Raw House Data Analysis

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Overview

Initial Observations from the Dataset

- Total Records: 5,000 rows
- Columns: 16
- Data Types:
  - Numerical: MLS, sold_price, zipcode, longitude, latitude, lot_acres, taxes, year_built, bedrooms, fireplaces,bathrooms,garage,sqrt_ft
  - Categorical (Objects): kitchen_features, floor_covering, HOA
- Missing Values:
  - lot_acres (10 missing)
  - fireplaces (25 missing)
  - sqrt_ft, garage, and HOA have None values (Need conversion to NaN)

Technology used in EDA

- Google Collab
- Python

- Libraries
  - Pandas: Read, clean, and manipulate data
  - NumPy: Handle numerical operations
  - Matplotlib & Seaborn: Create plots

Understanding Dataset Columns

Column Name	Description
MLS	Listing ID
sold_price	Sale price of the house
zipcode	Location identifier
longitude/latitude	Geographic location
lot_acres	Land area in acres
taxes	Annual property tax
year_built	Year house was built
bedrooms	Number of bedrooms
bathrooms	Number of bathrooms

Column Name	Description
sqrt_ft	Total square footage
garage	Number of garage spaces
kitchen_features	Kitchen specifications
fireplaces	Number of fireplaces
floor_covering	Type of flooring
HOA	Homeowners Association fee

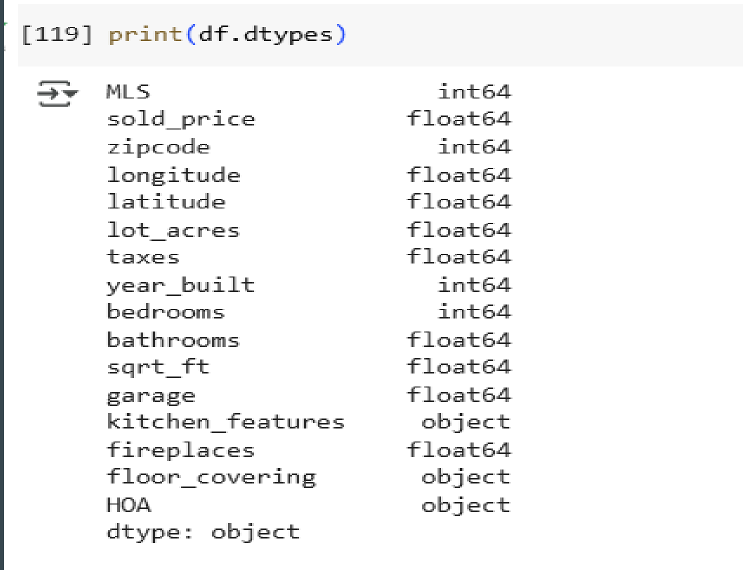
Potential Issues to Address

1. Bathrooms, Square Footage (sqrt_ft), and Garage columns are objects
   - Convert them to appropriate numerical types.
2. Missing Values Handling
   - lot_acres and fireplaces can be imputed or removed.
3. HOA contains None, which might indicate missing values
   - Need to check whether None means "No HOA" or a missing value.
4. Kitchen Features and Floor Covering are categorical
   - Need to encode or analyze further.

Potential Issues to Address

Missing Values Summary:

- lot_acres → 10 missing
- bathrooms → 6 missing
- sqrt_ft → 56 missing
- garage → 7 missing
- fireplaces → 25 missing
- HOA → 580 missing (possibly because many properties don't have HOA fees)



```
[119] print(df.dtypes)

MLS                     int64
sold_price            float64
zipcode                 int64
longitude             float64
latitude              float64
lot_acres             float64
taxes                 float64
year_built              int64
bedrooms                int64
bathrooms             float64
sqrt_ft               float64
garage                float64
kitchen_features       object
fireplaces            float64
floor_covering         object
HOA                    object
dtype: object
```

Potential Issues to Address

Handle missing values:

- lot_acres, bathrooms, sqrt_ft, garage, and fireplaces → Fill with median or mode.
- HOA → Treat missing values as zero (if None means no HOA).

Final Classification

Numerical (Continuous & Discrete)

- sold_price, longitude, latitude, lot_acres, taxes, year_built, bedrooms, fireplaces, bathrooms, sqrt_ft, garage, HOA

Categorical

- kitchen_features, floor_covering

Drop / Ignore

- MLS (just an ID, not useful for predictions)

Pandas/Seaborn Future Warning Fix

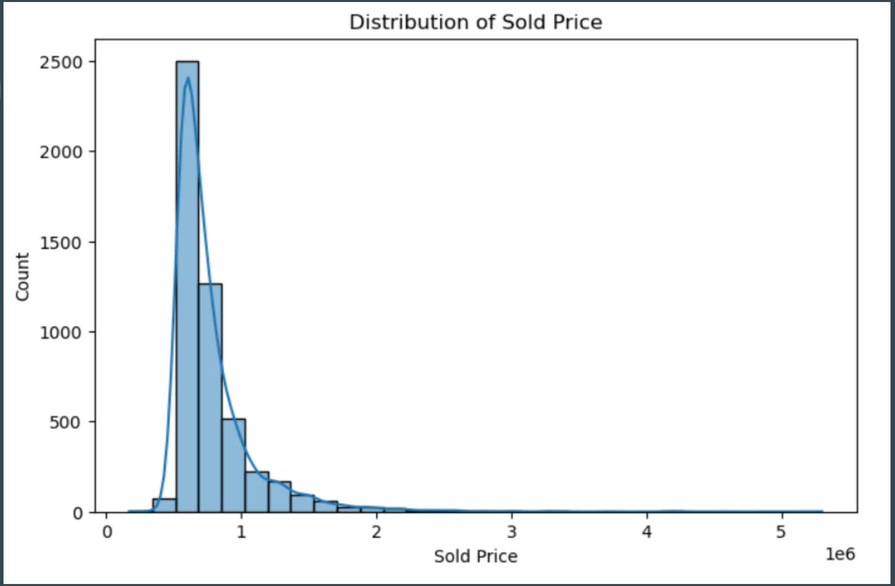
Instead of: df['lot_acres'].fillna(df['lot_acres'].median(), inplace=True)

Use: df['lot_acres'] = df['lot_acres'].fillna(df['lot_acres'].median())

Instead of: sns.kdeplot(df['sold_price'], shade= True, color= 'green')

Use: sns.kdeplot(df['sold_price'], shade= True, color= 'green')

Histogram (Frequency Plot)



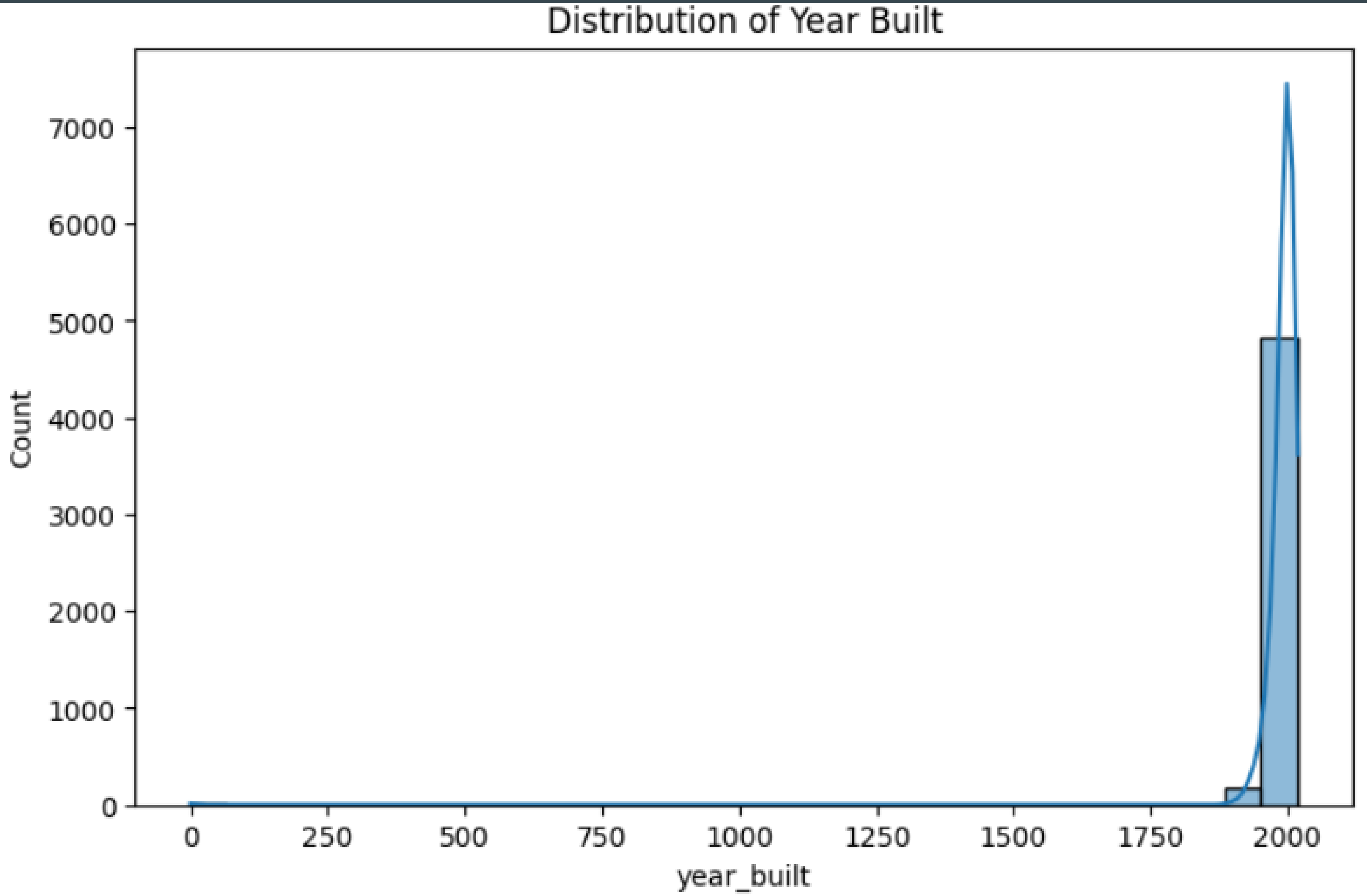
Used for: Checking the distribution of a numerical variable.

- The X-axis: Value of the variable (e.g., sold_price).
- The Y-axis: Count (frequency) of how many times a value appears.

Explanation

- sns.histplot() → Creates a histogram.
- bins=30 → Divides the data into 30 bins (smaller bins mean lower counts).
- kde=True → Adds a smooth curve (Kernel Density Estimation) to show distribution shape.

📌 Example:
If sold_price values range from 100K to 1M, this plot shows how many houses fall in each price range.


Distribution of Year Built
7000
6000
5000
4000
3000
2000
1000
0
Count
0
250
500
750
1000
1250
1500
1750
2000
year_built

Distribution Plot

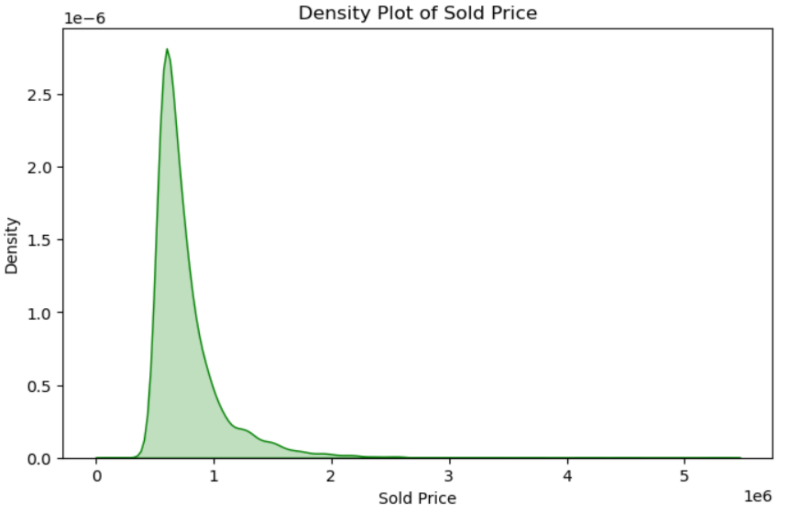
Used for: Checking if the data follows a normal distribution.

- Similar to a histogram but focuses more on smooth curves.

Explanation

- sns.kdeplot() → Creates a density plot.
- shade=True → Fills the area under the curve.
- This helps check if the data is skewed (left/right) or normally distributed.

Example:
If most house prices are between 200K-500K, the curve will peak there.



Pair Plot

Used for: Checking relationships between multiple numerical variables.

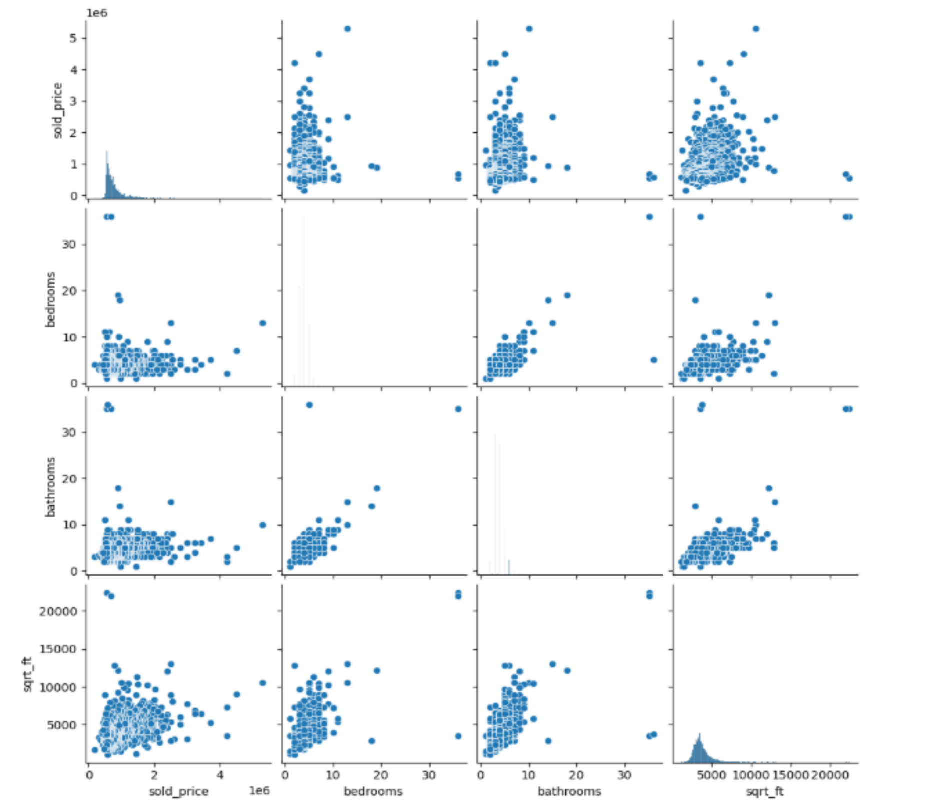
- It creates scatter plots + histograms for every combination.

Explanation

- sns.pairplot(df[columns]) → Plots all numerical columns.
- Helps detect correlations (e.g., larger houses have higher prices?).

Example:

- Sold Price vs Bedrooms → Do more bedrooms increase price?
- Sold Price vs sqrt_ft → Bigger houses → Higher price?



Box and Whisker Plot (Boxplot)

Used for: Identifying outliers in numerical data.

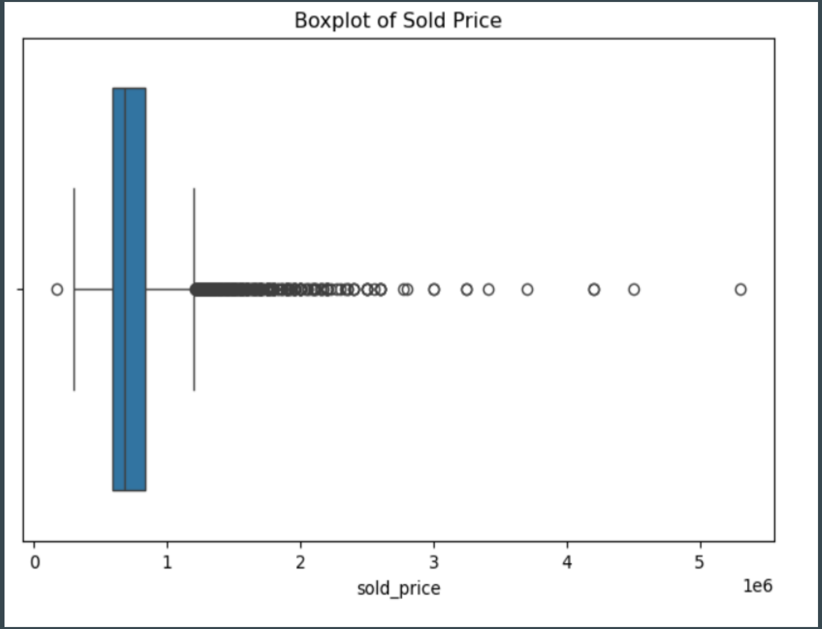
- Shows median, quartiles, and extreme values.

Explanation

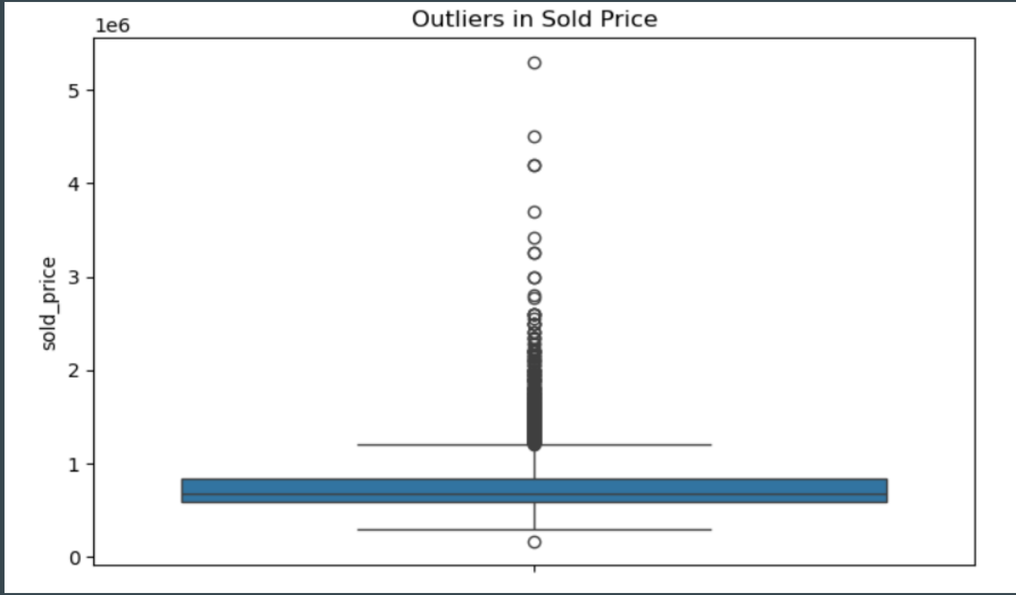
- sns.boxplot() → Creates a box plot.
- The box shows Q1 (25%), median (50%), and Q3 (75%).
- Outliers appear as individual dots beyond whiskers.

Example:
If most houses are under 500K, but some are 5M+,

those 5M+ values will appear as outliers.



Outlier Detection with Boxplot



Used for: Identifying extreme values in specific columns.

Explanation

- sns.boxplot(y=df['sold_price']) → Detects extreme price points.
- Outliers = Dots beyond whiskers (data points far from median).

Example:

- If 90% of house prices are below 1M, but some are 10M, those 10M houses are outliers

Correlation Matrix (Heatmap)

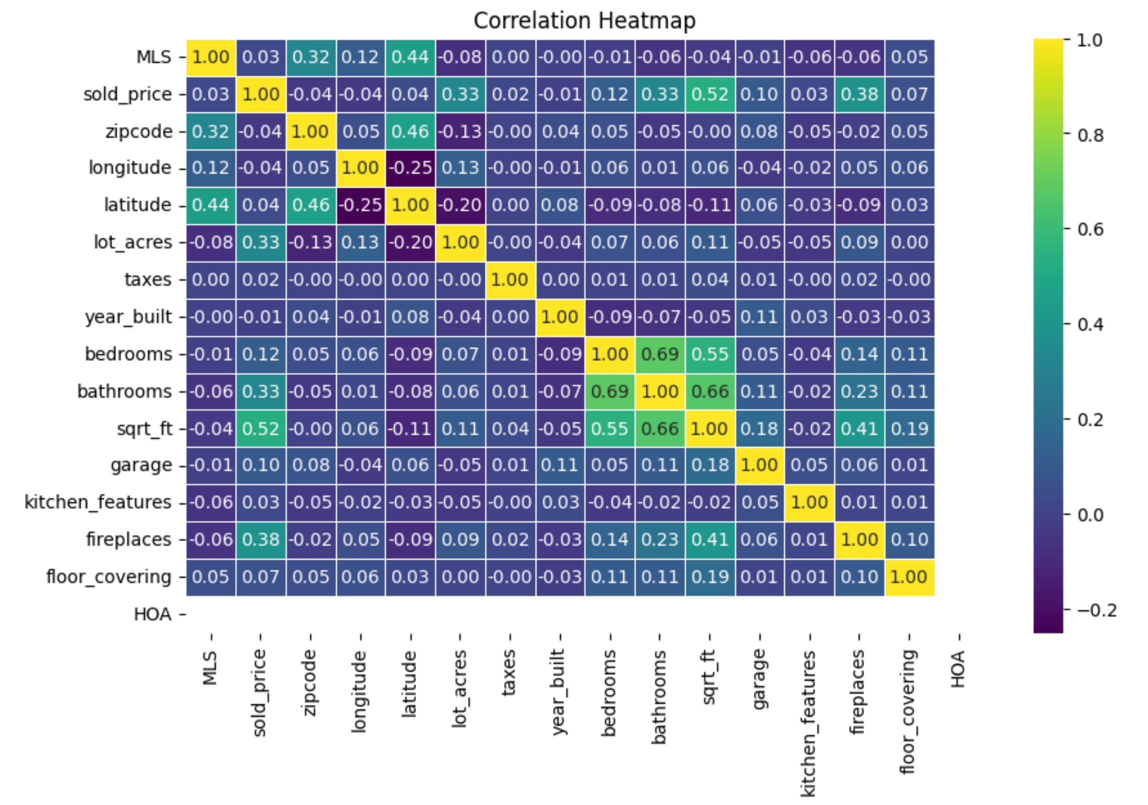
- Used for: Finding relationships between numerical columns.
- Shows which variables affect each other.

Explanation

- df.corr() → Calculates correlation between numerical columns.
- sns.heatmap() → Displays it as a color-coded matrix.
- Closer to +1 → Strong positive correlation (e.g., more sqft → higher price).
- Closer to -1 → Strong negative correlation.
- 0 means no relation.

Example:

- Sold Price & Square Feet = 0.85 → Bigger houses cost more.
- Sold Price & Bedrooms = 0.40 → Weak relation (more bedrooms don’t always mean higher price).



Correlation Heatmap

	MLS	sold_price	zipcode	longitude	latitude	lot_acres	taxes	year_built	bedrooms	bathrooms	sqrt_ft	garage	kitchen_features	fireplaces	floor_covering	HOA
MLS	1.00	0.03	0.32	0.12	0.44	-0.08	0.00	-0.00	-0.01	-0.06	-0.04	-0.01	-0.06	-0.06	0.05	
sold_price	0.03	1.00	-0.04	-0.04	0.04	0.33	0.02	-0.01	0.12	0.33	0.52	0.10	0.03	0.38	0.07	
zipcode	0.32	-0.04	1.00	0.05	0.46	-0.13	-0.00	0.04	0.05	-0.05	-0.00	0.08	-0.05	-0.02	0.05	
longitude	0.12	-0.04	0.05	1.00	-0.25	0.13	-0.00	-0.01	0.06	0.01	0.06	-0.04	-0.02	0.05	0.06	
latitude	0.44	0.04	0.46	-0.25	1.00	-0.20	0.00	0.08	-0.09	-0.08	-0.11	0.06	-0.03	-0.09	0.03	
lot_acres	-0.08	0.33	-0.13	0.13	-0.20	1.00	-0.00	-0.04	0.07	0.06	0.11	-0.05	-0.05	0.09	0.00	
taxes	0.00	0.02	-0.00	-0.00	0.00	-0.00	1.00	0.00	0.01	0.01	0.04	0.01	-0.00	0.02	-0.00	
year_built	-0.00	-0.01	0.04	-0.01	0.08	-0.04	0.00	1.00	-0.09	-0.07	-0.05	0.11	0.03	-0.03	-0.03	
bedrooms	-0.01	0.12	0.05	0.06	-0.09	0.07	0.01	-0.09	1.00	0.69	0.55	0.05	-0.04	0.14	0.11	
bathrooms	-0.06	0.33	-0.05	0.01	-0.08	0.06	0.01	-0.07	0.69	1.00	0.66	0.11	-0.02	0.23	0.11	
sqrt_ft	-0.04	0.52	-0.00	0.06	-0.11	0.11	0.04	-0.05	0.55	0.66	1.00	0.18	-0.02	0.41	0.19	
garage	-0.01	0.10	0.08	-0.04	0.06	-0.05	0.01	0.11	0.05	0.11	0.18	1.00	0.05	0.06	0.01	
kitchen_features	-0.06	0.03	-0.05	-0.02	-0.03	-0.05	-0.00	0.03	-0.04	-0.02	-0.02	0.05	1.00	0.01	0.01	
fireplaces	-0.06	0.38	-0.02	0.05	-0.09	0.09	0.02	-0.03	0.14	0.23	0.41	0.06	0.01	1.00	0.10	
floor_covering	0.05	0.07	0.05	0.06	0.03	0.00	-0.00	-0.03	0.11	0.11	0.19	0.01	0.01	0.10	1.00	
HOA																

Summary of Exploratory Data Analysis (EDA)

Key Insights & Steps

✓ Understanding Data: Identified numerical & categorical columns
✓ Handling Missing Values: Used Mean/Median/Mode for imputation
✓ Data Distribution: Checked skewness & outliers using histograms & boxplots
✓ Correlation Analysis: Found relationships using heatmaps & pair plots
✓ Outlier Detection: Used boxplots method to detect extreme values

Visualizations Used

✓ Histogram , Boxplot, Pairplot,Heatmap

Conclusion

✓ The dataset has been successfully cleaned and saved as a CSV file, ensuring it is ready for further data analysis and insights.

Question and Answer