Only for reference to hyper tuning using pipeline object of neighbours and sigma with models(above [29])

```
#imports for the entire project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV,
cross_val_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder,
OrdinalEncoder, MinMaxScaler
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.cluster import KMeans
from sklearn.metrics import mean_squared_error, r2_score,
mean_absolute_error, silhouette_score, davies_bouldin_score

#for a cleaner look in plots
plt.style.use('seaborn-v0_8-whitegrid')
#to ignore warnings for cleaner output
import warnings
warnings.filterwarnings('ignore')

print("Libraries imported successfully.")

Libraries imported successfully.

#Data Loading and Inspection
print("--- I. Data Loading and Inspection ---")

#Loading the dataset
df_raw = pd.read_csv('C:/Users/Zer0/Documents/mkd.csv', index_col=0) #
Ensure this path is correct for your environment
df = df_raw.copy() # copy df


#basic info
print("\nFirst 5 rows of the dataset:")
print(df.head())

print(f"\nShape of the dataset (rows, columns): {df.shape}")

print("\nData types of columns:")
print(df.info())
```

```python
print("\nSummary stats for numerical columns:")
print(df.describe())

print("\nSummary stats for object columns:")
print(df.describe(include='object'))

print("\nNumber of unique values in each column:")
for col in df.columns:
    print(f"- {col}: {df[col].nunique()} unique values")
```

```
--- I. Data Loading and Inspection ---

First 5 rows of the dataset:
   Size Size_unit      Property_type          Location Seller_name  \
0     2       BHK  Independent Floor       Uttam Nagar      seller
1     3       BHK  Independent House        Model Town      seller
2     2       BHK          Apartment  Sector 13 Rohini      seller
3     3       BHK          Apartment         DLF Farms      seller
4     3       BHK  Independent Floor       laxmi nagar      seller

      Seller_type Rent_price  Area_sqft          Status
Security_deposit  \
0  Verified Owner      8,500        500  Semi-Furnished
No
1  Verified Owner     48,000       1020       Furnished
No
2  Verified Owner     20,000        810     Unfurnished
No
3  Verified Owner     11,000        750  Semi-Furnished
No
4  Verified Owner     20,000       1300       Furnished
No

   Bathroom Facing_direction
0       1.0        NorthWest
1       3.0            South
2       2.0              NaN
3       1.0              NaN
4       2.0              NaN

Shape of the dataset (rows, columns): (14000, 12)

Data types of columns:
<class 'pandas.core.frame.DataFrame'>
Index: 14000 entries, 0 to 13999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Size              14000 non-null  int64
```

```
 1   Size_unit          14000 non-null  object
 2   Property_type      14000 non-null  object
 3   Location           14000 non-null  object
 4   Seller_name        14000 non-null  object
 5   Seller_type        14000 non-null  object
 6   Rent_price         14000 non-null  object
 7   Area_sqft          14000 non-null  int64
 8   Status             14000 non-null  object
 9   Security_deposit   14000 non-null  object
 10  Bathroom           6217 non-null   float64
 11  Facing_direction   2924 non-null   object
dtypes: float64(1), int64(2), object(9)
memory usage: 1.4+ MB
None

Summary stats for numerical columns:
               Size     Area_sqft     Bathroom
count  14000.000000  14000.000000  6217.000000
mean       3.106643   3116.115571     2.193663
std        1.155827   2255.780445     0.964027
min        0.000000    150.000000     1.000000
25%        2.000000   1000.000000     2.000000
50%        3.000000   2741.000000     2.000000
75%        4.000000   5896.000000     3.000000
max        9.000000  14521.000000     9.000000

Summary stats for object columns:
       Size_unit      Property_type Location           Seller_name  \
count      14000              14000    14000                 14000
unique         3                  7      381                   574
top          BHK  Independent Floor    Saket  B Kumar and Brothers
freq       13621               9273      698                  6914

       Seller_type Rent_price       Status Security_deposit
Facing_direction
count        14000      14000        14000            14000
2924
unique           4        654            3              459
8
top          Agent     3.01 L  Unfurnished               No
NorthEast
freq         13490       2233         7573             5813
932

Number of unique values in each column:
- Size: 10 unique values
- Size_unit: 3 unique values
- Property_type: 7 unique values
- Location: 381 unique values
- Seller_name: 574 unique values
```

```
- Seller_type: 4 unique values
- Rent_price: 654 unique values
- Area_sqft: 547 unique values
- Status: 3 unique values
- Security_deposit: 459 unique values
- Bathroom: 9 unique values
- Facing_direction: 8 unique values
```

```python
print("--- Data Cleaning and Preprocessing ---")

# 1. Get the initial number of rows
initial_rows = df.shape[0]

# 2. Drop duplicate rows
df.drop_duplicates(inplace=True)

# 3. Print information about dropped duplicates
print(f"\nDropped {initial_rows - df.shape[0]} duplicate rows.")
print(f"Shape after dropping duplicates: {df.shape}")
```

```
--- Data Cleaning and Preprocessing ---

Dropped 3827 duplicate rows.
Shape after dropping duplicates: (10173, 12)
```

```python
#Removing irrelevant columns
columns_to_drop_next = [] # Use a different name to avoid confusion if
cell is re-run

if 'Seller_name' in df.columns:
    columns_to_drop_next.append('Seller_name')
if 'Security_deposit' in df.columns:
    columns_to_drop_next.append('Security_deposit') #caused  target
leakage and overfitting

if columns_to_drop_next:
    df.drop(columns=columns_to_drop_next, axis=1, inplace=True)
    print(f"Dropped columns: {columns_to_drop_next}")
else:
    print("No further columns to drop (Seller_name,
Security_deposit).")


print("\nDataFrame columns after dropping:")
print(df.columns)
```

```
Dropped columns: ['Seller_name', 'Security_deposit']

DataFrame columns after dropping:
Index(['Size', 'Size_unit', 'Property_type', 'Location',
'Seller_type',
```

```
       'Rent_price', 'Area_sqft', 'Status', 'Bathroom',
'Facing_direction'],
      dtype='object')
```

```
# 1. Gets the initial number of rows BEFORE cleaning
initial_rows = df.shape[0]
#Logs how many rows have 'Size' exactly equal to 0
if 'Size' in df.columns:
    print(f"Number of rows where 'Size' is exactly 0: {(df['Size'] ==
0).sum()}")

    # 2. Filters out rows where 'Size' is exactly 0
    df = df[df['Size'] != 0]

    rows_removed = initial_rows - df.shape[0]
    print(f"Initial number of rows: {initial_rows}")
    print(f"Removed {rows_removed} rows where 'Size' was exactly 0.")
    print(f"New shape of DataFrame: {df.shape}")
else:
    print("Column 'Size' not found.")
```

```
Number of rows where 'Size' is exactly 0: 3
Initial number of rows: 10173
Removed 3 rows where 'Size' was exactly 0.
New shape of DataFrame: (10170, 10)
```

```
if 'Size' in df.columns:
    print(df['Size'].min())
```

```
1
```

```
#Converts 'Rent_price' to numeric
if 'Rent_price' in df.columns:
    print(f"\n'Rent_price' column before conversion (first 5): \
n{df['Rent_price'].head()}")
    print(f"Data type of 'Rent_price' before:
{df['Rent_price'].dtype}")

    def convert_price_to_numeric(price_str):
        price_str = str(price_str).replace(',', '') # Ensure it's a
string before replace
        price_str = price_str.strip().upper()
        if 'L' in price_str:
            return float(price_str.replace('L', '')) * 100000
        return float(price_str)

    df['Rent_price'] =
df['Rent_price'].apply(convert_price_to_numeric)

    print(f"\n'Rent_price' column after conversion (first 5): \
n{df['Rent_price'].head()}")
```

```
    print(f"Data type of 'Rent_price' after:
{df['Rent_price'].dtype}")
else:
    print("Column 'Rent_price' not found.")
```

```
'Rent_price' column before conversion (first 5):
0     8,500
1    48,000
2    20,000
3    11,000
4    20,000
Name: Rent_price, dtype: object
Data type of 'Rent_price' before: object

'Rent_price' column after conversion (first 5):
0     8500.0
1    48000.0
2    20000.0
3    11000.0
4    20000.0
Name: Rent_price, dtype: float64
Data type of 'Rent_price' after: float64
```

```
from sklearn.impute import KNNImputer
print("--- KNN Imputation for 'Bathroom' and related features ---")
num_features_for_knn = ['Bathroom', 'Area_sqft', 'Size']

# Check if all required columns exist
if all(col in df.columns for col in num_features_for_knn):
    print(f"Selected numerical features for KNN:
{num_features_for_knn}")

    df_subset_knn = df[num_features_for_knn].copy()

    original_index = df_subset_knn.index
    original_columns = df_subset_knn.columns

    scaler_knn = StandardScaler() # Use a different name for this
scaler

    scaled_values_array = scaler_knn.fit_transform(df_subset_knn)

    df_scaled_for_knn = pd.DataFrame(scaled_values_array,
columns=original_columns, index=original_index)

    print("\nSample of scaled data before KNN imputation:")
    print(df_scaled_for_knn.head())

    knn_imputer = KNNImputer(n_neighbors=5)
```

```
    imputed_scaled_values_array = 
knn_imputer.fit_transform(df_scaled_for_knn)

    print("\nSample of scaled and imputed data (NumPy array from 
KNNImputer):")
    print(imputed_scaled_values_array[:5])

    imputed_original_scale_array = 
scaler_knn.inverse_transform(imputed_scaled_values_array)

    df_imputed_original_scale = 
pd.DataFrame(imputed_original_scale_array, columns=original_columns, 
index=original_index)

    print("\nSample of imputed data (back to original scale):")
    print(df_imputed_original_scale.head())

    for col in original_columns:
        df[col] = df_imputed_original_scale[col]

    print(f"\nOriginal DataFrame 'df' updated with KNN imputed values 
for columns: {original_columns}.")
    print("Missing values count after KNN imputation for selected 
columns:")
    print(df[num_features_for_knn].isnull().sum())
else:
    print(f"One or more columns for KNN imputation not found in 
DataFrame: {num_features_for_knn}")

--- KNN Imputation for 'Bathroom' and related features ---
Selected numerical features for KNN: ['Bathroom', 'Area_sqft', 'Size']

Sample of scaled data before KNN imputation:
   Bathroom  Area_sqft      Size
0 -1.232181  -1.107162 -0.902441
1  0.843545  -0.882647 -0.072094
2 -0.194318  -0.973316 -0.902441
3 -1.232181  -0.999222 -0.072094
4 -0.194318  -0.761754 -0.072094

Sample of scaled and imputed data (NumPy array from KNNImputer):
[[-1.23218077 -1.1071621  -0.90244088]
 [ 0.84354517 -0.88264662 -0.07209403]
 [-0.1943178  -0.97331633 -0.90244088]
 [-1.23218077 -0.99922197 -0.07209403]
 [-0.1943178  -0.76175367 -0.07209403]]

Sample of imputed data (back to original scale):
   Bathroom  Area_sqft  Size
```

```
0       1.0      500.0   2.0
1       3.0     1020.0   3.0
2       2.0      810.0   2.0
3       1.0      750.0   3.0
4       2.0     1300.0   3.0

Original DataFrame 'df' updated with KNN imputed values for columns:
Index(['Bathroom', 'Area_sqft', 'Size'], dtype='object').
Missing values count after KNN imputation for selected columns:
Bathroom     0
Area_sqft    0
Size         0
dtype: int64
```

```
if 'Facing_direction' in df.columns:
    print(f"Handling 'Facing_direction' with
{df['Facing_direction'].isnull().sum()} missing values
({df['Facing_direction'].isnull().mean()*100:.2f}%).")

    fill_value = "Unknown"
    df['Facing_direction'].fillna(fill_value, inplace=True)

    print(f"Imputed 'Facing_direction' NaNs with '{fill_value}'.")
    print(df['Facing_direction'].value_counts(dropna=False))
else:
    print("Column 'Facing_direction' not found.")
```

```
Handling 'Facing_direction' with 7938 missing values (78.05%).
Imputed 'Facing_direction' NaNs with 'Unknown'.
Facing_direction
Unknown      7938
NorthEast     670
East          543
North         345
West          177
NorthWest     170
South         128
SouthEast     124
SouthWest      75
Name: count, dtype: int64
```

```
if 'Property_type' in df.columns:
    print(df['Property_type'].value_counts())
    wrong_value='ApartmentApartment'
    correct_value='Apartment'
    df['Property_type']=df['Property_type'].replace(wrong_value,
correct_value)
    print(f"Replaced '{wrong_value}' with '{correct_value}' in
'Property_type'.")
    print(df['Property_type'].value_counts())
```

```
else:
    print("Column 'Property_type' not found.")

Property_type
Independent Floor     6275
Apartment             1734
Villa                 1124
Independent House      688
Studio Apartment       288
Penthouse               60
ApartmentApartment       1
Name: count, dtype: int64
Replaced 'ApartmentApartment' with 'Apartment' in 'Property_type'.
Property_type
Independent Floor    6275
Apartment            1735
Villa                1124
Independent House     688
Studio Apartment      288
Penthouse              60
Name: count, dtype: int64

if 'Size_unit' in df.columns:
    print(df['Size_unit'].value_counts())
    wrong_value='BHKBHK'
    correct_value='BHK'
    df['Size_unit']=df['Size_unit'].replace(wrong_value,
correct_value)
    print(f"Replaced '{wrong_value}' with '{correct_value}' in
'Size_unit'.")
    print(df['Size_unit'].value_counts())
else:
    print("Column 'Size_unit' not found.")

Size_unit
BHK       9876
RK         288
BHKBHK       6
Name: count, dtype: int64
Replaced 'BHKBHK' with 'BHK' in 'Size_unit'.
Size_unit
BHK    9882
RK      288
Name: count, dtype: int64

if 'Bathroom' in df.columns:
    num_decimals = (df['Bathroom'] != np.floor(df['Bathroom'])).sum()
    if num_decimals > 0:
        print(f"Found approximately {num_decimals} decimal values in
'Bathroom' column.")
```

```
    df['Bathroom'] = df['Bathroom'].round(0).astype(int)

    print(f"Unique values in 'Bathroom' after rounding : 
{np.sort(df['Bathroom'].unique())}")
else:
    print("Column 'Bathroom' not found.")
```

```
Found approximately 2400 decimal values in 'Bathroom' column.
Unique values in 'Bathroom' after rounding : [1 2 3 4 5 6 7 8 9]
```

```
print("\nPreprocessing (initial cleaning) complete.")
df_cleaned = df.copy()
```

