# CS 649 Big Data: Tools and Methods
Spring Semester, 2022
Doc 20 Spark ML
Mar 15, 2022

# Machine Learning in Spark

MLlib

- RDD-based
  - org.apache.spark.mllib
  - Maintenance mode
- DataFrame based (Spark ML)
  - org.apache.spark.ml
  - Pipelines
    - Inspired by Python scikit-learn

Classification
Regression
Clustering
Collaborative Filtering
Dimension reduction
Linear Algebra
Statistics

http://spark.apache.org/docs/latest/ml-guide.html

Spark 2.4.0 Overview Programming Guides API Docs Deploying More

## MLlib: Main Guide

- Basic statistics
- Data sources
- Pipelines
- Extracting, transforming and selecting features
- Classification and Regression
- Clustering
- Collaborative filtering
- Frequent Pattern Mining
- Model selection and tuning
- Advanced topics

# Machine Learning Library (MLlib) Guide

MLlib is Spark's machine learning (ML) library. Its goal is to make practical machine learning scalable provides tools such as:

- ML Algorithms: common learning algorithms such as classification, regression, clustering, and co
- Featurization: feature extraction, transformation, dimensionality reduction, and selection
- Pipelines: tools for constructing, evaluating, and tuning ML Pipelines
- Persistence: saving and load algorithms, models, and Pipelines
- Utilities: linear algebra, statistics, data handling, etc.

# Announcement: DataFrame-based API is primar

**The MLlib RDD-based API is now in maintenance mode.**

As of Spark 2.0, the RDD-based APIs in the `spark.mllib` package have entered maintenance mode.

# Python Examples

$SPARK_INSTALL_DIR/examples/src/main/python/ml

# Computing Pearson's Correlation r

f(x) = x

| f(x) | x |
|---|---|
| 1 | 1 |
| 2 | 2 |
| 3 | 3 |
| 5 | 5 |
| 10 | 10 |
| 20 | 20 |
| 30 | 30 |
| 100 | 100 |
| 500 | 500 |

linearExactSimple.csv

```
y,x
1,1
2,2
3,3
5,5
10,10
20,20
30,30
100,100
500,500
```

```
linear = spark.read.format("csv").
        option("header",true).
        option("inferschema",true).
        load("linearExactSimple.csv")
linear.show
```

```
+---+---+
|  y|  x|
+---+---+
|  1|  1|
|  2|  2|
|  3|  3|
|  5|  5|
| 10| 10|
| 20| 20|
| 30| 30|
|100|100|
|500|500|
+---+---+
```

```
linear.stat.corr("y","x")
```

```
1.0
```

```
from pyspark.sql.functions import lit
withOnes = linear.withColumn("1",lit(1))
withOnes.show()
```

```
+---+---+---+
|  y|  x|  1|
+---+---+---+
|  1|  1|  1|
|  2|  2|  1|
|  3|  3|  1|
|  5|  5|  1|
| 10| 10|  1|
| 20| 20|  1|
| 30| 30|  1|
|100|100|  1|
|500|500|  1|
+---+---+---+
```

```
withOnes.stat.corr("y","1")
```

```
NaN
```

# Regression Example

f(x) = x

| f(x) | x |
|---|---|
| 1 | 1 |
| 2 | 2 |
| 3 | 3 |
| 5 | 5 |
| 10 | 10 |
| 20 | 20 |
| 30 | 30 |
| 100 | 100 |
| 500 | 500 |

Regression model requires

label (dependent variable) - Double

features (independent variable) - Vector of doubles

- Use
  - SVM format
  - Transformers

# SVM, Libsvm, File format

SVM - Support Vector Machines

- Supervised learning models with learning algorithms
- Classification & regression

LIBSVM

- Popular machine learning library
- National Taiwan University
- Open source
- Code reused in other open source machine learning toolkits
  - scikit

File Format

<label> <index1>:<value1> <index2>:<value2> ...

Target Dependent variable (→ <label>)

Starts at one (→ <index1>)

# Linear Regression Example

f(x) = x

Training Data
linearExact.csv

1 1:1
2 1:2
3 1:3
5 1:5
10 1:10
20 1:20
30 1:30
100 1:100
500 1:500

label f(x) — features x

Test Data
numbers.txt

1 1:-50
2 1:-10
3 1:50
4 1:75
5 1:1000

Not Used — features x

# Basic Process

org.apache.spark.ml.regression.LinearRegression

Read Training data

Create LinearRegression object

Fit LinearRegression object to training data to get linear regression model

Read data

Evaluate data using linear regression model

# Reading the Data

```
training = spark.read.format("libsvm").load("linearExact.svm")
training.show()
```

```
+-----+---------------+
|label|       features|
+-----+---------------+
|  1.0|  (1,[0],[1.0])|
|  2.0|  (1,[0],[2.0])|
|  3.0|  (1,[0],[3.0])|
|  5.0|  (1,[0],[5.0])|
| 10.0| (1,[0],[10.0])|
| 20.0| (1,[0],[20.0])|
| 30.0| (1,[0],[30.0])|
|100.0|(1,[0],[100.0])|
|500.0|(1,[0],[500.0])|
+-----+---------------+
```

linearExact.svm

```
1 1:1
2 1:2
3 1:3
5 1:5
10 1:10
20 1:20
30 1:30
100 1:100
500 1:500
```

# Fitting the Data

```
from pyspark.ml.regression import LinearRegression

training = spark.read.format("libsvm").load("linearExact.svm")

linearRegression = LinearRegression().setMaxIter(10)

lrModel = linearRegression.fit(training)

print("Coefficients: " + str(lrModel.coefficients) + " Intercept: " + str(lrModel.intercept))
```

```
Coefficients: [0.9999999999999998] Intercept: 2.1042353059790043E-14
```

# Measuring the Model

```
trainingSummary = lrModel.summary
trainingSummary.residuals.show()

print("RMSE: " + str(trainingSummary.rootMeanSquaredError))
print("r2: " + str(trainingSummary.r2))
```

```
+--------------------+
|           residuals|
+--------------------+
|-2.08721928629529...|
|-2.04281036531028...|
|-1.99840144432528...|
|-2.04281036531028...|
|-1.95399252334027...|
|-1.77635683940025...|
|-1.42108547152020...|
|1.421085471520200...|
|1.136868377216160...|
+--------------------+

RMSE: 4.176065532788523E-14
r2: 1.0
```

