Exploratory Data Analysis (EDA) & Data Cleaning for House Pricing Dataset

Data Loading & Initial Analysis

In [1]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
# Load the dataset
```

In [3]:
```
file_path = "raw_house_data.csv"
df = pd.read_csv(file_path)
```

In [4]:
```
# Initial exploration
```

In [5]:
```
print("Initial Dataset Info:")
print(df.info())
```

```
Initial Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   MLS               5000 non-null   int64
 1   sold_price        5000 non-null   float64
 2   zipcode           5000 non-null   int64
 3   longitude         5000 non-null   float64
 4   latitude          5000 non-null   float64
 5   lot_acres         4990 non-null   float64
 6   taxes             5000 non-null   float64
 7   year_built        5000 non-null   int64
 8   bedrooms          5000 non-null   int64
 9   bathrooms         4994 non-null   float64
 10  sqrt_ft           4944 non-null   float64
 11  garage            4993 non-null   float64
 12  kitchen_features  4967 non-null   object
 13  fireplaces        5000 non-null   object
 14  floor_covering    4999 non-null   object
 15  HOA               4438 non-null   object
dtypes: float64(8), int64(4), object(4)
memory usage: 625.1+ KB
None
```

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

Out[6]:

	MLS	sold_price	zipcode	longitude	latitude	lot_acres	taxes	year_built
0	21530491	5300000.0	85637	-110.378200	31.356362	2154.00	5272.00	1941
1	21529082	4200000.0	85646	-111.045371	31.594213	1707.00	10422.36	1997
2	3054672	4200000.0	85646	-111.040707	31.594844	1707.00	10482.00	1997
3	21919321	4500000.0	85646	-111.035925	31.645878	636.67	8418.58	1930
4	21306357	3411450.0	85750	-110.813768	32.285162	3.21	15393.00	1995

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

Out[7]:

	MLS	sold_price	zipcode	longitude	latitude	lot_acres	taxes	year_bu
4995	21810382	495000.0	85641	-110.661829	31.907917	4.98	2017.00	20
4996	21908591	550000.0	85750	-110.858556	32.316373	1.42	4822.01	19
4997	21832452	475000.0	85192	-110.755428	32.964708	12.06	1000.00	19
4998	21900515	550000.0	85745	-111.055528	32.296871	1.01	5822.93	20
4999	4111490	450000.0	85621	-110.913054	31.385259	4.16	2814.48	19

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

Out[8]: (5000, 16)

In [9]:
```
df.count()
```

Out[9]:
```
MLS                 5000
sold_price          5000
zipcode             5000
longitude           5000
latitude            5000
lot_acres           4990
taxes               5000
year_built          5000
bedrooms            5000
bathrooms           4994
sqrt_ft             4944
garage              4993
kitchen_features    4967
fireplaces          5000
floor_covering      4999
HOA                 4438
dtype: int64
```

In [10]:
```
df.describe()
```

Out[10]:

	MLS	sold_price	zipcode	longitude	latitude	lot_acre
count	5.000000e+03	5.000000e+03	5000.000000	5000.000000	5000.000000	4990.00000
mean	2.127070e+07	7.746262e+05	85723.025600	-110.912107	32.308512	4.66131
std	2.398508e+06	3.185556e+05	38.061712	0.120629	0.178028	51.68523
min	3.042851e+06	1.690000e+05	85118.000000	-112.520168	31.356362	0.00000
25%	2.140718e+07	5.850000e+05	85718.000000	-110.979260	32.277484	0.58000
50%	2.161469e+07	6.750000e+05	85737.000000	-110.923420	32.318517	0.99000
75%	2.180480e+07	8.350000e+05	85749.000000	-110.859078	32.394334	1.75750
max	2.192856e+07	5.300000e+06	86323.000000	-109.454637	34.927884	2154.00000

Data Cleaning

Data Type Conversion

In [11]:
```
convert_cols = ["bathrooms", "sqrt_ft", "garage", "fireplaces", "HOA"]
for col in convert_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce')
```

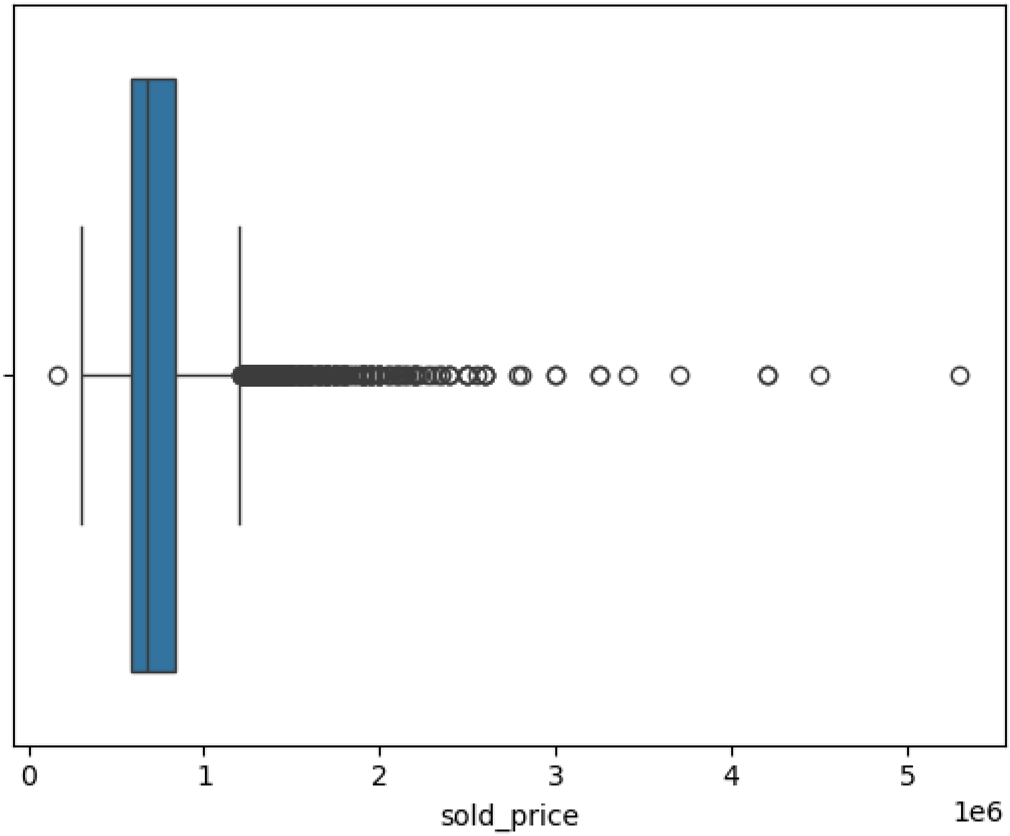
Handle missing values

In [12]:
```
df.fillna({"lot_acres":df["lot_acres"].median()}, inplace=True)
df.fillna({"sqrt_ft":df["sqrt_ft"].median()}, inplace=True)
```

```
df.fillna({"garage": 0}, inplace=True)
df.fillna({"HOA": 0}, inplace=True)
```

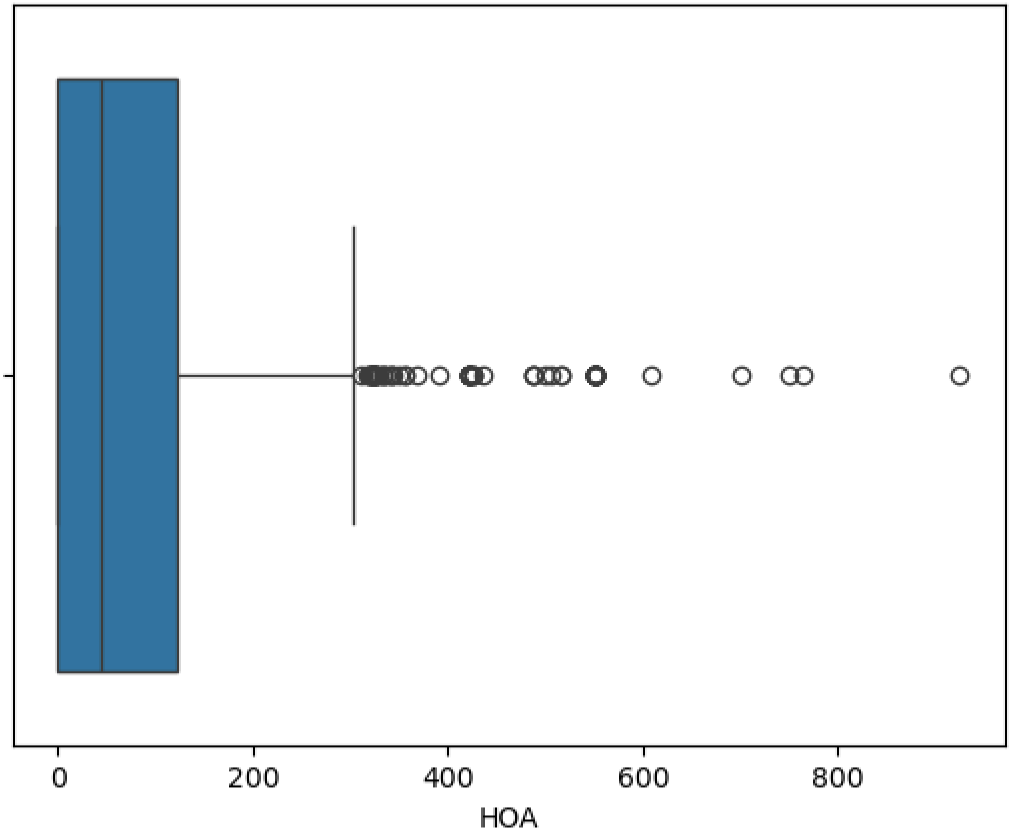
In [13]:
```
sns.boxplot(x=df['sold_price'])
```

Out[13]: <Axes: xlabel='sold_price'>



In [14]:
```
sns.boxplot(x=df['HOA'])
```

Out[14]: <Axes: xlabel='HOA'>



Outlier Removal using IQR method

In [15]:
```
column = df.select_dtypes(include=['float64', 'int64']).columns
```

In [16]:
```
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
```

In [17]:
```
outlier_cols = ["lot_acres", "sold_price", "taxes", "sqrt_ft", "HOA"]
for col in outlier_cols:
    df = remove_outliers(df, col)
```

In [18]:
```
# Summary Statistics After Cleaning:
```

In [19]:
```
print("\nSummary Statistics After Cleaning:")
print(df.describe())
```

```
Summary Statistics After Cleaning:
                MLS    sold_price       zipcode    longitude     latitude  \
count  3.733000e+03  3.733000e+03   3733.000000  3733.000000  3733.000000
mean   2.135377e+07  6.837639e+05  85726.135548  -110.916177    32.324772
std    2.101180e+06  1.362301e+05     32.688514     0.092688     0.134497
min    3.042851e+06  3.750000e+05  85118.000000  -111.430863    31.458609
25%    2.140831e+07  5.750000e+05  85718.000000  -110.975535    32.285978
50%    2.161784e+07  6.500000e+05  85737.000000  -110.922752    32.319066
75%    2.180678e+07  7.500000e+05  85750.000000  -110.861144    32.396889
max    2.192856e+07  1.185000e+06  85935.000000  -109.861617    34.314889

        lot_acres         taxes   year_built     bedrooms    bathrooms  \
count  3733.00000   3733.000000  3733.000000  3733.000000  3729.000000
mean      1.06910   6006.996552  1992.924993     3.850522     3.600697
std       0.84015   2092.235652    49.317624     0.826379     0.968307
min       0.00000    459.530000     0.000000     2.000000     2.000000
25%       0.51000   4708.000000  1987.000000     3.000000     3.000000
50%       0.87000   5945.000000  1999.000000     4.000000     4.000000
75%       1.20000   7272.620000  2005.000000     4.000000     4.000000
max       3.50000  11809.000000  2019.000000    18.000000    36.000000

           sqrt_ft       garage   fireplaces          HOA
count  3733.000000  3733.000000  3714.000000  3733.000000
mean   3423.058666     2.737209     1.721055    63.131372
std     617.383578     0.918898     1.000271    66.155298
min    1780.000000     0.000000     0.000000     0.000000
25%    2998.000000     2.000000     1.000000     3.000000
50%    3401.000000     3.000000     2.000000    44.000000
75%    3811.000000     3.000000     2.000000   100.000000
max    5125.000000    12.000000     8.000000   263.000000
```

In [20]:
```
df.head()
```

Out[20]:

LS	sold_price	zipcode	longitude	latitude	lot_acres	taxes	year_built	bedroom
40	1125000.0	85718	-110.883547	32.329763	1.33	8654.00	1986	
37	1100000.0	85750	-110.866891	32.321968	1.17	6565.93	1994	
50	1180000.0	85750	-110.868487	32.316324	1.30	9590.16	1993	
55	1175500.0	85718	-110.940650	32.347873	1.23	11674.00	2004	
03	1125478.0	85755	-110.973498	32.460529	1.71	3171.39	2017	

In [21]:
```
#df = df.drop(columns=['kitchen_features','floor_covering'])
```

In [22]:
```
print(df)
```

```
           MLS  sold_price  zipcode   longitude   latitude  lot_acres  \
398   21329440   1125000.0    85718 -110.883547  32.329763       1.33
400   21500337   1100000.0    85750 -110.866891  32.321968       1.17
411   21206450   1180000.0    85750 -110.868487  32.316324       1.30
412   21224755   1175500.0    85718 -110.940650  32.347873       1.23
428   21703603   1125478.0    85755 -110.973498  32.460529       1.71
...        ...         ...      ...         ...        ...        ...
4992   3056450    525000.0    85614 -110.980945  31.824287       3.01
4993  21908358    565000.0    85750 -110.820216  32.307646       0.83
4994  21909379    535000.0    85718 -110.922291  32.317496       0.18
4996  21908591    550000.0    85750 -110.858556  32.316373       1.42
4998  21900515    550000.0    85745 -111.055528  32.296871       1.01

         taxes  year_built  bedrooms  bathrooms  sqrt_ft  garage  \
398    8654.00        1986         4        5.0   5023.0     3.0
400    6565.93        1994         4        4.0   3870.0     3.0
411    9590.16        1993         4        3.0   5029.0     3.0
412   11674.00        2004         4        5.0   4143.0     3.0
428    3171.39        2017         3        4.0   3436.0     3.0
...        ...         ...       ...        ...      ...     ...
4992   5122.84        2007         3        3.0   3512.0     3.0
4993   4568.71        1986         4        3.0   2813.0     2.0
4994   4414.00        2002         3        2.0   2106.0     2.0
4996   4822.01        1990         4        3.0   2318.0     3.0
4998   5822.93        2009         4        4.0   3724.0     3.0

                                       kitchen_features  fireplaces  \
398   Compactor, Dishwasher, Garbage Disposal, Refri...         3.0
400   Dishwasher, Garbage Disposal, Refrigerator, Mi...         2.0
411   Dishwasher, Garbage Disposal, Refrigerator, Mi...         3.0
412   Dishwasher, Garbage Disposal, Refrigerator, Mi...         1.0
428                        Dishwasher, Garbage Disposal         1.0
...                                                 ...         ...
4992  Dishwasher, Garbage Disposal, Gas Range, Refri...         1.0
4993  Dishwasher, Double Sink, Electric Range, Garba...         2.0
4994  Dishwasher, Double Sink, Electric Range, Garba...         1.0
4996  Dishwasher, Double Sink, Electric Range, Garba...         1.0
4998  Dishwasher, Double Sink, Garbage Disposal, Gas...         1.0

                   floor_covering    HOA
398   Carpet, Natural Stone, Wood  179.0
400         Carpet, Natural Stone   58.0
411          Carpet, Ceramic Tile   40.0
412          Carpet, Ceramic Tile  159.0
428         Carpet, Natural Stone    0.0
...                           ...    ...
4992        Concrete, Other: Cork   37.0
4993         Carpet, Mexican Tile    6.0
4994                 Ceramic Tile  198.0
4996         Carpet, Ceramic Tile   43.0
4998         Carpet, Ceramic Tile    0.0

[3733 rows x 16 columns]
```

Save cleaned dataset

In [23]:
```
df.to_csv("cleaned_house_data.csv", index=False)
print("\nCleaned dataset saved as 'cleaned_house_data.csv'.")
```

```
Cleaned dataset saved as 'cleaned_house_data.csv'.
```

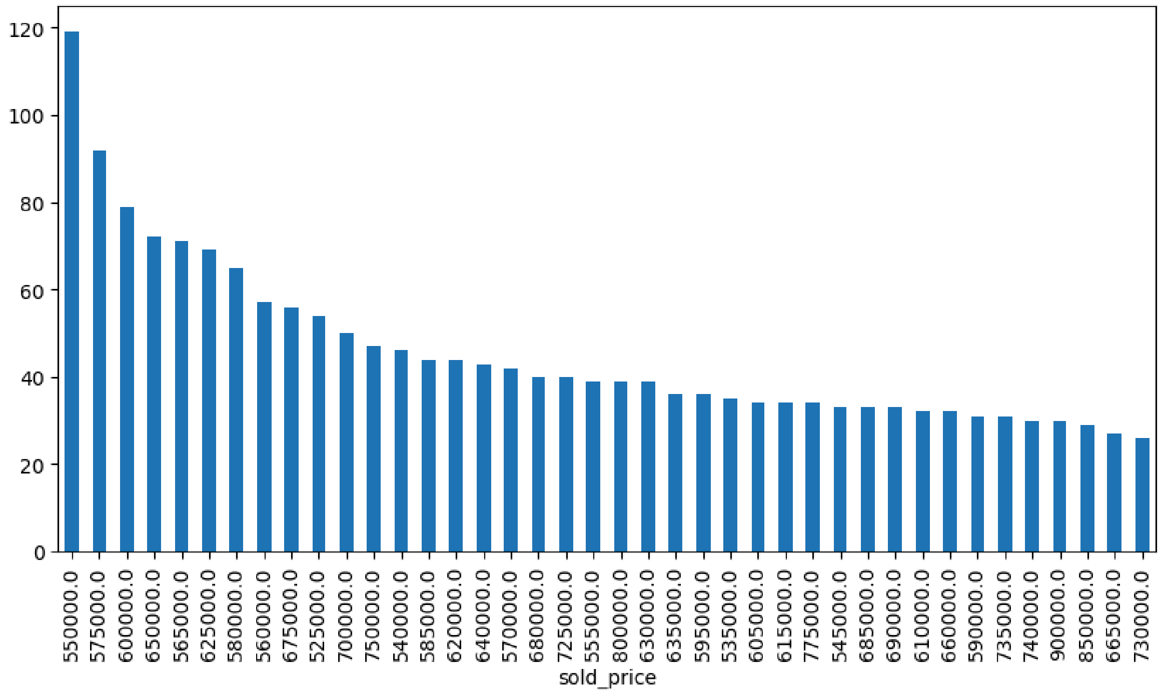
Data Visualization

Bar Chart

Used to compare categorical values such as sold price,lot acres.

In [24]:
```
df.sold_price.value_counts().nlargest(40).plot(kind='bar', figsize=(10,5))
```

Out[24]:
```
<Axes: xlabel='sold_price'>
```



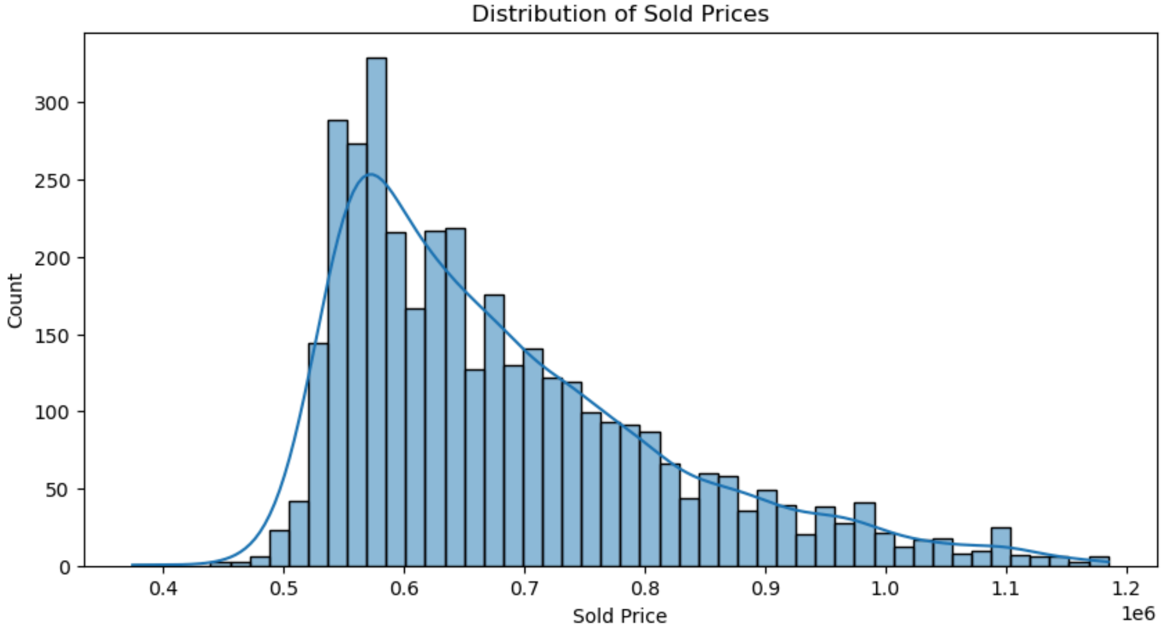
df.lot_acres.value_counts().nlargest(40).plot(kind='bar', figsize=(10,5))

Histogram of Sold Prices

- House prices were right-skewed, meaning some high-value properties affected the average.
- Suggested log transformation to normalize data for better model accuracy.

In [25]:
```
plt.figure(figsize=(10, 5))
sns.histplot(df["sold_price"], bins=50, kde=True) #Kernel Density Estimation
plt.title("Distribution of Sold Prices")
plt.xlabel("Sold Price")
```

```
plt.ylabel("Count")
plt.show()
```



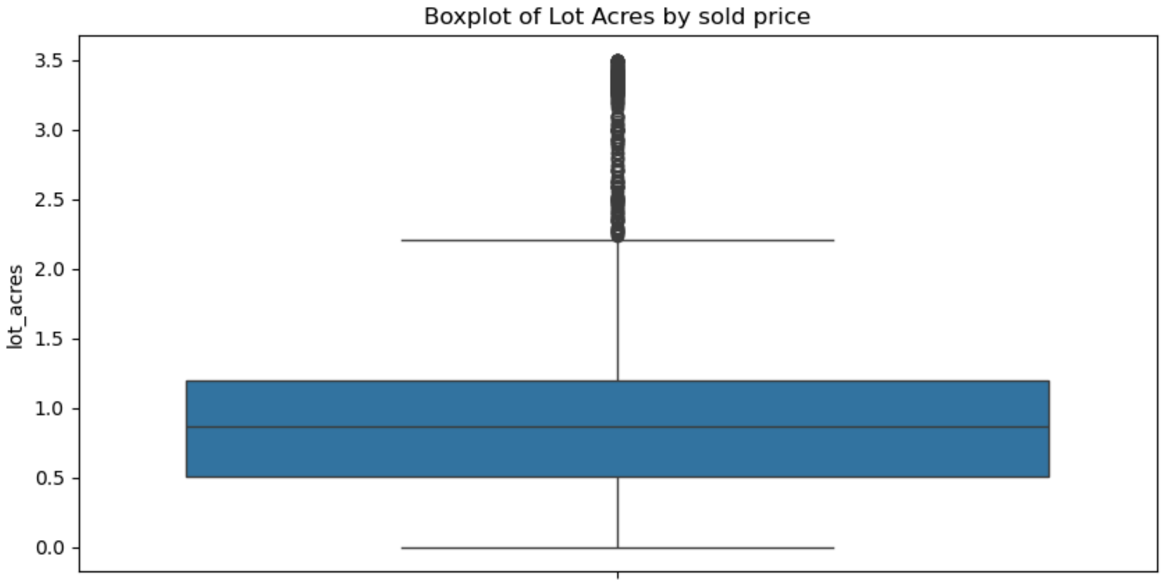
Boxplot of Lot Acres

Shows data distribution & outliers using quartiles.

- Before cleaning, several extreme outliers were identified in house prices.
- After applying IQR-based filtering, the data became more consistent and normally distributed.

In [26]:

```
plt.figure(figsize=(10, 5))
sns.boxplot(y=df["lot_acres"])
plt.title("Boxplot of Lot Acres by sold price")
plt.show()
```



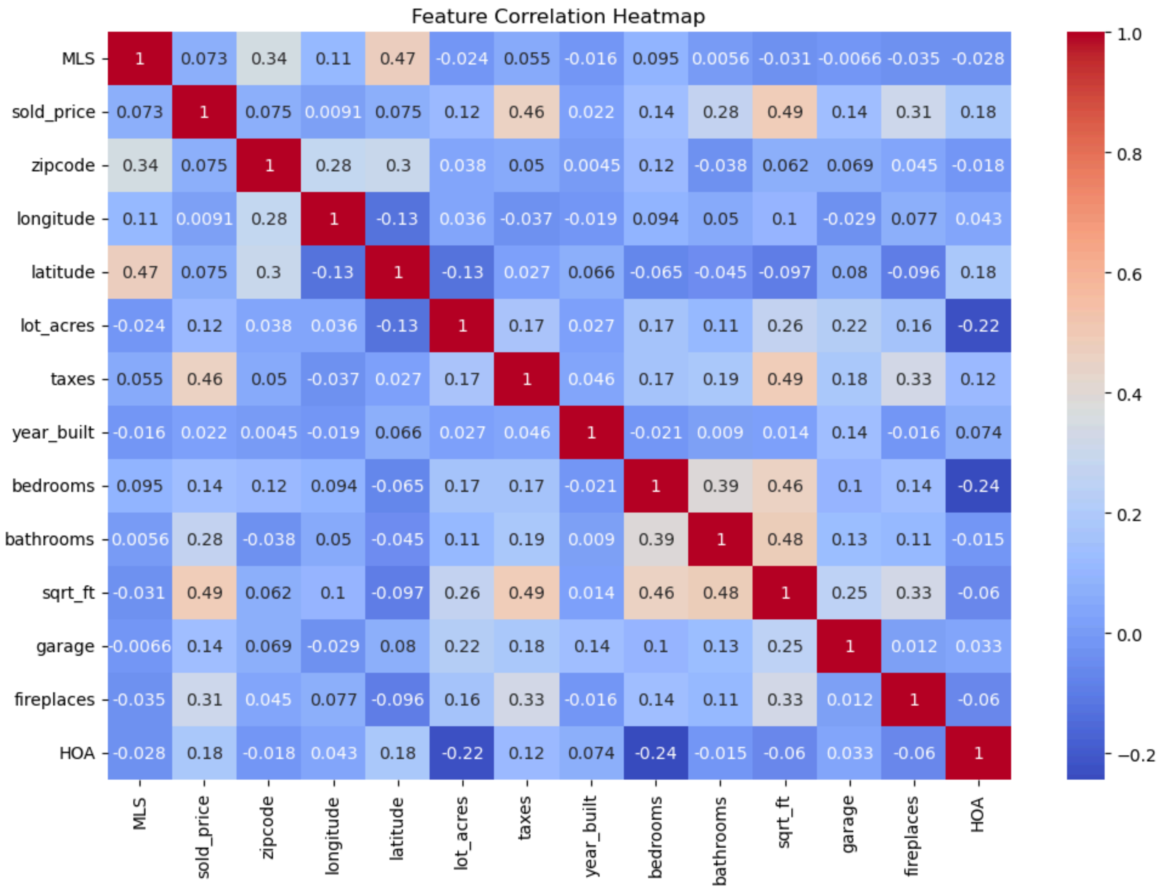
Correlation Heatmap

Helps identify feature relationships to select relevant predictors for modeling.

- Square footage, number of rooms, and overall quality had the highest correlation with house prices.
- Lot size had weak correlation, indicating it might not be a strong predictor.

In [27]:

```
plt.figure(figsize=(12, 8))
sns.heatmap(df[column].corr(), annot=True, cmap="coolwarm")
plt.title("Feature Correlation Heatmap")
plt.show()
```

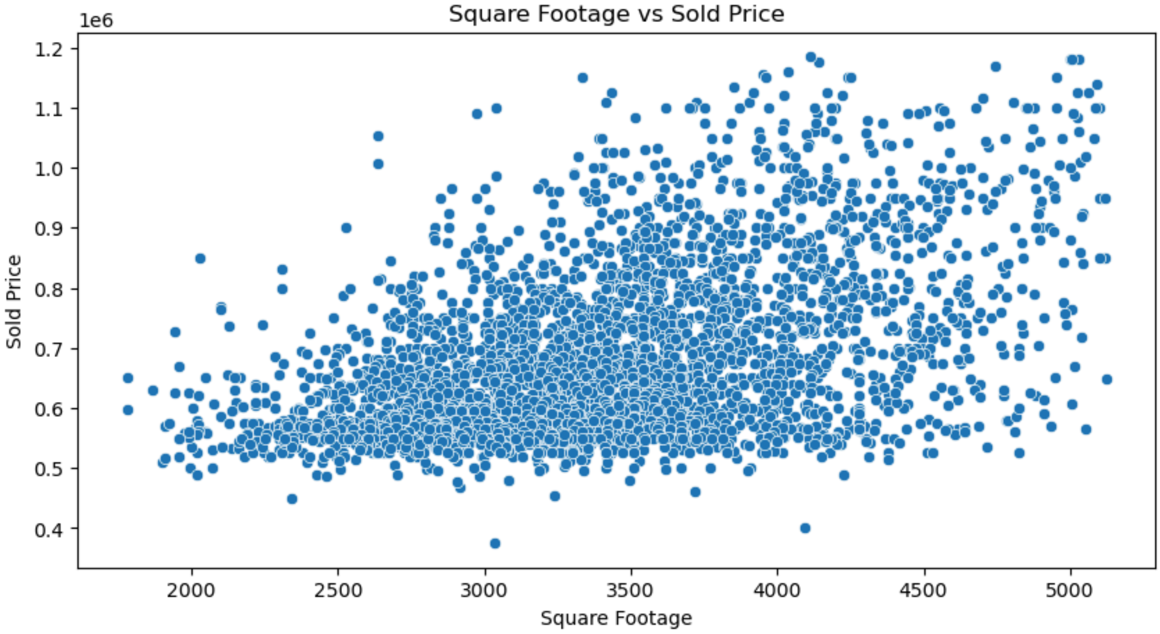


Scatter plot of Square Footage vs Price

A scatter plot is used to visualize the relationship between house size (square footage) and sold price. This helps identify whether larger homes tend to have higher prices.

In [28]:

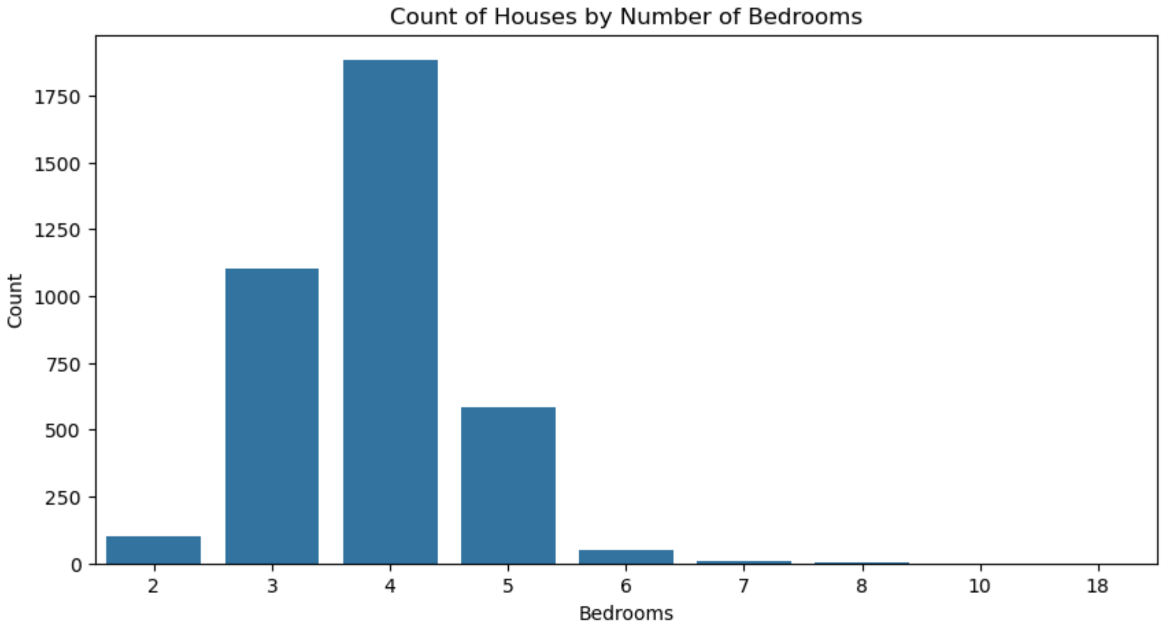
```
plt.figure(figsize=(10, 5))
sns.scatterplot(x=df["sqrt_ft"], y=df["sold_price"])
plt.title("Square Footage vs Sold Price")
plt.xlabel("Square Footage")
plt.ylabel("Sold Price")
plt.show()
```



Count Plot of Number of Bedrooms

A count plot is used to visualize the distribution of houses based on the number of bedrooms. This helps identify the most common house types in the dataset.

In [29]:
```
plt.figure(figsize=(10, 5))
sns.countplot(x=df["bedrooms"])
plt.title("Count of Houses by Number of Bedrooms")
plt.xlabel("Bedrooms")
plt.ylabel("Count")
plt.show()
```

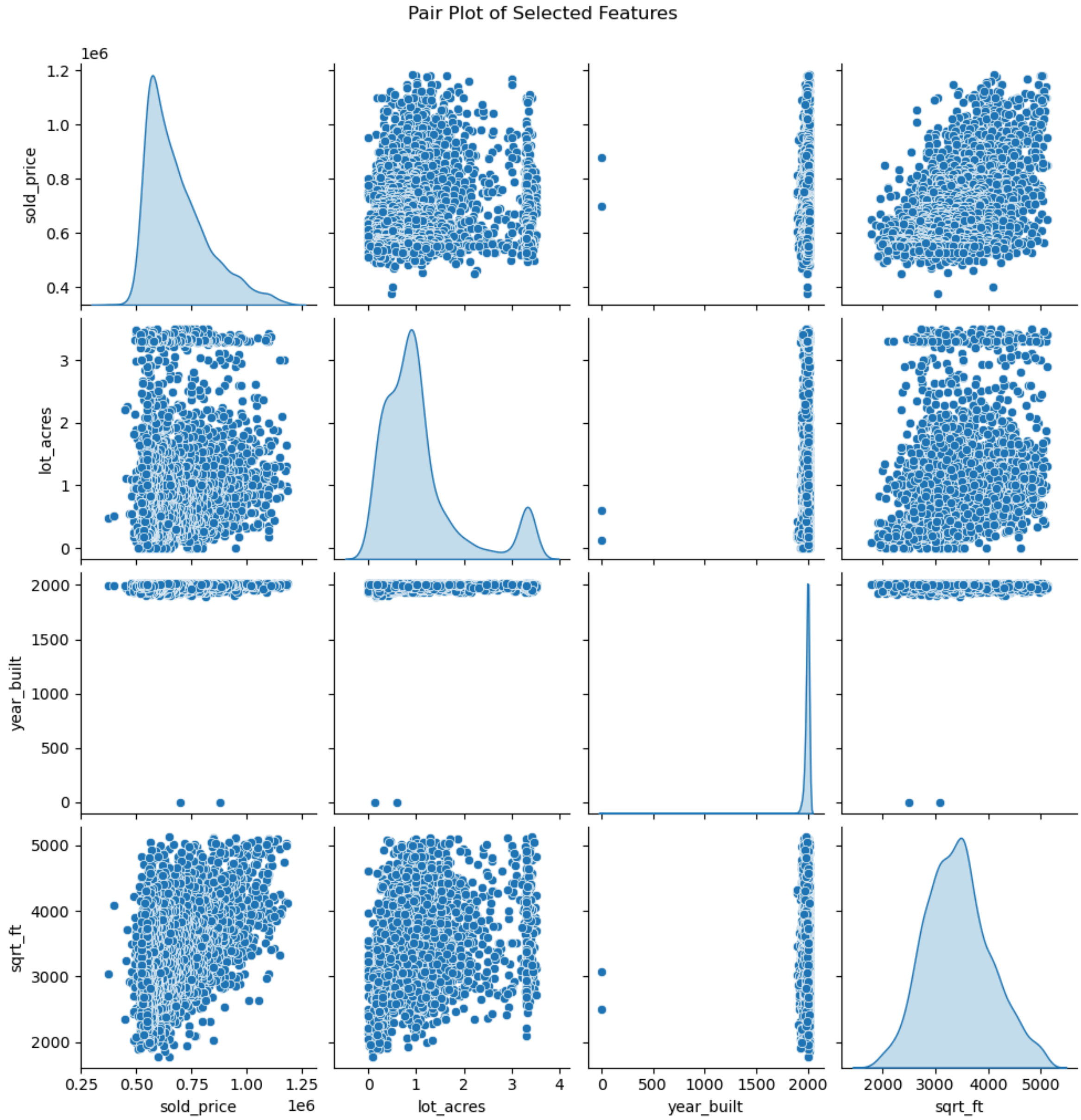


PairPlot of Selected Features

Displays pairwise relationships between multiple numerical variables.

- House price vs. square footage showed a strong positive correlation (larger homes tend to be more expensive).
- Year built vs. price suggested that newer homes generally have higher prices.
- Outliers were visible in some features like lot size.

In [30]:
```
selectedColumn = ['sold_price','lot_acres','year_built','sqrt_ft']
sns.pairplot(df[selectedColumn], diag_kind="kde")
plt.suptitle("Pair Plot of Selected Features", y=1.02)
plt.show()
```



In [ ]: