In [1]:
```
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
property_sales_df = pd.read_csv("nyc-rolling-sales.csv")
# Set the display options to show all columns
pd.set_option('display.max_columns', None)
property_sales_df.head(), property_sales_df.tail()
```

Out[2]:

```
(   Unnamed: 0  BOROUGH   NEIGHBORHOOD  \
0           4        1  ALPHABET CITY
1           5        1  ALPHABET CITY
2           6        1  ALPHABET CITY
3           7        1  ALPHABET CITY
4           8        1  ALPHABET CITY

                       BUILDING CLASS CATEGORY TAX CLASS AT PRESENT  BLOCK  \
0  07 RENTALS - WALKUP APARTMENTS                                 2A    392
1  07 RENTALS - WALKUP APARTMENTS                                  2    399
2  07 RENTALS - WALKUP APARTMENTS                                  2    399
3  07 RENTALS - WALKUP APARTMENTS                                 2B    402
4  07 RENTALS - WALKUP APARTMENTS                                 2A    404

   LOT EASE-MENT BUILDING CLASS AT PRESENT                ADDRESS  \
0    6                                  C2            153 AVENUE B
1   26                                  C7   234 EAST 4TH   STREET
2   39                                  C7   197 EAST 3RD   STREET
3   21                                  C4     154 EAST 7TH STREET
4   55                                  C2  301 EAST 10TH   STREET

  APARTMENT NUMBER  ZIP CODE  RESIDENTIAL UNITS  COMMERCIAL UNITS  \
0                    10009                  5                 0
1                    10009                 28                 3
2                    10009                 16                 1
3                    10009                 10                 0
4                    10009                  6                 0

   TOTAL UNITS LAND SQUARE FEET GROSS SQUARE FEET  YEAR BUILT  \
0            5             1633              6440        1900
1           31             4616             18690        1900
2           17             2212              7803        1900
3           10             2272              6794        1913
4            6             2369              4615        1900

   TAX CLASS AT TIME OF SALE BUILDING CLASS AT TIME OF SALE SALE PRICE  \
0                          2                             C2    6625000
1                          2                             C7          -
2                          2                             C7          -
3                          2                             C4    3936272
4                          2                             C2    8000000

            SALE DATE
0  2017-07-19 00:00:00
1  2016-12-14 00:00:00
2  2016-12-09 00:00:00
3  2016-09-23 00:00:00
4  2016-11-17 00:00:00  ,
       Unnamed: 0  BOROUGH NEIGHBORHOOD  \
84543        8409        5      WOODROW
84544        8410        5      WOODROW
84545        8411        5      WOODROW
84546        8412        5      WOODROW
84547        8413        5      WOODROW

                           BUILDING CLASS CATEGORY TAX CLASS AT PRESENT  \
84543  02 TWO FAMILY DWELLINGS                                       1
84544  02 TWO FAMILY DWELLINGS                                       1
84545  02 TWO FAMILY DWELLINGS                                       1
84546  22 STORE BUILDINGS                                            4
```

```
84547  35 INDOOR PUBLIC AND CULTURAL FACILITIES                      4

       BLOCK  LOT EASE-MENT BUILDING CLASS AT PRESENT               ADDRESS  \
84543   7349   34                                   B9          37 QUAIL LANE
84544   7349   78                                   B9       32 PHEASANT LANE
84545   7351   60                                   B2       49 PITNEY AVENUE
84546   7100   28                                   K6  2730 ARTHUR KILL ROAD
84547   7105  679                                   P9      155 CLAY PIT ROAD

      APARTMENT NUMBER  ZIP CODE  RESIDENTIAL UNITS  COMMERCIAL UNITS  \
84543                    10309                  2                 0
84544                    10309                  2                 0
84545                    10309                  2                 0
84546                    10309                  0                 7
84547                    10309                  0                 1

       TOTAL UNITS LAND SQUARE FEET GROSS SQUARE FEET  YEAR BUILT  \
84543            2             2400              2575        1998
84544            2             2498              2377        1998
84545            2             4000              1496        1925
84546            7           208033             64117        2001
84547            1            10796              2400        2006

       TAX CLASS AT TIME OF SALE BUILDING CLASS AT TIME OF SALE SALE PRICE  \
84543                          1                             B9     450000
84544                          1                             B9     550000
84545                          1                             B2     460000
84546                          4                             K6   11693337
84547                          4                             P9      69300

                SALE DATE
84543  2016-11-28 00:00:00
84544  2017-04-21 00:00:00
84545  2017-07-05 00:00:00
84546  2016-12-21 00:00:00
84547  2016-10-27 00:00:00  )
```

In [3]:
```
property_sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 84548 entries, 0 to 84547
Data columns (total 22 columns):
 #   Column                          Non-Null Count  Dtype 
---  ------                          --------------  ----- 
 0   Unnamed: 0                      84548 non-null  int64 
 1   BOROUGH                         84548 non-null  int64 
 2   NEIGHBORHOOD                    84548 non-null  object
 3   BUILDING CLASS CATEGORY         84548 non-null  object
 4   TAX CLASS AT PRESENT            84548 non-null  object
 5   BLOCK                           84548 non-null  int64 
 6   LOT                             84548 non-null  int64 
 7   EASE-MENT                       84548 non-null  object
 8   BUILDING CLASS AT PRESENT       84548 non-null  object
 9   ADDRESS                         84548 non-null  object
 10  APARTMENT NUMBER                84548 non-null  object
 11  ZIP CODE                        84548 non-null  int64 
 12  RESIDENTIAL UNITS               84548 non-null  int64 
 13  COMMERCIAL UNITS                84548 non-null  int64 
 14  TOTAL UNITS                     84548 non-null  int64 
 15  LAND SQUARE FEET                84548 non-null  object
 16  GROSS SQUARE FEET               84548 non-null  object
 17  YEAR BUILT                      84548 non-null  int64 
 18  TAX CLASS AT TIME OF SALE       84548 non-null  int64 
 19  BUILDING CLASS AT TIME OF SALE  84548 non-null  object
 20  SALE PRICE                      84548 non-null  object
 21  SALE DATE                       84548 non-null  object
dtypes: int64(10), object(12)
memory usage: 14.2+ MB
```

In [4]:
```
property_sales_df.isnull().values.any()
```

Out[4]:
```
False
```

In [5]:
```
property_sales_df.isnull()
```

Out[5]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILDIN CLASS PRESE
0	False	False	False	False	False	False	False	False	Fal
1	False	False	False	False	False	False	False	False	Fal
2	False	False	False	False	False	False	False	False	Fal
3	False	False	False	False	False	False	False	False	Fal
4	False	False	False	False	False	False	False	False	Fal
...	...	...	...	...	...	...	...	...	
84543	False	False	False	False	False	False	False	False	Fal
84544	False	False	False	False	False	False	False	False	Fal
84545	False	False	False	False	False	False	False	False	Fal
84546	False	False	False	False	False	False	False	False	Fal
84547	False	False	False	False	False	False	False	False	Fal

84548 rows × 22 columns

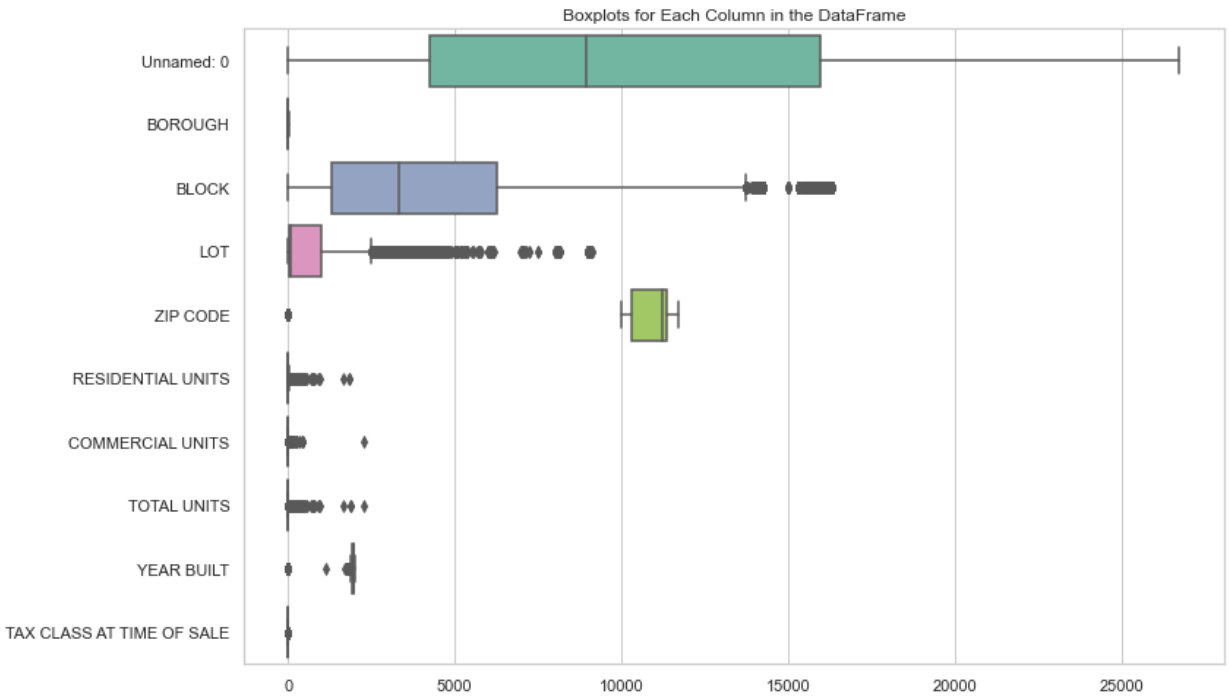
In [6]:
```
property_sales_df.isnull().sum()
```

Out[6]:
```
Unnamed: 0                        0
BOROUGH                           0
NEIGHBORHOOD                      0
BUILDING CLASS CATEGORY           0
TAX CLASS AT PRESENT              0
BLOCK                             0
LOT                               0
EASE-MENT                         0
BUILDING CLASS AT PRESENT         0
ADDRESS                           0
APARTMENT NUMBER                  0
ZIP CODE                          0
RESIDENTIAL UNITS                 0
COMMERCIAL UNITS                  0
TOTAL UNITS                       0
LAND SQUARE FEET                  0
GROSS SQUARE FEET                 0
YEAR BUILT                        0
TAX CLASS AT TIME OF SALE         0
BUILDING CLASS AT TIME OF SALE    0
SALE PRICE                        0
SALE DATE                         0
dtype: int64
```

In [7]:
```
sum(property_sales_df.duplicated())
```

Out[7]:
```
0
```

In [8]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="whitegrid")

# Create boxplots for each column
plt.figure(figsize=(12, 8))
sns.boxplot(data=property_sales_df, orient="h", palette="Set2")
plt.title('Boxplots for Each Column in the DataFrame')
plt.show()
```



In [9]:
```
# Clean the 'SALE PRICE' column by replacing non-numeric values with NaN. There are '-
property_sales_df['SALE PRICE'] = pd.to_numeric(property_sales_df['SALE PRICE'], error

# Convert the 'SALE PRICE' column to nullable integer type (Int64)
property_sales_df['SALE PRICE'] = property_sales_df['SALE PRICE'].astype('Int64')
```

In [10]:
```
print(property_sales_df['SALE PRICE'].unique())
```

```
<IntegerArray>
[ 6625000,     <NA>,  3936272,  8000000,  3192840, 16232000, 10350000,
        1,   499000,       10,
 ...
   681900,   412404,   239400,   441176,   306228,   774143,   523950,
   408092, 11693337,    69300]
Length: 10008, dtype: Int64
```

In [11]:
```
property_sales_df['SALE PRICE'].isna()
```

Out[11]:
```
0        False
1         True
2         True
3        False
4        False
         ...
84543    False
84544    False
84545    False
84546    False
84547    False
Name: SALE PRICE, Length: 84548, dtype: bool
```

In [12]:
```
null_count_before = property_sales_df['SALE PRICE'].isnull().sum()
```

In [13]:
```
# Drop null values from Sale Price column
property_sales_df.dropna(subset=['SALE PRICE'], inplace=True)
```

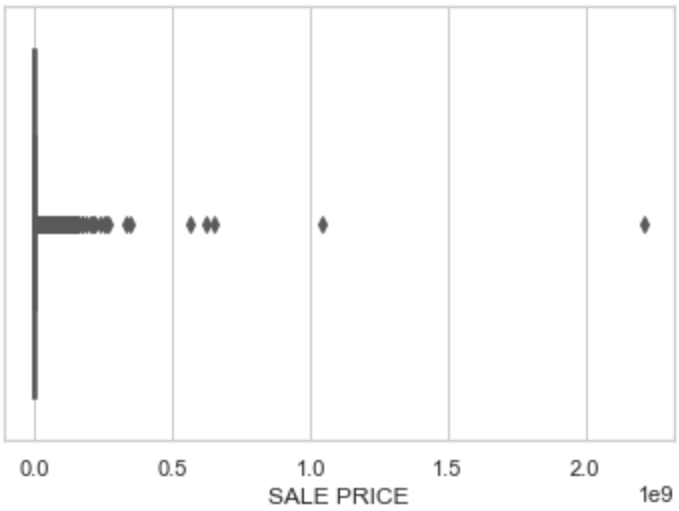
In [14]:
```
# Count null values after dropping
null_count_after = property_sales_df['SALE PRICE'].isnull().sum()
```

In [15]:
```
print(f'Null count before dropping: {null_count_before}')
print(f'Null count after dropping: {null_count_after}')
```

```
Null count before dropping: 14561
Null count after dropping: 0
```

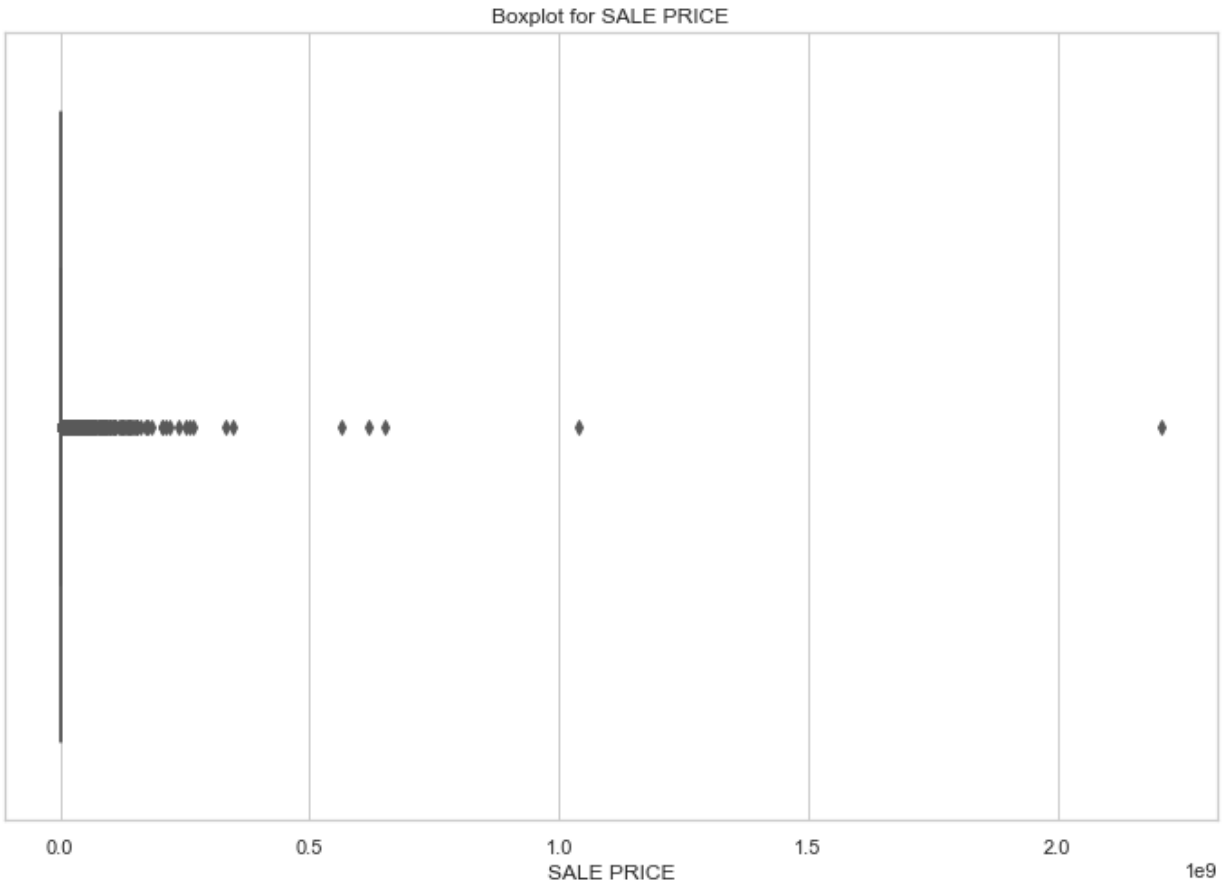
In [16]:
```
sns.boxplot(x=property_sales_df['SALE PRICE'], orient="h", palette="Set2")
```

Out[16]:
```
<AxesSubplot:xlabel='SALE PRICE'>
```



In [17]:
```
# Clean the 'SALE PRICE' column by replacing non-numeric values with NaN
property_sales_df['SALE PRICE'] = pd.to_numeric(property_sales_df['SALE PRICE'], error

# Convert the 'SALE PRICE' column to nullable integer type (Int64)
property_sales_df['SALE PRICE'] = property_sales_df['SALE PRICE'].astype('Int64')

# Drop missing values before creating the boxplot
property_sales_df_cleaned = property_sales_df.dropna(subset=['SALE PRICE'])

# Create boxplot for the 'SALE PRICE' column
plt.figure(figsize=(12, 8))
```

```
sns.boxplot(x=property_sales_df_cleaned['SALE PRICE'], orient="h", palette="Set2")
plt.title('Boxplot for SALE PRICE')
plt.show()
```



In [18]:
```
property_sales_df['SALE PRICE'].describe()
```

Out[18]:
```
count    6.998700e+04
mean     1.276456e+06
std      1.140526e+07
min      0.000000e+00
25%      2.250000e+05
50%      5.300000e+05
75%      9.500000e+05
max      2.210000e+09
Name: SALE PRICE, dtype: float64
```

In [19]:
```
# Check the authenticity of the max 'Sale Price' value
property_sales_df[property_sales_df['SALE PRICE'] == 2.210000e+09]
```

Out[19]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILDING CLASS AT PRESENT
7447	7451	1	MIDTOWN CBD	21 OFFICE BUILDINGS	4	1301	1		O4

In [20]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 50000]
```

Out[20]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLAS PRES
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
41	45	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2C	393	39		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84389	8255	5	WILLOWBROOK	05 TAX CLASS 1 VACANT LAND	1B	730	65		
84394	8260	5	WILLOWBROOK	44 CONDO PARKING	4	1965	1126		
84464	8330	5	WOODROW	01 ONE FAMILY DWELLINGS	1	7106	50		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

12164 rows × 22 columns

In [21]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 5000]
```

Out[21]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
209	213	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84194	8060	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	735	153		
84202	8068	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	744	14		
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84464	8330	5	WOODROW	01 ONE FAMILY DWELLINGS	1	7106	50		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

11441 rows × 22 columns

In [22]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 500]
```

Out[22]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
209	213	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84187	8053	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	734	13		
84194	8060	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	735	153		
84202	8068	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	744	14		
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

11236 rows × 22 columns

In [23]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 100]
```

Out[23]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
209	213	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84187	8053	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	734	13		
84194	8060	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	735	153		
84202	8068	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	744	14		
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

11140 rows × 22 columns

In [24]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 50]
```

Out[24]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
209	213	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84187	8053	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	734	13		
84194	8060	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	735	153		
84202	8068	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	744	14		
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

11140 rows × 22 columns

In [25]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 30]
```

Out[25]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
209	213	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84187	8053	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	734	13		
84194	8060	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	735	153		
84202	8068	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	744	14		
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

11140 rows × 22 columns

In [26]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 20]
```

Out[26]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
14	18	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
207	211	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
208	212	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
209	213	1	CHELSEA	01 ONE FAMILY DWELLINGS	1	772	29		
...	...	...	...	...	...	...	...	...	
84187	8053	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	734	13		
84194	8060	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	735	153		
84202	8068	5	WILLOWBROOK	01 ONE FAMILY DWELLINGS	1	744	14		
84301	8167	5	WILLOWBROOK	02 TWO FAMILY DWELLINGS	1	749	14		
84502	8368	5	WOODROW	02 TWO FAMILY DWELLINGS	1	6914	35		

11136 rows × 22 columns

In [27]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 10]
```

Out[27]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUIL CLA PRE
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
656	660	1	CHELSEA	13 CONDOS - ELEVATOR APARTMENTS	2	767	1110		
1653	1657	1	CLINTON	13 CONDOS - ELEVATOR APARTMENTS	2	1063	1129		
3409	3413	1	GRAMERCY	13 CONDOS - ELEVATOR APARTMENTS	2	876	1013		
3894	3898	1	GREENWICH VILLAGE-CENTRAL	13 CONDOS - ELEVATOR APARTMENTS	2	525	1714		
...	...	...	...	...	...	...	...	...	
80138	4004	5	NEW BRIGHTON	01 ONE FAMILY DWELLINGS	1	66	58		
80881	4747	5	NEW SPRINGVILLE	01 ONE FAMILY DWELLINGS	1	2410	11		
83181	7047	5	TODT HILL	33 EDUCATIONAL FACILITIES	4	683	1		
83182	7048	5	TODT HILL	33 EDUCATIONAL FACILITIES	4	683	301		
83291	7157	5	TOTTENVILLE	01 ONE FAMILY DWELLINGS	1	7863	232		

10369 rows × 22 columns

In [28]:
```
property_sales_df[property_sales_df['SALE PRICE'] < 5]
```

Out[28]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUIL CLA PRE
12	16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
656	660	1	CHELSEA	13 CONDOS - ELEVATOR APARTMENTS	2	767	1110		
1653	1657	1	CLINTON	13 CONDOS - ELEVATOR APARTMENTS	2	1063	1129		
3409	3413	1	GRAMERCY	13 CONDOS - ELEVATOR APARTMENTS	2	876	1013		
3894	3898	1	GREENWICH VILLAGE-CENTRAL	13 CONDOS - ELEVATOR APARTMENTS	2	525	1714		
...	...	...	...	...	...	...	...	...	
80138	4004	5	NEW BRIGHTON	01 ONE FAMILY DWELLINGS	1	66	58		
80881	4747	5	NEW SPRINGVILLE	01 ONE FAMILY DWELLINGS	1	2410	11		
83181	7047	5	TODT HILL	33 EDUCATIONAL FACILITIES	4	683	1		
83182	7048	5	TODT HILL	33 EDUCATIONAL FACILITIES	4	683	301		
83291	7157	5	TOTTENVILLE	01 ONE FAMILY DWELLINGS	1	7863	232		

10367 rows × 22 columns

In [29]:
```
cleaned_sales_price_df = property_sales_df[property_sales_df['SALE PRICE'] > 5000]
```

In [30]:
```
# New df without any unreasonable prices below $5,000.
cleaned_sales_price_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58514 entries, 0 to 84547
Data columns (total 22 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Unnamed: 0                      58514 non-null  int64
 1   BOROUGH                         58514 non-null  int64
 2   NEIGHBORHOOD                    58514 non-null  object
 3   BUILDING CLASS CATEGORY         58514 non-null  object
 4   TAX CLASS AT PRESENT            58514 non-null  object
 5   BLOCK                           58514 non-null  int64
 6   LOT                             58514 non-null  int64
 7   EASE-MENT                       58514 non-null  object
 8   BUILDING CLASS AT PRESENT       58514 non-null  object
 9   ADDRESS                         58514 non-null  object
 10  APARTMENT NUMBER                58514 non-null  object
 11  ZIP CODE                        58514 non-null  int64
 12  RESIDENTIAL UNITS               58514 non-null  int64
 13  COMMERCIAL UNITS                58514 non-null  int64
 14  TOTAL UNITS                     58514 non-null  int64
 15  LAND SQUARE FEET                58514 non-null  object
 16  GROSS SQUARE FEET               58514 non-null  object
 17  YEAR BUILT                      58514 non-null  int64
 18  TAX CLASS AT TIME OF SALE       58514 non-null  int64
 19  BUILDING CLASS AT TIME OF SALE  58514 non-null  object
 20  SALE PRICE                      58514 non-null  Int64
 21  SALE DATE                       58514 non-null  object
dtypes: Int64(1), int64(10), object(11)
memory usage: 10.3+ MB
```

In [31]:
```
cleaned_sales_price_df.head()
```

Out[31]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILDING CLASS AT PRESENT
0	4	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	392	6		C2
3	7	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	402	21		C4
4	8	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	404	55		C2
6	10	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	406	32		C4
9	13	1	ALPHABET CITY	08 RENTALS - ELEVATOR APARTMENTS	2	387	153		D9

In [32]:
```
cleaned_sales_price_df['BOROUGH'].value_counts()
```

Out[32]:
```
4    18081
3    15294
1    14293
5     5850
2     4996
Name: BOROUGH, dtype: int64
```

In [33]:
```
property_sales_df[property_sales_df['SALE PRICE'] > 1300000000]
```

Out[33]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILDING CLASS AT PRESENT
7447	7451	1	MIDTOWN CBD	21 OFFICE BUILDINGS	4	1301	1		O4

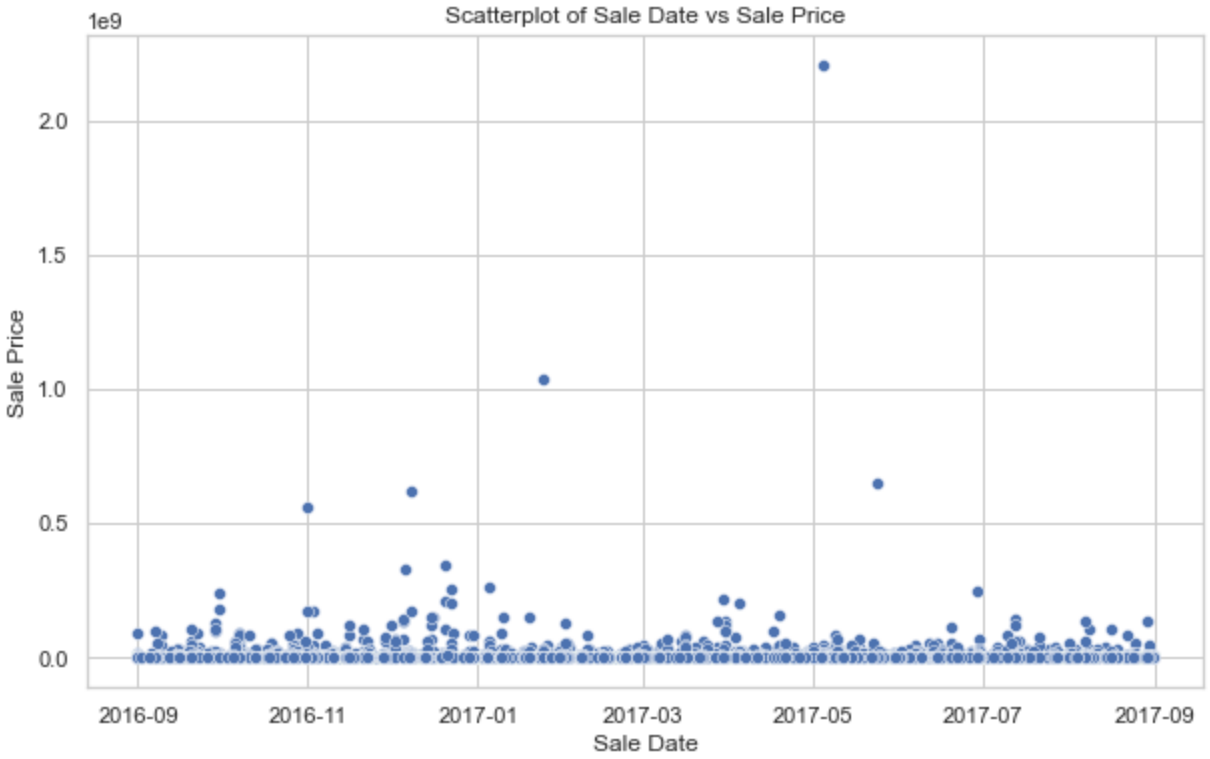
In [34]:
```
cleaned_sales_price_df.dtypes
```

Out[34]:
```
Unnamed: 0                       int64
BOROUGH                          int64
NEIGHBORHOOD                    object
BUILDING CLASS CATEGORY         object
TAX CLASS AT PRESENT            object
BLOCK                            int64
LOT                              int64
EASE-MENT                       object
BUILDING CLASS AT PRESENT       object
ADDRESS                         object
APARTMENT NUMBER                object
ZIP CODE                         int64
RESIDENTIAL UNITS                int64
COMMERCIAL UNITS                 int64
TOTAL UNITS                      int64
LAND SQUARE FEET                object
GROSS SQUARE FEET               object
YEAR BUILT                       int64
TAX CLASS AT TIME OF SALE        int64
BUILDING CLASS AT TIME OF SALE  object
SALE PRICE                       Int64
SALE DATE                       object
dtype: object
```

In [35]:
```
# Convert 'SALE DATE' from object to datetime
cleaned_sales_price_df['SALE DATE'] = pd.to_datetime(cleaned_sales_price_df['SALE DATE
```

In [36]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))  # Adjust the figure size as needed
sns.scatterplot(x='SALE DATE', y='SALE PRICE', data=cleaned_sales_price_df)

# Set plot labels and title
```

```
plt.xlabel('Sale Date')
plt.ylabel('Sale Price')
plt.title('Scatterplot of Sale Date vs Sale Price')

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



Note that there is not a significant correlation between 'SALE PRICE' and 'SALE DATE'.

In [37]:
```
cleaned_sales_price_df['BLOCK'].value_counts()
```

Out[37]:
```
5066     388
16       202
2135     196
4978     181
170      131
        ...
2465       1
11088      1
11090      1
11092      1
16316      1
Name: BLOCK, Length: 10482, dtype: int64
```

In [38]:
```
cleaned_sales_price_df['LOT'].value_counts()
```

Out[38]:
```
1       3309
20       690
12       680
40       662
23       638
        ...
3454       1
3469       1
3593       1
3605       1
679        1
Name: LOT, Length: 2356, dtype: int64
```

In [39]:
```
cleaned_sales_price_df['LAND SQUARE FEET'] = pd.to_numeric(cleaned_sales_price_df['LAN
```

In [40]:
```
cleaned_sales_price_df['LAND SQUARE FEET'].isna().sum()
```

Out[40]:
```
21012
```

In [41]:
```
cleaned_sales_price_df['LAND SQUARE FEET'].describe()
```

Out[41]:
```
count    3.750200e+04
mean     3.715316e+03
std      4.426534e+04
min      0.000000e+00
25%      1.402000e+03
50%      2.208500e+03
75%      3.325000e+03
max      4.252327e+06
Name: LAND SQUARE FEET, dtype: float64
```

In [42]:
```
cleaned_sales_price_df[cleaned_sales_price_df['LAND SQUARE FEET'] < 100]
```

Out[42]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLAS PRES
18354	52	2	BATHGATE	10 COOPS - ELEVATOR APARTMENTS	2	3035	48		
18355	53	2	BATHGATE	10 COOPS - ELEVATOR APARTMENTS	2	3035	48		
18356	54	2	BATHGATE	10 COOPS - ELEVATOR APARTMENTS	2	3044	40		
18746	444	2	BAYCHESTER	04 TAX CLASS 1 CONDOS	1A	4795	1009		
18747	445	2	BAYCHESTER	04 TAX CLASS 1 CONDOS	1A	4795	1027		
...	...	...	...	...	...	...	...	...	
49377	24026	3	WYCKOFF HEIGHTS	13 CONDOS - ELEVATOR APARTMENTS	2	3238	1025		
49378	24027	3	WYCKOFF HEIGHTS	13 CONDOS - ELEVATOR APARTMENTS	2	3248	1013		
49379	24028	3	WYCKOFF HEIGHTS	13 CONDOS - ELEVATOR APARTMENTS	2	3248	1015		
49380	24029	3	WYCKOFF HEIGHTS	13 CONDOS - ELEVATOR APARTMENTS	2	3328	1015		
55739	6341	4	FAR ROCKAWAY	05 TAX CLASS 1 VACANT LAND	1B	15793	11		

8067 rows × 22 columns

In [43]:
```
# Replace null values with 0
cleaned_sales_price_df['LAND SQUARE FEET'] = cleaned_sales_price_df['LAND SQUARE FEET'
```

In [44]:
```
cleaned_sales_price_df[cleaned_sales_price_df['LAND SQUARE FEET'] < 100]
```

Out[44]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLAS PRES
13	17	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
15	19	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
16	20	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
17	21	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	46		
18	22	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	49		
...	...	...	...	...	...	...	...	...	
84382	8248	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	1965	1122		
84383	8249	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2086	1009		
84384	8250	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2087	1002		
84385	8251	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2087	1021		
84388	8254	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2089	1006		

29079 rows × 22 columns

In [45]:
```
cleaned_sales_price_df['GROSS SQUARE FEET'] = pd.to_numeric(cleaned_sales_price_df['GR
```

In [46]:
```
cleaned_sales_price_df['GROSS SQUARE FEET'].isna().sum()
```

Out[46]:
```
21540
```

In [47]:
```
cleaned_sales_price_df['GROSS SQUARE FEET'].describe()
```

Out[47]:
```
count    3.697400e+04
mean     3.531155e+03
std      2.996708e+04
min      0.000000e+00
25%      8.680000e+02
50%      1.550000e+03
75%      2.341750e+03
max      3.750565e+06
Name: GROSS SQUARE FEET, dtype: float64
```

In [48]:
```
cleaned_sales_price_df['GROSS SQUARE FEET'] = cleaned_sales_price_df['GROSS SQUARE FEE
```

In [49]:
```
cleaned_sales_price_df[cleaned_sales_price_df['GROSS SQUARE FEET'] < 100]
```

Out[49]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLAS PRES
13	17	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
15	19	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
16	20	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
17	21	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	46		
18	22	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	49		
...	...	...	...	...	...	...	...	...	
84383	8249	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2086	1009		
84384	8250	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2087	1002		
84385	8251	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2087	1021		
84388	8254	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2089	1006		
84389	8255	5	WILLOWBROOK	05 TAX CLASS 1 VACANT LAND	1B	730	65		

30057 rows × 22 columns

In [50]:
```
cleaned_sales_price_df[(cleaned_sales_price_df['LAND SQUARE FEET'] < 100)\
                       & (cleaned_sales_price_df['GROSS SQUARE FEET'] < 100)]
```

Out[50]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLAS PRES
13	17	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
15	19	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
16	20	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40		
17	21	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	46		
18	22	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	49		
...	...	...	...	...	...	...	...	...	
84382	8248	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	1965	1122		
84383	8249	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2086	1009		
84384	8250	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2087	1002		
84385	8251	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2087	1021		
84388	8254	5	WILLOWBROOK	04 TAX CLASS 1 CONDOS	1A	2089	1006		

29075 rows × 22 columns

In [51]:
```
condition = (cleaned_sales_price_df['LAND SQUARE FEET'] < 100) & (cleaned_sales_price_

# Display only rows that satisfy the condition
filtered_rows = cleaned_sales_price_df[condition]
print(filtered_rows)
```

```
       Unnamed: 0  BOROUGH   NEIGHBORHOOD  \
13             17        1  ALPHABET CITY
15             19        1  ALPHABET CITY
16             20        1  ALPHABET CITY
17             21        1  ALPHABET CITY
18             22        1  ALPHABET CITY
...           ...      ...            ...
84382        8248        5    WILLOWBROOK
84383        8249        5    WILLOWBROOK
84384        8250        5    WILLOWBROOK
84385        8251        5    WILLOWBROOK
84388        8254        5    WILLOWBROOK

                            BUILDING CLASS CATEGORY TAX CLASS AT PRESENT  \
13     09 COOPS - WALKUP APARTMENTS                                    2
15     09 COOPS - WALKUP APARTMENTS                                    2
16     09 COOPS - WALKUP APARTMENTS                                    2
17     09 COOPS - WALKUP APARTMENTS                                    2
18     09 COOPS - WALKUP APARTMENTS                                    2
...                                              ...                  ...
84382  04 TAX CLASS 1 CONDOS                                          1A
84383  04 TAX CLASS 1 CONDOS                                          1A
84384  04 TAX CLASS 1 CONDOS                                          1A
84385  04 TAX CLASS 1 CONDOS                                          1A
84388  04 TAX CLASS 1 CONDOS                                          1A

       BLOCK   LOT EASE-MENT BUILDING CLASS AT PRESENT  \
13       373    40                                  C6
15       373    40                                  C6
16       373    40                                  C6
17       373    46                                  C6
18       373    49                                  C6
...      ...   ...       ...                      ...
84382   1965  1122                                  R3
84383   2086  1009                                  R3
84384   2087  1002                                  R3
84385   2087  1021                                  R3
84388   2089  1006                                  R3

                      ADDRESS APARTMENT NUMBER  ZIP CODE  RESIDENTIAL UNITS  \
13       327 EAST 3 STREET, 1C                      10009                  0
15     327 EAST 3RD STREET, 5A                      10009                  0
16       327 EAST 3 STREET, 2E                      10009                  0
17     317 EAST 3RD STREET, 12                      10009                  0
18     311 EAST 3RD STREET, 17                      10009                  0
...                        ...              ...       ...                ...
84382    1235 FOREST HILL ROAD               2L     10314                  1
84383         39 DREYER AVENUE                      10314                  1
84384     392 HAWTHORNE AVENUE                      10314                  1
84385     418 HAWTHORNE AVENUE                      10314                  1
84388         18 DARCEY AVENUE                      10314                  1

       COMMERCIAL UNITS  TOTAL UNITS  LAND SQUARE FEET  GROSS SQUARE FEET  \
13                    0            0               0.0                0.0
15                    0            0               0.0                0.0
16                    0            0               0.0                0.0
17                    0            0               0.0                0.0
18                    0            0               0.0                0.0
...                 ...          ...               ...                ...
84382                 0            1               0.0                0.0
```

```
84383                0           1              0.0               0.0
84384                0           1              0.0               0.0
84385                0           1              0.0               0.0
84388                0           1              0.0               0.0

       YEAR BUILT  TAX CLASS AT TIME OF SALE BUILDING CLASS AT TIME OF SALE  \
13           1920                         2                             C6
15           1920                         2                             C6
16           1920                         2                             C6
17           1925                         2                             C6
18           1920                         2                             C6
...           ...                       ...                            ...
84382        2015                         1                             R3
84383        1979                         1                             R3
84384        1980                         1                             R3
84385        1980                         1                             R3
84388        1980                         1                             R3

       SALE PRICE  SALE DATE
13         499000 2017-03-10
15         529500 2017-06-09
16         423000 2017-07-14
17         501000 2017-03-16
18         450000 2016-09-01
...           ...        ...
84382      430950 2017-06-01
84383      415500 2016-10-31
84384      335000 2016-10-20
84385      420000 2016-12-29
84388      407000 2016-10-13

[29075 rows x 22 columns]
```

It is the same 29,079 rows which have 0 values for both Land Square Feet and Gross Square Feet.

In [52]:
```
# Create sales_price_df with land and gross square feet more than 100.
cleaned_area_sales_df = cleaned_sales_price_df[(cleaned_sales_price_df['LAND SQUARE FE
                                                & (cleaned_sales_price_df['GROSS SQUARE
cleaned_area_sales_df.head()
```

Out[52]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILDING CLASS AT PRESENT
0	4	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	392	6		C2
3	7	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	402	21		C4
4	8	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	404	55		C2
6	10	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	406	32		C4
9	13	1	ALPHABET CITY	08 RENTALS - ELEVATOR APARTMENTS	2	387	153		D9

In [53]:
```
cleaned_area_sales_df
```

Out[53]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUILD CLASS PRESI
0	4	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	392	6		
3	7	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	402	21		
4	8	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	404	55		
6	10	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	406	32		
9	13	1	ALPHABET CITY	08 RENTALS - ELEVATOR APARTMENTS	2	387	153		
...	...	...	...	...	...	...	...	...	
84543	8409	5	WOODROW	02 TWO FAMILY DWELLINGS	1	7349	34		
84544	8410	5	WOODROW	02 TWO FAMILY DWELLINGS	1	7349	78		
84545	8411	5	WOODROW	02 TWO FAMILY DWELLINGS	1	7351	60		
84546	8412	5	WOODROW	22 STORE BUILDINGS	4	7100	28		
84547	8413	5	WOODROW	35 INDOOR PUBLIC AND CULTURAL FACILITIES	4	7105	679		

28453 rows × 22 columns

In [54]:
```
cleaned_area_sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 28453 entries, 0 to 84547
Data columns (total 22 columns):
 #   Column                          Non-Null Count  Dtype         
---  ------                          --------------  -----         
 0   Unnamed: 0                      28453 non-null  int64         
 1   BOROUGH                         28453 non-null  int64         
 2   NEIGHBORHOOD                    28453 non-null  object        
 3   BUILDING CLASS CATEGORY         28453 non-null  object        
 4   TAX CLASS AT PRESENT            28453 non-null  object        
 5   BLOCK                           28453 non-null  int64         
 6   LOT                             28453 non-null  int64         
 7   EASE-MENT                       28453 non-null  object        
 8   BUILDING CLASS AT PRESENT       28453 non-null  object        
 9   ADDRESS                         28453 non-null  object        
 10  APARTMENT NUMBER                28453 non-null  object        
 11  ZIP CODE                        28453 non-null  int64         
 12  RESIDENTIAL UNITS               28453 non-null  int64         
 13  COMMERCIAL UNITS                28453 non-null  int64         
 14  TOTAL UNITS                     28453 non-null  int64         
 15  LAND SQUARE FEET                28453 non-null  float64       
 16  GROSS SQUARE FEET               28453 non-null  float64       
 17  YEAR BUILT                      28453 non-null  int64         
 18  TAX CLASS AT TIME OF SALE       28453 non-null  int64         
 19  BUILDING CLASS AT TIME OF SALE  28453 non-null  object        
 20  SALE PRICE                      28453 non-null  Int64         
 21  SALE DATE                       28453 non-null  datetime64[ns]
dtypes: Int64(1), datetime64[ns](1), float64(2), int64(10), object(8)
memory usage: 5.0+ MB
```

In [55]:
```
# Choose appropriate columns to study
selected_columns = ['BOROUGH', 'BLOCK', 'LOT', 'ZIP CODE', 'RESIDENTIAL UNITS', 'COMME
                    'TOTAL UNITS', 'LAND SQUARE FEET', 'GROSS SQUARE FEET', 'SALE PRIC

real_estate_price_df = cleaned_area_sales_df[selected_columns]
real_estate_price_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 28453 entries, 0 to 84547
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   BOROUGH           28453 non-null  int64  
 1   BLOCK             28453 non-null  int64  
 2   LOT               28453 non-null  int64  
 3   ZIP CODE          28453 non-null  int64  
 4   RESIDENTIAL UNITS  28453 non-null  int64  
 5   COMMERCIAL UNITS  28453 non-null  int64  
 6   TOTAL UNITS       28453 non-null  int64  
 7   LAND SQUARE FEET  28453 non-null  float64
 8   GROSS SQUARE FEET  28453 non-null  float64
 9   SALE PRICE        28453 non-null  Int64  
dtypes: Int64(1), float64(2), int64(7)
memory usage: 2.4 MB
```

In [56]:
```
real_estate_price_df.describe()
```

Out[56]:

	BOROUGH	BLOCK	LOT	ZIP CODE	RESIDENTIAL UNITS	COMMERCIAL UNITS	TO U
count	28453.000000	28453.000000	28453.000000	28453.000000	28453.000000	28453.000000	28453.00
mean	3.538537	5555.606228	61.770639	10994.419253	3.044811	0.334692	3.37
std	1.018337	3777.336518	125.348953	514.698802	20.225415	14.230857	24.86
min	1.000000	5.000000	1.000000	0.000000	0.000000	0.000000	0.00
25%	3.000000	2690.000000	19.000000	10462.000000	1.000000	0.000000	1.00
50%	4.000000	4918.000000	38.000000	11221.000000	2.000000	0.000000	2.00
75%	4.000000	7837.000000	64.000000	11373.000000	2.000000	0.000000	2.00
max	5.000000	16319.000000	7501.000000	11694.000000	1844.000000	2261.000000	2261.00

In [57]:
```
real_estate_price_df['ZIP CODE'].value_counts()
```

Out[57]:
```
10314    841
10312    745
10306    645
11234    642
11434    515
        ...
10044      1
10803      1
10006      1
10167      1
11005      1
Name: ZIP CODE, Length: 179, dtype: int64
```

In [58]:
```
real_estate_price_df.isna().sum()
```

Out[58]:
```
BOROUGH              0
BLOCK                0
LOT                  0
ZIP CODE             0
RESIDENTIAL UNITS    0
COMMERCIAL UNITS     0
TOTAL UNITS          0
LAND SQUARE FEET     0
GROSS SQUARE FEET    0
SALE PRICE           0
dtype: int64
```

In [59]:
```
real_estate_price_df[(real_estate_price_df['RESIDENTIAL UNITS'] == 0)\
                     & (real_estate_price_df['COMMERCIAL UNITS'] == 0)]
```

Out[59]:

	BOROUGH	BLOCK	LOT	ZIP CODE	RESIDENTIAL UNITS	COMMERCIAL UNITS	TOTAL UNITS	LAND SQUARE FEET	GROSS SQUARE FEET	
5603	1	1771	44	10035	0	0	0	5973.0	24626.0	
21238	2	4036	16	10462	0	0	0	2375.0	432.0	
21240	2	4051	14	10462	0	0	0	2375.0	684.0	
26430	3	5941	40	11209	0	0	0	1808.0	5160.0	2
30100	3	5602	21	11219	0	0	0	2684.0	3943.0	
31045	3	229	10	11201	0	0	0	8530.0	29952.0	18
32125	3	3408	5	11207	0	0	0	7840.0	9520.0	
35155	3	3664	52	11207	0	0	0	2500.0	800.0	
37133	3	4522	20	11208	0	0	0	7878.0	6000.0	2
37153	3	4327	24	11207	0	0	0	19000.0	42112.0	10
37159	3	4303	39	11207	0	0	0	3420.0	3420.0	
37616	3	5147	7501	11226	0	0	0	5200.0	30000.0	
37693	3	5141	23	11218	0	0	0	9352.0	1782.0	
38523	3	7948	11	11203	0	0	0	4000.0	1800.0	1
38538	3	7927	6	11203	0	0	0	4000.0	1185.0	
38542	3	4882	37	11203	0	0	0	2000.0	600.0	
40372	3	6916	47	11214	0	0	0	3160.0	300.0	
41251	3	5322	51	11218	0	0	0	21992.0	200.0	15
41642	3	6810	1	11229	0	0	0	16500.0	5490.0	
41643	3	7298	41	11229	0	0	0	5030.0	1360.0	10
45721	3	488	1	11231	0	0	0	15000.0	15000.0	7
46725	3	7464	16	11235	0	0	0	14553.0	2800.0	1
48245	3	2770	1	11211	0	0	0	10145.0	30100.0	8
52278	4	16258	72	11694	0	0	0	6000.0	1685.0	
53401	4	3997	13	11356	0	0	0	10849.0	7112.0	2
54054	4	1961	1	11368	0	0	0	926.0	384.0	
55351	4	2507	62	11378	0	0	0	17485.0	17108.0	7
62058	4	3897	1	11375	0	0	0	13800.0	12445.0	3
62059	4	3718	70	11385	0	0	0	4000.0	3240.0	
62750	4	10829	56	11423	0	0	0	10719.0	1800.0	1
67079	4	2573	124	11378	0	0	0	106500.0	106000.0	20
67578	4	3802	2	11385	0	0	0	1450.0	1450.0	

	BOROUGH	BLOCK	LOT	ZIP CODE	RESIDENTIAL UNITS	COMMERCIAL UNITS	TOTAL UNITS	LAND SQUARE FEET	GROSS SQUARE FEET	
67579	4	2899	1	11379	0	0	0	4000.0	3000.0	
71103	4	3450	62	11385	0	0	0	2650.0	5600.0	2
71104	4	3450	62	11385	0	0	0	2650.0	5600.0	1
81560	5	1318	121	10303	0	0	0	2625.0	600.0	
82013	5	6760	49	10309	0	0	0	7160.0	1084.0	
82569	5	7187	1	10309	0	0	0	3014056.0	349503.0	7

In [60]:
```
# Check to ensure no 0 values for TOTAL UNITS
real_estate_price_df['TOTAL UNITS'].describe()
```

Out[60]:
```
count    28453.000000
mean         3.378062
std         24.867375
min          0.000000
25%          1.000000
50%          2.000000
75%          2.000000
max       2261.000000
Name: TOTAL UNITS, dtype: float64
```

In [61]:
```
# Further reduce df to exclude rows with 0 RESIDENTIAL and 0 COMMERCIAL UNITS
real_estate_price_df = real_estate_price_df[(real_estate_price_df['RESIDENTIAL UNITS']
                       | (real_estate_price_df['COMMERCIAL UNITS'] != 0)]
real_estate_price_df
```

Out[61]:

	BOROUGH	BLOCK	LOT	ZIP CODE	RESIDENTIAL UNITS	COMMERCIAL UNITS	TOTAL UNITS	LAND SQUARE FEET	GROSS SQUARE FEET	I
0	1	392	6	10009	5	0	5	1633.0	6440.0	662
3	1	402	21	10009	10	0	10	2272.0	6794.0	393
4	1	404	55	10009	6	0	6	2369.0	4615.0	80(
6	1	406	32	10009	8	0	8	1750.0	4226.0	31!
9	1	387	153	10009	24	0	24	4489.0	18523.0	162
...	...	...	...	...	...	...	...	...	...	
84543	5	7349	34	10309	2	0	2	2400.0	2575.0	4!
84544	5	7349	78	10309	2	0	2	2498.0	2377.0	5!
84545	5	7351	60	10309	2	0	2	4000.0	1496.0	4(
84546	5	7100	28	10309	0	7	7	208033.0	64117.0	116!
84547	5	7105	679	10309	0	1	1	10796.0	2400.0	(

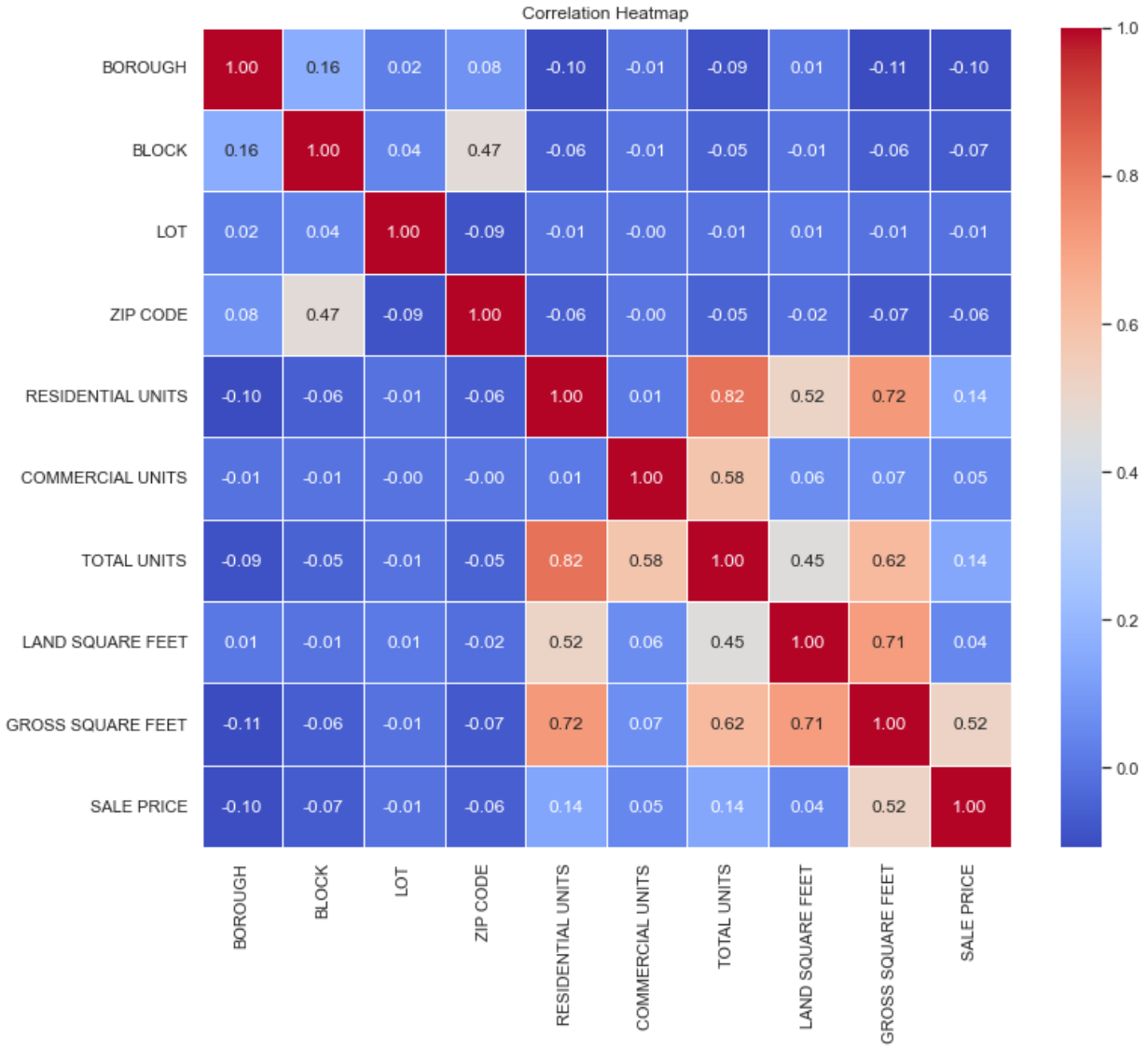
28415 rows × 10 columns

In [62]:
```
# Check correlations
real_estate_price_df.corr()
```

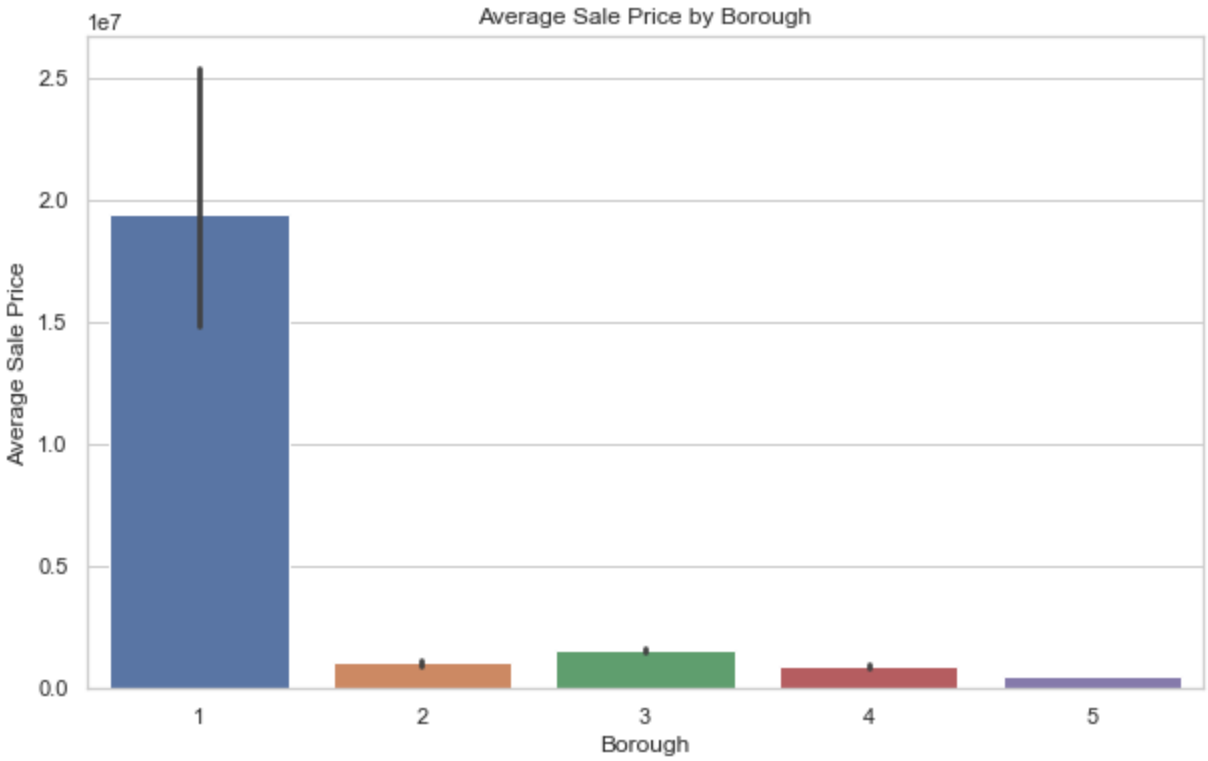
Out[62]:

	BOROUGH	BLOCK	LOT	ZIP CODE	RESIDENTIAL UNITS	COMMERCIAL UNITS	TOTAL UNITS	S
BOROUGH	1.000000	0.163071	0.023887	0.076966	-0.104796	-0.011437	-0.091748	0.
BLOCK	0.163071	1.000000	0.042334	0.466126	-0.055977	-0.006316	-0.049134	-0.
LOT	0.023887	0.042334	1.000000	-0.089428	-0.009030	-0.004537	-0.009936	0.
ZIP CODE	0.076966	0.466126	-0.089428	1.000000	-0.057055	-0.003570	-0.048428	-0.
RESIDENTIAL UNITS	-0.104796	-0.055977	-0.009030	-0.057055	1.000000	0.011839	0.820093	0.
COMMERCIAL UNITS	-0.011437	-0.006316	-0.004537	-0.003570	0.011839	1.000000	0.581891	0.
TOTAL UNITS	-0.091748	-0.049134	-0.009936	-0.048428	0.820093	0.581891	1.000000	0.
LAND SQUARE FEET	0.006034	-0.005711	0.009179	-0.021230	0.515057	0.061241	0.453959	1.
GROSS SQUARE FEET	-0.107883	-0.064526	-0.009274	-0.070754	0.719258	0.065629	0.622550	0.
SALE PRICE	-0.102624	-0.065475	-0.010423	-0.060251	0.138785	0.047692	0.140165	0.

In [63]:
```
# Create heatmap of correlations
plt.figure(figsize=(12, 10))
sns.heatmap(real_estate_price_df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linew

# Set title
plt.title('Correlation Heatmap')

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

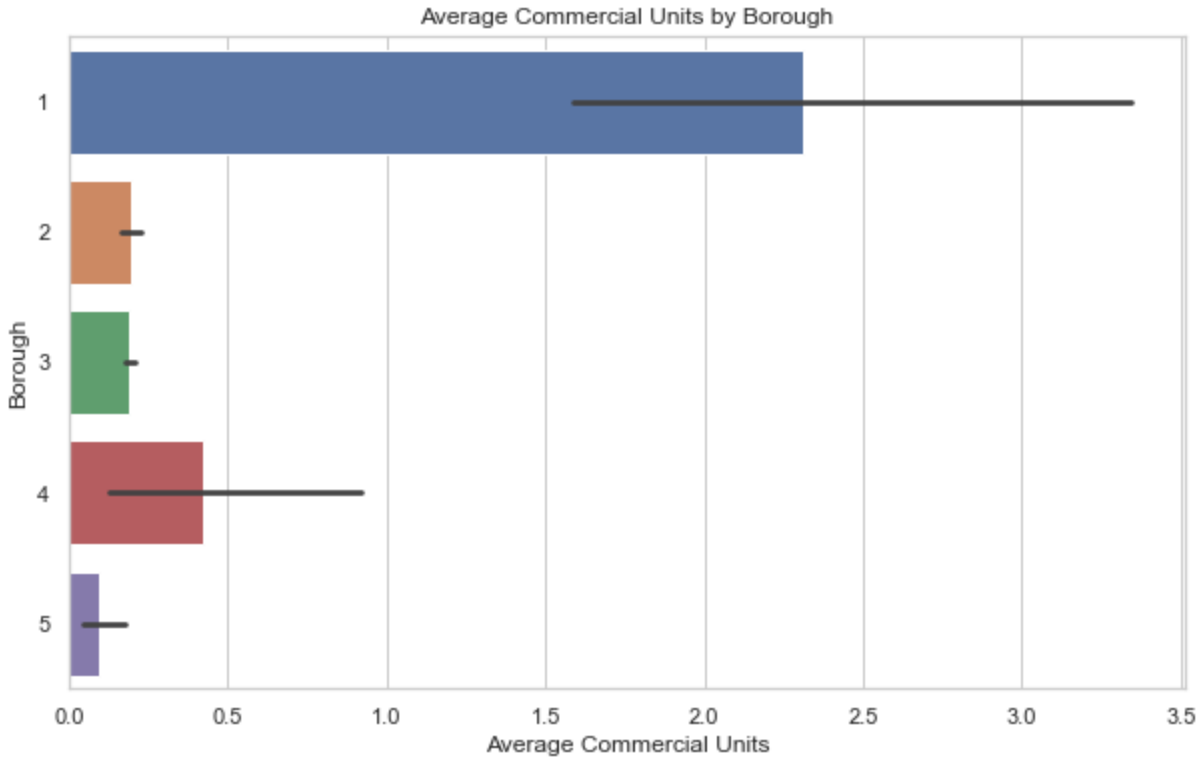


In [64]:
```
sns.set(style="whitegrid")

# Create a bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x='BOROUGH', y='SALE PRICE', data = real_estate_price_df, estimator=lambda

# Set labels and title
plt.xlabel('Borough')
plt.ylabel('Average Sale Price')
plt.title('Average Sale Price by Borough')

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

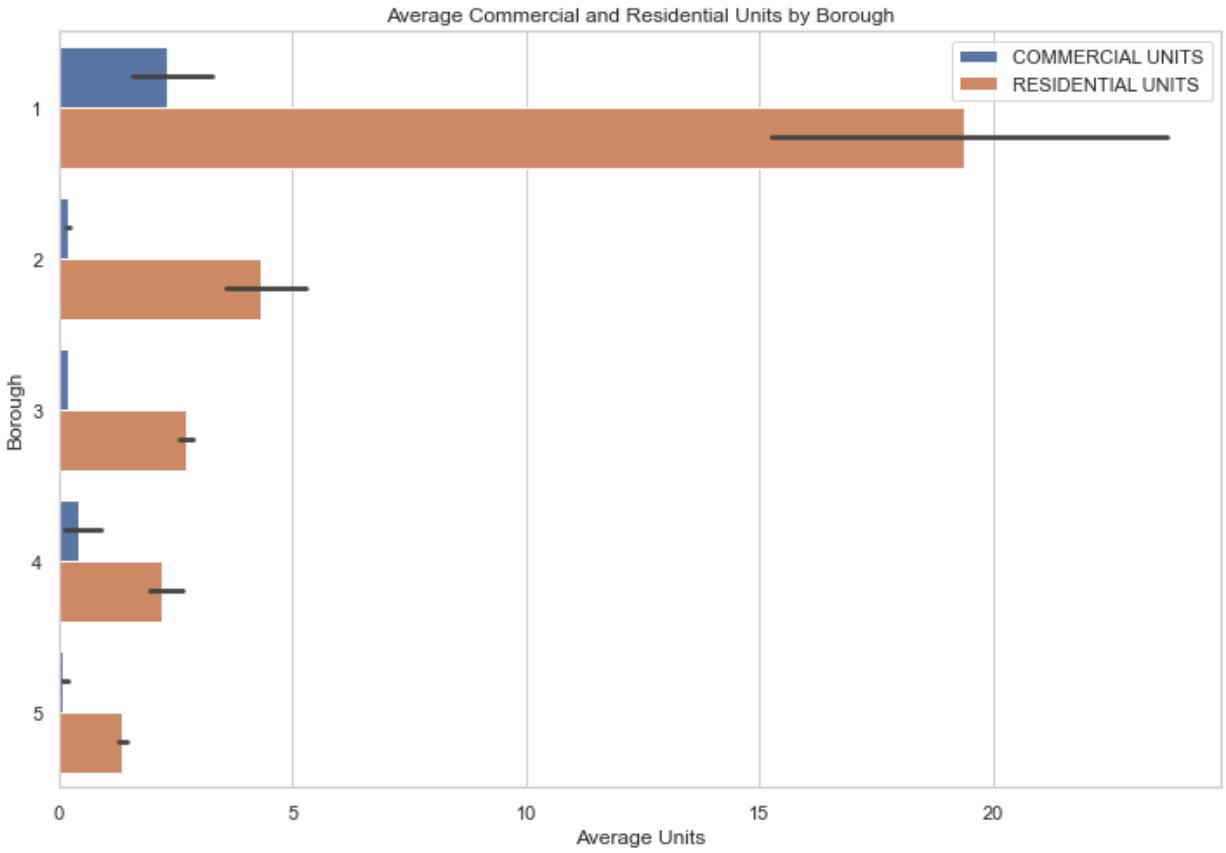


1=Manhattan has the highest average sale price by a lot.

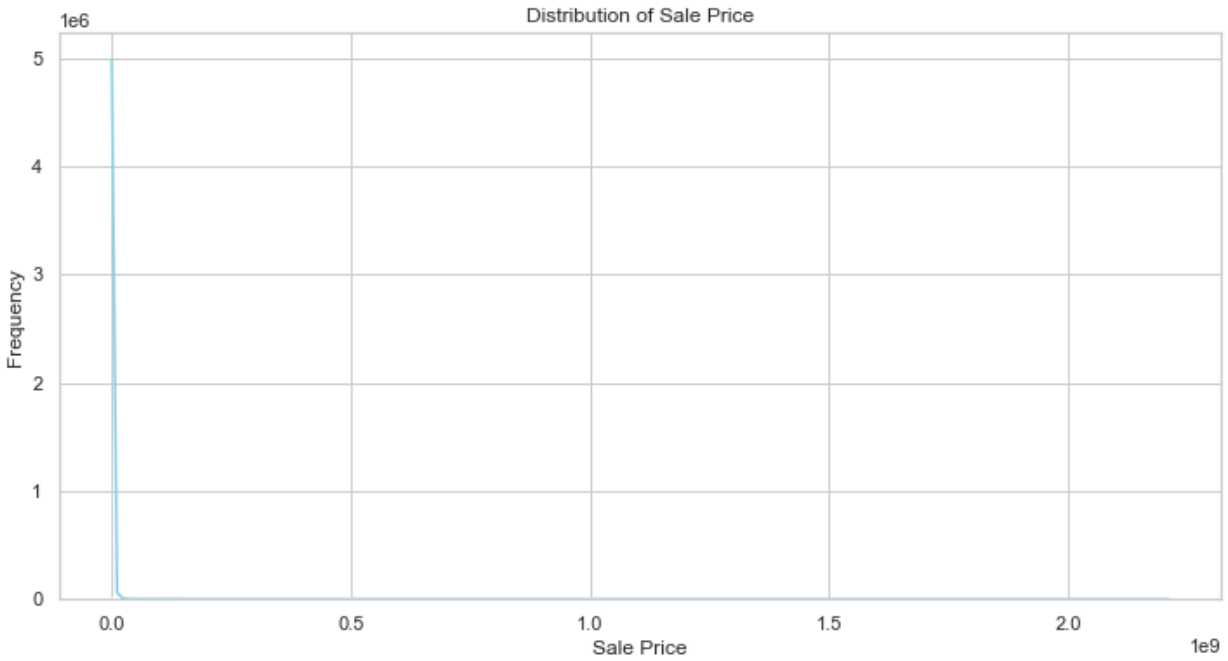
In [65]:
```
sns.set(style="whitegrid")

# Create a horizontal bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x='COMMERCIAL UNITS', y='BOROUGH', data=real_estate_price_df, estimator=la

# Set labels and title
plt.xlabel('Average Commercial Units')
plt.ylabel('Borough')
plt.title('Average Commercial Units by Borough')

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



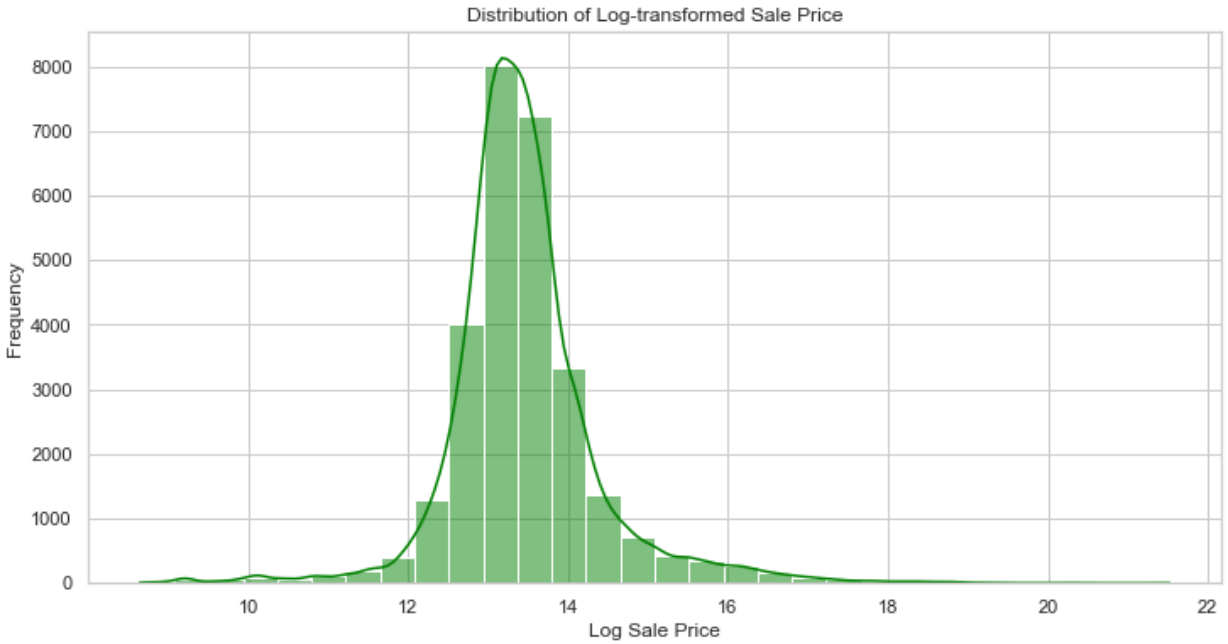
In [66]:
```
sns.set(style="whitegrid")

# Melt the DataFrame to plot both Commercial and Residential Units
melted_df = real_estate_price_df.melt(id_vars='BOROUGH', value_vars=['COMMERCIAL UNITS
                                      var_name='Unit Type', value_name='Average Units'

# Create a horizontal bar chart
plt.figure(figsize=(12, 8))
sns.barplot(x='Average Units', y='BOROUGH', hue='Unit Type', data=melted_df, orient='h

# Set labels and title
plt.xlabel('Average Units')
plt.ylabel('Borough')
plt.title('Average Commercial and Residential Units by Borough')

# Show the legend
plt.legend()

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



In [67]:
```
sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))

# Create a distribution plot for 'SALE PRICE'
sns.histplot(real_estate_price_df['SALE PRICE'], bins=2, kde=True, color='skyblue')

# Set labels and title
plt.xlabel('Sale Price')
plt.ylabel('Frequency')
plt.title('Distribution of Sale Price')

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



In [68]:
```
# Use log to better visualize
import numpy as np
sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))

# Take the logarithm of 'SALE PRICE'
real_estate_price_df['LOG SALE PRICE'] = np.log1p(real_estate_price_df['SALE PRICE'])

# Create a distribution plot for log-transformed 'SALE PRICE'
sns.histplot(real_estate_price_df['LOG SALE PRICE'], bins=30, kde=True, color='green')

# Set labels and title
plt.xlabel('Log Sale Price')
plt.ylabel('Frequency')
plt.title('Distribution of Log-transformed Sale Price')

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



In [69]:
```
# Check if 'LOG SALE PRICE' column exists before dropping
if 'LOG SALE PRICE' in real_estate_price_df.columns:
    real_estate_price_df = real_estate_price_df.drop('LOG SALE PRICE', axis=1)
else:
    print("'LOG SALE PRICE' column not found.")
```

In [70]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 1]

# Calculate the mean of residential units
mean_residential_units = filtered_df['RESIDENTIAL UNITS'].mean()

# Print the result
print(f"The mean of residential units in Manhattan is: {mean_residential_units}")
```

```
The mean of residential units in Manhattan is: 19.391666666666666
```

In [71]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 1]

# Calculate the mean of residential units
mean_commercial_units = filtered_df['COMMERCIAL UNITS'].mean()

# Print the result
print(f"The mean of commercial units in Manhattan is: {mean_commercial_units}")
```

```
The mean of commercial units in Manhattan is: 2.309375
```

In [72]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 2]

# Calculate the mean of residential units
mean_residential_units = filtered_df['RESIDENTIAL UNITS'].mean()

# Print the result
print(f"The mean of residential units in Bronx is: {mean_residential_units}")
```

```
The mean of residential units in Bronx is: 4.335684891240446
```

In [73]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 2]

# Calculate the mean of residential units
mean_commercial_units = filtered_df['COMMERCIAL UNITS'].mean()

# Print the result
print(f"The mean of residential units in Bronx is: {mean_commercial_units}")
```

```
The mean of residential units in Bronx is: 0.1966490299823633
```

In [81]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 3]

# Calculate the mean of residential units
mean_residential_units = filtered_df['RESIDENTIAL UNITS'].mean()

# Print the result
print(f"The mean of residential units in Brooklyn is: {mean_residential_units}")
```

```
The mean of residential units in Brooklyn is: 2.716373218349503
```

In [80]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 3]

# Calculate the mean of residential units
mean_commercial_units = filtered_df['COMMERCIAL UNITS'].mean()

# Print the result
print(f"The mean of commercial units in Brooklyn is: {mean_commercial_units}")
```

```
The mean of commercial units in Brooklyn is: 0.19187926697808122
```

In [76]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 4]

# Calculate the mean of residential units
mean_residential_units = filtered_df['RESIDENTIAL UNITS'].mean()

# Print the result
print(f"The mean of residential units in Queens is: {mean_residential_units}")
```

```
The mean of residential units in Queens is: 2.2180569731836317
```

In [79]:
```
# Filter the DataFrame for rows where borough is 1
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 4]

# Calculate the mean of residential units
mean_commercial_units = filtered_df['COMMERCIAL UNITS'].mean()

# Print the result
print(f"The mean of commercial units in Queens is: {mean_commercial_units}")
```

```
The mean of commercial units in Queens is: 0.4221954161640531
```

In [74]:
```
# Filter the DataFrame for rows where borough is 5
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 5]

# Calculate the mean of residential units
mean_residential_units = filtered_df['RESIDENTIAL UNITS'].mean()
```

```
# Print the result
print(f"The mean of residential units in Staten Island is: {mean_residential_units}")
```

```
The mean of residential units in Staten Island is: 1.3568094174954333
```

In [78]:
```
# Filter the DataFrame for rows where borough is 5
filtered_df = real_estate_price_df[real_estate_price_df['BOROUGH'] == 5]

# Calculate the mean of residential units
mean_commercial_units = filtered_df['COMMERCIAL UNITS'].mean()

# Print the result
print(f"The mean of commercial units in Staten Island is: {mean_commercial_units}")
```

```
The mean of commercial units in Staten Island is: 0.09843718286990055
```

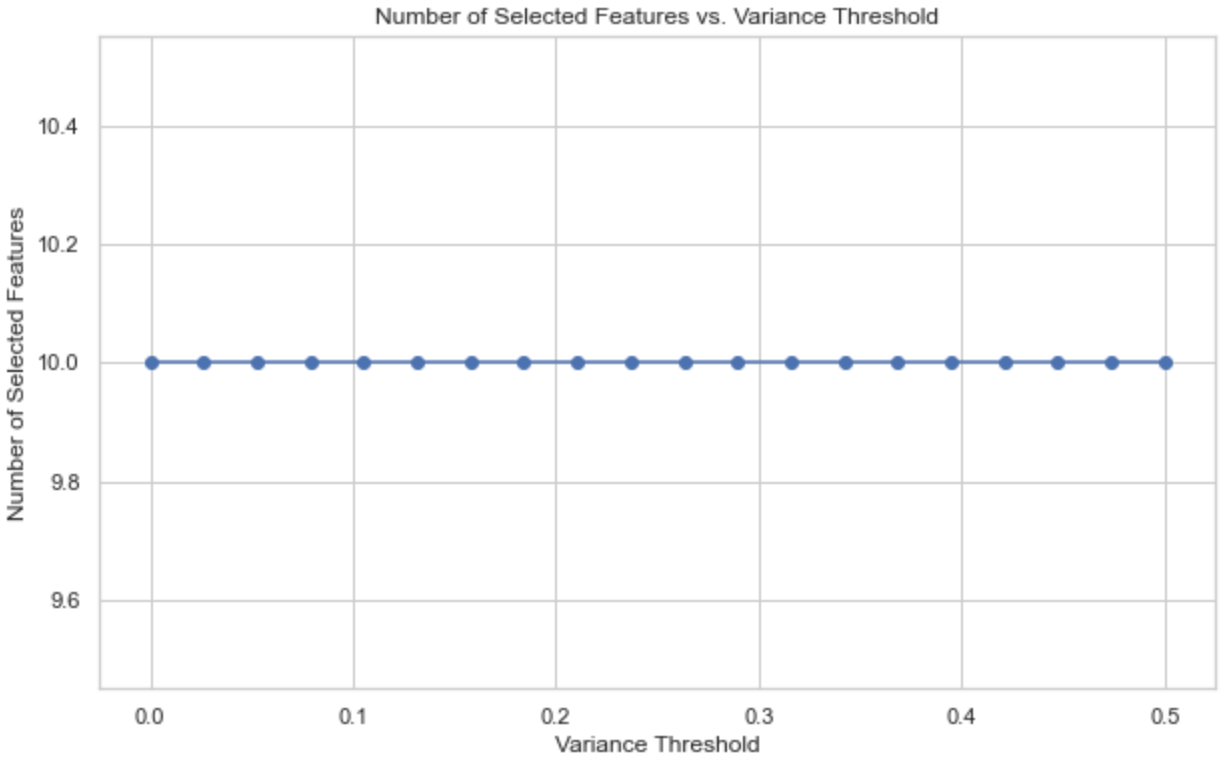
Try feature selection

In [70]:
```
# Variance threshold
from sklearn.feature_selection import VarianceThreshold


# Extracting the feature matrix (X) excluding non-numeric columns
X = real_estate_price_df.select_dtypes(include=['int64', 'float64'])

# Apply VarianceThreshold
selector = VarianceThreshold(threshold=0.8)
selected_features = selector.fit_transform(X)

# Convert the selected features back to a DataFrame
selected_features_variance_df = pd.DataFrame(selected_features, columns=X.columns[sele

# Display the selected features
print(selected_features_variance_df.head())
```

```
   BOROUGH  BLOCK    LOT  ZIP CODE  RESIDENTIAL UNITS  COMMERCIAL UNITS  \
0      1.0  392.0    6.0   10009.0                5.0               0.0
1      1.0  402.0   21.0   10009.0               10.0               0.0
2      1.0  404.0   55.0   10009.0                6.0               0.0
3      1.0  406.0   32.0   10009.0                8.0               0.0
4      1.0  387.0  153.0   10009.0               24.0               0.0

   TOTAL UNITS  LAND SQUARE FEET  GROSS SQUARE FEET  SALE PRICE
0          5.0            1633.0             6440.0   6625000.0
1         10.0            2272.0             6794.0   3936272.0
2          6.0            2369.0             4615.0   8000000.0
3          8.0            1750.0             4226.0   3192840.0
4         24.0            4489.0            18523.0  16232000.0
```

In [71]:
```
from sklearn.feature_selection import VarianceThreshold
import numpy as np
import matplotlib.pyplot as plt

threshold_values = np.linspace(0, 0.5, 20)

selected_features_count = []

for threshold in threshold_values:
    selector = VarianceThreshold(threshold=threshold)
```

```
    X_selected = selector.fit_transform(X)
    selected_features_count.append(X_selected.shape[1])

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(threshold_values, selected_features_count, marker='o', linestyle='-', color='
plt.title('Number of Selected Features vs. Variance Threshold')
plt.xlabel('Variance Threshold')
plt.ylabel('Number of Selected Features')
plt.grid(True)
plt.show()
```



In [72]:
```
# Try feature selection with variance threshold after normalization
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import VarianceThreshold

scaler = MinMaxScaler()
X_normalized = scaler.fit_transform(X)

# Apply VarianceThreshold
selector = VarianceThreshold(threshold=0.0001)
X_selected = selector.fit_transform(X_normalized)
# Convert the selected features back to a DataFrame
selected_features_variance_df = pd.DataFrame(X_selected, columns=X.columns[selector.ge

# Display the selected features
print(selected_features_variance_df.head())
```

```
   BOROUGH     BLOCK       LOT  ZIP CODE  RESIDENTIAL UNITS  TOTAL UNITS
0      0.0  0.023722  0.001348  0.855909           0.002711     0.001770
1      0.0  0.024335  0.005392  0.855909           0.005423     0.003982
2      0.0  0.024458  0.014559  0.855909           0.003254     0.002212
3      0.0  0.024580  0.008358  0.855909           0.004338     0.003097
4      0.0  0.023415  0.040981  0.855909           0.013015     0.010177
```

In [73]:
```
# Try feature selection with variance threshold after normalization
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import VarianceThreshold

scaler = MinMaxScaler()
X_normalized = scaler.fit_transform(X)

# Apply VarianceThreshold
selector = VarianceThreshold(threshold=0.001)
X_selected = selector.fit_transform(X_normalized)
# Convert the selected features back to a DataFrame
selected_features_variance_df = pd.DataFrame(X_selected, columns=X.columns[selector.ge

# Display the selected features
print(selected_features_variance_df.head())
```

```
   BOROUGH     BLOCK       LOT  ZIP CODE
0      0.0  0.023722  0.001348  0.855909
1      0.0  0.024335  0.005392  0.855909
2      0.0  0.024458  0.014559  0.855909
3      0.0  0.024580  0.008358  0.855909
4      0.0  0.023415  0.040981  0.855909
```

In [74]:
```
real_estate_price_df['BLOCK'].value_counts()
```

Out[74]:
```
1009     60
4452     57
2873     30
6979     24
1602     24
         ..
10477     1
10328     1
10834     1
10352     1
392       1
Name: BLOCK, Length: 9815, dtype: int64
```

In [75]:
```
real_estate_price_df['LOT'].value_counts()
```

Out[75]:
```
1      676
12     422
20     422
21     421
22     415
      ...
514      1
604      1
893      1
900      1
679      1
Name: LOT, Length: 664, dtype: int64
```

In [76]:
```
print(X.dtypes)
```

```
BOROUGH                 int64
BLOCK                   int64
LOT                     int64
ZIP CODE                int64
RESIDENTIAL UNITS       int64
COMMERCIAL UNITS        int64
TOTAL UNITS             int64
LAND SQUARE FEET      float64
GROSS SQUARE FEET     float64
SALE PRICE              Int64
dtype: object
```

In [70]:
```
# One-hot encode BOROUGH column

real_estate_price_df_encoded = pd.get_dummies(real_estate_price_df, columns=['BOROUGH'

# Display the resulting DataFrame
print(real_estate_price_df_encoded.head())
```

```
   BLOCK  LOT  ZIP CODE  RESIDENTIAL UNITS  COMMERCIAL UNITS  TOTAL UNITS  \
0    392    6     10009                  5                 0            5
3    402   21     10009                 10                 0           10
4    404   55     10009                  6                 0            6
6    406   32     10009                  8                 0            8
9    387  153     10009                 24                 0           24

   LAND SQUARE FEET  GROSS SQUARE FEET  SALE PRICE  BOROUGH_1  BOROUGH_2  \
0            1633.0             6440.0     6625000          1          0
3            2272.0             6794.0     3936272          1          0
4            2369.0             4615.0     8000000          1          0
6            1750.0             4226.0     3192840          1          0
9            4489.0            18523.0    16232000          1          0

   BOROUGH_3  BOROUGH_4  BOROUGH_5
0          0          0          0
3          0          0          0
4          0          0          0
6          0          0          0
9          0          0          0
```

In [71]:
```
# Drop BLOCK, LOT, ZIP CODE columns
real_estate_price_df_encoded = real_estate_price_df_encoded.drop(columns=['BLOCK', 'LO
real_estate_price_df_encoded.head()
```

Out[71]:

	RESIDENTIAL UNITS	COMMERCIAL UNITS	TOTAL UNITS	LAND SQUARE FEET	GROSS SQUARE FEET	SALE PRICE	BOROUGH_1	BOROUGH_2	BO
0	5	0	5	1633.0	6440.0	6625000	1	0	
3	10	0	10	2272.0	6794.0	3936272	1	0	
4	6	0	6	2369.0	4615.0	8000000	1	0	
6	8	0	8	1750.0	4226.0	3192840	1	0	
9	24	0	24	4489.0	18523.0	16232000	1	0	

In [79]:
```
# Try PCA
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Separate features and target variable
X = real_estate_price_df_encoded.drop('SALE PRICE', axis=1)
y = real_estate_price_df_encoded['SALE PRICE']

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Create a DataFrame with the principal components
pca_df = pd.DataFrame(data=X_pca, columns=['Principal Component 1', 'Principal Compone

# Concatenate the target variable to the PCA DataFrame
pca_df['SALE PRICE'] = y.values

# Display the resulting DataFrame with principal components and target variable
print(pca_df.head())
```

```
   Principal Component 1  Principal Component 2  SALE PRICE
0               0.773478              -0.280769     6625000
1               1.014380              -0.278699     3936272
2               0.801329              -0.279847     8000000
3               0.878845              -0.279311     3192840
4               1.852813              -0.274172    16232000
```

In [80]:
```
# Try PCA Linear Regression
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_pca, y)
```

Out[80]:
```
LinearRegression()
```

In [81]:
```
# PCA Linear Regression Model and Metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.decomposition import PCA

# Assuming X_pca is your principal components and y is your target variable (SALE PRIC
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_st

# Fit Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predictions on test set
y_pred = model.predict(X_test)

# Calculate regression metrics
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
explained_var = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 44696143299317.2
Mean Absolute Error (MAE): 1227557.9741111465
R-squared (R2): 0.10395883323056421
Explained Variance Score: 0.10483310982341232
Maximum Residual Error: 312251525.8804871
Median Absolute Error: 758104.4004410149
```

In [82]:
```
# Try Random Forest on PCA
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor()
model.fit(X_pca, y)
```

Out[82]:
```
RandomForestRegressor()
```

In [83]:
```
# PCA Random Forest and Metrics
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.decomposition import PCA

# Assuming X_pca is your principal components and y is your target variable (SALE PRIC
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_st

# Fit Random Forest Regression model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predictions on test set
y_pred = model.predict(X_test)

# Calculate regression metrics
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 34038452827932.94
Mean Absolute Error (MAE): 843683.3815387599
R-squared (R2): 0.31761774650849217
Explained Variance Score: 0.317675413112083
Maximum Residual Error: 269650484.42
Median Absolute Error: 190011.10349999997
```

In [84]:
```
# Try Gradient Boosting on PCA
from sklearn.ensemble import GradientBoostingRegressor
model = GradientBoostingRegressor()
model.fit(X_pca, y)
```

Out[84]:
```
GradientBoostingRegressor()
```

In [85]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.decomposition import PCA

# Assuming X_pca is your principal components and y is your target variable (SALE PRIC
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_st

# Fit Gradient Boosting Regression model
model = GradientBoostingRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predictions on test set
y_pred = model.predict(X_test)

# Calculate regression metrics
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 65248498095812.336
Mean Absolute Error (MAE): 949578.7345466504
R-squared (R2): -0.30806230802061463
Explained Variance Score: -0.30801578022817044
Maximum Residual Error: 411128520.50406146
Median Absolute Error: 265579.3603843944
```

In [86]:
```
# Try SVR on PCA
from sklearn.svm import SVR
model = SVR()
model.fit(X_pca, y)
```

Out[86]:
```
SVR()
```

In [87]:
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.decomposition import PCA

# Assuming X_pca is your PCA-transformed data and y is the target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_st

# Create SVR model
svr_model = SVR()

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

# Make predictions on the test set
y_pred = svr_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
evs = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
medae = median_absolute_error(y_test, y_pred)

# Print the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {evs}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {medae}")
```

```
Mean Squared Error (MSE): 50467174064776.16
Mean Absolute Error (MAE): 993620.1887153324
R-squared (R2): -0.011735290665426223
Explained Variance Score: 1.6675110267150295e-05
Maximum Residual Error: 329364051.6897238
Median Absolute Error: 239885.00726245693
```

In [88]:
```
import numpy as np

# Convert y to a numeric format to become a tensor
y = y.astype(np.float32)
```

In [89]:
```
'''
# Try Neural Network on PCA
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
model = Sequential([
    Dense(units=64, activation='relu', input_dim=2),  # Adjust input_dim based on the
    Dense(units=1)  # Output layer for regression
])
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X_pca, y, epochs=100, batch_size=32)
'''
```

Out[89]:
```
"\n# Try Neural Network on PCA\nfrom tensorflow.keras.models import Sequential\nfrom
tensorflow.keras.layers import Dense\nmodel = Sequential([\n    Dense(units=64, activ
ation='relu', input_dim=2),  # Adjust input_dim based on the number of principal comp
onents\n    Dense(units=1)  # Output layer for regression\n])\nmodel.compile(optimize
r='adam', loss='mean_squared_error')\nmodel.fit(X_pca, y, epochs=100, batch_size=32)
\n"
```

In [90]:
```
'''
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explain
from sklearn.decomposition import PCA

# Assuming X_pca is your PCA-transformed data and y is the target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_st

# Build the neural network model
model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1)  # Output layer with one neuron for regression
])

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')  # You can use different op

# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test, y_test)

# Make predictions on the test set
y_pred = model.predict(X_test).flatten()

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
evs = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
medae = median_absolute_error(y_test, y_pred)

# Print the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {evs}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {medae}")
'''
```

Out[90]:
```
'\nimport tensorflow as tf\nfrom sklearn.model_selection import train_test_split\nfro
m sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explained
_variance_score, max_error, median_absolute_error\nfrom sklearn.decomposition import
PCA\n\n# Assuming X_pca is your PCA-transformed data and y is the target variable\n\n
# Split the data into training and testing sets\nX_train, X_test, y_train, y_test = t
rain_test_split(X_pca, y, test_size=0.2, random_state=42)\n\n# Build the neural netwo
rk model\nmodel = tf.keras.Sequential([\n    tf.keras.layers.Dense(128, activation=
\'relu\', input_shape=(X_train.shape[1],)),\n    tf.keras.layers.Dense(64, activation
=\'relu\'),\n    tf.keras.layers.Dense(1)  # Output layer with one neuron for regress
ion\n])\n\n# Compile the model\nmodel.compile(optimizer=\'adam\', loss=\'mean_squared
_error\')  # You can use different optimizers and loss functions based on your prefer
ence\n\n# Train the model\nmodel.fit(X_train, y_train, epochs=50, batch_size=32, vali
dation_data=(X_test, y_test), verbose=2)\n\n# Make predictions on the test set\ny_pre
d = model.predict(X_test).flatten()\n\n# Evaluate the model\nmse = mean_squared_error
(y_test, y_pred)\nmae = mean_absolute_error(y_test, y_pred)\nr2 = r2_score(y_test, y_
pred)\nevs = explained_variance_score(y_test, y_pred)\nmax_err = max_error(y_test, y_
pred)\nmedae = median_absolute_error(y_test, y_pred)\n\n# Print the metrics\nprint
(f"Mean Squared Error (MSE): {mse}")\nprint(f"Mean Absolute Error (MAE): {mae}")\npri
nt(f"R-squared (R2): {r2}")\nprint(f"Explained Variance Score: {evs}")\nprint(f"Maxim
um Residual Error: {max_err}")\nprint(f"Median Absolute Error: {medae}")\n'
```

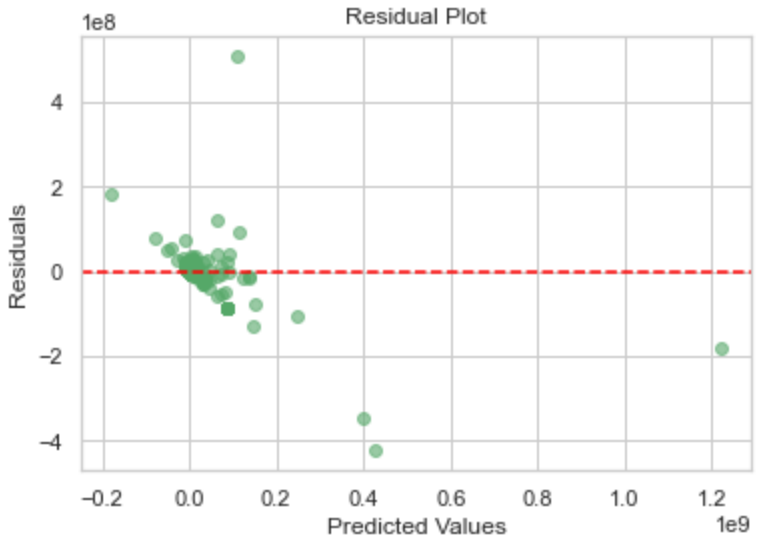
Try Linear Regression as baseline model

In [72]:
```
# Linear Regression on all Features
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair

X = real_estate_price_df_encoded[['RESIDENTIAL UNITS', 'COMMERCIAL UNITS', 'TOTAL UNIT
y = real_estate_price_df_encoded['SALE PRICE']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Initialize and train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f'Mean Squared Error (MSE): {mse:.2f}')
print(f'Mean Absolute Error (MAE): {mae:.2f}')
print(f'R-squared (R2): {r2:.2f}')
print(f'Explained Variance Score: {explained_var:.2f}')
print(f'Maximum Residual Error: {max_residual:.2f}')
print(f'Median Absolute Error: {median_ae:.2f}')
```

```
Mean Squared Error (MSE): 155075890534185.97
Mean Absolute Error (MAE): 1726621.12
R-squared (R2): 0.49
Explained Variance Score: 0.49
Maximum Residual Error: 510472987.36
Median Absolute Error: 504764.67
```

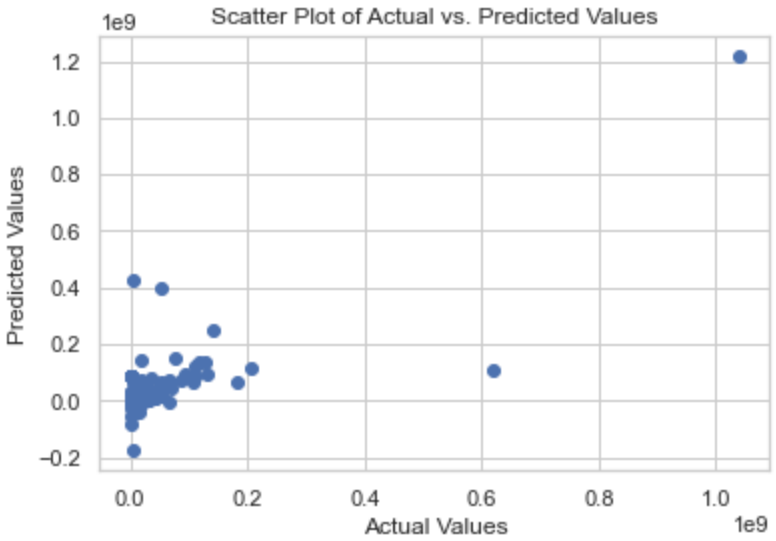
In [105…

```python
import matplotlib.pyplot as plt

# Calculate residuals
residuals = y_test - y_pred

# Residual Plot
plt.scatter(y_pred, residuals, c='g', alpha=0.6)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.axhline(y=0, color='red', linestyle='--')  # Add a horizontal line at y=0 for refe
plt.show()
```



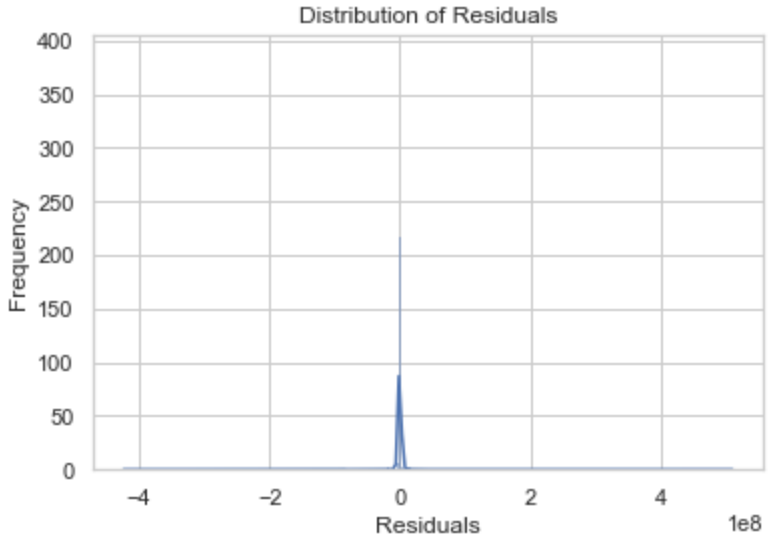
In [106…

```python
# Scatter Plot
plt.scatter(y_test, y_pred)
plt.title('Scatter Plot of Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



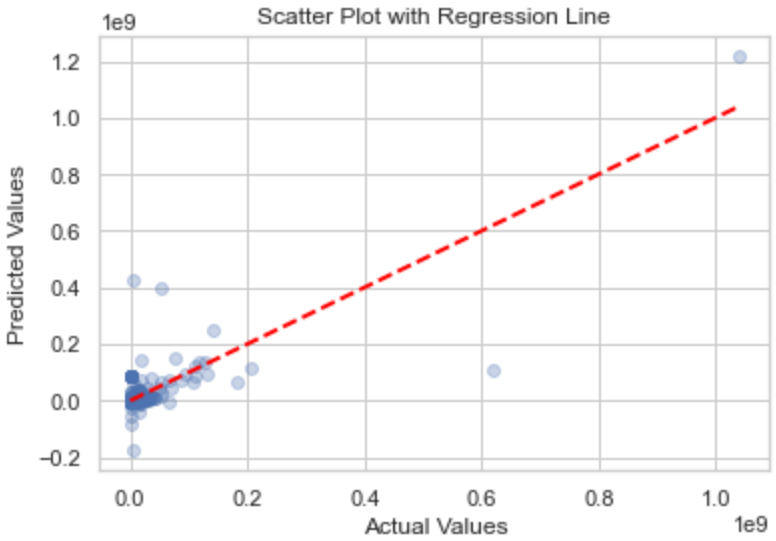
In [107…

```
# Distribution Plot
sns.histplot(y_test - y_pred, kde=True)
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



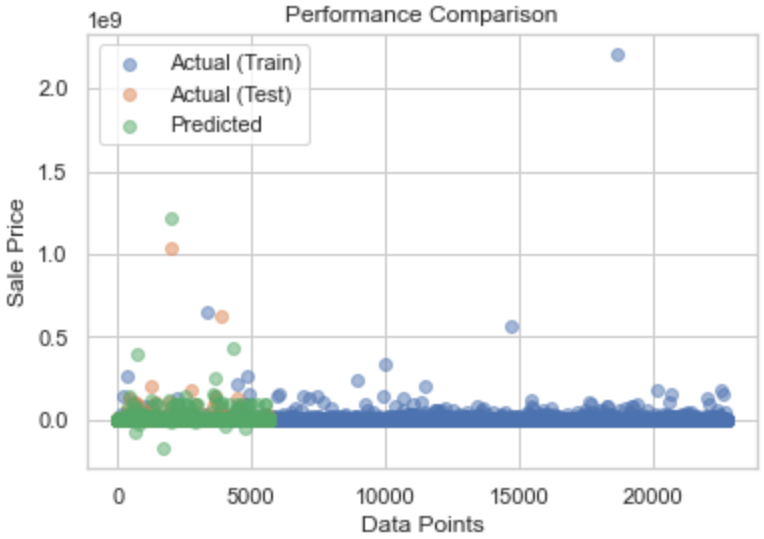
In [108…

```
import matplotlib.pyplot as plt

# Scatter Plot with Regression Line
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color
plt.title('Scatter Plot with Regression Line')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



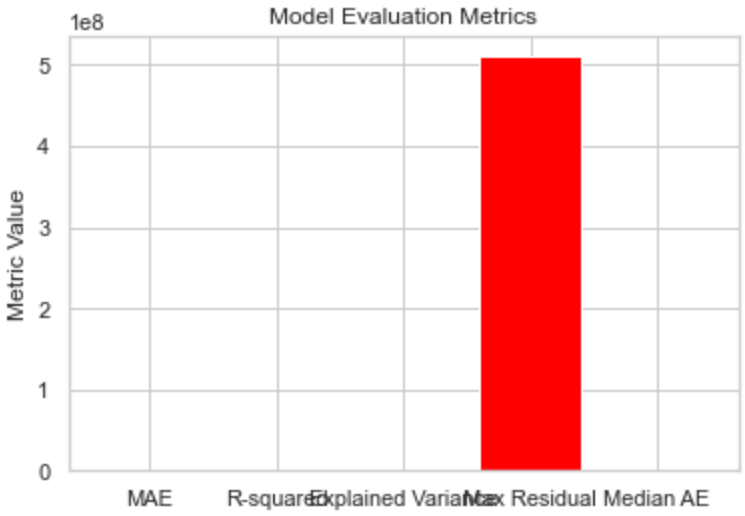
In [109…

```
# Performance Comparison Plot
plt.scatter(range(len(y_train)), y_train, label='Actual (Train)', alpha=0.5)
plt.scatter(range(len(y_test)), y_test, label='Actual (Test)', alpha=0.5)
plt.scatter(range(len(y_test)), y_pred, label='Predicted', alpha=0.5)
plt.legend()
plt.title('Performance Comparison')
plt.xlabel('Data Points')
plt.ylabel('Sale Price')
plt.show()
```



In [110…

```
# Metrics Comparison Bar Plot
metrics_names = ['MAE', 'R-squared', 'Explained Variance', 'Max Residual', 'Median AE'
metrics_values = [mae, r2, explained_var, max_residual, median_ae]
plt.bar(metrics_names, metrics_values, color=['green', 'orange', 'purple', 'red', 'brc
plt.title('Model Evaluation Metrics')
plt.ylabel('Metric Value')
plt.show()
```

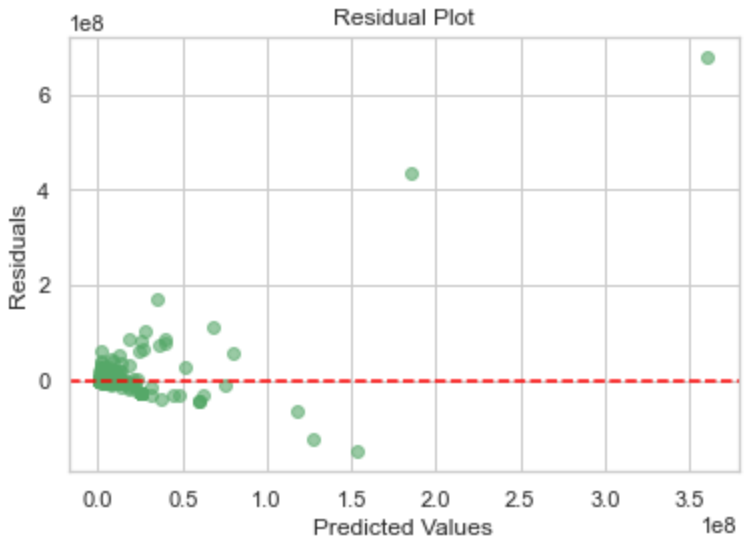


In [111…

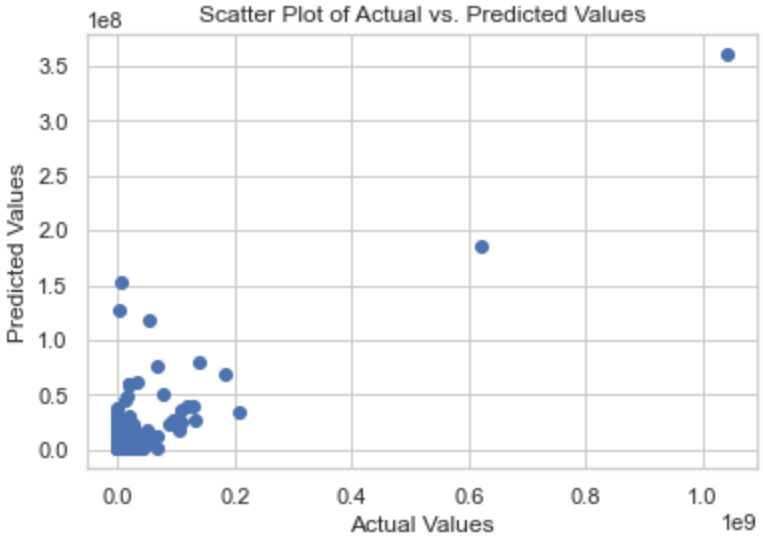
```
# Linear Regression on GROSS SQUARE FEET
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair

X = real_estate_price_df_encoded['GROSS SQUARE FEET']
y = real_estate_price_df_encoded['SALE PRICE']
# Reshape the input data to 2D array
X = X.values.reshape(-1, 1)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Initialize and train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f'Mean Squared Error (MSE): {mse:.2f}')
print(f'Mean Absolute Error (MAE): {mae:.2f}')
print(f'R-squared (R2): {r2:.2f}')
print(f'Explained Variance Score: {explained_var:.2f}')
print(f'Maximum Residual Error: {max_residual:.2f}')
print(f'Median Absolute Error: {median_ae:.2f}')
```

```
Mean Squared Error (MSE): 149623544146030.88
Mean Absolute Error (MAE): 1382152.65
R-squared (R2): 0.51
Explained Variance Score: 0.51
Maximum Residual Error: 679012110.35
Median Absolute Error: 491399.34
```

In [112…
```
import matplotlib.pyplot as plt

# Calculate residuals
residuals = y_test - y_pred

# Residual Plot
plt.scatter(y_pred, residuals, c='g', alpha=0.6)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.axhline(y=0, color='red', linestyle='--')  # Add a horizontal line at y=0 for refe
plt.show()
```

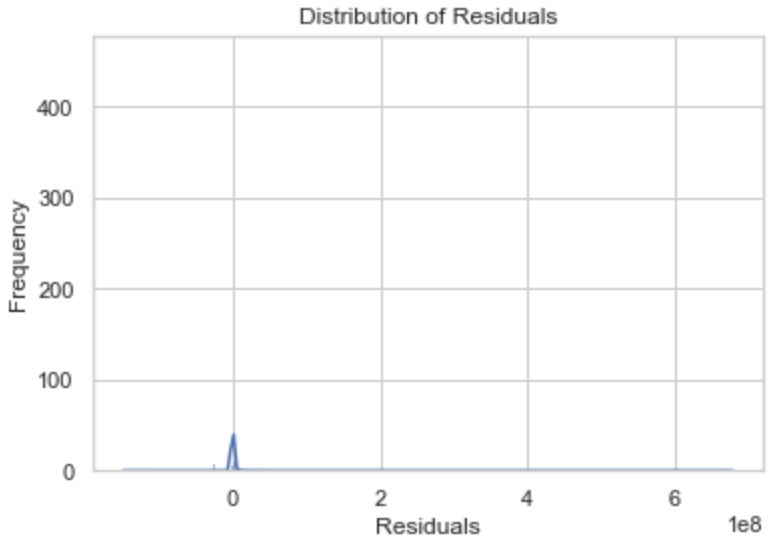


In [113…
```
# Scatter Plot
plt.scatter(y_test, y_pred)
plt.title('Scatter Plot of Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



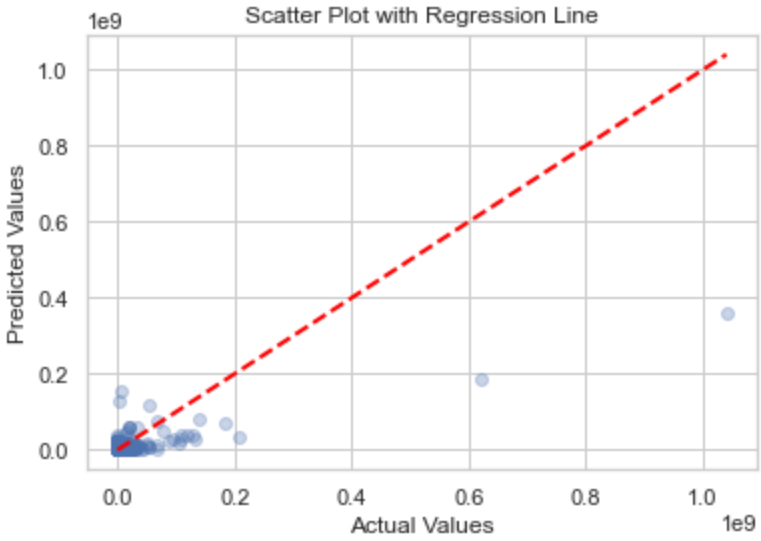
In [114…
```
# Distribution Plot
sns.histplot(y_test - y_pred, kde=True)
plt.title('Distribution of Residuals')
```

```
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



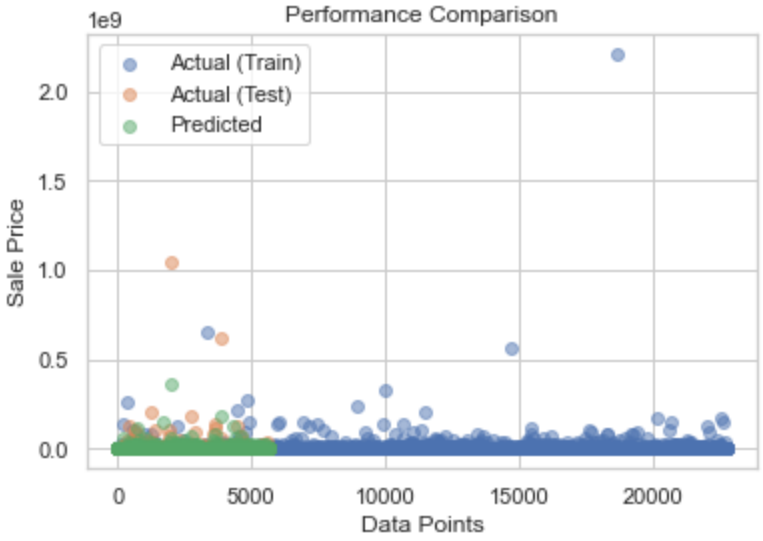
In [115…

```
import matplotlib.pyplot as plt

# Scatter Plot with Regression Line
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color
plt.title('Scatter Plot with Regression Line')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



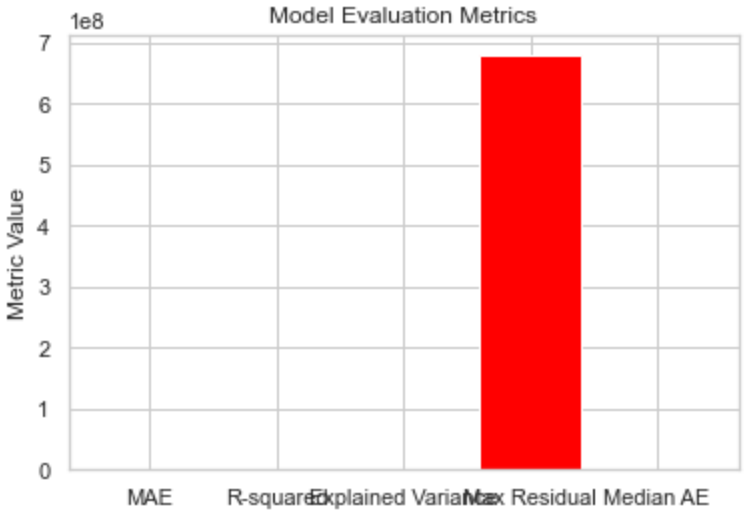
In [116…

```
# Performance Comparison Plot
plt.scatter(range(len(y_train)), y_train, label='Actual (Train)', alpha=0.5)
plt.scatter(range(len(y_test)), y_test, label='Actual (Test)', alpha=0.5)
plt.scatter(range(len(y_test)), y_pred, label='Predicted', alpha=0.5)
plt.legend()
plt.title('Performance Comparison')
plt.xlabel('Data Points')
plt.ylabel('Sale Price')
plt.show()
```



In [118…

```
# Metrics Comparison Bar Plot
metrics_names = ['MAE', 'R-squared', 'Explained Variance', 'Max Residual', 'Median AE'
metrics_values = [mae, r2, explained_var, max_residual, median_ae]
plt.bar(metrics_names, metrics_values, color=['green', 'orange', 'purple', 'red', 'brc
plt.title('Model Evaluation Metrics')
plt.ylabel('Metric Value')
plt.show()
```



In [93]:

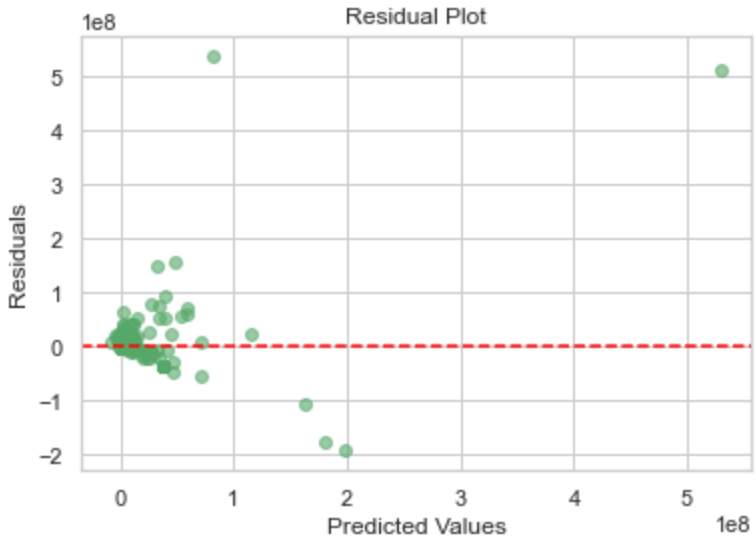
```
# Try Linear Regression on GROSS SQUARE FEET and TOTAL UNITS
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair

X = real_estate_price_df_encoded[['TOTAL UNITS', 'GROSS SQUARE FEET']]
y = real_estate_price_df_encoded['SALE PRICE']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Initialize and train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
```

```
y_pred = model.predict(X_test)

# Evaluate the model performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f'Mean Squared Error (MSE): {mse:.2f}')
print(f'Mean Absolute Error (MAE): {mae:.2f}')
print(f'R-squared (R2): {r2:.2f}')
print(f'Explained Variance Score: {explained_var:.2f}')
print(f'Maximum Residual Error: {max_residual:.2f}')
print(f'Median Absolute Error: {median_ae:.2f}')
```

```
Mean Squared Error (MSE): 139070168737840.92
Mean Absolute Error (MAE): 1535408.61
R-squared (R2): 0.54
Explained Variance Score: 0.54
Maximum Residual Error: 538656167.64
Median Absolute Error: 606237.63
```

In [95]:

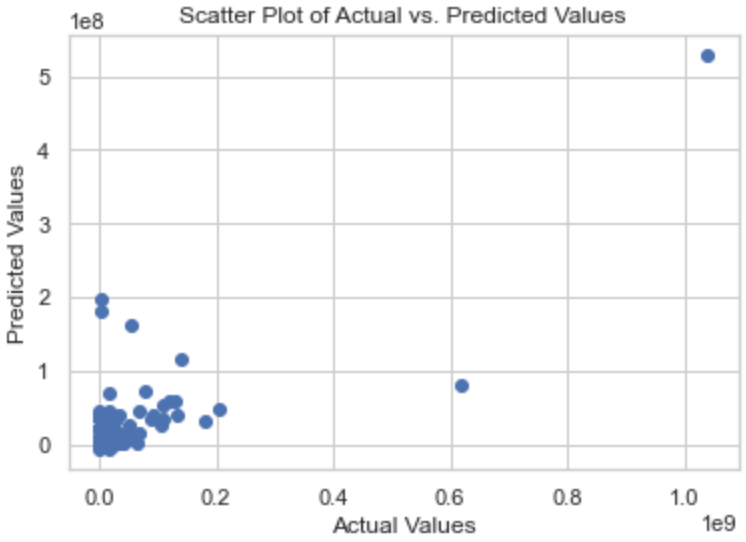
```
import matplotlib.pyplot as plt

# Calculate residuals
residuals = y_test - y_pred

# Residual Plot
plt.scatter(y_pred, residuals, c='g', alpha=0.6)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.axhline(y=0, color='red', linestyle='--')  # Add a horizontal line at y=0 for refe
plt.show()
```



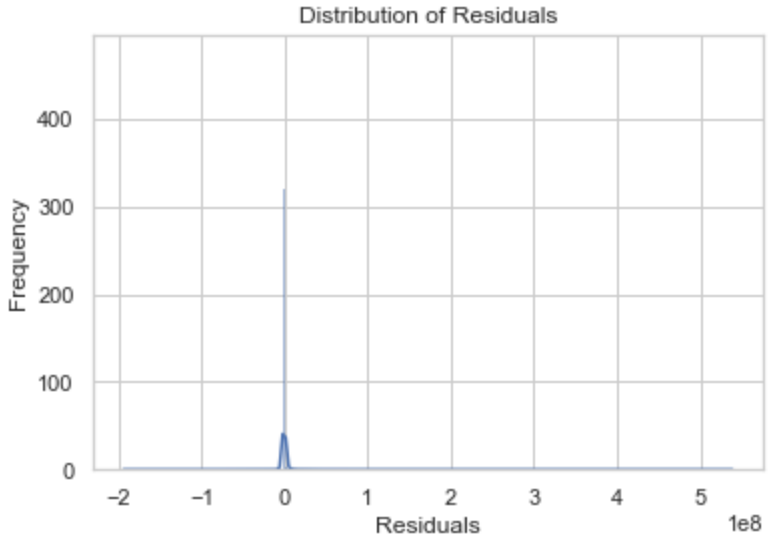
The residuals exhibit randomness which indicates their independence. The main

block of residual points resides around 0.

In [96]:
```
# Scatter Plot
plt.scatter(y_test, y_pred)
plt.title('Scatter Plot of Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```

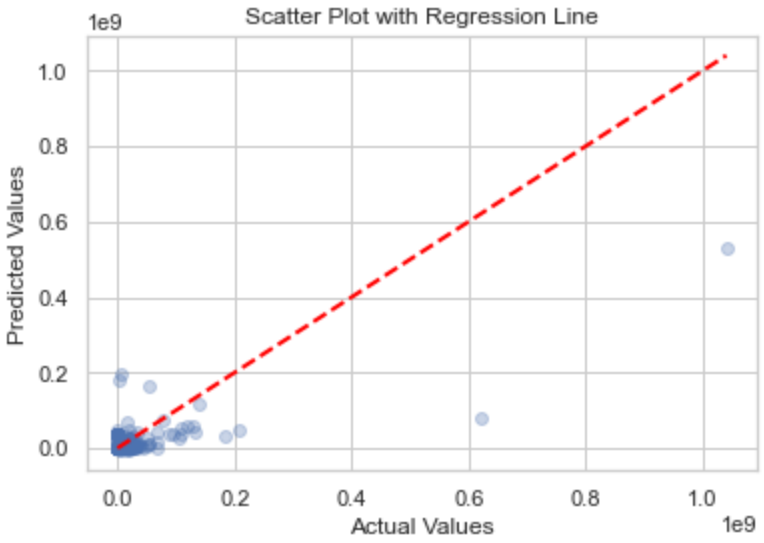


In [97]:
```
# Distribution Plot
sns.histplot(y_test - y_pred, kde=True)
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



In [103…
```
import matplotlib.pyplot as plt

# Scatter Plot with Regression Line
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color
plt.title('Scatter Plot with Regression Line')
```

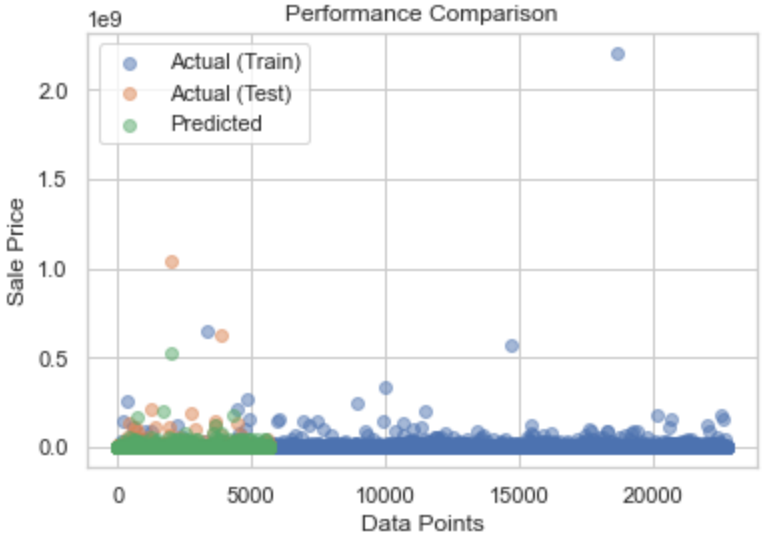
```
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



In [ ]:

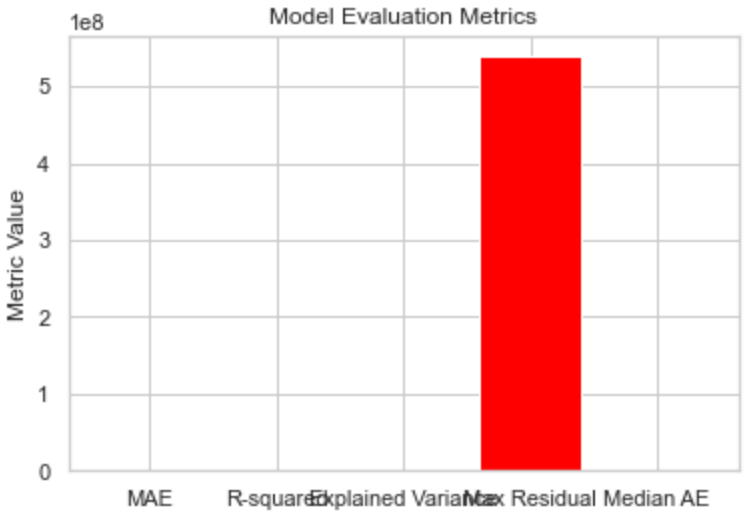
In [100…

```
# Performance Comparison Plot
plt.scatter(range(len(y_train)), y_train, label='Actual (Train)', alpha=0.5)
plt.scatter(range(len(y_test)), y_test, label='Actual (Test)', alpha=0.5)
plt.scatter(range(len(y_test)), y_pred, label='Predicted', alpha=0.5)
plt.legend()
plt.title('Performance Comparison')
plt.xlabel('Data Points')
plt.ylabel('Sale Price')
plt.show()
```



In [102…

```
# Metrics Comparison Bar Plot
metrics_names = ['MAE', 'R-squared', 'Explained Variance', 'Max Residual', 'Median AE'
metrics_values = [mae, r2, explained_var, max_residual, median_ae]
plt.bar(metrics_names, metrics_values, color=['green', 'orange', 'purple', 'red', 'brc
plt.title('Model Evaluation Metrics')
plt.ylabel('Metric Value')
plt.show()
```



Try Decision Tree

In [101…

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Initialize and train the Decision Tree Regressor
model_decision_tree = DecisionTreeRegressor(random_state=42)
model_decision_tree.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_decision_tree.predict(X_test)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 28495653781144.03
Mean Absolute Error (MAE): 874288.1754216434
R-squared (R2): 0.42873641936117024
Explained Variance Score: 0.4287532798778386
Maximum Residual Error: 220000000.0
Median Absolute Error: 223550.0
```

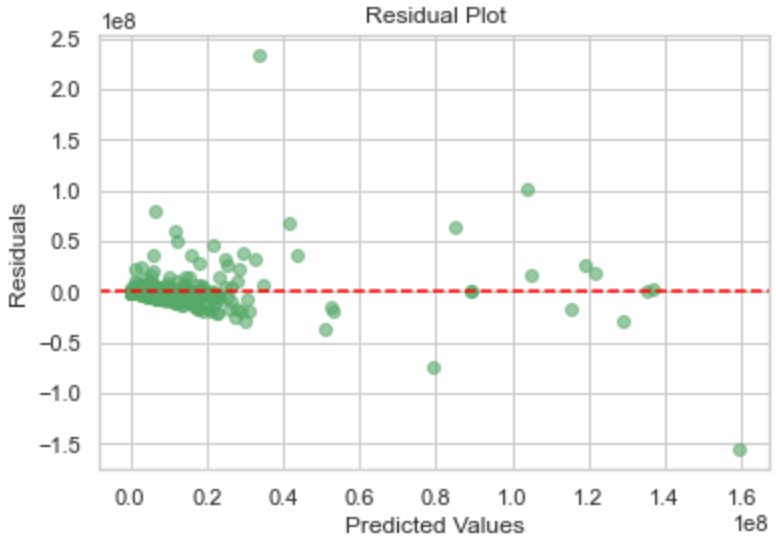
Try Random Forest

In [73]:
```
%%time
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Initialize and train the Random Forest Regressor
model_random_forest = RandomForestRegressor(random_state=42)
model_random_forest.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_random_forest.predict(X_test)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

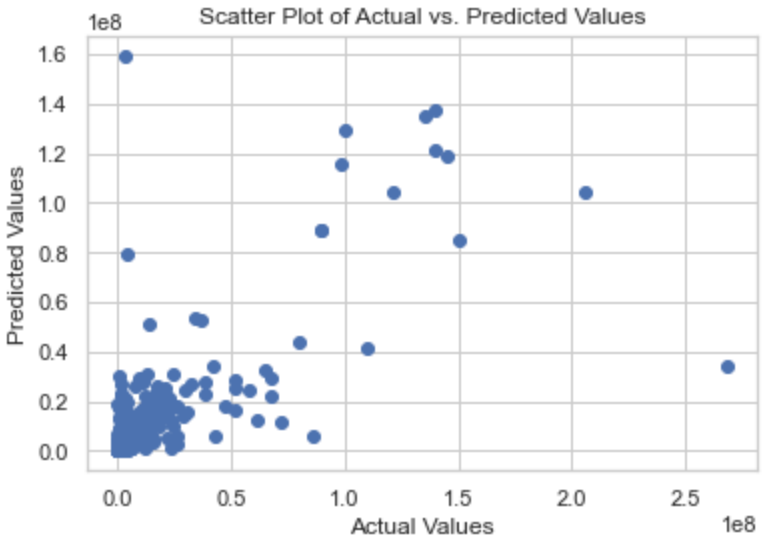
```
Mean Squared Error (MSE): 26042280118408.414
Mean Absolute Error (MAE): 775307.5338486986
R-squared (R2): 0.5873538937025908
Explained Variance Score: 0.5873993267307127
Maximum Residual Error: 234146834.95
Median Absolute Error: 188556.96000000002
CPU times: total: 6.69 s
Wall time: 7.29 s
```

In [74]:
```
import matplotlib.pyplot as plt

# Calculate residuals
residuals = y_test - y_pred
```

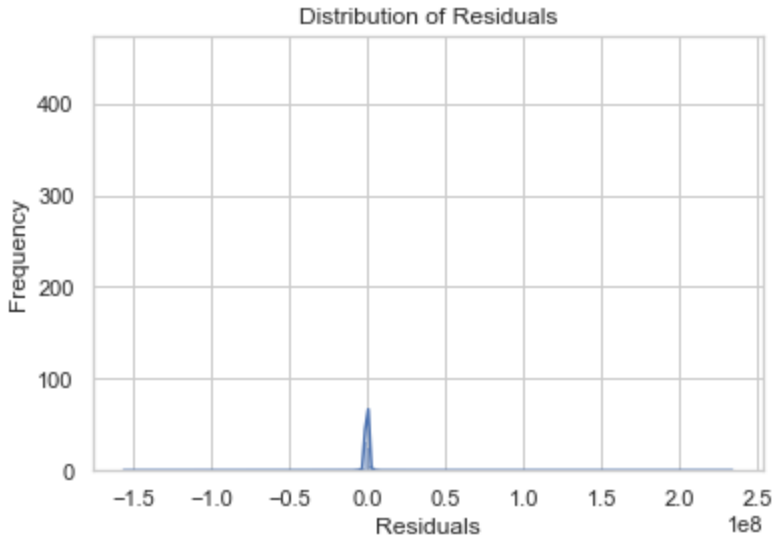
```
# Residual Plot
plt.scatter(y_pred, residuals, c='g', alpha=0.6)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.axhline(y=0, color='red', linestyle='--')  # Add a horizontal line at y=0 for refe
plt.show()
```



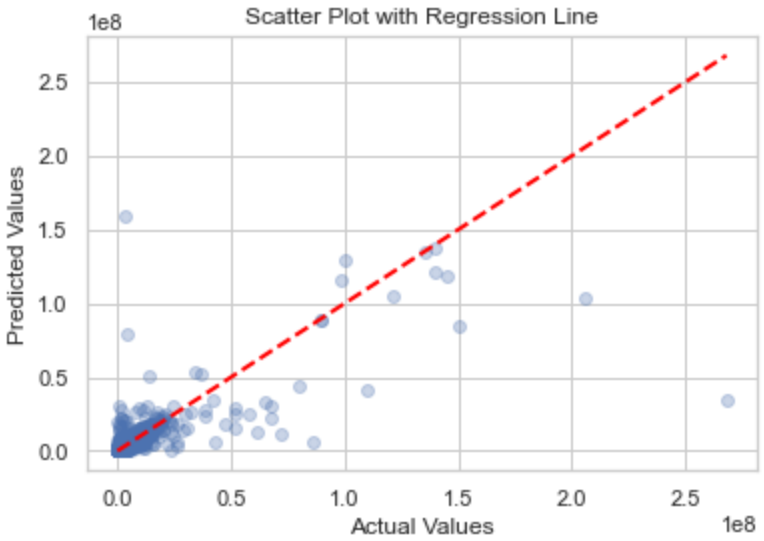
In [75]:
```
# Scatter Plot
plt.scatter(y_test, y_pred)
plt.title('Scatter Plot of Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



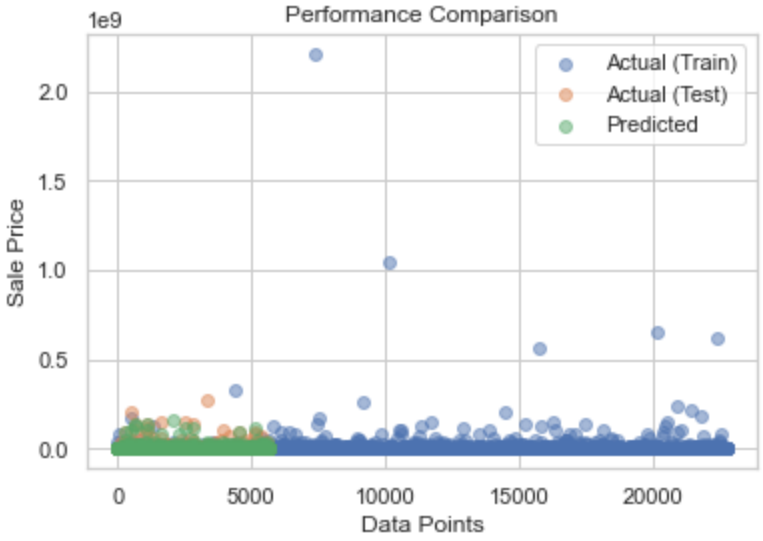
In [76]:
```
# Distribution Plot
sns.histplot(y_test - y_pred, kde=True)
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



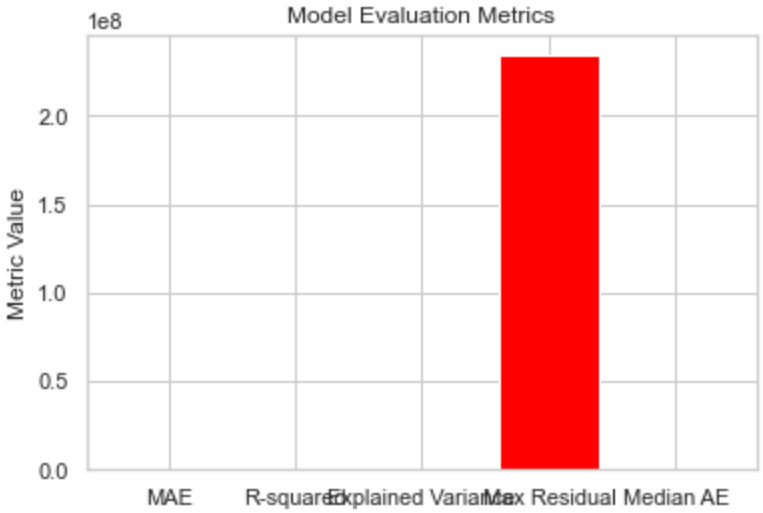
In [77]:
```
import matplotlib.pyplot as plt

# Scatter Plot with Regression Line
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color
plt.title('Scatter Plot with Regression Line')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



In [78]:
```
# Performance Comparison Plot
plt.scatter(range(len(y_train)), y_train, label='Actual (Train)', alpha=0.5)
plt.scatter(range(len(y_test)), y_test, label='Actual (Test)', alpha=0.5)
plt.scatter(range(len(y_test)), y_pred, label='Predicted', alpha=0.5)
plt.legend()
plt.title('Performance Comparison')
plt.xlabel('Data Points')
plt.ylabel('Sale Price')
plt.show()
```



In [79]:
```
# Metrics Comparison Bar Plot
metrics_names = ['MAE', 'R-squared', 'Explained Variance', 'Max Residual', 'Median AE'
metrics_values = [mae, r2, explained_var, max_residual, median_ae]
plt.bar(metrics_names, metrics_values, color=['green', 'orange', 'purple', 'red', 'brc
plt.title('Model Evaluation Metrics')
plt.ylabel('Metric Value')
plt.show()
```



In [ ]:
```
```

In [81]:
```
import numpy as np

# Create a new data df with one additional residential unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() + 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
```

```
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $12693147.12
```

In [82]:
```
import numpy as np

# Create a new data df with one less residential unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() - 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: {predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: 13619417.14
```

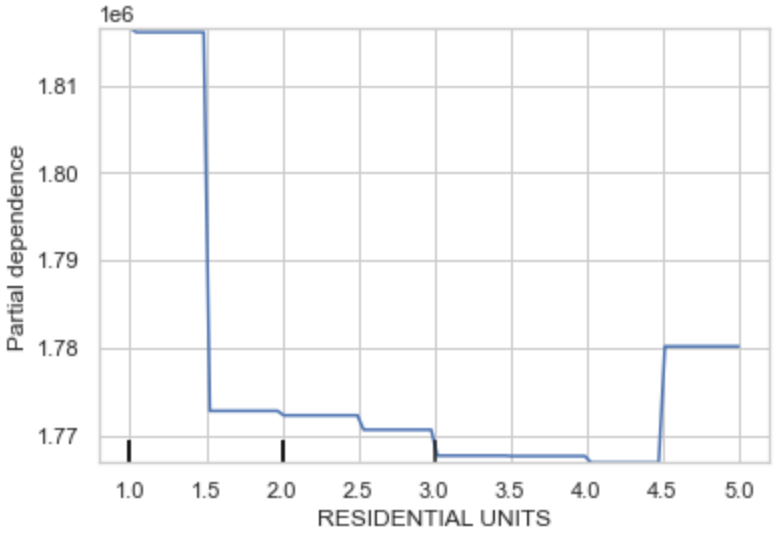
In [83]:
```
feature_importances = model_random_forest.feature_importances_
print("Feature Importance Scores:")
for feature, importance in zip(X.columns, feature_importances):
    print(f"{feature}: {importance}")
```

```
Feature Importance Scores:
RESIDENTIAL UNITS: 0.02383763156391659
COMMERCIAL UNITS: 0.08550317973383965
TOTAL UNITS: 0.06129051610973309
LAND SQUARE FEET: 0.09647072260352756
GROSS SQUARE FEET: 0.6979472731887629
BOROUGH_1: 0.02623194329742335
BOROUGH_2: 0.0018769358019488898
BOROUGH_3: 0.0008134735907364808
BOROUGH_4: 0.005571749674531837
BOROUGH_5: 0.00045657443557952135
```

In [84]:
```
from sklearn.inspection import plot_partial_dependence

# Select the feature index for 'RESIDENTIAL UNITS'
feature_index = X.columns.get_loc('RESIDENTIAL UNITS')
```

```
# Create partial dependence plots
plot_partial_dependence(model_random_forest, X_train, features=[feature_index], target
```

Out[84]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay at 0x296bf21634
0>
```



In [85]:
```
import numpy as np

# Create a new data df with one additional residential unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() + 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 1,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $583473.49
```

In [86]:
```
import numpy as np

# Create a new data df with one less residential unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() - 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
```

```
    'BOROUGH_1': 0,
    'BOROUGH_2': 1,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $669737.74
```

In [104…

```
import numpy as np

# Create a new data df with one additional residential unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() + 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 1,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1663263.7914285713
```

In [105…

```
import numpy as np

# Create a new data df with one less residential unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() - 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 1,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}
```

```
# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1095173.5571428572
```

In [106…

```
import numpy as np

# Create a new data df with one additional residential unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() + 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 1,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1260107.65
```

In [107…

```
import numpy as np

# Create a new data df with one less residential unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() - 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 1,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)
```

```
# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1182891.9
```

In [108…

```
import numpy as np

# Create a new data df with one additional residential unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() + 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 1
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $614241.55
```

In [109…

```
import numpy as np

# Create a new data df with one less residential unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean() - 1,
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 1
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $857385.06
```

In [87]:

```
import numpy as np
```

```
# Create a new data df with one additional commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() + 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $13185238.05
```

In [93]:

```
import numpy as np

# Create a new data df with one less commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() - 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $14735632.62
```

In [ ]:

In [94]:

```
import numpy as np

# Create a new data df with one additional commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() + 1,
```

```
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 1,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $643224.76
```

In [95]:

```
import numpy as np

# Create a new data df with one less commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() - 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 1,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $643347.62
```

In [96]:

```
import numpy as np

# Create a new data df with one additional commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() + 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 1,
    'BOROUGH_4': 0,
```

```
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1647062.06
```

In [97]:

```
import numpy as np

# Create a new data df with one less commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() - 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 1,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1134386.2771428572
```

In [98]:

```
import numpy as np

# Create a new data df with one more commercial unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() + 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 1,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
```

```
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1339586.33
```

In [101…

```
import numpy as np

# Create a new data df with one less commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() - 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 1,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $1041043.13
```

In [102…

```
import numpy as np

# Create a new data df with one more commercial unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() + 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 1
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

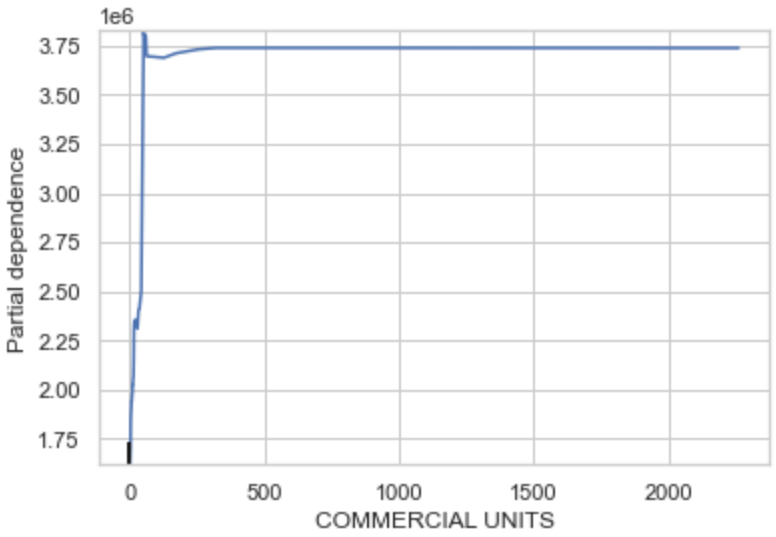
```
Predicted Sale Price for the New Data Point: $646237.26
```

In [103…
```
import numpy as np

# Create a new data df with one less commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() - 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 1
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $706012.26
```

In [89]:
```
from sklearn.inspection import plot_partial_dependence

# Select the feature index for 'Commercial UNITS'
feature_index = X.columns.get_loc('COMMERCIAL UNITS')

# Create partial dependence plots
plot_partial_dependence(model_random_forest, X_train, features=[feature_index], target
```

Out[89]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay at 0x296bee34c4
0>
```



In [110…
```
# Create a new data point with 1,000 less gross square feet than the mean
less_sqft_data_point = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean(),
```

```
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean() - 1000,
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
less_sqft_df = pd.DataFrame([less_sqft_data_point])

# Make predictions using the trained Random Forest Regressor
predicted_price_less_sqft = model_random_forest.predict(less_sqft_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point (1,000 less sqft): ${predicted_pri
```

```
Predicted Sale Price for the New Data Point (1,000 less sqft): $8216884.07
```

In [111…

```
# Create a new data point with 1,000 more gross square feet than the mean
more_sqft_data_point = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean(),
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean() + 1000,
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
more_sqft_df = pd.DataFrame([more_sqft_data_point])

# Make predictions using the trained Random Forest Regressor
predicted_price_more_sqft = model_random_forest.predict(more_sqft_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point (1,000 more sqft): ${predicted_pri
```

```
Predicted Sale Price for the New Data Point (1,000 more sqft): $19273101.05
```

In [112…

```
# Create a new data point with 300 less gross square feet than the mean
less_sqft_data_point = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean(),
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean() - 300,
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
less_sqft_df = pd.DataFrame([less_sqft_data_point])
```

```
# Make predictions using the trained Random Forest Regressor
predicted_price_less_sqft = model_random_forest.predict(less_sqft_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point (1,000 less sqft): ${predicted_pri
```

```
Predicted Sale Price for the New Data Point (1,000 less sqft): $13750465.283333335
```

In [113…

```
# Create a new data point with 300 more gross square feet than the mean
more_sqft_data_point = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean(),
    'TOTAL UNITS': X['TOTAL UNITS'].mean(),
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean() + 300,
    'BOROUGH_1': 1,
    'BOROUGH_2': 0,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
more_sqft_df = pd.DataFrame([more_sqft_data_point])

# Make predictions using the trained Random Forest Regressor
predicted_price_more_sqft = model_random_forest.predict(more_sqft_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point (1,000 more sqft): ${predicted_pri
```

```
Predicted Sale Price for the New Data Point (1,000 more sqft): $17790461.31
```

In [90]:

```
import numpy as np

# Create a new data df with one additional commercial unit more than mean
one_unit_more = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() + 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() + 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 1,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_more_df = pd.DataFrame([one_unit_more])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_more_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $643224.76
```

In [91]:
```
import numpy as np

# Create a new data df with one less commercial unit than mean
one_unit_less = {
    'RESIDENTIAL UNITS': X['RESIDENTIAL UNITS'].mean(),
    'COMMERCIAL UNITS': X['COMMERCIAL UNITS'].mean() - 1,
    'TOTAL UNITS': X['TOTAL UNITS'].mean() - 1,
    'LAND SQUARE FEET': X['LAND SQUARE FEET'].mean(),
    'GROSS SQUARE FEET': X['GROSS SQUARE FEET'].mean(),
    'BOROUGH_1': 0,
    'BOROUGH_2': 1,
    'BOROUGH_3': 0,
    'BOROUGH_4': 0,
    'BOROUGH_5': 0
}

# Convert the new data point to a DataFrame
one_unit_less_df = pd.DataFrame([one_unit_less])

# Make predictions using the trained Random Forest Regressor
predicted_price = model_random_forest.predict(one_unit_less_df)

# Display the predicted sale price
print(f"Predicted Sale Price for the New Data Point: ${predicted_price[0]}")
```

```
Predicted Sale Price for the New Data Point: $643347.62
```

In [ ]:

In [ ]:

Try SVR

In [103…
```
%%time
from sklearn.svm import SVR
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Support Vector Regressor
model_svr = SVR()
model_svr.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model_svr.predict(X_test_scaled)
```

```
# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 53364999706004.79
Mean Absolute Error (MAE): 1087655.4097198863
R-squared (R2): -0.014263302870199057
Explained Variance Score: 1.2646753423495305e-05
Maximum Residual Error: 256865218.03873628
Median Absolute Error: 238638.81921199046
CPU times: total: 28.1 s
Wall time: 32.4 s
```

Try kNN Regressor

In [104…

```
%%time
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the k-Nearest Neighbors Regressor
k = 5  # You can adjust the value of k
model_knn = KNeighborsRegressor(n_neighbors=k)
model_knn.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model_knn.predict(X_test_scaled)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 69611255467263.29
Mean Absolute Error (MAE): 899918.9297906036
R-squared (R2): 0.4034883536265532
Explained Variance Score: 0.40356793373796074
Maximum Residual Error: 471031816.6
Median Absolute Error: 190300.0
CPU times: total: 375 ms
Wall time: 501 ms
```

Try Lasso Regression

In [105…

```
%%time
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Lasso Regression model
alpha = 0.01  # You can adjust the regularization strength
model_lasso = Lasso(alpha=alpha)
model_lasso.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model_lasso.predict(X_test_scaled)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
```

```
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 65060404002762.15
Mean Absolute Error (MAE): 1358471.8190209807
R-squared (R2): 0.07084038716920427
Explained Variance Score: 0.07125492073213757
Maximum Residual Error: 309972630.0916606
Median Absolute Error: 465813.64168509934
CPU times: total: 453 ms
Wall time: 298 ms
```

Try Ridge Regression

In [126…

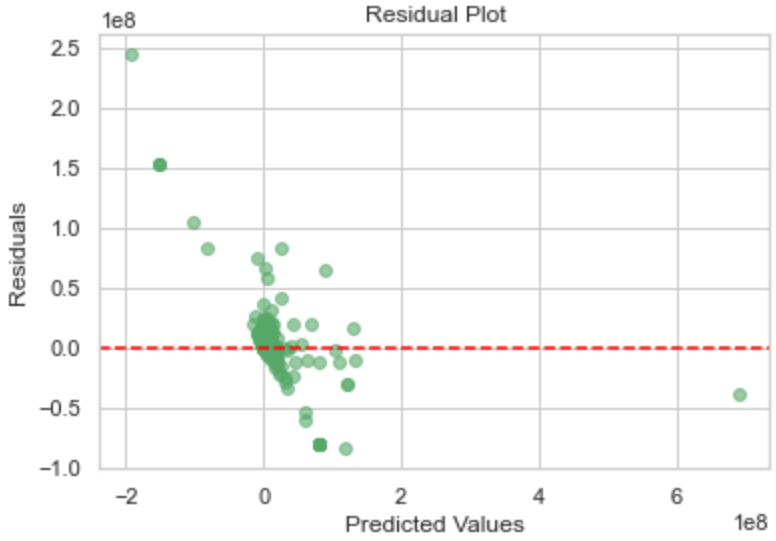
```
%%time
from sklearn.linear_model import Ridge
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Ridge Regression model
alpha = 0.01  # You can adjust the regularization strength
model_ridge = Ridge(alpha=alpha)
model_ridge.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model_ridge.predict(X_test_scaled)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
```

```
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 50297199319095.74
Mean Absolute Error (MAE): 1321224.6874237244
R-squared (R2): 0.5286346594630149
Explained Variance Score: 0.5287917340289177
Maximum Residual Error: 244856109.4587102
Median Absolute Error: 469387.2206523707
CPU times: total: 0 ns
Wall time: 141 ms
```

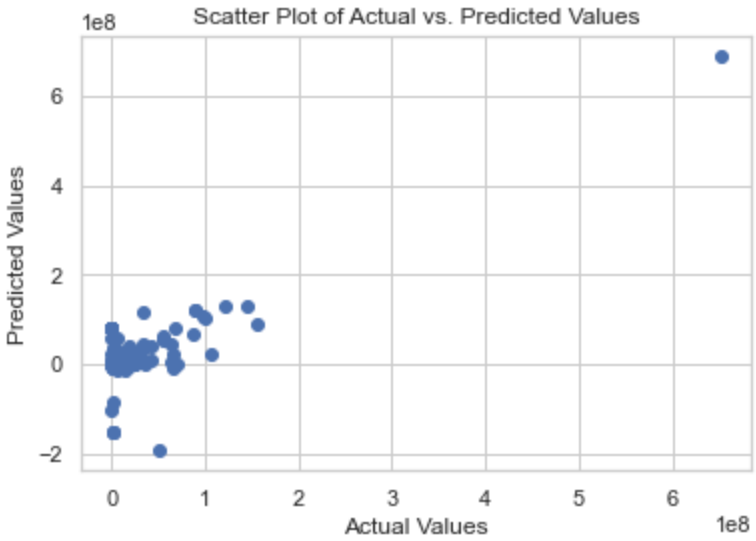
In [127…

```
import matplotlib.pyplot as plt

# Calculate residuals
residuals = y_test - y_pred

# Residual Plot
plt.scatter(y_pred, residuals, c='g', alpha=0.6)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.axhline(y=0, color='red', linestyle='--')  # Add a horizontal line at y=0 for refe
plt.show()
```



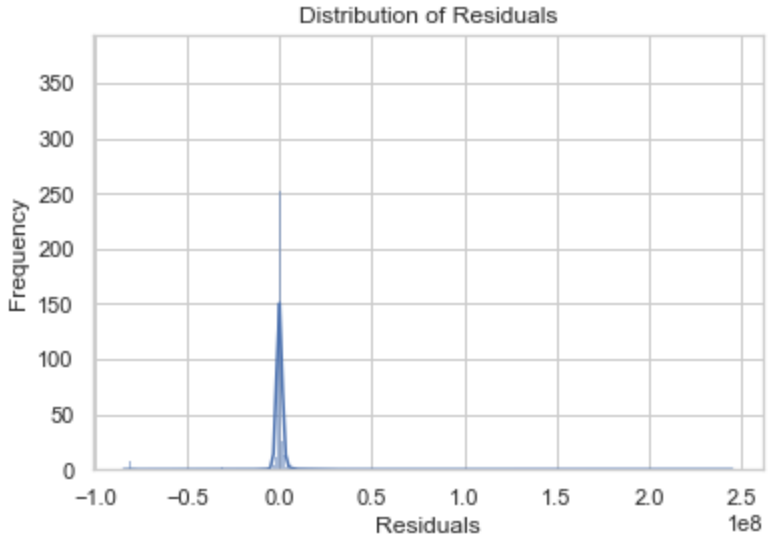
In [128…

```
# Scatter Plot
plt.scatter(y_test, y_pred)
plt.title('Scatter Plot of Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



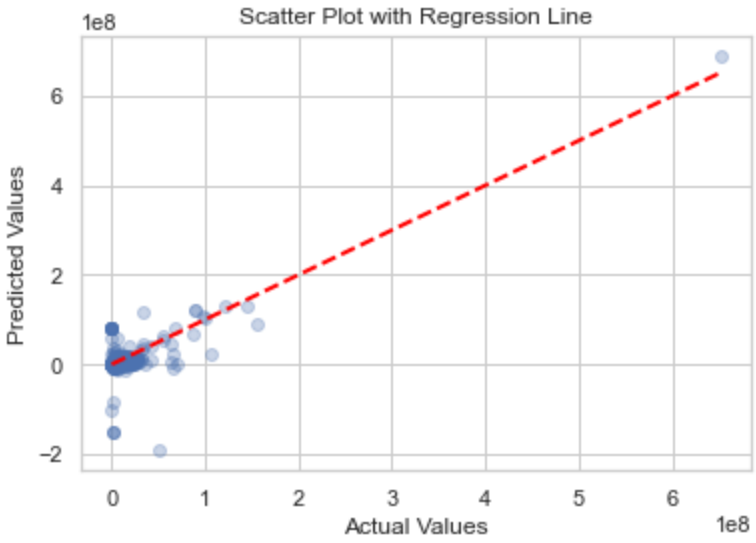
In [129…

```
# Distribution Plot
sns.histplot(y_test - y_pred, kde=True)
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



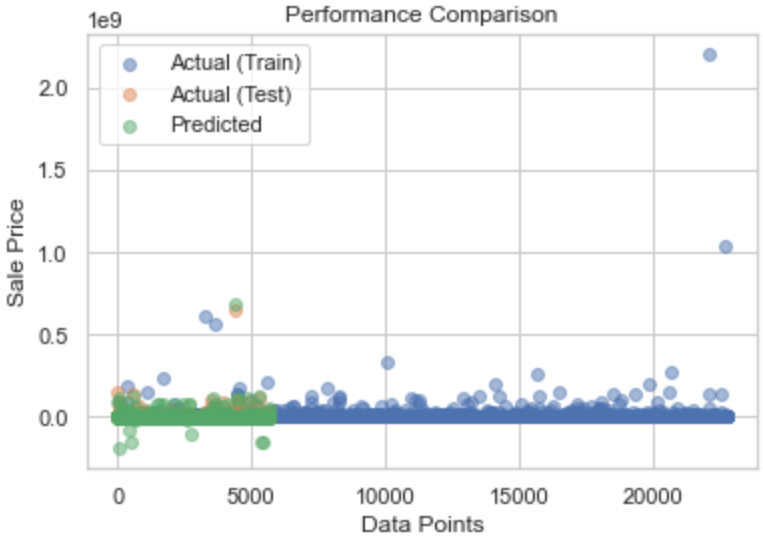
In [130…

```
import matplotlib.pyplot as plt

# Scatter Plot with Regression Line
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color
plt.title('Scatter Plot with Regression Line')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



In [133…

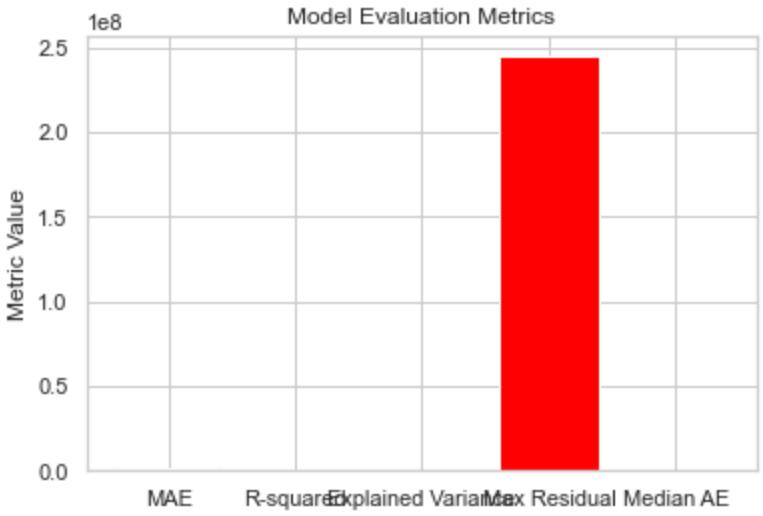
```
# Performance Comparison Plot
plt.scatter(range(len(y_train)), y_train, label='Actual (Train)', alpha=0.5)
plt.scatter(range(len(y_test)), y_test, label='Actual (Test)', alpha=0.5)
plt.scatter(range(len(y_test)), y_pred, label='Predicted', alpha=0.5)
plt.legend()
plt.title('Performance Comparison')
plt.xlabel('Data Points')
plt.ylabel('Sale Price')
plt.show()
```



In [ ]:

In [132…

```
# Metrics Comparison Bar Plot
metrics_names = ['MAE', 'R-squared', 'Explained Variance', 'Max Residual', 'Median AE'
metrics_values = [mae, r2, explained_var, max_residual, median_ae]
plt.bar(metrics_names, metrics_values, color=['green', 'orange', 'purple', 'red', 'brc
plt.title('Model Evaluation Metrics')
plt.ylabel('Metric Value')
plt.show()
```



Try Elastic Net Regression

In [107…

```
%%time
from sklearn.linear_model import ElasticNet
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Elastic Net Regression model
alpha = 0.01  # You can adjust the regularization strength
l1_ratio = 0.5  # You can adjust the balance between L1 and L2 regularization
model_en = ElasticNet(alpha=alpha, l1_ratio=l1_ratio)
model_en.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model_en.predict(X_test_scaled)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
explained_var = explained_variance_score(y_test, y_pred)
max_residual = max_error(y_test, y_pred)
median_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
```

```
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {explained_var}")
print(f"Maximum Residual Error: {max_residual}")
print(f"Median Absolute Error: {median_ae}")
```

```
Mean Squared Error (MSE): 151822233675479.1
Mean Absolute Error (MAE): 1696338.3263050753
R-squared (R2): 0.1688183981854715
Explained Variance Score: 0.168907993904035
Maximum Residual Error: 556148363.0909563
Median Absolute Error: 483345.95216699643
CPU times: total: 188 ms
Wall time: 112 ms
```

Try tuning RandomForest

In [134…

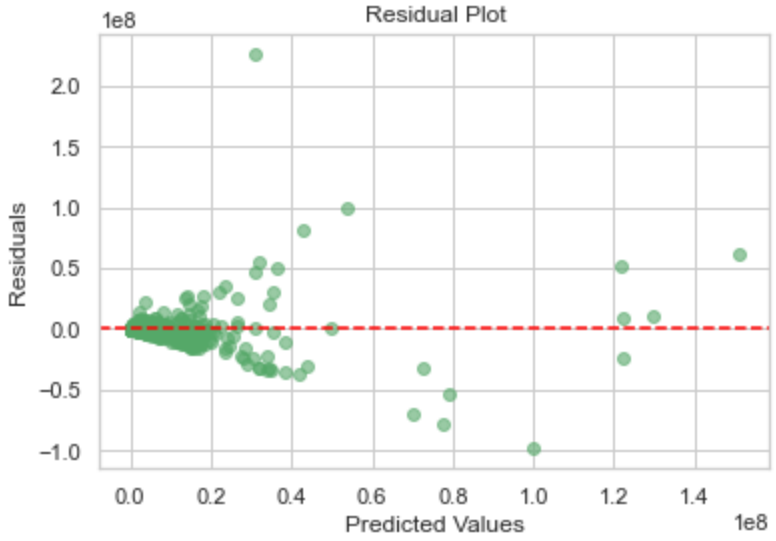
```
%%time
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.model_selection import GridSearchCV
# Separate features and target variable
X = real_estate_price_df_encoded.drop('SALE PRICE', axis=1)
y = real_estate_price_df_encoded['SALE PRICE']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Hyperparameter tuning using GridSearchCV
param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

rf = RandomForestRegressor(random_state=42)
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring='neg_mea
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")

# Train the random forest model with the best parameters
best_rf_model = RandomForestRegressor(random_state=42, **best_params)
best_rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = best_rf_model.predict(X_test)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
evs = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
med_ae = median_absolute_error(y_test, y_pred)
```

```
# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {evs}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {med_ae}")
```

```
Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 2, 'min_samples_split':
2, 'n_estimators': 150}
Mean Squared Error (MSE): 24172237304663.914
Mean Absolute Error (MAE): 789729.4074409158
R-squared (R2): 0.5405787804467665
Explained Variance Score: 0.5406321471820843
Maximum Residual Error: 226445484.61338624
Median Absolute Error: 180488.18492063496
CPU times: total: 12.3 s
Wall time: 7min 37s
```

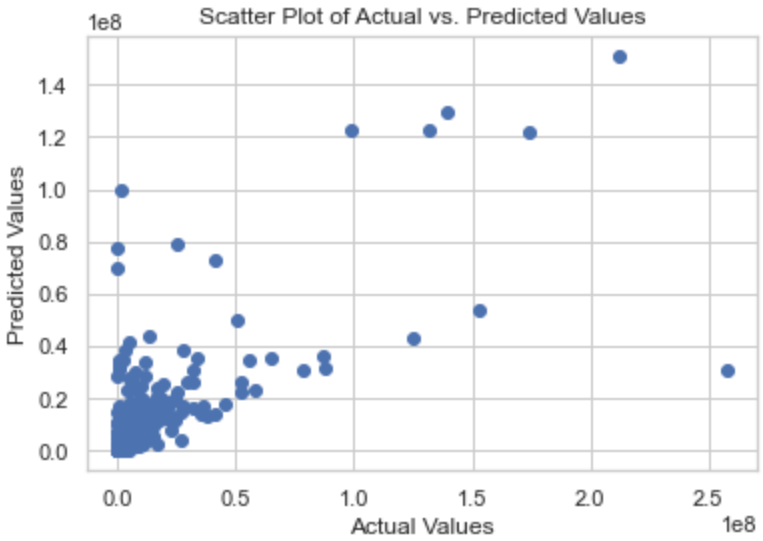
In [135…

```
import matplotlib.pyplot as plt

# Calculate residuals
residuals = y_test - y_pred

# Residual Plot
plt.scatter(y_pred, residuals, c='g', alpha=0.6)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.axhline(y=0, color='red', linestyle='--')  # Add a horizontal line at y=0 for refe
plt.show()
```



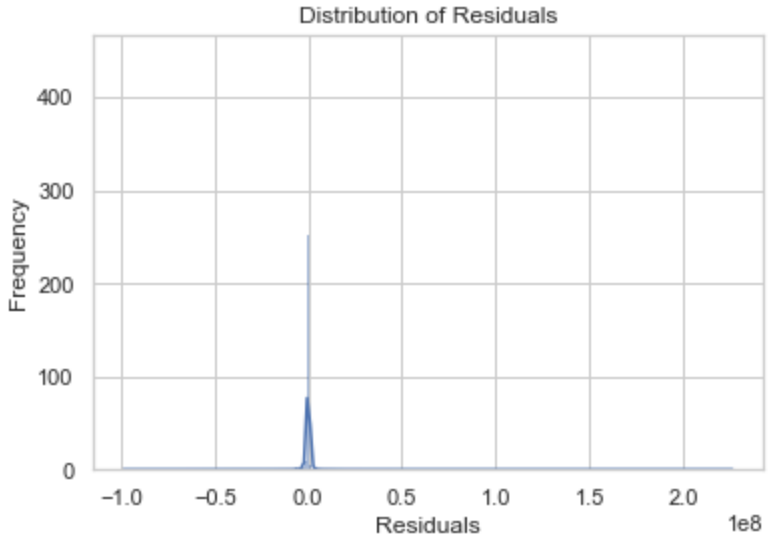
In [136…

```
# Scatter Plot
plt.scatter(y_test, y_pred)
plt.title('Scatter Plot of Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



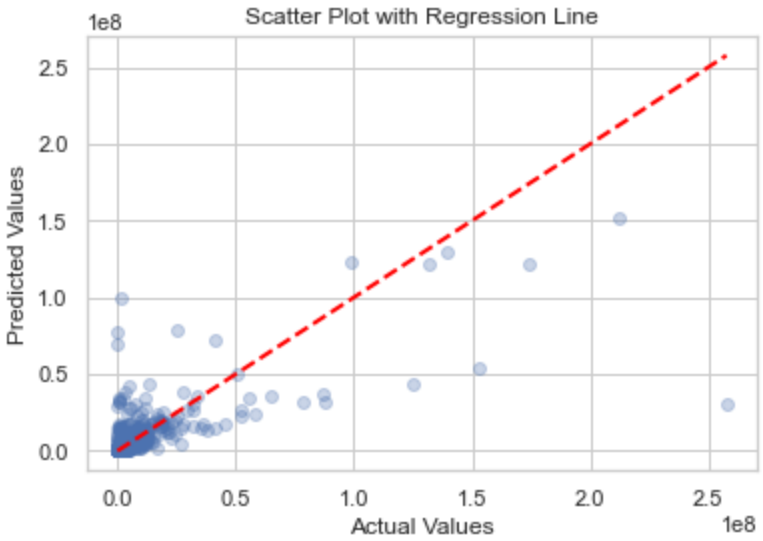
In [137…

```
# Distribution Plot
sns.histplot(y_test - y_pred, kde=True)
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



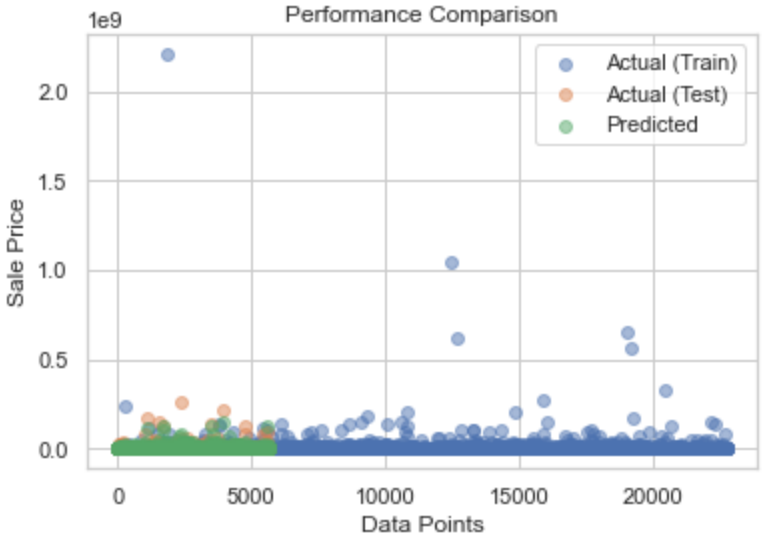
In [138…

```
import matplotlib.pyplot as plt

# Scatter Plot with Regression Line
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color
plt.title('Scatter Plot with Regression Line')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



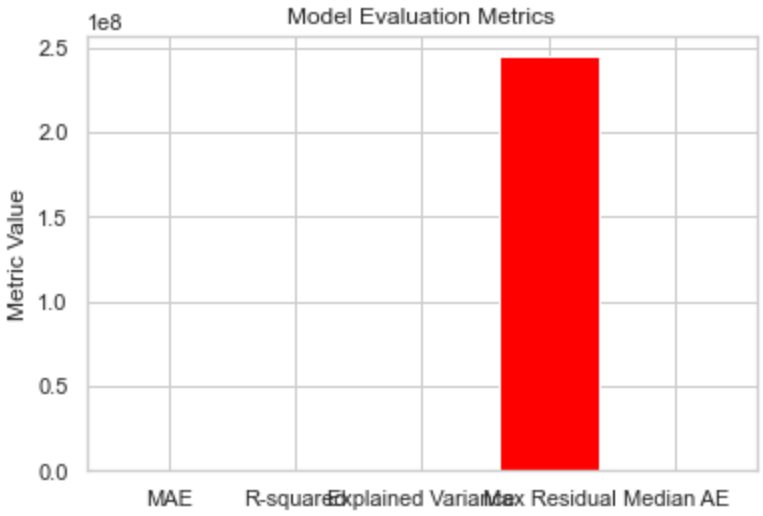
In [139…

```
# Performance Comparison Plot
plt.scatter(range(len(y_train)), y_train, label='Actual (Train)', alpha=0.5)
plt.scatter(range(len(y_test)), y_test, label='Actual (Test)', alpha=0.5)
plt.scatter(range(len(y_test)), y_pred, label='Predicted', alpha=0.5)
plt.legend()
plt.title('Performance Comparison')
plt.xlabel('Data Points')
plt.ylabel('Sale Price')
plt.show()
```



In [140…

```
# Metrics Comparison Bar Plot
metrics_names = ['MAE', 'R-squared', 'Explained Variance', 'Max Residual', 'Median AE'
metrics_values = [mae, r2, explained_var, max_residual, median_ae]
plt.bar(metrics_names, metrics_values, color=['green', 'orange', 'purple', 'red', 'brc
plt.title('Model Evaluation Metrics')
plt.ylabel('Metric Value')
plt.show()
```



Try tuning Ridge Regression

In [109…

```
%%time
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.model_selection import GridSearchCV


# Separate features and target variable
X = real_estate_price_df_encoded.drop('SALE PRICE', axis=1)
y = real_estate_price_df_encoded['SALE PRICE']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Hyperparameter tuning using GridSearchCV
param_grid = {
    'alpha': [0.01, 0.1, 1, 10, 100]
}

ridge = Ridge()
grid_search = GridSearchCV(estimator=ridge, param_grid=param_grid, cv=5, scoring='neg_
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")

# Train the Ridge Regression model with the best parameters
best_ridge_model = Ridge(**best_params)
best_ridge_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = best_ridge_model.predict(X_test)

# Evaluate the performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
evs = explained_variance_score(y_test, y_pred)
max_err = max_error(y_test, y_pred)
med_ae = median_absolute_error(y_test, y_pred)

# Display the metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")
print(f"Explained Variance Score: {evs}")
print(f"Maximum Residual Error: {max_err}")
print(f"Median Absolute Error: {med_ae}")
```

```
Best Hyperparameters: {'alpha': 100}
Mean Squared Error (MSE): 70716946459186.44
Mean Absolute Error (MAE): 1430639.1468653432
R-squared (R2): -0.4870235096423594
Explained Variance Score: -0.48690927330061395
Maximum Residual Error: 303048846.84214133
Median Absolute Error: 483846.73698667856
CPU times: total: 31.2 ms
Wall time: 196 ms
```

In [110…

```
%%time
from sklearn.linear_model import RidgeCV
import numpy as np

# Use RidgeCV for cross-validated alpha selection
alphas = np.logspace(-6, 6, 13)
model_ridge_cv = RidgeCV(alphas=alphas, store_cv_values=True)
model_ridge_cv.fit(X_train_scaled, y_train)

# Get the best alpha
best_alpha = model_ridge_cv.alpha_

# Initialize and train the Ridge Regression model with the best alpha
model_ridge_tuned = Ridge(alpha=best_alpha)
model_ridge_tuned.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_tuned = model_ridge_tuned.predict(X_test_scaled)

# Evaluate the performance
mse_tuned = mean_squared_error(y_test, y_pred_tuned)
mae_tuned = mean_absolute_error(y_test, y_pred_tuned)
r2_tuned = r2_score(y_test, y_pred_tuned)
explained_var_tuned = explained_variance_score(y_test, y_pred_tuned)
max_residual_tuned = max_error(y_test, y_pred_tuned)
median_ae_tuned = median_absolute_error(y_test, y_pred_tuned)

# Display the metrics for the tuned model
print("Metrics for Tuned Ridge Regression:")
print(f"Mean Squared Error (MSE): {mse_tuned}")
print(f"Mean Absolute Error (MAE): {mae_tuned}")
print(f"R-squared (R2): {r2_tuned}")
print(f"Explained Variance Score: {explained_var_tuned}")
print(f"Maximum Residual Error: {max_residual_tuned}")
print(f"Median Absolute Error: {median_ae_tuned}")
```

```
Metrics for Tuned Ridge Regression:
Mean Squared Error (MSE): 47629055053150.3
Mean Absolute Error (MAE): 1679933.9389470324
R-squared (R2): -0.0015353907703143932
Explained Variance Score: 0.00023881047306284486
Maximum Residual Error: 328109215.03413844
Median Absolute Error: 1170688.38013359
CPU times: total: 359 ms
Wall time: 348 ms
```

In [111…

```
# Get feature coefficients from the tuned Ridge Regression model
feature_coefficients = model_ridge_tuned.coef_

# Create a DataFrame to display feature importance
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': feature_coefficients
})

# Display feature importance
print("Feature Importance:")
print(feature_importance_df.sort_values(by='Coefficient', ascending=False))
```

```
Feature Importance:
             Feature   Coefficient
9          BOROUGH_5  53843.822412
4  GROSS SQUARE FEET   3844.909468
3   LAND SQUARE FEET   2030.988662
1   COMMERCIAL UNITS  -6325.196937
8          BOROUGH_4  -7232.477079
0  RESIDENTIAL UNITS  -7697.732528
7          BOROUGH_3  -8025.075479
2        TOTAL UNITS  -8854.302077
5          BOROUGH_1 -17614.582785
6          BOROUGH_2 -30769.869580
```

Try XGBoost Regression

In [112…

```
%%time
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the XGBoost Regressor
model_xgboost = XGBRegressor()
```

```
model_xgboost.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_xgboost = model_xgboost.predict(X_test_scaled)

# Evaluate the performance
mse_xgboost = mean_squared_error(y_test, y_pred_xgboost)
mae_xgboost = mean_absolute_error(y_test, y_pred_xgboost)
r2_xgboost = r2_score(y_test, y_pred_xgboost)
explained_var_xgboost = explained_variance_score(y_test, y_pred_xgboost)
max_residual_xgboost = max_error(y_test, y_pred_xgboost)
median_ae_xgboost = median_absolute_error(y_test, y_pred_xgboost)

print("Metrics for XGBoost Regression:")
print(f"Mean Squared Error (MSE): {mse_xgboost}")
print(f"Mean Absolute Error (MAE): {mae_xgboost}")
print(f"R-squared (R2): {r2_xgboost}")
print(f"Explained Variance Score: {explained_var_xgboost}")
print(f"Maximum Residual Error: {max_residual_xgboost}")
print(f"Median Absolute Error: {median_ae_xgboost}")
```

```
Metrics for XGBoost Regression:
Mean Squared Error (MSE): 711264446407468.1
Mean Absolute Error (MAE): 1349469.3190381401
R-squared (R2): 0.3576518616760782
Explained Variance Score: 0.35773578084573754
Maximum Residual Error: 1903387456.0
Median Absolute Error: 186047.1875
CPU times: total: 766 ms
Wall time: 735 ms
```

Try bagged regression with RandomForest

In [113…

```
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explair
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Random Forest Regressor
model_rf = RandomForestRegressor()
bagged_model_rf = BaggingRegressor(base_estimator=model_rf, n_estimators=10, random_st
bagged_model_rf.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_rf_bagged = bagged_model_rf.predict(X_test_scaled)
```

```
# Evaluate the performance
mse_rf_bagged = mean_squared_error(y_test, y_pred_rf_bagged)
mae_rf_bagged = mean_absolute_error(y_test, y_pred_rf_bagged)
r2_rf_bagged = r2_score(y_test, y_pred_rf_bagged)
explained_var_rf_bagged = explained_variance_score(y_test, y_pred_rf_bagged)
max_residual_rf_bagged = max_error(y_test, y_pred_rf_bagged)
median_ae_rf_bagged = median_absolute_error(y_test, y_pred_rf_bagged)

print("Metrics for Bagged Random Forest Regression:")
print(f"Mean Squared Error (MSE): {mse_rf_bagged}")
print(f"Mean Absolute Error (MAE): {mae_rf_bagged}")
print(f"R-squared (R2): {r2_rf_bagged}")
print(f"Explained Variance Score: {explained_var_rf_bagged}")
print(f"Maximum Residual Error: {max_residual_rf_bagged}")
print(f"Median Absolute Error: {median_ae_rf_bagged}")
```

```
Metrics for Bagged Random Forest Regression:
Mean Squared Error (MSE): 40830452373268.08
Mean Absolute Error (MAE): 840626.6911749778
R-squared (R2): 0.3436529360153082
Explained Variance Score: 0.3436944824052329
Maximum Residual Error: 278410760.62818587
Median Absolute Error: 181844.07421428582
```

Try Neural Network with Hyperparameter Tuning

In [115…

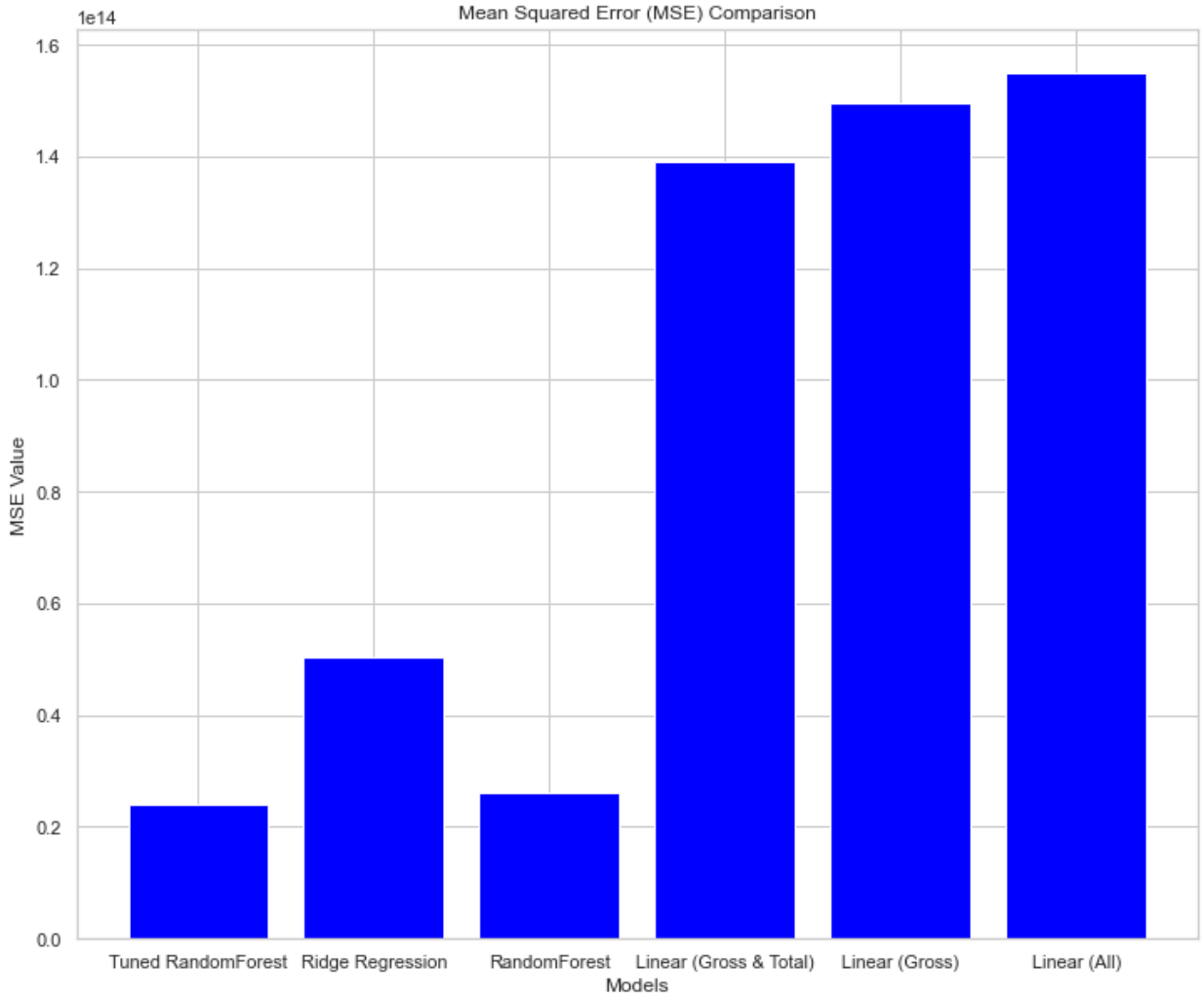
```
'''
%%time
import numpy as np
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.wrappers.scikit_learn import KerasRegressor
from sklearn.metrics import make_scorer, mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explain

# Assuming X and y are your feature matrix and target variable
X = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)
y = real_estate_price_df_encoded["SALE PRICE"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Define the neural network model
def create_model(optimizer='adam', activation='relu', neurons=64):
    model = Sequential([
        Dense(units=neurons, activation=activation, input_dim=X_train_scaled.shape[1])
        Dense(units=1)
    ])
```

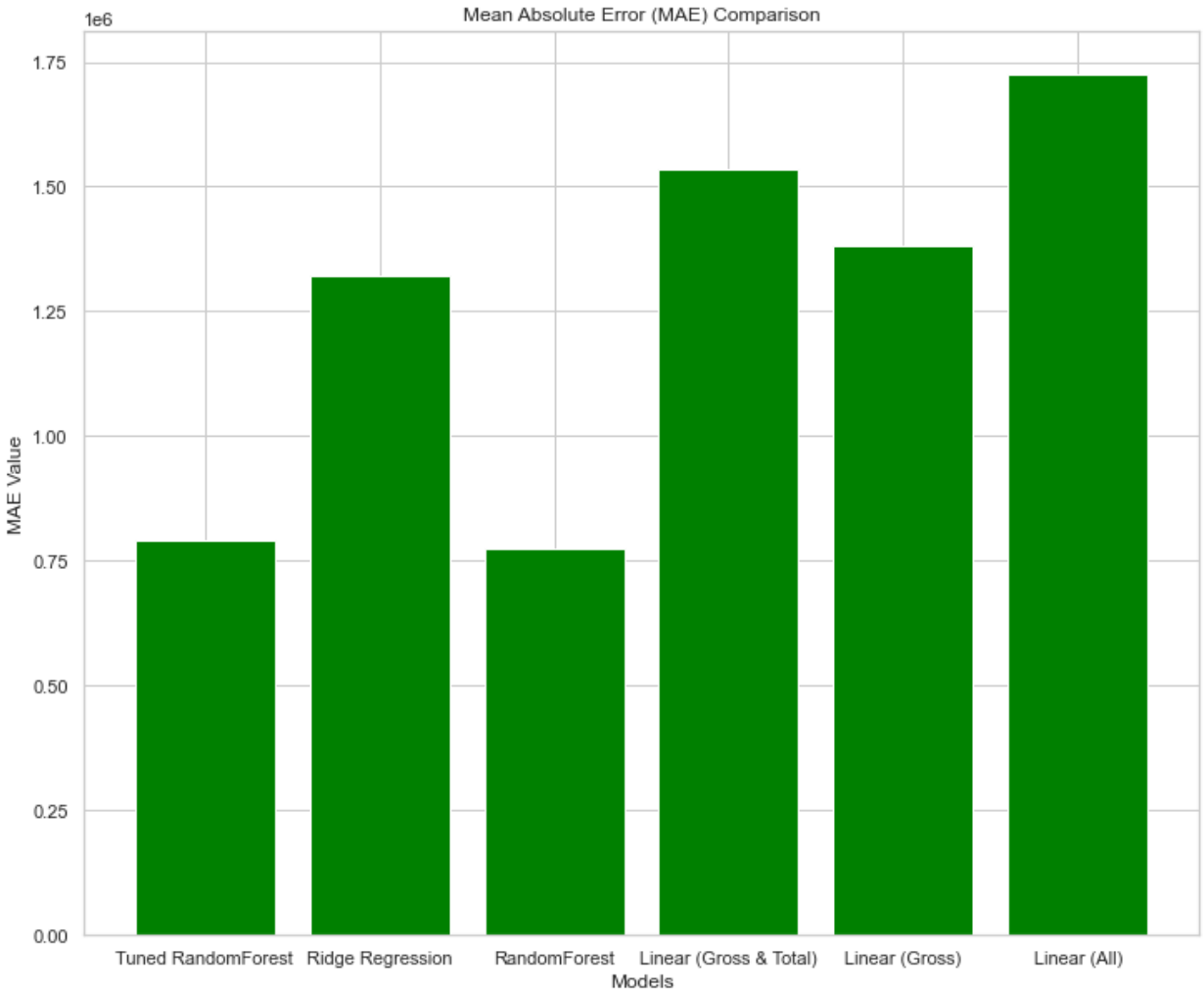
```
    model.compile(optimizer=optimizer, loss='mean_squared_error')
    return model

# Create a KerasRegressor with your neural network model
model_nn = KerasRegressor(build_fn=create_model, epochs=50, batch_size=66, verbose=0)

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'optimizer': ['adam', 'rmsprop'],
    'activation': ['relu', 'tanh'],
    'neurons': [32, 64, 128]
}

# Use GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(estimator=model_nn, param_grid=param_grid, scoring=make_scc
grid_result = grid_search.fit(X_train_scaled, y_train)

# Get the best parameters
best_params = grid_result.best_params_
print("Best Hyperparameters:", best_params)

# Make predictions on the test set using the best model
y_pred_nn = grid_result.predict(X_test_scaled)

# Evaluate the performance
mse_nn = mean_squared_error(y_test, y_pred_nn)
mae_nn = mean_absolute_error(y_test, y_pred_nn)
r2_nn = r2_score(y_test, y_pred_nn)
explained_var_nn = explained_variance_score(y_test, y_pred_nn)
max_residual_nn = max_error(y_test, y_pred_nn)
median_ae_nn = median_absolute_error(y_test, y_pred_nn)

# Print the metrics
print("Metrics for Neural Network Regression:")
print("Mean Squared Error (MSE):", mse_nn)
print("Mean Absolute Error (MAE):", mae_nn)
print("R-squared (R2):", r2_nn)
print("Explained Variance Score:", explained_var_nn)
print("Maximum Residual Error:", max_residual_nn)
print("Median Absolute Error:", median_ae_nn)
'''
```

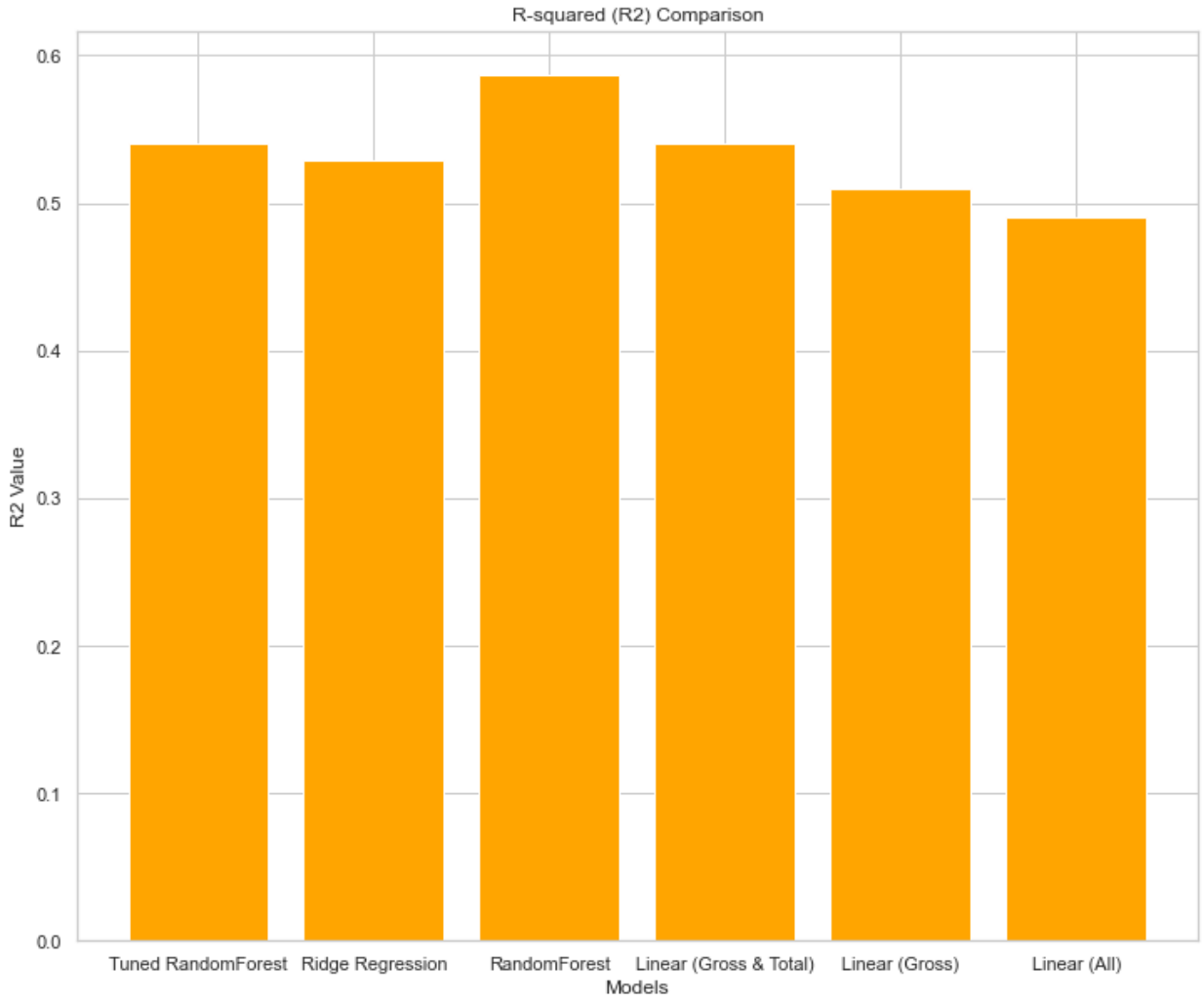
Out[115]:
```
'\n%%time\nimport numpy as np\nfrom sklearn.model_selection import GridSearchCV\nfrom
sklearn.preprocessing import StandardScaler\nfrom tensorflow.keras.models import Sequ
ential\nfrom tensorflow.keras.layers import Dense\nfrom tensorflow.keras.wrappers.sci
kit_learn import KerasRegressor\nfrom sklearn.metrics import make_scorer, mean_square
d_error\nfrom sklearn.model_selection import train_test_split\nfrom sklearn.metrics i
mport mean_squared_error, mean_absolute_error, r2_score, explained_variance_score, ma
x_error, median_absolute_error\n\n# Assuming X and y are your feature matrix and targ
et variable\nX = real_estate_price_df_encoded.drop("SALE PRICE", axis=1)\ny = real_es
tate_price_df_encoded["SALE PRICE"]\n\n# Split the data into training and testing set
s\nX_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_st
ate=82)\n\n# Standardize the features\nscaler = StandardScaler()\nX_train_scaled = sc
aler.fit_transform(X_train)\nX_test_scaled = scaler.transform(X_test)\n\n# Define the
neural network model\ndef create_model(optimizer=\'adam\', activation=\'relu\', neuro
ns=64):\n    model = Sequential([\n        Dense(units=neurons, activation=activatio
n, input_dim=X_train_scaled.shape[1]),\n        Dense(units=1)\n    ])\n    model.com
pile(optimizer=optimizer, loss=\'mean_squared_error\')\n    return model\n\n# Create
a KerasRegressor with your neural network model\nmodel_nn = KerasRegressor(build_fn=c
reate_model, epochs=50, batch_size=66, verbose=0)\n\n# Define the parameter grid for
hyperparameter tuning\nparam_grid = {\n    \'optimizer\': [\'adam\', \'rmsprop\'],\n
\'activation\': [\'relu\', \'tanh\'],\n    \'neurons\': [32, 64, 128]\n}\n\n# Use Gri
dSearchCV for hyperparameter tuning\ngrid_search = GridSearchCV(estimator=model_nn, p
aram_grid=param_grid, scoring=make_scorer(mean_squared_error, greater_is_better=Fals
e), cv=3)\ngrid_result = grid_search.fit(X_train_scaled, y_train)\n\n# Get the best p
arameters\nbest_params = grid_result.best_params_\nprint("Best Hyperparameters:", bes
t_params)\n\n# Make predictions on the test set using the best model\ny_pred_nn = gri
d_result.predict(X_test_scaled)\n\n# Evaluate the performance\nmse_nn = mean_squared_
error(y_test, y_pred_nn)\nmae_nn = mean_absolute_error(y_test, y_pred_nn)\nr2_nn = r2
_score(y_test, y_pred_nn)\nexplained_var_nn = explained_variance_score(y_test, y_pred
_nn)\nmax_residual_nn = max_error(y_test, y_pred_nn)\nmedian_ae_nn = median_absolute_
error(y_test, y_pred_nn)\n\n# Print the metrics\nprint("Metrics for Neural Network Re
gression:")\nprint("Mean Squared Error (MSE):", mse_nn)\nprint("Mean Absolute Error
(MAE):", mae_nn)\nprint("R-squared (R2):", r2_nn)\nprint("Explained Variance Score:",
explained_var_nn)\nprint("Maximum Residual Error:", max_residual_nn)\nprint("Median A
bsolute Error:", median_ae_nn)\n'
```

In [117…
```
import matplotlib.pyplot as plt

models = ['Tuned RandomForest', 'Ridge Regression', 'RandomForest', 'Linear (Gross & T
mse_values = [24172237304663.914, 50297199319095.74, 26042280118408.414, 139070168737
mae_values = [789729.41, 1321224.69, 775307.53, 1535408.61, 1382152.65, 1726621.12]
r2_values = [0.5406, 0.5286, 0.5874, 0.54, 0.51, 0.49]

# Plotting Mean Squared Error (MSE)
plt.figure(figsize=(12, 10))
plt.bar(models, mse_values, color='blue')
plt.title('Mean Squared Error (MSE) Comparison')
plt.xlabel('Models')
plt.ylabel('MSE Value')
plt.show()

# Plotting Mean Absolute Error (MAE)
plt.figure(figsize=(12, 10))
plt.bar(models, mae_values, color='green')
plt.title('Mean Absolute Error (MAE) Comparison')
plt.xlabel('Models')
plt.ylabel('MAE Value')
plt.show()

# Plotting R-squared (R2)
plt.figure(figsize=(12, 10))
```

```
plt.bar(models, r2_values, color='orange')
plt.title('R-squared (R2) Comparison')
plt.xlabel('Models')
plt.ylabel('R2 Value')
plt.show()
```

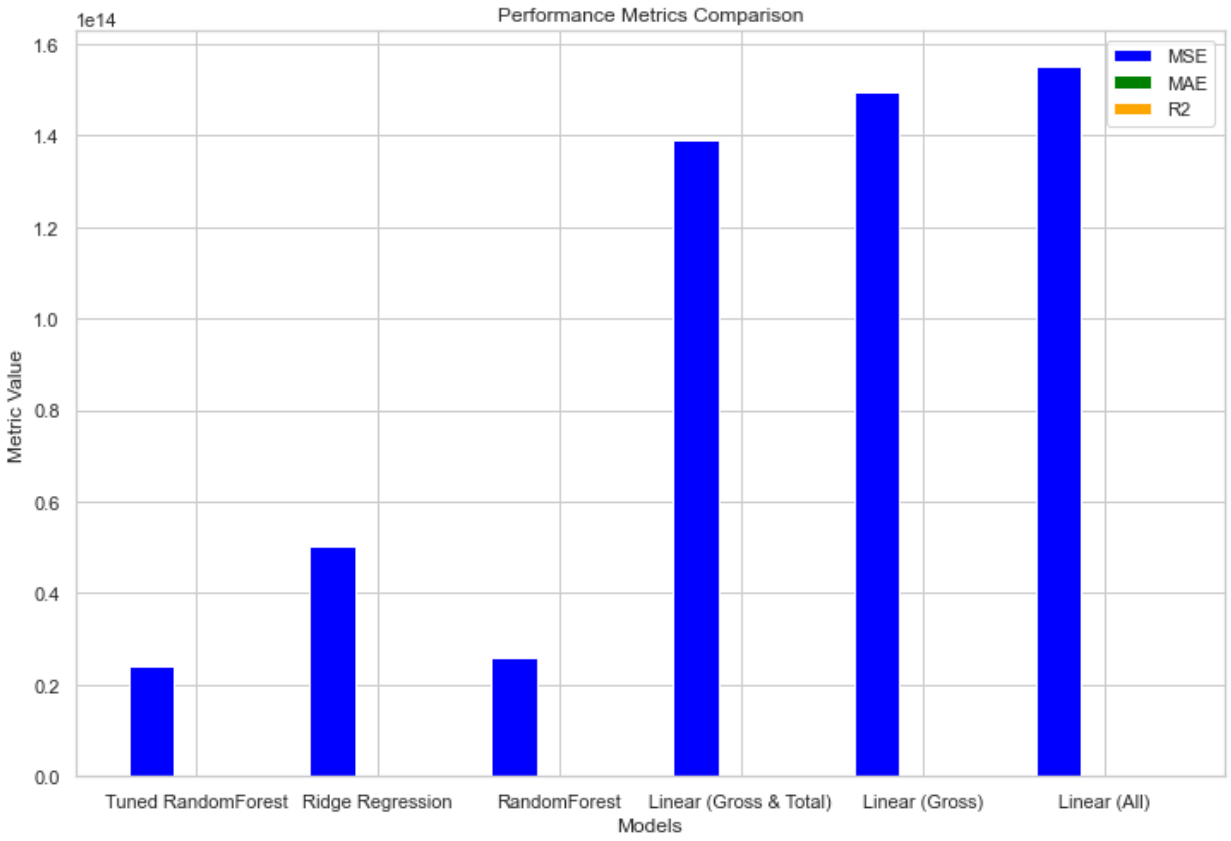



Mean Absolute Error (MAE) Comparison
1e6
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
MAE Value
Tuned RandomForest
Ridge Regression
RandomForest
Linear (Gross & Total)
Linear (Gross)
Linear (All)
Models



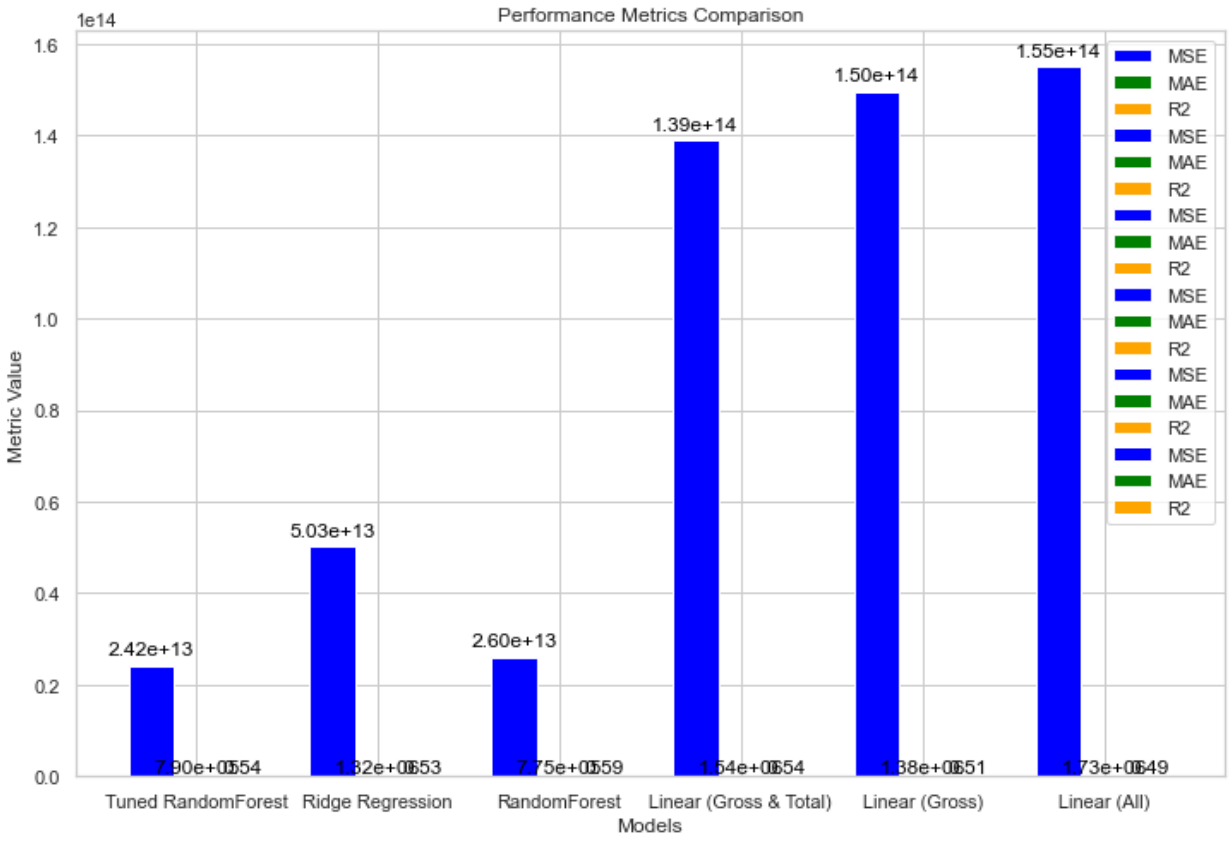
In [118…

```
import matplotlib.pyplot as plt
import numpy as np

models = ['Tuned RandomForest', 'Ridge Regression', 'RandomForest', 'Linear (Gross & T
mse_values = [24172237304663.914, 50297199319095.74, 26042280118408.414, 1390701687378
mae_values = [789729.41, 1321224.69, 775307.53, 1535408.61, 1382152.65, 1726621.12]
r2_values = [0.5406, 0.5286, 0.5874, 0.54, 0.51, 0.49]

bar_width = 0.25
index = np.arange(len(models))

# Plotting all metrics
plt.figure(figsize=(12, 8))

plt.bar(index - bar_width, mse_values, bar_width, label='MSE', color='blue')
plt.bar(index, mae_values, bar_width, label='MAE', color='green')
plt.bar(index + bar_width, r2_values, bar_width, label='R2', color='orange')

plt.title('Performance Metrics Comparison')
plt.xlabel('Models')
plt.ylabel('Metric Value')
plt.xticks(index, models)
plt.legend()
plt.show()
```



In [119…

```
import matplotlib.pyplot as plt
import numpy as np

models = ['Tuned RandomForest', 'Ridge Regression', 'RandomForest', 'Linear (Gross & T
mse_values = [24172237304663.914, 50297199319095.74, 26042280118408.414, 139070168737
mae_values = [789729.41, 1321224.69, 775307.53, 1535408.61, 1382152.65, 1726621.12]
r2_values = [0.5406, 0.5286, 0.5874, 0.54, 0.51, 0.49]

bar_width = 0.25
index = np.arange(len(models))

# Plotting all metrics with numerical values on top
plt.figure(figsize=(12, 8))

for i, model in enumerate(models):
    plt.bar(index[i] - bar_width, mse_values[i], bar_width, label='MSE', color='blue')
    plt.text(index[i] - bar_width, mse_values[i] + 0.01 * max(mse_values), f'{mse_valu

    plt.bar(index[i], mae_values[i], bar_width, label='MAE', color='green')
    plt.text(index[i], mae_values[i] + 0.01 * max(mae_values), f'{mae_values[i]:.2e}',

    plt.bar(index[i] + bar_width, r2_values[i], bar_width, label='R2', color='orange')
    plt.text(index[i] + bar_width, r2_values[i] + 0.01 * max(r2_values), f'{r2_values[

plt.title('Performance Metrics Comparison')
plt.xlabel('Models')
plt.ylabel('Metric Value')
plt.xticks(index, models)
plt.legend()
plt.show()
```



In [120…

```
!pip install tabulate
from tabulate import tabulate

# Assuming you have the metrics in a dictionary
metrics_dict = {
    'Model': models,
    'Mean Squared Error (MSE)': mse_values,
    'Mean Absolute Error (MAE)': mae_values,
    'R-squared (R2)': r2_values
}

# Convert the dictionary to a table
table = tabulate(metrics_dict, headers='keys', tablefmt='pretty')

# Print the table
print(table)
```

```
Requirement already satisfied: tabulate in c:\users\moshe\anaconda3\lib\site-packages
(0.8.9)
+-----------------------+--------------------------+---------------------------+----
------------+
|         Model         | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | R-s
quared (R2) |
+-----------------------+--------------------------+---------------------------+----
------------+
|   Tuned RandomForest  |    24172237304663.914    |         789729.41         |
0.5406     |
|    Ridge Regression   |    50297199319095.74     |        1321224.69         |
0.5286     |
|      RandomForest     |    26042280118408.414    |         775307.53         |
0.5874     |
| Linear (Gross & Total) |    139070168737840.92    |        1535408.61         |
0.54       |
|     Linear (Gross)    |    149623544146030.88    |        1382152.65         |
0.51       |
|      Linear (All)     |    155075890534231.84    |        1726621.12         |
0.49       |
+-----------------------+--------------------------+---------------------------+----
------------+
```

```
WARNING: Ignoring invalid distribution - (c:\users\moshe\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ensorflow-intel (c:\users\moshe\anaconda3\lib
\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\moshe\anaconda3\lib\site-pa
ckages)
WARNING: Ignoring invalid distribution - (c:\users\moshe\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ensorflow-intel (c:\users\moshe\anaconda3\lib
\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\moshe\anaconda3\lib\site-pa
ckages)

[notice] A new release of pip is available: 23.2.1 -> 23.3.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [121…

```python
from tabulate import tabulate

# Assuming you have the metrics in a dictionary
metrics_dict = {
    'Model': models,
    'Mean Squared Error (MSE)': mse_values,
    'Mean Absolute Error (MAE)': mae_values,
    'R-squared (R2)': r2_values
}

# Convert the dictionary to a table with pretty formatting
table = tabulate(metrics_dict, headers='keys', tablefmt='pretty')

# Print the table
print(table)
```

```
+------------------------+--------------------------+---------------------------+----
------------+
|         Model          | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | R-s
quared (R2) |
+------------------------+--------------------------+---------------------------+----
------------+
|   Tuned RandomForest   |    24172237304663.914    |         789729.41         |
0.5406      |
|    Ridge Regression    |    50297199319095.74     |        1321224.69         |
0.5286      |
|      RandomForest      |    26042280118408.414    |         775307.53         |
0.5874      |
| Linear (Gross & Total) |    139070168737840.92    |        1535408.61         |
0.54        |
|     Linear (Gross)     |    149623544146030.88    |        1382152.65         |
0.51        |
|      Linear (All)      |    155075890534231.84    |        1726621.12         |
0.49        |
+------------------------+--------------------------+---------------------------+----
------------+
```

In [ ]:

In [93]:

	1 Residential Unit More Than the Mean	One Residential
Manhattan	$12,693,147.12	$13,619,417.14
Bronx	$583,473.49	$669,737.74
Brooklyn	$1,663,263.79	$1,095,173.56
Queens	$1,260,107.65	$1,182,891.90
Staten Island	$614,241.55	$857,385.06

In [ ]:

Here is the table you requested:

Borough	1 Residential Unit More Than the Mean	One Residential Unit Less Than the		
Manhattan	\$12,693,147.12	\$13,619,417.14	\$13,185,238.05	\$14,735,632.62
Bronx	\$583,473.49	\$669,737.74	\$643,224.76	\$643,347.62
Brooklyn	\$1,663,263.79	\$1,095,173.56	\$1,647,062.06	\$1,134,386.28
Queens	\$1,260,107.65	\$1,182,891.90	\$1,339,586.33	\$1,041,043.13
Staten Island	\$614,241.55	\$857,385.06	\$646,237.26	\$706,012.26

Please note that the values are in US dollars.

In [ ]:

Borough	1 Residential Unit More Than the Mean	One Residential Unit Less Than the Mea		
Manhattan	$12,693,147.12	$13,619,417.14	$13,185,238.05	$14,735,632.62
Bronx	$583,473.49	$669,737.74	$643,224.76	$643,347.62
Brooklyn	$1,663,263.79	$1,095,173.56	$1,647,062.06	$1,134,386.28
Queens	$1,260,107.65	$1,182,891.90	$1,339,586.33	$1,041,043.13
Staten Island	$614,241.55	$857,385.06	$646,237.26	$706,012.26

In [1]:

```python
import pandas as pd
from IPython.display import display

# Define the data
data = {
    '1 Residential Unit More Than the Mean': ['$12,693,147.12', '$583,473.49', '$1,663
    'One Residential Unit Less Than the Mean': ['$13,619,417.14', '$669,737.74', '$1,0
    'One Commercial Unit More Than the Mean': ['$13,185,238.05', '$643,224.76', '$1,64
```

```
    'One Commercial Unit Less Than the Mean': ['$14,735,632.62', '$643,347.62', '$1,13
}

# Define the row labels
row_labels = ['Manhattan', 'Bronx', 'Brooklyn', 'Queens', 'Staten Island']

# Create the DataFrame
df = pd.DataFrame(data, index=row_labels)

# Display the DataFrame
display(df)
```

	1 Residential Unit More Than the Mean	One Residential Unit Less Than the Mean	One Commercial Unit More Than the Mean	One Commercial Unit Less Than the Mean
Manhattan	$12,693,147.12	$13,619,417.14	$13,185,238.05	$14,735,632.62
Bronx	$583,473.49	$669,737.74	$643,224.76	$643,347.62
Brooklyn	$1,663,263.79	$1,095,173.56	$1,647,062.06	$1,134,386.28
Queens	$1,260,107.65	$1,182,891.90	$1,339,586.33	$1,041,043.13
Staten Island	$614,241.55	$857,385.06	$646,237.26	$706,012.26

In [ ]: