

The background features several thin, overlapping rectangular outlines in orange and blue, creating a modern, architectural feel. These lines are positioned in the corners and along the sides of the slide.

# IMMO ELIZA

# DATA ANALYSIS

TEAM 5

Yusra  
Zelim  
Rasmita  
Muntadher

# OBJECTIVE

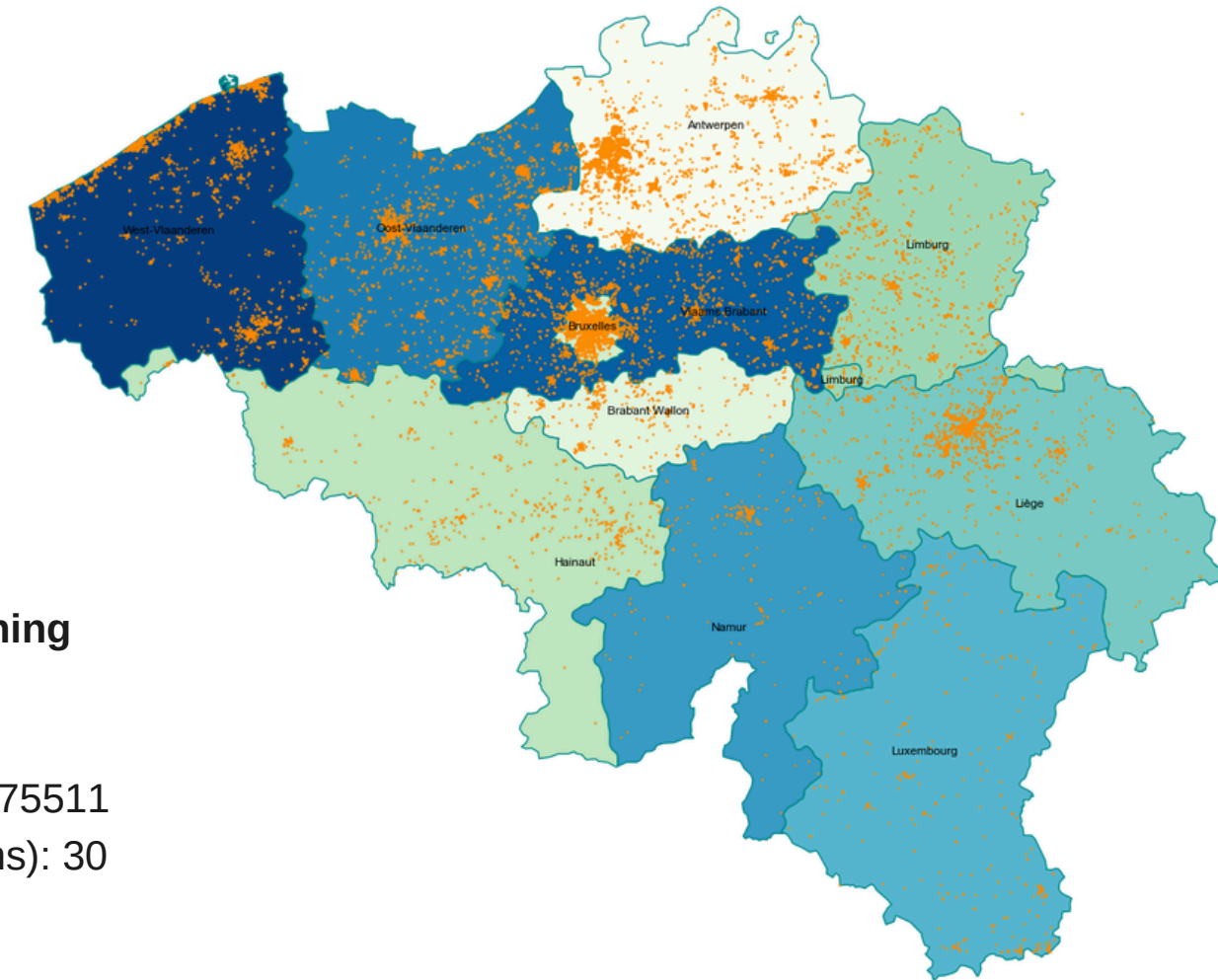
Perform an initial analysis of the scraped data to create visualizations and establish the foundation for the Machine Learning model.



# OBSERVATIONS AND FEATURES

**Observations:** These are the rows in your dataset, representing each individual instance .

**Features:** These are the columns in your dataset, representing the attributes or characteristics of each observation. For example, features in a real estate dataset could include "location," "price," "number of bedrooms."



## Before Data Cleaning

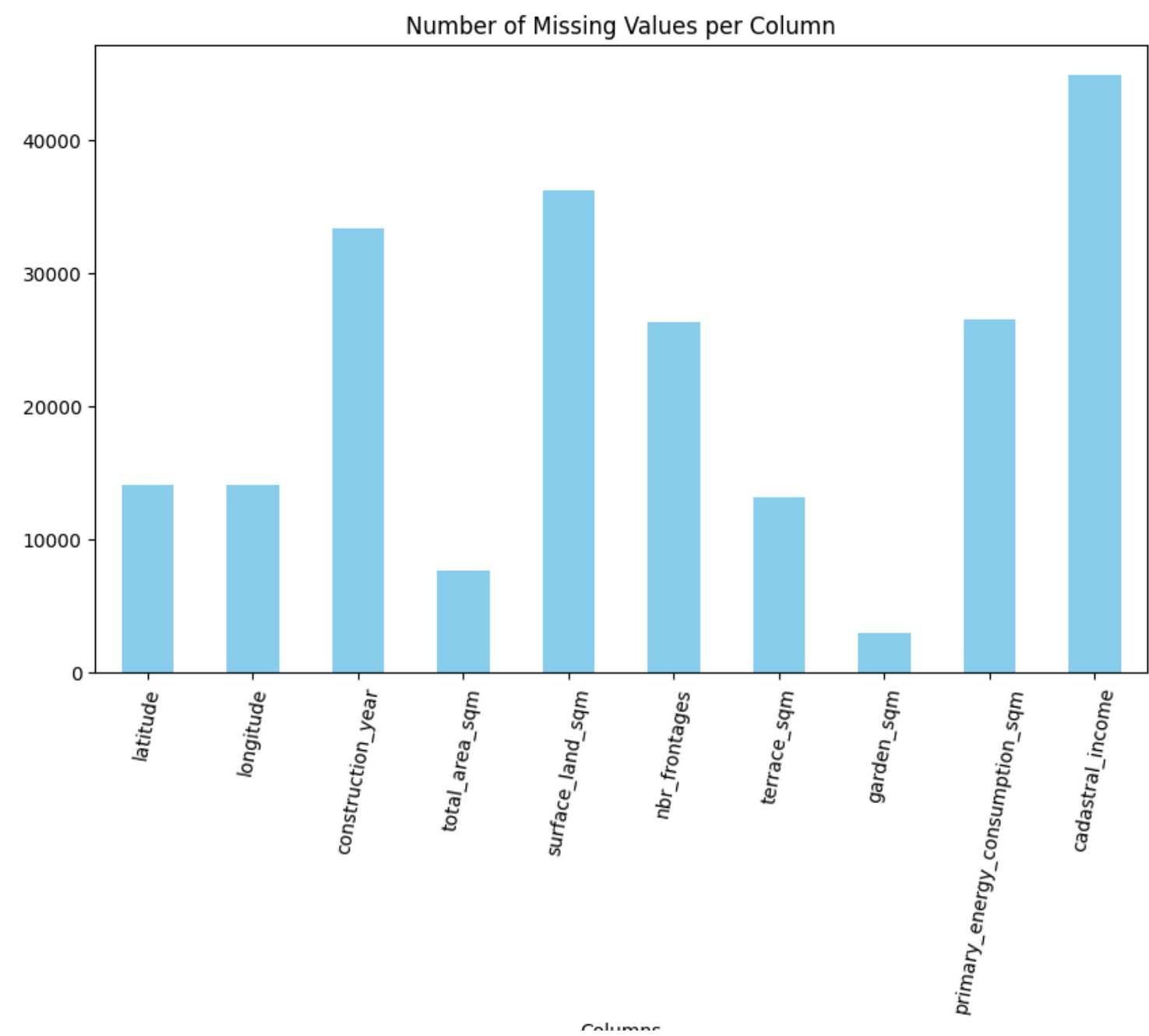
Number of (rows): 75511  
Number of (columns): 30

## After Data Cleaning

Number of (rows): 17258  
Number of (columns): 23

THE PROPORTION OF MISSING VALUES  
PER COLUMN.

- Construction year 44%
- Total area sqm 10.08%
- Surface land sqm 48.01%
- Frontages 34.89%
- Terrace sqm 17.40%
- Garden sqm 3.89%
- Latitude 18.67%
- Longitude 18.67%
- Primary Energy Consumption sqm 35.18%
- Cadastral Income 59.55%





# VARIABLES YOU WOULD DELETE .

## Variable Deletion in Real Estate Dataset for Immo Eliza

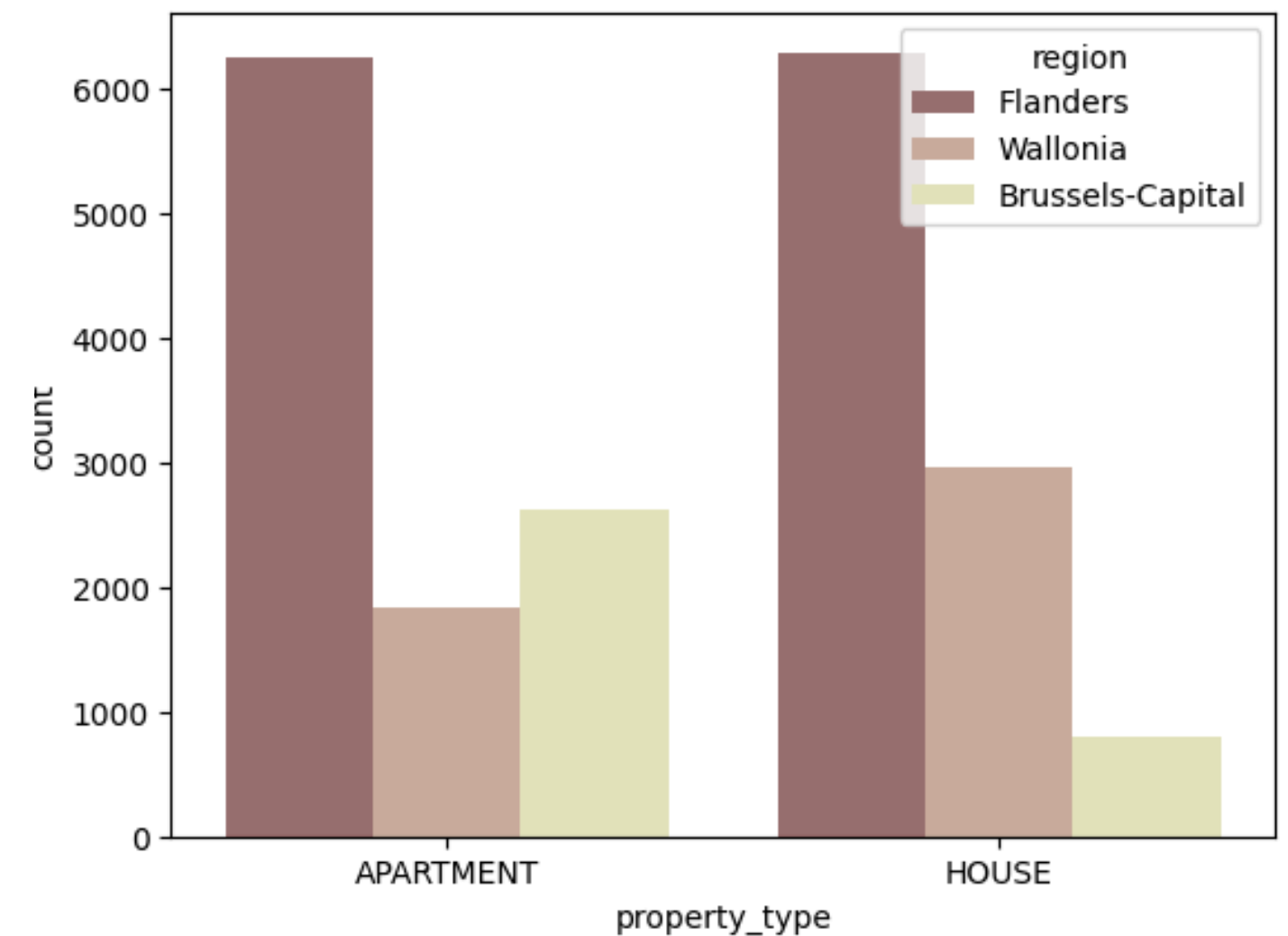
During this review, certain variables were identified as redundant or irrelevant for our specific objectives and were therefore removed. Also variables with a high percentage of missing values (e.g., more than 40%).

