```
import warnings
warnings.filterwarnings('ignore')

import lightgbm as lgb
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pickle
import seaborn as sns
import xgboost as xgb

from pandas.plotting import scatter_matrix
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
from sklearn.linear_model import ElasticNet, Lasso, LinearRegression, Ridge
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor

sns.set()
%matplotlib inline
```

```
from sklearn.neighbors import KNeighborsRegressor
```

```
# Reading the dataset into a data frame

sales_df = pd.read_csv("/content/Advertisement.csv")
sales_df.head()
```

	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

Data Preprocessing

```
sales_df.drop(['Unnamed: 0'], axis = 1, inplace = True)
sales_df.head()
```

	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

```
# Checking for missing values

sales_df.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
```

```
sales_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

```
sales_df.isnull().sum()
```

	0
TV	0
Radio	0
Newspaper	0
Sales	0

dtype: int64

```
# Checking for duplicate values

sales_df.duplicated().sum()
```

```
np.int64(0)
```

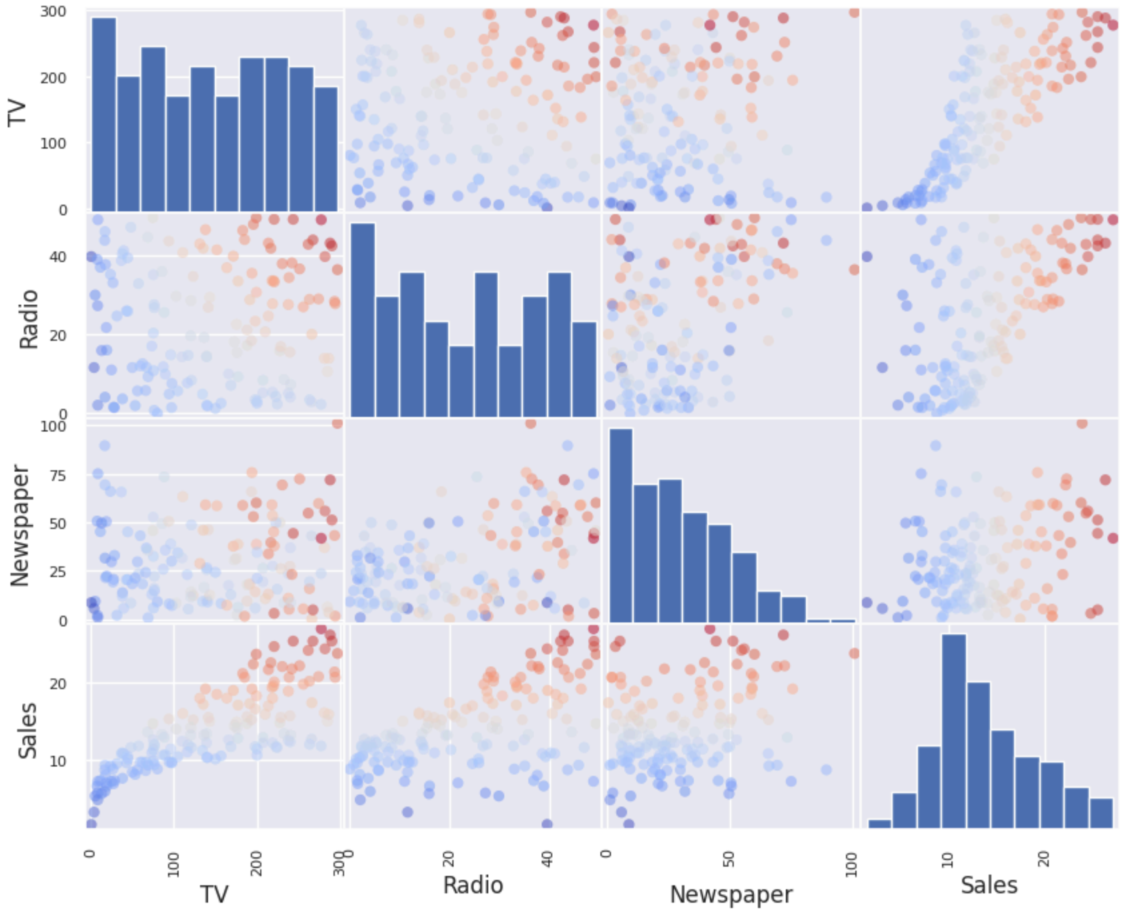
```
# Train test split

train_df, validation_df = train_test_split(sales_df, train_size = 0.75, random_state = 1)
train_df.head(2)
```

	TV	Radio	Newspaper	Sales
98	289.7	42.3	51.2	25.4
123	123.1	34.6	12.4	15.2

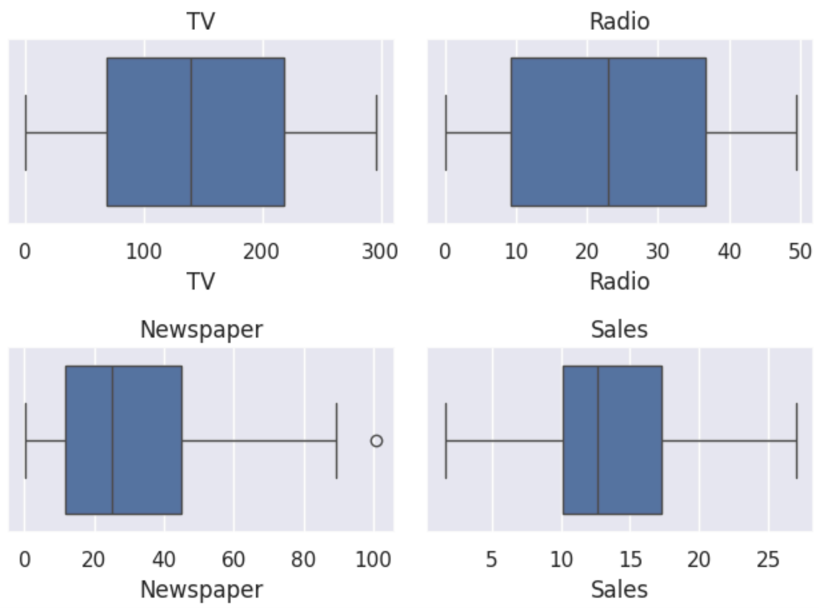
```
validation_df.head(2)
```

	TV	Radio	Newspaper	Sales
58	210.8	49.6	37.7	23.8
40	202.5	22.3	31.6	16.6

```
# Using scater-matrix plot

scatter_matrix(train_df, diagonal = "hist", marker = "o", c = train_df['Sales'], cmap = 'coolwarm', figsize = (10,8))
plt.show()
```

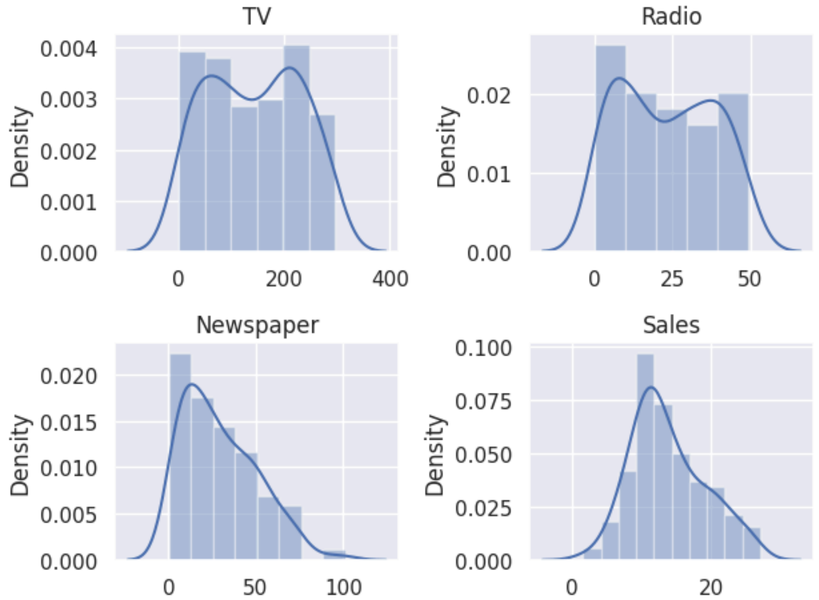



```
# Using box plot to see the distribution of each feature

plt.figure()

for col in train_df.select_dtypes(include = ['number']).columns:
    plt.subplot(2, 2, train_df.columns.get_loc(col) + 1)  # Adjust the subplot layout as needed
    sns.boxplot(x=train_df[col])
    plt.title(col)

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

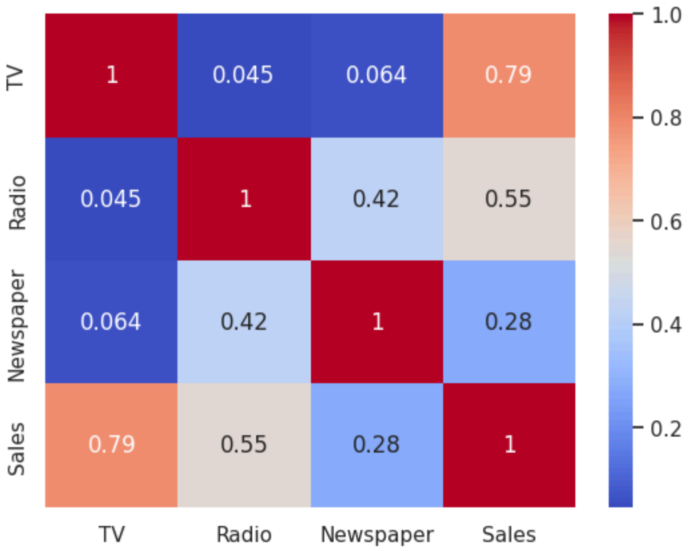



```
# Using distplot to see the distribution of each feature

plt.figure()

for col in train_df.select_dtypes(include = ['number']).columns:
    plt.subplot(2, 2, train_df.columns.get_loc(col) + 1)  # Adjust the subplot layout as needed
```

```
    sns.distplot(x=train_df[col])
    plt.title(col)

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




```
# Using heatmap to see the relationships

sns.heatmap(train_df.corr(), annot = True, cmap = "coolwarm")
plt.show()
```

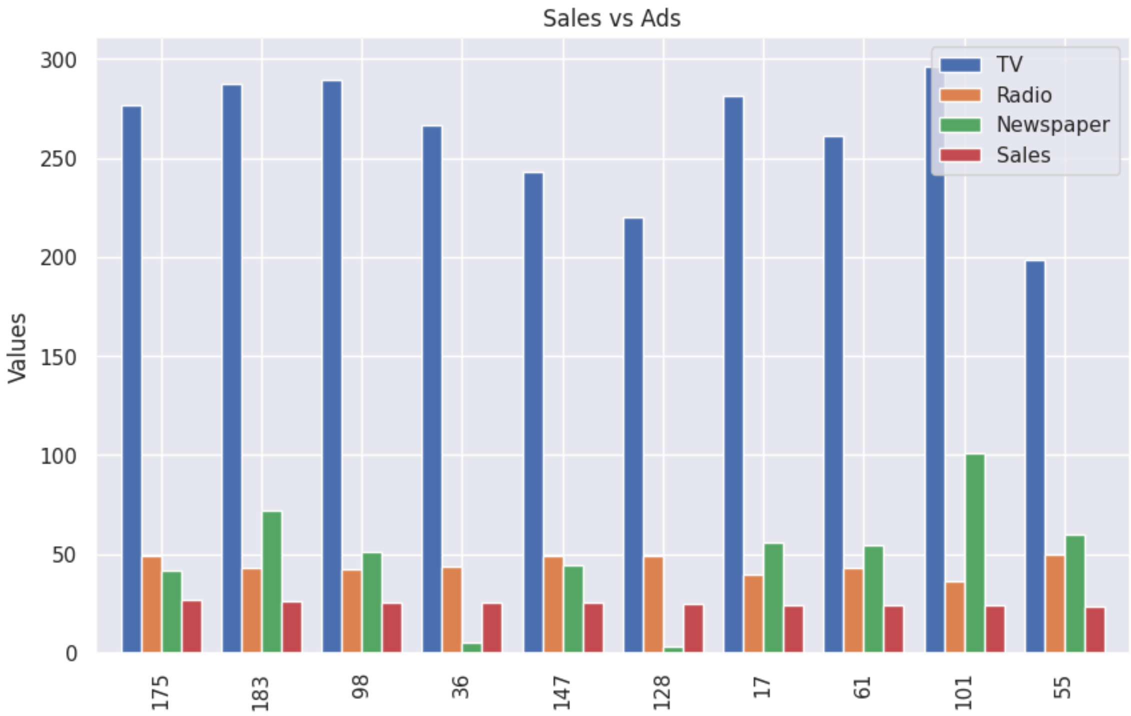



```
# Checking each variable against the target variable

def sales_per(col, color):
    avg_sales = train_df.groupby(col)['Sales'].mean().reset_index()
    plt.figure(figsize = (10, 6))
    plt.bar(avg_sales[col], avg_sales['Sales'], color = color)
    plt.title('Sales based on {} ads'.format(col))
    plt.xlabel(col)
    plt.ylabel('Sales')
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.show()
```

```
# Getting the ad details of top 10 selling products

top_10_products = train_df.nlargest(10, 'Sales')
top_10_products
```

	TV	Radio	Newspaper	Sales
175	276.9	48.9	41.8	27.0
183	287.6	43.0	71.8	26.2
98	289.7	42.3	51.2	25.4
36	266.9	43.8	5.0	25.4
147	243.2	49.0	44.3	25.4
128	220.3	49.0	3.2	24.7
17	281.4	39.6	55.8	24.4
61	261.3	42.7	54.7	24.2
101	296.4	36.3	100.9	23.8
55	198.9	49.4	60.0	23.7

```
ax = top_10_products.plot(kind='bar', figsize=(10, 6), width=0.8)
ax.set_ylabel('Values')
plt.title('Sales vs Ads')

plt.show()
```



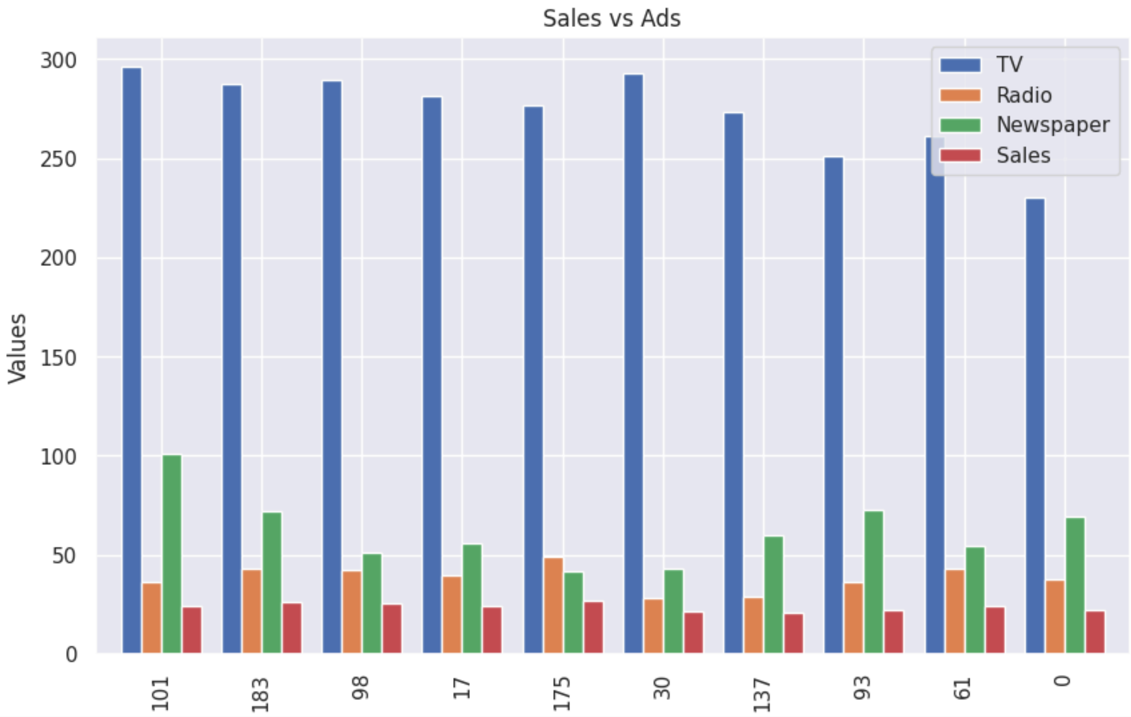

```
# Getting the sales details of products with more ads

train_df['Total_Ad_Spent'] = train_df['TV'] + train_df['Radio'] + train_df['Newspaper']
train_df.head(2)
```

	TV	Radio	Newspaper	Sales	Total_Ad_Spent
98	289.7	42.3	51.2	25.4	383.2
123	123.1	34.6	12.4	15.2	170.1

```
top_10_ads = train_df.nlargest(10, 'Total_Ad_Spent')
top_10_ads
```

	TV	Radio	Newspaper	Sales	Total_Ad_Spent
101	296.4	36.3	100.9	23.8	433.6
183	287.6	43.0	71.8	26.2	402.4
98	289.7	42.3	51.2	25.4	383.2
17	281.4	39.6	55.8	24.4	376.8
175	276.9	48.9	41.8	27.0	367.6
30	292.9	28.3	43.2	21.4	364.4
137	273.7	28.9	59.7	20.8	362.3
93	250.9	36.5	72.3	22.2	359.7
61	261.3	42.7	54.7	24.2	358.7
0	230.1	37.8	69.2	22.1	337.1

```
top_10_ads.drop(['Total_Ad_Spent'], axis = 1, inplace = True)
train_df.drop(['Total_Ad_Spent'], axis = 1, inplace = True)


ax = top_10_ads.plot(kind='bar', figsize=(10, 6), width=0.8)
ax.set_ylabel('Values')
plt.title('Sales vs Ads')

plt.show()
```



Deductions from the visuals

Unsupported Cell Type. Double-Click to inspect/edit the content.

```
# Splitting dependent and independent variable

raw_x_train = train_df.drop(['Sales'], axis = 1)
raw_y_train = train_df['Sales']

raw_x_val = validation_df.drop(['Sales'], axis = 1)
raw_y_val = validation_df['Sales']

raw_x_train.head(2)
```

	TV	Radio	Newspaper
98	289.7	42.3	51.2
123	123.1	34.6	12.4

```
raw_y_train
```

	Sales
98	25.4
123	15.2
119	6.6
53	21.2
33	17.4
...	...
133	19.6
137	20.8
72	8.8
140	10.9
37	14.7

150 rows × 1 columns

dtype: float64

```
raw_x_val.head(2)
```

	TV	Radio	Newspaper
58	210.8	49.6	37.7
40	202.5	22.3	31.6

```
# Building the models

# Linear Regression model
linear_model_raw = LinearRegression()
linear_model_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_lr = linear_model_raw.predict(raw_x_train)
raw_y_pred_val_lr = linear_model_raw.predict(raw_x_val)


print("Accuracy Scores for Linear Regression model on raw data")
raw_lr_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_lr)
raw_lr_rmse = mean_squared_error(raw_y_train, raw_y_pred_train_lr)
raw_train_lr_r2s = r2_score(raw_y_train, raw_y_pred_train_lr)
raw_val_lr_r2s = r2_score(raw_y_val, raw_y_pred_val_lr)
print("Mean Squared Error :", raw_lr_rmse)
print("R-squared Score (Train) :", raw_train_lr_r2s)
print("R-squared Score (Test) :", raw_val_lr_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Linear Regression model on raw data
Mean Squared Error : 3.086791346829135
R-squared Score (Train) : 0.890307557755665
R-squared Score (Test) : 0.9156213613792232
**************************************************************************************************
```

```
# Lasso Regression (L1 Regularization)
lasso_model_raw = Lasso()
lasso_model_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_lar = lasso_model_raw.predict(raw_x_train)
raw_y_pred_val_lar = lasso_model_raw.predict(raw_x_val)


print("Accuracy Scores for Lasso Regression (L1 Regularization) model on raw data")
raw_lar_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_lar)
raw_train_lar_r2s = r2_score(raw_y_train, raw_y_pred_train_lar)
raw_val_lar_r2s = r2_score(raw_y_val, raw_y_pred_val_lar)
print("Mean Squared Error :", raw_lar_rmse)
print("R-squared Score (Train) :", raw_train_lar_r2s)
print("R-squared Score (Test) :", raw_val_lar_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Lasso Regression (L1 Regularization) model on raw data
Mean Squared Error : 2.007667051817513
R-squared Score (Train) : 0.890134288627759
R-squared Score (Test) : 0.9141407522971794
**************************************************************************************************
```

```
# Ridge Regression (L2 Regularization)
ridge_model_raw = Ridge()
ridge_model_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_ridge = ridge_model_raw.predict(raw_x_train)
raw_y_pred_val_ridge = ridge_model_raw.predict(raw_x_val)


print("Accuracy Scores for Ridge Regression (L2 Regularization) model on raw data")
raw_ridge_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_ridge)
raw_train_ridge_r2s = r2_score(raw_y_train, raw_y_pred_train_ridge)
raw_val_ridge_r2s = r2_score(raw_y_val, raw_y_pred_val_ridge)
print("Mean Squared Error :", raw_ridge_rmse)
print("R-squared Score (Train) :", raw_train_ridge_r2s)
print("R-squared Score (Test) :", raw_val_ridge_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Ridge Regression (L2 Regularization) model on raw data
Mean Squared Error : 1.9731360610267696
R-squared Score (Train) : 0.890307557490011
R-squared Score (Test) : 0.9156174936169327
**************************************************************************************************
```

```
# Elastic Net Regression (L1 and L2 Regularizations)
enet_model_raw = ElasticNet()
enet_model_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_enet = enet_model_raw.predict(raw_x_train)
raw_y_pred_val_enet = enet_model_raw.predict(raw_x_val)


print("Accuracy Scores for Elastic Net Regression (L1 and L2 Regularizations) model on raw data")
raw_enet_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_enet)
raw_train_enet_r2s = r2_score(raw_y_train, raw_y_pred_train_enet)
raw_val_enet_r2s = r2_score(raw_y_val, raw_y_pred_val_enet)
print("Mean Squared Error :", raw_enet_rmse)
print("R-squared Score (Train) :", raw_train_enet_r2s)
print("R-squared Score (Test) :", raw_val_enet_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Elastic Net Regression (L1 and L2 Regularizations) model on raw data
Mean Squared Error : 1.9963873026756227
R-squared Score (Train) : 0.8902510395505827
R-squared Score (Test) : 0.9146231384451826
**************************************************************************************************
```

```
# Decission Tree regression - Choosing max depth as 6 after trying different values
dtree_raw = DecisionTreeRegressor(max_depth = 6)
dtree_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_dtree = dtree_raw.predict(raw_x_train)
raw_y_pred_val_dtree = dtree_raw.predict(raw_x_val)


print("Accuracy Scores for Decision Tree model on raw data")
raw_dtree_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_dtree)
raw_train_dtree_r2s = r2_score(raw_y_train, raw_y_pred_train_dtree)
raw_val_dtree_r2s = r2_score(raw_y_val, raw_y_pred_val_dtree)
print("Mean Squared Error :", raw_dtree_rmse)
print("R-squared Score (Train) :", raw_train_dtree_r2s)
print("R-squared Score (Test) :", raw_val_dtree_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Decision Tree model on raw data
Mean Squared Error : 1.173133205782313
R-squared Score (Train) : 0.9948414172626995
R-squared Score (Test) : 0.9498301601291492
**************************************************************************************************
```

```
# Random Forest regression - Choosing max depth as 6 after trying different values
# Choosing the parameters after trying different values
rf_raw = RandomForestRegressor(n_estimators = 500, random_state = 1, max_depth = 6)
rf_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_rf = rf_raw.predict(raw_x_train)
raw_y_pred_val_rf = rf_raw.predict(raw_x_val)


print("Accuracy Scores for Random Forest model on raw data")
raw_rf_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_rf)
raw_train_rf_r2s = r2_score(raw_y_train, raw_y_pred_train_rf)
raw_val_rf_r2s = r2_score(raw_y_val, raw_y_pred_val_rf)
print("Mean Squared Error :", raw_rf_rmse)
print("R-squared Score (Train) :", raw_train_rf_r2s)
print("R-squared Score (Test) :", raw_val_rf_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Random Forest model on raw data
Mean Squared Error : 0.40992725337108105
R-squared Score (Train) : 0.9954418189405353
R-squared Score (Test) : 0.9824691820511463
**************************************************************************************************
```

```
# Gradient Boosting Regression model
gb_raw = GradientBoostingRegressor(n_estimators = 100, max_depth = 3, random_state = 123)
gb_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_gb = gb_raw.predict(raw_x_train)
raw_y_pred_val_gb = gb_raw.predict(raw_x_val)


print("Accuracy Scores for Gradient Boost Regressor model on raw data")
raw_gb_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_gb)
raw_train_gb_r2s = r2_score(raw_y_train, raw_y_pred_train_gb)
raw_val_gb_r2s = r2_score(raw_y_val, raw_y_pred_val_gb)
print("Mean Squared Error :", raw_gb_rmse)
print("R-squared Score (Train) :", raw_train_gb_r2s)
print("R-squared Score (Test) :", raw_val_gb_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Gradient Boost Regressor model on raw data
Mean Squared Error : 0.39330203215430165
R-squared Score (Train) : 0.9988744334979055
R-squared Score (Test) : 0.9831801709500643
**************************************************************************************************
```

```
# XGBoost Regression model - Max depth = 2 after testing various values
xgb_raw = xgb.XGBRegressor(random_state = 111, max_depth = 2)
xgb_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_xgb = xgb_raw.predict(raw_x_train)
raw_y_pred_val_xgb = xgb_raw.predict(raw_x_val)


print("Accuracy Scores for XGBoost model on raw data")
raw_xgb_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_xgb)
raw_train_xgb_r2s = r2_score(raw_y_train, raw_y_pred_train_xgb)
raw_val_xgb_r2s = r2_score(raw_y_val, raw_y_pred_val_xgb)
print("Mean Squared Error :", raw_xgb_rmse)
print("R-squared Score (Train) :", raw_train_xgb_r2s)
print("R-squared Score (Test) :", raw_val_xgb_r2s)
print("**************" * 7)
```

```
Accuracy Scores for XGBoost model on raw data
Mean Squared Error : 0.4531219081746326
R-squared Score (Train) : 0.9973801988256545
R-squared Score (Test) : 0.9806219332441997
**************************************************************************************************
```

```
# Support Vector Regression model - Linear kernel
svr_linear_raw = SVR(kernel = 'linear')
svr_linear_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_svr_linear = svr_linear_raw.predict(raw_x_train)
raw_y_pred_val_svr_linear = svr_linear_raw.predict(raw_x_val)


print("Accuracy Scores for Support Vector Model with linear kernel on raw data")
raw_svr_linear_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_svr_linear)
raw_train_svr_linear_r2s = r2_score(raw_y_train, raw_y_pred_train_svr_linear)
raw_val_svr_linear_r2s = r2_score(raw_y_val, raw_y_pred_val_svr_linear)
print("Root Mean Squared Error :", raw_svr_linear_rmse)
print("R-squared Score (Train) :", raw_train_svr_linear_r2s)
print("R-squared Score (Test) :", raw_val_svr_linear_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Support Vector Model with linear kernel on raw data
Root Mean Squared Error : 1.9220583190995177
R-squared Score (Train) : 0.881634835018431
R-squared Score (Test) : 0.9178018680092217
**************************************************************************************************
```

```
# Support Vector Regression model - Poly kernel
svr_poly_raw = SVR(kernel = 'poly')
svr_poly_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_svr_poly = svr_poly_raw.predict(raw_x_train)
raw_y_pred_val_svr_poly = svr_poly_raw.predict(raw_x_val)


print("Accuracy Scores for Support Vector Model with poly kernel on raw data")
raw_svr_poly_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_svr_poly)
raw_train_svr_poly_r2s = r2_score(raw_y_train, raw_y_pred_train_svr_poly)
raw_val_svr_poly_r2s = r2_score(raw_y_val, raw_y_pred_val_svr_poly)
```

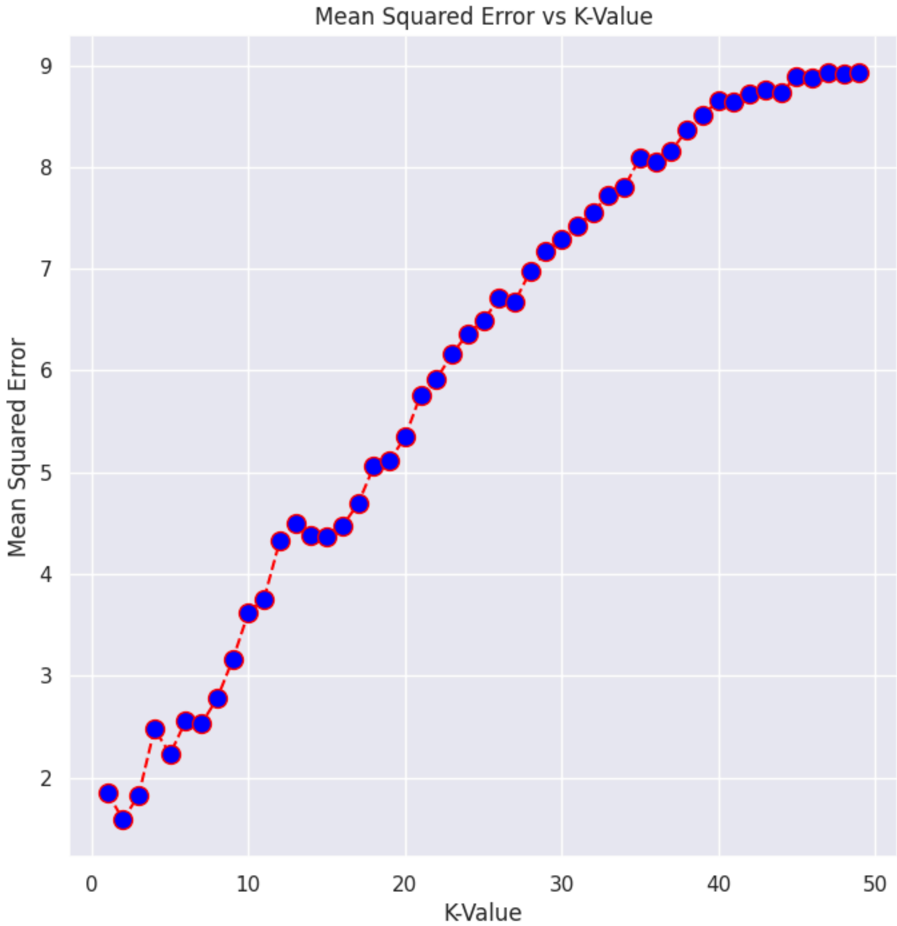
```
print("Root Mean Squared Error :", raw_svr_poly_rmse)
print("R-squared Score (Train) :", raw_train_svr_poly_r2s)
print("R-squared Score (Test) :", raw_val_svr_poly_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Support Vector Model with poly kernel on raw data
Root Mean Squared Error : 3.087389548470164
R-squared Score (Train) : 0.8462785174762764
R-squared Score (Test) : 0.8679656849689169
**************************************************************************************************
```

```
# Support Vector Regression model - RBF kernel
svr_rbf_raw = SVR(kernel = 'rbf')
svr_rbf_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_svr_rbf = svr_rbf_raw.predict(raw_x_train)
raw_y_pred_val_svr_rbf = svr_rbf_raw.predict(raw_x_val)


print("Accuracy Scores for Support Vector Model with rbf kernel on raw data")
raw_svr_rbf_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_svr_rbf)
raw_train_svr_rbf_r2s = r2_score(raw_y_train, raw_y_pred_train_svr_rbf)
raw_val_svr_rbf_r2s = r2_score(raw_y_val, raw_y_pred_val_svr_rbf)
print("Root Mean Squared Error :", raw_svr_rbf_rmse)
print("R-squared Score (Train) :", raw_train_svr_rbf_r2s)
print("R-squared Score (Test) :", raw_val_svr_rbf_r2s)
print("**************" * 7)
```

```
Accuracy Scores for Support Vector Model with rbf kernel on raw data
Root Mean Squared Error : 3.848044232597384
R-squared Score (Train) : 0.8541218680671167
R-squared Score (Test) : 0.835435769771242
**************************************************************************************************
```

```
# Function to find the best value of K based on mean squared error

def find_k(x_train, y_train, x_test, y_test):
    error_rate = []    # Finding the error rate for 50 iterations

    for i in range(1, 50):
        knn = KNeighborsRegressor(n_neighbors = i)    # Building the model with i neighbors
        knn.fit(x_train, y_train)
        y_pred = knn.predict(x_test)
        error_rate.append(mean_squared_error(y_test, y_pred))

# Ploting the error values to find the best value of k

    plt.figure(figsize = (8, 8))
    plt.plot(range(1,50), error_rate, color = 'red', linestyle = 'dashed', marker = 'o', markersize = 10, markerfacecolor = 'blue')
    plt.title("Mean Squared Error vs K-Value")
    plt.xlabel("K-Value")
    plt.ylabel("Mean Squared Error")
    plt.show()


find_k(raw_x_train, raw_y_train, raw_x_val, raw_y_val)
```



The error value is least in k = 2, proceeding with k = 2

```
# Building KNN regressor with k = 2
knn_raw = KNeighborsRegressor(n_neighbors = 2)
knn_raw.fit(raw_x_train, raw_y_train)
raw_y_pred_train_knn = knn_raw.predict(raw_x_train)
raw_y_pred_val_knn = knn_raw.predict(raw_x_val)

print("Accuracy Scores for KNN Regressor model on raw data")
raw_knn_rmse = mean_squared_error(raw_y_val, raw_y_pred_val_knn)
raw_train_knn_r2s = r2_score(raw_y_train, raw_y_pred_train_knn)
raw_val_knn_r2s = r2_score(raw_y_val, raw_y_pred_val_knn)
print("Mean Squared Error :", raw_knn_rmse)
print("R-squared Score (Train) :", raw_train_knn_r2s)
print("R-squared Score (Test) :", raw_val_knn_r2s)
print("**************" * 7)
```

```
Accuracy Scores for KNN Regressor model on raw data
Mean Squared Error : 1.5839000000000005
R-squared Score (Train) : 0.9758064493202534
R-squared Score (Test) : 0.9322634386446769
**************************************************************************************************
```

Considering the results, the Random Forest model appears to be the best among the three.

```
rf_raw
```

```
RandomForestRegressor
RandomForestRegressor(max_depth=6, n_estimators=500, random_state=1)
```

Start coding or generate with AI.

```
# Saving model for deployment

final_model = rf_raw
filename = '04_Sales_Predictions.sav'
pickle.dump(final_model, open(filename, 'wb'))
```

```
out_df = sales_df
```

```
# Splitting dependent and independent variable

x_final = out_df.drop(['Sales'], axis = 1)
y_final = out_df['Sales']
```

```
# Predicting the Rating using Random Forest model that was chosen as final model

y_pred = final_model.predict(x_final)
```

```
final_result = pd.DataFrame(y_pred)
final_result = final_result.rename(columns = {0 : "Predicted_Sales"})
final_result
```

	Predicted_Sales
0	21.772631
1	10.772412
2	8.735757
3	18.249825
4	13.835012
...	...
195	7.955268
196	9.821359
197	12.842530
198	24.842458
199	13.209785

200 rows × 1 columns

```
# Preparing the final data fram for output

final_result1 = pd.concat([sales_df, pd.DataFrame(final_result)], axis = 1)
final_result1.head(5)
```

	TV	Radio	Newspaper	Sales	Predicted_Sales
0	230.1	37.8	69.2	22.1	21.772631
1	44.5	39.3	45.1	10.4	10.772412
2	17.2	45.9	69.3	9.3	8.735757
3	151.5	41.3	58.5	18.5	18.249825