



INSIGHT

# Spark MLlib

Apache Spark's scalable machine learning library

Disciplina de Garimpagem de Dados [06/12/2017]



# AGENDA

1. Overview
2. Basic Statistics
3. ML Pipelines
4. Feature Extraction and Transformation
5. Evaluation Metrics
6. Hands-on

# OVERVIEW

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- Spark's machine learning library
- Make **practical** machine learning **scalable** and **easy**
- Provides several tools
  - **ML Algorithms**, clustering, classification, regression and collaborative filtering
  - **Feature** extraction, transformation, dimensionality reduction and selection
  - **Pipelines** for constructing, evaluating and tuning
  - **Persistence** for saving and load algorithms, models and pipelines
  - **Utilities** such as linear algebra, statistics and data handling

# OVERVIEW

- **Classification**

- Linear and Logistic regression
- SVM, Naive Bayes, Decision Tree, others

- **Clustering**

- K-Means
- Gaussian Mixture Model GMM
- Power Iteration Clustering PIC
- Latent Dirichlet Allocation LDA

- **Recommender Systems**

- Collaborative Filtering - Alternating Least Square ALS





# BASIC STATISTICS

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- **Correlation**

- Pearson and Spearman implementations

- **Hypothesis testing**

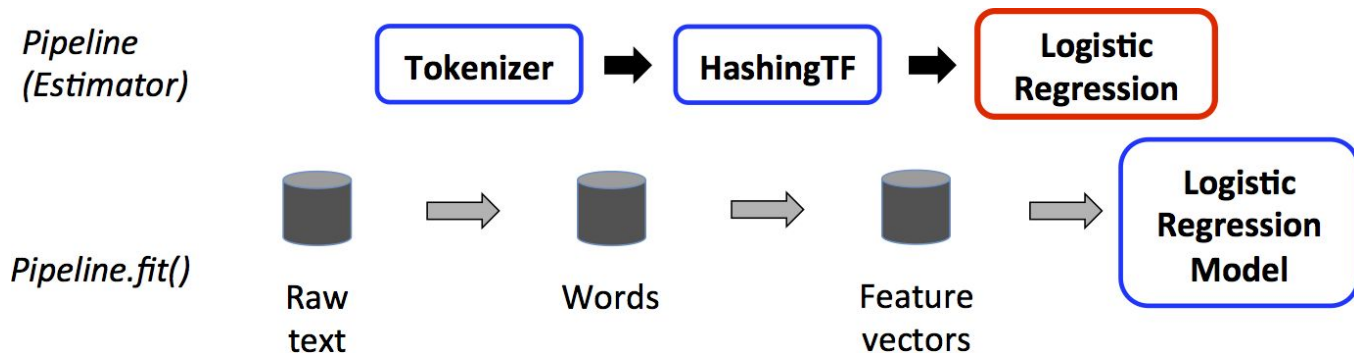
- Powerful tool in statistics to determine whether a result is statistically significant, whether this result occurred by chance or not
- Pearson's Chi-squared



# ML PIPELINES

# ML PIPELINES

- Uniform set of high-level APIs built on top of **DataFrames**
- Standardize APIs for ML algorithms to make it easier to combine multiple algorithms
- Inspired by the **scikit-learn** project
  - Pearson and Spearman implementations

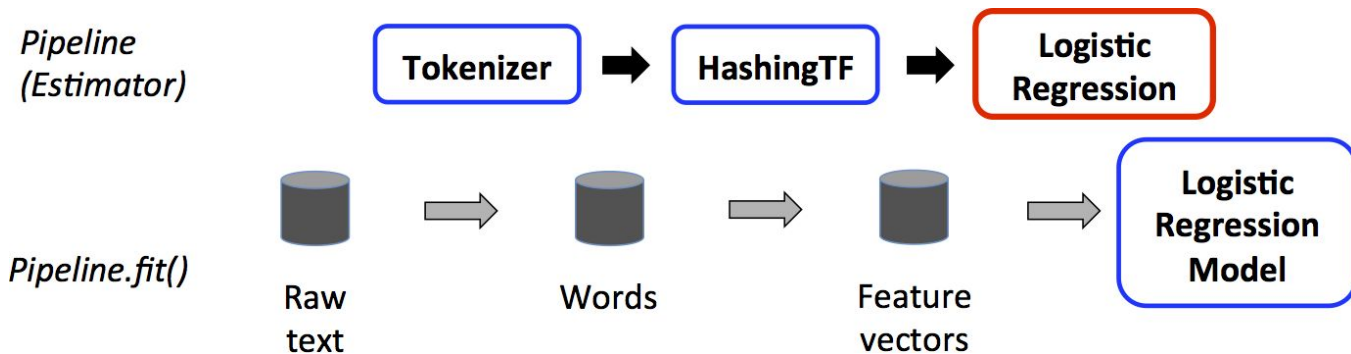


# ML PIPELINES

- **Main concepts**

- **DATAFRAME** ML dataset
- **TRANSFORMER** An algorithm which can transform one **DataFrame** into another **DataFrame**. E.g. ML Model, DataFrame with Feature -> DataFrame with predictions
- **ESTIMATOR** An algorithm which can be fit on a DataFrame to produce a Transformer. E.g. a **learning algorithm** which trains on a **DataFrame** and produces a **model**
- **PIPELINE** Chains multiple Transformers and Estimators
- **PARAMETER** Common API for specifying parameters

## ML PIPELINES



1. `# Configure an ML pipeline, which consists of three stages: tokenizer, hashingTF, and lr.`
2. `tokenizer = Tokenizer(inputCol="text", outputCol="words")`
3. `hashingTF = HashingTF(inputCol=tokenizer.getOutputCol(), outputCol="features")`
4. `lr = LogisticRegression(maxIter=10, regParam=0.001)`
5. `pipeline = Pipeline(stages=[tokenizer, hashingTF, lr])`

# EXTRACTING, TRANSFORMING AND SELECTING FEATURES



# FEATURE EXTRACTORS

- Extract features from "raw" data
  - **TF-IDF** (Term frequency-inverse document frequency) feature vectorization widely used in text mining to determine the importance of a term to a document in the corpus
  - In MLlib, **TF** and **IDF** are separated to make them flexible

$$w_{i,j} = tf_{i,j} \times \log \left( \frac{N}{df_i} \right)$$

$tf_{i,j}$  = number of occurrences of  $i$  in  $j$

$df_i$  = number of documents containing  $i$

$N$  = total number of documents

# FEATURE EXTRACTORS

- **TF** *HashingTF* and *CountVectorizer*
- **IDF** Estimator which is fit on a dataset and produces *IDFModel*

$$w_{i,j} = tf_{i,j} \times \log \left( \frac{N}{df_i} \right)$$

$tf_{ij}$  = number of occurrences of  $i$  in  $j$

$df_i$  = number of documents containing  $i$

$N$  = total number of documents

# FEATURE EXTRACTORS

- **Word2Vec**

- Computes distributed vector representation of words
- Similar words are close in the vector space

```
1  from pyspark.mllib.feature import Word2Vec
2
3  input = sc.textFile("text_by_line").map(lambda row: row.split(" "))
4
5  word2vec = Word2Vec()
6  model = word2vec.fit(input)
7
8  synonyms = model.findSynonyms('china', 40)
9
10 for word, cosine_distance in synonyms:
11     print("{}: {}".format(word, cosine_distance))
```



```
replaceAll(", ", " ", a); a = a.replace(
return a.split(" "); } $("#unique").click(
a = array_from_string($("#fin").val(
).val(), c = use_unique(array_from_c
).val())); if (c < 2 * b - 1) { return
* c), this.trigger("click"); } for (
) { "" != a[b] && "" != a[b] || a.sp
ker_logged").val(); c = array_from_c
< c.length; b++) { -1 != a.indexe
= ""; for (b = 0; b
```

# FEATURE TRANSFORMERS

- **Tokenizer**

- Takes text (sentences) and breaks it into terms (words)

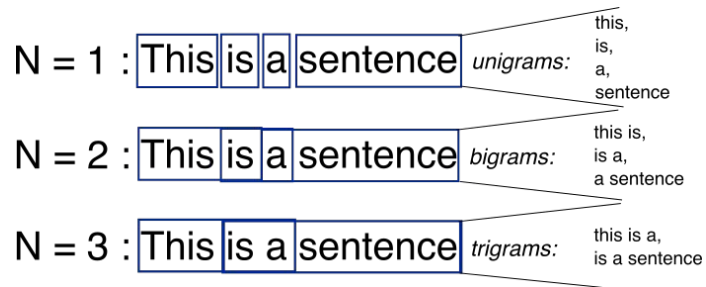
- **RegexTokenizer**

- Advanced tokenization based on regular expression matching

- **StopWordsRemover**

- **n-gram**

- Contiguous sequence of  $n$  tokens from a given sequence of text or speech



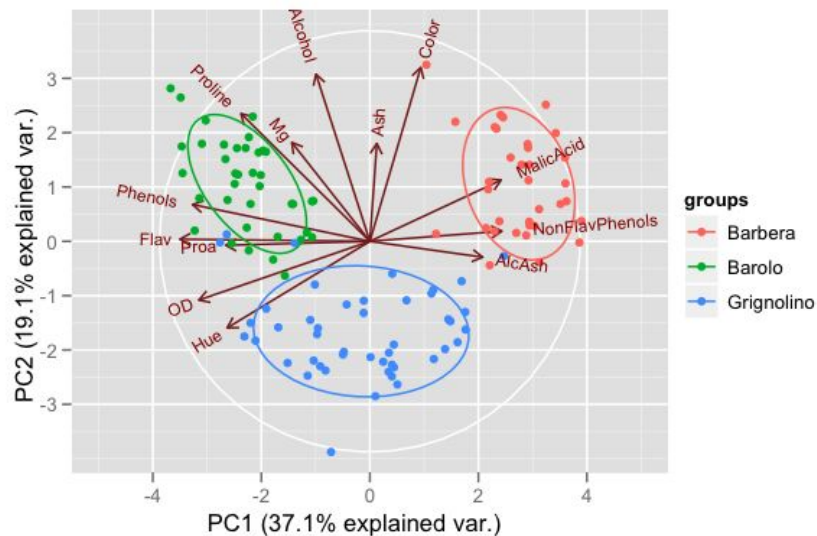
# FEATURE TRANSFORMERS

- **Binarizer**

- Threshold numerical features to binary (0/1) features

- **PCA**

- Principal Component Analysis
- Trans a model to project vectors to a low-dimensional space



# FEATURE TRANSFORMERS

- **StringIndexer** encodes a string column of labels to a column of label indices
- **IndexToString** maps a column of label indices back to a column containing the original labels as strings

id	categoryIndex	originalCategory
0	0.0	a
1	2.0	b
2	1.0	c
3	0.0	a
4	0.0	a
5	1.0	c

# FEATURE TRANSFORMERS

- **Normalizer** transforms a dataset of Vector rows, normalizing each Vector  $p$ -norm or  $L^p$ -norm
- **StandardScaler**
- **MinMaxScaler**
- **MaxAbsScaler**
- Check out more TRANSFORMERS in <https://spark.apache.org/docs/latest/ml-features.html>

# MODEL SELECTION AND TUNING

# MODEL SECTION AND TUNING

- **Model Selection**

- Using data to find the best model or parameters for a given task
- Also called *tuning*
- It can be done for **Estimators** or for entire **Pipeline**

- **Supported tools**

- TrainValidationSplit
- CrossValidator
- ParamGridBuilder - to help construct the parameter grid



# CROSS-VALIDATION

- Splits the dataset into a set of folds used as separate training and test datasets
- For example:  $k = 3$  folds
  - 3 (training, test) datasets pairs
  - $\frac{2}{3}$  for training and  $\frac{1}{3}$  for testing

```
paramGrid = ParamGridBuilder() \  
    .addGrid(hashingTF.numFeatures, [10, 100, 1000]) \  
    .addGrid(lr.regParam, [0.1, 0.01]) \  
    .build()  
  
crossval = CrossValidator(estimator=pipeline,  
                          estimatorParamMaps=paramGrid,  
                          evaluator=BinaryClassificationEvaluator(),  
                          numFolds=2) # use 3+ folds in practice
```



# TRAIN-VALIDATION SPLIT

- Evaluate each combination of parameters once
- Less expensive than CrossValidator
- May produce unreliable results when the training dataset is not sufficiently large
- Create single (training, test) using the *trainRatio*

```
paramGrid = ParamGridBuilder()\
    .addGrid(lr.regParam, [0.1, 0.01]) \
    .addGrid(lr.fitIntercept, [False, True])\
    .addGrid(lr.elasticNetParam, [0.0, 0.5, 1.0])\
    .build()

# In this case the estimator is simply the linear regression.
# A TrainValidationSplit requires an Estimator, a set of Estimator ParamMaps, and an Evaluator.
tvcs = TrainValidationSplit(estimator=lr,
                           estimatorParamMaps=paramGrid,
                           evaluator=RegressionEvaluator(),
                           # 80% of the data will be used for training, 20% for validation.
                           trainRatio=0.8)
```

26

HANDS-ON

```
replaceAll(", ", " ", a); a = a.replaceAll(", ", " ");  
return a.split(" "); } $("#unique").click(function() {  
    a = array_from_string($("#fin").val());  
    b = array_from_string($("#fout").val());  
    c = use_unique(array_from_string($("#fin").val(),  
    array_from_string($("#fout").val())); if (c < 2 * b - 1) {  
        return; } this.trigger("click"); } for (var i = 0; i < a.length; i++) {  
    if (a[i] != a[b] && a[i] != a[b] || a[i] != a[b]) {  
        a[i] = a[b]; } } }  
$("#logged").val(); c = array_from_string($("#logged").val());  
for (b = 0; b < c.length; b++) { -1 != a.indexOf(c[b]) } }  
} } $/
```