TP-ML-NANA-ROMARIC-v2

September 16, 2021

1 TRAVAUX PRATIQUES

1.0.1 COURS DE MACHINE LEARNING - UNIVERSITE VIRTUELLE DU BURKINA FASO - MASTER FD & IA

- ETUDIANT : NANA SIDWENDLUIAN ROMARIC
- ENSEIGNANT : MADAME BIRBA ELIANE

1.0.2 1. Chargement des données

```
[1]: #importing pyspark
import pyspark

#importing sparksession
from pyspark.sql import SparkSession

from pyspark.sql.functions import *

from pyspark.ml.classification import LogisticRegression
from pyspark.ml.evaluation import BinaryClassificationEvaluator

from pyspark.ml.classification import DecisionTreeClassifier

from pyspark.ml.classification import RandomForestClassifier
```

```
[2]: #creating a sparksession object and providing appName spark=SparkSession.builder.master("local").appName("tp").getOrCreate()
```

Constatant les resultats mitigés obtenus dans le fichier précédent, nous avons rétiré certaines lignes du dataset qui contenaient des anomalies. Il s'agit notamment des lignes où: * la variable EDU-CATION a des valeurs plus grandes que 4 * la variable MARRIAGE a des valeurs 0 (ZÉRO) * les variables PAY 0,PAY 1,PAY 2,....,PAY 6 ont des valeurs -2

```
[3]: datadft_bis = spark.read.format("csv").options(header=True,inferSchema=True).

→load("data/ccdefault-bis.csv")
```

1.0.3 2. Analyse exploratoire

```
[4]: datadft_bis.printSchema()
    root
     |-- ID: integer (nullable = true)
     |-- LIMIT_BAL: integer (nullable = true)
     |-- SEX: integer (nullable = true)
     |-- EDUCATION: integer (nullable = true)
     |-- MARRIAGE: integer (nullable = true)
     |-- AGE: integer (nullable = true)
     |-- PAY_0: integer (nullable = true)
     |-- PAY_2: integer (nullable = true)
     |-- PAY_3: integer (nullable = true)
     |-- PAY_4: integer (nullable = true)
     |-- PAY_5: integer (nullable = true)
     |-- PAY_6: integer (nullable = true)
     |-- BILL_AMT1: integer (nullable = true)
     |-- BILL_AMT2: integer (nullable = true)
     |-- BILL_AMT3: integer (nullable = true)
     |-- BILL AMT4: integer (nullable = true)
     |-- BILL_AMT5: integer (nullable = true)
     |-- BILL_AMT6: integer (nullable = true)
     |-- PAY_AMT1: integer (nullable = true)
     |-- PAY_AMT2: integer (nullable = true)
     |-- PAY_AMT3: integer (nullable = true)
     |-- PAY_AMT4: integer (nullable = true)
     |-- PAY_AMT5: integer (nullable = true)
     |-- PAY_AMT6: integer (nullable = true)
     |-- DEFAULT: integer (nullable = true)
[5]:
    datadft_bis.count()
[5]: 53104
    datadft_bis.where("ID is null").count()
[6]: 29946
    datadft_bis.where("ID is not null").count()
[7]: 23158
[8]: datadft_bis_clean=datadft_bis.where("ID is not null")
[9]: datadft_bis_clean.count()
```