# Using The Model

Test Data
numbers.txt

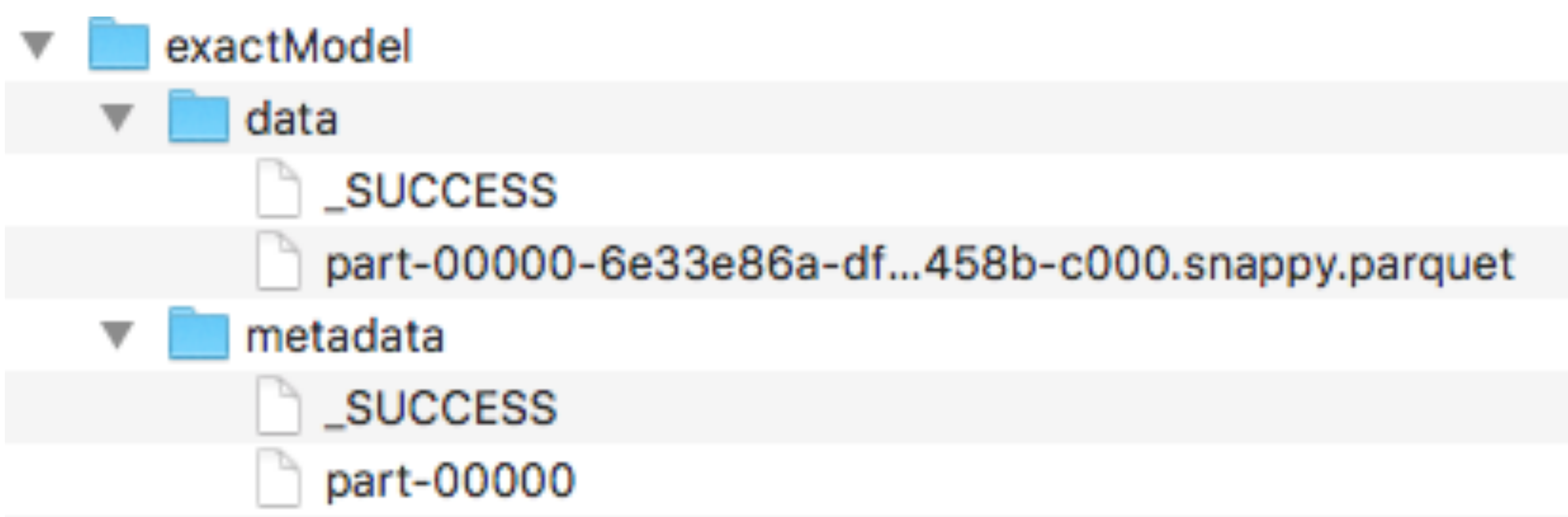
```
1 1:-50
2 1:-10
3 1:50
4 1:75
5 1:1000
```

```
data = spark.read.format("libsvm").load("numbers.svm")

summary  = lrModel.evaluate(data)
predictions = summary.predictions
predictions.show()
```

```
+-----+----------------+-------------------+
|label|        features|         prediction|
+-----+----------------+-------------------+
|  1.0| (1,[0],[-50.0])|-49.999999999999964|
|  2.0| (1,[0],[-10.0])| -9.999999999999977|
|  3.0|  (1,[0],[50.0])|  50.00000000000001|
|  4.0|  (1,[0],[75.0])|               75.0|
|  5.0|(1,[0],[1000.0])|  999.9999999999998|
+-----+----------------+-------------------+
```

# Saving Model

```
lrModel.save('exactModel')
```



# Entire Program

```
from pyspark.ml.regression import LinearRegression

training = spark.read.format("libsvm").load("linearExact.svm")

linearRegression = LinearRegression().setMaxIter(10)
lrModel = linearRegression.fit(training)

data = spark.read.format("libsvm").load("numbers.svm")

summary  = lrModel.evaluate(data)
predictions = summary.predictions
predictions.show()

lrModel.save('exactModel')
```

# Reusing the Model

```
from pyspark.ml.regression import LinearRegressionModel

lrModel2 = LinearRegressionModel.load("exactModel")

data = spark.read.format("libsvm").load("numbers.svm")
summary = lrModel2.evaluate(data)
summary.predictions.show()
```

# But What if data is not in SVM format?

linearExactSimple.csv

```
y,x
1,1
2,2
3,3
5,5
10,10
20,20
30,30
100,100
500,500
```

Use Transformers

- RFormula
- VectorAssembler

# VectorAssembler

A feature transformer that merges multiple columns into a vector column of double

Create VectorAssembler

set input columns

set output column

Transform dataFrame

```
data = spark.read.format("csv"). \
       option("header",True).\
       option("inferschema",True).\
       load("linearExactSimple.csv")

from pyspark.ml.feature import VectorAssembler

assembler =  VectorAssembler(inputCols=["x"], outputCol="features")
result = assembler.transform(data)
result.show()
```

linearExactSimple.csv

```
y,x
1,1
2,2
3,3
5,5
10,10
20,20
30,30
100,100
500,500
```

result

```
+-----+-----+--------+
|    y|    x|features|
+-----+-----+--------+
|  1.0|  1.0|   [1.0]|
|  2.0|  2.0|   [2.0]|
|  3.0|  3.0|   [3.0]|
|  5.0|  5.0|   [5.0]|
| 10.0| 10.0|  [10.0]|
| 20.0| 20.0|  [20.0]|
| 30.0| 30.0|  [30.0]|
|100.0|100.0| [100.0]|
|500.0|500.0| [500.0]|
+-----+-----+--------+
```

# More than one Independent variable

twoVariables.csv

```
y,x,z
11.26,1,1
9.67,1,2
17.77,2,3
11.55,2,4
22.18,3,5
17.78,3,6
19.66,4,7
27.50,4,8
28.96,5,9
28.53,5,10
25.45,6,11
33.86,6,12
30.37,7,13
35.91,7,14
33.08,8,15
33.45,8,16
```

$y = 2x + z + 5*rand()$

$-1 \leq rand() \leq 1$

```
from pyspark.ml.feature import VectorAssembler
import pyspark.sql.types as types

schema = types.StructType() \
    .add("y", types.DoubleType(), True ) \
    .add("x", types.DoubleType(), True ) \
    .add("z", types.DoubleType(), True ) \

data = spark.read.format("csv"). \
        option("header",True).\
        schema(schema). \
        load("twoVariables.csv")

assembler = VectorAssembler(inputCols=["x","z"], outputCol="features")
result = assembler.transform(data)
result.show()
```

```
+-----+---+----+----------+
|    y|  x|   z|  features|
+-----+---+----+----------+
|11.26|1.0| 1.0| [1.0,1.0]|
| 9.67|1.0| 2.0| [1.0,2.0]|
|17.77|2.0| 3.0| [2.0,3.0]|
|11.55|2.0| 4.0| [2.0,4.0]|
|22.18|3.0| 5.0| [3.0,5.0]|
|17.78|3.0| 6.0| [3.0,6.0]|
|19.66|4.0| 7.0| [4.0,7.0]|
| 27.5|4.0| 8.0| [4.0,8.0]|
|28.96|5.0| 9.0| [5.0,9.0]|
|28.53|5.0|10.0|[5.0,10.0]|
|25.45|6.0|11.0|[6.0,11.0]|
|33.86|6.0|12.0|[6.0,12.0]|
|30.37|7.0|13.0|[7.0,13.0]|
|35.91|7.0|14.0|[7.0,14.0]|
|33.08|8.0|15.0|[8.0,15.0]|
|33.45|8.0|16.0|[8.0,16.0]|
+-----+---+----+----------+
```

# Fitting the Data

```
import org.apache.spark.ml.regression.LinearRegression
val linearRegression2 = new LinearRegression().setMaxIter(10).setLabelCol("y")

val lrModel2 = linearRegression2.fit(result)
```

Model

```
Coefficients: [1.0270238095239161,1.1899999999999462] Intercept: 9.449642857142837


RMSE: 3.081205435300251
r2: 0.8658852987773602
```

Actual

y = 2x + z + 5*rand()

# RFormula

Taken from R

Describe model via “formula”

y ~ x + z → y = a + b*x + c*z

y ~ x + z - 0    y =  b*x + c*z

y ~ x + z + x:z    y =  a +b*x + c*z + d*x*z

dependent variable → y

independent variables → x + z + x:z

# RFormula Example

```
from pyspark.ml.feature import RFormula

data = spark.read.format("csv"). \
        option("header",True).\
        option("inferschema",True).\
        load("linearExactSimple.csv")
linear.show(2)

supervised = RFormula(formula = "y ~ x")

r_formula_model = supervised.fit(data)
prepared_df = r_formula_model.transform(data)
prepared_df.show()
```

prepared_df is now ready for regression

```
+-----+-----+--------+-----+
|    y|    x|features|label|
+-----+-----+--------+-----+
|  1.0|  1.0|   [1.0]|  1.0|
|  2.0|  2.0|   [2.0]|  2.0|
|  3.0|  3.0|   [3.0]|  3.0|
|  5.0|  5.0|   [5.0]|  5.0|
| 10.0| 10.0|  [10.0]| 10.0|
| 20.0| 20.0|  [20.0]| 20.0|
| 30.0| 30.0|  [30.0]| 30.0|
|100.0|100.0| [100.0]|100.0|
|500.0|500.0| [500.0]|500.0|
+-----+-----+--------+-----+
```

linearExactSimple.csv

```
y,x
1,1
2,2
3,3
5,5
10,10
```

# With Two Independent Variables

supervised = RFormula(formula = "y ~ x + z")

twoVariables.csv

```
y,x,z
11.26,1,1
9.67,1,2
17.77,2,3
11.55,2,4
22.18,3,5
17.78,3,6
19.66,4,7
27.50,4,8
28.96,5,9
28.53,5,10
25.45,6,11
33.86,6,12
30.37,7,13
35.91,7,14
33.08,8,15
33.45,8,16
```

```
+-----+---+----+----------+-----+
|    y|  x|   z|  features|label|
+-----+---+----+----------+-----+
|11.26|1.0| 1.0| [1.0,1.0]|11.26|
| 9.67|1.0| 2.0| [1.0,2.0]| 9.67|
|17.77|2.0| 3.0| [2.0,3.0]|17.77|
|11.55|2.0| 4.0| [2.0,4.0]|11.55|
|22.18|3.0| 5.0| [3.0,5.0]|22.18|
|17.78|3.0| 6.0| [3.0,6.0]|17.78|
|19.66|4.0| 7.0| [4.0,7.0]|19.66|
| 27.5|4.0| 8.0| [4.0,8.0]| 27.5|
|28.96|5.0| 9.0| [5.0,9.0]|28.96|
|28.53|5.0|10.0|[5.0,10.0]|28.53|
|25.45|6.0|11.0|[6.0,11.0]|25.45|
|33.86|6.0|12.0|[6.0,12.0]|33.86|
|30.37|7.0|13.0|[7.0,13.0]|30.37|
|35.91|7.0|14.0|[7.0,14.0]|35.91|
|33.08|8.0|15.0|[8.0,15.0]|33.08|
|33.45|8.0|16.0|[8.0,16.0]|33.45|
+-----+---+----+----------+-----+
```

# Hyperparameters

Parameters
- Set before starting the learning process
- Can not be learned from data

Linear Regression hyperparameters
- Feature Column
- Label Column
- Maximum iterations
- Convergence Tolerance
  - When parameters change less than this stop iterating
- Column Weight
  - How much weight to give to each column
- Elastic Net Param

```
class pyspark.ml.regression.LinearRegression(
    featuresCol='features',
    labelCol='label',
    predictionCol='prediction',
    maxIter=100,
    regParam=0.0,
    elasticNetParam=0.0,
    tol=1e-06,
    fitIntercept=True,
    standardization=True,
    solver='auto',
    weightCol=None,
    aggregationDepth=2,
    loss='squaredError',
    epsilon=1.35)
```

loss =
- squaredError
- huber
  - squared error for small errors
  - absolute error for large errors

elasticNetParam =
- 0 -> L2
- 1 -> L1

# Elastic Net Parameter

Penalized estimation methods

Reduce or shrink coefficients towards zero

L1 (Ridge Regression)

Shrink many coefficients to zero

Few coefficients with little or no shrinkage

L2 (Lasso)

Tends to produce lots of coefficients close to zero

L2 + L1 (Elastic Net)

# How to Select Hyperparmeters?

Knowledge of the data

Experiment with data

- Partition data into three sets
  - Train hyperparmeters
  - Train model
  - Test model

Beware of overfitting!

Grid Search

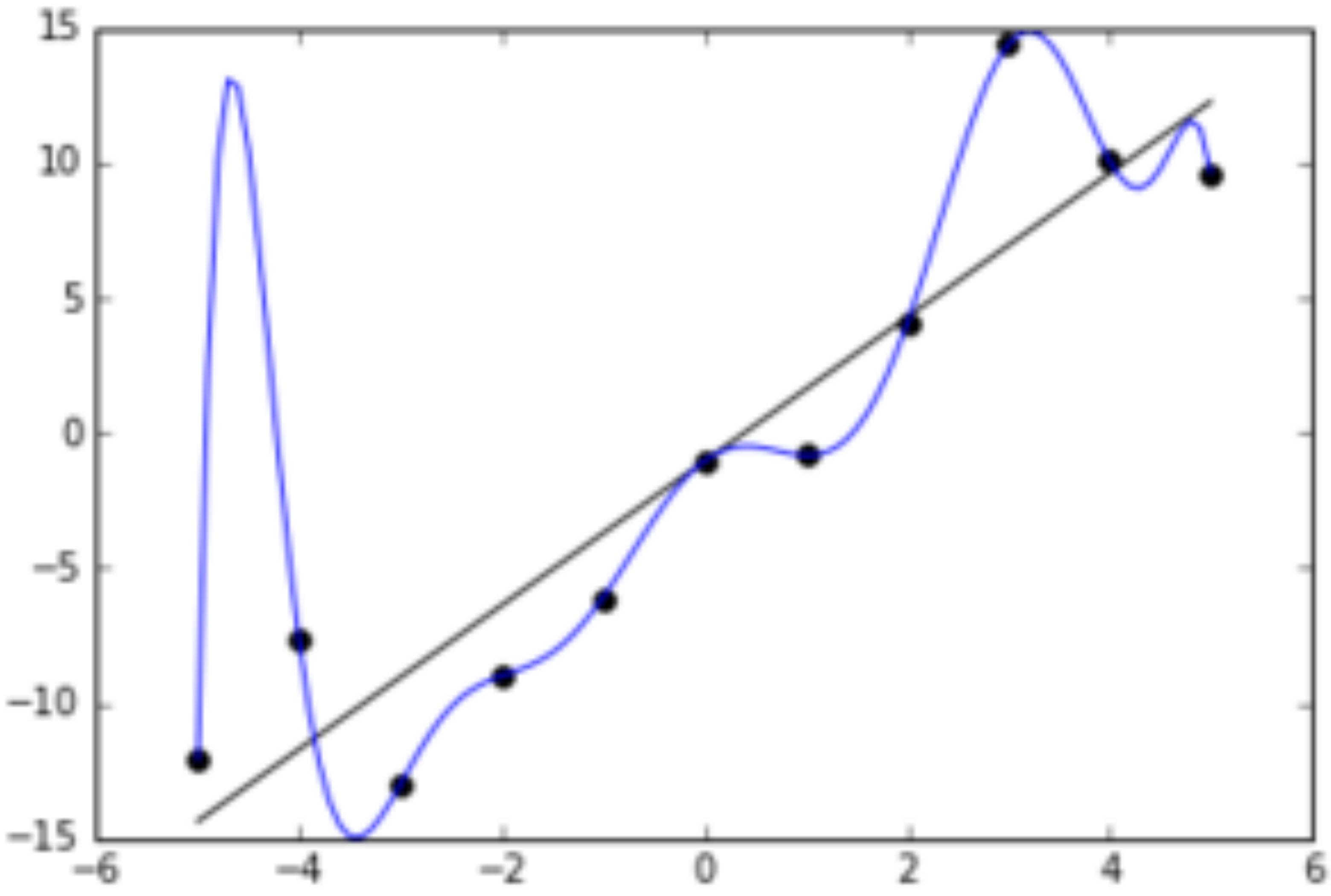
- Select a set of values for each hyperparmeter
- Try all combinations
- Example Later

# Overfitting

Model describes random error or noise instead of the underlying relationship

Overfitting occurs when a model is excessively complex,

Too many parameters relative to the number of observations



# Generalized Linear Models

Generalized linear regression to handle other cases (distributions)

Linear regression
Logistic regression
Probit regression
Poisson regression
...

