Final_IS457_122

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Whole Tale URL: https://dashboard.wholetale.org/run/5cbfee112744a50001c60b24

I wasn't sure how to publish my tale, but here is the URL.

Part 1

Q1:

```
# Loading the dataset
Airbnb_Sydney <- read.csv(file = "Airbnb Sydney.csv")

# Exploring dataset a little bit
head(Airbnb_Sydney)
```

```
##      id
## 1 12351
## 2 14250
## 3 15253
## 4 20865
## 5 38073
## 6 39348
##
description
## 1 Come stay with Vinh & Stuart (Awarded as one of Australia's top hosts by
Airbnb CEO Brian Chesky & key shareholder Ashton Kutcher. We're Sydney's #1 r
eviewed hosts too). Find out why we've been positively reviewed 500+ times. M
essage us and talk first BEFORE you make any reservation request - And please
read our listing to the end (hint hint). Everything you need to know is there
. We're pretty relaxed hosts, and we fully appreciate staying with someone el
se, in their home home, is not for every-one. This is not a business, or a ho
tel. We're casual Airbnb hosts, not hoteliers. If you're just looking for an
alternative to an expensive hotel, then we're not for you. Here you'll be tre
ated in the same way we treat family & friends when they stay. So... no fluff
y bathrobes... Please say hello and message us *BEFORE* you make your reserva
tion request... It'll help speed things up, and smooth things out... Please r
ead our listing all the way to the end. It will make getting a confirmed rese
rv
## 2 Beautifully renovated, spacious and quiet, our 3 Bedroom, 3 Bathroom hom
e is only a  10 minute walk to beaches in Fairlight or Forty Baskets,  or a 3
0 minute walk to Manly via the coastal promenade, or an Express bus runs ever
y 20 mins at your door. Our home is a thirty minute walk along the seashore p
romenade to Manly, one of Sydney's most beautiful beaches, with its village r
estaurants, cafes, and shopping.  If you prefer more variety, the Manly ferry
```

```
will take you to the Sydney CBD in 15 minutes.   The residence is sited in a 
sought-after family-friendly street only a short stroll to nearby North Harbo
ur reserve and Forty Baskets cafe and beach. It's a short walk further to exp
ress CBD buses, ferries, and Manly entertainment. Or there is a bus (#131 or 
#132) around the corner that drops you in Manly in 8 minutes.  Our home featu
res a stainless steel galley kitchen, including Ilve oven and gas cooktop. We
have two separate living areas on the ground floor. The front lounge enjoys P
&O
## 3 Penthouse living in a great central location: You will be staying in a u
nique apartment on the top floor of a centrally located boutique building.  A
spacious apartment spread over 2 levels, the space offers my guests a high le
vel of privacy and security. The room has its own bathroom and  balcony and t
he whole apartment is furnished to a luxury standard in a contemporary style 
with all mod cons.  Location is one if the best in the city with easy walking
to everything you may need. A charming two-level, two-bedroom, two-bathroom d
uplex apartment on the border of East Sydney, Darlinghurst and Kings Cross wi
th everything that Sydney has to offer within easy walking distance : Sydney 
CBD 10mins, Hyde Park 5 mins, Oxford St 10 mins, Kings Cross 5mins  The apart
ment is spacious, elegantly decorated in a modern contemporary style and very
well equipped with all mod cons.  The room is situated on the lower floor, it
is a spacious bedroom with large built in robes, own fridge and tea and coffe
## 4 Hi! We are a married professional couple with 2 kids.  When making a boo
king, please tell us a little bit about yourselves (ages & professions of eve
ryone in your group), the purpose of your visit and finally, your check in & 
out times. Thanks!    HOUSE : _________ * DUCTED AIR CONDITIONING IN ALL ROOM
S * BEDROOM 1 : QUEEN BED * BEDROOM 2 : QUEEN BED * BEDROOM 3 : QUEEN BED * B
ATHROOM : SHOWER, BATH & TOILET * KITCHEN : OVEN, STOVE TOP, DISHWASHER, MICR
OWAVE, FRIDGE * WASHING MACHINE & DRYER STUDIO : __________ * BEDROOM : QUEEN
BED * BATHROOM : SHOWER & TOILET * AIR CONDITIONER (in Studio area where ther
e is the Queen bed) * KITCHENETTE / STUDY : Oven, dishwasher, bar fridge & wa
shing machine, sofabed (wide single), computer, TV & desk.   * There is inter
nal access to the studio from the house but it can also be closed off to the 
front of the property with its own side access.  (Website hidden by Airbnb) *
*************************************************** LOCATION :  * 5 minute wa
lk
## 5 Welcome to my sanctuary - a bright, comfortable one bedroom apartment in
North Sydney. Free Wifi, heated pool/jacuzzi and everything else that you wil
l need to make your stay in Sydney very comfortable. Enjoy this fabulous Home
away from home, and have a fantastic stay in Sydney! The apartment is within 
walking distance of restaurants and shops, Luna Park and the North Sydney bus
iness district. Access to the Sydney CBD is easy by bus, train, taxi or ferry
.  It is also a short bus ride to the famous Balmoral Beach or Taronga Zoo. M
y apartment is situated in North Sydney which is 3 kms from the Sydney CBD.  
Here are some details about the apartment: You'll enjoy being centrally locat
ed just a couple blocks away from the train station so you can go anywhere qu
ickly in Sydney. The apartment also features several windows that let in tons
of natural light. It is comfortable and fully stocked. Here's what I have her
e: LIVING ROOM: 50" LCD TV DVD / blu ray player CD/Radio/Blue tooth syncing w
## 6
Fully self-contained sunny studio apartment.  10mn to walk to Bondi beach.  B
```

us to city at the door. Private 13m swimming pool. Sunny, studio apartment . Private terrace. bus at door to Bondi Junction and City Ground floor 1 bedroom with double bed plus kitchenette & study desk. own shower & toilet, share laundry, kitchen facilities Swimming pool 13m. Separate security private entrance Private entrance. Ground floor. Happy to indicate you the best spots for walking, dining, entertaining and best sightseeing location in Sydney. Upmarket area. Very nice and quiet neighbourhood . Very safe place. Bus at the door for the city.
##
neighborhood_overview
1 Pyrmont is an inner-city village of Sydney, only about 2kms from the Sydney CBD (Central Business District) / Core, right next door to Darling Harbour and Chinatown. https://www.airbnb.com.au/locations/sydney/pyrmont Pyrmont has a relaxed community feel with an inner city vibe. Pyrmont is only about 2kms (10 - 15 mins walk) from the centre of Sydney with an extensive range of local restaurants, wine bars, and pubs. There's some seriously good baristas and cafes right close to our home (Go and say hi to Damien & Tim at Bar Zini - it's one of our local faves). There's five star fine dining right through to greasy-spoon takeaways with some of Australia's finest dining restaurants within easy reach. * Darling Harbour and Cockle Bay * Exhibition and Convention Centres * Sydney Fish Markets * Pyrama Point Park * Jones Bay Wharf * The Star (Casino) with Food Halls, Bars, and the Lyric Theatre * Powerhouse Museum * National Maritime Museum Also (back on the food - notice a theme?): * Two groce
2 Balgowlah Heights is one of the most prestigious areas on the Northern Beaches. Filled with seaside character and a boutique way of living, this suburb offers everything you could need.   Located approximately 11km from the CBD, and only 2 kms from Manly, Balgowlah is surrounded by pristine water frontage including North Harbour, Forty Baskets, and Sydney Harbour. Filled with a vast array of public parks, pools, marinas, beaches, sporting facilities and Sydney Harbour National Park. Local Amenities •Forty Baskets Beach, Reef Beach, North Harbour Park, 40 Beans Cafe, Clontarf Beach, Castle Rock. •Nearby Spit to Manly walking track that leads left along the promenade to Manly or right through scenic Sydney Harbour National Park around to Clontarf. •Balgowlah Heights shops, offering a supermarket, delicatessen, boutique shops, cafes and more •Nearby Stockland Mall offers a vast range of cafes, supermarkets, eateries, boutique fashion stores, home wares shops and Fitness First Gym •Array
3 The location is really central and there is number of things to do and see all within a few kilometres; Stanley St (Sydney’s little Italy) is just around the corner which has some great restaurants and a real European feel. Darlinghurst is wall to wall of cafes, bars and restaurants to suite all tastes and budgets. Woolloomooloo marina is at the bottom of the hill with its ritzy restaurants and famous residents (Russell Crow has the penthouse at end of wharf) it is beautiful to hang out on a nice evening. The Australian Museum and The Art Gallery of NSW have both interesting exhibitions and evening events, The Bridge can be seen from my corner and the Opera House is a pleasant stroll through the Botanical Gardens and Domain. Chinatown and Darling Harbour are just at the back of the CBD and Sydney colourful nightlife of both Kings Cross & Oxford St are on your doorstep. I also have lots of more information on

```
things to do while in Sydney just ask me.  On booking you will receive my hou
## 4
BALMAIN is an older inner city village / suburb with numerous cafes, restaura
nts, parks, walks around the harbour, older-style pubs, markets, etc.  Our ho
use situated between Balmain and Rozelle shopping centres, in a quiet street 
with a small park at the end of it that has gated play equipment for small ch
ildren.
## 5 North Sydney, on Sydney's lower North Shore, starts at north end of the 
Harbour Bridge and is around 3km from the CBD and also closely located on rou
te to Sydney's famous Manly beach and other North shore village suburbs inclu
ding Neutral Bay, Crows Nest, McMahons Point, Kirribilli Chatswood and Mosman
(Balmoral Beach & Taronga Zoo). North Sydney is the second largest business c
entre to Sydney's CBD and located only a 5 minute drive directly over the Har
bour Bridge, making is an excellent alternative to the hustle and bustle of t
he CBD - whilst still being centrally located. The area is dominated by the I
T and advertising industries and café scene during the week and benefits from
the quieter peaceful surroundings at the weekend as the corporates go home to
the suburbs. North Sydney is a prosperous area with spectacular waterfront re
al estate and is location of official residences of the Australian Prime Mini
ster and Governor-General at Kirribilli Point. The area is easily accessible 
b
## 6
Upmarket area. Very nice and quiet neighbourhood . Very safe place.
##
house_rules
## 1 We look forward to welcoming you to stay you just as we would our family 
and friends. "Farm Gate Rules" - if a door is open, leave it open, if a door 
is closed, please leave it closed.  We'd ask that you'd please not eat in you
r room, or smoke inside the house. We've a kitchen and dining room for meals 
(and of course, feel free to use the fridge) and a sheltered, undercover area
outside that you're more than welcome to use if you smoke. We tend to work fr
om home, meet clients in our home office, and work by phone too. So this mean
s that our home would be better suited to guests wanting to be out sightseein
g during the day, rather than spending the days inside. (But why would you wa
nt to stay inside all day when there's so much to see and do anyway?) Every e
xperience we've ever had with Airbnb has been a positive one. Whether we've b
een hosting, or staying as guests, we've met kind & considerate people, had i
nteresting conversations, and made great new acquaintances & friends. We don'
t
## 2 Standard Terms and Conditions of Temporary Holiday Accommodation Note: V
ariances can be agreed on but only by arrangement with the owner in writing. 
Payment of booking constitutes the clients acceptance of these Terms and Cond
itions. Balance of the rental amount must be received in full according to AI
RBNB policies. If not the owner has the right to cancel the booking and attem
pt to re let it. The owners will make every effort to ensure the property is 
available as booked. However the owners reserve the right to make alterations
to bookings due to unforeseen circumstances. To maintain a good standard for 
our guests we require certain conditions to be complied with. We appreciate m
ost will respect our property but the occasional abuse requires that we state
the following conditions. Number of Guests should not exceed 6 adults or subs
```

```
equently agreed in writing or email, and no more than 8 people in the house a
t one time. Fees will apply for excess guests not agreed with the owners in a
dv
## 3
I am fairly easygoing and will try to accomodate guests reasonable requests.
I ask that guest treat my home with respect.  No Smoking inside of Apartment
No additional overnight guests.
## 4
PLEASE ENJOY YOURSELVES WITHOUT MAKING TOO MUCH NOISE AS WE HAVE VERY GOOD NE
IGHBOURS.  NO SMOKING INSIDE THE HOUSE.  SMOKING ALLOWED IN OUTSIDE AREAS ONL
Y. PLEASE LET US KNOW WHEN BOOKING, IF YOU PLAN TO BRING YOUR PET. PLEASE CLE
AN THE BBQ AFTER USE OR AN ADDITIONAL FEE MAY BE INCURRED. THANKS!
## 5 House Rules: •Smoking permitted outside only with the sliding doors clos
ed.  If smoking is detected in the apartment an additional cleaning fee will
apply of $350. •When using the BBQ, please do so with the balcony doors close
d.   •On arrival you will be given two sets of keys.  Each set of keys contai
n a security fob which allows you entry into the building and to my level.  I
f these keys are lost, the replacement cost is $200 for each set. •Please rem
ove shoes whilst inside the apartment as it's fully carpeted.   •This is a re
sidential building, so no parties are allowed. •For your own safety, please d
o not sleep with the gas heater running. •Kitchen knives and wooden chopping
boards are not to be placed in the dishwasher. •Please switch off all lights
and gas heater when you are not in the apartment or before leaving. ***ALL BR
EAKAGES AND ANY DAMAGE MUST BE PAID FOR & PLEASE DO NOT MOVE ANY FURNITURE***
On Exit: Empty fridge and take all your garbage out Turn on dishwasher Place
all
## 6
Only quiet people. No parties aloud.
##   host_id host_since host_response_time host_response_rate
## 1   17061    5/14/09 within a few hours               100%
## 2   55948   11/20/09 within a few hours                90%
## 3   59850    12/3/09     within an hour               100%
## 4   64282   12/19/09       within a day               100%
## 5  103476     4/4/10                N/A                N/A
## 6  168828    7/17/10                N/A                N/A
##   host_is_superhost
## 1                 f
## 2                 f
## 3                 f
## 4                 t
## 5                 f
## 6                 f
##
host_verifications
## 1  ['email', 'phone', 'manual_online', 'reviews', 'manual_offline', 'offli
ne_government_id', 'government_id', 'work_email']
## 2                                              ['email', 'phone', 'reviews', '
jumio', 'offline_government_id', 'government_id']
## 3                                  ['email', 'phone', 'facebook', 'reviews', '
jumio', 'offline_government_id', 'government_id']
```

```
## 4                                                      ['email', 'phone', '
reviews', 'jumio', 'government_id', 'work_email']
## 5                                                        ['email', 'phone',
'facebook', 'reviews', 'jumio', 'government_id']
## 6 ['email', 'phone', 'facebook', 'reviews', 'jumio', 'offline_government_i
d', 'selfie', 'government_id', 'identity_manual']
##   host_identity_verified         city zipcode property_type
## 1                      t      Pyrmont    2009     Townhouse
## 2                      t    Balgowlah    2093         House
## 3                      t Darlinghurst    2010     Apartment
## 4                      t      Balmain    2041         House
## 5                      t North Sydney    2060     Apartment
## 6                      f  North Bondi    2026   Guest suite
##         room_type accommodates bathrooms bedrooms beds bed_type
## 1    Private room            2         1        1    1 Real Bed
## 2 Entire home/apt            6         3        3    3 Real Bed
## 3    Private room            2         1        1    1 Real Bed
## 4 Entire home/apt            8         2        4    4 Real Bed
## 5 Entire home/apt            2         1        0    1 Real Bed
## 6 Entire home/apt            2         1        1    1 Real Bed
##
amenities
## 1
{TV,Internet,Wifi,"Air conditioning","Paid parking off premises",Breakfast,He
ating,"Smoke detector","Carbon monoxide detector","First aid kit","Safety car
d","Fire extinguisher",Essentials,Shampoo,"Lock on bedroom door","24-hour che
ck-in",Hangers,"Hair dryer",Iron,"Laptop friendly workspace","translation mis
sing: en.hosting_amenity_49","translation missing: en.hosting_amenity_50","Pr
ivate entrance","Hot water","Patio or balcony","Garden or backyard","Luggage
dropoff allowed","Well-lit path to entrance","Host greets you"}
## 2
{TV,Wifi,"Air conditioning",Kitchen,"Pets live on this property",Cat(s),"Free
street parking",Heating,Washer,Dryer,"Smoke detector",Essentials,Shampoo,Hang
ers,"Hair dryer",Iron,"Laptop friendly workspace","Hot water","Luggage dropof
f allowed",Other}
## 3 {TV,"Cable TV",Internet,Wifi,"Air conditioning",Kitchen,"Paid parking of
f premises","Pets allowed","Pets live on this property",Dog(s),"Free street p
arking","Buzzer/wireless intercom",Heating,Washer,Dryer,"Smoke detector","Fir
st aid kit","Fire extinguisher",Essentials,Shampoo,"24-hour check-in",Hangers
,"Hair dryer",Iron,"Laptop friendly workspace","translation missing: en.hosti
ng_amenity_49","translation missing: en.hosting_amenity_50","Self check-in",L
ockbox,"Hot water","Bed linens","Extra pillows and blankets",Microwave,"Coffe
e maker",Refrigerator,Dishwasher,"Dishes and silverware","Cooking basics",Ove
n,Stove,"Patio or balcony","Luggage dropoff allowed","Well-lit path to entran
ce"}
## 4
{TV,Internet,Wifi,"Air conditioning",Kitchen,"Pets allowed","Pets live on thi
s property",Cat(s),"Indoor fireplace",Heating,"Family/kid friendly",Washer,Dr
yer,"Smoke detector","First aid kit",Essentials,Shampoo,"24-hour check-in",Ha
ngers,"Hair dryer",Iron,"Laptop friendly workspace","Private entrance"}
```

```
## 5
{TV,"Cable TV",Wifi,"Air conditioning",Pool,Kitchen,"Free parking on premises
",Breakfast,Elevator,"Hot tub","Buzzer/wireless intercom",Heating,"Family/kid
friendly",Washer,"Smoke detector","First aid kit",Essentials,Shampoo,"24-hour
check-in",Hangers,"Hair dryer",Iron,"translation missing: en.hosting_amenity_
50"}
## 6
{Internet,Wifi,Pool,Kitchen,"Free street parking","Buzzer/wireless intercom",
Heating,"Smoke detector",Essentials,Hangers,Iron,"Hot water",Microwave,"Coffe
e maker",Refrigerator,"Dishes and silverware","Cooking basics","BBQ grill","G
arden or backyard","Long term stays allowed","Host greets you"}
##      price cleaning_fee guests_included extra_people minimum_nights
## 1 $100.00       $55.00               2      $395.00              2
## 2 $471.00      $100.00               6       $40.00              5
## 3 $109.00                            1       $10.00              2
## 4 $450.00                            6        $0.00              7
## 5 $159.00      $250.00               2       $25.00              2
## 6  $84.00       $90.00               1       $10.00              5
##   number_of_reviews review_scores_rating review_scores_accuracy
## 1               493                   95                     10
## 2                 1                  100                     10
## 3               300                   88                      9
## 4                15                   96                      9
## 5                63                   97                     10
## 6                 6                   87                      8
##   review_scores_cleanliness review_scores_checkin
## 1                         9                    10
## 2                        10                    10
## 3                         9                     9
## 4                         9                     9
## 5                        10                    10
## 6                         8                     9
##   review_scores_communication review_scores_location review_scores_value
## 1                          10                     10                  10
## 2                           8                     10                  10
## 3                           9                      9                   9
## 4                          10                     10                   9
## 5                          10                      9                   9
## 6                          10                      8                   8
##           cancellation_policy reviews_per_month
## 1 strict_14_with_grace_period              4.83
## 2 strict_14_with_grace_period              0.03
## 3 strict_14_with_grace_period              3.63
## 4 strict_14_with_grace_period              0.18
## 5 strict_14_with_grace_period              0.64
## 6 strict_14_with_grace_period              0.77
```

```r
names(Airbnb_Sydney)
```

```
##  [1] "id"                           "description"                 
##  [3] "neighborhood_overview"        "house_rules"                 
##  [5] "host_id"                      "host_since"                  
##  [7] "host_response_time"           "host_response_rate"          
##  [9] "host_is_superhost"            "host_verifications"          
## [11] "host_identity_verified"       "city"                        
## [13] "zipcode"                      "property_type"               
## [15] "room_type"                    "accommodates"                
## [17] "bathrooms"                    "bedrooms"                    
## [19] "beds"                         "bed_type"                    
## [21] "amenities"                    "price"                       
## [23] "cleaning_fee"                 "guests_included"             
## [25] "extra_people"                 "minimum_nights"              
## [27] "number_of_reviews"            "review_scores_rating"        
## [29] "review_scores_accuracy"       "review_scores_cleanliness"   
## [31] "review_scores_checkin"        "review_scores_communication" 
## [33] "review_scores_location"       "review_scores_value"         
## [35] "cancellation_policy"          "reviews_per_month"
```

```r
dim(Airbnb_Sydney)
```

```
## [1] 10815    36
```

```r
class(Airbnb_Sydney)
```

```
## [1] "data.frame"
```

```r
anyNA((Airbnb_Sydney))
```

```
## [1] TRUE
```

```r
sum(is.na.data.frame(Airbnb_Sydney))
```

```
## [1] 7
```

1.1

I combed through the csv file to look for possible missing values and found several possbilities including the usual NA values. I wrote a function to find and sum up the instances of these missing data for each column. My results show that the neighborhood_overview, house_rules, host_response_time host_response_rate, host_identity_verified, city, zipcode, bathrooms, bedrooms, cleaning_fee, review_scores_rating, review_scores_accuracy, review_scores_cleanliness, review_scores_checkin, and review_scores_communication columns have a missing values. Those missing values are NA, N/A and empty strings.

```r
missing_everything = function(x){
  # this function takes on argument and finds a list of possible missing valu
es and returns a vector with the number of times that missing value occurs
  z = sum(as.numeric(is.na(x)))
  y = sum(as.numeric(x==""))
  x = sum(as.numeric(x=="N/A"))
```

```r
  w = sum(as.numeric(x=="[]"))
  v = sum(as.numeric(x=="æ,%å•1/4"))
  u = sum(as.numeric(x=="#NAME?"))
  t = sum(as.numeric(x=="."))
  s = sum(as.numeric(x=="/"))
  r = sum(as.numeric(x=="(URL HIDDEN)"))
  q = sum(as.numeric(x=="(Other)"))
  return(c(z,y,x,w,v,u,t,s,r,q))
}

# calling the function using apply()
apply(Airbnb_Sydney,2,missing_everything)

##       id description neighborhood_overview house_rules host_id host_since
##  [1,]  0           0                     0           0       0          0
##  [2,]  0           0                   664        1639       0          0
##  [3,]  0           0                     0           0       0          0
##  [4,]  0           0                     0           0       0          0
##  [5,]  0           0                     0           0       0          0
##  [6,]  0           0                     0           0       0          0
##  [7,]  0           0                     0           0       0          0
##  [8,]  0           0                     0           0       0          0
##  [9,]  0           0                     0           0       0          0
## [10,]  0           0                     0           0       0          0
##       host_response_time host_response_rate host_is_superhost
##  [1,]                  0                  0                 0
##  [2,]                  0                  0                 0
##  [3,]               2483               2483                 0
##  [4,]                  0                  0                 0
##  [5,]                  0                  0                 0
##  [6,]                  0                  0                 0
##  [7,]                  0                  0                 0
##  [8,]                  0                  0                 0
##  [9,]                  0                  0                 0
## [10,]                  0                  0                 0
##       host_verifications host_identity_verified city zipcode property_type
##  [1,]                  0                      0    0       0             0
##  [2,]                  0                      0    8      21             0
##  [3,]                  0                      0    0       0             0
##  [4,]                  0                      0    0       0             0
##  [5,]                  0                      0    0       0             0
##  [6,]                  0                      0    0       0             0
##  [7,]                  0                      0    0       0             0
##  [8,]                  0                      0    0       0             0
##  [9,]                  0                      0    0       0             0
## [10,]                  0                      0    0       0             0
##       room_type accommodates bathrooms bedrooms beds bed_type amenities
##  [1,]         0            0         1        1    0        0         0
##  [2,]         0            0        NA       NA    0        0         0
##  [3,]         0            0        NA       NA    0        0         0
```

```
##  [4,]         0           0        NA       NA    0       0         0
##  [5,]         0           0        NA       NA    0       0         0
##  [6,]         0           0        NA       NA    0       0         0
##  [7,]         0           0        NA       NA    0       0         0
##  [8,]         0           0        NA       NA    0       0         0
##  [9,]         0           0        NA       NA    0       0         0
## [10,]         0           0        NA       NA    0       0         0
##       price cleaning_fee guests_included extra_people minimum_nights
##  [1,]     0            0               0            0              0
##  [2,]     0          621               0            0              0
##  [3,]     0            0               0            0              0
##  [4,]     0            0               0            0              0
##  [5,]     0            0               0            0              0
##  [6,]     0            0               0            0              0
##  [7,]     0            0               0            0              0
##  [8,]     0            0               0            0              0
##  [9,]     0            0               0            0              0
## [10,]     0            0               0            0              0
##       number_of_reviews review_scores_rating review_scores_accuracy
##  [1,]                 0                    1                      1
##  [2,]                 0                   NA                     NA
##  [3,]                 0                   NA                     NA
##  [4,]                 0                   NA                     NA
##  [5,]                 0                   NA                     NA
##  [6,]                 0                   NA                     NA
##  [7,]                 0                   NA                     NA
##  [8,]                 0                   NA                     NA
##  [9,]                 0                   NA                     NA
## [10,]                 0                   NA                     NA
##       review_scores_cleanliness review_scores_checkin
##  [1,]                         1                     1
##  [2,]                        NA                    NA
##  [3,]                        NA                    NA
##  [4,]                        NA                    NA
##  [5,]                        NA                    NA
##  [6,]                        NA                    NA
##  [7,]                        NA                    NA
##  [8,]                        NA                    NA
##  [9,]                        NA                    NA
## [10,]                        NA                    NA
##       review_scores_communication review_scores_location
##  [1,]                           1                      0
##  [2,]                          NA                      0
##  [3,]                          NA                      0
##  [4,]                          NA                      0
##  [5,]                          NA                      0
##  [6,]                          NA                      0
##  [7,]                          NA                      0
##  [8,]                          NA                      0
##  [9,]                          NA                      0
```

```
## [10,]                          NA                       0
##        review_scores_value cancellation_policy reviews_per_month
##  [1,]                    0                   0                 0
##  [2,]                    0                   0                 0
##  [3,]                    0                   0                 0
##  [4,]                    0                   0                 0
##  [5,]                    0                   0                 0
##  [6,]                    0                   0                 0
##  [7,]                    0                   0                 0
##  [8,]                    0                   0                 0
##  [9,]                    0                   0                 0
## [10,]                    0                   0                 0
```

1.2

To deal with this, I will be keeping the NA's in my dataset, but I will be replacing all other missing values with NA. This way I can easily exclude them when needed. I will keep the NA's in the dataset because I don't want to exlcude those rows that contain NA's from the dataset as I want to include that data in my analysis. I feel this is will help me get the most out of the data in terms of insights.

1.3

Handling the missing values this way will mean I will have to be mindful of the type of analysis I'm doing, and decide whether or not I have to explude the NA's. There will be cases where I have to exclude them to do an operation in R. However, I think my output and report should also reflect the amount of missing data, to help with the interpretation of my results. Knowing that there is missing data (and how much) could influence decisions that are made using this analysis. I think it would bias the results if I did not include the NA values.

1.4

I replaced the missing values "N/A" and "" with NA, to make missing values consistent and easy to exclude later.

```
# Replacing weird missing values with NA
Airbnb_Sydney$host_response_time[Airbnb_Sydney$host_response_time=="N/A"] <-
NA
Airbnb_Sydney$host_response_rate[Airbnb_Sydney$host_response_rate=="N/A"] <-
NA
Airbnb_Sydney$neighborhood_overview[Airbnb_Sydney$neighborhood_overview==""]
<- NA
Airbnb_Sydney$house_rules[Airbnb_Sydney$house_rules==""] <- NA
Airbnb_Sydney$zipcode[Airbnb_Sydney$zipcode==""] <- NA
Airbnb_Sydney$cleaning_fee[Airbnb_Sydney$cleaning_fee==""] <- NA

#apply(Airbnb_Sydney,2,missing_everything)
sum(is.na.data.frame(Airbnb_Sydney))
```

```
## [1] 7918
```

```r
apply(is.na(Airbnb_Sydney), 2, sum)
```

```
##                          id                 description 
##                           0                           0 
##       neighborhood_overview                 house_rules 
##                         664                        1639 
##                     host_id                  host_since 
##                           0                           0 
##          host_response_time          host_response_rate 
##                        2483                        2483 
##           host_is_superhost          host_verifications 
##                           0                           0 
##      host_identity_verified                        city 
##                           0                           0 
##                     zipcode               property_type 
##                          21                           0 
##                   room_type                accommodates 
##                           0                           0 
##                   bathrooms                    bedrooms 
##                           1                           1 
##                        beds                    bed_type 
##                           0                           0 
##                   amenities                       price 
##                           0                           0 
##                cleaning_fee             guests_included 
##                         621                           0 
##                extra_people              minimum_nights 
##                           0                           0 
##           number_of_reviews        review_scores_rating 
##                           0                           1 
##      review_scores_accuracy   review_scores_cleanliness 
##                           1                           1 
##       review_scores_checkin review_scores_communication 
##                           1                           1 
##      review_scores_location         review_scores_value 
##                           0                           0 
##         cancellation_policy           reviews_per_month 
##                           0                           0
```

1.5

```r
dim(Airbnb_Sydney)
```

```
## [1] 10815    36
```

```r
# The dim will reamin the same, because I have not removed any NA values yet.
```

1.6

I will remove any weird characters like dollar signs from (potentially) numeric columns. I will look at all data types. The date columns may need to be formatted, or broke up for more detailed analysis (for instance to look at a single year, month, or day). All classes of the columns should be doubled checked, because they may need to be re-assgined to be an integer from a character, for instance. I would double check that the data was read in correctly with the right headers. To analyze text data, I would parse and remove any strange characters to understand what words or how many words are in a row.

Q2

I looked at the overall distribution of the dataframe and decided to focus, at first, the the property type, the city, price and host since columns. I felt these variables would offer the most insight into the dataset.

```
# The funcitons below were used to help me understand the dataset:
# summary and str are commented out because output is so large
#summary(Airbnb_Sydney)
#str(Airbnb_Sydney)
names(Airbnb_Sydney)
```

```
##  [1] "id"                          "description"
##  [3] "neighborhood_overview"       "house_rules"
##  [5] "host_id"                     "host_since"
##  [7] "host_response_time"          "host_response_rate"
##  [9] "host_is_superhost"           "host_verifications"
## [11] "host_identity_verified"      "city"
## [13] "zipcode"                     "property_type"
## [15] "room_type"                   "accommodates"
## [17] "bathrooms"                   "bedrooms"
## [19] "beds"                        "bed_type"
## [21] "amenities"                   "price"
## [23] "cleaning_fee"                "guests_included"
## [25] "extra_people"                "minimum_nights"
## [27] "number_of_reviews"           "review_scores_rating"
## [29] "review_scores_accuracy"      "review_scores_cleanliness"
## [31] "review_scores_checkin"       "review_scores_communication"
## [33] "review_scores_location"      "review_scores_value"
## [35] "cancellation_policy"         "reviews_per_month"
```

Looking closer at the these columns, I see there are a large number of cities and property types to work with as character and factor variables. I also found an "Other" type in the city variable, which I have decided to leave in for now, but may turn into an NA. However, I don't think "other" means the same thing as NA, so I will decide on a case by case basis on what to do with that. I also looked at price. I removed the dollar sign from the data so I could look at it more closely. I also looked at the distribution and can see that the majority of the prices are at or below 200 dollars. I also looked at host_since variable, and we can see that we have data from 2009 to 2018 to work with. I also looked at cleaning fees, super host status, and review scores.

```
#Airbnb_Sydney$city
class(Airbnb_Sydney$city)

## [1] "factor"

anyNA(Airbnb_Sydney$city)

## [1] FALSE

head(summary(as.factor(Airbnb_Sydney$city)))

##   Bondi Beach  Surry Hills       Sydney        Manly Darlinghurst
##           555          500          463          389          373
##        Coogee
##           272

#Airbnb_Sydney$property_type
class(Airbnb_Sydney$property_type)

## [1] "factor"

anyNA(Airbnb_Sydney$property_type)

## [1] FALSE

head(summary(as.factor(Airbnb_Sydney$property_type)))

##        Aparthotel         Apartment Bed and breakfast              Boat
##                 2              6222                46                 8
##    Boutique hotel          Bungalow
##                26                62

#Airbnb_Sydney$property_type
class(Airbnb_Sydney$host_since)

## [1] "factor"

anyNA(Airbnb_Sydney$host_since)

## [1] FALSE

head(sort(as.Date(Airbnb_Sydney$host_since, tryFormats = c("%m/%d/%y")), decr
easing = T))

## [1] "2018-11-25" "2018-11-21" "2018-11-21" "2018-11-20" "2018-11-19"
## [6] "2018-11-19"

tail(sort(as.Date(Airbnb_Sydney$host_since, tryFormats = c("%m/%d/%y")), decr
easing = T))
```

```
## [1] "2009-05-17" "2009-05-14" "2009-05-14" "2009-05-14" "2009-04-20"
## [6] "2009-04-20"
```

```
#Airbnb_Sydney$price
anyNA(Airbnb_Sydney$price)
```

```
## [1] FALSE
```

```
class(Airbnb_Sydney$price)
```

```
## [1] "factor"
```

```
price_num = as.numeric(gsub("[\\$]", "", Airbnb_Sydney$price), length(2))
```

```
## Warning: NAs introduced by coercion
```

```
head(summary(price_num))
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##   0.0000  96.0000 150.0000 189.3062 226.0000 999.0000
```

```
#Airbnb_Sydney$cleaning_fee
anyNA(Airbnb_Sydney$cleaning_fee)
```

```
## [1] TRUE
```

```
class(Airbnb_Sydney$cleaning_fee)
```

```
## [1] "factor"
```

```
clean_fee = as.numeric(gsub("[\\$]", "", Airbnb_Sydney$cleaning_fee), length(
2))
head(summary(clean_fee))
```

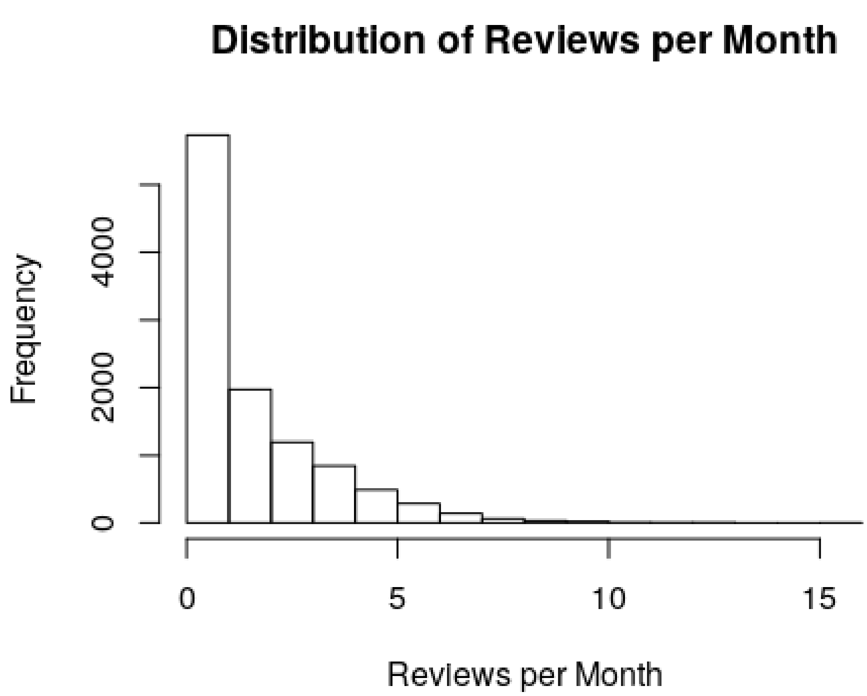
```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##   0.00000  40.00000  80.00000  94.47234 125.00000 800.00000
```

I also looked at the different review variables and super host variables. I thought these variables would also offer insight, and possbility overlap. Upon further inspection, I can see that the distribution of the review_rating and review_value columns are very similar (just on a different scale). Reviews_per_month looked interesting, but actually didn't hold much data, and we can see the distribution is really skewed. The superhost variable did not offer much in terms of insight at this stage, and is a collection of true and false values.

In general, it looks like the data from most variables is skewed, which will be something to keep in mind for analysis.

```
# Looking at some of the different "review" columns to see which my be useful
later and the superhost column

#Airbnb_Sydney$review_scores_value
class(Airbnb_Sydney$review_scores_value)
```

```
## [1] "integer"

summary(Airbnb_Sydney$review_scores_value)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   2.000   9.000  10.000   9.385  10.000  10.000

#Airbnb_Sydney$review_scores_rating
class(Airbnb_Sydney$review_scores_rating)

## [1] "integer"

summary(Airbnb_Sydney$review_scores_rating)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   20.00   92.00   96.00   94.19  100.00  100.00       1

#Airbnb_Sydney$reviews_per_month
class(Airbnb_Sydney$reviews_per_month)

## [1] "numeric"

summary(Airbnb_Sydney$reviews_per_month)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   0.020   0.270   0.950   1.572   2.310  15.180

hist(Airbnb_Sydney$reviews_per_month, main = "Distribution of Reviews per Mon
th", xlab = "Reviews per Month")
```



```r
#Airbnb_Sydney$host_is_superhost
class(Airbnb_Sydney$host_is_superhost)
```

```
## [1] "factor"
```

```r
summary(Airbnb_Sydney$host_is_superhost)
```

```
##    f    t 
## 8020 2795
```

```r
head(Airbnb_Sydney$host_is_superhost)
```

```
## [1] f f f t f f
## Levels: f t
```

Q3

3.1

We have mostly character vectors, which I will change to integer, dates and factors for visualization and analysis. Of the possible numerical variables, it looks like we have only discrete variables. To visualize this, I will use scatter plots, barplots, boxplots, and denisty plots.

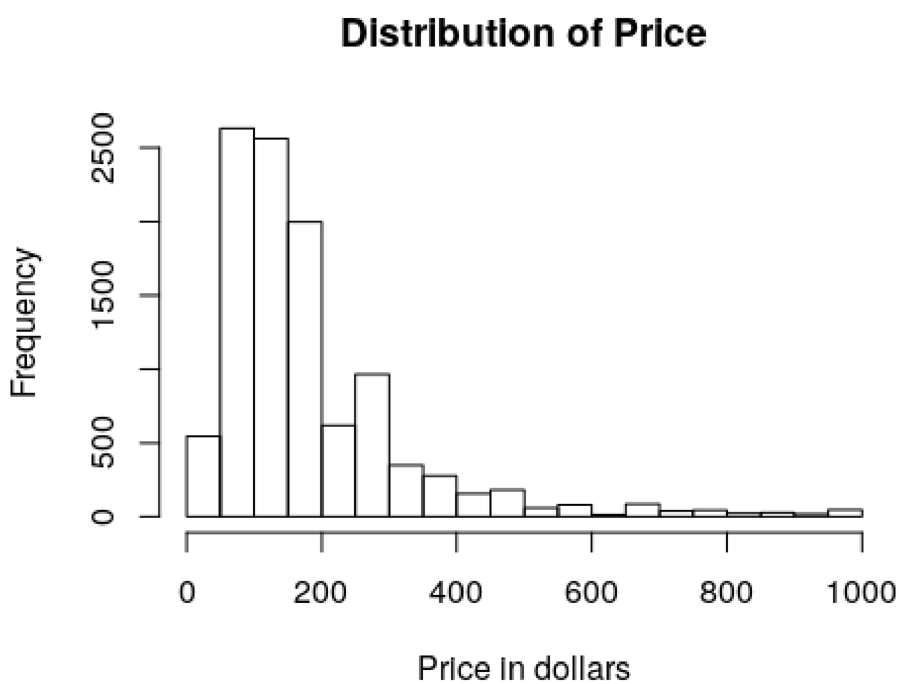
```r
# what types of data are there?
apply(Airbnb_Sydney, 2, class)
```

```
##                           id                  description 
##                  "character"                  "character" 
##       neighborhood_overview                  house_rules 
##                  "character"                  "character" 
##                      host_id                   host_since 
##                  "character"                  "character" 
##          host_response_time           host_response_rate 
##                  "character"                  "character" 
##            host_is_superhost           host_verifications 
##                  "character"                  "character" 
##       host_identity_verified                         city 
##                  "character"                  "character" 
##                      zipcode                property_type 
##                  "character"                  "character" 
##                    room_type                 accommodates 
##                  "character"                  "character" 
##                    bathrooms                     bedrooms 
##                  "character"                  "character" 
##                         beds                     bed_type 
##                  "character"                  "character" 
##                    amenities                        price 
##                  "character"                  "character" 
##                 cleaning_fee              guests_included 
##                  "character"                  "character" 
##                 extra_people               minimum_nights
```

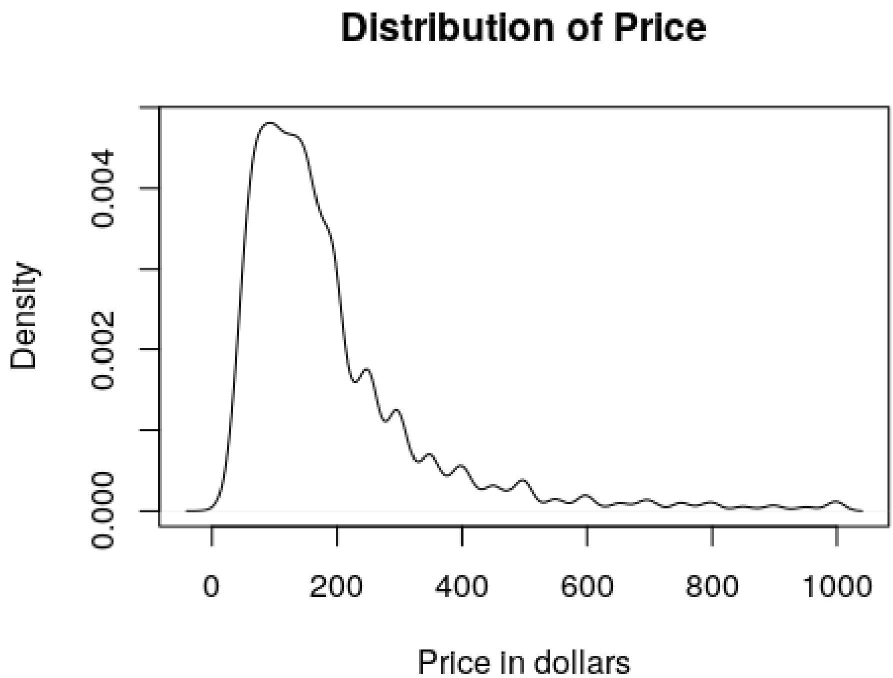
```
##                   "character"                          "character" 
##             number_of_reviews                 review_scores_rating 
##                   "character"                          "character" 
##        review_scores_accuracy            review_scores_cleanliness 
##                   "character"                          "character" 
##         review_scores_checkin          review_scores_communication 
##                   "character"                          "character" 
##        review_scores_location                  review_scores_value 
##                   "character"                          "character" 
##           cancellation_policy                    reviews_per_month 
##                   "character"                          "character"
```

3.2

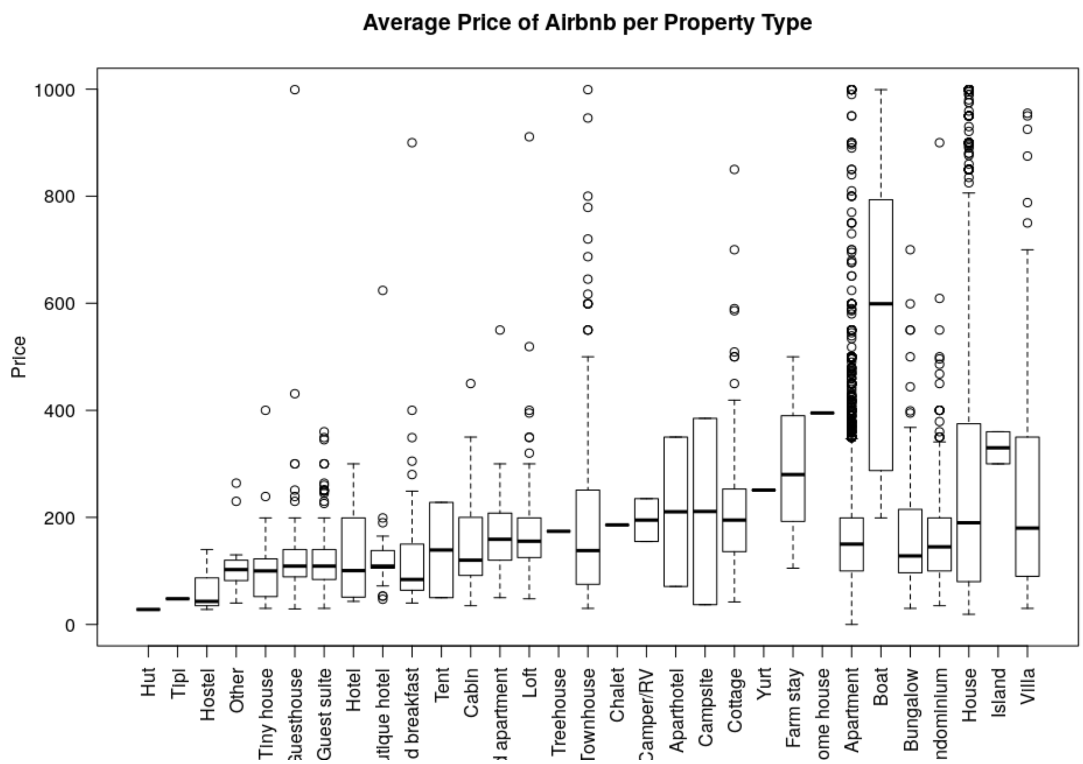
```
# exploring the price variable using histograms and density plots

hist(price_num, main = "Distribution of Price", xlab = "Price in dollars")
```



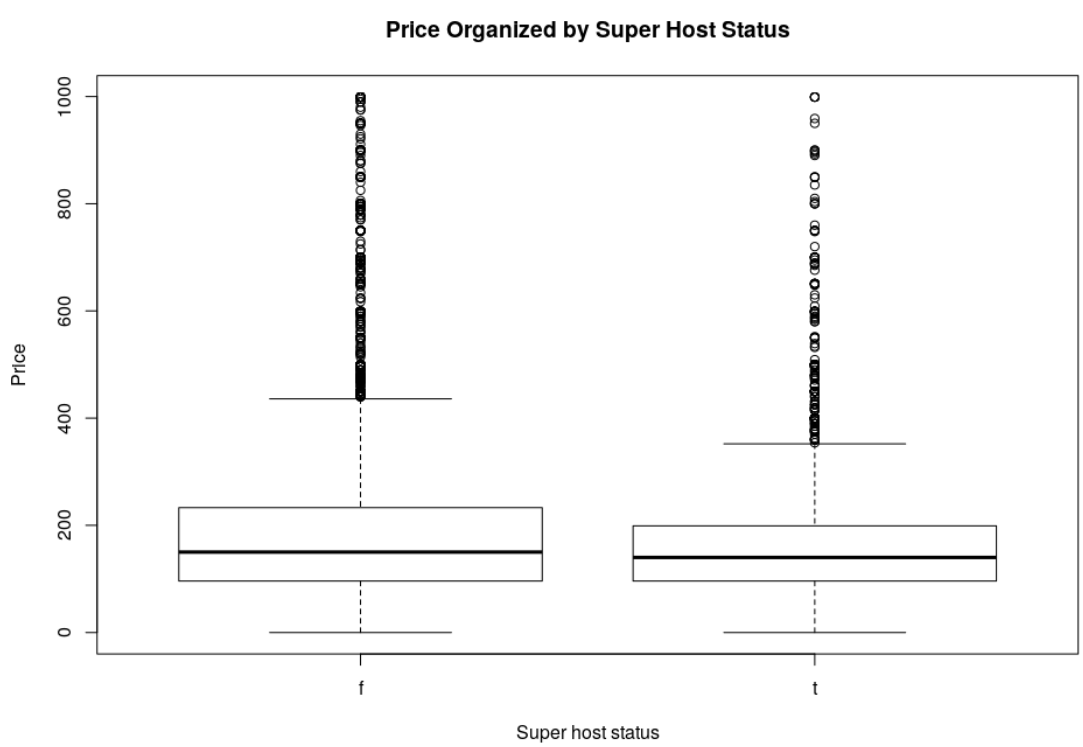

```
plot(density(price_num, na.rm = T), main = "Distribution of Price", xlab = "P
rice in dollars")
```



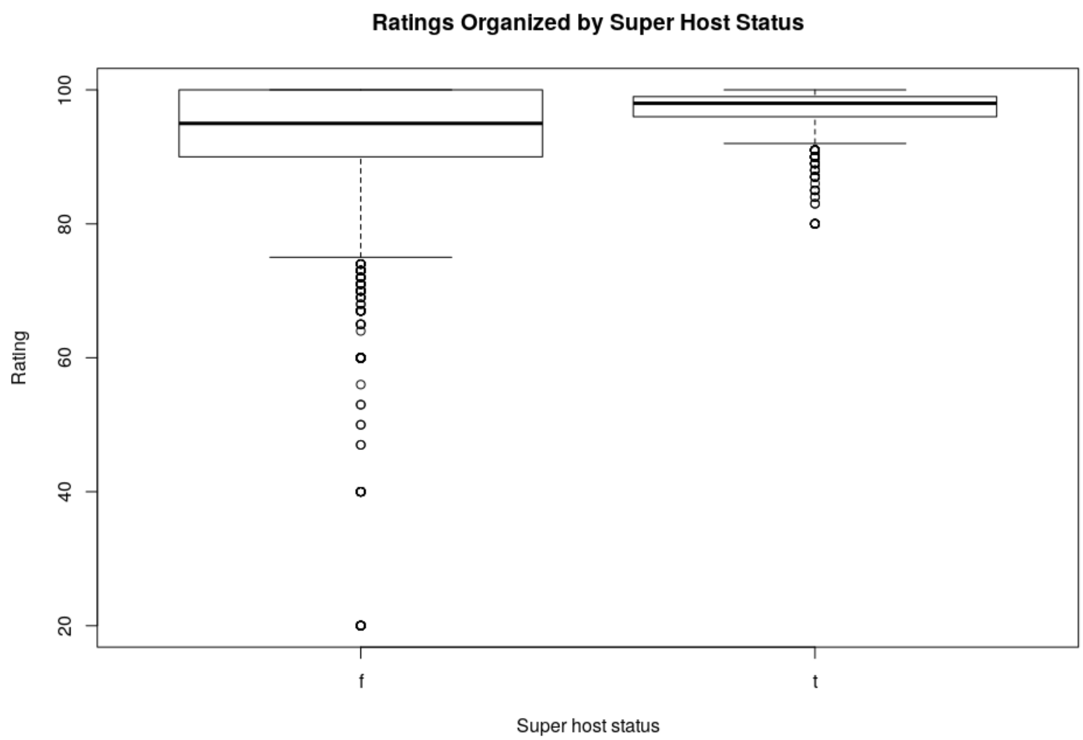

```r
# looking at price and other variables
# looking at review columns and super host

boxplot(price_num~
          as.factor(Airbnb_Sydney$property_type),
        at = rank(tapply(price_num, Airbnb_Sydney$property_type, mean)), las
=2,
        main = "Average Price of Airbnb per Property Type",
        ylab = "Price", cex.names=0.4)
```



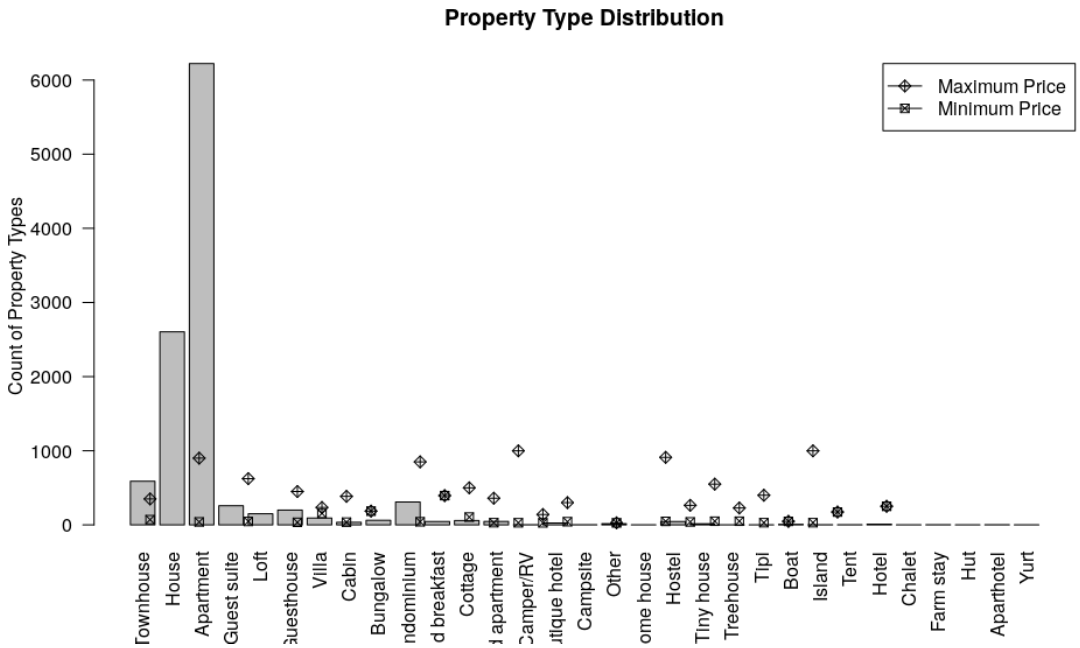

```r
plot(price_num~as.factor(Airbnb_Sydney$host_is_superhost), main = "Price Orga
nized by Super Host Status",
     xlab = "Super host status", ylab = "Price")
```



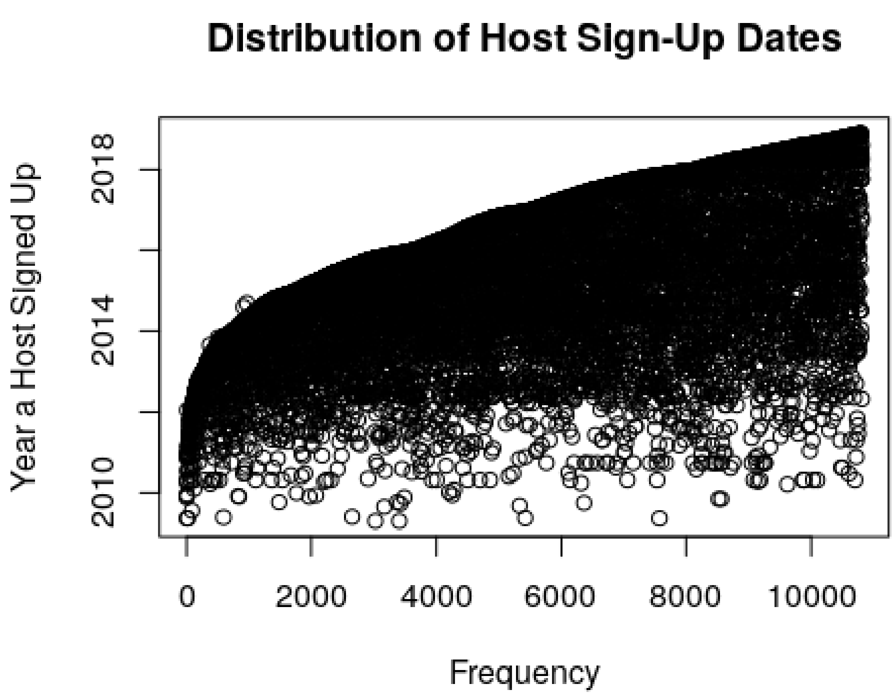
```
plot(Airbnb_Sydney$review_scores_rating~as.factor(Airbnb_Sydney$host_is_super
host), main = "Ratings Organized by Super Host Status",
     xlab = "Super host status", ylab = "Rating")
```



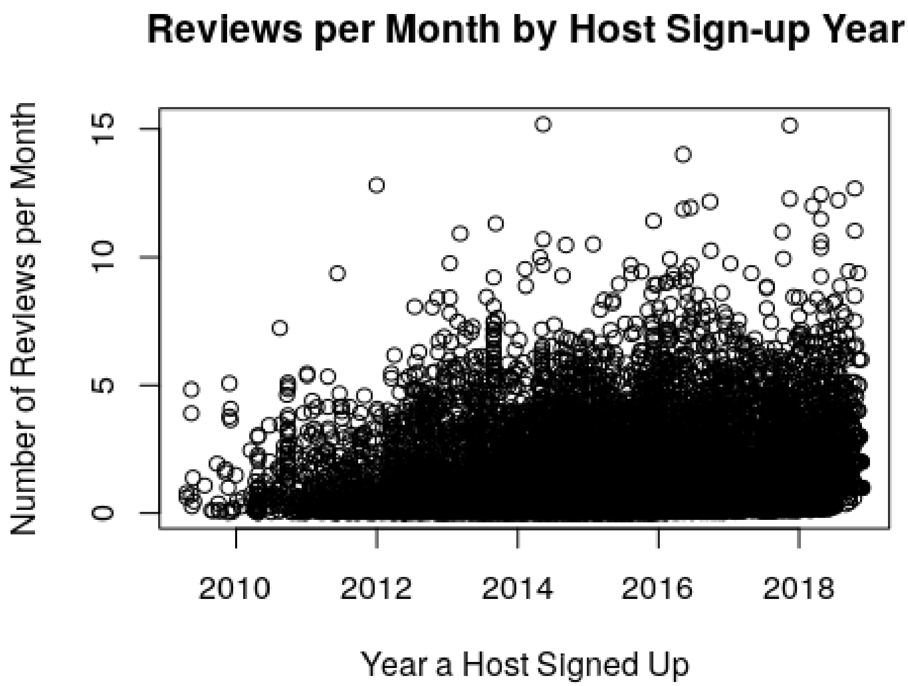

```
# looking at property type distribution with maximum and minimum plotted over
top

plot(sort(factor(Airbnb_Sydney$property_type,
                       levels = unique(Airbnb_Sydney$property_type)), decreas
ing = T), las=2, main = "Property Type Distribution", ylab = "Count of Proper
ty Types")

onemax <- by(price_num, Airbnb_Sydney$property_type, max)
means <- by(price_num, Airbnb_Sydney$property_type, min)

points(onemax, pch=9)
points(means, pch=7)
legend(legend = c("Maximum Price", "Minimum Price"), lty = c(1, 1), pch = c(9
, 7), "topright")
```




```r
# looking at host since dates and reviews

plot(as.Date(Airbnb_Sydney$host_since, tryFormats = c("%m/%d/%y")),
            main = "Distribution of Host Sign-Up Dates", xlab = "Frequency",
     ylab = "Year a Host Signed Up")
```



```r
plot(Airbnb_Sydney$reviews_per_month~as.Date(Airbnb_Sydney$host_since, tryFor
mats = c("%m/%d/%y")),
     main = "Reviews per Month by Host Sign-up Year", xlab = "Year a Host Sig
ned Up",
     ylab = "Number of Reviews per Month")
```



3.3

Visualizing the data showed me the distribution and potential relationship between the variables: price (reamed price_num), super_host, property_type, host_since, and review_per_month.

First, I focused on the price variable, which I converted to a numeric data type. I plotted it as both a histogram and a density plot. The density plot shows the overall trend better, because I have a smooth curve that that shows two peaks close together, and the sharp drop in the number of properties listed for more than 200 dollars a night. The histrogrm shows me more details, however, and I can see the individual frequencies for each category. For exploring the data, the histogram is better. As a presentation tool, the denisty plot is better.

Second, I looked at price in relation to property type using boxplots. I plotted the property type and ranked the properites according to the average price. Here we can see the trend in mean price, and also the amount of variance in price for each property type. Here is some data that will come in handy in the analysis phase. Property types that stand out are apartments, boats, houses, and townhomes. While some properites had massive variance, others did not, such as islands and cottages. Further analysis is needed here. I also organized price by super host status, but nothing interesting appeared at this initial stage, and may it require including other variables to see if super host status influences the data.

To get a better idea about what is going on with property types, I plotted a barchart to get a look at the distribution, and plotted the mean price overtop. So the same data, but looking at it in a different way. Here we can see that there are many apartment listed, followed by houses and townhomes. Here it makes sense that their is variance in the properities listed the most. It also looks like some averages are missing for some property types. The data looks to be skewed in favor of apartments, with little or no data for the majority of the property types.

I then looked at the distribution of host sign-up dates, and we can a drastic increase in hosts from 2010 to 2014. I also looked at the number of reviews organized by host sign up date, and we can see that the data is messy, but there is a general trend where there are more reviews for more recent dates. More analysis is needed here.

Q4

4.1

The number of reviews is the total number of reviews for listing, so we can use this varialbe to infer how often a listing has been rented and reviewed and how long it's been listed. This is useful for looking at a property's overall business. The number of reviews per month gives us more information on how often a listing was rented at time intervals. We can see how busy a property is or isn't and look for peak times. These variables are similar in that they convey information about freauency of use, but one gives us a total and one gives us a number for a short period of time.

From the analysis below, it looks like there are 25 host ids that are in the top 100 listings for number of reviews and for number of reviews per month.

```
# create a dataframe for reviews and host id
id_num = Airbnb_Sydney[,c("host_id", "number_of_reviews", "reviews_per_month"
)]

# subset and order by number of reviews
dis_num = id_num[order(id_num$number_of_reviews, decreasing = T), ]
top_total = head(dis_num, n=100L)

# subset and order by reviews per month
dis1_num = id_num[order(id_num$reviews_per_month, decreasing = T), ]
top_monthly = head(dis1_num, n=100L)

# check for overlapping host ids
top_monthly$host_id %in% top_total$host_id

##   [1]  TRUE FALSE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##  [12]  TRUE FALSE  TRUE FALSE FALSE FALSE  TRUE  TRUE FALSE FALSE FALSE
##  [23] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE  TRUE  TRUE
```

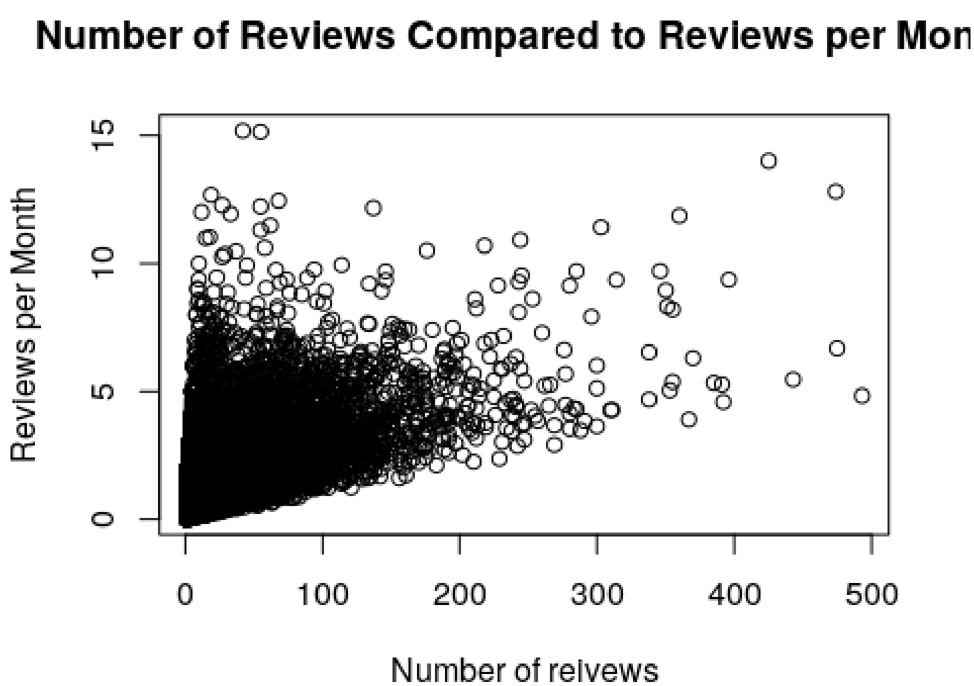
```
## [34] FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE FALSE  TRUE FALSE  TRUE
## [45]  TRUE  TRUE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE
## [56] FALSE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [67] FALSE  TRUE FALSE FALSE  TRUE FALSE  TRUE FALSE FALSE  TRUE FALSE
## [78] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE
## [89] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [100] FALSE
```

```
sum(as.numeric(top_monthly$host_id %in% top_total$host_id))
```

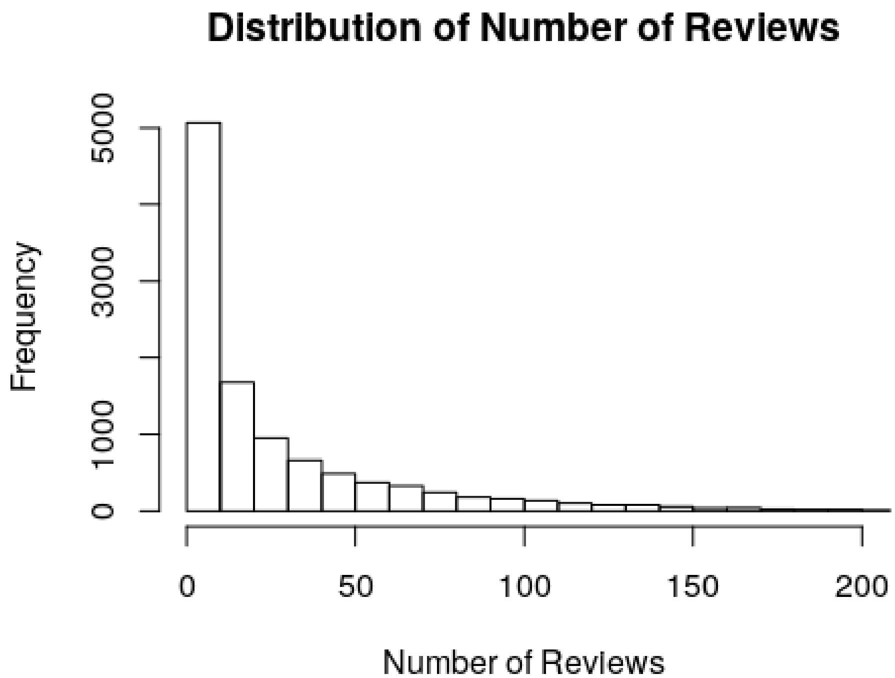
```
## [1] 25
```

Taking a look at this relationship visually, we can see that the two variables are closely related, with a higher number overall reviews being correlated with a higher number of reviews per month. This does suggest some colinearity between the two variables. I also looked at the distriubtion of both variables, and they look similar.

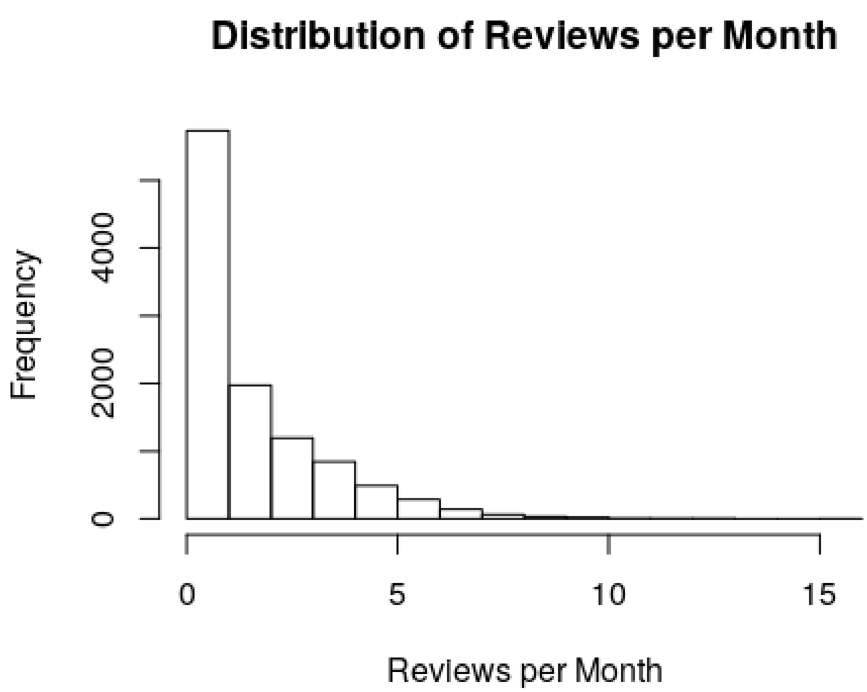
```
plot(Airbnb_Sydney$reviews_per_month~Airbnb_Sydney$number_of_reviews,
     main = "Number of Reviews Compared to Reviews per Month", xlab = "Number of reivews",
     ylab = "Reviews per Month")
```




```
hist(Airbnb_Sydney$number_of_reviews, xlim = c(0,200), breaks = 50,
     main = "Distribution of Number of Reviews", xlab = "Number of Reviews")
```



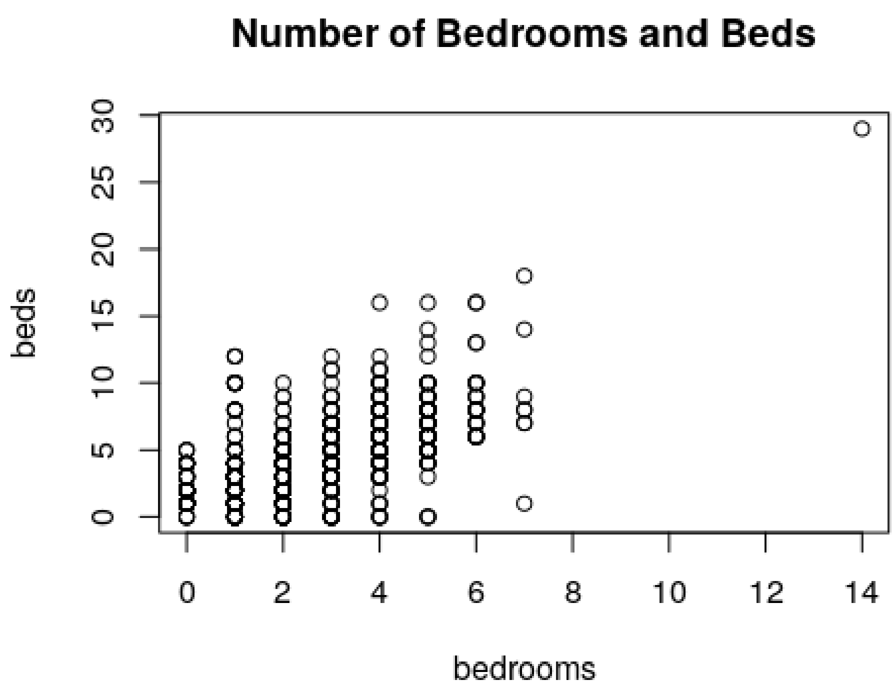

```
hist(Airbnb_Sydney$reviews_per_month,
     main = "Distribution of Reviews per Month", xlab = "Reviews per Month")
```



4.2

I also looked at the number of bedrooms and the number of beds in terms of a relationship. We can see that with an increase in bedrooms there is also an increase in the number of beds. This implies that their is a relationship between these two variables and possible colinearity. From both of these variables, we can infer the size of the property and how many peole can stay at this listing.

```
# number of bedrooms to number of beds

plot(Airbnb_Sydney[order(Airbnb_Sydney$bedrooms, decreasing = T),
              c("bedrooms", "beds")], type = "p", main = "Number of Bedrooms
and Beds")
```




```
# removed outliers

plot(Airbnb_Sydney[order(Airbnb_Sydney$bedrooms, decreasing = T),
              c("bedrooms", "beds")], type = "p", main = "Number of Bedrooms
and Beds",
     xlim = c(0,10), ylim = c(0,20))
```

Next, I looked at zipcode and cities, which do have considerable overlap. We can see from the dataframe that I created that each zipcode corresponds to one or two cities. We can also see the reverse when ordering by city. This means that we only need one of these variables in analysis, as they both represent similar data.

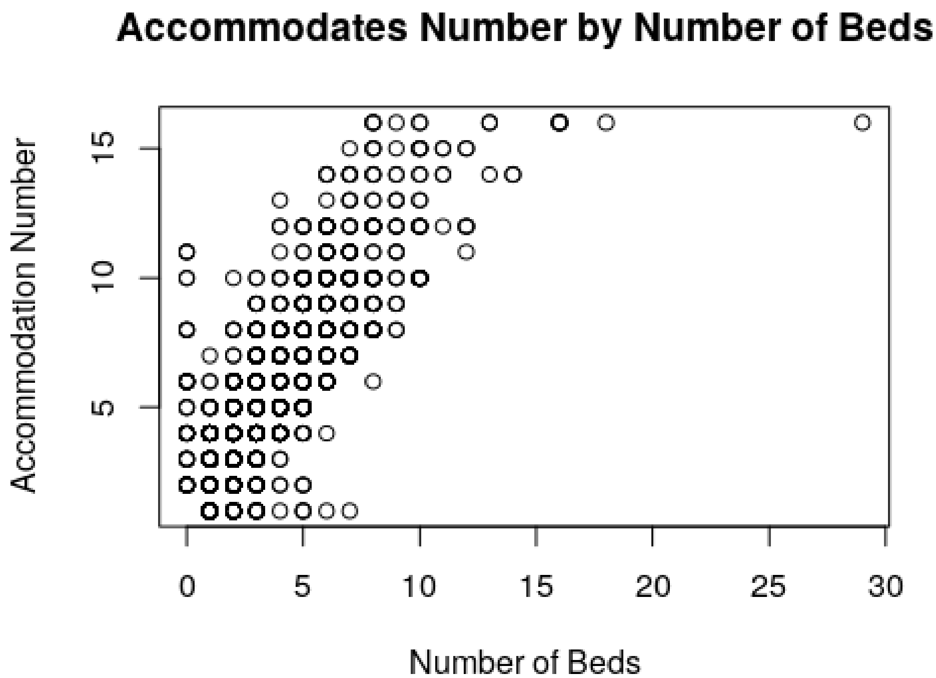
```
ord_zip = Airbnb_Sydney[order(Airbnb_Sydney$number_of_reviews, decreasing = T
), c("host_id","zipcode","city","number_of_reviews")]

top_zip = head(ord_zip, n=100L)
top_zip

##         host_id zipcode            city number_of_reviews
## 1         17061    2009         Pyrmont               493
## 298     4798499    2107          Avalon               475
## 2703    1553030    2020          Mascot               474
## 100     1943399    2016         Redfern               443
## 4241   71193770    2205       Arncliffe               425
## 2074     688781    2042         Newtown               396
## 57      1347315    2026           Bondi               392
## 183     1943399    <NA>         Redfern               391
## 262     4421400    2010     Surry Hills               385
## 780     3191055    2011    Woolloomooloo              370
## 22        17061    2009         Pyrmont               367
## 4307   71193770    2205       Arncliffe               360
## 285     4421400    2010     Darlinghurst              355
## 2228   32928357    2000    Millers Point              355
## 320     5169464    2016         Redfern               353
```

```
## 2087  30075514    2041           Balmain                 351
## 2839  35454201    2107      Avalon Beach                 350
## 3594  41011048    2020            Mascot                 346
## 198    3720786    2000     Millers Point                 338
## 1009  15354654    2010           Sydney                  338
## 3932  41498403    2044             Tempe                 314
## 210    3809995    2011            Sydney                 311
## 247    4367105    2042           Newtown                 310
## 4777  50707354    2038         Annandale                 303
## 3        59850    2010      Darlinghurst                 300
## 819    4421400    2010      Darlinghurst                 300
## 1443   7531199    2016           Redfern                 300
## 3191  48538672    2034            Coogee                 296
## 170    3437247    2010      Darlinghurst                 291
## 76      209719    2010      Darlinghurst                 288
## 393    6403880    2061     Milsons Point                 285
## 4383  78920515    2206          Earlwood                 285
## 440    4234278    2203      Dulwich Hill                 283
## 105    2020595    2100 Allambie Heights                  280
## 375     410489    2033        Kensington                 280
## 4294  73662200    2044             Tempe                 280
## 554    8939894    2061        Kirribilli                 277
## 1610   4421400    2010       Surry Hills                 277
## 2378  23817711    2011     Woolloomooloo                 276
## 26      425305    2011            Sydney                 269
## 130    2351093    2000            Sydney                 269
## 1205   6248691    2021        Paddington                 266
## 592    3809995    2011       Potts Point                 265
## 1263  18495707    2000            Sydney                 262
## 3549   6344154    2061        Kirribilli                 260
## 404    3455633    2042           Newtown                 257
## 418    4424088    2011       Potts Point                 255
## 4377  74564218    2000            Sydney                 253
## 495    8247293    2011       Potts Point                 252
## 119    2157195    2010       Surry Hills                 247
## 405    6538998    2016           Redfern                 247
## 1960  28356414    2229   Caringbah South                 247
## 379    3792649    2026       Bondi Beach                 245
## 2692  12060025    2095             Manly                 245
## 2474  11889319    2011       Potts Point                 244
## 4841   5383558    2016           Redfern                 244
## 4356   8530753    2000            Sydney                 243
## 4757  20381574    2016       Surry Hills                 243
## 66     1261500    2011       Potts Point                 242
## 1015  15492831    2024            Bronte                 241
## 1019    371323    2026       Bondi Beach                 241
## 3026  46909702    2007            Ultimo                 241
## 458    4155754    2011       Potts Point                 240
## 1320   2255025    2008        Darlington                 239
## 330    5512046    2010      Darlinghurst                 238
```

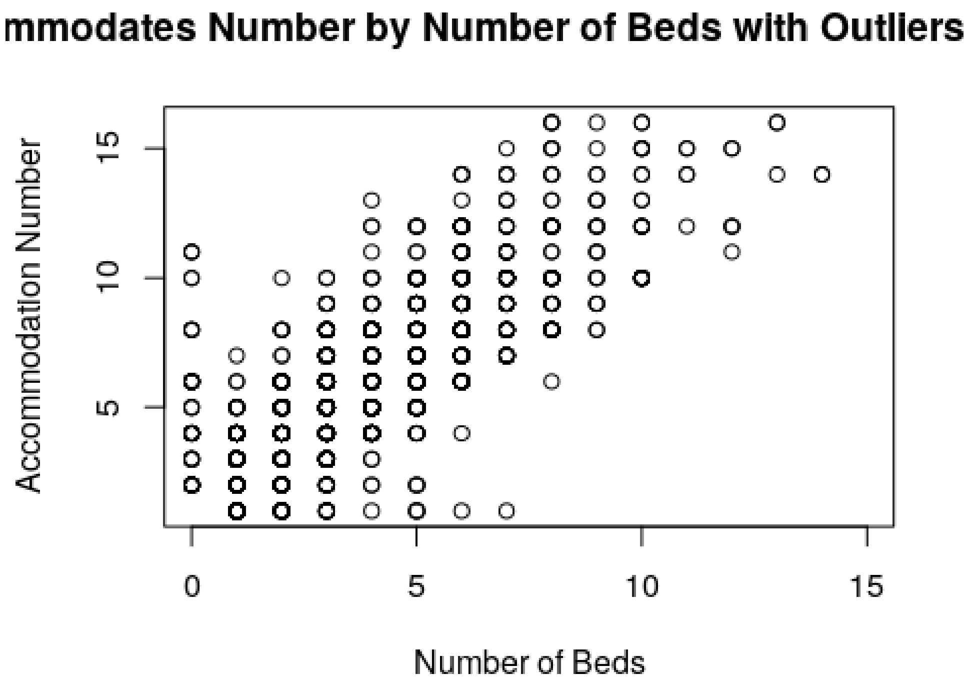
```
## 827      59850    2010     Darlinghurst                 238
## 1335   4945327    2007           Ultimo                 237
## 2761  13767099    2062         Cammeray                 237
## 428    7028222    2011      Potts Point                 234
## 1083   4519063    2068       Willoughby                 233
## 4033   8530753    2000           Sydney                 232
## 154    1261500    2011      Potts Point                 231
## 2531  38607216    2104          Bayview                 231
## 2865  16477385    2035         Maroubra                 230
## 10      279955    2088           Mosman                 229
## 4969  63558864    2217          Kogarah                 228
## 985    1560268    2010      Surry Hills                 226
## 1786   7736332    2042          Newtown                 225
## 2150  15885982    2011     Woolloomooloo                 225
## 4121  60423487    2037      Forest Lodge                 223
## 2917  45620575    2042          Newtown                 222
## 585    3699017    2024         Waverley                 219
## 840      57949    2010      Surry Hills                 219
## 4037   8530753    2000           Sydney                 218
## 6002  15542638    2017         Waterloo                 218
## 2375  19315857    2207     Bexley North                 215
## 2116  20493747    2010      Surry Hills                 214
## 792   11247892    2016          Redfern                 213
## 381    6245401    2230         Bundeena                 212
## 1649  18533922    2044        St Peters                 212
## 4870  74564218    2000           Sydney                 212
## 5215 105151106    2011      Potts Point                 211
## 24      402292    2036          Malabar                 210
## 924   13059157    2010     Darlinghurst                 210
## 2526   7058720    2026      Bondi Beach                 210
## 3016  10859587    2205      Wolli Creek                 210
## 605    9972513    2035         Maroubra                 209
## 2766   6599322    2010      Surry Hills                 208
## 767   11282313    2010     Darlinghurst                 207
## 1854  26709417    2011   Rushcutters Bay                 206
```

I also looked at the relationship between the number of beds and the number people a listing would accommodate. We can see that there is an increase in the number of beds and the number of people allowed to stay. It's not quite a linear looking relationship, but it is enough overlap to suggest the two are related.

```r
# number of beds and accommodation numbers
plot(Airbnb_Sydney$accommodates~Airbnb_Sydney$beds, type ="p",
     main = "Accommodates Number by Number of Beds", xlab = "Number of Beds",
ylab = "Accommodation Number")
```




```
# remove outliers
plot(Airbnb_Sydney$accommodates~Airbnb_Sydney$beds, type ="p", xlim= c(0,15),
main = "Accommodates Number by Number of Beds with Outliers Removed", xlab =
"Number of Beds",
ylab = "Accommodation Number")
```



Q5

1. I think that there is an optimal price range to attract a high volumne of customers. Listings that fall into this range will have more overall reviews, which will be measured by the number of reviews per month and total reviews. I will start by looking the range and distribution of overall price, and then look at that distriubtion by location (city), because I think that optimal price range will depend on the location. I will then group the prices into bins, and look at how many reviews per month fall into each price range bin. I will include other variable in this analysis such as property type, number of people staying there, and location.

2. I think that hosts who have been using Aribnb longer will have higher review ratings. I will use the host_since date variable, number of reviews, and ratings to investigate this. I think super host status will need to be held constant, as well as price, location, property type, and beds.

3. I think that a high cleaning fee will lead to lower review ratings and less customers. I will start this analysis by looking at the distribution of the cleaning fee, and then plot that as function of the total reviews and reviews per month, and reviews on cleanliness. I will include other functions such as property type, price, location and number of people staying that I think will influence the analysis. I think price and property type in particular will need to be held constant. So I would look at cleaning fees for apartments or houses only to and number of reviews to understand this relationship.

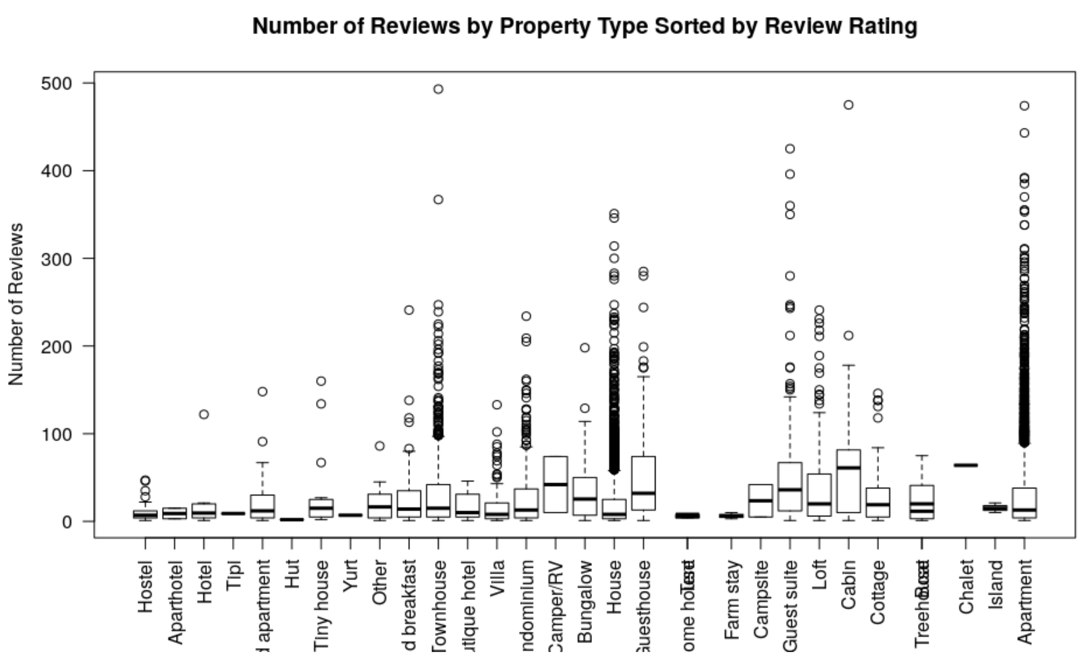
Part 2

Q6

6.1

Below, I have sorted the number of reviews by property type, and sorted them by their average review rating. We can see that apartments have the highest average reivews, and most total number of reivews. After that, we can see that islands and chalet's also have high average reviews, but not very many total reviews. Apartments have the most reviews overall, but not the highest average. Most of the property types in the data are apartments, so this makes sense.

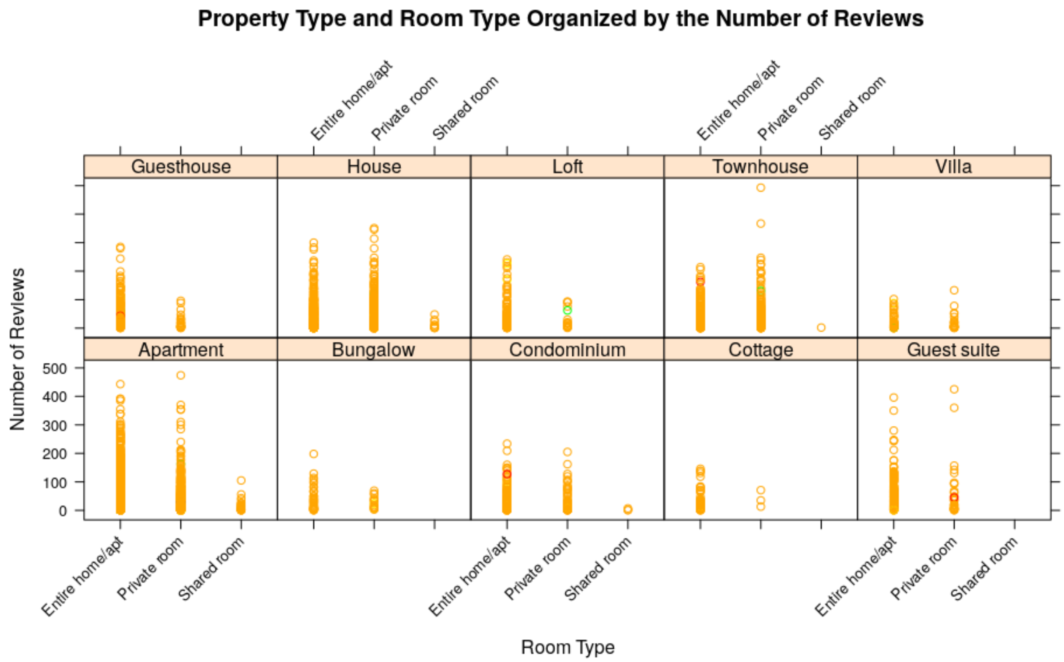
```
boxplot(Airbnb_Sydney$number_of_reviews~
          as.factor(Airbnb_Sydney$property_type),
        at = rank(tapply(Airbnb_Sydney$review_scores_rating,
                         Airbnb_Sydney$property_type, mean)), las =2,
        main = "Number of Reviews by Property Type Sorted by Review Rating",
        ylab = "Number of Reviews")
```



6.2

From the graph below, we can see that the room types with the highest total reviews for the top ten property types go to the entire home, or some cases just the private room. Shared rooms (across property types) do not have as many total reviews, or any at all. People seem to review the entire listing experience more than they do just a private room or shared room experience. In terms of the bed types, we can see that most of these listings have real beds (shown in orange), with a few execptions.

```
library(lattice)

# create table
pnum = as.data.frame(table(Airbnb_Sydney$property_type))

# order table
rpnum = pnum[order(-pnum$Freq), ]

# subset for the top 10 property types
order_prop = as.data.frame(Airbnb_Sydney[c(Airbnb_Sydney$property_type=="Apar
tment"
                           | Airbnb_Sydney$property_type=="House"
                           | Airbnb_Sydney$property_type=="Townhouse"
                           | Airbnb_Sydney$property_type=="Condominium"
                           | Airbnb_Sydney$property_type=="Guest suite"
                           | Airbnb_Sydney$property_type=="Guesthouse"
                           | Airbnb_Sydney$property_type=="Loft"
                           | Airbnb_Sydney$property_type=="Villa"
                           | Airbnb_Sydney$property_type=="Bungalow"
                           | Airbnb_Sydney$property_type=="Cottage"),
                           c("property_type", "number_of_reviews", "room_type
", "bed_type")])


# create factors from bed numbers
bed_col = cut(as.numeric(order_prop$bed_type), breaks = 5)
col_test = c("red", "blue", "green", "yellow", "orange")

# subset bed categories and colors
bed_color <- col_test[bed_col]

# plot everything
xyplot(number_of_reviews~order_prop$room_type|property_type, data = order_pro
p,
       col=as.character(bed_color), scales=list(x=list(rot=45)),
       main = "Property Type and Room Type Organized by the Number of Reviews
", xlab = "Room Type", ylab =
         "Number of Reviews",
       auto.key = T)
```

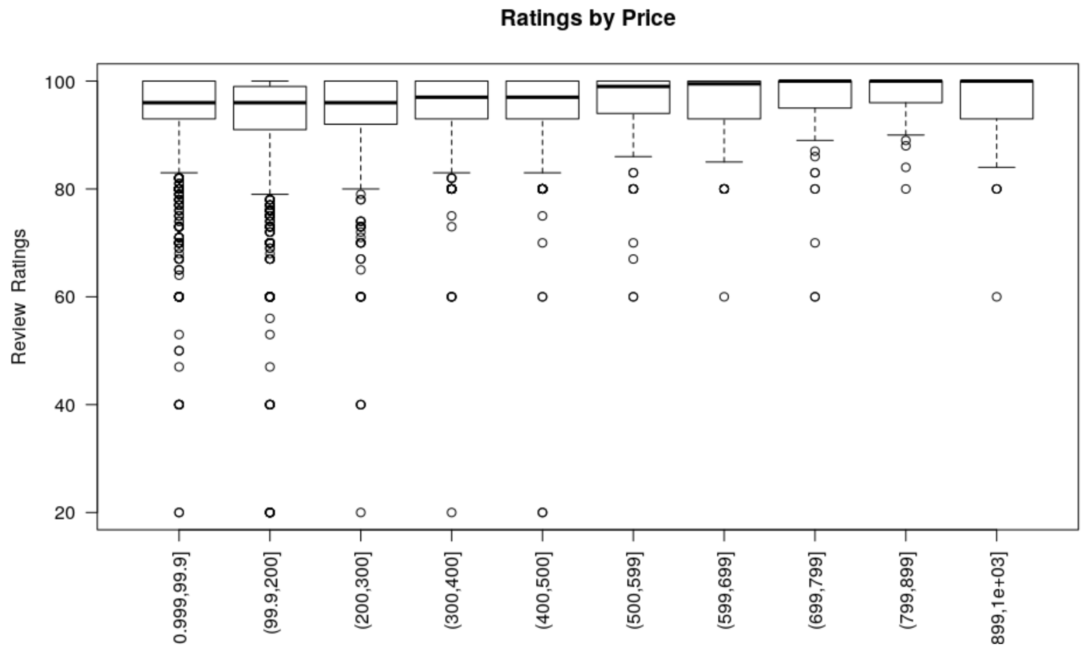


6.3

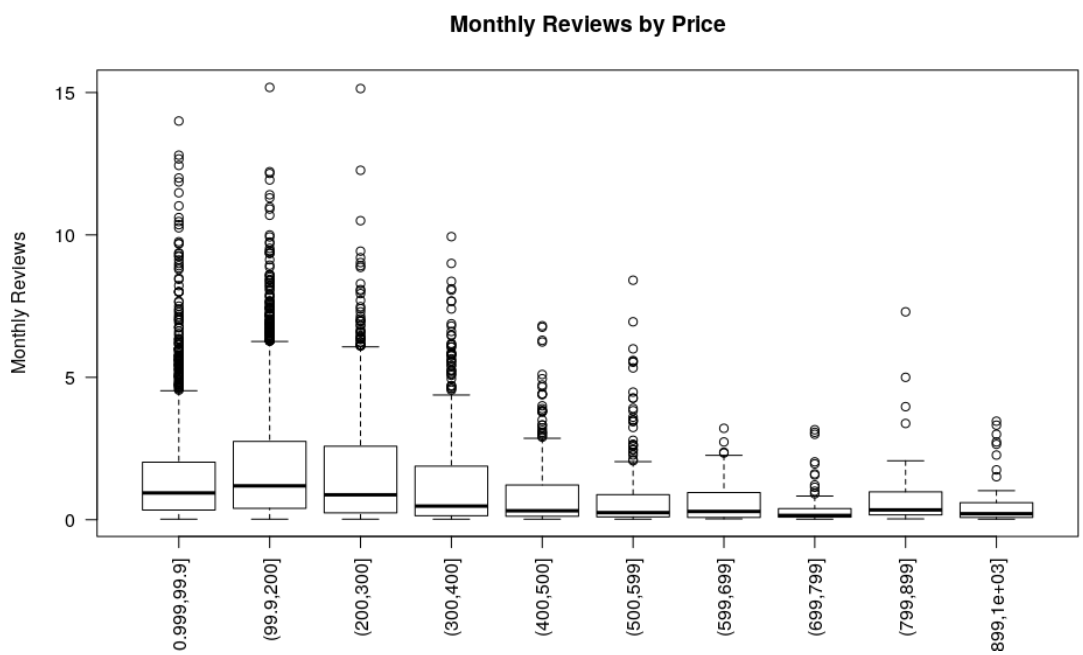
To explore my first hypothesis, I used boxplots to explore how price is related the number of reviews for a listing. I hypothesized that their is an optimal price range to get the most possible reviews. I created categories for price ranges, and plotted the number of reviews, review ratings, and monthly reviews in these categories.

From the visuals it is clear that the number of reviews vary the most (from 10 to less than 20) when the price is lower. Higher priced listings have a smaller range of ratings, as well as an average that is closer to 10. This could also be because higher priced listings are rented less (there's less data to work with). To further investigate this, we can look at the next graph, also a boxplot, and see that cheaper properties have more ratings per month, which could indicate that cheaper properties are rented more often. However, properties are are in the 100-300 range get the most reviews per month. This is also supported in the next graph, where we can see the total number of reviews are sorted by price category, and we see a similar pattern for the 100-200 dollar category. I used boxplots to show the distributions between different categories for easy comparison.

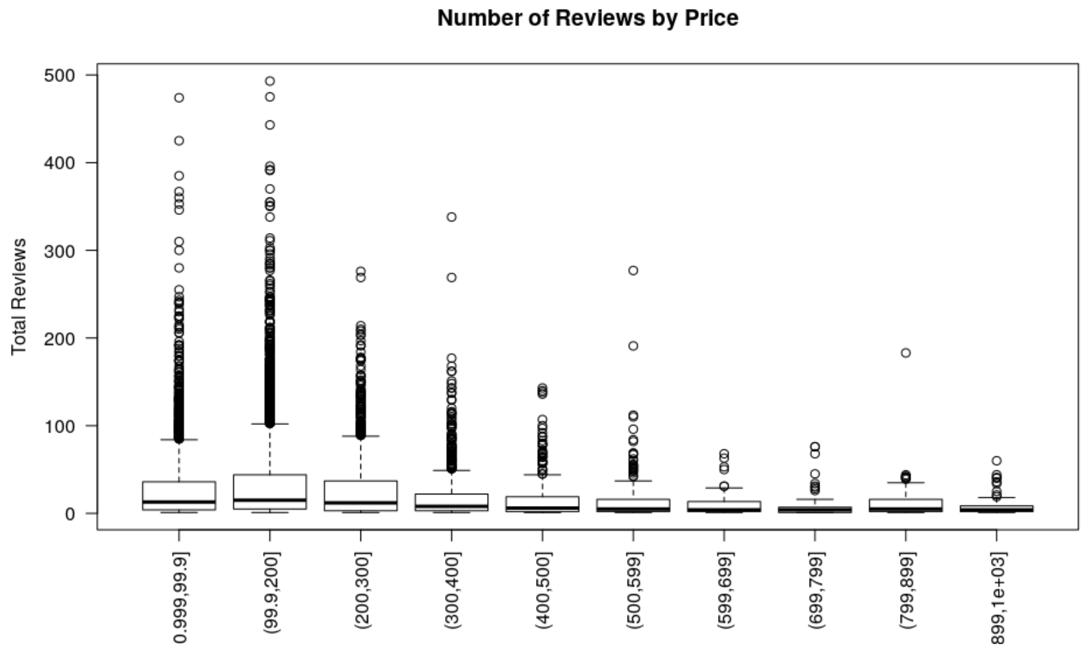
```
price_factor <- cut(x = as.numeric(price_num), breaks = 10)

plot(Airbnb_Sydney$review_scores_rating~price_factor, las=2,
     main = "Ratings by Price", xlab = "", ylab = "Review  Ratings")
```




```
plot(Airbnb_Sydney$reviews_per_month~price_factor, las= 2,
     main = "Monthly Reviews by Price", xlab = "", ylab = "Monthly Reviews")
```



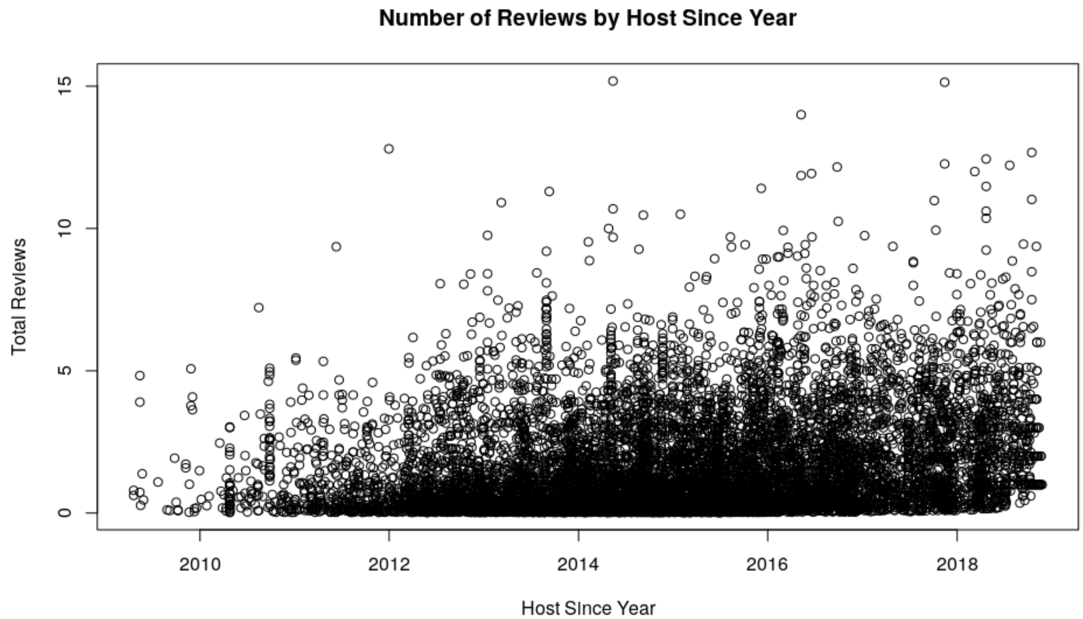

```
plot(Airbnb_Sydney$number_of_reviews~price_factor, las=2,
     main = "Number of Reviews by Price", xlab = "", ylab = "Total Reviews")
```



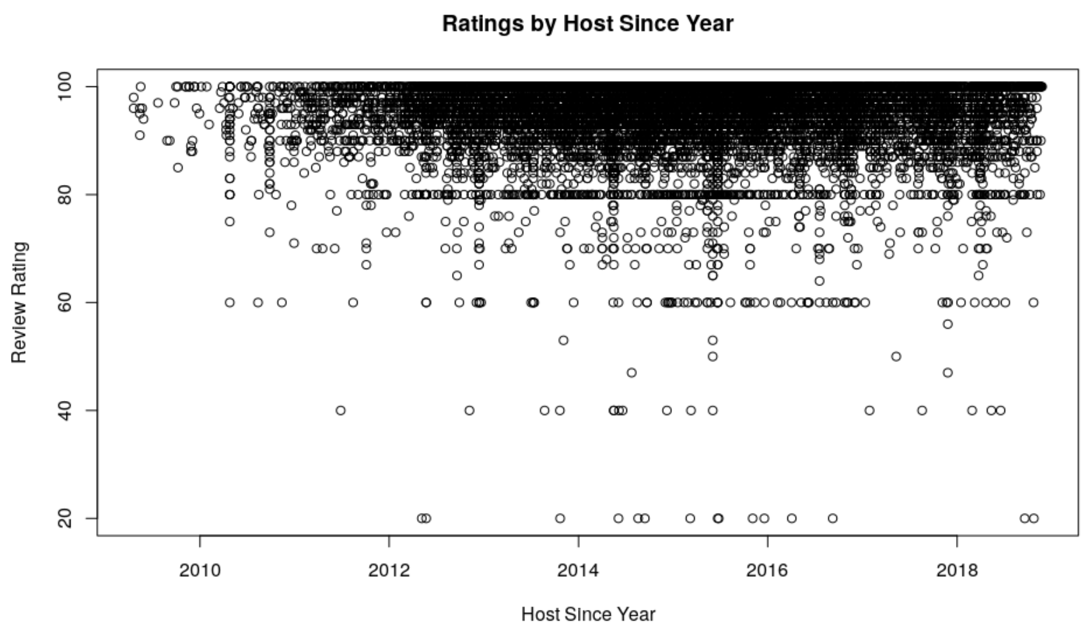
To explore my second hypothesis, I used scatterplots to explore how host sign up date is related the number of bookings and review ratings for a listing. I hypothesized that hosts how have used Aribnb longer will have better ratings.

The first and second visuals shows us that number of reviews and ratings grow with more recent host sign up dates, with the range of ratings increasing as more hosts sign up. The third visual shows host sign up dates by price, with the color indicating the number of beds in a listing. We can see that price tends to go up with the number of beds, and that listings with more beds have appeared with more recent listings. I used scatterplots to show the relationship between ratings, number of reviews, and price to host sign up.

```
library("RColorBrewer")

Airbnb_Sydney$host_data = as.Date(Airbnb_Sydney$host_since, tryFormats = c("%
m/%d/%y"))

plot(Airbnb_Sydney$reviews_per_month~as.Date(Airbnb_Sydney$host_since, tryFor
mats = c("%m/%d/%y")), main = "Number of Reviews by Host Since Year",
      xlab = "Host Since Year", ylab = "Total Reviews")
```

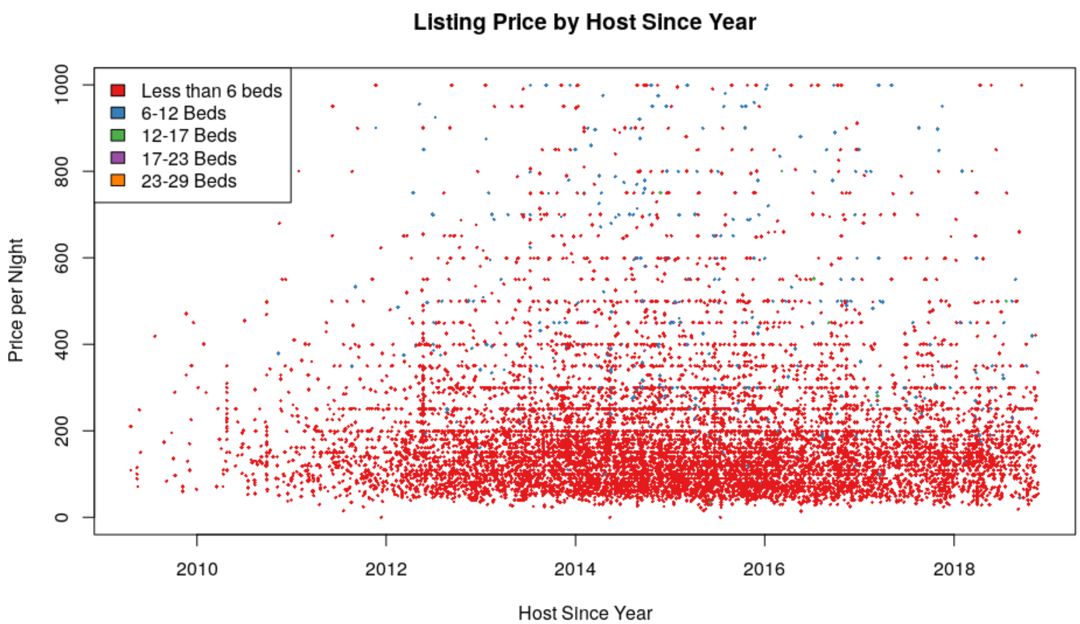



```
plot(Airbnb_Sydney$review_scores_rating~as.Date(Airbnb_Sydney$host_since, try
Formats = c("%m/%d/%y")), main = "Ratings by Host Since Year",
      xlab = "Host Since Year", ylab = "Review Rating")
```




```
beds_col = cut(as.numeric(Airbnb_Sydney$beds), breaks = 5, dig.lab = 1)
rCols <- brewer.pal(5, name = "Set1")
brCols <- rCols[beds_col]

plot(price_num~as.Date(Airbnb_Sydney$host_since, tryFormats = c("%m/%d/%y")),
```

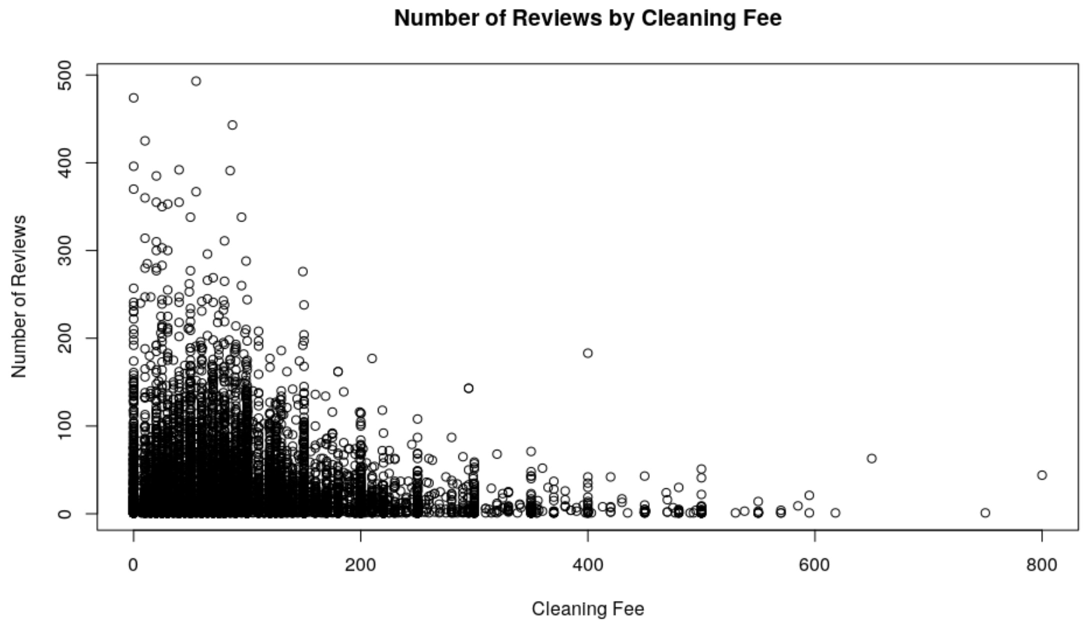
```
     col = brCols, pch = 18, cex = 0.5, main = "Listing Price by Host Since Y
ear",
      xlab = "Host Since Year", ylab = "Price per Night")
legend(legend =  c("Less than 6 beds","6-12 Beds", "12-17 Beds","17-23 Beds",
"23-29 Beds"), fill = rCols, "topleft")
```



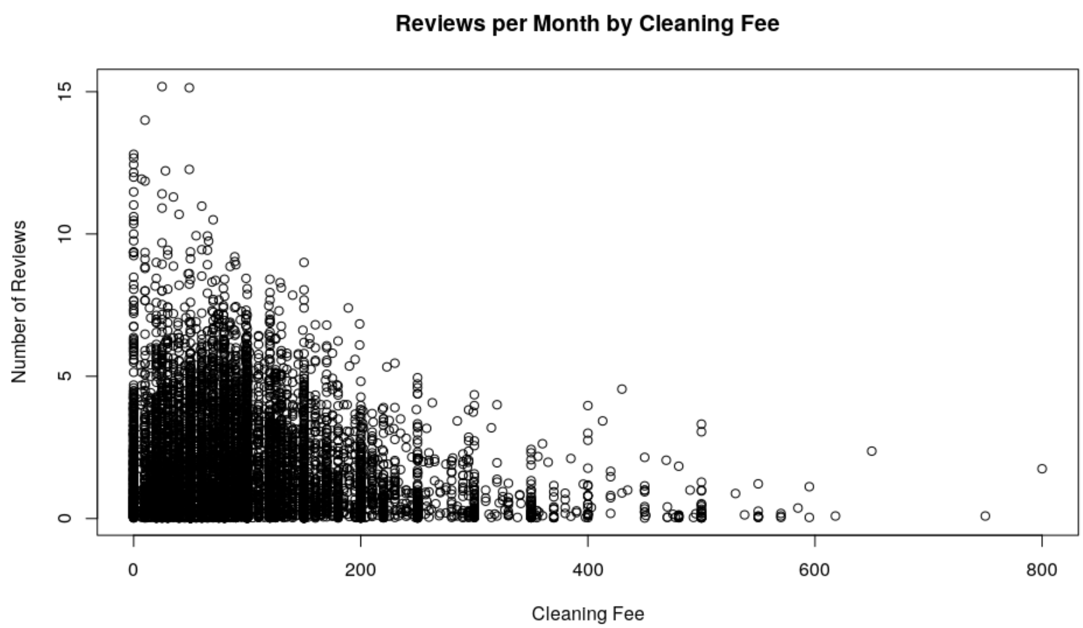
To explore my third hypothesis, I used scatterplots and a boxplot to explore how cleaning fees are related the number of bookings and review ratings for a listing. I hypothesized that listings with higher cleaning fees will have worse ratings.

The first and visual shows us that number of reviews by cleaning fee, and see can see the data is very skewed, with more reviews per month with less cleaning fees. There is a similar trend with the total number of reviews and cleaning fee. There is a steep drop in the number of reviews after 100 to 150 dollars. To look at this from another angle, I plotted property type by cleaning fee, and there are three property types that stand out in terms of cleaning fees- house, villa and apartment.

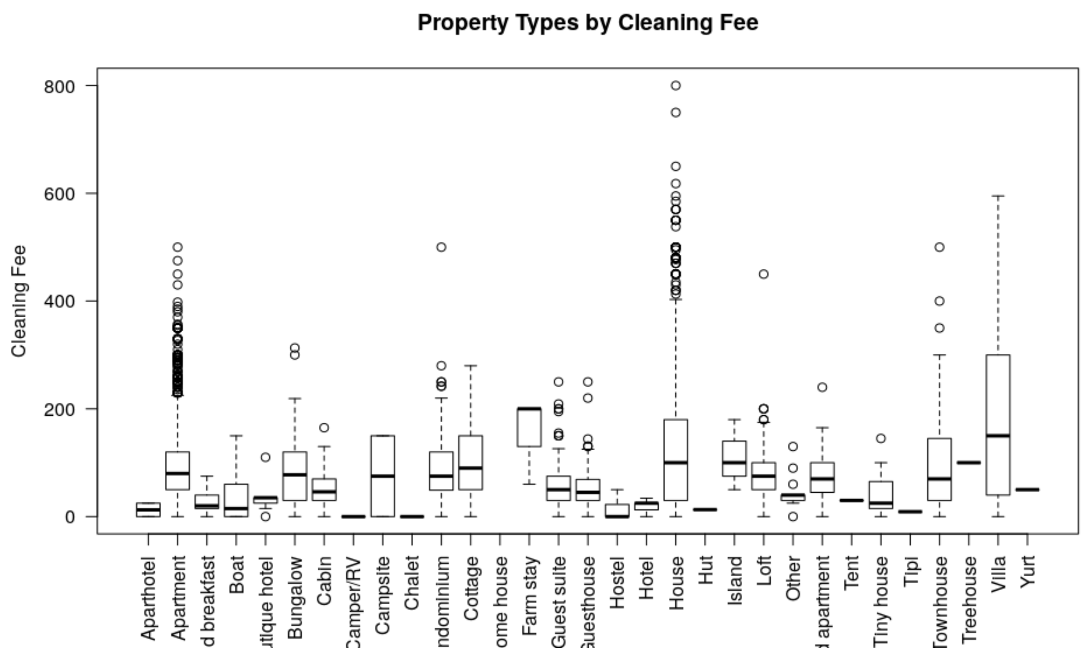
```
clean_num = as.numeric(gsub("[\\$]", "", Airbnb_Sydney$cleaning_fee), length(
2))
Airbnb_Sydney$clean_num = clean_num

plot(Airbnb_Sydney$number_of_reviews~clean_num, main = "Number of Reviews by
Cleaning Fee",
     xlab = "Cleaning Fee", ylab = "Number of Reviews")
```




```
plot(Airbnb_Sydney$reviews_per_month~clean_num, main = "Reviews per Month by
Cleaning Fee",
     xlab = "Cleaning Fee", ylab = "Number of Reviews")
```




```
plot(clean_num~as.factor(Airbnb_Sydney$property_type), las=2,
     main = "Property Types by Cleaning Fee",
     xlab = "", ylab = "Cleaning Fee")
```



Q7

7.1

I computed this step eariler. Here is the code again:

```
price_num = as.numeric(gsub("[\\$]", "", Airbnb_Sydney$price), length(2))

## Warning: NAs introduced by coercion

head(price_num)

## [1] 100 471 109 450 159  84
```

7.2

```
# convert to character
am_char = as.character.factor(Airbnb_Sydney$amenities)

# split on comma
am_char_split = strsplit(am_char,',')

# iterate over and get length for each item in list
am_length = lapply(am_char_split, length)
head(am_length)

## [[1]]
## [1] 29
##
## [[2]]
## [1] 20
##
```

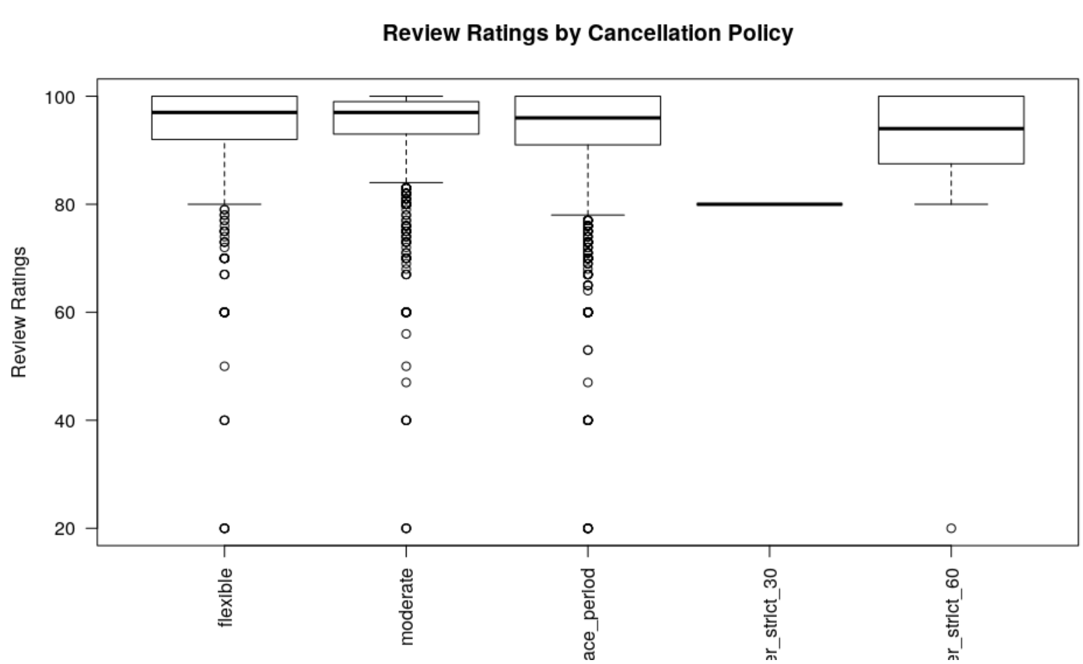
```
## [[3]]
## [1] 43
##
## [[4]]
## [1] 23
##
## [[5]]
## [1] 23
##
## [[6]]
## [1] 21

# add to dataframe
Airbnb_Sydney$am_length = I(am_length)
```

7.3

Below, I looked the average review score rating for each cancellation policy. The data is very skewed, with only a few values for the "strict 30 days" and "strict 60 days" categoies. We can see the ratings mean for the "strict 30 days" is the lowest at 80. The moderate, flexible and 14 day cancellation policy all have high review ratings between 93-95. This is further illustrated in the visual.

```
rev_cancel = Airbnb_Sydney[,c("review_scores_rating", "cancellation_policy",
"host_is_superhost")]

moderate = rev_cancel[rev_cancel$cancellation_policy=="moderate",]
flexible = rev_cancel[rev_cancel$cancellation_policy=="flexible",]
fourteen = rev_cancel[rev_cancel$cancellation_policy=="strict_14_with_grace_p
eriod",]
thirty = rev_cancel[rev_cancel$cancellation_policy=="super_strict_30",]
sixty = rev_cancel[rev_cancel$cancellation_policy=="super_strict_60",]

mod_mean = mean(moderate$review_scores_rating)
flex_mean = mean(flexible$review_scores_rating)
fourteen_mean = mean(fourteen$review_scores_rating, na.rm = T)
thirty_mean = mean(thirty$review_scores_rating)
sixty_mean = mean(sixty$review_scores_rating)

mod_mean

## [1] 95.00604

nrow(moderate)

## [1] 3314

flex_mean

## [1] 94.15888
```

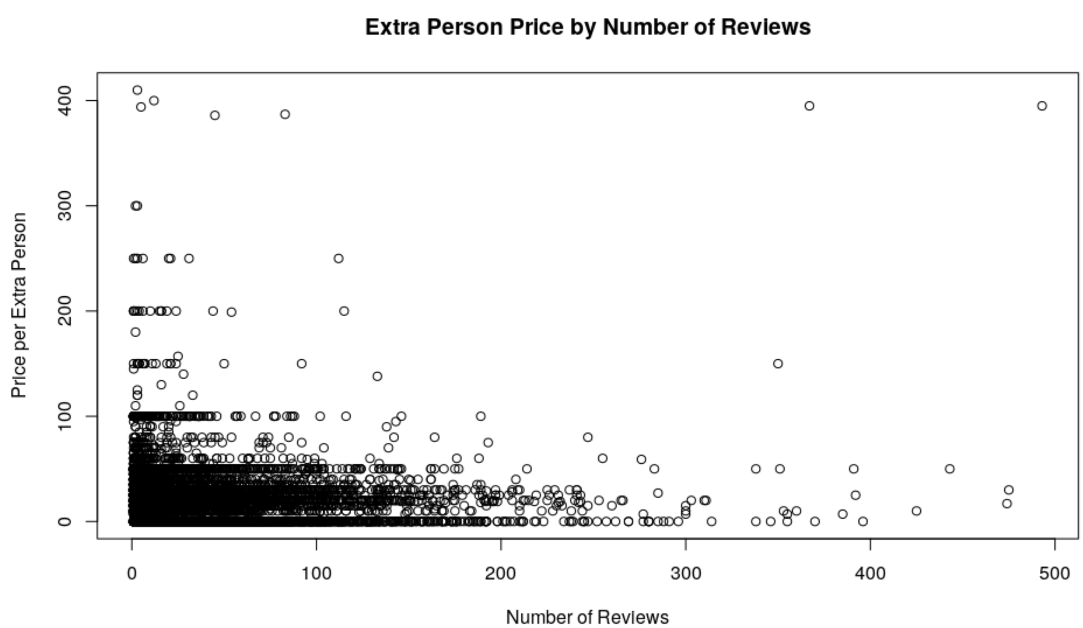
```
nrow(flexible)

## [1] 1391

fourteen_mean

## [1] 93.77102

nrow(fourteen)

## [1] 6089

thirty_mean

## [1] 80

nrow(thirty)

## [1] 1

sixty_mean

## [1] 89.8

nrow(sixty)

## [1] 20

plot(rev_cancel$review_scores_rating~rev_cancel$cancellation_policy, las=2, x
lab="", ylab = "Review Ratings",
     main = "Review Ratings by Cancellation Policy")
```



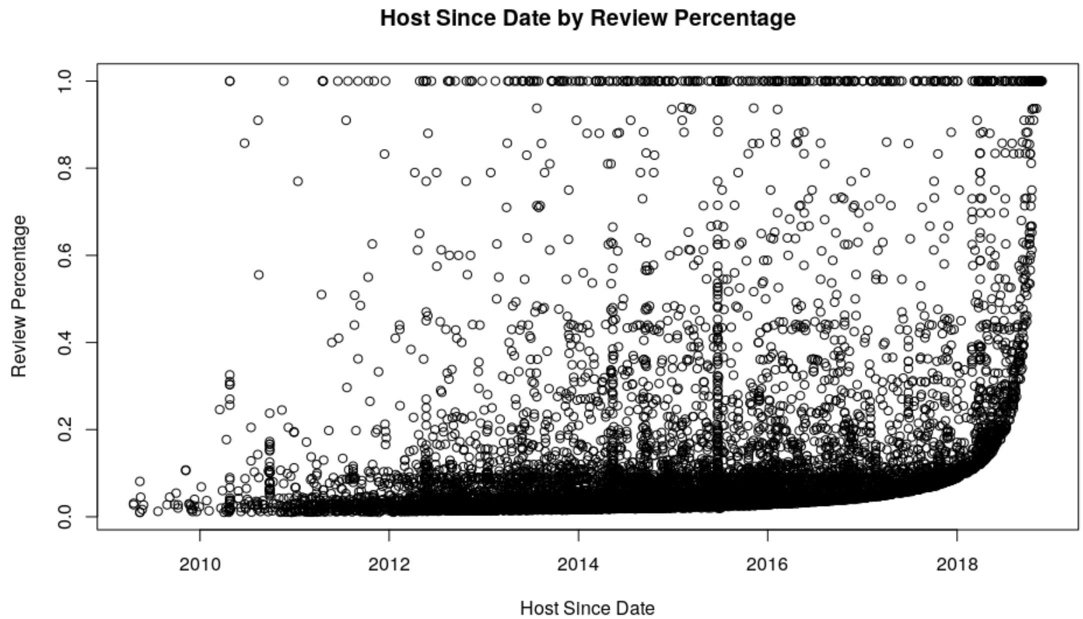
7.4

Below, I cleaned and plotted the extra people variable, which is the price to have one extra people stay one night at a listing. I looked at this variable in comparison to reviews per month divided by total number of reviews. I looked at a number of variables I cleaned to compare including cancellation polices and super hosts, host since data and reviews per month divided by total number of reviews, and extra person price by reviews per month divided by total number of reviews.

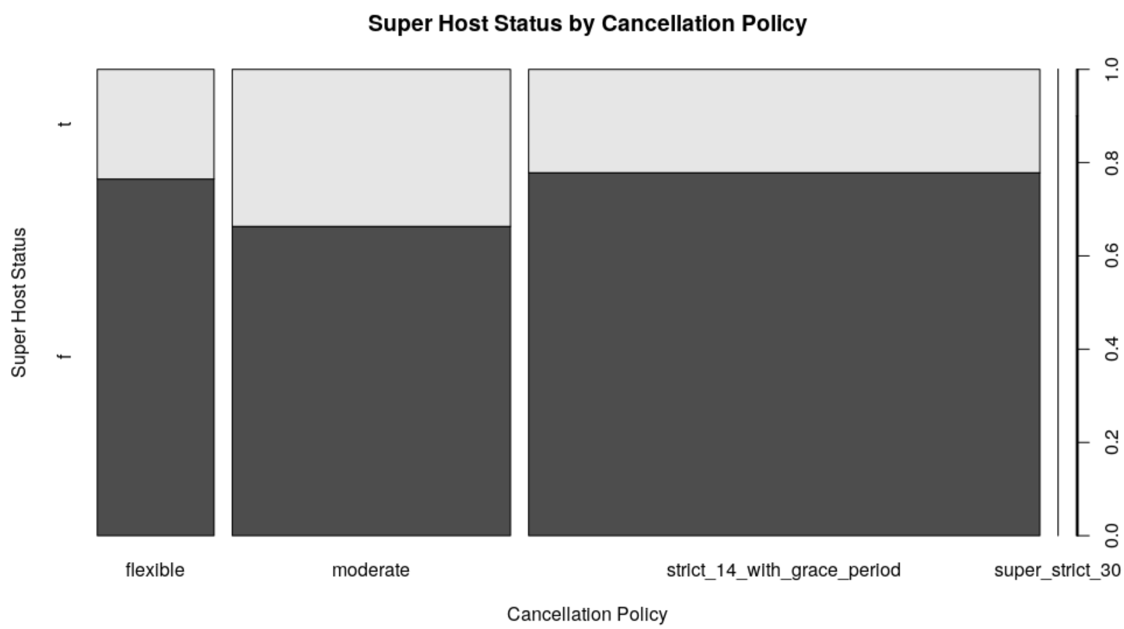
```
# clean extra person price and add to dataset
extra_num = as.numeric(gsub("[\\$]", "", Airbnb_Sydney$extra_people), length(
2))
Airbnb_Sydney$extra_num = extra_num

# add reviews per month divided by total number of reviews to dataset
Airbnb_Sydney$review_perc = Airbnb_Sydney$reviews_per_month/Airbnb_Sydney$num
ber_of_reviews

plot(Airbnb_Sydney$extra_num~Airbnb_Sydney$number_of_reviews, main = "Extra P
erson Price by Number of Reviews",
     ylab = "Price per Extra Person", xlab = "Number of Reviews")
```




```
plot(Airbnb_Sydney$review_perc~Airbnb_Sydney$host_data, main = "Host Since Da
te by Review Percentage",
     ylab = "Review Percentage", xlab = "Host Since Date")
```




```r
plot(rev_cancel$host_is_superhost~rev_cancel$cancellation_policy, main = "Sup
er Host Status by Cancellation Policy",
     ylab = "Super Host Status", xlab = "Cancellation Policy")
```



Q8

I chose reviews per month as my primary variable, which I think will offer more insights into possible buisness actions I can recommend. Reviews per month offers a snapshot of a listing's activity, and we can look at other variables in more detail with this as the predictor.

I examined price, number of amenities, number of host verifications, review ratings, the price of extra people, number of people a listing accommodates, cancellation policies, number of bathrooms, number of bedrooms, and the number of beds as possible response variables. I did find a possible positive relationship between the number of amenities and reviews per month, and a possible positive relationship between the number of people accommodated and reviews per month, in addition to the relationship I outline below.

Below, I've created a model to investigate a relationship between the reviews per month and the cleaning fees. The linear model shows that the residuals are not evenly distributed around the mean (or symmetrical), so the model points are far away from the actual points in some areas. So the model isn't an ideal fit. This could be an area for further investigation.

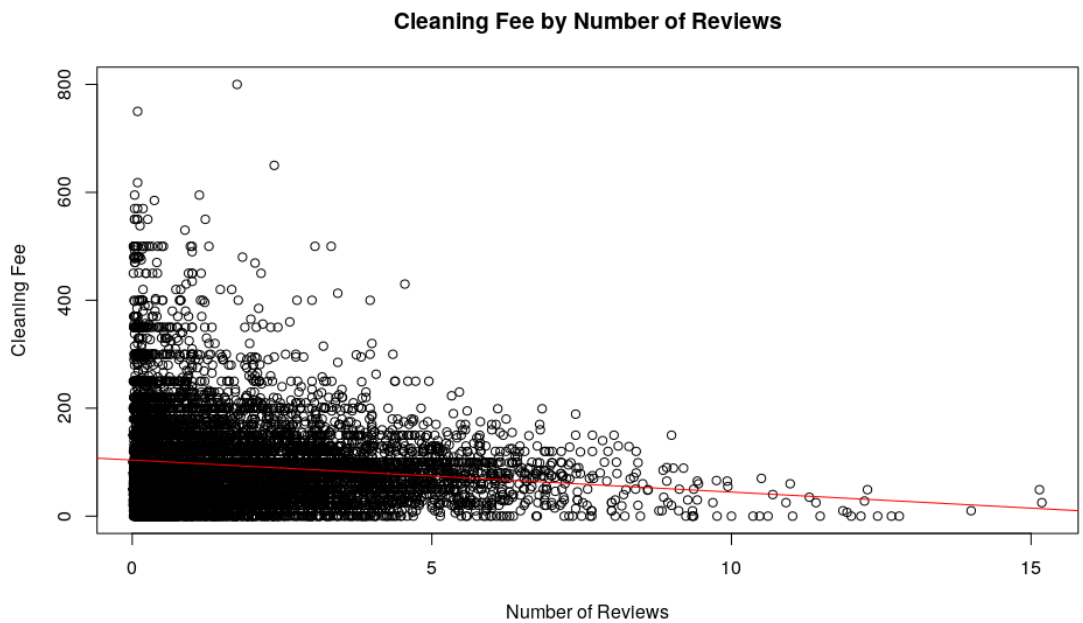
The model also shows that for the average number of reviews per month, there is a cleaning fee of roughly 103 dollars, and when the number of reviews per month increases by 1, the cleaning fee drops by roughly 5 dollars. So there is a possible negative relationship between cleaning fees and reviews per month.

We can see from the scatter plot and abline that there is a possible negative relationship. It's not an entirely linear relationship, as we can see there is a steep curve downward between 0-2 number of reviews. It appears that listings with high cleaning fees don't have a lot of reviews per month. This could be due to a number of reasons. High cleaning fees could belong to the more expensive properities which are rented less in general, or could be in locations that have less rentals.

According to the model, there is a statistically significant relationship here, as the p values are close to zero and below 5%.

```
clean_model = summary(lm(clean_num~Airbnb_Sydney$reviews_per_month))
clean_model

##
## Call:
## lm(formula = clean_num ~ Airbnb_Sydney$reviews_per_month)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -103.80  -53.51  -14.80   33.83  706.48
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     103.9219     1.0595   98.09   <2e-16 ***
## Airbnb_Sydney$reviews_per_month  -5.9414     0.4476  -13.27   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 79.21 on 10192 degrees of freedom
##   (621 observations deleted due to missingness)
```

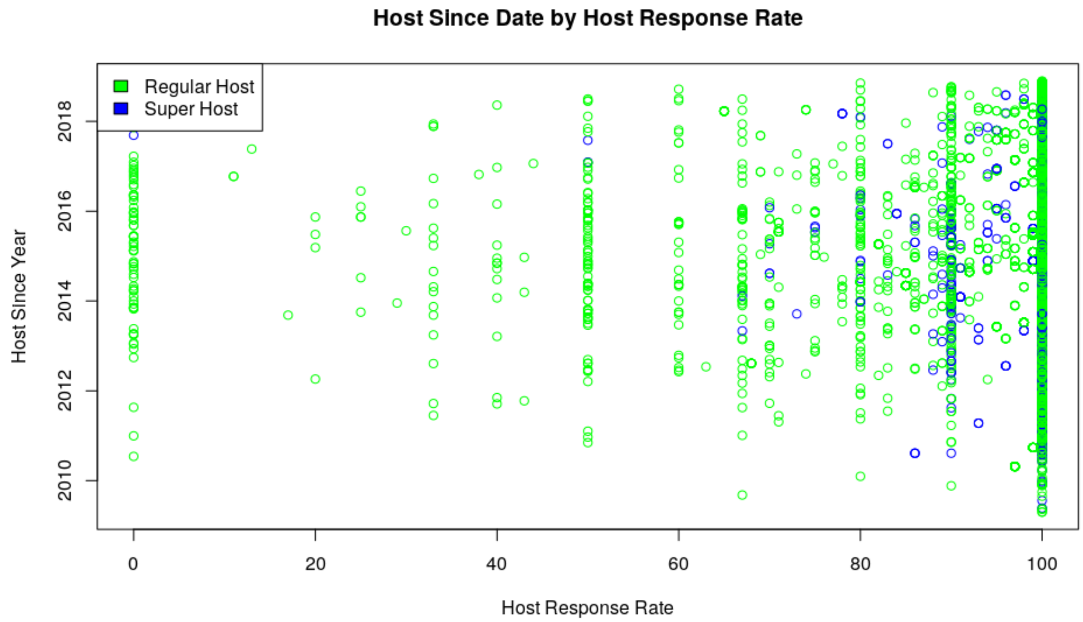
```
## Multiple R-squared:  0.01699,    Adjusted R-squared:  0.01689 
## F-statistic: 176.2 on 1 and 10192 DF,  p-value: < 2.2e-16

plot(clean_num~Airbnb_Sydney$reviews_per_month, main = "Cleaning Fee by Numbe
r of Reviews", ylab = "Cleaning Fee", xlab = "Number of Reviews")
abline(clean_model, col = "Red")

## Warning in abline(clean_model, col = "Red"): only using the first two of 8
## regression coefficients
```



Part 3

Q 9.1

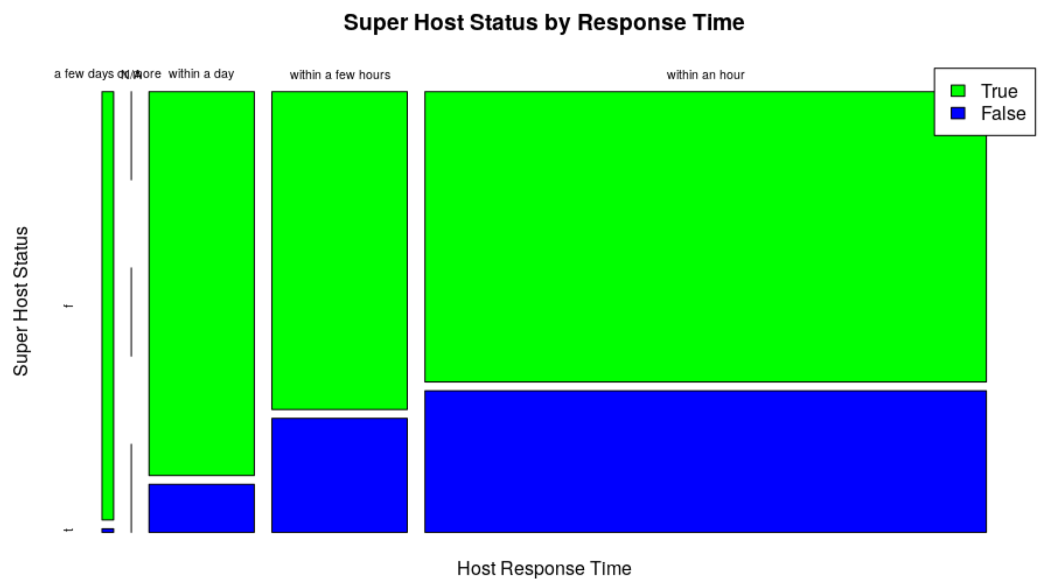
```
host_response_num = as.numeric(gsub("%", "", Airbnb_Sydney$host_response_rate
), length(2))

# look at host response rate by host since date, and super host status
colors = c("Green", "Blue")

plot(Airbnb_Sydney$host_data~host_response_num, col = colors[Airbnb_Sydney$ho
st_is_superhost],
     main = "Host Since Date by Host Response Rate", ylab = "Host Since Year"
, xlab = "Host Response Rate")
legend(legend = c("Regular Host", "Super Host"), fill= colors, "topleft")
```



9.2

From the mosaic plot below, we can see that super hosts tend to respond faster than regular hosts.

```
mosaicplot(table(Airbnb_Sydney$host_response_time,Airbnb_Sydney$host_is_super
host),
           color = c("Green", "Blue"), main = "Super Host Status by Response
Time",
           ylab = "Super Host Status", xlab = "Host Response Time")
legend(legend = c("True", "False"), fill = c("Green", "Blue"), "topright")
```



Q10

10.1

The top ten words suggest that aspects of the property are mentioned often, such as the type of property, rooms within the property, and the location of the property. Also proximity words such as 'walk' appear, also an indicator for importance of location.

```
# clean and split up description data
des = strsplit(gsub("[^[:alnum:] ]", "", Airbnb_Sydney$description), " +")
des_unique = length(unique(unlist(des)))

# make everything lower
des_lower = tolower(unlist(des))

# put into table and dataframe
des_freq = as.data.frame(table(des_lower))

stop_words = c("a", "able", "about", "across", "after", "all", "almost", "als
o", "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", "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", "on",
"only", "or", "other", "our", "own", "rather", "said", "say", "says", "she",
"should", "since", "so", "some", "than", "that", "the", "their",
"them", "then", "there", "these", "they", "this", "is", "to", "too", "was", "
```

```
us", "wants", "was", "we", "were", "what", "when", "where",
"which", "while", "who", "whom", "why", "will", "with", "would", "yet", "you"
, "your")

# remove stop words
top_des = as.data.frame(des_freq[!(des_freq$des_lower%in%stop_words),])

head(top_des[order(top_des$Freq, decreasing = T),], n=10L)

##       des_lower  Freq
## 2588  apartment 14622
## 23835      walk 10469
## 3851    bedroom 10176
## 21810    sydney  9657
## 19034      room  9544
## 13047   kitchen  9072
## 3616      beach  8855
## 3778        bed  8702
## 11756     house  7151
## 569           2  7137
```

10.2

The averages below show that lsitings with descriptions with the word 'beach' or 'beaches' in them are priced moderately higher than listings without those words in the description.

```
Airbnb_Sydney$price_num = price_num
# find words by subsetting and grep()
the_beach = Airbnb_Sydney[grep("beach", Airbnb_Sydney$description), c("host_i
d","price_num")]
the_beaches = Airbnb_Sydney[grep("beaches", Airbnb_Sydney$description), c("ho
st_id","price_num")]

# means
mean(the_beach$price_num, na.rm = T)

## [1] 218.986

mean(the_beaches$price_num, na.rm=T)

## [1] 216.5746

mean(Airbnb_Sydney$price_num, na.rm = T)

## [1] 189.3062

top_freq = function(input, word){
  # Find high frequency words in a dataset. Input is a vector and the string
to look for. Will return a row from a tabel with the word and the frequency.
  des = strsplit(gsub("[^[:alnum:] ]", "", input), " +")
  des_lower = tolower(unlist(des))
  des_freq = as.data.frame(table(des_lower))
```

```r
  top_des = as.data.frame(des_freq[!(des_freq$des_lower%in%stop_words),])
  word_freq = top_des[top_des$des_lower==word,]
  returnValue(word_freq)
}

# calling function

top_freq(Airbnb_Sydney$description, "apartment")

##      des_lower  Freq
## 2588 apartment 14622

top_freq(Airbnb_Sydney$description, "bed")

##      des_lower Freq
## 3778       bed 8702

row_freq = function(input, word){
  # function to indicate the frequency of a word in a list. Input is a list o
f vectors and the string to look for. Will return a list with integers to ind
icate the frequency of a word. ) means that word does not appear in that row.
  des = strsplit(gsub("[^[:alnum:] ]", "", input), " +")
  pattern = lapply(des, grep, pattern=word)
  lens = lapply(pattern, length)
  returnValue(lens)
}

head(row_freq(Airbnb_Sydney$description, "beach"))

## [[1]]
## [1] 0
##
## [[2]]
## [1] 3
##
## [[3]]
## [1] 0
##
## [[4]]
## [1] 0
##
## [[5]]
## [1] 0
##
## [[6]]
## [1] 1
```

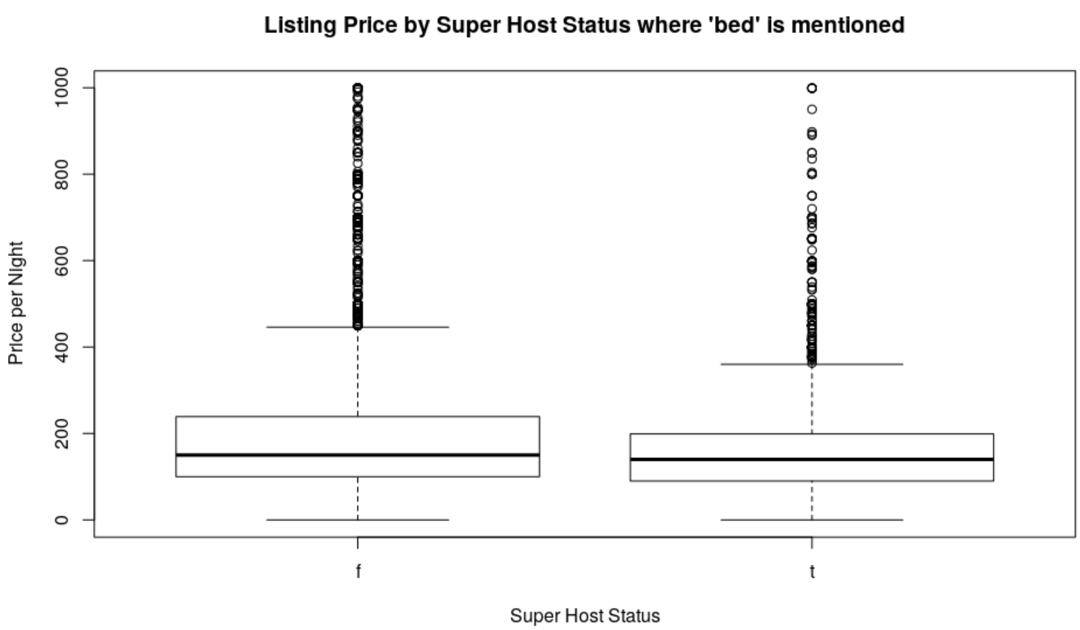
10.3

I looked the words ‘apartment’, ‘bed’, and ‘house’. I can see the average price of listings with those words differs quite a bit. I also compared this with super host status for further insight.

```
the_apt = Airbnb_Sydney[grep("apartment", Airbnb_Sydney$description),
                        c("host_is_superhost", "price_num")]
the_bed = Airbnb_Sydney[grep("bed", Airbnb_Sydney$description),
                        c("price_num", "host_is_superhost")]
sup_house = Airbnb_Sydney[grep("house", Airbnb_Sydney$description),
                          c("host_is_superhost", "price_num")]

mean(the_apt$price_num, na.rm = T)

## [1] 171.7812

mean(the_bed$price_num, na.rm = T)

## [1] 190.3527

mean(sup_house$price_num, na.rm = T)

## [1] 209.9777

mean(Airbnb_Sydney$price_num, na.rm = T)

## [1] 189.3062

plot(the_apt, main = "Listing Price by Super Host Status where 'Apartment' is
mentioned", xlab = "Super Host Status", ylab = "Price per Night")
```

```
plot(sup_house, main = "Listing Price by Super Host Status where 'House' is m
entioned", xlab = "Super Host Status", ylab = "Price per Night")
```


```
plot(as.numeric(the_bed$price_num)~the_bed$host_is_superhost, main = "Listing
Price by Super Host Status where 'bed' is mentioned", xlab = "Super Host Stat
us", ylab = "Price per Night")
```



10-2

10-2.1

I chose to look at cities, because I thought zipcodes would include a wider area, which could introduce more variability in the data. Cities seemed liked a good way to hold variables like price constant.

```
# Use for loop to get the number of host ids for each unique city name and ad
d to a dataframe
cities = data.frame()
for(i in unique(Airbnb_Sydney$city)){
  city_test = Airbnb_Sydney[Airbnb_Sydney$city==i, c("host_id")]
  city_len = length(Airbnb_Sydney[Airbnb_Sydney$city==i, c("host_id")])
  cities1 = data.frame("City" = i,city_len)
  cities = rbind(cities, cities1)
  returnValue(cities)
}

# print the top 100 cities with the most listings
head(cities[order(cities$city_len, decreasing = T),], n=100L)

##                     City city_len
## 7           Bondi Beach      555
## 49          Surry Hills      500
## 11               Sydney      463
## 73                Manly      389
## 3          Darlinghurst      373
## 16               Coogee      272
## 21                Bondi      222
## 79             Randwick      221
## 51              Redfern      206
## 27          Potts Point      198
## 6           North Bondi      191
## 39              Newtown      190
## 1              Pyrmont      178
## 60           Paddington      175
## 8               Mosman      167
## 48          Chippendale      155
## 19               Bronte      149
## 42       Bondi Junction      142
## 68             Maroubra      139
## 36             Waterloo      131
## 107        Avalon Beach      118
## 32               Ultimo      115
## 13        Elizabeth Bay      101
## 116              Mascot       95
## 44                Glebe       93
## 86              Zetland       93
## 184           Haymarket       92
```

```
## 46         Marrickville       90
## 188 Sydney Olympic Park       89
## 37           Camperdown       88
## 23         Erskineville       87
## 9            Alexandria       83
## 63            Fairlight       83
## 4               Balmain       79
## 93           Leichhardt       76
## 83            Annandale       75
## 62             Clovelly       72
## 66             Tamarama       72
## 75             Rose Bay       69
## 41        Bellevue Hill       67
## 40              Rozelle       66
## 5          North Sydney       65
## 90      Rushcutters Bay       64
## 29            Woollahra       63
## 18          Neutral Bay       62
## 56        Woolloomooloo       60
## 64             Rosebery       59
## 119          Freshwater       59
## 71           Palm Beach       57
## 2             Balgowlah       56
## 85             Waverley       52
## 112            Cronulla       50
## 121        Forest Lodge       50
## 251           Chatswood       50
## 22              Newport       49
## 31           Kirribilli       49
## 50             Cremorne       48
## 77             Vaucluse       46
## 137             Dee Why       46
## 179            Ashfield       46
## 30           Double Bay       43
## 92            Arncliffe       43
## 316         Wolli Creek       43
## 84        Millers Point       39
## 204              Rhodes       36
## 69           Kensington       35
## 94          Queenscliff       35
## 142         Strathfield       35
## 143             Burwood       35
## 148           Kingsford       35
## 105          Birchgrove       34
## 122        Dulwich Hill       34
## 53             Stanmore       33
## 70           Darlington       32
## 91            Lilyfield       32
## 34        Darling Point       31
## 76           Crows Nest       31
```

```
## 136           Mona Vale       30
## 320          Parramatta       30
## 178            Cammeray       28
## 172   Brighton-Le-Sands       27
## 123          Manly Vale       26
## 129      Wollstonecraft       26
## 113            Bundeena       25
## 132           Edgecliff       25
## 195      North Balgowlah      25
## 196                Ryde       25
## 57      Lane Cove North       24
## 89               Enmore       24
## 104           Narrabeen       24
## 158       McMahons Point      24
## 96            Petersham       23
## 45            Drummoyne       22
## 166            Lewisham       22
## 321      Wentworth Point      22
## 378           Bankstown       22
## 10               Avalon       21
## 97          Queens Park       21
## 111           Roseville       20
## 98           Sans Souci       19
```

```
# calculate weighted means by multiplying the number of reviews by review rat
ings
weighted = Airbnb_Sydney$number_of_reviews*Airbnb_Sydney$review_scores_rating

# add to dataframe
Airbnb_Sydney$weigted = weighted

# subset for certain columns
weight = Airbnb_Sydney[,c("host_id","weigted","city")]

# aggregate data by city and get mean, print top 100
head(aggregate(weight[2], by=list(weight$city), mean), n=100L)
```

```
##                              Group.1    weigted
## 1                                     3463.7500
## 2                  • Darling harbour   637.0000
## 3                        Abbotsford  1201.8750
## 4                       Agnes Banks  1500.0000
## 5                        Alexandria  2340.7470
## 6                       Alexandria   3648.0000
## 7                  Allambie Heights  5078.9091
## 8                           Allawah  1020.0000
## 9                   Allawah/Carlton  3267.0000
## 10                        Annandale  2520.6533
## 11                          Arcadia   843.0000
## 12                        Arncliffe  5755.6279
```

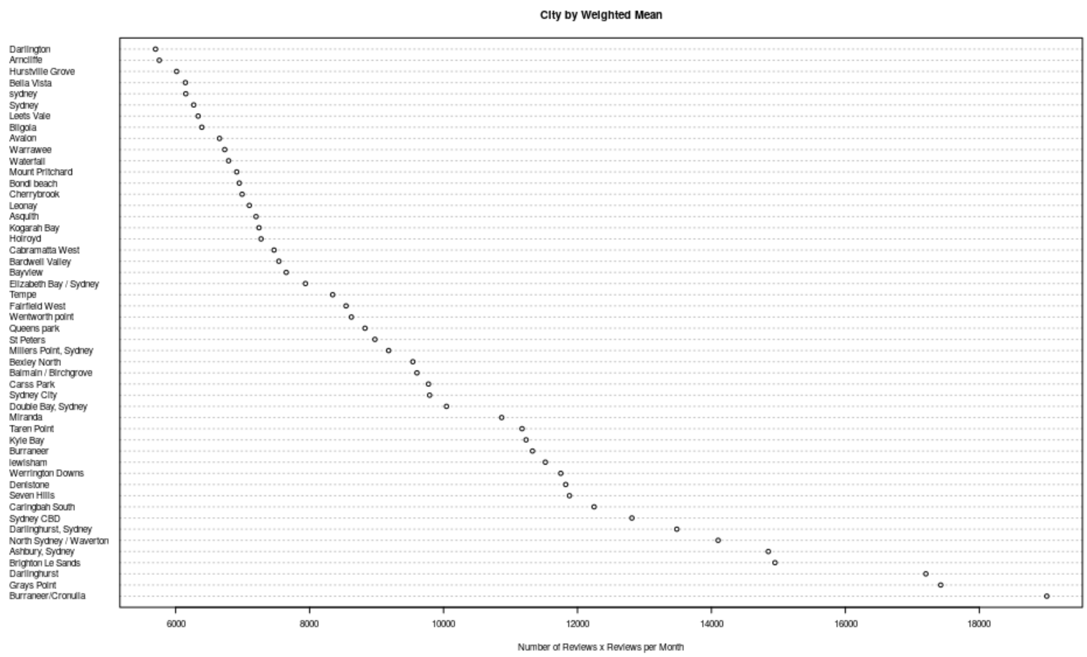
```
## 13                           Artarmon  1329.7143
## 14                    Ashbury, Sydney 14850.0000
## 15                          Ashfield  1690.9565
## 16     Ashfield, New South Wales, AU   651.0000
## 17                           Asquith  7200.0000
## 18                            Auburn  3999.0000
## 19                           Auburn   1692.0000
## 20                 Auburn / Lidcomb    582.0000
## 21                            Avalon  6654.8095
## 22                      Avalon Beach  3073.3644
## 23                         Balgowlah  1228.1786
## 24                 Balgowlah Heights  1237.8333
## 25                           Balmain  2605.7595
## 26              Balmain / Birchgrove  9603.0000
## 27                      Balmain East  2640.1667
## 28                    Balmoral Beach   422.0000
## 29                            Bangor  2570.5000
## 30                           Banksia   682.6667
## 31                    Banksia Sydney   200.0000
## 32                         Bankstown  1356.9545
## 33                         Bar Point  1000.0000
## 34                        Barangaroo  2466.5000
## 35                            Bardia   810.0000
## 36                   Bardwell Valley  7541.3333
## 37                         Barpoint    300.0000
## 38                    Baulkham Hills  2258.2857
## 39                           Bayview  7651.3333
## 40                       Beacon Hill  1978.7857
## 41                      Beaconsfield  3864.0769
## 42                    Beaumont Hills  2718.0000
## 43                          Beecroft  1255.5000
## 44                          Belfield   692.0000
## 45                       Bella Vista  6145.7143
## 46                     Bellevue Hill  1484.3433
## 47  Bellevue Hill (Double Bay side).  1372.0000
## 48             Bellevue Hill, Sydney   200.0000
## 49                           Belmore   861.7500
## 50                            Berala   742.6000
## 51                     Berowra Creek   300.0000
## 52                   Berowra Heights  2857.0000
## 53                    Berowra Waters  1504.0000
## 54                     Beverly Hills  3433.2000
## 55                            Bexley  3461.5000
## 56                      Bexley North  9541.6667
## 57                           Bilgola  6390.5000
## 58                     Bilgola Beach  2243.5294
## 59                   Bilgola Plateau  1528.9375
## 60                   Bilgola, Sydney   375.0000
## 61                        Birchgrove  1556.2059
## 62                         Blacktown   613.5000
```

```
## 63                        Blair Athol   100.0000
## 64                         Blakehurst   919.0000
## 65                              Bondi  1960.8198
## 66                             Bondi    341.0000
## 67                        bondi beach  1700.0000
## 68                        Bondi Beach  2376.6883
## 69                       Bondi beach   6950.0000
## 70                Bondi Beach, Sydney   639.0000
## 71                     Bondi Junction  2065.4507
## 72                    Bondi Junction     80.0000
## 73              Bondi Junction Sydney  3977.0000
## 74             Bondi Junction, Sydney  3284.0000
## 75                    Bondi, Tamarama   712.0000
## 76                             Botany  1529.3571
## 77                    Breakfast Point   784.0000
## 78                  Brighton Le Sands 14949.0000
## 79                  Brighton-Le-Sands  1392.2963
## 80                             Bronte         NA
## 81                            Bronte    300.0000
## 82                           Brooklyn  4985.0000
## 83                          Brookvale   460.0000
## 84                           Bundeena  3212.0400
## 85                        Bungarribee  1140.0000
## 86                          Burraneer 11328.0000
## 87                  Burraneer/Cronulla 19008.0000
## 88                            Burwood  1461.1143
## 89                           Cabarita   180.0000
## 90                         Cabramatta  1343.6667
## 91                    Cabramatta West  7469.0000
## 92                           Cammeray  2864.9643
## 93                        Campbelltown   869.0000
## 94                         camperdown  1316.0000
## 95                         Camperdown  1854.8068
## 96                            Campsie  1570.6000
## 97                         Canada Bay   100.0000
## 98                     Canley Heights   973.5000
## 99                         Canterbury  4982.0000
## 100                         Caringbah  1045.0000
```

From this graph we can see a clear downward trend when the cities are organized by weighted mean. We can see which cities have a high number of total reviews and reviews per month, and what that average is. This tells us which cities have the most sustained, overall activity.

```
# subet for a separate dataframe
city_df = Airbnb_Sydney[,c("city","number_of_reviews","review_scores_rating")
]

# calculate weighted means
m_w = city_df$number_of_reviews * city_df$review_scores_rating
```

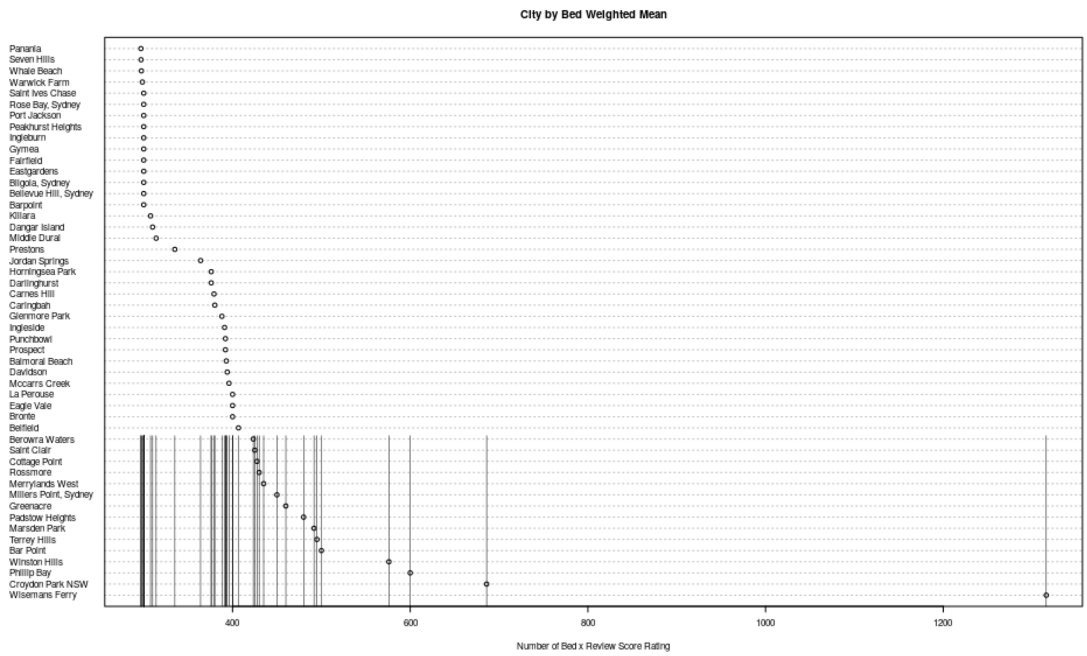
```r
city_df$weights = m_w

# use aggregate function
city_agg = aggregate(city_df$weights,
                     by=list(city = city_df$city),
                     mean)

city_100 =  head(city_agg[order(city_agg$x, decreasing = T),], n=50L)

dotchart(city_100$x, labels = city_100$city, cex = .5, main = "City by Weight
ed Mean", xlab = "Number of Reviews x Reviews per Month")
```



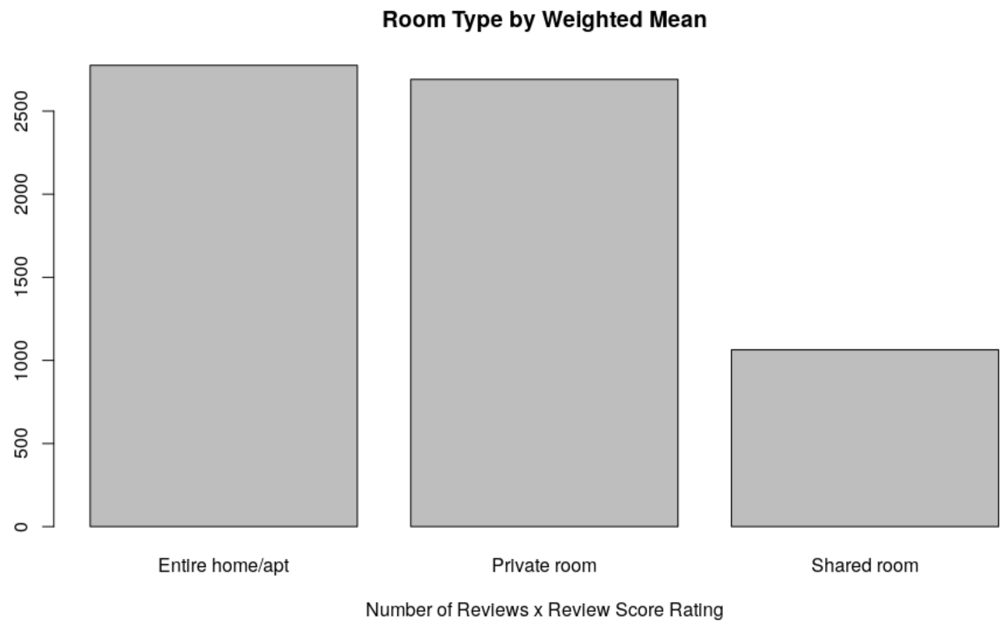
10-2.2

```r
city_beds = Airbnb_Sydney[,c("city","bedrooms","review_scores_rating")]


m_b = city_beds$bedrooms * city_beds$review_scores_rating
city_beds$weights = m_b

city_beds_agg = aggregate(city_beds$weights,
                     by=list(city = city_beds$city),
                     mean)

beds_100 =  head(city_beds_agg[order(city_beds_agg$x, decreasing = T),], n=50
L)

dotchart(beds_100$x, labels = beds_100$city, cex = .5, main = "City by Bed We
ighted Mean", xlab = "Number of Bed x Review Score Rating")
```

```
rug(beds_100$x, ticksize = 0.3)
```




```
rooms = Airbnb_Sydney[,c("room_type","number_of_reviews","review_scores_ratin
g")]

r_r = rooms$number_of_reviews * rooms$review_scores_rating
rooms$weights = r_r

rooms_agg = aggregate(rooms$weights,
                          by=list(room_type = rooms$room_type),
                          mean, na.rm =T)

barplot(rooms_agg$x, names.arg = rooms_agg$room_type, main = "Room Type by We
ighted Mean", xlab = "Number of Reviews x Review Score Rating")
```

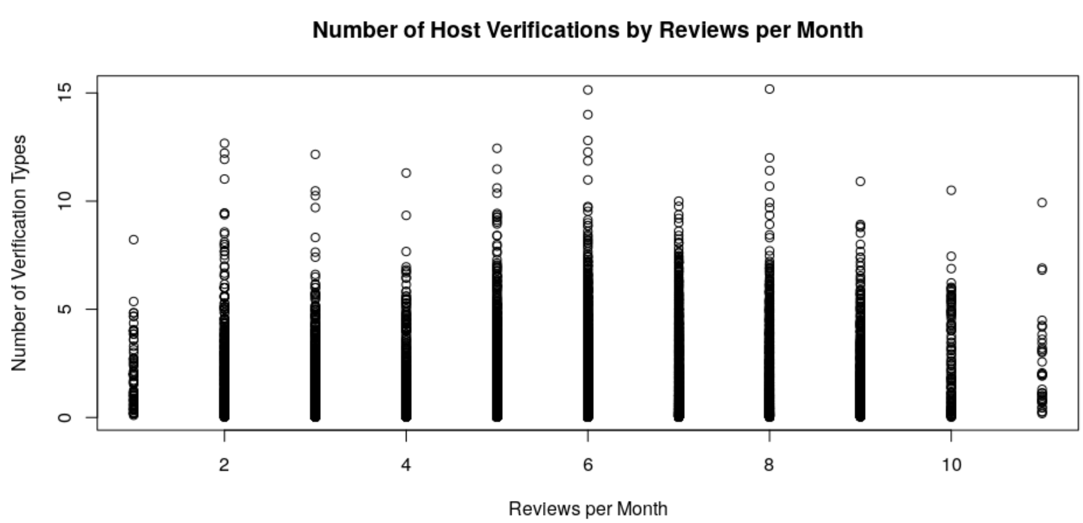


Part 4

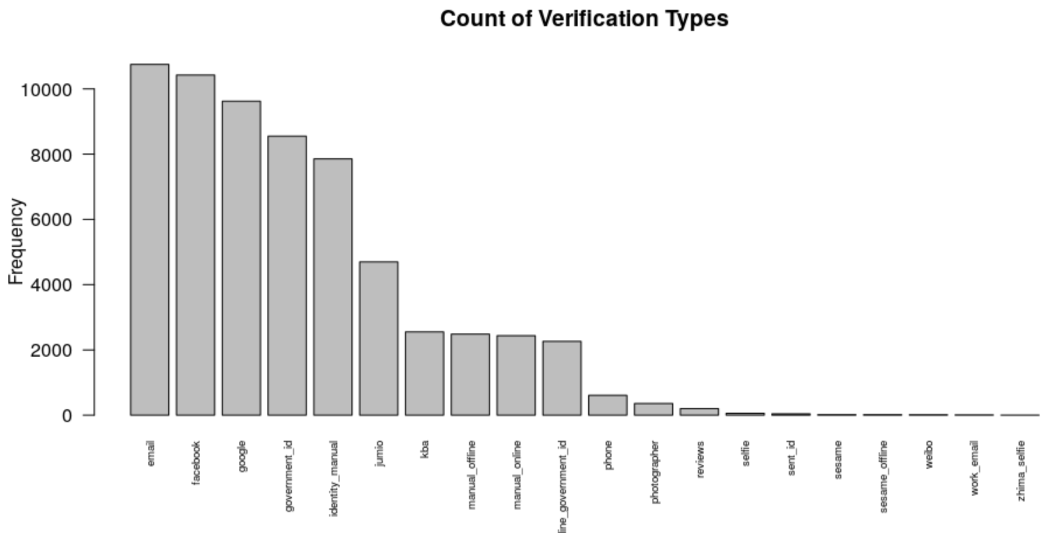
Below, I looked at the host verfication information for further insights. I split and cleaned verification information and plotted super host information and reviews per month. I also looked at a possbile linear relationship between the number of host verifications and reviews per month, and saw a positive relationship. We can also see some verification types are used way more than others, and that super hosts tend to have more types of verfication.

```
# convert and split host verification
ver_char = as.character.factor(Airbnb_Sydney$host_verifications)
ver_char_split = strsplit(ver_char,',')

# get number of verfications, assign to dataframe
ver_length = lapply(ver_char_split, length)
Airbnb_Sydney$ver_length = I(ver_length)

# clean data

ver_sub1 = gsub("^[\\[']", "", unlist(ver_char_split))

ver_sub2 = gsub("\\']", "", ver_sub1)

ver_sub3 = gsub(" '", "", ver_sub2)

ver_sub4 = gsub("'","", ver_sub3)

ver_sub5 = gsub("]", NA, ver_sub4)
```

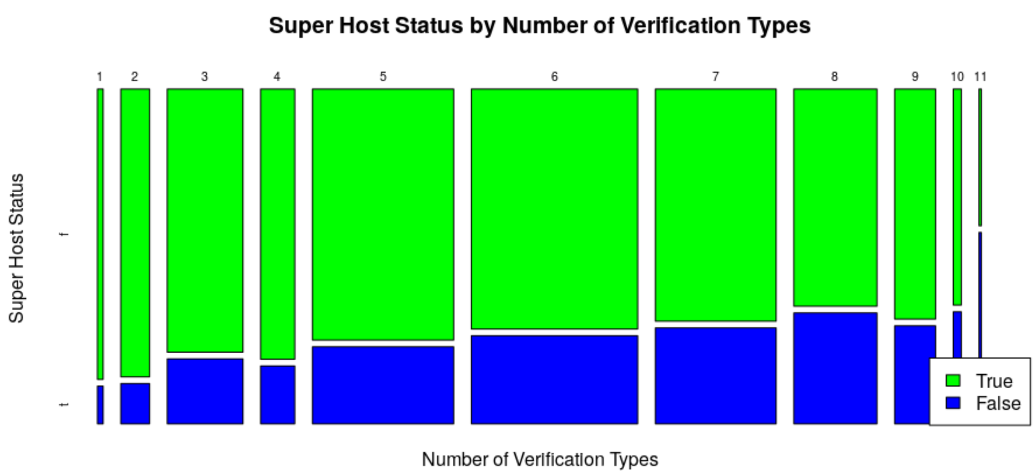
```
ver_df = as.data.frame(table(ver_sub5))

# fit linear model

summary(lm(as.numeric(Airbnb_Sydney$ver_length)~Airbnb_Sydney$reviews_per_mon
th))

##
## Call:
## lm(formula = as.numeric(Airbnb_Sydney$ver_length) ~ Airbnb_Sydney$reviews_
per_month)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5153 -0.8509  0.2101  1.2769  5.3239
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      5.65729    0.02446  231.30   <2e-16 ***
## Airbnb_Sydney$reviews_per_month  0.10439    0.01042   10.02   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.89 on 10813 degrees of freedom
## Multiple R-squared:  0.009204,   Adjusted R-squared:  0.009112
## F-statistic: 100.4 on 1 and 10813 DF,  p-value: < 2.2e-16

# plot linear model
plot(Airbnb_Sydney$reviews_per_month~as.numeric(Airbnb_Sydney$ver_length), ma
in = "Number of Host Verifications by Reviews per Month",
     xlab = "Reviews per Month", ylab = "Number of Verification Types")
```



```r
# plot number of verification type counts

barplot(ver_df$Freq[order(ver_df$Freq, decreasing = T)], names.arg = ver_df$v
er_sub5, las =2,
        main = "Count of Verification Types", ylab = "Frequency", cex.names =
0.6)
```




```r
# plot number of verification types by super host status

mosaicplot(table(as.numeric(Airbnb_Sydney$ver_length),Airbnb_Sydney$host_is_s
uperhost),
           color = c("Green", "Blue"), main = "Super Host Status by Number of
Verification Types",
           ylab = "Super Host Status", xlab = "Number of Verification Types")
legend(legend = c("True", "False"), fill = c("Green", "Blue"), "bottomright")
```



I also used a function to get the percentage of times a certain verification type was used in the dataset. We can see that percentage really high for email, phone, and facebook verification types.

```
ver_f = function(text){
  # this function take in a string of text to search verfification types and
a variable name to subset with
  # it returns the percentage of time a verification type was mentioned
  input = grepl(text, Airbnb_Sydney$host_verifications)
  yes_input = Airbnb_Sydney$host_verifications[input]
  len_input = round(length(yes_input)/length(Airbnb_Sydney$host_verifications
), 3)
  print(len_input)
}

ver_f("email")

## [1] 0.967

ver_f("phone")

## [1] 0.994

ver_f("government_id")

## [1] 0.791

ver_f("facebook")

## [1] 0.209

ver_f("reviews")

## [1] 0.89

ver_f("work_email")

## [1] 0.225

ver_f("jumio")

## [1] 0.726
```

Part 5

My analysis focused on the verfication types, price, property types, super host, cleaning fees, review ratings, and number of reviews. I found a number of interesting patterns: 1. Super hosts tend to have more vertification types listed. They also appear to respond faster to customer inquires than regular hosts. Super hosts also had a higher response rate, with the lowest response rate at about 63 percent. So, is it worth it to be a superhost? When comparing price and superhost status, there does not seem to be a significant difference- the average and range are roughly the same. When comparing reveiw ratings and super host status, super host do have a higher average, a higher number of reviews, and more reviews per month. Also, when looking at super host status and different description words, such as 'house', there is a small difference in price. A business action could be taken to encourage or incentivize regular hosts to upgrade to super hosts to increase traffic and reviews. 2. Additional costs and rules such as cancellation policies and cleaning fees had an effect on the number of reviews on listing. It appears there were fewer total reviews for listings that charged extra or were stricter on policies. Even a moderate increase in cleaning fees was associated with less reviews. It could also be that listings with higher cleaning fees were also more expensive, or rented less for other reasons. However, higher charges for extra people also led to less reviews overall. A business action to address this could include encouraging hosts to roll cleaning prices into the overall price, or allowing no extra people. Any way to reduce the number of extra costs would be a good action to take. 3. Location and property types significantly affected how often a listing is rented. Certain cities and property types where listed way more than others. Even location or property specific words in the listing description contributed to a difference in review numbers and ratings. I would recommend that hosts use certain words to attract more customers in their description. 4. Having extra perks, such as amenities, increased business. A higher number of amenities led to more reviews. I would encourage hosts to list all possible amenities in a listing to attract more buisness and reviews.

A general issue I struggled with was the skew of the data. The number of reviews and reviews per month was highly skewed, making it difficult to detect trends and find conclusions. The property type variable was also drastically skewed, with the vast majority of properities being apartments. This is reflected in my analysis and visualizations.

Part 6

Throughout this project, I iterated over the six divisions of data science to extract as much information as possible from a secondary dataset to generate insights from the data. There were some steps that I iterated over more than others, and that includes the data exploration step. After reading the data in as a csv file, I got some basic information about the data and then started to look at individual columns. The 50 Years of Data Science article mentions that data exploration is about 80% of the work, and that felt accurate while working with this dataset. I looked at many columns individually to understand their class, missing elements, and potential for insight. To get a better understanding of the data, I created several plots to look at the distribution of individual variables, and also to take a look at descriptive statistics with different variable combinations. This helped me determine the depth and richness of the information, provided hints at what to expect in the analysis phase, and highlighted what data needed to be cleaned. Hypothesis were formed at the conclusion of the data exploration phase. The data representation and transformation process for this project was simple- we worked with a csv file and did not have to do anything complicated to read it in, or to start exploring. The computing with data step was also a non-issue with this project because we just used R, and didn't combine any other computing methods or sources. I started the data cleaning process with some obvious fixes such as removing the dollar sign from price and converting the host_since variable to a proper date format. I also cleaned several of the character and list variables to do text analysis. This phase also required going back and reviewing my data explortion phase to decide what columns to focus on and what classes they needed to be. Cleaning the data allowed me to aggregate and group the data to start looking for potential relationships between variables. The data analysis phase followed next to further investigate potential relationships, with more data visualization to illustrate what was found. This was part of the data visualization and presentation phase of the lifecycle. After compiling the analysis, I created visuals to show the nature of the relationships I found and to show trends in the data. This phase included raw numbers from the analysis and data visualizations. The data modeling phase was touched on briefly in this project as we did some basic statistics. This analysis leaned toward the generative analysis side of things and not so much predictive analysis. The last division, science of data science, we left out of this project. Although there is potential to look at how I understood, cleaned, analyzed and visualized this data, we did not do this here. This project required me to keep the whole project and goal in mind even as I was working on individual parts of the project. As a result, I continued to go back and work on previous steps, and slowly came to conclusions after much tweaking. I did the project in the WholeTale tool to work in a virtual environment and have a reproducable product at the end of the class. I did my best to record my data lifecycle process by documenting my findings and by adding plenty of comments in my code, to illustrate my workflow. To me, the data science lifecycle is a constant practice of the science of science, and I added to it by processing this secondary dataset for insights but also by putting forth my own workflow and methods.