Regression_Task_:_Saad_Lahlali

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Contents

1 Settings

[3]:
```
import pyspark
sc = pyspark.SparkContext(appName="Regression Task")
```

[4]:
```
%matplotlib inline

import matplotlib
import numpy as np
import matplotlib.pyplot as plt
```

[5]:
```
from pyspark.sql.types import StructType, StructField
from pyspark.sql.types import DoubleType, IntegerType, StringType
from pyspark.ml.feature import VectorAssembler, StringIndexer, StandardScaler
from pyspark.sql import SQLContext
```

2 Data Preparation

2.1 Reading the data

[6]:
```
sqlContext = SQLContext(sc)
#indexer needed so that labels are 0 and 1

schema = StructType([ StructField("c"+str(0),StringType())]+
                    [ StructField("c"+str(i),DoubleType()) for i in range(1,9)])
# schema to cast data, can use inferschema also

raw_data = sqlContext.read.csv(
    "/content/drive/MyDrive/exo3_train.csv",schema=schema)



#droping rows with nulls
raw_data_nn = raw_data.dropna()

assembled_data = VectorAssembler(inputCols=["c"+str(i)
                for i in range(1,8)],outputCol="features").
 ↪transform(raw_data_nn)
```

```
/usr/local/lib/python3.7/dist-packages/pyspark/sql/context.py:79: FutureWarning:
Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  FutureWarning
```

2.2 Standardizing the data

[52]:
```
#standardizing the data
scale=StandardScaler(inputCol='features',outputCol='standardized_features')
data_scale=scale.fit(assembled_data)
data_scale_output=data_scale.transform(assembled_data)
```

2.3 Removing outliers

[125]:
```
"""
Applied according to :
How to remove outliers from multiple columns in pyspark
using mean and standard deviation
(from Stackoverflow)
"""

numeric_cols = ['c1', 'c2', 'c3', 'c4','c5','c6', 'c7']
mean_std = \
    train \
    .groupBy('c0', 'c8') \
    .agg( \
```

```
     *[f.mean(colName).alias('mean_{}'.format(colName)) for colName in␣
↪numeric_cols],\
     *[f.stddev(colName).alias('stddev_{}'.format(colName)) for colName in␣
↪numeric_cols])

mean_std_min_max = mean_std
for colName in numeric_cols:
    meanCol = 'mean_{}'.format(colName)
    stddevCol = 'stddev_{}'.format(colName)
    minCol = 'min_{}'.format(colName)
    maxCol = 'max_{}'.format(colName)
    mean_std_min_max = mean_std_min_max.withColumn(minCol, f.col(meanCol) - 5 *␣
↪f.col(stddevCol))
    mean_std_min_max = mean_std_min_max.withColumn(maxCol, f.col(meanCol) + 5 *␣
↪f.col(stddevCol))

outliers = train.join(mean_std_min_max, how = 'left', on = ['c0'])
for colName in numeric_cols:
    isOutlierCol = 'is_outlier_{}'.format(colName)
    minCol = 'min_{}'.format(colName)
    maxCol = 'max_{}'.format(colName)
    meanCol = 'mean_{}'.format(colName)
    stddevCol = 'stddev_{}'.format(colName)
    outliers = outliers.withColumn(isOutlierCol,
                                   f.when((f.col(colName) > f.col(maxCol)) |
                                          (f.col(colName) < f.col(minCol)), 1).
                                   otherwise(0))
    outliers = outliers.drop(minCol,maxCol, meanCol, stddevCol)
```

[132]:
```
print("With the mean and standard deviation, we have found",
      outliers.filter((f.col("is_outlier_c1")!=f.lit(0)) |
                (f.col("is_outlier_c2")!=f.lit(0)) |
                (f.col("is_outlier_c3")!=f.lit(0)) |
                (f.col("is_outlier_c4")!=f.lit(0)) |
                (f.col("is_outlier_c5")!=f.lit(0)) |
                (f.col("is_outlier_c6")!=f.lit(0)) |
                (f.col("is_outlier_c7")!=f.lit(0))).count(),
      "outliers. (*m)")
```

