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INSTITUTO TECNOLÓGICO DE TIJUANA

SUBDIRECCIÓN ACADÉMICA

DEPARTAMENTO DE SISTEMAS Y COMPUTACIÓN

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MATERIA: Datos Masivos

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Practice evaluatoria 4

Unidad 4

Introduction

This practice is for can see the best model for this example the data set is bank.csv is a data set about related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict if the client will subscribe a term deposit (variable y) and we try to do a prediction with teh models: SVM, Desicion tree, logistic regresion and multilayer perceptron those are machine learning models but supervised that is to say is a subcategory of machine learning and artificial intelligence. It is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weights until the model has been fitted appropriately, which occurs as part of the cross validation process. Supervised learning helps organizations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox.

In these case we used this types of models for create a comparation in this and obtaing valius information abou wich is the best in these case in spesific we based in the accuaracy and the error, and try to explain more about this models too.

Theoretical framework

- SVM
- Decision Three
- Logistic Regresion
- Multilayer perceptron

Start talk about the each of the models like SVM is a supervised machine learning algorithm that can be used for both classification or regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is a number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well, now let's move on to Decision three are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. A tree can be seen as a piecewise constant approximation, decision trees learn from data to approximate a sine curve with a set of if-then-else decision rules. The deeper the tree, the more complex the decision rules and the fitter the model, while logistic regresion is a supervised learning classification algorithm used to predict the probability of a target variable. The nature of target or dependent variable is dichotomous, which means there would be only two possible classes so the dependent variable is binary in nature having data coded as either 1 (stands for success/yes) or 0 (stands for failure/no) and multilayer perception is a neural network where the mapping between inputs and output is non-linear, has input and output layers, and one or more hidden layers with many neurons stacked together. And while in the Perceptron the neuron must have an activation function that imposes a threshold, like ReLU or sigmoid, neurons in a Multilayer Perceptron can use any arbitrary activation function.

Implementation

Why we used scala and spark like work environment?

Well Scala is a functional language, so computing can be distributed across the cores in a multicore server and across the servers in a Data Center. This makes Scala especially a great choice for multi-core CPUs and Cloud Coumputing distributed workloads. Learning Scala is indispensable for Big Data analysis scenarios and spark enables developers to perform operations on large volumes of data in clusters quickly and with fault tolerance. When we have to handle algorithms, working in memory and not on disk improves performance.

So we decide ussed because is a so lightweight work enviroment because this interfaz don't used a lot recurses and this does not go down the potential and the big power than have scala and spark and this is fantastic if work with big data because de dataset so big to do slower the recurses and the PC in general, and no it's so difficult to analizing in this type to envioroment.

Developement

Common Code
Every model needs certain library and is representate like here

```
import org.apache.spark.sql.SparkSession
import org.apache.spark.ml.classification.LinearSVC
import org.apache.spark.mllib.evaluation.MulticlassMetrics
import org.apache.spark.ml.linalg.Vectors
import org.apache.spark.ml.feature.StringIndexer
import org.apache.spark.ml.feature.VectorIndexer
import org.apache.spark.ml.feature.VectorAssembler
import org.apache.spark.ml.Pipeline
```

To do more small the error

```
import org.apache.log4j._
Logger.getLogger("org").setLevel(Level.ERROR)
```

Create a new session on spark

```
val spark = SparkSession.builder.appName("svm").getOrCreate()
```

Load the data set correspondet

```
val df  = spark.read.option("header","true").option("inferSchema",
"true").option("delimiter",";").format("csv").load("bank-full.csv")
df.head()
df.describe()
```

Define the colum "Y" like index

```
val labelIndexer = new
StringIndexer().setInputCol("y").setOutputCol("indexedY").fit(df)
```

```
val indexed = labelIndexer.transform(df).drop("y").withColumnRenamed("indexedY", "label")
```

