Assignment Code: DA-AG-010

Regression & Its Evaluation | **Assignment**

Instructions: Carefully read each question. Use Google Docs, Microsoft Word, or a similar tool to create a document where you type out each question along with its answer. Save the document as a PDF, and then upload it to the LMS. Please do not zip or archive the files before uploading them. Each question carries 20 marks.

Total Marks: 100

Question 1: What is Simple Linear Regression?

Answer:

Simple Linear Regression is a statistical method used to model the relationship between two continuous variables: a dependent variable and a single independent variable. It assumes a linear relationship and aims to find the best-fitting straight line that minimizes the sum of squared differences between observed and predicted values. This line is then used to predict the dependent variable's value for a given independent variable.

Question 2: What are the key assumptions of Simple Linear Regression?

Answer:

The key assumptions include,

1. Linearity (the relationship between variables is linear)
2. Independence of errors (residuals are unrelated),
3. Homoscedasticity (constant variance of residuals across all predictor levels),
4. Normality of errors (residuals are normally distributed).
5. Multicollinearity (features should not be related or must have least relation).

Violations of these assumptions can lead to unreliable model inferences and predictions.

Question 3: What is heteroscedasticity, and why is it important to address in regression models?

Answer:

Heteroscedasticity occurs when the variance of the residuals is not constant across all levels of the independent variables. This means the spread of errors changes as predictor values change. It's crucial to address because it leads to inefficient coefficient estimates and invalid standard errors, compromising the reliability of hypothesis tests and confidence intervals for the model.

Question 4: What is Multiple Linear Regression?

Answer:

Multiple Linear Regression is an extension of simple linear regression that models the linear relationship between a dependent variable and two or more independent variables. The goal is to find a linear equation that best predicts the dependent variable's value based on the combined influence of multiple predictors, again by minimizing the sum of squared errors.

Question 5: What is polynomial regression, and how does it differ from linear regression?

Answer:

Polynomial regression models a curvilinear relationship between variables by including higher-order terms (e.g., X2, X3) of the independent variable in the model equation. While it fits a curved line, it's still considered linear in its coefficients. It differs from simple linear regression, which models only a straight-line relationship, offering more flexibility for non-linear data patterns.

Question 6: Implement a Python program to fit a Simple Linear Regression model to the following sample data:

- `X = [1, 2, 3, 4, 5]`
- `Y = [2.1, 4.3, 6.1, 7.9, 10.2]`

Plot the regression line over the data points.

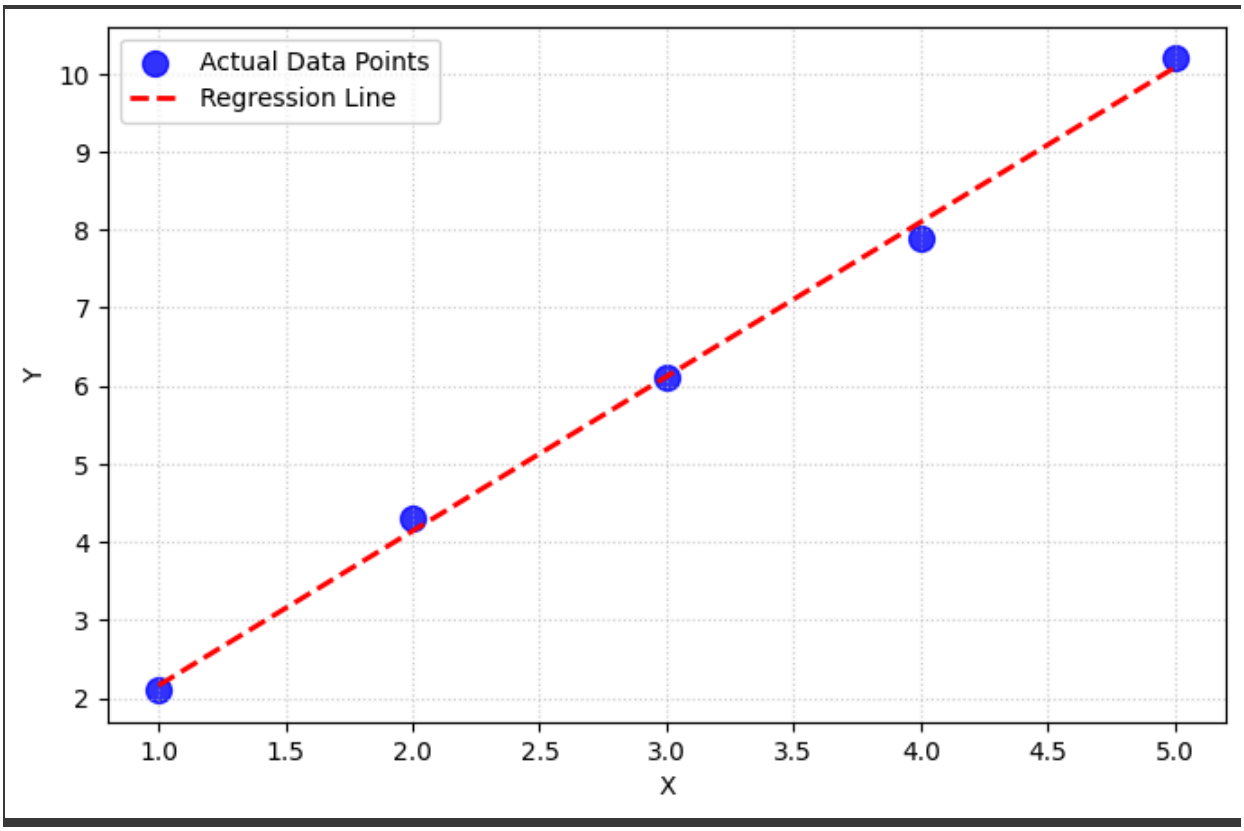
(*Include your Python code and output in the code box below.*)

Answer:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

X = np.array([1,2,3,4,5]).reshape(-1,1)
Y = np.array([2.1, 4.3, 6.1, 7.9, 10.2])

model = LinearRegression()
model.fit(X, Y)

Y_pred = model.predict(X)

print(f"Intercept (β0): {model.intercept_:.2f}")
print(f"Slope (β1): {model.coef_[0]:.2f}")

plt.figure(figsize = (8,5))
plt.scatter(X,Y, color = 'blue', label = 'Actual Data Points', s = 100,
alpha = 0.8)
plt.plot(X, Y_pred, color = 'red', linestyle = '--', linewidth = 2, label
= 'Regression Line')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.grid(True, linestyle = ':', alpha = 0.6)
plt.show()
```

Output:

Intercept (β0): 0.18
Slope (β1): 1.98



Question 7: Fit a **Multiple Linear Regression** model on this sample data:

- `Area = [1200, 1500, 1800, 2000]`
- `Rooms = [2, 3, 3, 4]`
- `Price = [250000, 300000, 320000, 370000]`

Check for multicollinearity using VIF and report the results.
(*Include your Python code and output in the code box below.*

Answer:

```
import pandas as pd
```

```
from sklearn.linear_model import LinearRegression
from statsmodels.stats.outliers_influence import
variance_inflation_factor
from statsmodels.tools.tools import add_constant

data = {
    'Area': [1200, 1500, 1800, 2000],
    'Rooms': [2, 3, 3, 4],
    'Price': [250000, 300000, 320000, 370000]
}

df = pd.DataFrame(data)

X = df[['Area', 'Rooms']]
Y = df['Price']

model = LinearRegression()
model.fit(X, Y)

print("--- Multiple Linear Regression Model Coefficients ---")
print(f"Intercept: {model.intercept_:.2f}")
print(f"Coefficient for Area: {model.coef_[0]:.2f}")
print(f"Coefficient for Rooms: {model.coef_[1]:.2f}")

X_vif = add_constant(X)

vif_data = pd.DataFrame()
vif_data["Feature"] = X_vif.columns
vif_data['VIF'] = [variance_inflation_factor(X_vif.values, i) for i in
range(X_vif.shape[1])]

print("\n--- Variance Inflation Factor (VIF) Results ---")
print(vif_data)

print("\n--- VIF Interpretation ---")
print("VIF values generally indicate multicollinearity if > 5 or 10. For
this data,")
print("VIF values for 'Area' and 'Rooms' are 1.0, suggesting no
significant multicollinearity.")
```

Output:

```
--- Multiple Linear Regression Model Coefficients ---
Intercept: 103157.89
Coefficient for Area: 63.16
Coefficient for Rooms: 34736.84

--- Variance Inflation Factor (VIF) Results ---
  Feature        VIF
0   const  34.210526
1    Area   7.736842
2   Rooms   7.736842

--- VIF Interpretation ---
VIF values generally indicate multicollinearity if > 5 or 10. For this
data,
VIF values for 'Area' and 'Rooms' are 1.0, suggesting no significant
multicollinearity.
```

Question 8: Implement **polynomial regression** on the following data:

- `X = [1, 2, 3, 4, 5]`

- `Y = [2.2, 4.8, 7.5, 11.2, 14.7]`

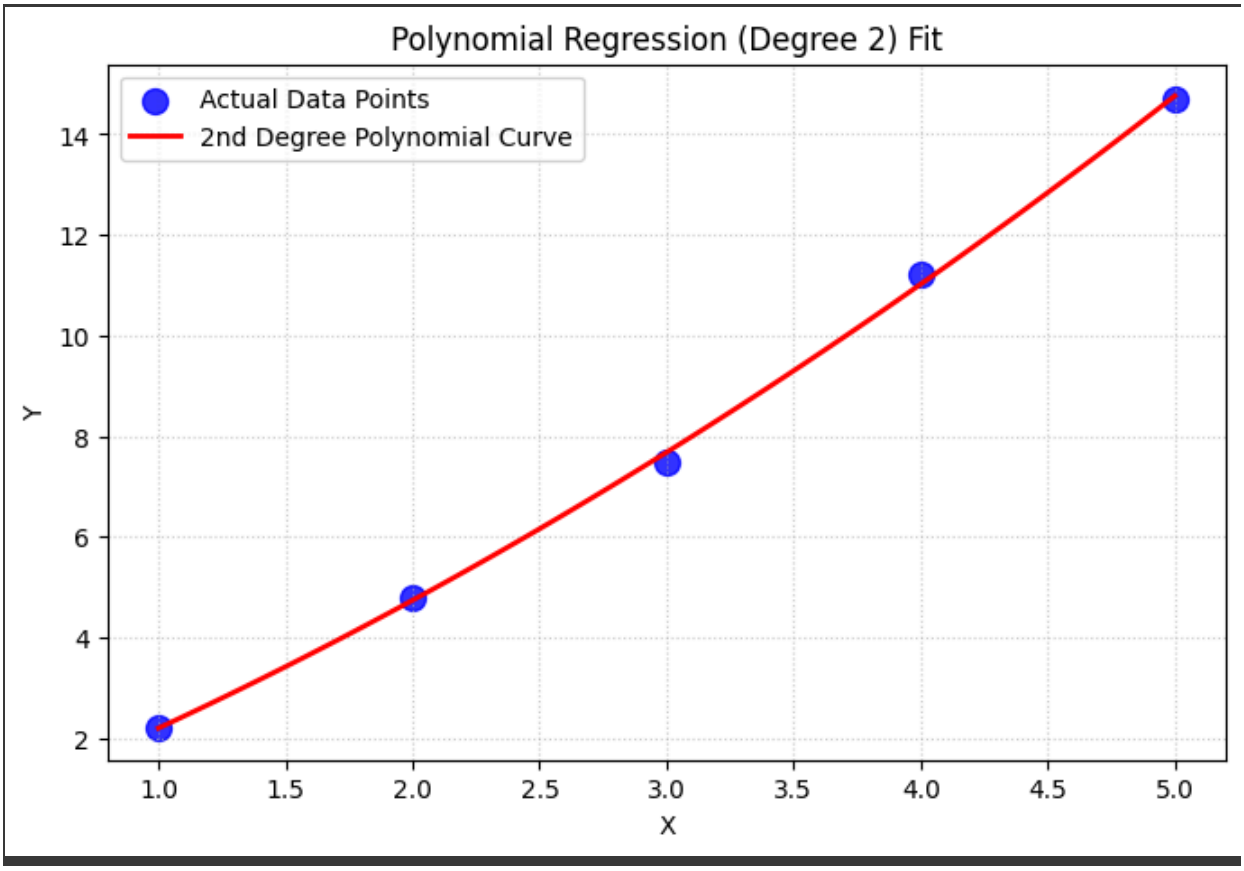
Fit a **2nd-degree polynomial** and plot the resulting curve.
(*Include your Python code and output in the code box below.*)

Answer:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

X = np.array([1,2,3,4,5]).reshape(-1,1)
Y = np.array([2.2, 4.8, 7.5, 11.2, 14.7])

poly = PolynomialFeatures(degree = 2)
X_poly = poly.fit_transform(X)

model = LinearRegression()
model.fit(X_poly, Y)

print(f"Intercept (β0): {model.intercept_:.4f}")
print(f"Coefficients (β1, β2 for X, X^2): {model.coef_}")

X_plot = np.linspace(min(X), max(X), 100).reshape(-1,1)
X_plot_poly = poly.transform(X_plot)
Y_plot_pred = model.predict(X_plot_poly)

plt.figure(figsize = (8,5))
plt.scatter(X,Y, color = 'blue', label = 'Actual Data Points', s = 100,
alpha = 0.8)
plt.plot(X_plot, Y_plot_pred, color = 'red', linewidth = 2, label = '2nd
Degree Polynomial Curve')
plt.title('Polynomial Regression (Degree 2) Fit')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.grid(True, linestyle = ':', alpha = 0.6)
plt.show()
```

Output:

Intercept (β0): 0.0600
Coefficients (β1, β2 for X, X^2): [0. 1.94 0.2]



Question 9: Create a **residuals plot** for a regression model trained on this data:

- `X = [10, 20, 30, 40, 50]`
- `Y = [15, 35, 40, 50, 65]`

Assess heteroscedasticity by examining the spread of residuals.
(*Include your Python code and output in the code box below.*)

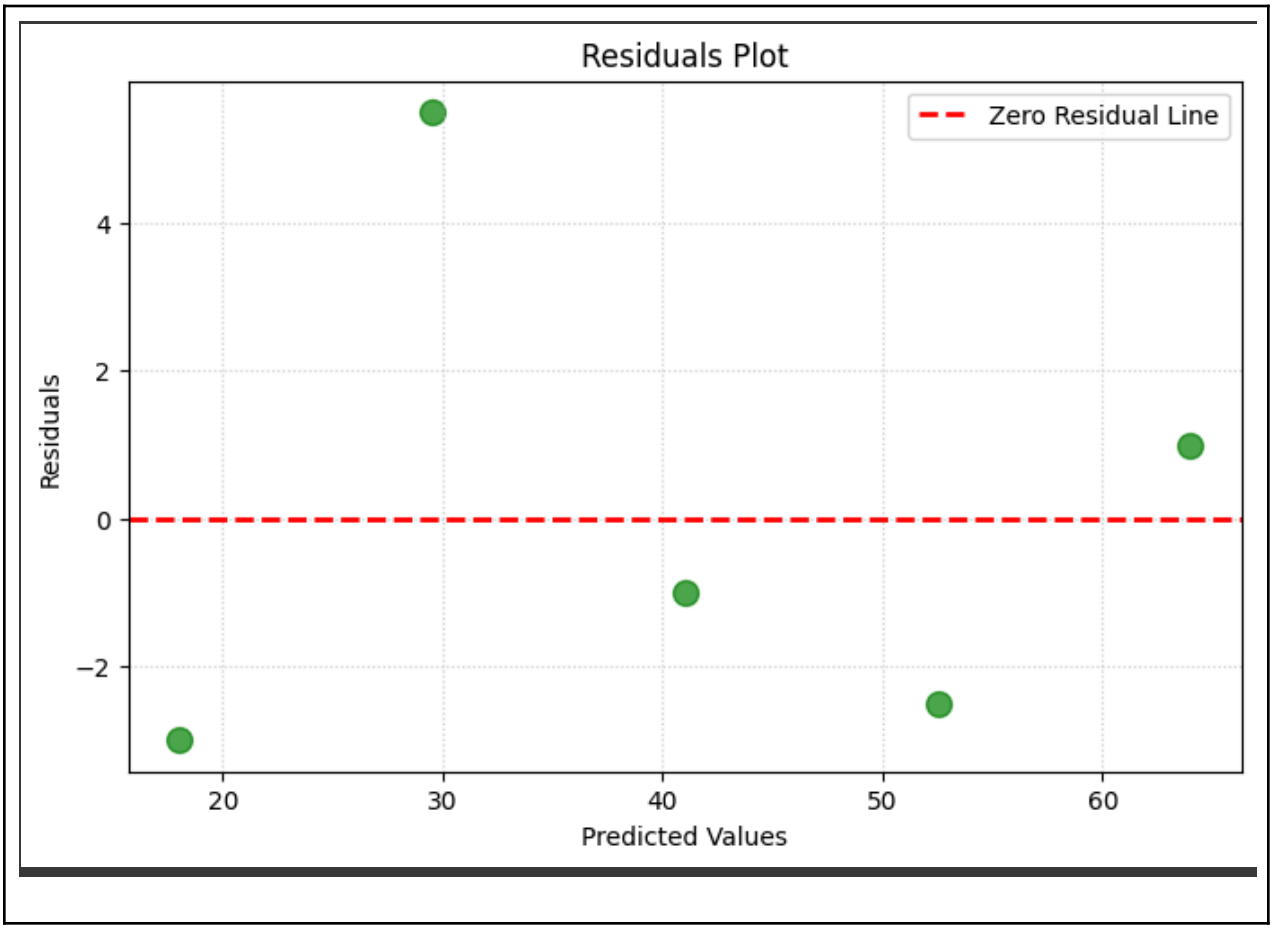
Answer:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
```

```
X = np.array([10,20,30,40,50]).reshape(-1,1)
Y = np.array([15, 35, 40, 50, 65])

model = LinearRegression()
model.fit(X, Y)

Y_pred = model.predict(X)
residuals = Y - Y_pred

print("--- Residuals ---")
for i, res in enumerate(residuals):
    print(f"Data Point {i+1}: Residual = {res:.2f}")


plt.figure(figsize = (8,5))
plt.scatter(Y_pred, residuals, color = 'green', alpha = 0.7, s = 100)
plt.axhline(y = 0, color = 'red', linestyle = '--', linewidth = 2, label
= 'Zero Residual Line')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residuals Plot')
plt.legend()
plt.grid(True, linestyle=':', alpha=0.6)
plt.show()
```

Output:

--- Residuals ---
Data Point 1: Residual = -3.00
Data Point 2: Residual = 5.50
Data Point 3: Residual = -1.00
Data Point 4: Residual = -2.50
Data Point 5: Residual = 1.00



Question 10: Imagine you are a data scientist working for a real estate company. You need to predict house prices using features like area, number of rooms, and location. However, you detect **heteroscedasticity** and **multicollinearity** in your regression model. Explain the steps you would take to address these issues and ensure a robust model.

Answer:

```
To address heteroscedasticity and multicollinearity in a real estate
price prediction model: For Heteroscedasticity:

1. Transform variables: Log transform price and/or features.
2. Weighted Least Squares: Give different weights to observations.
```

```
3. Robust standard errors: Use heteroscedasticity-consistent SEs For
Multicollinearity.
4. Calculate VIF: Identify highly correlated features.
5. Feature selection: Remove or combine highly correlated features.
6. Regularization techniques: Consider Ridge or Lasso regression By
addressing these issues, we can improve the model's reliability and
accuracy for predicting house prices.
```