```
import pandas as pd

# Load the dataset from the specified path
df = pd.read_csv('/content/Fish[1].csv')

# Display the first 5 rows of the dataset to understand its structure
print("Dataset Head:")
display(df.head())
```

Dataset Head:

	Species	Weight	Length1	Length2	Length3	Height	Width
0	Bream	242.0	23.2	25.4	30.0	11.5200	4.0200
1	Bream	290.0	24.0	26.3	31.2	12.4800	4.3056
2	Bream	340.0	23.9	26.5	31.1	12.3778	4.6961
3	Bream	363.0	26.3	29.0	33.5	12.7300	4.4555
4	Bream	430.0	26.5	29.0	34.0	12.4440	5.1340

```
print("\nDataset Info:")
# Display basic information about the dataset, including data types and non-null values
df.info()
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159 entries, 0 to 158
Data columns (total 7 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   Species  159 non-null    object 
 1   Weight   159 non-null    float64
 2   Length1  159 non-null    float64
 3   Length2  159 non-null    float64
 4   Length3  159 non-null    float64
 5   Height   159 non-null    float64
 6   Width    159 non-null    float64
dtypes: float64(6), object(1)
memory usage: 8.8+ KB
```

```
print("\nDataset Description:")
# Display descriptive statistics for numerical columns
display(df.describe())
```

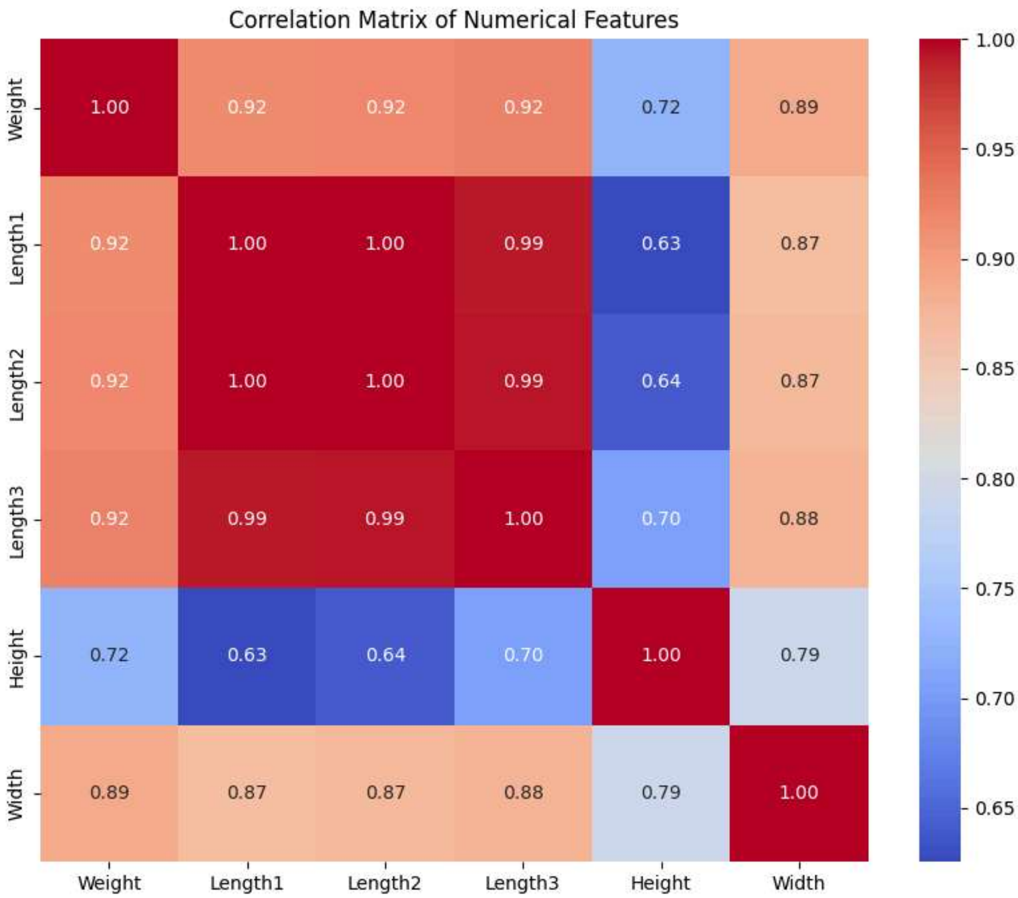
Dataset Description:

	Weight	Length1	Length2	Length3	Height	Width
count	159.000000	159.000000	159.000000	159.000000	159.000000	159.000000
mean	398.326415	26.247170	28.415723	31.227044	8.970994	4.417486
std	357.978317	9.996441	10.716328	11.610246	4.286208	1.685804
min	0.000000	7.500000	8.400000	8.800000	1.728400	1.047600
25%	120.000000	19.050000	21.000000	23.150000	5.944800	3.385650
50%	273.000000	25.200000	27.300000	29.400000	7.786000	4.248500
75%	650.000000	32.700000	35.500000	39.650000	12.365900	5.584500
max	1650.000000	59.000000	63.400000	68.000000	18.957000	8.142000

Correlation Analysis

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

# Calculate the correlation matrix for numerical columns
correlation_matrix = df.select_dtypes(include=['number']).corr()
```

```
# Plotting the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



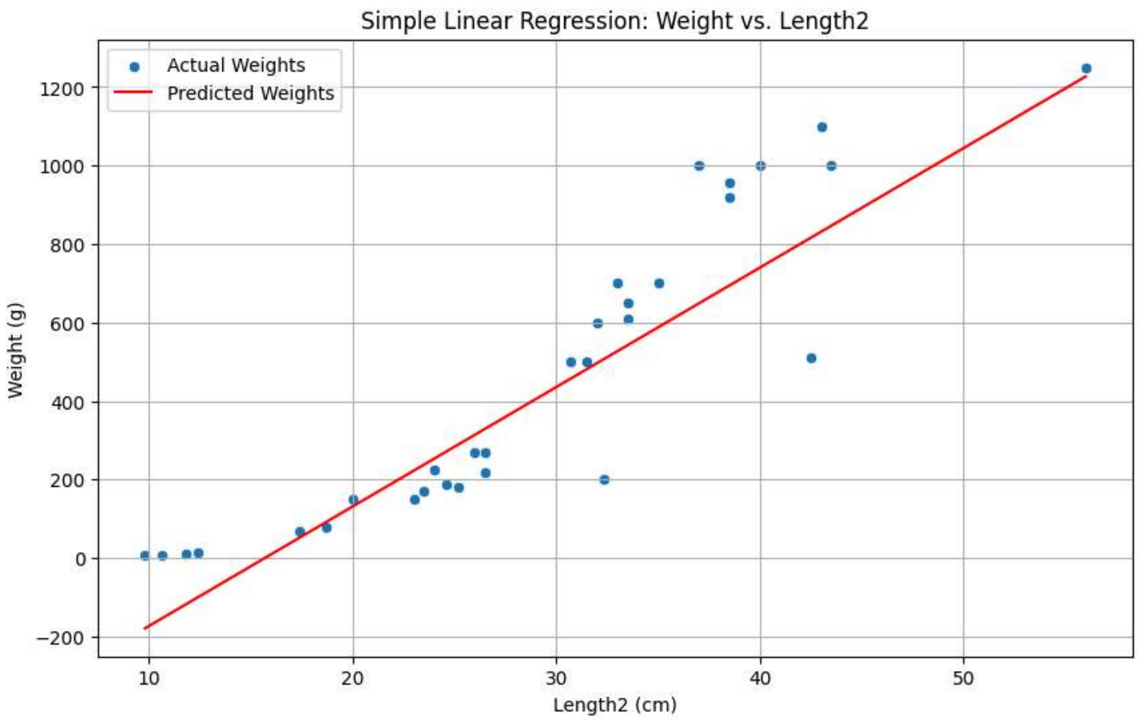
Simple Linear Regression

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np

# Define independent (X) and dependent (y) variables
# We'll use 'Length2' as the independent variable and 'Weight' as the dependent variable
X = df[['Length2']]
y = df['Weight']

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

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

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

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Model Coefficients (Slope): {model.coef_[0]:.2f}")
print(f"Model Intercept: {model.intercept_:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R-squared (R2) Score: {r2:.2f}")
```

```
Model Coefficients (Slope): 30.43
Model Intercept: -477.31
Mean Squared Error (MSE): 25604.52
R-squared (R2) Score: 0.82
```

Regression Plot

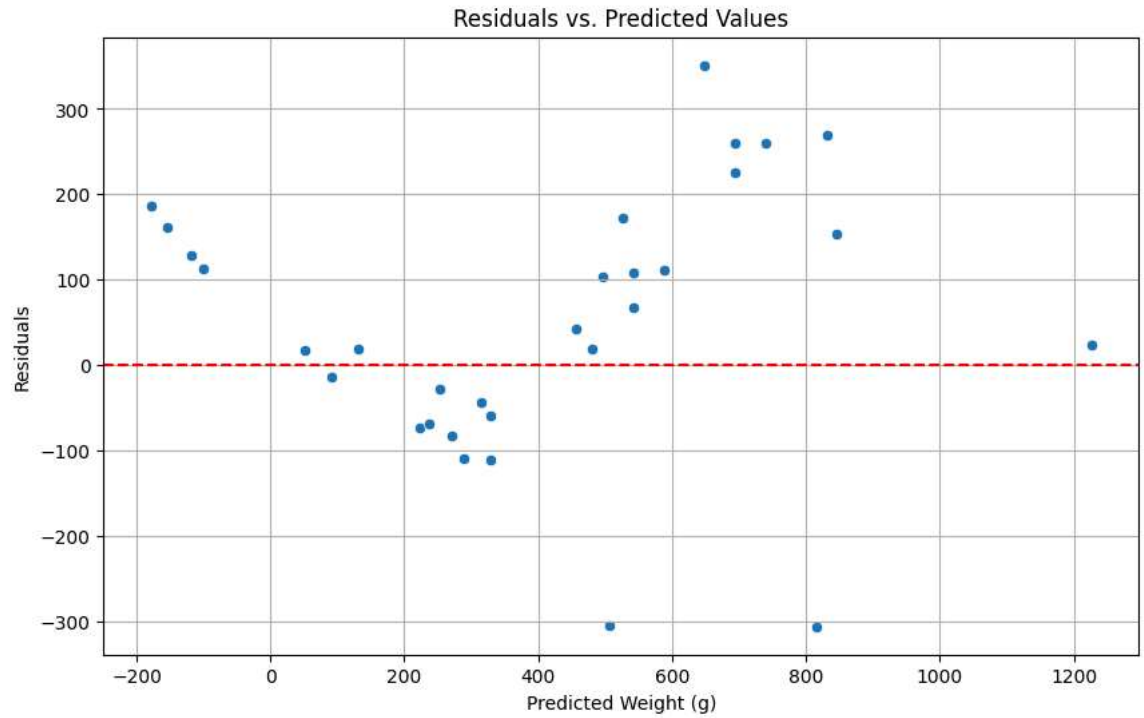
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_test['Length2'], y=y_test, label='Actual Weights')
sns.lineplot(x=X_test['Length2'], y=y_pred, color='red', label='Predicted Weights')
plt.title('Simple Linear Regression: Weight vs. Length2')
plt.xlabel('Length2 (cm)')
plt.ylabel('Weight (g)')
plt.legend()
plt.grid(True)
plt.show()
```



Residual Plot

A residual plot helps us to check the assumptions of linear regression. Ideally, residuals should be randomly scattered around zero, with no discernible pattern.

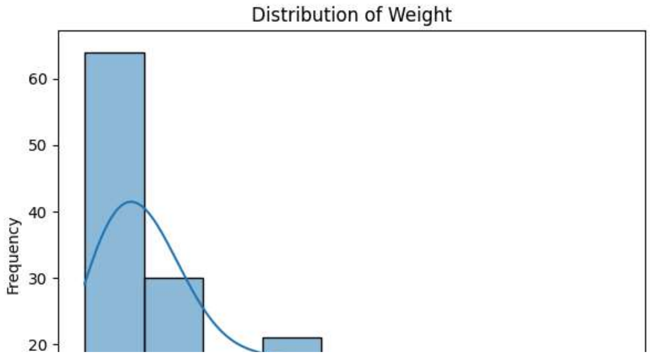
```
residuals = y_test - y_pred

plt.figure(figsize=(10, 6))
sns.scatterplot(x=y_pred, y=residuals)
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residuals vs. Predicted Values')
plt.xlabel('Predicted Weight (g)')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()
```

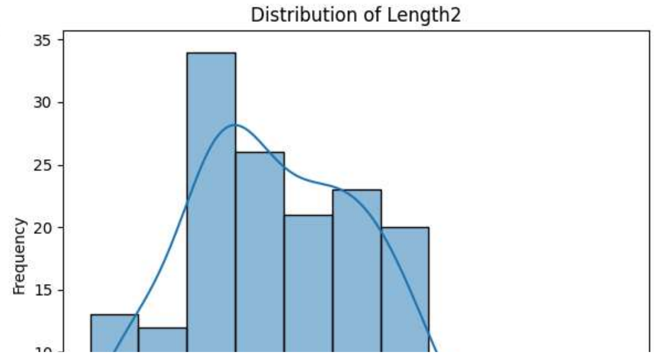


Distribution Plots

Let's also look at the distribution of the 'Weight' and 'Length2' columns to understand their spread and detect any outliers.

```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
sns.histplot(df['Weight'], kde=True)
plt.title('Distribution of Weight')
plt.xlabel('Weight (g)')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
sns.histplot(df['Length2'], kde=True)
plt.title('Distribution of Length2')
plt.xlabel('Length2 (cm)')
plt.ylabel('Frequency')

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


Distribution of Weight
Frequency
60
50
40
30
20


Distribution of Length2
Frequency
35
30
25
20
15