

# Airbnb Price Prediction

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Exploring patterns in airbnb dataset to understand the implications of different factors that affect the individual airbnb price

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MIS 381N Final Project, Summer 2022



# Traveling after summer classes?

Airbnb has revolutionized the travel industry with simple & convenient places to stay.

Hosts

How to list properties to generate additional income?

Travelers

What features should pay attention to find the optimally priced property?

Project Goals

Exploratory Data Analysis

Data Preprocessing

Modeling & Conclusion



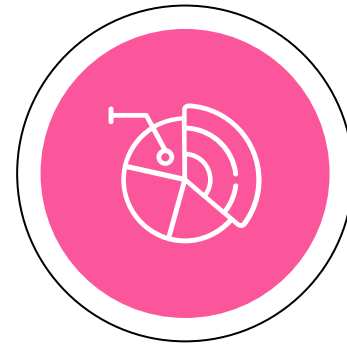
# Agenda



**Project Goals**



**Exploratory Data  
Analysis**



**Data  
Preprocessing**



**Modeling &  
Conclusion**

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# Data Description

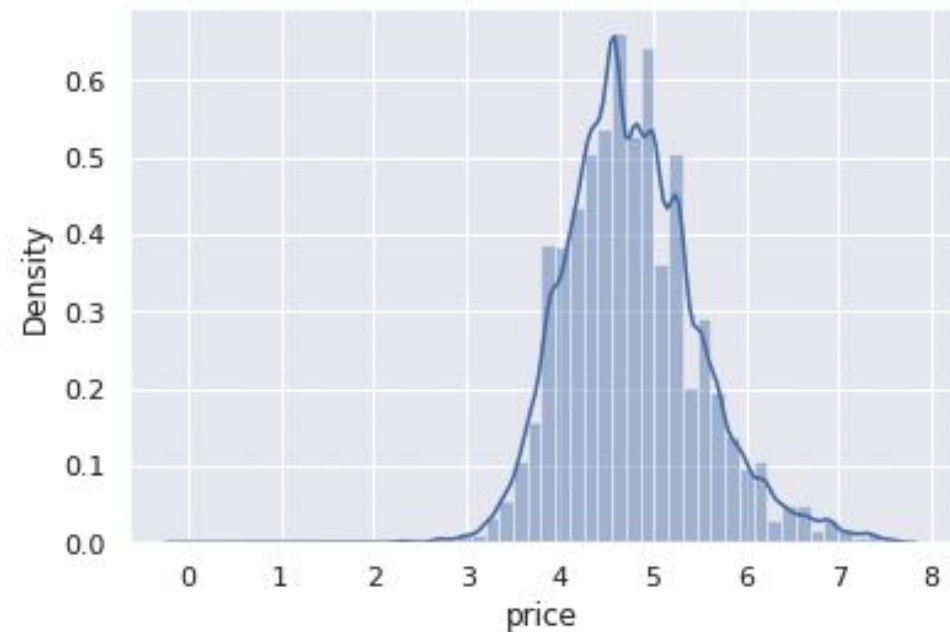
**Source:** Kaggle ([Dataset Here](#))

**Number of Features: 29**

- Number of numerical features: **9**
- Number of categorical features: **18**
- Number of date features: **2**

**Target:** log\_price

The dataset consists of **74,111** records





# Features

## Rating/Review Feature

first_review
last_review
number_of_reviews
review_score_rating

## Host-related Feature

cancellation_policy
host_has_profile_pic
host_identity_verified
host_response_rate
host_since

## Location Feature

city
description
latitude
longitude
neighbourhood
zipcode

## Property Feature

id
log_price
property_type
room_type
amenities
accommodates
bathrooms
bed_type
cleaning_fee
instant_bookable
bed
bedrooms
thumbnail_url
name

Project Goals

Exploratory Data Analysis

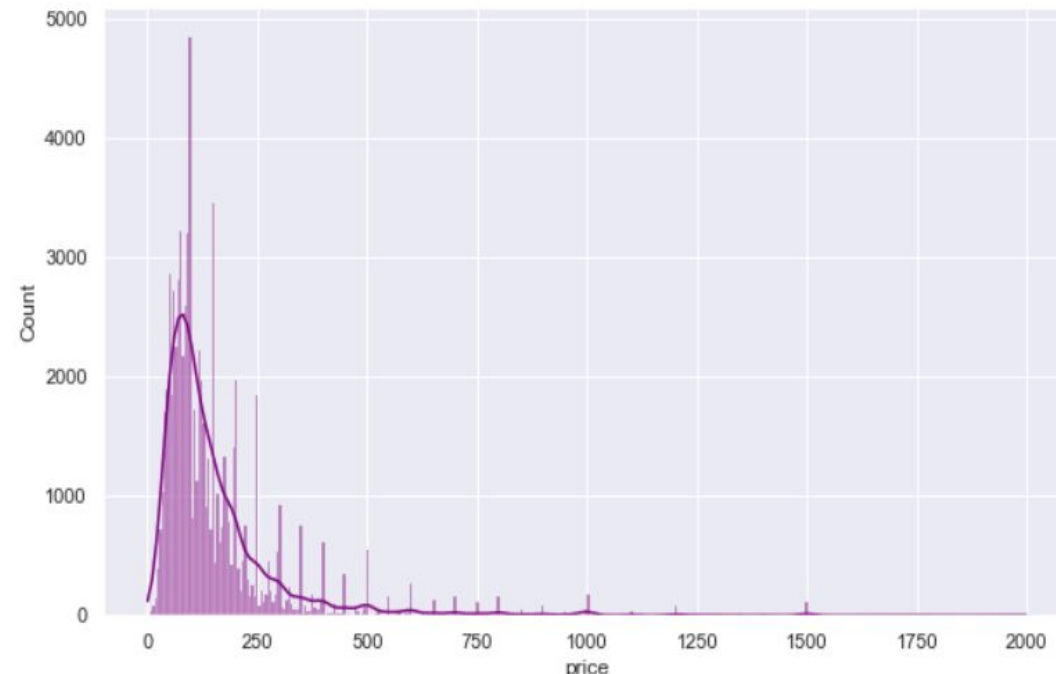
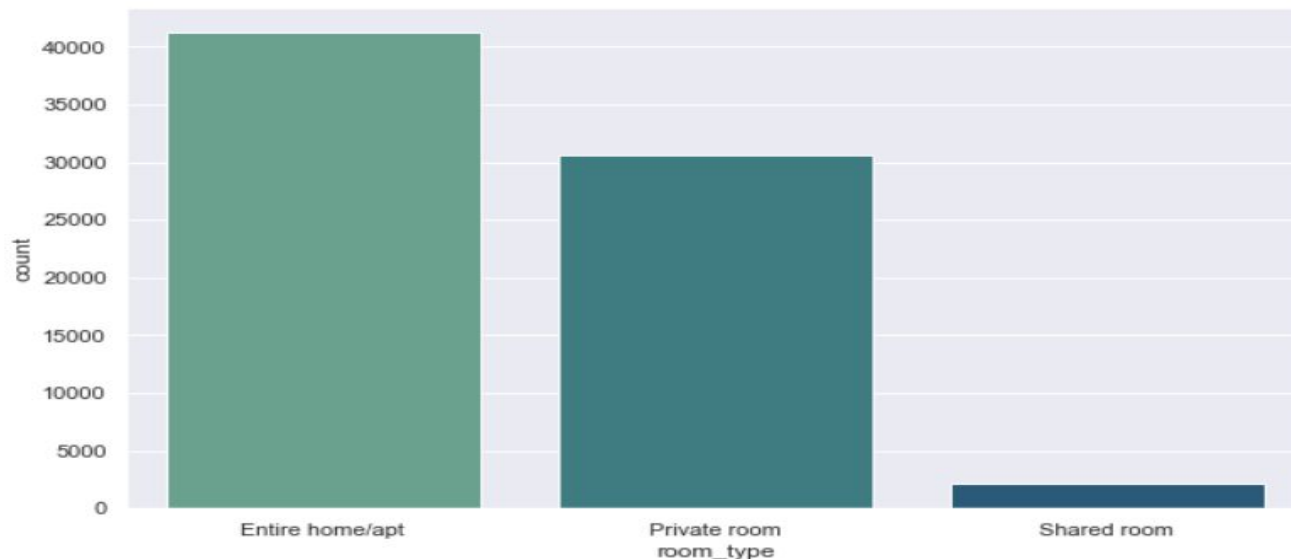
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# Exploratory Data Analysis

- Only 3% of the listings are for shared rooms
- 97.2% have real beds
- 73.9% of the listings are in NYC and LA
- Host response rate has a mean of 94.3%
- ~30% have a flexible cancellation policy
- Review scores > 85





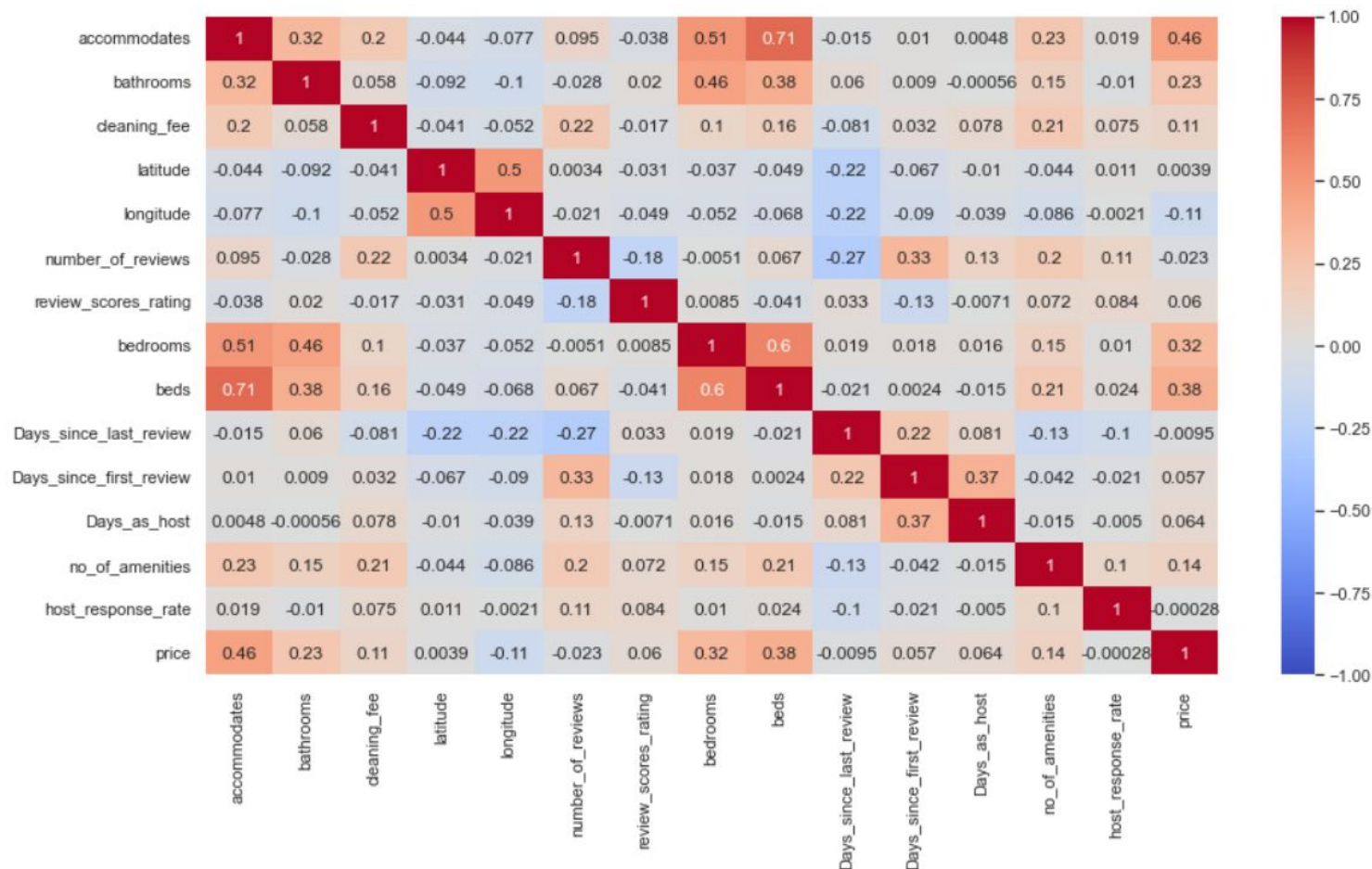
# Exploratory Data Analysis

- More expensive airbnb's also have a stricter cancellation policy
- Number of bedrooms and bathrooms have a significant impact on price
- Host features seem to have a negligible effect on price
- San Francisco has the highest avg number of ratings per airbnb, followed by Chicago
- SF has the highest average median price of airbnb's
- NYC has the highest number of expensive neighborhoods followed by LA





# Correlation between variables



- Number of people a room accommodates and bathrooms is correlated to the number of bedrooms
- Cleaning fee has a positive correlation with number of amenities offered
- Number of reviews is highly correlated with number of days elapsed since first review
- Number of bedrooms has a correlation with price





# Data Preprocessing

## Drop Columns

Dropped columns with **no predicting power** or **duplicate usage**



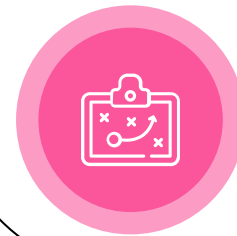
## Drop Null

Drop records with **null values**



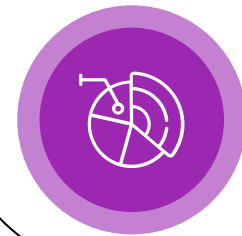
## Transform Variables

Encoding **categorical variables** and **dates**



## Split Train/Test

Split the data into **80% training data** and **20% testing data**



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# Linear Regression

## Results Summary

RMSE	0.4096
MAPE	0.0672
R <sup>2</sup>	0.63

- We used all features to fit linear regression model
- Features with p-value > 0.05:
  - number\_of\_reviews
  - property\_type: boutique hotel, bungalow, cabin, cave, chalet, earth house, island, serviced apartment, treehouse, villa, yurt, other
  - cancellation\_policy\_moderate
  - cleaning\_fee

