Step - 1 : Business Problem Understanding

- **Indentify relationship between total advertising spend and sales?**
- **Our next ad campaign will have a total spend of $200,000, how many units do we expect to sell as a result of this?**

Step - 2 : Data Understanding

Data

This sample data displays sales for a particular product as a function of advertising budgets (in dollars) for TV, radio, and newspaper media.

Indepenent variables

- TV: Advertising dollars spent on TV for a single product in a given market (in dollars)
- Radio: Advertising dollars spent on Radio
- Newspaper: Advertising dollars spent on Newspaper

Target Variable

- Sales: sales of a single product in a given market

- Collect & Load Data
- Dataset Understanding

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv("Advertising.csv")
df.head()
```

Out[2]:

	TV	radio	newspaper	sales
0	230100	37800	69200	22100
1	44500	39300	45100	10400
2	17200	45900	69300	9300
3	151500	41300	58500	18500
4	180800	10800	58400	12900

In [3]:
```
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    int64
 1   radio      200 non-null    int64
 2   newspaper  200 non-null    int64
 3   sales      200 non-null    int64
dtypes: int64(4)
memory usage: 6.4 KB
```

Step - 3 : Data Preprocessing

- by combining all the features, we get the "total spend"

In [4]:
```
df['total_spend'] = df['TV'] + df['radio'] + df['newspaper']
df.head()
```

Out[4]:

	TV	radio	newspaper	sales	total_spend
0	230100	37800	69200	22100	337100
1	44500	39300	45100	10400	128900
2	17200	45900	69300	9300	132400
3	151500	41300	58500	18500	251300
4	180800	10800	58400	12900	250000

In [5]:
```
df.drop(columns=['TV','radio','newspaper'],inplace=True)
df.head()
```

Out[5]:

	sales	total_spend
0	22100	337100
1	10400	128900
2	9300	132400
3	18500	251300
4	12900	250000

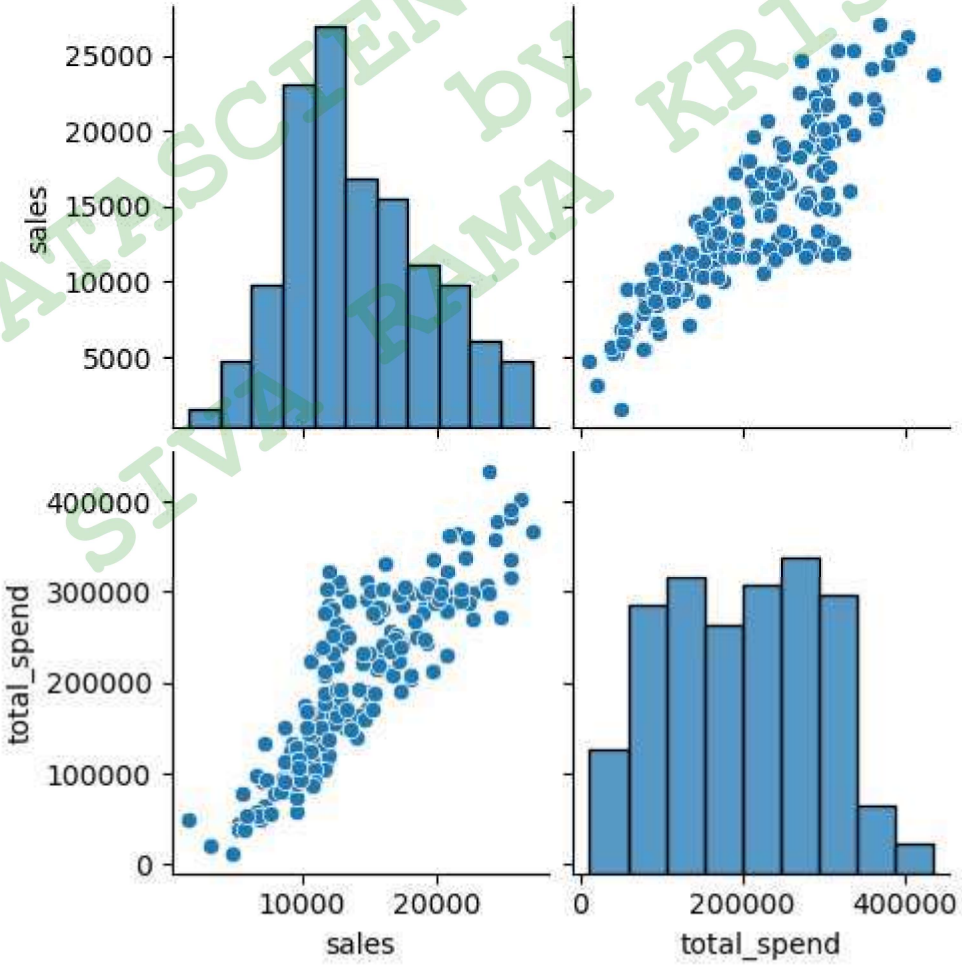
Exploratory Data Analysis (EDA)

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

Out[6]:

	sales	total_spend
count	200.000000	200.000000
mean	14022.500000	200860.500000
std	5217.456566	92985.180587
min	1600.000000	11700.000000
25%	10375.000000	123550.000000
50%	12900.000000	207350.000000
75%	17400.000000	281125.000000
max	27000.000000	433600.000000

In [7]:
```
sns.pairplot(df)
plt.show()
```



In [8]:
```
df.corr()
```

Out[8]:

	sales	total_spend
sales	1.000000	0.867712
total_spend	0.867712	1.000000

Data Cleaning

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
sales          0
total_spend    0
dtype: int64
```

Data Wangling

In [10]:
```
#no encoding is required (no categorical data)
```

create X and y

In [11]:
```
X = df[['total_spend']]
y = df['sales']
```

Train-Test Split

In [12]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,train_size=0.8,random
```


Step - 4 : Modelling

$$\hat{y} = \beta_0 + \beta_1 X$$

In [13]:
```
#import
from sklearn.linear_model import LinearRegression

#save the model
model = LinearRegression()

#fit
model.fit(X_train,y_train)

print("Intercept:",model.intercept_)
print("Coefficients:",model.coef_)
```

```
Intercept: 4389.814518436082
Coefficients: [0.04784052]
```

Step - 5 : Evaluation

Predictions

In [14]:
```
ypred_test = model.predict(X_test)
```

Mean Absolute Error (MAE) is the mean of the absolute value of the errors:

$$\frac{1}{n}\sum|y-\hat{y}|$$

In [15]:
```
from sklearn.metrics import mean_absolute_error
print("Test MAE:",mean_absolute_error(y_test,ypred_test))
```

```
Test MAE: 1915.90776501548
```

Mean Squared Error (MSE) is the mean of the squared errors:

$$\frac{1}{n}\sum(y-\hat{y})^2$$

In [16]:
```
from sklearn.metrics import mean_squared_error
print("Test MSE:",mean_squared_error(y_test,ypred_test))
```

```
Test MSE: 5868943.149727303
```

Root Mean Squared Error (RMSE) is the square root of the mean of the squared errors:

$$\sqrt{\frac{1}{n}\sum(y-\hat{y})^2}$$

In [17]:
```
print("Test RMSE:",np.sqrt(mean_squared_error(y_test,ypred_test)))
```

```
Test RMSE: 2422.590173704026
```

In [18]:
```
# Test R2
print("Test R2:",model.score(X_test,y_test))
```

```
Test R2: 0.7868779454628924
```

Model Selection

Checklist 1 : Check whether model is good or either having overfitting/underfitting problem

test accuracy = train accuracy

In [19]:
```
# prediction on train data
ypred_train = model.predict(X_train)

# Train R2
print("Train R2:",model.score(X_train,y_train))
```

```
Train R2: 0.7426281082244577
```

Checklist 2: whether the Test Accuracy = Cross validation Score

In [20]:
```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(model,X,y,cv=5)
print(scores)

print("Cross Validation Score:",scores.mean())
```

```
[0.74964192 0.79455226 0.76417134 0.74872042 0.65980565]
Cross Validation Score: 0.7433783178555419
```

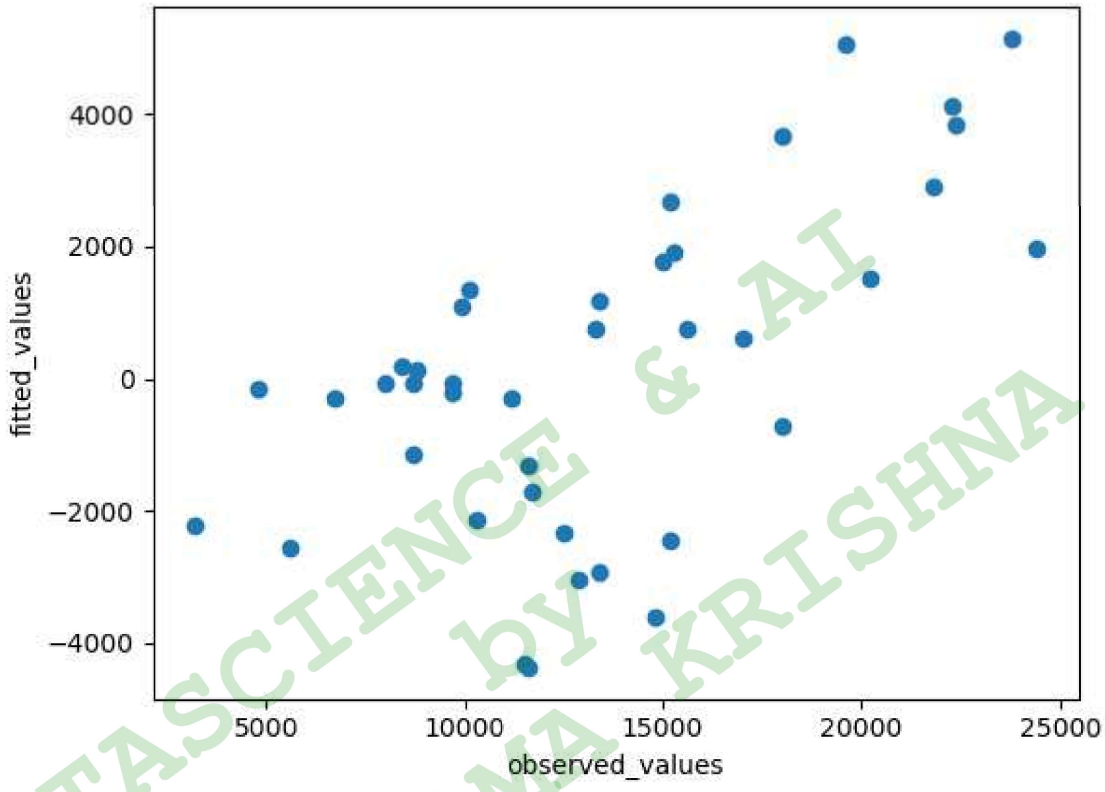
Checklist 3: check whether, it satisfies the Business Problem Requirements

Checklist 4 (only for Linear Regression) : Check for Assumptions

1. Linearity of Errors

In [21]:
```
error = y_test - ypred_test
```

In [22]:
```
plt.scatter(y_test,error)
plt.xlabel("observed_values")
plt.ylabel("fitted_values")
plt.show()
```

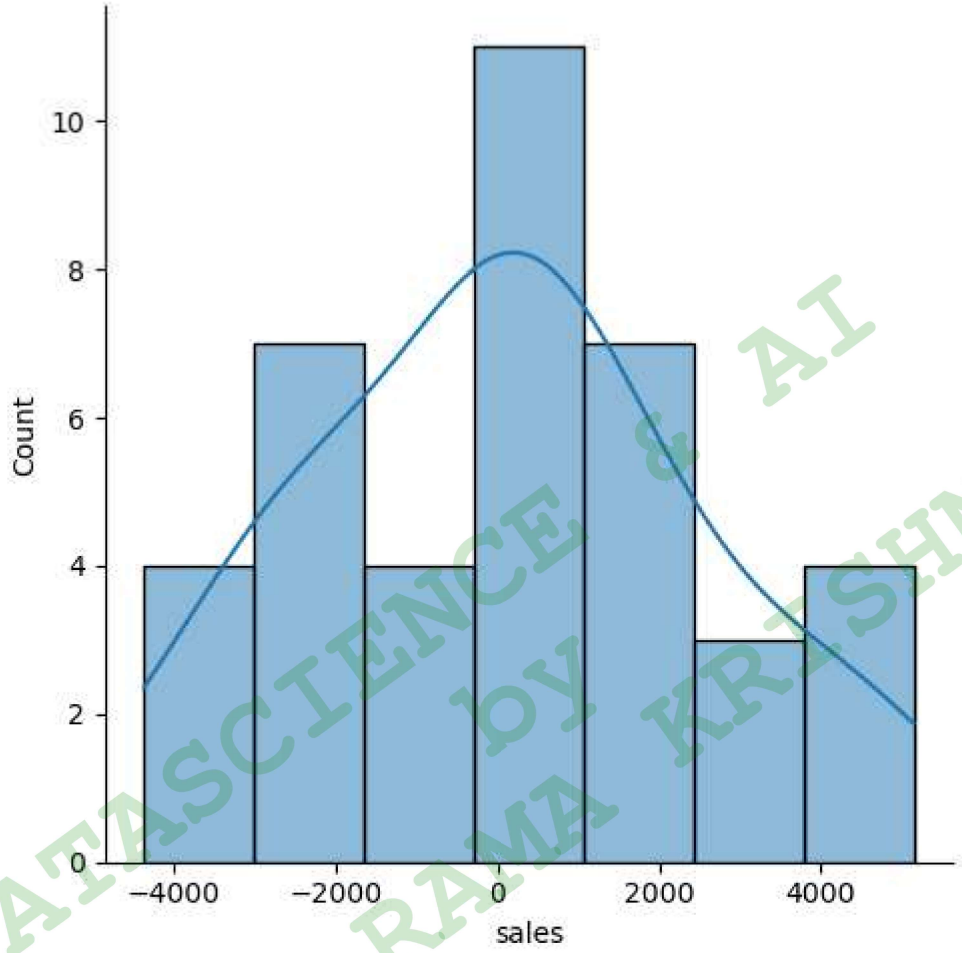


2. Normality of Errors

In [23]:
```
error.skew()
```

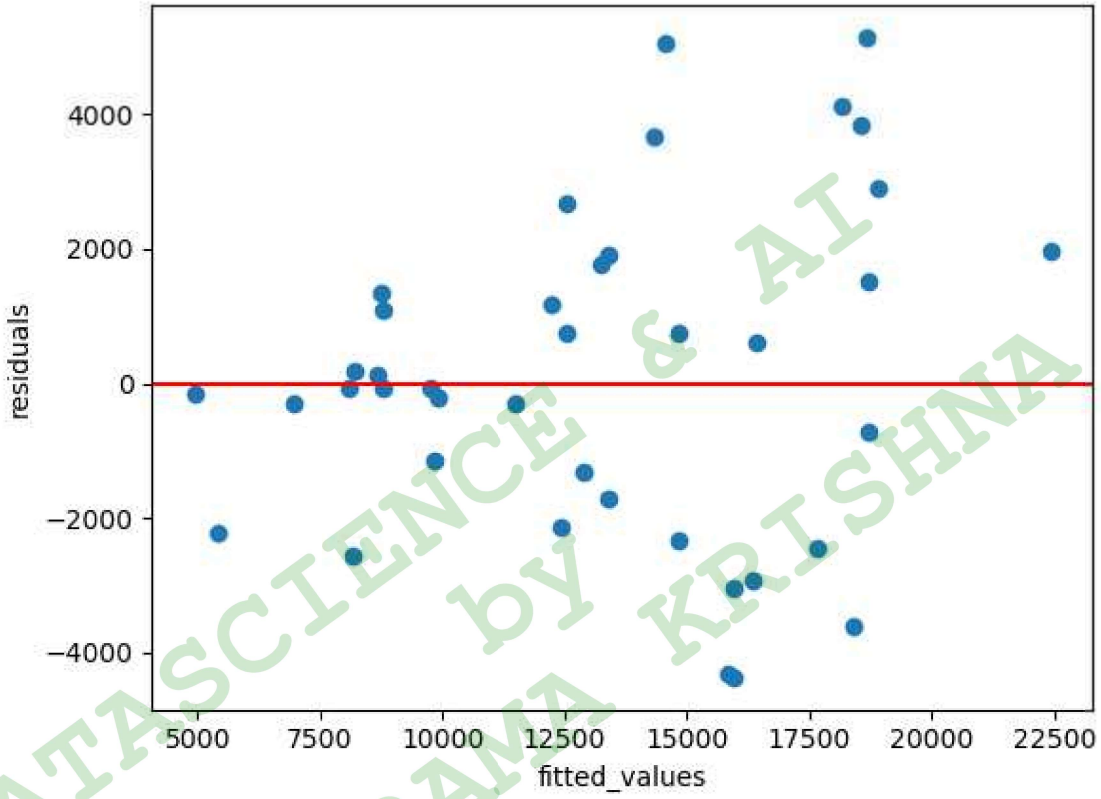
Out[23]: 0.17729242735315792

In [24]:
```
sns.displot(error,kde=True)
plt.show()
```



3. Equal Variance of Errors (Homoscadesicity)

In [25]:
```
plt.scatter(ypred_test,error)
plt.axhline(y=0,color='red')
plt.xlabel("fitted_values")
plt.ylabel("residuals")
plt.show()
```



4. Variables Significance

In [26]:
```
import statsmodels.formula.api as smf
model2=smf.ols("y~X",data=df).fit()
model2.summary()
```

Out[26]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.753
Model:	OLS	**Adj. R-squared:**	0.752
Method:	Least Squares	**F-statistic:**	603.4
Date:	Mon, 26 Jun 2023	**Prob (F-statistic):**	5.06e-62
Time:	01:08:51	**Log-Likelihood:**	-1855.4
No. Observations:	200	**AIC:**	3715.
Df Residuals:	198	**BIC:**	3721.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	4243.0282	438.525	9.676	0.000	3378.249	5107.807
X	0.0487	0.002	24.564	0.000	0.045	0.053

Omnibus:	6.851	**Durbin-Watson:**	1.967
Prob(Omnibus):	0.033	**Jarque-Bera (JB):**	6.692
Skew:	-0.373	**Prob(JB):**	0.0352
Kurtosis:	3.495	**Cond. No.**	5.28e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.28e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Final Model

In [27]:
```
#Modelling
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train,y_train)
print("Intercept:",model.intercept_)
print("Coefficients:",model.coef_)

#Prediction
ypred_train = model.predict(X_train)
ypred_test = model.predict(X_test)

#Evvalution
print("Train R2:",model.score(X_train,y_train))
print("Test R2:",model.score(X_test,y_test))
print("Cross Validation Score:",cross_val_score(model,X,y,cv=5).mean())
```

```
Intercept: 4389.814518436082
Coefficients: [0.04784052]
Train R2: 0.7426281082244577
Test R2: 0.7868779454628924
Cross Validation Score: 0.7433783178555419
```

$$\hat{y} = \beta_0 + \beta_1 X$$

$$Sales = 0.04784052(totalspend) + 4389.814518436082$$

Interpreting the coefficients

- A **1 unit increase in total Spend** is associated with an **increase of 0.0478 units in sales**.
- This basically means that for every $10000 dollars spend on Ads, we could expect 478 more units sold.

Use the model to make predictions on a new value. For a total spend of 200k on Ads, how many units could we expect to be sold?

In [28]:
```
new_data =pd.DataFrame({"total_spend":[200000]})
new_data
```

Out[28]:

	total_spend
0	200000

In [29]:
```
model.predict(new_data)
```

Out[29]:
```
array([13957.91946809])
```

Save a Model

In [30]:
```
from joblib import dump

dump(model,'sales_model.joblib')
```

Out[30]:
```
['sales_model.joblib']
```

Load a Model & Predict

In [31]:
```
from joblib import load

loaded_model = load('sales_model.joblib')

loaded_model.predict(new_data)
```

Out[31]:
```
array([13957.91946809])
```