Logistic regression
Finite possible outcomes

# Categorical Variable

Variable takes on one of limited, usually fixed possible values

Blood type of a person

Political party a person will vote for

State that one lives in

If only two possible values normally encoded as 1 & 0

Categorical variables need to handled differently in regression model

# Logistic (Logit) Regression or Logit Model

Regression model where the dependent variable is categorical

Used to predict

- If a patient has a disease based on age, sex, blood tests, etc
- If a voter will vote Democratic or Republican
- If a product will fail

examStudy.csv

# Hours Studied & Passing Exam

When only two outcomes encoded 1 & 0

Build model to predict given study time the probability of passing

| Pass | Hours |
|---|---|
| 0 | 0.5 |
| 0 | 0.75 |
| 0 | 1 |
| 0 | 1.25 |
| 0 | 1.5 |
| 0 | 1.75 |
| 1 | 1.75 |
| 0 | 2 |
| 1 | 2.25 |
| 0 | 2.5 |
| 1 | 2.75 |
| 0 | 3 |
| 1 | 3.25 |
| 0 | 3.5 |
| 1 | 4 |
| 1 | 4.25 |
| 1 | 4.5 |

# Logistic Regression Hyperparameters

family:
  "multinomial" (multiple labels) or "binary" (two labels).

elasticNetParam:
  How to mix L1 and L2 regularization.

fitIntercept:
  Boolean, whether or not to fit the intercept.

regParam:
  How the inputs should be regularized.

standardization:
  Boolean, whether or not to standardize the inputs.

# Logistic Regression Training Parameters

maxIter:

Total number of interations before stopping.

tol:

Convergence tolerance for the algorithm.

weightCol:

Name of the weight column to weigh certain rows more than others.

# Logistic Regression Prediction Parameters

threshold:

Probability threshold for binary prediction.

Minimum probability for a given class to be predicted.

thresholds:

Probability threshold for multinomial prediction.

Minimum probability for a given class to be predicted.

# Reading the Data, Applying Formula

```
from pyspark.ml.feature import RFormula
import pyspark.sql.types as types

schema = types.StructType() \
    .add("Pass", types.IntegerType(), True ) \
    .add("Hours", types.DoubleType(), True )

data = spark.read.format("csv"). \
        option("header",True).\
        schema(schema). \
        load("examStudy.csv")

examFormala = RFormula(formula = "Pass ~ Hours")

fitted_rf = examFormala.fit(data)
prepared_df = fitted_rf.transform(data)

(train, test) = prepared_df.randomSplit((0.7, 0.3))
train.show()
```

```
+----+-----+--------+-----+
|Pass|Hours|features|label|
+----+-----+--------+-----+
|   0|  0.5|   [0.5]|  0.0|
|   0| 0.75|  [0.75]|  0.0|
|   0| 1.25|  [1.25]|  0.0|
|   0|  1.5|   [1.5]|  0.0|
|   0| 1.75|  [1.75]|  0.0|
|   0|  2.0|   [2.0]|  0.0|
|   1| 1.75|  [1.75]|  1.0|
|   1| 2.75|  [2.75]|  1.0|
|   1| 3.25|  [3.25]|  1.0|
|   1|  4.0|   [4.0]|  1.0|
|   1| 4.25|  [4.25]|  1.0|
|   1|  4.5|   [4.5]|  1.0|
|   1| 4.75|  [4.75]|  1.0|
+----+-----+--------+-----+
```

# Training and Testing Data Sets

Need data to train model

Want to test the model

- Need data but want it to be similar to test data
- Divide data set randomly

```
(train, test) = prepared_df.randomSplit((0.7, 0.3))
```

# Fitting the Model

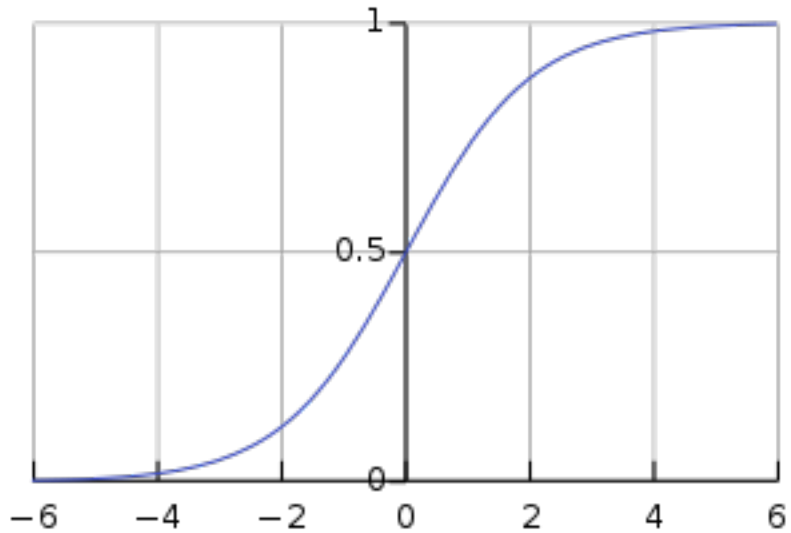
```
from pyspark.ml.classification import LogisticRegression

lr = LogisticRegression()
lr_model = lr.fit(train)
```

# Evaluate model using Test data

lr_model.evaluate(test).predictions.show()

```
+----+-----+--------+-----+--------------------+--------------------+----------+
|Pass|Hours|features|label|       rawPrediction|         probability|prediction|
+----+-----+--------+-----+--------------------+--------------------+----------+
|   0|  1.0|   [1.0]|  0.0|[4.27801503632846...|[0.98631958310440...|       0.0|
|   0|  2.5|   [2.5]|  0.0|[-1.8745690184952...|[0.13301393365332...|       1.0|
|   0|  3.0|   [3.0]|  0.0|[-3.9254303701031...|[0.01935176153455...|       1.0|
|   0|  3.5|   [3.5]|  0.0|[-5.9762917217110...|[0.00253179503666...|       1.0|
|   1| 2.25|  [2.25]|  1.0|[-0.8491383426912...|[0.29961364104257...|       1.0|
+----+-----+--------+-----+--------------------+--------------------+----------+
```

# Logistic Function




Not fitting data to a line
Fitting it to the logistic function

F(x)= 1/(1 + exp(Intercept + coefficient*x)

| Pass | Hours | features | label | rawPrediction | probability | prediction |
|---|---|---|---|---|---|---|
| 0 | 1.0 | [1.0] | 0.0 | [4.27801503632846... | [0.98631958310440... | 0.0 |
| 0 | 2.5 | [2.5] | 0.0 | [-1.8745690184952... | [0.13301393365332... | 1.0 |
| 0 | 3.0 | [3.0] | 0.0 | [-3.9254303701031... | [0.01935176153455... | 1.0 |
| 0 | 3.5 | [3.5] | 0.0 | [-5.9762917217110... | [0.00253179503666... | 1.0 |
| 1 | 2.25 | [2.25] | 1.0 | [-0.8491383426912... | [0.29961364104257... | 1.0 |

# Transformers, Estimators, Pipelines

Transformer

Converts data

Clean, add features, remove feature, format

Estimators

Models or variations of same model

Evaluator

See how an estimator performs

Pipeline

Specifying transformers and estimators together

# Using a Pipeline

Can create a pipeline of transformations and evaluators

Can be applied to multiple data frames

```
from pyspark.ml.classification import LogisticRegression
from pyspark.ml import Pipeline

exam_formula = RFormula(formula = "Pass ~ Hours")
lr = LogisticRegression().setLabelCol('label').setFeaturesCol("features")

pipeline = Pipeline().setStages([exam_formula, lr])
```

