



# Real Estate Price Prediction — Data Preprocessing & Feature Engineering

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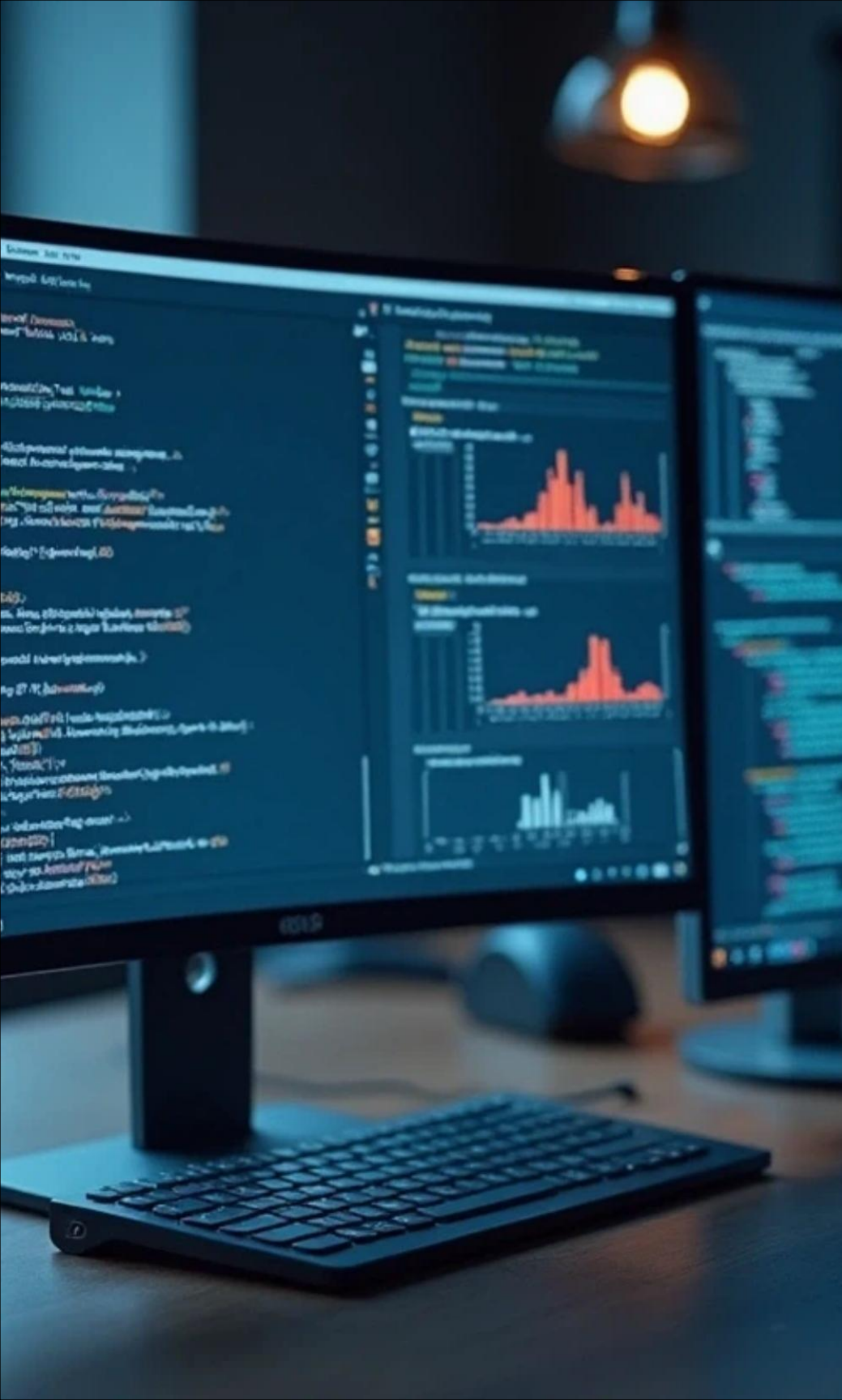
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# 1. Import Libraries

## Main Libraries

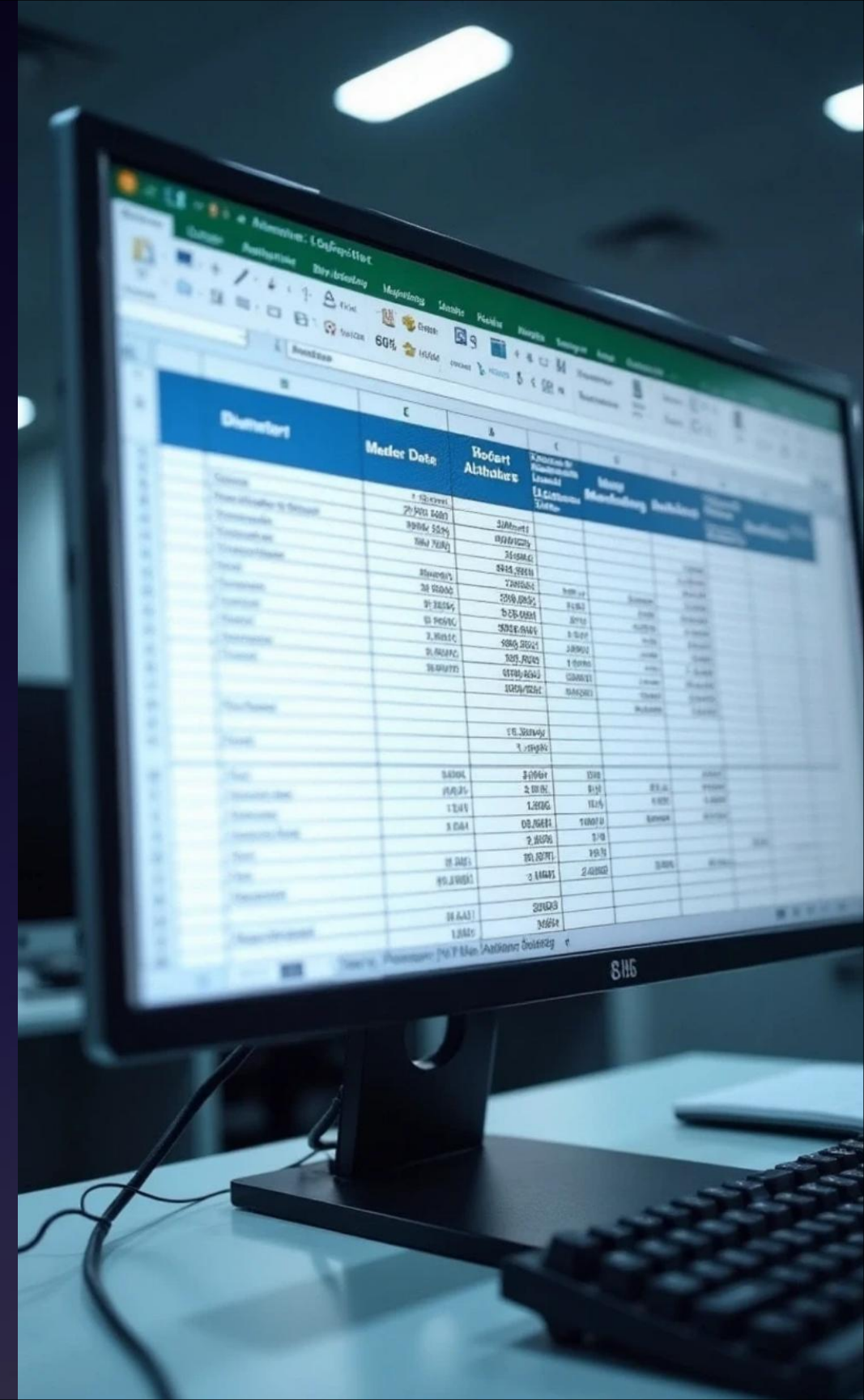
- NumPy: Essential for numerical calculations.
- Pandas: Key for data handling and analysis.
- Matplotlib: Ideal for generating visual charts.
- Seaborn: Specialized in statistical data visuals.
- category\_encoders: Designed for converting categorical variables.
- Scikit-learn: Essential tools for model selection and preparation.



## 2. Loading the Dataset

### Dataset details

- The dataset is loaded from an Excel file containing various property attributes.



# 3. Renaming Columns

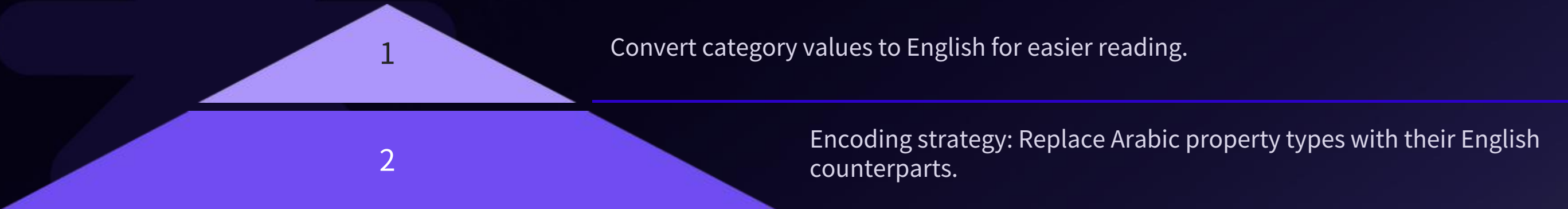
## Purpose

Standardize column names for easy data manipulation.

Column names were standardized to English for consistency and easier processing.

id	price	type	n_bedrooms	n_bathrooms	area	sub_location	location
1	9500000	شقة	3	2	140	أخرى مناطق	الجيزة
2	5800000	شقة	3	2	145	أكتوبر 6	الجيزة
3	15150000	فيلا	3	3	225	أكتوبر 6	الجيزة
4	11200000	شقة	3	2	150	أكتوبر 6	الجيزة
5	21918000	فيلا	4	4	265	الخميس التجمع	الجديد القاهرة m

# 4. Category Value Encoding



Number	Price	Type	Number of Bedrooms	Number of Bathrooms	Area	Sub-location	Location
1	9500000	Apartment	3	2	140	Other Areas	Giza
2	5800000	Apartment	3	2	145	October 6	Giza
3	15150000	Villa	3	3	225	October 6	Giza
4	11200000	Apartment	3	2	150	October 6	Giza
5	21918000	Villa	4	4	265	Fifth Residential Area	New Cairo

# 5. Data Analysis & Visualization

## Visualizing Price Distribution by Property Type



numerous outliers

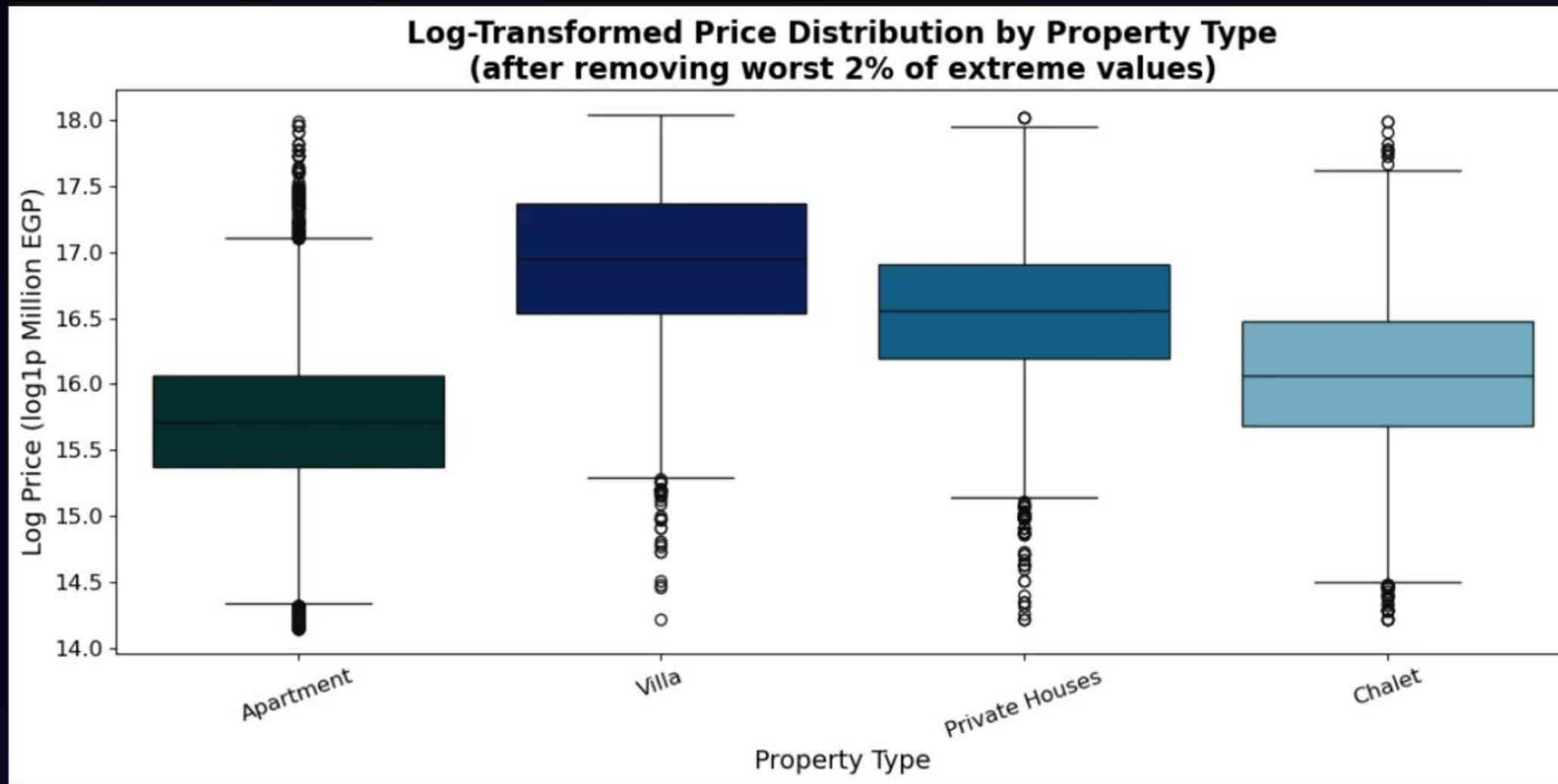
## 6. Outlier Removal & Log Transformation — Price

### Outlier Removal

Remove the top and bottom 1% of extreme values.

### Log Transformation

Apply log transformation to the price.



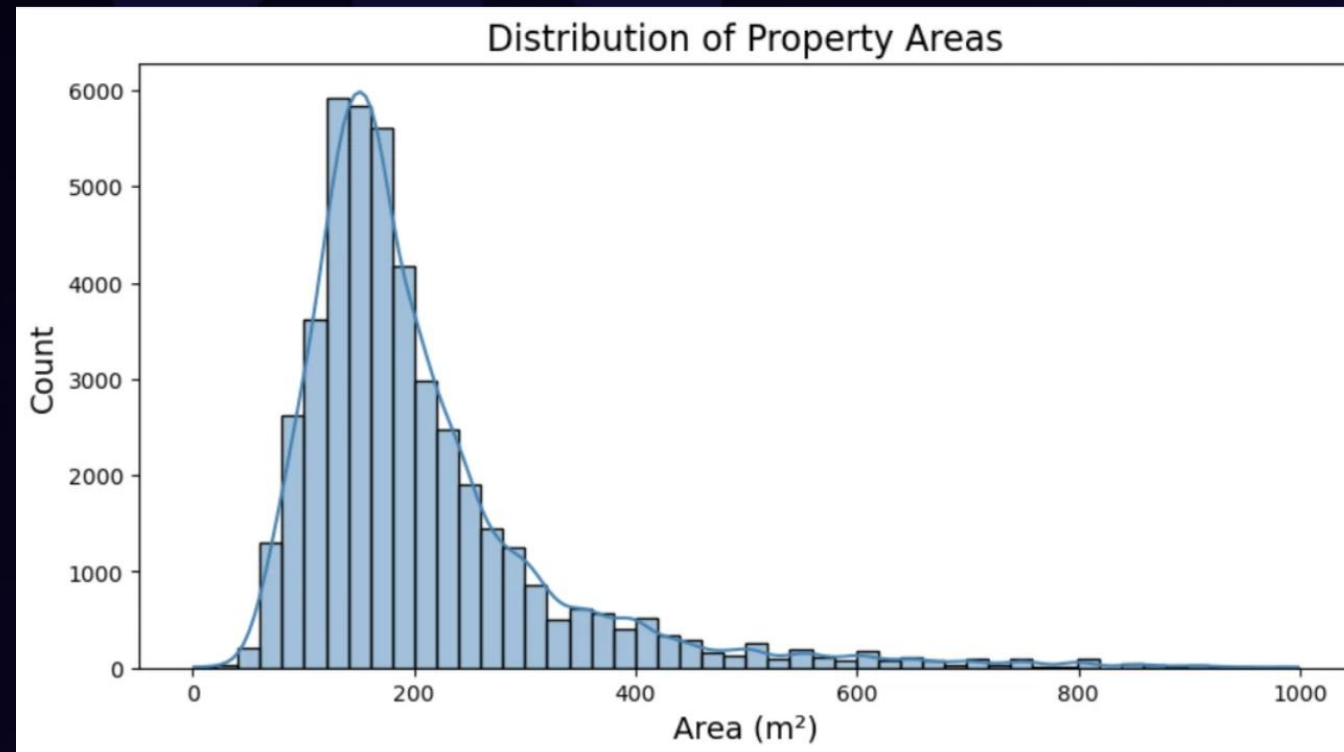


## 7. Outlier Removal & Log Transformation — Area

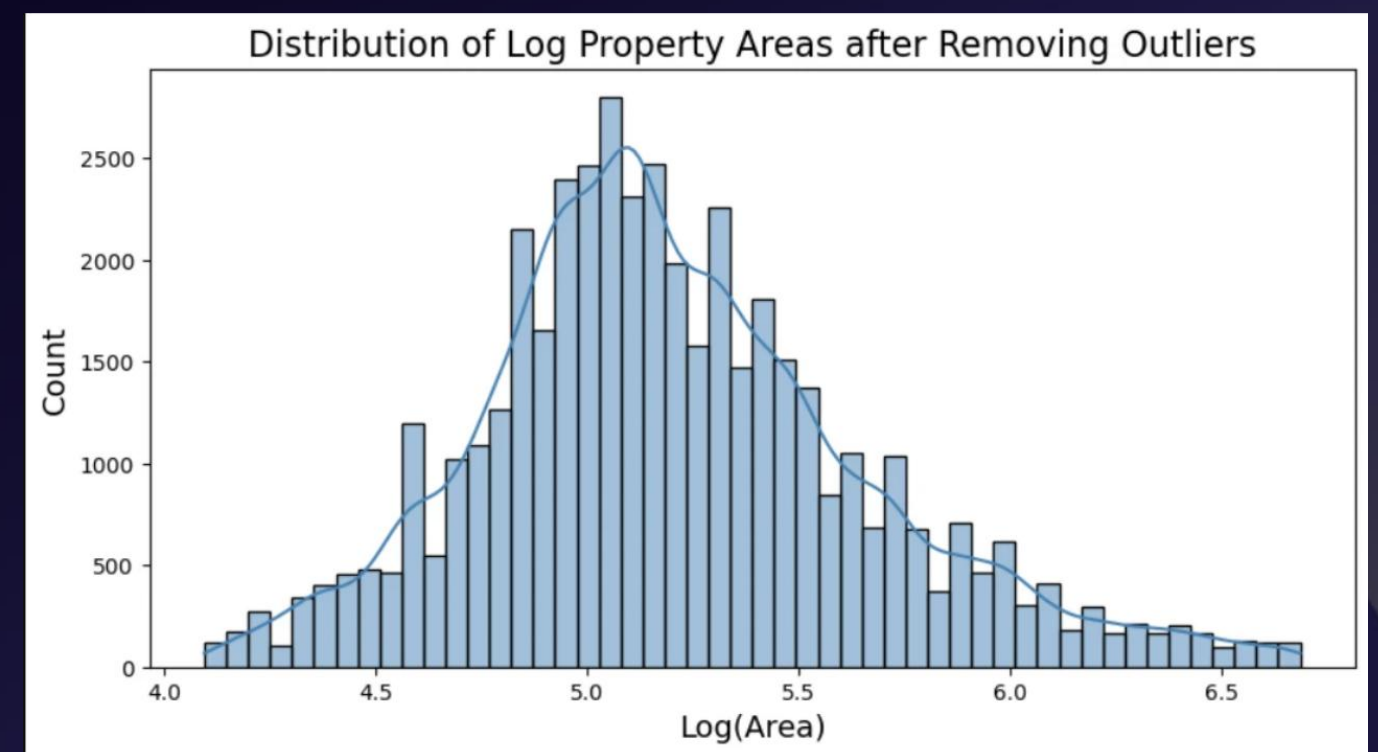
### Outlier Removal&Transformation - Area

Extreme values in the area column were removed using quantile filtering (top 0.5% and bottom 0.5%).

Logarithmic transformation was applied to area (and previously to price) to reduce skewness and stabilize variance.



Before Transformation



After Transformation

## 8. Correlation Analysis

### Visualizing Correlation with Price and Log Price

#### 🔗 Insights from Correlation Analysis

Log\_price offers greater stability as a target variable compared to raw price — the log transformation enhances linearity and minimizes the impact of outliers.

The variable n\_bedrooms exhibits the lowest correlation (~0.51) with both price and log\_price.

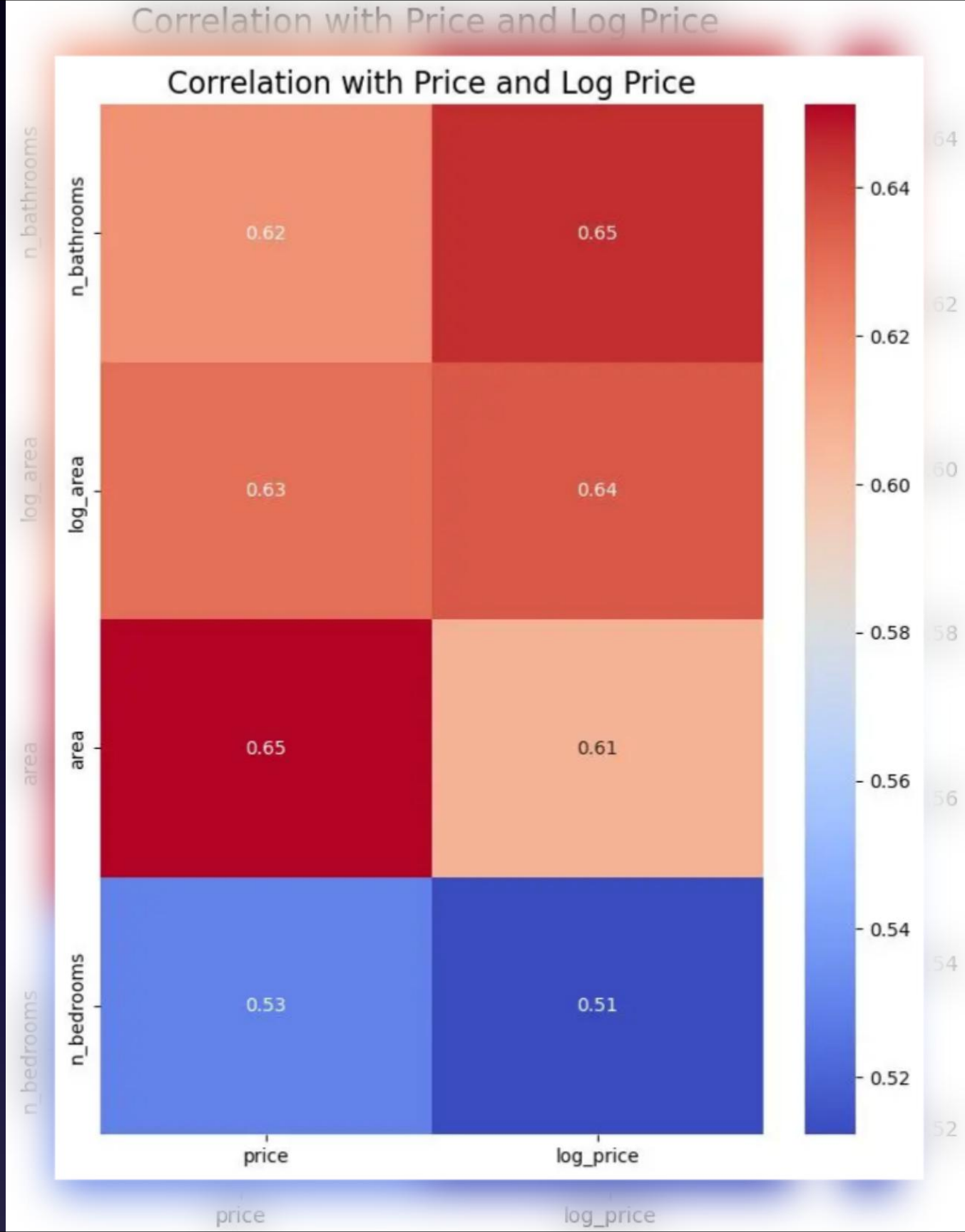
Log\_area demonstrates a robust and consistent correlation with log\_price (0.64), validating that log transformation mitigates skewness.

The variable area has a stronger correlation with raw price (0.65) compared to a slightly lower correlation with log\_price (0.61).

N\_bathrooms shows a higher correlation with log\_price (0.65) than with raw price (0.62).

#### ✓ Final Conclusion:

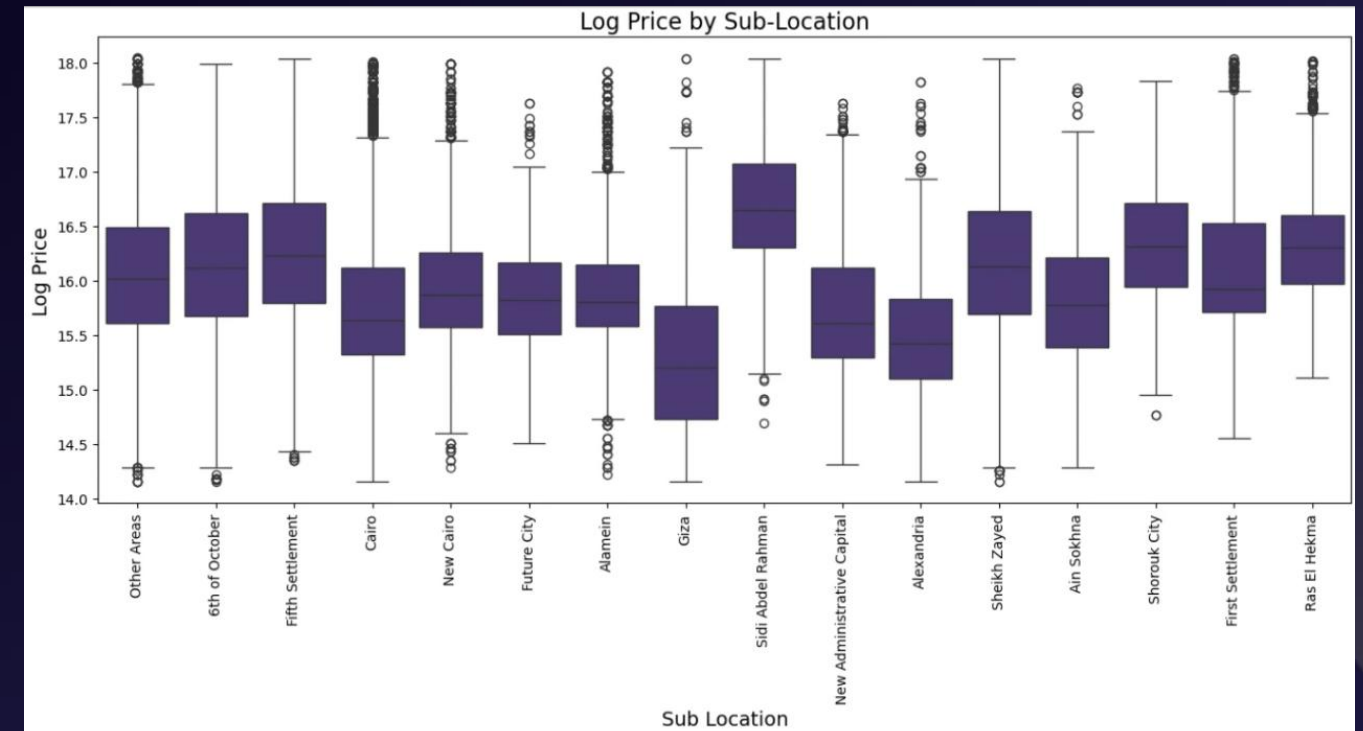
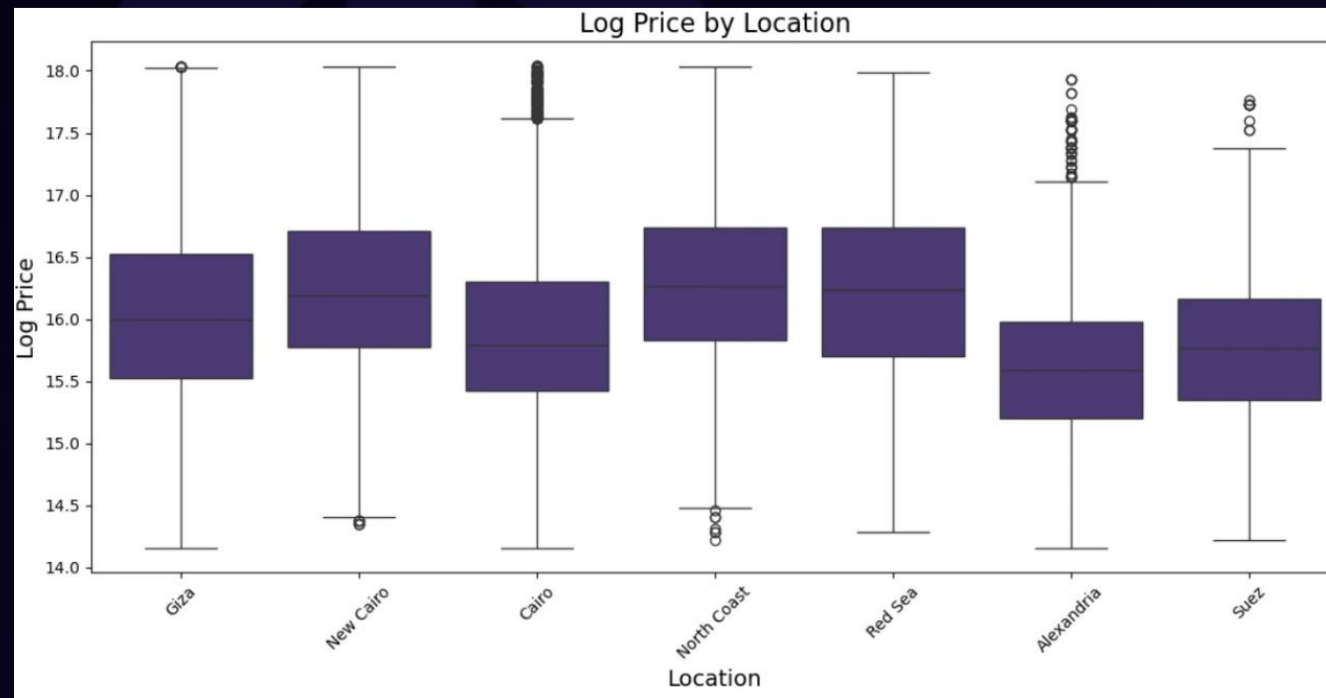
Log transformation boosts the stability of the model while strengthening the connection between essential numeric features and the target variable.



# 9. Aggregated Analysis by Property Type & Location

## Analysis

Calculate average and median log prices by property type and location.



There is a clear imbalance in the dataset: most listings are Apartments in Cairo.

Both property type and location are strong predictors of housing prices.

There is a clear imbalance in the dataset



## 10. Feature Engineering & Data Export

Additional Feature Creation and Saving Process



# Data Preparation Overview

1

## Dataset Copy

Create a copy to maintain the original data.

2

## Drop Area Column

Remove the area column for log\_area usage.

3

## Define Target & Features

Set log\_price as target and define feature matrix X.

4

## Train/Test Split

Split data with 80% training and 20% testing.

5

## Ensure Reproducibility

Utilize fixed random state for shuffling.





# Target Encoding

Purpose

Prepares categorical features to improve model accuracy.

Technique

Uses target averages in a cross-validation setup.

Features

Applies to location, type, and sub\_location.

Cross-Validation

Utilizes 6-fold to prevent data leakage.

Benefits

Captures target relationships while ensuring generalization.

DATA After Encoding

type	n_bedrooms	n_bathrooms	log_area	sub_location	location
15.724519	3	3	5.298317	16.279147	16.258963
15.723623	3	2	5.135798	16.273965	16.256207
15.723623	3	3	5.135798	16.342638	15.902682
16.927353	4	4	6.152733	16.139945	16.258745
15.72204	3	1	5.010635	15.809305	15.907546

Adding

# Adding New Features Overview

1

Bathroom-to-Bedroom Ratio

Indicates comfort level by comparing bathrooms to bedrooms.

3

Area per Room

Average space available for each room shows spaciousness.

5

Location–Area Interaction

Engages location data to reflect size impact on property price.

7

Log of Total Rooms

Applies a logarithmic transformation to the total number of rooms.

2

Total Number of Rooms

Sum of bedrooms and bathrooms for overall property size.

4

Area per Bedroom

Total area dedicated to bedrooms indicating living quality.

6

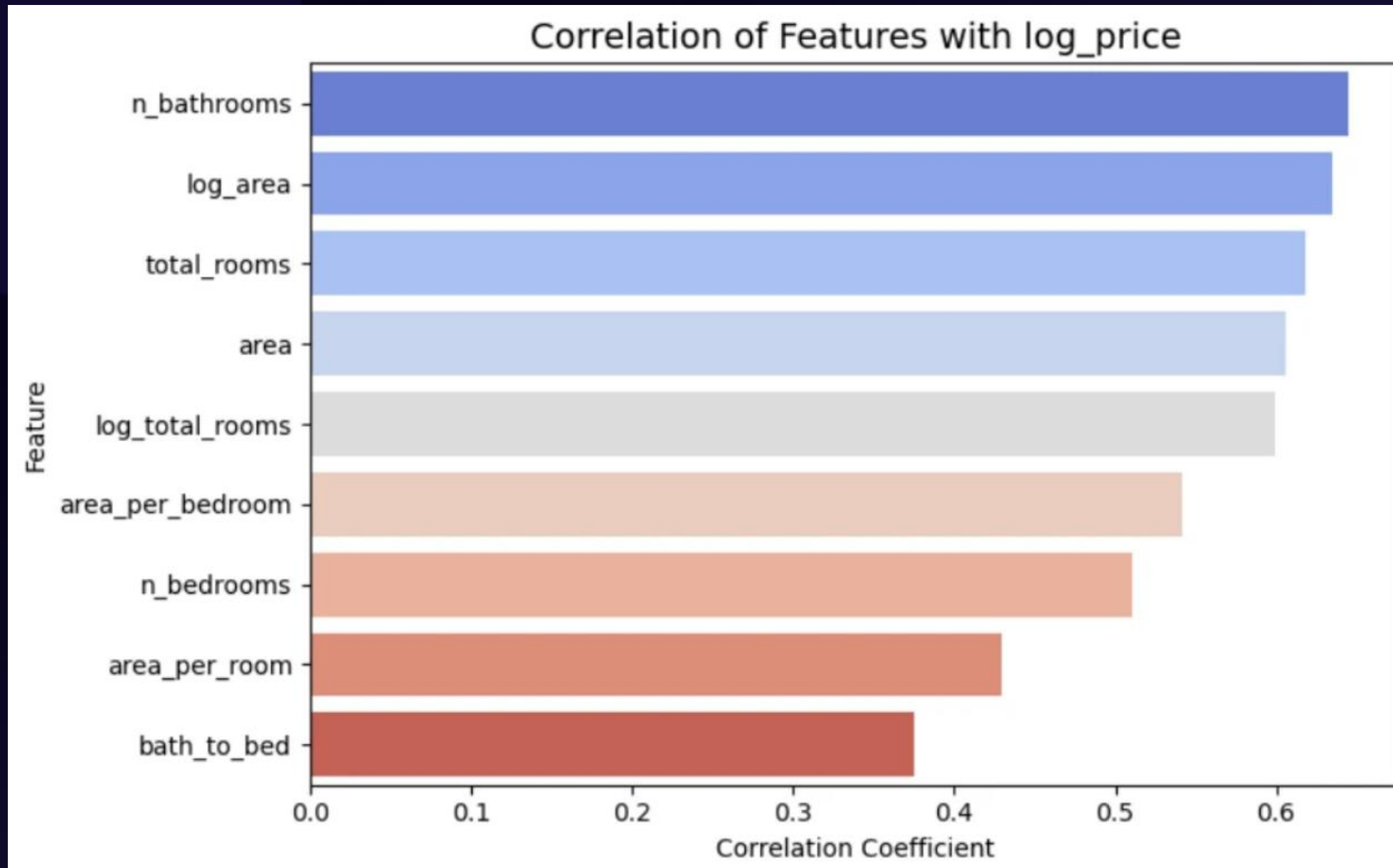
Location–Sub-Location Interaction

Captures the hierarchical relationship between a property's main location and its sub-location.

type	n_bedrooms	n_bathrooms	log_area	sub_location	location	bath_to_bed	total_rooms	area	area_per_room	area_per_bedroom	loc_area_interaction	loc_cross	log_total_rooms
15.724519	3	3	5.298317	16.279147	16.258963	1.000000	6	200.0	28.571429	50.0	86.145144	264.682048	1.945910
15.723623	3	2	5.135798	16.273965	16.256207	0.666666	5	170.0	28.333333	42.5	83.488601	264.552934	1.791759
15.723623	3	3	5.135798	16.342638	15.902682	1.000000	6	170.0	24.285714	42.5	81.672971	259.891776	1.945910
16.927353	4	4	6.152733	16.139945	16.258745	1.000000	8	470.0	52.222222	94.0	100.03571	262.415244	2.197225
15.72204	3	1	5.010635	15.809305	15.907546	0.333333	4	150.0	30.000000	37.5	79.706912	251.487241	1.609438

### Objective

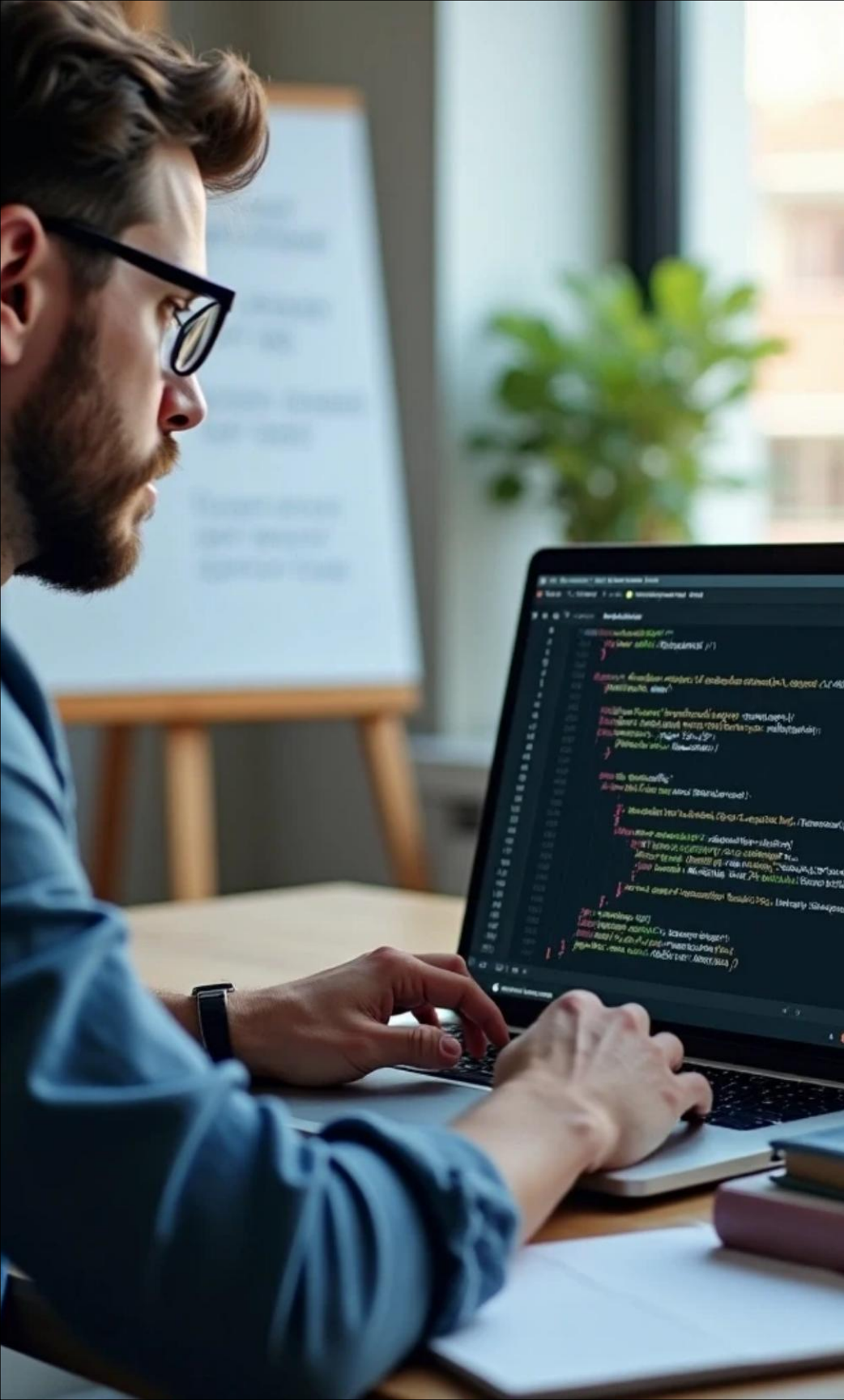
These engineered features enhance the dataset by offering structural, spatial, and relational insights. Collectively, they empower the regression model to better capture non-linear relationships and boost overall predictive accuracy.



# 11. Features Summary

Summary of key features for the final model inputs, showcasing their intended purpose and insights derived from them.

Feature Name	Type	Source	Description	Purpose / Insight
type	Encoded (Target)	● Original	Target-encoded representation of the property type.	Captures architectural and functional differences between property types.
n_bedrooms	Numeric	● Original	Number of bedrooms in the property.	Direct measure of property size; strongly influences price.
n_bathrooms	Numeric	● Original	Number of bathrooms in the property.	Indicates comfort level and modern facilities.
log_area	Numeric (log-transformed)	● Original (Transformed)	Logarithm of total built-up area.	Stabilizes skewed data; models proportional area effects.
location	Encoded (Target)	● Original	Target-encoded main city or district.	Captures macro-level price variation due to geography.
sub_location	Encoded (Target)	● Original	Target-encoded sub-region or neighborhood.	Adds micro-level geographical differentiation.
bath_to_bed	Numeric (Derived)	⦿ Engineered	Bathrooms-to-bedrooms ratio.	Reflects property luxury and comfort balance.
total_rooms	Numeric (Derived)	⦿ Engineered	Total count of rooms (bed + bath).	Simple proxy for overall property size.
log_total_rooms	Numeric (Transformed)	⦿ Engineered	Logarithm of total room count.	Reduces impact of large room counts on model stability.
area	Numeric (Derived)	⦿ Engineered	Actual property area (exponentiated from log_area).	Represents physical space and scale.
area_per_room	Numeric (Derived)	⦿ Engineered	Average area per room.	Indicates spaciousness and internal density.
area_per_bedroom	Numeric (Derived)	⦿ Engineered	Area divided by number of bedrooms.	Captures the space dedicated to private use.
loc_area_interaction	Numeric (Interaction)	⦿ Engineered	Interaction between log_area and location.	Models how the impact of area differs by location.
loc_cross	Numeric (Interaction)	⦿ Engineered	Product of sub_location and location.	Captures cross-geographic effects within regions.
log_price	Numeric (Target Variable)	● Original (Target)	Logarithm of property price.	Target variable: improves learning on wide price.



# Saving Train & Test Data

1

## Prepare CSV Files

Create separate CSV files for training and testing data.

2

## Save Encoded Data

Export the processed encoded data to CSV format.

3

## Data Processing Summary

Finalizes and saves the processed data sets for model training.

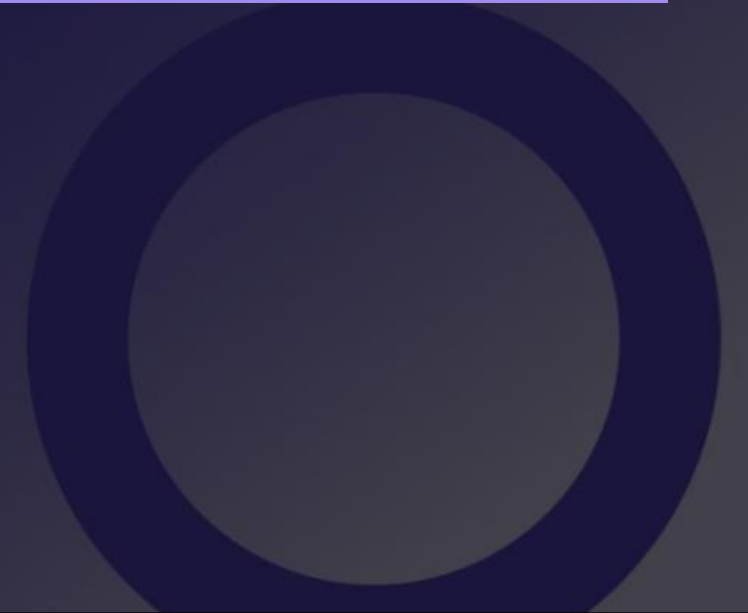




# Thank you!

Questions or feedback? Feel free to ask!

e-mail : [mwezzat16@gmail.com](mailto:mwezzat16@gmail.com)



The background is a solid dark purple. It features several large, overlapping, semi-transparent circles in a lighter shade of purple. At the bottom center, there is a dark purple, three-dimensional-looking pedestal or base. The text "Thank You" is centered in the middle of the image in a light purple, sans-serif font.

Thank You