# Model Selection - death_180days

Eduardo Yuki Yada

## Global parameters

```
k <- params$k # Number of folds for cross validation
grid_size <- params$grid_size # Number of parameter combination to tune on each model
repeats <- params$repeats
RUN_ALL_MODELS <- params$RUN_ALL_MODELS
Hmisc::list.tree(params)
```

```
##  params = list 5 (952 bytes)
## .  outcome_column = character 1= death_180days
## .  k = double 1= 10
## .  grid_size = double 1= 20
## .  repeats = double 1= 2
## .  RUN_ALL_MODELS = logical 1= TRUE
```

Minutes to run: 0

## Imports

```
library(tidyverse)
library(yaml)
library(tidymodels)
library(usemodels)
library(vip)
library(bonsai)
library(lightgbm)
library(caret)
library(pROC)

source("aux_functions.R")
predict <- stats::predict
```

Minutes to run: 0

## Loading data

```
load('dataset/processed_data.RData')
load('dataset/processed_dictionary.RData')

columns_list <- yaml.load_file("./auxiliar/columns_list.yaml")

outcome_column <- params$outcome_column
features_list <- params$features_list

df <- mutate(df, across(where(is.character), as.factor))
```

Minutes to run: 0.006

```
dir.create(file.path("./auxiliar/model_selection/hyperparameters/"),
           showWarnings = FALSE,
```

```
           recursive = TRUE)

dir.create(file.path("./auxiliar/model_selection/performance/"),
           showWarnings = FALSE,
           recursive = TRUE)
```

Minutes to run: 0

## Eligible features

```
cat_features_list = read_yaml(sprintf(
  "./auxiliar/significant_columns/categorical_%s.yaml",
  outcome_column
))

num_features_list = read_yaml(sprintf(
  "./auxiliar/significant_columns/numerical_%s.yaml",
  outcome_column
))

features_list = c(cat_features_list, num_features_list)
```

Minutes to run: 0

```
eligible_columns = df_names %>%
  filter(momento.aquisicao == 'Admissão t0') %>%
  .$variable.name

exception_columns = c('death_intraop', 'death_intraop_1', 'disch_outcomes_t0')

correlated_columns = c('year_procedure_1', # com year_adm_t0
                       'age_surgery_1', # com age
                       'admission_t0', # com admission_pre_t0_count
                       'atb', # com meds_antimicrobianos
                       'classe_meds_cardio_qtde', # com classe_meds_qtde
                       'suporte_hemod', # com proced_invasivos_qtde,
                       'radiografia', # com exames_imagem_qtde
                       'ecg' # com metodos_graficos_qtde
                       )

eligible_features = eligible_columns %>%
  base::intersect(c(columns_list$categorical_columns, columns_list$numerical_columns)) %>%
  setdiff(c(exception_columns, correlated_columns))

features = base::intersect(eligible_features, features_list)

gluedown::md_order(features, seq = TRUE, pad = TRUE)
```

```
## 01. sex
## 02. age
## 03. education_level
## 04. underlying_heart_disease
## 05. heart_disease
## 06. nyha_basal
## 07. hypertension
## 08. prior_mi
## 09. heart_failure
## 10. af
## 11. cardiac_arrest
## 12. valvopathy
## 13. diabetes
```

```
## 14. renal_failure
## 15. hemodialysis
## 16. stroke
## 17. copd
## 18. cancer
## 19. comorbidities_count
## 20. procedure_type_1
## 21. reop_type_1
## 22. procedure_type_new
## 23. cied_final_1
## 24. cied_final_group_1
## 25. admission_pre_t0_count
## 26. admission_pre_t0_180d
## 27. year_adm_t0
## 28. icu_t0
## 29. dialysis_t0
## 30. admission_t0_emergency
## 31. aco
## 32. antiarritmico
## 33. ieca_bra
## 34. dva
## 35. digoxina
## 36. estatina
## 37. diuretico
## 38. vasodilatador
## 39. insuf_cardiaca
## 40. espironolactona
## 41. antiplaquetario_ev
## 42. insulina
## 43. psicofarmacos
## 44. antifungico
## 45. classe_meds_qtde
## 46. meds_cardiovasc_qtde
## 47. meds_antimicrobianos
## 48. vni
## 49. ventilacao_mecanica
## 50. transplante_cardiaco
## 51. outros_proced_cirurgicos
## 52. icp
## 53. cateterismo
## 54. cateter_venoso_central
## 55. proced_invasivos_qtde
## 56. transfusao
## 57. interconsulta
## 58. equipe_multiprof
## 59. holter
## 60. teste_esforco
## 61. metodos_graficos_qtde
## 62. laboratorio
## 63. cultura
## 64. analises_clinicas_qtde
## 65. citologia
## 66. histopatologia_qtde
## 67. angiografia
## 68. aortografia
## 69. arteriografia
## 70. cintilografia
## 71. ecocardiograma
## 72. endoscopia
## 73. ultrassom
## 74. tomografia
```

```
## 75. ressonancia
## 76. exames_imagem_qtde
## 77. bic
## 78. hospital_stay
```

Minutes to run: 0

## Train test split (70%/30%)

```
set.seed(42)

if (outcome_column == 'readmission_30d') {
  df_split <- readRDS("./dataset/split_object.rds")
} else {
  df_split <- initial_split(df, prop = .7, strata = all_of(outcome_column))
}

df_train <- training(df_split) %>% dplyr::select(all_of(c(features, outcome_column)))
df_test <- testing(df_split) %>% dplyr::select(all_of(c(features, outcome_column)))

df_folds <- vfold_cv(df_train, v = k,
                     strata = all_of(outcome_column))
```

Minutes to run: 0.001

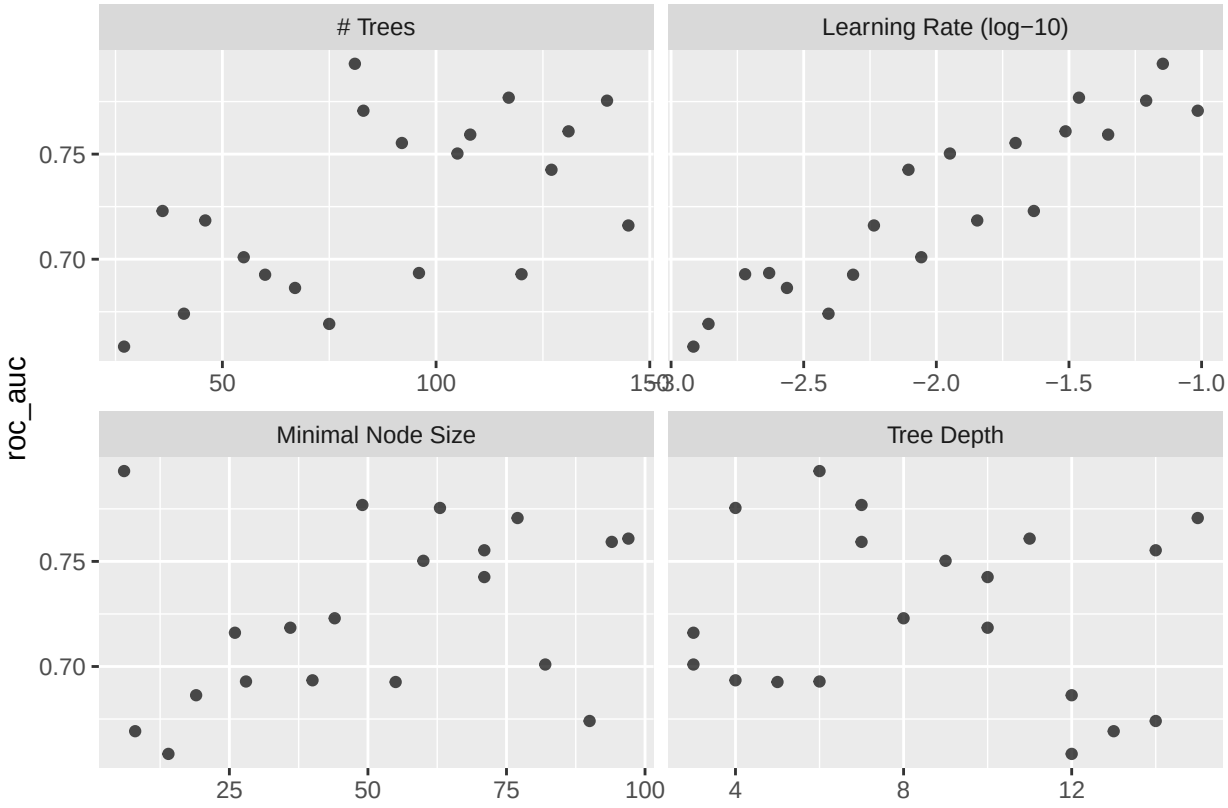
## Boosted Tree (XGBoost)

```
xgboost_recipe <-
  recipe(formula = sprintf("%s ~ .", outcome_column) %>% as.formula, data = df_train) %>%
  step_novel(all_nominal_predictors()) %>%
  step_unknown(all_nominal_predictors()) %>%
  step_other(all_nominal_predictors(), threshold = 0.05, other = ".merged") %>%
  step_dummy(all_nominal_predictors())

xgboost_spec <- boost_tree(
  trees = tune(),
  min_n = tune(),
  tree_depth = tune(),
  learn_rate = tune(),
) %>%
  set_engine("xgboost",
             nthread = 8) %>%
  set_mode("classification")

xgboost_grid <- grid_latin_hypercube(
  trees(range = c(25L, 150L)),
  min_n(range = c(2L, 100L)),
  tree_depth(range = c(2L, 15L)),
  learn_rate(range = c(-3, -1), trans = log10_trans()),
  size = grid_size
)

xgboost_workflow <-
  workflow() %>%
  add_recipe(xgboost_recipe) %>%
  add_model(xgboost_spec)

xgboost_tune <-
  xgboost_workflow %>%
  tune_grid(resamples = df_folds,
```

