ML model

• Data detail : https://bookdown.org/yih_huynh/Guide-to-R-Book/diamonds.html

```
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.3.2 --
## v ggplot2 3.4.0
                 v purrr
                             1.0.1
                 v dplyr
## v tibble 3.1.8
                             1.1.0
         1.3.0 v stringr 1.5.0
## v tidyr
## v readr
          2.1.3
                    v forcats 1.0.0
## -- Conflicts -----
                                         ## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                  masks stats::lag()
library(caret)
## Loading required package: lattice
##
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
##
      lift
tibble(diamonds)
## # A tibble: 53,940 x 10
##
     carat cut
                color clarity depth table price
                                                   Х
                  <ord> <ord>
##
     <dbl> <ord>
                                <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 0.23 Ideal
                 E
                        SI2
                                61.5
                                            326 3.95 3.98 2.43
                                       55
## 2 0.21 Premium E
                        SI1
                                59.8
                                       61
                                            326 3.89
                                                      3.84 2.31
## 3 0.23 Good
                   Ε
                        VS1
                                56.9
                                           327
                                                4.05 4.07 2.31
                                       65
## 4 0.29 Premium I
                       VS2
                                62.4 58 334 4.2
                                                      4.23 2.63
## 5 0.31 Good
                   J
                        SI2
                                63.3 58
                                            335 4.34 4.35 2.75
## 6 0.24 Very Good J
                        VVS2
                                62.8
                                       57
                                            336 3.94
                                                      3.96 2.48
## 7 0.24 Very Good I
                        VVS1
                                62.3 57
                                            336 3.95 3.98 2.47
## 8 0.26 Very Good H
                                61.9 55
                                            337 4.07 4.11 2.53
                        SI1
                                                      3.78 2.49
## 9 0.22 Fair
                   Ε
                        VS2
                                65.1
                                       61
                                            337 3.87
## 10 0.23 Very Good H
                                59.4
                                            338 4
                                                      4.05 2.39
                        VS1
                                       61
## # ... with 53,930 more rows
# check null
mean(complete.cases(diamonds))
## [1] 1
# train_test_split
train_test_data = function(data, train_size=0.7) {
 set.seed(7)
```

```
n = nrow(data)
id = sample(1:n, size = n*train_size)
train_data = data[id, ]
test_data = data[-id, ]
return(list(train_data, test_data))
}

split_data = train_test_data(diamonds)
train_data = split_data[[1]]
nrow(train_data)

## [1] 37758

test_data = split_data[[2]]
nrow(test_data)
## [1] 16182
```

Linear regression model

```
lm_model =
train(price ~ .,
     data = train_data,
     method="lm")
lm_model
## Linear Regression
##
## 37758 samples
##
       9 predictor
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 37758, 37758, 37758, 37758, 37758, 37758, ...
## Resampling results:
##
##
    RMSE
               Rsquared
                          MAE
    1128.136 0.9197066 741.9278
##
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
# score + evaluate model (Linear regression)
p1 = predict(lm_model, newdata= test_data)
RMSE(p1, test_data$price)
```

[1] 1245.287

set K fold cross validation

Logistic Regression model

[1] 1245.287

```
glm_model =
train(price~ .,
      data = train_data,
     method="glm",
      trControl = ctrl)
## + Fold1: parameter=none
## - Fold1: parameter=none
## + Fold2: parameter=none
## - Fold2: parameter=none
## + Fold3: parameter=none
## - Fold3: parameter=none
## + Fold4: parameter=none
## - Fold4: parameter=none
## + Fold5: parameter=none
## - Fold5: parameter=none
## Aggregating results
## Fitting final model on full training set
glm_model
## Generalized Linear Model
##
## 37758 samples
##
       9 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 30207, 30205, 30207, 30206
## Resampling results:
##
##
    RMSE
               Rsquared
    1129.125 0.9195944 741.9947
# score + evaluate model (Logistic Regression)
p2 = predict(glm_model, newdata= test_data)
RMSE(p2, test_data$price)
```

set grid search

```
grid = data.frame(k = c(3,7))
```

KNN model

```
knn_model =
train(price~.,
      data= train_data,
      method = "knn",
      trControl = ctrl,
      tuneGrid = grid)
## + Fold1: k=3
## - Fold1: k=3
## + Fold1: k=7
## - Fold1: k=7
## + Fold2: k=3
## - Fold2: k=3
## + Fold2: k=7
## - Fold2: k=7
## + Fold3: k=3
## - Fold3: k=3
## + Fold3: k=7
## - Fold3: k=7
## + Fold4: k=3
## - Fold4: k=3
## + Fold4: k=7
## - Fold4: k=7
## + Fold5: k=3
## - Fold5: k=3
## + Fold5: k=7
## - Fold5: k=7
## Aggregating results
## Selecting tuning parameters
## Fitting k = 7 on full training set
knn_model
## k-Nearest Neighbors
```

```
## k-Nearest Neighbors
##
37758 samples
## 9 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 30206, 30205, 30207, 30207
## Resampling results across tuning parameters:
##
```

```
## k RMSE Rsquared MAE
## 3 1024.520 0.9347872 547.7812
## 7 1012.071 0.9391815 540.8551
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 7.
```

```
# score + evaluate model (KNN)
p3 = predict(knn_model, newdata= test_data)
RMSE(p3, test_data$price)
```

[1] 981.4582