



Chapter 13: PCA and Logistic Regression

```
In [1]: import findspark
findspark.init()
```

```
In [2]: from pyspark.sql import SparkSession
```

```
In [3]: spark = SparkSession.builder.appName('PCA_sonar').getOrCreate()
```

```
In [4]: df = spark.read.csv('sonar_all_data.txt',inferSchema=True,header=False)
```

```
In [33]: str(df.schema.names)
```

```
Out[33]: "['_c0', '_c1', '_c2', '_c3', '_c4', '_c5', '_c6', '_c7', '_c8', '_c9', '_c10',
'_c11', '_c12', '_c13', '_c14', '_c15', '_c16', '_c17', '_c18', '_c19', '_c20',
'_c21', '_c22', '_c23', '_c24', '_c25', '_c26', '_c27', '_c28', '_c29', '_c30',
'_c31', '_c32', '_c33', '_c34', '_c35', '_c36', '_c37', '_c38', '_c39', '_c40',
'_c41', '_c42', '_c43', '_c44', '_c45', '_c46', '_c47', '_c48', '_c49', '_c50',
'_c51', '_c52', '_c53', '_c54', '_c55', '_c56', '_c57', '_c58', '_c59', 'label']"
```

```
In [6]: df = df.withColumnRenamed("_c60", "label")
```

```
In [7]: from pyspark.ml.linalg import Vectors
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.feature import StandardScaler
from pyspark.ml.feature import StringIndexer
from pyspark.ml.feature import PCA
```

```
In [8]: assembler = VectorAssembler(
    inputCols=['_c%d' % i for i in range(60)],
    outputCol="features")
output = assembler.transform(df)
```



```
In [9]: output.select("features").show(1, truncate=False)
```



In [13]: `final_data.show(3)`

```
+-----+-----+-----+
|      std_features|label|label_idx|
+-----+-----+-----+
|[-0.3985897356694...|    R|      1.0|
|[0.70184498705605...|    R|      1.0|
|[-0.1289179854363...|    R|      1.0|
+-----+-----+-----+
only showing top 3 rows
```

PCA

In [14]: `pca = PCA(k=15, inputCol="std_features", outputCol="pca")`
`model = pca.fit(final_data)`

In [15]: `model.explainedVariance`

Out[15]: DenseVector([0.2035, 0.189, 0.0855, 0.0568, 0.0501, 0.0406, 0.0328, 0.0305, 0.0257, 0.0249, 0.0208, 0.019, 0.0175, 0.0154, 0.0143])

In [16]: `percent = model.explainedVariance`
`type(percent)`

Out[16]: pyspark.ml.linalg.DenseVector

In [17]: `percent.values.sum()`

Out[17]: 0.8261807898020073

In [18]: `transformed = model.transform(final_data)`

In [19]: `transformed.show(3)`

```
+-----+-----+-----+-----+
|      std_features|label|label_idx|              pca|
+-----+-----+-----+-----+
|[-0.3985897356694...|    R|      1.0|[-1.9165444107164...|
|[0.70184498705605...|    R|      1.0|[0.47896904316845...|
|[-0.1289179854363...|    R|      1.0|[-3.8499400285258...|
+-----+-----+-----+-----+
only showing top 3 rows
```

In [20]: `final_data = transformed.select("label_idx", "pca")`

Logistic Regression

In [21]: `train_data, test_data = final_data.randomSplit([0.8, 0.2])`



In [22]: `from pyspark.ml.classification import LogisticRegression`

In [23]: `logistic = LogisticRegression(featuresCol='pca',
labelCol='label_idx',
predictionCol='prediction')`

In [24]: `# Fit the model to the data and call this model logisticModel
logisticModel = logistic.fit(train_data)`

In [25]: `# Create predictions for the testing data and show confusion matrix
test_model = logisticModel.transform(test_data)
test_model.groupBy('label_idx', 'prediction').count().show()`

```
+-----+-----+-----+
|label_idx|prediction|count|
+-----+-----+-----+
|      1.0|      1.0|   14|
|      0.0|      1.0|    2|
|      1.0|      0.0|   10|
|      0.0|      0.0|   19|
+-----+-----+-----+
```

In [26]: `# Calculate the elements of the confusion matrix
TN = test_model.filter('prediction = 0 AND label_idx = prediction').count()
TP = test_model.filter('prediction = 1 AND label_idx = prediction').count()
FN = test_model.filter('prediction = 0 AND label_idx != prediction').count()
FP = test_model.filter('prediction = 1 AND label_idx != prediction').count()`

In [27]: `# Calculate precision and recall
precision = TP / (TP + FP)
recall = TP / (TP + FN)
print('precision = {:.2f}\nrecall = {:.2f}'.format(precision, recall))`

```
precision = 0.88  
recall    = 0.58
```

In [28]: `acc =(TP+TN)/test_model.count()
acc`

Out[28]: 0.7333333333333333