HW1_JingQian_Q2

October 3, 2019

1 Load Spark

```
In [0]: # Install latest version of spark. If error, check the latest and replace "spark-2.4.4"
        !apt-get install openjdk-8-jdk-headless -qq > /dev/null
        !wget -q https://www-us.apache.org/dist/spark/spark-2.4.4/spark-2.4.4-bin-hadoop2.7.tgz
        !tar xf spark-2.4.4-bin-hadoop2.7.tgz
        !pip install -q findspark
        import os
        os.environ["JAVA_HOME"] = "/usr/lib/jvm/java-8-openjdk-amd64"
        os.environ["SPARK_HOME"] = "/content/spark-2.4.4-bin-hadoop2.7"
        import findspark
        findspark.init()
```

```
In [0]: #The entry point to using Spark SQL is an object called SparkSession.
        #It initiates a Spark Application which all the code for that Session will run on.
        from pyspark.sql import SparkSession
        spark = SparkSession.builder \
            .master("local[*]") \
            .appName("Learning_Spark") \
            .getOrCreate()
```

```
In [0]: import numpy as np
        import pandas as pd

        from google.colab import drive
        drive.mount('/content/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6b

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/gdrive
```

2 Q2. Binary classification with Spark MLlib

2.1 (1). Data loading

Read the csv file into a Dataframe. You could set "inferschema" to true and rename the columns with the following information: "age", "workclass", "fnlwgt","education", "education_num", "marital_status", "occupation", "relationship","race", "sex", "capital_gain", "capital_loss", "hours_per_week", "native_country","income".

```
In [0]: DATA_PATH = "/content/gdrive/My Drive/BigData/q1/adult_data.csv"
```

```
In [74]: data = spark.read.csv(DATA_PATH,inferSchema=True, header=False)
         print(data.count(),len(data.columns))
         data.show(5)
```

```
32561 15
+---+-----------------+--------+----------+----+-------------------+------------------+---------
|_c0|              _c1|     _c2|       _c3| _c4|                _c5|               _c6|
+---+-----------------+--------+----------+----+-------------------+------------------+---------
| 39|        State-gov| 77516.0| Bachelors|13.0|      Never-married|      Adm-clerical| Not-in-f
| 50| Self-emp-not-inc| 83311.0| Bachelors|13.0| Married-civ-spouse|   Exec-managerial|       Hu
| 38|          Private|215646.0|   HS-grad| 9.0|           Divorced| Handlers-cleaners| Not-in-f
| 53|          Private|234721.0|      11th| 7.0| Married-civ-spouse| Handlers-cleaners|       Hu
| 28|          Private|338409.0| Bachelors|13.0| Married-civ-spouse|    Prof-specialty|
+---+-----------------+--------+----------+----+-------------------+------------------+---------
only showing top 5 rows
```

```
In [75]: col_names = ["age", "workclass", "fnlwgt", "education", "education_num", "marital_statu
                      "occupation", "relationship", "race", "sex", "capital_gain", "capital_loss
                      "hours_per_week", "native_country", "income"]
         print(len(col_names))
         data = data.toDF(*col_names)
         data.show(5)
```

```
15
+---+-----------------+--------+----------+-------------+-------------------+------------------+
|age|        workclass|  fnlwgt| education|education_num|     marital_status|        occupation|
+---+-----------------+--------+----------+-------------+-------------------+------------------+
| 39|        State-gov| 77516.0| Bachelors|         13.0|      Never-married|      Adm-clerical|
| 50| Self-emp-not-inc| 83311.0| Bachelors|         13.0| Married-civ-spouse|   Exec-managerial|
| 38|          Private|215646.0|   HS-grad|          9.0|           Divorced| Handlers-cleaners|
| 53|          Private|234721.0|      11th|          7.0| Married-civ-spouse| Handlers-cleaners|
| 28|          Private|338409.0| Bachelors|         13.0| Married-civ-spouse|    Prof-specialty|
+---+-----------------+--------+----------+-------------+-------------------+------------------+
only showing top 5 rows
```

```
In [76]: data.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- workclass: string (nullable = true)
 |-- fnlwgt: double (nullable = true)
 |-- education: string (nullable = true)
 |-- education_num: double (nullable = true)
 |-- marital_status: string (nullable = true)
 |-- occupation: string (nullable = true)
 |-- relationship: string (nullable = true)
 |-- race: string (nullable = true)
 |-- sex: string (nullable = true)
 |-- capital_gain: double (nullable = true)
 |-- capital_loss: double (nullable = true)
 |-- hours_per_week: double (nullable = true)
 |-- native_country: string (nullable = true)
 |-- income: string (nullable = true)
```

2.2 (2). Data preprocessing

Convert the categorical variables into numeric variables with ML Pipelines and Feature Transformers . You will probably need OneHotEncoderEstimator, StringIndexer, and VectorAssembler. Split your data into training set and test set with ratio of 70% and 30% and set the seed to 100.

Reference: https://towardsdatascience.com/machine-learning-with-pyspark-and-mllib-solving-a-binary-classification-problem-96396065d2aa

```
In [77]: train, test = data.randomSplit([0.7, 0.3], seed = 100)
         print("Training Dataset Count: " + str(train.count()))
         print("Test Dataset Count: " + str(test.count()))
```

```
Training Dataset Count: 22838
Test Dataset Count: 9723
```

```
In [0]: from pyspark.ml.feature import OneHotEncoderEstimator, StringIndexer, VectorAssembler
        categoricalColumns = ['workclass','education','marital_status','occupation','relationshi
                              'race','sex','native_country']
        stages = []
        for categoricalCol in categoricalColumns:
            stringIndexer = StringIndexer(inputCol = categoricalCol, outputCol = categoricalCol
            encoder = OneHotEncoderEstimator(inputCols=[stringIndexer.getOutputCol()], outputCol
            stages += [stringIndexer, encoder]
        label_stringIdx = StringIndexer(inputCol = 'income', outputCol = 'label')
        stages += [label_stringIdx]
        numericCols = ['age','fnlwgt','education_num','capital_gain','capital_loss','hours_per_w
        assemblerInputs = [c + "classVec" for c in categoricalColumns] + numericCols
        assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
        stages += [assembler]
```

```
In [79]: from pyspark.ml import Pipeline
         pipeline = Pipeline(stages = stages)
         pipelineModel = pipeline.fit(train)
         train = pipelineModel.transform(train)

         selectedCols = ['label', 'features'] + col_names
         train = train.select(selectedCols)
         train.printSchema()
```

```
root
 |-- label: double (nullable = false)
 |-- features: vector (nullable = true)
 |-- age: integer (nullable = true)
 |-- workclass: string (nullable = true)
 |-- fnlwgt: double (nullable = true)
 |-- education: string (nullable = true)
 |-- education_num: double (nullable = true)
 |-- marital_status: string (nullable = true)
 |-- occupation: string (nullable = true)
 |-- relationship: string (nullable = true)
 |-- race: string (nullable = true)
 |-- sex: string (nullable = true)
 |-- capital_gain: double (nullable = true)
 |-- capital_loss: double (nullable = true)
 |-- hours_per_week: double (nullable = true)
 |-- native_country: string (nullable = true)
 |-- income: string (nullable = true)
```

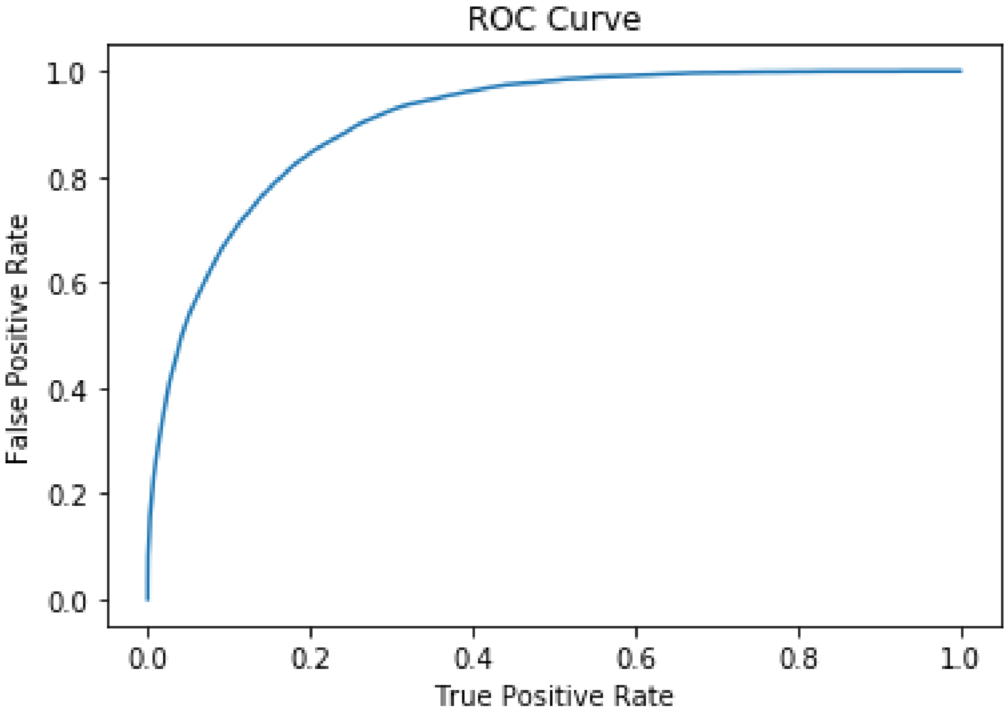
2.3 (3). Modelling

Train a logistic regression model with train set. Learn more about models provide in Spark MLlib here . After training, plot ROC curve and Precision-Recall curve of your training process.

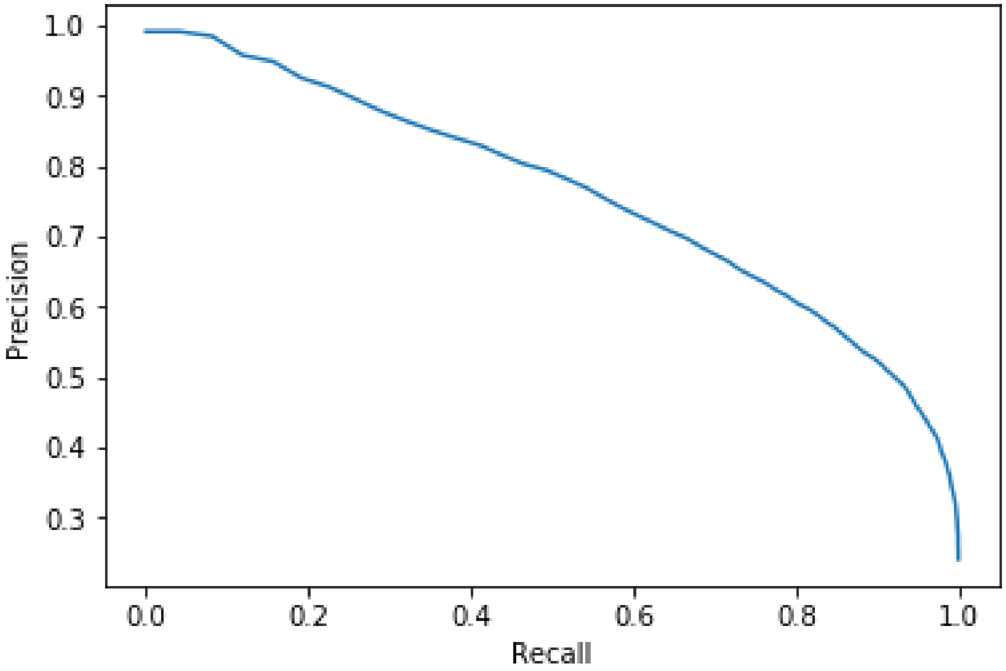
```
In [0]: from pyspark.ml.classification import LogisticRegression
        lr = LogisticRegression(featuresCol = 'features', labelCol = 'label', maxIter=10)
        lrModel = lr.fit(train)
```

```
In [81]: import matplotlib.pyplot as plt
         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))

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



```
Training set areaUnderROC: 0.9056654937412549
```



2.4 (4). Evaluation

Apply your trained model on the test set. Provide the value of area under ROC, accuracy, and confusion matrix. You should expect the accuracy to be around 85%.

```
In [82]: test = pipelineModel.transform(test)
         test = test.select(selectedCols)

         predictions = lrModel.transform(test)

         from pyspark.ml.evaluation import BinaryClassificationEvaluator
         evaluator = BinaryClassificationEvaluator()
         print('Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Test Area Under ROC 0.9027382028865563
```

```
In [84]: from pyspark.ml.evaluation import MulticlassClassificationEvaluator

         # Select (prediction, true label) and compute test error
         evaluator = MulticlassClassificationEvaluator(
             labelCol="label", predictionCol="prediction", metricName="accuracy")
         accuracy = evaluator.evaluate(predictions)
         print("Test accuracy: ", accuracy)
```

```
Test accuracy:  0.8484006993726216
```

```
In [87]: from sklearn.metrics import confusion_matrix
         y_true = test.select('label').collect()
         y_pred = predictions.select('prediction').collect()
         cnf_matrix = confusion_matrix(y_true, y_pred)
         cnf_matrix
```

```
Out[87]: array([[6860,  530],
                [ 944, 1389]])
```