Linear Regression

A linear regression model to predict house price

Data and libraries import:

In [1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split

df = pd.read_csv('data/house-prices.csv')
X = df[['SqFt', 'Bedrooms', 'Bathrooms', 'Offers', 'Brick', 'Neighborhood']]
y = df['Price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, rar
```

Preprocessing Data

showing Data's Info and Missed value count:

In [2]:
```
# Check for missing values
print("Missing values per column:\n", X_train.isna().sum())
# Display data info
print("\nData info:\n")
print(X_train.info())
# Display summary statistics
print("\nSummary statistics:\n")
print(X_train.describe())
```

```
Missing values per column:
 SqFt            2
Bedrooms        3
Bathrooms       1
Offers          2
Brick           0
Neighborhood    0
dtype: int64

Data info:

<class 'pandas.core.frame.DataFrame'>
Index: 115 entries, 4 to 102
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   SqFt          113 non-null    float64
 1   Bedrooms      112 non-null    float64
 2   Bathrooms     114 non-null    float64
 3   Offers        113 non-null    float64
 4   Brick         115 non-null    object 
 5   Neighborhood  115 non-null    object 
dtypes: float64(4), object(2)
memory usage: 6.3+ KB
None

Summary statistics:

              SqFt    Bedrooms   Bathrooms      Offers
count   113.000000  112.000000  114.000000  113.000000
mean   2008.761062    3.026786    2.464912    2.592920
std     214.247574    0.728565    0.518333    1.090848
min    1450.000000    2.000000    2.000000    1.000000
25%    1890.000000    3.000000    2.000000    2.000000
50%    2000.000000    3.000000    2.000000    3.000000
75%    2150.000000    3.000000    3.000000    3.000000
max    2590.000000    5.000000    4.000000    6.000000
```

Recovery Missed Values:

Replacing numerical missed values with *mean* and categorical missed values with *mode*

In [3]:

```python
# Fill missing numerical values with the mean
numerical_cols = ['SqFt', 'Bedrooms', 'Bathrooms', 'Offers']
for col in numerical_cols:
    X_train[col].fillna(X_train[col].mean(), inplace=True)
    X_test[col].fillna(X_train[col].mean(), inplace=True)  # Use train mean

# Fill missing categorical values with the mode
categorical_cols = ['Brick', 'Neighborhood']
for col in categorical_cols:
    X_train[col].fillna(X_train[col].mode()[0], inplace=True)
    X_test[col].fillna(X_train[col].mode()[0], inplace=True)  # Use train mc
```

```
print("Missing values per column after recovery:\n", X_train.isna().sum())
print(X_train.describe())
```

```
Missing values per column after recovery:
 SqFt           0
Bedrooms       0
Bathrooms      0
Offers         0
Brick          0
Neighborhood   0
dtype: int64
              SqFt    Bedrooms   Bathrooms      Offers
count   115.000000  115.000000  115.000000  115.000000
mean   2008.761062    3.026786    2.464912    2.592920
std     212.359893    0.718915    0.516055    1.081237
min    1450.000000    2.000000    2.000000    1.000000
25%    1895.000000    3.000000    2.000000    2.000000
50%    2000.000000    3.000000    2.000000    3.000000
75%    2145.000000    3.026786    3.000000    3.000000
max    2590.000000    5.000000    4.000000    6.000000
```

Removing Outliers:

removing outliers of numercial columns using IQR method. this method wouldn't be applied to *Bedroom* column because most of data are outlier.(due to distribution of this feature it should not include in training model)

In [4]:
```
n = X_train.shape[0]
# Detect outliers in X_train using the IQR method
for col in numerical_cols:
    if col == 'Bedrooms':
        continue
    Q1 = X_train[col].quantile(0.25)  # First quartile
    Q3 = X_train[col].quantile(0.75)  # Third quartile
    IQR = Q3 - Q1  # Inter-quartile range

    # Define outlier limits
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Remove outliers
    X_train = X_train[(X_train[col] >= lower_bound) & (X_train[col] <= upper
    y_train = y_train.loc[X_train.index]  # Keep labels aligned


# Display number of removed outliers
print(f"Original train size: {n}")
print(f"Train size after outlier removal: {X_train.shape[0]}")
print(f"Number of outliers removed: {n - X_train.shape[0]}")
print(f"Test size remains unchanged: {X_test.shape[0]}")
print(X_train.describe())
```

