# Credit card ML.R

### rocka

#### 2024-03-04

#### library(tidymodels)

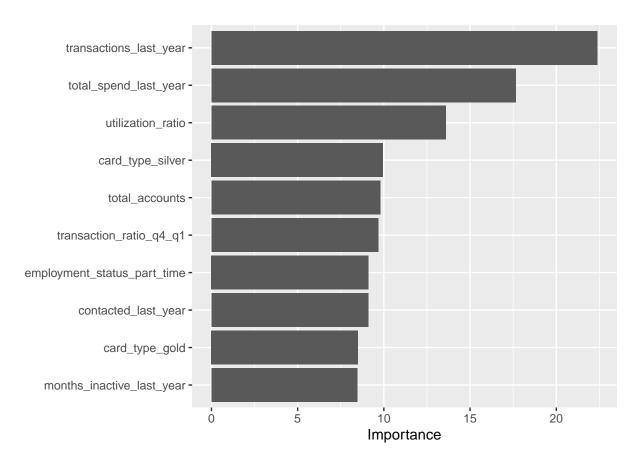
```
## Warning: package 'tidymodels' was built under R version 4.3.3
## -- Attaching packages ------ tidymodels 1.1.1 --
                1.0.5
## v broom
                          v recipes
                                        1.0.8
## v dials
                1.2.1
                         v rsample
                                        1.2.0
## v dplyr
                1.1.2
                       v tibble
                                        3.2.1
                3.4.4
## v ggplot2
                        v tidyr
                                        1.3.0
## v infer
                1.0.6
                                        1.1.2
                         v tune
## v modeldata
                1.3.0
                          v workflows
                                        1.1.4
## v parsnip
                1.2.0
                        v workflowsets 1.0.1
## v purrr
                1.0.2
                        v yardstick 1.3.0
## Warning: package 'dials' was built under R version 4.3.2
## Warning: package 'scales' was built under R version 4.3.2
## Warning: package 'ggplot2' was built under R version 4.3.2
## Warning: package 'infer' was built under R version 4.3.2
## Warning: package 'modeldata' was built under R version 4.3.2
## Warning: package 'parsnip' was built under R version 4.3.2
## Warning: package 'recipes' was built under R version 4.3.2
## Warning: package 'rsample' was built under R version 4.3.2
## Warning: package 'tune' was built under R version 4.3.2
## Warning: package 'workflows' was built under R version 4.3.2
## Warning: package 'workflowsets' was built under R version 4.3.2
## Warning: package 'yardstick' was built under R version 4.3.2
```

```
## -- Conflicts -----
                                          ----- tidymodels_conflicts() --
## x purrr::discard() masks scales::discard()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                     masks stats::lag()
## x recipes::step() masks stats::step()
\#\# * Use tidymodels\_prefer() to resolve common conflicts.
library(vip)
## Warning: package 'vip' was built under R version 4.3.3
##
## Attaching package: 'vip'
## The following object is masked from 'package:utils':
##
##
       vi
library(rpart.plot)
## Warning: package 'rpart.plot' was built under R version 4.3.2
## Loading required package: rpart
## Attaching package: 'rpart'
## The following object is masked from 'package:dials':
##
##
       prune
credit_card_df<-read.csv("customer.csv")</pre>
credit_card_df$customer_status <- factor(credit_card_df$customer_status,</pre>
                                         levels = c("closed_account", "active"))
#Splitting the data into training and testing sets
set.seed(7)
cdf_split<-initial_split(credit_card_df,prop=0.75,strata=customer_status)</pre>
cdf_training<-cdf_split %>% training()
cdf_testing<-cdf_split %>% testing()
cdf_split
## <Training/Testing/Total>
## <3470/1157/4627>
```

```
#Creating fold for cross validation
set.seed(7)
cdf folds <- vfold cv(cdf training, v = 5)
cdf recipe <-
 recipe(customer_status ~ ., data = cdf_training) %>%
 step_YeoJohnson(all_numeric(), -all_outcomes()) %>%
 step_normalize(all_numeric(), -all_outcomes()) %>%
 step_dummy(all_nominal(), -all_outcomes())
#Cross checking the feature engineering
(cdf_recipe %>%
   prep(training = cdf_training) %>%
   bake(new_data = NULL))
## # A tibble: 3,470 x 24
##
              age dependents income months_since_first_account total_accounts
##
     <dbl> <dbl>
                       <dbl> <dbl>
                                                          <dbl>
## 1 -2.17 -0.441
                       -0.272 -0.976
                                                                        -0.383
                                                        -0.172
## 2 -2.16 0.959
                       -1.05 -0.928
                                                                         1.45
                                                         1.40
## 3 -2.16 -0.315
                       0.493 -0.800
                                                        -0.793
                                                                         1.45
## 4 -2.13 2.00
                       -0.272 -0.896
                                                        1.94
                                                                         1.45
## 5 -2.13 0.0642
                       0.493 0.675
                                                        -0.0457
                                                                        -1.04
## 6 -2.13 0.702
                       1.25 -0.885
                                                        1.53
                                                                         0.857
## 7 -2.12 -0.441
                       1.25 -0.789
                                                        -0.0457
                                                                        1.45
## 8 -2.12 -0.692
                       0.493 - 0.996
                                                        -0.671
                                                                        -1.04
## 9 -2.10 -1.56
                       -0.272 -1.13
                                                        -2.18
                                                                         0.246
## 10 -2.10 1.48
                       -1.86 -0.925
                                                        -0.0457
                                                                         1.45
## # i 3,460 more rows
## # i 18 more variables: months_inactive_last_year <dbl>,
## #
      contacted_last_year <dbl>, credit_limit <dbl>, utilization_ratio <dbl>,
## #
      spend_ratio_q4_q1 <dbl>, total_spend_last_year <dbl>,
      transactions_last_year <dbl>, transaction_ratio_q4_q1 <dbl>,
## #
      customer_status <fct>, education_bachelors <dbl>,
## #
      education_doctorate <dbl>, education_masters <dbl>, ...
##Model 1 - Logistic Regression Model
#Specifying the model
logistic_model <- logistic_reg() %>%
 set_engine('glm') %>%
 set_mode('classification')
#Creating a workflow
cdf_wf <- workflow() %>%
 add_model(logistic_model) %>%
 add_recipe(cdf_recipe)
#Fitting the model
cdf_logistic_fit <- cdf_wf %>%
 fit(data = cdf_training)
#Exploring the model to see the importance of the predictors and plotting the same
```

```
cdf_trained_model <- cdf_logistic_fit %>%
    extract_fit_parsnip()

vip(cdf_trained_model)
```



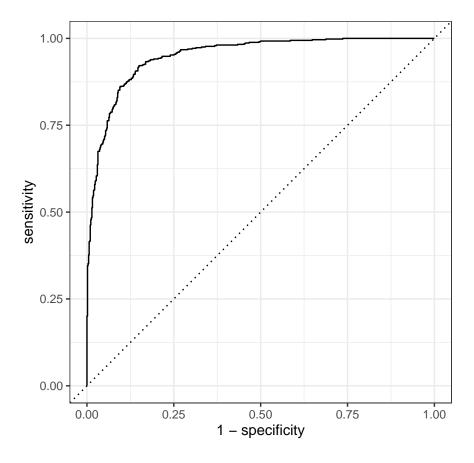
```
#Predicting using the test data
predictions_categories <- predict(cdf_logistic_fit, new_data = cdf_testing)
predictions_probabilities <- predict(cdf_logistic_fit, new_data = cdf_testing, type = 'prob')

test_results <-
    cdf_testing %>%
    dplyr::select(customer_status) %>%
    bind_cols(predictions_categories) %>%
    bind_cols(predictions_probabilities)

head(test_results)
```

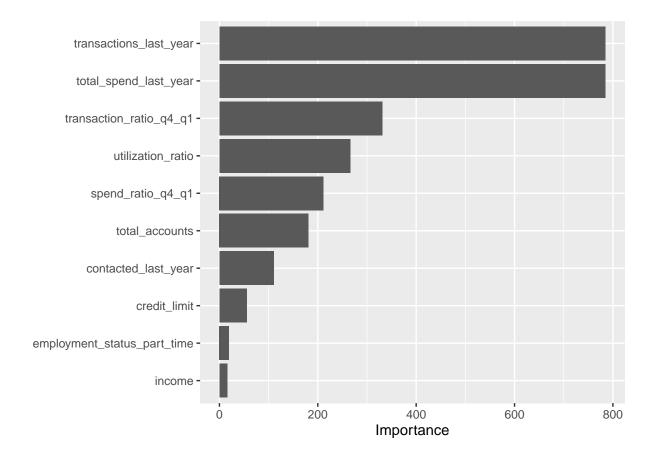
```
.pred_class .pred_closed_account .pred_active
##
    customer_status
## 1 closed_account
                            active
                                           0.3389566667
                                                          0.66104333
## 2 closed_account closed_account
                                           0.5113060000
                                                          0.48869400
## 3
             active
                            active
                                           0.0003688341
                                                          0.99963117
## 4 closed_account closed_account
                                           0.9797043905
                                                          0.02029561
## 5
             active closed_account
                                           0.6727272090
                                                          0.32727279
## 6
             active closed_account
                                           0.6263812123
                                                          0.37361879
```

```
## Truth
## Prediction closed_account active
## closed_account 451 63
## active 72 571
```



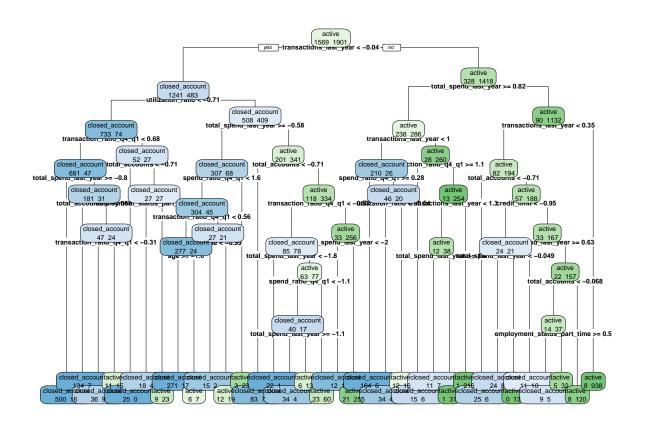
```
## # A tibble: 5 x 3
##
    .metric .estimator .estimate
##
    <chr>
            <chr>
                         <dbl>
## 1 accuracy binary
                           0.883
## 2 sens
             binary
                           0.862
## 3 spec
             binary
                           0.901
## 4 f_meas
             binary
                           0.870
## 5 roc_auc binary
                           0.949
##Model 2 -Decision Tree Model
#Specfying the model
tree_model <-</pre>
 decision_tree(cost_complexity = tune(),
               tree_depth = tune(),
               min_n = tune()) %>%
 set_engine('rpart') %>%
 set_mode('classification')
#Creating a workflow
tree_workflow <-</pre>
 workflow() %>%
 add model(tree model) %>%
 add_recipe(cdf_recipe)
#Creating a grid of hyperparameter values to test
tree grid <-
 grid_regular(cost_complexity(),
              tree_depth(),
              min_n(),
              levels = 2)
#Tuning decision tree workflow
set.seed(7)
tree_tuning <-</pre>
 tree_workflow %>%
 tune_grid(resamples = cdf_folds, grid = tree_grid)
#Showing top 5 best models (roc_auc metric)
tree_tuning %>% show_best('roc_auc')
## # A tibble: 5 x 9
    cost_complexity tree_depth min_n .metric .estimator mean
                                                                n std_err
##
              <dbl>
                       ## 1
       0.000000001
                           15 40 roc_auc binary
                                                      0.950
                                                               5 0.00401
## 2
       0.000000001
                           15
                                  2 roc_auc binary
                                                      0.906
                                                                5 0.00248
                                  2 roc_auc binary
## 3
       0.000000001
                            1
                                                      0.769
                                                                5 0.00793
## 4
       0.1
                                  2 roc_auc binary
                                                      0.769
                                                                5 0.00793
                           1
## 5
       0.1
                           15
                                  2 roc_auc binary
                                                      0.769
                                                                5 0.00793
## # i 1 more variable: .config <chr>
#Filtering out the best model based on roc_auc and checking the tree parameters for the same
(best_tree <-
```

```
tree_tuning %>%
    select_best(metric = 'roc_auc'))
## # A tibble: 1 x 4
##
     cost_complexity tree_depth min_n .config
               <dbl>
                           <int> <int> <chr>
##
        0.000000001
## 1
                              15
                                    40 Preprocessor1_Model7
#Finalizing workflow
final_tree_workflow <-</pre>
  tree_workflow %>%
  finalize_workflow(best_tree)
#Fitting the model to the training data
tree_wf_fit <-</pre>
  final_tree_workflow %>%
  fit(data = cdf_training)
#Exploring the model to see the importance of the predictors and plotting the same
tree_fit <-
  tree_wf_fit %>%
  extract_fit_parsnip()
vip(tree_fit)
```

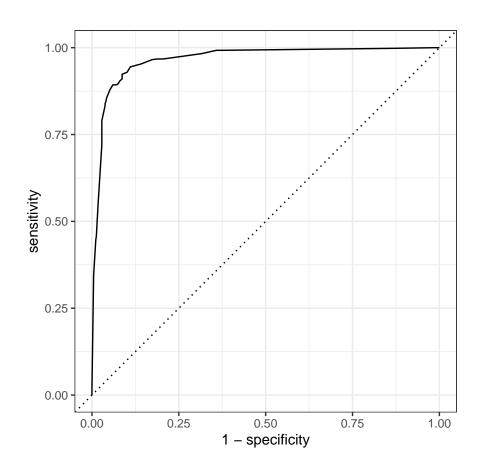


```
#Training the model and generating predictions on the test data
tree_last_fit <-
   final_tree_workflow %>%
   last_fit(cdf_split)

#Plotting the decsion tree
rpart.plot(tree_fit$fit, roundint = FALSE, extra = 1,cex=0.45)
```



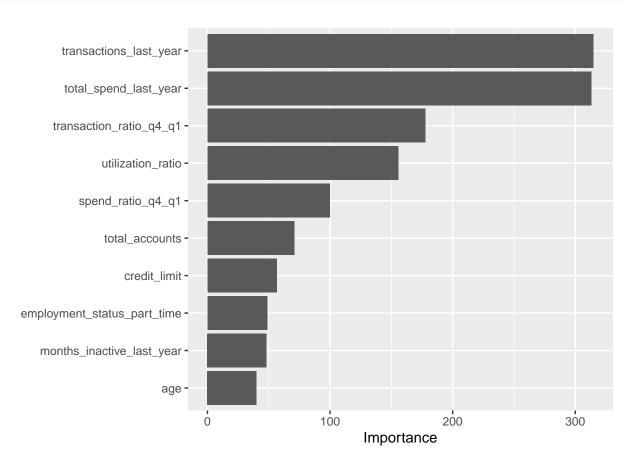
```
#Evaluating the model performance
#Peformance metrics
tree_last_fit %>% collect_metrics()
## # A tibble: 2 x 4
     .metric .estimator .estimate .config
##
     <chr>
              <chr>
                             <dbl> <chr>
                             0.913 Preprocessor1_Model1
## 1 accuracy binary
## 2 roc_auc binary
                             0.966 Preprocessor1_Model1
#roc_auc plot
tree_last_fit %>%
  collect_predictions() %>%
  roc_curve(truth = customer_status, .pred_closed_account) %>%
  autoplot()
```



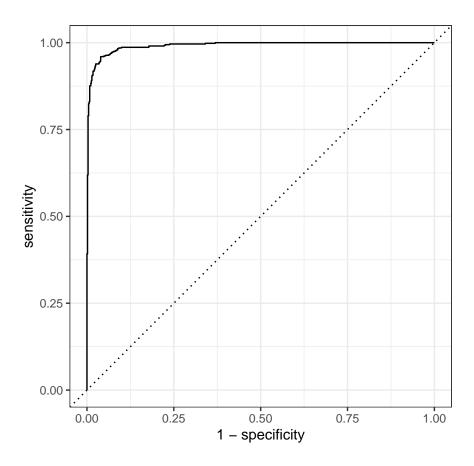
```
#Confusion Matrix
tree_predictions <- tree_last_fit %>% collect_predictions()
conf_mat(tree_predictions, truth = customer_status, estimate = .pred_class)
##
                   Truth
## Prediction
                    closed_account active
##
     closed_account
                               473
                                       51
                                      583
                                50
##
     active
## Model 3 - Random Forest
#Specifying the model
rf_model <-
  rand_forest(mtry = tune(),
              trees = tune(),
              min_n = tune()) %>%
  set_engine('ranger', importance = "impurity") %>%
  set_mode('classification')
#Creating a workflow
rf_workflow <-
  workflow() %>%
  add_model(rf_model) %>%
  add_recipe(cdf_recipe)
```

```
#Creating a grid of hyperparameter values to test
set.seed(7)
rf_grid <-
  grid_random(mtry() %>% range_set(c(2, 4)),
             trees(),
             min n(),
             size = 10)
#Tuning the hyperparameters created
set.seed(7)
rf_tuning <-
 rf_workflow %>%
 tune_grid(resamples = cdf_folds, grid = rf_grid)
## Warning: package 'ranger' was built under R version 4.3.2
rf_tuning %>% 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
       4 947
                 12 roc_auc binary
                                      0.987 5 0.000759 Preprocessor1_Model~
                4 1928
## 2
                                                5 0.000761 Preprocessor1_Model~
                                             5 0.00111 Preprocessor1_Model~
## 3
      3 207
## 4
       3 1455
                  7 roc_auc binary
                                      ## 5
       4 1114
                22 roc_auc binary
                                      0.986
                                             5 0.000816 Preprocessor1_Model~
# Selecting and viewing the paramaters of the best model based on roc_auc
(best_rf <-
   rf_tuning %>%
   select_best(metric = 'roc_auc'))
## # A tibble: 1 x 4
   mtry trees min_n .config
    <int> <int> <int> <chr>
          947
## 1
                  12 Preprocessor1_Model06
#Finalizing the workflow
final_rf_workflow <-</pre>
 rf workflow %>%
 finalize_workflow(best_rf)
#Fitting the model
rf_wf_fit <-
 final_rf_workflow %>%
 fit(data = cdf_training)
#Exploring the model to see the importance of the predictors and plotting the same
rf_fit <-
 rf wf fit %>%
 extract_fit_parsnip()
```

## vip(rf\_fit)



```
#Training the model and generating predictions on the test data
rf_last_fit <-
 final_rf_workflow %>%
 last_fit(cdf_split)
# Evaluating the model performance
# Performance metrics
rf_last_fit %>% collect_metrics()
## # A tibble: 2 x 4
     .metric .estimator .estimate .config
##
                           <dbl> <chr>
##
     <chr>
             <chr>
                          0.955 Preprocessor1_Model1
## 1 accuracy binary
## 2 roc_auc binary
                          0.991 Preprocessor1_Model1
# roc_auc plot
rf_last_fit %>% collect_predictions() %>%
 roc_curve(truth = customer_status, .pred_closed_account) %>%
 autoplot()
```



```
#Confusion matrix
rf_predictions <- rf_last_fit %>% collect_predictions()
conf_mat(rf_predictions, truth = customer_status, estimate = .pred_class)
```

```
## Truth
## Prediction closed_account active
## closed_account 502 31
## active 21 603
```