



airbnb

Airbnb Price Predictive model
CIS 512
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Data Cleaning



Drop column

Listing Url,
Scrape ID,
Name,
Summary,
Space,
Description,
Experiences Offered,
Neighborhood Overview,
Notes,
Access,
Interaction,
House Rules,
Thumbnail Url,
Medium Url,
Picture Url,
XL Picture Url,
Host URL,

Host Name,
Host About,
Host Acceptance Rate,
Host Thumbnail Url,
Host Picture Url,
Host Neighbourhood,
Host Listings Count,
Host Total Listings Count,
Host Verifications,
Neighbourhood,
Neighbourhood Cleansed,
Neighbourhood Group Cleansed,
State,
Zipcode,
Smart Location,
Country Code,
Geolocation,
Cancellation Policy

Latitude,
Longitude,
Square Feet,
Has Availability,
Availability 30,
Availability 60,
Availability 90,
Availability 365,
Calendar last Scraped,
First Review,
Review Scores Accuracy,
Review Scores Cleanliness,
Review Scores Checkin,
Review Scores Communication,
Review Scores Location,
Review Scores Value,
Jurisdiction Names

Columns	Data Description	Action Taken
Amenities	Multiple facilities and requirements	Split into categories; new column = Yes/No.
Price	Contains NA values.	Check weekly/monthly values; calculate mean price based on country.
Bedrooms, Beds, Bathrooms	Contains NA values	Use 'Accommodates' column to find actual numbers; otherwise, set to 0.
Host Location Match	Host location matches property location	Host Location (split) = "Street" or "City."
Last Rented (in months)	Findout Last time rented.	'Last Rented (in months)' = 'Last Scraped' - 'Last Review.'
Host Age	Determine host age.	'Host Age' = 'Last Scraped' - 'Host Since.'

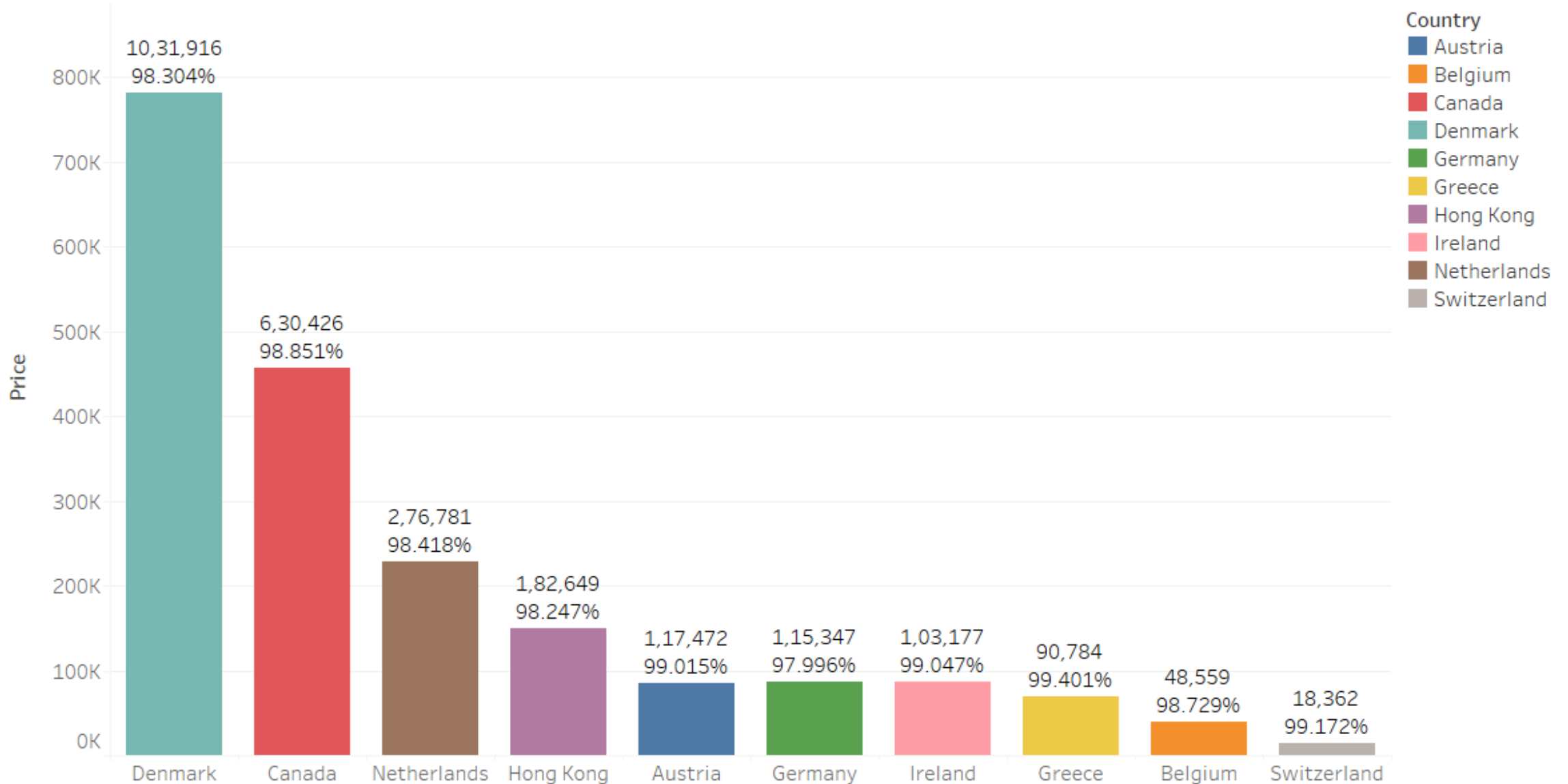
Columns	Data Description	Action Taken
Property Type	Unorganized property types.	Categorize based on house types.
Features	Long strings with essential details.	Split features; create new column with Yes/No.
Transit, Market, Weekly Price, Monthly Price, License	Long strings with mostly null values.	If empty, set to 'No'; else, set to 'Yes.'
Host Response Time, Beds, Security Deposit, Cleaning Fee, Review Scores Rating, Extra People, Reviews per Month	Contains NA values.	Fill with 0 for int/float; else, set to "Not Mention."



Data Analysis

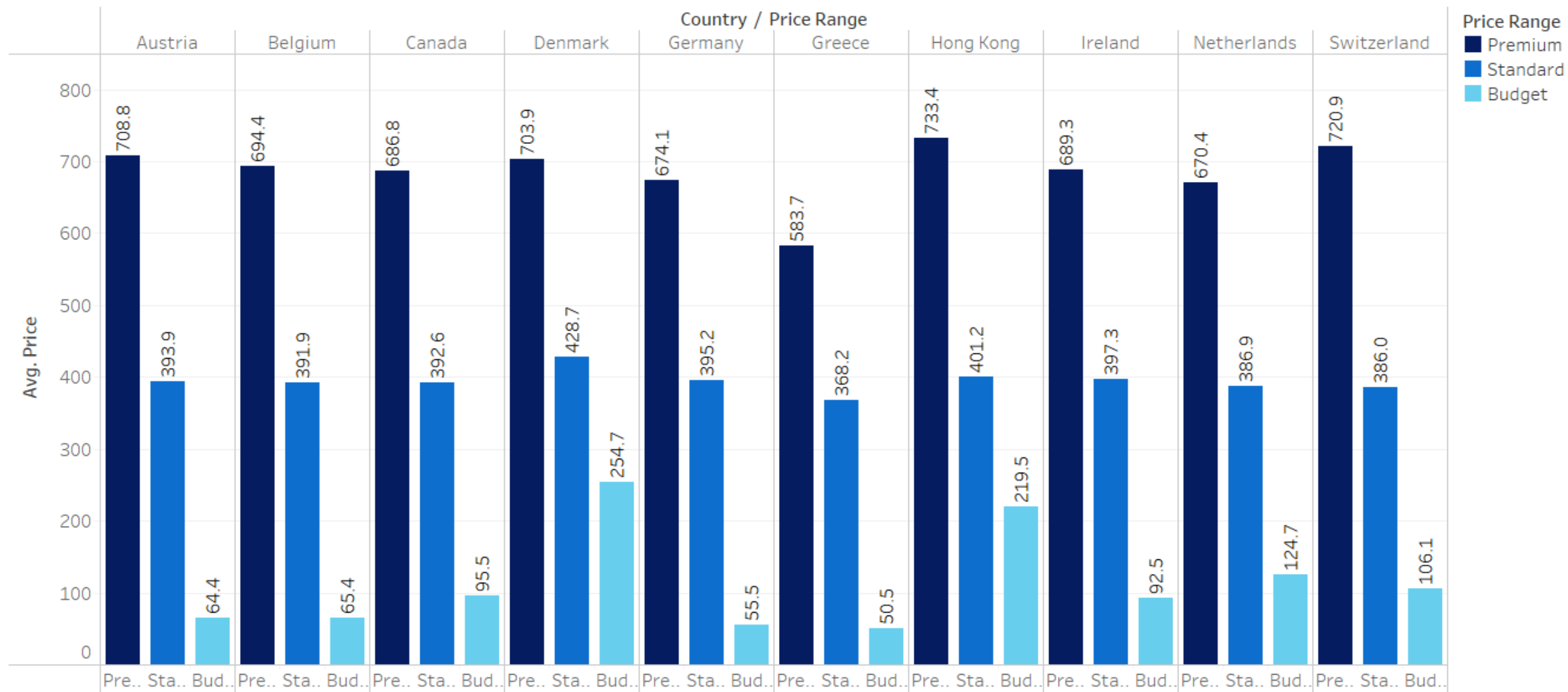


Total Revenue by Country



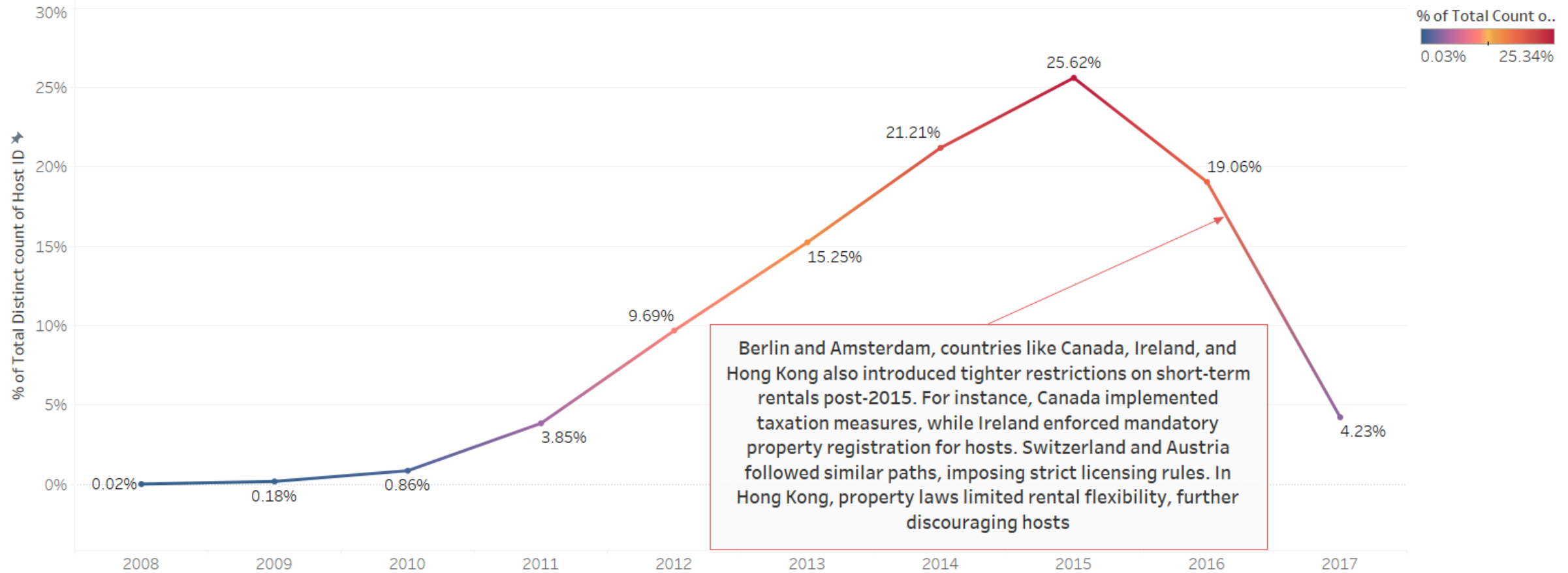
Shows which countries generate the highest revenue from Airbnb rentals, emphasizing quality hosts (Superhosts).

Average Airbnb Prices Across Countries



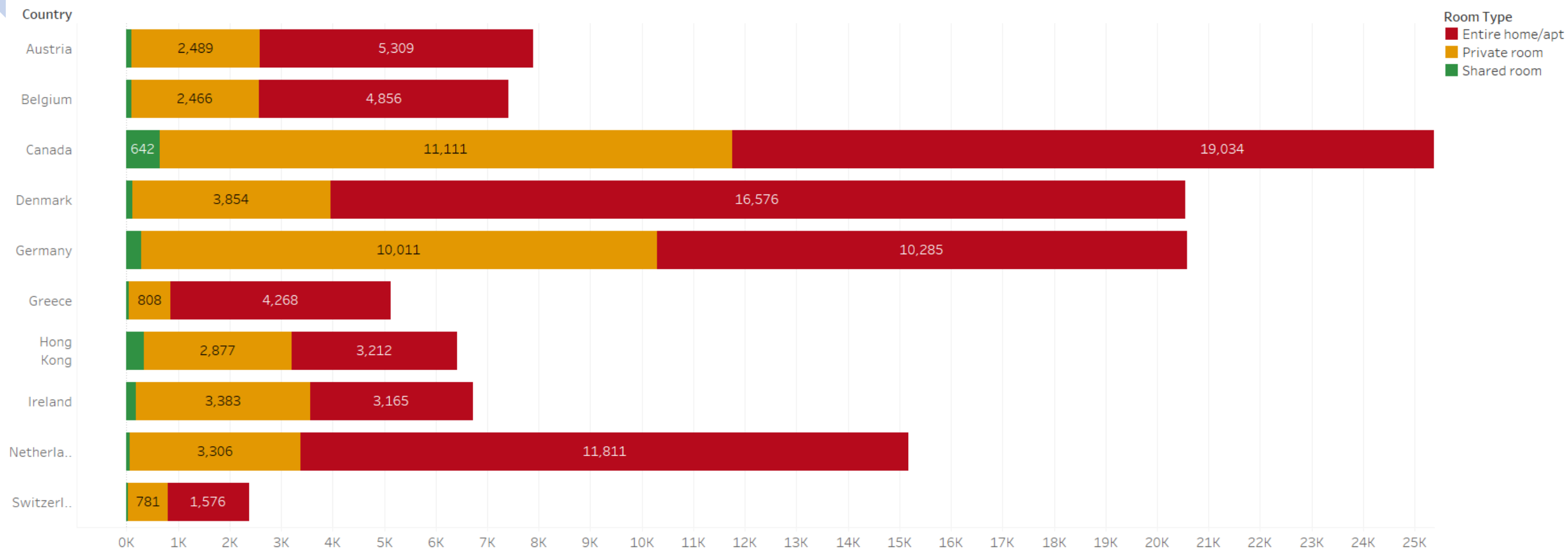
It compares average Airbnb prices across countries by Budget, Standard, and Premium categories, highlighting Denmark and Hong Kong as the most expensive, while Greece and Germany offer more affordable options.

Yearly Host Registration Rates on Airbnb



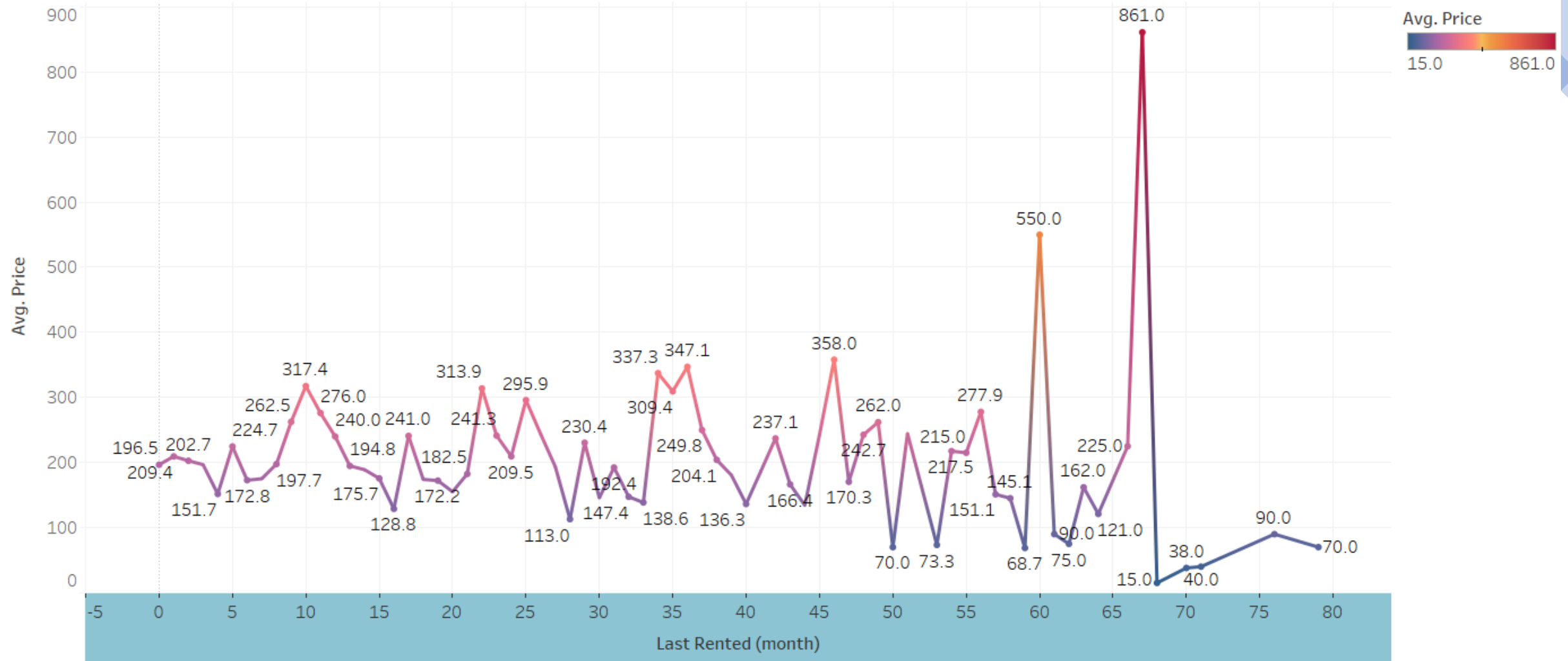
Host registrations began at 0.02% in 2008, gradually increasing to 25.63% by 2015. Following this peak, a significant drop occurred, with registrations falling to 4.23% by 2017. The rapid growth between 2011 and 2015 contrasts sharply with the steep decline in the subsequent years.

Room Type Distribution by Country



Shows the popularity of different room types in each country, helping investors understand which types of properties are more in demand.

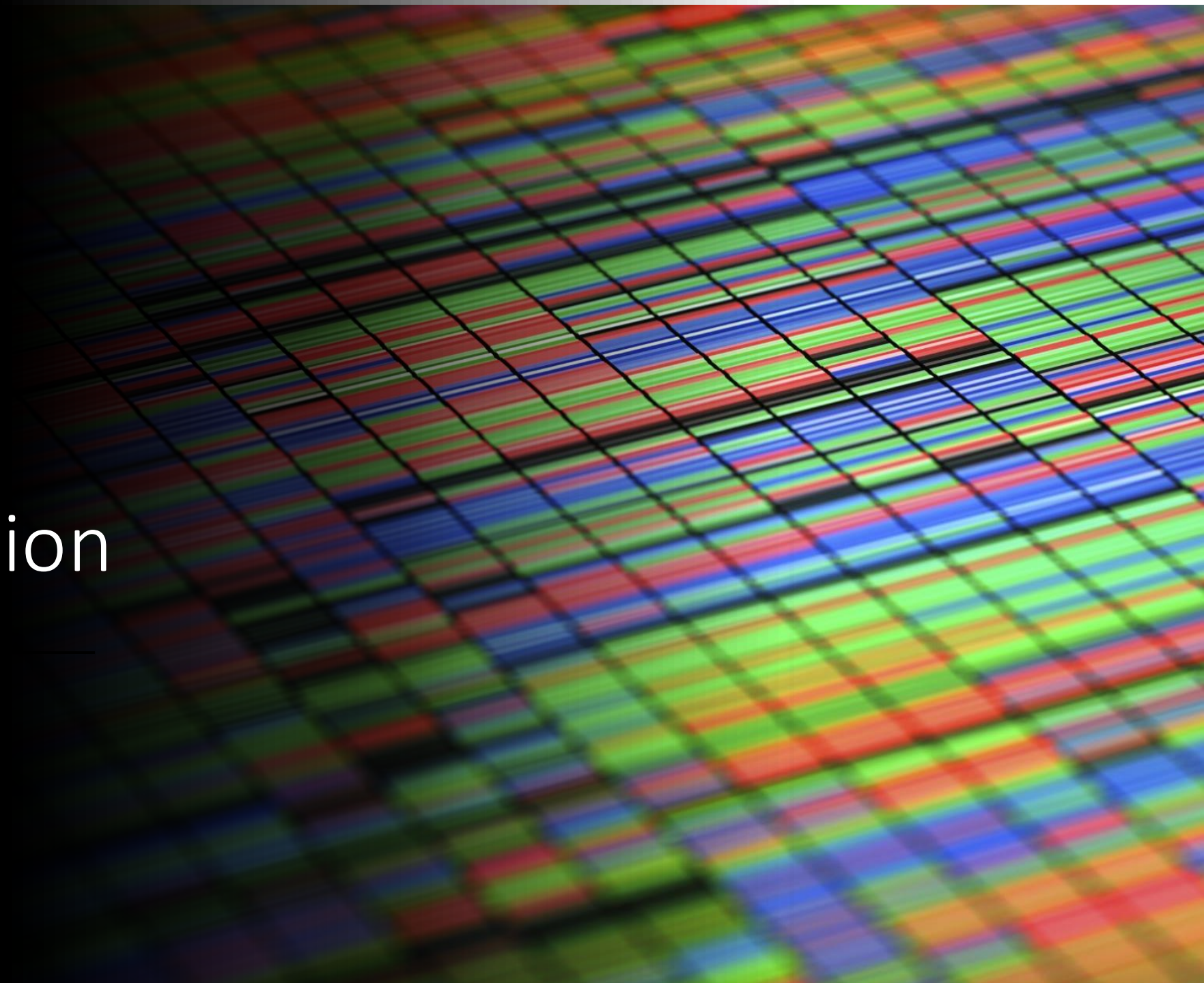
Current Average Price X Number of Months Since Last Rental

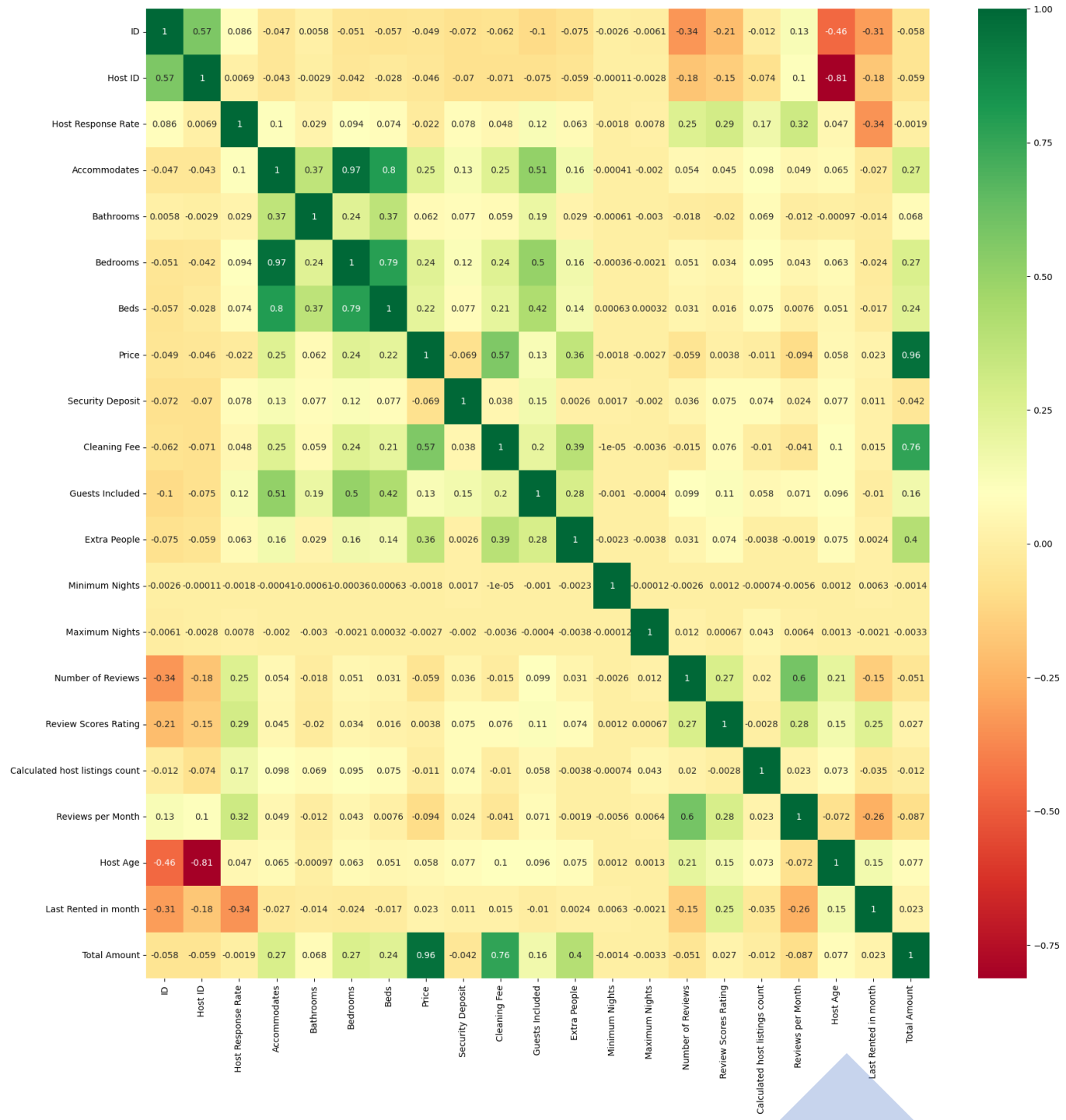


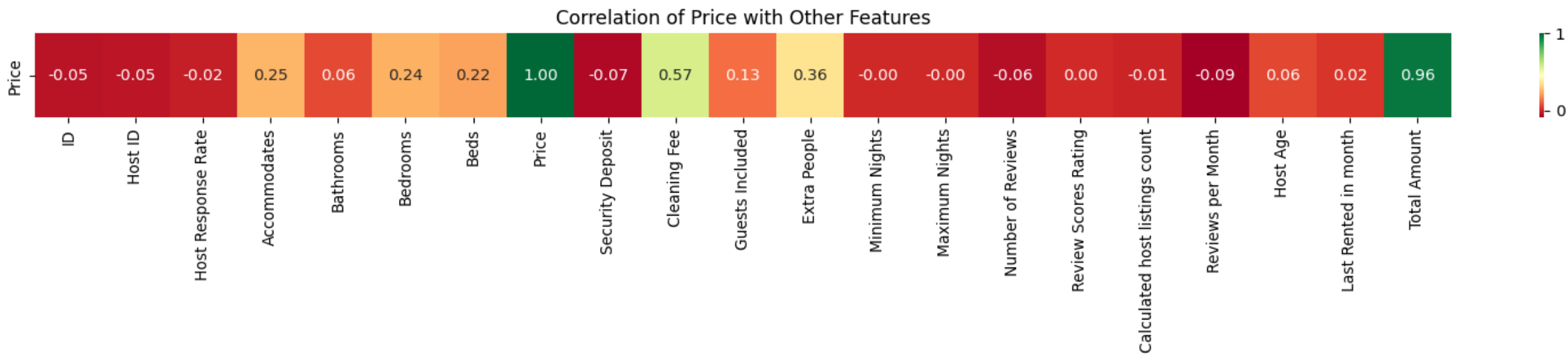
This chart displays the current average price of Airbnb Property X, indicating the number of months since its last rental. It provides insights into how rental availability may influence pricing.



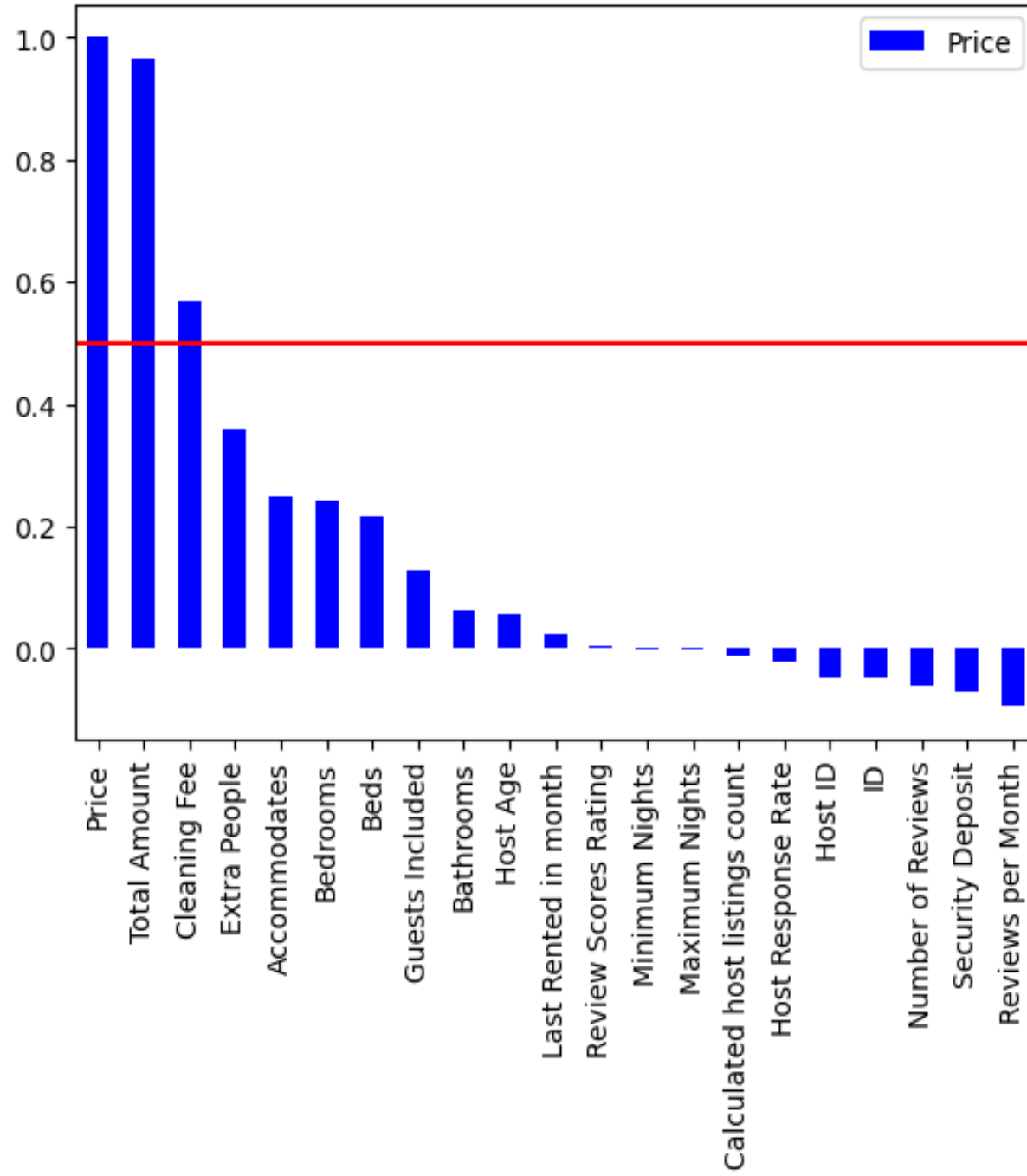
Data Correlation







Correlation with Price



Feature Engineering Process:

Feature Engineering Process:

- Converted categorical variables to numerical using one-hot encoding
- Created new columns for each category:
- 1 indicates presence
0 indicates absence
- Original categorical columns dropped

Categorical Variables Encoded:

- **Host Response Time**
- **Country**
- **Property Type**
- **Room Type**
- **Bed Type**
- **Cancellation Policy**

Example:

- Before: Room Type = "Entire home/apt"
- After: Room Type_Entire home/apt = 1, others = 0

Resulting Dataframe Shape:

- Rows: 123,061
- Columns: 91

Preparing Data for Modeling

Correlation Filtering:

Removed columns with correlation < 0.02 to price

Data Splitting:

Training Data: 75% (~92,295 rows)

Testing/Validation Data: 25% (~30,766 rows)

Data Standardization:

Applied StandardScaler to features

Standardizes features by removing the mean and scaling to unit variance

Dimensionality Reduction:

Performed Principal Component Analysis (PCA)

Reduced feature set to 57 columns for modeling

The background features a complex network of nodes and edges, resembling a graph or neural network. Nodes are represented by small circles in various colors (yellow, blue, purple, red) and are interconnected by thin lines. Some nodes are larger than others, suggesting different weights or importance. Text labels are scattered throughout the image, including numerical ranges and specific values.

Predictive Modeling

875.8965 - 874.8374
466/9583 - 472.8921
1-1043 - 6754

P - 2.1

15.683

34 - 87

[09] 209 - 9065 T
109 - 8418 - HR
GT - 87.9043

28.894
34.785
43.085
51.743
67.084

H - 6.8

57.264

3270

7843

29.625

2559

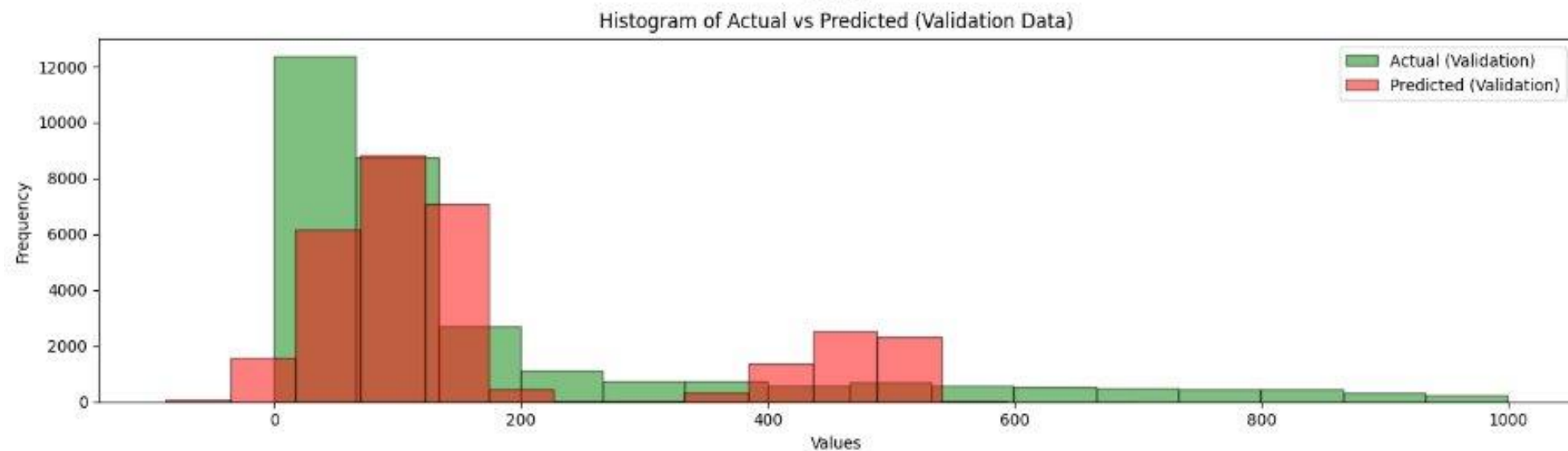
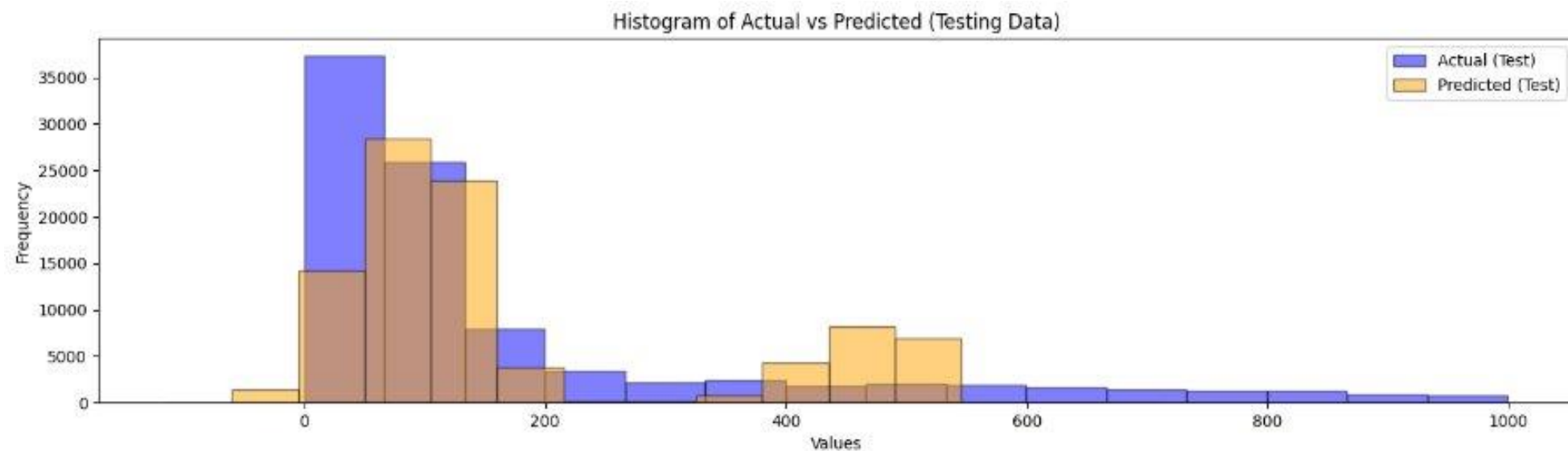
10.33

10-49

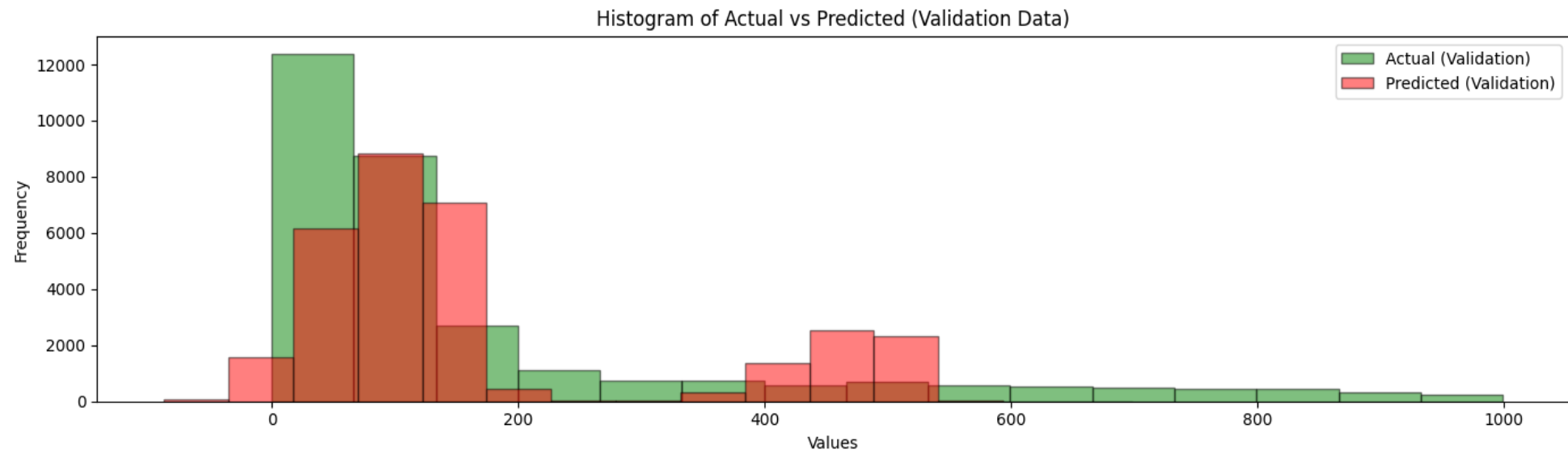
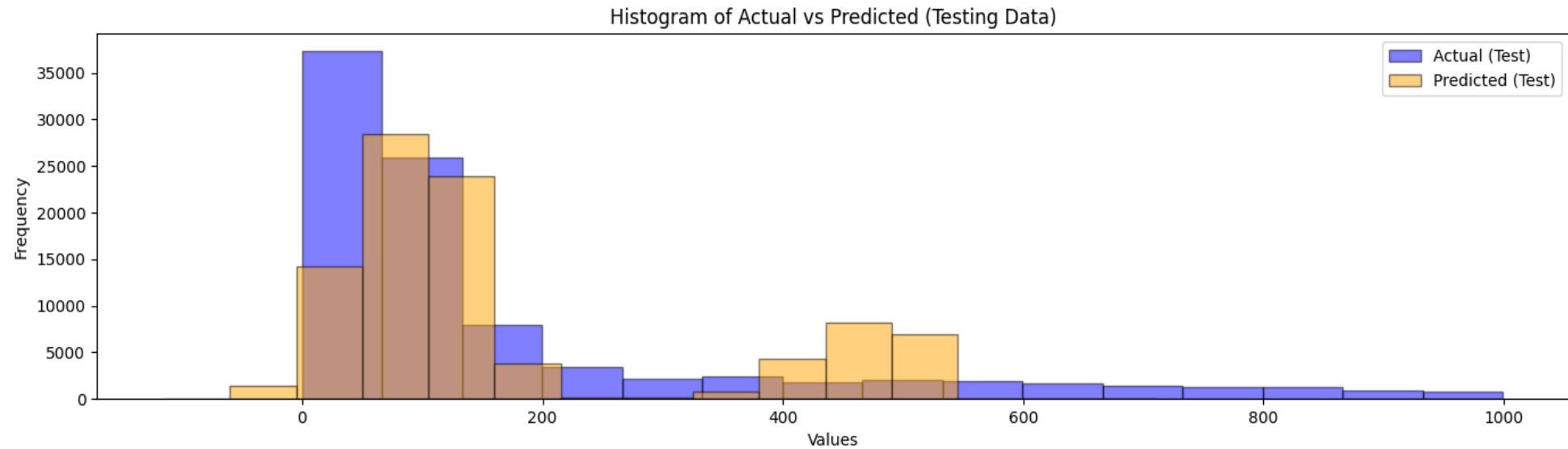
45.18

74.063

Linear Regression

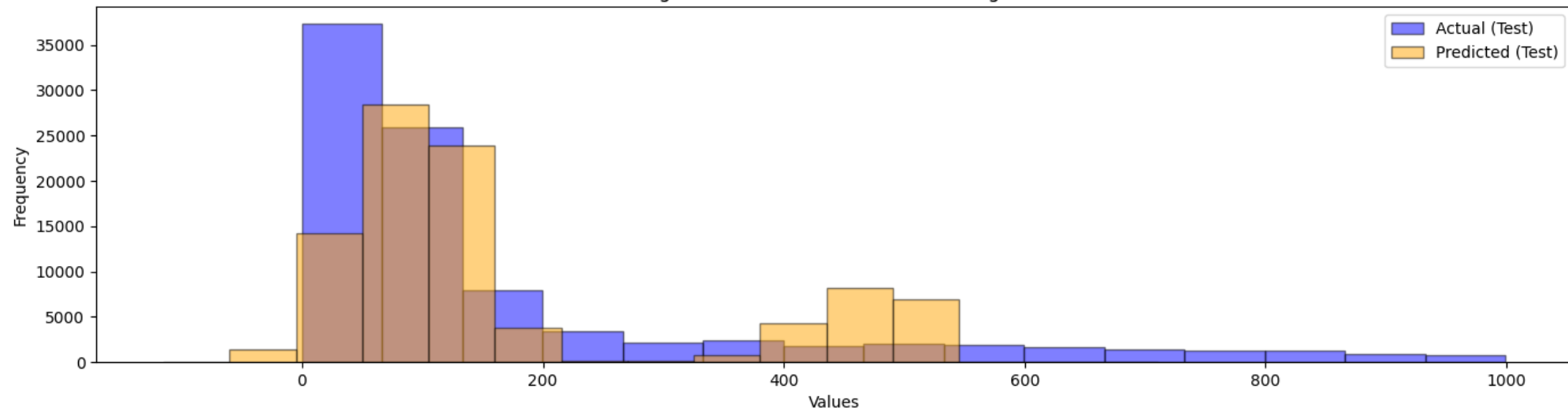


Random Forest Regression

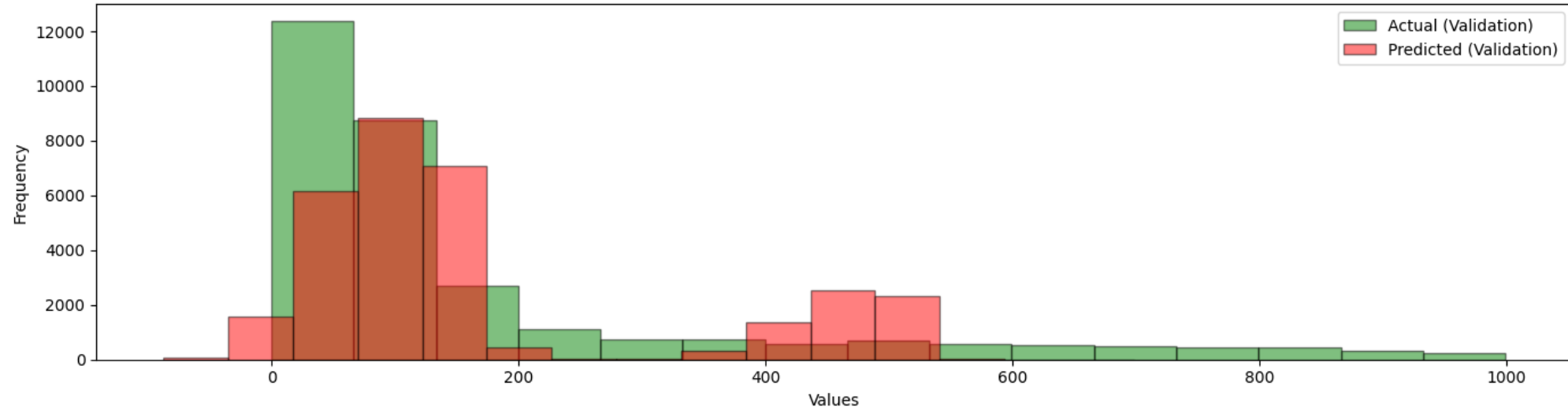


Lasso Regression

Histogram of Actual vs Predicted (Testing Data)

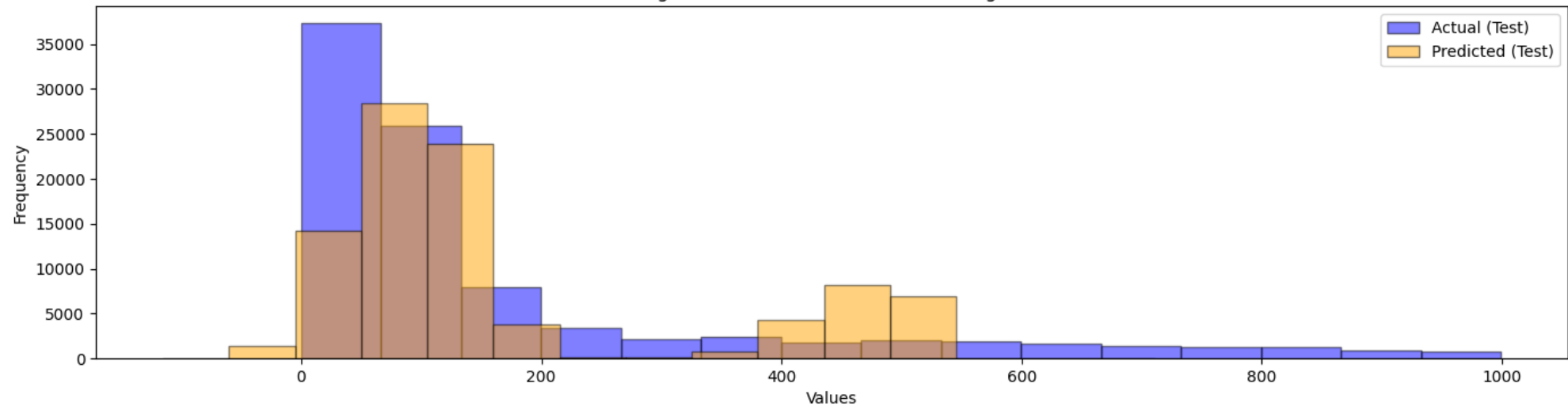


Histogram of Actual vs Predicted (Validation Data)

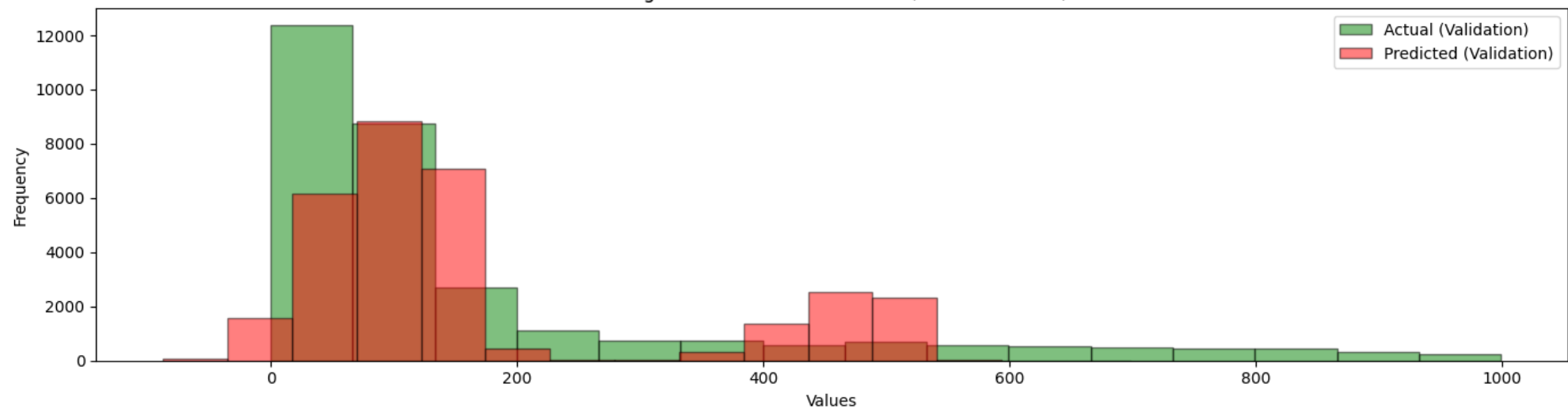


Ridge Regression

Histogram of Actual vs Predicted (Testing Data)



Histogram of Actual vs Predicted (Validation Data)



Model Performance Comparison

Train	Model	R ²	Adjusted R ²	Mean Squared Error (MSE)	Root Mean Square Error (RMSE)
	Linear Regression	0.55	0.55	21416.28	146.34
	Random Forest Regression	0.61	0.61	18478.35	135.94
	Lasso Regression	0.55	0.55	21416.22	146.34
	Ridge Ridge Regression	0.55	0.55	21416.2	146.34
Validation	Model	R ²	Adjusted R ²	Mean Squared Error (MSE)	Root Mean Square Error (RMSE)
	Linear Regression	0.56	0.56	20997.67	144.91
	Random Forest Regression	0.6	0.6	18809.03	137.15
	Lasso Regression	0.56	0.56	20997.88	144.91
	Ridge Ridge Regression	0.56	0.56	20997.76	144.91

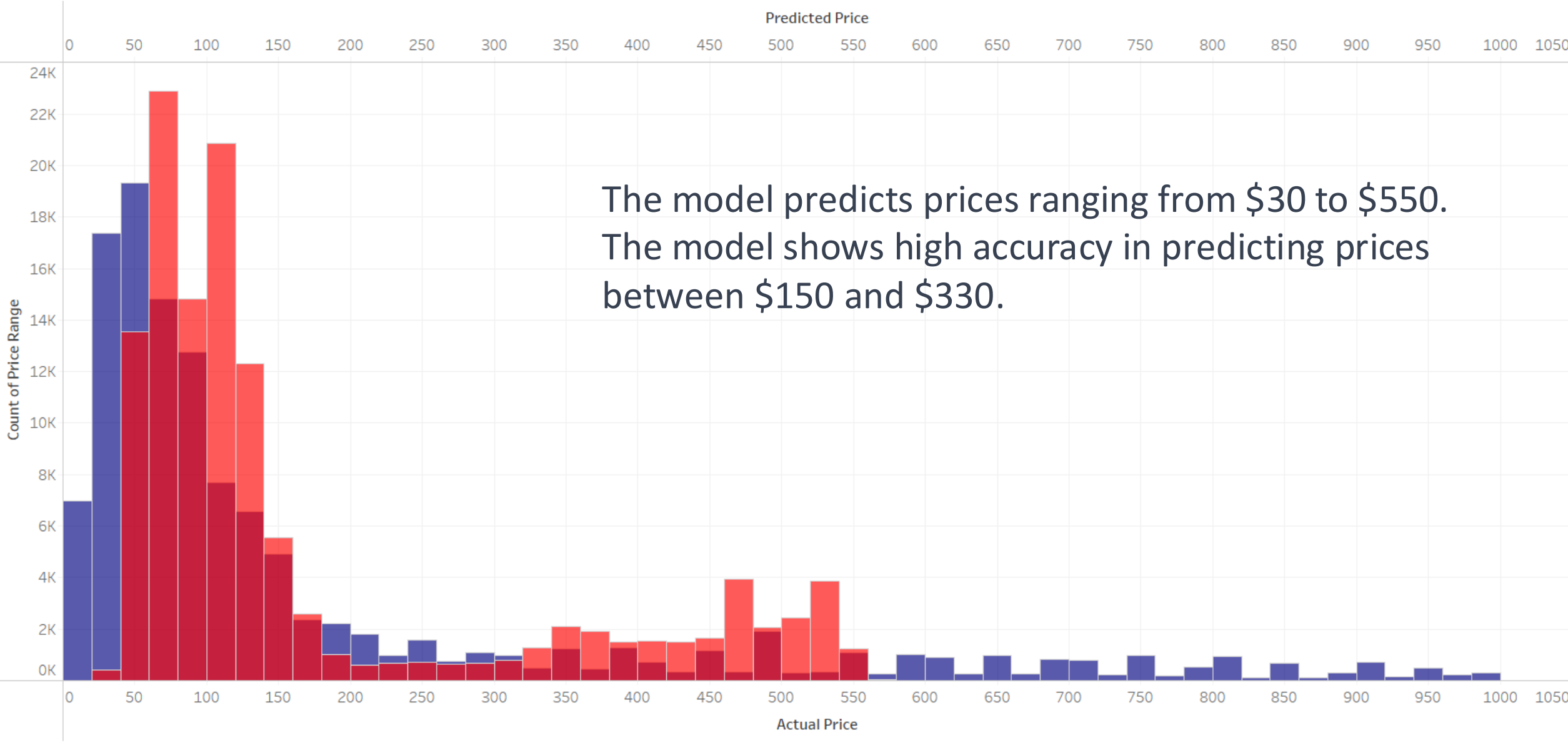
Winning Model: Random Forest Regression

- Key Insights:
 - **Superior Accuracy:** Outperforms other models in both training and validation sets
 - **Higher Explanatory Power:** R^2 of 0.60-0.61 vs 0.55-0.56 for other models
 - **Lower Prediction Errors:** ~12% lower MSE and ~6% lower RMSE compared to other models
 - **Consistent Performance:** Minimal difference between training and validation metrics, indicating good generalization
- Conclusion:
 - Random Forest Regression demonstrates superior performance in:
 - Capturing complex data patterns
 - Making accurate predictions
 - Generalizing well to unseen data

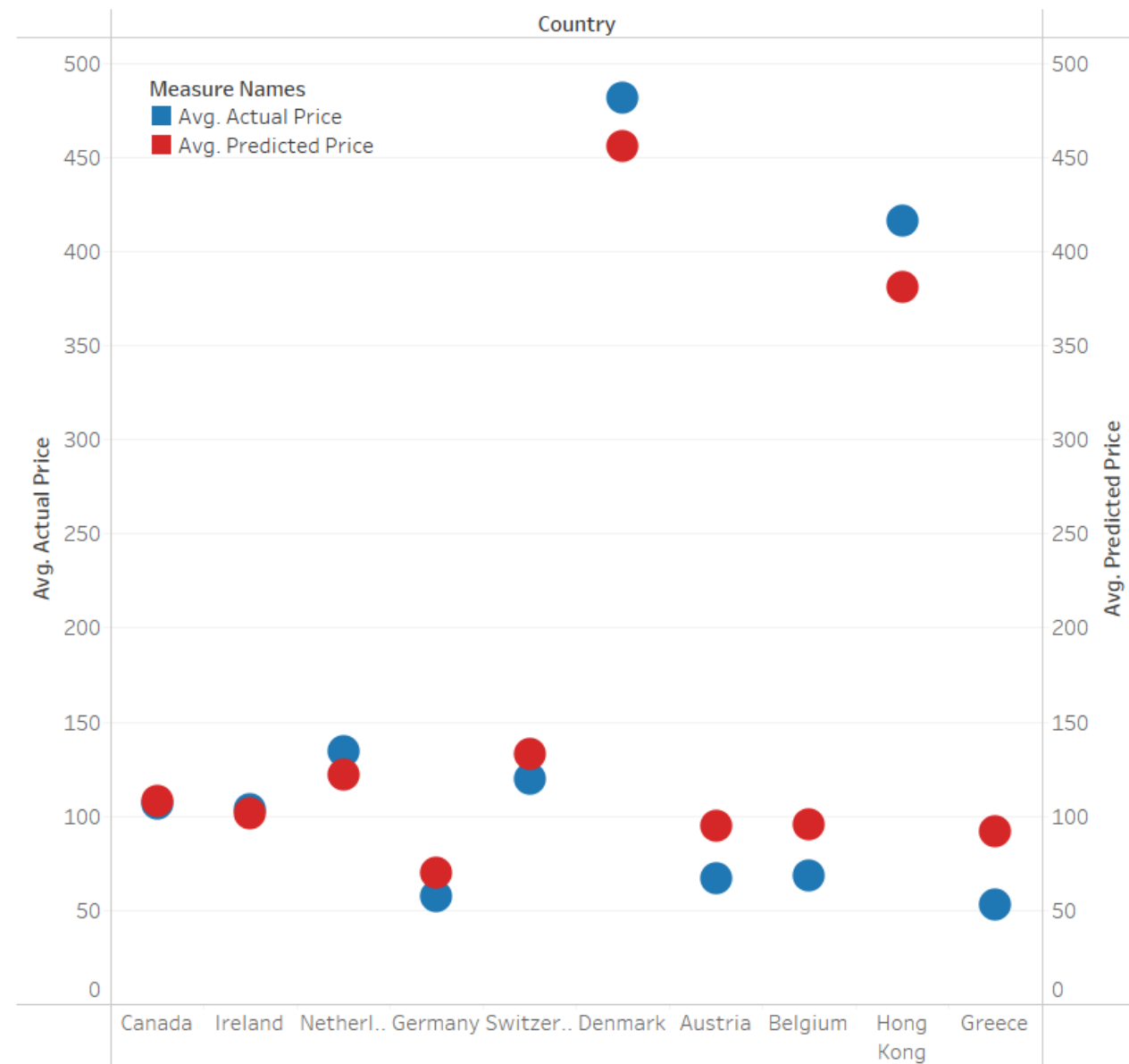
The background is a dark blue gradient with abstract, blurred lines and shapes representing data analysis. A prominent white line with circular markers starts from the top left and trends downwards towards the center. Other faint lines and shapes are visible in the background, suggesting a complex data environment.

Model-Based Outcome Data Analysis

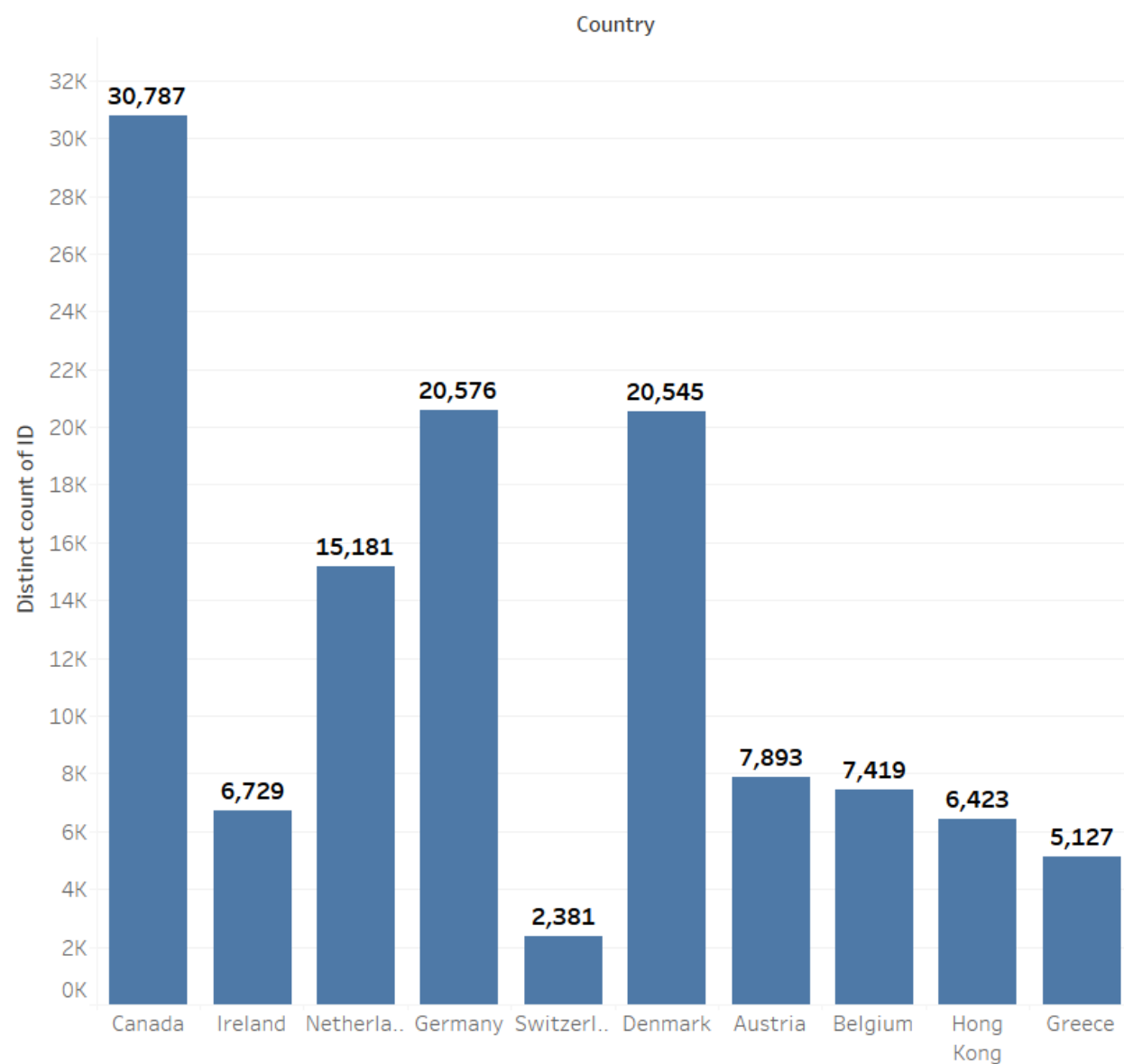
Actual V/S Pridicated Price Histogram



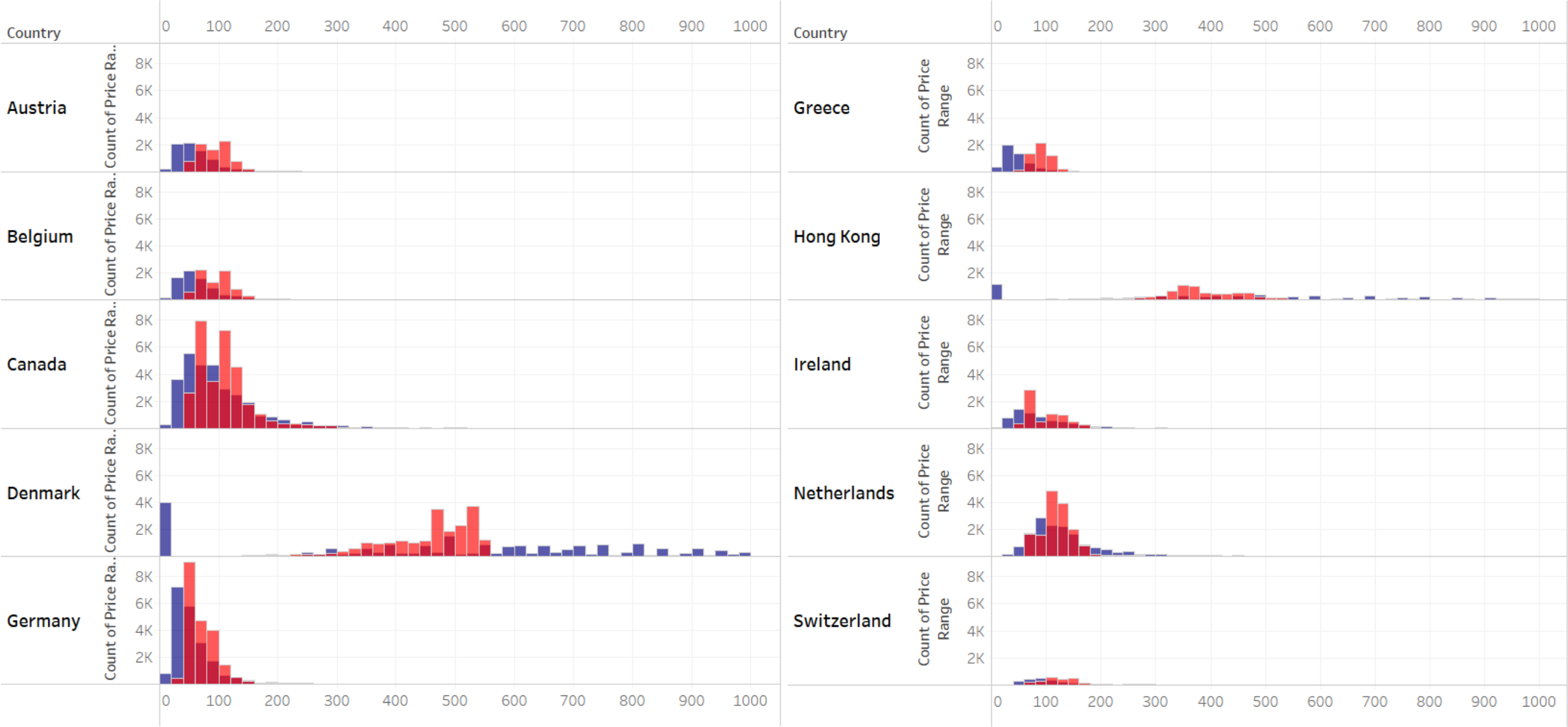
Actual V/S Pridicated Price by Contry



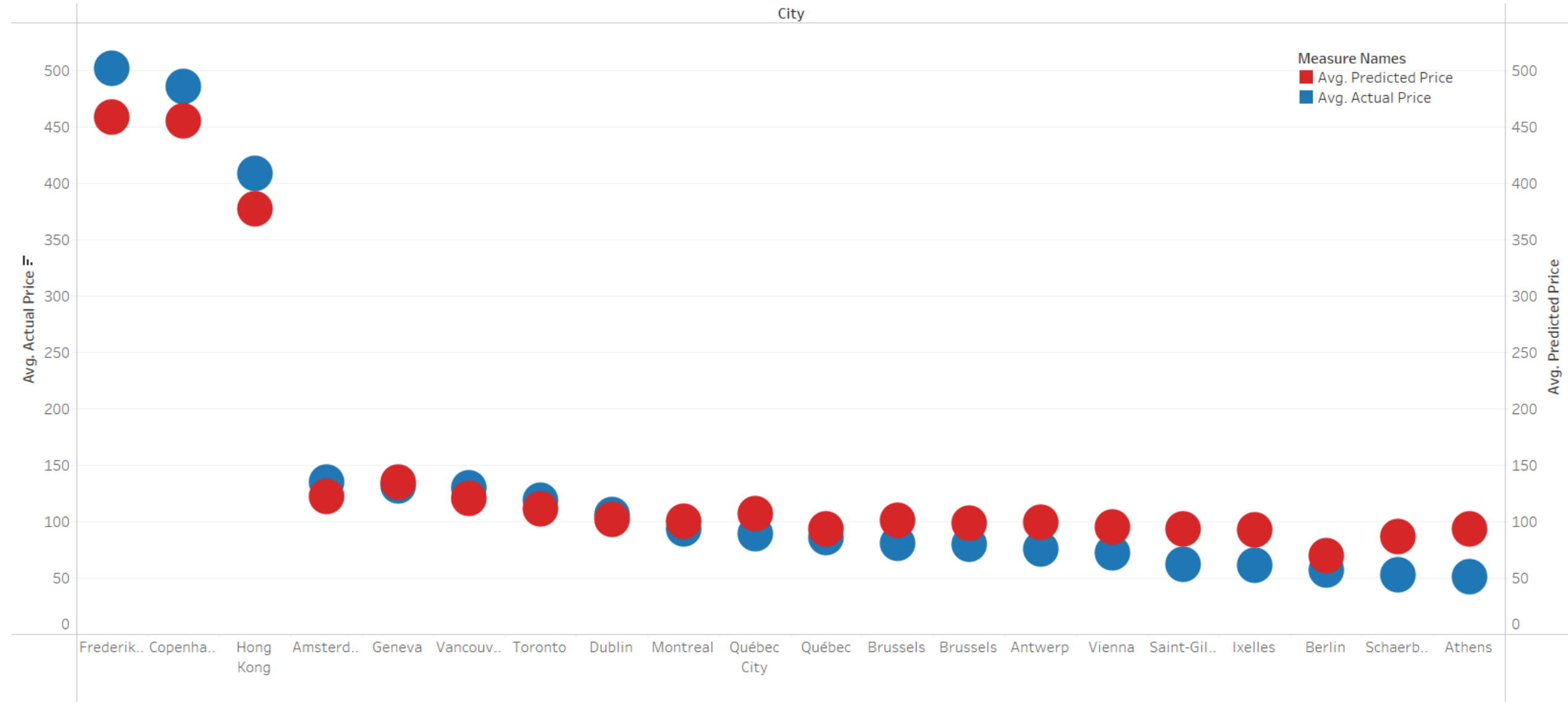
Number Of Listing by Contry



Actual V/S Pridicated Price Histogram by Contry in Detail

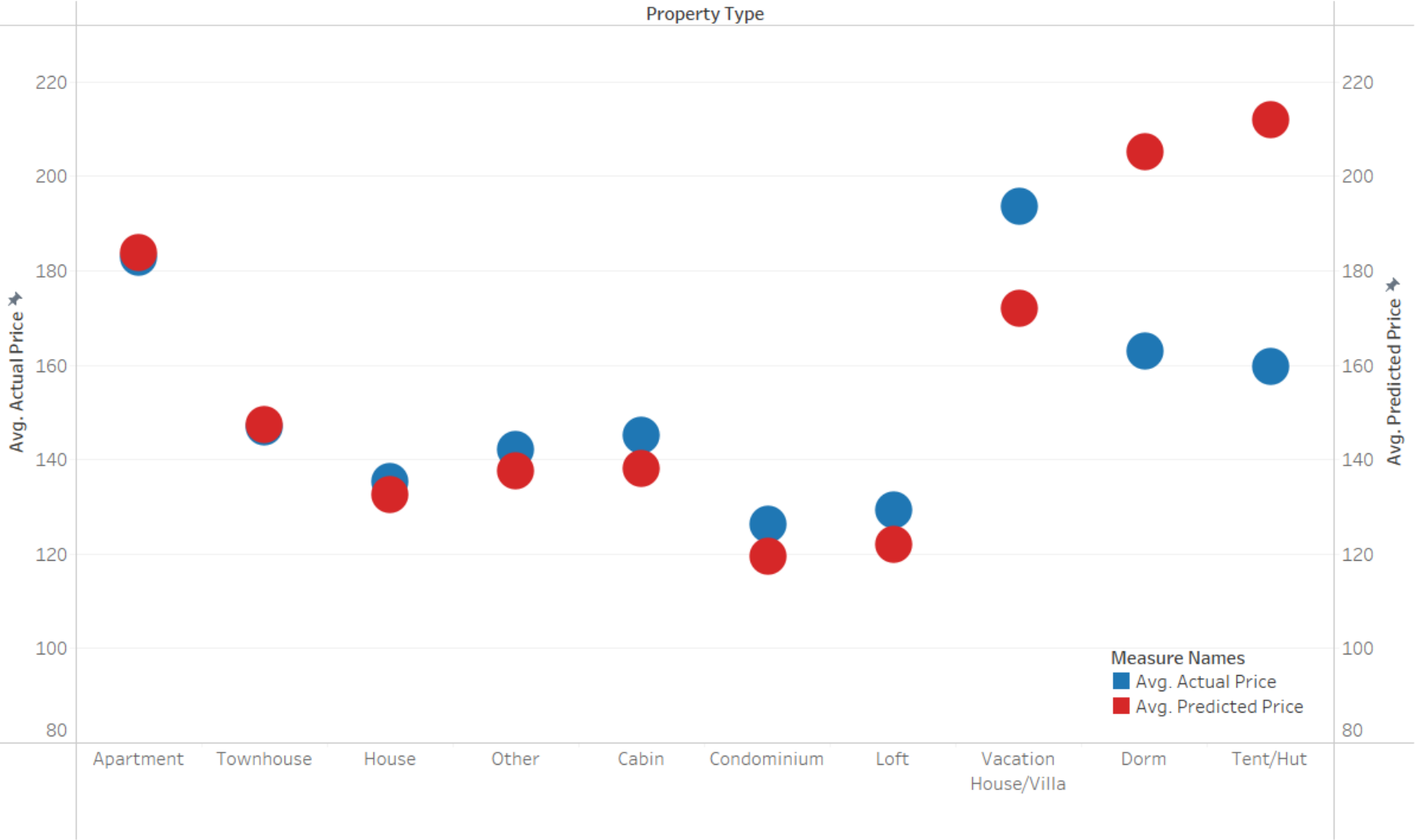


Actual V/S Pridicated Price by Top 20 City



In the graph, cities like **Geneva, Toronto, Dublin, Montreal, Québec** and **Berlin** show minimal differences between the actual and predicted average prices, indicating accurate predictions for these locations.

Actual V/S Pridicated Price by Property Type



Number Of Listing by Property Type

Property Type	
Apartment	97,592
House	16,210
Condominium	3,879
Loft	1,603
Townhouse	1,219
Vacation House/Villa	954
Other	649
Dorm	544
Cabin	388
Tent/Hut	23

In the chart, the **predicted prices** for **Apartment** and **Townhouse** closely match their **actual prices**, indicating accurate predictions for these property types. For **House**, the predicted price is also quite close to the actual price, showing a high level of prediction accuracy.

Conclusion

- **Canada, Netherlands, and Germany** are the top choices for investment, offering reliable price predictions and stable markets, particularly in **Toronto, Amsterdam, and Berlin**.
- Focus on major cities like **Toronto, Vancouver, Amsterdam, Rotterdam, Berlin, and Munich** where demand and price accuracy are high.
- Invest in **apartments and townhouses** for reliable returns. **Houses** are viable, but may have slight discrepancies in price predictions.



Any Questions?

