

SALES PREDICTION USING PYTHON

Sales prediction means predicting how much of a product people will buy based on factors such as the amount you spend to advertise your product, the segment of people you advertise for, or the platform you are advertising on about your product.

```
In [10]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```
In [2]: sales = pd.read_csv('C:/Users/Gayatri/Downloads/Advertising.csv', index_col=0)

sales.head()
```

```
Out[2]:
```

	TV	Radio	Newspaper	Sales
1	230.1	37.8	69.2	22.1
2	44.5	39.3	45.1	10.4
3	17.2	45.9	69.3	9.3
4	151.5	41.3	58.5	18.5
5	180.8	10.8	58.4	12.9

```
In [3]: # Exploratory Data Analysis
sales.shape
```

```
Out[3]: (200, 4)
```

```
In [4]: sales.info
```

```
Out[4]: <bound method DataFrame.info of          TV  Radio  Newspaper  Sales
1    230.1   37.8         69.2   22.1
2     44.5   39.3         45.1   10.4
3     17.2   45.9         69.3    9.3
4    151.5   41.3         58.5   18.5
5    180.8   10.8         58.4   12.9
..     ...   ...         ...   ...
196   38.2    3.7         13.8    7.6
197   94.2    4.9          8.1    9.7
198  177.0    9.3          6.4   12.8
199  283.6   42.0         66.2   25.5
200  232.1    8.6          8.7   13.4

[200 rows x 4 columns]>
```

```
In [5]: sales.describe
```

```
Out[5]: <bound method NDFrame.describe of          TV  Radio  Newspaper  Sales
1    230.1   37.8         69.2   22.1
2     44.5   39.3         45.1   10.4
3     17.2   45.9         69.3    9.3
4    151.5   41.3         58.5   18.5
```

```

5      180.8      10.8      58.4      12.9
..      ...      ...      ...      ...
196     38.2       3.7     13.8       7.6
197     94.2       4.9      8.1       9.7
198    177.0       9.3      6.4      12.8
199    283.6     42.0     66.2     25.5
200    232.1       8.6      8.7     13.4

```

```
[200 rows x 4 columns]>
```

```
In [6]: sales.isnull().sum()
```

```

Out[6]: TV          0
Radio        0
Newspaper    0
Sales        0
dtype: int64

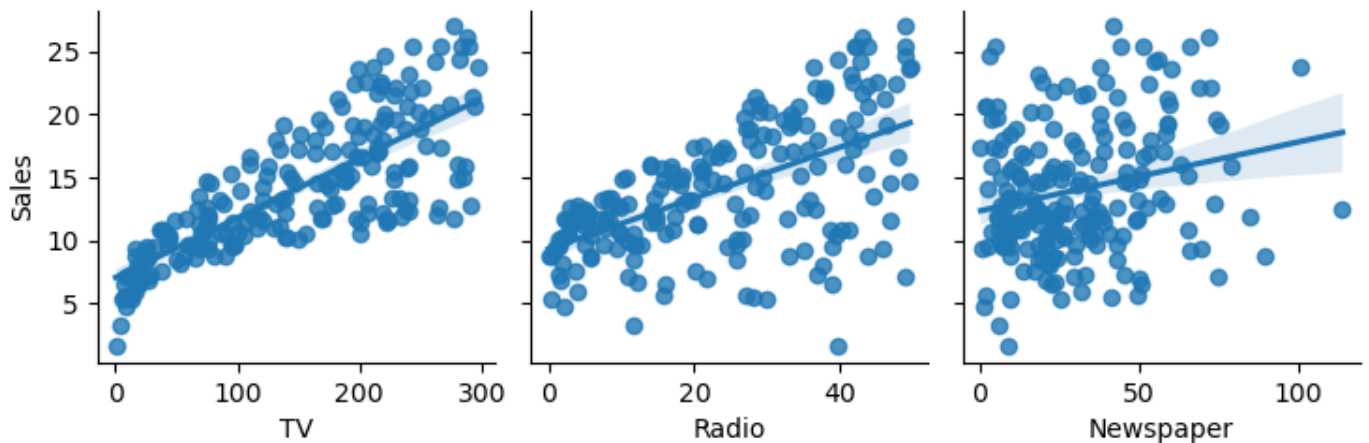
```

```

In [7]: # Check the main assumptions of linear Regression linearity , normality,mutlicolnearity
#1- linearity: which mean the relation between predictor(x) and outcome(y) must be linea
sns.pairplot(sales,x_vars=['TV','Radio','Newspaper'],y_vars='Sales',kind='reg')

```

```
Out[7]: <seaborn.axisgrid.PairGrid at 0x2b903ddc790>
```



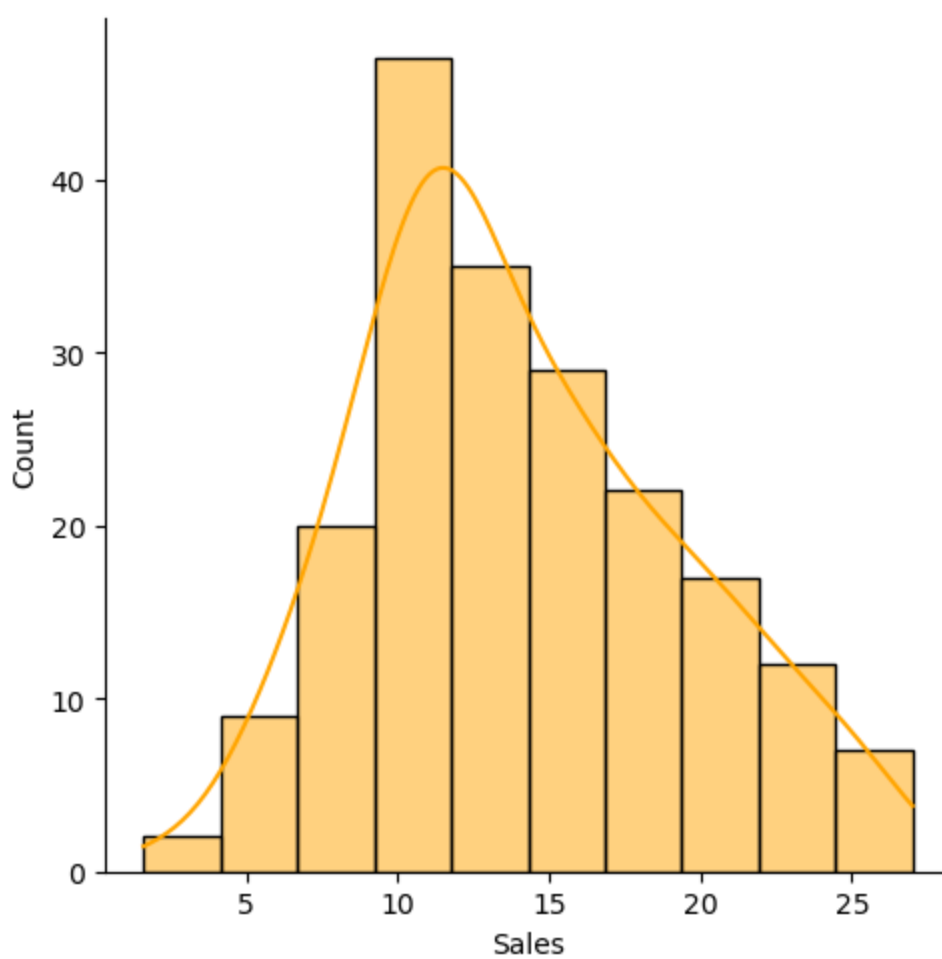
as we can see the relation between newspaper is not linear this will affect our model so may be we will remove this feature

2-Normality: we need the outcome variable(y) to be normally distributed

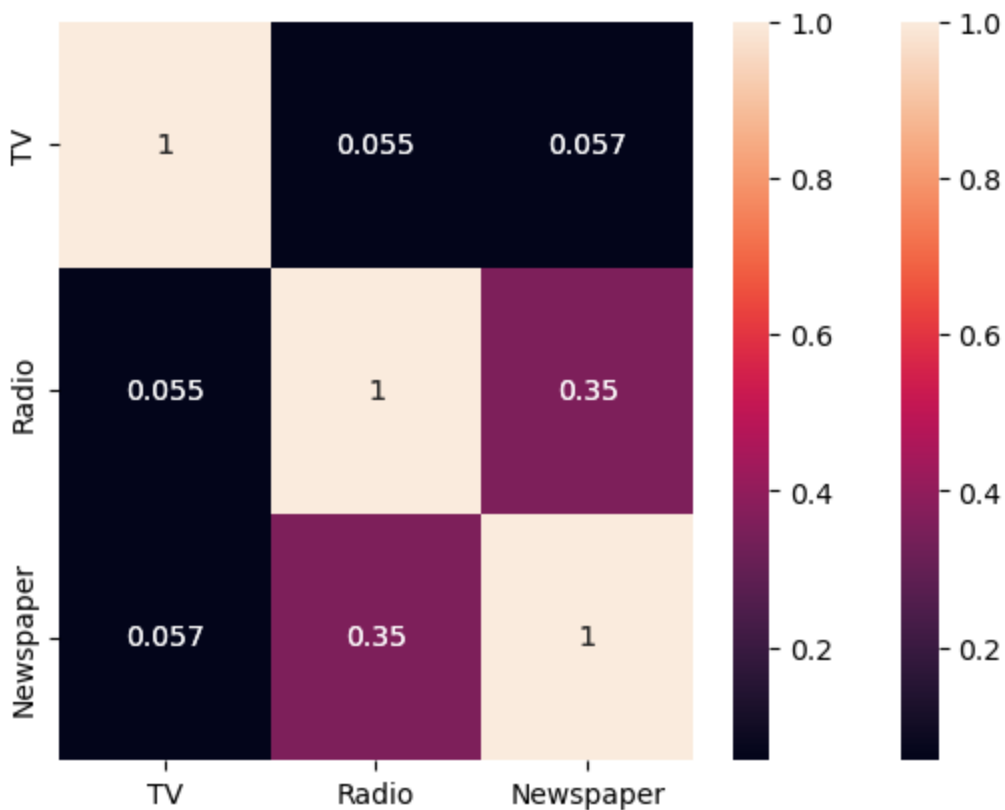
```

In [12]: sns.displot(sales.Sales,bins=10,color='orange',kde=True)
plt.show()

```



```
In [14]: sns.heatmap(sales.drop('Sales',axis=1).corr(),annot=True)
plt.show()
```



```
In [15]: from statsmodels.stats.outliers_influence import variance_inflation_factor
r = sales[["TV", "Radio", "Newspaper"]].values
vif_df = pd.DataFrame()
vif_df["VIF"] = [variance_inflation_factor(r, i) for i in range(3)]
```

```
vif_df["feature"] = ["TV", "Radio", "Newspaper"]
vif_df
```

```
Out[15]:
```

	VIF	feature
0	2.486772	TV
1	3.285462	Radio
2	3.055245	Newspaper

```
In [16]: X = sales.drop(['Sales', 'Newspaper'], axis=1)
y = sales[["Sales"]]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)

models = [('LinearRegression', LinearRegression())]
```

```
In [17]: lin_model = ols(formula="Sales ~ TV + Radio ", data=sales).fit()

print(lin_model.params, "\n")
print(lin_model.summary())
```

```
Intercept    2.921100
TV            0.045755
Radio         0.187994
dtype: float64
```

```

                                OLS Regression Results
=====
Dep. Variable:                  Sales    R-squared:                0.897
Model:                            OLS    Adj. R-squared:           0.896
Method:                 Least Squares    F-statistic:                859.6
Date:                    Mon, 26 Jun 2023    Prob (F-statistic):        4.83e-98
Time:                    14:37:56    Log-Likelihood:            -386.20
No. Observations:                200    AIC:                        778.4
Df Residuals:                    197    BIC:                        788.3
Df Model:                        2
Covariance Type:                nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	2.9211	0.294	9.919	0.000	2.340	3.502
TV	0.0458	0.001	32.909	0.000	0.043	0.048
Radio	0.1880	0.008	23.382	0.000	0.172	0.204

```

=====
Omnibus:                 60.022    Durbin-Watson:              2.081
Prob(Omnibus):            0.000    Jarque-Bera (JB):           148.679
Skew:                    -1.323    Prob(JB):                   5.19e-33
Kurtosis:                 6.292    Cond. No.                    425.
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
In [18]: # this model with Newspaper feature added
X = sales.drop(['Sales'], axis=1)
y = sales[["Sales"]]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)

models = [('LinearRegression', LinearRegression())]
```

```
In [19]: lin_model = ols(formula="Sales ~ TV + Radio + Newspaper ",data=sales).fit()

print(lin_model.params,"\n")
print(lin_model.summary())
```

```
Intercept      2.938889
TV              0.045765
Radio          0.188530
Newspaper      -0.001037
dtype: float64
```

OLS Regression Results						
=====						
Dep. Variable:	Sales	R-squared:		0.897		
Model:	OLS	Adj. R-squared:		0.896		
Method:	Least Squares	F-statistic:		570.3		
Date:	Mon, 26 Jun 2023	Prob (F-statistic):		1.58e-96		
Time:	14:39:01	Log-Likelihood:		-386.18		
No. Observations:	200	AIC:		780.4		
Df Residuals:	196	BIC:		793.6		
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	2.9389	0.312	9.422	0.000	2.324	3.554
TV	0.0458	0.001	32.809	0.000	0.043	0.049
Radio	0.1885	0.009	21.893	0.000	0.172	0.206
Newspaper	-0.0010	0.006	-0.177	0.860	-0.013	0.011
=====						
Omnibus:	60.414	Durbin-Watson:		2.084		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		151.241		
Skew:	-1.327	Prob(JB):		1.44e-33		
Kurtosis:	6.332	Cond. No.		454.		
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Adding the news paper or remove it not affect the model too much

```
In [ ]:
```