于python3.6创建pyspark虚拟 环境
- 5 conda activate pyspark # 激活(切换)到pyspark虚拟环境
- 6 conda install pyspark
- 7 2. 安装Spark
- 8 wget https://archive.apache.org/dist/spark/spark-3.5.0/spark-3.5.0-bin-hadoop3.tgz
- 9 tar -zxvf spark-3.5.0-bin-hadoop3.tgz
- 10 mv spark-3.5.0-bin-hadoop3/ spark
- 11 3. spark相关配置
- 12 在/etc/bash.bashrc中添加:
- 13 export SPARK\_HOME=/home/cmh/spark
- 14 export PATH=\$SPARK\_HOME/bin:\$PATH
- 15 export
  PYSPARK\_PYTHON=/home/cmh/anaconda3/envs/pyspark/bin/python
- 16 在spark/conf/spark-env.sh(该文件复制自spark-env.sh.template)中添加:
- 17 export JAVA\_HOME=/usr/lib/jvm/java-8-openjdk-amd64
- 18 export SPARK\_DIST\_CLASSPATH=\$(/home/cmh/hadoop/hadoop-3.3.6/bin/hadoop classpath)
- 19 export SPARK\_HISTORY\_OPTS="-Dspark.history.ui.port=18080 Dspark.history.fs.logDirectory=hdfs://localhost:9000/spark-logs"
- 20 在spark/conf/spark-defaults.conf(该文件复制自spark-defaults.conf.template)中添加:
- 21 spark.eventLog.enabled true
- spark.eventLog.dir hdfs://localhost:9000/sparklogs
- 23 创建hdfs://localhost:9000/spark-logs文件夹:
- 24 hdfs dfs -mkdir /spark-logs
- 25 4. 验证spark是否安装成功(终端环境)
- 26 pyspark
- 27 http://localhost:4040/



- 1 5. 程序测试
- 2 start-all.sh(开启Hadoop)
- 3 spark/sbin/start-all.sh (开启spark) (注意: 这里直接使用start-all.sh会与hadoop的start-all冲突)
- 4 spark/sbin/start-history-server.sh
- 5 # spark master: http://localhost:8080/
- 6 # spark history server: http://localhost:8080/
- 7 http://localhost:18080/
- 8 run-example SparkPi 10
- 9 spark/sbin/start-history-server.sh
- 10 spark/sbin/stop-all.sh





```
23/12/13 23:08:32 INFO TaskSetManager: Finished task 7.0 in stage 0.0 (TID 7) in 820 ms on 192.168.98.129 (executor driver) (1/10) 23/12/13 23:08:32 INFO TaskSetManager: Finished task 7.0 in stage 0.0 (TID 0) in 886 ms on 192.168.98.129 (executor driver) (2/10) 23/12/13 23:08:32 INFO Executor: Finished task 6.0 in stage 0.0 (TID 6). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO Executor: Finished task 1.0 in stage 0.0 (TID 1). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO Executor: Finished task 5.0 in stage 0.0 (TID 5). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO Executor: Finished task 5.0 in stage 0.0 (TID 5). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO TaskSetManager: Finished task 6.0 in stage 0.0 (TID 6). 10 1875 ms on 192.168.98.129 (executor driver) (3/10) 23/12/13 23:08:32 INFO TaskSetManager: Finished task 6.0 in stage 0.0 (TID 6). 10 1875 ms on 192.168.98.129 (executor driver) (5/10) 23/12/13 23:08:32 INFO TaskSetManager: Finished task 2.0 in stage 0.0 (TID 2). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO Executor: Finished task 2.0 in stage 0.0 (TID 2). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO Executor: Finished task 3.0 in stage 0.0 (TID 2). 1012 bytes result sent to driver 23/12/13 23:08:32 INFO Executor: Finished task 3.0 in stage 0.0 (TID 2) in 883 ms on 192.168.98.129 (executor driver) (6/10) 23/12/13 23:08:32 INFO Executor: Finished task 4.0 in stage 0.0 (TID 3) in 902 ms on 192.168.98.129 (executor driver) (7/10) 23/12/13 23:08:32 INFO Executor: Finished task 4.0 in stage 0.0 (TID 3) in 902 ms on 192.168.98.129 (executor driver) (8/10) 23/12/13 23:08:32 INFO Executor: Finished task 8.0 in stage 0.0 (TID 8) in 10 ms on 192.168.98.129 (executor driver) (8/10) 23/12/13 23:08:32 INFO Executor: Finished task 9.0 in stage 0.0 (TID 8) in 10 ms on 192.168.98.129 (executor driver) (9/10) 23/12/13 23:08:32 INFO TaskSetManager: Finished task 9.0 in stage 0.0 (TID 8) in 10 ms on 192.168.98.129 (executor driver) (9/10) 23/12/13 23:08:32
```