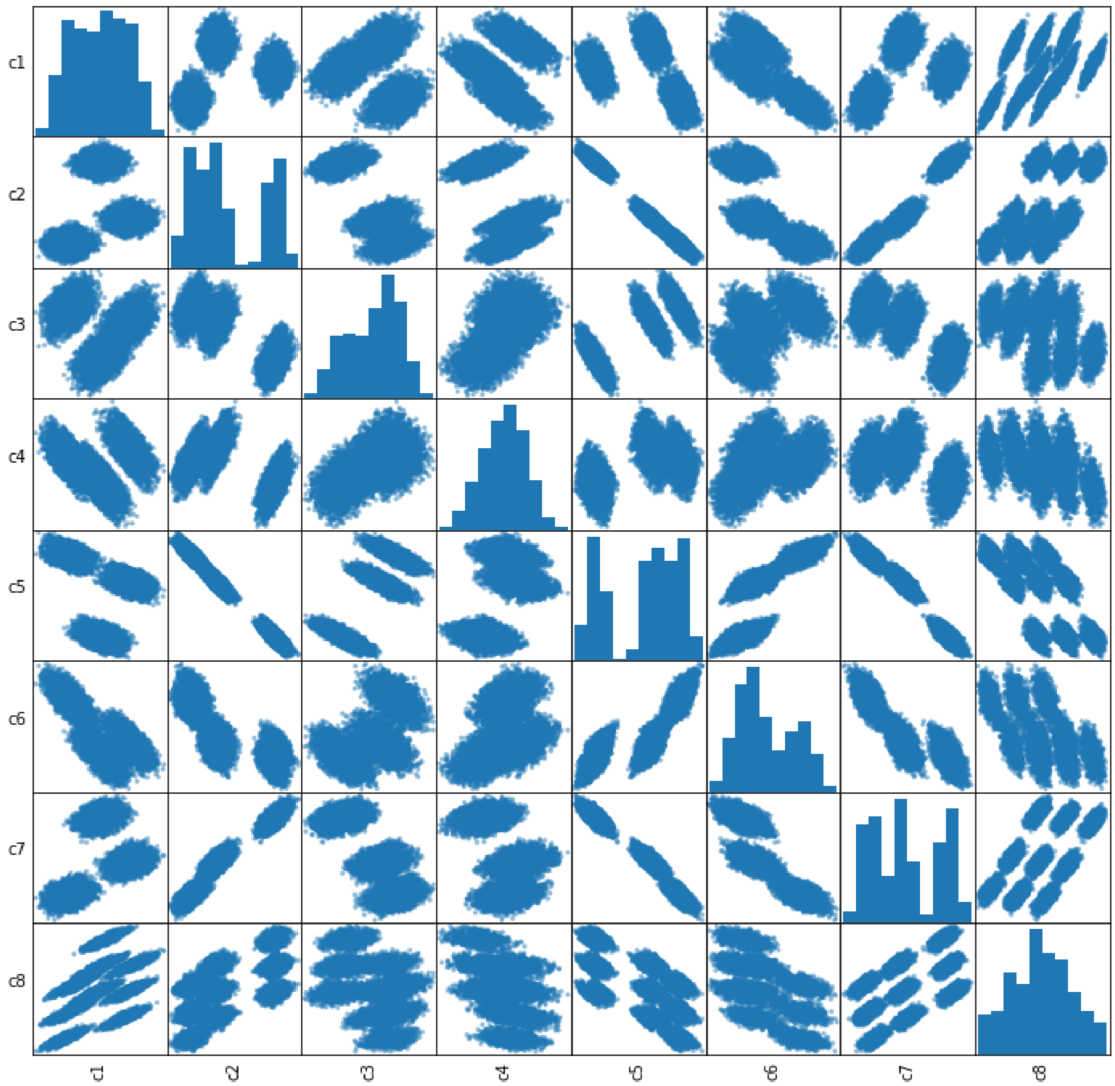
```
With the mean and standard deviation, we have found 0 outliers. (*m)
```

