REG Assignment 1

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In [ ]:
```
# imports
library(dplyr)
library(caret)
```

```
Attaching package: 'dplyr'


The following objects are masked from 'package:stats':

    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union


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    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union


Loading required package: ggplot2

Loading required package: lattice
```

In [ ]:
```
# set random seed
set.seed(42)
```

P1

1.1 Loading the Dataset

In [ ]:
```
data_path <- "data/raw/Bengaluru_House_Data.csv"
df <- read.csv(data_path)

# show the first 6 rows of the data frame
```

```
head(df)
```

A data.frame: 6 x 9

	area_type	availability	location	size	society	total_sqft	bath	b
	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<int>	
1	Super built-up Area	19-Dec	Electronic City Phase II	2 BHK	Coomee	1056	2	
2	Plot Area	Ready To Move	Chikka Tirupathi	4 Bedroom	Theanmp	2600	5	
3	Built-up Area	Ready To Move	Uttarahalli	3 BHK		1440	2	
4	Super built-up Area	Ready To Move	Lingadheeranahalli	3 BHK	Soiewre	1521	3	
5	Super built-up Area	Ready To Move	Kothanur	2 BHK		1200	2	
6	Super built-up Area	Ready To Move	Whitefield	2 BHK	DuenaTa	1170	2	

In [ ]:
```
# display the shape of the data frame
dim(df)
```

13320 · 9

So, this dataset has `13320` rows and `9` columns.

In [ ]:
```
# summary of the data frame
summary(df)
```

```
  area_type          availability          location              size          
 Length:13320       Length:13320       Length:13320       Length:13320      
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  



   society           total_sqft             bath           balcony     
 Length:13320       Length:13320       Min.   : 1.000   Min.   :0.000  
 Class :character   Class :character   1st Qu.: 2.000   1st Qu.:1.000  
 Mode  :character   Mode  :character   Median : 2.000   Median :2.000  
                                       Mean   : 2.693   Mean   :1.584  
                                       3rd Qu.: 3.000   3rd Qu.:2.000  
                                       Max.   :40.000   Max.   :3.000  
                                       NA's   :73       NA's   :609    
     price        
 Min.   :   8.0  
 1st Qu.:  50.0  
 Median :  72.0  
 Mean   : 112.6  
 3rd Qu.: 120.0  
 Max.   :3600.0  
```

Amongst the `9` columns, `6` of them are of `character` datatype and remaining `3` are of `numeric` datatype.

The `total_sqft` column should also be numeric, but it is of `character` datatype. So, we need to convert it to `numeric` datatype.

1.2 Preprocessing

1.2.1 Feature Engineering

In [ ]:
```
# check the unique values in the 'size' column
unique(df$size)
```

'2 BHK' · '4 Bedroom' · '3 BHK' · '4 BHK' · '6 Bedroom' · '3 Bedroom' · '1 BHK' · '1 RK' · '1 Bedroom' · '8 Bedroom' · '2 Bedroom' · '7 Bedroom' · '5 BHK' · '7 BHK' · '6 BHK' · '5 Bedroom' · '11 BHK' · '9 BHK' · '' · '9 Bedroom' · '27 BHK' · '10 Bedroom' · '11 Bedroom' · '10 BHK' · '19 BHK' · '16 BHK' · '43 Bedroom' · '14 BHK' · '8 BHK' · '12 Bedroom' · '13 BHK' · '18 Bedroom'

In [ ]:
```
# make 'size' into a numeric column
df <- df %>%
  mutate(size = case_when(
    grepl("^\\d+ BHK$", size) ~ as.numeric(gsub(" BHK", "", size)),
    grepl("^\\d+ Bedroom$", size) ~ as.numeric(gsub(" Bedroom", "", size)
    TRUE ~ NA_real_
  ))
```

```
Warning message:
"There were 2 warnings in `mutate()`.
The first warning was:
i In argument: `size = case_when(...)`.
Caused by warning:
! NAs introduced by coercion
i Run `dplyr::last_dplyr_warnings()` to see the 1 remaining warning."
```

We make `society` into a binary column, where:

- Assign `1` to the rows where `society` is not empty
- Assign `0` to the rows where `society` is empty

In [ ]:
```r
# make 'society' a binary column
df <- df %>%
  mutate(society = ifelse(society != "", 1, 0))
```

In [ ]:
```r
# make 'total_sqft' a numeric column
df <- df %>%
  mutate(total_sqft = case_when(
    # Check if the value is a single integer
    grepl("^\\d+$", total_sqft) ~ as.numeric(total_sqft),

    # Check if the value is a range of integers
    grepl("^\\d+ - \\d+$", total_sqft) ~ {
      # Extract the two integers from the range
      range_values <- as.numeric(strsplit(total_sqft, " - ")[[1]])
      # Calculate the midpoint
      sum(range_values) / 2
    },

    # For unknown values, set them to NA (nan)
    TRUE ~ NA_real_
  ))
```

```
Warning message:
"There was 1 warning in `mutate()`.
i In argument: `total_sqft = case_when(...)`.
Caused by warning:
! NAs introduced by coercion"
```

We can also make `availability` into a binary column, where:

- Assign `1` to the rows where `availability` is `Ready To Move`
- Assign `0` otherwise

In [ ]:
```r
# make 'availabiltiy' a binary column
df <- df %>%
  mutate(availability = case_when(
    grepl("Ready To Move", availability) ~ 1,
    TRUE ~ 0
  ))
```

In [ ]:
```r
# dataframe after feature engineering
head(df)
```

A data.frame: 6 x 9

	area_type	availability	location	size	society	total_sqft	bath	balco
	<chr>	<dbl>	<chr>	<dbl>	<dbl>	<dbl>	<int>	<in
1	Super built-up Area	0	Electronic City Phase II	2	1	1056	2	
2	Plot Area	1	Chikka Tirupathi	4	1	2600	5	
3	Built-up Area	1	Uttarahalli	3	0	1440	2	
4	Super built-up Area	1	Lingadheeranahalli	3	1	1521	3	
5	Super built-up Area	1	Kothanur	2	0	1200	2	
6	Super built-up Area	1	Whitefield	2	1	1170	2	

1.2.2 Handling Missing Values

In [ ]:
```
# check for missing values
colSums(is.na(df))
```

area_type: 0 **availability:** 0 **location:** 0 **size:** 29 **society:** 0 **total_sqft:** 138 **bath:** 73 **balcony:** 609 **price:** 0

So, we have missing values in the following columns:

- `size` : 29
- `total_sqft` : 138
- `bath` : 73
- `balcony` : 609

Since, all are numerical, we can use `mean` to fill the missing values.

In [ ]:
```
# impute missing values with mean in `total_sqft`, `bath` and `balcony` c

df$total_sqft[is.na(df$total_sqft)] <- mean(df$total_sqft, na.rm = TRUE)
df$bath[is.na(df$bath)] <- mean(df$bath, na.rm = TRUE)
df$balcony[is.na(df$balcony)] <- mean(df$balcony, na.rm = TRUE)


# drop the remaining rows with missing values
df <- na.omit(df)

# check for missing values again
```

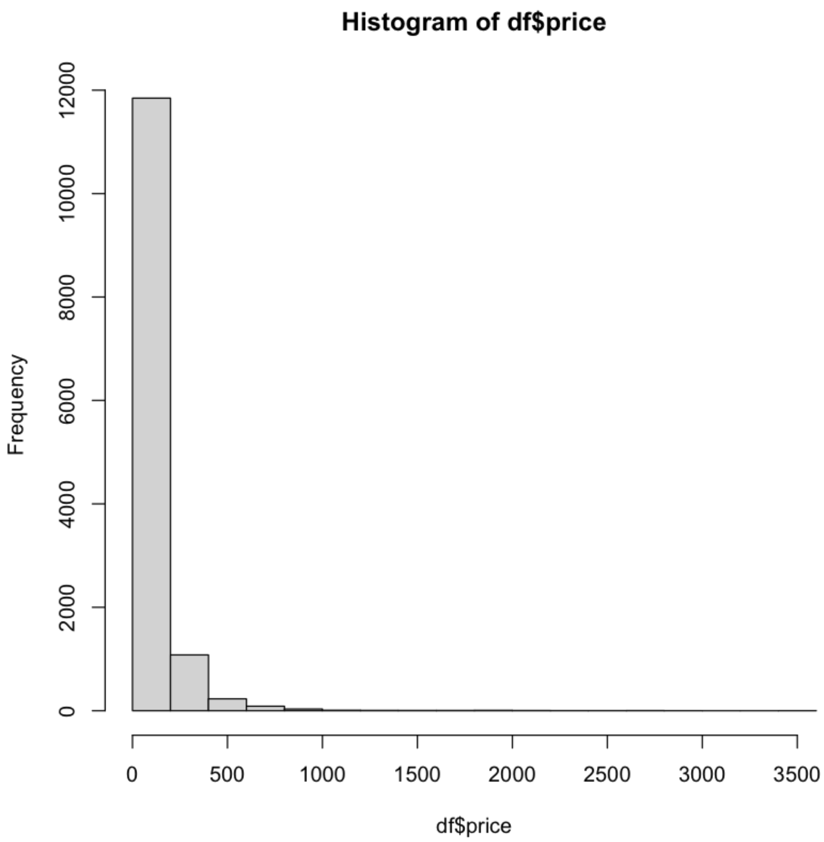
```
colSums(is.na(df))
```

area_type: 0 **availability:** 0 **location:** 0 **size:** 0 **society:** 0 **total_sqft:** 0 **bath:** 0 **balcony:** 0 **price:** 0

1.3 Exploratory Data Analysis

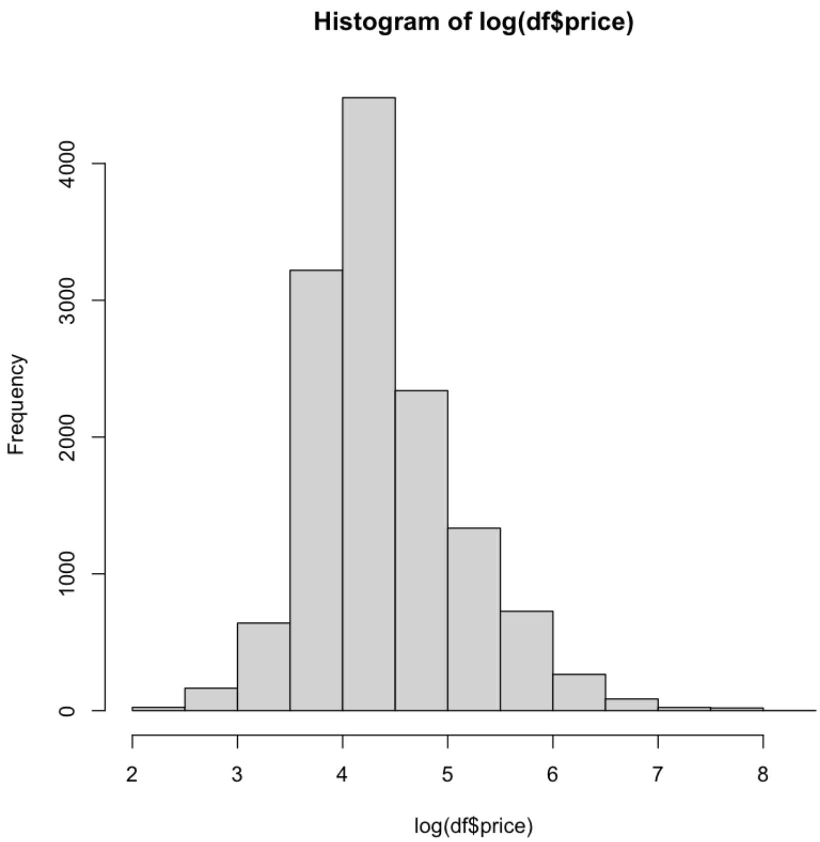
In [ ]:

```
# we plot the distribution of the target variable `price`

hist(df$price)
```



In [ ]:

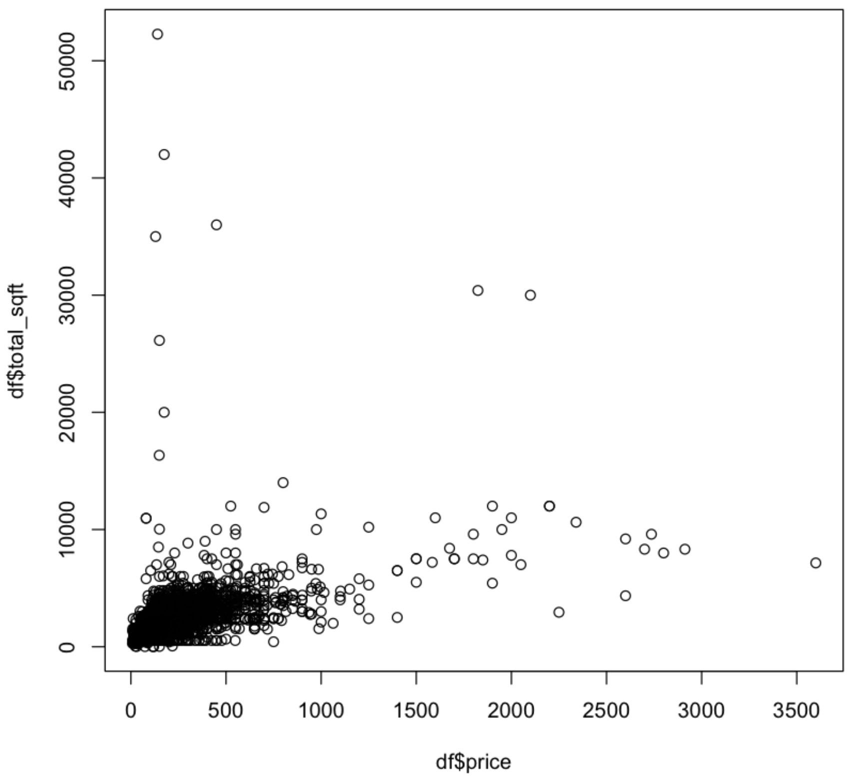
```
# we plot the distribution of the log(target) variable `log_price`

hist(log(df$price))
```



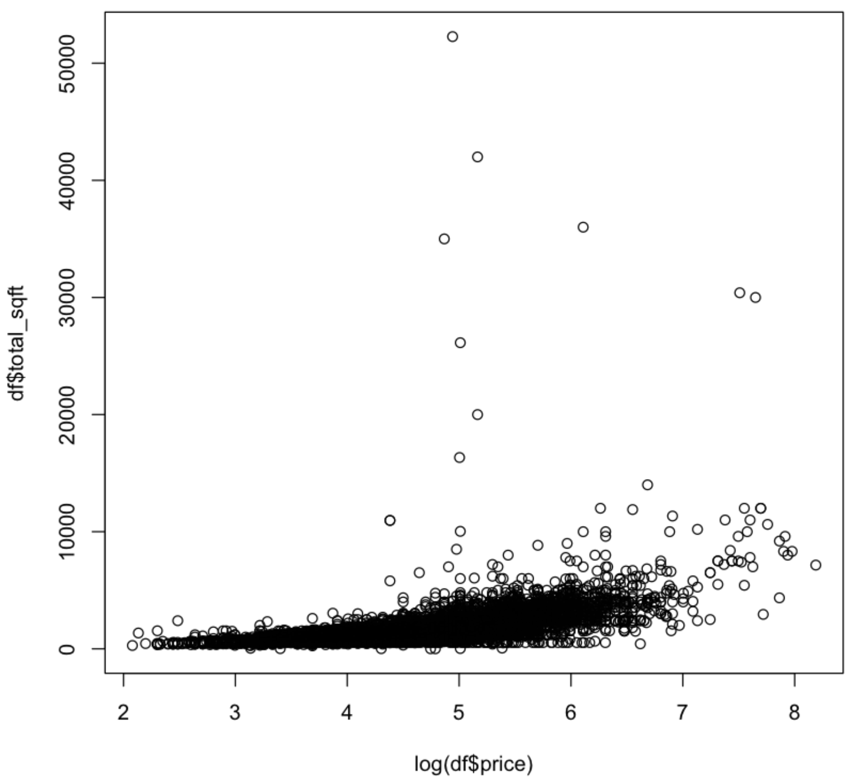
As seen from the plots, we can see that, the distribution of target variable `price` seems very skewed. But after applying `log` transformation, it looks more like a normal distribution.

So, we also experiment with the `log` transformed `price` as our target variable.

