IMPORTING REQUIRED LIBRARIES

In [1]:
```
import pandas as ps
import numpy as ns
import seaborn as sn
import matplotlib.pyplot as pl
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [2]:
```
df=ps.read_csv(r"C:\Users\Samdure\OneDrive\Desktop\American_Housing_Data.csv")
```

DATA CLEANING

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39981 entries, 0 to 39980
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Zip Code                 39981 non-null  int64  
 1   Price                    39981 non-null  float64
 2   Beds                     39981 non-null  int64  
 3   Baths                    39981 non-null  int64  
 4   Living Space             39981 non-null  int64  
 5   Address                  39981 non-null  object 
 6   City                     39981 non-null  object 
 7   State                    39981 non-null  object 
 8   Zip Code Population      39981 non-null  int64  
 9   Zip Code Density         39981 non-null  float64
 10  County                   39981 non-null  object 
 11  Median Household Income  39979 non-null  float64
 12  Latitude                 39981 non-null  float64
 13  Longitude                39981 non-null  float64
dtypes: float64(5), int64(5), object(4)
memory usage: 4.3+ MB
```

In [4]:
```
df.head(10)
```

Out[4]:

	Zip Code	Price	Beds	Baths	Living Space	Address	City	State	Zip Code Population	Zip Code Density	County	Median Household Income	Latitude	Longitude
0	10013	3999000.0	2	3	1967	74 GRAND ST APT 3	New York	New York	29563	20967.9	New York	370046.0	40.72001	-74.00472
1	10013	3999000.0	2	3	1967	74 GRAND ST APT 3	New York	New York	29563	20967.9	New York	370046.0	40.72001	-74.00472
2	10014	1650000.0	1	1	718	140 CHARLES ST APT 4D	New York	New York	29815	23740.9	New York	249880.0	40.73407	-74.00601
3	10014	760000.0	3	2	1538	38 JONES ST	New York	New York	29815	23740.9	New York	249880.0	40.73407	-74.00601
4	10014	1100000.0	1	1	600	81 BEDFORD ST APT 3F	New York	New York	29815	23740.9	New York	249880.0	40.73407	-74.00601
5	10017	764900.0	1	1	643	145 E 48TH ST APT 11E	New York	New York	15514	20107.7	New York	188289.0	40.75235	-73.97260
6	10021	2499000.0	2	2	1471	234 E 70TH ST APT 4	New York	New York	42484	46004.0	New York	261254.0	40.76963	-73.95899
7	10022	4580000.0	2	3	1800	641 5TH AVE # 29D	New York	New York	33303	28998.9	New York	281977.0	40.75856	-73.96787
8	10026	540000.0	2	1	750	45 CENTRAL PARK N # 4D	New York	New York	39401	39689.7	New York	117438.0	40.80302	-73.95348
9	10026	570000.0	1	1	589	300 W 110TH ST APT 19H	New York	New York	39401	39689.7	New York	117438.0	40.80302	-73.95348

In [5]:
```
df.tail(5)
```

Out[5]:

	Zip Code	Price	Beds	Baths	Living Space	Address	City	State	Zip Code Population	Zip Code Density	County	Median Household Income	Latitude	Longitude
39976	98199	2495000.0	4	4	3380	2626 27TH AVE W	Seattle	Washington	22890	2086.8	King	205611.0	47.65139	-122.40223
39977	98199	2295000.0	4	4	2878	3215 32ND AVE W	Seattle	Washington	22890	2086.8	King	205611.0	47.65139	-122.40223
39978	98199	950000.0	3	2	1380	3257 22ND AVE W	Seattle	Washington	22890	2086.8	King	205611.0	47.65139	-122.40223
39979	98199	425000.0	2	1	856	3711 26TH PL W APT 102	Seattle	Washington	22890	2086.8	King	205611.0	47.65139	-122.40223
39980	98199	1150000.0	3	3	2840	2911 25TH AVE W	Seattle	Washington	22890	2086.8	King	205611.0	47.65139	-122.40223

In [6]:
```
df.isnull()
```

Out[6]:

	Zip Code	Price	Beds	Baths	Living Space	Address	City	State	Zip Code Population	Zip Code Density	County	Median Household Income	Latitude	Longitude
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
39976	False	False	False	False	False	False	False	False	False	False	False	False	False	False
39977	False	False	False	False	False	False	False	False	False	False	False	False	False	False
39978	False	False	False	False	False	False	False	False	False	False	False	False	False	False
39979	False	False	False	False	False	False	False	False	False	False	False	False	False	False
39980	False	False	False	False	False	False	False	False	False	False	False	False	False	False

39981 rows × 14 columns

In [7]:
```
df.describe()
```

Out[7]:

	Zip Code	Price	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
count	39981.000000	3.998100e+04	39981.000000	39981.000000	39981.000000	39981.000000	39981.000000	39979.000000	39981.000000	39981.000000
mean	64833.391336	6.227771e+05	3.171682	2.466572	1901.522723	37726.201996	2379.412483	110837.259861	36.435668	-98.080576
std	25614.601116	9.469793e+05	1.308796	1.323042	1211.307257	18672.647445	2946.574792	47309.055715	4.446862	15.061145
min	10013.000000	1.800000e+03	1.000000	1.000000	2.000000	0.000000	0.000000	27475.000000	25.729830	-122.826870
25%	40215.000000	2.650000e+05	3.000000	2.000000	1200.000000	24465.000000	902.400000	76640.000000	33.239850	-111.636310
50%	74136.000000	3.999000e+05	3.000000	2.000000	1639.000000	35049.000000	1588.700000	100405.000000	36.166620	-96.839680
75%	85730.000000	6.749900e+05	4.000000	3.000000	2265.000000	46816.000000	2736.800000	135075.000000	39.283090	-85.656980
max	98199.000000	3.800000e+07	54.000000	66.000000	74340.000000	116469.000000	58289.600000	900203.000000	47.742370	-73.704510

In [8]:
```
df.shape
```

Out[8]:
```
(39981, 14)
```

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
Zip Code                   0
Price                      0
Beds                       0
Baths                      0
Living Space               0
Address                    0
City                       0
State                      0
Zip Code Population        0
Zip Code Density           0
County                     0
Median Household Income    2
Latitude                   0
Longitude                  0
dtype: int64
```

In [10]:
```
df.columns
```

Out[10]:
```
Index(['Zip Code', 'Price', 'Beds', 'Baths', 'Living Space', 'Address', 'City',
       'State', 'Zip Code Population', 'Zip Code Density', 'County',
       'Median Household Income', 'Latitude', 'Longitude'],
      dtype='object')
```

In [11]:
```
df.sample(4)
```

Out[11]:

	Zip Code	Price	Beds	Baths	Living Space	Address	City	State	Zip Code Population	Zip Code Density	County	Median Household Income	Latitude	Longitude
87	10306	798000.0	3	2	1750	305 HUSSON ST	Staten Island	New York	55805	2980.6	Richmond	118424.0	40.57149	-74.12430
10927	43207	164900.0	3	1	924	2943 PARSONS AVE	Columbus	Ohio	46038	768.8	Franklin	67173.0	39.89599	-82.96392
33837	92107	595000.0	2	2	986	4444 W POINT LOMA BLVD UNIT 37	San Diego	California	29753	3798.5	San Diego	133969.0	32.74020	-117.24357
807	19125	699995.0	3	3	2406	3000 CITYVIEW WALK # 169	Philadelphia	Pennsylvania	24948	7123.8	Philadelphia	115644.0	39.97611	-75.12472

In [12]:
```
df.columns
```

Out[12]:
```
Index(['Zip Code', 'Price', 'Beds', 'Baths', 'Living Space', 'Address', 'City',
       'State', 'Zip Code Population', 'Zip Code Density', 'County',
       'Median Household Income', 'Latitude', 'Longitude'],
      dtype='object')
```

In [13]:
```
df.drop(columns={'Address', 'City',
       'State','County','Zip Code'},inplace=True)
```

In [14]:
```
df
```

Out[14]:

	Price	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
0	3999000.0	2	3	1967	29563	20967.9	370046.0	40.72001	-74.00472
1	3999000.0	2	3	1967	29563	20967.9	370046.0	40.72001	-74.00472
2	1650000.0	1	1	718	29815	23740.9	249880.0	40.73407	-74.00601
3	760000.0	3	2	1538	29815	23740.9	249880.0	40.73407	-74.00601
4	1100000.0	1	1	600	29815	23740.9	249880.0	40.73407	-74.00601
...	...	...	...	...	...	...	...	...	...
39976	2495000.0	4	4	3380	22890	2086.8	205611.0	47.65139	-122.40223
39977	2295000.0	4	4	2878	22890	2086.8	205611.0	47.65139	-122.40223
39978	950000.0	3	2	1380	22890	2086.8	205611.0	47.65139	-122.40223
39979	425000.0	2	1	856	22890	2086.8	205611.0	47.65139	-122.40223
39980	1150000.0	3	3	2840	22890	2086.8	205611.0	47.65139	-122.40223

39981 rows × 9 columns

In [15]:
```
df.isnull().mean()*100
```

Out[15]:
```
Price                      0.000000
Beds                       0.000000
Baths                      0.000000
Living Space               0.000000
Zip Code Population        0.000000
Zip Code Density           0.000000
Median Household Income    0.005002
Latitude                   0.000000
Longitude                  0.000000
dtype: float64
```

In [16]:
```
df.dropna(inplace=True)
```

In [17]:
```
df.head(4)
```

Out[17]:

	Price	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
0	3999000.0	2	3	1967	29563	20967.9	370046.0	40.72001	-74.00472
1	3999000.0	2	3	1967	29563	20967.9	370046.0	40.72001	-74.00472
2	1650000.0	1	1	718	29815	23740.9	249880.0	40.73407	-74.00601
3	760000.0	3	2	1538	29815	23740.9	249880.0	40.73407	-74.00601

In [18]:
```
df.duplicated().sum()
```

Out[18]: 1447

In [19]:
```
df.drop_duplicates(inplace=True)
```

In [20]:
```
df.shape
```

Out[20]: (38532, 9)

In [21]:
```
df.head(5)
```

Out[21]:

	Price	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
0	3999000.0	2	3	1967	29563	20967.9	370046.0	40.72001	-74.00472
2	1650000.0	1	1	718	29815	23740.9	249880.0	40.73407	-74.00601
3	760000.0	3	2	1538	29815	23740.9	249880.0	40.73407	-74.00601
4	1100000.0	1	1	600	29815	23740.9	249880.0	40.73407	-74.00601
5	764900.0	1	1	643	15514	20107.7	188289.0	40.75235	-73.97260

In [22]:
```
df['Baths'].unique()
```

Out[22]:
```
array([ 3,  1,  2, 10,  4,  5,  9,  6, 11,  8,  7, 12, 24, 21, 20, 14, 15,
       28, 66, 18, 16, 17, 36, 19, 37, 42, 46, 56], dtype=int64)
```

SCALING

In [23]:
```
from sklearn.preprocessing import StandardScaler
```

In [24]:
```
#Price
Price_scaler=StandardScaler()
df['Price']=Price_scaler.fit_transform(ns.array(df['Price']).reshape(len(df['Price']),1))

#Beds
Beds_scaler=StandardScaler()
df['Beds']=Beds_scaler.fit_transform(ns.array(df['Beds']).reshape(len(df['Beds']),1))

#Baths
Baths_scaler=StandardScaler()
df['Baths']=Baths_scaler.fit_transform(ns.array(df['Baths']).reshape(len(df['Baths']),1))

#Living Space
Living_Space_scaler=StandardScaler()
df['Living Space']=Living_Space_scaler.fit_transform(ns.array(df['Living Space']).reshape(len(df['Living Space']),1))

#Zip Code Population
Zip_Code_Population_scaler=StandardScaler()
df['Zip Code Population']=Zip_Code_Population_scaler.fit_transform(ns.array(df['Zip Code Population']).reshape(len(df['Zip Code P

#Zip Code Density
Zip_Code_Density_scaler=StandardScaler()
df['Zip Code Density']=Zip_Code_Density_scaler.fit_transform(ns.array(df['Zip Code Density']).reshape(len(df['Zip Code Density'])

#Median Household Income
Median_Household_Income_scaler=StandardScaler()
df['Median Household Income']=Median_Household_Income_scaler.fit_transform(ns.array(df['Median Household Income']).reshape(len(df

#Latitude
Latitude_scaler=StandardScaler()
df['Latitude']=Latitude_scaler.fit_transform(ns.array(df['Latitude']).reshape(len(df['Latitude']),1))


#Longitude
Longitude_scaler=StandardScaler()
df['Longitude']=Longitude_scaler.fit_transform(ns.array(df['Longitude']).reshape(len(df['Longitude']),1))
```

In [25]:
```
df.head(5)
```

Out[25]:

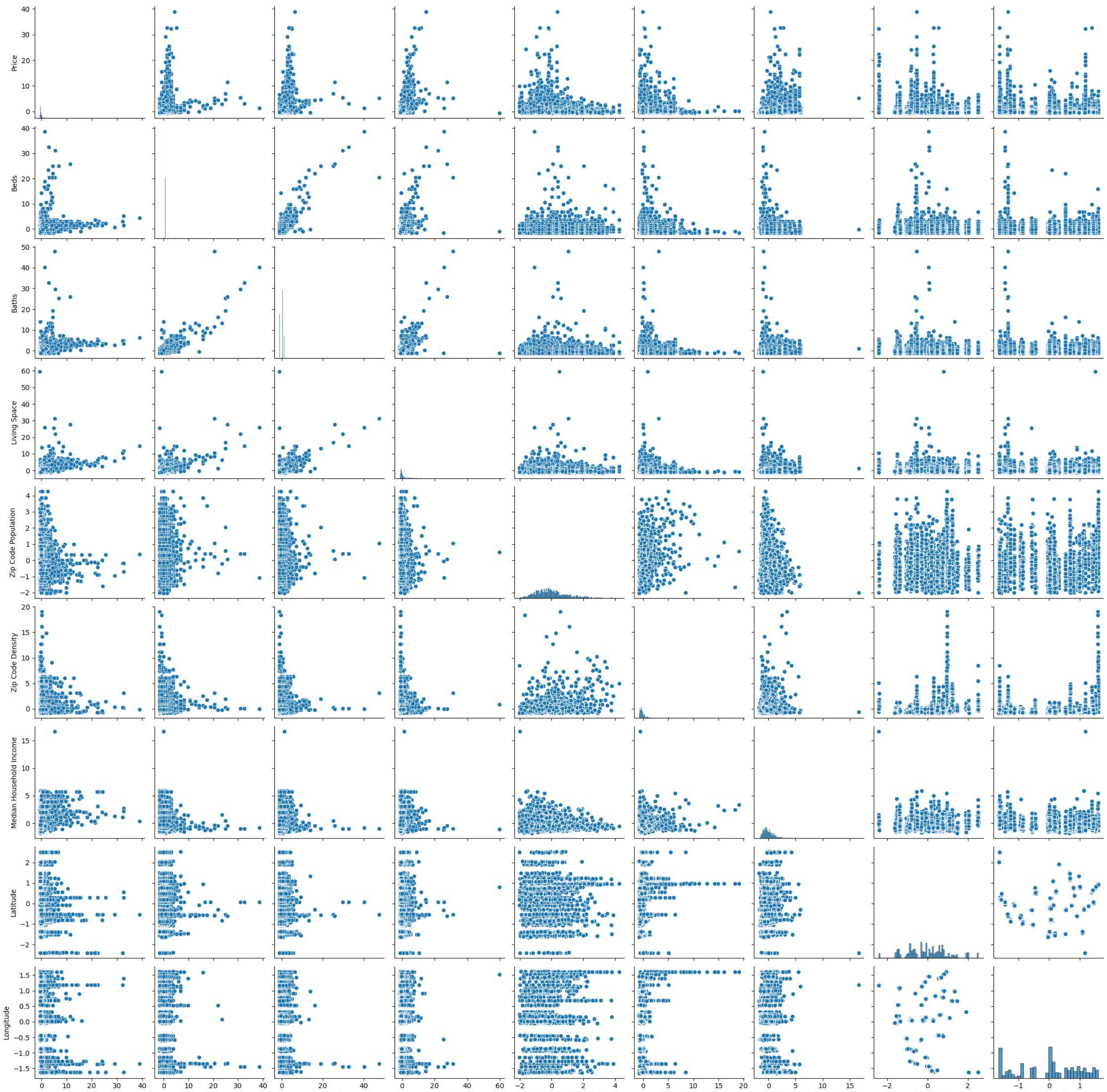
	Price	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
0	3.520793	-0.890824	0.403009	0.052402	-0.434679	6.338620	5.464918	0.955387	1.596649
2	1.069626	-1.652084	-1.099531	-0.974282	-0.421084	7.284213	2.929879	0.958548	1.596564
3	0.140917	-0.129564	-0.348261	-0.300238	-0.421084	7.284213	2.929879	0.958548	1.596564
4	0.495705	-1.652084	-1.099531	-1.071279	-0.421084	7.284213	2.929879	0.958548	1.596564
5	0.146030	-1.652084	-1.099531	-1.035933	-1.192575	6.045292	1.630546	0.962657	1.598782

In [26]:
```
import warnings
warnings.filterwarnings('ignore')
```

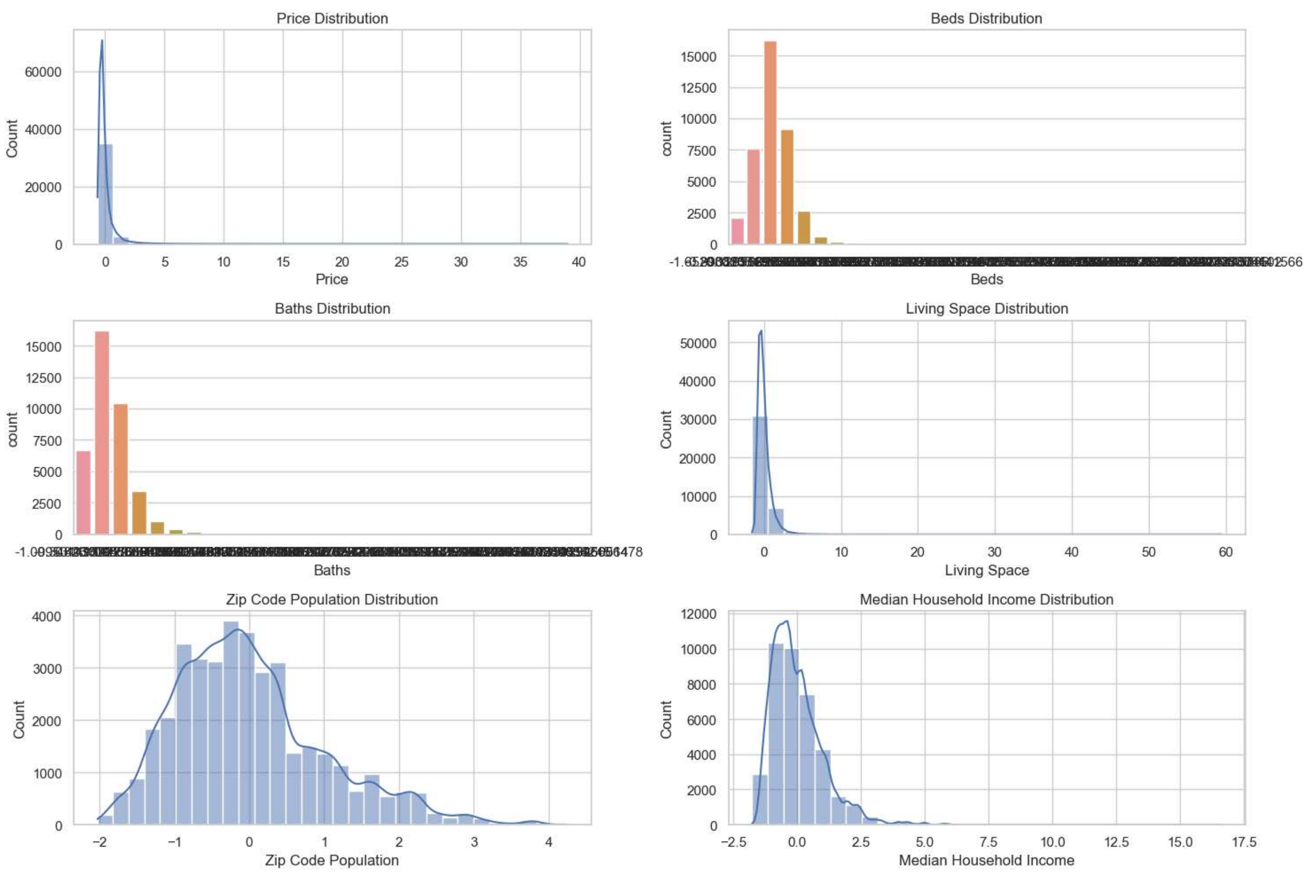
DATA VISUALIZATION

In [27]:
```
sn.pairplot(df)
```

Out[27]: <seaborn.axisgrid.PairGrid at 0x264b4d4b110>

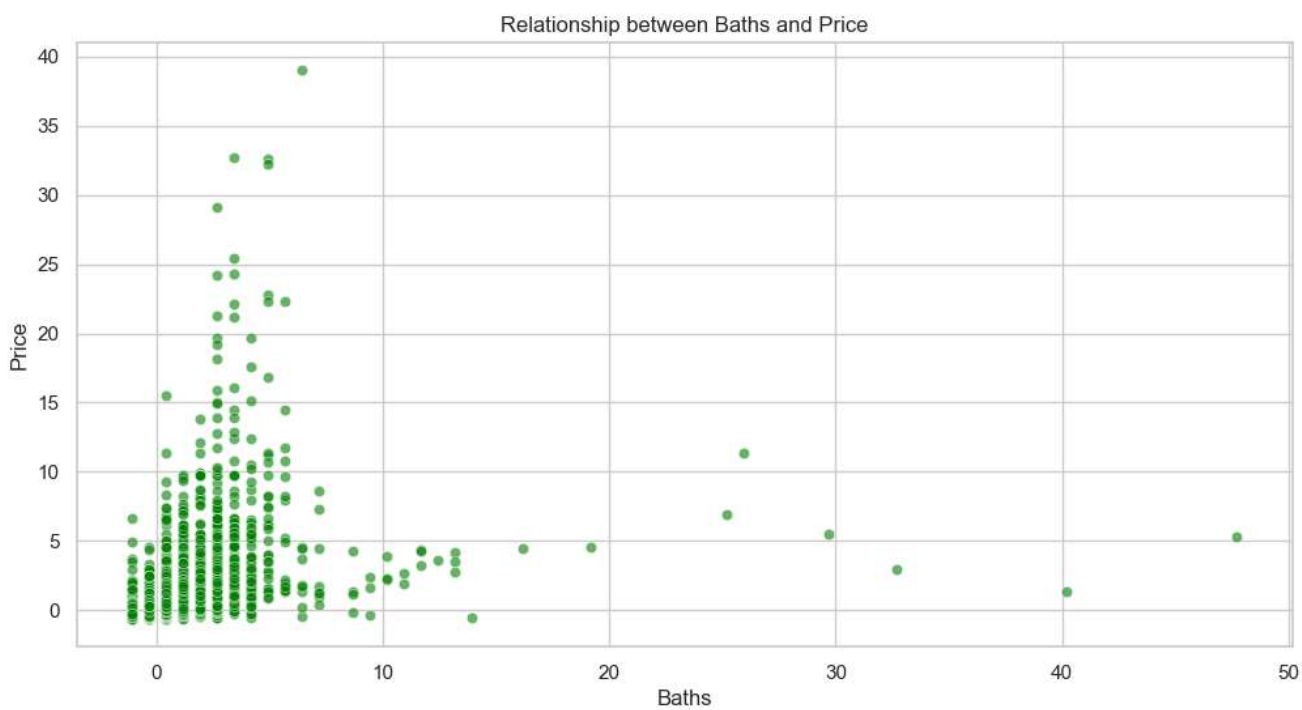


In [28]:
```python
sn.set(style='whitegrid')

fig, axs = pl.subplots(3, 2, figsize=(15, 10))

# Price distribution
sn.histplot(df['Price'], bins=30, ax=axs[0, 0], kde=True)
axs[0, 0].set_title('Price Distribution')

# Beds distribution
sn.countplot(x='Beds', data=df, ax=axs[0, 1])
axs[0, 1].set_title('Beds Distribution')

# Baths distribution
sn.countplot(x='Baths', data=df, ax=axs[1, 0])
axs[1, 0].set_title('Baths Distribution')

# Living Space distribution
sn.histplot(df['Living Space'], bins=30, ax=axs[1, 1], kde=True)
axs[1, 1].set_title('Living Space Distribution')

# Zip Code Population distribution
sn.histplot(df['Zip Code Population'], bins=30, ax=axs[2, 0], kde=True)
axs[2, 0].set_title('Zip Code Population Distribution')

# Median Household Income distribution
sn.histplot(df['Median Household Income'], bins=30, ax=axs[2, 1], kde=True)
axs[2, 1].set_title('Median Household Income Distribution')

pl.tight_layout()
pl.show()
```

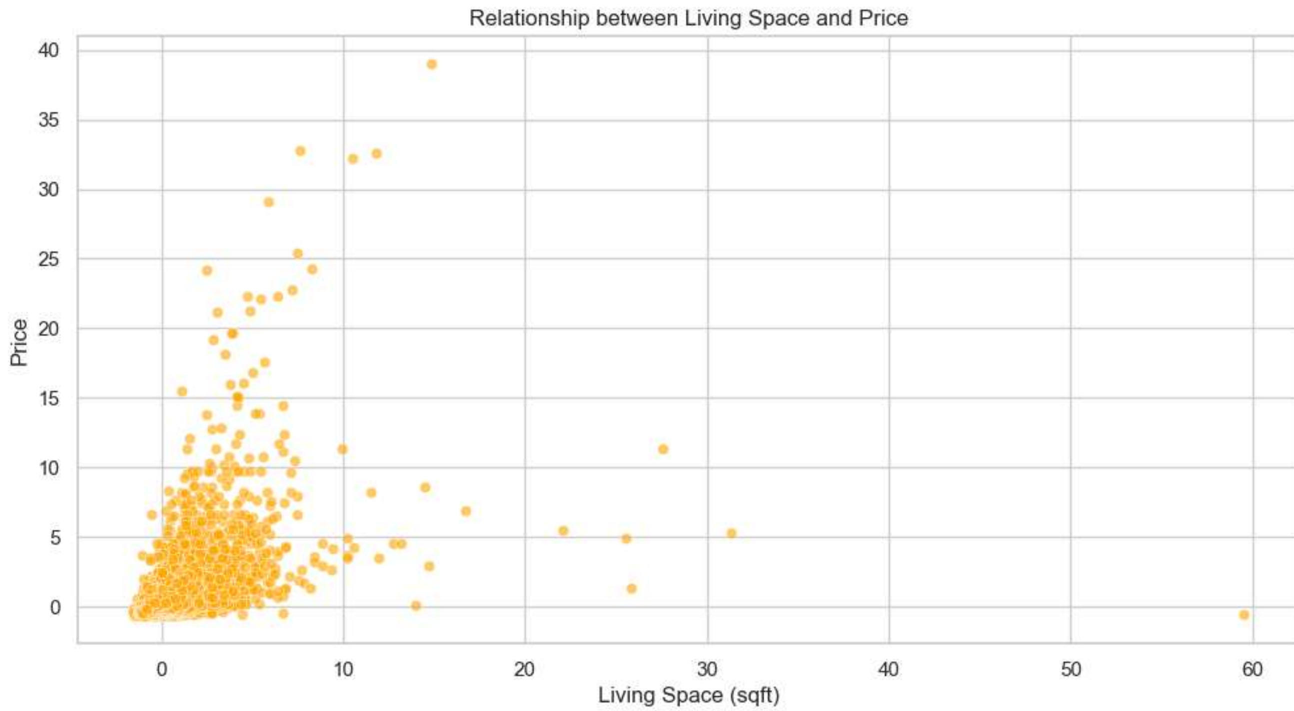


In [29]:
```
pl.figure(figsize=(12, 6))
sn.scatterplot(x='Beds', y='Price', data=df, color='blue', alpha=0.6)
pl.title('Relationship between Beds and Price')
pl.xlabel('Beds')
pl.ylabel('Price')
pl.show()
```

In [30]:
```
pl.figure(figsize=(12, 6))
sn.scatterplot(x='Baths', y='Price', data=df, color='green', alpha=0.6)
pl.title('Relationship between Baths and Price')
pl.xlabel('Baths')
pl.ylabel('Price')
pl.show()
```



In [31]:
```
pl.figure(figsize=(12, 6))
sn.scatterplot(x='Living Space', y='Price', data=df, color='orange', alpha=0.6)
pl.title('Relationship between Living Space and Price')
pl.xlabel('Living Space (sqft)')
pl.ylabel('Price')
pl.show()
```



In [32]:
```
df
```

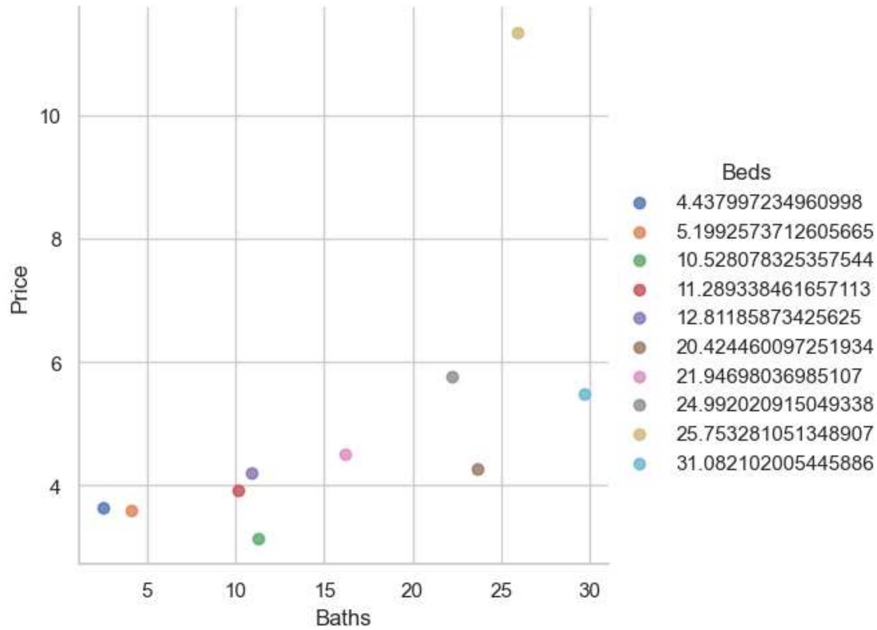
Out[32]:

	Price	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
0	3.520793	-0.890824	0.403009	0.052402	-0.434679	6.338620	5.464918	0.955387	1.596649
2	1.069626	-1.652084	-1.099531	-0.974282	-0.421084	7.284213	2.929879	0.958548	1.596564
3	0.140917	-0.129564	-0.348261	-0.300238	-0.421084	7.284213	2.929879	0.958548	1.596564
4	0.495705	-1.652084	-1.099531	-1.071279	-0.421084	7.284213	2.929879	0.958548	1.596564
5	0.146030	-1.652084	-1.099531	-1.035933	-1.192575	6.045292	1.630546	0.962657	1.598782
...	...	...	...	...	...	...	...	...	...
39976	1.951378	0.631697	1.154280	1.213896	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39977	1.742680	0.631697	1.154280	0.801249	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39978	0.339181	-0.129564	-0.348261	-0.430115	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39979	-0.208653	-0.890824	-1.099531	-0.860846	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39980	0.547880	-0.129564	0.403009	0.770013	-0.794665	-0.099833	1.995973	2.513491	-1.617405

38532 rows × 9 columns

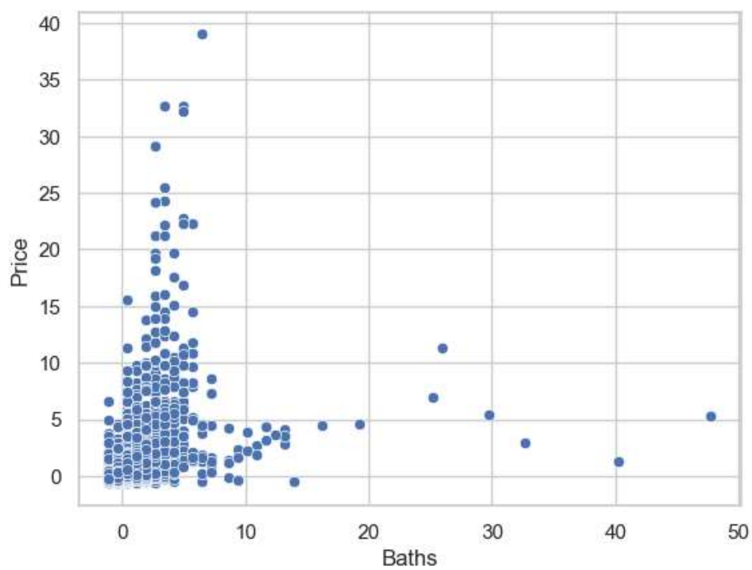
In [33]:
```
Median Household Income, have a high correlation with price
'Beds')[['Baths','Price']].mean().sort_values('Price', ascending=False).reset_index().head(10), x='Baths', y='Price', hue='Beds')
```

Out[33]: <seaborn.axisgrid.FacetGrid at 0x264ccb2d210>



In [34]:
```
sn.scatterplot(x='Baths',y='Price',data=df)
```

Out[34]: <Axes: xlabel='Baths', ylabel='Price'>



LINEAR REGRESSION MODEL

In [35]:
```
X = df.drop('Price',axis=1)
Y= df['Price']
```

In [36]:
```
X
```

Out[36]:

	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
0	-0.890824	0.403009	0.052402	-0.434679	6.338620	5.464918	0.955387	1.596649
2	-1.652084	-1.099531	-0.974282	-0.421084	7.284213	2.929879	0.958548	1.596564
3	-0.129564	-0.348261	-0.300238	-0.421084	7.284213	2.929879	0.958548	1.596564
4	-1.652084	-1.099531	-1.071279	-0.421084	7.284213	2.929879	0.958548	1.596564
5	-1.652084	-1.099531	-1.035933	-1.192575	6.045292	1.630546	0.962657	1.598782
...	...	...	...	...	...	...	...	...
39976	0.631697	1.154280	1.213896	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39977	0.631697	1.154280	0.801249	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39978	-0.129564	-0.348261	-0.430115	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39979	-0.890824	-1.099531	-0.860846	-0.794665	-0.099833	1.995973	2.513491	-1.617405
39980	-0.129564	0.403009	0.770013	-0.794665	-0.099833	1.995973	2.513491	-1.617405

38532 rows × 8 columns

In [37]:
```
Y
```

Out[37]:
```
0        3.520793
2        1.069626
3        0.140917
4        0.495705
5        0.146030
           ...   
39976    1.951378
39977    1.742680
39978    0.339181
39979   -0.208653
39980    0.547880
Name: Price, Length: 38532, dtype: float64
```

In [38]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [39]:
```
X_train, X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.2,random_state=42)
```

In [40]:
```
model = LinearRegression()
```

In [41]:
```
model.fit(X_train,Y_train)
```

Out[41]:
```
▾ LinearRegression
LinearRegression()
```

In [42]:
```
y_pred = model.predict(X_test)
y_pred
```

Out[42]:
```
array([-0.60675959,  1.76218257,  0.3105298 , ..., -0.34763035,
        0.1734936 , -0.42821048])
```

In [43]:
```
X_test
```

Out[43]:

	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
13412	-0.129564	-0.348261	-0.286264	-0.335687	0.085228	-1.193953	1.487314	0.668800
36437	0.631697	1.905550	2.290722	-0.295443	1.212198	1.327458	0.301761	-1.606663
10219	-0.129564	1.154280	0.590816	-0.748864	-0.552169	0.407560	0.402746	0.830379
37059	-0.129564	1.154280	0.032674	0.855454	0.155098	2.400007	0.185601	-1.583659
527	-0.890824	-0.348261	-0.167073	0.507013	5.745996	-0.063854	0.956839	1.606164
...	...	...	...	...	...	...	...	...
27479	-0.129564	0.403009	0.015412	0.073768	-0.398003	0.377709	0.558808	-0.446584
36363	0.631697	0.403009	0.265301	-0.208535	0.803646	0.764233	0.307116	-1.609700
25241	-0.129564	0.403009	-0.335584	-0.845212	-0.371303	-1.582460	-1.057238	-0.556380
29606	-0.129564	-0.348261	0.478201	-0.163112	-0.561206	-0.115772	-0.928613	-0.859181
31296	-0.890824	-0.348261	-0.708775	0.352887	-0.609935	-0.659103	-0.316463	-0.559348

7707 rows × 8 columns

In [44]:
```
Y_test
```

Out[44]:
```
13412   -0.422569
36437    0.901624
10219    0.015698
37059    0.495588
527      0.326659
           ...
27479   -0.134878
36363    0.390312
25241   -0.479961
29606    0.014654
31296   -0.433004
Name: Price, Length: 7707, dtype: float64
```

In [45]:
```
X_train
```

Out[45]:

	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
37751	0.631697	-0.348261	-0.394769	-0.368864	0.204884	-0.895359	0.460276	-1.553601
29600	-0.129564	-0.348261	-0.241876	-0.163112	-0.561206	-0.115772	-0.928613	-0.859181
25684	-0.129564	0.403009	0.613010	-0.486953	-0.537063	-0.116130	-1.032313	-0.568438
26492	0.631697	-0.348261	-0.249274	1.606121	0.390627	-0.683828	0.724966	-0.464011
2632	1.392957	-0.348261	0.285030	-0.921925	0.218013	-1.242770	0.632634	1.420763
...	...	...	...	...	...	...	...	...
6634	-0.129564	-0.348261	-0.176115	-0.105335	-0.238279	-0.906624	-1.379561	1.093294
11769	-0.129564	-1.099531	-0.196665	0.023328	-0.357629	-1.208383	0.746528	0.785786
39575	-0.890824	-0.348261	-0.599448	0.610482	0.220980	0.716091	2.488980	-1.608539
932	-0.890824	-1.099531	-0.750697	1.185175	1.465288	-1.213826	0.791183	1.523356
16356	-0.129564	-1.099531	-0.203242	0.351053	-0.347467	-0.692414	0.277075	0.040551

30825 rows × 8 columns

In [46]:
```
X_test
```

Out[46]:

	Beds	Baths	Living Space	Zip Code Population	Zip Code Density	Median Household Income	Latitude	Longitude
13412	-0.129564	-0.348261	-0.286264	-0.335687	0.085228	-1.193953	1.487314	0.668800
36437	0.631697	1.905550	2.290722	-0.295443	1.212198	1.327458	0.301761	-1.606663
10219	-0.129564	1.154280	0.590816	-0.748864	-0.552169	0.407560	0.402746	0.830379
37059	-0.129564	1.154280	0.032674	0.855454	0.155098	2.400007	0.185601	-1.583659
527	-0.890824	-0.348261	-0.167073	0.507013	5.745996	-0.063854	0.956839	1.606164
...	...	...	...	...	...	...	...	...
27479	-0.129564	0.403009	0.015412	0.073768	-0.398003	0.377709	0.558808	-0.446584
36363	0.631697	0.403009	0.265301	-0.208535	0.803646	0.764233	0.307116	-1.609700
25241	-0.129564	0.403009	-0.335584	-0.845212	-0.371303	-1.582460	-1.057238	-0.556380
29606	-0.129564	-0.348261	0.478201	-0.163112	-0.561206	-0.115772	-0.928613	-0.859181
31296	-0.890824	-0.348261	-0.708775	0.352887	-0.609935	-0.659103	-0.316463	-0.559348

7707 rows × 8 columns

In [47]:
```
mae=mean_absolute_error(Y_test,y_pred)
mse = mean_squared_error(Y_test, y_pred)
rmse= ns.sqrt(mse)
r2 =r2_score(Y_test,y_pred)
```

In [48]:
```
print('Mean Absolute Error',mae)
print('Mean Squared error',mse)
print('root Mean Squared error',rmse)
print('R2 score',r2)
```

```
Mean Absolute Error 0.32099721054789543
Mean Squared error 0.7689516707371317
root Mean Squared error 0.8768988942501477
R2 score 0.4134816287003974
```

In [49]:
```
model.coef_
```

Out[49]:
```
array([-0.07371379,  0.15864634,  0.3635581 , -0.01728186,  0.15404179,
        0.24577778, -0.06971322, -0.11222055])
```

In [50]:
```
model.intercept_
```

Out[50]:
```
-0.0037304625161884517
```