

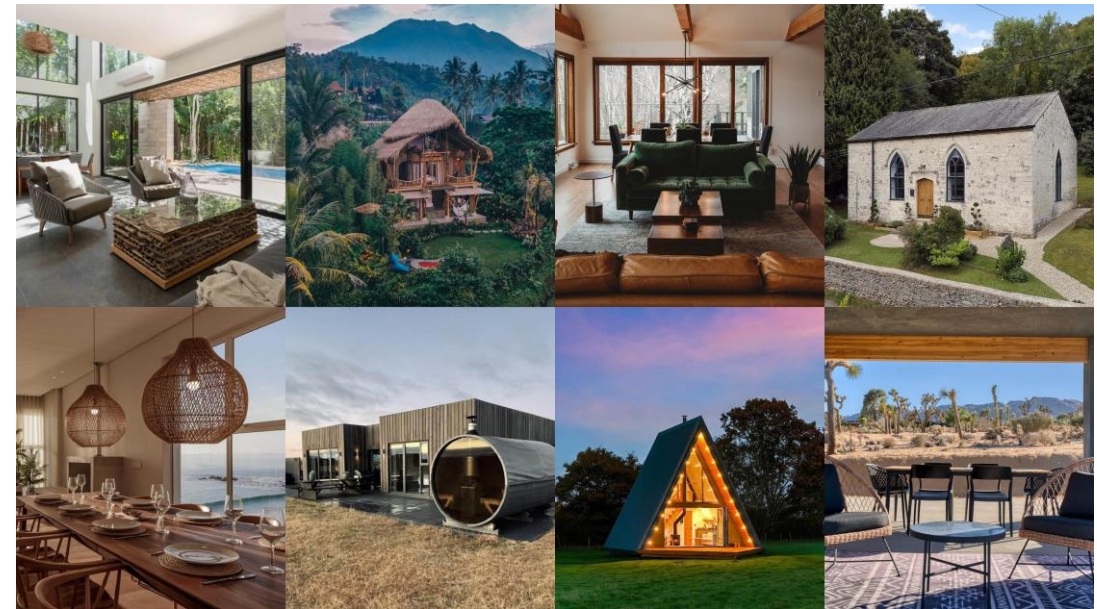
Airbnb Data Analysis: Lodge Prices

Tonghua Lin



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- 2 Data Cleaning
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Besides the chain hotels, Airbnb is another way to find a lodge while traveling. This project is trying to find the factors that can influence the price of a lodge.



AirBNB_Data

▲ 24

New Notebook

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Data Card Code (4) Discussion (0) Suggestions (0)


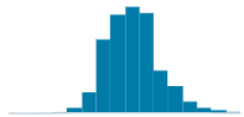

Airbnb_Data.csv (101.55 MB)

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Detail Compact Column
 10 of 29 columns

About this file
Add Suggestion

This dataset offers a detailed overview of Airbnb listings worldwide, providing information on property features, pricing, reviews, and host characteristics. It serves as a valuable resource for researchers and enthusiasts interested in exploring trends and patterns in the evolving landscape of modern hospitality.

id	# log_price	property_type	room_type	amenities	# ac
Airbnb id	Log price	Property type	Room type	Amenities of the Airbnb	No. c
		Apartment 66% House 22% Other (8597) 12%	Entire home/apt 56% Private room 41% Other (2163) 3%	67122 unique values	
344	21.2m				1

29 columns and 73000 rows

- ID
- Log_price
- Property_type
- Room_type
- Bathroom
- City
- ...

Introduction

Project Target:

- Predict the price by different factors
- Find a good city with low lodging prices



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Data Cleaning

Exclude text data and location name related data:

id amenities description name neighbourhood thumbnail_url

id	amenities	description	
6901257	["Wireless Internet","Air conditioning",Kitchen,	Beautiful, sunlit brownstone 1-bedroom in t	
6304928	["Wireless Internet","Air conditioning",Kitchen,	Enjoy travelling during your stay in Manhatt	
7919400	{TV,"Cable TV","Wireless Internet","Air conditic	The Oasis comes complete with a full backy.	
13418779	{TV,"Cable TV",Internet,"Wireless Internet",Kitc	This light-filled home-away-from-home is s	
3808709	{TV,Internet,"Wireless Internet","Air conditionir	Cool, cozy, and comfortable studio located i	
12422935	{TV,"Wireless Internet",Heating,"Smoke detecto	Beautiful private room overlooking scenic vi	
11825529	{TV,Internet,"Wireless Internet","Air conditionir	Warm and cozy studio with full kitchen and	
13971273	{TV,"Cable TV","Wireless Internet","Wheelchair	Arguably the best location (and safest) in dc	
180792	{TV,"Cable TV","Wireless Internet","Pets live on	Garden Studio with private entrance from th	
		thumbnail_url	zipcode
Beautiful brownstone 1-		https://a0.muscache.com/im/pic	11201
Superb 3BR Apt Located		https://a0.muscache.com/im/pic	10019
The Garden Oasis		https://a0.muscache.com/im/pic	10027
Beautiful Flat in the Hea		https://a0.muscache.com/im/pic	94117
Great studio in midtown			20009
Comfort Suite San Franc		https://a0.muscache.com/im/pic	94131
Beach Town Studio and Parking!!!11h		https://a0.muscache.com/im/pic	90292
Near LA Live, Staple's. St		https://a0.muscache.com/im/pic	90015
Cozy Garden Studio - Pl		https://a0.muscache.com/im/pic	94121

Deal with the NA missing data

log_price	property_type	room_type
0	0	0
accommodates	bathrooms	bed_type
0	200	0
cancellation_policy	cleaning_fee	city
0	0	0
first_review	host_has_profile_pic	host_identity_verified
15864	188	188
host_response_rate	host_since	instant_bookable
18299	188	0
last_review	latitude	longitude
15827	0	0
number_of_reviews	review_scores_rating	bedrooms
0	16722	91
beds		
131		

- For host_identity_verified related: Delete
- For bathrooms: 0
- For review related: 2017/11/01
- For beds and bedrooms and scores: average



Deal with the NA missing data

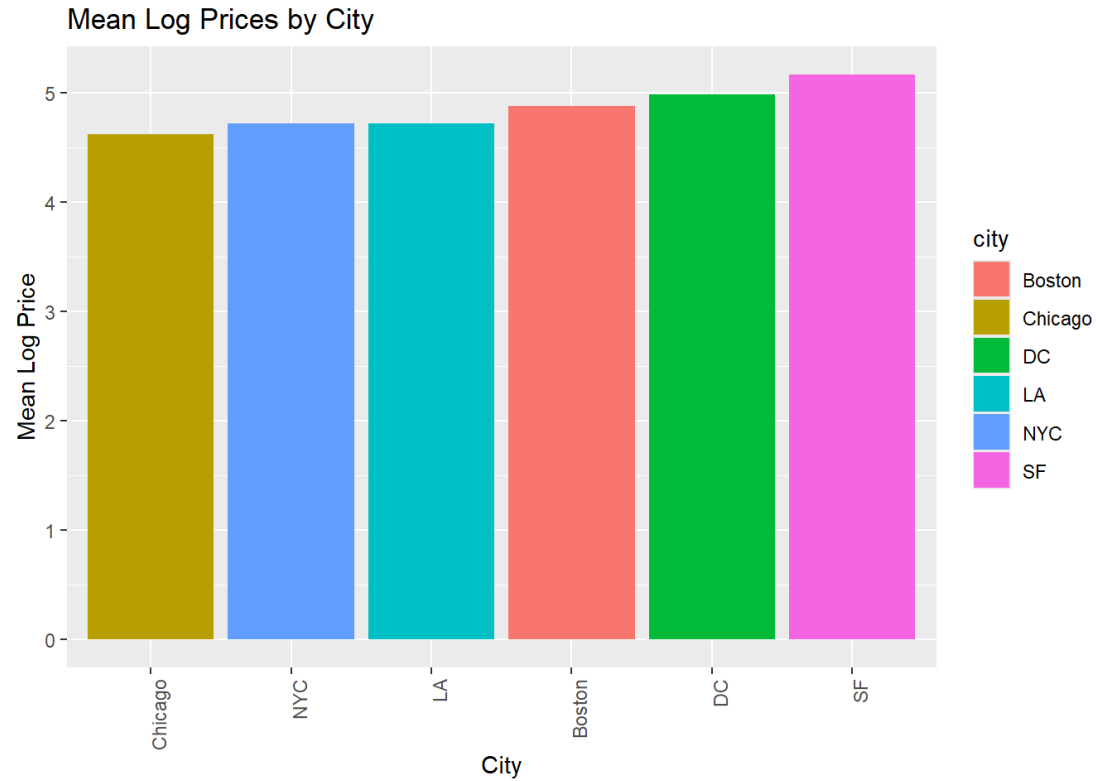
```
##          log_price      property_type      room_type
##              0              0              0
##      accommodates      bathrooms      bed_type
##              0              0              0
##      cancellation_policy      cleaning_fee      city
##              0              0              0
##      first_review  host_has_profile_pic  host_identity_verified
##              0              0              0
##      host_response_rate      host_since      instant_bookable
##              0              0              0
##      last_review      latitude      longitude
##              0              0              0
##      number_of_reviews  review_scores_rating      bedrooms
##              0              0              0
##              beds
##              0
```