2.4 Exploring the data

[8]:
```
import pandas as pd
```

[9]:
```
sampled_data = data_scale_output.select(["c"+str(i) for i in range(1,9)]).
                                        sample(False, 0.8).toPandas()
axs = pd.plotting.scatter_matrix(sampled_data, figsize=(12,12))
```

```
n = len(sampled_data.columns)
for i in range(n):
    v = axs[i, 0]
    v.yaxis.label.set_rotation(0)
    v.yaxis.label.set_ha('right')
    v.set_yticks(())
    h = axs[n-1, i]
    h.xaxis.label.set_rotation(90)
    h.set_xticks(())
```



The most important part of the previous visualization is the last colum since it represents the corelation between the taget values and the features. Therefor we notice some correlation between some of the variables and the target.

2.5 Split into training and validation

For the model selection, we have to divide our dataset into a training set and a validation set. We set the training ratio to be 80% of the dataset.

[10]:
```
train, val = data_scale_output.randomSplit([0.8, 0.2], seed=12345)
```

3 Model Selection

3.1 Linear Regression

[11]:
```
from pyspark.ml.regression import LinearRegression
from pyspark.ml.evaluation import RegressionEvaluator
```

[55]:
```
# Building the model
lr = LinearRegression(featuresCol = 'standardized_features',
                      labelCol='c8',
                      maxIter=10,
                      regParam=0.3,
                      elasticNetParam=0.8)

lr_model = lr.fit(train)
print("Coefficients: " + str(lr_model.coefficients))
print("Intercept: " + str(lr_model.intercept))

trainingSummary = lr_model.summary
print("RMSE: %f" % trainingSummary.rootMeanSquaredError)
print("r2: %f" % trainingSummary.r2)
```

```
Coefficients: [240.9285986458868,292.6629305671314,173.50830089598722,-217.70702
407591259,-114.51404850928375,203.0092587153934,-89.89095612048393]
Intercept: 186.17661860197106
RMSE: 222.477192
r2: 0.719846
```

[56]:
```
# Making the predictions
lr_predictions = lr_model.transform(val)
lr_predictions.select("prediction","c8","features").show(5)

lr_evaluator = RegressionEvaluator(predictionCol="prediction", \
                 labelCol="c8",metricName="r2")

print("R Squared (R2) on test data = %g" % lr_evaluator.
 ↪evaluate(lr_predictions))
```

```
+------------------+------+--------------------+
|        prediction|    c8|            features|
+------------------+------+--------------------+
| 528.4347866392004|1020.0|[446.0,461.0,-27...|
| 361.5438430116119| 354.0|[784.0,-848.0,196...|
| 551.8219666928418| 730.0|[515.0,202.0,-265...|
| 334.6315028322394| 220.0|[408.0,-14.0,-368...|
|471.15826441272804| 736.0|[829.0,-995.0,24...|
+------------------+------+--------------------+
only showing top 5 rows
```

```
R Squared (R2) on test data = 0.705601
```

