Final Project

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Contents

```
if (!require("pacman")){install.packages("pacman")}
```

```
## Loading required package: pacman
```

```
## Warning: package 'pacman' was built under R version 4.0.5
```

```
pacman::p_load(knitr, randomForest, dplyr, tidyverse, ggplot2, missForest, stats, readr, magrittr, data
```

##Import and Clean Data Set (2.1)##

Import the data set from drive.

```
library(readr)
housing_data_2016_2017 <- read_csv("C:\\Users\\twiz0\\Downloads\\housing_data_2016_2017.csv")
```

```
##
## -- Column specification --------------------------------------------------------
## cols(
##   .default = col_character(),
##   Keywords = col_logical(),
##   MaxAssignments = col_double(),
##   AssignmentDurationInSeconds = col_double(),
##   AutoApprovalDelayInSeconds = col_double(),
##   NumberOfSimilarHITs = col_logical(),
##   LifetimeInSeconds = col_logical(),
##   RejectionTime = col_logical(),
##   RequesterFeedback = col_logical(),
##   WorkTimeInSeconds = col_double(),
##   approx_year_built = col_double(),
##   community_district_num = col_double(),
##   num_bedrooms = col_double(),
##   num_floors_in_building = col_double(),
##   num_full_bathrooms = col_double(),
##   num_half_bathrooms = col_double(),
##   num_total_rooms = col_double(),
##   pct_tax_deductibl = col_double(),
##   sq_footage = col_double(),
```

```
##   walk_score = col_double(),
##   url = col_logical()
## )
## i Use `spec()` for the full column specifications.

## Warning: 758 parsing failures.
##  row col           expected
## 1473 url 1/0/T/F/TRUE/FALSE http://www.mlsli.com/homes-for-sale/10-Station-Sq-Forest-Hills-NY-11375-
## 1474 url 1/0/T/F/TRUE/FALSE http://www.mlsli.com/homes-for-sale/10-01-162nd-St-Beechhurst-NY-11357-1
## 1475 url 1/0/T/F/TRUE/FALSE http://www.mlsli.com/homes-for-sale/100-10-67th-Rd-Forest-Hills-NY-11375
## 1476 url 1/0/T/F/TRUE/FALSE http://www.mlsli.com/homes-for-sale/100-25-Queens-Blvd-Forest-Hills-NY-1
## 1477 url 1/0/T/F/TRUE/FALSE http://www.mlsli.com/homes-for-sale/10-11-162nd-St-Beechhurst-NY-11357-1
## .... ... .................. ....................................................................
## See problems(...) for more details.
```

```
#View(housing_data_2016_2017)
```

#Split Data#

Split Test and Training Sets. Retain 20% of data for testing.

```
set.seed(479)

#Split 20% Test/ 80% Train
K = 5

test_indices = sample(1 : nrow(housing_data_2016_2017), round(nrow(housing_data_2016_2017) / K))
train_indices = setdiff(1 : nrow(housing_data_2016_2017), test_indices)

housing_data_test = housing_data_2016_2017[test_indices, ]
housing_data_train = housing_data_2016_2017[train_indices, ]

#View(housing_data_train)
#View(housing_data_test)

#summary(housing_data_train)
#summary(housing_data_test)

#Count observations with missing target variable.
sum(is.na(housing_data_2016_2017$sale_price))
```

```
## [1] 1702
```

#Initial (Pre-Imputation) Data Clean-up (2.2)#

Data Clean-Up on Training Set

```
#Remove obviously unnecessary columns, reorder with objective variable (sale price) at head, remove obs
housing_data_train = housing_data_train %>%
  select(-(1:28), -url) %>%
    select(sale_price, everything()) %>%
      filter(!is.na(sale_price)) %>%
        select(-listing_price_to_nearest_1000)
```

```
#Unformat all prices
housing_data_train = housing_data_train %>%
  mutate(sale_price = parse_number(sale_price)) %>%
  mutate(common_charges = parse_number(common_charges)) %>%
  mutate(maintenance_cost = parse_number(maintenance_cost)) %>%
  mutate(parking_charges = parse_number(parking_charges)) %>%
  mutate(total_taxes = parse_number(total_taxes))

#Add feature for total bathrooms (whole plus half).
housing_data_train = housing_data_train %>%
  mutate(num_half_bathrooms = replace(num_half_bathrooms, is.na(num_half_bathrooms), 0)) %>%
  mutate(num_bathrooms = num_full_bathrooms + 0.5 * num_half_bathrooms)

#Separate dates sold as year, date, month, weekdays, and days of month.
housing_data_train = housing_data_train %>%
  mutate(date_of_sale = as_date(mdy(date_of_sale))) %>%
  mutate(month_of_year = month(date_of_sale)) %>%
  mutate(day_of_week = wday(date_of_sale)) %>%
  mutate(day_of_month = as.numeric(day(date_of_sale))) %>%
  mutate(year = year(date_of_sale)) %>%
    mutate(date_of_sale = as.numeric(date_of_sale))

#Extract zip codes from addresses.
housing_data_train = housing_data_train %>%
  mutate(zip_numeric = as.numeric(str_sub(full_address_or_zip_code, -5,-1))) %>%
  mutate(zip_factor = as.factor(zip_numeric))
```

```
## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion
```

```
#Create dummy variables for non-factor variables with potentially significant missing data.
housing_data_train = housing_data_train %>%
  mutate(common_charges_missing = as.factor(is.na(common_charges))) %>%
    mutate(common_charges = ifelse(is.na(common_charges), 0, common_charges)) %>%
  mutate(approx_year_built_missing = as.factor(is.na(approx_year_built))) %>%
  mutate(maintenance_cost_missing = as.factor(is.na(maintenance_cost))) %>%
    mutate(maintenance_cost = ifelse(is.na(maintenance_cost), 0, maintenance_cost)) %>%
  mutate(num_floors_in_building_missing = as.factor(is.na(num_floors_in_building))) %>%
  mutate(parking_charges_missing = as.factor(is.na(parking_charges))) %>%
    mutate(parking_charges = ifelse(is.na(parking_charges), 0, parking_charges)) %>%
  mutate(pct_tax_deductibl_missing = as.factor(is.na(pct_tax_deductibl))) %>%
  mutate(sq_footage_missing = as.factor(is.na(sq_footage))) %>%
  mutate(total_taxes_missing = as.factor(is.na(total_taxes)))

#Coerce yes/no to factors.
housing_data_train = housing_data_train %>%
  mutate(cats_allowed = factor(cats_allowed)) %>%
  mutate(dogs_allowed = factor(dogs_allowed))

#Garage exists to factor.
housing_data_train = housing_data_train %>%
  mutate(garage_exists = as.factor(!is.na(garage_exists)))

#Factorize character variables and set NA to "unknown" factor.
```

```
housing_data_train = housing_data_train %>%
  mutate(dining_room_type = replace_na(dining_room_type, "unknown")) %>%
  mutate(dining_room_type = factor(dining_room_type)) %>%
  mutate(coop_condo = factor(coop_condo, ordered = FALSE)) %>%
  mutate(fuel_type = ifelse(fuel_type %in% c("other", "Other"), "other", fuel_type)) %>%
  mutate(fuel_type = ifelse(is.na(fuel_type), "unknown", fuel_type)) %>%
  mutate(fuel_type = factor(fuel_type)) %>%
  mutate(kitchen_type = ifelse(kitchen_type %in% c("eat in", "Eat In", "Eat in"), "eat in", kitchen_type
  mutate(kitchen_type = replace_na(kitchen_type, "unknown")) %>%
  mutate(kitchen_type = ifelse(kitchen_type == "Combo", "combo", kitchen_type)) %>%
  mutate(kitchen_type = as.factor(kitchen_type))

#Take care of factors with only a few observations.
housing_data_train = housing_data_train %>%
  mutate(dining_room_type = recode(dining_room_type, "dining area" = "other")) %>%
  mutate(kitchen_type = recode(kitchen_type, "1955" = "unknown"))

#Fill in singular missing values in train data (found zip manually in raw data)
housing_data_train$zip_numeric[2] = 11354
housing_data_train$zip_factor[2] = "11354"

#Remove full address, model type, and date of sale
housing_data_train = housing_data_train %>%
  mutate(total_additional_charges = common_charges + maintenance_cost + parking_charges) %>%
  select(-full_address_or_zip_code, -model_type, -common_charges, -parking_charges, -maintenance_cost)

#summary(housing_data_train)
#sapply(housing_data_train, class)
```

Data Clean-Up on Test Set

```
#Remove obviously unnecessary columns, reorder with objective variable (sale price) at head, remove obs
housing_data_test = housing_data_test %>%
  select(-(1:28), -url) %>%
    select(sale_price, everything()) %>%
      filter(!is.na(sale_price)) %>%
        select(-listing_price_to_nearest_1000)

#Unformat all prices
housing_data_test = housing_data_test %>%
  mutate(sale_price = parse_number(sale_price)) %>%
  mutate(common_charges = parse_number(common_charges)) %>%
  mutate(maintenance_cost = parse_number(maintenance_cost)) %>%
  mutate(parking_charges = parse_number(parking_charges)) %>%
  mutate(total_taxes = parse_number(total_taxes))

#Add feature for total bathrooms (whole plus half).
housing_data_test = housing_data_test %>%
  mutate(num_half_bathrooms = replace(num_half_bathrooms, is.na(num_half_bathrooms), 0)) %>%
  mutate(num_bathrooms = num_full_bathrooms + 0.5 * num_half_bathrooms)

#Separate dates sold as year, date, month, weekdays, and days of month.
housing_data_test = housing_data_test %>%
```

```
  mutate(date_of_sale = as_date(mdy(date_of_sale))) %>%
  mutate(month_of_year = month(date_of_sale)) %>%
  mutate(day_of_week = wday(date_of_sale)) %>%
  mutate(day_of_month = as.numeric(day(date_of_sale))) %>%
  mutate(year = year(date_of_sale)) %>%
    mutate(date_of_sale = as.numeric(date_of_sale))

#Extract zip codes from addresses.
housing_data_test = housing_data_test %>%
  mutate(zip_numeric = as.numeric(str_sub(full_address_or_zip_code, -5,-1))) %>%
  mutate(zip_factor = as.factor(zip_numeric))

#Create dummy variables for non-factor variables with potentially significant missing data.
housing_data_test = housing_data_test %>%
  mutate(common_charges_missing = as.factor(is.na(common_charges))) %>%
    mutate(common_charges = ifelse(is.na(common_charges), 0, common_charges)) %>%
  mutate(approx_year_built_missing = as.factor(is.na(approx_year_built))) %>%
  mutate(maintenance_cost_missing = as.factor(is.na(maintenance_cost))) %>%
    mutate(maintenance_cost = ifelse(is.na(maintenance_cost), 0, maintenance_cost)) %>%
  mutate(num_floors_in_building_missing = as.factor(is.na(num_floors_in_building))) %>%
  mutate(parking_charges_missing = as.factor(is.na(parking_charges))) %>%
    mutate(parking_charges = ifelse(is.na(parking_charges), 0, parking_charges)) %>%
  mutate(pct_tax_deductibl_missing = as.factor(is.na(pct_tax_deductibl))) %>%
  mutate(sq_footage_missing = as.factor(is.na(sq_footage))) %>%
  mutate(total_taxes_missing = as.factor(is.na(total_taxes)))

#Coerce yes/no to factors.
housing_data_test = housing_data_test %>%
  mutate(cats_allowed = factor(cats_allowed)) %>%
  mutate(dogs_allowed = factor(dogs_allowed))

#Garage exists to factor.
housing_data_test = housing_data_test %>%
  mutate(garage_exists = as.factor(!is.na(garage_exists)))

#Factorize character variables and set NA to "unknown" factor.
housing_data_test = housing_data_test %>%
  mutate(dining_room_type = replace_na(dining_room_type, "unknown")) %>%
  mutate(dining_room_type = factor(dining_room_type)) %>%
  mutate(coop_condo = factor(coop_condo, ordered = FALSE)) %>%
  mutate(fuel_type = ifelse(fuel_type %in% c("other", "Other"), "other", fuel_type)) %>%
  mutate(fuel_type = ifelse(is.na(fuel_type), "unknown", fuel_type)) %>%
  mutate(fuel_type = factor(fuel_type)) %>%
  mutate(kitchen_type = ifelse(kitchen_type %in% c("eat in", "Eat In", "Eat in"), "eat in", kitchen_typ
  mutate(kitchen_type = replace_na(kitchen_type, "unknown")) %>%
  mutate(kitchen_type = ifelse(kitchen_type == "Combo", "combo", kitchen_type)) %>%
  mutate(kitchen_type = as.factor(kitchen_type))

#Take care of factors with only a few observations.
housing_data_test = housing_data_test %>%
  mutate(dining_room_type = recode(dining_room_type, "dining area" = "other")) %>%
  mutate(kitchen_type = recode(kitchen_type, "1955" = "unknown"))
```

```
#Fill in singular missing values easily available manually
housing_data_test = housing_data_test %>%
  mutate(dining_room_type = recode(dining_room_type, "dining area" = "other"))

#Remove full address, model type, and date of sale
housing_data_test = housing_data_test %>%
  mutate(total_additional_charges = common_charges + maintenance_cost + parking_charges) %>%
  select(-full_address_or_zip_code, -model_type, -common_charges, -parking_charges, -maintenance_cost)

#summary(housing_data_train)
#sapply(housing_data_test, class)
```

##Missingness in Features (2.3)

