```python
# !pip install pandas numpy matplotlib seaborn scikit-learn
# Importing necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Load the dataset
# Assuming 'house_prices.csv' is in the current directory
data = pd.read_csv('/content/house-prices MF ori.csv')
# Replace with actual file path
print("First 5 rows of the dataset:")
print(data.head())

# Dataset info
print("\nDataset Information:")
print(data.info())

# Check for missing values
print("\nMissing Values: ")
print(data.isnull().sum())

# Fill missing values (example: median for numerical columns)
data['SqFt'].fillna(data['SqFt'].median(), inplace=True)
data['Bedrooms'].fillna (data['Bedrooms'].median(), inplace=True)

# Handle outliers (example: capping)
upper_limit = data['Price'].quantile (0.95)
data['Price'] = np.where(data['Price'] > upper_limit, upper_limit, data['Price'])


# Encoding the 'Location' column using one-hot encoding
# Apply one-hot encoding to 'Home' column explicitly
# Include 'Home' column name while encoding
data = pd.get_dummies(data, columns=['Neighborhood', 'Home'], drop_first=True)

from sklearn.preprocessing import MinMaxScaler

# Normalize numerical columns
scaler=MinMaxScaler()
data[ [ 'SqFt', 'Bedrooms']]= scaler.fit_transform(data[['SqFt', 'Bedrooms']])

# Define features and target variable
X = data.drop('Price', axis=1)
y = data['Price']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) # Changed 'x' to 'X'
print (f"Training set size: {X_train.shape}")
print (f"Testing set size: {X_test.shape}")


# Display coefficients
print("Model Coefficients:", model.coef_)  # Changed 'copf_' to 'coef_'
print("Intercept: ", model.intercept_)


# Initialize and train the model
model = LinearRegression()
model.fit(X_train, y_train)


y_pred = model.predict(X_test)

#Evaluate the model
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score (y_test, y_pred)

print(f"RMSE: {rmse:.2f}")
print(f"R2: {r2:.2f}")


# Scatter plot of actual vs predicted prices
plt.figure(figsize=(8, 6))
plt.scatter (y_test, y_pred, alpha=0.7)
plt.title("Actual vs Predicted Prices")
plt.xlabel("Actual Prices")
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plt.ylabel("Predicted Prices")
plt.show()

# Residual plot
residuals = y_test - y_pred
plt.figure(figsize=(8, 6))
sns.histplot(residuals, kde=True, bins=30, color='blue')
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.show()
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First 5 rows of the dataset:
Home    Price SqFt Bedrooms Bathrooms Offers Brick Neighborhood
0       1 114300 1790      2         2         2         2        101
1       2 114200 2030      4         2         3         2        101
2       3 114800 1740      3         2         1         2        101
3       4         94700 1980         3         2         3         2        101
4       5 119800 2130      3         3         3         2        101

Dataset Information:
<class 'pandas.core.frame.DataFrame'> RangeIndex: 128 entries, 0 to 127
Data columns (total 8 columns):
      #    Column        Non-Null        Dty
                         Count           pe
     ----                ------------------  -------
      0    ------        128 non-null    int
           Home                          64
      1    Price         128 non-null    int
                                         64
      2    SqFt          128 non-null    int
                                         64
      3    Bedrooms      128 non-null    int
                                         64
      4    Bathrooms     128 non-null    int
                                         64
      5    Offers        128 non-null    int
                                         64
      6    Brick         128 non-null    int
                                         64
      7    Neighborhood  128 non-null    int
                                         64
dtypes: int64(8)
memory usage: 8.1 KB None
Missing Values:
Home    0
Price   0
SqFt    0
Bedrooms0
Bathrooms        0
Offers  0
Brick   0
Neighborhood     0
dtype: int64
Training set size: (102, 134)
Testing set size: (26, 134)
Model Coefficients: [ 3.96012842e+04 5.45124252e+03 8.13017724e+03 -6.45453118e+03
-1.27413706e+04 1.85749763e+04 -7.19045383e+03 -5.61674296e+03
-6.03471359e+03 -2.15627637e+04 -3.04023473e-12 -1.97446774e+04 1.10140751e+03 1.33781364e+03 -3.39578045e+03 -1.17084488e+04
0.00000000e+00 2.27373675e-12 2.41387912e+03 3.35975003e+03
1.72793723e+04 3.18371053e+03 9.12524628e+03 -2.74953356e+04
-3.63797881e-12 -3.63797881e-12 6.53745034e+03 1.04874619e+04
-7.29829897e+03 -1.01556054e+04 3.00434371e+03 1.95116618e+04 3.63797881e-12 9.09494702e-12 -2.49548010e+04 6.94529090e+03
1.25593798e+04 1.27329258e-11 -1.15135630e+04 -5.13533257e+03
9.85001160e+03 -3.57628397e+03 -9.09494702e-12 -6.61517308e+03
-7.41493051e+03 1.01027142e+03 5.45696821e-12 -1.27762136e+04
-9.19306254e+03 1.41710815e+04 5.72569978e+03 -9.32232069e-12 7.61268286e+03 -1.84037413e+03 -5.00021404e+03 -4.58704921e+03
1.79273095e+04 -1.19866728e+04 2.56367025e+03 1.75591339e+04
-1.63087802e+04 -3.63797881e-12 -8.52651283e-12 -1.51686991e+03
-1.29136640e+04 2.01494026e+03 1.59456673e+04 4.32881768e+01 1.72335828e+03 -6.09873348e+03 -9.09494702e-12 -3.39453858e+03
7.46231129e+03 2.36057001e+04 -1.45758537e+04 -1.81898940e-12
1.20328513e+04 1.78328246e+03 9.69121977e+03 -7.23175024e+03
-4.32599221e+03 -4.03072272e+03 -9.75537274e+03 8.55224079e+03 7.01699484e+03 9.83710532e+02 -1.81898940e-12 -3.18323146e-12
3.69725013e+03 1.91520138e+03 -1.81898940e-12 6.10484867e+03
1.04417796e+03 7.35544671e+03 5.77988014e+03 -4.04283690e+03
2.07492611e+03 -1.21227495e+04 -3.20820709e+03 2.27787310e+04
0.00000000e+00 -5.82371238e+03 0.00000000e+00 -1.39908751e+04
0.00000000e+00 5.36238417e+03 5.99461344e+03 1.88949021e+03
3.92426374e+03 5.95916581e+03 0.00000000e+00 0.00000000e+00
6.71526023e+02 -4.78677943e+03 -2.04816912e+04 -1.20786996e+04
8.14960135e+02 9.52735226e+03 -8.65206584e+03 0.00000000e+00
-9.20669202e+03 -1.19234496e+04 -1.16864593e+04 4.35743707e+03 0.00000000e+00 1.09835803e+04 -3.24850784e+03 -1.70560425e+04
1.92484674e+03 -1.46552740e+04 2.69577332e+03 0.00000000e+00
```
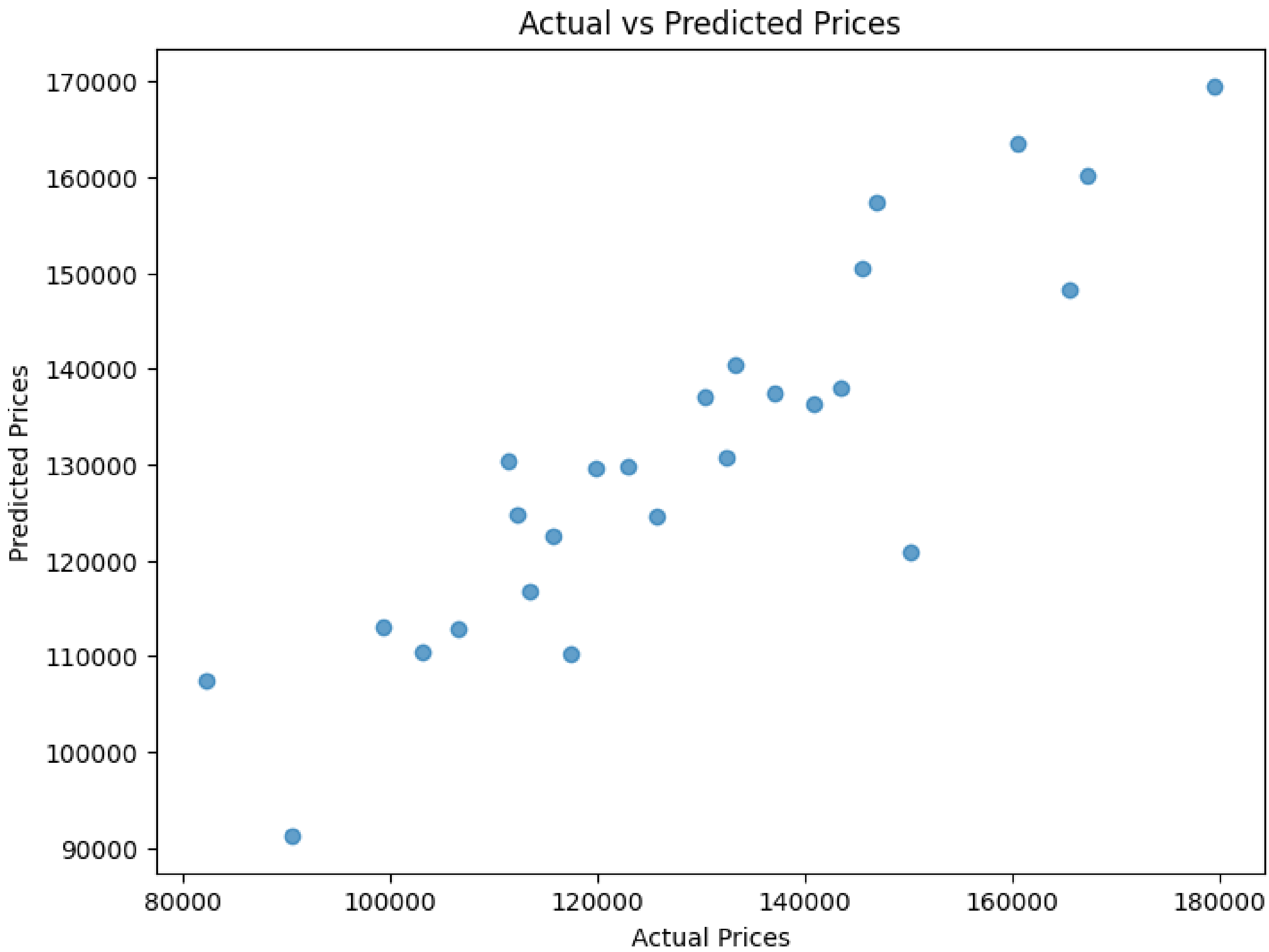
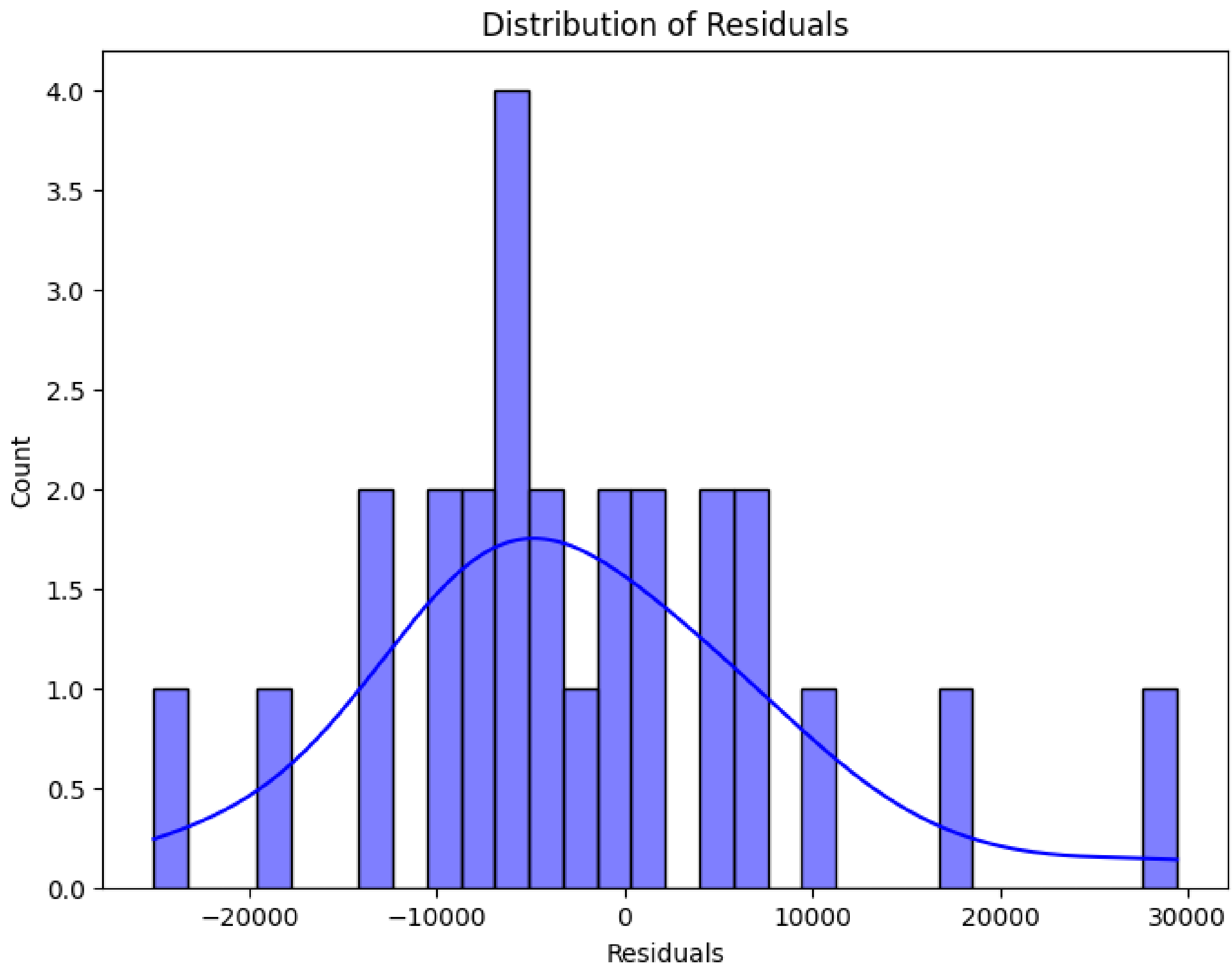


Actual vs Predicted Prices
Predicted Prices
Actual Prices
170000
160000
150000
140000
130000
120000
110000
100000
90000
80000
100000
120000
140000
160000
180000


Distribution of Residuals
Count
Residuals
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−20000
−10000
0
10000
20000
30000