SALES PREDICTION FORECASTING

In [1]:
```
#imporitng the libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
sp = pd.read_csv("C:/Users/yuvak/OneDrive/Pictures/sales prediction/advertising.csv"
```

In [3]:
```
sp.head()
```

Out[3]:

	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	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

In [4]:
```
len(sp)
```

Out[4]:
```
200
```

In [5]:
```
sp.shape
```

Out[5]:
```
(200, 4)
```

In [6]:
```
sp.index
```

Out[6]:
```
RangeIndex(start=0, stop=200, step=1)
```

In [7]:
```
sp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   TV         200 non-null    float64
 1   Radio      200 non-null    float64
 2   Newspaper  200 non-null    float64
 3   Sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
```

In [8]:
```
sp.dtypes
```

Out[8]:
```
TV           float64
Radio        float64
Newspaper    float64
Sales        float64
dtype: object
```

In [9]:
```
sp.describe()
```

Out[9]:

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

In [10]:
```
sp.isna()
```

Out[10]:

	TV	Radio	Newspaper	Sales
0	False	False	False	False
1	False	False	False	False
2	False	False	False	False
3	False	False	False	False
4	False	False	False	False
...	...	...	...	...
195	False	False	False	False
196	False	False	False	False
197	False	False	False	False
198	False	False	False	False
199	False	False	False	False

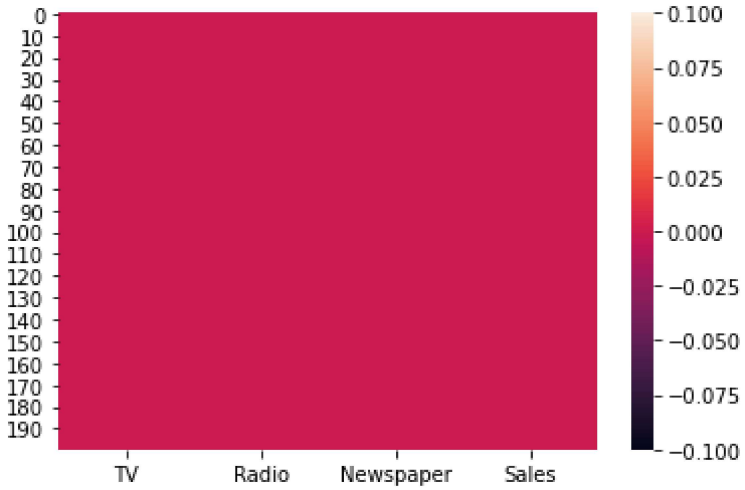
200 rows × 4 columns

In [11]:
```
sp.isna().sum()
```

Out[11]:
```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

In [12]:
```
sns.heatmap(sp.isna())
```

Out[12]:
```
<AxesSubplot:>
```

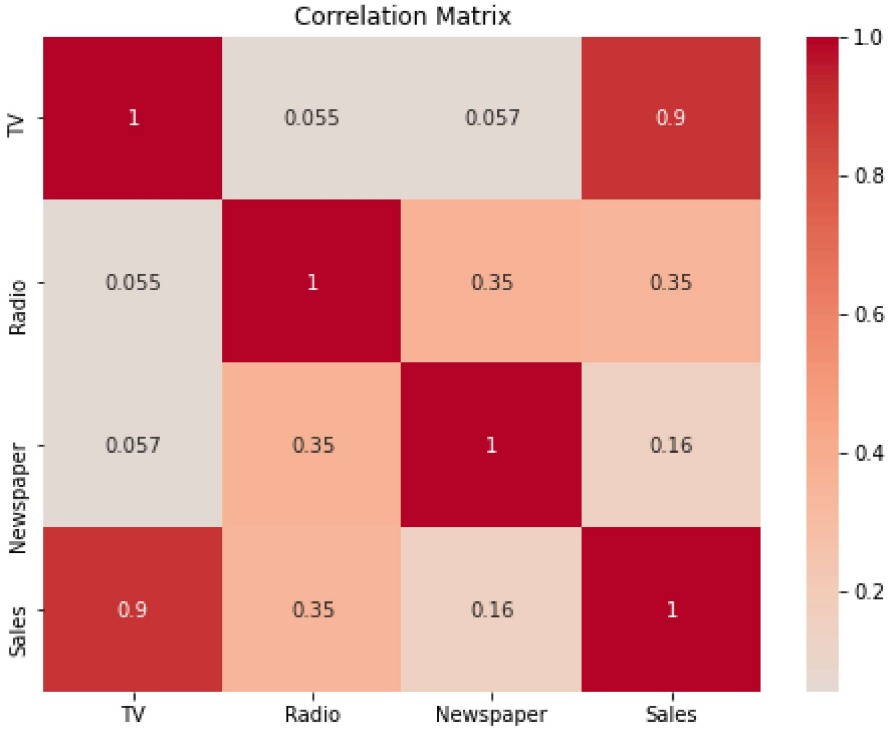


In [13]:
```
advertising_data = pd.DataFrame(sp)
```

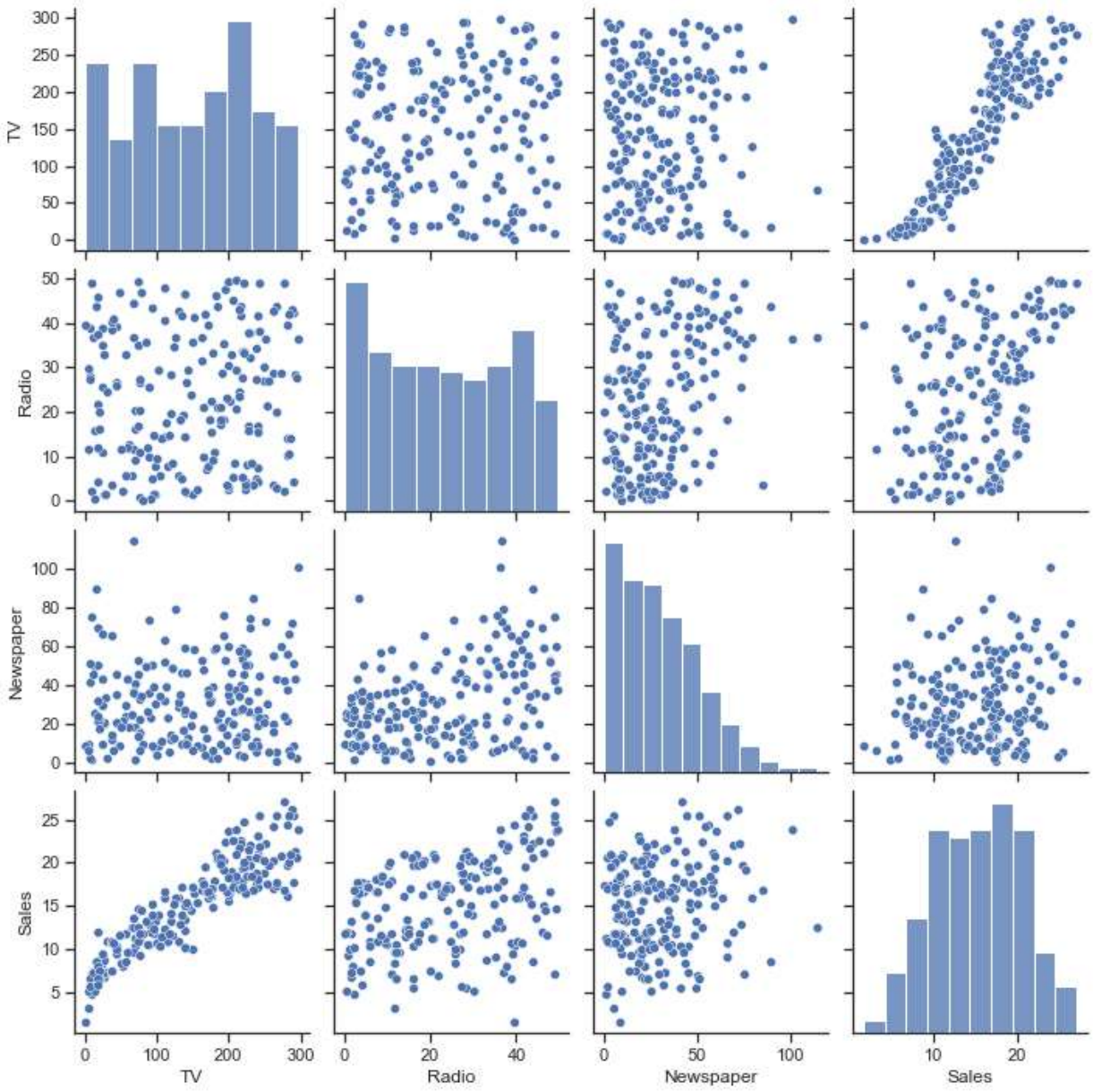
In [14]:
```
correlation_matrix = sp.corr()
print(correlation_matrix)
```

```
                 TV     Radio  Newspaper     Sales
TV         1.000000  0.054809   0.056648  0.901208
Radio      0.054809  1.000000   0.354104  0.349631
Newspaper  0.056648  0.354104   1.000000  0.157960
Sales      0.901208  0.349631   0.157960  1.000000
```

In [15]:
```
# Correlation matrix heatmap
correlation_matrix = advertising_data.corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Matrix')
plt.show()
```



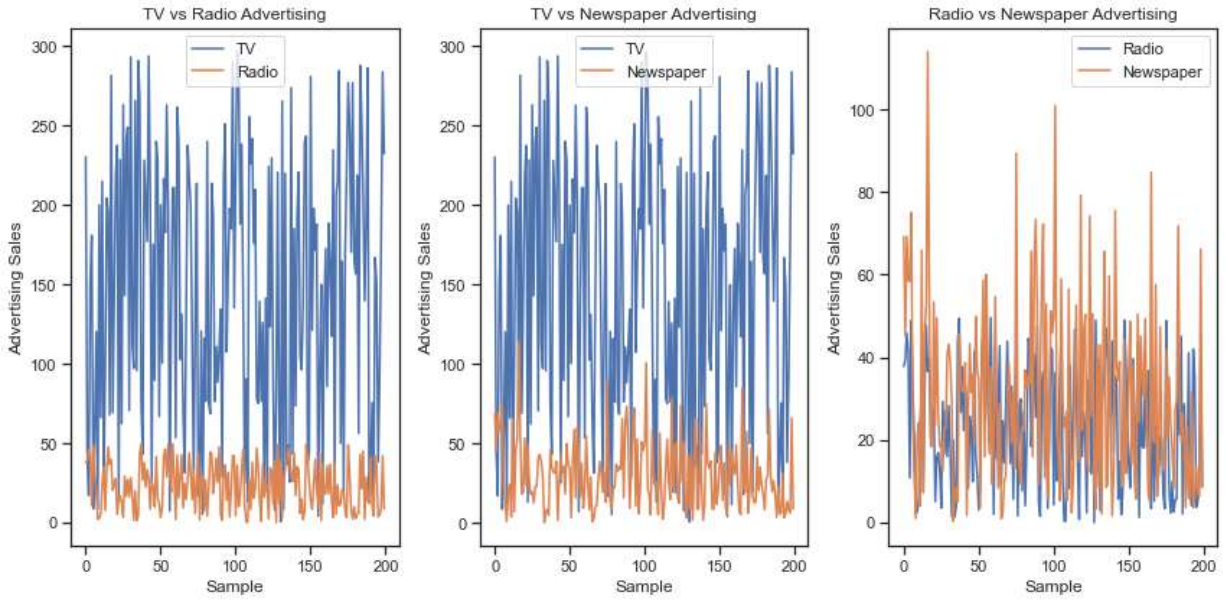
In [16]:
```
# Scatterplot matrix
sns.set(style='ticks')
sns.pairplot(advertising_data, kind='scatter')
plt.show()
```



In [17]:

```
# Line plot for each advertising type
plt.figure(figsize=(12, 6))

plt.subplot(131)
plt.plot(advertising_data['TV'], label='TV')
plt.plot(advertising_data['Radio'], label='Radio')
plt.xlabel('Sample')
plt.ylabel('Advertising Sales')
plt.title('TV vs Radio Advertising')
plt.legend()

plt.subplot(132)
plt.plot(advertising_data['TV'], label='TV')
plt.plot(advertising_data['Newspaper'], label='Newspaper')
plt.xlabel('Sample')
plt.ylabel('Advertising Sales')
plt.title('TV vs Newspaper Advertising')
plt.legend()

plt.subplot(133)
plt.plot(advertising_data['Radio'], label='Radio')
plt.plot(advertising_data['Newspaper'], label='Newspaper')
plt.xlabel('Sample')
plt.ylabel('Advertising Sales')
plt.title('Radio vs Newspaper Advertising')
```

```
plt.legend()

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



In [18]:
```
#Target and feature variables

x = sp[['TV','Radio','Newspaper']]  # Feature variable
y = sp['Sales']  # Target variable
```

In [19]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

In [20]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_sta
```

In [21]:
```
lr = LinearRegression()
```

In [22]:
```
lr.fit(x_train, y_train)
```

Out[22]:
```
▾ LinearRegression

LinearRegression()
```

In [23]:
```
y_pred = lr.predict(x_test)
```

In [24]:
```
# Assuming y_test and y_pred are your true and predicted values
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f"Mean Squared Error: {mse:.2f}")
print(f"Root Mean Squared Error: {rmse:.2f}")

mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error: {mae:.2f}")
```

```
Mean Squared Error: 2.72
Root Mean Squared Error: 1.65
Mean Absolute Error: 1.22
```

-Range for three errors indicates as 0 to positive infinity

Mean Squared Error (MSE):

Value: 2.72 Interpretation: A lower MSE indicates better model performance. The value of 2.72 suggests that, on average, the squared difference between predicted and true values is 2.72. Since it's a squared value, it's not directly interpretable in the original units of the target variable.

Root Mean Squared Error (RMSE):

Value: 1.65 Interpretation: RMSE is the square root of MSE. Like MSE, a lower RMSE indicates better model performance. The value of 1.65 suggests that, on average, the difference between predicted and true values is around 1.65 units (in the original units of the target variable).

Mean Absolute Error (MAE):

Value: 1.22 Interpretation: MAE represents the average absolute difference between predicted and true values. Like MSE and RMSE, a lower MAE is indicative of better model performance. The value of 1.22 suggests that, on average, the absolute difference between predicted and true values is 1.22 units (in the original units of the target variable).

In summary, lower values for all three metrics indicate better model performance. RMSE and MAE are directly interpretable in the original units of the target variable, making them useful for understanding the practical implications of the errors. Keep in mind that the acceptable ranges for these metrics can vary depending on the context of your problem and the nature of the data you're working with.

References:

1.Practical statistics for Data scientists Book

In [ ]: