

04_AutoML_example1

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1 AutoML and Ensemble Learning with H2O.ai

- [Introduction to H2O ai](#)
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```
In [1]: library( readr )
        library( dplyr )
        library( GGally )
```

Attaching package: dplyr

The following objects are masked from package:stats:

filter, lag

The following objects are masked from package:base:

intersect, setdiff, setequal, union

Loading required package: ggplot2

Registered S3 methods overwritten by 'ggplot2':

method	from
[.quosures	rlang
c.quosures	rlang
print.quosures	rlang

Registered S3 method overwritten by 'GGally':

method	from
+.gg	ggplot2

Attaching package: GGally

The following object is masked from package:dplyr:

```
nasa
```

2 Funky data example

```
In [3]: funky_data <- read_csv( "funkydata.csv" ) %>%  
      mutate( Y = factor( Y ) )
```

Parsed with column specification:

```
cols(  
  Gaussian1 = col_double(),  
  Gaussian2 = col_double(),  
  Moon1 = col_double(),  
  Moon2 = col_double(),  
  Circle1 = col_double(),  
  Circle2 = col_double(),  
  Y = col_double()  
)
```

```
In [4]: library( skimr )
```

Attaching package: skimr

The following object is masked from package:stats:

```
filter
```

```
In [5]: skim_to_wide( funky_data )
```

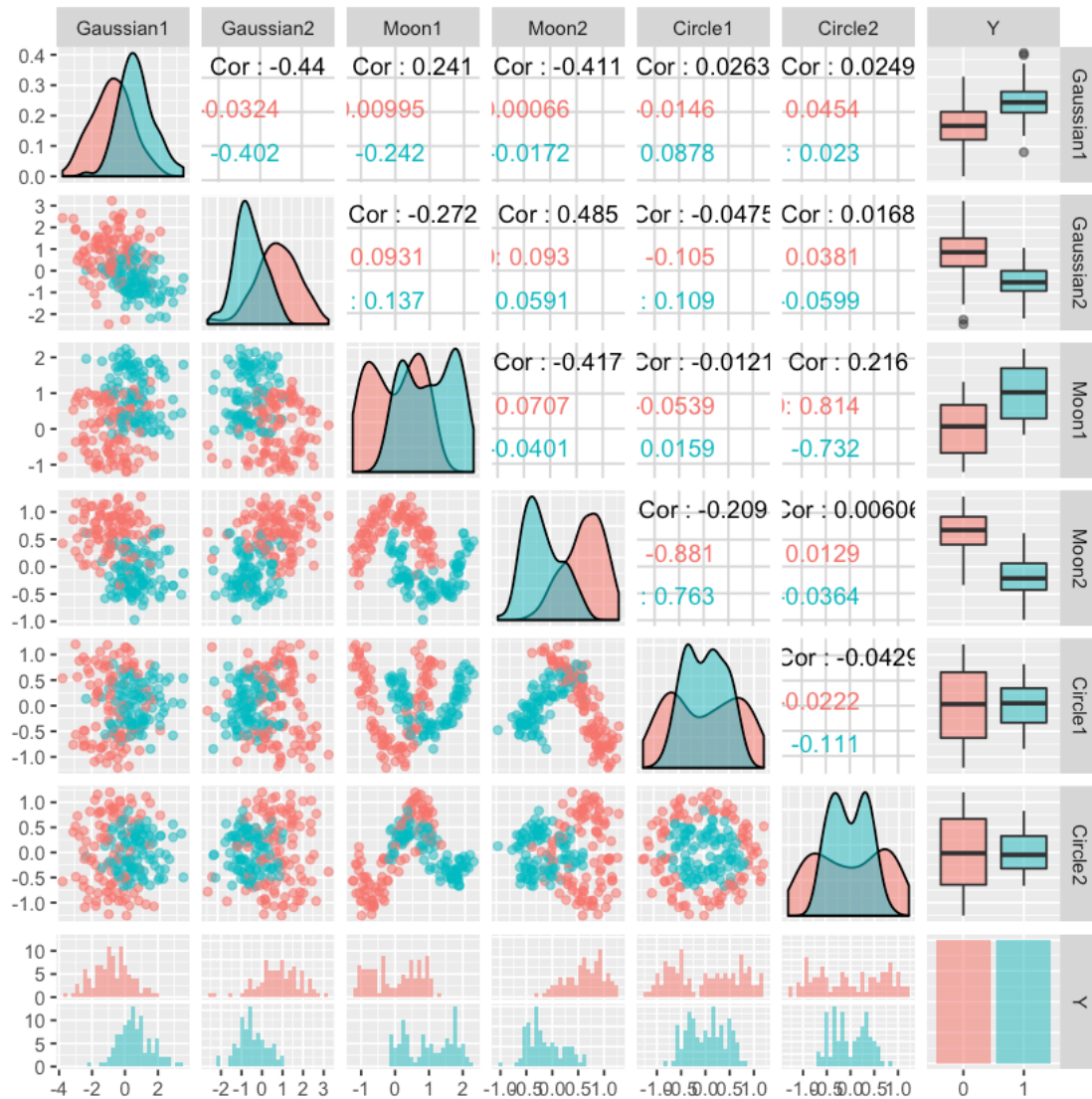
	type <chr>	variable <chr>	missing <chr>	complete <chr>	n <chr>	n_unique <chr>	top_counts <chr>	ord <chr>
	factor	Y	0	200	200	2	0: 100, 1: 100, NA: 0	FA
	numeric	Circle1	0	200	200	NA	NA	NA
	numeric	Circle2	0	200	200	NA	NA	NA
	numeric	Gaussian1	0	200	200	NA	NA	NA
	numeric	Gaussian2	0	200	200	NA	NA	NA
	numeric	Moon1	0	200	200	NA	NA	NA
	numeric	Moon2	0	200	200	NA	NA	NA

A tibble: 7 CE 16

```
In [6]: ggpairs( funky_data, aes( alpha=0.1, color=Y ) )
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.  
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
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`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
In [7]: library(h2o)
```

```
-----

Your next step is to start H2O:
> h2o.init()
```

For H2O package documentation, ask for help:

```
> ??h2o
```

After starting H2O, you can use the Web UI at <http://localhost:54321>

For more information visit <http://docs.h2o.ai>

Attaching package: h2o

The following objects are masked from package:stats:

```
cor, sd, var
```

The following objects are masked from package:base:

```
&&, %*%, %in%, ||, apply, as.factor, as.numeric, colnames,  
colnames<-, ifelse, is.character, is.factor, is.numeric, log,  
log10, log1p, log2, round, signif, trunc
```

```
In [8]: h2o.init()
```

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

Note: In case of errors look at the following log files:

```
/var/folders/8j/_h7w48591zq59klcljxctvcs25_0zh/T//RtmpaxYBGF/h2o_colettace_started_from_r.
```

```
/var/folders/8j/_h7w48591zq59klcljxctvcs25_0zh/T//RtmpaxYBGF/h2o_colettace_started_from_r.
```

Starting H2O JVM and connecting: . Connection successful!

R is connected to the H2O cluster:

```
H2O cluster uptime:      1 seconds 451 milliseconds  
H2O cluster timezone:    America/New_York  
H2O data parsing timezone: UTC  
H2O cluster version:     3.24.0.5  
H2O cluster version age:  8 days  
H2O cluster name:        H2O_started_from_R_colettace_yhm690  
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
H2O Internal Security: FALSE
H2O API Extensions:    Amazon S3, XGBoost, Algos, AutoML, Core V3, Core V4
R Version:             R version 3.6.0 (2019-04-26)

```

```
In [9]: funky_data = as.h2o( funky_data )
```

```
|=====| 100%
```

```
In [10]: class( funky_data )
```

```
'H2OFrame'
```

```
In [11]: summary( funky_data )
```

Warning message in summary.H2OFrame(funky_data):

Approximated quantiles computed! If you are interested in exact quantiles, please pass the `exact` argument.

Gaussian1	Gaussian2	Moon1	Moon2
Min. : -3.70164	Min. : -2.4650	Min. : -1.20354	Min. : -0.9726
1st Qu.: -0.92574	1st Qu.: -0.6316	1st Qu.: -0.09335	1st Qu.: -0.2183
Median : -0.01343	Median : 0.1066	Median : 0.46347	Median : 0.2632
Mean : -0.09543	Mean : 0.1677	Mean : 0.50255	Mean : 0.2487
3rd Qu.: 0.76956	3rd Qu.: 0.9259	3rd Qu.: 1.04960	3rd Qu.: 0.6657
Max. : 3.38425	Max. : 3.2245	Max. : 2.24426	Max. : 1.2825
Circle1	Circle2	Y	
Min. : -1.21187	Min. : -1.258472	0:100	
1st Qu.: -0.44734	1st Qu.: -0.474603	1:100	
Median : 0.04368	Median : -0.044858		
Mean : 0.01718	Mean : -0.002766		
3rd Qu.: 0.47565	3rd Qu.: 0.432842		
Max. : 1.19801	Max. : 1.200726		

2.1 Split into train val test

- H2O you give your “desired” train/val/test ratios and it gives you back approximately the proportions you want
- E.g., Say we want 500 samples for training, 100 samples for validation and 400 samples for test data:

```
In [12]: funky_splits <- h2o.splitFrame( funky_data, ratios=c(0.5) )
```

```
In [13]: funky_train <- funky_splits[[1]]
         funky_test  <- funky_splits[[2]]
```

```

In [14]: dim( funky_train )

1.97 2.7

In [15]: dim( funky_test )

1.103 2.7

In [16]: library(tictoc)

In [17]: tic()
aml_results <- h2o.automl(
  # x is omitted since we want to use all the columns except "Y" as predictors
  y = 'Y',
  training_frame = funky_train,
  leaderboard_frame = funky_test,
  max_runtime_secs = 360, # Default time is one hour!!
  exclude_algos = 'GBM',
)
toc()

|=====| 100%
318.586 sec elapsed

```

2.2 AutoML results

- Printing the results object shows you info from the winning “leader” model, and well as the “leaderboard” of how well the various models performed

```

In [18]: dim( aml_results@leaderboard )

1.208 2.6

In [22]: head( aml_results@leaderboard, 20 )

```

	model_id <chr>	auc <dbl>	logloss <dbl>	m <
A df[,6]: 20 6	XGBoost_grid_1_AutoML_20190627_121001_model_143	1.0000000	6.252269e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_122	1.0000000	6.911448e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_148	1.0000000	7.210843e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_124	1.0000000	5.184913e-02	0
	DeepLearning_grid_1_AutoML_20190627_121001_model_14	1.0000000	1.200763e-07	0
	DeepLearning_grid_1_AutoML_20190627_121001_model_7	1.0000000	1.795007e-02	0
	StackedEnsemble_BestOfFamily_AutoML_20190627_121001	1.0000000	3.869660e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_156	0.9996226	6.308121e-02	0
	DeepLearning_grid_1_AutoML_20190627_121001_model_3	0.9992453	6.517710e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_85	0.9992453	7.710078e-02	0
	StackedEnsemble_AllModels_AutoML_20190627_121001	0.9992453	1.011197e-01	0
	DeepLearning_grid_1_AutoML_20190627_121001_model_9	0.9992453	6.464990e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_25	0.9988679	8.680839e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_173	0.9988679	5.271640e-01	0
	XGBoost_grid_1_AutoML_20190627_121001_model_140	0.9988679	8.582076e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_50	0.9984906	7.613767e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_181	0.9984906	3.647458e-01	0
	XGBoost_grid_1_AutoML_20190627_121001_model_4	0.9984906	7.956581e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_157	0.9981132	8.424608e-02	0
	XGBoost_grid_1_AutoML_20190627_121001_model_7	0.9981132	1.473685e-01	0

```
In [20]: getParms( aml_results@leader )
          # or a synonym:
          # aml_results@leader@parameters
```

```
$model_id 'XGBoost_grid_1_AutoML_20190627_121001_model_143'
```

```
$training_frame 'automl_training_RTMP_sid_b932_3'
```

```
$nfolds 5
```

```
$keep_cross_validation_models FALSE
```

```
$keep_cross_validation_predictions TRUE
```

```
$fold_assignment 'Modulo'
```

```
$stopping_metric 'logloss'
```

```
$stopping_tolerance 0.05
```

```
$seed '-9118792347905751911'
```

```
$distribution 'bernoulli'
```

```
$ntrees 103
```

```
$max_depth 20
```

```
$min_rows 0.01
```

```

$learn_rate 0.05
$sample_rate 0.6
$col_sample_rate 0.8
$col_sample_rate_per_tree 0.8
$score_tree_interval 5
$booster 'dart'
$reg_lambda 0.01
$reg_alpha 0.001
$x 1. 'Gaussian1' 2. 'Gaussian2' 3. 'Moon1' 4. 'Moon2' 5. 'Circle1' 6. 'Circle2'
$y 'Y'

In [21]: as.data.frame( predict( aml_results@leader, funky_test ) )

|=====| 100%

```


	predict <fct>	p0 <dbl>	p1 <dbl>
	1	0.003199100	0.996800900
	0	0.990319550	0.009680446
	0	0.996739209	0.003260799
	0	0.994402945	0.005597057
	0	0.996943951	0.003056029
	1	0.002768338	0.997231662
	0	0.996874869	0.003125152
	0	0.994392037	0.005607983
	1	0.082000196	0.917999804
	0	0.980747581	0.019252392
	0	0.111670792	0.888329208
	1	0.006192982	0.993807018
	1	0.002698720	0.997301280
	0	0.996312141	0.003687858
	0	0.965337813	0.034662213
	0	0.965095460	0.034904540
	1	0.003074586	0.996925414
	0	0.995468318	0.004531683
	0	0.990804672	0.009195301
	1	0.021566689	0.978433311
	0	0.994225919	0.005774109
	1	0.005199194	0.994800806
	0	0.990367115	0.009632888
	0	0.933854520	0.066145495
	0	0.933238626	0.066761374
	0	0.995287836	0.004712182
	0	0.992851913	0.007148073
	0	0.989509702	0.010490319
	0	0.996046543	0.003953473
A df[,3]: 103 CE 3	1	0.076979578	0.923020422
	1	0.102084875	0.897915125
	1	0.011659980	0.988340020
	1	0.004415810	0.995584190
	0	0.333979487	0.666020513
	1	0.051807821	0.948192179
	0	0.196451485	0.803548515
	0	0.946147144	0.053852841
	0	0.995928228	0.004071767
	0	0.945539057	0.054460917
	1	0.003308177	0.996691823
	0	0.972926259	0.027073767
	1	0.004879534	0.995120466
	1	0.002771556	0.997228444
	0	0.992878377	0.007121624
	1	0.003055513	0.996944487
	0	0.932834148	0.067165881
	1	0.004070818	0.995929182
	0	0.985665262	0.014334713
	0	0.978906095	0.021093879
	0	0.650776029	0.349224001