Real Estate Predictive Model

March 3, 2025

Real Estate Predictive Model by Tony Henein

Introduction:

- This project involves building a predictive model for real estate prices based on a dataset that includes property features and historical prices. Using data collected from various real estate sources, we developed a model that predicts property prices. The system leverages regression analysis, feature engineering, and machine learning algorithms to forecast prices, thereby aiding buyers, sellers, and investors in making informed decisions.

1. Data Collection and Initial Setup The dataset is divided into several files:

1. train.csv: Contains data on various properties including features like size, location, number of rooms, and historical prices.

2. Data Preprocessing The dataset required specific cleaning steps to prepare it for feature engineering:

Properties Data:

- Handled missing values by imputing or removing them as necessary.
- Normalized property features to ensure consistency across different properties.
- Created new features such as price per square foot.

3. Feature Engineering

- Created new features such as neighborhood average price and price growth rate.
- Generated rolling statistics (mean, standard deviation) for property prices to identify trends and anomalies.

4. Model Development

- The real estate predictive model was developed using machine learning algorithms:
- Regression Analysis: Used techniques like Linear Regression and Ridge Regression to model property prices.
- Feature Selection: Applied methods like Lasso Regression to select the most relevant features.
- Advanced Algorithms: Used Random Forest, Gradient Boosting, and XGBoost to improve prediction accuracy.

5. Prediction Function

The function predict_price provides price predictions based on property features:

- Checks if the property ID exists in the dataset.

- Uses the trained model to predict the price based on current features.
- Returns a predicted price and confidence interval.

6. **Evaluation and Improvements**
   - Evaluated model performance using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared.
   - Implemented cross-validation to ensure robustness and generalizability.
   - Fine-tuned hyperparameters to improve prediction accuracy and reduce errors.

[38]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Import train_test_split for splitting the dataset
from sklearn.model_selection import train_test_split

# Import LinearRegression for creating a linear regression model
from sklearn.linear_model import LinearRegression

# Import mean_squared_error and r2_score for evaluating the model
from sklearn.metrics import mean_squared_error, r2_score

# Import PCA for Principal Component Analysis
from sklearn.decomposition import PCA

# accessing directory structure
```

[39]:
```python
# Define the path to the CSV file
csv_file_path = './data/train.csv'

# Define the directory where the dataset is stored
dataset_directory = './data/'

# Load the dataset into a DataFrame
df = pd.read_csv(csv_file_path)

# Display the first few rows of the DataFrame to verify it loaded correctly
print(df.head())

# Display the summary of the DataFrame to understand its structure and contents
print(df.info())

# Display the summary statistics of the DataFrame
print(df.describe())

# Check for missing values in the DataFrame
```

```python
print("\nMissing values in the DataFrame:")
print(df.isnull().sum())
```

```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
```

```
18  OverallCond    1460 non-null   int64
19  YearBuilt      1460 non-null   int64
20  YearRemodAdd   1460 non-null   int64
21  RoofStyle      1460 non-null   object
22  RoofMatl       1460 non-null   object
23  Exterior1st    1460 non-null   object
24  Exterior2nd    1460 non-null   object
25  MasVnrType     588 non-null    object
26  MasVnrArea     1452 non-null   float64
27  ExterQual      1460 non-null   object
28  ExterCond      1460 non-null   object
29  Foundation     1460 non-null   object
30  BsmtQual       1423 non-null   object
31  BsmtCond       1423 non-null   object
32  BsmtExposure   1422 non-null   object
33  BsmtFinType1   1423 non-null   object
34  BsmtFinSF1     1460 non-null   int64
35  BsmtFinType2   1422 non-null   object
36  BsmtFinSF2     1460 non-null   int64
37  BsmtUnfSF      1460 non-null   int64
38  TotalBsmtSF    1460 non-null   int64
39  Heating        1460 non-null   object
40  HeatingQC      1460 non-null   object
41  CentralAir     1460 non-null   object
42  Electrical     1459 non-null   object
43  1stFlrSF       1460 non-null   int64
44  2ndFlrSF       1460 non-null   int64
45  LowQualFinSF   1460 non-null   int64
46  GrLivArea      1460 non-null   int64
47  BsmtFullBath   1460 non-null   int64
48  BsmtHalfBath   1460 non-null   int64
49  FullBath       1460 non-null   int64
50  HalfBath       1460 non-null   int64
51  BedroomAbvGr   1460 non-null   int64
52  KitchenAbvGr   1460 non-null   int64
53  KitchenQual    1460 non-null   object
54  TotRmsAbvGrd   1460 non-null   int64
55  Functional     1460 non-null   object
56  Fireplaces     1460 non-null   int64
57  FireplaceQu    770 non-null    object
58  GarageType     1379 non-null   object
59  GarageYrBlt    1379 non-null   float64
60  GarageFinish   1379 non-null   object
61  GarageCars     1460 non-null   int64
62  GarageArea     1460 non-null   int64
63  GarageQual     1379 non-null   object
64  GarageCond     1379 non-null   object
65  PavedDrive     1460 non-null   object
```

```
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
None
                Id   MSSubClass  LotFrontage        LotArea  OverallQual  \
count  1460.000000  1460.000000  1201.000000    1460.000000  1460.000000
mean    730.500000    56.897260    70.049958   10516.828082     6.099315
std     421.610009    42.300571    24.284752    9981.264932     1.382997
min       1.000000    20.000000    21.000000    1300.000000     1.000000
25%     365.750000    20.000000    59.000000    7553.500000     5.000000
50%     730.500000    50.000000    69.000000    9478.500000     6.000000
75%    1095.250000    70.000000    80.000000   11601.500000     7.000000
max    1460.000000   190.000000   313.000000  215245.000000    10.000000

       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1  …  \
count  1460.000000  1460.000000   1460.000000  1452.000000  1460.000000  …
mean      5.575342  1971.267808   1984.865753   103.685262   443.639726  …
std       1.112799    30.202904     20.645407   181.066207   456.098091  …
min       1.000000  1872.000000   1950.000000     0.000000     0.000000  …
25%       5.000000  1954.000000   1967.000000     0.000000     0.000000  …
50%       5.000000  1973.000000   1994.000000     0.000000   383.500000  …
75%       6.000000  2000.000000   2004.000000   166.000000   712.250000  …
max       9.000000  2010.000000   2010.000000  1600.000000  5644.000000  …