```
Original train size: 115
Train size after outlier removal: 108
Number of outliers removed: 7
Test size remains unchanged: 13
              SqFt    Bedrooms   Bathrooms      Offers
count   108.000000  108.000000  108.000000  108.000000
mean   1999.699279    3.019263    2.458008    2.483202
std     196.360429    0.723194    0.516646    0.949603
min    1520.000000    2.000000    2.000000    1.000000
25%    1887.500000    3.000000    2.000000    2.000000
50%    2000.000000    3.000000    2.000000    3.000000
75%    2132.500000    3.026786    3.000000    3.000000
max    2440.000000    5.000000    4.000000    4.000000
```

Encode Categorical Data

encode *Brick* column using Label Encoding because it has binary values and encode *Neighborhood* column using One-Hot Encoding.

In [5]:
```python
from sklearn.preprocessing import LabelEncoder

label_encoders = {}  # Store LabelEncoders

# Label Encoding for Binary Categorical Data (Yes/No)
binary_cols = ['Brick']  # Binary categorical columns
for col in binary_cols:
    le = LabelEncoder()
    X_train[col] = le.fit_transform(X_train[col])  # Fit & transform train c
    X_test[col] = le.transform(X_test[col])  # Transform test data using sam
    label_encoders[col] = le  # Store encoder for future use

# One-Hot Encoding for Nominal Categorical Data (Neighborhood)
X_train = pd.get_dummies(X_train, columns=['Neighborhood'])
X_test = pd.get_dummies(X_test, columns=['Neighborhood'])

# Ensure test set has the same columns as train set
missing_cols = set(X_train.columns) - set(X_test.columns)
for col in missing_cols:
    X_test[col] = 0  # Add missing columns with default value 0

# Reorder columns to match train set
X_test = X_test[X_train.columns]

# Display final dataset info
print(f"Final train size: {X_train.shape[0]}")
print(f"Final test size: {X_test.shape[0]}")
print(X_train.head())  # Preview encoded data
```

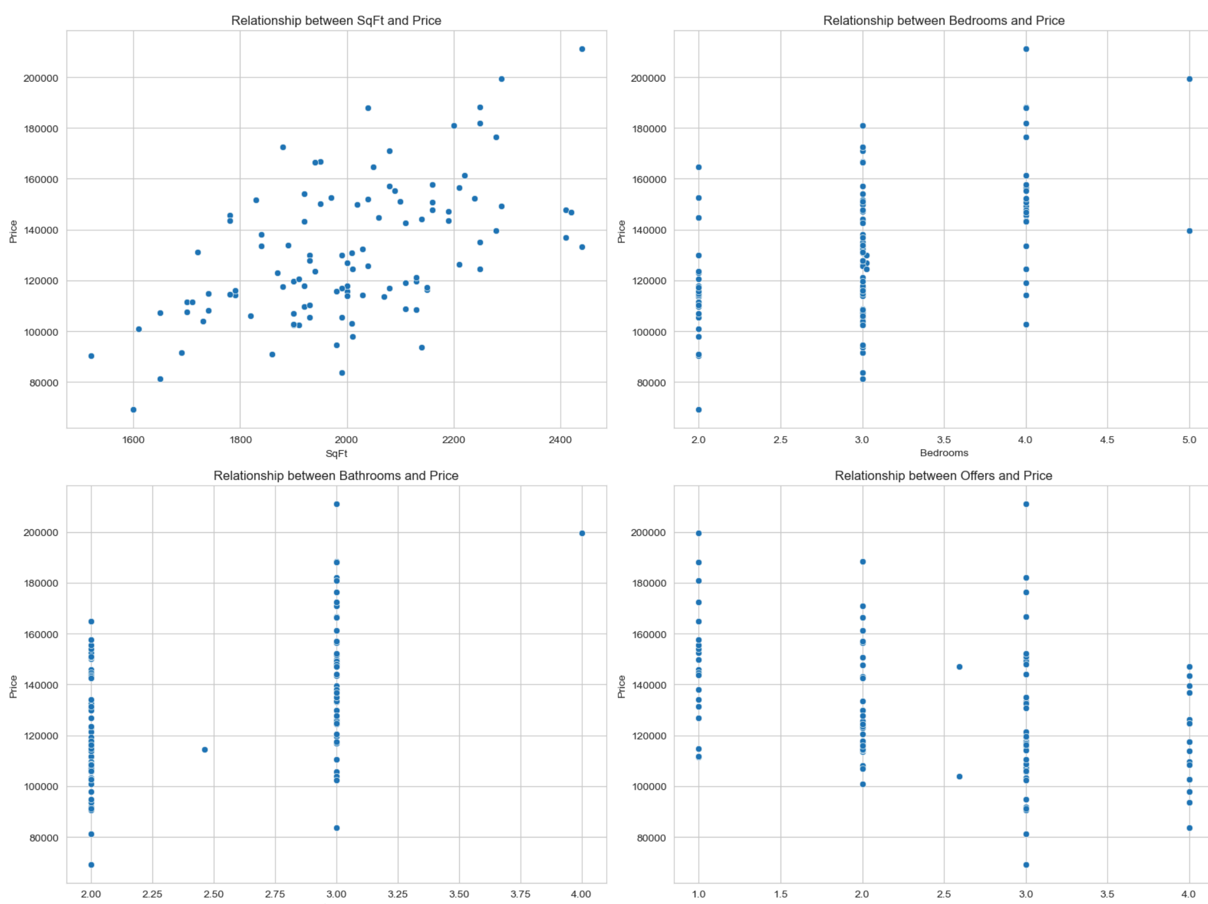
```
Final train size: 108
Final test size: 13
       SqFt  Bedrooms  Bathrooms  Offers  Brick  Neighborhood_East  \
4    2130.0       3.0        3.0     3.0      0               True   
96   2440.0       3.0        3.0     3.0      0               True   
113  2000.0       3.0        2.0     3.0      1              False   
36   1880.0       2.0        2.0     2.0      0              False   
80   2190.0       3.0        3.0     4.0      1               True   

     Neighborhood_North  Neighborhood_West  
4                 False              False  
96                False              False  
113                True              False  
36                 True              False  
80                False              False  
```

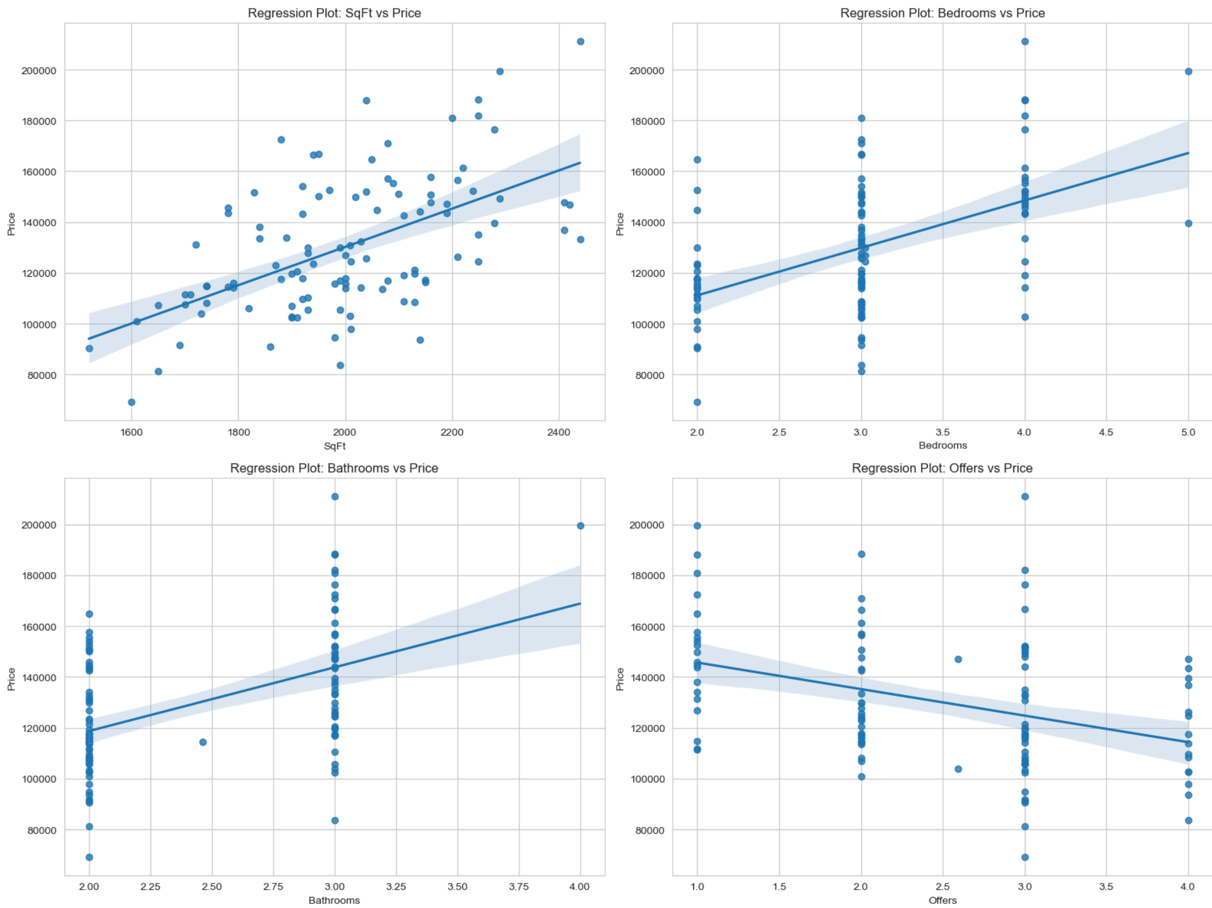
Data Analysis & Charts

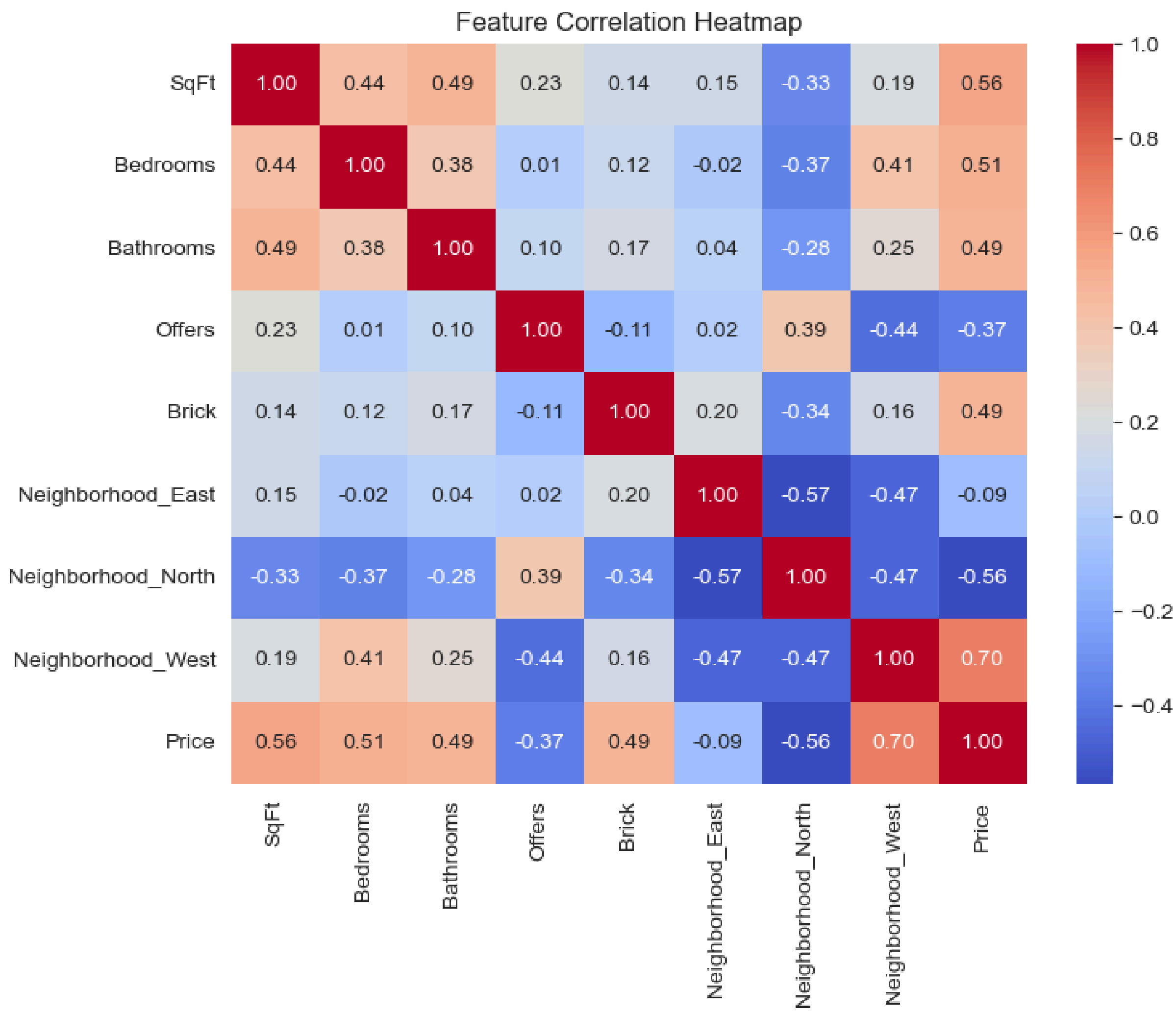
In [6]:

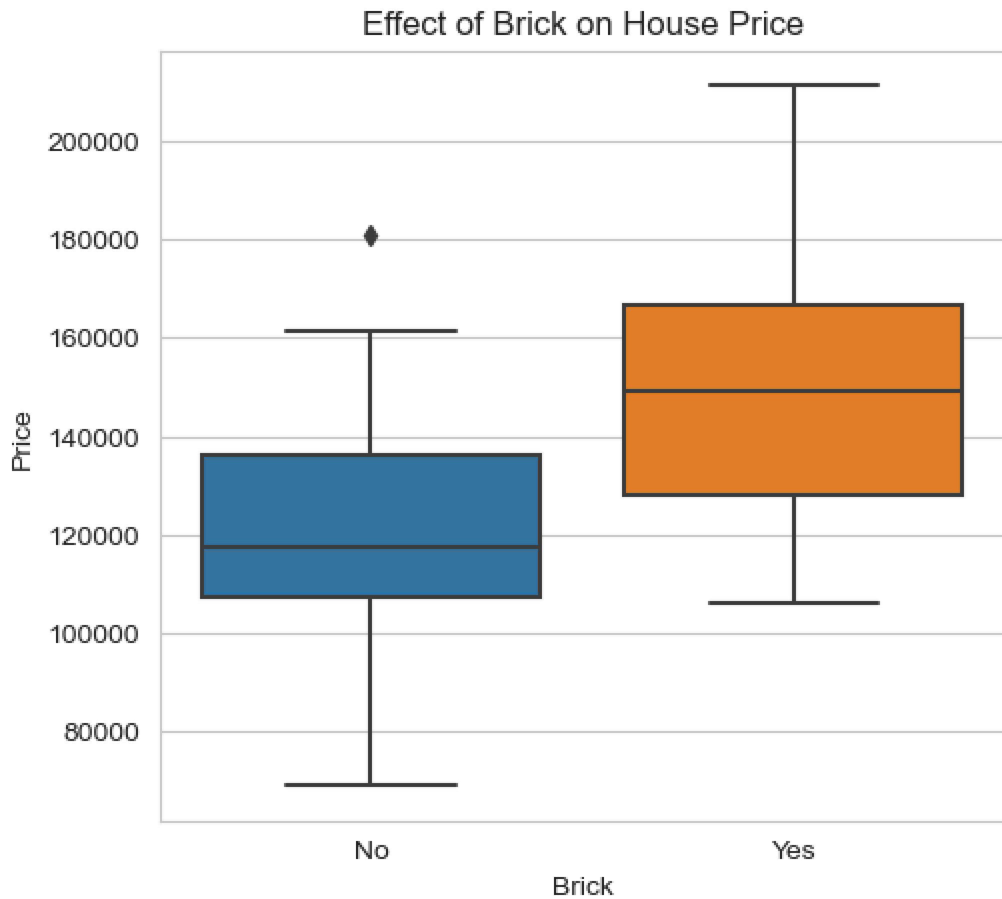
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Combine into a single DataFrame for visualization
df_visual = X_train.copy()
df_visual['Price'] = y_train  # Use y_train, not y

# Set Seaborn style
sns.set_style("whitegrid")

# Scatter Plots for Numerical Features
plt.figure(figsize=(16, 12))
for i, col in enumerate(numerical_cols):
    plt.subplot(2, 2, i+1)
    sns.scatterplot(x=df_visual[col], y=df_visual['Price'])
    plt.title(f'Relationship between {col} and Price')

plt.tight_layout()
plt.show()

# Regression Plots for Numerical Features
plt.figure(figsize=(16, 12))
for i, col in enumerate(numerical_cols):
    plt.subplot(2, 2, i+1)
    sns.regplot(x=df_visual[col], y=df_visual['Price'])
    plt.title(f'Regression Plot: {col} vs Price')

plt.tight_layout()
plt.show()

# Heatmap for Feature Correlation
plt.figure(figsize=(8, 6))
sns.heatmap(df_visual.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Feature Correlation Heatmap")
plt.show()
```

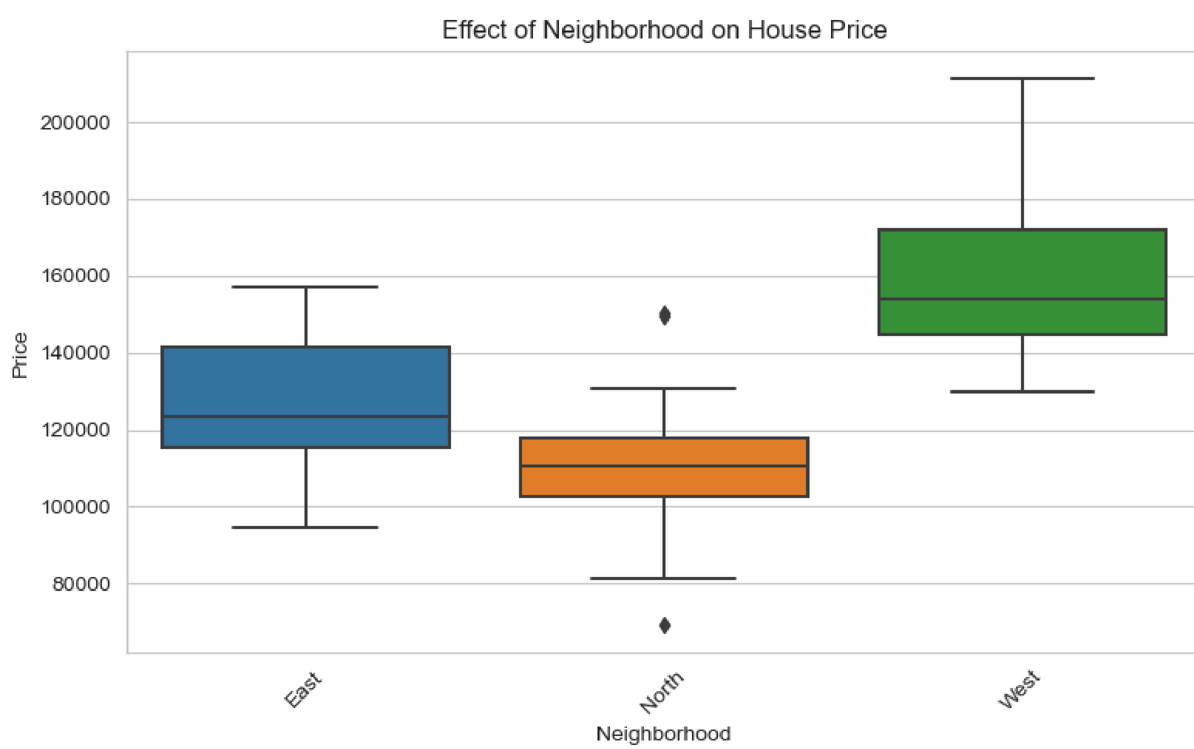
```
# Boxplots for Categorical Features
plt.figure(figsize=(12, 5))

# Brick vs Price (Binary Categorical)
plt.subplot(1, 2, 1)
sns.boxplot(x=df_visual['Brick'], y=df_visual['Price'])
plt.xticks([0, 1], ['No', 'Yes'])  # Convert 0/1 back to labels
plt.title("Effect of Brick on House Price")

# Neighborhood vs Price (One-Hot Encoded)
# plt.subplot(1, 2, 2)
# sns.boxplot(data=df_visual, y='Price')
# plt.title("Effect of Neighborhood on House Price")
# plt.xticks([])  # Remove x-axis labels since Neighborhood is one-hot encod

# Convert one-hot encoded neighborhoods back into a single categorical colum
df_visual['Neighborhood'] = df_visual[['Neighborhood_West', 'Neighborhood_No
df_visual['Neighborhood'] = df_visual['Neighborhood'].str.replace('Neighborh

plt.figure(figsize=(8, 5))
sns.boxplot(x=df_visual['Neighborhood'], y=df_visual['Price'])
plt.title("Effect of Neighborhood on House Price")
plt.xticks(rotation=45)
# plt.show()


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




Regression Plot: SqFt vs Price
Price
SqFt
200000
180000
160000
140000
120000
100000
80000
1600
1800
2000
2200
2400
Regression Plot: Bedrooms vs Price
Price
Bedrooms
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Regression Plot: Bathrooms vs Price
Price
Bathrooms
2.00
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
Regression Plot: Offers vs Price
Price
Offers
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Feature Correlation Heatmap
SqFt 1.00 0.44 0.49 0.23 0.14 0.15 -0.33 0.19 0.56
Bedrooms 0.44 1.00 0.38 0.01 0.12 -0.02 -0.37 0.41 0.51
Bathrooms 0.49 0.38 1.00 0.10 0.17 0.04 -0.28 0.25 0.49
Offers 0.23 0.01 0.10 1.00 -0.11 0.02 0.39 -0.44 -0.37
Brick 0.14 0.12 0.17 -0.11 1.00 0.20 -0.34 0.16 0.49
Neighborhood_East 0.15 -0.02 0.04 0.02 0.20 1.00 -0.57 -0.47 -0.09
Neighborhood_North -0.33 -0.37 -0.28 0.39 -0.34 -0.57 1.00 -0.47 -0.56
Neighborhood_West 0.19 0.41 0.25 -0.44 0.16 -0.47 -0.47 1.00 0.70
Price 0.56 0.51 0.49 -0.37 0.49 -0.09 -0.56 0.70 1.00
SqFt
Bedrooms
Bathrooms
Offers
Brick
Neighborhood_East
Neighborhood_North
Neighborhood_West
Price
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4





Normalize Data

normalizing numerical data using Min-Max Scaler

In [7]:
```python
from sklearn.preprocessing import MinMaxScaler
# Normalize features using Min-Max Scaling
scaler = MinMaxScaler()
X_train[numerical_cols] = scaler.fit_transform(X_train[numerical_cols])
X_test[numerical_cols] = scaler.transform(X_test[numerical_cols])  # Use tra
print("Normalized X_train:\n", X_train[:20])
```

```
Normalized X_train:
         SqFt  Bedrooms  Bathrooms    Offers  Brick  Neighborhood_East  \
4    0.663043  0.333333        0.5  0.666667      0               True
96   1.000000  0.333333        0.5  0.666667      0               True
113  0.521739  0.333333        0.0  0.666667      1              False
36   0.391304  0.000000        0.0  0.333333      0              False
80   0.728261  0.333333        0.5  1.000000      1               True
125  0.597826  0.000000        0.0  0.333333      0              False
84   0.000000  0.000000        0.0  0.666667      0              False
18   0.195652  0.000000        0.0  0.000000      1               True
10   0.554348  0.333333        0.0  0.666667      1               True
118  0.467391  0.333333        0.0  0.666667      1              False
11   0.380435  0.000000        0.0  0.333333      1               True
45   0.531262  0.333333        0.0  0.666667      0               True
70   0.467391  0.333333        0.5  0.666667      1              False
78   0.663043  0.333333        0.0  0.666667      0              False
0    0.293478  0.000000        0.0  0.333333      0               True
12   0.423913  0.333333        0.0  1.000000      0              False
42   0.510870  0.000000        0.0  0.666667      0               True
126  0.543478  0.333333        0.5  0.000000      0              False
24   0.750000  0.666667        0.5  0.333333      1               True
67   0.565217  0.666667        0.5  0.666667      0               True

     Neighborhood_North  Neighborhood_West
4                 False              False
96                False              False
113                True              False
36                 True              False
80                False              False
125                True              False
84                 True              False
18                False              False
10                False              False
118                True              False
11                False              False
45                False              False
70                False               True
78                 True              False
0                 False              False
12                 True              False
42                False              False
126               False               True
24                False              False
67                False              False
```

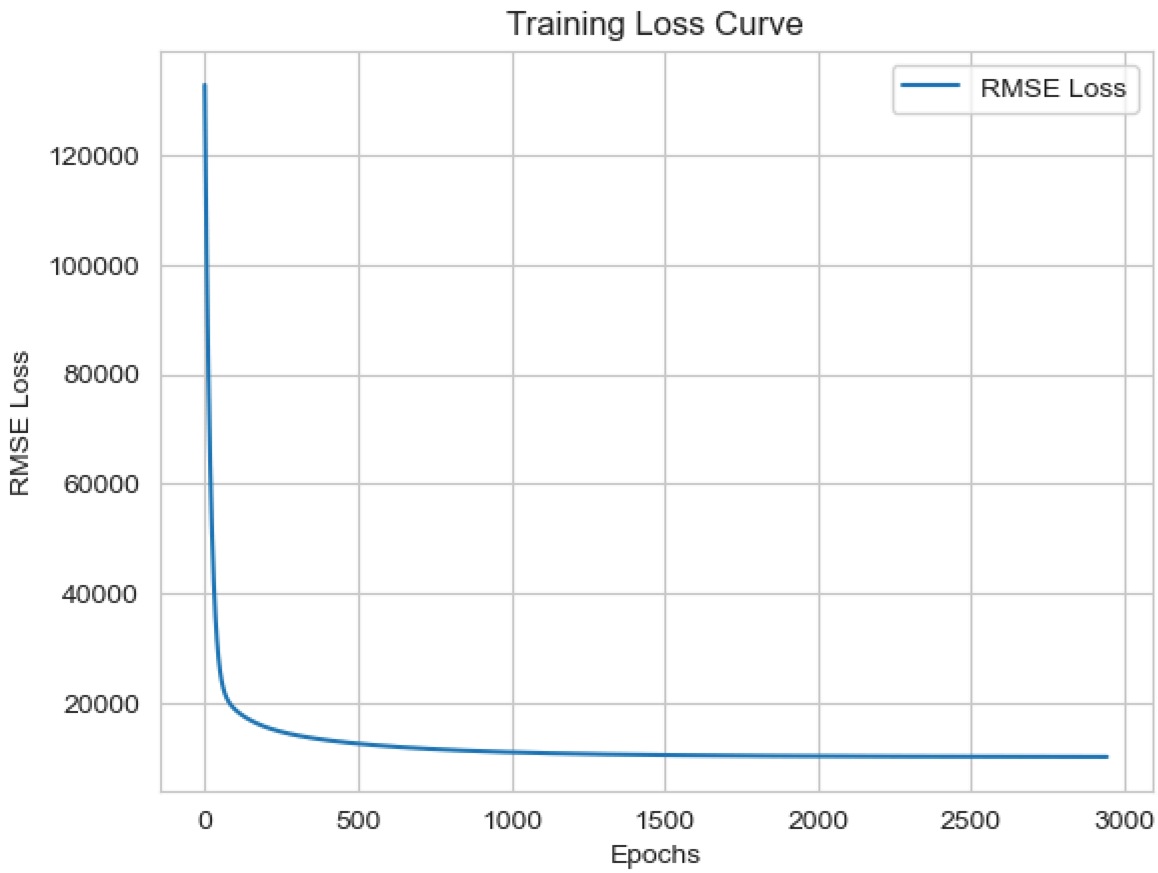
Train Model

training model using gradient descent

In [8]:
```
import numpy as np
import matplotlib.pyplot as plt

class LinearRegressionScratch:
    def __init__(self, learning_rate=0.01, epochs=1000, tolerance=1e-6, pati
        self.learning_rate = learning_rate
        self.epochs = epochs
        self.tolerance = tolerance  # Threshold for small RMSE change
        self.patience = patience  # Number of consecutive small changes befo
        self.W = None  # Weights
        self.b = 0  # Bias
        self.loss_history = []  # Store RMSE loss over epochs

    def compute_rmse(self, y_true, y_pred):
        """Compute Root Mean Squared Error (RMSE)"""
        mse = np.mean((y_pred - y_true) ** 2)
        return np.sqrt(mse)

    def fit(self, X_train, y_train):
        """Train the model using Gradient Descent with Convergence Counter""
        m, n = X_train.shape  # m = samples, n = features
        self.W = np.zeros(n)  # Initialize weights to zero
        self.b = 0  # Initialize bias

        no_change_count = 0  # Count epochs with small RMSE change

        for epoch in range(self.epochs):
            # Compute predictions
            y_pred = np.dot(X_train, self.W) + self.b

            # Compute RMSE loss
            loss = self.compute_rmse(y_train, y_pred)
            self.loss_history.append(loss)

            # Count consecutive small changes
            if epoch > 0 and abs(self.loss_history[-2] - loss) < self.tolera
                no_change_count += 1
            else:
                no_change_count = 0  # Reset counter if change is significar

            # Stop if we reach 10 consecutive small changes
            if no_change_count >= self.patience:
                print(f"Early stopping at epoch {epoch}, RMSE: {loss:.4f}")
                break

            # Compute gradients
            dW = (2/m) * np.dot(X_train.T, (y_pred - y_train))  # Gradient f
            db = (2/m) * np.sum(y_pred - y_train)  # Gradient for bias

            # Update parameters
            self.W -= self.learning_rate * dW
            self.b -= self.learning_rate * db
```

```
            # Print loss every 100 epochs
            if epoch % 100 == 0:
                print(f"Epoch {epoch}: RMSE Loss = {loss:.4f}")

    def predict(self, X_test):
        """Make predictions"""
        return np.dot(X_test, self.W) + self.b

    def plot_loss(self):
        """Plot RMSE loss over epochs"""
        plt.plot(range(len(self.loss_history)), self.loss_history, label="RM
        plt.xlabel("Epochs")
        plt.ylabel("RMSE Loss")
        plt.title("Training Loss Curve")
        plt.legend()
        plt.show()

# Ensure all data is numeric
X_train = X_train.astype(float)
X_test = X_test.astype(float)
y_train = y_train.astype(float)
y_test = y_test.astype(float)

# Train the model
model = LinearRegressionScratch(learning_rate=0.01, epochs=10000, tolerance=
model.fit(X_train, y_train)

# Plot RMSE loss curve
model.plot_loss()

# Test the model
y_test_pred = model.predict(X_test)

# Compute RMSE on test set
test_rmse = model.compute_rmse(y_test, y_test_pred)
print(f"Test Loss (RMSE): {test_rmse:.4f}")
```

```
Epoch 0: RMSE Loss = 132836.6645
Epoch 100: RMSE Loss = 18753.7405
Epoch 200: RMSE Loss = 15586.0958
Epoch 300: RMSE Loss = 14097.4410
Epoch 400: RMSE Loss = 13201.8796
Epoch 500: RMSE Loss = 12571.5401
Epoch 600: RMSE Loss = 12094.0674
Epoch 700: RMSE Loss = 11721.6439
Epoch 800: RMSE Loss = 11427.6264
Epoch 900: RMSE Loss = 11194.0029
Epoch 1000: RMSE Loss = 11007.4212
Epoch 1100: RMSE Loss = 10857.6447
Epoch 1200: RMSE Loss = 10736.7463
Epoch 1300: RMSE Loss = 10638.5741
Epoch 1400: RMSE Loss = 10558.3525
Epoch 1500: RMSE Loss = 10492.3721
Epoch 1600: RMSE Loss = 10437.7478
Epoch 1700: RMSE Loss = 10392.2302
Epoch 1800: RMSE Loss = 10354.0599
Epoch 1900: RMSE Loss = 10321.8549
Epoch 2000: RMSE Loss = 10294.5244
Epoch 2100: RMSE Loss = 10271.2029
Epoch 2200: RMSE Loss = 10251.1997
Epoch 2300: RMSE Loss = 10233.9602
Epoch 2400: RMSE Loss = 10219.0363
Epoch 2500: RMSE Loss = 10206.0637
Epoch 2600: RMSE Loss = 10194.7441
Epoch 2700: RMSE Loss = 10184.8323
Epoch 2800: RMSE Loss = 10176.1250
Epoch 2900: RMSE Loss = 10168.4527
Early stopping at epoch 2943, RMSE: 10165.4357
```




```
Test Loss (RMSE): 9584.2705
```

```
In [ ]:
```

```
In [ ]:
```