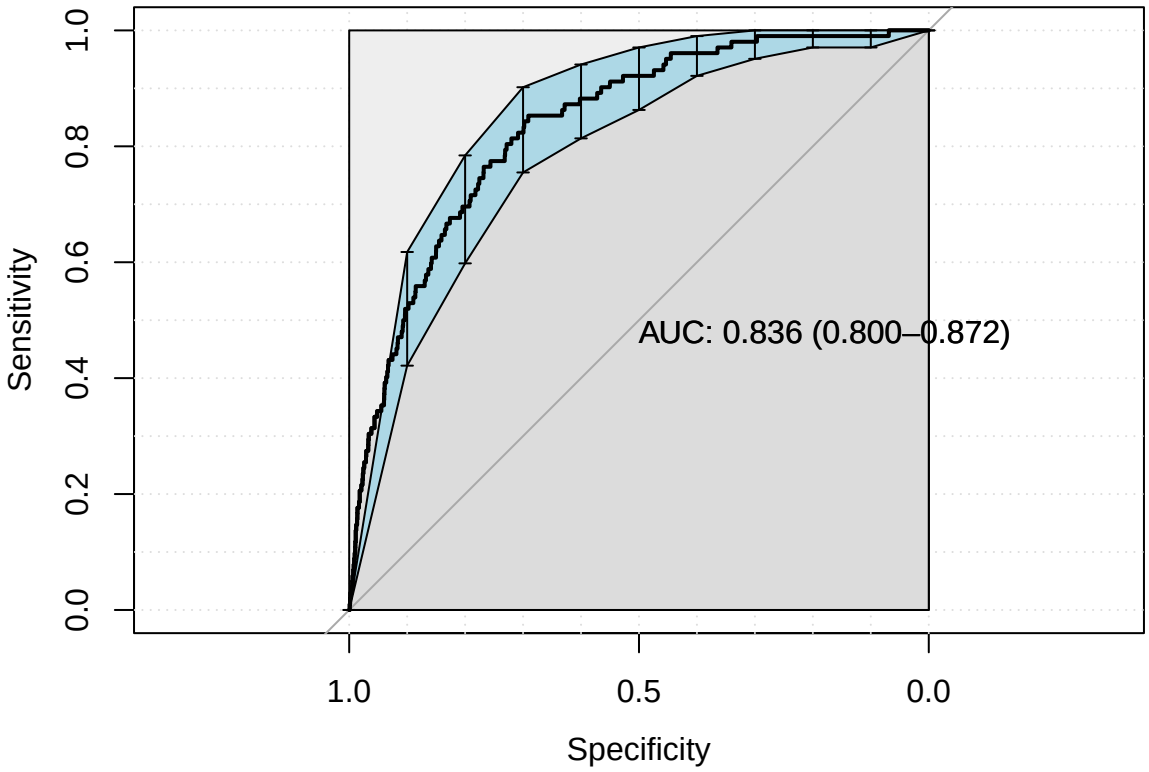
```
            grid = xgboost_grid)

xgboost_tune %>%
  show_best("roc_auc")
```

```
## # A tibble: 5 x 10
##   trees min_n tree_depth learn_rate .metric .estimator  mean     n std_err .config
##   <int> <int>      <int>      <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1    81     6          6     0.0714 roc_auc binary     0.793    10 0.00808 Preprocessor1_Model01
## 2   117    49          7     0.0345 roc_auc binary     0.777    10 0.00733 Preprocessor1_Model10
## 3   140    63          4     0.0618 roc_auc binary     0.775    10 0.00668 Preprocessor1_Model13
## 4    83    77         15     0.0967 roc_auc binary     0.771    10 0.00763 Preprocessor1_Model16
## 5   131    97         11     0.0307 roc_auc binary     0.761    10 0.00743 Preprocessor1_Model20
```

```
best_xgboost <- xgboost_tune %>%
  select_best("roc_auc")

autoplot(xgboost_tune, metric = "roc_auc")
```

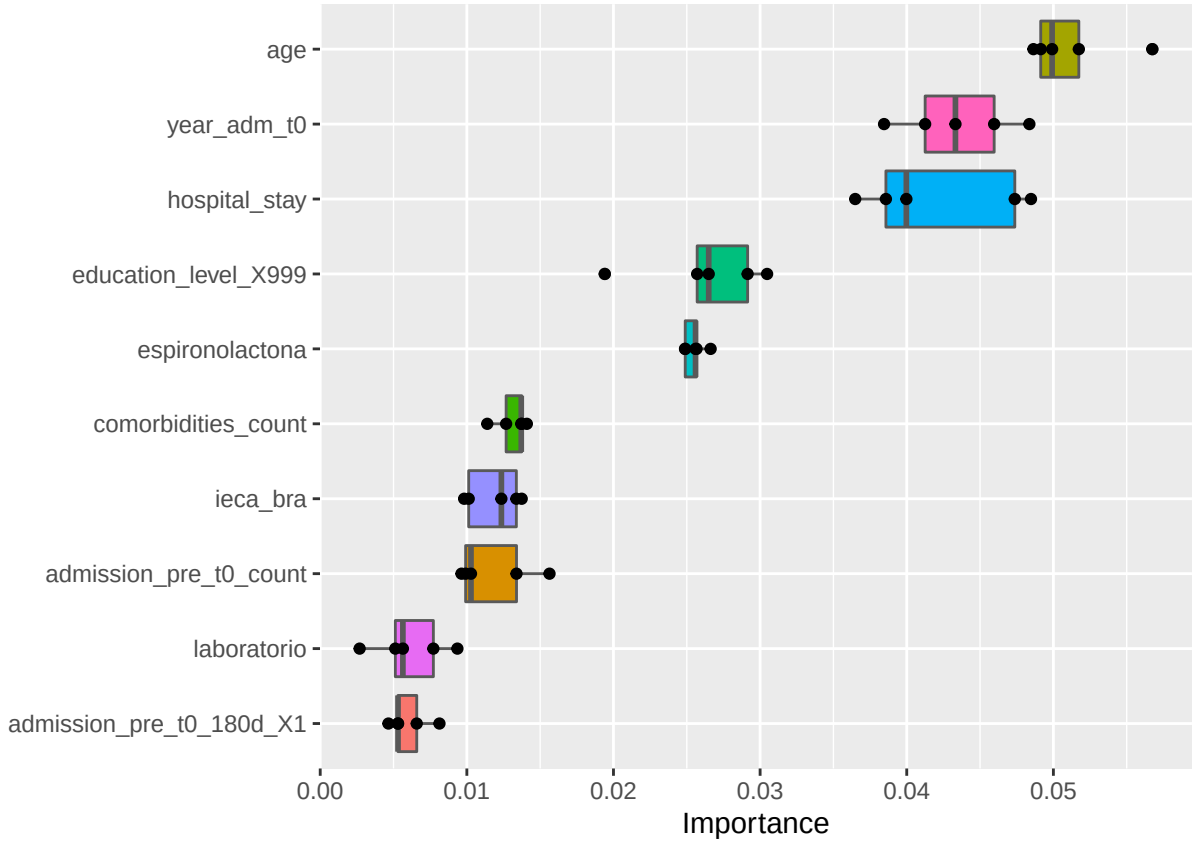



```
final_xgboost_workflow <-
  xgboost_workflow %>%
  finalize_workflow(best_xgboost)

last_xgboost_fit <-
  final_xgboost_workflow %>%
  last_fit(df_split)

final_xgboost_fit <- extract_workflow(last_xgboost_fit)

xgboost_auc <- validation(final_xgboost_fit, df_test)
```




```
## [1] "Optimal Threshold: 0.02"
## Confusion Matrix and Statistics
##
##     reference
## data    0    1
##    0 3198   15
##    1 1430   87
##
##                Accuracy : 0.6945
##                  95% CI : (0.6812, 0.7076)
##     No Information Rate : 0.9784
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0699
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.69101
##             Specificity : 0.85294
##          Pos Pred Value : 0.99533
##          Neg Pred Value : 0.05735
##              Prevalence : 0.97844
##          Detection Rate : 0.67611
##    Detection Prevalence : 0.67928
##       Balanced Accuracy : 0.77198
##
##        'Positive' Class : 0
##
```

```
extract_vip(final_xgboost_fit, pred_wrapper = predict,
            reference_class = "0")
```




```
xgboost_parameters <- xgboost_tune %>%
  show_best("roc_auc", n = 1) %>%
  select(-.metric, -.estimator, -.config, -mean, -n, -std_err) %>%
  as.list
```

Minutes to run: 3.582

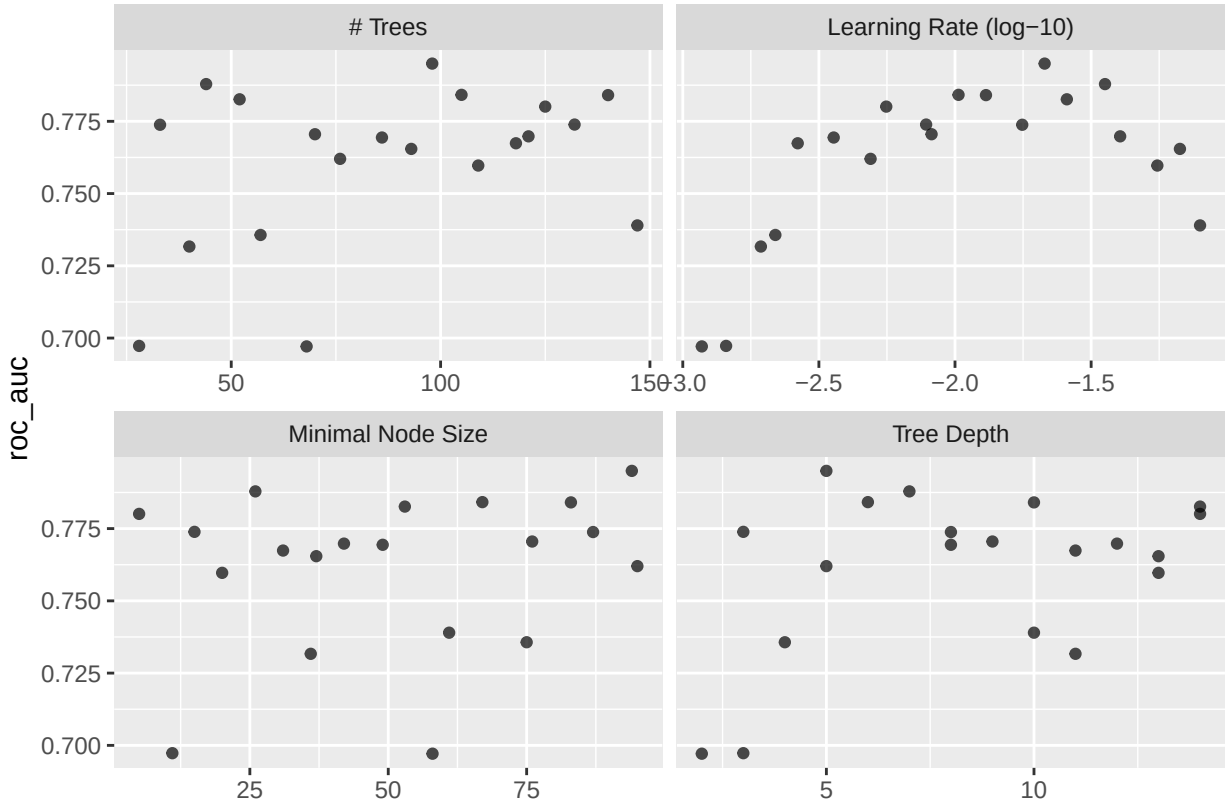
## Boosted Tree (LightGBM)

```
lightgbm_recipe <-
  recipe(formula = sprintf("%s ~ .", outcome_column) %>% as.formula, data = df_train) %>%
  step_novel(all_nominal_predictors()) %>%
  step_unknown(all_nominal_predictors()) %>%
  step_other(all_nominal_predictors(), threshold = 0.05, other = ".merged") %>%
  step_dummy(all_nominal_predictors())

lightgbm_spec <- boost_tree(
  trees = tune(),
  min_n = tune(),
  tree_depth = tune(),
  learn_rate = tune(),
  sample_size = 1
) %>%
  set_engine("lightgbm",
             nthread = 8) %>%
  set_mode("classification")

lightgbm_grid <- grid_latin_hypercube(
  trees(range = c(25L, 150L)),
  min_n(range = c(2L, 100L)),
  tree_depth(range = c(2L, 15L)),
  learn_rate(range = c(-3, -1), trans = log10_trans()),
  size = grid_size
```

```
)

lightgbm_workflow <-
  workflow() %>%
  add_recipe(lightgbm_recipe) %>%
  add_model(lightgbm_spec)

lightgbm_tune <-
  lightgbm_workflow %>%
  tune_grid(resamples = df_folds,
            grid = lightgbm_grid)

lightgbm_tune %>%
  show_best("roc_auc")
```

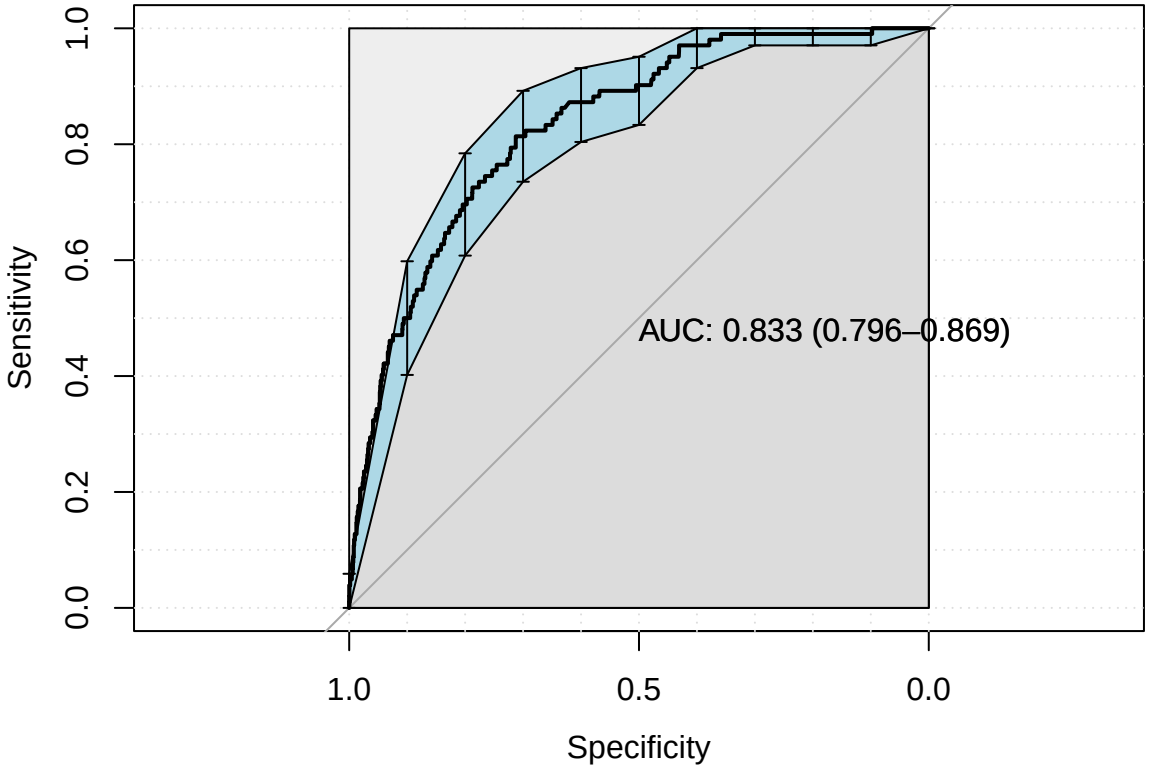
```
## # A tibble: 5 x 10
##   trees min_n tree_depth learn_rate .metric .estimator  mean     n std_err .config
##   <int> <int>      <int>      <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1    98    94          5     0.0213 roc_auc binary     0.795    10 0.00783 Preprocessor1_Model19
## 2    44    26          7     0.0356 roc_auc binary     0.788    10 0.00979 Preprocessor1_Model05
## 3   105    67          6     0.0103 roc_auc binary     0.784    10 0.00593 Preprocessor1_Model14
## 4   140    83         10     0.0130 roc_auc binary     0.784    10 0.00616 Preprocessor1_Model17
## 5    52    53         14     0.0258 roc_auc binary     0.783    10 0.00737 Preprocessor1_Model11
```

```
best_lightgbm <- lightgbm_tune %>%
  select_best("roc_auc")

autoplot(lightgbm_tune, metric = "roc_auc")
```




```
final_lightgbm_workflow <-
  lightgbm_workflow %>%
  finalize_workflow(best_lightgbm)

last_lightgbm_fit <-
```

```
  final_lightgbm_workflow %>%
  last_fit(df_split)

final_lightgbm_fit <- extract_workflow(last_lightgbm_fit)

lightgbm_auc <- validation(final_lightgbm_fit, df_test)
```




```
## [1] "Optimal Threshold: 0.02"
## Confusion Matrix and Statistics
##
##     reference
## data    0    1
##    0 3298   19
##    1 1330   83
##
##                Accuracy : 0.7148
##                  95% CI : (0.7017, 0.7276)
##     No Information Rate : 0.9784
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0723
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.71262
##             Specificity : 0.81373
##          Pos Pred Value : 0.99427
##          Neg Pred Value : 0.05874
##              Prevalence : 0.97844
##          Detection Rate : 0.69725
##    Detection Prevalence : 0.70127
##       Balanced Accuracy : 0.76317
##
```

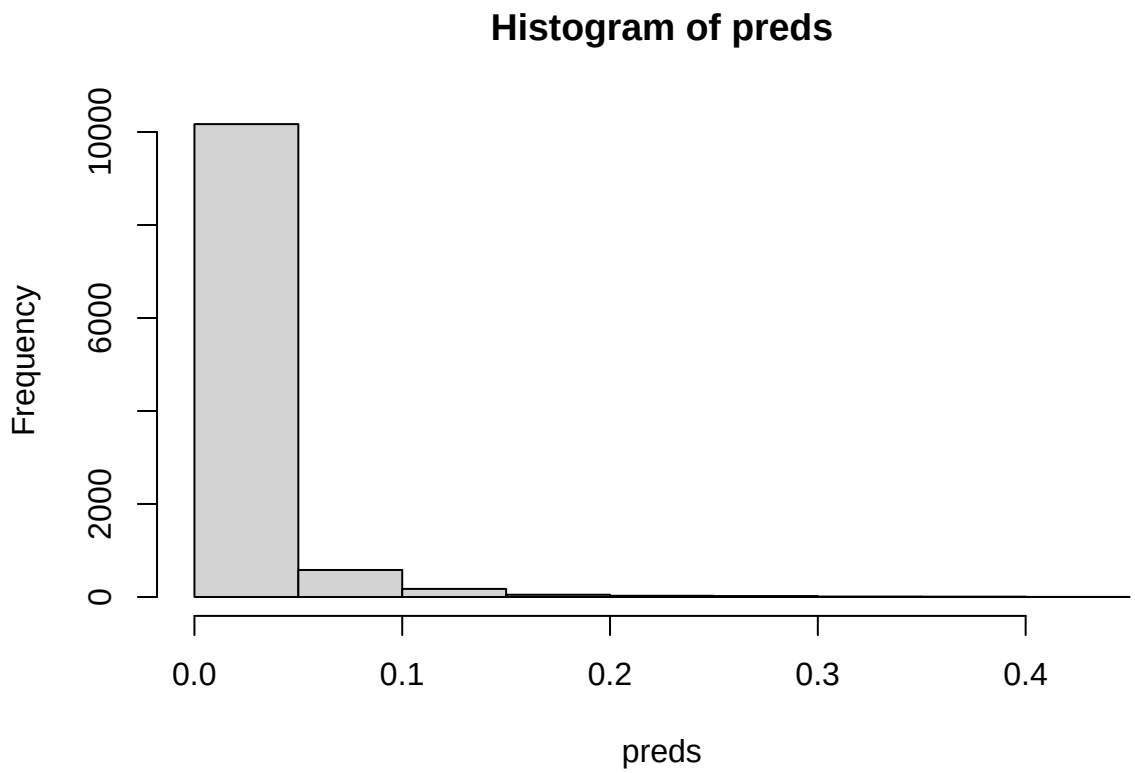
```
##        'Positive' Class : 0
##
```

```
lightgbm_parameters <- lightgbm_tune %>%
  show_best("roc_auc", n = 1) %>%
  select(-.metric, -.estimator, -.config, -mean, -n, -std_err) %>%
  as.list

Hmisc::list.tree(lightgbm_parameters)
```

```
##  lightgbm_parameters = list 4 (736 bytes)
## .  trees = integer 1= 98
## .  min_n = integer 1= 94
## .  tree_depth = integer 1= 5
## .  learn_rate = double 1= 0.021341
```

```
con <- file(sprintf('./auxiliar/model_selection/hyperparameters/%s.yaml', outcome_column), "w")
write_yaml(lightgbm_parameters, con)
close(con)
```

Minutes to run: 3.861

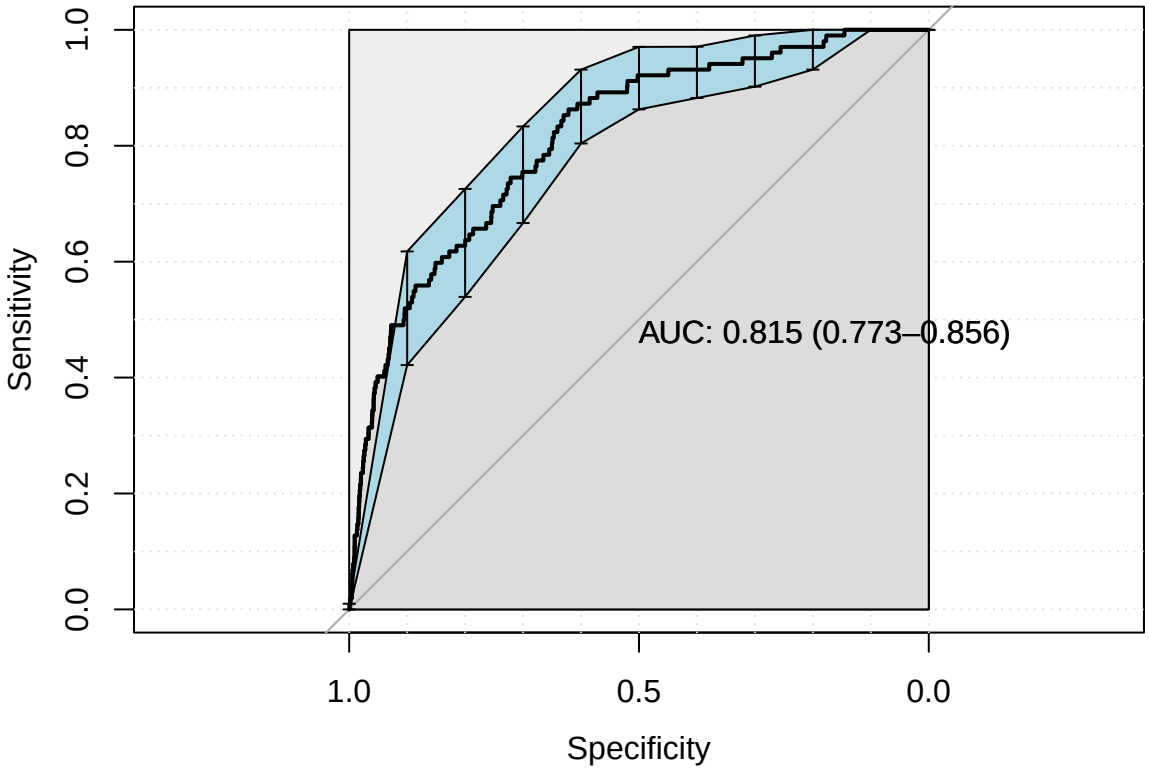



Minutes to run: 0.005

## GLM

```
glmnet_recipe <-
  recipe(formula = sprintf("%s ~ .", outcome_column) %>% as.formula, data = df_train) %>%
  step_novel(all_nominal_predictors()) %>%
  step_unknown(all_nominal_predictors()) %>%
  step_other(all_nominal_predictors(), threshold = 0.05, other = ".merged") %>%
  step_dummy(all_nominal_predictors()) %>%
  step_zv(all_predictors()) %>%
  step_normalize(all_numeric_predictors())
```

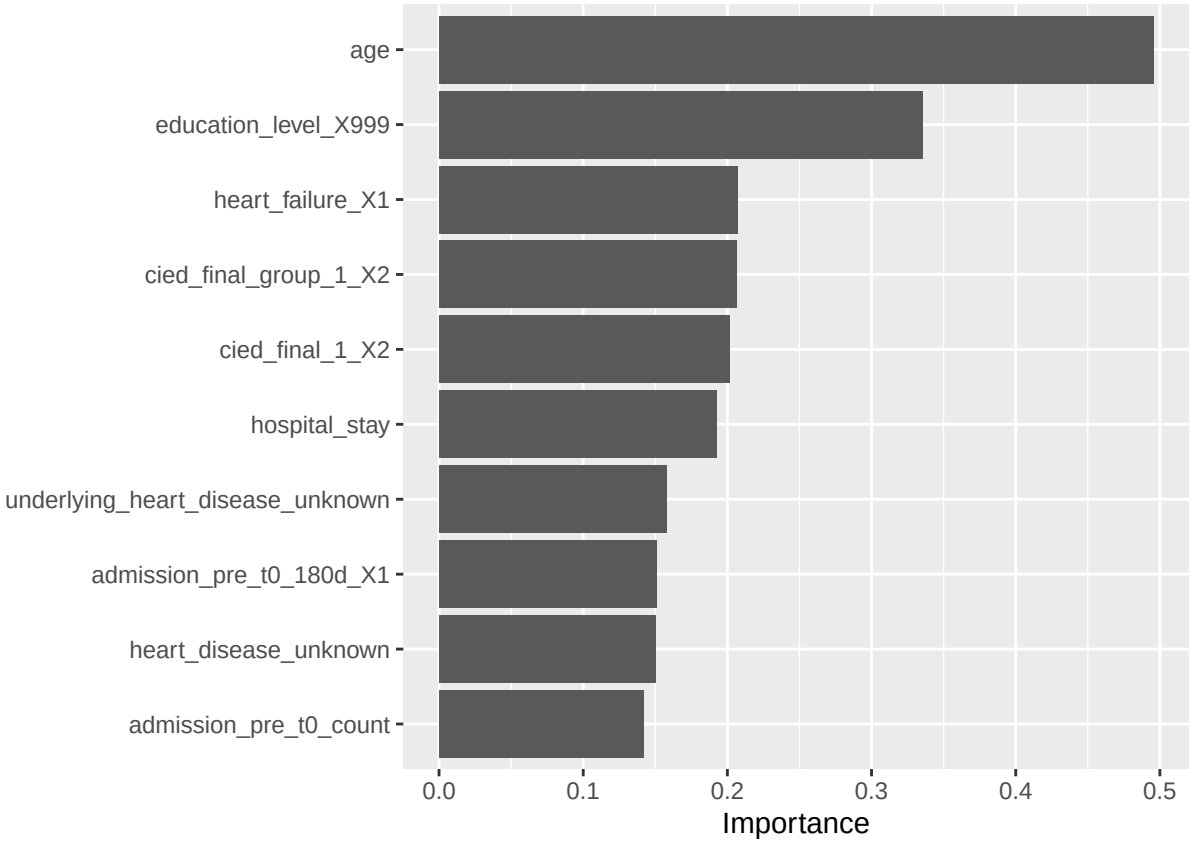
```r
glmnet_spec <-
  logistic_reg(penalty = 0) %>%
  set_mode("classification") %>%
  set_engine("glmnet")

glmnet_workflow <-
  workflow() %>%
  add_recipe(glmnet_recipe) %>%
  add_model(glmnet_spec)

glm_fit <- glmnet_workflow %>%
  fit(df_train)

glmnet_auc <- validation(glm_fit, df_test)
```



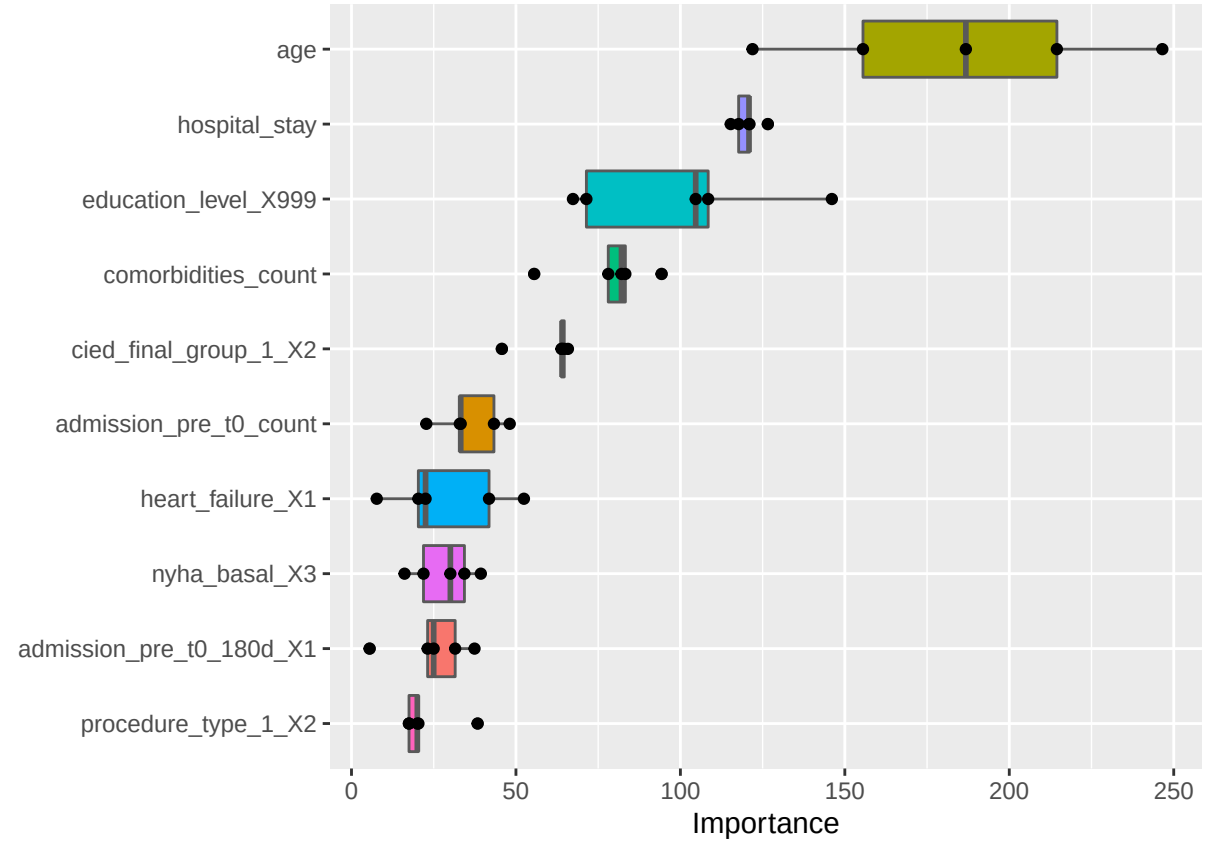

```
## [1] "Optimal Threshold: 0.02"
## Confusion Matrix and Statistics
##
##     reference
## data    0    1
##    0 2877   14
##    1 1751   88
##
##                Accuracy : 0.6268
##                  95% CI : (0.6129, 0.6407)
##     No Information Rate : 0.9784
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0519
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.62165
```

```
##             Specificity : 0.86275
##          Pos Pred Value : 0.99516
##          Neg Pred Value : 0.04785
##              Prevalence : 0.97844
##          Detection Rate : 0.60825
##    Detection Prevalence : 0.61121
##       Balanced Accuracy : 0.74220
##
##        'Positive' Class : 0
##
```

```
pfun_glmnet <- function(object, newdata) predict(object, newx = newdata)

extract_vip(glm_fit, pred_wrapper = pfun_glmnet,
            reference_class = "1", method = 'model')
```




```
extract_vip(glm_fit, pred_wrapper = pfun_glmnet,
            reference_class = "1", method = 'permute')
```




Minutes to run: 1.787

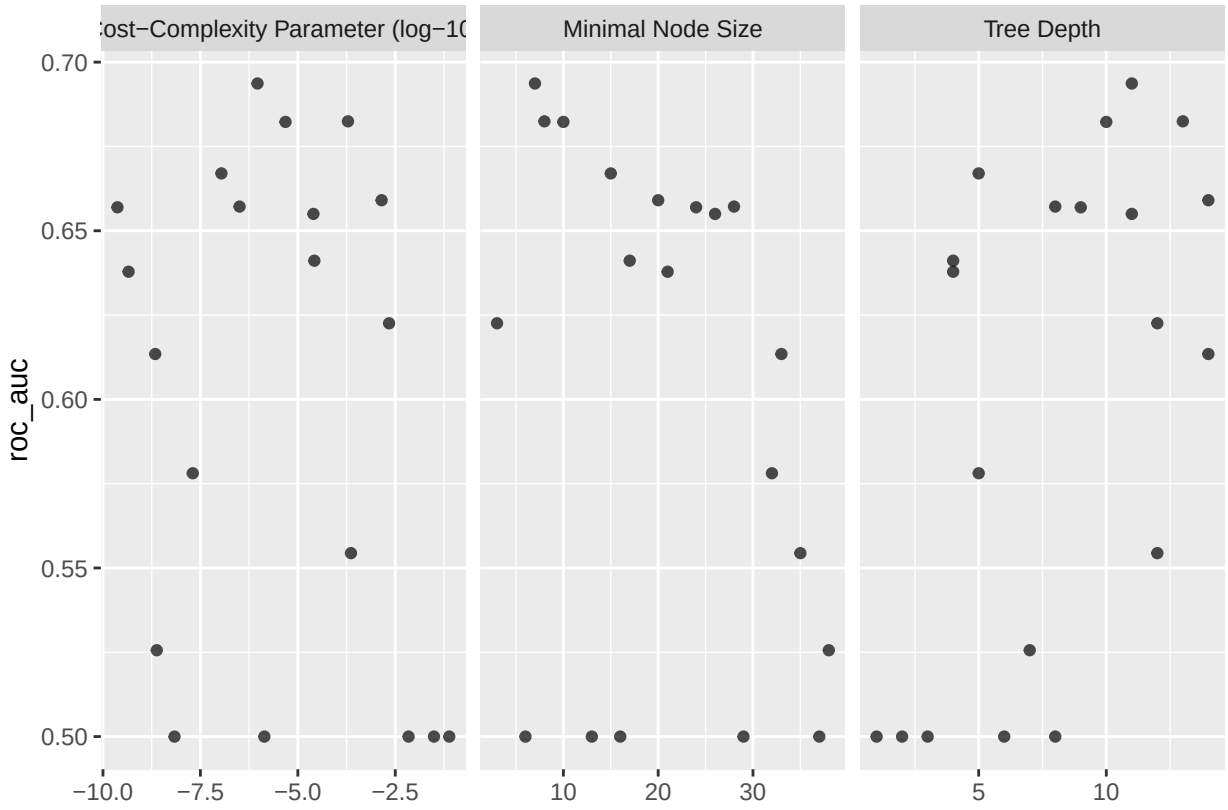
## Decision Tree

```
tree_recipe <-
  recipe(formula = sprintf("%s ~ .", outcome_column) %>% as.formula, data = df_train) %>%
  step_novel(all_nominal_predictors()) %>%
  step_unknown(all_nominal_predictors()) %>%
  step_other(all_nominal_predictors(), threshold = 0.05, other = ".merged") %>%
  step_dummy(all_nominal_predictors()) %>%
  step_zv(all_predictors())

tree_spec <-
  decision_tree(cost_complexity = tune(),
                tree_depth = tune(),
                min_n = tune()) %>%
  set_mode("classification") %>%
  set_engine("rpart")

tree_grid <- grid_latin_hypercube(cost_complexity(),
                                  tree_depth(),
                                  min_n(),
                                  size = grid_size)

tree_workflow <-
  workflow() %>%
  add_recipe(tree_recipe) %>%
  add_model(tree_spec)

tree_tune <-
  tree_workflow %>%
  tune_grid(resamples = df_folds,
            grid = tree_grid)
```

```
tree_tune %>%
  collect_metrics()
```

```
## # A tibble: 40 x 9
##    cost_complexity tree_depth min_n .metric  .estimator  mean     n std_err .config
##              <dbl>      <int> <int> <chr>    <chr>      <dbl> <int>   <dbl> <chr>
##  1        2.40e- 9          7    38 accuracy binary     0.979    10 0.00127 Preprocessor1_Model01
##  2        2.40e- 9          7    38 roc_auc  binary     0.526    10 0.0188  Preprocessor1_Model01
##  3        1.10e- 7          5    15 accuracy binary     0.978    10 0.00139 Preprocessor1_Model02
##  4        1.10e- 7          5    15 roc_auc  binary     0.667    10 0.0177  Preprocessor1_Model02
##  5        2.31e- 4         12    35 accuracy binary     0.979    10 0.00137 Preprocessor1_Model03
##  6        2.31e- 4         12    35 roc_auc  binary     0.554    10 0.0277  Preprocessor1_Model03
##  7        2.35e-10          9    24 accuracy binary     0.978    10 0.00130 Preprocessor1_Model04
##  8        2.35e-10          9    24 roc_auc  binary     0.657    10 0.0153  Preprocessor1_Model04
##  9        6.94e- 3          3    13 accuracy binary     0.979    10 0.00124 Preprocessor1_Model05
## 10        6.94e- 3          3    13 roc_auc  binary     0.5      10 0       Preprocessor1_Model05
## # ... with 30 more rows
## # i Use ‘print(n = ...)‘ to see more rows
```

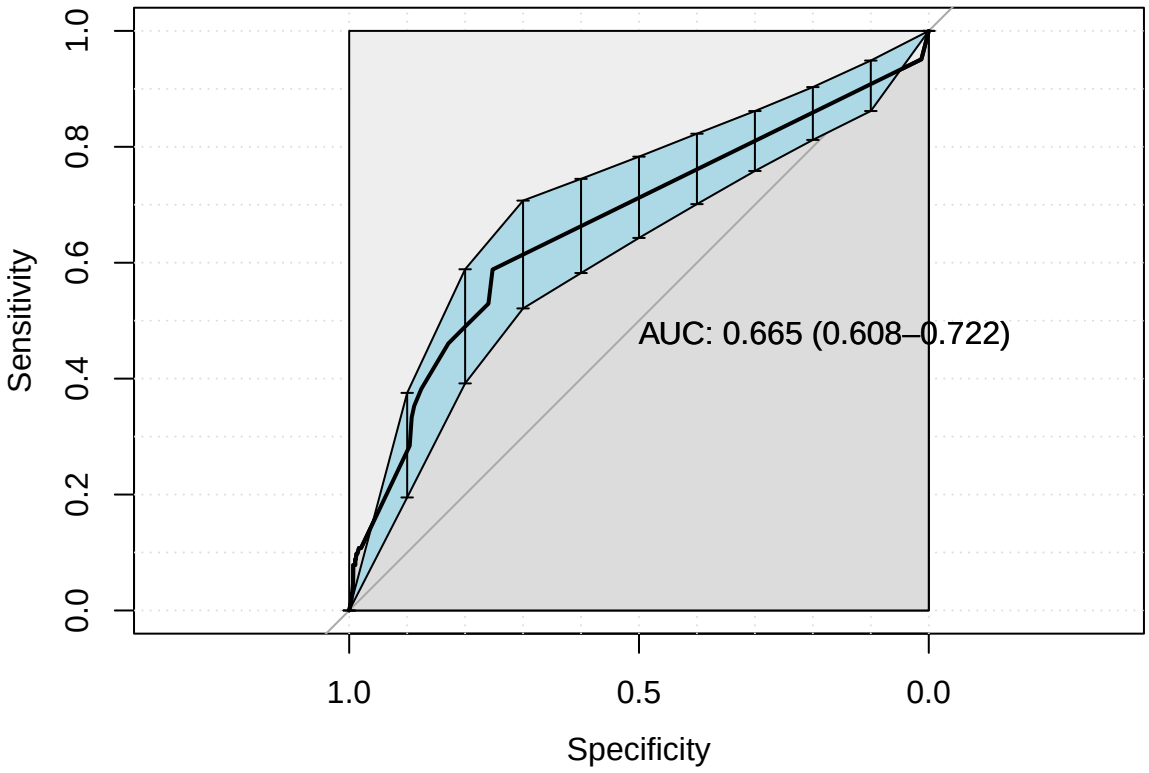
```
autoplot(tree_tune, metric = "roc_auc")
```




```
tree_tune %>%
  show_best("roc_auc")
```

```
## # A tibble: 5 x 9
##   cost_complexity tree_depth min_n .metric .estimator  mean     n std_err .config
##             <dbl>      <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1     0.000000923         11     7 roc_auc binary     0.694    10  0.0149 Preprocessor1_Model14
## 2     0.000193            13     8 roc_auc binary     0.682    10  0.0206 Preprocessor1_Model06
## 3     0.00000483          10    10 roc_auc binary     0.682    10  0.0213 Preprocessor1_Model20
## 4     0.000000110          5    15 roc_auc binary     0.667    10  0.0177 Preprocessor1_Model02
## 5     0.00141             14    20 roc_auc binary     0.659    10  0.0199 Preprocessor1_Model13
```

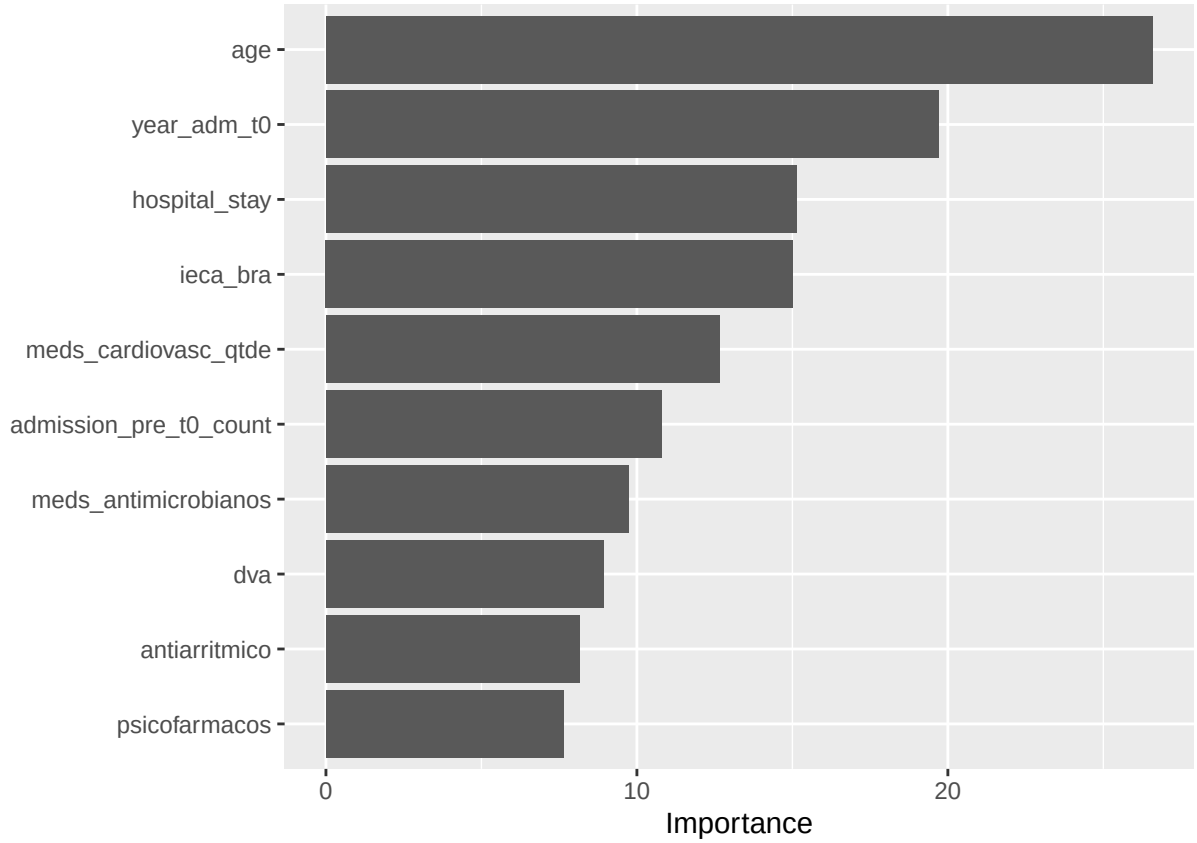
```r
best_tree <- tree_tune %>%
  select_best("roc_auc")

final_tree_workflow <-
  tree_workflow %>%
  finalize_workflow(best_tree)

last_tree_fit <-
  final_tree_workflow %>%
  last_fit(df_split)

final_tree_fit <- extract_workflow(last_tree_fit)

tree_auc <- validation(final_tree_fit, df_test)
```




```
## [1] "Optimal Threshold: 0.01"
## Confusion Matrix and Statistics
##
##     reference
## data    0    1
##    0 3483   42
##    1 1145   60
##
##                Accuracy : 0.749
##                  95% CI : (0.7364, 0.7614)
##     No Information Rate : 0.9784
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0542
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.75259
```

```
##             Specificity : 0.58824
##          Pos Pred Value : 0.98809
##          Neg Pred Value : 0.04979
##              Prevalence : 0.97844
##          Detection Rate : 0.73636
##    Detection Prevalence : 0.74524
##       Balanced Accuracy : 0.67041
##
##        'Positive' Class : 0
##
```

```r
extract_vip(final_tree_fit, pred_wrapper = predict,
            reference_class = "0", use_matrix = FALSE,
            method = 'model')
```




```r
# extract_vip(final_tree_fit, pred_wrapper = predict,
#             reference_class = "1", use_matrix = FALSE,
#             method = 'permute')
```

Minutes to run: 4.058

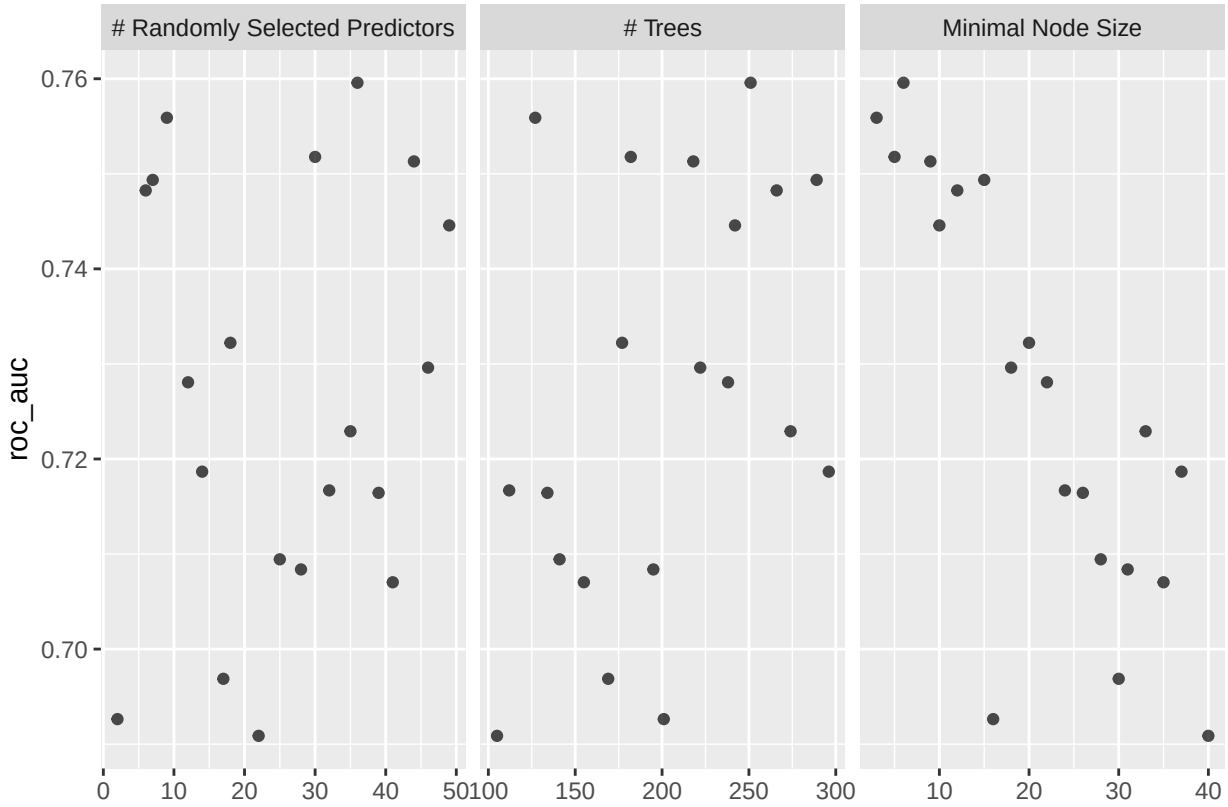
## Random Forest

```r
rf_recipe <-
  recipe(formula = sprintf("%s ~ .", outcome_column) %>% as.formula,
         data = df_train) %>%
  step_novel(all_nominal_predictors()) %>%
  step_unknown(all_nominal_predictors()) %>%
  step_other(all_nominal_predictors(), threshold = 0.05, other = ".merged") %>%
  step_dummy(all_nominal_predictors()) %>%
  step_zv(all_predictors()) %>%
  step_impute_mean(all_numeric_predictors())

rf_spec <-
```

```
  rand_forest(mtry = tune(),
              trees = tune(),
              min_n = tune()) %>%
  set_mode("classification") %>%
  set_engine("randomForest",
             probability = TRUE,
             nthread = 8)

rf_grid <- grid_latin_hypercube(mtry(range = c(1L, 50L)),
                                trees(range = c(100L, 300L)),
                                min_n(),
                                size = grid_size)

rf_workflow <-
  workflow() %>%
  add_recipe(rf_recipe) %>%
  add_model(rf_spec)

rf_tune <-
  rf_workflow %>%
  tune_grid(resamples = df_folds,
            grid = rf_grid)

rf_tune %>%
  collect_metrics()
```

```
## # A tibble: 40 x 9
##     mtry trees min_n .metric  .estimator  mean     n std_err .config
##    <int> <int> <int> <chr>    <chr>      <dbl> <int>   <dbl> <chr>
##  1    22   105    40 accuracy binary     0.979    10 0.00124 Preprocessor1_Model01
##  2    22   105    40 roc_auc  binary     0.691    10 0.0165  Preprocessor1_Model01
##  3     7   289    15 accuracy binary     0.979    10 0.00124 Preprocessor1_Model02
##  4     7   289    15 roc_auc  binary     0.749    10 0.0127  Preprocessor1_Model02
##  5     2   201    16 accuracy binary     0.979    10 0.00124 Preprocessor1_Model03
##  6     2   201    16 roc_auc  binary     0.693    10 0.0133  Preprocessor1_Model03
##  7    25   141    28 accuracy binary     0.979    10 0.00124 Preprocessor1_Model04
##  8    25   141    28 roc_auc  binary     0.709    10 0.0163  Preprocessor1_Model04
##  9    46   222    18 accuracy binary     0.979    10 0.00124 Preprocessor1_Model05
## 10    46   222    18 roc_auc  binary     0.730    10 0.0119  Preprocessor1_Model05
## # ... with 30 more rows
## # i Use `print(n = ...)` to see more rows
```

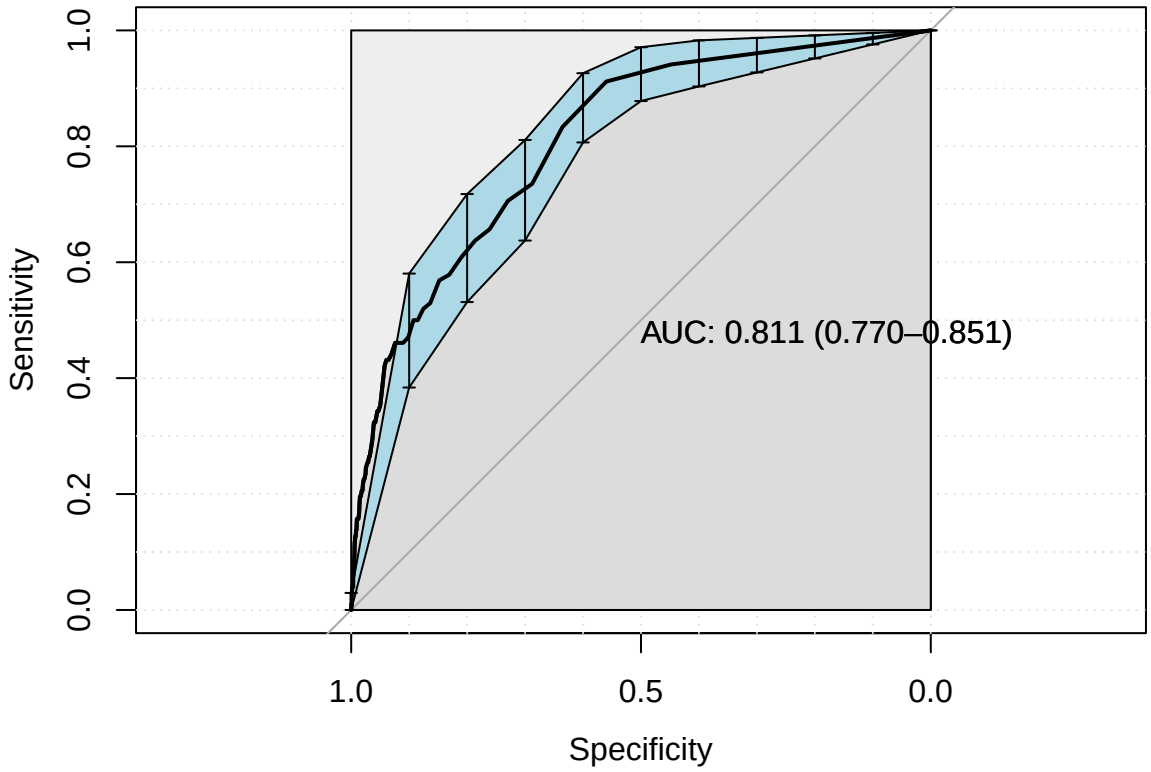
```
autoplot(rf_tune, metric = "roc_auc")
```




```
rf_tune %>%
  show_best("roc_auc")
```

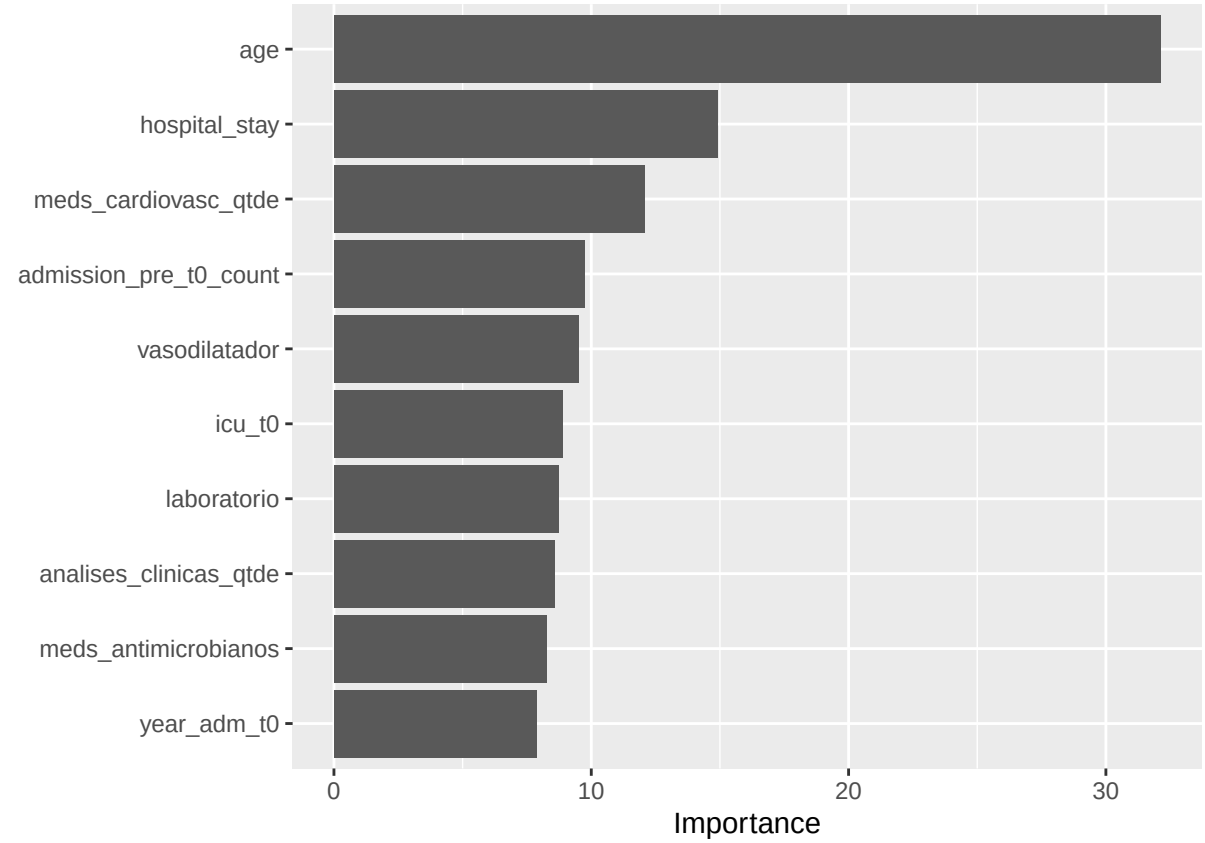
```
## # A tibble: 5 x 9
##    mtry trees min_n .metric .estimator  mean     n std_err .config
##   <int> <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1    36   251     6 roc_auc binary     0.760    10  0.0145 Preprocessor1_Model07
## 2     9   127     3 roc_auc binary     0.756    10  0.0123 Preprocessor1_Model12
## 3    30   182     5 roc_auc binary     0.752    10  0.0121 Preprocessor1_Model06
## 4    44   218     9 roc_auc binary     0.751    10  0.0127 Preprocessor1_Model16
## 5     7   289    15 roc_auc binary     0.749    10  0.0127 Preprocessor1_Model02
```

```
best_rf <- rf_tune %>%
  select_best("roc_auc")

final_rf_workflow <-
  rf_workflow %>%
  finalize_workflow(best_rf)

last_rf_fit <-
  final_rf_workflow %>%
  last_fit(df_split)

final_rf_fit <- extract_workflow(last_rf_fit)

rf_auc <- validation(final_rf_fit, df_test)
```




```
## [1] "Optimal Threshold: 0.01"
## Confusion Matrix and Statistics
##
##     reference
## data    0    1
##    0 2591    9
##    1 2037   93
##
##                Accuracy : 0.5674
##                  95% CI : (0.5532, 0.5816)
##     No Information Rate : 0.9784
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.044
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.55985
##             Specificity : 0.91176
##          Pos Pred Value : 0.99654
##          Neg Pred Value : 0.04366
##              Prevalence : 0.97844
##          Detection Rate : 0.54778
##    Detection Prevalence : 0.54968
##       Balanced Accuracy : 0.73581
##
##        'Positive' Class : 0
##
```

```
pfun_rf <- function(object, newdata) predict(object, data = newdata)

extract_vip(final_rf_fit, pred_wrapper = predict,
            reference_class = "1", use_matrix = FALSE,
            method = 'model')
```

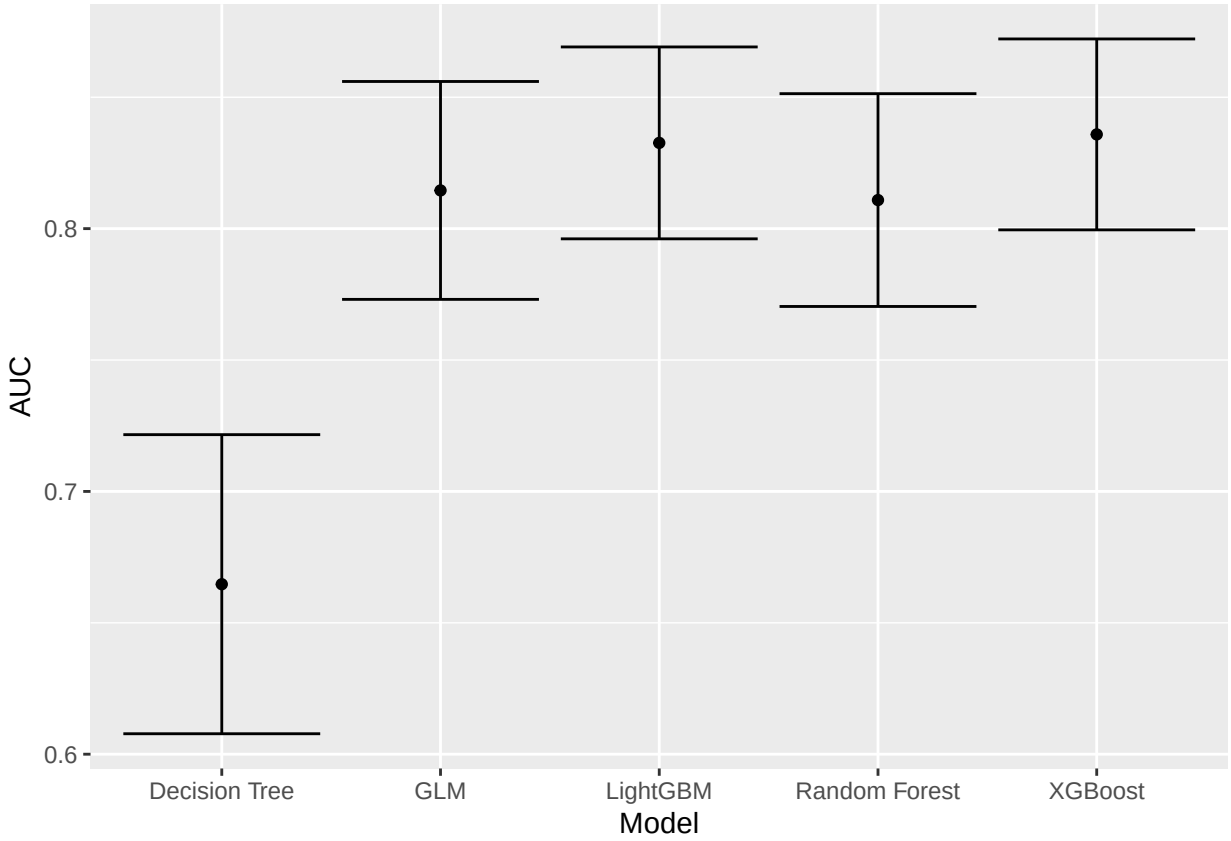



```
# extract_vip(final_rf_fit, pred_wrapper = predict,
#             reference_class = "1", use_matrix = FALSE,
#             method = 'permute')
```

Minutes to run: 55.491

## Models Comparison

```
if (RUN_ALL_MODELS) {
  df_auc <- tibble::tribble(
    ~Model, ~`AUC`, ~`Lower Limit`, ~`Upper Limit`,
    'XGBoost', as.numeric(xgboost_auc$auc), xgboost_auc$ci[1], xgboost_auc$ci[3],
    'LightGBM', as.numeric(lightgbm_auc$auc), lightgbm_auc$ci[1], lightgbm_auc$ci[3],
    'GLM', as.numeric(glmnet_auc$auc), glmnet_auc$ci[1], glmnet_auc$ci[3],
    'Decision Tree', as.numeric(tree_auc$auc), tree_auc$ci[1], tree_auc$ci[3],
    'Random Forest', as.numeric(rf_auc$auc), rf_auc$ci[1], rf_auc$ci[3]
  ) %>%
    mutate(Target = outcome_column)
} else {
  df_auc <- tibble::tribble(
    ~Model, ~`AUC`, ~`Lower Limit`, ~`Upper Limit`,
    'LightGBM', as.numeric(lightgbm_auc$auc), lightgbm_auc$ci[1], lightgbm_auc$ci[3]
  ) %>%
    mutate(Target = outcome_column)
}

df_auc %>%
  ggplot(aes(x = Model, y = AUC, ymin = `Lower Limit`, ymax = `Upper Limit`)) +
    geom_point() +
    geom_errorbar()
```




```
write_csv(df_auc, sprintf("./auxiliar/model_selection/performance/%s.csv", outcome_column))
```

Minutes to run: 0.01