

Business Growth Strategy for Hosts on **Airbnb Platform**

Meet the Team



Priyam Sarkar



Samridhi Vats



Priyanka Shinde



Nagraj Deshmukh

Executive Summary of Findings

Airbnb's business model embodies a quintessential platform-based structure, capitalizing on the network effect where the value of its service increases with each additional user, aligning with Metcalfe's Law. Our comprehensive analysis bolstered by predictive and prescriptive modelling provided strategic insights leading to value extraction for hosts of Airbnb platform. We undertook an exhaustive study of the potential new entrants and existing hosts to understand the competitive landscape better.

Superhost Program & Revenue Impact: Data from the Superhost Certification Program highlighted a stark contrast in earnings, with Superhosts significantly outperforming regular hosts. The rigorous statistical tests underscore the program's influence on revenue, customer satisfaction, and repeat bookings.

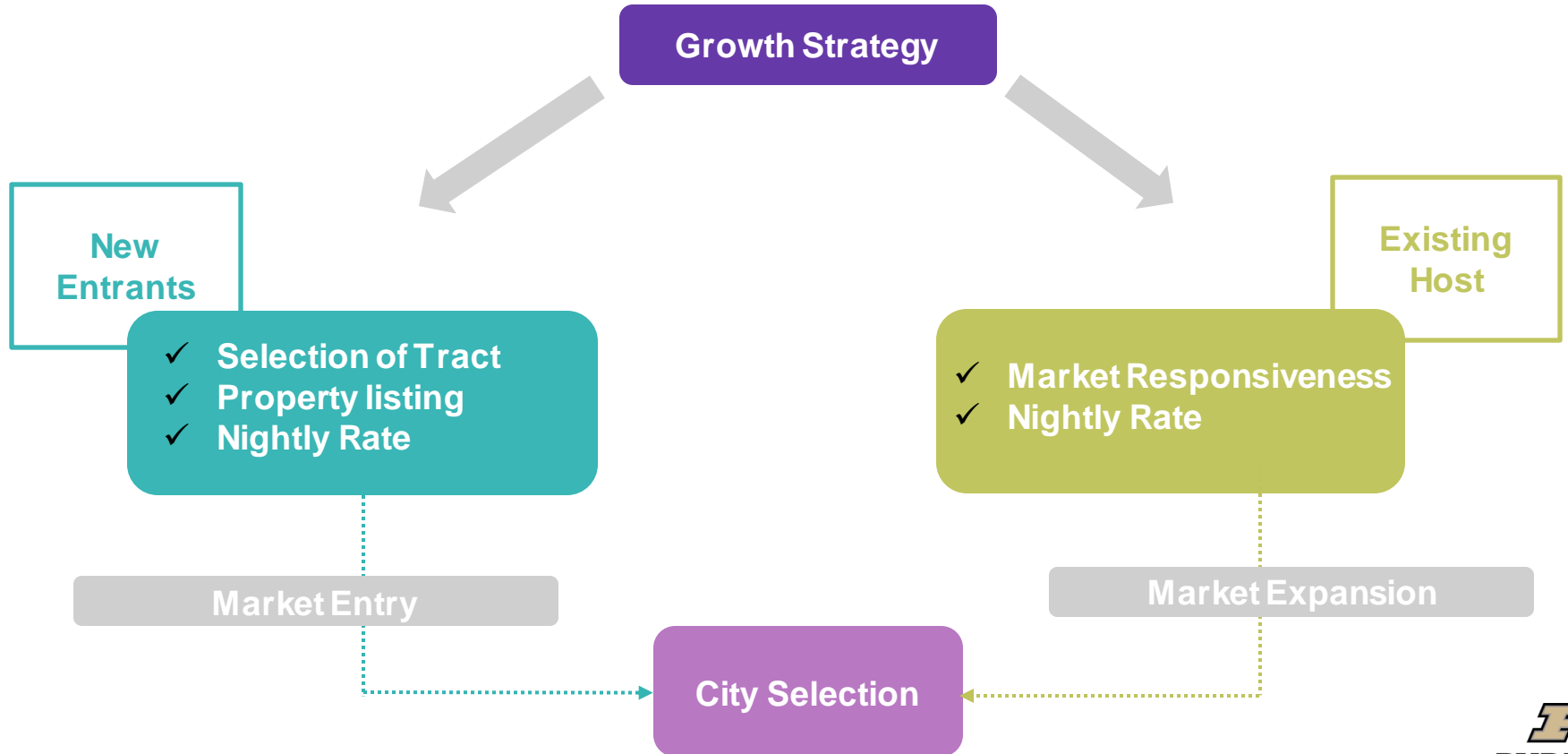
City Selection & Market Entry: Focused analysis on city and tract selection criteria revealed key indicators that guide potential new entrants in identifying lucrative city and tracts for market entry. The study demonstrated that certain tracts within chosen cities present substantial revenue-generating potential.

Market Expansion Strategy: For existing hosts, the model pinpoints factors in hosts' control that affect revenue on basis of seasonality demand. These controllable factors, along with responsive strategies to seasonality and market demands, are pivotal in driving revenue growth.

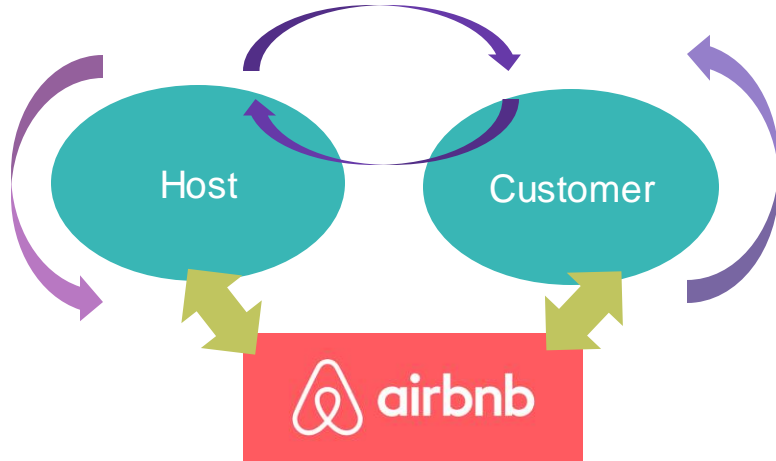
Challenges and Future Scope: Our project navigated through data inconsistencies and missing values to ensure robust model performance. The final recommendation underscores the vital role of data-driven strategies in maximizing value extraction for hosts of Airbnb platform to ultimately boost revenue growth. Due to time constraint, we have analyzed value extraction for hosts but for future scope, we can incorporate value creation for guests as well.

By integrating these findings, hosts can leverage key features for differentiation and competitive advantage, ultimately leading to sustained growth and value extraction on Airbnb platform.

Problem Statement



Network Effect of Airbnb



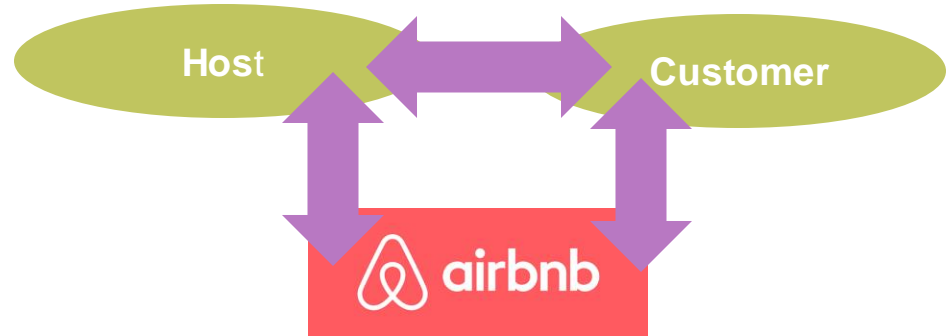
Correlation Matrix:

	Number of Hosts	Number of Superhosts	Rating Overall
Number of Hosts	1.000000	-0.109705	-0.896112
Number of Superhosts	-0.109705	1.000000	0.264264
Rating Overall	-0.896112	0.264264	1.000000
numReserv_pastYear	-0.868152	-0.063267	0.734875

Because of the Project Limitation, we will analyze one side of Network effect and we have chosen

Host.

Multi layered competition for Host in Airbnb platform

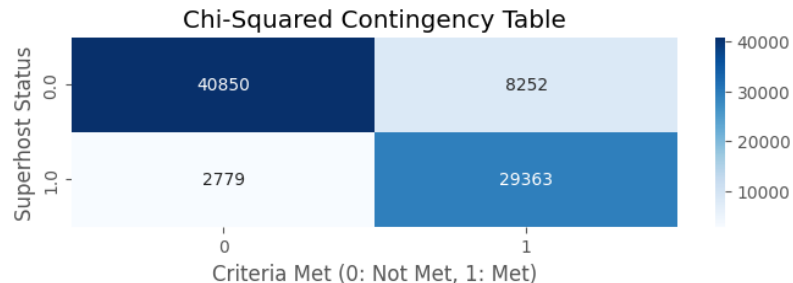


With intense competition, **value creation for host is challenging.**

However, **data driven business recommendation and growth strategy** can solve the problem.

