



Airbnb Global Price Analysis

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Part 1: Introduction



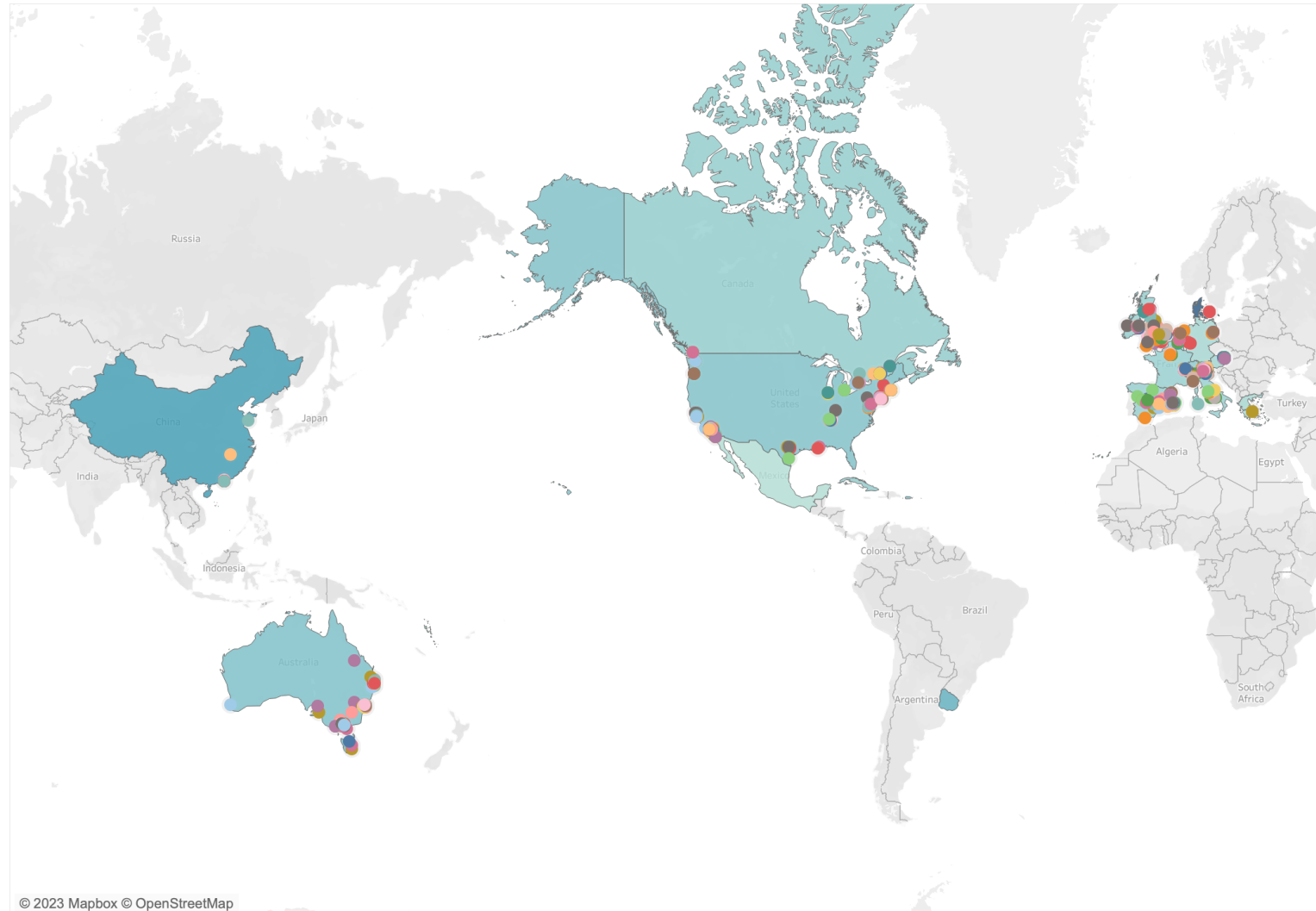
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Our Data

- **Data:** Airbnb's global price
- **Time Collected:** Last updated four months ago.
- **Data Size:** 1.94 GB
- **Data Source:** Kaggle by Joakim Arvidsson
- **Source Link:** <https://www.kaggle.com/datasets/joebeachcapital/airbnb>
- **Number of Columns:** 89
- **Number of Records:** 36,248,263
- **Data Type:** Structured



Our Data



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Why This Data

- **Why is it big data?**
 - Large amount of data
 - Complex structure
 - Cannot be captured, managed, and processed with a single database tool
- **Why choose this data set?**
 - To understand market trends
 - To reveal patterns and correlations by price data
 - Inform decision-making and market strategies
 - this data can be applied to other domains



Problem Statement

- **Goal:** Explore whether
 - 1. the rating scores of Airbnb listings affect the prices of their corresponding listings
 - 2. the features affect the prices of Airbnb
- **What we are doing:** Predicting future Airbnb prices using machine learning methods and statistical modeling





Part 2: Analysis



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Our Method for Data Analysis

WORDCOUNT

- Transit
- Amenities

SQL

- Response Time
- Property Type



Our Method for Machine Learning

Linear Regression

- Model 1: Price & Number of Different Rooms
- Model 2: Price & Ratings on the website





Part 2-1: Analysis Data Analysis



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Data Analysis -- Transit

Ten most frequent words with their average price

Transit	count	AveragePrice
phone	13248	9.730272202364587
email	13087	9.733401240855635
reviews	12718	9.731131643948403
jumio	7965	9.738031119090365
United States	5892	9.904449741756059
1.0	5706	9.570974576271187
United Kingdom	3762	9.66472602739726
Spain	3389	9.617452440033086
facebook	3288	9.789454545454545
France	3044	10.288540534253647



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Data Analysis -- Transit

- **Significantly frequent words: "phone", "reviews, and "email"**
 - customers take those three factors seriously
 - e.g. previous reviews, contact availability

[United Kingdom, 3762] [facebook, 3288]
[jumio, 7965] [phone, 13248]
[reviews, 12718]
[1.0, 5706] [email, 13087]
[Spain, 3389]
[France, 3044] [United States, 5892]



Data Analysis -- Amenities

Ten most frequent words with their average price

Amenity	count	AveragePrice
Wireless Internet	301897	139.894383855269
Kitchen	296850	141.42693088455155
Heating	285280	138.53689722531155
Essentials	272512	140.51520093750932
Washer	235544	142.11130688508692
TV	225280	154.405368044634
Internet	190759	144.2520076196168
Hangers	183868	138.5601776658159
Shampoo	183126	141.3421657196129
Smoke detector	177721	147.89176864200925



Data Analysis -- Amenities

- **TV leads to a higher price**
 - Hosts should provide TV to attract customers
 - Low-budget customers should seek rooms without TVs

[Internet, 190759] [Shampoo, 183126]
[Washer, 235544][Kitchen, 296850]
[Wireless Internet, 301897]
[Smokedetector, 177721] [Essentials, 272512]
[Hangers, 183868] [Heating, 285280]
[TV, 225280]



Data Analysis- Response Time

The relationship between the response time and the ratings

Host Response Time	Count_Number_of_Reviews	Avg_Review_Scores_Rating
within a few hours	5144	93.33547257876313
within an hour	18333	92.95301757066463
within a day	2047	92.86112469437653
a few days or more	119	89.8655462184874



Data Analysis- Response Time

- **Fast, but not too fast.**
 - Hosts should respond customers within a few hours.



Data Analysis- Property Types

The most common property types in the top 10 city's top neighborhood.

City	Neighbourhood	Property Type	AvgRating	COUNTS
Amsterdam	Oud-West	Apartment	94.33739130434783	1150
Berlin	Neukölln	Apartment	93.6020482809071	1367
Brooklyn	Williamsburg	Apartment	93.89115646258503	1617
Brooklyn	Williamsburg	Loft	94.4014598540146	137
København	Nørrebro	Apartment	94.19538572458544	1387
London	LB of Islington	House	92.35036496350365	137
London	LB of Islington	Apartment	92.46984924623115	398
Los Angeles	Mid-Wilshire	Apartment	92.56801195814649	669
Los Angeles	Mid-Wilshire	House	94.08243727598567	279
New York	Upper West Side	Apartment	93.18666666666667	900
Paris	Montmartre	Apartment	92.30014124293785	1416
Roma	Prati	Bed & Breakfast	91.61578947368422	190
Roma	Prati	Apartment	93.44505494505495	546
Toronto	Downtown Toronto	House	92.3	100
Toronto	Downtown Toronto	Apartment	93.54385964912281	456
Toronto	Downtown Toronto	Condominium	94.73451327433628	226



Data Analysis- Property Types

- **Apartment is the majority type**
 - Apartment owners in big cities can consider entering the Airbnb market

[London, House, 92.350364963503594]
[Los Angeles, House, 94.082437275985598]
[Toronto, Apartment, 93.543859649122794] [Roma, Apartment, 93.445054945054906]
[Los Angeles, Apartment, 92.5680119581464]
[Brooklyn, Loft, 94.401459854014604]
[Roma, Bed & Breakfast, 91.615789473684202] [Berlin, Apartment, 93.602048280907098]
[København, Apartment, 94.195385724585407]
[Brooklyn, Apartment, 93.891156462585002]
[Paris, Apartment, 92.300141242937798]
[Amsterdam, Apartment, 94.337391304347804]
[New York, Apartment, 93.186666666666596] [Toronto, House, 92.299999999999997]
[London, Apartment, 92.469849246231107]
[Toronto, Condominium, 94.734513274336194]





Part 2-2: Analysis Machine Learning



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Machine Learning -- Price & Rooms 1

- Independent Variables

- Accommodates Acc
- Bathrooms Bat
- Bedrooms Ber
- Beds Bed

- Dependent Variable

- Price Pri

- $Pri = 28.48 + 21.77 \text{ Acc} + 13.33 \text{ Bat} + 35.40 \text{ Ber} - 13.65 \text{ Bed}$

OLS Regression Results

Dep. Variable:	Price	R-squared:	0.164
Model:	OLS	Adj. R-squared:	0.164
Method:	Least Squares	F-statistic:	2.374e+04
Date:	Sun, 03 Dec 2023	Prob (F-statistic):	0.00
Time:	15:57:08	Log-Likelihood:	-3.0714e+06
No. Observations:	484544	AIC:	6.143e+06
Df Residuals:	484539	BIC:	6.143e+06
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	28.4832	0.484	58.846	0.000	27.535	29.432
Accommodates	21.7748	0.184	118.073	0.000	21.413	22.136
Bathrooms	13.3307	0.429	31.072	0.000	12.490	14.172
Bedrooms	35.4008	0.360	98.417	0.000	34.696	36.106
Beds	-13.6465	0.252	-54.056	0.000	-14.141	-13.152

Omnibus:	311633.729	Durbin-Watson:	0.850
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3347489.466
Skew:	3.051	Prob(JB):	0.00
Kurtosis:	14.339	Cond. No.	14.8

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



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Machine Learning -- Price & Rooms 2

- **Split the data:**
 - 70% training data
 - 30% testing data
- **Mean Squared Error:** 19624.42
- **Rsquared Error:** 16.51%
- **Reasons:**
 - Insufficient feature relevance
 - Underfitting
 - Lack of data



Machine Learning -- Price & Ratings 1

- Independent Variables
 - Review Scores Rating RSR
 - Review Scores Cleanliness RSC
 - Review Scores Location RSL
- Dependent Variable
 - Price Pri
- $Pri = -34.57 + 0.58 RSR + 0.01 RSC + 12.09 RSL$

```

OLS Regression Results
=====
Dep. Variable:          Price    R-squared:                0.008
Model:                  OLS      Adj. R-squared:           0.008
Method:                 Least Squares    F-statistic:           936.1
Date:                  Sun, 03 Dec 2023    Prob (F-statistic):     0.00
Time:                  16:40:00    Log-Likelihood:        -2.3070e+06
No. Observations:      361000    AIC:                   4.614e+06
Df Residuals:          360996    BIC:                   4.614e+06
Df Model:               3
Covariance Type:       nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----
const                -34.5742     3.251    -10.634     0.000    -40.947    -28.202
Review Scores Rating    0.5834     0.042     13.982     0.000     0.502     0.665
Review Scores Cleanliness 0.0133     0.324     0.041     0.967    -0.621     0.648
Review Scores Location  12.0860     0.335     36.128     0.000    11.430    12.742
=====
Omnibus:                227680.671    Durbin-Watson:           0.948
Prob(Omnibus):           0.000    Jarque-Bera (JB):        2193573.632
Skew:                    3.020    Prob(JB):                 0.00
Kurtosis:                13.458    Cond. No.                 1.28e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.28e+03. This might indicate that there are strong multicollinearity or other numerical problems.

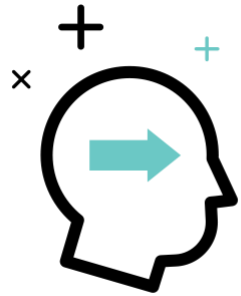


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Machine Learning -- Price & Ratings 2

- **Split the data:**
 - 70% training data
 - 30% testing data
- **Mean Squared Error:** 75000.15
- **Rsquared Error:** 34.73%
- **Reasons:**
 - Insufficient or Irrelevant Features
 - Non-linear Relationships
 - High Variance in the Target Variable





Part 3: Conclusion



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Conclusion

- Attach importance to phone communication, email communication, and reviews
- Providing TVs for customers to watch.
- Hosts should respond to customers within a few hours
- Apartment owners in big cities can consider entering the Airbnb market
- Accommodates, Bathrooms, Bedrooms, Beds, Review Scores Rating, and Review Scores

Location are all statistically significant predictors of Price

- The linear regression models are not good machine learning method