[9]: 23158

	s_clean.describe(dat	adft_bis_clean.col	umns).show()	
	+	·	•	
•		•	•	
•		•	•	
	+	•	•	•
· ·	+	•	•	
-+				
summary	ID	LIMIT_BAL	SEX	
EDUCATION	MARRIAGE	AGE	PAY_0	
PAY_2	PAY_3	PAY_4	PAY_5	
PAY_6	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AM7
BILL_AMT5	-	-	_	
PAY_AMT3	PAY_AMT4	PAY_AMT5	PAY_AMT6	
DEFAULT				
	+			
+				
	+	•	·	•
-+				
count	23158	23158	23158	
23158	23158	23158	23158	
23158	23158	23158	23158	
23158	23158	23158	23158	2315
	23158	721501	23158	
23158		23158		
23158	23158	23158	23158	
23158 23158	23158	23158	23158	05444000
23158 23158 mean 14	23158 916.514509024959 15	23158 6289.99395457294 1	23158	
23158 23158 mean 149 1861 1.56449	23158 916.514509024959 15 269798773642 35.245	23158 6289.99395457294 1 09888591415 0.180	23158 .5915450384316434 1 326453061577 0.1887	4686933241
23158 23158 mean 149 1861 1.56449 0.174453759	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584	23158 6289.99395457294 1 09888591415 0.180 851887037 0.091804	23158 .5915450384316434 1 326453061577 0.1887 1281630538 0.088263	4686933241 2351671128
23158 23158 mean 149 1861 1.56449 0.174453759 1282.0710769	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231	23158 6289.99395457294 1 09888591415 0.180 851887037 0.091804 5399 57343.2732101	23158 .5915450384316434 1 326453061577 0.1887 1281630538 0.088263 2177 53264.46122290	4686933241 2351671128
23158 23158 mean 149 1861 1.56449 0.174453759 1282.0710769 8870368775 4	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295	23158 6289.99395457294 1 09888591415 0.180 851887037 0.091804 5399 57343.2732101 6075.015243112532	23158 .5915450384316434 1 326453061577 0.1887 1281630538 0.088263 2177 53264.46122290 6121.004836341653	4686933241 2351671128
23158 23158 mean 149 1861 1.5644	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295 013904 5089.545815	23158 6289.99395457294 1 09888591415 0.180 851887037 0.091804 5399 57343.2732101 6075.015243112532 700838 5049.28387	23158 .5915450384316434 1 326453061577 0.1887 1281630538 0.088263 2177 53264.46122290 6121.004836341653	4686933241 2351671128
23158 23158 mean 149 1861 1.56449 0.174453759 1282.0710769 8870368775 4 5562.9769410 5334.334312	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295 013904 5089.545815 116763 0.2315398566	23158 6289.99395457294 1 09888591415 0.180 851887037 0.091804 5399 57343.2732101 6075.015243112532 700838 5049.28387	23158 .5915450384316434 1 326453061577 0.1887 1281630538 0.088263 2177 53264.46122290 6121.004836341653 5982382	4686933241 2351671128 3534 49786
23158 23158 mean 149 1861 1.5644	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295 013904 5089.545815	23158 6289.99395457294 1 09888591415 0.1803851887037 0.091804 5399 57343.27321013 6075.015243112532 700838 5049.283873 370153 7579.85957421701 0	23158 .5915450384316434 1 326453061577 0 .18874 1281630538 0 .088263 2177 53264 .46122290 6121 .004836341653 5982382 .4915586840970848 0	4686933241 2351671128 3534 49786
23158 23158 mean 149 1861 1.56449 0.174453759 1282.0710769 8870368775 4 5562.9769410 5334.3343129 stddev 80 5048 0.51874	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295 013904 5089.545815 116763 0.2315398566 614.422528409888 12	23158 6289.99395457294 1 09888591415 0.1803 851887037 0.091804 5399 57343.27321013 6075.015243112532 700838 5049.283873 370153 7579.85957421701 0 28745301381 0.9848	23158 .5915450384316434 1 326453061577 0 . 18874 1281630538 0 . 088263 2177 53264 . 46122290 6121 . 004836341653 5982382 .4915586840970848 0 565503867994	4686933241 2351671128 3534 49786
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23158 23158 mean 149 1861 1.5644 1861 1.5644 1861 1.5644 1861 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862 1862	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295 013904 5089.545815 116763 0.2315398566 614.422528409888 12 412618034684 9.2914 4615636 1.02233989 3186254 77602.34303	23158 6289.99395457294 1 09888591415 0.1803 851887037 0.091804 5399 57343.27321013 6075.015243112532 700838 5049.283873 370153 7579.85957421701 0 28745301381 0.98483 41110264 0.98887803 734612 75193.401053	23158 .5915450384316434 1 326453061577 0.18874 1281630538 0.088263 2177 53264.46122290 6121.004836341653 5982382 .4915586840970848 0 565503867994 901255524 0.9419114 589147 72368.629972 4456585 16902.04758	4686933241 2351671128 3534 49786 .700640636 434746279 41326 187008 203
23158 23158 mean 149 1861 1.5644 1861 1.5644 1861 1.5644 1861 1862 1862 1862 1862 1862 1862 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864 1864	23158 916.514509024959 15 269798773642 35.245 248294326 0.1332584 94965 59663.9061231 47915.041195267295 013904 5089.545815 116763 0.2315398566 614.422528409888 12 412618034684 9.2914 4615636 1.02233989 3186254 77602.34303 666815 64341.13974	23158 6289.99395457294 1 09888591415 0.1803 851887037 0.091804 5399 57343.27321013 6075.015243112532 700838 5049.283873 370153 7579.85957421701 0 28745301381 0.98483 41110264 0.98887803 734612 75193.401053	23158 .5915450384316434 1 326453061577 0.18874 1281630538 0.088263 2177 53264.46122290 6121.004836341653 5982382 .4915586840970848 0 565503867994 901255524 0.9419114 589147 72368.629972 4456585 16902.04758	4686933241 2351671128 3534 49786 .700640636 434746279 41326 187008 203

```
-1 l
              -1|
                                       -1|
                                               -165580 l
                          -1 l
                         -170000|
   -67526|
             -1572641
                                     -81334 l
   -339603|
                0|
                                         01
                             0|
   01
              01
                          01
                                      01
                30000|
                           1000000|
                                          21
      max |
   4|
              3|
                         79 l
                                                  8|
   81
              81
                          81
                                       81
                                               964511
   983931 l
              693131
                          891586|
                                     927171
   9616641
                         12270821
                                     8960401
              8735521
   621000|
              4265291
                          5286661
   ____+____
   +-----
   ______
   ______
   ______
[13]: datadft_bis_clean.describe("LIMIT_BAL",__
    →"BILL_AMT1", "PAY_AMT1", "BILL_AMT2", "PAY_AMT2").show()
   |summary|
             LIMIT_BAL| BILL_AMT1| PAY_AMT1|
              PAY_AMT2|
   BILL_AMT2|
   | count|
                23158
                          231581
                                       23158 l
   23158|
              23158
   mean | 156289.99395457294 | 61282.07107694965 | 6075.015243112532 | 59663.90612315399 |
   6121.004836341653
   | stddev|127579.85957421701|77602.34303734612|16902.04758187008|75193.4010558914
   7 | 20302.039638491944 |
                     -165580|
      min
                10000|
                                         0|
   -675261
                  01
      max |
               1000000|
                           964511
                                8735521
   983931
              1227082
[14]: datadft_bis_clean.describe("LIMIT_BAL", "AGE").show()
   |summary| LIMIT_BAL|
                            AGE
```

