House Price Prediction

Objective: To develop a predictive model using the house_price dataset to accurately predict the house price.

Members: Tyler, Humza, Angelina, Christine, Efaz, Nathan

Import Statements

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as ms

%matplotlib inline
```

Part 1: Data Understanding

Let's load the dataset and view it's content..

In [ ]:

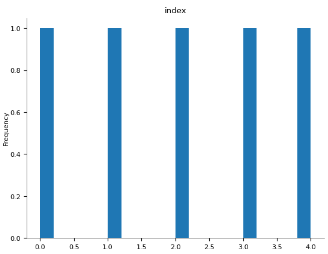
```
price = pd.read_csv('house_price.csv')
print('Size of house_price dataset: ',price.shape)
price.head(5)
```

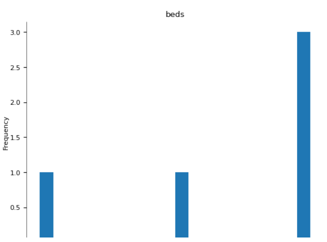
```
Size of house_price dataset:  (2016, 5)
```

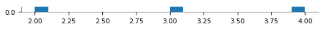
Out[ ]:

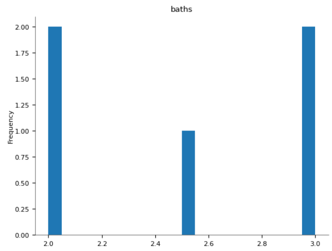
	beds	baths	size	lot_size	price
0	3	2.5	2590	6000.00	795000
1	4	2.0	2240	0.31	915000
2	4	3.0	2040	3783.00	950000
3	4	3.0	3800	5175.00	1950000
4	2	2.0	1042	NaN	950000

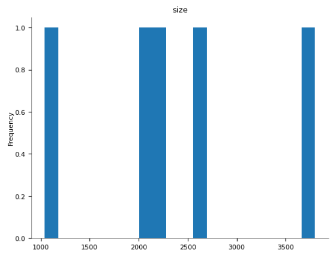
Distributions



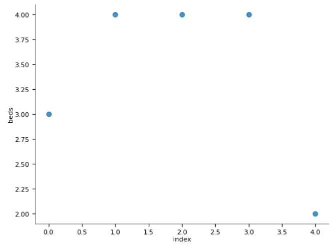


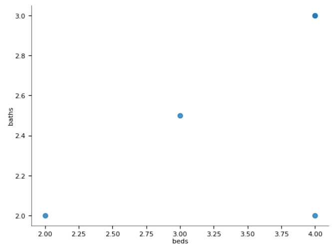


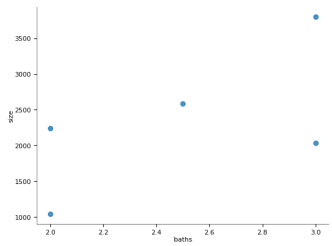


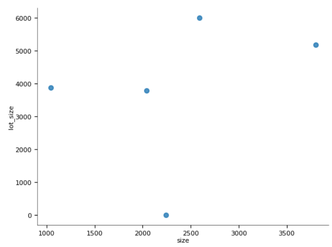


2-d distributions

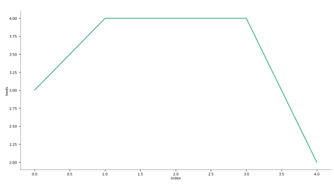


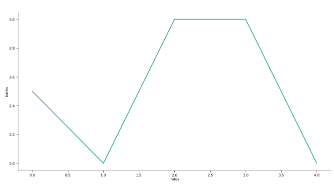


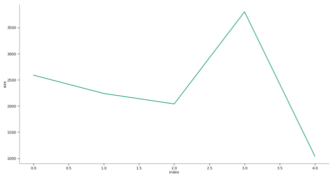


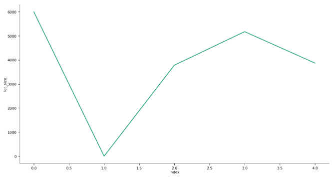


Time series

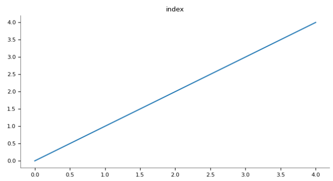


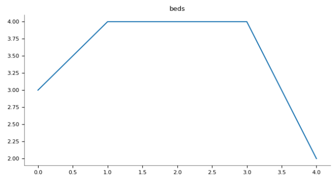


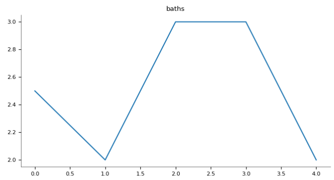


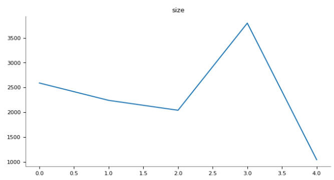


Values









Okay, it seems this dataset has 2016 rows and 5 columns. This tells us that there are 2016 houses with 5 attributes that relate to the amount of beds it contains, bathrooms, the square footage of the house, the square footage of the lot and the price of the house.

Now let's check on the datatypes of each column and see how many unique values exist in them

In [ ]:

```
data_types = price.dtypes

print("Data Types and Additional Information:")
for column in price.columns:
  print(f'Column: {column}')
  print(f' - Data Type: {data_types[column]}')
  print(f' - Number of Unique Values: {price[column].nunique()}')
  print(f' - Sample Values: {price[column].dropna().unique()[:5]}')
```

```
Data Types and Additional Information:
Column: beds
 - Data Type: int64
 - Number of Unique Values: 11
 - Sample Values: [3 4 2 1 5]
Column: baths
 - Data Type: float64
 - Number of Unique Values: 16
 - Sample Values: [2.5 2.  3.  1.  3.5]
Column: size
 - Data Type: int64
```

```
 - Number of Unique Values: 879
 - Sample Values: [2590 2240 2040 3800 1042]
Column: lot_size
 - Data Type: float64
 - Number of Unique Values: 959
 - Sample Values: [6.000e+03 3.100e-01 3.783e+03 5.175e+03 1.000e+00]
Column: price
 - Data Type: int64
 - Number of Unique Values: 767
 - Sample Values: [ 795000  915000  950000 1950000  740000]
```

In [ ]:

```
price.describe()
```

Out[ ]:

	beds	baths	size	lot_size	price
count	2016.000000	2016.000000	2016.000000	1669.000000	2.016000e+03
mean	2.857639	2.159970	1735.740575	3871.059694	9.636252e+05
std	1.255092	1.002023	920.132591	2719.402066	9.440954e+05
min	1.000000	0.500000	250.000000	0.230000	1.590000e+05
25%	2.000000	1.500000	1068.750000	1252.000000	6.017500e+05
50%	3.000000	2.000000	1560.000000	4000.000000	8.000000e+05
75%	4.000000	2.500000	2222.500000	6000.000000	1.105250e+06
max	15.000000	9.000000	11010.000000	9998.000000	2.500000e+07

We can clearly see that outliers do exist when looking at the minimum and maximum values of the dataset's descriptive statistics. We will deal with this later.

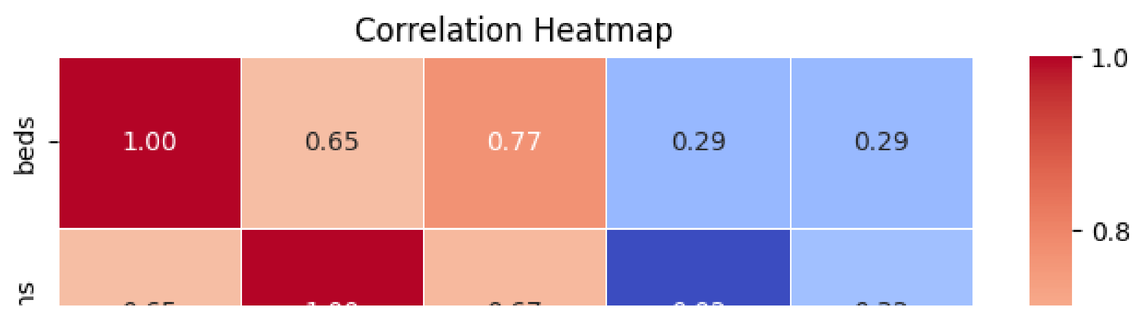
In [ ]:

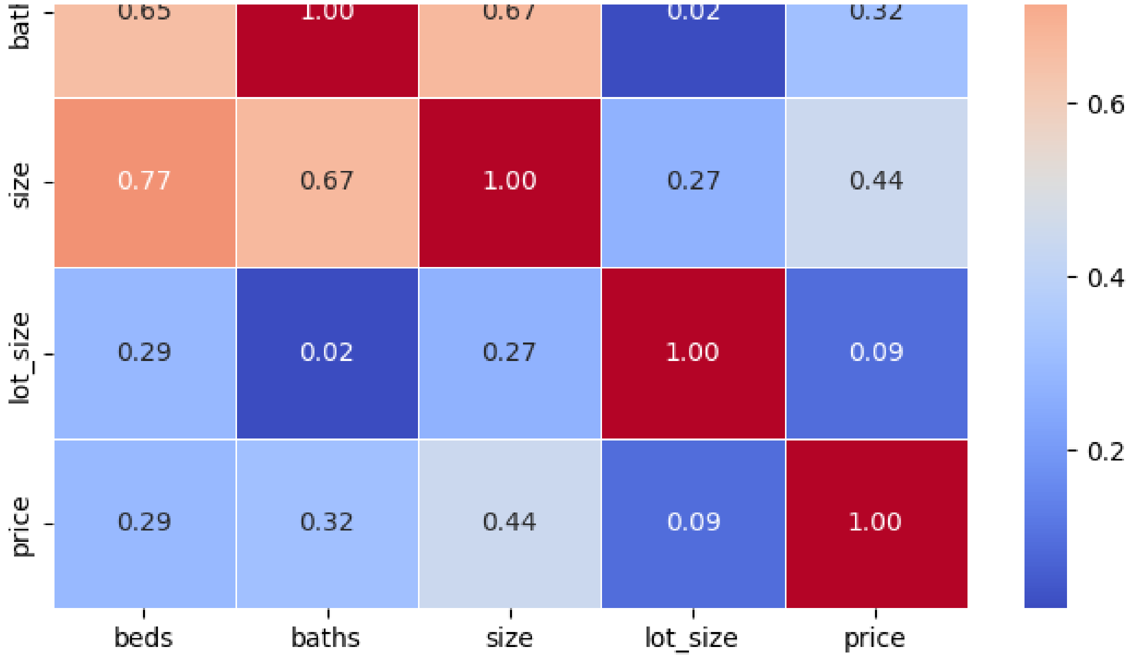
```
correlation_matrix = price.corr()

# Print correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)
```

```
Correlation Matrix:
              beds     baths      size  lot_size     price
beds      1.000000  0.652853  0.771929  0.291257  0.293516
baths     0.652853  1.000000  0.667655  0.016913  0.317325
size      0.771929  0.667655  1.000000  0.272596  0.444140
lot_size  0.291257  0.016913  0.272596  1.000000  0.091780
price     0.293516  0.317325  0.444140  0.091780  1.000000
```

In [ ]:

```
# Creating a correlation heatmap to see which variables are highly correlated with each o
ther or not correlated at all
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Heatmap')
plt.show()
```

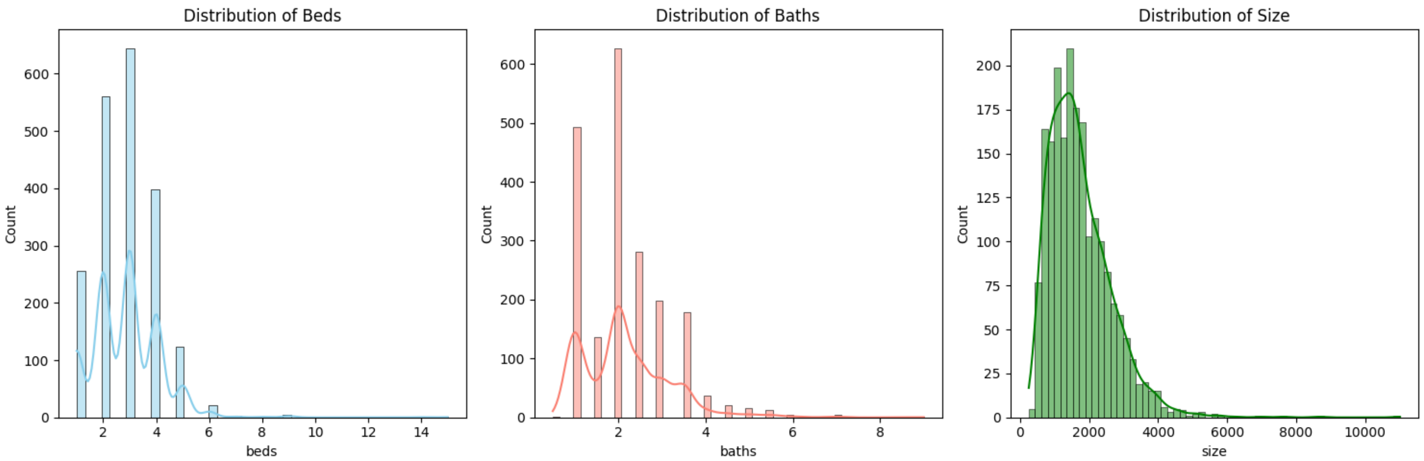




From looking at the correlation matrix and heatmap of the dataset, we can see that there is a strong correlation with beds, size and baths as they contain a r-squared value of 0.65.

In [ ]:

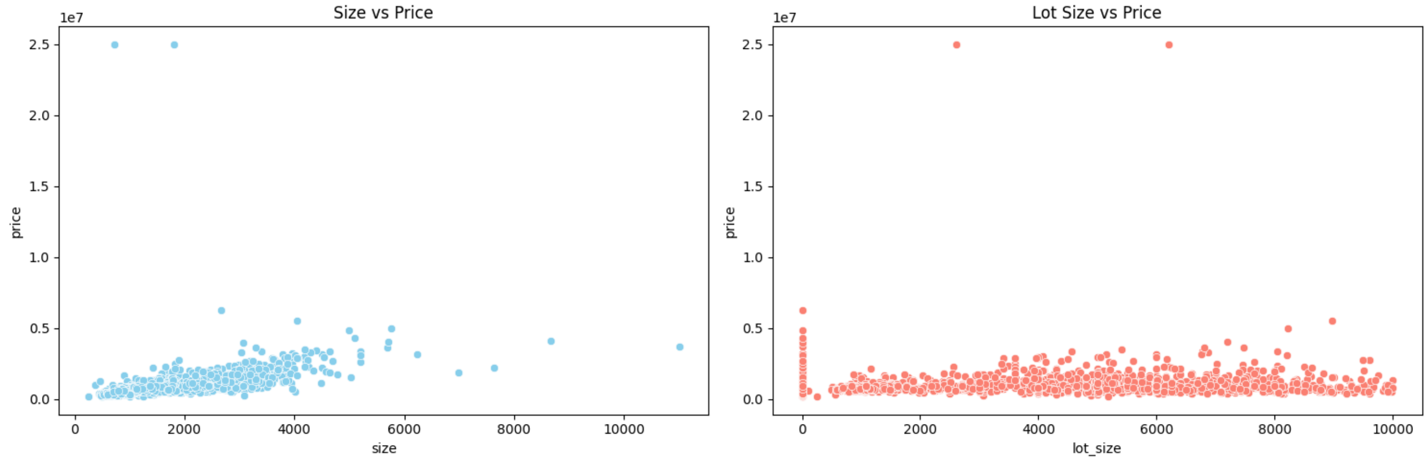
```
# Visualize the distribution of variables using histograms
plt.figure(figsize=(15, 5))
plt.subplot(1, 3, 1)
sns.histplot(price['beds'], kde=True, color='skyblue')
plt.title('Distribution of Beds') # beds distribution

plt.subplot(1, 3, 2)
sns.histplot(price['baths'], kde=True, color='salmon')
plt.title('Distribution of Baths') # baths distribution

plt.subplot(1, 3, 3)
sns.histplot(price['size'], kde=True, color='green')
plt.title('Distribution of Size') #house size distribution

plt.tight_layout()
plt.show()
```



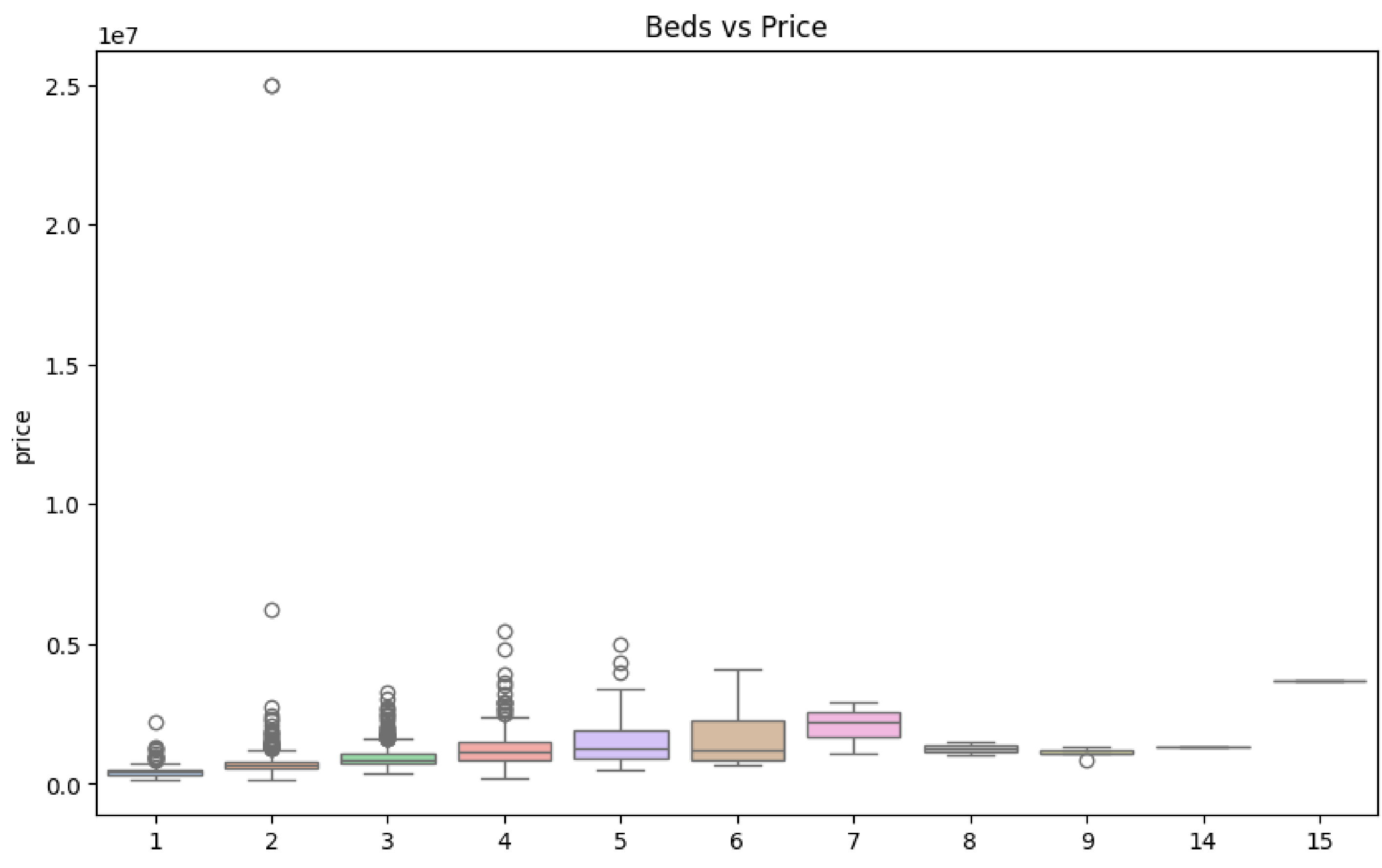
In [ ]:

