IN_SYS - SW06 - Multiple Linear Regression with Advertising Data

21/10/2024 - Eugen Rodel

Goals:

- Introduction into Multiple Linear Regression
- Repeat old topics as importing data from CSV file into Pandas, exploring and visualization of data, train model, make predictions

1. Description of the data

Preparation: Download the file 'Advertising.csv' from ILIAS to your laptop

The data set consists of 4 colums, three independent input variables (TV, Radio, Newspaper) and one dependent variable (Sales):

TV:

This column represents the advertising budget allocated to TV in thousands of CHF. It indicates how much money was spent on TV commercials to promote the product.

Radio:

This column represents the advertising budget spent on Radio in thousands of CHF. It indicates how much was allocated to radio advertising to reach potential customers.

Newspaper:

This column represents the advertising budget for Newspapers in thousands of CHF. It indicates the spending on newspaper ads to market the product.

Sales:

This column represents the Sales of the product in thousands of units. This is the **dependent variable** we are trying to predict in our regression model. It shows how much the product was sold, and our goal is to see how the different advertising channels (TV, radio, newspaper) contribute to these sales.

2. Load the necessary libraries: pandas, matplotlib, seaborn, sklearn (train_test_split, LinearRegression, mean_squared_error, r2_score)

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Set Seaborn style for plots
sns.set_style('whitegrid')
```

3. Load the 'Advertising.csv' file into a Pandas Dataframe called 'advertising_df'

Hint: **no** special options are needed to load the data, just a simple read Display first 5 rows of advertising_df to verify, that import worked

In [2]:
```
# Load the uploaded data from the CSV file
advertising_df = pd.read_csv('Advertising_2.csv',sep=';')

# Display the first few rows of the DataFrame to verify that the import worked
advertising_df.head()
```

Out[2]:

	Unnamed: 0	TV	radio	newspaper	sales
0	1	230.1	37.8	69.2	22.1
1	2	44.5	39.3	45.1	10.4
2	3	17.2	45.9	69.3	9.3
3	4	151.5	41.3	58.5	18.5
4	5	180.8	10.8	58.4	12.9

Goal for this Multiple Linear Regression Project: find the optimal parameters for this formular

$\textbf{Sales} = \beta_0 + \beta_1 * \textbf{TV} + \beta_2 * \textbf{Radio} + \beta_3 * \textbf{Newspaper}$

.

4. Data Exploration and Visualization

In [3]:
```
# check how many rows and columns we have in titanic_df
advertising_df.shape
```

Out[3]:
```
(200, 5)
```

In [4]:
```
advertising_df.columns
```

Out[4]:
```
Index(['Unnamed: 0', 'TV', 'radio', 'newspaper', 'sales'], dtype='object')
```

In [5]:
```
# Drop the unnecessary column 'Unnamed: 0' to clean up the data
advertising_df = advertising_df.drop(columns=['Unnamed: 0'])