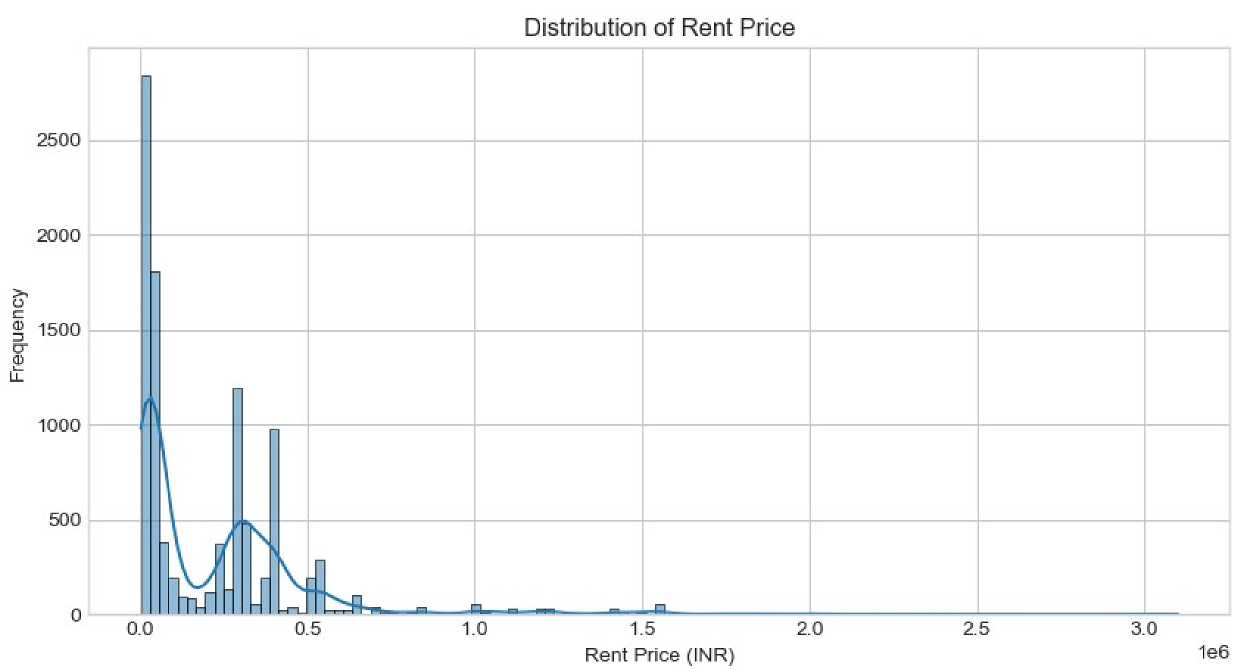
```
Preprocessing (initial cleaning) complete.
```

```
# Step III: Exploratory Data Analysis (EDA)
print("--- III. Exploratory Data Analysis (EDA) ---")

if not df_cleaned.empty:
    # 1. Univariate Analysis
    if 'Rent_price' in df_cleaned.columns:
        print("\nAnalyzing target variable 'Rent_price':")
        plt.figure(figsize=(10, 5))
        sns.histplot(df_cleaned['Rent_price'], kde=True)
        plt.title('Distribution of Rent Price')
        plt.xlabel('Rent Price (INR)')
        plt.ylabel('Frequency')
        plt.show()
        print(f"Rent Price Skewness: 
{df_cleaned['Rent_price'].skew():.2f}")

    if 'Area_sqft' in df_cleaned.columns:
        print("\nAnalyzing 'Area_sqft':")
        plt.figure(figsize=(10, 5))
        sns.histplot(df_cleaned['Area_sqft'], kde=True)
        plt.title('Distribution of Area (sqft)')
        plt.xlabel('Area (sqft)')
        plt.ylabel('Frequency')
        plt.show()

    if 'Bathroom' in df_cleaned.columns:
        print("\nAnalyzing 'Bathroom' counts:")
        plt.figure(figsize=(8, 5))
        sns.countplot(x='Bathroom', data=df_cleaned, 
palette='viridis')
        plt.title('Count of Bathrooms')
        plt.xlabel('Number of Bathrooms')
        plt.ylabel('Number of Properties')
        plt.show()
```

