Classification in Spark

By the end of this activity, you will be able to perform the following in Spark:

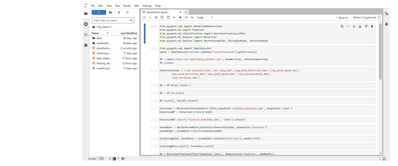
1. Generate a categorical variable from a numeric variable
2. Aggregate the features into one single column
3. Randomly split the data into training and test sets
4. Create a decision tree classifier to predict days with low humidity.

For this activity, you should have completed the creation of the JupyterLab container. If not follow, Steps 1-3 on the previous activity *Hand On: Data Exploration in Spark*, and then come back to Step 2 of this activity.

Step 1. Start the container. Open Docker Desktop and start your *jupyter-coursera* container.

When Jupyter starts running, click on the port to access JupyterLab in your browser:

Step 2. Open your notebook. Once you're in JupyterLab, go to the *big-data-4* folder and open the *classification.ipynb* notebook.



Step 3. Load classes and data. Execute the first cell in the notebook to load the classes used for this exercise.

```
[1]: from pyspark.sql import DataFrameNaFunctions
     from pyspark.ml import Pipeline
     from pyspark.ml.classification import DecisionTreeClassifier
     from pyspark.ml.feature import Binarizer
     from pyspark.ml.feature import VectorAssembler, StringIndexer, VectorIndexer
```

Next, execute the second cell which loads the weather data into a DataFrame and prints the columns.

```
[2]: from pyspark.sql import SparkSession
     spark = SparkSession.builder.appName("classification").getOrCreate()

     df = spark.read.csv('data/daily_weather.csv', header=True, inferSchema=True)
     df.columns
```

```
[2]: ['number',
      'air_pressure_9am',
      'air_temp_9am',
      'avg_wind_direction_9am',
      'avg_wind_speed_9am',
      'max_wind_direction_9am',
      'max_wind_speed_9am',
      'rain_accumulation_9am',
      'rain_duration_9am',
      'relative_humidity_9am',
      'relative_humidity_3pm']
```

Execute the third cell, which defines the columns in the weather data we will use for the decision tree classifier.

```
[3]: featureColumns = ['air_pressure_9am','air_temp_9am','avg_wind_direction_9am','avg_wind_speed_9am',
                      'max_wind_direction_9am','max_wind_speed_9am','rain_accumulation_9am',
                      'rain_duration_9am']
```

Step 4. Drop unused and missing data. We do not need the *number* column in our data, so let's remove it from the DataFrame:

```
[4]: df = df.drop('number')
```

Next, let's remove all rows with missing data:

```
[5]: df = df.na.drop()
```

We can print the number of rows and columns in our DataFrame:

```
[6]: df.count(), len(df.columns)
```

```
[6]: (1064, 10)
```

Step 5. Create categorical variable. Let's create a categorical variable to denote if the humidity is not low. If the value is less than 25%, then we want the categorical value to be 0, otherwise the categorical value should be 1. We can create this categorical variable as a column in a DataFrame using *Binarizer*:

```
[7]: binarizer = Binarizer(threshold=24.99999,inputCol='relative_humidity_3pm', outputCol='label')
     binarizedDF = binarizer.transform(df)
```

The *threshold* argument specifies the threshold value for the variable, *inputCol* is the input column to read, and *outputCol* is the name of the new categorical column. The second line applies the *Binarizer* and creates a new DataFrame with the categorical column. We can look at the first four values in the new DataFrame:

```
[8]: binarizedDF.select('relative_humidity_3pm', 'label').show(4)
```

```
+--------------------+-----+
|relative_humidity_3pm|label|
+--------------------+-----+
|   36.160000000000494|  1.0|
|     19.4265967985621|  0.0|
|   14.460000000000045|  0.0|
|   12.742547353761848|  0.0|
+--------------------+-----+
only showing top 4 rows
```

The first row's humidity value is greater than 25% and the label is 1. The other humidity values are less than 25% and have labels equal to 0.

Step 6. Aggregate features. Let's aggregate the features we will use to make predictions into a single column:

```
[9]: assembler = VectorAssembler(inputCols=featureColumns, outputCol='features')
     assembled = assembler.transform(binarizedDF)
```

The *inputCols* argument specifies our list of column names we defined earlier, and *outputCol* is the name of the new column. The second line creates a new DataFrame with the aggregated features in a column.

Step 7. Split training and test data. We can split the data by calling *randomSplit()*:

```
[10]: (trainingData, testData) = assembled.randomSplit([0.8,0.2],seed=13234)
```

The first argument is how many parts to split the data into and the *approximate* size of each. This specifies two sets of 80% and 20%. Normally, the seed should not be specified, but we use a specific value here so that everyone will get the same decision tree.

We can print the number of rows in each DataFrame to check the sizes (1095 * 80% = 851.2):

```
[11]: trainingData.count(), testData.count()
```

```
[11]: (846, 218)
```

Step 8. Create and train decision tree. Let's create the decision tree:

```
[12]: dt = DecisionTreeClassifier(labelCol='label', featuresCol='features', maxDepth=5,
                                  minInstancesPerNode=20, impurity='gini')
```

The *labelCol* argument is the column we are trying to predict, *featuresCol* specifies the aggregated features column, *maxDepth* is stopping criterion for tree induction based on maximum depth of tree, *minInstancesPerNode* is stopping criterion for tree induction based on minimum number of samples in a node, and *impurity* is the impurity measure used to split nodes.

We can create a model by training the decision tree. This is done by executing it in a *Pipeline*:

```
[13]: pipeline = Pipeline(stages=[dt])
      model = pipeline.fit(trainingData)
```

Let's make predictions using our test data set:

```
[14]: predictions = model.transform(testData)
```

Looking at the first ten rows in the prediction, we can see the prediction matches the input:

```
[15]: predictions.select('prediction', 'label').show(10)
```

```
+----------+-----+
|prediction|label|
+----------+-----+
|       1.0|  1.0|
|       1.0|  1.0|
|       0.0|  1.0|
|       1.0|  1.0|
|       1.0|  1.0|
|       1.0|  1.0|
|       1.0|  1.0|
|       1.0|  1.0|
|       0.0|  0.0|
|       1.0|  1.0|
+----------+-----+
only showing top 10 rows
```

Step 9. Save predictions to CSV. Finally, let's save the predictions to a CSV file. In the next Spark hands-on activity, we will evaluate the accuracy.

Let's save only the *prediction* and *label columns* to a CSV file:

```
[16]: predictions.select('prediction', 'label').write.mode('overwrite').csv('/home/jovyan/big-data-4/predictions', header=True)
```

You can see your *predictions* folder in the top left next to your notebooks and *data* folder.

Open the folder, and then open the CSV file:

Your full predictions will be displayed:

You can download the file locally by clicking *File* and then *Download*.

Step 10. Rename the file. To facilitate the location of the file on one of the following activities, right click on your CSV file and rename it to *predictions.csv*.

Step 11. Exiting the container. To exit JupyterLab, simply close the tab in your browser. To stop the container, go to Docker Desktop and click on the stop button. We recommend not to delete the container, as this container will be used for multiple activities across this specialization.

Go to next item ✓ Completed

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