21|

-1 l

-1 l

01

1|

```
count
                         23158
                                          23158
        mean | 156289.99395457294 | 35.24509888591415 |
     | stddev|127579.85957421701|9.291428745301381|
         minl
                        100001
                                             21
         max
                      1000000
                                             791
[15]: datadft_bis_clean.groupBy("SEX").count().orderBy(asc("count")).show() # SEXE ?__
      → HOMME=1 FEMME=2
     +---+
     |SEX|count|
     +---+
     | 1| 9459|
     | 2|13699|
     +---+
[16]: datadft_bis_clean.groupBy("DEFAULT").count().orderBy(asc("count")).show() #__
      → DÉFAUT DE PAIEMENT ? OUI=1 NON=0
     +----+
     |DEFAULT|count|
     +----+
           1 | 5362 |
           0 | 17796 |
     +----+
[17]: | datadft_bis_clean.groupBy(['DEFAULT', 'SEX']).count().orderBy(asc("DEFAULT")).
      →show()
     # repartition de la variable cible en fonction du sexe
     +----+
     |DEFAULT|SEX|count|
     +----+
           0 | 1 | 7081 |
           0| 2|10715|
           1 2 2984
           1 | 1 | 2378 |
     +----+
[18]: datadft_bis_clean.groupBy(['DEFAULT', 'EDUCATION']).count().

→orderBy(asc("DEFAULT")).show()
     # repartition de la variable cible en fonction du niveau d'instruction
```

```
+----+
|DEFAULT|EDUCATION|count|
+----+
     0|
             0|
     01
            1 | 6085 |
     0|
             2 | 8672 |
             3 | 2962 |
     0|
     01
                 69 l
             41
     1|
             2 | 2847 |
     1|
             1 | 1479 |
     1|
             3 | 1033 |
     1|
             4|
                 3|
+----+
```

```
[19]: datadft_bis_clean.groupBy(['DEFAULT','MARRIAGE']).count().

→orderBy(asc("DEFAULT")).show()

# repartition de la variable cible en fonction du statut matrimonial
```

```
+----+
|DEFAULT|MARRIAGE|count|
+----+
    01
           1 | 7792 |
0|
           2 | 9809 |
    0|
           3 | 195 |
           2| 2724|
    1|
           1 | 2564 |
    1|
     1|
           3| 74|
+----+
```

```
[20]: datadft_bis_clean.groupBy(['DEFAULT','AGE']).count().orderBy(asc("DEFAULT")).

→show()
```

```
+----+
|DEFAULT|AGE|count|
+----+
      0 | 42 | 452 |
      0 | 27 | 918 |
      0 | 39 | 566 |
      0| 31|
             708 l
      0 | 71 |
                31
      0 | 28 | 868 |
      0 | 56 | 104 |
      0 | 50 | 224 |
      0 | 22 | 344 |
      0| 58|
              62|
      0| 67|
             11|
```

```
0| 40|
                491
       0| 57|
                 761
       0| 32|
                6991
       0 | 60 |
                 31|
       0 | 73 |
                 1|
       0 | 65 |
                 17|
       0| 70|
                  6|
       0 | 48 |
                275
       0 | 25 | 722 |
   ----+
only showing top 20 rows
```

