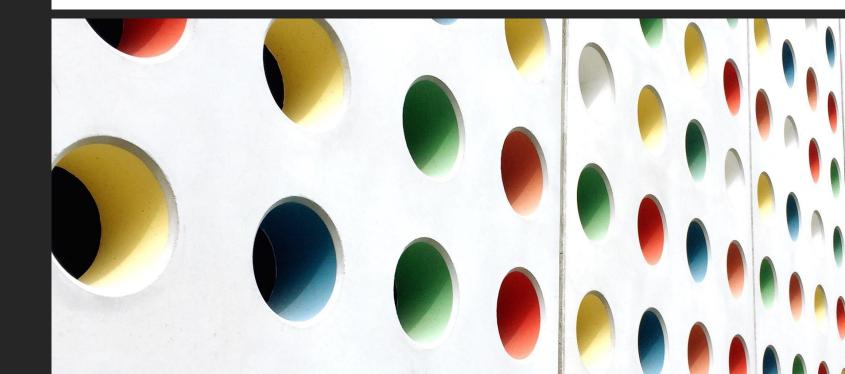
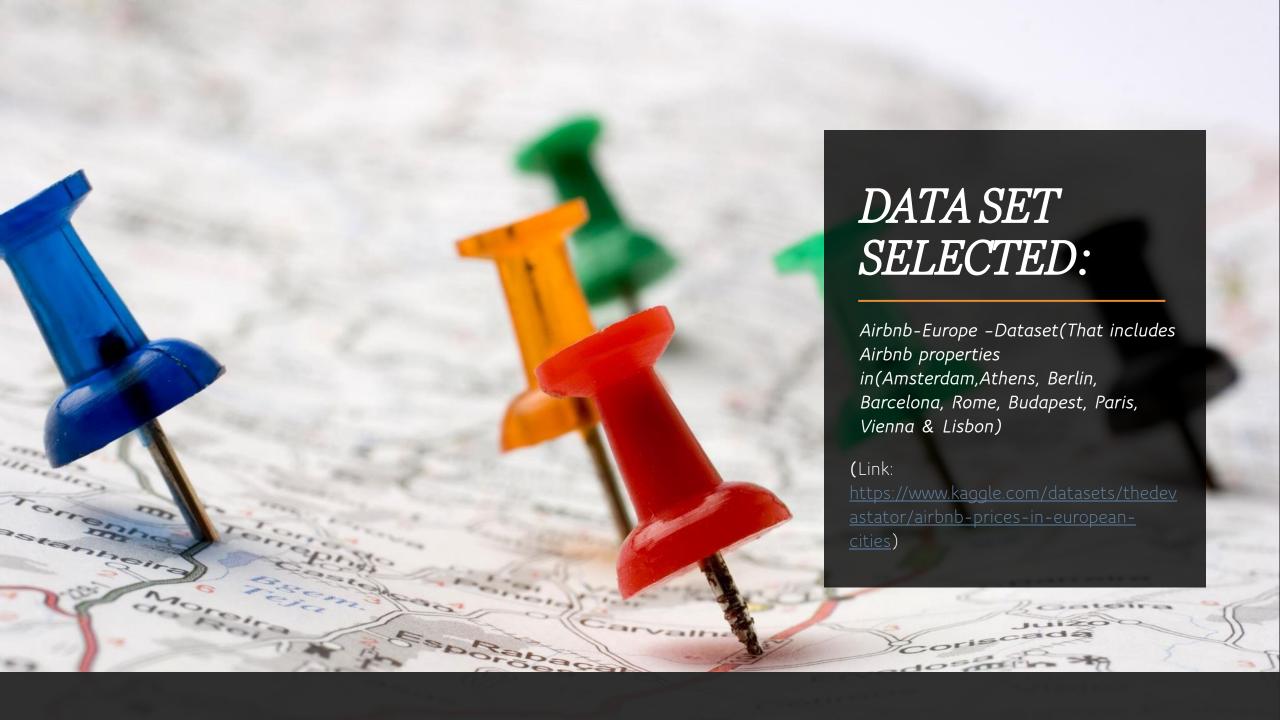
# Airbnb -Europe

BY: SEAN & TES

# (A) airbnb





## Project Description & Goals

#### PROJECT DESCRIPTION

 Analysis on Airbnb – Europe dataset, begin by identifying valuable questions and then to solve the questions.

#### PROJECT GOAL

- Using EDA & Statistical Modeling, produce an answer or solution to an identified question or problem.
- Communicating Insights using Impactful Dashboards to help stakeholders make decisions.

# Project Flow Structures



find dataset & identify problem



EDA & statistical modeling



Create visualization & dashboard to communicate insights

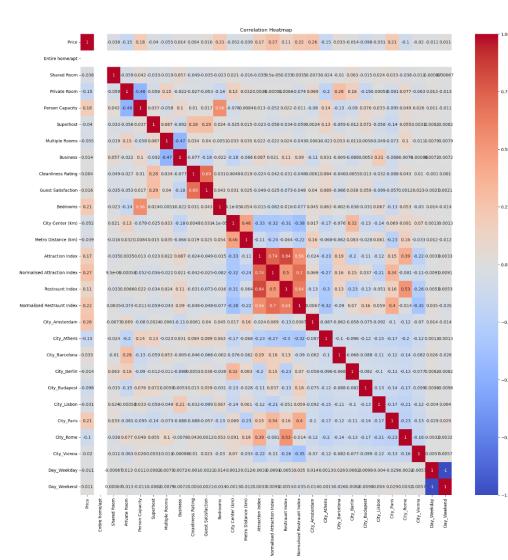
# PROBLEM IDENTIFIED

How important are each features to influence the Airbnb property:

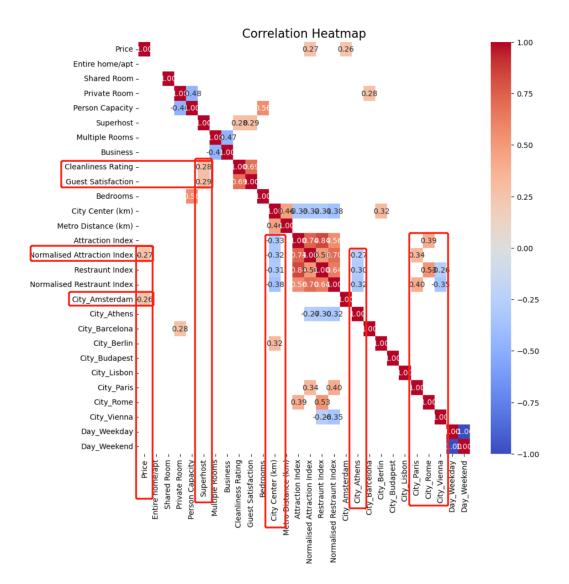
- 1. Price
- 2. Guest Satisfaction
- 3. Index

prediction across the 9 European cities?





# Using Heatmap



Only the parts of the heatmap with correlation coefficients greater than 0.25 in absolute value were extracted. Here are some pieces of information that can be observed from the heatmap:

- 1. The city of Amsterdam has the largest positive impact on prices in terms of the attraction index.
- 2. Superhosts were positively correlated with both cleanliness rating and customer satisfaction in the past.
- 3. The farther away from the city, the lower all the indices are.
- 4. The city of Athens has relatively low values for all indices. The restaurant index is also low in the city of Vienna. Both the cities of Paris and Rome show positive correlations with two indices.

## Findings @ EDA Level

- oNegative correlation between indexes and the distance to the city center and the subway station. We naturally prefer shorter distances.
- oThere is a significant positive correlation between indexes and price.

o However, it is harder to comprehend the negative correlation between indexes and Guest Satisfaction and Cleanliness Rating, which seems unreasonable for an attraction.

From the results of the regression analysis, the two factors that have the most significant impact on prices are:

- 1.City
- 2.Room type

#### OLS Regression Results

Dep. Variable:	Price	R-squared:			0.260	
Model:	OLS	Adj. R-squared:			0.260	
Method:	Least Squares	F-statistic:			611.2	
Date:	Thu, 13 Jul 2023	Prob (F-statistic):		0.00		
Time:	10:22:06	Log-Likelihood:		-2.87	-2.8786e+05	
No. Observations:	41714	AIC:		5.758e+05		
Df Residuals:	41689	BIC:		5.760e+05		
Df Model:	24					
Covariance Type:	nonrobust					
=======================================		========	========		========	=======
	coef	std err	t	P> t	[0.025	0.975]
Entire home/apt	-28.0361	9.741	-2.878	0.004	-47.129	-8.943
Shared Room	-192.1430	13.748	-13.976	0.000	-219.089	-165.197
Private Room	-86.1138	3.228	-26.677	0.000	-92.441	-79.787
Person Capacity	21.7643	1.278	17.033	0.000	19.260	24.269
Superhost	-1.6264	2.813	-0.578	0.563	-7.141	3.888
Multiple Rooms	11.8817	3.034	3.916	0.000	5.935	17.828
Business	40.1648	3.080	13.039	0.000	34.127	46.202
Cleanliness Rating	0.4696	0.149	3.157	0.002	0.178	0.761
Guest Satisfaction	0.7409	0.207	3.575	0.000	0.335	1.147
Bedrooms	7.1052	0.231	30.743	0.000	6.652	7.558
City Center (km)	0.3332	0.941	0.354	0.723	-1.511	2.177
Metro Distance (km)	0.8045	2.076	0.388	0.698	-3.264	4.873
Attraction Index	-0.0486	0.019	-2.616	0.009	-0.085	-0.012
Normalised Attraction	Index 5.6468	0.467	12.102	0.000	4.732	6.561
Restraunt Index	-0.0049	0.008	-0.634	0.526	-0.020	0.010
Normalised Restraunt	Index 0.8872	0.181	4.895	0.000	0.532	1.242
City_Amsterdam	291.3692	5.379	54.166	0.000	280.826	301.913
City_Athens	-136.8535	4.192	-32.645	0.000	-145.070	-128.637
City_Barcelona	53.6817	5.408	9.927	0.000	43.083	64.281
City_Berlin	-33.0317	6.899	-4.788	0.000	-46.555	-19.509
City_Budapest	-149.1238	4.371	-34.117	0.000	-157.691	-140.557
City_Lisbon	-44.4023	3.925	-11.312	0.000	-52.096	-36.708
City_Paris	80.6592	4.012	20.106	0.000	72.796	88.522
City_Rome	-64.6669	4.792	-13.496	0.000	-74.058	-55.275
City_Vienna	-25.6679	4.588	-5.595	0.000	-34.660	-16.675
Day_Weekday	-17.9140	5.021	-3.568	0.000	-27.756	-8.072
Day_Weekend	-10.1221	5.006	-2.022	0.043	-19.934	-0.310
Omnibus:	116159.888	Durbin-Wats			1.866	
Prob(Omnibus):	0.000	Jarque-Bera	(JB):	76944174		
Skew:	35.828	Prob(JB):			0.00	
Kurtosis: 2105.813 Cond. No. 1.27e+16						