Made the vector with the number columns in features

```
val vectorFeatures = (new VectorAssembler().setInputCols(Array("balance","day","duration","pdays","previous")).setOutputCol("features"))
```

Here transform feaure

```
val featurestrans = vectorFeatures.transform(indexed)
```

Join columns feature and label

```
val dataindexed = featureslabel.select("label","features")
dataindexed.show()
```

Creation of labelindex and featureindex for pipeline

```
val labelindexer = new StringIndexer().setInputCol("label").setOutputCol("indexedlabel").fit(dataindexed)
val featureIndexer = new VectorIndexer().setInputCol("features").setOutputCol("indexedfeatures").setMaxCategories(4).fit(dataindexed)
```

And training test and data

```
val Array(training, test) = dataindexed.randomSplit(Array(0.7, 0.3), seed = 1234L)
```

Is importat to sai only some this steps there are used on the models, sometimes can changed.

SVM

As we sai some steps on the code is so similar so here only explain the specific steps like these is where define the model, we define the max iteraccion and the param is go to train with differents.

```
val supportVM = new LinearSVC().setMaxIter(10).setRegParam(0.1)
```

Here train to model and need to transfor the test after we see the prediction

```
val modelSVM = supportVM.fit(training)

val predictions = modelSVM.transform(test)
predictions.show()
```

Here is a so important step because is the result and to do de metrics with the prediction, too to do the cofusion matrix for to do more real the results and print the accuacy and test error

```
val predictionAndLabels =
predictions.select($"prediction",$"label").as[(Double, Double)].rdd
val metrics = new MulticlassMetrics(predictionAndLabels)

println("Confusion matrix:")
println(metrics.confusionMatrix)

println("Accuracy: " + metrics.accuracy)
println(s"Tst Error = ${(1.0 - metrics.accuracy)}")
spark.stop()
```

RESULT

This is a example to result and repet the process 30 times

```
Confusion matrix:
12039.0  22.0
1599.0   22.0
Accuracy: 0.8833238995004502
Tst Error = 0.12047610058865769
```

Results SVM

Iter	SVM
1	0.8833
2	0.8835
3	0.8877
4	0.8820
5	0.8836
6	0.8865
7	0.8846

Iter	SVM
8	0.8797
9	0.8837
10	0.8838
11	0.8799
12	0.8839
13	0.8805
14	0.8830
15	0.8818
16	0.8805
17	0.8852
18	0.8811
19	0.8836
20	0.8796
21	0.8874
22	0.8865
23	0.8819
24	0.8823
25	0.8841
26	0.8878
27	0.8793
28	0.8874
29	0.8856
30	0.8842

AVERAGE: 0.883466667

DesicionTree

In these case start with the train of the model and we convert the the news labels too after start with pipeline than we help to do the predictions.

```
val dt = new DecisionTreeClassifier().setLabelCol("indexedLabel").setFeaturesCol("indexedFeatures")
val labelConverter = new IndexToString().setInputCol("prediction").setOutputCol("predictedLabel").setLabels(labelIndexer.labels)
val pipeline = new Pipeline().setStages(Array(labelIndexer, featureIndexer, dt, labelConverter))
```

An this is the final is the results, here used the pipeline and the trainingdata, after to do the prediction with the test data after print the prediction, the last part is evalute the prediction and print the accuracy and test error.

```
val model = pipeline.fit(trainingData)

val predictions = model.transform(testData)
predictions.select("predictedLabel", "label", "features").show(5)

val evaluator = new MulticlassClassificationEvaluator().setLabelCol("indexedLabel").setPredictionCol("prediction").setMetricName("accuracy")
val accuracy = evaluator.evaluate(predictions)
println(s"Test error = ${(1.0 - accuracy)}")
```

RESULT
This is a example to result and repet the process 30 times

```
Accuracy = 0.8907792083876189
Test Error = 0.10933129159924048
```

Iter	DescTree
1	0.8907
2	0.8951
3	0.8940
4	0.8901
5	0.8867
6	0.8809
7	0.8887
8	0.8903
9	0.8899
10	0.8804

Iter	DescTree
11	0.8874
12	0.8856
13	0.8912
14	0.8903
15	0.8878
16	0.8908
17	0.8856
18	0.8889
19	0.8875
20	0.8806
21	0.8874
22	0.8803
23	0.8907
24	0.8845
25	0.8874
26	0.8899
27	0.8867
28	0.8907
29	0.8887
30	0.8840

AVERAGE: 0.88776

Logistic Regression

In this model we start the explanation from the model since all the models are using the same data repository, in this model we start from the preparation of the vectors and the already established indexers

```
val data2 = assembler.transform(cleanData)

val featuresLabel = data2.withColumnRenamed("y", "label")

val finaldata = featuresLabel.select("label","features")
```

we proceed to divide the dataset to calculate and implement the logistic regression model

```
val Array(training, test) = finaldata.randomSplit(Array(0.7, 0.3), seed =
1234)
```

in this part we made a implementation of the model for obtain the results over data repository

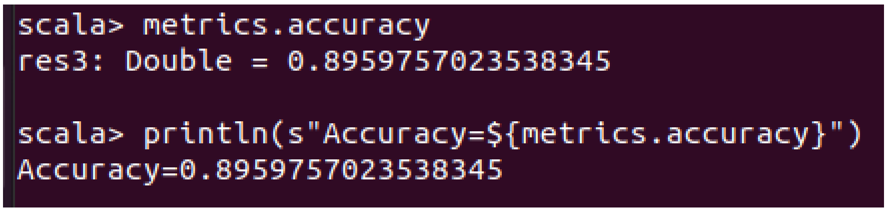
```
val lr = new LogisticRegression()

val model = lr.fit(training)

val results = model.transform(test)
```

we import the last library for the last step and obtain the most important results in this case the precision

```
import org.apache.spark.mllib.evaluation.MulticlassMetrics

val predictionAndLabels =
results.select($"prediction",$"label").as[(Double, Double)].rdd
val metrics = new MulticlassMetrics(predictionAndLabels)
```

for the last step we have to show the results of accuracy

```
println("Confusion matrix:")
println(metrics.confusionMatrix)

metrics.accuracy
println(s"Accuracy=${metrics.accuracy}")
```



```
scala> metrics.accuracy
res3: Double = 0.8959757023538345

scala> println(s"Accuracy=${metrics.accuracy}")
Accuracy=0.8959757023538345
```

Iter	LogiReg
1	0.8959
2	0.8959
3	0.8959

Iter	LogiReg
4	0.8959
5	0.8959
6	0.8959
7	0.8959
8	0.8959
9	0.8959
10	0.8959
11	0.8959
12	0.8959
13	0.8959
14	0.8959
15	0.8959
16	0.8959
17	0.8959
18	0.8959
19	0.8959
20	0.8959
21	0.8959
22	0.8959
23	0.8959
24	0.8959
25	0.8959
26	0.8959
27	0.8959
28	0.8959
29	0.8959
30	0.8959

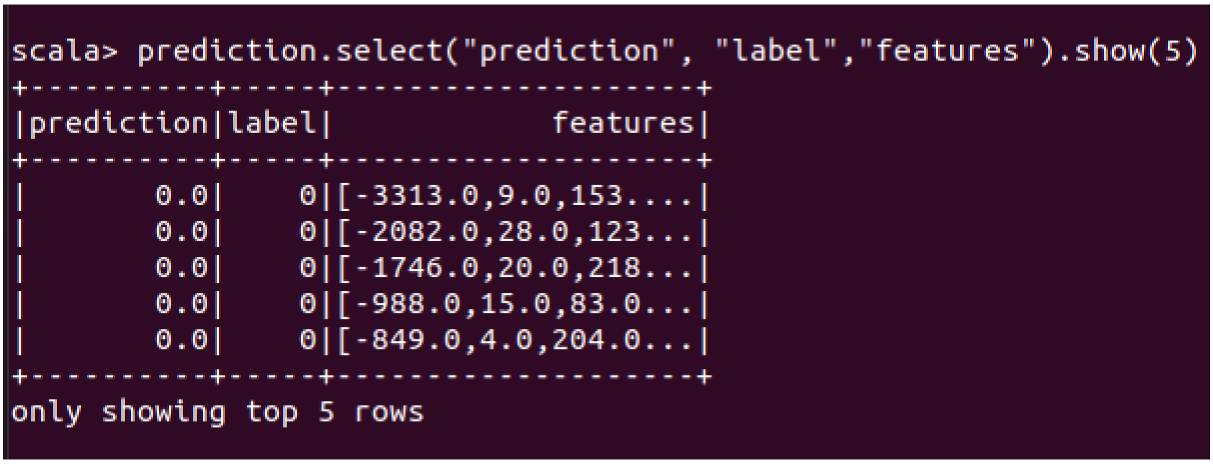
AVERAGE: 0.8959

we establish the parameters for the model and we can carry out the implementation

```
val trainer = new MultilayerPerceptronClassifier().setLayers(layers).setLabelCol("indexedLabel").setFeaturesCol("indexedFeatures").setBlockSize(128).setSeed(1234L).setMaxIter(100)


val labelConverter = new IndexToString().setInputCol("prediction").setOutputCol("predictedLabel").setLabels(labelIndexer.labels)
```

We proceed to establish the parameters within a pipeline that will be taken into account for the realization of the model, once done we implement the model in the divided dataset

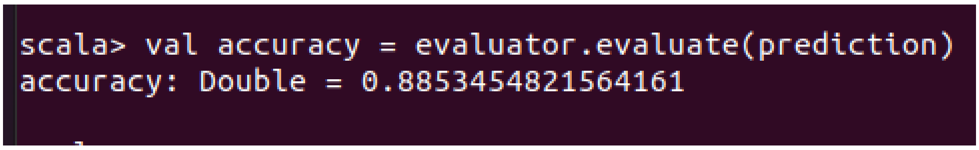
```
val pipeline = new Pipeline().setStages(Array(labelIndexer, featureIndexer, trainer, labelConverter))

val model = pipeline.fit(training)

val prediction = model.transform(test)
prediction.select("prediction", "label","features").show(5)
```



```
scala> prediction.select("prediction", "label","features").show(5)
+----------+-----+--------------------+
|prediction|label|            features|
+----------+-----+--------------------+
|       0.0|    0|[-3313.0,9.0,153....|
|       0.0|    0|[-2082.0,28.0,123...|
|       0.0|    0|[-1746.0,20.0,218...|
|       0.0|    0|[-988.0,15.0,83.0...|
|       0.0|    0|[-849.0,4.0,204.0...|
+----------+-----+--------------------+
only showing top 5 rows
```

for the step we show the result with obtain the accuracy

```
val evaluator = new MulticlassClassificationEvaluator().setLabelCol("indexedLabel").setPredictionCol("prediction").setMetricName("accuracy")

val accuracy = evaluator.evaluate(prediction)
```



```
scala> val accuracy = evaluator.evaluate(prediction)
accuracy: Double = 0.8853454821564161
```

Multilayer Perceptron

Iter	MultiPerc
1	0.8853
2	0.8853
3	0.8853
4	0.8853
5	0.8853
6	0.8853
7	0.8853
8	0.8853
9	0.8853
10	0.8853
11	0.8853
12	0.8853
13	0.8853
14	0.8853
15	0.8853
16	0.8853
17	0.8853
18	0.8853
19	0.8853
20	0.8853
21	0.8853
22	0.8853
23	0.8853
24	0.8853
25	0.8853
26	0.8853
27	0.8853
28	0.8853
29	0.8853

Iter	MultiPerc
30	0.8853

AVERAGE: 0.8853

Comparative table

Iter	SVM	DescTre	LogiReg	MultiPerc
1	0.8833	0.8907	0.8959	0.8853
2	0.8835	0.8951	0.8959	0.8853
3	0.8877	0.8940	0.8959	0.8853
4	0.8820	0.8901	0.8959	0.8853
5	0.8836	0.8867	0.8959	0.8853
6	0.8865	0.8809	0.8959	0.8853
7	0.8846	0.8887	0.8959	0.8853
8	0.8797	0.8903	0.8959	0.8853
9	0.8837	0.8899	0.8959	0.8853
10	0.8838	0.8804	0.8959	0.8853
11	0.8799	0.8874	0.8959	0.8853
12	0.8839	0.8856	0.8959	0.8853
13	0.8805	0.8912	0.8959	0.8853
14	0.8830	0.8903	0.8959	0.8853
15	0.8818	0.8878	0.8959	0.8853
16	0.8805	0.8908	0.8959	0.8853
17	0.8852	0.8856	0.8959	0.8853
18	0.8811	0.8889	0.8959	0.8853
19	0.8836	0.8875	0.8959	0.8853
20	0.8796	0.8806	0.8959	0.8853
21	0.8874	0.8874	0.8959	0.8853
22	0.8865	0.8803	0.8959	0.8853
23	0.8819	0.8907	0.8959	0.8853
24	0.8823	0.8845	0.8959	0.8853
25	0.8841	0.8874	0.8959	0.8853

Iter	SVM	DescTre	LogiReg	MultiPerc
26	0.8878	0.8899	0.8959	0.8853
27	0.8793	0.8867	0.8959	0.8853
28	0.8874	0.8907	0.8959	0.8853
29	0.8856	0.8887	0.8959	0.8853
30	0.8842	0.8840	0.8959	0.8853
AVG	0.883466667	0.88776	0.8959	0.8853

Explian about results

The results that we obtained were very varied as far as the models are concerned, some will not change their precision results and others their changes were small, giving 0.01 or 0.02, sometimes they were numbers further away than in decimal places. But thanks to the results, the different models are long or short in the execution process, having as the fastest model the logistic regression and the slowest the multilayer percetron, as the best in terms of precision, there is not one as such, since All had a similar precision in terms of the process of the 30 executions of each of the models, in any case it would be logistic regression in which it has better precision only by a small fraction of a decimal of 0.01 in other words 1%, all the model had a fairly high precision almost reached 0.9 which translates as 90%, the 4 models have a similar precision since none had a different precision I can say that the 4 precision models are quite good, maybe it is because of my computer that look like this.

Conclusion

Los modelos son diferentes en cuanto a la realizacion de procesas ya que cada modelo esta implementado o centrado para ciertos trabajos como el modelo de regresion logistica que hace comparaciones de 1 a 1, algunos de estos modelos como ya mencione estan dedicados para ciertas tareas que pueden realizar, al igual que otros modelos que no se vieron pero realizan tarea similiras en este caso sacar estadisticas, probabilidades y calculos que se requieran, estos modelos son algunos de los que utilizamos para nuestro proyecto final el cual nos deja en claro que si puede variar los resultados por muy pequeños que sean, algunos nos demostraran que su tiempo de ejecucion es el mas rapido o el mas lento, indenpendientemente del codigo ya que es el mismo repositorio de datos realizando funciones diferente. En conclusion podemos decir que los modelos tienes sus diferentes caracteristicas que los hace diferentes de los otros modelos y que nos permiten poder experimentarlos y comprobar por nuestros propias manos que son modelos que funcionan, que se utilizan y que pueden tener resultados para un repositorio de datos asi el cambio que pueden tener en su rendimiento estos nos ayuda a comprender un poco mas lo modelos que estamos utilizando, para que sirven y como debemos utilizarlos para adaptarnos a lo que nos pide un problema.

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