

Big data: architectures and data analytics

Spark MLlib

Classification: Parameter Tuning

Classification: Parameter Tuning

- The setting of the parameters of an algorithm is always a difficult task
- A “brute force” approach can be used to find the setting optimizing a quality index
 - The training data is split in two subsets
 - The first set is used to build a model
 - The second one is used to evaluate the quality of the model
 - The setting that maximizes a quality index (e.g., the prediction accuracy) is used to build the final model on the whole training dataset

Classification: Parameter Tuning

- One single split of the training set usually is biased
- Hence, the cross-validation approach is usually used
 - It creates **k splits** and **k models**
 - The **parameter setting** that achieves, on the average, the **best result on the k models** is selected as **final setting** of the algorithm's parameters

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Classification: Parameter Tuning

- Spark supports a **brute-force grid-based approach** to evaluate a set of possible parameter settings on a pipeline
- Input:
 - An MLlib pipeline
 - A set of values to be evaluated for each input parameter of the pipeline
 - All the possible combinations of the specified parameter values are considered and the related models are automatically generated and evaluated by Spark
 - A quality evaluation metric to evaluate the result of the input pipeline
- Output
 - The model associated with the best parameter setting, in term of quality evaluation metric

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Classification: Parameter Tuning - Example

- The following example shows how a grid-based approach can be used to tune a logistic regression classifier on a structured dataset
 - The pipeline that is repeated multiple times is based on the cross validation component
- The following parameters of the logistic regression algorithm are considered
 - Maximum iteration
 - 10, 100, 1000
 - Regulation parameter
 - 0.1, 0.01
 - 6 parameter configurations are evaluated (3 x 2)

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Classification: Parameter Tuning - Example

```
package it.polito.bigdata.spark.sparkmllib;

import org.apache.spark.api.java.*;
import org.apache.spark.sql.Dataset;
import org.apache.spark.sql.Row;
import org.apache.spark.sql.SparkSession;
import org.apache.spark.ml.Pipeline;
import org.apache.spark.ml.PipelineStage;
import org.apache.spark.ml.classification.LogisticRegression;
import org.apache.spark.ml.evaluation.BinaryClassificationEvaluator;
import org.apache.spark.ml.linalg.Vector;
import org.apache.spark.ml.linalg.Vectors;
import org.apache.spark.ml.feature.LabeledPoint;
import org.apache.spark.ml.param.ParamMap;
import org.apache.spark.ml.tuning.CrossValidator;
import org.apache.spark.ml.tuning.CrossValidatorModel;
import org.apache.spark.ml.tuning.ParamGridBuilder;
```

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Classification: Parameter Tuning - Example

```
public class SparkDriver {
    public static void main(String[] args) {
        String inputFileTraining;    String inputFileTest;  String outputPath;
        inputFileTraining=args[0];
        inputFileTest=args[1];
        outputPath=args[2];

        //Create a Spark Session object and set the name of the application
        //We use some Spark SQL transformation in this program
        SparkSession ss = SparkSession.builder()
            .appName("MLlib - logistic regression - Cross Validation")
            .getOrCreate();

        //Create a Java Spark Context from the Spark Session
        //When a Spark Session has already been defined this method
        //is used to create the Java Spark Context
        JavaSparkContext sc = new JavaSparkContext(ss.sparkContext());
    }
}
```

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Classification: Parameter Tuning - Example

```
// *****
//Training step
// *****

// Read training data from a text file
// Each line has the format: class-label, list of three numerical
// attribute values.
// E.g.,          1.0,5.8,0.5,1.7
JavaRDD<String> trainingData=sc.textFile(inputFileTraining);
```

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Classification: Parameter Tuning - Example

```
// Map each input record/data point of the input file to a LabeledPoint
JavaRDD<LabeledPoint> trainingRDD=trainingData.map(record ->
    {
        String[] fields = record.split(",");
        // Fields of 0 contains the id of the class
        double classLabel = Double.parseDouble(fields[0]);

        //The other three cells of fields contain the (numerical)
        // values of the three predictive attributes
        // Create an array of doubles containing those values
        double[] attributesValues = new double[3];

        attributesValues[0] = Double.parseDouble(fields[1]);
        attributesValues[1] = Double.parseDouble(fields[2]);
        attributesValues[2] = Double.parseDouble(fields[3]);
```

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Classification: Parameter Tuning - Example

```
        // Create a dense vector based on the content of
        // attributesValues
        Vector attrValues= Vectors.dense(attributesValues);

        // Return a LabeledPoint based on the content of
        // the current line
        return new LabeledPoint(classLabel, attrValues);
    });
```

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Classification: Parameter Tuning - Example

```
//Prepare training data.  
//We use LabeledPoint, which is a JavaBean.  
//We use Spark SQL to convert RDDs of JavaBeans  
//into Dataset<Row>. The columns of the Dataset are label  
//and features  
Dataset<Row> training =  
    ss.createDataFrame(trainingRDD, LabeledPoint.class).cache();
```

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Classification: Parameter Tuning - Example

```
//Create a LogisticRegression object.  
//LogisticRegression is an Estimator that is used to  
//create a classification model based on logistic regression.  
LogisticRegression lr = new LogisticRegression();  
  
//Define the pipeline that is used to create the logistic regression  
//model on the training data.  
//In this case the pipeline contains one single stage/step (the model  
//generation step).  
Pipeline pipeline = new Pipeline()  
    .setStages(new PipelineStage[] {lr});
```

