STA141A_FinalProj

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Factors Influencing Airbnb Listing Prices in New York City

Executive Summary

This project investigates the factors that influence the pricing of Airbnb listings in New York City (NYC). By analyzing a comprehensive dataset from Airbnb, we aim to identify key variables that significantly affect listing prices and develop predictive models to estimate prices based on these features. We employ exploratory data analysis (EDA) to understand data distributions and relationships, and we use both linear regression and polynomial regression models to predict prices. Our analysis reveals that factors such as location (borough and neighborhood), room type, minimum nights, availability, and number of reviews significantly impact Airbnb prices in NYC.

The decision trees model outperforms the linear regression model in predictive accuracy. These insights can help hosts optimize their pricing strategies and assist guests in making informed booking decisions.

1. Introduction

Project Description and Background

Airbnb has revolutionized the hospitality industry by allowing property owners to rent out their spaces to travelers worldwide. New York City, as one of the most visited cities globally, has a highly competitive and diverse short-term rental market. With thousands of listings across five boroughs, understanding what drives Airbnb prices can benefit hosts looking to optimize their rental income and guests seeking affordable options.

Project Goals

- Identify Key Factors Influencing Prices: Determine which features significantly impact Airbnb listing prices in NYC.
- Predictive Modeling: Develop models to predict listing prices based on these features.
- Provide Insights for Stakeholders: Offer actionable insights for hosts and guests to make informed decisions.

2. Data Description

Dataset Overview

We utilize the "New York City Airbnb Open Data" from Kaggle, which includes detailed information about Airbnb listings in NYC for the year 2019.

Data Source: Kaggle - New York City Airbnb Open Data Number of Observations: 48,895 listings Variables: id: Listing ID name: Name of the listing host_id: Host ID host_name: Host name neighbourhood_group: Borough (Manhattan, Brooklyn, etc.) neighbourhood: Specific neighborhood within the borough latitude: Latitude coordinate longitude: Longitude coordinate room_type: Type of room offered price: Price per night in USD minimum_nights: Minimum number of nights required to book number_of_reviews: Total

number of reviews last_review: Date of the last review reviews_per_month: Average number of reviews per month calculated_host_listings_count: Number of listings the host has availability_365: Number of days the listing is available per year

Summary Statistics

```
# Load necessary libraries
library(tidyverse)
library(GGally)
library(caret)
library(randomForest)
library(Matrix)
library(corrplot)
library(e1071)
library(DT)

# Read the data
df <- read.csv("AB_NYC_2019.csv")
df <- data.frame(lapply(df, function(x) gsub("\u2B50", "", x)))

df <- df %>%
  mutate(across(c(minimum_nights, price, number_of_reviews,
                  reviews_per_month, availability_365, latitude, longitude),
                as.numeric))


# View summary statistics
summary(df)
```

```
##       id                name              host_id           host_name
##  Length:48895       Length:48895       Length:48895       Length:48895
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  neighbourhood_group neighbourhood         latitude       longitude
##  Length:48895        Length:48895       Min.   :40.50   Min.   :-74.24
##  Class :character    Class :character   1st Qu.:40.69   1st Qu.:-73.98
##  Mode  :character    Mode  :character   Median :40.72   Median :-73.96
##                                         Mean   :40.73   Mean   :-73.95
##                                         3rd Qu.:40.76   3rd Qu.:-73.94
##                                         Max.   :40.91   Max.   :-73.71
##
##   room_type             price         minimum_nights    number_of_reviews
##  Length:48895       Min.   :    0.0   Min.   :   1.00   Min.   :  0.00
##  Class :character   1st Qu.:   69.0   1st Qu.:   1.00   1st Qu.:  1.00
##  Mode  :character   Median :  106.0   Median :   3.00   Median :  5.00
##                     Mean   :  152.7   Mean   :   7.03   Mean   : 23.27
##                     3rd Qu.:  175.0   3rd Qu.:   5.00   3rd Qu.: 24.00
##                     Max.   :10000.0   Max.   :1250.00   Max.   :629.00
##
##  last_review        reviews_per_month calculated_host_listings_count
```

```
##  Length:48895       Min.   : 0.010    Length:48895
##  Class :character   1st Qu.: 0.190    Class :character
##  Mode  :character   Median : 0.720    Mode  :character
##                     Mean   : 1.373
##                     3rd Qu.: 2.020
##                     Max.   :58.500
##                     NA's   :10052
##  availability_365
##  Min.   :  0.0
##  1st Qu.:  0.0
##  Median : 45.0
##  Mean   :112.8
##  3rd Qu.:227.0
##  Max.   :365.0
##
```

Observations: The average price is $152.72 with a standard deviation of $240.15. There are missing values in 'name', 'host_name', 'last_review', and 'reviews_per_month'. The 'price' variable is also highly skewed with extreme outliers.

3. Exploratory Data Analysis

Handling Missing Values

```r
# Check for missing values
colSums(is.na(df))
```

```
##                             id                           name
##                              0                              0
##                        host_id                      host_name
##                              0                              0
##           neighbourhood_group                  neighbourhood
##                              0                              0
##                       latitude                      longitude
##                              0                              0
##                      room_type                          price
##                              0                              0
##                minimum_nights              number_of_reviews
##                              0                              0
##                   last_review             reviews_per_month
##                              0                          10052
## calculated_host_listings_count               availability_365
##                              0                              0
```

```r
# Explore the data
str(df) #offers a compact preview of the data
```

```
## 'data.frame':    48895 obs. of  16 variables:
##  $ id                            : chr  "2539" "2595" "3647" "3831" ...
##  $ name                          : chr  "Clean & quiet apt home by the park" "Skylit Midtown Castle"
##  $ host_id                       : chr  "2787" "2845" "4632" "4869" ...
##  $ host_name                     : chr  "John" "Jennifer" "Elisabeth" "LisaRoxanne" ...
##  $ neighbourhood_group           : chr  "Brooklyn" "Manhattan" "Manhattan" "Brooklyn" ...
##  $ neighbourhood                 : chr  "Kensington" "Midtown" "Harlem" "Clinton Hill" ...
##  $ latitude                      : num  40.6 40.8 40.8 40.7 40.8 ...
##  $ longitude                     : num  -74 -74 -73.9 -74 -73.9 ...
```

```
##  $ room_type                     : chr  "Private room" "Entire home/apt" "Private room" "Entire home/
##  $ price                         : num  149 225 150 89 80 200 60 79 79 150 ...
##  $ minimum_nights                : num  1 1 3 1 10 3 45 2 2 1 ...
##  $ number_of_reviews             : num  9 45 0 270 9 74 49 430 118 160 ...
##  $ last_review                   : chr  "2018-10-19" "2019-05-21" "" "2019-07-05" ...
##  $ reviews_per_month             : num  0.21 0.38 NA 4.64 0.1 0.59 0.4 3.47 0.99 1.33 ...
##  $ calculated_host_listings_count: chr  "6" "2" "1" "1" ...
##  $ availability_365              : num  365 355 365 194 0 129 0 220 0 188 ...
```

```
head(df)
```

```
##     id                                              name host_id   host_name
## 1 2539                Clean & quiet apt home by the park    2787        John
## 2 2595                             Skylit Midtown Castle    2845    Jennifer
## 3 3647               THE VILLAGE OF HARLEM....NEW YORK !    4632   Elisabeth
## 4 3831                   Cozy Entire Floor of Brownstone    4869 LisaRoxanne
## 5 5022 Entire Apt: Spacious Studio/Loft by central park    7192       Laura
## 6 5099        Large Cozy 1 BR Apartment In Midtown East    7322       Chris
##   neighbourhood_group neighbourhood latitude longitude       room_type price
## 1            Brooklyn    Kensington 40.64749 -73.97237    Private room   149
## 2           Manhattan       Midtown 40.75362 -73.98377 Entire home/apt   225
## 3           Manhattan        Harlem 40.80902 -73.94190    Private room   150
## 4            Brooklyn  Clinton Hill 40.68514 -73.95976 Entire home/apt    89
## 5           Manhattan   East Harlem 40.79851 -73.94399 Entire home/apt    80
## 6           Manhattan   Murray Hill 40.74767 -73.97500 Entire home/apt   200
##   minimum_nights number_of_reviews last_review reviews_per_month
## 1              1                 9  2018-10-19              0.21
## 2              1                45  2019-05-21              0.38
## 3              3                 0                            NA
## 4              1               270  2019-07-05              4.64
## 5             10                 9  2018-11-19              0.10
## 6              3                74  2019-06-22              0.59
##   calculated_host_listings_count availability_365
## 1                              6              365
## 2                              2              355
## 3                              1              365
## 4                              1              194
## 5                              1                0
## 6                              1              129
```

Observation:

'name': 16 missing 'host_name': 21 missing 'last_review' and 'reviews_per_month': 10,052 missing (listings with zero reviews)

```
# Fill missing 'reviews_per_month' with 0
df$reviews_per_month[is.na(df$reviews_per_month)] <- 0

# Drop rows with missing 'name' and 'host_name'
df <- df %>% drop_na(name, host_name)
```

Handling outliers for Columns

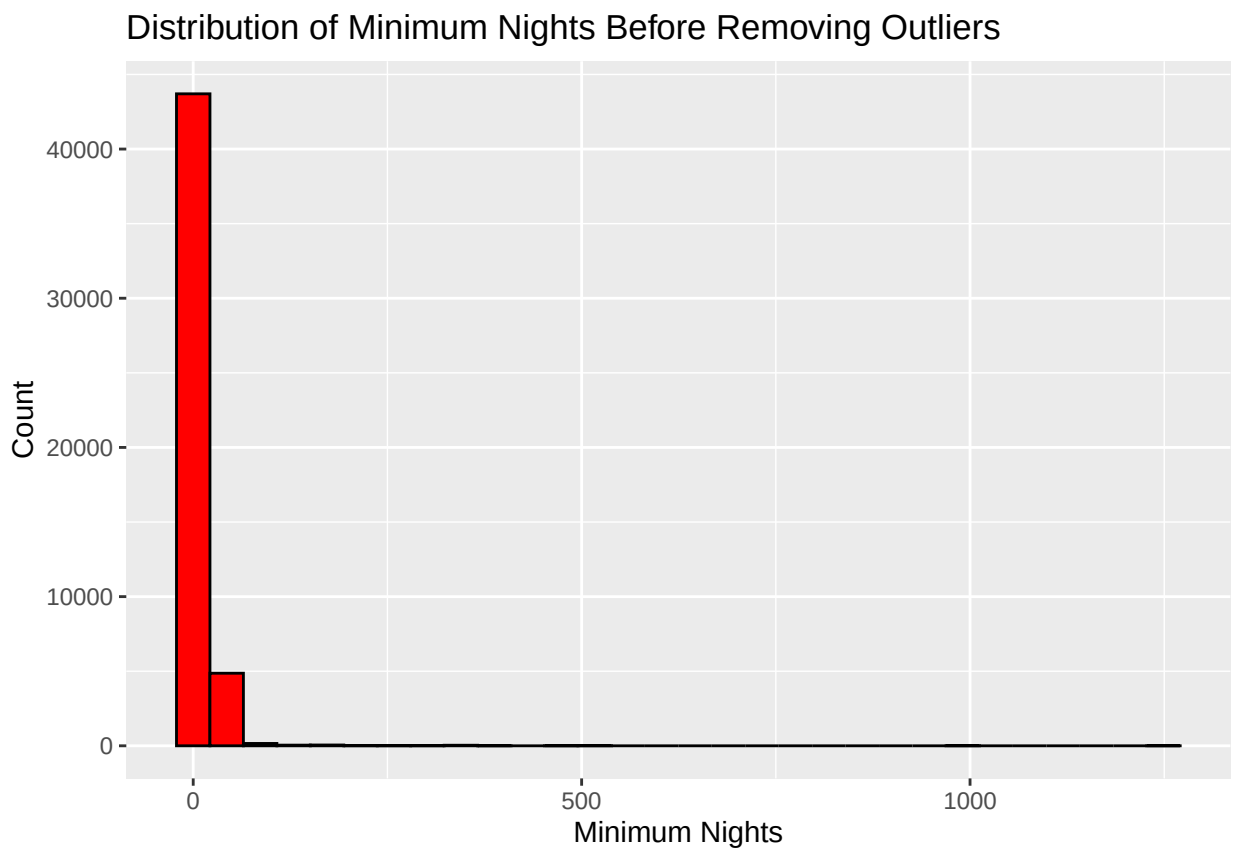
```
max(df$minimum_nights) #checking for information
```

```
## [1] 1250
```

```r
mean(df$minimum_nights) #comparative measure of minimum nights
```

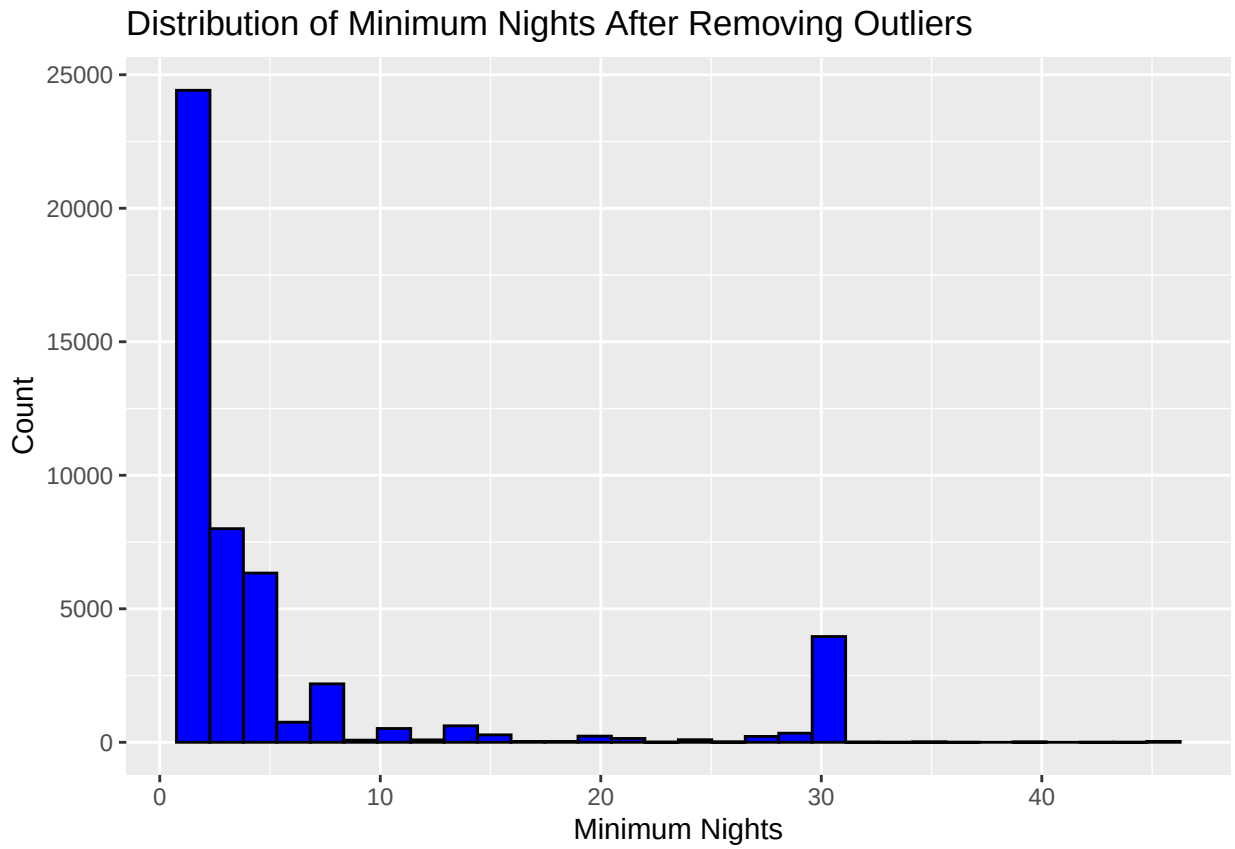
```
## [1] 7.029962
```

```r
df2 <- df
ggplot(df2, aes(x = minimum_nights)) +
  geom_histogram(color = "black", fill = 'red') +
  labs(title = "Distribution of Minimum Nights Before Removing Outliers",
                          x = "Minimum Nights", y = "Count")
```



Removing the Outliers

```r
# Define upper and lower quantiles
lower_quantile <- quantile(df$minimum_nights, 0.01)
upper_quantile <- quantile(df$minimum_nights, 0.99)

# Remove values outside this range
df <- df[df$minimum_nights >= lower_quantile & df$minimum_nights <= upper_quantile, ]

# Visualize the cleaned data
ggplot(df, aes(x = minimum_nights)) +
  geom_histogram(color = "black", fill = 'blue') +
  labs(title = "Distribution of Minimum Nights After Removing Outliers",
       x = "Minimum Nights", y = "Count")
```




```
max(df$minimum_nights)
```

```
## [1] 45
```

Analyzing Skewness and Transformations

```
# Check skewness of numerical variables
numeric_vars <- df %>% select(price, minimum_nights, number_of_reviews, reviews_per_month, availability
skewness_values <- sapply(numeric_vars, e1071::skewness)
print(skewness_values)
```

```
##             price    minimum_nights number_of_reviews reviews_per_month
##        18.6552004         2.3059163         3.6779410         3.2894295
##  availability_365
##         0.7712999
```

Observation:

'price' and 'minimum_nights' are highly skewed to the right.

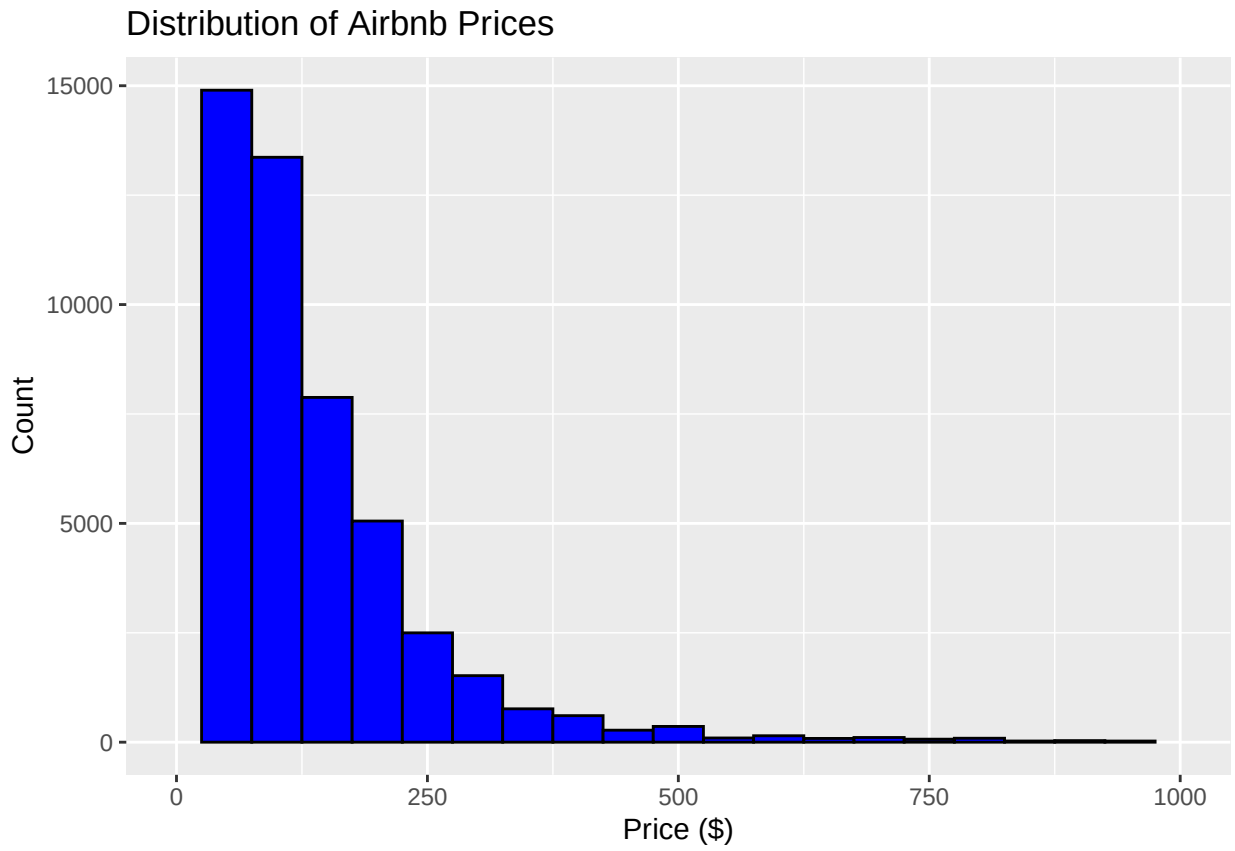
Log Transformation of Skewed Variables

```
# Apply log transformation to 'price' and 'minimum_nights'
df <- df %>%
  mutate(
    log_price = log(price + 1),             # <--- ADDED
    log_minimum_nights = log(minimum_nights + 1)
```

```
  )
```

Distribution of Prices

```
# Plot distribution of prices
ggplot(df, aes(x = price)) +
  geom_histogram(binwidth = 50, fill = "blue", color = "black") +
  xlim(0, 1000) +
  labs(title = "Distribution of Airbnb Prices", x = "Price ($)", y = "Count")
```

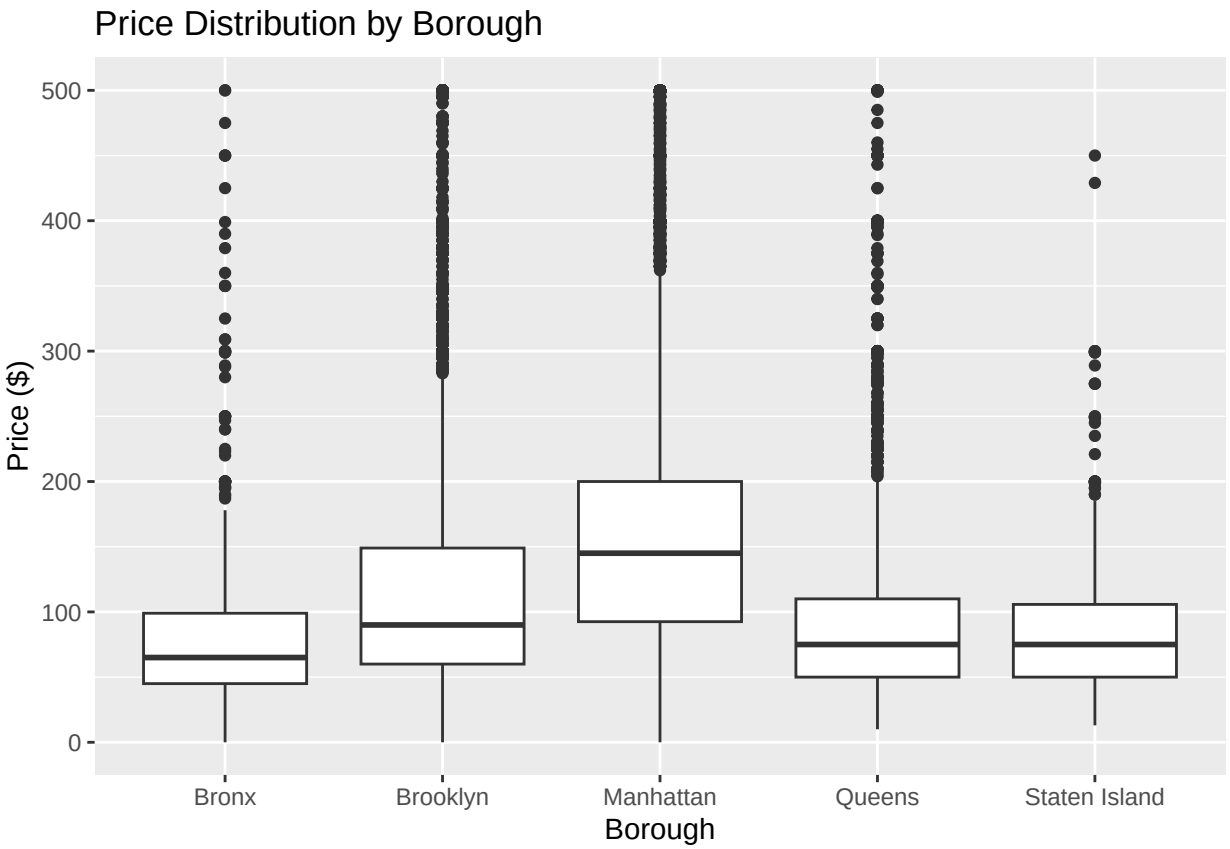


Observation:

The price distribution is right-skewed, with most listings priced below $500.

Price by Borough

```
# Boxplot of price by borough
ggplot(df, aes(x = neighbourhood_group, y = price)) +
  geom_boxplot() +
  ylim(0, 500) +
  labs(title = "Price Distribution by Borough", x = "Borough", y = "Price ($)")
```

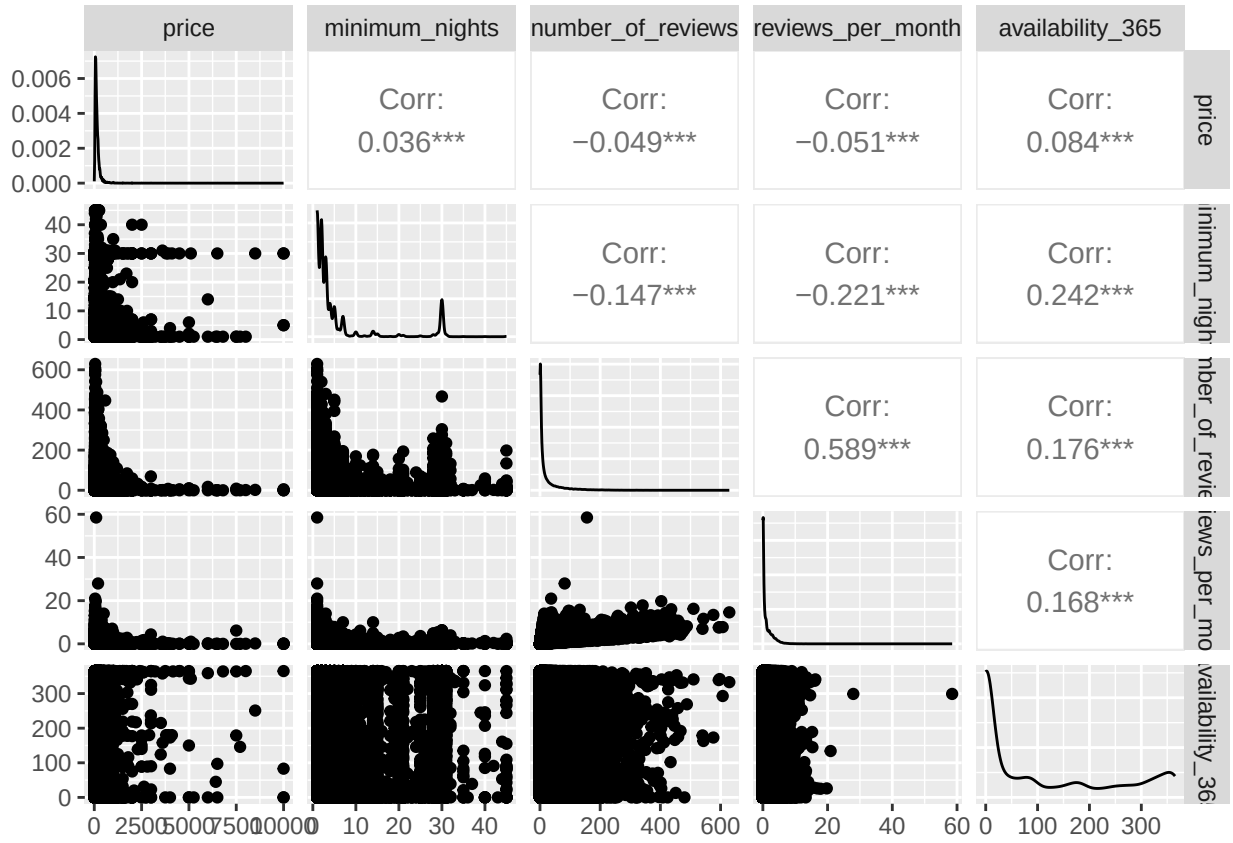


Observation:

Manhattan has higher median prices compared to other boroughs. Staten Island has a wider range of prices despite fewer listings.

Pairwise Scatter Plots

```
# Select numerical variables
numerical_vars <- df %>% select(price, minimum_nights, number_of_reviews, reviews_per_month, availabili

# Pairwise scatter plots
ggpairs(numerical_vars)
```



Observation:

Weak correlations between 'price' and other numerical variables. 'availability_365' shows some negative correlation with 'number_of_reviews'.

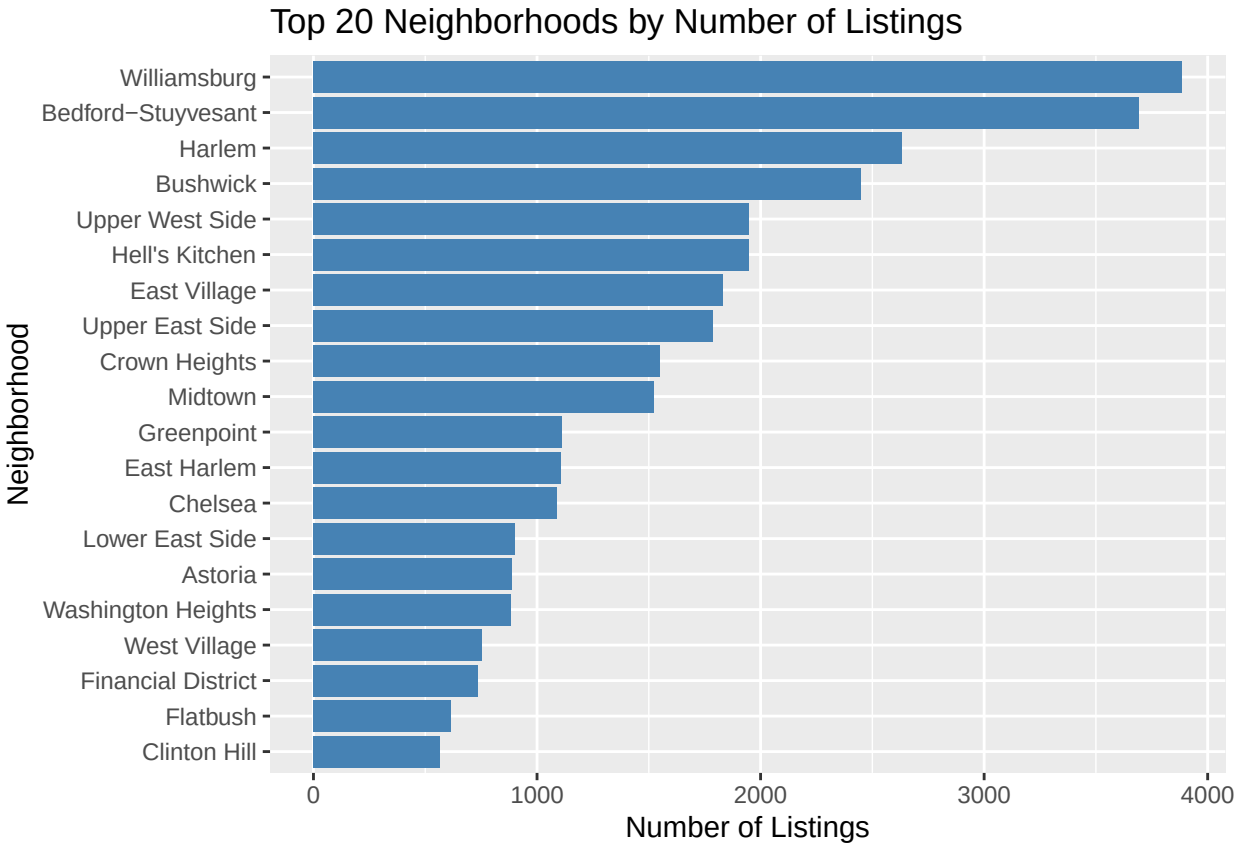
Exploring Location Data

Using Neighborhoods and Coordinates:

```
# Number of unique neighborhoods
num_neighbourhoods <- length(unique(df$neighbourhood))
cat("Number of unique neighborhoods:", num_neighbourhoods)
```

```
## Number of unique neighborhoods: 221
```

```
# Visualize the number of listings per neighborhood
top_neighbourhoods <- df %>%
  group_by(neighbourhood) %>%
  summarise(count = n()) %>%
  arrange(desc(count)) %>%
  top_n(20, count)

ggplot(top_neighbourhoods, aes(x = reorder(neighbourhood, count), y = count)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(title = "Top 20 Neighborhoods by Number of Listings", x = "Neighborhood", y = "Number of Listings
```



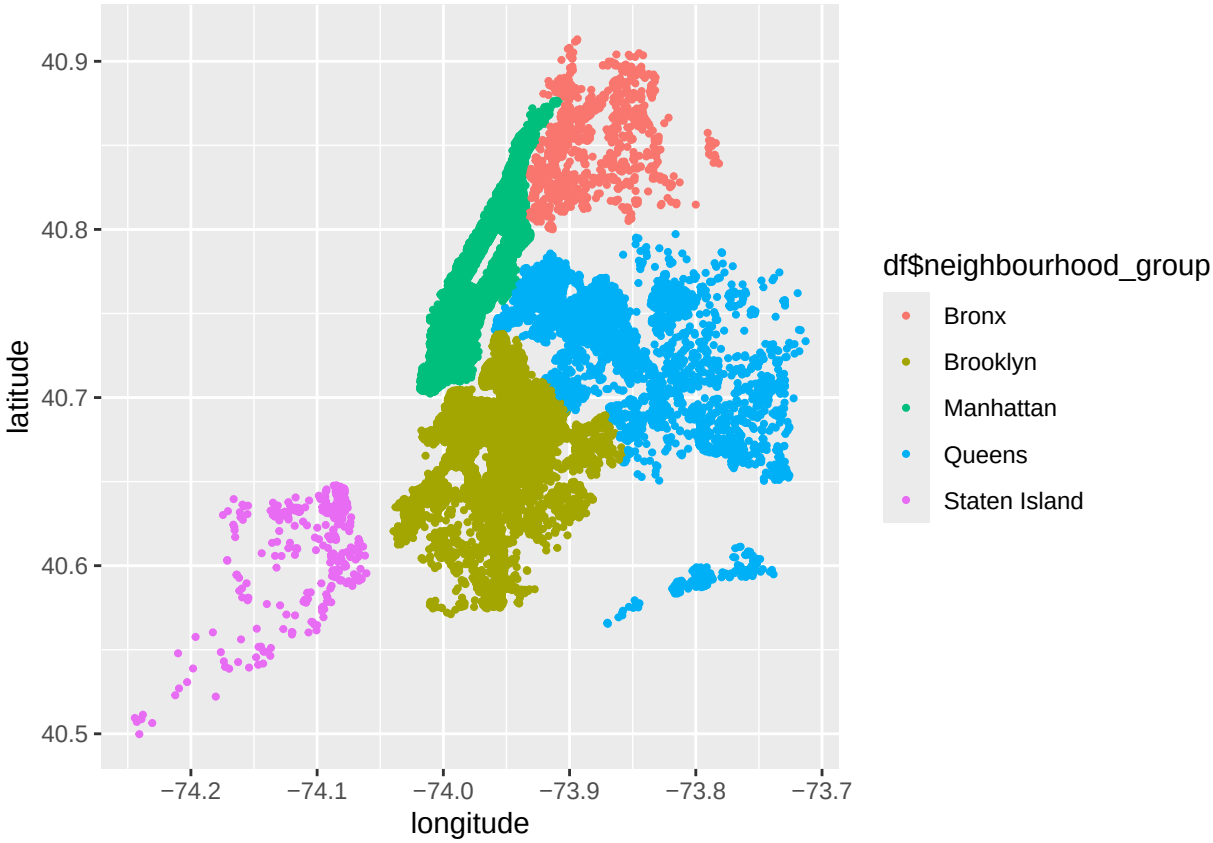
We have identified 221 unique neighbourhoods in New York, displaying the top 20 and the amount of listings. We can see Williamsburg and Bedford_Stuyevsant as the most popular by a decent margin.

Correlation Analysis

```r
# Compute correlation matrix
corr_matrix <- cor(numeric_vars)
corrplot(corr_matrix, method = "number", type = "upper")
```

Map of Borough

```
ggplot(data = df, aes(x = longitude, y = latitude, color = df$neighbourhood_group)) +
  geom_point(size = 0.75)
```



Map of Room Types Distribution

```
ggplot(data = df, aes(x = longitude, y = latitude, color = room_type)) +
  geom_point(size = 0.75)
```

Observation:

There is a moderate positive correlation between 'number_of_reviews' and 'reviews_per_month'. 'availability_365' has a weak correlation with other variables.

4. Methodology

Rationale for Method Selection

Exploratory Data Analysis (EDA): To understand data distributions, identify patterns, and detect anomalies. Data Preprocessing: To clean and prepare the data for modeling, ensuring reliable results. Linear Regression: As a baseline model to understand the linear relationships between variables.

Data Preprocessing Steps

Handling Missing Values: Imputed missing values appropriately. Outlier Removal: Removed listings with prices above the 99th percentile to reduce skewness. Encoding Categorical Variables: Converted categorical variables into factors and created dummy variables. Feature Scaling: Scaled numerical features where necessary.

5. Analysis and Findings

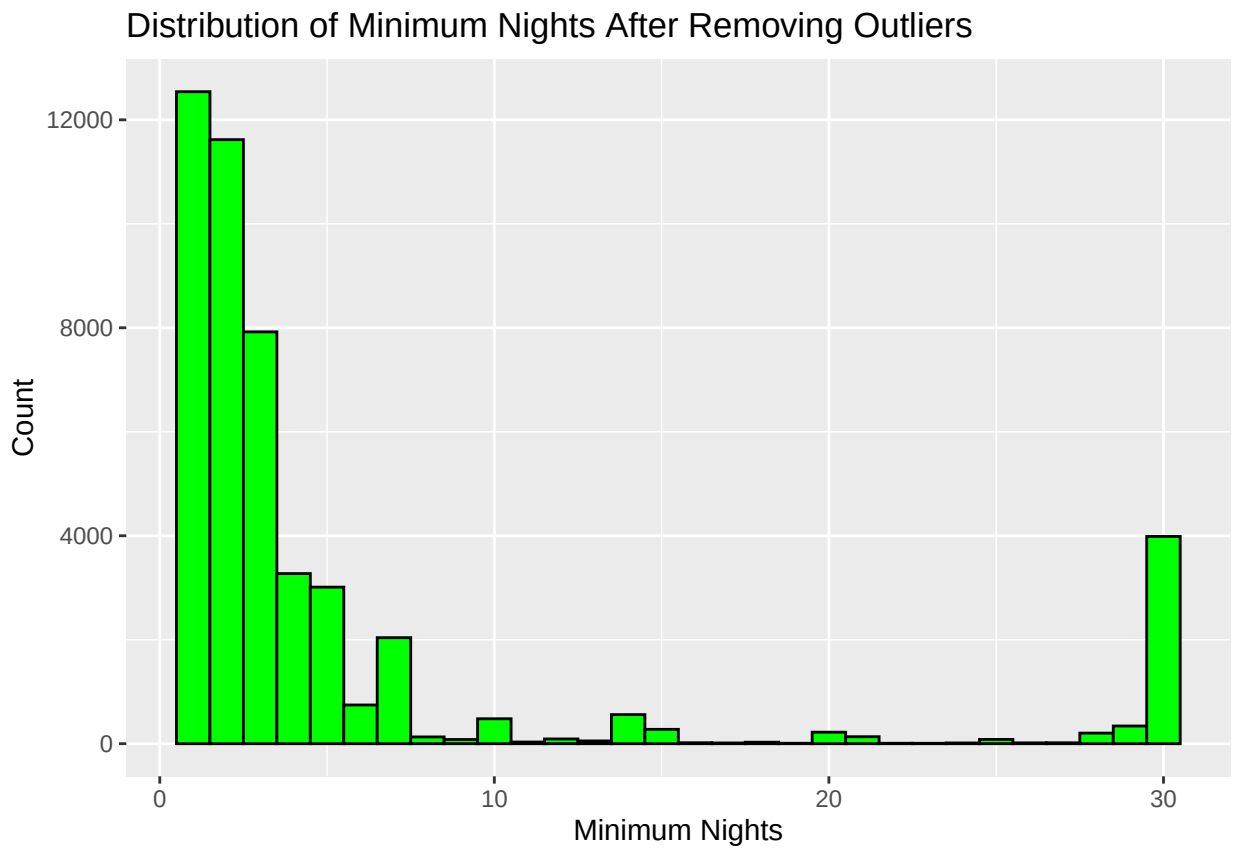
Data Cleaning and Preparation

```
# Remove extreme outliers in 'price' (above 99th percentile)
price_threshold <- quantile(df$price, 0.99)
df <- df %>% filter(price <= price_threshold)
```

```r
#must also account for lower outliers in price
sum(df$price == 0) #air bnb's with a price of 0 are questionable and removal may be advisable
```

```
## [1] 11
```

```r
df$price <- ifelse(df$price < 10, 10, df$price) # As a broader case, replace prices
#below $10 with 10 and above $1000 with 1000. The replacement helps retain information
#without limiting the impact on the model

# Replace minimum_nights above 30 with 30, same reasoning as before to keep information
# without negatively impacting the model accuracy
df$minimum_nights <- ifelse(df$minimum_nights > 30, 30, df$minimum_nights)

ggplot(df, aes(x = minimum_nights)) +
  geom_histogram(color = "black", fill = 'green') +
  labs(title = "Distribution of Minimum Nights After Removing Outliers",
                          x = "Minimum Nights", y = "Count")
```




```r
# One-hot encode 'room_type' and 'neighbourhood_group'
df_encoded <- df %>%
  mutate(
    borough_num = as.factor(neighbourhood_group),
    room_type_num = as.factor(room_type)
  )

df_encoded <- cbind(df_encoded, model.matrix(~ room_type + neighbourhood_group - 1, data = df_encoded))
```

Target Encoding for 'neighbourhood'

```
# Compute mean price per neighbourhood
neighbourhood_price <- df %>%
  group_by(neighbourhood) %>%
  summarise(mean_price = mean(log_price))

# Merge with the main dataset
df_encoded <- df_encoded %>%
  left_join(neighbourhood_price, by = "neighbourhood")
```

Feature Engineering

Interaction Terms

```
# Create interaction between room type and neighbourhood group
df_encoded <- df_encoded %>%
  mutate(
    interaction_term = interaction(room_type, neighbourhood_group)
  )

# One-hot encode the interaction term
df_encoded <- cbind(df_encoded, model.matrix(~ interaction_term - 1, data = df_encoded))
```

Using Geographical Coordinates

```
# Create features based on latitude and longitude
df_encoded <- df_encoded %>%
  mutate(
    lat_long = latitude * longitude
  )
```

Modeling

Splitting Data into Training and Testing Sets

```
set.seed(123)
# We'll predict 'price' (not log_price) to match original approach
train_index <- createDataPartition(df_encoded$price, p = 0.8, list = FALSE)

train_data <- df_encoded[train_index, ]
test_data  <- df_encoded[-train_index, ]
```

Feature Scaling

```
# Identify numeric features to scale
numeric_features <- c("log_minimum_nights", "number_of_reviews", "reviews_per_month", "availability_365

# Scale numeric features
preProcValues <- preProcess(train_data[, numeric_features], method = c("center", "scale"))
train_data[, numeric_features] <- predict(preProcValues, train_data[, numeric_features])
test_data[, numeric_features] <- predict(preProcValues, test_data[, numeric_features])
```

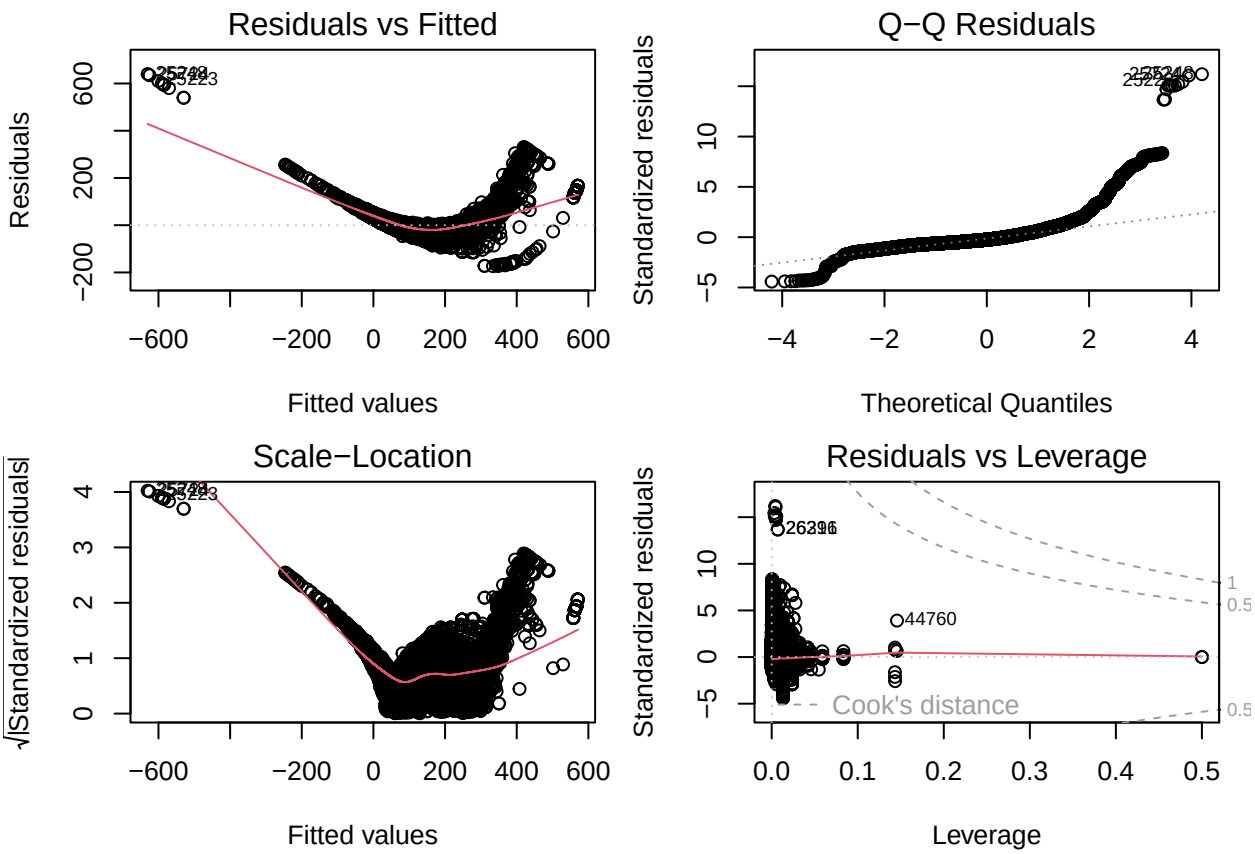
Linear Regression Model

```
# Fit linear regression model

# Create dummy variables again to ensure alignment
dummy_data <- model.matrix(~ neighbourhood_group + room_type - 1,
                           data = train_data)
train_data_encoded <- cbind(train_data, dummy_data)

dummy_test <- model.matrix(~ neighbourhood_group + room_type - 1,
                           data = test_data)
test_data_encoded <- cbind(test_data, dummy_test)

# Drop non-predictive or duplicated columns in both sets
drop_cols <- c("room_type", "neighbourhood_group", "neighbourhood",
               "name", "host_name", "id", "host_id", "last_review",
               "borough_num", "room_type_num", "latitude", "longitude",
               "interaction_term")

train_data_encoded <- train_data_encoded[, !(names(train_data_encoded)
                                             %in% drop_cols)]
test_data_encoded <- test_data_encoded[, !(names(test_data_encoded)
                                           %in% drop_cols)]

# Align columns
missing_cols <- setdiff(names(train_data_encoded), names(test_data_encoded))
test_data_encoded[missing_cols] <- 0
test_data_encoded <- test_data_encoded[, names(train_data_encoded)]

# Fit the linear regression model
lm_model <- lm(price ~ ., data = train_data_encoded)

# Predictions & Performance
lm_predictions <- predict(lm_model, newdata = test_data_encoded)
test_mae_lm <- mean(abs(lm_predictions - test_data_encoded$price))
rmse_lm <- sqrt(mean((lm_predictions - test_data_encoded$price)^2))
```

Findings: Significant Predictors: 'neighbourhood_group', 'room_type', 'minimum_nights', and 'availability_365'. Model Performance: Adjusted R-squared of approximately 0.35, indicating that the model explains about 35% of the variance in 'price'. An interesting observation to make is that the test lists the neighborhood group/ borough Staten Island and not significantly significant with a p value of 0.30. It is also noted that the Borough Queens is relatively large compared to its other neighbourhood groups but is still sigificant at an alpha level of .01

Residual Analysis for Linear Regression

```
# Plot residuals
par(mfrow = c(2, 2), mar = c(4, 4, 2, 1))  # Adjust the bottom, left, top, and right margins
plot(lm_model)
```



Observation:

Residuals vs Fitted: Indicates non-linearity. Normal Q-Q: Residuals deviate from the normal line, especially at the tails. Scale-Location: Heteroscedasticity is present. Residuals vs Leverage: No extreme outliers detected.

Findings:

Model Performance: RMSE of approximately $68.75, which is lower than the linear model's RMSE. Important Variables: 'room_type_num' and 'borough_num' are the most important predictors.

Polynomial Regression

```
# (1) Polynomial feature creation
# We'll manually create a squared term for 'log_minimum_nights'
train_data_encoded$log_minimum_nights_sq <- (train_data_encoded$log_minimum_nights)^2
test_data_encoded$log_minimum_nights_sq  <- (test_data_encoded$log_minimum_nights)^2

# Fit the polynomial regression using the updated train_data_encoded
poly_model <- lm(price ~ ., data = train_data_encoded)

# Predict on test set
poly_predictions <- predict(poly_model, newdata = test_data_encoded)
test_mae_poly <- mean(abs(poly_predictions - test_data_encoded$price))
rmse_poly <- sqrt(mean((poly_predictions - test_data_encoded$price)^2))
```

Decision Trees

```
# (2) Decision Tree
library(rpart)
tree_model <- rpart(price ~ ., data = train_data_encoded, method = "anova")

# Predictions & Performance
tree_predictions <- predict(tree_model, newdata = test_data_encoded)
test_mae_tree <- mean(abs(tree_predictions - test_data_encoded$price))
rmse_tree <- sqrt(mean((tree_predictions - test_data_encoded$price)^2))
```

Model Comparison

```
# Consolidate all model results
model_comparison <- data.frame(
  Model = c("Linear Regression",
            "Polynomial Regression", "Decision Tree"),
  MAE  = c(test_mae_lm, test_mae_poly, test_mae_tree),
  RMSE = c(rmse_lm, rmse_poly, rmse_tree)
)

model_comparison
```

```
##                   Model      MAE     RMSE
## 1     Linear Regression 25.13453 39.45833
## 2 Polynomial Regression 25.12411 39.44174
## 3         Decision Tree 13.16478 16.78395
```

Results:

We can see that the decision trees model performs the best, with an RMSE of 16.78395 and the Polynomial and Linear Regression having similar performances with 39.44174 and 39.45833 respectively.

6. Conclusions

Key Influencing Factors: Location (borough), room type, minimum nights, and availability significantly impact Airbnb listing prices in NYC.

Model Performance: Polynomial Regression can further improve over basic Linear Regression if the relationships are highly non-linear. Decision Trees are very interpretable and can perform better when tuned well.

Recommendations for Hosts: Optimize pricing strategies by considering the impact of room type and location. Adjust minimum nights and availability to influence pricing positively.

Recommendations for Guests: Look beyond popular boroughs like Manhattan to find more affordable options. Consider room types and booking durations to get better deals.