Importing the required libraries

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

from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
```

Loading the dataset

```
file_path = "./house_prices_dataset.csv"
df = pd.read_csv(file_path)
df
```

```
        Location  Size_sqft  Bedrooms  Bathrooms  House_Age  Garage  
Pool  \
0        Chicago       1395         3          1         26       1  
0
1        Houston       1528         4          2         28       1  
0
2    Los Angeles       2165         4          4         46       1  
0
3        Houston       1498         5          3         27       1  
0
4        Houston       1195         5          4         34       1  
1
..           ...        ...       ...        ...        ...     ...  
...
495     New York       4475         3          4         14       1  
1
496  Los Angeles       3854         3          4         16       1  
1
497     New York       2943         1          1         39       1  
0
498     New York       2111         1          4         17       0  
0
499     New York       3991         4          2          8       1  
0

     Distance_to_City_Center_miles         Price
0                        12.077516  7.257565e+05
1                        22.750817  7.264075e+05
2                        27.593580  1.050788e+06
```

```
3                           28.552394  7.240178e+05
4                           17.525116  7.342087e+05
..                                ...           ...
495                         22.624345  1.917976e+06
496                         27.292740  1.643563e+06
497                         22.882102  1.270751e+06
498                         18.116082  1.127655e+06
499                         19.796916  1.723863e+06

[500 rows x 9 columns]
```

Preprocessing and Handling the Missing Values

```
# dropping the duplicate rows and any missing values
df.drop_duplicates(inplace=True)
df.dropna(inplace= True)
df
```

```
        Location  Size_sqft  Bedrooms  Bathrooms  House_Age  Garage
Pool  \
0        Chicago       1395         3          1         26       1
0
1        Houston       1528         4          2         28       1
0
2    Los Angeles       2165         4          4         46       1
0
3        Houston       1498         5          3         27       1
0
4        Houston       1195         5          4         34       1
1
..           ...        ...       ...        ...        ...     ...
...
495     New York       4475         3          4         14       1
1
496  Los Angeles       3854         3          4         16       1
1
497     New York       2943         1          1         39       1
0
498     New York       2111         1          4         17       0
0
499     New York       3991         4          2          8       1
0

     Distance_to_City_Center_miles         Price
0                           12.077516  7.257565e+05
1                           22.750817  7.264075e+05
2                           27.593580  1.050788e+06
3                           28.552394  7.240178e+05
4                           17.525116  7.342087e+05
```

```
..                              ...           ...
495                       22.624345  1.917976e+06
496                       27.292740  1.643563e+06
497                       22.882102  1.270751e+06
498                       18.116082  1.127655e+06
499                       19.796916  1.723863e+06

[500 rows x 9 columns]
```

Encoding the categorical variable (Location)

```python
# encoding the categorical variables using OneHotEncoder
encoder = OneHotEncoder(drop='first', sparse_output=False)
encoded_location = encoder.fit_transform(df[['Location']])
#converting the encoded location into dataframe with proper columns
encoded_location_df = pd.DataFrame(encoded_location, columns =
encoder.get_feature_names_out(['Location']))
# adding the encoded location (categorical feature) to the dataframe
df = df.drop( columns= ['Location'])
df = pd.concat([df, encoded_location_df], axis  = 1)
df
```

```
     Size_sqft  Bedrooms  Bathrooms  House_Age  Garage  Pool  \
0         1395         3          1         26       1     0
1         1528         4          2         28       1     0
2         2165         4          4         46       1     0
3         1498         5          3         27       1     0
4         1195         5          4         34       1     1
..         ...       ...        ...        ...     ...   ...
495       4475         3          4         14       1     1
496       3854         3          4         16       1     1
497       2943         1          1         39       1     0
498       2111         1          4         17       0     0
499       3991         4          2          8       1     0

     Distance_to_City_Center_miles         Price  Location_Houston  \
0                        12.077516  7.257565e+05               0.0
1                        22.750817  7.264075e+05               1.0
2                        27.593580  1.050788e+06               0.0
3                        28.552394  7.240178e+05               1.0
4                        17.525116  7.342087e+05               1.0
..                             ...           ...               ...
495                      22.624345  1.917976e+06               0.0
496                      27.292740  1.643563e+06               0.0
497                      22.882102  1.270751e+06               0.0
498                      18.116082  1.127655e+06               0.0
499                      19.796916  1.723863e+06               0.0

     Location_Los Angeles  Location_New York  Location_San Francisco
0                     0.0                0.0                     0.0
```

```
1                           0.0                 0.0                        0.0
2                           1.0                 0.0                        0.0
3                           0.0                 0.0                        0.0
4                           0.0                 0.0                        0.0
..                          ...                 ...                        ...
495                         0.0                 1.0                        0.0
496                         1.0                 0.0                        0.0
497                         0.0                 1.0                        0.0
498                         0.0                 1.0                        0.0
499                         0.0                 1.0                        0.0

[500 rows x 12 columns]
```

Scaling the data

```python
# scaling the data using StandardScaler
X = df.drop(columns=['Price'])
y = df['Price']
X_scaled = StandardScaler().fit_transform(X)
```

Splitting into Train and Test data

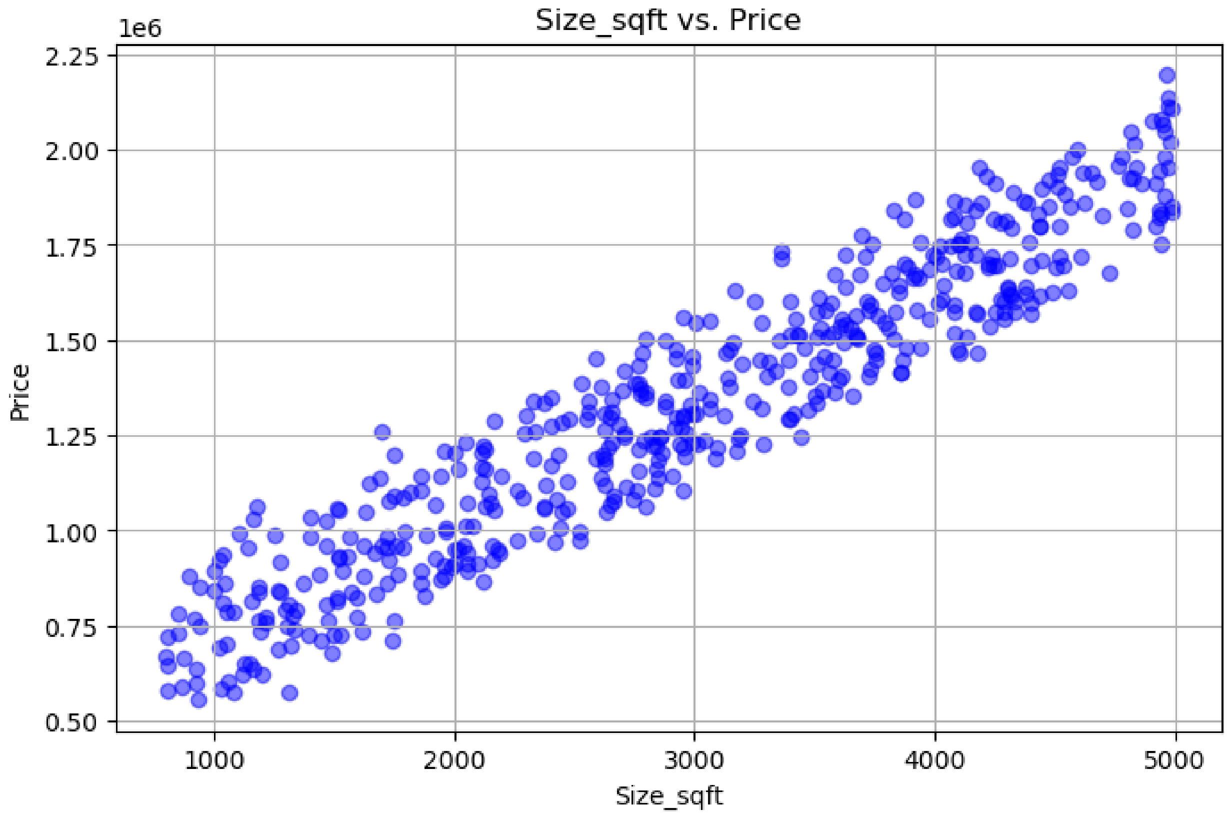
```python
# splitting the data into train and test in 80 / 20 ratio
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)
```

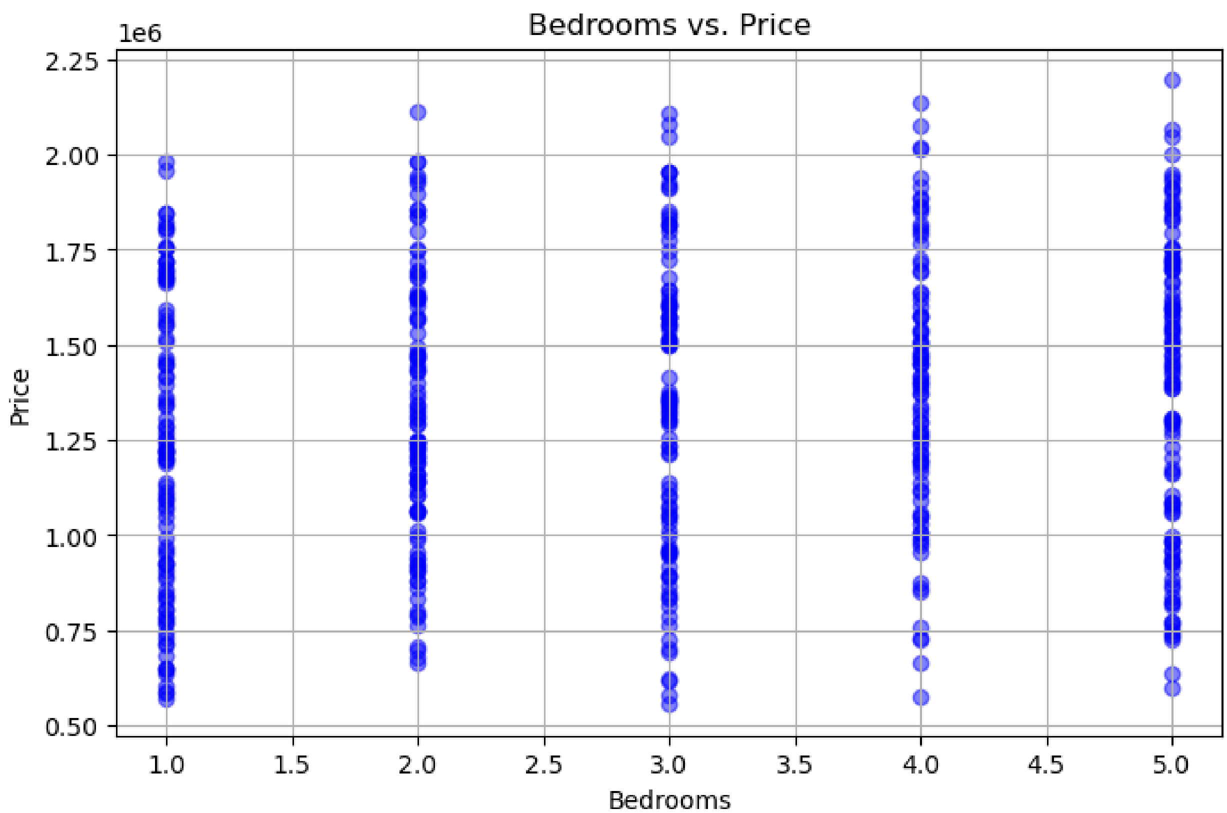
Exploratory data analysis

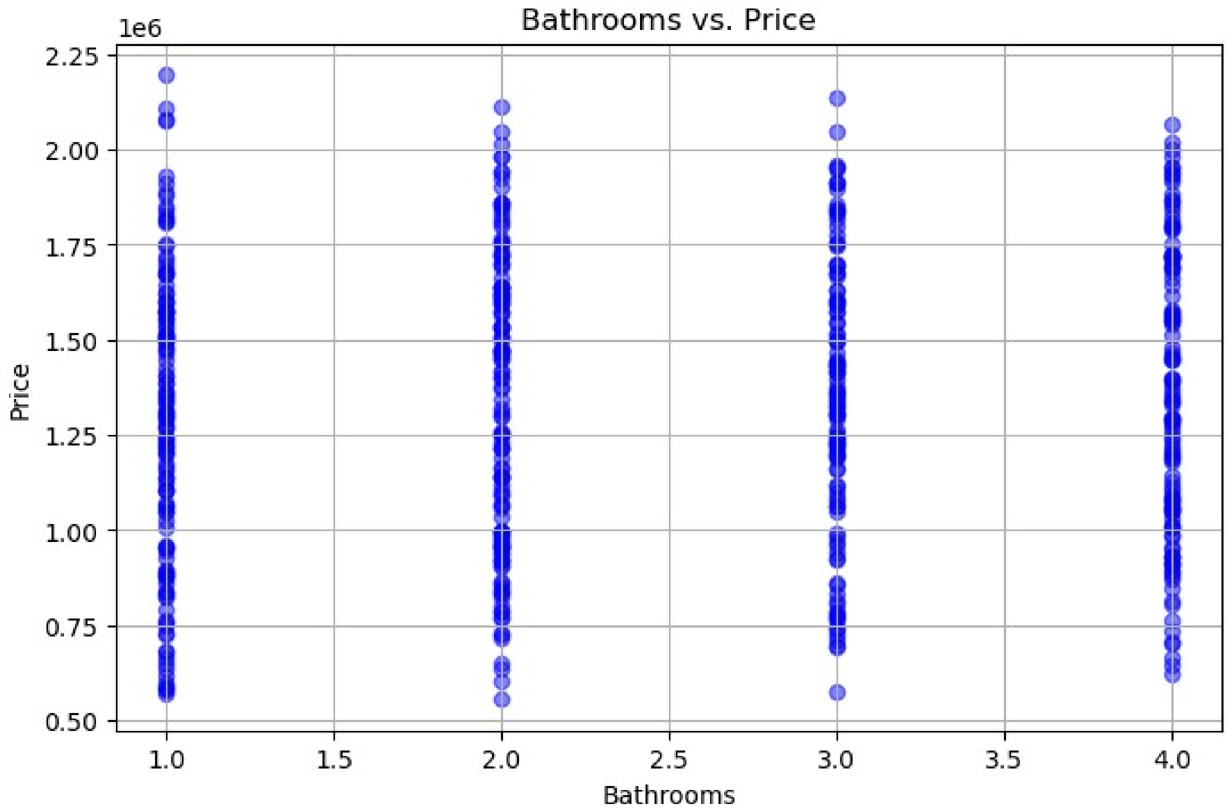
1.scatter plots between features and the house prices

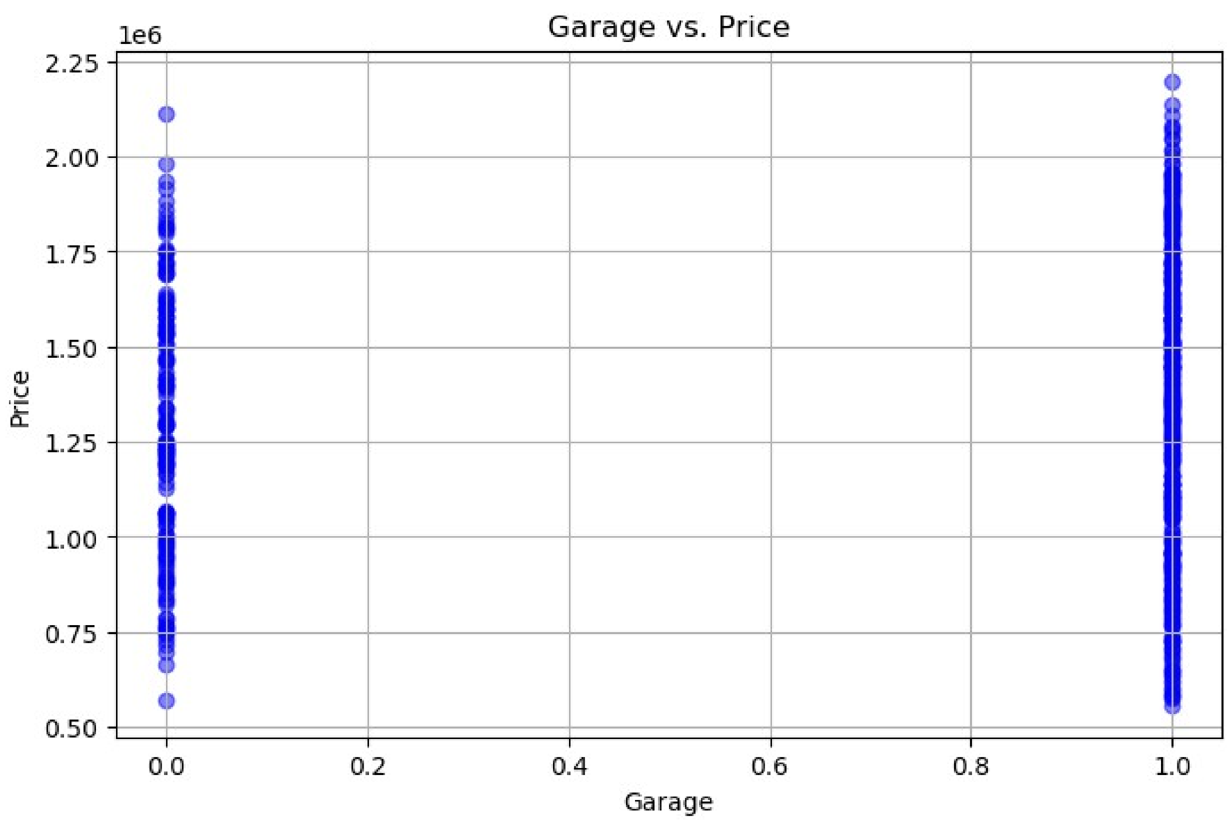
```python
# using scatter plot to understand the trends
features = ['Size_sqft', 'Bedrooms', 'Bathrooms', 'Garage', 'Pool',
'Distance_to_City_Center_miles']

for col in features:
    plt.figure(figsize=(8, 5))
    plt.scatter(df[col], df['Price'], alpha=0.5, color='blue')
    plt.title(f"{col} vs. Price")
    plt.xlabel(col)
    plt.ylabel("Price")
    plt.grid(True)
    plt.show()
```

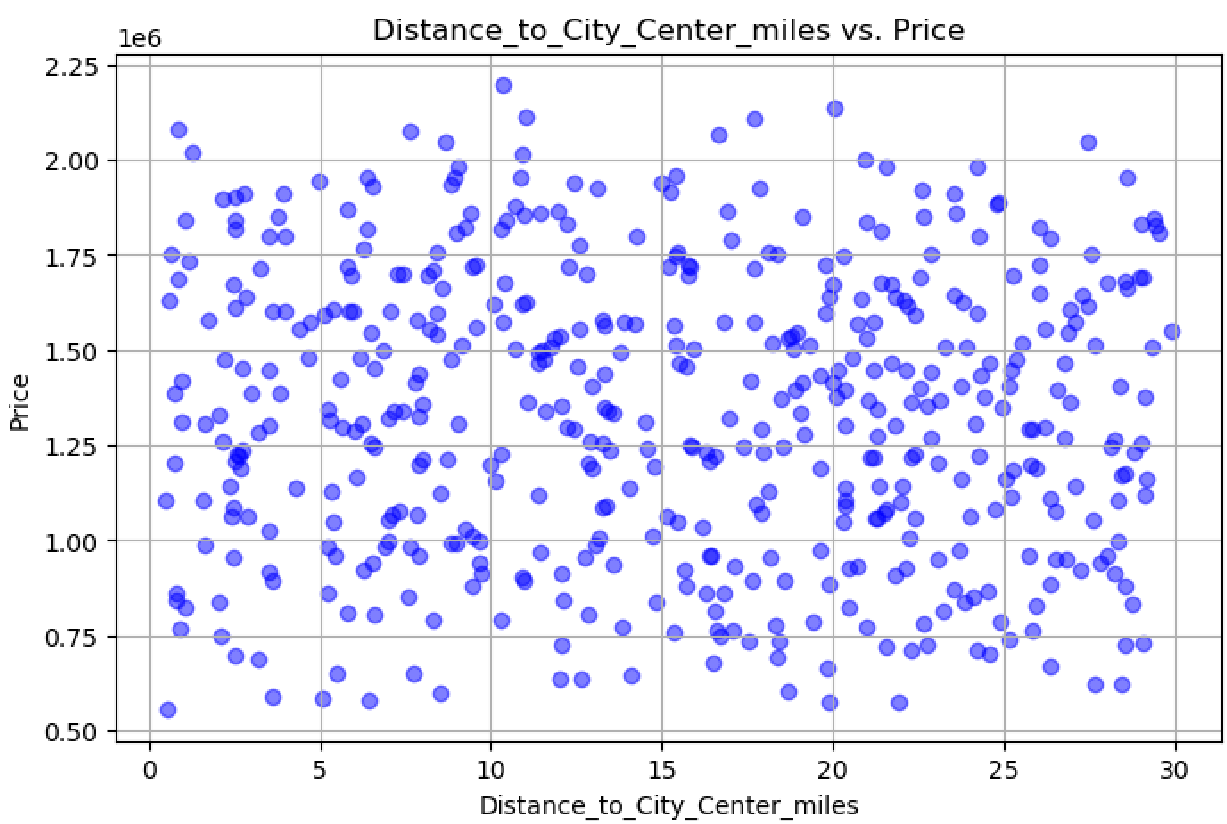

Size_sqft vs. Price
1e6
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
Price
1000
2000
3000
4000
5000
Size_sqft


Bedrooms vs. Price
1e6
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
Price
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Bedrooms


Bathrooms vs. Price
1e6
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
Price
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Bathrooms

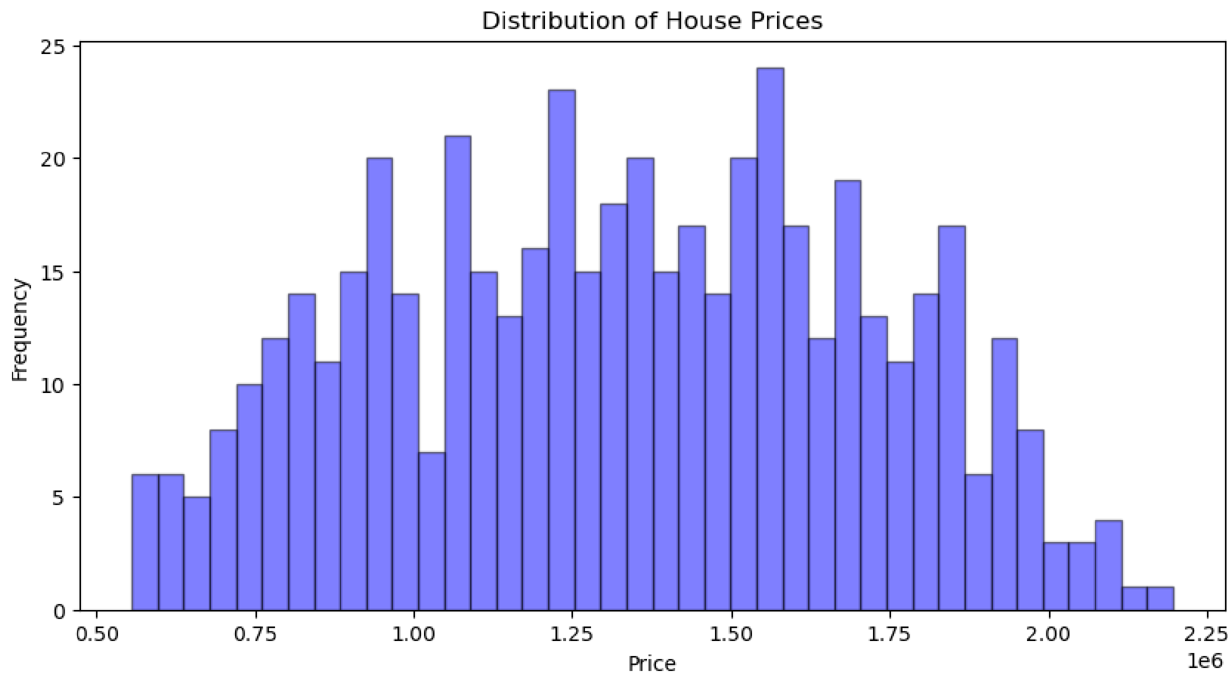

Garage vs. Price
1e6
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
Price
0.0
0.2
0.4
0.6
0.8
1.0
Garage


Pool vs. Price
1e6
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
Price
0.0
0.2
0.4
0.6
0.8
1.0
Pool


Distance_to_City_Center_miles vs. Price
1e6
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
Price
0
5
10
15
20
25
30
Distance_to_City_Center_miles

2.Histogram of the house prices

```
plt.figure(figsize=(10, 5))
plt.hist(df['Price'], bins=40, color='blue', edgecolor='black',
alpha=0.5)
plt.title("Distribution of House Prices")
plt.xlabel("Price")
plt.ylabel("Frequency")
plt.show()
```



3.Info about various statical measures of the given dataset

```
df.info()
df.describe()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 12 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Size_sqft                      500 non-null    int64
 1   Bedrooms                       500 non-null    int64
 2   Bathrooms                      500 non-null    int64
 3   House_Age                      500 non-null    int64
 4   Garage                         500 non-null    int64
 5   Pool                           500 non-null    int64
 6   Distance_to_City_Center_miles  500 non-null    float64
 7   Price                          500 non-null    float64
 8   Location_Houston               500 non-null    float64
```

```
 9   Location_Los Angeles          500 non-null    float64
 10  Location_New York             500 non-null    float64
 11  Location_San Francisco        500 non-null    float64
dtypes: float64(6), int64(6)
memory usage: 47.0 KB

         Size_sqft    Bedrooms   Bathrooms   House_Age      Garage  \
count   500.000000  500.000000  500.000000  500.000000  500.000000
mean   2971.950000    3.008000    2.458000   23.458000    0.702000
std    1169.733097    1.428291    1.114774   14.209435    0.457838
min     803.000000    1.000000    1.000000    0.000000    0.000000
25%    2005.000000    2.000000    1.000000   11.000000    0.000000
50%    2956.000000    3.000000    2.000000   23.000000    1.000000
75%    3980.500000    4.000000    3.000000   35.000000    1.000000
max    4988.000000    5.000000    4.000000   49.000000    1.000000

             Pool  Distance_to_City_Center_miles         Price  \
count  500.000000                     500.000000  5.000000e+02
mean     0.194000                      15.200508  1.329449e+06
std      0.395825                       8.373759  3.780628e+05
min      0.000000                       0.500343  5.558926e+05
25%      0.000000                       7.903742  1.029014e+06
50%      0.000000                      15.467201  1.336224e+06
75%      0.000000                      22.237744  1.619568e+06
max      1.000000                      29.916879  2.196013e+06

       Location_Houston  Location_Los Angeles  Location_New York  \
count        500.000000            500.000000         500.000000
mean           0.186000              0.182000           0.218000
std            0.389496              0.386231           0.413301
min            0.000000              0.000000           0.000000
25%            0.000000              0.000000           0.000000
50%            0.000000              0.000000           0.000000
75%            0.000000              0.000000           0.000000
max            1.000000              1.000000           1.000000

       Location_San Francisco
count              500.000000
mean                 0.190000
std                  0.392694
min                  0.000000
25%                  0.000000
50%                  0.000000
75%                  0.000000
max                  1.000000
```

Training the data using different models

1.Linear Regression

```
# using linear regression to train
model1 = LinearRegression()
model1.fit(X_train, y_train)
y_pred1 = model1.predict(X_test)

# performance metrics of linear regression
print("RMSE_LINEAR_REGRESSION : ", np.sqrt(mean_squared_error(y_pred1,
y_test)))
print("MAE_LINEAR_REGRESSION : ", mean_absolute_error(y_pred1,
y_test))
print("R2_SCORE_LINEAR_REGRESSION : ", r2_score(y_pred1, y_test))
```

```
RMSE_LINEAR_REGRESSION :  11719.545666352768
MAE_LINEAR_REGRESSION :  10334.125078503075
R2_SCORE_LINEAR_REGRESSION :  0.998960835812596
```

2.Neural Networks

```
# using multi layer feed forward network to train
model2 = MLPRegressor(hidden_layer_sizes= (100,
50),activation='relu' ,solver='adam', max_iter= 500, random_state= 42)
model2.fit(X_train, y_train)
y_pred2 = model2.predict(X_test)

# calculating performance metrics of neural networks
print("RMSE_NEURAL_NETWORKS : ", np.sqrt(mean_squared_error(y_pred2,
y_test)))
print("MAE_NEURAL_NETWOKS : ", mean_absolute_error(y_pred2, y_test))
print("R2_SCORE_NEURAL_NETWORKS : ", r2_score(y_pred2, y_test))
```

```
RMSE_NEURAL_NETWORKS :  1369368.162748587
MAE_NEURAL_NETWOKS :  1323044.0458968843
R2_SCORE_NEURAL_NETWORKS :  -8266.788117091606

/usr/lib/python3/dist-packages/sklearn/neural_network/
_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic
Optimizer: Maximum iterations (500) reached and the optimization
hasn't converged yet.
  warnings.warn(
```

3.Decision Tree

```
# using decision tree to train
model3 = DecisionTreeRegressor()
model3.fit(X_train, y_train)
```

```python
y_pred3 = model3.predict(X_test)

# calculating performance metrics of decision tree
print("RMSE_DECISION_TREE : ", np.sqrt(mean_squared_error(y_pred3,
y_test)))
print("MAE_DECISION_TREE : ", mean_absolute_error(y_pred3, y_test))
print("R2_SCORE_DECISION_TREE : ", r2_score(y_pred3, y_test))
```

```
RMSE_DECISION_TREE :  91841.89581855651
MAE_DECISION_TREE :  74880.42626300002
R2_SCORE_DECISION_TREE :  0.9390259587806761
```