        WoodDeckSF  OpenPorchSF  EnclosedPorch    3SsnPorch  ScreenPorch  \
count  1460.000000  1460.000000    1460.000000  1460.000000  1460.000000
mean     94.244521    46.660274      21.954110     3.409589    15.060959
std     125.338794    66.256028      61.119149    29.317331    55.757415
min       0.000000     0.000000       0.000000     0.000000     0.000000
25%       0.000000     0.000000       0.000000     0.000000     0.000000
50%       0.000000    25.000000       0.000000     0.000000     0.000000
75%     168.000000    68.000000       0.000000     0.000000     0.000000
max     857.000000   547.000000     552.000000   508.000000   480.000000
```

```
          PoolArea        MiscVal        MoSold        YrSold       SalePrice
count  1460.000000    1460.000000   1460.000000   1460.000000    1460.000000
mean      2.758904      43.489041      6.321918   2007.815753  180921.195890
std      40.177307     496.123024      2.703626      1.328095   79442.502883
min       0.000000       0.000000      1.000000   2006.000000   34900.000000
25%       0.000000       0.000000      5.000000   2007.000000  129975.000000
50%       0.000000       0.000000      6.000000   2008.000000  163000.000000
75%       0.000000       0.000000      8.000000   2009.000000  214000.000000
max     738.000000   15500.000000     12.000000   2010.000000  755000.000000

[8 rows x 38 columns]

Missing values in the DataFrame:
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

[40]:

```python
import os

# Ensure the file exists
if not os.path.exists(csv_file_path):
    # Notify if the file does not exist
    print(f"File '{csv_file_path}' does not exist.")
else:
    # Read the CSV file into a DataFrame
    df_data = pd.read_csv(csv_file_path)

    # Display the first 5 records
    print("DataFrame loaded successfully. Displaying the first 5 records:")
    print(df_data.head())  # Show the first 5 rows of the DataFrame
```

```
DataFrame loaded successfully. Displaying the first 5 records:
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1
```

```
  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
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2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

[41]:
```python
# Display the DataFrame
print("DataFrame loaded successfully. Displaying the first few rows:")
print(df_data.head())  # Print the first few rows of the DataFrame to the console

# List all columns and their types
print("\nColumns and their types:")
print(df_data.dtypes)  # Print columns and their types

# Display the summary statistics of the DataFrame
print("\nSummary statistics of the DataFrame:")
print(df_data.describe())  # Print summary statistics for numerical columns

# Check for missing values in the DataFrame
print("\nMissing values in the DataFrame:")
print(df_data.isnull().sum())  # Print the count of missing values for each column
```

```
DataFrame loaded successfully. Displaying the first few rows:
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
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  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
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1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
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4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12
```

```
  YrSold  SaleType  SaleCondition  SalePrice
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1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]

Columns and their types:
Id                 int64
MSSubClass         int64
MSZoning          object
LotFrontage      float64
LotArea            int64
                  …
MoSold             int64
YrSold             int64
SaleType          object
SaleCondition     object
SalePrice          int64
Length: 81, dtype: object

Summary statistics of the DataFrame:
                Id   MSSubClass  LotFrontage        LotArea  OverallQual  \
count  1460.000000  1460.000000  1201.000000    1460.000000  1460.000000
mean    730.500000    56.897260    70.049958   10516.828082     6.099315
std     421.610009    42.300571    24.284752    9981.264932     1.382997
min       1.000000    20.000000    21.000000    1300.000000     1.000000
25%     365.750000    20.000000    59.000000    7553.500000     5.000000
50%     730.500000    50.000000    69.000000    9478.500000     6.000000
75%    1095.250000    70.000000    80.000000   11601.500000     7.000000
max    1460.000000   190.000000   313.000000  215245.000000    10.000000

       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1  …  \
count  1460.000000  1460.000000   1460.000000  1452.000000  1460.000000  …
mean      5.575342  1971.267808   1984.865753   103.685262   443.639726  …
std       1.112799    30.202904     20.645407   181.066207   456.098091  …
min       1.000000  1872.000000   1950.000000     0.000000     0.000000  …
25%       5.000000  1954.000000   1967.000000     0.000000     0.000000  …
50%       5.000000  1973.000000   1994.000000     0.000000   383.500000  …
75%       6.000000  2000.000000   2004.000000   166.000000   712.250000  …
max       9.000000  2010.000000   2010.000000  1600.000000  5644.000000  …

        WoodDeckSF  OpenPorchSF  EnclosedPorch    3SsnPorch  ScreenPorch  \
count  1460.000000  1460.000000    1460.000000  1460.000000  1460.000000
mean     94.244521    46.660274      21.954110     3.409589    15.060959
```
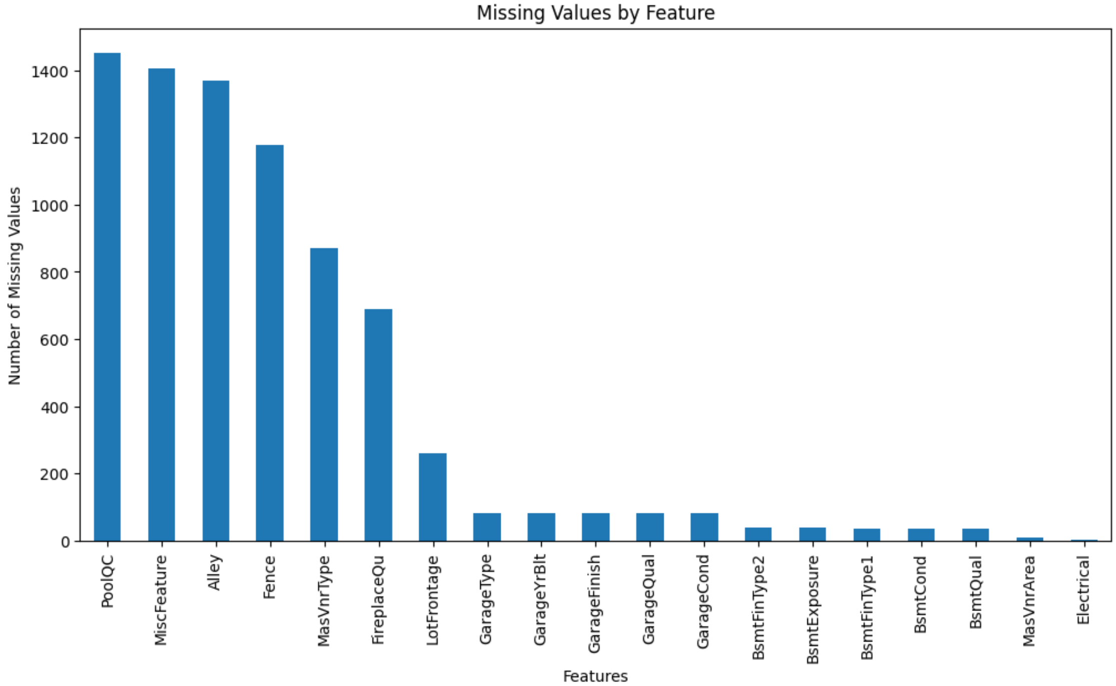

```
std     125.338794   66.256028     61.119149   29.317331    55.757415
min       0.000000    0.000000      0.000000    0.000000     0.000000
25%       0.000000    0.000000      0.000000    0.000000     0.000000
50%       0.000000   25.000000      0.000000    0.000000     0.000000
75%     168.000000   68.000000      0.000000    0.000000     0.000000
max     857.000000  547.000000    552.000000  508.000000   480.000000

          PoolArea       MiscVal       MoSold       YrSold      SalePrice
count  1460.000000   1460.000000  1460.000000  1460.000000    1460.000000
mean      2.758904     43.489041     6.321918  2007.815753  180921.195890
std      40.177307    496.123024     2.703626     1.328095   79442.502883
min       0.000000      0.000000     1.000000  2006.000000   34900.000000
25%       0.000000      0.000000     5.000000  2007.000000  129975.000000
50%       0.000000      0.000000     6.000000  2008.000000  163000.000000
75%       0.000000      0.000000     8.000000  2009.000000  214000.000000
max     738.000000  15500.000000    12.000000  2010.000000  755000.000000

[8 rows x 38 columns]

Missing values in the DataFrame:
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

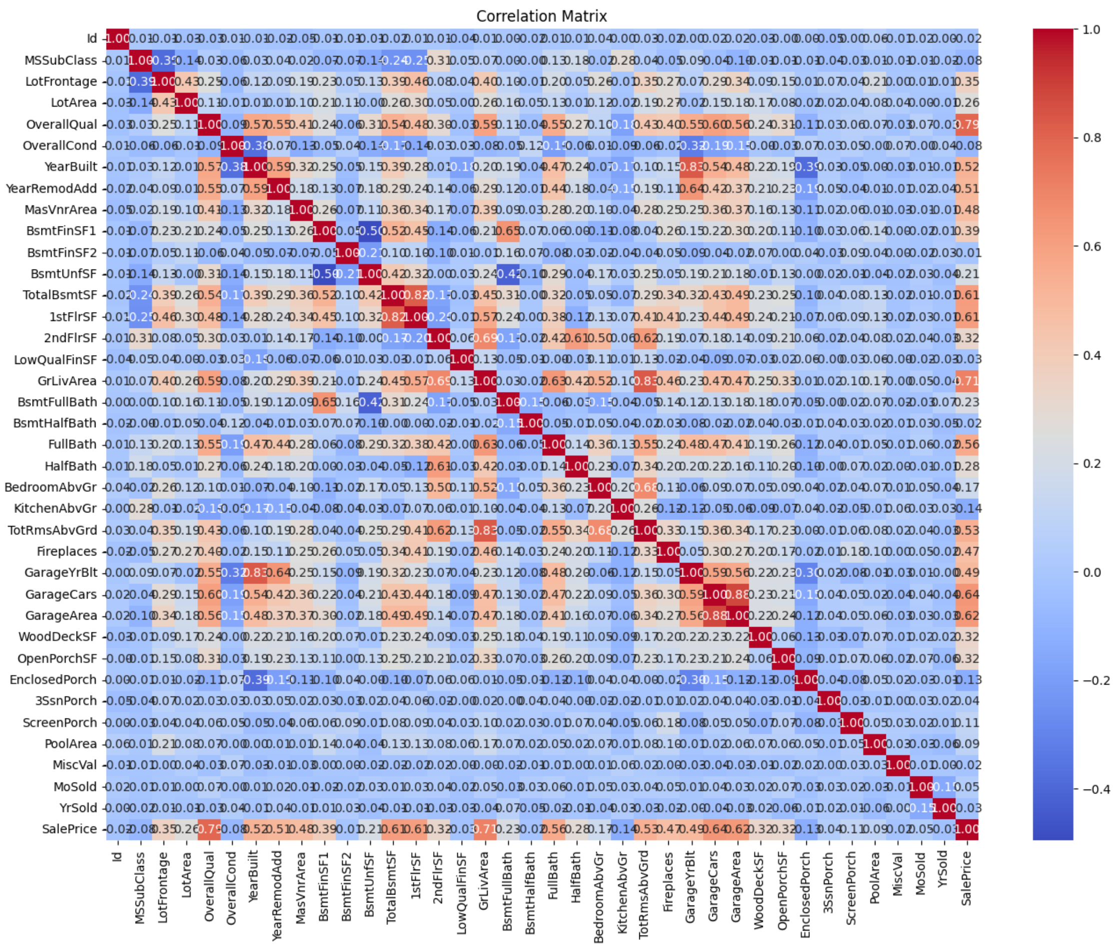
[42]:
```python
# Calculate the number of missing values for each column
missing_values = df_data.isnull().sum()

# Filter columns that have missing values
missing_values = missing_values[missing_values > 0]

# Sort the missing values in descending order
missing_values.sort_values(ascending=False, inplace=True)

# Plot the missing values by feature
plt.figure(figsize=(12, 6))
missing_values.plot(kind='bar')
plt.title('Missing Values by Feature')
plt.xlabel('Features')
```

```
plt.ylabel('Number of Missing Values')
plt.show()
```



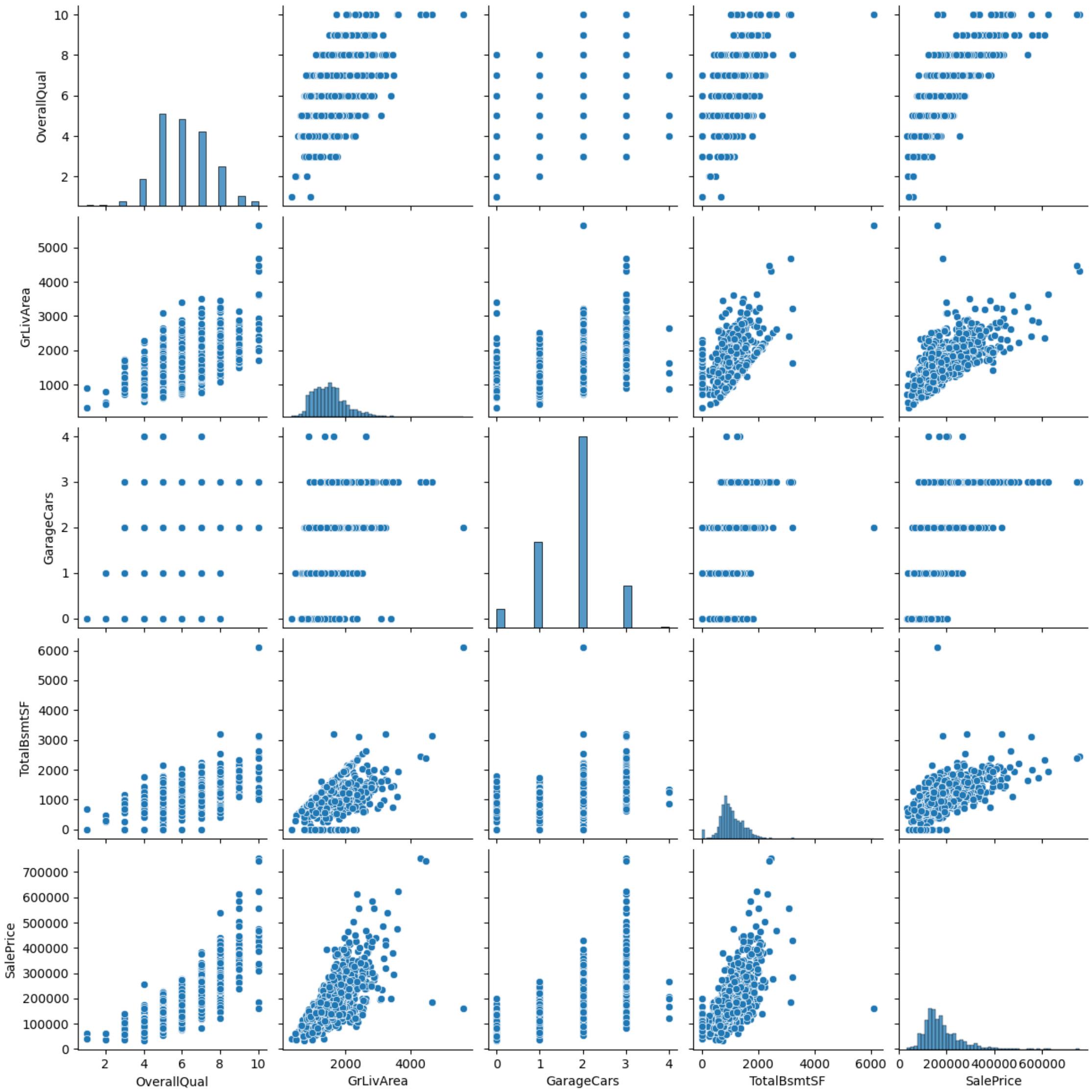
[43]:

```
# Select only numeric columns from the DataFrame
numeric_cols = df_data.select_dtypes(include=[np.number])

# Calculate the correlation matrix for the numeric columns
corr_matrix = numeric_cols.corr()

# Plot the correlation matrix using a heatmap
plt.figure(figsize=(16, 12))
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



[44]:
```python
import seaborn as sns

# Import necessary libraries
import matplotlib.pyplot as plt

# Pairplot for selected features
selected_features = ['OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF',␣
 ↪'SalePrice']

# Check if the selected features exist in the dataframe
missing_features = [feature for feature in selected_features if feature not in␣
 ↪df_data.columns]
if missing_features:
    raise ValueError(f"The following selected features are missing in the␣
 ↪dataframe: {missing_features}")