	coef	std err	t	P> t				
accommodates	0.0793	0.002	44.139	0.000				
bathrooms	0.1476	0.004	34.697	0.000				
host_response_rate	0.0008	0.000	5.425	0.000				
number_of_reviews	-9.315e-05	4.81e-05	-1.935	0.053	property_type_Timeshare	0.4897	0.077	6.368 0.000
review_scores_rating	0.0110	0.000	42.735	0.000	property_type_Tipi	0.6421	0.243	2.643 0.008
bedrooms	0.1376	0.004	37.491	0.000	property_type_Townhouse	-0.0327	0.013	-2.597 0.009
beds	-0.0409	0.003	-14.734	0.000	property_type_Train	0.6677	0.297	2.246 0.025
Days_since_last_review	0.0005	1.23e-05	43.528	0.000	property_type_Treehouse	0.3765	0.210	1.790 0.073
Days_as_host	5.048e-05	3.24e-06	15.600	0.000	property_type_Vacation home	0.3694	0.172	2.152 0.031
no_of_amenities	0.0066	0.000	21.808	0.000	property_type_Villa	0.0476	0.038	1.252 0.211
property_type_Bed & Breakfast	0.0911	0.023	3.889	0.000	property_type_Yurt	0.1708	0.172	0.995 0.320
property_type_Boat	0.2359	0.063	3.754	0.000	room_type_Private room	-0.5956	0.005	-123.024 0.000
property_type_Boutique hotel	0.1288	0.069	1.855	0.064	room_type_Shared room	-1.0389	0.013	-78.424 0.000
property_type_Bungalow	-0.0347	0.026	-1.360	0.174	bed_type_Couch	0.5274	0.044	11.871 0.000
property_type_Cabin	-0.1244	0.055	-2.262	0.024	bed_type_Futon	0.4860	0.031	15.687 0.000
property_type_Camper/RV	-0.2338	0.052	-4.467	0.000	bed_type_Pull-out Sofa	0.5555	0.032	17.270 0.000
property_type_Castle	0.3486	0.117	2.988	0.003	bed_type_Real Bed	0.5870	0.025	23.815 0.000
property_type_Cave	0.2649	0.297	0.891	0.373	cancellation_policy_moderate	0.0076	0.006	1.296 0.195
property_type_Chalet	0.1015	0.188	0.540	0.590	cancellation_policy_strict	0.0411	0.006	7.465 0.000
property_type_Condominium	0.0950	0.011	9.006	0.000	cancellation_policy_super_strict_30	0.2096	0.048	4.339 0.000
property_type_Dorm	-0.4148	0.042	-9.780	0.000	cancellation_policy_super_strict_60	0.7239	0.133	5.427 0.000
property_type_Earth House	0.0834	0.243	0.344	0.731	cleaning_fee_t	-0.0017	0.005	-0.322 0.748
property_type_Guest suite	-0.1229	0.042	-2.896	0.004	city_Chicago	-0.3475	0.012	-29.947 0.000
property_type_Guesthouse	-0.0645	0.021	-3.001	0.003	city_DC	-0.1398	0.011	-12.371 0.000
property_type_Hotel	-0.5097	0.058	-8.791	0.000	city_LA	-0.1792	0.010	-18.750 0.000
property_type_House	-0.0595	0.005	-11.396	0.000	city_NYC	0.0453	0.009	4.992 0.000
property_type_Hut	-0.3741	0.159	-2.353	0.019	city_SF	0.3028	0.011	27.905 0.000
property_type_In-law	-0.2195	0.053	-4.119	0.000	host_has_profile_pic_t	1.5330	0.035	43.542 0.000
property_type_Island	0.8016	0.420	1.907	0.057	host_identity_verified_t	-0.0232	0.005	-4.980 0.000
property_type_Loft	0.1478	0.015	10.169	0.000	instant_bookable_t	-0.0108	0.004	-2.451 0.014
property_type_Other	0.0318	0.021	1.478	0.139				
property_type_Serviced apartment	0.1899	0.109	1.749	0.080				
property_type_Tent	-0.2393	0.113	-2.125	0.034				

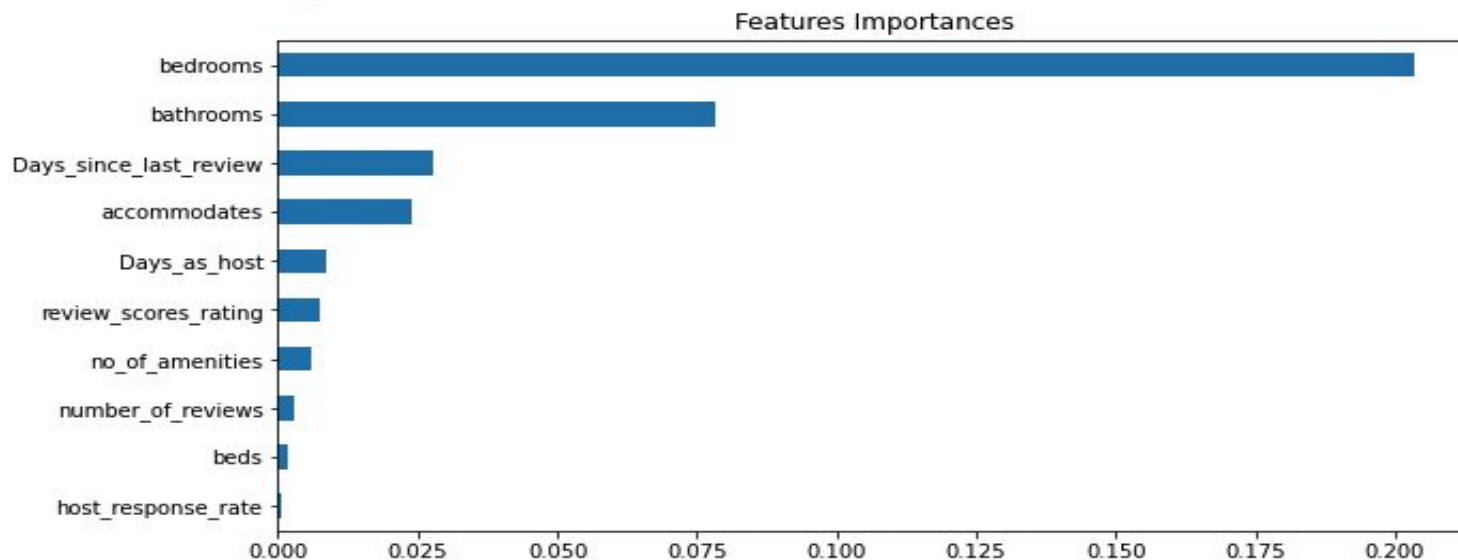
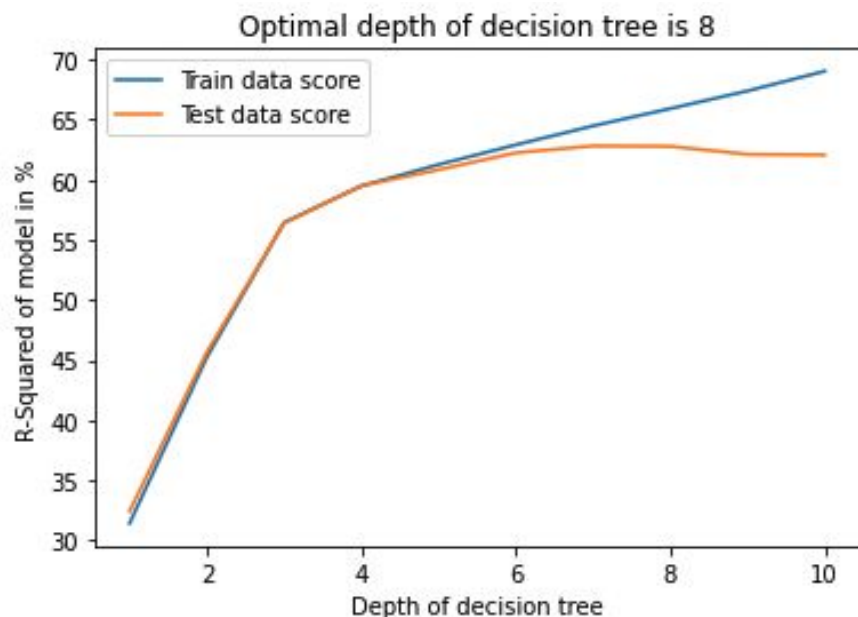


# Decision Tree Regressor

## Results Summary

RMSE	0.1702
MAPE	0.0674
R <sup>2</sup>	0.63

- Max depth of tree considered: 8
- Top 5 most important features: bathrooms, bedrooms, number of days since last review, number of people that can be accommodated and number of days as host





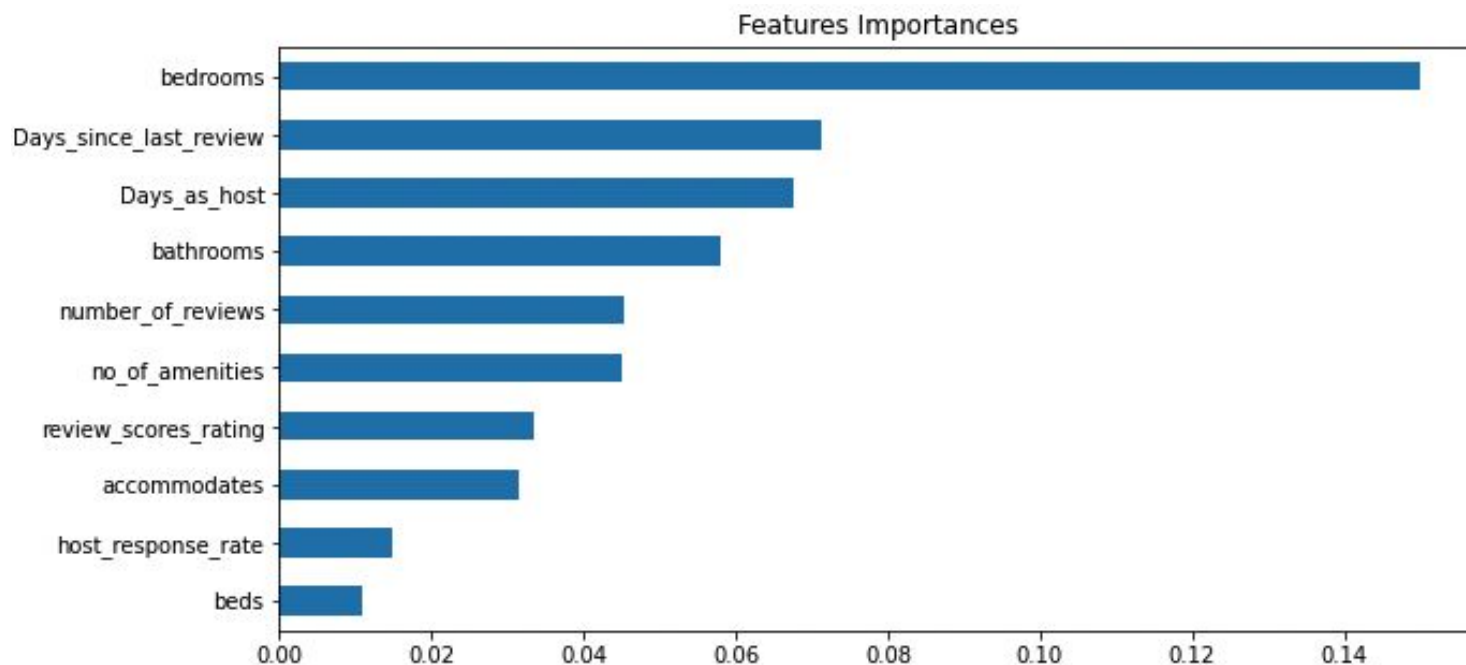
# Random Forest

## Results Summary

RMSE	0.3880
MAPE	0.063
R <sup>2</sup>	0.67

Values of Parameters selected after tuning:

- n\_estimators = 300
- max\_depth=80
- random\_state = 42



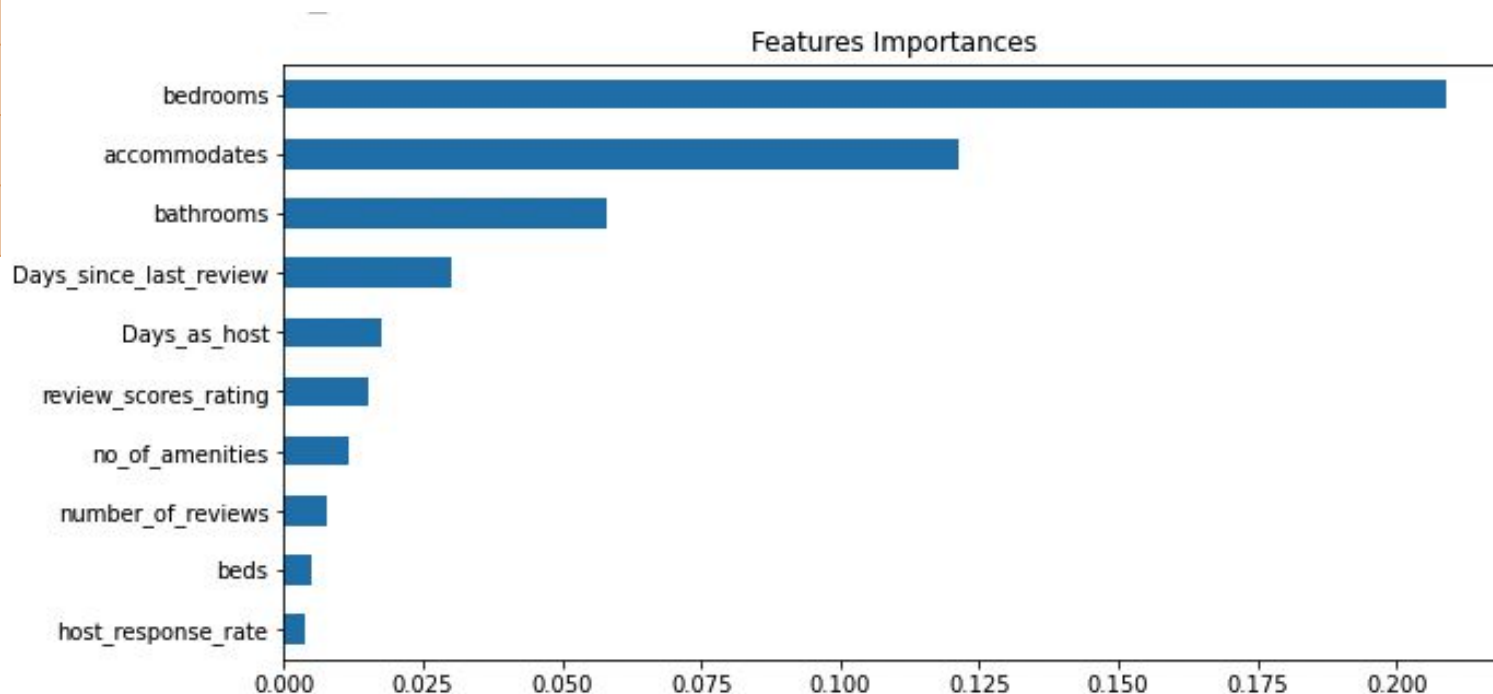


# Gradient Boosting

## Results Summary

RMSE	0.3844
MAPE	0.0631
R <sup>2</sup>	0.68

- Parameters tuned:
  - n\_estimators = 1000
  - max\_features = 'auto'





# Model Performance & Output Comparison

	Linear Regression	Decision Tree	Random Forest	Gradient Boosting
RMSE	0.4096	0.1702	0.3880	0.3844
MAPE	6.72%	6.73%	6.31%	6.31%
R^2	0.63	0.63	0.67	0.68

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# Insights & Conclusion

- **Gradient Boosting** yielded the best R-squared result, followed by Random Forest, Decision Tree, and OLS Linear Regression.
- Overall, **bedrooms, bathrooms, days\_since\_last\_review and days\_as\_host** are the top 4 features with the highest importances.



**Thanks!**

**Any Questions?**