# Findings @Modeling level

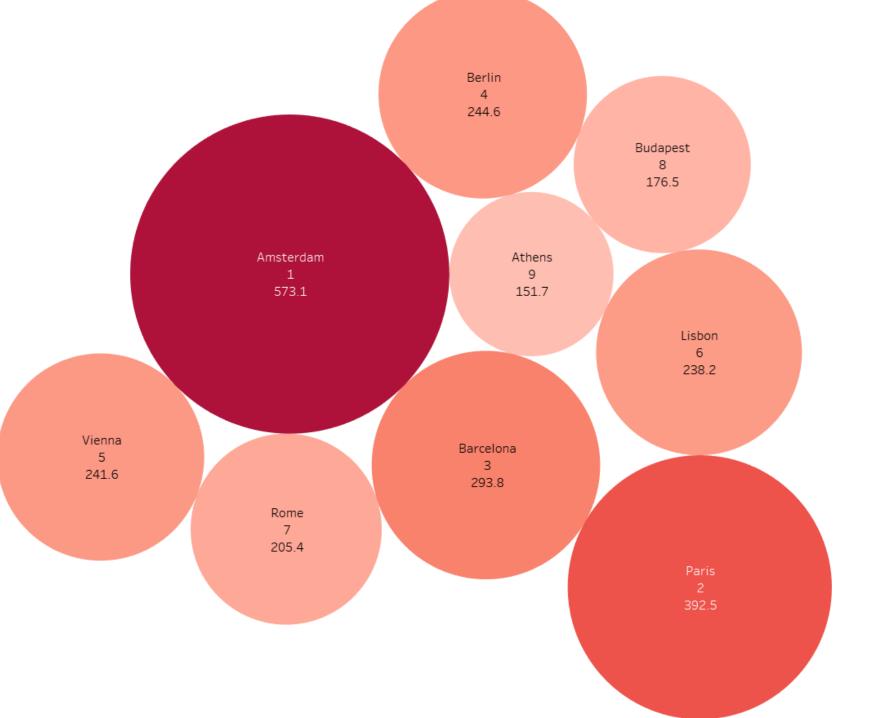
oR-square indicate approximately 26% of the variation in the Price can be explained by the independent variables included in the model.

- o The coefficient -192.143 indicate the negative r/ship and the significant decreases in price when room type is shared room.
- o The P-value of most of the variables is less than 0.05, indicating their statistical significance in explaining the variation in price.



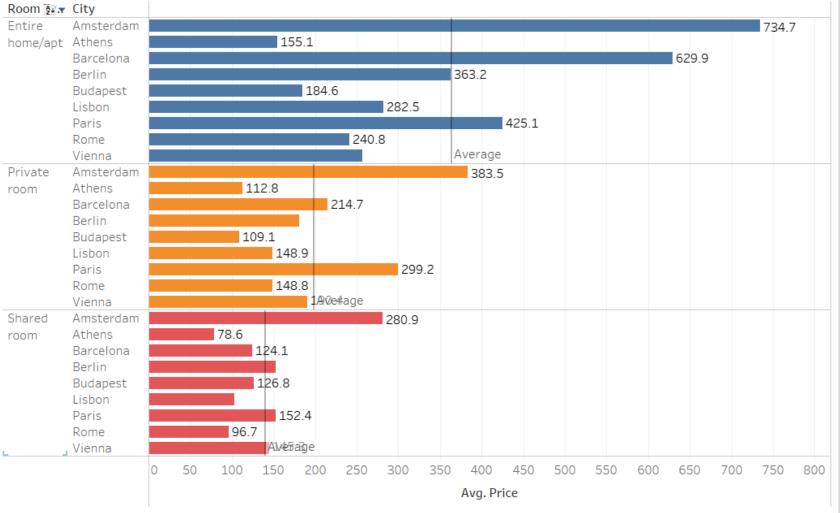
#### AVG Airbnb Rent by Cities

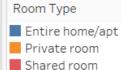




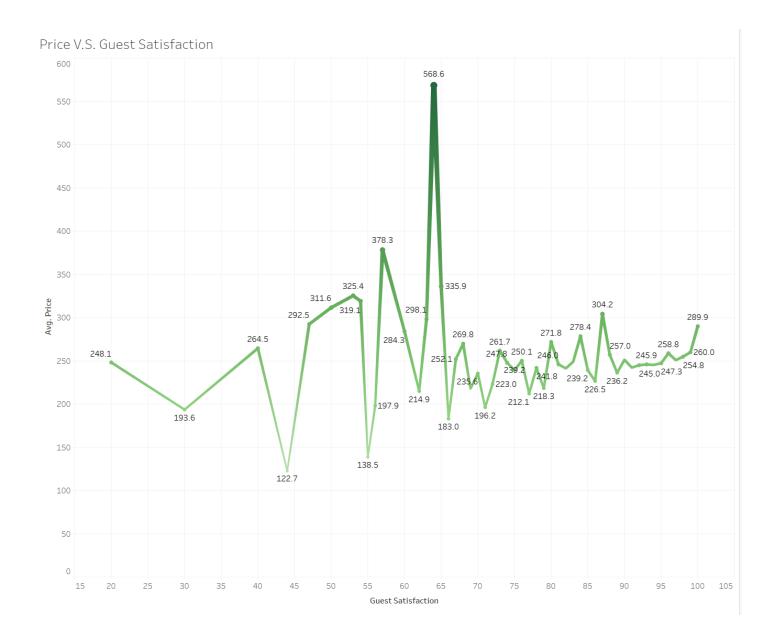
Average Prices and Rankings by City

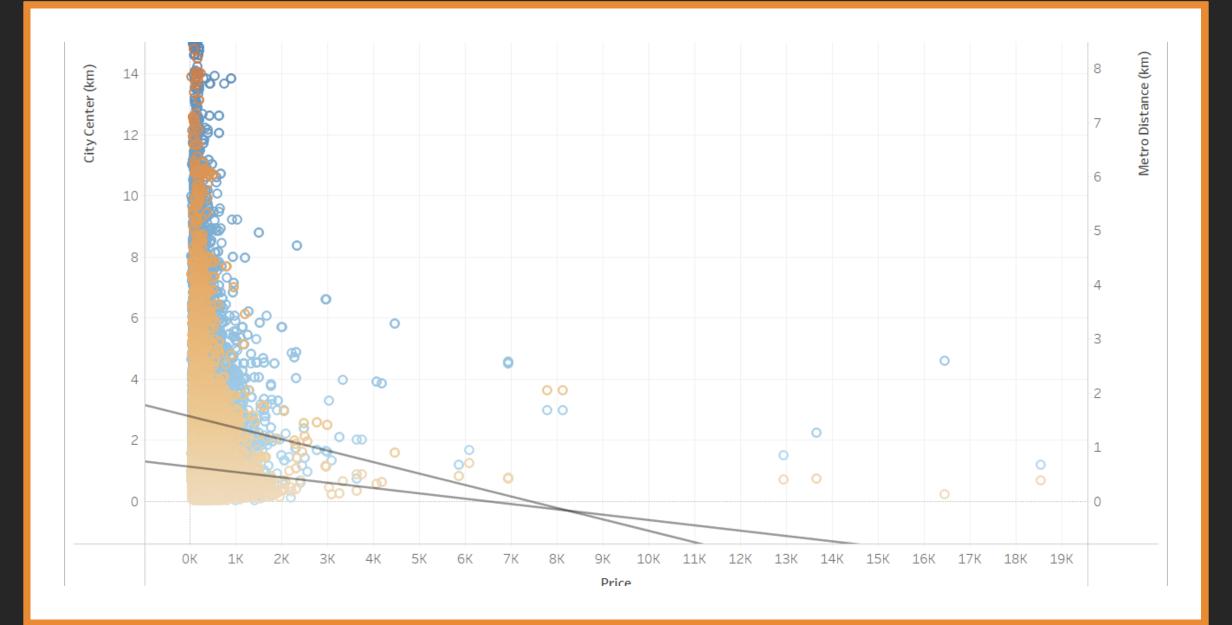
What are the average prices for different room types in each city?

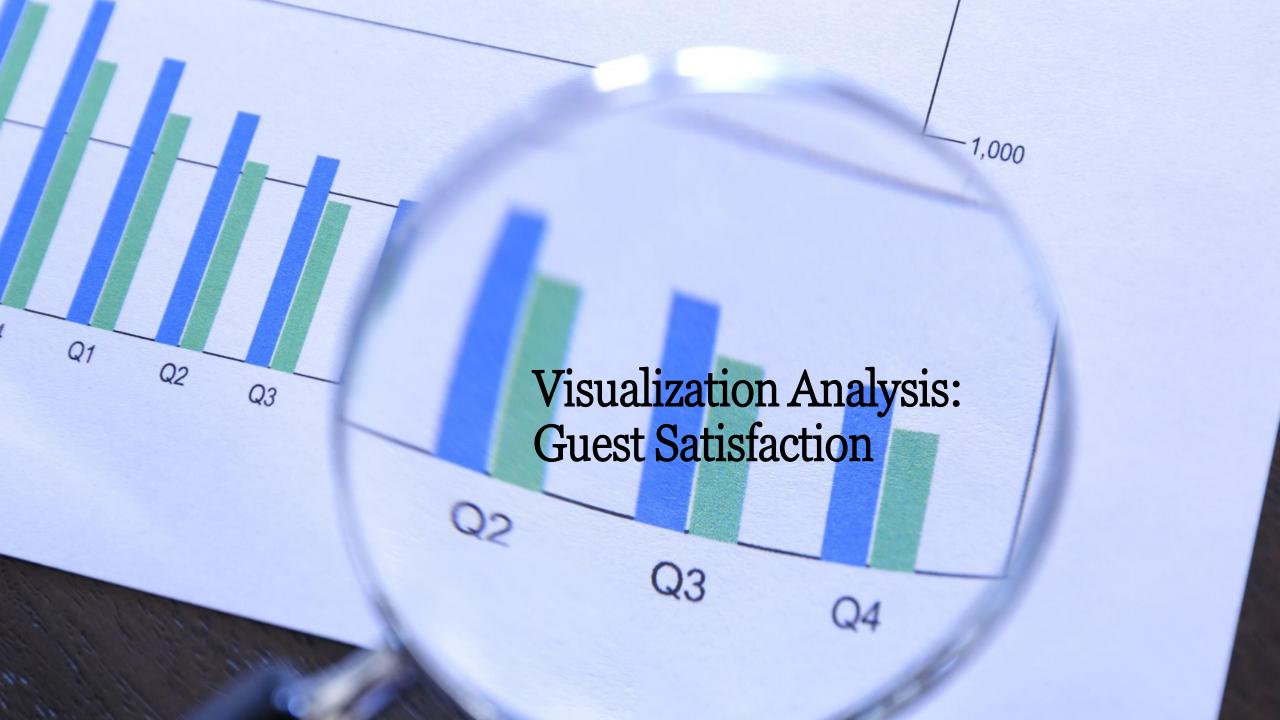


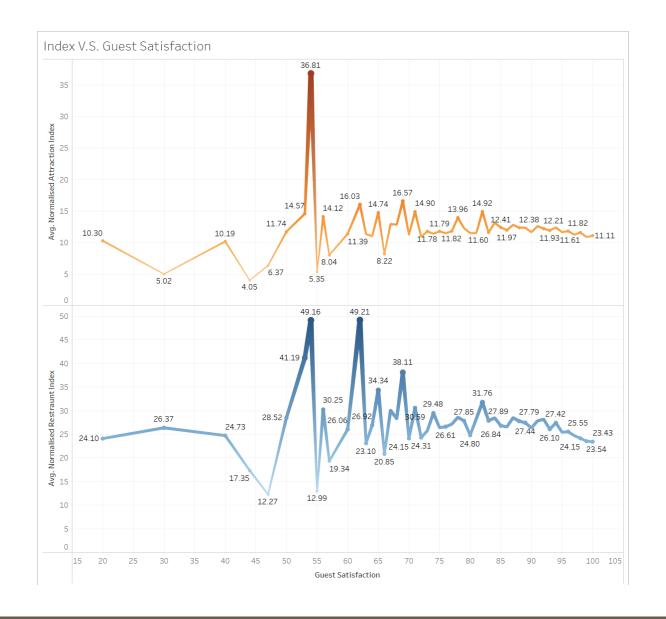


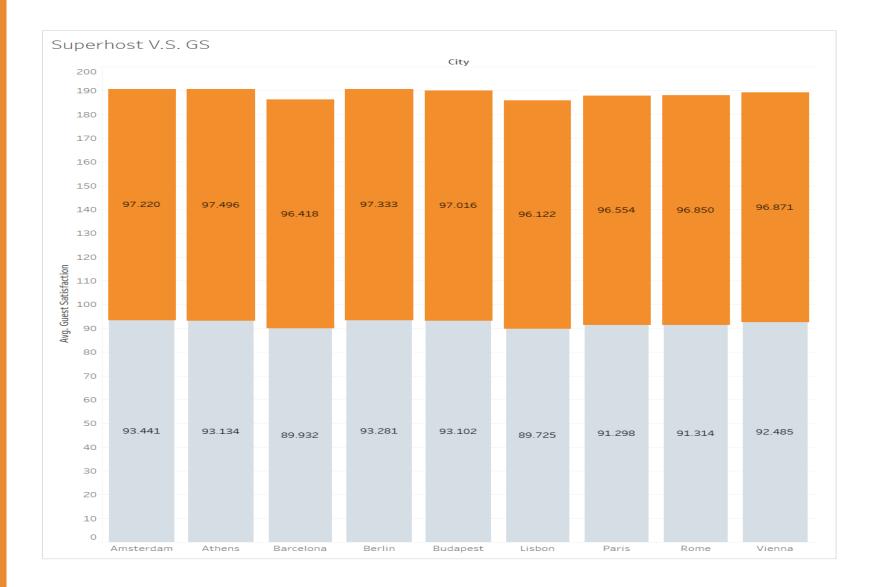
The relationship between customer satisfaction and prices is not clear, but it can be observed that houses with higher average prices tend to have lower overall satisfaction. This could be due to difficulties in meeting customer expectations.





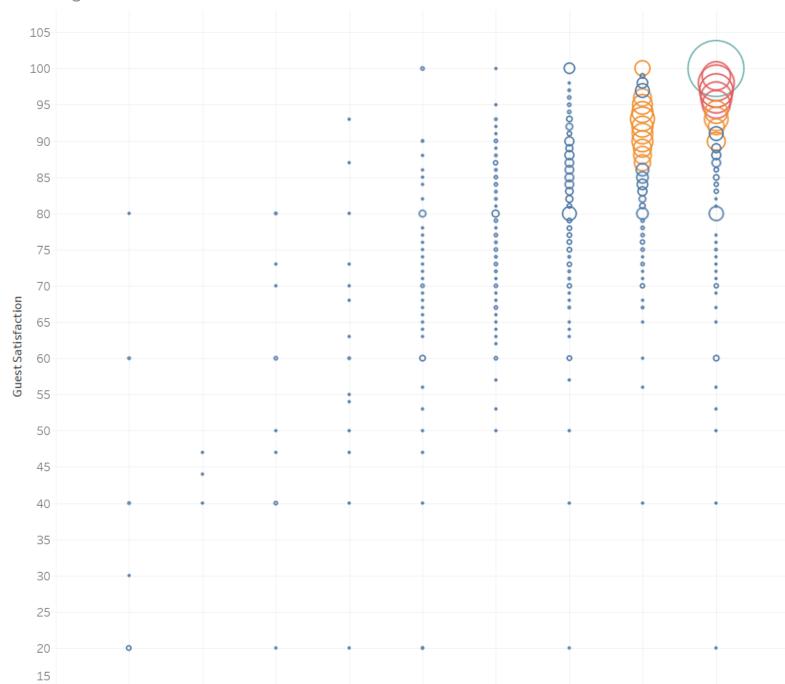






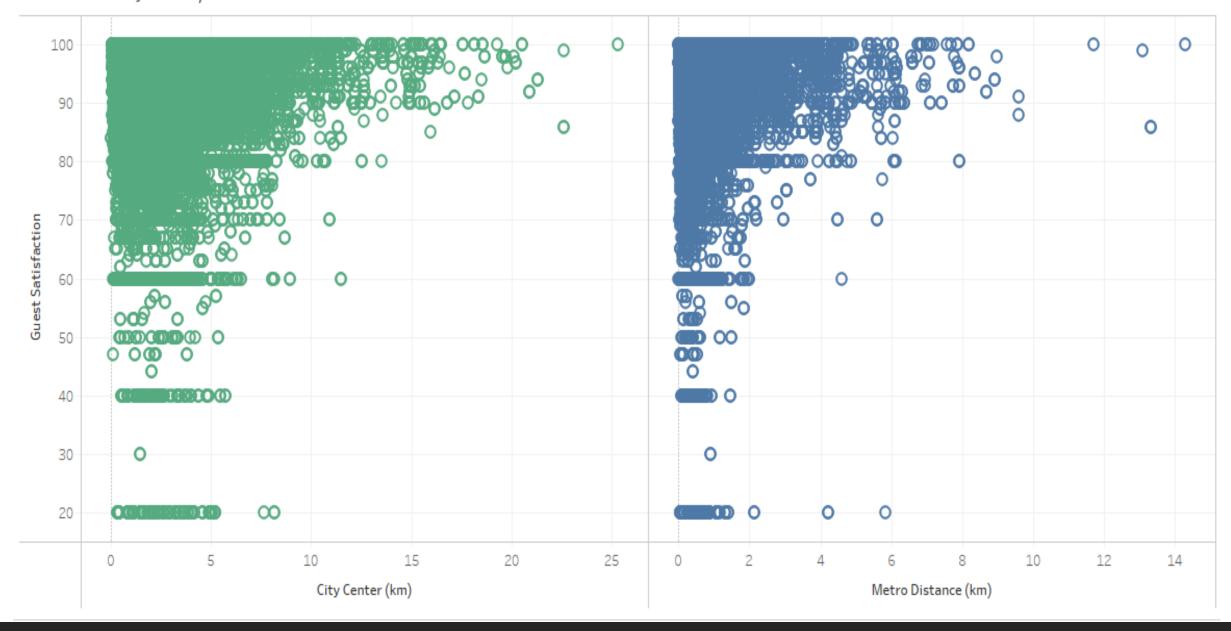
It can be seen that the average guest satisfaction of Superhosts is slightly higher than that of non-Superhosts, but the difference is not significant.

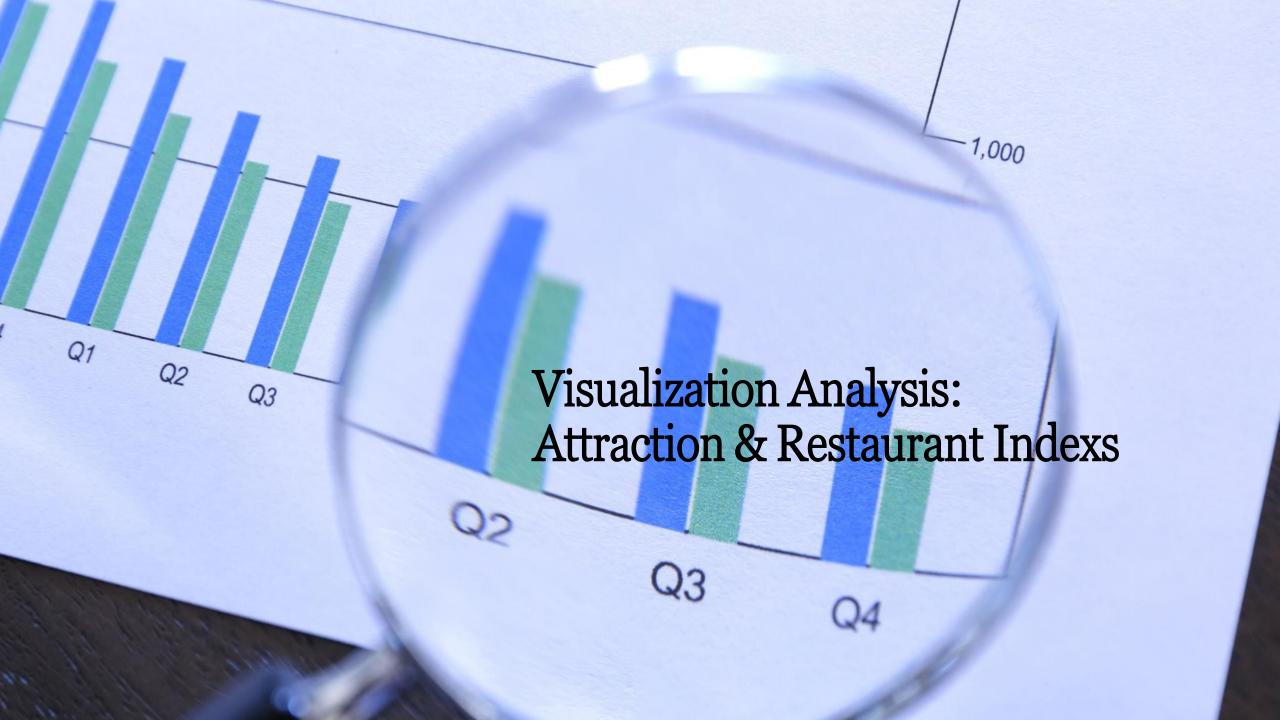
Cleaning V.S. GS



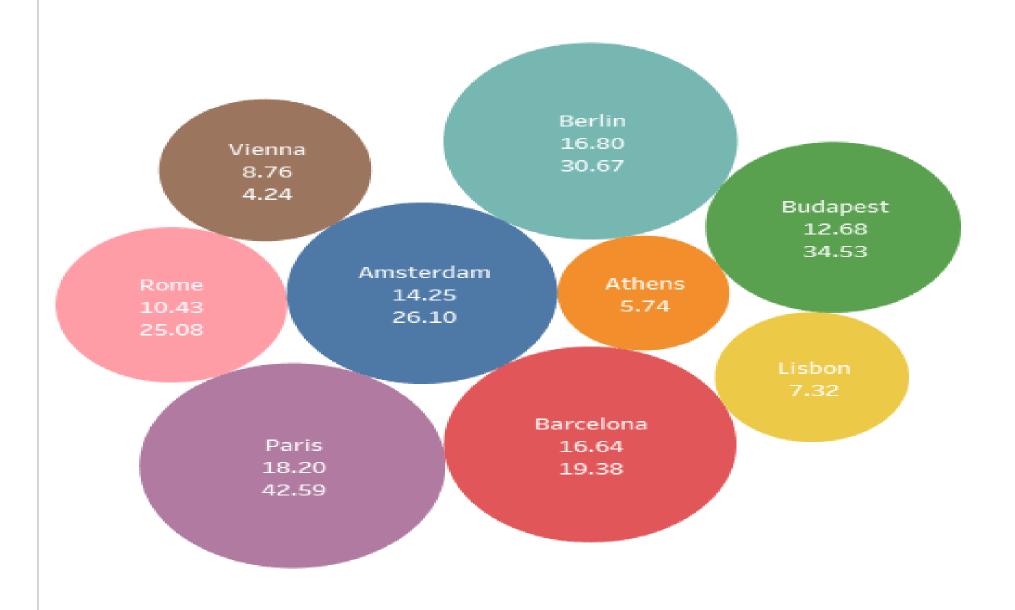
Clearly, higher cleanliness levels lead to higher customer satisfaction.

#### Distance to City Center/Metro Station VS Guest Satisfaction

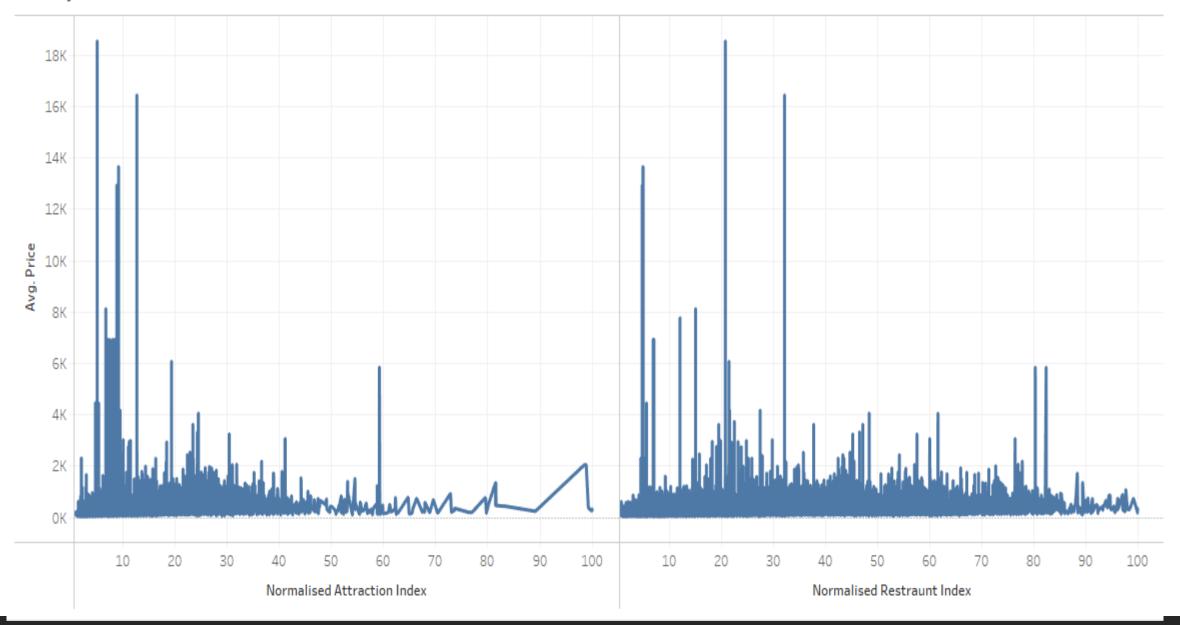


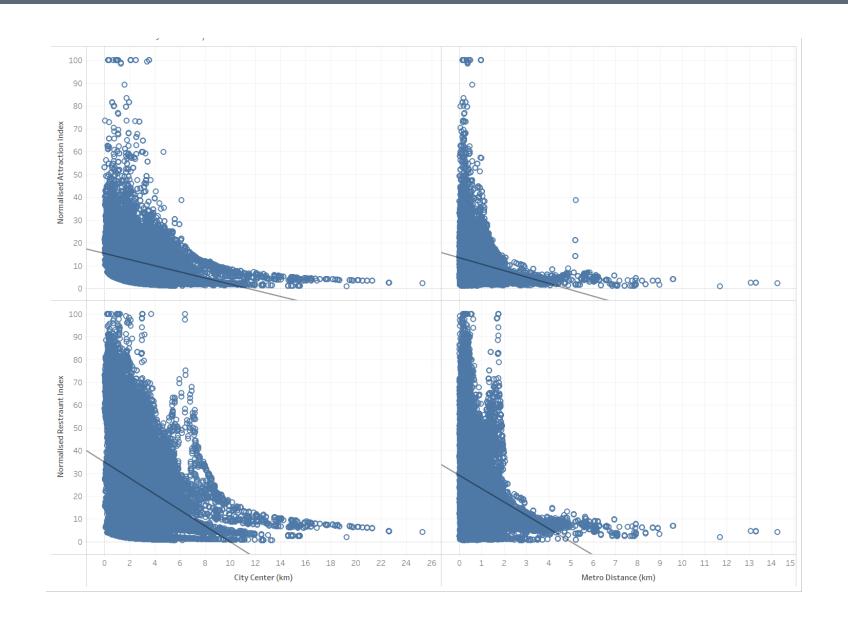


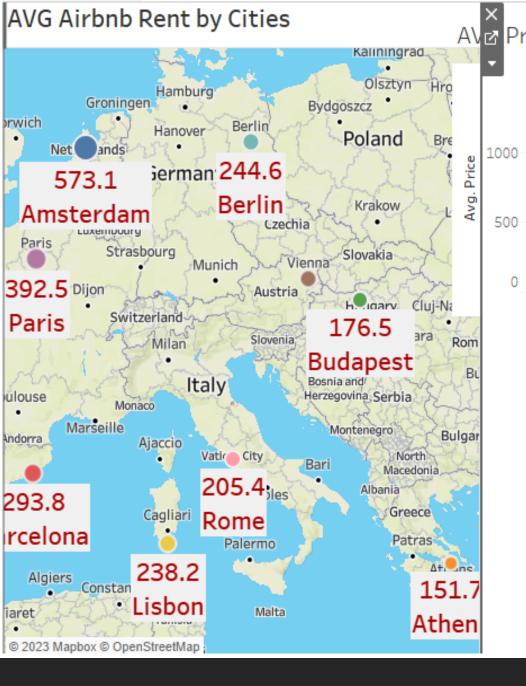
#### AVG Normalised Index By Cities

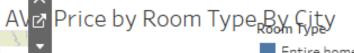


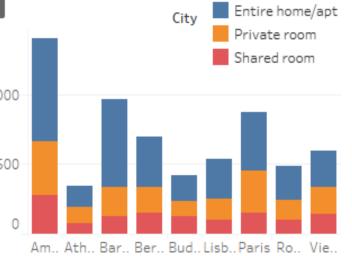
#### Price by Normalised Indexes



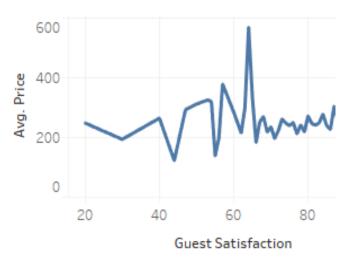








AVG Rent VS Guest Satisfaction



AVG Normalised Index By Cities





# Challenges

- Navigating how to work with GitHub as a team member when you must work on the same notebook was not as easy.
- oCreating robust and highly interactive dashboard needs time & practice.
- o If we had time, we would have tried creating classification(logistic model) specially with those columns with categorical data type.

# **THANAK YOU**

