FinalProject_IS457_35

35

April 29, 2019

```
# Load libraries

# install.packages("ggplot2")
# install.packages("dplyr")
# install.packages("lattice")
# install.packages("reshape2")

library(ggplot2)
library(dplyr)
library(lattice)
library(reshape2)
#require(RColorBrewer)
```

PART 1: Data Processing

Q1

1.1: What variables have missing values? What types/forms of missing values are they?

```
# Initial read of the data:
# airbnb <- read.csv(paste(getwd(),"/data/AirbnbSydney.csv", sep = ""), strin
gsAsFactors = FALSE)

# Read in airbnb data -- accounting for NA values
airbnb <- read.csv(paste(getwd(),"/data/AirbnbSydney.csv", sep = ""), strings
AsFactors = FALSE, na.strings = c("N/A","", "NA"))


# Number of missing values
missingvals <- sapply(airbnb, function(x) sum(is.na(x)))
missingvals[missingvals>0]

##       neighborhood_overview                    house_rules
##                         664                           1639
##          host_response_time             host_response_rate
##                        2483                           2483
##                        city                        zipcode
```

```
##                          8                          21
##                  bathrooms                    bedrooms
##                          1                           1
##               cleaning_fee        review_scores_rating
##                        621                           1
##     review_scores_accuracy   review_scores_cleanliness
##                          1                           1
##       review_scores_checkin review_scores_communication
##                          1                           1
```

```r
# Percent missing values
round(missingvals[missingvals >0]/length(airbnb[,1]), 2)
```

```
##       neighborhood_overview                 house_rules
##                        0.06                        0.15
##          host_response_time          host_response_rate
##                        0.23                        0.23
##                        city                     zipcode
##                        0.00                        0.00
##                   bathrooms                    bedrooms
##                        0.00                        0.00
##                cleaning_fee        review_scores_rating
##                        0.06                        0.00
##      review_scores_accuracy   review_scores_cleanliness
##                        0.00                        0.00
##       review_scores_checkin review_scores_communication
##                        0.00                        0.00
```

```r
summary(airbnb[,missingvals>0])
```

```
##  neighborhood_overview house_rules         host_response_time
##  Length:10815          Length:10815        Length:10815
##  Class :character      Class :character    Class :character
##  Mode  :character      Mode  :character    Mode  :character
##
##
##
##
##  host_response_rate     city               zipcode             bathrooms
##  Length:10815        Length:10815       Length:10815       Min.   : 0.000
##  Class :character    Class :character   Class :character   1st Qu.: 1.000
##  Mode  :character    Mode  :character   Mode  :character   Median : 1.000
##                                                            Mean   : 1.349
##                                                            3rd Qu.: 1.500
##                                                            Max.   :10.000
##                                                            NA's   :1
##     bedrooms       cleaning_fee       review_scores_rating
##  Min.   : 0.000   Length:10815       Min.   : 20.00
##  1st Qu.: 1.000   Class :character   1st Qu.: 92.00
##  Median : 1.000   Mode  :character   Median : 96.00
##  Mean   : 1.629                      Mean   : 94.19
```

```
##  3rd Qu.: 2.000                    3rd Qu.:100.00
##  Max.   :14.000                    Max.   :100.00
##  NA's   :1                         NA's   :1
##  review_scores_accuracy review_scores_cleanliness review_scores_checkin
##  Min.   : 2.00          Min.   : 2.000            Min.   : 2.000
##  1st Qu.: 9.00          1st Qu.: 9.000            1st Qu.:10.000
##  Median :10.00          Median :10.000            Median :10.000
##  Mean   : 9.64          Mean   : 9.398            Mean   : 9.782
##  3rd Qu.:10.00          3rd Qu.:10.000            3rd Qu.:10.000
##  Max.   :10.00          Max.   :10.000            Max.   :10.000
##  NA's   :1              NA's   :1                 NA's   :1
##  review_scores_communication
##  Min.   : 2.000
##  1st Qu.:10.000
##  Median :10.000
##  Mean   : 9.802
##  3rd Qu.:10.000
##  Max.   :10.000
##  NA's   :1
```

```
#sapply(airbnb[,missingvals>0], function(x) str(x))

# Clean the prices (drop $ and comma, as.numeric)
airbnb$price <- as.numeric(gsub("^\\$|,","",airbnb$price))
airbnb$cleaning_fee <- as.numeric(gsub("^\\$|,","",airbnb$cleaning_fee))
airbnb$extra_people <- as.numeric(gsub("^\\$|,","",airbnb$extra_people))

# Clean percents
airbnb$host_response_rate <- as.numeric(gsub("%$","", airbnb$host_response_ra
te))

# Store host_since as a date
airbnb$host_since <- as.Date(airbnb$host_since, format = "%m/%d/%y") #  add c
olumn of day units for comparing ages

# Add a column -- number of days as host as of max(date)
airbnb$host_number_of_days <- difftime(max(airbnb$host_since), airbnb$host_si
nce, units = "days")


# Store logicals as logical. R requires a capial T or F
airbnb$host_is_superhost <- as.logical(toupper(airbnb$host_is_superhost))
airbnb$host_identity_verified <- as.logical(toupper(airbnb$host_identity_veri
fied))
```

My answer

- Neighborhood_overview and house_rules are both text-heavy (paragraph or more) fields, NA on 6 and 15%. NA values are shown as empty strings: ""

- Host_response_time and host_response_rate are both absent from 23% of the observations. Response Time is an ordinal categorization of how long it takes to respond. Response Rate is a percentage that is imported as character, but will be converted to numeric. NA values are shown as valid character element “N/A”.
- City and zipcode are address components useful for aggregation. They are missing from 8 and 21 records (nearly zero percent) of these character vectors.
- Bathrooms is a numeric with decimals (due to half bath, .5). NA values are characters “NA”.
- Bedrooms is an integer numeric. NA values are characters “NA”.
- Cleaning_fee is a numerical (after cleaning) and missing from 6% of records.
- Review_scores_rating and review_scores_xxx are missing one observation in each column. These are integer values. NA values are characters “NA”.

1.2: How will you deal with missing values? Justify your methods.

For categorical data with missing values (such as city, zipcode, response_time), I imputed a value of “unknown.” This preserves the known data, and allows for omission of this value if necessary. I find it preferable to reduce the number of observations than to potentially impute incorrect values.

For numerical data, I used the median. This value is not affected by outliers. It is simply the value where half of the observations are higher, and half are lower.

1.3: Describe how your choice method may impact later analysis.

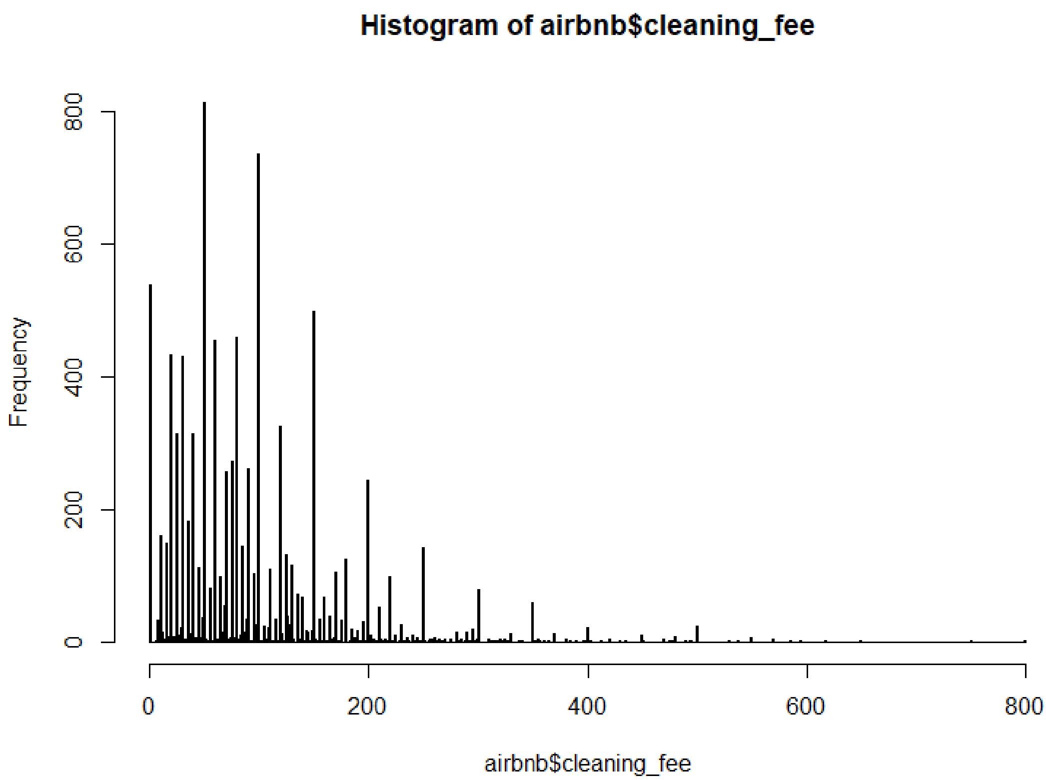
Imputing “unknown” for categorical data adds another category. It helps to preserve the known values for that observation, so na.rm() won’t remove the observation with the analyst possibly being unaware of its removal.

Imputing median values will increase the measure of centrality, while reducing the variance and standard deviation for those variables.

1.4: Implement methods to deal with missing values.

```
# NA neighborhood_overview and house_rules
# Do nothing, because these are descriptive text values and there is no way t
o impute them.

getmode <- function(v){
  # funcname: getmode
  # inputs  : a vector of elements
  # outputs : a single-value vector containing the most-frequently occuring v
alue
  # purpose : Calculate the mode
  # related : mean(), median()
```

```
  # auth/dt : ID35,

  uniqv <- unique(v)
  return(uniqv[which.max(tabulate(match(v, uniqv)))])
}

# NA host_response_time
# To preserve the integrity of these categorical data for comparative purpose
s,
# I will create a new category for NA values called "unknown"
airbnb$host_response_time[is.na(airbnb$host_response_time)] <- "unknown"

# NA host_response_rate
airbnb$host_response_rate[is.na(airbnb$host_response_rate)] <- median(airbnb$
host_response_rate, na.rm = TRUE)

# NA city
airbnb$city[is.na(airbnb$city)] <- "unknown"

# NA zipcode
airbnb$zipcode[is.na(airbnb$zipcode)] <- "unknown"

# NA bathrooms
airbnb$bathrooms[is.na(airbnb$bathrooms)] <- median(airbnb$bathrooms, na.rm =
TRUE)

# NA bedrooms
# Description calls this one a studio (no bedroom)
airbnb$bedrooms[is.na(airbnb$bedrooms)] <- 0

# NA cleaning fee
# The mode is 50
getmode(airbnb$cleaning_fee)

## [1] 50

# The distribution is positively skewed. This explains why the mean (94.4) is
greater than the median (80)
hist(airbnb$cleaning_fee, breaks = 1000)
```




```
# To clean this, I will use median. It lies between the mode and the mean, so
I'm using the central measure of centrality. :)
airbnb$cleaning_fee[is.na(airbnb$cleaning_fee)] <- median(airbnb$cleaning_fee
, na.rm = TRUE)


# NA review scores
# The review scores (review_scores_rating, review_scores_accuracy,
# review_scores_cleanliness, review_scores_checkin, and review_scores_communi
cation)
# are each missing one value. I will use median as the measure of centrality
# to fill in the missing values.

# These columns are being handled in the same way, and are next to each other
.
# I will use a for loop to go through each column, and assign the median valu
e
# of that column to any NA values.
for(i in 28:34){
  airbnb[is.na(airbnb[,i]),i] <- median(airbnb[,i], na.rm = TRUE)
}
```

1.5: After dealing with missing values, show the dimensions of the data.

```
# Show dimensions
dim(airbnb)

## [1] 10815    37
```

1.6: Comment on and explain any other data cleaning or preparation steps you think would be necessary from your inspection of the data (you do not have to carry them out).

host_since will need to be converted to date. host_response_time should become a factor (to compare levels) host_response_rate need the % sign scrubbed and converted to numeric (maybe even percentage, e.g. /100) price and cleaning_fee need $ scrubbed and converted to numeric

Q2

Conduct a preliminary exploration and describe what you find interesting or unexpected.

```
# This will create two lists: counts (table()) for categorical data, and summ
aries for continuous data
# This allows me to visually inspect the numerical distribution of each varia
ble (using View())
col_categories <- c(7,9,11:20,35)
col_continuous <- c(6,8,22:34,36)

counts <- lapply(airbnb[,col_categories], function(x) table(x))
summaries <- lapply(airbnb[,col_continuous], function(x) summary(x))
sds <- lapply(airbnb[,col_continuous], function(x) sd(x))

counts

## $host_response_time
## x
## a few days or more            unknown       within a day
##                119               2483               1078
## within a few hours     within an hour
##               1386               5749
##
## $host_is_superhost
## x
## FALSE  TRUE
##  8020  2795
##
```

```
## $host_identity_verified
## x
## FALSE  TRUE 
##  5631  5184 
## 
## $city
## x
##                 â\200¢ Darling harbour                          Abbotsford 
##                                     1                                   8 
##                                æ,‰å°¼                         Agnes Banks 
##                                     1                                   1 
##                            Alexandria                         Alexandria  
##                                    83                                   1 
##                      Allambie Heights                             Allawah 
##                                    11                                   3 
##                      Allawah/Carlton                            Annandale 
##                                     1                                  75 
##                               Arcadia                           Arncliffe 
##                                     2                                  43 
##                              Artarmon                     Ashbury, Sydney 
##                                     7                                   1 
##                             Ashfield      Ashfield, New South Wales, AU 
##                                    46                                   1 
##                               Asquith                              Auburn 
##                                     1                                   7 
##                               Auburn                   Auburn / Lidcomb  
##                                     1                                   1 
##                                Avalon                        Avalon Beach 
##                                    21                                 118 
##                             Balgowlah                   Balgowlah Heights 
##                                    56                                  12 
##                               Balmain                Balmain / Birchgrove 
##                                    79                                   1 
##                          Balmain East                      Balmoral Beach 
##                                    18                                   2 
##                                Bangor                             Banksia 
##                                     2                                   3 
##                        Banksia Sydney                           Bankstown 
##                                     1                                  22 
##                             Bar Point                          Barangaroo 
##                                     1                                   2 
##                                Bardia                      Bardwell Valley 
##                                     2                                   3 
##                             Barpoint                      Baulkham Hills 
##                                     1                                   7 
##                               Bayview                         Beacon Hill 
##                                     6                                  14 
##                          Beaconsfield                      Beaumont Hills 
##                                    13                                   2 
##                              Beecroft                            Belfield 
```

```
##                                  4                                  3
##                         Bella Vista                      Bellevue Hill
##                                  7                                 67
##    Bellevue Hill (Double Bay side).          Bellevue Hill, Sydney
##                                  1                                  1
##                             Belmore                             Berala
##                                  4                                 10
##                       Berowra Creek                    Berowra Heights
##                                  1                                  2
##                      Berowra Waters                      Beverly Hills
##                                  3                                  5
##                              Bexley                       Bexley North
##                                 10                                  3
##                             Bilgola                      Bilgola Beach
##                                  2                                 17
##                     Bilgola Plateau                    Bilgola, Sydney
##                                 16                                  1
##                          Birchgrove                          Blacktown
##                                 34                                  4
##                         Blair Athol                         Blakehurst
##                                  1                                  2
##                               Bondi                             Bondi 
##                                222                                  2
##                         bondi beach                        Bondi Beach
##                                  1                                555
##                        Bondi beach                Bondi Beach, Sydney
##                                  2                                  2
##                      Bondi Junction                    Bondi Junction 
##                                142                                  1
##               Bondi Junction Sydney             Bondi Junction, Sydney
##                                  1                                  2
##                     Bondi, Tamarama                             Botany
##                                  1                                 14
##                     Breakfast Point                 Brighton-Le-Sands
##                                  1                                 27
##                   Brighton Le Sands                             Bronte
##                                  1                                149
##                             Bronte                            Brooklyn
##                                  1                                  2
##                          Brookvale                           Bundeena
##                                  3                                 25
##                         Bungarribee                          Burraneer
##                                  1                                  1
##                  Burraneer/Cronulla                            Burwood
##                                  1                                 35
##                            Cabarita                         Cabramatta
##                                  1                                  3
##                     Cabramatta West                           Cammeray
##                                  1                                 28
##                        Campbelltown                         camperdown
```

```
##                                 2                                  1
##                        Camperdown                            Campsie
##                                88                                 10
##                        Canada Bay                     Canley Heights
##                                 1                                  2
##                        Canterbury                          Caringbah
##                                 8                                  1
##                   Caringbah South                        Carlingford
##                                 3                                  9
##                           Carlton                         Carnes Hill
##                                 6                                  9
##                          Carramar                          Carss Park
##                                 6                                  2
##                       Castle Cove                         Castle Hill
##                                 6                                  7
##                        Castlecrag                              Casula
##                                 5                                  8
##                   Centennial Park        Centennial Park, Sydney
##                                13                                  1
##                         Chatswood                  Chatswood Sydney 
##                                50                                  1
##                    Chatswood West                 Chatswood, Sydney 
##                                 4                                  1
##                        Cheltenham                         Cherrybrook
##                                 3                                  3
##                      Chester Hill                             Chifley
##                                 4                                  4
##                       Chippendale                       Chippendale 
##                               155                                  1
##                          Chiswick                        Church Point
##                                 8                                  4
##                        Clareville                            Clontarf
##                                 8                                 11
##                          Clovelly                   Coasters Retreat
##                                72                                  3
##                          Collaroy                     Collaroy Beach
##                                16                                  1
##                 Collaroy Plateau                                Como
##                                 5                                  1
##                           Concord                       Concord West
##                                 4                                  2
##                    Connells Point                              Coogee
##                                 5                                272
##                           Coogee  Coogee, New South Wales, Australia
##                                 1                                  1
##                     Cottage Point      Council of the City of Sydney
##                                 2                                  6
##                          Cremorne                     Cremorne Point
##                                48                                 13
##                            Cromer                           Cronulla
```

```
##                          5                        50
##                 Crows Nest       Crows Nest, Sydney
##                         31                         1
##                    Croydon              Croydon Park
##                         10                         7
##           Croydon Park NSW                 Curl Curl
##                          1                        10
##                 Daceyville             Dangar Island
##                          2                         4
##            darling harbour             Darling Point
##                          3                        31
##               Darlinghurst             Darlinghurst 
##                        373                         1
##        Darlinghurst Sydney       Darlinghurst, Sydney
##                          1                         1
##                 Darlington                  Davidson
##                         32                         2
##                Dawes Point                   Dee Why
##                          6                        46
##            Dee Why, Sydney                 Denistone
##                          1                         2
##             Denistone East               Dolls Point
##                          4                         3
##                 Double Bay        Double Bay, Sydney
##                         43                         1
##              Dover Heights                 Drummoyne
##                         15                        22
##              Duffys Forest              Dulwich Hill
##                          2                        34
##                     Dundas             Dundas Valley
##                          1                         4
##                      Dural                Eagle Vale
##                          3                         1
##                   Earlwood                East Hills
##                         15                         2
##             East Lindfield             Eastern Creek
##                          3                         1
##                Eastgardens              Eastgardens 
##                          9                         1
##                  Eastlakes                  Eastwood
##                          9                        10
##                  Edgecliff            Edmondson Park
##                         25                         3
##            Elanora Heights                Elderslie
##                          4                         4
##              Elizabeth Bay            Elizabeth Bay 
##                        101                         1
##       Elizabeth Bay / Sydney Elizabeth Bay /Potts Point
##                          1                         1
##                 Emu Plains                  Engadine
```

```
##                        1                        1
##                   Enmore                   Epping
##                       24                       14
##                Ermington              Erskineville
##                        8                       87
##                 Eveleigh                Fairfield
##                        4                        1
##           Fairfield West               Fairlight
##                        1                       83
##               Fairlight        Fairlight (Manly)
##                        1                        1
##                Five Dock             Forest lodge
##                        7                        1
##             Forest Lodge              Forestville
##                       50                        8
##           Frenchs Forest               Freshwater
##                        7                       59
##              Gladesville                    Glebe
##                        8                       93
##                Glenfield                Glenhaven
##                       18                        1
##            Glenmore Park                 Glenorie
##                        1                        1
##                 Glenwood                   Gordon
##                        1                        6
##                Granville              Grays Point
##                        3                        1
##    Great Mackerel Beach                Greenacre
##                        9                        2
##         Greenhills Beach                Greenwich
##                        2                       19
##               Greystanes              Greystanes 
##                        6                        1
##                Guildford           Guildford West
##                        5                        3
##                    Gymea               Haberfield
##                        1                        8
##              Harris Park                Haymarket
##                        1                       92
##                Heathcote                   Henley
##                        1                        3
##                Hillsdale                  Holroyd
##                       10                        1
##               Holsworthy                 Homebush
##                        3                       14
##            Homebush West          Horningsea Park
##                       16                        1
##                  Hornsby         Hornsby Heights
##                        8                        1
##             Hunters Hill             Huntleys Cove
```

```
##                      12                                    1
##           Hurlstone Park                          Hurstville
##                       8                                   18
##             Hurstville                      Hurstville Grove
##                       1                                    1
##       Hurstville Sydney                            Ingleburn
##                       1                                    2
##               Ingleside                              Jannali
##                       2                                    1
##          Jordan Springs                           Kellyville
##                       1                                    3
##              Kensington                              Killara
##                      35                                    6
##       Killarney Heights                        Kings Langley
##                       4                                    4
##               Kingsford                           Kingsgrove
##                      35                                    2
##               Kingswood                              Kirkham
##                       3                                    1
##              Kirribilli                              Kogarah
##                      49                                   18
##             Kogarah Bay                              Kurnell
##                       3                                    2
##           Kurraba Point                             Kyeemagh
##                       5                                    2
##               Kyle Bay                            La Perouse
##                       1                                    1
##               Lane Cove                      Lane Cove North
##                      18                                   24
##          Lane Cove West                             Lansvale
##                       8                                    1
##            Lavender Bay                           Leets Vale
##                      11                                    1
##              Leichhardt        Leichhardt Municipal Council
##                      76                                    1
##                  Leonay                             lewisham
##                       2                                    1
##                Lewisham                        Liberty Grove
##                      22                                    5
##                Lidcombe                          Lilli Pilli
##                      14                                    1
##              Lilyfield                             Lindfield
##                      32                                    6
##            Linley Point                          Little bay
##                       1                                    1
##             Little Bay                             Liverpool
##                      17                                    3
##                  Loftus                          Longueville
##                       1                                    9
##              Lovett Bay                       Lower Portland
```

```
##                                    3                                    2 
##                            Luddenham                              Lugarno 
##                                    2                                    1 
##                       Macquarie Park                             Maianbar 
##                                   14                                    5 
##                              Malabar                                Manly 
##                                   17                                  389 
##                               Manly                           Manly Beach 
##                                    1                                    4 
##                           Manly Vale                             Maroubra 
##                                   26                                  139 
##                       Maroubra Beach      Maroubra, New South Wales, AU 
##                                    1                                    1 
##                         Marrickville                        Marrickville  
##                                   90                                    1 
##                         Marsden Park                            Marsfield 
##                                    3                                   12 
##                               Mascot                          Matraville 
##                                   95                                    6 
##                        Mccarrs Creek                       McMahons Point 
##                                    1                                   24 
##                           Meadowbank                          Merrylands 
##                                    3                                   11 
##                      Merrylands West                         Middle Dural 
##                                    4                                    3 
##                        Millers Point                Millers Point, Sydney 
##                                   39                                    1 
##                      Milsons Passage                        Milsons Point 
##                                    4                                   16 
##                              Miranda                            Mona Vale 
##                                    3                                   30 
##                             Monterey                            Moorebank 
##                                    5                                    1 
##                          Morning Bay                             Mortdale 
##                                    4                                    2 
##                             Mortlake                               Mosman 
##                                    2                                  167 
##                        Mosman Sydney                         Mount Annan 
##                                    1                                    2 
##                          Mount Colah                         Mount Druitt 
##                                    1                                    1 
##                      Mount Pritchard                            Naremburn 
##                                    1                                   18 
##                            Narrabeen                           Narraweena 
##                                   24                                    1 
##                          Neutral Bay                      New South Wales 
##                                   62                                    1 
##                     New South Wales                             Newington 
##                                    1                                   10 
##                              Newport                              Newtown 
```

```
##                          49                                      190
##              North Balgowlah                             North Bondi
##                          25                                      191
##              North Curl Curl                             North Manly
##                          16                                       14
##              North Narrabeen                        North Parramatta
##                          17                                        8
##                   North Ryde                          North St Marys
##                          17                                        2
##            North Strathfield                            North Sydney
##                           1                                       65
##                North Sydney             North Sydney / Kirribilli
##                           1                                        1
##      North Sydney / Waverton                    North Sydney Council
##                           1                                        1
##             North Willoughby                             Northbridge
##                           6                                        6
##             Northern Beaches                               Northmead
##                           1                                        3
##                    Northwood                                     NSW
##                           2                                        1
##                     Oatlands                                  Oatley
##                           2                                        3
##                    Oran Park                           Orchard Hills
##                           1                                        1
##                 Oxford Falls                              Oxley Park
##                           2                                        5
##                   Paddington                                 Padstow
##                         175                                       15
##              Padstow Heights                                Pagewood
##                           1                                       10
##                   Palm Beach                                 Panania
##                          57                                        6
##                   Parramatta                               Peakhurst
##                          30                                        3
##            Peakhurst Heights                                Pemulwuy
##                           1                                        2
##                Pennant Hills                                 Penrith
##                           4                                        7
##                    Penshurst                               Petersham
##                           5                                       23
##                  Phillip Bay                       Pittwater Council
##                           1                                        1
##                     Plumpton                             Point Piper
##                           1                                        1
##                 Port Jackson                             Potts Point
##                           1                                      198
##                 Potts Point    Potts Point, New South Wales, AU
##                           1                                        1
##                     Prestons                                Prospect
```

```
##                          2                                  1
##                  Punchbowl                             Putney
##                          1                                  7
##                     Pymble                            pyrmont
##                          4                                  1
##                    Pyrmont                           Pyrmont 
##                        178                                  2
##               Quakers Hill                        Queens park
##                          1                                  1
##                Queens Park                        Queenscliff
##                         21                                 35
##                   Ramsgate                           Randwick
##                          1                                221
##                    Redfern                            Revesby
##                        206                                  4
##            Revesby Heights                             Rhodes
##                          1                                 36
##                    Rhodes                          Riverview
##                          1                                  2
##                  Riverwood                           Rockdale
##                         18                                  9
##                   Rose Bay                   Rose Bay, Sydney
##                         69                                  1
##                   Rosebery                           Rosehill
##                         59                                  2
##                  Roseville                           Rossmore
##                         20                                  1
##                 Rouse Hill                            Rozelle
##                          3                                 66
##          Rozelle / Balmain                    Rozelle, Sydney
##                          1                                  1
##            Rushcutters Bay                        Russell Lea
##                         64                                  6
##                  Rydalmere                               Ryde
##                          1                                 25
##                Saint Clair                        Saint Ives
##                          1                                  3
##          Saint Ives Chase                     Saint Leonards
##                          1                                  4
##                Saint Marys                       Saint Peters
##                          1                                 14
##                Sandringham                         Sans Souci
##                          8                                 19
##            Scotland Island                           Seaforth
##                         11                                 18
##                Seven Hills                       Seven Hills    
##                          1                                  1
##                 Smithfield                       South Coogee
##                          1                                 17
##           South Hurstville              South Wentworthville
```

```
##                                  1                                 6
##                            St Ives                       St Leonards
##                                  2                                17
##                          St Peters                  Stanhope Gardens
##                                  8                                 2
##                           Stanmore                       Strathfield
##                                 33                                35
##                  Strathfield South                       Summer Hill
##                                  3                                16
##                        Surry hills                       Surry Hills
##                                  2                               500
##                       Surry Hills                         Sutherland
##                                  1                                 2
##                           Sydenham                            sydney
##                                  8                                 3
##                             Sydney                           Sydney 
##                                463                                 8
##                         Sydney CBD                       Sydney City
##                                  2                                 1
##                Sydney Olympic Park               Sydney, Bondi Beach
##                                 89                                 1
##                           Sylvania                          Tamarama
##                                  3                                72
##                        Taren Point                           Telopea
##                                  1                                 4
##                              Tempe                      Terrey Hills
##                                 11                                 1
##                          The Ponds                         The Rocks
##                                  3                                14
##                         Thornleigh                        Toongabbie
##                                  1                                 3
##                         Turramurra                          Turrella
##                                  5                                 4
##                             Ultimo                           Ultimo 
##                                115                                 1
##                            unknown                          Vaucluse
##                                  8                                46
##                          Wahroonga                           Waitara
##                                  2                                 2
##                           Wareemba                          Warrawee
##                                  6                                 1
##                         Warriewood                      Warwick Farm
##                                  9                                 2
##                          Waterfall                          waterloo
##                                  1                                 1
##                           Waterloo                       Watsons Bay
##                                131                                 6
##                           Waverley                          Waverton
##                                 52                                12
##                    Wentworth point                   Wentworth Point
```

```
##                                    1                                   22
##                     Werrington Downs                          West Hoxton
##                   West Pennant Hills                          West Pymble
##                                    6                                    1
##                            West Ryde                             Westmead
##                                    4                                    5
##                          Whale Beach                     Wheeler Heights
##                                   11                                    1
##                           Wiley Park                          Willoughby
##                                    1                                   14
##                      Willoughby East                       Winston Hills
##                                    5                                    1
##                       Wisemans Ferry                          Wolli Creek
##                                    1                                   43
##                         Wolli Creek                       Wollstonecraft
##                                    1                                   26
##             Wollstonecraft, Sydney                              Woodbine
##                                    1                                    1
##                            Woollahra                        Woolloomooloo
##                                   63                                   60
##                       Woolloomooloo                            Woolooware
##                                    1                                    2
##                             Woolwich                              Yagoona
##                                    3                                    2
##                            Yowie Bay                              Zetland
##                                    1                                   93
##
## $zipcode
## x
##     2000     2007     2008     2009     2010     2011     2015     2016
##      551      127      187      183      876      442      102      210
##     2017     2018     2019     2020     2021     2022     2023     2024
##      228       70       14       96      189      169       69      201
##     2025     2026     2027     2028     2029     2030     2031     2032
##       64     1056       59       46       70       69      296       37
##     2033     2034     2035     2036     2037     2038     2039     2040
##       36      290      157       68      143       76       69      109
##     2041     2042     2043     2044     2045     2046     2047     2048
##      134      215       85       43        8       36       22       33
##     2049     2050     2060     2061     2062     2063     2064     2065
##       46       88      116       65       26        6        7      119
##     2066     2067     2068     2069     2070     2071     2072     2073
##       64       56       30       26        9        6        6        5
##     2074     2075     2076     2077     2079     2082     2083     2084
##        6        6        3       12        1        6       12        5
##     2085     2086     2087     2088     2089     2090     2091     2092
##        2        7       12      173       69       62        1       18
##     2093     2094     2095     2096     2097     2099     2100     2101
##      130       87      392      105       24       70       45       47
```

```
##     2102      2103      2104      2105      2106      2107      2108      2110 
##        9        30         6        23        49       194        70        15 
##     2111      2112      2113      2114      2115      2116      2117      2118 
##       12        35        31         9         8         1        11         9 
##     2119      2120      2121      2122      2125      2126      2127      2130 
##        7         5        14        22         6         3       123        16 
##     2131      2132      2133      2134      2135      2136      2137      2138 
##       49        10         8        35        35         3         9        45 
##     2140      2141      2142      2144      2145      2146      2147      2148 
##       30        25         6         8        20         3         6         5 
##     2150      2151      2152      2153      2154      2155      2156      2157 
##       30         9         4        15         7         8         1         1 
##     2158      2159      2160      2161      2162      2163      2164      2165 
##        6         2        15         8         4         6         1         2 
##     2166      2167      2170      2171      2173      2174      2190      2191 
##        7        18        17        12         3         3         2         3 
##     2192      2193      2194      2195      2196      2199      2200      2203 
##        4        17        10         1         1         2        22        35 
##     2204      2205      2206      2207      2208      2209      2210      2211 
##       93        92        15        16         2         5        24        16 
##     2212      2213      2216      2217      2218      2219      2220      2221 
##        5         8        43        27        10        30        21        11 
##     2222      2223      2224      2226      2227      2228      2229      2230 
##        4         5         3         2         1         4         6        87 
##     2231      2232      2233      2234      2557      2558      2560      2565 
##        2         4         3         2         1         1         4         4 
##     2567      2570      2745      2747      2748      2750      2753      2756 
##        2         6         3         5         1        10         1         2 
##     2759      2760      2761      2762      2763      2765      2766      2767 
##        1         8         1         1         1         3         1         1 
##     2768      2769      2770      2775 NSW 2025   unknown 
##        3         3         1         2         1        21 
## 
## $property_type
## x
##          Aparthotel          Apartment  Bed and breakfast 
##                   2               6222                 46 
##                Boat     Boutique hotel           Bungalow 
##                   8                 26                 62 
##               Cabin          Camper/RV           Campsite 
##                  35                  2                  2 
##              Chalet        Condominium            Cottage 
##                   1                309                 59 
##          Dome house          Farm stay        Guest suite 
##                   1                  3                258 
##          Guesthouse             Hostel              Hotel 
##                 200                 46                 10 
##               House                Hut             Island 
##                2604                  1                  3 
##                Loft              Other Serviced apartment
```

```
##                150                 16                 47 
##               Tent         Tiny house               Tipi 
##                  2                 15                  1 
##          Townhouse          Treehouse              Villa 
##                589                  1                 93 
##               Yurt 
##                  1 
## 
## $room_type
## x
## Entire home/apt    Private room     Shared room 
##            7922            2809              84 
## 
## $accommodates
## x
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15 
##  556 4200  766 2350  669 1208  251  430   84  163   31   49   12   19   13 
##   16 
##   14 
## 
## $bathrooms
## x
##    0  0.5    1  1.5    2  2.5    3  3.5    4  4.5    5  5.5    6    7    8 
##   13   19 7528  569 1881  334  307   59   64   16   10    3    9    1    1 
##   10 
##    1 
## 
## $bedrooms
## x
##    0    1    2    3    4    5    6    7   14 
##  682 5475 2819 1107  529  164   30    8    1 
## 
## $beds
## x
##    0    1    2    3    4    5    6    7    8    9   10   11   12   13   14 
##   69 4852 2623 1483  877  443  227   98   72   22   27    5    6    3    2 
##   16   18   29 
##    4    1    1 
## 
## $bed_type
## x
##        Airbed         Couch         Futon Pull-out Sofa      Real Bed 
##            11             8            12            46         10738 
## 
## $cancellation_policy
## x
##                    flexible                    moderate 
##                        1391                        3314 
## strict_14_with_grace_period             super_strict_30 
##                        6089                           1 
```

```
##             super_strict_60
##                          20
```

- host_response_time: Most hosts respond quickly (within an hour), although the imputed unknown category makes up the second-largest percentage.
- host_is_superhost: 2795 of the 10,815 are superhosts.
- host_identity_verified: just under half of listing have a verified host. This even number could make for good comparisons if splitting the data.
- city: What a mess! Invalid charactersets, inconsistent naming and upper/lower casing of city names (see: Bondi Beach, bondi beach, Bondi beach, "Bondi Beach, Sydney"). I will ignore if possible.
- zipcode: The distribution is uneven, and I don't know anything about the districts themselves. However, it's the cleanest geographic data available.
- property_type: Mostly Apartment (~58%) and House (~24%), although 31 property types total.
- room_type: Three categories. Predominantly Entire home/apt, 26% Private room, and only 84 in a Shared room.
- accommodates: Mostly 2, 4, 6, 3, 1, 5, then 8, 7, 10, and up to 16. Even numbers are more common.
- bathrooms: Mostly 1 or 2, but goes up to 10!
- bedrooms: Zero to four are "common" (>500), but continous up to 7 BR, then an outlier with 14 bedrooms.
- beds: Zero to 14, then 16, 18, and 29(!). Interesting about zero beds; maybe a couch?
- bed_type: Aha, couch is a type. 99.28% Real bed, with the remainder scattered around lesser bed types. There are 77 non-Real bed observations. It is plausible that the 69 zero beds observations are included in the 77.
- cancellation_policy: Five categories – flexible, moderate, strict and two levels of super_strict. I wonder if this affects reviews?

```
summaries

## $host_since
##         Min.      1st Qu.       Median         Mean      3rd Qu.
## "2009-04-20" "2013-11-08" "2015-02-01" "2015-02-04" "2016-05-29"
##         Max.
## "2018-11-25"
##
## $host_response_rate
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00  100.00  100.00   97.23  100.00  100.00
##
## $price
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0    96.0   150.0   203.2   230.0 10001.0
##
## $cleaning_fee
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

```
##    0.00   40.00   80.00   93.64  120.00  800.00
##
## $guests_included
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.969   2.000  16.000
##
## $extra_people
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00   10.00   17.07   25.00  410.00
##
## $minimum_nights
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   4.078   3.000 500.000
##
## $number_of_reviews
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    4.00   12.00   28.94   36.00  493.00
##
## $review_scores_rating
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   20.00   92.00   96.00   94.19  100.00  100.00
##
## $review_scores_accuracy
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    2.00    9.00   10.00    9.64   10.00   10.00
##
## $review_scores_cleanliness
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   9.000  10.000   9.398  10.000  10.000
##
## $review_scores_checkin
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000  10.000  10.000   9.782  10.000  10.000
##
## $review_scores_communication
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000  10.000  10.000   9.802  10.000  10.000
##
## $review_scores_location
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000  10.000  10.000   9.737  10.000  10.000
##
## $review_scores_value
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   9.000  10.000   9.385  10.000  10.000
##
## $reviews_per_month
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.020   0.270   0.950   1.572   2.310  15.180
```

```
sds
```

```
## $host_since
## [1] 681.2154
##
## $host_response_rate
## [1] 11.2011
##
## $price
## [1] 254.7939
##
## $cleaning_fee
## [1] 77.63737
##
## $guests_included
## [1] 1.584671
##
## $extra_people
## [1] 25.77062
##
## $minimum_nights
## [1] 12.66408
##
## $number_of_reviews
## [1] 42.66588
##
## $review_scores_rating
## [1] 7.471855
##
## $review_scores_accuracy
## [1] 0.7430775
##
## $review_scores_cleanliness
## [1] 0.9561665
##
## $review_scores_checkin
## [1] 0.6092216
##
## $review_scores_communication
## [1] 0.6054712
##
## $review_scores_location
## [1] 0.5801447
##
## $review_scores_value
## [1] 0.8401076
##
## $reviews_per_month
## [1] 1.744816
```

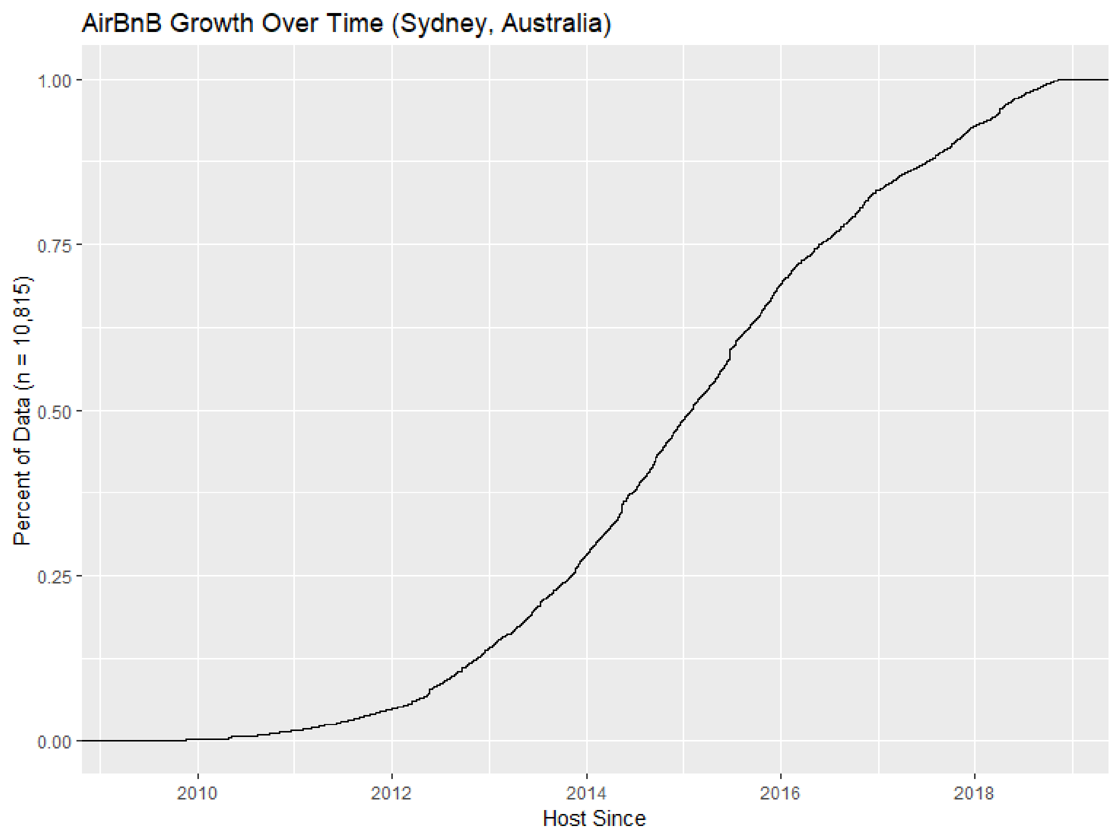
Summaries help with quartiles and ranges, skew can be somewhat interpreted by comparing median to mean.

- host_since: median and mean almost identical; six years from min to median, 3.5 years median to max. Listings have been added more frequently over time.
- host_response_rate: 1st quartile is 100%, so most hosts respond to inquiries.
- price: median of 150 and mean of 203 indicates positive skew. This is expected on this type of variable; prices have no upper limit, but are bound on the lower end by zero.
- cleaning_fee: same positive skew as price
- guests_included: strong positive skew. median is 1, 3rd quar is 2, and mean is 1.969. Max of 16
- extra_people: the max value of 410 may be influencing the mean
- minimum_nights: skewed HEAVILY by the max of 500. A 500 night minimum seems to go against the typical use case for AirBnB that I understand. Higher minimum night values will suppress the possible number of reviews per month. I want to explore this.
- number_of_reviews: median is 12; max is 493. Indicates popularity and longevity of a listing.
- review_scores_rating: the overall rating on a scale of 20 to 100 (the minimum is 20). Can I assume this relates to a 5 star rating scale, where each star is worth 20 points?
- review_scores_xxx: the xxx refers to subcategories of six review components: accuracy (of listing description), cleanliness, checkin, communication, location, and value.
- reviews_per_month: effectively – number_of_reviews / number of months listed. median .95, mean 1.5. max of 15.18 (averaging a new guest every other night!)

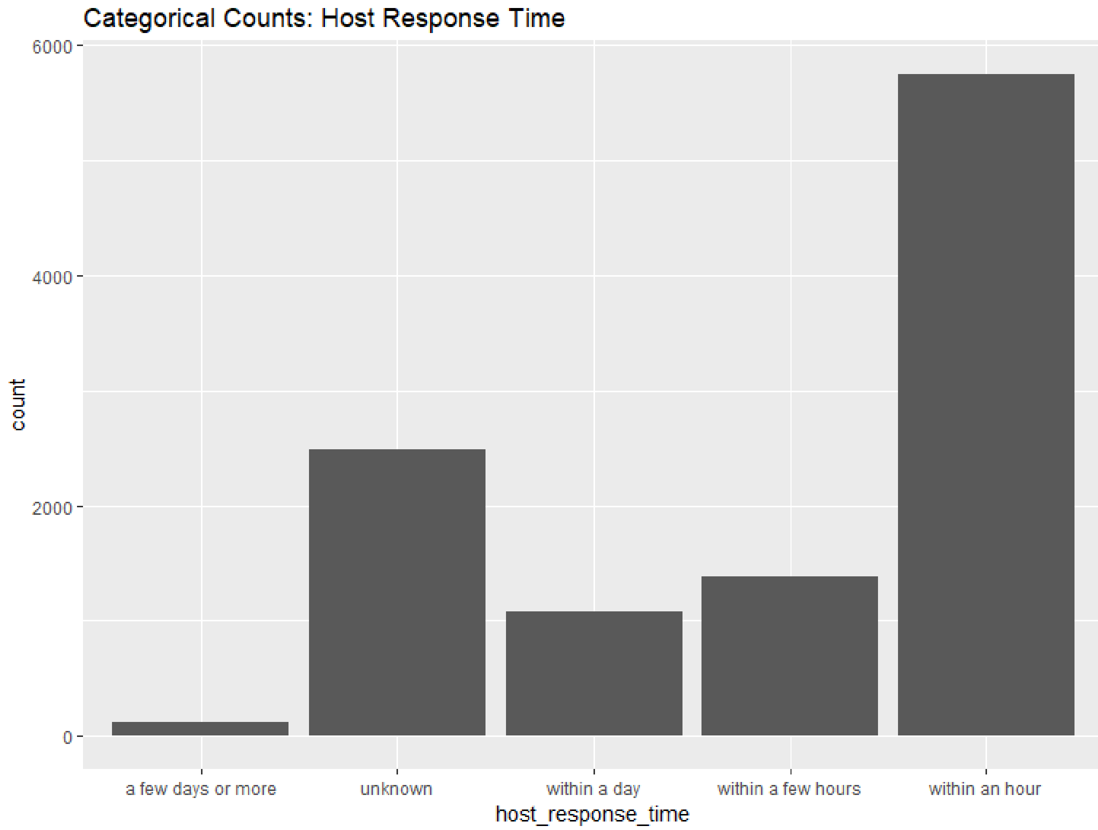
Q3

Explore comprehensively with charts, tables, and graphs # 3.1: Think about types of variables; choose appropriate graphs to find distributions and trends

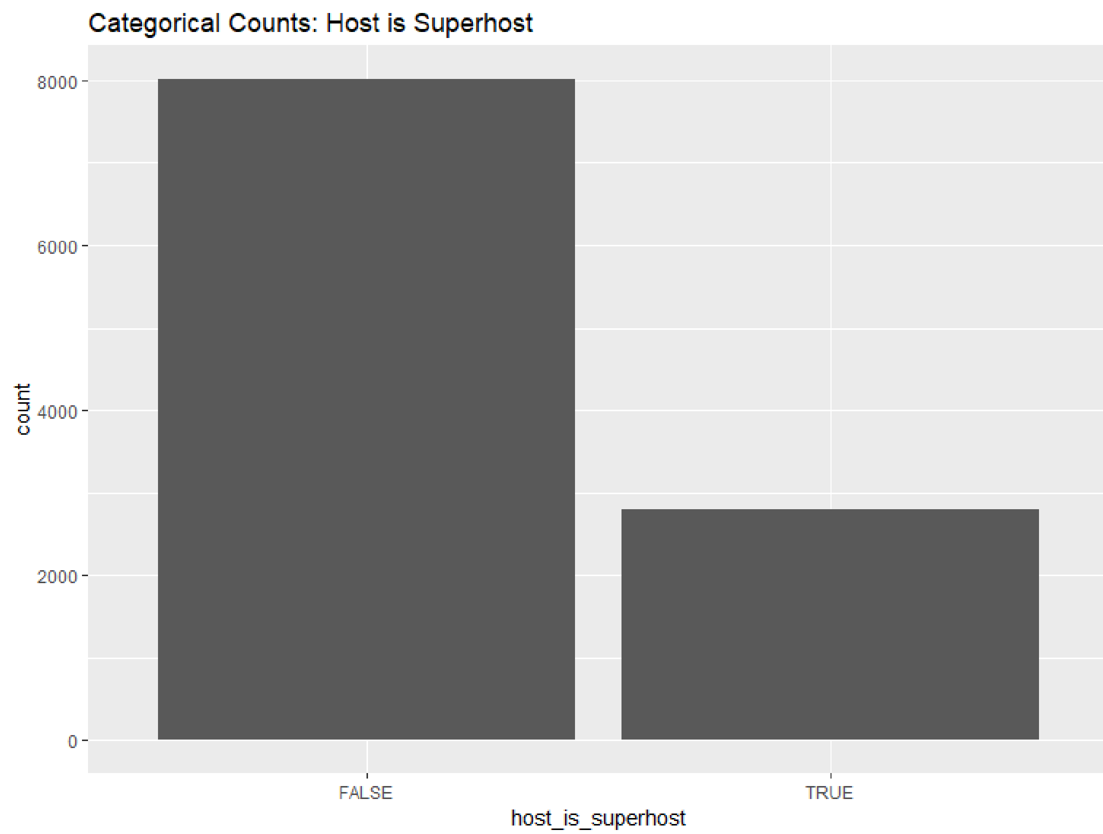
```
# Date / Host Growth Over Time
ggplot(data = airbnb, aes(x = host_since)) +
  stat_ecdf(geom = "step") +
  ggtitle("AirBnB Growth Over Time (Sydney, Australia)") +
  xlab("Host Since") +
  ylab("Percent of Data (n = 10,815)")
```



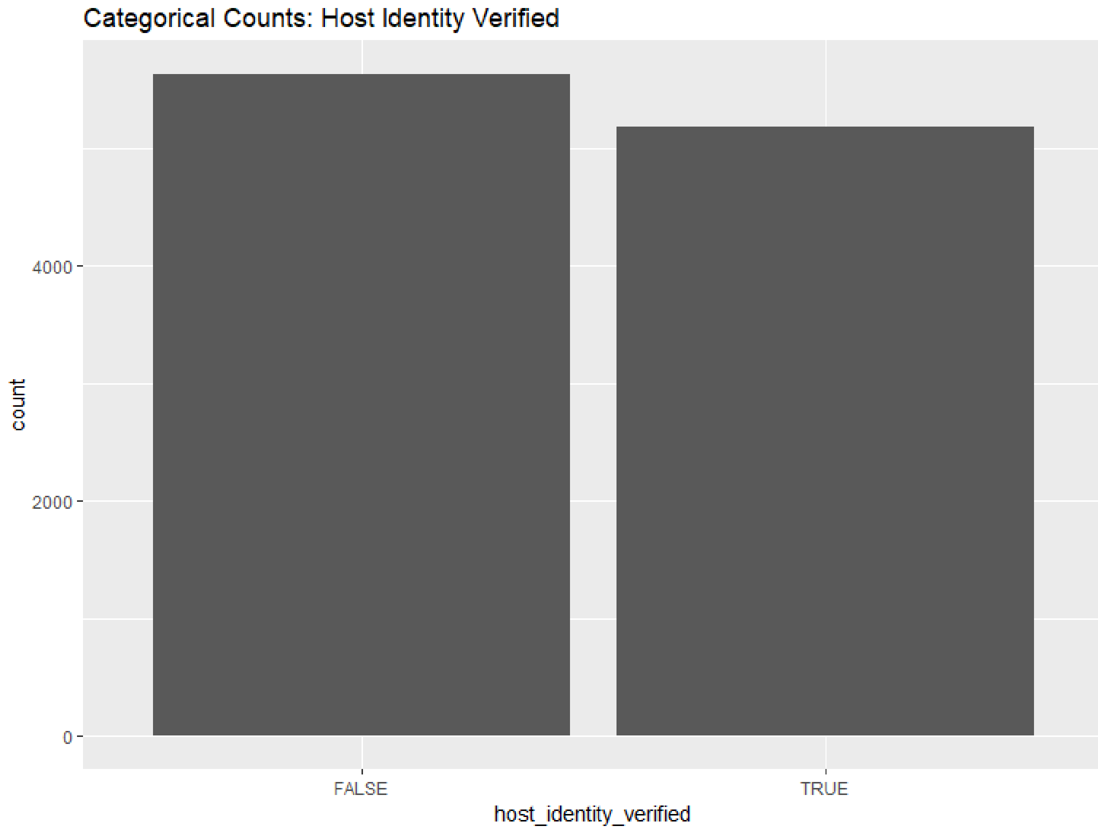

```r
# Categorical Graphs

ggplot(data = airbnb, aes(x = host_response_time)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Host Response Time")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



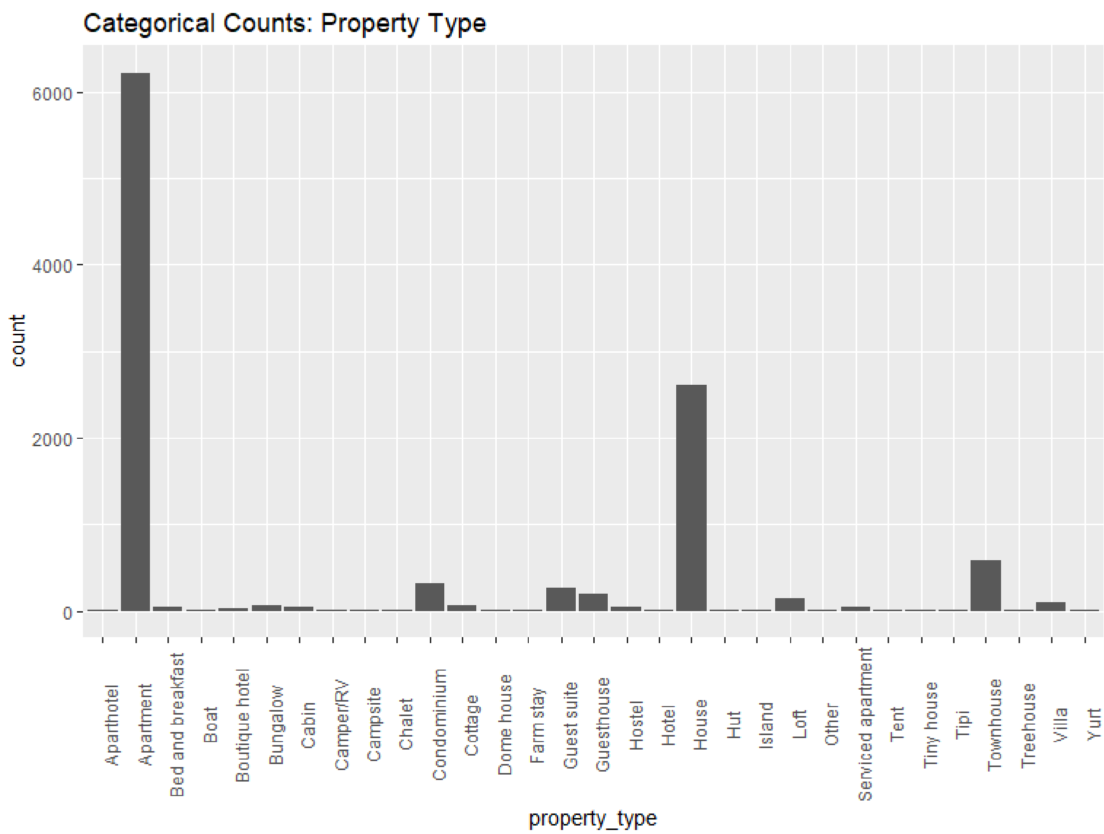

```
ggplot(data = airbnb, aes(x = host_is_superhost)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Host is Superhost")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



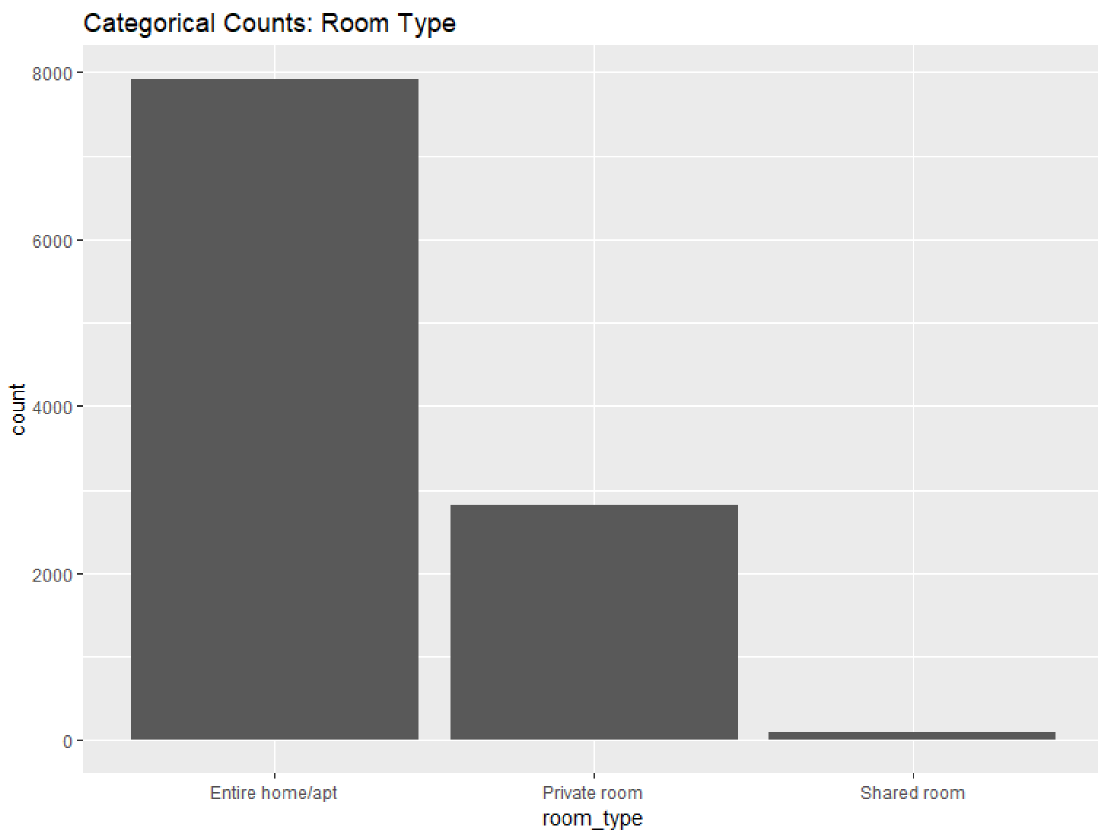

```
ggplot(data = airbnb, aes(x = host_identity_verified)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Host Identity Verified")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



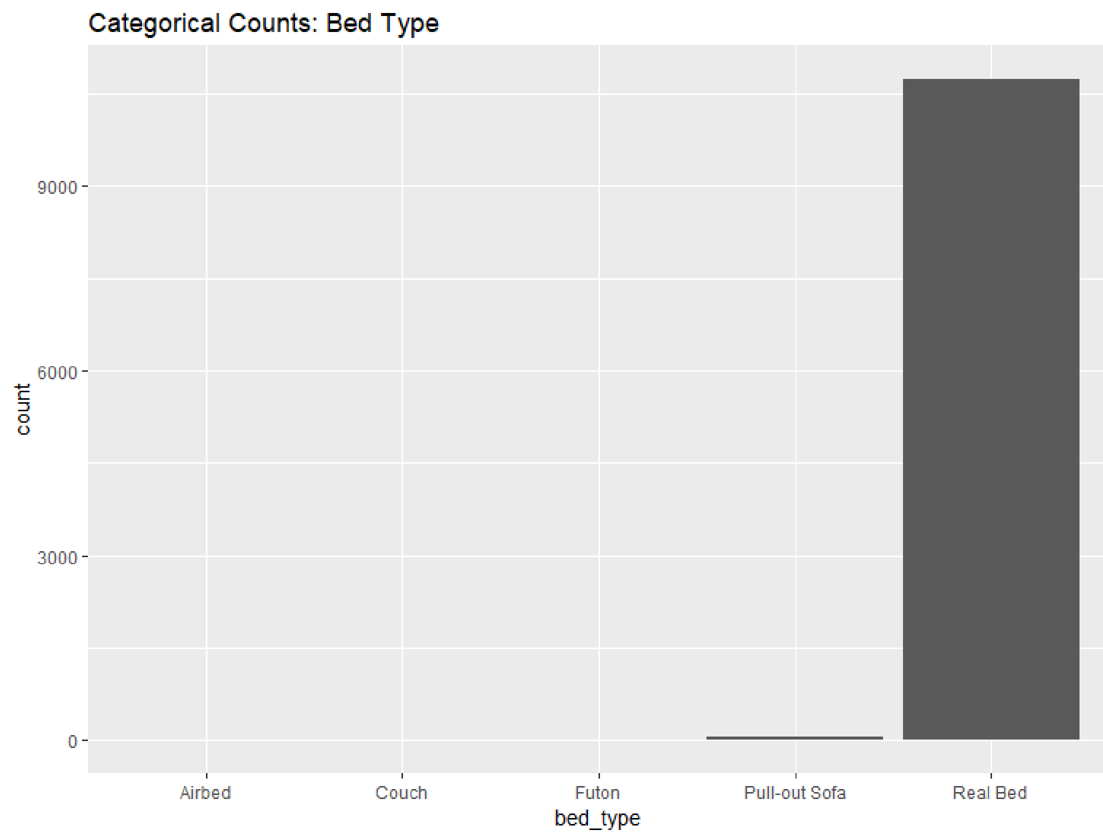

```
ggplot(data = airbnb, aes(x = property_type)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Property Type") +
  theme(axis.text.x = element_text(angle = 90))

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



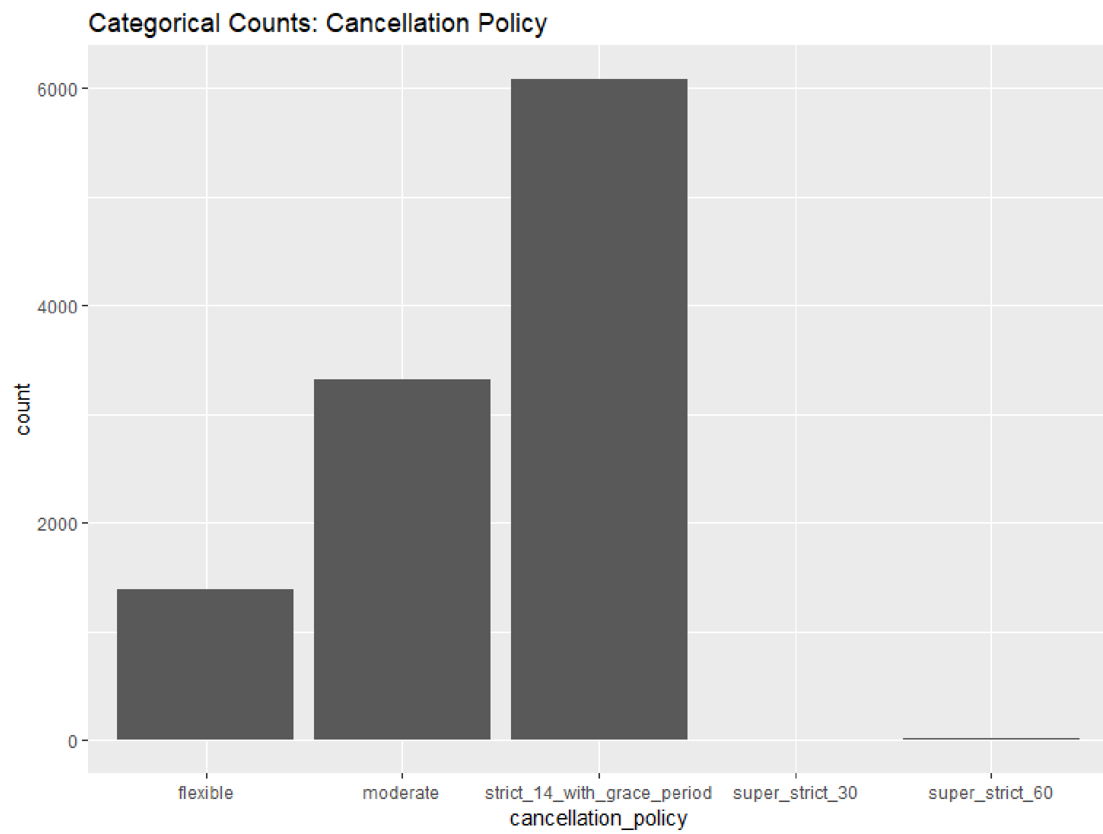

```
ggplot(data = airbnb, aes(x = room_type)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Room Type")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



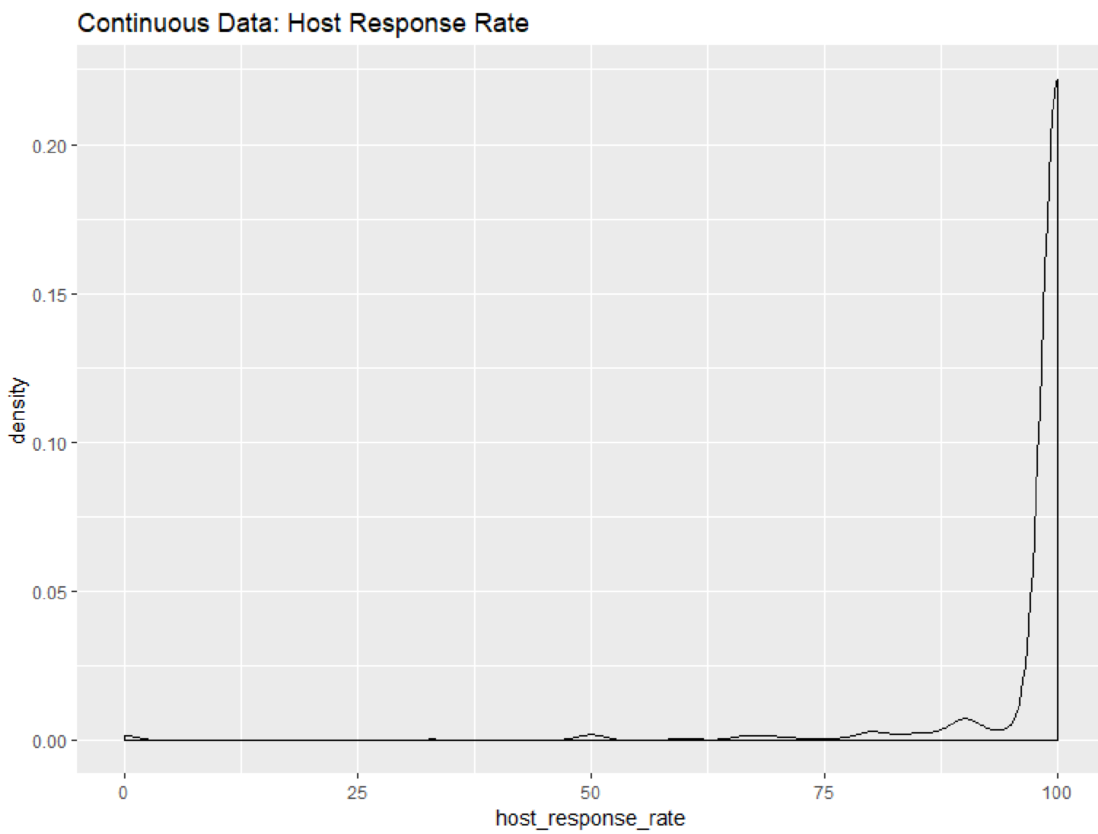

```
ggplot(data = airbnb, aes(x = bed_type)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Bed Type")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



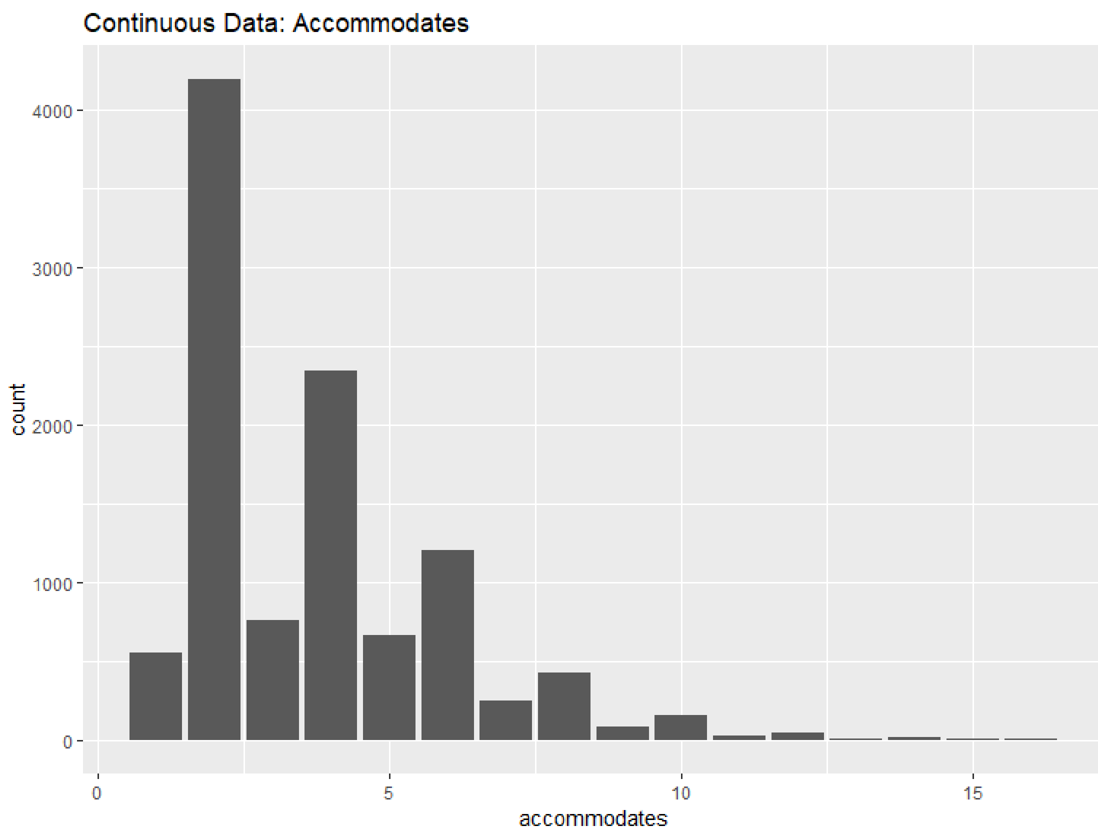

```
ggplot(data = airbnb, aes(x = cancellation_policy)) +
  geom_histogram(stat="count") +
  ggtitle("Categorical Counts: Cancellation Policy")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



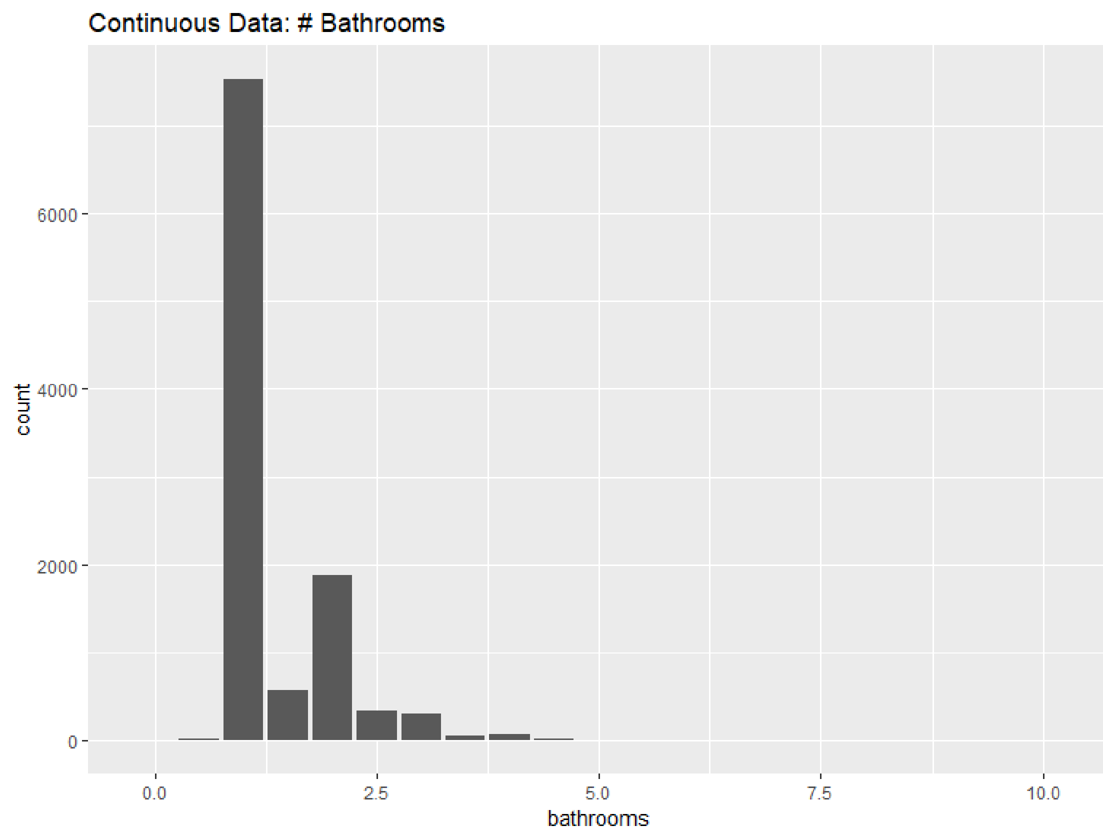

```
# Continuous Data Graphs

ggplot(data = airbnb, aes(x = host_response_rate)) +
  geom_density() +
  ggtitle("Continuous Data: Host Response Rate")
```



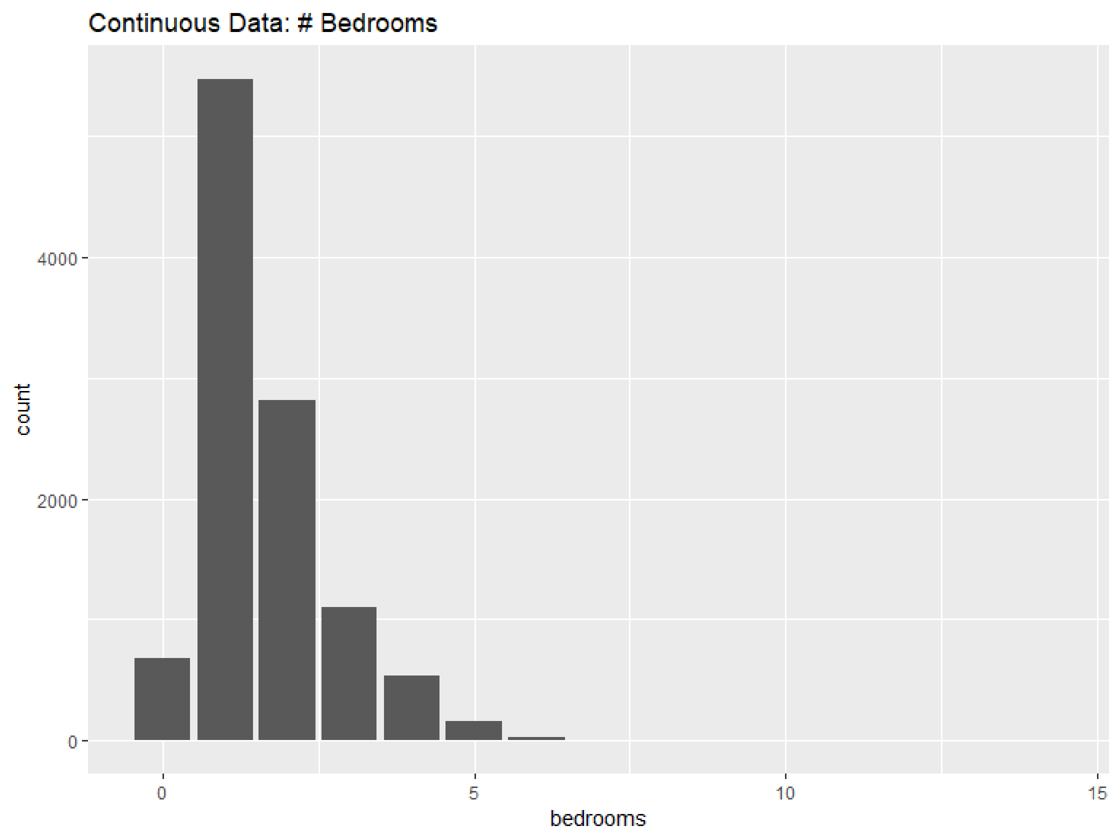

```
ggplot(data = airbnb, aes(x = accommodates)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: Accommodates")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



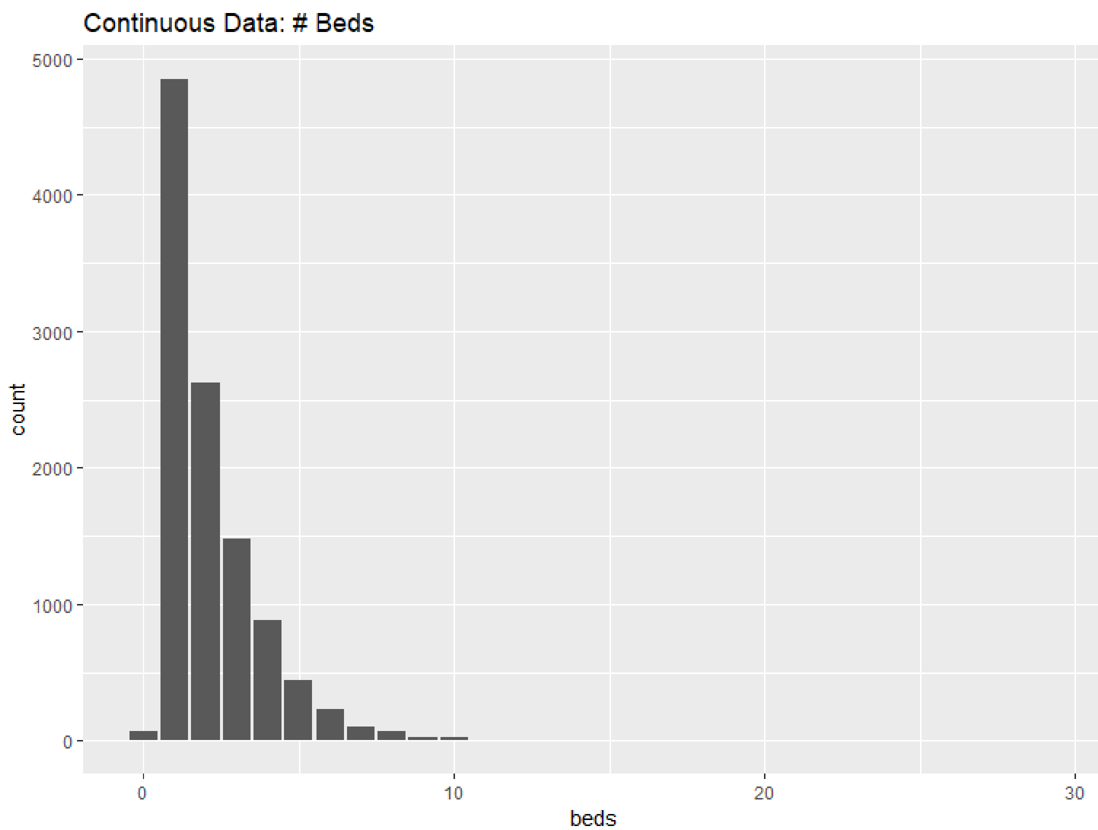

```
ggplot(data = airbnb, aes(x = bathrooms)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: # Bathrooms")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



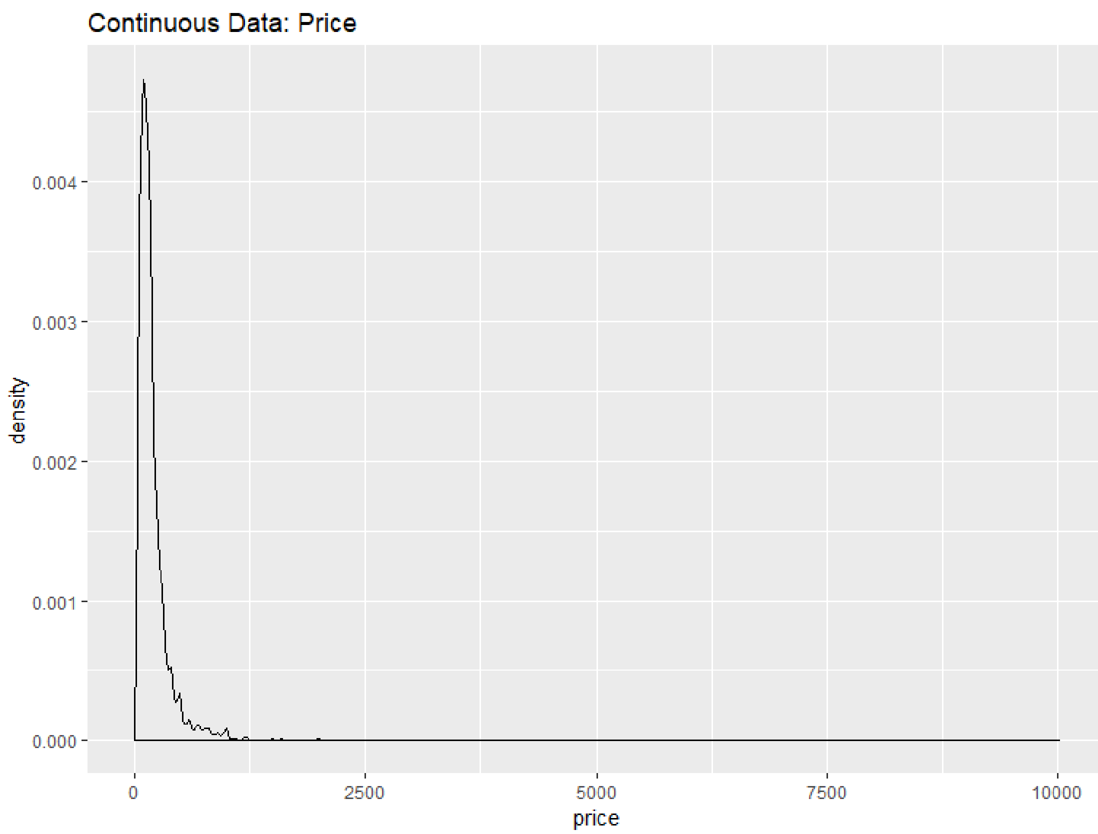

```
ggplot(data = airbnb, aes(x = bedrooms)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: # Bedrooms")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



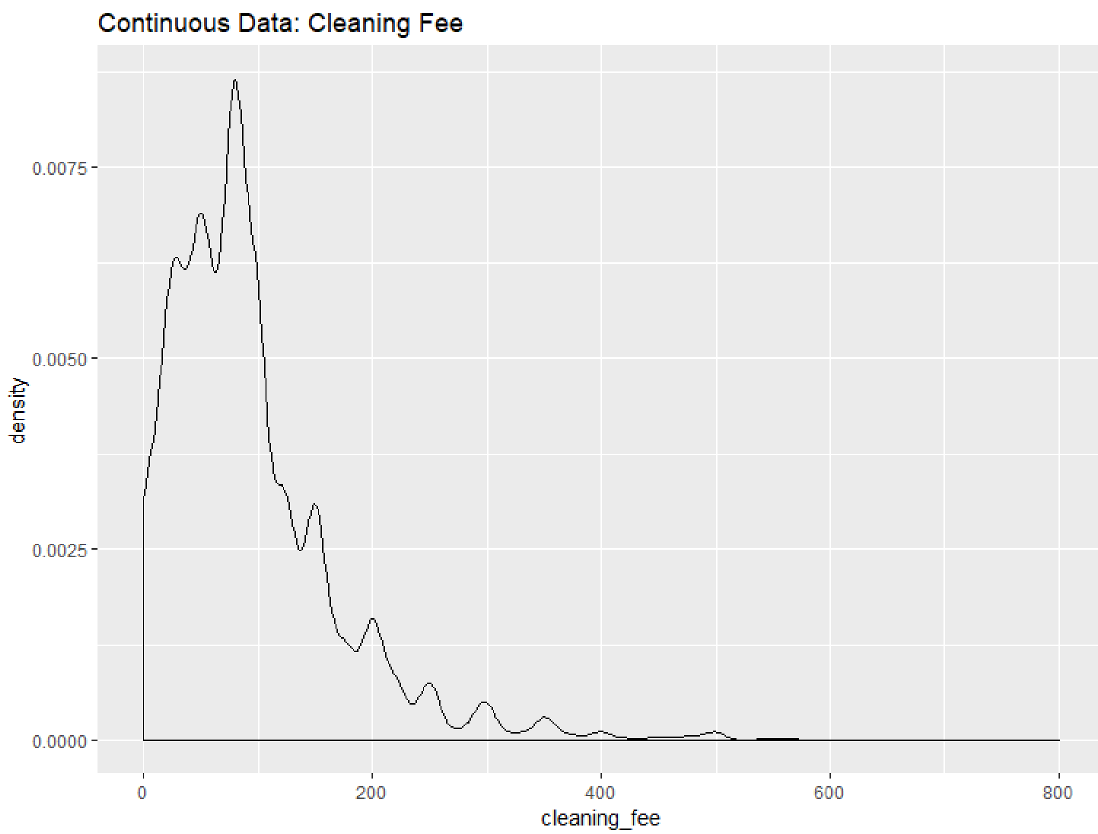

```
ggplot(data = airbnb, aes(x = beds)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: # Beds")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



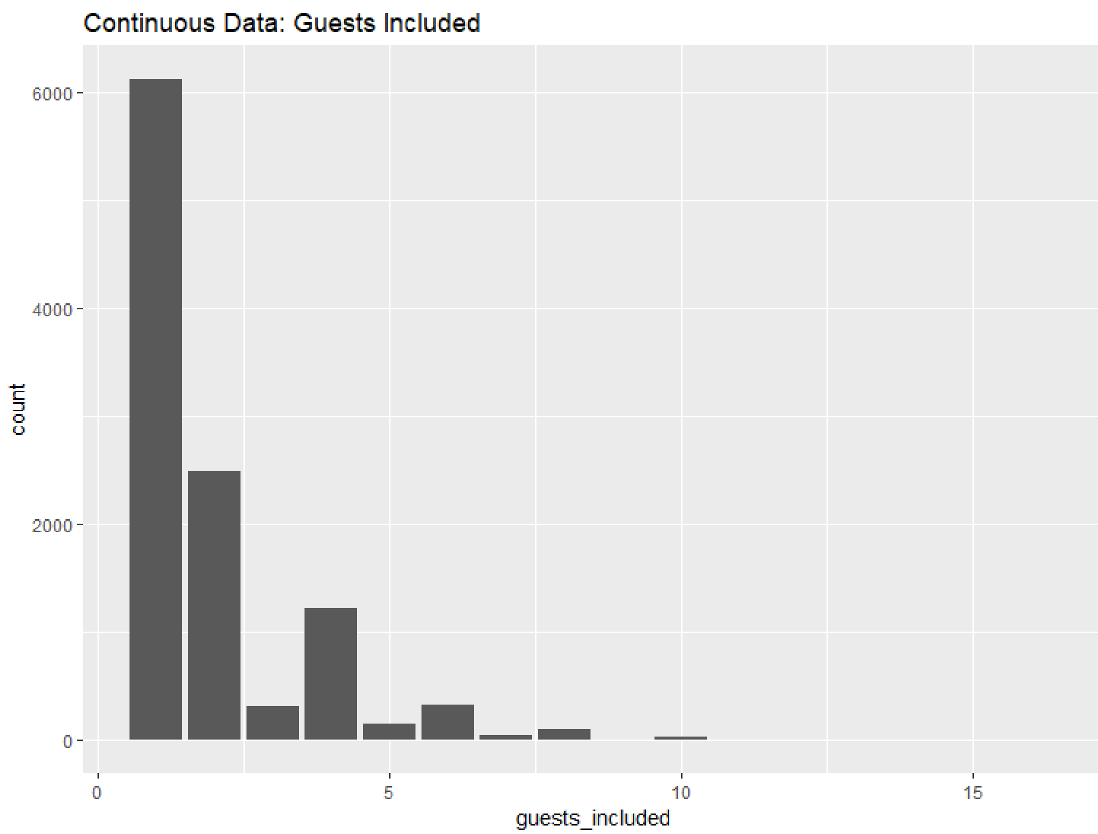

```r
ggplot(data = airbnb, aes(x = price)) +
  geom_density() +
  ggtitle("Continuous Data: Price")
```



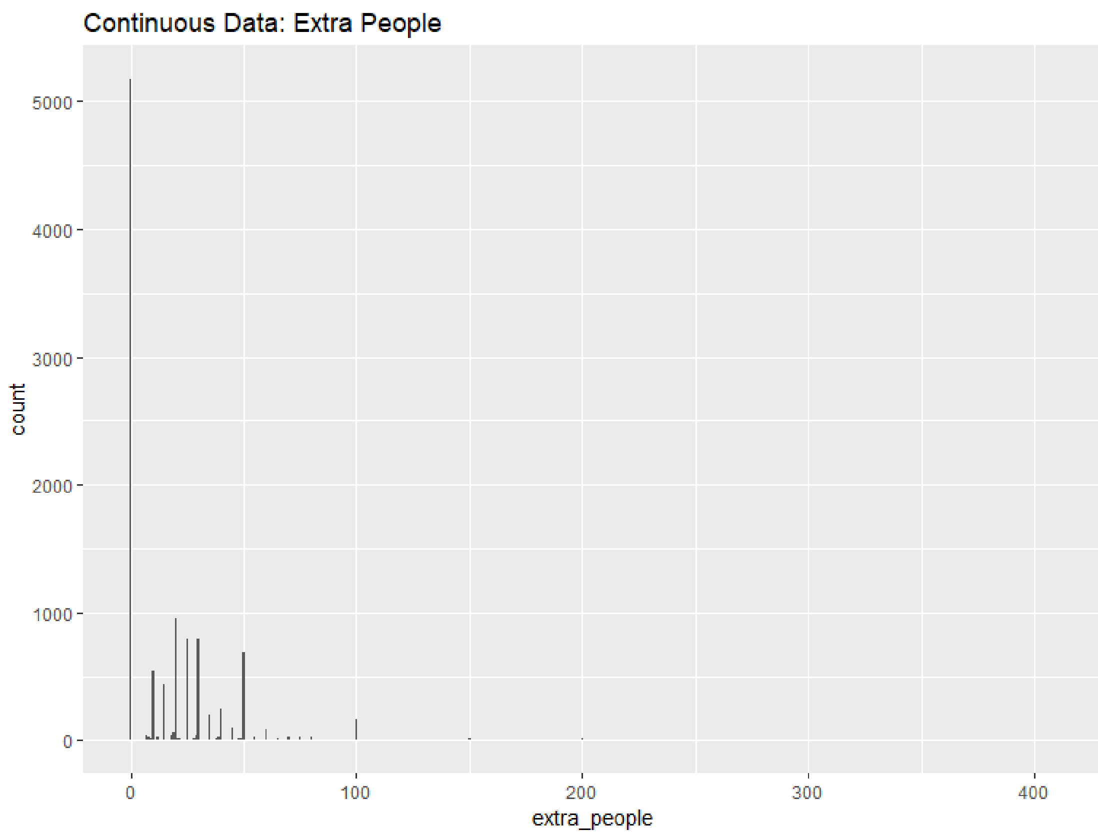

```
ggplot(data = airbnb, aes(x = cleaning_fee)) +
  geom_density() +
  ggtitle("Continuous Data: Cleaning Fee")
```



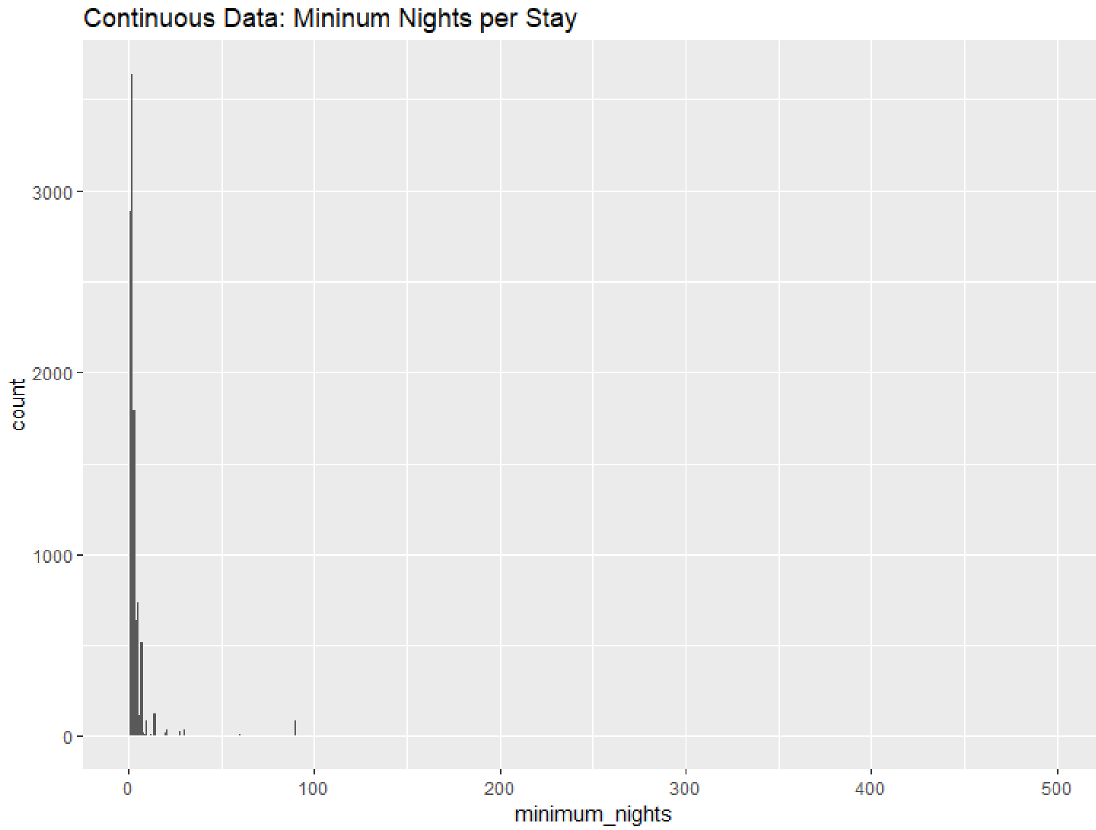

```
ggplot(data = airbnb, aes(x = guests_included)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: Guests Included")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



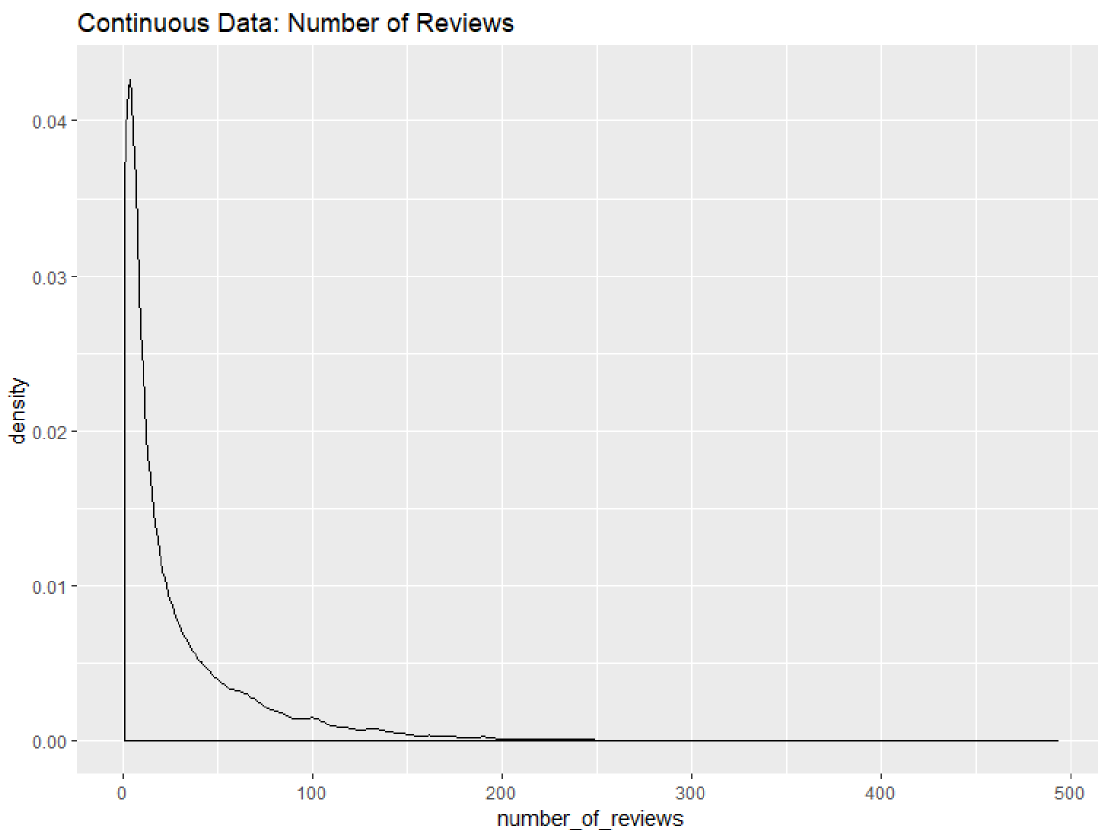

```
ggplot(data = airbnb, aes(x = extra_people)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: Extra People")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



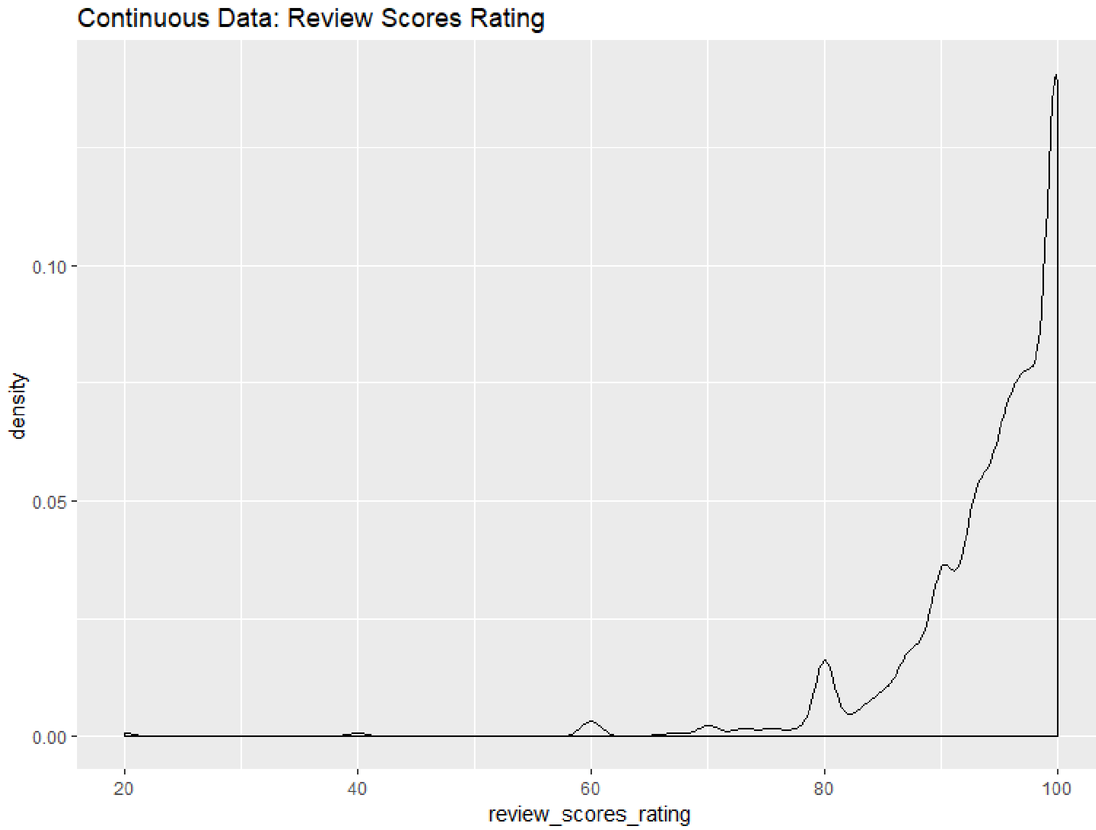

```
ggplot(data = airbnb, aes(x = minimum_nights)) +
  geom_histogram(stat="count") +
  ggtitle("Continuous Data: Mininum Nights per Stay")

## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



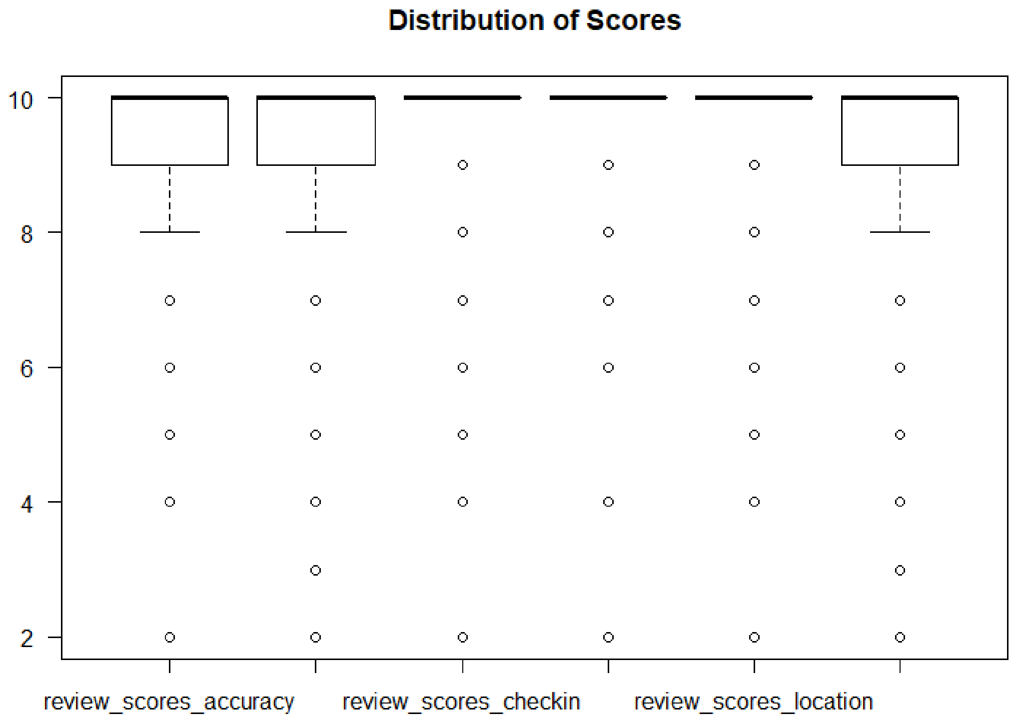

```
ggplot(data = airbnb, aes(x = number_of_reviews)) +
  geom_density() +
  ggtitle("Continuous Data: Number of Reviews")
```




```
ggplot(data = airbnb, aes(x = review_scores_rating)) +
  geom_density() +
  ggtitle("Continuous Data: Review Scores Rating")
```




```r
# What is the distribution of the different review scores?
boxplot(airbnb[29:34], las=1, main = "Distribution of Scores")
```



3.2: Compare different graph types to see which ones best convey trends, outliers, and patterns

For simply display of categorical data, the histogram counts work very well. I omitted the zipcode and city graphs, because there were too many variables to render.

For continuous data, histograms worked well for variables with fewer counts, and density plots worked better for variables with a wider spread of values.

For variables with similar value scale, a boxplot does a good job of showing distribution statistics in a side-by-side fashion.

3.3: Describe what you find from the graphs

Some of the categorical values have an even distribution (e.g., host_verified), but most have values that are more common than others. Bed_type is mostly "real bed". Property_type are predominantly house and apartment, even though there are 31 types.

Most of the review scores are focused on the high end of the scale, so they have a small standard deviations (<1). In retrospect, I could have done a litt

Q4

4.1: Compare and contrast review_per_month and number_of_reviews

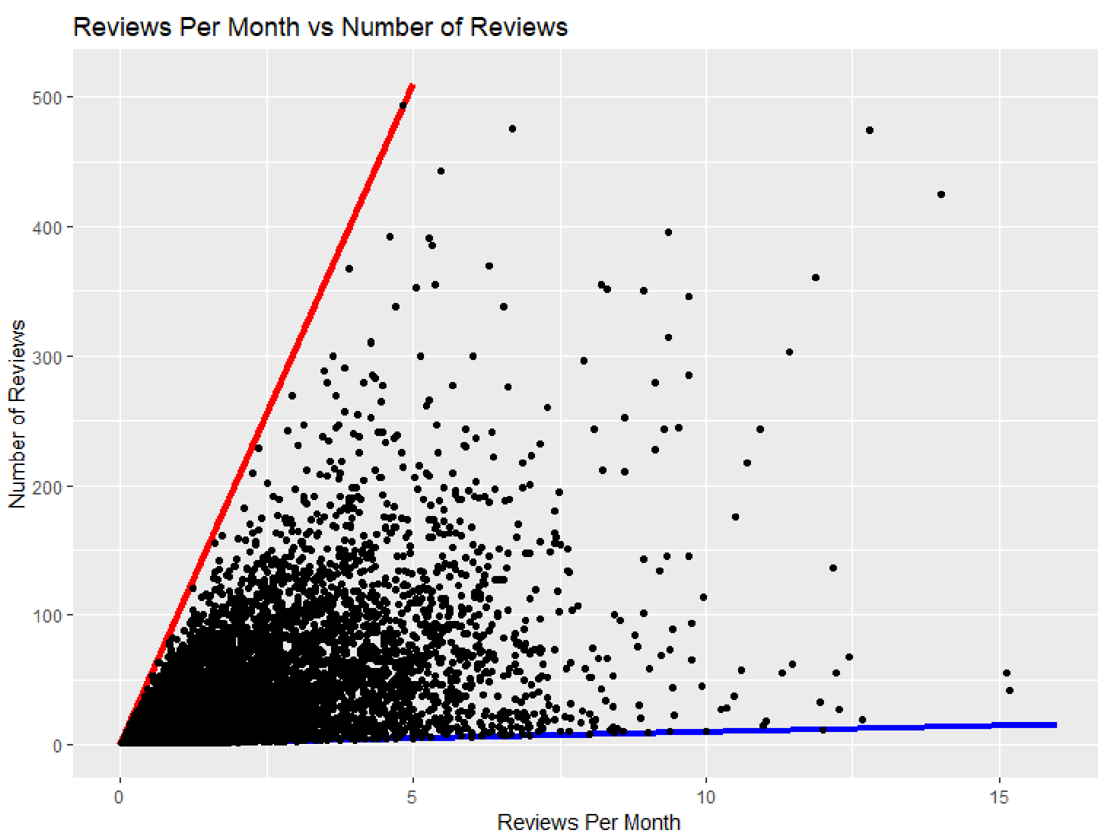
So my general theory is that number of reviews is partly a function of time (listings that have been around longer have more opportunities to be reviewed). So I want to explore what happens if we normalize the number of reviews by the number of months the listing has existed. I thought I could use host_since, but this is about the *host* and not the *property*.

```
# Errors of my ways: some host_ids have multiple listings
airbnb %>% select(host_id) %>% table() %>% sort(decreasing = TRUE) %>% head(1
5)

## .
##  36410227  15469257   2450066  15651267   7409213 103385102  15193662
##       156        65        58        53        42        37        35
## 101139031  21385139  27286333  38478183  33325403    113874 137278159
##        33        32        30        30        29        28        27
## 181584188
##        27

# Affirm that host_since is the same for all listings, using one of the top h
ost_ids
airbnb %>% select(host_id, host_since) %>% filter(host_id == '2450066') %>% h
ead(20)

##    host_id host_since
## 1  2450066 2012-05-23
## 2  2450066 2012-05-23
## 3  2450066 2012-05-23
## 4  2450066 2012-05-23
## 5  2450066 2012-05-23
## 6  2450066 2012-05-23
## 7  2450066 2012-05-23
## 8  2450066 2012-05-23
## 9  2450066 2012-05-23
## 10 2450066 2012-05-23
## 11 2450066 2012-05-23
## 12 2450066 2012-05-23
## 13 2450066 2012-05-23
## 14 2450066 2012-05-23
## 15 2450066 2012-05-23
## 16 2450066 2012-05-23
## 17 2450066 2012-05-23
## 18 2450066 2012-05-23
## 19 2450066 2012-05-23
## 20 2450066 2012-05-23
```

```
# YUP.

# Find rates
airbnb <- airbnb %>% mutate(months_listed = number_of_reviews / reviews_per_m
onth)
max(airbnb$months_listed) # 102 months max; 102.1 * 5 = 510.5. Use this in th
e red line.

## [1] 102.0704
```

Now I have calculated the number of months a listing has been available, but it is calculated using the two variables, so this data (months_listed) is literally a function of the two. Let's just plot them and have a look.

```
# A simple scatterplot of the two variables
ggplot(airbnb, aes(reviews_per_month, number_of_reviews)) +
  ggtitle("Reviews Per Month vs Number of Reviews") +
  geom_segment(aes(x = 0,xend = 5, y = 0, yend = 510.5), size = 1.5, color =
"red") +
  geom_segment(aes(x = 0,xend = 16, y = 0, yend = 16), size = 1.5, color = "b
lue") +
  geom_point() +
  xlab("Reviews Per Month") +
  ylab("Number of Reviews")
```



This graph shows a scatterplot of the two variables against each other. The blue line represents the max rate (1:1, that is, 30 reviews in one month). So a point near the blue line is receiving reviews as frequently as possible. The red line represents the minimum number of reviews a property could receive, for the given reviews per month and the maximum age of a listing in this dataset (102.1 months).

Now let's look at overlap between the top 100 of each variable

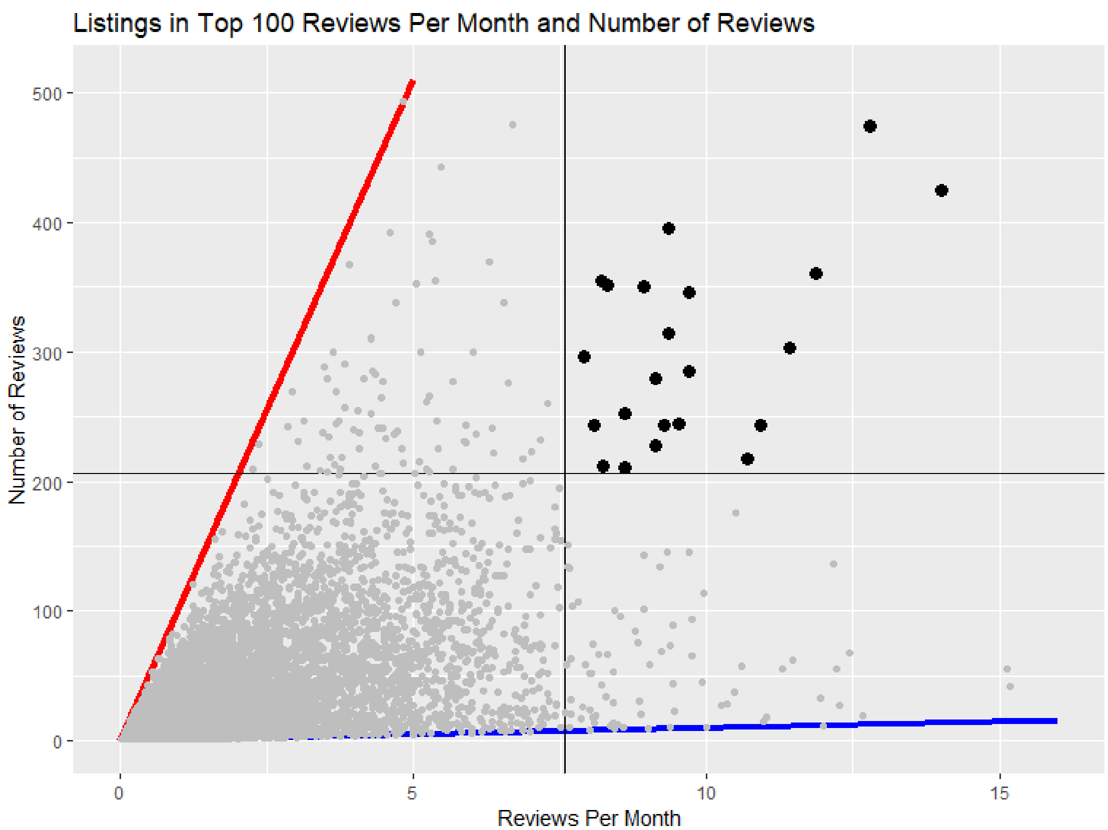
```r
#head(sort(airbnb$reviews_per_month, decreasing = TRUE), 100) # DELETE
# order() pulls the row values; I can use these to subset the IDs
top100rpm <- airbnb$id[head(order(airbnb$reviews_per_month, decreasing = TRUE
), 100)]

#head(sort(airbnb$number_of_reviews, decreasing = TRUE), 100)
top100nrev <- airbnb$id[head(order(airbnb$number_of_reviews, decreasing = TRU
E), 100)]

# How many values in the top 100 rate (rev per mo) are in the top 100 total (
num of reviews)
length(intersect(top100rpm, top100nrev))
```

```
## [1] 22
```

```r
# Which IDs are in both lists?
intersect(top100rpm, top100nrev)
```

```
##  [1] 12954762  7944819 13279754 15257722 15424010 17946780 10111445
##  [8] 13623082  7935975  5751561 11589811 15186470 15685660 13193475
## [15]  8412341 13582232 16123508  5796898 15474118  6327407 13499531
## [22]  9352316
```

```r
ggplot(airbnb, aes(reviews_per_month, number_of_reviews)) +
  ggtitle("Listings in Top 100 Reviews Per Month and Number of Reviews") +
  geom_segment(aes(x = 0,xend = 5, y = 0, yend = 510.5), size = 1.5, color =
"red") +
  geom_segment(aes(x = 0,xend = 16, y = 0, yend = 16), size = 1.5, color = "b
lue") +
  geom_vline(xintercept = min(airbnb$reviews_per_month[airbnb$id %in% top100r
pm])) +
  geom_hline(yintercept = min(airbnb$number_of_reviews[airbnb$id %in% top100n
rev])) +
  geom_point(color = "grey") +
  geom_point(data = airbnb[airbnb$id %in% intersect(top100rpm, top100nrev),],
size = 3) +
  xlab("Reviews Per Month") +
  ylab("Number of Reviews")
```



Discussion and findings

These two variables (number of reviews and reviews per month) both describe the populariy of a listing, but in different ways. Number of reviews is the total number of reviews. Properties with a high value here will have had the most guests visit. However, this metric is influenced by the length of time it has been around. Reviews per month attempts to account for the time a listing has been offered by normalizing the data against the number of months is has been available (and earlier I back-calculated the number of months). New listings with a strong opening can lead this metric. One potential drawback to the reviews_per_month variable is that it penalizes listings with higher minimum night stays. Listings with a seven-night minimum would have a four review_per_month ceiling.

22 listings are in both the top 100 review_per_month and the top 100 number_of_reviews. I have added reference lines to the graph illustrating the minimum value in the top 100 of each variable, then highlighted the values in the top 100 of each (the upper right quadrant).

The upper-right quadrant is the **best of the best** – popular for a long time and frequently reviewed. The upper-left quadrant contains **established favorites**. These properties have a lower review frequency, but they have been around long enough to achieve high review counts. The lower-right quadrant contains the **best new listings**. These listings have low counts, but are being reviewed frequently enough that it's expected they will work their way into the higher property counts. The lower-left quadrant contains **typical listings**.

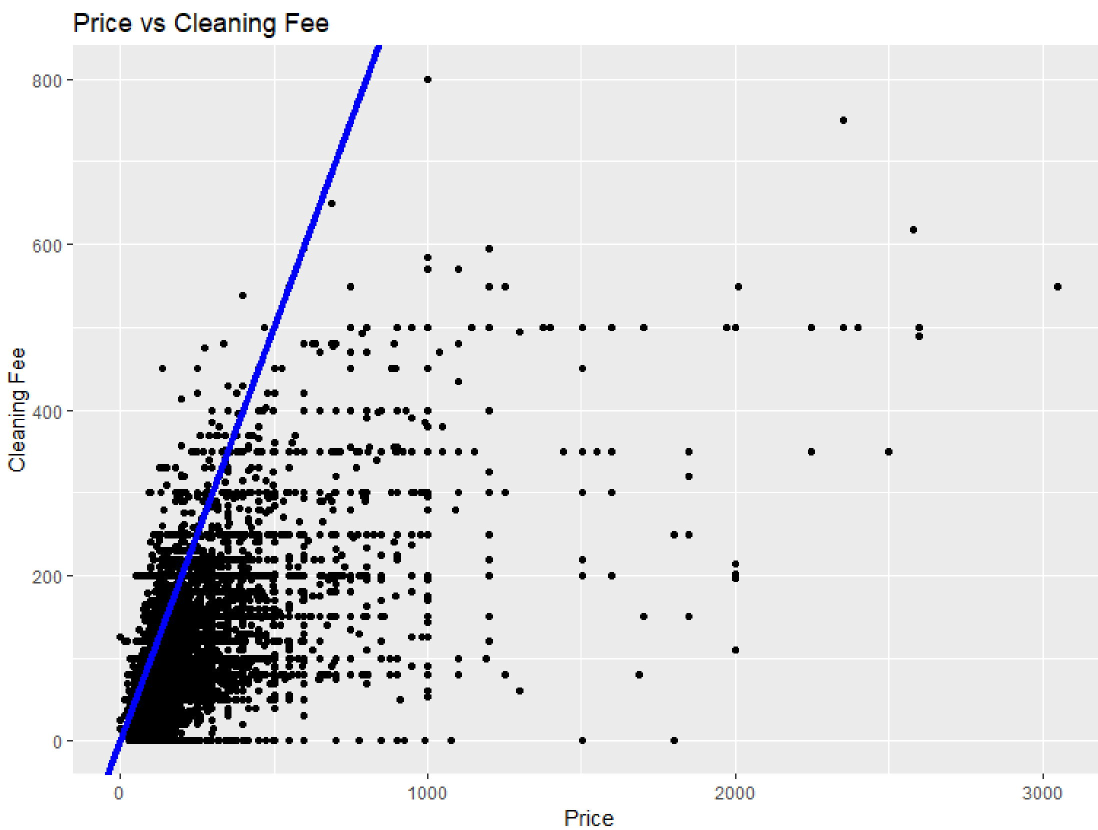
Ultimately, the right quadrants can be summarized as popular for a long time (upper right) and popular for a short time (lower right). Thus, reviews_per_month is better suited as a measure of popularity.

4.2: Analyze at least three other groups as in 4.1

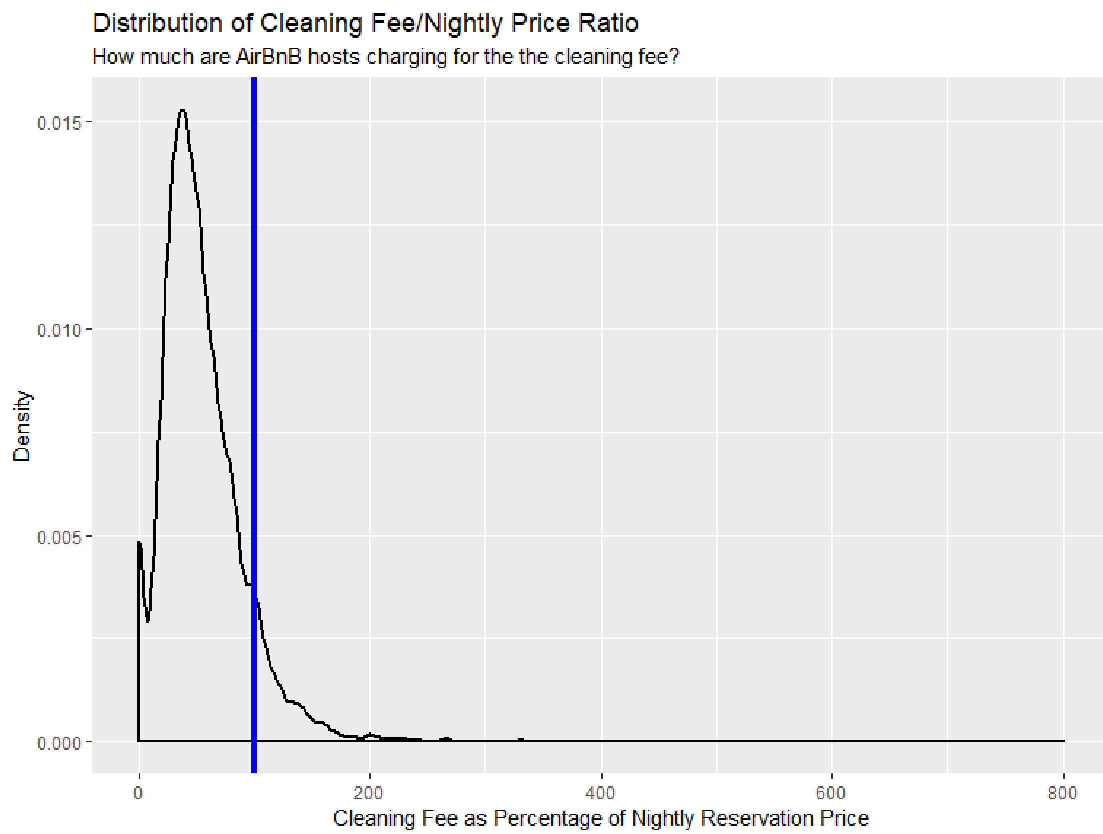
4.2.1: Cleaning Fee vs Price

Do expensive listings have higher cleaning fees? Or are hosts making up for low prices with high cleaning fees?

```
airbnb$cleaning_fee_pct <- airbnb$cleaning_fee / airbnb$price
summary(airbnb$cleaning_fee_pct) # bad news, we have infinite values

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.3077  0.4762     Inf  0.7080     Inf

airbnb %>% filter(price == 0) # dumb news, people have airbnbs with a price o
f 0

##         id
## 1 20563580
## 2 20718560
## 3 21372128
##

# Some outlier expensive price listings were messing up the graph, so I filte
red them
ggplot(airbnb %>% filter(price < 5000), aes(price, cleaning_fee)) +
  ggtitle("Price vs Cleaning Fee") +
  geom_point() +
  geom_abline(slope = 1, color = "blue", size = 1.5) +
  xlab("Price") +
  ylab("Cleaning Fee")
```




```
# 953 listings have a cleaning fee higher than the price
airbnb %>% filter(cleaning_fee > price) %>% count()

## # A tibble: 1 x 1
##       n
##   <int>
## 1   953

# This is 8.81% of all listings!
airbnb %>% filter(cleaning_fee > price) %>% count() / airbnb %>% count() * 10
0

##          n
## 1 8.811835

# What does the distribution of cleaning fee percentages look like?
ggplot(data = airbnb, aes(x = cleaning_fee_pct * 100)) +
  geom_density(size = 1) +
  ggtitle("Distribution of Cleaning Fee/Nightly Price Ratio", subtitle = "How
much are AirBnB hosts charging for the the cleaning fee?") +
  geom_vline(xintercept = 100, color = "blue", size = 1.5) +
  xlab("Cleaning Fee as Percentage of Nightly Reservation Price") +
  ylab("Density")

## Warning: Removed 3 rows containing non-finite values (stat_density).
```

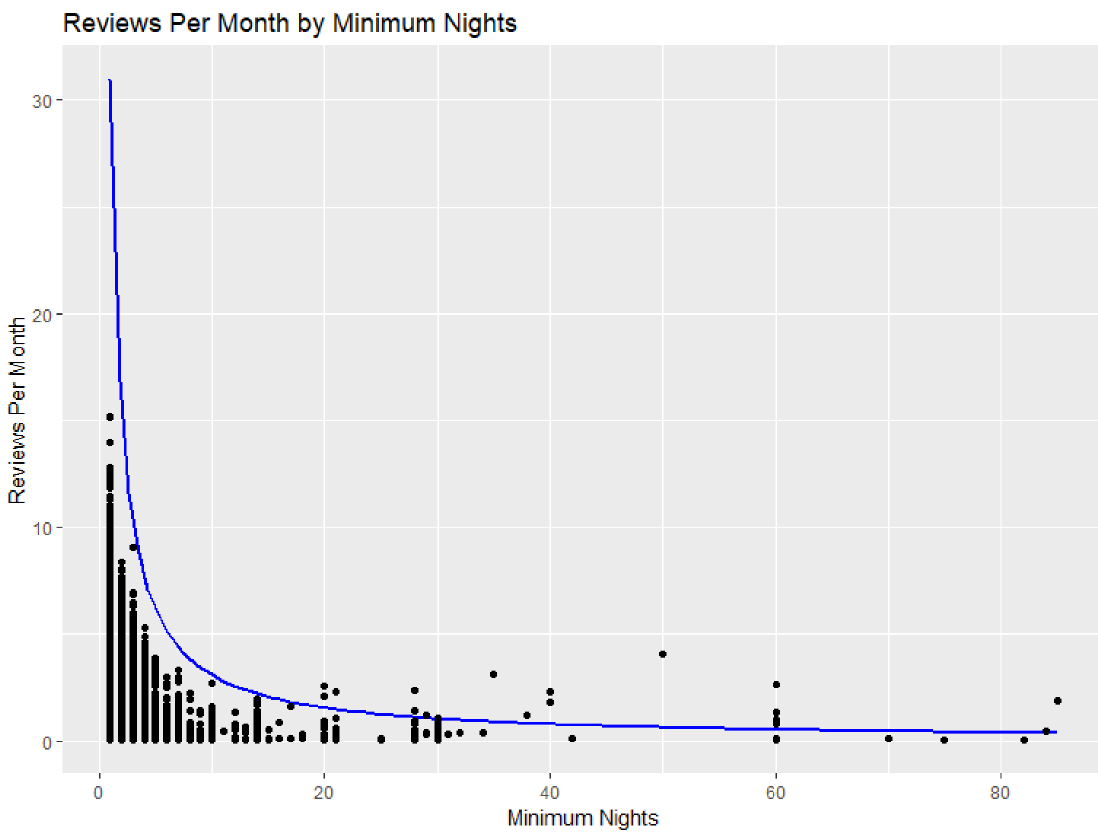


#

DISCUSS # PHIL - do not forget that you imputed a number of thPHILe median values ($80)
Consider Minimum Night Stays * Price, calc cleaning fee as pct of THAT

4.2.2: Minimum Night Stays

```
ggplot(data = airbnb %>% filter(minimum_nights < 90), aes(minimum_nights, rev
iews_per_month)) +
  stat_function(fun = function(x) 31/x, color = "blue", size = 1) +
  geom_point() +
  ggtitle("Reviews Per Month by Minimum Nights") +
  xlab("Minimum Nights") +
  ylab("Reviews Per Month")
```

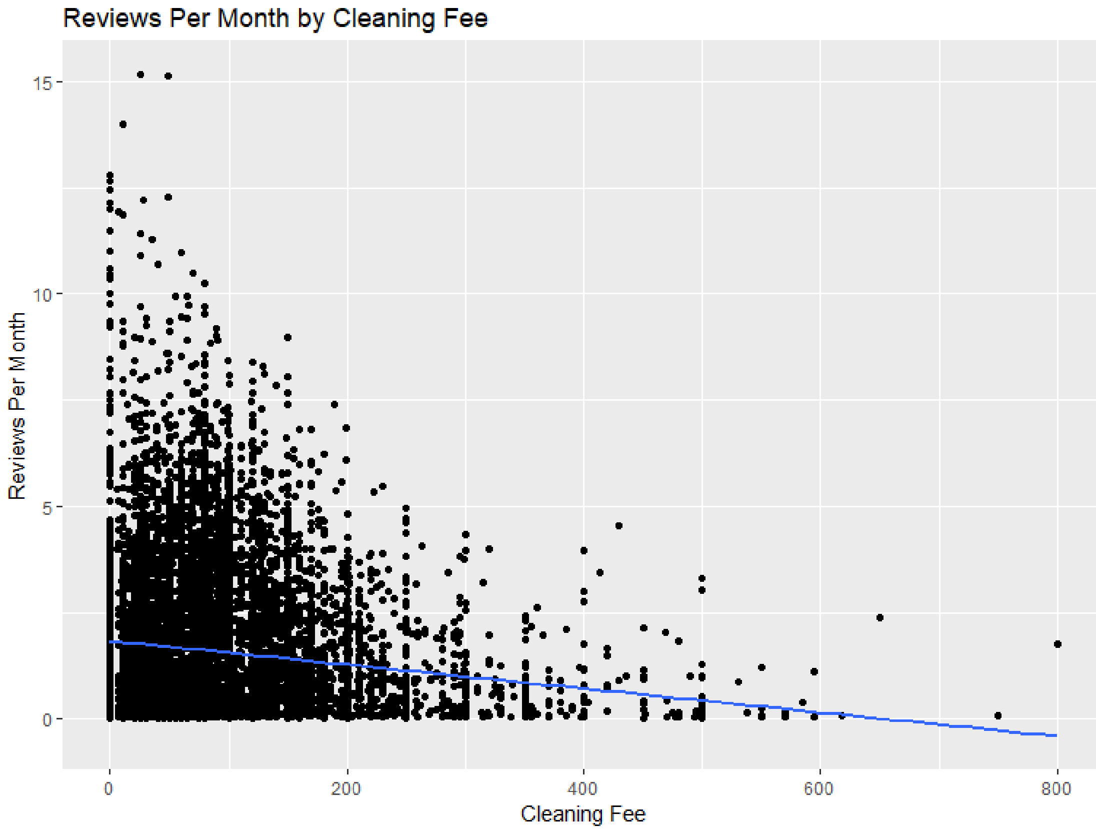


Something is wrong here. How can a listing with a 60-day minimum have 2 reviews per month? I filtered out minimum stays of 90 or more, because they are outliers and didn't add useful information. I have added a blue curve, which is the theoretical maximum reviews_per_month a listing can have (assumes all stays are for minimum length and 0% vacancy, and a 31-day month). It is possible that the listing has increased the minimum stay after amassing a high number/frequency of reviews.

4.2.3: Reviews_Per_Month

Because I determined reviews_per_month was a good indicator of popularity, I thought I would graph some other variables against it in a scatterplot and see if any patterns arise.

```
ggplot(data = airbnb, aes(cleaning_fee, reviews_per_month)) +
  geom_point() +
  geom_smooth(method = "lm", se=FALSE) +
  ggtitle("Reviews Per Month by Cleaning Fee") +
  xlab("Cleaning Fee") +
  ylab("Reviews Per Month")
```



Findings

Here I have a graph showing how the reviews_per_month relate to the cleaning fee. The blue line is the line of best fit. With a negative slope, this implies that as the cleaning fee increases, the reviews_per_month decreases.

Q5

Propose three different hypotheses for business analysis

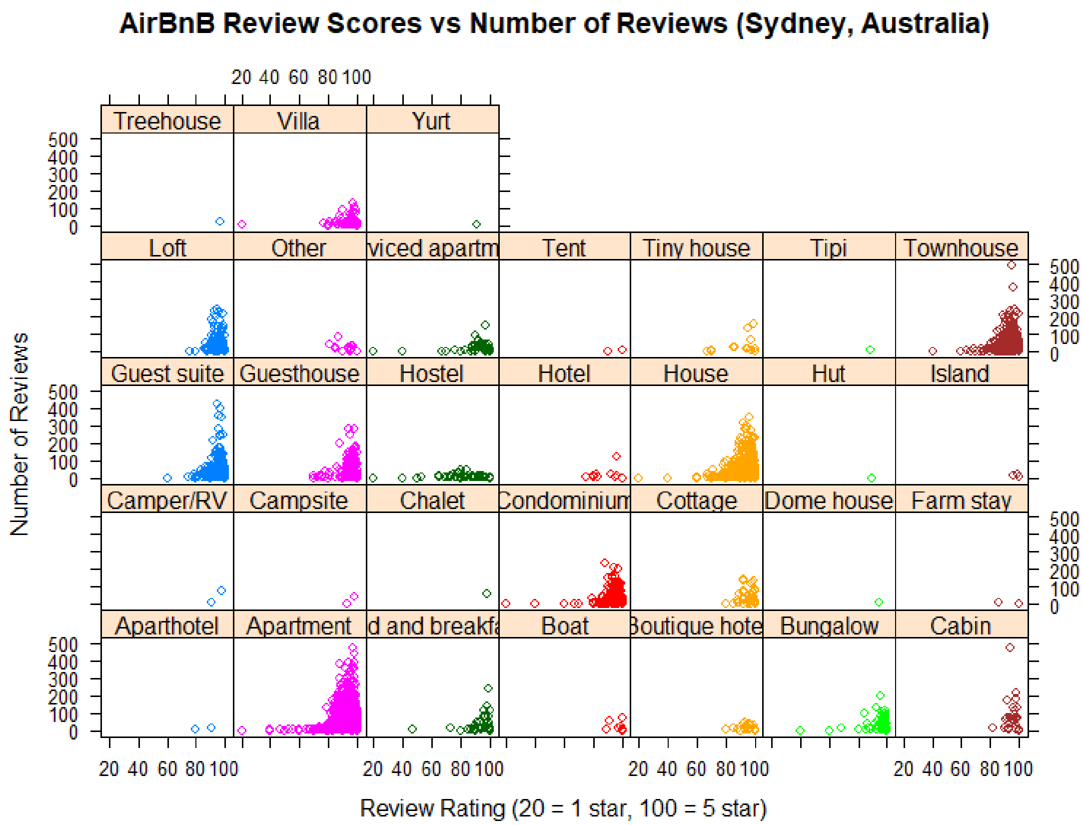
As a hypothetical AirBnB host, I'm looking at three ways in which to upgrade my listing. My goal is to either improve my overall rating from guests or be able to raise the price – or potentially both. The three upgrades I am considering are: a Pool, Cable TV subscription, or a BBQ Grill.

- Listings with a Pool will have a higher price than those without
- Listings with Cable TV will have a higher price than those without
- Listings with a BBQ Grill will have a higher price than those without

Q6

6.1: Make ONE plot to visualize relationship between review_scores_rating and number of reviews for all categories of property_type. Explain your findings.

```
xyplot(airbnb$number_of_reviews ~ airbnb$review_scores_rating | airbnb$proper
ty_type, groups = airbnb$property_type, xlab = "Review Rating (20 = 1 star, 1
00 = 5 star)", ylab = "Number of Reviews", main="AirBnB Review Scores vs Numb
er of Reviews (Sydney, Australia)")
```



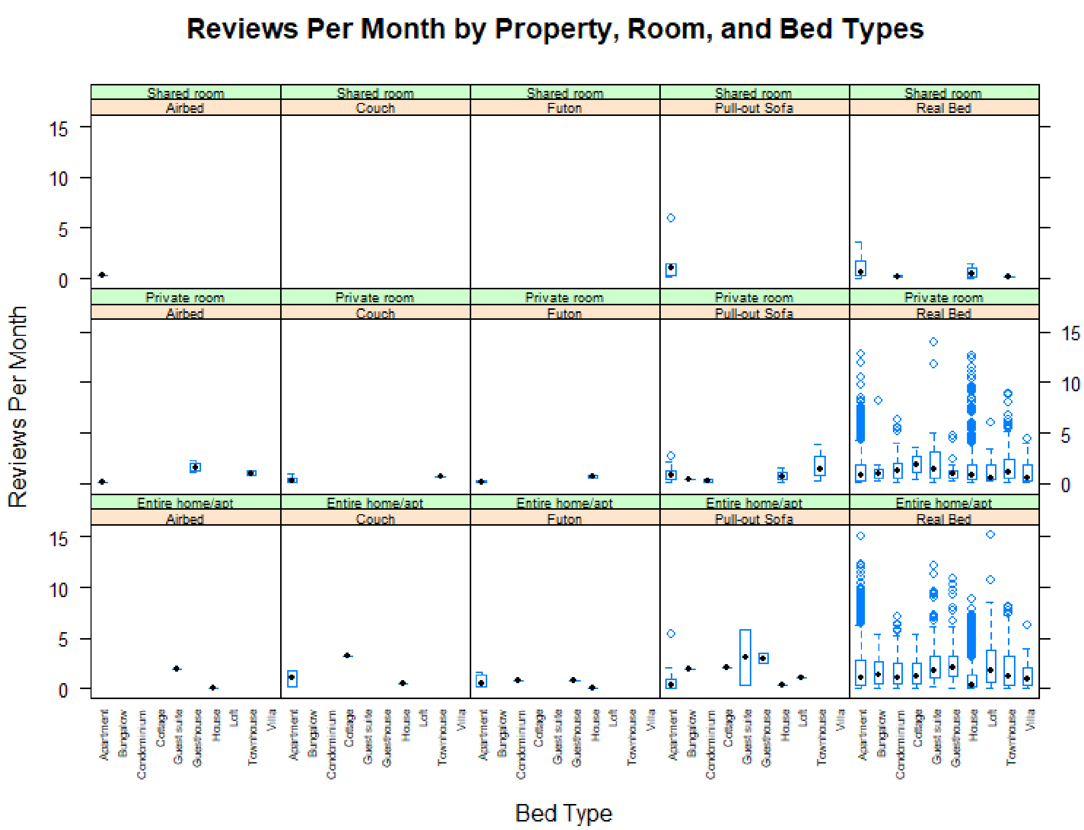
Findings

Although certain property types are more common than others, the distributions are largely similar: it is rare for a rental to get over 100 reviews if it is not at least a four-star property (rating = 80). This is why under the 100 review line, a variety of scores can be found (although still concentrated toward four- and five-star reviews). Poorly-reviewed rentals will see fewer guests and thus, reviews.

I'm unsure if all of these property types have been available for the same length of time. For example, hostels and boutique hotels seem to have a moderate number of reviews, but none over 100. I wonder if this is a newer addition to the property types.

6.2: Make ONE plot to show relationship among property types, room types, bed types, and reviews per month. Explain your findings.

```
# Get a target row count (10,546)
sum(head(sort(table(airbnb$property_type), decreasing = TRUE), 10))

## [1] 10546

# Subset the data frame to top property types
# Get a vector of property types
i <- names(head(sort(table(airbnb$property_type), decreasing = TRUE), 10))
# Subset
prairbnb <- airbnb[airbnb$property_type %in% i,]
# A double check
table(prairbnb$property_type)

##
##   Apartment    Bungalow Condominium     Cottage Guest suite  Guesthouse
##        6222          62         309          59         258         200
##       House        Loft   Townhouse       Villa
##        2604         150         589          93

# For best results, view on an 80" plasma 4k TV
bwplot(prairbnb$reviews_per_month ~ prairbnb$property_type | prairbnb$bed_typ
e + prairbnb$room_type,
       scales=list(x=list(rot=90, cex=0.5)),
       xlab='Bed Type', ylab='Reviews Per Month',
       par.strip.text=list(cex=.55),
       cex = .5,
       main = "Reviews Per Month by Property, Room, and Bed Types")
```



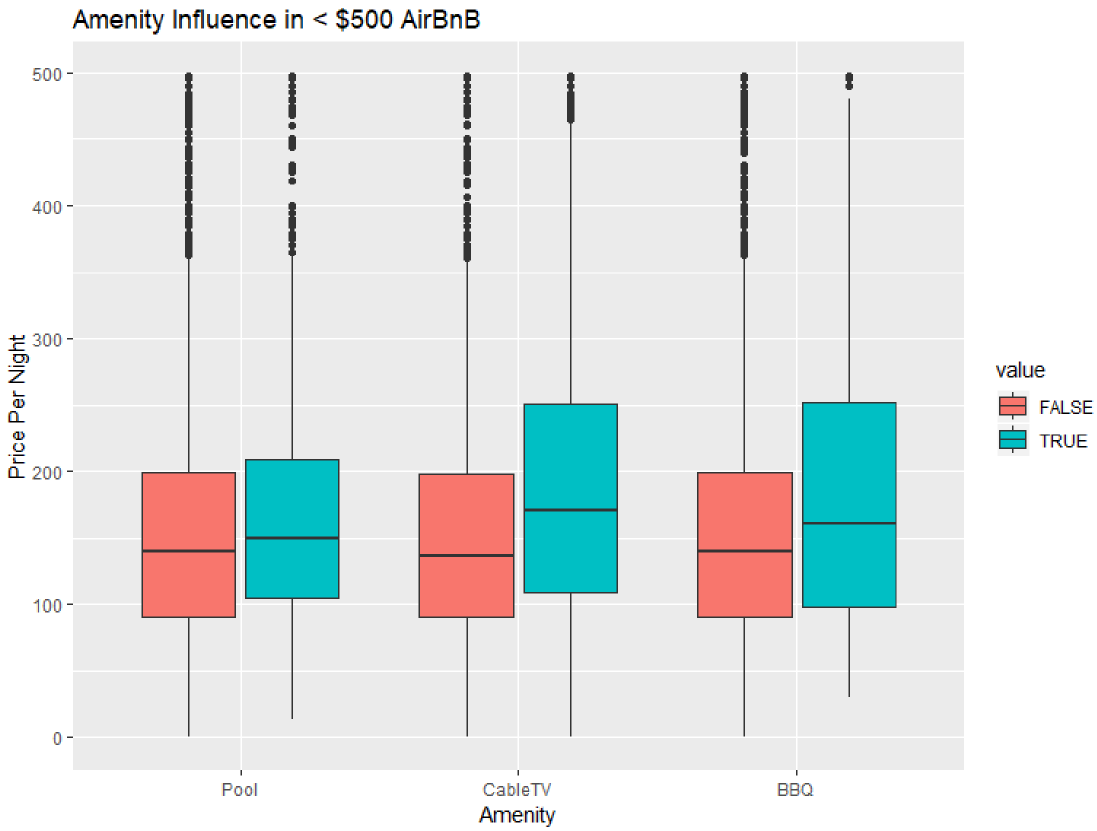
Findings

This layout is a grid of plots: each row contains one of three room types, and each column contains one of five bedtypes. The property types are shown in the boxplot inside each grid cell. This layout shows that "real bed" is the most common bed type (due to the visual density of the boxplots). Real beds are also found at the most popular listings: all listings with over 10 reviews per month have a real bed. Futons, couches, and airbeds are not common, and the listings that have them do not have more than five reviews per month. The pull-out sofa is the second-most popular bed type, and it has a couple listings that break the five review per month level. In the Real Bed > Entire Home and Private Room graphs, the large amount of outliers above the whiskers indicate a positively-skewed distribution.

6.3: Make some plots to explore hypotheses in Q5. Explain your choice and describe interesting findings.

```
# Create the variables I need. grep() returns row numbers (i.e. row names)
airbnb$has_pool <- rownames(airbnb) %in% grep("Pool", airbnb$amenities)
airbnb$has_cable <- rownames(airbnb) %in% grep("Cable TV", airbnb$amenities)
airbnb$has_bbq <- rownames(airbnb) %in% grep("BBQ ", airbnb$amenities)
```

```r
# ggplot boxplots require data in long format. melt() in reshape2 can help wi
th that
mair <- airbnb %>% filter(price < 500) %>% select(c("id", Pool = "has_pool",
CableTV = "has_cable", BBQ = "has_bbq", "price")) %>% melt(id=c("id", "price"
))
ggplot(mair, aes(x=factor(variable), y=price)) +
  geom_boxplot(aes(fill = value))+
  ggtitle("Amenity Influence in < $500 AirBnB") +
  xlab("Amenity") +
  ylab("Price Per Night")
```




```r
# Get the numbers
mair %>% group_by(variable, value) %>% summarise(count = n(), mean_price = me
an(price))
```

```
## # A tibble: 6 x 4
## # Groups:   variable [?]
##   variable value count mean_price
##   <fct>    <lgl> <int>      <dbl>
## 1 Pool     FALSE  8451       161.
## 2 Pool     TRUE   1748       173.
## 3 CableTV  FALSE  8113       155.
## 4 CableTV  TRUE   2086       195.
## 5 BBQ      FALSE  8645       159.
## 6 BBQ      TRUE   1554       189.
```

First, I filtered the data to eliminate any properties over $500/night. I did this because my hypothetical rental is not in the extreme luxury class. I want to analyze my peer class. Second, I had to format this data into a long table (due to ggplot's handling of boxplot). This has the benefit of placing my plots next to each other for easy comparison.

The boxplot shows that the presensce of all of my potential amenities increase the price (at mean and at IQR points). The table indicates that pool, cable, and bbq will increase the mean by 12, 40, and 30 dollars per night. To my surprise, the pool had the smallest effect on price, and was also associated with the lowest prices. Perhaps a pool is less novel in Sydney? Due to the large cost of installation, ongoing costs, and small return, I will rule out the pool.

Cable TV and BBQ Grill are both cost-effective. Cable has an ongoing cost that will eat into profits, so I will compare the monthly cost against my occupancy rates and my planned price increase.

The BBQ Grill is more of a one-time expense with a strong return. I will choose that one first.

Q7

7.1: Clean the price

Price was cleaned back in step 1 with the following:

```
# airbnb$price <- as.numeric(gsub("^\\$|,","",airbnb$price))
```

7.2: Add number of amenities as column

```
# Amenities are separated by a comma and opened with a curly brace. Count the
curly brace and commas for num of amenities
# This statement is using lapply to make a vector 10815 elements long. gregex
pr returns a list, and I need to get the
# length of the first element of the list
airbnb$number_of_amenities <- sapply(airbnb$amenities, function(x) length(gre
gexpr("\\{|,",x)[[1]]))

# Problem with the above is that it counts empty curly brace as 1
airbnb$number_of_amenities <- sapply(airbnb$amenities, function(x) length(str
split(x,",")[[1]]))
# This does the same.

# Clean up the ones; using a within() statment to minimize typing airbnb$
airbnb <- within(airbnb, number_of_amenities[number_of_amenities == 1] <- 0)
```

7.3: Calculate mean review_scores_rating against cancellation policies. What do you find?

```
# Using Base R
by(airbnb$review_scores_rating, airbnb$cancellation_policy, mean)

## airbnb$cancellation_policy: flexible
## [1] 94.15888
## --------------------------------------------------------
## airbnb$cancellation_policy: moderate
## [1] 95.00604
## --------------------------------------------------------
## airbnb$cancellation_policy: strict_14_with_grace_period
## [1] 93.77139
## --------------------------------------------------------
## airbnb$cancellation_policy: super_strict_30
## [1] 80
## --------------------------------------------------------
## airbnb$cancellation_policy: super_strict_60
## [1] 89.8

# Using dplyr
airbnb %>% group_by(cancellation_policy) %>% summarise(mean = mean(review_sco
res_rating))

## # A tibble: 5 x 2
##   cancellation_policy          mean
##   <chr>                       <dbl>
## 1 flexible                     94.2
## 2 moderate                     95.0
## 3 strict_14_with_grace_period  93.8
## 4 super_strict_30              80
## 5 super_strict_60              89.8
```

Findings

The super-strict cancellation policies have the worst scores – under 90. These are less guest-friendly. The highest mean was for the moderate policy, which sits between flexible and strict_14_with_grace_period on the guest-friendly scale. Why wouldn't flexible – as the most guest-friendly – have the highest ratings? Perhaps the hosts who choose the flexible policy are more care-free and less professional in their rental? It could also be statistical noise; are 95.00 and 94.15 meaningfully different?

```
# Here is a t-test
t.test(airbnb$review_scores_rating[airbnb$cancellation_policy == "flexible"],
airbnb$review_scores_rating[airbnb$cancellation_policy == "moderate"])

##
##  Welch Two Sample t-test
```

```
##
## data:  airbnb$review_scores_rating[airbnb$cancellation_policy == "flexible
"] and airbnb$review_scores_rating[airbnb$cancellation_policy == "moderate"]
## t = -3.2849, df = 2062.9, p-value = 0.001037
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.3529094 -0.3414036
## sample estimates:
## mean of x mean of y
##  94.15888  95.00604

# I have run the t-test, and I THINK that because the p value is < .05, I wil
l reject the null hypothesis.
# Then again, I feel in this class we would find the standard deviation which
for "flexible" is 8.67.
sd(airbnb$review_scores_rating[airbnb$cancellation_policy == "flexible"])

## [1] 8.665896

# In this case, I could argue that the mean for "strict_14" falls within +/-
8.67 of the mean flexible. Therefore they are
# not statistically different.
```

Other manipulations

Here I use dplyr to get mean scores by types

```
airbnb %>% group_by(property_type) %>% summarise(mean = mean(review_scores_ra
ting)) %>% arrange(desc(mean))

## # A tibble: 31 x 2
##    property_type  mean
##    <chr>         <dbl>
##  1 Island         98.3
##  2 Chalet         98
##  3 Boat           97
##  4 Treehouse      97
##  5 Cottage        95.9
##  6 Cabin          95.9
##  7 Loft           95.6
##  8 Guest suite    95.5
##  9 Campsite       95.5
## 10 Farm stay      95.3
## # ... with 21 more rows

airbnb %>% group_by(room_type) %>% summarise(mean = mean(review_scores_rating
)) %>% arrange(desc(mean))

## # A tibble: 3 x 2
##   room_type        mean
```

```
##   <chr>            <dbl>
## 1 Private room      94.6
## 2 Entire home/apt   94.1
## 3 Shared room       84.9
```

```
airbnb %>% group_by(bed_type) %>% summarise(mean = mean(review_scores_rating)
) %>% arrange(desc(mean))
```

```
## # A tibble: 5 x 2
##   bed_type       mean
##   <chr>         <dbl>
## 1 Futon          94.6
## 2 Real Bed       94.2
## 3 Pull-out Sofa  92.6
## 4 Couch          92
## 5 Airbed         81.8
```

```
airbnb %>% group_by(number_of_amenities) %>% summarise(mean = mean(review_sco
res_rating)) %>% arrange(desc(mean))
```

```
## # A tibble: 87 x 2
##    number_of_amenities  mean
##                  <dbl> <dbl>
##  1                  80 100
##  2                  95 100
##  3                  97 100
##  4                  79  99
##  5                  81  99
##  6                  69  98.6
##  7                  77  98.5
##  8                  89  98
##  9                 101  98
## 10                  74  97.6
## # ... with 77 more rows
```

I added amenity data in 6.3. I will add word count data in 10. I will add spatial data in part 4.

Q8: Linear Modeling

Explain 10 variables; evaluate one

In question four, I established that reviews_per_month was the preferred measure of popularity (the right quadrants were either popular for a long time, or popular for a short time). I will use reviews_per_month as the dependent variable in this exercise.

Reviews per month is a mix of occupancy rate and minimum night stay.

- Price: I don't think price will affect reviews_per month. Expensive listings could be frequently reviewed ($R^2 = 0.008$)

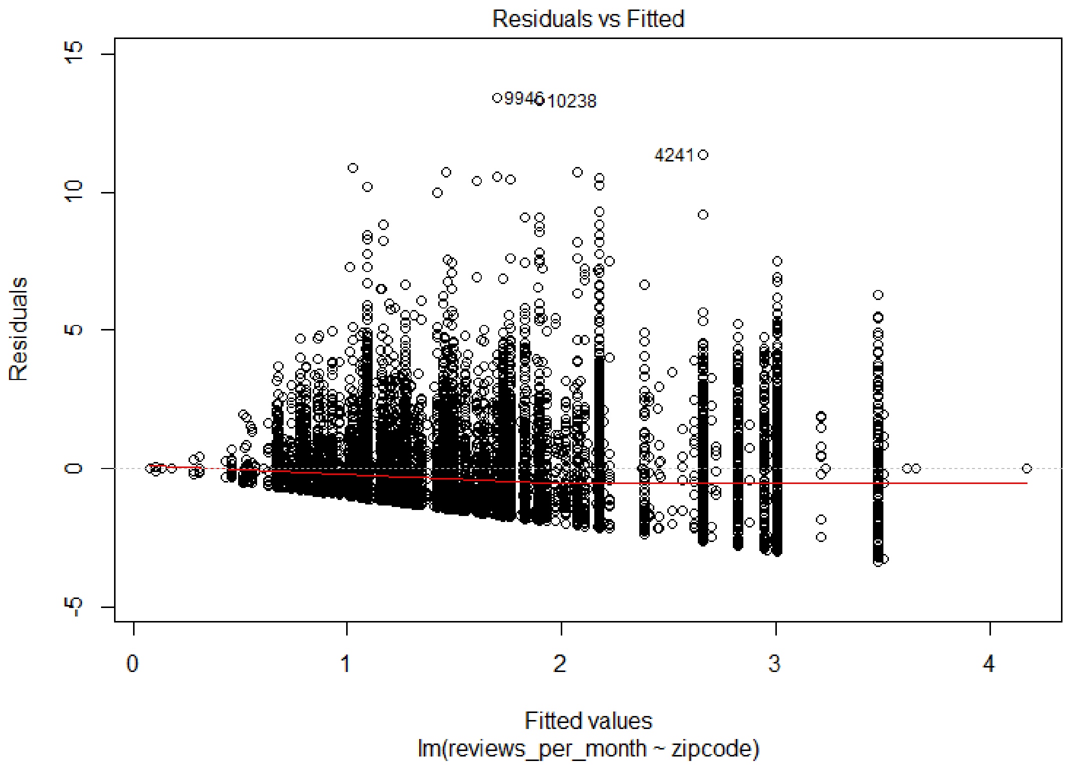
- Host_is_superhost: ($R^2 = 0.088$)
- Number_of_verifications: This could help, but I'm not sure that that buyers care more about the NUMBER of verifications, but just that there is at least one.
- Cleaning_fee: This might have a small impact ($R^2 = 0.01566$)
- Review_scores_communication: Perhaps hosts with good communication skills will be more likely to receive reviews? Apparently not ($R^2 = 0.006$)
- Host_response_rate: Building off the previous variable, perhaps responsive hosts will be more likely to receive reviews? ($R^2 = 0.009$)
- Room_type: Perhaps shared_room will be less popular than a private room, which may be less popular than an entire house/apt? ($R^2 = 0.005$)
- Number_of_amentities: I think guests will be attracted to listings with a number of amenities, because 1. guests like amenities and 2. multiple amenities can be found on listings with complete descriptions. ($R^2 = 0.009$)
- Zipcode: I believe certain zipcodes will be more popular than others. ($R^2 = 0.147$)
- Minimum_nights: I think this one will have the most correlation (negative slope). ($R^2 = 0.015$)

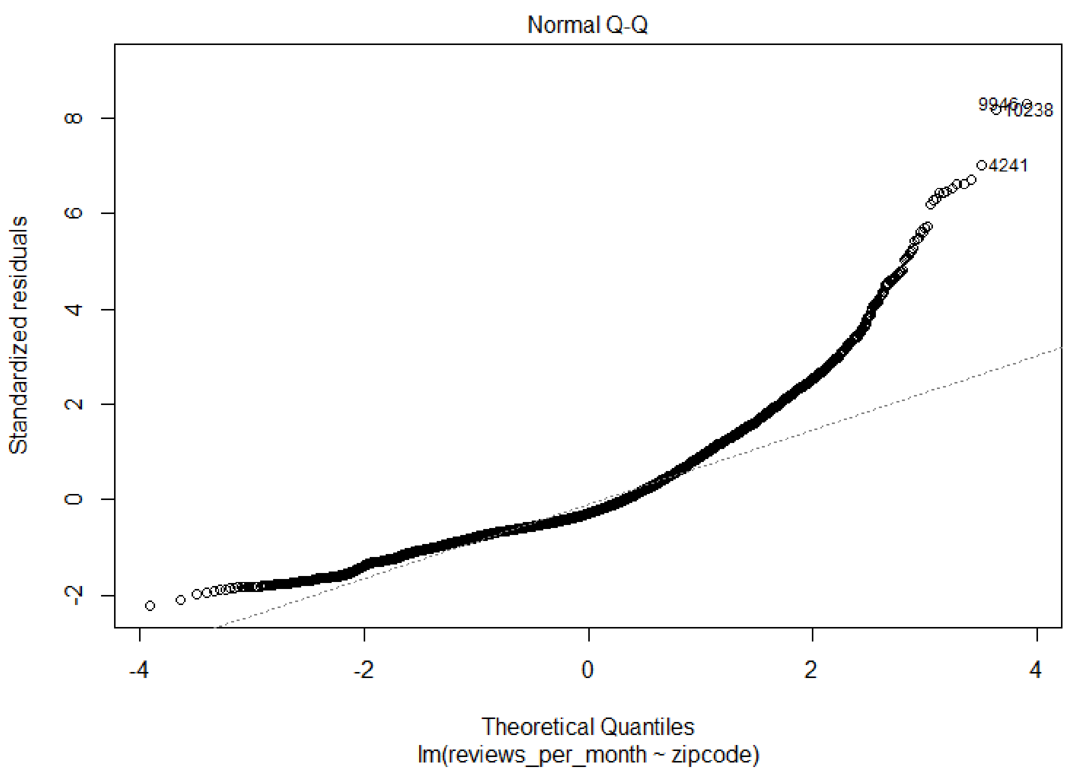
```
# Zipcode was my winning -- although weak -- correlation. Here's the model an
d charts
amodel <- lm(reviews_per_month ~ zipcode, data = airbnb)
summary(amodel)

##
## Call:
## lm(formula = reviews_per_month ~ zipcode, data = airbnb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.3773 -1.0018 -0.4533  0.6927 13.4386
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.00178    0.06932  43.304  < 2e-16 ***
## zipcode2007     -0.05871    0.16016  -0.367 0.713960
## zipcode2008     -0.34467    0.13771  -2.503 0.012333 *
## zipcode2009     -0.17768    0.13883  -1.280 0.200614
## zipcode2010     -0.82550    0.08847  -9.331  < 2e-16 ***
## zipcode2011     -1.27714    0.10390 -12.292  < 2e-16 ***
## zipcode2015     -1.30041    0.17539  -7.414 1.31e-13 ***
## zipcode2016     -1.17478    0.13196  -8.903  < 2e-16 ***
## zipcode2017     -1.10717    0.12813  -8.641  < 2e-16 ***
## zipcode2018     -1.40035    0.20646  -6.783 1.24e-11 ***
## zipcode2019     -1.50821    0.44036  -3.425 0.000617 ***
## zipcode2020     -0.93095    0.17995  -5.173 2.34e-07 ***
## zipcode2021     -1.55448    0.13716 -11.333  < 2e-16 ***
## zipcode2022     -1.92912    0.14308 -13.483  < 2e-16 ***
## zipcode2023     -2.32395    0.20779 -11.184  < 2e-16 ***
~~~ manually truncated by author
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.627 on 10609 degrees of freedom
## Multiple R-squared:  0.1468, Adjusted R-squared:  0.1304
## F-statistic: 8.907 on 205 and 10609 DF,  p-value: < 2.2e-16
```

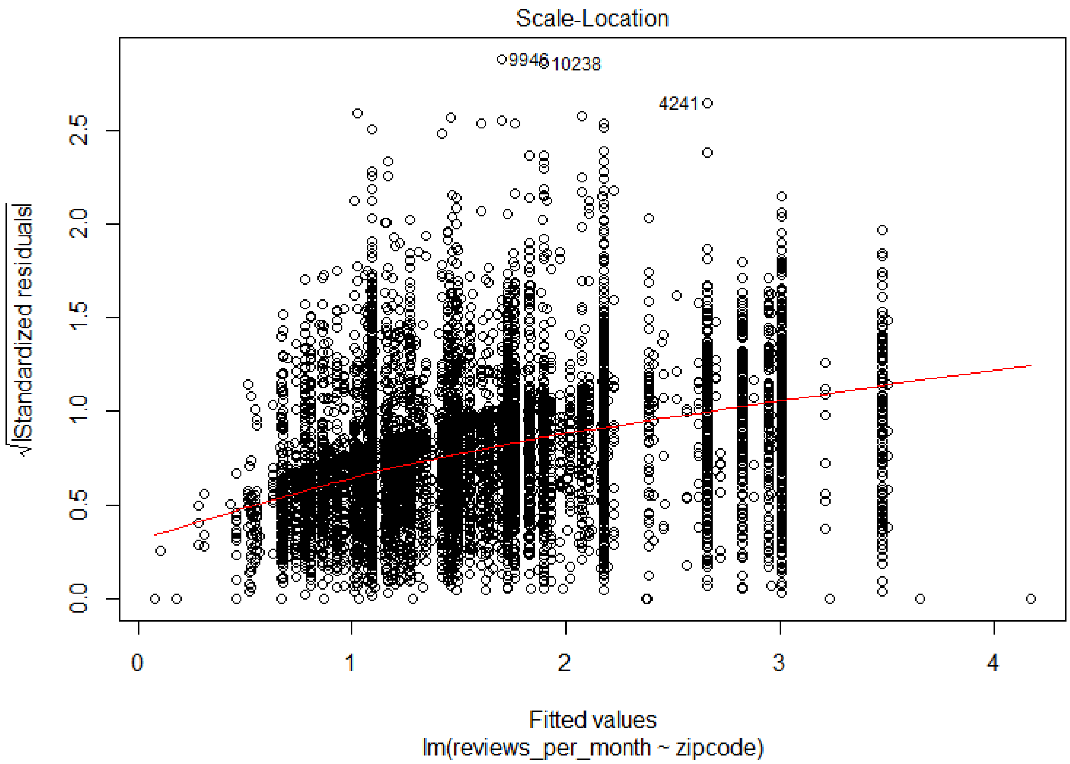
```
plot(amodel, ask = FALSE)
```

```
## Warning: not plotting observations with leverage one:
##   1826, 2608, 6910, 7042, 7195, 7661, 7719, 8222, 9759
```

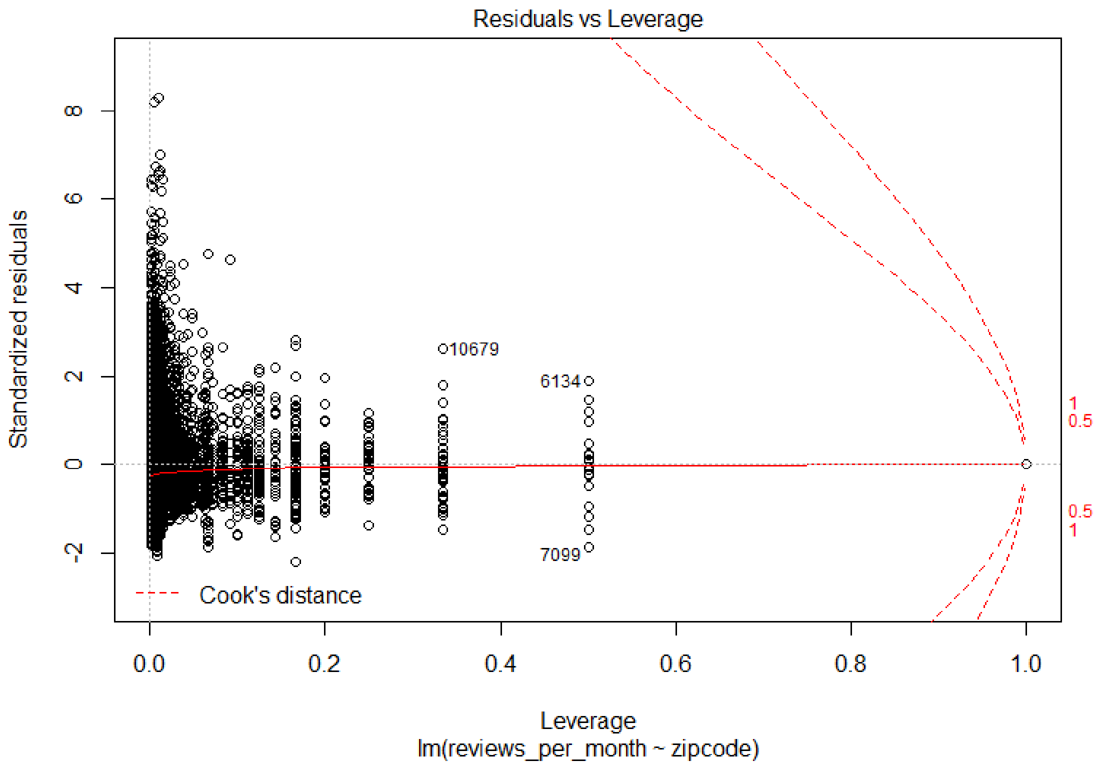

Residuals vs Fitted
Residuals
15
10
5
0
-5
0
1
2
3
4
9946
10238
4241
Fitted values
lm(reviews_per_month ~ zipcode)


Normal Q-Q
Standardized residuals
8
6
4
2
0
-2
-4
-2
0
2
4
9946
10238
4241
Theoretical Quantiles
lm(reviews_per_month ~ zipcode)

```
## Warning: not plotting observations with leverage one:
##   1826, 2608, 6910, 7042, 7195, 7661, 7719, 8222, 9759
```




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

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



The first plot, Residuals vs Fitted, is a scatterplot of residuals (observed y - predicted y). We want this to be approximately zero. This plot helps us to assess the assumptions of linearity (is red line a line around y=0?) and homoscedasticity (is the spread of residuals even along the x axis?). This model has linearity, but the residuals have larger positive values than negative. So the model is not entirely homoscedastic.

The second plot, Normal Q-Q, compares the residuals to "ideal" normal observations. We want observations to lie along the 45 degree line in the plot. This model follows fairly closely, but at the extreme theoretical quantiles deviate from the line.

The third plot, Scale-Location, shows square-rooted standardized residual vs predicted value and can help visualize homoscedasticity. We want a horizontal line and equal spread of points. This model has some slope in the red line, but is it flat enough? The spread of points seems fairly even.

The fourth plot, Residuals vs Leverage, helps to find outliers and overly-influential observations. Here we look for values at the upper-right and lower-left portions of the plot. No outliers exceed the 0.5 Cook's distance.

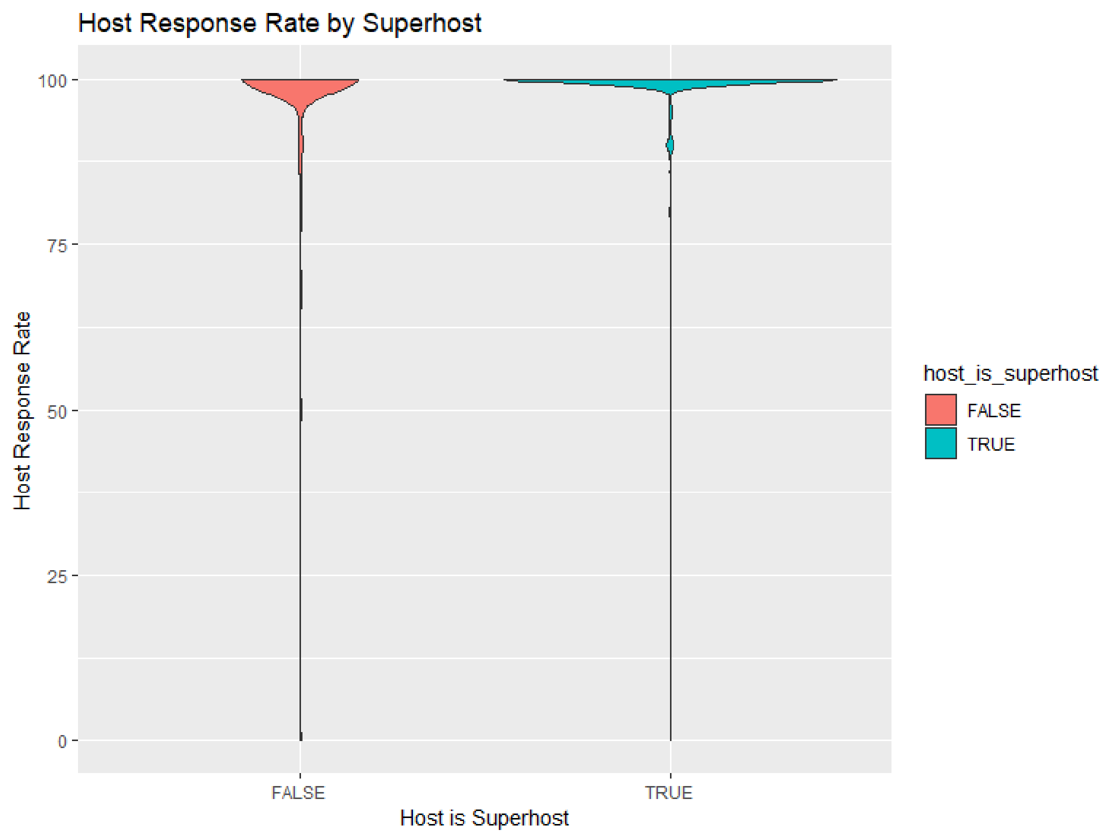
In all, the diagnostic plots of this model show that it meets the assumptions of linearity, normality, and homoscedasticity. I believe this to be a good model, although the correlation level is small.

PART 3: Further Analysis

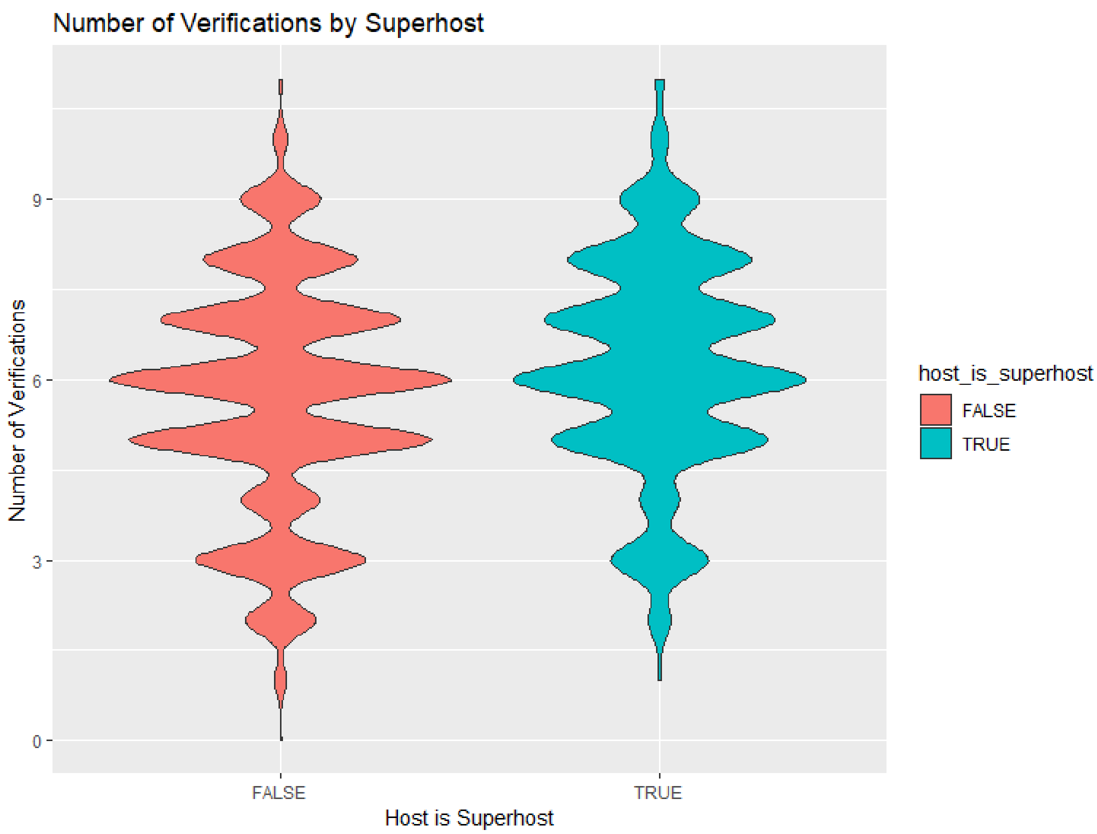
Q9

9.1: Explore relationships (if any) between superhost and host_since, host_response_time, host_response_rate. host_verifications, host_identity_verified

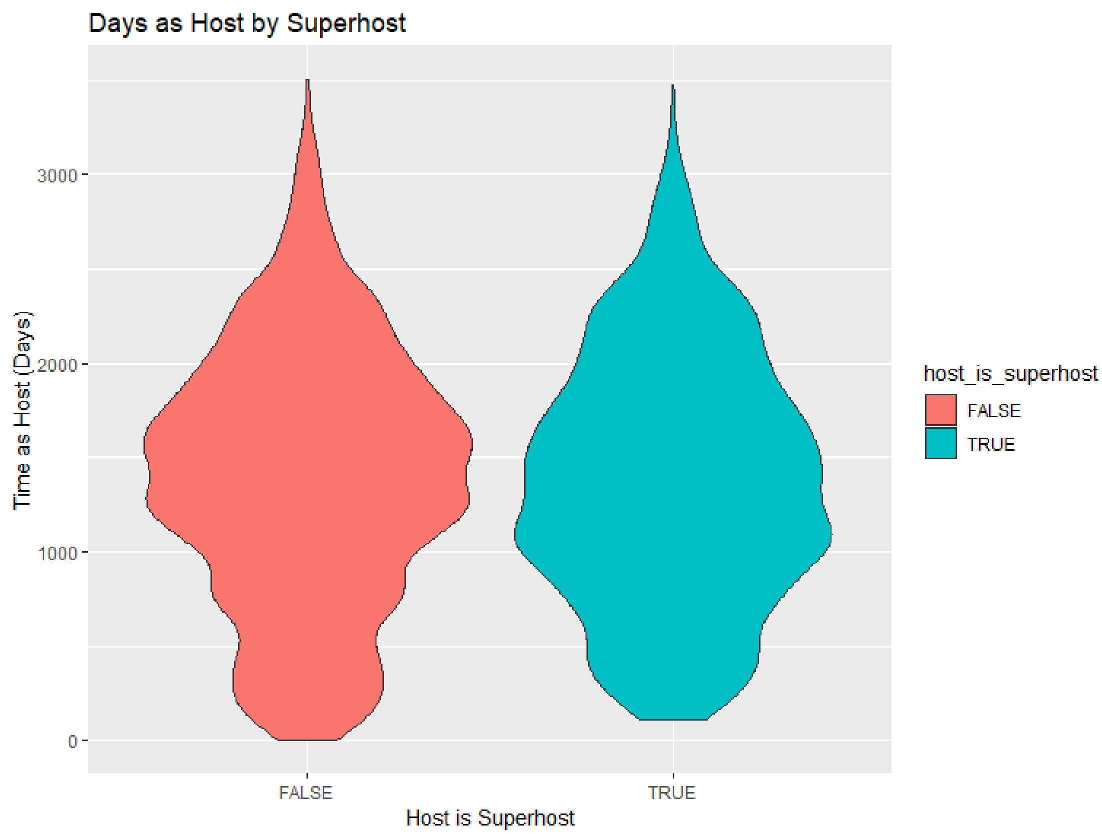
```
# STEP 1: Make host_verifications useful
# Get table of verification counts
#table(sapply(airbnb$host_verifications, function(x) length(strsplit(x,",")[[
1]])))
#airbnb %>% select(host_verifications, number_of_verifications) %>% filter(ho
st_verifications == "[]")

# Split amenities on comma, assign comma count (or 1 if no commas)
airbnb$number_of_verifications <- sapply(airbnb$host_verifications, function(
x) length(strsplit(x,",")[[1]]))

# Clean up the ones; some values of 1 are empty; these are []
airbnb <- within(airbnb, number_of_verifications[host_verifications == "[]"]
<- 0)


# Some graphs
ggplot(airbnb, aes(host_is_superhost, host_response_rate, fill = host_is_supe
rhost)) +
  geom_violin() +
  labs(x = "Host is Superhost", y = "Host Response Rate", title = "Host Respo
nse Rate by Superhost")
```




```
ggplot(airbnb, aes(host_is_superhost, number_of_verifications, fill = host_is
_superhost)) +
  geom_violin() +
  labs(x = "Host is Superhost", y = "Number of Verifications", title = "Numbe
r of Verifications by Superhost")
```




```r
ggplot(airbnb, aes(host_is_superhost, host_number_of_days, fill = host_is_sup
erhost)) +
  geom_violin() +
  labs(x = "Host is Superhost", y = "Time as Host (Days)", title = "Days as H
ost by Superhost")
```




```r
# Some models
zmodel1 <- lm(host_response_rate ~ host_is_superhost, data = airbnb)
summary(zmodel1)

##
## Call:
## lm(formula = host_response_rate ~ host_is_superhost, data = airbnb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -99.272   0.728   3.480   3.480   3.480
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            96.5200     0.1244  776.16   <2e-16 ***
## host_is_superhostTRUE   2.7520     0.2446   11.25   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.14 on 10813 degrees of freedom
## Multiple R-squared:  0.01157,    Adjusted R-squared:  0.01148
## F-statistic: 126.6 on 1 and 10813 DF,  p-value: < 2.2e-16

#zmodel2 <- lm(host_response_time ~ host_is_superhost, data = airbnb) # this
one is failing
```

```r
#summary(zmodel2)
zmodel3 <- lm(number_of_verifications ~ host_is_superhost, data = airbnb)
summary(zmodel3)
```

```
##
## Call:
## lm(formula = number_of_verifications ~ host_is_superhost, data = airbnb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.6845 -1.2111  0.3155  1.3155  5.3155
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              5.68454    0.02107  269.83   <2e-16 ***
## host_is_superhostTRUE  0.52655    0.04144   12.71   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.887 on 10813 degrees of freedom
## Multiple R-squared:  0.01471,    Adjusted R-squared:  0.01462
## F-statistic: 161.5 on 1 and 10813 DF,  p-value: < 2.2e-16
```

```r
zmodel4 <- lm(host_identity_verified ~ host_is_superhost, data = airbnb)
summary(zmodel4)
```

```
##
## Call:
## lm(formula = host_identity_verified ~ host_is_superhost, data = airbnb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5152 -0.4668 -0.4668  0.5332  0.5332
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.466833   0.005574  83.753  < 2e-16 ***
## host_is_superhostTRUE 0.048373   0.010964   4.412 1.03e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4992 on 10813 degrees of freedom
## Multiple R-squared:  0.001797,   Adjusted R-squared:  0.001705
## F-statistic: 19.46 on 1 and 10813 DF,  p-value: 1.035e-05
```

```r
zmodel5 <- lm(as.numeric(host_number_of_days) ~ host_is_superhost, data = air
bnb)
summary(zmodel5)
```

```
##
## Call:
```

```
## lm(formula = as.numeric(host_number_of_days) ~ host_is_superhost,
##     data = airbnb)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1393.64  -478.83     4.99   453.99  2112.36
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1393.642      7.607 183.213   <2e-16 ***
## host_is_superhostTRUE  -15.632     14.963  -1.045    0.296
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 681.2 on 10813 degrees of freedom
## Multiple R-squared:  0.0001009,  Adjusted R-squared:  8.457e-06
## F-statistic: 1.091 on 1 and 10813 DF,  p-value: 0.2962
```

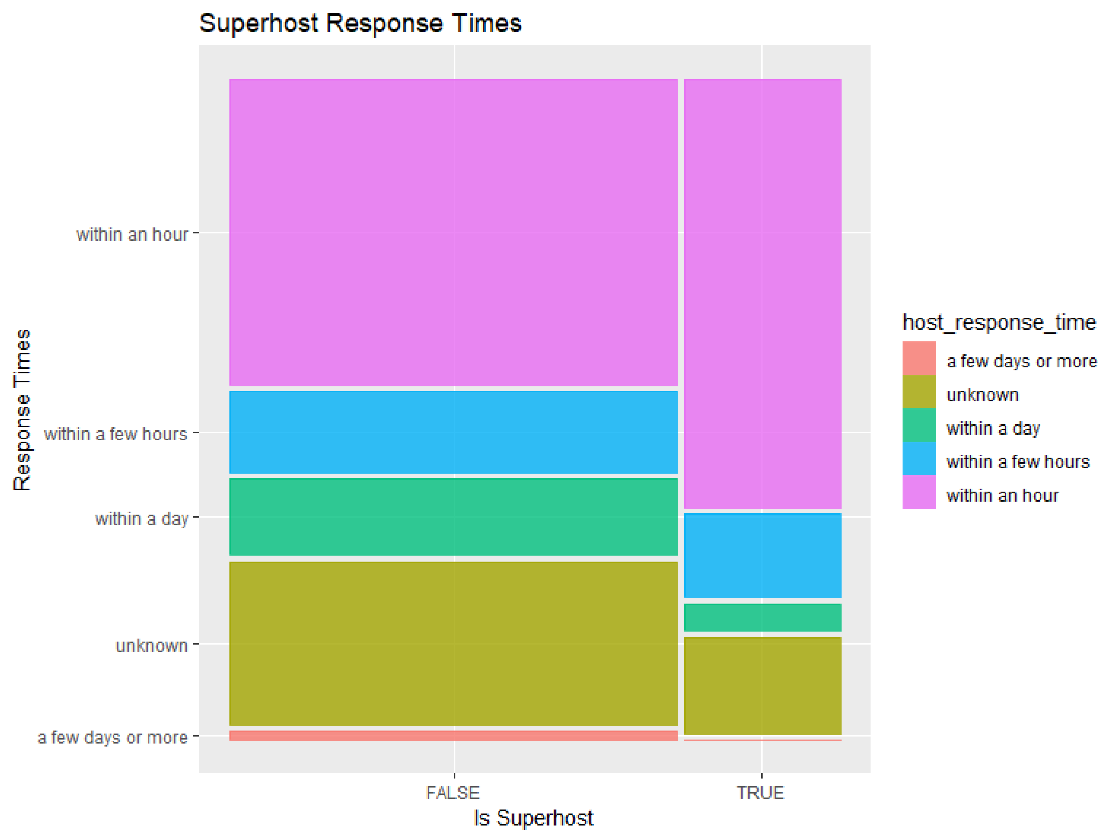
All of these models have small (<0.1) R^2 values. I'm beginning to think I should just burn this project down and start with something else.

9.2: Create mosaic plot for host_response_time by superhost. What do you learn?

```
library("ggmosaic")
```

```
## Warning: package 'ggmosaic' was built under R version 3.5.2
```

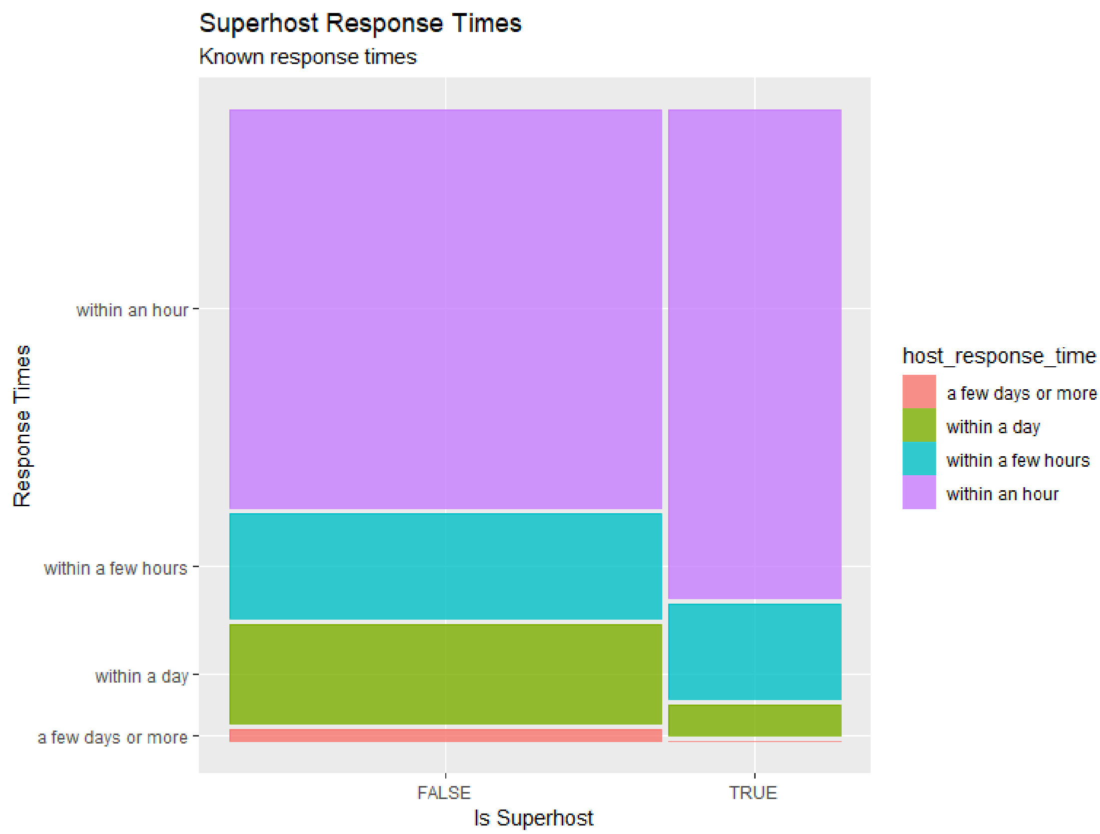
```
ggplot(data = airbnb) +
  geom_mosaic(aes(product(host_response_time, host_is_superhost), fill=host_r
esponse_time), na.rm=TRUE) +
  labs(x="Is Superhost", y="Response Times", title="Superhost Response Times"
)
```



Findings

A mosaic plot shows percentages of observations across categorical variables. Here we can see the distribution of host_is_superhost along the x-axis: Superhosts (TRUE) make up less than a third of the total observations (because the FALSE column is more than twice as wide as TRUE). However, we can see the response time distribution along the y-axis, and the data show that over half of Superhosts respond within an hour. This graph includes some imputed data from the cleanup phase. The "unknown" response doesn't necessarily help us in comparing these two groups (although it does describe the condition of our data). If we want, we can remove "unknown" to compare known response times:

```
ggplot(data = airbnb %>% filter(host_response_time != "unknown")) +
  geom_mosaic(aes(product(host_response_time, host_is_superhost), fill=host_r
esponse_time), na.rm=TRUE) +
  labs(x="Is Superhost", y="Response Times", title="Superhost Response Times"
, subtitle = "Known response times")
```



Here we can see that, based on known response times, Superhosts respond more quickly than non-Superhosts.

Q10

10.1: Extract unique words in description and eliminate stop words. Store in dataframe and sort decreasing. What do you infer from words with top 10 frequency?

```
# Get all "words", splitting on space
#all_words <- unlist(strsplit(airbnb[1:3,2], "[[:space:]]"))
# Extract only alpha letters
#regmatches(all_words, regexpr("[[:alpha:]]+", all_words))
#grep("[[:alpha:]]",unlist(strsplit(airbnb[1:3,2], "[[:space:]]|,|.")), value
= TRUE)
#unlist(grep("[[:alpha:]]", airbnb[1:3,2], value=TRUE))

# After wrangling with "what is a word" and handling punctuation, I've decide
d to leverage libraries built to deal with this
# https://www.tidytextmining.com/tidytext.html
```

```
#install.packages("tidytext")
library(tidytext)

## Warning: package 'tidytext' was built under R version 3.5.3

# Load the stop words (to be omitted from analysis) into a tidytext-compatibl
e data frame
#is457_stop_words <- c("a", "able", "about", "across", "after", "all", "almos
t", "also", "among", "and", "are", "almost", "at", "almost", "also", "am", "a
mong", "an", "and", "any", "are", "as", "at", "be", "because", "been", "but",
"by", "can", "cannot", "could", "dear", "did", "do", "does", "either", "else"
, "ever", "every", "for", "from", "get", "got", "had", "has", "have", "he", "
her", "hers", "him", "his", "how", "however", "i", "if", "in", "into", "is",
"it", "its", "just", "least", "let", "like", "likely", "may", "me", "might",
"most", "must", "my", "neither", "no", "nor", "not", "of", "off", "often", "o
n", "only", "or", "other", "our", "own", "rather", "said", "say", "says", "sh
e", "should", "since", "so", "some", "than", "that", "the", "their", "them",
"then", "there", "these", "they", "this", "is", "to", "too", "was", "us", "wa
nts", "was", "we", "were", "what", "when", "where", "which", "while", "who",
"whom", "why", "will", "with", "would", "yet", "you", "your")
is457_stop_words_df <- data.frame(lexicon = "is457", word = c("a", "able", "a
bout", "across", "after", "all", "almost", "also", "among", "and", "are", "al
most", "at", "almost", "also", "am", "among", "an", "and", "any", "are", "as"
, "at", "be", "because", "been", "but", "by", "can", "cannot", "could", "dear
", "did", "do", "does", "either", "else", "ever", "every", "for", "from", "ge
t", "got", "had", "has", "have", "he", "her", "hers", "him", "his", "how", "h
owever", "i", "if", "in", "into", "is", "it", "its", "just", "least", "let",
"like", "likely", "may", "me", "might", "most", "must", "my", "neither", "no"
, "nor", "not", "of", "off", "often", "on", "only", "or", "other", "our", "ow
n", "rather", "said", "say", "says", "she", "should", "since", "so", "some",
"than", "that", "the", "their", "them", "then", "there", "these", "they", "th
is", "is", "to", "too", "was", "us", "wants", "was", "we", "were", "what", "w
hen", "where", "which", "while", "who", "whom", "why", "will", "with", "would
", "yet", "you", "your"))

# Subset ID and Description
text_df <- airbnb[,1:2]

# Unnest_tokens does some heavy-lifting: it splits out each word, converts to
lowercase
tidy_txt <- text_df %>% unnest_tokens(word, description)

# Remove ("anti-join") the stop words for this class (tidytext comes with its
own dictionaries of stop words)
tidy_txt <- tidy_txt %>% anti_join(is457_stop_words_df)

## Warning: Column `word` joining character vector and factor, coercing into
## character vector
```

```r
# Count'em and keep the top 10
tidy_txt %>% count(word, sort = TRUE) %>% head(10)
```

```
## # A tibble: 10 x 2
##    word          n
##    <chr>     <int>
##  1 apartment 14658
##  2 bedroom   10692
##  3 walk      10680
##  4 sydney     9734
##  5 room       9702
##  6 kitchen    9340
##  7 beach      8965
##  8 bed        8872
##  9 2          7575
## 10 house      7236
```

```r
# 10.2a: Explore whether beach affects price of a listing. What is the differ
ence in average price?

# Get "beach" and "beaches" listing IDs
has_beach <- tidy_txt$id[tidy_txt$word == "beach"]
has_beaches <- tidy_txt$id[tidy_txt$word == "beaches"]

# These vectors have every mention of the word
paste(length(has_beach),"mentions of beach, and",length(has_beaches),"mention
s of beaches.")
```

```
## [1] "8965 mentions of beach, and 2054 mentions of beaches."
```

```r
# Show unique listings with these words
paste(length(unique(has_beach)),"listings have beach, and",length(unique(has_
beaches)),"listings have beaches.")
```

```
## [1] "4016 listings have beach, and 1550 listings have beaches."
```

```r
# union() removes duplicates
beachy <- union(has_beach, has_beaches)
paste(length(beachy),"listings in total mention beach or beaches.")
```

```
## [1] "4655 listings in total mention beach or beaches."
```

```r
# How do beach listings prices compare to non-beach?
# Convert beachy vector to a data frame to merge into airbnb as a logical col
umn
beachy <- data.frame(id = beachy, beach_desc = TRUE)

airbnb <- merge(airbnb, beachy, all.x = TRUE, by="id")
airbnb$beach_desc[is.na(airbnb$beach_desc)] <- FALSE
```

```r
# I still have 4655 listings with beach, now as a logical column in airbnb
table(airbnb$beach_desc)
```

```
##
## FALSE  TRUE
##  6160  4655
```

```r
mean(airbnb$price)
```

```
## [1] 203.1568
```

```r
by(airbnb$price, airbnb$beach_desc, mean)
```

```
## airbnb$beach_desc: FALSE
## [1] 177.6529
## --------------------------------------------------------
## airbnb$beach_desc: TRUE
## [1] 236.9063
```

```r
airbnb %>% group_by(beach_desc) %>% summarise(mean(price))
```

```
## # A tibble: 2 x 2
##   beach_desc `mean(price)`
##   <lgl>              <dbl>
## 1 FALSE               178.
## 2 TRUE                237.
```

Findings

The average price for all listings is $203.16. Listings that mention “beach” or “beaches” average price is $236.91 ($33.75 above average). Listings without those words average $177.25 ($25.51 below average).

Compared to each other, a beach listing is priced 33% higher.

10.2b: Explore multiple high frequency words. Write a function to get word frequency by row.

```r
count_word_in_desc <- function(w, v){
  # funcname: count_word_in_desc
  # inputs  : A word (character string) to search for, a vector to search in
  # outputs : count of words (integer)
  # purpose : Count appearances of a string
  # related : N/A
  # auth/dt : ID35, 2019-04-25

  w <- tolower(w)
  v <- tolower(v)
```

```r
  if(attr(gregexpr(w,v)[[1]], "match.length")[1] == -1){
    return(0)
  }
  else{
    return(length(attr(gregexpr(w,v)[[1]], "match.length")))
  }
}

# Now to find some top words! I dug a little
# Beach, just for comparison to the tidytext. This one finds 4,694 beach list
ings, but the results are similar.
airbnb$wc_beach <- unlist(lapply(airbnb$description, function(x) count_word_i
n_desc("beach",x)))
airbnb %>% group_by(wc_beach>0) %>% summarise(n = n(), avg_price = mean(price
), avg_review = mean(review_scores_rating))
```

```
## # A tibble: 2 x 4
##   `wc_beach > 0`     n avg_price avg_review
##   <lgl>          <int>     <dbl>      <dbl>
## 1 FALSE           6121      177.       93.8
## 2 TRUE            4694      237.       94.6
```

```r
# What listings are different?
diffs <- airbnb$description[airbnb$beach_desc == FALSE & airbnb$wc_beach > 0]
table(regmatches(diffs, regexpr("beach[[:alpha:]]*", diffs)))
```

```
## 
##          beachâ            beaché          beaches      beachfront 
##               1                 1                1               4 
##       beachside beachvolleyball           beachy 
##              19                 1                7
```

10.3: Select at least 3 other words from your dataframe and do similar analysis. What conclusions do you find?

```r
airbnb$wc_kitchen <- unlist(lapply(airbnb$description, function(x) count_word
_in_desc("kitchen",x)))
airbnb$wc_restaurants <- unlist(lapply(airbnb$description, function(x) count_
word_in_desc("restaurants",x)))
airbnb$wc_bus <- unlist(lapply(airbnb$description, function(x) count_word_in_
desc("bus",x)))
airbnb$wc_walk <- unlist(lapply(airbnb$description, function(x) count_word_in
_desc("walk",x)))
airbnb$wc_balcony <- unlist(lapply(airbnb$description, function(x) count_word
_in_desc("balcony",x)))

#airbnb$wc_kitchen[airbnb$wc_kitchen > 0]
airbnb %>% group_by(wc_kitchen>0) %>% summarise(n = n(), avg_price = mean(pri
ce), avg_review = mean(review_scores_rating))
```

```
## # A tibble: 2 x 4
##   `wc_kitchen > 0`     n avg_price avg_review
##   <lgl>            <int>     <dbl>      <dbl>
## 1 FALSE             3848      211.       94.3
## 2 TRUE              6967      199.       94.1
```

```
airbnb %>% group_by(wc_restaurants>0) %>% summarise(n = n(), avg_price = mean
(price), avg_review = mean(review_scores_rating))
```

```
## # A tibble: 2 x 4
##   `wc_restaurants > 0`     n avg_price avg_review
##   <lgl>                <int>     <dbl>      <dbl>
## 1 FALSE                 6309      214.       94.0
## 2 TRUE                  4506      188.       94.4
```

```
airbnb %>% group_by(wc_bus>0) %>% summarise(n = n(), avg_price = mean(price),
avg_review = mean(review_scores_rating))
```

```
## # A tibble: 2 x 4
##   `wc_bus > 0`     n avg_price avg_review
##   <lgl>        <int>     <dbl>      <dbl>
## 1 FALSE         5422      230.       94.2
## 2 TRUE          5393      176.       94.2
```

```
airbnb %>% group_by(wc_walk>0) %>% summarise(n = n(), avg_price = mean(price)
, avg_review = mean(review_scores_rating))
```

```
## # A tibble: 2 x 4
##   `wc_walk > 0`     n avg_price avg_review
##   <lgl>         <int>     <dbl>      <dbl>
## 1 FALSE          3610      222.       93.9
## 2 TRUE           7205      194.       94.3
```

```
airbnb %>% group_by(wc_balcony>0) %>% summarise(n = n(), avg_price = mean(pri
ce), avg_review = mean(review_scores_rating))
```

```
## # A tibble: 2 x 4
##   `wc_balcony > 0`     n avg_price avg_review
##   <lgl>            <int>     <dbl>      <dbl>
## 1 FALSE             7812      207.       94.1
## 2 TRUE              3003      193.       94.4
```

Findings

Scanning the top words, I looked for words that indicated something possibly unique about a listing (e.g. kitchen) versus something more routine (e.g., bed). I focused on a few areas: food (kitchen vs restaurants), transportation (bus vs walking), and the balcony (just curious about it more than anything).

Effect on Review Score

What I found is that these words had a small effect on the average review (the largest spread was 0.4, or just under a quarter-star difference: “walk” and “restaurants” both scored higher than their non-walk and non-restaurant counterparts).

Effect on Price

Food: Presence of either “kitchen” or “restaurant” is tied to a lower average price. Kitchen is $12 less than non-kitchen, and restaurant is $26 less than non-restaurant.

Transportation: Presence of “bus” and “walk” are both linked to lower average price. Bus is $54 less than non-bus, and walk is $28 less than non-walk. It seems that nobody really wants to think about taking the bus.

Balcony: Presence of “balcony” is also related to lower average price – $14 less if the description mentions “balcony”.

Q10(2)

Q10(2).1 Choose between zip code or city. Justify. Calculate number of listings for each in category. Filter to top 100.

Explore whether top 100 have higher weighted ratings. Graph and explain your findings.

The city data is very messy, with case and formatting issues. I’m going to use zip code data.

```
# Grab the top 100, but exclude the "unknown" that I imputed earlier.
#head(sort(table(airbnb$zipcode[airbnb$zipcode != "unknown"]), decreasing = T
RUE), 100)

# I have just been learning the dplyr tools with this project, and I find thi
s much more readable:
# How many listings in the top 100?
airbnb %>% select(zipcode) %>% filter(zipcode != "unknown") %>% table() %>% s
ort(decreasing = TRUE) %>% head(100) %>% sum()

## [1] 10291

# Filter the top 100 zipcodes
zip100 <- airbnb %>% select(zipcode) %>% filter(zipcode != "unknown") %>% tab
le() %>% sort(decreasing = TRUE) %>% head(100) %>% row.names()

airbnb %>% filter(zipcode %in% zip100) %>% select(c(zipcode, review_scores_ra
ting, number_of_reviews)) %>% group_by(zipcode) %>% summarise(wmean = weighte
d.mean(review_scores_rating, number_of_reviews))
```

```
## # A tibble: 100 x 2
##    zipcode wmean
##    <chr>   <dbl>
##  1 2000     93.1
##  2 2007     93.3
##  3 2008     92.9
##  4 2009     93.9
##  5 2010     93.9
##  6 2011     94.4
##  7 2015     96.3
##  8 2016     94.1
##  9 2017     94.2
## 10 2018     95.0
## # ... with 90 more rows
```

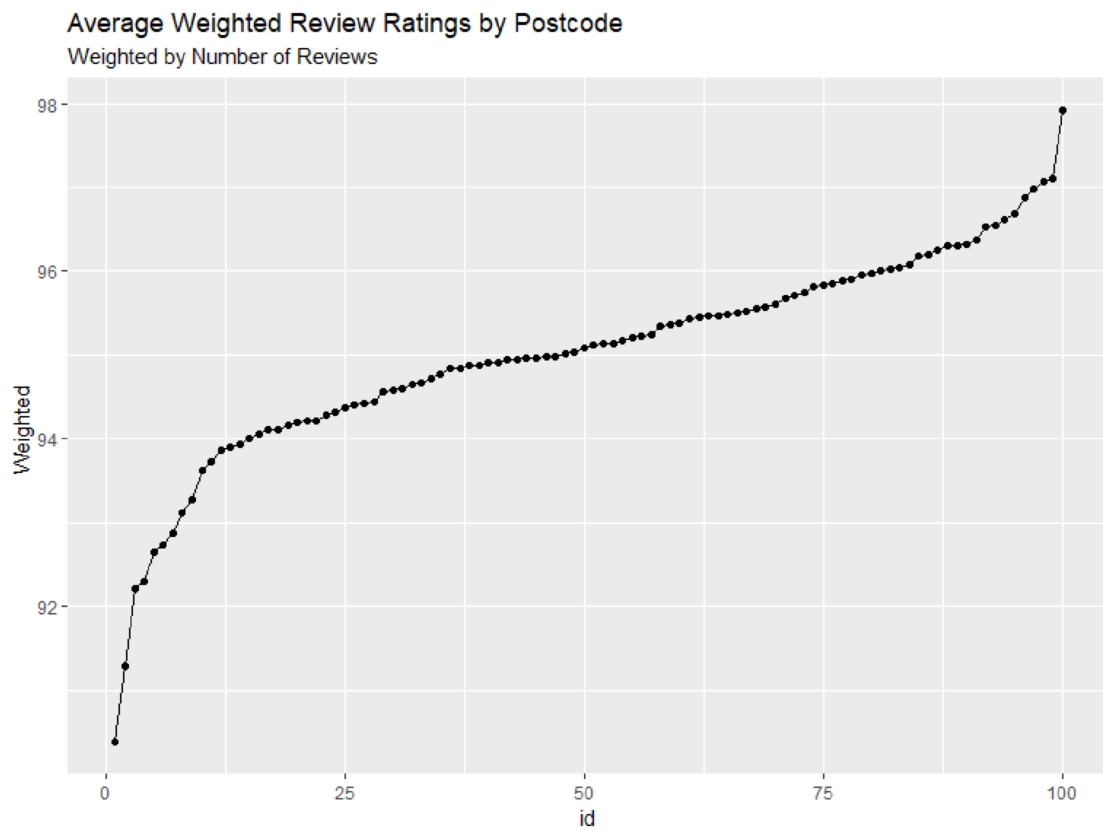
```
# How many observations (listings) are not in the top 100 postal codes?
airbnb %>% filter(!(zipcode %in% zip100)) %>% count()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1   524
```

This makes little sense. The top 100 zipcodes is most of the data set – 10,291 of the 10,815 observations. Can I reduce this number, like show the top 50? Am I supposed to use the inconsistently-named cities? Or am I actually to compare 10,291 to 524 observations?

Instead, I will show the trend of the top 100, putting each of the 100 zipcodes on the x-axis and showing the weighted mean.

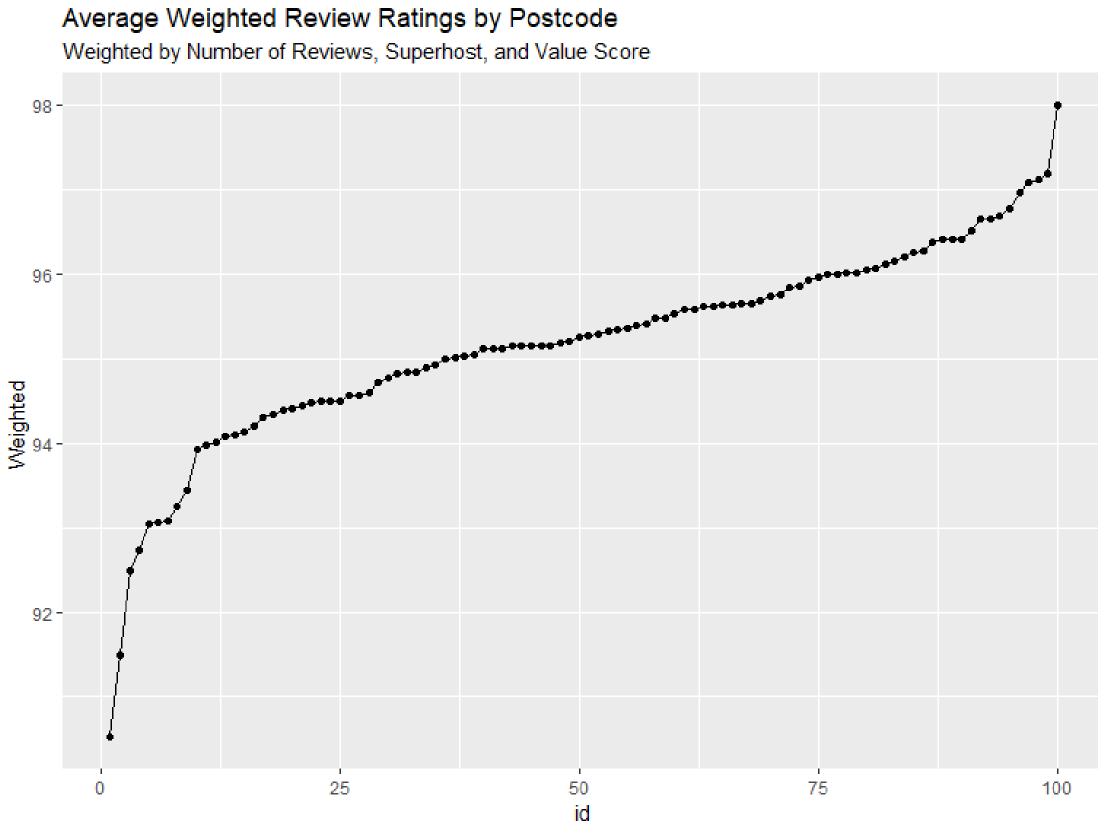
```
wmeans <- airbnb %>% filter(zipcode %in% zip100) %>% select(c(zipcode, review
_scores_rating, number_of_reviews)) %>% group_by(zipcode) %>% summarise(wmean
= weighted.mean(review_scores_rating, number_of_reviews))
wmeans <- sort(wmeans$wmean)

wmeans <- data.frame(wmean = wmeans) # make a data.frame
wmeans$id <- as.numeric(row.names(wmeans)) # add an id

ggplot(wmeans, aes(x = id, y = wmean)) +
  geom_point() +
  geom_line() +
  labs("x = ID", y = "Weighted ", title = "Average Weighted Review Ratings by
Postcode", subtitle = "Weighted by Number of Reviews")
```



Q10(2).2: Choose two other aspects from description that may improve the weighted mean of review_scores_rating

```
# Superhosts should count for twice as much as regular hosts
#    as.numeric(airbnb$host_is_superhost) + 1 # I dunno, this was breaking th
e weighted mean
# Let's emphasize value


wmeans <- airbnb %>% filter(zipcode %in% zip100) %>% select(c(zipcode, review
_scores_rating, number_of_reviews, host_is_superhost, review_scores_value)) %
>% group_by(zipcode) %>% summarise(wmean = weighted.mean(review_scores_rating
, (number_of_reviews * review_scores_value)))
wmeans <- sort(wmeans$wmean)

wmeans <- data.frame(wmean = wmeans) # make a data.frame
wmeans$id <- as.numeric(row.names(wmeans)) # add an id

ggplot(wmeans, aes(x = id, y = wmean)) +
  geom_point() +
  geom_line() +
  labs("x = ID", y = "Weighted ", title = "Average Weighted Review Ratings by
```

```
Postcode", subtitle = "Weighted by Number of Reviews, Superhost, and Value Sc
ore")
```



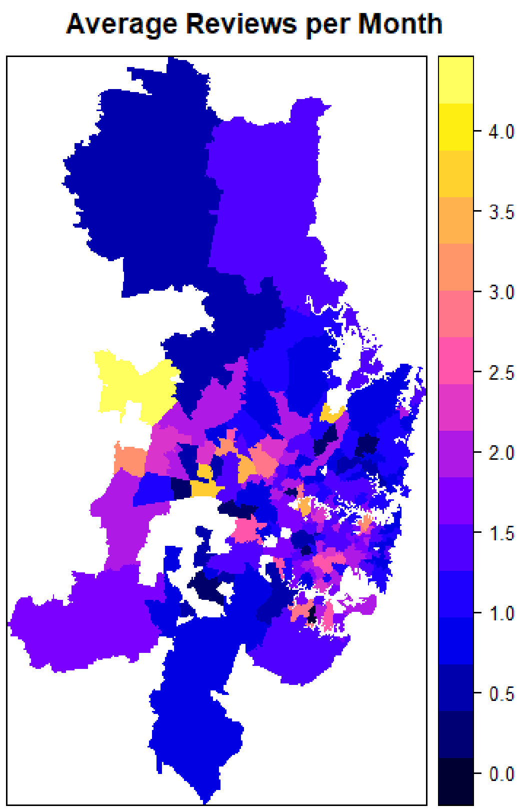
I don’t think I chose the right variables to add to the graph, and the Superhost weighted value was breaking for me. What stands out is that most of the average scores are between 94 and 97. Extreme values are likely caused by lower n values.

PART 4: Your Turn

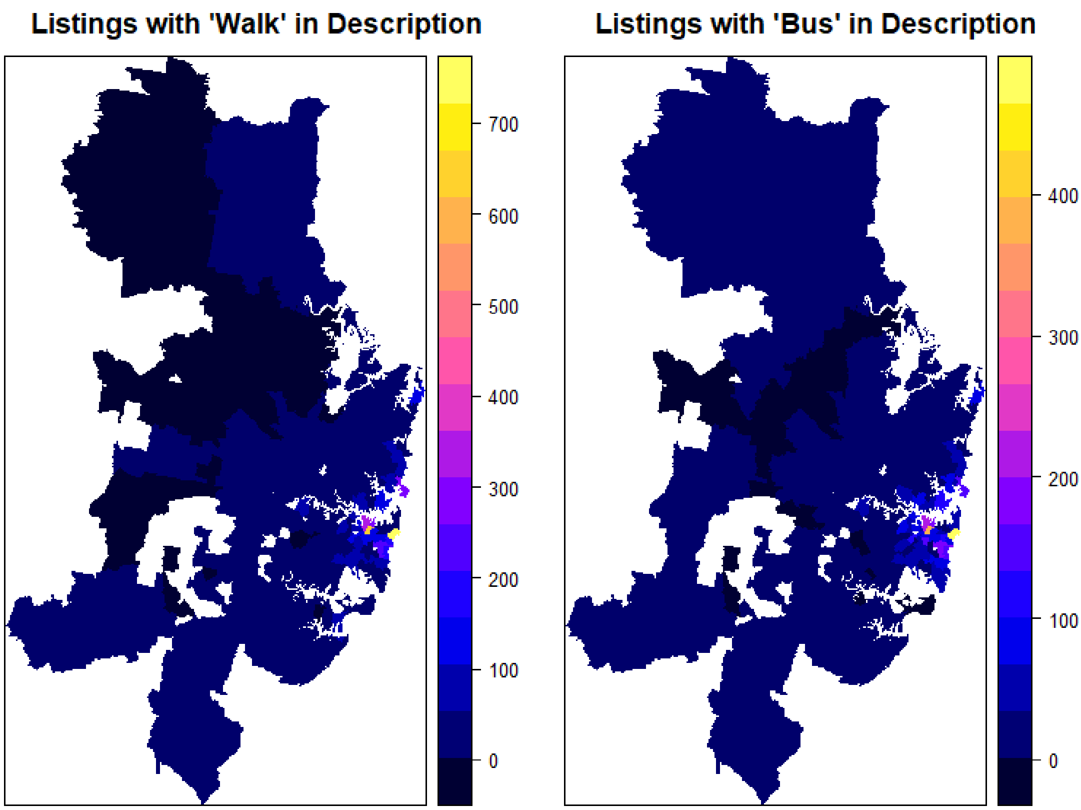
Conduct further analysis

```
#install.packages(c("sp", "rgdal"))
library(sp)

## Warning: package 'sp' was built under R version 3.5.3

library(rgdal)

## Warning: package 'rgdal' was built under R version 3.5.3

# Postal Areas ASGS Ed 2016 Digital Boundaries in ESRI Shapefile Format
# Shapefile from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.5
5.003July%202016?OpenDocument
```

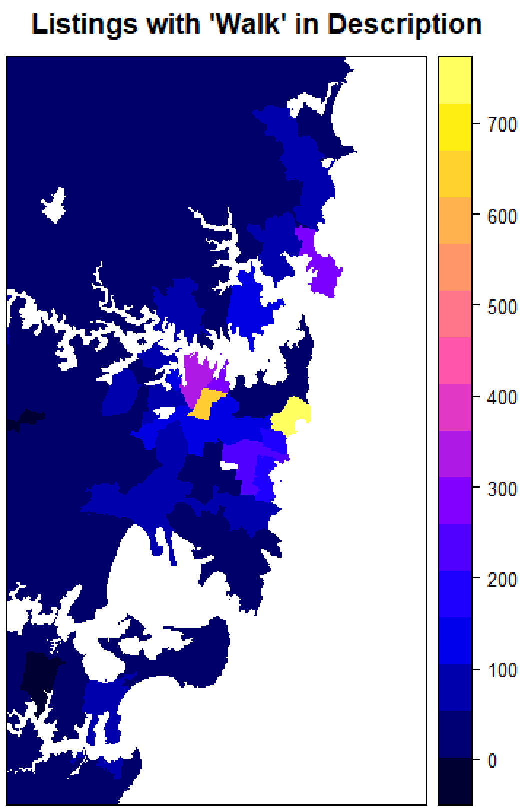
```
# direct link: http://www.abs.gov.au/ausstats/subscriber.nsf/log?openagent&12
70055003_poa_2016_aust_shape.zip&1270.0.55.003&Data%20Cubes&4FB811FA48EECA7AC
A25802C001432D0&0&July%202016&13.09.2016&Previous
# Processed in ArcGIS to inner join postal codes
# Post-processed data available for download at: https://github.com/mapsquatc
h/IS457/tree/master/data
shape <- readOGR(dsn = ".\\data", layer = "sydneyGIS")

## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\Phil\Documents\IS457\data", layer: "sydneyGIS"
## with 203 features
## It has 5 fields

# de-factor the merge field
shape$POA_CODE16 <- as.character(shape$POA_CODE16)

# Summarize by postcode; mutate new variables for NUMBER of listings mentioni
ng walk or bus (the word counts could do multiples per listing)
attrtable <- airbnb %>% mutate(n_walk = wc_walk > 0, n_bus = wc_bus > 0) %>%
group_by(zipcode) %>% summarise(n = n(), walk = sum(n_walk), bus = sum(n_bus)
, avg_rev_mo = mean(reviews_per_month))

sydneylyr <- merge(shape, attrtable, by.x = "POA_CODE16", by.y = "zipcode")

# Plot Average Reviews Per Month
spplot(sydneylyr, "avg_rev_mo", main = "Average Reviews per Month", col = "tr
ansparent")
```

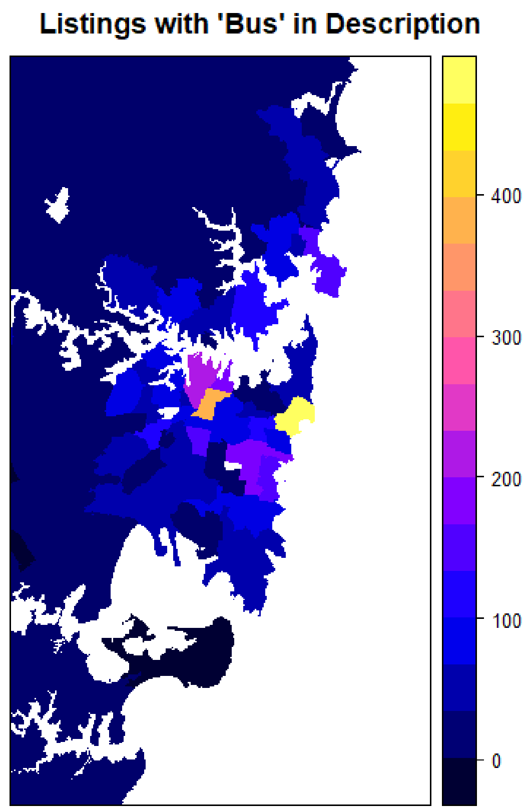



```
# Side by side plot
# Plot Walk Mentions
sp_out_walk <- spplot(sydneylyr, "walk", main = "Listings with 'Walk' in Desc
ription", col = "transparent")
print(sp_out_walk, split=c(1, 1, 2, 1), more=TRUE)
# Plot Bus Mentions
sp_out_bus <- spplot(sydneylyr, "bus", main = "Listings with 'Bus' in Descrip
tion", col = "transparent")
print(sp_out_bus, split=c(2, 1, 2, 1), more=FALSE)
```




```
# Now zoom in to harbor area
scale.parameter = 0.3  # scaling parameter. less than 1 is zooming in, more t
han 1 zooming out.
xshift = 0.35  # Shift to right in map units.
yshift = -0.2  # Shift to left in map units.
original.bbox = sydneylyr@bbox  # Pass bbox of your Spatial* Object.

edges = original.bbox
edges[1, ] <- (edges[1, ] - mean(edges[1, ])) * scale.parameter + mean(edges[
1, ]) + xshift
edges[2, ] <- (edges[2, ] - mean(edges[2, ])) * scale.parameter + mean(edges[
2, ]) + yshift

# Plot Walk Mentions - ZOOM IN
sp_out_walk <- spplot(sydneylyr, "walk", main = "Listings with 'Walk' in Desc
ription", col = "transparent", xlim = edges[1, ], ylim = edges[2, ])
print(sp_out_walk, split=c(1, 1, 2, 1), more=TRUE)
# Plot Bus Mentions - ZOOM IN
sp_out_bus <- spplot(sydneylyr, "bus", main = "Listings with 'Bus' in Descrip
tion", col = "transparent", xlim = edges[1, ], ylim = edges[2, ])
print(sp_out_bus, split=c(2, 1, 2, 1), more=FALSE)
```





Findings

To start with, postal codes are dynamic features that change over time. These are from 2016, which is within the date range of our analysis, and thus a suitable dataset for use.

I wanted to further explore the transportation options in the description. My hypothesis was that there would be more mentions of bus in postcodes a little further from the most central.

My methodology was to take the word counts of each target word in the description, and calculate (mutate) a logical variable for analysis that would contain TRUE if the listing contained the target word. Then, summing the raw counts, display them on the map.

I also attempted this with normalizing the data by listings, so it created a density – or percent of listings in a postcode containing the target words. However, this was skewed by the more rural postcodes with fewer listings, and the map appeared a mess.

In using the raw counts, there is an inherent bias where postcodes with more listings will have more listings containing the target words, assuming an even distribution. In effect, this ultimately shows the postcodes with the most listings.

However, the side by side choropleth maps still provide some value, because the color ramp is symbolized relative to each target word, and we can compare the colors to detect any patterns.

In this analysis, I see higher values for “bus” through the periphery (the medium shades of blue), and thus my hypothesis seems to be supported, but not strongly. More statistical analysis is required (but impossible due to time contstraints).

PART 5: Conclusion

Most of the techniques and analyses employed in this project failed to find strong correlations. However, there were a few observations that stood out:

Airbnb hosts looking to upgrade their properties may be interested to know that a cable TV subscription or BBQ grill are both correlated with a higher price than a swimming pool.

Guests may not want to think of logistics when browsing Airbnb. Descriptions containing the following words all had lower prices than those that did not: walk, bus, restaurants, kitchen.

On the contrary, expect to pay (or charge) more beach properties. Listings with “beach” or “beaches” in the listing had prices 33% higher on average.

As a guest, you can expect quicker responses from an Airbnb Superhost.

Check those cleaning fees! You may be surprised to know that nearly 1 in 12 properties charge a cleaning fee that is greater than the price per night.

Final note: For this project, I wanted to learn to use Github with RStudio. You can view any of my files or check my commit history at https://github.com/mapsquatch/IS457. I found it to be rather easy to use.

PART 6: Lifecycle of Data Science

The Lifecycle of Data Science refers to the entire process of gathering information from data. Donoho breaks this process down into the six divisions of Greater Data Science (Donoho, 2017). We were able to experience these divisions in this project and in this class.

GDS1: Data Exploration and Preparation.

This step is also called “exploratory data analysis,” and it often the most time-intensive task – often estimated as taking 80% of the time. During this step it is the analyst’s job to understand the dataset – both the data and the metadata. For this project, we first had to understand the when (2010-2018), where (Sydney, Australia), why (lodging), who(users: hosts and guests), how (user-collected), and what (data about the property, and the users’ self-reported experience).

Additionally we had to analyze the integrity of these data and plan to deal with missing or faulty data. We did have NA values, but the data were consistent for the most part.

I would add that the 80% of time might be relevant for someone who was adept with the software tools used for later steps, but R is still new to me, and I feel I spent a lot of time fighting to figure out a command or parameter to get things to render correctly.

I would have welcomed a more complete metadata document, but the field_name and descriptions on the project assignment were enough to get started.

GDS2: Data Representation and Transformation.

Data scientists must always consider the format of data. This project employed heavy use of the data frame in R. New variables were added to the data frame, ensuring one observation for each listing. I found that factors generally created more problems than they solved, so I made sure to cast them to numerics or characters whenever appropriate.

Using built-in functions to calculate new data was also important. I used time functions to calculate a number based on days elapsed. I also used regular expressions to parse data from fields of comma-separated values (amenities and verifications).

In hindsight, I could have possibly found more relationships by transforming data using log() or other methods.

GDS3: Computing with Data.

The data were provided as a comma-separated value dataset, which is stored in plaintext and is a common format. Data were processed in R, with spatial data coming from ArcGIS.

GDS4: Data Visualization and Presentation.

This project relied heavily on data visualization. I used many different types of graphs, and I feel that I'm still learning which ones work best. All semester long we've worked with Base R, so I viewed it as an opportunity to learn to work with ggplot2. I think by default ggplot graphs look a little cleaner. I also like the syntax for creating the graphs, although it takes a little while to learn. Only after creating some lattice graphics did I discover facets in ggplot. I would like to work with those in the future.

Building a good graph can be a very time-consuming process, but it is nice that it is repeatable once it is built.

GDS5: Data Modeling.

This division is dealing with the two major schools of thought: generative modeling based on existing data (more traditional), and predictive modeling (such as machine learning). Analysis in this project was descriptive, and any use of statistics to predict was done on the assumption that the future conditions would the same as the past.

GDS6: Science about Data Science.

This division refers to how data scientists are doing data science. In this project we employed various methodologies, but they were all rather basic. As I learned fundamentals, I did not explore different workflows in the context of what others were doing. I was simply trying to get results.

References

Donoho, D. (2017). 50 Years of Data Science. *Journal of Computational and Graphical Statistics*, *26*(4), 745–766. https://doi.org/10.1080/10618600.2017.1384734