Sales Prediction

Linear Regression Model

Prediction or Interpretation

- This model will be focussed on Prediction rather Interpretaion
- Model will have more explanation over the model prediction performance using performance metrics

In [1]:
```
# Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
# will import regression models later while building it
```

In [2]:
```
# importing csv fie and creating dataframe

df = pd.read_csv('advertising.csv')
df.head()
```

Out[2]:

	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

Dataset Description and attributes summary

In [3]:
```
df.columns
```

Out[3]:
```
Index(['TV', 'Radio', 'Newspaper', 'Sales'], dtype='object')
```

In [4]:
```
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
```

```
 3   Sales       200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
```

In [5]:

```
df.describe()
```

Out[5]:

	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

- This dataset has three feature with different mode of advertising - TV, Radio, Newspaper
- We are gonna findout the best contributor to achieve maximum sales
- All columns has numerical values of float datatype.
- TV - Holds high share in advertising campaign followed by Newspaper and Radio
- Its pretty clear visual ads attract more customers compared to Radio

Data Cleaning

In [6]:

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

Out[6]:

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

This dataset is pretty clean. Since our concern is on the model performance we dive into the next section.

Feature Selection

In [7]:

```
df.head()
```

Out[7]:

	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 [8]:

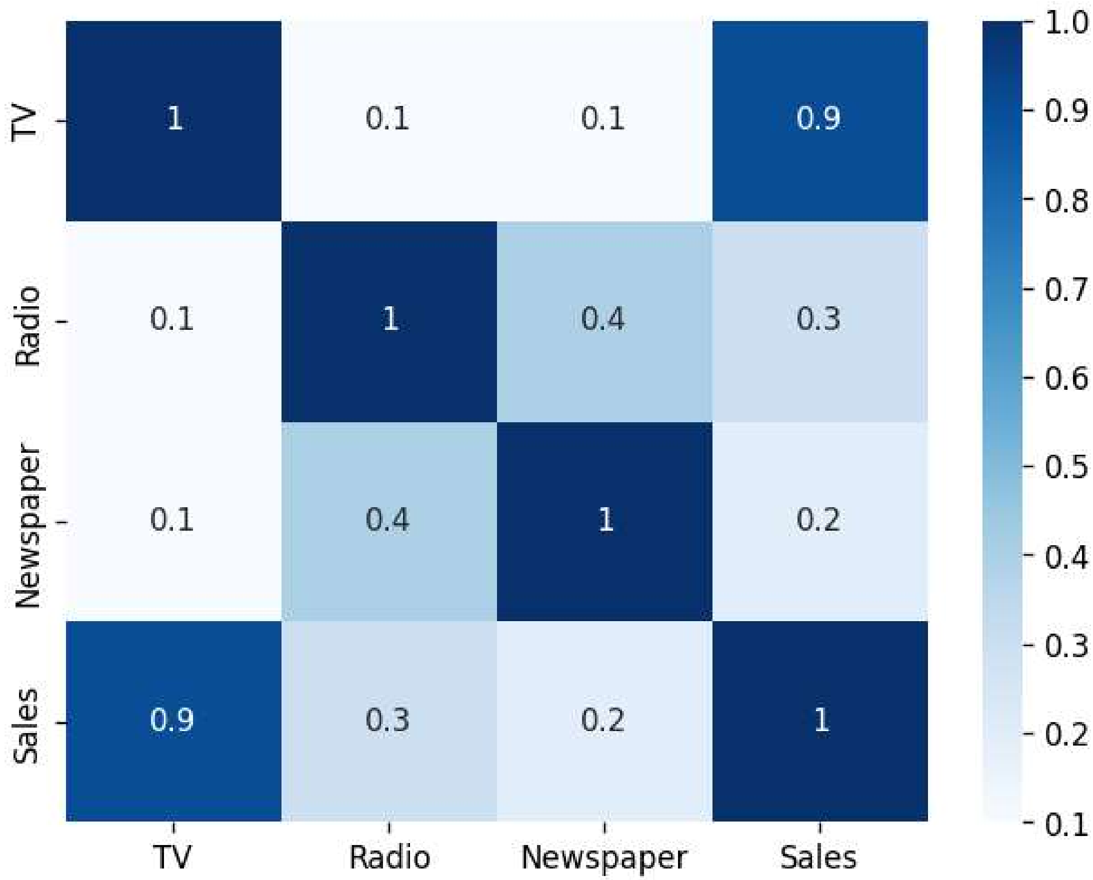
```
np.round(df.corr(),2)
```

Out[8]:

	TV	Radio	Newspaper	Sales
TV	1.00	0.05	0.06	0.90
Radio	0.05	1.00	0.35	0.35
Newspaper	0.06	0.35	1.00	0.16
Sales	0.90	0.35	0.16	1.00

In [9]:

```
plt.figure(dpi=120)
sns.heatmap(np.round(df.corr(),1),annot=True, cmap="Blues")
plt.show()
```

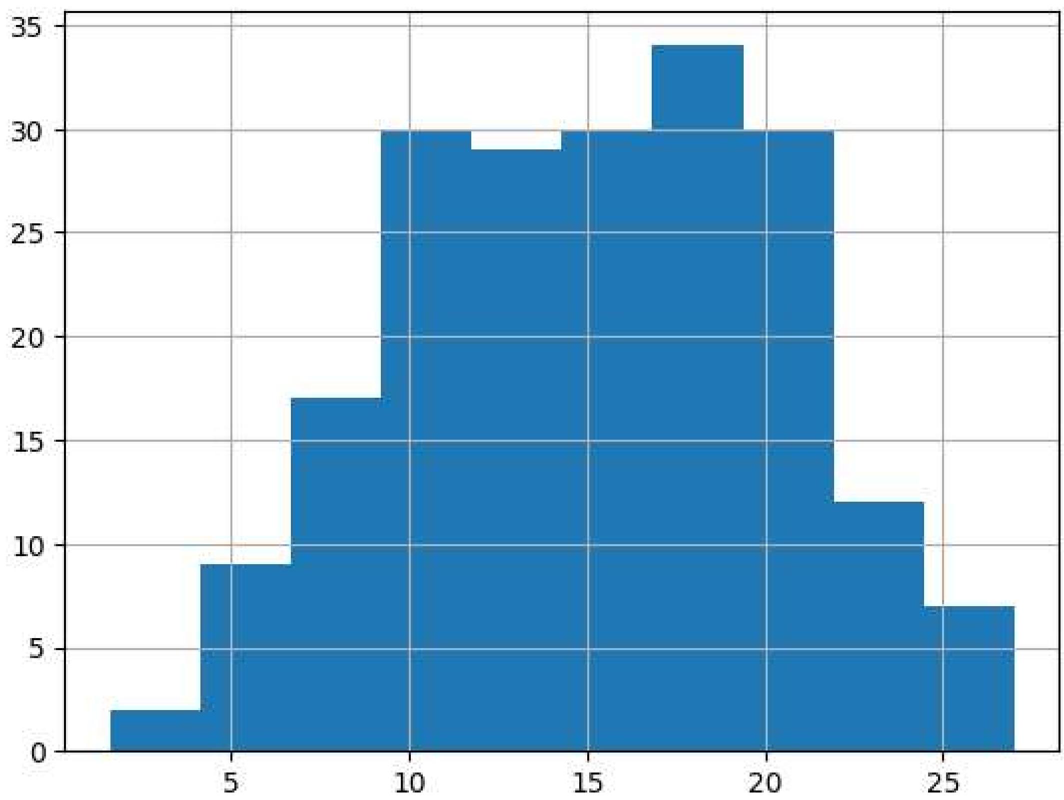


As mentioned before TV advertising has maximum correlation with sales.

Determining Normality

In [10]:
```
df['Sales'].hist()
```

Out[10]: <AxesSubplot:>



In [11]:
```
from scipy.stats.mstats import normaltest
normaltest(df['Sales'].values)
```

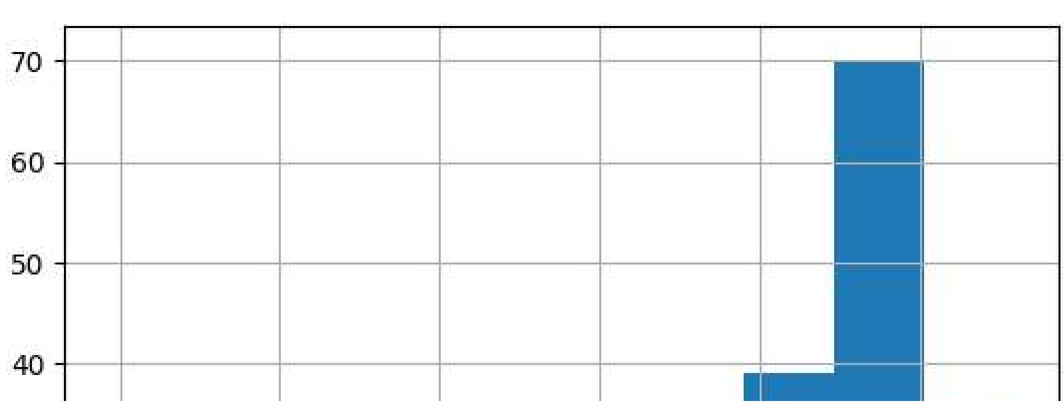
Out[11]: NormaltestResult(statistic=7.100749912891184, pvalue=0.0287138711844335)

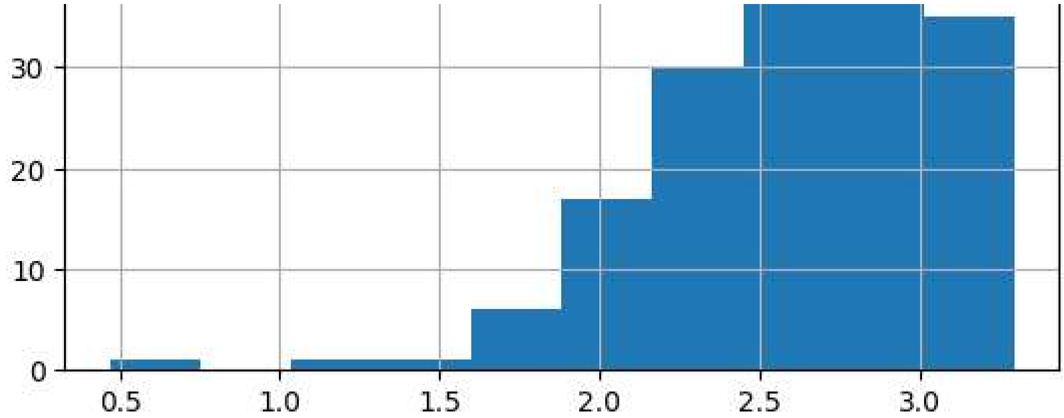
Since p-value is less than 0.05 we can conclude the distribution is Normal. Even though we will try the transformation to compare the pvalues

Log Transformation

In [12]:
```
np.log(df.Sales).hist()
```

Out[12]: <AxesSubplot:>





Clearly shows the distribution is left skewed. so no good after transformation.

In [13]:
```
normaltest(np.log(df['Sales']).values)
```

Out[13]:
```
NormaltestResult(statistic=58.29670316124151, pvalue=2.1929652606684847e-13)
```

Nope Nope Nope all Bad... we have made it worse so lets keep the original format for rest of the model build

In [14]:
```
y = df.Sales
x = df.drop(columns = ['Sales'])
```

Polynomial feature creation

In [15]:
```
from sklearn.preprocessing import PolynomialFeatures
pf = PolynomialFeatures(degree = 2, include_bias = False)
x_pf = pf.fit_transform(x)
```

Train Test Split

In [16]:
```
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x, y, random_state=10, train_
xtrain_pf, xtest_pf, ytrain_pf, ytest_pf = train_test_split(x_pf, y, random_s
```

Linear Model Build

Stock Linear Regression

In [17]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error as mae
from sklearn.metrics import mean_squared_error as mse
from sklearn.metrics import r2_score as r2
lrmodel = LinearRegression()
lrmodel.fit(xtrain, ytrain)
lrypred = lrmodel.predict(xtest)
```

In [18]:

```
# score for non polynomial feature
print('Stock LR Non-Polynomial Score :', lrmodel.score(xtest, ytest))
print('Mean Absolute Error :', mae(ytest, lrypred))
print('Mean Squared Error :', mse(ytest, lrypred))
print('Root Mean Squared Error :', np.sqrt(mse(ytest, lrypred)))
print('R2 Score :', r2(ytest,lrypred))
```

```
Stock LR Non-Polynomial Score : 0.8886717577059424
Mean Absolute Error : 1.5748043429197127
Mean Squared Error : 4.448475475432899
Root Mean Squared Error : 2.10914093304191
R2 Score : 0.8886717577059424
```

In [19]:

```
# score for polynomial feature
lrmodel.fit(xtrain_pf, ytrain_pf)
lrypred = lrmodel.predict(xtest_pf)
print(' Stock LR Polynomial Score :', lrmodel.score(xtest_pf, ytest_pf))
print('Mean Absolute Error :', mae(ytest, lrypred))
print('Mean Squared Error :', mse(ytest, lrypred))
print('Root Mean Squared Error :', np.sqrt(mse(ytest, lrypred)))
print('R2 Score :', r2(ytest,lrypred))
```

```
 Stock LR Polynomial Score : 0.9389652287353996
Mean Absolute Error : 1.089077274110421
Mean Squared Error : 2.4388392156778353
Root Mean Squared Error : 1.5616783329731623
R2 Score : 0.9389652287353996
```

Dataset with polynomial feature performs well in stock linear regression model

Lasso Regression

In [20]:

```
from sklearn.linear_model import LassoCV
lassomodel = LassoCV()
lassomodel.fit(xtrain, ytrain)
lassoypred = lassomodel.predict(xtest)
```

In [21]:

```
# score for non polynomial feature
print('Lasso LR Non-Polynomial Score :', lassomodel.score(xtest, ytest))
print('Mean Absolute Error :', mae(ytest, lassoypred))
print('Mean Squared Error :', mse(ytest, lassoypred))
print('Root Mean Squared Error :', np.sqrt(mse(ytest, lassoypred)))
print('R2 Score :', r2(ytest,lassoypred))
```

```
Lasso LR Non-Polynomial Score : 0.8888142958595117
Mean Absolute Error : 1.5856164924556566
Mean Squared Error : 4.442779908275812
Root Mean Squared Error : 2.107790290393191
R2 Score : 0.8888142958595117
```

In [22]:

```
# score for polynomial feature
lassomodel.fit(xtrain_pf, ytrain_pf)
lassoypred = lrmodel.predict(xtest_pf)
print('Lasso LR Non-Polynomial Score :', lassomodel.score(xtest_pf, ytest_pf)
```

```
print('Mean Absolute Error :', mae(ytest_pf, lassoypred))
print('Mean Squared Error :', mse(ytest_pf, lassoypred))
print('Root Mean Squared Error :', np.sqrt(mse(ytest_pf, lassoypred)))
print('R2 Score :', r2(ytest_pf,lassoypred))
```

```
Lasso LR Non-Polynomial Score : 0.8706431811737638
Mean Absolute Error : 1.089077274110421
Mean Squared Error : 2.4388392156778353
Root Mean Squared Error : 1.5616783329731623
R2 Score : 0.9389652287353996
```

Here also polynomial feature dataset performs well in Lasso Linear Regression model

Ridge Regression

In [23]:

```
from sklearn.linear_model import RidgeCV
ridgemodel = RidgeCV()
ridgemodel.fit(xtrain, ytrain)
ypred = ridgemodel.predict(xtest)
```

In [24]:

```
# score for non polynomial feature
print('Ridge LR Non-Polynomial Score :', ridgemodel.score(xtest, ytest))
print('Mean Absolute Error :', mae(ytest, ypred))
print('Mean Squared Error :', mse(ytest, ypred))
print('Root Mean Squared Error :', np.sqrt(mse(ytest, ypred)))
print('R2 Score :', r2(ytest,ypred))
```

```
Ridge LR Non-Polynomial Score : 0.8886742389546507
Mean Absolute Error : 1.5748689868770613
Mean Squared Error : 4.448376329216271
Root Mean Squared Error : 2.1091174289774077
R2 Score : 0.8886742389546507
```

In [25]:

```
ridgemodel.fit(xtrain_pf, ytrain_pf)
ypred = ridgemodel.predict(xtest_pf)
print('Ridge LR Non-Polynomial Score :', ridgemodel.score(xtest_pf, ytest_pf)
print('Mean Absolute Error :', mae(ytest_pf, ypred))
print('Mean Squared Error :', mse(ytest_pf, ypred))
print('Root Mean Squared Error :', np.sqrt(mse(ytest_pf, ypred)))
print('R2 Score :', r2(ytest_pf,ypred))
```

```
Ridge LR Non-Polynomial Score : 0.9389616502427018
Mean Absolute Error : 1.0890465429473049
Mean Squared Error : 2.438982205782387
Root Mean Squared Error : 1.5617241132102644
R2 Score : 0.9389616502427018
c:\Users\shankesh\AppData\Local\Programs\Python\Python310\lib\site-packages\s
klearn\base.py:450: UserWarning: X does not have valid feature names, but Rid
geCV was fitted with feature names
  warnings.warn(
c:\Users\shankesh\AppData\Local\Programs\Python\Python310\lib\site-packages\s
klearn\base.py:450: UserWarning: X does not have valid feature names, but Rid
geCV was fitted with feature names
  warnings.warn(
```

Same here, polynomial feature wins

Same here, polynomial feature wins

Best Model

Stock LR

- Stock LR Polynomial Score : 0.9389652287353996
- Mean Absolute Error : 1.089077274110421
- Mean Squared Error : 2.4388392156778353
- Root Mean Squared Error : 1.5616783329731623
- R2 Score : 0.9389652287353996

Lasso LR

- Lasso LR Non-Polynomial Score : 0.8706431811737638
- Mean Absolute Error : 1.089077274110421
- Mean Squared Error : 2.4388392156778353
- Root Mean Squared Error : 1.5616783329731623
- R2 Score : 0.9389652287353996

Ridge LR

- Ridge LR Non-Polynomial Score : 0.9389616502427018
- Mean Absolute Error : 1.0890465429473049
- Mean Squared Error : 2.438982205782387
- Root Mean Squared Error : 1.5617241132102644
- R2 Score : 0.9389616502427018

For my dataset both Stock and Ridge performs well

Insights on my models

- According to my dataset all three models have similar mae, mse and r2 values
- Only the prediction score varies for same test data

Next Step Analysis