H2O Machine Learning & Deep Learning London Workshop

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Data Science for IoT Meetup
Barclays Eagle Venture Labs
21st & 24th November, 2016

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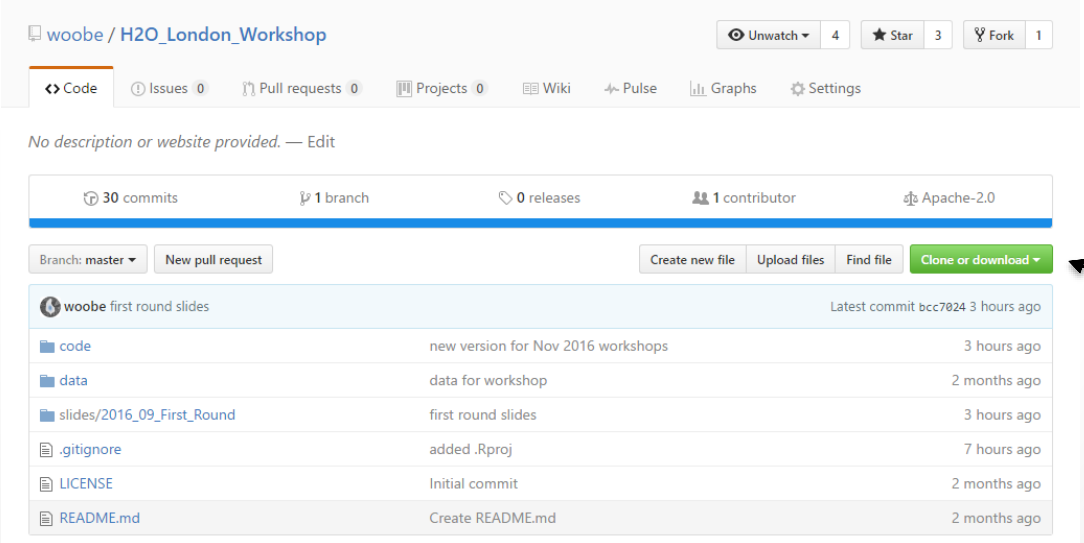


Example 1: Classification

(Use Case: Predictive Maintenance)

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

https://archive.ics.uci.edu/ml/datasets/SECOM

Data Set Information:

A complex modern semi-conductor manufacturing process is normally under consistent surveillance via the monitoring of signals/variables collected from sensors and or process measurement points. However, not all of these signals are equally valuable in a specific monitoring system. The measured signals contain a combination of useful information, irrelevant information as well as noise. It is often the case that useful information is buried in the latter two. Engineers typically have a much larger number of signals than are actually required. If we consider each type of signal as a feature, then feature selection may be applied to identify the most relevant signals. The Process Engineers may then use these signals to determine key factors contributing to yield excursions downstream in the process. This will enable an increase in process throughput, decreased time to learning and reduce the per unit production costs.

To enhance current business improvement techniques the application of feature selection as an intelligent systems technique is being investigated.

The dataset presented in this case represents a selection of such features where each example represents a single production entity with associated measured features and the labels represent a simple pass/fail yield for in house line testing, figure 2, and associated date time stamp. Where –1 corresponds to a pass and 1 corresponds to a fail and the data time stamp is for that specific test point.

Using feature selection techniques it is desired to rank features according to their impact on the overall yield for the product, causal relationships may also be considered with a view to identifying the key features.

Results may be submitted in terms of feature relevance for predictability using error rates as our evaluation metrics. It is suggested that cross validation be applied to generate these results. Some baseline results are shown below for basic feature selection techniques using a simple kernel ridge classifier and 10 fold cross validation.

Baseline Results: Pre-processing objects were applied to the dataset simply to standardize the data and remove the constant features and then a number of different feature selection objects selecting 40 highest ranked features were applied with a simple classifier to achieve some initial results. 10 fold cross validation was used and the balanced error rate (*BER) generated as our initial performance metric to help investigate this dataset.

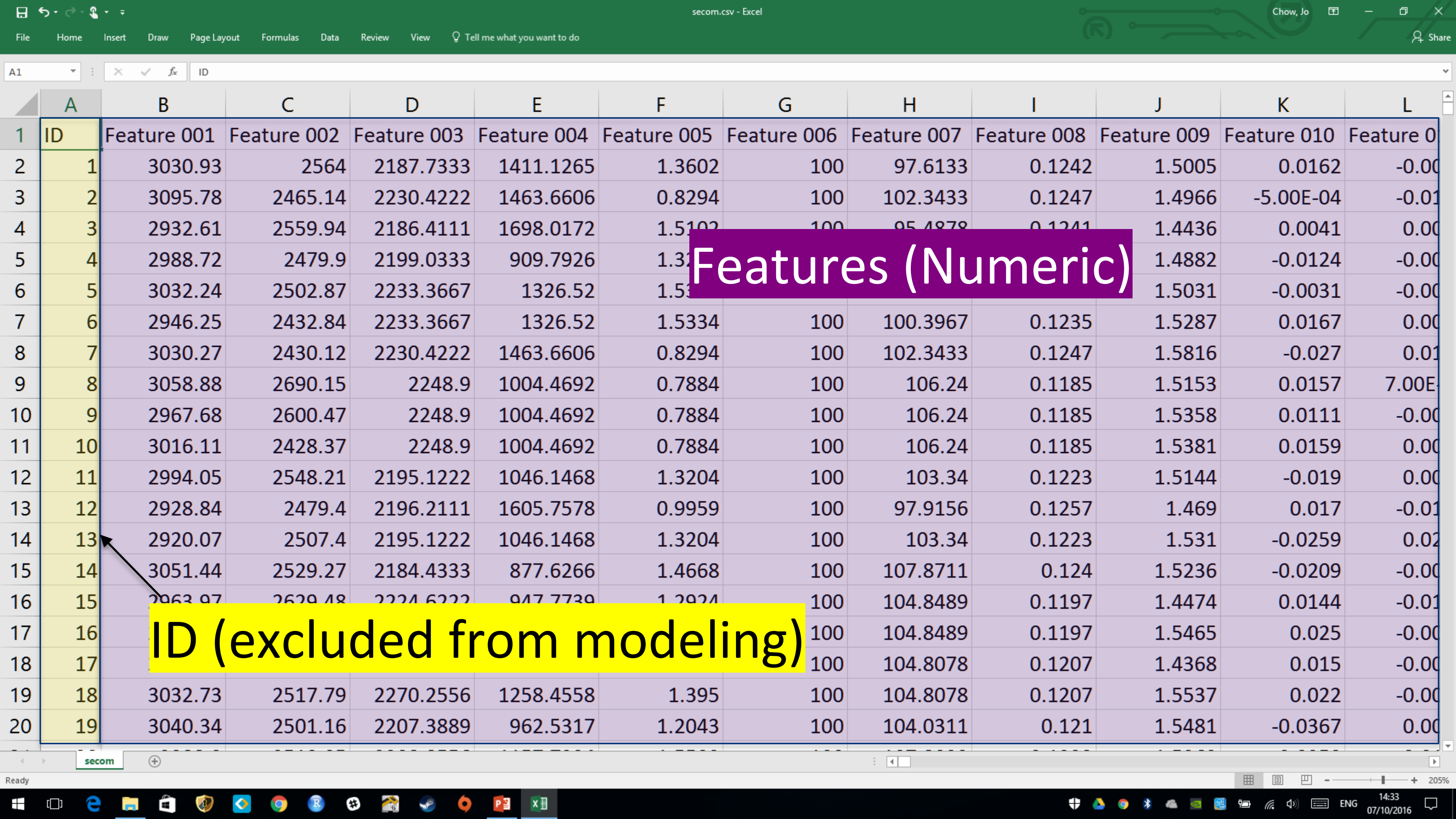
SECOM Dataset: 1567 examples 591 features, 104 fails

We want to predict fails in the future.

FSmethod (40 features) BER % True + % True - %
S2N (signal to noise) 34.5 +-2.6 57.8 +-5.3 73.1 +2.1
Ttest 33.7 +-2.1 59.6 +-4.7 73.0 +-1.8
Relief 40.1 +-2.8 48.3 +-5.9 71.6 +-3.2
Pearson 34.1 +-2.0 57.4 +-4.3 74.4 +-4.9
Ftest 33.5 +-2.2 59.1 +-4.8 73.8 +-1.8
Gram Schmidt 35.6 +-2.4 51.2 +-11.8 77.5 +-2.3

The ML Problem – Pass/Fail

- Inputs
  - 591 features
- Output
  - Classification
    - -1 = pass
    - 1 = fail
- Size: 1567 Samples



	A	B	C	D	E	F	G	H	I	J	K	L
1	ID	Feature 001	Feature 002	Feature 003	Feature 004	Feature 005	Feature 006	Feature 007	Feature 008	Feature 009	Feature 010	Feature 0
2	1	3030.93	2564	2187.7333	1411.1265	1.3602	100	97.6133	0.1242	1.5005	0.0162	-0.00
3	2	3095.78	2465.14	2230.4222	1463.6606	0.8294	100	102.3433	0.1247	1.4966	-5.00E-04	-0.01
4	3	2932.61	2559.94	2186.4111	1698.0172	1.5102	100	95.4878	0.1241	1.4436	0.0041	0.00
5	4	2988.72	2479.9	2199.0333	909.7926	[illegible]	[illegible]	[illegible]	[illegible]	1.4882	-0.0124	-0.00
6	5	3032.24	2502.87	2233.3667	1326.52	[illegible]	[illegible]	[illegible]	[illegible]	1.5031	-0.0031	-0.00
7	6	2946.25	2432.84	2233.3667	1326.52	1.5334	100	100.3967	0.1235	1.5287	0.0167	0.00
8	7	3030.27	2430.12	2230.4222	1463.6606	0.8294	100	102.3433	0.1247	1.5816	-0.027	0.01
9	8	3058.88	2690.15	2248.9	1004.4692	0.7884	100	106.24	0.1185	1.5153	0.0157	7.00E
10	9	2967.68	2600.47	2248.9	1004.4692	0.7884	100	106.24	0.1185	1.5358	0.0111	-0.00
11	10	3016.11	2428.37	2248.9	1004.4692	0.7884	100	106.24	0.1185	1.5381	0.0159	0.00
12	11	2994.05	2548.21	2195.1222	1046.1468	1.3204	100	103.34	0.1223	1.5144	-0.019	0.00
13	12	2928.84	2479.4	2196.2111	1605.7578	0.9959	100	97.9156	0.1257	1.469	0.017	-0.01
14	13	2920.07	2507.4	2195.1222	1046.1468	1.3204	100	103.34	0.1223	1.531	-0.0259	0.02
15	14	3051.44	2529.27	2184.4333	877.6266	1.4668	100	107.8711	0.124	1.5236	-0.0209	-0.00
16	15	2963.97	2629.48	2224.6222	947.7739	1.2924	100	104.8489	0.1197	1.4474	0.0144	-0.01
17	16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	100	104.8489	0.1197	1.5465	0.025	-0.00
18	17	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	100	104.8078	0.1207	1.4368	0.015	-0.00
19	18	3032.73	2517.79	2270.2556	1258.4558	1.395	100	104.8078	0.1207	1.5537	0.022	-0.00
20	19	3040.34	2501.16	2207.3889	962.5317	1.2043	100	104.0311	0.121	1.5481	-0.0367	0.00

secom.csv - Excel

	VJ	VK	VL	VM	VN	VO	VP	VQ	VR	VS	VT	VU
1	Feature 581	Feature 582	Feature 583	Feature 584	Feature 585	Feature 586	Feature 587	Feature 588	Feature 589	Feature 590	Date	Classification
2			0.5005	0.0118	0.0035	2.363					2008-07-19	-1
3	0.006	[illegible]	[illegible]	[illegible]	[illegible]	4.4447	0.0096	0.0201	0.006	208.2045	2008-07-19	-1
4	0.0148	[illegible]	[illegible]	[illegible]	[illegible]	3.1745	0.0584	0.0484	0.0148	82.8602	2008-07-19	1
5	0.0044	73.8432	0.499	0.0103	0.0025	2.0544	0.0202	0.0149	0.0044	73.8432	2008-07-19	-1
6			0.48	0.4766	0.1045	99.3032	0.0202	0.0149	0.0044	73.8432	2008-07-19	-1
7	0.0052	44.0077	0.4949	0.0189	0.0044	3.8276	0.0342	0.0151	0.0052	44.0077	2008-07-19	-1
8			0.501	0.0143	0.0042	2.8515	0.0342	0.0151	0.0052	44.0077	2008-07-19	-1
9	0.0063	95.031	0.4984	0.0106	0.0034	2.1261	0.0204	0.0194	0.0063	95.031	2008-07-19	-1
10	0.0045	111.6525	0.4993	0.0172	0.0046	3.4456	0.0111	0.0124	0.0045	111.6525	2008-07-19	-1
11	0.0073	90.2294	0.4967	0.0152	0.0038	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2008-07-19	-1
12	0.0071	57.8122	0.4925	0.0158	0.0041	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2008-07-19	1
13	0.0081	75.5077	0.4987	0.0427	0.0092	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2008-07-19	1
14	0.0034	52.2039	0.495	0.0153	0.0041	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2008-07-20	-1
15			0.5034	0.0151	0.0038	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2008-07-21	-1
16	0.0084	142.908	0.5077	0.0094	0.0026	1.8483	0.0202	0.0289	0.0084	142.908	2008-07-21	1
17	0.0045	100.2745	0.5058	0.0078	0.0021	1.5352	0.0174	0.0174	0.0045	100.2745	2008-07-22	-1
18	0.0042	82.0989	0.5005	0.0108	0.0034	2.1574	0.0184	0.0151	0.0042	82.0989	2008-07-22	-1
19			0.5015	0.0105	0.0027	2.0979	0.0184	0.0151	0.0042	82.0989	2008-07-22	-1
20			0.4948	0.0117	0.0034	2.3737	0.0184	0.0151	0.0042	82.0989	2008-07-22	-1

Features (Numeric)

Response (Classification)
-1 (Pass) or 1 (Fail)

Workshop #1

Example 1: Classification

Step 1: R Packages

step_01_install_packages.R

```r
# ------------------------------------------------------------------------------
# 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.
if (! ("methods" %in% rownames(installed.packages()))) { install.packages("methods") }
if (! ("statmod" %in% rownames(installed.packages()))) { install.packages("statmod") }
if (! ("stats" %in% rownames(installed.packages()))) { install.packages("stats") }
if (! ("graphics" %in% rownames(installed.packages()))) { install.packages("graphics") }
if (! ("RCurl" %in% rownames(installed.packages()))) { install.packages("RCurl") }
if (! ("jsonlite" %in% rownames(installed.packages()))) { install.packages("jsonlite") }
if (! ("tools" %in% rownames(installed.packages()))) { install.packages("tools") }
if (! ("utils" %in% rownames(installed.packages()))) { install.packages("utils") }

# 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/10/R")))

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

# Finally, let's run a demo to see H2O at work.
demo(h2o.kmeans)

```

step_01_install_packages.R

Package ‘h2oEnsemble’

```r
# ---------------------------------------------------------------------------
# Install "h2oEnsemble" for model stacking
# Reference: https://github.com/h2oai/h2o-3/tree/master/h2o-r/ensemble
# ---------------------------------------------------------------------------

# Install stable version (1.8)
install.packages(
  "https://h2o-release.s3.amazonaws.com/h2o-ensemble/R/h2oEnsemble_0.1.8.tar.gz",
  repos = NULL)

# Quick test
library(h2oEnsemble)
```

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

Example 1: Classification

Step 2: Exploratory Analysis

step_02_exploratory_analysis.R

Importing SECOM data

```r
# ---------------------------------------------------------------------------
# Step 2: Data Exploration
# ---------------------------------------------------------------------------

# 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")

# (Optional) Demo - Importing files using URLs
secom <- h2o.importFile(
  path = "https://github.com/woobe/H2O_London_Workshop/raw/master/data/secom.csv",
  destination_frame = "secom")

# (Optional) Demo - Converting R data frame into H2O data frame
hdf_iris <- as.h2o(iris)

# (Optional) Turning off progress bar in R
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

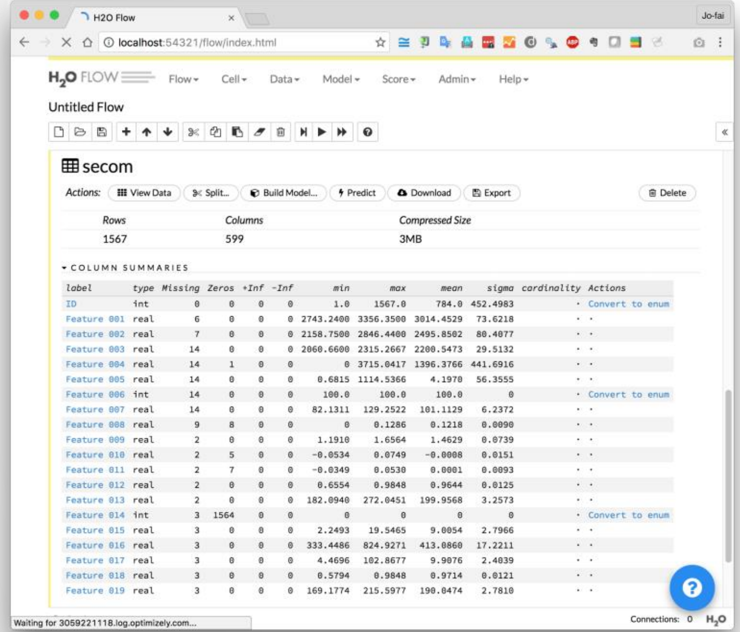
```r
# Basic exploratory analysis
print(dim(secom)) # 1567 x 599
print(summary(secom$Classification))
# alternatively, use H2O flow to look at data (localhost:54321)

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

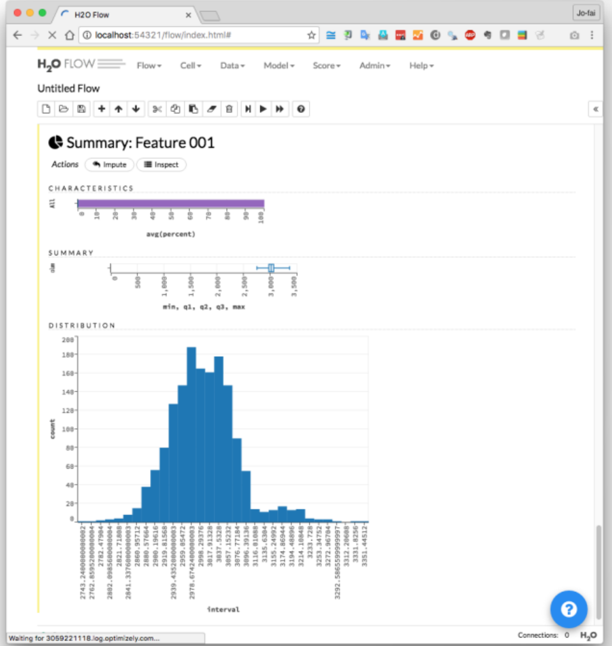
Convert -1 and 1 to categorical value

```
> # 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)





Example 1: Classification

Step 3: Building Models

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Go to file/function | Addins | H2O_London_Workshop

step_03_basic_models.R

Source on Save | Run | Source

```r


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

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

print(target)
print(features)


# ------------------------------------------------------------------------------
# Train H2O models with default value
# ------------------------------------------------------------------------------

# Turn off progress bar (if you want to ...)
# h2o.no_progress()

# GBM
model_gbm <- h2o.gbm(x = features, y = target,
                     training_frame = secom)

# Random Forest
model_drf <- h2o.randomForest(x = features, y = target,
                              training_frame = secom)

# Deep Neural Network
model_dnn <- h2o.deeplearning(x = features, y = target,
                              training_frame = secom)

# Use R / Flow to look at models
print(summary(model_gbm))
print(summary(model_drf))
print(summary(model_dnn))

# Look at variable importance
print(h2o.varimp(model_gbm))
h2o.varimp_plot(model_gbm)
```

22:1 (Untitled) R Script

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
> print(target)
[1] "Classification"
>
> print(features)
  [1] "Feature 001"       "Feature 002"       "Feature 003"       "Feature 004"       "Feature 005"
  [6] "Feature 006"       "Feature 007"       "Feature 008"       "Feature 009"       "Feature 010"
 [11] "Feature 011"       "Feature 012"       "Feature 013"       "Feature 014"       "Feature 015"
 [16] "Feature 016"       "Feature 017"       "Feature 018"       "Feature 019"       "Feature 020"
 [21] "Feature 021"       "Feature 022"       "Feature 023"       "Feature 024"       "Feature 025"
 [26] "Feature 026"       "Feature 027"       "Feature 028"       "Feature 029"       "Feature 030"
 [31] "Feature 031"       "Feature 032"       "Feature 033"       "Feature 034"       "Feature 035"
 [36] "Feature 036"       "Feature 037"       "Feature 038"       "Feature 039"       "Feature 040"
 [41] "Feature 041"       "Feature 042"       "Feature 043"       "Feature 044"       "Feature 045"
 [46] "Feature 046"       "Feature 047"       "Feature 048"       "Feature 049"       "Feature 050"
 [51] "Feature 051"       "Feature 052"       "Feature 053"       "Feature 054"       "Feature 055"
 [56] "Feature 056"       "Feature 057"       "Feature 058"       "Feature 059"       "Feature 060"
 [61] "Feature 061"       "Feature 062"       "Feature 063"       "Feature 064"       "Feature 065"
 [66] "Feature 066"       "Feature 067"       "Feature 068"       "Feature 069"       "Feature 070"
 [71] "Feature 071"       "Feature 072"       "Feature 073"       "Feature 074"       "Feature 075"
 [76] "Feature 076"       "Feature 077"       "Feature 078"       "Feature 079"       "Feature 080"
 [81] "Feature 081"       "Feature 082"       "Feature 083"       "Feature 084"       "Feature 085"
 [86] "Feature 086"       "Feature 087"       "Feature 088"       "Feature 089"       "Feature 090"
 [91] "Feature 091"       "Feature 092"       "Feature 093"       "Feature 094"       "Feature 095"
 [96] "Feature 096"       "Feature 097"       "Feature 098"       "Feature 099"       "Feature 100"
[101] "Feature 101"       "Feature 102"       "Feature 103"       "Feature 104"       "Feature 105"
[106] "Feature 106"       "Feature 107"       "Feature 108"       "Feature 109"       "Feature 110"
[111] "Feature 111"       "Feature 112"       "Feature 113"       "Feature 114"       "Feature 115"
[116] "Feature 116"       "Feature 117"       "Feature 118"       "Feature 119"       "Feature 120"
[121] "Feature 121"       "Feature 122"       "Feature 123"       "Feature 124"       "Feature 125"
[126] "Feature 126"       "Feature 127"       "Feature 128"       "Feature 129"       "Feature 130"
[131] "Feature 131"       "Feature 132"       "Feature 133"       "Feature 134"       "Feature 135"
[136] "Feature 136"       "Feature 137"       "Feature 138"       "Feature 139"       "Feature 140"
[141] "Feature 141"       "Feature 142"       "Feature 143"       "Feature 144"       "Feature 145"
[146] "Feature 146"       "Feature 147"       "Feature 148"       "Feature 149"       "Feature 150"
[151] "Feature 151"       "Feature 152"       "Feature 153"       "Feature 154"       "Feature 155"
[156] "Feature 156"       "Feature 157"       "Feature 158"       "Feature 159"       "Feature 160"
[161] "Feature 161"       "Feature 162"       "Feature 163"       "Feature 164"       "Feature 165"
[166] "Feature 166"       "Feature 167"       "Feature 168"       "Feature 169"       "Feature 170"
[171] "Feature 171"       "Feature 172"       "Feature 173"       "Feature 174"       "Feature 175"
[176] "Feature 176"       "Feature 177"       "Feature 178"       "Feature 179"       "Feature 180"
[181] "Feature 181"       "Feature 182"       "Feature 183"       "Feature 184"       "Feature 185"
[186] "Feature 186"       "Feature 187"       "Feature 188"       "Feature 189"       "Feature 190"
[191] "Feature 191"       "Feature 192"       "Feature 193"       "Feature 194"       "Feature 195"
[196] "Feature 196"       "Feature 197"       "Feature 198"       "Feature 199"       "Feature 200"
[201] "Feature 201"       "Feature 202"       "Feature 203"       "Feature 204"       "Feature 205"
```

