Name: **SHREYASH SAHARE**

Student ID: **110988918**

Statistical Modeling Techniques:

Data Preprocessing

In [17]:
```
lon_wknds = read.csv("london_weekends.csv")
```

In [18]:
```
head(lon_wknds)
```

	X	realSum	room_type	room_shared	room_private	person_capacity	host_is_superhost	multi	biz	c
	<int>	<dbl>	<chr>	<chr>	<chr>	<dbl>	<chr>	<int>	<int>	
1	0	121.1223	Private room	False	True	2	False	0	0	
2	1	195.9124	Private room	False	True	2	False	1	0	
3	2	193.3253	Private room	False	True	3	False	1	0	
4	3	180.3899	Private room	False	True	2	False	1	0	
5	4	405.7010	Entire home/apt	False	False	3	False	0	1	
6	5	354.1946	Entire home/apt	False	False	2	False	0	1	

In [19]:
```
null_count <- colSums(is.na(lon_wknds))
print(null_count)
```

```
                          X                     realSum 
                          0                           0 
                  room_type                 room_shared 
                          0                           0 
               room_private             person_capacity 
                          0                           0 
          host_is_superhost                       multi 
                          0                           0 
                        biz         cleanliness_rating 
                          0                           0 
guest_satisfaction_overall                    bedrooms 
                          0                           0 
                       dist                  metro_dist 
                          0                           0 
                 attr_index             attr_index_norm 
                          0                           0 
                 rest_index             rest_index_norm 
                          0                           0 
                        lng                         lat 
                          0                           0 
```

Here we can see that there are no null values present in the dataset. Therefore, there is no need to clean the dataset.

In [20]:
```
names(lon_wknds)
```

'X' · 'realSum' · 'room_type' · 'room_shared' · 'room_private' · 'person_capacity' · 'host_is_superhost' · 'multi' · 'biz' · 'cleanliness_rating' · 'guest_satisfaction_overall' · 'bedrooms' · 'dist' · 'metro_dist' · 'attr_index' · 'attr_index_norm' · 'rest_index' · 'rest_index_norm' · 'lng' · 'lat'

In [21]:
```
# installing and importing the required packages
install.packages("corrplot")
library(ggplot2)
library(corrplot)
```

```
Installing package into ‘/usr/local/lib/R/site-library’
(as ‘lib’ is unspecified)
```

In [22]:
```
lon_wknds <- data.frame(lon_wknds)
```

In [23]:
```
head(lon_wknds)
```

	X	realSum	room_type	room_shared	room_private	person_capacity	host_is_superhost	multi	biz	c
	<int>	<dbl>	<chr>	<chr>	<chr>	<dbl>	<chr>	<int>	<int>	
1	0	121.1223	Private room	False	True	2	False	0	0	
2	1	195.9124	Private room	False	True	2	False	1	0	
3	2	193.3253	Private room	False	True	3	False	1	0	
4	3	180.3899	Private room	False	True	2	False	1	0	
5	4	405.7010	Entire home/apt	False	False	3	False	0	1	
6	5	354.1946	Entire home/apt	False	False	2	False	0	1	

In [24]:
```
# checking the number of unique values in non-numeric columns
unique_values_1 <- unique(lon_wknds$room_type)
num_unique_1 <- length(unique_values_1)

unique_values_2 <- unique(lon_wknds$room_private)
num_unique_2 <- length(unique_values_2)

unique_values_3 <- unique(lon_wknds$room_shared)
num_unique_3 <- length(unique_values_3)
```

In [25]:
```
cat("Number of unique values in room_type: ", num_unique_1, "\n")
cat("Number of unique values in room_private: ", num_unique_2, "\n")
cat("Number of unique values in room_shared: ", num_unique_3)
```

```
Number of unique values in room_type:  3
Number of unique values in room_private:  2
Number of unique values in room_shared:  2
```

In [26]:
```
unique_values_1
```

'Private room' · 'Entire home/apt' · 'Shared room'

```
In [27]: lon_wknds$room_type_encoded <- as.numeric(factor(lon_wknds$room_type, levels = c('Privat

         # Check the result
         head(lon_wknds$room_type_encoded)
```

1 · 1 · 1 · 1 · 2 · 2

In a similar way, we encode the columns "room_shared", "room_private" and "host_is_superhost" in order to check the correlation between the attributes in the dataset.

```
In [28]: lon_wknds$room_private_encoded <- as.numeric(factor(lon_wknds$room_private, levels = c('
         lon_wknds$room_shared_encoded <- as.numeric(factor(lon_wknds$room_shared, levels = c('Tr
         lon_wknds$room_host_encoded <- as.numeric(factor(lon_wknds$host_is_superhost, levels = c
```

```
In [29]: head(lon_wknds)
```

	X	realSum	room_type	room_shared	room_private	person_capacity	host_is_superhost	multi	biz
	<int>	<dbl>	<chr>	<chr>	<chr>	<dbl>	<chr>	<int>	<int>
1	0	121.1223	Private room	False	True	2	False	0	0
2	1	195.9124	Private room	False	True	2	False	1	0
3	2	193.3253	Private room	False	True	3	False	1	0
4	3	180.3899	Private room	False	True	2	False	1	0
5	4	405.7010	Entire home/apt	False	False	3	False	0	1
6	5	354.1946	Entire home/apt	False	False	2	False	0	1

```
In [30]: # keeping the columns best suitable to predict the price of Airbnb listing
         lon_wknds <- subset(lon_wknds, select = -c(room_type, room_private, room_shared, host_is
         head(lon_wknds)
```

A data.frame: 6 ×

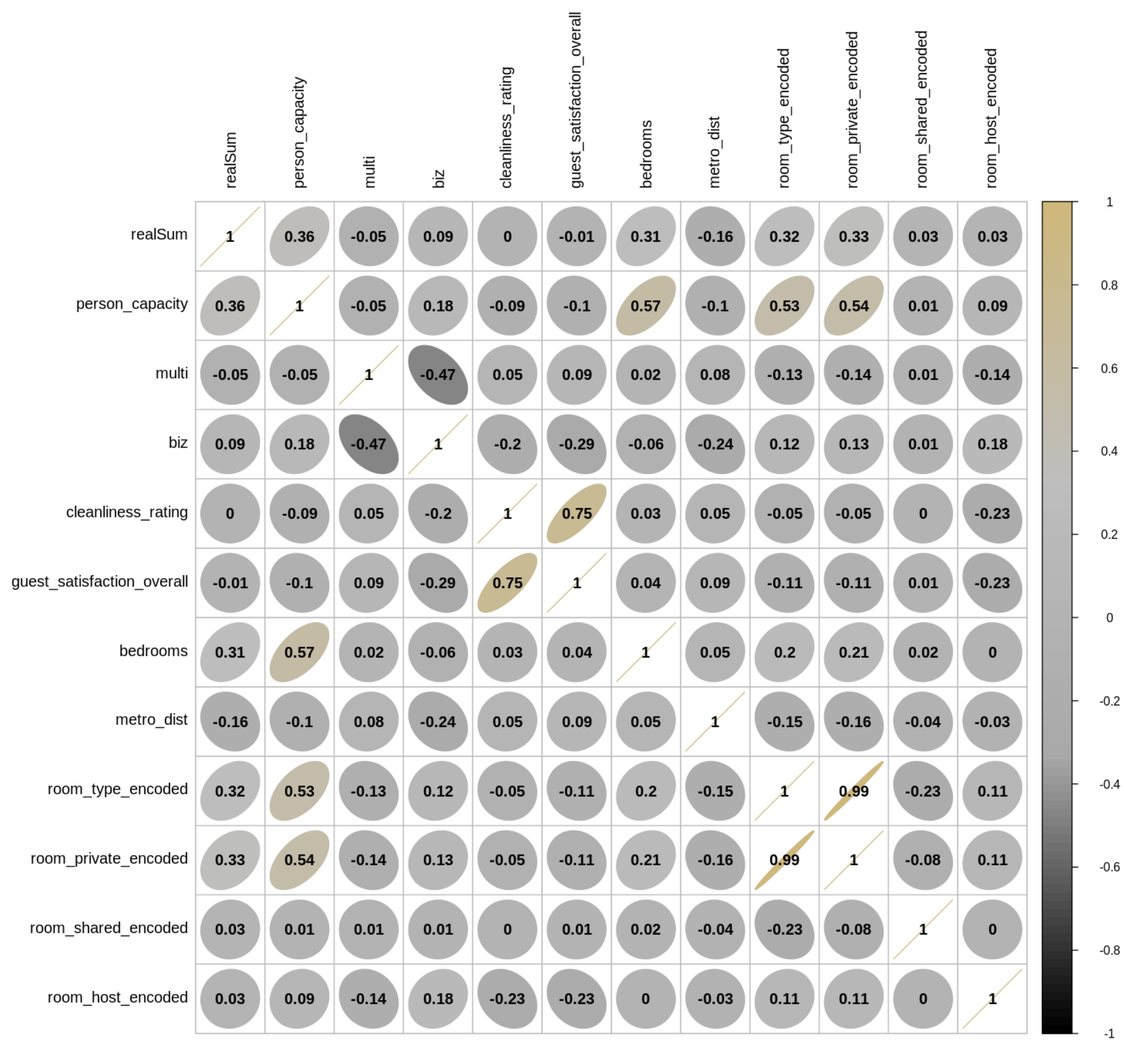
	realSum	person_capacity	multi	biz	cleanliness_rating	guest_satisfaction_overall	bedrooms	dist
	<dbl>	<dbl>	<int>	<int>	<dbl>	<dbl>	<int>	<dbl>
1	121.1223	2	0	0	6	69	1	5.734117
2	195.9124	2	1	0	10	96	1	4.788905
3	193.3253	3	1	0	10	95	1	4.596677
4	180.3899	2	1	0	9	87	1	2.054769
5	405.7010	3	0	1	7	65	0	4.491277
6	354.1946	2	0	1	9	93	0	4.467894

```
In [31]: #training and test set
         set.seed(1111)
         n = floor(0.8 * nrow(lon_wknds)) #find the number corresponding to 80% of the data
         index = sample(seq_len(nrow(lon_wknds)), size = n) #randomly sample indicies to be inclu

         train = lon_wknds[index, ] #set the training set to be the randomly sampled rows of the
         test = lon_wknds[-index, ] #set the testing set to be the remaining rows
```

```
cat("There are", dim(train)[1], "rows and",dim(train)[2],"columns in the training set. "
cat("There are", dim(test)[1], "rows and",dim(test)[2],"columns in the testing set.")  #
```

```
There are 4303 rows and 13 columns in the training set. There are 1076 rows and 13 colum
ns in the testing set.
```

In [68]:
```
# generating a correlation plot
col4 = colorRampPalette(c("black", "darkgrey", "grey","#CFB87C"))
corrplot(cor(train[,-8]), method = "ellipse", col = col4(100),  addCoef.col = "black", t
```



Regression Modeling

In [33]:
```
# fitting a multiple linear regression model
model_wknds <- lm(realSum ~ ., data = train)

summary(model_wknds)
```

```
Call:
lm(formula = realSum ~ ., data = train)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
 -932.4  -105.6   -38.5    43.7 12740.5 

Coefficients: (1 not defined because of singularities)
                            Estimate Std. Error t value Pr(>|t|)    
(Intercept)                -191.1881    78.1570  -2.446  0.01448 *  
person_capacity              40.3261     7.4466   5.415 6.45e-08 ***
multi                        -0.9893    16.0066  -0.062  0.95072    
biz                          14.3408    16.4034   0.874  0.38203    
cleanliness_rating            5.4522     8.2624   0.660  0.50936    
guest_satisfaction_overall    0.8339     0.8541   0.976  0.32898    
bedrooms                    168.8604    13.6456  12.375  < 2e-16 ***
dist                        -28.2780     3.3129  -8.536  < 2e-16 ***
metro_dist                   -2.2541     6.9431  -0.325  0.74545    
room_type_encoded          -257.3392    84.4595  -3.047  0.00233 ** 
room_private_encoded        445.6634    87.5348   5.091 3.71e-07 ***
room_shared_encoded               NA         NA      NA       NA    
room_host_encoded            -1.2152    17.5474  -0.069  0.94479    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 409.7 on 4291 degrees of freedom
Multiple R-squared:  0.2126,	Adjusted R-squared:  0.2106 
F-statistic: 105.3 on 11 and 4291 DF,  p-value: < 2.2e-16
```

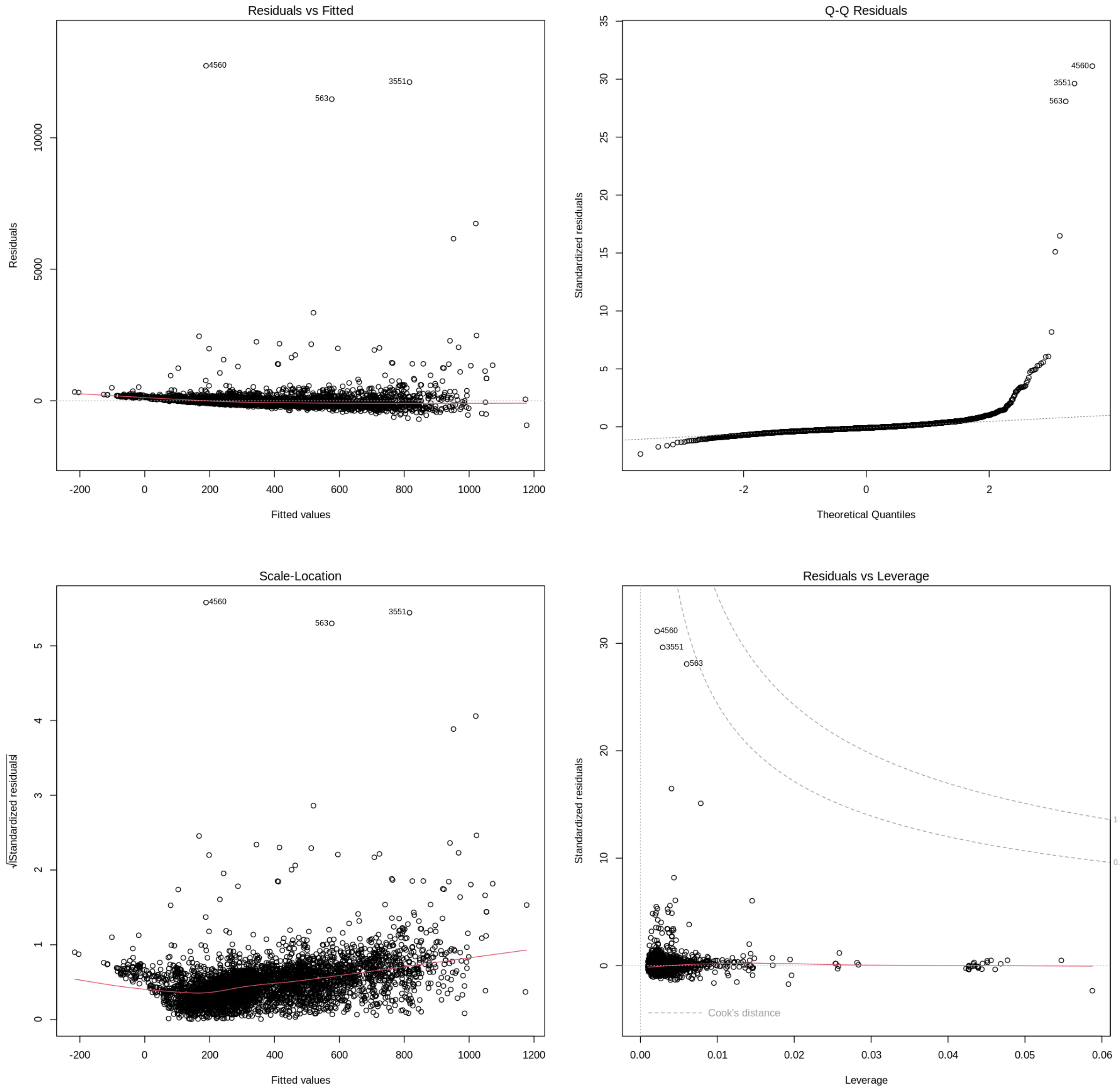
In [34]:
```
# checking the coefficients for the MLR model
coeff_wknds <- coef(model_wknds)
print(coeff_wknds)
```

```
               (Intercept)            person_capacity 
              -191.1880583                 40.3261107 
                     multi                        biz 
                -0.9893159                 14.3408212 
        cleanliness_rating guest_satisfaction_overall 
                 5.4522454                  0.8338866 
                  bedrooms                       dist 
               168.8604274                -28.2780164 
                metro_dist          room_type_encoded 
                -2.2541405               -257.3391547 
      room_private_encoded        room_shared_encoded 
               445.6634414                         NA 
         room_host_encoded 
                -1.2151846 
```

It can be observed from the above result that the column "room_shared_encoded" has "NA" value as the coefficient. This means that the aforementioned variable was not included in the model as a predictor. Therefore, we need to assess the model fitting process and the model diagnostics to understand and determine the reason for this result.

Diagnostics of the Model

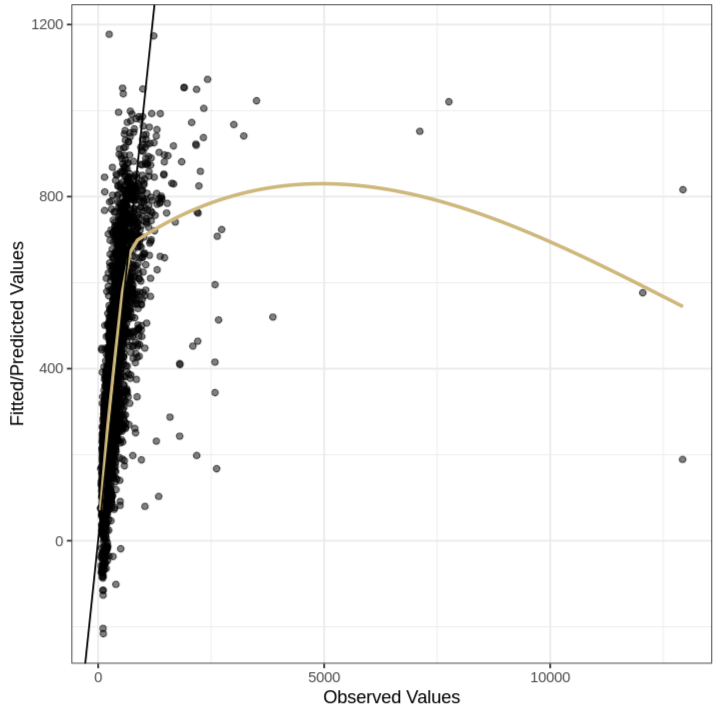
In [35]:
```
# diagnostic to check modeling assumptions
options(repr.plot.width=15, repr.plot.height=15)
par(mfrow = c(2, 2))
plot(model_wknds)
```



In [36]:
```
# plotting the diagnostics
train.diagnostics = data.frame(yhat = fitted(model_wknds), r = resid(model_wknds), y = t
                               room_priv = train$room_private_encoded, room_shared = tra
                               biz = train$biz, guest = train$guest_satisfaction_overall
```

In [37]:
```
library(ggplot2)

options(repr.plot.width = 6, repr.plot.height = 6)
ggplot(train.diagnostics, aes(x = y, y = yhat)) +
    geom_point(alpha = 0.5) +
    geom_smooth(se = F, col = "#CFB87C") +
    geom_abline(intercept = 0, slope = 1)+
    xlab("Observed Values") +
    ylab("Fitted/Predicted Values") +
    theme_bw()
```

```
`geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



It can be observed from the diagnostic plots that there are outliers present in the dataset that are potentially high leverage and highly influential points (563, 3551, 4560). Apart from those outliers, the other data points are almost equally distributed about the regression line (red line). Therefore, we can first transform the data using the `cube root` transformation and then remove the above points from the dataset and re-fit the regression model to check for modeling assumptions.

In [38]:
```
# Apply cube root transformation to numerical columns
train_transformed <- train
numeric_columns <- sapply(train, is.numeric)
train_transformed[, numeric_columns] <- lapply(train[, numeric_columns], function(x) x^(

head(train_transformed)
```

A data.frame: 6

	realSum	person_capacity	multi	biz	cleanliness_rating	guest_satisfaction_overall	bedrooms	di
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<db
2486	6.143718	1.259921	1	0	2.154435	4.610436	1.000000	1.7167
2098	6.658150	1.259921	0	0	2.154435	4.530655	1.000000	1.5323
794	5.441298	1.259921	0	1	2.080084	4.447960	1.000000	1.4104
326	7.534999	1.709976	0	0	2.154435	4.610436	1.259921	2.1448
3034	6.421726	1.587401	0	0	2.080084	4.447960	1.000000	1.7171
991	6.647522	1.259921	0	1	2.000000	4.362071	0.000000	1.6547

In [39]:
```
print(colSums(is.na(train_transformed)))
```

```
                 realSum          person_capacity
                       0                        0
                   multi                      biz
                       0                        0
      cleanliness_rating guest_satisfaction_overall
                       0                        0
                bedrooms                     dist
                       0                        0
              metro_dist        room_type_encoded
                       0                        0
```

```
        room_private_encoded         room_shared_encoded
                           0                           0
           room_host_encoded
                           0
```

In [40]:
```
# points to be removed
points_rem <- c(563, 3551, 4560)
```

In [41]:
```
# Remove the specified points from the dataset using subsetting
train_new <- train_transformed[!rownames(train_transformed) %in% points_rem, ]

# Check if the specified points are removed
if (nrow(train_new) == (nrow(train_transformed) - length(points_rem))) {
  print("Specified points have been successfully removed.")
} else {
  print("Some specified points may not have been removed.")
}
```

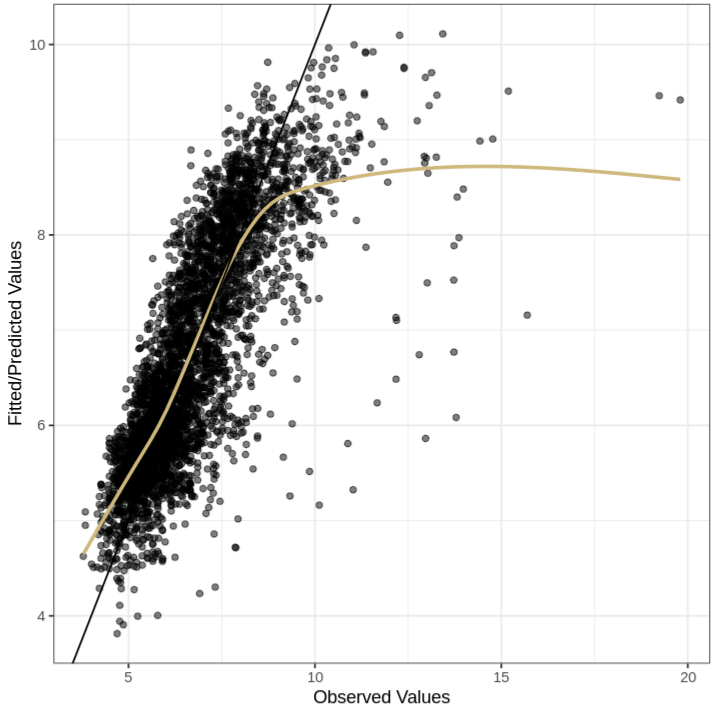
```
[1] "Specified points have been successfully removed."
```

In [42]:
```
model_wknds_new <- lm(realSum ~ ., data = train_new)
summary(model_wknds_new)
```

```
Call:
lm(formula = realSum ~ ., data = train_new)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2164 -0.5493 -0.1542  0.3779 10.3796 

Coefficients: (1 not defined because of singularities)
                            Estimate Std. Error t value Pr(>|t|)    
(Intercept)                 -2.19848    0.43425  -5.063 4.31e-07 ***
person_capacity              2.23080    0.10407  21.437  < 2e-16 ***
multi                        0.09173    0.03606   2.544  0.01099 *  
biz                          0.10392    0.03692   2.815  0.00491 ** 
cleanliness_rating           0.93359    0.20238   4.613 4.08e-06 ***
guest_satisfaction_overall  -0.02058    0.09415  -0.219  0.82701    
bedrooms                     0.66799    0.05388  12.397  < 2e-16 ***
dist                        -1.20667    0.06017 -20.055  < 2e-16 ***
metro_dist                  -0.36251    0.05915  -6.129 9.66e-10 ***
room_type_encoded          -11.05698    1.04322 -10.599  < 2e-16 ***
room_private_encoded        16.46261    1.06873  15.404  < 2e-16 ***
room_shared_encoded               NA         NA      NA       NA    
room_host_encoded           -0.35145    0.15129  -2.323  0.02023 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9224 on 4288 degrees of freedom
Multiple R-squared:  0.6301,	Adjusted R-squared:  0.6292 
F-statistic: 664.1 on 11 and 4288 DF,  p-value: < 2.2e-16
```

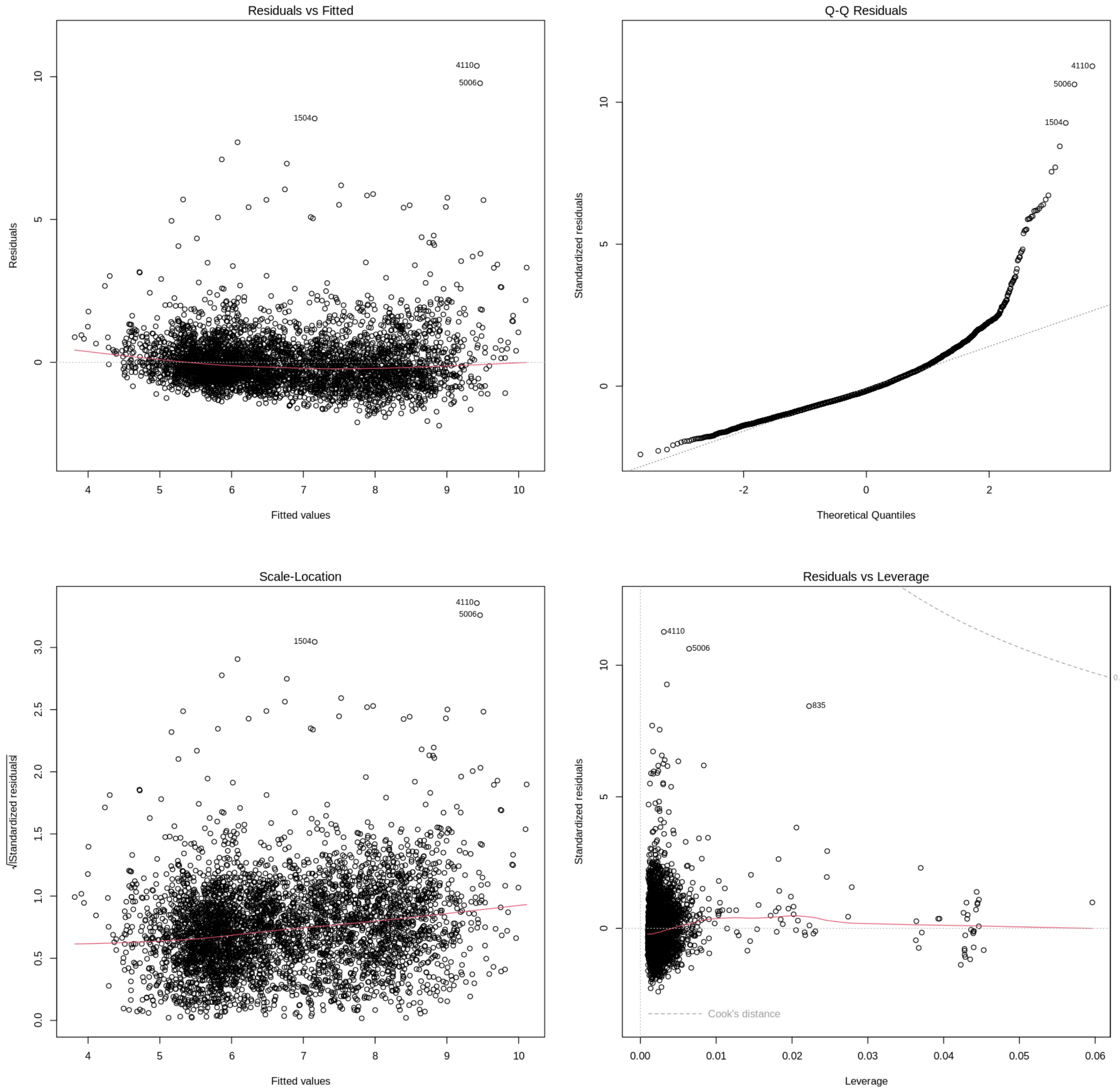
In [43]:
```
# rechecking the diagnostics
train_new.diagnostics = data.frame(yhat = fitted(model_wknds_new), r = resid(model_wknds
                               room_priv = train_new$room_private_encoded, room_shared =
                               biz = train_new$biz, guest = train_new$guest_satisfaction

options(repr.plot.width = 6, repr.plot.height = 6)
ggplot(train_new.diagnostics, aes(x = y, y = yhat)) +
    geom_point(alpha = 0.5) +
    geom_smooth(se = F, col = "#CFB87C") +
    geom_abline(intercept = 0, slope = 1)+
    xlab("Observed Values") +
    ylab("Fitted/Predicted Values") +
    theme_bw()
```

```
`geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



In [44]:

```
# re-plotting the diagnostics to check modeling assumptions
options(repr.plot.width=15, repr.plot.height=15)
par(mfrow = c(2, 2))
plot(model_wknds_new)
```



We keep removing the outliers till we have an even distribution of data around the regression line (red line) in all the plots.

In [45]:
```
# points to be removed
points_rem <- c(1504, 4110, 5006)
```

In [46]:
```
# Remove the specified points from the dataset using subsetting
train_new_1 <- train_new[!rownames(train_new) %in% points_rem, ]

# Check if the specified points are removed
if (nrow(train_new_1) == (nrow(train_new) - length(points_rem))) {
  print("Specified points have been successfully removed.")
} else {
  print("Some specified points may not have been removed.")
}
```

```
[1] "Specified points have been successfully removed."
```

In [47]:
```
# re-fitting the model
model_wknds_new <- lm(realSum ~ ., data = train_new_1)
```

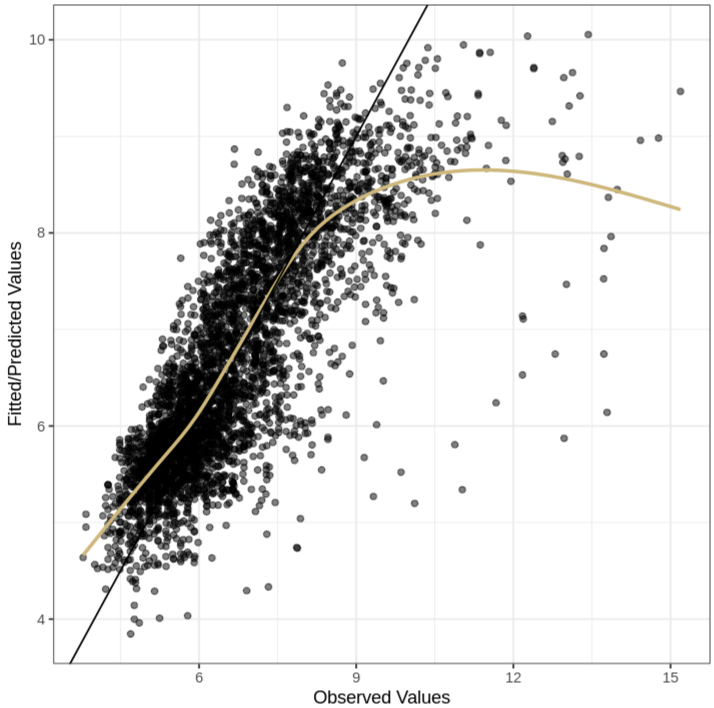
```
summary(model_wknds_new)
```

```
Call:
lm(formula = realSum ~ ., data = train_new_1)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.1929 -0.5450 -0.1495  0.3843  7.6468 

Coefficients: (1 not defined because of singularities)
                            Estimate Std. Error t value Pr(>|t|)    
(Intercept)                 -2.13224    0.41775  -5.104 3.47e-07 ***
person_capacity              2.25920    0.10019  22.549  < 2e-16 ***
multi                        0.08993    0.03469   2.592  0.00957 ** 
biz                          0.10397    0.03553   2.927  0.00344 ** 
cleanliness_rating           0.91524    0.19460   4.703 2.64e-06 ***
guest_satisfaction_overall  -0.02912    0.09054  -0.322  0.74778    
bedrooms                     0.63023    0.05186  12.152  < 2e-16 ***
dist                        -1.17005    0.05796 -20.185  < 2e-16 ***
metro_dist                  -0.37003    0.05690  -6.503 8.79e-11 ***
room_type_encoded          -10.95832    1.00314 -10.924  < 2e-16 ***
room_private_encoded        16.28556    1.02773  15.846  < 2e-16 ***
room_shared_encoded               NA         NA      NA       NA    
room_host_encoded           -0.32364    0.14559  -2.223  0.02627 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.887 on 4285 degrees of freedom
Multiple R-squared:  0.6435,	Adjusted R-squared:  0.6426 
F-statistic: 703.2 on 11 and 4285 DF,  p-value: < 2.2e-16
```

