

AML Project: AirBnB (New York) Dataset

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The project aims to analyze the AirBnB data set available at OpenDataSoft and apply techniques learned as part of the course and some additional methods to predict the price that a new property should expect to charge based on its features. The data for New York City was extracted and used for the purpose of this project. Analysis, filtering, and extraction of categorical variables from the data set was done using Python. The combined, cleansed data file was loaded into a database (MySQL) from where it is read for regression. Extraction of derived columns and running the regression models was performed in R and the following methods were used- Linear Regression, Tree, Ridge/Lasso Regression, and XGBoost. Validation set and k-fold cross validation techniques are used. The output of the predicted prices (for data without prices in data set) is written to a CSV file at the end.

The required packages need to be installed. Please uncomment any packages that are not installed to make sure the program runs successfully.

```
print("Installing required packages")

## [1] "Installing required packages"

#install.packages("RMySQL")
#install.packages("MASS")
#install.packages("tidyverse")
#install.packages("glmnet")
#install.packages("tree")
#install.packages("xgboost")
#install.packages("caret")

library(RMySQL)

## Loading required package: DBI

library(MASS)
library(tidyverse)

## -- Attaching packages -----
----- tidyverse 1.3.0 -----

## v ggplot2 3.2.1      v purrr   0.3.3
## v tibble  2.1.3      v dplyr   0.8.3
## v tidyr   1.0.0      v stringr 1.4.0
## v readr   1.3.1      v forcats 0.4.0

## -- Conflicts -----
----- tidyverse_conflicts() -----
```

```

## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
## x dplyr::select() masks MASS::select()

library(glmnet)

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
## expand, pack, unpack

## Loaded glmnet 3.0-2

library(tree)

## Registered S3 method overwritten by 'tree':
## method from
## print.tree cli

library(xgboost)

##
## Attaching package: 'xgboost'

## The following object is masked from 'package:dplyr':
##
## slice

library(caret)

## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
## lift

```

The data is available as a CSV file and was loaded into MySQL database for this project. The user can choose to read from either source. For the purpose of this markdown, we read from the CSV file.

The regression models can be run with price or log of price (which has distribution closer to normal). The variable log_regression controls this feature and is set to FALSE for the purpose of this markdown.

```

print("NOTE: The data set is available as a cleaned CSV file and was loaded
into MySQL database for this project")

```

```
## [1] "NOTE: The data set is available as a cleaned CSV file and was loaded into MySQL database for this project"
```

```
read_from <- 0
r_user <- "r_user"
r_password <- "r_password"
db_name <- "aml"
log_regression <- FALSE
if(as.integer(read_from)==1){
  print(paste("Connecting to database with user",r_user))
  mydb <- dbConnect(MySQL(), user=r_user, password=r_password,
dbname=db_name, host="localhost")
  print(paste("Showing list of tables available in schema",db_name))
  tableNames <- dbListTables(mydb)
  print(tableNames)
  print(paste("Checking columns in table",tableNames[1]))
  colNames <- dbListFields(mydb, tableNames[1])
  print(colNames)
  print(paste("Fetching all data from ",tableNames[1]))
  tableQuery <- paste("SELECT * FROM ",db_name,".",tableNames[1],sep="")
  resultSet <- dbSendQuery(mydb, tableQuery)
  airData <- fetch(resultSet,n=-1)
  dbDisconnect(mydb)
} else {
  if(as.integer(read_from)==0){
    print("Reading from CSV")
  } else{
    print("Invalid input, defaulting to reading from CSV")
  }
  airData <- read.csv("final_project.csv")
}
```

```
## [1] "Reading from CSV"
```

Dimensions of airData.

```
print("Dimensions of airData:")
```

```
## [1] "Dimensions of airData:"
```

```
print(dim(airData))
```

```
## [1] 19273 130
```

Changing boolean columns to integer (0/1) columns so as to later convert them to factors.

```
print("Converting boolean columns to integers")
```

```
## [1] "Converting boolean columns to integers"
```

```
airData[,31:130] <- lapply(airData[,31:130],as.integer)
```

Deriving new features: 1. featureCount: Number of 0/1 features provided by each listing. 2. yearsAsHost: (2019 - first year as host)

```
print("Deriving new features from data set")
## [1] "Deriving new features from data set"
print("Deriving number of features as numerical feature")
## [1] "Deriving number of features as numerical feature"
airData$featureCount <- apply(airData[,31:130],1,sum)
print("Deriving yearAsHost as numerical feature")
## [1] "Deriving yearAsHost as numerical feature"
airData$yearsAsHost <- (2019 - airData$hostYear)
```

Converting categorical columns to factors.

```
print("Converting categorical columns to factors")
## [1] "Converting categorical columns to factors"
airData[,31:130] <- lapply(airData[,31:130],as.factor)
airData$neighbourhoodCleansed <- as.factor(airData$neighbourhoodCleansed)
airData$neighbourhoodGroupCleansed <-
as.factor(airData$neighbourhoodGroupCleansed)
airData$bedType <- as.factor(airData$bedType)
airData$cancellationPolicy <- as.factor(airData$cancellationPolicy)
airData$propertyType <- as.factor(airData$propertyType)
airData$roomType <- as.factor(airData$roomType)
airData <- as.data.frame(airData)
```

Summary of airData after above manipulations.

```
print("Summary of airData:")
## [1] "Summary of airData:"
print(summary(airData))
##          id          hostYear  hostResponseHours
##  Min.   :   2515   Min.   :2008   Min.   : 1.000
## 1st Qu.: 4941141   1st Qu.:2013   1st Qu.: 1.000
##  Median : 9906178   Median :2014   Median : 1.000
##   Mean   : 9832847   Mean   :2014   Mean   : 9.231
## 3rd Qu.:14834468   3rd Qu.:2015   3rd Qu.:12.000
##   Max.   :18516103   Max.   :2017   Max.   :72.000
##
##      neighbourhoodCleansed neighbourhoodGroupCleansed  accommodates
##   Harlem          :2481      Bronx          :    15      Min.   : 1.000
##   East Village     :1828      Brooklyn         :   212      1st Qu.: 2.000
```

```

## Upper West Side:1750      Manhattan      :18902      Median : 2.000
## Hell's Kitchen :1557      Queens       : 140      Mean   : 2.803
## Upper East Side:1520      Staten Island: 4      3rd Qu.: 4.000
## Chelsea         :1056                                     Max.   :16.000
## (Other)         :9081
##      bathrooms      bedType      bedrooms      beds
## Min.   :0.000      Airbed       : 133      Min.   :0.000      Min.   : 0.000
## 1st Qu.:1.000      Couch        : 67      1st Qu.:1.000      1st Qu.: 1.000
## Median :1.000      Futon        : 186      Median :1.000      Median : 1.000
## Mean   :1.098      Pull-out Sofa: 205      Mean   :1.093      Mean   : 1.506
## 3rd Qu.:1.000      Real Bed     :18682      3rd Qu.:1.000      3rd Qu.: 2.000
## Max.   :6.500                                     Max.   :6.000      Max.   :14.000
##
##      TV      cancellationPolicy      cleaningFee
## Min.   :0.0000      flexible      :5799      Min.   : 0.00
## 1st Qu.:0.0000      moderate      :4250      1st Qu.: 0.00
## Median :1.0000      strict        :9220      Median : 40.00
## Mean   :0.6886      super_strict_30: 4      Mean   : 47.86
## 3rd Qu.:1.0000                                     3rd Qu.: 75.00
## Max.   :2.0000                                     Max.   :600.00
##
##      extraPeople      guestsIncluded      maximumNights      minimumNights
## Min.   : 0.00      Min.   : 1.000      Min.   : 1.0      Min.   : 1.00
## 1st Qu.: 0.00      1st Qu.: 1.000      1st Qu.: 30.0      1st Qu.: 1.00
## Median : 0.00      Median : 1.000      Median :1125.0      Median : 2.00
## Mean   : 14.05      Mean   : 1.435      Mean   : 696.8      Mean   : 4.21
## 3rd Qu.: 25.00      3rd Qu.: 2.000      3rd Qu.:1125.0      3rd Qu.: 3.00
## Max.   :300.00      Max.   :16.000      Max.   :1125.0      Max.   :1250.00
##
##      price      propertyType      roomType
## Min.   : 0.0      Apartment :18092      Entire home/apt:10818
## 1st Qu.: 88.0      House     : 294      Private room : 7880
## Median :133.0      Loft      : 264      Shared room  : 575
## Mean   :165.1      Condominium: 191
## 3rd Qu.:200.0      Townhouse : 178
## Max.   :999.0      Other     : 101
##      (Other)      : 153
##      securityDeposit      numberOfReviews      reviewScoresAccuracy      reviewScoresCheckin
## Min.   : 0.0      Min.   : 0.00      Min.   : 0.000      Min.   : 0.000
## 1st Qu.: 0.0      1st Qu.: 1.00      1st Qu.: 6.000      1st Qu.: 7.000
## Median : 0.0      Median : 5.00      Median : 9.000      Median :10.000
## Mean   :122.9      Mean   : 16.91      Mean   : 7.212      Mean   : 7.358
## 3rd Qu.:200.0      3rd Qu.: 19.00      3rd Qu.:10.000      3rd Qu.:10.000
## Max.   :999.0      Max.   :432.00      Max.   :10.000      Max.   :10.000
##
##      reviewScoresCleanliness      reviewScoresCommunication      reviewScoresLocation
## Min.   : 0.000      Min.   : 0.000      Min.   : 0.000
## 1st Qu.: 6.000      1st Qu.: 8.000      1st Qu.: 7.000
## Median : 9.000      Median :10.000      Median :10.000
## Mean   : 6.957      Mean   : 7.394      Mean   : 7.265

```

```

## 3rd Qu.:10.000      3rd Qu.:10.000      3rd Qu.:10.000
## Max.    :10.000      Max.    :10.000      Max.    :10.000
##
## reviewScoresRating reviewScoresValue reviewsperMonth  checkIn24Hours
## Min.    : 0.00      Min.    : 0.000      Min.    : 0.000      0:14476
## 1st Qu.: 60.00      1st Qu.: 6.000      1st Qu.: 0.060      1: 4797
## Median : 92.00      Median : 9.000      Median : 0.420
## Mean    : 70.64      Mean    : 7.063      Mean    : 1.028
## 3rd Qu.: 98.00      3rd Qu.:10.000      3rd Qu.: 1.460
## Max.    :100.00      Max.    :10.000      Max.    :125.920
##
## accessibleHeightToilet airConditioning BBQgrill  babyBath  babyMonitor
## 0:19272      0: 2732      0:19272      0:19255      0:19264
## 1: 1      1:16541      1: 1      1: 18      1: 9
##
##
##
##
##
## babySitterRecommendations bathTub  bedLinens breakfast
## 0:19211      0:18825      0:19265      0:17882
## 1: 62      1: 448      1: 8      1: 1391
##
##
##
##
##
## buzzerOrWirelessIntercom cableTV  carbonMonoxideDetector cats
## 0:9731      0:12835      0: 8174      0:18596
## 1:9542      1: 6438      1:11099      1: 677
##
##
##
##
##
## changingTable childrenBooksAndToys childrenDinnerware
## 0:19253      0:19210      0:19231
## 1: 20      1: 63      1: 42
##
##
##
##
##
## cleaningBeforeCheckout coffeemaker cookingBasics crib
## 0:19272      0:19266      0:19265      0:19237
## 1: 1      1: 7      1: 8      1: 36
##
##
##
##

```

```

##
## dishesAndSilverware dishwasher dogs      doorman  doormanEntry dryer
## 0:19265          0:19271    0:18526    0:16544    0:18933    0:11162
## 1:      8          1:      2    1:   747    1:  2729    1:   340    1:  8111
##
##
##
##
## elevator  essentials extraPillowsBlankets familyAndKidFriendly
## 0:11421    0: 3232    0:19269          0:10810
## 1: 7852    1:16041    1:      4          1: 8463
##
##
##
##
## fireExtinguisher fireplaceGuards firstAidKit freeParkingOnPremises
## 0:14376          0:19261          0:14181    0:18402
## 1: 4897          1:      12          1: 5092    1:   871
##
##
##
##
## freeParkingOnStreet gameConsole gardenOrBackyard railsInShowerToilet
## 0:19269          0:19220    0:19270          0:19272
## 1:      4          1:   53    1:      3          1:      1
##
##
##
##
## gym        hairdryer hangers    heating    highchair hottub    hotwater
## 0:17535    0: 9072    0: 7893    0: 1215    0:19217    0:18135    0:19267
## 1: 1738    1:10201    1:11380    1:18058    1:   56    1: 1138    1:      6
##
##
##
##
## indoorFireplace internet  iron      keypad    kitchen
## 0:18442          0: 5891    0:9734    0:19131    0: 1004
## 1:  831          1:13382    1:9539    1:  142    1:18269
##
##
##
##
## laptopFriendlyWorkspace lockOnBedroomDoor lockbox    longTermStaysAllowed

```

```

## 0:9335          0:15388          0:18630    0:19271
## 1:9938          1: 3885          1: 643    1: 2
##
##
##
##
## luggageDropOffAllowed microwave otherPets outletCovers oven
## 0:19271          0:19266    0:19244    0:19251    0:19264
## 1: 2            1: 7      1: 29     1: 22     1: 9
##
##
##
##
## packNPlayTravelCrib pathToEntranceLitAtNight patioOrBalcony petsAllowed
## 0:19180          0:19272          0:19270    0:16973
## 1: 93           1: 1            1: 3      1: 2300
##
##
##
##
## petsLiveOnThisProperty pool      privateBathroom privatEntrance
## 0:17756          0:18984    0:19271    0:18734
## 1: 1517         1: 289     1: 2       1: 539
##
##
##
##
## privateLivingRoom refrigerator shades      safetyCard selfCheckIn shampoo
## 0:18986          0:19264          0:19088    0:17077    0:18102    0: 7196
## 1: 287          1: 9            1: 185     1: 2196    1: 1171    1:12077
##
##
##
##
## smartlock smokeDetector smokingAllowed stairGates stepFreeaccess
## 0:19207    0: 4141      0:18355      0:19250    0:19271
## 1: 66      1:15132      1: 918       1: 23     1: 2
##
##
##
##
## stove      suitableForEvents tableCornerGuards washer      washerDryer
## 0:19265    0:18587          0:19266          0:11093    0:19267
## 1: 8        1: 686          1: 7            1: 8180    1: 6

```



```

##
##
##
##
## wheelchairAccessible wideClearanceToBed wideClearanceShowerToilet
## 0:17632 0:19272 0:19272
## 1: 1641 1: 1 1: 1
##
##
##
##
## wideDoorway wideHallwayClearance windowGuards wirelessInternet
## 0:19272 0:19272 0:19153 0: 533
## 4: 1 1: 1 1: 120 1:18740
##
##
##
##
## hosting_amenity_49 hosting_amenity_50 hostHasProfilePic
## 0:12997 0:11648 0: 79
## 1: 6276 1: 7625 1:19194
##
##
##
##
## hostIdentityVerified hostIsSuperhost instantBookable isLocationExact
## 0: 6586 0:17569 0:15645 0: 3368
## 1:12687 1: 1704 1: 3628 1:15905
##
##
##
##
## requireGuestPhoneVerification requireGuestProfilePicture featureCount
## 0:18595 0:18680 Min. : 2.00
## 1: 678 1: 593 1st Qu.:14.00
## Median :17.00
## Mean :17.65
## 3rd Qu.:21.00
## Max. :51.00
##
## yearsAsHost
## Min. : 2.000
## 1st Qu.: 4.000
## Median : 5.000
## Mean : 5.087

```

```
## 3rd Qu.: 6.000
## Max.    :11.000
##
```

Dropping columns that have been used to derive other columns, have repeated information or have low count which may cause issues when training and test data sets have different levels.

```
print("Dropping columns from airData that have been used to derive other
columns, have repeated information, or have low count for certain levels")
```

```
## [1] "Dropping columns from airData that have been used to derive other
columns, have repeated information, or have low count for certain levels"
```

```
dropColumns <-
c("id","hostYear","accessibleHeightToilet","BBQgrill","babyBath","babyMonitor",
"babySitterRecommendations","bathTub","bedLinens","breakfast","changingTable",
"cats","childrenBooksAndToys","childrenDinnerware","cleaningBeforeCheckout",
"coffeemaker","cookingBasics","crib","dishesAndSilverware","dishwasher","dogs",
"doormanEntry","extraPillowsBlankets","fireplaceGuards","freeParkingOnStreet",
"gameConsole","gardenOrBackyard","railsInShowerToilet","highchair","hotwater",
"indoorFireplace","keypad","lockbox","longTermStaysAllowed","luggageDropOffAllowed",
"microwave","otherPets","outletCovers","oven","packNPlayTravelCrib",
"pathToEntranceLitAtNight","patioOrBalcony","privateBathroom","privateEntrance",
"privateLivingRoom","refrigerator","shades","safetyCard","smartlock","stairGates",
"stepFreeaccess","stove","suitableForEvents","tableCornerGuards",
"washerDryer","wideClearanceToBed","wideClearanceShowerToilet","wideDoorway",
"wideHallwayClearance","windowGuards","hosting_amenity_49","hosting_amenity_50")
airDataClean <- airData[,!(names(airData) %in% dropColumns)]
airDataClean <- as.data.frame(airDataClean)
```

Column names in cleaned data set.

```
print("Columns in cleaned airData set")
```

```
## [1] "Columns in cleaned airData set"
```

```
print(names(airDataClean))
```

```
## [1] "hostResponseHours"      "neighbourhoodCleansed"
## [3] "neighbourhoodGroupCleansed" "accommodates"
## [5] "bathrooms"             "bedType"
## [7] "bedrooms"              "beds"
## [9] "TV"                    "cancellationPolicy"
## [11] "cleaningFee"           "extraPeople"
## [13] "guestsIncluded"        "maximumNights"
## [15] "minimumNights"         "price"
## [17] "propertyType"          "roomType"
## [19] "securityDeposit"       "numberOfReviews"
## [21] "reviewScoresAccuracy"  "reviewScoresCheckin"
## [23] "reviewScoresCleanliness" "reviewScoresCommunication"
```

```
## [25] "reviewScoresLocation"      "reviewScoresRating"
## [27] "reviewScoresValue"        "reviewsperMonth"
## [29] "checkIn24Hours"           "airConditioning"
## [31] "buzzerOrWirelessIntercom" "cableTV"
## [33] "carbonMonoxideDetector"    "doorman"
## [35] "dryer"                     "elevator"
## [37] "essentials"                "familyAndKidFriendly"
## [39] "fireExtinguisher"          "firstAidKit"
## [41] "freeParkingOnPremises"     "gym"
## [43] "hairdryer"                 "hangers"
## [45] "heating"                   "hottub"
## [47] "internet"                  "iron"
## [49] "kitchen"                   "laptopFriendlyWorkspace"
## [51] "lockOnBedroomDoor"         "petsAllowed"
## [53] "petsLiveOnThisProperty"    "pool"
## [55] "selfCheckIn"               "shampoo"
## [57] "smokeDetector"             "smokingAllowed"
## [59] "washer"                    "wheelchairAccessible"
## [61] "wirelessInternet"          "hostHasProfilePic"
## [63] "hostIdentityVerified"      "hostIsSuperhost"
## [65] "instantBookable"           "isLocationExact"
## [67] "requireGuestPhoneVerification" "requireGuestProfilePicture"
## [69] "featureCount"              "yearsAsHost"
```

Clubbing infrequent neighborhoods into 'Other' category so as to reduce the probability of issues caused due to different levels in training and test data sets.

```
print("Clubbing infrequent neighborhoods into 'Other' category")
## [1] "Clubbing infrequent neighborhoods into 'Other' category"

neighborhoodList <- unique(airDataClean$neighbourhoodCleansed)

print("Converting column as character to replace with Other")
## [1] "Converting column as character to replace with Other"

airDataClean$neighbourhoodCleansed <-
as.character(airDataClean$neighbourhoodCleansed)
print("Neighborhood summary before cleansing")
## [1] "Neighborhood summary before cleansing"

print(summary(airDataClean$neighbourhoodCleansed))

##      Length      Class      Mode
##      19273 character character

print("Clubbing infrequent neighborhoods into 'Other'")
## [1] "Clubbing infrequent neighborhoods into 'Other'"
```

```

for(n in neighborhoodList)
{
  tempList <- airDataClean$neighbourhoodCleansed == n
  rcount <- length(which(tempList))
  print(paste(n,":",rcount))
  if(rcount <= 300){
    print(paste("Changing ",n," to Other"))
    airDataClean$neighbourhoodCleansed[tempList] <- "Other"
  }
}

```

```

## [1] "Long Island City : 28"
## [1] "Changing Long Island City to Other"
## [1] "Lower East Side : 947"
## [1] "Midtown : 946"
## [1] "Kips Bay : 409"
## [1] "Little Italy : 89"
## [1] "Changing Little Italy to Other"
## [1] "Murray Hill : 253"
## [1] "Changing Murray Hill to Other"
## [1] "Morningside Heights : 388"
## [1] "NoHo : 77"
## [1] "Changing NoHo to Other"
## [1] "Nolita : 284"
## [1] "Changing Nolita to Other"
## [1] "Roosevelt Island : 57"
## [1] "Changing Roosevelt Island to Other"
## [1] "SoHo : 350"
## [1] "Stuyvesant Town : 38"
## [1] "Changing Stuyvesant Town to Other"
## [1] "Hell's Kitchen : 1557"
## [1] "Greenwich Village : 373"
## [1] "Harlem : 2481"
## [1] "Inwood : 223"
## [1] "Changing Inwood to Other"
## [1] "East Harlem : 1038"
## [1] "East Village : 1828"
## [1] "Financial District : 387"
## [1] "Flatiron District : 88"
## [1] "Changing Flatiron District to Other"
## [1] "Flatbush : 6"
## [1] "Changing Flatbush to Other"
## [1] "Gramercy : 302"
## [1] "Upper West Side : 1750"
## [1] "Theater District : 171"
## [1] "Changing Theater District to Other"
## [1] "Tribeca : 155"
## [1] "Changing Tribeca to Other"
## [1] "Two Bridges : 54"
## [1] "Changing Two Bridges to Other"

```

[1] "Upper East Side : 1520"
[1] "Washington Heights : 851"
[1] "West Village : 769"
[1] "Williamsburg : 62"
[1] "Changing Williamsburg to Other"
[1] "Ditmars Steinway : 15"
[1] "Changing Ditmars Steinway to Other"
[1] "Astoria : 37"
[1] "Changing Astoria to Other"
[1] "Battery Park City : 63"
[1] "Changing Battery Park City to Other"
[1] "Bedford-Stuyvesant : 31"
[1] "Changing Bedford-Stuyvesant to Other"
[1] "Prospect-Lefferts Gardens : 9"
[1] "Changing Prospect-Lefferts Gardens to Other"
[1] "Bushwick : 30"
[1] "Changing Bushwick to Other"
[1] "Chinatown : 354"
[1] "Chelsea : 1056"
[1] "Civic Center : 41"
[1] "Changing Civic Center to Other"
[1] "Concourse : 2"
[1] "Changing Concourse to Other"
[1] "Jamaica Hills : 1"
[1] "Changing Jamaica Hills to Other"
[1] "Greenpoint : 6"
[1] "Changing Greenpoint to Other"
[1] "Crown Heights : 13"
[1] "Changing Crown Heights to Other"
[1] "East Flatbush : 3"
[1] "Changing East Flatbush to Other"
[1] "Elmhurst : 8"
[1] "Changing Elmhurst to Other"
[1] "Sunset Park : 4"
[1] "Changing Sunset Park to Other"
[1] "Mariners Harbor : 1"
[1] "Changing Mariners Harbor to Other"
[1] "Sunnyside : 13"
[1] "Changing Sunnyside to Other"
[1] "Ridgewood : 18"
[1] "Changing Ridgewood to Other"
[1] "Far Rockaway : 1"
[1] "Changing Far Rockaway to Other"
[1] "Fort Greene : 9"
[1] "Changing Fort Greene to Other"
[1] "Fresh Meadows : 1"
[1] "Changing Fresh Meadows to Other"
[1] "Gravesend : 2"
[1] "Changing Gravesend to Other"
[1] "Kensington : 3"

```
## [1] "Changing Kensington to Other"
## [1] "Rockaway Beach : 1"
## [1] "Changing Rockaway Beach to Other"
## [1] "Marble Hill : 3"
## [1] "Changing Marble Hill to Other"
## [1] "Port Morris : 1"
## [1] "Changing Port Morris to Other"
## [1] "Kingsbridge : 2"
## [1] "Changing Kingsbridge to Other"
## [1] "Midwood : 2"
## [1] "Changing Midwood to Other"
## [1] "Red Hook : 2"
## [1] "Changing Red Hook to Other"
## [1] "Bensonhurst : 1"
## [1] "Changing Bensonhurst to Other"
## [1] "Concourse Village : 1"
## [1] "Changing Concourse Village to Other"
## [1] "Corona : 2"
## [1] "Changing Corona to Other"
## [1] "Highbridge : 2"
## [1] "Changing Highbridge to Other"
## [1] "Carroll Gardens : 3"
## [1] "Changing Carroll Gardens to Other"
## [1] "Flushing : 3"
## [1] "Changing Flushing to Other"
## [1] "South Slope : 1"
## [1] "Changing South Slope to Other"
## [1] "Prospect Heights : 4"
## [1] "Changing Prospect Heights to Other"
## [1] "Stapleton : 1"
## [1] "Changing Stapleton to Other"
## [1] "Fort Hamilton : 1"
## [1] "Changing Fort Hamilton to Other"
## [1] "Brooklyn Heights : 4"
## [1] "Changing Brooklyn Heights to Other"
## [1] "Jamaica : 2"
## [1] "Changing Jamaica to Other"
## [1] "Riverdale : 1"
## [1] "Changing Riverdale to Other"
## [1] "Park Slope : 3"
## [1] "Changing Park Slope to Other"
## [1] "Rego Park : 2"
## [1] "Changing Rego Park to Other"
## [1] "Morrisania : 2"
## [1] "Changing Morrisania to Other"
## [1] "Throgs Neck : 1"
## [1] "Changing Throgs Neck to Other"
## [1] "Jackson Heights : 2"
## [1] "Changing Jackson Heights to Other"
## [1] "Mott Haven : 1"
```

```

## [1] "Changing Mott Haven to Other"
## [1] "Cypress Hills : 1"
## [1] "Changing Cypress Hills to Other"
## [1] "Arrochar : 1"
## [1] "Changing Arrochar to Other"
## [1] "Bay Ridge : 2"
## [1] "Changing Bay Ridge to Other"
## [1] "Borough Park : 1"
## [1] "Changing Borough Park to Other"
## [1] "Forest Hills : 2"
## [1] "Changing Forest Hills to Other"
## [1] "New Brighton : 1"
## [1] "Changing New Brighton to Other"
## [1] "Maspeth : 1"
## [1] "Changing Maspeth to Other"
## [1] "Vinegar Hill : 1"
## [1] "Changing Vinegar Hill to Other"
## [1] "Brownsville : 1"
## [1] "Changing Brownsville to Other"
## [1] "Bellerose : 1"
## [1] "Changing Bellerose to Other"
## [1] "Longwood : 1"
## [1] "Changing Longwood to Other"
## [1] "Clinton Hill : 4"
## [1] "Changing Clinton Hill to Other"
## [1] "Boerum Hill : 1"
## [1] "Changing Boerum Hill to Other"
## [1] "Morris Heights : 1"
## [1] "Changing Morris Heights to Other"
## [1] "Canarsie : 1"
## [1] "Changing Canarsie to Other"
## [1] "Ozone Park : 1"
## [1] "Changing Ozone Park to Other"
## [1] "Woodside : 1"
## [1] "Changing Woodside to Other"
## [1] "Bath Beach : 1"
## [1] "Changing Bath Beach to Other"

print("Converting neighborhood as factor post-clubbing")

## [1] "Converting neighborhood as factor post-clubbing"

airDataClean$neighbourhoodCleansed <-
as.factor(airDataClean$neighbourhoodCleansed)

print("Summary of neighborhood column post clubbing")

## [1] "Summary of neighborhood column post clubbing"

print(summary(airDataClean$neighbourhoodCleansed))

```

##	Chelsea	Chinatown	East Harlem
##	1056	354	1038
##	East Village	Financial District	Gramercy
##	1828	387	302
##	Greenwich Village	Harlem	Hell's Kitchen
##	373	2481	1557
##	Kips Bay	Lower East Side	Midtown
##	409	947	946
##	Morningside Heights	Other	SoHo
##	388	1967	350
##	Upper East Side	Upper West Side	Washington Heights
##	1520	1750	851
##	West Village		
##	769		

Extract data without price information as data set to predict on at the end.

```
print("Extract data without price as predict data set")
## [1] "Extract data without price as predict data set"
airDataPredict <- airDataClean[airDataClean$price == 0,]
print(paste("Number of rows in airDataPredict:", nrow(airDataPredict)))
## [1] "Number of rows in airDataPredict: 131"
```

Extract data set with valid price information to use for building training and test data sets.

```
print("Extract valid data with price as actual data set")
## [1] "Extract valid data with price as actual data set"
airDataValid <- airDataClean[airDataClean$price > 0,]
print(paste("Number of rows in airDataValid:", nrow(airDataValid)))
## [1] "Number of rows in airDataValid: 19142"
```

Log transform price if required.

```
if(log_regression){
  airDataValid$price <- log(airDataValid$price)
}
```

Create training and sample tests by sampling 95% of data for training set and 5% for test set.

```
print("Creating sample training set and test sets")
## [1] "Creating sample training set and test sets"
train <- sample(1:nrow(airDataValid), 0.95*nrow(airDataValid))
airDataTrain <- airDataValid[train,]
airDataTest <- airDataValid[-train,]
```


Linear Regression: Price vs Everything.

```
print("Running Linear Regression Model: Price vs Everything")

## [1] "Running Linear Regression Model: Price vs Everything"

lm1 <- lm(price~.,data=airDataTrain)
print("Summary of Linear Regression")

## [1] "Summary of Linear Regression"

print(summary(lm1))

##
## Call:
## lm(formula = price ~ ., data = airDataTrain)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -514.04  -39.75   -4.77   26.99  904.86
##
## Coefficients:
##                                Estimate Std. Error t value
## (Intercept)                   -1.386103   23.661112  -0.059
## hostResponseHours              -0.047165    0.040678  -1.159
## neighbourhoodCleansedChinatown -31.028809    4.946381  -6.273
## neighbourhoodCleansedEast Harlem -70.362687    3.602816 -19.530
## neighbourhoodCleansedEast Village -27.316559    3.132938  -8.719
## neighbourhoodCleansedFinancial District -37.997174    4.897226  -7.759
## neighbourhoodCleansedGramercy      -29.522401    5.230841  -5.644
## neighbourhoodCleansedGreenwich Village   8.277170    4.850873   1.706
## neighbourhoodCleansedHarlem          -75.597872    3.075542 -24.580
## neighbourhoodCleansedHell's Kitchen    -15.283612    3.226681  -4.737
## neighbourhoodCleansedKips Bay         -27.640052    4.679288  -5.907
## neighbourhoodCleansedLower East Side   -33.244748    3.618505  -9.187
## neighbourhoodCleansedMidtown           -2.493174    3.706684  -0.673
## neighbourhoodCleansedMorningside Heights -67.348538    4.844746 -13.901
## neighbourhoodCleansedOther            -21.555978    3.205641  -6.724
## neighbourhoodCleansedSoHo              24.843834    4.975777   4.993
## neighbourhoodCleansedUpper East Side   -33.938207    3.232933 -10.498
## neighbourhoodCleansedUpper West Side   -29.619841    3.148623  -9.407
## neighbourhoodCleansedWashington Heights -79.477200    3.812532 -20.846
## neighbourhoodCleansedWest Village      10.456850    3.804379   2.749
## neighbourhoodGroupCleansedBrooklyn     31.530886   20.787084   1.517
## neighbourhoodGroupCleansedManhattan    81.615634   20.211702   4.038
## neighbourhoodGroupCleansedQueens      11.855518   21.107152   0.562
## neighbourhoodGroupCleansedStaten Island -33.181092   49.133333  -0.675
## accommodates                    15.867516    0.689854  23.001
## bathrooms                       59.336945    1.976715  30.018
## bedTypeCouch                    11.331045   12.245096   0.925
## bedTypeFuton                     19.920931    9.146332   2.178
```

## bedTypePull-out Sofa	16.440314	8.914900	1.844
## bedTypeReal Bed	16.412054	7.039755	2.331
## bedrooms	30.420432	1.221160	24.911
## beds	2.634716	1.123543	2.345
## TV	8.964447	1.419963	6.313
## cancellationPolicymoderate	-5.264101	1.717846	-3.064
## cancellationPolicystrict	-7.126372	1.562511	-4.561
## cancellationPolicysuper_strict_30	64.939468	44.924193	1.446
## cleaningFee	0.283760	0.015419	18.404
## extraPeople	0.015059	0.026381	0.571
## guestsIncluded	2.600795	0.782856	3.322
## maximumNights	0.001010	0.001127	0.896
## minimumNights	-0.116080	0.038184	-3.040
## propertyTypeBed & Breakfast	19.046868	10.572002	1.802
## propertyTypeBoat	187.108591	77.991940	2.399
## propertyTypeBoutique hotel	49.649615	26.088743	1.903
## propertyTypeBungalow	-52.494227	77.512013	-0.677
## propertyTypeCabin	78.369087	77.610233	1.010
## propertyTypeCastle	111.624567	77.519928	1.440
## propertyTypeCondominium	51.461825	5.971218	8.618
## propertyTypeDorm	-32.909670	44.806708	-0.734
## propertyTypeGuest suite	171.753594	54.901057	3.128
## propertyTypeGuesthouse	16.775622	21.767825	0.771
## propertyTypeHostel	-8.334471	22.836205	-0.365
## propertyTypeHouse	23.529344	4.996240	4.709
## propertyTypeHut	-32.138453	77.877729	-0.413
## propertyTypeLighthouse	29.887377	77.587456	0.385
## propertyTypeLoft	52.360398	5.084780	10.297
## propertyTypeOther	41.084368	8.341148	4.926
## propertyTypeServiced apartment	94.799199	38.845659	2.440
## propertyTypeTimeshare	102.976647	13.607063	7.568
## propertyTypeTownhouse	22.138879	6.204668	3.568
## propertyTypeVacation home	185.882999	77.598523	2.395
## propertyTypeVilla	-15.844696	38.811528	-0.408
## roomTypePrivate room	-58.723827	1.602457	-36.646
## roomTypeShared room	-72.898881	3.777639	-19.297
## securityDeposit	-0.013277	0.003501	-3.792
## numberOfReviews	-0.065135	0.024643	-2.643
## reviewScoresAccuracy	0.950880	1.037882	0.916
## reviewScoresCheckin	-1.881277	1.086623	-1.731
## reviewScoresCleanliness	4.220609	0.824670	5.118
## reviewScoresCommunication	-2.268170	1.135158	-1.998
## reviewScoresLocation	0.422377	0.916654	0.461
## reviewScoresRating	0.326521	0.117344	2.783
## reviewScoresValue	-6.306832	1.063625	-5.930
## reviewsperMonth	-1.610618	0.440165	-3.659
## checkIn24Hours1	-1.299334	1.641293	-0.792
## airConditioning1	-1.122820	1.877579	-0.598
## buzzerOrWirelessIntercom1	-1.741814	1.428461	-1.219
## cableTV1	10.770992	1.543699	6.977

## carbonMonoxideDetector1	1.165293	1.601707	0.728
## doorman1	7.950986	2.190256	3.630
## dryer1	-0.310951	3.407495	-0.091
## elevator1	8.353844	1.610309	5.188
## essentials1	-10.588924	1.847402	-5.732
## familyAndKidFriendly1	2.668674	1.330909	2.005
## fireExtinguisher1	2.719266	1.632304	1.666
## firstAidKit1	2.847427	1.659956	1.715
## freeParkingOnPremises1	-1.741520	2.932166	-0.594
## gym1	19.095249	2.529974	7.548
## hairdryer1	-2.547332	1.713685	-1.486
## hangers1	-5.790698	1.741407	-3.325
## heating1	-3.832088	2.593456	-1.478
## hottub1	-4.918711	2.585287	-1.903
## internet1	-1.805301	1.546928	-1.167
## iron1	-3.459870	1.686572	-2.051
## kitchen1	-7.318994	2.862023	-2.557
## laptopFriendlyWorkspace1	-1.306653	1.609633	-0.812
## lockOnBedroomDoor1	-2.804050	1.750691	-1.602
## petsAllowed1	-6.967597	1.946391	-3.580
## petsLiveOnThisProperty1	-2.961472	2.442083	-1.213
## pool1	17.905360	5.109975	3.504
## selfCheckIn1	9.143911	2.860155	3.197
## shampoo1	3.912367	1.500874	2.607
## smokeDetector1	-6.340369	1.853096	-3.422
## smokingAllowed1	-0.300668	2.847226	-0.106
## washer1	3.188479	3.414901	0.934
## wheelchairAccessible1	12.373064	2.370779	5.219
## wirelessInternet1	-1.964830	3.781742	-0.520
## hostHasProfilePic1	-13.621731	8.815305	-1.545
## hostIdentityVerified1	-1.429651	1.434768	-0.996
## hostIsSuperhost1	15.260998	2.264191	6.740
## instantBookable1	-4.451783	1.691223	-2.632
## isLocationExact1	-0.131177	1.696189	-0.077
## requireGuestPhoneVerification1	-12.652511	5.390762	-2.347
## requireGuestProfilePicture1	5.663180	5.732609	0.988
## featureCount	0.760911	0.537129	1.417
## yearsAsHost	0.316785	0.387069	0.818
##	Pr(> t)		
## (Intercept)	0.953286		
## hostResponseHours	0.246274		
## neighbourhoodCleansedChinatown	3.62e-10 ***		
## neighbourhoodCleansedEast Harlem	< 2e-16 ***		
## neighbourhoodCleansedEast Village	< 2e-16 ***		
## neighbourhoodCleansedFinancial District	9.02e-15 ***		
## neighbourhoodCleansedGramercy	1.69e-08 ***		
## neighbourhoodCleansedGreenwich Village	0.087965 .		
## neighbourhoodCleansedHarlem	< 2e-16 ***		
## neighbourhoodCleansedHell's Kitchen	2.19e-06 ***		
## neighbourhoodCleansedKips Bay	3.55e-09 ***		

## neighbourhoodCleansedLower East Side	< 2e-16	***
## neighbourhoodCleansedMidtown	0.501200	
## neighbourhoodCleansedMorningside Heights	< 2e-16	***
## neighbourhoodCleansedOther	1.82e-11	***
## neighbourhoodCleansedSoHo	6.00e-07	***
## neighbourhoodCleansedUpper East Side	< 2e-16	***
## neighbourhoodCleansedUpper West Side	< 2e-16	***
## neighbourhoodCleansedWashington Heights	< 2e-16	***
## neighbourhoodCleansedWest Village	0.005990	**
## neighbourhoodGroupCleansedBrooklyn	0.129322	
## neighbourhoodGroupCleansedManhattan	5.41e-05	***
## neighbourhoodGroupCleansedQueens	0.574339	
## neighbourhoodGroupCleansedStaten Island	0.499476	
## accommodates	< 2e-16	***
## bathrooms	< 2e-16	***
## bedTypeCouch	0.354794	
## bedTypeFuton	0.029417	*
## bedTypePull-out Sofa	0.065179	.
## bedTypeReal Bed	0.019746	*
## bedrooms	< 2e-16	***
## beds	0.019037	*
## TV	2.80e-10	***
## cancellationPolicymoderate	0.002185	**
## cancellationPolicystrict	5.13e-06	***
## cancellationPolicysuper_strict_30	0.148325	
## cleaningFee	< 2e-16	***
## extraPeople	0.568139	
## guestsIncluded	0.000895	***
## maximumNights	0.370270	
## minimumNights	0.002369	**
## propertyTypeBed & Breakfast	0.071620	.
## propertyTypeBoat	0.016447	*
## propertyTypeBoutique hotel	0.057043	.
## propertyTypeBungalow	0.498262	
## propertyTypeCabin	0.312615	
## propertyTypeCastle	0.149900	
## propertyTypeCondominium	< 2e-16	***
## propertyTypeDorm	0.462665	
## propertyTypeGuest suite	0.001760	**
## propertyTypeGuesthouse	0.440918	
## propertyTypeHostel	0.715140	
## propertyTypeHouse	2.50e-06	***
## propertyTypeHut	0.679847	
## propertyTypeLighthouse	0.700087	
## propertyTypeLoft	< 2e-16	***
## propertyTypeOther	8.49e-07	***
## propertyTypeServiced apartment	0.014680	*
## propertyTypeTimeshare	3.98e-14	***
## propertyTypeTownhouse	0.000361	***
## propertyTypeVacation home	0.016610	*

## propertyTypeVilla	0.683097	
## roomTypePrivate room	< 2e-16	***
## roomTypeShared room	< 2e-16	***
## securityDeposit	0.000150	***
## numberOfReviews	0.008220	**
## reviewScoresAccuracy	0.359588	
## reviewScoresCheckin	0.083414	.
## reviewScoresCleanliness	3.12e-07	***
## reviewScoresCommunication	0.045720	*
## reviewScoresLocation	0.644961	
## reviewScoresRating	0.005398	**
## reviewScoresValue	3.09e-09	***
## reviewsperMonth	0.000254	***
## checkIn24Hours1	0.428573	
## airConditioning1	0.549837	
## buzzerOrWirelessIntercom1	0.222722	
## cableTV1	3.11e-12	***
## carbonMonoxideDetector1	0.466909	
## doorman1	0.000284	***
## dryer1	0.927291	
## elevator1	2.15e-07	***
## essentials1	1.01e-08	***
## familyAndKidFriendly1	0.044962	*
## fireExtinguisher1	0.095749	.
## firstAidKit1	0.086296	.
## freeParkingOnPremises1	0.552562	
## gym1	4.64e-14	***
## hairdryer1	0.137174	
## hangers1	0.000885	***
## heating1	0.139533	
## hottub1	0.057111	.
## internet1	0.243216	
## iron1	0.040240	*
## kitchen1	0.010558	*
## laptopFriendlyWorkspace1	0.416934	
## lockOnBedroomDoor1	0.109243	
## petsAllowed1	0.000345	***
## petsLiveOnThisProperty1	0.225267	
## pool1	0.000459	***
## selfCheckIn1	0.001391	**
## shampoo1	0.009149	**
## smokeDetector1	0.000624	***
## smokingAllowed1	0.915901	
## washer1	0.350473	
## wheelchairAccessible1	1.82e-07	***
## wirelessInternet1	0.603379	
## hostHasProfilePic1	0.122307	
## hostIdentityVerified1	0.319053	
## hostIsSuperhost1	1.63e-11	***
## instantBookable1	0.008488	**

```
## isLocationExact1                0.938357
## requireGuestPhoneVerification1  0.018932 *
## requireGuestProfilePicture1    0.323220
## featureCount                    0.156609
## yearsAsHost                     0.413128
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 77.4 on 18068 degrees of freedom
## Multiple R-squared:  0.5992, Adjusted R-squared:  0.5966
## F-statistic: 234.9 on 115 and 18068 DF,  p-value: < 2.2e-16

print("Using Linear Regression Model for prediction")

## [1] "Using Linear Regression Model for prediction"

print("WARNING!!!: This step may fail in case the training set and test set
have different levels. If this occurs, re-running the code usually fixes
it.")

## [1] "WARNING!!!: This step may fail in case the training set and test set
have different levels. If this occurs, re-running the code usually fixes it."

lm1Pred <- predict(lm1, airDataTest)
print(paste("Test MSE:", mean((airDataTest$price - lm1Pred) ^ 2)))

## [1] "Test MSE: 6130.21599833604"
```

Running Principal Component Analysis in numerical features to analyze factor loading of each against first 3 PCs.

```
print("Running PCA on numerical features")

## [1] "Running PCA on numerical features"

pcaDF <-
data.frame(cbind(hostResponseHours=airDataValid$hostResponseHours,accommodate
s=airDataValid$accommodates,bathrooms=airDataValid$bathrooms,bedrooms=airData
Valid$bedrooms,beds=airDataValid$beds,TV=airDataValid$TV,cleaningFee=airDataV
alid$cleaningFee,extraPeople=airDataValid$extraPeople,guestsIncluded=airDataV
alid$guestsIncluded,maximumNights=airDataValid$maximumNights,minimumNights=ai
rDataValid$minimumNights,price=airDataValid$price,securityDeposit=airDataVali
d$securityDeposit,numberOfReviews=airDataValid$numberOfReviews,reviewScoresAc
curacy=airDataValid$reviewScoresAccuracy,reviewScoresCheckin=airDataValid$rev
iewScoresCheckin,reviewScoresCleanliness=airDataValid$reviewScoresCleanliness
,reviewScoresCommunication=airDataValid$reviewScoresCommunication,reviewScore
sLocation=airDataValid$reviewScoresLocation,reviewScoresLocation=airDataValid
$reviewScoresLocation,reviewScoresRating=airDataValid$reviewScoresRating,revi
ewScoresValue=airDataValid$reviewScoresValue,reviewspersMonth=airDataValid$rev
iewspersMonth))
pcaModel <- prcomp(pcaDF,scale.=TRUE,center=TRUE)
print("Summary of PCA Model")
```

```
## [1] "Summary of PCA Model"
```

```
print(summary(pcaModel))
```

```
## Importance of components:
```

```
##          PC1      PC2      PC3      PC4      PC5      PC6
## Standard deviation  2.8700 1.9640 1.16666 1.13561 1.00818 1.0003
## Proportion of Variance 0.3581 0.1677 0.05918 0.05607 0.04419 0.0435
## Cumulative Proportion 0.3581 0.5258 0.58502 0.64109 0.68528 0.7288
##          PC7      PC8      PC9     PC10     PC11     PC12
## Standard deviation  0.99088 0.97523 0.91901 0.87159 0.77786 0.70400
## Proportion of Variance 0.04269 0.04135 0.03672 0.03303 0.02631 0.02155
## Cumulative Proportion 0.77147 0.81282 0.84954 0.88257 0.90888 0.93043
##          PC13     PC14     PC15     PC16     PC17     PC18
## Standard deviation  0.68109 0.66843 0.60992 0.42687 0.2300 0.16019
## Proportion of Variance 0.02017 0.01943 0.01617 0.00792 0.0023 0.00112
## Cumulative Proportion 0.95060 0.97002 0.98620 0.99412 0.9964 0.99754
##          PC19     PC20     PC21     PC22     PC23
## Standard deviation  0.13649 0.12205 0.1177 0.09645 1.072e-16
## Proportion of Variance 0.00081 0.00065 0.0006 0.00040 0.000e+00
## Cumulative Proportion 0.99835 0.99899 0.9996 1.00000 1.000e+00
```

```
print("Rotation Matrix of PCA Model")
```

```
## [1] "Rotation Matrix of PCA Model"
```

```
print(pcaModel$rotation)
```

```
##          PC1          PC2          PC3
## hostResponseHours  0.010623765 -0.007706717 -0.18499252
## accommodates       0.063732043  0.433984113  0.02134112
## bathrooms         0.009975546  0.266840841 -0.12242621
## bedrooms          0.025473654  0.364391600 -0.02061117
## beds              0.051321852  0.418914350  0.02779839
## TV                 0.022849329  0.141432471 -0.06684028
## cleaningFee        0.075166481  0.308855500 -0.11693451
## extraPeople        0.060479077  0.133465184  0.16490221
## guestsIncluded     0.076333846  0.327590430  0.15867777
## maximumNights     -0.005899567  0.037846809 -0.09498251
## minimumNights     -0.015018446  0.006629710 -0.15811710
## price              0.015448283  0.377032375 -0.14213289
## securityDeposit    0.044306385  0.158417754 -0.09346542
## numberOfReviews    0.127160608  0.028293594  0.63398279
## reviewScoresAccuracy 0.342630272 -0.053178947 -0.06501591
## reviewScoresCheckin 0.342944200 -0.052538004 -0.05923336
## reviewScoresCleanliness 0.340897084 -0.045027804 -0.05775156
## reviewScoresCommunication 0.342973450 -0.053822732 -0.06104353
## reviewScoresLocation 0.342565870 -0.049776293 -0.06655161
## reviewScoresLocation.1 0.342565870 -0.049776293 -0.06655161
## reviewScoresRating  0.342773576 -0.052045062 -0.06853238
## reviewScoresValue   0.342486951 -0.054990316 -0.06611126
```

## reviewsperMonth	0.140758080	0.029555194	0.61725736
##	PC4	PC5	PC6
## hostResponseHours	0.11468152	0.4768823601	-0.530426737
## accommodates	-0.14393054	0.0109854904	0.006117475
## bathrooms	-0.25578886	0.1485500307	-0.034180704
## bedrooms	-0.26634366	0.1826668956	0.041951750
## beds	-0.20003260	0.0871710705	0.037126329
## TV	0.14091974	-0.4058946367	-0.505656909
## cleaningFee	0.31160668	-0.1201743935	-0.001795881
## extraPeople	0.50121519	0.0301580023	0.153196526
## guestsIncluded	0.18692646	0.0524654193	0.134475346
## maximumNights	-0.23814466	-0.5597261480	0.332404369
## minimumNights	0.14008885	0.4257551554	0.526300789
## price	-0.04362853	-0.0834066517	-0.115507220
## securityDeposit	0.54328882	-0.1433795872	0.080135986
## numberOfReviews	0.02866579	0.0664847294	-0.094188157
## reviewScoresAccuracy	-0.01938522	-0.0002550280	0.005479408
## reviewScoresCheckin	-0.022261918	0.0036082138	0.008543965
## reviewScoresCleanliness	-0.01323716	-0.0050488529	0.001222884
## reviewScoresCommunication	-0.02145754	0.0023628008	0.010235701
## reviewScoresLocation	-0.02127709	-0.0038897114	0.007649949
## reviewScoresLocation.1	-0.02127709	-0.0038897114	0.007649949
## reviewScoresRating	-0.01851883	0.0007029437	0.004302680
## reviewScoresValue	-0.02792812	0.0019930679	0.007730111
## reviewsperMonth	-0.09412678	-0.0008205797	-0.023099828
##	PC7	PC8	PC9
## hostResponseHours	0.3355708341	0.566864405	-0.058980363
## accommodates	0.0091476687	0.001937219	-0.001244235
## bathrooms	-0.0455993059	-0.076933701	-0.007965630
## bedrooms	0.0632854178	-0.085536980	-0.006094501
## beds	0.0369257938	-0.028320443	-0.023427949
## TV	-0.4934633492	0.141484043	0.427113854
## cleaningFee	-0.0711042933	0.077608445	-0.242276495
## extraPeople	0.3741437985	-0.065394366	0.520768713
## guestsIncluded	0.2064639975	-0.045557635	0.247246049
## maximumNights	0.3038405190	0.629564261	0.011941815
## minimumNights	-0.5532262039	0.395300794	0.176931144
## price	-0.1266365811	0.013591642	-0.047679061
## securityDeposit	-0.0380049983	-0.018977744	-0.593988262
## numberOfReviews	-0.1444883131	0.194542361	-0.148224489
## reviewScoresAccuracy	0.0002082373	-0.016575063	0.010217946
## reviewScoresCheckin	0.0032382472	-0.016638715	0.010205570
## reviewScoresCleanliness	-0.0036408610	-0.019763040	0.007612665
## reviewScoresCommunication	0.0015953378	-0.019287792	0.009535240
## reviewScoresLocation	0.0016900906	-0.008994315	0.004260073
## reviewScoresLocation.1	0.0016900906	-0.008994315	0.004260073
## reviewScoresRating	-0.0010108374	-0.022504100	0.012530115
## reviewScoresValue	0.0017354049	-0.020319219	0.014349402
## reviewsperMonth	-0.1091575553	0.197053494	-0.114655031
##	PC10	PC11	PC12

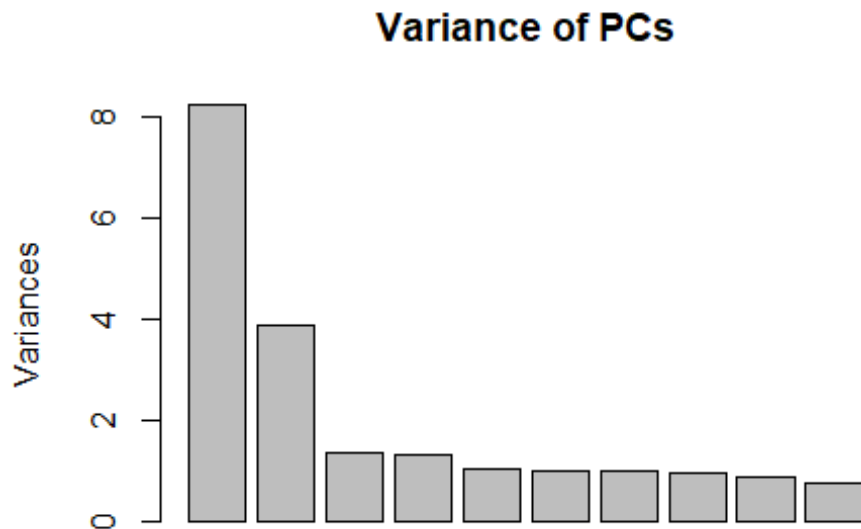
## hostResponseHours	3.759995e-02	-0.037598424	0.0338447302
## accommodates	2.622319e-01	-0.014876237	0.0686369642
## bathrooms	-8.345226e-01	-0.165817479	0.2248775596
## bedrooms	8.141674e-02	-0.247236504	-0.6201060152
## beds	2.337677e-01	-0.115920020	-0.0542707355
## TV	1.891869e-02	-0.270775108	-0.0747216557
## cleaningFee	-2.996961e-02	0.567650450	-0.1452802011
## extraPeople	-2.817751e-01	0.073145154	-0.3150466887
## guestsIncluded	2.328287e-01	-0.176930136	0.6200777645
## maximumNights	-8.414694e-02	-0.072539985	-0.0314629879
## minimumNights	2.425072e-02	-0.023691289	-0.0021928475
## price	-7.726768e-02	0.468409522	0.1510952722
## securityDeposit	-7.340979e-02	-0.485405975	-0.0082187877
## numberOfReviews	-9.361614e-02	0.038311411	-0.1243650213
## reviewScoresAccuracy	1.752297e-03	-0.007825300	0.0052071997
## reviewScoresCheckin	7.899421e-03	-0.010212244	-0.0051972929
## reviewScoresCleanliness	3.205107e-05	0.002544175	0.0031547747
## reviewScoresCommunication	7.240649e-03	-0.011483686	-0.0051808577
## reviewScoresLocation	3.745000e-03	0.010434534	-0.0016693948
## reviewScoresLocation.1	3.745000e-03	0.010434534	-0.0016693948
## reviewScoresRating	-2.671173e-03	-0.005094931	0.0017325495
## reviewScoresValue	1.675310e-03	-0.012593420	-0.0007386662
## reviewsperMonth	-9.646931e-02	0.032892007	0.0787243978
##	PC13	PC14	PC15
## hostResponseHours	0.045101492	-0.012740088	0.007086225
## accommodates	0.072403628	-0.103406172	-0.352800607
## bathrooms	-0.034763136	0.171523004	-0.097766490
## bedrooms	-0.056973377	0.102198222	0.531035757
## beds	0.113309722	-0.021585964	-0.538164823
## TV	0.024254560	0.088634032	0.006772006
## cleaningFee	0.028518542	0.598589310	-0.016195704
## extraPeople	0.109420941	-0.203691672	-0.149120045
## guestsIncluded	-0.187766959	0.243271962	0.356949320
## maximumNights	-0.077714150	-0.004726907	0.018666802
## minimumNights	0.016966797	-0.041238963	-0.003976291
## price	-0.064308811	-0.658400561	0.301017205
## securityDeposit	0.056459886	-0.206969824	0.017121997
## numberOfReviews	-0.663876370	-0.053969721	-0.129153419
## reviewScoresAccuracy	-0.006904114	-0.005897608	0.003729282
## reviewScoresCheckin	-0.014617176	-0.003279478	-0.003228543
## reviewScoresCleanliness	0.002580730	-0.007527287	0.003826496
## reviewScoresCommunication	-0.018740070	-0.005639855	-0.003315280
## reviewScoresLocation	-0.004317425	-0.019230525	0.002515401
## reviewScoresLocation.1	-0.004317425	-0.019230525	0.002515401
## reviewScoresRating	-0.008794778	-0.009399030	0.005968689
## reviewScoresValue	0.002457585	-0.003116225	0.001319768
## reviewsperMonth	0.686787221	0.006509022	0.190514409
##	PC16	PC17	PC18
## hostResponseHours	0.002734262	-0.004788514	0.001006052
## accommodates	0.756267545	0.001130522	-0.010100455

## bathrooms	0.046495875	0.008956450	-0.001478290
## bedrooms	0.025332154	0.001303373	-0.008052979
## beds	-0.628735525	-0.004784490	0.004868690
## TV	-0.030228371	0.009471549	0.001767942
## cleaningFee	-0.012491736	-0.001071584	0.010774217
## extraPeople	0.023758038	0.001362257	0.002031904
## guestsIncluded	-0.089961501	0.009515004	-0.004503719
## maximumNights	-0.017558622	-0.011758880	0.001654749
## minimumNights	0.006294102	-0.003616091	-0.002267408
## price	-0.139161548	-0.012502452	0.023535595
## securityDeposit	0.003306071	0.003311821	0.000919025
## numberOfReviews	0.001741909	-0.002996495	-0.009993529
## reviewScoresAccuracy	0.007765761	-0.194494077	0.227839361
## reviewScoresCheckin	0.002514669	0.079240819	0.486962404
## reviewScoresCleanliness	-0.009142728	-0.580828194	-0.542864587
## reviewScoresCommunication	0.001366255	-0.008312346	0.482666536
## reviewScoresLocation	-0.009414401	0.519060136	-0.297066376
## reviewScoresLocation.1	-0.009414401	0.519060136	-0.297066376
## reviewScoresRating	-0.002456447	-0.273115020	0.006505995
## reviewScoresValue	-0.000288166	-0.066142665	-0.074406047
## reviewsperMonth	-0.012221994	0.003012105	0.014578591
##	PC19	PC20	PC21
## hostResponseHours	-0.0006866173	-0.0027474425	0.0001815162
## accommodates	-0.0014902581	-0.0036621723	0.0038389343
## bathrooms	-0.0073052603	0.0013471827	-0.0010296893
## bedrooms	-0.0018601975	0.0052103999	0.0023966721
## beds	0.0056933800	0.0055737511	0.0043828780
## TV	-0.0013165148	-0.0002538783	0.0002024053
## cleaningFee	0.0076092030	-0.0037412572	-0.0007715564
## extraPeople	0.0022983650	0.0014848696	-0.0006644462
## guestsIncluded	-0.0003912556	-0.0016889240	0.0001572761
## maximumNights	0.0001558799	-0.0023745095	0.0005642854
## minimumNights	-0.0010420589	-0.0001813681	-0.0006859989
## price	0.0062781012	-0.0054291511	-0.0101092127
## securityDeposit	0.0030645341	-0.0023187785	-0.0023312803
## numberOfReviews	0.0122447795	-0.0004897797	-0.0012296908
## reviewScoresAccuracy	0.3194417507	0.8219935057	0.0783886251
## reviewScoresCheckin	-0.3258322228	-0.0746034398	-0.5087331332
## reviewScoresCleanliness	-0.4376800242	0.0480382177	-0.2009758423
## reviewScoresCommunication	-0.2971905427	-0.2231266337	0.2740977725
## reviewScoresLocation	-0.0692621582	0.0724232630	0.0821402199
## reviewScoresLocation.1	-0.0692621582	0.0724232630	0.0821402199
## reviewScoresRating	0.1883482593	-0.3350103459	0.6367131792
## reviewScoresValue	0.6829913042	-0.3792036725	-0.4477004784
## reviewsperMonth	-0.0008793112	-0.0030579705	0.0063010504
##	PC22	PC23	
## hostResponseHours	0.0019034908	-2.372948e-18	
## accommodates	-0.0013923189	1.307853e-16	
## bathrooms	0.0016417702	9.466267e-17	
## bedrooms	-0.0003170390	-4.764127e-17	

```
## beds -0.0022960187 5.444345e-17
## TV 0.0006178135 -5.343026e-17
## cleaningFee 0.0013760036 4.970285e-17
## extraPeople 0.0009916549 -5.814551e-18
## guestsIncluded 0.0006935043 -5.588022e-17
## maximumNights -0.0010728195 -7.502198e-17
## minimumNights -0.0003127416 2.841532e-17
## price 0.0040251978 -1.542974e-16
## securityDeposit -0.0005599607 -3.346111e-17
## numberOfReviews -0.0009298338 -5.033139e-17
## reviewScoresAccuracy 0.0302726502 -1.458515e-16
## reviewScoresCheckin -0.5106302395 2.902152e-16
## reviewScoresCleanliness 0.1061053514 1.322417e-17
## reviewScoresCommunication 0.6540866676 -4.796392e-16
## reviewScoresLocation -0.0065733661 7.071068e-01
## reviewScoresLocation.1 -0.0065733661 -7.071068e-01
## reviewScoresRating -0.4960707889 -1.112250e-16
## reviewScoresValue 0.2303120943 -1.192665e-16
## reviewsperMonth -0.0005533699 4.983270e-17
```

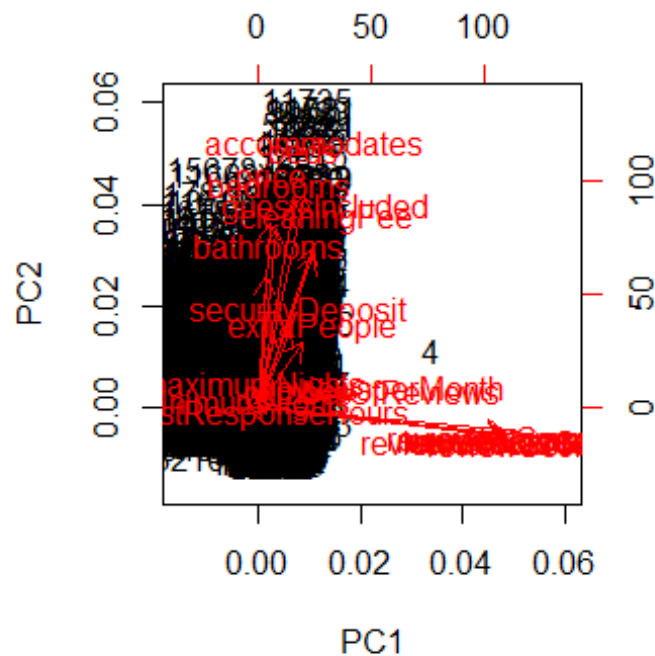
Screepplot

```
print("PCA Screepplot")
## [1] "PCA Screepplot"
screepplot(pcaModel, main="Variance of PCs")
```



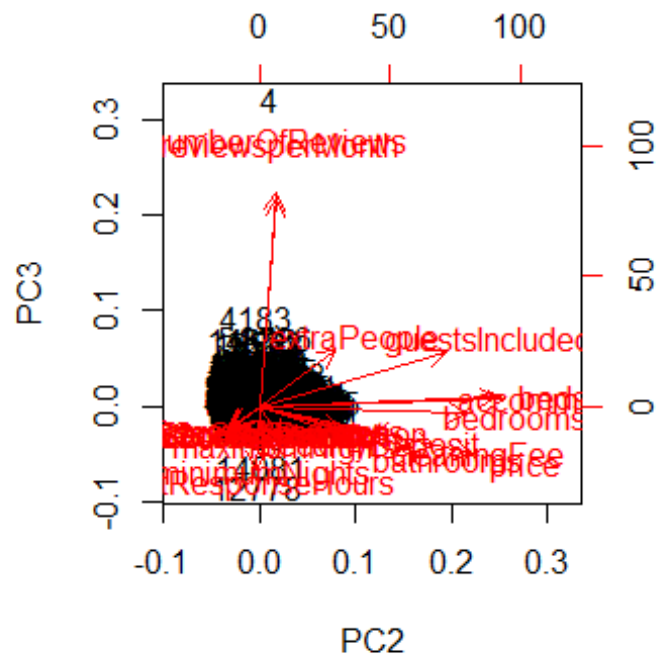
Biplot: PC1 vs PC2

```
print("Plotting Biplot: PC1 vs PC2 (Please wait till plot appears to  
continue)")  
  
## [1] "Plotting Biplot: PC1 vs PC2 (Please wait till plot appears to  
continue)"  
  
biplot(pcaModel,choices = c(1,2))
```



Biplot: PC2 vs PC3

```
print("Plotting Biplot: PC2 vs PC3 (Please wait till plot appears to  
continue)")  
  
## [1] "Plotting Biplot: PC2 vs PC3 (Please wait till plot appears to  
continue)"  
  
biplot(pcaModel,choices = c(2,3))
```

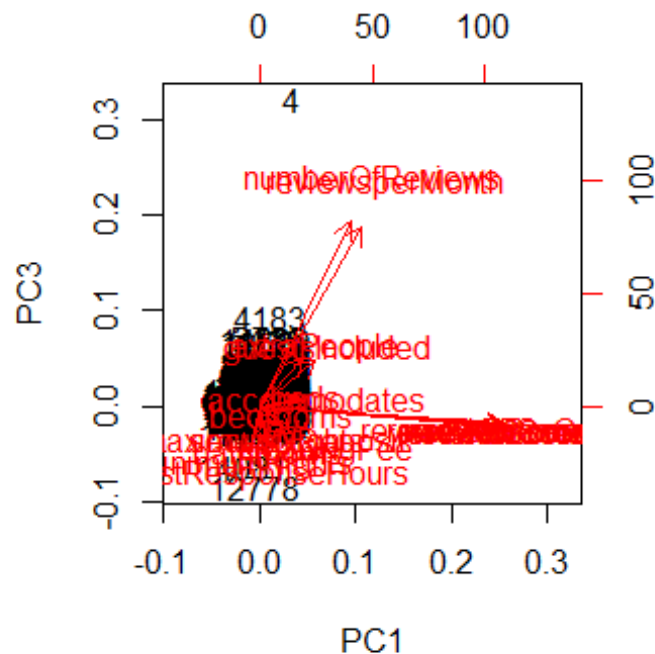


Biplot: PC1 vs PC3

```
print("Plotting Biplot: PC1 vs PC3 (Please wait till plot appears to
continue)")

## [1] "Plotting Biplot: PC1 vs PC3 (Please wait till plot appears to
continue)"

biplot(pcaModel,choices = c(1,3))
```



Removing features with similar factor loadings to avoid issues like collinearity.

```
print("Reviews per month and number of reviews have similar factor loadings
as do all the individual review columns")

## [1] "Reviews per month and number of reviews have similar factor loadings
as do all the individual review columns"

print("Removing Reviews per month, the individual review scores except Review
score rating")

## [1] "Removing Reviews per month, the individual review scores except
Review score rating"

dropColumns <-
c("reviewsperMonth", "reviewScoresAccuracy", "reviewScoresCheckin", "reviewScore
sCleanliness", "reviewScoresCommunication", "reviewScoresLocation", "reviewScore
sValue")
airDataValid <- airDataValid[,!(names(airDataValid) %in% dropColumns)]
airDataValid <- as.data.frame(airDataValid)
```

Summary after removing features with similar factor loading.

```
print("Summary after deletion of columns")

## [1] "Summary after deletion of columns"

print(summary(airDataValid))
```

```

## hostResponseHours      neighbourhoodCleansed neighbourhoodGroupCleansed
## Min.   : 1.000    Harlem           :2475    Bronx           : 15
## 1st Qu.: 1.000    Other           :1948    Brooklyn        : 212
## Median : 1.000    East Village    :1819    Manhattan       :18771
## Mean   : 9.246    Upper West Side:1738    Queens          : 140
## 3rd Qu.:12.000    Hell's Kitchen :1549    Staten Island: 4
## Max.   :72.000    Upper East Side:1507
##                      (Other)       :8106
## accommodates      bathrooms      bedType      bedrooms
## Min.   : 1.000    Min.   :0.000    Airbed       : 132    Min.   :0.000
## 1st Qu.: 2.000    1st Qu.:1.000    Couch        : 65     1st Qu.:1.000
## Median : 2.000    Median :1.000    Futon        : 185    Median :1.000
## Mean   : 2.779    Mean   :1.092    Pull-out Sofa: 204    Mean   :1.085
## 3rd Qu.: 4.000    3rd Qu.:1.000    Real Bed     :18556    3rd Qu.:1.000
## Max.   :16.000    Max.   :5.000                      Max.   :6.000
##
##      beds      TV      cancellationPolicy
## Min.   : 0.000    Min.   :0.0000    flexible     :5741
## 1st Qu.: 1.000    1st Qu.:0.0000    moderate     :4234
## Median : 1.000    Median :1.0000    strict       :9163
## Mean   : 1.494    Mean   :0.6877    super_strict_30: 4
## 3rd Qu.: 2.000    3rd Qu.:1.0000
## Max.   :12.000    Max.   :2.0000
##
## cleaningFee      extraPeople      guestsIncluded      maximumNights
## Min.   : 0.00    Min.   : 0.00    Min.   : 1.000    Min.   : 1
## 1st Qu.: 0.00    1st Qu.: 0.00    1st Qu.: 1.000    1st Qu.: 30
## Median : 40.00    Median : 0.00    Median : 1.000    Median :1125
## Mean   : 47.39    Mean   : 14.01    Mean   : 1.427    Mean   : 696
## 3rd Qu.: 75.00    3rd Qu.: 25.00    3rd Qu.: 2.000    3rd Qu.:1125
## Max.   :600.00    Max.   :300.00    Max.   :16.000    Max.   :1125
##
## minimumNights      price      propertyType
## Min.   : 1.000    Min.   : 10.0    Apartment :18001
## 1st Qu.: 1.000    1st Qu.: 89.0    House     : 280
## Median : 2.000    Median :135.0    Loft      : 253
## Mean   : 4.142    Mean   :166.3    Condominium: 187
## 3rd Qu.: 4.000    3rd Qu.:200.0    Townhouse : 171
## Max.   :1250.000    Max.   :999.0    Other     : 99
##                      (Other)       : 151
##      roomType      securityDeposit      numberOfReviews
## Entire home/apt:10705    Min.   : 0.0    Min.   : 0.00
## Private room : 7864    1st Qu.: 0.0    1st Qu.: 1.00
## Shared room : 573    Median : 0.0    Median : 5.00
##                      Mean   :123.1    Mean   : 16.97
##                      3rd Qu.:200.0    3rd Qu.: 19.00
##                      Max.   :999.0    Max.   :432.00
##
## reviewScoresRating      checkIn24Hours      airConditioning
## Min.   : 0.00    0:14387    0: 2721

```

```

## 1st Qu.: 67.00      1: 4755      1:16421
## Median : 92.00
## Mean   : 70.83
## 3rd Qu.: 98.00
## Max.   :100.00
##
## buzzerOrWirelessIntercom cableTV carbonMonoxideDetector doorman
## 0:9681      0:12787    0: 8110      0:16449
## 1:9461      1: 6355     1:11032      1: 2693
##
##
##
##
## dryer      elevator essentials familyAndKidFriendly fireExtinguisher
## 0:11122    0:11362    0: 3182     0:10766      0:14298
## 1: 8020    1: 7780    1:15960     1: 8376      1: 4844
##
##
##
##
## firstAidKit freeParkingOnPremises gym      hairdryer hangers heating
## 0:14085    0:18278      0:17424    0: 8997     0: 7828     0: 1206
## 1: 5057    1: 864      1: 1718    1:10145    1:11314    1:17936
##
##
##
##
## hottub      internet iron      kitchen laptopFriendlyWorkspace
## 0:18021    0: 5862    0:9660     0: 1002     0:9270
## 1: 1121    1:13280    1:9482     1:18140    1:9872
##
##
##
##
## lockOnBedroomDoor petsAllowed petsLiveOnThisProperty pool
## 0:15274      0:16871     0:17632      0:18857
## 1: 3868      1: 2271     1: 1510      1: 285
##
##
##
##
## selfCheckIn shampoo smokeDetector smokingAllowed washer
## 0:17978    0: 7129    0: 4090     0:18229      0:11051
## 1: 1164    1:12013    1:15052     1: 913       1: 8091
##

```



```
##
##
##
##
## wheelchairAccessible wirelessInternet hostHasProfilePic
## 0:17526          0: 526          0: 79
## 1: 1616          1:18616        1:19063
##
##
##
##
##
## hostIdentityVerified hostIsSuperhost instantBookable isLocationExact
## 0: 6524          0:17447        0:15530        0: 3346
## 1:12618          1: 1695        1: 3612        1:15796
##
##
##
##
## requireGuestPhoneVerification requireGuestProfilePicture featureCount
## 0:18472          0:18558          Min.   : 2.00
## 1: 670           1: 584           1st Qu.:14.00
##                                     Median :17.00
##                                     Mean    :17.64
##                                     3rd Qu.:21.00
##                                     Max.    :51.00
##
## yearsAsHost
## Min.   : 2.000
## 1st Qu.: 4.000
## Median : 5.000
## Mean    : 5.086
## 3rd Qu.: 6.000
## Max.    :11.000
##
```

Using K-fold validation on Linear Model to check if model still performs comparably after removing features based on PCA. The aim is to achieve close to same R-squared model with a much smaller set of features.

```
print("Retraining linear model with repeated k-fold cross validation")
## [1] "Retraining linear model with repeated k-fold cross validation"
train.control <- trainControl(method="repeatedcv",number=10,repeats=3)
lm2 <- train(price~.,data=airDataValid,method="lm",trControl=train.control)
## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient
## fit may be misleading
```

```
## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient
## fit may be misleading

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## fit may be misleading

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## fit may be misleading

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient
## fit may be misleading
```

Summary of K-fold model.

```
print("Summary of Linear Regression")

## [1] "Summary of Linear Regression"

print(summary(lm2))
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -514.11  -39.94   -5.08   27.23  899.36
##
## Coefficients:
##                                     Estimate Std. Error t value
## (Intercept)                        5.665e+00  2.364e+01   0.240
## hostResponseHours                  -2.667e-02  3.949e-02  -0.675
## neighbourhoodCleansedChinatown     -3.274e+01  4.837e+00  -6.769
## `neighbourhoodCleansedEast Harlem` -7.058e+01  3.480e+00 -20.283
## `neighbourhoodCleansedEast Village` -2.733e+01  3.065e+00  -8.919
## `neighbourhoodCleansedFinancial District` -3.623e+01  4.792e+00  -7.560
## neighbourhoodCleansedGramercy      -2.964e+01  5.142e+00  -5.765
## `neighbourhoodCleansedGreenwich Village`  7.824e+00  4.745e+00   1.649
## neighbourhoodCleansedHarlem        -7.552e+01  2.970e+00 -25.426
## `neighbourhoodCleansedHell's Kitchen`  -1.488e+01  3.156e+00  -4.716
## `neighbourhoodCleansedKips Bay`      -2.885e+01  4.582e+00  -6.296
## `neighbourhoodCleansedLower East Side` -3.225e+01  3.540e+00  -9.109
## neighbourhoodCleansedMidtown        -2.622e+00  3.610e+00  -0.726
## `neighbourhoodCleansedMorningside Heights` -6.683e+01  4.733e+00 -14.120
## neighbourhoodCleansedOther         -2.161e+01  3.142e+00  -6.879
## neighbourhoodCleansedSoHo           2.442e+01  4.869e+00   5.016
## `neighbourhoodCleansedUpper East Side` -3.386e+01  3.164e+00 -10.702
## `neighbourhoodCleansedUpper West Side` -3.074e+01  3.077e+00  -9.991
## `neighbourhoodCleansedWashington Heights` -7.903e+01  3.698e+00 -21.371
## `neighbourhoodCleansedWest Village`    9.385e+00  3.732e+00   2.515
## neighbourhoodGroupCleansedBrooklyn    2.936e+01  2.081e+01   1.410
## neighbourhoodGroupCleansedManhattan    8.031e+01  2.026e+01   3.963
## neighbourhoodGroupCleansedQueens      1.146e+01  2.114e+01   0.542
## `neighbourhoodGroupCleansedStaten Island` -4.091e+01  4.386e+01  -0.933
## accommodates                       1.565e+01  6.766e-01  23.136
## bathrooms                          5.933e+01  1.928e+00  30.777
## bedTypeCouch                       5.684e+00  1.184e+01   0.480
## bedTypeFuton                       1.551e+01  8.887e+00   1.745
## `bedTypePull-out Sofa`             1.347e+01  8.713e+00   1.546
## `bedTypeReal Bed`                  1.261e+01  6.872e+00   1.835
## bedrooms                          3.069e+01  1.195e+00  25.679
## beds                              2.470e+00  1.099e+00   2.248
## TV                                9.528e+00  1.387e+00   6.872
## cancellationPolicymoderate          -4.676e+00  1.676e+00  -2.790
## cancellationPolicystrict            -7.381e+00  1.523e+00  -4.846
## cancellationPolycysuper_strict_30    7.576e+01  3.905e+01   1.940
## cleaningFee                        2.903e-01  1.492e-02  19.457
## extraPeople                        2.075e-02  2.576e-02   0.805
## guestsIncluded                     2.267e+00  7.665e-01   2.958
## maximumNights                      5.594e-04  1.100e-03   0.509
```

## minimumNights	-1.196e-01	3.707e-02	-3.226
## `propertyTypeBed & Breakfast`	2.229e+01	1.050e+01	2.123
## propertyTypeBoat	1.894e+02	7.821e+01	2.422
## `propertyTypeBoutique hotel`	2.728e+01	2.368e+01	1.152
## propertyTypeBungalow	-5.078e+01	7.776e+01	-0.653
## propertyTypeCabin	8.068e+01	7.785e+01	1.036
## propertyTypeCastle	1.138e+02	7.776e+01	1.463
## propertyTypeCondominium	5.173e+01	5.842e+00	8.855
## propertyTypeDorm	-3.372e+01	4.494e+01	-0.750
## `propertyTypeGuest suite`	1.718e+02	5.507e+01	3.119
## propertyTypeGuesthouse	1.828e+01	2.181e+01	0.838
## propertyTypeHostel	-1.339e+01	2.286e+01	-0.586
## propertyTypeHouse	2.305e+01	4.920e+00	4.684
## propertyTypeHut	-4.032e+01	7.810e+01	-0.516
## propertyTypeLighthouse	1.948e+01	7.781e+01	0.250
## propertyTypeLoft	5.226e+01	5.007e+00	10.436
## propertyTypeOther	3.885e+01	8.122e+00	4.784
## `propertyTypeServiced apartment`	1.344e+02	3.486e+01	3.854
## propertyTypeTimeshare	1.007e+02	1.328e+01	7.585
## propertyTypeTownhouse	2.317e+01	6.107e+00	3.793
## `propertyTypeVacation home`	1.895e+02	7.784e+01	2.435
## propertyTypeVilla	-2.490e+01	3.485e+01	-0.715
## `roomTypePrivate room`	-5.959e+01	1.563e+00	-38.122
## `roomTypeShared room`	-7.367e+01	3.691e+00	-19.959
## securityDeposit	-1.092e-02	3.415e-03	-3.197
## numberOfReviews	-1.146e-01	2.135e-02	-5.368
## reviewScoresRating	-1.929e-01	1.588e-02	-12.147
## checkIn24Hours1	-1.017e+00	1.604e+00	-0.634
## airConditioning1	-5.668e-01	1.836e+00	-0.309
## buzzerOrWirelessIntercom1	-1.190e+00	1.397e+00	-0.852
## cableTV1	1.087e+01	1.510e+00	7.199
## carbonMonoxideDetector1	1.233e+00	1.565e+00	0.788
## doorman1	9.324e+00	2.139e+00	4.360
## dryer1	1.328e+00	3.307e+00	0.401
## elevator1	8.761e+00	1.573e+00	5.570
## essentials1	-1.076e+01	1.807e+00	-5.957
## familyAndKidFriendly1	2.486e+00	1.302e+00	1.908
## fireExtinguisher1	2.506e+00	1.593e+00	1.573
## firstAidKit1	3.677e+00	1.620e+00	2.270
## freeParkingOnPremises1	-1.743e+00	2.859e+00	-0.610
## gym1	1.881e+01	2.466e+00	7.627
## hairdryer1	-2.180e+00	1.676e+00	-1.301
## hangers1	-5.750e+00	1.703e+00	-3.375
## heating1	-3.964e+00	2.539e+00	-1.561
## hottub1	-5.525e+00	2.518e+00	-2.194
## internet1	-1.990e+00	1.513e+00	-1.315
## iron1	-3.102e+00	1.649e+00	-1.881
## kitchen1	-8.075e+00	2.798e+00	-2.886
## laptopFriendlyWorkspace1	-1.008e+00	1.572e+00	-0.641
## lockOnBedroomDoor1	-3.277e+00	1.707e+00	-1.920

## petsAllowed1	-6.981e+00	1.903e+00	-3.669
## petsLiveOnThisProperty1	-3.356e+00	2.385e+00	-1.407
## pool1	1.629e+01	4.996e+00	3.260
## selfCheckIn1	9.135e+00	2.800e+00	3.262
## shampoo1	3.542e+00	1.465e+00	2.418
## smokeDetector1	-5.792e+00	1.814e+00	-3.193
## smokingAllowed1	-1.438e+00	2.783e+00	-0.517
## washer1	1.410e+00	3.315e+00	0.425
## wheelchairAccessible1	1.250e+01	2.310e+00	5.412
## wirelessInternet1	-8.504e-01	3.711e+00	-0.229
## hostHasProfilePic1	-1.472e+01	8.836e+00	-1.666
## hostIdentityVerified1	-1.561e+00	1.403e+00	-1.113
## hostIsSuperhost1	1.632e+01	2.201e+00	7.414
## instantBookable1	-5.241e+00	1.646e+00	-3.184
## isLocationExact1	1.712e-01	1.658e+00	0.103
## requireGuestPhoneVerification1	-9.042e+00	5.316e+00	-1.701
## requireGuestProfilePicture1	5.374e+00	5.641e+00	0.953
## featureCount	6.047e-01	5.254e-01	1.151
## yearsAsHost	4.283e-01	3.736e-01	1.146
##	Pr(> t)		
## (Intercept)	0.810638		
## hostResponseHours	0.499429		
## neighbourhoodCleansedChinatown	1.34e-11 ***		
## `neighbourhoodCleansedEast Harlem`	< 2e-16 ***		
## `neighbourhoodCleansedEast Village`	< 2e-16 ***		
## `neighbourhoodCleansedFinancial District`	4.20e-14 ***		
## neighbourhoodCleansedGramercy	8.30e-09 ***		
## `neighbourhoodCleansedGreenwich Village`	0.099193 .		
## neighbourhoodCleansedHarlem	< 2e-16 ***		
## `neighbourhoodCleansedHell's Kitchen`	2.43e-06 ***		
## `neighbourhoodCleansedKips Bay`	3.12e-10 ***		
## `neighbourhoodCleansedLower East Side`	< 2e-16 ***		
## neighbourhoodCleansedMidtown	0.467631		
## `neighbourhoodCleansedMorningside Heights`	< 2e-16 ***		
## neighbourhoodCleansedOther	6.21e-12 ***		
## neighbourhoodCleansedSoHo	5.32e-07 ***		
## `neighbourhoodCleansedUpper East Side`	< 2e-16 ***		
## `neighbourhoodCleansedUpper West Side`	< 2e-16 ***		
## `neighbourhoodCleansedWashington Heights`	< 2e-16 ***		
## `neighbourhoodCleansedWest Village`	0.011916 *		
## neighbourhoodGroupCleansedBrooklyn	0.158411		
## neighbourhoodGroupCleansedManhattan	7.42e-05 ***		
## neighbourhoodGroupCleansedQueens	0.587807		
## `neighbourhoodGroupCleansedStaten Island`	0.350991		
## accommodates	< 2e-16 ***		
## bathrooms	< 2e-16 ***		
## bedTypeCouch	0.631243		
## bedTypeFuton	0.081039 .		
## `bedTypePull-out Sofa`	0.122114		
## `bedTypeReal Bed`	0.066476 .		

## bedrooms	< 2e-16	***
## beds	0.024593	*
## TV	6.55e-12	***
## cancellationPolicymoderate	0.005281	**
## cancellationPolicystrict	1.27e-06	***
## cancellationPolicysuper_strict_30	0.052395	.
## cleaningFee	< 2e-16	***
## extraPeople	0.420684	
## guestsIncluded	0.003098	**
## maximumNights	0.611069	
## minimumNights	0.001257	**
## `propertyTypeBed & Breakfast`	0.033781	*
## propertyTypeBoat	0.015450	*
## `propertyTypeBoutique hotel`	0.249475	
## propertyTypeBungalow	0.513692	
## propertyTypeCabin	0.300041	
## propertyTypeCastle	0.143445	
## propertyTypeCondominium	< 2e-16	***
## propertyTypeDorm	0.453056	
## `propertyTypeGuest suite`	0.001817	**
## propertyTypeGuesthouse	0.401960	
## propertyTypeHostel	0.558194	
## propertyTypeHouse	2.83e-06	***
## propertyTypeHut	0.605661	
## propertyTypeLighthouse	0.802309	
## propertyTypeLoft	< 2e-16	***
## propertyTypeOther	1.73e-06	***
## `propertyTypeServiced apartment`	0.000117	***
## propertyTypeTimeshare	3.49e-14	***
## propertyTypeTownhouse	0.000149	***
## `propertyTypeVacation home`	0.014895	*
## propertyTypeVilla	0.474914	
## `roomTypePrivate room`	< 2e-16	***
## `roomTypeShared room`	< 2e-16	***
## securityDeposit	0.001391	**
## numberOfReviews	8.05e-08	***
## reviewScoresRating	< 2e-16	***
## checkIn24Hours1	0.526227	
## airConditioning1	0.757506	
## buzzerOrWirelessIntercom1	0.394082	
## cableTV1	6.28e-13	***
## carbonMonoxideDetector1	0.430972	
## doorman1	1.31e-05	***
## dryer1	0.688076	
## elevator1	2.58e-08	***
## essentials1	2.61e-09	***
## familyAndKidFriendly1	0.056355	.
## fireExtinguisher1	0.115840	
## firstAidKit1	0.023231	*
## freeParkingOnPremises1	0.542138	

```

## gym1                2.52e-14 ***
## hairdryer1          0.193193
## hangers1            0.000739 ***
## heating1            0.118523
## hottub1             0.028234 *
## internet1           0.188424
## iron1               0.060003 .
## kitchen1            0.003901 **
## laptopFriendlyWorkspace1 0.521430
## lockOnBedroomDoor1  0.054906 .
## petsAllowed1        0.000244 ***
## petsLiveOnThisProperty1 0.159463
## pool1               0.001117 **
## selfCheckIn1        0.001107 **
## shampoo1            0.015627 *
## smokeDetector1      0.001409 **
## smokingAllowed1     0.605261
## washer1             0.670602
## wheelchairAccessible1 6.32e-08 ***
## wirelessInternet1   0.818755
## hostHasProfilePic1  0.095655 .
## hostIdentityVerified1 0.265760
## hostIsSuperhost1    1.28e-13 ***
## instantBookable1    0.001453 **
## isLocationExact1    0.917736
## requireGuestPhoneVerification1 0.088954 .
## requireGuestProfilePicture1 0.340768
## featureCount        0.249781
## yearsAsHost         0.251705
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 77.65 on 19033 degrees of freedom
## Multiple R-squared:  0.5951, Adjusted R-squared:  0.5928
## F-statistic: 259 on 108 and 19033 DF, p-value: < 2.2e-16

print(lm2)

## Linear Regression
##
## 19142 samples
## 62 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 3 times)
## Summary of sample sizes: 17228, 17227, 17227, 17227, 17229, 17228, ...
## Resampling results:
##
## RMSE      Rsquared    MAE
## 78.16914  0.5874553  50.29873

```

```
##  
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

Removing features from Linear Model with high p-values.

```
print("Removing features with high p-values in cross validated linear model")  
## [1] "Removing features with high p-values in cross validated linear model"  
  
dropColumns <-  
c("hostResponseHours", "neighbourhoodGroupCleansed", "bedType", "beds", "extraPeople", "maximumNights", "checkIn24Hours", "airConditioning", "buzzerOrWirelessInternet", "dryer", "familyAndKidFriendly", "fireExtinguisher", "firstAidKit", "freeParkingOnPremises", "hairdryer", "hangers", "heating", "hottub", "internet", "iron", "kitchen", "laptopFriendlyWorkspace", "lockOnBedroomDoor", "petsLiveOnThisProperty", "selfCheckIn", "shampoo", "smokingAllowed", "washer", "wirelessInternet", "hostHasProfilePic", "hostIdentityVerified", "instantBookable", "isLocationExact", "requireGuestPhoneVerification", "requireGuestProfilePicture", "featureCount", "yearsAsHost")  
airDataValid <- airDataValid[,!(names(airDataValid) %in% dropColumns)]  
airDataValid <- as.data.frame(airDataValid)
```

Summary of data set after removal of features.

```
print("Summary after deletion of columns")  
## [1] "Summary after deletion of columns"  
  
print(summary(airDataValid))  
  
##      neighbourhoodCleansed  accommodates      bathrooms  
## Harlem          :2475      Min.   : 1.000      Min.    :0.000  
## Other           :1948      1st Qu.: 2.000      1st Qu.:1.000  
## East Village    :1819      Median : 2.000      Median :1.000  
## Upper West Side:1738      Mean    : 2.779      Mean    :1.092  
## Hell's Kitchen :1549      3rd Qu.: 4.000      3rd Qu.:1.000  
## Upper East Side:1507      Max.    :16.000      Max.     :5.000  
## (Other)         :8106  
##      bedrooms      TV      cancellationPolicy  
## Min.   :0.000      Min.   :0.0000      flexible      :5741  
## 1st Qu.:1.000      1st Qu.:0.0000      moderate      :4234  
## Median :1.000      Median :1.0000      strict        :9163  
## Mean    :1.085      Mean    :0.6877      super_strict_30: 4  
## 3rd Qu.:1.000      3rd Qu.:1.0000  
## Max.    :6.000      Max.    :2.0000  
##  
##      cleaningFee      guestsIncluded      minimumNights      price  
## Min.   : 0.00      Min.   : 1.000      Min.   : 1.000      Min.   : 10.0  
## 1st Qu.: 0.00      1st Qu.: 1.000      1st Qu.: 1.000      1st Qu.: 89.0  
## Median : 40.00      Median : 1.000      Median : 2.000      Median :135.0  
## Mean    : 47.39      Mean    : 1.427      Mean    : 4.142      Mean    :166.3  
## 3rd Qu.: 75.00      3rd Qu.: 2.000      3rd Qu.: 4.000      3rd Qu.:200.0
```



```

## Max. :600.00 Max. :16.000 Max. :1250.000 Max. :999.0
##
##      propertyType      roomType      securityDeposit
## Apartment :18001 Entire home/apt:10705 Min. : 0.0
## House : 280 Private room : 7864 1st Qu.: 0.0
## Loft : 253 Shared room : 573 Median : 0.0
## Condominium: 187 Mean :123.1
## Townhouse : 171 3rd Qu.:200.0
## Other : 99 Max. :999.0
## (Other) : 151
## numberOfReviews reviewScoresRating cableTV carbonMonoxideDetector
## Min. : 0.00 Min. : 0.00 0:12787 0: 8110
## 1st Qu.: 1.00 1st Qu.: 67.00 1: 6355 1:11032
## Median : 5.00 Median : 92.00
## Mean : 16.97 Mean : 70.83
## 3rd Qu.: 19.00 3rd Qu.: 98.00
## Max. :432.00 Max. :100.00
##
## doorman elevator essentials gym petsAllowed pool
## 0:16449 0:11362 0: 3182 0:17424 0:16871 0:18857
## 1: 2693 1: 7780 1:15960 1: 1718 1: 2271 1: 285
##
##
##
##
## smokeDetector wheelchairAccessible hostIsSuperhost
## 0: 4090 0:17526 0:17447
## 1:15052 1: 1616 1: 1695
##
##
##
##
##

```

Using K-fold validation on Linear Model to check if model still performs comparably after removing features based on p-values. The aim is to achieve close to same R-squared model with a much smaller set of features.

```

print("Retraining linear model with repeated k-fold cross validation")
## [1] "Retraining linear model with repeated k-fold cross validation"
train.control <- trainControl(method="repeatedcv",number=10,repeats=3)
lm3 <- train(price~.,data=airDataValid,method="lm",trControl=train.control)
## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient
## fit may be misleading
## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient
## fit may be misleading

```

```
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## fit may be misleading
```

Summary of K-fold model

```
print("Summary of Linear Regression")

## [1] "Summary of Linear Regression"
```

```
print(summary(lm3))
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -521.33  -39.97   -5.71   27.14  895.89
##
## Coefficients:
##                                     Estimate Std. Error t value
## (Intercept)                        74.98239     3.76614  19.910
## neighbourhoodCleansedChinatown      -32.29262     4.85327   -6.654
## `neighbourhoodCleansedEast Harlem`   -70.72683     3.48853  -20.274
## `neighbourhoodCleansedEast Village`  -26.94199     3.07905   -8.750
## `neighbourhoodCleansedFinancial District` -36.54804     4.81209   -7.595
## neighbourhoodCleansedGramercy       -30.27116     5.17033   -5.855
## `neighbourhoodCleansedGreenwich Village`  7.59746     4.77357    1.592
## neighbourhoodCleansedHarlem          -74.95405     2.96750  -25.258
## `neighbourhoodCleansedHell's Kitchen`   -15.79077     3.16646   -4.987
## `neighbourhoodCleansedKips Bay`        -30.02821     4.60714   -6.518
## `neighbourhoodCleansedLower East Side`  -32.23106     3.55594   -9.064
## neighbourhoodCleansedMidtown          -2.73585     3.61804   -0.756
## `neighbourhoodCleansedMorningside Heights` -66.61796     4.73675  -14.064
## neighbourhoodCleansedOther           -32.80271     3.04366  -10.777
## neighbourhoodCleansedSoHo             24.65450     4.89290    5.039
## `neighbourhoodCleansedUpper East Side`  -34.25711     3.17934  -10.775
## `neighbourhoodCleansedUpper West Side`  -31.13937     3.09165  -10.072
## `neighbourhoodCleansedWashington Heights` -78.77315     3.70312  -21.272
## `neighbourhoodCleansedWest Village`     9.68040     3.75370    2.579
## accommodates                        16.58471     0.55864   29.687
## bathrooms                          60.12775     1.91176   31.451
## bedrooms                          31.43630     1.15731   27.163
## TV                                 9.17734     1.36551    6.721
## cancellationPolicymoderate           -5.01875     1.66583   -3.013
## cancellationPolicystrict             -8.19915     1.50180   -5.460
## cancellationPolicysuper_strict_30    64.01483    39.23118    1.632
## cleaningFee                          0.30057     0.01480   20.309
## guestsIncluded                       2.59663     0.72828    3.565
## minimumNights                       -0.11693     0.03726   -3.138
## `propertyTypeBed & Breakfast`         25.25500    10.50638    2.404
## propertyTypeBoat                    203.82930    78.41415    2.599
## `propertyTypeBoutique hotel`          30.80298    23.71069    1.299
## propertyTypeBungalow                 -55.79836    78.25616   -0.713
## propertyTypeCabin                     89.24455    78.25960    1.140
## propertyTypeCastle                   117.84411    78.26117    1.506
## propertyTypeCondominium               52.68935     5.85792    8.995
## propertyTypeDorm                     -25.64820    45.21056   -0.567
## `propertyTypeGuest suite`            164.38148    55.37552    2.968
```

## propertyTypeGuesthouse	17.76576	21.89237	0.812
## propertyTypeHostel	-12.68207	22.76451	-0.557
## propertyTypeHouse	12.49786	4.80199	2.603
## propertyTypeHut	-22.88089	78.35598	-0.292
## propertyTypeLighthouse	20.85363	78.29605	0.266
## propertyTypeLoft	53.65344	5.02030	10.687
## propertyTypeOther	46.05459	7.98749	5.766
## `propertyTypeServiced apartment`	132.88281	35.03730	3.793
## propertyTypeTimeshare	105.15306	13.27982	7.918
## propertyTypeTownhouse	24.66136	6.10609	4.039
## `propertyTypeVacation home`	181.35300	78.29776	2.316
## propertyTypeVilla	-25.49723	35.06686	-0.727
## `roomTypePrivate room`	-60.70211	1.48249	-40.946
## `roomTypeShared room`	-73.27667	3.52769	-20.772
## securityDeposit	-0.01025	0.00341	-3.006
## numberOfReviews	-0.11046	0.02033	-5.433
## reviewScoresRating	-0.19633	0.01561	-12.582
## cableTV1	12.10858	1.37094	8.832
## carbonMonoxideDetector1	2.74906	1.41997	1.936
## doorman1	11.98476	2.04470	5.861
## elevator1	10.68763	1.40502	7.607
## essentials1	-10.76535	1.60247	-6.718
## gym1	19.45066	2.39740	8.113
## petsAllowed1	-6.46179	1.76779	-3.655
## pool1	17.80043	4.93093	3.610
## smokeDetector1	-4.71966	1.70954	-2.761
## wheelchairAccessible1	14.25975	2.22030	6.422
## hostIsSuperhost1	16.87090	2.08539	8.090
##	Pr(> t)		
## (Intercept)	< 2e-16	***	
## neighbourhoodCleansedChinatown	2.93e-11	***	
## `neighbourhoodCleansedEast Harlem`	< 2e-16	***	
## `neighbourhoodCleansedEast Village`	< 2e-16	***	
## `neighbourhoodCleansedFinancial District`	3.22e-14	***	
## neighbourhoodCleansedGramercy	4.85e-09	***	
## `neighbourhoodCleansedGreenwich Village`	0.111498		
## neighbourhoodCleansedHarlem	< 2e-16	***	
## `neighbourhoodCleansedHell's Kitchen`	6.19e-07	***	
## `neighbourhoodCleansedKips Bay`	7.32e-11	***	
## `neighbourhoodCleansedLower East Side`	< 2e-16	***	
## neighbourhoodCleansedMidtown	0.449558		
## `neighbourhoodCleansedMorningside Heights`	< 2e-16	***	
## neighbourhoodCleansedOther	< 2e-16	***	
## neighbourhoodCleansedSoHo	4.73e-07	***	
## `neighbourhoodCleansedUpper East Side`	< 2e-16	***	
## `neighbourhoodCleansedUpper West Side`	< 2e-16	***	
## `neighbourhoodCleansedWashington Heights`	< 2e-16	***	
## `neighbourhoodCleansedWest Village`	0.009919	**	
## accommodates	< 2e-16	***	
## bathrooms	< 2e-16	***	

```

## bedrooms < 2e-16 ***
## TV 1.86e-11 ***
## cancellationPolycymoderate 0.002592 **
## cancellationPolycystrict 4.83e-08 ***
## cancellationPolycysuper_strict_30 0.102752
## cleaningFee < 2e-16 ***
## guestsIncluded 0.000364 ***
## minimumNights 0.001705 **
## `propertyTypeBed & Breakfast` 0.016236 *
## propertyTypeBoat 0.009346 **
## `propertyTypeBoutique hotel` 0.193919
## propertyTypeBungalow 0.475841
## propertyTypeCabin 0.254148
## propertyTypeCastle 0.132140
## propertyTypeCondominium < 2e-16 ***
## propertyTypeDorm 0.570513
## `propertyTypeGuest suite` 0.002996 **
## propertyTypeGuesthouse 0.417086
## propertyTypeHostel 0.577467
## propertyTypeHouse 0.009258 **
## propertyTypeHut 0.770281
## propertyTypeLighthouse 0.789978
## propertyTypeLoft < 2e-16 ***
## propertyTypeOther 8.25e-09 ***
## `propertyTypeServiced apartment` 0.000150 ***
## propertyTypeTimeshare 2.54e-15 ***
## propertyTypeTownhouse 5.39e-05 ***
## `propertyTypeVacation home` 0.020558 *
## propertyTypeVilla 0.467172
## `roomTypePrivate room` < 2e-16 ***
## `roomTypeShared room` < 2e-16 ***
## securityDeposit 0.002651 **
## numberOfReviews 5.61e-08 ***
## reviewScoresRating < 2e-16 ***
## cableTV1 < 2e-16 ***
## carbonMonoxideDetector1 0.052883 .
## doorman1 4.67e-09 ***
## elevator1 2.94e-14 ***
## essentials1 1.89e-11 ***
## gym1 5.23e-16 ***
## petsAllowed1 0.000258 ***
## pool1 0.000307 ***
## smokeDetector1 0.005772 **
## wheelchairAccessible1 1.37e-10 ***
## hostIsSuperhost1 6.32e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 78.2 on 19076 degrees of freedom

```

```
## Multiple R-squared:  0.5885, Adjusted R-squared:  0.5871
## F-statistic: 419.6 on 65 and 19076 DF,  p-value: < 2.2e-16

print(lm3)

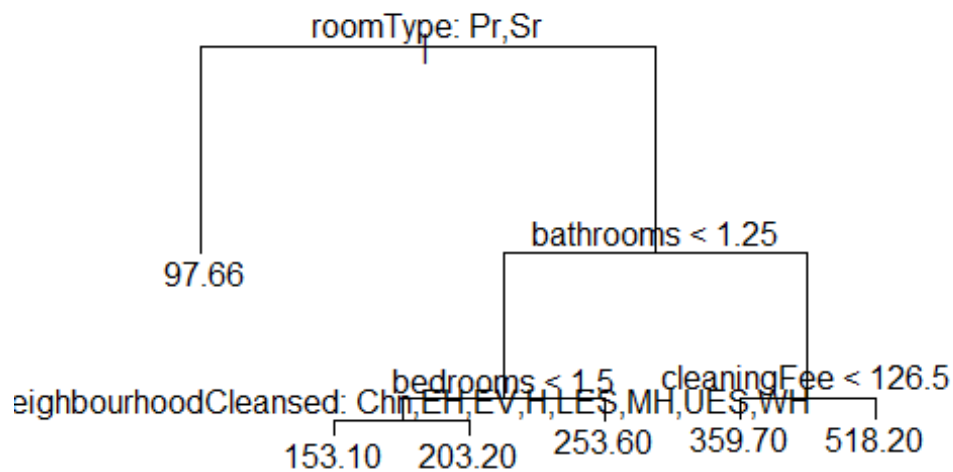
## Linear Regression
##
## 19142 samples
##    25 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 3 times)
## Summary of sample sizes: 17228, 17228, 17227, 17228, 17228, 17228, ...
## Resampling results:
##
##    RMSE      Rsquared   MAE
##  78.52298   0.583468   50.50286
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

Using Regression Tree to model price vs features.

```
print("Creating Regression Tree for prediction")
## [1] "Creating Regression Tree for prediction"
airTree <- tree(price~., data=airDataTrain)
```

Tree plot.

```
print("Plotting Tree")
## [1] "Plotting Tree"
plot(airTree)
text(airTree,pretty=TRUE)
```



Tree-based prediction.

```

print("Using Tree Model to predict for Test data")
## [1] "Using Tree Model to predict for Test data"
treePred <- predict(airTree, airDataTest)
print(paste("Test MSE:", mean((airDataTest$price - treePred) ^ 2)))
## [1] "Test MSE: 7471.89554988577"

```

Pruning tree to get best tree.

```

print("Using Cross Validation to get Pruned Tree")
## [1] "Using Cross Validation to get Pruned Tree"
cvtree <- cv.tree(airTree, FUN=prune.tree, K=10)

```

Pruning: Sizes considered

```

print("Sizes considered:")
## [1] "Sizes considered:"
print(cvtree$size)
## [1] 6 5 4 3 2 1

```

Pruning: k-values considered

```
print("Various alphas (k's) considered:")
```

```
## [1] "Various alphas (k's) considered:"
```

```
print(cvtree$k)
```

```
## [1]      -Inf  4457445  6423652  7416235  48021749  67434626
```

Pruning: misclassification rates for corresponding k-values

```
print("Corresponding misclassification rates:")
```

```
## [1] "Corresponding misclassification rates:"
```

```
print(cvtree$dev)
```

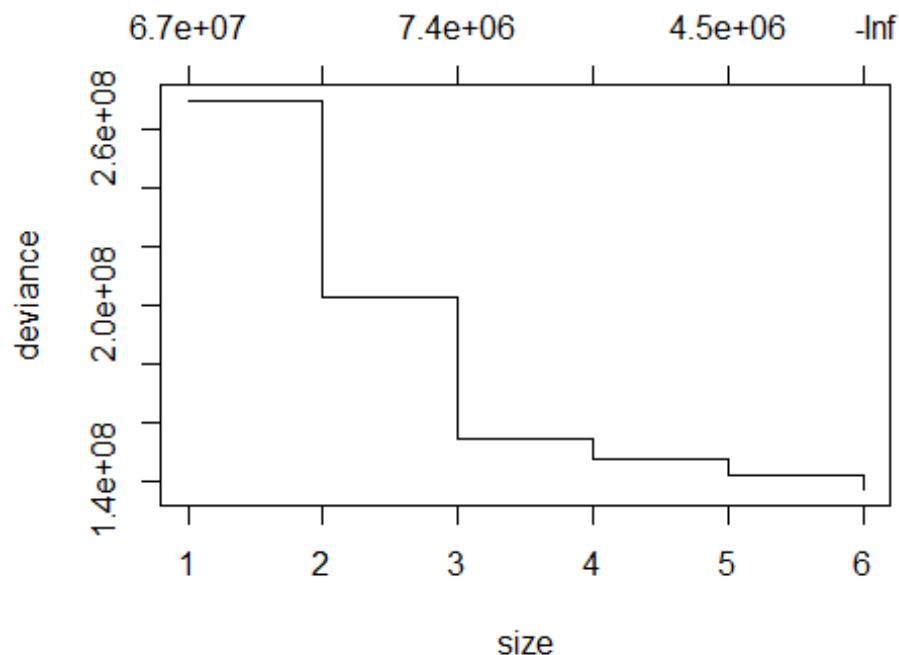
```
## [1] 137147120 141796176 147723058 154722397 202653593 270084492
```

Pruning: Plot of misclassification rate

```
print("plot of misclassification rate:")
```

```
## [1] "plot of misclassification rate:"
```

```
plot.tree.sequence(cvtree)
```



Extracting best tree model.

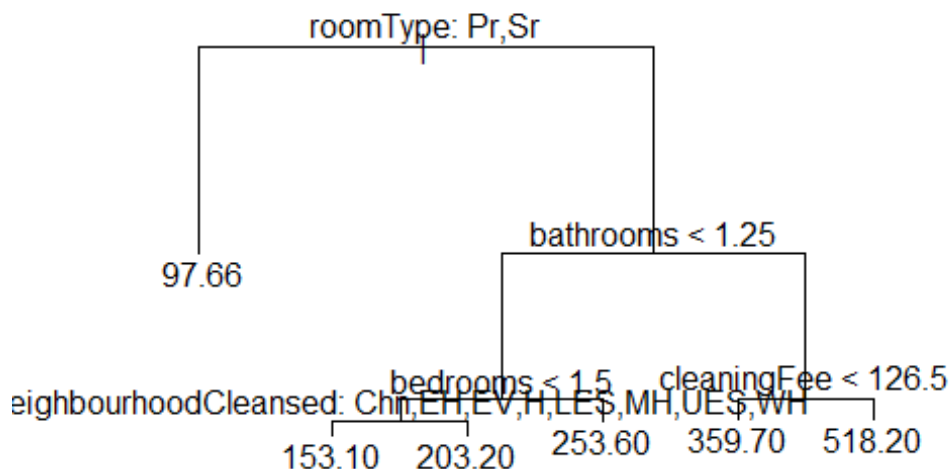
```
print("Extracting best tree from CV model")
```



```
## [1] "Extracting best tree from CV model"
bestTree <- prune.tree(airTree, best=cvtree$size[which.min(cvtree$dev)])
```

Plotting best tree.

```
print("Plotting best tree")
## [1] "Plotting best tree"
plot(bestTree)
text(bestTree,pretty=TRUE)
```



Using best tree for prediction on test data.

```
print("Using Best Tree Model to predict for Test data")
## [1] "Using Best Tree Model to predict for Test data"
treePred2 <- predict(bestTree, airDataTest)
print(paste("Test MSE:", mean((airDataTest$price - treePred2) ^ 2)))
## [1] "Test MSE: 7471.89554988577"
```

Linear model with interaction. It is possible that the pricing of a listing in NYC is subjective and/or dependent on features not available in this set (like age of building, rent control etc.). It is also possible that the true relationship between price and some of the features in non-linear. Running a linear model with interaction or higher polynomial order might

reveal these relationships. However, running a interaction model with even 27 variables for polynomial degree=2 takes prohibitively long time (~10 minutes). Running more complex models is not possible unless dedicated machines are available and/or time is not a constraint. The output of the quadratic model is pasted here for reference and there are indications that the relationship of price with at least some of these features may be non-linear.

```
print("Linear Regression with interaction")
## [1] "Linear Regression with interaction"

#lmi <- lm(price~(.)^2,data=airDataTrain)
#print(summary(lmi))
#lmiPred <- predict(lmi,airDataTest)
#print(mean((airDataTest$price - lmiPred) ^ 2))
print("Linear Regression with interaction runs prohibitively long (~10
minutes for polynomial degree 2)")

## [1] "Linear Regression with interaction runs prohibitively long (~10
minutes for polynomial degree 2)"

print("The output of the above commented code is pasted below for reference")
## [1] "The output of the above commented code is pasted below for reference"

print("*****")
## [1] "*****"

print("Residual standard error: 70.57 on 17072 degrees of freedom")
## [1] "Residual standard error: 70.57 on 17072 degrees of freedom"

print("Multiple R-squared:  0.684,  Adjusted R-squared:  0.6635")
## [1] "Multiple R-squared:  0.684,\tAdjusted R-squared:  0.6635"

print("F-statistic: 33.27 on 1111 and 17072 DF,  p-value: < 2.2e-16")
## [1] "F-statistic: 33.27 on 1111 and 17072 DF,  p-value: < 2.2e-16"

print("*****")
## [1] "*****"

print("This indicates that the relationship between price and othe features
may be non-linear and/or there may be an interaction effect between certain
features.")
## [1] "This indicates that the relationship between price and othe features
may be non-linear and/or there may be an interaction effect between certain
features."
```

Using data set with all columns for Ridge and Lasso regression. Recreating training and test data sets from this data set.

```
print("Recreating training and test data sets with all columns in cleaned
dataSet")

## [1] "Recreating training and test data sets with all columns in cleaned
dataSet"

airDataNew <- airDataClean[airDataClean$price > 0,]

if(log_regression){
  airDataNew$price <- log(airDataNew$price)
}

airDataTrain <- airDataNew[train,]
airDataTest <- airDataNew[-train,]
```

glm (Ridge/Lasso/Elastic Net) requires data to be split into two objects: a model matrix with all features and a label object with the response.

```
featureSet <- model.matrix(price~.,airDataTrain)[,-1]
responseSet <- airDataTrain$price
```

Running Ridge regression model.

```
print("Running Ridge Regression Model")

## [1] "Running Ridge Regression Model"

print("Using Cross Validation to determine value of Shrinkage Parameter")

## [1] "Using Cross Validation to determine value of Shrinkage Parameter"

cv <- cv.glmnet(featureSet, responseSet, alpha=0)
minLambda <- cv$lambda.min
print(paste("Min. Lambda determined: ",minLambda))

## [1] "Min. Lambda determined: 7.28207895394829"

ridgeModel <- glmnet(featureSet, responseSet, alpha=0, lambda=minLambda)
print(summary(ridgeModel))

##           Length Class      Mode
## a0           1    -none-   numeric
## beta        115   dgMatrix S4
## df            1    -none-   numeric
## dim           2    -none-   numeric
## lambda        1    -none-   numeric
## dev.ratio      1    -none-   numeric
## nulldev        1    -none-   numeric
## npasses        1    -none-   numeric
## jerr           1    -none-   numeric
```

```

## offset      1    -none-    logical
## call       5    -none-    call
## nobs       1    -none-    numeric

print(coef(ridgeModel))

## 116 x 1 sparse Matrix of class "dgCMatrix"
##                                     s0
## (Intercept)                      25.043539761
## hostResponseHours                 -0.039603960
## neighbourhoodCleansedChinatown    -13.654989883
## neighbourhoodCleansedEast Harlem -51.720351044
## neighbourhoodCleansedEast Village -10.335189986
## neighbourhoodCleansedFinancial District -20.541644538
## neighbourhoodCleansedGramercy     -12.883093447
## neighbourhoodCleansedGreenwich Village 23.668712529
## neighbourhoodCleansedHarlem        -56.451700566
## neighbourhoodCleansedHell's Kitchen  0.553424969
## neighbourhoodCleansedKips Bay       -10.849036469
## neighbourhoodCleansedLower East Side -16.191388834
## neighbourhoodCleansedMidtown        13.475026658
## neighbourhoodCleansedMorningside Heights -48.186784120
## neighbourhoodCleansedOther          -5.552506097
## neighbourhoodCleansedSoHo           39.335445730
## neighbourhoodCleansedUpper East Side -16.863818214
## neighbourhoodCleansedUpper West Side -12.558955419
## neighbourhoodCleansedWashington Heights -60.176767465
## neighbourhoodCleansedWest Village    25.868568448
## neighbourhoodGroupCleansedBrooklyn   -6.962422080
## neighbourhoodGroupCleansedManhattan  41.412957060
## neighbourhoodGroupCleansedQueens     -25.279363666
## neighbourhoodGroupCleansedStaten Island -64.990841678
## accommodates                       14.376611974
## bathrooms                           56.816726053
## bedTypeCouch                         5.413123281
## bedTypeFuton                         12.393776859
## bedTypePull-out Sofa                 9.845004385
## bedTypeReal Bed                      11.827860818
## bedrooms                             28.020448692
## beds                                5.642655602
## TV                                   9.824073249
## cancellationPolycymoderate           -4.429111284
## cancellationPolycystrict             -5.826180115
## cancellationPolycysuper_strict_30    64.501598706
## cleaningFee                          0.292998222
## extraPeople                           0.010252366
## guestsIncluded                       3.148255736
## maximumNights                        0.001111189
## minimumNights                        -0.111734515
## propertyTypeBed & Breakfast          18.296985749

```

## propertyTypeBoat	187.582436507
## propertyTypeBoutique hotel	46.919576463
## propertyTypeBungalow	-50.633094209
## propertyTypeCabin	77.846360392
## propertyTypeCastle	104.297230049
## propertyTypeCondominium	50.611500558
## propertyTypeDorm	-34.422643201
## propertyTypeGuest suite	162.115788503
## propertyTypeGuesthouse	13.056811104
## propertyTypeHostel	5.276471103
## propertyTypeHouse	20.663935954
## propertyTypeHut	-34.905016186
## propertyTypeLighthouse	29.850676484
## propertyTypeLoft	51.926833711
## propertyTypeOther	37.824416922
## propertyTypeServiced apartment	88.733575298
## propertyTypeTimeshare	98.016744314
## propertyTypeTownhouse	20.566627679
## propertyTypeVacation home	183.360915282
## propertyTypeVilla	-14.295025364
## roomTypePrivate room	-55.252579318
## roomTypeShared room	-67.266866825
## securityDeposit	-0.010197838
## numberOfReviews	-0.069674940
## reviewScoresAccuracy	0.081488460
## reviewScoresCheckin	-0.853682725
## reviewScoresCleanliness	1.419621984
## reviewScoresCommunication	-0.855844252
## reviewScoresLocation	-0.462290473
## reviewScoresRating	0.041035068
## reviewScoresValue	-1.497753171
## reviewsperMonth	-1.523936975
## checkIn24Hours1	-0.857422781
## airConditioning1	0.853827404
## buzzerOrWirelessIntercom1	-1.152413942
## cableTV1	11.394115083
## carbonMonoxideDetector1	1.233845313
## doorman1	8.912556864
## dryer1	1.374740077
## elevator1	7.896844295
## essentials1	-9.281113779
## familyAndKidFriendly1	3.905972489
## fireExtinguisher1	3.221546292
## firstAidKit1	2.579599060
## freeParkingOnPremises1	-2.620506541
## gym1	19.267061221
## hairdryer1	-1.690504110
## hangers1	-5.304232986
## heating1	-3.389636633
## hottub1	-4.777520593

```
## internet1 -1.436545199
## iron1 -3.082232969
## kitchen1 -6.646908205
## laptopFriendlyWorkspace1 -0.639189669
## lockOnBedroomDoor1 -3.250060944
## petsAllowed1 -6.078464179
## petsLiveOnThisProperty1 -3.845922966
## pool1 17.052716545
## selfCheckIn1 10.228325098
## shampoo1 4.127420520
## smokeDetector1 -5.447946148
## smokingAllowed1 -0.886073773
## washer1 2.844872414
## wheelchairAccessible1 12.086076800
## wirelessInternet1 -2.255280422
## hostHasProfilePic1 -13.497110568
## hostIdentityVerified1 -1.084456368
## hostIsSuperhost1 15.260718439
## instantBookable1 -4.306107639
## isLocationExact1 0.371599873
## requireGuestPhoneVerification1 -9.282581713
## requireGuestProfilePicture1 2.956270521
## featureCount 0.420047543
## yearsAsHost 0.407190999

ridgeTest <- model.matrix(price~.,airDataTest)[, -1]
ridgePred <- predict(ridgeModel,ridgeTest)
print(paste("RMSE:",RMSE(ridgePred, airDataTest$price)))

## [1] "RMSE: 78.3890763404307"

print(paste("R-squared:",R2(ridgePred, airDataTest$price)))

## [1] "R-squared: 0.560859666021504"
```

Running LASSO regression model.

```
print("Running Lasso Regression Model")

## [1] "Running Lasso Regression Model"

print("Using Cross Validation to determine value of Shrinkage Parameter")

## [1] "Using Cross Validation to determine value of Shrinkage Parameter"

cv <- cv.glmnet(featureSet, responseSet, alpha=1)
minLambda <- cv$lambda.min
print(paste("Min. Lambda determined: ",minLambda))

## [1] "Min. Lambda determined: 0.0468097358807009"
```

```
lassoModel <- glmnet(featureSet, responseSet, alpha=1, lambda=minLambda)
print(summary(lassoModel))
```

```
##           Length Class      Mode
## a0           1    -none-  numeric
## beta        115   dgCMatrx S4
## df           1    -none-  numeric
## dim           2    -none-  numeric
## lambda        1    -none-  numeric
## dev.ratio     1    -none-  numeric
## nulldev       1    -none-  numeric
## npasses       1    -none-  numeric
## jerr          1    -none-  numeric
## offset        1    -none-  logical
## call          5    -none-  call
## nobs          1    -none-  numeric
```

```
print(coef(lassoModel))
```

```
## 116 x 1 sparse Matrix of class "dgCMatrx"
##                                     s0
## (Intercept)                      1.083313e+01
## hostResponseHours                 -4.120741e-02
## neighbourhoodCleansedChinatown    -2.853248e+01
## neighbourhoodCleansedEast Harlem  -6.820004e+01
## neighbourhoodCleansedEast Village -2.495130e+01
## neighbourhoodCleansedFinancial District -3.528480e+01
## neighbourhoodCleansedGramercy     -2.692041e+01
## neighbourhoodCleansedGreenwich Village 1.033748e+01
## neighbourhoodCleansedHarlem        -7.332343e+01
## neighbourhoodCleansedHell's Kitchen -1.283230e+01
## neighbourhoodCleansedKips Bay      -2.512141e+01
## neighbourhoodCleansedLower East Side -3.079013e+01
## neighbourhoodCleansedMidtown       .
## neighbourhoodCleansedMorningside Heights -6.469314e+01
## neighbourhoodCleansedOther         -1.918424e+01
## neighbourhoodCleansedSoHo          2.690373e+01
## neighbourhoodCleansedUpper East Side -3.157926e+01
## neighbourhoodCleansedUpper West Side -2.720527e+01
## neighbourhoodCleansedWashington Heights -7.721025e+01
## neighbourhoodCleansedWest Village  1.260491e+01
## neighbourhoodGroupCleansedBrooklyn  1.886843e+01
## neighbourhoodGroupCleansedManhattan 6.957408e+01
## neighbourhoodGroupCleansedQueens    .
## neighbourhoodGroupCleansedStaten Island -4.157853e+01
## accommodates                      1.587934e+01
## bathrooms                         5.949907e+01
## bedTypeCouch                      7.166551e+00
## bedTypeFuton                      1.580840e+01
## bedTypePull-out Sofa              1.246381e+01
```

## bedTypeReal Bed	1.319597e+01
## bedrooms	3.034575e+01
## beds	2.564823e+00
## TV	8.940970e+00
## cancellationPolicymoderate	-5.046291e+00
## cancellationPolicystrict	-6.930013e+00
## cancellationPolicysuper_strict_30	6.090565e+01
## cleaningFee	2.843693e-01
## extraPeople	1.341034e-02
## guestsIncluded	2.551104e+00
## maximumNights	8.629911e-04
## minimumNights	-1.130853e-01
## propertyTypeBed & Breakfast	1.849352e+01
## propertyTypeBoat	1.823427e+02
## propertyTypeBoutique hotel	4.750546e+01
## propertyTypeBungalow	-4.609131e+01
## propertyTypeCabin	7.278802e+01
## propertyTypeCastle	1.055791e+02
## propertyTypeCondominium	5.131636e+01
## propertyTypeDorm	-2.914546e+01
## propertyTypeGuest suite	1.666482e+02
## propertyTypeGuesthouse	1.492195e+01
## propertyTypeHostel	-5.657774e+00
## propertyTypeHouse	2.301196e+01
## propertyTypeHut	-2.556598e+01
## propertyTypeLighthouse	2.386969e+01
## propertyTypeLoft	5.226207e+01
## propertyTypeOther	4.000240e+01
## propertyTypeServiced apartment	9.124248e+01
## propertyTypeTimeshare	1.014449e+02
## propertyTypeTownhouse	2.181640e+01
## propertyTypeVacation home	1.799646e+02
## propertyTypeVilla	-1.309771e+01
## roomTypePrivate room	-5.879000e+01
## roomTypeShared room	-7.253163e+01
## securityDeposit	-1.286394e-02
## numberOfReviews	-6.571702e-02
## reviewScoresAccuracy	2.966535e-01
## reviewScoresCheckin	-9.949108e-01
## reviewScoresCleanliness	4.511431e+00
## reviewScoresCommunication	-1.543589e+00
## reviewScoresLocation	.
## reviewScoresRating	1.834673e-01
## reviewScoresValue	-5.742365e+00
## reviewsperMonth	-1.592578e+00
## checkIn24Hours1	-9.924278e-01
## airConditioning1	-5.623663e-01
## buzzerOrWirelessIntercom1	-1.324278e+00
## cableTV1	1.099844e+01
## carbonMonoxideDetector1	1.258457e+00


```

## doorman1                8.245811e+00
## dryer1                  .
## elevator1              8.622926e+00
## essentials1            -1.009085e+01
## familyAndKidFriendly1  2.634717e+00
## fireExtinguisher1      3.025391e+00
## firstAidKit1           3.074645e+00
## freeParkingOnPremises1 -1.303091e+00
## gym1                   1.944936e+01
## hairdryer1             -2.164501e+00
## hangers1               -5.425258e+00
## heating1               -3.509780e+00
## hottub1                -4.433442e+00
## internet1              -1.507958e+00
## iron1                  -3.135484e+00
## kitchen1               -6.963046e+00
## laptopFriendlyWorkspace1 -8.247768e-01
## lockOnBedroomDoor1     -2.295287e+00
## petsAllowed1           -6.507069e+00
## petsLiveOnThisProperty1 -2.251488e+00
## pool1                  1.771080e+01
## selfCheckIn1           9.676471e+00
## shampoo1               4.016852e+00
## smokeDetector1         -5.815790e+00
## smokingAllowed1        .
## washer1                3.447717e+00
## wheelchairAccessible1  1.258175e+01
## wirelessInternet1      -1.468102e+00
## hostHasProfilePic1     -1.295706e+01
## hostIdentityVerified1  -9.797188e-01
## hostIsSuperhost1       1.562294e+01
## instantBookable1       -4.046998e+00
## isLocationExact1       9.913903e-02
## requireGuestPhoneVerification1 -1.086545e+01
## requireGuestProfilePicture1 4.347151e+00
## featureCount           4.672462e-01
## yearsAsHost            2.825844e-01

```

```

lassoTest <- model.matrix(price~.,airDataTest)[, -1]
lassoPred <- predict(lassoModel,lassoTest)
print(paste("RMSE:",RMSE(lassoPred, airDataTest$price)))

## [1] "RMSE: 78.2508024632149"

print(paste("R-squared:",R2(lassoPred, airDataTest$price)))

## [1] "R-squared: 0.563446444064143"

```

XGBoost is a library designed and optimized for boosting trees algorithms. Gradient boosting trees model is originally proposed by Friedman et al. The underlying algorithm of XGBoost is similar, specifically it is an extension of the classic gbm algorithm. By employing

multi-threads and imposing regularization, XGBoost is able to utilize more computational power and get more accurate prediction. XGBoost requires training and test data to be prepared similar to requirements of Ridge/Lasso regression models.

```
print("Using XGBoost")
## [1] "Using XGBoost"
print("Creating matrices for training and test data for XGBoost")
## [1] "Creating matrices for training and test data for XGBoost"
xgbTestData <- model.matrix(price~.,airDataTest)[,-1]
xgbPredData <- model.matrix(price~.,airDataPredict)[,-1]
xgbTestLabel <- airDataTest$price
```

XGBoost can be used with caret to set up training controls for the cross validation approach. The xgbGrid defines the values or list/range of values for each parameter that needs to be estimated. An average CV run for XGBoost (2 parameters with 3 values each) runs for ~45-50 minutes. The values below were estimated during earlier test runs and have been fixed to provide optimum results and reduce runtime for the markdown.

```
print("Setting up XGBoost Training Controls")
## [1] "Setting up XGBoost Training Controls"
xgb_trcontrol = trainControl(method="cv", number=5, allowParallel=TRUE,
verboseIter=TRUE, returnData=FALSE)
print("Setting up XGBoost Grid")
## [1] "Setting up XGBoost Grid"
xgbGrid <- expand.grid(nrounds=100, max_depth=10, colsample_bytree=0.5,
eta=0.1, gamma=0, min_child_weight=50, subsample=0.9)
xgb1 <- train(featureSet, responseSet, trControl=xgb_trcontrol,
tuneGrid=xgbGrid, method="xgbTree")
## + Fold1: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## - Fold1: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## + Fold2: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## - Fold2: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## + Fold3: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## - Fold3: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## + Fold4: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## - Fold4: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
```

```

gamma=0, min_child_weight=50, subsample=0.9
## + Fold5: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## - Fold5: nrounds=100, max_depth=10, colsample_bytree=0.5, eta=0.1,
gamma=0, min_child_weight=50, subsample=0.9
## Aggregating results
## Fitting final model on full training set

```

Best tuning parameters.

```

print("Best Tuning Parameters")
## [1] "Best Tuning Parameters"

print(xgb1$bestTune)

##      nrounds max_depth eta gamma colsample_bytree min_child_weight subsample
## 1         100         10 0.1     0              0.5              50         0.9

```

Summary of XGBoost model.

```

print("Summary of XGBoost model")
## [1] "Summary of XGBoost model"

print(xgb1)

## eXtreme Gradient Boosting
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 14547, 14549, 14547, 14547, 14546
## Resampling results:
##
##      RMSE      Rsquared   MAE
##  70.25147  0.6679247  43.54998
##
## Tuning parameter 'nrounds' was held constant at a value of 100
##  0.5
## Tuning parameter 'min_child_weight' was held constant at a value
##  of 50
## Tuning parameter 'subsample' was held constant at a value of 0.9

```

Using XGBoost model to predict on test data.

```

print("Using XGBoost model to predict on Test Data")
## [1] "Using XGBoost model to predict on Test Data"

xgbPred <- predict(xgb1,xgbTestData)
print(paste("RMSE:",RMSE(xgbPred, airDataTest$price)))

## [1] "RMSE: 72.2505609015715"

```

```
print(paste("R-squared:",R2(xgbPred, airDataTest$price)))
```

```
## [1] "R-squared: 0.628885183117991"
```

Using XGBoost model for pure prediction.

```
print("Using XGBoost model to predict on Unknown Data")
```

```
## [1] "Using XGBoost model to predict on Unknown Data"
```

```
xgbPred <- predict(xgb1,xgbPredData)
```

```
airDataPredict$price <- xgbPred
```

```
print("Printing head and tail for predicted data")
```

```
## [1] "Printing head and tail for predicted data"
```

```
print(head(airDataPredict))
```

```
##      hostResponseHours neighbourhoudCleansed neighbourhoudGroupCleansed
## 140                24                SoHo                Manhattan
## 424                1                Gramercy                Manhattan
## 462                1                Upper West Side                Manhattan
## 583                72                Washington Heights                Manhattan
## 692                12                Chelsea                Manhattan
## 1171               24                Chelsea                Manhattan
##      accommodates bathrooms  bedType bedrooms  beds TV cancellationPolicy
## 140                8          3 Real Bed          4   6   1                flexible
## 424               10          3 Real Bed          4   4   0                strict
## 462               10          6 Real Bed          6   6   1                flexible
## 583                2          1 Real Bed          1   1   1                flexible
## 692                6          2 Real Bed          2   2   1                strict
## 1171               2          1 Real Bed          1   2   1                strict
##      cleaningFee extraPeople guestsIncluded maximumNights minimumNights
## 140           250          100             6             12             2
## 424           450           12             4             1125             1
## 462           250            0             1             1125             4
## 583            0            0             1             1125             1
## 692           299            0             1             1125             10
## 1171           80            0             1             1125             3
##      price propertyType      roomType securityDeposit numberOfReviews
## 140  758.2528   Apartment Entire home/apt             0             9
## 424  642.8275   Apartment Entire home/apt            800            23
## 462  813.4902    House Entire home/apt             0             2
## 583  219.2037   Apartment Entire home/apt             0             0
## 692  527.8794   Apartment Entire home/apt             0             0
## 1171 205.9745   Apartment Entire home/apt             0            15
##      reviewScoresAccuracy reviewScoresCheckin reviewScoresCleanliness
## 140                10             10             10
## 424                 9             10             9
## 462                10             10            10
## 583                 0              0             0
## 692                 0              0             0
```

## 1171	10	10	10
##	reviewScoresCommunication	reviewScoresLocation	reviewScoresRating
## 140	10	10	98
## 424	9	9	88
## 462	10	10	100
## 583	0	0	0
## 692	0	0	0
## 1171	10	10	93
##	reviewScoresValue	reviewsperMonth	checkIn24Hours
## 140	10	0.82	0
## 424	9	2.41	1
## 462	10	0.21	1
## 583	0	0.00	0
## 692	0	0.00	0
## 1171	9	1.88	0
##	buzzerOrWirelessIntercom	cableTV	carbonMonoxideDetector
## 140	1	1	1
## 424	0	0	1
## 462	1	1	1
## 583	1	1	0
## 692	0	0	1
## 1171	0	0	0
##	doorman	dryer	
## 140	0	1	1
## 424	0	1	1
## 462	0	1	0
## 583	1	0	0
## 692	1	1	0
## 1171	0	0	0
##	elevator	essentials	familyAndKidFriendly
## 140	0	1	1
## 424	0	1	1
## 462	0	1	0
## 583	1	0	0
## 692	1	1	1
## 1171	0	0	1
##	fireExtinguisher	firstAidKit	
## 140	0	1	1
## 424	0	1	1
## 462	0	1	0
## 583	1	0	0
## 692	1	1	0
## 1171	0	0	0
##	freeParkingOnPremises	gym	hairdryer
## 140	0	0	0
## 424	0	0	1
## 462	0	0	1
## 583	0	0	0
## 692	0	0	1
## 1171	0	0	0
##	hangers	heating	hottub
## 140	1	1	0
## 424	0	1	0
## 462	1	1	0
## 583	0	1	0
## 692	1	1	0
## 1171	0	1	0
##	internet		
## 140	1		
## 424	1		
## 462	1		
## 583	0		
## 692	0		
## 1171	0		
##	iron	kitchen	laptopFriendlyWorkspace
## 140	0	1	1
## 424	0	1	0
## 462	1	1	1
## 583	0	1	0
## 692	1	1	1
## 1171	0	1	0
##	lockOnBedroomDoor	petsAllowed	
## 140	0	0	0
## 424	0	0	1
## 462	0	0	0
## 583	0	0	0
## 692	1	1	1
## 1171	0	0	0
##	petsLiveOnThisProperty	pool	selfCheckIn
## 140	1	0	0
## 424	0	0	0
## 462	0	0	1
## 583	0	0	0
## 692	0	0	1
## 1171	0	0	0
##	shampoo	smokeDetector	
## 140	0	1	
## 424	0	1	
## 462	1	1	
## 583	0	0	
## 692	1	1	
## 1171	0	0	

```

##      smokingAllowed washer wheelchairAccessible wirelessInternet
## 140      1      1      0      1
## 424      0      1      0      1
## 462      0      1      0      1
## 583      0      0      0      1
## 692      0      1      0      1
## 1171     0      1      0      1
##      hostHasProfilePic hostIdentityVerified hostIsSuperhost
## 140      1      1      0
## 424      1      1      0
## 462      1      0      0
## 583      1      0      0
## 692      1      0      0
## 1171     1      1      0
##      instantBookable isLocationExact requireGuestPhoneVerification
## 140      0      1      0
## 424      1      0      0
## 462      0      1      0
## 583      0      1      0
## 692      1      1      0
## 1171     0      0      0
##      requireGuestProfilePicture featureCount yearsAsHost
## 140      0      23      4
## 424      0      18      4
## 462      0      24      4
## 583      0      9      4
## 692      0      22      3
## 1171     0      10      8

print(tail(airDataPredict))

##      hostResponseHours neighbourhoodCleansed neighbourhoodGroupCleansed
## 17992      1      Hell's Kitchen      Manhattan
## 18377      1      Hell's Kitchen      Manhattan
## 18811      1      Other      Manhattan
## 19050      1      Upper East Side      Manhattan
## 19055      1      Upper West Side      Manhattan
## 19154      1      Chelsea      Manhattan
##      accommodates bathrooms bedType bedrooms beds TV cancellationPolicy
## 17992      4      1 Real Bed      2      2      1      strict
## 18377      1      1 Real Bed      1      1      1      strict
## 18811      3      1 Real Bed      1      2      0      flexible
## 19050      3      2 Real Bed      3      3      1      flexible
## 19055      2      1 Real Bed      1      1      1      flexible
## 19154     16      1 Real Bed      0      1      0      strict
##      cleaningFee extraPeople guestsIncluded maximumNights minimumNights
## 17992      70      0      1      365      30
## 18377      0      0      1      1125      1
## 18811      0     30      2      1125      1
## 19050      0      0      1      1125      1

```

##	19055	100	0	1	1125	1
##	19154	0	0	1	1125	1
##		price	propertyType	roomType	securityDeposit	
##	17992	238.2175	Apartment	Entire home/apt	0	
##	18377	164.2854	Apartment	Private room	0	
##	18811	144.5242	Apartment	Entire home/apt	0	
##	19050	318.6658	Apartment	Entire home/apt	0	
##	19055	282.7828	Apartment	Entire home/apt	0	
##	19154	317.8828	Other	Private room	0	
##		numberOfReviews	reviewScoresAccuracy	reviewScoresCheckin		
##	17992	6	9	10		
##	18377	0	0	0		
##	18811	2	10	7		
##	19050	0	0	0		
##	19055	0	0	0		
##	19154	0	0	0		
##		reviewScoresCleanliness	reviewScoresCommunication			
##	17992	10	10			
##	18377	0	0			
##	18811	5	8			
##	19050	0	0			
##	19055	0	0			
##	19154	0	0			
##		reviewScoresLocation	reviewScoresRating	reviewScoresValue		
##	17992	10	97	10		
##	18377	0	0	0		
##	18811	9	76	7		
##	19050	0	0	0		
##	19055	0	0	0		
##	19154	0	0	0		
##		reviewsperMonth	checkIn24Hours	airConditioning		
##	17992	0.57	1	1		
##	18377	0.00	0	0		
##	18811	0.04	0	1		
##	19050	0.00	1	1		
##	19055	0.00	0	1		
##	19154	0.00	0	1		
##		buzzerOrWirelessIntercom	cableTV	carbonMonoxideDetector	doorman	
##	17992	1	1	1	0	
##	18377	1	1	0	0	
##	18811	0	0	0	0	
##	19050	1	1	0	1	
##	19055	1	1	0	0	
##	19154	0	0	0	0	
##		dryer	elevator	essentials	familyAndKidFriendly	fireExtinguisher
##	17992	1	0	1	0	0
##	18377	0	0	0	0	0
##	18811	0	0	0	0	0
##	19050	1	1	1	1	0
##	19055	1	1	0	1	0

## 19154	0	0	0	1	0	
##	firstAidKit	freeParkingOnPremises	gym	hairdryer	hangers	heating
## 17992	0		0	0	1	1
## 18377	0		0	0	0	1
## 18811	0		0	0	0	1
## 19050	0		0	0	1	0
## 19055	0		0	0	0	1
## 19154	0		0	0	0	0
##	hottub	internet	iron	kitchen	laptopFriendlyWorkspace	
## 17992	0	1	1	1		1
## 18377	0	1	0	1		0
## 18811	1	0	0	1		0
## 19050	0	1	1	1		1
## 19055	0	1	0	1		0
## 19154	0	0	0	1		0
##	lockOnBedroomDoor	petsAllowed	petsLiveOnThisProperty	pool		
## 17992		0		0	0	0
## 18377		0		0	0	0
## 18811		0		0	0	0
## 19050		0		0	0	0
## 19055		0		0	1	0
## 19154		0	1		0	0
##	selfCheckIn	shampoo	smokeDetector	smokingAllowed	washer	
## 17992	0	1	1	0	1	
## 18377	0	0	0	0	0	
## 18811	0	0	0	0	0	
## 19050	0	0	0	0	1	
## 19055	0	0	0	0	1	
## 19154	0	0	0	0	0	
##	wheelchairAccessible	wirelessInternet	hostHasProfilePic			
## 17992		0	1		1	
## 18377		0	1		1	
## 18811		0	1		1	
## 19050		0	1		1	
## 19055		0	1		1	
## 19154		1	0		1	
##	hostIdentityVerified	hostIsSuperhost	instantBookable	isLocationExact		
## 17992		1	0	0		0
## 18377		0	0	0		0
## 18811		0	0	0		1
## 19050		0	0	0		1
## 19055		0	0	0		1
## 19154		0	0	0		0
##	requireGuestPhoneVerification	requireGuestProfilePicture				
## 17992		0		0		
## 18377		0		0		
## 18811		1		1		
## 19050		0		0		
## 19055		0		0		
## 19154		0		0		


```
##          featureCount yearsAsHost
## 17992           22           5
## 18377            7           4
## 18811            9           9
## 19050           19           4
## 19055           15           5
## 19154            8           2

print("Writing predicted data to file predictedPrices.csv")
## [1] "Writing predicted data to file predictedPrices.csv"

if(log_regression){
  airDataPredict$price <- exp(airDataPredict$price)
}

write.csv(airDataPredict,"predictedPrices.csv")

print("----- End of Algorithmic Machine Learning Project -----")
## [1] "----- End of Algorithmic Machine Learning Project -----"
```

End of Markdown.