پریسا سادات عمادی - شماره دانشجویی: ۴۰۱۳۶۲۴۰۲۰

تمرین ششم

In [ ]:
```
!pip install pyspark
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting pyspark
  Downloading pyspark-3.4.0.tar.gz (310.8 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 310.8/310.8 MB 4.2 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: py4j==0.10.9.7 in /usr/local/lib/python3.9/dist-packages (from pyspark) (0.1
0.9.7)
Building wheels for collected packages: pyspark
  Building wheel for pyspark (setup.py) ... done
  Created wheel for pyspark: filename=pyspark-3.4.0-py2.py3-none-any.whl size=311317145 sha256=e1963cdade1d
27f4e160a8a36ba7b9dfd921412230ed23b4602acac73ef9fd53
  Stored in directory: /root/.cache/pip/wheels/9f/34/a4/159aa12d0a510d5ff7c8f0220abbea42e5d81ecf588c4fd884
Successfully built pyspark
Installing collected packages: pyspark
Successfully installed pyspark-3.4.0
```

In [ ]:
```
from pyspark.sql import SparkSession
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
```

In [ ]:
```
spark = SparkSession.builder.appName('ml-diabetes').getOrCreate()
df = spark.read.csv('ML_hw_dataset.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)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- month: string (nullable = true)
 |-- day_of_week: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- emp_var_rate: double (nullable = true)
 |-- cons_price_idx: double (nullable = true)
 |-- cons_conf_idx: double (nullable = true)
 |-- euribor3m: double (nullable = true)
 |-- nr_employed: double (nullable = true)
 |-- y: integer (nullable = true)
```

In [ ]:
```
df.show(10)
```

```
+---+-----------+--------+----------------+-------+-------+----+--------+-----+-----------+--------+------
--+-----+--------+-----------+------------+-------------+------------+---------+-----------+---+
|age|        job| marital|       education|default|housing|loan| contact|month|day_of_week|duration|campai
gn|pdays|previous|   poutcome|emp_var_rate|cons_price_idx|cons_conf_idx|euribor3m|nr_employed|  y|
+---+-----------+--------+----------------+-------+-------+----+--------+-----+-----------+--------+------
--+-----+--------+-----------+------------+-------------+------------+---------+-----------+---+
| 44|blue-collar| married|        basic.4y|unknown|    yes|  no|cellular|  aug|        thu|     210|
1|  999|       0|nonexistent|         1.4|       93.444|       -36.1|    4.963|     5228.1|  0|
| 53| technician| married|         unknown|     no|     no|  no|cellular|  nov|        fri|     138|
1|  999|       0|nonexistent|        -0.1|         93.2|       -42.0|    4.021|     5195.8|  0|
| 28| management|  single|university.degree|     no|    yes|  no|cellular|  jun|        thu|     339|
3|    6|       2|    success|        -1.7|       94.055|       -39.8|    0.729|     4991.6|  1|
| 39|   services| married|     high.school|     no|     no|  no|cellular|  apr|        fri|     185|
2|  999|       0|nonexistent|        -1.8|       93.075|       -47.1|    1.405|     5099.1|  0|
| 55|    retired| married|        basic.4y|     no|    yes|  no|cellular|  aug|        fri|     137|
1|    3|       1|    success|        -2.9|       92.201|       -31.4|    0.869|     5076.2|  1|
| 30| management|divorced|        basic.4y|     no|    yes|  no|cellular|  jul|        tue|      68|
8|  999|       0|nonexistent|         1.4|       93.918|       -42.7|    4.961|     5228.1|  0|
| 37|blue-collar| married|        basic.4y|     no|    yes|  no|cellular|  may|        thu|     204|
1|  999|       0|nonexistent|        -1.8|       92.893|       -46.2|    1.327|     5099.1|  0|
| 39|blue-collar|divorced|        basic.9y|     no|    yes|  no|cellular|  may|        fri|     191|
1|  999|       0|nonexistent|        -1.8|       92.893|       -46.2|    1.313|     5099.1|  0|
| 36|     admin.| married|university.degree|     no|     no|  no|cellular|  jun|        mon|     174|
1|    3|       1|    success|        -2.9|       92.963|       -40.8|    1.266|     5076.2|  1|
| 27|blue-collar|  single|        basic.4y|     no|    yes|  no|cellular|  apr|        thu|     191|
2|  999|       1|    failure|        -1.8|       93.075|       -47.1|     1.41|     5099.1|  0|
+---+-----------+--------+----------------+-------+-------+----+--------+-----+-----------+--------+------
--+-----+--------+-----------+------------+-------------+------------+---------+-----------+---+
only showing top 10 rows
```

In [ ]:
```python
df.groupby('y').count().show()
```

```
+---+-----+
|  y|count|
+---+-----+
|  1| 4640|
|  0|36548|
+---+-----+
```

In [ ]:
```python
df.describe().show()
```

```
+-------+------------------+--------+--------+---------+-------+-------+-----+---------+-----+-----------+--
---------------+------------------+------------------+------------------+--------+-------------------+----
--------------+------------------+------------------+------------------+-------------------+
|summary|               age|     job| marital|education|default|housing| loan|  contact|month|day_of_week|
duration|          campaign|             pdays|          previous|poutcome|        emp_var_rate|     cons_pr
ice_idx|     cons_conf_idx|         euribor3m|       nr_employed|                  y|
+-------+------------------+--------+--------+---------+-------+-------+-----+---------+-----+-----------+--
---------------+------------------+------------------+------------------+--------+-------------------+----
--------------+------------------+------------------+------------------+-------------------+
|  count|             41188|   41188|   41188|    41188|  41188|  41188|41188|    41188|41188|      41188|
41188|             41188|             41188|             41188|   41188|              41188|             4
1188|             41188|             41188|             41188|              41188|
|   mean| 40.02406040594348|    null|    null|     null|   null|   null| null|     null| null|       null|25
8.2850101971448| 2.567592502670681| 962.4754540157328|0.17296299893172767|    null|0.08188550063125699| 93.
57566436827325|-40.50260027191949|3.6212908128582826|5167.035910942904|0.11265417111780131|
| stddev|10.421249980934071|    null|    null|     null|   null|   null| null|     null| null|       null|25
9.2792488364662|2.7700135429023405|186.91090734474142|0.49490107983929005|    null| 1.5709597405170228|0.57
88400489541238| 4.628197856174544| 1.734447404851268|72.25152766826125| 0.3161734269429653|
|    min|                17| admin.|divorced| basic.4y|     no|     no|   no| cellular|  apr|        fri|
0|                 1|                 0|                 0| failure|               -3.4|             92.201
|             -50.8|             0.634|            4963.6|                  0|
|    max|                98|unknown| unknown|  unknown|    yes|    yes|  yes|telephone|  sep|        wed|
4918|                56|               999|                 7| success|                1.4|              94.
767|             -26.9|             5.045|            5228.1|                  1|
+-------+------------------+--------+--------+---------+-------+-------+-----+---------+-----+-----------+--
---------------+------------------+------------------+------------------+--------+-------------------+----
--------------+------------------+------------------+------------------+-------------------+
```

In [ ]:
```python
df.columns
```

Out[ ]:
```
['age',
 'job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'duration',
 'campaign',
 'pdays',
 'previous',
 'poutcome',
 'emp_var_rate',
 'cons_price_idx',
 'cons_conf_idx',
 'euribor3m',
 'nr_employed',
 'y']
```

Fill Null values

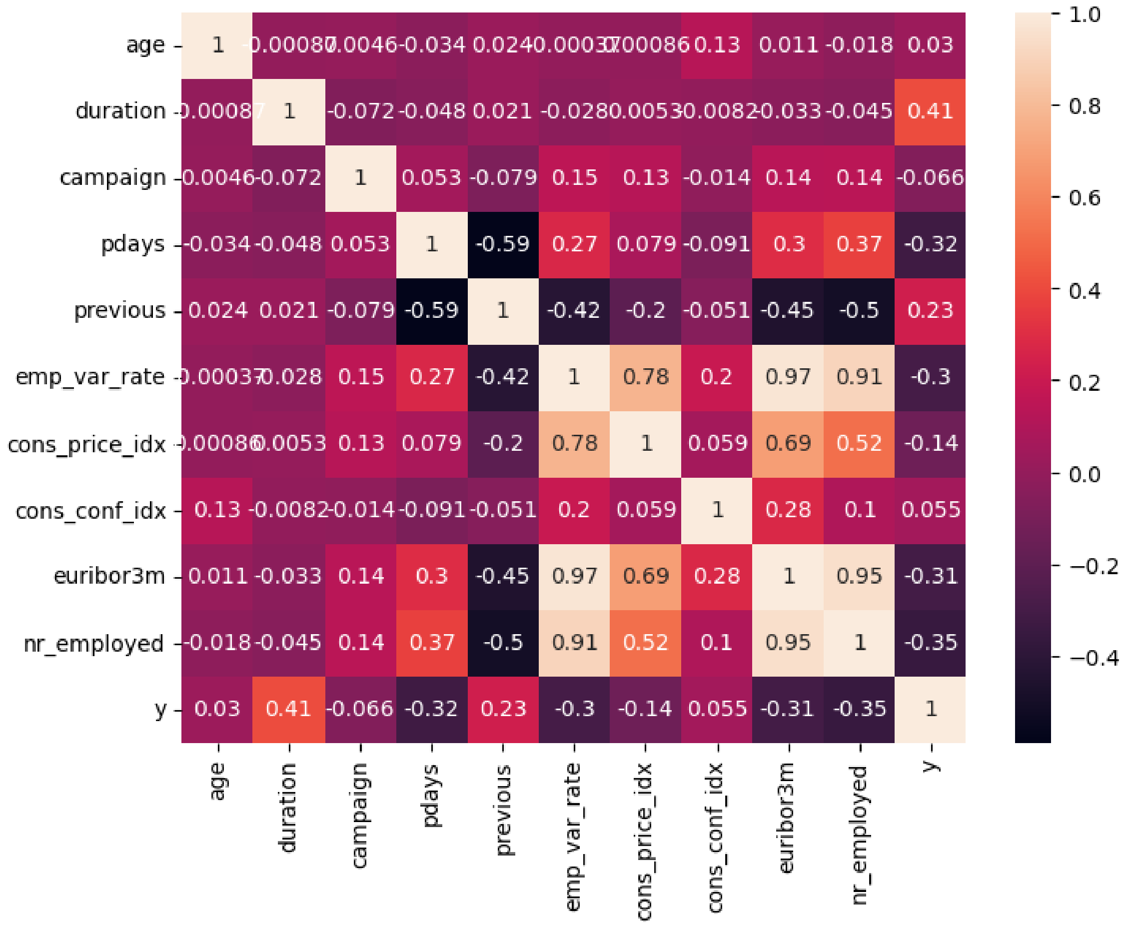
In [ ]:
```
## See if we have missing values
from pyspark.sql.functions import when, count
df.select([count(when(df[c]==None, c)).alias(c) for c in df.columns]).show()
```

```
+---+---+-------+---------+-------+-------+----+-------+-----+-----------+--------+--------+-----+--------+
--------+------------+--------------+-------------+---------+-----------+---+
|age|job|marital|education|default|housing|loan|contact|month|day_of_week|duration|campaign|pdays|previous|
poutcome|emp_var_rate|cons_price_idx|cons_conf_idx|euribor3m|nr_employed|  y|
+---+---+-------+---------+-------+-------+----+-------+-----+-----------+--------+--------+-----+--------+
--------+------------+--------------+-------------+---------+-----------+---+
|  0|  0|      0|        0|      0|      0|   0|      0|    0|          0|       0|       0|    0|       0|
0|           0|             0|            0|        0|          0|  0|
+---+---+-------+---------+-------+-------+----+-------+-----+-----------+--------+--------+-----+--------+
--------+------------+--------------+-------------+---------+-----------+---+
```

Correlation Matrix

In [ ]:
```
Correlation_matrix = df.toPandas().corr()
fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(Correlation_matrix, annot=True)
plt.show()
```

```
<ipython-input-9-738b4ffef13b>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is dep
recated. In a future version, it will default to False. Select only valid columns or specify the value of n
umeric_only to silence this warning.
  Correlation_matrix = df.toPandas().corr()
```



Indexing and One-Hot-Encoding

In [ ]:
```
from pyspark.ml.feature import StringIndexer
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.functions import vector_to_array
import pyspark.sql.functions as F
from pyspark.ml import Pipeline
from pyspark.pandas import concat, Series
```

```
/usr/local/lib/python3.9/dist-packages/pyspark/pandas/__init__.py:50: UserWarning: 'PYARROW_IGNORE_TIMEZON
E' environment variable was not set. It is required to set this environment variable to '1' in both driver
and executor sides if you use pyarrow>=2.0.0. pandas-on-Spark will set it for you but it does not work if t
here is a Spark context already launched.
  warnings.warn(
```

In [ ]:
```
df = StringIndexer(inputCol='job', outputCol='si_job').fit(df).transform(df)
df = StringIndexer(inputCol='marital', outputCol='si_marital').fit(df).transform(df)
df = StringIndexer(inputCol='education', outputCol='si_education').fit(df).transform(df)
df = StringIndexer(inputCol='default', outputCol='si_default').fit(df).transform(df)
df = StringIndexer(inputCol='housing', outputCol='si_housing').fit(df).transform(df)
df = StringIndexer(inputCol='loan', outputCol='si_loan').fit(df).transform(df)
df = StringIndexer(inputCol='contact', outputCol='si_contact').fit(df).transform(df)
df = StringIndexer(inputCol= 'poutcome', outputCol='si_poutcome').fit(df).transform(df)
df = StringIndexer(inputCol='month', outputCol='si_month').fit(df).transform(df)
df = StringIndexer(inputCol='day_of_week', outputCol='si_day').fit(df).transform(df)
```

Select Features for Classification

In [ ]:
```
df.show()
```

```
+---+-----------+--------+-----------------+-------+-------+----+---------+-----+-----------+--------+-----
---+-----+--------+-----------+------------+--------------+-------------+---------+-----------+---+------+-
---------+------------+----------+----------+-------+----------+-----------+--------+------+
|age|        job| marital|        education|default|housing|loan|  contact|month|day_of_week|duration|campa
ign|pdays|previous|   poutcome|emp_var_rate|cons_price_idx|cons_conf_idx|euribor3m|nr_employed|  y|si_job|s
i_marital|si_education|si_default|si_housing|si_loan|si_contact|si_poutcome|si_month|si_day|
+---+-----------+--------+-----------------+-------+-------+----+---------+-----+-----------+--------+-----
---+-----+--------+-----------+------------+--------------+-------------+---------+-----------+---+------+-
---------+------------+----------+----------+-------+----------+-----------+--------+------+
| 44|blue-collar| married|         basic.4y|unknown|    yes|  no| cellular|  aug|        thu|     210|
1|  999|       0|nonexistent|         1.4|        93.444|        -36.1|    4.963|     5228.1|  0|   1.0|
0.0|         4.0|       1.0|       0.0|    0.0|       0.0|        0.0|     2.0|   0.0|
| 53| technician| married|          unknown|     no|     no|  no| cellular|  nov|        fri|     138|
1|  999|       0|nonexistent|        -0.1|          93.2|        -42.0|    4.021|     5195.8|  0|   2.0|
0.0|         6.0|       0.0|       1.0|    0.0|       0.0|        0.0|     4.0|   4.0|
| 28| management|  single|university.degree|     no|    yes|  no| cellular|  jun|        thu|     339|
3|    6|       2|    success|        -1.7|        94.055|        -39.8|    0.729|     4991.6|  1|   4.0|
1.0|         0.0|       0.0|       0.0|    0.0|       0.0|        2.0|     3.0|   0.0|
| 39|   services| married|      high.school|     no|     no|  no| cellular|  apr|        fri|     185|
2|  999|       0|nonexistent|        -1.8|        93.075|        -47.1|    1.405|     5099.1|  0|   3.0|
0.0|         1.0|       0.0|       1.0|    0.0|       0.0|        0.0|     5.0|   4.0|
| 55|    retired| married|         basic.4y|     no|    yes|  no| cellular|  aug|        fri|     137|
1|    3|       1|    success|        -2.9|        92.201|        -31.4|    0.869|     5076.2|  1|   5.0|
0.0|         4.0|       0.0|       0.0|    0.0|       0.0|        2.0|     2.0|   4.0|
| 30| management|divorced|         basic.4y|     no|    yes|  no| cellular|  jul|        tue|      68|
8|  999|       0|nonexistent|         1.4|        93.918|        -42.7|    4.961|     5228.1|  0|   4.0|
2.0|         4.0|       0.0|       0.0|    0.0|       0.0|        0.0|     1.0|   3.0|
| 37|blue-collar| married|         basic.4y|     no|    yes|  no| cellular|  may|        thu|     204|
1|  999|       0|nonexistent|        -1.8|        92.893|        -46.2|    1.327|     5099.1|  0|   1.0|
0.0|         4.0|       0.0|       0.0|    0.0|       0.0|        0.0|     0.0|   0.0|
| 39|blue-collar|divorced|         basic.9y|     no|    yes|  no| cellular|  may|        fri|     191|
1|  999|       0|nonexistent|        -1.8|        92.893|        -46.2|    1.313|     5099.1|  0|   1.0|
2.0|         2.0|       0.0|       0.0|    0.0|       0.0|        0.0|     0.0|   4.0|
| 36|     admin.| married|university.degree|     no|     no|  no| cellular|  jun|        mon|     174|
1|    3|       1|    success|        -2.9|        92.963|        -40.8|    1.266|     5076.2|  1|   0.0|
0.0|         0.0|       0.0|       1.0|    0.0|       0.0|        2.0|     3.0|   1.0|
| 27|blue-collar|  single|         basic.4y|     no|    yes|  no| cellular|  apr|        thu|     191|
2|  999|       1|    failure|        -1.8|        93.075|        -47.1|     1.41|     5099.1|  0|   1.0|
1.0|         4.0|       0.0|       0.0|    0.0|       0.0|        1.0|     5.0|   0.0|
| 34|  housemaid|  single|university.degree|     no|     no|  no|telephone|  may|        fri|      62|
2|  999|       0|nonexistent|         1.1|        93.994|        -36.4|    4.864|     5191.0|  0|   8.0|
1.0|         0.0|       0.0|       1.0|    0.0|       1.0|        0.0|     0.0|   4.0|
| 41| management| married|university.degree|     no|    yes|  no| cellular|  aug|        thu|     789|
1|  999|       0|nonexistent|         1.4|        93.444|        -36.1|    4.964|     5228.1|  0|   4.0|
0.0|         0.0|       0.0|       0.0|    0.0|       0.0|        0.0|     2.0|   0.0|
| 55| management| married|university.degree|     no|     no|  no| cellular|  aug|        mon|     372|
3|  999|       0|nonexistent|         1.4|        93.444|        -36.1|    4.965|     5228.1|  1|   4.0|
0.0|         0.0|       0.0|       1.0|    0.0|       0.0|        0.0|     2.0|   1.0|
| 33|   services|divorced|      high.school|     no|    yes|  no| cellular|  may|        tue|      75|
5|  999|       0|nonexistent|        -1.8|        92.893|        -46.2|    1.291|     5099.1|  0|   3.0|
2.0|         1.0|       0.0|       0.0|    0.0|       0.0|        0.0|     0.0|   3.0|
| 26|     admin.| married|      high.school|     no|     no| yes|telephone|  jun|        mon|    1021|
1|  999|       0|nonexistent|         1.4|        94.465|        -41.8|     4.96|     5228.1|  0|   0.0|
0.0|         1.0|       0.0|       1.0|    1.0|       1.0|        0.0|     3.0|   1.0|
| 52|   services| married|      high.school|unknown|    yes|  no| cellular|  jul|        thu|     117|
2|  999|       0|nonexistent|         1.4|        93.918|        -42.7|    4.962|     5228.1|  0|   3.0|
0.0|         1.0|       1.0|       0.0|    0.0|       0.0|        0.0|     1.0|   0.0|
| 35|   services| married|      high.school|     no|     no|  no| cellular|  apr|        thu|    1034|
2|  999|       0|nonexistent|        -1.8|        93.075|        -47.1|    1.365|     5099.1|  1|   3.0|
0.0|         1.0|       0.0|       1.0|    0.0|       0.0|        0.0|     5.0|   0.0|
| 27|     admin.|  single|university.degree|     no|     no|  no|telephone|  oct|        tue|     540|
1|  999|       0|nonexistent|        -0.1|        93.798|        -40.4|     4.86|     5195.8|  1|   0.0|
1.0|         0.0|       0.0|       1.0|    0.0|       1.0|        0.0|     6.0|   3.0|
| 28|blue-collar| married|         basic.9y|unknown|     no|  no|telephone|  may|        thu|     140|
1|  999|       0|nonexistent|         1.1|        93.994|        -36.4|     4.86|     5191.0|  0|   1.0|
0.0|         2.0|       1.0|       1.0|    0.0|       1.0|        0.0|     0.0|   0.0|
| 26| unemployed|  single|         basic.9y|     no|    yes| yes| cellular|  jul|        mon|     104|
4|  999|       0|nonexistent|         1.4|        93.918|        -42.7|     4.96|     5228.1|  0|   9.0|
1.0|         2.0|       0.0|       0.0|    1.0|       0.0|        0.0|     1.0|   1.0|
+---+-----------+--------+-----------------+-------+-------+----+---------+-----+-----------+--------+-----
---+-----+--------+-----------+------------+--------------+-------------+---------+-----------+---+------+-
---------+------------+----------+----------+-------+----------+-----------+--------+------+
only showing top 20 rows
```

```
In [ ]: assembler = VectorAssembler(inputCols = ['age', 'duration', 'campaign', 'pdays', 'previous',
                                          'emp_var_rate', 'cons_price_idx', 'cons_conf_idx', 'euribor3m', '
                                          'si_job', 'si_marital', 'si_education', 'si_default', 'si_housing
                                          'si_contact', 'si_poutcome', 'si_month', 'si_day'],
                                outputCol = 'features')
        output = assembler.transform(df)
        final_data = output.select('features', 'y')
```

```
In [ ]: final_data.show()
```

```
+--------------------+---+
|            features|  y|
+--------------------+---+
|[44.0,210.0,1.0,9...|  0|
|[53.0,138.0,1.0,9...|  0|
|[28.0,339.0,3.0,6...|  1|
|[39.0,185.0,2.0,9...|  0|
|[55.0,137.0,1.0,3...|  1|
|[30.0,68.0,8.0,99...|  0|
|(20,[0,1,2,3,5,6,...|  0|
|[39.0,191.0,1.0,9...|  0|
|[36.0,174.0,1.0,3...|  1|
|[27.0,191.0,2.0,9...|  0|
|[34.0,62.0,2.0,99...|  0|
|(20,[0,1,2,3,5,6,...|  0|
|[55.0,372.0,3.0,9...|  1|
|[33.0,75.0,5.0,99...|  0|
|[26.0,1021.0,1.0,...|  0|
|[52.0,117.0,2.0,9...|  0|
|[35.0,1034.0,2.0,...|  1|
|[27.0,540.0,1.0,9...|  1|
|[28.0,140.0,1.0,9...|  0|
|[26.0,104.0,4.0,9...|  0|
+--------------------+---+
only showing top 20 rows
```

```
In [ ]: (trainingData, testData) = final_data.randomSplit([0.8, 0.2])
```

Modeling

```
In [ ]: from pyspark.ml.evaluation import BinaryClassificationEvaluator
        from sklearn.metrics import precision_score, recall_score
        binary_evaluator = BinaryClassificationEvaluator(rawPredictionCol='prediction', labelCol='y')
```

Logestic Regression

```
In [ ]: from pyspark.ml.classification import LogisticRegression

        lr = LogisticRegression(labelCol="y", featuresCol="features", maxIter=10)
        model = lr.fit(trainingData)

        predictions = model.transform(testData)
        print('Logistic Regression Accuracy:', binary_evaluator.evaluate(predictions))
        preds = predictions.toPandas()['prediction'].values
        tar = predictions.toPandas()['y'].values
        print('Logistic Regression Precision:', precision_score(tar, preds))
        print('Logistic Regression Recall:', recall_score(tar, preds))
```

```
Logistic Regression Accuracy: 0.7012789470136336
Logistic Regression Precision: 0.6736474694589878
Logistic Regression Recall: 0.4279379157427938
```

SVM

```
In [ ]: from pyspark.ml.classification import LinearSVC

        lsvc = LinearSVC(maxIter=20, regParam=0.1, labelCol="y", featuresCol="features")
        model = lsvc.fit(trainingData)
```

```
predictions = model.transform(testData)
print('SVM Accuracy:', binary_evaluator.evaluate(predictions))
preds = predictions.toPandas()['prediction'].values
tar = predictions.toPandas()['y'].values
print('SVM Precision:', precision_score(tar, preds))
print('SVM Recall:', recall_score(tar, preds))
```

```
SVM Accuracy: 0.5901305700205359
SVM Precision: 0.5718849840255591
SVM Recall: 0.1984478935698448
```

Decision Tree

In [ ]:

```
from pyspark.ml.classification import DecisionTreeClassifier

dt = DecisionTreeClassifier(labelCol="y", featuresCol="features", maxDepth=5)
model = dt.fit(trainingData)

predictions = model.transform(testData)
print('DecisionTree Accuracy:', binary_evaluator.evaluate(predictions))
preds = predictions.toPandas()['prediction'].values
tar = predictions.toPandas()['y'].values
print('DecisionTree Precision:', precision_score(tar, preds))
print('DecisionTree Recall:', recall_score(tar, preds))
```

```
DecisionTree Accuracy: 0.7566220920574618
DecisionTree Precision: 0.6475195822454308
DecisionTree Recall: 0.549889135254989
```

Random Forest

In [ ]:

```
from pyspark.ml.classification import RandomForestClassifier

rf = RandomForestClassifier(labelCol="y", featuresCol="features", maxDepth=5)
model = rf.fit(trainingData)

predictions = model.transform(testData)
print('RandomForest Accuracy:', binary_evaluator.evaluate(predictions))
preds = predictions.toPandas()['prediction'].values
tar = predictions.toPandas()['y'].values
print('RandomForest Precision:', precision_score(tar, preds))
print('RandomForest Recall:', recall_score(tar, preds))
```

```
RandomForest Accuracy: 0.6106847854087069
RandomForest Precision: 0.7536231884057971
RandomForest Recall: 0.23059866962305986
```

In [ ]: