Exercise 4b

Date: 22/01/2025

Linear Regression - Multivariate dataset

Aim: To build a Linear Regression model to predict the price of house based on features in multivariate housing dataset.

Algorithm:

The Linear Regression algorithm aims to model the relationship between multiple independent variables (features) and a dependent variable (target) by fitting a linear equation to observed data.It assumes that there is a linear relationship between the features and the target, and it tries to minimize the difference between predicted and actual target values.

The model is represented by the equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Where:

- y is the dependent variable (target).
- β_0 is the intercept (constant term).
- $(\beta_1, \beta_2, \ldots, \beta_n)$ are the coefficients (weights) of the features $(x_1, x_2, \ldots, x_n)$, representing the impact of each feature on the target variable.

Step 1: Import Libraries

- Import necessary Python libraries like pandas, numpy, matplotlib, and scikit-learn modules for data preprocessing, model building, and evaluation.

Step 2: Load the Dataset

- Load the multivariate dataset using pandas read_csv() function.
- Use df.info() to examine the structure of the dataset, checking for data types, null values, and the number of records.

Step 3: Prepare the Data

- Check for missing or null values in the dataset using df.isna().sum().
- Handle missing values by using techniques like mean imputation, deletion, or other relevant methods depending on the data.
- Drop irrelevant columns (e.g., non-feature columns such as address or names).

Step 4: Feature Selection and Target Variable

- Identify and separate the features (independent variables) and the target variable (dependent variable).
- In this case, features could be multiple columns representing the house's characteristics, and the target is the price of the house.

Step 5: Data Transformation and Scaling

- Standardize the features using techniques like StandardScaler from scikit-learn to ensure the features are on a similar scale.

Step 6: Train-Test Split

- Split the dataset into training and testing sets using train_test_split. Typically, 80% of the data is used for training, and 20% is used for testing.

Step 7: Train the Model

- Initialize the Linear Regression model and fit it on the training data (X_train, y_train).
- The model learns the best-fit line by minimizing the sum of squared errors between actual and predicted values.

Step 8: Make Predictions

- After training the model, use it to make predictions on the test data (X_test).

Step 9: Evaluate the Model

- Evaluate the model's performance using key metrics such as R-squared and Mean Squared Error (MSE).
- R-squared indicates how well the model explains the variance in the target variable, with values closer to 1 being better.
- MSE calculates the average squared difference between the actual and predicted values, with lower values indicating better predictions.

Step 10: Visualize the Results

- Create a scatter plot comparing the actual vs. predicted values, and draw the best-fit line on the plot.

Import the libraries

In [71]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Load the Dataset

In [72]:
```
df = pd.read_csv("housing.csv",sep=',')
```

In [73]:
```
df
```

Out[73]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.45857	5.682861	7.009188	4.09	23086.80050	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.64245	6.002900	6.730821	3.09	40173.07217	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	61287.06718	5.865890	8.512727	5.13	36882.15940	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	63345.24005	7.188236	5.586729	3.26	34310.24283	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.19723	5.040555	7.839388	4.23	26354.10947	6.309435e+05	USNS Raymond\nFPO AE 09386
...	...	...	...	...	...	...	...
4995	60567.94414	7.830362	6.137356	3.46	22837.36103	1.060194e+06	USNS Williams\nFPO AP 30153-7653
4996	78491.27543	6.999135	6.576763	4.02	25616.11549	1.482618e+06	PSC 9258, Box 8489\nAPO AA 42991-3352
4997	63390.68689	7.250591	4.805081	2.13	33266.14549	1.030730e+06	4215 Tracy Garden Suite 076\nJoshualand, VA 01...
4998	68001.33124	5.534388	7.130144	5.44	42625.62016	1.198657e+06	USS Wallace\nFPO AE 73316
4999	65510.58180	5.992305	6.792336	4.07	46501.28380	1.298950e+06	37778 George Ridges Apt. 509\nEast Holly, NV 2...

5000 rows × 7 columns

In [74]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Avg. Area Income             5000 non-null   float64
 1   Avg. Area House Age          5000 non-null   float64
 2   Avg. Area Number of Rooms    5000 non-null   float64
 3   Avg. Area Number of Bedrooms 5000 non-null   float64
 4   Area Population              5000 non-null   float64
 5   Price                        5000 non-null   float64
 6   Address                      5000 non-null   object 
dtypes: float64(6), object(1)
memory usage: 273.6+ KB
```

Drop unnecessary columns

In [75]:
```
df = df.drop(columns=['Address'])
```

Check for null values

In [76]:
```
df.isna().sum()
```

Out[76]:
```
Avg. Area Income               0
Avg. Area House Age            0
Avg. Area Number of Rooms      0
Avg. Area Number of Bedrooms   0
Area Population                0
Price                          0
dtype: int64
```

Split features and target

In [77]:
```
X = df.drop(columns=['Price'])
y = df['Price']
```

Log transform target variable

In [78]:
```
y_log = np.log1p(y)
```

Scale the features

In [79]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Split dataset into train and test data

In [80]:
```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_log, test_size=0.2, random_state=42)
```

Apply Linear Regression

In [81]:
```
model=LinearRegression()
model.fit(X_train, y_train)
```

Out[81]:
```
▾ LinearRegression
LinearRegression()
```

In [82]:
```
y_pred = model.predict(X_test)
```

Performance metrics

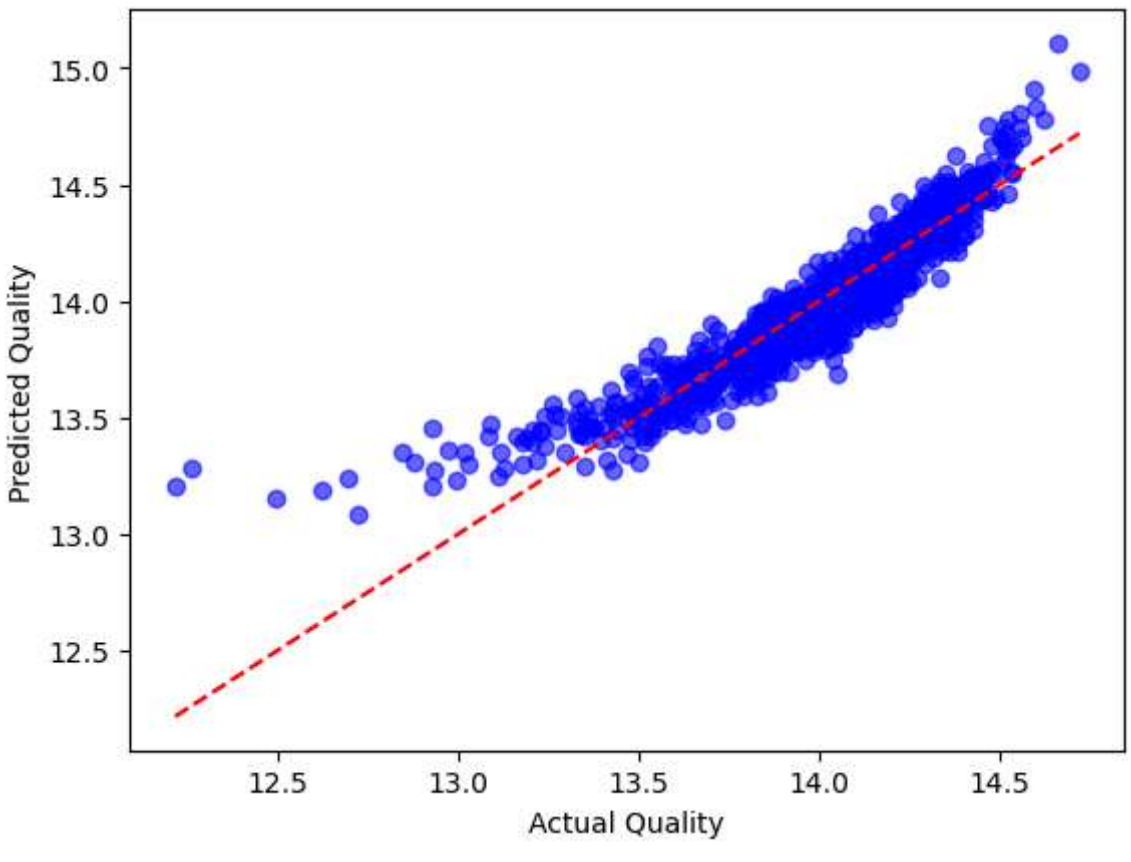
In [83]:
```
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
```

In [84]:
```
print(f'R-squared: {r2:.4f}')
print(f'Mean Squared Error: {mse:.4f}')
```

```
R-squared: 0.8570
Mean Squared Error: 0.0150
```

Plot the graph

In [85]:
```
plt.scatter(y_test, y_pred, color='blue', alpha=0.6)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--')
plt.xlabel('Actual Quality')
plt.ylabel('Predicted Quality')
plt.show()
```



Result

A Linear Regression model was built to predict the house price based on the given features, achieving an R-squared value of 0.8570 and a Mean Squared Error (MSE) of 0.0150.
