Generación de modelos inteligentes utilizando PySpark y MLLib

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1. Preparación del ambiente de trabajo para Big Data en Colab

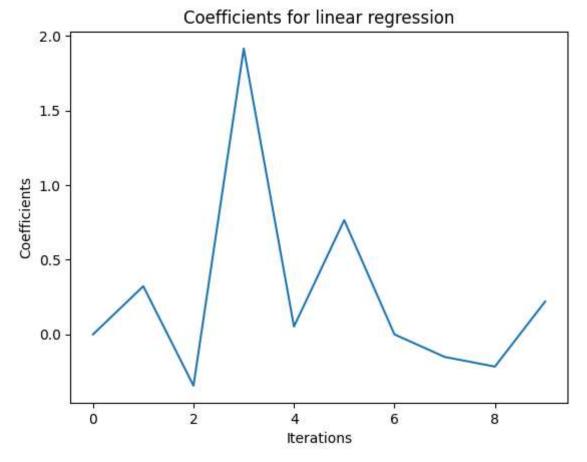
```
In [4]: !pip install pyspark py4j
        Requirement already satisfied: pyspark in /usr/local/lib/python3.10/dist-packages (3.
        Requirement already satisfied: py4j in /usr/local/lib/python3.10/dist-packages (0.10.
        9.7)
In [5]: from pyspark.sql import SparkSession
        import matplotlib.pyplot as plt
In [7]: from google.colab import drive
        drive.mount('/content/drive')
        Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
        ount("/content/drive", force remount=True).
In [8]: spark = SparkSession.builder.appName("tec").getOrCreate()
In [9]: def plt plot(lst, x, y, t):
          plt.plot(lst)
          plt.xlabel(str(x))
          plt.ylabel(str(y))
          plt.title(str(t))
          plt.show()
```

2. Genera un modelo de regresión utilizando PySpark y MLlib

Regression:

• Linear Regression:

```
lr = LinearRegression(maxIter=10, regParam=0.3, elasticNetParam=0.8)
In [13]:
         # Fit the model
In [14]:
         lrModel = lr.fit(training)
In [15]: # Print the coefficients and intercept for linear regression
         print("Coefficients: %s" % str(lrModel.coefficients))
         print("Intercept: %s" % str(lrModel.intercept))
         Coefficients: [0.0,0.3229251667740594,-0.3438548034562219,1.915601702345841,0.0528805
         8680386255,0.765962720459771,0.0,-0.15105392669186676,-0.21587930360904645,0.22025369
         188813431
         Intercept: 0.15989368442397356
In [16]: plt.plot(lrModel.coefficients)
         plt.xlabel("Iterations")
         plt.ylabel("Coefficients")
         plt.title("Coefficients for linear regression")
         plt.show()
```



```
In [17]: # Summarize the model over the training set and print out some metrics
    trainingSummary = lrModel.summary
    print("numIterations: %d" % trainingSummary.totalIterations)
    print("objectiveHistory: %s" % str(trainingSummary.objectiveHistory))
    trainingSummary.residuals.show()
    print("RMSE: %f" % trainingSummary.rootMeanSquaredError)
    print("r2: %f" % trainingSummary.r2)
```

```
numIterations: 6
objectiveHistory: [0.499999999999999, 0.4967620357443381, 0.49363616643404634, 0.49
36351537897608, 0.4936351214177871, 0.49363512062528014, 0.4936351206216114]
  -----+
           residuals
  -9.889232683103197
  0.5533794340053553
  -5.204019455758822
 -20.566686715507508
    -9.4497405180564
  -6.909112502719487
  -10.00431602969873
  2.0623978070504845
  3.1117508432954772
  -15.89360822941938
  -5.036284254673026
  6.4832158769943335
  12.429497299109002
  -20.32003219007654
    -2.0049838218725
 -17.867901734183793
   7.646455887420495
 -2.2653482182417406
 -0.10308920436195645
  -1.380034070385301
+----+
only showing top 20 rows
RMSE: 10.189077
r2: 0.022861
```

3. Genera un modelo de clasificación utilizando PySpark y MLlib:

Classification:

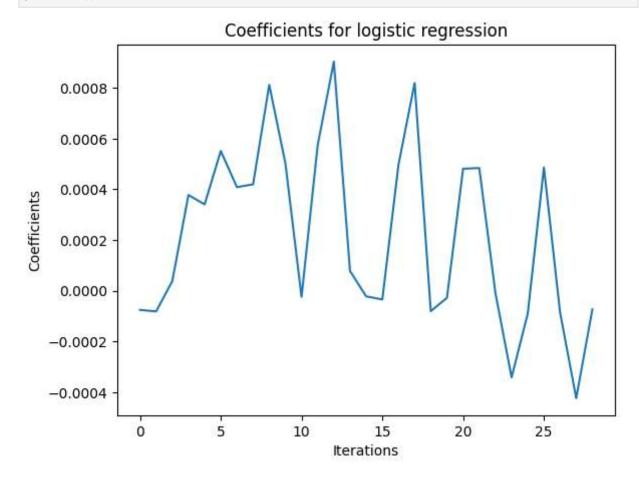
• Logistic Regression:

```
In [19]: from pyspark.ml.classification import LogisticRegression
In [21]: # Load training data
    training = spark.read.format("libsvm").load("/content/drive/MyDrive/Colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/colab_Notebooks/c
```

Coefficients: (692,[272,300,323,350,351,378,379,405,406,407,428,433,434,435,455,456,461,462,483,484,489,490,496,511,512,517,539,540,568],[-7.520689871384125e-05,-8.115773 146847006e-05,3.814692771846427e-05,0.0003776490540424338,0.0003405148366194403,0.000 5514455157343107,0.0004085386116096912,0.0004197467332749452,0.0008119171358670031,0.000502770837266875,-2.3929260406600902e-05,0.0005745048020902297,0.000903754642680367 7,7.818229700243899e-05,-2.1787551952911914e-05,-3.402165821789542e-05,0.000496651736 0637633,0.0008190557828370372,-8.017982139522613e-05,-2.743169403783527e-05,0.0004810 832226238988,0.0004840801762677878,-8.926472920009901e-06,-0.00034148812330427297,-8.950592574121382e-05,0.00048645469116892156,-8.478698005186097e-05,-0.0004234783215831 7705,-7.296535777631246e-05])

In [30]: plt.plot(lrModel.coefficients)
 plt.xlabel("Iterations")
 plt.ylabel("Coefficients")
 plt.title("Coefficients for logistic regression")
 plt.show()

Intercept: -0.5991460286401438



```
In [25]: # We can also use the multinomial family for binary classification
    mlr = LogisticRegression(maxIter=10, regParam=0.3, elasticNetParam=0.8, family="multir")
In [26]: # Fit the model
    mlrModel = mlr.fit(training)
In [27]: # Print the coefficients and intercepts for logistic regression with multinomial famil
    print("Multinomial coefficients: " + str(mlrModel.coefficientMatrix))
    print("Multinomial intercepts: " + str(mlrModel.interceptVector))
```

```
Multinomial coefficients: 2 X 692 CSRMatrix
(0,272) 0.0001
(0,300) 0.0001
(0,350) -0.0002
(0,351) - 0.0001
(0,378) -0.0003
(0,379) -0.0002
(0,405) -0.0002
(0,406) - 0.0004
(0,407) -0.0002
(0,433) - 0.0003
(0,434) -0.0005
(0,435) - 0.0001
(0,456) 0.0
(0,461) - 0.0002
(0,462) -0.0004
(0,483) 0.0001
Multinomial intercepts: [0.27505875857180895,-0.27505875857180895]
```

4. Genera un agrupamiento utilizando PySpark y MLlib:

Clustering:

K-means:

```
import plotly.graph_objects as go
In [39]:
                                 from pyspark.ml.clustering import KMeans
                                  from pyspark.ml.evaluation import ClusteringEvaluator
In [31]: # Loads data.
                                  dataset = spark.read.format("libsvm").load("/content/drive/MyDrive/Colab Notebooks/content/drive/MyDrive/Colab Notebooks/content/drive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/MyDrive/My
In [32]: # Trains a k-means model.
                                 kmeans = KMeans().setK(2).setSeed(1)
                                 model = kmeans.fit(dataset)
In [33]: # Make predictions
                                 predictions = model.transform(dataset)
In [34]: # Evaluate clustering by computing Silhouette score
                                 evaluator = ClusteringEvaluator()
In [35]: silhouette = evaluator.evaluate(predictions)
                                 print("Silhouette with squared euclidean distance = " + str(silhouette))
                                 Silhouette with squared euclidean distance = 0.9997530305375207
In [41]: # Shows the result.
                                 cen list = list()
                                  centers = model.clusterCenters()
```

```
print("Cluster Centers: ")
for center in centers:
  print(center)
  cen_list.append(center)
fig = go.Figure( go.Scatter(x=cen_list[0], y=cen_list[1] ) )
fig.show()

Cluster Centers:
[9.1 9.1 9.1]
```

[0.1 0.1 0.1]