## PySpark for BigMart Sales

```
In [1]:
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName('Analysis-BigMart').getOrCreate()
data = spark.read.csv('train.csv', header = True, inferSchema = True)
data.printSchema()
    |-- Item_Identifier: string (nullable = true)
    |-- Item_Weight: double (nullable = true)
    |-- Item_Fat_Content: string (nullable = true)
    |-- Item_Visibility: double (nullable = true)
    |-- Item_Type: string (nullable = true)
    |-- Item_MRP: double (nullable = true)
    |-- Outlet_Identifier: string (nullable = true)
    |-- Outlet_Establishment_Year: integer (nullable = true)
    |-- Outlet_Size: string (nullable = true)
    |-- Outlet_Location_Type: string (nullable = true)
    |-- Outlet_Type: string (nullable = true)
    |-- Item_Outlet_Sales: double (nullable = true)
  In [2]:
data.show(5, truncate=False)
   |Item_Identifier|Item_Weight|Item_Fat_Content|Item_Visibility|Item_Type
                                                                                                                                     Item MRP Outlet Identifier Outlet Establishment Year O
   249.8092 OUT049
                                                                                                                                                                                1999
                                                                                                                                |48.2692 |OUT018
                                                                                                                                                                                2009
                                                                                                                                    |141.618 |OUT049
                                                                                                                                                                                11999
                                                                                                                                                                                                                             IM
                                                                                                                                                                                1998
                                                                                                                                    53.8614 OUT013
                                                                                                                                                                                1987
                                                                                                                                                                                                                             Н
                                                Supermarket Type1 994.7052
                                                                                                       -----
   only showing top 5 rows
  In [3]:
data.describe().show()
   |summary|Item_Identifier| Item_Weight|Item_Fat_Content| Item_Visibility| Item_Type| Item_MRP|Outlet_Identifier|Outlet_
  | count | 8523 | 7060 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 | 8523 |
                                                                                                                                                                                                           null
                                                                                                                                                                                                           null
                                                                                                                                                                          31.29
                                                                                                                                                                                                         OUT010|
                                                                                                                                                                                                        OUT049
```

```
AnalysisBigMartSales
    In [4]:
import pyspark.sql.functions as f
# null values in each column
data_agg = data.agg(*[f.count(f.when(f.isnull(c), c)).alias(c) for c in data.columns])
data_agg.show()
      | \texttt{Item\_Identifier} | \texttt{Item\_Weight} | \texttt{Item\_Fat\_Content} | \texttt{Item\_Visibility} | \texttt{Item\_MRP} | \texttt{Outlet\_Identifier} | \texttt{Outlet\_Establishment\_Year} | \texttt{Outlet\_Size} | \texttt{Outl
      utlet_Location_Type|Outlet_Type|Item_Outlet_Sales|
      ------
                                              0 1463
                                                                                                                                                                                                                             0
                                                                                                                                                                                                                                                                                                                                                                                                                                  2410
                               0|
     0
      Fill NA with mean and mode
    In [5]:
data.agg({'Item_Weight': 'mean'}).show()
      +----+
      avg(Item_Weight)
     12.857645184136183
    In [6]:
data = data.fillna( { 'Item_Weight':12.857645184136183 } )
    In [7]:
data.groupBy('Outlet_Size').count().show()
      |Outlet_Size|count|
                        High| 932|
                            null| 2410|
                       Medium | 2793|
                        Small 2388
```

```
In [8]:
data = data.fillna( { 'Outlet Size':'Medium' } )
In [9]:
```

```
import pyspark.sql.functions as f
# null values in each column
data_agg = data.agg(*[f.count(f.when(f.isnull(c), c)).alias(c) for c in data.columns])
data_agg.show()
           | \texttt{Item\_Identifier} | \texttt{Item\_Weight} | \texttt{Item\_Fat\_Content} | \texttt{Item\_Visibility} | \texttt{Item\_MRP} | \texttt{Outlet\_Identifier} | \texttt{Outlet\_Establishment\_Year} | \texttt{Outlet\_Size} | \texttt{Outl
           utlet_Location_Type|Outlet_Type|Item_Outlet_Sales|
            -----
                                                                                  0
                                                                                                                                                                                                                                                   0
                                                                                                                                                                                                                                                                                                                                                     0
                                                                                                                                                                                                                                                                                                                                                                                                          0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                 0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          0
                                                                   0
```

