Industrial IoT Data Science with H2O

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H2O Hands-on Workshop
La Fosse Associates
27th & 28th September, 2016

About Me: Civil Engineer → Data Scientist

- 2005 - 2015
- Water Engineer
  - Consultant for Utilities
  - EngD Research
    - Machine learning + Water Engineering
  - ***Discovered H2O in 2014!***

- 2015 - Present
- Data Scientist
  - Virgin Media (UK)
  - Domino Data Lab (US)
  - H2O.ai (US)

Why? Long story – see bit.ly/joe_h2o_talk2

Agenda

- **Workshop #1**
  - About H2O
  - Data Munging in H2O
  - Case 1 (Basics)
    - Classification
    - Importing data
    - Exploring data
    - Training models
    - Evaluating models
    - Tuning models (manual)
- **Workshop #2**
  - Case 1 (Advanced)
    - Early stopping
    - Tuning models (auto)
    - Stacking models
    - Saving/loading models
  - Case 2
    - Anomaly detection
  - Other H2O features

About H2O

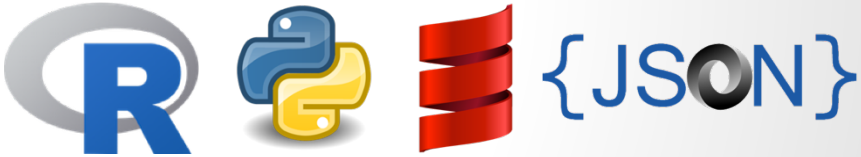
About H2O.ai

- **H2O.ai, the Company**
  - Team: 80 (71 shown)
  - Founded in 2012,
  - HQ: Mountain View, California

- **H2O, the Platform**
  - Open Source (Apache 2.0)
  - R, Python, Scala, Java and Web Interfaces
  - Distributed Algorithms that Scale to Big Data
  - Works with Laptop, Cloud, Hadoop & Spark

H2O Platform Overview

- Core algorithms written in high performance Java.
- Fast, distributed and scalable.
- APIs available in R, Python, Scala, REST/JSON and web.
- Works with laptop, cloud, Hadoop and Spark



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

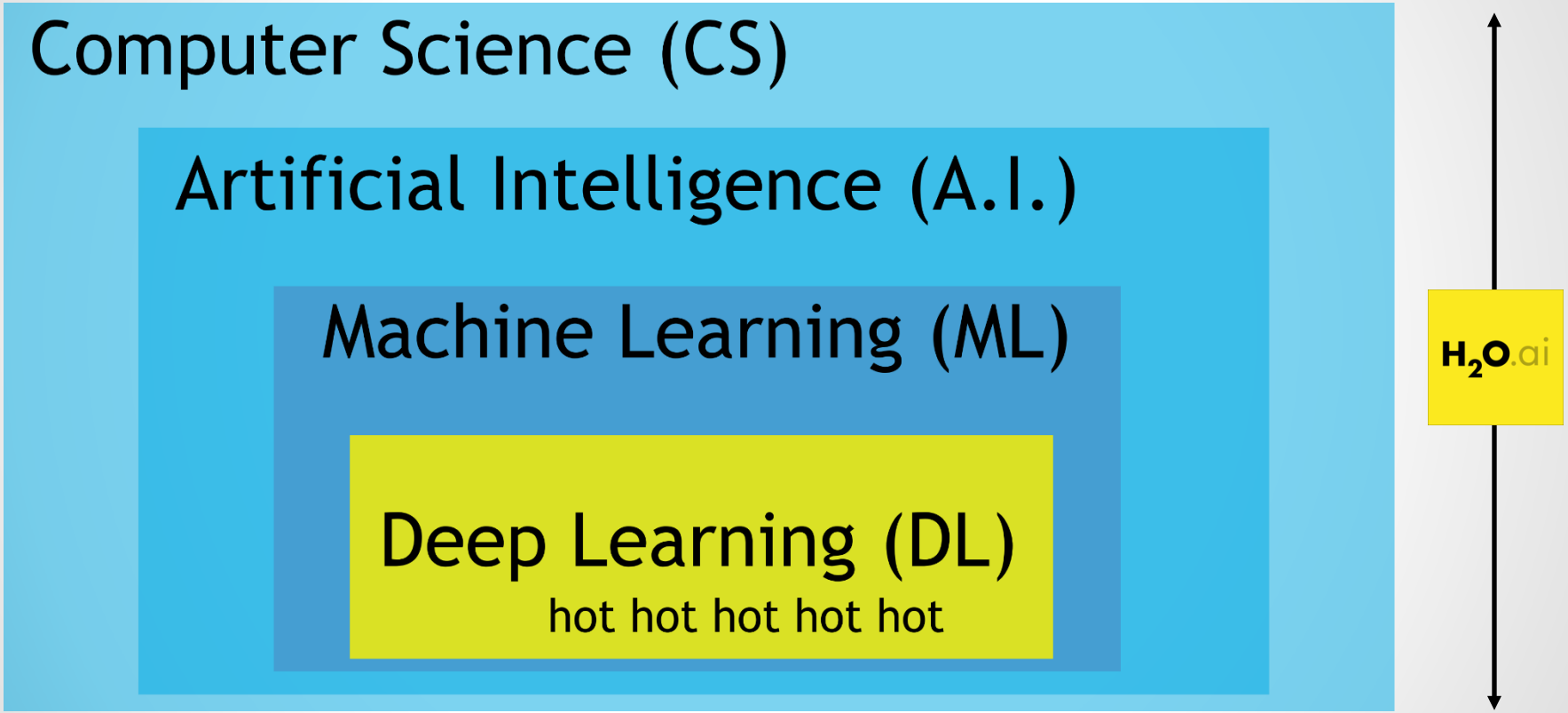
- Scalable Data Frames
- Sort, Slice, Log Transform

Workshop

Joe's Strata Hadoop London Talk
bit.ly/joe_h2o_talk4

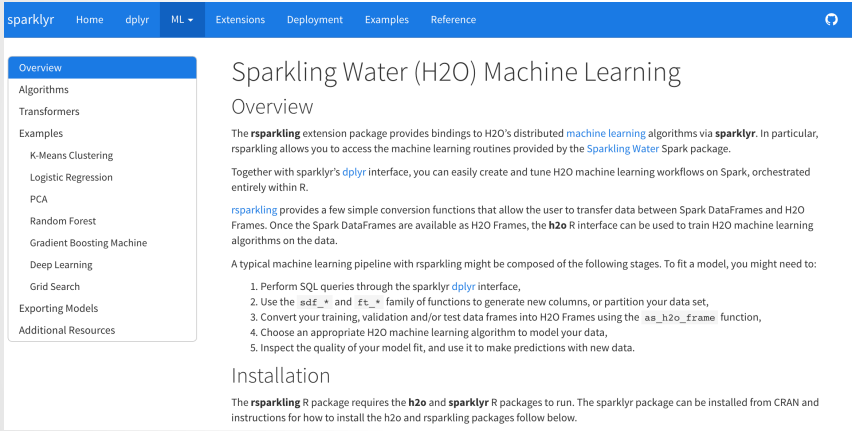
Joe's LondonR Talk
bit.ly/joe_h2o_talk3

H2O Overview



New Stuff!

H2O + RStudio
RSparkling



Deep Water: Next-Gen Deep Learning in H2O

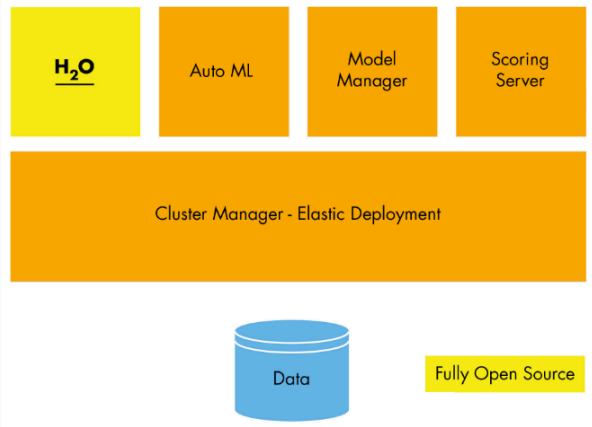
New Stuff!

COMMUNITY BLOG DOCUMENTATION SUPPORT

H2O.ai PRODUCT USE CASES CUSTOMERS COMPANY H2O OPEN TOUR DOWNLOAD

STEAM

The Steam AI engine is an end-to-end platform that streamlines the entire process of building and deploying smart applications. Now data scientists and developers can launch turnkey compute environments for collaboratively training and deploying predictive models and integrate those models into real-time smart applications.



Data Munging in H2O

by Jan Gorecki & Matt Dowle

(see pdf in repo)

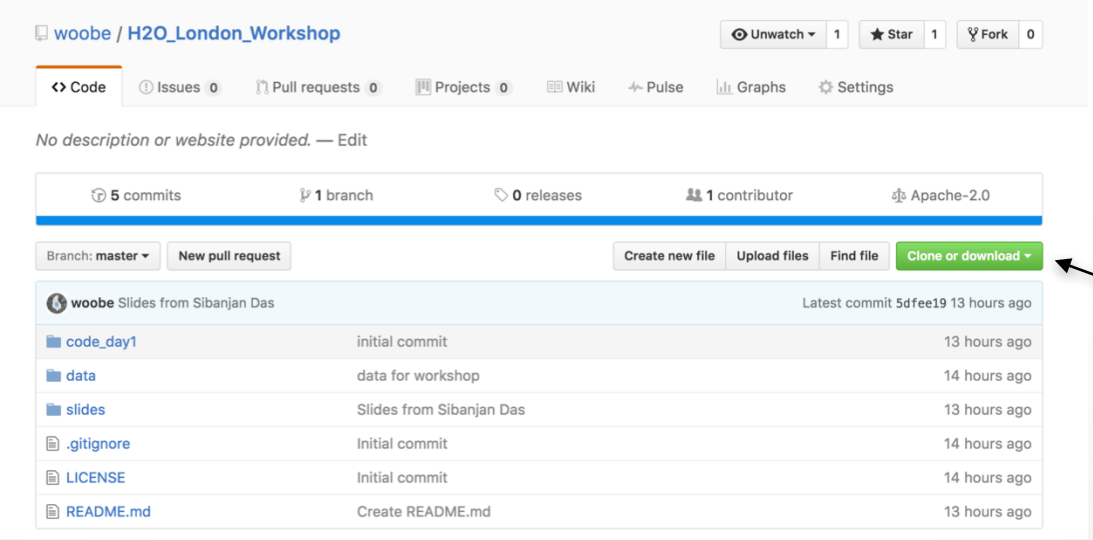
Workshop #1

Use Case 1: Classification

Download Data & Code for Workshop

- Please go to

bit.ly/h2o_iot_workshop1



Workshop #1

Use Case 1: Classification

Step 1: R Packages

step_01_install_packages.R

Package ‘h2o’

```
# ------------------------------------------------------------------------------
# Step 1: Install R Packages for Workshop
# ------------------------------------------------------------------------------

# ------------------------------------------------------------------------------
# Install "h2o" for machine learning
# Reference: http://www.h2o.ai/download/h2o/r
# ------------------------------------------------------------------------------

# The following two commands remove any previously installed H2O packages for R.
if ("package:h2o" %in% search()) { detach("package:h2o", unload=TRUE) }
if ("h2o" %in% rownames(installed.packages())) { remove.packages("h2o") }

# Next, we download packages that H2O depends on.
pkgs <- c("methods","statmod","stats","graphics","RCurl","jsonlite","tools","utils")
for (pkg in pkgs) {
  if (! (pkg %in% rownames(installed.packages()))) { install.packages(pkg) }
}

# Now we download, install and initialize the H2O package for R.
install.packages("h2o",
                 type="source",
                 repos=(c("http://h2o-release.s3.amazonaws.com/h2o/rel-turing/7/R")))

# Quick test
suppressPackageStartupMessages(library(h2o))
h2o.init(nthreads = -1)
```

```
> suppressPackageStartupMessages(library(h2o))
> h2o.init(nthreads = -1)
 Connection successful!

R is connected to the H2O cluster:
    H2O cluster uptime:         1 minutes 891 milliseconds
    H2O cluster version:        3.10.0.7
    H2O cluster version age:    6 days
    H2O cluster name:           H2O_started_from_R_jofaichow_ayn543
    H2O cluster total nodes:    1
    H2O cluster total memory:   3.28 GB
    H2O cluster total cores:    8
    H2O cluster allowed cores:  8
    H2O cluster healthy:        TRUE
    H2O Connection ip:          localhost
    H2O Connection port:        54321
    H2O Connection proxy:       NA
    R Version:                  R version 3.3.0 (2016-05-03)
```

step_01_install_packages.R

Package ‘h2oEnsemble’

```
30 # ------------------------------------------------------------------------------
31 # Install "h2oEnsemble" for model stacking
32 # Reference: https://github.com/h2oai/h2o-3/tree/master/h2o-r/ensemble
33 # ------------------------------------------------------------------------------
34
35 # Install stable version (1.8)
36 install.packages(
37   "https://h2o-release.s3.amazonaws.com/h2o-ensemble/R/h2oEnsemble_0.1.8.tar.gz",
38   repos = NULL)
39
40 # Quick test
41 library(h2oEnsemble)
```

```
> library(h2oEnsemble)
h2oEnsemble (beta) for H2O >=3.0
Version: 0.1.8
Package created on 2016-03-29
```

Workshop #1

Use Case 1: Classification

Step 2: Exploratory Analysis

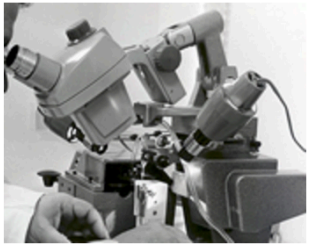
Data for Use Case 1: SECOM

UCI Machine Learning Repository

Center for Machine Learning and Intelligent Systems

SECOM Data Set

Download: Data Folder, Data Set Description



Abstract: Data from a semi-conductor manufacturing process

Data Set Characteristics:	Multivariate	**Number of Instances:**	1567	**Area:**	Computer
Attribute Characteristics:	Real	**Number of Attributes:**	591	**Date Donated**	2008-11-19
Associated Tasks:	Classification, Causal-Discovery	**Missing Values?**	Yes	**Number of Web Hits:**	37895

Source:

Authors: Michael McCann, Adrian Johnston

step_02_exploratory_analysis.R

Importing SECOM data

```
1  # ------------------------------------------------------------------------
2  # Step 2: Data Exploration
3  # ------------------------------------------------------------------------
4
5  # Start and connect to a local H2O cluster
6  library(h2o)
7  h2o.init(nthreads = -1)
8
9  # Import data from a local CSV file
10 # Source: https://archive.ics.uci.edu/ml/machine-learning-databases/secom/
11 secom <- h2o.importFile(path = "./data/secom.csv", destination_frame = "secom")
12
13 # (Optional) Demo - Importing files using URLs
14 secom <- h2o.importFile(
15   path = "https://github.com/woobe/H2O_London_Workshop/raw/master/data/secom.csv",
16   destination_frame = "secom")
17
18 # (Optional) Demo - Converting R data frame into H2O data frame
19 hdf_iris <- as.h2o(iris)
20
21 # (Optional) Turning off progress bar in R
22 h2o.no_progress()
```

Optional (different ways to import data)

```
java version "1.8.0_72"
Java(TM) SE Runtime Environment (build 1.8.0_72-b15)
Java HotSpot(TM) 64-Bit Server VM (build 25.72-b15, mixed mode)

Starting H2O JVM and connecting: ... Connection successful!

R is connected to the H2O cluster:
    H2O cluster uptime:         2 seconds 721 milliseconds
    H2O cluster version:        3.10.0.7
    H2O cluster version age:    7 days, 10 hours and 4 minutes
    H2O cluster name:           H2O_started_from_R_jofaichow_cow128
    H2O cluster total nodes:    1
    H2O cluster total memory:   3.56 GB
    H2O cluster total cores:    8
    H2O cluster allowed cores:  8
    H2O cluster healthy:        TRUE
    H2O Connection ip:          localhost
    H2O Connection port:        54321
    H2O Connection proxy:       NA
    R Version:                  R version 3.3.0 (2016-05-03)

>
> # Import data from a local CSV file
> # Source: https://archive.ics.uci.edu/ml/machine-learning-databases/secom/
> secom <- h2o.importFile(path = "./data/secom.csv", destination_frame = "secom")
  |=================================================================================| 100%
```

step_02_exploratory_analysis.R

Basic exploratory analysis

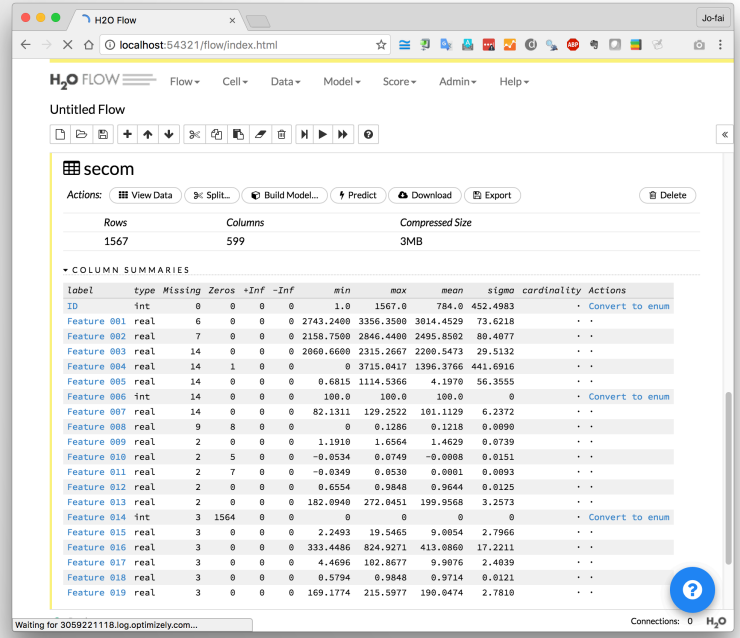
```
25 # Basic exploratory analysis
26 print(dim(secom)) # 1567 x 599
27 print(summary(secom$Classification))
28 # alternatively, use H2O flow to look at data (localhost:54321)
29
30 # Convert Classification to factor
31 secom$Classification <- as.factor(secom$Classification)
32 print(summary(secom$Classification))
```

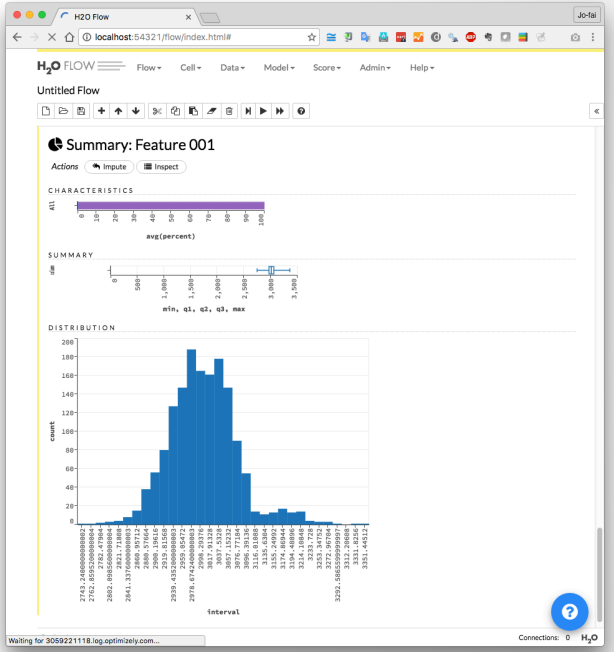
Convert -1 and 1 to categorical value

```
> # Basic exploratory analysis
> print(dim(secom)) # 1567 x 599
[1] 1567  599
> print(summary(secom$Classification))
 Classification
 Min.   :-1.0000
 1st Qu.:-1.0000
 Median :-1.0000
 Mean   :-0.8673
 3rd Qu.:-1.0000
 Max.   : 1.0000
```

```
> # Convert Classification to factor
> secom$Classification <- as.factor(secom$Classification)
> print(summary(secom$Classification))
 Classification
 -1:1463
 1 : 104
```

Use H2O Flow (localhost:54321)





Workshop #1

Use Case 1: Classification

Step 3: Building & Evaluating Models

step_03_basic_models.R

Define features & target

```r
# ------------------------------------------------------------------------------
# Loading data (same as previous steps)
# ------------------------------------------------------------------------------

# Start and connect to a local H2O cluster
library(h2o)
h2o.init(nthreads = -1)

# Import data from a local CSV file
# Source: https://archive.ics.uci.edu/ml/machine-learning-databases/secom/
secom <- h2o.importFile(path = "./data/secom.csv", destination_frame = "secom")

# Convert Classification to factor
secom$Classification <- as.factor(secom$Classification)


# ------------------------------------------------------------------------------
# Define Targets and Features
# ------------------------------------------------------------------------------

target <- "Classification"
features <- setdiff(colnames(secom), c("ID", "Classification"))

print(target)
print(features)
```

```
> print(target)
[1] "Classification"
> print(features)
  [1] "Feature 001"  "Feature 002"  "Feature 003"  "Feature 004"
  [5] "Feature 005"  "Feature 006"  "Feature 007"  "Feature 008"
  [9] "Feature 009"  "Feature 010"  "Feature 011"  "Feature 012"
 [13] "Feature 013"  "Feature 014"  "Feature 015"  "Feature 016"
 [17] "Feature 017"  "Feature 018"  "Feature 019"  "Feature 020"
 [21] "Feature 021"  "Feature 022"  "Feature 023"  "Feature 024"
 [25] "Feature 025"  "Feature 026"  "Feature 027"  "Feature 028"
 [29] "Feature 029"  "Feature 030"  "Feature 031"  "Feature 032"
 [33] "Feature 033"  "Feature 034"  "Feature 035"  "Feature 036"
 [37] "Feature 037"  "Feature 038"  "Feature 039"  "Feature 040"
 [41] "Feature 041"  "Feature 042"  "Feature 043"  "Feature 044"
 [45] "Feature 045"  "Feature 046"  "Feature 047"  "Feature 048"
 [49] "Feature 049"  "Feature 050"  "Feature 051"  "Feature 052"
 [53] "Feature 053"  "Feature 054"  "Feature 055"  "Feature 056"
 [57] "Feature 057"  "Feature 058"  "Feature 059"  "Feature 060"
 [61] "Feature 061"  "Feature 062"  "Feature 063"  "Feature 064"
 [65] "Feature 065"  "Feature 066"  "Feature 067"  "Feature 068"
 [69] "Feature 069"  "Feature 070"  "Feature 071"  "Feature 072"
 [73] "Feature 073"  "Feature 074"  "Feature 075"  "Feature 076"
 [77] "Feature 077"  "Feature 078"  "Feature 079"  "Feature 080"
 [81] "Feature 081"  "Feature 082"  "Feature 083"  "Feature 084"
 [85] "Feature 085"  "Feature 086"  "Feature 087"  "Feature 088"
 [89] "Feature 089"  "Feature 090"  "Feature 091"  "Feature 092"
 [93] "Feature 093"  "Feature 094"  "Feature 095"  "Feature 096"
 [97] "Feature 097"  "Feature 098"  "Feature 099"  "Feature 100"
[101] "Feature 101"  "Feature 102"  "Feature 103"  "Feature 104"
[105] "Feature 105"  "Feature 106"  "Feature 107"  "Feature 108"
```

step_03_basic_models.R

Split data with a random seed

```
32 # ------------------------------------------------------------------------------
33 # Split data into training / test
34 # ------------------------------------------------------------------------------
35
36 # Split
37 # i.e. using 60% of data for training and 40% for test
38 secom_splits <- h2o.splitFrame(data = secom, ratios = 0.6, seed = 1234)
39 secom_train <- secom_splits[[1]]
40 secom_test  <- secom_splits[[2]]
41
42 # Check
43 summary(secom_train$Classification) # 882 : 62 ... % of 1 = 0.07029478
44 summary(secom_test$Classification) # 581 : 42 ... % of 1 = 0.07228916
```

```
> summary(secom_train$Classification)
 Classification
 -1:882
 1 : 62
```

```
> summary(secom_test$Classification)
 Classification
 -1:581
 1 : 42
```

Classification 1 samples ≈ 7%

step_03_basic_models.R

Train H2O models with default values

```
47 # ------------------------------------------------------------------------------
48 # Train H2O models with default value
49 # ------------------------------------------------------------------------------
50
51 # Turn off progress bar (if you want to ...)
52 # h2o.no_progress()
53
54 # GBM
55 model_gbm <- h2o.gbm(x = features, y = target,
56                      training_frame = secom_train)
57
58 # Random Forest
59 model_drf <- h2o.randomForest(x = features, y = target,
60                               training_frame = secom_train)
61
62 # Deep Neural Network
63 model_dnn <- h2o.deeplearning(x = features, y = target,
64                               training_frame = secom_train)
```

```
> # GBM
> model_gbm <- h2o.gbm(x = features, y = target,
+                      training_frame = secom_train)
  |======================================================================| 100%
Warning message:
In .h2o.startModelJob(algo, params, h2oRestApiVersion) :
  Dropping constant columns: [Feature 516, Feature 234, Feature 233, Feature 236, Feature 235, Feature
510, Feature 238, Feature 513, Feature 237, Feature 479, Feature 515, Feature 514, Feature 193, Featur
e 192, Feature 195, Feature 194, Feature 075, Feature 230, Feature 232, Feature 231, Feature 529, Feat
ure 244, Feature 365, Feature 401, Feature 400, Feature 006, Feature 403, Feature 402, Feature 405, Fe
ature 404, Feature 241, Feature 482, Feature 243, Feature 242, Feature 180, Feature 179, Feature 459,
Feature 050, Feature 053, Feature 450, Feature 210, Feature 331, Feature 452, Feature 330, Feature 451
, Feature 191, Feature 070, Feature 190, Feature 506, Feature 505, Feature 508, Feature 507, Feature 5
09, Feature 465, Feature 343, Feature 464, Feature 467, Feature 466, Feature 227, Feature 348, Feature
502, Feature 504, Feature 503, Feature 463, Feature 187, Feature 462, Feature 399, Feature 277, Featur
e 398, Feature 315, Feature 314, Feature 316, Feature 150, Feature 395, Feature 39 [... truncated]
```

H2O automatically ignores
Columns with constant values

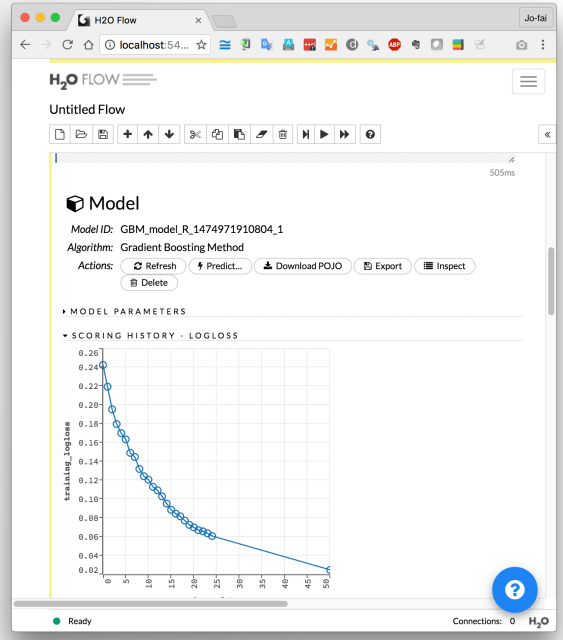
step_03_basic_models.R

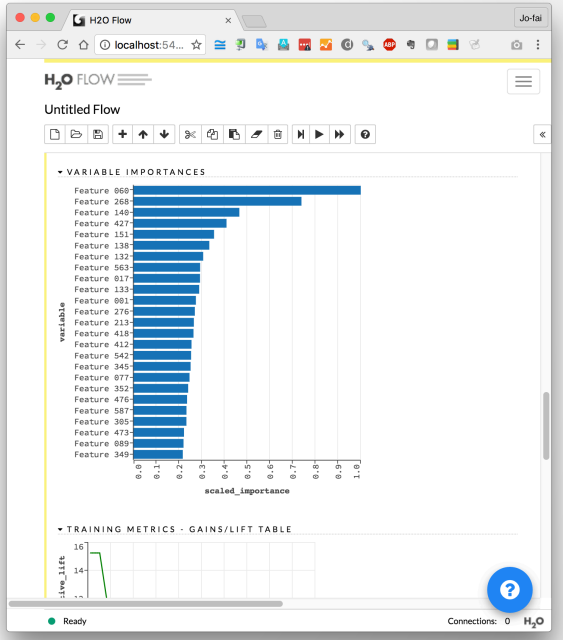
summary(model_xxx)

```
> print(summary(model_gbm))
Model Details:
==============

H2OBinomialModel: gbm
Model Key:  GBM_model_R_1474971910804_1
Model Summary:
  number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth mean_depth
1              50                       50               10880         5         5    5.00000
  min_leaves max_leaves mean_leaves
1          6         21    12.38000

H2OBinomialMetrics: gbm
** Reported on training data. **

MSE:  0.002598174
RMSE:  0.05097229
LogLoss:  0.0248643
Mean Per-Class Error:  0
AUC:  1
Gini:  1

Confusion Matrix for F1-optimal threshold:
        -1  1    Error    Rate
-1     882  0 0.000000  =0/882
1        0 62 0.000000   =0/62
Totals 882 62 0.000000  =0/944

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                       max f1  0.628627 1.000000  61
2                       max f2  0.628627 1.000000  61
3                 max f0point5  0.628627 1.000000  61
4                 max accuracy  0.628627 1.000000  61
5                max precision  0.956650 1.000000   0
6                   max recall  0.628627 1.000000  61
7              max specificity  0.956650 1.000000   0
8             max absolute_mcc  0.628627 1.000000  61
9   max min_per_class_accuracy  0.628627 1.000000  61
10 max mean_per_class_accuracy  0.628627 1.000000  61
```

```
Scoring History:
             timestamp   duration number_of_trees training_rmse training_logloss training_auc
1 2016-09-27 11:25:31  0.021 sec               0       0.24772          0.24231      0.50000
2 2016-09-27 11:25:32  0.722 sec               1       0.24010          0.21926      0.83663
3 2016-09-27 11:25:32  1.001 sec               2       0.22980          0.19523      0.92679
4 2016-09-27 11:25:32  1.178 sec               3       0.22041          0.17966      0.94964
5 2016-09-27 11:25:32  1.320 sec               4       0.21468          0.16997      0.96445
  training_lift training_classification_error
1       1.00000                       0.93432
2       9.13548                       0.08581
3      12.18065                       0.04449
4      13.70323                       0.03496
5      15.22581                       0.03708

---
              timestamp   duration number_of_trees training_rmse training_logloss training_auc
21 2016-09-27 11:25:34  3.500 sec              20       0.12174          0.06986      0.99996
22 2016-09-27 11:25:34  3.631 sec              21       0.11797          0.06696      1.00000
23 2016-09-27 11:25:35  3.726 sec              22       0.11645          0.06571      1.00000
24 2016-09-27 11:25:35  3.841 sec              23       0.11373          0.06369      1.00000
25 2016-09-27 11:25:35  3.967 sec              24       0.10979          0.06082      1.00000
26 2016-09-27 11:25:37  6.596 sec              50       0.05097          0.02486      1.00000
   training_lift training_classification_error
21      15.22581                       0.00106
22      15.22581                       0.00000
23      15.22581                       0.00000
24      15.22581                       0.00000
25      15.22581                       0.00000
26      15.22581                       0.00000

Variable Importances: (Extract with `h2o.varimp`)
=================================================

Variable Importances:
     variable relative_importance scaled_importance percentage
1 Feature 060            9.594806          1.000000   0.050880
2 Feature 268            7.089089          0.738847   0.037592
3 Feature 140            4.466067          0.465467   0.023683
4 Feature 427            3.924058          0.408977   0.020809
5 Feature 151            3.397748          0.354124   0.018018
```

Use H2O Flow (localhost:54321)





step_03_basic_models.R

Evaluate models with test data

```
72 # ------------------------------------------------
73 # Evaluate model performance on unseen data
74 # ------------------------------------------------
75
76 h2o.performance(model_gbm, newdata = secom_test)
77 h2o.performance(model_drf, newdata = secom_test)
78 h2o.performance(model_dnn, newdata = secom_test)
```

```
> h2o.performance(model_gbm, newdata = secom_test)
H2OBinomialMetrics: gbm

MSE:  0.06408139
RMSE:  0.253143
LogLoss:  0.2678549
Mean Per-Class Error:  0.2928858
AUC:  0.7041841
Gini:  0.4083682

Confusion Matrix for F1-optimal threshold:
        -1   1    Error      Rate
-1     379 202 0.347676  =202/581
1       10  32 0.238095    =10/42
Totals 389 234 0.340289  =212/623

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                        max f1  0.016032 0.231884 201
2                        max f2  0.016032 0.398010 201
3                  max f0point5  0.053221 0.196078  63
4                  max accuracy  0.492634 0.930979   0
5                 max precision  0.244674 0.333333   5
6                    max recall  0.005088 1.000000 378
7               max specificity  0.492634 0.998279   0
8              max absolute_mcc  0.016032 0.214472 201
9    max min_per_class_accuracy  0.016481 0.659208 196
10 max mean_per_class_accuracy  0.016032 0.707114 201
```

Workshop #1

Use Case 1: Classification

Step 4: Tuning Models

step_04_manual_tuning.R

?h2o.gbm ?h2o.deeplearning …

h2o.gbm {h2o} R Documentation

Gradient Boosting Machine

Description

Builds gradient boosted classification trees and gradient boosted regression trees on a parsed data set.

Usage

```
h2o.gbm(x, y, training_frame, model_id, checkpoint, ignore_const_cols = TRUE,
  distribution = c("AUTO", "gaussian", "bernoulli", "multinomial", "poisson",
  "gamma", "tweedie", "laplace", "quantile", "huber"), quantile_alpha = 0.5,
  tweedie_power = 1.5, huber_alpha = 0.9, ntrees = 50, max_depth = 5,
  min_rows = 10, learn_rate = 0.1, learn_rate_annealing = 1,
  sample_rate = 1, sample_rate_per_class, col_sample_rate = 1,
  col_sample_rate_change_per_level = 1, col_sample_rate_per_tree = 1,
  nbins = 20, nbins_top_level = 1024, nbins_cats = 1024,
  validation_frame = NULL, balance_classes = FALSE, class_sampling_factors,
  max_after_balance_size = 5, seed, build_tree_one_node = FALSE,
  nfolds = 0, fold_column = NULL, fold_assignment = c("AUTO", "Random",
  "Modulo", "Stratified"), keep_cross_validation_predictions = FALSE,
  keep_cross_validation_fold_assignment = FALSE,
  score_each_iteration = FALSE, score_tree_interval = 0,
  stopping_rounds = 0, stopping_metric = c("AUTO", "deviance", "logloss",
  "MSE", "AUC", "misclassification", "mean_per_class_error"),
  stopping_tolerance = 0.001, max_runtime_secs = 0, offset_column = NULL,
  weights_column = NULL, min_split_improvement = 1e-05,
  histogram_type = c("AUTO", "UniformAdaptive", "Random", "QuantilesGlobal",
  "RoundRobin"), max_abs_leafnode_pred, pred_noise_bandwidth = 0)
```

Arguments

x	A vector containing the names or indices of the predictor variables to use in building the GBM model. If x is missing,then all columns except y are used.
y	The name or index of the response variable. If the data does not contain a header, this is the column index number starting at 0, and increasing from left to right. (The response must be either an integer or a categorical variable).
training_frame	An H2OFrame object containing the variables in the model.
model_id	(Optional) The unique id assigned to the resulting model. If none is given, an id will automatically be generated.
checkpoint	"Model checkpoint (provide the model_id) to resume training with."
ignore_const_cols	A logical value indicating whether or not to ignore all the constant columns in the training frame.
distribution	A character string. The distribution function of the response. Must be "AUTO", "bernoulli", "multinomial", "poisson", "gamma", "tweedie", "laplace", "quantile", "huber" or "gaussian"
quantile_alpha	Desired quantile for Quantile regression, must be between 0 and 1. Default is 0.5.
tweedie_power	Tweedie power for Tweedie regression, must be between 1 and 2. Default is 1.5.
huber_alpha	Desired quantile for Huber/M-regression (threshold between quadratic and linear loss, must be between 0 and 1). Default is 0.9.
ntrees	A nonnegative integer that determines the number of trees to grow. Default is 50.
max_depth	Maximum depth to grow the tree. Default is 5.
min_rows	Minimum number of rows to assign to teminal nodes. Default is 10.
learn_rate	Learning rate (from 0.0 to 1.0). Default is 0.1.
learn_rate_annealing	Scale the learning rate by this factor after each tree (e.g., 0.99 or 0.999). Default is 1.
sample_rate	Row sample rate per tree (from 0.0 to 1.0). Default is 1.
sample_rate_per_class	Row sample rate per tree per class (one per class, from 0.0 to 1.0).
col_sample_rate	Column sample rate per split (from 0.0 to 1.0). Default is 1.
col_sample_rate_change_per_level	Relative change of the column sampling rate for every level (from 0.0 to 2.0). Default is 1.
col_sample_rate_per_tree	Column sample rate per tree (from 0.0 to 1.0). Default is 1.
nbins	For numerical columns (real/int), build a histogram of (at least) this many bins, then split at the best point. Default is 20.
nbins_top_level	For numerical columns (real/int), build a histogram of (at most) this many bins at the root level, then decrease by factor of two per level. Default is 1024.
nbins_cats	For categorical columns (factors), build a histogram of this many bins, then split at the best point. Higher values can lead to more overfitting. Default is 1024.
validation_frame	An H2OFrame object indicating the validation dataset used to contruct the confusion matrix. Defaults to NULL. If left as NULL, this defaults to the training data when nfolds = 0.

step_04_manual_tuning.R

```
29 # ------------------------------------------------------------
30 # Train H2O models with default / manual settings
31 # ------------------------------------------------------------
32
33 # Check out all parameters
34 # ?h2o.gbm
35 # ?h2o.deeplearning
36 # ?h2o.randomForest
37
38 # GBM with default settings
39 model_gbm1 <- h2o.gbm(x = features, y = target,
40                       training_frame = secom_train)
41
42 # GBM with manual settings
43 model_gbm2 <- h2o.gbm(x = features, y = target,
44                       training_frame = secom_train,
45                       validation_frame = secom_test,
46                       model_id = "gbm_tuning", # define an ID
47                       ntrees = 40,             # default = 50
48                       max_depth = 7,           # default = 5
49                       sample_rate = 0.75,      # default = 1
50                       col_sample_rate = 0.75,  # default = 1
51                       learn_rate = 0.05)       # default = 0.1
```

step_04_manual_tuning.R

Default

```
> h2o.performance(model_gbm1, newdata = secom_test)
H2OBinomialMetrics: gbm

MSE:  0.06408139
RMSE:  0.253143
LogLoss:  0.2678549
Mean Per-Class Error:  0.2928858
AUC:  0.7041841
Gini:  0.4083682

Confusion Matrix for F1-optimal threshold:
        -1   1    Error      Rate
-1     379 202 0.347676  =202/581
1       10  32 0.238095    =10/42
Totals 389 234 0.340289  =212/623

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                        max f1  0.016032 0.231884 201
2                        max f2  0.016032 0.398010 201
3                  max f0point5  0.053221 0.196078  63
4                  max accuracy  0.492634 0.930979   0
5                 max precision  0.244674 0.333333   5
6                    max recall  0.005088 1.000000 378
7               max specificity  0.492634 0.998279   0
8              max absolute_mcc  0.016032 0.214472 201
9    max min_per_class_accuracy  0.016481 0.659208 196
10 max mean_per_class_accuracy  0.016032 0.707114 201
```

Manual settings

```
> h2o.performance(model_gbm2, newdata = secom_test)
H2OBinomialMetrics: gbm

MSE:  0.06190533
RMSE:  0.2488078
LogLoss:  0.2377858
Mean Per-Class Error:  0.3158348
AUC:  0.7431153
Gini:  0.4862306

Confusion Matrix for F1-optimal threshold:
        -1   1    Error      Rate
-1     463 118 0.203098  =118/581
1       18  24 0.428571    =18/42
Totals 481 142 0.218299  =136/623

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                        max f1  0.046956 0.260870 127
2                        max f2  0.039038 0.410765 164
3                  max f0point5  0.046956 0.196721 127
4                  max accuracy  0.342333 0.930979   0
5                 max precision  0.213427 0.400000   4
6                    max recall  0.015282 1.000000 358
7               max specificity  0.342333 0.998279   0
8              max absolute_mcc  0.039038 0.231566 164
9    max min_per_class_accuracy  0.039038 0.690476 164
10 max mean_per_class_accuracy  0.039038 0.710987 164
```

Better performance with manual settings

step_04_manual_tuning.R

Using the model for predictions

```
66 # ------------------------------------------------
67 # Making predictions
68 # ------------------------------------------------
69
70 yhat_test <- h2o.predict(model_gbm2, secom_test)
71 print(head(yhat_test))
72 print(summary(yhat_test))
```

```
> print(head(yhat_test))
  predict        p-1         p1
1      -1 0.9758252 0.02417485
2       1 0.8462699 0.15373015
3       1 0.8631695 0.13683051
4       1 0.8481034 0.15189664
5       1 0.8737211 0.12627893
6      -1 0.9832580 0.01674202
> print(summary(yhat_test))
 predict p-1                p1
 -1:482  Min.   :0.6577   Min.   :0.01198
 1 :141  1st Qu.:0.9543   1st Qu.:0.01858
         Median :0.9732   Median :0.02651
         Mean   :0.9597   Mean   :0.04030
         3rd Qu.:0.9811   3rd Qu.:0.04534
         Max.   :0.9880   Max.   :0.34233
```

End of Workshop #1

Industrial IoT Data Science with H2O

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@matlabulous

H2O Hands-on Workshop
La Fosse Associates
27th & 28th September, 2016

Agenda

- **Workshop #1**
  - About H2O
  - Data Munging in H2O
  - Case 1 (Basics)
    - Classification
    - Importing data
    - Exploring data
    - Training models
    - Evaluating models
    - Tuning models (manual)

- **Workshop #2**
  - Case 1 (Advanced)
    - Early stopping
    - Tuning models (auto)
    - Stacking models
    - Saving/loading models
  - Case 2
    - Anomaly detection
  - Other H2O features

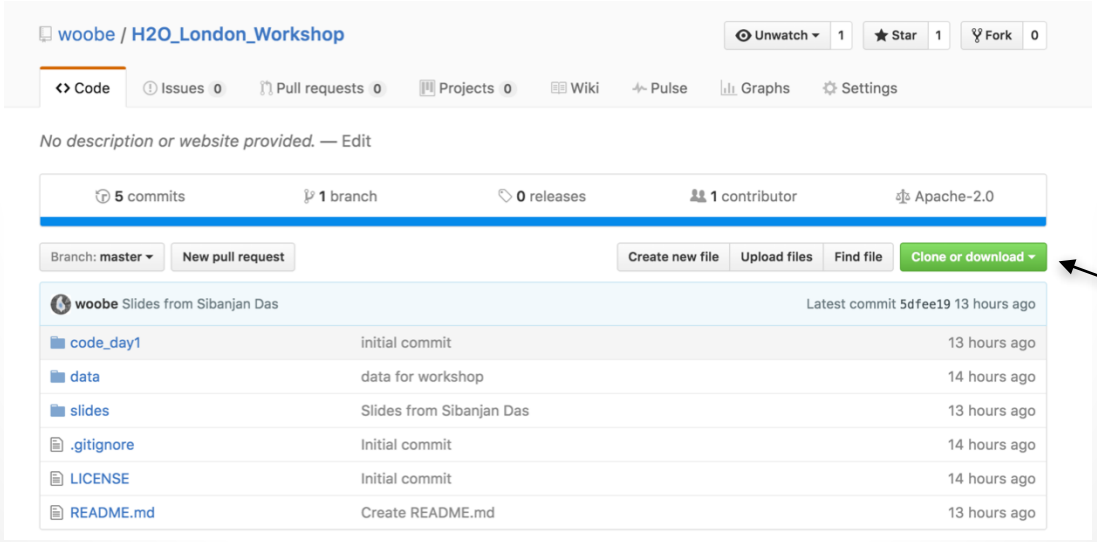
Workshop #2

Use Case 1: Classification

Download Data & Code for Workshop

- Please go to

bit.ly/h2o_iot_workshop1



[RECAP] Data for Use Case 1: SECOM

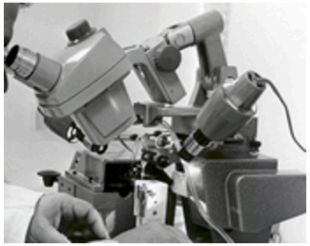
UCI Machine Learning Repository

Center for Machine Learning and Intelligent Systems

SECOM Data Set

Download: Data Folder, Data Set Description

Abstract: Data from a semi-conductor manufacturing process



Data Set Characteristics:	Multivariate	**Number of Instances:**	1567	**Area:**	Computer
Attribute Characteristics:	Real	**Number of Attributes:**	591	**Date Donated**	2008-11-19
Associated Tasks:	Classification, Causal-Discovery	**Missing Values?**	Yes	**Number of Web Hits:**	37895

Source:

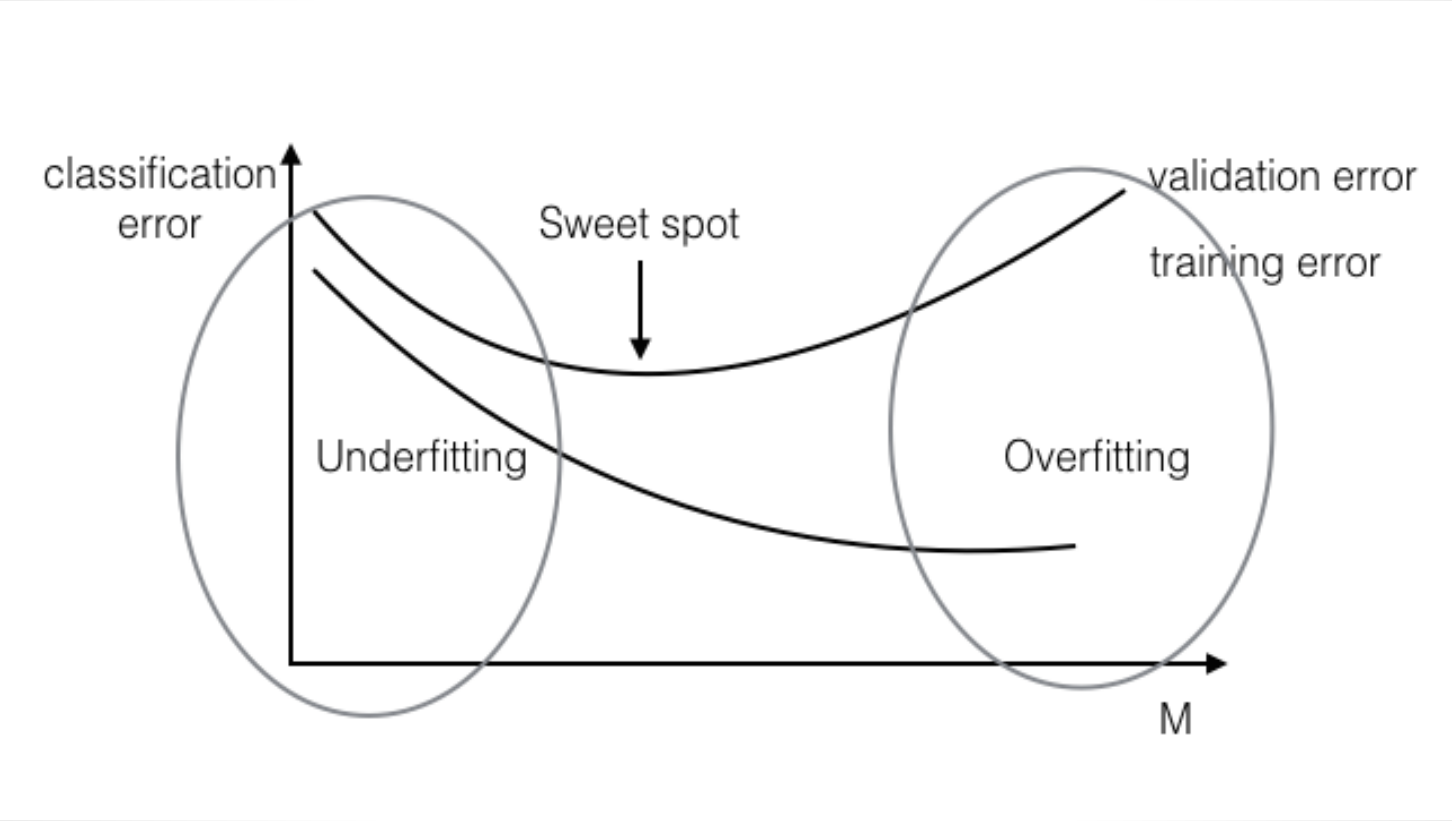
Authors: Michael McCann, Adrian Johnston

Workshop #2

Use Case 1: Classification

Step 5: Tuning Models with Early Stopping

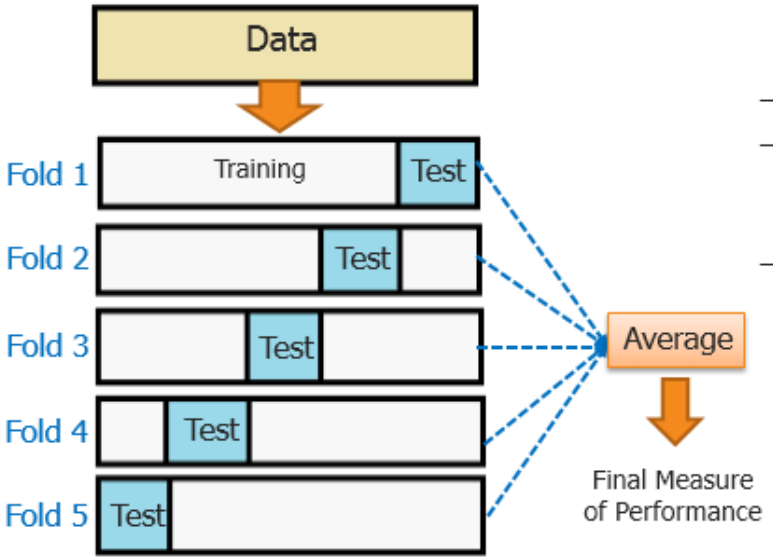
Underfitting and Overfitting



Cross Validation

Cross-Validation (CV)

edureka!



- → Technique to validate models/classifiers
- → Method to estimate how accurately the model generalizes to unseen data i.e., how well it performs/predicts
- → K-fold CV
  - » Most popular
  - » k is typically set to 10
  - » Every sample/record is used both in training and test sets

step_05_early_stopping.R

```r
# ------------------------------------------------------------------------------
# Loading and preparing data (same as previous steps)
# ------------------------------------------------------------------------------

# Start and connect to a local H2O cluster
library(h2o)
h2o.init(nthreads = -1)

# Import data from a local CSV file
secom <- h2o.importFile(path = "./data/secom.csv", destination_frame = "secom")

# Convert Classification to factor
secom$Classification <- as.factor(secom$Classification)

# Define Targets and Features
target <- "Classification"
features <- setdiff(colnames(secom), c("ID", "Classification"))

# Split
secom_splits <- h2o.splitFrame(data = secom, ratios = 0.6, seed = 1234)
secom_train <- secom_splits[[1]]  # 882 : 62 ... 7% of 1
secom_test  <- secom_splits[[2]]  # 581 : 42 ... 7% of 1
```

- Workshop 1 Recap
- Previous steps
  - Connect to H2O
  - Import data
  - Convert data type
  - Define target and features
  - Split data into training/test

step_05_early_stopping.R

```r
# ------------------------------------------------------------------------------
# Train H2O models with early stopping
# ------------------------------------------------------------------------------

# GBM with default settings
model_gbm1 <- h2o.gbm(x = features,
                      y = target,
                      training_frame = secom_train,
                      ntrees = 50)  # default = 50

# GBM with early stopping and cross validation
model_gbm2 <- h2o.gbm(x = features,
                      y = target,
                      training_frame = secom_train,
                      model_id = "gbm_early_stop", # define an ID

                      # Settings for Early Stopping w/ Cross Validation
                      nfolds = 5,
                      ntrees = 200,
                      stopping_metric = "AUC",
                      score_tree_interval = 3,
                      stopping_rounds = 20)


# ------------------------------------------------------------------------------
# Evaluate model performance on unseen data
# ------------------------------------------------------------------------------

print(model_gbm1)
print(model_gbm2)

h2o.performance(model_gbm1, newdata = secom_test)
h2o.performance(model_gbm2, newdata = secom_test)
```

- Two GBMs
  - Default settings
  - Early stopping with cross validation
  - Evaluate models

step_05_early_stopping.R

Default 50 trees

```
> print(model_gbm1)
Model Details:
==============

H2OBinomialModel: gbm
Model ID:  GBM_model_R_1475069583054_2087
Model Summary:
  number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth
1              50                       50               10885         5         5
  mean_depth min_leaves max_leaves mean_leaves
1    5.00000          6         21    12.38000
```

```
> print(model_gbm2)
Model Details:
==============

H2OBinomialModel: gbm
Model ID:  gbm_early_stop
Model Summary:
  number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth
1             158                      158               34081         5         5
  mean_depth min_leaves max_leaves mean_leaves
1    5.00000          6         21    12.17722
```

Stopped at 158th tree with early stopping

step_05_early_stopping.R

Default 50 trees

```
> h2o.performance(model_gbm1, newdata = secom_test)
H2OBinomialMetrics: gbm

MSE:  0.06408139
RMSE:  0.253143
LogLoss:  0.2678549
Mean Per-Class Error:  0.2928858
AUC:  0.7041841
Gini:  0.4083682

Confusion Matrix for F1-optimal threshold:
        -1   1    Error      Rate
-1     379 202 0.347676  =202/581
1       10  32 0.238095    =10/42
Totals 389 234 0.340289  =212/623
```

With early stopping

```
> h2o.performance(model_gbm2, newdata = secom_test)
H2OBinomialMetrics: gbm

MSE:  0.06717936
RMSE:  0.2591898
LogLoss:  0.4121121
Mean Per-Class Error:  0.3679002
AUC:  0.7218671
Gini:  0.4437341

Confusion Matrix for F1-optimal threshold:
        -1  1    Error     Rate
-1     527 54 0.092943  =54/581
1       27 15 0.642857   =27/42
Totals 554 69 0.130016  =81/623
```

Better AUC (early stopping objective)

Workshop #2

Use Case 1: Classification

Step 6: Tuning Models with Grid Search

Full Grid Search

- GBM Grid Example
  - Max depth
    - try 5, 6 and 7
  - Sample rate
    - try 0.8, 0.9 and 1
  - 3 x 3 = 9 possible combinations

	Max Depth	Sample Rate
Model 1	5	0.8
Model 2	5	0.9
Model 3	5	1.0
Model 4	6	0.8
Model 5	6	0.9
Model 6	6	1.0
Model 7	7	0.8
Model 8	7	0.9
Model 9	7	1.0

step_06_grid_search.R

```r
# ------------------------------------------------------------------------------
# Train H2O models with early stopping and grid search
# ------------------------------------------------------------------------------

# Define parameters for grid search
param_gbm <- list(
  max_depth = c(5, 6, 7),
  sample_rate = c(0.8, 0.9, 1)
)

# GBM with early stopping, cross validation and grid search
grid_gbm <- h2o.grid(

  # Core parameters for model training
  x = features,
  y = target,
  training_frame = secom_train,
  ntrees = 100,

  # Parameters for grid search
  grid_id = "my_gbm_grid",
  hyper_params = param_gbm,
  algorithm = "gbm",

  # Parameters for early stopping & cross validation
  nfolds = 3,
  stopping_metric = "logloss",
  score_tree_interval = 3,
  stopping_rounds = 20

)
```

- Define parameters search space
- Core settings
- Grid search settings
- Combined with early stopping and cross validation

step_06_grid_search.R

Sort and extract models based on specific metric

```r
# ------------------------------------------------------------------------------
# Extract the model and evaluate model performance on unseen data
# ------------------------------------------------------------------------------

# Sort models by metric "logloss"
grid_sort <- h2o.getGrid("my_gbm_grid", sort_by = "logloss", decreasing = FALSE)
print(grid_sort)

# Extract the best model
model_ids <- grid_sort@model_ids
best_gbm <- h2o.getModel(model_ids[[1]])

# Evaluate
h2o.performance(best_gbm, newdata = secom_test)
```

```
> # Sort models by metric "logloss"
> grid_sort <- h2o.getGrid("my_gbm_grid", sort_by = "logloss", decreasing = FALSE)
> print(grid_sort)
H2O Grid Details
================

Grid ID: my_gbm_grid
Used hyper parameters:
  -  max_depth
  -  sample_rate
Number of models: 9
Number of failed models: 0

Hyper-Parameter Search Summary: ordered by increasing logloss
  max_depth sample_rate           model_ids             logloss
1         5         0.8 my_gbm_grid_model_0  0.3989474186984012
2         5         0.9 my_gbm_grid_model_3 0.41058755077960957
3         5         1.0 my_gbm_grid_model_6 0.42449170943216347
4         7         0.8 my_gbm_grid_model_2 0.43034423783274595
5         6         0.8 my_gbm_grid_model_1   0.440581300385333
6         7         0.9 my_gbm_grid_model_5  0.4617179142530345
7         6         0.9 my_gbm_grid_model_4 0.47081986284541355
8         6         1.0 my_gbm_grid_model_7  0.4744610428831065
9         7         1.0 my_gbm_grid_model_8  0.4855019969560252
```

step_06_grid_search.R

Random (instead of full) Grid Search

```
# ------------------------------------------------------------------------------
# Train H2O models with early stopping and RANDOM grid search
# ------------------------------------------------------------------------------

# Define parameters for grid search
param_gbm <- list(
  max_depth = c(4, 5, 6, 7, 8), sample_rate = c(0.6, 0.7, 0.8, 0.9, 1)
)

# Define criteria for random grid search
search_criteria <- list(
  strategy = "RandomDiscrete",
  max_models = 5,
  seed = 1234,
  max_runtime_secs = 600
)

# GBM with early stopping, cross validation and RANDOM grid search
ran_grid_gbm <- h2o.grid(

  # Core parameters for model training
  x = features, y = target,
  training_frame = secom_train,
  ntrees = 200,

  # Parameters for grid search
  grid_id = "random_gbm_grid",
  hyper_params = param_gbm,
  search_criteria = search_criteria, # <- added this for Random Grid Search
  algorithm = "gbm",

  # Parameters for early stopping & cross validation
  nfolds = 5,
  stopping_metric = "logloss",
  score_tree_interval = 3,
  stopping_rounds = 20

)
```

```
> # Sort models by metric "logloss"
> ran_grid_sort <- h2o.getGrid("random_gbm_grid",
+                              sort_by = "logloss", decreasing = FALSE)
> print(ran_grid_sort)
H2O Grid Details
================

Grid ID: random_gbm_grid
Used hyper parameters:
  -  max_depth
  -  sample_rate
Number of models: 5
Number of failed models: 0

Hyper-Parameter Search Summary: ordered by increasing logloss
  max_depth sample_rate               model_ids             logloss
1         4         0.8 random_gbm_grid_model_3 0.33992979268268186
2         4         0.9 random_gbm_grid_model_0  0.3604323057000522
3         6         0.7 random_gbm_grid_model_1  0.4209052037025763
4         6         0.8 random_gbm_grid_model_4  0.4209146622322222
5         8         1.0 random_gbm_grid_model_2  0.5544583797661401
```

Workshop #2

Use Case 1: Classification

Step 7: Stacking Models with h2oEnsemble

step_07_stacking_models.R

```r
# ------------------------------------------------------------------------------
# Train multiple H2O models
# ------------------------------------------------------------------------------

# Train a GBM 1
model_gbm1 <- h2o.gbm(x = features,
                      y = target,
                      training_frame = secom_train,
                      nfolds = 5,
                      fold_assignment = "Modulo",
                      keep_cross_validation_predictions = TRUE)

# Train a GBM 2
model_gbm2 <- h2o.gbm(x = features,
                      y = target,
                      training_frame = secom_train,
                      sample_rate = 0.8,
                      nfolds = 5,
                      fold_assignment = "Modulo",
                      keep_cross_validation_predictions = TRUE)

# Train a DRF 1
model_drf1 <- h2o.randomForest(x = features,
                               y = target,
                               training_frame = secom_train,
                               nfolds = 5,
                               fold_assignment = "Modulo",
                               keep_cross_validation_predictions = TRUE)

# Train a DRF 2
model_drf2 <- h2o.randomForest(x = features,
                               y = target,
                               training_frame = secom_train,
                               ntrees = 200,
                               nfolds = 5,
                               fold_assignment = "Modulo",
                               keep_cross_validation_predictions = TRUE)
```

- Four H2O models
  - Two GBM
  - Two DRF
  - Specific settings:
    - fold_assignment
    - Keep_cross_validation_predictions

step_07_stacking_models.R

```
68  # ------------------------------------------------------------------------
69  # Model stacking
70  # ------------------------------------------------------------------------
71
72  # Load h2oEnsemble
73  library(h2oEnsemble)
74
75  # Define a list of all models
76  models <- list(model_gbm1, model_gbm2, model_drf1, model_drf2)
77
78  # Define the metalearner
79  custom_dnn_metalearner <- function(...,
80                             hidden = c(200, 200, 200),
81                             epochs = 1000,
82                             activation = "RectifierWithDropout",
83                             input_dropout_ratio = 0.2,
84                             l1 = 1e-7,
85                             l2 = 1e-7
86  ) {
87    h2o.deeplearning.wrapper(...,
88                             hidden = hidden,
89                             epochs = epochs,
90                             activation = activation,
91                             input_dropout_ratio = input_dropout_ratio,
92                             l1 = l1, l2 = l2
93    )
94  }
95  metalearner <- "custom_dnn_metalearner"
96
97  # Use h2oEnsemble::h2o.stack for model stacking
98  model_stack <- h2o.stack(models = models,
99                           metalearner = metalearner,
100                          response_frame = secom_train[, target])
101
102 # Evalute ensemble performance on test data
103 print(h2o.ensemble_performance(model_stack, secom_test))
```

```
> print(h2o.ensemble_performance(model_stack, secom_test))

Base learner performance, sorted by specified metric:
                              learner       AUC
1 GBM_model_R_1475073231344_2140 0.7041841
2 GBM_model_R_1475073231344_2703 0.7042660
3 DRF_model_R_1475073231344_3242 0.7287517
4 DRF_model_R_1475073231344_4365 0.7425006


H2O Ensemble Performance on <newdata>:
----------------
Family: binomial

Ensemble performance (AUC): 0.753729202524383
```

Better AUC than any individual model

Workshop #2

Use Case 1: Classification

Step 8: Saving / Loading Models

Step_08_saving_loading.R

```r
# ------------------------------------------------------------------------
# Train a H2O model
# ------------------------------------------------------------------------

# Train a GBM
model_gbm <- h2o.gbm(x = features,
                     y = target,
                     model_id = "default_gbm",
                     training_frame = secom_train)

# ------------------------------------------------------------------------
# Saving / Loading H2O model
# ------------------------------------------------------------------------

# Save model to disk
h2o.saveModel(model_gbm, path = "./models/")

# Load model from disk
model_gbm_from_disk <- h2o.loadModel(path = "./models/default_gbm/")
print(model_gbm_from_disk)
```

```
> h2o.saveModel(model_gbm, path = "./models/")
[1] "/Users/jofaichow/Documents/Repo/H2O_London_Workshop/models/default_gbm"
>
> model_gbm_from_disk <- h2o.loadModel(path = "./models/default_gbm/")
> print(model_gbm_from_disk)
Model Details:
==============

H2OBinomialModel: gbm
Model ID:  default_gbm
Model Summary:
  number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth
1              50                       50               10880         5         5
  mean_depth min_leaves max_leaves mean_leaves
1    5.00000          6         21    12.38000
```

Workshop #2

Use Case 2: Anomaly Detection

use_case_2_anomaly_detection.R

```r
# ------------------------------------------------------
# Step 8: Using Deep Learning for Anomaly Detection
# ------------------------------------------------------

# Start and connect to a local H2O cluster
library(h2o)
h2o.init(nthreads = -1)

# Import data from a local CSV file
mtcar <- read.csv("./data/auto_design.csv")
mtcar$gear <- as.factor(mtcar$gear)
mtcar$carb <- as.factor(mtcar$carb)
mtcar$cyl <- as.factor(mtcar$cyl)
mtcar$vs  <- as.factor(mtcar$vs)
mtcar$am  <- as.factor(mtcar$am)
mtcar$ID  <- 1:nrow(mtcar)

# Print it out
print(mtcar)

# Convert R data frame into H2O data frame
h2o_mtcar  <- as.h2o(mtcar)
```

```
> print(mtcar)
                     X  mpg cyl  disp  hp  drat      wt    qsec vs am gear carb ID
1            Mazda RX4 21.0   6 160.0 110  3.90   2.620   16.46  0  1    4    4  1
2        Mazda RX4 Wag 21.0   6 160.0 110  3.90   2.875   17.02  0  1    4    4  2
3           Datsun 710 22.8   4 108.0  93  3.85   2.320   18.61  1  1    4    1  3
4       Hornet 4 Drive 21.4   6 258.0 110  3.08   3.215   19.44  1  0    3    1  4
5    Hornet Sportabout 18.7   8 360.0 175  3.15   3.440   17.02  0  0    3    2  5
6              Valiant 18.1   6 225.0 105  2.76   3.460   20.22  1  0    3    1  6
7           Duster 360 14.3   8 360.0 245  3.21   3.570   15.84  0  0    3    4  7
8            Merc 240D 24.4   4 146.7  62  3.69   3.190   20.00  1  0    4    2  8
9             Merc 230 22.8   4 140.8  95  3.92   3.150   22.90  1  0    4    2  9
10            Merc 280 19.2   6 167.6 123  3.92   3.440   18.30  1  0    4    4 10
11           Merc 280C 17.8   6 167.6 210 800.00 900.000 1000.00  1  0    4    4 11
12          Merc 450SE 16.4   8 275.8 180  3.07   4.070   17.40  0  0    3    3 12
13          Merc 450SL 17.3   8 275.8 180  3.07   3.730   17.60  0  0    3    3 13
14         Merc 450SLC 15.2   8 275.8 180  3.07   3.780   18.00  0  0    3    3 14
15  Cadillac Fleetwood 10.4   8 472.0 205  2.93   5.250   17.98  0  0    3    4 15
16 Lincoln Continental 10.4   8 460.0 215  3.00   5.424   17.82  0  0    3    4 16
17   Chrysler Imperial 14.7   8 440.0 230  3.23   5.345   17.42  0  0    3    4 17
18            Fiat 128 32.4   4 780.0 2100 400.00 200.000 700.00  1  1    4    1 18
19         Honda Civic 80.4  10  75.7 100  4.93   1.615  150.52  1  1    4    2 19
20      Toyota Corolla 33.9   4  71.1  65  4.22   1.835   19.90  1  1    4    1 20
21      Toyota Corona 21.5   4 120.1  97  3.70   2.465   20.01  1  0    3    1 21
22   Dodge Challenger 15.5   8 318.0 150  2.76   3.520   16.87  0  0    3    2 22
23        AMC Javelin 15.2   8 304.0 150  3.15   3.435   17.30  0  0    3    2 23
24         Camaro Z28 13.3   8 350.0 245  3.73   3.840   15.41  0  0    3    4 24
25   Pontiac Firebird 19.2   8 400.0 175  3.08   3.845   17.05  0  0    3    2 25
26          Fiat X1-9 27.3   4  79.0  66  4.08   1.935   18.90  1  1    4    1 26
27      Porsche 914-2 26.0   4 120.3  91  4.43   2.140   16.70  0  1    5    2 27
28       Lotus Europa 30.4   4  95.1 113  3.77   1.513   16.90  1  1    5    2 28
29     Ford Pantera L 15.8   8 351.0 264  4.22   3.170   14.50  0  1    5    4 29
30       Ferrari Dino 19.7   6 900.0 700  3.62 200.770  150.50  0  1    5    6 30
31      Maserati Bora 15.0   8 301.0 335  3.54   3.570   14.60  0  1    5    8 31
32        Volvo 142E 21.4   4 121.0 109  4.11   2.780   18.60  1  1    4    2 32
```

use_case_2_anomaly_detection.R

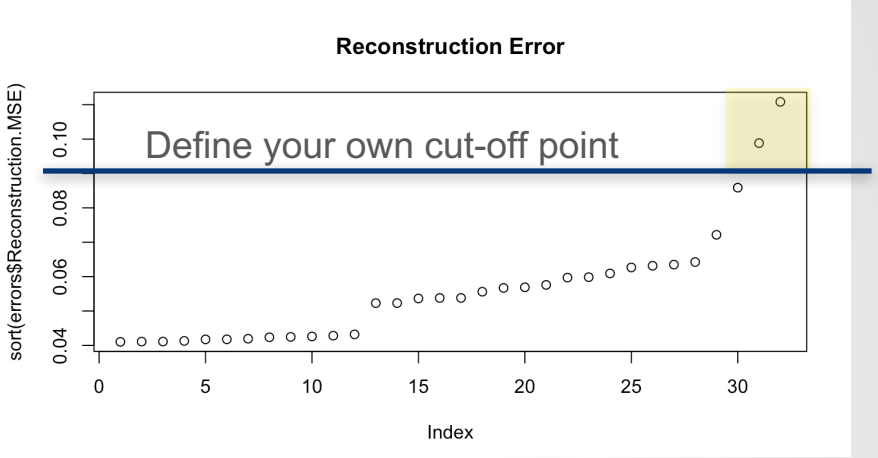
```r
# ------------------------------------------------------------------------
# Training an unsupervised deep neural network with autoencoder
# ------------------------------------------------------------------------

# Use a bigger DNN
model <- h2o.deeplearning(x = 1:10,
                          training_frame = h2o_mtcar,
                          autoencoder = TRUE,
                          activation = "RectifierWithDropout",
                          hidden = c(50, 50, 50),
                          epochs = 100)

# Calculate reconstruction errors (MSE)
errors <- h2o.anomaly(model, h2o_mtcar, per_feature = FALSE)
print(errors)
errors <- as.data.frame(errors)

# Plot
plot(sort(errors$Reconstruction.MSE), main = "Reconstruction Error")

# Outliers (define 0.09 as the cut-off point)
row_outliers <- which(errors > 0.09) # based on plot above
mtcar[row_outliers,]
```




```
> row_outliers <- which(errors > 0.09) # based on plot above
> mtcar[row_outliers,]
          X  mpg cyl  disp  hp drat  wt qsec vs am gear carb ID
11 Merc 280C 17.8   6 167.6 210  800 900 1000  1  0    4    4 11
18  Fiat 128 32.4   4 780.0 2100 400 200  700  1  1    4    1 18
```

Identify the outliers

Thanks!

- Ajit and Sibanjan
- La Fosse Associates

- Slides & Code
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