Super Host Certification Program

```
# Criteria for Superhost
min_trips = 10
min_response_rate = 90
max_cancellations = 0
min_5_star_prop = 80
```



Revenue

t-test : 12.39, p : 0.0000

Customer Satisfaction (average rating)

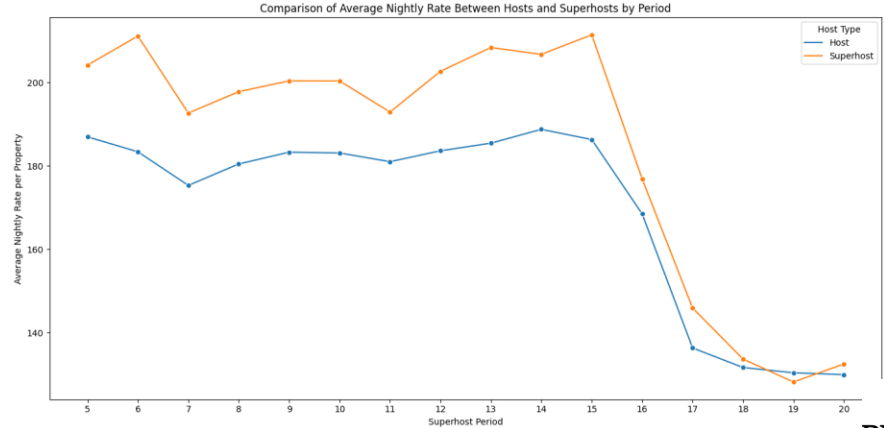
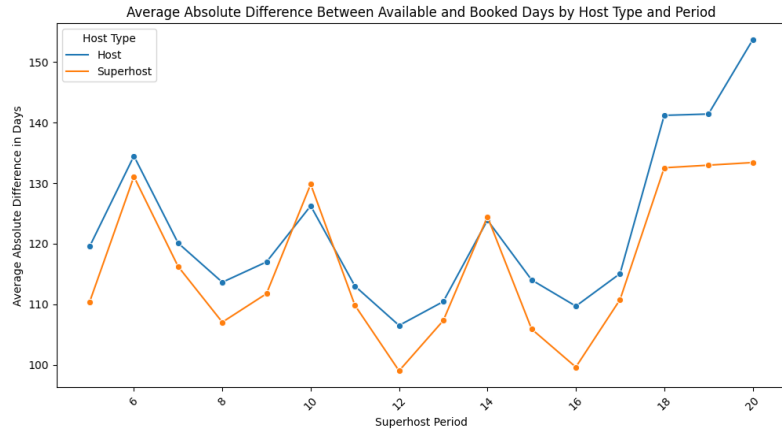
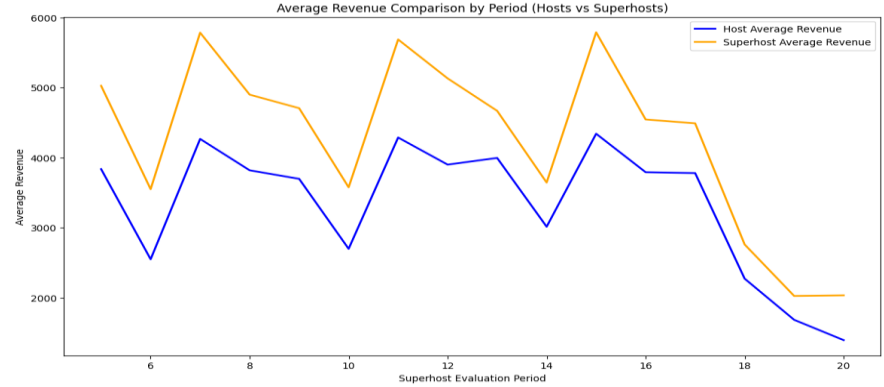
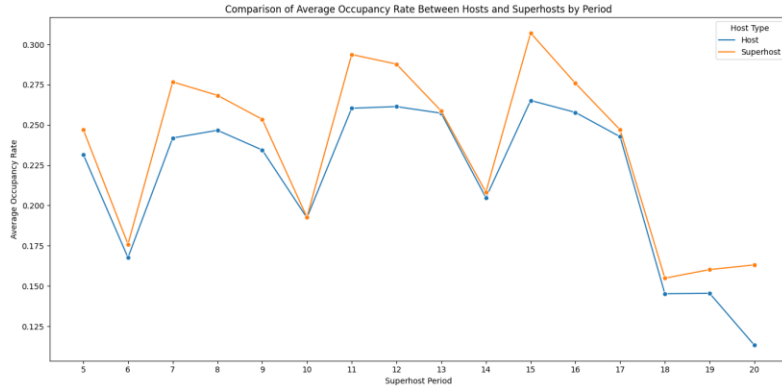
t-test : 127.10, p : 0.0000

