Simple Linear Regression

Build a model which predicts sales based on the money spent on different platforms for marketing

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

Exploring our dataset

In [2]:
```
advertising = pd.read_csv('advertising.csv')
```

In [3]:
```
advertising.head()
```

Out[3]:

	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 [4]:
```
advertising.isnull().sum()
```

Out[4]:
```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

In [5]:
```
advertising.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
```

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

Out[6]:

	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

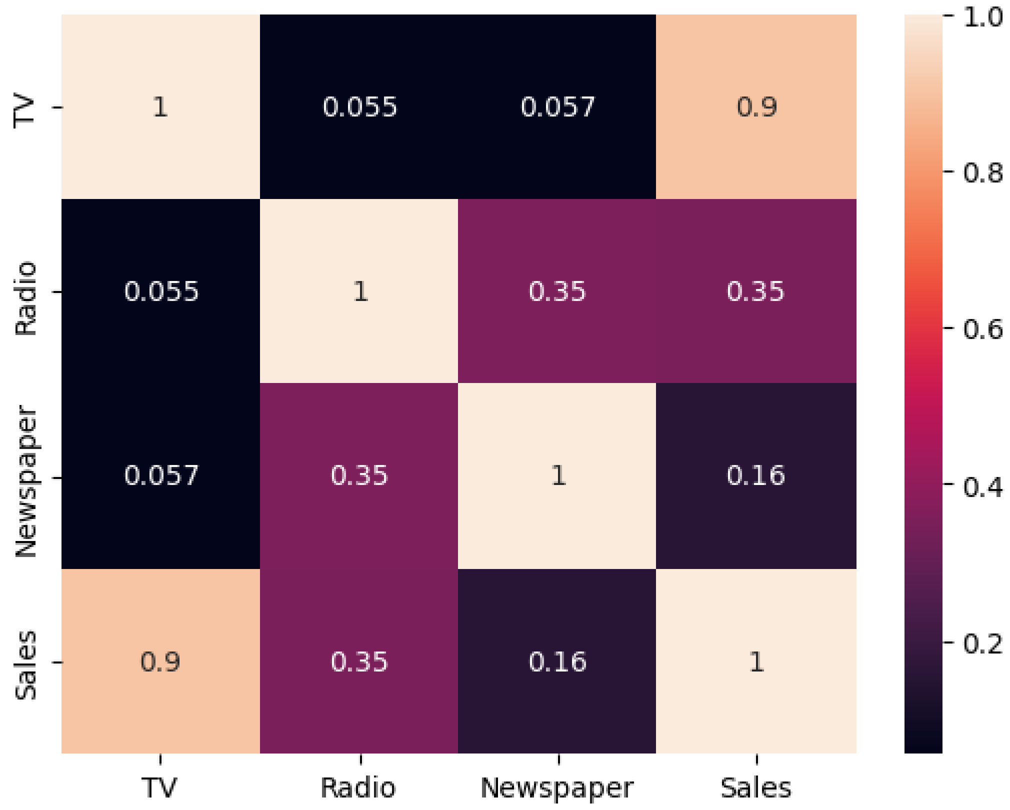
Time to do some Visualization

In [7]:
```
correlation = advertising.corr()
correlation
```

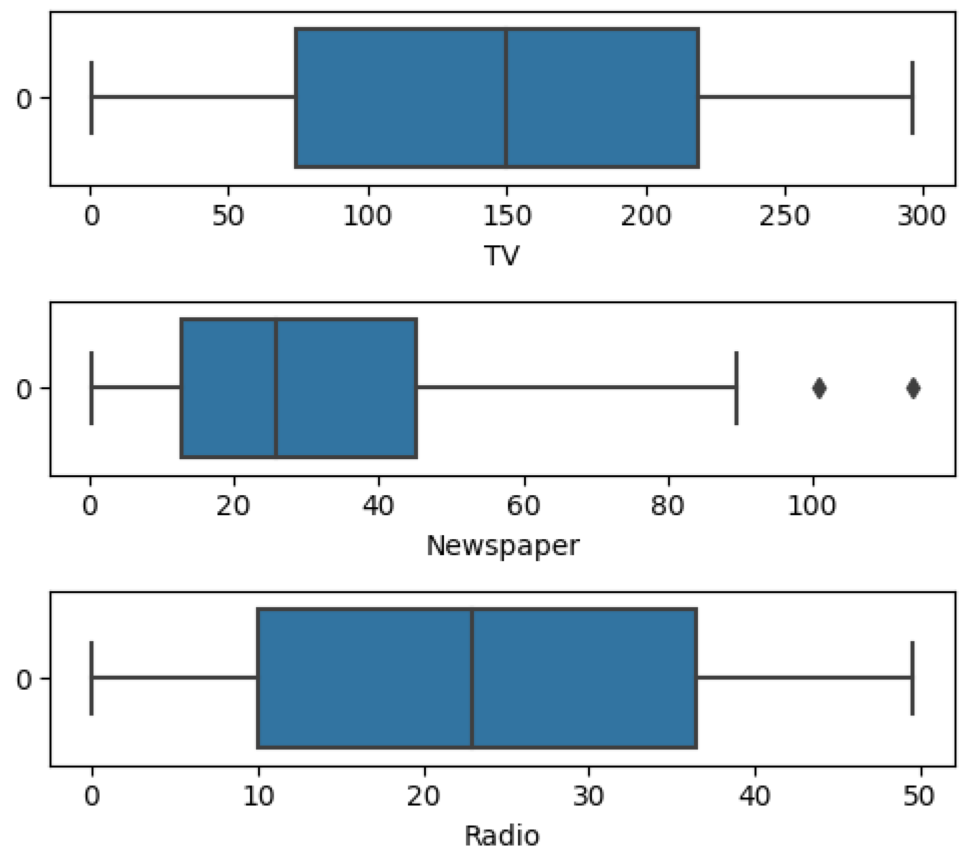
Out[7]:

	TV	Radio	Newspaper	Sales
TV	1.000000	0.054809	0.056648	0.901208
Radio	0.054809	1.000000	0.354104	0.349631
Newspaper	0.056648	0.354104	1.000000	0.157960
Sales	0.901208	0.349631	0.157960	1.000000

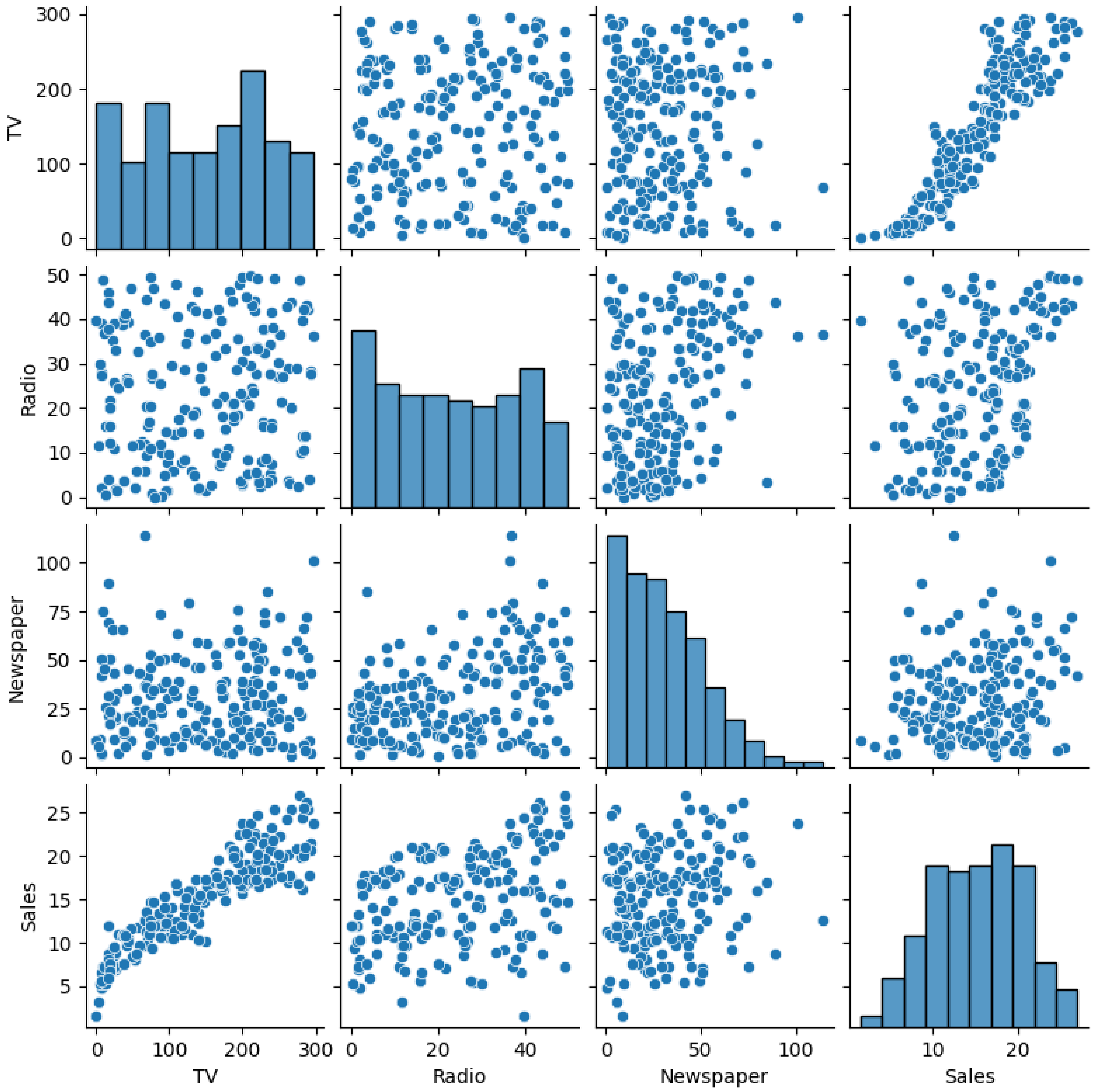
In [8]:
```
sns.heatmap(correlation, annot=True)
plt.show()
```



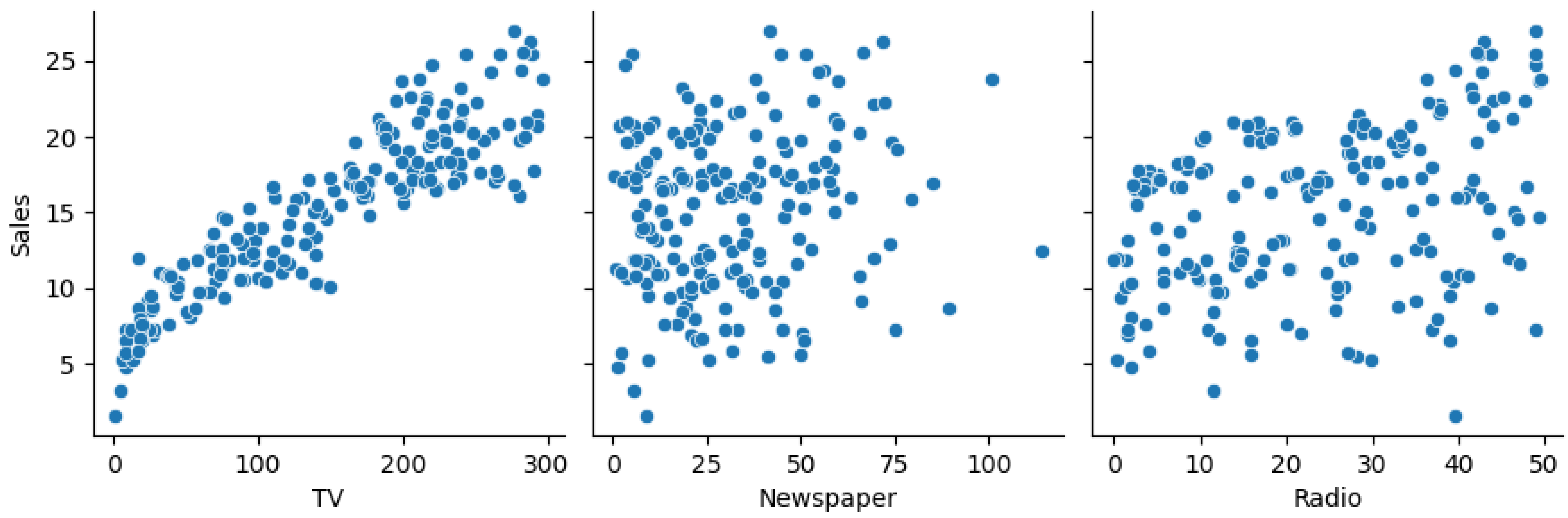
In [9]:
```
fig, axs = plt.subplots(3, figsize = (5,4.5))
plt1 = sns.boxplot(advertising['TV'], ax = axs[0], orient='h')
plt2 = sns.boxplot(advertising['Newspaper'], ax = axs[1], orient='h')
plt3 = sns.boxplot(advertising['Radio'], ax = axs[2], orient='h')
plt1.set_xlabel('TV')
plt2.set_xlabel('Newspaper')
plt3.set_xlabel('Radio')
plt.tight_layout()
```



In [10]:
```
sns.pairplot(advertising, height=2, aspect=1, kind='scatter')
plt.show()
```



In [11]:
```
sns.pairplot(advertising, x_vars=['TV', 'Newspaper', 'Radio'], y_vars='Sales', height=3, aspect=1, kind='scatter')
plt.show()
```



choosing TV as independent variable and Sales as depenent variable

In [12]:
```
X = advertising['TV']
y = advertising['Sales']
```

In [13]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size = 0.3, random_state = 44)
```

In [14]:
```
y_train.shape
```

Out[14]: (140,)

In [15]:
```
X_train_sm = sm.add_constant(X_train)

model = sm.OLS(y_train, X_train_sm).fit()
```

In [16]:
```
coefficients = model.params
coefficients
```

Out[16]:
```
const    6.572498
TV       0.058265
dtype: float64
```

In [17]:
```
intercept = coefficients[0]
slope = coefficients[1]
```

In [18]:
```
model.summary()
```

Out[18]:

OLS Regression Results

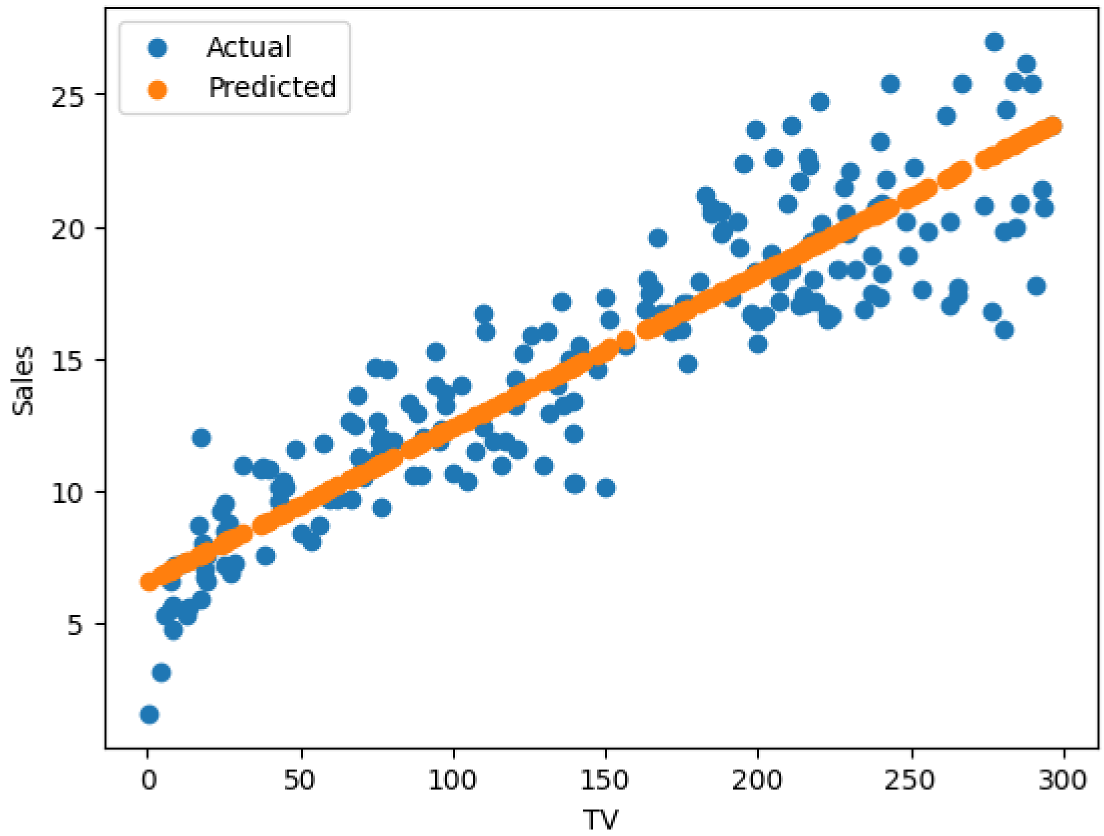
Dep. Variable:	Sales	**R-squared:**	0.829
Model:	OLS	**Adj. R-squared:**	0.828
Method:	Least Squares	**F-statistic:**	670.6
Date:	Thu, 27 Apr 2023	**Prob (F-statistic):**	7.75e-55
Time:	01:42:54	**Log-Likelihood:**	-315.16
No. Observations:	140	**AIC:**	634.3
Df Residuals:	138	**BIC:**	640.2
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.5725	0.385	17.062	0.000	5.811	7.334
TV	0.0583	0.002	25.896	0.000	0.054	0.063

Omnibus:	0.106	**Durbin-Watson:**	2.218
Prob(Omnibus):	0.949	**Jarque-Bera (JB):**	0.187
Skew:	-0.063	**Prob(JB):**	0.911
Kurtosis:	2.872	**Cond. No.**	337.

