Published in Towards Data Science

Susan Li Follow

May 6, 2018 · 6 min read · Listen



# Machine Learning with PySpark and MLlib — Solving a Binary Classification Problem


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Apache Spark, once a component of the Hadoop ecosystem, is now becoming the big-data platform of choice for enterprises. It is a powerful open source engine that provides real-time stream processing, interactive processing, graph processing, in-memory processing as well as batch processing with very fast speed, ease of use and standard interface.

In the industry, there is a big demand for a powerful engine that can do all of above. Sooner or later, your company or your clients will be using Spark to develop sophisticated models that would enable you to discover new opportunities or avoid risk. Spark is not hard to learn, if you already known Python and SQL, it is very easy to get started. Let's give it a try today!

We will use the same data set when we built a Logistic Regression in Python, and it is related to direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict whether the client will subscribe (Yes/No) to a term deposit. The dataset can be downloaded from Kaggle.

```
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName('ml-bank').getOrCreate()
df = spark.read.csv('bank.csv', header = True, inferSchema = True)
df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- deposit: string (nullable = true)
```

Figure 1

Input variables: age, job, marital, education, default, balance, housing, loan, contact, day, month, duration, campaign, pdays, previous, poutcome.

Output variable: deposit

Have a peek of the first five observations. Pandas data frame is prettier than Spark DataFrame.show().

```
import pandas as pd
pd.DataFrame(df.take(5), columns=df.columns).transpose()
```

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **age** | 59 | 56 | 41 | 55 | 54 |
| **job** | admin. | admin. | technician | services | admin. |
| **marital** | married | married | married | married | married |
| **education** | secondary | secondary | secondary | secondary | tertiary |
| **default** | no | no | no | no | no |
| **balance** | 2343 | 45 | 1270 | 2476 | 184 |
| **housing** | yes | no | yes | yes | no |
| **loan** | no | no | no | no | no |
| **contact** | unknown | unknown | unknown | unknown | unknown |
| **day** | 5 | 5 | 5 | 5 | 5 |
| **month** | may | may | may | may | may |
| **duration** | 1042 | 1467 | 1389 | 579 | 673 |
| **campaign** | 1 | 1 | 1 | 1 | 2 |
| **pdays** | -1 | -1 | -1 | -1 | -1 |
| **previous** | 0 | 0 | 0 | 0 | 0 |
| **poutcome** | unknown | unknown | unknown | unknown | unknown |
| **deposit** | yes | yes | yes | yes | yes |

Figure 2

Our classes are perfect balanced.

```
import pandas as pd
pd.DataFrame(df.take(5), columns=df.columns).transpose()
```

| | deposit | count |
|---|---|---|
| **0** | no | 5873 |
| **1** | yes | 5289 |

Figure 3

## Summary statistics for numeric variables

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| summary | count | mean | stddev | min | max |
| age | 11162 | 41.231947679627304 | 11.913369192215518 | 18 | 95 |
| balance | 11162 | 1528.5385235620856 | 3225.413325946149 | -6847 | 81204 |
| day | 11162 | 15.658036194230425 | 8.420739541006462 | 1 | 31 |
| duration | 11162 | 371.99381831213043 | 347.12838571630687 | 2 | 3881 |
| campaign | 11162 | 2.508421429851281 | 2.7220771816614824 | 1 | 63 |
| pdays | 11162 | 51.33040673714388 | 108.75828197197717 | -1 | 854 |
| previous | 11162 | 0.8325568894463358 | 2.292007218670508 | 0 | 58 |

Figure 4

## Correlations between independent variables.

```
numeric_data = df.select(numeric_features).toPandas()

axs = pd.scatter_matrix(numeric_data, figsize=(8, 8));

n = len(numeric_data.columns)
for i in range(n):
    v = axs[i, 0]
    v.yaxis.label.set_rotation(0)
    v.yaxis.label.set_ha('right')
    v.set_yticks(())
    h = axs[n-1, i]
    h.xaxis.label.set_rotation(90)
    h.set_xticks(())
```

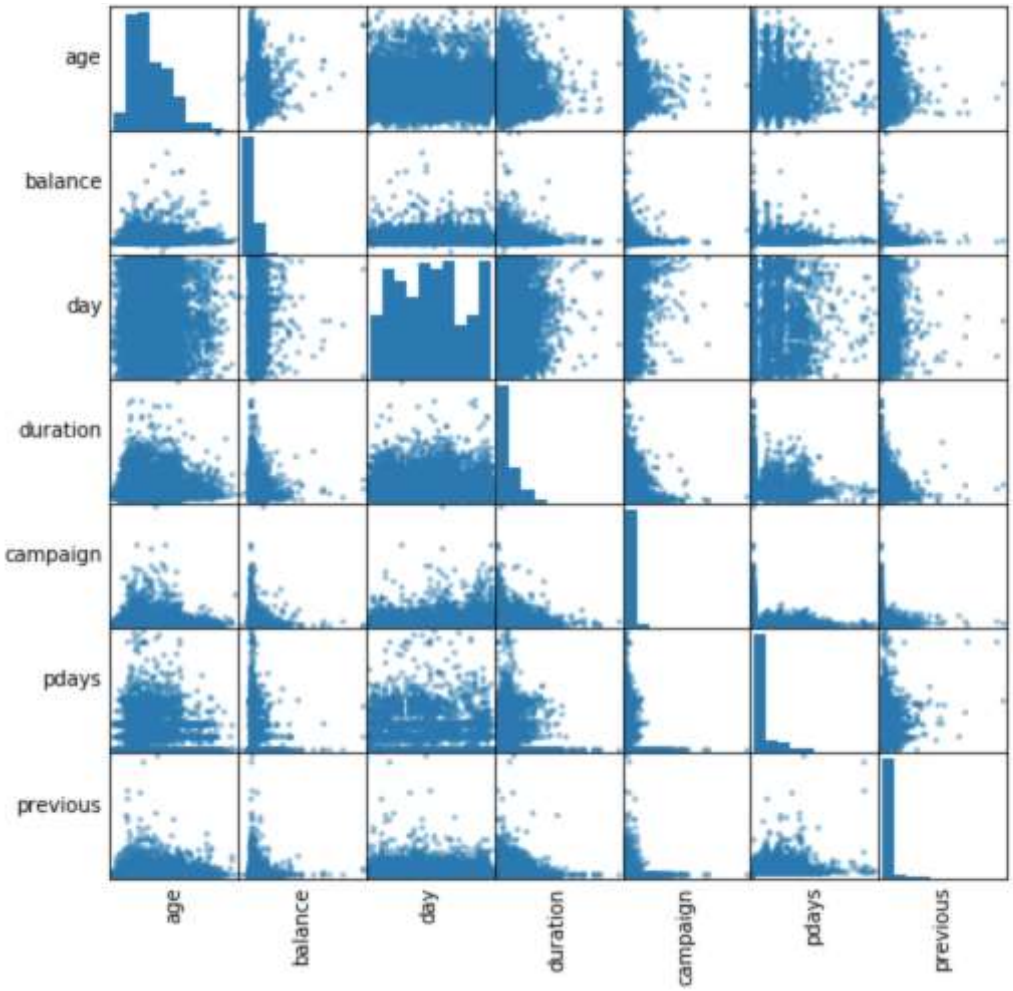



Figure 5

It's obvious that there aren't highly correlated numeric variables. Therefore, we will keep all of them for the model. However, day and month columns are not really useful, we will remove these two columns.

```
df = df.select('age', 'job', 'marital', 'education', 'default',
'balance', 'housing', 'loan', 'contact', 'duration', 'campaign',
'pdays', 'previous', 'poutcome', 'deposit')
cols = df.columns
df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- deposit: string (nullable = true)
```

Figure 6

## Preparing Data for Machine Learning

The process includes Category Indexing, One-Hot Encoding and VectorAssembler — a feature transformer that merges multiple columns into a vector column.

```
from pyspark.ml.feature import OneHotEncoderEstimator,
StringIndexer, VectorAssembler

categoricalColumns = ['job', 'marital', 'education', 'default',
'housing', 'loan', 'contact', 'poutcome']
stages = []

for categoricalCol in categoricalColumns:
    stringIndexer = StringIndexer(inputCol = categoricalCol,
outputCol = categoricalCol + 'Index')
    encoder = OneHotEncoderEstimator(inputCols=
[stringIndexer.getOutputCol()], outputCols=[categoricalCol +
"classVec"])
    stages += [stringIndexer, encoder]

label_stringIdx = StringIndexer(inputCol = 'deposit', outputCol =
'label')
stages += [label_stringIdx]

numericCols = ['age', 'balance', 'duration', 'campaign', 'pdays',
'previous']
assemblerInputs = [c + "classVec" for c in categoricalColumns] +
numericCols
```

The above code are taken from databricks' official site and it indexes each categorical column using the StringIndexer, then converts the indexed categories into one-hot encoded variables. The resulting output has the binary vectors appended to the end of each row. We use the StringIndexer again to encode our labels to label indices. Next, we use the VectorAssembler to combine all the feature columns into a single vector column.

### Pipeline

We use Pipeline to chain multiple Transformers and Estimators together to specify our machine learning workflow. A Pipeline's stages are specified as an ordered array.

```
from pyspark.ml import Pipeline
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(df)
df = pipelineModel.transform(df)
selectedCols = ['label', 'features'] + cols
df = df.select(selectedCols)
df.printSchema()
```

```
root
 |-- label: double (nullable = false)
 |-- features: vector (nullable = true)
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- deposit: string (nullable = true)
```

Figure 7

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| label | 1 | 1 | 1 | 1 | 1 |
| features | (0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, ... | (0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, ... | (0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ... | (0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, ... | (0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, ... |
| age | 59 | 56 | 41 | 55 | 54 |
| job | admin. | admin. | technician | services | admin. |
| marital | married | married | married | married | married |
| education | secondary | secondary | secondary | secondary | tertiary |
| default | no | no | no | no | no |
| balance | 2343 | 45 | 1270 | 2476 | 184 |
| housing | yes | no | yes | yes | no |
| loan | no | no | no | no | no |
| contact | unknown | unknown | unknown | unknown | unknown |
| duration | 1042 | 1467 | 1389 | 579 | 673 |
| campaign | 1 | 1 | 1 | 1 | 2 |
| pdays | -1 | -1 | -1 | -1 | -1 |
| previous | 0 | 0 | 0 | 0 | 0 |
| poutcome | unknown | unknown | unknown | unknown | unknown |
| deposit | yes | yes | yes | yes | yes |

Figure 8

As you can see, we now have features column and label column.

Randomly split data into train and test sets, and set seed for reproducibility.

```
train, test = df.randomSplit([0.7, 0.3], seed = 2018)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

*Training Dataset Count: 7764*

*Test Dataset Count: 3398*

## Logistic Regression Model

```
from pyspark.ml.classification import LogisticRegression

lr = LogisticRegression(featuresCol = 'features', labelCol =
'label', maxIter=10)
lrModel = lr.fit(train)
```

```
import matplotlib.pyplot as plt
import numpy as np

beta = np.sort(lrModel.coefficients)

plt.plot(beta)
plt.ylabel('Beta Coefficients')
plt.show()
```

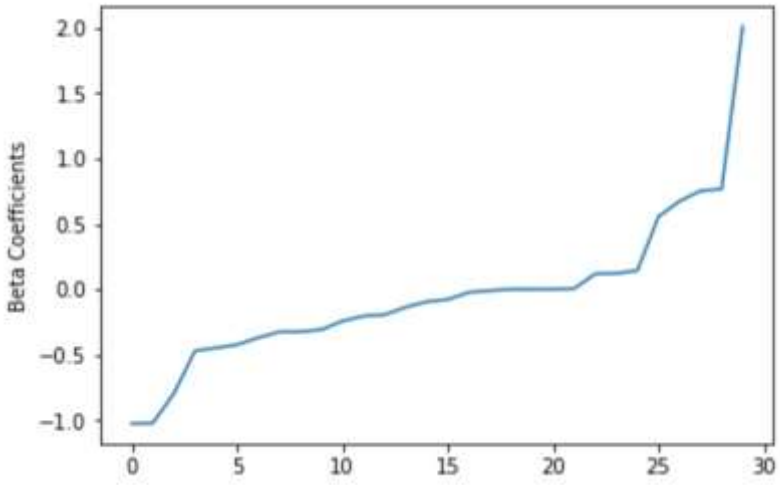


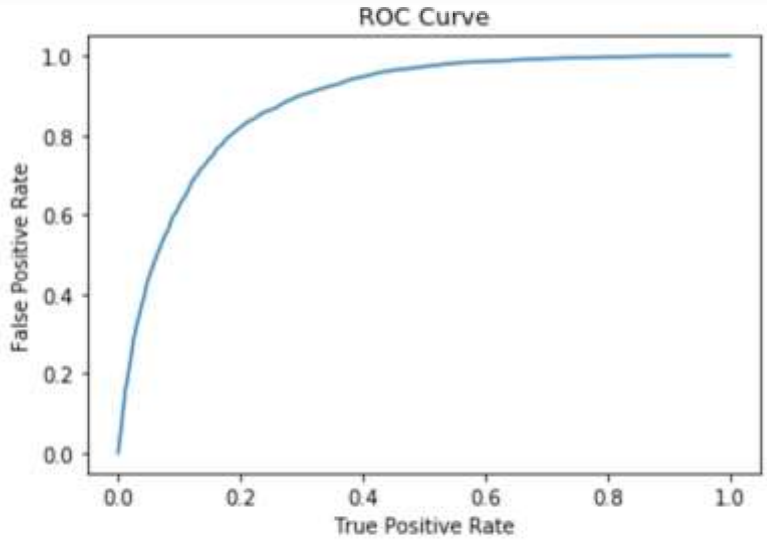

Figure 9

Summarize the model over the training set, we can also obtain the **receiver-operating characteristic and areaUnderROC**.

```
trainingSummary = lrModel.summary

roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'],roc['TPR'])
plt.ylabel('False Positive Rate')
plt.xlabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()

print('Training set areaUnderROC: ' +
str(trainingSummary.areaUnderROC))
```




```
Training set areaUnderROC: 0.8849092421146739
```

Figure 10

## Precision and recall.

```
pr = trainingSummary.pr.toPandas()
plt.plot(pr['recall'],pr['precision'])
plt.ylabel('Precision')
plt.xlabel('Recall')
plt.show()
```

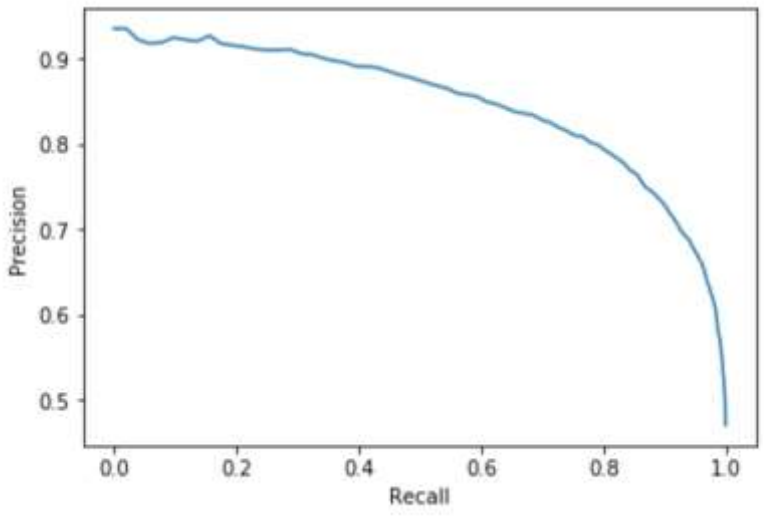



Figure 11

```
predictions = lrModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction',
'prediction', 'probability').show(10)
```

```
+---+----------+-----+--------------------+----------+--------------------+
|age|       job|label|       rawPrediction|prediction|         probability|
+---+----------+-----+--------------------+----------+--------------------+
| 37|management|  0.0|[1.19871810716723...|       0.0|[0.76829666339830...|
| 40|management|  0.0|[2.20534940465796...|       0.0|[0.90072886169926...|
| 53|management|  0.0|[1.02590348276690...|       0.0|[0.73612093009497...|
| 32|management|  0.0|[1.25795481657702...|       0.0|[0.77867383994058...|
| 54|management|  0.0|[1.33232096924268...|       0.0|[0.79122429116078...|
| 40|management|  0.0|[1.57095096412779...|       0.0|[0.82791913346617...|
| 56|management|  0.0|[3.06095963426752...|       0.0|[0.95525333386804...|
| 50|management|  0.0|[-0.8102603273804...|       1.0|[0.30783502428597...|
| 47|management|  0.0|[0.67024288891379...|       0.0|[0.66155754396054...|
| 44|management|  0.0|[1.29756265761715...|       0.0|[0.78542449653716...|
+---+----------+-----+--------------------+----------+--------------------+
only showing top 10 rows
```

Figure 12

**Evaluate our Logistic Regression model.**

```
from pyspark.ml.evaluation import BinaryClassificationEvaluator

evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
```

*Test Area Under ROC 0.8858324614449619*

## Decision Tree Classifier

Decision trees are widely used since they are easy to interpret, handle categorical features, extend to the multi-class classification, do not require feature scaling, and are able to capture non-linearities and feature interactions.

```
from pyspark.ml.classification import DecisionTreeClassifier

dt = DecisionTreeClassifier(featuresCol = 'features', labelCol
```

```
+---+----------+-----+--------------+----------+--------------------+
|age|       job|label| rawPrediction|prediction|         probability|
+---+----------+-----+--------------+----------+--------------------+
| 37|management|  0.0|[1130.0,387.0]|       0.0|[0.74489123269611...|
| 40|management|  0.0| [1333.0,86.0]|       0.0|[0.93939393939393...|
| 53|management|  0.0|[1130.0,387.0]|       0.0|[0.74489123269611...|
| 32|management|  0.0|[1130.0,387.0]|       0.0|[0.74489123269611...|
| 54|management|  0.0| [1333.0,86.0]|       0.0|[0.93939393939393...|
| 40|management|  0.0|  [373.0,30.0]|       0.0|[0.92555831265508...|
| 56|management|  0.0| [1333.0,86.0]|       0.0|[0.93939393939393...|
| 50|management|  0.0|[788.0,1230.0]|       1.0|[0.39048562933597...|
| 47|management|  0.0|[788.0,1230.0]|       1.0|[0.39048562933597...|
| 44|management|  0.0|[1130.0,387.0]|       0.0|[0.74489123269611...|
+---+----------+-----+--------------+----------+--------------------+
only showing top 10 rows
```

Figure 13

**Evaluate our Decision Tree model.**

```
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions,
{evaluator.metricName: "areaUnderROC"})))
```

*Test Area Under ROC: 0.7807240050065357*

One simple decision tree performed poorly because it is too weak given the range of different features. The prediction accuracy of decision trees can be improved by Ensemble methods, such as Random Forest and Gradient-Boosted Tree.

## Random Forest Classifier

```
from pyspark.ml.classification import RandomForestClassifier

rf = RandomForestClassifier(featuresCol = 'features', labelCol =
'label')
rfModel = rf.fit(train)
predictions = rfModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction',
```

```
+---+----------+-----+--------------------+----------+--------------------+
|age|       job|label|       rawPrediction|prediction|         probability|
+---+----------+-----+--------------------+----------+--------------------+
| 37|management|  0.0|[14.0335043427458...|       0.0|[0.70167521713729...|
| 40|management|  0.0|[15.5696428848403...|       0.0|[0.77848214424201...|
| 53|management|  0.0|[14.0604626680319...|       0.0|[0.70302313340159...|
| 32|management|  0.0|[14.9300431640802...|       0.0|[0.74650215820401...|
| 54|management|  0.0|[14.4483343905905...|       0.0|[0.72241671952952...|
| 40|management|  0.0|[15.0798534256099...|       0.0|[0.75399267128049...|
| 56|management|  0.0|[18.2682164556330...|       0.0|[0.91341082278165...|
| 50|management|  0.0|[5.99972486043756...|       1.0|[0.29998624302187...|
| 47|management|  0.0|[10.8585049161417...|       0.0|[0.54292524580708...|
| 44|management|  0.0|[10.6040194546245...|       0.0|[0.53020097273122...|
+---+----------+-----+--------------------+----------+--------------------+
only showing top 10 rows
```

Figure 14

### Evaluate our Random Forest Classifier.

```
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions,
{evaluator.metricName: "areaUnderROC"})))
```

*Test Area Under ROC: 0.8846453518867426*

## Gradient-Boosted Tree Classifier

```
from pyspark.ml.classification import GBTClassifier

gbt = GBTClassifier(maxIter=10)
gbtModel = gbt.fit(train)
predictions = gbtModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction',
'prediction', 'probability').show(10)
```

```
+---+----------+-----+--------------------+----------+--------------------+
|age|       job|label|       rawPrediction|prediction|         probability|
+---+----------+-----+--------------------+----------+--------------------+
| 37|management|  0.0|[0.57808138910181...|       0.0|[0.76063477260811...|
| 40|management|  0.0|[1.37467582901950...|       0.0|[0.93987672346171...|
| 53|management|  0.0|[-0.0012929624008...|       1.0|[0.49935351915983...|
| 32|management|  0.0|[0.61900313605401...|       0.0|[0.77521678642033...|
| 54|management|  0.0|[0.98157815641818...|       0.0|[0.87687413211579...|
| 40|management|  0.0|[0.96138354833170...|       0.0|[0.87244668327834...|
| 56|management|  0.0|[1.39120025731353...|       0.0|[0.94171733839668...|
| 50|management|  0.0|[-0.6141629093446...|       1.0|[0.22647458093662...|
| 47|management|  0.0|[-0.0439971283470...|       1.0|[0.47801561939801...|
| 44|management|  0.0|[0.26452511568224...|       0.0|[0.62926156628314...|
+---+----------+-----+--------------------+----------+--------------------+
only showing top 10 rows
```

Figure 15

**Evaluate our Gradient-Boosted Tree Classifier.**

```
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions,
{evaluator.metricName: "areaUnderROC"})))
```

*Test Area Under ROC: 0.8940728473145346*

Gradient-Boosted Tree achieved the best results, we will try tuning this model with the ParamGridBuilder and the CrossValidator. Before that we can use explainParams() to print a list of all params and their definitions to understand what params available for tuning.

```
print(gbt.explainParams())
```

```
cacheNodeIds: If false, the algorithm will pass trees to executors to match instances with nodes. If true, the algori
thm will cache node IDs for each instance. Caching can speed up training of deeper trees. Users can set how often sho
uld the cache be checkpointed or disable it by setting checkpointInterval. (default: False)
checkpointInterval: set checkpoint interval (>= 1) or disable checkpoint (-1). E.g. 10 means that the cache will get
checkpointed every 10 iterations. Note: this setting will be ignored if the checkpoint directory is not set in the Sp
arkContext. (default: 10)
featuresCol: features column name. (default: features)
labelCol: label column name. (default: label)
lossType: Loss function which GBT tries to minimize (case-insensitive). Supported options: logistic (default: logisti
c)
maxBins: Max number of bins for discretizing continuous features.  Must be >=2 and >= number of categories for any ca
tegorical feature. (default: 32)
maxDepth: Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node; depth 1 means 1 internal node + 2 leaf n
odes. (default: 5)
maxIter: max number of iterations (>= 0). (default: 20, current: 10)
maxMemoryInMB: Maximum memory in MB allocated to histogram aggregation. If too small, then 1 node will be split per i
teration, and its aggregates may exceed this size. (default: 256)
minInfoGain: Minimum information gain for a split to be considered at a tree node. (default: 0.0)
minInstancesPerNode: Minimum number of instances each child must have after split. If a split causes the left or righ
t child to have fewer than minInstancesPerNode, the split will be discarded as invalid. Should be >= 1. (default: 1)
predictionCol: prediction column name. (default: prediction)
seed: random seed. (default: -7674267899484452859)
stepSize: Step size (a.k.a. learning rate) in interval (0, 1] for shrinking the contribution of each estimator. (defa
ult: 0.1)
subsamplingRate: Fraction of the training data used for learning each decision tree, in range (0, 1]. (default: 1.0)
```

Figure 16

```
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

paramGrid = (ParamGridBuilder()
             .addGrid(gbt.maxDepth, [2, 4, 6])
             .addGrid(gbt.maxBins, [20, 60])
             .addGrid(gbt.maxIter, [10, 20])
             .build())

cv = CrossValidator(estimator=gbt, estimatorParamMaps=paramGrid,
evaluator=evaluator, numFolds=5)

# Run cross validations.  This can take about 6 minutes since it is
training over 20 trees!
cvModel = cv.fit(train)
predictions = cvModel.transform(test)
evaluator.evaluate(predictions)
```

*0.8981050997838095*

To sum it up, we have learned how to build a binary classification application using PySpark and MLlib Pipelines API. We tried four algorithms and gradient boosting performed best on our data set.

Source code can be found on Github. I look forward to hearing feedback or questions.