

# Introduction to AirBnB Price Prediction

AirBnB is short for its original name, [AirBedandBreakfast.com](https://www.airbnb.com), the popular home-sharing platform, is an online marketplace for arranging or offering homestays or tourism experiences and it presents unique pricing challenges. So understanding how to accurately predict AirBnB prices is crucial for hosts and guests alike.



# Importance of Accurate Pricing

## Maximize Revenue

Optimal pricing helps hosts earn the most from their listings.

## Attract Guests

Competitive pricing makes listings more appealing to potential guests.

## Maintain Occupancy

Accurate pricing avoids vacant days and maintains high occupancy rates.

## Improve Competitiveness

Precise pricing gives hosts an edge over similar listings.

# Machine Learning for Price Prediction

1

## Regression Models

Predict continuous price values based on listing features.

2

## Classification Models

Classify listings into price tiers or ranges.

3

## Ensemble Methods

Combine multiple models for improved accuracy.

4

## Neural Networks

Leverage complex non-linear relationships in data.

# Data Collection and Preprocessing

## Scraping Listings

Collect comprehensive data on Airbnb properties and hosts.

## Cleaning and Transforming

Handle missing values, outliers, and feature engineering.

## Exploratory Analysis

Uncover trends, patterns, and relationships in the data.



Airbnb\_Open\_Data

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General

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1	id	NAME	host id	host_iden	host name	neighbour	neighbour lat	long	country	country cc	instant_	bc	cancellatic	room type	Constructi	price	service fee	minimum	number of last	review reviews	pe review rat	calculated	availability	house_rul	license				
2	1001254	Clean & qu	8E+10	unconfirm	Madaline	Brooklyn	Kensington	40.64749	-73.9724	United Sta	US	FALSE	strict	Private ro	2020	\$966	\$193	10	9	10/19/202	0.21	4	6	286	Clean up and treat the home the way you'd like your home				
3	1002102	Skylit Mid	5.23E+10	verified	Jenna	Manhattan	Midtown	40.75362	-73.9838	United Sta	US	FALSE	moderate	Entire hon	2007	\$142	\$28	30	45	5/21/2022	0.38	4	2	228	Pet friendly but please confirm with me if the pet you are p				
4	1002403	THE VILLA	7.88E+10		Elise	Manhattan	Harlem	40.80902	-73.9419	United Sta	US	TRUE	flexible	Private ro	2005	\$620	\$124	3	0			5	1	352	I encourage you to use my kitchen, cooking and laundry fac				
5	1002755		8.51E+10	unconfirm	Garry	Brooklyn	Clinton Hil	40.68514	-73.9598	United Sta	US	TRUE	moderate	Entire hon	2005	\$368	\$74	30	270	7/5/2019	4.64	4	1	322					
6	1003689	Entire Apt	9.2E+10	verified	Lyndon	Manhattan	East Harle	40.79851	-73.944	United Sta	US	FALSE	moderate	Entire hon	2009	\$204	\$41	10	9	11/19/201	0.1	3	1	289	Please no smoking in the house, porch or on the property (				
7	1004098	Large Cozy	4.55E+10	verified	Michelle	Manhattan	Murray Hil	40.74767	-73.975	United Sta	US	TRUE	flexible	Entire hon	2013	\$577	\$115	3	74	6/22/2015	0.59	3	1	374	No smoking, please, and no drugs.				
8	1004650	BlissArts	6.13E+10		Alberta	Brooklyn	Bedford-Si	40.68688	-73.956	United Sta	US	FALSE	moderate	Private ro	2015	\$71	\$14	45	49	10/5/2017	0.4	5	1	224	Please no shoes in the house so bring slippers or extra sock				
9	1005202	BlissArts	9.08E+10	unconfirm	Emma	Brooklyn	Bedford-Si	40.68688	-73.956	United Sta	US	FALSE	moderate	Private ro	2009	\$1,060	\$212	45	49	10/5/2017	0.4	5	1	219	House Guidelines for our BnB We are delighted to welcome				
10	1005754	Large Furn	7.94E+10	verified	Evelyn	Manhattan	Hell's Kitcl	40.76489	-73.9849	United Sta	US	TRUE	strict	Private ro	2005	\$1,018	\$204	2	430	6/24/2015	3.47	3	1	180	- Please clean up after yourself when using the kitchen. - W				
11	1006307	Cozy Clear	7.55E+10	unconfirm	Carl	Manhattan	Upper We	40.80178	-73.9672	United Sta	US	FALSE	strict	Private ro	2015	\$291	\$58	2	118	7/21/2017	0.99	5	1	375	NO SMOKING OR PETS ANYWHERE ON THE PROPERTY 1. B				
12	1006859	Cute & Co	1.28E+09	verified	Miranda	Manhattan	Chinatown	40.71344	-73.9904	United Sta	US	FALSE	flexible	Entire hon	2004	\$319	\$64	1	160	6/9/2019	1.33	3	4	1					
13	1007411	Beautiful	1.88E+10	verified	Alan	Manhattan	Upper We	40.80316	-73.9655	United Sta	US	TRUE	flexible	Entire hon	2008	\$606	\$121	5	53	6/22/2015	0.43	4	1	163	My ideal guests would be warm, friendly, and respectful of				
14	1007964	Central Mi	8.81E+10	verified		Manhattan	Hell's Kitcl	40.76076	-73.9887	United Sta	US	FALSE	strict	Private ro	2008	\$714	\$143	2	188	6/23/2015	1.5	4	1	258	- One of the bedroom closets is not accessible to guests - P				
15	1008516	Lovely Roc	2.68E+10	verified	Darcy	brookln	South Slop	40.66829	-73.9878	United Sta	US	TRUE	moderate	Private ro	2010	\$580	\$116	4	167	6/24/2015	1.34	4	3	47					
16	1009068	Wonderfu	8.89E+10	verified	Leonardo	Manhattan	Upper We	40.79826	-73.9611	United Sta	US	FALSE	flexible	Private ro	2019	\$149	\$30	2	113	7/5/2019	0.91	3	1	68					
17	1009621	West Villaj	4.66E+10	verified	Daniel	Manhattan	West Villaj	40.7353	-74.0053	United Sta	US	TRUE	flexible	Entire hon	2018	\$578		90	27	10/31/201	0.22	3	1	100	Arrival time can be no later than 9:00PM unless pre-arrang				
18	1010173	Only 2 sto	6.26E+10	unconfirm	Heather	Brooklyn	Williamsb	40.70837	-73.9535	United States			moderate	Entire hon	2009	\$778		2	148	6/29/2015	1.2	3	1	197	Absolutely no smoking in the building, handling of art work				
19	1010725	Perfect for	8.04E+10	verified	Ryan	Brooklyn	Fort Greer	40.69169	-73.9719	United States			flexible	Entire hon	2006	\$656		2	198	6/28/2015	1.72	5	1	96	- Please be mindful of the neighbors, quiet time after 10PM				
20	1011277	Chelsea Pe	7.39E+10	verified	Alberta	manhatan	Chelsea	40.74192	-73.995	United States			moderate	Private ro	2008	\$460		1	260	7/1/2019	2.12	3	1	325					
21	1011830	Hip Histori	7.21E+10		Martin	Brooklyn	Crown Hei	40.67592	-73.9469	United States			moderate	Entire hon	2004	\$1,095		3	53	6/22/2015	4.44	5	1	345	LAUNDRY - Laundry can be done by the visitor before 10 pr				
22	1012382	Huge 2 BR	7.98E+10	verified	Audrey	Manhattan	East Harle	40.79685	-73.9487	United States			moderate	Entire hon	2013	\$281	\$56	7	0			3	2	347	No smoking, No pets. No shoes in the house. Visitors are p				
23	1012934	Sweet and	8.66E+10	verified	Alissa	Brooklyn	Williamsb	40.71842	-73.9572	United States			flexible	Entire hon	2016	\$477	\$95	3	9	12/28/202	0.07	3	1	193	- No smoking or open flames on the property - Please respi				
24	1013487	CBG CtyBC	5.38E+10	verified	Mary	Brooklyn	Park Slope	40.68069	-73.9771	United States			moderate	Private ro	2013	\$133	\$27	2	130	7/1/2019	1.09	4	6	54	Arrival time can be no later than 10:00PM. No visitors allow				
25	1014039	CBG Helps	8.77E+10		William	Brooklyn	Park Slope	40.67989	-73.978	United States			moderate	Private ro	2017	\$1,050	\$210	1	39	1/1/2019	0.37	3	6	9					
26	1014591	CBG Helps	5.78E+10	unconfirm	Charlotte	Brooklyn	Park Slope	40.68001	-73.9787	United States			strict	Private ro	2005	\$816	\$163	2	71	7/2/2019	0.61	4	6	344	We take great care of our home and expect you to do the s				
27	1015144	MAISON D	4.84E+10		Miranda	Brooklyn	Bedford-Si	40.68371	-73.9403	United States			strict	Entire hon	2006	\$1,175	\$235	2	88	6/19/2015	0.73	4	2	372					
28	1015696	Sunny Bed	8.17E+10		Carlos	Brooklyn	Windsor T	40.65599	-73.9752	United States			moderate	Private ro	2021	\$530	\$106	1	19	6/23/2015	1.37	5	2	344	Quiet neighborhood, middle apartment of big house, quiet				
29	1016248	Magnifiqu	3.88E+10	verified	Adrianna	Manhattan	Inwood	40.86754	-73.9264	United States			strict	Private ro	2017	\$274	\$55	4	0			1	96	To treat our home with respect. No smoking inside but fee					
30	1016800	Midtown I	1.94E+10	unconfirm	Andrew	Manhattan	Hell's Kitcl	40.76715	-73.9853	United States			moderate	Entire hon	2016	\$209	\$42	10	58	8/13/2017	0.49	1	1	103	Please no pets or smoking in the house, though you can go				
31	1017353	SPACIOUS,	5.14E+10	verified	Daryl	Manhattan	Inwood	40.86482	-73.9211	United States			strict	Private ro	2021	\$432	\$86	3	108	6/15/2015	1.11	3	3	172	My ideal guests would be warm, friendly, and respectful of				
32	1017905	Modern 1	8.64E+10	unconfirm	Tyler	Manhattan	East Villag	40.7292	-73.9854	United States			flexible	Entire hon	2010	\$666	\$133	14	29	4/19/2015	0.24	1	1	56	Just be respectful, clean, and quiet after 10:00PM!				
33	1018457	front room	6.94E+10	unconfirm	Byron	Manhattan	Harlem	40.82245	-73.951	United States			flexible	Private ro	2004	\$770	\$154	3	242	6/1/2019	2.04	3	3	105	No loud noises or loud music. Please help us save the plan				
34	1019010	Spacious 1	8.04E+10	verified	Mary	Manhattan	Harlem	40.81305	-73.9547	United States			flexible	Private ro	2007	\$512	\$102	2	88	6/14/2015	1.42	1	1	169					

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# Feature Engineering



# Supervised Learning Models

1

## Multiple Linear Regression

Extends simple linear regression to model the relationship between one dependent variable and multiple independent variables.

2

## Decision Trees

Is a non-linear model that splits the data into regions and fits a constant model within each region. Random Forest, ensemble method for improved accuracy.

3

## Random Forest

Builds an ensemble of decision trees and averages their predictions to improve accuracy and control over fitting.

4

## Gradient Boosting Regression

Builds an ensemble of decision trees sequentially, where each tree corrects the errors of the previous ones.

5

## XGBoost Regression

XGBoost, short for Extreme Gradient Boosting, It leverages an ensemble of decision trees, using a boosting technique to iteratively improve the model by minimizing errors from previous iterations. This method enhances the overall prediction accuracy significantly.

# Model Evaluation

Metric	Description	Importance
RMSE	Root Mean Squared Error	Measures overall prediction accuracy
R-squared	Coefficient of Determination	Indicates model's explanatory power
MAE	Mean Absolute Error	Captures average magnitude of errors
MAPE	Mean Absolute Percentage Error	Is crucial for measuring the accuracy of a regression model by expressing prediction errors as a percentage, making it easy to interpret and compare across different datasets



## Model In A Nutshell

making money by charging guests a service fee. The fee from hosts is generally 3%. The platform takes 15% of the total paid amount.

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# Conclusions and Future

## Insights

1

Actionable insights to optimize Airbnb pricing strategies.

## Limitations

2

Addressing data availability and model complexities.

## Future Research

3

Incorporating dynamic pricing, market trends, and user behavior.