Initial Result and Code

Note: So far this is what I have for my project, and things will be subject to change as I progress through the capstone and towards the final results and report.

Load the Dataset

data <- read.csv('C:/Users/Ryan/Desktop/Capstone/listings.csv')  
str(data)

## 'data.frame': 37728 obs. of 106 variables:  
## $ id : int 109 344 2708 2732 2864 3021 5728 5729 5843 6033 ...  
## $ listing\_url : Factor w/ 37728 levels "https://www.airbnb.com/rooms/10000255",..: 481 21558 14528 14722 15900 17441 34749 34752 34828 34939 ...  
## $ scrape\_id : num 2.02e+13 2.02e+13 2.02e+13 2.02e+13 2.02e+13 ...  
## $ last\_scraped : Factor w/ 4 levels "2020-04-14","2020-04-15",..: 2 2 1 1 1 2 1 1 1 2 ...  
## $ name : Factor w/ 37000 levels "","'20s Showplace With Mid-Century Decor in Hancock Park",..: 3922 14623 22062 36970 582 17228 34285 36983 4521 25634 ...  
## $ summary : Factor w/ 32576 levels "","'Casita Esme' is truly charming. The enclosed private yard is landscaped with an ever-green lawn (synthetic gr"| \_\_truncated\_\_,..: 363 26822 19244 1 6815 2816 19518 19519 9291 19371 ...  
## $ space : Factor w/ 25077 levels "","'Cloud 9' is stylishly appointed with a modern surf side chic decor and all the modern entertainment and living"| \_\_truncated\_\_,..: 346 4269 6317 19840 17777 14927 5282 5283 12277 23901 ...  
## $ description : Factor w/ 34500 levels "","'Casita Esme' is truly charming. The enclosed private yard is landscaped with an ever-green lawn (synthetic gr"| \_\_truncated\_\_,..: 388 28403 20383 28632 7179 2930 20672 20673 9767 20512 ...  
## $ experiences\_offered : Factor w/ 1 level "none": 1 1 1 1 1 1 1 1 1 1 ...  
## $ neighborhood\_overview : Factor w/ 20880 levels "","-- 2 miles to Santa Monica beach -- 2 miles to Venice Beach -- near Getty Center + Hammer Museum -- walkable"| \_\_truncated\_\_,..: 1 10851 19684 16928 20367 16940 10155 10155 10156 1 ...  
## $ notes : Factor w/ 15294 levels "","---------------------------------------------------------------------------------------------------------- CORO"| \_\_truncated\_\_,..: 1 7137 2217 1 5076 1 8081 8081 8081 140 ...  
## $ transit : Factor w/ 19034 levels "","-- easy street parking [be careful during street cleaning!] -- close to major bus routes on Santa Monica Blvd -"| \_\_truncated\_\_,..: 1 10582 12807 16324 9901 3080 18502 18503 18502 5724 ...  
## $ access : Factor w/ 18252 levels "","--- More Amenities - 60\" TV with premium cable & Amazon fire stick - High speed internet - A/C - 2 car priva"| \_\_truncated\_\_,..: 1 10577 8682 1 4582 1 16139 16156 17986 3990 ...  
## $ interaction : Factor w/ 19206 levels "","- A comprehensive House guide to show how to operate the home. We are on call at all times to assist you with your stay!",..: 1 3731 6190 1 5149 1 3636 3637 3636 1 ...  
## $ house\_rules : Factor w/ 21353 levels "","---Check-in/Check-out: Check-in is at 2 p.m. or anytime thereafter provided you let us know the time. Ring the"| \_\_truncated\_\_,..: 7585 9301 9776 6394 1 11170 2421 2421 2421 5408 ...  
## $ thumbnail\_url : logi NA NA NA NA NA NA ...  
## $ medium\_url : logi NA NA NA NA NA NA ...  
## $ picture\_url : Factor w/ 36591 levels "https://a0.muscache.com/4ea/air/v2//pictures/0007dab7-df39-47ed-9eb6-6b839f58d52c.jpg?t=r:w1200-h720-sfit,e:fjpg-c85",..: 10887 29868 10470 3438 6290 12906 18960 34937 6668 11253 ...  
## $ xl\_picture\_url : logi NA NA NA NA NA NA ...  
## $ host\_id : int 521 767 3008 3041 3207 3415 9171 9171 9171 11619 ...  
## $ host\_url : Factor w/ 21996 levels "https://www.airbnb.com/users/show/10000147",..: 16760 19803 11874 12046 12741 13581 21255 21255 21255 1338 ...  
## $ host\_name : Factor w/ 7957 levels "","(Ana)","(Email hidden by Airbnb)",..: 5706 5019 1384 7786 924 5390 6393 6393 6393 6408 ...  
## $ host\_since : Factor w/ 3566 levels "","2008-06-27",..: 2 3 6 7 8 9 19 19 19 22 ...  
## $ host\_location : Factor w/ 924 levels ""," California, United States",..: 706 115 462 734 74 462 462 462 462 462 ...  
## $ host\_about : Factor w/ 13047 levels "","'Pocahontas' at heart. Nature and the wind are my guides. My dream is to someday create a food forest. I create"| \_\_truncated\_\_,..: 11361 11439 12948 7640 1971 10068 12362 12362 12362 6874 ...  
## $ host\_response\_time : Factor w/ 6 levels "","a few days or more",..: 4 4 5 6 3 4 6 6 6 6 ...  
## $ host\_response\_rate : Factor w/ 64 levels "","0%","10%",..: 4 31 4 4 64 27 4 4 4 4 ...  
## $ host\_acceptance\_rate : Factor w/ 99 levels "","0%","10%",..: 2 27 93 70 99 29 98 98 98 93 ...  
## $ host\_is\_superhost : Factor w/ 3 levels "","f","t": 2 2 3 2 2 2 3 3 3 2 ...  
## $ host\_thumbnail\_url : Factor w/ 21917 levels "","https://a0.muscache.com/defaults/user\_pic-50x50.png?v=3",..: 21010 21497 14365 19715 9552 20054 10458 10458 10458 14702 ...  
## $ host\_picture\_url : Factor w/ 21917 levels "","https://a0.muscache.com/defaults/user\_pic-225x225.png?v=3",..: 21010 21497 14365 19715 9552 20054 10458 10458 10458 14702 ...  
## $ host\_neighbourhood : Factor w/ 456 levels "","Å pinut","Adams Point",..: 94 54 159 346 34 193 98 98 98 455 ...  
## $ host\_listings\_count : int 1 1 2 2 1 6 8 8 8 15 ...  
## $ host\_total\_listings\_count : int 1 1 2 2 1 6 8 8 8 15 ...  
## $ host\_verifications : Factor w/ 491 levels "['email', 'facebook', 'reviews', 'jumio', 'government\_id', 'work\_email']",..: 101 280 101 295 64 278 116 116 116 289 ...  
## $ host\_has\_profile\_pic : Factor w/ 3 levels "","f","t": 3 3 3 3 3 3 3 3 3 3 ...  
## $ host\_identity\_verified : Factor w/ 3 levels "","f","t": 3 3 3 2 3 3 2 2 2 3 ...  
## $ street : Factor w/ 431 levels " Los Angeles, CA, United States",..: 70 44 179 311 34 179 179 179 179 427 ...  
## $ neighbourhood : Factor w/ 165 levels "","Alhambra",..: 31 21 60 119 16 13 33 33 33 165 ...  
## $ neighbourhood\_cleansed : Factor w/ 264 levels "Acton","Adams-Normandie",..: 54 32 102 194 23 104 57 57 57 264 ...  
## $ neighbourhood\_group\_cleansed : Factor w/ 3 levels "City of Los Angeles",..: 2 2 1 2 2 1 1 1 1 1 ...  
## $ city : Factor w/ 404 levels ""," Los Angeles",..: 67 41 157 292 33 157 157 157 157 399 ...  
## $ state : Factor w/ 11 levels "","åŠ å\210©ç¦\217å°¼äºš",..: 8 8 8 8 8 8 8 8 8 8 ...  
## $ zipcode : Factor w/ 330 levels "","0000","10001",..: 81 236 53 117 138 53 67 67 67 219 ...  
## $ market : Factor w/ 38 levels "","California - Los Angeles - Beach Cities and South Bay",..: 28 28 28 28 28 28 28 28 28 28 ...  
## $ smart\_location : Factor w/ 431 levels " Los Angeles, CA",..: 70 44 179 312 34 179 179 179 179 427 ...  
## $ country\_code : Factor w/ 1 level "US": 1 1 1 1 1 1 1 1 1 1 ...  
## $ country : Factor w/ 1 level "United States": 1 1 1 1 1 1 1 1 1 1 ...  
## $ latitude : num 34 34.2 34.1 34 33.9 ...  
## $ longitude : num -118 -118 -118 -118 -118 ...  
## $ is\_location\_exact : Factor w/ 2 levels "f","t": 2 2 2 2 2 2 2 2 2 2 ...  
## $ property\_type : Factor w/ 46 levels "Aparthotel","Apartment",..: 16 26 2 2 2 22 39 23 26 7 ...  
## $ room\_type : Factor w/ 4 levels "Entire home/apt",..: 1 1 3 3 1 1 3 3 1 1 ...  
## $ accommodates : int 6 6 1 1 2 2 2 3 5 4 ...  
## $ bathrooms : num 2 1 1.5 1 1 1 1 1 1 1 ...  
## $ bedrooms : int 2 3 1 1 1 1 1 1 2 1 ...  
## $ beds : int 3 3 1 1 1 2 1 1 2 1 ...  
## $ bed\_type : Factor w/ 6 levels "","Airbed","Couch",..: 6 6 6 5 6 6 6 2 6 6 ...  
## $ amenities : Factor w/ 35004 levels "{\"Air conditioning\",\"Fire extinguisher\",Essentials,Shampoo,Hangers}",..: 2309 1106 589 1482 2830 7690 13971 1156 1334 2236 ...  
## $ square\_feet : int NA NA NA NA NA NA 64 400 NA NA ...  
## $ price : Factor w/ 871 levels "$0.00","$1,000.00",..: 135 188 777 174 787 161 762 112 420 804 ...  
## $ weekly\_price : Factor w/ 611 levels "","$1,000.00",..: 581 1 314 538 314 529 293 1 1 1 ...  
## $ monthly\_price : Factor w/ 668 levels "","$1,000.00",..: 310 1 657 145 62 258 1 1 423 1 ...  
## $ security\_deposit : Factor w/ 223 levels "","$0.00","$1,000.00",..: 174 2 164 1 36 103 36 61 88 61 ...  
## $ cleaning\_fee : Factor w/ 319 levels "","$0.00","$1,000.00",..: 115 8 300 8 283 253 120 230 8 120 ...  
## $ guests\_included : int 3 6 1 1 1 1 1 2 2 2 ...  
## $ extra\_people : Factor w/ 100 levels "$0.00","$10.00",..: 35 1 1 1 35 95 14 14 14 35 ...  
## $ minimum\_nights : int 30 2 30 1 2 3 30 30 1 5 ...  
## $ maximum\_nights : int 730 14 366 180 730 730 1125 1125 90 30 ...  
## $ minimum\_minimum\_nights : int 30 2 1 1 2 3 1 30 1 5 ...  
## $ maximum\_minimum\_nights : int 30 2 30 1 2 3 30 30 5 5 ...  
## $ minimum\_maximum\_nights : int 730 14 1125 180 730 730 1125 1125 1125 1125 ...  
## $ maximum\_maximum\_nights : int 730 14 1125 180 730 730 1125 1125 1125 1125 ...  
## $ minimum\_nights\_avg\_ntm : num 30 2 28.8 1 2 3 29.9 30 2.3 5 ...  
## $ maximum\_nights\_avg\_ntm : num 730 14 1125 180 730 ...  
## $ calendar\_updated : Factor w/ 91 levels "1 week ago","10 months ago",..: 13 77 26 26 16 2 90 12 14 40 ...  
## $ has\_availability : Factor w/ 1 level "t": 1 1 1 1 1 1 1 1 1 1 ...  
## $ availability\_30 : int 0 0 30 30 0 0 0 16 14 30 ...  
## $ availability\_60 : int 0 0 32 60 0 12 12 19 38 47 ...  
## $ availability\_90 : int 0 1 32 90 0 42 42 28 61 47 ...  
## $ availability\_365 : int 14 73 281 365 0 317 249 230 136 47 ...  
## $ calendar\_last\_scraped : Factor w/ 4 levels "2020-04-14","2020-04-15",..: 2 2 1 1 1 2 1 1 1 2 ...  
## $ number\_of\_reviews : int 2 8 24 21 0 23 309 228 126 25 ...  
## $ number\_of\_reviews\_ltm : int 0 2 8 3 0 0 69 73 48 3 ...  
## $ first\_review : Factor w/ 2850 levels "","2009-05-26",..: 100 1451 735 76 1 506 3 6 70 4 ...  
## $ last\_review : Factor w/ 1680 levels "","2010-03-28",..: 348 1501 1651 1570 1 1150 1647 1643 1650 1656 ...  
## $ review\_scores\_rating : int 80 97 97 94 NA 81 96 95 92 88 ...  
## $ review\_scores\_accuracy : int 10 10 10 9 NA 8 10 9 10 8 ...  
## $ review\_scores\_cleanliness : int 10 10 10 9 NA 8 10 10 10 8 ...  
## $ review\_scores\_checkin : int 6 10 10 9 NA 8 10 10 10 9 ...  
## $ review\_scores\_communication : int 8 10 10 9 NA 9 10 10 10 9 ...  
## $ review\_scores\_location : int 10 10 10 10 NA 9 10 9 10 9 ...  
## $ review\_scores\_value : int 8 10 10 9 NA 8 9 9 9 9 ...  
## $ requires\_license : Factor w/ 2 levels "f","t": 1 1 2 2 1 2 2 2 2 2 ...  
## $ license : Factor w/ 5538 levels "","#HSR19-002081",..: 1 1 1 275 1 1 1997 1997 1997 1 ...  
## $ jurisdiction\_names : Factor w/ 12 levels "","{\"Arkansas State\"}",..: 4 1 3 9 1 3 3 3 3 3 ...  
## $ instant\_bookable : Factor w/ 2 levels "f","t": 1 2 2 1 1 1 2 2 2 2 ...  
## $ is\_business\_travel\_ready : Factor w/ 1 level "f": 1 1 1 1 1 1 1 1 1 1 ...  
## $ cancellation\_policy : Factor w/ 9 levels "flexible","luxury\_moderate",..: 7 1 7 7 7 7 5 5 5 7 ...  
## [list output truncated]

Removing Redundant and not relevant variables for analysis e.g.(Repeated variables that represent the same thing)

data$listing\_url<-NULL # Not useful for analysis knowing the URL  
data$scrape\_id<-NULL # Not useful for analysis knowing the scrape ID  
data$experiences\_offered<-NULL # There is only one value it is none, since theres are all living spaces no experiences offered  
data$thumbnail\_url<-NULL #URL Links not useful for analysis and most are NA values  
data$medium\_url<-NULL #URL Links not useful for analysis and most are NA values  
data$picture\_url<-NULL #URL Links not useful for analysis  
data$xl\_picture\_url<-NULL #URL Links not useful for analysis and most are NA values  
data$thumbnail\_url<-NULL #URL Links not useful for analysis  
data$medium\_url<-NULL #URL Links not useful for analysis  
data$picture\_url<-NULL #URL Links not useful for analysis  
data$xl\_picture\_url<-NULL #URL Links not useful for analysis  
data$host\_url<-NULL #URL Links not useful for analysis  
data$host\_thumbnail\_url<-NULL #URL Links not useful for analysis  
data$host\_picture\_url<-NULL #URL Links not useful for analysis  
data$host\_name<-NULL #Already have ID , not need two have both   
data$country\_code<-NULL # We already know it's in the US and in LA metro area  
data$country<-NULL# We already know it's in the US  
data$state<-NULL #We already know it's in CA since it's in LA metro area  
data$host\_neighbourhood<-NULL # The location of the host maybe not be useful  
data$host\_location<-NULL  
data$host\_has\_profile\_pic<-NULL  
data$neighbourhood<-NULL #There is already a cleansed version of the neighbourhood, so this should be more accurate to go off of  
data$is\_location\_exact<- NULL # I believe that using the general location of the long and lat shuold be sufficient for analysis  
  
  
#These are redundant numbers that are already shown by minimum\_nights and maximum\_nights column   
data$maximum\_maximum\_nights<-NULL  
data$maximum\_minimum\_nights<-NULL  
data$maximum\_nights\_avg\_ntm<-NULL  
data$minimum\_maximum\_nights<-NULL  
data$minimum\_minimum\_nights<-NULL  
data$minimum\_nights\_avg\_ntm<-NULL  
  
  
  
  
data$market<-NULL # Already shown by City/Neighbourhod,it's going to be in LA metropolitan area,thus redundant information  
data$smart\_location<-NULL # Already shown by City/Neighbourhood  
data$host\_listings\_count<-NULL # Doubled, there is already a total listings count  
  
  
data$jurisdiction\_names<-NULL #We already know that it is within the LA metro area  
data$number\_of\_reviews\_ltm<-NULL # Not really useful to know the amount last month, more interested in total  
data$calculated\_host\_listings\_count<-NULL #Repeated total listing counts for each host  
  
data$license<-NULL # License number/ID not important for the analysis  
data$is\_business\_travel\_ready<-NULL #When checking the structure of the dataset, only one factor and it's all false

Fixing the Data types of variables

str(data)

## 'data.frame': 37728 obs. of 73 variables:  
## $ id : int 109 344 2708 2732 2864 3021 5728 5729 5843 6033 ...  
## $ last\_scraped : Factor w/ 4 levels "2020-04-14","2020-04-15",..: 2 2 1 1 1 2 1 1 1 2 ...  
## $ name : Factor w/ 37000 levels "","'20s Showplace With Mid-Century Decor in Hancock Park",..: 3922 14623 22062 36970 582 17228 34285 36983 4521 25634 ...  
## $ summary : Factor w/ 32576 levels "","'Casita Esme' is truly charming. The enclosed private yard is landscaped with an ever-green lawn (synthetic gr"| \_\_truncated\_\_,..: 363 26822 19244 1 6815 2816 19518 19519 9291 19371 ...  
## $ space : Factor w/ 25077 levels "","'Cloud 9' is stylishly appointed with a modern surf side chic decor and all the modern entertainment and living"| \_\_truncated\_\_,..: 346 4269 6317 19840 17777 14927 5282 5283 12277 23901 ...  
## $ description : Factor w/ 34500 levels "","'Casita Esme' is truly charming. The enclosed private yard is landscaped with an ever-green lawn (synthetic gr"| \_\_truncated\_\_,..: 388 28403 20383 28632 7179 2930 20672 20673 9767 20512 ...  
## $ neighborhood\_overview : Factor w/ 20880 levels "","-- 2 miles to Santa Monica beach -- 2 miles to Venice Beach -- near Getty Center + Hammer Museum -- walkable"| \_\_truncated\_\_,..: 1 10851 19684 16928 20367 16940 10155 10155 10156 1 ...  
## $ notes : Factor w/ 15294 levels "","---------------------------------------------------------------------------------------------------------- CORO"| \_\_truncated\_\_,..: 1 7137 2217 1 5076 1 8081 8081 8081 140 ...  
## $ transit : Factor w/ 19034 levels "","-- easy street parking [be careful during street cleaning!] -- close to major bus routes on Santa Monica Blvd -"| \_\_truncated\_\_,..: 1 10582 12807 16324 9901 3080 18502 18503 18502 5724 ...  
## $ access : Factor w/ 18252 levels "","--- More Amenities - 60\" TV with premium cable & Amazon fire stick - High speed internet - A/C - 2 car priva"| \_\_truncated\_\_,..: 1 10577 8682 1 4582 1 16139 16156 17986 3990 ...  
## $ interaction : Factor w/ 19206 levels "","- A comprehensive House guide to show how to operate the home. We are on call at all times to assist you with your stay!",..: 1 3731 6190 1 5149 1 3636 3637 3636 1 ...  
## $ house\_rules : Factor w/ 21353 levels "","---Check-in/Check-out: Check-in is at 2 p.m. or anytime thereafter provided you let us know the time. Ring the"| \_\_truncated\_\_,..: 7585 9301 9776 6394 1 11170 2421 2421 2421 5408 ...  
## $ host\_id : int 521 767 3008 3041 3207 3415 9171 9171 9171 11619 ...  
## $ host\_since : Factor w/ 3566 levels "","2008-06-27",..: 2 3 6 7 8 9 19 19 19 22 ...  
## $ host\_about : Factor w/ 13047 levels "","'Pocahontas' at heart. Nature and the wind are my guides. My dream is to someday create a food forest. I create"| \_\_truncated\_\_,..: 11361 11439 12948 7640 1971 10068 12362 12362 12362 6874 ...  
## $ host\_response\_time : Factor w/ 6 levels "","a few days or more",..: 4 4 5 6 3 4 6 6 6 6 ...  
## $ host\_response\_rate : Factor w/ 64 levels "","0%","10%",..: 4 31 4 4 64 27 4 4 4 4 ...  
## $ host\_acceptance\_rate : Factor w/ 99 levels "","0%","10%",..: 2 27 93 70 99 29 98 98 98 93 ...  
## $ host\_is\_superhost : Factor w/ 3 levels "","f","t": 2 2 3 2 2 2 3 3 3 2 ...  
## $ host\_total\_listings\_count : int 1 1 2 2 1 6 8 8 8 15 ...  
## $ host\_verifications : Factor w/ 491 levels "['email', 'facebook', 'reviews', 'jumio', 'government\_id', 'work\_email']",..: 101 280 101 295 64 278 116 116 116 289 ...  
## $ host\_identity\_verified : Factor w/ 3 levels "","f","t": 3 3 3 2 3 3 2 2 2 3 ...  
## $ street : Factor w/ 431 levels " Los Angeles, CA, United States",..: 70 44 179 311 34 179 179 179 179 427 ...  
## $ neighbourhood\_cleansed : Factor w/ 264 levels "Acton","Adams-Normandie",..: 54 32 102 194 23 104 57 57 57 264 ...  
## $ neighbourhood\_group\_cleansed : Factor w/ 3 levels "City of Los Angeles",..: 2 2 1 2 2 1 1 1 1 1 ...  
## $ city : Factor w/ 404 levels ""," Los Angeles",..: 67 41 157 292 33 157 157 157 157 399 ...  
## $ zipcode : Factor w/ 330 levels "","0000","10001",..: 81 236 53 117 138 53 67 67 67 219 ...  
## $ latitude : num 34 34.2 34.1 34 33.9 ...  
## $ longitude : num -118 -118 -118 -118 -118 ...  
## $ property\_type : Factor w/ 46 levels "Aparthotel","Apartment",..: 16 26 2 2 2 22 39 23 26 7 ...  
## $ room\_type : Factor w/ 4 levels "Entire home/apt",..: 1 1 3 3 1 1 3 3 1 1 ...  
## $ accommodates : int 6 6 1 1 2 2 2 3 5 4 ...  
## $ bathrooms : num 2 1 1.5 1 1 1 1 1 1 1 ...  
## $ bedrooms : int 2 3 1 1 1 1 1 1 2 1 ...  
## $ beds : int 3 3 1 1 1 2 1 1 2 1 ...  
## $ bed\_type : Factor w/ 6 levels "","Airbed","Couch",..: 6 6 6 5 6 6 6 2 6 6 ...  
## $ amenities : Factor w/ 35004 levels "{\"Air conditioning\",\"Fire extinguisher\",Essentials,Shampoo,Hangers}",..: 2309 1106 589 1482 2830 7690 13971 1156 1334 2236 ...  
## $ square\_feet : int NA NA NA NA NA NA 64 400 NA NA ...  
## $ price : Factor w/ 871 levels "$0.00","$1,000.00",..: 135 188 777 174 787 161 762 112 420 804 ...  
## $ weekly\_price : Factor w/ 611 levels "","$1,000.00",..: 581 1 314 538 314 529 293 1 1 1 ...  
## $ monthly\_price : Factor w/ 668 levels "","$1,000.00",..: 310 1 657 145 62 258 1 1 423 1 ...  
## $ security\_deposit : Factor w/ 223 levels "","$0.00","$1,000.00",..: 174 2 164 1 36 103 36 61 88 61 ...  
## $ cleaning\_fee : Factor w/ 319 levels "","$0.00","$1,000.00",..: 115 8 300 8 283 253 120 230 8 120 ...  
## $ guests\_included : int 3 6 1 1 1 1 1 2 2 2 ...  
## $ extra\_people : Factor w/ 100 levels "$0.00","$10.00",..: 35 1 1 1 35 95 14 14 14 35 ...  
## $ minimum\_nights : int 30 2 30 1 2 3 30 30 1 5 ...  
## $ maximum\_nights : int 730 14 366 180 730 730 1125 1125 90 30 ...  
## $ calendar\_updated : Factor w/ 91 levels "1 week ago","10 months ago",..: 13 77 26 26 16 2 90 12 14 40 ...  
## $ has\_availability : Factor w/ 1 level "t": 1 1 1 1 1 1 1 1 1 1 ...  
## $ availability\_30 : int 0 0 30 30 0 0 0 16 14 30 ...  
## $ availability\_60 : int 0 0 32 60 0 12 12 19 38 47 ...  
## $ availability\_90 : int 0 1 32 90 0 42 42 28 61 47 ...  
## $ availability\_365 : int 14 73 281 365 0 317 249 230 136 47 ...  
## $ calendar\_last\_scraped : Factor w/ 4 levels "2020-04-14","2020-04-15",..: 2 2 1 1 1 2 1 1 1 2 ...  
## $ number\_of\_reviews : int 2 8 24 21 0 23 309 228 126 25 ...  
## $ first\_review : Factor w/ 2850 levels "","2009-05-26",..: 100 1451 735 76 1 506 3 6 70 4 ...  
## $ last\_review : Factor w/ 1680 levels "","2010-03-28",..: 348 1501 1651 1570 1 1150 1647 1643 1650 1656 ...  
## $ review\_scores\_rating : int 80 97 97 94 NA 81 96 95 92 88 ...  
## $ review\_scores\_accuracy : int 10 10 10 9 NA 8 10 9 10 8 ...  
## $ review\_scores\_cleanliness : int 10 10 10 9 NA 8 10 10 10 8 ...  
## $ review\_scores\_checkin : int 6 10 10 9 NA 8 10 10 10 9 ...  
## $ review\_scores\_communication : int 8 10 10 9 NA 9 10 10 10 9 ...  
## $ review\_scores\_location : int 10 10 10 10 NA 9 10 9 10 9 ...  
## $ review\_scores\_value : int 8 10 10 9 NA 8 9 9 9 9 ...  
## $ requires\_license : Factor w/ 2 levels "f","t": 1 1 2 2 1 2 2 2 2 2 ...  
## $ instant\_bookable : Factor w/ 2 levels "f","t": 1 2 2 1 1 1 2 2 2 2 ...  
## $ cancellation\_policy : Factor w/ 9 levels "flexible","luxury\_moderate",..: 7 1 7 7 7 7 5 5 5 7 ...  
## $ require\_guest\_profile\_picture : Factor w/ 2 levels "f","t": 2 1 1 1 1 1 1 1 1 1 ...  
## $ require\_guest\_phone\_verification : Factor w/ 2 levels "f","t": 1 1 1 1 1 1 1 1 1 1 ...  
## $ calculated\_host\_listings\_count\_entire\_homes : int 1 1 0 1 1 1 1 1 1 3 ...  
## $ calculated\_host\_listings\_count\_private\_rooms: int 0 0 2 1 0 3 3 3 3 3 ...  
## $ calculated\_host\_listings\_count\_shared\_rooms : int 0 0 0 0 0 0 0 0 0 0 ...  
## $ reviews\_per\_month : num 0.02 0.17 0.34 0.19 NA 0.29 2.36 1.76 1.16 0.19 ...

#These should be a character data type  
data$name<-as.character(data$name)  
data$summary<-as.character(data$summary)  
data$space<-as.character(data$space)  
data$description<-as.character(data$description)  
data$neighborhood\_overview<-as.character(data$neighborhood\_overview)  
data$notes<-as.character(data$notes)  
data$transit<-as.character(data$transit)  
data$access<-as.character(data$access)  
data$interaction<-as.character(data$interaction)  
data$house\_rules<-as.character(data$house\_rules)  
data$host\_since<-as.Date(data$host\_since)  
data$host\_about<-as.character(data$host\_about)  
  
#Was not numeric  
data$host\_response\_rate<-gsub('[%]','',data$host\_response\_rate)  
data$host\_response\_rate<-as.numeric(data$host\_response\_rate)

## Warning: NAs introduced by coercion

data$host\_acceptance\_rate<-gsub('[%]','',data$host\_acceptance\_rate)  
data$host\_acceptance\_rate<-as.numeric(data$host\_acceptance\_rate)

## Warning: NAs introduced by coercion

#Prices was not numeric  
data$price<-gsub('[$]','',data$price)  
data$price<-as.numeric(data$price)

## Warning: NAs introduced by coercion

data$weekly\_price<-gsub('[$]','',data$weekly\_price)  
data$weekly\_price<-as.numeric(data$weekly\_price)

## Warning: NAs introduced by coercion

data$monthly\_price<-gsub('[$]','',data$monthly\_price)  
data$monthly\_price<-as.numeric(data$monthly\_price)

## Warning: NAs introduced by coercion

data$security\_deposit<-gsub('[$]','',data$security\_deposit)  
data$security\_deposit<-as.numeric(data$security\_deposit)

## Warning: NAs introduced by coercion

data$cleaning\_fee<-gsub('[$]','',data$cleaning\_fee)  
data$cleaning\_fee<-as.numeric(data$cleaning\_fee)

## Warning: NAs introduced by coercion

data$extra\_people<-gsub('[$]','',data$extra\_people)  
data$extra\_people<-as.numeric(data$extra\_people)  
  
#After looking closely at the weekly price and monthly price , the amount don't actually checkout if you multiply the per night  
#By 7 and there are many missing NA values for them as well.  
  
length(which(is.na(data$monthly\_price)==TRUE))

## [1] 37512

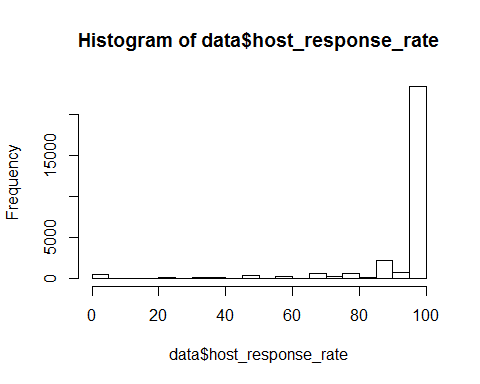
length(which(is.na(data$weekly\_price)==TRUE))

## [1] 35238

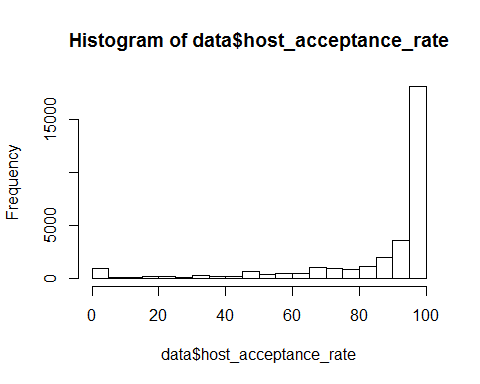
data$weekly\_price<-NULL  
data$monthly\_price<-NULL  
#Better to remove the weekly/monthly prices due to the number of missing values, moreover AirBnb prices per night anyways  
  
  
#Changing dates to datatype  
data$last\_scraped<-as.Date(data$last\_scraped)  
data$calendar\_last\_scraped<-as.Date(data$calendar\_last\_scraped)  
data$first\_review<-as.Date(data$first\_review)  
data$last\_review<-as.Date(data$last\_review)  
  
  
#Cleaning amenities  
  
data$amenities<-as.character(data$amenities)  
data$amenities<-strsplit(data$amenities,",")  
data$amenities<-gsub("[{}]","",data$amenities)  
data$amenities<-gsub('["\"]',"",data$amenities)

Visualiztions of variables (histogram and boxplots)

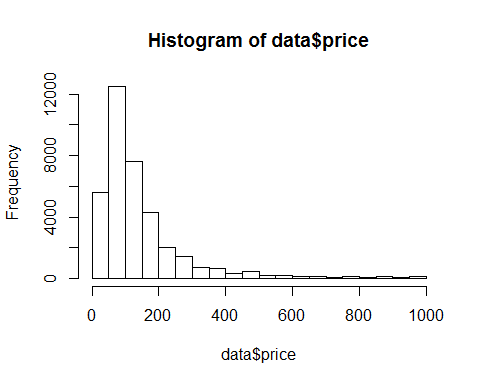
#Histograms  
hist(data$host\_response\_rate)



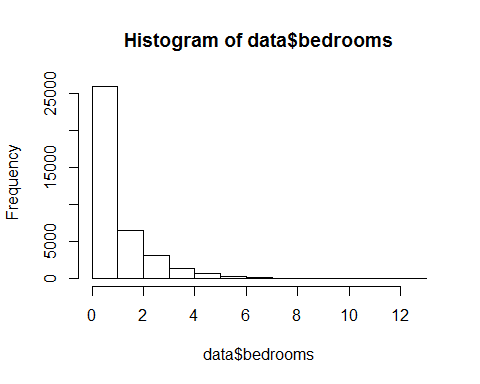
hist(data$host\_acceptance\_rate)



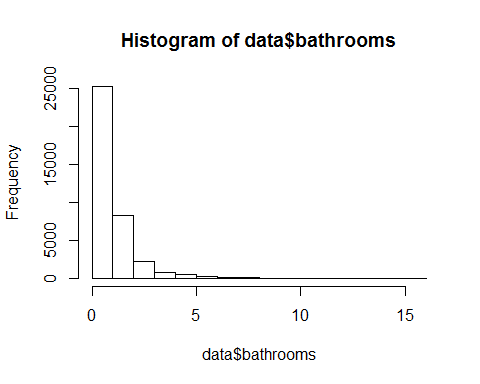
hist(data$price)



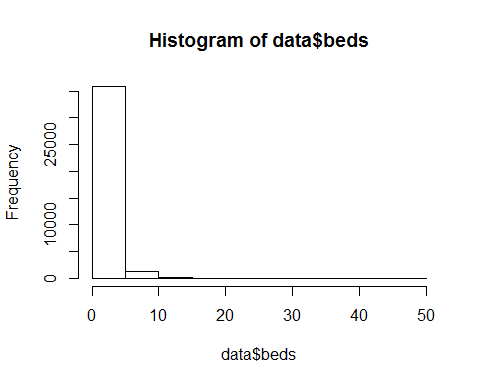
hist(data$bedrooms)



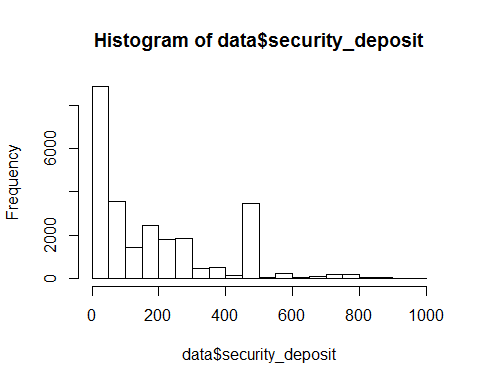
hist(data$bathrooms)



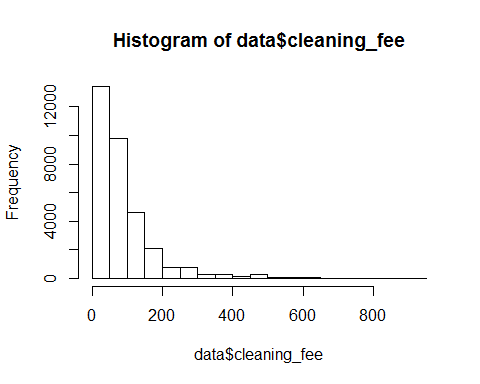
hist(data$beds)



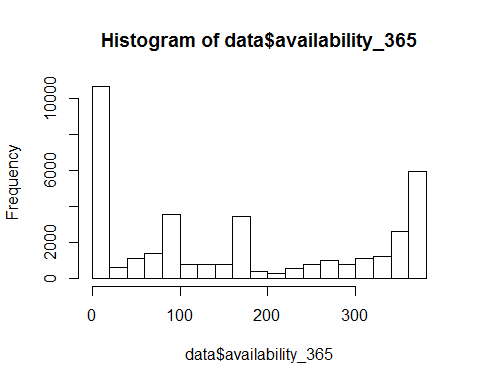
hist(data$security\_deposit)



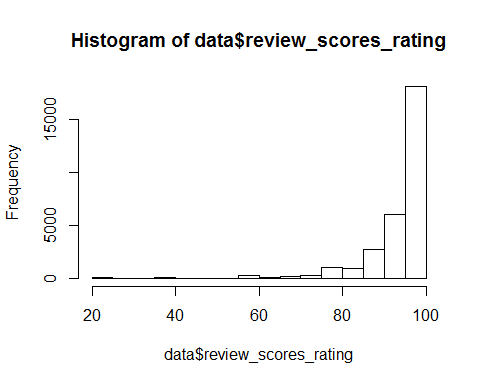
hist(data$cleaning\_fee)



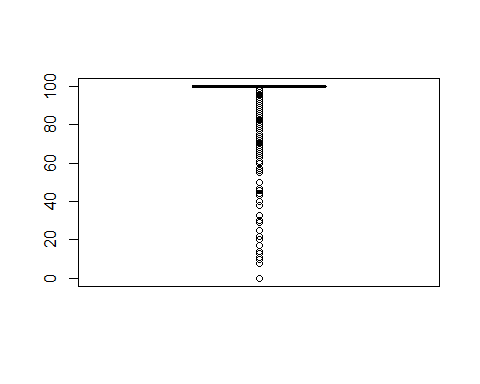
hist(data$availability\_365)



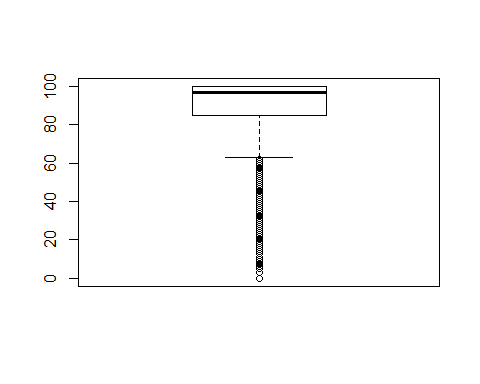
hist(data$review\_scores\_rating)



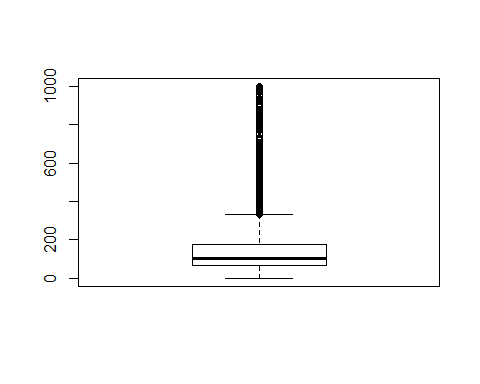
#Boxplots  
boxplot(data$host\_response\_rate)



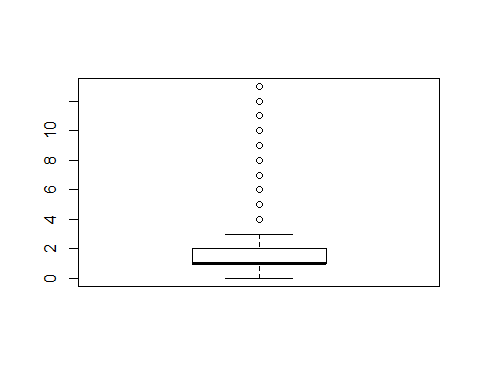
boxplot(data$host\_acceptance\_rate)



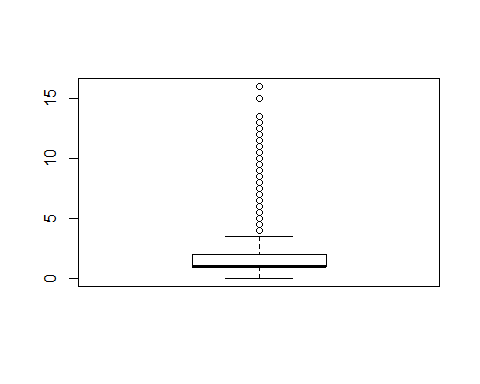
boxplot(data$price)



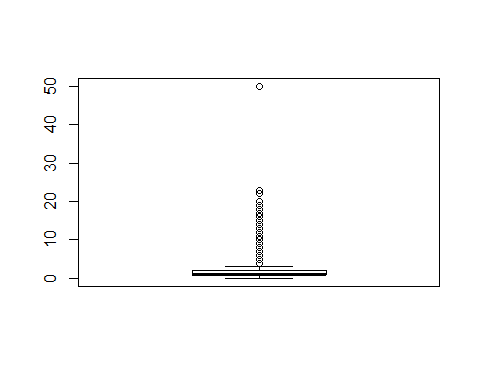
boxplot(data$bedrooms)



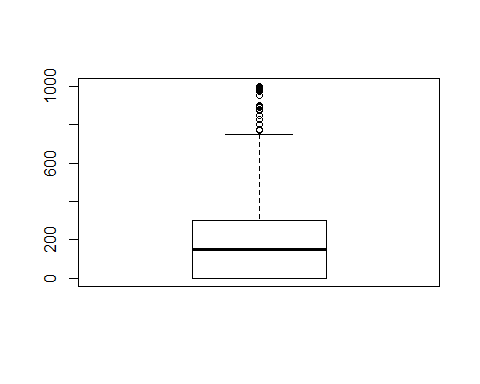
boxplot(data$bathrooms)



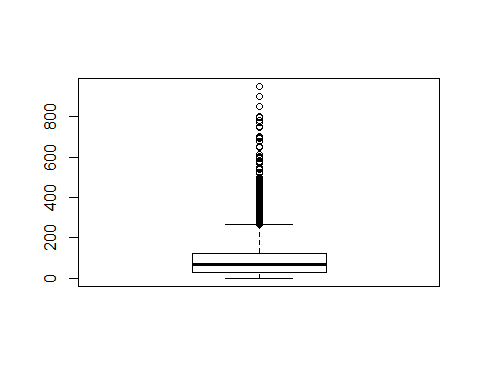
boxplot(data$beds)



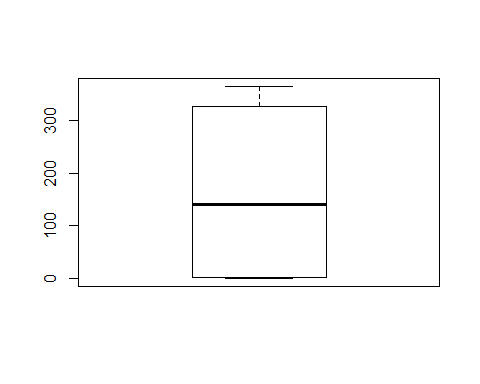
boxplot(data$security\_deposit)



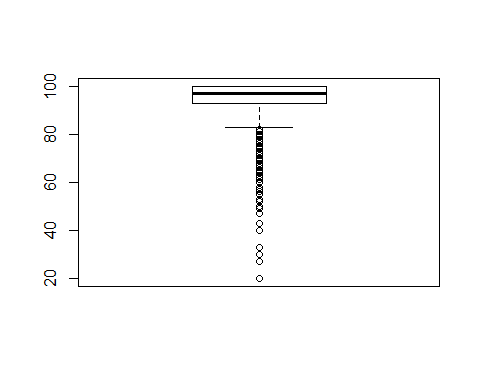
boxplot(data$cleaning\_fee)



boxplot(data$availability\_365)



boxplot(data$review\_scores\_rating)  
boxplot(data$review\_scores\_rating)



Dealing with the outliers in the dataset

#Decided to replace the outlier values with the median values, if I used mean instead extreme outliers could possibly affect the mean  
  
boxplot.stats(data$price)

## $stats  
## [1] 0 69 105 175 334  
##   
## $n  
## [1] 36702  
##   
## $conf  
## [1] 104.1258 105.8742  
##   
## $out  
## [1] 395 450 900 399 600 395 350 550 340 369 418 550 515 699 595 500 695  
## [18] 361 375 450 750 450 350 525 575 350 335 550 350 550 585 375 399 400  
## [35] 350 450 400 425 500 400 590 899 610 450 489 500 695 349 499 450 750  
## [52] 350 700 350 500 375 395 565 459 340 490 430 374 850 510 449 900 359  
## [69] 699 825 425 350 400 700 409 350 382 649 399 799 499 632 450 790 399  
## [86] 525 750 525 495 350 400 350 550 349 365 958 525 899 595 795 420 595  
## [103] 450 500 360 425 650 475 350 349 650 900 795 350 395 575 390 525 375  
## [120] 749 950 750 350 410 495 799 695 799 725 699 795 500 400 350 575 536  
## [137] 660 380 900 445 350 600 379 500 600 525 395 550 400 540 850 345 895  
## [154] 450 361 600 350 829 450 425 350 389 699 395 624 475 450 450 349 349  
## [171] 700 500 773 600 350 420 400 349 650 400 425 495 500 336 442 444 650  
## [188] 350 499 500 850 595 450 344 350 350 725 395 495 795 425 750 495 450  
## [205] 400 445 350 500 350 556 375 545 525 375 500 425 399 925 347 375 750  
## [222] 478 335 350 400 360 720 450 350 500 475 525 950 750 575 349 340 700  
## [239] 400 475 825 400 550 450 400 550 399 350 775 900 395 495 900 350 450  
## [256] 750 550 550 550 450 990 375 922 500 427 450 535 500 400 450 400 500  
## [273] 725 450 640 375 524 400 380 900 372 450 360 500 748 450 415 619 475  
## [290] 969 650 500 600 449 650 598 540 472 560 450 400 450 695 500 395 450  
## [307] 425 350 400 400 350 400 550 400 600 400 900 495 480 350 424 450 550  
## [324] 599 350 449 829 500 395 450 430 350 400 340 350 549 575 400 499 600  
## [341] 550 750 350 524 535 685 380 425 369 750 400 400 349 575 799 519 350  
## [358] 900 750 900 700 800 500 600 425 750 350 850 550 430 495 350 500 380  
## [375] 367 975 349 800 749 400 425 380 800 375 349 349 350 350 400 375 350  
## [392] 600 549 450 995 500 350 350 399 389 350 545 495 400 425 470 400 480  
## [409] 495 400 900 350 700 500 400 450 425 394 550 400 950 650 875 550 398  
## [426] 999 359 350 500 499 600 375 340 435 350 500 599 349 850 595 349 399  
## [443] 550 349 400 695 349 400 449 395 420 900 350 825 600 350 500 625 382  
## [460] 436 340 550 425 550 599 349 450 350 350 445 450 995 550 379 900 650  
## [477] 350 365 445 350 600 500 475 350 700 350 449 449 400 424 350 350 350  
## [494] 500 400 359 449 395 425 599 600 399 525 995 695 650 500 650 550 950  
## [511] 600 360 350 400 680 380 475 480 385 600 700 400 339 419 600 750 750  
## [528] 700 348 850 699 575 475 373 400 690 850 589 650 700 350 825 545 399  
## [545] 399 950 450 351 350 925 475 450 950 350 475 625 395 375 399 795 535  
## [562] 399 625 400 500 345 590 500 675 700 876 495 500 378 850 459 425 450  
## [579] 450 375 680 395 550 450 425 500 849 450 350 845 749 399 500 350 950  
## [596] 339 650 450 446 350 460 395 645 650 350 999 450 425 550 750 450 500  
## [613] 499 650 465 800 400 349 450 400 500 495 900 450 700 375 500 490 450  
## [630] 600 350 450 675 750 450 480 525 620 395 350 400 375 699 550 499 360  
## [647] 425 777 389 630 500 398 359 410 695 500 350 850 389 550 650 600 349  
## [664] 500 350 350 395 400 695 600 490 675 700 400 550 400 500 350 400 350  
## [681] 400 695 500 395 449 375 450 400 482 500 999 865 375 400 360 595 400  
## [698] 375 459 360 645 465 699 599 595 349 545 400 500 425 350 499 345 496  
## [715] 349 900 550 350 600 490 500 900 666 500 350 380 775 395 669 350 690  
## [732] 395 600 400 350 450 350 399 899 425 500 420 395 600 349 650 350 799  
## [749] 350 500 350 675 400 375 500 398 475 995 850 990 495 750 403 595 390  
## [766] 777 859 650 450 350 425 400 700 900 790 350 349 800 400 450 450 399  
## [783] 650 525 399 800 400 800 350 400 400 585 389 525 400 449 489 343 600  
## [800] 598 499 400 875 499 400 390 350 530 367 975 650 600 600 346 385 350  
## [817] 629 500 500 349 400 699 449 380 690 350 500 512 489 799 400 500 800  
## [834] 500 400 590 600 625 500 349 599 565 550 400 400 396 590 900 950 375  
## [851] 850 499 599 400 400 499 800 500 695 600 579 349 575 599 481 349 350  
## [868] 485 399 349 501 499 435 400 399 799 599 999 380 350 399 800 399 600  
## [885] 500 350 500 349 399 850 350 595 795 650 450 399 359 500 349 350 999  
## [902] 368 395 399 399 479 750 399 365 600 695 450 549 600 995 380 372 900  
## [919] 345 450 435 999 400 400 415 379 950 550 400 385 340 999 430 355 349  
## [936] 700 660 350 750 750 336 350 860 650 595 354 400 950 350 750 525 500  
## [953] 752 650 900 500 800 350 349 600 495 815 890 400 395 450 469 350 500  
## [970] 700 600 500 460 500 500 400 399 598 485 345 499 600 395 680 375 450  
## [987] 399 500 600 499 450 350 400 400 700 450 890 450 850 550 590 700 890  
## [1004] 385 500 450 800 349 350 400 795 410 500 500 395 600 345 980 396 700  
## [1021] 450 350 700 595 995 450 495 750 349 500 385 449 400 500 350 420 450  
## [1038] 389 380 450 699 800 795 650 449 591 450 399 399 437 495 350 360 508  
## [1055] 520 600 449 359 450 600 389 600 500 495 615 550 350 550 450 385 450  
## [1072] 375 399 554 380 349 450 399 499 410 499 499 750 375 750 380 350 500  
## [1089] 795 699 550 750 999 895 395 404 600 599 350 380 380 880 525 500 500  
## [1106] 430 539 500 500 495 500 335 499 400 400 649 499 350 350 400 999 460  
## [1123] 750 645 750 350 500 525 398 350 350 375 450 995 500 995 429 369 400  
## [1140] 490 399 350 500 650 350 500 500 585 750 950 500 625 495 380 400 950  
## [1157] 399 350 450 750 449 550 350 650 399 350 647 767 375 400 501 450 350  
## [1174] 800 399 350 450 499 649 895 695 723 599 800 500 349 875 385 500 549  
## [1191] 999 350 550 999 350 935 400 420 900 349 340 335 350 550 500 595 550  
## [1208] 465 799 996 700 650 350 750 570 404 425 350 400 485 400 600 700 400  
## [1225] 450 750 500 350 895 350 550 389 350 900 525 400 995 525 400 480 550  
## [1242] 345 700 512 495 850 400 355 750 350 500 499 800 500 350 750 395 350  
## [1259] 850 895 358 420 350 399 500 800 800 700 448 550 995 500 600 350 425  
## [1276] 410 525 450 375 350 335 400 795 700 500 500 999 850 399 340 999 415  
## [1293] 599 699 365 520 626 609 704 617 640 490 950 564 500 499 450 340 364  
## [1310] 450 350 599 350 650 795 900 600 425 500 595 495 959 495 350 931 375  
## [1327] 898 725 600 800 350 350 400 350 355 510 399 376 400 900 370 480 399  
## [1344] 475 600 400 380 450 990 350 600 353 950 945 360 449 399 575 350 399  
## [1361] 360 800 348 349 700 700 428 414 400 400 399 651 700 480 375 750 350  
## [1378] 999 350 600 749 399 400 350 950 399 450 388 499 399 894 550 750 489  
## [1395] 480 375 594 398 450 650 849 750 350 395 950 800 525 506 360 850 450  
## [1412] 372 472 400 550 500 349 399 956 399 699 700 350 350 599 350 350 699  
## [1429] 450 495 429 800 399 490 383 350 458 400 625 750 450 440 399 495 350  
## [1446] 339 480 385 350 958 900 350 500 399 350 700 350 595 350 379 480 700  
## [1463] 385 500 350 478 455 450 395 390 499 780 400 400 750 650 600 900 375  
## [1480] 350 479 700 599 395 450 800 375 600 350 360 750 575 365 425 596 900  
## [1497] 500 425 399 499 695 680 389 359 339 379 349 389 349 399 449 500 499  
## [1514] 599 400 459 339 397 399 569 645 350 645 450 399 350 800 500 499 599  
## [1531] 399 550 595 337 500 500 800 359 499 378 373 450 350 349 698 600 549  
## [1548] 448 369 400 365 490 375 995 380 380 490 630 673 693 600 995 500 499  
## [1565] 348 500 589 598 899 610 899 475 899 899 351 401 800 850 475 349 350  
## [1582] 650 550 950 449 749 400 450 450 600 400 500 599 600 400 780 337 350  
## [1599] 350 385 395 350 600 342 350 988 375 550 399 500 550 800 675 350 600  
## [1616] 500 425 600 526 349 399 400 400 365 439 695 925 645 585 355 600 550  
## [1633] 599 500 550 399 375 360 525 349 550 500 499 500 550 349 390 700 750  
## [1650] 450 400 350 335 899 450 420 450 695 380 375 750 480 390 379 399 850  
## [1667] 900 500 349 350 339 349 395 950 475 795 750 450 349 428 350 450 350  
## [1684] 397 395 395 399 500 506 649 449 549 500 564 620 498 500 350 800 650  
## [1701] 450 599 349 650 359 350 835 799 550 400 350 931 349 850 475 350 400  
## [1718] 380 596 799 835 399 700 800 400 350 375 650 444 385 430 849 375 799  
## [1735] 800 599 395 400 450 900 750 600 374 349 350 375 792 475 900 550 350  
## [1752] 360 375 385 700 350 499 350 995 600 385 488 380 380 380 380 800 599  
## [1769] 999 550 498 350 600 500 360 420 349 349 795 369 622 750 600 350 499  
## [1786] 899 499 400 450 500 500 500 999 495 628 519 598 380 600 395 950 450  
## [1803] 500 349 990 978 599 875 398 950 777 350 399 450 481 500 544 350 500  
## [1820] 335 398 689 500 425 400 400 425 599 989 424 450 350 775 335 350 425  
## [1837] 749 899 499 399 499 395 399 335 400 800 350 495 600 340 667 350 500  
## [1854] 443 424 358 342 989 342 342 799 750 399 350 392 600 570 350 350 350  
## [1871] 375 850 349 450 650 599 650 349 350 405 433 500 500 500 850 395 399  
## [1888] 400 345 335 349 350 950 385 695 499 375 850 499 349 350 800 399 395  
## [1905] 350 459 999 695 342 350 399 495 425 349 525 980 900 425 999 995 750  
## [1922] 648 465 371 823 700 419 500 500 350 347 350 850 569 399 450 555 595  
## [1939] 395 431 350 500 365 750 795 850 349 350 399 777 749 749 749 450 525  
## [1956] 450 995 400 700 695 550 400 400 399 695 649 455 350 440 420 399 425  
## [1973] 750 499 400 400 395 850 425 400 399 830 375 800 905 395 350 499 550  
## [1990] 350 485 395 440 350 525 900 500 349 600 975 399 351 399 448 650 499  
## [2007] 595 400 550 500 840 525 520 350 368 390 549 500 899 500 500 650 397  
## [2024] 399 852 900 999 999 500 395 350 450 474 365 549 800 400 400 550 555  
## [2041] 499 550 550 491 400 549 379 439 409 469 750 500 591 525 689 350 550  
## [2058] 500 350 500 395 495 420 700 346 350 495 449 908 492 492 825 492 500  
## [2075] 435 350 450 350 900 800 350 400 499 395 355 349 486 599 700 400 600  
## [2092] 900 900 600 429 479 339 389 779 339 379 799 979 480 450 795 990 650  
## [2109] 500 700 499 900 900 400 450 450 720 440 520 499 650 750 429 449 450  
## [2126] 399 420 475 360 350 900 502 389 350 369 339 400 348 337 390 588 525  
## [2143] 400 706 345 399 500 385 385 700 650 800 395 689 668 870 500 900 750  
## [2160] 450 845 374 995 500 600 500 370 795 999 500 700 600 800 999 495 700  
## [2177] 349 500 380 460 500 800 639 495 395 399 350 533 349 500 464 900 800  
## [2194] 438 500 999 589 395 888 395 700 999 999 999 999 999 999 375 400 550  
## [2211] 999 999 850 999 999 500 999 525 999 999 399 595 385 499 799 399 999  
## [2228] 999 999 999 999 999 999 999 999 999 999 690 999 999 999 599 345 750  
## [2245] 999 999 999 999 350 999 999 999 999 349 999 999 999 999 999 550 406  
## [2262] 340 406 425 850 590 450 550 350 550 500 400 500 405 550 455 349 550  
## [2279] 450 499 399 345 459 399 375 450 400 350 412 490 335 349 495 995 530  
## [2296] 860 640 600 475 754 480 650 350 599 800 850 350 519 549 589 589 448  
## [2313] 375 599 399 377 649 499 480 395 950 399 395 700 480 600 460 515 430  
## [2330] 445 435 420 400 399 899 899 699 380 375 450 495 349 899 800 349 449  
## [2347] 400 800 349 349 349 475 379 895 400 591 400 369 675 350 925 613 425  
## [2364] 900 498 495 350 500 389 589 595 927 400 395 900 750 385 349 689 850  
## [2381] 350 699 380 499 499 449 350 355 575 349 509 827 425 611 399 399 399  
## [2398] 735 625 389 399 700 500 368 399 350 400 420 500 895 425 409 950 725  
## [2415] 550 350 999 399 500 600 499 499 444 350 400 585 339 500 369 540 350  
## [2432] 650 450 400 375 499 390 500 375 525 575 525 389 350 350 615 500 350  
## [2449] 650 499 379 349 370 350 460 400 900 350 399 850 605 719 350 345 385  
## [2466] 500 525 370 500 560 355 400 550 450 450 730 499 349 997 875 399 480  
## [2483] 349 550 550 950 950 655 385 350 550 350 375 900 999 700 899 899 482  
## [2500] 895 499 995 499 899 889 350 798 500 700 475 790 388 350 460 430 400  
## [2517] 480 519 595 930 335 350 350 600 595 399 500 695 500 695 899 450 400  
## [2534] 500 500 375 549 532 400 451 500 461 399 399 399 399 499 449 349 349  
## [2551] 349 349 349 599 499 897 465 399 399 600 349 969 550 400 495 999 350  
## [2568] 500 349 398 666 450 400 795 400 475 490 399 400 363 632 350 785 875  
## [2585] 706 399 400 399 690 499 999 799 400 999 338 595 950 399 350 500 999  
## [2602] 999 350 343 400 400 349 499 350 700 400 950 400 789 900 849 800 675  
## [2619] 900 399 900 900 695 390 795 700 645 500 790 500 775 860 875 599 995  
## [2636] 850 399 600 400 700 400 500 359 350 380 400 349 388 359 350 549 699  
## [2653] 349 575 350 650 990 350 549 599 900 785 406 475 444 400 399 350 399  
## [2670] 799 368 500 495 375 399 390 890 890 575 981 750 800 570 410 600 412  
## [2687] 835 700 800 419 599 350 350 600 399 400 350 360 460 400 500 900 680  
## [2704] 375 350 375 599 589 499 599 599 375 499 659 785 600 699 350 800 800  
## [2721] 399 425 449 589 800 799 550 605 650 930 500 900 950 349 600 450 550  
## [2738] 350 650 399 399 368 380 350 599 415 350 999 350 375 499 549 350 345  
## [2755] 400 375 424 424 375 390 499 499 399 350 700 367 499 499 900 999 800  
## [2772] 499 600 424 424 424 424 424 457 424 444 630 595 950 345 510 625 390  
## [2789] 950 600 675 399 700 399 799 599 500 385 599 490 350 450 349 499 499  
## [2806] 499 499 400 350 399 499 424 424 475 350 442 998 950 350 499 400 799  
## [2823] 398 800 984 500 995 699 700 789 349 350 349 500 399 434 825 350 495  
## [2840] 499 690 450 400 349 895 675 999 500 500 425 600 499 335 429 389 389  
## [2857] 399 399 346 399 350 450 358 375 399 534 990 500 995 499 600 395 395  
## [2874] 595 850 495 500 861 899 499 350 499 499 999 499 450 375 337 495 499  
## [2891] 400 640 699 499 449 619 335 900 699 499 369 749 499 660 833 600 600  
## [2908] 350 349 450 400 379 509 637 799 450 345 416

data$price[which(data$price>334)]<-median(data$price,na.rm=TRUE) #334 is the uppper whisker, no values that are below the lower whisker  
  
boxplot.stats(data$host\_acceptance\_rate)

## $stats  
## [1] 63 85 97 100 100  
##   
## $n  
## [1] 31814  
##   
## $conf  
## [1] 96.86713 97.13287  
##   
## $out  
## [1] 0 33 35 62 13 13 24 24 50 60 35 56 47 33 0 35 44 60 55 60 0 17 50  
## [24] 60 50 29 59 55 60 46 44 0 46 20 50 62 0 50 44 60 59 0 59 31 57 0  
## [47] 16 16 60 60 25 0 50 0 59 60 53 0 0 44 0 57 29 60 0 29 14 0 0  
## [70] 25 59 60 0 0 0 8 0 13 0 50 25 50 13 33 46 59 29 46 46 60 43 0  
## [93] 18 42 42 56 47 33 0 50 0 0 32 40 0 59 25 0 0 58 58 0 0 56 57  
## [116] 33 13 47 61 25 0 55 53 50 53 37 13 57 62 0 0 0 0 33 47 60 42 0  
## [139] 13 18 0 22 20 0 0 0 50 0 47 33 50 0 33 56 17 40 0 0 33 20 0  
## [162] 0 0 0 50 46 50 0 0 44 44 52 19 43 0 33 25 0 50 52 58 0 0 61  
## [185] 0 50 50 30 47 0 45 30 44 44 53 44 29 0 57 55 33 54 50 30 46 62 30  
## [208] 25 17 47 16 0 59 0 14 0 25 50 38 0 33 43 13 51 43 0 59 46 55 29  
## [231] 0 54 60 0 0 44 33 46 62 50 0 44 38 29 51 40 53 40 13 0 25 30 18  
## [254] 56 0 0 0 0 25 21 44 59 59 25 33 0 26 38 49 52 39 59 0 0 0 43  
## [277] 35 47 29 50 13 49 0 0 50 0 44 57 54 30 48 50 43 0 55 62 62 62 58  
## [300] 25 59 25 50 0 0 33 0 0 44 0 39 0 43 50 20 33 0 40 39 62 0 60  
## [323] 18 50 56 32 0 0 0 55 36 62 50 0 61 0 25 50 50 50 60 60 0 44 55  
## [346] 9 49 0 43 0 0 13 54 20 33 0 40 25 50 59 0 0 0 0 40 0 60 0  
## [369] 50 32 32 32 38 38 0 46 0 0 50 38 59 59 0 28 44 44 59 0 0 0 0  
## [392] 53 46 43 50 34 50 50 33 36 28 32 54 9 38 47 0 16 56 58 50 58 51 33  
## [415] 0 60 60 0 32 36 0 55 36 0 60 0 29 25 0 25 0 62 13 0 50 0 25  
## [438] 0 33 62 48 58 0 56 50 40 60 57 0 50 50 60 0 55 25 0 36 32 60 0  
## [461] 61 33 62 38 0 40 62 0 62 50 55 55 55 55 55 50 50 62 43 33 36 51 48  
## [484] 47 44 39 50 50 45 50 50 50 42 61 39 50 0 0 0 40 33 25 60 13 52 29  
## [507] 29 32 50 50 0 33 33 0 0 61 55 0 50 40 0 62 46 40 53 40 50 50 0  
## [530] 0 0 41 50 33 59 59 59 40 40 40 40 40 39 59 50 0 62 54 44 44 0 25  
## [553] 43 50 28 0 13 36 50 33 0 33 54 62 15 60 28 0 0 50 33 20 55 50 62  
## [576] 43 43 0 25 33 23 28 58 50 39 0 0 55 7 0 0 50 58 0 0 50 0 50  
## [599] 62 15 47 0 40 0 25 0 59 57 57 43 39 58 56 0 0 21 33 52 52 52 50  
## [622] 38 0 52 50 52 52 0 50 58 34 34 46 50 39 0 27 56 43 0 0 0 43 41  
## [645] 0 50 25 56 0 50 57 50 51 57 0 0 60 21 0 39 50 58 18 25 57 32 25  
## [668] 55 0 0 41 21 18 0 0 0 33 0 40 51 25 25 50 0 50 21 28 53 0 33  
## [691] 0 34 0 23 56 0 33 0 25 0 57 40 0 57 0 17 0 25 49 59 0 0 0  
## [714] 51 58 28 28 44 56 18 13 0 20 0 0 55 0 0 50 22 0 46 0 0 50 33  
## [737] 0 20 20 52 55 0 25 0 50 60 22 50 0 0 50 56 60 0 35 60 17 20 57  
## [760] 53 55 29 0 0 49 0 37 0 27 60 17 0 32 32 0 52 33 0 58 0 0 33  
## [783] 0 62 50 40 38 40 62 33 0 58 57 29 36 35 47 50 33 33 0 0 0 20 55  
## [806] 38 59 0 50 33 0 0 0 43 0 0 50 44 57 54 44 30 33 46 59 0 50 60  
## [829] 30 51 51 51 0 62 57 59 38 59 39 59 57 20 58 0 55 58 56 50 0 0 59  
## [852] 0 50 56 62 59 0 46 45 0 59 17 30 47 36 0 50 40 50 25 62 55 52 50  
## [875] 56 0 59 50 0 0 0 39 55 55 33 43 60 47 55 25 38 25 59 25 46 0 25  
## [898] 43 33 40 40 55 25 0 30 0 0 0 0 50 62 58 0 47 0 46 50 0 50 0  
## [921] 54 0 20 61 59 42 39 0 52 26 0 18 53 0 0 0 58 58 50 0 0 17 50  
## [944] 55 47 47 61 27 50 46 54 23 39 53 61 61 61 59 52 0 0 0 50 50 44 37  
## [967] 25 43 58 60 58 31 57 0 43 33 55 32 0 62 32 21 56 61 0 0 49 20 32  
## [990] 54 0 57 9 0 0 29 57 28 53 23 0 50 0 50 25 0 23 0 0 0 0 23  
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## [1036] 20 44 55 33 33 50 50 58 50 59 43 25 0 0 0 0 29 21 0 22 0 23 37  
## [1059] 40 25 0 50 37 33 3 25 50 0 43 44 0 37 0 54 18 56 43 0 21 32 50  
## [1082] 62 0 0 50 50 50 60 25 29 0 54 20 20 34 0 0 50 33 20 0 0 55 22  
## [1105] 0 50 29 36 55 40 24 54 44 29 33 39 0 50 50 50 17 0 44 46 25 33 33  
## [1128] 55 44 38 37 0 37 48 0 47 33 0 60 0 56 36 0 47 53 50 57 50 0 0  
## [1151] 0 59 0 62 41 27 0 0 36 37 33 25 61 0 31 0 0 62 37 50 56 37 48  
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## [1243] 0 58 48 0 0 61 0 0 33 56 30 43 58 58 58 0 0 61 50 62 0 61 0  
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## [1427] 24 24 0 0 0 33 43 0 52 0 55 0 50 40 39 50 0 11 0 38 39 50 37  
## [1450] 50 39 37 0 9 54 0 55 50 23 38 50 14 5 39 36 0 50 24 43 27 0 50  
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## [1519] 50 0 50 0 44 0 0 55 40 50 48 50 31 0 58 0 39 29 53 43 50 51 40  
## [1542] 0 18 0 11 24 33 55 13 30 57 38 0 33 24 60 33 52 59 44 0 0 0 54  
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## [1588] 38 55 50 0 29 33 60 25 24 57 44 57 62 40 24 50 60 0 36 50 59 18 50  
## [1611] 25 0 33 0 33 0 50 0 32 0 0 33 0 37 50 0 36 57 25 44 37 0 39  
## [1634] 54 50 19 19 0 50 50 0 55 58 0 0 50 56 13 13 13 13 13 58 0 53 50  
## [1657] 62 13 13 51 7 5 18 7 7 54 13 7 9 18 13 20 21 13 7 22 7 18 30  
## [1680] 13 18 7 52 13 11 18 9 22 24 27 51 7 13 41 13 52 58 14 56 53 0 0  
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## [1726] 25 0 33 0 58 38 59 59 33 50 0 25 56 9 50 0 53 48 0 51 0 0 27  
## [1749] 50 0 50 60 39 0 60 53 50 0 0 24 33 35 35 59 31 33 55 44 50 0 20  
## [1772] 60 50 33 0 50 0 57 50 0 38 38 46 41 33 33 59 43 52 50 60 17 0 25  
## [1795] 28 46 33 60 0 39 33 62 0 46 0 50 0 50 56 50 25 39 0 0 0 0 0  
## [1818] 50 50 13 25 50 27 50 55 0 50 0 50 0 50 0 0 0 0 42 28 0 58 50  
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## [1864] 35 46 0 0 62 56 0 39 0 50 0 50 0 50 50 50 50 61 33 0 35 50 43  
## [1887] 50 50 50 61 61 33 55 61 0 23 36 0 60 0 50 38 50 50 50 0 55 0 50  
## [1910] 55 0 0 61 50 50 50 50 61 0 50 0 56 0 25 61 50 50 33 50 58 0 56  
## [1933] 58 25 54 57 50 0 0 55 19 18 34 0 50 0 60 46 0 0 0 0 0 0 50  
## [1956] 50 38 0 31 54 33 0 50 39 54 0 51 55 0 25 25 23 55 44 0 40 0 51  
## [1979] 7 10 0 39 0 0 0 39 0 48 0 0 50 0 60 0 61 44 0 50 46 0 57  
## [2002] 0 0 50 44 50 0 46 0 39 13 7 7 9 7 13 39 0 55 0 0 25 0 61  
## [2025] 0 50 13 0 0 0 20 50 13 50 0 50 50 60 60 38 50 50 33 60 55 61 25  
## [2048] 61 61 25 43 25 54 60 45 59 61 0 0 52 20 45 0 25 44 0 0 13 13 13  
## [2071] 13 32 50 0 50 13 0 50 0 61 28 39 52 9 0 0 0 29 57 57 0 22 50  
## [2094] 0 53 7 13 33 22 0 13 20 0 44 52 50 40 50 52 50 33 50 25 42 0 0  
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## [2163] 29 0 50 44 50 7 44 44 61 0 35 50 55 59 59 0 0 50 61 33 0 50 0  
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## [2232] 50 38 46 55 45 56 44 0 0 0 56 0 0 0 50 50 52 50 0 33 17 33 61  
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## [2370] 33 50 0 50 0 56 25 50 55 19 17 61 44 0 50 0 33 0 40 0 61 13 52  
## [2393] 0 0 0 7 10 7 7 17 50 20 60 40 55 49 0 53 0 60 50 0 50 25 54  
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## [2439] 55 0 49 0 26 0 0 0 37 38 0 0 0 62 33 50 0 33 0 18 61 40 0  
## [2462] 46 50 33 0 57 0 0 55 55 55 50 50 59 62 35 31 0 0 44 7 51 0 11  
## [2485] 0 0 0 40 13 0 40 0 47 0 7 43 50 0 9 58 55 60 50 0 0 50 50  
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## [2554] 27 51 0 35 35 44 50 50 0 0 0 43 27 61 0 31 0 53 33 7 56 54 0  
## [2577] 44 0 53 60 54 50 0 51 56 31 50 0 33 54 7 33 7 33 0 33 53 56 60  
## [2600] 33 19 19 19 19 19 50 50 0 11 0 50 54 60 39 50 60 25 0 27 38 48 55  
## [2623] 30 0 0 7 50 54 51 50 20 50 40 20 33 0 33 35 25 53 35 35 35 35 50  
## [2646] 56 56 56 33 61 0 50 50 19 0 48 0 17 33 0 19 19 19 29 50 17 0 39  
## [2669] 46 60 50 33 33 50 33 50 43 0 0 0 51 7 6 6 36 56 0 8 25 19 33  
## [2692] 50 56 19 0 38 50 54 56 33 42 59 50 50 43 60 50 56 38 33 31 50 25 42  
## [2715] 0 50 5 5 50 50 29 50 51 0 50 50 0 0 40 50 61 60 53 48 50 50 50  
## [2738] 50 50 44 33 0 8 59 33 50 50 33 0 48 41 53 43 48 38 23 7 50 52 29  
## [2761] 60 60 33 50 38 0 48 50 0 39 50 47 59 59 59 17 0 25 41 54 50 50 50  
## [2784] 50 50 50 57 17 17 33 33 15 51 59 13 34 59 55 20 50 34 34 46 43 34 59  
## [2807] 34 58 23 57 33 33 33 47 7 60 0 0 0 56 56 33 46 17 0 51 0 50 59  
## [2830] 59 50 14 25 0 57 29 25 41 7 33 60 13 11 50 55 43 0 48 0 33 40 34  
## [2853] 32 29 29 17 29 29 33 18 55 55 56 51 0 0 60 50 50 50 33 0 0 0 7  
## [2876] 33 40 25 55 61 51 58 0 57 50 50 35 35 50 55 38 33 0 33 33 29 29 29  
## [2899] 50 33 7 40 29 38 34 34 55 60 33 33 0 54 60 0 57 50 33 60 57 0 33  
## [2922] 0 34 50 61 0 23 50 51 52 61 53 50 18 50 50 25 29 33 40 25 0 50 7  
## [2945] 50 33 25 17 50 51 40 25 51 50 61 44 50 48 48 48 44 32 50 36 0 29 56  
## [2968] 17 55 50 50 50 33 21 48 51 61 48 50 0 60 46 53 25 50 29 50 50 50 25  
## [2991] 20 59 0 50 50 47 53 53 55 51 51 40 0 48 33 54 0 51 61 50 50 0 0  
## [3014] 0 11 62 7 52 38 20 50 29 48 50 40 19 55 53 7 7 40 53 48 40 0 62  
## [3037] 17 45 50 33 48 42 43 50 60 60 48 0 50 52 42 42 50 62 50 0 0 33 47  
## [3060] 55 42 48 56 57 60 9 42 42 57 17 53 51 39 40 50 44 0 0 0 44 44 50  
## [3083] 33 60 48 50 25 55 54 33 55 50 0 29 50 50 60 50 27 0 40 56 50 45 45  
## [3106] 40 45 48 25 25 25 60 25 33 9 47 54 35 25 50 55 48 50 60 58 50 21 57  
## [3129] 0 0 50 33 50 57 60 50 47 0 50 0 46 48 43 61 33 36 0 50 33 50 62  
## [3152] 56 51 54 53 0 13 60 50 50 57 0 60 0 44 0 62 0 62 57 0 0 33 34  
## [3175] 15 15 44 40 20 0 0 55 50 50 7 52 46 44 50 50 46 56 33 16 0 57 0  
## [3198] 62 33 42 17 51 17 0 0 50 60 40 60 57 14 0 50 44 44 18 50 13 52 50  
## [3221] 0 0 57 60 0 52 50 61 56 50 33 44 25 51 50 50 51 51 62 0 46 53 42  
## [3244] 60 43 33 33 51 25 18 50 0 0 16 44 50 52 50 37 50 0 33 25 56 0 0  
## [3267] 59 40 43 44 56 0 56 0 52 29 51 50 7 33 33 50 50 0 50 53 25 20 29  
## [3290] 47 0 56 29 60 60 33 36 61 50 0 53 53 33 53 61 0 0 0 7 43 0 20  
## [3313] 56 25 48 59 59 59 59 59 50 59 59 59 59 59 59 59 59 50 20 40 0 25 31  
## [3336] 48 50 50 0 25 50 0 33 54 45 40 33 40 57 50 50 45 45 45 45 45 45 45  
## [3359] 45 50 0 0 55 51 0 45 45 45 45 0 0 0 57 56 0 37 40 0 46 46 40  
## [3382] 56 40 50 47 60 60 60 48 0 60 0 55 60 0 33 61 47 33 29 55 50 33 55  
## [3405] 55 55 55 55 55 27 13 33 60 62 31 33 55 50 57 50 29 53 50 54 54 31 44  
## [3428] 61 33 0 33 44 30 50 62 7 33 0 55 0 59 59 59 59 59 50 33 61 60 57  
## [3451] 50 50 25 22 43 50 33 42 50 33 38 50 20 0 43 33 33 51 33 33 33 33 47  
## [3474] 25 0 50 50 50 50 50 53 24 50 0 33 49 33 33 33 38 33 33 33 50 0 62  
## [3497] 33 29 43 57 58 61 50 50 33 40 20 0 53 29 50 0 0 58 33 50 40 43 0  
## [3520] 33 51 25 41 40 44 50 39 33 40 57 44 53 60 50 50 50 53 0 60 60 51 20  
## [3543] 9 0 14 59 50 59 42 36 48 50 50 50 51 13 20 0 50 0 50 0 44 50 47  
## [3566] 0 44 25 50 0 44 48 36 7 50 50 50 33 33 46 56 0 58 50 36 55 50 47  
## [3589] 38 57 13 0 55 57 62 55 55 0 62 60 53 50 62 55 44 33 50 61 50 31 50  
## [3612] 0 0 50 50 50 50 25 25 0 33 62 0 50 0 60 33 62 25 56 7 0 46 56  
## [3635] 47 61 0 17 50 61 0 14 52 51 33 50 40 51 7 0 0 0 58 0 50 40 33  
## [3658] 59 0 50 0 50 50 53 50 50 21 50 61 61 40 50 44 53 62 50 48 25 0 44  
## [3681] 50 50 50 58 58 31 53 50 35 35 40 50 0 51 40 50 50 51 60 51 54 51 53  
## [3704] 50 31 50 25 50 0 50 43 48 0 44 55 55 0 58 47 0 30 0 20 46 46 59  
## [3727] 58 58 58 60 58 0 61 50 25 0 0 50 0 0 50 17 0 42 58 50 33 29 0  
## [3750] 29 29 29 29 29 60 55 20 29 40 25 51 29 0 0 29 29 29 29 29 29 29 50  
## [3773] 50 0 42 33 46 0 44 40 0 59 0 16 62 62 62 56 0 45 59 0 52 0 0  
## [3796] 25 58 33 51 55 51 59 45 45 59 59 60 59 59 59 50 0 59 59 50 59 59 59  
## [3819] 59 56 56 56 56 56 56 56 56 56 56 56 56 59 59 59 59 59 59 59 0 33 59  
## [3842] 33 0 0

data$host\_acceptance\_rate[which(data$host\_acceptance\_rate<63)]<-median(data$host\_acceptance\_rate,na.rm=TRUE)   
  
boxplot.stats(data$bedrooms)

## $stats  
## [1] 0 1 1 2 3  
##   
## $n  
## [1] 37625  
##   
## $conf  
## [1] 0.9918545 1.0081455  
##   
## $out  
## [1] 4 4 5 5 5 4 7 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4  
## [24] 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 6 4 5 5 4  
## [47] 4 4 4 4 5 4 5 4 4 5 4 4 4 4 4 5 5 4 5 5 4 5 5  
## [70] 4 5 4 4 4 5 4 7 6 4 4 4 5 5 4 4 4 5 4 5 4 6 7  
## [93] 4 5 4 5 5 4 5 5 4 4 4 7 4 4 6 5 6 7 6 4 4 4 4  
## [116] 5 4 4 8 7 5 4 4 4 5 4 4 4 5 5 4 4 6 4 4 7 4 4  
## [139] 4 4 5 4 5 6 4 4 4 4 4 4 4 4 4 4 4 4 4 5 4 4 4  
## [162] 7 4 4 5 5 4 4 4 5 4 4 5 4 4 5 4 4 4 5 8 8 5 4  
## [185] 5 4 4 5 5 4 4 4 4 6 5 5 4 6 5 4 4 5 4 4 4 4 5  
## [208] 4 4 5 5 4 5 4 4 6 4 4 4 6 6 4 5 4 5 4 7 4 4 5  
## [231] 5 4 4 4 7 4 5 4 4 4 4 5 4 5 4 6 4 5 4 4 5 4 4  
## [254] 4 7 4 5 5 5 4 4 4 4 5 5 4 5 5 4 4 4 4 5 5 4 5  
## [277] 4 6 8 4 4 4 5 4 6 6 5 4 4 4 4 5 4 4 4 4 4 4 4  
## [300] 5 4 4 4 4 4 4 5 4 5 4 6 4 4 4 5 4 4 4 4 4 5 4  
## [323] 4 4 4 4 4 4 4 4 4 6 5 4 5 4 6 4 4 4 4 4 4 4 5  
## [346] 4 6 5 5 4 7 4 5 4 4 6 4 4 4 7 4 4 5 4 6 6 4 4  
## [369] 4 4 6 5 4 4 5 4 4 4 5 9 5 4 4 4 4 5 7 6 4 4 7  
## [392] 5 4 4 5 5 4 4 4 4 5 5 5 4 7 4 4 4 5 4 4 4 4 4  
## [415] 4 6 4 5 4 4 4 7 4 4 4 4 6 6 4 5 4 5 4 4 5 4 4  
## [438] 4 4 4 6 4 5 4 5 4 4 5 5 4 4 6 4 5 5 5 4 5 4 4  
## [461] 4 4 6 4 11 4 4 6 4 4 5 4 6 6 5 4 4 4 4 4 4 5 5  
## [484] 5 5 4 4 4 4 7 5 5 5 4 4 5 7 5 4 5 5 4 4 4 6 6  
## [507] 9 7 7 5 4 4 4 4 4 4 4 5 4 4 4 4 4 7 5 4 4 4 5  
## [530] 5 4 4 4 6 4 4 4 4 4 6 4 4 4 4 5 4 5 4 5 4 5 5  
## [553] 5 6 4 4 4 5 5 5 4 5 4 5 9 4 4 4 4 4 4 4 4 4 4  
## [576] 5 4 5 4 4 4 5 4 4 4 4 4 5 6 4 6 5 5 4 4 4 4 5  
## [599] 4 5 4 4 4 4 5 5 4 6 6 4 4 4 6 6 4 4 4 5 5 4 4  
## [622] 4 5 4 9 4 5 4 5 4 6 4 5 4 4 5 6 4 4 4 4 4 5 4  
## [645] 4 4 4 4 6 4 5 5 8 7 5 5 4 5 5 5 6 5 4 9 4 6 6  
## [668] 6 4 5 4 7 5 4 4 4 6 5 4 4 4 4 4 6 5 6 5 6 4 5  
## [691] 5 4 4 4 5 4 4 6 4 4 4 4 4 8 4 10 5 5 5 4 5 7 4  
## [714] 4 4 4 5 6 5 4 4 4 4 4 5 4 4 5 5 4 4 4 4 4 5 4  
## [737] 4 4 5 4 4 4 4 4 7 7 5 4 4 4 4 5 4 5 7 4 4 5 5  
## [760] 4 5 5 4 4 4 5 4 4 5 6 4 4 4 4 4 4 4 5 6 5 5 4  
## [783] 4 4 5 5 5 6 4 4 4 4 4 4 4 4 4 5 6 4 6 5 5 7 4  
## [806] 4 4 4 4 7 4 5 4 4 4 4 5 4 6 4 6 4 6 5 12 4 4 5  
## [829] 4 4 4 4 5 4 4 5 5 5 5 5 4 4 7 7 4 4 5 5 5 4 4  
## [852] 4 5 4 5 6 8 4 6 4 4 4 4 4 4 7 4 4 4 5 4 5 5 4  
## [875] 6 4 5 5 4 4 4 11 5 5 7 4 4 4 5 4 4 4 5 4 4 5 4  
## [898] 6 5 5 4 4 4 7 6 6 4 6 5 4 4 4 4 8 4 6 4 5 4 4  
## [921] 4 5 4 5 6 5 5 4 4 4 5 4 4 4 5 5 4 6 6 5 4 4 5  
## [944] 4 4 7 10 4 6 5 4 8 9 4 5 4 5 4 4 4 5 5 4 4 6 7  
## [967] 8 7 5 4 9 5 6 5 4 4 5 4 4 4 4 5 5 5 4 4 6 7 7  
## [990] 4 4 7 4 4 5 4 5 4 4 5 5 5 4 4 5 5 4 5 4 5 4 5  
## [1013] 4 5 4 5 7 7 4 4 11 4 6 5 4 4 4 5 10 6 4 5 4 4 6  
## [1036] 4 5 4 5 5 4 4 4 5 7 7 5 7 5 4 5 4 6 4 4 4 4 4  
## [1059] 7 5 6 4 4 4 4 4 4 4 4 5 4 4 5 4 7 4 4 5 4 4 4  
## [1082] 5 4 4 4 4 4 4 4 4 4 4 4 4 5 5 4 4 6 5 4 4 6 5  
## [1105] 5 6 4 4 6 6 4 6 4 4 4 7 4 4 5 5 8 6 5 5 4 4 5  
## [1128] 4 6 5 4 5 7 4 8 4 4 4 4 5 7 5 4 5 4 4 4 4 4 4  
## [1151] 4 4 4 5 4 4 5 4 4 4 4 4 5 5 10 5 6 5 5 4 4 5 7  
## [1174] 4 4 4 5 4 4 4 5 4 4 4 4 5 4 5 4 4 4 6 4 4 4 5  
## [1197] 5 4 4 4 5 4 5 5 5 5 4 4 5 4 4 6 7 4 5 4 6 4 4  
## [1220] 4 5 4 7 4 4 5 5 4 5 6 5 6 5 5 5 6 5 7 6 5 5 5  
## [1243] 5 4 4 6 5 5 5 4 4 5 6 4 4 5 4 4 6 6 4 5 4 4 5  
## [1266] 6 4 4 4 5 5 4 4 4 5 4 6 8 5 5 7 5 5 4 4 4 4 4  
## [1289] 5 4 6 9 4 4 4 5 4 7 5 4 5 4 4 5 4 4 4 4 5 5 4  
## [1312] 5 4 4 4 4 5 4 4 5 4 5 5 4 4 5 4 4 9 4 4 5 5 6  
## [1335] 4 4 4 4 4 4 4 5 4 4 4 4 7 6 4 5 6 10 4 4 4 4 4  
## [1358] 5 4 4 4 4 4 11 6 4 4 4 4 4 4 5 4 5 4 5 4 4 4 4  
## [1381] 5 4 4 5 4 7 4 4 6 5 4 4 4 4 4 8 4 4 4 5 4 4 4  
## [1404] 4 5 10 4 4 4 5 4 5 4 5 4 4 4 5 4 5 4 4 7 4 4 4  
## [1427] 4 5 5 4 4 5 4 4 4 8 8 8 4 4 4 6 5 6 4 4 4 4 4  
## [1450] 6 5 4 4 6 5 6 4 5 4 4 4 4 4 4 4 4 5 4 5 4 4 5  
## [1473] 5 4 5 4 5 4 8 7 5 4 5 6 4 7 4 5 4 6 12 4 5 5 4  
## [1496] 4 6 7 4 4 5 4 4 4 4 4 12 4 4 4 5 6 6 5 5 5 4 4  
## [1519] 4 9 4 4 4 4 4 4 4 4 4 5 4 4 4 5 5 5 4 5 5 5 7  
## [1542] 5 4 5 4 4 4 4 6 4 4 4 5 7 4 4 5 5 4 4 5 8 4 5  
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## [1588] 6 4 4 4 4 5 4 5 5 5 4 8 4 4 4 6 4 4 4 4 4 8 5  
## [1611] 7 4 5 4 5 4 4 4 4 4 4 4 4 5 4 6 4 4 4 5 4 6 4  
## [1634] 4 4 5 4 8 5 4 4 5 4 4 5 4 5 4 6 4 4 5 4 4 5 4  
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## [1680] 4 4 4 5 4 5 4 4 5 6 4 4 4 5 4 7 4 5 5 4 4 5 5  
## [1703] 4 7 4 5 4 4 5 4 5 6 4 4 4 5 5 8 6 5 4 6 4 5 4  
## [1726] 4 4 4 4 5 5 6 4 5 4 4 5 4 4 5 5 4 5 5 4 4 4 4  
## [1749] 5 4 6 5 4 4 5 5 4 5 5 10 4 7 6 4 4 4 4 6 5 5 5  
## [1772] 4 5 6 4 7 5 4 4 5 4 5 4 6 6 4 5 5 4 5 4 4 4 4  
## [1795] 4 5 4 4 4 9 4 4 6 4 5 4 5 6 7 8 4 4 4 4 4 4 4  
## [1818] 4 4 4 4 5 4 4 4 4 4 6 5 5 4 4 4 4 4 4 5 4 5 5  
## [1841] 4 4 4 6 4 4 4 4 4 5 5 4 5 4 4 4 4 4 4 4 4 5 4  
## [1864] 4 11 5 4 4 5 5 4 4 5 5 6 4 4 4 4 7 4 4 5 6 4 4  
## [1887] 4 6 5 5 5 5 4 4 4 5 4 6 4 5 5 4 5 5 5 4 4 4 4  
## [1910] 4 5 4 4 6 4 4 4 5 5 4 4 4 5 4 8 4 5 5 8 4 4 4  
## [1933] 7 4 5 5 4 5 5 5 8 4 4 6 5 6 5 5 5 6 4 5 5 5 4  
## [1956] 4 4 4 4 4 4 4 4 6 5 4 4 5 5 5 5 4 5 4 7 4 4 5  
## [1979] 5 4 4 5 4 4 4 4 4 4 4 4 5 5 4 5 4 4 4 4 6 5 4  
## [2002] 4 5 4 4 4 6 4 4 4 4 4 4 4 4 4 6 4 6 4 4 5 4 4  
## [2025] 6 4 5 5 4 4 8 4 7 5 4 4 5 4 5 4 6 6 4 9 5 4 4  
## [2048] 4 4 6 6 6 6 6 4 4 4 6 6 5 4 4 4 5 4 4 5 4 4 4  
## [2071] 4 4 5 4 5 4 6 4 7 4 5 7 4 4 4 6 4 5 5 4 5 4 4  
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## [2163] 4 4 4 4 4 4 5 5 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4  
## [2186] 4 5 4 4 4 5 4 4 6 5 4 6 5 5 5 4 4 4 4 5 6 5 4  
## [2209] 4 5 6 4 6 5 4 7 4 5 5 4 6 7 5 4 6 6 5 4 5 10 4  
## [2232] 4 4 4 7 5 4 4 5 4 7 5 13 4 4 4 5 4 4 4 4 4 5 6  
## [2255] 4 4 9 5 4 4 8 5 5 6 4 7 4 5 4 5 5 4 6 4 5 4 5  
## [2278] 6 6 4 4 4 7 5 6 4 5 5 7

data$bedrooms[which(data$bedrooms>3)]<-median(data$bedrooms,na.rm=TRUE)#3 is the upper whisker, no values that are below the lower whisker  
  
boxplot.stats(data$bathrooms)

## $stats  
## [1] 0.0 1.0 1.0 2.0 3.5  
##   
## $n  
## [1] 37691  
##   
## $conf  
## [1] 0.9918616 1.0081384  
##   
## $out  
## [1] 11.0 4.0 11.0 11.0 8.0 8.0 8.0 8.0 8.0 8.0 8.0 8.0 8.0  
## [14] 8.0 8.0 4.5 4.0 8.0 8.0 8.0 7.5 4.5 4.5 5.0 4.0 4.0  
## [27] 5.5 8.0 11.0 11.0 11.0 5.0 11.0 11.0 11.0 11.0 11.0 11.0 11.0  
## [40] 11.0 11.0 4.5 4.0 4.0 4.0 4.5 11.0 5.0 4.5 4.5 4.5 4.0  
## [53] 4.0 4.0 8.0 8.0 8.0 8.0 11.5 4.5 4.5 4.0 4.5 6.5 4.5  
## [66] 4.5 6.5 7.5 5.5 4.5 4.5 5.0 4.0 4.5 8.0 4.0 4.5 5.5  
## [79] 11.0 11.0 4.0 5.0 4.5 8.0 4.0 4.0 5.0 7.5 5.0 4.5 5.0  
## [92] 4.5 4.5 4.0 6.0 7.5 5.5 5.5 4.5 4.0 4.0 4.0 4.0 6.5  
## [105] 6.0 4.0 5.0 4.0 7.0 7.5 5.5 4.5 7.0 4.0 4.0 4.5 8.0  
## [118] 4.0 4.5 5.0 4.0 4.0 4.5 5.5 4.5 6.0 4.5 5.0 4.5 13.5  
## [131] 6.5 4.0 7.5 5.5 4.0 8.0 8.0 5.5 5.5 4.0 8.0 8.0 8.0  
## [144] 8.0 8.0 8.0 8.0 8.0 4.5 4.5 7.5 5.0 4.5 4.0 5.0 4.0  
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## [1249] 5.0 9.5 4.0 4.5 5.0 4.0 5.5 9.0 5.5 7.0 4.0 4.0 4.0  
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## [1275] 6.0 8.5 6.0 5.5 4.5 6.5 6.5 4.0 6.0 4.0 4.5 5.5 5.5  
## [1288] 5.0 4.0 4.0 4.5 4.5 6.5 4.5 4.5 5.0 4.0 11.0 6.0 4.5  
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## [1314] 4.5 5.5 4.0 8.5 4.0 4.5 4.5 4.5 5.5 15.0 5.0 4.5 5.0  
## [1327] 5.0 4.5 8.0 4.5 12.0 5.0 8.0 4.5 8.0 5.5 5.5 4.0 4.0  
## [1340] 5.0 4.0 5.0 6.0 8.5 4.0 6.0 4.0 4.0 9.5

data$bathrooms[which(data$bathrooms>3.5)]<-median(data$bathrooms,na.rm=TRUE)#3.5 is the upper whisker, no values that are below the lower whisker  
  
boxplot.stats(data$beds)

## $stats  
## [1] 0 1 1 2 3  
##   
## $n  
## [1] 37340  
##   
## $conf  
## [1] 0.9918235 1.0081765  
##   
## $out  
## [1] 5 4 5 5 5 5 4 5 5 9 5 5 6 4 4 4 4 4 7 4 4 4 4  
## [24] 4 6 4 8 4 4 4 11 5 6 6 8 4 7 4 5 4 4 5 4 4 4 4  
## [47] 15 4 4 6 6 5 4 5 6 5 4 8 4 9 5 5 8 6 4 5 5 4 4  
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## [300] 7 4 4 11 4 5 4 5 4 4 4 4 4 5 4 4 4 4 5 5 5 5 5  
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## [2830] 7 4 4 6 5 5 5 4 6 6 4 4 4 4 4 4 4 5 5 4 5 5 4  
## [2853] 4 6 4 4 4 4 4 4 5 4 4 4 4 6 7 4 4 4 4 4 4 4 4  
## [2876] 5 4 4 4 4 4 4 9 6 5 5 19 5 4 4 4 7 4 4 4 4 4 4  
## [2899] 5 8 8 4 4 8 5 5 5 5 4 6 4 4 4 6 7 4 4 5 5 6 6  
## [2922] 6 6 6 6 6 4 6 4 5 7 6 5 4 4 6 4 4 4 6 5 5 5 4  
## [2945] 4 5 9 5 6 6 8 4 7 4 8 4 4 6 4 4 5 4 4 4 8 6 4  
## [2968] 6 5 5 6 6 4 6 6 4 6 4 4 5 4 5 4 4 5 5 5 5 4 5  
## [2991] 4 5 5 14 4 4 4 6 5 8 4 4 4 4 5 4 5 6 6 4 6 4 14  
## [3014] 5 5 5 4 5 5 5 4 4 4 7 5 5 4 4 4 6 5 5 4 4 5 4  
## [3037] 6 4 4 4 4 20 4 5 4 4 5 4 4 8 6 7 4 4 5 7 6 5 4  
## [3060] 5 5 4 4 5 5 4 4 5 5 4 4 6 7 4 9 6 4 4 4 6 5 4  
## [3083] 4 4 9 5 5 4 4 6 4 4 4 4 4 4 5 6 6 4 5 7 5 6 4  
## [3106] 4 5 5 6 4 5 5 4 5 4 4 4 4 4 4 5 4 5 5 7 6 4 14  
## [3129] 4 6 4 4 5 5 4 7 4 4 6 4 5 4 4 6 4 4 4 6 9 4 4  
## [3152] 4 4 4 5 4 5 4 4 5 4 4 4 4 4 10 4 4 4 4 4 6 6 4  
## [3175] 4 8 5 7 9 4 10 4 4 12 4 5 4 6 5 4 4 4 4 4 4 5 5  
## [3198] 4 6 4 5 5 10 11 5 4 4 4 4 4 5 4 6 6 6 4 4 5 4 4  
## [3221] 5 11 7 4 6 4 5 4 5 5 4 4 5 4 4 5 5 5 4 5 6 5 4  
## [3244] 4 5 4 5 7 6 5 4 8 4 4 8 5 4 6 6 5 4 5 6 4 4 4  
## [3267] 4 4 4 4 4 5 4 6 5 4 4 5 5 4 6 4 4 5 5 4 4 4 4  
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## [3336] 4 4 5 4 7 4 5 4 8 4 4 4 5 4 4 4 4 5 4 4 4 4 6  
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## [3382] 6 6 4 5 4 6 6 4 4 4 6 4 5 5 4 8 7 4 5 5 9 9 9  
## [3405] 4 5 4 4 4 4 4 4 6 5 5 7 6 4 4 7 4 4 6 4 4 6 4  
## [3428] 4 4 5 5 8 8 4 6 7 7 4 4 6 6 7 4 5 4 6 4 5 4 4  
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## [3474] 4 5 4 4 4 4 4 4 10 9 4 4 5 4 6 4 7 4 4 7 7 7 4  
## [3497] 4 6 4 4 6 4 4 4 4 6 4 8 6 6 4 5 5 6 5 13 4 4 16  
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## [3658] 5 15 4 8 4 6 4 5 6 7 8 8 8 4 4 5 7 6 4 7 8 6 8  
## [3681] 7 4 6 5 9 12 10 7 7 8 4 4 8 15 4 10 7 4 5 4 4 7 7  
## [3704] 5 7 4 9 6 4 5 6 11 4 8 4 6 6 4 5 9 4 4 6 4 4 5  
## [3727] 4 4 5 6 4 5 14 4 4 5 5 7 6 4 6 6 4 4 4 9 4 4 4  
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## [3842] 4 4 8 4 5 4 4 4 5 8 8 4 4 5 4 4 4 6 9 5 6 5 6  
## [3865] 4 5 8 5 8 4 4 4 8 5 6 6 5 4 6 16 5 6 5 6 6 5 4  
## [3888] 6 4 6 4 6 6 6 8 5 11 4 7 4 4 4 6 12 4 4 4 6 7 5  
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## [3957] 6 6 4 6 6 6 6 6 6 6 6 4 4 6 4 5 4 4 4 4 6 4 16  
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## [4049] 4 5 6 4 7 4 4 5 4 5 4 10 5 4 7 4 4 6 6 6 5 4 4  
## [4072] 6 6 7 4 7 5 5 4 6 6 6 5 4 5 4 5 8 5 6 4 5 5 4  
## [4095] 4 5 5 6 4 4 5 5 7 4 5 6 5 4 4 4 6 8 6 4 7 6 4  
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## [4164] 8 6 8 4 5 4 6 7 4 4 6 5 6 5 4 5 4 5 6 6 4 5 4  
## [4187] 4 4 6 4 6 6 4 4 4 4 4 6 4 7 4 9 4 5 4 4 20 4 5  
## [4210] 4 5 8 4 4 4 8 4 6 4 10 12 14 16 5 4 4 4 5 5 4 4 8  
## [4233] 4 5 6 5 6 4 9 4 4 5 4 5 4 4 5 4 4 4 4 5 4 4 5  
## [4256] 4 4 7 14 6 5 4 4 6 6 4 4 4 8 6 5 6 4 8 8 5 10 6  
## [4279] 5 5 6 4 6 4 4 6 5 4 6 5 4 5 4 5 5 6 5 4 4 6 5  
## [4302] 4 4 6 4 4 4 5 4 4 6 4 6 4 4 4 4 4 4 4 8 4 4 4  
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## [4348] 4 4 4 4 5 4 10 4 7 7 4 4 5 5 5 4 4 4 4 4 5 6 5  
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## [4417] 4 4 6 5 4 5 6 5 6 4 4 7 4 6 5 4 4 5 4 4 8 4 4  
## [4440] 5 4 6 5 4 4 8 6 4 4 4 7 7 5 4 5 5 6 6 5 7 5 4  
## [4463] 5 6 7 4 4 4 5 4 5 8 4 4 4 4 6 4 7 4 5 5 6 4 5  
## [4486] 4 7 6 4 4 6 4 4 4 7 5 6 6 5 8 6 5 5 6 4 5 6 8  
## [4509] 7 5 8 4 4 6 4 5 5 5 7 4 4 5 6 4 4 4 4 4 4 4 8  
## [4532] 5 5 5 6 6 5 4 4 6 5 5 5 4 6 5 6 4 4 5 8 5 5 8  
## [4555] 4 4 5 5 8 5 4 11 6 4 4 4 5 5 4 6 4 4 4 5 5 5 5  
## [4578] 6 4 5 6 5 6 5 5 5 6 6 5 4 4 4 5 6 4 6 4 4 4 7  
## [4601] 11 4 4 6 4 5 7 4 5 4 6 4 5 4 4 6 5 5 4 5 5 4 5  
## [4624] 6 6 4 5 5 4 5 4 5 6 5 6 5 4 4 4 4 5 4 7 9 7 6  
## [4647] 4 4 5 13 4 4 4 6 8 4 4 7 5 5 4 4 5 4 6 4 6 6 5  
## [4670] 6 6 4 9 4 4 5 4 4 4 4 6 6 6 6 6 6 4 4 6 5 6 6  
## [4693] 6 5 4 4 6 6 4 6 4 5 8 4 5 4 4 4 5 4 4 4 5 6 5  
## [4716] 5 4 5 6 4 6 6 5 6 7 4 10 4 9 5 4 4 6 5 4 4 6 5  
## [4739] 5 5 6 5 7 4 4 4 4 5 6 4 4 4 5 5 5 5 6 4 7 4 5  
## [4762] 8 4 4 4 8 4 6 5 10 8 8 6 4 5 4 4 6 4 4 6 9 5 6  
## [4785] 5 5 5 4 4 4 4 4 4 5 8 4 4 7 5 5 6 4 7 4 7 4 6  
## [4808] 4 4 4 4 5 4 5 5 4 6 4 4 4 4 5 7 5 4 4 6 4 8 6  
## [4831] 5 7 5 5 4 5 5 9 5 4 5 6 4 5 5 4 7 4 4 4 4 4 4  
## [4854] 4 5 4 7 8 4 5 4 6 4 5 5 4 8 6 6 4 5 4 4 5 4 4  
## [4877] 6 7 4 4 4 5 5 5 4 5 5 6 5 7 4 5 5 4 5 5 4 10 4  
## [4900] 6 4 4 8 5 4 5 4 4 6 4 5 4 4 4 4 4 4 6 5 4 4 9  
## [4923] 6 4 5 4 16 12 4 6 5 4 5 4 4 4 6 5 4 5 5 4 7 22 5  
## [4946] 5 5 4 4 4 4 5 4 4 4 5 6 6 6 6 4 4 6 4 6 6 8 6  
## [4969] 4 4 8 9 4 10 9 4 9 4 4 9 6 4 4 4 9 6 4 5 4 5 5  
## [4992] 4 4 5 10 4 5 5 4 4 4 6 7 6 4 7 5 4 4 5 4 6 4 4  
## [5015] 8 5 4 6 5 22 6 4 4 17 4 6 14 5 5 4 5 10 6 6 4 6 4  
## [5038] 4 5 5 5 7 4 4 4 6 4 4 6 5 5 5 4 6 4 4 9 6 4 5  
## [5061] 10 5 5 5 4 4 6 5 7 9 5 5 4 5 7 7 6 4 4 4 5 4 5  
## [5084] 6 6 4 8 4 4 4 12 4 5 6 4 4 10 6 5 4 7

data$beds[which(data$beds>3)]<-median(data$beds,na.rm=TRUE) #3 is the upper whisker, no values that are below the lower whisker  
  
boxplot.stats(data$security\_deposit)

## $stats  
## [1] 0 0 150 300 750  
##   
## $n  
## [1] 25265  
##   
## $conf  
## [1] 147.0179 152.9821  
##   
## $out  
## [1] 950 800 850 799 800 800 900 800 995 800 800 800 800 800 800 900 800  
## [18] 900 800 825 800 800 800 800 800 800 800 800 800 800 900 800 800 800  
## [35] 800 989 900 800 777 800 800 999 800 800 800 800 890 800 800 800 900  
## [52] 850 900 900 950 800 900 800 800 800 800 800 800 800 800 800 800 800  
## [69] 800 850 800 900 950 800 900 800 800 800 800 800 800 800 800 800 950  
## [86] 800 800 800 900 800 800 800 850 800 800 850 800 800 800 800 800 800  
## [103] 800 800 800 800 800 800 800 800 900 800 800 800 800 900 800 800 800  
## [120] 850 800 850 995 800 800 950 800 900 899 800 850 900 950 850 800 800  
## [137] 800 985 800 800 850 800 800 800 800 900 950 950 800 800 800 900 800  
## [154] 800 800 800 999 999 950 800 850 800 850 970 800 800 999 800 980 900  
## [171] 800 800 800 800 900 800 900 900 900 950 900 900 850 950 800 850 900  
## [188] 800 800 800 800 800 900 800 800 800 800 800 900 800 850 800 800 800  
## [205] 874 900 800 800 900 900 900 880 900 895 875 850 800 800 950 800 800  
## [222] 800 800 800 850 950 800 850 800 800 990 990 800 800 900 800 770 800  
## [239] 875 850 800 900 800 800 799 800 800 900 800 800 800 800

data$security\_deposit[which(data$security\_deposit>750)]<-median(data$security\_deposit,na.rm=TRUE) # 750 is the upper whisker, no values that are below the lower whisker  
  
boxplot.stats(data$cleaning\_fee)

## $stats  
## [1] 0 30 70 125 265  
##   
## $n  
## [1] 32715  
##   
## $conf  
## [1] 69.17014 70.82986  
##   
## $out  
## [1] 400 275 300 300 300 400 300 450 500 500 300 300 450 500 300 500 300  
## [18] 420 275 350 275 275 450 300 299 333 360 540 540 420 420 275 350 400  
## [35] 300 480 333 320 500 420 327 650 300 651 333 275 350 300 399 368 475  
## [52] 300 350 300 950 500 651 360 550 500 471 300 485 300 300 300 350 300  
## [69] 300 300 500 300 600 300 300 500 295 400 350 350 500 325 285 500 300  
## [86] 350 500 300 399 333 300 500 500 340 350 290 350 333 350 400 350 300  
## [103] 300 300 275 350 300 300 350 650 295 300 350 350 300 300 300 300 500  
## [120] 275 399 300 500 400 300 500 350 300 285 300 349 275 350 350 675 350  
## [137] 295 300 350 325 300 500 450 300 400 285 300 500 300 500 450 400 300  
## [154] 300 325 395 500 495 350 300 395 599 500 300 500 380 350 375 500 350  
## [171] 350 340 550 500 350 350 300 500 550 500 500 500 898 291 500 400 350  
## [188] 300 350 450 300 500 275 300 650 275 300 500 450 300 300 300 450 300  
## [205] 320 500 275 275 350 275 300 300 300 295 350 350 300 300 750 300 350  
## [222] 300 575 375 300 300 300 500 300 425 350 350 310 300 300 285 595 350  
## [239] 300 575 400 300 300 275 500 300 300 350 300 275 400 400 400 290 350  
## [256] 850 310 310 300 350 500 500 285 299 275 345 375 350 500 600 300 320  
## [273] 300 300 400 300 500 450 375 350 375 300 350 350 300 350 275 425 400  
## [290] 300 299 375 375 500 350 350 350 300 500 300 350 280 295 500 650 300  
## [307] 350 500 350 500 290 500 300 300 500 500 400 750 300 350 650 395 400  
## [324] 400 500 600 300 850 500 400 300 275 300 269 450 300 395 550 750 300  
## [341] 300 300 599 310 399 300 360 269 300 750 650 420 390 350 750 275 280  
## [358] 489 750 500 550 300 300 350 650 350 350 495 400 475 450 600 350 595  
## [375] 300 300 310 500 500 350 750 500 320 280 300 400 400 500 460 350 500  
## [392] 500 400 365 400 300 300 350 395 500 300 300 500 450 500 379 500 400  
## [409] 600 395 300 300 300 600 500 500 353 275 300 350 275 400 899 699 500  
## [426] 500 300 400 350 300 495 300 500 300 300 300 325 450 495 300 275 350  
## [443] 850 269 500 399 500 395 375 400 500 500 300 595 400 550 550 359 350  
## [460] 390 390 300 269 300 395 350 350 450 400 300 350 300 500 350 400 300  
## [477] 310 350 300 350 300 300 300 450 269 350 300 288 275 350 495 350 300  
## [494] 350 750 750 400 300 750 300 350 350 385 350 300 350 299 288 350 779  
## [511] 300 300 500 288 299 300 375 500 395 350 395 300 400 500 280 300 350  
## [528] 295 300 288 288 400 650 350 269 269 300 395 288 288 300 500 525 300  
## [545] 400 380 330 300 350 400 390 400 300 300 300 350 648 300 400 500 400  
## [562] 385 380 300 380 550 430 500 300 750 350 300 500 350 350 500 333 783  
## [579] 333 333 333 333 400 395 600 500 350 300 300 300 280 400 750 404 500  
## [596] 380 385 330 595 300 300 304 303 350 650 300 300 500 299 650 500 500  
## [613] 750 500 300 603 350 350 500 495 425 300 340 288 350 300 295 300 385  
## [630] 300 275 410 300 410 410 410 500 375 400 399 369 400 350 520 400 300  
## [647] 300 300 300 550 300 380 500 385 385 380 380 380 380 380 380 380 380  
## [664] 380 350 380 380 325 274 500 615 450 600 600 275 464 300 350 360 360  
## [681] 450 275 280 300 280 275 375 300 500 550 600 395 750 350 800 950 500  
## [698] 400 650 300 300 450 500 300 300 500 350 380 400 300 400 300 300 300  
## [715] 300 325 400 322 299 299 450 450 395 600 300 350 300 275 399 375 350  
## [732] 300 435 500 650 435 435 375 500 295 550 330 395 350 299 425 398 650  
## [749] 300 350 500 500 385 500 750 545 291 500 350 350 270 350 410 298 298  
## [766] 298 395 545 350 410 300 300 300 390 390 300 275 385 330 360 395 300  
## [783] 355 455 450 350 300 470 500 299 650 850 700 444 300 500 700 470 295  
## [800] 500 300 410 545 410 410 410 410 410 360 350 450 500 350 345 345 350  
## [817] 300 435 350 345 295 300 300 300 300 500 360 450 300 400 450 350 749  
## [834] 600 435 500 395 350 300 500 500 300 300 380 350 500 500 500 500 295  
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## [868] 295 350 400 410 300 300 300 300 300 300 300 650 295 410 300 300 360  
## [885] 299 295 650 295 295 495 295 295 410 410 410 410 350 350 345 300 350  
## [902] 300 350 345 295 450 650 490 290 450 950 350 300 400 650 470 525 350  
## [919] 300 295 525 295 525 525 330 500 525 450 375 360 300 300 295 345 525  
## [936] 410 410 300 300 345 300 410 300 500 525 300 300 300 300 359 360 350  
## [953] 600 389 650 295 350 500 295 399 350 500 295 295 500 300 400 280 578  
## [970] 800 550 300 350 450 525 380 295 500 750 500 650 300 400 400 410 410  
## [987] 300 295 300 400 500 295 410 450 295 450 650 300 300 450 650 500 295  
## [1004] 300 360 500 269 389 500 295 499 400 300 300 300 300 300 300 410 489  
## [1021] 350 299 500 400 500 300 495 444 300 300 550 435 400 650 269 318 300  
## [1038] 410 410 300 500 300 410 500 300 300 410 470 385 300 295 300 300 385  
## [1055] 385 650 320 450 500 295 300 300 295 295 295 295 295 295 345 299 269  
## [1072] 400 360 499 345 300 500 600 295 300 400 364 399 600 500 300 300 345  
## [1089] 300 400 495 300 600 605 525 295 410 300 295 345 300 300 300 300 295  
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## [1140] 350 300 300 300 300 269 275 380 300 345 295 500 300 300 500 380 450  
## [1157] 295 570 300 380 380 380 410 380 300 345 295 799 300 650 295 650 500  
## [1174] 300 300 600 300 400 450 400 300 475 300 290 290 290 375 350 295 295  
## [1191] 295 300 350 500 295 295 295 400 500 350 580 295 350 300 470 500 275  
## [1208] 300 295 295 425 450 550 295 295 295 295 300 295 399 500 600 650 399  
## [1225] 600 550 380 380 380 380 380 380 650 425 450 500 600 300 424 400 399  
## [1242] 570 300 360 375 300 345 500 295 575 400 400 295 295 295 400 350 350  
## [1259] 425 500 295 410 410 300 299 500 545 295 295 471 599 280 295 295 400  
## [1276] 295 295 300 500 300 384 345 295 300 295 490 350 300 300 500 614 295  
## [1293] 525 495 275 350 450 295 295 295 300 300 410 410 300 350 499 382 395  
## [1310] 540 540 295 400 350 500 500 345 350 500 600 500 410 295 295 275 300  
## [1327] 450 377 300 300 350 295 295 350 300 300 410 300 300 300 295 350 295  
## [1344] 400 350 269 350 300 365 300 410 300 300 400 350 350 300 333 279 350  
## [1361] 300 345 285 500 350 495 350 380 299 345 380 380 295 295 500 295 295  
## [1378] 350 365 575 600 395 300 300 400 350 500 799 350 500 300 410 410 295  
## [1395] 395 400 275 295 300 375 300 450 350 295 650 275 300 770 500 550 500  
## [1412] 500 500 300 295 400 295 399 299 650 410 300 600 500 500 284 700 400  
## [1429] 400 425 750 300 350 349 295 300 275 500 500 300 520 400 300 500 300  
## [1446] 500 395 450 350 295 410 410 300 500 550 350 350 550 275 410 400 285  
## [1463] 500 500 500 550 300 400 489 400 475 295 295 500 300 299 295 345 500  
## [1480] 350 500 295 300 300 425 410 410 410 500 300 380 410 500 300 410 300  
## [1497] 380 380 380 380 380 380 380 300 296 295 345 400 450 500 360 325 599  
## [1514] 379 299 399 295 345 295 345 295 345 300 350 550 400 300 300 300 300  
## [1531] 400 500 500 350 390 400 495 500 350 275 300 492 295 500 350 500 600  
## [1548] 300 350 495 280 350 300 450 295 300 295 345 275 289 500 410 410 600  
## [1565] 350 350 304 300 500 300 500 300 300 300 300 300 300 500 350 595 750  
## [1582] 800 299 750 350 350 300 300 300 275 650 280 325 325 296 295 295 295  
## [1599] 410 375 295 345 345 650 750 399 350 500 300 350 800 500 499 350 400  
## [1616] 491 425 550 500 295 350 300 350 350 450 300 300 400 380 599 350 500  
## [1633] 500 300 295 650 500 410 425 449 400 500 500 410 410 300 410 500 295  
## [1650] 300 500 350 300 350 599 380 275 350 269 400 540 350 500 500 500 400  
## [1667] 410 410 390 375 345 295 295 399 499 599 350 380 295 300 300 300 285  
## [1684] 380 350 295 500 300 410 295 295 295 750 390 400 400 299 499 499 395  
## [1701] 300 295 295 295 600 495 750 495 550 395 575 350 380 295 295 295 400  
## [1718] 450 480 295 295 295 495 399 300 300 295 500 380 380 380 380 380 380  
## [1735] 380 380 380 380 380 380 280 500 350 295 295 295 295 295 450 450 350  
## [1752] 500 275 295 295 295 500 300 350 270 300 500 300 410 300 399 300 350  
## [1769] 300 350 300 300 300 300 300 300 480 480 500 699 300 500 449 400 600  
## [1786] 295 296 295 295 295 295 295 295 295 295 800 345 500 425 300 399 399  
## [1803] 399 390 600 600 299 299 389 300 694 350 375 475 595 600 300 300 284  
## [1820] 300 444 295 295 295 295 295 275 444 390 300 300 300 600 300 400 399  
## [1837] 299 650 400 295 345 345 295 400 275 295 400 400 350 500 289 300 300  
## [1854] 350 350 350 650 410 300 299 299 299 299 498 350 410 410 300 595 375  
## [1871] 275 295 299 300 300 300 300 299 275 300 575 450 295 500 295 295 300  
## [1888] 275 360 400 295 691 550 550 300 300 300 300 500 400 350 350 300 400  
## [1905] 300 300 499 350 800 300 795 359 300 289 269 300 295 359 600 300 550  
## [1922] 650 395 395 500 500 450 500 290 450 500 450 499 450 550

data$cleaning\_fee[which(data$cleaning\_fee>265)]<-median(data$cleaning\_fee,na.rm=TRUE) # 265 is the upper whisker, no values that are below the lower whisker  
  
boxplot.stats(data$availability\_365) #No outliers

## $stats  
## [1] 0 1 141 327 365  
##   
## $n  
## [1] 37728  
##   
## $conf  
## [1] 138.3482 143.6518  
##   
## $out  
## integer(0)

boxplot.stats(data$review\_scores\_rating)

## $stats  
## [1] 83 93 97 100 100  
##   
## $n  
## [1] 29665  
##   
## $conf  
## [1] 96.93579 97.06421  
##   
## $out  
## [1] 80 81 78 80 81 80 67 82 82 70 80 81 81 70 76 82 80 77 80 72 75 82 78  
## [24] 81 77 80 60 78 82 80 80 78 80 82 82 82 82 77 79 40 77 64 73 82 82 82  
## [47] 80 60 60 82 69 80 70 75 82 80 80 73 82 75 82 20 80 20 80 80 80 82 77  
## [70] 80 80 82 80 64 60 80 80 80 80 60 76 71 80 77 80 80 80 30 80 60 75 73  
## [93] 70 80 80 81 80 76 80 80 80 80 80 72 81 80 80 20 65 70 80 60 80 70 80  
## [116] 80 80 80 80 60 73 80 80 81 80 82 80 81 80 80 78 60 80 60 80 76 80 80  
## [139] 80 60 73 80 20 80 80 70 60 60 81 20 80 82 40 78 81 60 80 50 60 75 20  
## [162] 80 40 80 80 80 80 71 82 78 75 80 60 68 80 70 82 79 79 80 80 20 80 70  
## [185] 80 80 80 80 80 80 75 80 82 80 73 80 70 73 60 73 20 72 40 60 70 80 71  
## [208] 53 71 40 82 75 80 80 20 73 80 82 60 80 80 80 75 80 81 80 80 76 80 80  
## [231] 80 80 80 80 80 73 73 60 60 78 80 80 80 80 80 75 60 60 80 60 72 80 80  
## [254] 80 80 80 80 20 80 80 80 75 70 80 70 76 20 80 60 80 78 73 80 60 80 80  
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## [300] 70 80 75 73 70 60 40 60 82 80 80 81 60 80 76 77 82 77 82 81 81 82 50  
## [323] 67 82 60 80 75 75 20 80 80 80 73 80 80 60 80 67 80 20 60 80 82 80 77  
## [346] 60 81 80 80 76 80 20 80 80 66 80 75 80 77 81 60 68 80 80 60 80 60 80  
## [369] 70 80 80 20 70 73 56 20 20 80 80 82 80 80 80 80 79 80 80 72 80 79 76  
## [392] 80 80 50 78 68 80 78 82 80 40 80 73 80 80 60 60 80 20 80 73 80 80 80  
## [415] 75 78 60 81 80 80 81 73 80 80 70 80 80 80 80 50 70 20 80 80 60 80 75  
## [438] 70 60 81 81 80 58 80 78 60 76 80 20 76 80 82 80 82 80 80 65 20 80 80  
## [461] 72 80 80 72 82 80 70 75 55 80 65 80 80 80 78 75 80 81 40 50 80 20 80  
## [484] 80 80 71 80 81 76 20 73 75 75 80 77 82 60 80 80 73 80 76 76 80 80 78  
## [507] 80 80 74 20 80 80 60 60 81 73 60 20 79 80 77 80 60 80 82 76 80 80 40  
## [530] 40 80 40 60 80 80 60 80 80 47 80 80 20 40 80 80 80 76 60 80 80 65 80  
## [553] 73 67 79 82 80 75 80 75 81 78 20 81 80 80 80 82 80 60 80 75 80 76 60  
## [576] 30 78 20 80 60 80 78 82 78 81 80 76 82 20 70 66 80 80 80 80 75 78 60  
## [599] 20 80 80 74 80 82 20 80 73 80 82 80 80 80 78 76 80 80 60 80 27 73 69  
## [622] 64 80 80 80 80 82 80 80 60 73 70 63 75 60 78 82 60 20 73 60 80 80 40  
## [645] 70 79 82 60 80 78 80 80 20 82 80 80 73 76 70 70 73 80 80 80 60 80 80  
## [668] 80 80 81 76 69 66 20 82 76 80 81 60 80 80 60 40 80 73 82 80 80 75 80  
## [691] 80 77 70 40 80 60 74 73 77 50 60 82 70 80 80 53 80 80 80 70 20 20 78  
## [714] 80 20 80 80 80 82 80 80 60 82 80 81 20 55 80 74 60 77 60 77 70 80 80  
## [737] 80 82 56 73 70 68 40 60 79 80 81 77 80 80 73 70 80 82 81 60 80 73 82  
## [760] 80 82 73 81 40 20 73 77 80 80 67 80 77 73 77 60 73 80 80 60 80 80 70  
## [783] 20 80 76 60 82 80 77 76 60 82 60 70 80 60 40 82 76 82 82 40 33 82 80  
## [806] 74 64 60 79 82 82 20 77 76 70 77 80 77 74 82 81 40 75 82 30 60 76 80  
## [829] 60 71 79 80 78 80 70 64 82 69 80 80 73 69 82 82 78 81 82 20 80 80 60  
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## [875] 70 20 82 80 80 80 80 60 81 75 79 80 80 70 77 79 80 60 82 80 20 50 78  
## [898] 80 80 80 80 80 80 79 70 60 71 80 78 79 80 20 78 20 20 70 80 79 78 76  
## [921] 70 80 80 80 80 80 82 82 81 81 78 77 77 80 20 80 80 73 70 80 61 75 80  
## [944] 60 20 80 80 80 80 71 80 80 73 60 80 80 80 20 81 82 20 60 80 70 76 78  
## [967] 74 71 60 70 69 80 70 60 70 80 78 81 80 72 60 76 70 80 80 80 72 77 60  
## [990] 20 60 76 80 82 47 68 68 68 60 77 77 60 73 80 70 77 70 80 80 60 60 82  
## [1013] 75 63 80 80 81 80 77 82 80 60 82 70 60 79 80 74 81 73 40 60 60 80 80  
## [1036] 80 73 80 40 73 82 60 40 70 73 60 78 80 80 60 70 81 73 80 80 70 80 80  
## [1059] 75 80 80 75 80 80 80 80 75 76 80 80 80 60 70 75 60 73 60 70 20 80 80  
## [1082] 80 80 76 77 60 63 80 68 80 78 80 80 79 82 80 77 73 82 55 60 70 73 80  
## [1105] 73 80 75 56 75 68 80 80 78 80 80 80 50 80 77 60 80 75 71 65 70 74 82  
## [1128] 70 81 70 76 80 75 80 77 75 80 82 80 64 70 76 80 73 79 70 80 70 81 60  
## [1151] 80 68 80 80 74 82 74 79 76 80 80 65 75 80 75 76 80 80 80 70 20 71 81  
## [1174] 80 81 80 80 81 75 82 77 68 20 80 60 76 82 63 60 80 75 60 57 80 80 78  
## [1197] 40 80 75 80 80 50 80 80 82 60 69 80 80 73 80 79 80 82 73 80 20 20 77  
## [1220] 50 73 81 80 80 80 78 80 74 80 60 82 80 60 80 70 80 70 82 20 20 73 80  
## [1243] 80 75 80 73 81 80 80 67 80 80 40 20 77 80 81 70 78 80 80 70 60 40 80  
## [1266] 80 73 60 73 73 20 80 67 78 62 75 81 80 73 80 80 72 80 60 60 80 80 80  
## [1289] 80 70 70 72 40 60 80 80 60 73 80 68 20 20 50 60 74 20 20 20 60 52 50  
## [1312] 80 60 20 75 50 80 74 80 60 71 20 80 60 80 60 53 82 60 75 40 80 65 76  
## [1335] 60 80 40 82 70 80 70 81 20 73 69 81 40 50 20 80 82 80 20 80 40 80 60  
## [1358] 82 20 75 80 40 80 76 75 73 60 78 71 80 60 60 73 65 77 80 78 80 80 79  
## [1381] 80 40 60 80 53 82 20 78 77 80 60 20 72 60 60 80 80 77 80 80 73 82 78  
## [1404] 60 80 20 77 79 80 56 60 80 80 76 20 74 80 80 80 80 60 80 71 82 73 80  
## [1427] 73 76 80 80 60 80 20 73 82 80 80 60 73 78 75 63 76 40 81 81 73 65 60  
## [1450] 70 43 76 70 80 78 73 73 80 77 78 72 80 80 80 73 80 77 80 78 73 60 60  
## [1473] 60 70 67 80 80 60 78 80 80 77 53 80 62 80 63 20 70 60 80 20 68 82 20  
## [1496] 80 60 76 80 60 70 70 80 71 70 75 73 60 77 62 73 72 20 80 80 80 81 73  
## [1519] 80 80 82 70 74 82 80 80 80 80 60 78 60 80 20 76 60 73 60 20 72 70 74  
## [1542] 70 40 50 55 40 75 81 75 50 20 20 80 20 80 20 80 70 79 80 40 80 80 80  
## [1565] 80 60 71 80 80 60 60 80 40 80 20 71 60 20 50 60 76 81 80 80 80 78 69  
## [1588] 80 60 69 70 80 80 60 60 80 70 20 73 75 60 80 78 72 80 20 80 73 72 20  
## [1611] 70 73 70 73 72 80 75 80 82 80 80 80 75 65 80 60 80 80 82 80 80 80 80  
## [1634] 82 60 77 20 40 60 80 80 77 82 80 80 77 77 73 20 73 40 80 73 65 70 80  
## [1657] 80 60 20 60 80 80 82 82 80 78 81 80 64 70 81 40 70 74 20 80 77 67 81  
## [1680] 80 60 60 60 80 82 80 50 60 80 80 81 80 60 69 80 80 80 60 78 64 82 81  
## [1703] 73 53 80 75 73 70 80 60 60 60 78 78 70 80 80 80 80 67 20 20 60 70 40  
## [1726] 80 75 80 80 73 77 80 20 80 80 80 40 80 73 60 80 62 80 60 73 76 80 69  
## [1749] 80 79 72 80 80 60 80 80 60 82 60 80 82 82 80 75 80 80 79 80 80 80 65  
## [1772] 65 60 80 80 50 78 20 80 20 80 70 20 60 60 60 60 73 80 82 80 80 20 67  
## [1795] 73 67 80 80 70 80 60 80 60 20 80 80 60 80 60 40 49 56 60 63 80 76 60  
## [1818] 60 80 82 80 73 40 80 71 60 65 77 80 78 77 80 76 60 60 80 80 70 60 76  
## [1841] 70 80 82 80 80 78 80 60 80 66 76 80 60 77 60 80 67 20 60 60 70 65 40  
## [1864] 60 80 80 80 78 60 73 80 80 80 80 63 76 80 80 73 82 82 75 40 80 70 73  
## [1887] 20 40 65 80 63 80 80 60 80 82 80 60 20 80 50 60 60 75 80 60 80 20 73  
## [1910] 73 80 82 80 67 80 75 80 20 60 77 80 80 67 80 80 40 52 80 60 73 30 67  
## [1933] 70 73 80 77 80 80 80 60 80 76 80 78 72 80 80 80 80 80 20 80 80 73 80  
## [1956] 60 60 66 75 70 76 80 40 70 75 78 80 73 60 74 65 65 73 67 80 60 80 80  
## [1979] 80 80 20 80 60 80 60 80 40 78 80 73 80 70 75 80 60 73 80 40 80 80 80  
## [2002] 80 80 80 80 80 20 80 80 73 80 75 20 70 80 80 60 82 71 40 80 80 60 80  
## [2025] 73 73 80 73 70 80 70 73 30 80 80 60 80 80 20 20 80 67 80 60 80 73 60  
## [2048] 60 53 40 73 80 60 80 60 50 80 76 80 80 60 73 60 80 50 80 70 20 60 80  
## [2071] 64 80 70 73 80 60 73 80 20 80 67 73 80 80 70 73 60 40 80 80 80 40 70  
## [2094] 40 60 73 20 60 80 80 80 80 73 60 80 60 60 60 20 80 20 20 80 20 40 60  
## [2117] 20 60 80 50 80 60 60 80 80 67 73 80 20 80 67 80 73 80 80 40 73 60 20  
## [2140] 20 60 80 20 40 60 60 70 60 60 80 40 60 20 40 80 80 60 40 50

data$review\_scores\_rating[which(data$review\_scores\_rating<83)]<-median(data$review\_scores\_rating,na.rm=TRUE) # 83 is the lower whisker, no values above the upper whisker

Correlation of the numerical attributes in the dataset

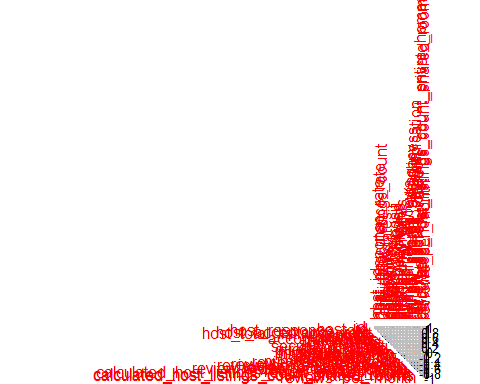
#First create an numerical attribute dataframe of the dataset  
#Then create a correlation matrix  
#Remove any highly correlated attributes to one another  
  
num\_cols\_only <- unlist(lapply(data,is.numeric)) #When you lapply is.numeric , it returns a list therefore you need to unlist to use it to make a numeric dataframe  
data\_numeric<-data[,num\_cols\_only]  
cor\_matrix<-cor(data\_numeric,use="complete.obs")  
library(corrplot)

## Warning: package 'corrplot' was built under R version 3.6.3

## corrplot 0.84 loaded

corrplot(cor\_matrix,type="upper")

## Warning in corrplot(cor\_matrix, type = "upper"): Not been able to  
## calculate text margin, please try again with a clean new empty window using  
## {plot.new(); dev.off()} or reduce tl.cex



#Bedrooms and bathrooms is moderately postively correlated, we can remove bathrooms and keep bedrooms  
#Availability 365 is moderately postively correlated with the other availability values which makes sense  
#Accomadates number is moderately postively correlated with bedrooms,which makes sense as if you have more rooms you can accomodate more people

Dealing with NA values or missing values in the dataset

#Now that the outliers have been replaced, I will want to replace any NA values with the mean value  
#If there are records with missing values that are non numerical, I will remove that record if it is logical to do so  
  
data$price[which(is.na(data$price)==TRUE)]<-mean(data$price,na.rm=TRUE)  
data$bedrooms[which(is.na(data$bedrooms)==TRUE)]<-mean(data$bedrooms,na.rm=TRUE)  
data$bathrooms[which(is.na(data$bathrooms)==TRUE)]<-mean(data$bathrooms,na.rm=TRUE)  
data$beds[which(is.na(data$beds)==TRUE)]<-mean(data$beds,na.rm=TRUE)  
data$security\_deposit[which(is.na(data$security\_deposit)==TRUE)]<-mean(data$security\_deposit,na.rm=TRUE)  
data$review\_scores\_rating[which(is.na(data$review\_scores\_rating)==TRUE)]<-mean(data$review\_scores\_rating,na.rm=TRUE)  
data$review\_scores\_accuracy[which(is.na(data$review\_scores\_accuracy)==TRUE)]<-mean(data$review\_scores\_accuracy,na.rm=TRUE)  
data$review\_scores\_checkin[which(is.na(data$review\_scores\_checkin)==TRUE)]<-mean(data$review\_scores\_checkin,na.rm=TRUE)  
data$review\_scores\_cleanliness[which(is.na(data$review\_scores\_cleanliness)==TRUE)]<-mean(data$review\_scores\_cleanliness,na.rm=TRUE)  
data$review\_scores\_value[which(is.na(data$review\_scores\_value)==TRUE)]<-mean(data$review\_scores\_value,na.rm=TRUE)  
data$review\_scores\_location[which(is.na(data$review\_scores\_location)==TRUE)]<-mean(data$review\_scores\_location,na.rm=TRUE)  
data$review\_scores\_communication[which(is.na(data$review\_scores\_communication)==TRUE)]<-mean(data$review\_scores\_communication,na.rm=TRUE)  
data$cleaning\_fee[which(is.na(data$cleaning\_fee)==TRUE)]<-mean(data$cleaning\_fee,na.rm=TRUE)  
  
data<-data[which(!data$host\_is\_superhost==""),] # Only 3 values that were blank in the dataset, removed  
data<-data[which(!data$bed\_type==""),] #10 blank values removed  
data<-data[which(!data$host\_response\_time==""),] # Only 3 values that were blank in the dataset, which also happens to be the same rows of the superhost that were blank  
data<-data[which(!data$price==0),]#I also removed prices that were at 0, since it doesn't make sense for a listing to be at 0 for the context of the problem,since if it is 0 then that means it's free AirBnb.  
  
#After removing the blank values in the dataset, there was still blank factors in the str(data)  
str(data)

## 'data.frame': 37710 obs. of 71 variables:  
## $ id : int 109 344 2708 2732 2864 3021 5728 5729 5843 6033 ...  
## $ last\_scraped : Date, format: "2020-04-15" "2020-04-15" ...  
## $ name : chr "Amazing bright elegant condo park front \*UPGRADED\*" "Family perfect;Pool;Near Studios!" "Mirrored Mini-Suite with Fireplace - W. Hollywood" "Zen Life at the Beach" ...  
## $ summary : chr "\*\*\* Unit upgraded with new bamboo flooring, brand new Ultra HD 50\" Sony TV, new paint, new lighting, new mattr"| \_\_truncated\_\_ "This home is perfect for families; aspiring child actors w/parents; and friends vacationing for the summer or h"| \_\_truncated\_\_ "Our best memory foam pillows you'll ever sleep on. Handmade Amish wildflower soap. SoCal: beaches, Walk of Fa"| \_\_truncated\_\_ "" ...  
## $ space : chr "\*\*\* Unit upgraded with new bamboo flooring, brand new Ultra HD 50\" Sony TV, new paint, new lighting, new mattr"| \_\_truncated\_\_ "Cheerful & comfortable; near studios, amusement parks, downtown, beaches! Central and modern; private, conveni"| \_\_truncated\_\_ "Flickering fireplace. BlendtecÂ® Designer 625 Blender Bundle with Twister Jar MORE THAN JUST SMOOTHIES: From h"| \_\_truncated\_\_ "This is a beautiful three story townhouse that will enhance your Santa Monica experience. This airy, light fil"| \_\_truncated\_\_ ...  
## $ description : chr "\*\*\* Unit upgraded with new bamboo flooring, brand new Ultra HD 50\" Sony TV, new paint, new lighting, new mattr"| \_\_truncated\_\_ "This home is perfect for families; aspiring child actors w/parents; and friends vacationing for the summer or h"| \_\_truncated\_\_ "Our best memory foam pillows you'll ever sleep on. Handmade Amish wildflower soap. SoCal: beaches, Walk of Fa"| \_\_truncated\_\_ "This is a beautiful three story townhouse that will enhance your Santa Monica experience. This airy, light fil"| \_\_truncated\_\_ ...  
## $ neighborhood\_overview : chr "" "Quiet-yet-close to all the fun in LA! Hollywood, Universal Studios, beaches, great hikes and more are all minutes away." "We are minutes away from the Mentor Language Institute, Kings College, Musicians Institute, and many film schoo"| \_\_truncated\_\_ "This is the best part of Santa Monica. Quiet, calm, safe." ...  
## $ notes : chr "" "One dog may be on premises, friendly and cared for by caretaker. A great addition to stabilize kids-away-from-"| \_\_truncated\_\_ "BlendtecÂ® Designer 625 Blender Bundle with Twister Jar MORE THAN JUST SMOOTHIES: From hot soup to ice cream an"| \_\_truncated\_\_ "" ...  
## $ transit : chr "" "Short drive to subway and elevated trains running to major tourist spots in LA; freeways minutes away as well. "| \_\_truncated\_\_ "There are many buses; bus stops going in every direction are just around the corner. The subway is five minutes"| \_\_truncated\_\_ "Walking distance to all transportation: buses, train." ...  
## $ access : chr "" "Pool, patio and self-contained main house all accessible freely by guests. Garage, pool house and back caretak"| \_\_truncated\_\_ "Kitchen with new refrigerator, dishwasher, stove and oven with new plank floors. Jacuzzi and sundeck New gym wi"| \_\_truncated\_\_ "" ...  
## $ interaction : chr "" "Host and caretaker may be available throughout your stay to assist in troubleshooting with local information/am"| \_\_truncated\_\_ "I am friendly and available to help you with your needs even before you arrive. I am seldom seen as I am in and"| \_\_truncated\_\_ "" ...  
## $ house\_rules : chr "Camelot NEW RESIDENTSâ\200\231 GENERAL INFORMATION File: New Residents Info 1 Created on 12/13/05 Hello, a"| \_\_truncated\_\_ "Host asks that guests refrain from partying loudly into the evening on back patio/pool area. Guest swim at the"| \_\_truncated\_\_ "I just have one rule. The Golden Rule Do unto others as you would have them do unto you. This is a no smoking d"| \_\_truncated\_\_ "ABOUT YOU. Friendly travelers or people coming to LA for work are welcome to stay .I am open to interns who vi"| \_\_truncated\_\_ ...  
## $ host\_id : int 521 767 3008 3041 3207 3415 9171 9171 9171 11619 ...  
## $ host\_since : Date, format: "2008-06-27" "2008-07-11" ...  
## $ host\_about : chr "Search for me on the Internet with the keyword pppaolo\n\nPolyhedric Lateral Thinker Entrepreneur, a Human Netw"| \_\_truncated\_\_ "Single mother, CEO and Owner of an international coaching and training business. \n\nLove to travel! Family-fo"| \_\_truncated\_\_ "Writer.\nLiterary Manager.\nPhotographer.\nProducing Partner.\nI work all the time.\nI wear many hats.\nProfess"| \_\_truncated\_\_ "I have been teaching yoga and meditation for 30 years.\nWorld-traveled,passionate,love life and committed to ma"| \_\_truncated\_\_ ...  
## $ host\_response\_time : Factor w/ 6 levels "","a few days or more",..: 4 4 5 6 3 4 6 6 6 6 ...  
## $ host\_response\_rate : num 100 67 100 100 NA 63 100 100 100 100 ...  
## $ host\_acceptance\_rate : num 97 97 94 73 NA 97 99 99 99 94 ...  
## $ host\_is\_superhost : Factor w/ 3 levels "","f","t": 2 2 3 2 2 2 3 3 3 2 ...  
## $ host\_total\_listings\_count : int 1 1 2 2 1 6 8 8 8 15 ...  
## $ host\_verifications : Factor w/ 491 levels "['email', 'facebook', 'reviews', 'jumio', 'government\_id', 'work\_email']",..: 101 280 101 295 64 278 116 116 116 289 ...  
## $ host\_identity\_verified : Factor w/ 3 levels "","f","t": 3 3 3 2 3 3 2 2 2 3 ...  
## $ street : Factor w/ 431 levels " Los Angeles, CA, United States",..: 70 44 179 311 34 179 179 179 179 427 ...  
## $ neighbourhood\_cleansed : Factor w/ 264 levels "Acton","Adams-Normandie",..: 54 32 102 194 23 104 57 57 57 264 ...  
## $ neighbourhood\_group\_cleansed : Factor w/ 3 levels "City of Los Angeles",..: 2 2 1 2 2 1 1 1 1 1 ...  
## $ city : Factor w/ 404 levels ""," Los Angeles",..: 67 41 157 292 33 157 157 157 157 399 ...  
## $ zipcode : Factor w/ 330 levels "","0000","10001",..: 81 236 53 117 138 53 67 67 67 219 ...  
## $ latitude : num 34 34.2 34.1 34 33.9 ...  
## $ longitude : num -118 -118 -118 -118 -118 ...  
## $ property\_type : Factor w/ 46 levels "Aparthotel","Apartment",..: 16 26 2 2 2 22 39 23 26 7 ...  
## $ room\_type : Factor w/ 4 levels "Entire home/apt",..: 1 1 3 3 1 1 3 3 1 1 ...  
## $ accommodates : int 6 6 1 1 2 2 2 3 5 4 ...  
## $ bathrooms : num 2 1 1.5 1 1 1 1 1 1 1 ...  
## $ bedrooms : num 2 3 1 1 1 1 1 1 2 1 ...  
## $ beds : num 3 3 1 1 1 2 1 1 2 1 ...  
## $ bed\_type : Factor w/ 6 levels "","Airbed","Couch",..: 6 6 6 5 6 6 6 2 6 6 ...  
## $ amenities : chr "c(TV, \\Cable TV\\, Internet, Wifi, \\Air conditioning\\, \\Wheelchair accessible\\, Pool, Kitchen, \\Free park"| \_\_truncated\_\_ "c(Internet, Wifi, \\Air conditioning\\, Pool, Kitchen, \\Pets live on this property\\, Dog(s), \\Free street pa"| \_\_truncated\_\_ "c(Internet, Wifi, \\Air conditioning\\, \\Wheelchair accessible\\, Kitchen, \\Free parking on premises\\, Gym, "| \_\_truncated\_\_ "c(Internet, Wifi, Kitchen, Heating, Washer, Dryer, \\Smoke detector\\, Essentials, Shampoo, Hangers, \\Hair dry"| \_\_truncated\_\_ ...  
## $ square\_feet : int NA NA NA NA NA NA 64 400 NA NA ...  
## $ price : num 122 168 79 155 80 145 75 105 303 85 ...  
## $ security\_deposit : num 500 0 450 182 100 ...  
## $ cleaning\_fee : num 240 100 84 100 75 60 25 50 100 25 ...  
## $ guests\_included : int 3 6 1 1 1 1 1 2 2 2 ...  
## $ extra\_people : num 25 0 0 0 25 9 15 15 15 25 ...  
## $ minimum\_nights : int 30 2 30 1 2 3 30 30 1 5 ...  
## $ maximum\_nights : int 730 14 366 180 730 730 1125 1125 90 30 ...  
## $ calendar\_updated : Factor w/ 91 levels "1 week ago","10 months ago",..: 13 77 26 26 16 2 90 12 14 40 ...  
## $ has\_availability : Factor w/ 1 level "t": 1 1 1 1 1 1 1 1 1 1 ...  
## $ availability\_30 : int 0 0 30 30 0 0 0 16 14 30 ...  
## $ availability\_60 : int 0 0 32 60 0 12 12 19 38 47 ...  
## $ availability\_90 : int 0 1 32 90 0 42 42 28 61 47 ...  
## $ availability\_365 : int 14 73 281 365 0 317 249 230 136 47 ...  
## $ calendar\_last\_scraped : Date, format: "2020-04-15" "2020-04-15" ...  
## $ number\_of\_reviews : int 2 8 24 21 0 23 309 228 126 25 ...  
## $ first\_review : Date, format: "2011-08-15" "2016-06-14" ...  
## $ last\_review : Date, format: "2016-05-15" "2019-10-19" ...  
## $ review\_scores\_rating : num 97 97 97 94 96.2 ...  
## $ review\_scores\_accuracy : num 10 10 10 9 9.61 ...  
## $ review\_scores\_cleanliness : num 10 10 10 9 9.42 ...  
## $ review\_scores\_checkin : num 6 10 10 9 9.75 ...  
## $ review\_scores\_communication : num 8 10 10 9 9.72 ...  
## $ review\_scores\_location : num 10 10 10 10 9.7 ...  
## $ review\_scores\_value : num 8 10 10 9 9.43 ...  
## $ requires\_license : Factor w/ 2 levels "f","t": 1 1 2 2 1 2 2 2 2 2 ...  
## $ instant\_bookable : Factor w/ 2 levels "f","t": 1 2 2 1 1 1 2 2 2 2 ...  
## $ cancellation\_policy : Factor w/ 9 levels "flexible","luxury\_moderate",..: 7 1 7 7 7 7 5 5 5 7 ...  
## $ require\_guest\_profile\_picture : Factor w/ 2 levels "f","t": 2 1 1 1 1 1 1 1 1 1 ...  
## $ require\_guest\_phone\_verification : Factor w/ 2 levels "f","t": 1 1 1 1 1 1 1 1 1 1 ...  
## $ calculated\_host\_listings\_count\_entire\_homes : int 1 1 0 1 1 1 1 1 1 3 ...  
## $ calculated\_host\_listings\_count\_private\_rooms: int 0 0 2 1 0 3 3 3 3 3 ...  
## $ calculated\_host\_listings\_count\_shared\_rooms : int 0 0 0 0 0 0 0 0 0 0 ...  
## $ reviews\_per\_month : num 0.02 0.17 0.34 0.19 NA 0.29 2.36 1.76 1.16 0.19 ...

#Removed for analysis  
levels(data$host\_is\_superhost)[which(levels(data$host\_is\_superhost)=="")]<-NA   
levels(data$bed\_type)[which(levels(data$bed\_type)=="")]<-NA   
levels(data$host\_response\_time)[which(levels(data$host\_response\_time)=="")]<-NA  
levels(data$host\_identity\_verified)[which(levels(data$host\_identity\_verified)=="")]<-NA

Backward elimination and checking assumptions of the linear regression model

#Still trying to figure out the best way incorporate amenities into my models,and still a work in progress for the final results/report  
model<-lm(price~bedrooms+property\_type+beds+host\_is\_superhost+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+  
 review\_scores\_rating+bed\_type+review\_scores\_accuracy+review\_scores\_checkin+review\_scores\_cleanliness+  
 review\_scores\_communication+review\_scores\_location+review\_scores\_value,data=data)  
  
library(MASS)

## Warning: package 'MASS' was built under R version 3.6.3

summary(model)

##   
## Call:  
## lm(formula = price ~ bedrooms + property\_type + beds + host\_is\_superhost +   
## neighbourhood\_cleansed + cleaning\_fee + security\_deposit +   
## review\_scores\_rating + bed\_type + review\_scores\_accuracy +   
## review\_scores\_checkin + review\_scores\_cleanliness + review\_scores\_communication +   
## review\_scores\_location + review\_scores\_value, data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -189.972 -32.463 -8.119 22.527 254.250   
##   
## Coefficients:  
## Estimate  
## (Intercept) 1.238e+01  
## bedrooms 2.247e+01  
## property\_typeApartment -1.632e+01  
## property\_typeBarn -2.555e+01  
## property\_typeBed and breakfast -2.668e+01  
## property\_typeBoat -2.088e+01  
## property\_typeBoutique hotel 2.198e+01  
## property\_typeBungalow -1.478e+01  
## property\_typeBus 7.729e+01  
## property\_typeCabin 2.786e+00  
## property\_typeCamper/RV -1.045e+01  
## property\_typeCampsite -3.328e+01  
## property\_typeCasa particular (Cuba) -3.070e+01  
## property\_typeCastle -4.489e+00  
## property\_typeCave -2.574e+01  
## property\_typeChalet -7.520e+01  
## property\_typeCondominium -1.404e+01  
## property\_typeCottage -5.189e+00  
## property\_typeDome house -4.307e+01  
## property\_typeDorm -8.815e+01  
## property\_typeEarth house -9.842e+00  
## property\_typeFarm stay -1.453e+01  
## property\_typeGuest suite -1.422e+01  
## property\_typeGuesthouse -3.026e+00  
## property\_typeHostel -4.755e+01  
## property\_typeHotel 2.161e+01  
## property\_typeHouse -2.308e+01  
## property\_typeHouseboat -5.149e+01  
## property\_typeHut -5.759e+01  
## property\_typeIgloo -4.867e+01  
## property\_typeIsland -5.746e+01  
## property\_typeLoft -3.427e+00  
## property\_typeMinsu (Taiwan) -3.502e+01  
## property\_typeNature lodge -6.751e+01  
## property\_typeOther -2.920e+00  
## property\_typePension (South Korea) -1.713e+01  
## property\_typeResort 9.509e+01  
## property\_typeServiced apartment 1.132e+01  
## property\_typeTent 9.285e-01  
## property\_typeTiny house -8.724e+00  
## property\_typeTipi -1.744e+00  
## property\_typeTownhouse -2.122e+01  
## property\_typeTrain 1.106e+01  
## property\_typeTreehouse 2.315e+01  
## property\_typeVacation home -7.140e+01  
## property\_typeVilla -2.135e+01  
## property\_typeYurt -2.844e+01  
## beds 6.690e+00  
## host\_is\_superhostt 1.560e+00  
## neighbourhood\_cleansedAdams-Normandie -1.899e+01  
## neighbourhood\_cleansedAgoura Hills -8.454e+00  
## neighbourhood\_cleansedAgua Dulce -5.255e-01  
## neighbourhood\_cleansedAlhambra -2.990e+01  
## neighbourhood\_cleansedAlondra Park -1.986e+01  
## neighbourhood\_cleansedAltadena -2.011e+01  
## neighbourhood\_cleansedAngeles Crest -5.614e+01  
## neighbourhood\_cleansedArcadia -2.828e+01  
## neighbourhood\_cleansedArleta -5.052e+01  
## neighbourhood\_cleansedArlington Heights -5.012e+01  
## neighbourhood\_cleansedArtesia -3.448e+01  
## neighbourhood\_cleansedAthens -3.311e+01  
## neighbourhood\_cleansedAtwater Village -1.356e+01  
## neighbourhood\_cleansedAvalon -1.608e+01  
## neighbourhood\_cleansedAvocado Heights -2.716e+01  
## neighbourhood\_cleansedAzusa -2.226e+01  
## neighbourhood\_cleansedBaldwin Hills/Crenshaw -2.849e+01  
## neighbourhood\_cleansedBaldwin Park -2.675e+01  
## neighbourhood\_cleansedBel-Air -6.627e+00  
## neighbourhood\_cleansedBell -3.477e+01  
## neighbourhood\_cleansedBell Gardens -3.022e+01  
## neighbourhood\_cleansedBellflower -3.947e+01  
## neighbourhood\_cleansedBeverly Crest -8.525e+00  
## neighbourhood\_cleansedBeverly Grove 1.053e+01  
## neighbourhood\_cleansedBeverly Hills 1.950e+00  
## neighbourhood\_cleansedBeverlywood -2.823e+01  
## neighbourhood\_cleansedBoyle Heights -2.841e+01  
## neighbourhood\_cleansedBradbury -3.368e+00  
## neighbourhood\_cleansedBrentwood -3.122e+00  
## neighbourhood\_cleansedBroadway-Manchester -3.433e+01  
## neighbourhood\_cleansedBurbank -1.555e+01  
## neighbourhood\_cleansedCalabasas -1.925e+01  
## neighbourhood\_cleansedCanoga Park -3.144e+01  
## neighbourhood\_cleansedCarson -3.797e+01  
## neighbourhood\_cleansedCarthay 2.620e-01  
## neighbourhood\_cleansedCastaic -4.469e+01  
## neighbourhood\_cleansedCastaic Canyons -3.149e+01  
## neighbourhood\_cleansedCentral-Alameda -4.184e+01  
## neighbourhood\_cleansedCentury City 5.559e-01  
## neighbourhood\_cleansedCerritos -4.032e+01  
## neighbourhood\_cleansedCharter Oak -5.907e+01  
## neighbourhood\_cleansedChatsworth -2.200e+01  
## neighbourhood\_cleansedChatsworth Reservoir 8.791e+01  
## neighbourhood\_cleansedChesterfield Square -5.606e+01  
## neighbourhood\_cleansedCheviot Hills -1.313e+01  
## neighbourhood\_cleansedChinatown -1.841e+01  
## neighbourhood\_cleansedCitrus -1.190e+01  
## neighbourhood\_cleansedClaremont -1.069e+01  
## neighbourhood\_cleansedCommerce -3.820e+00  
## neighbourhood\_cleansedCompton -2.067e+01  
## neighbourhood\_cleansedCovina -3.493e+01  
## neighbourhood\_cleansedCudahy -1.142e+02  
## neighbourhood\_cleansedCulver City -3.606e+00  
## neighbourhood\_cleansedCypress Park -4.463e+01  
## neighbourhood\_cleansedDel Aire -1.983e+01  
## neighbourhood\_cleansedDel Rey 4.562e+00  
## neighbourhood\_cleansedDesert View Highlands 7.772e+00  
## neighbourhood\_cleansedDiamond Bar -2.937e+01  
## neighbourhood\_cleansedDowney -3.207e+01  
## neighbourhood\_cleansedDowntown 9.459e+00  
## neighbourhood\_cleansedDuarte -3.796e+01  
## neighbourhood\_cleansedEagle Rock -2.003e+01  
## neighbourhood\_cleansedEast Compton -3.742e+01  
## neighbourhood\_cleansedEast Hollywood -3.190e+01  
## neighbourhood\_cleansedEast Los Angeles -3.096e+01  
## neighbourhood\_cleansedEast Pasadena -1.359e+01  
## neighbourhood\_cleansedEast San Gabriel -4.539e+01  
## neighbourhood\_cleansedEast Whittier 7.690e+00  
## neighbourhood\_cleansedEcho Park -1.525e+01  
## neighbourhood\_cleansedEl Monte -2.676e+01  
## neighbourhood\_cleansedEl Segundo -1.412e+01  
## neighbourhood\_cleansedEl Sereno -3.416e+01  
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## neighbourhood\_cleansedElysian Valley -1.222e+01  
## neighbourhood\_cleansedEncino -2.133e+01  
## neighbourhood\_cleansedExposition Park -2.018e+01  
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## neighbourhood\_cleansedGardena -3.528e+01  
## neighbourhood\_cleansedGlassell Park -2.074e+01  
## neighbourhood\_cleansedGlendale -4.572e+00  
## neighbourhood\_cleansedGlendora -3.477e+01  
## neighbourhood\_cleansedGramercy Park 1.327e+01  
## neighbourhood\_cleansedGranada Hills -1.189e+01  
## neighbourhood\_cleansedGreen Meadows -2.686e+01  
## neighbourhood\_cleansedGreen Valley -1.940e+01  
## neighbourhood\_cleansedGriffith Park -5.625e+01  
## neighbourhood\_cleansedHacienda Heights -3.854e+01  
## neighbourhood\_cleansedHancock Park -3.327e+00  
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## neighbourhood\_cleansedHawaiian Gardens -4.673e+01  
## neighbourhood\_cleansedHawthorne -3.876e+01  
## neighbourhood\_cleansedHermosa Beach -5.296e-01  
## neighbourhood\_cleansedHighland Park -2.457e+01  
## neighbourhood\_cleansedHistoric South-Central -6.303e+01  
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## neighbourhood\_cleansedJefferson Park -2.384e+01  
## neighbourhood\_cleansedKoreatown -2.438e+01  
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## neighbourhood\_cleansedLa Habra Heights -1.100e+00  
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## neighbourhood\_cleansedLa Puente -2.687e+01  
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## neighbourhood\_cleansedManhattan Beach 4.370e+00  
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## neighbourhood\_cleansedToluca Lake -9.936e+00  
## neighbourhood\_cleansedTopanga 9.437e+00  
## neighbourhood\_cleansedTorrance -2.728e+01  
## neighbourhood\_cleansedTujunga -3.994e+01  
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## neighbourhood\_cleansedUnincorporated Santa Monica Mountains -5.557e+00  
## neighbourhood\_cleansedUnincorporated Santa Susana Mountains -1.177e+01  
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## neighbourhood\_cleansedVermont Knolls -4.607e+01  
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## neighbourhood\_cleansedVincent -3.701e+00  
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## neighbourhood\_cleansedWatts -5.916e+01  
## neighbourhood\_cleansedWest Adams -2.790e+01  
## neighbourhood\_cleansedWest Carson -2.706e+01  
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## neighbourhood\_cleansedWest Hills -2.409e+01  
## neighbourhood\_cleansedWest Hollywood 3.658e+00  
## neighbourhood\_cleansedWest Los Angeles -2.811e+01  
## neighbourhood\_cleansedWest Puente Valley -2.516e+01  
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## neighbourhood\_cleansedWestwood -6.939e-01  
## neighbourhood\_cleansedWhittier -2.965e+01  
## neighbourhood\_cleansedWillowbrook -2.021e+01  
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## neighbourhood\_cleansedWindsor Square -7.199e+00  
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## neighbourhood\_cleansedWoodland Hills -1.945e+01  
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## security\_deposit 2.394e-02  
## review\_scores\_rating 1.740e-01  
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## bed\_typePull-out Sofa 1.162e+01  
## bed\_typeReal Bed 2.405e+01  
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## review\_scores\_location 3.957e+00  
## review\_scores\_value -3.419e+00  
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## (Intercept) 2.846e+01  
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## property\_typeApartment 4.222e+00  
## property\_typeBarn 1.799e+01  
## property\_typeBed and breakfast 6.355e+00  
## property\_typeBoat 1.172e+01  
## property\_typeBoutique hotel 5.195e+00  
## property\_typeBungalow 4.537e+00  
## property\_typeBus 5.221e+01  
## property\_typeCabin 7.858e+00  
## property\_typeCamper/RV 5.959e+00  
## property\_typeCampsite 1.858e+01  
## property\_typeCasa particular (Cuba) 3.695e+01  
## property\_typeCastle 1.188e+01  
## property\_typeCave 2.637e+01  
## property\_typeChalet 2.161e+01  
## property\_typeCondominium 4.350e+00  
## property\_typeCottage 5.746e+00  
## property\_typeDome house 1.350e+01  
## property\_typeDorm 1.888e+01  
## property\_typeEarth house 1.170e+01  
## property\_typeFarm stay 1.043e+01  
## property\_typeGuest suite 4.438e+00  
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## property\_typeHostel 5.904e+00  
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## property\_typeHouse 4.253e+00  
## property\_typeHouseboat 5.209e+01  
## property\_typeHut 2.366e+01  
## property\_typeIgloo 5.208e+01  
## property\_typeIsland 3.700e+01  
## property\_typeLoft 4.591e+00  
## property\_typeMinsu (Taiwan) 5.537e+01  
## property\_typeNature lodge 3.734e+01  
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## property\_typeTreehouse 1.628e+01  
## property\_typeVacation home 3.696e+01  
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## host\_is\_superhostt 6.372e-01  
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## neighbourhood\_cleansedAngeles Crest 3.709e+01  
## neighbourhood\_cleansedArcadia 2.628e+01  
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## neighbourhood\_cleansedBel-Air 2.674e+01  
## neighbourhood\_cleansedBell 3.673e+01  
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## neighbourhood\_cleansedBellflower 2.748e+01  
## neighbourhood\_cleansedBeverly Crest 2.635e+01  
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## neighbourhood\_cleansedBradbury 4.505e+01  
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## neighbourhood\_cleansedCarthay 2.670e+01  
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## neighbourhood\_cleansedCastaic Canyons 2.840e+01  
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## neighbourhood\_cleansedChatsworth 2.695e+01  
## neighbourhood\_cleansedChatsworth Reservoir 5.801e+01  
## neighbourhood\_cleansedChesterfield Square 2.804e+01  
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## neighbourhood\_cleansedDowney 2.665e+01  
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## neighbourhood\_cleansedEast Compton 4.500e+01  
## neighbourhood\_cleansedEast Hollywood 2.614e+01  
## neighbourhood\_cleansedEast Los Angeles 2.645e+01  
## neighbourhood\_cleansedEast Pasadena 2.685e+01  
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## neighbourhood\_cleansedGreen Meadows 3.132e+01  
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## neighbourhood\_cleansedHarbor City 2.829e+01  
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## neighbourhood\_cleansedParamount 3.078e+01  
## neighbourhood\_cleansedPasadena 2.615e+01  
## neighbourhood\_cleansedPico-Robertson 2.628e+01  
## neighbourhood\_cleansedPico-Union 2.650e+01  
## neighbourhood\_cleansedPico Rivera 2.728e+01  
## neighbourhood\_cleansedPlaya del Rey 2.647e+01  
## neighbourhood\_cleansedPlaya Vista 2.672e+01  
## neighbourhood\_cleansedPomona 2.642e+01  
## neighbourhood\_cleansedPorter Ranch 2.864e+01  
## neighbourhood\_cleansedQuartz Hill 3.259e+01  
## neighbourhood\_cleansedRancho Dominguez 3.487e+01  
## neighbourhood\_cleansedRancho Palos Verdes 2.669e+01  
## neighbourhood\_cleansedRancho Park 2.682e+01  
## neighbourhood\_cleansedRedondo Beach 2.619e+01  
## neighbourhood\_cleansedReseda 2.636e+01  
## neighbourhood\_cleansedRidge Route 5.803e+01  
## neighbourhood\_cleansedRolling Hills 3.357e+01  
## neighbourhood\_cleansedRolling Hills Estates 3.487e+01  
## neighbourhood\_cleansedRosemead 2.644e+01  
## neighbourhood\_cleansedRowland Heights 2.614e+01  
## neighbourhood\_cleansedSan Dimas 2.714e+01  
## neighbourhood\_cleansedSan Fernando 3.078e+01  
## neighbourhood\_cleansedSan Gabriel 2.633e+01  
## neighbourhood\_cleansedSan Marino 2.975e+01  
## neighbourhood\_cleansedSan Pasqual 2.804e+01  
## neighbourhood\_cleansedSan Pedro 2.646e+01  
## neighbourhood\_cleansedSanta Clarita 2.638e+01  
## neighbourhood\_cleansedSanta Fe Springs 3.968e+01  
## neighbourhood\_cleansedSanta Monica 2.609e+01  
## neighbourhood\_cleansedSawtelle 2.615e+01  
## neighbourhood\_cleansedSepulveda Basin 3.488e+01  
## neighbourhood\_cleansedShadow Hills 2.761e+01  
## neighbourhood\_cleansedSherman Oaks 2.617e+01  
## neighbourhood\_cleansedSierra Madre 2.840e+01  
## neighbourhood\_cleansedSignal Hill 2.725e+01  
## neighbourhood\_cleansedSilver Lake 2.614e+01  
## neighbourhood\_cleansedSouth Diamond Bar 5.801e+01  
## neighbourhood\_cleansedSouth El Monte 3.673e+01  
## neighbourhood\_cleansedSouth Gate 2.808e+01  
## neighbourhood\_cleansedSouth Park 2.933e+01  
## neighbourhood\_cleansedSouth Pasadena 2.662e+01  
## neighbourhood\_cleansedSouth San Gabriel 2.742e+01  
## neighbourhood\_cleansedSouth San Jose Hills 3.126e+01  
## neighbourhood\_cleansedSouth Whittier 2.877e+01  
## neighbourhood\_cleansedSoutheast Antelope Valley 2.965e+01  
## neighbourhood\_cleansedStevenson Ranch 3.038e+01  
## neighbourhood\_cleansedStudio City 2.618e+01  
## neighbourhood\_cleansedSun Valley 2.666e+01  
## neighbourhood\_cleansedSun Village 3.356e+01  
## neighbourhood\_cleansedSunland 3.082e+01  
## neighbourhood\_cleansedSylmar 2.777e+01  
## neighbourhood\_cleansedTarzana 2.639e+01  
## neighbourhood\_cleansedTemple City 2.633e+01  
## neighbourhood\_cleansedToluca Lake 2.674e+01  
## neighbourhood\_cleansedTopanga 2.622e+01  
## neighbourhood\_cleansedTorrance 2.620e+01  
## neighbourhood\_cleansedTujunga 2.788e+01  
## neighbourhood\_cleansedTujunga Canyons 3.450e+01  
## neighbourhood\_cleansedUnincorporated Catalina Island 3.555e+01  
## neighbourhood\_cleansedUnincorporated Santa Monica Mountains 2.644e+01  
## neighbourhood\_cleansedUnincorporated Santa Susana Mountains 2.945e+01  
## neighbourhood\_cleansedUniversal City 3.968e+01  
## neighbourhood\_cleansedUniversity Park 2.680e+01  
## neighbourhood\_cleansedVal Verde 3.675e+01  
## neighbourhood\_cleansedValinda 2.840e+01  
## neighbourhood\_cleansedValley Glen 2.632e+01  
## neighbourhood\_cleansedValley Village 2.643e+01  
## neighbourhood\_cleansedVan Nuys 2.625e+01  
## neighbourhood\_cleansedVenice 2.608e+01  
## neighbourhood\_cleansedVermont-Slauson 2.874e+01  
## neighbourhood\_cleansedVermont Knolls 2.878e+01  
## neighbourhood\_cleansedVermont Square 2.658e+01  
## neighbourhood\_cleansedVermont Vista 3.487e+01  
## neighbourhood\_cleansedVernon 3.968e+01  
## neighbourhood\_cleansedVeterans Administration 2.976e+01  
## neighbourhood\_cleansedView Park-Windsor Hills 2.659e+01  
## neighbourhood\_cleansedVincent 3.675e+01  
## neighbourhood\_cleansedWalnut 2.661e+01  
## neighbourhood\_cleansedWatts 2.790e+01  
## neighbourhood\_cleansedWest Adams 2.658e+01  
## neighbourhood\_cleansedWest Carson 2.734e+01  
## neighbourhood\_cleansedWest Compton 3.487e+01  
## neighbourhood\_cleansedWest Covina 2.647e+01  
## neighbourhood\_cleansedWest Hills 2.660e+01  
## neighbourhood\_cleansedWest Hollywood 2.612e+01  
## neighbourhood\_cleansedWest Los Angeles 2.635e+01  
## neighbourhood\_cleansedWest Puente Valley 2.976e+01  
## neighbourhood\_cleansedWest Whittier-Los Nietos 3.128e+01  
## neighbourhood\_cleansedWestchester 2.623e+01  
## neighbourhood\_cleansedWestlake 2.613e+01  
## neighbourhood\_cleansedWestlake Village 3.078e+01  
## neighbourhood\_cleansedWestmont 2.777e+01  
## neighbourhood\_cleansedWestwood 2.615e+01  
## neighbourhood\_cleansedWhittier 2.674e+01  
## neighbourhood\_cleansedWillowbrook 2.878e+01  
## neighbourhood\_cleansedWilmington 2.752e+01  
## neighbourhood\_cleansedWindsor Square 2.724e+01  
## neighbourhood\_cleansedWinnetka 2.669e+01  
## neighbourhood\_cleansedWoodland Hills 2.621e+01  
## cleaning\_fee 5.979e-03  
## security\_deposit 1.855e-03  
## review\_scores\_rating 8.342e-02  
## bed\_typeCouch 9.358e+00  
## bed\_typeFuton 7.619e+00  
## bed\_typePull-out Sofa 8.446e+00  
## bed\_typeReal Bed 6.219e+00  
## review\_scores\_accuracy 6.026e-01  
## review\_scores\_checkin 6.186e-01  
## review\_scores\_cleanliness 4.527e-01  
## review\_scores\_communication 6.199e-01  
## review\_scores\_location 5.684e-01  
## review\_scores\_value 5.576e-01  
## t value  
## (Intercept) 0.435  
## bedrooms 50.622  
## property\_typeApartment -3.866  
## property\_typeBarn -1.420  
## property\_typeBed and breakfast -4.198  
## property\_typeBoat -1.781  
## property\_typeBoutique hotel 4.232  
## property\_typeBungalow -3.258  
## property\_typeBus 1.480  
## property\_typeCabin 0.355  
## property\_typeCamper/RV -1.754  
## property\_typeCampsite -1.791  
## property\_typeCasa particular (Cuba) -0.831  
## property\_typeCastle -0.378  
## property\_typeCave -0.976  
## property\_typeChalet -3.479  
## property\_typeCondominium -3.229  
## property\_typeCottage -0.903  
## property\_typeDome house -3.190  
## property\_typeDorm -4.668  
## property\_typeEarth house -0.841  
## property\_typeFarm stay -1.393  
## property\_typeGuest suite -3.203  
## property\_typeGuesthouse -0.691  
## property\_typeHostel -8.055  
## property\_typeHotel 2.848  
## property\_typeHouse -5.427  
## property\_typeHouseboat -0.988  
## property\_typeHut -2.434  
## property\_typeIgloo -0.935  
## property\_typeIsland -1.553  
## property\_typeLoft -0.746  
## property\_typeMinsu (Taiwan) -0.633  
## property\_typeNature lodge -1.808  
## property\_typeOther -0.424  
## property\_typePension (South Korea) -0.327  
## property\_typeResort 2.546  
## property\_typeServiced apartment 2.340  
## property\_typeTent 0.055  
## property\_typeTiny house -1.309  
## property\_typeTipi -0.076  
## property\_typeTownhouse -4.723  
## property\_typeTrain 0.299  
## property\_typeTreehouse 1.422  
## property\_typeVacation home -1.932  
## property\_typeVilla -4.653  
## property\_typeYurt -1.313  
## beds 15.912  
## host\_is\_superhostt 2.449  
## neighbourhood\_cleansedAdams-Normandie -0.700  
## neighbourhood\_cleansedAgoura Hills -0.310  
## neighbourhood\_cleansedAgua Dulce -0.018  
## neighbourhood\_cleansedAlhambra -1.141  
## neighbourhood\_cleansedAlondra Park -0.697  
## neighbourhood\_cleansedAltadena -0.766  
## neighbourhood\_cleansedAngeles Crest -1.513  
## neighbourhood\_cleansedArcadia -1.076  
## neighbourhood\_cleansedArleta -1.508  
## neighbourhood\_cleansedArlington Heights -1.898  
## neighbourhood\_cleansedArtesia -1.209  
## neighbourhood\_cleansedAthens -0.901  
## neighbourhood\_cleansedAtwater Village -0.511  
## neighbourhood\_cleansedAvalon -0.596  
## neighbourhood\_cleansedAvocado Heights -0.922  
## neighbourhood\_cleansedAzusa -0.833  
## neighbourhood\_cleansedBaldwin Hills/Crenshaw -1.070  
## neighbourhood\_cleansedBaldwin Park -0.981  
## neighbourhood\_cleansedBel-Air -0.248  
## neighbourhood\_cleansedBell -0.947  
## neighbourhood\_cleansedBell Gardens -0.867  
## neighbourhood\_cleansedBellflower -1.436  
## neighbourhood\_cleansedBeverly Crest -0.324  
## neighbourhood\_cleansedBeverly Grove 0.403  
## neighbourhood\_cleansedBeverly Hills 0.075  
## neighbourhood\_cleansedBeverlywood -1.029  
## neighbourhood\_cleansedBoyle Heights -1.071  
## neighbourhood\_cleansedBradbury -0.075  
## neighbourhood\_cleansedBrentwood -0.119  
## neighbourhood\_cleansedBroadway-Manchester -1.154  
## neighbourhood\_cleansedBurbank -0.594  
## neighbourhood\_cleansedCalabasas -0.718  
## neighbourhood\_cleansedCanoga Park -1.177  
## neighbourhood\_cleansedCarson -1.425  
## neighbourhood\_cleansedCarthay 0.010  
## neighbourhood\_cleansedCastaic -1.545  
## neighbourhood\_cleansedCastaic Canyons -1.109  
## neighbourhood\_cleansedCentral-Alameda -1.492  
## neighbourhood\_cleansedCentury City 0.020  
## neighbourhood\_cleansedCerritos -1.455  
## neighbourhood\_cleansedCharter Oak -1.945  
## neighbourhood\_cleansedChatsworth -0.816  
## neighbourhood\_cleansedChatsworth Reservoir 1.515  
## neighbourhood\_cleansedChesterfield Square -2.000  
## neighbourhood\_cleansedCheviot Hills -0.482  
## neighbourhood\_cleansedChinatown -0.691  
## neighbourhood\_cleansedCitrus -0.355  
## neighbourhood\_cleansedClaremont -0.397  
## neighbourhood\_cleansedCommerce -0.096  
## neighbourhood\_cleansedCompton -0.728  
## neighbourhood\_cleansedCovina -1.292  
## neighbourhood\_cleansedCudahy -1.968  
## neighbourhood\_cleansedCulver City -0.138  
## neighbourhood\_cleansedCypress Park -1.500  
## neighbourhood\_cleansedDel Aire -0.736  
## neighbourhood\_cleansedDel Rey 0.174  
## neighbourhood\_cleansedDesert View Highlands 0.173  
## neighbourhood\_cleansedDiamond Bar -1.115  
## neighbourhood\_cleansedDowney -1.204  
## neighbourhood\_cleansedDowntown 0.362  
## neighbourhood\_cleansedDuarte -1.358  
## neighbourhood\_cleansedEagle Rock -0.759  
## neighbourhood\_cleansedEast Compton -0.831  
## neighbourhood\_cleansedEast Hollywood -1.220  
## neighbourhood\_cleansedEast Los Angeles -1.170  
## neighbourhood\_cleansedEast Pasadena -0.506  
## neighbourhood\_cleansedEast San Gabriel -1.705  
## neighbourhood\_cleansedEast Whittier 0.221  
## neighbourhood\_cleansedEcho Park -0.583  
## neighbourhood\_cleansedEl Monte -1.011  
## neighbourhood\_cleansedEl Segundo -0.535  
## neighbourhood\_cleansedEl Sereno -1.276  
## neighbourhood\_cleansedElysian Park -0.457  
## neighbourhood\_cleansedElysian Valley -0.440  
## neighbourhood\_cleansedEncino -0.808  
## neighbourhood\_cleansedExposition Park -0.763  
## neighbourhood\_cleansedFairfax -0.157  
## neighbourhood\_cleansedFlorence -2.596  
## neighbourhood\_cleansedFlorence-Firestone -1.648  
## neighbourhood\_cleansedGardena -1.332  
## neighbourhood\_cleansedGlassell Park -0.779  
## neighbourhood\_cleansedGlendale -0.175  
## neighbourhood\_cleansedGlendora -1.293  
## neighbourhood\_cleansedGramercy Park 0.449  
## neighbourhood\_cleansedGranada Hills -0.440  
## neighbourhood\_cleansedGreen Meadows -0.858  
## neighbourhood\_cleansedGreen Valley -0.628  
## neighbourhood\_cleansedGriffith Park -2.005  
## neighbourhood\_cleansedHacienda Heights -1.467  
## neighbourhood\_cleansedHancock Park -0.125  
## neighbourhood\_cleansedHarbor City -0.944  
## neighbourhood\_cleansedHarbor Gateway -1.868  
## neighbourhood\_cleansedHarvard Heights -1.167  
## neighbourhood\_cleansedHarvard Park -2.693  
## neighbourhood\_cleansedHasley Canyon -0.598  
## neighbourhood\_cleansedHawaiian Gardens -0.806  
## neighbourhood\_cleansedHawthorne -1.473  
## neighbourhood\_cleansedHermosa Beach -0.020  
## neighbourhood\_cleansedHighland Park -0.935  
## neighbourhood\_cleansedHistoric South-Central -2.353  
## neighbourhood\_cleansedHollywood -0.198  
## neighbourhood\_cleansedHollywood Hills -0.184  
## neighbourhood\_cleansedHollywood Hills West -0.244  
## neighbourhood\_cleansedHuntington Park -1.024  
## neighbourhood\_cleansedHyde Park -1.500  
## neighbourhood\_cleansedIndustry -0.909  
## neighbourhood\_cleansedInglewood -1.187  
## neighbourhood\_cleansedIrwindale -1.657  
## neighbourhood\_cleansedJefferson Park -0.892  
## neighbourhood\_cleansedKoreatown -0.932  
## neighbourhood\_cleansedLa Canada Flintridge -0.086  
## neighbourhood\_cleansedLa Crescenta-Montrose -0.210  
## neighbourhood\_cleansedLa Habra Heights -0.039  
## neighbourhood\_cleansedLa Mirada -1.386  
## neighbourhood\_cleansedLa Puente -0.910  
## neighbourhood\_cleansedLa Verne -1.550  
## neighbourhood\_cleansedLadera Heights -0.242  
## neighbourhood\_cleansedLake Balboa -0.987  
## neighbourhood\_cleansedLake Hughes 1.452  
## neighbourhood\_cleansedLake Los Angeles -0.681  
## neighbourhood\_cleansedLake View Terrace -1.469  
## neighbourhood\_cleansedLakewood -0.957  
## neighbourhood\_cleansedLancaster -2.023  
## neighbourhood\_cleansedLarchmont -0.357  
## neighbourhood\_cleansedLawndale -1.320  
## neighbourhood\_cleansedLeimert Park -1.284  
## neighbourhood\_cleansedLennox -1.382  
## neighbourhood\_cleansedLeona Valley -0.444  
## neighbourhood\_cleansedLincoln Heights -0.482  
## neighbourhood\_cleansedLomita -1.065  
## neighbourhood\_cleansedLong Beach -0.614  
## neighbourhood\_cleansedLopez/Kagel Canyons -1.058  
## neighbourhood\_cleansedLos Feliz -0.380  
## neighbourhood\_cleansedLynwood -1.832  
## neighbourhood\_cleansedMalibu -0.156  
## neighbourhood\_cleansedManchester Square -0.386  
## neighbourhood\_cleansedManhattan Beach 0.166  
## neighbourhood\_cleansedMar Vista -0.559  
## neighbourhood\_cleansedMarina del Rey 1.004  
## neighbourhood\_cleansedMayflower Village -1.504  
## neighbourhood\_cleansedMaywood -1.219  
## neighbourhood\_cleansedMid-City -0.741  
## neighbourhood\_cleansedMid-Wilshire -0.343  
## neighbourhood\_cleansedMission Hills -0.701  
## neighbourhood\_cleansedMonrovia -0.711  
## neighbourhood\_cleansedMontebello -1.047  
## neighbourhood\_cleansedMontecito Heights -0.605  
## neighbourhood\_cleansedMonterey Park -1.024  
## neighbourhood\_cleansedMount Washington -0.518  
## neighbourhood\_cleansedNorth El Monte -0.843  
## neighbourhood\_cleansedNorth Hills -1.308  
## neighbourhood\_cleansedNorth Hollywood -0.882  
## neighbourhood\_cleansedNorth Whittier -0.019  
## neighbourhood\_cleansedNortheast Antelope Valley -1.861  
## neighbourhood\_cleansedNorthridge -0.886  
## neighbourhood\_cleansedNorthwest Antelope Valley -1.932  
## neighbourhood\_cleansedNorthwest Palmdale -2.106  
## neighbourhood\_cleansedNorwalk -1.650  
## neighbourhood\_cleansedPacific Palisades -0.125  
## neighbourhood\_cleansedPacoima -0.931  
## neighbourhood\_cleansedPalmdale -1.936  
## neighbourhood\_cleansedPalms -0.741  
## neighbourhood\_cleansedPalos Verdes Estates 0.146  
## neighbourhood\_cleansedPanorama City -1.536  
## neighbourhood\_cleansedParamount -0.643  
## neighbourhood\_cleansedPasadena -0.418  
## neighbourhood\_cleansedPico-Robertson -0.376  
## neighbourhood\_cleansedPico-Union -0.759  
## neighbourhood\_cleansedPico Rivera -1.422  
## neighbourhood\_cleansedPlaya del Rey -0.221  
## neighbourhood\_cleansedPlaya Vista 0.088  
## neighbourhood\_cleansedPomona -1.283  
## neighbourhood\_cleansedPorter Ranch -0.682  
## neighbourhood\_cleansedQuartz Hill -1.730  
## neighbourhood\_cleansedRancho Dominguez -1.834  
## neighbourhood\_cleansedRancho Palos Verdes -0.909  
## neighbourhood\_cleansedRancho Park -1.300  
## neighbourhood\_cleansedRedondo Beach -0.184  
## neighbourhood\_cleansedReseda -1.043  
## neighbourhood\_cleansedRidge Route -0.477  
## neighbourhood\_cleansedRolling Hills -1.226  
## neighbourhood\_cleansedRolling Hills Estates 1.221  
## neighbourhood\_cleansedRosemead -1.569  
## neighbourhood\_cleansedRowland Heights -1.473  
## neighbourhood\_cleansedSan Dimas -1.357  
## neighbourhood\_cleansedSan Fernando -1.431  
## neighbourhood\_cleansedSan Gabriel -1.130  
## neighbourhood\_cleansedSan Marino -0.361  
## neighbourhood\_cleansedSan Pasqual -0.797  
## neighbourhood\_cleansedSan Pedro -0.925  
## neighbourhood\_cleansedSanta Clarita -0.837  
## neighbourhood\_cleansedSanta Fe Springs -1.512  
## neighbourhood\_cleansedSanta Monica 0.243  
## neighbourhood\_cleansedSawtelle -0.403  
## neighbourhood\_cleansedSepulveda Basin 1.542  
## neighbourhood\_cleansedShadow Hills -0.908  
## neighbourhood\_cleansedSherman Oaks -0.649  
## neighbourhood\_cleansedSierra Madre -0.361  
## neighbourhood\_cleansedSignal Hill -0.886  
## neighbourhood\_cleansedSilver Lake -0.187  
## neighbourhood\_cleansedSouth Diamond Bar -0.564  
## neighbourhood\_cleansedSouth El Monte -0.955  
## neighbourhood\_cleansedSouth Gate -0.737  
## neighbourhood\_cleansedSouth Park -1.693  
## neighbourhood\_cleansedSouth Pasadena -0.645  
## neighbourhood\_cleansedSouth San Gabriel -1.617  
## neighbourhood\_cleansedSouth San Jose Hills -1.360  
## neighbourhood\_cleansedSouth Whittier -1.015  
## neighbourhood\_cleansedSoutheast Antelope Valley -0.615  
## neighbourhood\_cleansedStevenson Ranch -1.503  
## neighbourhood\_cleansedStudio City -0.230  
## neighbourhood\_cleansedSun Valley -0.671  
## neighbourhood\_cleansedSun Village -0.557  
## neighbourhood\_cleansedSunland -0.969  
## neighbourhood\_cleansedSylmar -1.313  
## neighbourhood\_cleansedTarzana -0.803  
## neighbourhood\_cleansedTemple City -1.283  
## neighbourhood\_cleansedToluca Lake -0.372  
## neighbourhood\_cleansedTopanga 0.360  
## neighbourhood\_cleansedTorrance -1.041  
## neighbourhood\_cleansedTujunga -1.433  
## neighbourhood\_cleansedTujunga Canyons 0.630  
## neighbourhood\_cleansedUnincorporated Catalina Island -0.374  
## neighbourhood\_cleansedUnincorporated Santa Monica Mountains -0.210  
## neighbourhood\_cleansedUnincorporated Santa Susana Mountains -0.400  
## neighbourhood\_cleansedUniversal City -0.366  
## neighbourhood\_cleansedUniversity Park -1.798  
## neighbourhood\_cleansedVal Verde -0.821  
## neighbourhood\_cleansedValinda -1.636  
## neighbourhood\_cleansedValley Glen -0.695  
## neighbourhood\_cleansedValley Village -0.630  
## neighbourhood\_cleansedVan Nuys -1.056  
## neighbourhood\_cleansedVenice 0.310  
## neighbourhood\_cleansedVermont-Slauson -1.220  
## neighbourhood\_cleansedVermont Knolls -1.601  
## neighbourhood\_cleansedVermont Square -1.672  
## neighbourhood\_cleansedVermont Vista -1.050  
## neighbourhood\_cleansedVernon 0.224  
## neighbourhood\_cleansedVeterans Administration 0.060  
## neighbourhood\_cleansedView Park-Windsor Hills -0.600  
## neighbourhood\_cleansedVincent -0.101  
## neighbourhood\_cleansedWalnut -0.973  
## neighbourhood\_cleansedWatts -2.120  
## neighbourhood\_cleansedWest Adams -1.050  
## neighbourhood\_cleansedWest Carson -0.990  
## neighbourhood\_cleansedWest Compton -1.423  
## neighbourhood\_cleansedWest Covina -1.436  
## neighbourhood\_cleansedWest Hills -0.906  
## neighbourhood\_cleansedWest Hollywood 0.140  
## neighbourhood\_cleansedWest Los Angeles -1.067  
## neighbourhood\_cleansedWest Puente Valley -0.845  
## neighbourhood\_cleansedWest Whittier-Los Nietos -0.845  
## neighbourhood\_cleansedWestchester -0.666  
## neighbourhood\_cleansedWestlake -0.363  
## neighbourhood\_cleansedWestlake Village 0.447  
## neighbourhood\_cleansedWestmont -0.454  
## neighbourhood\_cleansedWestwood -0.027  
## neighbourhood\_cleansedWhittier -1.109  
## neighbourhood\_cleansedWillowbrook -0.702  
## neighbourhood\_cleansedWilmington -1.374  
## neighbourhood\_cleansedWindsor Square -0.264  
## neighbourhood\_cleansedWinnetka -0.825  
## neighbourhood\_cleansedWoodland Hills -0.742  
## cleaning\_fee 55.775  
## security\_deposit 12.900  
## review\_scores\_rating 2.086  
## bed\_typeCouch -0.265  
## bed\_typeFuton 0.979  
## bed\_typePull-out Sofa 1.376  
## bed\_typeReal Bed 3.867  
## review\_scores\_accuracy -0.355  
## review\_scores\_checkin -2.194  
## review\_scores\_cleanliness 7.682  
## review\_scores\_communication 0.297  
## review\_scores\_location 6.962  
## review\_scores\_value -6.131  
## Pr(>|t|)   
## (Intercept) 0.663571   
## bedrooms < 2e-16 \*\*\*  
## property\_typeApartment 0.000111 \*\*\*  
## property\_typeBarn 0.155548   
## property\_typeBed and breakfast 2.69e-05 \*\*\*  
## property\_typeBoat 0.074862 .   
## property\_typeBoutique hotel 2.32e-05 \*\*\*  
## property\_typeBungalow 0.001124 \*\*   
## property\_typeBus 0.138780   
## property\_typeCabin 0.722949   
## property\_typeCamper/RV 0.079408 .   
## property\_typeCampsite 0.073338 .   
## property\_typeCasa particular (Cuba) 0.405956   
## property\_typeCastle 0.705545   
## property\_typeCave 0.329101   
## property\_typeChalet 0.000503 \*\*\*  
## property\_typeCondominium 0.001245 \*\*   
## property\_typeCottage 0.366471   
## property\_typeDome house 0.001425 \*\*   
## property\_typeDorm 3.05e-06 \*\*\*  
## property\_typeEarth house 0.400389   
## property\_typeFarm stay 0.163754   
## property\_typeGuest suite 0.001361 \*\*   
## property\_typeGuesthouse 0.489408   
## property\_typeHostel 8.21e-16 \*\*\*  
## property\_typeHotel 0.004405 \*\*   
## property\_typeHouse 5.77e-08 \*\*\*  
## property\_typeHouseboat 0.322938   
## property\_typeHut 0.014942 \*   
## property\_typeIgloo 0.349978   
## property\_typeIsland 0.120387   
## property\_typeLoft 0.455393   
## property\_typeMinsu (Taiwan) 0.527023   
## property\_typeNature lodge 0.070617 .   
## property\_typeOther 0.671278   
## property\_typePension (South Korea) 0.743757   
## property\_typeResort 0.010905 \*   
## property\_typeServiced apartment 0.019275 \*   
## property\_typeTent 0.956127   
## property\_typeTiny house 0.190617   
## property\_typeTipi 0.939501   
## property\_typeTownhouse 2.33e-06 \*\*\*  
## property\_typeTrain 0.764969   
## property\_typeTreehouse 0.154941   
## property\_typeVacation home 0.053406 .   
## property\_typeVilla 3.28e-06 \*\*\*  
## property\_typeYurt 0.189211   
## beds < 2e-16 \*\*\*  
## host\_is\_superhostt 0.014328 \*   
## neighbourhood\_cleansedAdams-Normandie 0.483694   
## neighbourhood\_cleansedAgoura Hills 0.756577   
## neighbourhood\_cleansedAgua Dulce 0.985862   
## neighbourhood\_cleansedAlhambra 0.253939   
## neighbourhood\_cleansedAlondra Park 0.486080   
## neighbourhood\_cleansedAltadena 0.443682   
## neighbourhood\_cleansedAngeles Crest 0.130195   
## neighbourhood\_cleansedArcadia 0.281854   
## neighbourhood\_cleansedArleta 0.131478   
## neighbourhood\_cleansedArlington Heights 0.057747 .   
## neighbourhood\_cleansedArtesia 0.226541   
## neighbourhood\_cleansedAthens 0.367545   
## neighbourhood\_cleansedAtwater Village 0.609044   
## neighbourhood\_cleansedAvalon 0.551232   
## neighbourhood\_cleansedAvocado Heights 0.356520   
## neighbourhood\_cleansedAzusa 0.405046   
## neighbourhood\_cleansedBaldwin Hills/Crenshaw 0.284588   
## neighbourhood\_cleansedBaldwin Park 0.326741   
## neighbourhood\_cleansedBel-Air 0.804278   
## neighbourhood\_cleansedBell 0.343788   
## neighbourhood\_cleansedBell Gardens 0.386058   
## neighbourhood\_cleansedBellflower 0.150924   
## neighbourhood\_cleansedBeverly Crest 0.746260   
## neighbourhood\_cleansedBeverly Grove 0.687189   
## neighbourhood\_cleansedBeverly Hills 0.940537   
## neighbourhood\_cleansedBeverlywood 0.303715   
## neighbourhood\_cleansedBoyle Heights 0.284267   
## neighbourhood\_cleansedBradbury 0.940414   
## neighbourhood\_cleansedBrentwood 0.905374   
## neighbourhood\_cleansedBroadway-Manchester 0.248618   
## neighbourhood\_cleansedBurbank 0.552480   
## neighbourhood\_cleansedCalabasas 0.472559   
## neighbourhood\_cleansedCanoga Park 0.239174   
## neighbourhood\_cleansedCarson 0.154031   
## neighbourhood\_cleansedCarthay 0.992169   
## neighbourhood\_cleansedCastaic 0.122277   
## neighbourhood\_cleansedCastaic Canyons 0.267547   
## neighbourhood\_cleansedCentral-Alameda 0.135726   
## neighbourhood\_cleansedCentury City 0.984065   
## neighbourhood\_cleansedCerritos 0.145672   
## neighbourhood\_cleansedCharter Oak 0.051830 .   
## neighbourhood\_cleansedChatsworth 0.414425   
## neighbourhood\_cleansedChatsworth Reservoir 0.129661   
## neighbourhood\_cleansedChesterfield Square 0.045555 \*   
## neighbourhood\_cleansedCheviot Hills 0.630012   
## neighbourhood\_cleansedChinatown 0.489680   
## neighbourhood\_cleansedCitrus 0.722923   
## neighbourhood\_cleansedClaremont 0.691546   
## neighbourhood\_cleansedCommerce 0.923278   
## neighbourhood\_cleansedCompton 0.466648   
## neighbourhood\_cleansedCovina 0.196449   
## neighbourhood\_cleansedCudahy 0.049061 \*   
## neighbourhood\_cleansedCulver City 0.890575   
## neighbourhood\_cleansedCypress Park 0.133637   
## neighbourhood\_cleansedDel Aire 0.461843   
## neighbourhood\_cleansedDel Rey 0.862007   
## neighbourhood\_cleansedDesert View Highlands 0.862769   
## neighbourhood\_cleansedDiamond Bar 0.265025   
## neighbourhood\_cleansedDowney 0.228783   
## neighbourhood\_cleansedDowntown 0.717037   
## neighbourhood\_cleansedDuarte 0.174563   
## neighbourhood\_cleansedEagle Rock 0.447802   
## neighbourhood\_cleansedEast Compton 0.405755   
## neighbourhood\_cleansedEast Hollywood 0.222302   
## neighbourhood\_cleansedEast Los Angeles 0.241893   
## neighbourhood\_cleansedEast Pasadena 0.612653   
## neighbourhood\_cleansedEast San Gabriel 0.088236 .   
## neighbourhood\_cleansedEast Whittier 0.825444   
## neighbourhood\_cleansedEcho Park 0.559919   
## neighbourhood\_cleansedEl Monte 0.312209   
## neighbourhood\_cleansedEl Segundo 0.592991   
## neighbourhood\_cleansedEl Sereno 0.201865   
## neighbourhood\_cleansedElysian Park 0.647665   
## neighbourhood\_cleansedElysian Valley 0.659819   
## neighbourhood\_cleansedEncino 0.418894   
## neighbourhood\_cleansedExposition Park 0.445669   
## neighbourhood\_cleansedFairfax 0.874917   
## neighbourhood\_cleansedFlorence 0.009425 \*\*   
## neighbourhood\_cleansedFlorence-Firestone 0.099322 .   
## neighbourhood\_cleansedGardena 0.182904   
## neighbourhood\_cleansedGlassell Park 0.436223   
## neighbourhood\_cleansedGlendale 0.861111   
## neighbourhood\_cleansedGlendora 0.196121   
## neighbourhood\_cleansedGramercy Park 0.653098   
## neighbourhood\_cleansedGranada Hills 0.659742   
## neighbourhood\_cleansedGreen Meadows 0.391149   
## neighbourhood\_cleansedGreen Valley 0.530147   
## neighbourhood\_cleansedGriffith Park 0.044921 \*   
## neighbourhood\_cleansedHacienda Heights 0.142254   
## neighbourhood\_cleansedHancock Park 0.900163   
## neighbourhood\_cleansedHarbor City 0.344974   
## neighbourhood\_cleansedHarbor Gateway 0.061827 .   
## neighbourhood\_cleansedHarvard Heights 0.243386   
## neighbourhood\_cleansedHarvard Park 0.007084 \*\*   
## neighbourhood\_cleansedHasley Canyon 0.550135   
## neighbourhood\_cleansedHawaiian Gardens 0.420476   
## neighbourhood\_cleansedHawthorne 0.140820   
## neighbourhood\_cleansedHermosa Beach 0.983955   
## neighbourhood\_cleansedHighland Park 0.350044   
## neighbourhood\_cleansedHistoric South-Central 0.018649 \*   
## neighbourhood\_cleansedHollywood 0.843081   
## neighbourhood\_cleansedHollywood Hills 0.853732   
## neighbourhood\_cleansedHollywood Hills West 0.807238   
## neighbourhood\_cleansedHuntington Park 0.305969   
## neighbourhood\_cleansedHyde Park 0.133662   
## neighbourhood\_cleansedIndustry 0.363580   
## neighbourhood\_cleansedInglewood 0.235158   
## neighbourhood\_cleansedIrwindale 0.097522 .   
## neighbourhood\_cleansedJefferson Park 0.372149   
## neighbourhood\_cleansedKoreatown 0.351180   
## neighbourhood\_cleansedLa Canada Flintridge 0.931102   
## neighbourhood\_cleansedLa Crescenta-Montrose 0.833356   
## neighbourhood\_cleansedLa Habra Heights 0.969080   
## neighbourhood\_cleansedLa Mirada 0.165797   
## neighbourhood\_cleansedLa Puente 0.362998   
## neighbourhood\_cleansedLa Verne 0.121137   
## neighbourhood\_cleansedLadera Heights 0.808956   
## neighbourhood\_cleansedLake Balboa 0.323435   
## neighbourhood\_cleansedLake Hughes 0.146476   
## neighbourhood\_cleansedLake Los Angeles 0.496047   
## neighbourhood\_cleansedLake View Terrace 0.141930   
## neighbourhood\_cleansedLakewood 0.338416   
## neighbourhood\_cleansedLancaster 0.043112 \*   
## neighbourhood\_cleansedLarchmont 0.720881   
## neighbourhood\_cleansedLawndale 0.186796   
## neighbourhood\_cleansedLeimert Park 0.198980   
## neighbourhood\_cleansedLennox 0.166837   
## neighbourhood\_cleansedLeona Valley 0.657222   
## neighbourhood\_cleansedLincoln Heights 0.629656   
## neighbourhood\_cleansedLomita 0.286962   
## neighbourhood\_cleansedLong Beach 0.539079   
## neighbourhood\_cleansedLopez/Kagel Canyons 0.290110   
## neighbourhood\_cleansedLos Feliz 0.703665   
## neighbourhood\_cleansedLynwood 0.066958 .   
## neighbourhood\_cleansedMalibu 0.875852   
## neighbourhood\_cleansedManchester Square 0.699269   
## neighbourhood\_cleansedManhattan Beach 0.868083   
## neighbourhood\_cleansedMar Vista 0.576313   
## neighbourhood\_cleansedMarina del Rey 0.315290   
## neighbourhood\_cleansedMayflower Village 0.132686   
## neighbourhood\_cleansedMaywood 0.222970   
## neighbourhood\_cleansedMid-City 0.458778   
## neighbourhood\_cleansedMid-Wilshire 0.731682   
## neighbourhood\_cleansedMission Hills 0.483425   
## neighbourhood\_cleansedMonrovia 0.477374   
## neighbourhood\_cleansedMontebello 0.294944   
## neighbourhood\_cleansedMontecito Heights 0.545114   
## neighbourhood\_cleansedMonterey Park 0.305983   
## neighbourhood\_cleansedMount Washington 0.604294   
## neighbourhood\_cleansedNorth El Monte 0.399269   
## neighbourhood\_cleansedNorth Hills 0.190742   
## neighbourhood\_cleansedNorth Hollywood 0.377519   
## neighbourhood\_cleansedNorth Whittier 0.984996   
## neighbourhood\_cleansedNortheast Antelope Valley 0.062702 .   
## neighbourhood\_cleansedNorthridge 0.375574   
## neighbourhood\_cleansedNorthwest Antelope Valley 0.053389 .   
## neighbourhood\_cleansedNorthwest Palmdale 0.035216 \*   
## neighbourhood\_cleansedNorwalk 0.098970 .   
## neighbourhood\_cleansedPacific Palisades 0.900314   
## neighbourhood\_cleansedPacoima 0.351748   
## neighbourhood\_cleansedPalmdale 0.052891 .   
## neighbourhood\_cleansedPalms 0.458521   
## neighbourhood\_cleansedPalos Verdes Estates 0.883704   
## neighbourhood\_cleansedPanorama City 0.124552   
## neighbourhood\_cleansedParamount 0.520032   
## neighbourhood\_cleansedPasadena 0.675931   
## neighbourhood\_cleansedPico-Robertson 0.706718   
## neighbourhood\_cleansedPico-Union 0.447999   
## neighbourhood\_cleansedPico Rivera 0.155158   
## neighbourhood\_cleansedPlaya del Rey 0.825320   
## neighbourhood\_cleansedPlaya Vista 0.930048   
## neighbourhood\_cleansedPomona 0.199326   
## neighbourhood\_cleansedPorter Ranch 0.495455   
## neighbourhood\_cleansedQuartz Hill 0.083675 .   
## neighbourhood\_cleansedRancho Dominguez 0.066707 .   
## neighbourhood\_cleansedRancho Palos Verdes 0.363109   
## neighbourhood\_cleansedRancho Park 0.193726   
## neighbourhood\_cleansedRedondo Beach 0.853889   
## neighbourhood\_cleansedReseda 0.297094   
## neighbourhood\_cleansedRidge Route 0.633051   
## neighbourhood\_cleansedRolling Hills 0.220146   
## neighbourhood\_cleansedRolling Hills Estates 0.222104   
## neighbourhood\_cleansedRosemead 0.116593   
## neighbourhood\_cleansedRowland Heights 0.140736   
## neighbourhood\_cleansedSan Dimas 0.174880   
## neighbourhood\_cleansedSan Fernando 0.152452   
## neighbourhood\_cleansedSan Gabriel 0.258464   
## neighbourhood\_cleansedSan Marino 0.718461   
## neighbourhood\_cleansedSan Pasqual 0.425195   
## neighbourhood\_cleansedSan Pedro 0.354957   
## neighbourhood\_cleansedSanta Clarita 0.402350   
## neighbourhood\_cleansedSanta Fe Springs 0.130571   
## neighbourhood\_cleansedSanta Monica 0.808130   
## neighbourhood\_cleansedSawtelle 0.687272   
## neighbourhood\_cleansedSepulveda Basin 0.122972   
## neighbourhood\_cleansedShadow Hills 0.364143   
## neighbourhood\_cleansedSherman Oaks 0.516196   
## neighbourhood\_cleansedSierra Madre 0.717859   
## neighbourhood\_cleansedSignal Hill 0.375439   
## neighbourhood\_cleansedSilver Lake 0.851695   
## neighbourhood\_cleansedSouth Diamond Bar 0.572771   
## neighbourhood\_cleansedSouth El Monte 0.339438   
## neighbourhood\_cleansedSouth Gate 0.460828   
## neighbourhood\_cleansedSouth Park 0.090398 .   
## neighbourhood\_cleansedSouth Pasadena 0.519212   
## neighbourhood\_cleansedSouth San Gabriel 0.105785   
## neighbourhood\_cleansedSouth San Jose Hills 0.173701   
## neighbourhood\_cleansedSouth Whittier 0.310101   
## neighbourhood\_cleansedSoutheast Antelope Valley 0.538695   
## neighbourhood\_cleansedStevenson Ranch 0.132854   
## neighbourhood\_cleansedStudio City 0.818243   
## neighbourhood\_cleansedSun Valley 0.502121   
## neighbourhood\_cleansedSun Village 0.577724   
## neighbourhood\_cleansedSunland 0.332555   
## neighbourhood\_cleansedSylmar 0.189181   
## neighbourhood\_cleansedTarzana 0.421855   
## neighbourhood\_cleansedTemple City 0.199583   
## neighbourhood\_cleansedToluca Lake 0.710181   
## neighbourhood\_cleansedTopanga 0.718954   
## neighbourhood\_cleansedTorrance 0.297656   
## neighbourhood\_cleansedTujunga 0.151931   
## neighbourhood\_cleansedTujunga Canyons 0.528755   
## neighbourhood\_cleansedUnincorporated Catalina Island 0.708756   
## neighbourhood\_cleansedUnincorporated Santa Monica Mountains 0.833525   
## neighbourhood\_cleansedUnincorporated Santa Susana Mountains 0.689420   
## neighbourhood\_cleansedUniversal City 0.714402   
## neighbourhood\_cleansedUniversity Park 0.072118 .   
## neighbourhood\_cleansedVal Verde 0.411630   
## neighbourhood\_cleansedValinda 0.101835   
## neighbourhood\_cleansedValley Glen 0.486777   
## neighbourhood\_cleansedValley Village 0.528436   
## neighbourhood\_cleansedVan Nuys 0.290976   
## neighbourhood\_cleansedVenice 0.756519   
## neighbourhood\_cleansedVermont-Slauson 0.222474   
## neighbourhood\_cleansedVermont Knolls 0.109409   
## neighbourhood\_cleansedVermont Square 0.094563 .   
## neighbourhood\_cleansedVermont Vista 0.293593   
## neighbourhood\_cleansedVernon 0.822964   
## neighbourhood\_cleansedVeterans Administration 0.952186   
## neighbourhood\_cleansedView Park-Windsor Hills 0.548542   
## neighbourhood\_cleansedVincent 0.919787   
## neighbourhood\_cleansedWalnut 0.330495   
## neighbourhood\_cleansedWatts 0.033971 \*   
## neighbourhood\_cleansedWest Adams 0.293864   
## neighbourhood\_cleansedWest Carson 0.322350   
## neighbourhood\_cleansedWest Compton 0.154704   
## neighbourhood\_cleansedWest Covina 0.150915   
## neighbourhood\_cleansedWest Hills 0.365134   
## neighbourhood\_cleansedWest Hollywood 0.888620   
## neighbourhood\_cleansedWest Los Angeles 0.286084   
## neighbourhood\_cleansedWest Puente Valley 0.397964   
## neighbourhood\_cleansedWest Whittier-Los Nietos 0.397912   
## neighbourhood\_cleansedWestchester 0.505381   
## neighbourhood\_cleansedWestlake 0.716616   
## neighbourhood\_cleansedWestlake Village 0.654637   
## neighbourhood\_cleansedWestmont 0.649897   
## neighbourhood\_cleansedWestwood 0.978832   
## neighbourhood\_cleansedWhittier 0.267458   
## neighbourhood\_cleansedWillowbrook 0.482428   
## neighbourhood\_cleansedWilmington 0.169467   
## neighbourhood\_cleansedWindsor Square 0.791525   
## neighbourhood\_cleansedWinnetka 0.409504   
## neighbourhood\_cleansedWoodland Hills 0.458047   
## cleaning\_fee < 2e-16 \*\*\*  
## security\_deposit < 2e-16 \*\*\*  
## review\_scores\_rating 0.036981 \*   
## bed\_typeCouch 0.791333   
## bed\_typeFuton 0.327581   
## bed\_typePull-out Sofa 0.168867   
## bed\_typeReal Bed 0.000110 \*\*\*  
## review\_scores\_accuracy 0.722308   
## review\_scores\_checkin 0.028232 \*   
## review\_scores\_cleanliness 1.61e-14 \*\*\*  
## review\_scores\_communication 0.766834   
## review\_scores\_location 3.42e-12 \*\*\*  
## review\_scores\_value 8.80e-10 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 51.83 on 37385 degrees of freedom  
## Multiple R-squared: 0.3614, Adjusted R-squared: 0.3559   
## F-statistic: 65.31 on 324 and 37385 DF, p-value: < 2.2e-16

stepAIC(model,direction="backward") #Through backward elimination, we eliminated the attribute review\_score\_accuracy and review\_score\_communication

## Start: AIC=298075.7  
## price ~ bedrooms + property\_type + beds + host\_is\_superhost +   
## neighbourhood\_cleansed + cleaning\_fee + security\_deposit +   
## review\_scores\_rating + bed\_type + review\_scores\_accuracy +   
## review\_scores\_checkin + review\_scores\_cleanliness + review\_scores\_communication +   
## review\_scores\_location + review\_scores\_value  
##   
## Df Sum of Sq RSS AIC  
## - review\_scores\_communication 1 236 100419423 298074  
## - review\_scores\_accuracy 1 339 100419526 298074  
## <none> 100419187 298076  
## - review\_scores\_rating 1 11689 100430876 298078  
## - review\_scores\_checkin 1 12931 100432118 298079  
## - host\_is\_superhost 1 16111 100435298 298080  
## - review\_scores\_value 1 100979 100520166 298112  
## - bed\_type 4 127334 100546521 298115  
## - review\_scores\_location 1 130176 100549363 298123  
## - review\_scores\_cleanliness 1 158499 100577686 298133  
## - security\_deposit 1 447000 100866187 298241  
## - beds 1 680076 101099263 298328  
## - property\_type 45 2216048 102635235 298809  
## - neighbourhood\_cleansed 263 7599659 108018846 300301  
## - bedrooms 1 6883321 107302508 300574  
## - cleaning\_fee 1 8355958 108775145 301088  
##   
## Step: AIC=298073.8  
## price ~ bedrooms + property\_type + beds + host\_is\_superhost +   
## neighbourhood\_cleansed + cleaning\_fee + security\_deposit +   
## review\_scores\_rating + bed\_type + review\_scores\_accuracy +   
## review\_scores\_checkin + review\_scores\_cleanliness + review\_scores\_location +   
## review\_scores\_value  
##   
## Df Sum of Sq RSS AIC  
## - review\_scores\_accuracy 1 242 100419665 298072  
## <none> 100419423 298074  
## - review\_scores\_rating 1 11607 100431030 298076  
## - review\_scores\_checkin 1 14590 100434013 298077  
## - host\_is\_superhost 1 16128 100435551 298078  
## - review\_scores\_value 1 101536 100520959 298110  
## - bed\_type 4 127222 100546645 298114  
## - review\_scores\_location 1 132482 100551905 298121  
## - review\_scores\_cleanliness 1 160265 100579688 298132  
## - security\_deposit 1 447243 100866666 298239  
## - beds 1 680057 101099480 298326  
## - property\_type 45 2215965 102635388 298807  
## - neighbourhood\_cleansed 263 7599466 108018889 300299  
## - bedrooms 1 6883772 107303195 300572  
## - cleaning\_fee 1 8355818 108775241 301086  
##   
## Step: AIC=298071.9  
## price ~ bedrooms + property\_type + beds + host\_is\_superhost +   
## neighbourhood\_cleansed + cleaning\_fee + security\_deposit +   
## review\_scores\_rating + bed\_type + review\_scores\_checkin +   
## review\_scores\_cleanliness + review\_scores\_location + review\_scores\_value  
##   
## Df Sum of Sq RSS AIC  
## <none> 100419665 298072  
## - review\_scores\_rating 1 11527 100431192 298074  
## - host\_is\_superhost 1 16027 100435692 298076  
## - review\_scores\_checkin 1 16966 100436630 298076  
## - bed\_type 4 127160 100546825 298112  
## - review\_scores\_value 1 124302 100543967 298117  
## - review\_scores\_location 1 133447 100553112 298120  
## - review\_scores\_cleanliness 1 171146 100590811 298134  
## - security\_deposit 1 447074 100866739 298237  
## - beds 1 679934 101099598 298324  
## - property\_type 45 2215804 102635469 298805  
## - neighbourhood\_cleansed 263 7599394 108019058 300297  
## - bedrooms 1 6885315 107304980 300571  
## - cleaning\_fee 1 8355580 108775244 301084

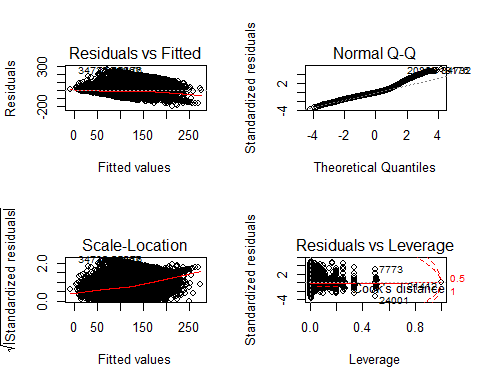
##   
## Call:  
## lm(formula = price ~ bedrooms + property\_type + beds + host\_is\_superhost +   
## neighbourhood\_cleansed + cleaning\_fee + security\_deposit +   
## review\_scores\_rating + bed\_type + review\_scores\_checkin +   
## review\_scores\_cleanliness + review\_scores\_location + review\_scores\_value,   
## data = data)  
##   
## Coefficients:  
## (Intercept)   
## 12.66367   
## bedrooms   
## 22.47472   
## property\_typeApartment   
## -16.33764   
## property\_typeBarn   
## -25.56432   
## property\_typeBed and breakfast   
## -26.66146   
## property\_typeBoat   
## -20.84395   
## property\_typeBoutique hotel   
## 21.97274   
## property\_typeBungalow   
## -14.79717   
## property\_typeBus   
## 77.22083   
## property\_typeCabin   
## 2.78239   
## property\_typeCamper/RV   
## -10.46939   
## property\_typeCampsite   
## -33.27789   
## property\_typeCasa particular (Cuba)   
## -30.72970   
## property\_typeCastle   
## -4.49097   
## property\_typeCave   
## -25.75819   
## property\_typeChalet   
## -75.18795   
## property\_typeCondominium   
## -14.06511   
## property\_typeCottage   
## -5.19384   
## property\_typeDome house   
## -43.08072   
## property\_typeDorm   
## -88.22256   
## property\_typeEarth house   
## -9.82721   
## property\_typeFarm stay   
## -14.55306   
## property\_typeGuest suite   
## -14.22810   
## property\_typeGuesthouse   
## -3.04343   
## property\_typeHostel   
## -47.56467   
## property\_typeHotel   
## 21.58366   
## property\_typeHouse   
## -23.09836   
## property\_typeHouseboat   
## -51.52236   
## property\_typeHut   
## -57.55767   
## property\_typeIgloo   
## -48.34794   
## property\_typeIsland   
## -57.49526   
## property\_typeLoft   
## -3.45276   
## property\_typeMinsu (Taiwan)   
## -33.84689   
## property\_typeNature lodge   
## -67.52380   
## property\_typeOther   
## -2.94271   
## property\_typePension (South Korea)   
## -16.94183   
## property\_typeResort   
## 95.04635   
## property\_typeServiced apartment   
## 11.29189   
## property\_typeTent   
## 0.97082   
## property\_typeTiny house   
## -8.73269   
## property\_typeTipi   
## -1.79817   
## property\_typeTownhouse   
## -21.23897   
## property\_typeTrain   
## 11.01195   
## property\_typeTreehouse   
## 23.14500   
## property\_typeVacation home   
## -71.42162   
## property\_typeVilla   
## -21.36637   
## property\_typeYurt   
## -28.43470   
## beds   
## 6.68942   
## host\_is\_superhostt   
## 1.55576   
## neighbourhood\_cleansedAdams-Normandie   
## -19.08174   
## neighbourhood\_cleansedAgoura Hills   
## -8.49832   
## neighbourhood\_cleansedAgua Dulce   
## -0.54177   
## neighbourhood\_cleansedAlhambra   
## -29.94986   
## neighbourhood\_cleansedAlondra Park   
## -19.90672   
## neighbourhood\_cleansedAltadena   
## -20.15897   
## neighbourhood\_cleansedAngeles Crest   
## -56.21595   
## neighbourhood\_cleansedArcadia   
## -28.31758   
## neighbourhood\_cleansedArleta   
## -50.57486   
## neighbourhood\_cleansedArlington Heights   
## -50.19522   
## neighbourhood\_cleansedArtesia   
## -34.53171   
## neighbourhood\_cleansedAthens   
## -33.21781   
## neighbourhood\_cleansedAtwater Village   
## -13.59321   
## neighbourhood\_cleansedAvalon   
## -16.12898   
## neighbourhood\_cleansedAvocado Heights   
## -27.22726   
## neighbourhood\_cleansedAzusa   
## -22.28855   
## neighbourhood\_cleansedBaldwin Hills/Crenshaw   
## -28.55774   
## neighbourhood\_cleansedBaldwin Park   
## -26.79176   
## neighbourhood\_cleansedBel-Air   
## -6.66306   
## neighbourhood\_cleansedBell   
## -34.83124   
## neighbourhood\_cleansedBell Gardens   
## -30.27911   
## neighbourhood\_cleansedBellflower   
## -39.49325   
## neighbourhood\_cleansedBeverly Crest   
## -8.56094   
## neighbourhood\_cleansedBeverly Grove   
## 10.47786   
## neighbourhood\_cleansedBeverly Hills   
## 1.89673   
## neighbourhood\_cleansedBeverlywood   
## -28.28427   
## neighbourhood\_cleansedBoyle Heights   
## -28.44193   
## neighbourhood\_cleansedBradbury   
## -3.44844   
## neighbourhood\_cleansedBrentwood   
## -3.16325   
## neighbourhood\_cleansedBroadway-Manchester   
## -34.35577   
## neighbourhood\_cleansedBurbank   
## -15.59956   
## neighbourhood\_cleansedCalabasas   
## -19.28785   
## neighbourhood\_cleansedCanoga Park   
## -31.47853   
## neighbourhood\_cleansedCarson   
## -38.01954   
## neighbourhood\_cleansedCarthay   
## 0.23702   
## neighbourhood\_cleansedCastaic   
## -44.73803   
## neighbourhood\_cleansedCastaic Canyons   
## -31.53606   
## neighbourhood\_cleansedCentral-Alameda   
## -41.87742   
## neighbourhood\_cleansedCentury City   
## 0.49933   
## neighbourhood\_cleansedCerritos   
## -40.37060   
## neighbourhood\_cleansedCharter Oak   
## -59.11166   
## neighbourhood\_cleansedChatsworth   
## -22.04220   
## neighbourhood\_cleansedChatsworth Reservoir   
## 87.87155   
## neighbourhood\_cleansedChesterfield Square   
## -56.14295   
## neighbourhood\_cleansedCheviot Hills   
## -13.16047   
## neighbourhood\_cleansedChinatown   
## -18.44377   
## neighbourhood\_cleansedCitrus   
## -12.02910   
## neighbourhood\_cleansedClaremont   
## -10.74033   
## neighbourhood\_cleansedCommerce   
## -3.88392   
## neighbourhood\_cleansedCompton   
## -20.73100   
## neighbourhood\_cleansedCovina   
## -34.97257   
## neighbourhood\_cleansedCudahy   
## -114.28082   
## neighbourhood\_cleansedCulver City   
## -3.64831   
## neighbourhood\_cleansedCypress Park   
## -44.68741   
## neighbourhood\_cleansedDel Aire   
## -19.87645   
## neighbourhood\_cleansedDel Rey   
## 4.50569   
## neighbourhood\_cleansedDesert View Highlands   
## 7.72710   
## neighbourhood\_cleansedDiamond Bar   
## -29.42037   
## neighbourhood\_cleansedDowney   
## -32.12804   
## neighbourhood\_cleansedDowntown   
## 9.41233   
## neighbourhood\_cleansedDuarte   
## -38.02063   
## neighbourhood\_cleansedEagle Rock   
## -20.08071   
## neighbourhood\_cleansedEast Compton   
## -37.33381   
## neighbourhood\_cleansedEast Hollywood   
## -31.95450   
## neighbourhood\_cleansedEast Los Angeles   
## -31.01641   
## neighbourhood\_cleansedEast Pasadena   
## -13.63704   
## neighbourhood\_cleansedEast San Gabriel   
## -45.46364   
## neighbourhood\_cleansedEast Whittier   
## 7.63624   
## neighbourhood\_cleansedEcho Park   
## -15.29978   
## neighbourhood\_cleansedEl Monte   
## -26.81699   
## neighbourhood\_cleansedEl Segundo   
## -14.16882   
## neighbourhood\_cleansedEl Sereno   
## -34.20989   
## neighbourhood\_cleansedElysian Park   
## -13.15680   
## neighbourhood\_cleansedElysian Valley   
## -12.29208   
## neighbourhood\_cleansedEncino   
## -21.35902   
## neighbourhood\_cleansedExposition Park   
## -20.24254   
## neighbourhood\_cleansedFairfax   
## -4.18004   
## neighbourhood\_cleansedFlorence   
## -72.23932   
## neighbourhood\_cleansedFlorence-Firestone   
## -46.89878   
## neighbourhood\_cleansedGardena   
## -35.32696   
## neighbourhood\_cleansedGlassell Park   
## -20.79934   
## neighbourhood\_cleansedGlendale   
## -4.61772   
## neighbourhood\_cleansedGlendora   
## -34.78981   
## neighbourhood\_cleansedGramercy Park   
## 13.22026   
## neighbourhood\_cleansedGranada Hills   
## -11.92649   
## neighbourhood\_cleansedGreen Meadows   
## -26.94871   
## neighbourhood\_cleansedGreen Valley   
## -19.48472   
## neighbourhood\_cleansedGriffith Park   
## -56.25004   
## neighbourhood\_cleansedHacienda Heights   
## -38.58367   
## neighbourhood\_cleansedHancock Park   
## -3.36992   
## neighbourhood\_cleansedHarbor City   
## -26.73924   
## neighbourhood\_cleansedHarbor Gateway   
## -50.68108   
## neighbourhood\_cleansedHarvard Heights   
## -30.99308   
## neighbourhood\_cleansedHarvard Park   
## -80.94504   
## neighbourhood\_cleansedHasley Canyon   
## -26.96151   
## neighbourhood\_cleansedHawaiian Gardens   
## -46.77069   
## neighbourhood\_cleansedHawthorne   
## -38.80019   
## neighbourhood\_cleansedHermosa Beach   
## -0.57102   
## neighbourhood\_cleansedHighland Park   
## -24.61640   
## neighbourhood\_cleansedHistoric South-Central   
## -63.09728   
## neighbourhood\_cleansedHollywood   
## -5.21594   
## neighbourhood\_cleansedHollywood Hills   
## -4.85802   
## neighbourhood\_cleansedHollywood Hills West   
## -6.42799   
## neighbourhood\_cleansedHuntington Park   
## -33.45215   
## neighbourhood\_cleansedHyde Park   
## -39.93837   
## neighbourhood\_cleansedIndustry   
## -24.72370   
## neighbourhood\_cleansedInglewood   
## -31.11506   
## neighbourhood\_cleansedIrwindale   
## -55.66209   
## neighbourhood\_cleansedJefferson Park   
## -23.88308   
## neighbourhood\_cleansedKoreatown   
## -24.41714   
## neighbourhood\_cleansedLa Canada Flintridge   
## -2.40175   
## neighbourhood\_cleansedLa Crescenta-Montrose   
## -5.90499   
## neighbourhood\_cleansedLa Habra Heights   
## -1.12932   
## neighbourhood\_cleansedLa Mirada   
## -42.18509   
## neighbourhood\_cleansedLa Puente   
## -26.90934   
## neighbourhood\_cleansedLa Verne   
## -42.22016   
## neighbourhood\_cleansedLadera Heights   
## -6.55187   
## neighbourhood\_cleansedLake Balboa   
## -26.37567   
## neighbourhood\_cleansedLake Hughes   
## 65.37886   
## neighbourhood\_cleansedLake Los Angeles   
## -23.86780   
## neighbourhood\_cleansedLake View Terrace   
## -58.27599   
## neighbourhood\_cleansedLakewood   
## -25.82915   
## neighbourhood\_cleansedLancaster   
## -53.63474   
## neighbourhood\_cleansedLarchmont   
## -9.55364   
## neighbourhood\_cleansedLawndale   
## -35.21984   
## neighbourhood\_cleansedLeimert Park   
## -34.65890   
## neighbourhood\_cleansedLennox   
## -38.51499   
## neighbourhood\_cleansedLeona Valley   
## -14.95577   
## neighbourhood\_cleansedLincoln Heights   
## -12.99628   
## neighbourhood\_cleansedLomita   
## -29.62747   
## neighbourhood\_cleansedLong Beach   
## -16.06142   
## neighbourhood\_cleansedLopez/Kagel Canyons   
## -42.12271   
## neighbourhood\_cleansedLos Feliz   
## -10.01933   
## neighbourhood\_cleansedLynwood   
## -51.90205   
## neighbourhood\_cleansedMalibu   
## -4.13548   
## neighbourhood\_cleansedManchester Square   
## -11.02129   
## neighbourhood\_cleansedManhattan Beach   
## 4.32345   
## neighbourhood\_cleansedMar Vista   
## -14.70387   
## neighbourhood\_cleansedMarina del Rey   
## 26.31406   
## neighbourhood\_cleansedMayflower Village   
## -42.31807   
## neighbourhood\_cleansedMaywood   
## -38.97465   
## neighbourhood\_cleansedMid-City   
## -19.43720   
## neighbourhood\_cleansedMid-Wilshire   
## -9.00388   
## neighbourhood\_cleansedMission Hills   
## -21.63103   
## neighbourhood\_cleansedMonrovia   
## -18.95226   
## neighbourhood\_cleansedMontebello   
## -28.65295   
## neighbourhood\_cleansedMontecito Heights   
## -16.20650   
## neighbourhood\_cleansedMonterey Park   
## -26.87831   
## neighbourhood\_cleansedMount Washington   
## -13.76471   
## neighbourhood\_cleansedNorth El Monte   
## -24.30321   
## neighbourhood\_cleansedNorth Hills   
## -35.37737   
## neighbourhood\_cleansedNorth Hollywood   
## -23.12420   
## neighbourhood\_cleansedNorth Whittier   
## -0.75225   
## neighbourhood\_cleansedNortheast Antelope Valley   
## -60.58760   
## neighbourhood\_cleansedNorthridge   
## -23.53671   
## neighbourhood\_cleansedNorthwest Antelope Valley   
## -71.02754   
## neighbourhood\_cleansedNorthwest Palmdale   
## -67.18439   
## neighbourhood\_cleansedNorwalk   
## -44.81072   
## neighbourhood\_cleansedPacific Palisades   
## -3.34407   
## neighbourhood\_cleansedPacoima   
## -27.34141   
## neighbourhood\_cleansedPalmdale   
## -51.55780   
## neighbourhood\_cleansedPalms   
## -19.50368   
## neighbourhood\_cleansedPalos Verdes Estates   
## 4.25976   
## neighbourhood\_cleansedPanorama City   
## -43.04878   
## neighbourhood\_cleansedParamount   
## -19.86700   
## neighbourhood\_cleansedPasadena   
## -10.97231   
## neighbourhood\_cleansedPico-Robertson   
## -9.94606   
## neighbourhood\_cleansedPico-Union   
## -20.15915   
## neighbourhood\_cleansedPico Rivera   
## -38.84580   
## neighbourhood\_cleansedPlaya del Rey   
## -5.90144   
## neighbourhood\_cleansedPlaya Vista   
## 2.30097   
## neighbourhood\_cleansedPomona   
## -33.94808   
## neighbourhood\_cleansedPorter Ranch   
## -19.56695   
## neighbourhood\_cleansedQuartz Hill   
## -56.43130   
## neighbourhood\_cleansedRancho Dominguez   
## -64.00279   
## neighbourhood\_cleansedRancho Palos Verdes   
## -24.29058   
## neighbourhood\_cleansedRancho Park   
## -34.90930   
## neighbourhood\_cleansedRedondo Beach   
## -4.86517   
## neighbourhood\_cleansedReseda   
## -27.52334   
## neighbourhood\_cleansedRidge Route   
## -27.77759   
## neighbourhood\_cleansedRolling Hills   
## -41.22812   
## neighbourhood\_cleansedRolling Hills Estates   
## 42.61316   
## neighbourhood\_cleansedRosemead   
## -41.53387   
## neighbourhood\_cleansedRowland Heights   
## -38.54727   
## neighbourhood\_cleansedSan Dimas   
## -36.88984   
## neighbourhood\_cleansedSan Fernando   
## -44.09798   
## neighbourhood\_cleansedSan Gabriel   
## -29.80122   
## neighbourhood\_cleansedSan Marino   
## -10.79284   
## neighbourhood\_cleansedSan Pasqual   
## -22.40850   
## neighbourhood\_cleansedSan Pedro   
## -24.51402   
## neighbourhood\_cleansedSanta Clarita   
## -22.13153   
## neighbourhood\_cleansedSanta Fe Springs   
## -60.04387   
## neighbourhood\_cleansedSanta Monica   
## 6.28053   
## neighbourhood\_cleansedSawtelle   
## -10.57781   
## neighbourhood\_cleansedSepulveda Basin   
## 53.72853   
## neighbourhood\_cleansedShadow Hills   
## -25.09891   
## neighbourhood\_cleansedSherman Oaks   
## -17.02917   
## neighbourhood\_cleansedSierra Madre   
## -10.32583   
## neighbourhood\_cleansedSignal Hill   
## -24.20302   
## neighbourhood\_cleansedSilver Lake   
## -4.93560   
## neighbourhood\_cleansedSouth Diamond Bar   
## -32.84979   
## neighbourhood\_cleansedSouth El Monte   
## -35.15615   
## neighbourhood\_cleansedSouth Gate   
## -20.76421   
## neighbourhood\_cleansedSouth Park   
## -49.70875   
## neighbourhood\_cleansedSouth Pasadena   
## -17.20402   
## neighbourhood\_cleansedSouth San Gabriel   
## -44.38613   
## neighbourhood\_cleansedSouth San Jose Hills   
## -42.54189   
## neighbourhood\_cleansedSouth Whittier   
## -29.24026   
## neighbourhood\_cleansedSoutheast Antelope Valley   
## -18.31108   
## neighbourhood\_cleansedStevenson Ranch   
## -45.71835   
## neighbourhood\_cleansedStudio City   
## -6.05904   
## neighbourhood\_cleansedSun Valley   
## -17.93947   
## neighbourhood\_cleansedSun Village   
## -18.70979   
## neighbourhood\_cleansedSunland   
## -29.97395   
## neighbourhood\_cleansedSylmar   
## -36.51402   
## neighbourhood\_cleansedTarzana   
## -21.22463   
## neighbourhood\_cleansedTemple City   
## -33.83073   
## neighbourhood\_cleansedToluca Lake   
## -9.98494   
## neighbourhood\_cleansedTopanga   
## 9.39932   
## neighbourhood\_cleansedTorrance   
## -27.32643   
## neighbourhood\_cleansedTujunga   
## -39.95888   
## neighbourhood\_cleansedTujunga Canyons   
## 21.71401   
## neighbourhood\_cleansedUnincorporated Catalina Island   
## -13.41923   
## neighbourhood\_cleansedUnincorporated Santa Monica Mountains   
## -5.59299   
## neighbourhood\_cleansedUnincorporated Santa Susana Mountains   
## -11.83932   
## neighbourhood\_cleansedUniversal City   
## -14.52643   
## neighbourhood\_cleansedUniversity Park   
## -48.22265   
## neighbourhood\_cleansedVal Verde   
## -30.22794   
## neighbourhood\_cleansedValinda   
## -46.50724   
## neighbourhood\_cleansedValley Glen   
## -18.36630   
## neighbourhood\_cleansedValley Village   
## -16.70667   
## neighbourhood\_cleansedVan Nuys   
## -27.77637   
## neighbourhood\_cleansedVenice   
## 8.02749   
## neighbourhood\_cleansedVermont-Slauson   
## -35.09455   
## neighbourhood\_cleansedVermont Knolls   
## -46.13291   
## neighbourhood\_cleansedVermont Square   
## -44.49811   
## neighbourhood\_cleansedVermont Vista   
## -36.67407   
## neighbourhood\_cleansedVernon   
## 8.75701   
## neighbourhood\_cleansedVeterans Administration   
## 1.77381   
## neighbourhood\_cleansedView Park-Windsor Hills   
## -15.99616   
## neighbourhood\_cleansedVincent   
## -3.66396   
## neighbourhood\_cleansedWalnut   
## -25.93735   
## neighbourhood\_cleansedWatts   
## -59.18776   
## neighbourhood\_cleansedWest Adams   
## -27.95621   
## neighbourhood\_cleansedWest Carson   
## -27.10836   
## neighbourhood\_cleansedWest Compton   
## -49.63880   
## neighbourhood\_cleansedWest Covina   
## -38.05633   
## neighbourhood\_cleansedWest Hills   
## -24.13930   
## neighbourhood\_cleansedWest Hollywood   
## 3.60461   
## neighbourhood\_cleansedWest Los Angeles   
## -28.19095   
## neighbourhood\_cleansedWest Puente Valley   
## -25.24084   
## neighbourhood\_cleansedWest Whittier-Los Nietos   
## -26.47242   
## neighbourhood\_cleansedWestchester   
## -17.52923   
## neighbourhood\_cleansedWestlake   
## -9.53602   
## neighbourhood\_cleansedWestlake Village   
## 13.73837   
## neighbourhood\_cleansedWestmont   
## -12.61814   
## neighbourhood\_cleansedWestwood   
## -0.75137   
## neighbourhood\_cleansedWhittier   
## -29.68313   
## neighbourhood\_cleansedWillowbrook   
## -20.27005   
## neighbourhood\_cleansedWilmington   
## -37.86489   
## neighbourhood\_cleansedWindsor Square   
## -7.23688   
## neighbourhood\_cleansedWinnetka   
## -22.07372   
## neighbourhood\_cleansedWoodland Hills   
## -19.48029   
## cleaning\_fee   
## 0.33349   
## security\_deposit   
## 0.02393   
## review\_scores\_rating   
## 0.17269   
## bed\_typeCouch   
## -2.47330   
## bed\_typeFuton   
## 7.44929   
## bed\_typePull-out Sofa   
## 11.61426   
## bed\_typeReal Bed   
## 24.03258   
## review\_scores\_checkin   
## -1.31612   
## review\_scores\_cleanliness   
## 3.44794   
## review\_scores\_location   
## 3.94972   
## review\_scores\_value   
## -3.46092

model<-lm(price~bedrooms+property\_type+beds+host\_is\_superhost+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+  
 review\_scores\_rating+bed\_type+review\_scores\_checkin+review\_scores\_cleanliness  
 +review\_scores\_location+review\_scores\_value,data=data) # removed due to backward regression  
  
par(mfrow=c(2,2))#Easier to look at the plots in a 2x2 window  
plot(model)

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced  
  
## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced

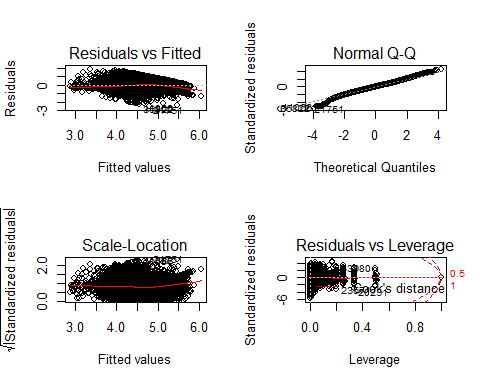


#Based on the plots, it looks like there isn't constant variance, but the other assumptions are upheld   
#To address this I transformed the dependent variable by taking the natural log of the price  
  
  
model<-lm(log(price)~bedrooms+property\_type+beds+host\_is\_superhost+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+  
 review\_scores\_rating+bed\_type+review\_scores\_checkin+review\_scores\_cleanliness  
 +review\_scores\_location+review\_scores\_value,data=data)  
  
  
plot(model)

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced  
  
## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced

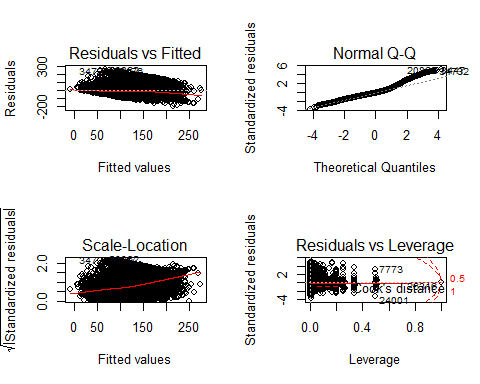


In addition, I created a variation to the above model, since the context of the problem is to help new listers determine their price per night, it wouldn’t make sense for them to have a rating or superhost on AirBnb.

model2<-lm(price~bedrooms+property\_type+beds+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+bed\_type,data=data)  
par(mfrow=c(2,2))#Easier to look at the plots in a 2x2 window  
plot(model2)

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640  
  
## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced  
  
## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced

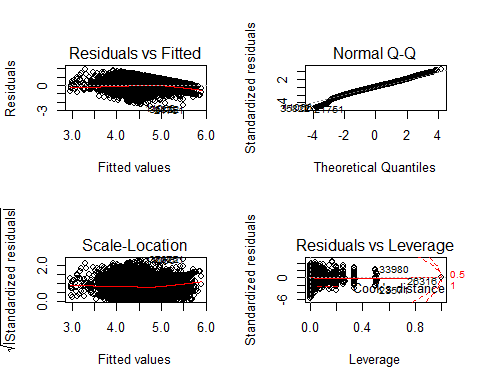


#Again, need to log the price as there isn't constant variance and for a better model  
  
model2<-lm(log(price)~bedrooms+property\_type+beds+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+bed\_type,data=data)  
plot(model2)

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning: not plotting observations with leverage one:  
## 15268, 25910, 31768, 36640

## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced  
  
## Warning in sqrt(crit \* p \* (1 - hh)/hh): NaNs produced



Spliting the dataset into a training set and test set using 10 cross fold validation. Then create the above model using the 10 fold cross validation. The benefit of 10 cross fold validation, is that it can use the entire dataset to train the model on.

It seems that the dataset provided by insideairbnb website doesn’t show when they host actually put up their listing, but provides when they scraped the listing off of the website. I also checked actual AirBnb website as well,there’s no way to find out the actual time they put up the listing.However, I do find it important to know when they scraped off the listing, since it means that, that was the price per night of their listing on the date of the scraping, which means that the host still thought that their property was worth that much at the time of the scrap and market conditions are still represented at the time of the scraping.

#Looking at the dataset of when the data is scraped,it is all in 2020 with a few days difference for some of the listings  
library(caret)

## Warning: package 'caret' was built under R version 3.6.3

## Loading required package: lattice

## Loading required package: ggplot2

train\_cv<-trainControl(method="cv",number=10) #10 cross fold validation  
  
model\_cv<-train(log(price)~bedrooms+property\_type+beds+host\_is\_superhost+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+  
 review\_scores\_rating+bed\_type+review\_scores\_checkin+review\_scores\_cleanliness  
 +review\_scores\_location+review\_scores\_value,data=data,trControl=train\_cv,method="lm")

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

print(model\_cv)

## Linear Regression   
##   
## 37710 samples  
## 13 predictor  
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold)   
## Summary of sample sizes: 33940, 33939, 33938, 33940, 33939, 33939, ...   
## Resampling results:  
##   
## RMSE Rsquared MAE   
## 0.4448096 0.4087386 0.3465547  
##   
## Tuning parameter 'intercept' was held constant at a value of TRUE

#By printing our model, we have three metrics we can look at for our model, RMSE,R2,and MAE.We can look at these measures  
  
  
#I looked into the warning message, which may be the result of colinearity of the independent variables, however I already looked into numberic variables in the model and I didn't find anything of the sort.Thus, I think it MAY be an false warning.   
  
  
  
#The model variation we did above, I will do again for the 10 cross fold validation  
  
model2\_cv<-train(log(price)~bedrooms+property\_type+beds+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+bed\_type,data=data,trControl=train\_cv,method="lm")

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

print(model2\_cv)

## Linear Regression   
##   
## 37710 samples  
## 7 predictor  
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold)   
## Summary of sample sizes: 33940, 33938, 33939, 33938, 33939, 33938, ...   
## Resampling results:  
##   
## RMSE Rsquared MAE   
## 0.4466335 0.4037924 0.3481002  
##   
## Tuning parameter 'intercept' was held constant at a value of TRUE

Multinomial Logistic Model using 10 Fold Cross Validation

#First split the price into categories such as low , medium , high.I think this is important to look at since when it comes to the tourism or hospitality industry, as a consumer myself I look at the price as a way to determine the luxary of an accomadation.Higher the price the more luxurious it is. I'm thinking of renaming these categories to other categories that will fit the context of the problem better, these could be temporary names.  
  
  
range(data$price)

## [1] 10 334

#10 is the loweest , 334 is the highest price , I want to split it between low, medium and high  
#Thus, lowest I will set it as 10-118 as low inclusively, 119- 226 inclusively as medium, and 227-334 inclusively as high.  
  
data$price\_level<-NA  
  
data$price\_level[which(data$price<=118)]<-"Low"  
data$price\_level[which(data$price>=119)]<-"Medium"  
data$price\_level[which(data$price>=227)]<-"High"  
  
  
data$price\_level<-as.factor(data$price\_level)

train\_cv<-trainControl(method="cv",number=10)  
  
model\_log\_cv<-train(price\_level~bedrooms+property\_type+beds+host\_is\_superhost+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+  
 review\_scores\_rating+bed\_type+review\_scores\_checkin+review\_scores\_cleanliness  
 +review\_scores\_location+review\_scores\_value,data=data,trControl=train\_cv,method="multinom")

## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 28001.390112  
## iter 20 value 27201.463075  
## iter 30 value 25552.132562  
## iter 40 value 24256.918990  
## iter 50 value 23872.501896  
## iter 60 value 23716.742475  
## iter 70 value 23650.258980  
## iter 80 value 23612.053603  
## iter 90 value 23588.271823  
## iter 100 value 23579.164255  
## final value 23579.164255   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 28001.611416  
## iter 20 value 27204.519820  
## iter 30 value 25565.791308  
## iter 40 value 24290.604570  
## iter 50 value 23913.481915  
## iter 60 value 23763.391853  
## iter 70 value 23704.078311  
## iter 80 value 23672.771768  
## iter 90 value 23657.951269  
## iter 100 value 23652.916292  
## final value 23652.916292   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 28001.390333  
## iter 20 value 27201.466137  
## iter 30 value 25552.146806  
## iter 40 value 24256.956560  
## iter 50 value 23872.552217  
## iter 60 value 23716.804839  
## iter 70 value 23650.340915  
## iter 80 value 23612.157184  
## iter 90 value 23588.399303  
## iter 100 value 23579.312113  
## final value 23579.312113   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27980.450376  
## iter 20 value 27167.346547  
## iter 30 value 25487.250681  
## iter 40 value 24358.690398  
## iter 50 value 23836.532762  
## iter 60 value 23650.317269  
## iter 70 value 23567.976573  
## iter 80 value 23533.730512  
## iter 90 value 23507.119576  
## iter 100 value 23495.249065  
## final value 23495.249065   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27980.674287  
## iter 20 value 27170.459571  
## iter 30 value 25503.209059  
## iter 40 value 24396.690679  
## iter 50 value 23882.752990  
## iter 60 value 23705.306230  
## iter 70 value 23638.690766  
## iter 80 value 23612.417322  
## iter 90 value 23582.292800  
## iter 100 value 23573.669307  
## final value 23573.669307   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27980.450599  
## iter 20 value 27167.349657  
## iter 30 value 25487.267238  
## iter 40 value 24358.732561  
## iter 50 value 23836.589430  
## iter 60 value 23650.389616  
## iter 70 value 23568.069449  
## iter 80 value 23533.834642  
## iter 90 value 23507.251145  
## iter 100 value 23495.404228  
## final value 23495.404228   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27935.069064  
## iter 20 value 27170.230492  
## iter 30 value 25548.120938  
## iter 40 value 24385.801781  
## iter 50 value 23905.353812  
## iter 60 value 23731.374892  
## iter 70 value 23662.901637  
## iter 80 value 23624.914470  
## iter 90 value 23597.227317  
## iter 100 value 23583.955646  
## final value 23583.955646   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27935.287500  
## iter 20 value 27173.122986  
## iter 30 value 25563.396046  
## iter 40 value 24421.782725  
## iter 50 value 23951.069844  
## iter 60 value 23782.255355  
## iter 70 value 23722.654220  
## iter 80 value 23685.833630  
## iter 90 value 23667.040387  
## iter 100 value 23659.370665  
## final value 23659.370665   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27935.069283  
## iter 20 value 27170.233403  
## iter 30 value 25548.136980  
## iter 40 value 24385.842068  
## iter 50 value 23905.410374  
## iter 60 value 23731.443791  
## iter 70 value 23662.988997  
## iter 80 value 23625.021712  
## iter 90 value 23597.356062  
## iter 100 value 23584.104932  
## final value 23584.104932   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27912.108969  
## iter 20 value 27122.982697  
## iter 30 value 25720.687629  
## iter 40 value 24373.265021  
## iter 50 value 23845.408590  
## iter 60 value 23655.584291  
## iter 70 value 23578.922498  
## iter 80 value 23527.156032  
## iter 90 value 23504.374145  
## iter 100 value 23493.375692  
## final value 23493.375692   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27912.331551  
## iter 20 value 27126.033121  
## iter 30 value 25735.234345  
## iter 40 value 24413.981910  
## iter 50 value 23892.574697  
## iter 60 value 23697.994682  
## iter 70 value 23638.989755  
## iter 80 value 23600.001680  
## iter 90 value 23579.903148  
## iter 100 value 23572.027705  
## final value 23572.027705   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27912.109192  
## iter 20 value 27122.985756  
## iter 30 value 25720.702777  
## iter 40 value 24373.310365  
## iter 50 value 23845.466526  
## iter 60 value 23655.659002  
## iter 70 value 23579.016487  
## iter 80 value 23527.270526  
## iter 90 value 23504.510720  
## iter 100 value 23493.532229  
## final value 23493.532229   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27927.718784  
## iter 20 value 27126.207449  
## iter 30 value 25554.046860  
## iter 40 value 24211.239976  
## iter 50 value 23810.111927  
## iter 60 value 23644.050841  
## iter 70 value 23593.034144  
## iter 80 value 23546.964177  
## iter 90 value 23517.590081  
## iter 100 value 23505.929536  
## final value 23505.929536   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27927.943995  
## iter 20 value 27129.306340  
## iter 30 value 25652.785072  
## iter 40 value 24295.202974  
## iter 50 value 23851.645677  
## iter 60 value 23691.937729  
## iter 70 value 23642.741409  
## iter 80 value 23609.021412  
## iter 90 value 23586.073282  
## iter 100 value 23578.769998  
## final value 23578.769998   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27927.719009  
## iter 20 value 27126.210569  
## iter 30 value 25554.081686  
## iter 40 value 24211.385627  
## iter 50 value 23810.189858  
## iter 60 value 23644.118786  
## iter 70 value 23593.097255  
## iter 80 value 23547.070708  
## iter 90 value 23517.711218  
## iter 100 value 23506.072239  
## final value 23506.072239   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27922.385087  
## iter 20 value 27139.974085  
## iter 30 value 25449.341353  
## iter 40 value 24350.621632  
## iter 50 value 23902.738656  
## iter 60 value 23706.972802  
## iter 70 value 23628.340692  
## iter 80 value 23579.920097  
## iter 90 value 23545.986852  
## iter 100 value 23534.433244  
## final value 23534.433244   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27922.600565  
## iter 20 value 27142.977317  
## iter 30 value 25466.724072  
## iter 40 value 24385.693261  
## iter 50 value 23944.337614  
## iter 60 value 23744.985170  
## iter 70 value 23681.454039  
## iter 80 value 23642.876444  
## iter 90 value 23618.290011  
## iter 100 value 23611.368677  
## final value 23611.368677   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27922.385302  
## iter 20 value 27139.977070  
## iter 30 value 25449.359256  
## iter 40 value 24350.660861  
## iter 50 value 23902.789363  
## iter 60 value 23707.041008  
## iter 70 value 23628.425277  
## iter 80 value 23580.024961  
## iter 90 value 23546.118343  
## iter 100 value 23534.584454  
## final value 23534.584454   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27934.494752  
## iter 20 value 27141.861586  
## iter 30 value 25532.750821  
## iter 40 value 24321.373336  
## iter 50 value 23810.698897  
## iter 60 value 23630.831875  
## iter 70 value 23555.153300  
## iter 80 value 23516.412234  
## iter 90 value 23489.320907  
## iter 100 value 23479.177093  
## final value 23479.177093   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27934.713491  
## iter 20 value 27144.900271  
## iter 30 value 25548.405940  
## iter 40 value 24364.852762  
## iter 50 value 23857.673555  
## iter 60 value 23685.804279  
## iter 70 value 23619.831480  
## iter 80 value 23588.740746  
## iter 90 value 23565.913066  
## iter 100 value 23559.391093  
## final value 23559.391093   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27934.494971  
## iter 20 value 27141.864638  
## iter 30 value 25532.767220  
## iter 40 value 24321.421747  
## iter 50 value 23810.756706  
## iter 60 value 23630.905536  
## iter 70 value 23555.250421  
## iter 80 value 23516.528344  
## iter 90 value 23489.459841  
## iter 100 value 23479.336845  
## final value 23479.336845   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27910.368021  
## iter 20 value 27136.971397  
## iter 30 value 25523.826760  
## iter 40 value 24257.186517  
## iter 50 value 23826.651346  
## iter 60 value 23650.156096  
## iter 70 value 23593.919874  
## iter 80 value 23546.447127  
## iter 90 value 23517.582846  
## iter 100 value 23508.620618  
## final value 23508.620618   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27910.587548  
## iter 20 value 27139.840733  
## iter 30 value 25538.823234  
## iter 40 value 24295.031014  
## iter 50 value 23870.061379  
## iter 60 value 23711.998307  
## iter 70 value 23653.591134  
## iter 80 value 23609.075554  
## iter 90 value 23591.177870  
## iter 100 value 23585.283582  
## final value 23585.283582   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37285.802465   
## iter 10 value 27910.368240  
## iter 20 value 27136.974255  
## iter 30 value 25523.842349  
## iter 40 value 24257.229050  
## iter 50 value 23826.704977  
## iter 60 value 23650.226138  
## iter 70 value 23594.004950  
## iter 80 value 23546.556342  
## iter 90 value 23517.716739  
## iter 100 value 23508.774052  
## final value 23508.774052   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37284.703853   
## iter 10 value 27928.448545  
## iter 20 value 27170.470287  
## iter 30 value 25550.899665  
## iter 40 value 24305.133655  
## iter 50 value 23855.896020  
## iter 60 value 23676.179196  
## iter 70 value 23610.389144  
## iter 80 value 23572.560689  
## iter 90 value 23542.885391  
## iter 100 value 23534.614070  
## final value 23534.614070   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37284.703853   
## iter 10 value 27928.666584  
## iter 20 value 27173.322316  
## iter 30 value 25564.818394  
## iter 40 value 24340.227206  
## iter 50 value 23897.339152  
## iter 60 value 23735.146912  
## iter 70 value 23672.098497  
## iter 80 value 23641.161510  
## iter 90 value 23617.164237  
## iter 100 value 23611.917113  
## final value 23611.917113   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37284.703853   
## iter 10 value 27928.448763  
## iter 20 value 27170.473145  
## iter 30 value 25550.914267  
## iter 40 value 24305.173038  
## iter 50 value 23855.947175  
## iter 60 value 23676.247412  
## iter 70 value 23610.474836  
## iter 80 value 23572.669333  
## iter 90 value 23543.020067  
## iter 100 value 23534.767928  
## final value 23534.767928   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37286.901077   
## iter 10 value 27926.384123  
## iter 20 value 27117.947660  
## iter 30 value 25513.909255  
## iter 40 value 24170.006297  
## iter 50 value 23789.564196  
## iter 60 value 23638.506972  
## iter 70 value 23584.978486  
## iter 80 value 23535.631573  
## iter 90 value 23505.494903  
## iter 100 value 23497.544132  
## final value 23497.544132   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37286.901077   
## iter 10 value 27926.607724  
## iter 20 value 27121.061718  
## iter 30 value 25527.013832  
## iter 40 value 24209.858326  
## iter 50 value 23834.158086  
## iter 60 value 23688.824729  
## iter 70 value 23639.359103  
## iter 80 value 23597.457755  
## iter 90 value 23577.803611  
## iter 100 value 23571.224210  
## final value 23571.224210   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 37286.901077   
## iter 10 value 27926.384347  
## iter 20 value 27117.950787  
## iter 30 value 25513.922995  
## iter 40 value 24170.048570  
## iter 50 value 23789.617706  
## iter 60 value 23638.574329  
## iter 70 value 23585.063836  
## iter 80 value 23535.734704  
## iter 90 value 23505.623788  
## iter 100 value 23497.690546  
## final value 23497.690546   
## stopped after 100 iterations  
## # weights: 972 (646 variable)  
## initial value 41428.669406   
## iter 10 value 30077.976576  
## iter 20 value 29435.274334  
## iter 30 value 28122.706953  
## iter 40 value 27032.361161  
## iter 50 value 26578.349489  
## iter 60 value 26359.252003  
## iter 70 value 26292.764353  
## iter 80 value 26265.228017  
## iter 90 value 26249.121578  
## iter 100 value 26242.377040  
## final value 26242.377040   
## stopped after 100 iterations

print(model\_log\_cv)

## Penalized Multinomial Regression   
##   
## 37710 samples  
## 13 predictor  
## 3 classes: 'High', 'Low', 'Medium'   
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold)   
## Summary of sample sizes: 33939, 33939, 33939, 33939, 33939, 33939, ...   
## Resampling results across tuning parameters:  
##   
## decay Accuracy Kappa   
## 0e+00 0.6781490 0.2746292  
## 1e-04 0.6781225 0.2746001  
## 1e-01 0.6785734 0.2743263  
##   
## Accuracy was used to select the optimal model using the largest value.  
## The final value used for the model was decay = 0.1.

#Using a 10 fold cross validation and multinomial logistic regression takes a long time to train the model.   
  
#Again we have some metrics to look at for our multinomial regression model.

I made a confusion matrix here to see more metrics of the multinomial logistic regression.

log\_predictions <-predict(model\_log\_cv,data)  
actual\_values <-data$price\_level  
  
  
confusionMatrix(log\_predictions,actual\_values)

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction High Low Medium  
## High 228 356 131  
## Low 1243 21564 6633  
## Medium 1436 2154 3965  
##   
## Overall Statistics  
##   
## Accuracy : 0.683   
## 95% CI : (0.6783, 0.6877)  
## No Information Rate : 0.6384   
## P-Value [Acc > NIR] : < 2.2e-16   
##   
## Kappa : 0.2847   
##   
## Mcnemar's Test P-Value : < 2.2e-16   
##   
## Statistics by Class:  
##   
## Class: High Class: Low Class: Medium  
## Sensitivity 0.078431 0.8957 0.3696  
## Specificity 0.986007 0.4224 0.8669  
## Pos Pred Value 0.318881 0.7325 0.5248  
## Neg Pred Value 0.927585 0.6965 0.7757  
## Prevalence 0.077088 0.6384 0.2845  
## Detection Rate 0.006046 0.5718 0.1051  
## Detection Prevalence 0.018960 0.7807 0.2003  
## Balanced Accuracy 0.532219 0.6591 0.6183

Multinomial Logistic Regression Model Variation

model2\_log\_cv<-train(price\_level~bedrooms+property\_type+beds+neighbourhood\_cleansed+cleaning\_fee+security\_deposit+bed\_type,data=data,trControl=train\_cv,method="multinom")

## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27219.148994  
## iter 20 value 25940.011037  
## iter 30 value 24469.980018  
## iter 40 value 23934.318848  
## iter 50 value 23734.630249  
## iter 60 value 23651.468436  
## iter 70 value 23597.353251  
## iter 80 value 23571.531836  
## iter 90 value 23563.266358  
## iter 100 value 23559.043710  
## final value 23559.043710   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27222.425527  
## iter 20 value 25958.038986  
## iter 30 value 24492.752287  
## iter 40 value 23966.564561  
## iter 50 value 23762.275153  
## iter 60 value 23716.576769  
## iter 70 value 23662.255299  
## iter 80 value 23641.007193  
## iter 90 value 23636.894935  
## iter 100 value 23636.395184  
## final value 23636.395184   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27219.152271  
## iter 20 value 25940.029331  
## iter 30 value 24470.005433  
## iter 40 value 23934.358810  
## iter 50 value 23734.709044  
## iter 60 value 23651.577262  
## iter 70 value 23597.457177  
## iter 80 value 23571.656474  
## iter 90 value 23563.408849  
## iter 100 value 23559.217550  
## final value 23559.217550   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37284.703853   
## iter 10 value 27138.999496  
## iter 20 value 25930.281299  
## iter 30 value 24387.613040  
## iter 40 value 23858.679484  
## iter 50 value 23688.076709  
## iter 60 value 23609.516657  
## iter 70 value 23571.743414  
## iter 80 value 23553.335934  
## iter 90 value 23547.519040  
## iter 100 value 23542.789033  
## final value 23542.789033   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37284.703853   
## iter 10 value 27140.842516  
## iter 20 value 25947.199129  
## iter 30 value 24427.299692  
## iter 40 value 23893.107696  
## iter 50 value 23751.664788  
## iter 60 value 23681.766048  
## iter 70 value 23639.811389  
## iter 80 value 23624.128561  
## iter 90 value 23620.750631  
## iter 100 value 23620.247182  
## final value 23620.247182   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37284.703853   
## iter 10 value 27139.001338  
## iter 20 value 25930.298492  
## iter 30 value 24387.656496  
## iter 40 value 23858.721587  
## iter 50 value 23688.111112  
## iter 60 value 23609.593615  
## iter 70 value 23571.840305  
## iter 80 value 23553.454898  
## iter 90 value 23547.659630  
## iter 100 value 23542.966917  
## final value 23542.966917   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26896.885347  
## iter 20 value 25606.940644  
## iter 30 value 24433.103180  
## iter 40 value 23890.926792  
## iter 50 value 23678.046506  
## iter 60 value 23611.276826  
## iter 70 value 23582.903024  
## iter 80 value 23565.808206  
## iter 90 value 23559.417154  
## iter 100 value 23554.401431  
## final value 23554.401431   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26898.582360  
## iter 20 value 25623.039927  
## iter 30 value 24463.256615  
## iter 40 value 23917.871023  
## iter 50 value 23729.342097  
## iter 60 value 23676.110561  
## iter 70 value 23653.561800  
## iter 80 value 23639.286389  
## iter 90 value 23636.385809  
## iter 100 value 23635.998887  
## final value 23635.998887   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26896.887045  
## iter 20 value 25606.956990  
## iter 30 value 24433.136212  
## iter 40 value 23890.960369  
## iter 50 value 23678.109386  
## iter 60 value 23611.364856  
## iter 70 value 23583.006846  
## iter 80 value 23565.935159  
## iter 90 value 23559.570772  
## iter 100 value 23554.599574  
## final value 23554.599574   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27526.390048  
## iter 20 value 26401.795878  
## iter 30 value 24667.719661  
## iter 40 value 24030.890423  
## iter 50 value 23793.862214  
## iter 60 value 23653.407486  
## iter 70 value 23600.123802  
## iter 80 value 23573.218072  
## iter 90 value 23566.813923  
## iter 100 value 23562.973957  
## final value 23562.973957   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27529.512888  
## iter 20 value 26418.626987  
## iter 30 value 24711.449899  
## iter 40 value 24057.834464  
## iter 50 value 23830.780308  
## iter 60 value 23722.187749  
## iter 70 value 23659.971897  
## iter 80 value 23644.545459  
## iter 90 value 23640.476991  
## iter 100 value 23639.987902  
## final value 23639.987902   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27526.393173  
## iter 20 value 26401.812995  
## iter 30 value 24667.766800  
## iter 40 value 24030.924986  
## iter 50 value 23793.899965  
## iter 60 value 23653.491793  
## iter 70 value 23600.216297  
## iter 80 value 23573.343955  
## iter 90 value 23566.958864  
## iter 100 value 23563.150149  
## final value 23563.150149   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27104.277314  
## iter 20 value 25547.933729  
## iter 30 value 24428.918196  
## iter 40 value 23937.953171  
## iter 50 value 23751.714377  
## iter 60 value 23673.198353  
## iter 70 value 23616.793169  
## iter 80 value 23593.655037  
## iter 90 value 23585.926627  
## iter 100 value 23581.278321  
## final value 23581.278321   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27105.970761  
## iter 20 value 25568.912060  
## iter 30 value 24460.316458  
## iter 40 value 23961.405090  
## iter 50 value 23772.366520  
## iter 60 value 23695.783811  
## iter 70 value 23671.167963  
## iter 80 value 23661.916981  
## iter 90 value 23658.748286  
## iter 100 value 23658.363570  
## final value 23658.363570   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27104.279008  
## iter 20 value 25547.955060  
## iter 30 value 24428.952857  
## iter 40 value 23937.983393  
## iter 50 value 23751.789255  
## iter 60 value 23673.288433  
## iter 70 value 23616.887592  
## iter 80 value 23593.773434  
## iter 90 value 23586.061578  
## iter 100 value 23581.449437  
## final value 23581.449437   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26794.274411  
## iter 20 value 25606.465372  
## iter 30 value 24458.813216  
## iter 40 value 23939.617169  
## iter 50 value 23721.951628  
## iter 60 value 23619.746551  
## iter 70 value 23587.752715  
## iter 80 value 23567.293132  
## iter 90 value 23560.290459  
## iter 100 value 23555.369859  
## final value 23555.369859   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26795.976361  
## iter 20 value 25623.859561  
## iter 30 value 24488.231989  
## iter 40 value 23964.305574  
## iter 50 value 23777.414043  
## iter 60 value 23713.186898  
## iter 70 value 23659.724107  
## iter 80 value 23639.173991  
## iter 90 value 23635.531892  
## iter 100 value 23635.072103  
## final value 23635.072103   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26794.276111  
## iter 20 value 25606.482994  
## iter 30 value 24458.845355  
## iter 40 value 23939.646595  
## iter 50 value 23722.003210  
## iter 60 value 23619.825153  
## iter 70 value 23587.851105  
## iter 80 value 23567.415918  
## iter 90 value 23560.434231  
## iter 100 value 23555.553551  
## final value 23555.553551   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26808.350205  
## iter 20 value 25454.574375  
## iter 30 value 24376.304865  
## iter 40 value 23898.929510  
## iter 50 value 23693.191262  
## iter 60 value 23602.729120  
## iter 70 value 23567.727726  
## iter 80 value 23548.195501  
## iter 90 value 23541.719314  
## iter 100 value 23536.416878  
## final value 23536.416878   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26810.054256  
## iter 20 value 25473.045670  
## iter 30 value 24405.924725  
## iter 40 value 23931.918742  
## iter 50 value 23723.466559  
## iter 60 value 23658.799964  
## iter 70 value 23625.727126  
## iter 80 value 23615.617183  
## iter 90 value 23613.583837  
## iter 100 value 23613.340363  
## final value 23613.340363   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26808.351911  
## iter 20 value 25454.593165  
## iter 30 value 24376.337434  
## iter 40 value 23898.968620  
## iter 50 value 23693.257293  
## iter 60 value 23602.811668  
## iter 70 value 23567.830821  
## iter 80 value 23548.314171  
## iter 90 value 23541.859460  
## iter 100 value 23536.602669  
## final value 23536.602669   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26547.266183  
## iter 20 value 25654.659842  
## iter 30 value 24484.063375  
## iter 40 value 23832.778970  
## iter 50 value 23645.605365  
## iter 60 value 23588.289884  
## iter 70 value 23564.012387  
## iter 80 value 23545.879201  
## iter 90 value 23538.863953  
## iter 100 value 23533.762304  
## final value 23533.762304   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26548.990186  
## iter 20 value 25590.492181  
## iter 30 value 24357.793861  
## iter 40 value 23821.987089  
## iter 50 value 23690.413299  
## iter 60 value 23646.240366  
## iter 70 value 23626.154725  
## iter 80 value 23616.360840  
## iter 90 value 23613.599983  
## iter 100 value 23613.160705  
## final value 23613.160705   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 26547.267908  
## iter 20 value 25654.673538  
## iter 30 value 24484.089249  
## iter 40 value 23832.814857  
## iter 50 value 23645.676947  
## iter 60 value 23588.386238  
## iter 70 value 23564.111859  
## iter 80 value 23546.005637  
## iter 90 value 23539.015070  
## iter 100 value 23533.956257  
## final value 23533.956257   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27006.573813  
## iter 20 value 25647.000793  
## iter 30 value 24451.867101  
## iter 40 value 23885.097537  
## iter 50 value 23678.541420  
## iter 60 value 23601.113016  
## iter 70 value 23573.692101  
## iter 80 value 23561.338996  
## iter 90 value 23556.073135  
## iter 100 value 23550.903355  
## final value 23550.903355   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27008.307424  
## iter 20 value 25664.231968  
## iter 30 value 24481.758964  
## iter 40 value 23910.854010  
## iter 50 value 23717.266894  
## iter 60 value 23669.638473  
## iter 70 value 23640.935341  
## iter 80 value 23630.125207  
## iter 90 value 23628.108961  
## iter 100 value 23627.863155  
## final value 23627.863155   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37285.802465   
## iter 10 value 27006.575547  
## iter 20 value 25647.018286  
## iter 30 value 24451.899891  
## iter 40 value 23885.129161  
## iter 50 value 23678.599813  
## iter 60 value 23601.189087  
## iter 70 value 23573.793059  
## iter 80 value 23561.459202  
## iter 90 value 23556.216585  
## iter 100 value 23551.098883  
## final value 23551.098883   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37286.901077   
## iter 10 value 27048.251548  
## iter 20 value 25658.311723  
## iter 30 value 24447.348898  
## iter 40 value 23908.379713  
## iter 50 value 23712.241453  
## iter 60 value 23643.521560  
## iter 70 value 23608.292257  
## iter 80 value 23586.285795  
## iter 90 value 23579.749168  
## iter 100 value 23574.684913  
## final value 23574.684913   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37286.901077   
## iter 10 value 27049.963235  
## iter 20 value 25675.425960  
## iter 30 value 24478.700088  
## iter 40 value 23931.795954  
## iter 50 value 23767.357821  
## iter 60 value 23690.502076  
## iter 70 value 23667.186659  
## iter 80 value 23655.024418  
## iter 90 value 23653.072317  
## iter 100 value 23652.792618  
## final value 23652.792618   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 37286.901077   
## iter 10 value 27048.253260  
## iter 20 value 25658.329076  
## iter 30 value 24447.383267  
## iter 40 value 23908.409002  
## iter 50 value 23712.308870  
## iter 60 value 23643.592864  
## iter 70 value 23608.399603  
## iter 80 value 23586.405703  
## iter 90 value 23579.890675  
## iter 100 value 23574.870057  
## final value 23574.870057   
## stopped after 100 iterations  
## # weights: 954 (634 variable)  
## initial value 41428.669406   
## iter 10 value 29628.295478  
## iter 20 value 28604.425809  
## iter 30 value 27069.345259  
## iter 40 value 26582.864136  
## iter 50 value 26391.162507  
## iter 60 value 26328.284306  
## iter 70 value 26299.302554  
## iter 80 value 26287.002275  
## iter 90 value 26282.515451  
## iter 100 value 26281.269242  
## final value 26281.269242   
## stopped after 100 iterations

print(model2\_log\_cv)

## Penalized Multinomial Regression   
##   
## 37710 samples  
## 7 predictor  
## 3 classes: 'High', 'Low', 'Medium'   
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold)   
## Summary of sample sizes: 33939, 33938, 33939, 33939, 33939, 33939, ...   
## Resampling results across tuning parameters:  
##   
## decay Accuracy Kappa   
## 0e+00 0.6769559 0.2707465  
## 1e-04 0.6769559 0.2707465  
## 1e-01 0.6771946 0.2702641  
##   
## Accuracy was used to select the optimal model using the largest value.  
## The final value used for the model was decay = 0.1.

log2\_prediction<-predict(model2\_log\_cv,data)  
confusionMatrix(log2\_prediction,actual\_values)

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction High Low Medium  
## High 219 337 124  
## Low 1257 21600 6707  
## Medium 1431 2137 3898  
##   
## Overall Statistics  
##   
## Accuracy : 0.682   
## 95% CI : (0.6772, 0.6867)  
## No Information Rate : 0.6384   
## P-Value [Acc > NIR] : < 2.2e-16   
##   
## Kappa : 0.2801   
##   
## Mcnemar's Test P-Value : < 2.2e-16   
##   
## Statistics by Class:  
##   
## Class: High Class: Low Class: Medium  
## Sensitivity 0.075335 0.8972 0.3633  
## Specificity 0.986754 0.4160 0.8678  
## Pos Pred Value 0.322059 0.7306 0.5221  
## Neg Pred Value 0.927410 0.6963 0.7741  
## Prevalence 0.077088 0.6384 0.2845  
## Detection Rate 0.005807 0.5728 0.1034  
## Detection Prevalence 0.018032 0.7840 0.1980  
## Balanced Accuracy 0.531045 0.6566 0.6155