Scalable Machine Learning in R with H2O

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Introduction

- Statistician & Machine Learning Scientist at H2O.ai in Mountain View, California, USA
- Ph.D. in Biostatistics with Designated Emphasis in Computational Science and Engineering from UC Berkeley (focus on Machine Learning)
- Written a handful of machine learning R packages

Agenda

- Who/What is H2O?
- H2O Platform
  - H2O Distributed Computing
  - H2O Machine Learning
- H2O in R

H2O.ai

H2O.ai, the Company

- Team: 60; Founded in 2012
- Mountain View, CA
- Stanford & Purdue Math & Systems Engineers

H2O, the Platform

- Open Source Software (Apache 2.0 Licensed)
- R, Python, Scala, Java and Web Interfaces
- Distributed Algorithms that Scale to Big Data

Scientific Advisory Council

Dr. Trevor Hastie

- John A. Overdeck Professor of Mathematics, Stanford University
- PhD in Statistics, Stanford University
- Co-author, *The Elements of Statistical Learning: Prediction, Inference and Data Mining*
- Co-author with John Chambers, *Statistical Models in S*
- Co-author, *Generalized Additive Models*

Dr. Robert Tibshirani

- Professor of Statistics and Health Research and Policy, Stanford University
- PhD in Statistics, Stanford University
- Co-author, *The Elements of Statistical Learning: Prediction, Inference and Data Mining*
- Author, *Regression Shrinkage and Selection via the Lasso*
- Co-author, *An Introduction to the Bootstrap*

Dr. Steven Boyd

- Professor of Electrical Engineering and Computer Science, Stanford University
- PhD in Electrical Engineering and Computer Science, UC Berkeley
- Co-author, *Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers*
- Co-author, *Linear Matrix Inequalities in System and Control Theory*
- Co-author, *Convex Optimization*

H2O Platform

H2O Platform Overview

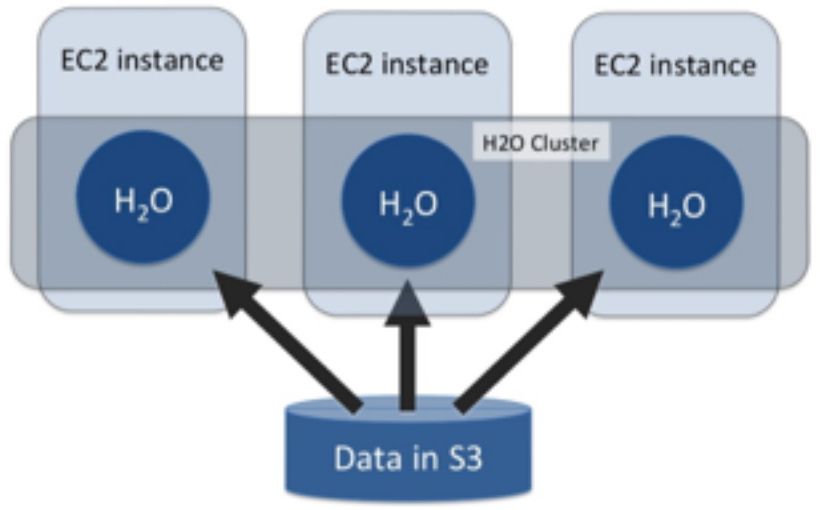
- Distributed implementations of cutting edge ML algorithms.
- Core algorithms written in high performance Java.
- APIs available in R, Python, Scala, REST/JSON.
- Interactive Web GUI.

H2O Platform Overview

- Write code in high-level language like R (or use the web GUI) and output production-ready models in Java.
- To scale, just add nodes to your H2O cluster.
- Works with Hadoop, Spark and your laptop.

H2O Distributed Computing

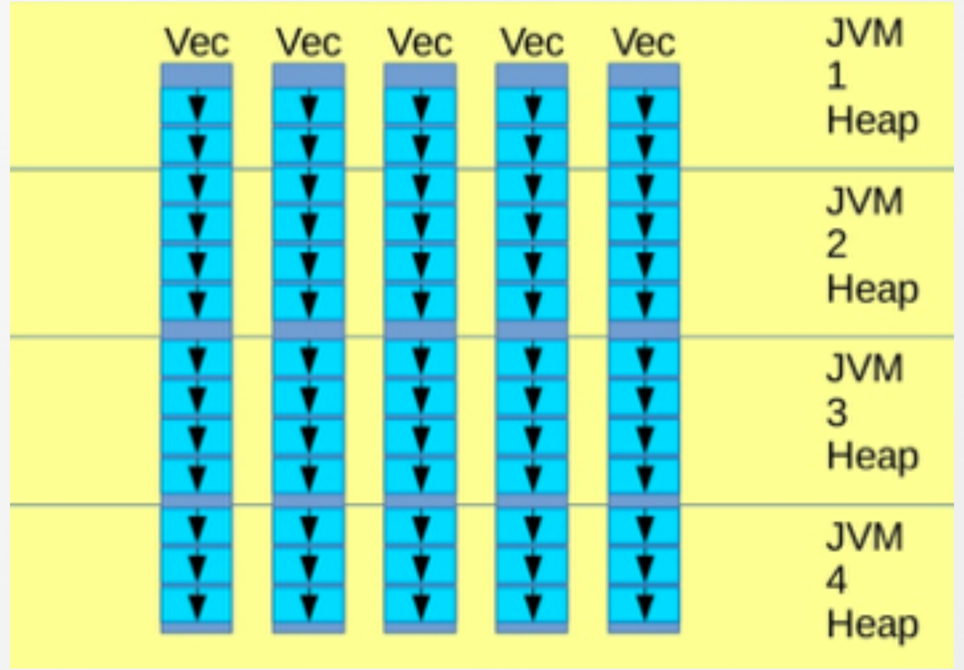
H2O Cluster



- Multi-node cluster with shared memory model.
- All computations in memory.
- Each node sees only some rows of the data.
- No limit on cluster size.

H2O Frame

- Distributed data frames (collection of distributed arrays).
- Columns are distributed across the cluster
- Single row is on a single machine.
- Syntax is the same as R's data.frame or Python's pandas.DataFrame



H2O Communication

Network Communication

- H2O requires network communication to JVMs in unrelated process or machine memory spaces.
- Performance is network dependent.

Reliable RPC

- H2O implements a reliable RPC which retries failed communications at the RPC level.
- We can pull cables from a running cluster, and plug them back in, and the cluster will recover.

Optimizations

- Message data is compressed in a variety of ways (because CPU is cheaper than network).
- Short messages are sent via 1 or 2 UDP packets; larger message use TCP for congestion control.

Data Processing in H2O

Map Reduce

- Map/Reduce is a nice way to write blatantly parallel code; we support a particularly fast and efficient flavor.
- Distributed fork/join and parallel map: within each node, classic fork/join.

Group By

- We have a GroupBy operator running at scale.
- GroupBy can handle millions of groups on billions of rows, and runs Map/Reduce tasks on the group members.

Ease of Use

- H2O has overloaded all the basic data frame manipulation functions in R and Python.
- Tasks such as imputation and one-hot encoding of categoricals is performed inside the algorithms.

H2O on Spark

Spark + H_2O

SPARKLING WATER

Sparkling Water

- Sparkling Water is transparent integration of H2O into the Spark ecosystem.
- H2O runs inside the Spark Executor JVM.

Features

- Provides access to high performance, distributed machine learning algorithms to Spark workflows.
- Alternative to the default MLlib library in Spark.

SparkR Implementation Details

- Central controller:
  - Explicitly “broadcast” auxiliary objects to worker nodes
- Distributed workers:
  - Scala code spans Rscript processes
  - Scala communicates with worker processes via stdin/stout using custom protocol
  - Serializes data via R serialization, simple binary serialization of integers, strings, raw byes
- Hides distributed operations
  - Same function names for local and distributed computation
  - Allows same code for simple case, distributed case

H2O vs SparkR

- Although SparkML / MLlib (in Scala) supports a good number of algorithms, SparkR still only supports GLMs.
- Major differences between H2O and Spark:
    - In SparkR, R each worker has to be able to access local R interpreter.
    - In H2O, there is only a (potentially local) instance of R driving the distributed computation in Java.

H2O Machine Learning

Current Algorithm Overview

Statistical Analysis

- Linear Models (GLM)
- Naïve Bayes

Ensembles

- Random Forest
- Distributed Trees
- Gradient Boosting Machine
- R Package - Stacking / Super Learner

Deep Neural Networks

- Multi-layer Feed-Forward Neural Network
- Auto-encoder
- Anomaly Detection
- Deep Features

Clustering

- K-Means

Dimension Reduction

- Principal Component Analysis
- Generalized Low Rank Models

Solvers & Optimization

- Generalized ADMM Solver
- L-BFGS (Quasi Newton Method)
- Ordinary Least-Square Solver
- Stochastic Gradient Descent

Data Munging

- Scalable Data Frames
- Sort, Slice, Log Transform

H2O in R

h2o R Package

Installation

- Java 7 or later; R 3.1 and above; Linux, Mac, Windows
- The easiest way to install the h2o R package is CRAN.
- Latest version: http://www.h2o.ai/download/h2o/r

Design

All computations are performed in highly optimized Java code in the H2O cluster, initiated by REST calls from R.

h2o R Package

```
> library(h2o)
> localH2O <- h2o.init(nthreads = -1, max_mem_size = "8G")

H2O is not running yet, starting it now...

Note:  In case of errors look at the following log files:
    /var/folders/2j/jg4sl53d5q53tc2_nzm9fz5h0000gn/T//RtmpAXY9gj/h2o_me_started_from_r.out
    /var/folders/2j/jg4sl53d5q53tc2_nzm9fz5h0000gn/T//RtmpAXY9gj/h2o_me_started_from_r.err

java version "1.8.0_45"
Java(TM) SE Runtime Environment (build 1.8.0_45-b14)
Java HotSpot(TM) 64-Bit Server VM (build 25.45-b02, mixed mode)

.Successfully connected to http://127.0.0.1:54321/

R is connected to the H2O cluster:
    H2O cluster uptime:         1 seconds 96 milliseconds
    H2O cluster version:        3.3.0.99999
    H2O cluster name:           H2O_started_from_R_me_kfo618
    H2O cluster total nodes:    1
    H2O cluster total memory:   7.11 GB
    H2O cluster total cores:    8
    H2O cluster allowed cores:  8
    H2O cluster healthy:        TRUE

>
```

Load Data into R

Example

```
library(h2o)  # First install from CRAN
localH2O <- h2o.init()  # Initialize the H2O cluster

# Data directly into H2O cluster (avoids R)
train <- h2o.importFile(path = "train.csv")

# Data into H2O from R data.frame
train <- as.h2o(my_df)
```

Train a Model & Predict

Example

```
y <- "Class"
x <- setdiff(names(train), y)

fit <- h2o.gbm(x = x, y = y, training_frame = train)

pred <- h2o.predict(fit, test)
```

Grid Search

Example

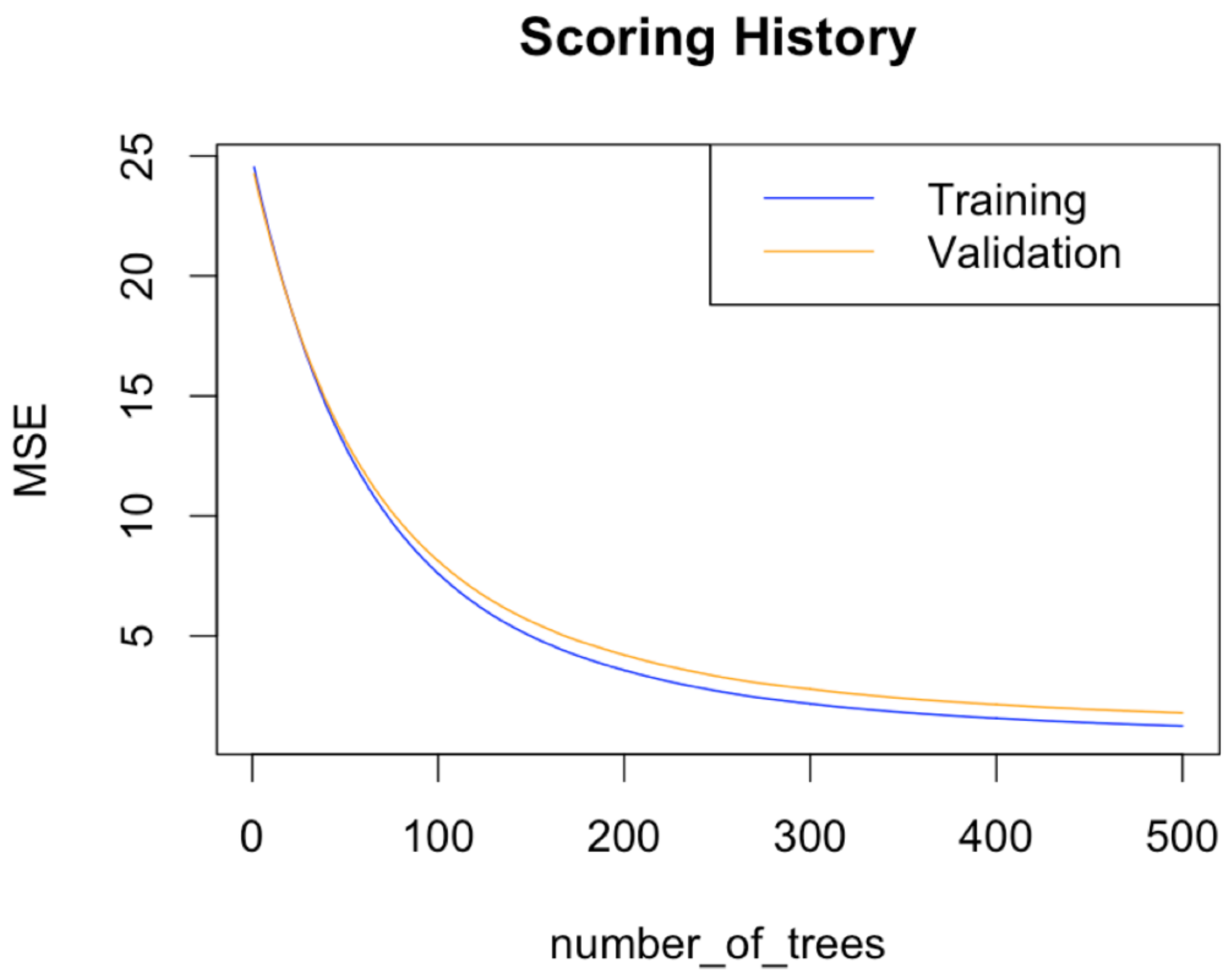
```
hidden_opt <- list(c(200,200), c(100,300,100), c(500,500))
l1_opt <- c(1e-5,1e-7)
hyper_params <- list(hidden = hidden_opt, l1 = l1_opt)

model_grid <- h2o.grid("deeplearning",
        hyper_params = hyper_params,
        x = x, y = y,
        training_frame = train,
        validation_frame = test)
```

H2O Ensemble

Example

```
library(h2oEnsemble)  #Install from GitHub

learner <- c("h2o.randomForest.1",
             "h2o.deeplearning.1",
             "h2o.deeplearning.2")

metalearner <- "h2o.glm.wrapper"

family <- "binomial"
```

Plotting Results



`plot(fit)` plots scoring history over time.

H2O R Code

https://github.com/h2oai/h2o-3/blob/master/h2o-r/h2o-package/R/gbm.R

https://github.com/h2oai/h2o-3/blob/26017bd1f5e0f025f6735172a195df4e794f311a/h2o-r/h2o-package/R/models.R#L103

H2O Resources

- H2O Online Training: http://learn.h2o.ai
- H2O Tutorials: https://github.com/h2oai/h2o-tutorials
- H2O Slidedecks: http://www.slideshare.net/0xdata
- H2O Video Presentations: https://www.youtube.com/user/0xdata
- H2O Community Events & Meetups: http://h2o.ai/events

Tutorial: Intro to H2O Algorithms

The “Intro to H2O” tutorial introduces five popular supervised machine learning algorithms in the context of a binary classification problem.

The training module demonstrates how to train models and evaluating model performance on a test set.

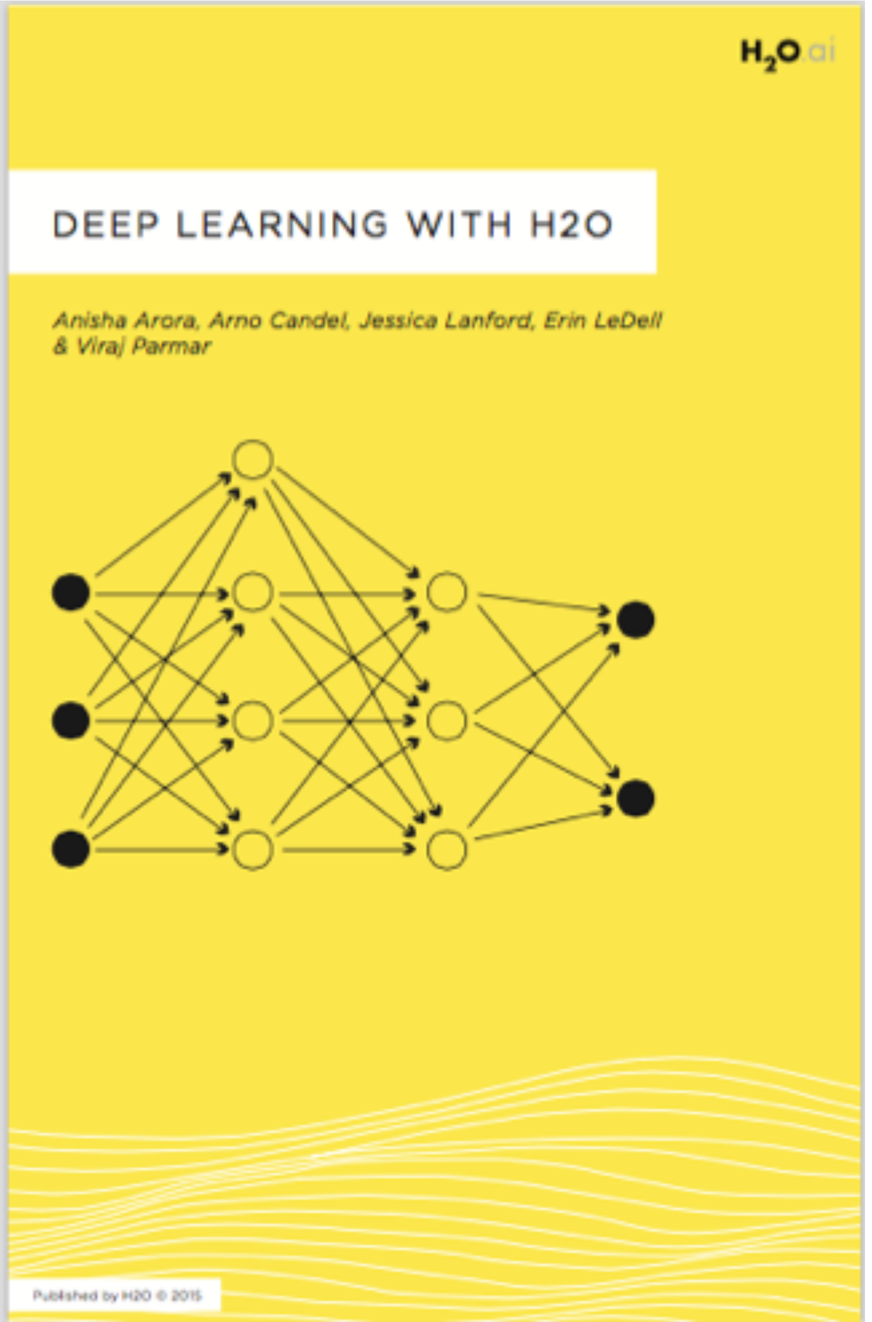
- Generalized Linear Model (GLM)
- Random Forest (RF)
- Gradient Boosting Machine (GBM)
- Deep Learning (DL)
- Naive Bayes (NB)

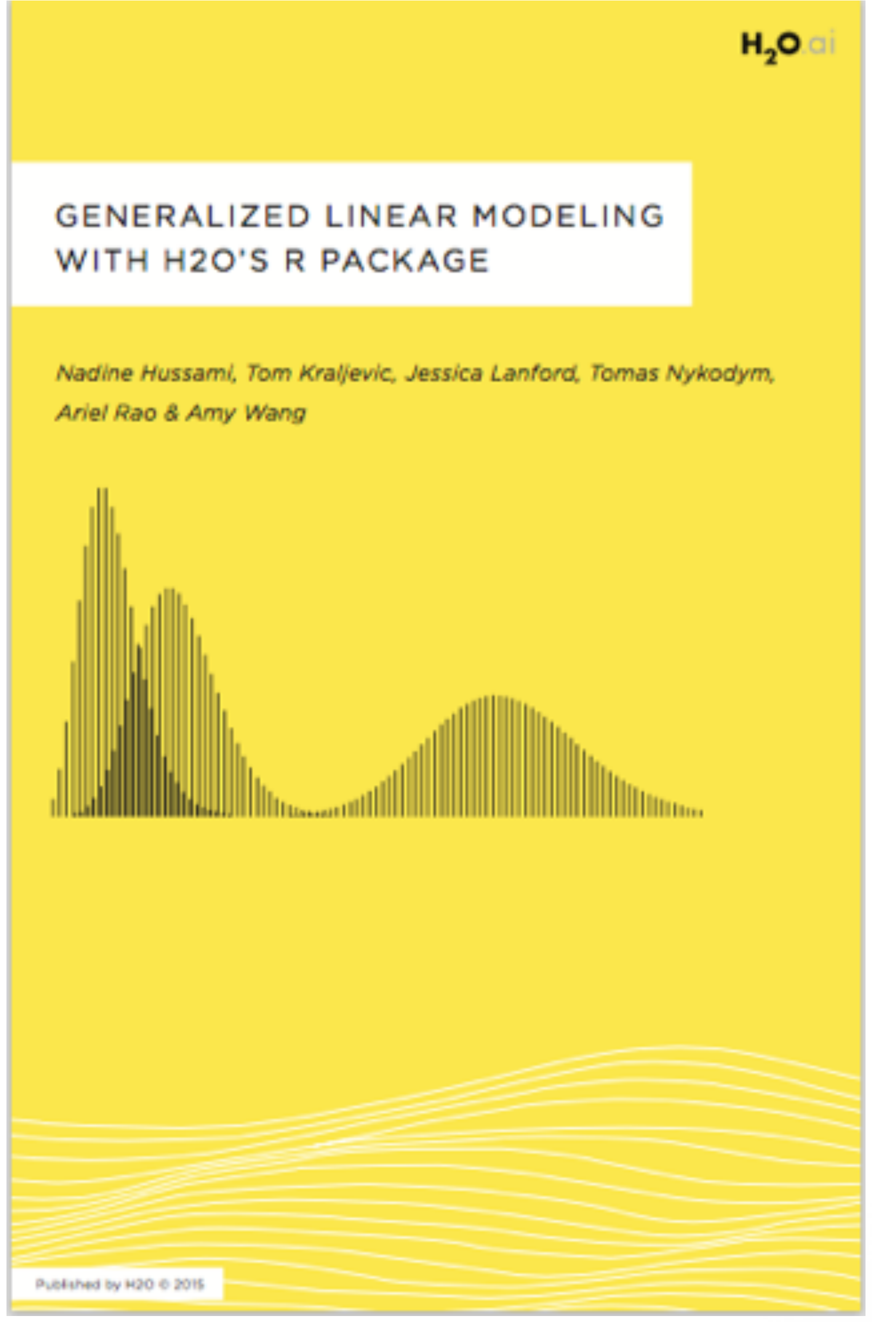
Tutorial: Grid Search for Model Selection

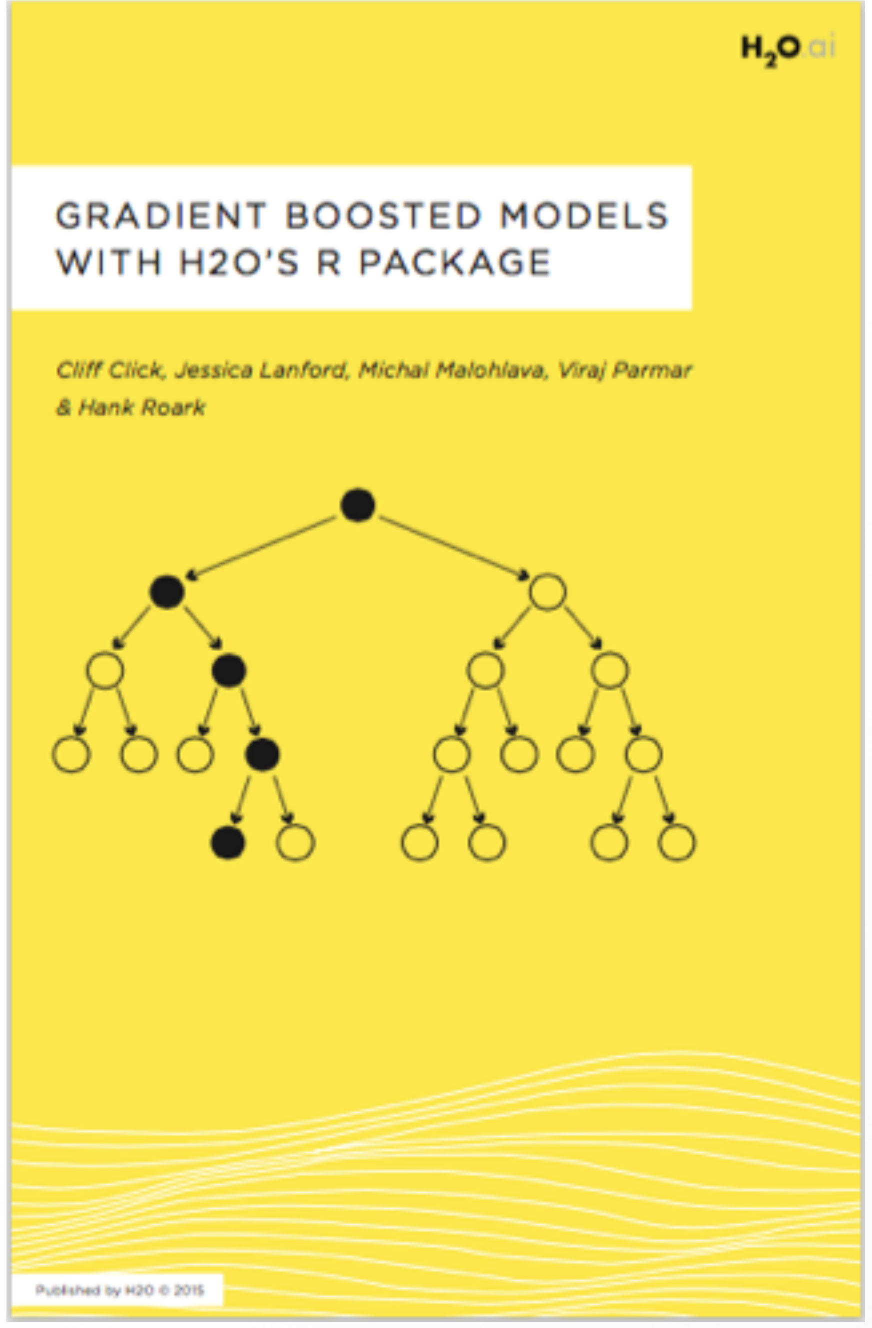
```
> print(gbm_gridperf)
H2O Grid Details
================

Grid ID: gbm_grid2
Used hyper parameters:
  -  sample_rate
  -  max_depth
  -  learn_rate
  -  col_sample_rate
Number of models: 72
Number of failed models: 0

Hyper-Parameter Search Summary: ordered by decreasing auc
  sample_rate max_depth learn_rate col_sample_rate         model_ids               auc
1           1         3       0.19               1 gbm_grid2_model_38 0.685166598389755
2         0.9         3       0.15               1 gbm_grid2_model_53 0.684956999713052
3         0.8         5       0.06               1 gbm_grid2_model_22 0.684843506375254
4         0.6         4       0.07               1  gbm_grid2_model_4 0.684327718715252
5        0.95         4       0.13               1 gbm_grid2_model_48 0.684042497773235
```

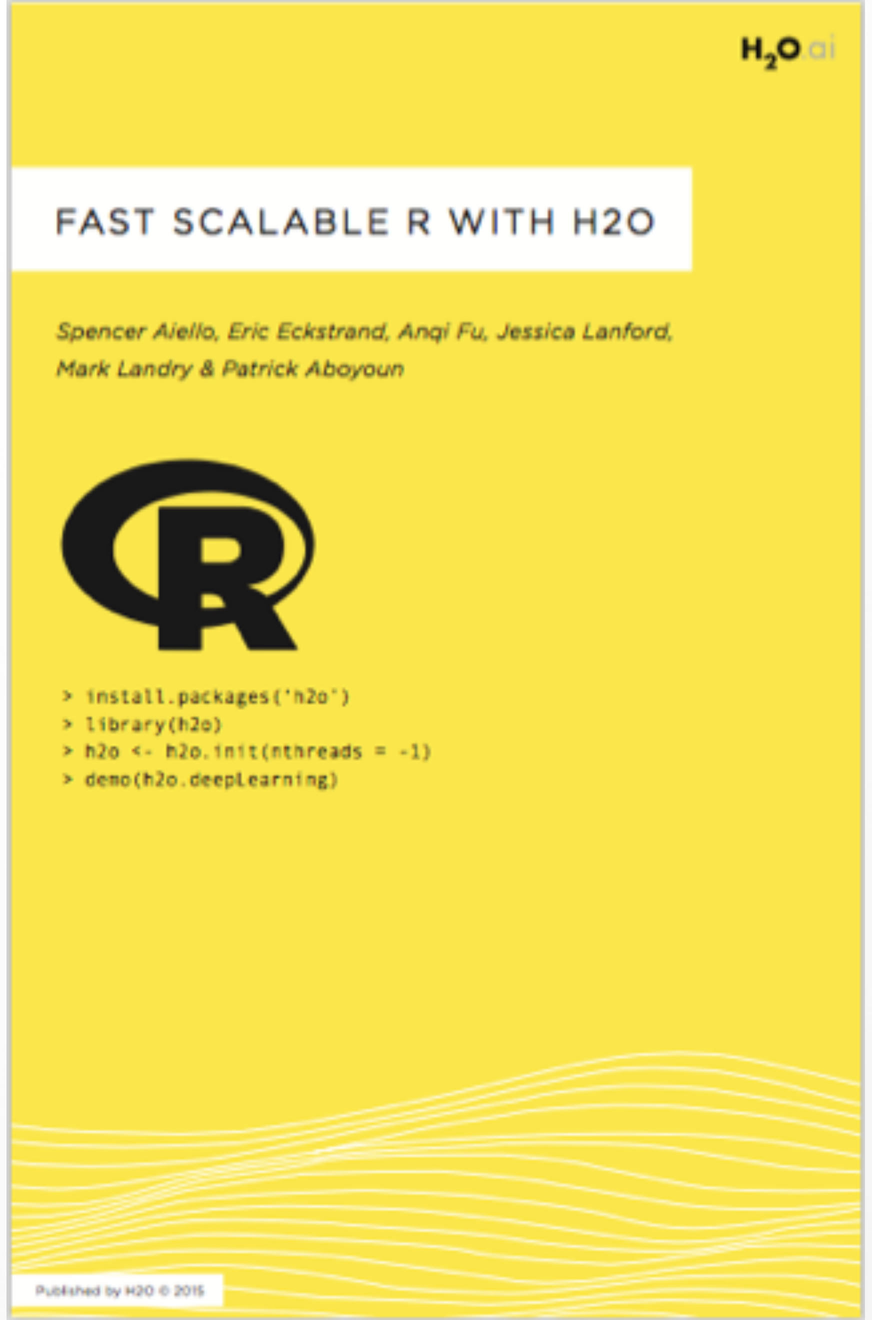
The second training module demonstrates how to find the best set of model parameters for each model using Grid Search.

H2O Booklets









http://www.h2o.ai/docs

Thank you!

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http://www.stat.berkeley.edu/~ledell