In [ ]:
```
# plot target vs 'total_sqft'

plot(df$price, df$total_sqft)
```



In [ ]:
```
# plot log(target) vs 'total_sqft'

plot(log(df$price), df$total_sqft)
```



1.4 Train Test Split

In [ ]:
```
# train test split
train_indices <- createDataPartition(df$price, p = 0.75, list = FALSE)
train_df <- df[train_indices, ]
test_df <- df[-train_indices, ]
```

1.5 Model Fitting

We use various models to fit the data and compare their performance using `R2` scores.

1.5.1 Target: `price`

In [ ]:
```
# this model uses 'size', 'society', 'bath', 'total_sqft' as features and

model_1_1 <- lm(price ~ size + society + bath + total_sqft, data = train_
summary(model_1_1)
```

```
Call:
lm(formula = price ~ +size + society + bath + total_sqft, data = train_df)

Residuals:
     Min       1Q   Median       3Q      Max 
-2901.46   -30.71   -12.71    10.42  2809.23 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -54.422074   3.414788 -15.937  < 2e-16 ***
size         -7.113568   2.096188  -3.394 0.000693 ***
society     -11.178459   2.409528  -4.639 3.54e-06 ***
bath         32.001607   2.057284  15.555  < 2e-16 ***
total_sqft    0.069974   0.001105  63.323  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 115.2 on 9964 degrees of freedom
Multiple R-squared:  0.4325,	Adjusted R-squared:  0.4323 
F-statistic:  1898 on 4 and 9964 DF,  p-value: < 2.2e-16
```

In [ ]:
```
# this model uses 'size', 'society', 'bath', 'total_sqft' as well as the

model_1_2 <- lm(price ~  size + society + bath + total_sqft + I(total_sqf
summary(model_1_2)
```

```
Call:
lm(formula = price ~ size + society + bath + total_sqft + I(total_sqft^2),
    data = train_df)

Residuals:
     Min       1Q   Median       3Q      Max
-1203.70   -31.91    -8.76    18.13  2764.04

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)     -9.062e+01  3.282e+00 -27.607  < 2e-16 ***
size            -4.755e+00  1.941e+00  -2.450   0.0143 *
society         -1.764e+01  2.236e+00  -7.892 3.29e-15 ***
bath             1.705e+01  1.939e+00   8.794  < 2e-16 ***
total_sqft       1.242e-01  1.676e-03  74.104  < 2e-16 ***
I(total_sqft^2) -2.657e-06  6.505e-08 -40.847  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 106.6 on 9963 degrees of freedom
Multiple R-squared:  0.5139,    Adjusted R-squared:  0.5137
F-statistic:  2107 on 5 and 9963 DF,  p-value: < 2.2e-16
```

1.5.2 Target: `log(price)`

In [ ]:

```
# this model uses 'size', 'society', 'bath', 'total_sqft' as features and

model_2_1 <- lm(log(price) ~ size + society + bath + total_sqft, data = t
summary(model_2_1)
```

```
Call:
lm(formula = log(price) ~ size + society + bath + total_sqft,
    data = train_df)

Residuals:
     Min       1Q   Median       3Q      Max
-10.8015  -0.2927  -0.0348   0.2533   2.8373

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.322e+00  1.494e-02 222.398  < 2e-16 ***
size        5.263e-02  9.169e-03   5.741  9.7e-09 ***
society     2.342e-02  1.054e-02   2.222   0.0263 *
bath        1.942e-01  8.998e-03  21.576  < 2e-16 ***
total_sqft  2.528e-04  4.833e-06  52.303  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.504 on 9964 degrees of freedom
Multiple R-squared:  0.512,     Adjusted R-squared:  0.5118
F-statistic:  2613 on 4 and 9964 DF,  p-value: < 2.2e-16
```

In [ ]:

```
# this model uses 'size', 'society', 'bath', 'total_sqft' as well as the

model_2_2 <- lm(log(price) ~ size + society + bath + total_sqft + I(total
summary(model_2_2)
```

```
Call:
lm(formula = log(price) ~ size + society + bath + total_sqft + 
    I(total_sqft^2), data = train_df)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.9864 -0.2693 -0.0294  0.2300  2.5579 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)      3.134e+00  1.385e-02 226.230  < 2e-16 ***
size             6.490e-02  8.190e-03   7.924 2.54e-15 ***
society         -1.020e-02  9.434e-03  -1.081     0.28    
bath             1.164e-01  8.182e-03  14.228  < 2e-16 ***
total_sqft       5.350e-04  7.074e-06  75.621  < 2e-16 ***
I(total_sqft^2) -1.382e-08  2.745e-10 -50.340  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.45 on 9963 degrees of freedom
Multiple R-squared:  0.6109,    Adjusted R-squared:  0.6107 
F-statistic:  3129 on 5 and 9963 DF,  p-value: < 2.2e-16
```

In [ ]:

```r
# this model uses 'size', 'society', 'bath', 'total_sqft' as well as the

model_2_3 <- lm(log(price) ~ size + society + bath + total_sqft + I(total
summary(model_2_3)
```

```
Call:
lm(formula = log(price) ~ size + society + bath + total_sqft + 
    I(total_sqft^3), data = train_df)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.3325 -0.2734 -0.0266  0.2374  3.1772 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)      3.211e+00  1.388e-02 231.382  < 2e-16 ***
size             6.588e-02  8.384e-03   7.858 4.31e-15 ***
society          5.704e-07  9.646e-03   0.000        1    
bath             1.296e-01  8.351e-03  15.518  < 2e-16 ***
total_sqft       4.283e-04  5.928e-06  72.237  < 2e-16 ***
I(total_sqft^3) -2.813e-13  6.340e-15 -44.369  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4606 on 9963 degrees of freedom
Multiple R-squared:  0.5925,    Adjusted R-squared:  0.5923 
F-statistic:  2897 on 5 and 9963 DF,  p-value: < 2.2e-16
```

P2

We obtained the following results:

Model	Target	Adj R2 Score
model_1_1	`price`	`0.4323`
model_1_2	`price`	`0.5137`
model_2_1	`log(price)`	`0.5118`
model_2_2	`log(price)`	`0.6107`
model_2_3	`log(price)`	`0.5923`

Based on the above results, we can say that `model_2_3`, which fits the data with `log(price)` as the target variable against `size`, `society`, `total_sqft`, `bath` and `total_sqft^3` as the features is the best.

This can be attributed to the following reasons:

- It obtains a respectable `Adj R2` score of `0.5923`
- It has a low Residual Standard Error.
- The coefficients of the features are also interpretable (the are positive, which matched the intuition corresponding to housing prices).

P3

3.a

In [ ]:
```
data_3a_1 <- data.frame(total_sqft = 2000, size = 3, bath = 2, society =
data_3a_2 <- data.frame(total_sqft = 2000, size = 3, bath = 2, society =

# predict the price for the two data points
price_3a_1 <- exp(predict(model_2_3, data_3a_1))
price_3a_2 <- exp(predict(model_2_3, data_3a_2))

# the builder should expect the following as premiuim for society:
price_3a_1 - price_3a_2
```

1: 5.24848021825619e-05

3.b

In [ ]:
```
data_3b_1 <- data.frame(total_sqft = 3000, size = 5, bath = 4, society =
data_3b_2 <- data.frame(total_sqft = 3000, size = 5, bath = 4, society =

# predict the price for the two data points
price_3b_1 <- exp(predict(model_2_3, data_3b_1))
price_3b_2<- exp(predict(model_2_3, data_3b_2))

# the builder should expect the following as premiuim for society:
price_3b_1 - price_3b_2
```

1: 2.25655872702742

3.c

In [ ]:
```
data_3c_1 = data.frame(total_sqft = 2000, size = 3, bath = 3, society = 1
data_3c_2 = data.frame(total_sqft = 2000, size = 3, bath = 4, society = 1

# predict the price for the two data points
price_3c_1 <- exp(predict(model_2_3, data_3c_1))
price_3c_2 <- exp(predict(model_2_3, data_3c_2))

# the builder should expect the following as premiuim for 4 bathrooms ove
price_3c_1 - price_3c_2
```

1: 14.4920341014985

3.d

In [ ]:
```
data_3d_1 = data.frame(total_sqft = 1500, size = 2, bath = 2, society = 1
data_3d_2 = data.frame(total_sqft = 1500, size = 3, bath = 2, society = 1

# predict the price for the two data points
price_3d_1 <- exp(predict(model_2_3, data_3d_1))
price_3d_2 <- exp(predict(model_2_3, data_3d_2))

# the builder should expect the following as premiuim for 3 BHK over 2 BH
price_3d_1 - price_3d_2
```

1: 4.74159728018292