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

In [19]:
```
plt.scatter(advertising.TV, advertising.Sales, label='Actual')
plt.scatter(advertising.TV, intercept + slope*advertising.TV, label='Predicted')
plt.xlabel('TV')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



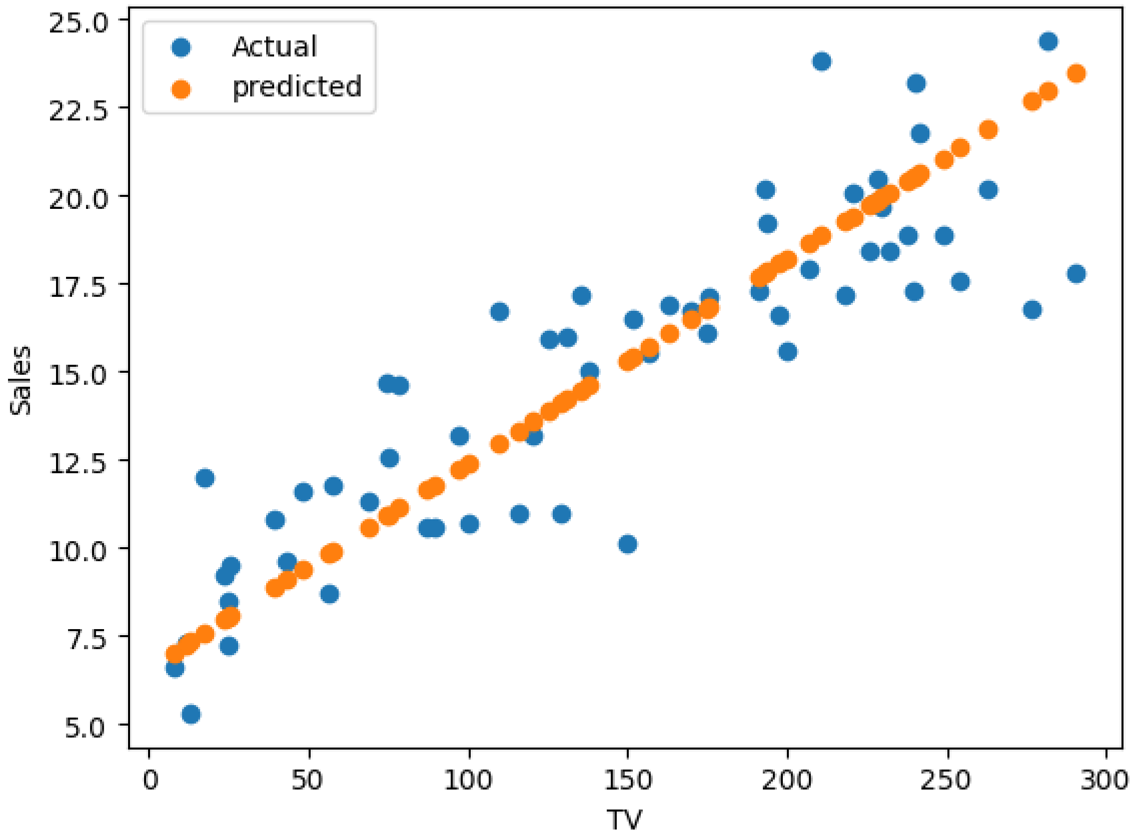
Testing our model

In [20]:
```
X_test_sm = sm.add_constant(X_test)
y_pred = model.predict(X_test_sm)
d = pd.DataFrame({'actual': y_test, 'predicted':y_pred})
d.head()
```

Out[20]:

	actual	predicted
135	11.6	9.386712
73	11.0	14.112028
157	10.1	15.300640
28	18.9	21.068905
23	20.5	19.874466

In [21]:
```
plt.scatter(X_test, y_test, label = 'Actual')
plt.scatter(X_test, d.predicted, label = 'predicted')
plt.xlabel('TV')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



Calculating RMSE

In [22]:
```
np.sqrt(((d['actual'] - d['predicted'])**2).sum()/60)
```

Out[22]: 2.293212682024496

Coefficient of Determination

In [23]:
```
r2_score(y_test, y_pred)
```

Out[23]: 0.7418242381629321