advertising_df.head()
```

Out[5]:

	TV	radio	newspaper	sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

In [6]:
```
advertising_df.describe()
```

Out[6]:

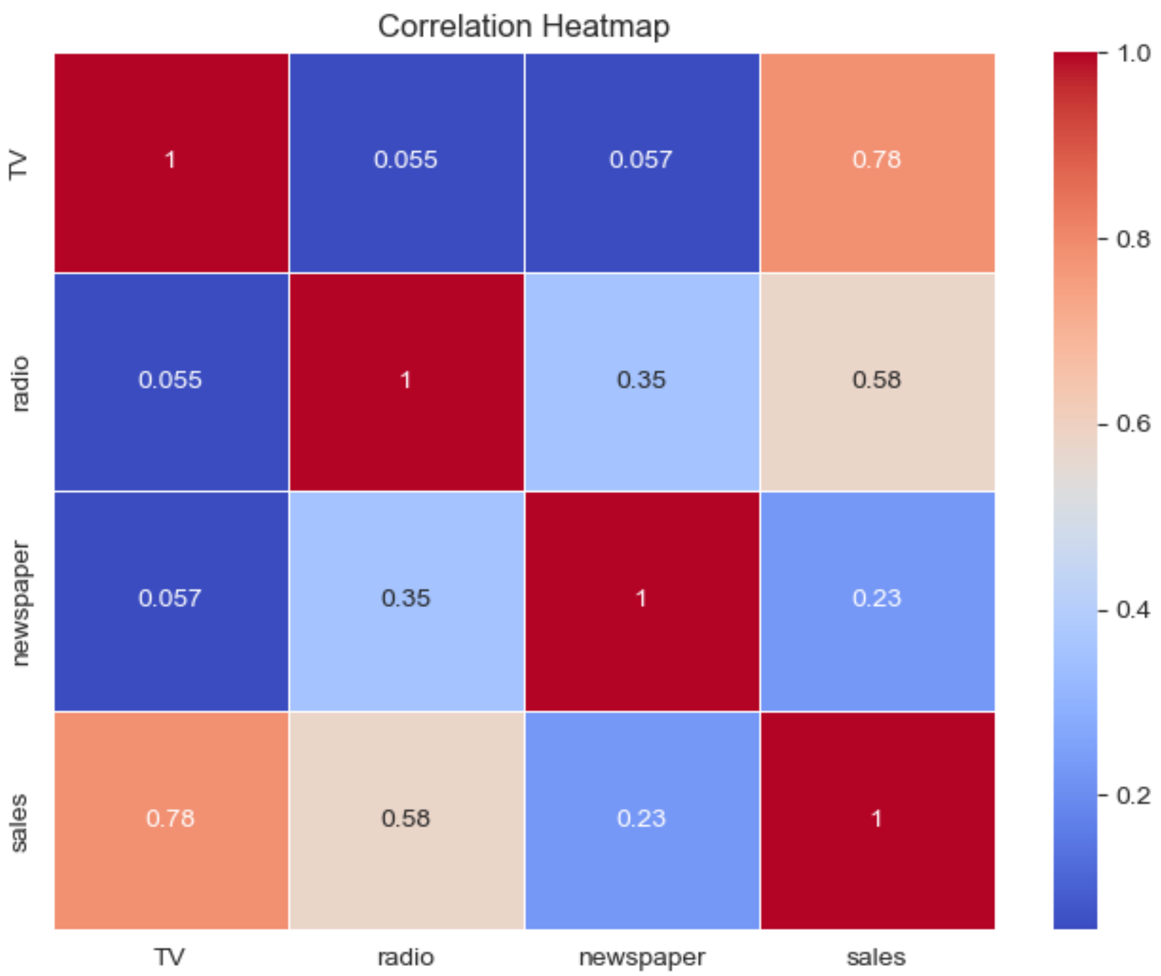
	TV	radio	newspaper	sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	14.022500
std	85.854236	14.846809	21.778621	5.217457
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	10.375000
50%	149.750000	22.900000	25.750000	12.900000
75%	218.825000	36.525000	45.100000	17.400000
max	296.400000	49.600000	114.000000	27.000000

Heatmap:

Displays the correlation between features. This helps us see which features are most correlated with sales.

In [7]:
```
# Heatmap to show the correlation between features
plt.figure(figsize=(8, 6))   # Set the plot size in inch: figsize(width, height)
sns.heatmap(advertising_df.corr(), annot=True, cmap='coolwarm', linewidths=0.5)
```

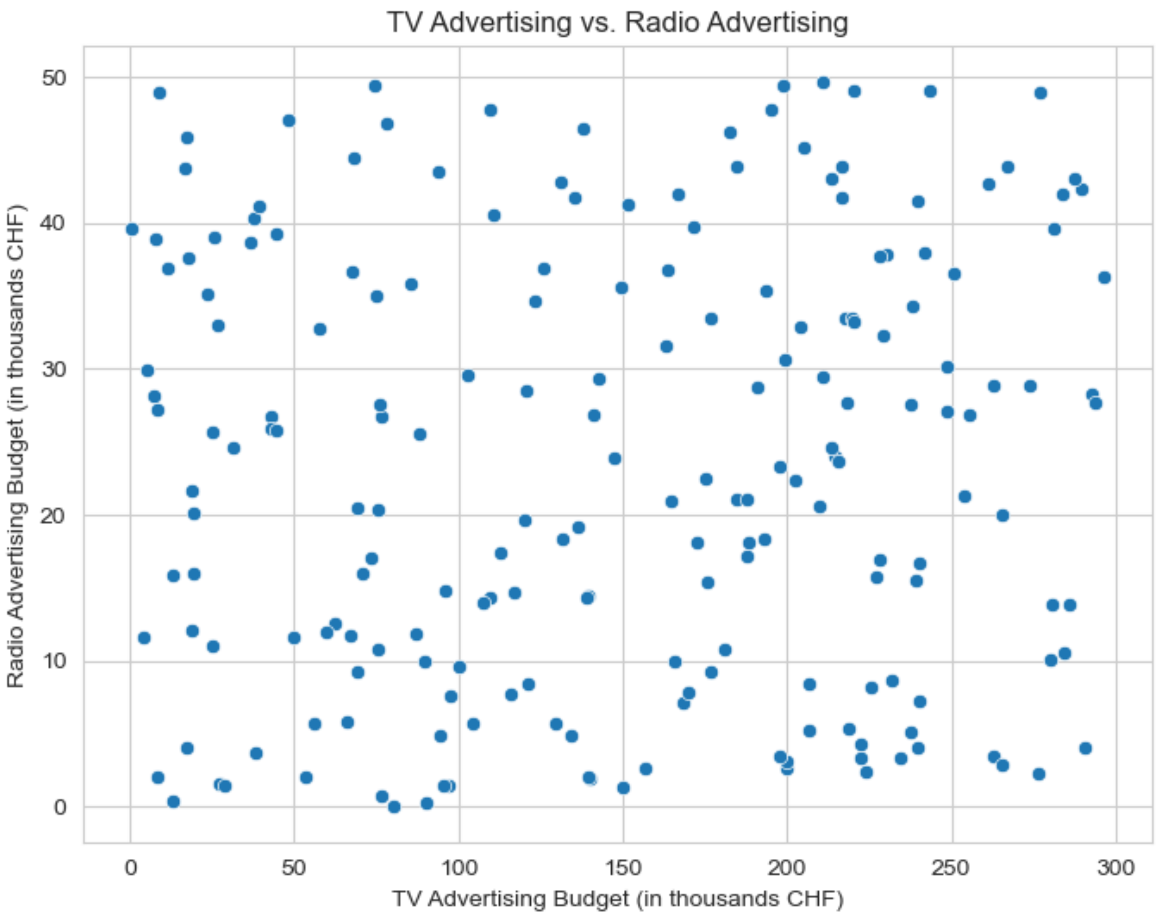
```
plt.title('Correlation Heatmap')
plt.show()
```



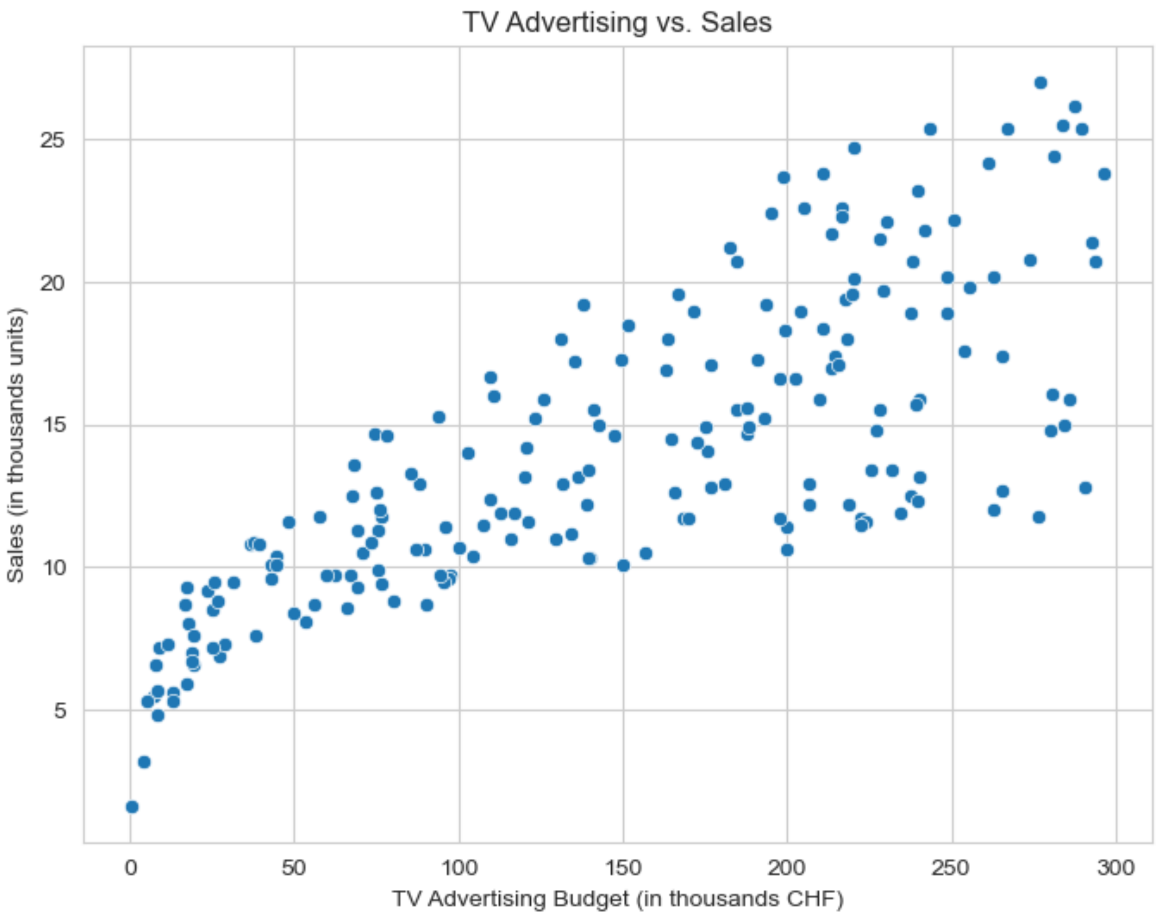
Scatterplot, to visualize the correlation between two variables

Question: based on the heatmap data above, what do you expect for the scatter plot of TV vs Radio advertising?

In [8]:
```
# Scatter plot of TV advertising vs. Radio advertising using circles (dots)
plt.figure(figsize=(8, 6))
sns.scatterplot(data=advertising_df, x='TV', y='radio', marker='o')
plt.title('TV Advertising vs. Radio Advertising')
plt.xlabel('TV Advertising Budget (in thousands CHF)')
plt.ylabel('Radio Advertising Budget (in thousands CHF)')
plt.show()
```



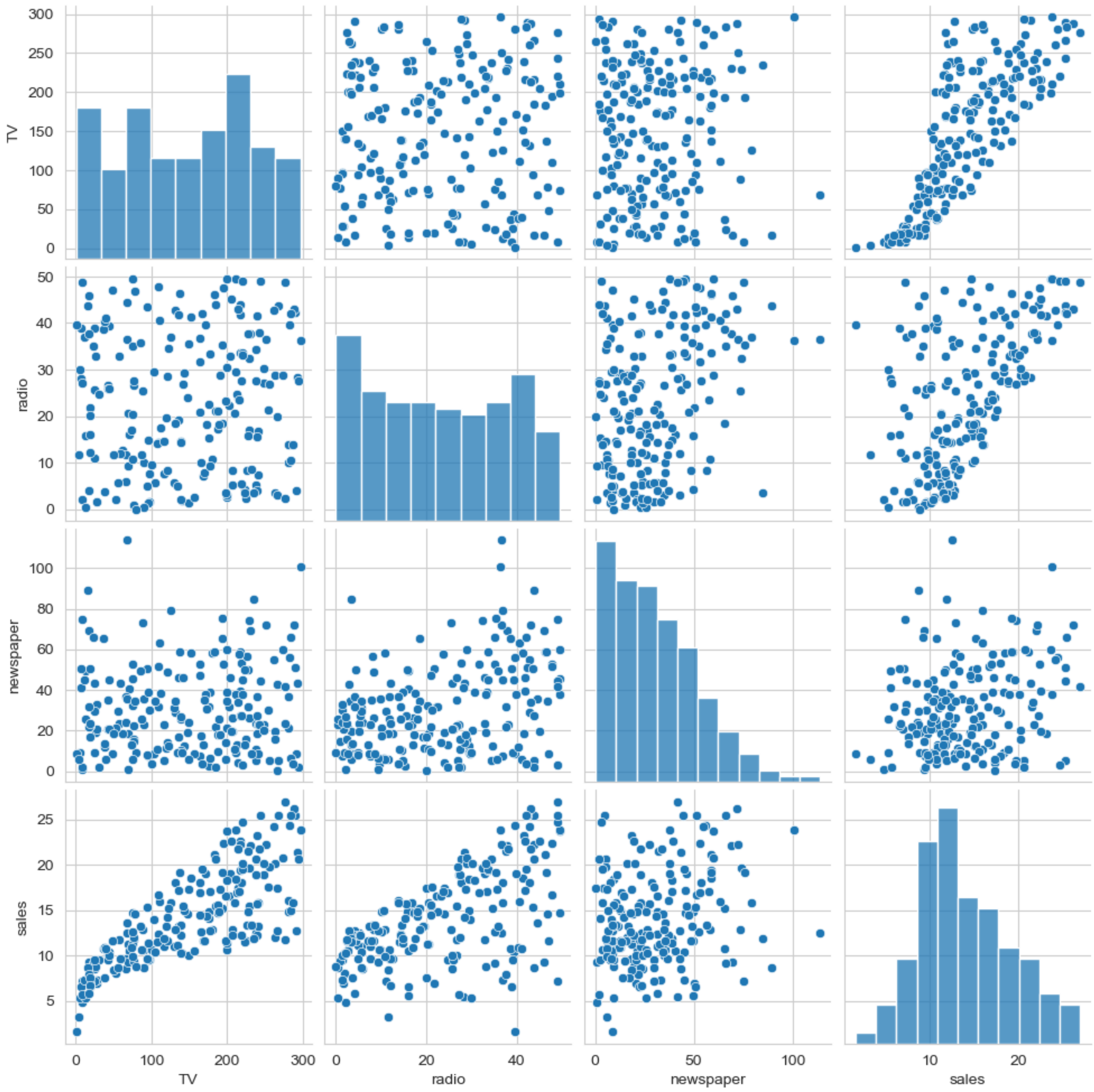
In [9]:
```
# Scatter plot of TV advertising vs. Sales using circles (dots)
plt.figure(figsize=(8, 6))
sns.scatterplot(data=advertising_df, x='TV', y='sales', marker='o')
plt.title('TV Advertising vs. Sales')
plt.xlabel('TV Advertising Budget (in thousands CHF)')
plt.ylabel('Sales (in thousands units)')
plt.show()
```



Pairplot

to visualize the relationship between all features

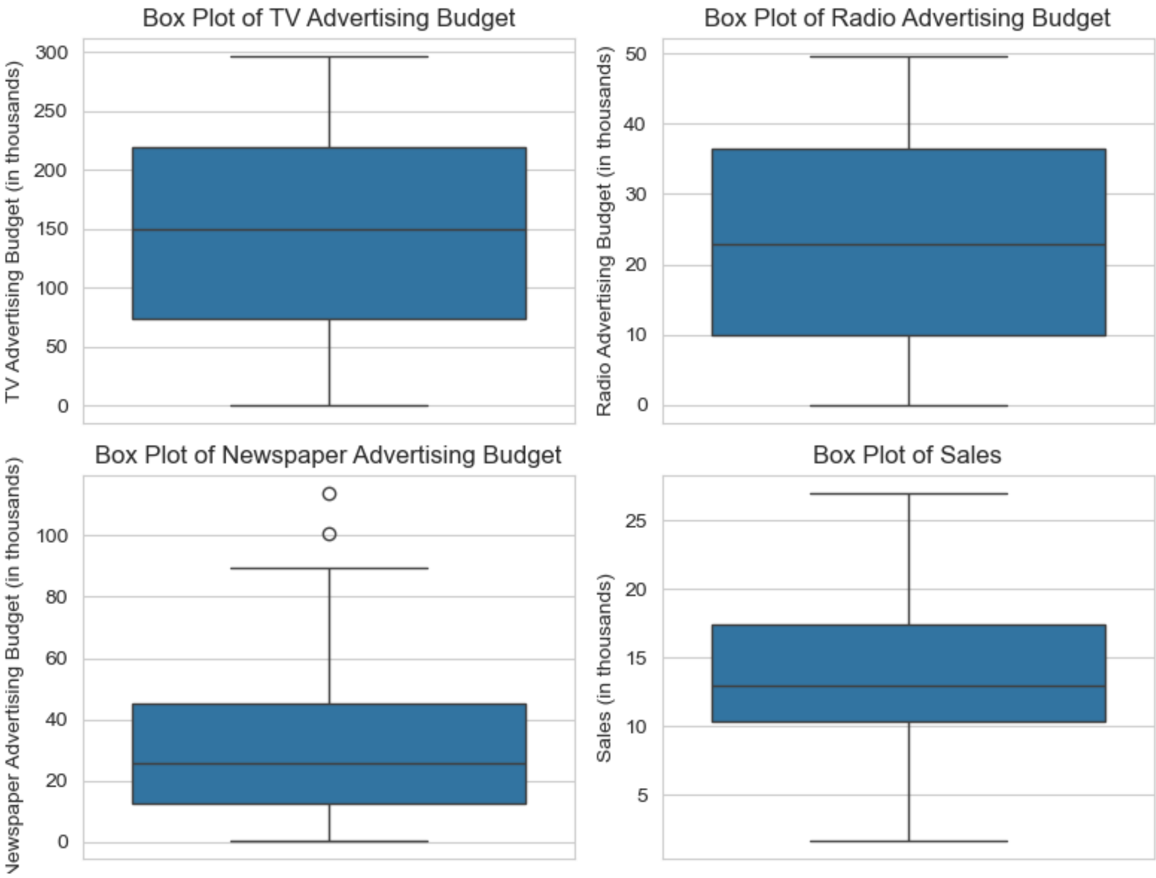
In [10]:
```
# Pairplot to visualize the relationships between all features
sns.pairplot(advertising_df)
plt.show()
```



Create Box Plots for each of the four features, but group them in one plot

In [11]:
```
# Box plots for all features in the dataset
plt.figure(figsize=(8, 6))

# Box plot for TV Advertising Budget
plt.subplot(2, 2, 1)
sns.boxplot(data=advertising_df, y='TV')
plt.title('Box Plot of TV Advertising Budget')
plt.ylabel('TV Advertising Budget (in thousands)')

# Box plot for Radio Advertising Budget
plt.subplot(2, 2, 2)
sns.boxplot(data=advertising_df, y='radio')
plt.title('Box Plot of Radio Advertising Budget')
plt.ylabel('Radio Advertising Budget (in thousands)')

# Box plot for Newspaper Advertising Budget
plt.subplot(2, 2, 3)
sns.boxplot(data=advertising_df, y='newspaper')
plt.title('Box Plot of Newspaper Advertising Budget')
```

```
plt.ylabel('Newspaper Advertising Budget (in thousands)')

# Box plot for Sales
plt.subplot(2, 2, 4)
sns.boxplot(data=advertising_df, y='sales')
plt.title('Box Plot of Sales')
plt.ylabel('Sales (in thousands)')

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



5. Multiple Linear Regression

Split Data into Inndependent Input Data and Dependend Output Data

In [12]:
```
# Prepare the data: Define independent input features (X) and dependend output t
X = advertising_df[['TV', 'radio', 'newspaper']]
y = advertising_df['sales']
```

Assistant

The error occurs because you're trying to access multiple columns from the DataFrame using incorrect syntax. When selecting multiple columns from a pandas DataFrame, you need to use a list of column names inside square brackets.

Would you like me to provide the corrected code?

Split data into train and test data

In [13]:
```
# Split the data into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

Train the model

In [14]:
```
# Initialize and train the Multiple Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[14]:
```
▾ LinearRegression  i ?

LinearRegression()
```

Use trained modek for prediction, input is the test data

In [15]:
```
# Make predictions on the test set
y_pred = model.predict(X_test)
```

Evaluation of the trained model

In [16]:
```
# Make predictions on the test set
y_pred = model.predict(X_test)
```

In [17]:
```
# print out the input data and the predicted sales

# Input data for prediction (the test data):
print(X_test)
```

```
         TV  radio  newspaper
95    163.3   31.6       52.9
15    195.4   47.7       52.9
30    292.9   28.3       43.2
158    11.7   36.9       45.2
128   220.3   49.0        3.2
115    75.1   35.0       52.7
69    216.8   43.9       27.2
170    50.0   11.6       18.4
174   222.4    3.4       13.1
45    175.1   22.5       31.5
66     31.5   24.6        2.2
182    56.2    5.7       29.7
165   234.5    3.4       84.8
78      5.4   29.9        9.4
186   139.5    2.1       26.6
177   170.2    7.8       35.2
56      7.3   28.1       41.4
152   197.6   23.3       14.2
82     75.3   20.3       32.5
68    237.4   27.5       11.0
124   229.5   32.3       74.2
16     67.8   36.6      114.0
148    38.0   40.3       11.9
93    250.9   36.5       72.3
65     69.0    9.3        0.9
60     53.5    2.0       21.4
84    213.5   43.0       33.8
67    139.3   14.5       10.2
125    87.2   11.8       25.9
132     8.4   27.2        2.1
9     199.8    2.6       21.2
18     69.2   20.5       18.3
55    198.9   49.4       60.0
75     16.9   43.7       89.4
150   280.7   13.9       37.0
104   238.2   34.3        5.3
135    48.3   47.0        8.5
137   273.7   28.9       59.7
164   117.2   14.7        5.4
76     27.5    1.6       20.7
```

In [18]:

```python
# the predicted data for the test input data
print(y_pred)
```

```
[16.4080242  20.88988209 21.55384318 10.60850256 22.11237326 13.10559172
 21.05719192  7.46101034 13.60634581 15.15506967  9.04831992  6.65328312
 14.34554487  8.90349333  9.68959028 12.16494386  8.73628397 16.26507258
 10.27759582 18.83109103 19.56036653 13.25103464 12.33620695 21.30695132
  7.82740305  5.80957448 20.75753231 11.98138077  9.18349576  8.5066991
 12.46646769 10.00337695 21.3876709  12.24966368 18.26661538 20.13766267
 14.05514005 20.85411186 11.0174441   4.56899622]
```

In [19]:

```python
# To compare the predicted results from the Multiple Linear Regression Model wit
# which we know from the original data in Advertising.csv, lets combine them in 

# Create a DataFrame from X_test
results_df = X_test.copy()

# Add the actual sales values to the new DataFrame results_df into a new column 
```

```
results_df['Actual Sales'] = y_test

# Add the predicted sales values to the new DataFrame results_df into a new colu
results_df['Predicted Sales'] = y_pred

results_df.sort_index()
```

Out[19]:

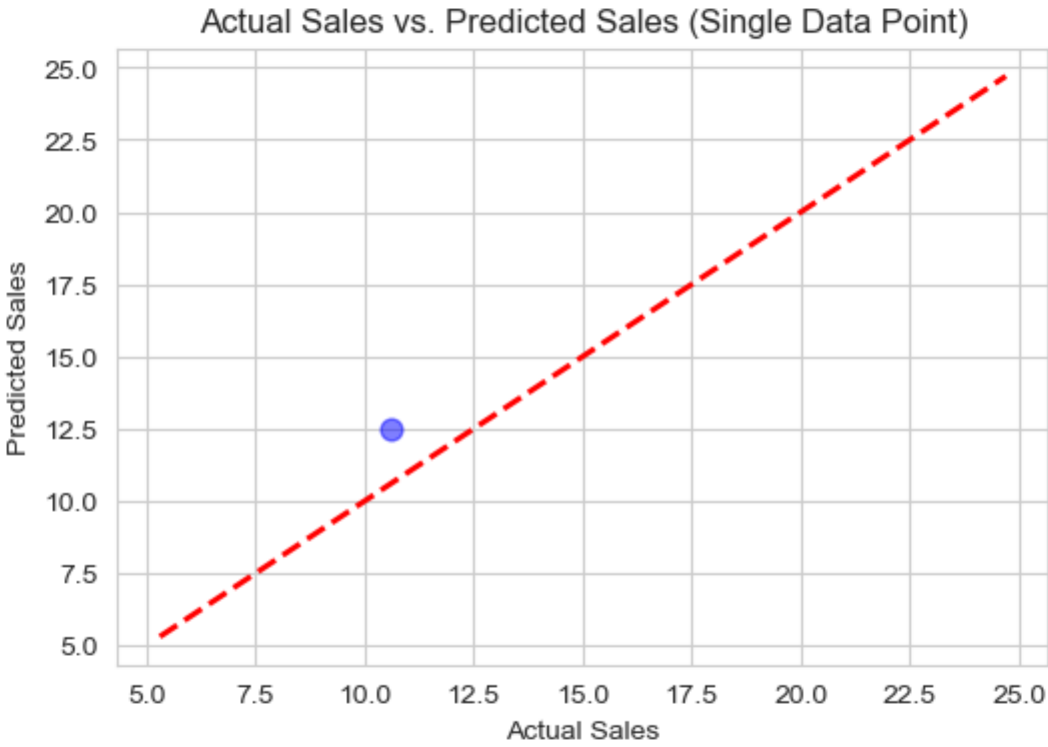
	TV	radio	newspaper	Actual Sales	Predicted Sales
9	199.8	2.6	21.2	10.6	12.466468
15	195.4	47.7	52.9	22.4	20.889882
16	67.8	36.6	114.0	12.5	13.251035
18	69.2	20.5	18.3	11.3	10.003377
30	292.9	28.3	43.2	21.4	21.553843
45	175.1	22.5	31.5	14.9	15.155070
55	198.9	49.4	60.0	23.7	21.387671
56	7.3	28.1	41.4	5.5	8.736284
60	53.5	2.0	21.4	8.1	5.809574
65	69.0	9.3	0.9	9.3	7.827403
66	31.5	24.6	2.2	9.5	9.048320
67	139.3	14.5	10.2	13.4	11.981381
68	237.4	27.5	11.0	18.9	18.831091
69	216.8	43.9	27.2	22.3	21.057192
75	16.9	43.7	89.4	8.7	12.249664
76	27.5	1.6	20.7	6.9	4.568996
78	5.4	29.9	9.4	5.3	8.903493
82	75.3	20.3	32.5	11.3	10.277596
84	213.5	43.0	33.8	21.7	20.757532
93	250.9	36.5	72.3	22.2	21.306951
95	163.3	31.6	52.9	16.9	16.408024
104	238.2	34.3	5.3	20.7	20.137663
115	75.1	35.0	52.7	12.6	13.105592
124	229.5	32.3	74.2	19.7	19.560367
125	87.2	11.8	25.9	10.6	9.183496
128	220.3	49.0	3.2	24.7	22.112373
132	8.4	27.2	2.1	5.7	8.506699
135	48.3	47.0	8.5	11.6	14.055140
137	273.7	28.9	59.7	20.8	20.854112
148	38.0	40.3	11.9	10.9	12.336207
150	280.7	13.9	37.0	16.1	18.266615
152	197.6	23.3	14.2	16.6	16.265073

	TV	radio	newspaper	Actual Sales	Predicted Sales
158	11.7	36.9	45.2	7.3	10.608503
164	117.2	14.7	5.4	11.9	11.017444
165	234.5	3.4	84.8	11.9	14.345545
170	50.0	11.6	18.4	8.4	7.461010
174	222.4	3.4	13.1	11.5	13.606346
177	170.2	7.8	35.2	11.7	12.164944
182	56.2	5.7	29.7	8.7	6.653283
186	139.5	2.1	26.6	10.3	9.689590

In [20]:
```
# As an example, let's just plot one prediction vs actual sales,
# so we just use the first row of results_df
first_row = results_df.sort_index().iloc[0]

first_row
```

Out[20]:
```
TV                  199.800000
radio                 2.600000
newspaper            21.200000
Actual Sales         10.600000
Predicted Sales      12.466468
Name: 9, dtype: float64
```

In [21]:
```
# Scatter plot: Actual Sales vs. Predicted Sales for the first data point
plt.figure(figsize=(6, 4))
plt.scatter(first_row['Actual Sales'], first_row['Predicted Sales'], color='blue
plt.plot([results_df['Actual Sales'].min(), results_df['Actual Sales'].max()],
         [results_df['Actual Sales'].min(), results_df['Actual Sales'].max()],
         color='red', linestyle='--', linewidth=2)  # 45-degree reference line
plt.title('Actual Sales vs. Predicted Sales (Single Data Point)')
plt.xlabel('Actual Sales')
plt.ylabel('Predicted Sales')
plt.show()
```



In [22]:
```
# Let's visualize the actaul sales vs the predicted sales for all test data

# Scatter plot: Actual Sales vs. Predicted Sales with enhanced markers for visib
plt.figure(figsize=(8, 6))
sns.scatterplot(x=results_df['Actual Sales'], y=results_df['Predicted Sales'], s
plt.plot([results_df['Actual Sales'].min(), results_df['Actual Sales'].max()],
         [results_df['Actual Sales'].min(), results_df['Actual Sales'].max()],
         color='red', linestyle='--', linewidth=2)  # 45-degree line for referen
plt.title('Actual Sales vs. Predicted Sales')
plt.xlabel('Actual Sales')
plt.ylabel('Predicted Sales')
plt.show()
```

In [23]:
```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Display the model evaluation results
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error (MSE): 3.17
R² Score: 0.90
```

Model Evaluation Metrics

1. **Mean Squared Error (MSE): 3.17**

- The **Mean Squared Error (MSE)** measures the **average squared difference** between the predicted values and the actual values.
- In our case, an MSE of **3.17** means that, on average, the **squared error** between the predicted sales and actual sales is **3.17**.
- The **lower** the MSE, the better the model's predictions are, as it means the predictions are closer to the actual values.

2. **R^2 Score: 0.90**

- The **R^2 score**, also known as the **coefficient of determination**, measures how well the independent variables (TV, radio, newspaper advertising budgets) explain the variance in the dependent variable (sales).
- An R^2 score of **0.90** means that **90%** of the variability in sales can be explained by

the advertising spending.

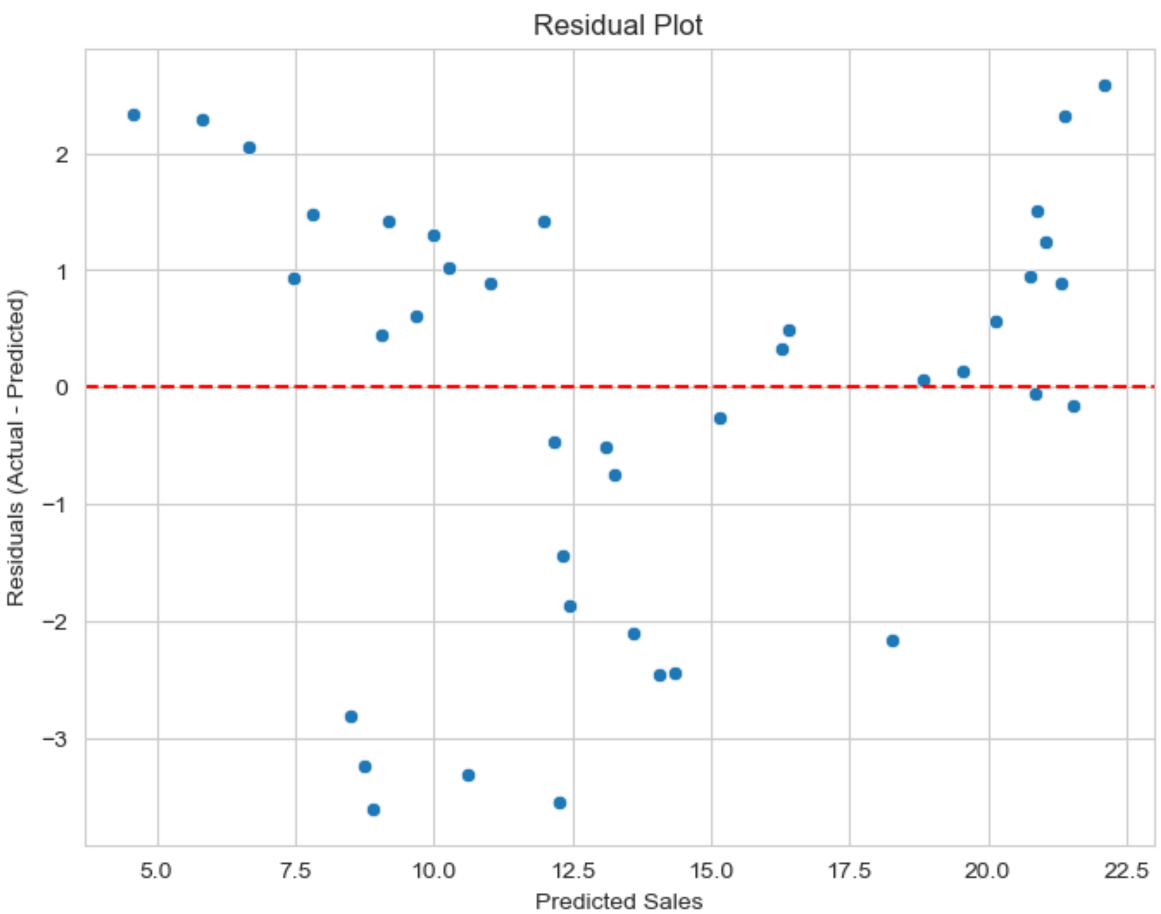
- The **closer the R^2 value is to 1**, the better the model explains the variance in the target variable. In this case, an R^2 score of **0.90** indicates a strong relationship between the advertising budgets and sales, meaning our model is performing well.

These metrics help us understand how well our model fits the data and can be used to predict future sales based on advertising spending.

Residual Plot

For a good trained model the residual plot (the difference between trained and actual data) should be in a random pattern above and below the zero line.

In [24]:
```
residuals = y_test - y_pred
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_pred, y=residuals)
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residual Plot')
plt.xlabel('Predicted Sales')
plt.ylabel('Residuals (Actual - Predicted)')
plt.show()
```



In [ ]:

In [ ]: