In [174…

```
##IMPORTING ALL THE LIBRARIES
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import make_pipeline
from category_encoders import TargetEncoder
from sklearn.preprocessing import RobustScaler
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from sklearn.metrics import r2_score, mean_squared_error

import joblib
```

In [175…

```
plt.style.use('tableau-colorblind10')
sns.set_style('whitegrid')
```

In [176…

```
# Reading the file
brookdf = pd.read_csv('BrooklynDataFinal.csv', index_col=[0])
brookdf.head()
```

Out[176]:

	Borough	Neighborhood	Building_Class_Category	Tax Class At Present	Block	Lot	Ease-Ment	Building Class At Present	address	Apartment Number	...	Total Units	Land_Square_Fe
9	3	BATH BEACH	01 ONE FAMILY DWELLINGS	1	6399	8	NaN	S1	1653 BATH AVENUE	NaN	...	2.0	1,26
10	3	BATH BEACH	01 ONE FAMILY DWELLINGS	1	6399	107	NaN	S1	1655 BATH AVENUE	NaN	...	2.0	1,26
12	3	BATH BEACH	01 ONE FAMILY DWELLINGS	1	6405	148	NaN	S1	1865 BATH AVENUE	NaN	...	2.0	1,12
16	3	BATH BEACH	01 ONE FAMILY DWELLINGS	1	6442	32	NaN	S1	2014 BATH AVENUE	NaN	...	2.0	1,24
21	3	BATH BEACH	01 ONE FAMILY DWELLINGS	1	6461	141	NaN	A5	1173 SHORE PARKWAY	NaN	...	1.0	1,66

5 rows × 23 columns

In [177…
```
brookdf.shape
```
Out[177]:
```
(7815, 23)
```

In [178…
```
#Data Clean up
```

In [179…
```
brookdf['Sale_Price'].quantile([0, 0.25, 0.5, 0.75, 0.9, 0.95, 0.99, 0.997, 1])
```

Out[179]:
```
0.000            0.0
0.250            0.0
0.500       597500.0
0.750      1400000.0
0.900      2800000.0
0.950      4500000.0
0.990     15750000.0
0.997     36746400.0
1.000    228447600.0
Name: Sale_Price, dtype: float64
```

In [180…
```
brookdf['Year Built'].quantile([0, 0.25, 0.5, 0.75, 0.9, 0.95, 0.99, 0.997, 1])
```

Out[180]:
```
0.000    1800.000
0.250    1910.000
0.500    1925.000
0.750    1935.000
0.900    1987.000
0.950    2005.000
0.990    2019.000
0.997    2021.134
1.000    2022.000
Name: Year Built, dtype: float64
```

In [181…
```
#Masking the data where the year built is less than 1900 and sale price is less than 100000 and more than 1e7
mask = (brookdf['Year Built'] > 1900) & (brookdf['Sale_Price'] > 100000) & (brookdf['Sale_Price'] < 1e7)
brookdf = brookdf[mask]
```

In [182…
```
brookdf.shape
```

Out[182]:
```
(3522, 23)
```

In [183…
```
# Feature Engineering
#It appears that there are a substantial amount of missing values in a majority of the columns.
#To address this issue a 50% missing value cutoff. Columns that exceed this threshold will be removed.
req_cols = []

for col in brookdf.columns:
    is_na = round(brookdf[col].isna().sum() / len(brookdf) * 100, 2)
    if is_na < 50:
        req_cols.append(col)
    print(f"{col} has {is_na} % of nan values")

print(f"{len(req_cols)} has less than 50% of nan values")
```

```
brookdf = brookdf[req_cols]
print(brookdf.shape)
```

```
Borough has 0.0 % of nan values
Neighborhood has 0.0 % of nan values
Building_Class_Category has 0.0 % of nan values
Tax Class At Present has 0.0 % of nan values
Block has 0.0 % of nan values
Lot has 0.0 % of nan values
Ease-Ment has 100.0 % of nan values
Building Class At Present has 0.0 % of nan values
address has 0.0 % of nan values
Apartment Number has 99.83 % of nan values
Zip Code has 0.0 % of nan values
Residential_Units has 0.2 % of nan values
Commercial_Units has 0.03 % of nan values
Total Units has 0.03 % of nan values
Land_Square_Feet has 0.2 % of nan values
Gross Square Feet has 0.2 % of nan values
Year Built has 0.0 % of nan values
Tax_Class_At_Time_Of_Sale has 0.0 % of nan values
Building_Class_At_Time_Of_Sale has 0.0 % of nan values
Sale_Price has 0.0 % of nan values
sale date has 0.0 % of nan values
latitude has 0.31 % of nan values
longitude has 0.31 % of nan values
21 has less than 50% of nan values
(3522, 21)
```

In [184…

```
### Categorical Columns
cat_cols = brookdf.select_dtypes('object').columns
k = 0
cardinality_cols = []

for col in cat_cols:
    value_counts = brookdf[col].value_counts(normalize=True).round(2)
    if len(value_counts) > 5 or len(value_counts) < 2:
        cardinality_cols.append(col)
    else:
        print("====================================================================")
        print(col)
        print(value_counts)

cardinality_cols.remove('Neighborhood')
cardinality_cols.remove('Building_Class_At_Time_Of_Sale')
```

```
print(f"Removed Columns: {cardinality_cols}")
brookdf.drop(columns=cardinality_cols, axis=1, inplace=True)
```

```
Removed Columns: ['Building_Class_Category', 'Tax Class At Present', 'Building Class At Present', 'address', 'Land_Squa
re_Feet', 'Gross Square Feet', 'sale date']
```

In [185…

```
#Checking and normalizing the Neighborhoods
brookdf['Neighborhood'].value_counts(normalize=True).round(2)
```

Out[185]:

```
EAST NEW YORK              0.08
BUSHWICK                   0.08
BEDFORD STUYVESANT         0.06
CROWN HEIGHTS              0.05
FLATBUSH-EAST              0.04
CANARSIE                   0.04
BAY RIDGE                  0.03
CYPRESS HILLS              0.03
MARINE PARK                0.03
GREENPOINT                 0.03
SHEEPSHEAD BAY             0.03
WILLIAMSBURG-EAST          0.03
GRAVESEND                  0.03
BROWNSVILLE                0.03
FLATBUSH-CENTRAL           0.02
GERRITSEN BEACH            0.02
OCEAN HILL                 0.02
FLATBUSH-NORTH             0.02
OCEAN PARKWAY-SOUTH        0.02
MADISON                    0.02
OCEAN PARKWAY-NORTH        0.02
WYCKOFF HEIGHTS            0.02
PARK SLOPE                 0.02
MIDWOOD                    0.02
FLATBUSH-LEFFERTS GARDEN   0.01
BOROUGH PARK               0.01
BENSONHURST                0.01
MILL BASIN                 0.01
BERGEN BEACH               0.01
BRIGHTON BEACH             0.01
SUNSET PARK                0.01
FORT GREENE                0.01
MANHATTAN BEACH            0.01
FLATLANDS                  0.01
OLD MILL BASIN             0.01
CLINTON HILL               0.01
CARROLL GARDENS            0.01
PROSPECT HEIGHTS           0.01
SEAGATE                    0.01
BATH BEACH                 0.01
KENSINGTON                 0.01
DYKER HEIGHTS              0.01
PARK SLOPE SOUTH           0.01
WINDSOR TERRACE            0.01
WILLIAMSBURG-NORTH         0.01
```

```
BOERUM HILL                 0.01
RED HOOK                    0.01
GOWANUS                     0.00
COBBLE HILL                 0.00
BROOKLYN HEIGHTS            0.00
WILLIAMSBURG-CENTRAL        0.00
CONEY ISLAND                0.00
WILLIAMSBURG-SOUTH          0.00
NAVY YARD                   0.00
DOWNTOWN-FULTON MALL        0.00
BUSH TERMINAL               0.00
COBBLE HILL-WEST            0.00
DOWNTOWN-METROTECH          0.00
DOWNTOWN-FULTON FERRY       0.00
SPRING CREEK                0.00
Name: Neighborhood, dtype: float64
```

In [186…

```
#Normalizing the neghborhood data
neighborhood = brookdf['Neighborhood'].value_counts(normalize=True).round(2)
idx = np.where(neighborhood > 0.01)[0].max()
places = neighborhood.index[:idx]
brookdf['Neighborhood'] =brookdf['Neighborhood'].apply(lambda x: x if x in places else 'OTHER')
brookdf['Neighborhood'].value_counts(normalize=True)
```

Out[186]:
```
OTHER                    0.238217
EAST NEW YORK            0.081204
BUSHWICK                 0.077513
BEDFORD STUYVESANT       0.057638
CROWN HEIGHTS            0.046281
FLATBUSH-EAST            0.042022
CANARSIE                 0.035775
BAY RIDGE                0.034923
CYPRESS HILLS            0.034639
MARINE PARK              0.032368
SHEEPSHEAD BAY           0.030380
GREENPOINT               0.030380
WILLIAMSBURG-EAST        0.027257
GRAVESEND                0.025554
BROWNSVILLE              0.025270
GERRITSEN BEACH          0.022714
FLATBUSH-CENTRAL         0.022714
OCEAN HILL               0.022430
FLATBUSH-NORTH           0.021863
OCEAN PARKWAY-SOUTH      0.020159
MADISON                  0.019591
OCEAN PARKWAY-NORTH      0.017604
WYCKOFF HEIGHTS          0.017036
PARK SLOPE               0.016468
Name: Neighborhood, dtype: float64
```

In [187…
```
#Normalizing Building class
building_class = brookdf['Building_Class_At_Time_Of_Sale'].value_counts(normalize=True).round(2)
idx = np.where(building_class > 0.01)[0].max()
places = building_class.index[:idx]
brookdf['Building_Class_At_Time_Of_Sale'] =brookdf['Building_Class_At_Time_Of_Sale'].apply(lambda x: x if x in places e
brookdf['Building_Class_At_Time_Of_Sale'].value_counts(normalize=True)
```

Out[187]:
```
OTHER    0.187394
B1       0.133731
C0       0.131175
A5       0.089722
B2       0.074673
A1       0.069563
B3       0.063884
B9       0.059057
A9       0.051107
S2       0.044293
C3       0.033504
C2       0.032936
C1       0.028961
Name: Building_Class_At_Time_Of_Sale, dtype: float64
```

In [188…
```
brookdf.shape
```

Out[188]:
```
(3522, 14)
```

In [189…
```
#Removed Column
num_cols = brookdf.select_dtypes('number').columns

low_var_cols = []
for col in num_cols:
    scaled = (brookdf[col] - brookdf[col].mean()) / brookdf[col].std()
    variance = scaled.var()
    if variance == 0 or brookdf[col].std() == 0:
        low_var_cols.append(col)
#     else:
#         print(col, variance)

brookdf.drop(columns=low_var_cols, axis=1, inplace=True)
print(f"Removed Columns: {low_var_cols}")
print(brookdf.shape, len(low_var_cols))
```

```
Removed Columns: ['Borough']
(3522, 13) 1
```

In [190…
```
#Gathering age when the building was built
brookdf['age'] = 2023 - (brookdf['Year Built'] + brookdf['Year Built']) // 2
brookdf.drop(['Zip Code', 'Year Built'], axis=1, inplace=True)
```

In [191…
```
#corrleation between saleprice and other columns
corr = brookdf.drop('Sale_Price', axis=1).corr()
```

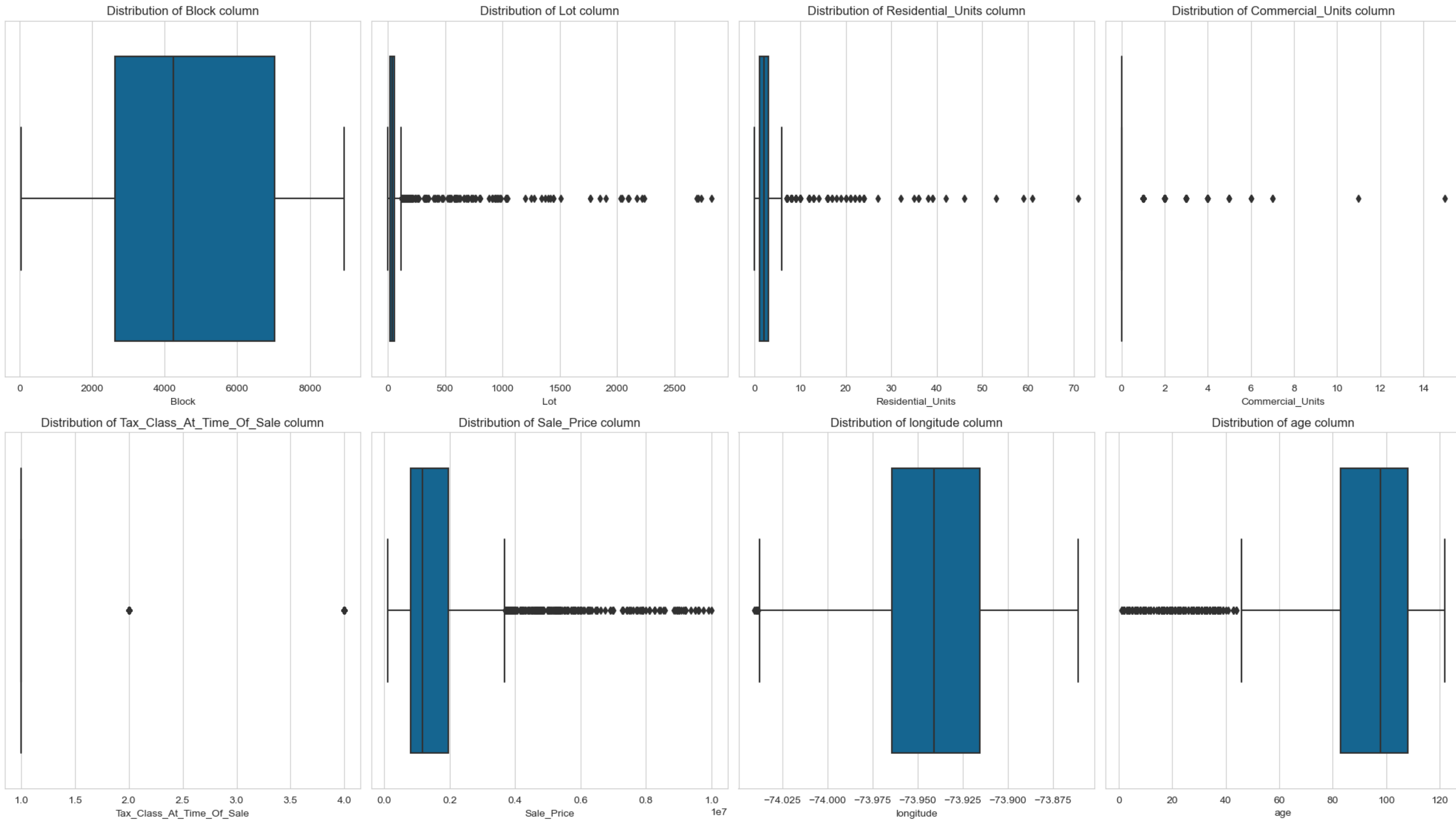
```
upper = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
drop = [column for column in upper.columns if any(np.abs(upper[column]) > 0.7)]
print(f"columns dropped are: {drop}")
brookdf.drop(columns=drop, axis=1, inplace=True)
```

```
columns dropped are: ['Total Units', 'latitude']
```

```
C:\Users\seema\AppData\Local\Temp\ipykernel_2756\21742755.py:3: DeprecationWarning: `np.bool` is a deprecated alias for
the builtin `bool`. To silence this warning, use `bool` by itself. Doing this will not modify any behavior and is safe.
If you specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecatio
ns
  upper = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
```

In [192…

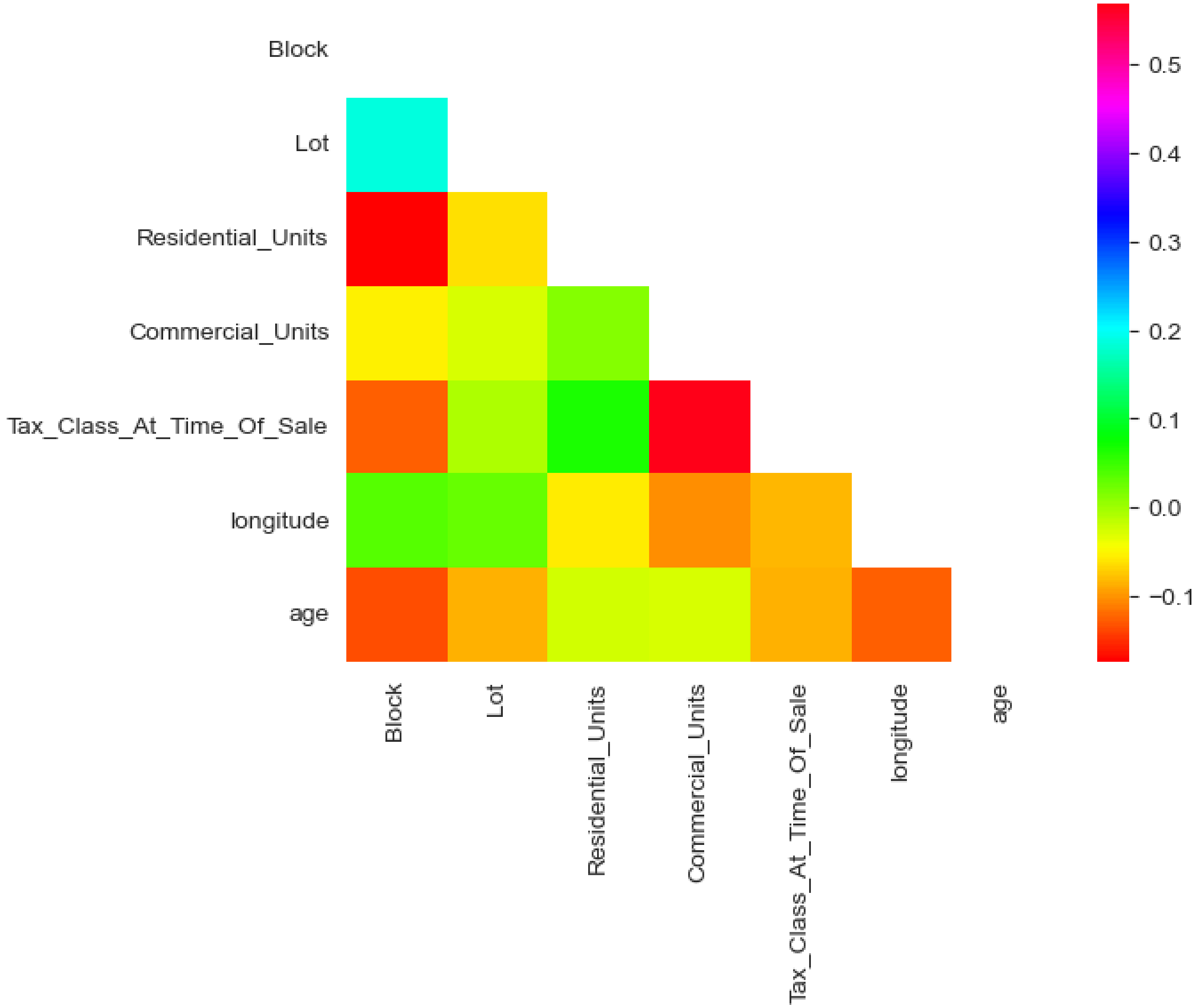
```
num_cols = brookdf.select_dtypes('number').columns
k = 0
plt.figure(figsize=(20, 100))
for col in num_cols:
    plt.subplot(18, 4, k + 1)
    sns.boxplot(data=brookdf, x=col)
    plt.xlabel(col)
    plt.title(f"Distribution of {col} column")
    k += 1
plt.tight_layout()
```



In [193…

```
corr = brookdf.drop('Sale_Price', axis=1).corr()
mask = np.triu(np.ones_like(corr))
sns.heatmap(corr, mask=mask, cmap='hsv')
```

Out[193]: <AxesSubplot:>



In [194…
```
brookdf.shape
```
Out[194]:
```
(3522, 10)
```

In [195…
```
brookdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3522 entries, 9 to 25607
Data columns (total 10 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Neighborhood                  3522 non-null   object 
 1   Block                         3522 non-null   int64  
 2   Lot                           3522 non-null   int64  
 3   Residential_Units             3515 non-null   float64
 4   Commercial_Units              3521 non-null   float64
 5   Tax_Class_At_Time_Of_Sale     3522 non-null   int64  
 6   Building_Class_At_Time_Of_Sale  3522 non-null   object 
 7   Sale_Price                    3522 non-null   float64
 8   longitude                     3511 non-null   float64
 9   age                           3522 non-null   float64
dtypes: float64(5), int64(3), object(2)
memory usage: 302.7+ KB
```

In [196…

```
drop_cols = ['Block', 'Lot']
brookdf.drop(columns=drop_cols, axis=1, inplace=True)
```