```
# Visualize the relationship between variables and price using scatter plots
plt.figure(figsize=(15, 5))
plt.subplot(1, 2, 1)
sns.scatterplot(x='size', y='price', data=price, color='skyblue')
plt.title('Size vs Price')

# Visualize the relationship between the lot_size and price of the house using scatter pl
ots
```

```
plt.subplot(1, 2, 2)
sns.scatterplot(x='lot_size', y='price', data=price, color='salmon')
plt.title('Lot Size vs Price')

plt.tight_layout()
plt.show()

# Visualize the relationship between categorical variable (beds) and price using box plot
s
plt.figure(figsize=(10, 6))
sns.boxplot(x='beds', y='price', data=price, palette='pastel')
plt.title('Beds vs Price')
plt.show()

# Visualize the relationship between categorical variable (baths) and price using box plo
ts
plt.figure(figsize=(10, 6))
sns.boxplot(x='baths', y='price', data=price, palette='pastel')
plt.title('Baths vs Price')
plt.show()
```

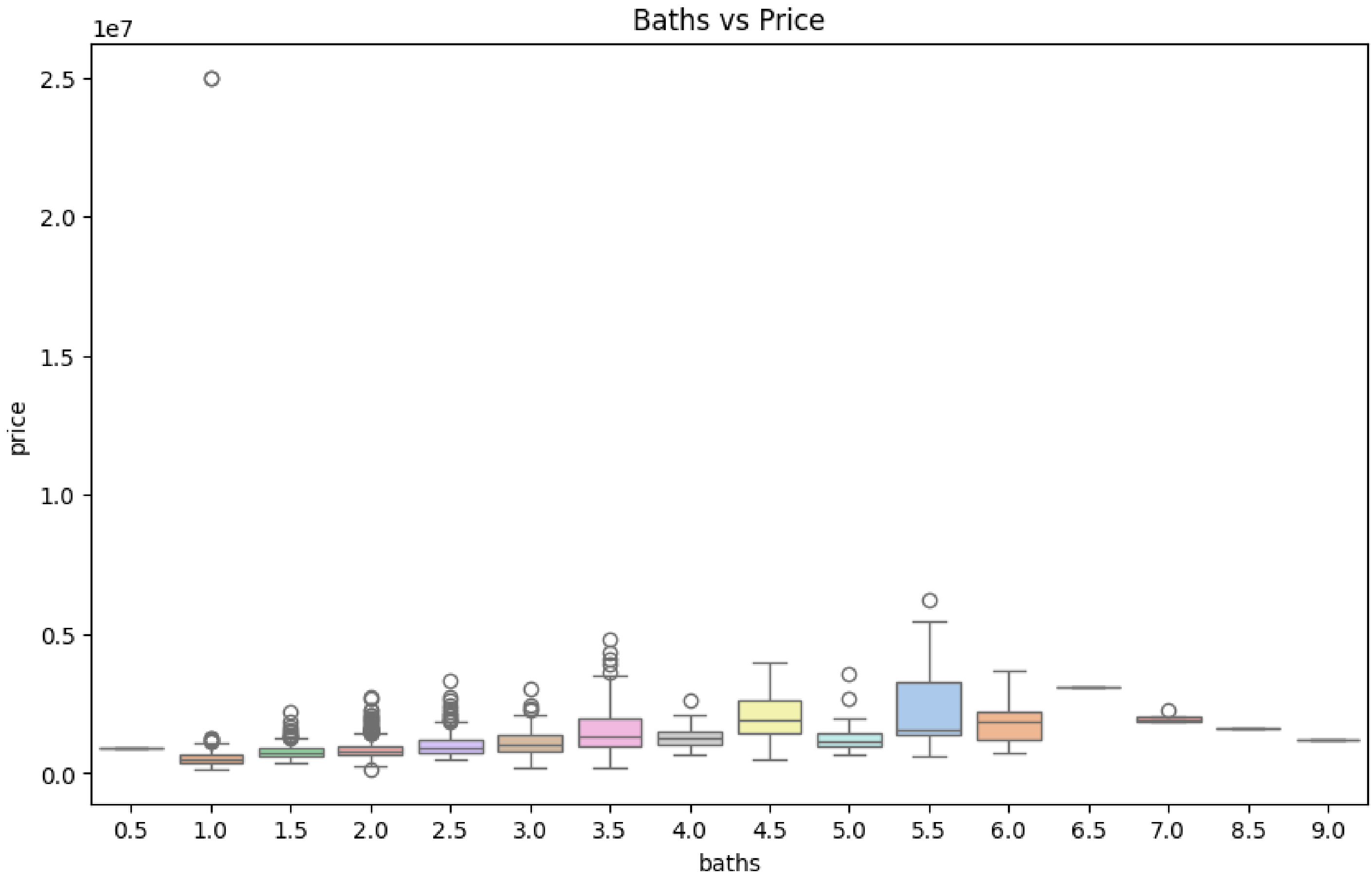



```
<ipython-input-8-9605d5501b63>:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(x='beds', y='price', data=price, palette='pastel')
```



beds

```
<ipython-input-8-9605d5501b63>:23: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(x='baths', y='price', data=price, palette='pastel')
```



Part 2: Data Preprocessing

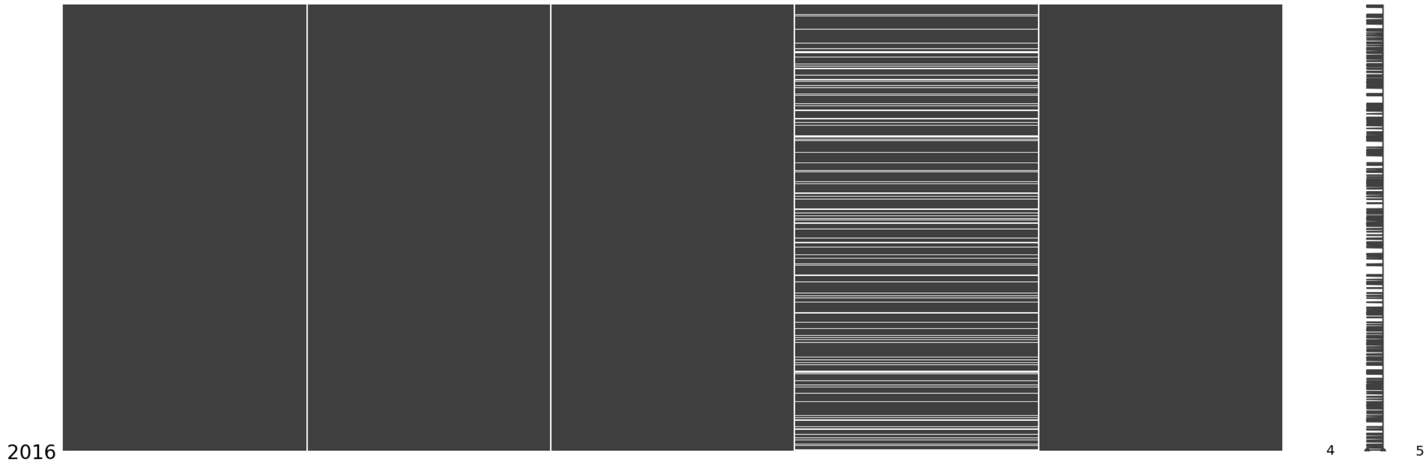
Before we build a machine learning model, let's first clean up any missing values, outliers and duplicated rows in the dataset.

Cleaning

In [ ]:

```
#Checking for Missing Values
missing_values = price.isnull().sum()
print("Missing values:\n", missing_values)
ms.matrix(price)
plt.show()
```

```
Missing values:
 beds          0
baths         0
size          0
lot_size    347
price         0
dtype: int64
```



There approximately looks to be 347 missing values in the lot_size category, so let's fix that.

In [ ]:

```
mean = price['lot_size'].mean() # calculating the means of the column lot_size
median = price['lot_size'].median() # calculating the median of the column lot_size

print('Mean of lot_size: ',mean) # printing the mean and median of the column
print('Median of lot_size: ',median)
```

```
Mean of lot_size:  3871.059694427802
Median of lot_size:  4000.0
```

It would make the most sense if we fill in the missing values with the mean of lot_size as the median only accounts for the middle of the entire dataset after being sorted

In [ ]:

```
price['lot_size'].fillna(price['lot_size'].mean(),inplace = True) # Filling in missing va
lues with the mean of lot_size
missing= price.isnull().sum() # checking for any null values after filling in
print('Missing Values after Imputing',missing)
```

```
Missing Values after Imputing beds        0
baths       0
size        0
lot_size    0
price       0
dtype: int64
```

Cool, everything looks good now for missing values, now let's check for duplicated data.

In [ ]:

```
# Checking duplicated records
duplicates = price.duplicated().sum()
print('Number of Duplicated Entries: ',duplicates)
```

```
Number of Duplicated Entries:  9
```

9 duplicated entries exist....let's drop the duplicated rows

In [ ]:

```
price = price.drop_duplicates() # dropping duplicated rows and checking if there are any
left just in case
duplicates = price.duplicated().sum()
print('Number of Duplicated Entries: ',duplicates)
```

```
Number of Duplicated Entries:  0
```

Transformation

Transformation

From the Data Understanding phase, we created box-plots to visualize each feature according to price. As we can see, many outliers exist, so let's identify them using IQR

In [ ]:

```
def detect_outliers(column): # this function detects outliers based on Q1, Q3 and IQR and 
returns the two quartile limits
  Q1 = column.quantile(0.25) # calcualtes the 25th percentile
  Q3 = column.quantile(0.75) # calculates the 75th percentile
  IQR = Q3-Q1 # calculates the IQR using Q1 and Q3
  lower = Q1-1.5*IQR # sets lower bound
  upper = Q3+1.5*IQR # sets upper bound
  return (column < lower) | (column > upper) # returns a updated column based upon the b
ounds set above
```

In [ ]:

```
outliers_beds = detect_outliers(price['beds']).sum() # detects the outliers of each categ
ory and sums them up
outliers_baths = detect_outliers(price['baths']).sum()
outliers_size = detect_outliers(price['size']).sum()
outliers_lot = detect_outliers(price['lot_size']).sum()
outlier_summary = { # prints out the outliers as a dictionary array
    'Beds Outliers':outliers_beds,
    'Baths Outliers':outliers_baths,
    'Size Outliers': outliers_size,
    'Lot Size Outliers': outliers_lot
}

outlier_summary
```

Out[ ]:

```
{'Beds Outliers': 9,
 'Baths Outliers': 62,
 'Size Outliers': 40,
 'Lot Size Outliers': 0}
```

Outlier Analysis

- **Beds: 9 outliers**
- **Baths: 62 outliers**
- **Size Outliers: 40 outliers**
- **Lot_Size Outliers: 0**

Let's try to adjust the dataset so that there aren't many outliers

In [ ]:

```
# Beds
Q1_beds = price['beds'].quantile(0.25) # calculates Q1 and Q3
Q3_beds = price['beds'].quantile(0.75)
IQR_beds = Q3_beds - Q1_beds
lower_beds = Q1_beds-1.5*IQR_beds # Calculates the upper and lower bounds
upper_beds = Q3_beds+1.5*IQR_beds

price['beds']=price['beds'].clip(lower=lower_beds,upper=upper_beds)
```

In [ ]:

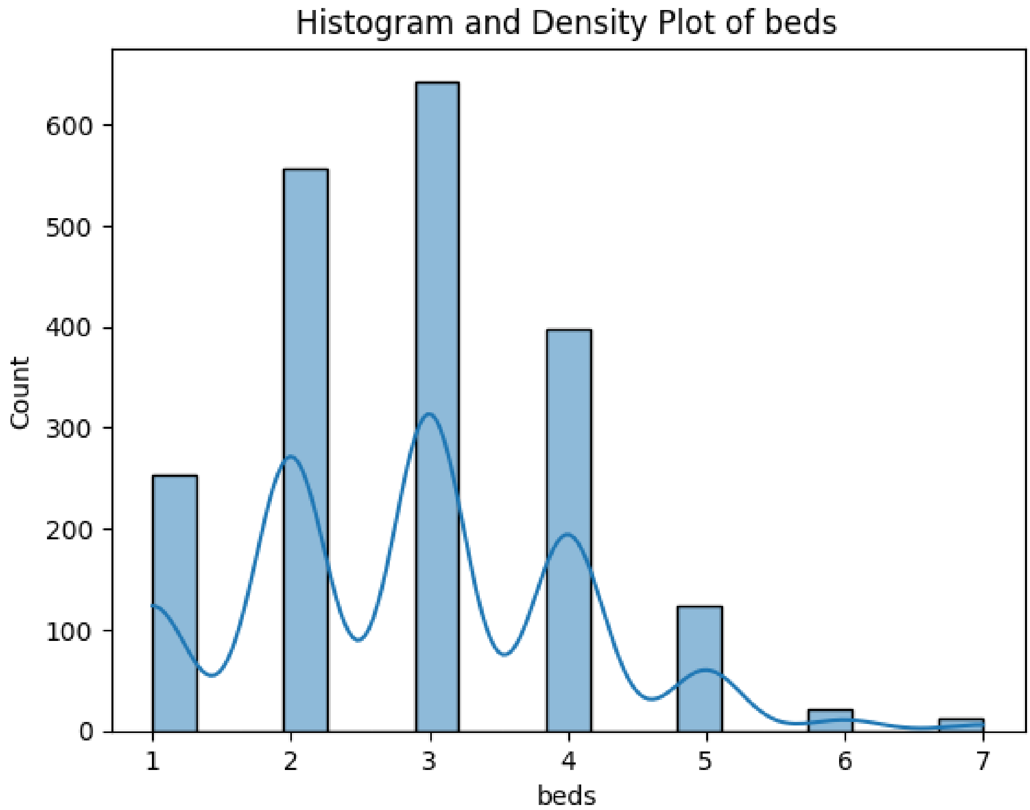
```
# Baths
Q1_baths = price['baths'].quantile(0.25)
Q3_baths = price['baths'].quantile(0.75)
IQR_baths = Q3_baths - Q1_baths
lower_baths = Q1_baths-1.5*IQR_baths
upper_baths = Q3_baths+1.5*IQR_baths

price['baths']=price['baths'].clip(lower=lower_baths,upper=upper_baths)
```

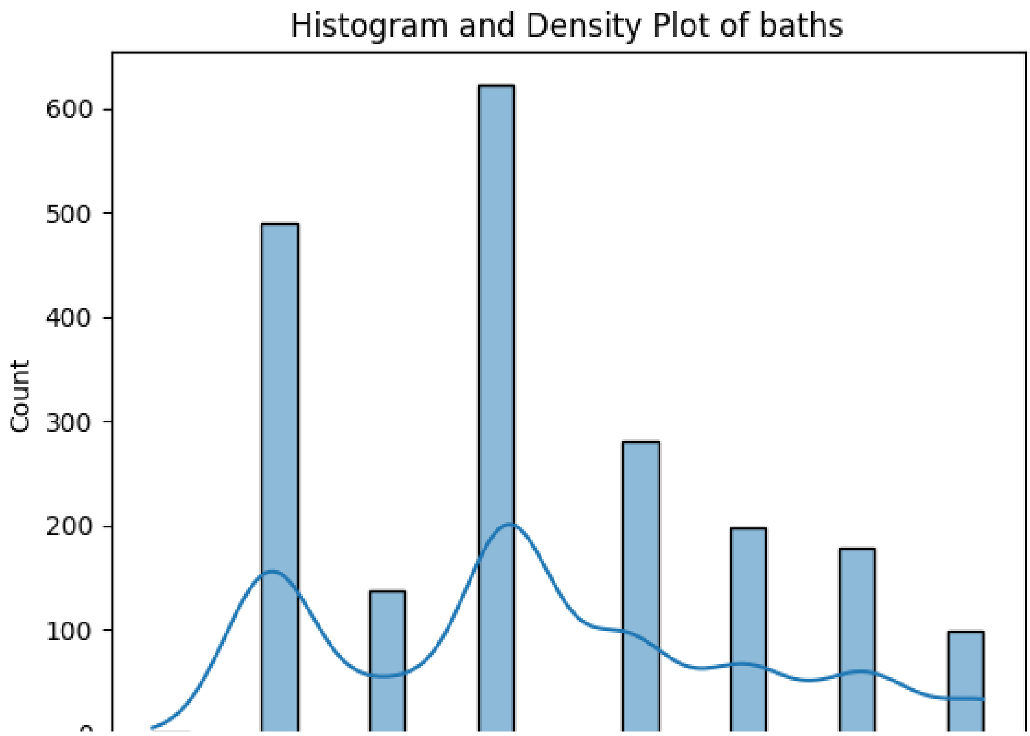
In [ ]:

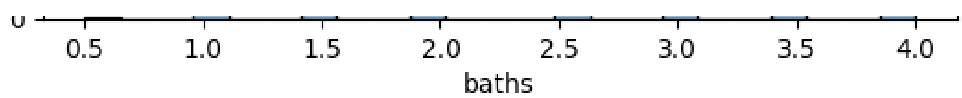
```
# Size
Q1_size = price['size'].quantile(0.25)
Q3_size = price['size'].quantile(0.75)
IQR_size = Q3_size - Q1_size
lower_size = Q1_size-1.5*IQR_size
upper_size = Q3_size+1.5*IQR_size

price['size']=price['size'].clip(lower=lower_size,upper=upper_size)
```

In [ ]:

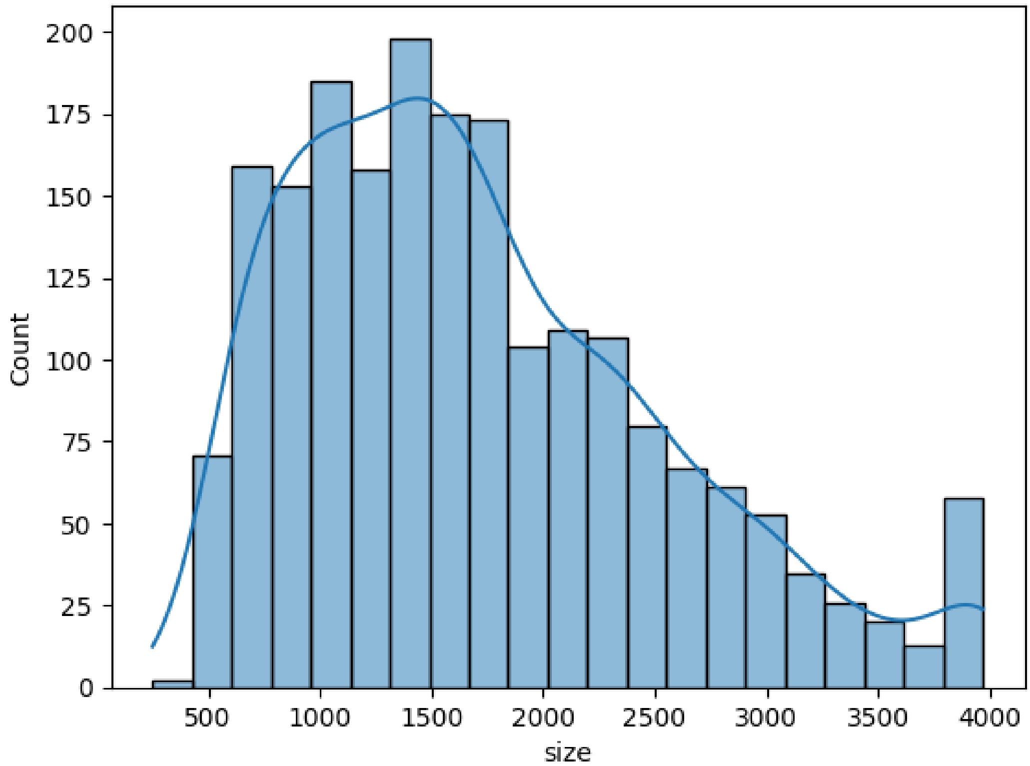
```
for col in price.select_dtypes(include=['number']).columns: # Let's look at the normalize
d distribution after removing outliers
  sns.histplot(price[col],kde=True)
  plt.title(f"Histogram and Density Plot of {col}")
  plt.show()
```



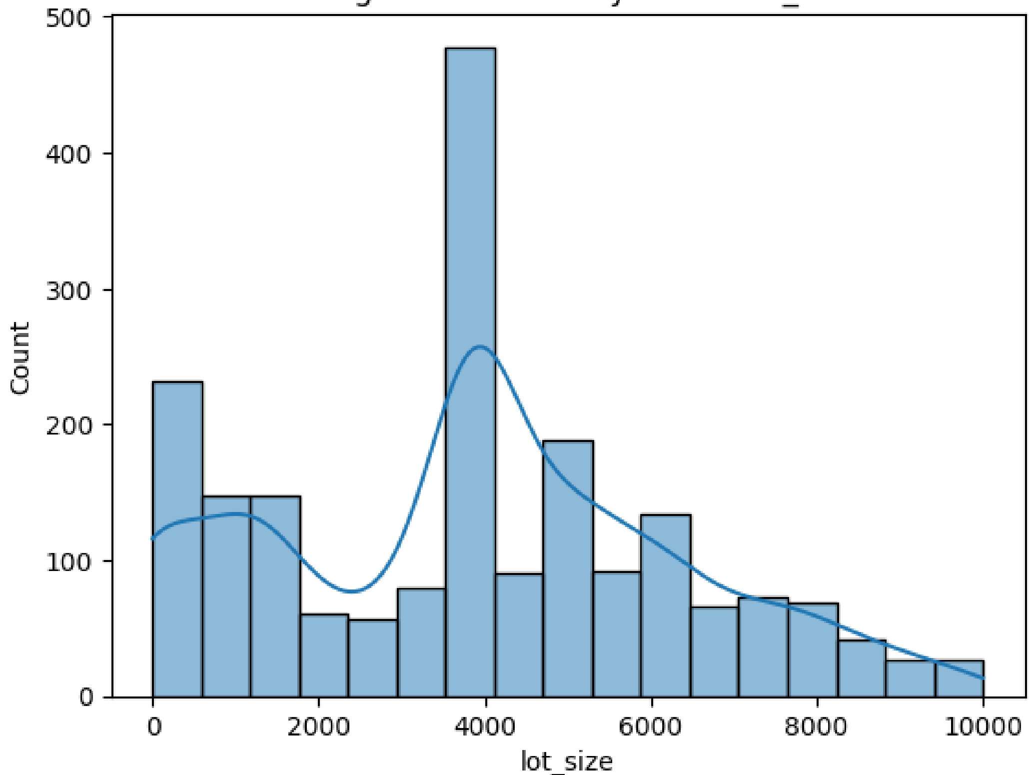




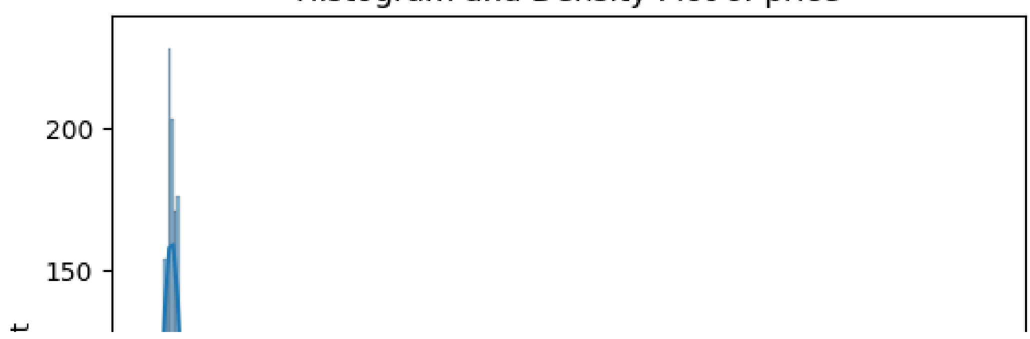
Histogram and Density Plot of size

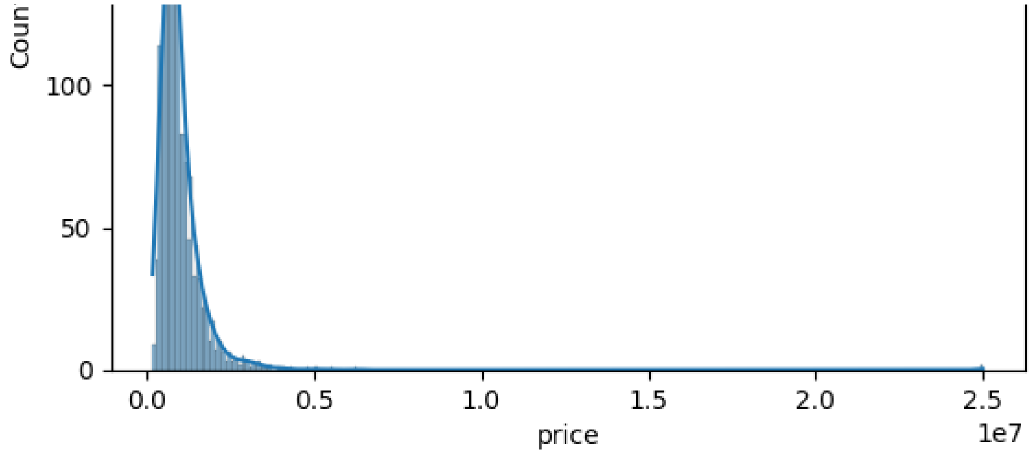


Histogram and Density Plot of lot_size



Histogram and Density Plot of price





As we can see from the histogram density plots of each variable, we no longer have outliers. Now we can start the model development phase!

Part 3 Model Development and Evaluation

In [ ]:

```
from sklearn.model_selection import train_test_split #Provides a function to split data i
nto training and testing sets.
from sklearn.pipeline import Pipeline # Allows sequential application of a list of transf
ormations and a final estimator.
from sklearn.linear_model import LinearRegression #Loads a linear regression model for pr
edictive analysis.
from sklearn.preprocessing import OneHotEncoder, PolynomialFeatures

from sklearn.metrics import mean_squared_error, r2_score # Imports functions to compute m
odel metrics.
import numpy as np #Imports the NumPy library for numerical computations.
import matplotlib.pyplot as plt # Loads the matplotlib library for plotting graphs.
from sklearn.tree import DecisionTreeRegressor #create a model based on decision trees fo
r regression tasks
from sklearn.tree import plot_tree
```

Data Splitting

In [ ]:

```
X = price.drop('price',axis=1) # setting up our X set that uses every column except pric
e
y = price['price'] # sets up the y set that only contains the price variable

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
) # splits the X and y sets into train/test containing 20% of the dataset randomly
```

LinearRegression, PolynomialRegression and DecisionTree

LinearRegression

In [ ]:

```
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [ ]:

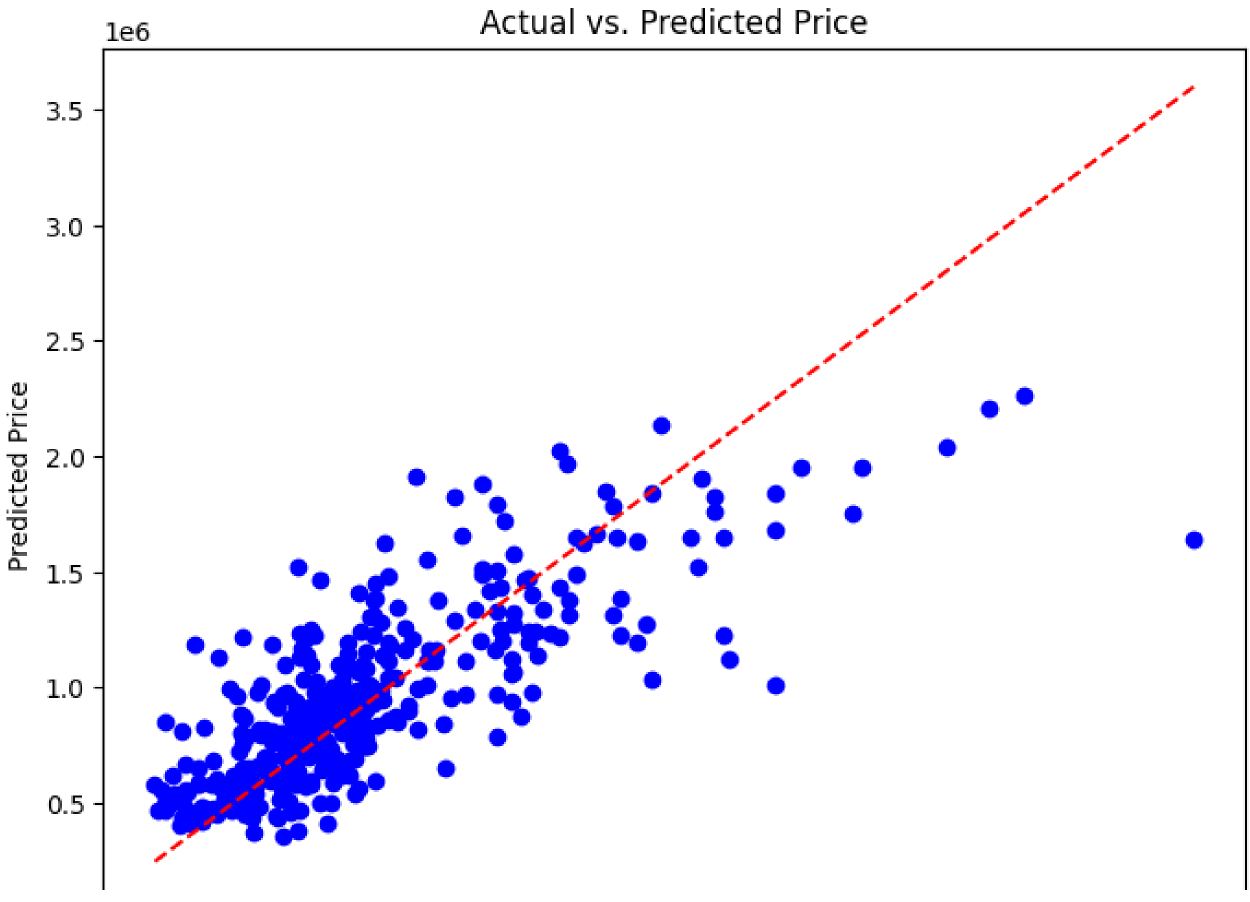
```
rmse = np.sqrt(mean_squared_error(y_test,y_pred)) # calculates RMSE
r2 = r2_score(y_test,y_pred) # calculate r-squared
```

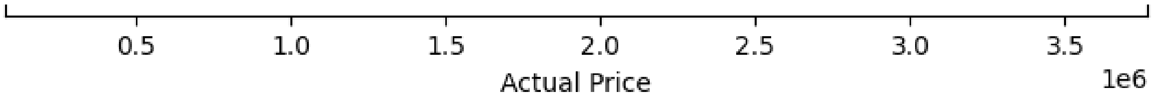
```
print("RMSE: ",rmse)
print('R^2: ',r2)

print("Coefficients of Regression: ",model.coef_) #prints the coefficient of each column
print("Intercepts of Regression: ",model.intercept_) # prints the overall intercept for t
he dataset
```

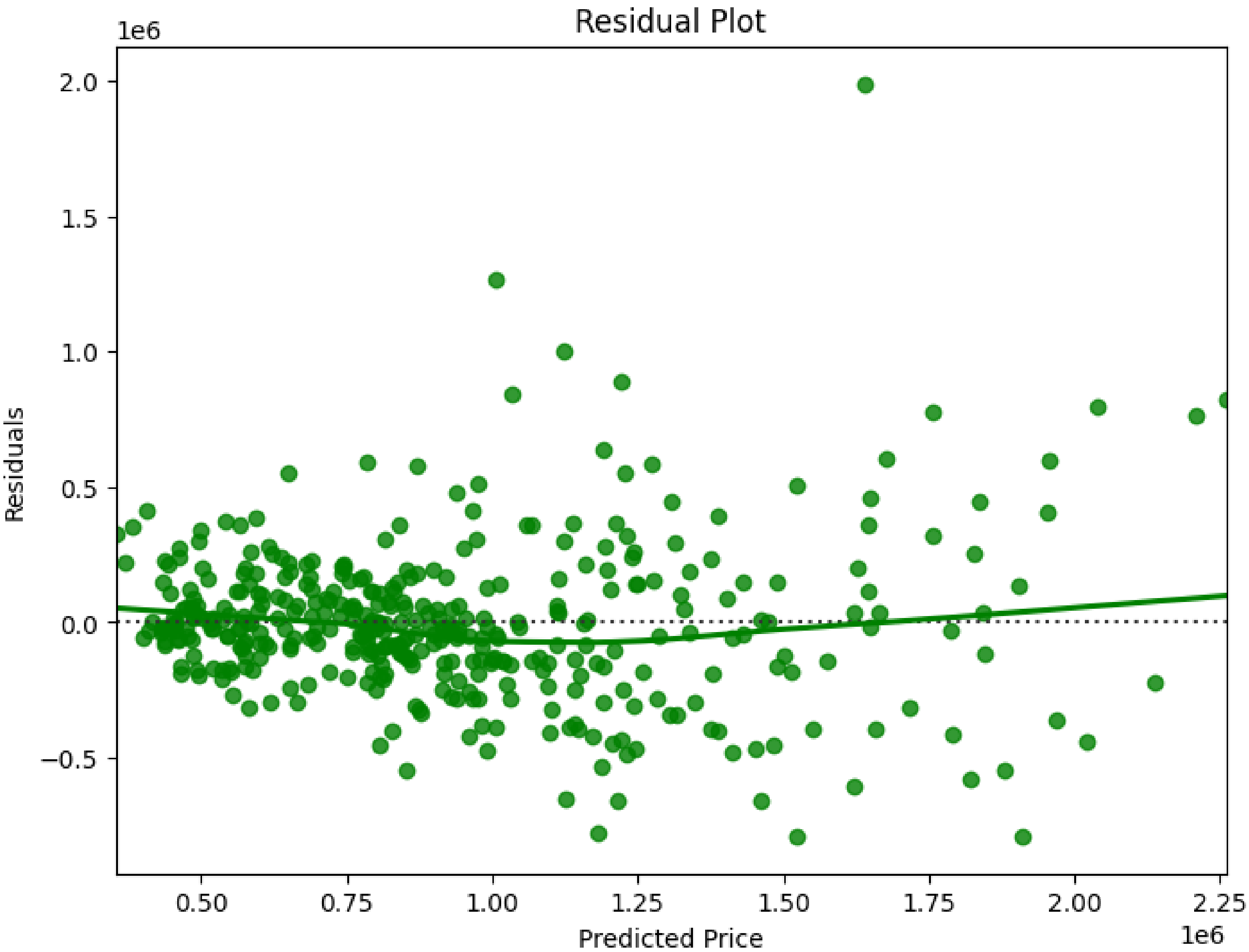
```
RMSE:  290184.16884769243
R^2:  0.6327489925647252
Coefficients of Regression:  [-1.03708032e+05  6.23314762e+04  5.68195016e+02 -6.39932842
e+00]
Intercepts of Regression:  181141.75421554246
```

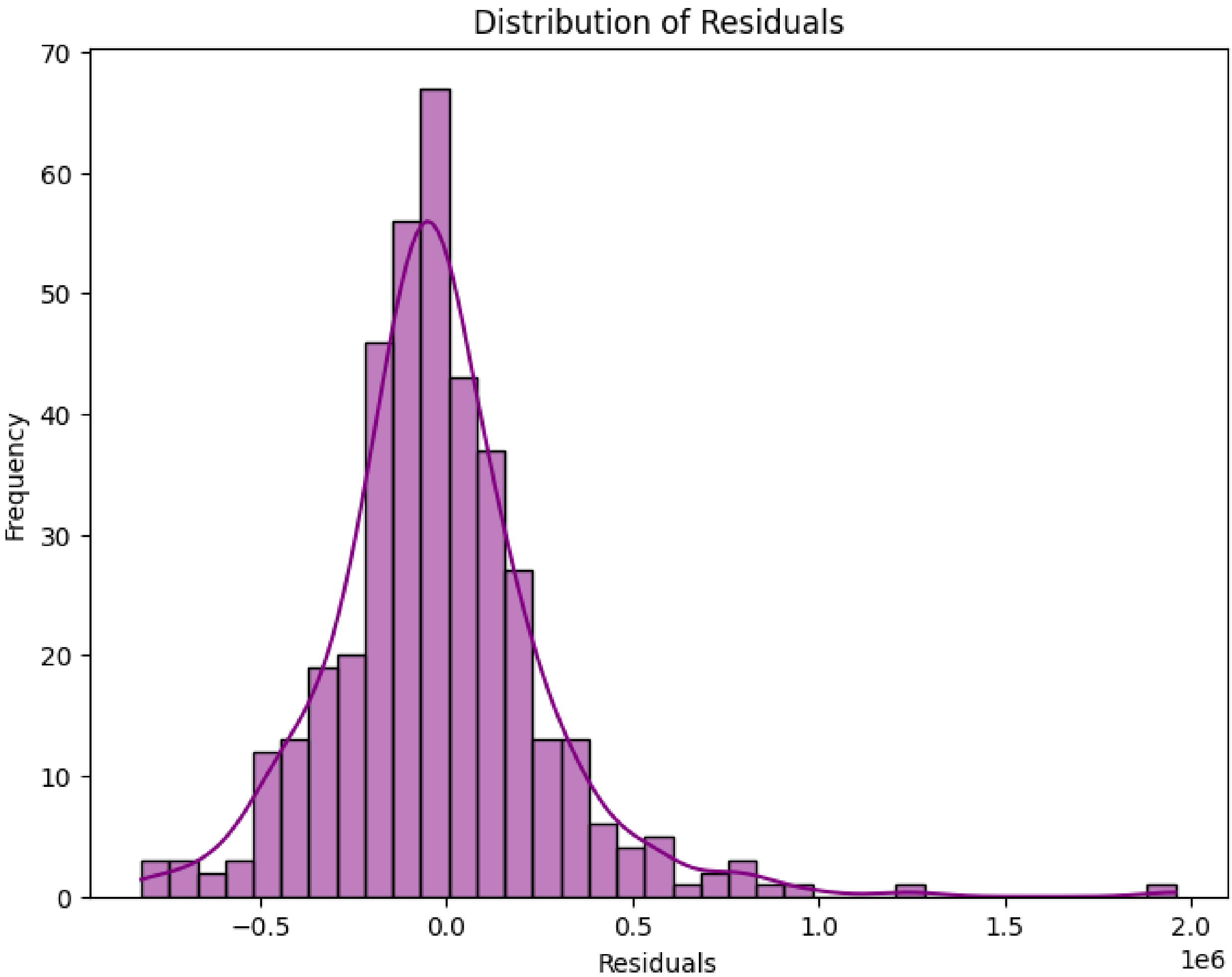
In [ ]:

```
# Scatter plot of actual vs. predicted values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], '--', color='red')
# Plotting the diagonal line
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs. Predicted Price')
plt.show()

# Residual plot
residuals = y_test - y_pred
plt.figure(figsize=(8, 6))
sns.residplot(x=y_pred, y=residuals, lowess=True, color='green')
plt.xlabel('Predicted Price')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

# Distribution plot of residuals
plt.figure(figsize=(8, 6))
sns.histplot(residuals, kde=True, color='purple')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals')
plt.show()
```




0.5
1.0
1.5
2.0
2.5
3.0
3.5
1e6
Actual Price


Residual Plot
1e6
2.0
1.5
1.0
0.5
0.0
−0.5
Residuals
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
1e6
Predicted Price


Distribution of Residuals
70
60
50
40
30
20
10
0
Frequency
−0.5
0.0
0.5
1.0
1.5
2.0
1e6
Residuals

Actual vs Predicted Plot:

- **Majority of the data lie along the regression line, so we can say the LinearRegression model predicts the house prices well.**

Residuals Plot

- **There are a lot of data points very close to the line, and no particular pattern exist so we can say that the predicted data is normally distributed.**

Residual Distribution Plot:

- **The residuals seem to be roughly normal with a slight right-skewed tail, but we can choose to ignore it and say it looks normally distributed.**

PolynomialRegression

In [ ]:

```
numerical_features = ['beds','baths', 'size','lot_size'] #Defines a list of numerical fea
tures to be transformed.
X_numerical_train = X_train[numerical_features] #Extracts the columns for the numerical f
eatures from the training data.
X_numerical_test = X_test[numerical_features] #Extracts the same columns for the numerica
l features from the test data.
poly_features = PolynomialFeatures(degree=2) #Creates an instance of PolynomialFeatures t
o generate polynomial and
# interaction features up to the second degree
X_poly_train = poly_features.fit_transform(X_numerical_train) #Fits the PolynomialFeature
s transformer to the training data
# and then transforms the training data, expanding it with polynomial features.
X_poly_test = poly_features.transform(X_numerical_test)
```

In [ ]:

```
# Creates an instance of the LinearRegression model.
poly_regression_model = LinearRegression()

#  Trains the linear regression model on the transformed training data (X_poly_train),
poly_regression_model.fit(X_poly_train, y_train)
```

Out[ ]:

```
▾ LinearRegression
LinearRegression()
```

In [ ]:

```
y_pred_poly = poly_regression_model.predict(X_poly_test)

### Calculates the Root Mean Squared Error (RMSE) between the actual target values in the
test set (y_test) and
# the predicted values (y_pred_poly). RMSE quantifies the model's prediction error.
rmse_poly = np.sqrt(mean_squared_error(y_test, y_pred_poly))

### Computes the R-squared (R²) score for the polynomial regression model's predictions
r2_poly = r2_score(y_test, y_pred_poly)
```

In [ ]:

```
print("Polynomial Regression - RMSE:", rmse_poly, "R2:", r2_poly) # print the metrics
```

```
Polynomial Regression - RMSE: 285722.56827141094 R2: 0.6439551936515422
```

DecisionTree

In [ ]:

```
tree_model = DecisionTreeRegressor() # creates a DecisionTree model

tree_model.fit(X_train,y_train) # fits the model to our training sets
y_pred = tree_model.predict(X_test) # tests the set and predicts values for price

rmse = np.sqrt(mean_squared_error(y_test,y_pred)) # calculates rmse
r2 = r2_score(y_test,y_pred) # calculates r-squared

print("RMSE: ",rmse)
print('R^2: ',r2)
```

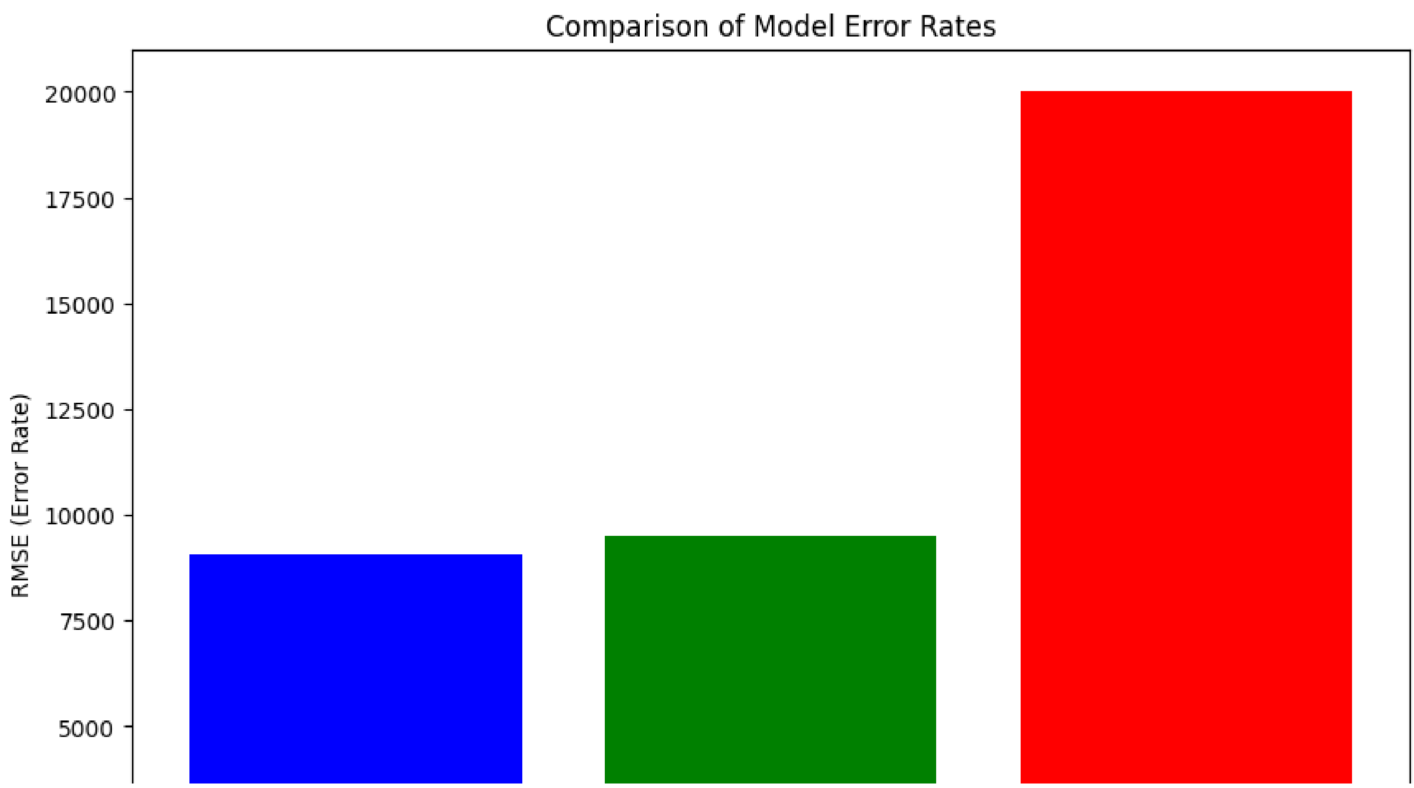
```
RMSE:  421237.5731992992
R^2:  0.2261268678187246
```

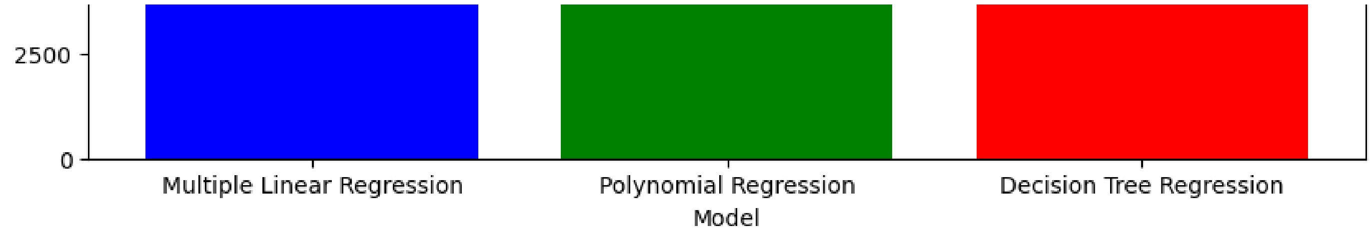
Model Comparison

RMSE

In [ ]:

```
# Define the models and their RMSE values
models = ['Multiple Linear Regression', 'Polynomial Regression', 'Decision Tree Regressi
on']
rmse_values = [9055.96, 9502.89, 20000.66]  # Replace these values with the actual RMSE
values obtained

# Set the positions for the bars
positions = np.arange(len(models))

# Plotting
plt.figure(figsize=(10, 7))
plt.bar(positions, rmse_values, color=['blue', 'green', 'red'])

# Labels and title
plt.xlabel('Model')
plt.ylabel('RMSE (Error Rate)')
plt.title('Comparison of Model Error Rates')
plt.xticks(positions, models)

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

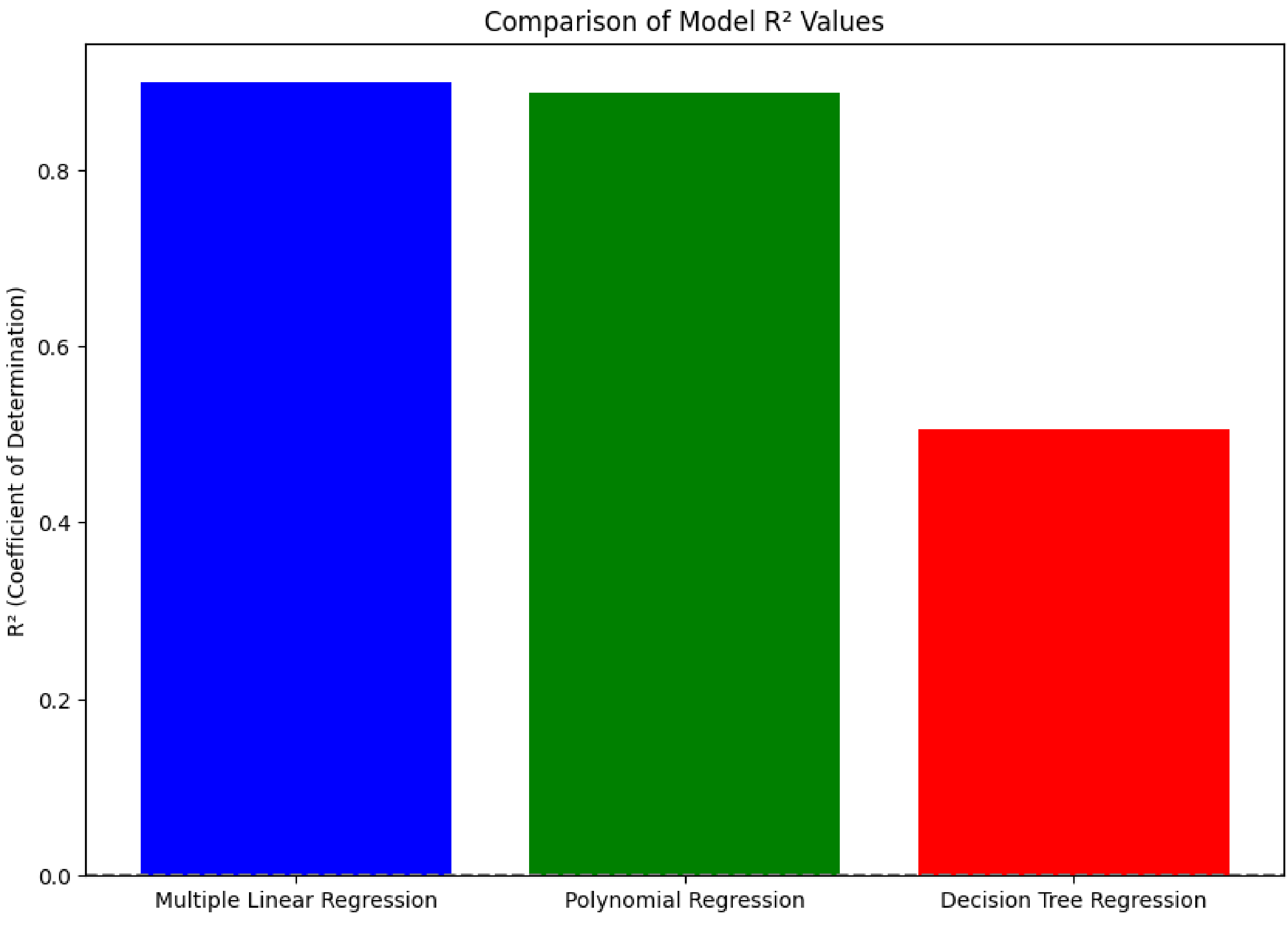




R^2

In [ ]:

```
# Define the models and their R² values
models = ['Multiple Linear Regression', 'Polynomial Regression', 'Decision Tree Regressi
on']
r2_values = [0.899, 0.888, 0.506]  # Replace these values with the actual R² values obta
ined

# Set the positions for the bars
positions = np.arange(len(models))

# Plotting
plt.figure(figsize=(10, 7))
plt.bar(positions, r2_values, color=['blue', 'green', 'red'])

# Labels and title
plt.xlabel('Model')
plt.ylabel('R² (Coefficient of Determination)')
plt.title('Comparison of Model R² Values')
plt.xticks(positions, models)

# Adding a horizontal line for R²=0 to indicate the baseline performance
plt.axhline(y=0, color='gray', linestyle='--')

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



Results

LinearRegression Model:

- **RMSE: 290184.16884769243**
- **R^2: 0.6327489925647252**

PolynomialRegression Model:

- **RMSE: 285722.56827141094**
- **R^2: 0.6439551936515422**

DecisionTree Model:

- **RMSE: 416353.14834879886**
- **R^2: 0.17588443727393532**

Which Model Is Best?

If we look at the two graphs above for RMSE and R^2, we can see that there is a higher error rate if we use RMSE for Decision Trees but, when we compare it to the R^2 metrics, it has a much lower R^2 value compared to the other two.

All three models have varying amounts of error but the model that does best for RMSE seem to be PolynomialRegression while R^2 is LinearRegression.

If it were up to us, we would pick LinearRegression more as it averages out much better than the other two models.