notebook

March 30, 2025

1 Start of the House Prices Data Analysis, For Qafza Workshop Project

1.1 Importing Required Libraries

[41]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
import matplotlib.pyplot as plt
import seaborn as sns
```

1.2 Start of Data Exploration and Cleaning!

[42]:
```
#Load Dataset
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
#Explore the shape of the dataset
train.shape
```

[42]:
```
(1460, 81)
```

[43]:
```
#Explore Data Types and nulls
#train.info()
#Explore Statsitical Summary
train.describe()
```

[43]:
```
                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]
```

1.2.1 Counting Missing Values of each column!

[44]:
```python
missing_values = train.isnull().sum().sort_values(ascending=False)
missing_values = missing_values[missing_values > 0]
missing_values
```

[44]:
```
PoolQC          1453
MiscFeature     1406
Alley           1369
Fence           1179
MasVnrType       872
FireplaceQu      690
```

```
LotFrontage      259
GarageQual        81
GarageFinish      81
GarageType        81
GarageYrBlt       81
GarageCond        81
BsmtFinType2      38
BsmtExposure      38
BsmtCond          37
BsmtQual          37
BsmtFinType1      37
MasVnrArea         8
Electrical         1
dtype: int64
```

1.2.2 Handling Missing Values

[45]:
```
#Dropping Columns from both datasets since these columns has a lot of missing␣
↪values more than 90% (PoolQC (1453 missing, ~99%), MiscFeature (1406␣
↪missing, ~96%), Alley (1369 missing, ~94%))
train.drop(columns=['PoolQC', 'MiscFeature', 'Alley'], inplace=True)
test.drop(columns=['PoolQC', 'MiscFeature', 'Alley'], inplace=True)
```

[46]:
```
#Replacing Non Numerics NULLs with NONE for features of the house which makes␣
↪sense!
fill_none_columns = ['Fence', 'MasVnrType', 'FireplaceQu', 'GarageType',␣
↪'GarageFinish', 'GarageQual', 'GarageCond', 'BsmtQual', 'BsmtCond',␣
↪'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2']
for i in fill_none_columns:
    train[i] = train[i].fillna("None")
    test[i] = test[i].fillna("None")
```

[47]:
```
# Fill LotFrontage on median per Neighborhood
train["LotFrontage"] = train.groupby("Neighborhood")["LotFrontage"].
↪transform(lambda x: x.fillna(x.median()))
test["LotFrontage"] = test.groupby("Neighborhood")["LotFrontage"].
↪transform(lambda x: x.fillna(x.median()))
```

[48]:
```
# Fill null numerics with 0
null_numerics = ['GarageYrBlt', 'MasVnrArea']
for i in null_numerics:
    train[i] = train[i].fillna(0)
    test[i] = test[i].fillna(0)
```

[49]:
```
# Filling 1 Elictrical Missing value with The most common value using Mode!
train.fillna({'Electrical': train['Electrical'].mode()[0]}, inplace=True)
test.fillna({'Electrical': test['Electrical'].mode()[0]}, inplace=True)
```

[50]:
```python
#Checking Missing Values again!
missing_values = train.isnull().sum().sort_values(ascending=False)
missing_values = missing_values[missing_values > 0]
missing_values
```

[50]: Series([], dtype: int64)

1.3 Start OF EDA

Calculate Skewness of nemeric data, and Create Correlation Matrix

[12]:
```python
#Identify skewness for numerical Values
numerical_features = train.select_dtypes(include=np.number)
numerical_features.skew()
# Selecting only numeric values for the Matrix
# Create a correlation Matrix for numerical Values
corr_matrix = numerical_features.corr()
top_corr_features = corr_matrix['SalePrice'].sort_values(ascending=False)[:15]
print(top_corr_features)
```