Impute using missForest. Check out line 245 issue.

```
#Impute missing values in training data
housing_data_train_imp = missForest(data.frame(housing_data_train))$ximp
```

```
##   missForest iteration 1 in progress...done!
##   missForest iteration 2 in progress...done!
##   missForest iteration 3 in progress...done!
```

```
#Impute missing values in test data.
housing_data_test_imp = cbind("sale_price" = NA, housing_data_test[2:ncol(housing_data_test)])
housing_data_test_train_imp = rbind(housing_data_test_imp, housing_data_train_imp)
housing_data_test_train_imp = missForest(data.frame(housing_data_test_train_imp))$ximp
```

```
##   missForest iteration 1 in progress...done!
##   missForest iteration 2 in progress...done!
##   missForest iteration 3 in progress...done!
##   missForest iteration 4 in progress...done!
```

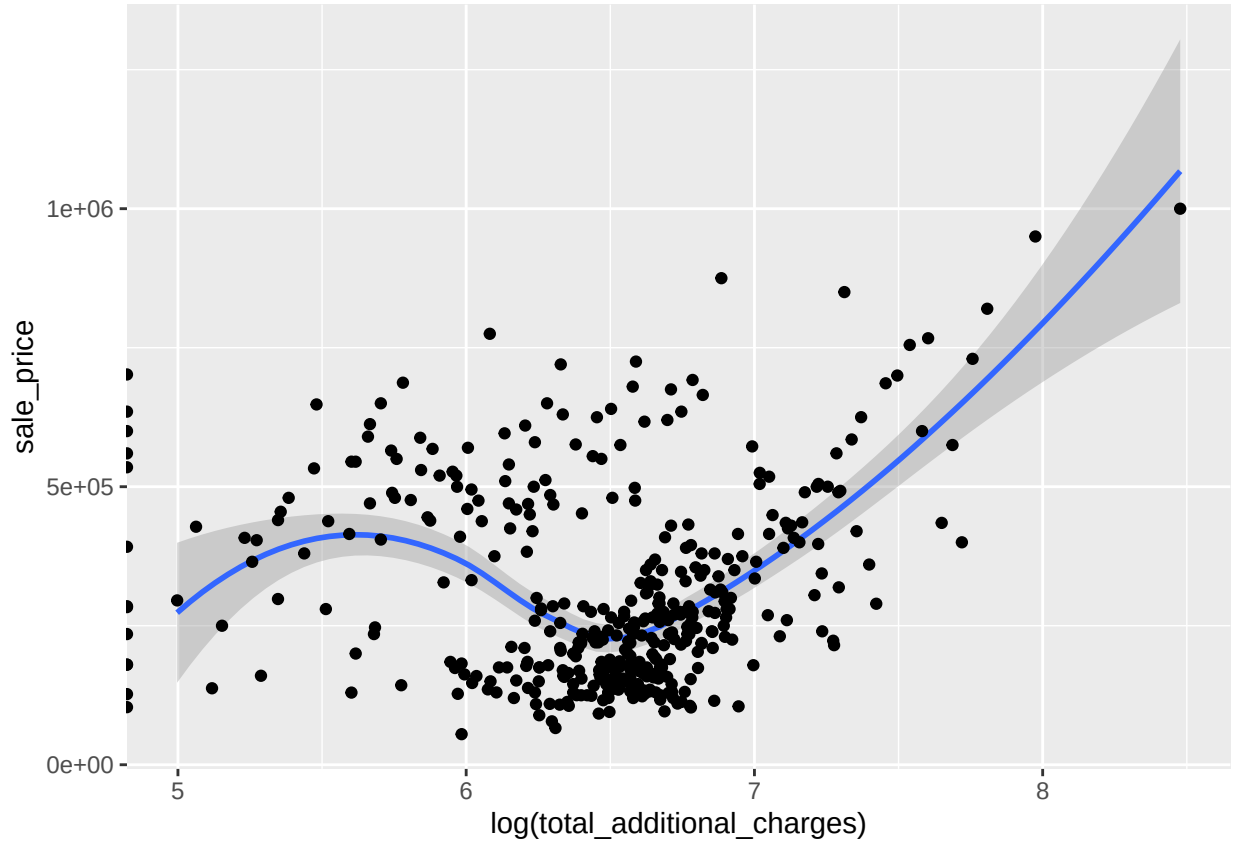
```
housing_data_test_imp = housing_data_test_train_imp[1:nrow(housing_data_test_imp), ]
```

Playing with visualizations to consider feature transformations.

```
#Not a linear relationship.
ggplot(housing_data_train_imp) +
  aes(x = log(total_additional_charges), y = sale_price) +
  geom_smooth() +
  geom_jitter()
```

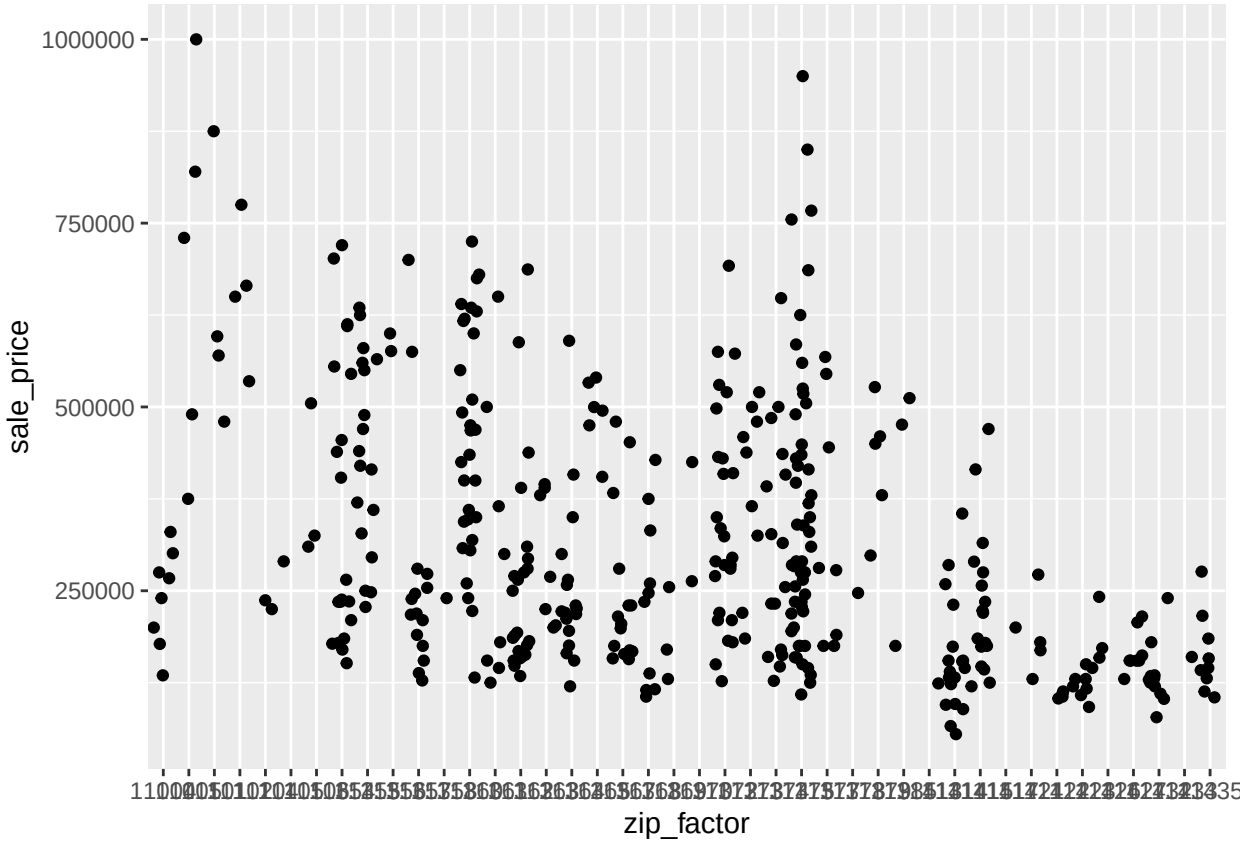
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

```
## Warning: Removed 13 rows containing non-finite values (stat_smooth).
```



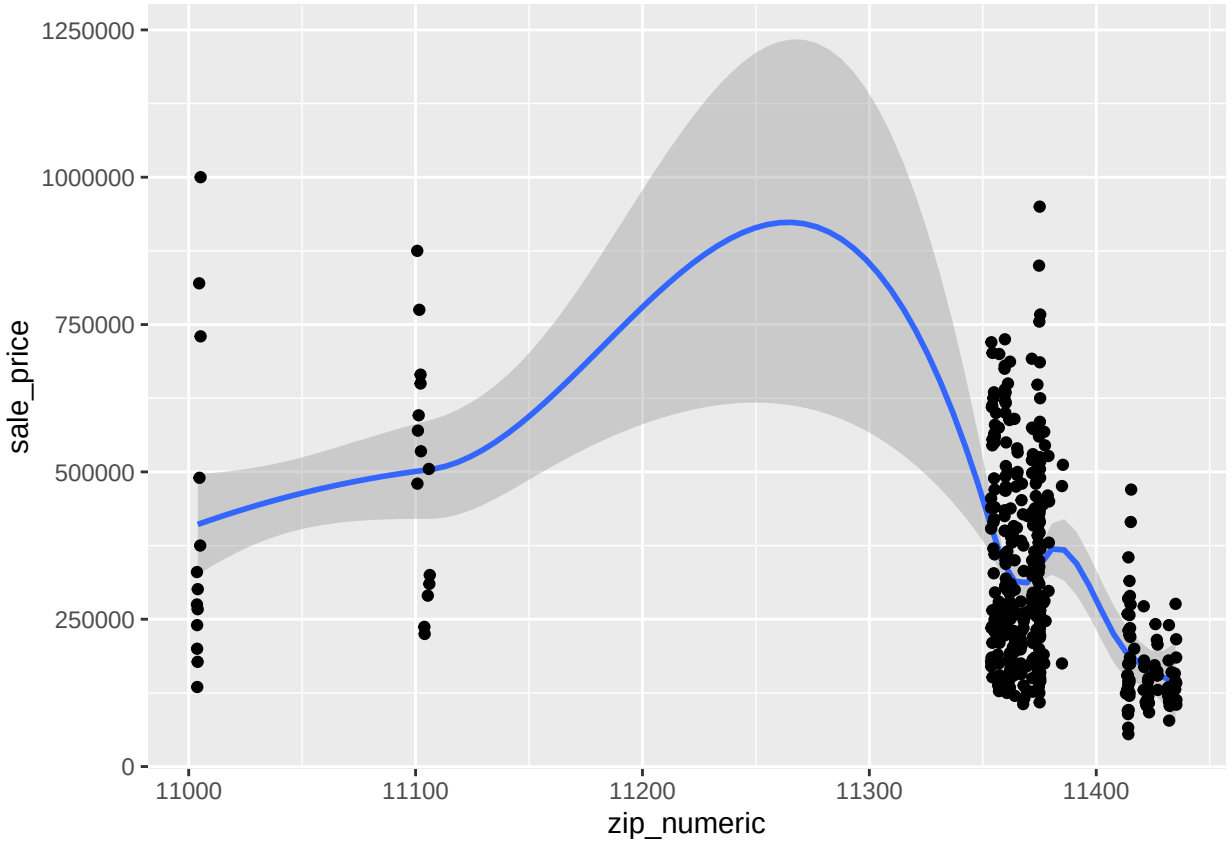

```
#Note how the relative lack of data in zip codes (just two zips?) below 11300 as well as the lack of de


ggplot(housing_data_train_imp) +
  aes(x = zip_factor, y = sale_price) +
  geom_smooth() +
  geom_jitter()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



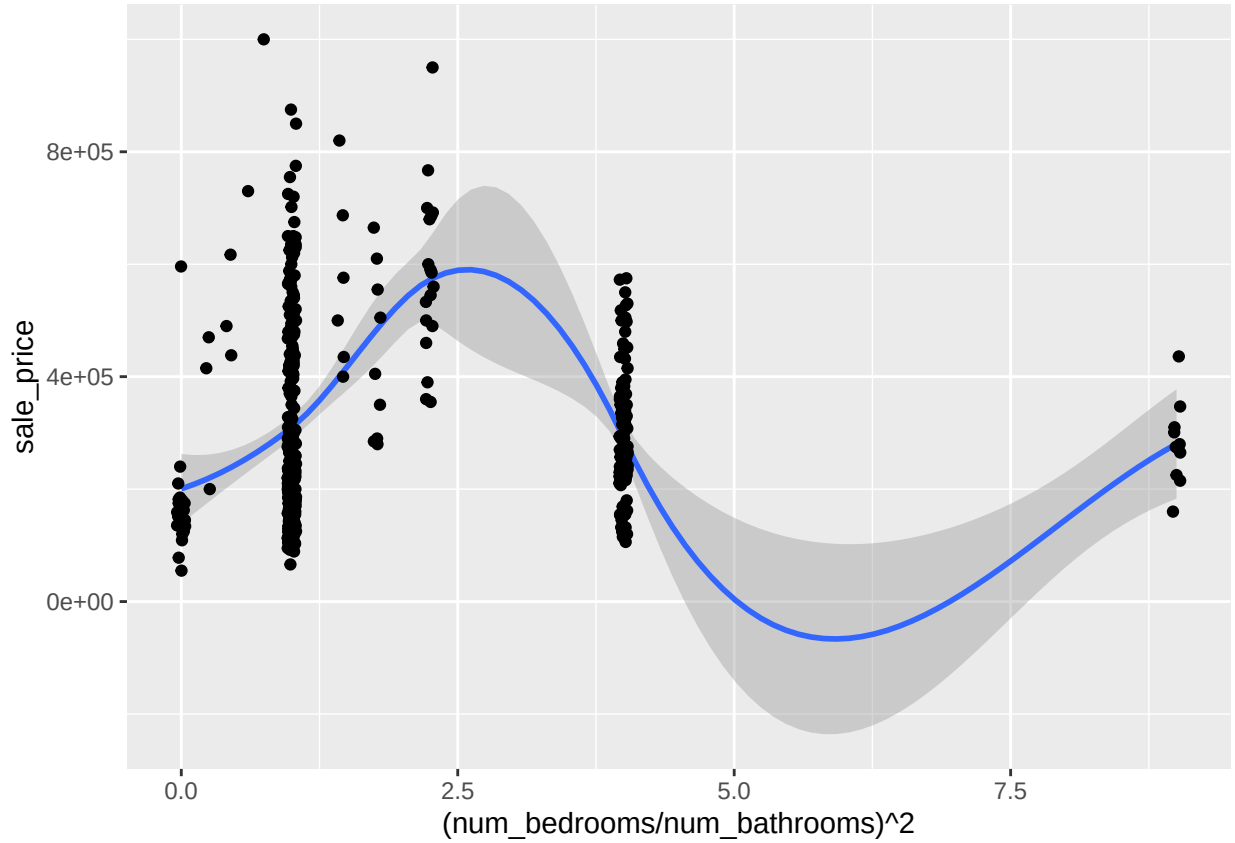

```
ggplot(housing_data_train_imp) +
  aes(x = zip_numeric, y = sale_price) +
  geom_smooth() +
  geom_jitter()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



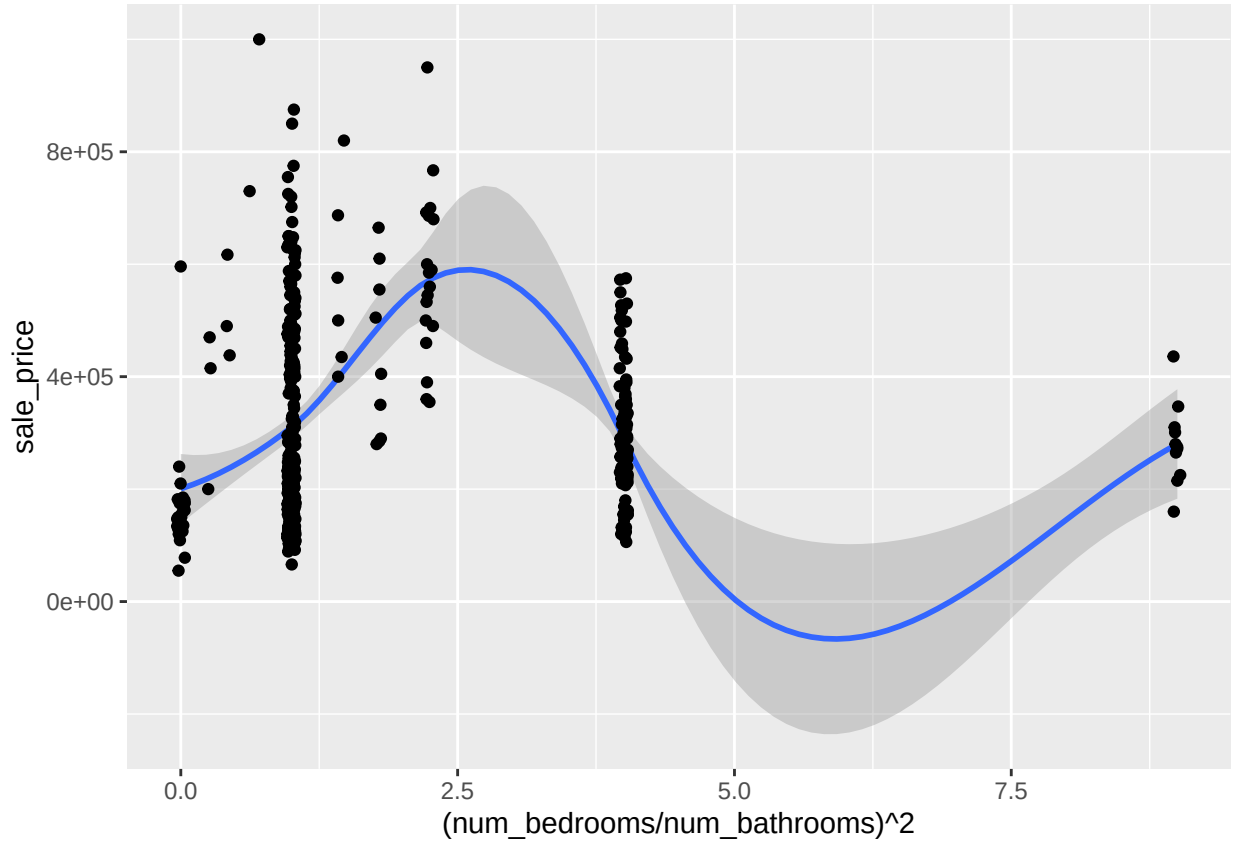

```
#Visualize effect of interactions between #bedrooms and #bathrooms on sale price
ggplot(housing_data_train_imp) +
  aes(x = (num_bedrooms / num_bathrooms)^2, y = sale_price) +
  geom_smooth() +
  geom_jitter()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
ggplot(housing_data_train_imp) +
  aes(x = (num_bedrooms / num_bathrooms)^2, y = sale_price) +
  geom_smooth() +
  geom_jitter()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Feature Transformations

Add feature transformations to be included in models.

```
#Training Data Transformations

housing_data_train_imp = housing_data_train_imp %>%
  mutate(log_tot_add_charges = log(total_additional_charges)) %>%
  mutate(log_tot_add_charges = ifelse(log_tot_add_charges == -Inf, 0, log_tot_add_charges)) %>%
    select(-num_half_bathrooms) %>%
    mutate(num_missing = (as.numeric(common_charges_missing) + as.numeric(approx_year_built_missing) + a
      select(-common_charges_missing, -approx_year_built_missing, -maintenance_cost_missing, -num_floors

housing_data_train_imp = housing_data_train_imp %>%
  mutate(bedroom_sq_ft_ratio = num_bedrooms / sq_footage) %>%
  mutate(bedroom_bathroom_ratio = num_bedrooms / num_bathrooms) %>%
    select(-zip_numeric)

#Test Data Transformations


housing_data_test_imp = housing_data_test_imp %>%
  mutate(log_tot_add_charges = log(total_additional_charges)) %>%
  mutate(log_tot_add_charges = ifelse(log_tot_add_charges == -Inf, 0, log_tot_add_charges)) %>%
    select(-num_half_bathrooms) %>%
    mutate(num_missing = (as.numeric(common_charges_missing) + as.numeric(approx_year_built_missing) + a
      select(-common_charges_missing, -approx_year_built_missing, -maintenance_cost_missing, -num_floors
```

```
housing_data_test_imp = housing_data_test_imp %>%
  mutate(bedroom_sq_ft_ratio = num_bedrooms / sq_footage) %>%
  mutate(bedroom_bathroom_ratio = num_bedrooms / num_bathrooms) %>%
    select(-zip_numeric)


#head(housing_data_train_imp)
#head(housing_data_test_imp)
```

Split into X, y test and training sets.

```
X_train = housing_data_train_imp[ , 2:ncol(housing_data_train_imp)]
y_train = housing_data_train_imp[ , 1]

X_test = housing_data_test_imp[ , 2:ncol(housing_data_test_imp)]
y_test = housing_data_test[ ,1]
```

##Regression Tree Modeling (3.1)

Load YARF

```
Sys.setenv(JAVA_HOME = '/usr/lib/jvm/jdk1.8.0_65')

if (!pacman::p_isinstalled(YARF)){
  pacman::p_install_gh("kapelner/YARF/YARFJARs", ref = "dev")
  pacman::p_install_gh("kapelner/YARF/YARF", ref = "dev", force = TRUE)
}
options(java.parameters = "-Xmx4000m")
pacman::p_load(YARF)
```

```
## YARF can now make use of 7 cores.
```

```
library(YARF, YARFJARs)
```

Create one tree model.

```
mod_YARF = YARF(y = y_train, X = X_train, num_trees = 1)
```

```
## YARF initializing with a fixed 1 trees...
## YARF factors created...
## YARF after data preprocessed... 87 total features...
## Beginning YARF regression model construction...done.
## Calculating OOB error...done.
```

```
illustrate_trees(mod_YARF, max_depth = 5, length_in_px_per_half_split = 30, font_size = 14, line_rgb_co

mod_YARF
```

```
## YARF v1.1 for regression
## Missing data feature ON.
```

```
## 1 trees, training data n = 411 and p = 87
## Model construction completed within 0.02 minutes.
## OOB results on 36.74% of the observations (260 missing):
##   R^2: 0.79675
##   RMSE: 131556.1
##   MAE: 91496.32
##   L2: 2.613356e+12
##   L1: 13815945
```

Tree Metrics? Nope.. Just a free space to check out some things.

```
#housing_data_test
#housing_data_train_imp
```

##Linear Modeling (3.2)

Create OLS Model

```
#summary(X_train)
#str(X_train)

mod_ols = lm(y_train ~ ., X_train)
mod_ols
```

```
##
## Call:
## lm(formula = y_train ~ ., data = X_train)
##
## Coefficients:
##              (Intercept)         approx_year_built           cats_allowedyes
##               -1.446e+09                 3.831e+02                 1.478e+04
##   community_district_num           coop_condocondo              date_of_sale
##                3.691e+03                 2.213e+05                -1.936e+03
##    dining_room_typeother    dining_room_typeformal   dining_room_typeunknown
##                7.971e+03                 1.898e+04                -3.191e+03
##          dogs_allowedyes              fuel_typegas             fuel_typenone
##               -6.963e+03                 2.068e+04                 5.355e+04
##             fuel_typeoil            fuel_typeother          fuel_typeunknown
##                3.470e+04                 5.636e+04                 2.944e+04
##        garage_existsTRUE         kitchen_typecombo        kitchen_typeeat in
##                6.624e+03                 1.710e+04                -7.028e+02
##   kitchen_typeefficiency              num_bedrooms    num_floors_in_building
##               -9.270e+03                 9.546e+04                 3.255e+03
##       num_full_bathrooms           num_total_rooms         pct_tax_deductibl
##                1.933e+04                 5.545e+03                -1.125e+03
##               sq_footage               total_taxes                walk_score
##               -4.312e+01                 6.032e-02                -7.724e+02
##            num_bathrooms             month_of_year               day_of_week
##                8.853e+04                 6.252e+04                 2.240e+02
##              day_of_month                      year           zip_factor11005
##                1.690e+03                 7.329e+05                 3.230e+04
##          zip_factor11101           zip_factor11102           zip_factor11104
##                1.359e+05                 1.211e+05                 6.448e+04
```

```
##          zip_factor11105          zip_factor11106          zip_factor11354
##               -6.936e+03                1.151e+05                2.487e+04
##          zip_factor11355          zip_factor11356          zip_factor11357
##               -2.281e+04               -1.402e+05               -5.195e+04
##          zip_factor11358          zip_factor11360          zip_factor11361
##                5.849e+04               -2.299e+04                1.078e+04
##          zip_factor11362          zip_factor11363          zip_factor11364
##               -5.029e+04               -9.965e+03               -2.801e+04
##          zip_factor11365          zip_factor11367          zip_factor11368
##               -3.576e+04               -2.449e+04               -1.180e+05
##          zip_factor11369          zip_factor11370          zip_factor11372
##               -3.285e+04               -2.531e+04                6.362e+04
##          zip_factor11373          zip_factor11374          zip_factor11375
##               -8.468e+03                5.270e+03                4.913e+04
##          zip_factor11377          zip_factor11378          zip_factor11379
##                3.933e+04               -5.072e+03               -5.762e+04
##          zip_factor11385          zip_factor11413          zip_factor11414
##               -3.403e+04               -6.652e+04               -1.591e+05
##          zip_factor11415          zip_factor11417          zip_factor11421
##               -6.599e+04               -3.246e+05               -8.964e+04
##          zip_factor11422          zip_factor11423          zip_factor11426
##               -7.721e+04               -9.578e+04               -1.097e+04
##          zip_factor11427          zip_factor11432          zip_factor11433
##               -5.776e+04               -8.979e+04               -4.251e+05
##          zip_factor11435   total_taxes_missingTRUE  total_additional_charges
##               -6.729e+04               -1.644e+04                8.901e+01
##      log_tot_add_charges             num_missing       bedroom_sq_ft_ratio
##               -1.234e+04                2.224e+02               -1.102e+08
##   bedroom_bathroom_ratio
##                7.974e+04
```

```
View(data.frame(coefficients(mod_ols)), "OLS Model Coefficients")
```

OLS In-Sample Metrics

```
RMSE = summary(mod_ols)$sigma
RMSE
```

```
## [1] 64677.72
```

```
r_squared = summary(mod_ols)$r.square

View(data.frame(cbind("R Squared" = r_squared, "RMSE" = RMSE)),  title = "OLS Model In-Sample Errors")
```

##Random Forest Modeling (3.3)

Create RF Model

```
rf_mod = randomForest(y_train ~ . , data = X_train, ntree = 6000, mtry = 25)

rf_mod_YARF = YARF(X = X_train, y = y_train, num_trees = 6000, mtry = 25)
```

```
## YARF initializing with a fixed 6000 trees...
## YARF factors created...
## YARF after data preprocessed... 87 total features...
## Beginning YARF regression model construction...done.
## Calculating OOB error...done.
```

##Performance Results for Random Forest (4)

RF Metrics

```
rf_mod
```

```
##
## Call:
##  randomForest(formula = y_train ~ ., data = X_train, ntree = 6000,      mtry = 25)
##                Type of random forest: regression
##                      Number of trees: 6000
## No. of variables tried at each split: 25
##
##           Mean of squared residuals: 5977895159
##                     % Var explained: 80.89
```

```
rf_mod_YARF
```

```
## YARF v1.1 for regression
## Missing data feature ON.
## 6000 trees, training data n = 411 and p = 87
## Model construction completed within 0.93 minutes.
## OOB results on all observations:
##   R^2: 0.77309
##   RMSE: 84254.63
##   MAE: 58324.4
##   L2: 2.917625e+12
##   L1: 23971329
```

```
oob_se = sd(housing_data_train$sale_price - rf_mod$predicted)
oob_se
```

```
## [1] 77279.66
```

```
View(data.frame(cbind("R-Squared" = max(rf_mod$rsq), "OOB_SE" = oob_se)), "Random Forest Metrics")
```

#Break open the test data.

Out-of-sample OLS model metrics

```
y_test = as.matrix(y_test)

y_hat_oos = predict(mod_ols, X_test)
oos_residuals = y_test - y_hat_oos

R_sq_oos = 1 - sum(oos_residuals^2) / sum((y_test - mean(y_test))^2)
```

```
RMSE_oos = sqrt(mean(oos_residuals^2))
ooss_e = sd(y_hat_oos - y_test)

RMSE_oos
```

```
## [1] 69535.17
```

```
R_sq_oos
```

```
## [1] 0.8625976
```

```
ooss_e
```

```
## [1] 69821.17
```

Create a final OLS model and compute final in-sample statistics for whole data set.

```
train = cbind(X_train, "sale_price" = y_train)
test = cbind(X_test, y_test)
full = rbind(train, test)

head(train)
```

```
##   approx_year_built cats_allowed community_district_num coop_condo date_of_sale
## 1              1955           no                      25      co-op        16847
## 2              1955           no                      25      co-op        16847
## 3              2004           no                      24      condo        16848
## 4              2002           no                      25      condo        16848
## 5              1949          yes                      26      co-op        16849
## 6              1950           no                      29      co-op        16850
##   dining_room_type dogs_allowed fuel_type garage_exists kitchen_type
## 1            combo           no       gas         FALSE       eat in
## 2           formal           no       oil         FALSE       eat in
## 3            combo           no   unknown         FALSE   efficiency
## 4            combo           no       gas         FALSE       eat in
## 5            combo          yes       gas         FALSE       eat in
## 6            combo           no       gas         FALSE   efficiency
##   num_bedrooms num_floors_in_building num_full_bathrooms num_total_rooms
## 1            2               6.000000                  1               5
## 2            1               7.000000                  1               4
## 3            1               1.000000                  1               3
## 4            3               6.306667                  2               5
## 5            2               2.000000                  1               4
## 6            1               4.490000                  1               3
##   pct_tax_deductibl sq_footage total_taxes walk_score num_bathrooms
## 1            44.290   993.1100     2058.53         82             1
## 2            44.000   890.0000     2663.36         89             1
## 3            42.550   550.0000     5500.00         90             1
## 4            42.120   966.9858     2260.00         94             2
## 5            39.000   675.0000     2641.52         71             1
## 6            41.015   711.8900     2299.87         72             1
```

```
##   month_of_year day_of_week day_of_month year zip_factor total_taxes_missing
## 1             2           3           16 2016      11355                TRUE
## 2             2           3           16 2016      11354                TRUE
## 3             2           4           17 2016      11368               FALSE
## 4             2           4           17 2016      11354               FALSE
## 5             2           5           18 2016      11426                TRUE
## 6             2           6           19 2016      11423                TRUE
##   total_additional_charges log_tot_add_charges num_missing bedroom_sq_ft_ratio
## 1                      767            6.642487          13         0.002013876
## 2                      604            6.403574          12         0.001123596
## 3                      167            5.117994          11         0.001818182
## 4                      275            5.616771          13         0.003102424
## 5                      660            6.492240          11         0.002962963
## 6                      660            6.492240          14         0.001404711
##   bedroom_bathroom_ratio sale_price
## 1                    2.0     228000
## 2                    1.0     235500
## 3                    1.0     137550
## 4                    1.5     545000
## 5                    2.0     241700
## 6                    1.0     145000
```

```
head(test)
```

```
##   approx_year_built cats_allowed community_district_num coop_condo date_of_sale
## 1              1926           no                     25      condo        17123
## 2              1982          yes                     25      condo        17100
## 3              1947          yes                     26      co-op        17058
## 4              1956           no                     28      co-op        17156
## 5              1950          yes                     26      co-op        17106
## 6              1950           no                     24      co-op        17037
##   dining_room_type dogs_allowed fuel_type garage_exists kitchen_type
## 1          unknown           no       oil         FALSE       eat in
## 2            combo           no       gas         FALSE       eat in
## 3            combo          yes       gas         FALSE   efficiency
## 4            combo           no       gas          TRUE       eat in
## 5            combo           no       oil         FALSE       eat in
## 6           formal           no       gas          TRUE       eat in
##   num_bedrooms num_floors_in_building num_full_bathrooms num_total_rooms
## 1            3                     6                  2              6
## 2            2                    22                  3              7
## 3            1                     2                  1              3
## 4            1                     6                  1              3
## 5            2                     2                  1              4
## 6            2                     6                  1              4
##   pct_tax_deductibl sq_footage total_taxes walk_score num_bathrooms
## 1          38.96668  2000.0000    5359.000         96             2
## 2          41.70799  1419.0000    5807.000         82             3
## 3          43.31925   730.4336    2273.023         74             1
## 4          20.00000   921.6717    2585.406         91             1
## 5          43.11997   903.7003    2685.371         77             1
## 6          43.53132  1100.0000    2557.847         87             1
##   month_of_year day_of_week day_of_month year zip_factor total_taxes_missing
## 1            11           6           18 2016      11355               FALSE
```

```
## 2            10           4           26 2016      11360               FALSE
## 3             9           4           14 2016      11004                TRUE
## 4            12           4           21 2016      11375                TRUE
## 5            11           3            1 2016      11362                TRUE
## 6             8           4           24 2016      11355                TRUE
##   total_additional_charges log_tot_add_charges num_missing bedroom_sq_ft_ratio
## 1                      821            6.710523          11         0.001500000
## 2                     1017            6.924612          11         0.001409443
## 3                      497            6.208590          13         0.001369050
## 4                      740            6.606650          11         0.001084985
## 5                      810            6.697034          13         0.002213123
## 6                      886            6.786717          11         0.001818182
##   bedroom_bathroom_ratio sale_price
## 1              1.5000000     830000
## 2              0.6666667     790000
## 3              1.0000000     189000
## 4              1.0000000     205000
## 5              2.0000000     248500
## 6              2.0000000     355000
```

```
X = full[ , 1:(ncol(full) - 1)]
y = full[ , ncol(full)]

ols_mod_final = lm(y ~ ., X)
summary(ols_mod_final)
```

```
##
## Call:
## lm(formula = y ~ ., data = X)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -231664  -34006     -26   28740  257163
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -2.008e+09  6.031e+09  -0.333 0.739305
## approx_year_built         4.561e+02  2.830e+02   1.612 0.107656
## cats_allowedyes           1.320e+04  9.561e+03   1.380 0.168178
## community_district_num    3.243e+03  1.157e+03   2.803 0.005277 **
## coop_condocondo           2.254e+05  2.941e+04   7.663 1.13e-13 ***
## date_of_sale             -2.713e+03  8.344e+03  -0.325 0.745233
## dining_room_typeother     1.260e+04  1.089e+04   1.158 0.247533
## dining_room_typeformal    2.216e+04  8.157e+03   2.717 0.006836 **
## dining_room_typeunknown   1.783e+03  7.878e+03   0.226 0.821088
## dogs_allowedyes          -2.475e+03  1.053e+04  -0.235 0.814328
## fuel_typegas              3.651e+04  2.185e+04   1.671 0.095494 .
## fuel_typenone             7.711e+04  4.680e+04   1.648 0.100099
## fuel_typeoil              4.559e+04  2.238e+04   2.037 0.042216 *
## fuel_typeother            2.750e+04  3.166e+04   0.868 0.385615
## fuel_typeunknown          4.645e+04  2.555e+04   1.818 0.069714 .
## garage_existsTRUE         3.438e+03  8.892e+03   0.387 0.699228
## kitchen_typecombo         1.008e+04  2.731e+04   0.369 0.712176
## kitchen_typeeat in       -8.320e+03  2.664e+04  -0.312 0.754943
```

```
## kitchen_typeefficiency   -1.584e+04  2.665e+04  -0.594 0.552569
## num_bedrooms              1.485e+05  2.687e+04   5.526 5.57e-08 ***
## num_floors_in_building    3.122e+03  7.352e+02   4.247 2.64e-05 ***
## num_full_bathrooms        4.243e+04  2.787e+04   1.522 0.128620
## num_total_rooms           5.348e+03  5.108e+03   1.047 0.295702
## pct_tax_deductibl        -7.033e+02  9.524e+02  -0.738 0.460603
## sq_footage               -4.118e+01  1.499e+01  -2.747 0.006264 **
## total_taxes              -6.408e-01  3.889e+00  -0.165 0.869190
## walk_score               -5.379e+02  3.726e+02  -1.444 0.149494
## num_bathrooms             1.761e+04  4.117e+04   0.428 0.668969
## month_of_year             8.602e+04  2.548e+05   0.338 0.735843
## day_of_week              -6.184e+02  2.179e+03  -0.284 0.776703
## day_of_month              2.547e+03  8.370e+03   0.304 0.761039
## year                      1.018e+06  3.061e+06   0.333 0.739536
## zip_factor11005           4.645e+04  4.294e+04   1.082 0.279960
## zip_factor11101           1.481e+05  4.084e+04   3.626 0.000321 ***
## zip_factor11102           1.057e+05  3.718e+04   2.843 0.004666 **
## zip_factor11104           2.968e+04  4.586e+04   0.647 0.517842
## zip_factor11105           8.436e+04  5.139e+04   1.641 0.101403
## zip_factor11106           8.865e+04  3.965e+04   2.236 0.025864 *
## zip_factor11354           1.322e+04  2.601e+04   0.508 0.611436
## zip_factor11355          -1.708e+04  2.669e+04  -0.640 0.522465
## zip_factor11356          -1.607e+05  4.336e+04  -3.706 0.000237 ***
## zip_factor11357          -4.121e+04  2.597e+04  -1.587 0.113323
## zip_factor11358          -2.341e+03  4.261e+04  -0.055 0.956209
## zip_factor11360          -2.826e+04  2.518e+04  -1.122 0.262364
## zip_factor11361           3.818e+02  2.923e+04   0.013 0.989584
## zip_factor11362          -4.514e+04  2.495e+04  -1.809 0.071070 .
## zip_factor11363          -7.976e+03  3.254e+04  -0.245 0.806460
## zip_factor11364          -4.016e+04  2.479e+04  -1.620 0.105917
## zip_factor11365          -6.191e+04  3.102e+04  -1.996 0.046528 *
## zip_factor11367          -3.881e+04  2.444e+04  -1.588 0.113019
## zip_factor11368          -1.262e+05  2.930e+04  -4.307 2.03e-05 ***
## zip_factor11369          -6.403e+04  3.944e+04  -1.624 0.105174
## zip_factor11370          -1.095e+04  4.323e+04  -0.253 0.800135
## zip_factor11372           6.277e+04  2.551e+04   2.461 0.014243 *
## zip_factor11373          -2.509e+04  3.115e+04  -0.805 0.420987
## zip_factor11374          -7.162e+03  2.692e+04  -0.266 0.790335
## zip_factor11375           3.574e+04  2.444e+04   1.463 0.144272
## zip_factor11377           2.718e+04  3.077e+04   0.883 0.377576
## zip_factor11378          -1.012e+04  6.732e+04  -0.150 0.880545
## zip_factor11379          -7.473e+04  3.707e+04  -2.016 0.044392 *
## zip_factor11385          -6.615e+04  4.014e+04  -1.648 0.100003
## zip_factor11413          -7.259e+04  6.775e+04  -1.071 0.284565
## zip_factor11414          -1.526e+05  2.426e+04  -6.288 7.62e-10 ***
## zip_factor11415          -6.320e+04  2.570e+04  -2.460 0.014286 *
## zip_factor11417          -2.093e+05  5.170e+04  -4.048 6.08e-05 ***
## zip_factor11421          -9.484e+04  3.548e+04  -2.673 0.007791 **
## zip_factor11422          -7.737e+04  4.159e+04  -1.860 0.063514 .
## zip_factor11423          -9.562e+04  3.063e+04  -3.122 0.001913 **
## zip_factor11426          -9.692e+03  4.201e+04  -0.231 0.817661
## zip_factor11427          -7.236e+04  3.078e+04  -2.351 0.019143 *
## zip_factor11432          -9.672e+04  2.890e+04  -3.347 0.000885 ***
## zip_factor11433          -4.365e+05  7.009e+04  -6.228 1.09e-09 ***
```

```
## zip_factor11435          -7.904e+04  2.811e+04  -2.812 0.005146 **
## total_taxes_missingTRUE  -6.655e+03  2.692e+04  -0.247 0.804857
## total_additional_charges  8.184e+01  1.557e+01   5.255 2.29e-07 ***
## log_tot_add_charges      -1.101e+04  3.609e+03  -3.050 0.002426 **
## num_missing              -1.874e+03  3.360e+03  -0.558 0.577404
## bedroom_sq_ft_ratio      -1.078e+08  1.868e+07  -5.773 1.46e-08 ***
## bedroom_bathroom_ratio    2.463e+04  2.890e+04   0.852 0.394495
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 63310 on 449 degrees of freedom
## Multiple R-squared:  0.894,  Adjusted R-squared:  0.8756
## F-statistic: 48.57 on 78 and 449 DF,  p-value: < 2.2e-16
```

```
summary(ols_mod_final)$r.sq
```

```
## [1] 0.8940442
```

```
R_sq_final = summary(ols_mod_final)$r.sq
RMSE_final = summary(ols_mod_final)$sigma
```

```
RMSE_Rsq_table = data.frame(cbind("RMSE" = c(RMSE, RMSE_oos, RMSE_final), "R Squared" = c(r_squared, R_s

View(RMSE_Rsq_table)
```