04 Performance Measures

2021-01-06

Contents

Loading Libraries

```
library(tidyverse)
library(tidyquant)
library(broom)
library(umap)
```

```r
library(readxl)
library(h2o)
library(readxl)
library(rsample)
library(recipes)
library(PerformanceAnalytics)
library(h2o)
library(cowplot)
library(glue)

library(h2o)
library(tidyquant)
library(broom)
library(umap)
library(tidyverse)
library(readxl)
library(rsample)
library(recipes)
library(PerformanceAnalytics)  # for skewers
```

Loading Data

```r
product_backorders_tbl <- read_csv("product_backorders.csv")

# Split into test and train
set.seed(seed = 1113)
split_obj <- rsample::initial_split(product_backorders_tbl, prop = 0.85)


# Assign training and test data
train_readable_tbl<- training(split_obj)
test_readable_tbl <- testing(split_obj)


  recipe_obj <- recipe( went_on_backorder~., data = train_readable_tbl) %>%
  step_zv(all_predictors()) %>%
  prep()

train_tbl <- bake(recipe_obj, new_data = train_readable_tbl)
test_tbl  <- bake(recipe_obj, new_data = test_readable_tbl)

 #set the predictor names
 predictors <- c("national_inv", "lead_time", "forecast_3_month", "sales_3_month")

# #specify the response
 response <- "went_on_backorder"



 h2o.init()
```

```
##  Connection successful!
##
## R is connected to the H2O cluster:
##     H2O cluster uptime:         4 hours 42 minutes
##     H2O cluster timezone:       Europe/Berlin
##     H2O data parsing timezone:  UTC
##     H2O cluster version:        3.32.0.1
##     H2O cluster version age:    2 months and 30 days
##     H2O cluster name:           H2O_started_from_R_ahmed_cgv301
##     H2O cluster total nodes:    1
##     H2O cluster total memory:   1.02 GB
##     H2O cluster total cores:    4
##     H2O cluster allowed cores:  4
##     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, Algos, AutoML, Core V3, TargetEncoder, Core V4
##     R Version:                  R version 4.0.3 (2020-10-10)
```

```r
# Split data into a training and a validation data frame
# Setting the seed is just for reproducability
split_h2o <- h2o.splitFrame(as.h2o(train_tbl), ratios = c(0.85), seed = 1234)
```

```
##   |                                                                              |
```

```r
train_h2o <- split_h2o[[1]]
valid_h2o <- split_h2o[[2]]
test_h2o  <- as.h2o(test_tbl)
```

```
##   |                                                                              |
```

```r
# Set the target and predictors
y <- response
x <- setdiff(names(train_h2o), y)

automl_models_h2o <- h2o.automl(
  x = x,
  y = y,
  training_frame    = train_h2o,
  validation_frame  = valid_h2o,
  leaderboard_frame = test_h2o,
  max_runtime_secs  = 15,
  nfolds            = 5
)
```

```
##   |                                                                              |
## 03:17:11.229: User specified a validation frame with cross-validation still enabled. Please note tha
## 03:17:11.230: AutoML: XGBoost is not available; skipping it.   |
```

```r
leaderboard_Model <- automl_models_h2o@leaderboard


 Model<-automl_models_h2o@leader


   h2o.saveModel(Model,path = "ml_journal-Automated_Machine_learning_2_model")
```

```
## [1] "D:\\Mechatronics_master\\Third semester\\Data science\\Machine learning\\ml_journal-AhmedShaheer
```

Leader board Visualization

```r
automl_models_h2o@leaderboard %>%
              as_tibble() %>%
              select(-c(mean_per_class_error, rmse, mse))
```

```
## # A tibble: 12 x 4
##    model_id                                                auc logloss aucpr
##    <chr>                                                 <dbl>   <dbl> <dbl>
##  1 StackedEnsemble_AllModels_AutoML_20210108_031711    0.938   0.200 0.696
##  2 StackedEnsemble_BestOfFamily_AutoML_20210108_031711 0.933   0.207 0.682
##  3 GBM_2_AutoML_20210108_031711                        0.928   0.307 0.649
##  4 GBM_3_AutoML_20210108_031711                        0.909   0.314 0.618
##  5 GBM_1_AutoML_20210108_031711                        0.904   0.312 0.568
##  6 GBM_grid__1_AutoML_20210108_031711_model_1          0.887   0.286 0.529
##  7 GBM_4_AutoML_20210108_031711                        0.869   0.324 0.585
##  8 DRF_1_AutoML_20210108_031711                        0.854   0.692 0.525
##  9 XRT_1_AutoML_20210108_031711                        0.760   3.01  0.387
## 10 GBM_5_AutoML_20210108_031711                        0.741   0.347 0.325
## 11 DeepLearning_1_AutoML_20210108_031711               0.734   0.452 0.269
## 12 GLM_1_AutoML_20210108_031711                        0.679   0.353 0.196
```

data preparation and Visulatization

```r
data_transformed_tbl <- automl_models_h2o@leaderboard %>%
  as_tibble() %>%
  select(-c(aucpr, mean_per_class_error, rmse, mse)) %>%
  mutate(model_type = str_extract(model_id, "[^_]+")) %>%
  slice(1:15) %>%
  rownames_to_column(var = "rowname") %>%

  mutate(
  model_id   = as_factor(model_id) %>% reorder(auc),
  model_type = as.factor(model_type)
  ) %>%

  pivot_longer(cols = -c(model_id, model_type, rowname),
```

```
                     names_to = "key",
                     values_to = "value",
                     names_transform = list(key = forcats::fct_inorder)
                     ) %>%
        mutate(model_id = paste0(rowname, ". ", model_id) %>% as_factor() %>% fct_rev())

data_transformed_tbl
```

```
## # A tibble: 24 x 5
##    rowname model_id                                 model_type     key    value
##    <chr>   <fct>                                    <fct>          <fct>  <dbl>
##  1 1       1. StackedEnsemble_AllModels_AutoML_2021~ StackedEnsemb~ auc    0.938
##  2 1       1. StackedEnsemble_AllModels_AutoML_2021~ StackedEnsemb~ loglo~ 0.200
##  3 2       2. StackedEnsemble_BestOfFamily_AutoML_2~ StackedEnsemb~ auc    0.933
##  4 2       2. StackedEnsemble_BestOfFamily_AutoML_2~ StackedEnsemb~ loglo~ 0.207
##  5 3       3. GBM_2_AutoML_20210108_031711           GBM            auc    0.928
##  6 3       3. GBM_2_AutoML_20210108_031711           GBM            loglo~ 0.307
##  7 4       4. GBM_3_AutoML_20210108_031711           GBM            auc    0.909
##  8 4       4. GBM_3_AutoML_20210108_031711           GBM            loglo~ 0.314
##  9 5       5. GBM_1_AutoML_20210108_031711           GBM            auc    0.904
## 10 5       5. GBM_1_AutoML_20210108_031711           GBM            loglo~ 0.312
## # ... with 14 more rows
```

