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Oasis Infobyte (Data Science) - Task-5

Sales Prediction

Importing Libraries

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from google.colab import files


uploaded = files.upload()

<IPython.core.display.HTML object>

Saving Advertising.csv to Advertising (1).csv

df = pd.read_csv('Advertising.csv')

df

        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
..     ...    ...        ...    ...
195   38.2    3.7       13.8    7.6
196   94.2    4.9        8.1    9.7
197  177.0    9.3        6.4   12.8
198  283.6   42.0       66.2   25.5
199  232.1    8.6        8.7   13.4

[200 rows x 4 columns]

df.columns

Index(['TV', 'Radio', 'Newspaper', 'Sales'], dtype='object')
```

There are total 5 columns in the Dataset

```
df.info
```

```
<bound method DataFrame.info of         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
..     ...    ...        ...    ...
195   38.2    3.7       13.8    7.6
196   94.2    4.9        8.1    9.7
197  177.0    9.3        6.4   12.8
198  283.6   42.0       66.2   25.5
199  232.1    8.6        8.7   13.4

[200 rows x 4 columns]>
```

There are 200 Rows and 4 Columns

```
df.shape
```

```
(200, 4)
```

```
df.head(2)
```

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4

Displaying the first 2 entries of the dataset

```
df.iloc[1]
```

```
TV           44.5
Radio        39.3
Newspaper    45.1
Sales        10.4
Name: 1, dtype: float64
```

```
df.describe()
```

	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

Preprocessing the Data

checking the null values

```
df.isnull()
```

```
        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 x 4 columns]
```

```
df.isnull().sum()
```

```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

There are no null values in the datset

```
df.describe
```

```
<bound method NDFrame.describe of         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
..     ...    ...        ...    ...
195   38.2    3.7       13.8    7.6
196   94.2    4.9        8.1    9.7
197  177.0    9.3        6.4   12.8
198  283.6   42.0       66.2   25.5
199  232.1    8.6        8.7   13.4

[200 rows x 4 columns]>
```

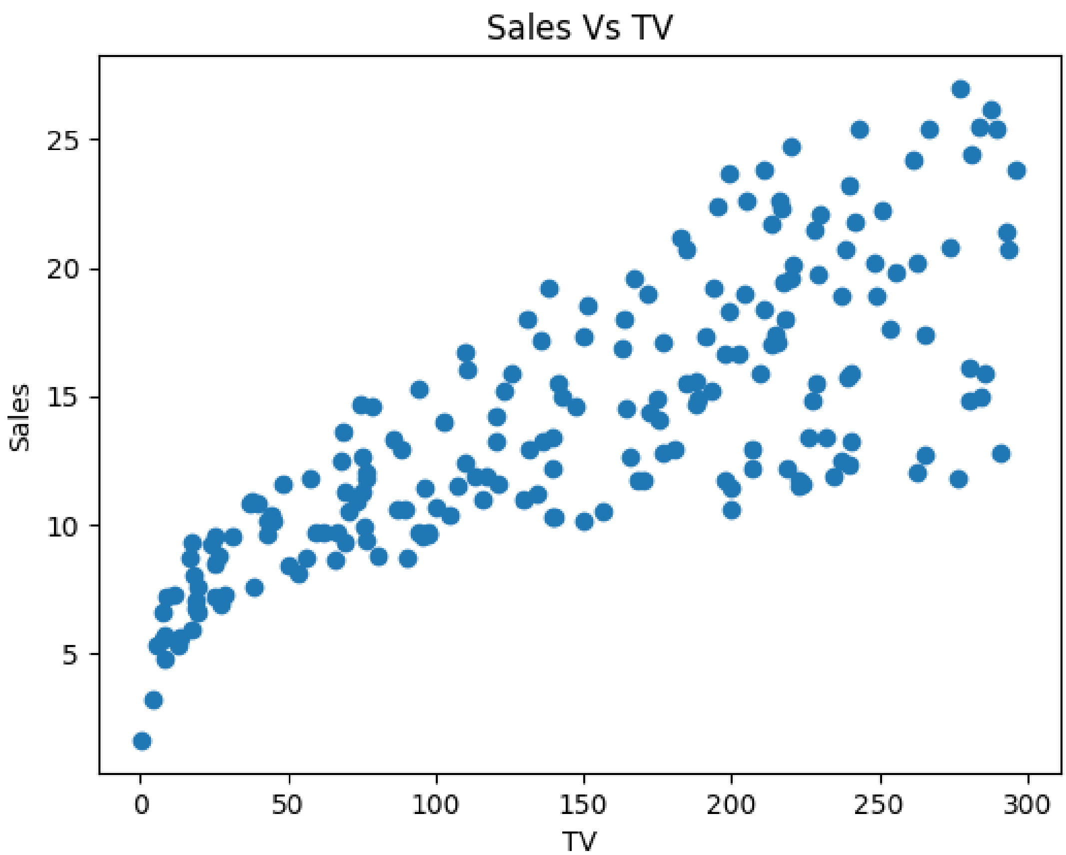
```
df.duplicated().sum()
```

```
0
```

Data Visualization

```
plt.scatter(df['TV'], df['Sales'])
plt.title("Sales Vs TV")
plt.xlabel('TV')
plt.ylabel('Sales')
```

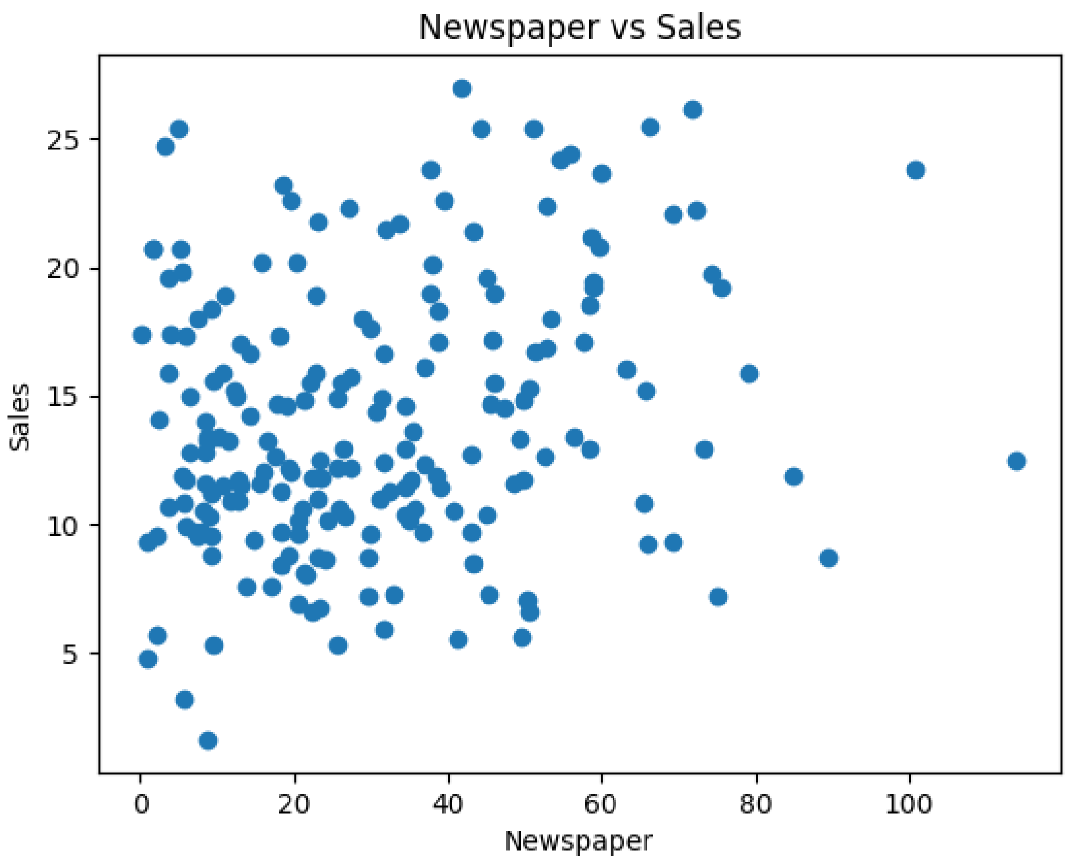
```
Text(0, 0.5, 'Sales')
```



The horizontal axis represents the TV advertising expenditure, measured in monetary units, while the vertical axis signifies the sales figures. The graph shows a positive trend, indicating that increased investment in television advertising is often associated with higher sales.

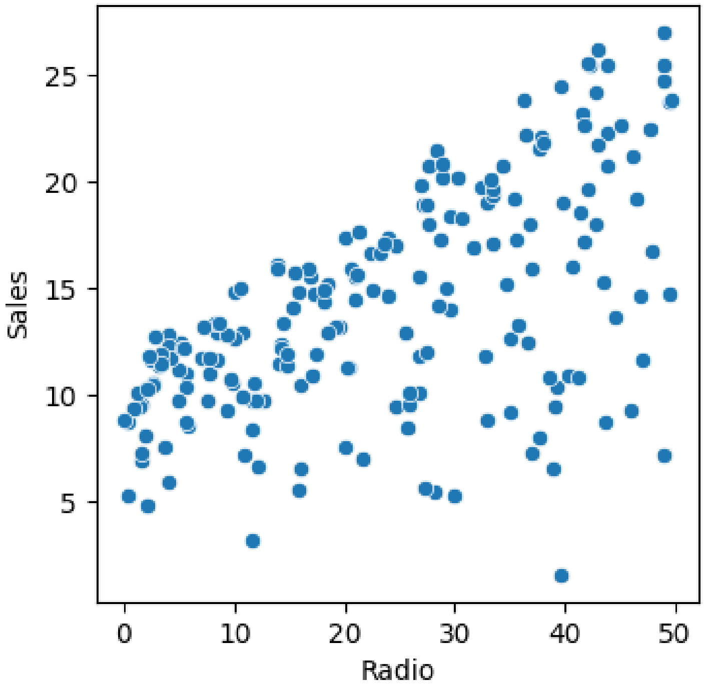
```
plt.scatter(x=df['Newspaper'], y=df['Sales'])
plt.title("Newspaper vs Sales")
plt.xlabel("Newspaper")
plt.ylabel("Sales")
```

```
Text(0, 0.5, 'Sales')
```



The horizontal axis represents the Newspaper advertising expenditure, measured in monetary units, while the vertical axis signifies the sales figures The graph reveals the impact of newspaper advertising on sales performance. The expenditure on newspaper advertising increases along the horizontal axis, the sales figures, indicated on the vertical axis, exhibit varying patterns

```
plt.figure(figsize=(4,4))
sns.scatterplot(data=df,x=df['Radio'],y=df['Sales'])
plt.show()
```




```
x=df.drop('Sales',axis=1)

x

        TV  Radio  Newspaper
0    230.1   37.8       69.2
1     44.5   39.3       45.1
2     17.2   45.9       69.3
3    151.5   41.3       58.5
4    180.8   10.8       58.4
..     ...    ...        ...
195   38.2    3.7       13.8
196   94.2    4.9        8.1
197  177.0    9.3        6.4
198  283.6   42.0       66.2
199  232.1    8.6        8.7

[200 rows x 3 columns]

y=df['Sales']

y

0      22.1
1      10.4
2       9.3
3      18.5
4      12.9
       ...
```

```
195     7.6
196     9.7
197    12.8
198    25.5
199    13.4
Name: Sales, Length: 200, dtype: float64
```

Importing train_test_split to train and test the dataset

```
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x,y,
test_size=0.2, random_state=42)

x_train.shape

(160, 3)
```

x_train shape of (160, 3) it means there are 160 training samples, and each sample has 4 features or input variables

```
x_test.shape

(40, 3)
```

x_test has a shape (40,3) it means that there are 40 test samples, and each samples has 4 features or input variables

Creating a Model

```
model = LinearRegression()
```

Fit the model into the training data

```
model.fit(x_train, y_train)

LinearRegression()
```

Make predictions on the test data

```
y_pred=model.predict(x_test)

y_pred

array([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])

from sklearn.metrics import r2_score, mean_squared_error,
mean_absolute_error

import numpy as np
```

Evaluate the model for its accuracy

R-squared

```
r_squared =r2_score(y_test, y_pred)

print("R-Squared", r_squared)

R-Squared 0.899438024100912

y_pred = model.predict([[8.6, 2.1, 1]])

print(*y_pred)

3.7638119165871475
```

Mean Absolute Error

```
from sklearn import metrics

y_pred = model.predict(x_test)

mae = mean_absolute_error(y_test, y_pred)

print("MAE", mae)

MAE 1.4607567168117603

y_pred = model.predict([[8.6, 2.1, 1]])

print(*y_pred)
```

```
3.7638119165871475
```

Root Mean Square Error

```
y_pred = model.predict(x_test)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("RMSE", rmse)
RMSE 1.78159966153345
y_pred = model.predict([[8.6, 2.1, 1]])
print(*y_pred)
3.7638119165871475
```

Decision Tree Regressor

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor()
model.fit(x_train, y_train)
DecisionTreeRegressor()
y_pred = model.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
print("MSE", mse)
MSE 1.7012500000000004
```

Using Linear Regression

```
model_lr = LinearRegression()
model_lr.fit(x_train, y_train)
LinearRegression()
y_pred_lr = model_lr.predict(x_test)
mse_lr = mean_squared_error(y_test, y_pred_lr)
print('Linear Regression MSE:', mse_lr)
Linear Regression MSE: 3.1740973539761033
```

Using Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor

model_rf = RandomForestRegressor(n_estimators=100)

model_rf.fit(x_train, y_train)

RandomForestRegressor()

y_pred_rf = model_rf.predict(x_test)

mse_rf = mean_squared_error(y_test, y_pred_rf)

print('Random Forest MSE:', mse_rf)

Random Forest MSE: 0.5559962249999993
```

All the three algorithms

```
print('Linear Regression R^2:', model.score(x_test, y_test))
print('Decision Tree R^2:', model.score(x_test, y_test))
print('Random Forest R^2:', model.score(x_test, y_test))

Linear Regression R^2: 0.9461008776923572
Decision Tree R^2: 0.9461008776923572
Random Forest R^2: 0.9461008776923572
```

End of the Code

```
```