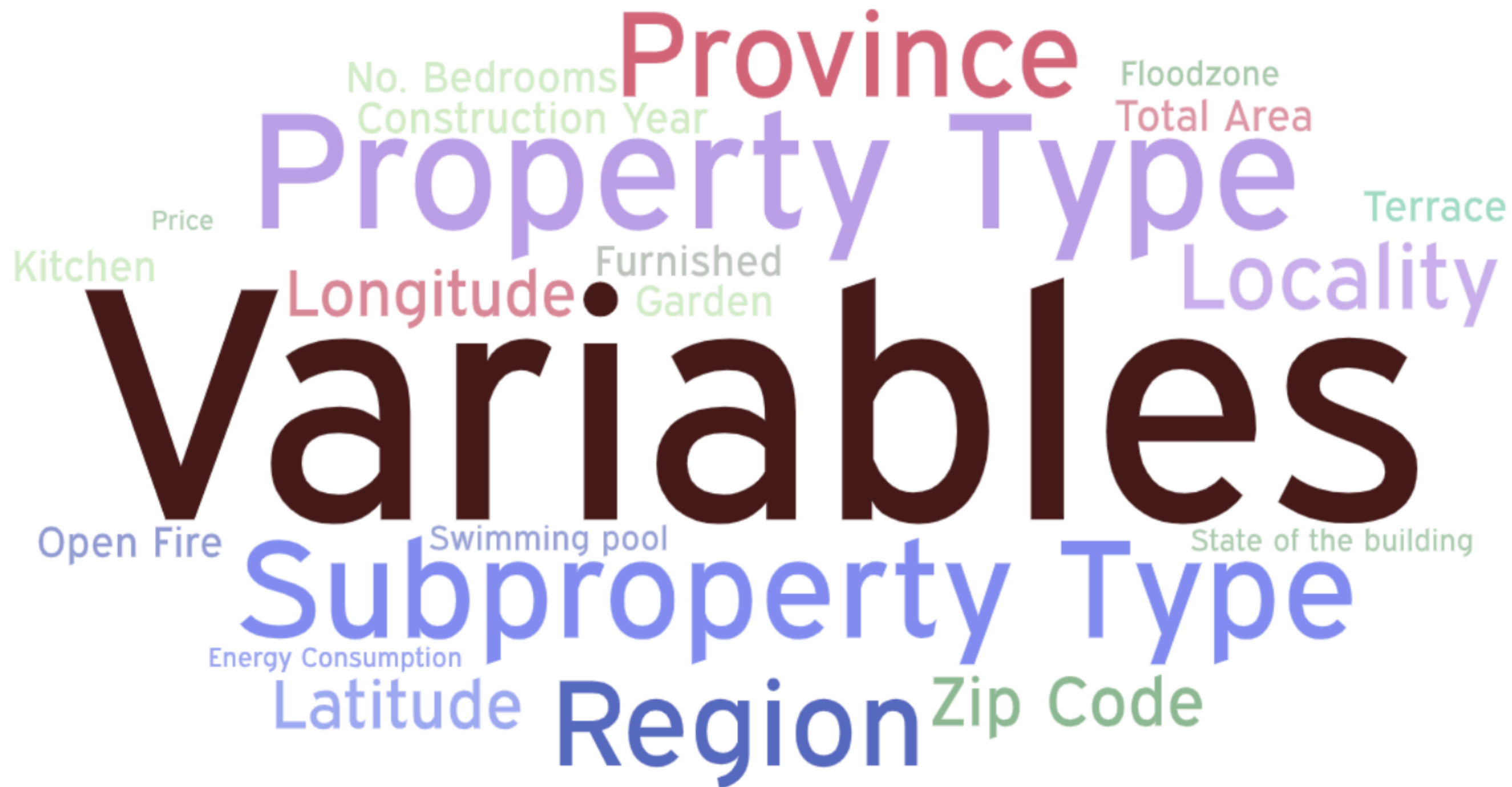
1. Surface land sqm
2. Frontages
3. Cadastral Home
4. Terrace FL
5. Garden FL
6. Primary Energy Consumption
7. Heating type



## REMOVING THESE VARIABLES IS EXPECTED TO

- **Improve Model Simplicity:** Fewer variables reduce model complexity, which can lead to better interpretability and faster computation.
- **Focus on Key Features:** Concentrating on variables that have a more direct impact on property prices will help refine the accuracy of predictions.





# QUANTITATIVE

- Price
- Total Area
- No. of bedrooms
- Terrace(sqm)
- Garden(sqm)
- Primary Energy Consumption per sqm



# QUALITATIVE

## Nominal

- ID
- Property Type
- Sub property type
- Location data

## Ordinal

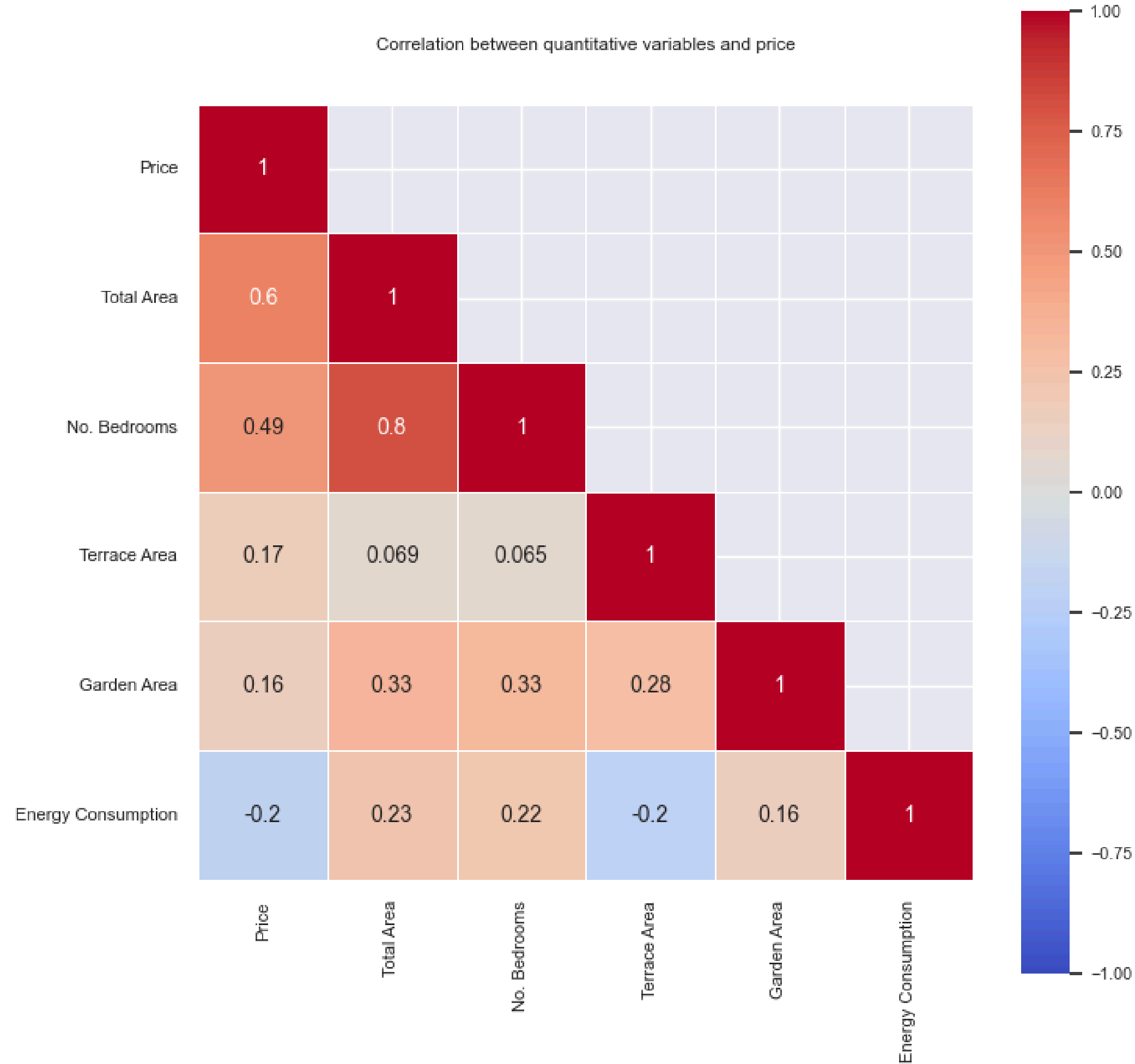
- Construction year
- State of building
- Kitchen level

## Binary

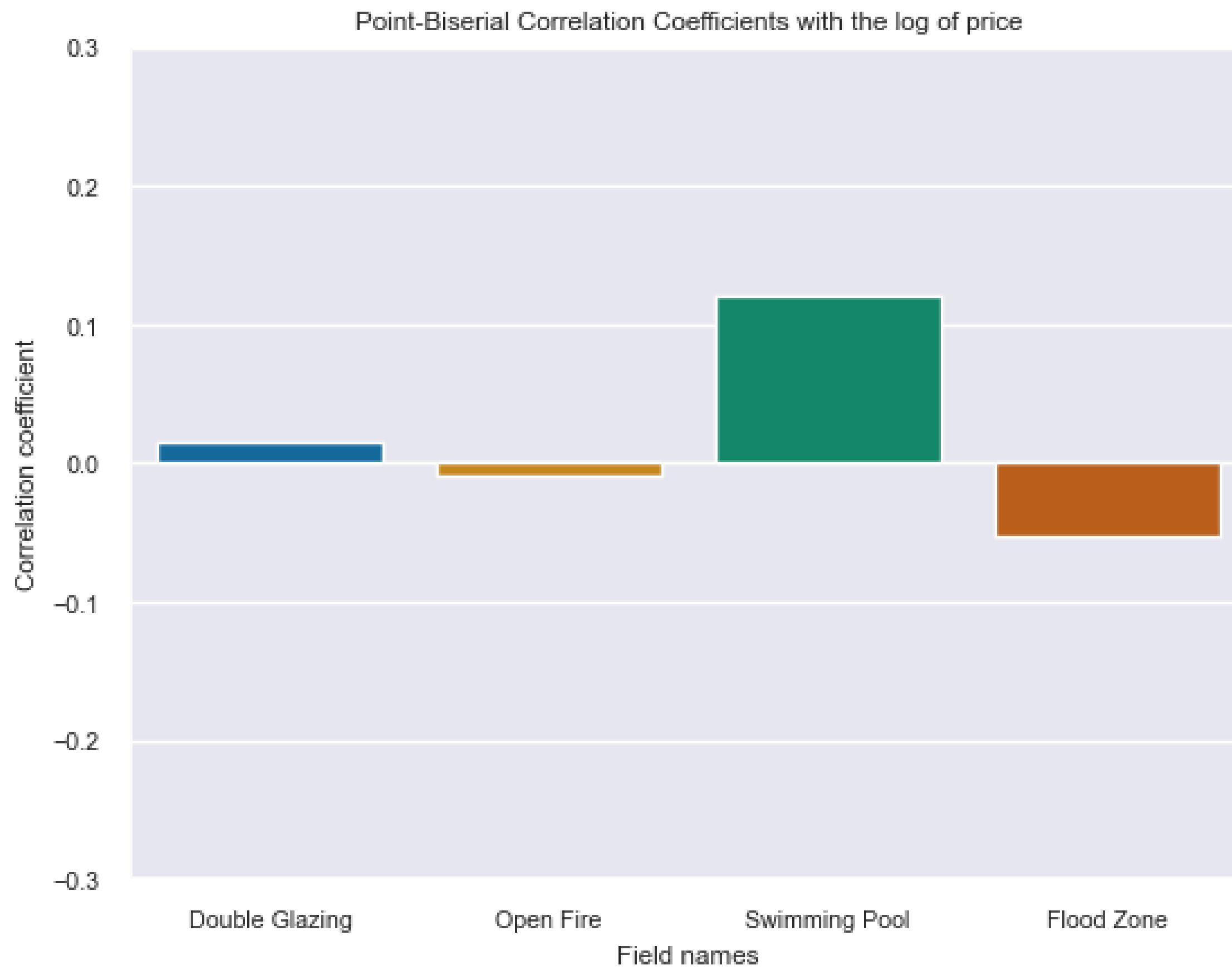
- Swimming pool
- Double glazing
- Furnished
- Open Fire
- Flood zone

# CONVERSION METHODS

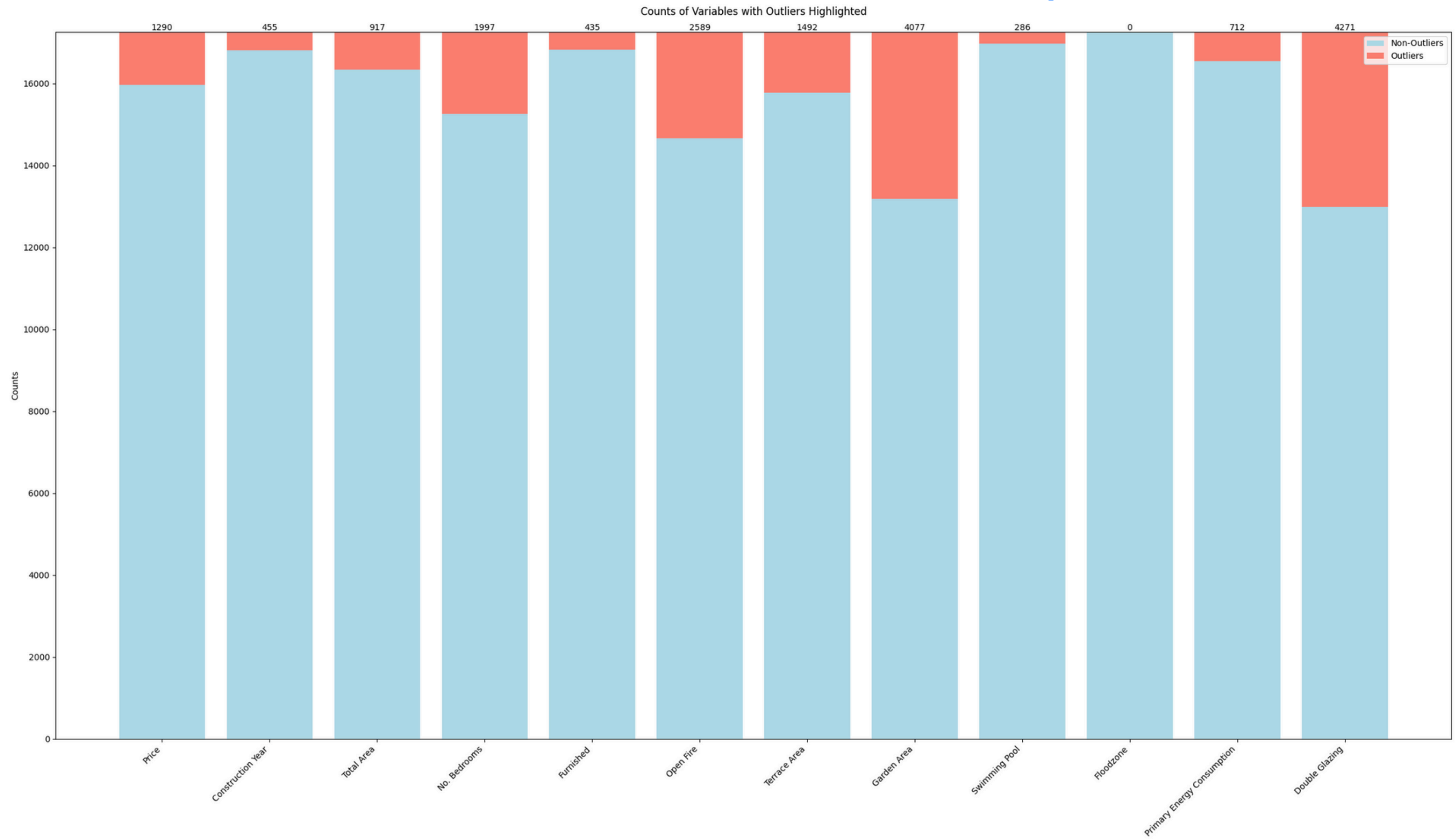
- Numeric Encoding
- Label Encoding
- One hot encoding
- Frequency encoding



Method:Spearman's

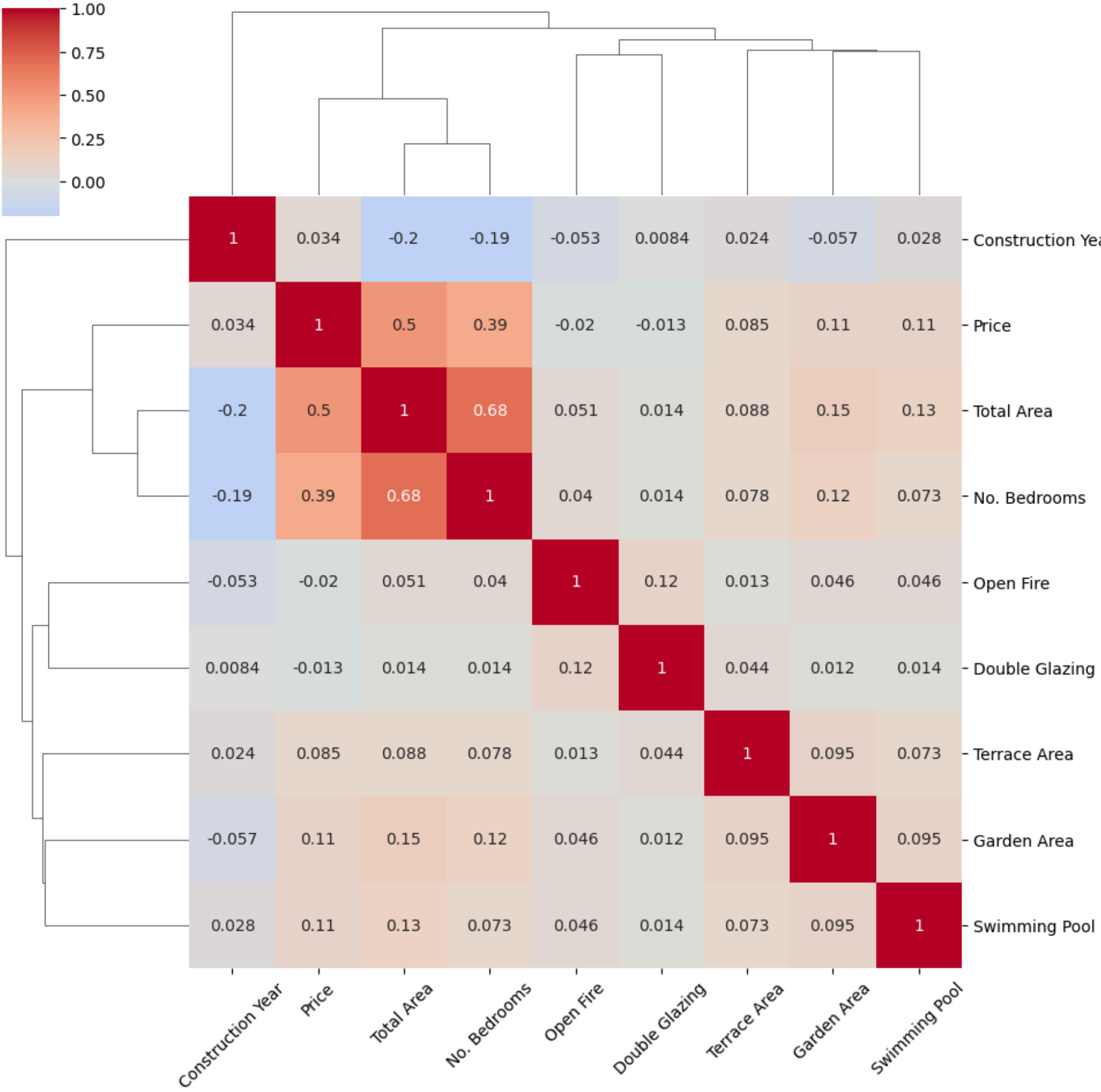


Method: Point biserial

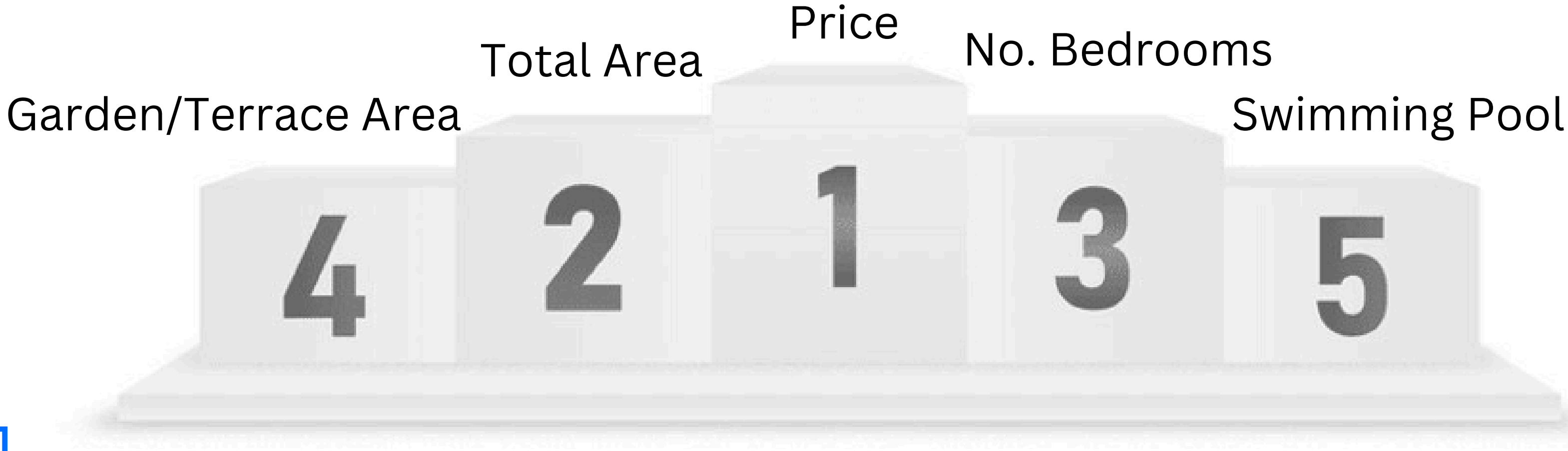




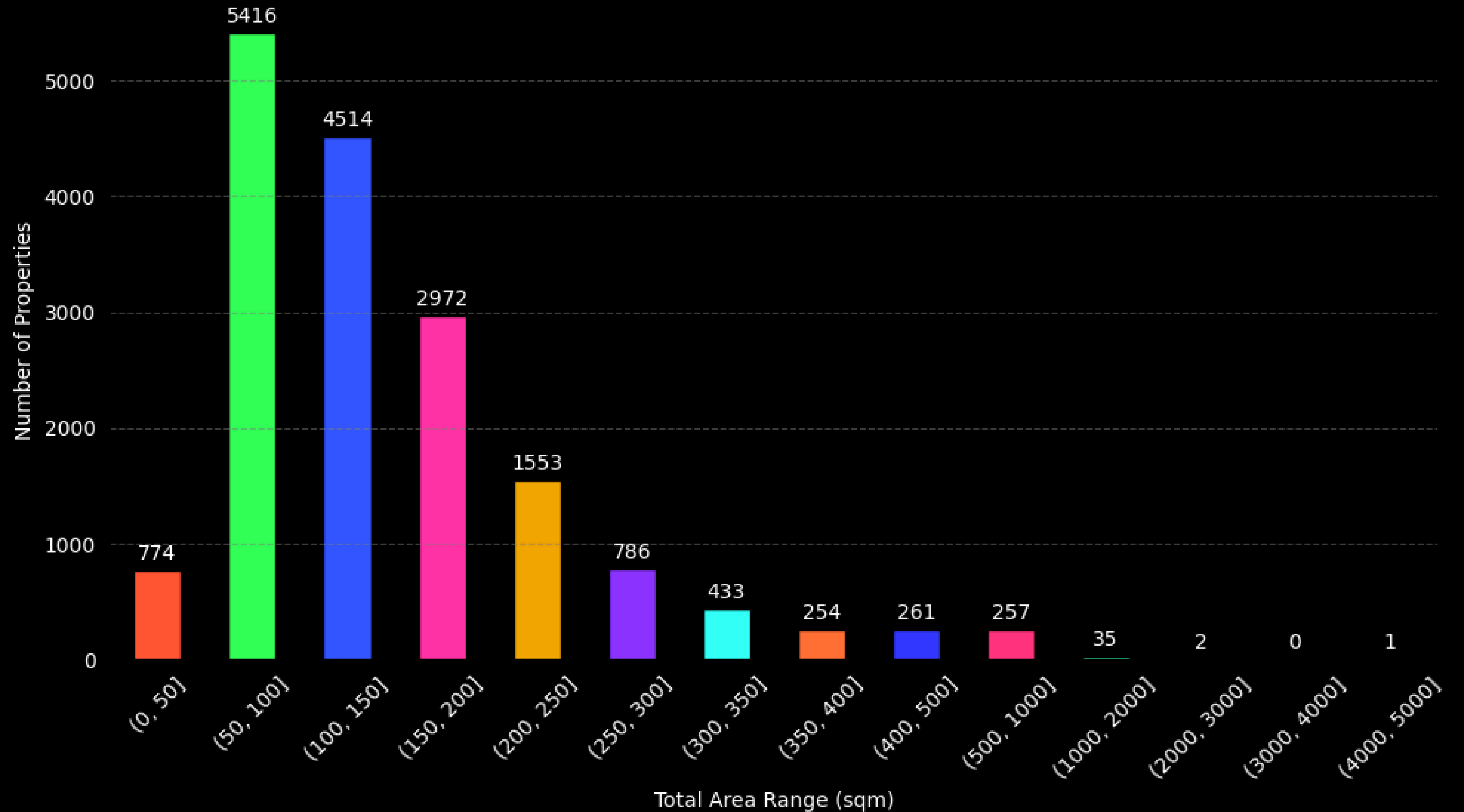
Clustermap of correlated variables



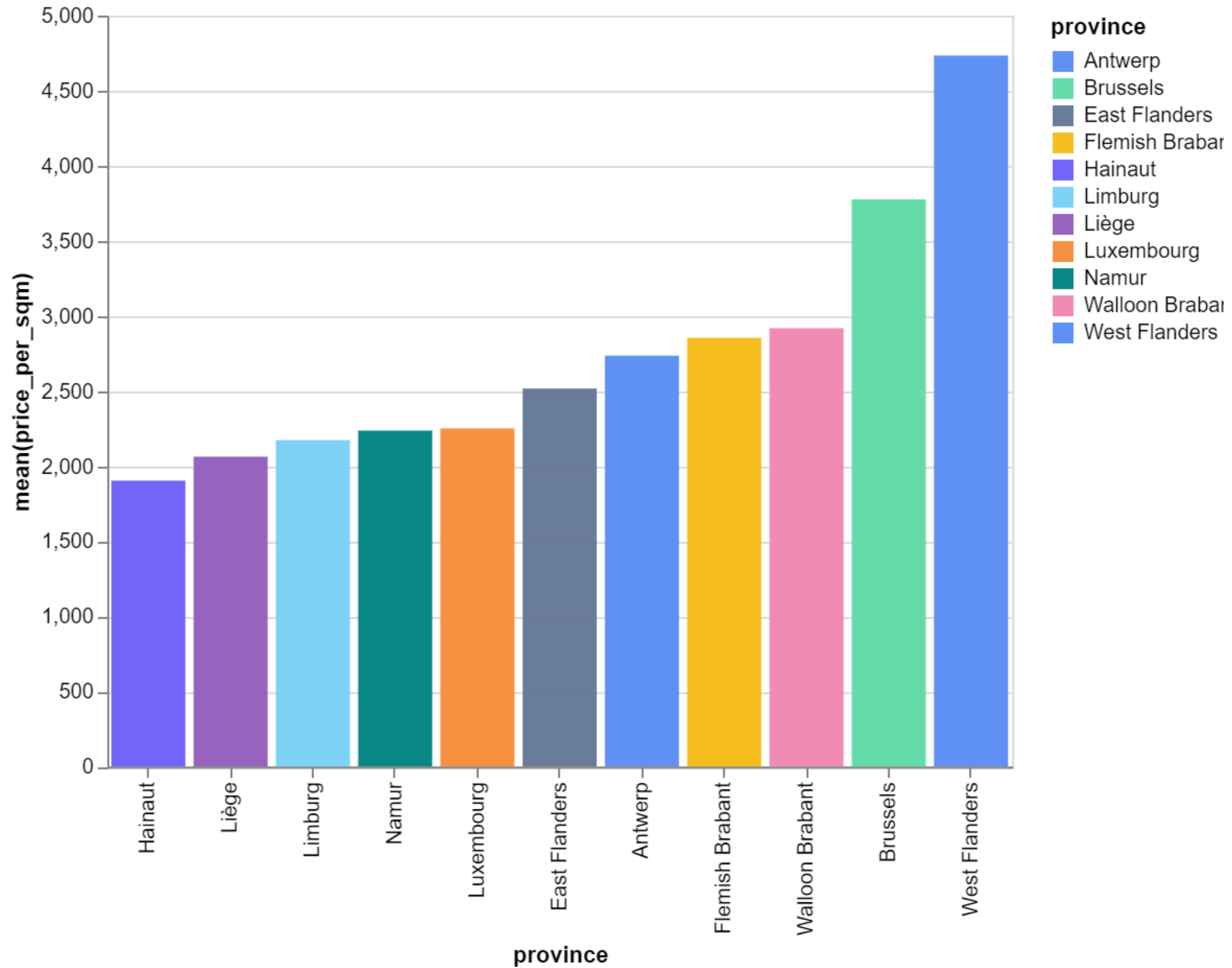
# Top 5 variables



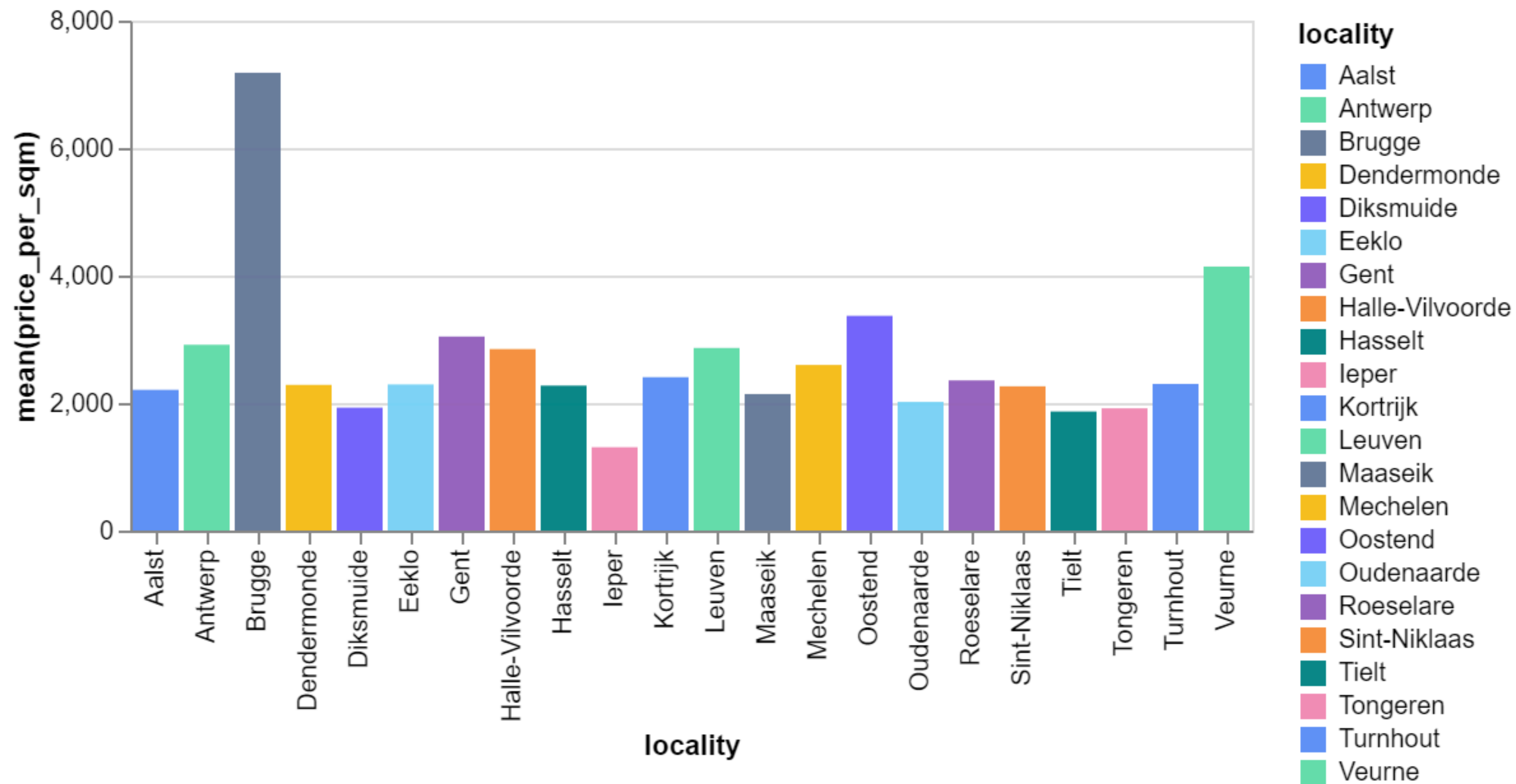
Distribution of Properties by Total Area (sqm)



Average Prices per sqm in Belgium

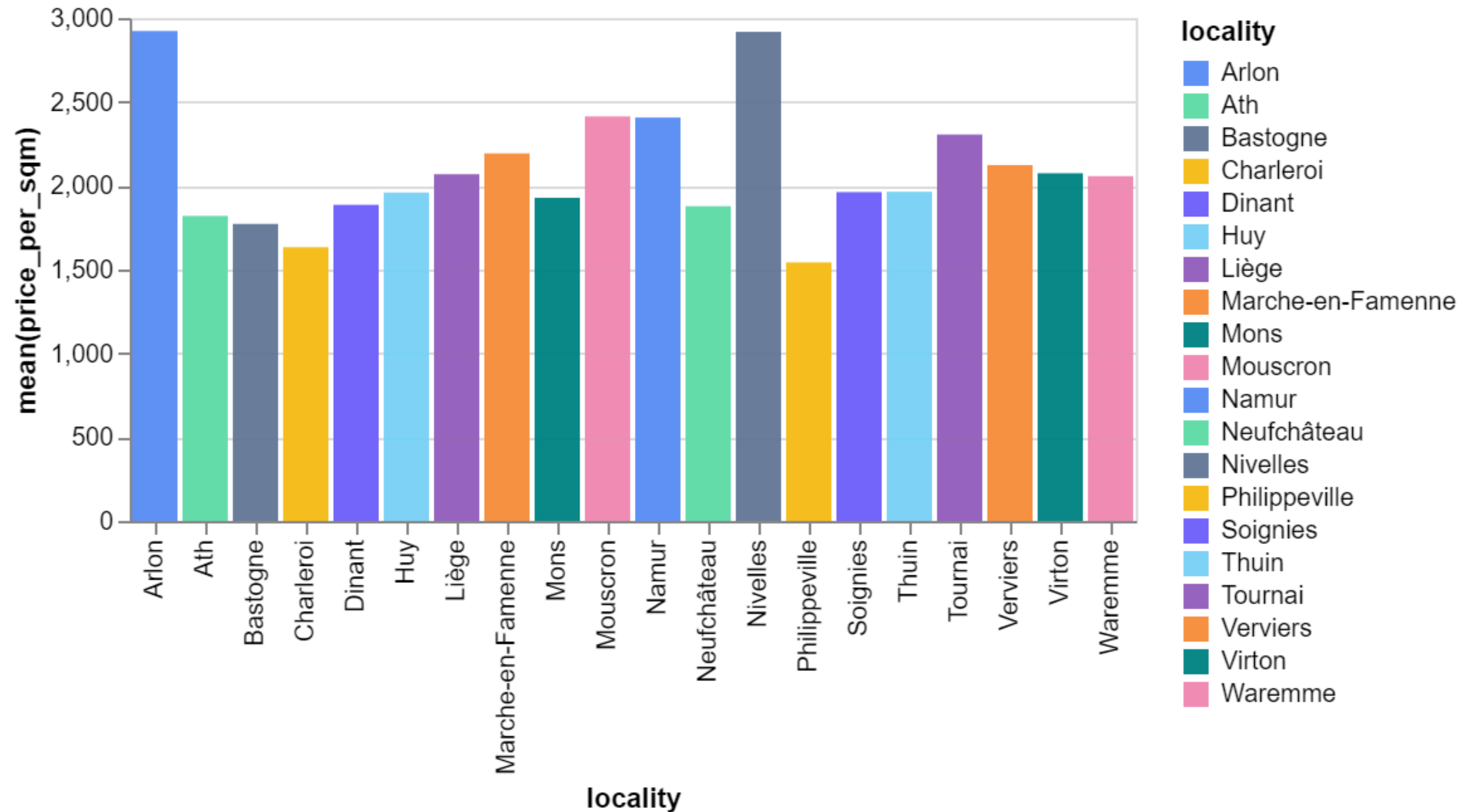


Average Prices per sqm in Flanders





Average Prices per sqm in Wallonia



# Conclusion

- **Price** is most correlated with the values of **total area** and **number of bedrooms**.
- Ordinal variables in our dataset have low correlation with price.
- **Garden area** has the most outliers.
- **Brugge** is the most expensive and **leper** is the least expensive locality in Flanders.
- **Nivelles** is the most expensive and **Philippeville** is the least expensive locality in Wallonia.
- **West Flanders** is the most expensive and **Hainaut** is the least expensive province in all of Belgium.

The background features several overlapping rectangles in blue and orange. A large orange rectangle is centered behind the text. Other blue and orange rectangles are positioned around the edges, some overlapping each other and the central orange rectangle. The text "THANK YOU" is centered in a bold, black, sans-serif font.

**THANK YOU**