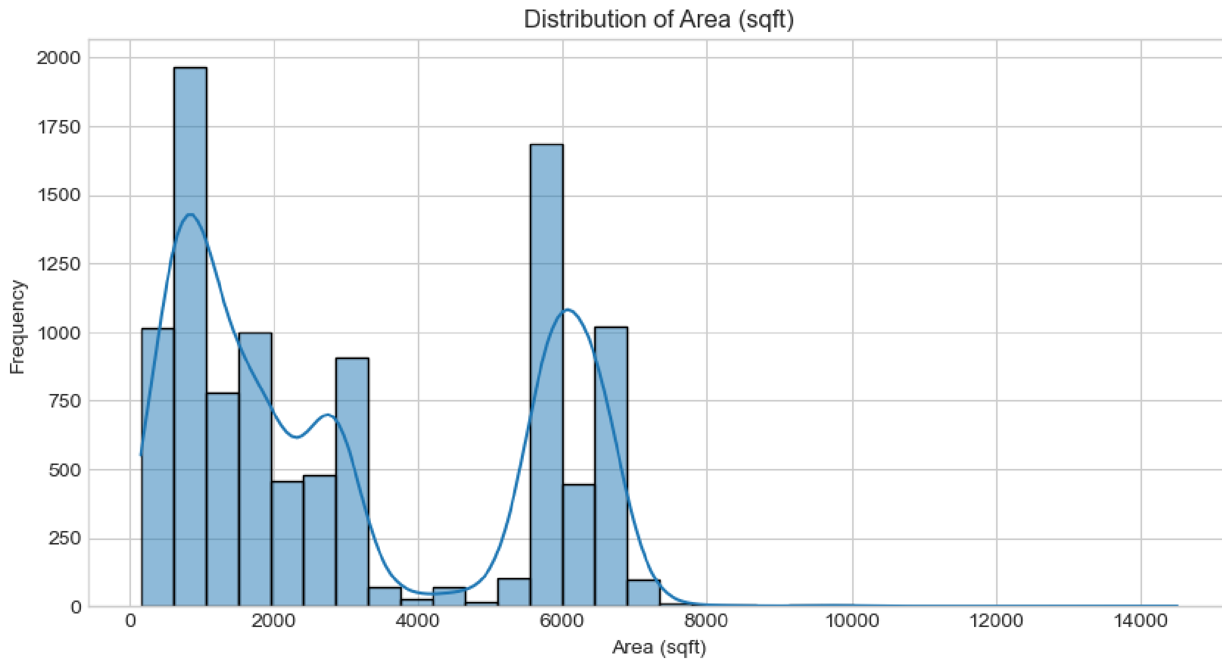
```
    if 'Property_type' in df_cleaned.columns:
        print("\nAnalyzing 'Property_type':")
        plt.figure(figsize=(12, 6))
        df_cleaned['Property_type'].value_counts().plot(kind='bar')
        plt.title('Distribution of Property Types')
        plt.xlabel('Property Type')
        plt.ylabel('Count')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()

    # 2. Bivariate Analysis
    if 'Area_sqft' in df_cleaned.columns and 'Rent_price' in
df_cleaned.columns:
        print("\nRent Price vs. Area_sqft:")
        plt.figure(figsize=(10, 6))
        sns.scatterplot(x='Area_sqft', y='Rent_price',
data=df_cleaned, alpha=0.5)
        plt.title('Rent Price vs. Area (sqft)')
        plt.xlabel('Area (sqft)')
        plt.ylabel('Rent Price (INR)')
        plt.show()

    if 'Property_type' in df_cleaned.columns and 'Rent_price' in
df_cleaned.columns:
        print("\nRent Price by Property Type:")
        plt.figure(figsize=(12, 7))
        sns.boxplot(x='Property_type', y='Rent_price',
data=df_cleaned, palette='Set2')
        plt.title('Rent Price by Property Type')
        plt.xlabel('Property Type')
        plt.ylabel('Rent Price (INR)')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()

    if 'Bathroom' in df_cleaned.columns and 'Rent_price' in
df_cleaned.columns:
        print("\nRent Price by Number of Bathrooms:")
        plt.figure(figsize=(10, 6))
        sns.boxplot(x='Bathroom', y='Rent_price', data=df_cleaned,
palette='coolwarm')
        plt.title('Rent Price by Number of Bathrooms')
        plt.xlabel('Number of Bathrooms')
        plt.ylabel('Rent Price (INR)')
        plt.show()

    # 3. Correlation Analysis
    numerical_df = df_cleaned.select_dtypes(include=np.number)
```

```
    if not numerical_df.empty:
        plt.figure(figsize=(10, 8))
        correlation_matrix = numerical_df.corr()
        sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f", linewidths=.5)
        plt.title('Correlation Matrix of Numerical Features')
        plt.show()
    else:
        print("No numerical features found for correlation analysis.")
else:
    print("df_cleaned is empty. Skipping EDA.")

print("\nEDA complete.")
df_eda_done = df_cleaned.copy()
```