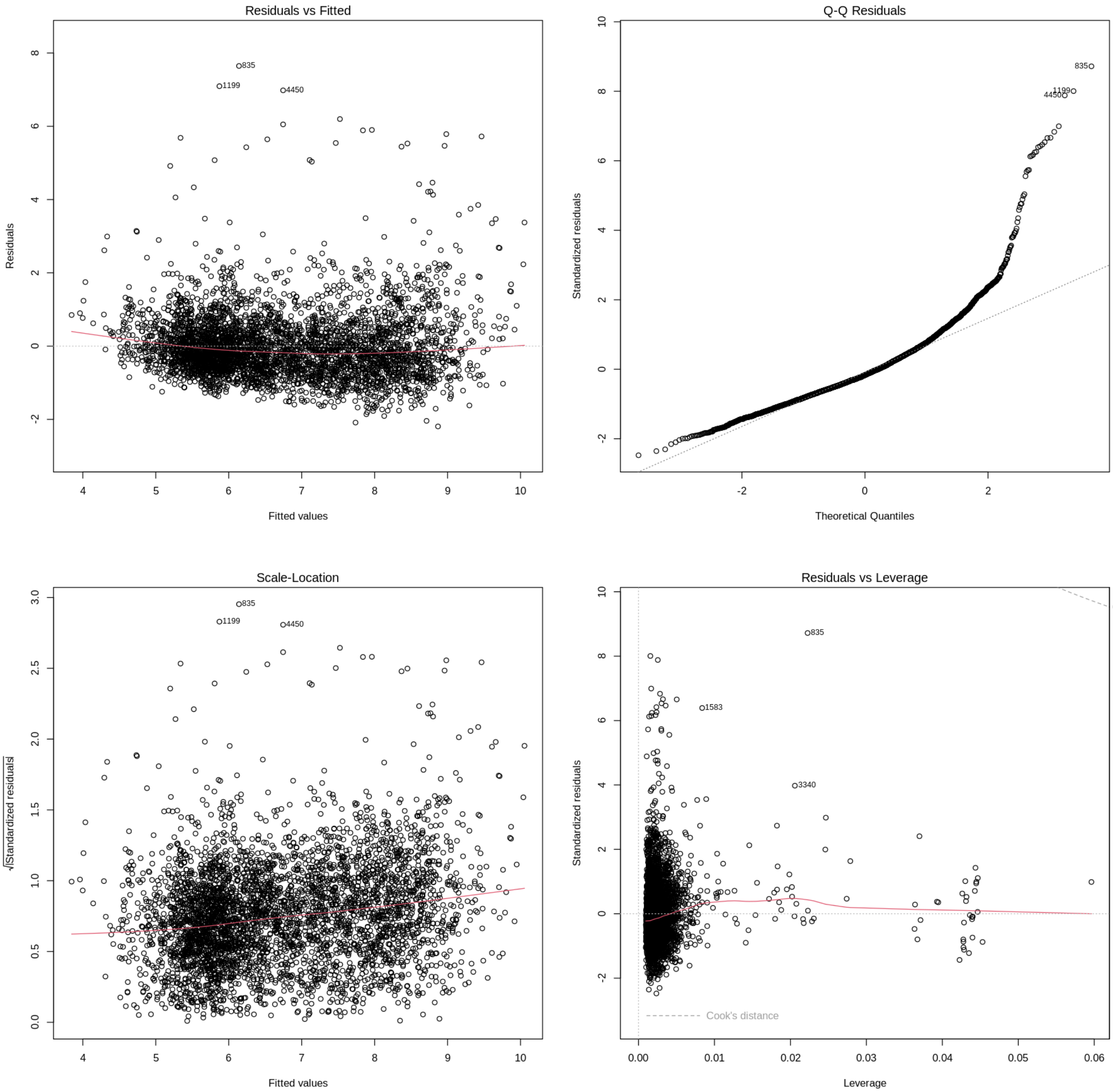
In [48]:

```
# rechecking the diagnostics
train_new.diagnostics = data.frame(yhat = fitted(model_wknds_new), r = resid(model_wknds
                               room_priv = train_new_1$room_private_encoded, room_shared
                               biz = train_new_1$biz, guest = train_new_1$guest_satisfac

options(repr.plot.width = 6, repr.plot.height = 6)
ggplot(train_new.diagnostics, aes(x = y, y = yhat)) +
    geom_point(alpha = 0.5) +
    geom_smooth(se = F, col = "#CFB87C") +
    geom_abline(intercept = 0, slope = 1)+
    xlab("Observed Values") +
    ylab("Fitted/Predicted Values") +
    theme_bw()
```

```
`geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



In [49]:
```
# re-plotting the diagnostics to check modeling assumptions
options(repr.plot.width=15, repr.plot.height=15)
par(mfrow = c(2, 2))
plot(model_wknds_new)
```



From the above diagnostic plots, it is observed that it is following all the modeling assumptions almost perfectly for a dataset with large number of data points. Notably, there are no high leverage points in the dataset since all the points are well within `Cook's Distance`. Therefore, we can now proceed with model selection.

Model Selection

We can now select the best model according to various methods. This can be fulfilled by using two types of selection techniques:

1. **Backward Selection:** Using MSPE as a criterion

2. **Forward Selection:** Using AIC, BIC and R_a^2 criteria.

Backward Selection

For this dataset, let us keep the $\alpha_{crit} = 0.01$

In [50]:
```
model_wknds_new <- lm(realSum ~ ., data = train_new_1)
summary(model_wknds_new)
```

```
Call:
lm(formula = realSum ~ ., data = train_new_1)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.1929 -0.5450 -0.1495  0.3843  7.6468 

Coefficients: (1 not defined because of singularities)
                            Estimate Std. Error t value Pr(>|t|)    
(Intercept)                 -2.13224    0.41775  -5.104 3.47e-07 ***
person_capacity              2.25920    0.10019  22.549  < 2e-16 ***
multi                        0.08993    0.03469   2.592  0.00957 ** 
biz                          0.10397    0.03553   2.927  0.00344 ** 
cleanliness_rating           0.91524    0.19460   4.703 2.64e-06 ***
guest_satisfaction_overall  -0.02912    0.09054  -0.322  0.74778    
bedrooms                     0.63023    0.05186  12.152  < 2e-16 ***
dist                        -1.17005    0.05796 -20.185  < 2e-16 ***
metro_dist                  -0.37003    0.05690  -6.503 8.79e-11 ***
room_type_encoded          -10.95832    1.00314 -10.924  < 2e-16 ***
room_private_encoded        16.28556    1.02773  15.846  < 2e-16 ***
room_shared_encoded               NA         NA      NA       NA    
room_host_encoded           -0.32364    0.14559  -2.223  0.02627 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.887 on 4285 degrees of freedom
Multiple R-squared:  0.6435,	Adjusted R-squared:  0.6426 
F-statistic: 703.2 on 11 and 4285 DF,  p-value: < 2.2e-16
```

In [51]:
```
# first update
model_wknds_new <- update(model_wknds_new, . ~ . -guest_satisfaction_overall)
predicted_values <- predict(model_wknds_new, newdata = test)
mspe_1 <- mean((test$realSum - predicted_values)^2)
summary(model_wknds_new)
```

```
Warning message in predict.lm(model_wknds_new, newdata = test):
“prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases”
Call:
lm(formula = realSum ~ person_capacity + multi + biz + cleanliness_rating + 
    bedrooms + dist + metro_dist + room_type_encoded + room_private_encoded + 
    room_shared_encoded + room_host_encoded, data = train_new_1)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.1925 -0.5441 -0.1492  0.3844  7.6609 

Coefficients: (1 not defined because of singularities)
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)           -2.17503    0.39596  -5.493 4.18e-08 ***
person_capacity        2.25859    0.10016  22.550  < 2e-16 ***
multi                  0.09041    0.03466   2.609  0.00912 ** 
biz                    0.10586    0.03503   3.021  0.00253 ** 
cleanliness_rating     0.87029    0.13537   6.429 1.43e-10 ***
bedrooms               0.62989    0.05185  12.149  < 2e-16 ***
dist                  -1.16944    0.05793 -20.188  < 2e-16 ***
metro_dist            -0.37072    0.05686  -6.520 7.83e-11 ***
room_type_encoded    -10.95671    1.00302 -10.924  < 2e-16 ***
room_private_encoded  16.28707    1.02761  15.849  < 2e-16 ***
room_shared_encoded         NA         NA      NA       NA    
room_host_encoded     -0.32149    0.14542  -2.211  0.02711 *  
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8869 on 4286 degrees of freedom
Multiple R-squared:  0.6435,	Adjusted R-squared:  0.6427 
F-statistic: 773.7 on 10 and 4286 DF,  p-value: < 2.2e-16
```

In [52]:
```
# second update
model_wknds_new <- update(model_wknds_new, . ~ . -room_host_encoded)
predicted_values_1 <- predict(model_wknds_new, newdata = test)
mspe_2 <- mean((test$realSum - predicted_values_1)^2)
summary(model_wknds_new)
```

```
Warning message in predict.lm(model_wknds_new, newdata = test):
“prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases”
Call:
lm(formula = realSum ~ person_capacity + multi + biz + cleanliness_rating + 
    bedrooms + dist + metro_dist + room_type_encoded + room_private_encoded + 
    room_shared_encoded, data = train_new_1)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2084 -0.5447 -0.1420  0.3863  7.6961 

Coefficients: (1 not defined because of singularities)
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)           -2.65407    0.33155  -8.005 1.53e-15 ***
person_capacity        2.25210    0.10016  22.484  < 2e-16 ***
multi                  0.09575    0.03459   2.768  0.00566 ** 
biz                    0.09889    0.03491   2.833  0.00464 ** 
cleanliness_rating     0.92471    0.13317   6.944 4.40e-12 ***
bedrooms               0.63284    0.05185  12.204  < 2e-16 ***
dist                  -1.16990    0.05795 -20.187  < 2e-16 ***
metro_dist            -0.37275    0.05687  -6.554 6.27e-11 ***
room_type_encoded    -10.94478    1.00346 -10.907  < 2e-16 ***
room_private_encoded  16.26077    1.02801  15.818  < 2e-16 ***
room_shared_encoded         NA         NA      NA       NA    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8873 on 4287 degrees of freedom
Multiple R-squared:  0.6431,	Adjusted R-squared:  0.6424 
F-statistic: 858.3 on 9 and 4287 DF,  p-value: < 2.2e-16
```

In [53]:
```
# third update
model_wknds_new <- update(model_wknds_new, . ~ . -room_shared_encoded)
predicted_values_2 <- predict(model_wknds_new, newdata = test)
mspe_3 <- mean((test$realSum - predicted_values_2)^2)
summary(model_wknds_new)
```

```
Call:
lm(formula = realSum ~ person_capacity + multi + biz + cleanliness_rating + 
    bedrooms + dist + metro_dist + room_type_encoded + room_private_encoded, 
    data = train_new_1)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2084 -0.5447 -0.1420  0.3863  7.6961 

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)           -2.65407    0.33155  -8.005 1.53e-15 ***
person_capacity        2.25210    0.10016  22.484  < 2e-16 ***
multi                  0.09575    0.03459   2.768  0.00566 ** 
biz                    0.09889    0.03491   2.833  0.00464 ** 
cleanliness_rating     0.92471    0.13317   6.944 4.40e-12 ***
```

```
bedrooms                 0.63284    0.05185  12.204  < 2e-16 ***
dist                    -1.16990    0.05795 -20.187  < 2e-16 ***
metro_dist              -0.37275    0.05687  -6.554 6.27e-11 ***
room_type_encoded      -10.94478    1.00346 -10.907  < 2e-16 ***
room_private_encoded    16.26077    1.02801  15.818  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8873 on 4287 degrees of freedom
Multiple R-squared:  0.6431,    Adjusted R-squared:  0.6424
F-statistic: 858.3 on 9 and 4287 DF,  p-value: < 2.2e-16
```

Here, we can see that the p-values of all our predictors are lesser than $\alpha_{crit} = 0.01$. Therefore, we need not proceed with any further updates on the model.

Forward Selection

In [54]:
```
# choosing the best model for each size
install.packages("leaps")
library(leaps)
library(MASS)

reg1 = regsubsets(realSum ~ ., data = train_new_1)
rs = summary(reg1)
rs$which
```

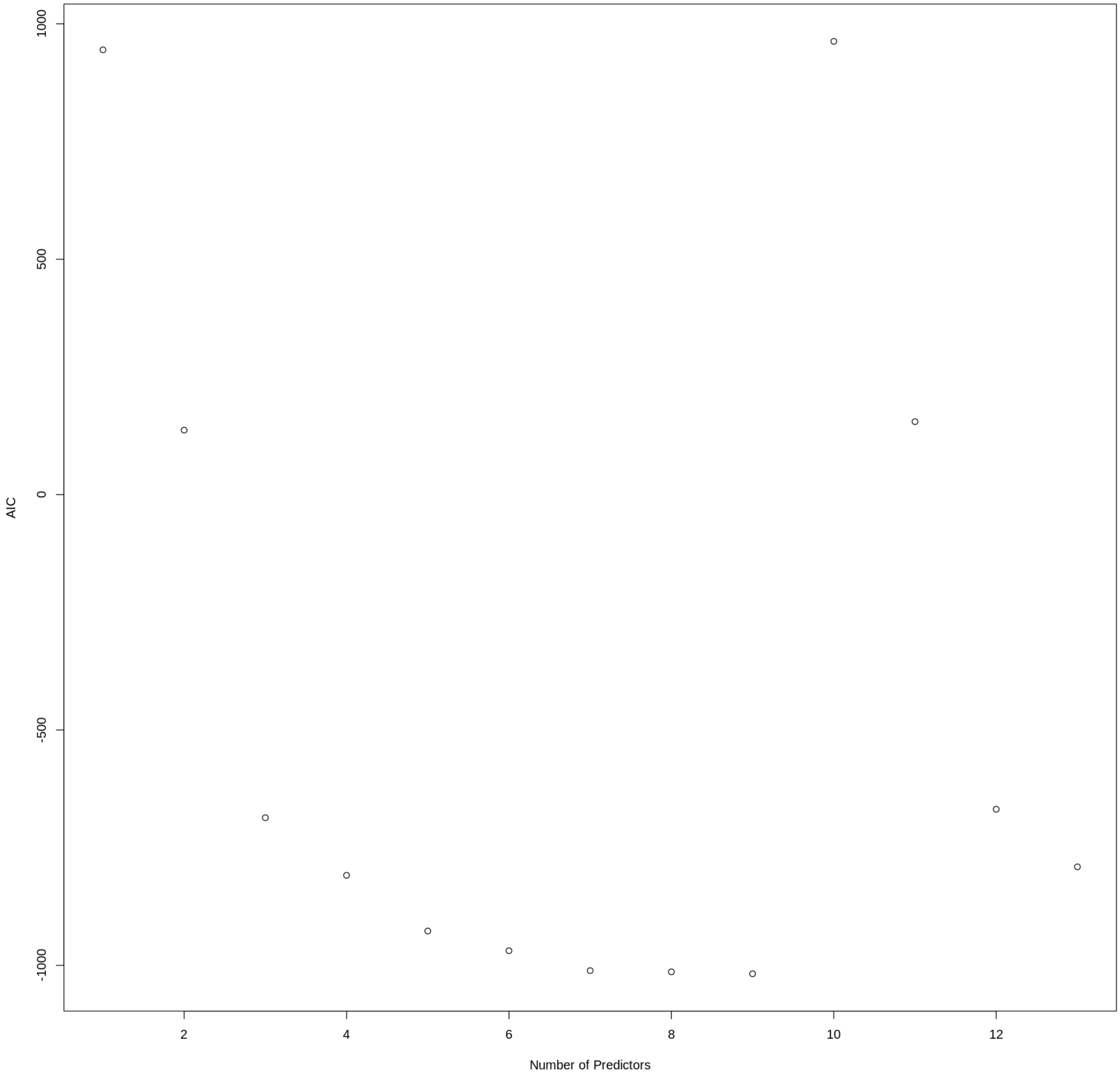
```
Installing package into ‘/usr/local/lib/R/site-library’
(as ‘lib’ is unspecified)

Warning message in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax, force.in = f
orce.in, :
“1  linear dependencies found”
Reordering variables and trying again:
```

A matrix: 9 × 13 of t

	(Intercept)	person_capacity	multi	biz	cleanliness_rating	guest_satisfaction_overall	bedrooms	dist
1	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
3	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
4	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
5	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
6	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
7	TRUE	TRUE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE
8	TRUE	TRUE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE
9	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE

In [55]:
```
# getting the number of predictors for the best model using AIC
n = dim(train_new_1)[1];
AIC = 2*(2:14) + n*log(rs$rss/n)
plot(AIC ~ I(1:13), xlab = "Number of Predictors", ylab = "AIC")
```

```
Warning message in 2 * (2:14) + n * log(rs$rss/n):
“longer object length is not a multiple of shorter object length”
```

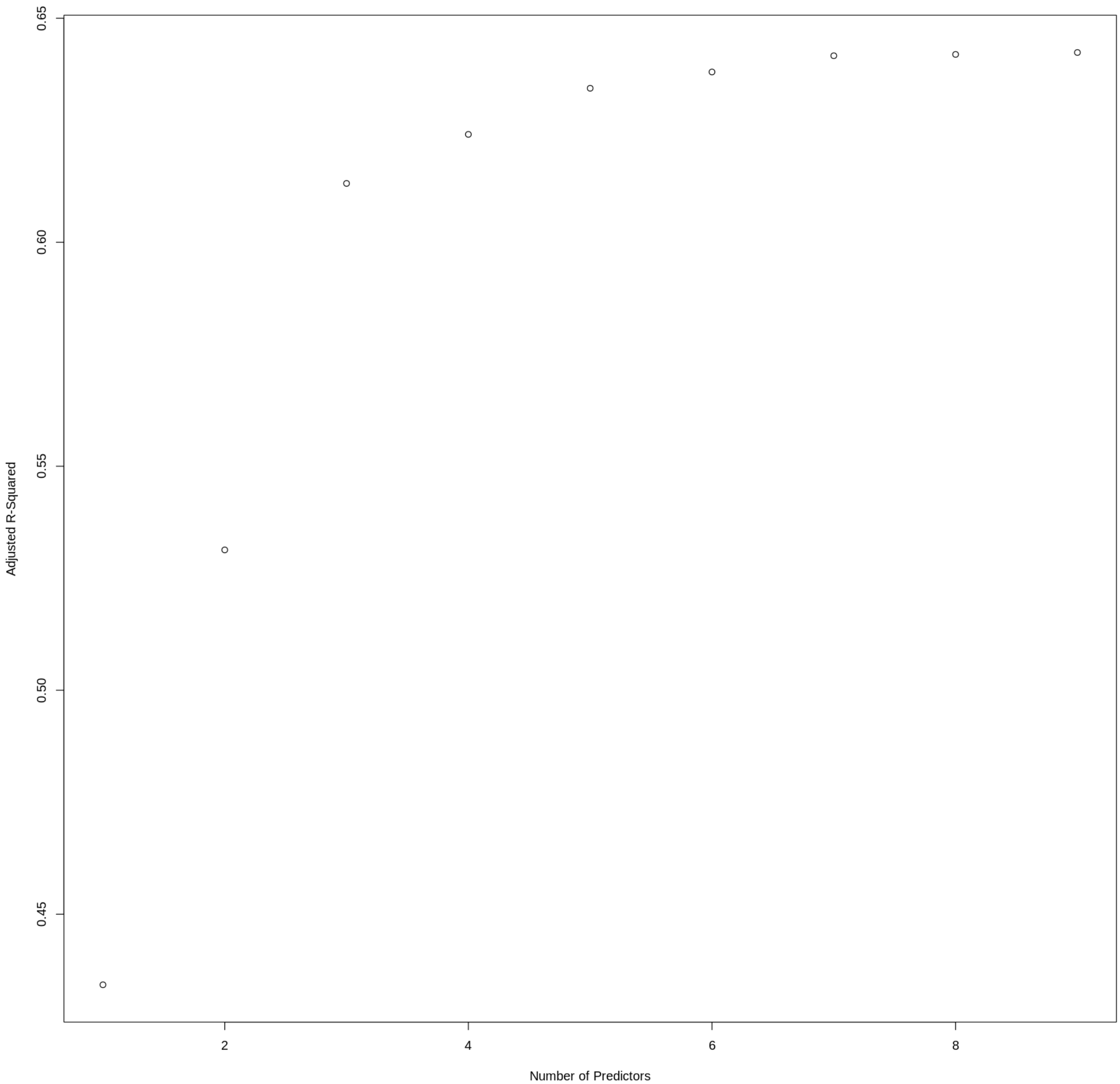


It can be observed in the above plot that the best model size for the lowest AIC is $k = 9$.

In [56]:
```
rs$adjr2
```

0.434250645196204 · 0.531321518704489 · 0.613130043990843 · 0.624078512815006 · 0.634370241397012 · 0.638005934053297 · 0.64162994916227 · 0.64192658792319 · 0.642353338237643

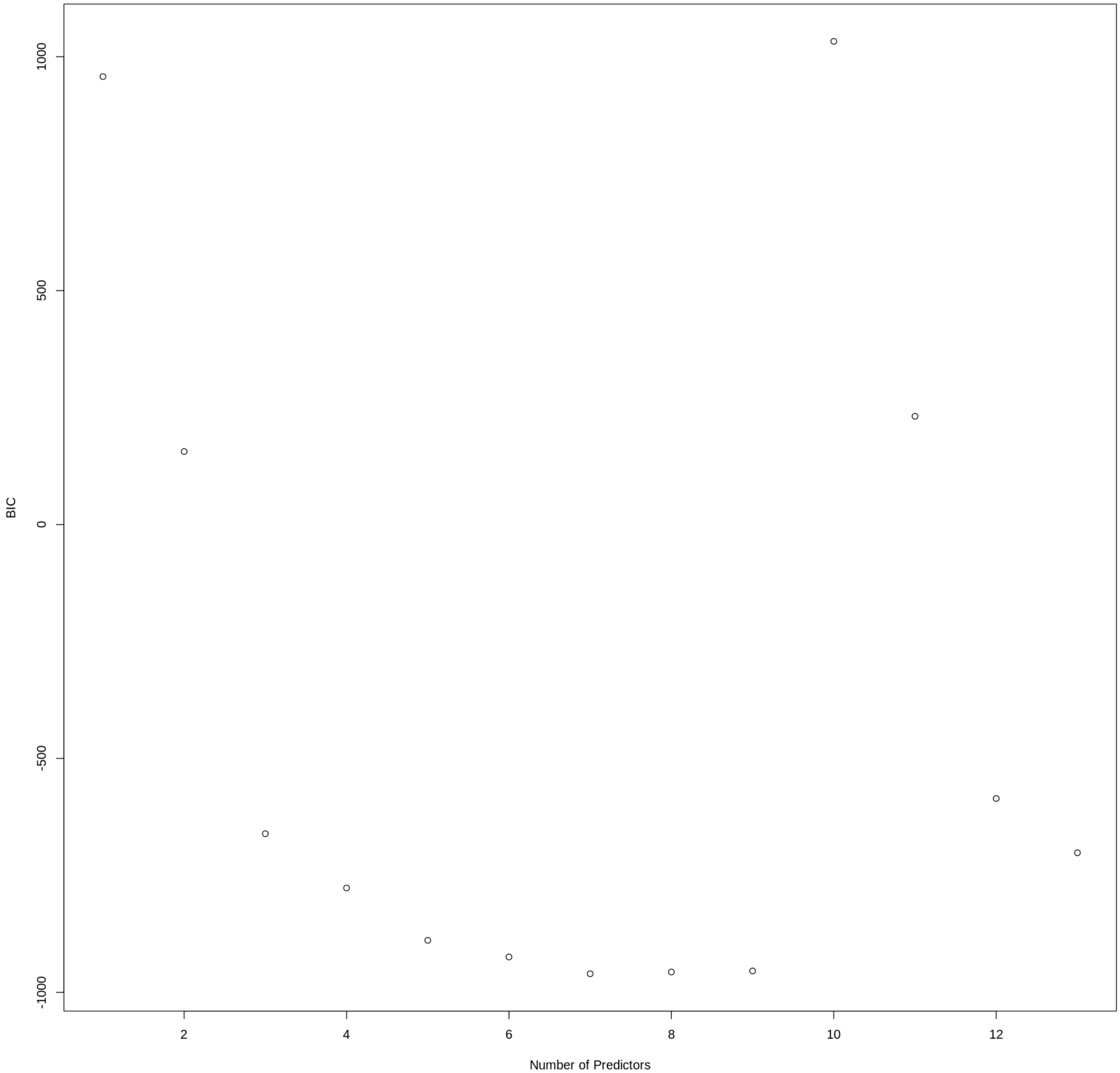
In [57]:
```
# getting the number of predictors for the best model using R2a
plot(1:9, rs$adjr2, xlab = "Number of Predictors", ylab = "Adjusted R-Squared")
```



It can be observed in the above plot that the best model size for the highest R_a^2 values is $k = 9$.

In [58]:
```
# getting the number of predictors for the best model using BIC
BIC = log(n)*(2:14) + n*log(rs$rss/n)
plot(BIC ~ I(1:13), xlab = "Number of Predictors", ylab = "BIC")
```

```
Warning message in log(n) * (2:14) + n * log(rs$rss/n):
“longer object length is not a multiple of shorter object length”
```



It can be observed in the above plot that the best model size for the lowest BIC is $k = 7$.

We can see that out of the three criteria, **AIC** and R_a^2 have the best models with size $k = 9$ while the **BIC** criterion has the best model with size $k = 7$. Therefore, we can proceed with the model with $k = 9$ for regression modeling with the following equation:

`realSum` = $\widehat{\beta}_0 + \widehat{\beta}_1 \times$ `person_capacity` $+ \widehat{\beta}_2 \times$ `multi` $+ \widehat{\beta}_3 \times$ `biz` + $\widehat{\beta}_4 \times$ `cleanliness_rating` + $\widehat{\beta}_5 \times$ `bedrooms` + $\widehat{\beta}_6 \times$ `dist` + $\widehat{\beta}_7 \times$ `metro_dist` + $\widehat{\beta}_8 \times$ `room_type_encoded` + $\widehat{\beta}_9 \times$ `room_private_encoded`

In [59]:
```
# computing the MSPE for the above best model
model_wknds_fs <- lm(realSum ~ person_capacity + multi + biz + cleanliness_rating + bedr
predicted_values_fs <- predict(model_wknds_fs, newdata = test)
mspe_fs <- mean((test$realSum - predicted_values_fs)^2)
summary(model_wknds_fs)
```

```
Call:
lm(formula = realSum ~ person_capacity + multi + biz + cleanliness_rating +
```

```
    bedrooms + dist + metro_dist + room_type_encoded + room_private_encoded,
    data = train_new_1)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2084 -0.5447 -0.1420  0.3863  7.6961

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           -2.65407    0.33155  -8.005 1.53e-15 ***
person_capacity        2.25210    0.10016  22.484  < 2e-16 ***
multi                  0.09575    0.03459   2.768  0.00566 **
biz                    0.09889    0.03491   2.833  0.00464 **
cleanliness_rating     0.92471    0.13317   6.944 4.40e-12 ***
bedrooms               0.63284    0.05185  12.204  < 2e-16 ***
dist                  -1.16990    0.05795 -20.187  < 2e-16 ***
metro_dist            -0.37275    0.05687  -6.554 6.27e-11 ***
room_type_encoded    -10.94478    1.00346 -10.907  < 2e-16 ***
room_private_encoded  16.26077    1.02801  15.818  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8873 on 4287 degrees of freedom
Multiple R-squared:  0.6431,    Adjusted R-squared:  0.6424
F-statistic: 858.3 on 9 and 4287 DF,  p-value: < 2.2e-16
```

Comparison of MSPE values between backward selection and forward selection

In [60]:
```
cat("The mean square prediction error (MSPE) on the test dataset for the best model as c
```

```
The mean square prediction error (MSPE) on the test dataset for the best model as comput
ed in backward selection is:  229556.4
```

In [61]:
```
cat("The mean square prediction error (MSPE) on the test dataset for the best model as c
```

```
The mean square prediction error (MSPE) on the test dataset for the best model as comput
ed in forward selection is:  229556.4
```

Therefore, for both type of model selection techniques, the MSPE values remain the same. Hence, the best model has been selected for regression modeling and predicting the prices of the Airbnb listings (`realSum`)

ANOVA Testing

In [62]:
```
# perform ANOVA test
anova_result <- anova(model_wknds_fs)
print(anova_result)
```

```
Analysis of Variance Table

Response: realSum
                       Df Sum Sq Mean Sq   F value    Pr(>F)
person_capacity         1 3708.3  3708.3 4710.4276 < 2.2e-16 ***
multi                   1   23.1    23.1   29.3838 6.264e-08 ***
biz                     1   41.0    41.0   52.1147 6.163e-13 ***
cleanliness_rating      1   50.4    50.4   64.0454 1.552e-15 ***
bedrooms                1    1.4     1.4    1.7328    0.1881
dist                    1  931.1   931.1 1182.7272 < 2.2e-16 ***
metro_dist              1   74.4    74.4   94.4498 < 2.2e-16 ***
room_type_encoded       1 1054.7  1054.7 1339.7718 < 2.2e-16 ***
room_private_encoded    1  197.0   197.0  250.2023 < 2.2e-16 ***
```

```
Residuals               4287 3375.0     0.8
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Hypothesis Testing

Distance vs. Listing Price

Null Hypothesis: There is no significant impact of the distance from the city center and the listing price.

Alternative Hypothesis: There is a significant impact of the distance from the city center and the listing price.

In [63]:
```
# testing the hypothesis using the regression coefficients of the optimized model `model_
test_result <- summary(model_wknds_fs)$coefficients['dist', 'Pr(>|t|)']

# significance level is set as 0.01
if (test_result < 0.01) {
  cat("Reject the null hypothesis.")
} else {
  cat("Do not reject the null hypothesis.")
}
```

```
Reject the null hypothesis.
```

Cleanliness Ratings vs. Listing Price

Null Hypothesis: There is no significant impact of the cleanliness ratings on the listing price.

Alternative Hypothesis: There is a significant impact of the cleanliness ratings on the listing price.

In [64]:
```
# testing the hypothesis using the regression coefficients of the optimized model `model_
test_result_guest <- summary(model_wknds_fs)$coefficients['cleanliness_rating', 'Pr(>|t|

# significance level is set as 0.01
if (test_result_guest < 0.01) {
  cat("Reject the null hypothesis.")
} else {
  cat("Do not reject the null hypothesis.")
}
```

```
Reject the null hypothesis.
```

Person Capacity vs. Listing Price

Null Hypothesis: There is no significant impact of the maximum person capacity of a room on the listing price.

Alternative Hypothesis: There is a significant impact of the maximum person capacity of a room on the listing price.

In [65]:
```
# Calculate Pearson's correlation coefficient
correlation <- cor(lon_wknds$person_capacity, lon_wknds$realSum)
print(correlation)
```

```
[1] 0.3841969
```

In [66]:
```
test_result <- cor.test(lon_wknds$person_capacity, lon_wknds$realSum)
```

```
if (test_result$p.value < 0.01) {
  cat("Reject the null hypothesis")
} else {
  cat("Do not reject the null hypothesis")
}
```

```
Reject the null hypothesis
```

Room Type vs. Listing Price

Null Hypothesis: There is no significant difference in the prices between private rooms and shared rooms.

Alternative Hypothesis: There is a significant difference in the prices between private rooms and shared rooms.

In [67]:

```
# Subset the data for shared rooms
shared_rooms <- lon_wknds[lon_wknds$room_type == 3, "realSum"]

# Subset the data for private rooms
private_rooms <- lon_wknds[lon_wknds$room_type == 1, "realSum"]

# Perform a t-test
t_test_result <- t.test(shared_rooms, private_rooms)

# Print the t-test result
print(t_test_result)
```

```
        Welch Two Sample t-test

data:  shared_rooms and private_rooms
t = -2.1622, df = 32.441, p-value = 0.03808
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -84.730300  -2.551048
sample estimates:
mean of x mean of y 
 178.4475  222.0881 
```

Formal Report:

- **Introduction:**

I am interested in looking into elements like guest and cleanliness ratings that have a big impact on price. Determining the critical elements is crucial because they provide the framework for enhancing the guest experience and optimizing all marketing tactics. The dataset was obtained via Kaggle datasets which was initially gathered by researchers to determine what factors influence pricing. With the use of statistical analysis on this dataset, I want to provide useful answers to the following questions: finding out the most influential factor on price listing, the difference in prices of different room types, and the effect of distance from the city center, cleanliness ratings, listings established for business purposes and maximum person capacity of rooms on the price of the listing.

- **Methods implemented and results:**

To facilitate computation and allow for the formation of correlation between the variables, data preprocessing was performed followed by splitting the dataset into training and testing data.

1. *Regression Modeling*: Using `realSum` as the response variable and the other columns as predictor variables, we design a linear regression model in this section to check for underperforming predictors.

2. *Model Diagnostics*: To verify modeling assumptions, including homoscedasticity, error normality, non-constant variances, and the existence of high leverage points, we generate diagnostic plots. Observations show that the model hardly fits into any of the categories. We perform a cube root data transformation to standardize the data, stabilize variance, and reinforce the model against outliers. Furthermore, we manually eliminated the outliers from the training dataset twice to fit the modeling assumptions.

3. *Model Selection*: This operation is carried out using two techniques - backward and forward selection. For backward selection, the significance level is set as $\alpha_{crit} = 0.01$ and the model is updated till a point where the p-values of all the predictor variables are below α_{crit}. In the case of forward selection, different selection criteria are implemented which resulted in the best model having **9** predictors. This can be determined using the `regsubsets()` function.

4. *ANOVA Testing*: To find the most influential predictor variable in the best model selected previously, we conduct an ANOVA test and check which predictor has the highest `F-value` and the lowest `Pr(>f)` value. Consequently, `person_capacity` turned out to be the most influential predictor. It is also observed that listings established for business purposes influence pricing.

5. *Hypothesis Testing*: Rejecting the null hypotheses indicates significant relationships between variables. The distance from the city center, cleanliness ratings, person capacity, and room type all impact listing prices in Airbnb accommodations, based on the conducted hypothesis tests.

- **Conclusions:**

The analysis reveals the significant impact of various factors on listing prices and its critical understanding for optimizing pricing strategies. Through this project, I learned the application of statistical methods for analyzing data and uncovering trends and insights of the dataset.

Future research could be conducted by exploring variables such as property amenities, seasonal trends, and neighborhood characteristics that influence pricing and investigating how those factors vary across different geographical locations.