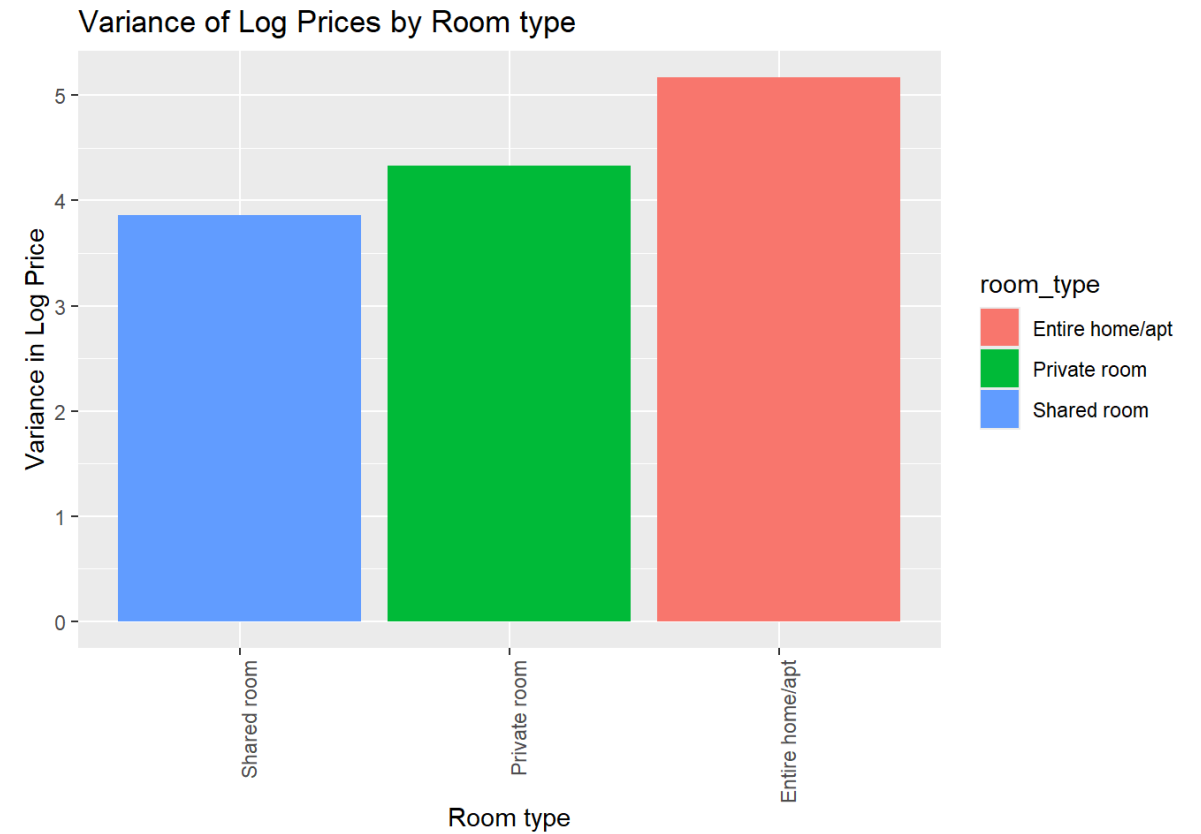
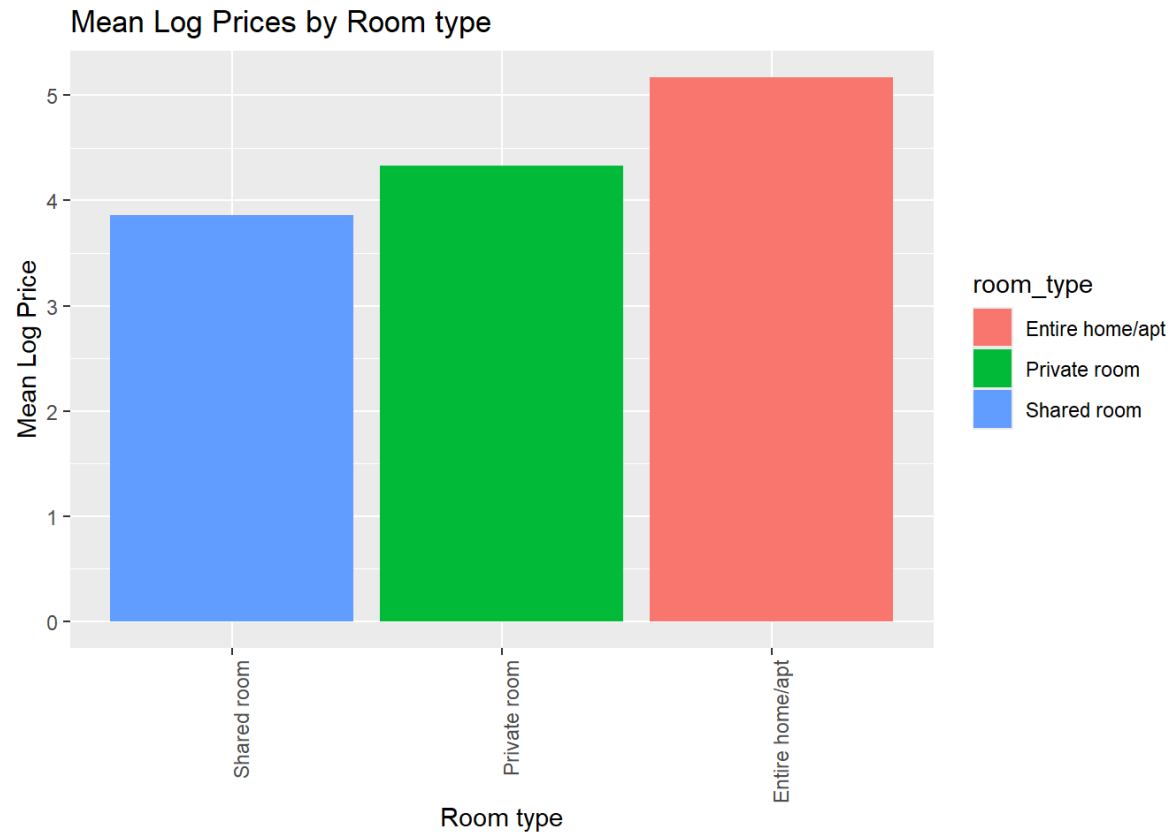
Transform the date data to number: using 2017/11/01 as baseline

```
## # A tibble: 6 × 22
##   log_price property_type room_type      accommodates bathrooms bed_type
##   <dbl> <chr>          <chr>          <dbl>      <dbl> <chr>
## 1     5.01 Apartment    Entire home/apt      3          1 Real Bed
## 2     5.13 Apartment    Entire home/apt      7          1 Real Bed
## 3     4.98 Apartment    Entire home/apt      5          1 Real Bed
## 4     6.62 House        Entire home/apt      4          1 Real Bed
## 5     4.74 Apartment    Entire home/apt      2          1 Real Bed
## 6     4.44 Apartment    Private room         2          1 Real Bed
## # 16 more variables: cancellation_policy <chr>, cleaning_fee <lgl>,
## # city <chr>, first_review <dbl>, host_has_profile_pic <lgl>,
## # host_identity_verified <lgl>, host_response_rate <dbl>, host_since <dbl>,
## # instant_bookable <lgl>, last_review <dbl>, latitude <dbl>, longitude <dbl>,
## # number_of_reviews <dbl>, review_scores_rating <dbl>, bedrooms <dbl>,
## # beds <dbl>
```

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Means and variances across cities



Means and variances across room types



```
## Two Sample t-test
##
## data:  DataSet$log_price[DataSet$city == "NYC"] and DataSet$log_price[DataSet$city == "LA"]
## t = -0.21408, df = 54615, p-value = 0.4152
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##      -Inf 0.008644347
## sample estimates:
## mean of x mean of y
##  4.719238  4.720531

##
## Two Sample t-test
##
## data:  DataSet$log_price[DataSet$city == "NYC"] and DataSet$log_price[DataSet$city == "Boston"]
## t = -13.927, df = 35639, p-value < 2.2e-16
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##      -Inf -0.1453337
## sample estimates:
## mean of x mean of y
##  4.719238  4.884035
```

T-test results

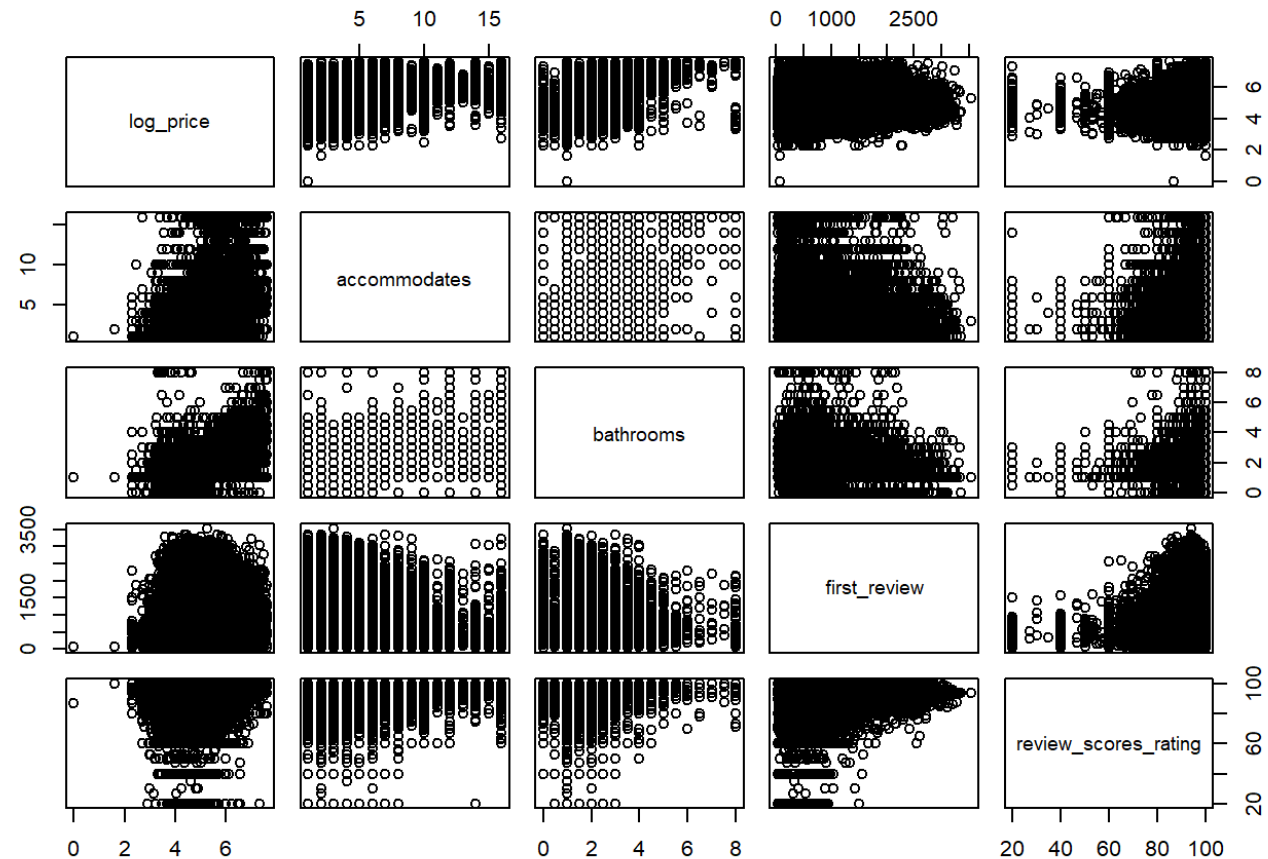


```
## Two Sample t-test
##
## data: DataSet$log_price[DataSet$room_type == "Private room"] and DataSet$log_price[DataSet$room_type == "Shared room"]
## t = 41.153, df = 32698, p-value = 1
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##      -Inf 0.4854585
## sample estimates:
## mean of x mean of y
##  4.327647  3.860847

## Two Sample t-test
##
## data: DataSet$log_price[DataSet$room_type == "Private room"] and DataSet$log_price[DataSet$room_type == "Entire home/apt"]
## t = -196.9, df = 71760, p-value < 2.2e-16
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##      -Inf -0.8325653
## sample estimates:
## mean of x mean of y
##  4.327647  5.167226
```

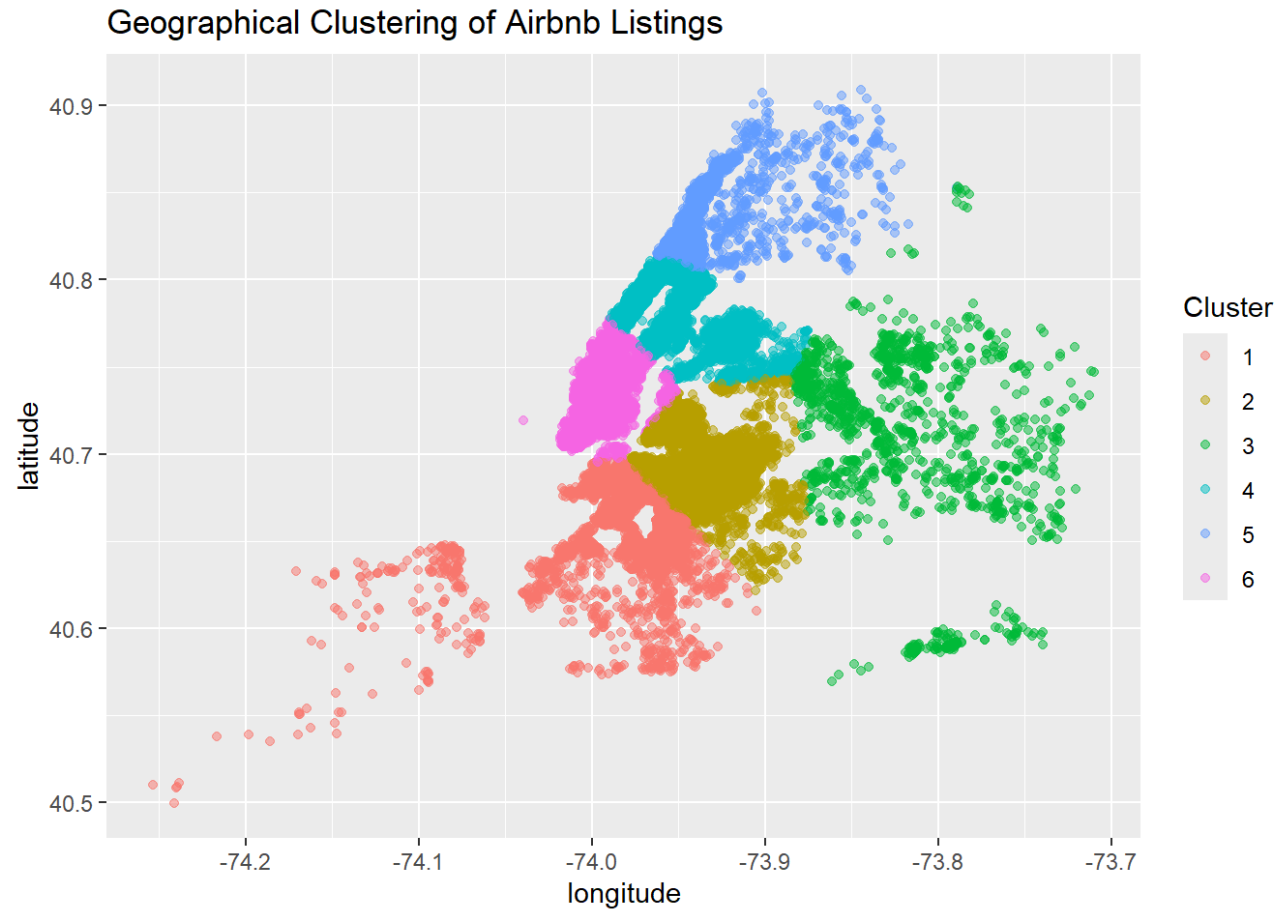
T-test results

Explore

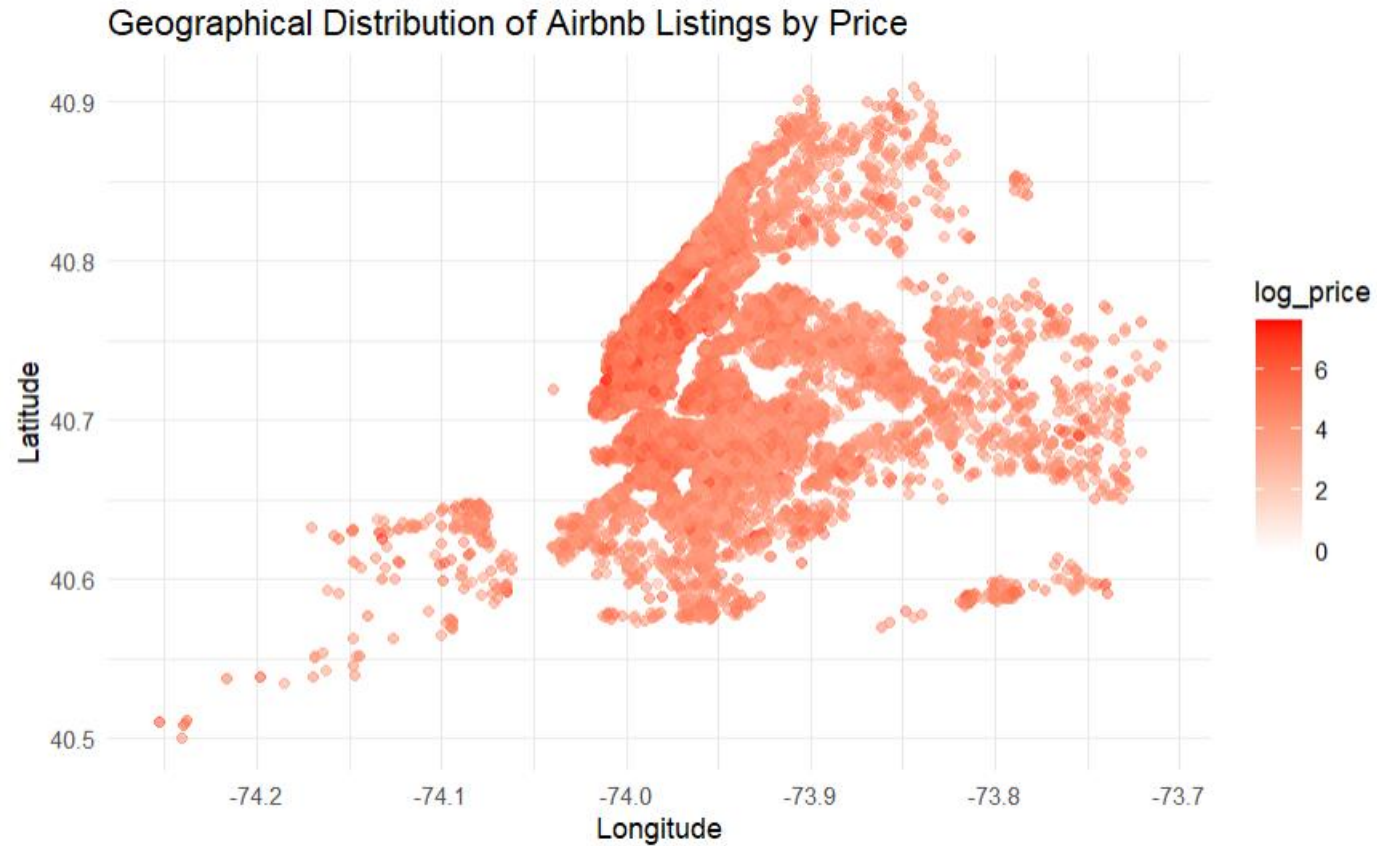


Multi-variables visualization: significant relationship pattern

Explore



K-means cluster in NYC



Prices across latitude and longitude

Explore

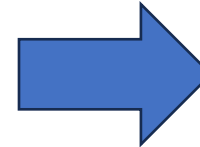
```
## $ log_price      : num [1:73923] 5.01 5.13 4.98 6.62 4.74 ...
## $ property_type  : Factor w/ 35 levels "Apartment", "Bed & Breakfast",...: 1 1 1 18 1 1 1 12 18 18 ...
## $ room_type      : Factor w/ 3 levels "Entire home/apt",...: 1 1 1 1 1 2 1 1 2 2 ...
## $ accommodates   : num [1:73923] 3 7 5 4 2 2 3 2 2 2 ...
## $ bathrooms      : num [1:73923] 1 1 1 1 1 1 1 1 1 1 ...
## $ bed_type       : Factor w/ 5 levels "Airbed", "Couch",...: 5 5 5 5 5 5 5 5 5 5 ...
## $ cancellation_policy : Factor w/ 5 levels "flexible", "moderate",...: 3 3 2 1 2 3 2 2 2 2 ...
## $ cleaning_fee    : Factor w/ 2 levels "FALSE", "TRUE": 2 2 2 2 2 2 2 2 2 2 ...
## $ city            : Factor w/ 6 levels "Boston", "Chicago",...: 5 5 5 6 3 6 4 4 6 4 ...
## $ first_review     : num [1:73923] 501 88 185 927 904 66 236 320 627 212 ...
## $ host_has_profile_pic : Factor w/ 2 levels "FALSE", "TRUE": 2 2 2 2 2 2 2 2 2 2 ...
## $ host_identity_verified : Factor w/ 2 levels "FALSE", "TRUE": 2 1 2 2 2 2 1 2 1 1 ...
## $ host_response_rate : num [1:73923] 94.4 100 100 94.4 100 ...
## $ host_since       : num [1:73923] 2046 135 372 927 976 ...
## $ instant_bookable  : Factor w/ 2 levels "FALSE", "TRUE": 1 2 2 1 2 2 2 1 1 2 ...
```

Simple analysis about category variables



Explore

```
##                property_type
## room_type      Apartment Bed & Breakfast Boat Boutique hotel Bungalow Cabin
## Entire home/apt 28820          57   56          22   313   58
## Private room    18648          361   9          47   51   12
## Shared room     1372           43   0          0    2    1
##                property_type
## room_type      Camper/RV Casa particular Castle Cave Chalet Condominium
## Entire home/apt 73             0    7    1    3    1631
## Private room    17             1    6    1    3    984
## Shared room     4              0    0    0    0    39
##                property_type
## room_type      Dorm Earth House Guest suite Guesthouse Hostel House Hut
## Entire home/apt 3              3      71    412    2 7513    5
## Private room    66             1      52    68    23 8540    2
## Shared room     73             0      0     18    45 450    1
##                property_type
## room_type      In-law Island Lighthouse Loft Other Parking Space
## Entire home/apt 62    0          1 784 353          0
## Private room    8     1          0 408 223          0
## Shared room     1     0          0 49 31            1
##                property_type
## room_type      Serviced apartment Tent Timeshare Tipi Townhouse Train
## Entire home/apt          16    6      59    2    787    1
## Private room            5    11      17    1    872    1
## Shared room             0    1      0    0    26    0
##                property_type
## room_type      Treehouse Vacation home Villa Yurt
## Entire home/apt 4              9    83    6
## Private room    3              2    92    3
## Shared room     0              0    4    0
```



```
##                broad_category
## room_type      Apartment House Other Unique Stays
## Entire home/apt 31251 8761 609        602
## Private room    20045 9566 632        296
## Shared room     1460 483 80          138
```

- Apartment
- House
- Unique Stays
- Other



Explore

```
##                bed_type
## room_type      Airbed Couch Futon Pull-out Sofa Real Bed
## Entire home/apt    100    53    168                211    40691
## Private room        275    61    485                256    29462
## Shared room         102   153    97                115    1694
```

```
##                host_has_profile_pic
## room_type      FALSE  TRUE
## Entire home/apt    127 41096
## Private room        90 30449
## Shared room         9  2152
```

```
##                cancellation_policy
## room_type      flexible moderate strict super_strict_30 super_strict_60
## Entire home/apt    9762    10544  20788                112                17
## Private room        11767    8079  10693                0                0
## Shared room         955     391   815                0                0
```

```
##                city
## room_type      Boston Chicago    DC    LA    NYC    SF
## Entire home/apt    2146    2217  3882 12998 16163 3817
## Private room        1276    1401  1668 8472 15205 2517
## Shared room         46     101   137  974  805   98
```

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Regression Model

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	29.248008	0.600812	48.681	< 2e-16	***
accommodates	0.273277	0.004733	57.739	< 2e-16	***
bathrooms	0.109863	0.003081	35.664	< 2e-16	***
first_review	0.050307	0.004387	11.467	< 2e-16	***
host_response_rate	-0.022973	0.002441	-9.412	< 2e-16	***
host_since	-0.012076	0.003161	-3.820	0.000134	***
last_review	0.055619	0.003949	14.085	< 2e-16	***
latitude	0.439013	0.107776	4.073	4.64e-05	***
longitude	-29.682742	0.583046	-50.910	< 2e-16	***
number_of_reviews	-0.037284	0.003188	-11.697	< 2e-16	***
review_scores_rating	0.062223	0.002419	25.726	< 2e-16	***
bedrooms	0.164799	0.003909	42.154	< 2e-16	***
beds	-0.083314	0.004403	-18.921	< 2e-16	***
property_typeHouse	-0.026082	0.006361	-4.101	4.12e-05	***
property_typeOther	0.164041	0.018252	8.988	< 2e-16	***
property_typeUnique Stays	-0.147914	0.020725	-7.137	9.62e-13	***
room_typePrivate room	-0.832712	0.005918	-140.701	< 2e-16	***
room_typeShared room	-1.444050	0.015385	-93.862	< 2e-16	***
bed_typeCouch	0.202804	0.049919	4.063	4.86e-05	***
bed_typeFuton	-0.018888	0.038075	-0.496	0.619852	
bed_typePull-out Sofa	0.083466	0.040135	2.080	0.037561	*
bed_typeReal Bed	0.085573	0.030014	2.851	0.004359	**
cancellation_policymoderate	-0.032916	0.006855	-4.802	1.57e-06	***
cancellation_policystrict	0.017643	0.006361	2.774	0.005545	**
cleaning_feeTRUE	-0.054722	0.005999	-9.122	< 2e-16	***
cityChicago	-23.045924	0.446837	-51.576	< 2e-16	***
cityDC	-7.617708	0.206776	-36.840	< 2e-16	***
cityLA	-63.654096	1.321949	-48.152	< 2e-16	***
cityNYC	-3.756324	0.099393	-37.793	< 2e-16	***
citySF	-69.149846	1.399629	-49.406	< 2e-16	***
host_has_profile_picTRUE	-0.141855	0.043393	-3.269	0.001079	**
host_identity_verifiedTRUE	-0.042862	0.005556	-7.714	1.23e-14	***
instant_bookableTRUE	-0.022839	0.005690	-4.014	5.98e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Exclude some insignificant variables

Coefficients:

##	Estimate	Std. Error	t value	Pr(> t)	
## (Intercept)	29.510709	0.598271	49.327	< 2e-16	***
## accommodates	0.274852	0.004729	58.126	< 2e-16	***
## bathrooms	0.108939	0.003063	35.564	< 2e-16	***
## first_review	0.043438	0.003877	11.205	< 2e-16	***
## host_response_rate	-0.023557	0.002438	-9.661	< 2e-16	***
## last_review	0.057329	0.003856	14.866	< 2e-16	***
## latitude	0.469393	0.107767	4.356	1.33e-05	***
## longitude	-29.945648	0.580588	-51.578	< 2e-16	***
## number_of_reviews	-0.037664	0.003182	-11.837	< 2e-16	***
## review_scores_rating	0.060655	0.002415	25.120	< 2e-16	***
## bedrooms	0.162782	0.003885	41.902	< 2e-16	***
## beds	-0.082977	0.004402	-18.850	< 2e-16	***
## property_typeOther	0.172636	0.018159	9.507	< 2e-16	***
## property_typeUnique Stays	-0.142209	0.020631	-6.893	5.50e-12	***
## room_typePrivate room	-0.838806	0.005773	-145.301	< 2e-16	***
## room_typeShared room	-1.432679	0.015241	-94.001	< 2e-16	***
## bed_typeReal Bed	0.047190	0.014833	3.181	0.001466	**
## cleaning_feeTRUE	-0.055430	0.005773	-9.601	< 2e-16	***
## cityChicago	-23.245231	0.444999	-52.237	< 2e-16	***
## cityDC	-7.664944	0.206408	-37.135	< 2e-16	***
## cityLA	-64.152643	1.317369	-48.698	< 2e-16	***
## cityNYC	-3.774646	0.099272	-38.023	< 2e-16	***
## citySF	-69.734870	1.394238	-50.016	< 2e-16	***
## host_has_profile_picTRUE	-0.143900	0.043421	-3.314	0.000920	***
## host_identity_verifiedTRUE	-0.048705	0.005340	-9.121	< 2e-16	***
## instant_bookableTRUE	-0.019855	0.005678	-3.497	0.000472	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1



Regression Model

```
##          (Intercept)          accommodates
##          29.51070890          0.27485198 ##          cityChicago          cityDC
##          bathrooms          first_review ##          -23.24523069          -7.66494418
##          0.10893871          0.04343812 ##          cityLA          cityNYC
##          host_response_rate          last_review ##          -64.15264317          -3.77464607
##          -0.02355706          0.05732861 ##          citySF          host_has_profile_picTRUE
##          latitude          longitude ##          -69.73487033          -0.14390002
##          0.46939271          -29.94564776 ##          host_identity_verifiedTRUE          instant_bookableTRUE
##          number_of_reviews          review_scores_rating ##          -0.04870497          -0.01985495
##          -0.03766385          0.06065545

##          bedrooms          beds
##          0.16278239          -0.08297697
##          property_typeOther          property_typeUnique Stays
##          0.17263609          -0.14220902
##          room_typePrivate room          room_typeShared room
##          -0.83880579          -1.43267918
##          bed_typeReal Bed          cleaning_feeTRUE
##          0.04719036          -0.05543024
```

R-squared: 0.58

Find the variables that have
coefficients higher than 0.5

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From the results, there are several intuitive insights.

- More bathrooms, bedrooms, accommodates can increase the price.
- However, more beds can lead to lower price. It may be because more beds implied sharing room.
- Shared room and Private room can decrease the price compared with Entire Home/Apt

bathrooms

0.10893871

bedrooms

0.16278239

accommodates

0.27485198

beds

-0.08297697

room_typePrivate room

-0.83880579

room_typeShared room

-1.43267918

Also, there are some interesting results.

- In `property_type`, others will increase the price while unique stays decrease the price. We can see some fantastic types in unique stays, such as castle, island. But their price is lower than normal house.
- Review scores don't increase the price significantly. That's kind of reasonable since we have good lodges in every point of price range.
- `host_has_profile_pic` seems quite significant. It may be caused by amount of data. There are only 1% of hosts don't have a picture for their lodges.
- The latitude and longitude is significantly influencing the price. Which is weird. From the early analysis, we can see that dealing with location related number is difficult.

`property_typeOther`
0.17263609

`property_typeUnique Stays`
-0.14220902

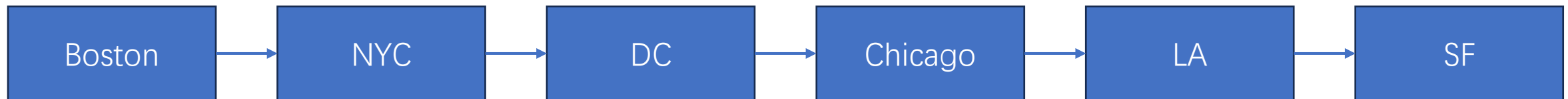
`review_scores_rating`
0.06065545

`latitude`
0.46939271

`longitude`
-29.94564776

Finally, we can get the city related influence. Boston is the most expensive city for lodging, followed by NYC and DC. While SF, La and Chicago are much cheaper.

cityChicago	cityDC
-23.24523069	-7.66494418
cityLA	cityNYC
-64.15264317	-3.77464607
citySF	host_has_profile_picTRUE
-69.73487033	-0.14390002



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Conclusion and Extension

- Cleaned up the data set about Airbnb lodges
- Analyzed data by preliminary methods like MVA and T-test
- Used multiple regression to get a predicting model
- Draw some insights from the model

There are some following direction can be explored afterwards.

- The influence of property_type can be analyzed further, since the board classification is still crude.
- The location of data, namely the latitude and longitude can be explored more. Classic cluster and regression methods may not be able to deal with this part.
- About the text type of data, we can use text mining methods to put them to use.



Conclusion and Extension

- There is a lots of works before we actually run the regression. We need to clean up the data, explore with many methods for a clear direction.
- Analysis is a dynamic process; we need to run the model and do the analysis iteratively.
- Finally, I should go to SF, LA or Chicago for a holiday travel. Otherwise, I should prepare for an expensive lodging.

Thank you for your attention!

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