Final tibble to visualize

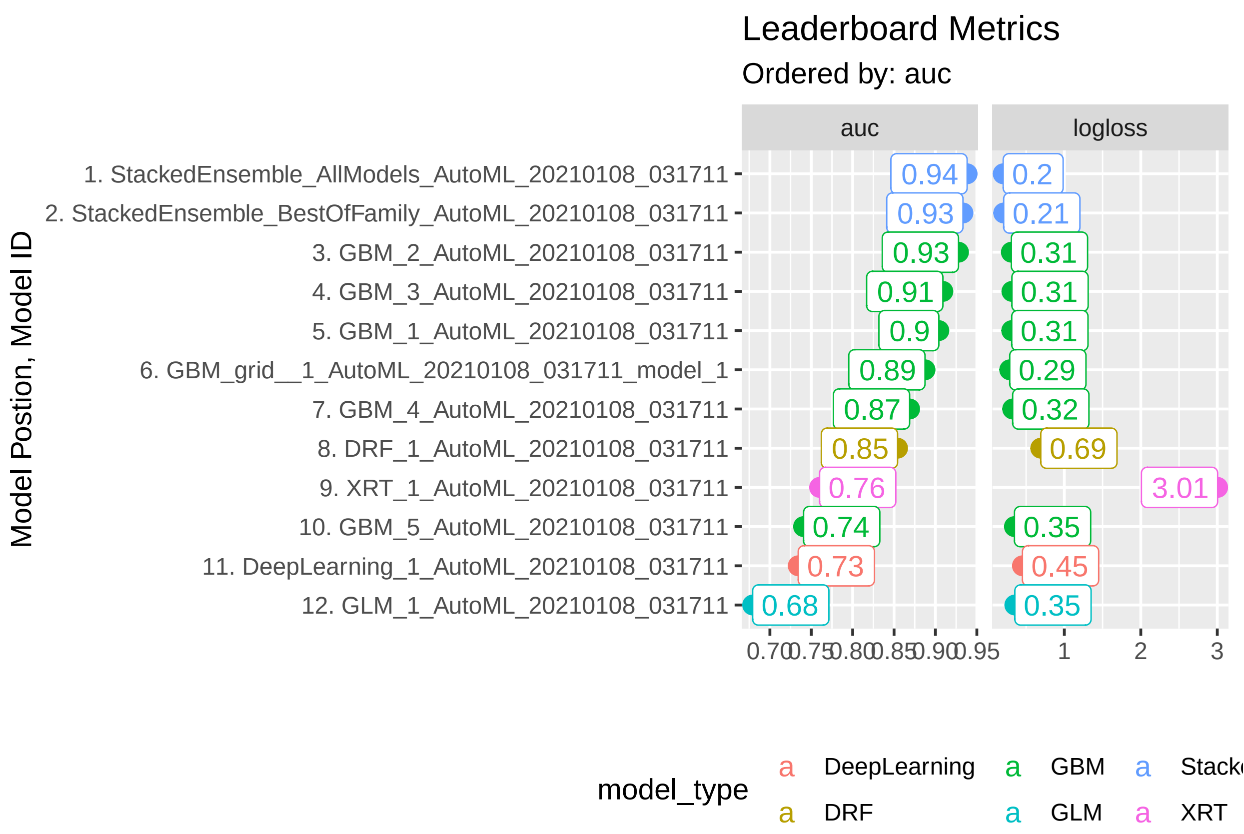
```
data_transformed_tbl
```

```
## # A tibble: 24 x 5
##    rowname model_id                                 model_type     key    value
##    <chr>   <fct>                                    <fct>          <fct>  <dbl>
##  1 1       1. StackedEnsemble_AllModels_AutoML_2021~ StackedEnsemb~ auc    0.938
##  2 1       1. StackedEnsemble_AllModels_AutoML_2021~ StackedEnsemb~ loglo~ 0.200
##  3 2       2. StackedEnsemble_BestOfFamily_AutoML_2~ StackedEnsemb~ auc    0.933
##  4 2       2. StackedEnsemble_BestOfFamily_AutoML_2~ StackedEnsemb~ loglo~ 0.207
##  5 3       3. GBM_2_AutoML_20210108_031711           GBM            auc    0.928
##  6 3       3. GBM_2_AutoML_20210108_031711           GBM            loglo~ 0.307
##  7 4       4. GBM_3_AutoML_20210108_031711           GBM            auc    0.909
##  8 4       4. GBM_3_AutoML_20210108_031711           GBM            loglo~ 0.314
##  9 5       5. GBM_1_AutoML_20210108_031711           GBM            auc    0.904
## 10 5       5. GBM_1_AutoML_20210108_031711           GBM            loglo~ 0.312
## # ... with 14 more rows
```

Visualization

```
data_transformed_tbl %>%
        ggplot(aes(value, model_id, color = model_type)) +
        geom_point(size = 3) +
        geom_label(aes(label = round(value, 2), hjust = "inward")) +
```

```r
    # Facet to break out logloss and auc
    facet_wrap(~ key, scales = "free_x") +
    labs(title = "Leaderboard Metrics",
         subtitle = paste0("Ordered by: ", "auc"),
         y = "Model Postion, Model ID", x = "") +
    theme(legend.position = "bottom")
```



Grid Search

```r
grid_search_model <- h2o.loadModel("ml_journal-Automated_Machine_learning_2_model/StackedEnsemble_AllMo

grid_search_model
```

```
## Model Details:
## ==============
##
## H2OBinomialModel: stackedensemble
## Model ID:  StackedEnsemble_AllModels_AutoML_20210107_224531
## Number of Base Models: 10
##
## Base Models (count by algorithm type):
##
## deeplearning          drf          gbm          glm
##            1            2            6            1
##
```

```
## Metalearner:
##
## Metalearner algorithm: glm
## Metalearner cross-validation fold assignment:
##   Fold assignment scheme: AUTO
##   Number of folds: 5
##   Fold column: NULL
## Metalearner hyperparameters:
##
##
## H2OBinomialMetrics: stackedensemble
## ** Reported on training data. **
##
## MSE:  0.04664896
## RMSE:  0.2159837
## LogLoss:  0.1665542
## Mean Per-Class Error:  0.1411272
## AUC:  0.9695554
## AUCPR:  0.8361613
## Gini:  0.9391108
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          No  Yes    Error        Rate
## No     8521  284 0.032254   =284/8805
## Yes     303  909 0.250000   =303/1212
## Totals 8824 1193 0.058600  =587/10017
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.256367    0.755925 212
## 2                       max f2  0.135270    0.821907 266
## 3                 max f0point5  0.424893    0.789763 157
## 4                 max accuracy  0.293859    0.941400 199
## 5                max precision  0.997190    1.000000   0
## 6                   max recall  0.027349    1.000000 378
## 7              max specificity  0.997190    1.000000   0
## 8             max absolute_mcc  0.175042    0.723872 248
## 9   max min_per_class_accuracy  0.124218    0.911414 272
## 10 max mean_per_class_accuracy  0.114705    0.913524 277
## 11                     max tns  0.997190 8805.000000   0
## 12                     max fns  0.997190 1201.000000   0
## 13                     max fps  0.019690 8805.000000 399
## 14                     max tps  0.027349 1212.000000 378
## 15                     max tnr  0.997190    1.000000   0
## 16                     max fnr  0.997190    0.990924   0
## 17                     max fpr  0.019690    1.000000 399
## 18                     max tpr  0.027349    1.000000 378
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
## H2OBinomialMetrics: stackedensemble
## ** Reported on validation data. **
##
## MSE:  0.06603241
## RMSE:  0.2569677
```

```
## LogLoss:  0.2243434
## Mean Per-Class Error:  0.1681104
## AUC:  0.925822
## AUCPR:  0.6400195
## Gini:  0.8516441
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          No Yes    Error       Rate
## No     1930 174 0.082700  =174/2104
## Yes      72 212 0.253521    =72/284
## Totals 2002 386 0.103015  =246/2388
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.179216    0.632836 221
## 2                       max f2  0.112725    0.744298 260
## 3                 max f0point5  0.482100    0.625000 111
## 4                 max accuracy  0.482100    0.910804 111
## 5                max precision  0.997476    1.000000   0
## 6                   max recall  0.024669    1.000000 385
## 7              max specificity  0.997476    1.000000   0
## 8             max absolute_mcc  0.179216    0.583687 221
## 9   max min_per_class_accuracy  0.114479    0.866197 259
## 10 max mean_per_class_accuracy  0.112725    0.869605 260
## 11                     max tns  0.997476 2104.000000   0
## 12                     max fns  0.997476  282.000000   0
## 13                     max fps  0.019476 2104.000000 399
## 14                     max tps  0.024669  284.000000 385
## 15                     max tnr  0.997476    1.000000   0
## 16                     max fnr  0.997476    0.992958   0
## 17                     max fpr  0.019476    1.000000 399
## 18                     max tpr  0.024669    1.000000 385
##
## Gains/Lift Table: Extract with 'h2o.gainsLift(<model>, <data>)' or 'h2o.gainsLift(<model>, valid=<T/
## H2OBinomialMetrics: stackedensemble
## ** Reported on cross-validation data. **
## ** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **
##
## MSE:  0.06744484
## RMSE:  0.2597014
## LogLoss:  0.2337148
## Mean Per-Class Error:  0.2156106
## AUC:  0.9138266
## AUCPR:  0.623122
## Gini:  0.8276533
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##           No  Yes    Error         Rate
## No     11528  632 0.051974   =632/12160
## Yes      625 1023 0.379248    =625/1648
## Totals 12153 1655 0.091034  =1257/13808
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold        value idx
```

```
## 1                        max f1  0.255882     0.619437 212
## 2                        max f2  0.078528     0.698761 306
## 3                  max f0point5  0.331120     0.632699 186
## 4                  max accuracy  0.331120     0.912080 186
## 5                 max precision  0.999404     0.937500   0
## 6                    max recall  0.017271     1.000000 387
## 7               max specificity  0.999404     0.999836   0
## 8              max absolute_mcc  0.255882     0.567738 212
## 9    max min_per_class_accuracy  0.086554     0.838816 300
## 10 max mean_per_class_accuracy  0.077422     0.842540 307
## 11                      max tns  0.999404 12158.000000   0
## 12                      max fns  0.999404  1618.000000   0
## 13                      max fps  0.008532 12160.000000 399
## 14                      max tps  0.017271  1648.000000 387
## 15                      max tnr  0.999404     0.999836   0
## 16                      max fnr  0.999404     0.981796   0
## 17                      max fpr  0.008532     1.000000 399
## 18                      max tpr  0.017271     1.000000 387
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

```
test_tbl
```

```
## # A tibble: 2,857 x 23
##        sku national_inv lead_time in_transit_qty forecast_3_month
##      <dbl>        <dbl>     <dbl>          <dbl>            <dbl>
##  1 1.12e6            7         8              0                0
##  2 1.12e6            0        12              0              163
##  3 1.13e6          150         8              0              325
##  4 1.13e6            0         8              0                3
##  5 1.13e6            3         3              0               16
##  6 1.13e6          -62         8              0              120
##  7 1.13e6            0         8              0                2
##  8 1.13e6           11         2             10               27
##  9 1.13e6            1         2              4                4
## 10 1.14e6           -1         8              0                9
## # ... with 2,847 more rows, and 18 more variables: forecast_6_month <dbl>,
## #   forecast_9_month <dbl>, sales_1_month <dbl>, sales_3_month <dbl>,
## #   sales_6_month <dbl>, sales_9_month <dbl>, min_bank <dbl>,
## #   potential_issue <fct>, pieces_past_due <dbl>, perf_6_month_avg <dbl>,
## #   perf_12_month_avg <dbl>, local_bo_qty <dbl>, deck_risk <fct>,
## #   oe_constraint <fct>, ppap_risk <fct>, stop_auto_buy <fct>, rev_stop <fct>,
## #   went_on_backorder <fct>
```

test performance with new data output from previous test

```
h2o.performance(grid_search_model, newdata = as.h2o(test_tbl))
```

```
##   |                                                                              |
```

```
## H2OBinomialMetrics: stackedensemble
##
## MSE:  0.06315357
## RMSE:  0.2513037
## LogLoss:  0.2183313
## Mean Per-Class Error:  0.1711951
## AUC:  0.9297926
## AUCPR:  0.6499886
## Gini:  0.8595852
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          No Yes    Error       Rate
## No     2339 184 0.072929  =184/2523
## Yes      90 244 0.269461    =90/334
## Totals 2429 428 0.095905  =274/2857
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.201687    0.640420 221
## 2                       max f2  0.096409    0.728395 284
## 3                 max f0point5  0.389786    0.656385 154
## 4                 max accuracy  0.389786    0.918446 154
## 5                max precision  0.996593    1.000000   0
## 6                   max recall  0.031624    1.000000 370
## 7              max specificity  0.996593    1.000000   0
## 8             max absolute_mcc  0.187938    0.593279 227
## 9   max min_per_class_accuracy  0.106826    0.853293 275
## 10 max mean_per_class_accuracy  0.096409    0.863535 284
## 11                     max tns  0.996593 2523.000000   0
## 12                     max fns  0.996593  332.000000   0
## 13                     max fps  0.020097 2523.000000 399
## 14                     max tps  0.031624  334.000000 370
## 15                     max tnr  0.996593    1.000000   0
## 16                     max fnr  0.996593    0.994012   0
## 17                     max fpr  0.020097    1.000000 399
## 18                     max tpr  0.031624    1.000000 370
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

Grid Search

```
search_grid_01 <- h2o.grid(
  algorithm = "deeplearning",
  grid_id = "search_grid_01",
 x = x,
    y = y,

    # training and validation frame and crossfold validation
    training_frame   = train_h2o,
    validation_frame = valid_h2o,
    nfolds = 5,
```

```r
    # Hyperparamters: Use deeplearning_h2o@allparameters to see all
    hyper_params = list(
        # Use some combinations (the first one was the original)
        hidden = list(c(10, 10, 10), c(50, 20, 10), c(20, 20, 20)),
        epochs = c(10, 50, 20)
    )
)
```

```
##   |                                                                              |
```

```r
search_grid_01
```

```
## H2O Grid Details
## ================
##
## Grid ID: search_grid_01
## Used hyper parameters:
##   -  epochs
##   -  hidden
## Number of models: 108
## Number of failed models: 0
##
## Hyper-Parameter Search Summary: ordered by increasing logloss
##              epochs       hidden              model_ids            logloss
## 1 10.401183024268088 [50, 20, 10] search_grid_01_model_94  0.593392794267379
## 2 10.396790876881736 [10, 10, 10] search_grid_01_model_19 0.6872272269441417
## 3  10.39353646494803 [10, 10, 10] search_grid_01_model_91 0.7753158814829997
## 4 10.390115491579332 [10, 10, 10] search_grid_01_model_10 0.8019901718186699
## 5 10.379148529101434 [50, 20, 10] search_grid_01_model_76 0.8212459493715552
##
## ---
##                epochs       hidden              model_ids            logloss
## 103  20.79287977545045 [20, 20, 20] search_grid_01_model_72  3.982996617678043
## 104  52.01446341563045 [20, 20, 20] search_grid_01_model_62  3.999608770441817
## 105  52.00488790148506 [10, 10, 10] search_grid_01_model_56  4.741461845786739
## 106 52.012464918336036 [20, 20, 20] search_grid_01_model_98   4.87022132619315
## 107  20.79885310027837 [50, 20, 10] search_grid_01_model_15 5.1541284744691325
## 108  51.99653962675832 [20, 20, 20] search_grid_01_model_71  6.757877764291338
```

sort accoding to auc high to low

```r
h2o.getGrid(grid_id = "search_grid_01", sort_by = "auc", decreasing = TRUE)
```

```
## H2O Grid Details
## ================
##
## Grid ID: search_grid_01
## Used hyper parameters:
##   -  epochs
```

```
##   -  hidden
## Number of models: 108
## Number of failed models: 0
##
## Hyper-Parameter Search Summary: ordered by decreasing auc
##               epochs       hidden              model_ids                auc
## 1  51.98202355143529 [50, 20, 10] search_grid_01_model_50 0.6766130247588783
## 2 10.401183024268088 [50, 20, 10] search_grid_01_model_94 0.6759369161583418
## 3  20.78583674094471 [50, 20, 10] search_grid_01_model_78   0.65798493289314
## 4 20.798433494599845 [50, 20, 10] search_grid_01_model_24 0.6345598332907512
## 5  10.40730809032598 [20, 20, 20] search_grid_01_model_16  0.628448158852836
##
## ---
##                 epochs       hidden              model_ids                auc
## 103  10.39973847867544 [50, 20, 10]  search_grid_01_model_4 0.5210769333642055
## 104 51.993617845941706 [10, 10, 10] search_grid_01_model_38 0.5207654263940342
## 105 52.002001061293505 [10, 10, 10] search_grid_01_model_92 0.5156528198055059
## 106 20.785329625967172 [10, 10, 10] search_grid_01_model_57 0.5130598392788708
## 107  20.79758024534127 [20, 20, 20] search_grid_01_model_45 0.5100362381036024
## 108 20.802074059358134 [20, 20, 20] search_grid_01_model_90 0.5007095672186382
```

```
search_grid_01_model_1 <- h2o.getModel("search_grid_01_model_1")
search_grid_01_model_1 %>% h2o.auc(train = T, valid = T, xval = T)
```

```
##     train     valid      xval
## 0.6521814 0.6270526 0.5897518
```

```
search_grid_01_model_1 %>%
    h2o.performance(newdata = as.h2o(test_tbl))
```

```
##   |                                                                              |
```

```
## H2OBinomialMetrics: deeplearning
##
## MSE:  0.1052787
## RMSE:  0.3244668
## LogLoss:  0.3974823
## Mean Per-Class Error:  0.404194
## AUC:  0.6518983
## AUCPR:  0.2197715
## Gini:  0.3037967
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          No Yes    Error       Rate
## No     1964 559 0.221562  =559/2523
## Yes     196 138 0.586826   =196/334
## Totals 2160 697 0.264263  =755/2857
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.158513    0.267701 206
## 2                       max f2  0.040741    0.445923 350
```

```
## 3                 max f0point5  0.378959    0.266749  74
## 4                 max accuracy  0.932781    0.885194  10
## 5                max precision  0.932781    0.607143  10
## 6                   max recall  0.000034    1.000000 399
## 7              max specificity  0.999862    0.998018   0
## 8             max absolute_mcc  0.783253    0.166765  22
## 9   max min_per_class_accuracy  0.102825    0.577844 269
## 10 max mean_per_class_accuracy  0.050803    0.603219 333
## 11                     max tns  0.999862 2518.000000   0
## 12                     max fns  0.999862  328.000000   0
## 13                     max fps  0.000034 2523.000000 399
## 14                     max tps  0.000034  334.000000 399
## 15                     max tnr  0.999862    0.998018   0
## 16                     max fnr  0.999862    0.982036   0
## 17                     max fpr  0.000034    1.000000 399
## 18                     max tpr  0.000034    1.000000 399
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

H2o Performance

load model

```r
stacked_ensemble_h2o <- h2o.loadModel("ml_journal-Automated_Machine_learning_2_model/StackedEnsemble_Al

performance_h2o <- h2o.performance(stacked_ensemble_h2o, newdata = as.h2o(test_tbl))
```

```
##   |                                                                              |
```

```r
typeof(performance_h2o)
```

```
## [1] "S4"
```

```r
performance_h2o %>% slotNames()
```

```
## [1] "algorithm" "on_train"  "on_valid"  "on_xval"   "metrics"
```

```r
performance_h2o@metrics
```

```
## $model
## $model$`__meta`
## $model$`__meta`$schema_version
## [1] 3
##
## $model$`__meta`$schema_name
## [1] "ModelKeyV3"
##
## $model$`__meta`$schema_type
```

```
## [1] "Key<Model>"
##
##
## $model$name
## [1] "StackedEnsemble_AllModels_AutoML_20210108_015304"
##
## $model$type
## [1] "Key<Model>"
##
## $model$URL
## [1] "/3/Models/StackedEnsemble_AllModels_AutoML_20210108_015304"
##
##
## $model_checksum
## [1] "-2137875469075093584"
##
## $frame
## $frame$name
## [1] "test_tbl_sid_90af_462"
##
##
## $frame_checksum
## [1] "-1590291148178685696"
##
## $description
## NULL
##
## $scoring_time
## [1] 1.610073e+12
##
## $predictions
## NULL
##
## $MSE
## [1] 0.05601617
##
## $RMSE
## [1] 0.2366774
##
## $nobs
## [1] 2857
##
## $custom_metric_name
## NULL
##
## $custom_metric_value
## [1] 0
##
## $r2
## [1] 0.457412
##
## $logloss
## [1] 0.196452
##
```

```
## $AUC
## [1] 0.9417586
##
## $pr_auc
## [1] 0.7119371
##
## $Gini
## [1] 0.8835172
##
## $mean_per_class_error
## [1] 0.1758813
##
## $domain
## [1] "No"  "Yes"
##
## $cm
## $cm$`__meta`
## $cm$`__meta`$schema_version
## [1] 3
##
## $cm$`__meta`$schema_name
## [1] "ConfusionMatrixV3"
##
## $cm$`__meta`$schema_type
## [1] "ConfusionMatrix"
##
##
## $cm$table
## Confusion Matrix: Row labels: Actual class; Column labels: Predicted class
##          No Yes  Error          Rate
## No     2406 117 0.0464 = 117 / 2,523
## Yes     102 232 0.3054 =   102 / 334
## Totals 2508 349 0.0767 = 219 / 2,857
##
##
## $thresholds_and_metric_scores
## Metrics for Thresholds: Binomial metrics as a function of classification thresholds
##   threshold       f1       f2 f0point5 accuracy precision   recall specificity
## 1  0.998898 0.011905 0.007474 0.029240 0.883794  1.000000 0.005988    1.000000
## 2  0.996792 0.029499 0.018643 0.070621 0.884844  1.000000 0.014970    1.000000
## 3  0.995788 0.058140 0.037147 0.133690 0.886594  1.000000 0.029940    1.000000
## 4  0.994837 0.074928 0.048184 0.168394 0.887644  1.000000 0.038922    1.000000
## 5  0.993040 0.096591 0.062777 0.209360 0.888694  0.944444 0.050898    0.999604
##   absolute_mcc min_per_class_accuracy mean_per_class_accuracy  tns fns fps tps
## 1     0.072744               0.005988                0.502994 2523 332   0   2
## 2     0.115079               0.014970                0.507485 2523 329   0   5
## 3     0.162889               0.029940                0.514970 2523 324   0  10
## 4     0.185820               0.038922                0.519461 2523 321   0  13
## 5     0.205079               0.050898                0.525251 2522 317   1  17
##        tnr      fnr      fpr      tpr idx
## 1 1.000000 0.994012 0.000000 0.005988   0
## 2 1.000000 0.985030 0.000000 0.014970   1
## 3 1.000000 0.970060 0.000000 0.029940   2
## 4 1.000000 0.961078 0.000000 0.038922   3
```

```
## 5 0.999604 0.949102 0.000396 0.050898   4
##
## ---
##     threshold       f1       f2 f0point5 accuracy precision   recall
## 395  0.020644 0.214860 0.406227 0.146056 0.145607  0.120360 1.000000
## 396  0.020348 0.213282 0.403967 0.144890 0.137557  0.119371 1.000000
## 397  0.020043 0.211526 0.401442 0.143594 0.128456  0.118272 1.000000
## 398  0.019719 0.210129 0.399426 0.142564 0.121106  0.117399 1.000000
## 399  0.019222 0.209667 0.398758 0.142224 0.118656  0.117111 1.000000
## 400  0.018879 0.209339 0.398283 0.141983 0.116906  0.116906 1.000000
##     specificity absolute_mcc min_per_class_accuracy mean_per_class_accuracy tns
## 395    0.032501     0.062545               0.032501                0.516250  82
## 396    0.023385     0.052834               0.023385                0.511692  59
## 397    0.013080     0.039331               0.013080                0.506540  33
## 398    0.004756     0.023630               0.004756                0.502378  12
## 399    0.001982     0.015234               0.001982                0.500991   5
## 400    0.000000     0.000000               0.000000                0.500000   0
##     fns  fps tps      tnr      fnr      fpr      tpr idx
## 395   0 2441 334 0.032501 0.000000 0.967499 1.000000 394
## 396   0 2464 334 0.023385 0.000000 0.976615 1.000000 395
## 397   0 2490 334 0.013080 0.000000 0.986920 1.000000 396
## 398   0 2511 334 0.004756 0.000000 0.995244 1.000000 397
## 399   0 2518 334 0.001982 0.000000 0.998018 1.000000 398
## 400   0 2523 334 0.000000 0.000000 1.000000 1.000000 399
##
## $max_criteria_and_metric_scores
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.323580    0.679356 188
## 2                       max f2  0.125719    0.745243 270
## 3                 max f0point5  0.520073    0.705795 135
## 4                 max accuracy  0.480941    0.927896 144
## 5                max precision  0.998898    1.000000   0
## 6                   max recall  0.025434    1.000000 378
## 7              max specificity  0.998898    1.000000   0
## 8             max absolute_mcc  0.323580    0.636047 188
## 9   max min_per_class_accuracy  0.087553    0.865636 294
## 10 max mean_per_class_accuracy  0.071412    0.872407 306
## 11                     max tns  0.998898 2523.000000   0
## 12                     max fns  0.998898  332.000000   0
## 13                     max fps  0.018879 2523.000000 399
## 14                     max tps  0.025434  334.000000 378
## 15                     max tnr  0.998898    1.000000   0
## 16                     max fnr  0.998898    0.994012   0
## 17                     max fpr  0.018879    1.000000 399
## 18                     max tpr  0.025434    1.000000 378
##
## $gains_lift_table
## Gains/Lift Table: Avg response rate: 11.69 %, avg score: 12.70 %
##    group cumulative_data_fraction lower_threshold     lift cumulative_lift
## 1      1               0.01015051        0.983449 8.258930        8.258930
## 2      2               0.02030102        0.949574 6.784121        7.521526
## 3      3               0.03010151        0.896397 6.109923        7.061934
## 4      4               0.04025201        0.854943 7.963969        7.289404
```

```
## 5      5             0.05005250        0.803196 5.498931        6.938822
## 6      6             0.10010501        0.429004 5.024664        5.981743
## 7      7             0.15015751        0.211347 3.170324        5.044603
## 8      8             0.20021001        0.115391 1.794523        4.232083
## 9      9             0.29996500        0.046491 0.930423        3.134098
## 10    10             0.40007000        0.034363 0.358905        2.439693
## 11    11             0.50017501        0.029974 0.029909        1.957399
## 12    12             0.59993000        0.027532 0.090041        1.646899
## 13    13             0.70003500        0.025604 0.089726        1.424223
## 14    14             0.79978999        0.023861 0.030014        1.250328
## 15    15             0.89989499        0.022050 0.000000        1.111241
## 16    16             1.00000000        0.018589 0.000000        1.000000
##    response_rate    score cumulative_response_rate cumulative_score
## 1       0.965517 0.992662                 0.965517         0.992662
## 2       0.793103 0.971039                 0.879310         0.981850
## 3       0.714286 0.921029                 0.825581         0.962048
## 4       0.931034 0.880146                 0.852174         0.941395
## 5       0.642857 0.829368                 0.811189         0.919459
## 6       0.587413 0.621150                 0.699301         0.770305
## 7       0.370629 0.310652                 0.589744         0.617087
## 8       0.209790 0.158233                 0.494755         0.502374
## 9       0.108772 0.069594                 0.366394         0.358450
## 10      0.041958 0.039293                 0.285214         0.278591
## 11      0.003497 0.031784                 0.228831         0.229195
## 12      0.010526 0.028698                 0.192532         0.195857
## 13      0.010490 0.026513                 0.166500         0.171641
## 14      0.003509 0.024746                 0.146171         0.153319
## 15      0.000000 0.022992                 0.129911         0.138821
## 16      0.000000 0.020904                 0.116906         0.127017
##    capture_rate cumulative_capture_rate        gain cumulative_gain
## 1      0.083832                0.083832  725.893042      725.893042
## 2      0.068862                0.152695  578.412141      652.152591
## 3      0.059880                0.212575  510.992301      606.193427
## 4      0.080838                0.293413  696.396861      628.940380
## 5      0.053892                0.347305  449.893071      593.882166
## 6      0.251497                0.598802  402.466396      498.174281
## 7      0.158683                0.757485  217.032369      404.460310
## 8      0.089820                0.847305   79.452284      323.208304
## 9      0.092814                0.940120   -6.957664      213.409820
## 10     0.035928                0.976048  -64.109543      143.969279
## 11     0.002994                0.979042  -97.009129       95.739871
## 12     0.008982                0.988024  -90.995903       64.689873
## 13     0.008982                0.997006  -91.027386       42.422305
## 14     0.002994                1.000000  -96.998634       25.032823
## 15     0.000000                1.000000 -100.000000       11.124076
## 16     0.000000                1.000000 -100.000000        0.000000
##    kolmogorov_smirnov
## 1            0.083436
## 2            0.149920
## 3            0.206630
## 4            0.286675
## 5            0.336604
## 6            0.564716
## 7            0.687727
```

```
## 8            0.732759
## 9            0.724900
## 10           0.652227
## 11           0.542260
## 12           0.439471
## 13           0.336285
## 14           0.226714
## 15           0.113357
## 16           0.000000
##
## $residual_deviance
## [1] 1122.527
##
## $null_deviance
## [1] 2061.286
##
## $AIC
## [1] 1138.527
##
## $null_degrees_of_freedom
## [1] 2856
##
## $residual_degrees_of_freedom
## [1] 2849
```

```r
# Classifier Summary Metrics

h2o.auc(performance_h2o, train = T, valid = T, xval = T)
```

```
## [1] 0.9417586
```

```r
# our value is [1] 0.9037603

h2o.auc(stacked_ensemble_h2o, train = T, valid = T, xval = T)
```

```
##     train     valid      xval
## 0.9787684 0.9548814 0.9304988
```

```r
#     train     valid      xval
# 0.9320589 0.8932458 0.8576325

h2o.giniCoef(performance_h2o)
```

```
## [1] 0.8835172
```

```r
# [1] 0.8075205

h2o.logloss(performance_h2o)
```

```
## [1] 0.196452
```

```r
# [1] 0.2362433

# result for the training data
h2o.confusionMatrix(stacked_ensemble_h2o)
```

```
## Confusion Matrix (vertical: actual; across: predicted)  for max f1 @ threshold = 0.341126899054185:
##           No  Yes    Error        Rate
## No      8579  237 0.026883   =237/8816
## Yes      227  974 0.189009   =227/1201
## Totals  8806 1211 0.046321  =464/10017
```

```r
# Confusion Matrix (vertical: actual; across: predicted)  for max f1 @ threshold = 0.268791256959701

# result for the hold out set
h2o.confusionMatrix(performance_h2o)
```

```
## Confusion Matrix (vertical: actual; across: predicted)  for max f1 @ threshold = 0.323579611938672:
##           No Yes    Error       Rate
## No      2406 117 0.046373  =117/2523
## Yes      102 232 0.305389   =102/334
## Totals  2508 349 0.076654  =219/2857
```

```r
# Confusion Matrix (vertical: actual; across: predicted)  for max f1 @ threshold = 0.258178237257322
```

performance table

```r
performance_tbl <- performance_h2o %>%
    h2o.metric() %>%
    as.tibble()

performance_tbl %>%
  glimpse()
```

```
## Rows: 400
## Columns: 20
## $ threshold               <dbl> 0.9988981, 0.9967924, 0.9957879, 0.9948373,...
## $ f1                      <dbl> 0.01190476, 0.02949853, 0.05813953, 0.07492...
## $ f2                      <dbl> 0.007473842, 0.018642804, 0.037147103, 0.04...
## $ f0point5                <dbl> 0.02923977, 0.07062147, 0.13368984, 0.16839...
## $ accuracy                <dbl> 0.8837942, 0.8848442, 0.8865943, 0.8876444,...
## $ precision               <dbl> 1.0000000, 1.0000000, 1.0000000, 1.0000000,...
## $ recall                  <dbl> 0.005988024, 0.014970060, 0.029940120, 0.03...
## $ specificity             <dbl> 1.0000000, 1.0000000, 1.0000000, 1.0000000,...
## $ absolute_mcc            <dbl> 0.07274403, 0.11507888, 0.16288896, 0.18581...
## $ min_per_class_accuracy  <dbl> 0.005988024, 0.014970060, 0.029940120, 0.03...
## $ mean_per_class_accuracy <dbl> 0.5029940, 0.5074850, 0.5149701, 0.5194611,...
## $ tns                     <dbl> 2523, 2523, 2523, 2523, 2522, 2522, 2522, 2...
## $ fns                     <dbl> 332, 329, 324, 321, 317, 313, 312, 311, 309...
## $ fps                     <dbl> 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 2, 3, 4, 4, 4...
```

```
## $ tps                        <dbl> 2, 5, 10, 13, 17, 21, 22, 23, 25, 27, 29, 3...
## $ tnr                        <dbl> 1.0000000, 1.0000000, 1.0000000, 1.0000000,...
## $ fnr                        <dbl> 0.9940120, 0.9850299, 0.9700599, 0.9610778,...
## $ fpr                        <dbl> 0.0000000000, 0.0000000000, 0.0000000000, 0...
## $ tpr                        <dbl> 0.005988024, 0.014970060, 0.029940120, 0.03...
## $ idx                        <int> 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1...
```

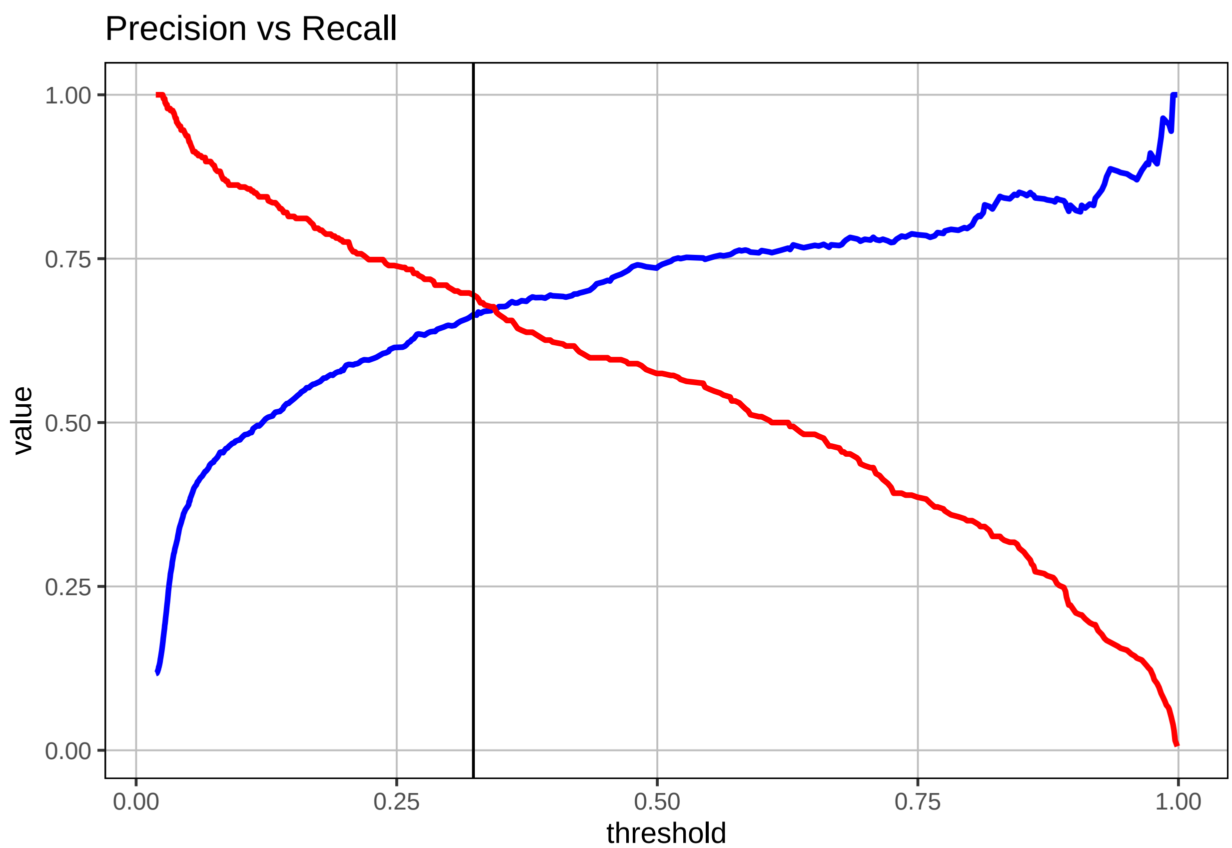
```
# save our theme
theme_new <- theme(
      legend.position  = "bottom",
      legend.key       = element_blank(),
      panel.background = element_rect(fill   = "transparent"),
      panel.border     = element_rect(color = "black", fill = NA, size = 0.5),
      panel.grid.major = element_line(color = "grey", size = 0.333)
      )
```

Visualize the trade of between the precision and the recall and the optimal threshold

```
performance_tbl %>%
    filter(f1 == max(f1))
```

```
## # A tibble: 1 x 20
##   threshold    f1    f2 f0point5 accuracy precision recall specificity
##       <dbl> <dbl> <dbl>    <dbl>    <dbl>     <dbl>  <dbl>       <dbl>
## 1     0.324 0.679 0.688    0.671    0.923     0.665  0.695       0.954
## # ... with 12 more variables: absolute_mcc <dbl>, min_per_class_accuracy <dbl>,
## #   mean_per_class_accuracy <dbl>, tns <dbl>, fns <dbl>, fps <dbl>, tps <dbl>,
## #   tnr <dbl>, fnr <dbl>, fpr <dbl>, tpr <dbl>, idx <int>
```

```
performance_tbl %>%
    ggplot(aes(x = threshold)) +
    geom_line(aes(y = precision), color = "blue", size = 1) +
    geom_line(aes(y = recall), color = "red", size = 1) +

    # Insert line where precision and recall are harmonically optimized
    geom_vline(xintercept = h2o.find_threshold_by_max_metric(performance_h2o, "f1")) +
    labs(title = "Precision vs Recall", y = "value") +
    theme_new
```



ROC Plot

```
path <- "/StackedEnsemble_AllModels_AutoML_20210108_015304"

load_model_performance_metrics <- function(path, test_tbl) {

    model_h2o <- h2o.loadModel(path)
    perf_h2o  <- h2o.performance(model_h2o, newdata = as.h2o(test_tbl))

    perf_h2o %>%
        h2o.metric() %>%
        as_tibble() %>%
        mutate(auc = h2o.auc(perf_h2o)) %>%
        select(tpr, fpr, auc)

}


#model_metrics_tbl <- fs::dir_info(path = "ml_journal-Automated_Machine_learning_2_model/") %>%
#    select(path) %>%
#    mutate(metrics = map(path, load_model_performance_metrics, test_tbl)) %>%
#    unnest(cols = metrics)

#model_metrics_tbl %>%
#    mutate(
#        # Extract the model names
#        path = str_split(path, pattern = "/", simplify = T)[,2] %>% as_factor(),
```

```
#        auc  = auc %>% round(3) %>% as.character() %>% as_factor()
#        ) %>%
#    ggplot(aes(fpr, tpr, color = path, linetype = auc)) +
#    geom_line(size = 1) +
#
#    # just for demonstration purposes
#    geom_abline(color = "red", linetype = "dotted") +
#
#    theme_new +
#    theme(
#      legend.direction = "vertical",
#      ) +
#    labs(
#        title = "ROC Plot",
#        subtitle = "Performance of 3 Top Performing Models"
#    )
```

Percision vs Recall plot

```
# Precision vs Recall

load_model_performance_metrics <- function(path, test_tbl) {

    model_h2o <- h2o.loadModel(path)
    perf_h2o  <- h2o.performance(model_h2o, newdata = as.h2o(test_tbl))

    perf_h2o %>%
        h2o.metric() %>%
        as_tibble() %>%
        mutate(auc = h2o.auc(perf_h2o)) %>%
        select(tpr, fpr, auc, precision, recall)

}

#model_metrics_tbl <- fs::dir_info(path = "ml_journal-Automated_Machine_learning_2_model/") %>%
#    select(path) %>%
#    mutate(metrics = map(path, load_model_performance_metrics, test_tbl)) %>%
#    unnest(cols = metrics)
#
#model_metrics_tbl %>%
#    mutate(
#        path = str_split(path, pattern = "/", simplify = T)[,2] %>% as_factor(),
#        auc  = auc %>% round(3) %>% as.character() %>% as_factor()
#    ) %>%
#    ggplot(aes(recall, precision, color = path, linetype = auc)) +
#    geom_line(size = 1) +
#    theme_new +
#    theme(
#      legend.direction = "vertical",
#      ) +
#    labs(
#        title = "Precision vs Recall Plot",
```

```r
#         subtitle = "Performance of 3 Top Performing Models"
#    )
```

getting predictions_tbl from previous session

```r
predictions <- h2o.predict(stacked_ensemble_h2o, newdata = as.h2o(test_tbl))
```

```
##   |                                                                              |
##   |                                                                              |
```

```r
typeof(predictions)
```

```
## [1] "environment"
```

```r
# [1] "environment"

predictions_tbl <- predictions %>% as_tibble()

# No     0.938624996 0.06137500
# Yes    0.767573922 0.23242608
# No     0.934670085 0.06532991
# Yes    0.580364130 0.41963587
# Yes    0.738244189 0.26175581
# Yes    0.767517540 0.23248246
# Yes    0.580365130 0.41963487
# No     0.940360179 0.05963982
# Yes    0.616682970 0.38331703
# Yes    0.111431957 0.88856804

# Gain & Lift

ranked_predictions_tbl <- predictions_tbl %>%
    bind_cols(test_tbl) %>%
    select(predict:Yes, went_on_backorder) %>%
    arrange(desc(Yes))

ranked_predictions_tbl
```

```
## # A tibble: 2,857 x 4
##    predict       No   Yes went_on_backorder
##    <fct>      <dbl> <dbl> <fct>
##  1 Yes     0.000523 0.999 Yes
##  2 Yes     0.00168  0.998 Yes
##  3 Yes     0.00280  0.997 Yes
##  4 Yes     0.00334  0.997 Yes
##  5 Yes     0.00348  0.997 Yes
##  6 Yes     0.00388  0.996 Yes
##  7 Yes     0.00397  0.996 Yes
##  8 Yes     0.00435  0.996 Yes
##  9 Yes     0.00437  0.996 Yes
## 10 Yes     0.00449  0.996 Yes
## # ... with 2,847 more rows
```

Gain and Lift calculations

```
ranked_predictions_tbl %>%
    mutate(ntile = ntile(Yes, n = 10)) %>%
    group_by(ntile) %>%
    summarise(
        cases = n(),
        responses = sum(went_on_backorder == "Yes")
    ) %>%
    arrange(desc(ntile))
```

```
## # A tibble: 10 x 3
##    ntile cases responses
##    <int> <int>     <int>
##  1    10   285       200
##  2     9   285        82
##  3     8   285        32
##  4     7   286        12
##  5     6   286         1
##  6     5   286         3
##  7     4   286         3
##  8     3   286         1
##  9     2   286         0
## 10     1   286         0
```

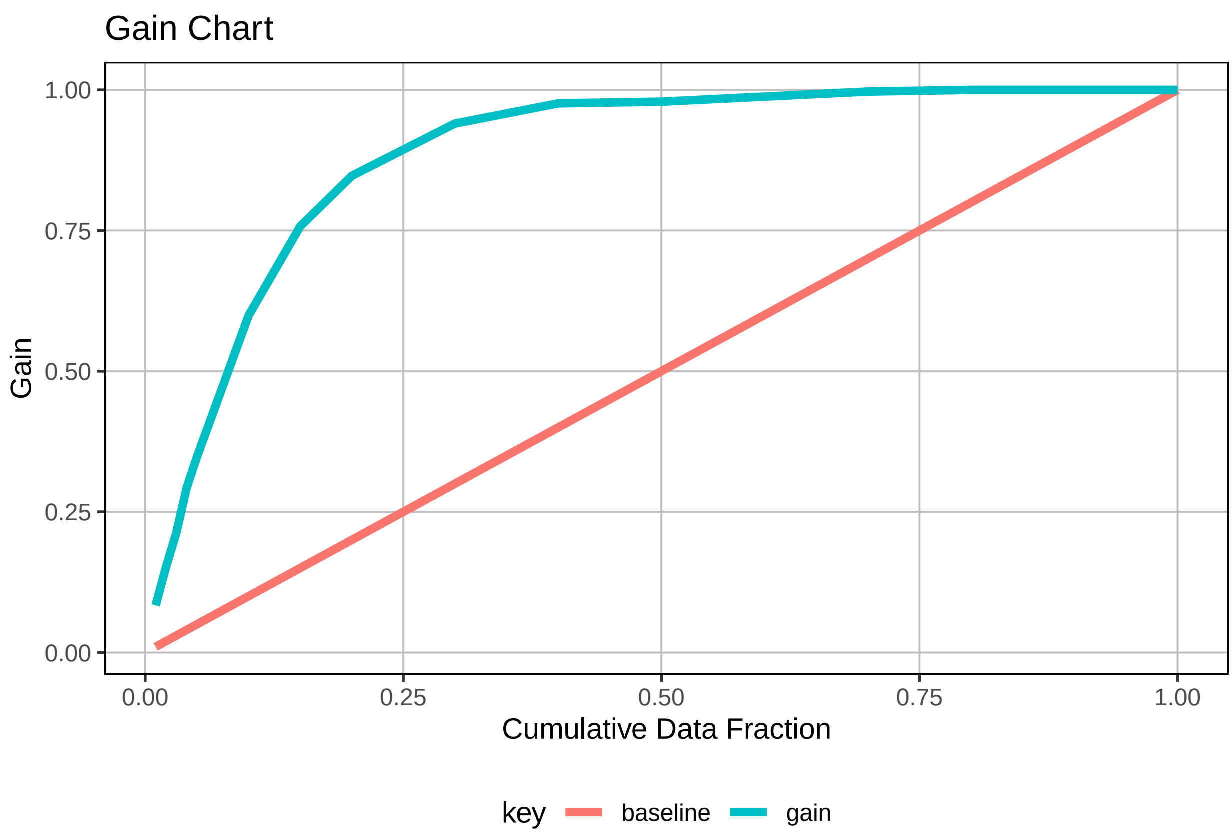
```
calculated_gain_lift_tbl <- ranked_predictions_tbl %>%
    mutate(ntile = ntile(Yes, n = 10)) %>%
    group_by(ntile) %>%
    summarise(
        cases = n(),
        responses = sum(went_on_backorder == "Yes")
    ) %>%
    arrange(desc(ntile)) %>%

    # Add group numbers (opposite of ntile)
    mutate(group = row_number()) %>%
    select(group, cases, responses) %>%

    # Calculations
    mutate(
        cumulative_responses = cumsum(responses),
        pct_responses        = responses / sum(responses),
        gain                 = cumsum(pct_responses),
        cumulative_pct_cases = cumsum(cases) / sum(cases),
        lift                 = gain / cumulative_pct_cases,
        gain_baseline        = cumulative_pct_cases,
        lift_baseline        = gain_baseline / cumulative_pct_cases
    )

calculated_gain_lift_tbl
```

```
## # A tibble: 10 x 10
```

```
##    group cases responses cumulative_resp~ pct_responses  gain cumulative_pct_~
##    <int> <int>     <int>            <int>         <dbl> <dbl>            <dbl>
##  1     1   285       200              200       0.599   0.599           0.0998
##  2     2   285        82              282       0.246   0.844           0.200
##  3     3   285        32              314       0.0958  0.940           0.299
##  4     4   286        12              326       0.0359  0.976           0.399
##  5     5   286         1              327       0.00299 0.979           0.499
##  6     6   286         3              330       0.00898 0.988           0.600
##  7     7   286         3              333       0.00898 0.997           0.700
##  8     8   286         1              334       0.00299 1.00            0.800
##  9     9   286         0              334       0       1.00            0.900
## 10    10   286         0              334       0       1.00            1
## # ... with 3 more variables: lift <dbl>, gain_baseline <dbl>,
## #   lift_baseline <dbl>
```

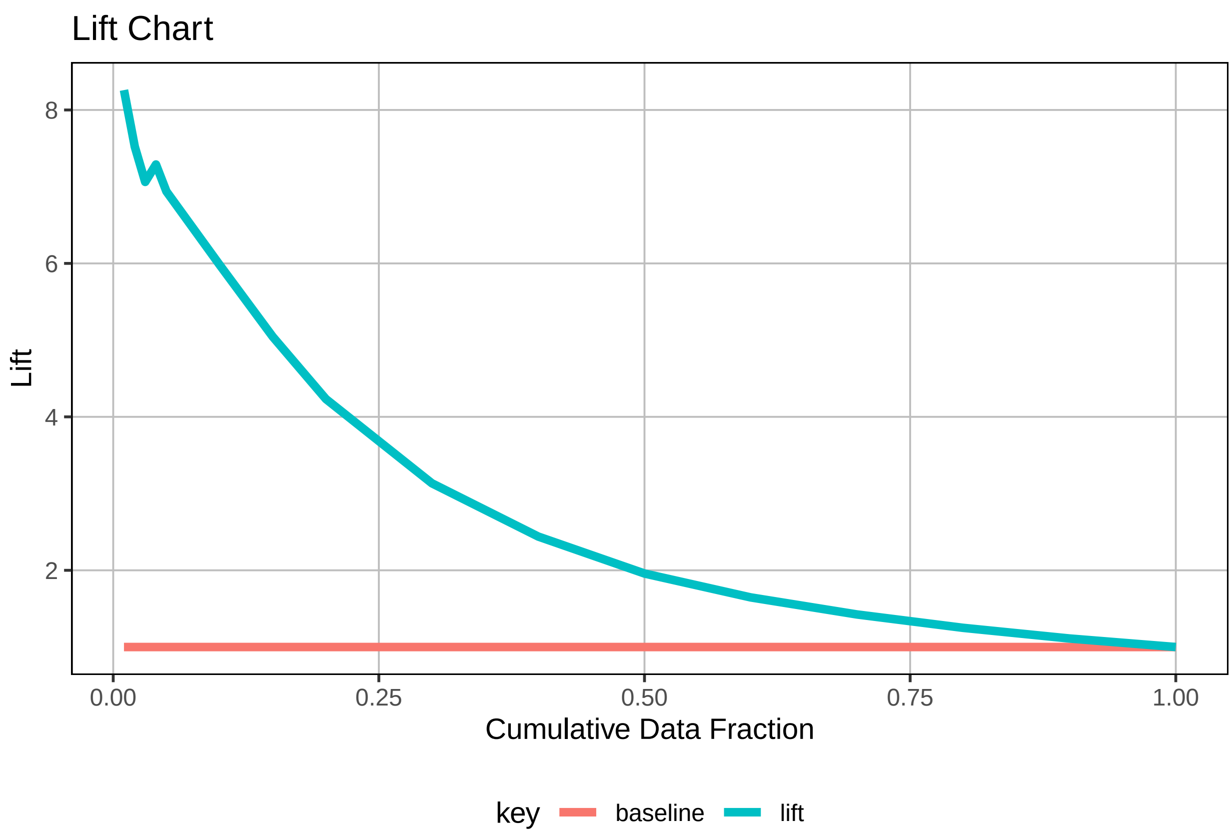
Gain Plot

```
gain_lift_tbl <- performance_h2o %>%
    h2o.gainsLift() %>%
    as.tibble()

## Gain Chart

gain_transformed_tbl <- gain_lift_tbl %>%
    select(group, cumulative_data_fraction, cumulative_capture_rate, cumulative_lift) %>%
    select(-contains("lift")) %>%
    mutate(baseline = cumulative_data_fraction) %>%
    rename(gain     = cumulative_capture_rate) %>%
    # prepare the data for the plotting (for the color and group aesthetics)
    pivot_longer(cols = c(gain, baseline), values_to = "value", names_to = "key")

gain_transformed_tbl %>%
    ggplot(aes(x = cumulative_data_fraction, y = value, color = key)) +
    geom_line(size = 1.5) +
    labs(
        title = "Gain Chart",
        x = "Cumulative Data Fraction",
        y = "Gain"
    ) +
    theme_new
```



Lift Plot

```
lift_transformed_tbl <- gain_lift_tbl %>%
    select(group, cumulative_data_fraction, cumulative_capture_rate, cumulative_lift) %>%
    select(-contains("capture")) %>%
    mutate(baseline = 1) %>%
    rename(lift = cumulative_lift) %>%
    pivot_longer(cols = c(lift, baseline), values_to = "value", names_to = "key")

lift_transformed_tbl %>%
    ggplot(aes(x = cumulative_data_fraction, y = value, color = key)) +
    geom_line(size = 1.5) +
    labs(
        title = "Lift Chart",
        x = "Cumulative Data Fraction",
        y = "Lift"
    ) +
    theme_new
```



Cowplot block

Visualization

```
# set values to test the function while building it
h2o_leaderboard <- automl_models_h2o@leaderboard
newdata <- test_tbl
order_by <- "auc"
max_models <- 4
size <- 1

plot_h2o_performance <- function(h2o_leaderboard, newdata, order_by = c("auc", "logloss"),
                                 max_models = 3, size = 1.5) {

    # Inputs
    leaderboard_tbl <- h2o_leaderboard %>%
        as_tibble() %>%
        slice(1:max_models)

    newdata_tbl <- newdata %>%
        as_tibble()

     # Selecting the first, if nothing is provided
    order_by      <- tolower(order_by[[1]])
```

```r
# Convert string stored in a variable to column name (symbol)
order_by_expr <- rlang::sym(order_by)

# Turn of the progress bars ( opposite h2o.show_progress())
h2o.no_progress()

# 1. Model metrics

get_model_performance_metrics <- function(model_id, test_tbl) {

    model_h2o <- h2o.getModel(model_id)
    perf_h2o  <- h2o.performance(model_h2o, newdata = as.h2o(test_tbl))

    perf_h2o %>%
        h2o.metric() %>%
        as.tibble() %>%
        select(threshold, tpr, fpr, precision, recall)
}
    model_metrics_tbl <- leaderboard_tbl %>%
    mutate(metrics = map(model_id, get_model_performance_metrics, newdata_tbl)) %>%
    unnest(cols = metrics) %>%
    mutate(
      model_id = as_factor(model_id) %>%
                  # programmatically reorder factors depending on order_by
                  fct_reorder(!! order_by_expr,
                              .desc = ifelse(order_by == "auc", TRUE, FALSE)),
      auc      = auc %>%
                  round(3) %>%
                  as.character() %>%
                  as_factor() %>%
                  fct_reorder(as.numeric(model_id)),
      logloss  = logloss %>%
                  round(4) %>%
                  as.character() %>%
                  as_factor() %>%
                  fct_reorder(as.numeric(model_id))
    )


# 1A. ROC Plot

p1 <- model_metrics_tbl %>%
    ggplot(aes(fpr, tpr, color = model_id, linetype = !! order_by_expr)) +
    geom_line(size = size) +
    theme_new +
    labs(title = "ROC", x = "FPR", y = "TPR") +
    theme(legend.direction = "vertical")


# 1B. Precision vs Recall

p2 <- model_metrics_tbl %>%
    ggplot(aes(recall, precision, color = model_id, linetype = !! order_by_expr)) +
```

```r
    geom_line(size = size) +
    theme_new +
    labs(title = "Precision Vs Recall", x = "Recall", y = "Precision") +
    theme(legend.position = "none")


# 2. Gain / Lift

get_gain_lift <- function(model_id, test_tbl) {

    model_h2o <- h2o.getModel(model_id)
    perf_h2o  <- h2o.performance(model_h2o, newdata = as.h2o(test_tbl))

    perf_h2o %>%
        h2o.gainsLift() %>%
        as.tibble() %>%
        select(group, cumulative_data_fraction, cumulative_capture_rate, cumulative_lift)

}

gain_lift_tbl <- leaderboard_tbl %>%
    mutate(metrics = map(model_id, get_gain_lift, newdata_tbl)) %>%
    unnest(cols = metrics) %>%
    mutate(
        model_id = as_factor(model_id) %>%
            fct_reorder(!! order_by_expr,
                        .desc = ifelse(order_by == "auc", TRUE, FALSE)),
        auc  = auc %>%
            round(3) %>%
            as.character() %>%
            as_factor() %>%
            fct_reorder(as.numeric(model_id)),
        logloss = logloss %>%
            round(4) %>%
            as.character() %>%
            as_factor() %>%
            fct_reorder(as.numeric(model_id))
    ) %>%
    rename(
        gain = cumulative_capture_rate,
        lift = cumulative_lift
    )

# 2A. Gain Plot

p3 <- gain_lift_tbl %>%
    ggplot(aes(cumulative_data_fraction, gain,
                      color = model_id, linetype = !! order_by_expr)) +
    geom_line(size = size,) +
    geom_segment(x = 0, y = 0, xend = 1, yend = 1,
                 color = "red", size = size, linetype = "dotted") +
    theme_new +
    expand_limits(x = c(0, 1), y = c(0, 1)) +
```

```r
        labs(title = "Gain",
             x = "Cumulative Data Fraction", y = "Gain") +
        theme(legend.position = "none")

    # 2B. Lift Plot

    p4 <- gain_lift_tbl %>%
        ggplot(aes(cumulative_data_fraction, lift,
                          color = model_id, linetype = !! order_by_expr)) +
        geom_line(size = size) +
        geom_segment(x = 0, y = 1, xend = 1, yend = 1,
                     color = "red", size = size, linetype = "dotted") +
        theme_new +
        expand_limits(x = c(0, 1), y = c(0, 1)) +
        labs(title = "Lift",
             x = "Cumulative Data Fraction", y = "Lift") +
        theme(legend.position = "none")


    # Combine using cowplot

    # cowplot::get_legend extracts a legend from a ggplot object
    p_legend <- get_legend(p1)
    # Remove legend from p1
    p1 <- p1 + theme(legend.position = "none")

    # cowplot::plt_grid() combines multiple ggplots into a single cowplot object
    p <- cowplot::plot_grid(p1, p2, p3, p4, ncol = 2)

    # cowplot::ggdraw() sets up a drawing layer
    p_title <- ggdraw() +

        # cowplot::draw_label() draws text on a ggdraw layer / ggplot object
        draw_label("H2O Model Metrics", size = 18, fontface = "bold",
                   color = "#2C3E50")

    p_subtitle <- ggdraw() +
        draw_label(glue("Ordered by {toupper(order_by)}"), size = 10,
                   color = "#2C3E50")

    # Combine everything
    ret <- plot_grid(p_title, p_subtitle, p, p_legend,

                     # Adjust the relative spacing, so that the legends always fits
                     ncol = 1, rel_heights = c(0.05, 0.05, 1, 0.05 * max_models))

    h2o.show_progress()

    return(ret)

}

automl_models_h2o@leaderboard %>%
```

```r
plot_h2o_performance(newdata = test_tbl, order_by = "logloss",
                     size = 0.5, max_models = 4)
```