A Taste of Random Decision Forests on Apache Spark

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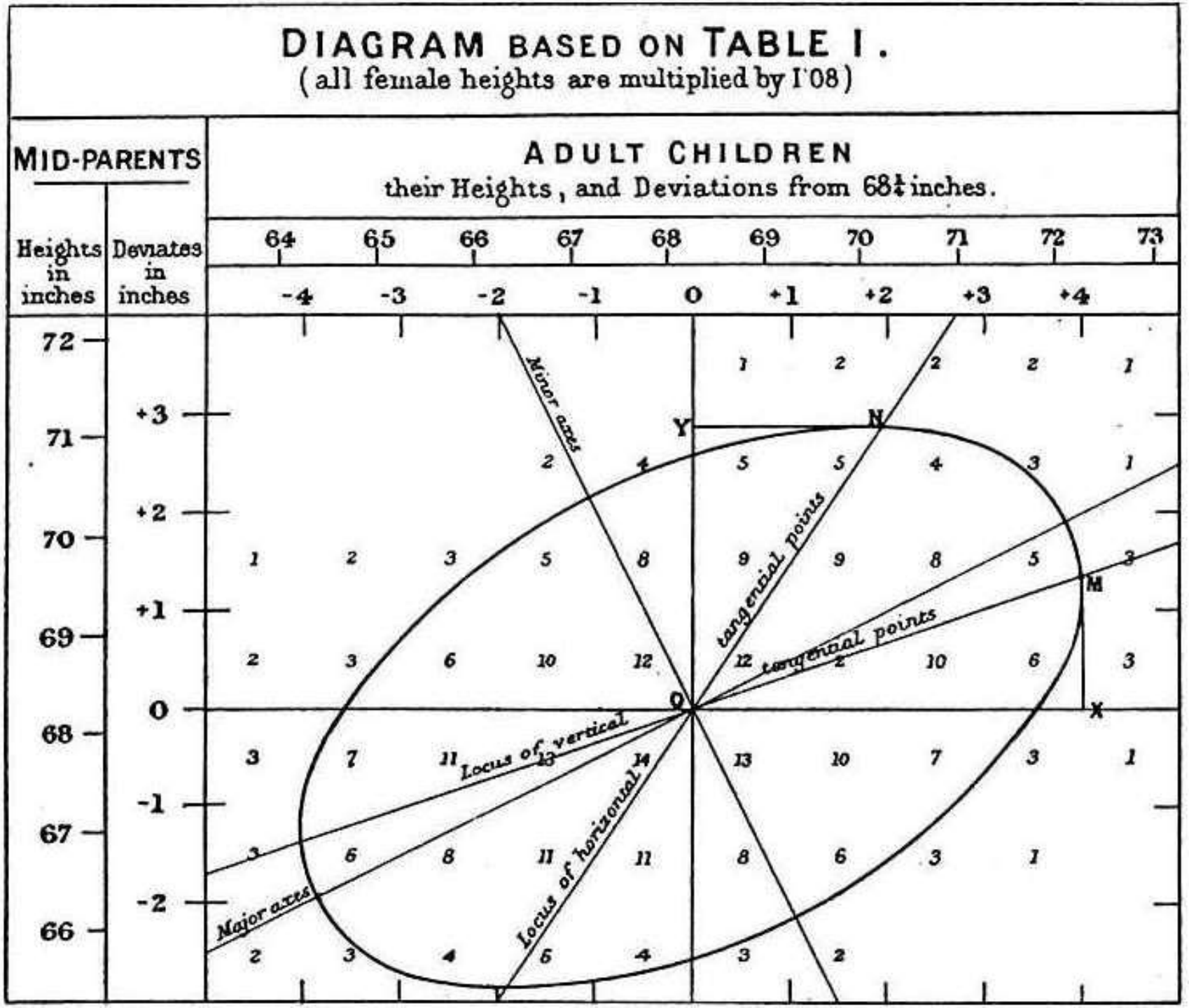
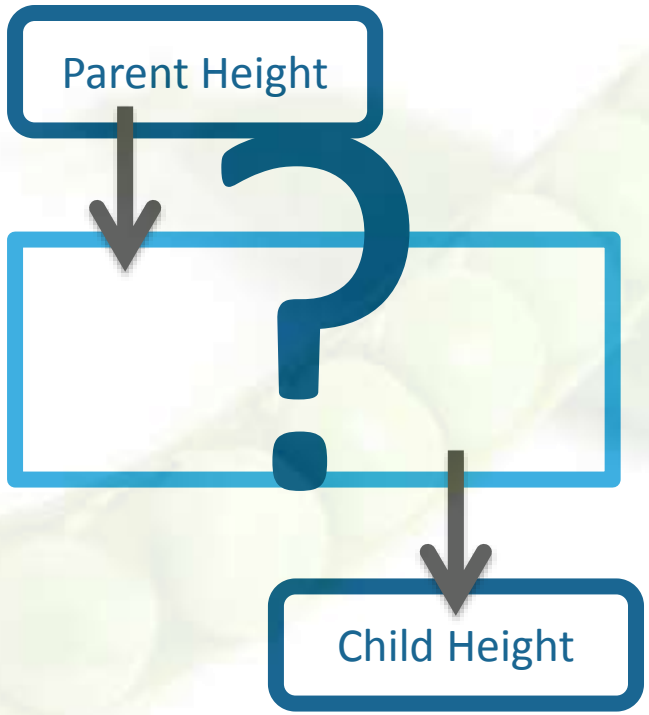
The Roots of Prediction

Regression to the mean as an early predictive model?

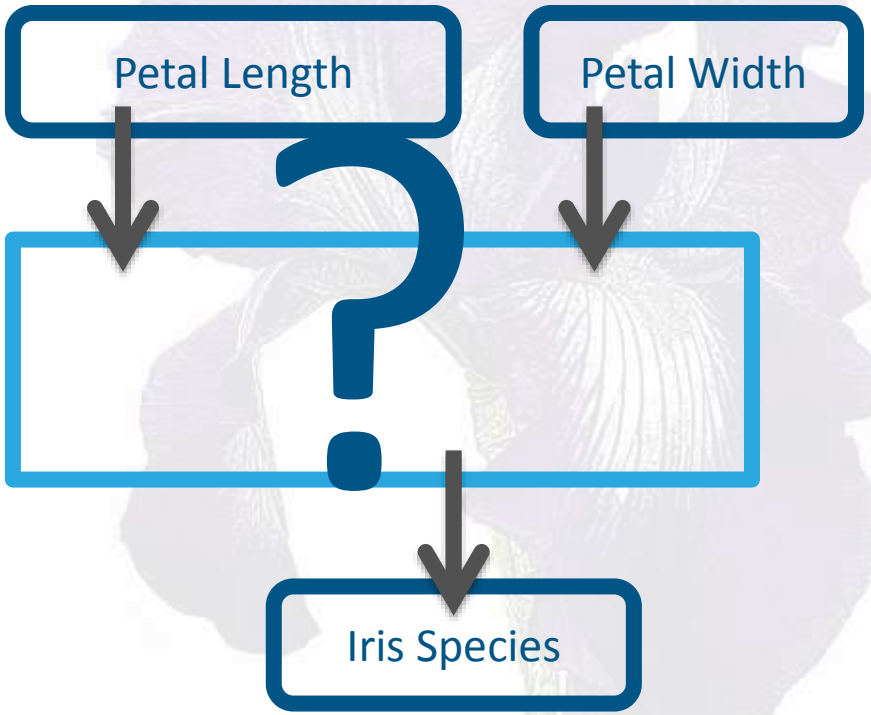


Input + Model = Output

Galton's Regression

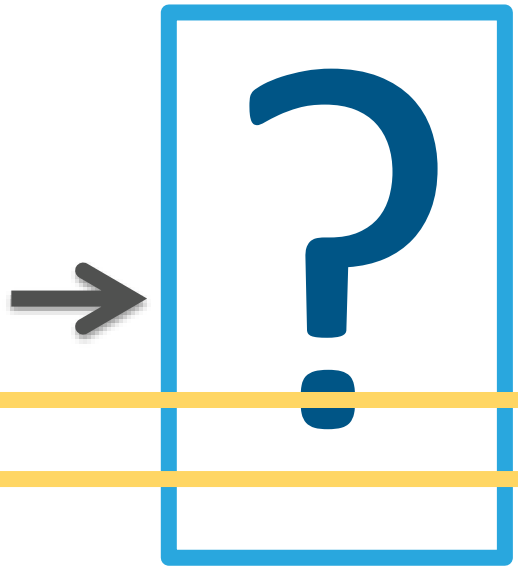


Classifying Iris Species



Feature Vectors in the Iris Data Set

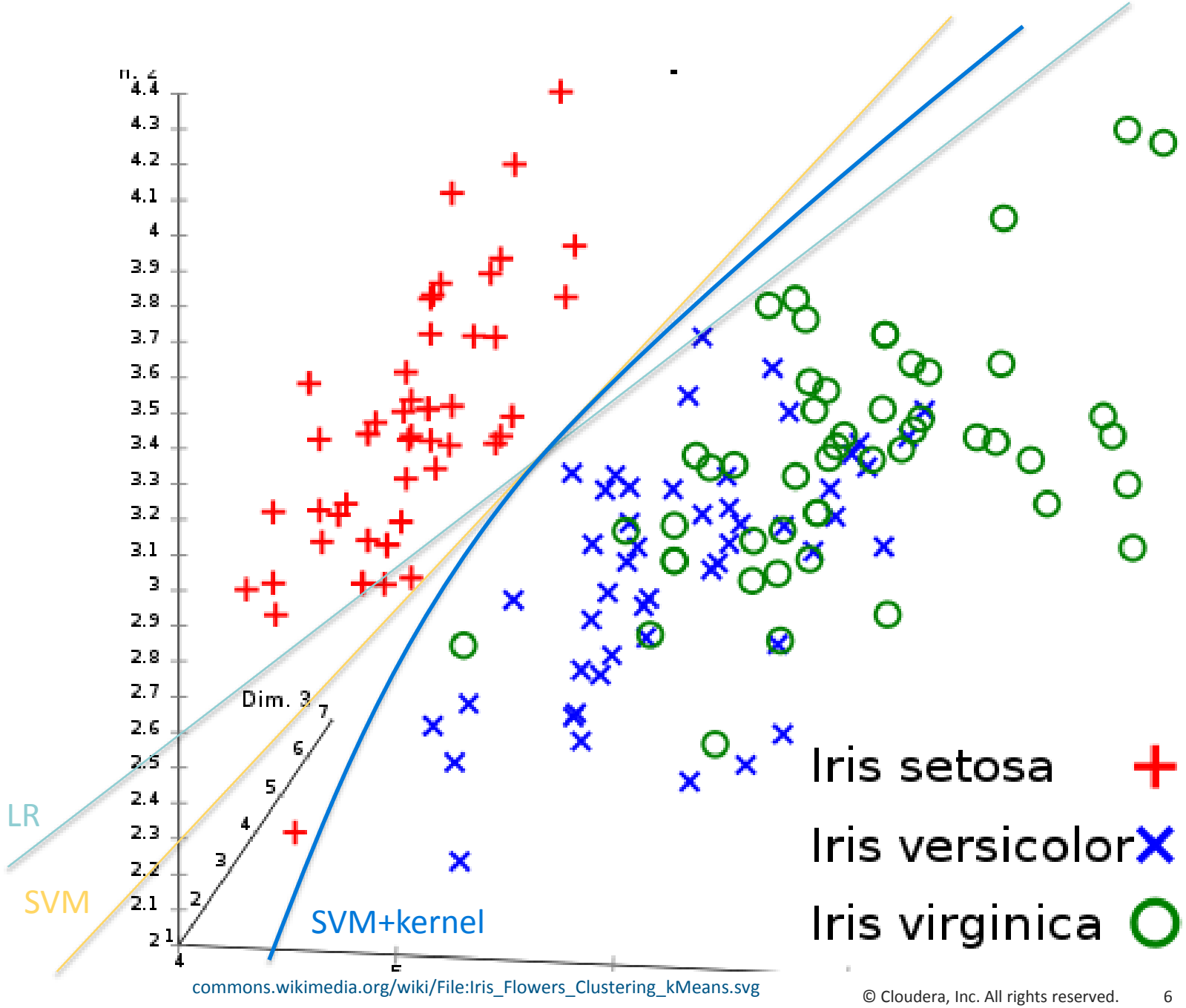
Sepal Length	Sepal Width	Petal Length	Petal Width
5.1	3.5	1.4	0.2
4.9	3.0	1.4	0.2
7.0	3.2	4.7	1.4
6.3	3.3	6.0	2.5
6.4	3.2	4.5	1.5
…	…	…	…



Species
Iris-setosa
Iris-setosa
Iris-versacolor
Iris-virginica
Iris-versacolor
…

```
6.4,3.2,4.5,1.5,Iris-versacolor
```

Classically,
classification has been
linear models,
drawing ideal
category dividing lines



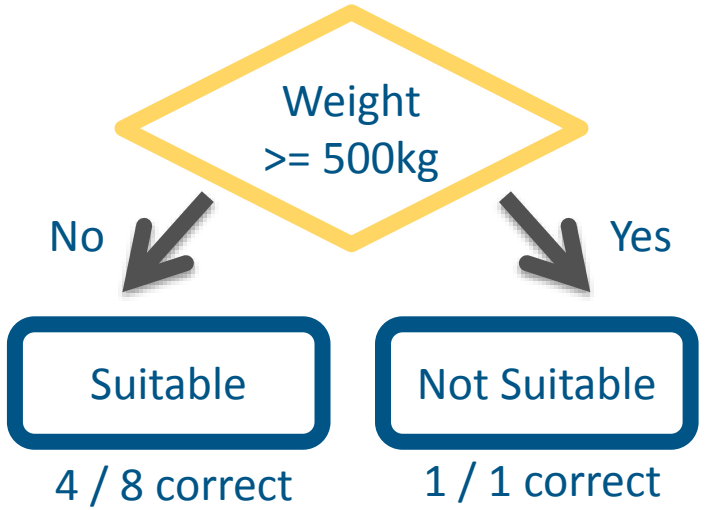
commons.wikimedia.org/wiki/File:Iris_Flowers_Clustering_kMeans.svg

Introducing Decision Trees

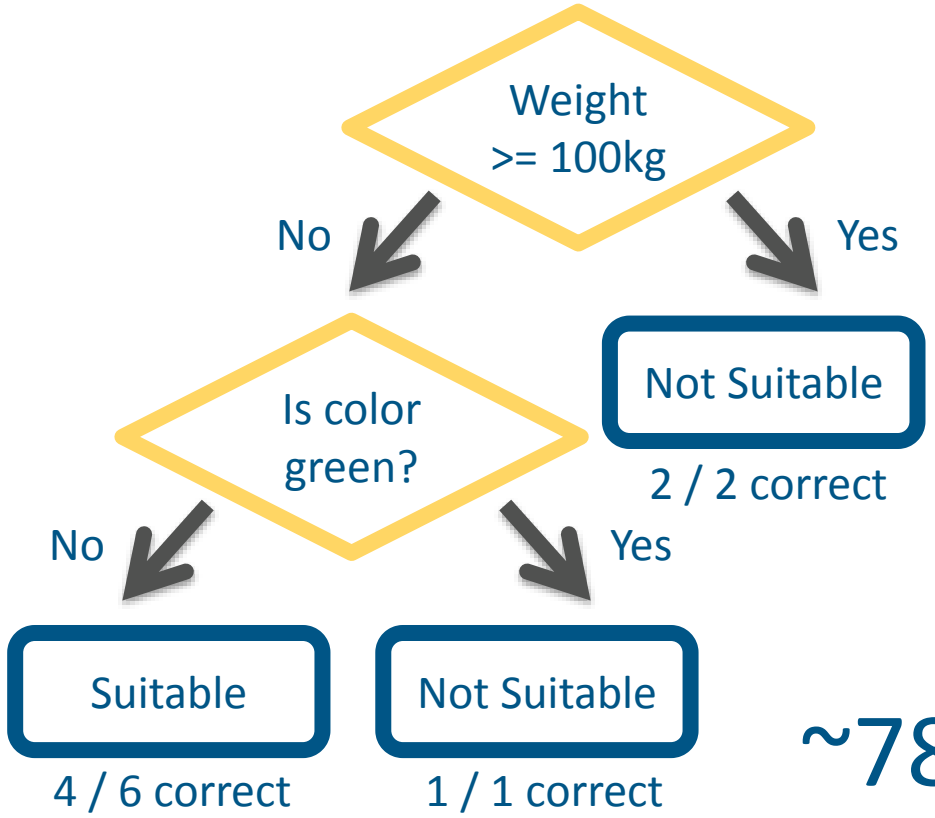
Good Pet Data Set

Name	Weight (kg)	Legs	Color	Suitable Pet?
Fido	20.5	4	Brown	**Yes**
Mr. Slither	3.1	0	Green	**No**
Nemo	0.2	0	Tan	**Yes**
Dumbo	1390.8	4	Grey	**No**
Kitty	12.1	4	Grey	**Yes**
Jim	150.9	2	Tan	**No**
Millie	0.1	100	Brown	**No**
McPigeon	1.0	2	Grey	**No**
Spot	10.0	4	Brown	**Yes**

Possible Decision Trees

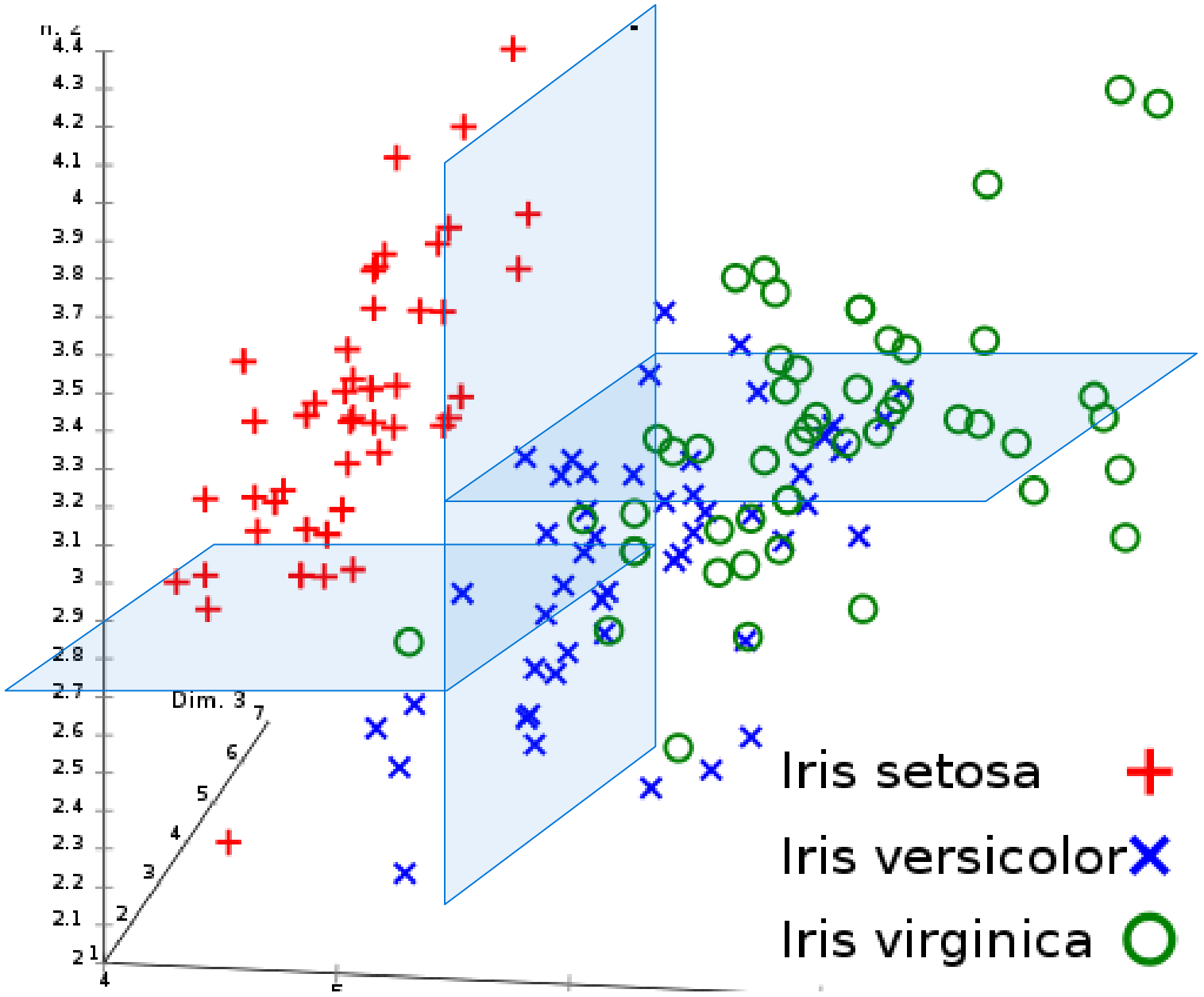


~56%



~78%

Simple decision trees create axis-aligned, stair-step decision boundaries



commons.wikimedia.org/wiki/File:Iris_Flowers_Clustering_kMeans.svg

Interpreting Models

Linear Models give Coefficients

```
> library("e1071")
> model <- svm(Species ~ ., data = iris,
               method = "C-classification")
> model$SV
```

```
Sepal.Length Sepal.Width Petal.Length Petal.Width
9    -1.74301699 -0.36096697  -1.33575163  -1.3110521
14   -1.86378030 -0.13153881  -1.50569459  -1.4422448
16   -0.17309407  3.08045544  -1.27910398  -1.0486668
...
```

Decision Trees give Decisions

```
> library("party")
> cf <- cforest(Species ~ ., data = iris)
> party:::prettytree(cf@ensemble[[1]],
                     names(cf@data@get("input")))
```

```
1) Petal.Length <= 1.9; ...
  2)*  weights = 0
1) Petal.Length > 1.9
  3) Petal.Width <= 1.7; ...
    4) Petal.Length <= 4.8; ...
      5) Sepal.Length <= 5.5; ...
        6)*  weights = 0
...
```

Decision Trees in MLlib

Covertype Data Set

581,012 examples

54 features (elevation, slope, soil type, etc.) predicting forest cover type (spruce, aspen, etc.)

Encoding as LabeledPoint

Building a Decision Tree in MLlib

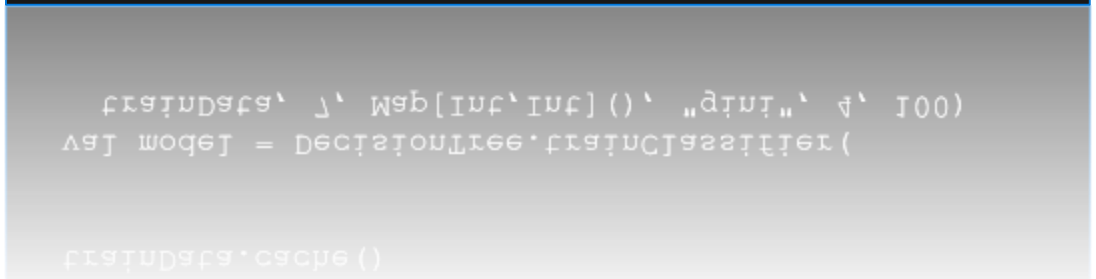
```
import org.apache.spark.mllib.linalg._
import org.apache.spark.mllib.regression._
import org.apache.spark.mllib.tree._

val rawData = sc.textFile("/user/ds/covtype.data")

val data = rawData.map { line =>
  val values = line.split(',').map(_.toDouble)
  val featureVector = Vectors.dense(values.init)
  val label = values.last - 1
  LabeledPoint(label, featureVector)
}

val Array(trainData, testData) =
   data.randomSplit(Array(0.9, 0.1))
trainData.cache()


val model = DecisionTree.trainClassifier(
  trainData, 7, Map[Int,Int](), "gini", 4, 100)
```



```
DecisionTreeModel classifier
      of depth 4 with 31 nodes
  If (feature 0 <= 3042.0)
   If (feature 0 <= 2509.0)
    If (feature 3 <= 0.0)
     If (feature 12 <= 0.0)
      Predict: 3.0
     Else (feature 12 > 0.0)
      Predict: 5.0
    Else (feature 3 > 0.0)
     If (feature 0 <= 2465.0)
      Predict: 2.0
     Else (feature 0 > 2465.0)
      Predict: 2.0
   Else (feature 0 > 2509.0)
  ...
```


Evaluating a Decision Tree

```
import org.apache.spark.mllib.evaluation._
import org.apache.spark.mllib.tree.model._
import org.apache.spark.rdd._

def getMetrics(model: DecisionTreeModel,
               data: RDD[LabeledPoint]) = {
  val predictionsAndLabels = data.map(example =>
    (model.predict(example.features), example.label)
  )
  new MulticlassMetrics(predictionsAndLabels)
}

val metrics = getMetrics(model, testData)

metrics.confusionMatrix
metrics.precision
```

```
14406.0  6459.0   6.0     0.0  0.0  0.0  416.0
5706.0   22086.0  415.0   13.0 0.0  11.0 40.0
0.0      439.0    3056.0  65.0 0.0  13.0 0.0
0.0      0.0      139.0   98.0 0.0  0.0  0.0
0.0      926.0    28.0    2.0  0.0  0.0  0.0
0.0      461.0    1186.0  37.0 0.0  61.0 0.0
1120.0   27.0     0.0     0.0  0.0  0.0  925.0
```

0.6988527889097195

~ 70% accuracy

Better Than Random Guessing?

```
def classProbabilities(data: RDD[LabeledPoint]) = {
  val countsByCategory =
    data.map(_.label).countByValue()
  val counts =
    countsByCategory.toArray.sortBy(_._1).map(_._2)
  counts.map(_.toDouble / counts.sum)
}

val trainProbs = classProbabilities(trainData)
val testProbs = classProbabilities(testData)

trainProbs.zip(testProbs).map {
  case (trainProb, testProb) => trainProb * testProb
}.sum
```

```
7758    10303   1302    86   348  636  755
10383   13789   1743    116  466  851  1011
1310    1740    220     15   59   107  128
102     136     17      1    5    8    10
348     462     58      4    16   28   34
636     845     107     7    29   52   62
751     997     126     8    34   62   73
```

0.37682125742281786

~ 38% accuracy

Hyperparameters

```
trainClassifier(trainData,
    7, Map[Int,Int](),
    "gini", 4, 100)
```

Impurity: Gini

Measure how much decision decreases impurity using Gini impurity (vs. entropy)

Maximum Depth: 4

Build trees to depth of 4 decisions before terminating in a prediction

Maximum Bins: 100

Consider 100 different decision rules for a feature when choosing a next best decision

Decisions Should Make Lower Impurity Subsets

Gini Impurity

- 1 minus probability that random guess *i* (probability p_i) is correct
- Lower is better

$$1 - \sum p_i^2$$

Entropy

- Information theory concept
- Measures mixed-ness, unpredictability of population
- Lower is better

$$-\sum p_i \log p_i$$

Tuning Hyperparameters

```
val evaluations =
  for (impurity <- Array("gini", "entropy");
       depth    <- Array(1, 20);
       bins     <- Array(10, 300)) yield {

    val model = DecisionTree.trainClassifier(
        trainData, 7, Map[Int,Int](),
        impurity, depth, bins)

    val accuracy =
      getMetrics(model, testData).precision

    ((impurity, depth, bins), accuracy)
  }

evaluations.sortBy(_._2).reverse.foreach(println)
```

```
((entropy,20,300),0.9125545571245186)
((gini,20,300),0.9042533162173727)
((gini,20,10),0.8854428754813863)
((entropy,20,10),0.8848951647411211)
((gini,1,300),0.6358065896448438)
((gini,1,10),0.635566961959777)
...
```

~ 91% accuracy

One-Hot / 1-of-n Encoding

…,cat,…		…,1,0,0,…
…,dog,…		…,0,1,0,…
…,fish,…		…,0,0,1,…

Categoricals Revisited

```
2596,51,3,258,0,510,221,232,148,6279,
1,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,
5
```

← Wilderness Type (4 features)

← Soil Type (40 features)


```
2596,51,3,258,0,510,221,232,148,6279,
0,
26,
5
```

← Wilderness Type (0 – 3)

← Soil Type (0 – 39)

Categoricals Revisited

```
val data = rawData.map { line =>
  val values = line.split(',').map(_.toDouble)

  val wilderness = values.slice(10, 14).
    indexOf(1.0).toDouble
  val soil = values.slice(14, 54).
    indexOf(1.0).toDouble

  val vector = Vectors.dense(
    values.slice(0, 10) :+ wilderness :+ soil)
  val label = values.last - 1

  LabeledPoint(label, vector)
}

...
  DecisionTree.trainClassifier(trainData,
    7, Map(10 -> 4, 11 -> 40),
    impurity, depth, bins)
...
```

```
((entropy,30,300),0.9438383977425239)
((entropy,30,40),0.938934581368939)
((gini,30,300),0.937127912178671)
((gini,30,40),0.9329467634811934)
((entropy,20,40),0.9280773598540899)
((gini,20,300),0.924963006297536)
...
```

~ 94% accuracy

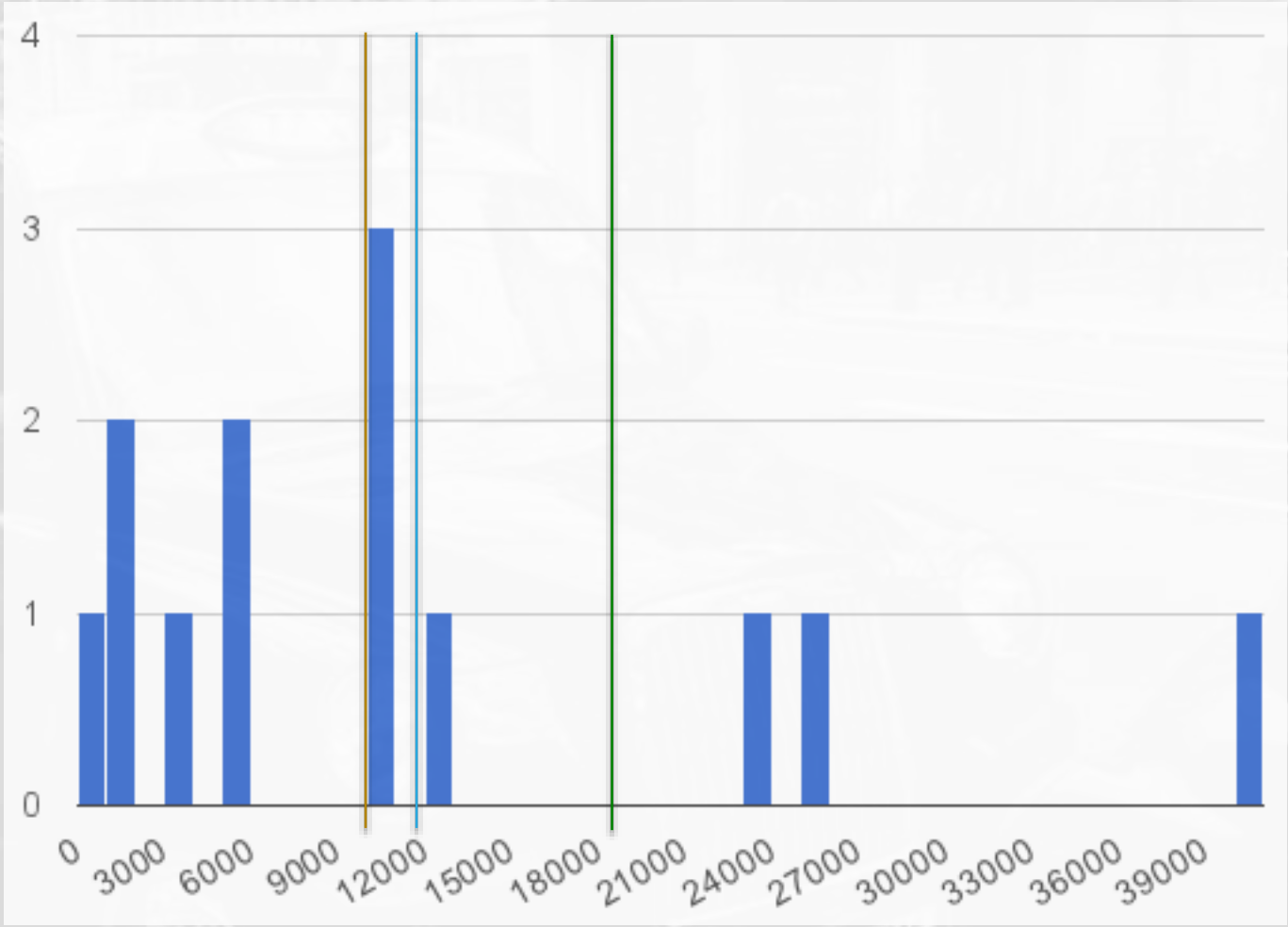
Decision Trees to Random Decision Forests

Wisdom of the Crowds: How many black cabs operate in London?

My Guess 10,000

Mean Guess 11,170

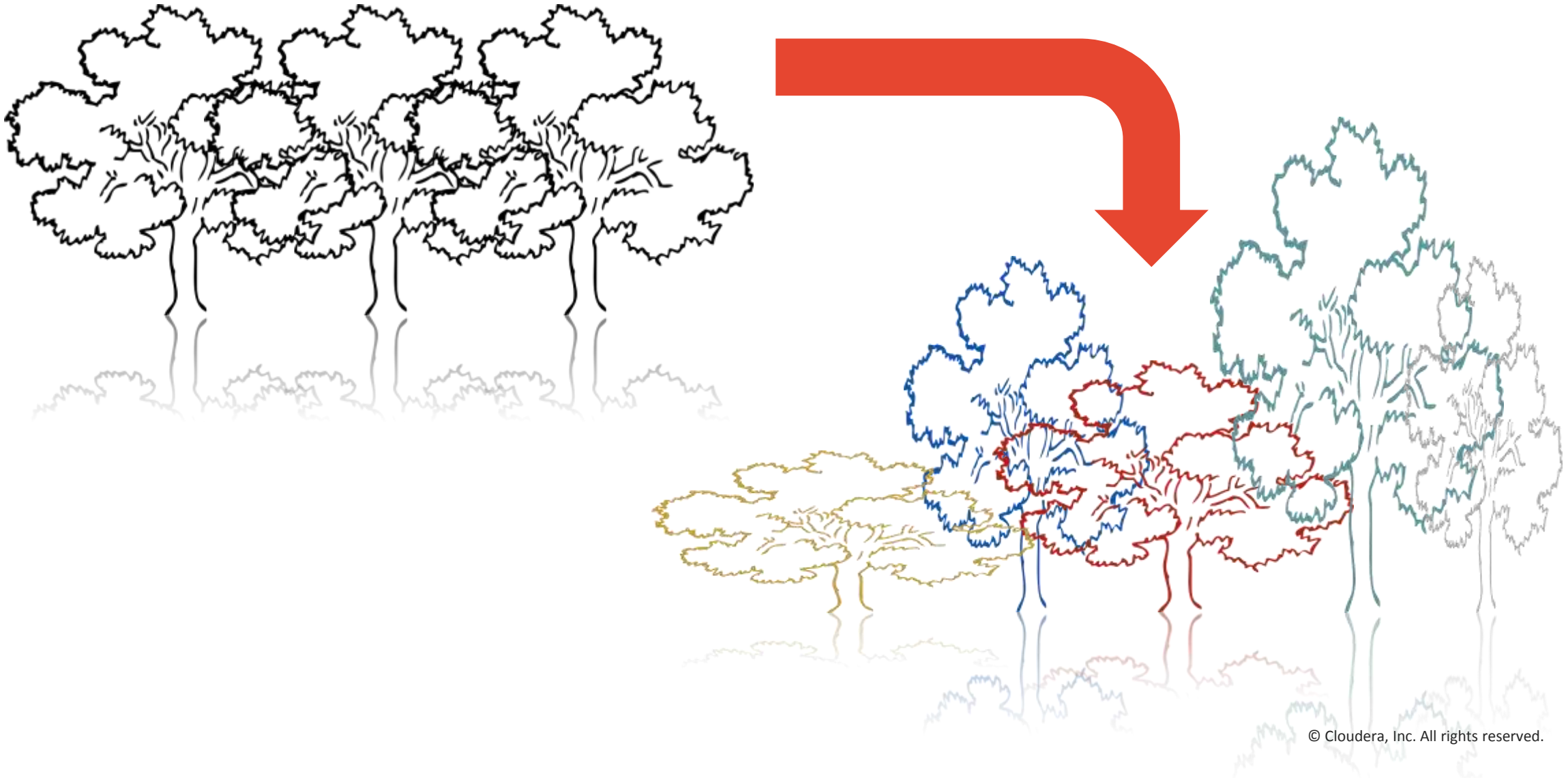
Correct 19,000



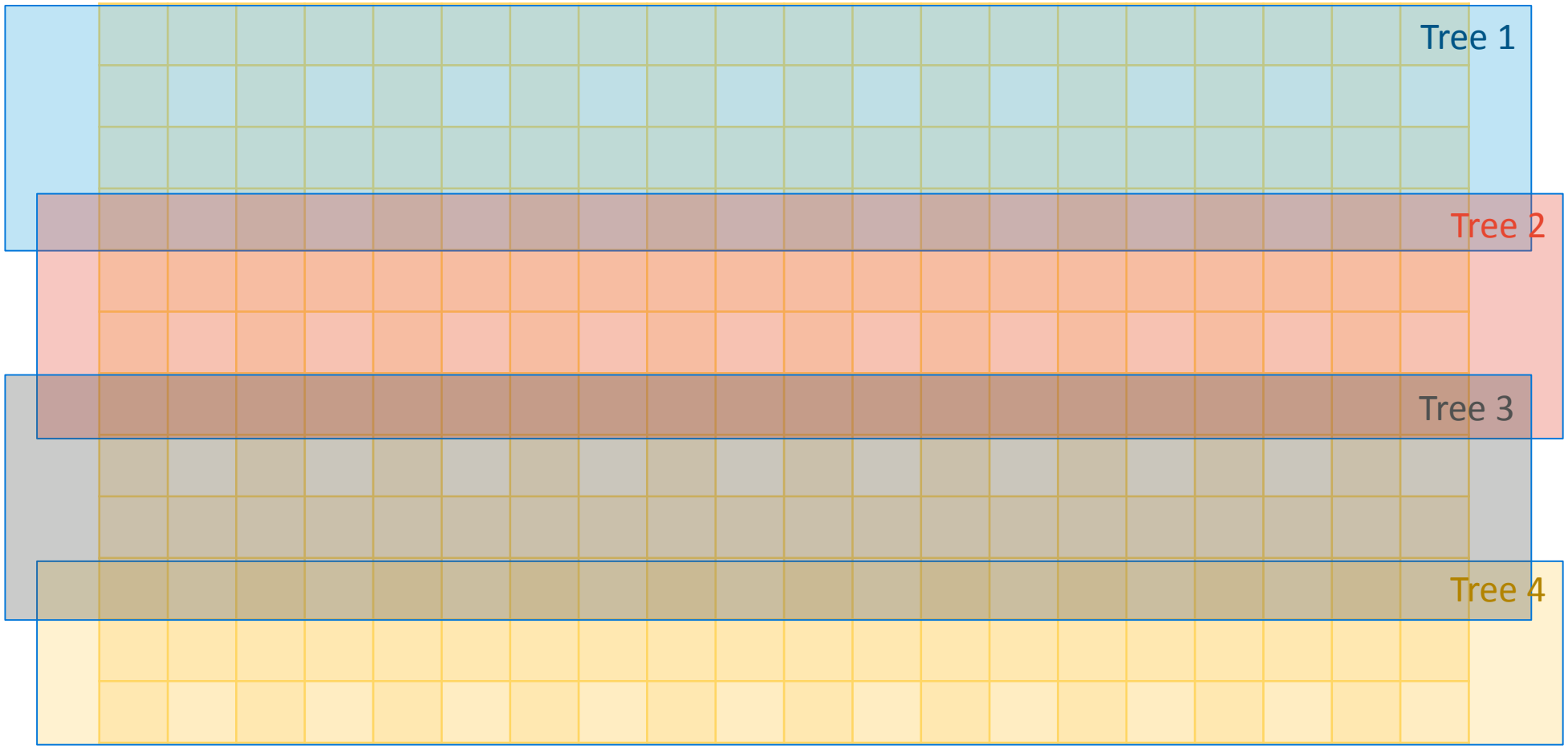
Random Decision Forests leverage the wisdom of a crowd of Decision Trees