运行pyspark程序: spark-submit [options] [app arguments]

### 3.任务一

1. 编写 Spark 程序,统计application\_data.csv中所有用户的贷款金额AMT\_CREDIT 的分布情

况。以10000元为区间进行输出。输出格式示例:

((20000,30000),1234)

表示20000到30000元之间(包括20000元,但不包括30000元)有1234条记录。

- 设计思路:通过遍历每个区间,将AMT\_CREDIT值分配到相应的区间中,然后统计每个区间的记录数量,最终按照区间范围格式化输出。使用groupBy和count方法统计每个区间的记录数量。
- 运行结果:

```
|bin range
                    record count
 {100000, 110000}
 {1000000, 1010000}|2587
 [1010000, 1020000]
                     656
 {1020000, 1030000}|1438
 {1030000, 1040000}|868
 [1040000, 1050000] | 1463
 {1050000, 1060000}|905
 {1060000, 1070000}|725
 {1070000, 1080000}|3252
 {1080000, 1090000}|760
 {1090000, 1100000}|768
 {110000, 120000}
                     1930
 {1100000, 1110000} 421
 {1110000, 1120000}|1009
 {1120000, 1130000} | 4199
 {1130000, 1140000}|492
 {1140000, 1150000}|301
 {1150000, 1160000}|379
 {1160000, 1170000}|365
{1170000, 1180000}|474
only showing top 20 rows
```

2. 编写Spark程序,统计application\_data.csv中客户贷款金额AMT\_CREDIT 比客户收入

AMT\_INCOME\_TOTAL差值最高和最低的各十条记录。差值=AMT\_CREDIT-AMT\_INCOME\_TOTAL。输出格式:

- <SK\_ID\_CURR><NAME\_CONTRACT\_TYPE><AMT\_CREDIT>
  <AMT INCOME TOTAL>, <差值>
- 设计思路:在df中添加新列"dif",计算出差值并填入,然后分别按照差值升序和降序排列df,从而得到差值最高和最低的各十条记录。
- 运行结果:

```
SK ID CURR|NAME CONTRACT TYPE|AMT CREDIT|AMT INCOME TOTAL|
                   Cash loans | 4050000.0|
                                                   405000.0|3645000.0|
    433294
    210956
                   Cash loans
                                4031032.5
                                                   430650.0|3600382.5
    434170
                   Cash loans
                                4050000.0
                                                   450000.0|3600000.0
                   Cash loans!
                                                   458550.0|3569130.0
    315893
                                4027680.01
                   Cash loans | 3860019.0|
                                                   292050.0|3567969.0|
    238431
                   Cash loans
                                                   587250.0|3462750.0|
                                4050000.0
                   Cash loans | 4050000.0|
                                                   760846.5|3289153.5
    117337
    120926
                   Cash loans | 4050000.0|
                                                   783000.0|3267000.0|
    117085
                   Cash loans | 3956274.0|
                                                   749331.0|3206943.0|
    228135
                   Cash loans | 4050000.0|
                                                   864900.0|3185100.0|
```