3.1.1 Parameters tuning

[86]:
```python
from pyspark.ml.tuning import ParamGridBuilder, TrainValidationSplit,␣
 ↪CrossValidator
from pyspark.ml.evaluation import RegressionEvaluator

lr = LinearRegression(featuresCol = 'standardized_features',
                      labelCol='c8',
                      solver="normal")

# Evaluate model
lr_evaluator = RegressionEvaluator(predictionCol="prediction",
                                   labelCol="c8",
                                   metricName="rmse")

# Create ParamGrid for Cross Validation
lr_paramGrid = (ParamGridBuilder()
             .addGrid(lr.regParam, [1e-2, 1e-3, 1e-4, 1e-5])
             .addGrid(lr.elasticNetParam, [0.0, 0.25])
             .addGrid(lr.maxIter, [1, 2, 5])
             .build())

# Create 4-fold CrossValidator
lr_cv = CrossValidator(estimator = lr,
                    estimatorParamMaps = lr_paramGrid,
                    evaluator = lr_evaluator,
                    numFolds = 4)

# Run cross validations
lr_cv_Model = lr_cv.fit(data_scale_output)
print(lr_cv_Model)

# Get Model Summary Statistics
lr_cv_Summary = lr_cv_Model.bestModel.summary
print("Coefficient Standard Errors: " + str(lr_cv_Summary.
 ↪coefficientStandardErrors))
```

```
CrossValidatorModel_9a6729a15d9a
Coefficient Standard Errors: [2.6750193208107875, 12.496692273090728,
2.5127277408447344, 1.5465671392467242, 14.840759881676508, 6.373236267906828,
8.546833266216035, 3.8375043042082986]
```

[149]:
```python
print("The best model has the following parameters:")
print("\t"*6,"MaxIter=", lr_cv_Model.bestModel.getMaxIter())
```

```
print("\t"*6,"NetParam=", lr_cv_Model.bestModel.getElasticNetParam())
print("\t"*6,"RegParam=", lr_cv_Model.bestModel.getRegParam())
```

```
The best model has the following parameters:
                                                 MaxIter= 1
                                                 NetParam= 0.0
                                                 RegParam= 0.001
```

[61]:
```
# Use velidation set here so we can measure the accuracy of our model on new␣
 ↪data
lr_predictions = lr_cv_Model.transform(val)

lr_score = lr_cv_Summary.rootMeanSquaredError

# cvModel uses the best model found from the Cross Validation
# Evaluate best model
print('RMSE:', lr_score)
```

```
RMSE: 82.00958198000126
```

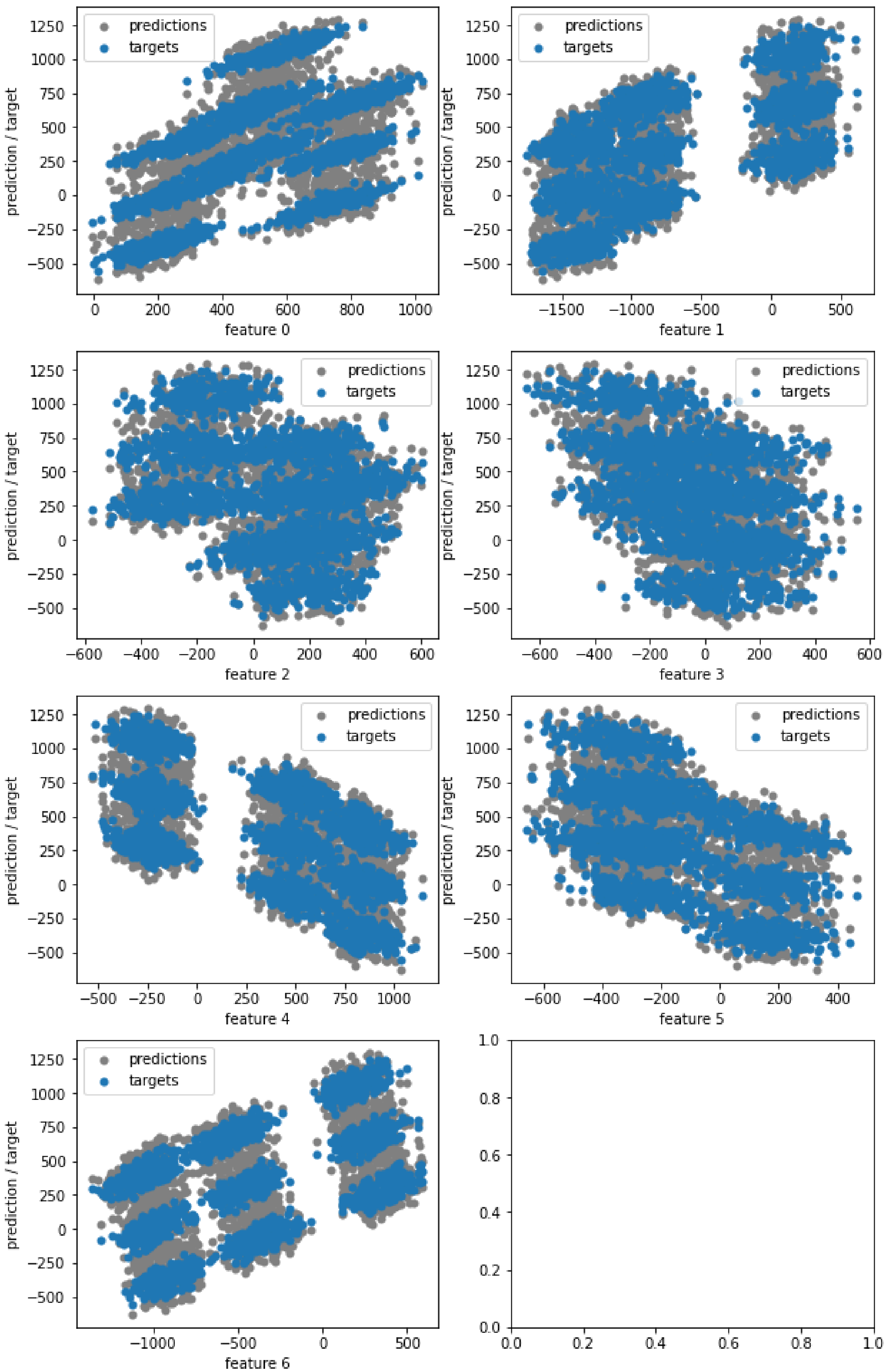
[60]:
```
lr_predictions.select("prediction","c8","features").show(10)

lr_evaluator = RegressionEvaluator(predictionCol="prediction", \
                 labelCol="c8",metricName="r2")

print("R Squared (R2) on test data = %g" % lr_evaluator.
 ↪evaluate(lr_predictions))
```

```
+-------------------+------+--------------------+
|         prediction|    c8|            features|
+-------------------+------+--------------------+
|  927.0563429044515|1020.0|[446.0,461.0,-27...|
|   438.671052424401| 354.0|[784.0,-848.0,196...|
|  811.0902390756099| 730.0|[515.0,202.0,-265...|
|  280.9446575758557| 220.0|[408.0,-14.0,-368...|
|  719.5481187387066| 736.0|[829.0,-995.0,24...|
|   693.980796280758| 631.0|[672.0,-842.0,238...|
| 1037.3125565078024|1179.0|[732.0,222.0,-240...|
|  832.7614185609549| 959.0|[438.0,62.0,-451...|
| 236.28262055046167| 389.0|[322.0,-1484.0,29...|
|-177.21209555850294|-320.0|[200.0,-1283.0,27...|
+-------------------+------+--------------------+
only showing top 10 rows

R Squared (R2) on test data = 0.960351
```

3.1.2 Visualization of LR

From the following visualization we notice how the target and the predictions superpose in the space which attests of the relative good predictions made by the model.

[185]:
```
ft = [w.features for w in lr_predictions.select('features').collect()]
pred = [w.prediction for w in lr_predictions.select('prediction').collect()]
true = [w.c8 for w in lr_predictions.select('c8').collect()]

sort = sorted(range(len(true)), key=lambda k: true[k])
sorted_pred = [pred[i] for i in sort]
sorted_true = [true[i] for i in sort]

fig, ax = plt.subplots(7//2+1, 7%2+1,figsize=(10,17))

for i in range(7):
  c = [f[i] for f in ft]
  sorted_c = [c[i] for i in sort]
  ax[i//2, i%2].scatter(sorted_c, sorted_pred, color='grey', linewidth=0.1,␣
 ↪label= 'predictions')
  ax[i//2, i%2].scatter(sorted_c, sorted_true, linewidth=0.1, label= 'targets')
  ax[i//2, i%2].set_xlabel('feature '+ str(i))
  ax[i//2, i%2].set_ylabel('prediction / target')
  ax[i//2, i%2].legend()
plt.show()
```


predictions
targets
prediction / target
feature 0
feature 1
feature 2
feature 3
feature 4
feature 5
feature 6

3.2 Decision Tree Regression

[ ]:
```
from pyspark.ml.regression import DecisionTreeRegressor
dt = DecisionTreeRegressor(featuresCol ='features', labelCol = 'c8')
dt_model = dt.fit(train)
dt_predictions = dt_model.transform(val)
dt_evaluator = RegressionEvaluator(
    labelCol="c8", predictionCol="prediction", metricName="rmse")
rmse = dt_evaluator.evaluate(dt_predictions)
print("Root Mean Squared Error (RMSE) on validation data = %g" % rmse)
```

```
Root Mean Squared Error (RMSE) on validation data = 237.499
```

[ ]:
```
dt_model.featureImportances
```

[ ]:
```
SparseVector(7, {0: 0.2846, 1: 0.0203, 2: 0.0698, 3: 0.0222, 4: 0.454, 6:
0.1491})
```

3.2.1 Parameters tuning

[ ]:
```
# Evaluate model
evaluator = RegressionEvaluator(
    labelCol="c8", predictionCol="prediction", metricName="rmse")

# Create ParamGrid for Cross Validation
paramGrid = ParamGridBuilder().addGrid(dt.maxDepth,
                                       [2, 5, 10, 20, 30]).
                                       addGrid(dt.maxBins,
                                               [10, 40, 100]).
                                               build()

# Create 5-fold CrossValidator
cvs = CrossValidator(estimator=dt,
                     estimatorParamMaps=paramGrid,
                     evaluator=evaluator,
                     # 80% of the data will be used for training, 20% for␣
 ↪validation.
                     numFolds=5)

# Run cross validations
cvs_model = cvs.fit(train)
print(cvs_Model)
```

```
CrossValidatorModel_a7f5e34b3bba
```

[ ]:
```
cvs_predictions = cvs_model.transform(val)
evaluator.evaluate(cvs_predictions)
```

[ ]: 145.0533679351754

[ ]:
```python
# Use velidation set here so we can measure the accuracy of our model on new␣
 ↪data
dt_predictions = cvs_model.transform(val)

# cvModel uses the best model found from the Cross Validation
# Evaluate best model
print('RMSE:', evaluator.evaluate(dt_predictions))
```

```
RMSE: 145.0533679351754
```

[ ]:
```python
dt_predictions.select("prediction","c8","features").show(10)

evaluator = RegressionEvaluator(predictionCol="prediction", \
                 labelCol="c8",metricName="r2")

print("R Squared (R2) on test data = %g" % evaluator.evaluate(dt_predictions))
```

```
+----------+------+--------------------+
|prediction|    c8|            features|
+----------+------+--------------------+
|    1034.0|1020.0|[446.0,461.0,-27...|
|     701.0| 354.0|[784.0,-848.0,196...|
|     741.0| 730.0|[515.0,202.0,-265...|
|     232.0| 220.0|[408.0,-14.0,-368...|
|     739.0| 736.0|[829.0,-995.0,24...|
|     613.0| 631.0|[672.0,-842.0,238...|
|    1168.0|1179.0|[732.0,222.0,-240...|
|     938.0| 959.0|[438.0,62.0,-451...|
|     394.0| 389.0|[322.0,-1484.0,29...|
|    -330.0|-320.0|[200.0,-1283.0,27...|
+----------+------+--------------------+
only showing top 10 rows

R Squared (R2) on test data = 0.874884
```

[ ]:
```python
dt_evaluator = RegressionEvaluator(
    labelCol="c8", predictionCol="prediction", metricName="rmse")
dtr_rmse = dt_evaluator.evaluate(dt_predictions)
print("Root Mean Squared Error (RMSE) on validation data = %g" % rmse)
```

```
Root Mean Squared Error (RMSE) on validation data = 112.314
```

3.3 Gradient-boosted tree regression

[18]:
```
from pyspark.ml.regression import GBTRegressor
gbt = GBTRegressor(featuresCol = 'features', labelCol = 'c8', maxIter=10)
gbt_model = gbt.fit(train)
gbt_predictions = gbt_model.transform(val)
gbt_predictions.select('prediction', 'c8', 'features').show(5)
```

```
+------------------+------+--------------------+
|        prediction|    c8|            features|
+------------------+------+--------------------+
| 514.5688085108319|1020.0|[446.0,461.0,-27....|
| 623.8457698169174| 354.0|[784.0,-848.0,196...|
|1010.8209828200846| 730.0|[515.0,202.0,-265...|
| 364.8186941829988| 220.0|[408.0,-14.0,-368...|
| 571.1635744816143| 736.0|[829.0,-995.0,24....|
+------------------+------+--------------------+
only showing top 5 rows
```

[ ]:
```
gbt_evaluator = RegressionEvaluator(
    labelCol="c8", predictionCol="prediction", metricName="rmse")
rmse = gbt_evaluator.evaluate(gbt_predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

```
Root Mean Squared Error (RMSE) on test data = 182.743
```

3.3.1 Parameters tuning

[19]:
```
# Evaluate model
evaluator = RegressionEvaluator(
    labelCol="c8", predictionCol="prediction", metricName="rmse")

# Create ParamGrid for Cross Validation
paramGrid = ParamGridBuilder()\
  .addGrid(gbt.maxDepth, [2, 5, 10])\
  .addGrid(gbt.maxIter, [10, 50])\
  .build()

# Create 5-fold CrossValidator
gb = CrossValidator(estimator=gbt,
                    estimatorParamMaps=paramGrid,
                    evaluator=evaluator,
                    # 80% of the data will be used for training, 20% for␣
 ↪validation.
                    numFolds=5)
```

```python
# Run cross validations
gb_model = gb.fit(train)
print(gb_model)
```

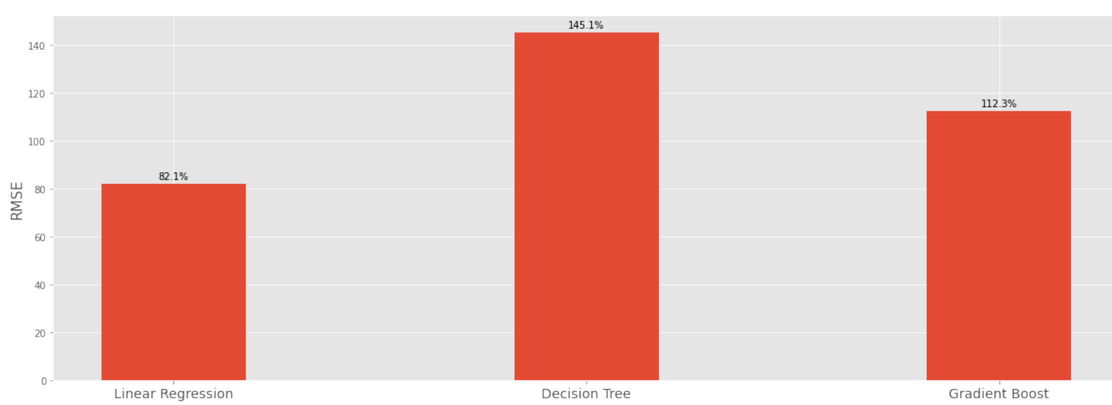
```
CrossValidatorModel_5e8522c33aa8
```

[20]:
```python
evaluator = RegressionEvaluator(
    labelCol="c8", predictionCol="prediction", metricName="rmse")
gb_predictions = gb_model.bestModel.transform(val)
gb_score = evaluator.evaluate(gb_predictions)
print('Rmse obtained is', gb_score)
```

```
Rmse obtained is 127.95867390709157
```

3.4 Comparing results

```
[ ]: I = ['Linear Regression', 'Decision Tree', 'Gradient Boost']
L = [lr_score, dtr_rmse, gb_score]

labels = L
x = np.arange(len(labels))
width = 0.35

fig, ax = plt.subplots(figsize=(20,7))
rects1 = ax.bar(x, L, width)

def autolabel(rects, labels):
    i=0
    for rect in rects:
        height = rect.get_height()
        ax.annotate(s = str(labels[i])+'%',
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')
        i+=1

labels1 = [round(A_SVM_sorte, 1) for A_SVM_sorte in L]
autolabel(rects1, labels1)


ax.set_ylabel('RMSE', size = 15)
ax.set_xticks(x)
ax.set_xticklabels(I, size = 14)

plt.show()
```



We get much better results on the Linear Regression than in the two other models. Therefore we will choose this model for the rest of the project.

3.5 Ensemble Method

[36]:
```
lr_df = lr_predictions.select(lr_predictions["c0"].alias("c0_lr"),␣
↪lr_predictions["prediction"].alias("lr_pred"), lr_predictions["c8"])
gb_df = gb_predictions.select(gb_predictions["c0"].alias("c0_gb"),␣
↪gb_predictions["prediction"].alias("gb_pred"))
```

[142]:
```
from pyspark.sql.functions import col
# finding good compromize between weight of prediction to Gradient Boost and␣
↪Linear Regression
for lr_a in range(0,15):

  marksColumns = [col('lr_pred')] + [col('gb_pred')]*lr_a

  averageFunc = sum(x for x in marksColumns)/len(marksColumns)

  df = gb_df.join(lr_df, lr_df["c0_lr"]==gb_df["c0_gb"], "inner")

  ens = df.withColumn('ens_pred', averageFunc).select(col("c0_gb").
↪alias("index"), col("ens_pred").alias("prediction"), col("c8").
↪alias("label"))

  evaluator = RegressionEvaluator(
      labelCol="label", predictionCol="prediction", metricName="rmse")
  score = evaluator.evaluate(ens)
  print(lr_a, score)
```

```
0 222.50513985032347
1 148.66018770825247
2 133.34879846641687
3 128.55487052280907
4 126.73643162225233
5 125.98846107999964
6 125.68639417619252
7 125.5878893870486
8 125.58736711333606
9 125.63489774271443
10 125.70545467580429
11 125.78598818210368
12 125.86953638095635
13 125.9523657479568
14 126.03250974003987
```

The ensemble method path was not conclusive, the results were worse than for a simple Linear Regression

4 Testing

4.1 Reading the data

[ ]:
```
schema = StructType([ StructField("c"+str(0),StringType())]+[␣
↪StructField("c"+str(i),DoubleType()) for i in range(1,9)])
# schema to cast data, can use inferschema also

raw_data = sqlContext.read.csv("/content/drive/MyDrive/exo3_predict.
↪csv",schema=schema)

assembled_data = VectorAssembler(inputCols=["c"+str(i) for i in␣
↪range(1,8)],outputCol="features").transform(raw_data)

#standardizing the data
scale=StandardScaler(inputCol='features',outputCol='standardized_features')
data_scale=scale.fit(assembled_data)
data_scale_output=data_scale.transform(assembled_data)
```

4.2 Making the predictions

[ ]:
```
test_lr_predictions = lr_cv_Model.transform(data_scale_output)
```

4.3 Saving the results

[ ]:
```
pred = [w.prediction for w in test_lr_predictions.select('prediction').
↪collect()]
ind = [w.c0 for w in test_lr_predictions.select('c0').collect()]

with open('exo3.csv','wb') as file:
  for p, i in zip(pred, ind):
    file.write((str(i)+','+str(p)+'\n').encode())
```