# **Label Encoding**

```
In [10]:
from pyspark.ml.feature import StringIndexer
# create object of StringIndexer class and specify input and output column
SI_Fat = StringIndexer(inputCol='Item_Fat_Content',outputCol='Item_Fat_Content_Index')
SI_Type = StringIndexer(inputCol='Item_Type',outputCol='Item_Type_Index')
SI_Size = StringIndexer(inputCol='Outlet_Size',outputCol='Outlet_Size_Index')
SI_Location = StringIndexer(inputCol='Outlet_Location_Type',outputCol='Outlet_Location_Type_Index')
SI_Out_Type = StringIndexer(inputCol='Outlet_Type',outputCol='Outlet_Type_Index')
# transform the data
data = SI Fat.fit(data).transform(data)
data = SI Type.fit(data).transform(data)
data = SI_Size.fit(data).transform(data)
data = SI_Location.fit(data).transform(data)
data = SI_Out_Type.fit(data).transform(data)
# view the transformed data
data.first()
 Row(Item_Identifier='FDA15', Item_Weight=9.3, Item_Fat_Content='Low Fat', Item_Visibility=0.016047301, Item_Type='Dairy', Item_MRP=249.809
 2, Outlet_Identifier='0UT049', Outlet_Establishment_Year=1999, Outlet_Size='Medium', Outlet_Location_Type='Tier 1', Outlet_Type='Supermark
 et Type1', Item Outlet Sales=3735.138, Item Fat Content Index=0.0, Item Type Index=4.0, Outlet Size Index=0.0, Outlet Location Type Index=
 2.0, Outlet_Type_Index=0.0)
```

## One Hot Encoding

```
In [11]:
from pyspark.ml.feature import OneHotEncoder
OHE = OneHotEncoder(inputCols=['Item_Fat_Content_Index', 'Item_Type_Index', 'Outlet_Size_Index', 'Outlet_
Location_Type_Index', 'Outlet_Type_Index'],outputCols=['Item_Fat_Content_OHE', 'Item_Type_OHE', 'Outlet_S
ize_OHE', 'Outlet_Location_Type_OHE', 'Outlet_Type_OHE'])

# transform the data
data = OHE.fit(data).transform(data)

In [12]:
data.take(1)

[Row(Item_Identifier='FDA15', Item_Meight=9.3, Item_Fat_Content='Low Fat', Item_Visibility=0.016047301, Item_Type='Dairy', Item_MRP=249.80
92, Outlet_Identifier='OUT049', Outlet_Establishment_Year=1999, Outlet_Size='Medium', Outlet_Location_Type='Tier 1', Outlet_Type='Supermar
ket Type1', Item_Outlet_Sales=3735.138, Item_Fat_Content_Index=0.0, Item_Type_Index=4.0, Outlet_Size_Index=0.0, Outlet_Location_Type_Index
=2.0, Outlet_Type_Index=0.0, Outlet_Type_OHE=SparseVector(3, (0: 1.0)), Item_Fat_Content_OHE=SparseVector(4, (0: 1.0)), Outlet_Size_OHE=SparseVector(2, {}}), Item_Type_OHE=SparseVector(15, {4: 1.0}))]
```

