Practice Project - Linear Regression based : Using dataset (Advertising.csv)

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1. Introduction

• Regression is a statistical technique which helps you to measure the relationship between the independent variables and dependent variables

• It helps you to understand one unit change in the independent variables is going to cause how many units change in the dependent variable

• Dependent or predicted variable is represented as ‘y’

2. Linear Regression Steps:

2.1 Importing Our Libraries

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2.2 Reading the data

Here two important things

1. index_col is by default none and header is 0

1. Make use of proper function depending on the extension of the file

In [ ]:
```
data = pd.read_csv(r'Advertising.csv',index_col = 0)
```

In [ ]:
```
data.head()
```

Out[ ]:

	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

2.3 Assumptions Check

Assumption 1: There should be no outliers in the data

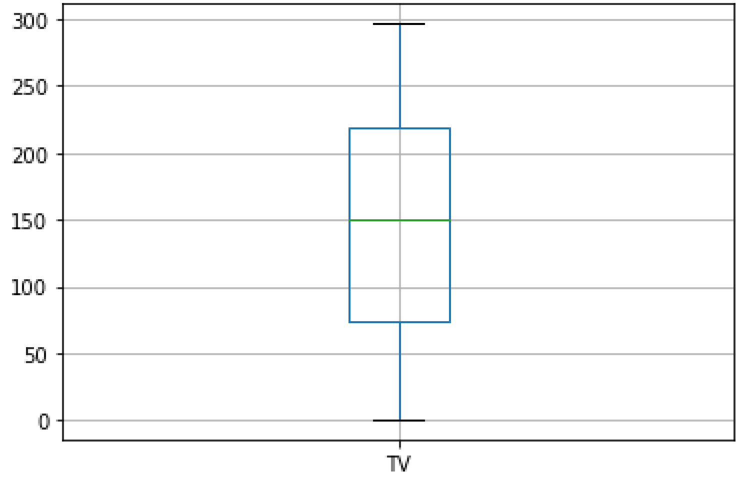
In [ ]:
```
data.describe()
```

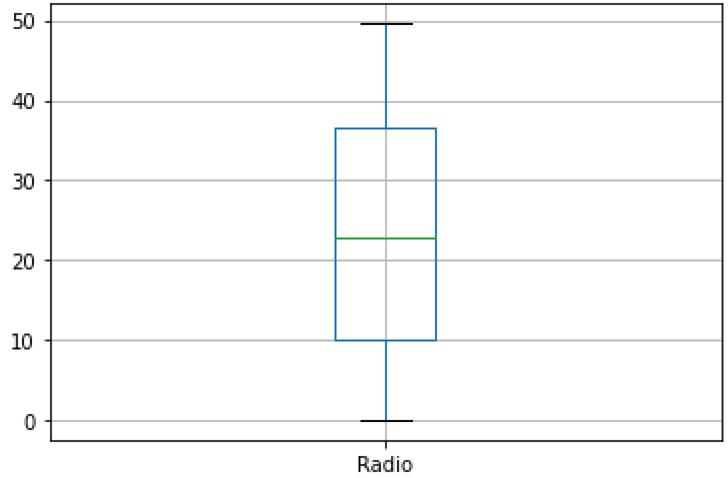
Out[ ]:

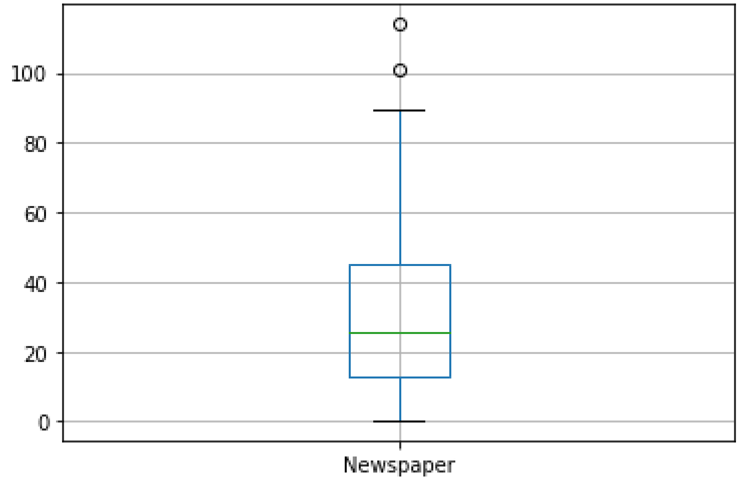
	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	14.022500
std	85.854236	14.846809	21.778621	5.217457
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	10.375000
50%	149.750000	22.900000	25.750000	12.900000

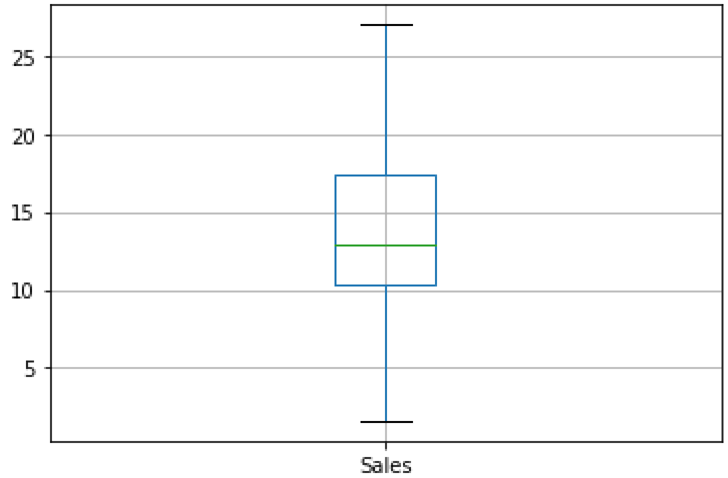
	TV	Radio	Newspaper	Sales
75%	218.825000	36.525000	45.100000	17.400000
max	296.400000	49.600000	114.000000	27.000000

In [ ]:
```
for i in data.columns:
    data.boxplot(column=i)
    plt.show()
```







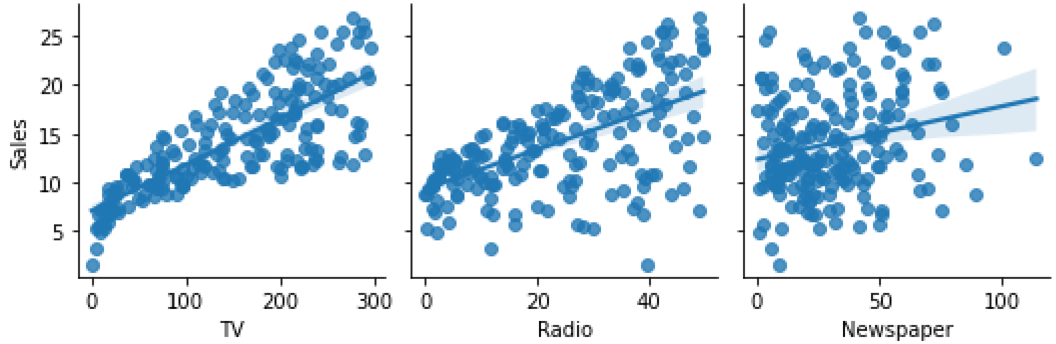


Assumption 2: Assumption of Linearity : Every independent variable should have a linear relationship with the dependent variable

In [ ]:

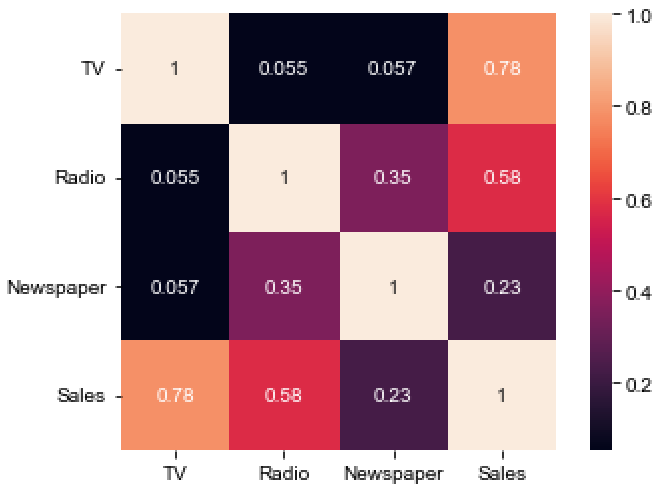
```
sns.pairplot(data,x_vars=['TV','Radio','Newspaper'],
            y_vars="Sales",kind='reg')
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x251f619a040>



Assumption 3: Assumption of no multicollinearity means the independewnt variable should not be correalated with each other

In [ ]:
```
corr = data.corr()
sns.heatmap(corr, annot=True, square=True)
plt.yticks(rotation=0)
sns.set(rc = {'figure.figsize':(15,8)})
plt.show()
```



2.4 Preprocessing and Understanding the data

In [ ]:
```
data.shape
```

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

In [ ]:
```
data.isnull()
```

Out[ ]:

	TV	Radio	Newspaper	Sales
1	False	False	False	False
2	False	False	False	False
3	False	False	False	False
4	False	False	False	False
5	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	False	False	False	False

200 rows × 4 columns

In [ ]:
```
data.isnull().sum()
```

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

So as there are no null values in the data we don't need any sort of missing values handling bt lets consider a example where we have missing values and we treat it using mean median and mode or we can delete the column itself.

2.5 Splitting the data into train and test

In [ ]:
```
x = data[['TV', 'Radio', 'Newspaper']]
y = data[['Sales']]
```

In [ ]:
```
import sklearn
```

In [ ]:
```
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=10)
```

In [ ]:
```
print(x_train.shape)
print(x_test.shape)
```

```
(160, 3)
(40, 3)
```

In [ ]:
```
print(y_train.shape)
print(y_test.shape)
```

```
(160, 1)
(40, 1)
```

2.6 Running your First Machine Leraning Algorithm

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

lm =LinearRegression()

lm.fit(x_train,y_train)
```

Out[ ]:
```
LinearRegression()
```

In [ ]:
```
print(lm.intercept_)
```

```
[3.25409711]
```

In [ ]:
```
print(lm.coef_)
```

```
[[ 0.0437726   0.19343299 -0.00222879]]
```

In [ ]:
```
y_pred = lm.predict(x_test)
print(y_pred)
```

```
[[18.1625299 ]
 [12.92663232]
 [18.0531098 ]
 [23.64464668]
 [20.70438374]
 [14.28227997]
 [14.94493548]
 [21.38232981]
 [21.17508238]
 [12.73110461]
 [24.00312134]
 [ 7.21544071]
 [12.24762152]
 [19.24345998]
 [19.38241854]
 [13.45643798]
 [19.6247089 ]
 [ 9.2531648 ]
 [21.13268075]
 [20.90762408]
 [15.53485445]
 [10.92529369]
 [22.82955184]
 [15.8122438 ]
 [17.42515749]
 [ 8.16218669]
 [11.89783444]
 [12.70337575]
 [21.74138085]
 [ 7.96215368]
 [12.50099965]
 [20.45535282]
 [ 4.72120047]
 [ 4.72259288]
 [16.75292333]
 [15.75804986]
 [ 6.74415499]
 [17.73477354]
```

```
 [ 9.01591827]
 [13.617599  ]]
```

2.7 Evaluation

2.7.1 RMSE:

- Root Mean Square error is an absolute measure of the goodness for the fit
- It gives an absolute number on how much your predicted results deviate from the actual number
- Low the RMSE better the model

2.7.2 R Squared:

- It tells you how well the regression model is predicting as compared to the mean model
- Lies between (0-1)
- If R squared is close to 1 → very good model

In [ ]:
```
from sklearn.metrics import r2_score,mean_squared_error

r2 = r2_score(y_test,y_pred)

rmse = np.sqrt(mean_squared_error(y_test,y_pred))

print('R-squared', r2)
print('RMSE', rmse)
```

```
R-squared 0.8353672324670594
RMSE 2.58852984462781
```

2.8 Finalizing Stuff

In [ ]:
```
new_data = pd.DataFrame()
new_data = (x_test)

new_data['Actual_Sales'] = y_test
new_data['Predicted_Sales'] = y_pred
```

In [ ]:
```
new_data
```

Out[ ]:

	TV	Radio	Newspaper	Actual_Sales	Predicted_Sales
60	210.7	29.5	9.3	18.4	18.162530
6	8.7	48.9	75.0	7.2	12.926632
21	218.4	27.7	53.4	18.0	18.053110
199	283.6	42.0	66.2	25.5	23.644647
53	216.4	41.7	39.6	22.6	20.704384
20	147.3	23.9	19.1	14.6	14.282280
163	188.4	18.1	25.6	14.9	14.944935
56	198.9	49.4	60.0	23.7	21.382330
70	216.8	43.9	27.2	22.3	21.175082
3	17.2	45.9	69.3	9.3	12.731105
99	289.7	42.3	51.2	25.4	24.003121
11	66.1	5.8	24.2	8.6	7.215441
76	16.9	43.7	89.4	8.7	12.247622
143	220.5	33.2	37.9	20.1	19.243460
125	229.5	32.3	74.2	19.7	19.382419
64	102.7	29.6	8.4	14.0	13.456438
110	255.4	26.9	5.5	19.8	19.624709
79	5.4	29.9	9.4	5.3	9.253165
112	241.7	38.0	23.2	21.8	21.132681
186	205.0	45.1	19.6	22.6	20.907624
155	187.8	21.1	9.5	15.6	15.534854
131	0.7	39.6	8.7	1.6	10.925294
62	261.3	42.7	54.7	24.2	22.829552
88	110.7	40.6	63.2	16.0	15.812244

	TV	Radio	Newspaper	Actual_Sales	Predicted_Sales
103	280.2	10.1	21.4	14.8	17.425157
122	18.8	21.7	50.4	7.0	8.162187
137	25.6	39.0	9.3	9.5	11.897834
2	44.5	39.3	45.1	10.4	12.703376
48	239.9	41.5	18.5	23.2	21.741381
173	19.6	20.1	17.0	7.6	7.962154
160	131.7	18.4	34.6	12.9	12.501000
40	228.0	37.7	32.0	21.5	20.455353
77	27.5	1.6	20.7	6.9	4.721200
92	28.6	1.5	33.0	7.3	4.722593
36	290.7	4.1	8.5	12.8	16.752923
179	276.7	2.3	23.7	11.8	15.758050
128	80.2	0.0	9.2	8.8	6.744155
170	284.3	10.6	6.4	15.0	17.734774
47	89.7	9.9	35.7	10.6	9.015918
175	222.4	3.4	13.1	11.5	13.617599

In [ ]:

```
#new_data.to_csv('predictions.csv')
```