# Apprentissage Statistique New York city Airbnb

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## Import Packages

# Import Raw data

# Data manipulations / Cleaning the data

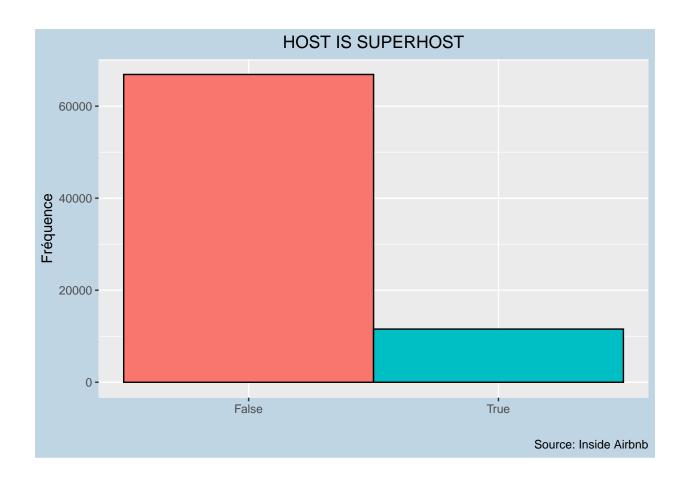
Dealing with missing values

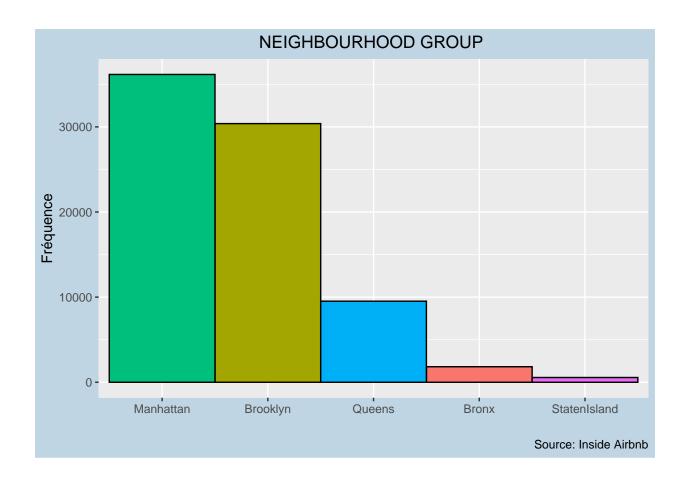
Dealing with categorical variables

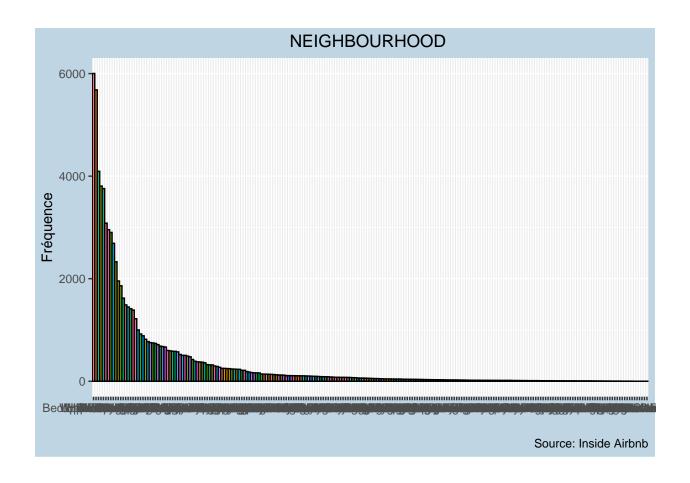
## Data analysis / Data visualisation

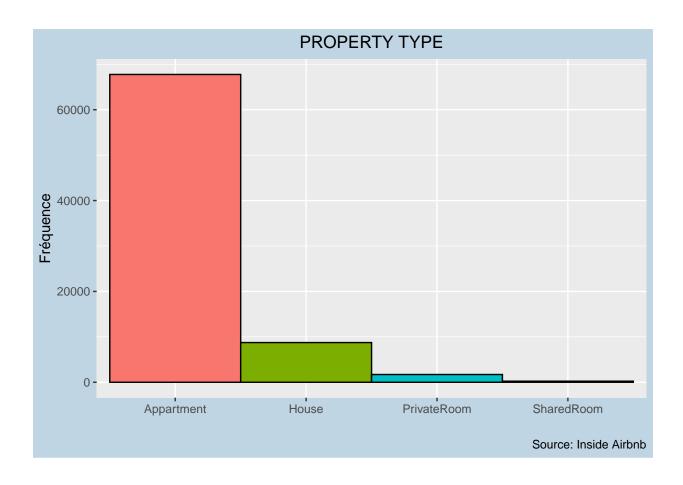
Data visualisation

Frequence of discrete variables







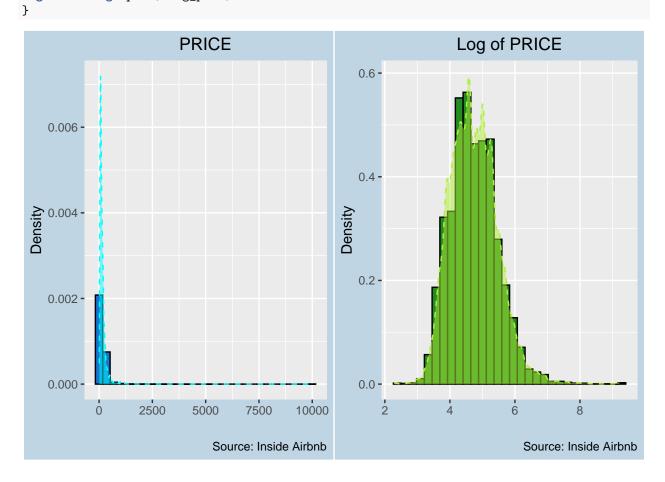


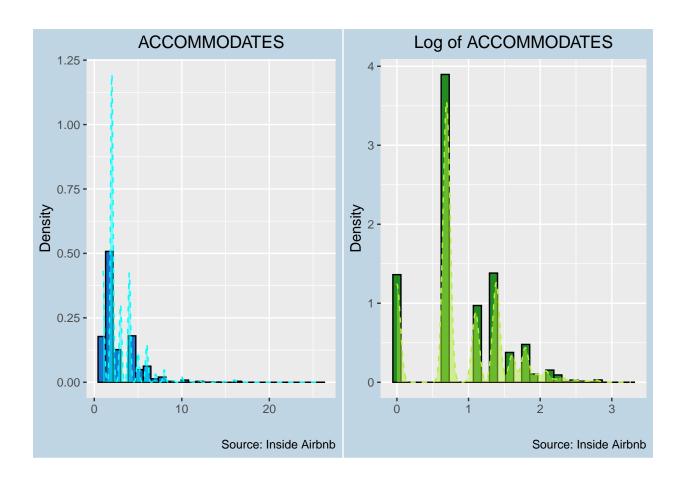


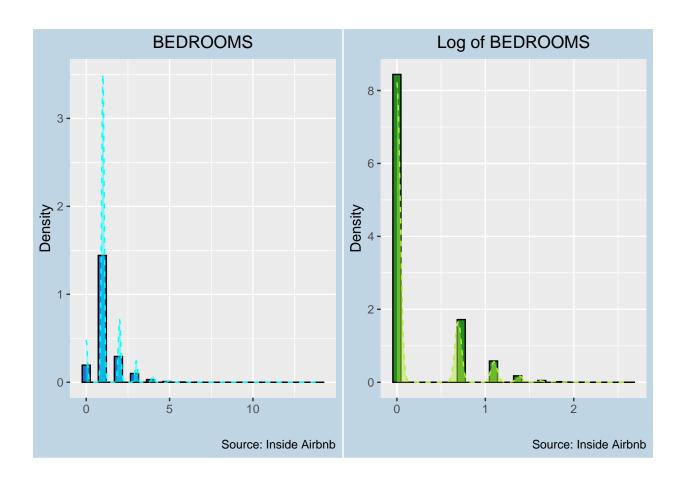
#### Density and log of continuous variables

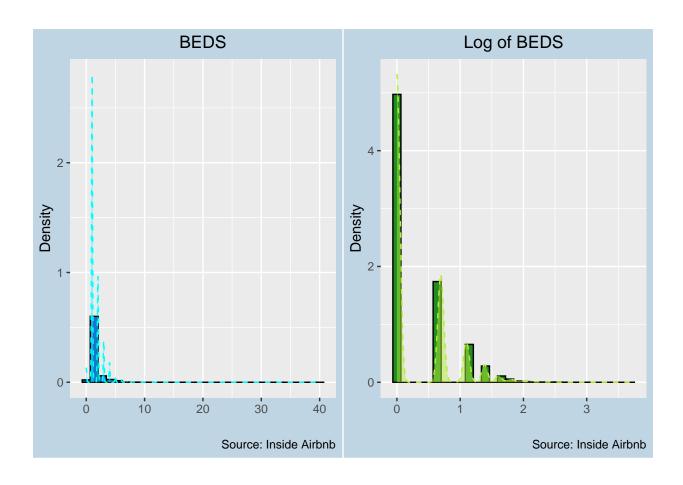
```
features_numeric <- names(select_if(data[,-c(1,6:7)],is.numeric))</pre>
# Without id, latitude and longitude
for (i in features_numeric){
 plot <- ggplot(mapping = aes(x = data[,i])) +</pre>
   geom_histogram(colour="black", fill="dodgerblue3",
                   aes(y = ..density..)) + theme +
    ggtitle(str_replace_all(toupper(i), c("_" = " "))) +
    labs(x = "", y = "Density", caption = tag_source) +
    geom_density(fill = "cyan", colour = "cyan",
                 alpha = 0.5, lwd=0.5, linetype = "dashed")
  log_plot <- ggplot(mapping = aes(x = log(data[,i]))) +</pre>
   geom_histogram(colour="black", fill="forestgreen",
                   aes(y= ..density..)) + theme +
   labs(x = "", y = "Density", caption = tag_source) +
   ggtitle(str_replace_all(paste("Log of",toupper(i)),
                            c("" = "")) +
    geom_density(fill = "olivedrab2", colour = "olivedrab2",
                 alpha = 0.5, lwd=0.5, linetype = "dashed")
```

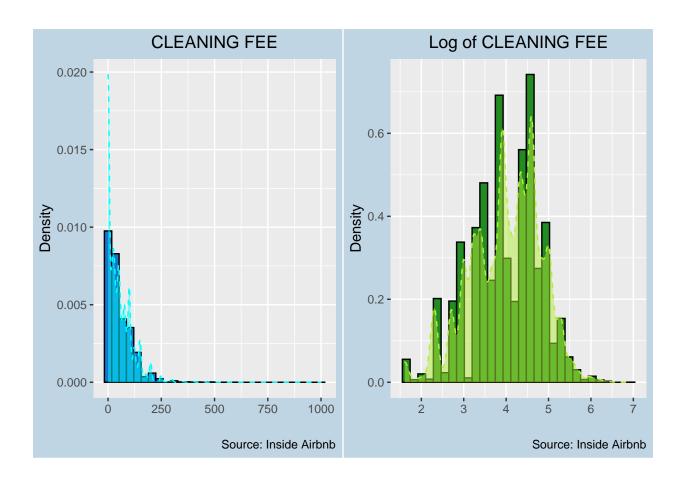
```
grid.arrange(plot, log_plot, ncol=2)
```

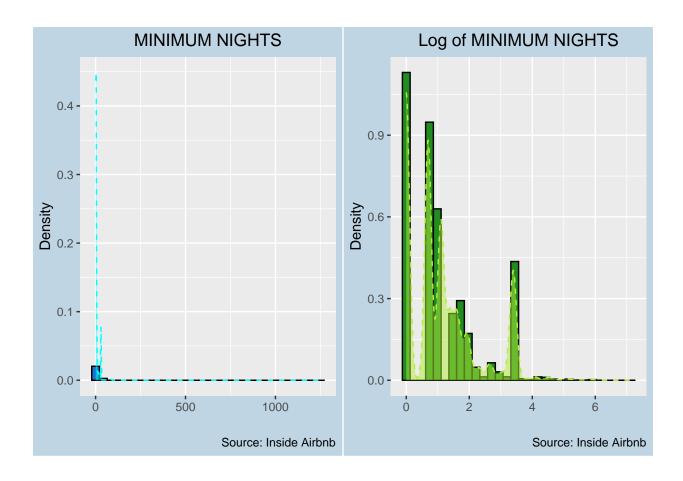


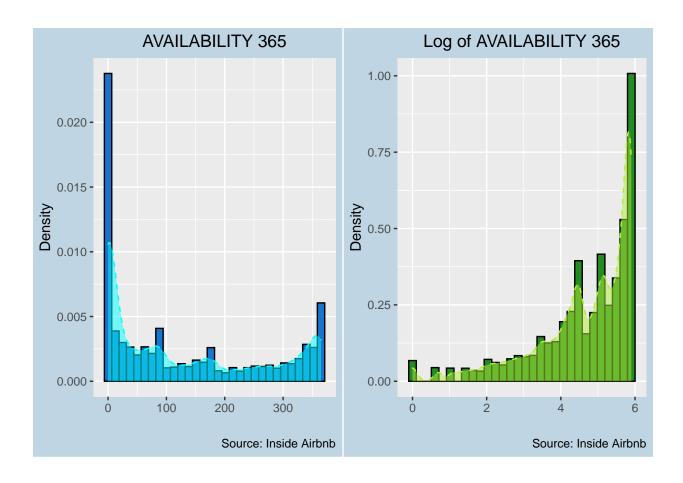


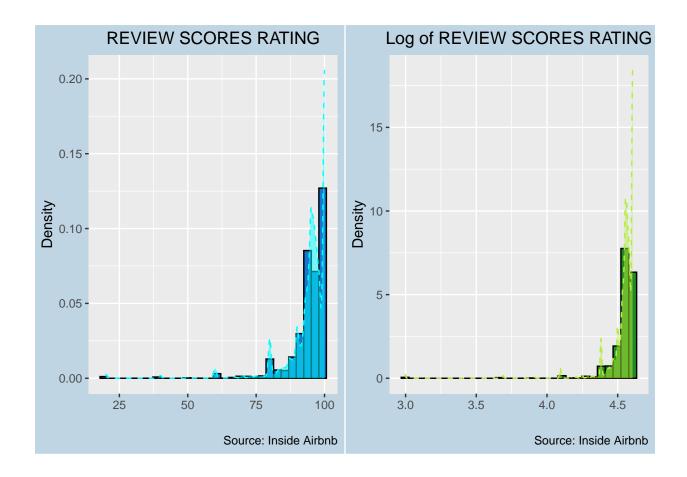




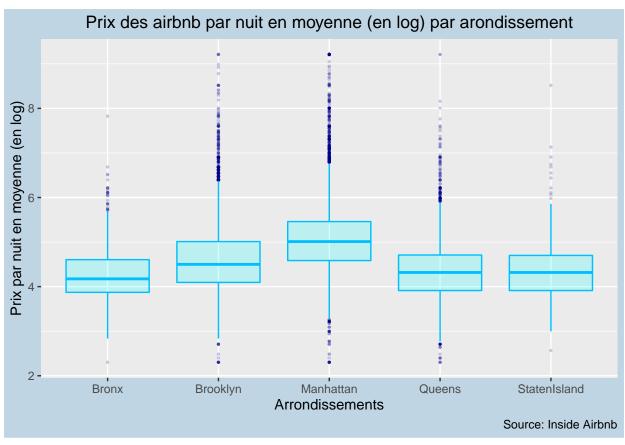


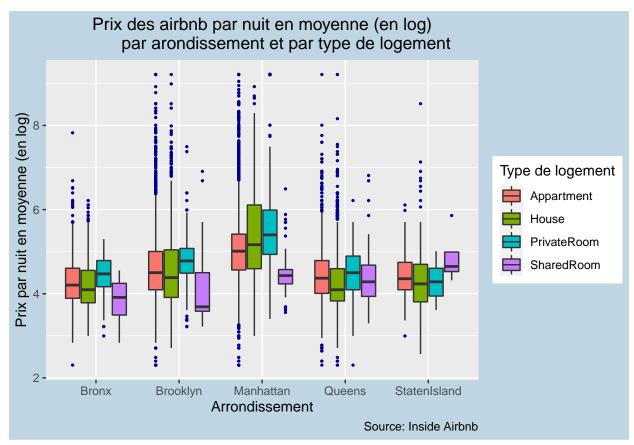


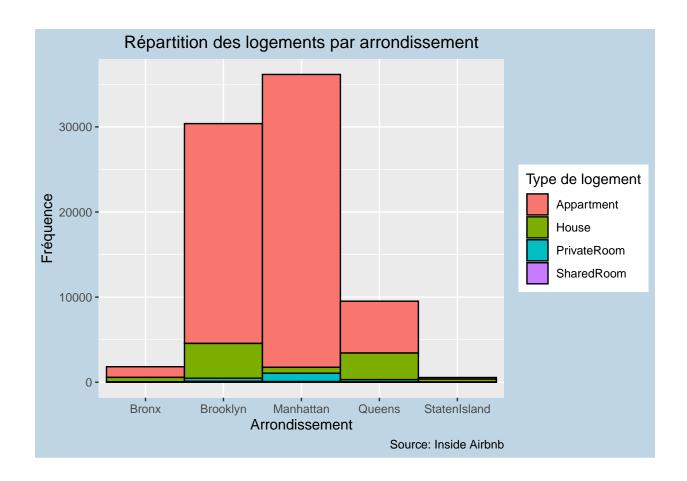




#### **Boxplot**

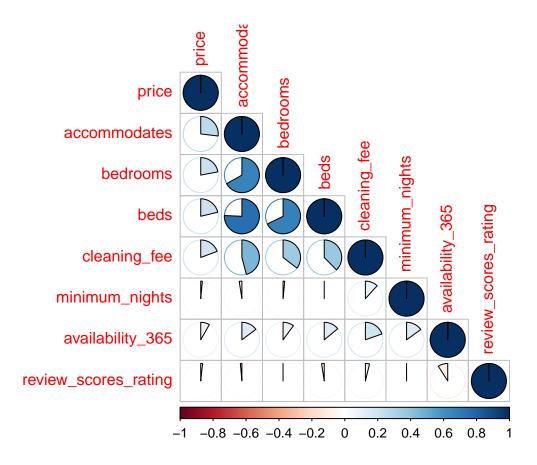






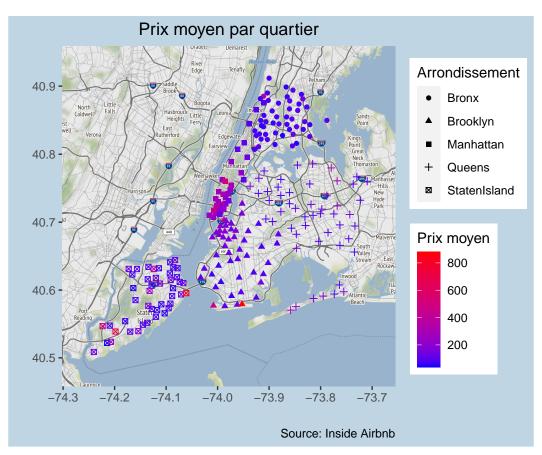
#### Correlation matrix

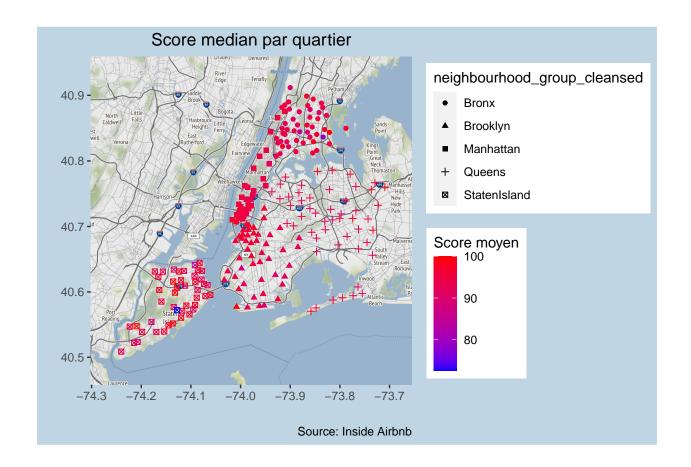
```
corrplot(cor(data[,features_numeric]), method = "pie", type = "lower")
```



#### Spatial Heatmap

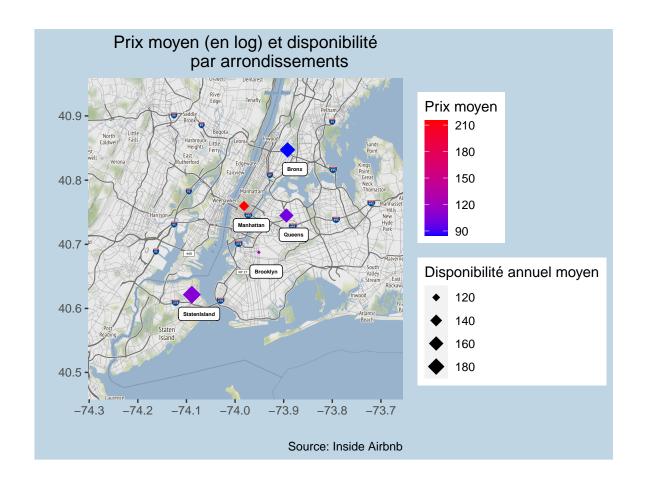
#### Evolution des prix par quartier





#### Evolution des prix par Arrondissement

```
# # ===== Prix moyen par arrondissements ===== ====
ggmap(map) +
  geom_point(by_borough, shape = 18,
            mapping = aes(x = longitude, y = latitude,
                          col = prix_moyen, size = disponibilité_moyen)) +
  scale_colour_gradient(low = "blue", high = "red") +
 theme + labs(x = "", y = "", caption = tag_source,
              size = "Disponibilité annuel moyen",
              col = "Prix moyen") +
  ggtitle("Prix moyen (en log) et disponibilité
         par arrondissements") +
  geom_label(by_borough,
            mapping = aes(longitude, latitude,
                          label = neighbourhood_group_cleansed),
            size = 1.5, fontface = "bold",
            nudge_x = 0.015, nudge_y = -0.03)
```



## Models

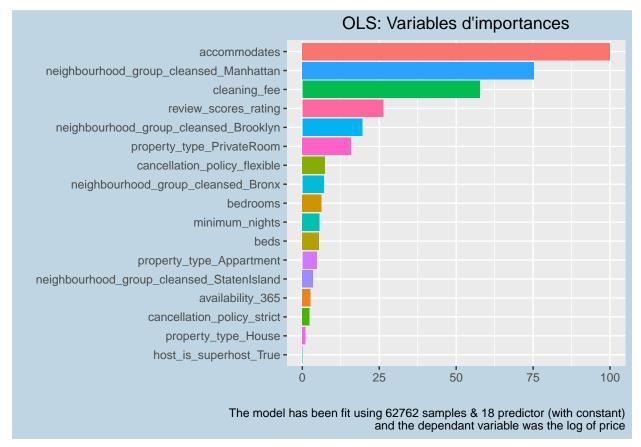
Setting up the theme

Split the data and setting seeds

Allow for Parallel computing

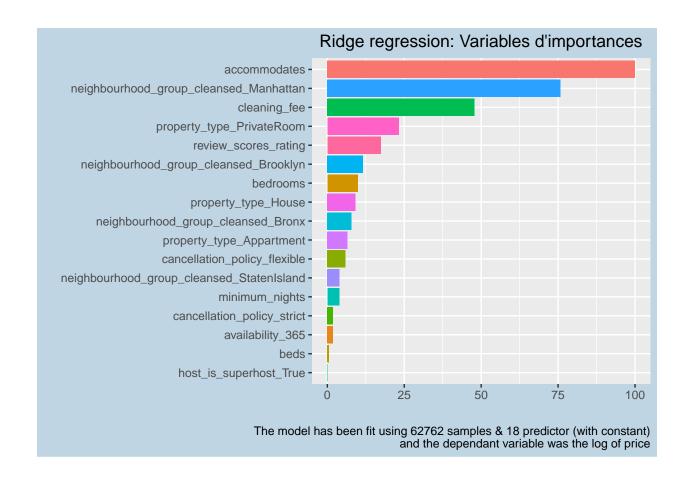
## Ordinary Least Square model

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
## Residuals:
##
      Min
               1Q Median
                               3Q
                                      Max
## -3.0010 -0.3237 -0.0203 0.2907 5.0917
##
## Coefficients:
##
                                              Estimate Std. Error t value
## (Intercept)
                                              2.951e+00 4.543e-02 64.954
## host_is_superhost_True
                                             -6.473e-03 6.052e-03 -1.069
## neighbourhood_group_cleansed_Bronx
                                             -1.170e-01 1.492e-02 -7.843
## neighbourhood_group_cleansed_Brooklyn
                                              1.412e-01 7.072e-03 19.963
## neighbourhood_group_cleansed_Manhattan
                                             5.374e-01 7.250e-03 74.123
## neighbourhood_group_cleansed_StatenIsland -1.120e-01
                                                        2.515e-02
                                                                   -4.454
## property_type_Appartment
                                              2.154e-01 3.819e-02
                                                                    5.639
## property_type_House
                                              8.116e-02 3.861e-02
                                                                   2.102
## property_type_PrivateRoom
                                             6.662e-01 4.057e-02 16.420
                                              1.708e-01 1.742e-03 98.065
## accommodates
## bedrooms
                                             2.694e-02 3.760e-03
                                                                   7.165
## beds
                                            -1.875e-02 2.940e-03 -6.376
## cleaning_fee
                                             2.397e-03 4.205e-05 57.002
## minimum nights
                                            -7.098e-04 1.095e-04 -6.482
## availability 365
                                             6.086e-05 1.665e-05
                                                                   3.655
## review_scores_rating
                                             6.824e-03 2.566e-04 26.590
## cancellation_policy_flexible
                                             4.845e-02 5.909e-03
                                                                   8.199
                                            -1.829e-02 5.578e-03 -3.279
## cancellation_policy_strict
##
                                            Pr(>|t|)
## (Intercept)
                                              < 2e-16 ***
## host_is_superhost_True
                                             0.284868
## neighbourhood_group_cleansed_Bronx
                                            4.46e-15 ***
## neighbourhood_group_cleansed_Brooklyn
                                              < 2e-16 ***
## neighbourhood_group_cleansed_Manhattan
                                              < 2e-16 ***
## neighbourhood_group_cleansed_StatenIsland 8.45e-06 ***
## property_type_Appartment
                                            1.72e-08 ***
## property_type_House
                                            0.035568 *
## property_type_PrivateRoom
                                             < 2e-16 ***
## accommodates
                                              < 2e-16 ***
## bedrooms
                                            7.84e-13 ***
## beds
                                            1.83e-10 ***
## cleaning_fee
                                             < 2e-16 ***
## minimum nights
                                            9.12e-11 ***
## availability_365
                                            0.000258 ***
## review_scores_rating
                                             < 2e-16 ***
                                            2.48e-16 ***
## cancellation_policy_flexible
## cancellation_policy_strict
                                            0.001042 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.5221 on 62744 degrees of freedom
## Multiple R-squared: 0.4917, Adjusted R-squared: 0.4915
## F-statistic: 3570 on 17 and 62744 DF, p-value: < 2.2e-16
```



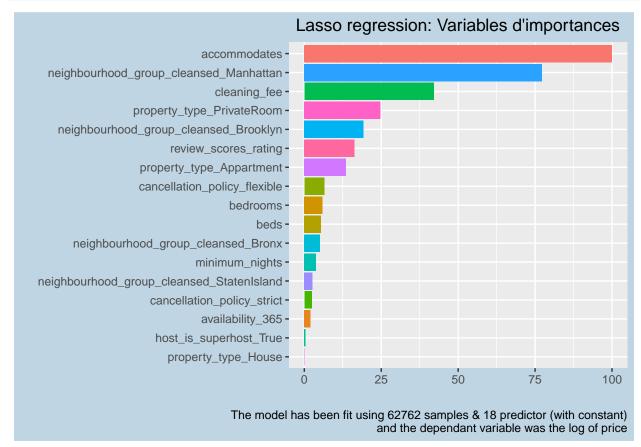
#### Ridge regression

```
cancellation_policy_moderate,
                   data = data_train,
                   method = "glmnet",
                   tuneGrid = expand.grid(alpha = 0,
                                           lambda = seq(0, 1, 0.01)),
                   preProcess = c("scale", "center"),
                   trControl = K5_CV_seed)
ridge_fit$bestTune
   alpha lambda
## 5
        0
           0.04
ridge_pred <- predict(ridge_fit, data_test)</pre>
postResample(pred = ridge_pred, obs = data_test$log_price)
                             MAE
        RMSE Rsquared
## 0.5157762 0.4914722 0.3880052
ridge_varImp <- data.frame(variables = row.names(varImp(ridge_fit)$importance),</pre>
                           varImp(ridge_fit)$importance)
ggplot(data = ridge_varImp, mapping = aes(x=reorder(variables, Overall),
                                        y=Overall,
                                        fill=variables)) +
  coord_flip() + geom_bar(stat = "identity", position = "dodge") +
  theme_models + labs(x = "", y = "", caption = tag_source_models) +
  ggtitle("Ridge regression: Variables d'importances")
```



#### Lasso regression

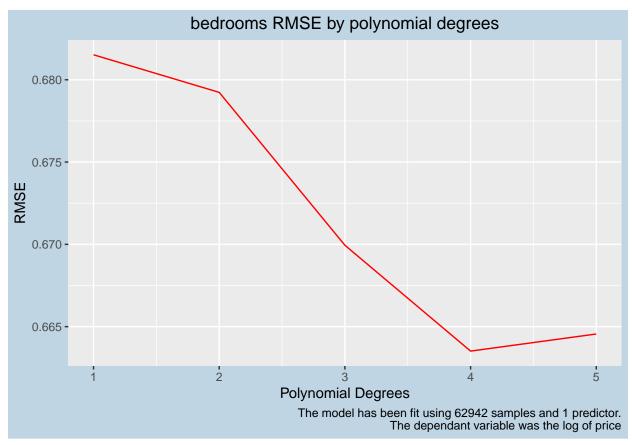
```
set.seed(777)
lasso_fit <- train(log_price ~ . -</pre>
                      host_is_superhost_False -
                      property_type_SharedRoom -
                      neighbourhood_group_cleansed_Queens -
                      cancellation_policy_moderate,
                    data = data_train,
                    method = "glmnet",
                    tuneGrid = expand.grid(alpha = 1,
                                            lambda = seq(0, 1, 0.01)),
                    preProcess = c("scale", "center"),
                    trControl = K5_CV_seed)
lasso_fit$bestTune
     alpha lambda
## 1
         1
lasso_pred <- predict(lasso_fit, data_test)</pre>
postResample(pred = lasso_pred, obs = data_test$log_price)
```

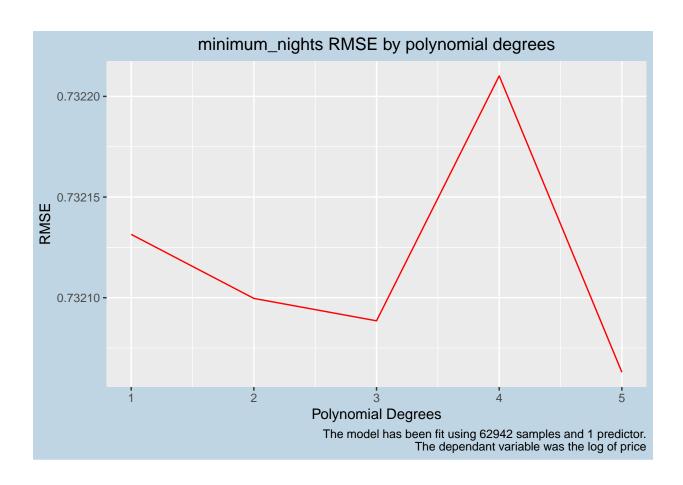


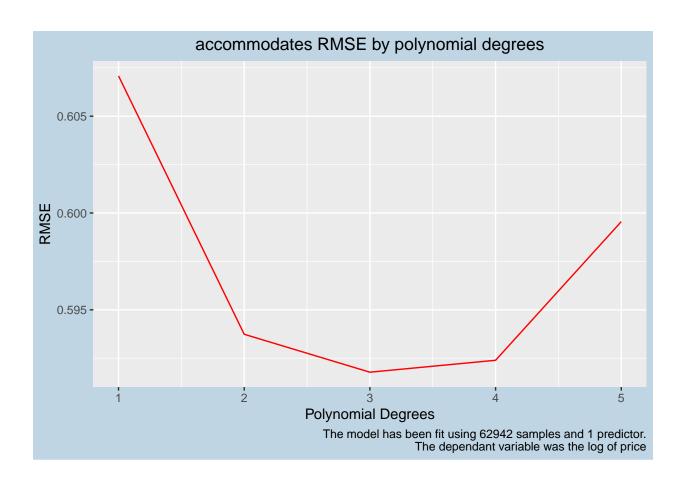
### Polynomial Models

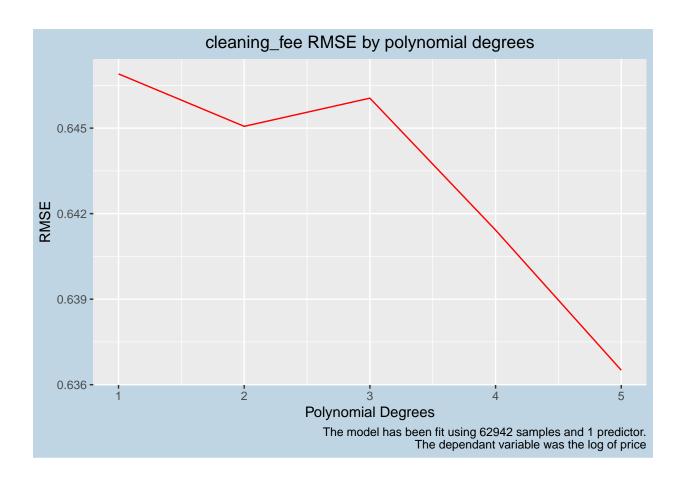
#### Polynomial plots

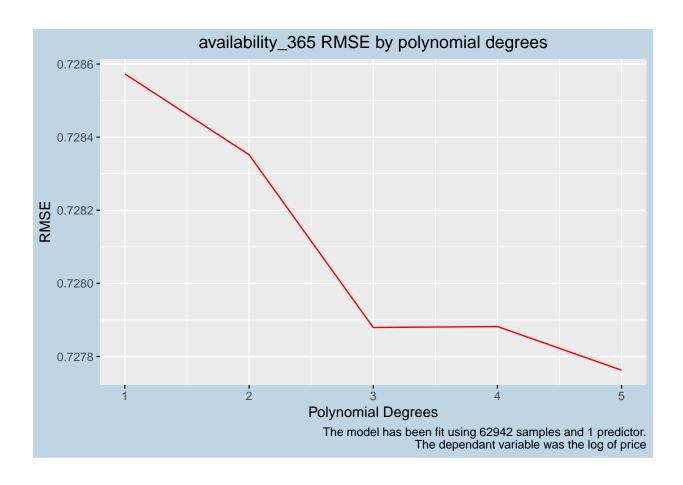
```
for (l in list){
  RMSE <- rep(0,max_degree)</pre>
  for (d in 1:max_degree) {
    PolyRegressor <- train(as.formula(bquote(log_price ~ poly(.(as.name(1)), .(d)))),
                            data = data_train,
                            method = "lm",
                            trControl = K5_CV_seed)
    RMSE[d] <- PolyRegressor$results$RMSE</pre>
  }
  tem_data = data.frame(1:max_degree, RMSE)
  plot <- ggplot(aes(x = 1:max_degree,y = RMSE), data = tem_data) +</pre>
    geom_line(col="red") + theme_models +
    labs(x = "Polynomial Degrees", y = "RMSE",
         caption = "The model has been fit using 62942 samples and 1 predictor.
         The dependant variable was the log of price") +
    ggtitle(paste(1,"RMSE by polynomial degrees"))
  print(plot)
```

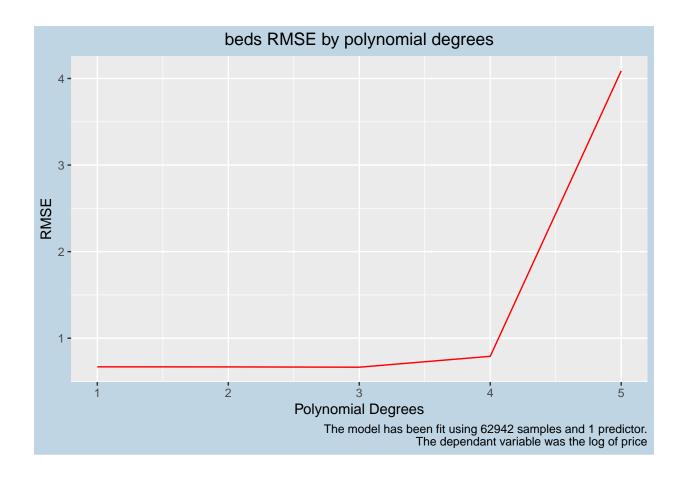












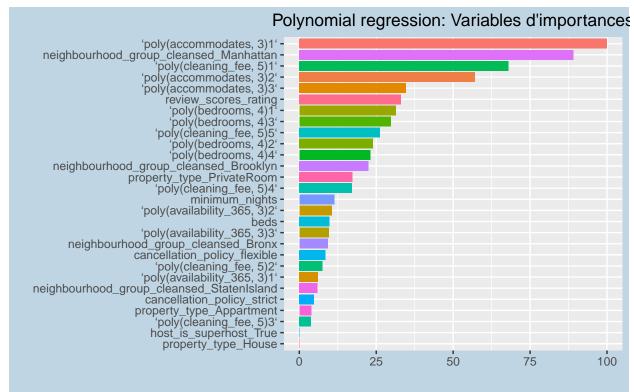
#### **Polynomial Regression**

## lm(formula = .outcome ~ ., data = dat)

```
set.seed(777)
poly_fit <- train(log_price ~ poly(accommodates,3) +</pre>
                    poly(availability_365,3) +
                    poly(bedrooms,4) +
                    poly(cleaning_fee,5) +. -
                    host_is_superhost_False -
                    property_type_SharedRoom -
                    neighbourhood_group_cleansed_Queens -
                    cancellation_policy_moderate -
                    accommodates -
                    availability_365 -
                    bedrooms -
                    cleaning_fee,
                  data = data_train,
                  method = "lm" ,
                  trControl = K5_CV_seed)
summary(poly_fit)
##
## Call:
```

```
##
## Residuals:
      Min
                1Q Median
                                       Max
  -4.3662 -0.3077 -0.0224 0.2698 5.2174
## Coefficients:
                                               Estimate Std. Error t value
## (Intercept)
                                              3.741e+00 4.386e-02 85.297
## `poly(accommodates, 3)1`
                                              7.230e+01 8.971e-01
                                                                    80.596
## `poly(accommodates, 3)2`
                                             -2.752e+01 5.938e-01 -46.354
## `poly(accommodates, 3)3`
                                              1.585e+01 5.553e-01 28.553
## `poly(availability_365, 3)1`
                                              3.066e+00 5.393e-01
                                                                     5.685
## `poly(availability_365, 3)2`
                                              4.758e+00 5.129e-01
                                                                     9.276
## `poly(availability_365, 3)3`
                                              4.287e+00 5.041e-01
                                                                     8.504
## `poly(bedrooms, 4)1`
                                              2.066e+01 7.992e-01
                                                                    25.846
## `poly(bedrooms, 4)2`
                                              1.170e+01 5.857e-01 19.984
## `poly(bedrooms, 4)3`
                                             -1.333e+01 5.429e-01 -24.558
## `poly(bedrooms, 4)4`
                                              1.065e+01 5.529e-01 19.257
## `poly(cleaning_fee, 5)1`
                                              3.396e+01 6.166e-01 55.072
## `poly(cleaning_fee, 5)2`
                                             -3.590e+00 5.255e-01
                                                                    -6.832
## `poly(cleaning_fee, 5)3`
                                              2.008e+00 5.158e-01
                                                                     3.893
## `poly(cleaning_fee, 5)4`
                                              7.498e+00 5.150e-01 14.558
                                             -1.105e+01 5.083e-01 -21.737
## `poly(cleaning_fee, 5)5`
## host is superhost True
                                              5.616e-03
                                                         5.861e-03
                                                                     0.958
## neighbourhood_group_cleansed_Bronx
                                             -1.179e-01 1.433e-02 -8.229
## neighbourhood_group_cleansed_Brooklyn
                                              1.279e-01 6.803e-03 18.798
## neighbourhood_group_cleansed_Manhattan
                                                         6.999e-03 71.918
                                              5.034e-01
## neighbourhood_group_cleansed_StatenIsland -1.345e-01 2.415e-02 -5.567
## property_type_Appartment
                                              1.449e-01 3.670e-02
                                                                     3.949
## property_type_House
                                              3.228e-02 3.709e-02
                                                                     0.870
## property_type_PrivateRoom
                                              5.704e-01
                                                         3.900e-02 14.627
## beds
                                             -2.525e-02 2.903e-03 -8.700
## minimum_nights
                                             -1.050e-03 1.057e-04 -9.936
                                              6.716e-03 2.465e-04
                                                                    27.244
## review_scores_rating
## cancellation_policy_flexible
                                              4.403e-02 5.778e-03
                                                                     7.621
## cancellation_policy_strict
                                             -2.508e-02 5.363e-03 -4.677
##
                                             Pr(>|t|)
## (Intercept)
                                              < 2e-16 ***
## `poly(accommodates, 3)1`
                                              < 2e-16 ***
## `poly(accommodates, 3)2`
                                              < 2e-16 ***
## `poly(accommodates, 3)3`
                                              < 2e-16 ***
## `poly(availability_365, 3)1`
                                             1.32e-08 ***
## `poly(availability_365, 3)2`
                                              < 2e-16 ***
## `poly(availability_365, 3)3`
                                              < 2e-16 ***
## `poly(bedrooms, 4)1`
                                              < 2e-16 ***
                                              < 2e-16 ***
## `poly(bedrooms, 4)2`
## `poly(bedrooms, 4)3`
                                              < 2e-16 ***
## `poly(bedrooms, 4)4`
                                              < 2e-16 ***
## `poly(cleaning_fee, 5)1`
                                              < 2e-16 ***
## `poly(cleaning_fee, 5)2`
                                             8.43e-12 ***
## `poly(cleaning_fee, 5)3`
                                             9.91e-05 ***
## `poly(cleaning_fee, 5)4`
                                              < 2e-16 ***
## `poly(cleaning_fee, 5)5`
                                              < 2e-16 ***
## host_is_superhost_True
                                                0.338
```

```
## neighbourhood_group_cleansed_Bronx
                                             < 2e-16 ***
                                           < 2e-16 ***
## neighbourhood_group_cleansed_Brooklyn
## neighbourhood group cleansed Manhattan < 2e-16 ***
## neighbourhood_group_cleansed_StatenIsland 2.61e-08 ***
## property_type_Appartment
                                            7.85e-05 ***
## property_type_House
                                               0.384
## property_type_PrivateRoom
                                              < 2e-16 ***
## beds
                                              < 2e-16 ***
## minimum_nights
                                              < 2e-16 ***
## review_scores_rating
                                             < 2e-16 ***
## cancellation_policy_flexible
                                            2.55e-14 ***
## cancellation_policy_strict
                                            2.92e-06 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.5012 on 62733 degrees of freedom
## Multiple R-squared: 0.5317, Adjusted R-squared: 0.5315
## F-statistic: 2544 on 28 and 62733 DF, p-value: < 2.2e-16
poly_pred <- predict(poly_fit, data_test)</pre>
postResample(pred = poly_pred, obs = data_test$log_price)
##
        RMSE Rsquared
                            MAF.
## 0.4950583 0.5313251 0.3693402
# RMSE 0.5016245
poly_varImp <- data.frame(variables = row.names(varImp(poly_fit)$importance),</pre>
                          varImp(poly_fit)$importance)
ggplot(data = poly_varImp, mapping = aes(x=reorder(variables, Overall),
                                         y=0verall,
                                         fill=variables)) +
  coord_flip() + geom_bar(stat = "identity", position = "dodge") +
  theme_models +
  labs(x = "", y = "",
       caption = "The model has been fit using 62762 samples & 23 predictor (with constant) and the dep
       The variable bedrooms was taken to the 4th polynomial degree, the variable availability_365 was
       3rd polynomial degree and the variable bedrooms was taken to the 2nd polynomial degree.") +
  ggtitle("Polynomial regression: Variables d'importances")
```



del has been fit using 62762 samples & 23 predictor (with constant) and the dependant variable was the log of price.

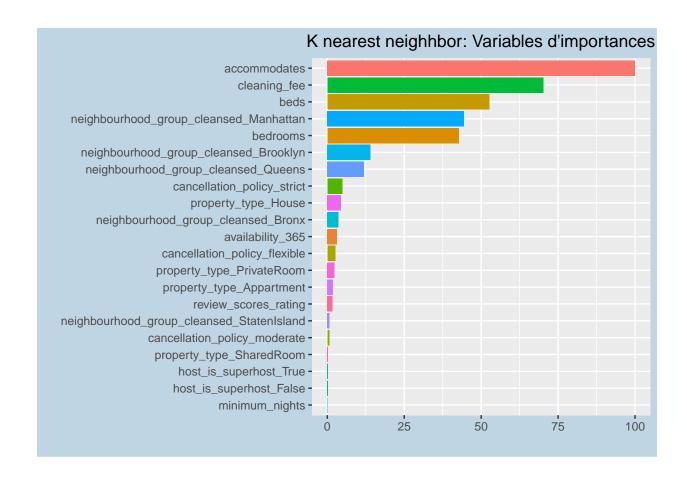
The variable bedrooms was taken to the 4th polynomial degree, the variable availability\_365 was taken to the

3rd polynomial degree and the variable bedrooms was taken to the 2nd polynomial degree.

#### **KNN**

#### PreProcess / Standardize

#### **KNN Regression**



## **Boosting**

#### **XG**boost

```
# Grid <- expand.grid(nrounds = 0:50,
                          max_depth = 5,
#
                          eta = 0.3,
#
                          qamma = 0.01,
#
                          colsample_bytree = 0.5,
#
                          min \ child \ weight = 0,
#
                          subsample = 0.5)
Grid <- expand.grid(nrounds = 47,</pre>
                     max_depth = 5,
                     eta = 0.3,
                     gamma = 0.01,
                     colsample_bytree = 0.5,
                     min_child_weight = 0,
                     subsample = 0.5)
set.seed(777)
xgboost_fit <-</pre>
                 train(log_price~.,
                         data = data_train,
                         method = "xgbTree",
```

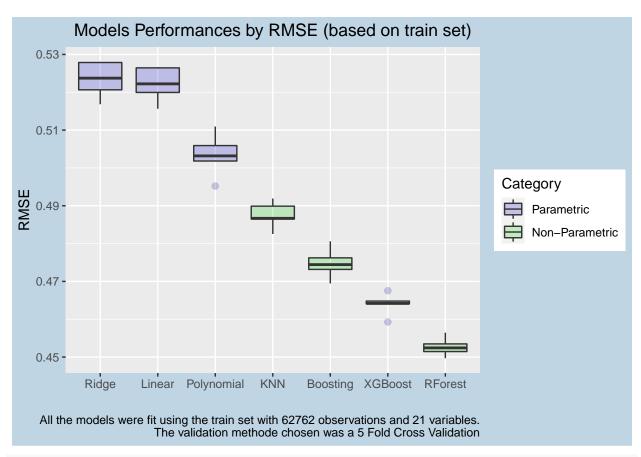
#### Random forest

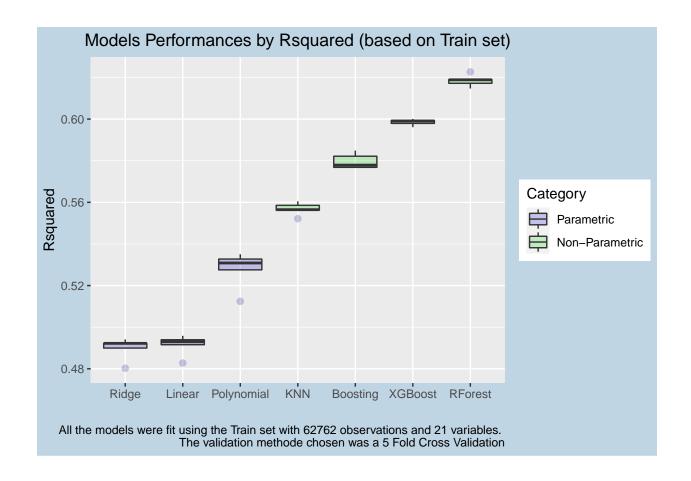
```
# Grid <- expand.grid(.mtry=c(1:5))</pre>
Grid <- expand.grid(.mtry=5)</pre>
set.seed(777)
rf_fit <- train(log_price ~ .,</pre>
                   data = data_train,
                   method = "rf",
                   trControl = K5_CV_seed,
                   tuneGrid = Grid,
                   allowParallel = TRUE)
# plot(rf_fit)
# rf_fit$bestTune
rf_pred <- predict(rf_fit, newdata = data_test)</pre>
#RMSE for Random Forest
postResample(pred = rf_pred, obs = data_test$log_price)
        RMSE Rsquared
## 0.4418751 0.6271526 0.3233835
       RMSE Rsquared
                             MAE
# 0.4418751 0.6271526 0.3233835
```

#### Comparaison of models (Train set)

RMSE and R2 based on Train set

```
Polynomial = poly_fit,
               KNN = knn_fit,
               Boosting = gbm_fit,
               XGBoost = xgboost_fit,
               RForest = rf_fit)
res <- resamples(models)</pre>
models_list = c("Linear", "Ridge", "Polynomial", "KNN",
                "Boosting", "XGBoost", "RForest")
df = data.frame()
for (i in models_list){
 x = data.frame (model = i,
                  RMSE = res$values[paste(i, "RMSE", sep = "~")],
                  Rsquared = res$values[paste(i, "Rsquared", sep = "~")])
 x <- x %>% rename(RMSE = paste(i, ".RMSE", sep = ""))
 x <- x %>% rename(Rsquared = paste(i, ".Rsquared", sep = ""))
 df <- rbind(df,x)</pre>
}
df$Category <- factor(ifelse(df$model %in% c("KNN", "Boosting", "XGBoost",</pre>
                                              "RForest"), 1, 0),
                      labels = c("Parametric", "Non-Parametric"))
theme_models2 <- theme(plot.title = element_text(hjust = 0.5),</pre>
               plot.background = element_rect(fill = "#BFD5E3"))
# RMSE
ggplot(data = df, aes(x = fct_reorder(model, RMSE, .desc = T),
                      y = RMSE, fill = Category)) +
  geom_boxplot(outlier.colour = "darkblue", outlier.size = 2, alpha=0.2) +
 theme_models2 +
 labs(x = "", y = "RMSE",
       caption = "All the models were fit using the train set with 62762 observations and 21 variables.
       The validation methode chosen was a 5 Fold Cross Validation") +
  ggtitle("Models Performances by RMSE (based on train set)") +
  scale_fill_manual(values=c("blue3", "green3"))
```





## Comparaison of models (Test set)

```
pred_list = c("ols_pred", "ridge_pred", "poly_pred", "knn_pred",
                 "gbm_pred", "xgboost_pred", "rf_pred")
models_list = c("Linear", "Ridge", "Polynomial", "KNN",
                 "Boosting", "XGBoost", "RForest")
df = data.frame()
for (i in pred_list){
  if (i == "knn_pred"){
    x = as.data.frame(postResample(pred = get(i),
                                      obs = data_test_standardized$log_price))
    names(x)[1] \leftarrow i
    x \leftarrow t(x)
  }
  else {
    x = as.data.frame(postResample(pred = get(i), obs = data_test$log_price))
    names(x)[1] \leftarrow i
    x \leftarrow t(x)
  }
  df <- rbind(df,x)</pre>
}
```

