magicbricks-exploratory-analysis

January 11, 2026

1 Data Analysis Process

1. Problem Finding
2. Data Warnings
    - 2.1 Data Gathering (csv, xlsx, db, api)
    - 2.2 Data Assessing
    - 2.3 Data Preprocessing
3. EDA –> Exploratory data Analysis –> Visualise Data, Statiscal Methods
4. Reporting, colclusions, summary, Advisories
5. Dashboarding –> Power Bi and Tableau

[36]:
```
# importing mojor libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

# addition libraries
import warnings
warnings.filterwarnings('ignore')
```

[37]:
```
# importing dataset
df = pd.read_csv('Magicbricks.csv')
```

2 Data Assessing

[38]:
```
df.head()
```

[38]:
```
     Area  BHK  Bathroom Furnishing   Location       District  \
0   950.0    2       2.0  Furnished  Karol Bagh  Central Delhi
1   535.0    2       1.0  Furnished  Karol Bagh  Central Delhi
2  1280.0    3       3.0  Furnished  Karol Bagh  Central Delhi
3  1135.0    3       3.0  Furnished  Karol Bagh  Central Delhi
4  1135.0    3       3.0  Furnished  Karol Bagh  Central Delhi

                                         Locality  Parking        Status  \
```

```
0  DDA MIG Flats Prasad Nagar Phase 2, Prasad Nag…      1.0  Ready_to_move
1                             Dev Nagar, Karol Bagh      1.0  Ready_to_move
2                                        Karol Bagh      2.0  Ready_to_move
3                         The Amaryllis, Karol Bagh      2.0   Almost_ready
4                         The Amaryllis, Karol Bagh      2.0   Almost_ready

    Transaction           Type  Per_Sqft     Price
0        Resale      Apartment    8761.0  12500000
1  New_Property      Apartment    7290.0   3900000
2        Resale  Builder_Floor   14092.0  15000000
3        Resale      Apartment   22222.0  25000000
4        Resale      Apartment   22222.0  25000000
```

[39]:
```
# shape
df.shape
```

[39]: (1214, 13)

2.1 Data Card: Magicbricks Property Listings (Sample)

2.1.1 1. Dataset Overview

- **Dataset Name:** Magicbricks Property Listings – Sample
- **Source:** Magicbricks (Indian real estate listing platform)
- **Type:** Structured tabular data
- **Domain:** Real Estate / Housing
- **Geographic Coverage:** Central Delhi, India
- **Purpose:**
  - Property price analysis
  - Real estate market insights
  - Predictive modeling (e.g., price estimation)
  - Academic or demonstration use

2.1.2 2. Data Description

Each row represents a **single residential property listing**.

Column Name	Description	Data Type
Area	Super built-up area of the property (in sq. ft.)	Float
BHK	Number of bedrooms	Integer
Bathroom	Number of bathrooms	Float
Furnishing	Furnishing status (e.g., Furnished)	Categorical
Location	Broad locality / area name	Categorical

Column Name	Description	Data Type
District	Administrative district	Categorical
Locality	Detailed address or society name	Text
Parking	Number of parking spaces	Float
Status	Construction status (Ready to move, Almost ready)	Categorical
Transaction	Sale type (Resale / New Property)	Categorical
Type	Property type (Apartment / Builder Floor)	Categorical
Per_Sqft	Price per square foot (INR)	Float
Price	Total property price (INR)	Integer

3 Types of Error

- **completeness**
- **Validity** –> dtypes(No. of children in float), Duplicacy issue(eg. patient_id),salary(-10000), age in negetive
- **Accuracy** –> body weight(13kg of adult), age 100
- **Inconsistency** –> New York City, NYC

4 Types of Data

- **Dirty Data** –> completeness, validity, accuracy, Inconsistency
- **Massy Data** –> Strutral issue –> Eg. pivot tables, sparsity issue

[40]:
```
# seeking information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1214 entries, 0 to 1213
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Area         1214 non-null   float64
 1   BHK          1214 non-null   int64
 2   Bathroom     1212 non-null   float64
 3   Furnishing   1214 non-null   object
 4   Location     1214 non-null   object
 5   District     1214 non-null   object
 6   Locality     1214 non-null   object
 7   Parking      1182 non-null   float64
 8   Status       1214 non-null   object
 9   Transaction  1214 non-null   object
 10  Type         1209 non-null   object
 11  Per_Sqft     973 non-null    float64
 12  Price        1214 non-null   int64
dtypes: float64(4), int64(2), object(7)
memory usage: 123.4+ KB
```

5 Point

- The dataset contains null values, requiring proper handling.
- Bathroom and Parking are stored as float types, though they should be integers, indicating a data validity issue.
- There are 6 numerical features and 7 categorical (object-type) features in the dataset.
- Data cleaning and type conversion are needed before analysis.

[41]:
```
df.describe()
```

[41]:
```
              Area          BHK     Bathroom      Parking       Per_Sqft  \
count  1214.000000  1214.000000  1212.000000  1182.000000     973.000000
mean   1451.850751     2.778418     2.523927     1.708122   15574.885920
std    1586.472855     0.946811     1.017723     5.717177   21574.389007
min      28.000000     1.000000     1.000000     1.000000    1259.000000
25%     800.000000     2.000000     2.000000     1.000000    6154.000000
50%    1150.000000     3.000000     2.000000     1.000000   10838.000000
75%    1620.000000     3.000000     3.000000     2.000000   17647.000000
max   24300.000000    10.000000     7.000000   114.000000  183333.000000

              Price
count  1.214000e+03
mean   2.079898e+07
std    2.561308e+07
min    1.000000e+06
25%    5.600000e+06
50%    1.400000e+07
75%    2.500000e+07
max    2.400000e+08
```

6 Key Observations

- The dataset includes 1,214 residential property listings, with missing values primarily in the Bathroom, Parking, and Price per Sq. Ft. fields, indicating areas that may require data cleaning or imputation.

- The majority of listings are 2–3 BHK units, with an average built-up area of approximately 1,450 sq. ft., suggesting a market focus on mid-sized family homes.

- Most properties feature 2 bathrooms and 1 parking space, though the presence of unusually high values points to potential outliers or luxury developments.

- The median property price is around 1.4 crore, while prices span a wide range—from 10 lakh to 24 crore—highlighting strong market segmentation.

- Significant gaps between minimum and maximum values across price, area, and parking indicate high variability and the presence of outliers, which may influence summary statistics and should be handled carefully in further analysis.

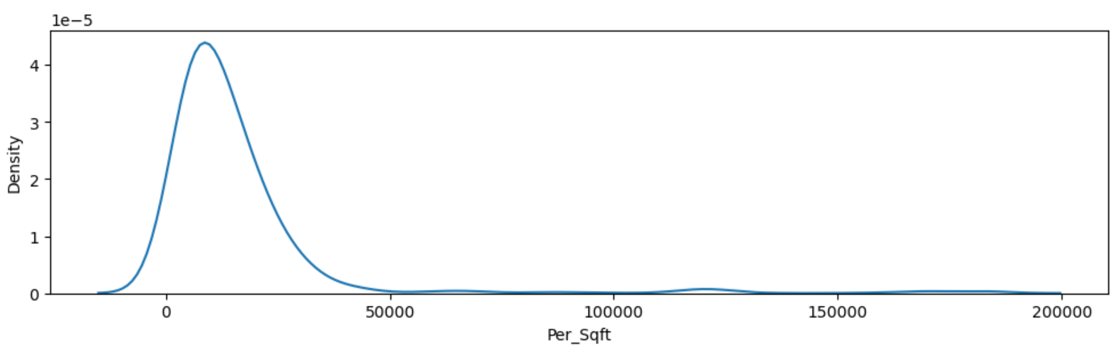
[42]:
```
# completness
df.isnull().sum().sum()
```

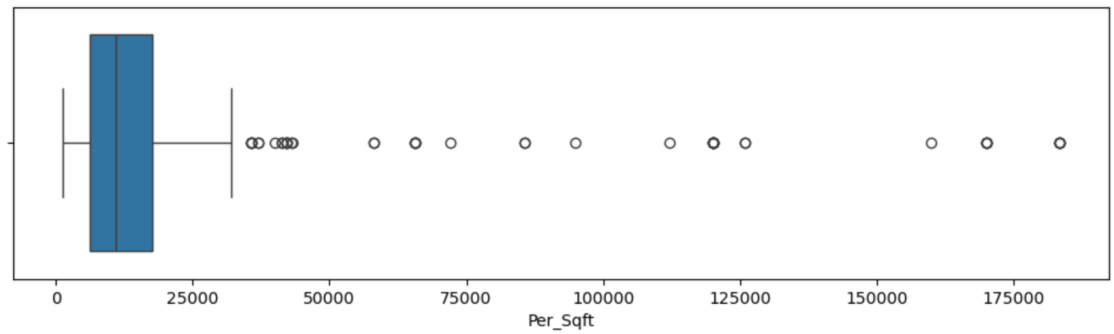
[42]: np.int64(280)

[43]:
```
# percentage
df.isnull().mean()*100
```

[43]:
```
Area            0.000000
BHK             0.000000
Bathroom        0.164745
Furnishing      0.000000
Location        0.000000
District        0.000000
Locality        0.000000
Parking         2.635914
Status          0.000000
Transaction     0.000000
Type            0.411862
Per_Sqft       19.851730
Price           0.000000
dtype: float64
```

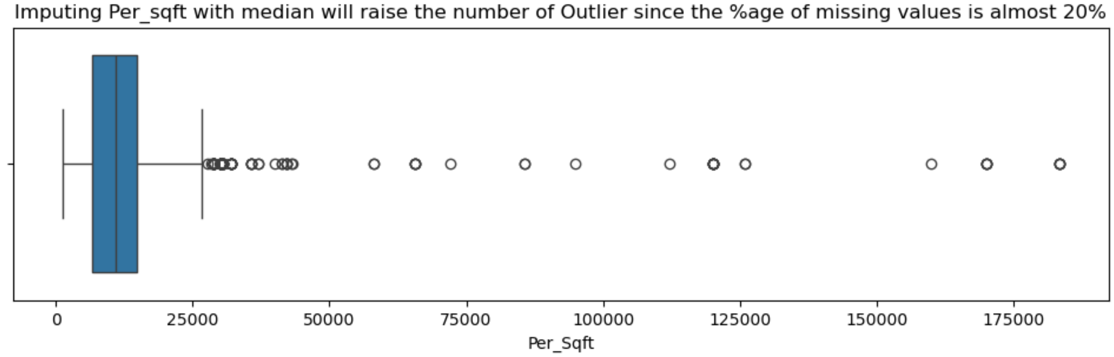
[44]:
```
df.Per_Sqft.describe()
# visualisation
plt.figure(figsize=(12,3))
sns.kdeplot(data=df, x='Per_Sqft')
plt.show()
plt.figure(figsize=(12,3))
sns.boxplot(data=df,x='Per_Sqft')
plt.show()

print('skewness',df.Per_Sqft.skew())
```






```
skewness 5.264871991245157
```

[45]:
```
plt.figure(figsize=(12,3))
plt.title('Imputing Per_sqft with median will raise the number of Outlier since␣
↪the %age of missing values is almost 20%')
sns.boxplot(x=df.Per_Sqft.fillna(df.Per_Sqft.median()))
plt.show()
```



[46]:
```
df.columns
```

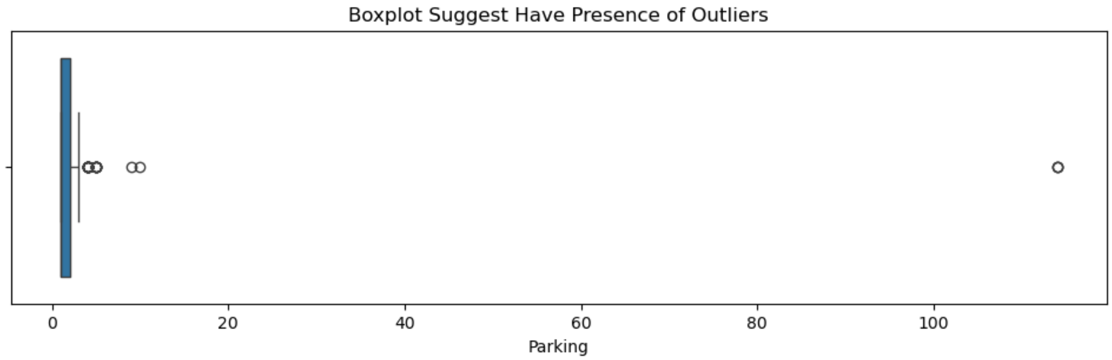
[46]:
```
Index(['Area', 'BHK', 'Bathroom', 'Furnishing', 'Location', 'District',
       'Locality', 'Parking', 'Status', 'Transaction', 'Type', 'Per_Sqft',
       'Price'],
      dtype='object')
```

[47]:
```
# 'Area' --> 'Price'
# 'per_sqft' --> price/area
df.Per_Sqft = df.Per_Sqft.fillna(df.Price/df.Area)
```

[48]:
```
df.Per_Sqft.isnull().sum()
# df.per_sqft is free from issue of completeness
```

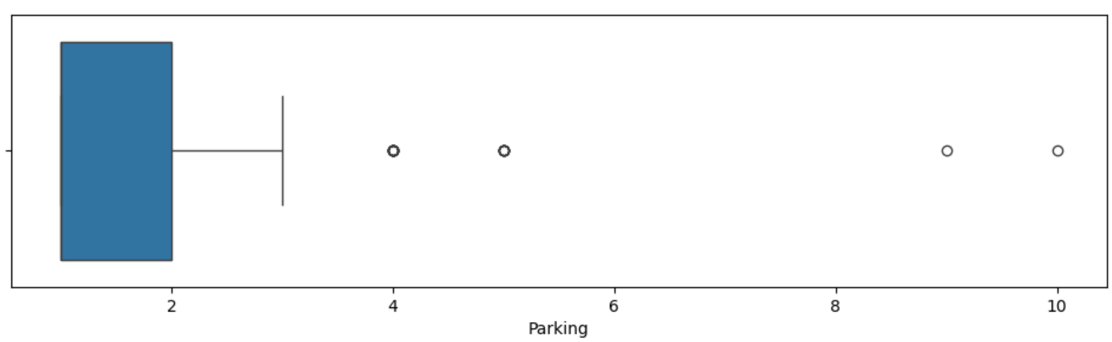
[48]: np.int64(0)

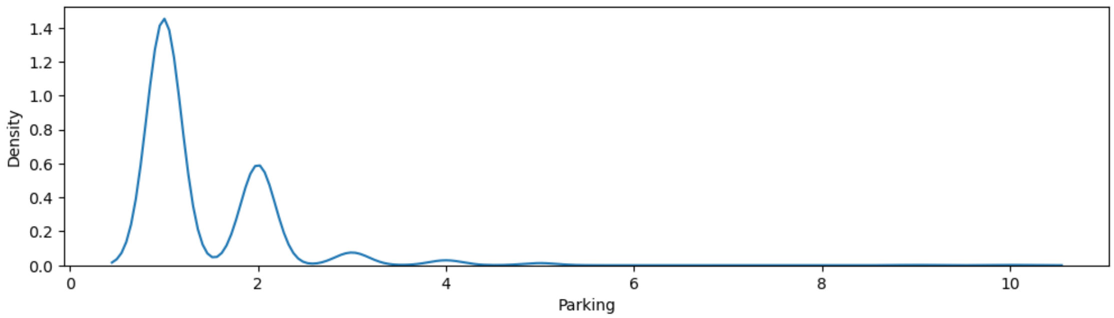
[49]:
```
# outlier
plt.figure(figsize=(12,3))
plt.title('Boxplot Suggest Have Presence of Outliers')
sns.boxplot(x=df.Parking)
plt.show()
```



[50]:
```
df[df.Parking>100]
df.Parking = np.where(df.Parking>100,1,df.Parking)
```

[51]:
```
plt.figure(figsize=(12,3))
sns.boxplot(x=df.Parking)
plt.show()
plt.figure(figsize=(12,3))
sns.kdeplot(x=df.Parking)
plt.show()
df.Parking.skew()
```



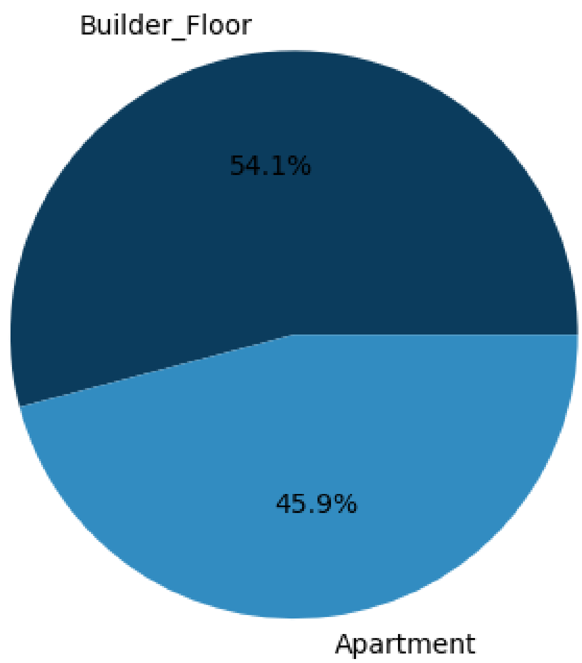


[51]: np.float64(3.5598955904673226)

[52]:
```
df.Parking = df.Parking.fillna(1)
df.Parking = df.Parking.astype(int)
df.Parking.sample(5)
```

[52]:
```
84     2
226    2
880    1
727    1
509    1
Name: Parking, dtype: int64
```

[53]:
```
df.isnull().sum()
colors = ["#0B3C5D", "#328CC1"]
temp = df.Type.value_counts().reset_index()
plt.pie(temp['count'],labels=temp.Type,autopct='%1.1f%%',colors=colors)
plt.show()
temp
```



[53]:

	Type	count
0	Builder_Floor	654
1	Apartment	555

[54]:
```
df.Type.mode().values
df.Type.fillna('Builder_Floor',inplace=True)
```

[55]:
```
df.isnull().sum().sum()
```

[55]: np.int64(2)

[56]:
```
df.dropna(inplace=True)
```

[57]:
```
df.shape
```

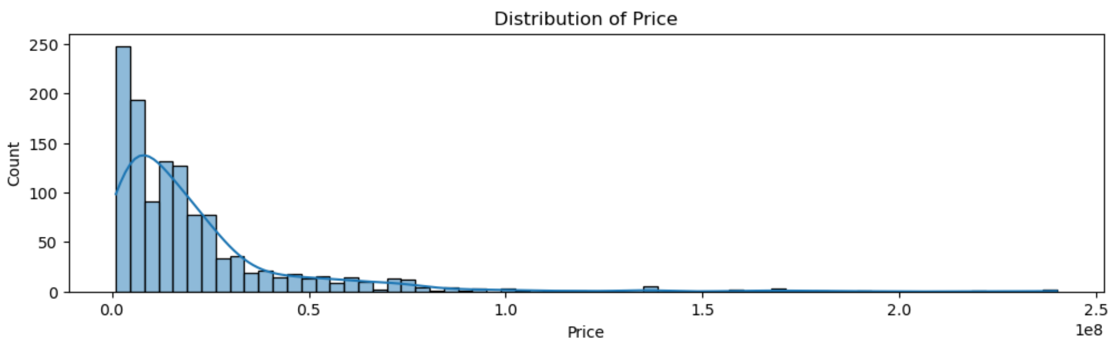
[57]: (1212, 13)

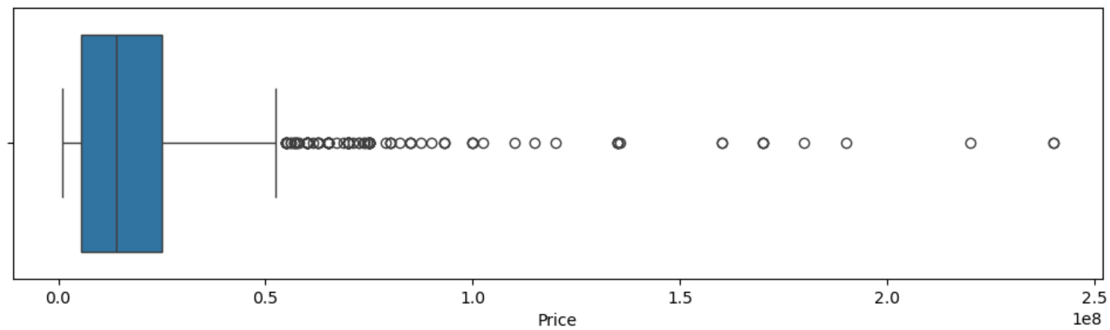
[58]:
```
# numerical
# categorical
df.columns
num = list(df.describe().columns)
cat = []
```

```python
for i in df.columns:
    if i not in num:
        cat.append(i)

print('Numerical:\t', num)
print('Categorical:\t', cat)
```

```
Numerical:       ['Area', 'BHK', 'Bathroom', 'Parking', 'Per_Sqft', 'Price']
Categorical:     ['Furnishing', 'Location', 'District', 'Locality', 'Status',
'Transaction', 'Type']
```

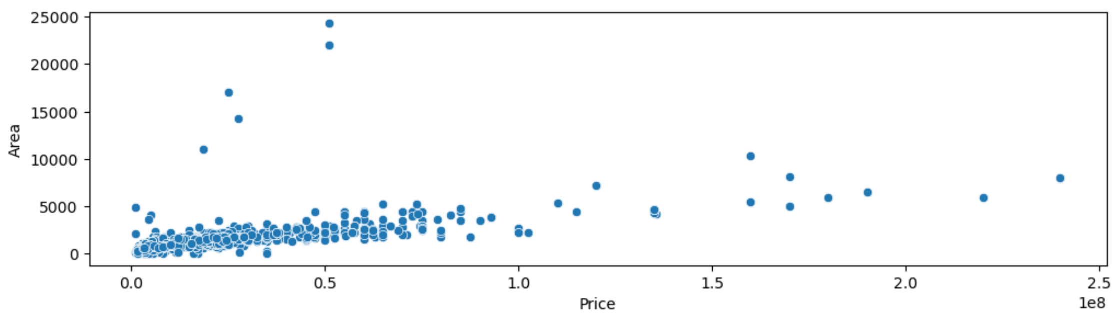
[59]:
```python
# univariable
# numberical columns

# distribution
plt.figure(figsize=(12,3))
plt.title('Distribution of Price')
sns.histplot(df.Price,kde=True)
plt.show()
plt.figure(figsize=(12,3))
sns.boxplot(x=df.Price)
plt.show()
df.Area.skew()
```





[59]: np.float64(8.099780784747038)

[60]:
```
# bivariate analysis
plt.figure(figsize=(12,3))
sns.scatterplot(data=df,x='Price',y='Area')
plt.show()
```



7 Potential issue

Area above 10k sqft is very affordable which is not possilble in Delhi like location

[61]:
```
df[df.Area>10000]
```

[61]:
```
        Area  BHK  Bathroom      Furnishing           Location     District  \
429  22050.0    4       4.0  Semi-Furnished    Greater Kailash  South Delhi
431  22050.0    4       4.0  Semi-Furnished    Greater Kailash  South Delhi
515  10350.0    4       7.0  Semi-Furnished     Friends Colony  South Delhi
603  24300.0    4       5.0  Semi-Furnished              Saket  South Delhi
806  14220.0    3       3.0  Semi-Furnished      Paschim Vihar   West Delhi
835  17010.0    3       3.0  Semi-Furnished       Punjabi Bagh   West Delhi
978  11050.0    3       3.0     Unfurnished  Chittaranjan Park  South Delhi

                             Locality  Parking         Status   Transaction  \
429                 Greater Kailash 1        2   Almost_ready  New_Property
431                 Greater Kailash 1        2   Almost_ready  New_Property
515  Maharani Bagh, New Friends Colony        3  Ready_to_move  New_Property
603                             Saket        2  Ready_to_move        Resale
806             Paschim Vihar Block B4        1  Ready_to_move  New_Property
835                 Punjabi Bagh West        2  Ready_to_move        Resale
978                 Chittaranjan Park        1  Ready_to_move  New_Property

             Type  Per_Sqft     Price
429  Builder_Floor   30556.0  51000000
```

```
431  Builder_Floor   30556.0   51000000
515      Apartment   15459.0  160000000
603  Builder_Floor   12500.0   51000000
806  Builder_Floor   10943.0   27500000
835  Builder_Floor   15278.0   25000000
978  Builder_Floor   12916.0   18500000
```

[62]:
```
22050.0*30556.0
```

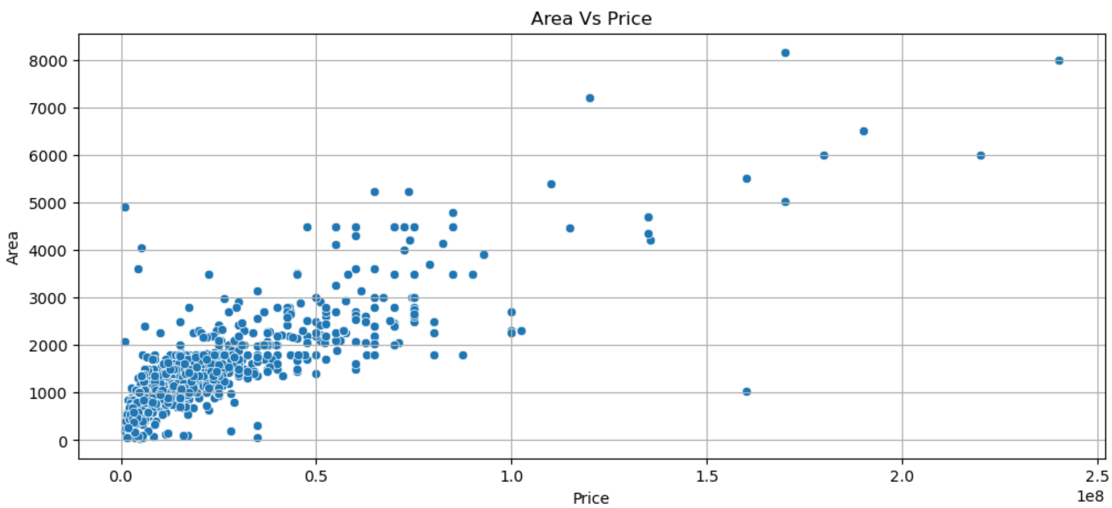
[62]: 673759800.0

[63]:
```
(673759800.0/51000000)/10
```

[63]: 1.3210976470588236

[64]:
```
df.Area = np.where(df.Area>10000,df.Area/10,df.Area)
```

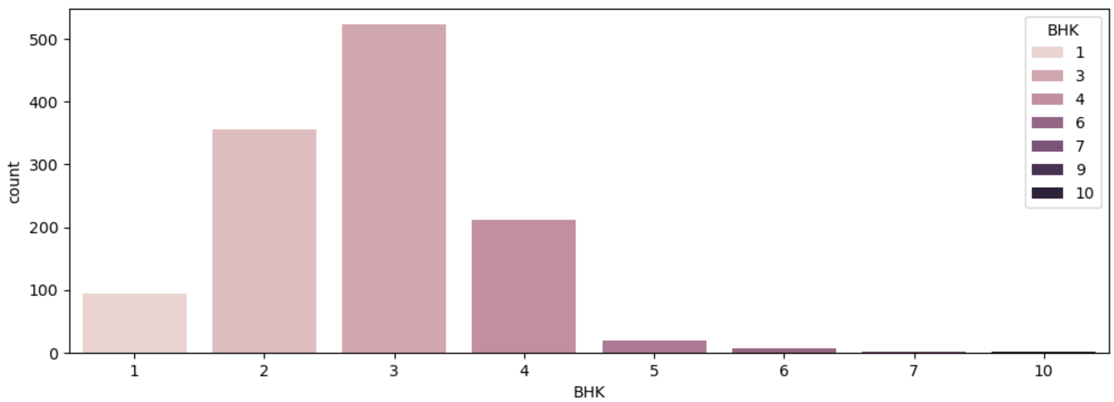
[65]:
```
# bivariate analysis
plt.figure(figsize=(12,5))
plt.title('Area Vs Price')
sns.scatterplot(data=df,x='Price',y='Area')
plt.grid()
plt.show()
```



[66]:
```
# plotly
px.
↪scatter(df,x="Price",y="Area",hover_data=["Area","Location","Price"],height=500,color='Pric
↪Vs Price')
```

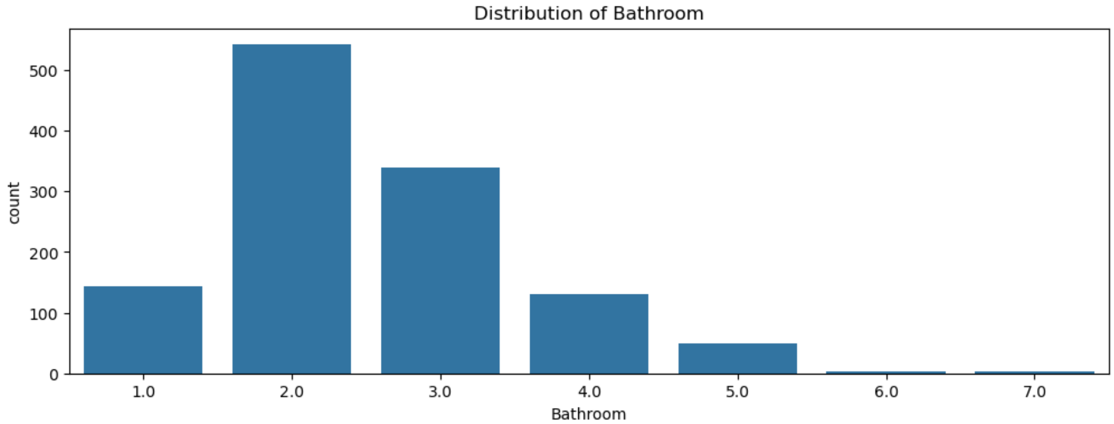
8 Exploratory Analysis

[67]:
```
# univeriate analysis
num
# BHK
plt.figure(figsize=(12,4))
sns.countplot(data=df,x='BHK',hue='BHK')
temp = df.BHK.value_counts().reset_index()
temp
px.pie(temp,names='BHK',values='count',color_discrete_sequence=px.colors.
↪sequential.Blues,height=400,title='Distribution of BHK')
# feature engg --> 5,6,7,10 --> 4+ BHK Enteries
```



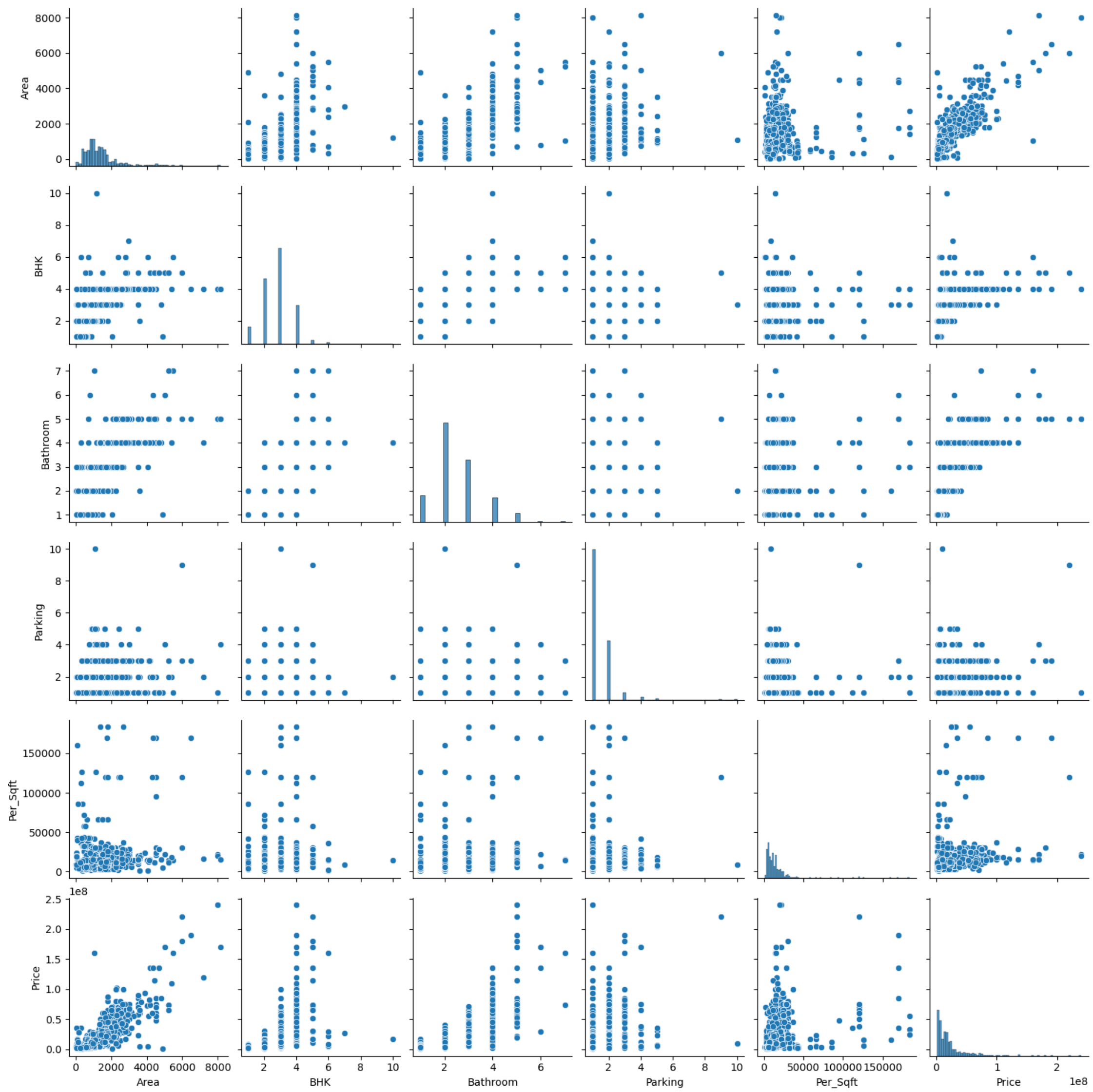
- 3 BHK apartment have higher number of listing on MagicBricks including strong demand and builder preference
- 2 BHK units follow, driven by affordability and suitability for smaller or nuclear families
- 4 BHK and 1 BHK configuration show moderate to low

[68]:
```
df.Bathroom.value_counts()
plt.figure(figsize=(12,4))
sns.countplot(data=df,x='Bathroom')
plt.title('Distribution of Bathroom')
plt.show()
```



- Descriptive Statistics: Summarizing key variables such as price, area, location, and number of bathrooms.
- Visualizations: Bar charts, scatter plots, and distribution graphs to uncover trends and patterns in housing data.
- Market Insights: Identifying dominant property configurations, pricing trends, and regional preferences.
- Data Cleaning & Preparation: Handling missing values, outliers, and formatting for analytical clarity.

[71]:
```
# multivarite analysis
sns.pairplot(df)
plt.show()
```



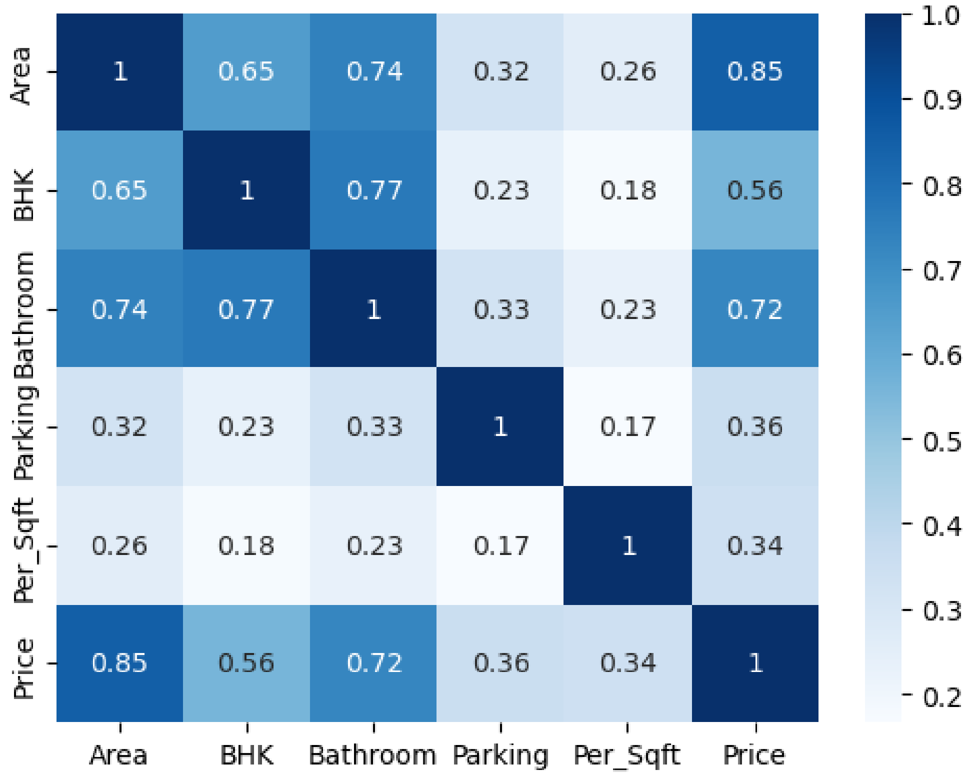
[76]:
```python
df.corr(numeric_only=True)
```

[76]:

	Area	BHK	Bathroom	Parking	Per_Sqft	Price
Area	1.000000	0.651160	0.740293	0.324508	0.257313	0.847225
BHK	0.651160	1.000000	0.767598	0.232556	0.175552	0.559619
Bathroom	0.740293	0.767598	1.000000	0.325204	0.230032	0.724435
Parking	0.324508	0.232556	0.325204	1.000000	0.166187	0.355349
Per_Sqft	0.257313	0.175552	0.230032	0.166187	1.000000	0.338885
Price	0.847225	0.559619	0.724435	0.355349	0.338885	1.000000

[78]:
```python
# corr
# heatmap
sns.heatmap(df.corr(numeric_only=True),cmap='Blues',annot=True)
```

```
plt.show()
```



The heatmap reveals how different real estate features relate to property price:

Highly Correlated with Price: - Area (0.85): Strongest predictor of price. - Bathroom (0.72): Indicates property luxury and size. - BHK (0.56): Moderately influential.

Feature Relationships: - Bathroom & BHK (0.77) and Bathroom & Area (0.74): These features scale together, reflecting property size and layout. **Weak Correlations:** - Parking (0.36) and Per_Sqft (0.34): Minimal impact on price, suggesting external factors may influence them.

[79]:
```
cat
```

[79]:
```
['Furnishing',
 'Location',
 'District',
 'Locality',
 'Status',
 'Transaction',
 'Type']
```

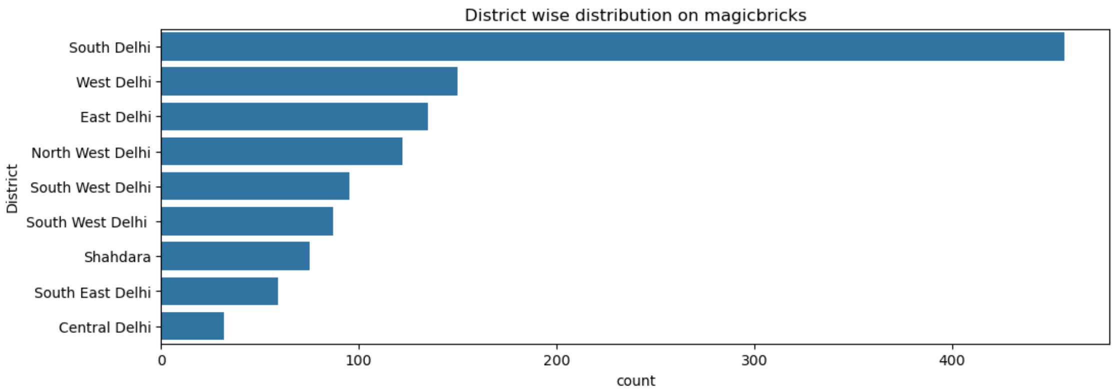
[82]:
```
df.District.value_counts().reset_index()
```

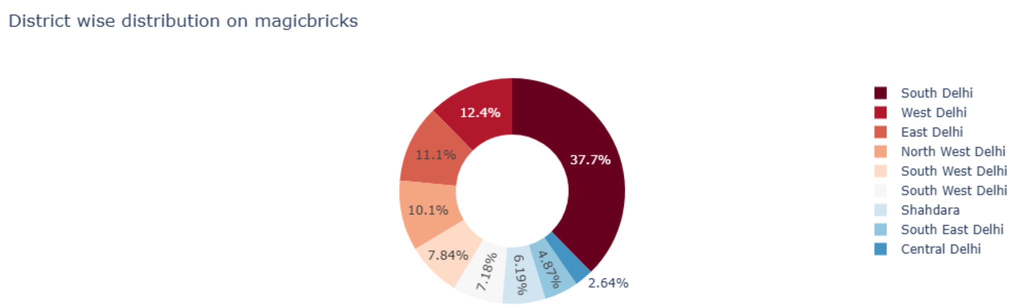
[82]:

	District	count
0	South Delhi	457
1	West Delhi	150
2	East Delhi	135
3	North West Delhi	122
4	South West Delhi	95
5	South West Delhi	87
6	Shahdara	75
7	South East Delhi	59
8	Central Delhi	32

[92]:

```
temp = df.District.value_counts().reset_index()
plt.figure(figsize=(12,4))
sns.countplot(data=df,y='District',order=temp.District)
plt.title('District wise distribution on magicbricks')
plt.show()

px.pie(temp,values='count',names='District',height=400,
        color_discrete_sequence=px.colors.sequential.RdBu,hole=0.5,
        title='District wise distribution on magicbricks').show()
temp
```



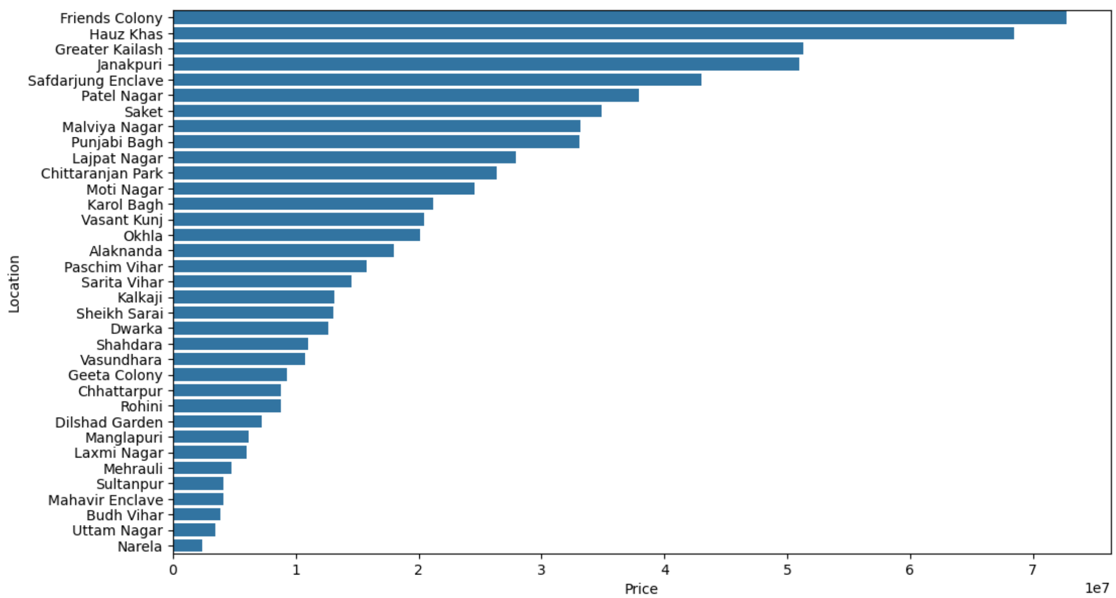


[92]:
```
             District  count
0         South Delhi    457
1          West Delhi    150
2          East Delhi    135
3    North West Delhi    122
4    South West Delhi     95
5   South West Delhi      87
6            Shahdara     75
7    South East Delhi     59
8       Central Delhi     32
```

[93]:
```
# location
# price
# bivariate
df.loc[:,['Location','Price']].sample(5)
```

[93]:
```
        Location     Price
795   Moti Nagar  14200000
693  Vasant Kunj  20000000
957    Alaknanda  19000000
67      Shahdara   6500000
756       Dwarka   2400000
```

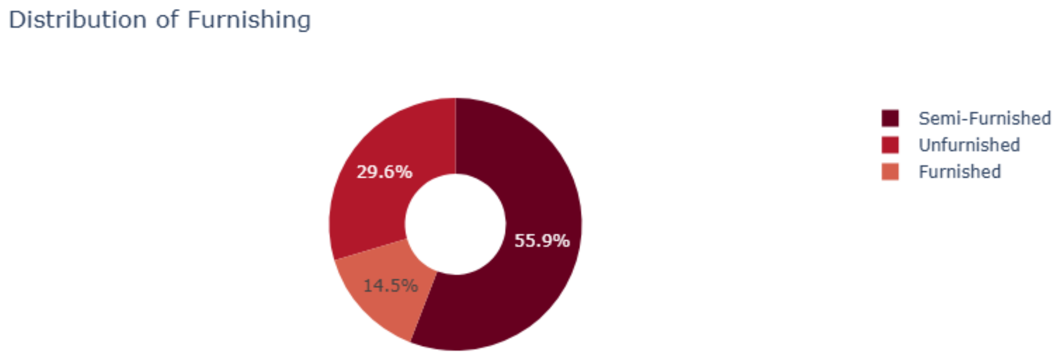
[94]:
```
temp = df.groupby('Location')['Price'].mean().sort_values(ascending=False).
  ↪reset_index()
plt.figure(figsize=(12,7))
sns.barplot(data=df,y='Location',x='Price',ci=False,order=temp.Location)
plt.show()
```

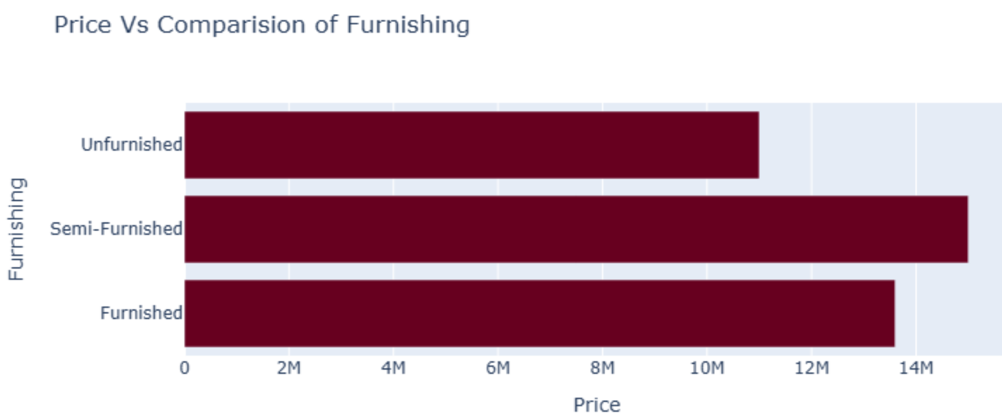


8.1 Property Price Insights by Location

- Premium Localities: Friends Colony, Hauz Khas, and Greater Kailash top the chart with the highest property prices, indicating their status as upscale, well-developed neighborhoods favored for luxury living and investment.
- Mid-Tier Zones: Areas like Patel Nagar, Saket, and Malviya Nagar show moderate pricing, suggesting balanced demand and accessibility—ideal for middle-income buyers seeking urban convenience.
- Affordable Segments: Narela, Uttam Nagar, Budh Vihar, and Mahavir Enclave reflect the lowest property prices, positioning them as budget-friendly options, likely with developing infrastructure and emerging residential appeal.
- Investment Implication: The wide price disparity across locations highlights strategic opportunities for both premium investments and affordable housing development, depending on buyer goals and urban growth trends.

[99]:
```
temp = df.Furnishing.value_counts().reset_index()

px.pie(temp,names='Furnishing',values='count',title='Distribution of␣
↪Furnishing',hole=0.4,
       color_discrete_sequence=px.colors.sequential.RdBu).show()

temp2 = df.groupby('Furnishing')['Price'].median().reset_index()

px.bar(temp2,x='Price',y='Furnishing',title='Price Vs Comparision of␣
↪Furnishing',color_discrete_sequence=px.colors.sequential.RdBu).show()
```





8.2 Property Price Insights by Furnishing Status

- Semi-Furnished Leads in Value
  Properties labeled as Semi-Furnished command the highest average price, suggesting a strong buyer preference for partial readiness without full customization costs.
- Furnished Homes Rank Second
  Furnished properties are priced slightly lower than semi-furnished ones, indicating that while convenience is valued, buyers may not always pay a premium for fully furnished setups.
- Unfurnished Properties Are Least Expensive
  Unfurnished homes show the lowest price range, making them attractive for budget-conscious buyers or investors seeking flexibility in interior design.
- Market Implication
  The pricing trend highlights that moderate furnishing strikes the best balance between cost

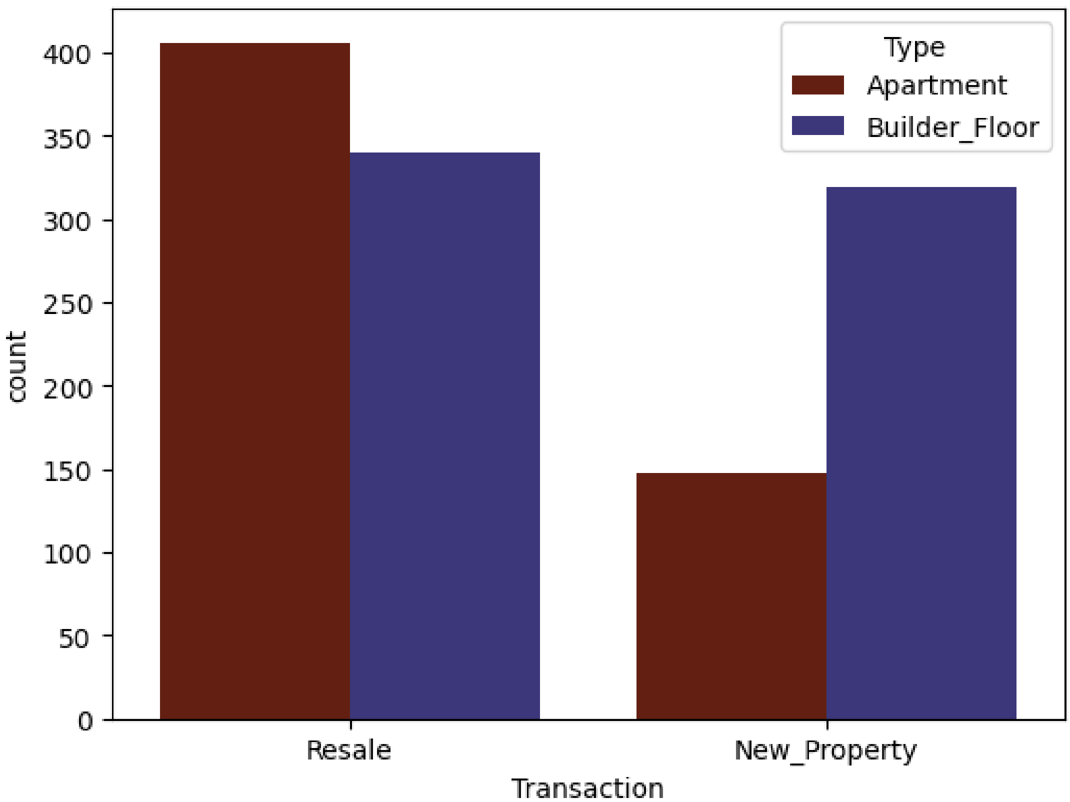
and buyer appeal, offering developers and sellers a strategic edge in mid-tier segments.

[100]:
```
df.Transaction.value_counts()
```

[100]:
```
Transaction
Resale          746
New_Property    466
Name: count, dtype: int64
```

[103]:
```
colors = ['#701705','#312C85']
sns.countplot(data=df,x='Transaction',hue='Type',palette=colors)
```

[103]: <Axes: xlabel='Transaction', ylabel='count'>



9 Property Transaction Insights by Type

- *Apartments Dominate Resale Market*
  Resale transactions are more frequent for Apartments, with counts exceeding 400, indicating strong secondary market activity and buyer preference for established units.
- *Builder Floors Lead in New Properties*
  Builder_Floor properties show higher counts in New_Property transactions, suggesting they

are more commonly developed and sold as fresh inventory.

- *Segmented Demand Patterns*
  The chart highlights a clear split: Apartments are favored for resale, while Builder_Floors drive new property listings—reflecting distinct buyer and developer strategies across transaction types.

```
[ ]:
```