In [197…

```
brookdf.shape
```

Out[197]:

```
(3522, 8)
```

In [198…

```
brookdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3522 entries, 9 to 25607
Data columns (total 8 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Neighborhood                  3522 non-null   object 
 1   Residential_Units             3515 non-null   float64
 2   Commercial_Units              3521 non-null   float64
 3   Tax_Class_At_Time_Of_Sale     3522 non-null   int64  
 4   Building_Class_At_Time_Of_Sale  3522 non-null   object 
 5   Sale_Price                    3522 non-null   float64
 6   longitude                     3511 non-null   float64
 7   age                           3522 non-null   float64
dtypes: float64(5), int64(1), object(2)
memory usage: 247.6+ KB
```

In [199…

```
brookdf.dropna().info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3506 entries, 9 to 25607
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Neighborhood                 3506 non-null   object 
 1   Residential_Units            3506 non-null   float64
 2   Commercial_Units             3506 non-null   float64
 3   Tax_Class_At_Time_Of_Sale    3506 non-null   int64  
 4   Building_Class_At_Time_Of_Sale  3506 non-null   object 
 5   Sale_Price                   3506 non-null   float64
 6   longitude                    3506 non-null   float64
 7   age                          3506 non-null   float64
dtypes: float64(5), int64(1), object(2)
memory usage: 246.5+ KB
```

In [200…

```
brookdf.dropna(inplace=True)
```

In [201…

```
brookdf.shape
```

Out[201]:

```
(3506, 8)
```

In [202…

```
def treat_categorical(brookdf):
    cat_cols = brookdf.select_dtypes('object').columns
    k = 0
    cardinality_cols = []
    for col in cat_cols:
        value_counts = brookdf[col].value_counts(normalize=True).round(2)
        if len(value_counts) > 5 or len(value_counts) < 2:
            cardinality_cols.append(col)
    return cardinality_cols

def get_low_variance_cols(brookdf):
    num_cols = brookdf.drop('Sale_Price', axis=1).select_dtypes('number').columns
    low_var_cols = []
    for col in num_cols:
        scaled = (brookdf[col] - brookdf[col].mean()) / brookdf[col].std()
        variance = scaled.var().round(2)
        if variance == 0 or brookdf[col].std() == 0:
            low_var_cols.append(col)
    return low_var_cols

def treat_na(brookdf):
    req_cols = []
```

```
    for col in brookdf.columns:
        is_na = round(brookdf[col].isna().sum() / len(brookdf) * 100, 2)
        if is_na < 50:
            req_cols.append(col)
    return req_cols
def wrangle(filepath):
    # Import data
    brookdf = pd.read_csv(filepath, index_col=[0])
    print(f"Imported Data, Shape: {brookdf.shape}")

    # Filter out the relevant data by sale_price and year_built
    mask = (brookdf['Year Built'] > 1900) & (brookdf['Sale_Price'] > 100000) & (brookdf['Sale_Price'] < 1e7)
    brookdf = brookdf[mask]
    print(f"Created mask, Shape: {brookdf.shape}")

    # Remove features which have majority missing values
    req_cols = treat_na(brookdf)
    brookdf = brookdf[req_cols]
    print(f"Filtered Columns by NaN, Shape: {brookdf.shape}")

    # Remove high and low cardinality categorical columns
    drop_cols = treat_categorical(brookdf)
    if 'Neighborhood' in drop_cols:
        drop_cols.remove('Neighborhood')
    if 'Building_Class_At_Time_Of_Sale' in drop_cols:
        drop_cols.remove('Building_Class_At_Time_Of_Sale')
    brookdf.drop(columns=drop_cols, axis=1, inplace=True)
    print(f"Dropped Columns by Cardinality, Shape: {brookdf.shape}")

    # Reduce the cardinality of neighborhood column
    neighborhood = brookdf['Neighborhood'].value_counts(normalize=True).round(2)
    idx = np.where(neighborhood > 0.01)[0].max()
    places = neighborhood.index[:idx]
    brookdf['Neighborhood'] =brookdf['Neighborhood'].apply(lambda x: x if x in places else 'OTHER')

    # Reduce the cardinality of building_class_at_sale column
    building_class = brookdf['Building_Class_At_Time_Of_Sale'].value_counts(normalize=True).round(2)
    idx = np.where(building_class > 0.01)[0].max()
    places = building_class.index[:idx]
    brookdf['Building_Class_At_Time_Of_Sale'] =brookdf['Building_Class_At_Time_Of_Sale'].apply(lambda x: x if x in plac


    # Calculate age of the house
    brookdf['age'] = 2023 - (brookdf['Year Built'] + brookdf['Year Built']) // 2
```

```
    # Drop unwanted columns
    drop = ['Zip Code', 'Year Built']
    brookdf.drop(columns=drop, axis=1, inplace=True)
    print(f"Dropped Columns by redundancy, Shape: {brookdf.shape}")

    # Drop columns with multicollinearity
    corr = brookdf.drop('Sale_Price', axis=1).corr()
    upper = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
    drop = [column for column in upper.columns if any(np.abs(upper[column]) > 0.7)]
    brookdf.drop(columns=drop, axis=1, inplace=True)
    print(f"Dropped Columns by collinearity, Shape: {brookdf.shape}")

    # Drop unwanted columns
    drop_cols = ['Block', 'Lot']
    brookdf.drop(columns=drop_cols, axis=1, inplace=True)
    print(f"Dropped Columns manually, Shape: {brookdf.shape}")

    # Drop missing values
    brookdf.dropna(inplace=True)
    print(f"Dropped NaN values, Shape: {brookdf.shape}")

    return brookdf
```

In [203…

```
brookdf.shape
```

Out[203]:

```
(3506, 8)
```

In [204…

```
brookdf.info
```

Out[204]:
```
<bound method DataFrame.info of           Neighborhood  Residential_Units  Commercial_Units  \
9                OTHER               1.0               1.0
12               OTHER               1.0               1.0
21               OTHER               1.0               0.0
26               OTHER               1.0               0.0
61               OTHER               2.0               0.0
...                ...               ...               ...
25600  WYCKOFF HEIGHTS               0.0               1.0
25601  WYCKOFF HEIGHTS               0.0               1.0
25604  WYCKOFF HEIGHTS               0.0               1.0
25605  WYCKOFF HEIGHTS               0.0               1.0
25607  WYCKOFF HEIGHTS               0.0               0.0

       Tax_Class_At_Time_Of_Sale Building_Class_At_Time_Of_Sale  Sale_Price  \
9                              1                          OTHER    800000.0
12                             1                          OTHER    955000.0
21                             1                             A5    843000.0
26                             1                             A5    880000.0
61                             1                             B2   1388000.0
...                          ...                            ...         ...
25600                          4                          OTHER   6500000.0
25601                          4                          OTHER   6500000.0
25604                          4                          OTHER   1250000.0
25605                          4                          OTHER    925000.0
25607                          4                          OTHER    495000.0

       longitude    age
9     -74.008802   93.0
12    -74.003951  103.0
21    -74.012745   73.0
26    -74.013811   78.0
61    -74.001930   93.0
...          ...    ...
25600 -73.922701   63.0
25601 -73.922211   92.0
25604 -73.917162   92.0
25605 -73.914681   92.0
25607 -73.919767   92.0

[3506 rows x 8 columns]>
```

In [205…
```python
Brooklyn = wrangle('BrooklynDataFinal.csv')
print(Brooklyn.shape)
Brooklyn.head()
```

```
Imported Data, Shape: (7815, 23)
Created mask, Shape: (3522, 23)
Filtered Columns by NaN, Shape: (3522, 21)
Dropped Columns by Cardinality, Shape: (3522, 14)
Dropped Columns by redundancy, Shape: (3522, 13)
Dropped Columns by collinearity, Shape: (3522, 11)
Dropped Columns manually, Shape: (3522, 9)
Dropped NaN values, Shape: (3506, 9)
(3506, 9)
```

```
C:\Users\seema\AppData\Local\Temp\ipykernel_2756\2540135087.py:75: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use `bool` by itself. Doing this will not modify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  upper = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
```

Out[205]:

	Borough	Neighborhood	Residential_Units	Commercial_Units	Tax_Class_At_Time_Of_Sale	Building_Class_At_Time_Of_Sale	Sale_Price	long
9	3	OTHER	1.0	1.0	1	OTHER	800000.0	-74.0(
12	3	OTHER	1.0	1.0	1	OTHER	955000.0	-74.0(
21	3	OTHER	1.0	0.0	1	A5	843000.0	-74.0'
26	3	OTHER	1.0	0.0	1	A5	880000.0	-74.0'
61	3	OTHER	2.0	0.0	1	B2	1388000.0	-74.0(

In [206…

```
Brooklyn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3506 entries, 9 to 25607
Data columns (total 9 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Borough                      3506 non-null   int64  
 1   Neighborhood                 3506 non-null   object 
 2   Residential_Units            3506 non-null   float64
 3   Commercial_Units             3506 non-null   float64
 4   Tax_Class_At_Time_Of_Sale    3506 non-null   int64  
 5   Building_Class_At_Time_Of_Sale  3506 non-null   object 
 6   Sale_Price                   3506 non-null   float64
 7   longitude                    3506 non-null   float64
 8   age                          3506 non-null   float64
dtypes: float64(5), int64(2), object(2)
memory usage: 273.9+ KB
```

In [207…

```
viz_df = Brooklyn.copy()
```

In [208…

```
brookdf['Sale_Price'] = brookdf['Sale_Price'].astype(np.float64)
print(brookdf.dtypes)
```

```
Neighborhood                       object
Residential_Units                 float64
Commercial_Units                  float64
Tax_Class_At_Time_Of_Sale           int64
Building_Class_At_Time_Of_Sale     object
Sale_Price                        float64
longitude                         float64
age                               float64
dtype: object
```

In [209…

```
median_home_price = viz_df['Sale_Price'].median()
median_home_price
```

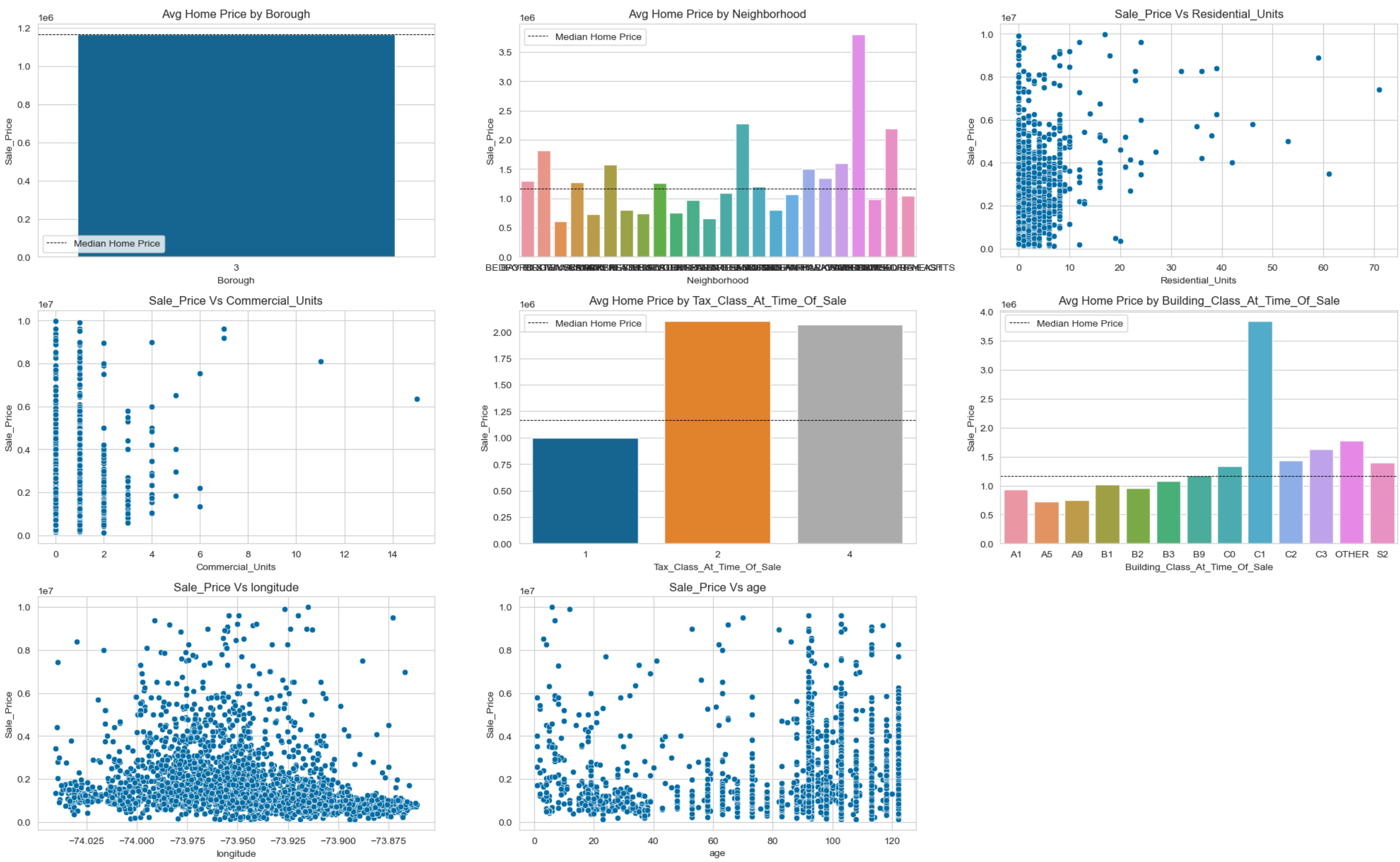
Out[209]:

```
1165000.0
```

In [210…

```
#plotting the original data
k = 0
plt.figure(figsize=(20, 20))
for col in viz_df.drop('Sale_Price', axis=1).columns:
    plt.subplot(5, 3, k + 1)
    if viz_df[col].dtype == 'float64':
        sns.scatterplot(data=viz_df, x=col, y='Sale_Price')
```

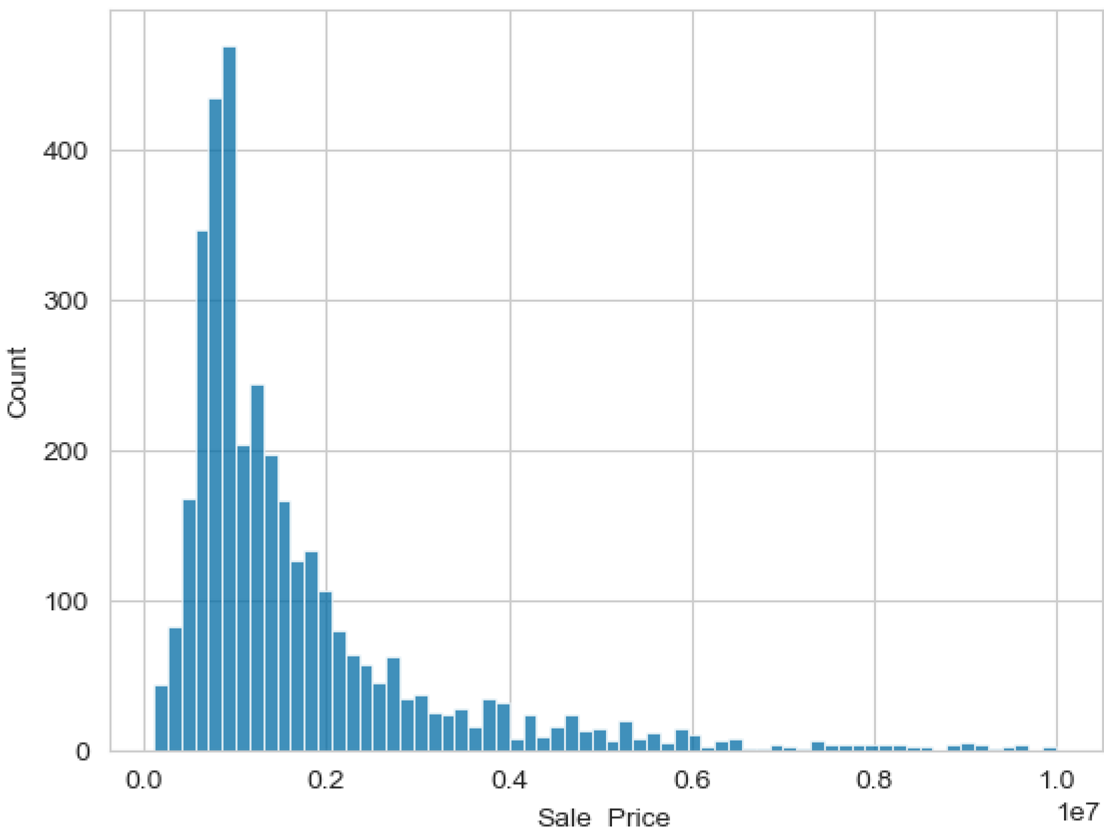
```
        plt.title(f"Sale_Price Vs {col}")
    else:
        group = viz_df[[col, 'Sale_Price']].groupby(by=col).median()
        sns.barplot(data=group, x=group.index, y='Sale_Price')
        plt.axhline(y=median_home_price, label='Median Home Price', color='black', linestyle='--', linewidth=0.7)
        plt.title(f"Avg Home Price by {col}")
        plt.legend()
    k += 1
plt.tight_layout()
```



In [211…

```
sns.histplot(viz_df['Sale_Price'])
```

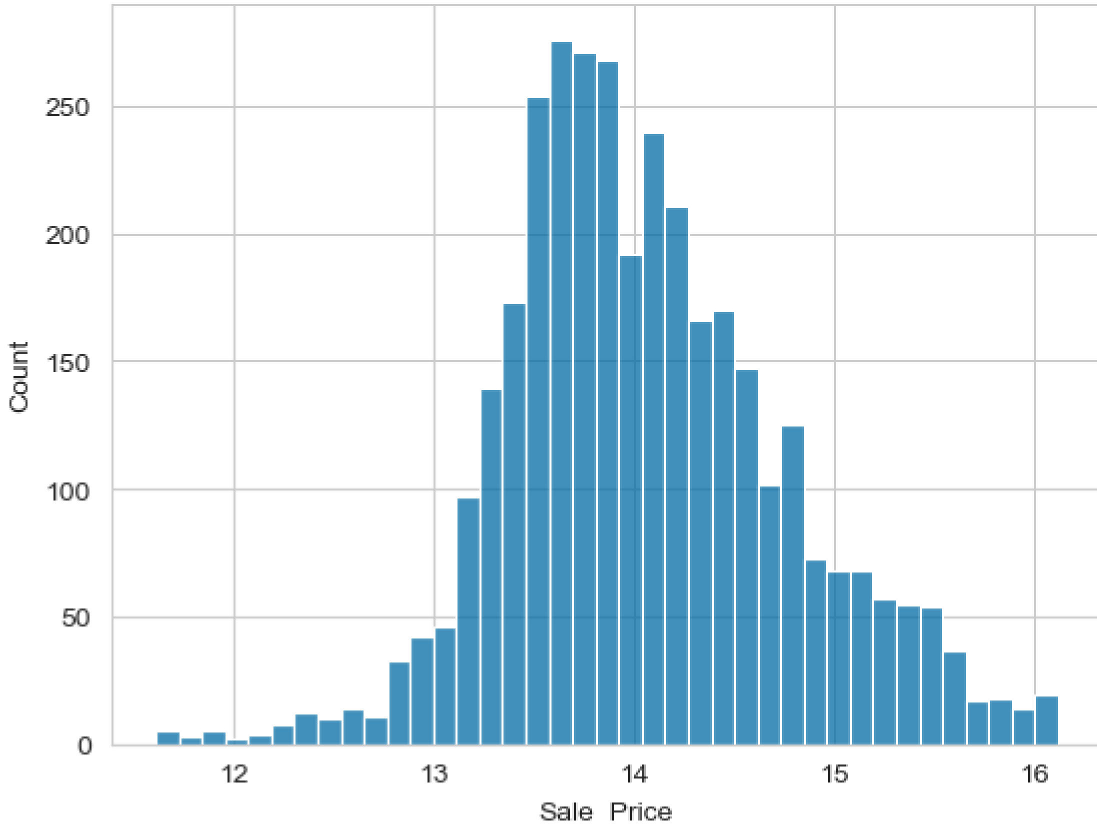
Out[211]: <AxesSubplot:xlabel='Sale_Price', ylabel='Count'>



In [212…

```
#Normalizing the Target Column for Improved Model Performance using log transformation effectively converts the target
sns.histplot(np.log(viz_df['Sale_Price']))
```

Out[212]: <AxesSubplot:xlabel='Sale_Price', ylabel='Count'>



In [213…
```
#Creating the trianing and test set
X_train, X_test, y_train, y_test = train_test_split(Brooklyn.drop('Sale_Price', axis=1), Brooklyn['Sale_Price'],
                                                    test_size=0.2, random_state=42)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[213]:
```
((2804, 8), (702, 8), (2804,), (702,))
```

In [214…
```
X_train.columns
```

Out[214]:
```
Index(['Borough', 'Neighborhood', 'Residential_Units', 'Commercial_Units',
       'Tax_Class_At_Time_Of_Sale', 'Building_Class_At_Time_Of_Sale',
       'longitude', 'age'],
      dtype='object')
```

In [215…
```
#caluclating the RMSE
y_mean = Brooklyn['Sale_Price'].mean()
```

```
print("Baseline R2 Score:", r2_score(y_test, [y_mean] * len(y_test)))
print("Baseline Root Mean Squared Error:", mean_squared_error(y_test, [y_mean] * len(y_test), squared=False))
```

```
Baseline R2 Score: -0.00065086991283624944
Baseline Root Mean Squared Error: 1354178.5558621555
```

In [108…

```
#RandomForestRegressor¶
```

In [216…

```
def train_model(model):
    model.fit(X_train, np.log(y_train))
    print(f"Train R-Squared: {r2_score(y_train, np.exp(model.predict(X_train))).round(2)}")
    print(f"Test R-Squared: {r2_score(y_test, np.exp(model.predict(X_test))).round(2)}")
    print(f"Train Root Mean Squared Error: {mean_squared_error(y_train, np.exp(model.predict(X_train)), squared=False).
    print(f"Test Root Mean Squared Error: {mean_squared_error(y_test, np.exp(model.predict(X_test)), squared=False).rou
    return model
```

In [217…

```
rf = make_pipeline(
    TargetEncoder(),
    RobustScaler(),
    RandomForestRegressor(random_state=42, n_jobs=-1)
)
rf = train_model(rf)
```

```
Train R-Squared: 0.88
Test R-Squared: 0.46
Train Root Mean Squared Error: 507246.84
Test Root Mean Squared Error: 998322.9
```

In [218…

```
#parameter tuning

params = {
    'randomforestregressor__n_estimators': np.arange(25, 126, 25),
    'randomforestregressor__min_samples_split': np.arange(2, 26, 5)
}
rf_grid = RandomizedSearchCV(
    estimator = rf,
    param_distributions=params,
    scoring='neg_mean_squared_error',
    verbose=1,
    random_state=42,
    n_jobs=-1
)
rf_grid = train_model(rf_grid)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Train R-Squared: 0.69
Test R-Squared: 0.45
Train Root Mean Squared Error: 816336.73
Test Root Mean Squared Error: 999615.78
```

In [219…
```
rf_grid.best_estimator_
```

Out[219]:
```
Pipeline(steps=[('targetencoder',
                 TargetEncoder(cols=['Neighborhood',
                                     'Building_Class_At_Time_Of_Sale'])),
                ('robustscaler', RobustScaler()),
                ('randomforestregressor',
                 RandomForestRegressor(min_samples_split=12, n_jobs=-1,
                                       random_state=42))])
```

In [ ]:
```
#XGBooster Model
```

In [220…
```
xgb = make_pipeline(
    TargetEncoder(),
    RobustScaler(),
    XGBRegressor(random_state=42, n_jobs=-1),
)
xgb = train_model(xgb)
```

```
Train R-Squared: 0.86
Test R-Squared: 0.38
Train Root Mean Squared Error: 541187.39
Test Root Mean Squared Error: 1069777.83
```

In [114…
```
#CatBoost Regressor
```

In [221…
```
cat = CatBoostRegressor(
    cat_features=list(X_train.select_dtypes('object').columns),
    verbose=0
)
cat = train_model(cat)
```

```
Train R-Squared: 0.64
Test R-Squared: 0.43
Train Root Mean Squared Error: 886780.14
Test Root Mean Squared Error: 1020447.63
```

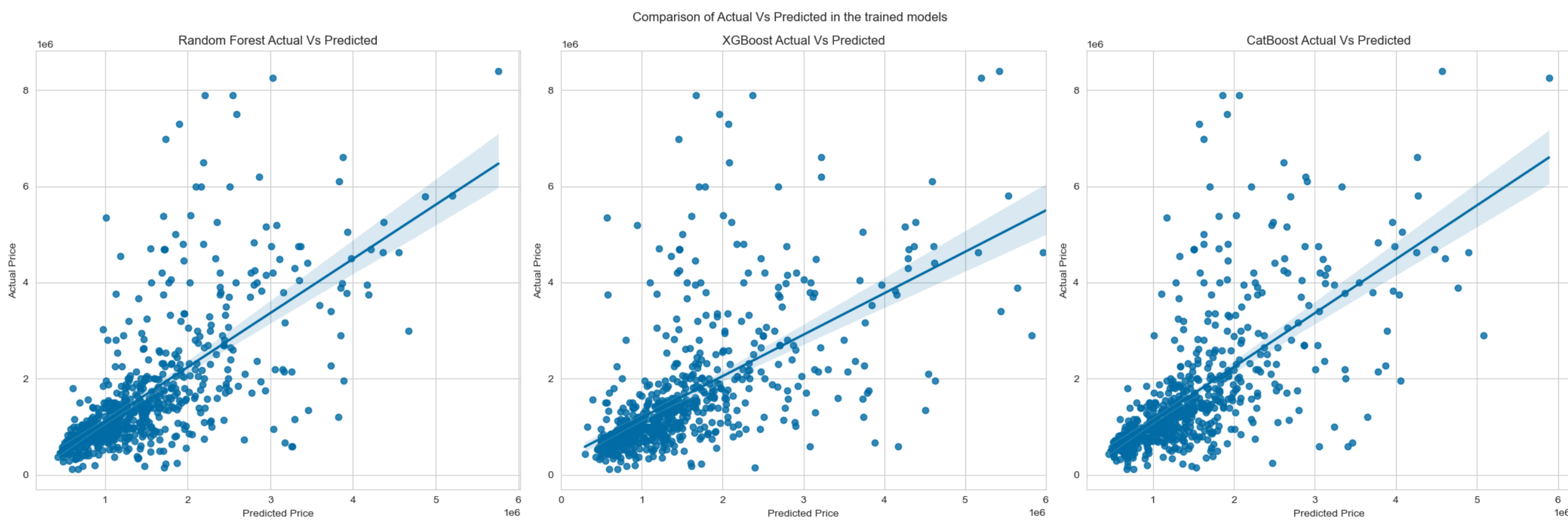
In [222…
```
#Plots between different models and predictions and analysis
```

```
plt.figure(figsize=(21, 7))
plt.subplot(1, 3, 1)
preds = np.exp(rf_grid.predict(X_test))
sns.regplot(x=preds, y=y_test)
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Random Forest Actual Vs Predicted');

plt.subplot(1, 3, 2)
preds = np.exp(xgb.predict(X_test))
sns.regplot(x=preds, y=y_test)
plt.xlim(0, 6e6)
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('XGBoost Actual Vs Predicted');

plt.subplot(1, 3, 3)
preds = np.exp(cat.predict(X_test))
sns.regplot(x=preds, y=y_test)
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('CatBoost Actual Vs Predicted');

plt.suptitle('Comparison of Actual Vs Predicted in the trained models')
plt.tight_layout()
```



In [239…

```
#XGGBoost and CatBoost models have generated results with a very close RMSE. RandomForest has closer train and test RMS
```

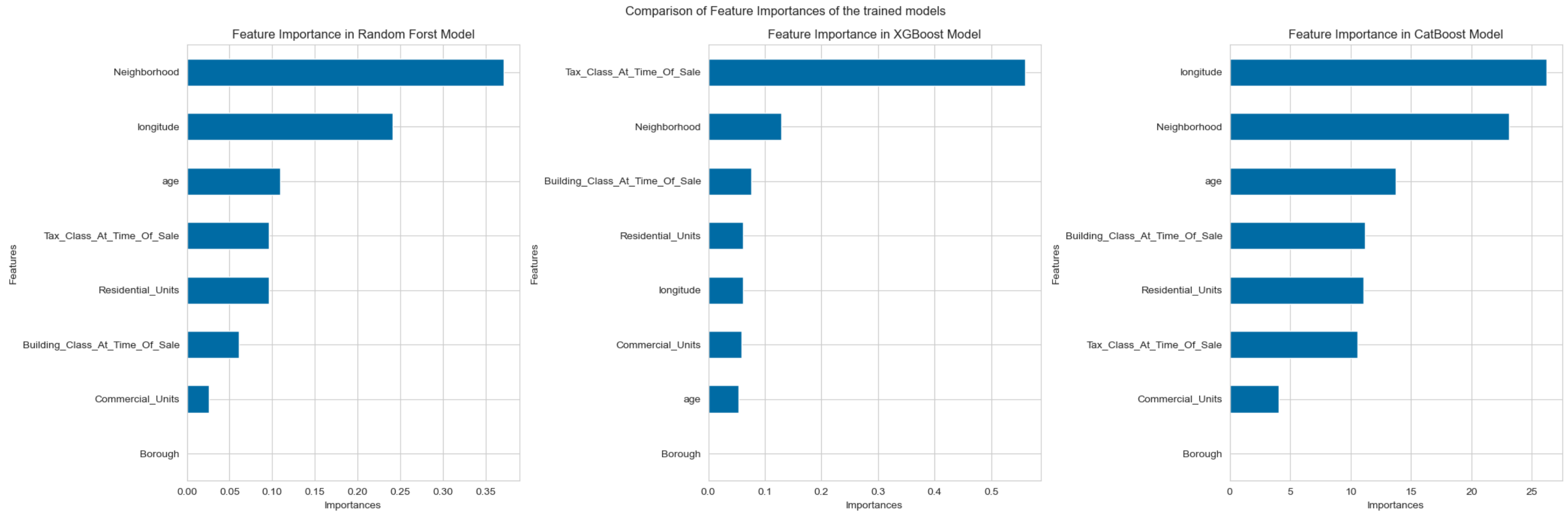
In [223…

```
#plots to compare of features of the trained model
plt.figure(figsize=(21, 7))
feat_imp = rf_grid.best_estimator_.named_steps['randomforestregressor'].feature_importances_
rf_feat_imp = pd.Series(feat_imp, index=X_train.columns).sort_values()
plt.subplot(1, 3, 1)
rf_feat_imp.plot(kind='barh')
plt.xlabel('Importances')
plt.ylabel('Features')
plt.title('Feature Importance in Random Forst Model');

feat_imp = xgb.named_steps['xgbregressor'].feature_importances_
xgb_feat_imp = pd.Series(feat_imp, index=X_train.columns).sort_values()
plt.subplot(1, 3, 2)
xgb_feat_imp.plot(kind='barh')
plt.xlabel('Importances')
plt.ylabel('Features')
plt.title('Feature Importance in XGBoost Model');

feat_imp = cat.get_feature_importance()
cat_feat_imp = pd.Series(feat_imp, index=X_train.columns).sort_values()
plt.subplot(1, 3, 3)
cat_feat_imp.plot(kind='barh')
plt.xlabel('Importances')
plt.ylabel('Features')
plt.title('Feature Importance in CatBoost Model')

plt.suptitle('Comparison of Feature Importances of the trained models')
plt.tight_layout();
```



In [224…
```
joblib.dump(rf_grid, 'randomforest.pkl', compress=9)
```
Out[224]:
```
['randomforest.pkl']
```

In [225…
```
joblib.dump(xgb, 'xgboost.pkl', compress=9)
```
Out[225]:
```
['xgboost.pkl']
```

In [226…
```
joblib.dump(cat, 'catboost.pkl', compress=9)
```
Out[226]:
```
['catboost.pkl']
```

In [231…
```
def predict_house_price(Borough, Neighborhood, Residential_Units, Commercial_Units,
       Tax_Class_At_Time_Of_Sale, Building_Class_At_Time_Of_Sale,
       latitude, age):

    params_dict = {
        'Borough': Borough,
        'Neighborhood': Neighborhood,
        'Residential_Units': Residential_Units,
        'Commercial_Units': Commercial_Units,
        'Tax_Class_At_Time_Of_Sale': Tax_Class_At_Time_Of_Sale,
        'Building_Class_At_Time_Of_Sale': Building_Class_At_Time_Of_Sale,
        'latitude': latitude,
        'age': age
```

```
    }

    brookdf = pd.DataFrame(params_dict, index=[0])

    with open('randomforest.pkl', 'rb') as f:
        rf_grid = joblib.load(f)

    rf_grid_pred = rf_grid.predict(brookdf)

    avg = (np.exp(rf_grid_pred)).round(2)[0]

    return f"The Predicted House Price is ${avg}"
```

In [232…

```
predict_house_price(
    Borough = 3,
    Neighborhood = "BATH BEACH",
    Residential_Units = 1,
    Commercial_Units = 1,
    Tax_Class_At_Time_Of_Sale = 1,
    Building_Class_At_Time_Of_Sale = 'S1',
    latitude = 40.6029517,
    age = 103
)
```

```
C:\Users\seema\anaconda3\lib\site-packages\sklearn\base.py:493: FutureWarning: The feature names should match those tha
t were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- latitude
Feature names seen at fit time, yet now missing:
- longitude

  warnings.warn(message, FutureWarning)
```

Out[232]:

```
'The Predicted House Price is $1053100.22'
```

In [237…

```
def predict_house_price(Borough, Neighborhood, Residential_Units, Commercial_Units,
       Tax_Class_At_Time_Of_Sale, Building_Class_At_Time_Of_Sale,
       latitude, age):

    params_dict = {
        'Borough': Borough,
        'Neighborhood': Neighborhood,
        'Residential_Units': Residential_Units,
        'Commercial_Units': Commercial_Units,
        'Tax_Class_At_Time_Of_Sale': Tax_Class_At_Time_Of_Sale,
```

```
        'Building_Class_At_Time_Of_Sale': Building_Class_At_Time_Of_Sale,
        'latitude': latitude,
        'age': age
    }

    df = pd.DataFrame(params_dict, index=[0])

    with open('xgboost.pkl', 'rb') as f:
        xgb = joblib.load(f)

    xgb_pred = xgb.predict(brookdf)

    avg = (np.exp(xgb_pred)).round(2)[0]

    return f"The Predicted House Price is ${avg}"
```

In [238…

```
predict_house_price(
    Borough = 3,
    Neighborhood = "BATH BEACH",
    Residential_Units = 1,
    Commercial_Units = 1,
    Tax_Class_At_Time_Of_Sale = 1,
    Building_Class_At_Time_Of_Sale = 'S1',
    latitude = 40.6029517,
    age = 103
)
```

```
C:\Users\seema\anaconda3\lib\site-packages\sklearn\base.py:493: FutureWarning: The feature names should match those tha
t were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- Sale_Price
Feature names seen at fit time, yet now missing:
- Borough

  warnings.warn(message, FutureWarning)
```

Out[238]:

```
'The Predicted House Price is $2104829.0'
```

In [ ]: