Please ask questions via the mobile app!

Engage

Fast Analytics on Big Data with H20

0xdata.com, h2o.ai

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Team

About H2O and 0xdata

- H2O is a platform for distributed in memory predictive analytics and machine learning
- Pure Java, Apache v2 Open Source
- Easy deployment with a single jar, automatic cloud discovery
- https://github.com/0xdata/h2o
- https://github.com/0xdata/h2o-dev
- Google group h2ostream
- ~15000 commits over two years, **very** active developers

Overview

- H2O Architecture
- GLM on H2O
  - demo
- Random Forest

H2O Architecture

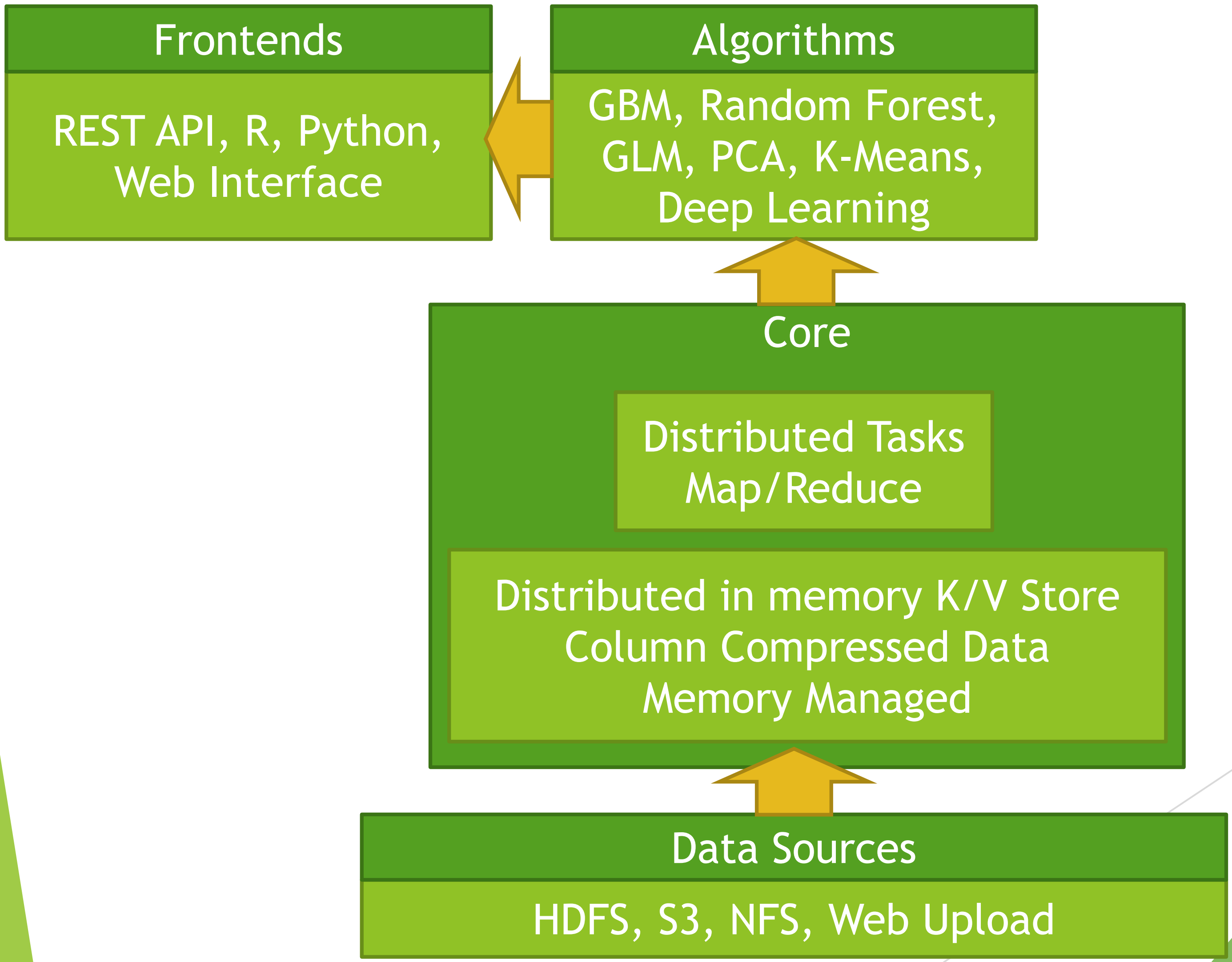
Practical Data Science

- Data scientists are not necessarily trained as computer scientists
- A “typical” data science team is about 20% CS, working mostly on UI and visualization tools
- An example is Netflix
  - Statisticians prototype in R
  - When done, developers recode the code in Java and Hadoop

What we want from modern machine learning platform

Requirements	Solution
Fast & Interactive	In-Memory
Big Data (no sampling)	Distributed
Flexibility	Open Source
Extensibility	API/SDK
Portability	Java, REST/JSON
Infrastructure	Cloud or On-Premise Hadoop or Private Cluster

H2O Architecture

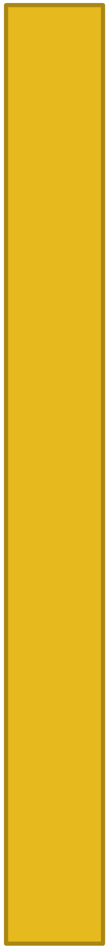


Distributed Data Taxonomy

Vector

Distributed Data Taxonomy

Vector

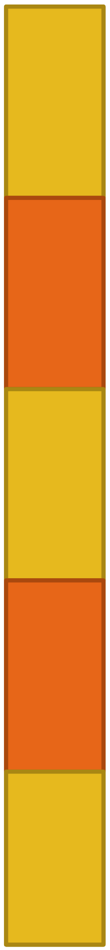


The vector may be very large ~ billions of rows

- Store compressed (often 2-4x)
- Access as Java primitives with on the fly decompression
- Support fast Random access
- Modifiable with Java memory semantics

Distributed Data Taxonomy

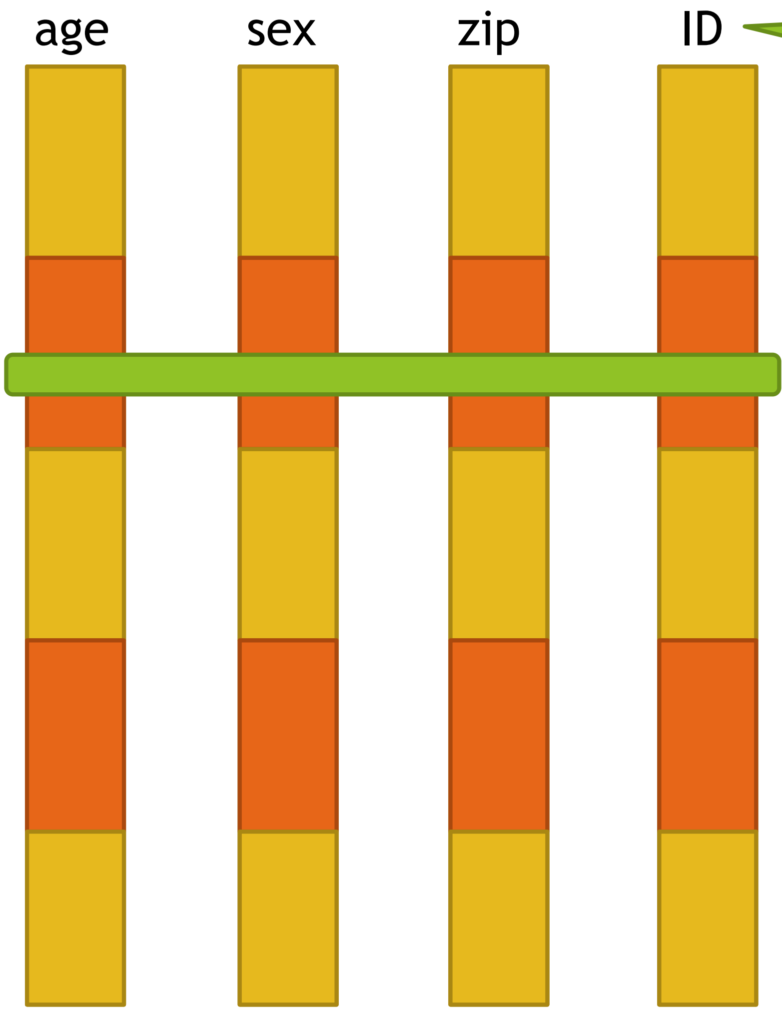
Vector



Large vectors must be distributed over multiple JVMs

- Vector is split into chunks
- Chunk is a unit of parallel access
- Each chunk ~ 1000 elements
- Per chunk compression
- Homed to a single node
- Can be spilled to disk
- GC very cheap

Distributed Data Taxonomy



Distributed data frame

A row is always stored in a single JVM

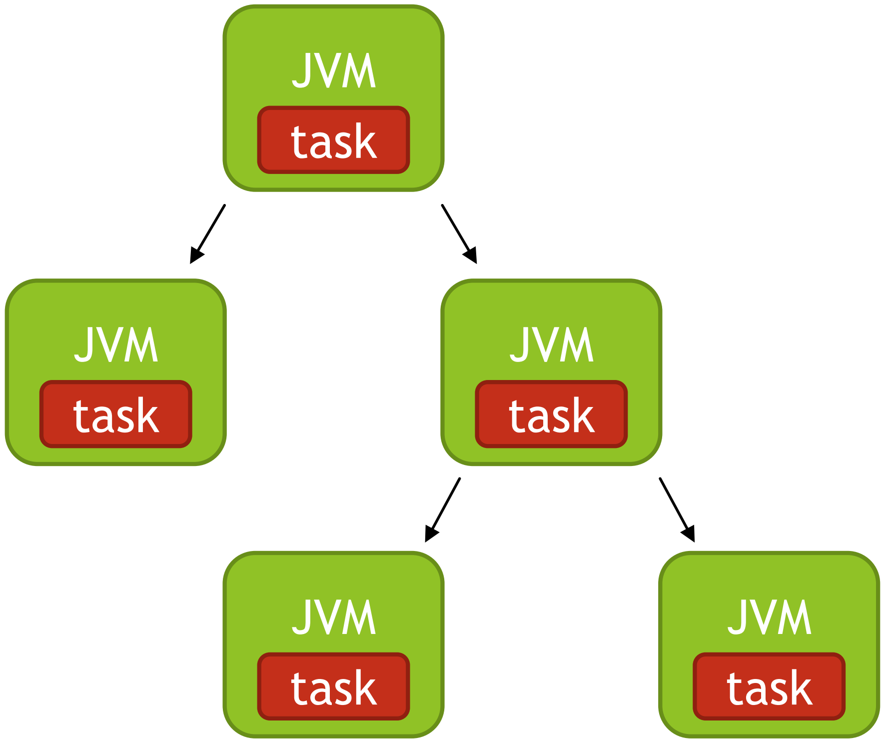
- Similar to R frame
- Adding and removing columns is cheap
- Row-wise access

Distributed Data Taxonomy

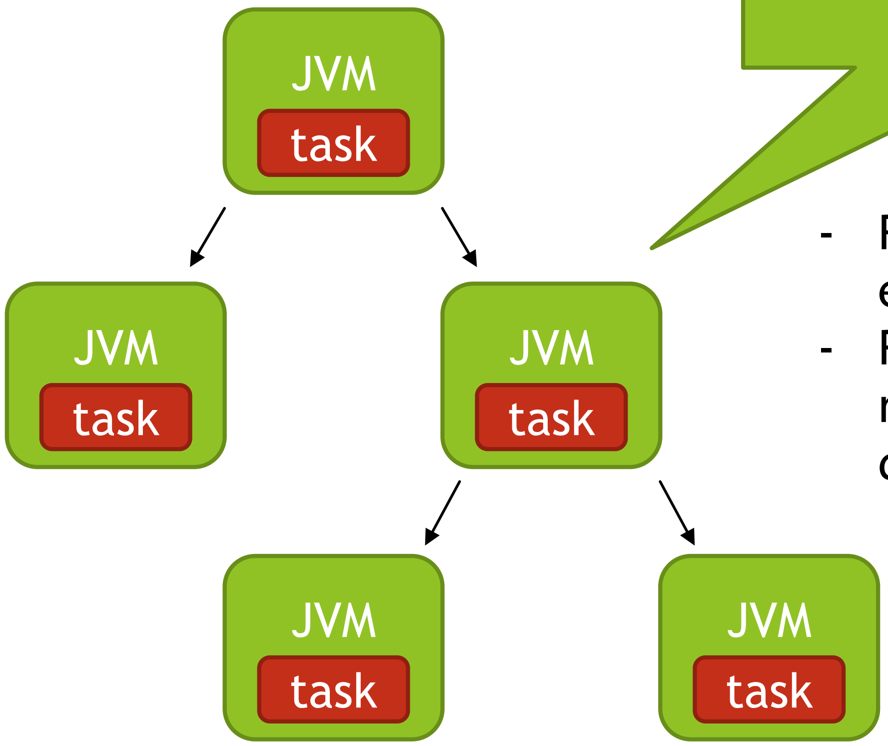
- Elem – a java double
- Chunk – a collection of thousands to millions of elems
- Vec – a collection of Chunks
- Frame – a collection of Vecs

- Row i - i’th elements of all the vecs in a frame

Distributed Fork/Join



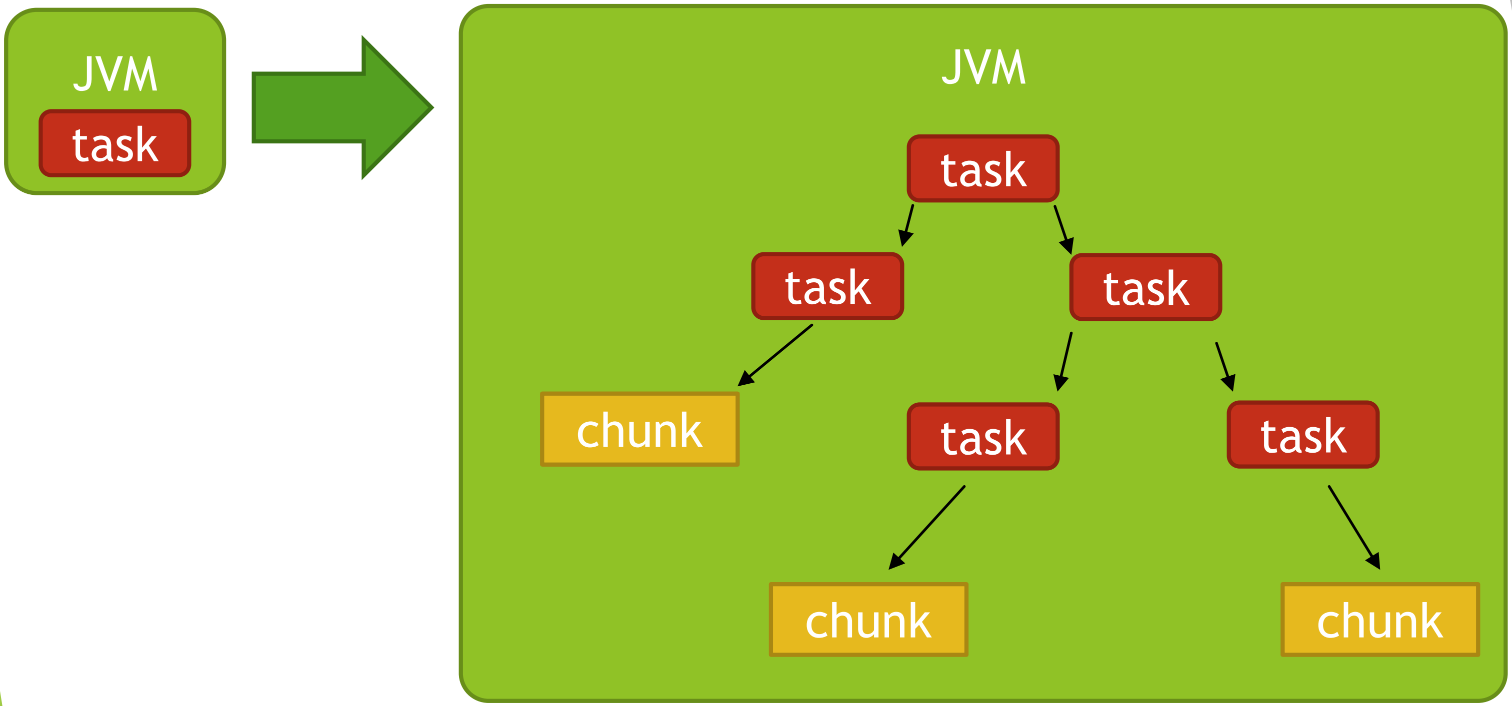
Distributed Fork/Join



Task is distributed in a tree pattern

- Results are reduced at each inner node
- Returns with a single result when all subtasks done

Distributed Fork/Join



- On each node the task is parallelized over home chunks using Fork/Join
- No blocked thread using continuation passing style

Distributed Code

- Simple tasks
  - Executed on a single remote node
- Map/Reduce
  - Two operations
    - map(x) -> y
    - reduce(y, y) -> y
  - Automatically distributed amongst the cluster and worker threads inside the nodes

Distributed Code

```
double sumY2 = new MRTask2(){
   double map(double x){
       return x*x;
   }
   double reduce(double x, double y){
       return x + y;
   }
}.doAll(vec);
```

Demo

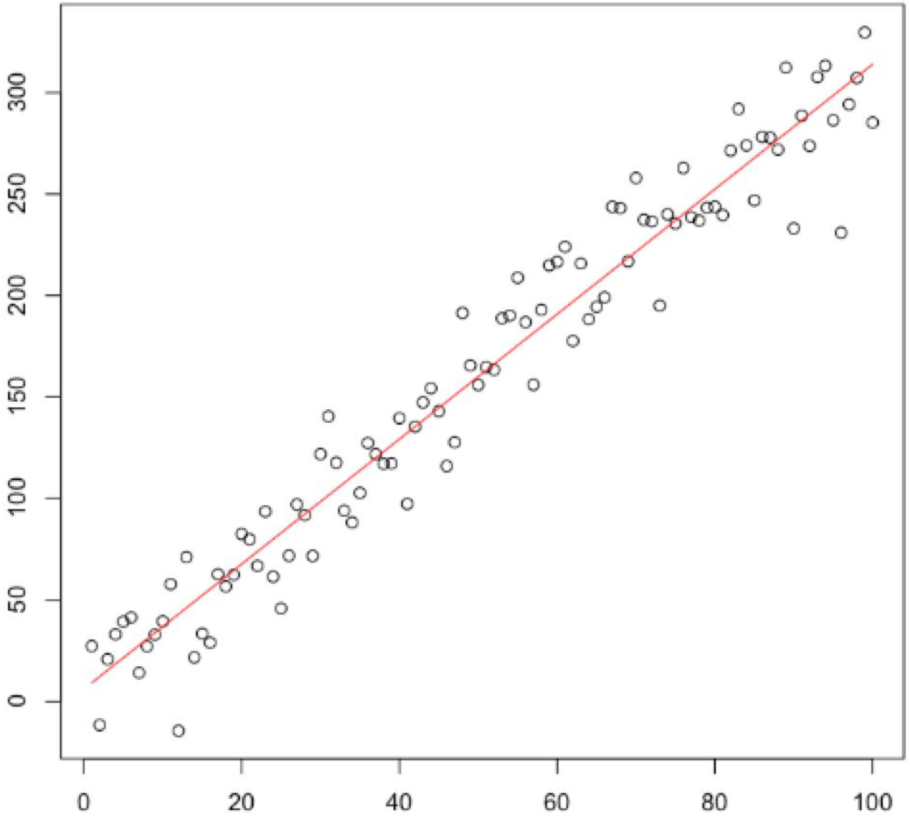
GLM

CTR Prediction Contest

- Kaggle contest- clickthrought rate prediction
- Data
  - 11 days worth of clickthrough data from Avazu
  - ~ 8GB, ~ 44 million rows
  - Mostly categoricals
- Large number of features (predictors), good fit for linear models

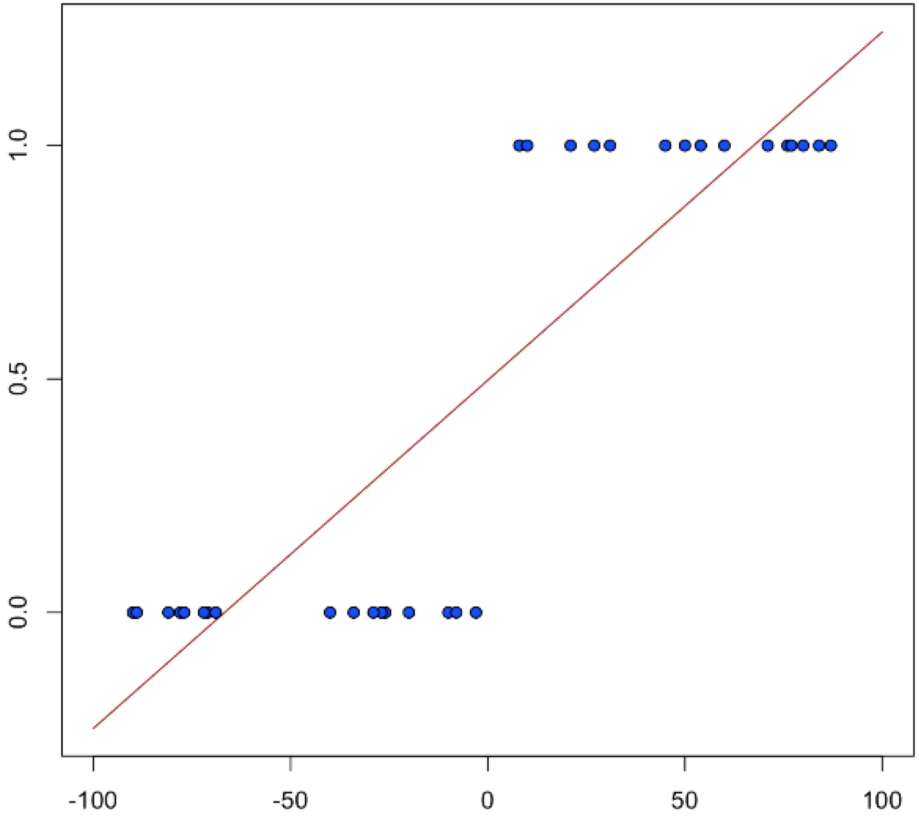
Linear Regression

- Least Squares Fit



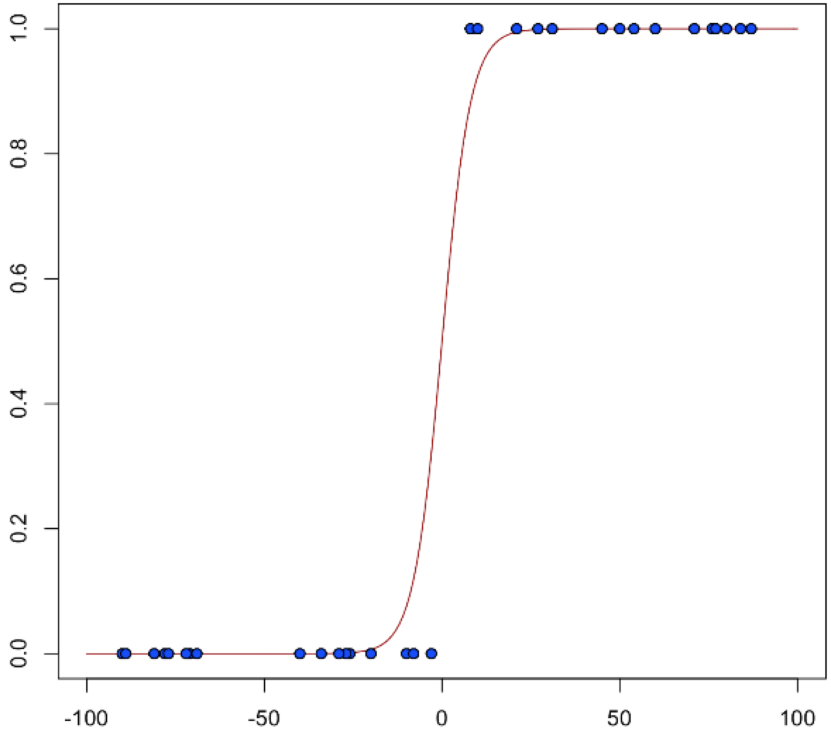
Logistic Regression

- Least Squares Fit



Logistic Regression

- GLM Fit



Generalized Linear Modelling

- Solved by iterative reweighted least squares
- Computation in two parts
  - Compute $X^T X$
  - Compute inverse of $X^T X$ (Cholesky Decomposition)
- Assumption
  - Number of rows >> number of cols
  - (use strong rules to filter out inactive columns)
- Complexity
  - Nrows * Ncols2/N*P +Ncols3/P

Generalized Linear Modelling

- Solved by iterative reweighted least squares
- Computation in two parts
  - Compute $X^T X$ Distributed
  - Compute inverse of $X^T X$ (Cholesky Decomposition) Single Node
- Assumption
  - Number of rows >> number of cols
  - (use strong rules to filter out inactive columns)
- Complexity
  - Nrows * Ncols2/N*P +Ncols3/P

Random Forest

How Big is Big?

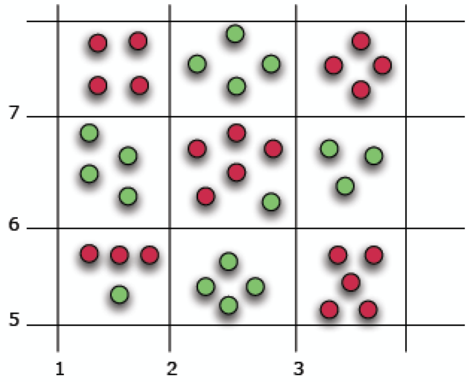
- Data set size is relative
  - Does the data fit in one machine’s RAM
  - Does the data fit in one machine’s disk
  - Does the data fit in several machine’s RAM
  - Does the data fit in several machine’s disk

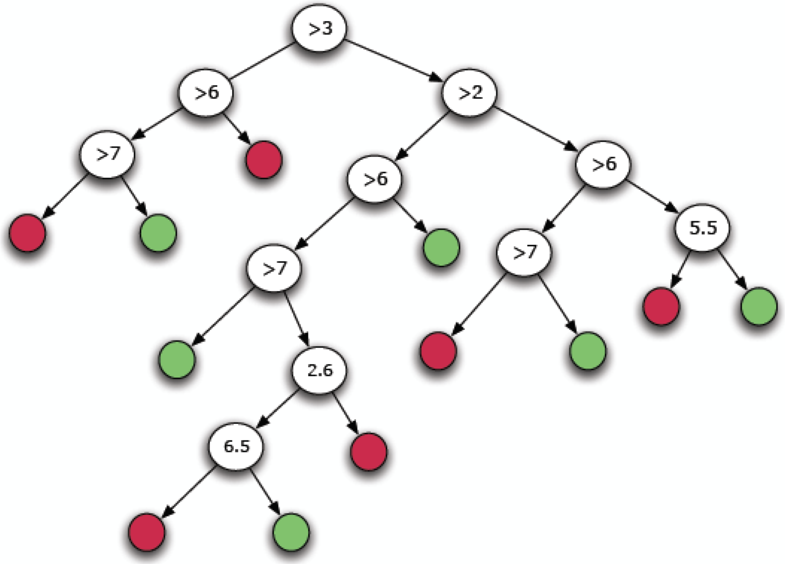
Why so Random?

- Introducing
  - Random Forest
  - Bagging
  - Out of bag error estimate
  - Confusion matrix

- Leo Breiman: Random Forests. Machine Learning, 2001

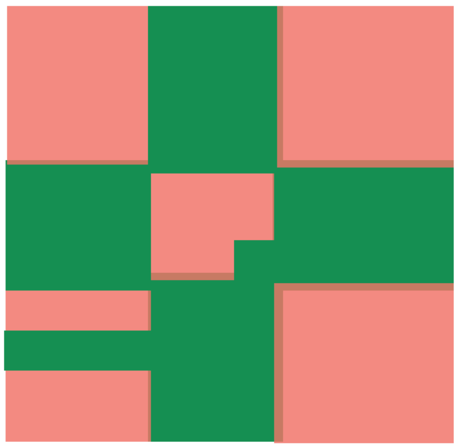
Classification Trees

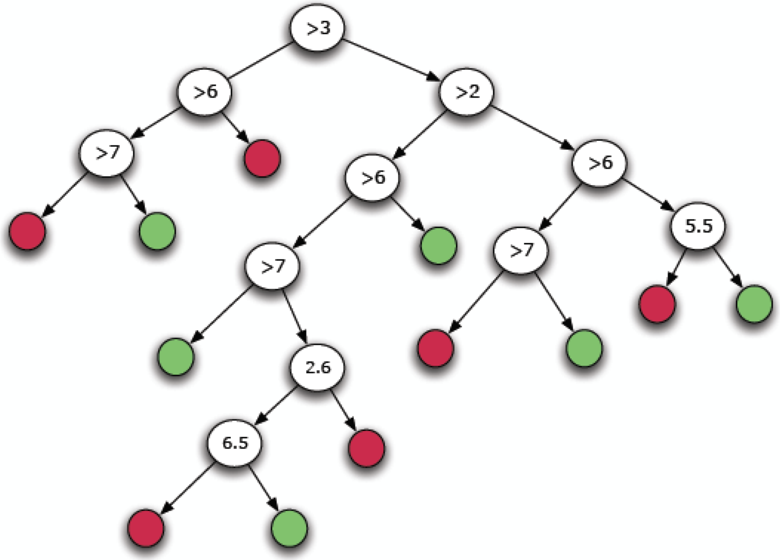




- Consider a supervised learning problem with a simple data set with two classes and two features **x** in [1,4] and **y** in [5,8]
- We can build a classification tree to predict of new observations

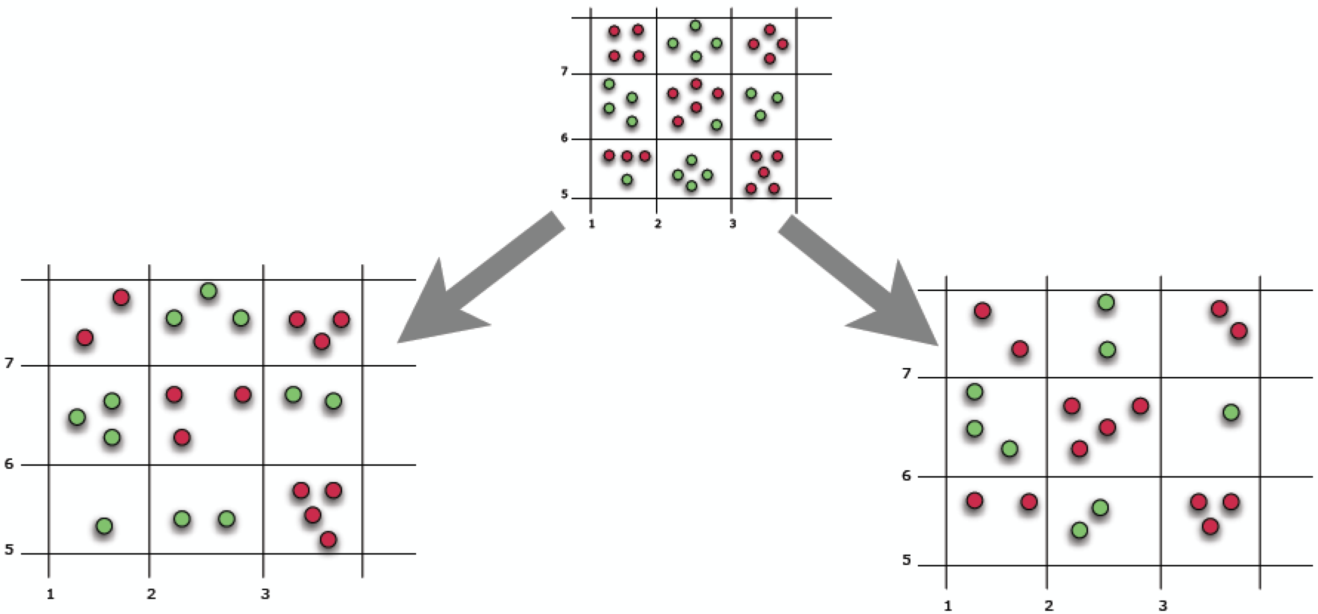
Classification Trees





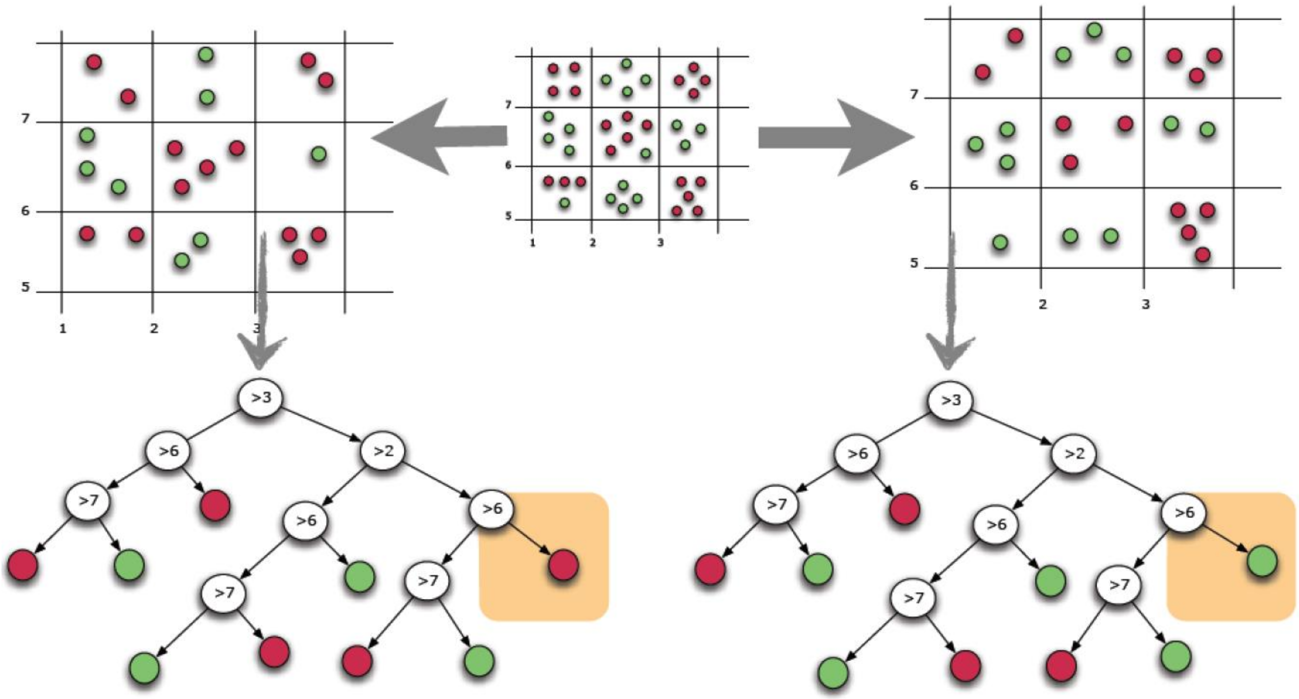
- Classification trees often overfit the data

Random Forest



- Overfiting is avoided by building multiple randomized and far less precise (partial) trees
  - All these trees in fact underfit
- Result is obtained by a vote over the ensemble of the decision trees
  - Different voting strategies possible

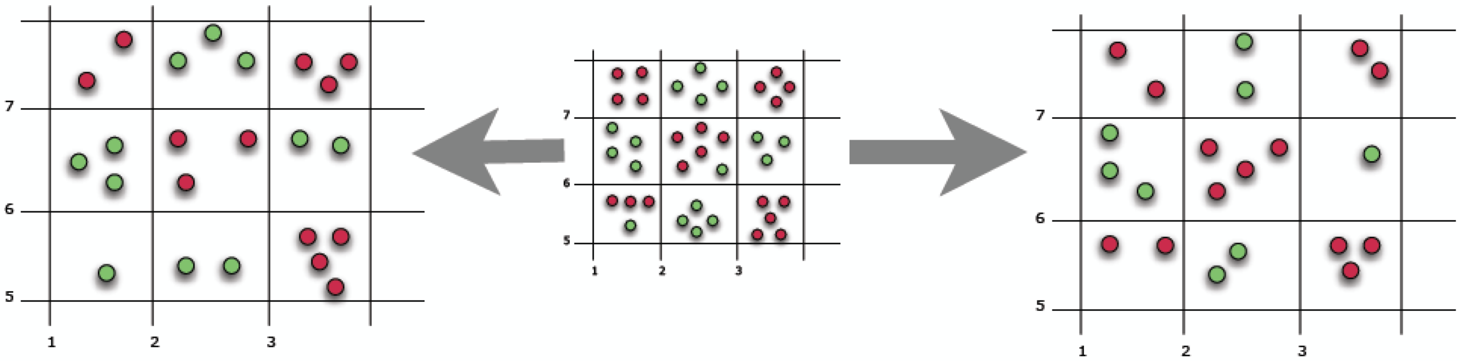
Random Forest



- Each tree sees a different part of the training set and captures the information it contains

Random Forest

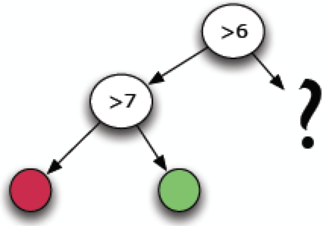
- Each tree sees a different random selection of the training set (without replacement)



- At each split, a random subset of features is selected over which the decision should maximize gain
  - Gini Impurity
  - Information gain

Random Forest

- Each tree sees a different random selection of the training set (without replacement)
  - Bagging
- At each split, a random subset of features is selected over which the decision should maximize gain



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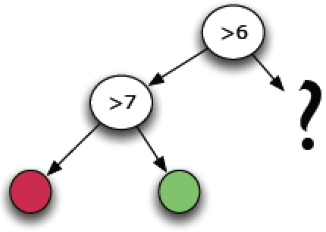

  - Gini Impurity $I_G(f) = \sum_{i=1}^{m} f_i(1-f_i) = \sum_{i=1}^{m}(f_i - f_i^2) = \sum_{i=1}^{m} f_i - \sum_{i=1}^{m} f_i^2 = 1 - \sum_{i=1}^{m} f_i^2$
  - Information gain

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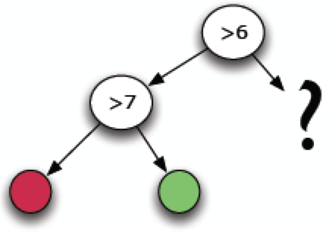
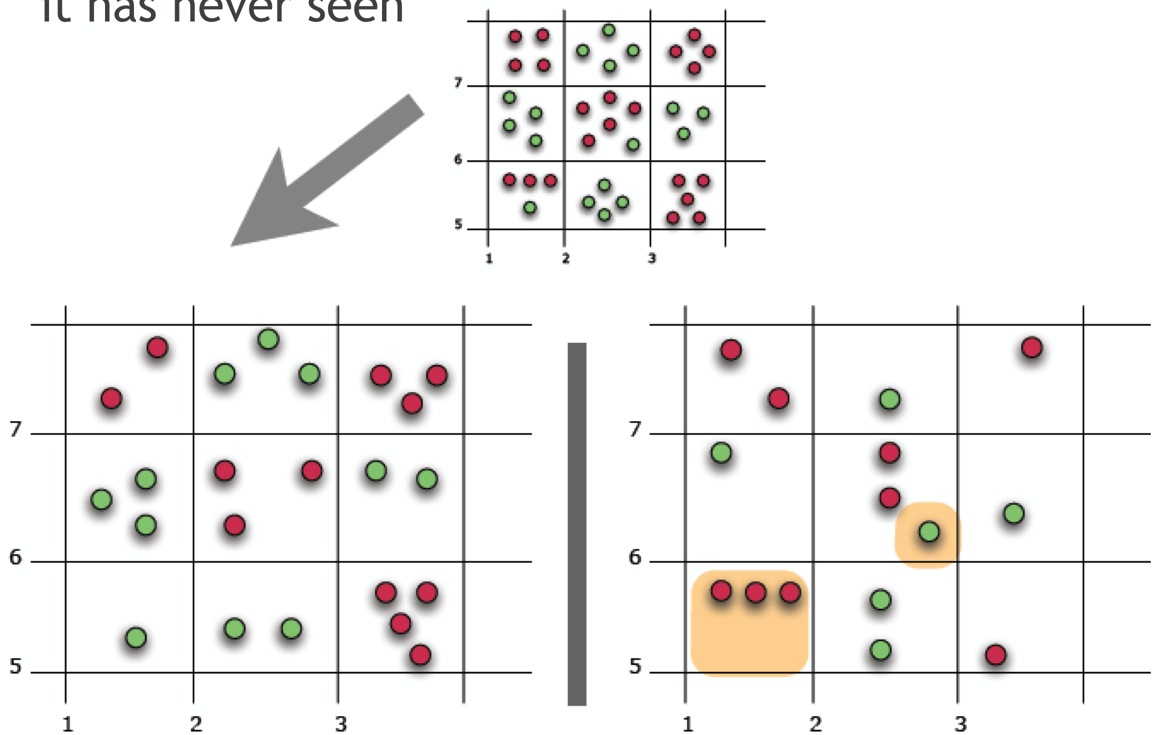


  - Gini Impurity
  - Information gain $I_E(f) = -\sum_{i=1}^{m} f_i \log_2 f_i$

Validating the trees

- We can exploit the fact that each tree sees only a subset of the training data
- Each tree in the forest is validated on the training data it has never seen



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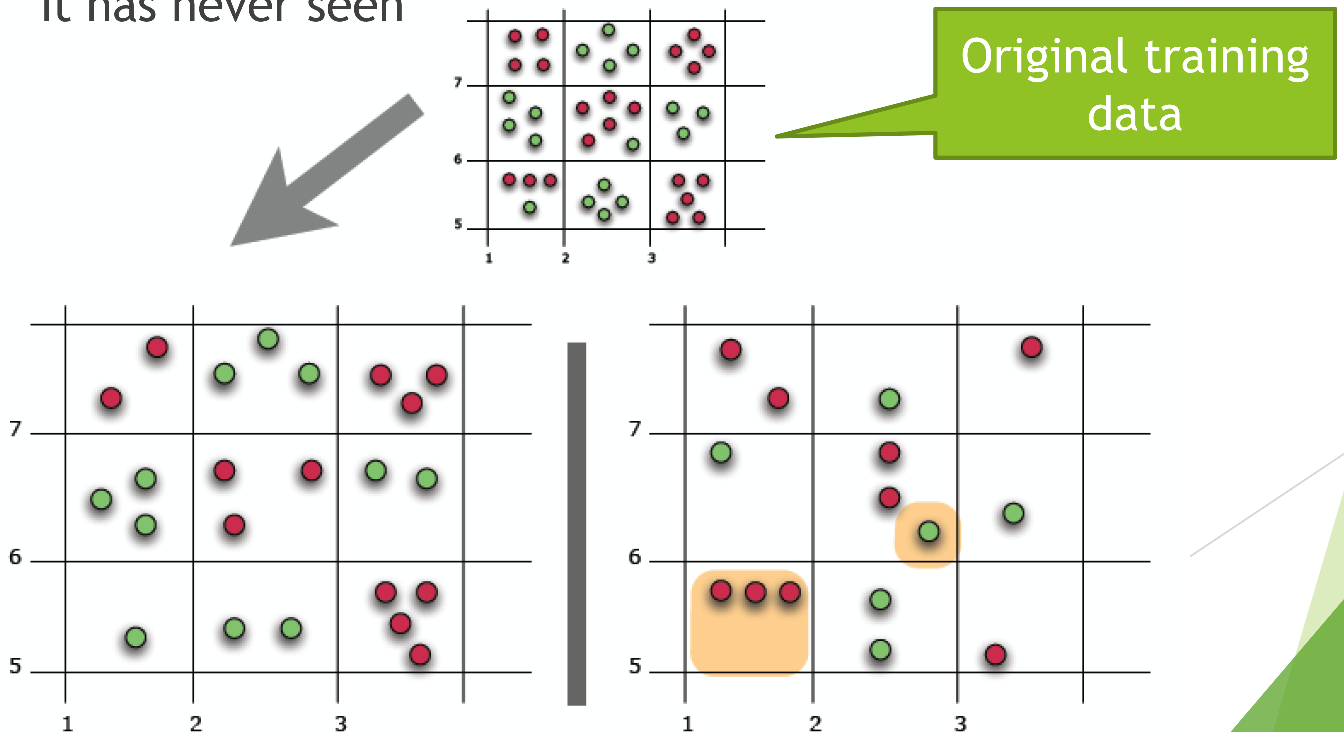

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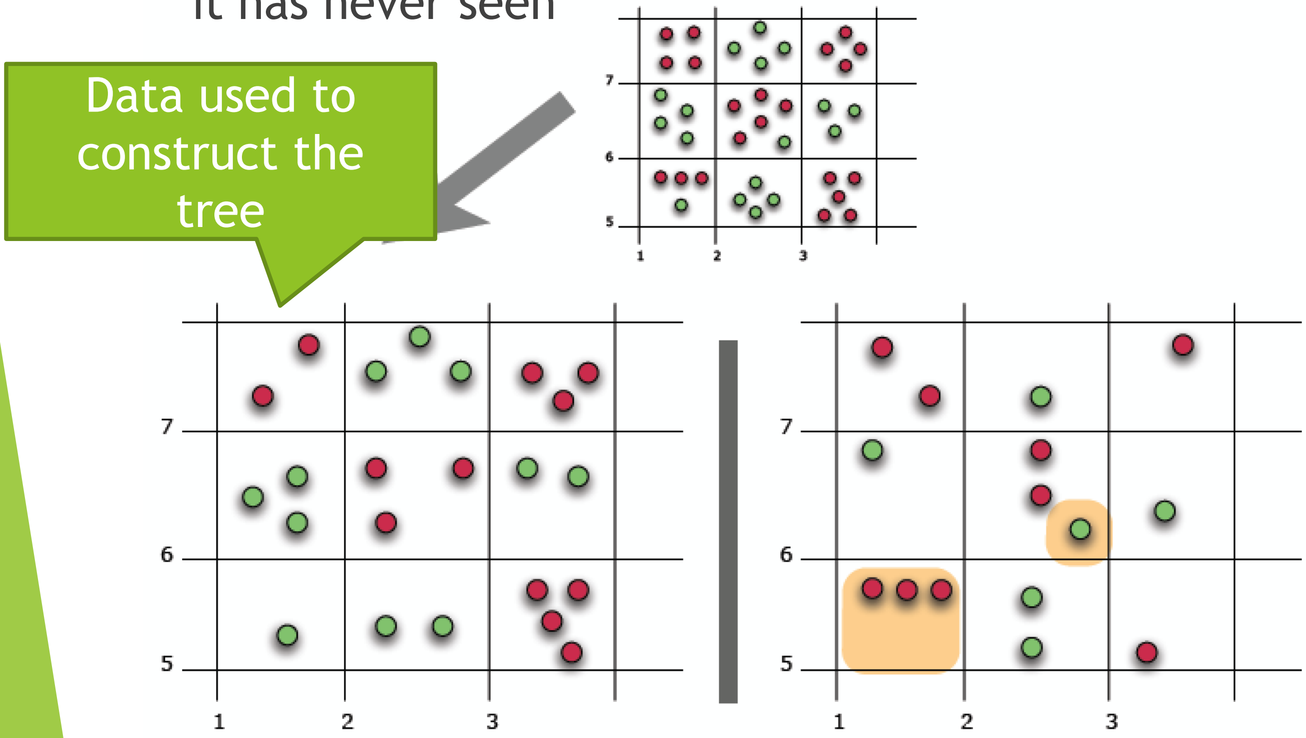

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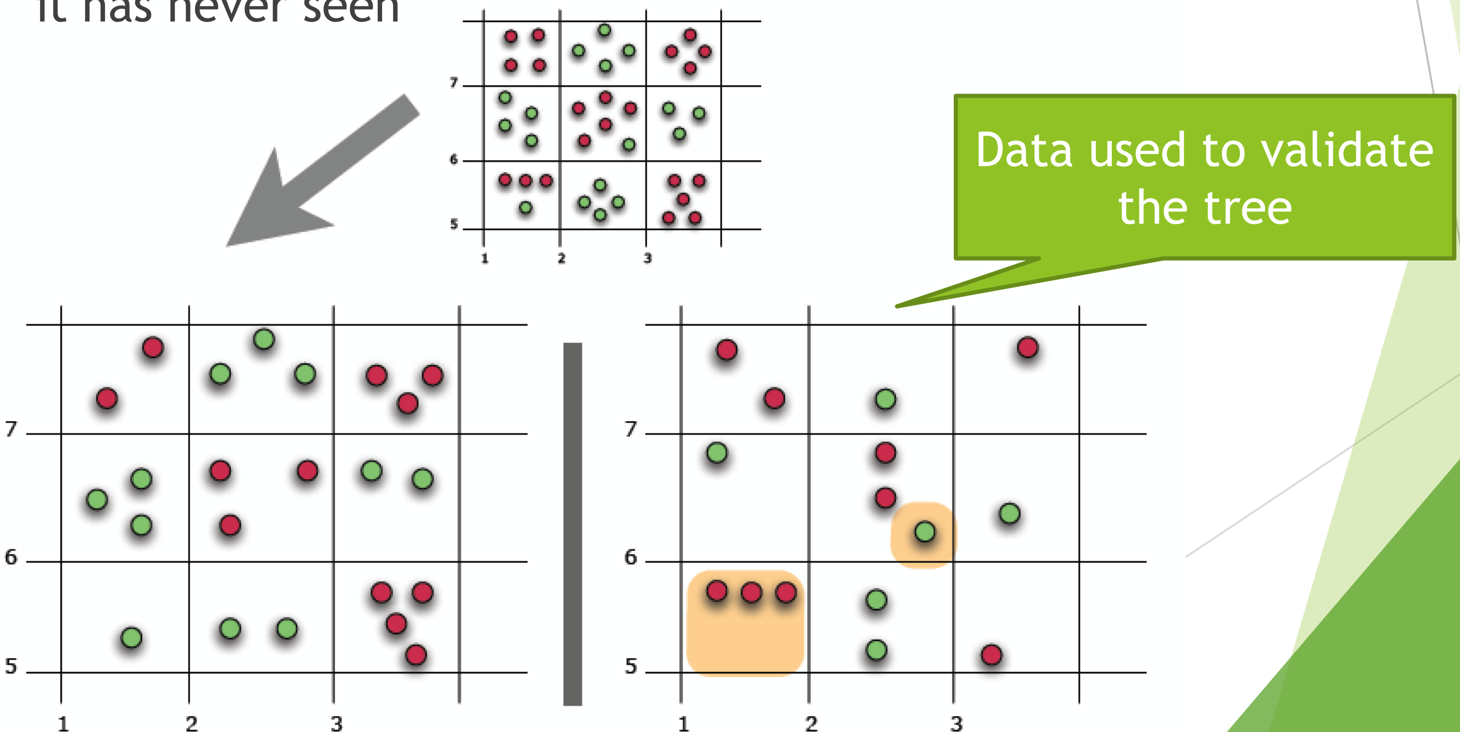

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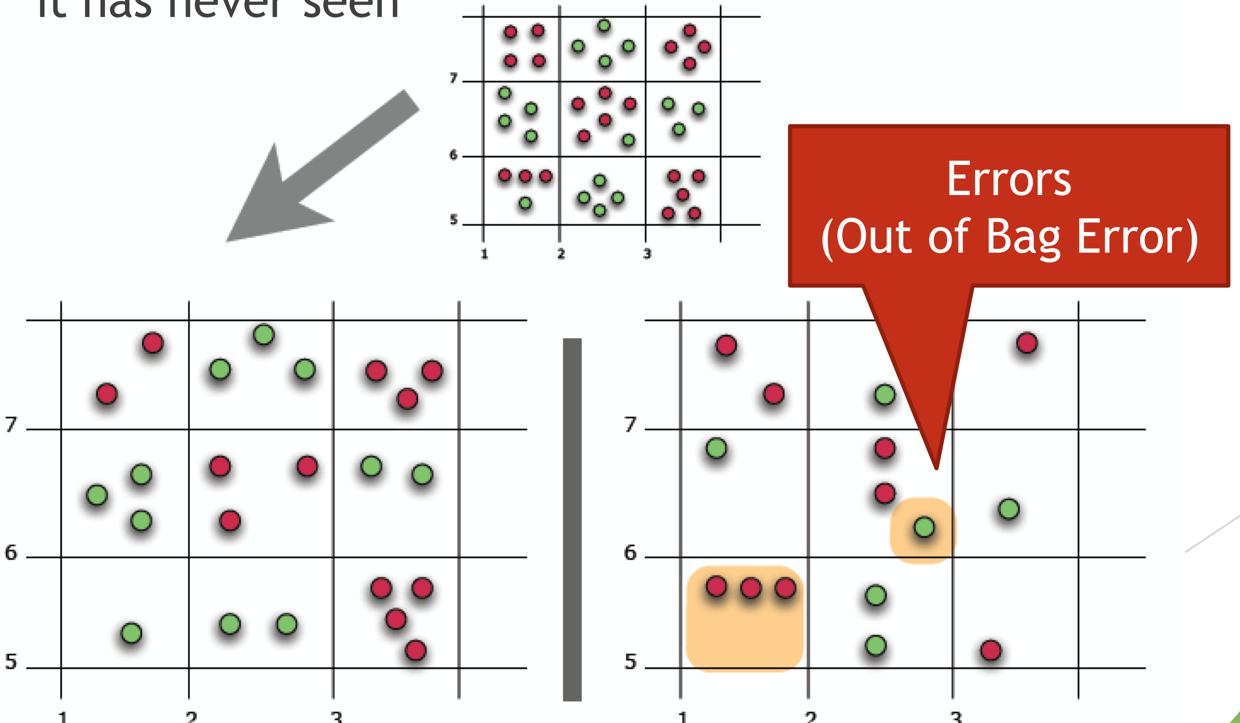

Validating the Forest

- Confusion Matrix is build for the forest and training data
  - During a vote, trees trained on the current row are ignored

actual/ assigned	Red	Green	
Red	15	5	33%
Green	1	10	10%

Distributing and Parallelizing

- How do we sample?
- How do we select splits?
- How do we estimate OOBE?

Distributing and Parallelizing

- How do we sample?
- How do we select splits?
- How do we estimate OOBE?
- When random data sample fits in memory, RF building parallelize extremely well
  - Parallel tree building is trivial
  - Validation requires trees to be collocated with data
    - Moving trees to data
    - (large training datasets can produce huge trees!)

Random Forest in H2O

- Trees must be built in parallel over randomized data samples
- To calculate gains, feature sets must be sorted at each split

Random Forest in H2O

- Trees must be built in parallel over randomized data samples
  - H2O reads data and distributes them over the nodes
  - Each node builds trees in parallel on a sample of the data that fits locally
- To calculate gains, feature sets must be sorted at each split

Random Forest in H2O

- Trees must be built in parallel over randomized data samples
- To calculate gains, feature sets must be sorted at each split
  - the values are discretized -> instead of sorting features are represented as arrays of their cardinality
  - { (2, **red**), (3.4, **red**), (5, **green**), (6.1, **green**) }
    becomes
    { (1, **red**), (2, **red**), (3, **green**), (4, **green**) }
  - But trees can be very large (~100k splits)

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Binning

Lessons Learned

- Java Random is not really random
  - Small seeds give very bad random sequences resulting in poor RF performance
    - And we of course started with a deterministic seed of 42:)
  - But determinism is important for debugging
- Linux kernel drops TCP connections silently when under stress
  - Sender opens connection, sends, closes w/o exceptions, but receiver never sees the data
  - Need to recycle TCP connections and use TCP reliable delayer
- Good Diagnostics to detect hardware issues is needed
  - Specific UDP packet drops with 100% chance

Demo

Continued

Q & A

Thank you

Please evaluate this talk via the mobile app!

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