History

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/media/SUPPORT/Repo/H2O_London_Workshop - master - RStudio

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step_03_basic_models.R

```r


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

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

print(target)
print(features)


# ------------------------------------------------------------------------------
# Train H2O models with default value
# ------------------------------------------------------------------------------

# Turn off progress bar (if you want to ...)
# h2o.no_progress()

# GBM
model_gbm <- h2o.gbm(x = features, y = target,
                     training_frame = secom)

# Random Forest
model_drf <- h2o.randomForest(x = features, y = target,
                              training_frame = secom)

# Deep Neural Network
model_dnn <- h2o.deeplearning(x = features, y = target,
                              training_frame = secom)

# Use R / Flow to look at models
print(summary(model_gbm))
print(summary(model_drf))
print(summary(model_dnn))

# Look at variable importance
print(h2o.varimp(model_gbm))
h2o.varimp_plot(model_gbm)
```

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
> # GBM
> model_gbm <- h2o.gbm(x = features, y = target,
+                      training_frame = secom)
  |==========================================================================================| 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 515, Feature 514, Feature 193, Feature 192, Feature 195, Feature 194, Feature 230,
Feature 232, Feature 231, Feature 529, Feature 244, Feature 365, Feature 401, Feature 400, Feature 006, Feature 403, Fe
ature 402, Feature 405, Feature 404, Feature 241, Feature 482, Feature 243, Feature 242, Feature 180, Feature 179, Feat
ure 459, Feature 050, Feature 053, Feature 450, Feature 331, Feature 452, Feature 330, Feature 451, Feature 191, Featur
e 070, Feature 190, Feature 506, Feature 505, Feature 508, Feature 507, Feature 509, Feature 465, Feature 464, Feature
467, Feature 466, Feature 227, Feature 502, Feature 504, Feature 503, Feature 463, Feature 187, Feature 462, Feature 39
9, Feature 277, Feature 398, Feature 315, Feature 314, Feature 316, Feature 150, Feature 395, Feature 397, Feature 396,
 Feature 329, Date.year, Feature 323, Feature 326... <truncated>
>
```

Environment Files Plots Spark Packages Help Git Viewer

History

Sun, Nov 20, 2016 8:11 pm

/media/SUPPORT/Repo/H2O_London_Workshop - master - RStudio

step_03_basic_models.R

```r


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

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

print(target)
print(features)


# ---------------------------------------------------------------------------
# Train H2O models with default value
# ---------------------------------------------------------------------------

# Turn off progress bar (if you want to ...)
# h2o.no_progress()

# GBM
model_gbm <- h2o.gbm(x = features, y = target,
                     training_frame = secom)

# Random Forest
model_drf <- h2o.randomForest(x = features, y = target,
                              training_frame = secom)

# Deep Neural Network
model_dnn <- h2o.deeplearning(x = features, y = target,
                              training_frame = secom)

# Use R / Flow to look at models
print(summary(model_gbm))
print(summary(model_drf))
print(summary(model_dnn))

# Look at variable importance
print(h2o.varimp(model_gbm))
h2o.varimp_plot(model_gbm)
```

Console /media/SUPPORT/Repo/H2O_London_Workshop/

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

H2OBinomialModel: gbm
Model Key:  GBM_model_R_1479672080021_139
Model Summary:
  number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth mean_depth min_leaves
1              50                       50               11781         5         5    5.00000          7
  max_leaves mean_leaves
1         20    13.82000

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

MSE:  0.005638814
RMSE:  0.07509204
LogLoss:  0.03756363
Mean Per-Class Error:  0
AUC:  1
Gini:  1

Confusion Matrix for F1-optimal threshold:
         -1   1    Error     Rate
-1     1463   0 0.000000  =0/1463
1         0 104 0.000000   =0/104
Totals 1463 104 0.000000  =0/1567

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                       max f1  0.399934 1.000000  98
2                       max f2  0.399934 1.000000  98
3                 max f0point5  0.399934 1.000000  98
4                 max accuracy  0.399934 1.000000  98
5                max precision  0.960024 1.000000   0
6                   max recall  0.399934 1.000000  98
7              max specificity  0.960024 1.000000   0
8             max absolute_mcc  0.399934 1.000000  98
9   max min_per_class_accuracy  0.399934 1.000000  98
10 max mean_per_class_accuracy  0.399934 1.000000  98

Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F>, xval=<T/F>)`
```

/media/SUPPORT/Repo/H2O_London_Workshop - master - RStudio

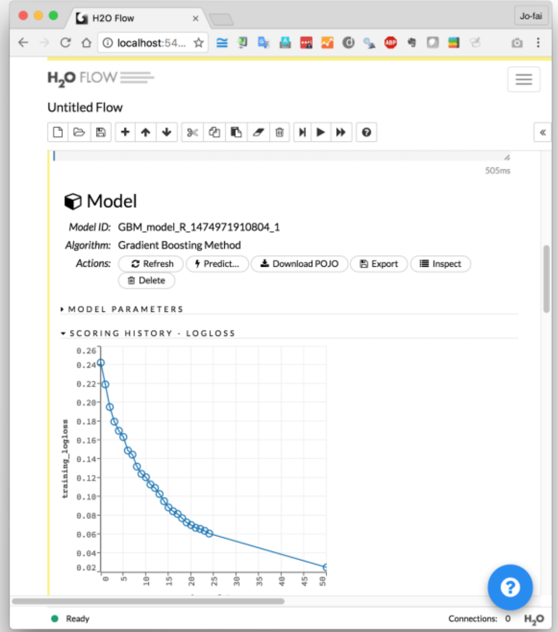
step_03_basic_models.R

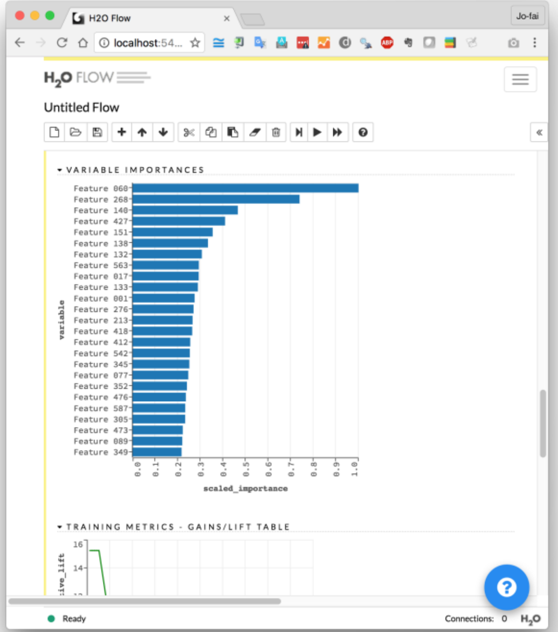
```r


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

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

print(target)
print(features)


# ----------------------------------------------------------------------------
# Train H2O models with default value
# ----------------------------------------------------------------------------

# Turn off progress bar (if you want to ...)
# h2o.no_progress()

# GBM
model_gbm <- h2o.gbm(x = features, y = target,
                     training_frame = secom)

# Random Forest
model_drf <- h2o.randomForest(x = features, y = target,
                              training_frame = secom)

# Deep Neural Network
model_dnn <- h2o.deeplearning(x = features, y = target,
                              training_frame = secom)

# Use R / Flow to look at models
print(summary(model_gbm))
print(summary(model_drf))
print(summary(model_dnn))

# Look at variable importance
print(h2o.varimp(model_gbm))
h2o.varimp_plot(model_gbm)
```

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
> print(h2o.varimp(model_gbm))
Variable Importances:
     variable relative_importance scaled_importance percentage
1 Feature 060           21.270756          1.000000   0.067994
2 Feature 065           10.369788          0.487514   0.033148
3 Feature 563            9.856809          0.463397   0.031508
4 Feature 349            9.147681          0.430059   0.029241
5 Feature 030            8.751948          0.411455   0.027976

