housing-price-prediction

February 19, 2024

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

[2]:
```
df = pd.read_csv("/content/Housing.csv")
df.head()
```

[2]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	\
0	13300000	7420	4	2	3	yes	no	no	
1	12250000	8960	4	4	4	yes	no	no	
2	12250000	9960	3	2	2	yes	no	yes	
3	12215000	7500	4	2	2	yes	no	yes	
4	11410000	7420	4	1	2	yes	yes	yes	

	hotwaterheating	airconditioning	parking	prefarea	furnishingstatus
0	no	yes	2	yes	furnished
1	no	yes	3	no	furnished
2	no	no	2	yes	semi-furnished
3	no	yes	3	yes	furnished
4	no	yes	2	no	furnished

Data Cleaning:

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             545 non-null    int64
 1   area              545 non-null    int64
 2   bedrooms          545 non-null    int64
 3   bathrooms         545 non-null    int64
 4   stories           545 non-null    int64
 5   mainroad          545 non-null    object
 6   guestroom         545 non-null    object
 7   basement          545 non-null    object
```

```
 8   hotwaterheating   545 non-null    object
 9   airconditioning   545 non-null    object
 10  parking           545 non-null    int64
 11  prefarea          545 non-null    object
 12  furnishingstatus  545 non-null    object
dtypes: int64(6), object(7)
memory usage: 55.5+ KB
```

[4]:
```
df.describe()
```

[4]:

	price	area	bedrooms	bathrooms	stories	parking
count	5.450000e+02	545.000000	545.000000	545.000000	545.000000	545.000000
mean	4.766729e+06	5150.541284	2.965138	1.286239	1.805505	0.693578
std	1.870440e+06	2170.141023	0.738064	0.502470	0.867492	0.861586
min	1.750000e+06	1650.000000	1.000000	1.000000	1.000000	0.000000
25%	3.430000e+06	3600.000000	2.000000	1.000000	1.000000	0.000000
50%	4.340000e+06	4600.000000	3.000000	1.000000	2.000000	0.000000
75%	5.740000e+06	6360.000000	3.000000	2.000000	2.000000	1.000000
max	1.330000e+07	16200.000000	6.000000	4.000000	4.000000	3.000000

[5]:
```
print("\033[1mMissing values:\033[0m")
print(df.isnull().sum())
```

Missing values:
```
price             0
area              0
bedrooms          0
bathrooms         0
stories           0
mainroad          0
guestroom         0
basement          0
hotwaterheating   0
airconditioning   0
parking           0
prefarea          0
furnishingstatus  0
dtype: int64
```

[6]:
```
# Convert categorical variables to numerical using one-hot encoding
df = pd.get_dummies(df, columns=['mainroad', 'guestroom', 'basement',␣
↪'hotwaterheating',
                                 'airconditioning', 'prefarea',␣
↪'furnishingstatus'], drop_first=True)
```

[7]:
```
# Verify changes
print("\033[1mDataFrame after cleaning:\033[0m")
df.head()
```

DataFrame after cleaning:

[7]:

	price	area	bedrooms	bathrooms	stories	parking	mainroad_yes	\
0	13300000	7420	4	2	3	2	1	
1	12250000	8960	4	4	4	3	1	
2	12250000	9960	3	2	2	2	1	
3	12215000	7500	4	2	2	3	1	
4	11410000	7420	4	1	2	2	1	

	guestroom_yes	basement_yes	hotwaterheating_yes	airconditioning_yes	\
0	0	0	0	1	
1	0	0	0	1	
2	0	1	0	0	
3	0	1	0	1	
4	1	1	0	1	

	prefarea_yes	furnishingstatus_semi-furnished	furnishingstatus_unfurnished
0	1	0	0
1	0	0	0
2	1	1	0
3	1	0	0
4	0	0	0

Feature Selection:

[8]:
```
df.corr()
```

[8]:

	price	area	bedrooms	bathrooms	\
price	1.000000	0.535997	0.366494	0.517545	
area	0.535997	1.000000	0.151858	0.193820	
bedrooms	0.366494	0.151858	1.000000	0.373930	
bathrooms	0.517545	0.193820	0.373930	1.000000	
stories	0.420712	0.083996	0.408564	0.326165	
parking	0.384394	0.352980	0.139270	0.177496	
mainroad_yes	0.296898	0.288874	-0.012033	0.042398	
guestroom_yes	0.255517	0.140297	0.080549	0.126469	
basement_yes	0.187057	0.047417	0.097312	0.102106	
hotwaterheating_yes	0.093073	-0.009229	0.046049	0.067159	

```
airconditioning_yes              0.452954  0.222393  0.160603   0.186915
prefarea_yes                     0.329777  0.234779  0.079023   0.063472
furnishingstatus_semi-furnished  0.063656  0.006156  0.050040   0.029834
furnishingstatus_unfurnished    -0.280587 -0.142278 -0.126252  -0.132107

                                  stories   parking  mainroad_yes  \
price                            0.420712  0.384394      0.296898
area                             0.083996  0.352980      0.288874
bedrooms                         0.408564  0.139270     -0.012033
bathrooms                        0.326165  0.177496      0.042398
stories                          1.000000  0.045547      0.121706
parking                          0.045547  1.000000      0.204433
mainroad_yes                     0.121706  0.204433      1.000000
guestroom_yes                    0.043538  0.037466      0.092337
basement_yes                    -0.172394  0.051497      0.044002
hotwaterheating_yes              0.018847  0.067864     -0.011781
airconditioning_yes              0.293602  0.159173      0.105423
prefarea_yes                     0.044425  0.091627      0.199876
furnishingstatus_semi-furnished -0.003648  0.041327      0.011450
furnishingstatus_unfurnished    -0.082972 -0.165705     -0.133123

                                 guestroom_yes  basement_yes  \
price                                 0.255517      0.187057
area                                  0.140297      0.047417
bedrooms                              0.080549      0.097312
bathrooms                             0.126469      0.102106
stories                               0.043538     -0.172394
parking                               0.037466      0.051497
mainroad_yes                          0.092337      0.044002
guestroom_yes                         1.000000      0.372066
basement_yes                          0.372066      1.000000
hotwaterheating_yes                  -0.010308      0.004385
airconditioning_yes                   0.138179      0.047341
prefarea_yes                          0.160897      0.228083
furnishingstatus_semi-furnished       0.005821      0.050284
furnishingstatus_unfurnished         -0.099023     -0.117935

                                 hotwaterheating_yes  airconditioning_yes  \
price                                       0.093073             0.452954
area                                       -0.009229             0.222393
bedrooms                                    0.046049             0.160603
bathrooms                                   0.067159             0.186915
stories                                     0.018847             0.293602
parking                                     0.067864             0.159173
mainroad_yes                               -0.011781             0.105423
guestroom_yes                              -0.010308             0.138179
basement_yes                                0.004385             0.047341
```

hotwaterheating_yes	1.000000	-0.130023
airconditioning_yes	-0.130023	1.000000
prefarea_yes	-0.059411	0.117382
furnishingstatus_semi-furnished	0.063819	-0.053179
furnishingstatus_unfurnished	-0.059194	-0.094086

	prefarea_yes \
price	0.329777
area	0.234779
bedrooms	0.079023
bathrooms	0.063472
stories	0.044425
parking	0.091627
mainroad_yes	0.199876
guestroom_yes	0.160897
basement_yes	0.228083
hotwaterheating_yes	-0.059411
airconditioning_yes	0.117382
prefarea_yes	1.000000
furnishingstatus_semi-furnished	-0.011535
furnishingstatus_unfurnished	-0.081271

	furnishingstatus_semi-furnished \
price	0.063656
area	0.006156
bedrooms	0.050040
bathrooms	0.029834
stories	-0.003648
parking	0.041327
mainroad_yes	0.011450
guestroom_yes	0.005821
basement_yes	0.050284
hotwaterheating_yes	0.063819
airconditioning_yes	-0.053179
prefarea_yes	-0.011535
furnishingstatus_semi-furnished	1.000000
furnishingstatus_unfurnished	-0.588405

	furnishingstatus_unfurnished
price	-0.280587
area	-0.142278
bedrooms	-0.126252
bathrooms	-0.132107
stories	-0.082972
parking	-0.165705
mainroad_yes	-0.133123
guestroom_yes	-0.099023

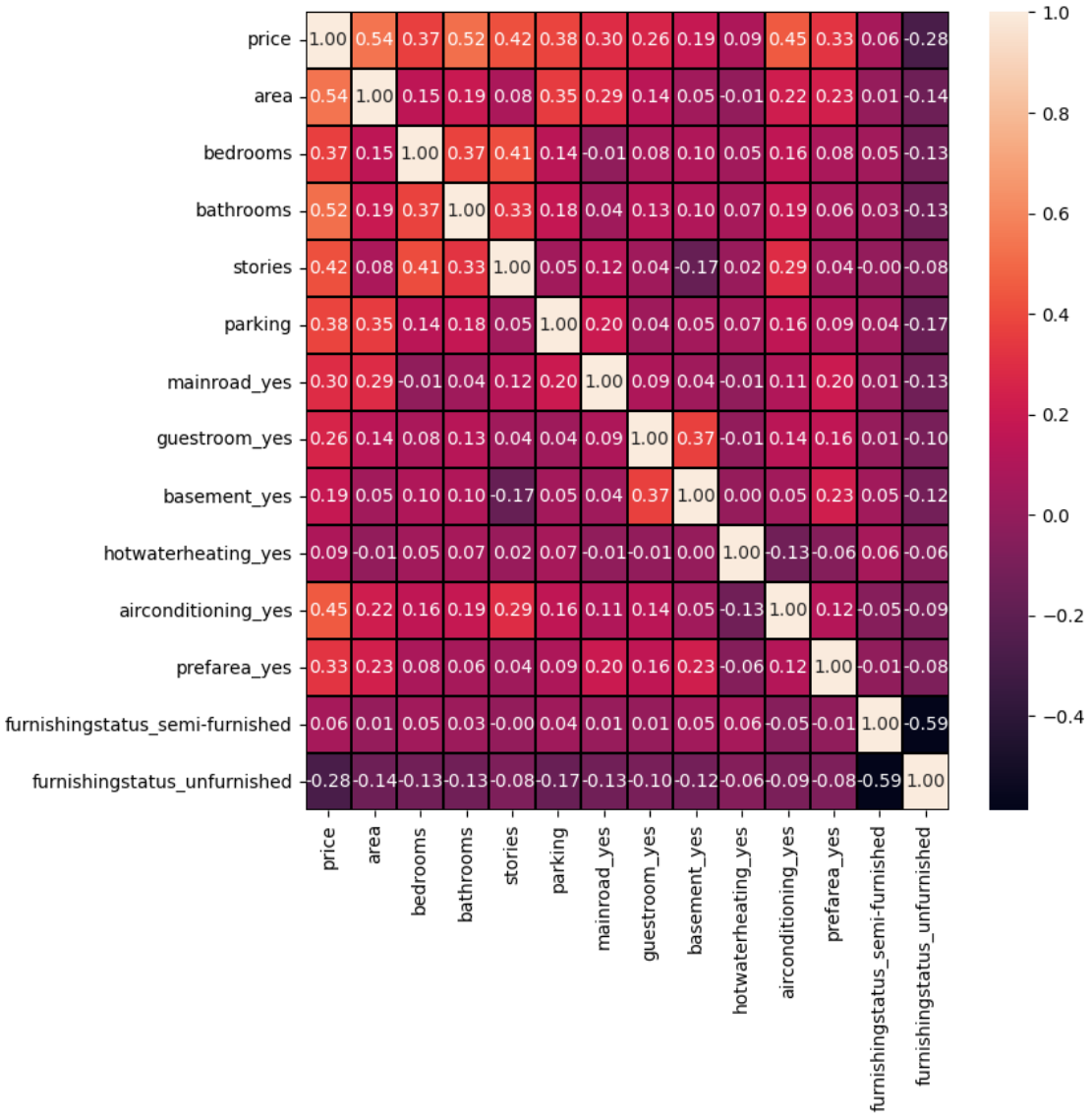
```
basement_yes                      -0.117935
hotwaterheating_yes               -0.059194
airconditioning_yes               -0.094086
prefarea_yes                      -0.081271
furnishingstatus_semi-furnished   -0.588405
furnishingstatus_unfurnished       1.000000
```

[9]:
```
import matplotlib.pyplot as plt
import seaborn as sns

corr = df.corr()

fig, ax = plt.subplots(figsize=(8, 8))
sns.heatmap(corr, annot=True, linewidths=0.2, linecolor="black", fmt=".2f",␣
 ↪ax=ax)

plt.show()
```



[10]:
```
# Find features with correlation greater than a threshold with the target␣
↪variable
threshold = 0.5
high_corr_features = corr.index[abs(corr['price']) > threshold].tolist()

# Print selected features
print("\033[1mFeatures with high correlation with the target variable:\033[0m")
print(high_corr_features)
```

Features with high correlation with the target variable:
['price', 'area', 'bathrooms']

[11]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression

# Assuming X contains the features and y contains the target variable (price)
X = df.drop(columns=['price'])  # Features
y = df['price']  # Target variable

# Initialize a linear regression model
model = LinearRegression()

# Initialize RFE
rfe = RFE(model, n_features_to_select=3)
# Fit RFE
rfe.fit(X, y)

# Get selected features
selected_features = X.columns[rfe.support_]
# Print selected features
print("\033[1mSelected features using RFE:\033[0m")
print(selected_features)
```

Selected features using RFE:
Index(['bathrooms', 'mainroad_yes', 'airconditioning_yes'], dtype='object')

[12]:
```
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler

# Assuming X contains the features and y contains the target variable (price)
X = df.drop(columns=['price'])  # Features
y = df['price']  # Target variable

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Initialize Lasso regression model
lasso = Lasso(alpha=0.1)

# Fit Lasso model
lasso.fit(X_scaled, y)

# Get coefficients and select non-zero coefficient features
selected_features = X.columns[lasso.coef_ != 0]

# Print selected features
print("\033[1mSelected features using Lasso regularization:\033[0m")
print(selected_features)
```

```
Selected features using Lasso regularization:
Index(['area', 'bedrooms', 'bathrooms', 'stories', 'parking', 'mainroad_yes',
       'guestroom_yes', 'basement_yes', 'hotwaterheating_yes',
       'airconditioning_yes', 'prefarea_yes',
       'furnishingstatus_semi-furnished', 'furnishingstatus_unfurnished'],
      dtype='object')
```

Model Training:

[13]:
```
from sklearn.linear_model import LinearRegression

# Assuming X contains the selected features and y contains the target variable (price)
X = df[selected_features]  # Selected features
y = df['price']  # Target variable

# Initialize and fit the linear regression model
model = LinearRegression()
model.fit(X, y)
```

[13]:
```
LinearRegression()
```

Model Evaluation:

[14]:
```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.model_selection import train_test_split

# Assuming X_test contains the selected features and y_test contains the actual target variable values for the test set
X_test = df[selected_features]  # Selected features from the test set
y_test = df['price']  # Actual target variable values for the test set

# Make predictions on the test set
y_pred = model.predict(X_test)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)

# Calculate R-squared
r_squared = r2_score(y_test, y_pred)

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_pred)

print("\033[1mMean Squared Error (MSE):\033[0m", mse)
print("\033[1mR-squared:\033[0m", r_squared)
print("\033[1mMean Absolute Error (MAE):\033[0m", mae)
```

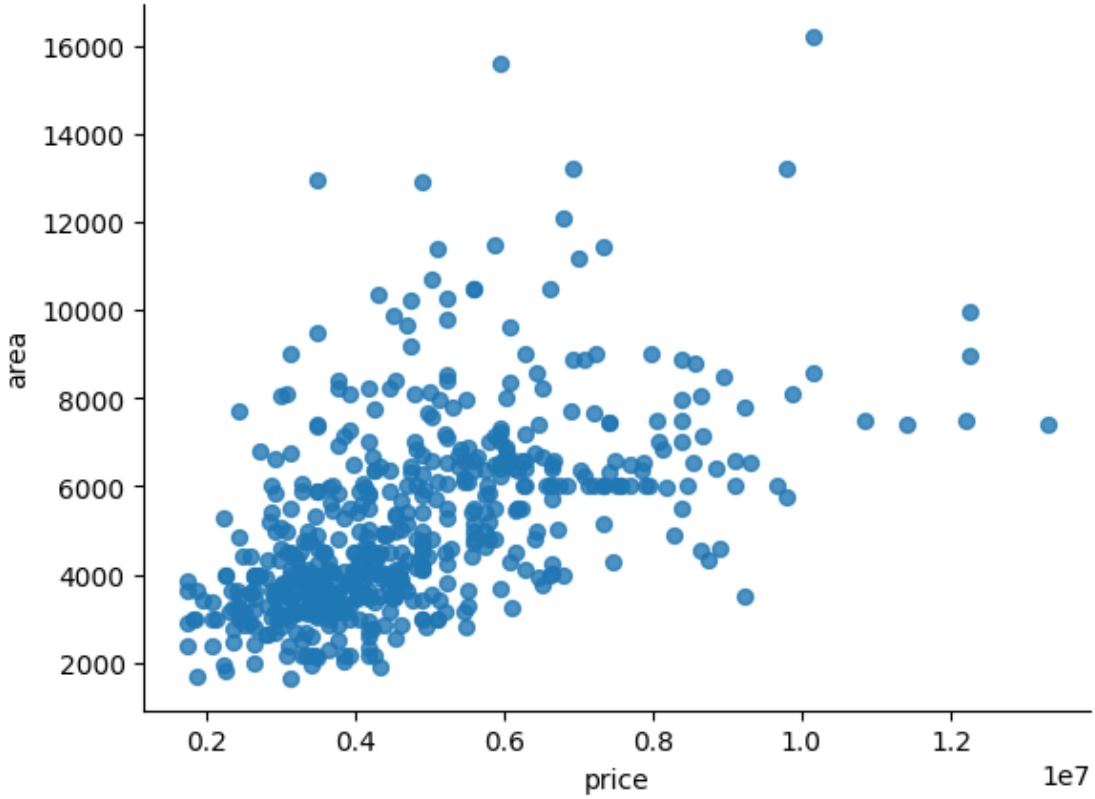
```
Mean Squared Error (MSE): 1111187722284.4001
```

R-squared: 0.6818018485540142
Mean Absolute Error (MAE): 775054.3287400283

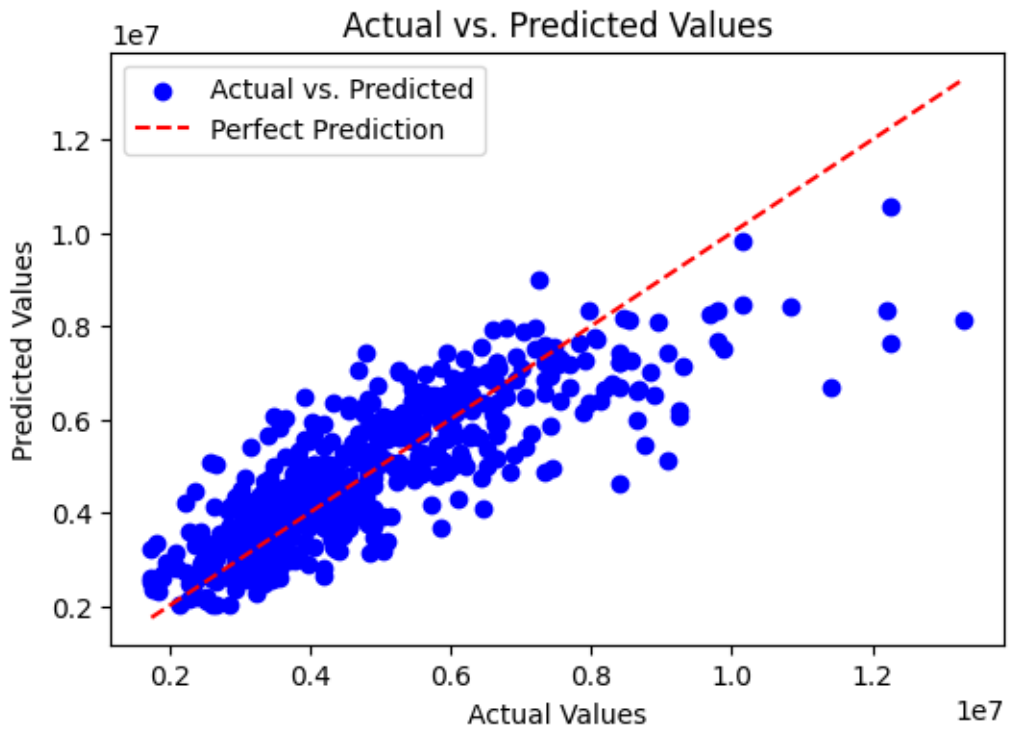
Visualization:

[15]:
```
# price vs area
plt.figure(figsize=(6, 4))
df.plot(kind='scatter', x='price', y='area', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

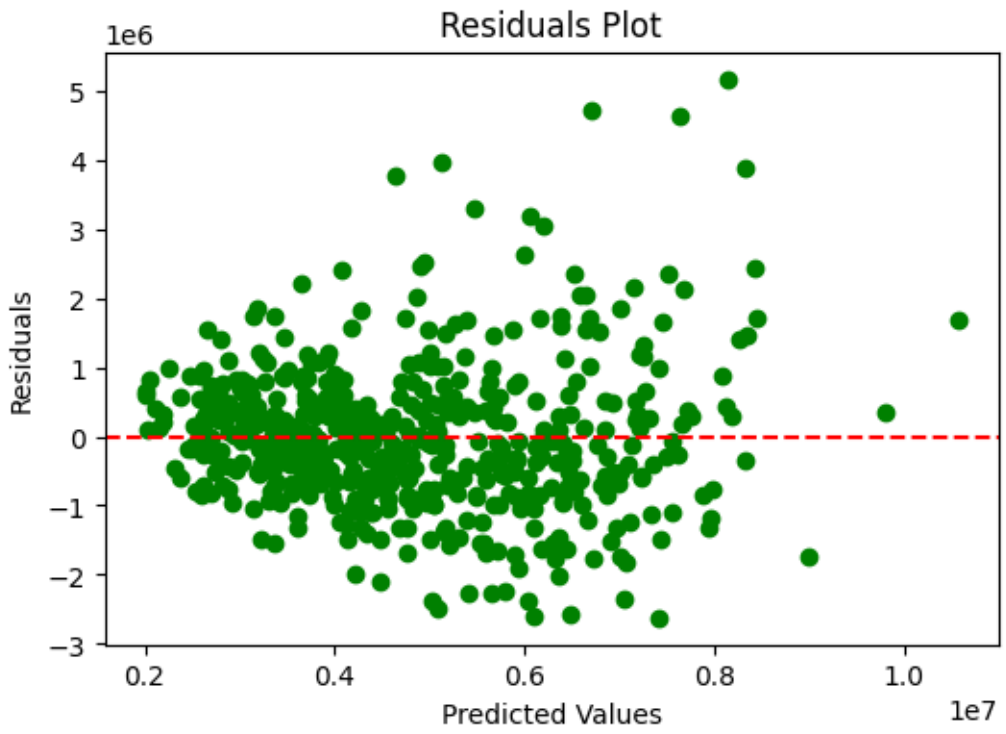
```
<Figure size 600x400 with 0 Axes>
```



[16]:
```
# Plotting the predicted vs. actual values
plt.figure(figsize=(6, 4))
plt.scatter(y_test, y_pred, color='blue', label='Actual vs. Predicted')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
 ↪linestyle='--', label='Perfect Prediction')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted Values')
plt.legend()
plt.show()
```



[17]:
```
# Plotting residuals
residuals = y_test - y_pred
plt.figure(figsize=(6, 4))
plt.scatter(y_pred, residuals, color='green')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residuals Plot')
plt.axhline(y=0, color='red', linestyle='--')
plt.show()
```


Residuals Plot
1e6
5
4
3
2
1
0
−1
−2
−3
Residuals
0.2
0.4
0.6
0.8
1.0
1e7
Predicted Values