

# **Information and Airbnb, An Analysis on the Impact of Reviews and Ratings on Airbnb Prices in Canada\***

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## **1 Introduction**

In the changing landscape of modern travel, Airbnb has emerged as a transformative force, reshaping traditional notions of accommodation and hospitality. No longer are travelers confined to hotels; people have the choice to choose between various forms of accommodation and find the option most suitable for their needs. With Airbnb's vacation rentals, travelers have the option to gain access to more space, kitchens, home amenities, and lower cost (Guttentag, 2016). Central to Airbnb's allure are the wealth of user-generated reviews and ratings, which serve as vital sources of information for prospective guests navigating a vast array of listings. These reviews not only offer insights into the quality and character of accommodations but also play a pivotal role in shaping consumer decisions. However, in this growing world of shared experiences, a fundamental question persists: What effect do these reviews and ratings have on Airbnb pricing strategies? This question lies at the heart of our inquiry, as we delve into the relationship between information, consumer behavior, and pricing dynamics within the Airbnb marketplace in Canada. Through statistical analysis and data visualization, this

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\*Code and data are available at: [https://github.com/alainahu/airbnb\\_analysis](https://github.com/alainahu/airbnb_analysis)

paper endeavors to continue to explore the relationship between reviews, ratings, and Airbnb prices.

In an econometric analysis on Airbnb reviews and price in Boston, Lawani et al. find that reviews serve as a good proxy for rooms' quality and reviews affect both the host price and neighboring host price. Peng et al. (2020) build a machine learning model and use natural language processing to predict Airbnb prices in nine cities across the United States, Australia, and Europe. Their research concludes that customer reviews, house features, and geographical data are all predictive factors for Airbnb rental prices.

## 2 Data

```
Rows: 87059 Columns: 9
-- Column specification -----
Delimiter: ","
chr (1): city
dbl (8): review, guest_satisfaction_overall, accuracy_rating, cleanliness_ra...
i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.

Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
i Please use `after_stat(density)` instead.

Warning: Removed 102 rows containing non-finite values (`stat_bin()`).

Warning: Removed 2 rows containing missing values (`geom_bar()`).

Min. 1st Qu. Median Mean 3rd Qu. Max.
26.00 68.67 93.83 107.66 126.33 634.33

summary_df <- airbnb |>
  summarise(
    Mean_New_Price = mean(new_price, na.rm = TRUE),
    Median_New_Price = median(new_price, na.rm = TRUE),
    SD_New_Price = sd(new_price, na.rm = TRUE))
```

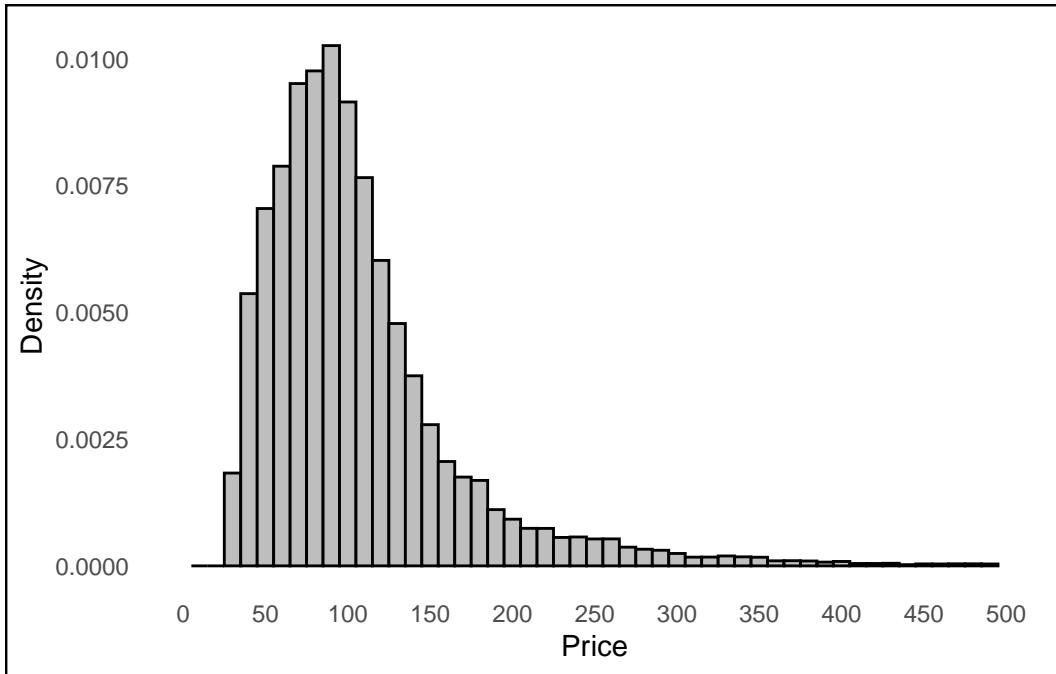


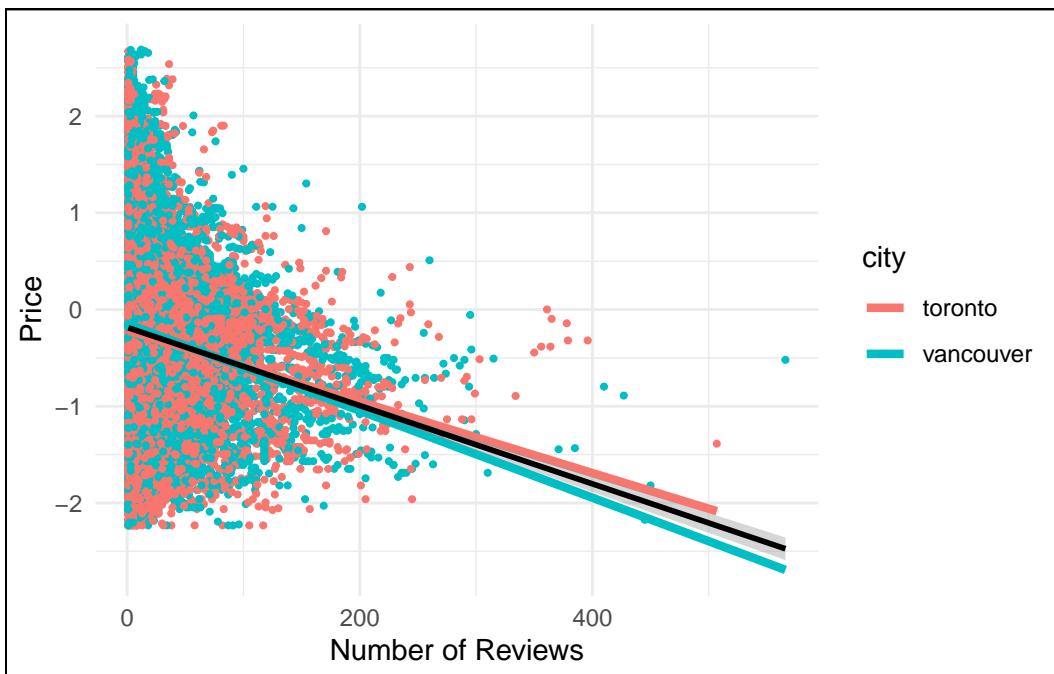
Figure 1: Distribution of Airbnb prices per night (including cleaning fees)

Table 1: Summary Statistics for the Reviews and Ratings

Variable	Mean	Median	Standard Deviation	Min	Max
Accuracy Rating	9.47	10	0.98	0	10
Cleanliness Rating	9.28	10	1.14	0	10
Guest Overall Satisfaction	93.47	95	7.78	20	100
Location Rating	9.48	10	0.95	0	10
Number of Reviews	14.90	7	23.86	1	566
Value Rating	9.29	9	1.00	0	10

Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
i Please use `linewidth` instead.

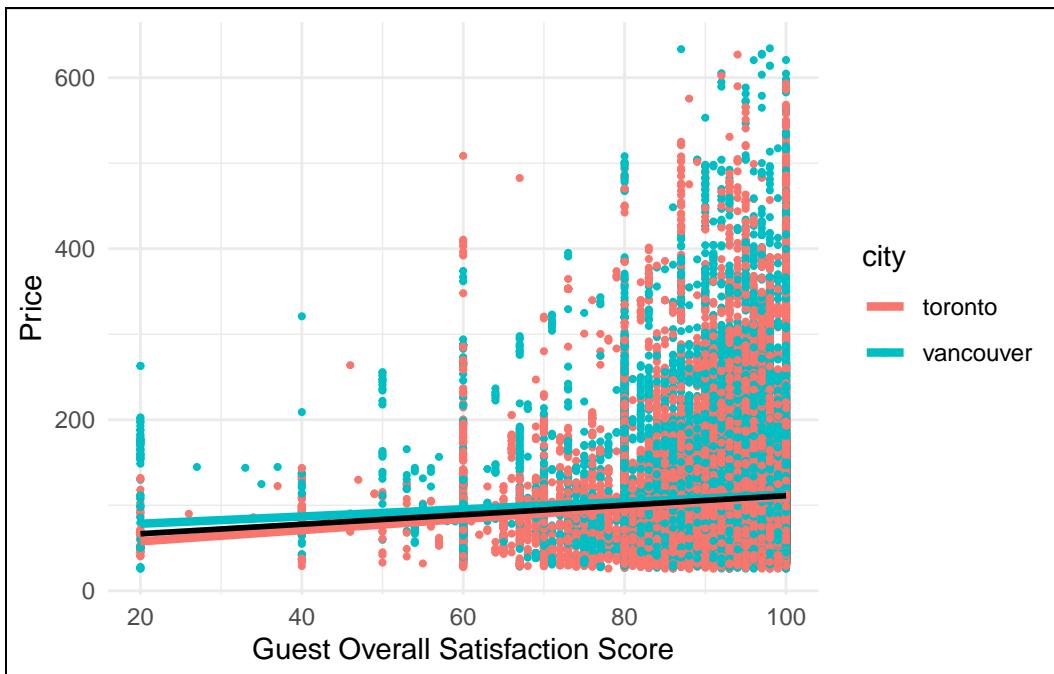
```
`geom_smooth()` using formula = 'y ~ x'  
`geom_smooth()` using formula = 'y ~ x'
```



```
<ggproto object: Class ScaleDiscrete, Scale, gg>
  aesthetics: colour
  axis_order: function
  break_info: function
  break_positions: function
  breaks: waiver
  call: call
  clone: function
  dimension: function
  drop: TRUE
  expand: waiver
  get_breaks: function
  get_breaks_minor: function
  get_labels: function
  get_limits: function
  guide: legend
  is_discrete: function
  is_empty: function
  labels: waiver
  limits: NULL
  make_sec_title: function
  make_title: function
  map: function
```

```
map_df: function
n.breaks.cache: NULL
na.translate: TRUE
na.value: NA
name: waiver
palette: function
palette.cache: NULL
position: left
range: environment
rescale: function
reset: function
scale_name: brewer
train: function
train_df: function
transform: function
transform_df: function
super: <ggproto object: Class ScaleDiscrete, Scale, gg>
```

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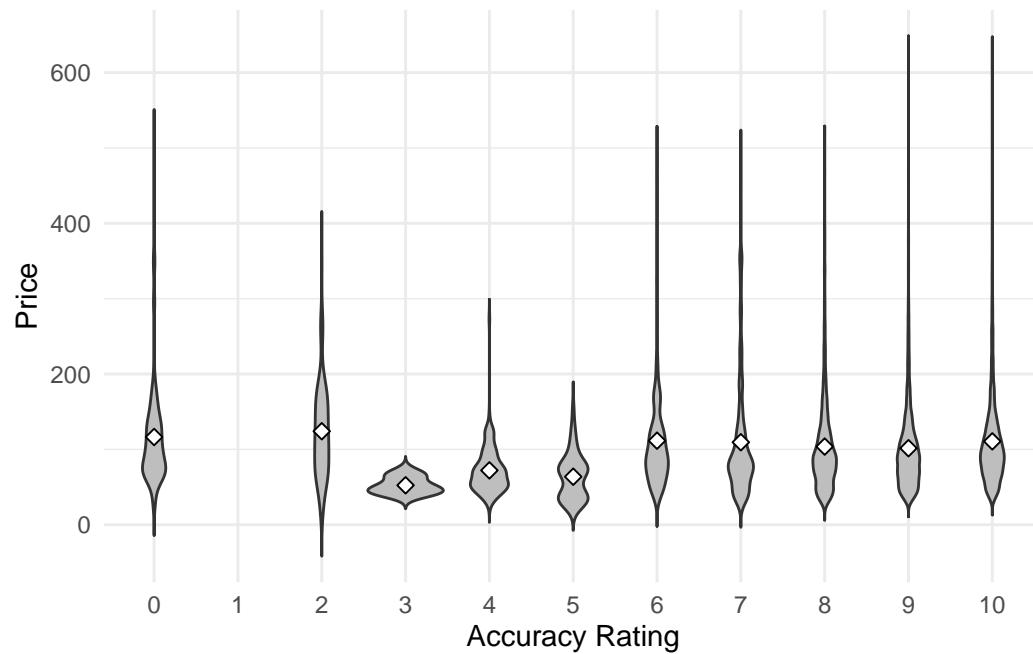
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<ggproto object: Class ScaleDiscrete, Scale, gg>
```

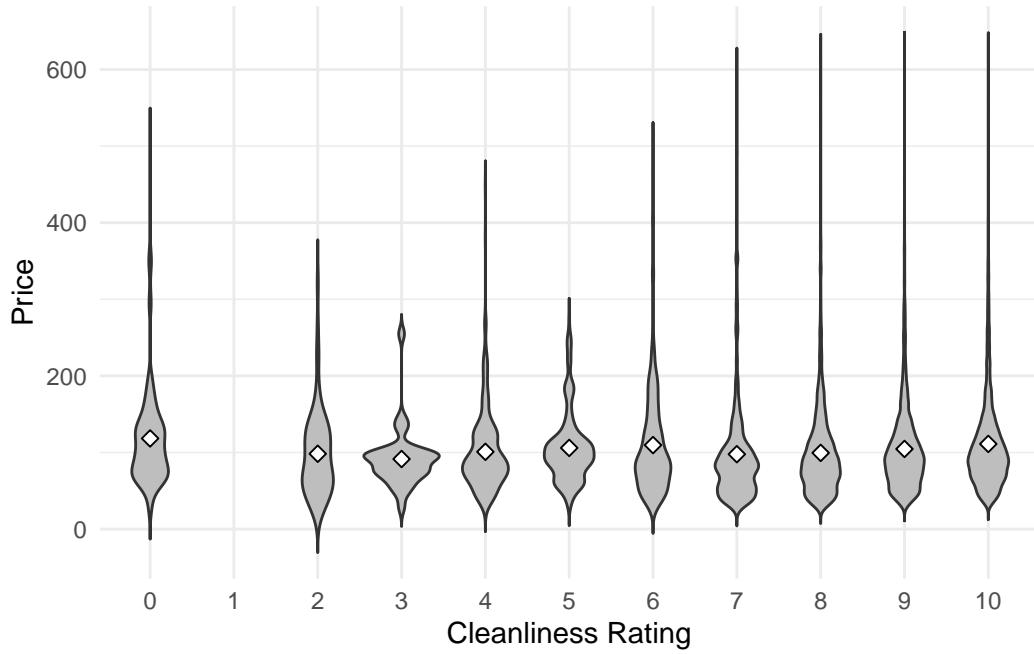
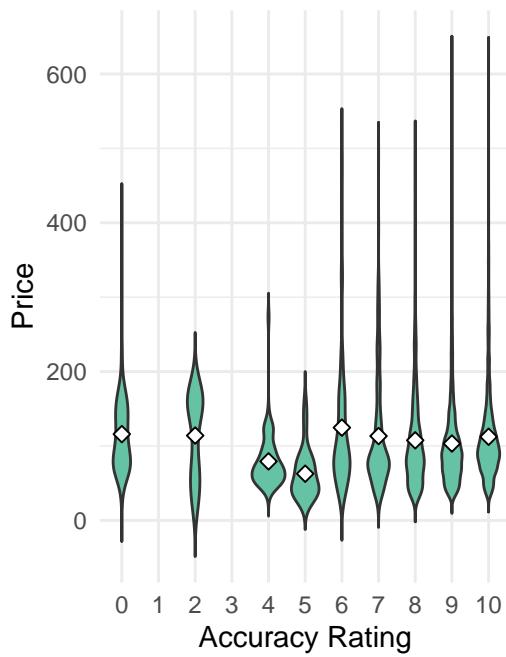
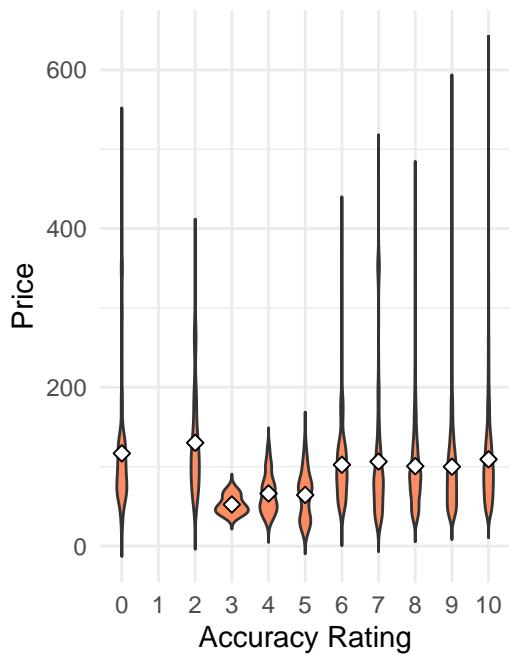
```
aesthetics: colour
axis_order: function