#### Vectorizing into single Feature

```
from pyspark.ml.feature import VectorAssembler

inputcol = ['Item_Fat_Content_Index', 'Item_Type_Index', 'Outlet_Size_Index', 'Outlet_Location_Type_Inde
x', 'Outlet_Type_Index', 'Item_Fat_Content_OHE', 'Item_Type_OHE', 'Outlet_Size_OHE', 'Outlet_Location_Type
_OHE', 'Outlet_Type_OHE', 'Item_Weight', 'Item_Visibility', 'Item_MRP', 'Outlet_Establishment_Year']
# specify the input and output columns of the vector assembler
assembler = VectorAssembler(inputCols=inputcol, outputCol='features')

# fill the null values
data = data.fillna(0)

# transform the data
final_data = assembler.transform(data)
```

```
In [14]:
final_data.take(1)
```

[Row(Item\_Identifier='FDA15', Item\_Weight=9.3, Item\_Fat\_Content='Low Fat', Item\_Visibility=0.016047301, Item\_Type='Dairy', Item\_MRP=249.80 92, Outlet\_Identifier='OUT049', Outlet\_Establishment\_Year=1999, Outlet\_Size='Medium', Outlet\_Location\_Type='Tier 1', Outlet\_Type='Supermar ket Type1', Item\_Outlet\_Sales=3735.138, Item\_Fat\_Content\_Index=0.0, Item\_Type\_Index=4.0, Outlet\_Size\_Index=0.0, Outlet\_Location\_Type\_Index = 2.0, Outlet\_Type\_Index=0.0, Outlet\_Type\_OHE=SparseVector(3, {0: 1.0}), Item\_Fat\_Content\_OHE=SparseVector(4, {0: 1.0}), Outlet\_Size\_OHE=SparseVector(2, {}), Item\_Type\_OHE=SparseVector(15, {4: 1.0}), features=SparseVector(35, {1: 4.0, 3: 2.0, 5: 1.0, 13: 1.0, 24: 1.0, 28: 1.0, 31: 9.3, 32: 0.016, 33: 249.8092, 34: 1999.0}))]

```
In [15]: |
df_train = final_data.select(['features', 'Item_Outlet_Sales'])
```

```
In [16]:

df_train.take(1)
```

[Row(features=SparseVector(35, {1: 4.0, 3: 2.0, 5: 1.0, 13: 1.0, 24: 1.0, 28: 1.0, 31: 9.3, 32: 0.016, 33: 249.8092, 34: 1999.0}), Item\_Outlet\_Sales=3735.138)]

```
In [17]:
```

 $df_{train.show(5)}$ 

only showing top 5 rows

## Split train and test

```
In [18]:
```

train\_df, test\_df = df\_train.randomSplit([0.8, 0.2])

