```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme(color_codes = True)

df = pd.read_csv("C:\\Users\\HP\\Downloads\\archive\\MagicBricks.csv")

df.head(6)
```

```
     Area  BHK  Bathroom      Furnishing  \
0   800.0    3       2.0  Semi-Furnished
1   750.0    2       2.0  Semi-Furnished
2   950.0    2       2.0       Furnished
3   600.0    2       2.0  Semi-Furnished
4   650.0    2       2.0  Semi-Furnished
5  1300.0    4       3.0  Semi-Furnished

                                          Locality  Parking
Price  \
0                                Rohini Sector 25      1.0
6500000
1            J R Designers Floors, Rohini Sector 24      1.0
5000000
2               Citizen Apartment, Rohini Sector 13      1.0
15500000
3                                Rohini Sector 24      1.0
4200000
4  Rohini Sector 24 carpet area 650 sqft status R...      1.0
6200000
5                                Rohini Sector 24      1.0
15500000

          Status   Transaction           Type  Per_Sqft
0  Ready_to_move  New_Property  Builder_Floor       NaN
1  Ready_to_move  New_Property      Apartment    6667.0
2  Ready_to_move        Resale      Apartment    6667.0
3  Ready_to_move        Resale  Builder_Floor    6667.0
4  Ready_to_move  New_Property  Builder_Floor    6667.0
5  Ready_to_move  New_Property  Builder_Floor    6667.0
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Area         1259 non-null   float64
 1   BHK          1259 non-null   int64
 2   Bathroom     1257 non-null   float64
```

```
 3   Furnishing   1254 non-null   object
 4   Locality     1259 non-null   object
 5   Parking      1226 non-null   float64
 6   Price        1259 non-null   int64
 7   Status       1259 non-null   object
 8   Transaction  1259 non-null   object
 9   Type         1254 non-null   object
 10  Per_Sqft     1018 non-null   float64
dtypes: float64(4), int64(2), object(5)
memory usage: 108.3+ KB
```

```
#Check the number of unique value from all of the object datatype
df.select_dtypes(include='object').nunique()
```

```
Furnishing       3
Locality       365
Status           2
Transaction      2
Type             2
dtype: int64
```

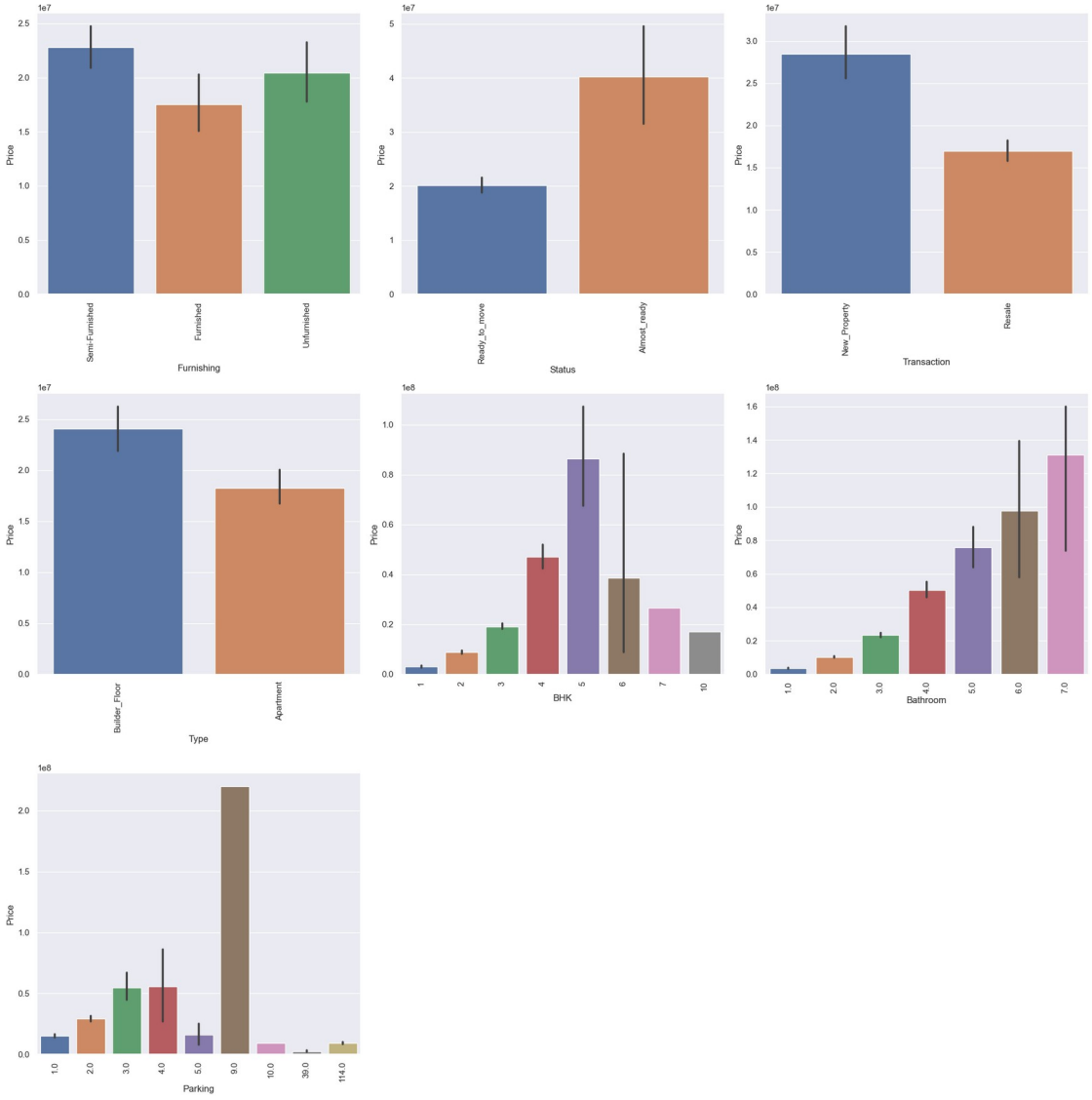
```
# Dropping of 'Locality' column because its irrelevant
df.drop(columns='Locality', inplace=True)
df.head()
```

```
    Area  BHK  Bathroom      Furnishing  Parking     Price
Status  \
0  800.0    3       2.0  Semi-Furnished      1.0   6500000
Ready_to_move
1  750.0    2       2.0  Semi-Furnished      1.0   5000000
Ready_to_move
2  950.0    2       2.0       Furnished      1.0  15500000
Ready_to_move
3  600.0    2       2.0  Semi-Furnished      1.0   4200000
Ready_to_move
4  650.0    2       2.0  Semi-Furnished      1.0   6200000
Ready_to_move

    Transaction           Type  Per_Sqft
0  New_Property  Builder_Floor       NaN
1  New_Property      Apartment    6667.0
2        Resale      Apartment    6667.0
3        Resale  Builder_Floor    6667.0
4  New_Property  Builder_Floor    6667.0
```

```
# data preprocessing 1
```

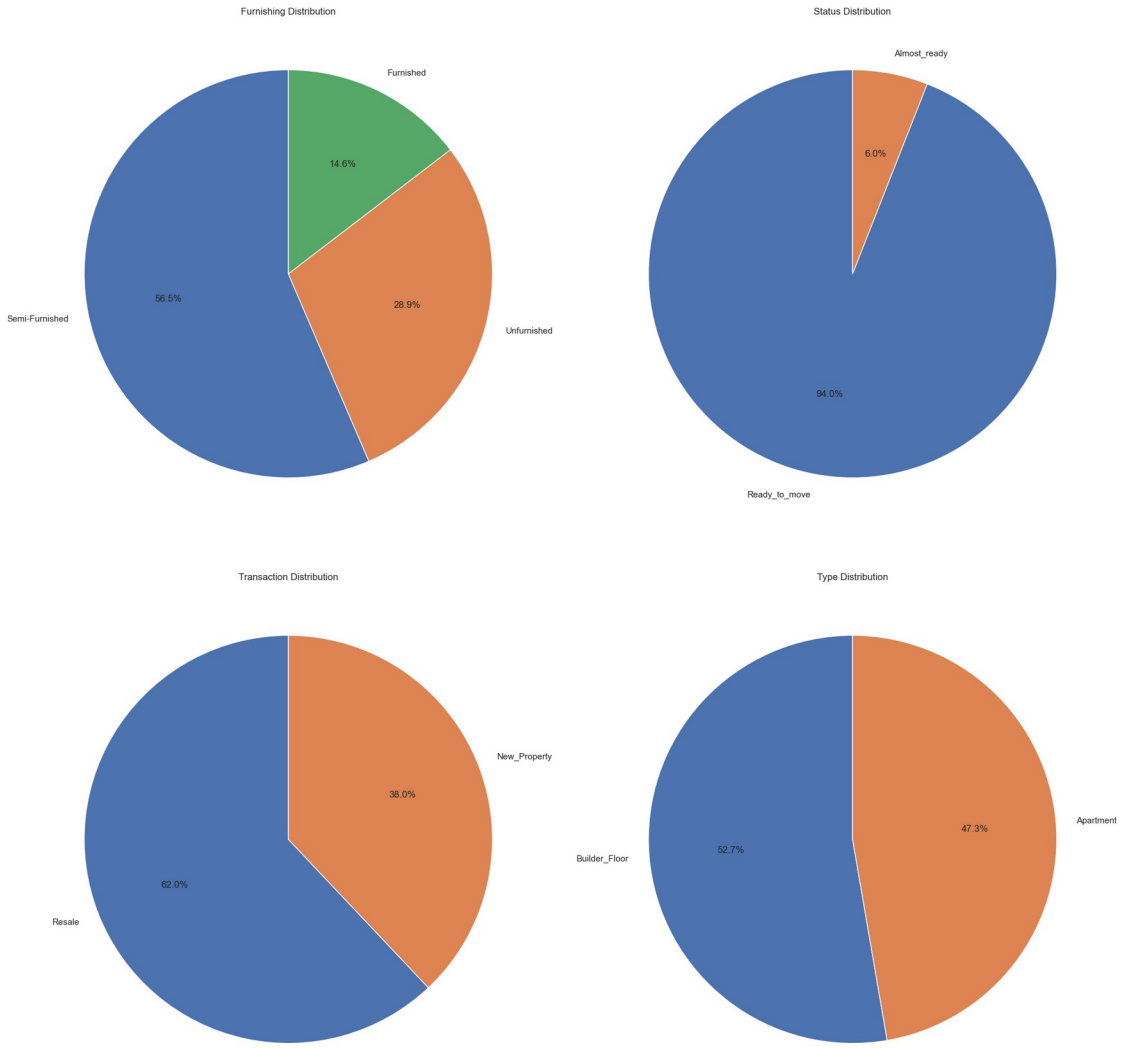
```
# list of categorical variables to plot
cat_vars = ['Furnishing', 'Status', 'Transaction', 'Type', 'BHK',
'Bathroom', 'Parking']
```

```
# create figure with subplots
fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(20, 20))
axs = axs.ravel()

# create barplot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.barplot(x=var, y='Price', data=df, ax=axs[i],
estimator=np.mean)
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# adjust spacing between subplots
fig.tight_layout()

# remove the eigth subplot
fig.delaxes(axs[7])

# remove the ninth subplot
fig.delaxes(axs[8])

# show plot
plt.show()
```



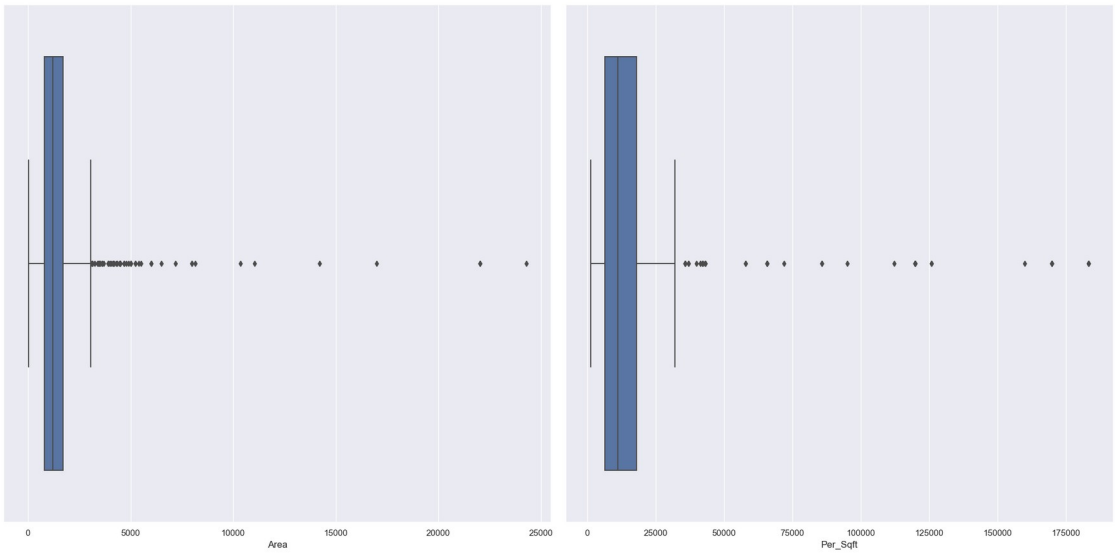

```
cat_vars = ['Furnishing', 'Status', 'Transaction', 'Type']

# create a figure and axes
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 20))

# create a pie chart for each categorical variable
for i, var in enumerate(cat_vars):
    if i < len(axs.flat):
        # count the number of occurrences for each category
        cat_counts = df[var].value_counts()

        # create a pie chart
        axs.flat[i].pie(cat_counts, labels=cat_counts.index,
autopct='%1.1f%%', startangle=90)

        # set a title for each subplot
```

```
        axs.flat[i].set_title(f'{var} Distribution')

# adjust spacing between subplots
fig.tight_layout()

# show the plot
plt.show()
```

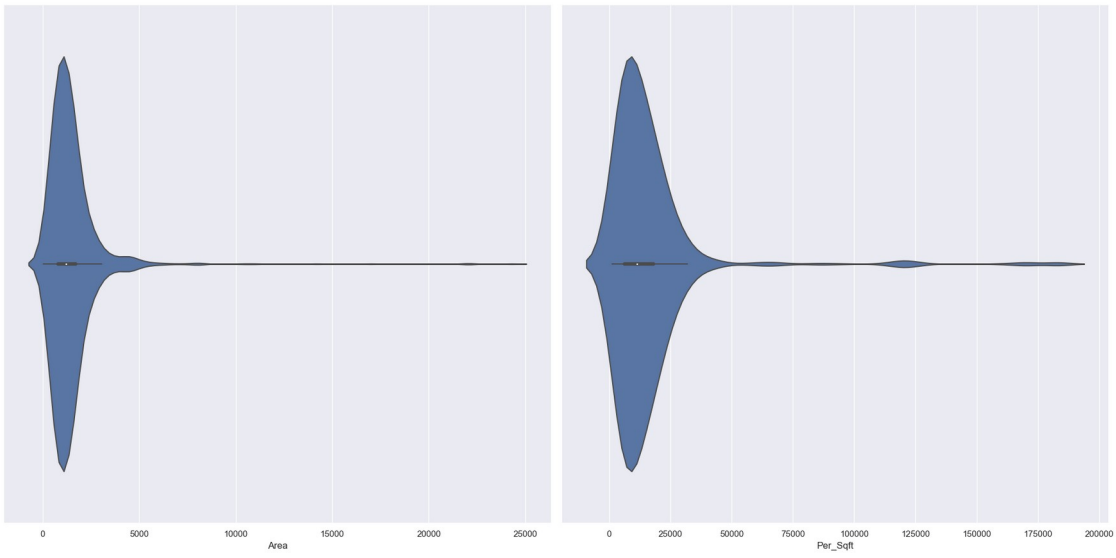



```
num_vars = ['Area', 'Per_Sqft']

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.boxplot(x=var, data=df, ax=axs[i])

fig.tight_layout()
```

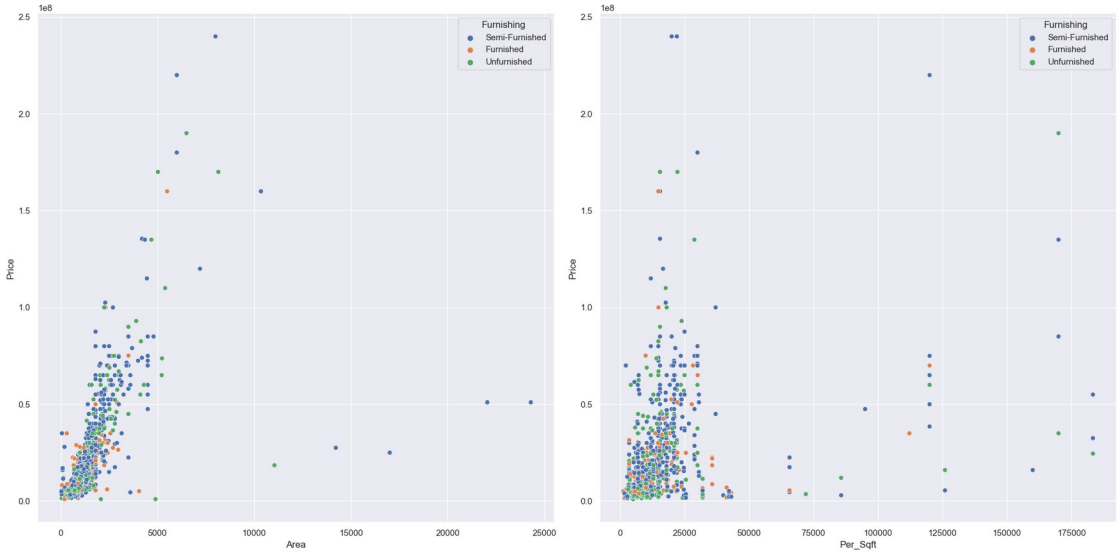
```
plt.show()
```



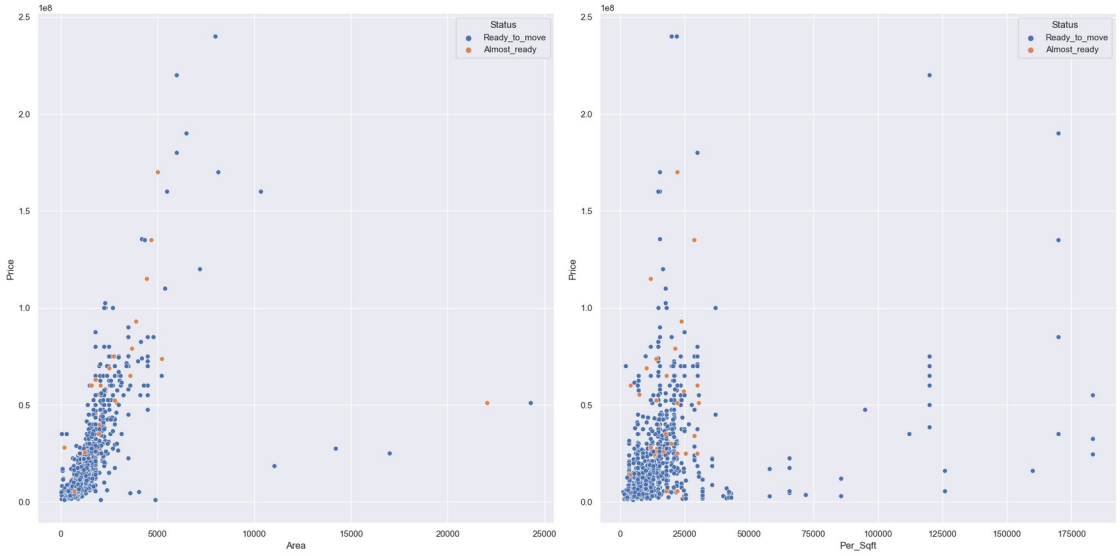

```
num_vars = ['Area', 'Per_Sqft']

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.violinplot(x=var, data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



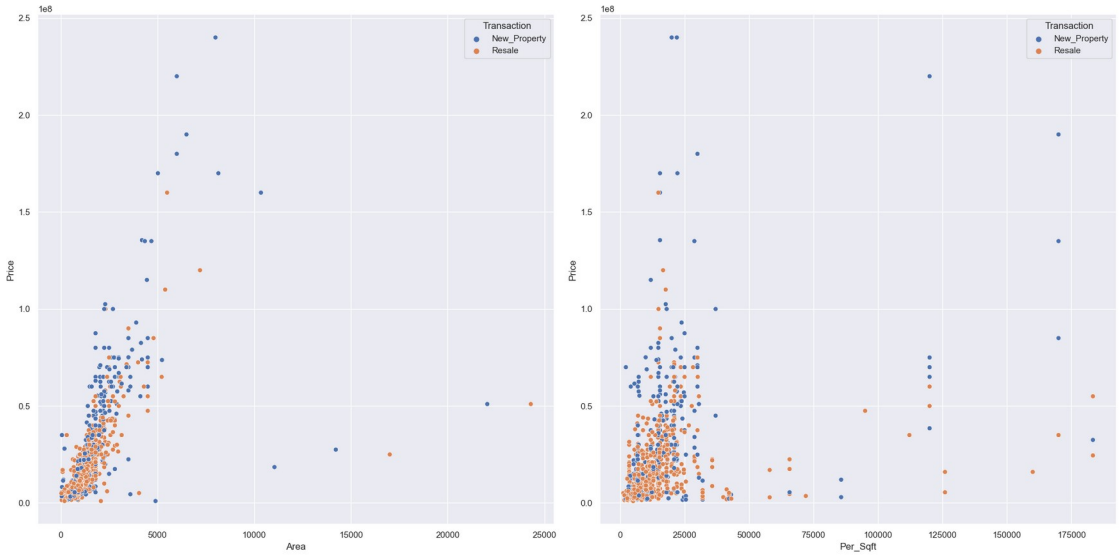
```
num_vars = ['Area', 'Per_Sqft']

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.scatterplot(x=var, y='Price', hue='Furnishing', data=df,
ax=axs[i])

fig.tight_layout()

plt.show()
```




```
num_vars = ['Area', 'Per_Sqft']

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.scatterplot(x=var, y='Price', hue='Status', data=df,
ax=axs[i])

fig.tight_layout()

plt.show()
```

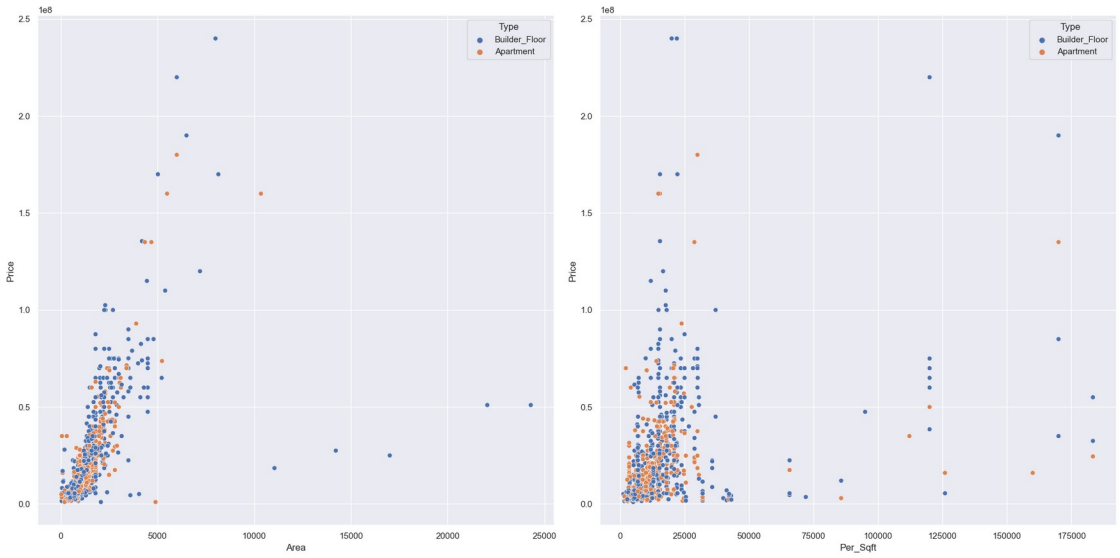



```
num_vars = ['Area', 'Per_Sqft']

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.scatterplot(x=var, y='Price', hue='Transaction', data=df,
ax=axs[i])

fig.tight_layout()

plt.show()
```




```
num_vars = ['Area', 'Per_Sqft']

fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(20, 10))
```

```
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.scatterplot(x=var, y='Price', hue='Type', data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```




```
# data pre processing 2

df.shape
```

```
(1259, 10)
```

```
#Check missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

```
Per_Sqft      19.142176
Parking        2.621128
Furnishing     0.397141
Type           0.397141
Bathroom       0.158856
dtype: float64
```

```
# handling of null values with the median
df['Per_Sqft'].fillna(df['Per_Sqft'].median(), inplace=True)
df['Parking'].fillna(df['Parking'].median(), inplace=True)

# drop of 3 columns which have null values less than 1%
df.dropna(subset=['Furnishing', 'Type', 'Bathroom'], inplace=True)
df.head()
```

```
    Area  BHK  Bathroom      Furnishing  Parking     Price
Status  \
0  800.0    3       2.0  Semi-Furnished      1.0   6500000
Ready_to_move
1  750.0    2       2.0  Semi-Furnished      1.0   5000000
Ready_to_move
2  950.0    2       2.0       Furnished      1.0  15500000
Ready_to_move
3  600.0    2       2.0  Semi-Furnished      1.0   4200000
Ready_to_move
4  650.0    2       2.0  Semi-Furnished      1.0   6200000
Ready_to_move

    Transaction           Type  Per_Sqft
0  New_Property  Builder_Floor   11291.5
1  New_Property      Apartment    6667.0
2        Resale      Apartment    6667.0
3        Resale  Builder_Floor    6667.0
4  New_Property  Builder_Floor    6667.0
```

```python
# handling of the object data types

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

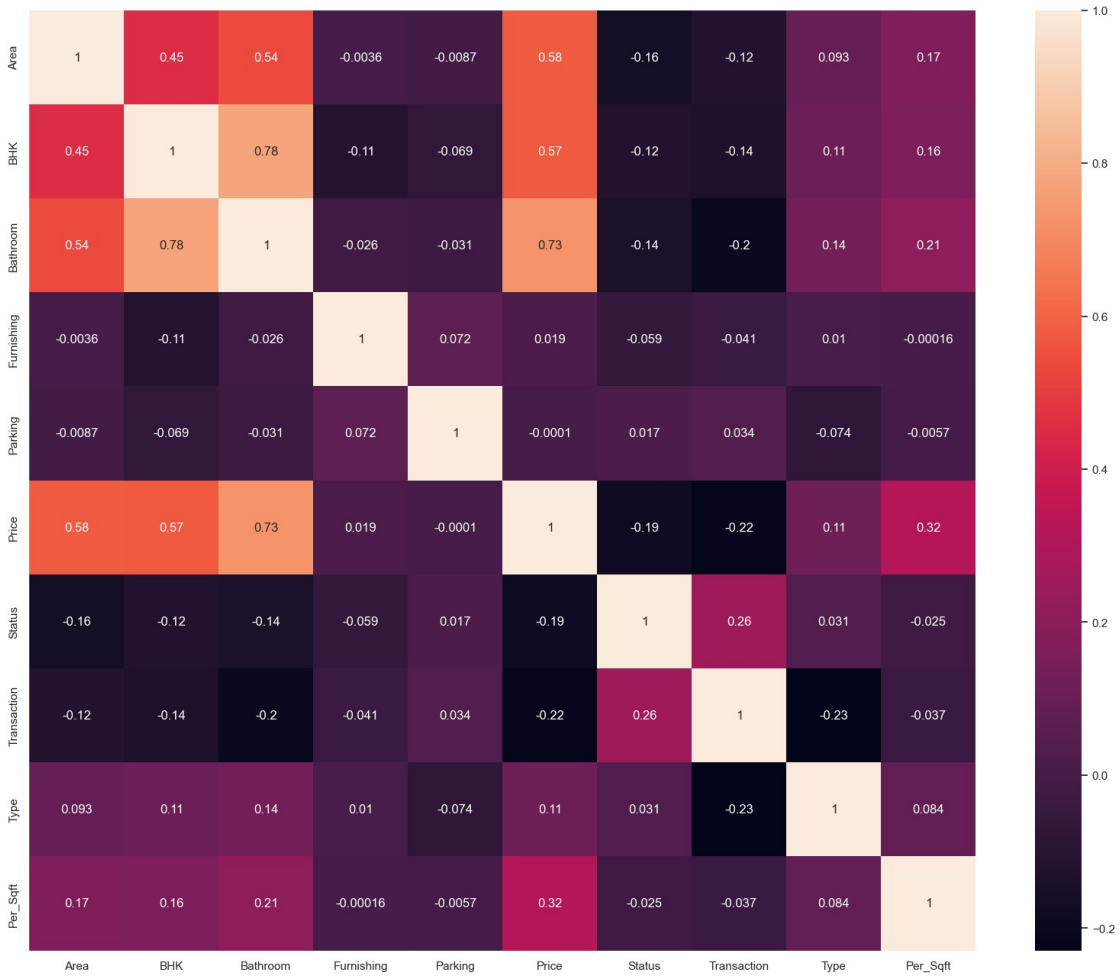
```
Furnishing: ['Semi-Furnished' 'Furnished' 'Unfurnished']
Status: ['Ready_to_move' 'Almost_ready']
Transaction: ['New_Property' 'Resale']
Type: ['Builder_Floor' 'Apartment']
```

```python
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
Furnishing: [1 0 2]
Status: [1 0]
Transaction: [0 1]
Type: [1 0]
```

```
# corelation heat map

#Correlation Heatmap
plt.figure(figsize=(20, 16))
sns.heatmap(df.corr(), fmt='.2g', annot=True)
```

```
<AxesSubplot:>
```




```
# train test dataset
from sklearn.model_selection import train_test_split

# Perform train-test split
X_train, X_test, y_train, y_test = train_test_split(df.drop('Price',
axis=1), df['Price'], test_size=0.2, random_state=0)

# removal of the outliers
# Concatenate X_train and y_train for outlier removal
```

```
train_df = pd.concat([X_train, y_train], axis=1)

# Calculate the IQR values for each column
Q1 = train_df.quantile(0.25)
Q3 = train_df.quantile(0.75)
IQR = Q3 - Q1

# Remove outliers from X_train
train_df = train_df[~((train_df < (Q1 - 1.5 * IQR)) | (train_df > (Q3
+ 1.5 * IQR))).any(axis=1)]

# Separate X_train and y_train after outlier removal
X_train = train_df.drop('Price', axis=1)
y_train = train_df['Price']

# using Decision tree for the problem solving

from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import load_boston


# Create a DecisionTreeRegressor object
dtree = DecisionTreeRegressor()

# Define the hyperparameters to tune and their values
param_grid = {
    'max_depth': [2, 4, 6, 8],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': ['auto', 'sqrt', 'log2'],
    'random_state': [0, 42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(dtree, param_grid, cv=5,
scoring='neg_mean_squared_error')

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 4,
'min_samples_split': 2, 'random_state': 42}
```

```
from sklearn.tree import DecisionTreeRegressor
dtree = DecisionTreeRegressor(random_state=42, max_depth=6,
```

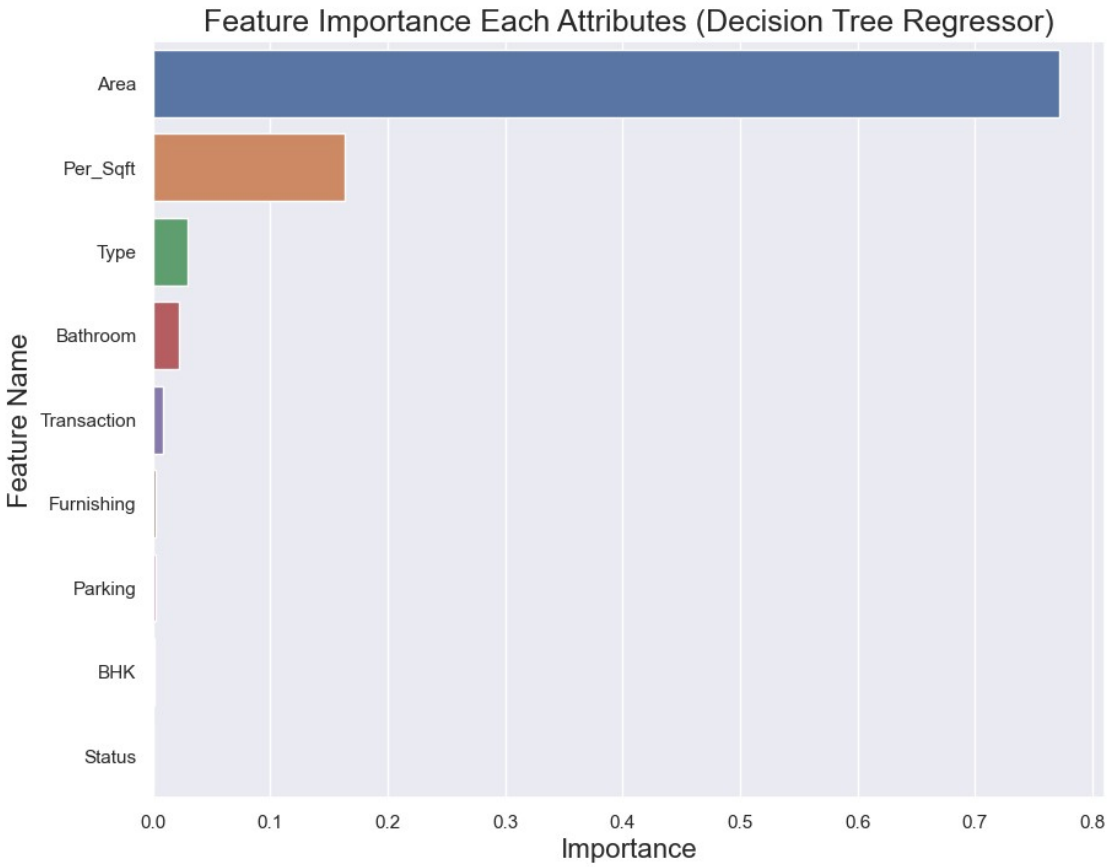
```
max_features='auto', min_samples_leaf=4, min_samples_split=2)
dtree.fit(X_train, y_train)
```

```
DecisionTreeRegressor(max_depth=6, max_features='auto',
min_samples_leaf=4,
                      random_state=42)
```

```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = dtree.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 8490104.759742005
MAPE is 0.48423957735847867
MSE is 517184355319855.8
R2 score is 0.4080663111331838
RMSE score is 22741687.609319054
```

```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Decision Tree
Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```

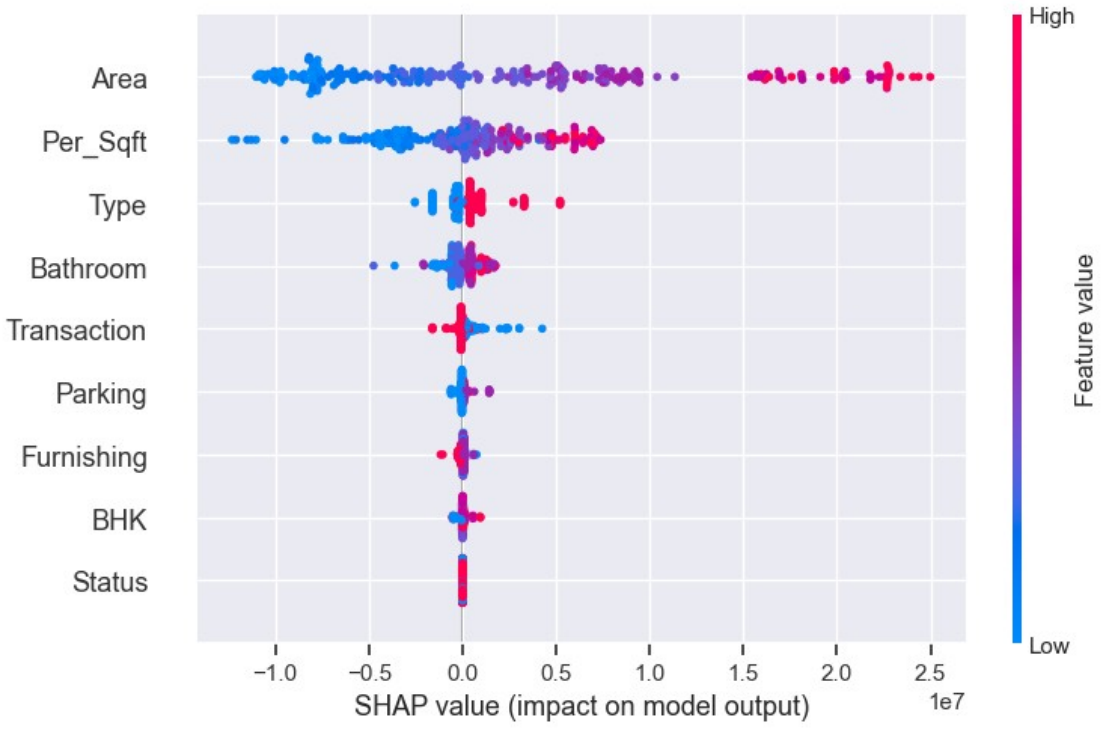



```
!pip install shap
```

```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```

```
Collecting shap
  Downloading shap-0.41.0-cp39-cp39-win_amd64.whl (435 kB)
     ---------------------------------- 435.6/435.6 kB 353.6 kB/s
eta 0:00:00
Collecting slicer==0.0.7
  Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
Requirement already satisfied: tqdm>4.25.0 in c:\users\hp\anaconda3\
lib\site-packages (from shap) (4.64.1)
Requirement already satisfied: scikit-learn in c:\users\hp\anaconda3\
lib\site-packages (from shap) (1.0.2)
Requirement already satisfied: cloudpickle in c:\users\hp\anaconda3\
lib\site-packages (from shap) (2.0.0)
Requirement already satisfied: packaging>20.9 in c:\users\hp\
anaconda3\lib\site-packages (from shap) (21.3)
Requirement already satisfied: numpy in c:\users\hp\anaconda3\lib\
site-packages (from shap) (1.21.5)
Requirement already satisfied: pandas in c:\users\hp\anaconda3\lib\
```

```
site-packages (from shap) (1.4.4)
Requirement already satisfied: scipy in c:\users\hp\anaconda3\lib\
site-packages (from shap) (1.9.1)
Requirement already satisfied: numba in c:\users\hp\anaconda3\lib\
site-packages (from shap) (0.55.1)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\
hp\anaconda3\lib\site-packages (from packaging>20.9->shap) (3.0.9)
Requirement already satisfied: colorama in c:\users\hp\anaconda3\lib\
site-packages (from tqdm>4.25.0->shap) (0.4.5)
Requirement already satisfied: llvmlite<0.39,>=0.38.0rc1 in c:\users\
hp\anaconda3\lib\site-packages (from numba->shap) (0.38.0)
Requirement already satisfied: setuptools in c:\users\hp\anaconda3\
lib\site-packages (from numba->shap) (63.4.1)
Requirement already satisfied: pytz>=2020.1 in c:\users\hp\anaconda3\
lib\site-packages (from pandas->shap) (2022.1)
Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\hp\
anaconda3\lib\site-packages (from pandas->shap) (2.8.2)
Requirement already satisfied: joblib>=0.11 in c:\users\hp\anaconda3\
lib\site-packages (from scikit-learn->shap) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\hp\
anaconda3\lib\site-packages (from scikit-learn->shap) (2.2.0)
Requirement already satisfied: six>=1.5 in c:\users\hp\anaconda3\lib\
site-packages (from python-dateutil>=2.8.1->pandas->shap) (1.16.0)
Installing collected packages: slicer, shap
Successfully installed shap-0.41.0 slicer-0.0.7
```



```
explainer = shap.Explainer(dtree, X_test)
shap_values = explainer(X_test)
shap.plots.waterfall(shap_values[0])
```