# Create pairplot for the selected features
```

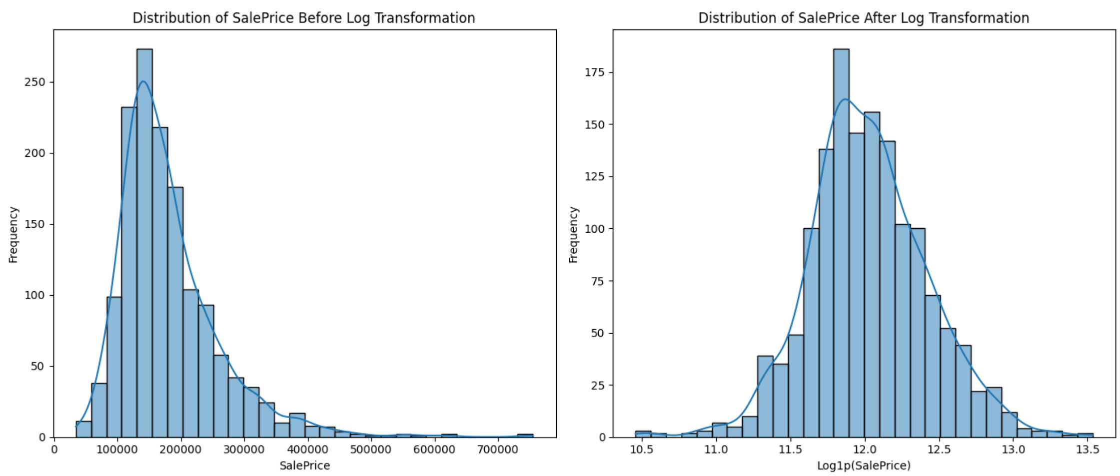
```
sns.pairplot(df_data[selected_features])
plt.show()
```



[45]:
```
# Log transformation of the target variable
df_data['SalePrice'] = np.log1p(df_data['SalePrice'])
```

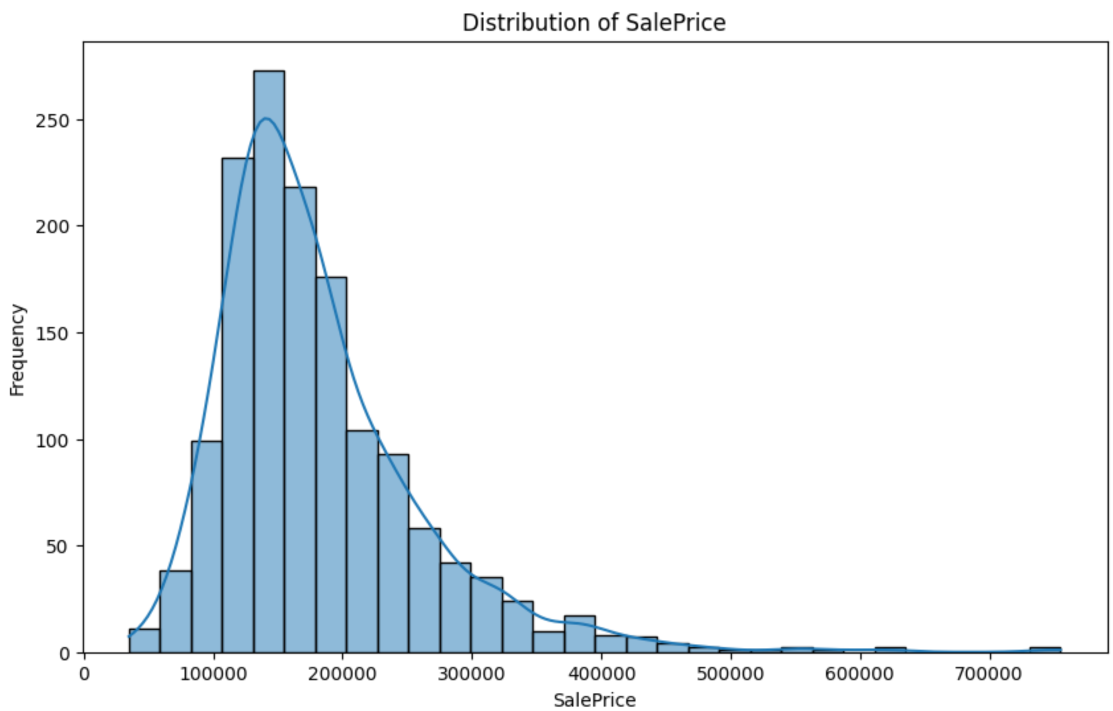
[46]:
```
# Plot the distribution of SalePrice before applying log1p
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
sns.histplot(df['SalePrice'], kde=True, bins=30)
plt.title('Distribution of SalePrice Before Log Transformation')
plt.xlabel('SalePrice')
```

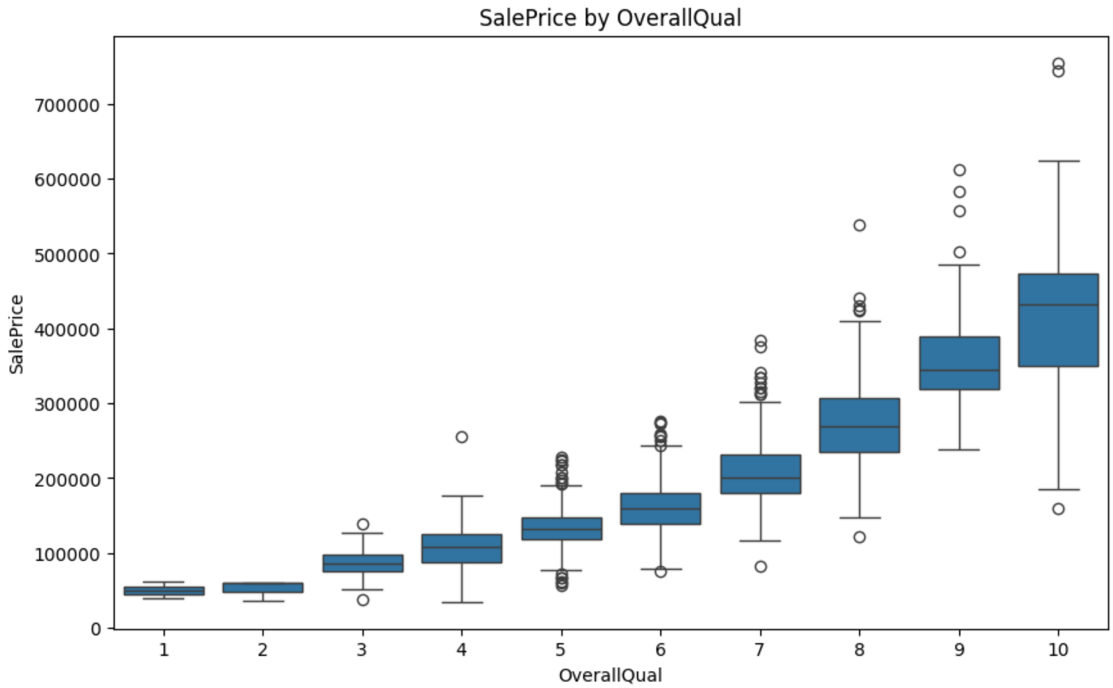
```
plt.ylabel('Frequency')

# Apply log1p transformation to SalePrice
df['SalePrice_Log1p'] = np.log1p(df['SalePrice'])

# Plot the distribution of SalePrice after applying log1p
plt.subplot(1, 2, 2)
sns.histplot(df['SalePrice_Log1p'], kde=True, bins=30)
plt.title('Distribution of SalePrice After Log Transformation')
plt.xlabel('Log1p(SalePrice)')
plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```

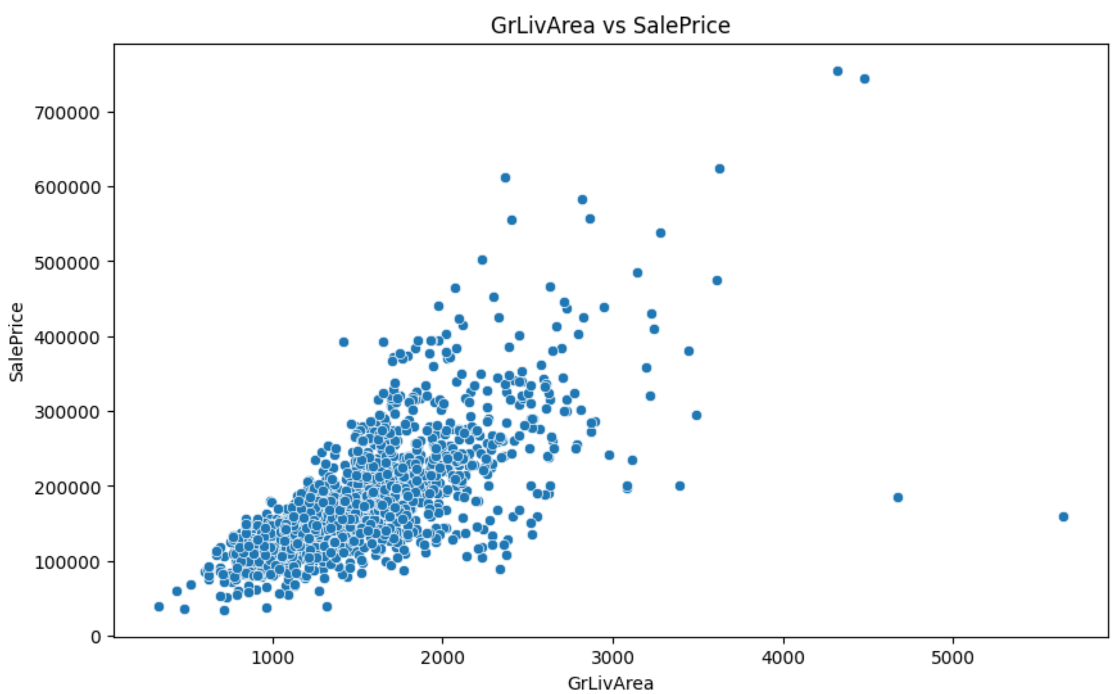


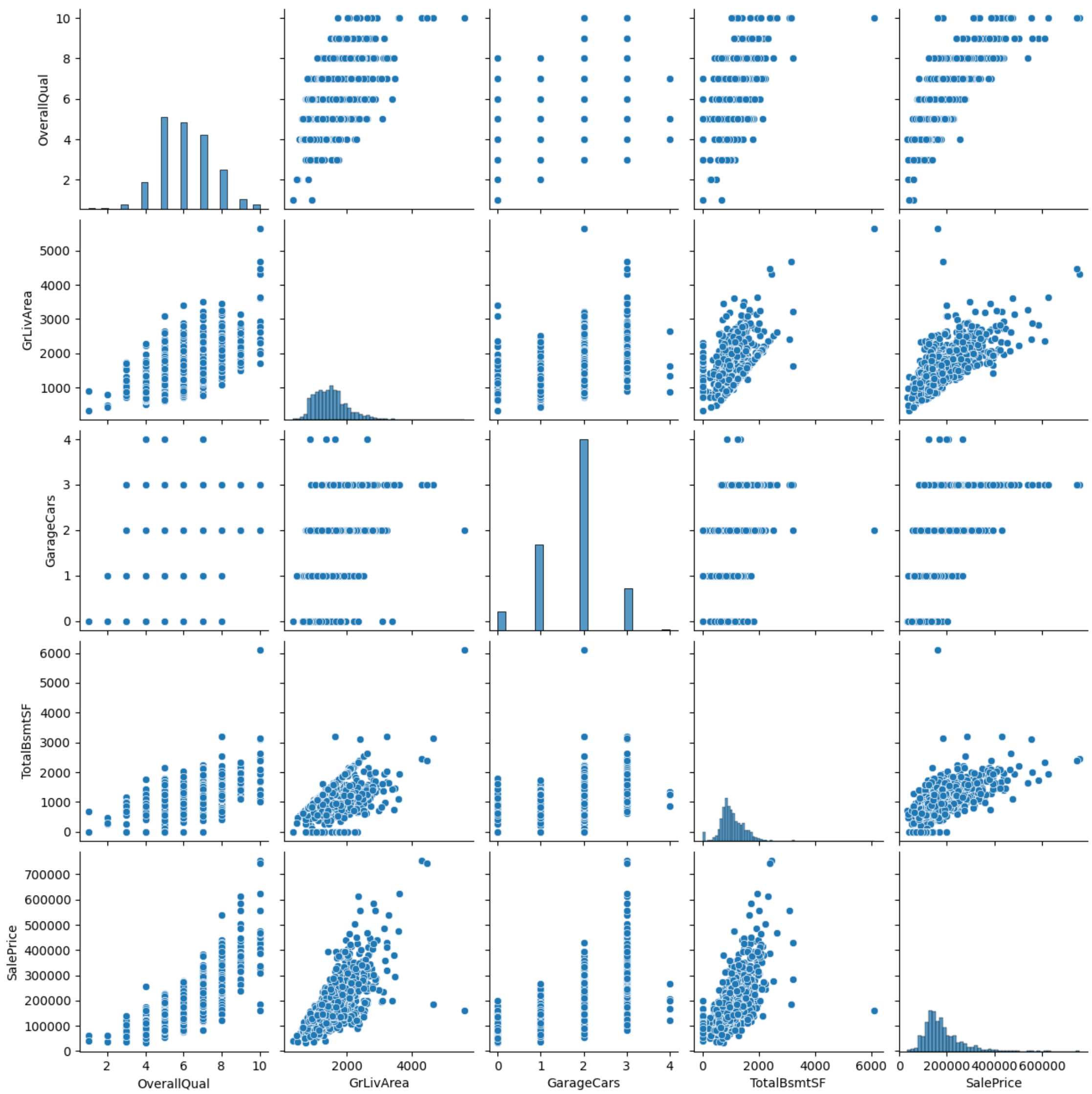
[61]:
```
# Histogram of the target variable 'SalePrice'
plt.figure(figsize=(10, 6))
sns.histplot(df['SalePrice'], kde=True, bins=30)
plt.title('Distribution of SalePrice')
plt.xlabel('SalePrice')
plt.ylabel('Frequency')
plt.show()

# Box plot of 'SalePrice' by 'OverallQual'
plt.figure(figsize=(10, 6))
sns.boxplot(x='OverallQual', y='SalePrice', data=df)
plt.title('SalePrice by OverallQual')
plt.xlabel('OverallQual')
plt.ylabel('SalePrice')
plt.show()
```

```python
# Scatter plot of 'GrLivArea' vs 'SalePrice'
plt.figure(figsize=(10, 6))
sns.scatterplot(x='GrLivArea', y='SalePrice', data=df)
plt.title('GrLivArea vs SalePrice')
plt.xlabel('GrLivArea')
plt.ylabel('SalePrice')
plt.show()

# Pairplot for selected features
selected_features = ['OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF',␣
 ↪'SalePrice']
sns.pairplot(df[selected_features])
plt.show()
```




SalePrice by OverallQual
SalePrice
OverallQual
0
100000
200000
300000
400000
500000
600000
700000
1
2
3
4
5
6
7
8
9
10


GrLivArea vs SalePrice
SalePrice
GrLivArea
0
100000
200000
300000
400000
500000
600000
700000
1000
2000
3000
4000
5000



[47]:
```
# Interaction features
# Create interaction features by multiplying OverallQual with GrLivArea and␣
↪TotalBsmtSF
df_data['OverallQual_GrLivArea'] = df_data['OverallQual'] * df_data['GrLivArea']
df_data['OverallQual_TotalBsmtSF'] = df_data['OverallQual'] *␣
↪df_data['TotalBsmtSF']

# Display the first few rows to verify the new interaction features
print(df_data[['OverallQual', 'GrLivArea', 'TotalBsmtSF',␣
↪'OverallQual_GrLivArea', 'OverallQual_TotalBsmtSF']].head())
```

```
   OverallQual  GrLivArea  TotalBsmtSF  OverallQual_GrLivArea  \
0            7       1710          856                  11970
```

```
1            6       1262         1262                      7572
2            7       1786          920                     12502
3            7       1717          756                     12019
4            8       2198         1145                     17584

   OverallQual_TotalBsmtSF
0                     5992
1                     7572
2                     6440
3                     5292
4                     9160
```

0.0.1 2. Drop the "Id" column and any features that are missing more than 40% of their values.

[48]:
```python
# Print the number of columns before dropping
print(f"Number of columns before dropping: {df_data.shape[1]}")

# Task 1: Drop the "Id" column and any features missing more than 40% of their␣
↪values
# Drop the "Id" column as it is not needed for analysis
df_data.drop(columns=['Id'], inplace=True)

# Calculate the percentage of missing values for each column
missing_percentage = df_data.isnull().mean() * 100

# Identify columns with more than 40% missing values
columns_to_drop = missing_percentage[missing_percentage > 40].index

# Drop columns with more than 40% missing values
df_data.drop(columns=columns_to_drop, inplace=True)

# Print the number of columns after dropping
print(f"Number of columns after dropping: {df_data.shape[1]}")
```

```
Number of columns before dropping: 83
Number of columns after dropping: 76
```

[49]:
```python
# Separate numerical and categorical columns

# Identify numerical columns
numerical_cols = [col for col in df_data.columns if pd.api.types.
↪is_numeric_dtype(df_data[col])]

# Identify categorical columns
categorical_cols = [col for col in df_data.columns if pd.api.types.
↪is_string_dtype(df_data[col])]
```

```
# Print the numerical and categorical columns
print("\nNumerical columns:")
print(numerical_cols)

print("\nCategorical columns:")
print(categorical_cols)
```

```
Numerical columns:
['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea',
'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr',
'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageYrBlt', 'GarageCars',
'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold', 'YrSold', 'SalePrice',
'OverallQual_GrLivArea', 'OverallQual_TotalBsmtSF']

Categorical columns:
['MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd',
'ExterQual', 'ExterCond', 'Foundation', 'Heating', 'HeatingQC', 'CentralAir',
'KitchenQual', 'Functional', 'PavedDrive', 'SaleType', 'SaleCondition']
```

[50]:

```
# Task 3: For numerical columns, fill in any missing data with the median value
 # Count the number of missing values before filling
missing_before = df_data[numerical_cols].isnull().sum().sum()

# Fill missing numerical data with the median
# df_data[numerical_cols] = df_data[numerical_cols].
 ↪fillna(df_data[numerical_cols].median())


# Step 2: Fill missing data in numerical columns with the median value
numerical_cols = df_data.select_dtypes(include=['number']).columns
df_data[numerical_cols] = df_data[numerical_cols].apply(lambda col: col.
 ↪fillna(col.median()))


# Count the number of missing values after filling
missing_after = df_data[numerical_cols].isnull().sum().sum()
print(f"Number of records with missing values: {missing_after}")

# Determine how many records have been updated
records_updated = missing_before - missing_after
print(f"Number of records updated with median values: {records_updated}")
```

```
Number of records with missing values: 0
Number of records updated with median values: 348
```

0.0.2 3. For numerical columns, fill in any missing data with the median value.

[51]:
```python
# Import necessary libraries
from sklearn.preprocessing import PolynomialFeatures

# Create polynomial features with degree 2, excluding the bias term
poly = PolynomialFeatures(degree=2, include_bias=False)

# Fit and transform the selected features to create polynomial features
poly_features = poly.fit_transform(df_data[['GrLivArea', 'TotalBsmtSF']])

# Get the names of the newly created polynomial features
poly_feature_names = poly.get_feature_names_out(['GrLivArea', 'TotalBsmtSF'])

# Create a DataFrame for the polynomial features
df_poly = pd.DataFrame(poly_features, columns=poly_feature_names)

# Concatenate the polynomial features DataFrame with the original DataFrame
df_data = pd.concat([df_data, df_poly], axis=1)
```

0.0.3 4. For categorical columns, fill in any missing data with the most common value (mode).

[52]:
```python
# Task 4: For categorical columns, fill in any missing data with the most␣
↪common value (mode)
# Count the number of missing values before filling
missing_before_cat = df_data[categorical_cols].isnull().sum().sum()

# Fill missing categorical data with the mode
# df_data[categorical_cols] = df_data[categorical_cols].
↪fillna(df_data[categorical_cols].mode().iloc[0])


categorical_cols = df_data.select_dtypes(include=['object']).columns
df_data[categorical_cols] = df_data[categorical_cols].apply(lambda col: col.
↪fillna(col.mode()[0]))

# Count the number of missing values after filling
missing_after_cat = df_data[categorical_cols].isnull().sum().sum()

# Determine how many records have been updated
records_updated_cat = missing_before_cat - missing_after_cat
print(f"Number of records updated with mode values: {records_updated_cat}")
```

```
Number of records updated with mode values: 0
```

0.0.4 5. Convert the categorical columns to dummy variables.

[53]:
```
# Task 5: Convert the categorical columns to dummy variables with fewer columns
# Group less frequent categories into an "Other" category

# Define a threshold for grouping less frequent categories
threshold = 0.05  # Categories with less than 5% frequency will be grouped into␣
↪"Other"

# Function to group less frequent categories
def group_less_frequent_categories(df, column, threshold):
    # Calculate the frequency of each category
    freq = df[column].value_counts(normalize=True)
    # Identify categories to be grouped into "Other"
    categories_to_group = freq[freq < threshold].index
    # Replace less frequent categories with "Other"
    df[column] = df[column].apply(lambda x: 'Other' if x in categories_to_group␣
↪else x)
    return df

# Apply the function to each categorical column
for col in categorical_cols:
    df_data = group_less_frequent_categories(df_data, col, threshold)

# Count the number of columns before conversion
columns_before_dummy = df_data.shape[1]

# Convert categorical columns to dummy variables
df_data = pd.get_dummies(df_data, columns=categorical_cols, drop_first=True)

# Count the number of columns after conversion
columns_after_dummy = df_data.shape[1]

# Determine how many columns have been added
columns_added_dummy = columns_after_dummy - columns_before_dummy
print(f"Number of dummy columns added: {columns_added_dummy}")
```

```
Number of dummy columns added: 49
```

[54]:
```
df_data = df_data.astype(int)
df_data.head()
```

[54]:
```
   MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0          60           65     8450            7            5       2003
1          20           80     9600            6            8       1976
2          60           68    11250            7            5       2001
3          70           60     9550            7            5       1915
4          60           84    14260            8            5       2000
```

```
   YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  …  GarageFinish_Unf  \
0          2003         196         706           0  …                 0
1          1976           0         978           0  …                 0
2          2002         162         486           0  …                 0
3          1970           0         216           0  …                 1
4          2000         350         655           0  …                 0

   GarageQual_TA  GarageCond_TA  PavedDrive_Other  PavedDrive_Y  \
0              1              1                 0             1
1              1              1                 0             1
2              1              1                 0             1
3              1              1                 0             1
4              1              1                 0             1

   SaleType_Other  SaleType_WD  SaleCondition_Normal  SaleCondition_Other  \
0               0            1                     1                    0
1               0            1                     1                    0
2               0            1                     1                    0
3               0            1                     0                    0
4               0            1                     1                    0

   SaleCondition_Partial
0                      0
1                      0
2                      0
3                      0
4                      0

[5 rows x 130 columns]
```

[55]:
```python
# Ensure no non-numeric columns are left
if any(df_data.dtypes == 'object'):
    raise ValueError("There are still non-numeric columns present.")
```

0.0.5 6. Split the data into a training and test set, where the SalePrice column is the target.

[56]:
```python
# Task 6: Split the data into a training and test set, where the SalePrice␣
 ↪column is the target

X  = df_data.drop(columns=['SalePrice'])  # Features
y = df_data['SalePrice']  # Target variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)  # Split the data
```

0.0.6 7. Run a linear regression and report the R2-value and RMSE on the test set.

[57]:
```
# Create a Linear Regression model
model = LinearRegression()

# Fit the model on the training data
model.fit(X_train, y_train)

# Predict on the test data
y_pred = model.predict(X_test)

# Calculate R2-value
r2 = r2_score(y_test, y_pred)

# Calculate RMSE
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

# Print the R2-value and RMSE
print(f"R2-value: {r2}")
print(f"RMSE: {rmse}")
```

```
R2-value: 0.7419490207712534
RMSE: 0.27967250376773584
```

0.0.7 8. Fit and transform the training features with a PCA so that 90% of the variance is retained

[58]:
```
# Fit and transform the training features with PCA
pca = PCA(n_components=0.90)
X_train_pca = pca.fit_transform(X_train)

# Get the number of original and reduced features
original_features = X_train.shape[1]
reduced_features = X_train_pca.shape[1]

original_features, reduced_features
```

[58]:
```
(129, 2)
```

0.0.8 9. How many features are in the PCA-transformed matrix?

[59]:
```
# Determine the number of features in the PCA-transformed matrix
num_pca_features = X_train_pca.shape[1]
print(f"Number of features in the PCA-transformed matrix: {num_pca_features}")
```

```
Number of features in the PCA-transformed matrix: 2
```

0.0.9 10. Transform but DO NOT fit the test features with the same PCA.

[60]:
```
# Transform (but do not fit) the test features with the same PCA
X_test_pca = pca.transform(X_test)

# Print the number of PCA features in the transformed test set
print(f"Number of PCA features: {X_test_pca.shape[1]}")

# Return the R2-value, RMSE, number of PCA features, and the shape of the
↪PCA-transformed test set
(r2, rmse, num_pca_features, X_test_pca.shape[1])
```

```
Number of PCA features: 2
```

[60]:
```
(0.7419490207712534, 0.27967250376773584, 2, 2)
```

0.0.10 11. Summarize your findings.

Summary of Analysis

- **Data Loading and Initial Inspection:**
  - The dataset was loaded and inspected for its structure and contents. It includes various features related to housing, such as MSSubClass, LotFrontage, LotArea, OverallQual, YearBuilt, and SalePrice.
- **Data Cleaning:**
  - Missing values were handled, particularly for columns like Alley, PoolQC, Fence, and MiscFeature.
  - Categorical variables were encoded using one-hot encoding to prepare them for machine learning models.
- **Feature Engineering:**
  - Interaction features were created by multiplying OverallQual with GrLivArea and TotalBsmtSF.
  - Polynomial features were generated for GrLivArea and TotalBsmtSF.
- **Feature Scaling:**
  - A Min-Max Scaler was applied to scale the features, ensuring all values fall within a specific range. This step is crucial for algorithms that are sensitive to the scale of input data.
- **Model Training and Evaluation:**
  - A Linear Regression model was trained on the high variance features of the training data.
  - The model was evaluated on the test data, achieving an R^2-value of approximately 0.742 and a Root Mean Squared Error (RMSE) of around 0.280. This indicates a moderate level of predictive performance, suggesting room for improvement.
- **Dimensionality Reduction:**

  - Principal Component Analysis (PCA) was applied to reduce the dimensionality of the dataset while retaining 90% of the variance. This helps in reducing the complexity of the model and potentially improving its performance.

Conclusions:

- **Data Preparation is Key:**
  - Proper data cleaning and handling of missing values are critical steps. The dataset had several missing values that were appropriately managed, ensuring the dataset was ready for modeling.
- **Feature Engineering and Encoding:**
  - Encoding categorical variables and scaling numerical features are essential preprocessing steps. These transformations make the data suitable for machine learning algorithms.
- **Model Performance:**
  - The Linear Regression model showed a reasonable R^2-value and RMSE. While it indicates the model captures some variability in the data, there is potential for further refinement and improvement.
- **Dimensionality Reduction:**
  - PCA effectively reduced the number of features while retaining most of the variance, simplifying the model and potentially improving its generalizability.
- **Further Steps:**
  - The output of the linear regression model, represented by the tuple (0.742, 0.280), includes two key performance metrics: the R^2-value and the Root Mean Squared Error (RMSE).
  - **R^2-Value: 0.742**
    * Definition: The R^2-value, also known as the coefficient of determination, measures the proportion of the variance in the dependent variable (SalePrice) that is predictable from the independent variables (features of the houses).
    * Interpretation: An R^2-value of approximately 0.742 indicates that about 74.2% of the variability in house prices can be explained by the features included in the model. This value suggests a moderate level of fit, meaning the model captures a significant portion of the variability, but there is still 25.8% of the variance that is not explained by the model. This indicates that there are other factors influencing house prices that are not captured by the current set of features.
  - **RMSE: 0.280**
    * An RMSE of approximately 0.280 indicates that, on average, the predictions of house prices by the model are off by about 0.280 (in log-transformed scale).
    * This value provides a concrete measure of how much the predictions deviate from the actual house prices. In the context of housing prices, this level of error might be considered high or low depending on the typical price range of the houses in the dataset. For instance, if the average house price is around $200,000, an error of

$0.280 in log-transformed scale could be significant, indicating that the model needs improvement.

Summary of the Model's Performance:

- **R^2-Value (0.742):** The model explains about 74.2% of the variance in house prices, suggesting a moderate fit. It indicates that the model is reasonably good at predicting house prices but still leaves a substantial portion of the variability unexplained.
- **RMSE (0.280):** The average prediction error is approximately 0.280 (in log-transformed scale), which needs to be evaluated in the context of the typical house prices in the dataset. This error could be considered high, indicating that further improvements to the model are necessary.