### Applying various models in Pyspark Api

```
In [30]:
# Linear Regression Model
from pyspark.ml.regression import LinearRegression
from pyspark.ml.evaluation import RegressionEvaluator
lr = LinearRegression(featuresCol = 'features', labelCol='Item_Outlet_Sales', maxIter=150, regParam=0.0,
elasticNetParam=0.0)
lr_model = lr.fit(train_df)
trainingSummary = lr model.summary
print("RMSE: %f" % trainingSummary.rootMeanSquaredError)
print("R2: %f" % trainingSummary.r2)
# Predict and Evaluate
lr_predictions = lr_model.transform(test_df)
lr_predictions.select("prediction","Item_Outlet_Sales","features").show(5)
lr_evaluator = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricName="r
mse")
print("Root Mean Square Error (RMSE) on test data = %g" % 1r evaluator.evaluate(1r predictions))
lr_evaluator_r2 = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales", metricName
="r2")
print("R Squared (R2) on test data = %g" % lr_evaluator_r2.evaluate(lr_predictions))
 RMSE: 1133.476559
 R2: 0.554448
  +----
        prediction|Item_Outlet_Sales|
 729.2843759230018 331.5684 (35, [0,1,2,3,4,6,...]
  384.5975328735367
                      425.4462 (35,[0,1,2,3,4,6,...
 1136.7232229275978
                        945.436 (35,[0,1,2,3,4,6,...
                     317.5866 | (35, [0,1,2,3,4,6,...|
 I-153.25180773547618
 -30.22022594201553
                       113.8518 (35,[0,1,2,3,4,6,...
 only showing top 5 rows
 Root Mean Square Error (RMSE) on test data = 1106.76
 R Squared (R2) on test data = 0.593892
```

```
In [23]:
  Lasso Regression Model
lar = LinearRegression(featuresCol = 'features', labelCol='Item_Outlet_Sales', maxIter=100, regParam=0.3,
elasticNetParam=1)
lar_model = lar.fit(train_df)
trainingSummary = lar_model.summary
print("RMSE: %f" % trainingSummary.rootMeanSquaredError)
print("R2: %f" % trainingSummary.r2)
# Predict and Evaluate
lar_predictions = lar_model.transform(test_df)
lar_predictions.select("prediction","Item_Outlet_Sales","features").show(5)
lar_evaluator = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricName=
print("Root Mean Square Error (RMSE) on test data = %g" % lar_evaluator.evaluate(lar_predictions))
lar_evaluator_r2 = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricNam
print("R Squared (R2) on test data = %g" % lar evaluator r2.evaluate(lar predictions))
 RMSE: 1133.589738
 R2: 0.554359
         prediction|Item_Outlet_Sales|
                                        features
 723.1792481893208
                       331.5684 (35,[0,1,2,3,4,6,...
                       425.4462 (35,[0,1,2,3,4,6,...|
945.436 (35,[0,1,2,3,4,6,...|
 378.63698723577545
 1130.646491530053
                       317.5866 | (35, [0,1,2,3,4,6,...
 -158.85101700072846
                        113.8518 | (35,[0,1,2,3,4,6,...|
 -35.82258349095355
 only showing top 5 rows
 Root Mean Square Error (RMSE) on test data = 1106.86
 R Squared (R2) on test data = 0.593819
```

```
In [26]:
# Decision Tree Regression Model
from pyspark.ml.regression import DecisionTreeRegressor
dt = DecisionTreeRegressor(featuresCol = 'features', labelCol='Item_Outlet_Sales', maxDepth=15, minInstan
cesPerNode=100)
dt_model = dt.fit(train_df)
# Predict and Evaluate
dt predictions = dt model.transform(test df)
dt_predictions.select("prediction","Item_Outlet_Sales","features").show(5)
df_evaluator = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricName="r
mse")
print("Root Mean Square Error (RMSE) on test data = %g" % df_evaluator.evaluate(dt_predictions))
df_evaluator_r2 = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricName
print("R Squared (R2) on test data = %g" % df_evaluator_r2.evaluate(dt_predictions))
        prediction|Item_Outlet_Sales|
                      331.5684|(35,[0,1,2,3,4,6,...|
425.4462|(35,[0,1,2,3,4,6,...|
 394.03078252427184
 283.3360183206108
 500.69881896551715
                       945.436 (35, [0,1,2,3,4,6,...
                      317.5866|(35,[0,1,2,3,4,6,...|
113.8518|(35,[0,1,2,3,4,6,...|
 223.94658571428573
 283.3360183206108
 only showing top 5 rows
 Root Mean Square Error (RMSE) on test data = 1057.63
 R Squared (R2) on test data = 0.629148
In [27]:
## GBT Regression Model
from pyspark.ml.regression import GBTRegressor
gbt = GBTRegressor(featuresCol = 'features', labelCol='Item_Outlet_Sales', maxIter=10)