---
            variable relative_importance scaled_importance percentage
474      Feature 582            0.000000          0.000000   0.000000
475      Feature 587            0.000000          0.000000   0.000000
476      Feature 590            0.000000          0.000000   0.000000
477       Date.month            0.000000          0.000000   0.000000
478 Date.day-of-week            0.000000          0.000000   0.000000
479        Date.hour            0.000000          0.000000   0.000000
>
```

Use H2O Flow (localhost:54321)

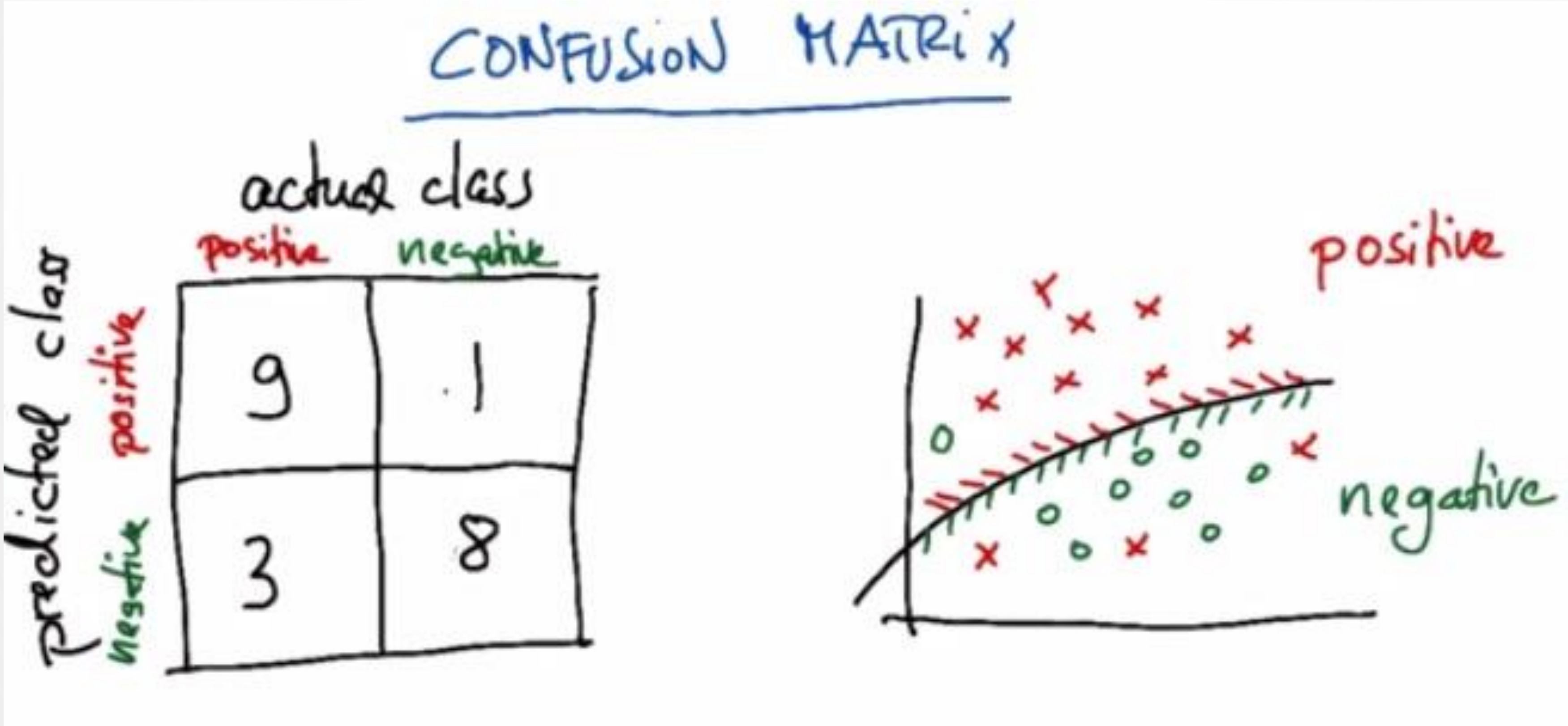




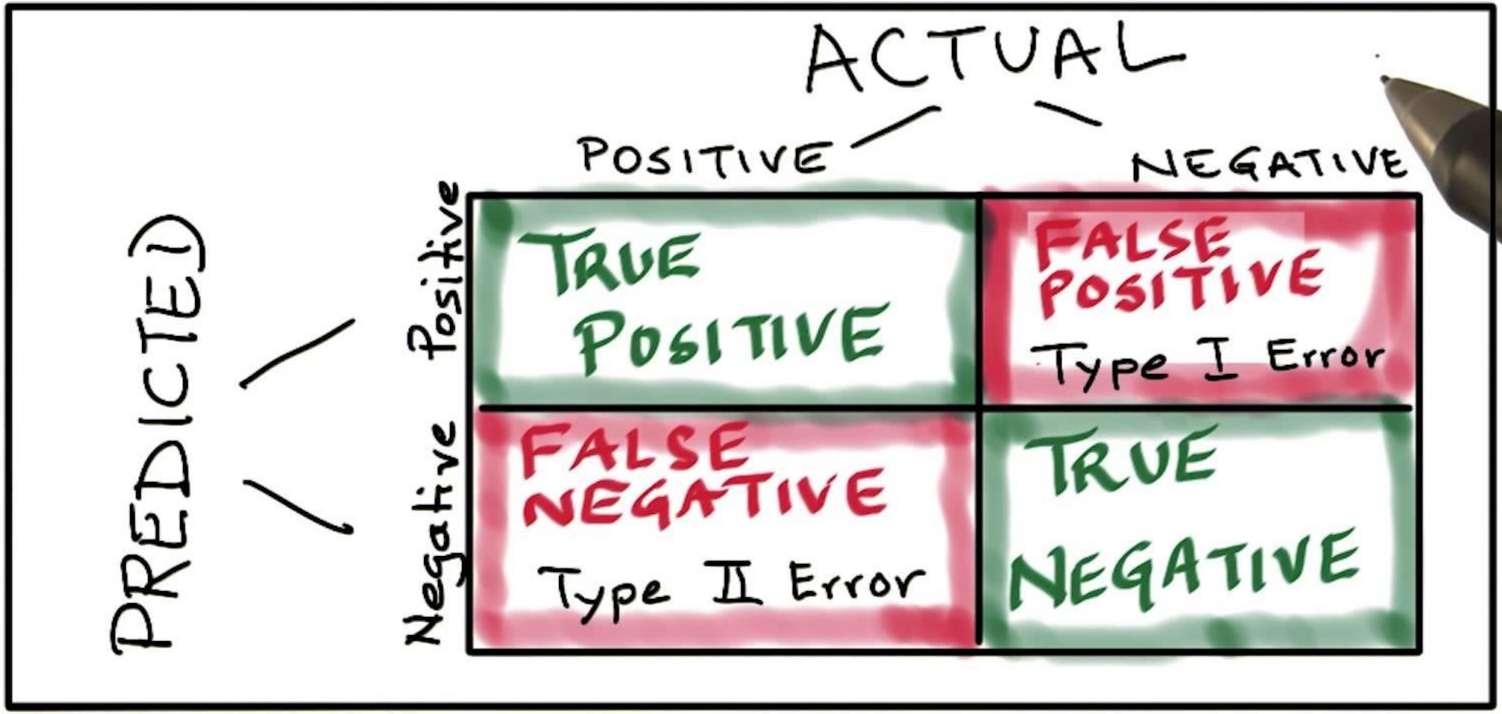
Example 1: Classification

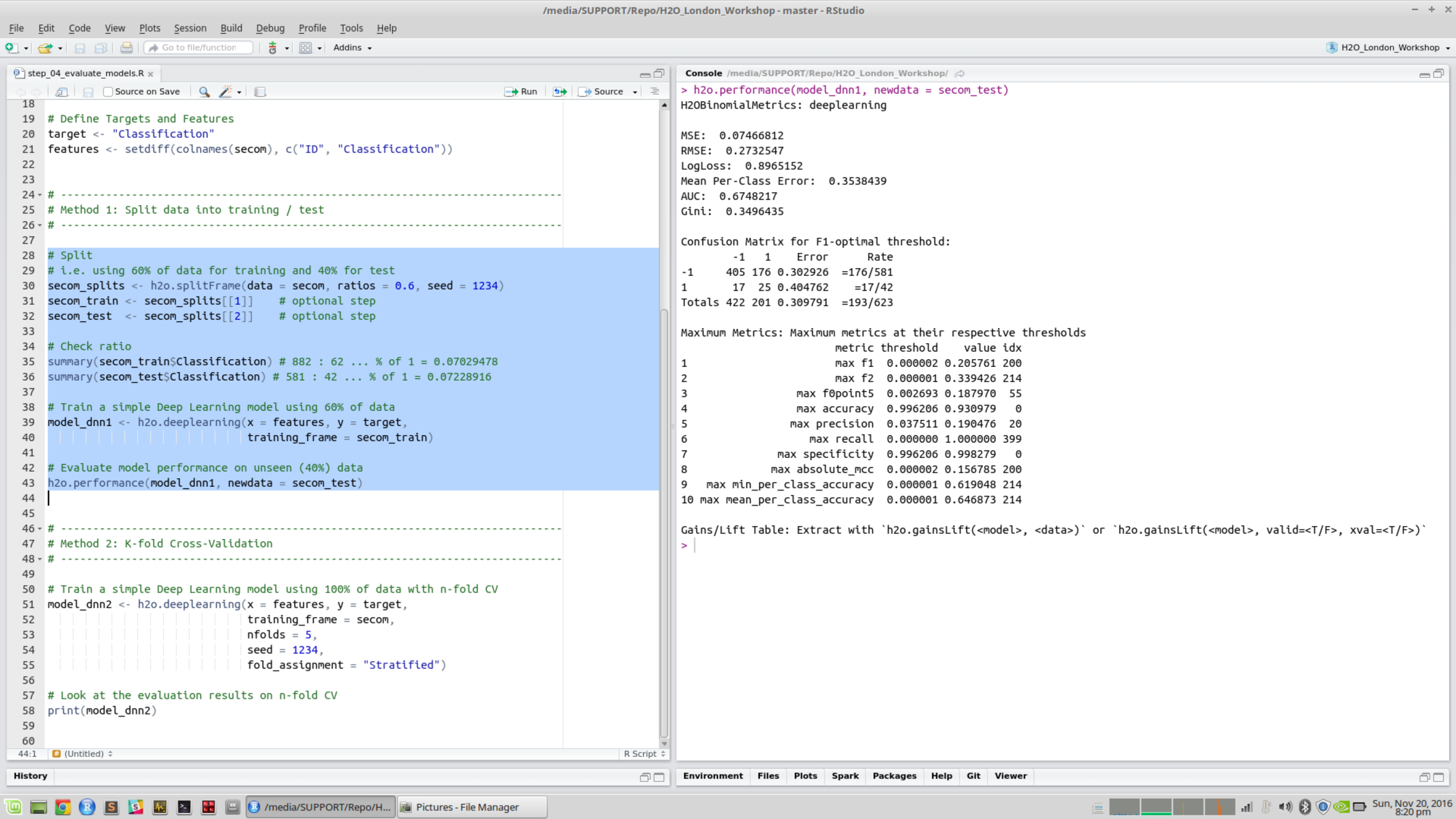
Step 4: Evaluating Models

Confusion Matrix



The Confusion Matrix

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File Edit Code View Plots Session Build Debug Profile Tools Help
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Addins
H2O_London_Workshop
step_04_evaluate_models.R
Source on Save
Run
Source
# Define Targets and Features
target <- "Classification"
features <- setdiff(colnames(secom), c("ID", "Classification"))
# ---
# Method 1: Split data into training / test
# ---
# Split
# i.e. using 60% of data for training and 40% for test
secom_splits <- h2o.splitFrame(data = secom, ratios = 0.6, seed = 1234)
secom_train <- secom_splits[[1]]   # optional step
secom_test <- secom_splits[[2]]   # optional step
# Check ratio
summary(secom_train$Classification) # 882 : 62 ... % of 1 = 0.07029478
summary(secom_test$Classification) # 581 : 42 ... % of 1 = 0.07228916
# Train a simple Deep Learning model using 60% of data
model_dnn1 <- h2o.deeplearning(x = features, y = target,
                               training_frame = secom_train)
# Evaluate model performance on unseen (40%) data
h2o.performance(model_dnn1, newdata = secom_test)
# ---
# Method 2: K-fold Cross-Validation
# ---
# Train a simple Deep Learning model using 100% of data with n-fold CV
model_dnn2 <- h2o.deeplearning(x = features, y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified")
# Look at the evaluation results on n-fold CV
print(model_dnn2)
44:1
(Untitled)
R Script
Console /media/SUPPORT/Repo/H2O_London_Workshop/
> h2o.performance(model_dnn1, newdata = secom_test)
H2OBinomialMetrics: deeplearning
MSE: 0.07466812
RMSE: 0.2732547
LogLoss: 0.8965152
Mean Per-Class Error: 0.3538439
AUC: 0.6748217
Gini: 0.3496435
Confusion Matrix for F1-optimal threshold:
        -1   1   Error   Rate
-1   405 176 0.302926 =176/581
1   17 25 0.404762   =17/42
Totals 422 201 0.309791 =193/623
Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold   value idx
1   max f1 0.000002 0.205761 200
2   max f2 0.000001 0.339426 214
3   max f0point5 0.002693 0.187970 55
4   max accuracy 0.996206 0.930979   0
5   max precision 0.037511 0.190476 20
6   max recall 0.000000 1.000000 399
7   max specificity 0.996206 0.998279   0
8   max absolute_mcc 0.000002 0.156785 200
9   max min_per_class_accuracy 0.000001 0.619048 214
10 max mean_per_class_accuracy 0.000001 0.646873 214
Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F>, xval=<T/F>)`
>
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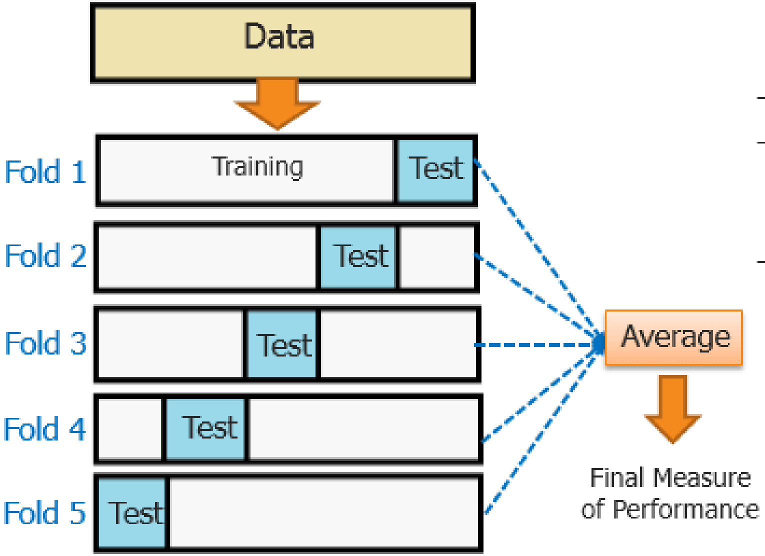
8:20 pm

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

Slide 46

www.edureka.in/data-science

/media/SUPPORT/Repo/H2O_London_Workshop - master - RStudio

step_04_evaluate_models.R

```r

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


# ------------------------------------------------------------------------------
# Method 1: Split data into training / test
# ------------------------------------------------------------------------------

# Split
# i.e. using 60% of data for training and 40% for test
secom_splits <- h2o.splitFrame(data = secom, ratios = 0.6, seed = 1234)
secom_train <- secom_splits[[1]]    # optional step
secom_test  <- secom_splits[[2]]    # optional step

# Check ratio
summary(secom_train$Classification) # 882 : 62 ... % of 1 = 0.07029478
summary(secom_test$Classification) # 581 : 42 ... % of 1 = 0.07228916

# Train a simple Deep Learning model using 60% of data
model_dnn1 <- h2o.deeplearning(x = features, y = target,
                               training_frame = secom_train)

# Evaluate model performance on unseen (40%) data
h2o.performance(model_dnn1, newdata = secom_test)


# ------------------------------------------------------------------------------
# Method 2: K-fold Cross-Validation
# ------------------------------------------------------------------------------

# Train a simple Deep Learning model using 100% of data with n-fold CV
model_dnn2 <- h2o.deeplearning(x = features, y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified")

# Look at the evaluation results on n-fold CV
print(model_dnn2)


```

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
H2OBinomialMetrics: deeplearning
** Reported on cross-validation data. **
** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **

MSE:  0.08972877
RMSE:  0.2995476
LogLoss:  0.6970678
Mean Per-Class Error:  0.4119072
AUC:  0.6058744
Gini:  0.2117488

Confusion Matrix for F1-optimal threshold:
         -1   1    Error       Rate
-1     1144 319 0.218045  =319/1463
1        63  41 0.605769    =63/104
Totals 1207 360 0.243778  =382/1567

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                       max f1  0.002525 0.176724 317
2                       max f2  0.000044 0.295883 391
3                 max f0point5  0.020865 0.137755 213
4                 max accuracy  0.999999 0.932355   0
5                max precision  0.020865 0.123288 213
6                   max recall  0.000000 1.000000 399
7              max specificity  0.999999 0.998633   0
8             max absolute_mcc  0.002525 0.104257 317
9   max min_per_class_accuracy  0.000086 0.574846 387
10 max mean_per_class_accuracy  0.000044 0.598990 391

Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F>, xval=<T/F>)`
Cross-Validation Metrics Summary:
                             mean          sd  cv_1_valid  cv_2_valid  cv_3_valid   cv_4_valid  cv_5_valid
accuracy                0.7087468  0.14202245  0.88782054  0.79591835   0.4781145    0.9235474  0.45833334
auc                     0.6190499 0.026494274  0.62117493  0.66482586  0.62324876   0.63509935   0.5509008
err                    0.29125318  0.14202245  0.11217949  0.20408164   0.5218855    0.0764526   0.5416667
err_count                    88.2   40.267605        35.0        70.0       155.0         25.0       156.0
f0point5               0.19044691 0.063521884  0.21367522  0.17006803  0.12160229    0.3508772  0.09601182
f1                       0.201924 0.025374223  0.22222222  0.22222222  0.17989418   0.24242425  0.14285715
f2                      0.2723356  0.04121469  0.23148148  0.32051283  0.34552845   0.18518518  0.27896994
lift_top_group              1.308   1.8497913         0.0         0.0         0.0         6.54         0.0
logloss                0.69674987  0.04815367   0.6732423    0.636079    0.641785     0.822235  0.71040815
max_per_class_error    0.65172094  0.08798135   0.7619048  0.54545456   0.5503597         0.84   0.5608856
mcc                    0.17012891 0.034879416  0.16248225  0.16829523  0.17033629   0.25242126 0.097109556
```

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Example 1: Classification

Step 5: Tuning Models

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step_05_manual_tuning.R

Source on Save | Run | Source

```r
# ------------------------------------------------------------------------------
# Train H2O models with default / manual settings
# ------------------------------------------------------------------------------

# Check out all parameters
# ?h2o.gbm
# ?h2o.deeplearning
# ?h2o.randomForest

# Deep Learning model with CV and default value
model_dnn1 <- h2o.deeplearning(x = features,
                               y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified")
print(model_dnn1)

# Deep Learning model with manual settings
# ?h2o.deeplearning
model_dnn2 <- h2o.deeplearning(x = features,
                               y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified",
                               score_duty_cycle = 1,

                               # Manual tweaks
                               activation = "RectifierWithDropout",
                               balance_classes = TRUE,
                               hidden = c(100, 100, 100),
                               epochs = 100)
print(model_dnn2)

# Use R / Flow to look at models
print(model_dnn1)
print(model_dnn2)

# ------------------------------------------------------------------------------
# Making predictions
# ------------------------------------------------------------------------------
```

41:1 (Untitled) R Script

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
H2OBinomialMetrics: deeplearning
** Reported on cross-validation data. **
** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **

MSE:  0.08972877
RMSE:  0.2995476
LogLoss:  0.6970678
Mean Per-Class Error:  0.4119072
AUC:  0.6058744
Gini:  0.2117488

Confusion Matrix for F1-optimal threshold:
         -1   1    Error       Rate
-1     1144 319 0.218045  =319/1463
1        63  41 0.605769    =63/104
Totals 1207 360 0.243778  =382/1567

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                       max f1  0.002525 0.176724 317
2                       max f2  0.000044 0.295883 391
3                 max f0point5  0.020865 0.137755 213
4                 max accuracy  0.999999 0.932355   0
5                max precision  0.020865 0.123288 213
6                   max recall  0.000000 1.000000 399
7              max specificity  0.999999 0.998633   0
8             max absolute_mcc  0.002525 0.104257 317
9   max min_per_class_accuracy  0.000086 0.574846 387
10 max mean_per_class_accuracy  0.000044 0.598990 391

Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F>, xval=<T/F>)`
Cross-Validation Metrics Summary:
                             mean          sd  cv_1_valid  cv_2_valid  cv_3_valid   cv_4_valid   cv_5_valid
accuracy                0.7087468  0.14202245  0.88782054  0.79591835   0.4781145    0.9235474   0.45833334
auc                     0.6190499 0.026494274  0.62117493  0.66482586  0.62324876   0.63509935    0.5509008
err                    0.29125318  0.14202245  0.11217949  0.20408164   0.5218855    0.0764526    0.5416667
err_count                    88.2   40.267605        35.0        70.0       155.0         25.0        156.0
f0point5               0.19044691 0.063521884  0.21367522  0.17006803  0.12160229    0.3508772   0.09601182
f1                       0.201924 0.025374223  0.22222222  0.22222222  0.17989418   0.24242425   0.14285715
f2                      0.2723356  0.04121469  0.23148148  0.32051283  0.34552845   0.18518518   0.27896994
lift_top_group              1.308   1.8497913         0.0         0.0         0.0         6.54          0.0
logloss                0.69674987  0.04815367   0.6732423    0.636079    0.641785     0.822235   0.71040815
max_per_class_error    0.65172094  0.08798135   0.7619048  0.54545456   0.5503597         0.84    0.5608856
mcc                    0.17012891 0.034879416  0.16248225  0.16829523  0.17033629   0.25242126  0.097109556
```

History | Environment Files Plots Spark Packages Help Git Viewer

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/media/SUPPORT/Repo/H2O_London_Workshop - master - RStudio

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step_05_manual_tuning.R*

Source on Save | Run | Source

```r
# Check out all parameters
# ?h2o.gbm
# ?h2o.deeplearning
# ?h2o.randomForest

# Deep Learning model with CV and default value
model_dnn1 <- h2o.deeplearning(x = features,
                               y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified")
print(model_dnn1)

# Deep Learning model with manual settings
# ?h2o.deeplearning
model_dnn2 <- h2o.deeplearning(x = features,
                               y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified",

                               # Manual tweaks
                               activation = "RectifierWithDropout",
                               balance_classes = TRUE,
                               hidden = c(50, 50, 50),
                               epochs = 100)
print(model_dnn2)

# Use R / Flow to look at models
print(model_dnn1)
print(model_dnn2)

# ------------------------------------------------------------------------
# Making predictions
# ------------------------------------------------------------------------

yhat <- h2o.predict(model_dnn2, secom)
print(head(yhat))
print(summary(yhat))
```

57:1 | (Untitled) | R Script

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
H2OBinomialMetrics: deeplearning
** Reported on cross-validation data. **
** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **

MSE:  0.07248065
RMSE:  0.2692223
LogLoss:  0.4506603
Mean Per-Class Error:  0.3919272
AUC:  0.6879634
Gini:  0.3759267

Confusion Matrix for F1-optimal threshold:
         -1   1    Error       Rate
-1     1315 148 0.101162  =148/1463
1        71  33 0.682692    =71/104
Totals 1386 181 0.139757  =219/1567

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                       max f1  0.033625 0.231579 172
2                       max f2  0.003561 0.342298 315
3                 max f0point5  0.033625 0.199275 172
4                 max accuracy  1.000000 0.932993   0
5                max precision  0.931569 0.357143  13
6                   max recall  0.000002 1.000000 399
7              max specificity  1.000000 0.999316   0
8             max absolute_mcc  0.003561 0.172113 315
9   max min_per_class_accuracy  0.001171 0.644231 354
10 max mean_per_class_accuracy  0.001171 0.652259 354

Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F>, xval=<T/F>)`
Cross-Validation Metrics Summary:
                              mean          sd  cv_1_valid  cv_2_valid  cv_3_valid  cv_4_valid  cv_5_valid
accuracy                0.82608616 0.040651035   0.9230769   0.8600583   0.7744108    0.795107   0.7777778
auc                      0.6986671 0.013941814  0.69906723  0.69371283  0.73040515  0.66860926   0.7015411
err                     0.17391384 0.040651035  0.07692308  0.13994169  0.22558923  0.20489296  0.22222222
err_count                     54.0   11.721775        24.0        48.0        67.0        67.0        64.0
f0point5                0.23526171  0.04821312  0.37037036   0.1923077  0.19543974  0.21885522  0.19933555
f1                      0.27503464 0.024445241  0.33333334  0.22580644  0.26373628   0.2795699  0.27272728
f2                      0.36008653 0.043195467   0.3030303   0.2734375   0.4054054  0.38690478  0.43165466
lift_top_group            3.269126    2.105467    7.428571         0.0         0.0        3.27    5.647059
logloss                 0.44672656  0.05261717  0.42377242  0.50482506  0.35533702  0.55806434  0.39163405
max_per_class_error      0.5077285  0.11780413  0.71428573   0.6818182  0.36842105        0.48  0.29411766
mcc                      0.2376755 0.031912867  0.29840672  0.16440463  0.23739722   0.2212242   0.2669447
```

History

Environment Files Plots Spark Packages Help Git Viewer

/media/SUPPORT/Repo/H... | Pictures - File Manager | Sun, Nov 20, 2016 8:23 pm

Comparison: Default vs. Manual

Default Settings

```
H2OBinomialMetrics: deeplearning
** Reported on cross-validation data. **
** 5-fold cross-validation on training data

MSE:  0.08972877
RMSE:  0.2995476
LogLoss:  0.6970678
Mean Per-Class Error:  0.4119072
AUC:  0.6058744
Gini:  0.2117488

Confusion Matrix for F1-optimal threshold:
         -1   1    Error       Rate
-1     1144 319 0.218045  =319/1463
1        63  41 0.605769    =63/104
Totals 1207 360 0.243778  =382/1567
```

Manual Tweaks

```
H2OBinomialMetrics: deeplearning
** Reported on cross-validation data. **
** 5-fold cross-validation on training data

MSE:  0.07248065
RMSE:  0.2692223
LogLoss:  0.4506603
Mean Per-Class Error:  0.3919272
AUC:  0.6879634
Gini:  0.3759267

Confusion Matrix for F1-optimal threshold:
         -1   1    Error       Rate
-1     1315 148 0.101162  =148/1463
1        71  33 0.682692    =71/104
Totals 1386 181 0.139757  =219/1567
```

Smaller Errors

Fewer false positives

/media/SUPPORT/Repo/H2O_London_Workshop - master - RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

Making Predictions

step_05_manual_tuning.R*

```r
# Check out all parameters
# ?h2o.gbm
# ?h2o.deeplearning
# ?h2o.randomForest

# Deep Learning model with CV and default value
model_dnn1 <- h2o.deeplearning(x = features,
                               y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified")
print(model_dnn1)

# Deep Learning model with manual settings
# ?h2o.deeplearning
model_dnn2 <- h2o.deeplearning(x = features,
                               y = target,
                               training_frame = secom,
                               nfolds = 5,
                               seed = 1234,
                               fold_assignment = "Stratified",

                               # Manual tweaks
                               activation = "RectifierWithDropout",
                               balance_classes = TRUE,
                               hidden = c(50, 50, 50),
                               epochs = 100)
print(model_dnn2)

# Use R / Flow to look at models
print(model_dnn1)
print(model_dnn2)

# ---------------------------------------------------------------------------
# Making predictions
# ---------------------------------------------------------------------------

yhat <- h2o.predict(model_dnn2, secom)
print(head(yhat, 40))
print(summary(yhat))
```

Console /media/SUPPORT/Repo/H2O_London_Workshop/

```
> print(head(yhat, 40))
```

	predict	p-1	p1
1	-1	1.000000e+00	1.152322e-15
2	-1	1.000000e+00	2.203204e-16
3	1	1.197242e-05	9.999880e-01
4	-1	1.000000e+00	6.160491e-16
5	-1	1.000000e+00	5.075575e-13
6	-1	1.000000e+00	3.021475e-08
7	-1	1.000000e+00	1.530499e-16
8	-1	1.000000e+00	6.463078e-14
9	-1	1.000000e+00	5.099715e-11
10	-1	1.000000e+00	1.501379e-15
11	1	4.556583e-05	9.999544e-01
12	1	9.744068e-05	9.999026e-01
13	-1	1.000000e+00	7.235294e-17
14	-1	1.000000e+00	1.117404e-26
15	1	4.242277e-05	9.999576e-01
16	-1	1.000000e+00	4.651994e-09
17	-1	1.000000e+00	3.355911e-23
18	-1	1.000000e+00	5.910014e-19
19	-1	1.000000e+00	2.524364e-16
20	-1	1.000000e+00	6.455791e-13
21	-1	1.000000e+00	1.634878e-13
22	-1	1.000000e+00	2.045357e-16
23	-1	1.000000e+00	6.730709e-12
24	1	1.139797e-04	9.998860e-01
25	-1	1.000000e+00	3.814657e-09
26	-1	1.000000e+00	1.002225e-12
27	-1	1.000000e+00	1.170781e-11
28	-1	1.000000e+00	4.475900e-09
29	-1	1.000000e+00	9.521416e-15
30	-1	1.000000e+00	3.137428e-13
31	-1	1.000000e+00	1.220719e-08
32	-1	1.000000e+00	1.262628e-12
33	-1	1.000000e+00	2.133081e-13
34	-1	1.000000e+00	2.116694e-12
35	-1	1.000000e+00	6.076701e-12
36	-1	1.000000e+00	5.224696e-12
37	-1	1.000000e+00	3.816010e-08
38	-1	1.000000e+00	5.701559e-13
39	1	1.443873e-06	9.999986e-01
40	-1	1.000000e+00	1.531729e-10

Sun, Nov 20, 2016 8:24 pm

End of Workshop #1

(to be continued …)

Workshop #1 Recap

Workshop #1 Recap

- Introduction to H2O
  - H2O's Interface
    - Flow (Web) and R
  - MNIST Example
    - Hand-written Digits
    - 28 x 28 Pixels
    - Labels: 0 to 9
- Example 1
  - SECOM Data
  - 591 Features (sensors)
  - One Output
    - Pass = -1
    - Fail = 1
  - Binary Classification

Workshop #2 Agenda

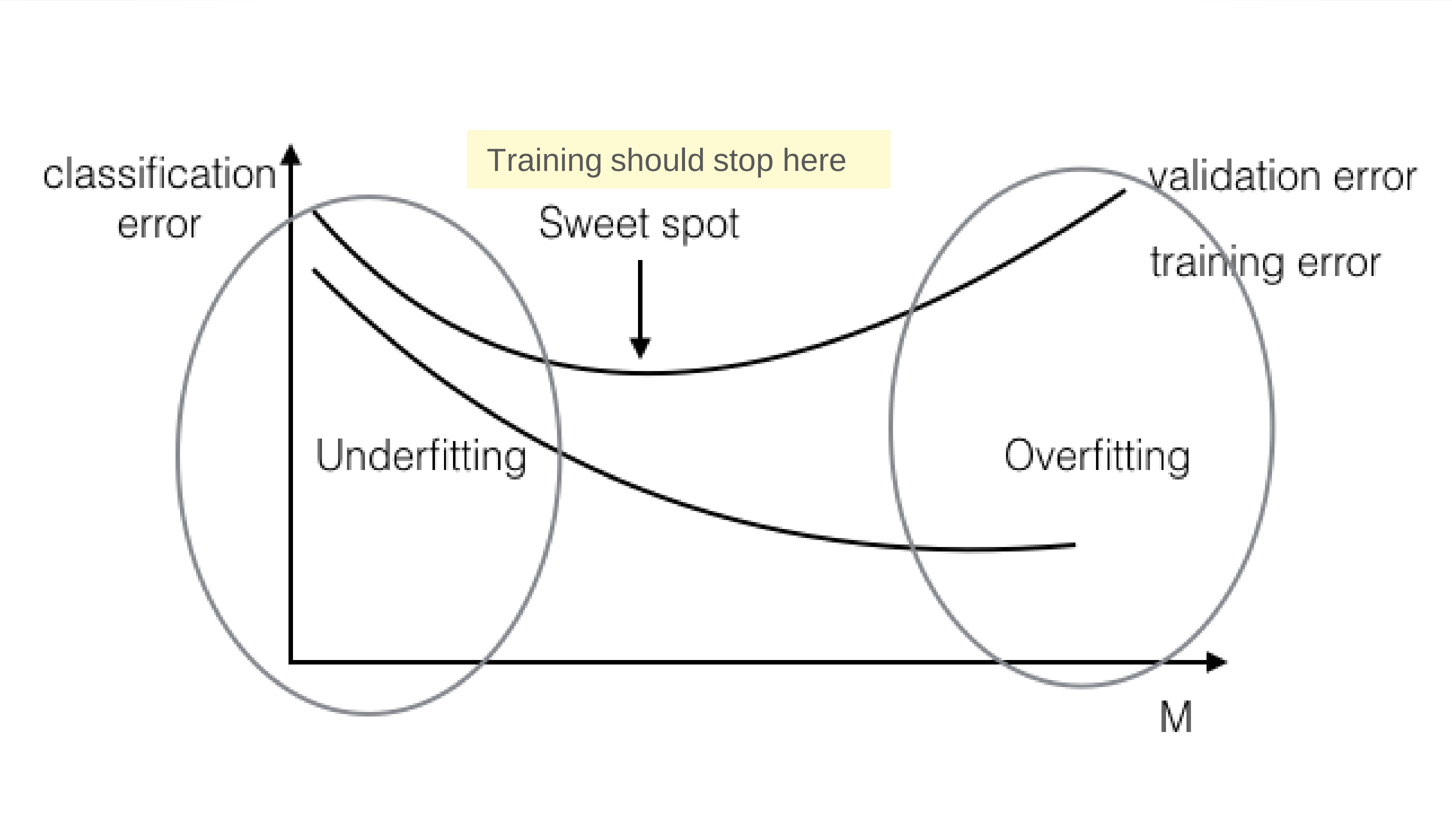
- Example 1 (cont'd)
  6. Full/Random Grid Search
  7. Model Stacking
  8. Saving/Loading Models
  9. Deploying Models with H2O Steam

- Example 2
  - Anomaly Detection using Deep Auto Encoder

- Deep Water
  - Motivation
  - Demo

Early Stopping and Grid Search

Underfitting and Overfitting



Grid Search

- Grid Search Example
  - Parameter 1
    - 5, 6 and 7
  - Parameter 2
    - 0.8, 0.9 and 1.0
  - Full Grid Search
    - 3 x 3 = 9 Combinations
  - Random Grid Search
    - Randomly picks n out of 9

	Parameter 1	Parameter 2
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_full_and_random_grid_search.R

```r
# -----------------------------------------------------
# Train H2O models with FULL grid search
# -----------------------------------------------------

# Define parameters for grid search
param_dnn <- list(
  activation = c("Tanh", "Rectifier"),
  hidden = list(c(50,50), c(50,50,50), c(100,100)),
  balance_classes = c(TRUE, FALSE)
)

# DNN with early stopping and FULL grid search
full_grid_dnn <- h2o.grid(

  # Core parameters for model training
  x = features,
  y = target,
  training_frame = secom_train,
  validation_frame = secom_valid,
  epochs = 100,

  # Parameters for grid search
  grid_id = "full_grid_dnn",
  hyper_params = param_dnn,
  algorithm = "deeplearning",

  # Parameters for early stopping
  stopping_metric = "logloss",
  stopping_rounds = 10

)
```

Define search range

H2O Grid Search Function
(Default = Full Grid Search)

Core parameters

Define H2O algorithm for gird search

Settings for early stopping

step_06_full_and_random_grid_search.R

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

Grid ID: full_grid_dnn
Used hyper parameters:
  -  activation
  -  balance_classes
  -  hidden
Number of models: 12
Number of failed models: 0

Hyper-Parameter Search Summary: ordered by increasing logloss
   activation balance_classes       hidden              model_ids             logloss
1        Tanh           false     [50, 50]  full_grid_dnn_model_2 0.40711800843533374
2   Rectifier           false [50, 50, 50]  full_grid_dnn_model_7 0.48874743693102923
3   Rectifier           false     [50, 50]  full_grid_dnn_model_3  0.4982381350341734
4        Tanh           false   [100, 100] full_grid_dnn_model_10  0.5086143941843354
5        Tanh           false [50, 50, 50]  full_grid_dnn_model_6  0.6951631654420898
6   Rectifier           false   [100, 100] full_grid_dnn_model_11  0.7255411856345131
7        Tanh            true     [50, 50]  full_grid_dnn_model_0  0.8135149329182292
8   Rectifier            true     [50, 50]  full_grid_dnn_model_1  0.8196504509768745
9   Rectifier            true [50, 50, 50]  full_grid_dnn_model_5  0.8967032178246215
10       Tanh            true   [100, 100]  full_grid_dnn_model_8  0.9060965911951484
11  Rectifier            true   [100, 100]  full_grid_dnn_model_9  0.9210162435224971
12       Tanh            true [50, 50, 50]  full_grid_dnn_model_4  1.1898727562847378
```

Full Grid Search
Comparing logloss from all 12 models

step_06_full_and_random_grid_search.R

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

# Define criteria for random grid search
search_criteria <- list(
  strategy = "RandomDiscrete",     # Ask H2O to run random grid search
  max_models = 5,                  # e.g. only want to test 5 random models
  max_runtime_secs = 600,          # e.g. only have 600 sec to run this
  seed = 1234                      # reproducible random parameters combinations
)

# DNN with early stopping and RANDOM grid search
random_grid_dnn <- h2o.grid(

  # Core parameters for model training
  x = features,
  y = target,
  training_frame = secom_train,
  validation_frame = secom_valid,
  epochs = 100,

  # Parameters for grid search
  grid_id = "random_grid_dnn",
  hyper_params = param_dnn,
  algorithm = "deeplearning",
  search_criteria = search_criteria, # <- added this for Random Grid Search

  # Parameters for early stopping
  stopping_metric = "logloss",
  stopping_rounds = 10

)
```

Define search criteria for RANDOM grid search

step_06_full_and_random_grid_search.R

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

Grid ID: random_grid_dnn
Used hyper parameters:
  -  activation
  -  balance_classes
  -  hidden
Number of models: 5
Number of failed models: 0

Hyper-Parameter Search Summary: ordered by increasing logloss
  activation balance_classes      hidden               model_ids             logloss
1       Tanh           false     [50, 50] random_grid_dnn_model_0 0.44293730219504907
2  Rectifier           false     [50, 50] random_grid_dnn_model_3  0.5668445883973072
3       Tanh           false [50, 50, 50] random_grid_dnn_model_1  0.5810266574346342
4       Tanh            true   [100, 100] random_grid_dnn_model_4  0.8644619887482393
5  Rectifier            true [50, 50, 50] random_grid_dnn_model_2  0.9745825958041073
> |
```

Only searched five models with RANDOM grid search

h2oEnsemble
Model Stacking

Common Types of Ensemble Methods

Bagging

- Reduces variance and increases accuracy
- Robust against outliers or noisy data
- Often used with Decision Trees (i.e. Random Forest)

Boosting

- Also reduces variance and increases accuracy
- Not robust against outliers or noisy data
- Flexible – can be used with any loss function

Stacking

- Used to ensemble a diverse group of strong learners
- Involves training a second-level machine learning algorithm called a “metalearner” to learn the optimal combination of the base learners

H2O Overview

- H2O Ensemble is a scalable implementation of the Super Learner algorithm for H2O.
- H2O is an open-source, distributed machine learning library written in Java with APIs in R, Python, Scala and REST/JSON.
- Produced by H2O.ai in Mountain View, CA.
- H2O.ai advisers are Trevor Hastie, Rob Tibshirani and Stephen Boyd from Stanford.

step_07_stacking_models.R

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

# Train a Gradient Boosting Machine model
model_gbm <- h2o.gbm(x = features,
                     y = target,
                     training_frame = secom_train,
                     model_id = "gradient_boosting_machine",
                     nfolds = 5,
                     fold_assignment = "Modulo",
                     keep_cross_validation_predictions = TRUE)

# Train a Distributed Random Forest model
model_drf <- h2o.randomForest(x = features,
                              y = target,
                              training_frame = secom_train,
                              model_id = "random_forest",
                              nfolds = 5,
                              fold_assignment = "Modulo",
                              keep_cross_validation_predictions = TRUE)

# Train a Deep Learning model
model_dnn <- h2o.deeplearning(x = features,
                              y = target,
                              training_frame = secom_train,
                              model_id = "deep_learning",
                              nfolds = 5,
                              fold_assignment = "Modulo",
                              keep_cross_validation_predictions = TRUE)
```

Build three different H2O models

step_07_stacking_models.R

```r
# Load h2oEnsemble
library(h2oEnsemble)

# Define a list of all models
models <- list(model_gbm, model_drf, model_dnn)

# Define the metalearner
custom_dnn_metalearner <- function(...,
                                   hidden = c(400, 400, 400),
                                   epochs = 1000,
                                   activation = "RectifierWithDropout",
                                   input_dropout_ratio = 0.2,
                                   l1 = 1e-7,
                                   l2 = 1e-7
) {
  h2o.deeplearning.wrapper(...,
                           hidden = hidden,
                           epochs = epochs,
                           activation = activation,
                           input_dropout_ratio = input_dropout_ratio,
                           l1 = l1, l2 = l2
  )
}
metalearner <- "custom_dnn_metalearner"

# Use h2oEnsemble::h2o.stack for model stacking
model_stack <- h2o.stack(models = models,
                         metalearner = metalearner,
                         response_frame = secom_train[, target])

# Evalute ensemble performance on test data
print(h2o.ensemble_performance(model_stack, secom_test))
```

Using h2o.stack(…) function to create ensemble

step_07_stacking_models.R

```
> # Evalute ensemble performance on test data
> print(h2o.ensemble_performance(model_stack, secom_test))
  |=====================================================================| 100%
  |=====================================================================| 100%
  |=====================================================================| 100%

Base learner performance, sorted by specified metric:
                   learner       AUC
3            deep_learning 0.6439226
2            random_forest 0.6966232
1 gradient_boosting_machine 0.7041841


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

Ensemble performance (AUC): 0.720781083517744
```

Ensemble has better performance (e.g. higher AUC) when compared to individual models

Saving / Loading H2O 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_from_disk <- h2o.loadModel(path = "./models/default_gbm/")
print(model_from_disk)
```

Deploying Models with H2O Steam

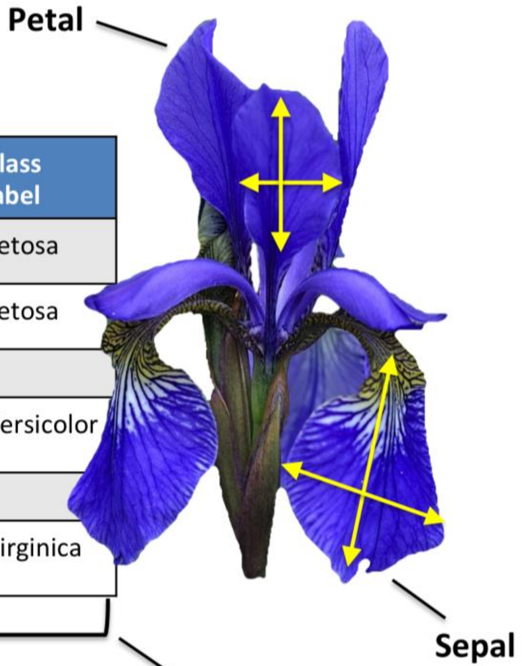
Iris Dataset

Samples
(instances, observations)

	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
…					
50	6.4	3.5	4.5	1.2	Versicolor
…					
150	5.9	3.0	5.0	1.8	Virginica

Features
(attributes, measurements, dimensions)

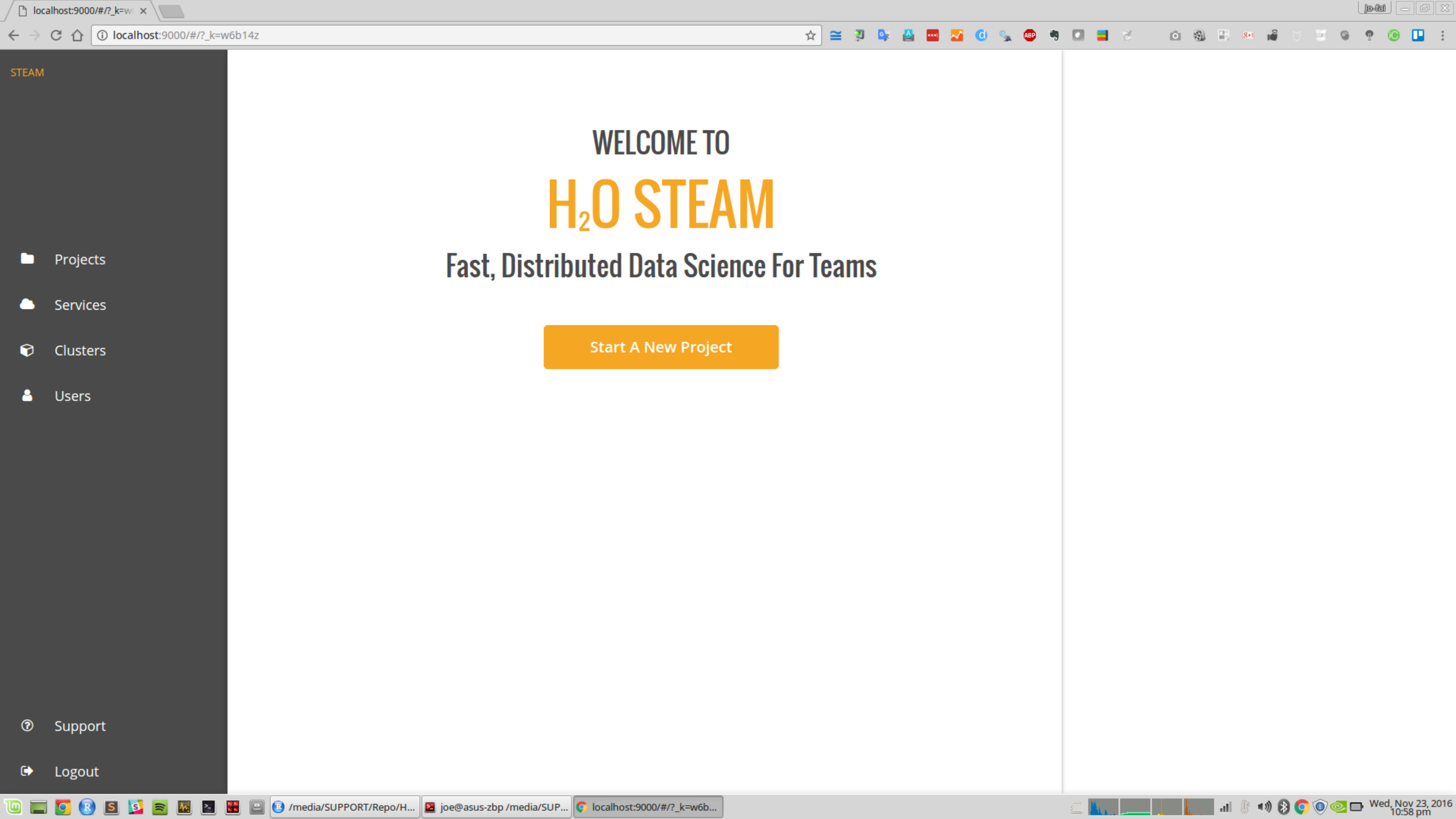
Class labels
(targets)



step_09_deploy_model_with_steam.R

```r
# Import data from a R data frame
data(iris)
d_iris <- as.h2o(iris)

# Quick look
head(d_iris)
summary(d_iris)

# Define Targets and Features
target <- "Species"
features <- setdiff(colnames(d_iris), c("Species"))

# ---------------------------------------------------------------
# Train a H2O Model
# ---------------------------------------------------------------

# Train three basic H2O models
model_dnn <- h2o.deeplearning(x = features,
                              y = target,
                              model_id = "iris_deep_learning",
                              training_frame = d_iris)

model_drf <- h2o.randomForest(x = features,
                              y = target,
                              model_id = "iris_random_forest",
                              training_frame = d_iris)

model_gbm <- h2o.gbm(x = features,
                     y = target,
                     model_id = "iris_gbm",
                     training_frame = d_iris)
```

Build three different models with the classic Iris dataset


localhost:9000/#/?_k=w6b14z
STEAM
Projects
Services
Clusters
Users
Support
Logout
WELCOME TO
H2O STEAM
Fast, Distributed Data Science For Teams
Start A New Project
/media/SUPPORT/Repo/H...
joe@asus-zbp /media/SUP...
localhost:9000/#/?_k=w6b...
Wed, Nov 23, 2016
10:58 pm

localhost:9000/#/newproject?_k=9vms5b

STEAM

1. Select H2O Cluster

Select an H2O cluster to import models and datasets from.

CLUSTER	DATASETS	MODELS	
joe	N/A	N/A	Connect

… Or Connect To A New H2O Cluster

Connect to a H2O cluster where your existing models and data sets are located.

localhost

54321

Connect

- Projects
- Services
- Clusters
- Users

- Support
- Logout

/media/SUPPORT/Repo/H... joe@asus-zbp /media/SUP... localhost:9000/#/newproje... Wed, Nov 23, 2016 10:58 pm localhost:9000/#/newproject?_k=sl92dl

STEAM

Projects

Services

Clusters

Users

Support

Logout

1. Select H2O Cluster

H2O_started_from_R_joe_eon283
localhost:54321
✖ use a different cluster

2. Select Dataframe

iris

3. Select Model Category

Multinomial

4. Pick Models To Import

Models in a project must share the same feature set and response column to enable comparison. By default, Steam picks the most optimized model format for you to import. Advanced users can choose your own model type here.

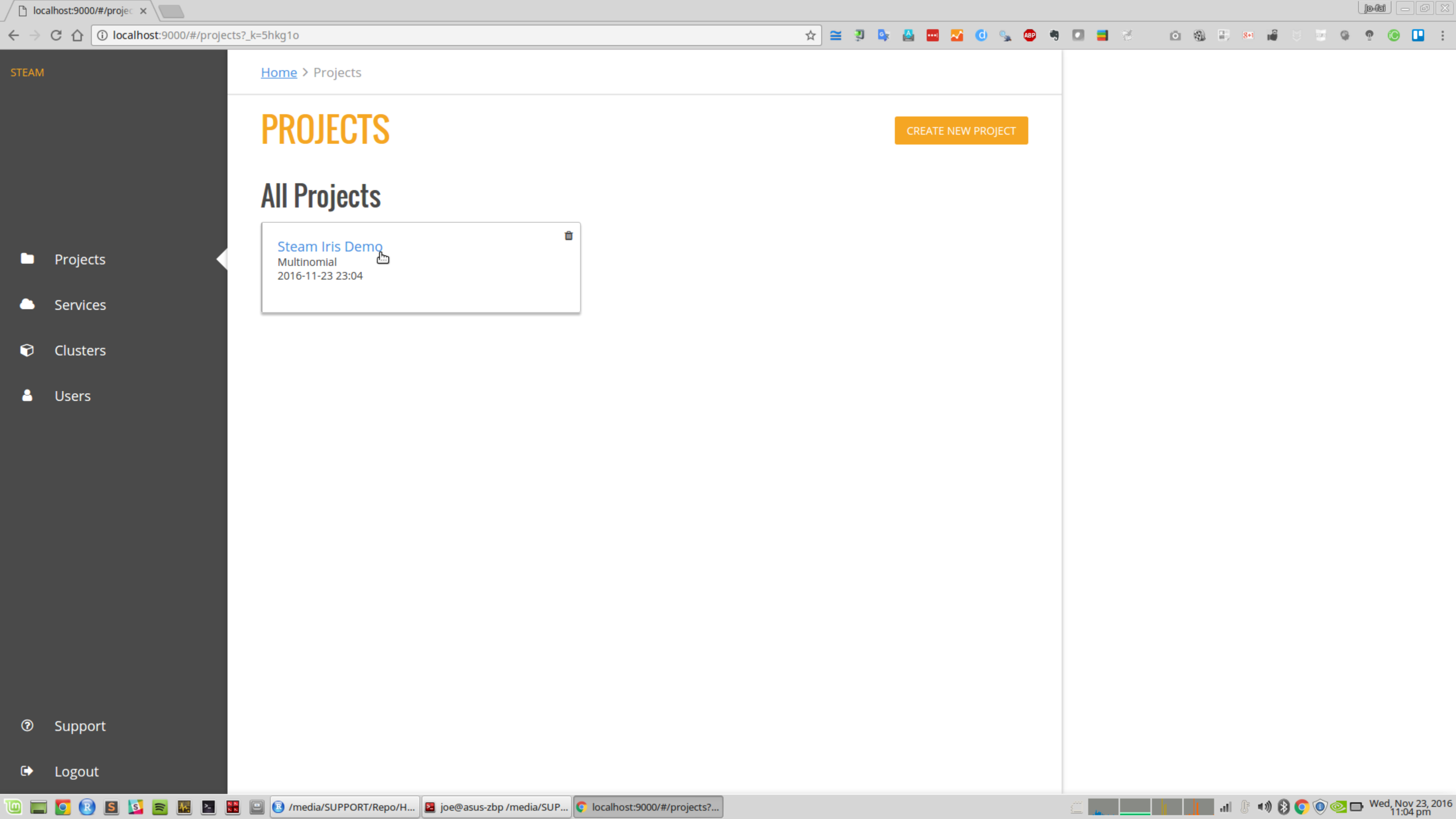
MODEL	RESPONSE COLUMN	CATEGORICAL	
iris_deep_learning	Species	Multinomial	☑ Select for Import
iris_random_forest	Species	Multinomial	☑ Select for Import
iris_gbm	Species	Multinomial	☑ Select for Import

5. Name Project

Steam Iris Demo

Create Project

/media/SUPPORT/Repo/H... joe@asus-zbp /media/SUP... localhost:9000/#/newproje... Wed, Nov 23, 2016 11:04 pm


localhost:9000/#/projec
localhost:9000/#/projects?_k=5hkg1o
STEAM
Home > Projects
PROJECTS
CREATE NEW PROJECT
All Projects
Steam Iris Demo
Multinomial
2016-11-23 23:04
Projects
Services
Clusters
Users
Support
Logout
/media/SUPPORT/Repo/H...
joe@asus-zbp /media/SUP...
localhost:9000/#/projects?...
Wed, Nov 23, 2016
11:04 pm

STEAM

< Projects

Steam ...

- Models
- Deployment
- Configurations
- Collaborators

Home > Projects > 5 > Models

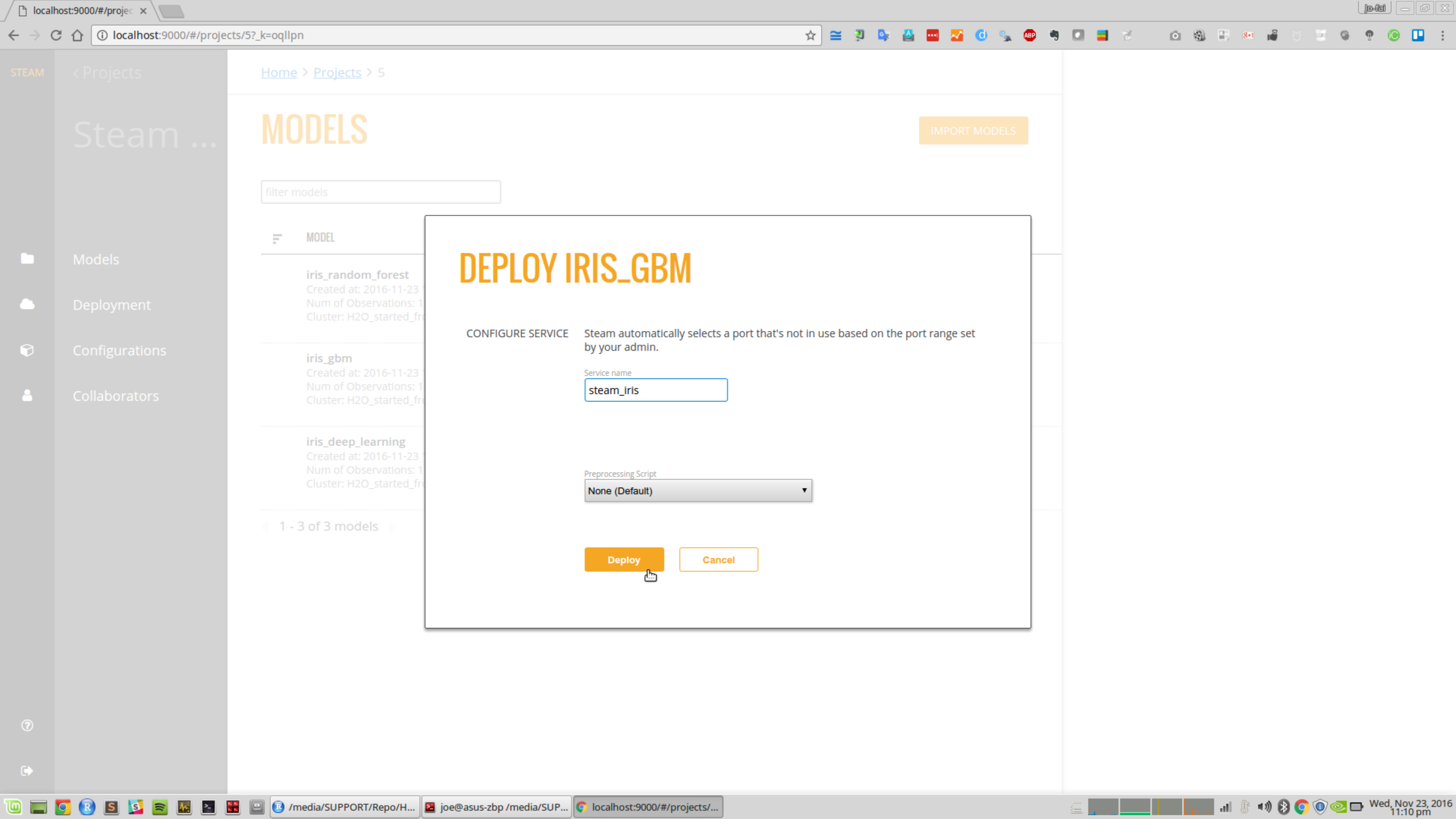
MODELS

IMPORT MODELS

filter models

MODEL	MSE	LOGLOSS	R^2	ACTIONS
iris_random_forest Created at: 2016-11-23 11:04:38 Num of Observations: 150 Cluster: H2O_started_from_R_joe_eon283	0.034834	0.122869	0.947749	view model details label as deploy model delete model
iris_gbm Created at: 2016-11-23 11:04:40 Num of Observations: 150 Cluster: H2O_started_from_R_joe_eon283	0.002838	0.018819	0.995744	view model details label as deploy model delete model
iris_deep_learning Created at: 2016-11-23 11:04:37 Num of Observations: 150 Cluster: H2O_started_from_R_joe_eon283	0.127301	0.577885	0.809048	view model details label as deploy model delete model

1 - 3 of 3 models


localhost:9000/#/projects/5?_k=oqllpn
STEAM
< Projects
Steam ...
Models
Deployment
Configurations
Collaborators
Home > Projects > 5
MODELS
IMPORT MODELS
filter models
MODEL
iris_random_forest
Created at: 2016-11-23
Num of Observations: 1
Cluster: H2O_started_fr
iris_gbm
Created at: 2016-11-23
Num of Observations: 1
Cluster: H2O_started_fr
iris_deep_learning
Created at: 2016-11-23
Num of Observations: 1
Cluster: H2O_started_fr
1 - 3 of 3 models
DEPLOY IRIS_GBM
CONFIGURE SERVICE
Steam automatically selects a port that's not in use based on the port range set by your admin.
Service name
steam_iris
Preprocessing Script
None (Default)
Deploy
Cancel
/media/SUPPORT/Repo/H...
joe@asus-zbp /media/SUP...
localhost:9000/#/projects/...
Wed, Nov 23, 2016
11:10 pm

localhost:9000/#/projects/5/deployment?_k=0nrxw3

STEAM

< Projects

Steam ...

Models

Deployment

Configurations

Collaborators

Home > Projects > 5 > Deployment

DEPLOYMENT

UPLOAD NEW PACKAGE

DEPLOYED SERVICES | PACKAGING

steam_iris @ 192.168.1.80:41788

started

✖ Stop Service

Model	7
Status	OK

192.168.1.80:41788

/media/SUPPORT/Repo/H... joe@asus-zbp /media/SUP... localhost:9000/#/projects/...

Wed, Nov 23, 2016 11:10 pm

Prediction Service

Steam

Select input parameters, OR enter your own custom query string to predict

MODEL INPUT PARAMETERS

Parameters

1. Sepal.Length	1.2
2. Sepal.Width	0.6
3. Petal.Length	0.8
4. Petal.Width	1.1

Query String

The parameters above gets automatically built into a REST API query string. You can also input your own string if that's easier for you.

http://192.168.1.80:41788/predict? Sepal.Length=1.2&Sepal.Width=0.6&Petal.Length=0.8&Petal.Width=1.1

PREDICT CLEAR

PREDICTION RESULTS

Model Predictions

Predicting setosa

Index	Labels	Probability
0	setosa	0.7998
1	versicolor	0.1513
2	virginica	0.0489

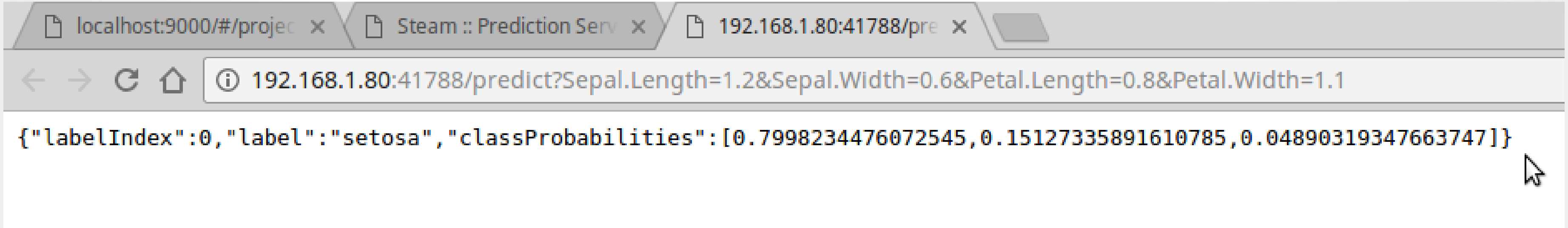
Model Runtime Stats

Service started	2016-11-23 23:10:20 UTC
Uptime	28 s

MORE STATS

BATCH PREDICTION *OPTIONAL

Select a Batch JSON file



The Classic REST API Service

Thanks!

- Organisers & Contributors
  - Ajit Jaokar
  - Sibanjan Das
- Key Resources
  - docs.h2o.ai
  - github.com/h2oai/h2o-meetups
- Slides & Code
  - bit.ly/h2o_iot_workshop1
- Contact
  - joe@h2o.ai
  - @matlabulous
  - github.com/woobe