# Reading data

```
from pyspark.ml.feature import RFormula
import pyspark.sql.types as types

schema = types.StructType() \
    .add("Pass", types.IntegerType(), True ) \
    .add("Hours", types.DoubleType(), True )

data = spark.read.format("csv"). \
        option("header",True).\
        schema(schema). \
        load("examStudy.csv")

(train, test) = data.randomSplit((0.7, 0.3))
```

```
+----+-----+
|Pass|Hours|
+----+-----+
|   0| 0.75|
|   0|  1.0|
|   0| 1.25|
|   0|  1.5|
|   0|  2.0|
|   0|  2.5|
|   0|  3.0|
|   0|  3.5|
|   1| 1.75|
|   1| 2.75|
|   1| 3.25|
|   1|  4.0|
|   1|  4.5|
+----+-----+
```

# Using the Pipeline

pipeline_model = pipeline.fit(train)

pipeline_model.transform(test).show()

```
+----+-----+--------+-----+--------------------+--------------------+----------+
|Pass|Hours|features|label|       rawPrediction|         probability|prediction|
+----+-----+--------+-----+--------------------+--------------------+----------+
|   0|  0.5|   [0.5]|  0.0|[3.20443890334995...|[0.96100097970834...|       0.0|
|   0| 1.75|  [1.75]|  0.0|[1.57204004098768...|[0.82807423779535...|       0.0|
|   1| 2.25|  [2.25]|  1.0|[0.91908049604277...|[0.71485471339150...|       0.0|
|   1| 4.25|  [4.25]|  1.0|[-1.6927576837368...|[0.15541352205043...|       1.0|
|   1| 4.75|  [4.75]|  1.0|[-2.3457172286817...|[0.08740679247853...|       1.0|
+----+-----+--------+-----+--------------------+--------------------+----------+
```

# Extracting, transforming and selecting features

Feature Extractors

- TF-IDF
- Word2Vec
- CountVectorizer

Feature Selectors

- VectorSlicer
- RFormula
- ChiSqSelector

Feature Transformers

- Tokenizer
- StopWordsRemover
- n-gram
- Binarizer
- PCA
- PolynomialExpansion
- Discrete Cosine Transform (DCT)
- StringIndexer
- IndexToString
- OneHotEncoder
- VectorIndexer
- Interaction
- Normalizer
- StandardScaler
- MinMaxScaler
- MaxAbsScaler
- Bucketizer
- ElementwiseProduct
- SQLTransformer
- VectorAssembler
- QuantileDiscretizer
- Imputer

# Scaling Data

StandardScaler

transforms a dataset of Vector rows, normalizing each feature to have unit standard deviation and/or zero mean

```
+--------------+--------------------------------+
|      features|scaledFeatures                  |
+--------------+--------------------------------+
|[1.0,0.1,-1.0]| [1.0,0.018156825980064073,-0.5]|
|[2.0,1.1, 1.0]| [2.0,0.19972508578070483,  0.5]|
|[3.0,10.1,3.0]| [3.0,1.8338394239864713,   1.5]|
+--------------+--------------------------------+
```

# Scaling Data - MinMaxScaler

transforms a dataset of Vector rows, rescaling each feature to a specific range

```
Features scaled to range: [0.0, 1.0]
+--------------+--------------+
|      features|scaledFeatures|
+--------------+--------------+
|[1.0,0.1,-1.0]| [0.0,0.0,0.0]|
| [2.0,1.1,1.0]| [0.5,0.1,0.5]|
|[3.0,10.1,3.0]| [1.0,1.0,1.0]|
+--------------+--------------+
```

# Example

```
from pyspark.ml.feature import MinMaxScaler
from pyspark.ml.linalg import Vectors

dataFrame = spark.createDataFrame((
  (0, Vectors.dense(1.0, 0.1, -1.0)),
  (1, Vectors.dense(2.0, 1.1, 1.0)),
  (2, Vectors.dense(3.0, 10.1, 3.0))
)).toDF("id", "features")

scaler = MinMaxScaler().setInputCol("features").setOutputCol("scaledFeatures")

# Compute summary statistics and generate MinMaxScalerModel
scalerModel = scaler.fit(dataFrame)

# rescale each feature to range [min, max].
scaledData = scalerModel.transform(dataFrame)
scaledData.show()
```

```
+---+--------------+--------------+
| id|      features|scaledFeatures|
+---+--------------+--------------+
|  0|[1.0,0.1,-1.0]| [0.0,0.0,0.0]|
|  1| [2.0,1.1,1.0]| [0.5,0.1,0.5]|
|  2|[3.0,10.1,3.0]| [1.0,1.0,1.0]|
+---+--------------+--------------+
```

# Scaling Data MaxAbsScaler

transforms a dataset of Vector rows, rescaling each feature to range [-1, 1]

```
+--------------+----------------+
|      features|  scaledFeatures|
+--------------+----------------+
|[1.0,0.1,-8.0]|[0.25,0.01,-1.0]|
|[2.0,1.0,-4.0]|[0.5, 0.1, -0.5]|
|[4.0,10.0,8.0]|[1.0, 1.0,  1.0]|
+--------------+----------------+
```

# Binning Data - Bucketizer

transforms a column of continuous features to a column of feature buckets

splits: Parameter for mapping continuous features into buckets

```
from pyspark.ml.feature import Bucketizer
values = [(0.1,), (0.4,), (1.2,), (1.5,), (float("nan"),), (float("nan"),)]
df = spark.createDataFrame(values, ["values"])
bucketizer = Bucketizer(splits=[-float("inf"), 0.5, 1.4, float("inf")], \
                                  inputCol="values", outputCol="buckets")
bucketed = bucketizer.setHandleInvalid("keep").transform(df).collect()
bucketed
```

```
[Row(values=0.1, buckets=0.0),
 Row(values=0.4, buckets=0.0),
 Row(values=1.2, buckets=1.0),
 Row(values=1.5, buckets=2.0),
 Row(values=nan, buckets=3.0),
 Row(values=nan, buckets=3.0)]
```

# Binning Data - Binarizer

Binarization is the process of thresholding numerical features to binary (0/1) features

```
from pyspark.ml.feature import Binarizer

binarizer = Binarizer(). \
  setInputCol("feature"). \
  setOutputCol("binarized_feature"). \
  setThreshold(0.5)
```

```
Binarizer output with Threshold = 0.5
+---+-------+-----------------+
| id|feature|binarized_feature|
+---+-------+-----------------+
|  0|    0.1|              0.0|
|  1|    0.8|              1.0|
|  2|    0.2|              0.0|
+---+-------+-----------------+
```

# QuantileDiscretizer

column with continuous features -> a column with binned categorical features

numBuckets = 3

| id | hour |
|---|---|
| 0 | 18.0 |
| 1 | 19.0 |
| 2 | 8.0 |
| 3 | 5.0 |
| 4 | 2.2 |

| id | hour | result |
|---|---|---|
| 0 | 18.0 | 2.0 |
| 1 | 19.0 | 2.0 |
| 2 | 8.0 | 1.0 |
| 3 | 5.0 | 1.0 |
| 4 | 2.2 | 0.0 |

# StringIndexer

encodes a string column of labels to a column of label indices

```
 id | category
----|----------
 0  | a
 1  | b
 2  | c
 3  | a
 4  | a
 5  | c
```

```
 id | category | categoryIndex
----|----------|---------------
 0  | a        | 0.0
 1  | b        | 2.0
 2  | c        | 1.0
 3  | a        | 0.0
 4  | a        | 0.0
 5  | c        | 1.0
```

What happens when test data contains category that training data does not?

throw an exception (which is the default)
skip the row containing the unseen label entirely
put unseen labels in a special additional bucket, at index numLabels

# OneHotEncoder

maps a column of label indices to a column of binary vectors

allows algorithms which expect continuous features, such as Logistic Regression, to use categorical features

```
+---+--------+-------------+-------------+
| id|category|categoryIndex|  categoryVec|
+---+--------+-------------+-------------+
|  0|       a|          0.0|(2,[0],[1.0])|
|  1|       b|          2.0|    (2,[],[])|
|  2|       c|          1.0|(2,[1],[1.0])|
|  3|       a|          0.0|(2,[0],[1.0])|
|  4|       a|          0.0|(2,[0],[1.0])|
|  5|       c|          1.0|(2,[1],[1.0])|
+---+--------+-------------+-------------+
```

# SQLTransformer

implements the transformations which are defined by SQL statement

SELECT a, a + b AS a_b FROM __THIS__
SELECT a, SQRT(b) AS b_sqrt FROM __THIS__ where a > 5
SELECT a, b, SUM(c) AS c_sum FROM __THIS__ GROUP BY a, b

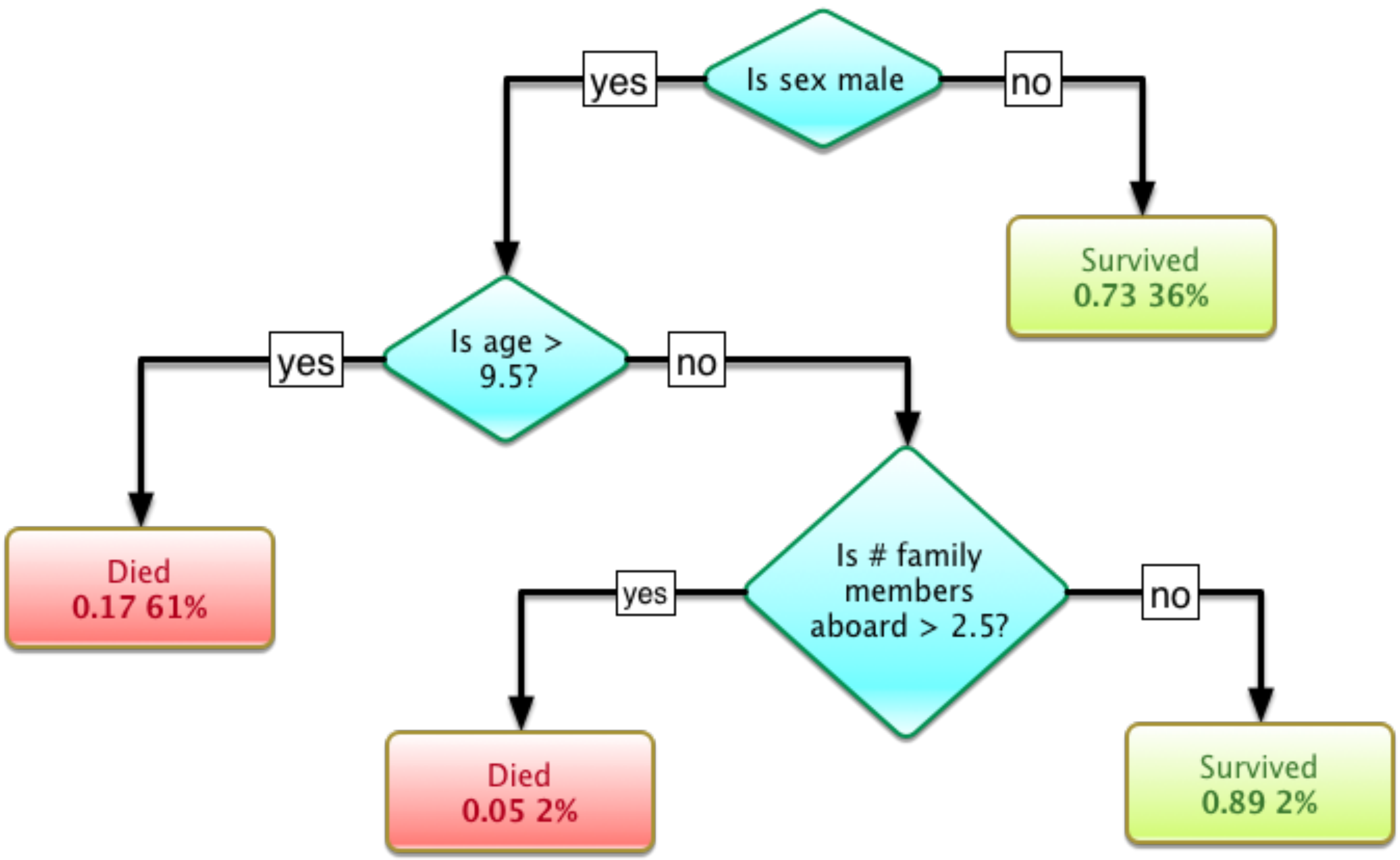
```
from pyspark.ml.feature import SQLTransformer

df = spark.createDataFrame(((0, 1.0, 3.0), (2, 2.0, 5.0))).toDF("id", "v1", "v2")

sqlTrans = SQLTransformer().setStatement(
  "SELECT *, (v1 + v2) AS v3, (v1 * v2) AS v4 FROM __THIS__")

sqlTrans.transform(df).show()
```

| id | v1 | v2 |
|---|---|---|
| 0 | 1.0 | 3.0 |
| 2 | 2.0 | 5.0 |

| id | v1 | v2 | v3 | v4 |
|---|---|---|---|---|
| 0 | 1.0 | 3.0 | 4.0 | 3.0 |
| 2 | 2.0 | 5.0 | 7.0 | 10.0 |

| Model | Features Count | Training Examples | Output Classes |
| --- | --- | --- | --- |
| Logistic Regression | 1 to 10 million | no limit | Features x Classes < 10 million |
| Decision Trees | 1,000s | no limit | Features x Classes < 10,000s |
| Random Forest | 10,000s | no limit | Features x Classes < 100,000s |
| Gradient Boosted Trees | 1,000s | no limit | Features x Classes < 10,000s |

# Decision Trees

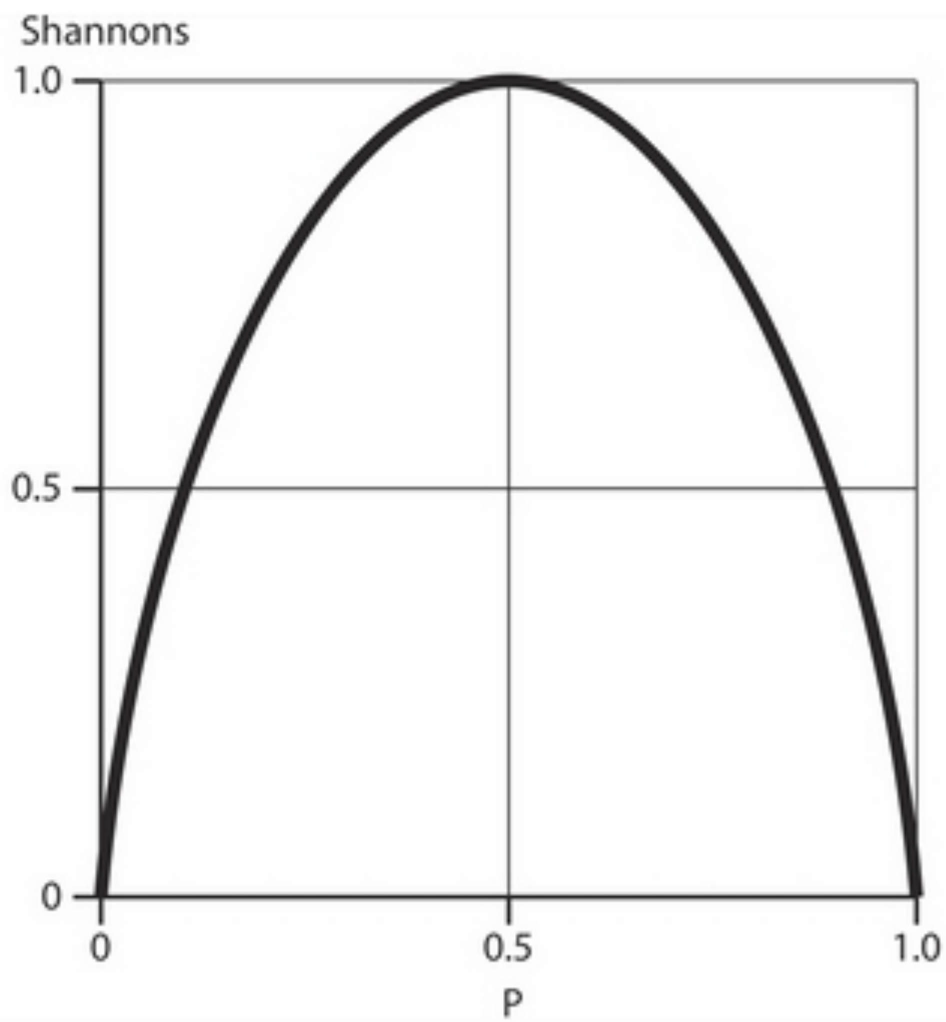


# How to Decide Which Question to Ask First

Information

$$I(e) = -log_2 P(e)$$

P(e) = probability of event e






D20

# Which card was selected from Deck of Cards

Is it red? (a Heart or a Diamond)
Is it a picture card? (a Jack, Queen, or King)

P(red) = 26/52 = 1/2

I(red) = -log2(1/2) = 1

P(picture) = 12/52 = 3/13

I(picture) = -log2(3/13) = 2.12

P(black) = 26/52 = 1/2

I(black) = -log2(1/2) = 1

P(not picture) = 40/52 = 10/13

I(picture) = -log2(10/13) = 0.38

# How to Decide Which Question to Ask First

Entropy - Measure of uncertainty or disorder  or order)

$$H(X) = \sum_i P(x_i) I(P(x_i))$$

Lower values of H indicate more order, less uncertainty

H(red or not red) = P(red)*I(red) + P(not red)*I(not red)
= 1/2 * 1 + 1/2 * 1
= 1

H(picture or not picture) = 3/13 * 2.12 + 10/13 * 0.38
= 0.78

# Information Gain

How much does entropy decreases


Decision Tree Building

For root node which feature will produce the most information gain (biggest entropy loss)

Repeat on each subnode

# How to Use

Create a DecisionTreeClassifier

Fit the classifier to your training data

Use the classifier to transform data

# But data needs to be in correct format

Need svm format

If categorical the categories need to be integers

# Iris Example

```
+------------+-----------+------------+-----------+----------+
|sepal_length|sepal_width|petal_length|petal_width|   species|
+------------+-----------+------------+-----------+----------+
|         5.1|        3.5|         1.4|        0.2|    setosa|
|         4.9|        3.0|         1.4|        0.2|    setosa|
|         4.7|        3.2|         1.3|        0.2|    setosa|
|         4.6|        3.1|         1.5|        0.2|    setosa|

|         7.0|        3.2|         4.7|        1.4|versicolor|
|         6.4|        3.2|         4.5|        1.5|versicolor|
|         6.9|        3.1|         4.9|        1.5|versicolor|
|         5.5|        2.3|         4.0|        1.3|versicolor|
|         6.5|        2.8|         4.6|        1.5|versicolor|
|         5.7|        2.8|         4.5|        1.3|versicolor|

|         6.3|        3.3|         6.0|        2.5| virginica|
|         5.8|        2.7|         5.1|        1.9| virginica|
|         7.1|        3.0|         5.9|        2.1| virginica|
|         6.3|        2.9|         5.6|        1.8| virginica|
```

# Reading the File

```
iris = spark.read.format("csv"). \
        option("header",True).\
        option("inferschema",True).\
        load("iris.txt")
iris.schema
```

```
StructType(List(StructField(sepal_length,DoubleType,true),
                StructField(sepal_width,DoubleType,true),
                StructField(petal_length,DoubleType,true),
                StructField(petal_width,DoubleType,true),
                StructField(species,StringType,true)))
```

# StringIndexer - convert column to index

```
from pyspark.ml.feature import StringIndexer

irisIndexer = StringIndexer(inputCol="species", outputCol="label").fit(iris)
irisIndexer.transform(iris).show(150)
```

```
+------------+-----------+------------+-----------+----------+------------+
|sepal_length|sepal_width|petal_length|petal_width|   species|label       |
+------------+-----------+------------+-----------+----------+------------+
|         5.1|        3.5|         1.4|        0.2|    setosa|         2.0|
|         4.9|        3.0|         1.4|        0.2|    setosa|         2.0|
|         4.7|        3.2|         1.3|        0.2|    setosa|         2.0|
|         4.6|        3.1|         1.5|        0.2|    setosa|         2.0|

|         7.0|        3.2|         4.7|        1.4|versicolor|         0.0|
|         6.4|        3.2|         4.5|        1.5|versicolor|         0.0|

|         6.0|        3.0|         4.8|        1.8| virginica|         1.0|
|         6.9|        3.1|         5.4|        2.1| virginica|         1.0|
|         6.7|        3.1|         5.6|        2.4| virginica|         1.0|
```

# Convert Format

```
from pyspark.ml.feature import VectorAssembler

iris_assembler = VectorAssembler(inputCols=["sepal_length","sepal_width",  \
                                            "petal_length", "petal_width"], outputCol="features")
iris_assembler.transform(iris).show()
```

```
+------------+-----------+------------+-----------+-------+-----------------+
|sepal_length|sepal_width|petal_length|petal_width|species|         features|
+------------+-----------+------------+-----------+-------+-----------------+
|         5.1|        3.5|         1.4|        0.2| setosa|[5.1,3.5,1.4,0.2]|
|         4.9|        3.0|         1.4|        0.2| setosa|[4.9,3.0,1.4,0.2]|
|         4.7|        3.2|         1.3|        0.2| setosa|[4.7,3.2,1.3,0.2]|
|         4.6|        3.1|         1.5|        0.2| setosa|[4.6,3.1,1.5,0.2]|
|         5.0|        3.6|         1.4|        0.2| setosa|[5.0,3.6,1.4,0.2]|
```