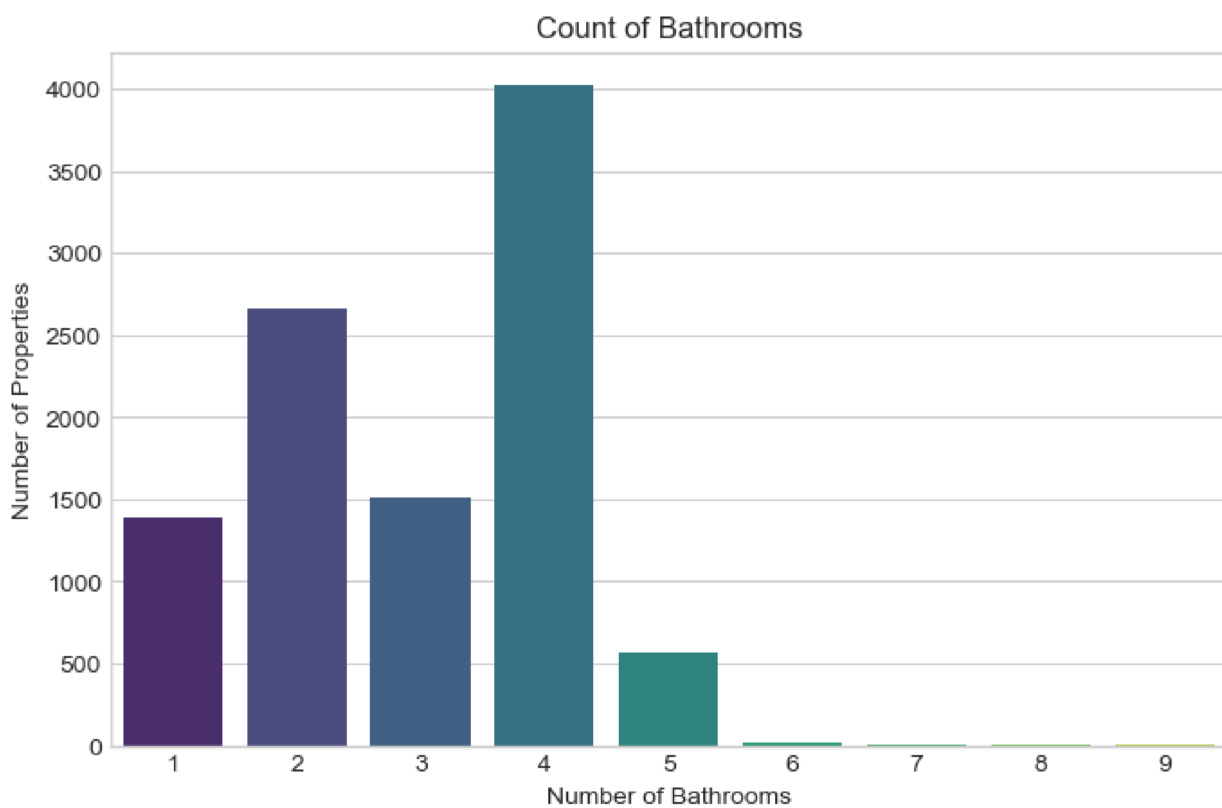
```
--- III. Exploratory Data Analysis (EDA) ---

Analyzing target variable 'Rent_price':
```



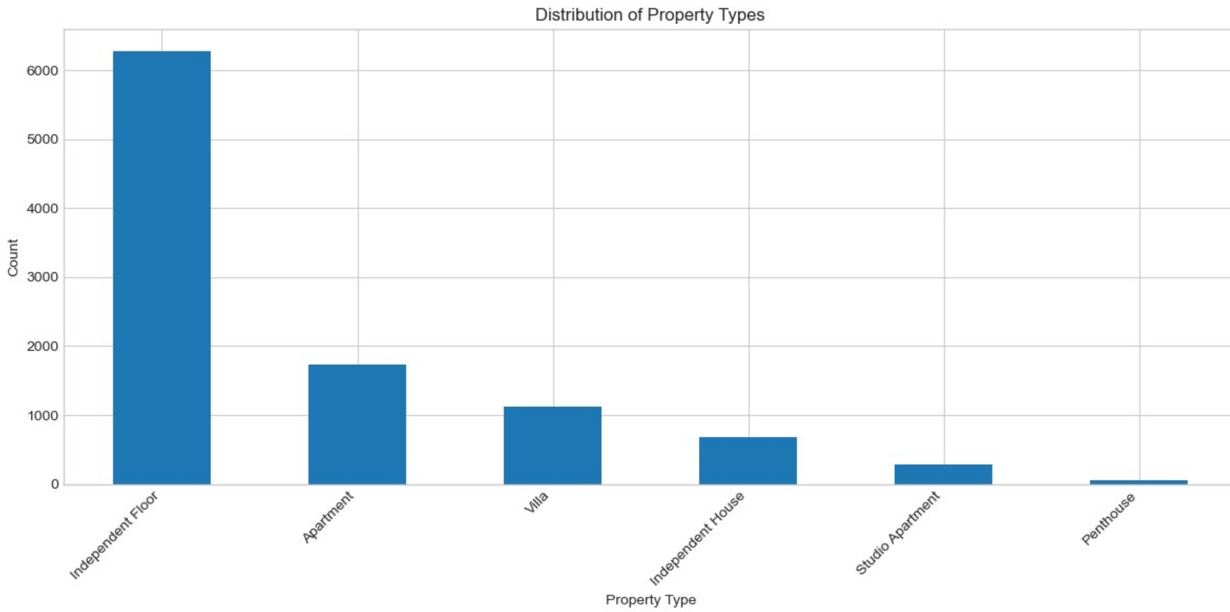

```
Rent Price Skewness: 2.94

Analyzing 'Area_sqft':
```




```
Analyzing 'Bathroom' counts:
```