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Classification: Parameter Tuning - Example

```
//We use a ParamGridBuilder to construct a grid of parameter values to
//search over.
//We set 3 values for lr.setMaxIter and 2 values for lr.regParam.
//This grid will evaluate 3 x 2 = 6 parameter settings for
//the input pipeline.
ParamMap[] paramGrid = new ParamGridBuilder()
    .addGrid(lr.setMaxIter(), new int[]{10, 100, 1000})
    .addGrid(lr.regParam(), new double[]{0.1, 0.01})
    .build();
```

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Classification: Parameter Tuning - Example

```
//We use a ParamGridBuilder to construct a grid of parameter values to
//search over.
//We set 3 values for lr.setMaxIter and 2 values for lr.regParam.
//This grid will evaluate 3 x 2 = 6 parameter settings for
//the input pipeline.
```

```
ParamMap[] paramGrid = new ParamGridBuilder()
    .addGrid(lr.setMaxIter(), new int[]{10, 100, 1000})
    .addGrid(lr.regParam(), new double[]{0.1, 0.01})
    .build();
```

There is one call to the addGrid method for each parameter that we want to set. Each call to the addGrid method is characterized by

- The parameter we want to consider
- The list of values to test/to consider

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Classification: Parameter Tuning - Example

```
//We now treat the Pipeline as an Estimator, wrapping it in a
//CrossValidator instance. This allows us to jointly choose parameters
//for all Pipeline stages.
//CrossValidator requires
// - an Estimator
// - a set of Estimator ParamMaps
// - an Evaluator.
CrossValidator cv = new CrossValidator()
    .setEstimator(pipeline)
    .setEstimatorParamMaps(paramGrid)
    .setEvaluator(new BinaryClassificationEvaluator())
    .setNumFolds(3);
```

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Classification: Parameter Tuning - Example

Here, we set

- The pipeline to be evaluated
- The set of parameter values to be considered
- The evaluator (i.e., the object that is used to compute the quality measure that is used to evaluate the quality of the model)
- The number of folds to consider (i.e., the number or repetitions)

```
// - an Evaluator.
CrossValidator cv = new CrossValidator()
    .setEstimator(pipeline)
    .setEstimatorParamMaps(paramGrid)
    .setEvaluator(new BinaryClassificationEvaluator())
    .setNumFolds(3);
```

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Classification: Parameter Tuning - Example

```
// Run cross-validation. The result is the logistic regression model
// based on the best set of parameters (based on the results of the
// cross-validation operation).
CrossValidatorModel model = cv.fit(training);

// Now, the classification model can be used to predict the class label
// of new unlabeled data
```

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Classification: Parameter Tuning - Example

```
// Run cross-validation. The result is the logistic regression model
// based on the best set of parameters (based on the results of the
// cross-validation operation).
CrossValidatorModel model = cv.fit(training);

// Now, the classification model can be used to predict the class label
// of new unlabeled data
```

The returned model is the one associated with the best parameter setting, based on the result of the cross-validation test

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Classification: Parameter Tuning - Example

```
// *****
// Prediction step
// *****

// Read unlabeled data
// For the unlabeled data only the predictive attributes are available
// The class label is not available and must be predicted by applying
// the classification model inferred during the previous phase
JavaRDD<String> unlabeledData=sc.textFile(inputFileTest);
```

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Classification: Parameter Tuning - Example

```
// Map each unlabeled input record/data point of the input file to
// a LabeledPoint
JavaRDD<LabeledPoint> unlabeledRDD=unlabeledData.map(record ->
{
    String[] fields = record.split(",");

    //The last three cells of fields contain the (numerical) values of the
    //three predictive attributes
    //Create an array of doubles containing those three values
    double[] attributesValues = new double[3];

    attributesValues[0] = Double.parseDouble(fields[1]);
    attributesValues[1] = Double.parseDouble(fields[2]);
    attributesValues[2] = Double.parseDouble(fields[3]);
```

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Classification: Parameter Tuning - Example

```

//Create a dense vector based in the content of attributesValues
Vector attrValues= Vectors.dense(attributesValues);

//The class label is unknown.
//To create a LabeledPoint a class label value must be specified
//also for the unlabeled data. I set it to -1 (an invalid value).
//The specified value does not impact on the prediction because
//the label column is not used to perform the prediction
double classLabel = -1;

//Return a new LabeledPoint
return new LabeledPoint(classLabel, attrValues);
});

//Create the DataFrame based on the new test data
Dataset<Row> test =
    ss.createDataFrame(unlabeledRDD, LabeledPoint.class);

```

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Classification: Parameter Tuning - Example

```

//Make predictions on test documents using the transform()
//method.
//The transform will only use the 'features' columns
Dataset<Row> predictions = model.transform(test);

//The returned Dataset<Row> has the following schema (attributes)
// - features: vector (values of the attributes)
// - label: double (value of the class label)
// - rawPrediction: vector (nullable = true)
// - probability: vector (The i-th cell contains the probability that the
//                       current record belongs to the i-th class)
// - prediction: double (the predicted class label)

//Select only the features (i.e., the value of the attributes) and
//the predicted class for each record
Dataset<Row> predictionsDF=predictions.select("features", "prediction");

```

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Classification: Parameter Tuning - Example

```
// Save the result in an HDFS file
JavaRDD<Row> predictionsRDD = predictionsDF.javaRDD();
predictionsRDD.saveAsTextFile(outputPath);

// Close the Spark Context object
sc.close();
}
}
```

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