commons.wikimedia.org/wiki/File:Walking_the_Avenue_of_the_Baobabs.jpg

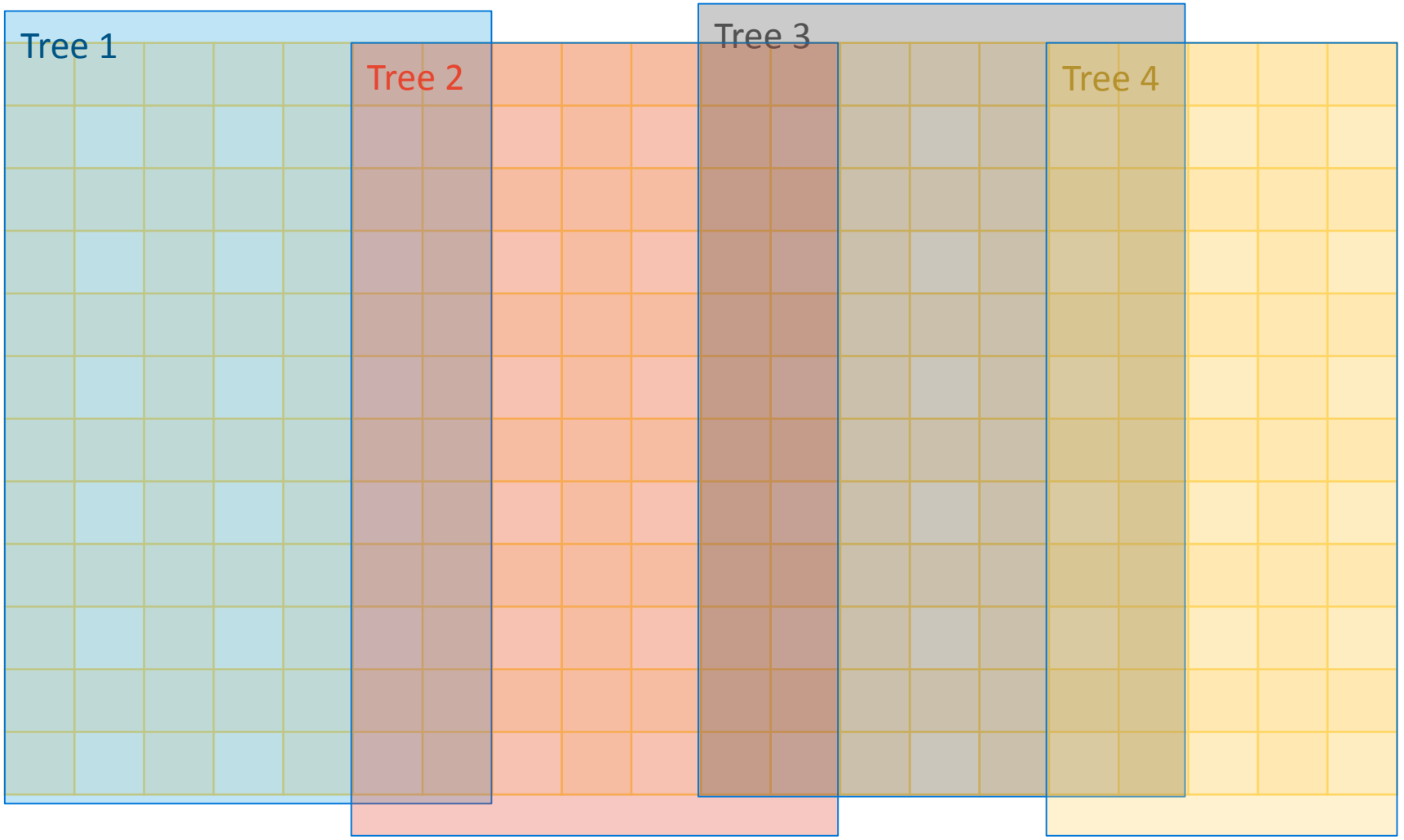
How to Create a Crowd?



Trees See Subsets of Examples



Or Subsets of Features



Diversity of Opinion

```
If (feature 0 <= 4199.0)
 If (feature 1 <= 14.0)
   Predict: 3.0
...
```

```
If (feature 11 <= 0,5)
  Predict: 1.0
...
```

```
If (feature 0 <= 3042.0)
 If (feature 0 <= 2509.0)
  If (feature 3 <= 0.0)
   If (feature 12 <= 0.0)
    Predict: 3.0
...
```

Random Decision Forests

```
RandomForest.trainClassifier(trainData,
  7, Map(10 -> 4, 11 -> 40),
  20, "auto", "entropy", 30, 300)
```

Number of Trees: 20

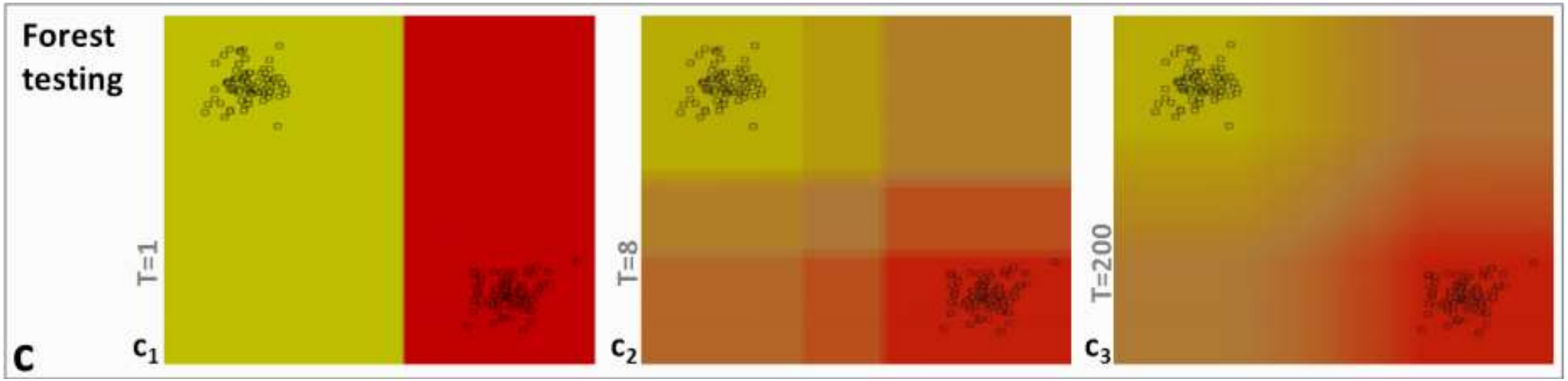
How many different decision trees to build

Feature Subset Strategy: auto

Intelligently pick a number of different features to try at each node

~ 96% accuracy

Forests Learn More Complex Boundaries



A. Criminisi, J. Shotton and E. Konukoglu. "Decision Forests for Classification, Regression, Density Estimation, Manifold Learning and Semi-Supervised Learning." p. 26

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Use random decision forests for regression

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Thank You

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