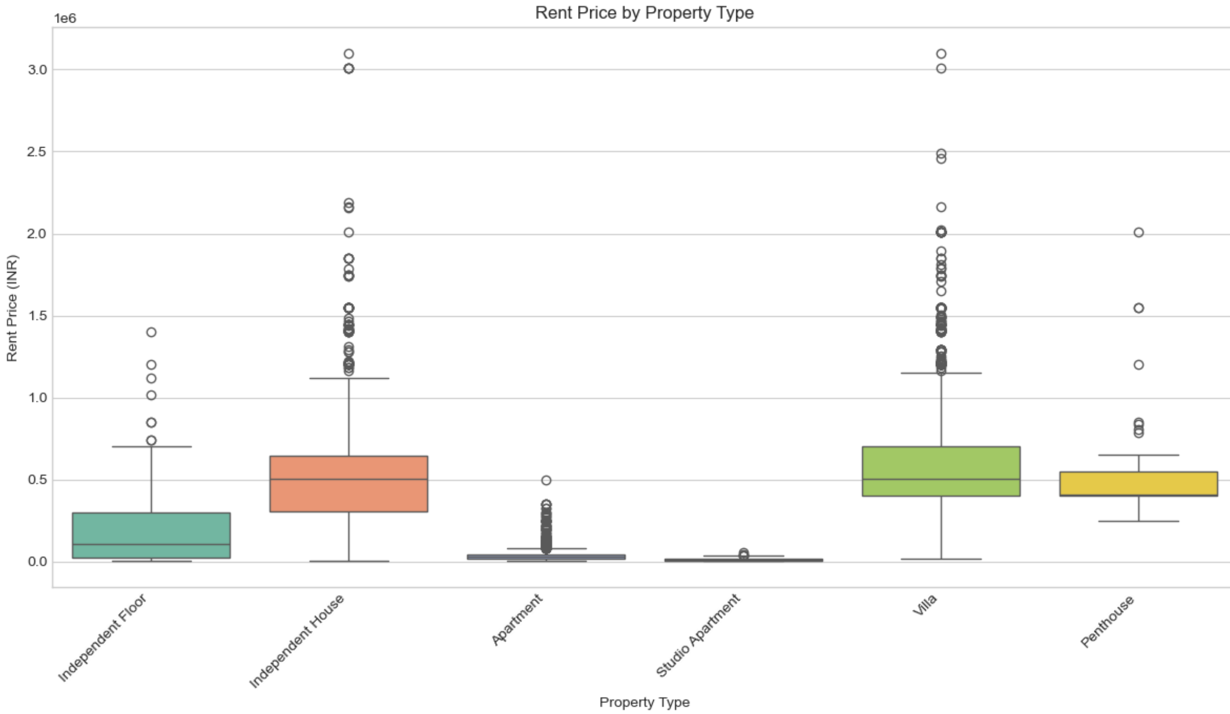


`Analyzing 'Property_type':`

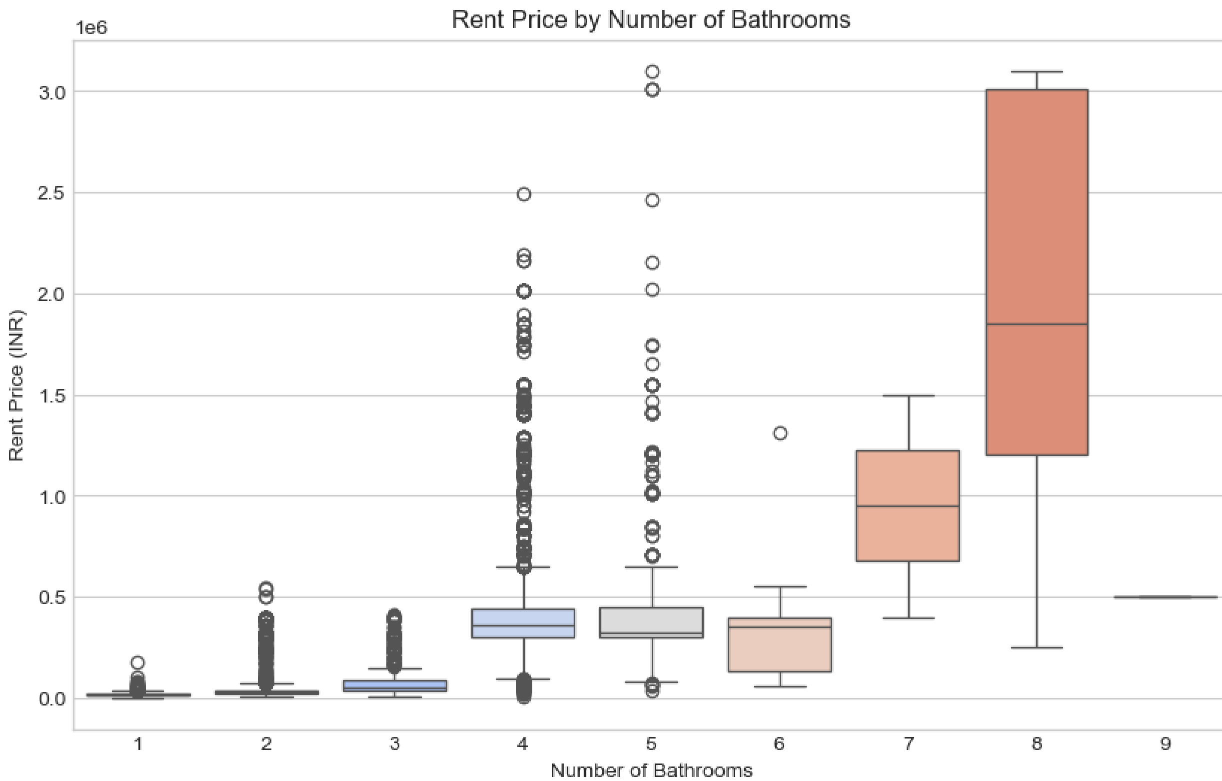


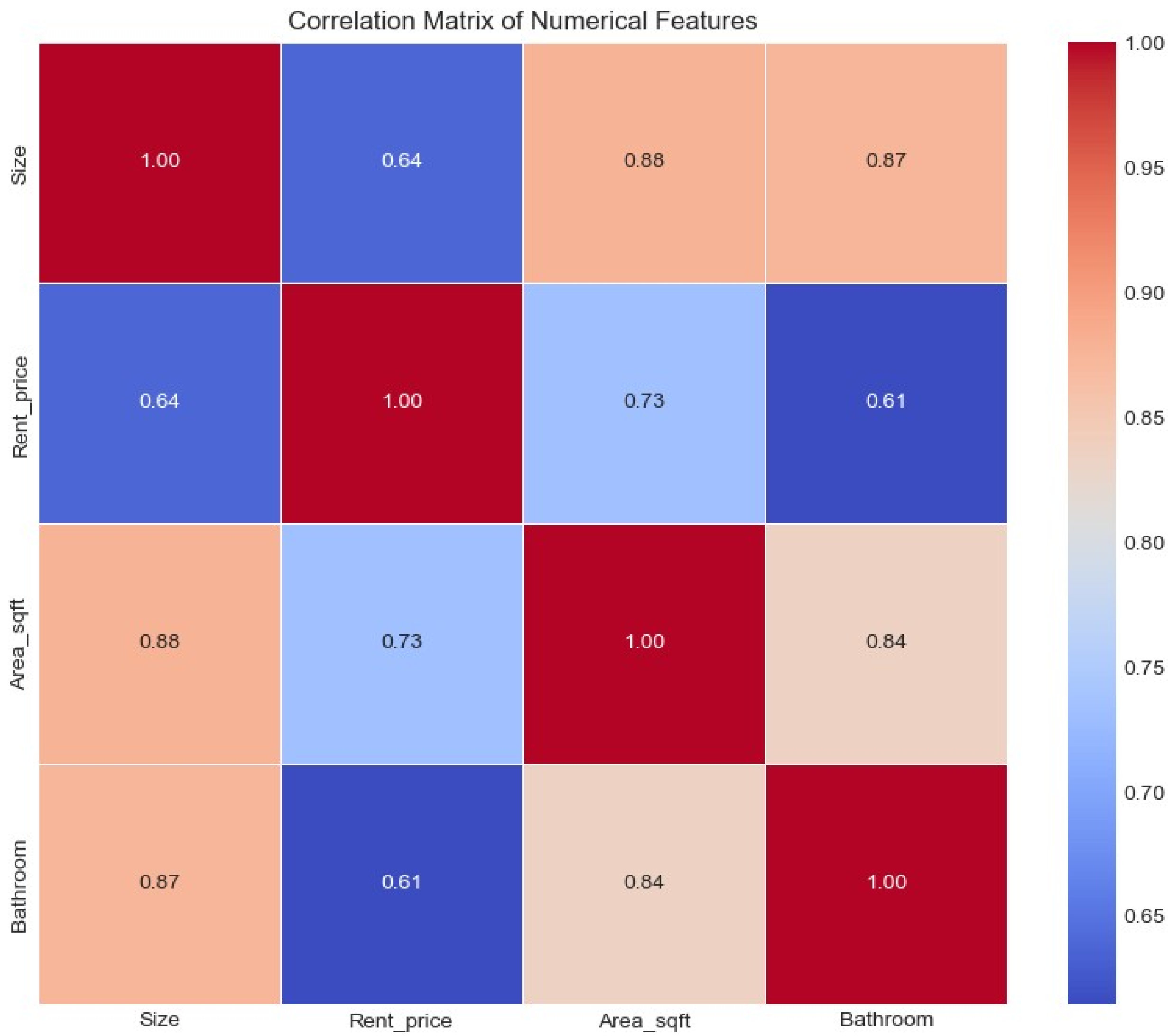

`Rent Price vs. Area_sqft:`

```
Rent Price by Property Type:
```



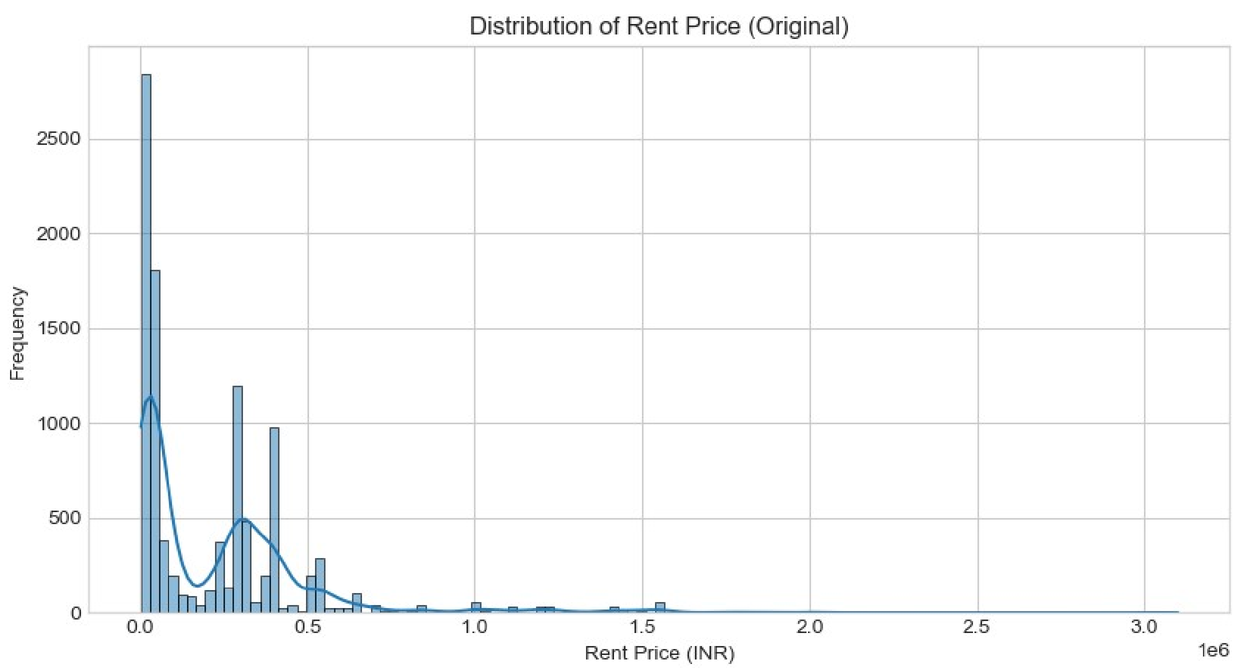

```
Rent Price by Number of Bathrooms:
```


Rent Price by Number of Bathrooms
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Rent Price (INR)
1
2
3
4
5
6
7
8
9
Number of Bathrooms

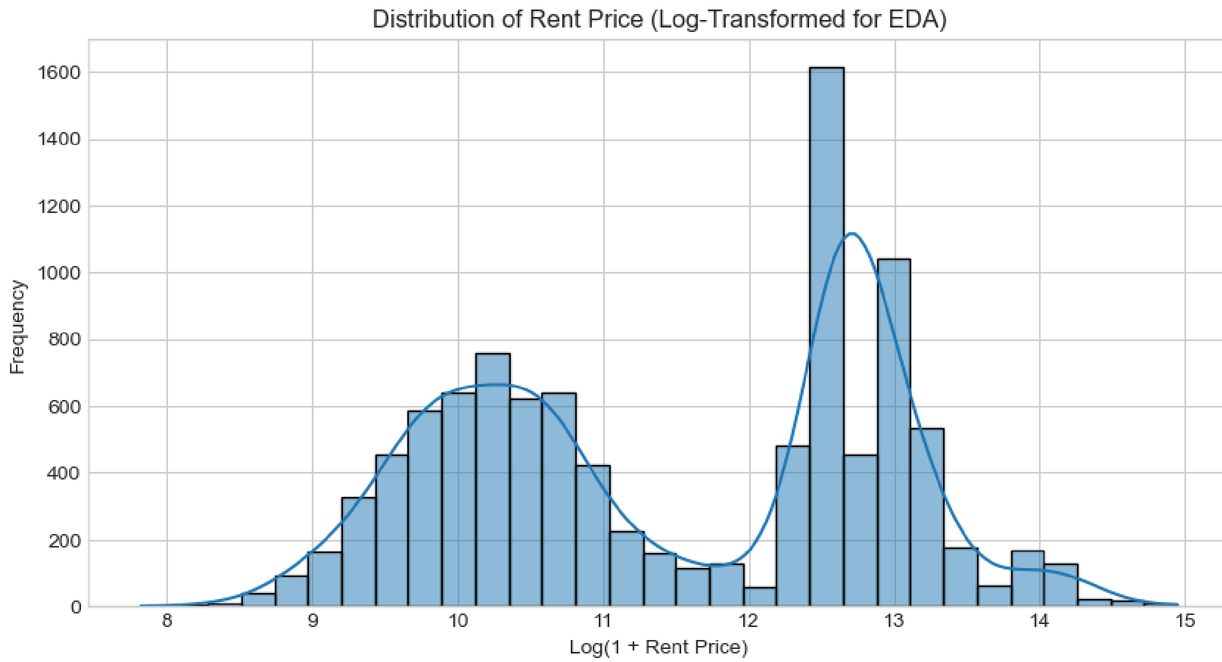



```
EDA complete.

print("--- IV. Feature Engineering ---")
from category_encoders import CatBoostEncoder

--- IV. Feature Engineering ---

from sklearn.linear_model import Ridge
import xgboost as xgb

# --- II. Exploratory Data Analysis (Brief) ---
print("\n--- II. Exploratory Data Analysis (Brief) ---")

plt.figure(figsize=(10, 5))
sns.histplot(df_cleaned['Rent_price'], kde=True)
plt.title('Distribution of Rent Price (Original)')
```

```
plt.xlabel('Rent Price (INR)')
plt.ylabel('Frequency')
plt.show()
print(f"Skewness of original Rent_price:
{df_cleaned['Rent_price'].skew():.2f}")

# Attempt log transformation for EDA
rent_price_log_transformed = np.log1p(df_cleaned['Rent_price'])
plt.figure(figsize=(10, 5))
sns.histplot(rent_price_log_transformed, kde=True)
plt.title('Distribution of Rent Price (Log-Transformed for EDA)')
plt.xlabel('Log(1 + Rent Price)')
plt.ylabel('Frequency')
plt.show()
print(f"Skewness of log-transformed Rent_price:
{rent_price_log_transformed.skew():.2f}")



--- II. Exploratory Data Analysis (Brief) ---
```




```
Skewness of original Rent_price: 2.94
```




```
Skewness of log-transformed Rent_price: -0.05

EDA Observation:
Log-transforming 'Rent_price' significantly reduced its skewness
(e.g., from a high value to near 0).
However, the log-transformed distribution appeared to be bimodal
(having two distinct peaks).
Initial modeling attempts with the log-transformed target, when
evaluated on the original scale
(after back-transformation), resulted in worse RMSE and MAE compared
to modeling the original
'Rent_price' directly. This suggests that while the transformation
helps with symmetry, the
bimodality introduces complexities that the models (or the simple
back-transformation)
struggle with, leading to poorer predictive accuracy on the original
scale.
Therefore, for the main modeling pipeline, we will proceed with the
original 'Rent_price'
as the target and rely on robust models or specific strategies (if
bimodality persists as an issue)
rather than a global log transformation of the target.


# --- III. Feature Engineering Setup ---
print("\n--- III. Feature Engineering Setup ---")

X = df_cleaned.drop(['Rent_price'], axis=1)
```

```
y = df_cleaned['Rent_price']

numerical_features_knn = []
if 'Size' in X.columns: numerical_features_knn.append('Size')
if 'Bathroom' in X.columns: numerical_features_knn.append('Bathroom')
if 'Area_sqft' in X.columns:
numerical_features_knn.append('Area_sqft')

if not all(f in X.columns for f in ['Size', 'Bathroom', 'Area_sqft']):
    print("Warning: One or more of 'Size', 'Bathroom', 'Area_sqft' are
missing. KNN Imputation might be affected.")
    numerical_features_knn = [f for f in ['Size', 'Bathroom',
'Area_sqft'] if f in X.columns]


categorical_ohe_features = []
for col in ['Property_type', 'Seller_type', 'Size_unit', 'Status',
'Facing_direction']:
    if col in X.columns:
        categorical_ohe_features.append(col)

catboost_feature = []
if 'Location' in X.columns:
    catboost_feature.append('Location')
else:
    print("ERROR: 'Location' column not found for CatBoostEncoding ")


all_pipeline_features = numerical_features_knn +
categorical_ohe_features + catboost_feature
unknown_cols = [col for col in X.columns if col not in
all_pipeline_features]
if unknown_cols:
    print(f"Warning: The following columns are in X but not assigned
to a pipeline: {unknown_cols}. )

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

print(f"X_train shape: {X_train.shape}, X_test shape: {X_test.shape}")
print(f"Numerical features for KNN & Scaling:
{numerical_features_knn}")
print(f"Categorical features for OHE: {categorical_ohe_features}")
print(f"Feature for CatBoostEncoding: {catboost_feature}")


# --- IV. Preprocessing Pipelines ---
print("\n--- IV. Preprocessing Pipelines ---")

numeric_transformer = Pipeline(steps=[
```

```
    ('imputer_knn', KNNImputer()),
    ('scaler', StandardScaler())
])

ohe_transformer = Pipeline(steps=[
    ('imputer_cat', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore',
sparse_output=False))
])


transformers_list = []
has_knn_step = False
if numerical_features_knn:
    transformers_list.append(('num_knn', numeric_transformer,
numerical_features_knn))
    has_knn_step = True

has_cb_step = False
if categorical_ohe_features:
    transformers_list.append(('ohe', ohe_transformer,
categorical_ohe_features))
if catboost_feature:
    transformers_list.append(('cb',
CatBoostEncoder(handle_unknown='value', handle_missing='value'),
catboost_feature))
    has_cb_step = True

if not transformers_list:
    print("ERROR: No features available for preprocessing. Exiting.")
    preprocessor = None # Avoid NameError later if script continues
else:
    preprocessor = ColumnTransformer(
        transformers=transformers_list,
        remainder='drop'
    )

# --- V. Model Definition and Hyperparameter Grids ---
print("\n--- V. Model Definition and Hyperparameter Grids ---")


from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
import xgboost as xgb

models_and_params = {
    'Ridge': {
        'model': Ridge(random_state=42),
        'params': {
```

```
            'regressor__alpha': [0.1, 1.0, 10.0, 50.0, 100.0]
        }
    },
    'RandomForestRegressor': {
        'model': RandomForestRegressor(random_state=42, n_jobs=-1),
        'params': {
            'regressor__n_estimators': [100, 200],
            'regressor__max_depth': [10, 20, None],
            'regressor__min_samples_split': [2, 5, 10],
            'regressor__min_samples_leaf': [1, 2, 4]
        }
    },
    'GradientBoostingRegressor': {
        'model': GradientBoostingRegressor(random_state=42),
        'params': {
            'regressor__n_estimators': [100, 200],
            'regressor__learning_rate': [0.01, 0.05, 0.1],
            'regressor__max_depth': [3, 5, 7],
            'regressor__subsample': [0.7, 0.8, 1.0]
        }
    },
    'XGBRegressor': {
        'model': xgb.XGBRegressor(random_state=42, n_jobs=-1,
objective='reg:squarederror'),
        'params': {

            'regressor__n_estimators': [100, 150],
            'regressor__learning_rate': [0.01, 0.05, 0.1],
            'regressor__max_depth': [3, 4, 5],
            'regressor__colsample_bytree': [0.7, 0.8, 0.9],
            'regressor__subsample': [0.7, 0.8, 0.9],
            'regressor__gamma': [0, 0.1, 0.2],
            'regressor__reg_alpha': [0, 0.01, 0.1],
            'regressor__reg_lambda': [1, 0.1, 0.01]
        }
    }
}


for model_name in models_and_params:
    if has_knn_step:

        models_and_params[model_name]['params']
['preprocessor__num_knn__imputer_knn__n_neighbors'] = [3, 5, 7, 9]
    if has_cb_step:
        models_and_params[model_name]['params']
['preprocessor__cb__sigma'] = [0.05, 0.1, 0.2, 0.4]


print("XGBoost params after conditional additions:",
```

```
models_and_params['XGBRegressor']['params'])


# --- VI. GridSearchCV for Model Training and Tuning ---
print("\n--- VI. GridSearchCV for Model Training and Tuning ---")

best_estimators = {}
results_summary = []


if preprocessor is None:
    print("ERROR: Preprocessor not defined. Cannot proceed with
GridSearchCV.")
    # exit() or handle
else:
    for name, config in models_and_params.items():
        print(f"\n--- Tuning {name} ---")
        model = config['model']
        param_grid = config['params']

        pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                                   ('regressor', model)])


        grid_search = GridSearchCV(pipeline, param_grid, cv=3,
                                   scoring='neg_mean_squared_error',
                                   verbose=1, n_jobs=-1)

        try:
            grid_search.fit(X_train, y_train)


            best_cv_rmse = np.sqrt(-grid_search.best_score_)

            print(f"Best parameters for {name}:
{grid_search.best_params_}")
            print(f"Best CV RMSE (Original Scale):
{best_cv_rmse:.2f}")

            best_estimators[name] = grid_search.best_estimator_


            y_pred_test = grid_search.predict(X_test)

            rmse_original = np.sqrt(mean_squared_error(y_test,
y_pred_test))
            mae_original = mean_absolute_error(y_test, y_pred_test)
            r2_original = r2_score(y_test, y_pred_test)

            print(f"Test RMSE (Original Scale) for {name}:
```

```
{rmse_original:.2f}")
            print(f"Test MAE (Original Scale) for {name}:
{mae_original:.2f}")
            print(f"Test R2 (Original Scale) for {name}:
{r2_original:.4f}")

            results_summary.append({
                'Model': name,
                'Best CV RMSE (Original)': best_cv_rmse,
                'Test RMSE (Original)': rmse_original,
                'Test MAE (Original)': mae_original,
                'Test R2 (Original)': r2_original,
                'Best Params': grid_search.best_params_
            })

        except Exception as e:
            print(f"ERROR during GridSearchCV for {name}: {e}")
            results_summary.append({
                'Model': name,
                'Best CV RMSE (Original)': np.nan,
                'Test RMSE (Original)': np.nan,
                'Test MAE (Original)': np.nan,
                'Test R2 (Original)': np.nan,
                'Best Params': str(e)
            })


# --- VII. Results Comparison ---
print("\n--- VII. Results Comparison ---")
if not results_summary:
    print("No models were tuned. Results summary is empty.")
else:
    results_df = pd.DataFrame(results_summary)
    results_df = results_df.sort_values(by='Test RMSE (Original)',
ascending=True)
    print(results_df[['Model', 'Test RMSE (Original)', 'Test MAE
(Original)', 'Test R2 (Original)', 'Best CV RMSE (Original)']])

    if not results_df.empty and results_df['Test RMSE
(Original)'].notna().any():
        best_model_name_from_df = results_df.iloc[0]['Model']
        best_overall_pipeline_from_df =
best_estimators.get(best_model_name_from_df)
        print(f"\nBest overall model based on Test RMSE (Original
Scale): {best_model_name_from_df}")
        if best_overall_pipeline_from_df:
            print("Best parameters for the best model:")
            best_params_dict = results_df.iloc[0]['Best Params']
            if isinstance(best_params_dict, dict):
                 for k, v in best_params_dict.items():
```

```
                    print(f"  {k}: {v}")
            else:
                print(f"  {best_params_dict}")
        else:
            print(f"Could not retrieve the best pipeline for
{best_model_name_from_df} from 'best_estimators'. This might happen if
its GridSearchCV failed.")
    else:
        print("\nNo models were successfully trained and evaluated, or
results are all NaN.")
        best_overall_pipeline_from_df = None
```

--- III. Feature Engineering Setup --- X_train shape: (8136, 9), X_test shape: (2034, 9) Numerical features for KNN & Scaling: ['Size', 'Bathroom', 'Area_sqft'] Categorical features for OHE: ['Property_type', 'Seller_type', 'Size_unit', 'Status', 'Facing_direction'] Feature for CatBoostEncoding: ['Location']

--- IV. Preprocessing Pipelines ---

--- V. Model Definition and Hyperparameter Grids --- XGBoost params after conditional additions: {'regressor__n_estimators': [100, 150], 'regressor__learning_rate': [0.01, 0.05, 0.1], 'regressor__max_depth': [3, 4, 5], 'regressor__colsample_bytree': [0.7, 0.8, 0.9], 'regressor__subsample': [0.7, 0.8, 0.9], 'regressor__gamma': [0, 0.1, 0.2], 'regressor__reg_alpha': [0, 0.01, 0.1], 'regressor__reg_lambda': [1, 0.1, 0.01], 'preprocessor__num_knn__imputer_knn__n_neighbors': [3, 5, 7, 9], 'preprocessor__cb__sigma': [0.05, 0.1, 0.2, 0.4]}

--- VI. GridSearchCV for Model Training and Tuning ---

--- Tuning Ridge --- Fitting 3 folds for each of 80 candidates, totalling 240 fits Best parameters for Ridge: {'preprocessor__cb__sigma': 0.05, 'preprocessor__num_knn__imputer_knn__n_neighbors': 3, 'regressor__alpha': 50.0} Best CV RMSE (Original Scale): 137829.08 Test RMSE (Original Scale) for Ridge: 131942.56 Test MAE (Original Scale) for Ridge: 78776.34 Test R2 (Original Scale) for Ridge: 0.7930

--- Tuning RandomForestRegressor --- Fitting 3 folds for each of 864 candidates, totalling 2592 fits Best parameters for RandomForestRegressor: {'preprocessor__cb__sigma': 0.05, 'preprocessor__num_knn__imputer_knn__n_neighbors': 7, 'regressor__max_depth': 10, 'regressor__min_samples_leaf': 2, 'regressor__min_samples_split': 10, 'regressor__n_estimators': 200} Best CV RMSE (Original Scale): 95588.18 Test RMSE (Original Scale) for RandomForestRegressor: 90949.09 Test MAE (Original Scale) for RandomForestRegressor: 43666.99 Test R2 (Original Scale) for RandomForestRegressor: 0.9016

--- Tuning GradientBoostingRegressor --- Fitting 3 folds for each of 864 candidates, totalling 2592 fits Best parameters for GradientBoostingRegressor: {'preprocessor__cb__sigma': 0.05, 'preprocessor__num_knn__imputer_knn__n_neighbors': 9, 'regressor__learning_rate': 0.05, 'regressor__max_depth': 5, 'regressor__n_estimators': 100, 'regressor__subsample': 0.7} Best CV RMSE (Original Scale): 98531.55 Test RMSE (Original Scale) for GradientBoostingRegressor:

95310.22 Test MAE (Original Scale) for GradientBoostingRegressor: 45558.64 Test R2 (Original Scale) for GradientBoostingRegressor: 0.8920

--- Tuning XGBRegressor --- Fitting 3 folds for each of 69984 candidates, totalling 209952 fits Best parameters for XGBRegressor: {'preprocessor__cb__sigma': 0.05, 'preprocessor__num_knn__imputer_knn__n_neighbors': 3, 'regressor__colsample_bytree': 0.9, 'regressor__gamma': 0.1, 'regressor__learning_rate': 0.05, 'regressor__max_depth': 5, 'regressor__n_estimators': 100, 'regressor__reg_alpha': 0.1, 'regressor__reg_lambda': 1, 'regressor__subsample': 0.8} Best CV RMSE (Original Scale): 96414.59 Test RMSE (Original Scale) for XGBRegressor: 92050.17 Test MAE (Original Scale) for XGBRegressor: 44714.89 Test R2 (Original Scale) for XGBRegressor: 0.8992

--- VII. Results Comparison --- Model Test RMSE (Original) Test MAE (Original) 1
RandomForestRegressor 90949.087599 43666.988835
3 XGBRegressor 92050.168191 44714.887717
2 GradientBoostingRegressor 95310.224543 45558.642010
0 Ridge 131942.564854 78776.344741

Test R2 (Original) Best CV RMSE (Original)
1 0.901639 95588.179749
3 0.899243 96414.593659
2 0.891980 98531.551378
0 0.792988 137829.078117

Best overall model based on Test RMSE (Original Scale): RandomForestRegressor Best parameters for the best model: preprocessor__cb__sigma: 0.05
preprocessor__num_knn__imputer_knn__n_neighbors: 7 regressor__max_depth: 10
regressor__min_samples_leaf: 2 regressor__min_samples_split: 10 regressor__n_estimators: 200

```
import joblib
import os
import sklearn

MODEL_ARTIFACTS_PATH = 'trained_rental_model_artifacts.joblib'
print(f"Attempting to save artifacts to:
{os.path.abspath(MODEL_ARTIFACTS_PATH)}")



print("\n--- Saving Trained Models and Artifacts ---")



if 'best_model_name_from_df' in locals() or 'best_model_name_from_df'
in globals():
    current_best_model_name = best_model_name_from_df
    print(f"Best model identified as: {current_best_model_name}")
elif not results_df.empty and results_df['Test RMSE
(Original)'].notna().any():
```

```
    # If best_model_name_from_df wasn't explicitly set but results_df
exists, try to derive it
    results_df_sorted = results_df.sort_values(by='Test RMSE
(Original)', ascending=True)
    current_best_model_name = results_df_sorted.iloc[0]['Model']
    print(f"Best model derived from results_df:
{current_best_model_name}")
else:
    current_best_model_name = None
    print("Warning: Could not determine the best_model_name_from_df.
It will be saved as None.")

artifacts_to_save = {
    'best_estimators': best_estimators,
    'results_summary_df': results_df,
    'numerical_features_knn': numerical_features_knn,
    'categorical_ohe_features': categorical_ohe_features,
    'catboost_feature': catboost_feature,
    'best_overall_model_name': current_best_model_name,
    'sklearn_version': sklearn.__version__,
    'xgboost_version': xgb.__version__,
}



if preprocessor is not None:
    artifacts_to_save['preprocessor_template'] = preprocessor
    print("Included 'preprocessor_template' (fitted preprocessor
structure) in saved artifacts.")


joblib.dump(artifacts_to_save, MODEL_ARTIFACTS_PATH)
print(f"\nSuccessfully saved artifacts to {MODEL_ARTIFACTS_PATH}")
print("These artifacts include your trained models, results, and
feature definitions.")
```

```
Attempting to save artifacts to: e:\acad_doc\
trained_rental_model_artifacts.joblib

--- Saving Trained Models and Artifacts ---
Best model identified as: RandomForestRegressor
Included 'preprocessor_template' (fitted preprocessor structure) in
saved artifacts.

Successfully saved artifacts to trained_rental_model_artifacts.joblib
These artifacts include your trained models, results, and feature
definitions.
```

```
import joblib

MODEL_ARTIFACTS_PATH = 'trained_rental_model_artifacts.joblib'


loaded_artifacts = joblib.load(MODEL_ARTIFACTS_PATH)

best_estimators = loaded_artifacts['best_estimators']
results_df = loaded_artifacts['results_summary_df']
numerical_features_knn = loaded_artifacts['numerical_features_knn']
categorical_ohe_features =
loaded_artifacts['categorical_ohe_features']
catboost_feature = loaded_artifacts['catboost_feature']
best_overall_model_name = loaded_artifacts['best_overall_model_name']

print("Successfully loaded artifacts.")
print(f"Sklearn version used for training:
{loaded_artifacts.get('sklearn_version', 'N/A')}")
print(f"XGBoost version used for training:
{loaded_artifacts.get('xgboost_version', 'N/A')}")
print(f"Best overall model was: {best_overall_model_name}")


if best_overall_model_name and best_overall_model_name in
best_estimators:
    my_best_pipeline = best_estimators[best_overall_model_name]
    print(f"\nLoaded pipeline for the best model
('{best_overall_model_name}'):")
    print(my_best_pipeline)


# predictions = my_best_pipeline.predict(X_new)
# print(f"Predictions: {predictions[:5]}")
elif best_estimators:
    print("\nBest overall model name not found or specified, but other
models are available in 'best_estimators'.")
    print(f"Available models: {list(best_estimators.keys())}")
```

```
Successfully loaded artifacts.
Sklearn version used for training: 1.4.2
XGBoost version used for training: 2.1.1
Best overall model was: RandomForestRegressor

Loaded pipeline for the best model ('RandomForestRegressor'):
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num_knn',

Pipeline(steps=[('imputer_knn',
```

```
KNNImputer(n_neighbors=7)),

('scaler',

StandardScaler())]),
                                                  ['Size', 'Bathroom',
                                                   'Area_sqft']),
                                                 ('ohe',

Pipeline(steps=[('imputer_cat',

SimpleImputer(strategy='most_frequent')),

('onehot',

OneHotEncoder(handle_unknown='ignore',

sparse_output=False))]),
                                                  ['Property_type',
                                                   'Seller_type',
'Size_unit',
                                                   'Status',

'Facing_direction']),
                                                 ('cb',

CatBoostEncoder(sigma=0.05),
                                                  ['Location'])])),
                ('regressor',
                 RandomForestRegressor(max_depth=10,
min_samples_leaf=2,
                                       min_samples_split=10,
n_estimators=200,
                                       n_jobs=-1, random_state=42))])

input_dict={'Property_type':'Independent Floor',
'Seller_type':'Owner',
'Size_unit':'BHK','Status':'Furnished','Facing_direction':'North','Siz
e' :2,'Bathroom':1,'Area_sqft':350,'Location':'Lajpat Nagar' }
input_df_raw = pd.DataFrame([input_dict])
predictions = my_best_pipeline.predict(input_df_raw)
print(f"Predictions: {predictions[:5]}")

Predictions: [17936.2957136]
```