## 603 final code

## December 1, 2021

```
[39]: import pyspark
     from pyspark.sql import SparkSession
     from pyspark.sql.types import FloatType, StructType, StringType, StructField,
      →IntegerType
     from pyspark.ml.regression import LinearRegression
     from pyspark.ml.feature import VectorAssembler
     import matplotlib.pyplot as plt
     from matplotlib.pyplot import figure
     import numpy as np
[40]: spark = SparkSession.builder.getOrCreate()
     sc = spark.sparkContext
     combined_schema = StructType([
         StructField('STATION', StringType()),
         StructField('NAME', StringType()),
         StructField('LATITUDE', FloatType()),
         StructField('LONGITUDE', FloatType()),
         StructField('ELEVATION', FloatType()),
         StructField('AWND', FloatType()),
         StructField('PRCP', FloatType()),
         StructField('SNOW', FloatType()),
         StructField('SNWD', FloatType()),
         StructField('TAVG', FloatType()),
         StructField('CRASHCOUNT', IntegerType()),
         StructField('YEAR', IntegerType()),
         StructField('MONTH', IntegerType()),
         StructField('DAY', IntegerType())
     ])
[41]: combinedDF = spark.read.options(header = 'True').schema(combined_schema).
      combinedDF = combinedDF.drop('STATION', 'NAME', 'ELEVATION', 'LATITUDE', L
      # elevation, latitude and longitude have a large number of missing values
     combinedDF.show(30)
```

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```
AWND | PRCP | SNOW | SNWD | TAVG | CRASHCOUNT | MONTH | DAY |
+----+
|10.74| 0.0| 0.0| 0.0|50.0|
                                   49|
                                          41
                                              11
| 8.28| 0.0| 0.0| 0.0|40.0|
                                   35|
                                          4|
                                              2|
|10.51| 0.0| 0.0| 0.0|40.0|
                                   49 l
                                          41 31
| 4.25|0.04| 0.0| 0.0|37.0|
                                   38|
                                          4 | 4 |
| 8.05|0.11| 0.0| 0.0|48.0|
                                   60|
                                          4|
                                              5|
| 5.59| 0.0| 0.0| 0.0|47.0|
                                   49 l
                                          4|
                                              61
| 5.82| 0.0| 0.0| 0.0|50.0|
                                          4| 7|
                                   52|
| 4.92| 0.0| 0.0| 0.0|64.0|
                                   64|
                                          4 8
| 6.71| 0.0| 0.0| 0.0|73.0|
                                          4| 9|
                                   59|
| 7.61| 0.0| 0.0| 0.0|76.0|
                                          4 | 10 |
                                   70|
| 9.62| 0.0| 0.0| 0.0|72.0|
                                   55|
                                          4 | 11 |
|10.29|0.67| 0.0| 0.0|55.0|
                                          4 | 12 |
                                   49|
| 5.14| 0.0| 0.0| 0.0|54.0|
                                   53|
                                          4 | 13 |
| 5.59| 0.0| 0.0| 0.0|54.0|
                                   581
                                          4 | 14 |
| 8.28| 0.0| 0.0| 0.0|56.0|
                                   52|
                                          4 | 15 |
| 6.04| 0.0| 0.0| 0.0|60.0|
                                   46|
                                          4 | 16 |
| 5.82| 0.0| 0.0| 0.0|65.0|
                                          4 | 17 |
                                   62|
9.17 | 0.04 | 0.0 | 0.0 | 63.0 |
                                   64 l
                                          4 | 18 |
| 7.83|0.79| 0.0| 0.0|66.0|
                                   73|
                                          4 | 19 |
|10.29|0.07| 0.0| 0.0|54.0|
                                          4 | 20 |
                                   47|
| 4.92| 0.0| 0.0| 0.0|47.0|
                                   40 l
                                          4 | 21 |
|11.18| 0.0| 0.0| 0.0|46.0|
                                          4 | 22 |
                                   52|
| 6.26| 0.0| 0.0| 0.0|51.0|
                                   46|
                                          41 231
| 6.93| 0.0| 0.0| 0.0|56.0|
                                          4| 24|
                                   47|
| 7.16| 0.0| 0.0| 0.0|58.0|
                                          4 | 25 |
                                   65 l
| 4.25| 0.0| 0.0| 0.0|55.0|
                                   55|
                                          4| 26|
| 4.47| 0.0| 0.0| 0.0|55.0|
                                          4 | 27 |
                                   44|
| 5.37| 0.0| 0.0| 0.0|57.0|
                                   541
                                          4| 28|
                                          4| 29|
| 7.16|0.26| 0.0| 0.0|56.0|
                                   661
| 7.83|0.22| 0.0| 0.0|56.0|
                                   62|
                                          4| 30|
+----+
only showing top 30 rows
```

```
[42]: features = combinedDF.columns
    features.pop(5)

vectorAssembler = VectorAssembler(inputCols = features, outputCol = 'features')

vDF = vectorAssembler.transform(combinedDF)
 vDF = vDF.select(['features', 'CRASHCOUNT'])

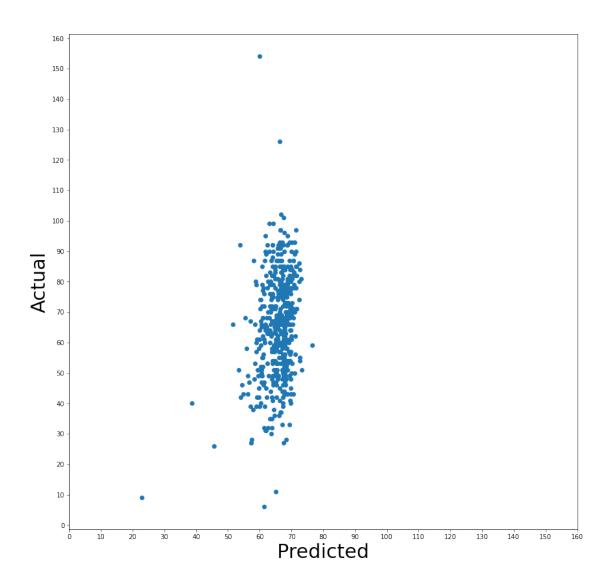
split = vDF.randomSplit([.8, .2], seed = 12345)
```

```
trainingData = split[0]
               testData = split[1]
               →maxIter = 10, regParam = .3, elasticNetParam = .8)
               lrModel = lr.fit(trainingData)
[43]: #print('Coefficients:', str(lrModel.coefficients))
               count = 0
               print('Coefficients per feature:')
               for item in lrModel.coefficients:
                         print(features[count] + ':', item)
                         count += 1
               print()
               trainingSummary = lrModel.summary
               print('RMSE:', trainingSummary.rootMeanSquaredError)
               print('R squared:', trainingSummary.r2)
             Coefficients per feature:
             AWND: 0.6590887741121741
             PRCP: 0.0
             SNOW: -1.3372764638638435
             SNWD: -0.7240295709285356
             TAVG: 0.17799762976077024
             MONTH: 0.04447601690300508
             DAY: -0.05181953403363659
             RMSE: 15.65479033763715
             R squared: 0.06788566821269193
[44]: | lr_predictions = lrModel.transform(testData)
               lr predictions.select('prediction', 'CRASHCOUNT', 'features').show(5, False)
               from pyspark.ml.evaluation import RegressionEvaluator
               lr_evaluator = RegressionEvaluator(predictionCol = 'prediction', labelCol = 'prediction', labelC
                 print('R squared on test data:', lr_evaluator.evaluate(lr_predictions))
               testResult = lrModel.evaluate(testData)
               print('RMSE on test data:', testResult.rootMeanSquaredError)
```

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## 0.1 Slightly worse

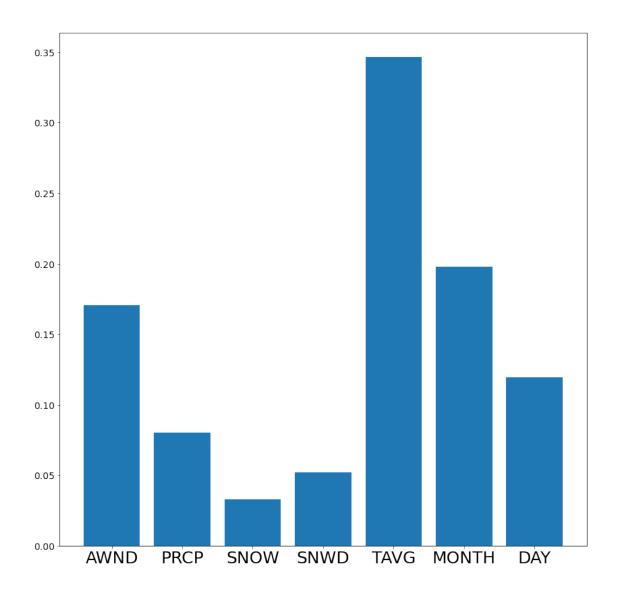
```
[45]: pdDF = lr_predictions.toPandas()
    fig, ax = plt.subplots()
    fig.set_size_inches(14,14)
    plt.scatter(pdDF.prediction, pdDF.CRASHCOUNT)
    ax.xaxis.set_ticks(np.arange(0, 170, 10))
    ax.yaxis.set_ticks(np.arange(0, 170, 10))
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    ax.xaxis.label.set_size(30)
    ax.yaxis.label.set_size(30)
```



## [46]: trainingData.describe().show()

+-	+-	+
summary		CRASHCOUNT
+-	+-	+
1	count	1975
1	mean 6	5.54886075949366
1	stddev 1	6.21894640101575
1	min	41
1	max	109

```
[47]: from pyspark.ml.regression import DecisionTreeRegressor
      dt = DecisionTreeRegressor(featuresCol = 'features', labelCol = 'CRASHCOUNT')
      dtModel = dt.fit(trainingData)
      dtPredictions = dtModel.transform(testData)
      dtEvaluator = RegressionEvaluator(
          labelCol = "CRASHCOUNT", predictionCol = "prediction", metricName = "rmse")
      rmse = dtEvaluator.evaluate(dtPredictions)
      print("Root Mean Squared Error (RMSE) on test data: ", rmse)
     Root Mean Squared Error (RMSE) on test data: 16.805152604072795
[48]: dtModel.featureImportances
[48]: SparseVector(7, {0: 0.1706, 1: 0.0803, 2: 0.0329, 3: 0.052, 4: 0.3466, 5: 0.198,
      6: 0.1196})
[49]: features
[49]: ['AWND', 'PRCP', 'SNOW', 'SNWD', 'TAVG', 'MONTH', 'DAY']
[50]: fig, ax = plt.subplots()
      fig.set_size_inches(14,14)
      plt.bar(features, dtModel.featureImportances)
      plt.xticks(fontsize=25)
      plt.yticks(fontsize=14)
[50]: (array([0. , 0.05, 0.1 , 0.15, 0.2 , 0.25, 0.3 , 0.35, 0.4]),
       [Text(0, 0, ''),
       Text(0, 0, '')])
```



1 It seems that year is by far the best predictor