SK_ID_CURR NAME	CONTRACT_TYPE	+ AMT_CREDIT AN	T_INCOME_TOTAL	dif
+	+			
114967	Cash loans	562491.0	1.17E8	-1.16437509E8
336147	Cash loans	675000.0	1.800009E7	-1.732509E7
385674	Cash loans	1400503.5	1.35E7	-1.20994965E7
190160	Cash loans	1431531.0	9000000.0	-7568469.0
252084	Cash loans	790830.0	6750000.0	-5959170.0
337151	Cash loans	450000.0	4500000.0	-4050000.0
317748	Cash loans	835380.0	4500000.0	-3664620.0
310601	Cash loans	675000.0	3950059.5	-3275059.5
432980	Cash loans	1755000.0	4500000.0	-2745000.0
157471	Cash loans	953460.0	3600000.0	-2646540.0
+				

#### 4.任务二

基于Hive或者Spark SQL对application data.csv进行如下统计:

1. 统计所有男性客户(CODE\_GENDER=M)的小孩个数(CNT\_CHILDREN)类型占比情况。

输出格式为: <CNT\_CHILDREN>, <类型占比> 例: 0, 0.1234 表示没有小孩的男性客户占总男性客户数量的占比为0.1234。

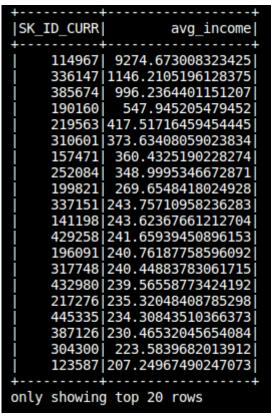
- 设计思路: 首先筛选出男性客户, 然后统计小孩个数类型占比, 并按照占比降序排序, 最后输出结果。
- 运行结果:

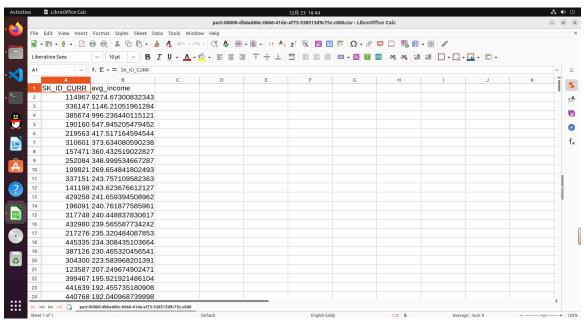
存为csv。

2. 统计每个客户出生以来每天的平均收入(avg\_income)=总收入 (AMT\_INCOME\_TOTAL)/ 出生天数(DAYS\_BIRTH),统计每日收入大于1的客户,并按照从大到小排序,保

#### 输出格式: <SK ID CURR>, <avg income>

- 设计思路:为df新增一列avg\_income,通过公式计算并填入,这里需要把出生天数取绝对值,然后筛选avg\_income大于1的客户,再按照从大到小排序,最后保存为csv文件。
- 运行结果:





#### 5.任务三

根据给定的数据集,基于Spark MLlib 或者Spark ML编写程序对贷款是否违约进行分类,并评估

实验结果的准确率。可以训练多个模型,比较模型的表现。

- 1、该任务可视为一个"二分类"任务,因为数据集只存在两种情况,违约(Class=1)和其他(Class=0)。
- 2、可根据时间特征的先后顺序按照8: 2的比例将数据集application\_data.csv拆分成训练集和测

试集,时间小的为训练集,其余为测试集;也可以按照8:2的比例随机拆分数据集。最后评估模

型的性能,评估指标可以为accuracy、f1-score等。

3、基于数据集application\_data.csv,可以自由选择特征属性的组合,自行选用一种或多种分类

算法对目标属性TARGET进行预测。

- 设计思路:在实验二中数据清洗后得到的train.csv和test.csv数据基础上进行模型 训练与评估,对类别型变量进行独热编码处理,而后分别构建logistic模型和随机 森林模型,构建pipeline流水线进行模型的训练和评估,最后计算出accuracy
- 运行结果:

Logistic Regression Model Accuracy: 0.6708912078965459

Random Forest Model Accuracy: 0.6690078136635321