break_info: function
break_positions: function
breaks: waiver
call: call
clone: function
dimension: function
drop: TRUE
expand: waiver
get_breaks: function
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n.breaks.cache: NULL
na.translate: TRUE
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name: waiver
palette: function
palette.cache: NULL
position: left
range: environment
rescale: function
reset: function
scale_name: manual
train: function
train_df: function
transform: function
transform_df: function
super: <ggproto object: Class ScaleDiscrete, Scale, gg>
```

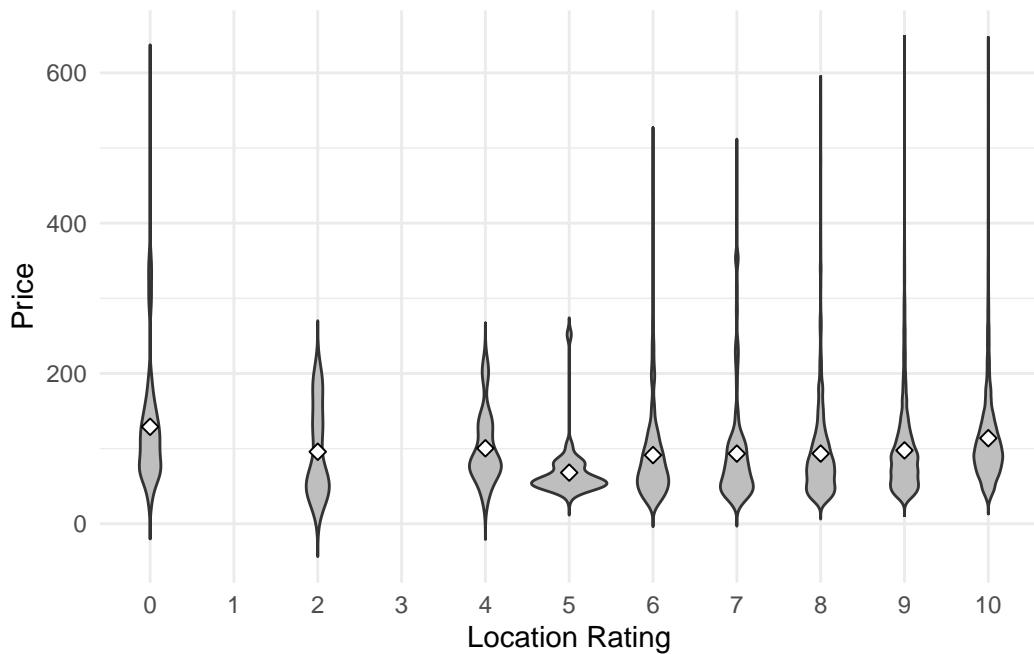
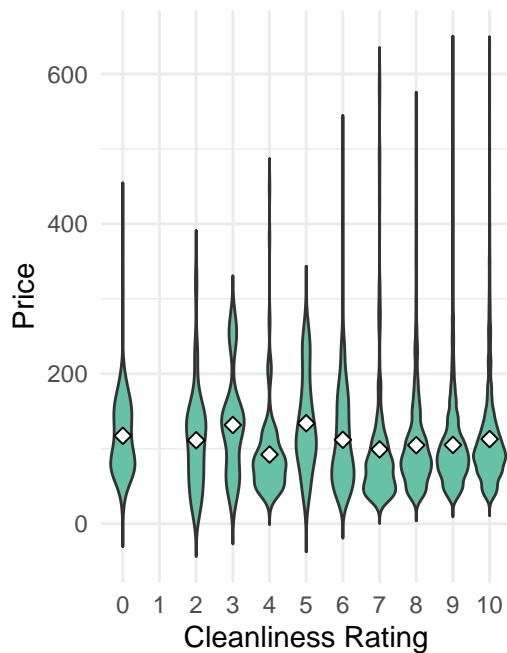
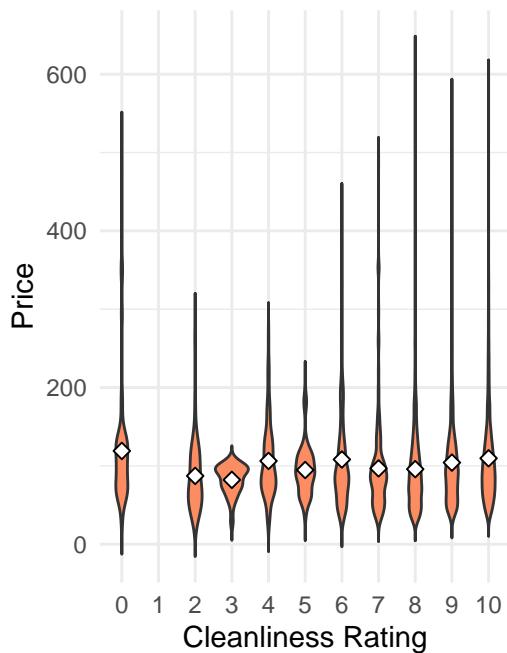
```
unique_values <- unique(airbnb$accuracy_rating)

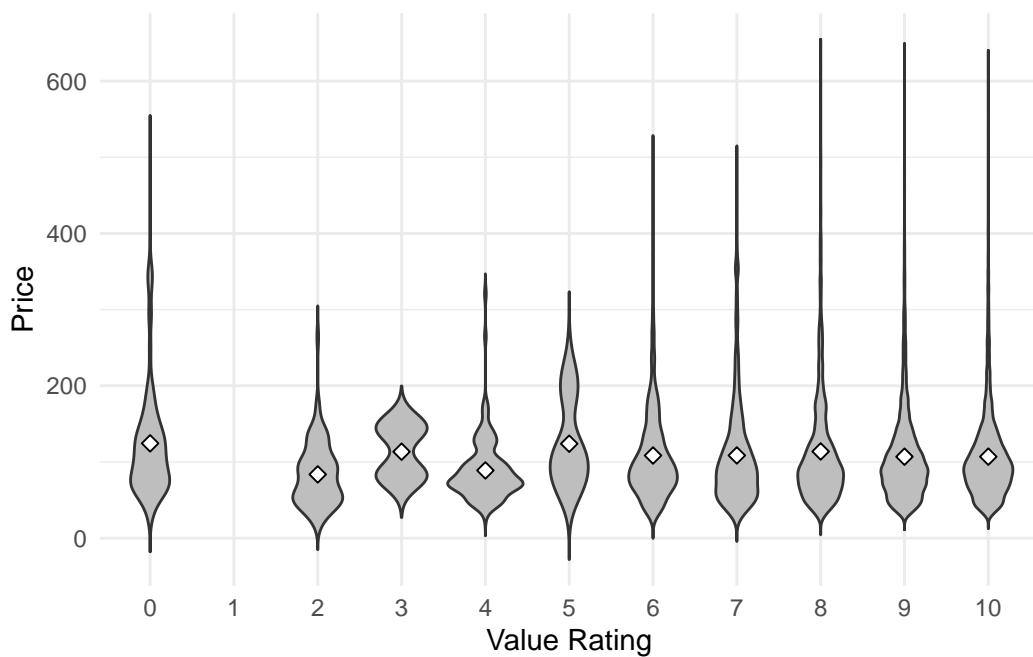
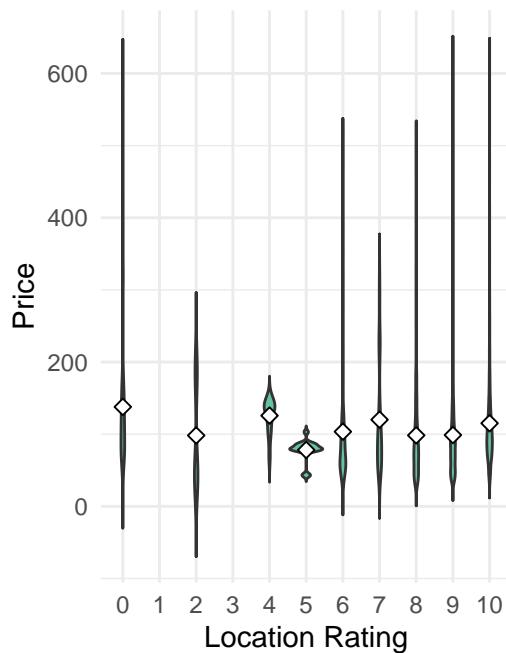
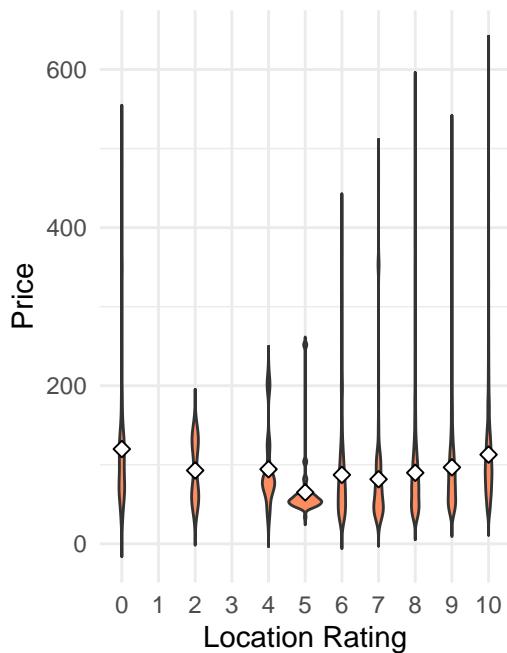
# Print the unique values
print(unique_values)
```

```
[1] 10 9 8 7 0 6 2 5 4 3
```









Warning: Groups with fewer than two data points have been dropped.  
Groups with fewer than two data points have been dropped.