# Using Pipeline

```
from pyspark.ml import Pipeline

pipeline = Pipeline(stages=[iris_indexer, iris_assembler])
pipeline.fit(iris).transform(iris).show()
```

```
+------------+-----------+------------+-----------+-------+-----+-----------------+
|sepal_length|sepal_width|petal_length|petal_width|species|label|         features|
+------------+-----------+------------+-----------+-------+-----+-----------------+
|         5.1|        3.5|         1.4|        0.2| setosa|  2.0|[5.1,3.5,1.4,0.2]|
|         4.9|        3.0|         1.4|        0.2| setosa|  2.0|[4.9,3.0,1.4,0.2]|
|         4.7|        3.2|         1.3|        0.2| setosa|  2.0|[4.7,3.2,1.3,0.2]|
```

```
from pyspark.ml.classification import DecisionTreeClassifier

tree = DecisionTreeClassifier()

pipeline = Pipeline(stages=[iris_indexer, iris_assembler, tree])

(training_data, test_data) = iris.randomSplit([0.7, 0.3])
iris_model = pipeline.fit(training_data)

predictions = iris_model.transform(test_data)
predictions.select("label", "features","probability","prediction").show()
```

```
+-----+-----------------+-------------+----------+
|label|         features|  probability|prediction|
+-----+-----------------+-------------+----------+
|  2.0|[4.3,3.0,1.1,0.1]|[0.0,0.0,1.0]|       2.0|
|  2.0|[4.5,2.3,1.3,0.3]|[0.0,0.0,1.0]|       2.0|
|  2.0|[4.6,3.6,1.0,0.2]|[0.0,0.0,1.0]|       2.0|
|  2.0|[4.8,3.1,1.6,0.2]|[0.0,0.0,1.0]|       2.0|
|  2.0|[4.8,3.4,1.6,0.2]|[0.0,0.0,1.0]|       2.0|
|  0.0|[4.9,2.4,3.3,1.0]|[1.0,0.0,0.0]|       0.0|
|  2.0|[4.9,3.0,1.4,0.2]|[0.0,0.0,1.0]|       2.0|
|  2.0|[4.9,3.1,1.5,0.1]|[0.0,0.0,1.0]|       2.0|
|  0.0|[5.0,2.3,3.3,1.0]|[1.0,0.0,0.0]|       0.0|
|  2.0|[5.0,3.2,1.2,0.2]|[0.0,0.0,1.0]|       2.0|
|  2.0|[5.0,3.4,1.5,0.2]|[0.0,0.0,1.0]|       2.0|
|  2.0|[5.1,3.4,1.5,0.2]|[0.0,0.0,1.0]|       2.0|
|  2.0|[5.1,3.5,1.4,0.3]|[0.0,0.0,1.0]|       2.0|
|  2.0|[5.2,3.4,1.4,0.2]|[0.0,0.0,1.0]|       2.0|
|  0.0|[5.4,3.0,4.5,1.5]|[1.0,0.0,0.0]|       0.0|
|  2.0|[5.4,3.4,1.5,0.4]|[0.0,0.0,1.0]|       2.0|
|  2.0|[5.4,3.4,1.7,0.2]|[0.0,0.0,1.0]|       2.0|
|  0.0|[5.5,2.3,4.0,1.3]|[1.0,0.0,0.0]|       0.0|
|  0.0|[5.7,2.6,3.5,1.0]|[1.0,0.0,0.0]|       0.0|
|  0.0|[5.7,2.8,4.5,1.3]|[1.0,0.0,0.0]|       0.0|
+-----+-----------------+-------------+----------+
```

# Some Information about The Tree

Pipeline does not give access to tree (python)
So only use pipeline to transform data

```
pipeline = Pipeline(stages=[iris_indexer, iris_assembler])
pipeline_model = pipeline.fit(training_data)
iris_transformed = pipeline_model.transform(training_data)

iris_tree = DecisionTreeClassifier()
raw_model = iris_tree.fit(iris_transformed)
```

```
raw_model.featureImportances
```

```
SparseVector(4, {0: 0.0291, 2: 0.5744, 3: 0.3965})
```

**raw_model.toDebugString**

```
DecisionTreeClassificationModel (
  uid=DecisionTreeClassifier_e1ee1b355b47) of depth 4 with 11 nodes
  If (feature 2 <= 2.45)
    Predict: 2.0
  Else (feature 2 > 2.45)
    If (feature 3 <= 1.75)
      If (feature 2 <= 4.95)
        If (feature 0 <= 4.95)
          Predict: 1.0
        Else (feature 0 > 4.95)
          Predict: 0.0
      Else (feature 2 > 4.95)
        If (feature 3 <= 1.65)
          Predict: 1.0
        Else (feature 3 > 1.65)
          Predict: 0.0
    Else (feature 3 > 1.75)
      Predict: 1.0
```

# DecisionTree & Iris

Features are continuous

Decision tree bins the values

This dataset bins each feature into two bins

- Feature 2
  - Values <= 2.45
  - Values > 2.45

- Feature 3
  - Depends on values of Feature 2 & 1

Can set maximum number of bins

Can bin values before using tree model

# Categorical Features

If have mixed categorical and continuous features

Use VectorIndexer

- Specify how many values needed to be considered continuous

```
from pyspark.ml.feature import VectorIndexer
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml import Pipeline
from pyspark.ml.feature import StringIndexer


iris_indexer = StringIndexer(inputCol="species", outputCol="label")
iris_assembler = VectorAssembler(inputCols=["sepal_length","sepal_width", "petal_length",
"petal_width"], outputCol="features_first")
featureIndexer =\
    VectorIndexer(inputCol="features_first", outputCol="features", maxCategories=4)

full_pipeline = Pipeline(stages=[iris_indexer, iris_assembler, featureIndexer])

(training_data, test_data) = iris.randomSplit([0.7, 0.3])
iris_model = full_pipeline.fit(training_data)
iris_transformed = iris_model.transform(training_data)
```

# Tree Ensembles

Gradient-Boosted

Random Forests

- Create multiple decision trees
- Sample training data for each tree
- Classification
  - Majority vote
- Regression
  - Average

```
from pyspark.ml.feature import VectorIndexer
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml import Pipeline
from pyspark.ml.feature import StringIndexer

iris_indexer = StringIndexer(inputCol="species", outputCol="label")
iris_assembler = VectorAssembler(inputCols=["sepal_length","sepal_width", "petal_length",
"petal_width"], outputCol="features_first")
featureIndexer =\
    VectorIndexer(inputCol="features_first", outputCol="features", maxCategories=4)

full_pipeline = Pipeline(stages=[iris_indexer, iris_assembler, featureIndexer])

(training_data, test_data) = iris.randomSplit([0.7, 0.3])
iris_model = full_pipeline.fit(training_data)
iris_transformed = iris_model.transform(training_data)
test_transformed = iris_model.transform(test_data)
```

```
from pyspark.ml.classification import RandomForestClassifier

forest_classifier = RandomForestClassifier(numTrees = 3)

iris_forest_model = forest_classifier.fit(iris_transformed)
iris_forest_model.trees
```

```
[DecisionTreeClassificationModel (uid=dtc_2eb2f52c851c) of depth 4 with 11 nodes,
 DecisionTreeClassificationModel (uid=dtc_5d145ec5624f) of depth 5 with 11 nodes,
 DecisionTreeClassificationModel (uid=dtc_f9859ed404fb) of depth 4 with 9 nodes]
```

prediction = iris_forest_model.transform(test_transformed)
prediction.select("label", "probability","prediction" ).show()

```
+-----+-------------+----------+
|label|  probability|prediction|
+-----+-------------+----------+
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  0.0|[0.0,1.0,0.0]|       1.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
|  2.0|[0.0,0.0,1.0]|       2.0|
```

# Decision Trees - Hyperparameters

impurity:
Metric to calculate information gain. “entropy” or “gini”.

maxBins:
Total number of bins used for discretizing continuous features and for choosing how to split on features at each node.

maxDepth:
Determines how deep the total tree can be.

minInfoGain:
Minimum information gain that can be used for a split. A higher value can prevent overfitting.

minInstancePerNode:
Minimum number of instances that need to be in a node. A higher value can prevent overfitting.

# Decision Tree

Easy to understand
Easy to interpret
Handles categorical features
Handles multi-class classification
Does not require feature scaling