Exploratory Data Analysis for Airbnb in Paris, France*

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We gather Airbnb Data from Paris for analysis from Cox (2021). Code for this EDA is based on `Telling Stories with Data` Alexander (2023).

1 Data

The whole dataset is at 96MB, so we will create a parquet file with the variables we want.

```
airbnb_data <- read_csv("data/airbnb_data.csv", show_col_types = FALSE)

airbnb_data_selected <-
  airbnb_data |>
  select(
    host_id,
    host_response_time,
    host_is_superhost,
    host_total_listings_count,
    neighbourhood_cleansed,
    bathrooms,
    bedrooms,
    price,
    number_of_reviews,
    review_scores_rating,
    review_scores_accuracy,
    review_scores_value
  )
```

*Code and data are available at: https://github.com/alainahu/mini_essay8.

```r
write_parquet(
  x = airbnb_data_selected,
  sink =
    "2023-12-12-paris-airbnblistings-select_variables.parquet"
  )

rm(airbnb_data)
```

2 Distribution and Properties of Individual Variables

An important aspect of Airbnb data is price. Here we look at the distribution and properties of prices of Airbnbs in Paris. First, we need to clean and organize the data for prices in a way that it can be analyzed.

```r
airbnb_data_selected$price |>
  head()
```

```
[1] "$150.00" "$146.00" "$110.00" "$140.00" "$180.00" "$71.00"
```

```r
airbnb_data_selected$price |>
  str_split("") |>
  unlist() |>
  unique()
```

```
 [1] "$" "1" "5" "0" "." "4" "6" "8" "7" "3" "2" "9" NA  ","
```

```r
airbnb_data_selected |>
  select(price) |>
  filter(str_detect(price, ","))
```

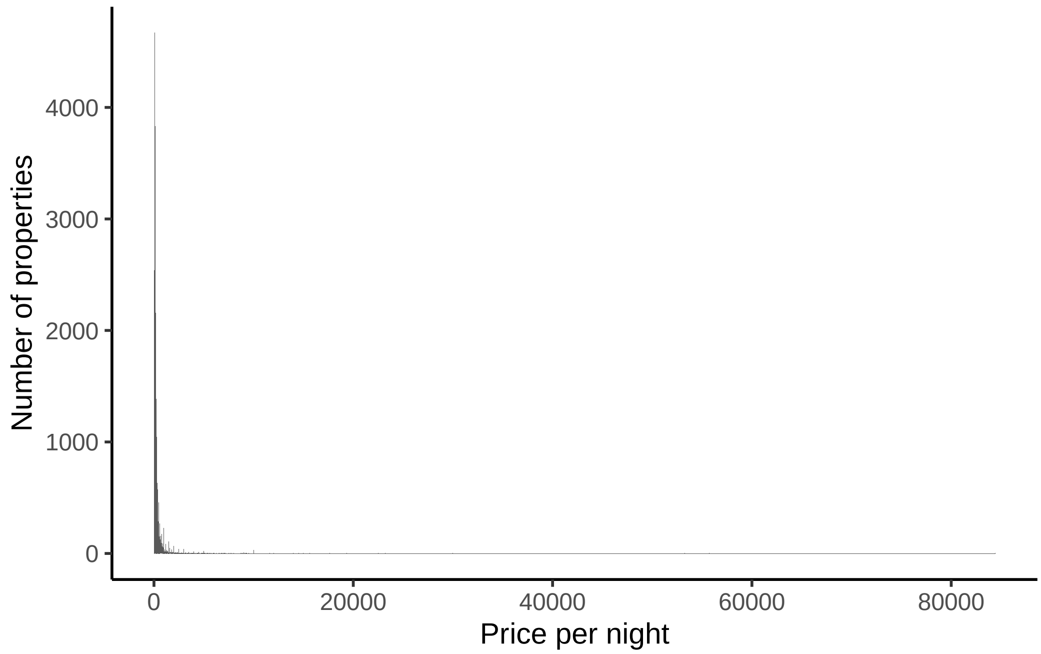
```
# A tibble: 1,550 x 1
   price
   <chr>
 1 $1,200.00
 2 $8,000.00
 3 $7,000.00
 4 $1,997.00
```

```
 5 $1,000.00
 6 $1,286.00
 7 $2,300.00
 8 $1,500.00
 9 $1,200.00
10 $1,357.00
# i 1,540 more rows
```

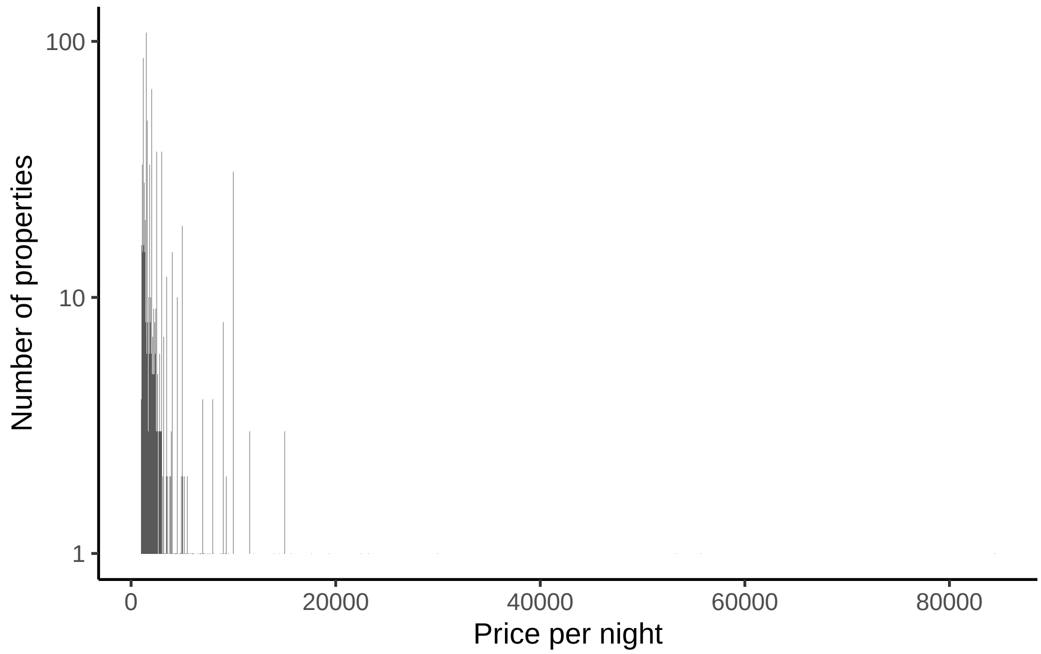
```
airbnb_data_selected <-
  airbnb_data_selected |>
  mutate(
    price = str_remove_all(price, "[\\$,]"),
    price = as.integer(price)
  )
```

Now that the values have been formatted in a way that can be plotted. We look at the distribution of prices. Since the prices are likely to be skewed and have outliers, we use the log scale for prices.

```
airbnb_data_selected |>
  ggplot(aes(x = price)) +
  geom_histogram(binwidth = 10) +
  theme_classic() +
  labs(
    x = "Price per night",
    y = "Number of properties"
  )
```

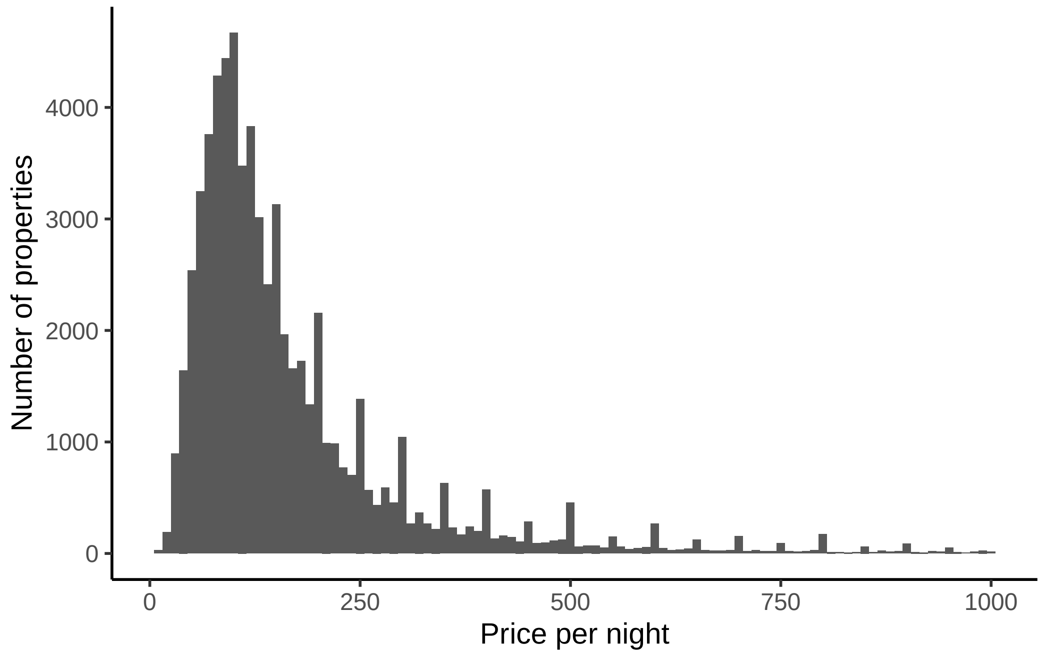



```
airbnb_data_selected |>
  filter(price > 1000) |>
  ggplot(aes(x = price)) +
  geom_histogram(binwidth = 10) +
  theme_classic() +
  labs(
    x = "Price per night",
    y = "Number of properties"
  ) +
  scale_y_log10()
```

