



Multi-City Analysis of AirBnB Markets: Key Determinants, Dynamics, Value, and Predictive Modelling with Machine Learning

Author: Sharayu Zodpe
Supervisor: Charles Nwankire



Masters in Business Analytics

This study analyzes key determinants of AirBnB listing prices across eleven major cities using machine learning algorithms by developing predictive models. The work will further analyze the dynamics of markets in relation to the value assessment of cities so as to optimize pricing strategies to enhance booking experiences for both hosts and travellers.

01. INTRODUCTION

Airbnb revolutionized hospitality by enabling hosts to rent spaces, but pricing optimization remains a challenge [1]. While this offers travelers diverse and affordable options, it also presents challenges in price optimization and value assessment. Existing pricing tools, such as "Smart Pricing," lack the granularity needed for personalized strategies, making it difficult for hosts to set competitive rates [2]. Additionally, travelers struggle to assess listings due to pricing variability and inconsistent amenities. To enhance Airbnb's global expansion, more accurate, context-sensitive pricing models are needed, incorporating local demand trends and urban complexities [3].

02. RESEARCH QUESTIONS

- What are the most influential factors affecting AirBnB listing prices, and which machine learning model performs best: CatBoost, Random Forest, or Neural Networks?
- Which are the biggest differences in market characteristics in terms of Airbnb across the eleven cities?
- 2.a. Which city offers the best value for travellers?

03. RESEARCH APPROACH

Research Design:

- Quantitative Analysis: Focus on statistical and machine learning techniques.
- Descriptive and Exploratory: Describe Airbnb listing features and market trends; explore key pricing factors and emerging patterns.

Data Collection and Tools:

- Dataset: Airbnb Listings and Reviews from Inside Airbnb (over 60,000 listings across eleven major cities- data as of July 2024).
 - <https://insideAirBnB.com/get-the-data/>

Tools: Python for data processing and machine learning; Tableau for visualizations.

04. DATA ANALYSIS

Data Cleaning and Preprocessing

City-Wise Model Training

EDA (Market Dynamics)

Price Standardization

Data Cleaning: handled missing values. Retained necessary columns

Data normalization: Standardized dataset for consistency.

Amenities Transformation:

Transformed list to binary columns

Structure data:

Organized necessary fields and categories for effective visualization.

Manage Skewness and Outliers

Assess feature importance

Train and test models: Random Forest, Neural Networks, CatBoost,

Hyperparameter Tuning

Cross-Validation: Evaluated model stability and accuracy.

Compare model performance: Metrics used - RMSE, MAE and R-squared.

Compute descriptive statistics: Mean

Develop visualizations: Histograms, box plots, heatmaps, scatter plots in Tableau.

Apply dynamic filters:

Interactive exploration of variables and subsets.

Analyze market trends: Examine trends across cities.

Identify patterns: Analyze visualizations for trends, correlations, and anomalies.

References

- [1] 'Morgan Stanley: AirBnB's Threat to Hotels Is Only Getting Sharper', <https://www.hospitalityireland.com/hotel/morgan-stanley-AirBnBs-threat-hotels-getting-sharper-34954>.
- [2] 'Customized Regression Model for AirBnB Dynamic Pricing', <https://doi.org/10.1145/3219819.3219830>
- [3] 'Learning-based AirBnB Price Prediction Model', <https://doi.org/10.1109/ECIT52743.2021.00068>.

05. RESULTS AND FINDINGS

1. Factors Influencing AirBnB Listing Prices and Model Performance:

Property Attributes

- Accommodates:** Larger properties command higher prices.
- Bedrooms:** More rooms and amenities increase value.
- Room Type:** Entire homes/apartments cost more for privacy.

Host Attributes

- Experience:** Longer tenure and larger portfolios increase pricing.
- Engagement:** Higher response rates link to premium listings.

Location-Specific Attributes

- Prime Areas:** High prices in neighborhoods like Shinjuku (Tokyo), Eixample (Barcelona), and Commercial Triangle (Athens).
- Regulations:** Stricter policies (e.g., minimum_nights in Barcelona) influence pricing.

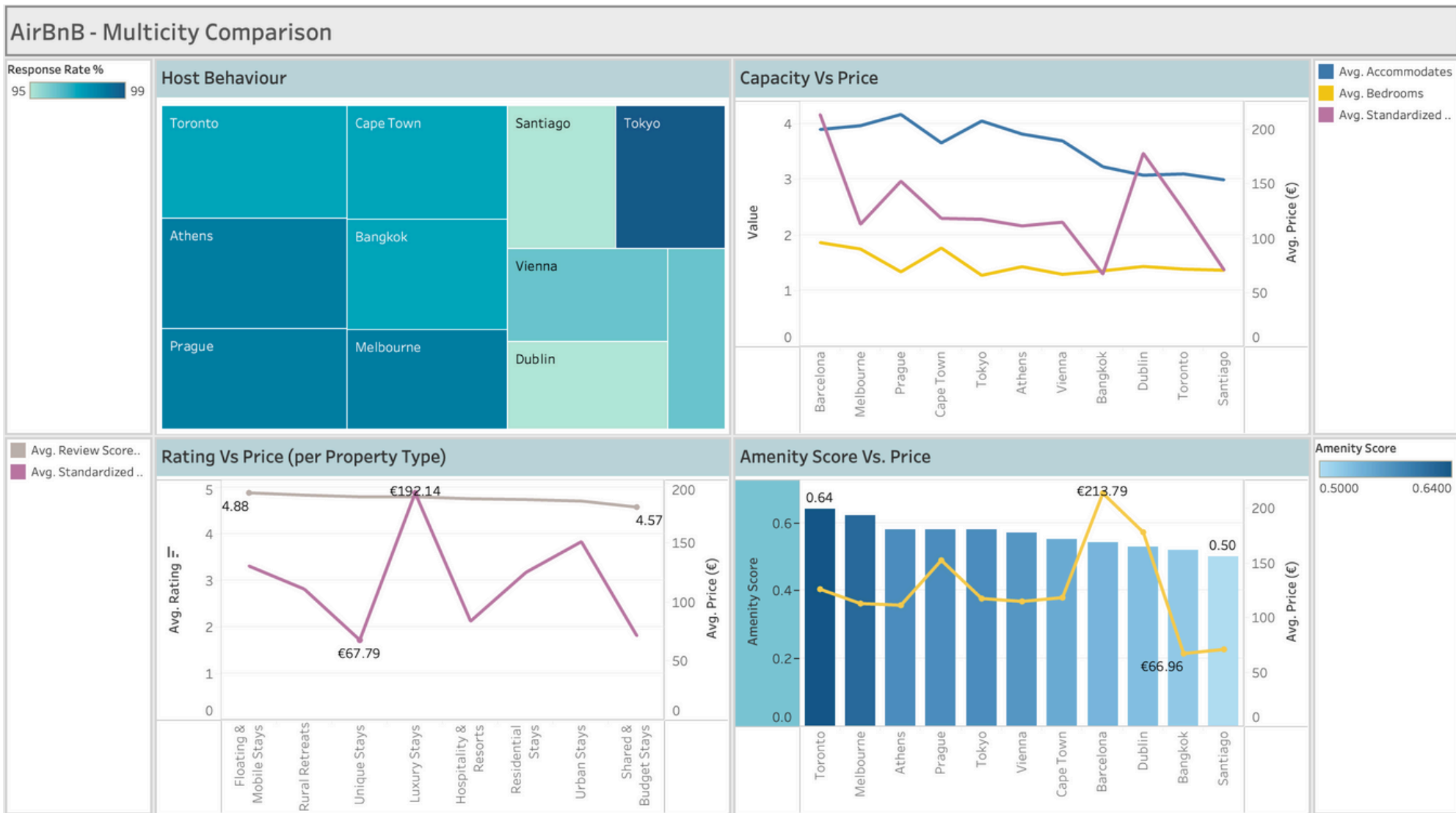
Model Performance:

CatBoost

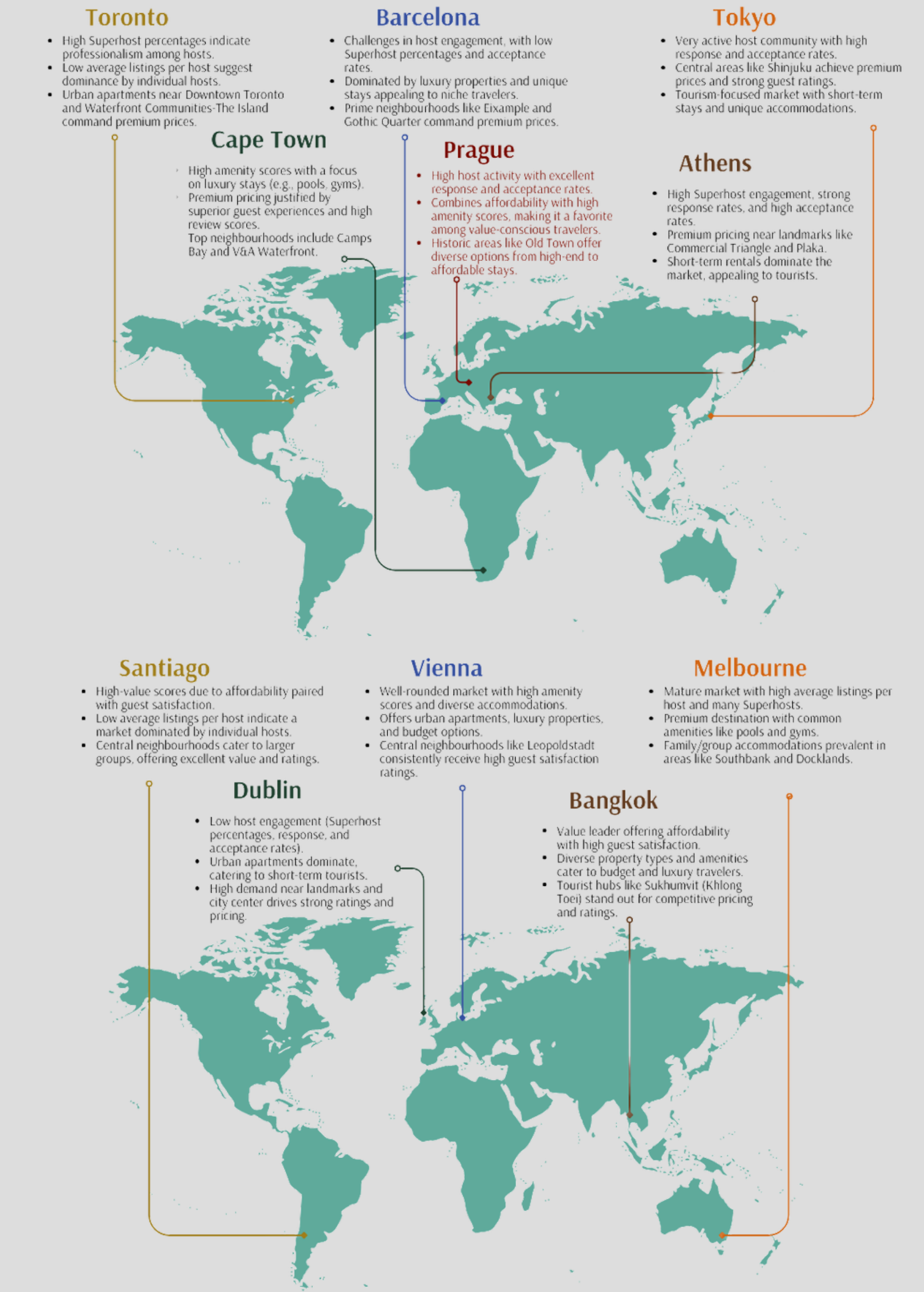
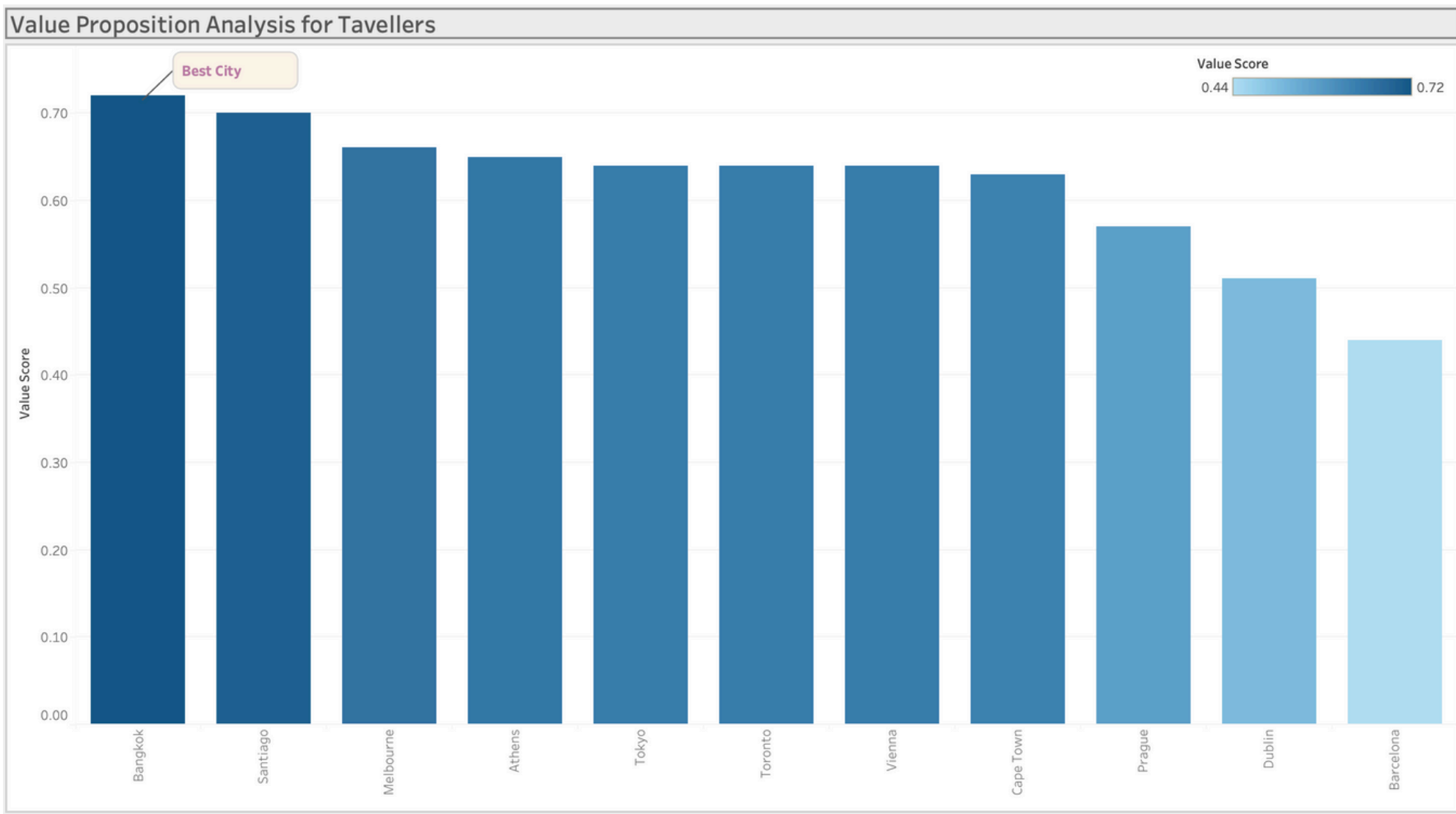
- Best performer with the lowest RMSE and MAE, and the highest R2.
- Excels in handling categorical variables and nonlinear relationships.

Though many factors affecting price were common across the cities, their relative importance and influence varied greatly which is demonstrated by the features for each city.

2. AirBnB Market Trends:



2 a. Best Value City for Travellers:



06. RECOMMENDATIONS FOR STAKEHOLDERS

For New Hosts

- Set competitive pricing based on local market trends.
- Focus on high-demand neighbourhoods like Shinjuku (Tokyo) or Eixample (Barcelona).
- Prioritize key price drivers like guest capacity and bedrooms; offer essentials.

For Existing Hosts

- Adjust pricing based on demand trends and city-specific factors.
- Upgrade amenities and focus on guest feedback to boost ratings.
- Expand into high-performing neighbourhoods.

For Budget Travellers

- Choose affordable cities like Santiago or Bangkok for value-driven stays.
- Focus on top-rated, budget-friendly neighbourhoods with essential amenities.

For Experience Seekers

- Explore unique stays in Barcelona or luxury in Cape Town.
- Stay in culturally rich areas like Plaka (Athens) or Shinjuku (Tokyo).

For Airbnb Platform

- Enhance dynamic pricing tools with neighbourhood trends and seasonal demand data.
- Add detailed neighbourhood profiles and personalized recommendations.
- Provide city-specific onboarding for new hosts to set competitive strategies.