[21]: datadft_bis_clean.groupBy(['DEFAULT','LIMIT_BAL']).count().

→orderBy(desc("DEFAULT")).orderBy(desc("count")).show()

```
|DEFAULT|LIMIT_BAL|count|
       0|
             50000 | 2137 |
I
       0|
             20000 | 1070 |
       0|
             100008
                     946|
       0|
             30000| 867|
       0|
            200000| 811|
       1|
             50000|
                     790
       0|
            150000| 626|
            100000| 620|
       0|
             20000| 593|
       1|
       0|
            180000|
                     567
             60000| 537|
       0|
       1|
             30000| 522|
            140000|
                      488|
       0|
       0|
             70000|
                      480|
            5000001
                      458
       0|
       0|
            130000|
                      448|
       0|
            210000|
                      431
       0|
            120000|
                      430
       0|
            230000
                      429|
       0|
            360000|
                      4101
only showing top 20 rows
```

[22]: datadft_bis_clean.createOrReplaceTempView("dataView")
spark.sql("SELECT DEFAULT, avg(LIMIT_BAL) AS BALANCE FROM dataView GROUP BY

→DEFAULT ORDER BY BALANCE DESC").show()

+----+

```
BALANCE
    DEFAULT
      ----+
         0 | 168451 . 11260957518 |
         1 | 115928.32525177173 |
       ----+-----+
[23]: datadft_bis_clean
[23]: DataFrame[ID: int, LIMIT_BAL: int, SEX: int, EDUCATION: int, MARRIAGE: int, AGE:
    int, PAY_0: int, PAY_2: int, PAY_3: int, PAY_4: int, PAY_5: int, PAY_6: int,
    BILL_AMT1: int, BILL_AMT2: int, BILL_AMT3: int, BILL_AMT4: int, BILL_AMT5: int,
    BILL_AMT6: int, PAY_AMT1: int, PAY_AMT2: int, PAY_AMT3: int, PAY_AMT4: int,
    PAY_AMT5: int, PAY_AMT6: int, DEFAULT: int]
    1.0.4 3. Preparation des données
    Renommons la colonne DEFAULT en label
[24]: \# datadft_bis = datadft.
     →withColumn("ID", "LIMIT_BAL", "SEX", "EDUCATION", "MARRIAGE", "AGE", "PAY_0", "PAY_2", "PAY_3", "PAY
    renamedDatadft_bis_clean = datadft_bis_clean.
     [25]: renamedDatadft_bis_clean.show(5)
    ---+---+
    | ID|LIMIT_BAL|SEX|EDUCATION|MARRIAGE|AGE|PAY_0|PAY_2|PAY_3|PAY_4|PAY_5|PAY_6|BI
    LL_AMT1|BILL_AMT2|BILL_AMT3|BILL_AMT4|BILL_AMT5|BILL_AMT6|PAY_AMT1|PAY_AMT2|PAY_
    AMT3|PAY_AMT4|PAY_AMT5|PAY_AMT6|label|
    ---+----
    | 2|
                                2 | 26 |
                                             2|
                                                  0|
                                                      0|
          120000| 2|
                                       -1|
                                                           0|
                                                     01
    2682
            1725
                    2682
                            3272
                                   3455
                                           3261
                                                          1000
    1000
           1000
                    01
                         2000
                                1|
                                2| 34|
                                                      0|
    | 3|
           90000| 2|
                         21
                                        0|
                                             0|
                                                  0|
                                                           01
                                                                0|
    29239|
            14027
                    13559|
                            14331|
                                   14948|
                                           15549|
                                                   1518|
                                                           1500|
    1000
           1000|
                  1000|
                         5000
                                0|
    | 4|
           50000| 2|
                         2|
                                1 | 37 |
                                        0|
                                             0|
                                                  0| 0|
                                                           0|
                                                                0|
                            28314
                                           29547
                                                   2000
    46990
           48233|
                    49291
                                   28959
                                                           2019
```

1 | 57 | -1 |

19146|

19619|

0|

0|

0|

20024|

19131

-1|

2000

25001

0|

0|

36681 l

01

1815 l

0|

01

2 | 37 |

1200

| 5|

8617|

100001

| 6|

64400|

1100|

50000

5670

9000

50000 1

57069

1069|

35835

689 l

57608

1000|

1|

20940

19394|

679 l

```
657 l
          1000|
                  1000
                          1008
    ______
    ---+---+
    only showing top 5 rows
[26]: # colonne des etiquettes
    colLabel = "label"
    # colonne numerique
    colNum = [col for col in renamedDatadft_bis_clean.columns if col!= colLabel]
[27]: colNum
[27]: ['ID',
     'LIMIT BAL',
     'SEX',
     'EDUCATION',
     'MARRIAGE',
     'AGE',
     'PAY_O',
     'PAY_2',
     'PAY_3',
     'PAY_4',
     'PAY_5',
     'PAY_6',
     'BILL_AMT1',
     'BILL_AMT2',
     'BILL_AMT3',
     'BILL_AMT4',
     'BILL_AMT5',
     'BILL_AMT6',
     'PAY_AMT1',
     'PAY_AMT2',
     'PAY_AMT3',
     'PAY_AMT4',
     'PAY_AMT5',
     'PAY AMT6']
[28]: from pyspark.ml.feature import VectorAssembler, StandardScaler
    va = VectorAssembler().setInputCols(colNum).

-setOutputCol("to_be_scaled_features")
    featuredDatadft_bis_clean = va.transform(renamedDatadft_bis_clean)
```

```
scaler = StandardScaler().setInputCol("to_be_scaled_features").
      ⇔setOutputCol("features")
     dataset_bis = scaler.fit(featuredDatadft_bis_clean).

¬transform(featuredDatadft_bis_clean).select("features", "label")

     dataset_bis.show(5)
     +----+
                features|label|
     +----+
     |[2.32168783618879...|
                           1 |
     |[3.48253175428319...|
                           0|
                           0|
     |[4.64337567237759...|
     |[5.80421959047199...|
                           0|
     1 [6.96506350856639...]
                           01
    +----+
    only showing top 5 rows
    1.0.5 4. Application des modèles
[29]: trainSetb, testSetb = dataset_bis.randomSplit([0.8,0.2])
[30]: trainSetb.count()
[30]: 18494
[31]: testSetb.count()
[31]: 4664
[32]: trainSetb.show(5)
     +----+
                features|label|
     +----+
     |(24,[0,1,2,3,4,5,...|
                           01
     |(24,[0,1,2,3,4,5,...|
                           01
     |(24,[0,1,2,3,4,5,...]
                           01
     |(24,[0,1,2,3,4,5,...|
                           0|
     |(24,[0,1,2,3,4,5,...|
                           0|
    only showing top 5 rows
```