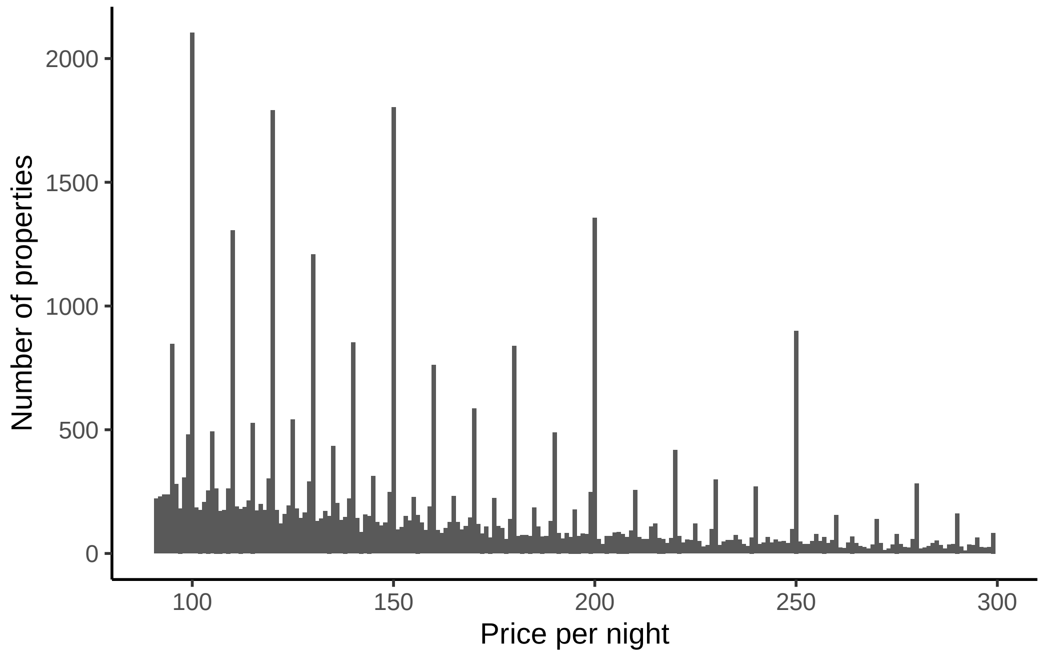


To zoom in, we look at prices that are less than $1000. From this, we can see that most prices are less than $300.

```
airbnb_data_selected |>
  filter(price < 1000) |>
  ggplot(aes(x = price)) +
  geom_histogram(binwidth = 10) +
  theme_classic() +
  labs(
    x = "Price per night",
    y = "Number of properties"
  )
```




```r
airbnb_data_selected |>
  filter(price > 90) |>
  filter(price < 300) |>
  ggplot(aes(x = price)) +
  geom_histogram(binwidth = 1) +
  theme_classic() +
  labs(
    x = "Price per night",
    y = "Number of properties"
  )
```



We will remove all prices greater than $999.

```
airbnb_data_less_1000 <-
  airbnb_data_selected |>
  filter(price < 1000)
```

From these listings that are less than or equal to $999, we are interested in seeing if the hosts of these listings are superhosts. On Airbnb, superhosts are especially experienced hosts, and hosts are either a superhost or not a superhost.

```
airbnb_data_less_1000 |>
  filter(is.na(host_is_superhost))
```

```
# A tibble: 83 x 12
    host_id host_response_time host_is_superhost host_total_listings_count
      <dbl> <chr>              <lgl>                                 <dbl>
 1 29138344 within an hour     NA                                        3
 2  5869840 within a few hours NA                                        7
 3 35125972 within an hour     NA                                        3
 4 13827149 within a few hours NA                                        3
 5 62919059 within a few hours NA                                        3
 6 22167607 N/A                NA                                        2
 7 10259782 N/A                NA                                        2
```

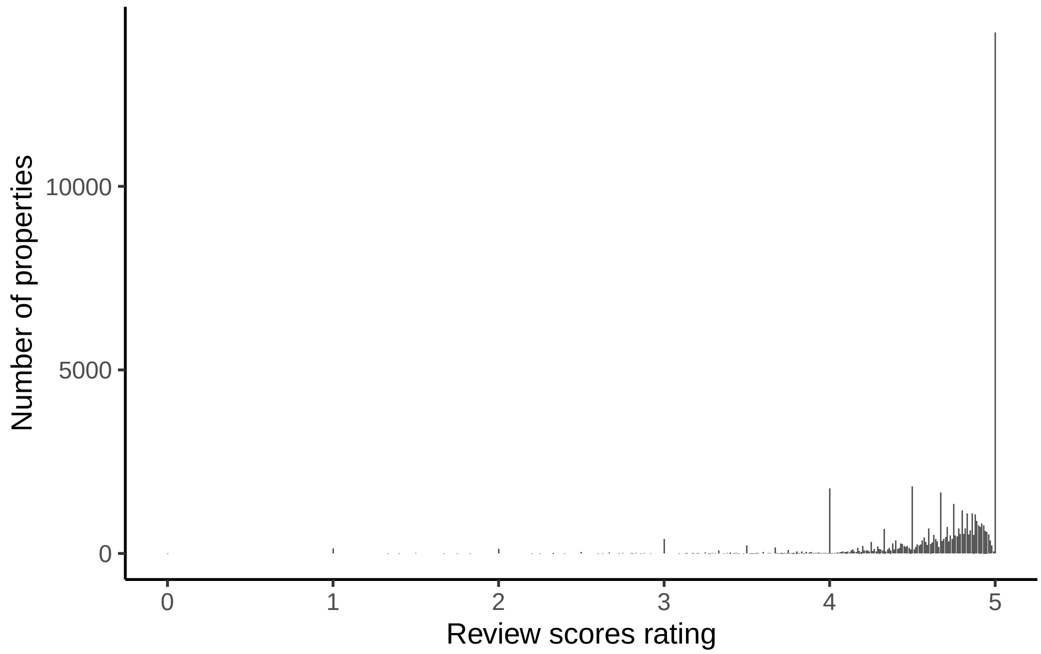
```
 8 62919059 within a few hours NA                                        3
 9 20056470 N/A                NA                                        4
10 20056470 N/A                NA                                        4
# i 73 more rows
# i 8 more variables: neighbourhood_cleansed <chr>, bathrooms <lgl>,
#   bedrooms <dbl>, price <int>, number_of_reviews <dbl>,
#   review_scores_rating <dbl>, review_scores_accuracy <dbl>,
#   review_scores_value <dbl>
```

In the data right now, the superhost is a true/false variable, but we want to turn it into a binary variable.

```
airbnb_data_no_superhost_nas <-
  airbnb_data_less_1000 |>
  filter(!is.na(host_is_superhost)) |>
  mutate(
    host_is_superhost_binary =
      as.numeric(host_is_superhost)
  )
```

Next, we look at the reviews in the listings.

```
airbnb_data_no_superhost_nas |>
  ggplot(aes(x = review_scores_rating)) +
  geom_bar() +
  theme_classic() +
  labs(
    x = "Review scores rating",
    y = "Number of properties"
  )
```



We want to deal with the NAs in the review_scores_rating variable. This process is slightly more complicated.

```
airbnb_data_no_superhost_nas |>
  filter(is.na(review_scores_rating)) |>
  nrow()
```

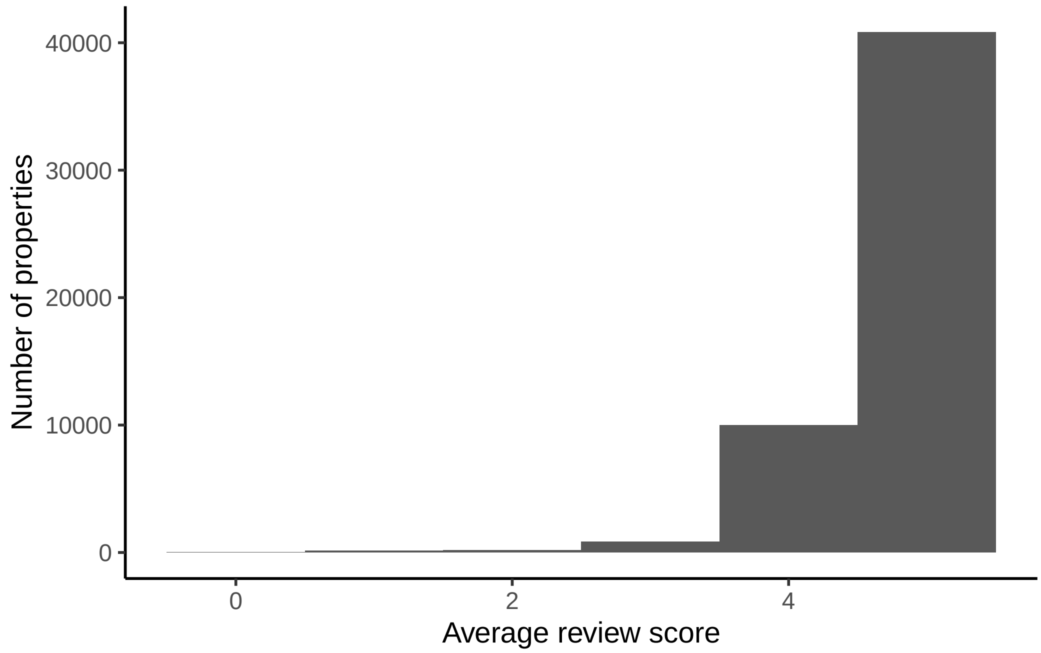
```
[1] 13497
```

```
airbnb_data_no_superhost_nas |>
  filter(is.na(review_scores_rating)) |>
  select(number_of_reviews) |>
  table()
```

```
number_of_reviews
    0
13497
```

Instead, we can just focus on those that are not missing and the main review score variable.

```
airbnb_data_no_superhost_nas |>
  filter(!is.na(review_scores_rating)) |>
  ggplot(aes(x = review_scores_rating)) +
  geom_histogram(binwidth = 1) +
  theme_classic() +
  labs(
    x = "Average review score",
    y = "Number of properties"
  )
```



For simplicity, we will remove all with NA in the main review score.

```
airbnb_data_has_reviews <-
  airbnb_data_no_superhost_nas |>
  filter(!is.na(review_scores_rating))
```

Another important variable to look at is the response time of hosts.

```
airbnb_data_has_reviews |>
  count(host_response_time)
```

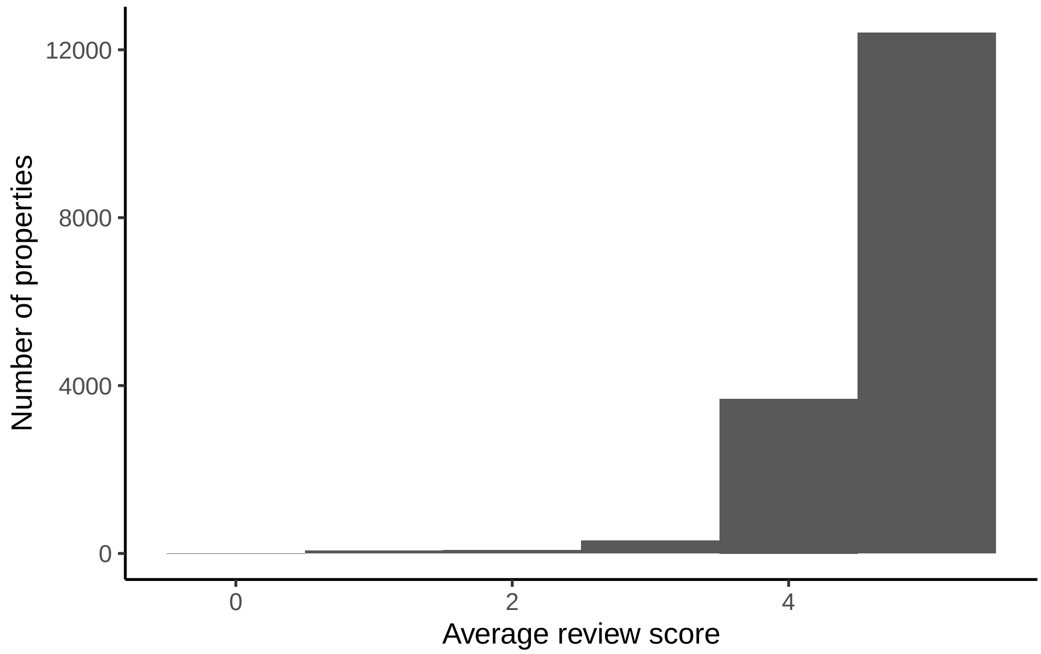
```
# A tibble: 6 x 2
```

```
  host_response_time      n
  <chr>               <int>
1 N/A                 16531
2 a few days or more   1243
3 within a day         5297
4 within a few hours   6811
5 within an hour      22094
6 <NA>                    2
```

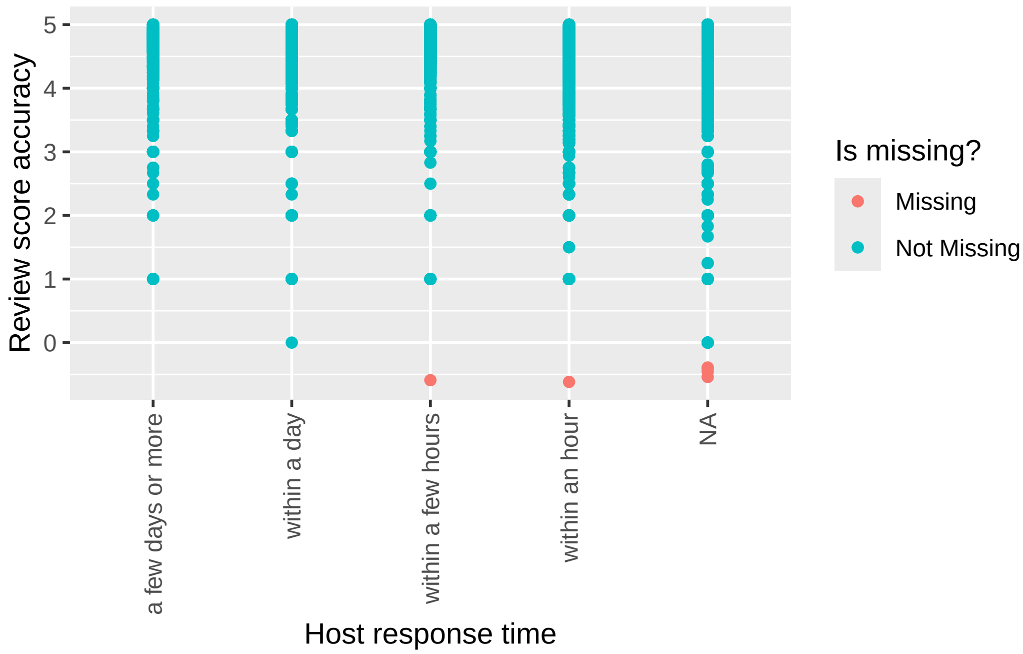
```
airbnb_data_has_reviews <-
  airbnb_data_has_reviews |>
  mutate(
    host_response_time = if_else(
      host_response_time == "N/A",
      NA_character_,
      host_response_time
    ),
    host_response_time = factor(host_response_time)
  )
```

Let's look at the distribution of review scores.

```
airbnb_data_has_reviews |>
  filter(is.na(host_response_time)) |>
  ggplot(aes(x = review_scores_rating)) +
  geom_histogram(binwidth = 1) +
  theme_classic() +
  labs(
    x = "Average review score",
    y = "Number of properties"
  )
```




```r
airbnb_data_has_reviews |>
  ggplot(aes(
    x = host_response_time,
    y = review_scores_accuracy
  )) +
  geom_miss_point() +
  labs(
    x = "Host response time",
    y = "Review score accuracy",
    color = "Is missing?"
  ) +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```

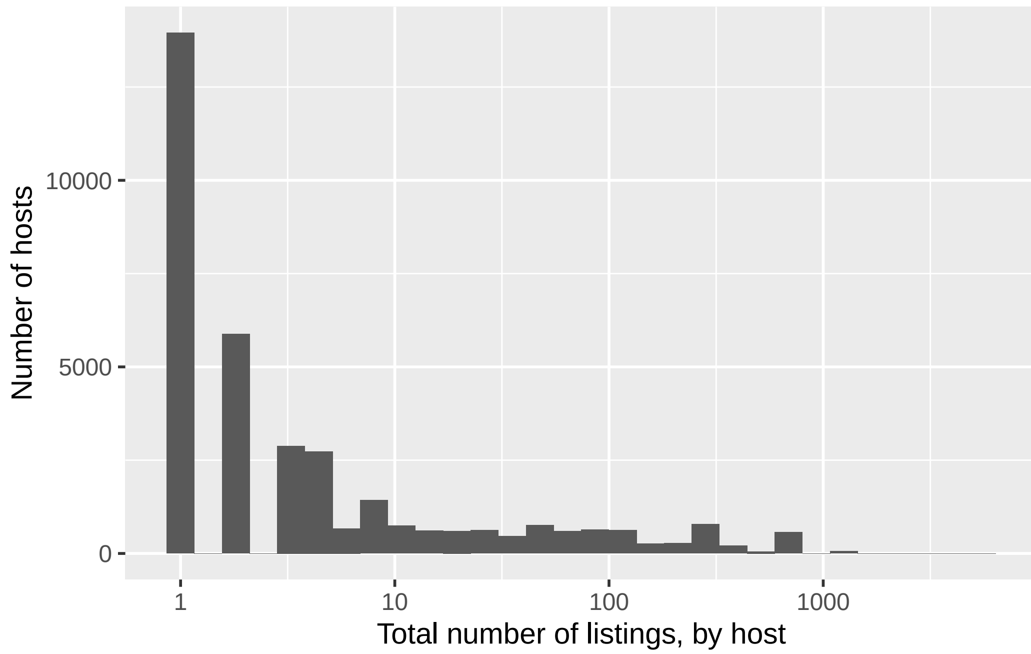


Removing anyone with a response time of NA

```
airbnb_data_selected <-
  airbnb_data_has_reviews |>
  filter(!is.na(host_response_time))
```

We look at the number of properties Airbnb hosts have.

```
airbnb_data_selected |>
  ggplot(aes(x = host_total_listings_count)) +
  geom_histogram() +
  scale_x_log10() +
  labs(
    x = "Total number of listings, by host",
    y = "Number of hosts"
  )
```




```
airbnb_data_selected |>
  filter(host_total_listings_count >= 500) |>
  head()
```

```
# A tibble: 6 x 13
   host_id host_response_time host_is_superhost host_total_listings_count
     <dbl> <fct>              <lgl>                                 <dbl>
1 50502817 within an hour     FALSE                                   778
2 50502817 within an hour     FALSE                                   778
3 50502817 within an hour     FALSE                                   778
4 50502817 within an hour     FALSE                                   778
5 50502817 within an hour     FALSE                                   778
6 50502817 within an hour     FALSE                                   778
# i 9 more variables: neighbourhood_cleansed <chr>, bathrooms <lgl>,
#   bedrooms <dbl>, price <int>, number_of_reviews <dbl>,
#   review_scores_rating <dbl>, review_scores_accuracy <dbl>,
#   review_scores_value <dbl>, host_is_superhost_binary <dbl>
```

For simplicity, we focus on hosts with one propety.

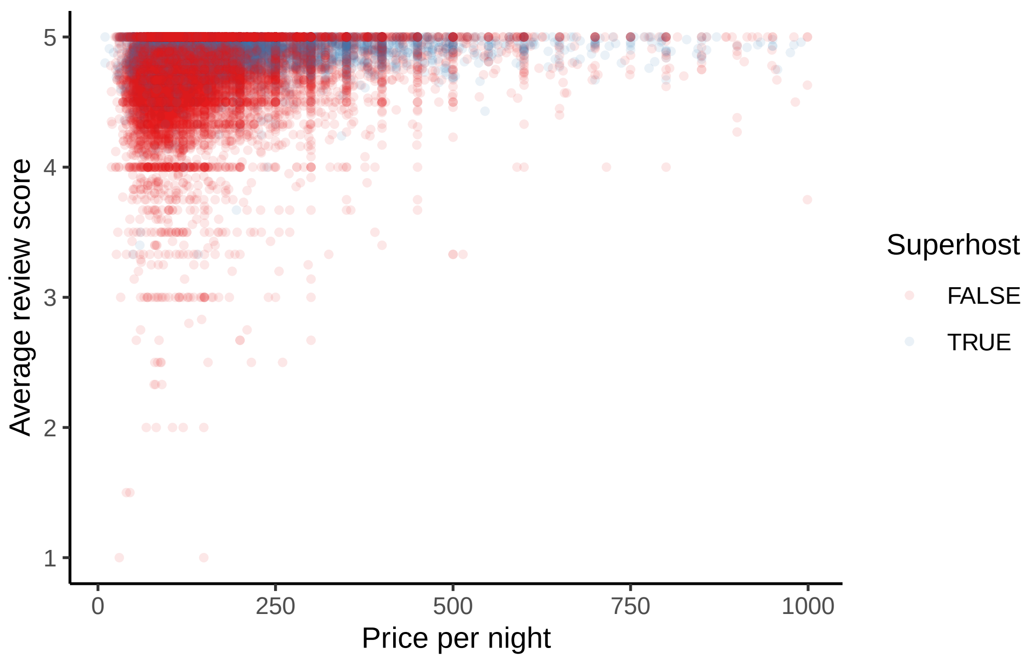
```
airbnb_data_selected <-
  airbnb_data_selected |>
```

```
  add_count(host_id) |>
  filter(n == 1) |>
  select(-n)
```

3 Relationship between Variables

We want to look at the relationship between price and reviews, and whether they are a super host, for properties that have more than one review.

```
airbnb_data_selected |>
  filter(number_of_reviews > 1) |>
  ggplot(aes(x = price, y = review_scores_rating,
             color = host_is_superhost)) +
  geom_point(size = 1, alpha = 0.1) +
  theme_classic() +
  labs(
    x = "Price per night",
    y = "Average review score",
    color = "Superhost"
  ) +
  scale_color_brewer(palette = "Set1")
```



Looking deeper at superhosts data.

```r
airbnb_data_selected |>
  count(host_is_superhost) |>
  mutate(
    proportion = n / sum(n),
    proportion = round(proportion, digits = 2)
  )
```

```
# A tibble: 2 x 3
  host_is_superhost     n proportion
  <lgl>             <int>      <dbl>
1 FALSE             15820       0.72
2 TRUE               6227       0.28
```

```r
airbnb_data_selected |>
  tabyl(host_response_time, host_is_superhost) |>
  adorn_percentages("col") |>
  adorn_pct_formatting(digits = 0) |>
  adorn_ns() |>
  adorn_title()
```

```
                    host_is_superhost
 host_response_time             FALSE          TRUE
 a few days or more        6%   (953)  0%     (24)
       within a day       22% (3,511) 12%    (770)
 within a few hours       24% (3,802) 26% (1,614)
     within an hour       48% (7,554) 61% (3,819)
```

Finally, let's look at neighborhoods.

```r
airbnb_data_selected |>
  tabyl(neighbourhood_cleansed) |>
  adorn_pct_formatting() |>
  arrange(-n) |>
  filter(n > 100) |>
  adorn_totals("row") |>
  head()
```

```
 neighbourhood_cleansed    n percent
      Buttes-Montmartre 2842   12.9%
             Popincourt 2202   10.0%
               Entrepôt 1713    7.8%
              Vaugirard 1681    7.6%
           Ménilmontant 1438    6.5%
        Buttes-Chaumont 1430    6.5%
```

We build a model to get a better idea of the relationships that exist in our data. Here, we try to forecast whether someone is a superhost. We expect that superhost status will be associated with faster responses and better reviews.

```
logistic_reg_superhost_response_review <-
  glm(
    host_is_superhost ~
      host_response_time +
      review_scores_rating,
    data = airbnb_data_selected,
    family = binomial
  )
```

Below is a table displaying the regression results.

```
modelsummary(logistic_reg_superhost_response_review)
```

From this, we can see that there is a positive relationship with the different factors and the probability of the host being a superhost.

Last, we save the analysis dataset.

```
write_parquet(
  x = airbnb_data_selected,
  sink = "2023-12-12-paris-airbnblistings-analysis_dataset.parquet"
  )
```

References

Alexander, Rohan. 2023. *Telling Stories with Data*. Chapman & Hall.
Cox, Murray. 2021. *Inside Airbnb*. http://insideairbnb.com/.

	(1)
(Intercept)	−16.262
	(0.481)
host_response_timewithin a day	2.019
	(0.211)
host_response_timewithin a few hours	2.695
	(0.210)
host_response_timewithin an hour	2.972
	(0.209)
review_scores_rating	2.624
	(0.089)
Num.Obs.	22 047
AIC	24 165.0
BIC	24 205.0
Log.Lik.	−12 077.507
RMSE	0.43