main

August 25, 2024

```
[ ]: import pandas as pd
     import numpy as np
     import plotly.express as px
     import plotly.graph_objects as go
     import matplotlib.pyplot as plt
     import seaborn as sns
     from scipy import stats

     from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LinearRegression

     from sklearn.metrics import mean_absolute_percentage_error
     from sklearn.metrics import mean_squared_error
     from sklearn.metrics import r2_score

     import warnings
     warnings.simplefilter(action='ignore', category=FutureWarning)
```

Data Description: Data Source: - This data is acquired from https://docs.google.com/spreadsheets/d/1caaR9pT24GNmq3rDQpMiIMJrmiTGarbs/edit?gid=1150341366#gid= as .xlsx file and converted to data.csv file. - This dataset contains the following columns: 1. Id: To count the records. 2. MSSubClass: Identifies the type of dwelling involved in the sale. 3. MSZoning: Identifies the general zoning classification of the sale. 4. LotArea: Lot size in square feet. 5. LotConfig: Configuration of the lot 6. BldgType: Type of dwelling 7. OverallCond: Rates the overall condition of the house 8. YearBuilt: Original construction year 9. YearRemodAdd: Remodel date (same as construction date if no remodeling or additions). 11. BsmtFinSF2: Type 2 finished square feet. 12. TotalBsmtSF: Total square feet of basement area 13. SalePrice: To be predicted Data Question: - What factors are significant in predciting sale price of houses? And what price is the house based on given factors's information? The response variable: SalePrice The possible predictors: MSSubClass, MSZoning, LotArea, LotConfig, BldgType, OverallCond, YearBuilt, YearRemodAdd, BsmtFinSF2, TotalBsmtSF

```
[ ]: # Load and show the first 10 rows of the data to see data's structure
     df = pd.read_csv('data.csv')
     df.head(10)
```

```
[ ]:    Id  MSSubClass MSZoning  LotArea LotConfig BldgType  OverallCond  \
     0   0          60       RL     8450    Inside     1Fam            5
```

```
1   1         20       RL     9600      FR2     1Fam            8
2   2         60       RL    11250   Inside     1Fam            5
3   3         70       RL     9550   Corner     1Fam            5
4   4         60       RL    14260      FR2     1Fam            5
5   5         50       RL    14115   Inside     1Fam            5
6   6         20       RL    10084   Inside     1Fam            5
7   7         60       RL    10382   Corner     1Fam            6
8   8         50       RM     6120   Inside     1Fam            5
9   9        190       RL     7420   Corner   2fmCon            6

   YearBuilt  YearRemodAdd Exterior1st  BsmtFinSF2  TotalBsmtSF  SalePrice
0       2003          2003     VinylSd         0.0        856.0   208500.0
1       1976          1976     MetalSd         0.0       1262.0   181500.0
2       2001          2002     VinylSd         0.0        920.0   223500.0
3       1915          1970     Wd Sdng         0.0        756.0   140000.0
4       2000          2000     VinylSd         0.0       1145.0   250000.0
5       1993          1995     VinylSd         0.0        796.0   143000.0
6       2004          2005     VinylSd         0.0       1686.0   307000.0
7       1973          1973     HdBoard        32.0       1107.0   200000.0
8       1931          1950     BrkFace         0.0        952.0   129900.0
9       1939          1950     MetalSd         0.0        991.0   118000.0
```

[ ]:
```python
# Check data type of each variable an correct the data type
df.info()
# Count categorical columns
categorical_columns = df.select_dtypes(include=['object', 'category', 'bool'])
print(f'Number of categorical columns: {len(categorical_columns.columns)}')
print(categorical_columns.columns)

# Count numeric columns:
numeric_columns = df.select_dtypes(include=['number'])
print(f'Number of numeric columns: {len(numeric_columns.columns)}')
print(numeric_columns.columns)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Id            2919 non-null   int64
 1   MSSubClass    2919 non-null   int64
 2   MSZoning      2915 non-null   object
 3   LotArea       2919 non-null   int64
 4   LotConfig     2919 non-null   object
 5   BldgType      2919 non-null   object
 6   OverallCond   2919 non-null   int64
 7   YearBuilt     2919 non-null   int64
 8   YearRemodAdd  2919 non-null   int64
 9   Exterior1st   2918 non-null   object
 10  BsmtFinSF2    2918 non-null   float64
 11  TotalBsmtSF   2918 non-null   float64
 12  SalePrice     1460 non-null   float64
dtypes: float64(3), int64(6), object(4)
memory usage: 296.6+ KB
Number of categorical columns: 4
Index(['MSZoning', 'LotConfig', 'BldgType', 'Exterior1st'], dtype='object')
Number of numeric columns: 9
Index(['Id', 'MSSubClass', 'LotArea', 'OverallCond', 'YearBuilt',
       'YearRemodAdd', 'BsmtFinSF2', 'TotalBsmtSF', 'SalePrice'],
      dtype='object')
```

- This dataset has 2919 entries and 13 columns.
- That includes: 4 categorical variables: 'MSZoning', 'LotConfig', 'BldgType', 'Exterior1st' 9 numeric varibles: 'Id', 'MSSubClass', 'LotArea', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'BsmtFinSF2', 'TotalBsmtSF', 'SalePrice'

[ ]:
```
# Drop Id column
if 'Id' in df.columns:
    df.drop('Id', axis=1, inplace=True)

# Check data statistic of numeric variables
df.describe()
```

[ ]:
```
        MSSubClass        LotArea  OverallCond    YearBuilt  YearRemodAdd  \
count  2919.000000    2919.000000  2919.000000  2919.000000   2919.000000
mean     57.137718   10168.114080     5.564577  1971.312778   1984.264474
std      42.517628    7886.996359     1.113131    30.291442     20.894344
min      20.000000    1300.000000     1.000000  1872.000000   1950.000000
25%      20.000000    7478.000000     5.000000  1953.500000   1965.000000
50%      50.000000    9453.000000     5.000000  1973.000000   1993.000000
75%      70.000000   11570.000000     6.000000  2001.000000   2004.000000
max     190.000000  215245.000000     9.000000  2010.000000   2010.000000

        BsmtFinSF2  TotalBsmtSF      SalePrice
count  2918.000000  2918.000000    1460.000000
mean     49.582248  1051.777587  180921.195890
std     169.205611   440.766258   79442.502883
min       0.000000     0.000000   34900.000000
25%       0.000000   793.000000  129975.000000
50%       0.000000   989.500000  163000.000000
75%       0.000000  1302.000000  214000.000000
max    1526.000000  6110.000000  755000.000000
```

[ ]:
```
# Check missing/null values of data
df.isnull().sum()
```

[ ]:
```
MSSubClass         0
MSZoning           4
LotArea            0
LotConfig          0
BldgType           0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
Exterior1st        1
BsmtFinSF2         1
TotalBsmtSF        1
SalePrice       1459
dtype: int64
```

- MSZoning has 4 null values
- Exterior1st has 1 null values
- BsmtFinSF2 has 1 null values
- TotalBsmtSF has 1 null values
- SalePrice has 1459 null values

[ ]:
```python
# Replace null values with mean values and remove duplicate rows if any in the␣
↪dataset
df. drop_duplicates(inplace=True)

# Fill na for categorical variables
df['MSZoning'].fillna(df['MSZoning'].mode()[0], inplace = True)
df['Exterior1st'].fillna(df['Exterior1st'].mode()[0], inplace = True)

# Fill na for numeric variables
df['BsmtFinSF2'].fillna(df['BsmtFinSF2'].mean(), inplace = True)
df['TotalBsmtSF'].fillna(df['TotalBsmtSF'].mean(), inplace = True)
df['SalePrice'].fillna(df['SalePrice'].mean(), inplace = True)
df.shape
```

[ ]:
```
(2911, 12)
```

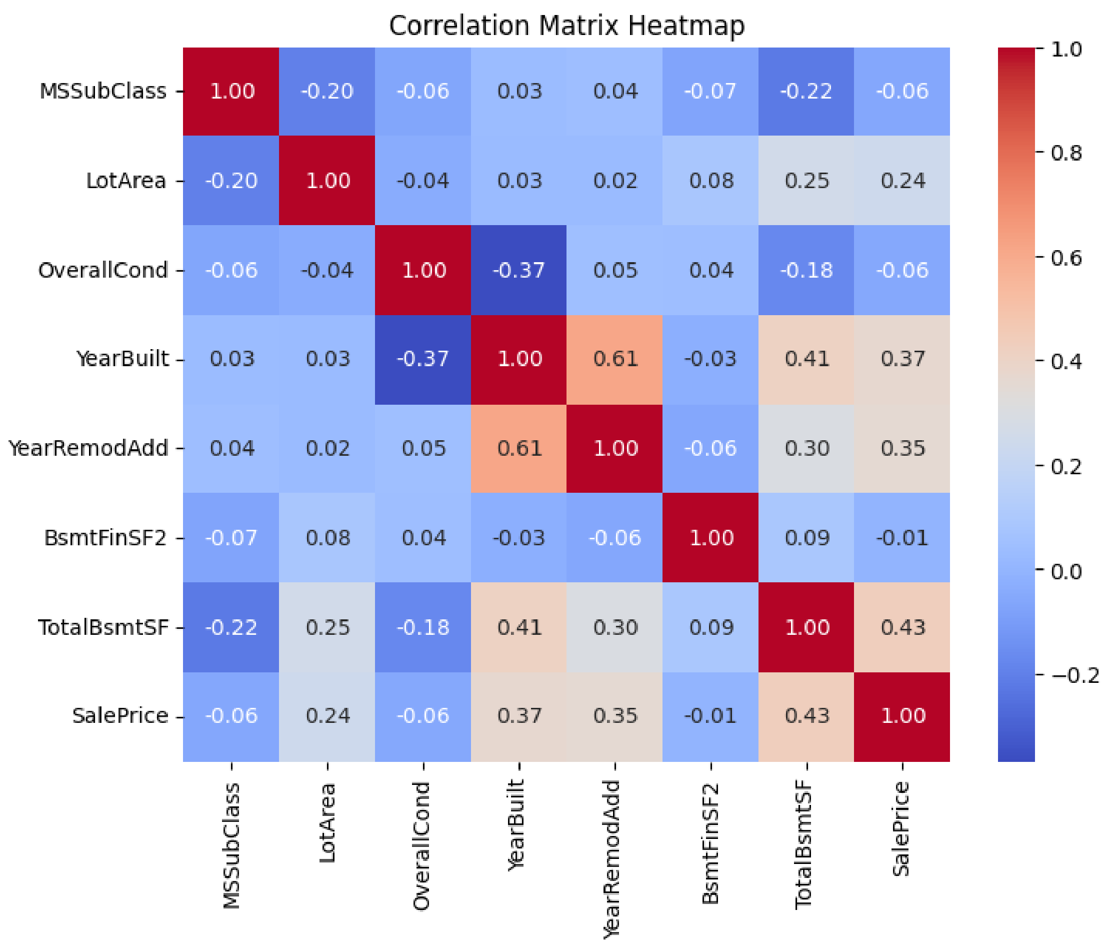
After cleaning: - This dataset has 2911 entries and 12 columns. - That includes: 4 categorical variables: ‘MSZoning’, ‘LotConfig’, ‘BldgType’, ‘Exterior1st’ 9 numeric varibles: ‘MSSubClass’, ‘LotArea’, ‘OverallCond’, ‘YearBuilt’, ‘YearRemodAdd’, ‘BsmtFinSF2’, ‘TotalBsmtSF’, ‘SalePrice’

[ ]:
```python
# Plot bar chart to see the distribution of each variable

# Plot categorical variables:
for col in categorical_columns:
    unique_values = df[col].unique()
    print(f'Values of {col}: ', unique_values)
    value_count = df[col].value_counts().reset_index()
    value_count.columns = ['Category', 'Count']
    plot = px.bar(value_count, x='Category', y='Count', title=f'{col} Category␣
↪Distribution')
    plot.show()
```

```
Values of MSZoning:  ['RL' 'RM' 'C (all)' 'FV' 'RH']

Values of LotConfig:  ['Inside' 'Corner' 'FR2' 'CulDSac' 'FR3']

Values of BldgType:  ['1Fam' 'TwnhsE' 'Duplex' 'Twnhs' '2fmCon']

Values of Exterior1st:  ['VinylSd' 'Wd Sdng' 'HdBoard' 'BrkFace' 'WdShing'
'MetalSd' 'CemntBd'
 'Stucco' 'Plywood' 'AsbShng' 'Stone' 'ImStucc' 'CBlock' 'BrkComm']
```

[ ]:
```
# Plot Numerical Variables
numeric_columns = df.select_dtypes(include=['number'])
for col in numeric_columns:
    fig = px.histogram(df, x=col, nbins=30, title=f'Histogram of {col}')
    # Customize the appearance if needed
    fig.update_layout(
        xaxis_title=col,
        yaxis_title='Counts',
        bargap=0.1,  # Adjust the gap between bars
        title_x=0.5   # Center the title
    )
    fig.show()
```

[ ]:
```
# Explore relationship between numerical variables

# Select only numerical columns
numerical_df = df.select_dtypes(include='number')

# Compute the correlation matrix for the numerical columns
correlation_matrix = numerical_df.corr()

# Plotting the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, fmt='.2f', cmap='coolwarm',␣
↪cbar=True)

# Update layout for better readability
plt.title('Correlation Matrix Heatmap')
plt.show()
```



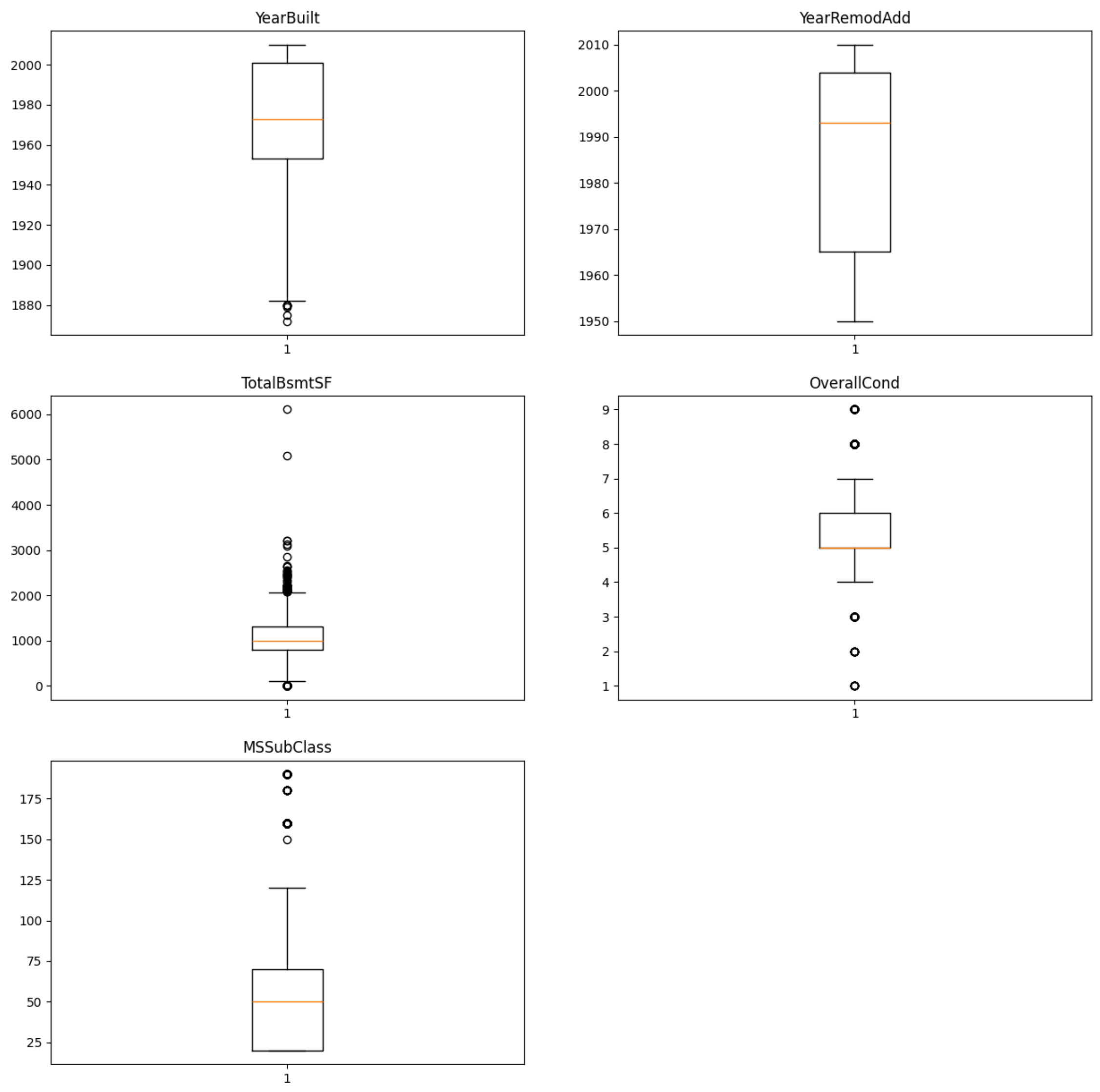
- TotalBsmtSF and SalePrice have a positive correlation (~0.43), indicating that as the total basement area increases, the sale price tends to increase.
- YearBuilt, YearRemodAdd also show a positive correlation (0.35~0.37) with SalePrice, suggesting that newer houses tend to have higher sale prices.
- OverallCond, MSSubclass have a slight negative correlation with SalePrice (-0.05~-0.06), meaning that the overall condition rating may slightly decrease as sale price increases, though the effect is very minimal.
- LotArea and SalePrice have a correlation of 0.24 suggests that, in general, larger lot areas tend to be associated with higher sale prices. However, the relationship is not very strong, implying that other factors likely play a more significant role in determining the sale price of a property.

[ ]:
```
# Explore relationship between SalePrice and other categorical varialbe using␣
 ↪correlation rattio

# Function to calculate the correlation ratio ( ²)
def correlation_ratio(categories, measurements):
    fcat, _ = pd.factorize(categories)
    cat_num = np.max(fcat) + 1
    y_avg_array = np.zeros(cat_num)
    n_array = np.zeros(cat_num)

    for i in range(cat_num):
        cat_measures = measurements[fcat == i]
        n_array[i] = len(cat_measures)
        y_avg_array[i] = np.mean(cat_measures)

    y_total_avg = np.sum(y_avg_array * n_array) / np.sum(n_array)
    numerator = np.sum(n_array * (y_avg_array - y_total_avg) ** 2)
    denominator = np.sum((measurements - y_total_avg) ** 2)

    if numerator == 0:
        return 0.0
    else:
        return np.sqrt(numerator / denominator)

# Calculate the correlation ratio for each categorical variable
for col in categorical_columns:
    # Ensure there are no missing values in the column and SalePrice
    eta_squared = correlation_ratio(df[col].dropna(), df['SalePrice'].
 ↪loc[df[col].dropna().index])
    print(f"Correlation Ratio ( ²) for {col}: {eta_squared}")
```

```
Correlation Ratio ( ²) for MSZoning: 0.22669722318599306
Correlation Ratio ( ²) for LotConfig: 0.10523387811917098
Correlation Ratio ( ²) for BldgType: 0.12899402011999697
Correlation Ratio ( ²) for Exterior1st: 0.27626786820716165
```

- ^{2} between 0.1 and 0.3: There is a weak to moderate association between categorical variables (MSZoning,LotConfig, BldgType, Exterior1st) and numeric variables (SalePrice). The numeric values show some variation across categories, but the relationship is not strong.

[ ]:
```
# Detect outliers using Boxplot
feature = ['YearBuilt', 'YearRemodAdd', 'TotalBsmtSF','OverallCond',␣
 ↪'MSSubClass']
plt.figure(figsize=(15,15))
for i,col in enumerate(feature):
    plt.subplot(3,2,i+1)
    plt.boxplot(df[col])
    plt.title(f'{col}')
plt.show()
```

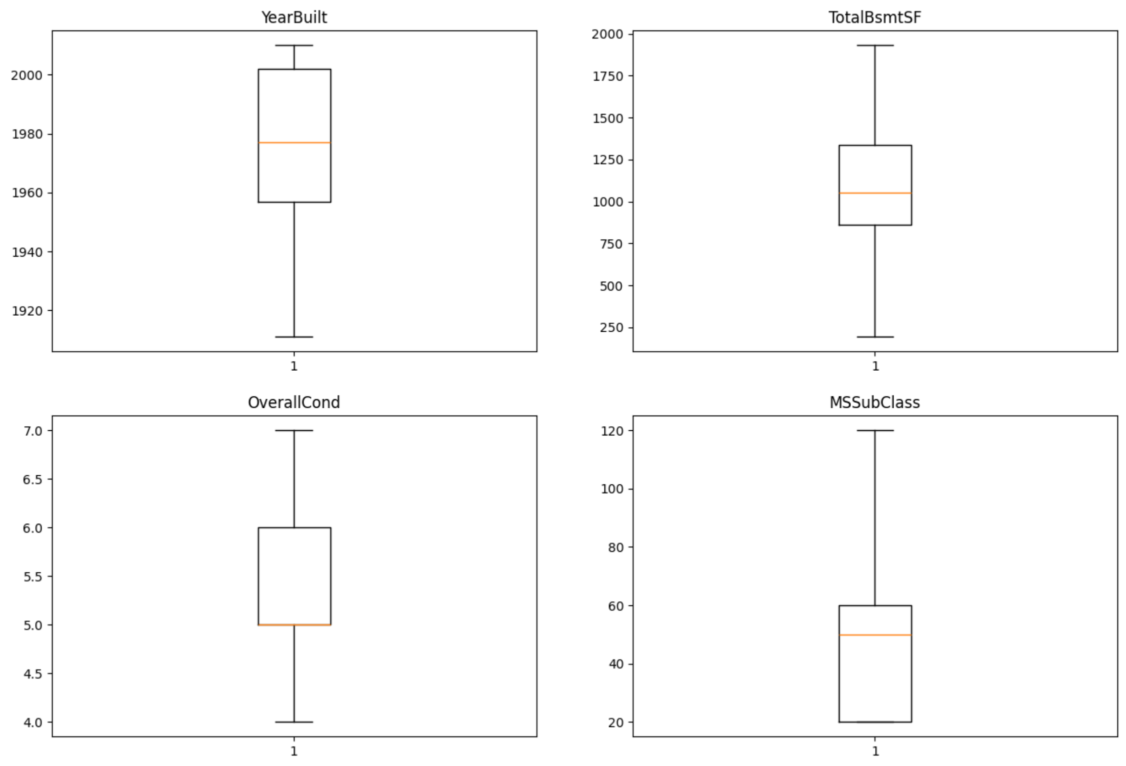


- The graph shows there are too some outliers in MSSubClass, OverallCond.

[ ]:
```
# Handle outliers using Z-score

# Calculate Z-scores
z_scores = np.abs(stats.zscore(df[['YearBuilt', 'TotalBsmtSF','OverallCond',␣
  ↪'MSSubClass']]))

# Set a threshold for Z-score (common choice is 3)
threshold = 2

# Identify outliers
outliers = np.where(z_scores > threshold)
```

```
# Remove outliers
df = df[(z_scores < threshold).all(axis=1)]

# Reset index
df = df.reset_index(drop=True)
```

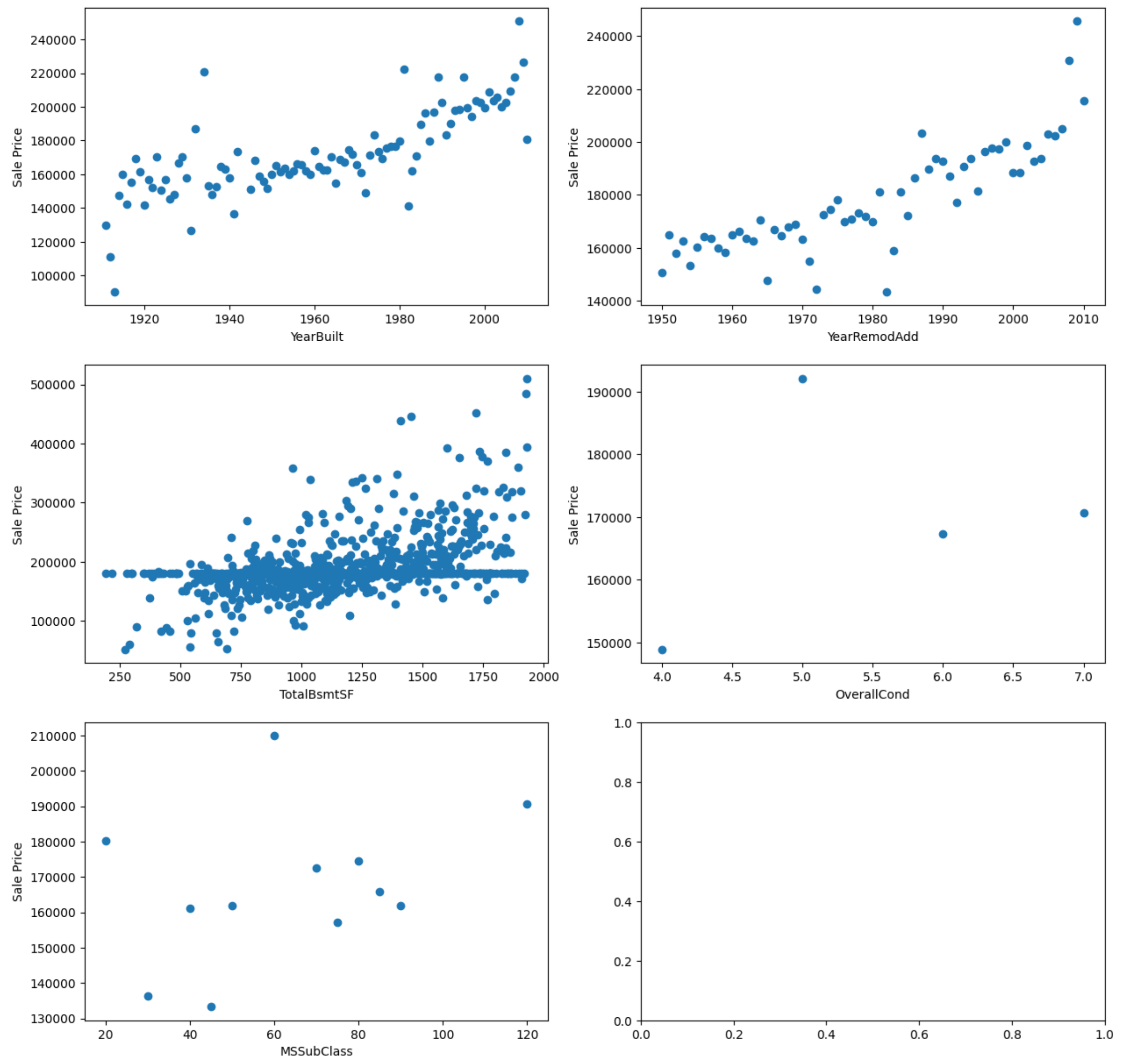
[ ]:
```
# Boxplot after handling outliers
feature = ['YearBuilt', 'TotalBsmtSF','OverallCond', 'MSSubClass']
plt.figure(figsize=(15,10))
for i,col in enumerate(feature):
    plt.subplot(2,2,i+1)
    plt.boxplot(df[col])
    plt.title(f'{col}')
plt.show()
```



All of the outliers are removed from the dataset.

[ ]:
```
# Plot the graphs to see relationships between SalePrice and 5 significant␣
↪variables
feature = ['YearBuilt', 'YearRemodAdd', 'TotalBsmtSF','OverallCond',␣
↪'MSSubClass']
plt.subplots(3,2, figsize=(15,15))
```

```
for i, col in enumerate(feature):
    grouped_data = df.groupby(col)['SalePrice'].mean()
    plt.subplot(3,2,i+1)
    plt.scatter(grouped_data.index, grouped_data.values)
    plt.xlabel(f'{col}')
    plt.ylabel('Sale Price')
plt.show()
```



Based on the graphs, I decided to use linear models to build a ML model to predict the house's prices.

```
[ ]: # Build Linear Regression Model
X = df.drop(['SalePrice', 'MSZoning','LotArea','LotConfig',␣
 ↪'BldgType','Exterior1st','BsmtFinSF2'], axis= 1)
```

```
Y = df['SalePrice']

# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.3,␣
 ↪random_state=50)

# Fit a linear regression model
model = LinearRegression()
model.fit(X_train, Y_train)

# Predict on the test set
Y_pred = model.predict(X_test)
```

```
[ ]: # Calculate residuals
residuals = Y_test - Y_pred
# Evaluate model

mae = mean_absolute_percentage_error(Y_test, Y_pred)
print("MAE:", mae)
mse = mean_squared_error(Y_test, Y_pred)
print("MSE:", mse)
rmse = np.sqrt(mse)
print("RMSE:", rmse)
r2 = r2_score(Y_test, Y_pred)
print("R²:", r2)
```

```
MAE: 0.1682407531839539
MSE: 1623478473.0801294
RMSE: 40292.41210302666
R²: 0.2588271652481561
```

The statistics show that the Linear Regression Model has low performance and needs to be polished or replaced by other linear models or non-linear models to improve prediction performance.