Repeat bookings

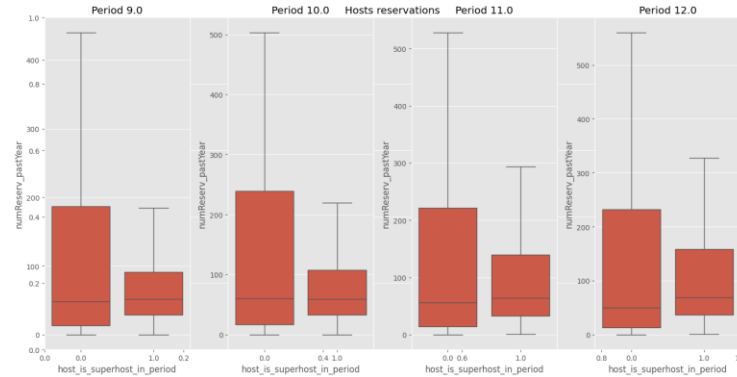
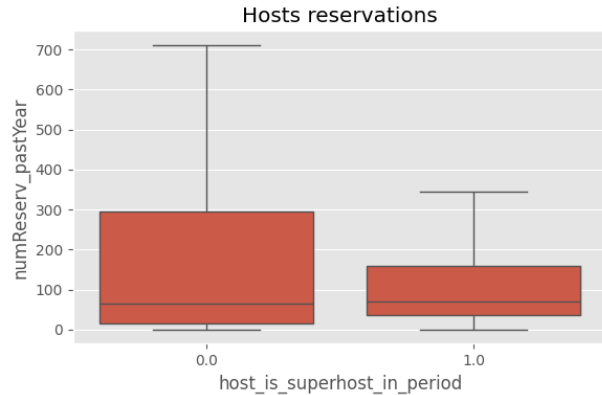
t-test : -37.58, p: 0.0000

1. Superhosts, on average, generate higher revenue than non-Superhosts.
2. Superhosts have higher customer satisfaction ratings.
3. Non-Superhosts have a higher number of reservations on average compared to Super hosts.

Super Value Creation!



Superhost Status Boosts New Entrants' Business



1. Easier for new entrants to achieve superhost status initially.
2. Challenges in retaining superhost status for more than 3 evaluation periods.

Superhost status might provide an initial reservation boost but leads to increased cancellations, potentially resulting in status loss within a few periods.

Avg. consecutive period for which a host retains its superhost status ~ 3

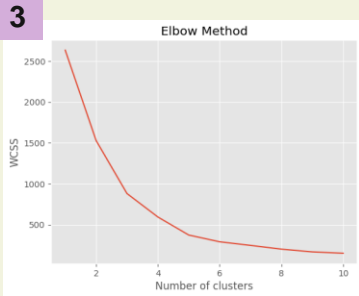
Market Entry Strategy of New host

1

```
# List of new variables for clustering
new_vars_for_clustering = [
    'booking_rate_per_host',
    'revenue_per_host',
    'superhosts_per_host',
    'reservations_per_host',
    'cancellations_per_host'
]
```

2

```
# Plot the elbow graph
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



5

Cluster 0:
[17031010100, 17031010201, 17031010202, 17031010203]

Cluster 1:
[17031300500] ← Selected tract

Cluster 2:
[17031020302, 17031030104, 17031140500, 17031140501, 17031140502, 17031140503]

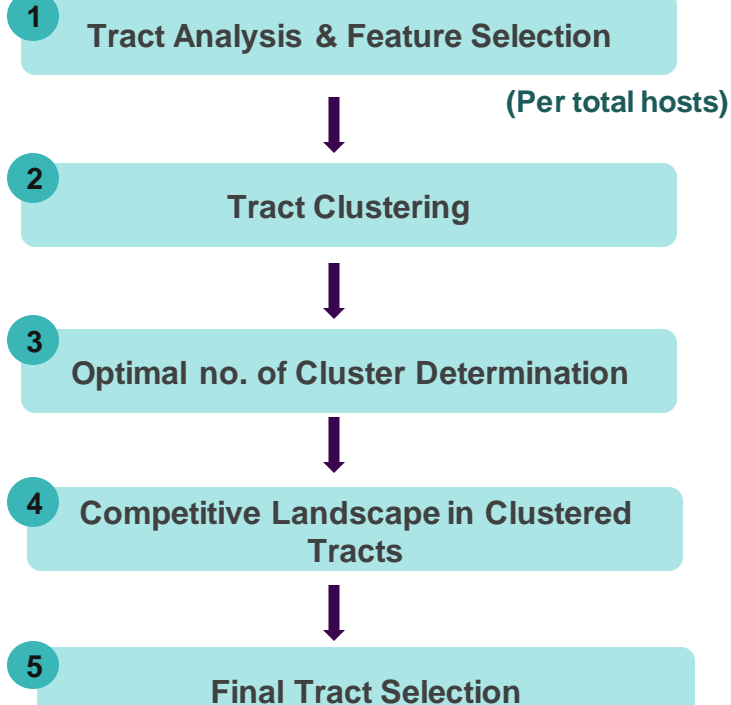
4

Cluster centers (in the original feature space):

	booking_rate_per_host	revenue_per_host	superhosts_per_host	\
0	1.028510	0.432229	38.175886	
1	100.000000	100.000000	100.000000	
2	46.662498	12.742170	92.132505	

	reservations_per_host	cancellations_per_host
0	0.028495	0.512315
1	100.000000	13.333333
2	0.238468	30.740741

For a chosen city, which tract(s) to venture into?



Revenue Drivers in the “Chosen Tract”

Analyzing Competitive environment within
High potential Tracts

Finalized Tract in Chicago

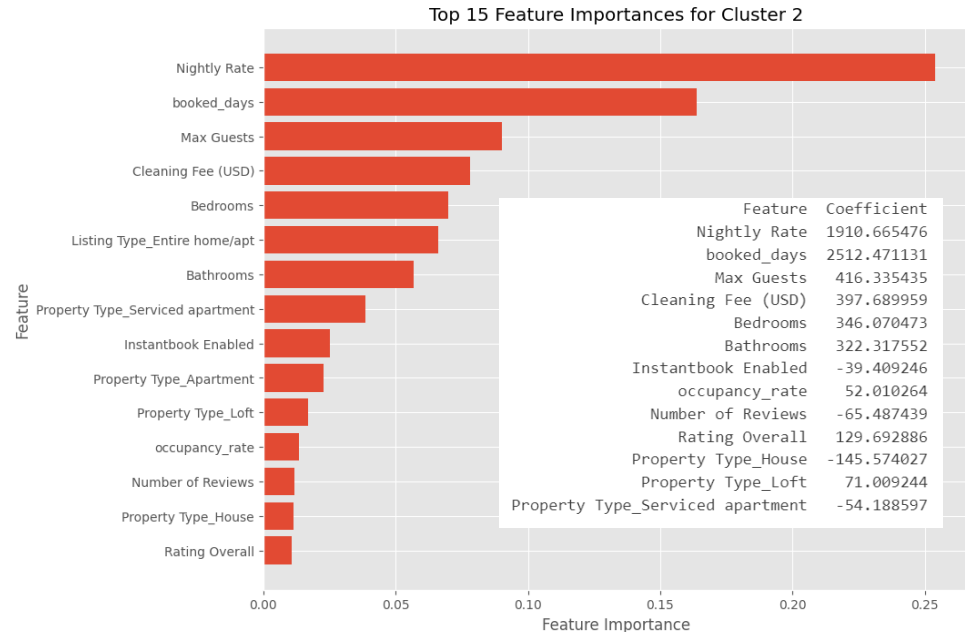
```
##Cluster Mapping  
tracts_cluster_2 = [17031300500]
```

XGBoost Model

```
# Define the Gradient Boosting model  
model = Pipeline(steps=[  
    ('preprocessor', preprocessor),  
    ('regressor', xgb.XGBRegressor(objective='reg:squarederror',  
    | n_estimators=100, learning_rate=0.1, max_depth=5))  
])
```

Predictive analysis to help hosts
understand key features for differentiation
and competitive positioning

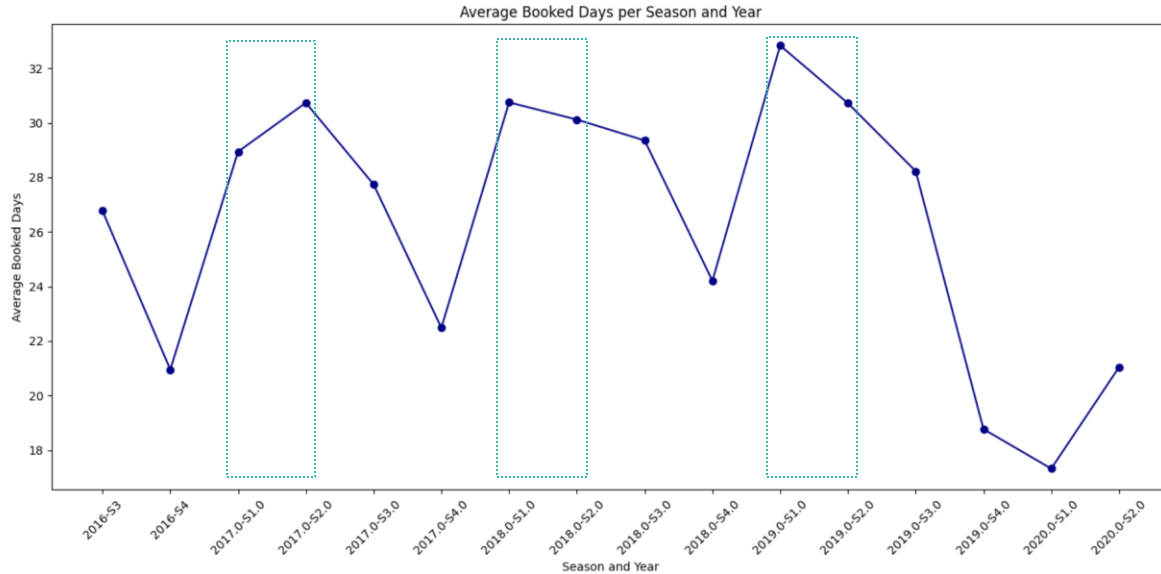
Important Feature for Tract 2



Root Mean Squared Error: 1802.19
R-squared: 0.84
Mean Absolute Percentage Error (MAPE): 34.15%

Market Responsiveness

Assessing Demand Seasonality Needs



Demand Seasonality in
booking pattern



Market Responsive

Controllable
factor

Uncontrollable
Factor

Impact of Controllable Factors and Seasonality on Revenue

OLS Regression Results

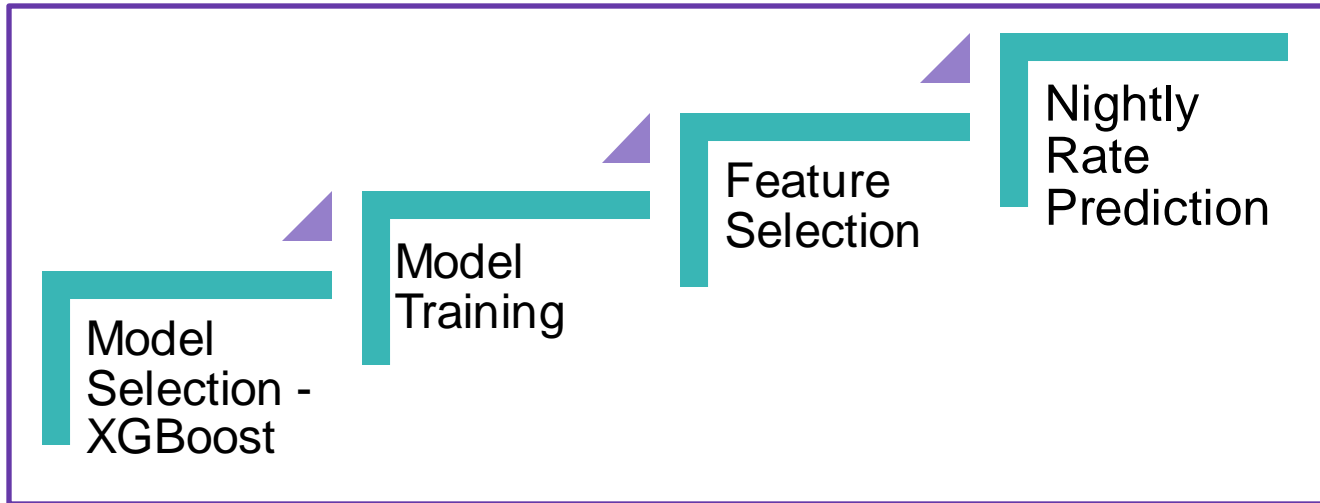
```
=====
Dep. Variable:          revenue    R-squared:                0.612
Model:                  OLS        Adj. R-squared:           0.612
Method:                 Least Squares    F-statistic:             3062.
Date:                   Fri, 08 Dec 2023    Prob (F-statistic):       0.00
Time:                   21:19:05          Log-Likelihood:          -3.8232e+05
No. Observations:       44703           AIC:                    7.647e+05
Df Residuals:           44679           BIC:                    7.649e+05
Df Model:                23
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t
const	-2344.9933	172.678	-13.580	0.000
season_Nightly Rate_interaction	-0.3974	0.063	-6.318	0.000
season_Cleaning Fee (USD)_interaction	-0.3973	0.183	-2.167	0.030
season_Max Guests_interaction	-29.9202	3.106	-9.634	0.000
season_Minimum Stay_interaction	2.5334	0.722	3.507	0.000
season_Pets Allowed_interaction	28.7440	14.093	2.040	0.041
season_Instantbook Enabled_interaction	-33.3185	10.800	-3.085	0.002
season_available_days_interaction	-0.2573	0.083	-3.109	0.002
season_Number of Photos_interaction	-2.1301	0.551	-3.869	0.000
season_hostResponseAverage_pastYear_interaction	1.9046	0.184	10.348	0.000

Controllable Factors

1. Nightly Rate
2. Cleaning Fee (USD)
3. Maximum Guests
4. Minimum Stay
5. Pets Allowed
6. Instant Book Enabled
7. Available Days
8. Number of Photos
9. Response Time

Nightly Rate Recommendation for Both Existing Host and New Host



Nightly Rate Recommendation for Both Existing Host and New Host

Training - RMSE: 95.75188150425886, MAPE: 47.12527571068168%, R-Squared: 0.6168818766374641
Validation - RMSE: 100.09587339162654, MAPE: 47.40330429732502%, R-Squared: 0.5841805267888589

Input Values to predict Nightly Rate:

Cleaning Fee (USD): [35]

Bathrooms: [3]

Max Guests: [4]

Bedrooms: [3]

Rating Overall: [4]

census_tract: [17031671800]

Number of Reviews: [10]

Number of Photos: [20]

Listing Type_Entire home/apt: [1]

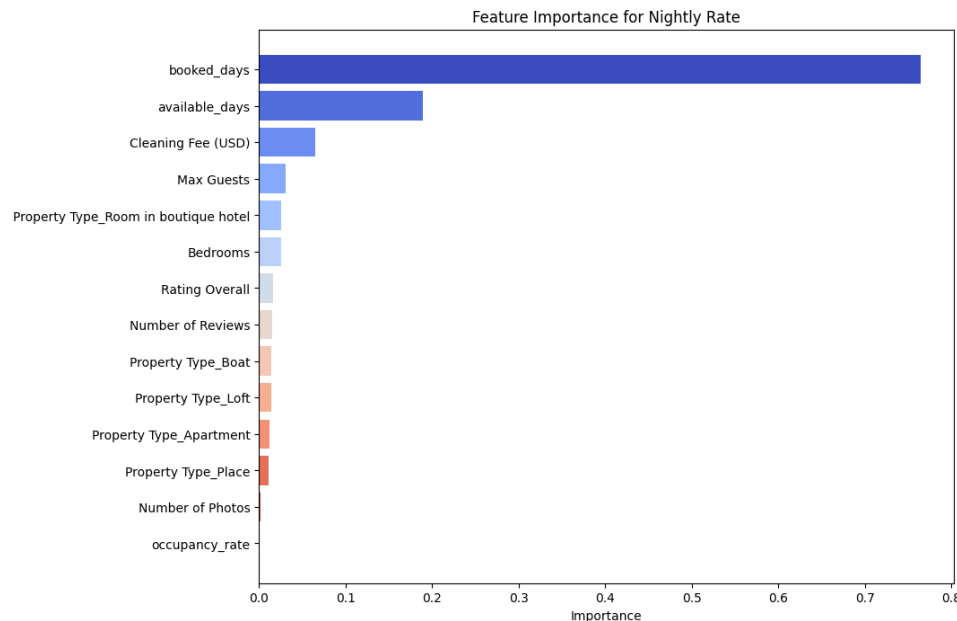
Property Type_Apartment: [1]

Property Type_Loft: [1]

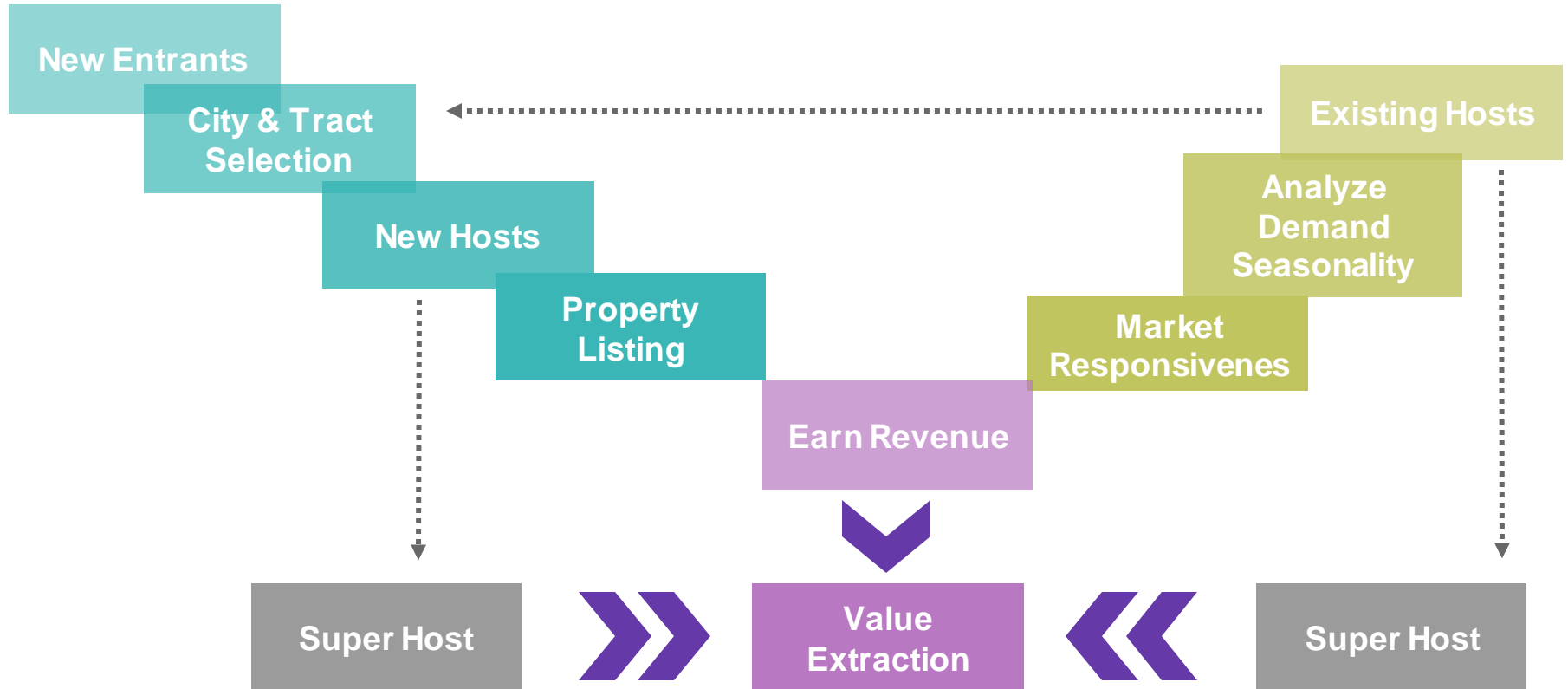
Property Type_Place: [1]

Property Type_Boat: [1]

Predicted Nightly Rate: 466.2528



Conclusion



Basis of City Selection and Outcome

Selection Criteria

```
# Combined score per host
city_metrics['combined_score_per_host'] = (
    city_metrics['booking_rate_per_host'] +
    city_metrics['revenue_per_host'] +
    city_metrics['superhosts_per_host'] +
    city_metrics['reservations_per_host'] -
    city_metrics['cancellations_per_host']
)
```



Outcome

	City	combined_score_per_host
7	Oakland	241.477518
1	Chicago	230.376751
2	Dallas	168.390218
9	Washington	75.956511
0	Boston	73.689445
3	Houston	66.607554
8	Philadelphia	65.699838
4	Los Angeles	39.032313
6	New York	21.995084
5	Miami	-17.080418

Challenges and Future Scope

- ❑ Lots of Missing data in the dataset
- ❑ Difficulty in determining between impute and remove
- ❑ Categorical variable with too many levels, which causes linear dependency on each other.

- ❑ Binary column contains non-binary value
- ❑ pre_year_superhost column contains values other than 0 and 1

- ❑ Few Columns definition are missing in dataset
- ❑ Example : Response Rate is an important parameter for super host classification and missing in data description



Due to the time constraint , we have analyzed value creation for host. For future scope we can incorporate value creation for guest as well.

Thank You!