```
SalePrice       1.000000
OverallQual     0.790982
GrLivArea       0.708624
GarageCars      0.640409
GarageArea      0.623431
TotalBsmtSF     0.613581
1stFlrSF        0.605852
FullBath        0.560664
TotRmsAbvGrd    0.533723
YearBuilt       0.522897
YearRemodAdd    0.507101
MasVnrArea      0.472614
Fireplaces      0.466929
BsmtFinSF1      0.386420
LotFrontage     0.349876
Name: SalePrice, dtype: float64
```

1.3.1 Subsettign the dataset for most Correlated features with Sale PRice

[13]:
```python
# Final Columns Included in selection of features for visualization
selected_features = [
    'SalePrice',
    'GrLivArea',
    'TotalBsmtSF',
    'GarageArea',
    'OverallQual',
    'FullBath',
    'TotRmsAbvGrd'
]
```

```python
# Creating the sub-dataframe for analysis process
df_analysis = train[selected_features].copy()

# Check the shape and first few rows
print(df_analysis.shape)
df_analysis.head()
```

```
(1460, 7)
```

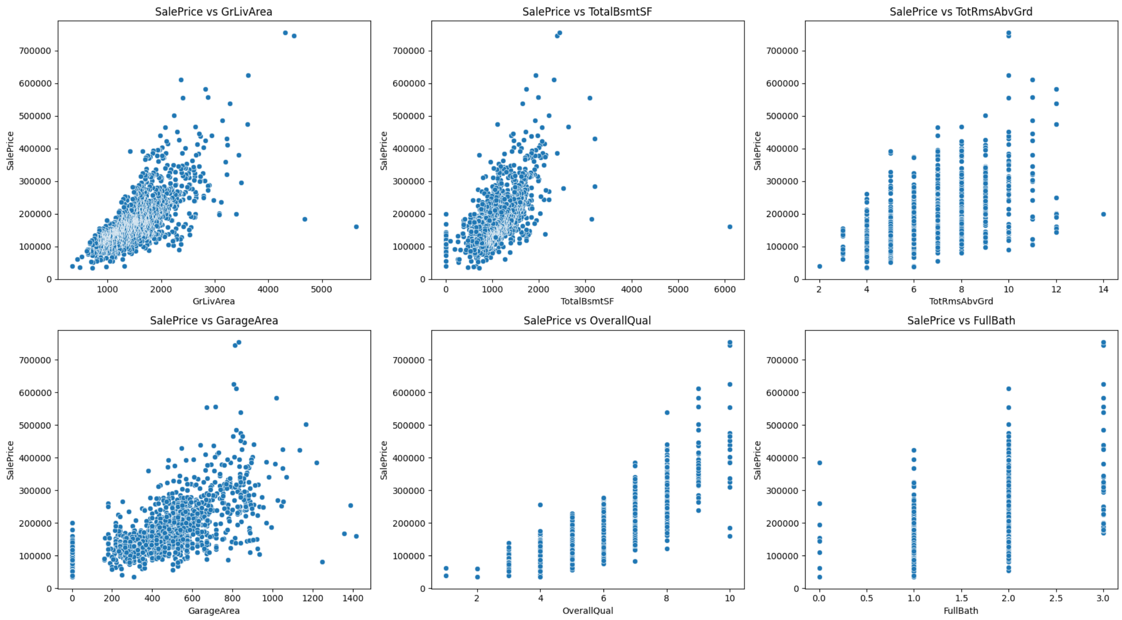
[13]:

```
   SalePrice  GrLivArea  TotalBsmtSF  GarageArea  OverallQual  FullBath  \
0     160000       5642         6110        1418           10         2
1     184750       4676         3138         884           10         3
2     745000       4476         2396         813           10         3
3     755000       4316         2444         832           10         3
4     625000       3627         1930         807           10         3

   TotRmsAbvGrd
0            12
1            11
2            10
3            10
4            10
```

1.3.2 Plotting the data to spot outliers!

[18]:

```python
top_features = ["GrLivArea", "TotalBsmtSF", "TotRmsAbvGrd", "GarageArea",␣
↪"OverallQual", "FullBath"]
fig, axes = plt.subplots(2, 3, figsize=(18, 10))

for i, feature in enumerate(top_features):
    row, col = divmod(i, 3)
    sns.scatterplot(x=df_analysis[feature], y=df_analysis["SalePrice"],␣
↪ax=axes[row, col])
    axes[row, col].set_title(f"SalePrice vs {feature}")

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



1.3.3 Removing outliers using Interquartile Range (IQR) Method

[19]:
```
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

# Apply to large numerical columns
outlier_columns = ['SalePrice', 'GrLivArea', 'TotalBsmtSF', 'GarageArea']
for col in outlier_columns:
    df_analysis = remove_outliers(df_analysis, col)
```

1.3.4 Compute key statistical measures (Min, Max, mean, median, standard deviation, skewness)

[20]:
```
# Select only numeric columns for analysis
numeric_cols = df_analysis.select_dtypes(include=['number'])

# Compute summary statistics
summary_stats = pd.DataFrame({
    'Min': numeric_cols.min(),
    'Max': numeric_cols.max(),
```

```
    'Mean': numeric_cols.mean(),
    'Median': numeric_cols.median(),
    'Standard Deviation': numeric_cols.std(),
    'Skewness': numeric_cols.skew()
})

# Display the summary statistics
summary_stats
```

[20]:

```
                Min     Max           Mean    Median  Standard Deviation  \
SalePrice     34900  340000  169520.997727  159217.0        57244.979120
GrLivArea       438    2640    1444.128788    1427.0          421.722347
TotalBsmtSF     105    1907    1030.675758     974.5          325.180441
GarageArea        0     954     452.440152     464.5          192.772917
OverallQual       1      10       5.993182       6.0            1.232286
FullBath          0       3       1.519697       2.0            0.527836
TotRmsAbvGrd      3      12       6.334848       6.0            1.441820

              Skewness
SalePrice     0.709241
GrLivArea     0.435271
TotalBsmtSF   0.458321
GarageArea   -0.152735
OverallQual   0.066534
FullBath     -0.032142
TotRmsAbvGrd  0.454969
```

1.3.5 Create the Corr Matrix

[21]:

```
analysis_corr_matrix = numeric_cols.corr()
top_corr_features = analysis_corr_matrix['SalePrice'].
  ↪sort_values(ascending=False)
print(top_corr_features)
```

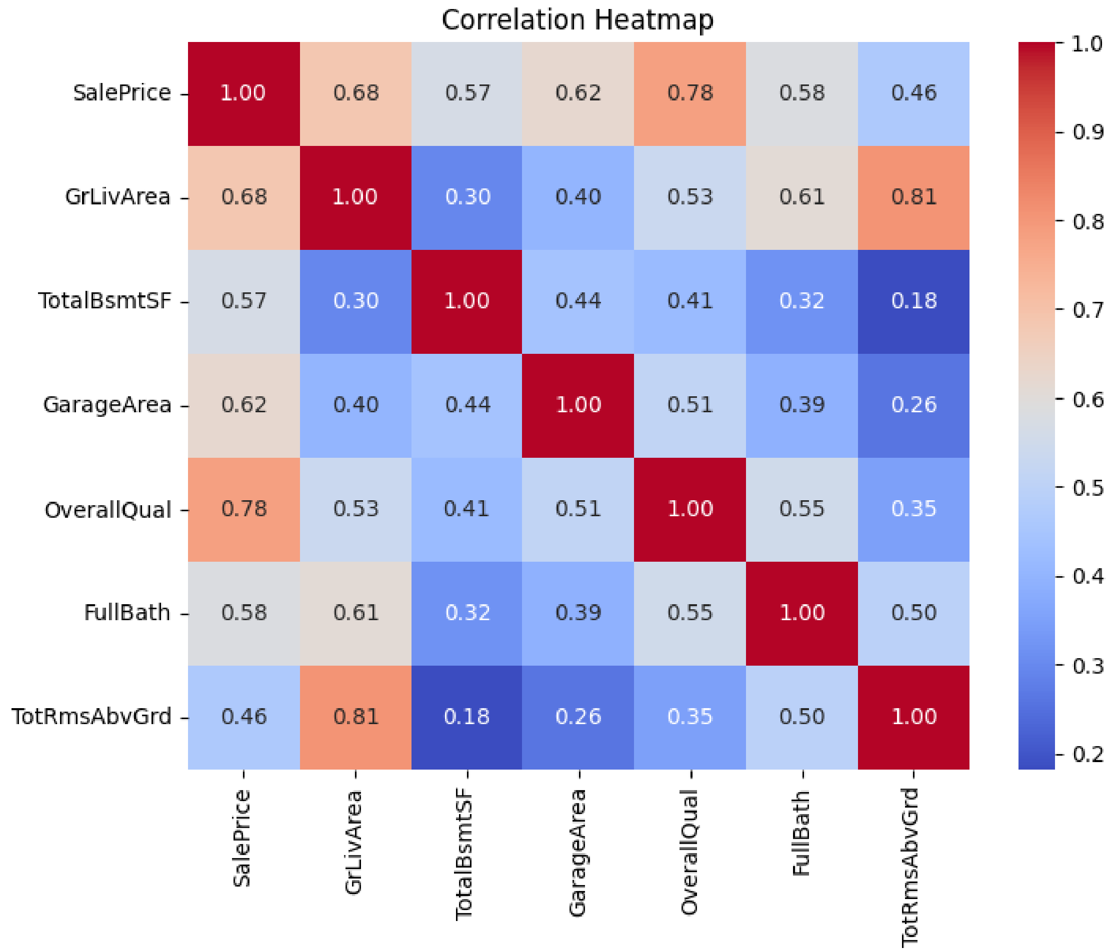
```
SalePrice       1.000000
OverallQual     0.780186
GrLivArea       0.683798
GarageArea      0.619517
FullBath        0.583587
TotalBsmtSF     0.567059
TotRmsAbvGrd    0.462772
Name: SalePrice, dtype: float64
```

Visualizing COrrelations using Heatmap

[22]:

```
#Plotting a Heatmap to visualize correlations
plt.figure(figsize=(8, 6))
sns.heatmap(df_analysis.corr(), annot=True, cmap='coolwarm', fmt=".2f")
```

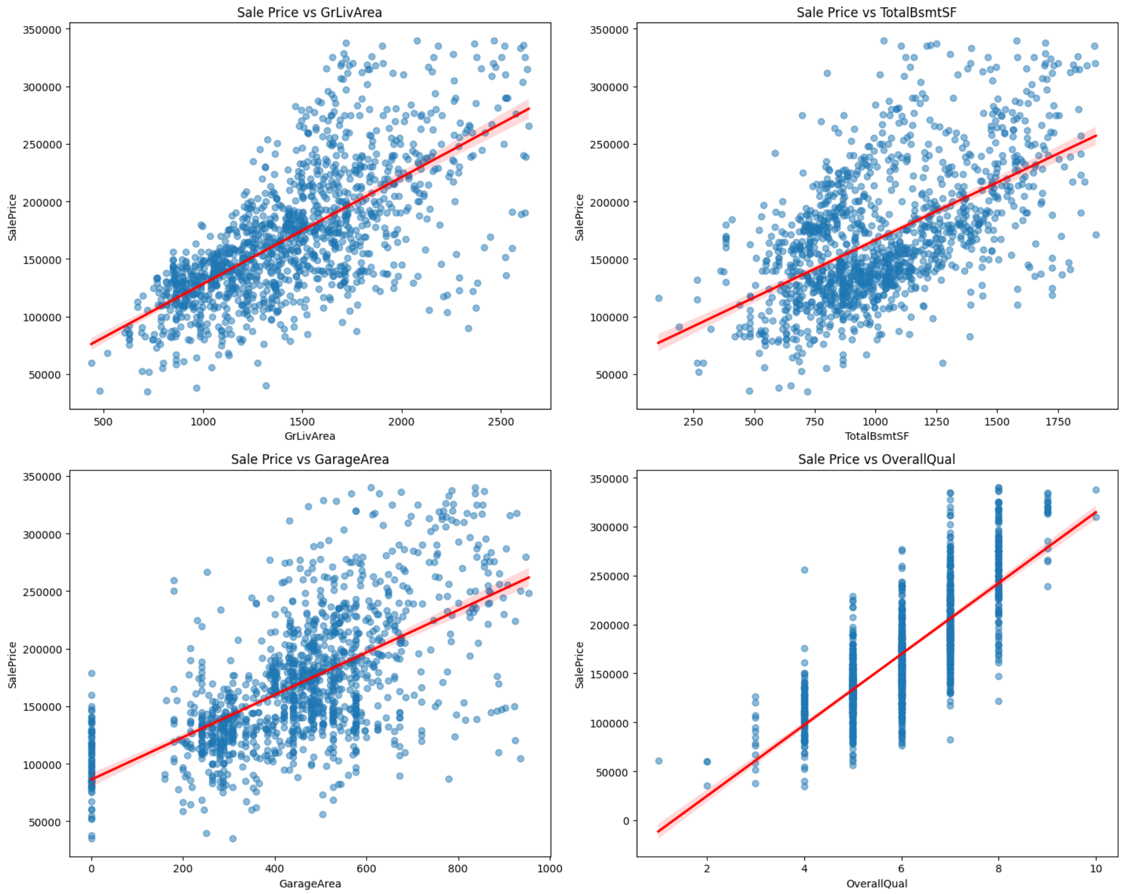
```
plt.title('Correlation Heatmap')
plt.show()
```



1.4 Data Visualization, After Identifying the significant relationships!

[24]:
```
#Creating a regresion plot charts for Sale Price with Significant relationships
features = ["GrLivArea", "TotalBsmtSF", "GarageArea", "OverallQual"]

# Set up the figure size
plt.figure(figsize=(15, 12))

# Create regplots for each feature
for i, feature in enumerate(features, 1):
    plt.subplot(2, 2, i)  # Create a 3-row, 2-column subplot
    sns.regplot(x=df_analysis[feature], y=df_analysis["SalePrice"],␣
↪scatter_kws={'alpha':0.5}, line_kws={"color":"red"})
    plt.title(f"Sale Price vs {feature}")
```

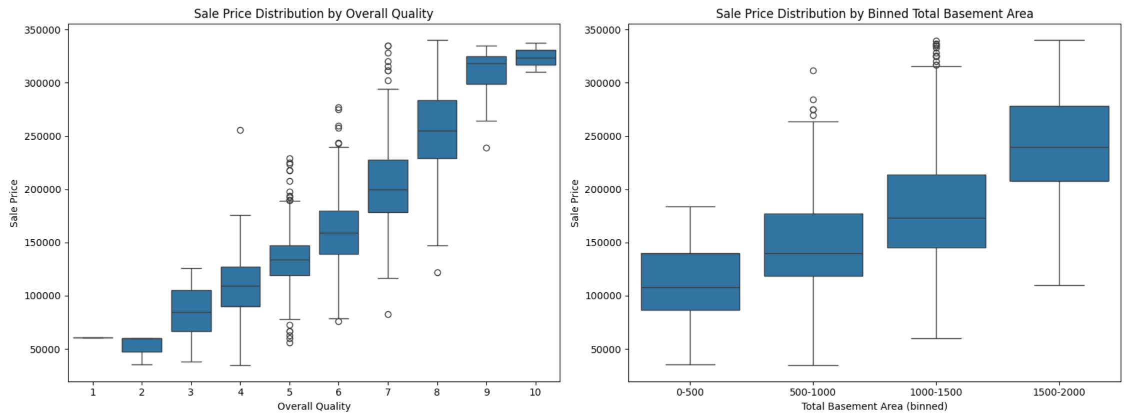
```
plt.tight_layout()
plt.show()
```



Visulaizing Correlations using Box Plots

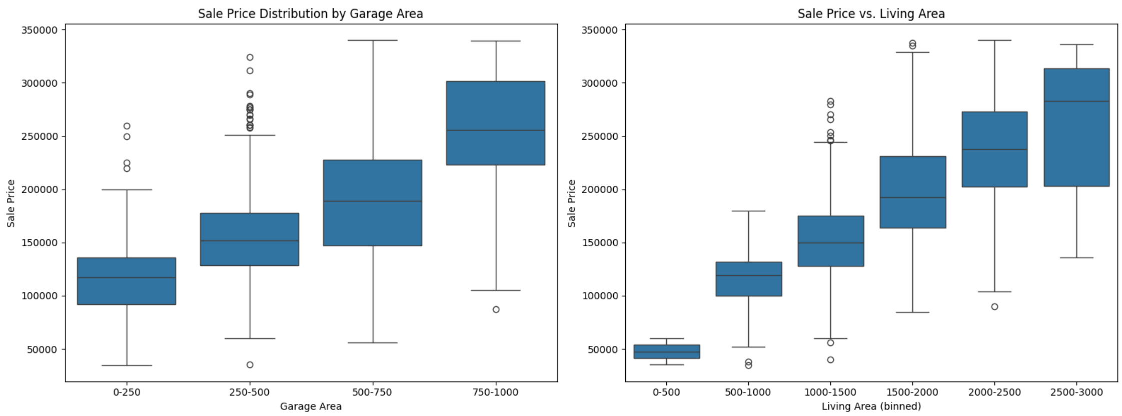
[31]:
```
# Create Box Plot Visualizing Sale Price Distibution by Overall Quality and Sale Price Distribution by Binned Total Basement Area
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Box Plot for Sale Price by Overall Quality
sns.boxplot(x=df_analysis['OverallQual'], y=df_analysis['SalePrice'], ax=axes[0])
axes[0].set_xlabel("Overall Quality")
axes[0].set_ylabel("Sale Price")
axes[0].set_title("Sale Price Distribution by Overall Quality")

# Create Bins the Total Basement Area
df_analysis['BsmtSF_Binned'] = pd.cut(df_analysis['TotalBsmtSF'],
```

```
                                          bins=[0, 500, 1000, 1500, 2000],
                                          labels=["0-500", "500-1000", "1000-1500",␣
 ↪"1500-2000"])

# Create the Box Plots
sns.boxplot(x=df_analysis['BsmtSF_Binned'], y=df_analysis['SalePrice'],␣
 ↪ax=axes[1])
axes[1].set_xlabel("Total Basement Area (binned)")
axes[1].set_ylabel("Sale Price")
axes[1].set_title("Sale Price Distribution by Binned Total Basement Area")

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

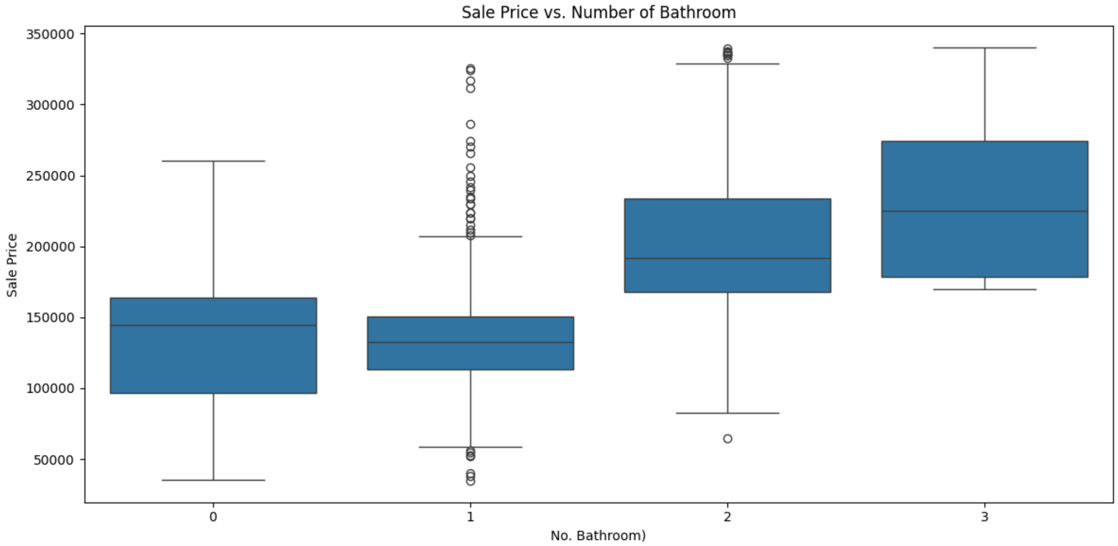


[35]:
```
fig, axes = plt.subplots(1, 2, figsize=(16, 6))
df_analysis['GarageArea_Binned'] = pd.cut(df_analysis['GarageArea'],
                                              bins=[0, 250, 500, 750, 1000],
                                              labels=["0-250", "250-500",␣
 ↪"500-750", "750-1000"],
                                              include_lowest=True,
                                              right=True
                                              )
sns.boxplot(x=df_analysis['GarageArea_Binned'], y=df_analysis['SalePrice'],␣
 ↪ax=axes[0])
axes[0].set_xlabel("Garage Area")
axes[0].set_ylabel("Sale Price")
axes[0].set_title("Sale Price Distribution by Garage Area")

df_analysis['GrLivArea_Binned'] = pd.cut(df_analysis['GrLivArea'], [0, 500,␣
 ↪1000, 1500, 2000, 2500, 3000],
                                         labels=["0-500", "500-1000",␣
 ↪"1000-1500", "1500-2000", "2000-2500", "2500-3000"])
```

```
sns.boxplot(x=df_analysis['GrLivArea_Binned'], y=df_analysis['SalePrice'],␣
↪ax=axes[1])
axes[1].set_title("Sale Price vs. Living Area")
axes[1].set_xlabel("Living Area (binned)")
axes[1].set_ylabel("Sale Price")

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

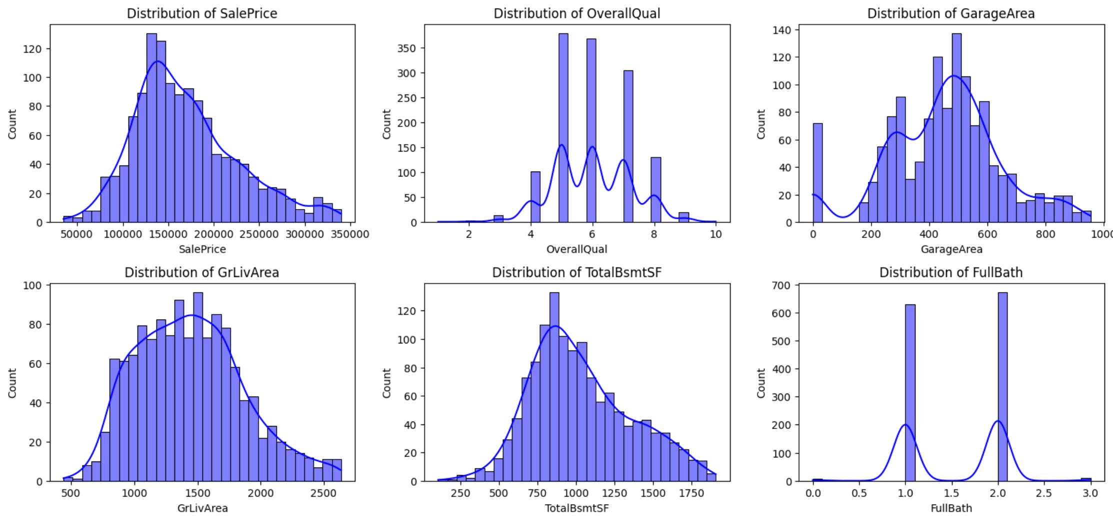


[37]:
```
fig, ax = plt.subplots(figsize=(12, 6))

sns.boxplot(x=df_analysis['FullBath'], y=df_analysis['SalePrice'], ax=ax)
ax.set_title("Sale Price vs. Number of Bathroom")
ax.set_xlabel("No. Bathroom)")
ax.set_ylabel("Sale Price")

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



Visualizing Distribution of data using Histograms

[38]:
```
features = ['SalePrice', 'OverallQual', 'GarageArea', 'GrLivArea',␣
↪'TotalBsmtSF', 'FullBath']

plt.figure(figsize=(15, 10))

for i, feature in enumerate(features, 1):
    plt.subplot(3, 3, i)  # Arrange plots in a 2x3 grid
    sns.histplot(df_analysis[feature], bins=30, kde=True, color='blue')
    plt.title(f'Distribution of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')

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



Key Findings:

House prices are most strongly influenced by Overall Quality, Living Area, and Basement Area.

Some attributes like Full Bathrooms and Garage Area also impact pricing but to a lesser extent.

The dataset had several outliers that were removed for better model performance.