

```
# Import Libraries
```

```
library(tidyverse)
```

```
## — Attaching packages ————— tidyverse 1.3.0 —
```

```
## ✓ ggplot2 3.3.1      ✓ purrr 0.3.4
```

```
## ✓ tibble 3.0.1       ✓ dplyr 1.0.0
```

```
## ✓ tidyr 1.1.2        ✓ stringr 1.4.0
```

```
## ✓ readr 1.3.1        ✓ forcats 0.5.0
```

```
## — Conflicts ————— tidyverse_conflicts() —
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag() masks stats::lag()
```

```
library(readxl)
```

```
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 https://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
```

```
# Read the Excel Sheets
```

```
path <- "bank_term_deposit_marketing_analysis.xlsx"
```

```
sheets <- excel_sheets(path)
```

```
# Explore Data in each Sheet
```

```
sheets %>%
```

```
  map(~ read_excel(path = path, sheet = .)) %>%
```

```
  set_names(sheets)
```

```
## New names:
## * `` -> ...2
## * `` -> ...3
## * `` -> ...4
## * `` -> ...5
## * `` -> ...6
## * ...
```

```
## New names:
## * `` -> ...2
## * `` -> ...4
```

```
## $PROCEDURE
## # A tibble: 14 x 1
##   `BANK MARKETING ANALYSIS PROCEDURE`
##   <chr>
## 1 <NA>
## 2 STEP 1: COLLECT INFORMATION
## 3 1) CLIENT INFORMATION: AGE, JOB, MARITAL STATUS, EDUCATION LEVEL
## 4 2) CLIENT LOAN HISTORY: DEFAULT HISTORY, HOME LOAN, PERSONAL LOAN, CURRENT B...
## 5 3) MARKETING HISTORY: CONTACT TYPE, DAY LAST CONTACT, MONTH LAST CONTACT, LA...
## 6 4) SUBSCRIPTION HISTORY: ENROLLED IN TERM LOAN? (Y/N)
## 7 <NA>
## 8 STEP 2: MERGE INFORMATION
## 9 1) PERFORM VLOOKUP
## 10 <NA>
## 11 STEP 3: MARKETING ANALYSIS
## 12 1) DAILY RANGE: WHAT IS NORMAL HIT RATE?
## 13 2) WHAT FEATURES CONTRIBUTE TO TERM LOAN ENROLLMENT?
## 14 - Job Analysis
##
## $`DATA DESCRIPTION`
## # A tibble: 70 x 1
##   bank_info
##   <chr>
## 1 Citation Request:
## 2 This dataset is public available for research. The details are described in ...
## 3 Please include this citation if you plan to use this database:
## 4 <NA>
## 5 [Moro et al., 2011] S. Moro, R. Laureano and P. Cortez. Using Data Mining fo...
## 6 In P. Novais et al. (Eds.), Proceedings of the European Simulation and Model...
## 7 <NA>
## 8 Available at: [pdf] http://hdl.handle.net/1822/14838
## 9 [bib] http://www3.dsi.uminho.pt/pcortez/bib/2011-esm-1.txt
## 10 <NA>
## # ... with 60 more rows
##
## $`Step 1 - Collect Information`
## # A tibble: 1 x 2
##   Step Description
##   <dbl> <chr>
## 1 1 Collect Client Information
##
## $CLIENT_INFO
## # A tibble: 45,211 x 5
##   ID      AGE JOB      MARITAL EDUCATION
##   <chr> <dbl> <chr>      <chr>   <chr>
## 1 2836    58 management married  tertiary
## 2 2837    44 technician single   secondary
## 3 2838    33 entrepreneur married  secondary
## 4 2839    47 blue-collar married  unknown
## 5 2840    33 unknown    single   unknown
## 6 2841    35 management married  tertiary
## 7 2842    28 management single   tertiary
## 8 2843    42 entrepreneur divorced tertiary
## 9 2844    58 retired    married  primary
## 10 2845    43 technician single   secondary
## # ... with 45,201 more rows
##
## $LOAN_HISTORY
## # A tibble: 45,211 x 5
##   ID      DEFAULT BALANCE HOUSING LOAN
##   <chr> <chr>      <dbl> <chr>   <chr>
```

```

## 1 2836 no 2143 yes no
## 2 2837 no 29 yes no
## 3 2838 no 2 yes yes
## 4 2839 no 1506 yes no
## 5 2840 no 1 no no
## 6 2841 no 231 yes no
## 7 2842 no 447 yes yes
## 8 2843 yes 2 yes no
## 9 2844 no 121 yes no
## 10 2845 no 593 yes no
## # ... with 45,201 more rows
##
## `$MARKETING HISTORY`
## # A tibble: 45,211 x 9
##   ID CONTACT DAY MONTH DURATION CAMPAIGN PDAYS PREVIOUS POUTCOME
##   <chr> <chr> <dbl> <chr> <dbl> <dbl> <dbl> <dbl> <chr>
## 1 2836 unknown 5 may 261 1 -1 0 unknown
## 2 2837 unknown 5 may 151 1 -1 0 unknown
## 3 2838 unknown 5 may 76 1 -1 0 unknown
## 4 2839 unknown 5 may 92 1 -1 0 unknown
## 5 2840 unknown 5 may 198 1 -1 0 unknown
## 6 2841 unknown 5 may 139 1 -1 0 unknown
## 7 2842 unknown 5 may 217 1 -1 0 unknown
## 8 2843 unknown 5 may 380 1 -1 0 unknown
## 9 2844 unknown 5 may 50 1 -1 0 unknown
## 10 2845 unknown 5 may 55 1 -1 0 unknown
## # ... with 45,201 more rows
##
## `$SUBSCRIPTION HISTORY`
## # A tibble: 45,211 x 2
##   ID TERM_DEPOSIT
##   <chr> <chr>
## 1 2836 no
## 2 2837 no
## 3 2838 no
## 4 2839 no
## 5 2840 no
## 6 2841 no
## 7 2842 no
## 8 2843 no
## 9 2844 no
## 10 2845 no
## # ... with 45,201 more rows
##
## `$Step 2 - Merge Information`
## # A tibble: 1 x 2
##   Step Description
##   <dbl> <chr>
## 1 2 Perform Data Merge
##
## $CLIENT_MERGE
## # A tibble: 10,006 x 20
##   `VLOOKUP MERGE ... ...2 ...3 ...4 ...5 ...6 ...7 ...8 ...9 ...10 ...11
##   <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>
## 1 1. DIFFICULT TO... <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
## 2 2. COMPUTATIONA... <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
## 3 3. EVERY CELL C... <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
## 4 <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
## 5 <NA> CLIE... <NA> <NA> <NA> LOAN... <NA> <NA> <NA> MARK... <NA>
## 6 <NA> 2.0 3.0 4.0 5.0 2.0 3.0 4.0 5.0 2.0 3.0
## 7 ID AGE JOB MARI... EDUC... DEFA... BALA... HOUS... LOAN CONT... DAY
## 8 2836 58 mana... marr... tert... no 2143 yes no unkn... 5

```

```
## 9 2837 44 tech... sing... seco... no 29 yes no unkn... 5
## 10 2838 33 entr... marr... seco... no 2 yes yes unkn... 5
## # ... with 9,996 more rows, and 9 more variables: ...12 <chr>, ...13 <chr>,
## # ...14 <chr>, ...15 <chr>, ...16 <chr>, ...17 <chr>, ...18 <chr>,
## # ...19 <chr>, ...20 <chr>
##
## $`Step 3 - Marketing Analysis`
## # A tibble: 1 x 2
## Step Description
## <dbl> <chr>
## 1 3 Perform Marketing Analysis
##
## $`DAILY RANGE`
## # A tibble: 28 x 4
## `HIT RATE` ...2 `DAILY SUMMARY` ...4
## <dbl> <lgl> <chr> <dbl>
## 1 0.0386 NA MEAN 0.0351
## 2 0.0360 NA MEDIAN 0.0362
## 3 0.0551 NA SD 0.0138
## 4 0.0613 NA LOWER CONF 0.00755
## 5 0.0427 NA UPPER CONF 0.0627
## 6 0.0391 NA <NA> NA
## 7 0.0451 NA <NA> NA
## 8 0.0166 NA <NA> NA
## 9 0.0222 NA <NA> NA
## 10 0.0179 NA <NA> NA
## # ... with 18 more rows
##
## $`JOB ANALYSIS`
## # A tibble: 0 x 0
##
## $Sheet3
## # A tibble: 0 x 0
```

```
# Join Data by ID Column
data_joined_tbl <- sheets[4:7] %>%
  map(~ read_excel(path = path, sheet = .)) %>%
  reduce(left_join)
```

```
## Joining, by = "ID"
## Joining, by = "ID"
## Joining, by = "ID"
```

```
# Start H2O Cluster
h2o.init(max_mem_size = "4g")
```

```
## Connection successful!
##
## R is connected to the H2O cluster:
##   H2O cluster uptime:      15 minutes 41 seconds
##   H2O cluster timezone:    Asia/Kolkata
##   H2O data parsing timezone: UTC
##   H2O cluster version:     3.30.1.3
##   H2O cluster version age: 24 days
##   H2O cluster name:        H2O_started_from_R_priyarajpurohit_exx530
##   H2O cluster total nodes: 1
##   H2O cluster total memory: 3.85 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, TargetEncoder, Core V4
##   R Version:                R version 3.6.3 (2020-02-29)
```

```
#Data Preparation
data_joined_tbl <- data_joined_tbl %>%
  mutate_if(is.character, as.factor)

train <- as.h2o(data_joined_tbl)
```

```
## Warning in use.package("data.table"): data.table cannot be used without R
## package bit64 version 0.9.7 or higher. Please upgrade to take advantage of
## data.table speedups.
```

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

```
h2o.describe(train)
```

##	Label	Type	Missing	Zeros	PosInf	NegInf	Min	Max	Mean
## 1	ID	enum	0	1	0	0	0	45210	NA
## 2	AGE	int	0	0	0	0	18	95	4.093621e+01
## 3	JOB	enum	0	5171	0	0	0	11	NA
## 4	MARITAL	enum	0	5207	0	0	0	2	NA
## 5	EDUCATION	enum	0	6851	0	0	0	3	NA
## 6	DEFAULT	enum	0	44396	0	0	0	1	1.802659e-02
## 7	BALANCE	int	0	3514	0	0	-8019	102127	1.362272e+03
## 8	HOUSING	enum	0	20081	0	0	0	1	5.558382e-01
## 9	LOAN	enum	0	37967	0	0	0	1	1.602265e-01
## 10	CONTACT	enum	0	29285	0	0	0	2	NA
## 11	DAY	int	0	0	0	0	1	31	1.580642e+01
## 12	MONTH	enum	0	2932	0	0	0	11	NA
## 13	DURATION	int	0	3	0	0	0	4918	2.581631e+02
## 14	CAMPAIGN	int	0	0	0	0	1	63	2.763841e+00
## 15	PDAYS	int	0	0	0	0	-1	871	4.019783e+01
## 16	PREVIOUS	int	0	36954	0	0	0	275	5.803234e-01
## 17	POUTCOME	enum	0	4901	0	0	0	3	NA
## 18	TERM_DEPOSIT	enum	0	39922	0	0	0	1	1.169848e-01

##	Sigma	Cardinality
## 1	NA	45211
## 2	10.6187620	NA
## 3	NA	12
## 4	NA	3
## 5	NA	4
## 6	0.1330489	2
## 7	3044.7658292	NA
## 8	0.4968778	2
## 9	0.3668200	2
## 10	NA	3
## 11	8.3224762	NA
## 12	NA	12
## 13	257.5278123	NA
## 14	3.0980209	NA
## 15	100.1287460	NA
## 16	2.3034410	NA
## 17	NA	4
## 18	0.3214057	2

```
y <- "TERM_DEPOSIT"
```

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

```
#H2O AutoML Training
```

```
aml <- h2o.automl(
  y = y,
  x = x,
  training_frame = train,
  project_name = "term_deposit",
  max_runtime_secs = 300,
  balance_classes = TRUE,
  #max_models = 10,
  seed = 1)
```

##	
	0%
## 18:25:24.295: New models will be added to existing leaderboard term_deposit@@TERM_DEPOSIT (leaderboard frame=null) with already 28 models.	
	1%
=	1%
==	2%
==	3%
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```

===== | 92%
===== | 92%
===== | 93%
===== | 94%
===== | 94%
===== | 95%
===== | 95%
===== | 96%
===== | 97%

```

```
## 18:30:15.196: StackedEnsemble_BestOfFamily_AutoML_20201022_182524 [StackedEnsemble best (built using top model from each algorithm type)] failed: water.exceptions.H2OIllegalArgumentExcept
ion: Failed to find the xval predictions frame. . . Looks like keep_cross_validation_predictio
ns wasn't set when building the models, or the frame was deleted.
```

```
## 18:30:16.209: StackedEnsemble_AllModels_AutoML_20201022_182524 [StackedEnsemble all (built u
sing all AutoML models)] failed: water.exceptions.H2OIllegalArgumentException: Failed to find t
he xval predictions frame. . . Looks like keep_cross_validation_predictions wasn't set when bu
ilding the models, or the frame was deleted.
```

```

===== | 100%

```

```
#View AutoML Leaderboard
```

```
lb <- aml@leaderboard
```

```
print(lb)
```

```
##
##              model_id      auc  logloss
## 1  XGBoost_grid__1_AutoML_20201022_182524_model_2 0.9356780 0.1967353
## 2  XGBoost_grid__1_AutoML_20201022_180957_model_2 0.9356780 0.1967353
## 3 StackedEnsemble_BestOfFamily_AutoML_20201022_180957 0.9350219 0.2166654
## 4      GBM_grid__1_AutoML_20201022_182524_model_2 0.9332449 0.2048228
## 5      GBM_grid__1_AutoML_20201022_180957_model_2 0.9332449 0.2048228
## 6  StackedEnsemble_AllModels_AutoML_20201022_180957 0.9331147 0.2060752
##      aucpr mean_per_class_error      rmse      mse
## 1 0.6303982      0.1673404 0.2488460 0.06192432
## 2 0.6303982      0.1673404 0.2488460 0.06192432
## 3 0.6310380      0.1621620 0.2543648 0.06470145
## 4 0.6190190      0.1749242 0.2540487 0.06454074
## 5 0.6190190      0.1749242 0.2540487 0.06454074
## 6 0.6320502      0.1646369 0.2509036 0.06295260
##
## [53 rows x 7 columns]
```

```
print(lb, n = nrow(lb))
```

##		model_id	auc	logloss
## 1	XGBoost_grid__1_AutoML_20201022_182524_model_2		0.9356780	0.1967353
## 2	XGBoost_grid__1_AutoML_20201022_180957_model_2		0.9356780	0.1967353
## 3	StackedEnsemble_BestOfFamily_AutoML_20201022_180957		0.9350219	0.2166654
## 4	GBM_grid__1_AutoML_20201022_182524_model_2		0.9332449	0.2048228
## 5	GBM_grid__1_AutoML_20201022_180957_model_2		0.9332449	0.2048228
## 6	StackedEnsemble_AllModels_AutoML_20201022_180957		0.9331147	0.2060752
## 7	GBM_grid__1_AutoML_20201022_180957_model_1		0.9329840	0.1998278
## 8	GBM_grid__1_AutoML_20201022_182524_model_1		0.9329840	0.1998278
## 9	XGBoost_grid__1_AutoML_20201022_182524_model_1		0.9325188	0.2012839
## 10	XGBoost_grid__1_AutoML_20201022_180957_model_1		0.9325188	0.2012839
## 11	GBM_5_AutoML_20201022_180957		0.9315950	0.2340688
## 12	GBM_5_AutoML_20201022_182524		0.9310546	0.2378464
## 13	XGBoost_grid__1_AutoML_20201022_180957_model_4		0.9304512	0.2051540
## 14	GBM_2_AutoML_20201022_182524		0.9303961	0.2256216
## 15	XGBoost_grid__1_AutoML_20201022_182524_model_4		0.9303429	0.2048351
## 16	GBM_2_AutoML_20201022_180957		0.9302493	0.2235782
## 17	GBM_grid__1_AutoML_20201022_180957_model_3		0.9302468	0.2123839
## 18	XGBoost_1_AutoML_20201022_182524		0.9301496	0.2058485
## 19	GBM_3_AutoML_20201022_182524		0.9296739	0.2264755
## 20	GBM_3_AutoML_20201022_180957		0.9294973	0.2296272
## 21	XGBoost_grid__1_AutoML_20201022_182524_model_3		0.9294347	0.2087894
## 22	XGBoost_grid__1_AutoML_20201022_180957_model_3		0.9294347	0.2087894
## 23	XGBoost_3_AutoML_20201022_182524		0.9293704	0.2053813
## 24	XGBoost_2_AutoML_20201022_182524		0.9291699	0.2121849
## 25	XGBoost_3_AutoML_20201022_180957		0.9290737	0.2056809
## 26	GBM_1_AutoML_20201022_182524		0.9290262	0.2223897
## 27	GBM_grid__1_AutoML_20201022_182524_model_3		0.9289238	0.2180805
## 28	GBM_4_AutoML_20201022_180957		0.9285313	0.2421198
## 29	XGBoost_2_AutoML_20201022_180957		0.9279268	0.2194895
## 30	GBM_4_AutoML_20201022_182524		0.9277236	0.2445372
## 31	GBM_1_AutoML_20201022_180957		0.9263077	0.2388728
## 32	GBM_grid__1_AutoML_20201022_180957_model_4		0.9251986	0.2801308
## 33	XGBoost_1_AutoML_20201022_180957		0.9212617	0.2567543
## 34	DRF_1_AutoML_20201022_182524		0.9129661	0.3840614
## 35	XRT_1_AutoML_20201022_182524		0.9079611	0.2985438
## 36	GLM_1_AutoML_20201022_180957		0.9069214	0.2400166
## 37	GLM_1_AutoML_20201022_182524		0.9067093	0.2397973
## 38	XRT_1_AutoML_20201022_180957		0.9020821	0.3256563
## 39	GBM_grid__1_AutoML_20201022_182524_model_4		0.9018473	0.3381990
## 40	GBM_grid__1_AutoML_20201022_180957_model_5		0.8950291	0.3385584
## 41	DeepLearning_grid__1_AutoML_20201022_182524_model_1		0.8946814	0.2777782
## 42	DeepLearning_grid__3_AutoML_20201022_182524_model_1		0.8857072	0.2913048
## 43	DeepLearning_1_AutoML_20201022_182524		0.8852609	0.2795636
## 44	DeepLearning_grid__2_AutoML_20201022_180957_model_1		0.8842133	0.2556144
## 45	DeepLearning_grid__2_AutoML_20201022_182524_model_1		0.8780543	0.2740725
## 46	DeepLearning_grid__2_AutoML_20201022_180957_model_2		0.8765819	0.5752285
## 47	DeepLearning_grid__1_AutoML_20201022_180957_model_1		0.8719760	0.2679993
## 48	DeepLearning_grid__3_AutoML_20201022_180957_model_1		0.8692540	0.3134560
## 49	DeepLearning_grid__1_AutoML_20201022_180957_model_2		0.8643338	0.5129829
## 50	DeepLearning_grid__2_AutoML_20201022_182524_model_2		0.8597253	0.5016307
## 51	DeepLearning_grid__1_AutoML_20201022_182524_model_2		0.8540015	0.3872542
## 52	DRF_1_AutoML_20201022_180957		0.8306920	1.6339417
## 53	DeepLearning_1_AutoML_20201022_180957		0.8300519	0.3654677
##	aucpr mean_per_class_error	rmse	mse	
## 1	0.6303982	0.1673404	0.2488460	0.06192432
## 2	0.6303982	0.1673404	0.2488460	0.06192432
## 3	0.6310380	0.1621620	0.2543648	0.06470145
## 4	0.6190190	0.1749242	0.2540487	0.06454074
## 5	0.6190190	0.1749242	0.2540487	0.06454074
## 6	0.6320502	0.1646369	0.2509036	0.06295260

```
## 7 0.6147040 0.1774892 0.2508573 0.06292938
## 8 0.6147040 0.1774892 0.2508573 0.06292938
## 9 0.6178210 0.1624412 0.2513834 0.06319361
## 10 0.6178210 0.1624412 0.2513834 0.06319361
## 11 0.6141615 0.1808666 0.2723323 0.07416490
## 12 0.6126850 0.1844423 0.2743283 0.07525604
## 13 0.6066089 0.1688106 0.2540210 0.06452666
## 14 0.6138666 0.1863686 0.2666936 0.07112549
## 15 0.6054021 0.1770424 0.2538020 0.06441547
## 16 0.6138750 0.1829718 0.2654296 0.07045286
## 17 0.6127362 0.1677809 0.2586092 0.06687871
## 18 0.6103736 0.1763310 0.2532572 0.06413921
## 19 0.6117829 0.1738852 0.2675636 0.07159029
## 20 0.6107208 0.1788176 0.2694537 0.07260529
## 21 0.6006786 0.1745010 0.2564203 0.06575138
## 22 0.6006786 0.1745010 0.2564203 0.06575138
## 23 0.6137425 0.1819538 0.2527652 0.06389025
## 24 0.6081160 0.1686919 0.2537222 0.06437494
## 25 0.6131600 0.1703810 0.2529245 0.06397081
## 26 0.6110695 0.1727226 0.2644352 0.06992598
## 27 0.6108366 0.1762797 0.2619030 0.06859316
## 28 0.6087903 0.1698850 0.2766374 0.07652827
## 29 0.6077885 0.1752221 0.2550462 0.06504856
## 30 0.6059858 0.1856767 0.2778675 0.07721037
## 31 0.6042230 0.1889074 0.2735924 0.07485281
## 32 0.5789561 0.1869553 0.2938106 0.08632469
## 33 0.5922735 0.1922122 0.2653683 0.07042034
## 34 0.5646684 0.1847008 0.2838098 0.08054803
## 35 0.5580078 0.1865876 0.2825120 0.07981301
## 36 0.5496125 0.1970992 0.2670000 0.07128898
## 37 0.5506528 0.2074031 0.2667996 0.07118201
## 38 0.5464658 0.1895219 0.2832367 0.08022302
## 39 0.5068837 0.1905388 0.3140848 0.09864925
## 40 0.5146294 0.1915177 0.3142071 0.09872612
## 41 0.5253416 0.2154294 0.2907789 0.08455237
## 42 0.4886886 0.2224349 0.2974873 0.08849869
## 43 0.4933892 0.2194074 0.2768825 0.07666391
## 44 0.4938987 0.2259416 0.2762350 0.07630578
## 45 0.4869933 0.2303299 0.2778627 0.07720770
## 46 0.4767087 0.2491287 0.4220132 0.17809512
## 47 0.5003377 0.2511806 0.2825800 0.07985148
## 48 0.4669421 0.2442798 0.3099441 0.09606537
## 49 0.4669419 0.2591776 0.4013121 0.16105144
## 50 0.4443261 0.2552644 0.4026107 0.16209537
## 51 0.4682556 0.2576376 0.3332676 0.11106727
## 52 0.4493111 0.1980239 0.3036473 0.09220170
## 53 0.3886545 0.2766686 0.3449946 0.11902127
##
## [53 rows x 7 columns]
```

```
# Ensemble Exploration ----
```

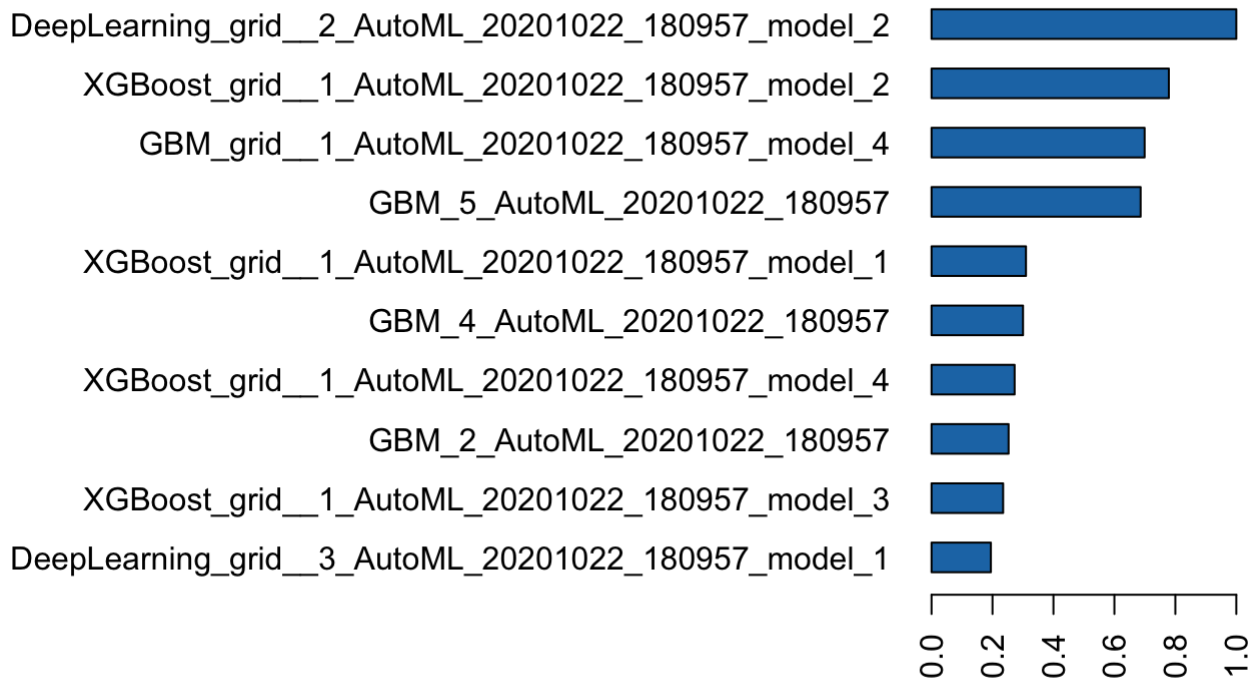
```
model_ids <- as.data.frame(aml@leaderboard$model_id)[,1]
se <- h2o.getModel(grep("StackedEnsemble_AllModels", model_ids, value = TRUE)[1])
metalearner <- h2o.getModel(se@model$metalearner$name)

h2o.varimp(metalearner)
```

##	variable	relative_importance
## 1	DeepLearning_grid__2_AutoML_20201022_180957_model_2	0.346650843
## 2	XGBoost_grid__1_AutoML_20201022_180957_model_2	0.269919970
## 3	GBM_grid__1_AutoML_20201022_180957_model_4	0.242369833
## 4	GBM_5_AutoML_20201022_180957	0.237822020
## 5	XGBoost_grid__1_AutoML_20201022_180957_model_1	0.107409688
## 6	GBM_4_AutoML_20201022_180957	0.104062635
## 7	XGBoost_grid__1_AutoML_20201022_180957_model_4	0.094490941
## 8	GBM_2_AutoML_20201022_180957	0.087640253
## 9	XGBoost_grid__1_AutoML_20201022_180957_model_3	0.081433076
## 10	DeepLearning_grid__3_AutoML_20201022_180957_model_1	0.067484828
## 11	GBM_1_AutoML_20201022_180957	0.063001922
## 12	GBM_3_AutoML_20201022_180957	0.030522733
## 13	DeepLearning_1_AutoML_20201022_180957	0.026747155
## 14	GBM_grid__1_AutoML_20201022_180957_model_5	0.020859414
## 15	DeepLearning_grid__1_AutoML_20201022_180957_model_2	0.006714708
## 16	GBM_grid__1_AutoML_20201022_180957_model_2	0.000000000
## 17	GBM_grid__1_AutoML_20201022_180957_model_1	0.000000000
## 18	GBM_grid__1_AutoML_20201022_180957_model_3	0.000000000
## 19	XGBoost_3_AutoML_20201022_180957	0.000000000
## 20	XGBoost_2_AutoML_20201022_180957	0.000000000
## 21	XGBoost_1_AutoML_20201022_180957	0.000000000
## 22	GLM_1_AutoML_20201022_180957	0.000000000
## 23	XRT_1_AutoML_20201022_180957	0.000000000
## 24	DeepLearning_grid__2_AutoML_20201022_180957_model_1	0.000000000
## 25	DeepLearning_grid__1_AutoML_20201022_180957_model_1	0.000000000
## 26	DRF_1_AutoML_20201022_180957	0.000000000
##	scaled_importance	percentage
## 1	1.00000000	0.193970690
## 2	0.77865084	0.151035441
## 3	0.69917566	0.135619586
## 4	0.68605637	0.133074828
## 5	0.30984978	0.060101776
## 6	0.30019438	0.058228911
## 7	0.27258247	0.052873009
## 8	0.25281996	0.049039663
## 9	0.23491383	0.045566397
## 10	0.19467666	0.037761566
## 11	0.18174461	0.035253127
## 12	0.08805036	0.017079190
## 13	0.07715878	0.014966541
## 14	0.06017413	0.011672018
## 15	0.01937024	0.003757258
## 16	0.00000000	0.000000000
## 17	0.00000000	0.000000000
## 18	0.00000000	0.000000000
## 19	0.00000000	0.000000000
## 20	0.00000000	0.000000000
## 21	0.00000000	0.000000000
## 22	0.00000000	0.000000000
## 23	0.00000000	0.000000000
## 24	0.00000000	0.000000000
## 25	0.00000000	0.000000000
## 26	0.00000000	0.000000000

```
h2o.varimp_plot(metalearner)
```

## Variable Importance: GLM



```
# Baselearner Variable Importance
```

```
xgb <- h2o.getModel(grep("XGBoost", model_ids, value = TRUE)[1])
```

```
h2o.varimp(xgb)
```

```
## Variable Importances:
```

```
##           variable relative_importance scaled_importance percentage
## 1      DURATION      12787.352539          1.000000    0.412424
## 2 POUTCOME.success      2143.389404          0.167618    0.069130
## 3           DAY      1705.303711          0.133359    0.055000
## 4          PDAYS      1413.857666          0.110567    0.045600
## 5    HOUSING.no      1285.888184          0.100559    0.041473
##
## ---
##           variable relative_importance scaled_importance percentage
## 46 EDUCATION.unknown      12.700191          0.000993    0.000410
## 47   JOB.services         8.025841          0.000628    0.000259
## 48   JOB.unknown         6.445179          0.000504    0.000208
## 49   DEFAULT.yes         5.249918          0.000411    0.000169
## 50  JOB.entrepreneur         4.777218          0.000374    0.000154
## 51   JOB.unemployed         1.840618          0.000144    0.000059
```

```
h2o.varimp_plot(xgb)
```



Variable Importance: XGBOOST