1.0.6 4.1 Logistic Regression

```
[33]: from pyspark.ml.classification import LogisticRegression
            from pyspark.ml.evaluation import BinaryClassificationEvaluator
            lr_b = LogisticRegression(maxIter=100, regParam=0.0001, elasticNetParam=0.1)
            lrModel_b = lr_b.fit(trainSetb)
[34]: # trainingSummary = lrModel.summary
            print("Coefficients: " + str(lrModel_b.coefficients))
            print("Intercept: " + str(lrModel_b.intercept))
          Coefficients: [-0.02094330588103058,-0.17998491808473413,-0.04570017072716318,-0
           .11032980661501554,0.08180686709890893,0.04774788768784148,0.07102923985889595,0
           .07978566469835958,-0.3711038032003112,0.2841025868205868,0.002833425120911844,0
           .049224513407792644, 0.015627669327713645, -0.015931441855878616, -0.15447222157692, -0.015931441855878616, -0.015447222157692, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.015931441855878616, -0.0159314418578616, -0.0159314418578616, -0.015931441855878616, -0.0159314418578616, -0.0159314418578616, -0.0159314418578616, -0.0159314418578616, -0.0159314418578616, -0.0159314418578616, -0.0159314418616, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.01594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.0015941644, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594164, -0.001594404, -0.001594404, 
          014, -0.14494741912990822, -0.007457465858492866, -0.05608250525945112, -0.047916706
          055974104,0.02873570956534439]
          Intercept: -0.928546893254043
[35]: summary = lrModel_b.summary
            print("Training set areaUnderROC:", summary.areaUnderROC)
            summary.roc.show()
            summary.pr.show()
           Training set areaUnderROC: 0.7524071908449781
           +----+
                                              FPR.I
                                                                                         TPR I
                                               0.01
                                                                                         0.01
           |4.907459338194055E-4|0.002600472813238...|
           0.001051598429613... 0.004964539007092199
           0.001542344363432... 0.007565011820330969
           10.001752664049355... | 0.0111111111111111111
           0.002243409983174425 0.013711583924349883
           0.002383623107122... 0.017494089834515367
           0.002734155916993... 0.02056737588652482
           |0.003084688726864...| 0.02364066193853428|
           0.003295008412787437 | 0.027186761229314422 |
           |0.003715647784632...|0.030023640661938536|
           0.003996074032529445 0.0333333333333333333
           0.004136287156477846 | 0.037115839243498816 |
           0.004416713404374649 | 0.04042553191489362
           [0.004837352776219...] 0.04326241134751773
           0.005047672462142457 | 0.04680851063829787
           0.00532809871003926 | 0.050118203309692674 |
           10.00574873808188446410.0529550827423167851
```

```
0.005959057767807066 0.056501182033096925
     0.006449803701626472 0.0591016548463357
    +----+
    only showing top 20 rows
                  recall
                                precision
     +----+
                     0.0|0.61111111111111111
     0.002600472813238... 0.6111111111111111
     |0.004964539007092199|0.58333333333333334|
     0.007565011820330969 0.5925925925925926
     |0.011111111111111112|0.652777777777778|
     0.013711583924349883 0.644444444444445
     |0.017494089834515367|0.6851851851851852|
     0.02056737588652482 | 0.6904761904761905 |
     | 0.02364066193853428|0.6944444444444444|
     [0.027186761229314422]0.7098765432098766]
     [0.030023640661938536]0.705555555555556]
     0.03333333333333330.712121212121212121
     0.037115839243498816 0.7268518518518519
     0.04042553191489362 | 0.7307692307692307 |
     0.04326241134751773 | 0.7261904761904762 |
     0.04680851063829787 | 0.733333333333333333333
     0.050118203309692674 0.7361111111111111
     |0.052955082742316785|0.7320261437908496|
     [0.056501182033096925]0.7376543209876543]
     0.0591016548463357|0.7309941520467836|
    +----+
    only showing top 20 rows
[36]: # make predictions on the test data
     lr_predictions_b = lrModel_b.transform(testSetb)
     lr_predictions_b.select("prediction", "label", "features").show(25)
     lr_evaluator_b = BinaryClassificationEvaluator()
     print('Test Area Under ROC', lr_evaluator_b.evaluate(lr_predictions_b))
```

+	+	+	+
pred	liction la	bel fe	eatures
+		+	+
1	0.0	1 (24,[0,1,2,3,4	4,5,…
1	0.01	0 (24,[0,1,2,3,4	4,5,…
	0.01	1 (24,[0,1,2,3,4	4,5,…
1	0.0	0 (24,[0,1,2,3,4	4,5,…
1	0.0	0 (24,[0,1,2,3,4	4,5,

```
0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.0
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 1 | (24, [0,1,2,3,4,5,...]
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.0
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 1 | [2.32168783618879...|
        0.01
                 0 | [0.00139301270171...|
        0.01
                 0 | [0.00185735026895...|
        0.01
                 0 | [0.00336644736247...]
        0.01
                 0 | [0.00359861614609...|
        0.01
                 0 | [0.00429512249694...|
        0.01
                 0 | [0.00464337567237...|
        0.01
                 0 | [0.00499162884780...|
        0.01
                 0 | [0.00684897911675...|
        1.01
                 1 | [0.00835807621027...|
    ----+
only showing top 25 rows
```

Test Area Under ROC 0.7364789966745253

1.0.7 4.2 Decision Tree

```
0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 1|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.0
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.0
                 0|(24,[0,1,2,3,4,5,...|
        0.0
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.0
                 1|(24,[0,1,2,3,4,5,...|
        0.0
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 0|(24,[0,1,2,3,4,5,...|
                 0|(24,[0,1,2,3,4,5,...|
        0.01
        0.01
                 0|(24,[0,1,2,3,4,5,...|
        0.01
                 1 | [2.32168783618879... |
        0.01
                 0 | [0.00139301270171...|
        0.01
                 0 | [0.00185735026895...|
        0.01
                 0 | [0.00336644736247...|
        0.0
                 0 | [0.00359861614609...|
        0.01
                 0 | [0.00429512249694...|
        0.01
                 0 | [0.00464337567237...|
        0.0
                 0 | [0.00499162884780...|
        1.01
                 0 | [0.00684897911675...|
        1.01
                 1 | [0.00835807621027...|
     -----+
only showing top 25 rows
```

Test Area Under ROC: 0.43740745891175686

1.0.8 4.3 Random Forest

```
[41]: from pyspark.ml.classification import RandomForestClassifier

rf = RandomForestClassifier(featuresCol = "features", labelCol = "label")

rfModel_b = rf.fit(trainSetb)

rf_predictions_b = rfModel_b.transform(testSetb)

rf_predictions_b.select("prediction", "label", "features").show(25)
```

```
+----+
|prediction|label|
    ----+
      0.0
             1|(24,[0,1,2,3,4,5,...|
      0.01
             0|(24,[0,1,2,3,4,5,...|
      0.0
             1|(24,[0,1,2,3,4,5,...|
      0.0
             0|(24,[0,1,2,3,4,5,...|
      0.0
             0|(24,[0,1,2,3,4,5,...|
      0.0
             0|(24,[0,1,2,3,4,5,...|
      0.01
             0|(24,[0,1,2,3,4,5,...|
```

```
0.01
                  0|(24,[0,1,2,3,4,5,...|
         0.01
                  0|(24,[0,1,2,3,4,5,...|
         0.01
                  1|(24,[0,1,2,3,4,5,...|
         0.0
                  0|(24,[0,1,2,3,4,5,...|
         0.01
                  0|(24,[0,1,2,3,4,5,...|
                  0|(24,[0,1,2,3,4,5,...|
         0.0
         0.0
                  0|(24,[0,1,2,3,4,5,...|
         0.01
                  0|(24,[0,1,2,3,4,5,...|
         0.0
                  1 | [2.32168783618879...|
         0.0
                  0 | [0.00139301270171...|
         0.01
                  0 | [0.00185735026895...|
                  0|[0.00336644736247...|
         0.01
         0.01
                  0 | [0.00359861614609...|
         0.01
                  0 | [0.00429512249694...|
         0.01
                  0 | [0.00464337567237...|
         0.01
                  0 | [0.00499162884780...|
         0.01
                  0 | [0.00684897911675...|
         1.0|
                  1 | [0.00835807621027...|
only showing top 25 rows
```

```
[42]: rf_evaluator2 = BinaryClassificationEvaluator(labelCol="label")
accuracy = rf_evaluator2.evaluate(rf_predictions_b)
print("Accuracy = %s" % (accuracy))
print("Test Error = %s" % (1.0 - accuracy))
```

Accuracy = 0.7793560340791312 Test Error = 0.22064396592086877

Test Area Under ROC: 0.7793560340791312