Housing Price Analysis Using Linear Regression

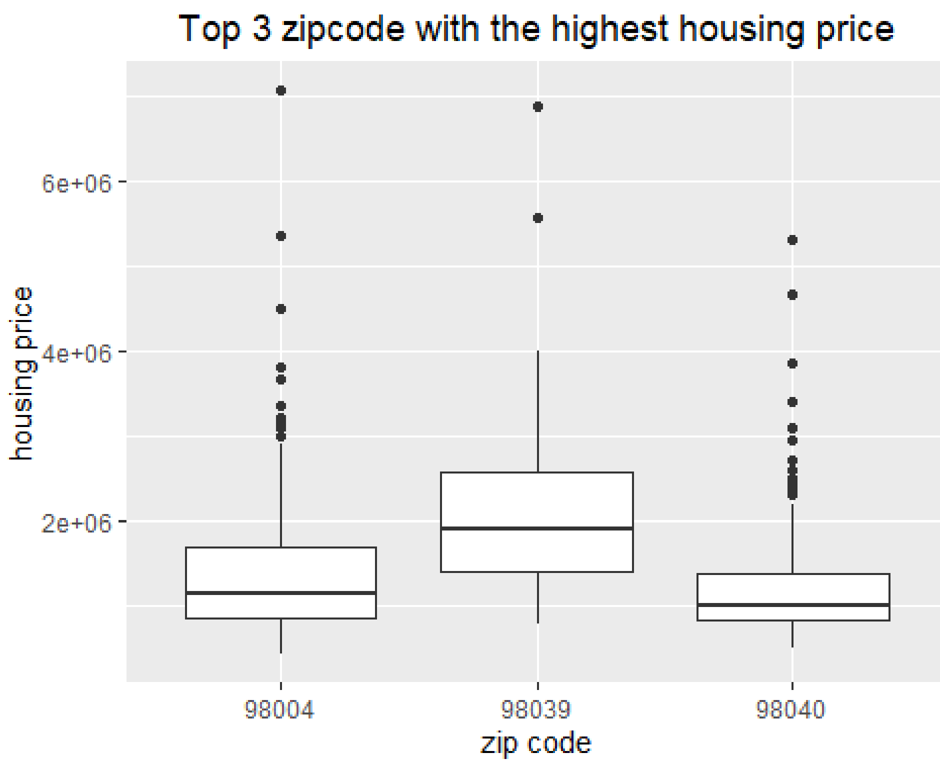
Part 1. EDA

I first noticed that *'zipcode'* is the only variable that is not numeric. Thus, I decided to rank the zipcodes by their average housing price to get a sense of how they are related to each other.

```
ave.zip = tapply(price, zipcode, mean)
head(sort(ave.zip)) #bottom 5 zip code with the lowest average housing price

##    98002    98168    98032    98001    98148    98023
## 234284.0 240328.4 251296.2 280804.7 284908.6 286732.8

tail(sort(ave.zip)) #top 5 zip code with the highest average housing price

##     98109     98102     98112     98040     98004     98039
##  879623.6  901258.2 1095499.4 1194230.0 1355927.1 2160606.6

top.zip = housing[c(which(zipcode == "98039"),
                    which(zipcode == "98004"),
                    which(zipcode == "98040")),]
```

I sorted the zipcodes and found the top 5 and bottom 5 zipcodes whose housing prices are the most and least expensive respectively. Below is boxplots for the top 3 zipcodes.

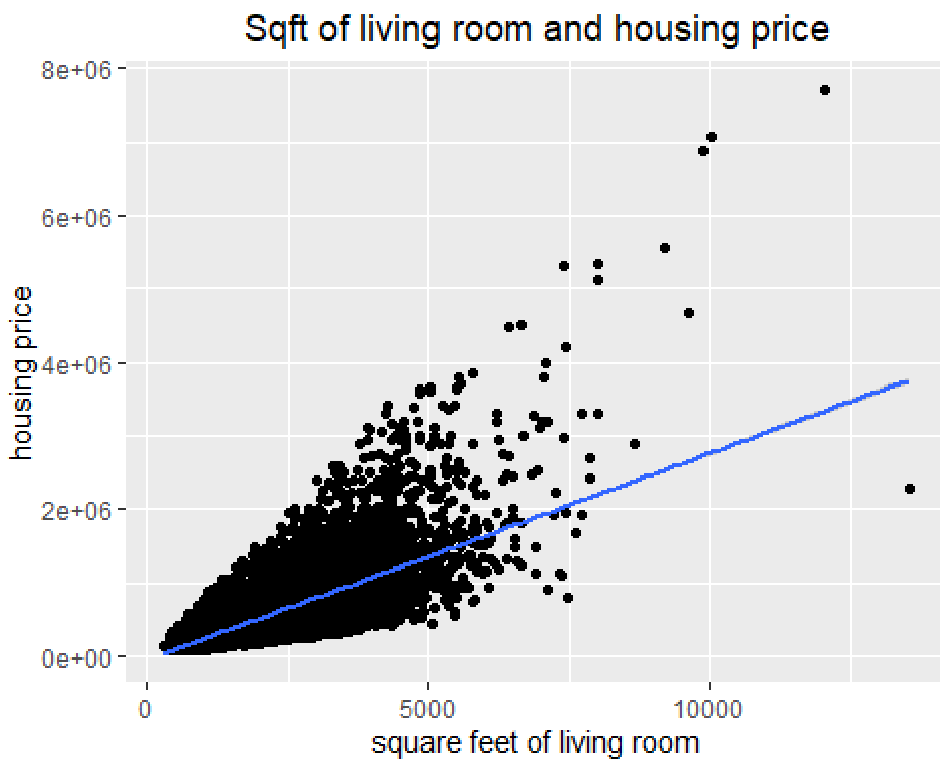
```
#generate boxplot
library(ggplot2) # for ggplot
p = ggplot(top.zip, aes(x = as.factor(zipcode), y = price))+
  geom_boxplot()+
  xlab("zip code")+
  ylab("housing price")+
  labs(title = "Top 3 zipcode with the highest housing price")+
  theme(plot.title = element_text(hjust = 0.5))
p
```

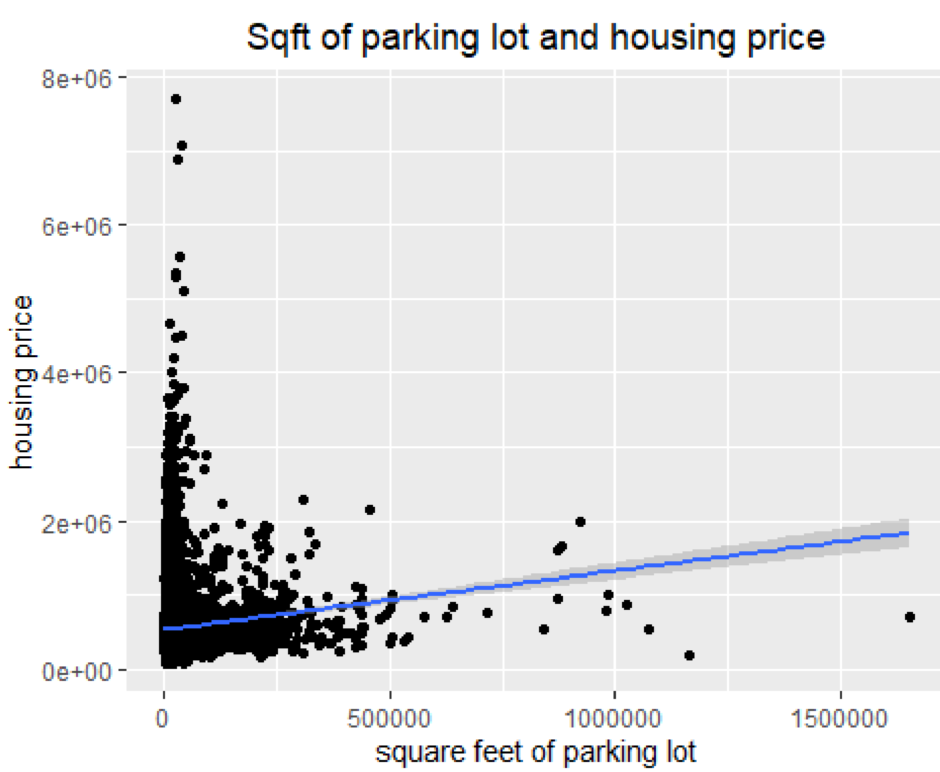


Part 2. EDA (continued)

Now I decided to look at how quantitative variables are related to housing price by plotting scatterplots. Below are the scatterplots for '*square feet of a living room'* and '*square feet of a parking lot*', which indicate that these variables seem to have a positive correlation with *housing price*. '*Square feet of a living room'* seems to be more correlated with housing price than '*square feet of a parking lot'* does.

```
#square feet of living room and housing price

p1 = ggplot(housing, aes(x = sqft_living, y = price))+
  geom_point()+
  geom_smooth(method=lm)+
  xlab("square feet of living room")+
  ylab("housing price")+
  labs(title = "Sqft of living room and housing price")+
  theme(plot.title = element_text(hjust = 0.5))
p1

## `geom_smooth()` using formula 'y ~ x'
```


Sqft of living room and housing price
housing price
8e+06
6e+06
4e+06
2e+06
0e+00
0
5000
10000
square feet of living room


Sqft of parking lot and housing price
housing price
8e+06
6e+06
4e+06
2e+06
0e+00
0
500000
1000000
1500000
square feet of parking lot

Part 3. Modeling

Before applying linear regression model on the data, I used k-fold cross validation for model assessment. I used K = 10, since it was a commonly accepted value for the number of splits.

Next I fit a linear regression model as follow:

Housing price ~ bedrooms + bathrooms + sqft_living + sqft_lot

Cross Validation error, which is an estimate of test MSE (Mean Square Error), was calculated by averaging ten CV errors.

Here we got $66,351,069,200 for test MSE, and 0.502 for adjusted r-squared value. Given the adjusted r-squared value, this model does not seem to have enough variables related to housing price. These two values will be used for feature selection afterwards.

```
#variables: bedroom, bathroom, sqft_living, sqft_lot
library(caret)

## Loading required package: lattice

##k-fold cross validation (approach 1)
k = 10 #number of folds
n = length(housing[,1])
set.seed(1)
folds = createFolds(seq(1:n),k) #split the data in k groups

cv.error.10 = rep(0,k)
for (i in 1:k){
  index = unlist(folds[i],use.names = FALSE)
  train = housing[-index,]
  test = housing[index,]
  model = lm(price ~ bedrooms + bathrooms + sqft_living + sqft_lot,
             data = train)
  cv.error.10[i] = mean((test$price - predict(model, test))^2)
}
mean(cv.error.10) ##CV ERROR WHEN K = 10

## [1] 66351069200
```

```
#cv MSE is $66,351,069,200

summary(model)$adj.r.squared

## [1] 0.5022257

#adj r squared is 0.502
```

I also tried glm function for k-fold cross validation. Not surprisingly we got a similar result for test MSE ($66,351,830,466).

```
##k-fold cross validation (approach 2: using glm)
library(boot) #for glm

##
## Attaching package: 'boot'

## The following object is masked from 'package:lattice':
##
##     melanoma

set.seed(1)
cv.error.10.2 = rep(0,10)
for(i in 1:10){
  glm.fit = glm(price ~ bedrooms + bathrooms + sqft_living + sqft_lot,
                data = housing)
  cv.error.10.2[i] = cv.glm(housing,glm.fit, K = 10)$delta[1]
}
mean(cv.error.10.2)

## [1] 66351830466

#cv MSE is $66,351,830,466
```

Part 4. Feature Engineering

I added '*zipcode*' variable to improve the linear model previously built. Similarly, k-fold cross validation was used, and as a result, the **test MSE decreased dramatically** from $66,351,069,200 to $35,510,919,131. This result indicates that '***zipcode***' **is a significant factor for predicting housing price.**

```
#adding zipcode in the linear model

library(boot) #for glm
set.seed(1)
cv.error.zip = rep(0,10)
for(i in 1:10){
  glm.fit.zip = glm(price ~ bedrooms + bathrooms + sqft_living + sqft_lot + a
s.factor(zipcode),
                data = housing)
  cv.error.zip[i] = cv.glm(housing, glm.fit.zip, K = 10)$delta[1]
}
mean(cv.error.zip)

## [1] 35510919131

#CV MSE is $35,510,919,131 (decreased from the previous model)
```

Part 5. Prediction

Using the improved linear model, I tried to predict a housing price for a fancy house. The predicted housing price is $14,761,285, given the features of the house. The only concern here is the fact that the fancy house data are quite extreme compared to the values in the dataset used for modeling – the maximum housing price in the given dataset is $7,700,000. Thus, the model we built might not be able to extrapolated to this extreme case.

```
fancy$zipcode = as.factor(fancy$zipcode)
predict(glm.fit.zip, fancy)

##        1
## 14761285
```

```
#predicted housing price for the fancy house is $14,761,285
```

Part 6. Feature Engineering

Lastly, I tried out some different models to see if there is any room for improvement. I juggled them around by adding new variables, interaction terms, or quadratic terms. Based on the test MSE and adjusted r-squared value, I ultimately landed on my final model below:

*Housing price ~ bedrooms + bathrooms + bedrooms*bathrooms + sqft_living + sqft_living^2 + sqft_lot + zipcode*

```
#improving the linear model based on the CV MSE
k = 10 #number of folds
n = length(housing[,1])
set.seed(1)
folds = createFolds(seq(1:n),k) #split the data in k groups


#adding terms
cv.error0 = rep(0,k)
cv.error1 = rep(0,k)
cv.error2 = rep(0,k)
cv.error3 = rep(0,k)
cv.error4 = rep(0,k)
cv.error5 = rep(0,k)

for (i in 1:k){
  index = unlist(folds[i],use.names = FALSE)
  train = housing[-index,]
  test = housing[index,]

  #adding zipcode
  m0 = lm(price ~ bedrooms + bathrooms + sqft_living + sqft_lot + as.factor(z
ipcode),
                 data = train)
  m1 = lm(price ~ bedrooms + bathrooms + sqft_living + I(sqft_living^2) + sqf
t_lot + as.factor(zipcode),
```

```
              data = train)
  m2 = lm(price ~ bedrooms + bathrooms + sqft_living + I(sqft_lot^2) + as.fac
tor(zipcode),
          data = train)
  m3 = lm(price ~ bedrooms + bathrooms + sqft_living + sqft_lot + yr_built +
as.factor(zipcode),
          data = train)
  m4 = lm(price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above
+ as.factor(zipcode))
  m5 = lm(price ~ bedrooms + bathrooms + bedrooms*bathrooms + sqft_living + I
(sqft_living^2) + sqft_lot + as.factor(zipcode),
          data = train)
  cv.error0[i] = mean((test$price - predict(m0, test))^2)
  cv.error1[i] = mean((test$price - predict(m1, test))^2)
  cv.error2[i] = mean((test$price - predict(m2, test))^2)
  cv.error3[i] = mean((test$price - predict(m3, test))^2)
  cv.error4[i] = mean((test$price - predict(m4, test))^2)
  cv.error5[i] = mean((test$price - predict(m5, test))^2)
}
mean(cv.error0)

## [1] 35494949727

mean(cv.error1)

## [1] 32870191570

mean(cv.error2)

## [1] 35552317005

mean(cv.error3)

## [1] 35157847543

mean(cv.error4)

## [1] 34834352240

mean(cv.error5) #lowest CV ERROR

## [1] 32839272557

summary(m0)$adj.r.squared

## [1] 0.7379652

summary(m1)$adj.r.squared

## [1] 0.767428

summary(m2)$adj.r.squared
```

```
## [1] 0.7373796
summary(m3)$adj.r.squared
## [1] 0.7405543
summary(m4)$adj.r.squared
## [1] 0.7406675
summary(m5)$adj.r.squared #highest adjusted r squared
## [1] 0.7683188
```