# gbt = GBTRegressor(featuresCol = 'features', labelCol='Item_Outlet_Sales', maxIter=10, maxDepth=15, min
InstancesPerNode=100)
gbt_model = gbt.fit(train_df)
# Predict and Evaluate
gbt predictions = gbt model.transform(test df)
gbt_predictions.select("prediction","Item_Outlet_Sales","features").show(5)
gbt_evaluator = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricName=
"rmse")
print("Root Mean Square Error (RMSE) on test data = %g" % gbt_evaluator.evaluate(gbt_predictions))
gbt_evaluator_r2 = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricNam
e="r2")
print("R Squared (R2) on test data = %g" % gbt_evaluator_r2.evaluate(gbt_predictions))
       prediction Item_Outlet_Sales
 477.42167799114003
                      331.5684 (35,[0,1,2,3,4,6,...
                      425.4462|(35,[0,1,2,3,4,6,...|
945.436|(35,[0,1,2,3,4,6,...|
 342.25790791842667
 541.6654409408936
                      317.5866|(35,[0,1,2,3,4,6,...|
 245.1703909636694
 311.27774749352017
                       113.8518 (35, [0,1,2,3,4,6,...]
  t-----t
 only showing top 5 rows
 Root Mean Square Error (RMSE) on test data = 1047.03
 R Squared (R2) on test data = 0.636544
```

```
In [29]:
# RandomForest Regression Model
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.ml.regression import RandomForestRegressor
rf = RandomForestRegressor(featuresCol = 'features', labelCol='Item_Outlet_Sales', minInstancesPerNode=15
0)
rf_evaluator = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales",metricName="r
mse")
paramGrid = ParamGridBuilder() \
    .addGrid(rf.maxDepth, [5, 6, 10]) \
    .addGrid(rf.numTrees, [200, 400]) \
    .build()
cv = CrossValidator(estimator=rf, estimatorParamMaps=paramGrid, evaluator=rf_evaluator, numFolds=5, paral
lelism=5)
cv model = cv.fit(train df)
rf_predictions = cv_model.transform(test_df)
rf_predictions.select("prediction","Item_Outlet_Sales","features").show(5)
print("Root Mean Square Error (RMSE) on test data = %g" % gbt_evaluator.evaluate(gbt_predictions))
rf_evaluator_r2 = RegressionEvaluator(predictionCol="prediction", labelCol="Item_Outlet_Sales", metricName
="r2")
print("R Squared (R2) on test data = %g" % rf_evaluator_r2.evaluate(rf_predictions))
       prediction|Item_Outlet_Sales|
                                      features
 +----
 441.65932039560516
                     331.5684 (35,[0,1,2,3,4,6,...
 325.619648765012
                      425.4462 (35,[0,1,2,3,4,6,...
 473.97048510979783
                      945.436 (35,[0,1,2,3,4,6,...
 309.47752994468544
                     317.5866 (35,[0,1,2,3,4,6,...
 319.80938730928233
                      113.8518 (35,[0,1,2,3,4,6,...
 +-----
 only showing top 5 rows
 Root Mean Square Error (RMSE) on test data = 1047.03
 R Squared (R2) on test data = 0.61196
```

#### Results

```
In [33]:
import numpy as np
import matplotlib.pyplot as plt
models = ['LinearRegression', 'LassoRegression', 'DecisionTreeRegressor',
                 'GBTRegressor', 'RandomForestRegressor']
data = [1106.76, 1106.86, 1057.63, 1047.03, 1047.03]
plt.barh(models, data)
for index, value in enumerate(data):
    plt.text(value, index,
              str(value))
plt.show()
                                                                          1047.03
  Random Forest Regressor \\
                                                                          1047.03
           GBTRegressor ·
                                                                          1057.63
   DecisionTreeRegressor -
                                                                             11φ6.86
        LassoRegression -
                                                                             11¢6.76
        LinearRegression -
                                200
                                         400
                                                   600
                                                            800
                       Ó
                                                                     1000
```

Here we can easily see that RFR and GBT outplayed all the other models as they have least RMSE scores on test\_dataset.

Improvements can be done as we can apply ANN and also can change the parameters in CrossValidations and other models' arguments as well.

We can even apply word embeddings as in case of neuralNets as well.