Simple Regression

In [3]:
```
import pandas as pd
import numpy as np
import os
from sklearn.model_selection import train_test_split, cross_val_score,c
ross_val_predict
from sklearn.metrics import mean_squared_error, r2_score
```

In [4]:
```
df = pd.read_csv("advertising.csv", usecols = [1,2,3,4])
```

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

Out[8]:

	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	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

In [9]:
```
df = df.iloc[:,1:len(df)]
```

In [113]:
```
```

Out[113]:

	TV	radio	newspaper	sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4

	TV	radio	newspaper	sales
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

In [10]:
```
df.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
radio	200.0	23.2640	14.846809	0.0	9.975	22.90	36.525	49.6
newspaper	200.0	30.5540	21.778621	0.3	12.750	25.75	45.100	114.0
sales	200.0	14.0225	5.217457	1.6	10.375	12.90	17.400	27.0

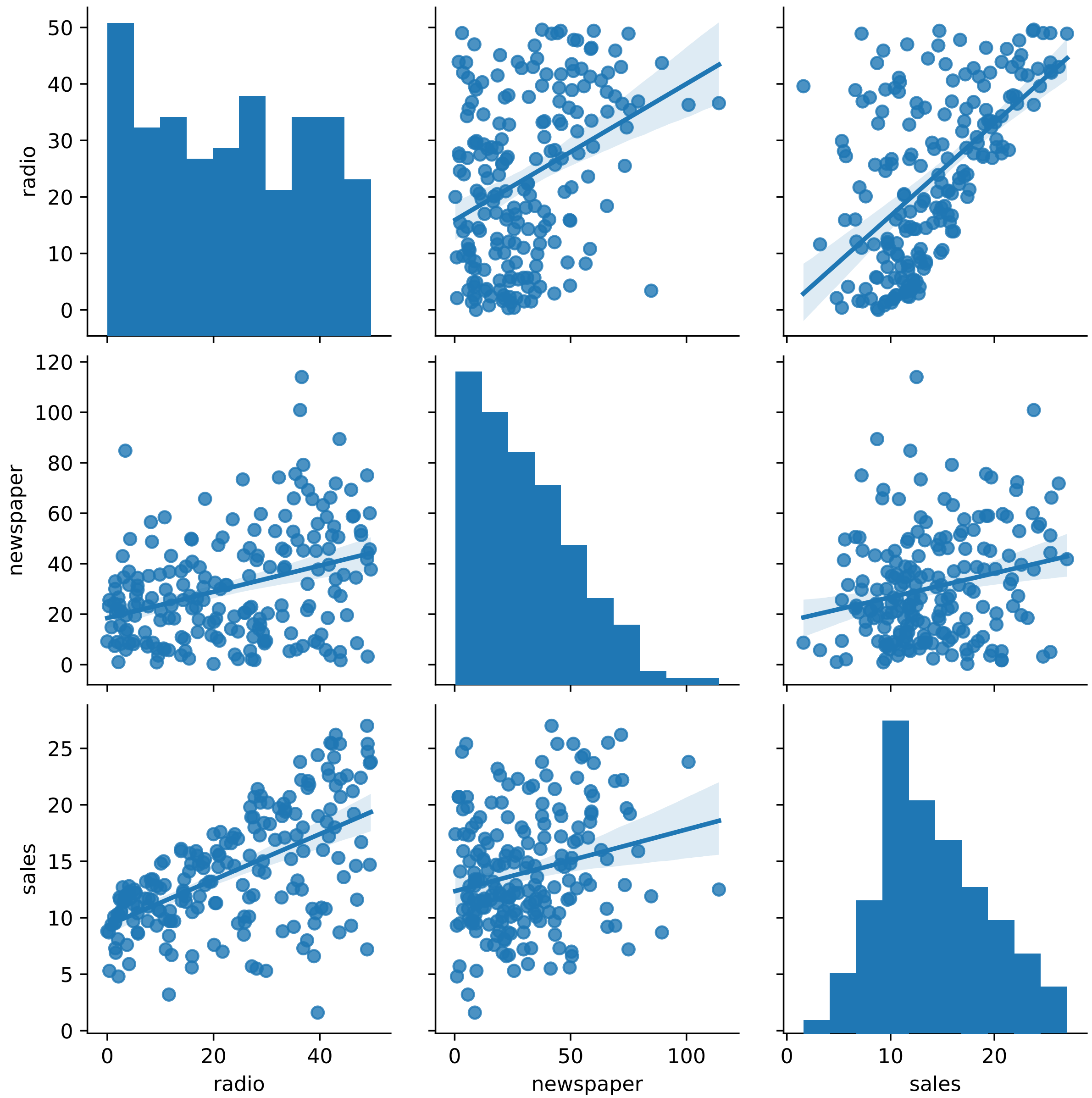
In [11]:
```
df.corr()
```

Out[11]:

	radio	newspaper	sales
radio	1.000000	0.354104	0.576223
newspaper	0.354104	1.000000	0.228299
sales	0.576223	0.228299	1.000000

In [12]:
```
import seaborn as sns
sns.pairplot(df, kind = "reg")
```

Out[12]: <seaborn.axisgrid.PairGrid at 0x2f0e04a9390>



Modelling with Stats

In [36]:
```python
X = df[["TV"]]
```

In [15]:
```python
import statsmodels.api as sm
```

In [37]:
```python
X = sm.add_constant(X)
```

In [38]:
```python
y = df["sales"]
```

In [39]:
```python
lm = sm.OLS(y,X)
```

In [40]:
```python
model = lm.fit()
```

In [41]:
```python
model.summary() #coef and TV kısmında tv nin 1 biriminin satış üzerinde ki etkisi
```

Out[41]:

OLS Regression Results

Dep. Variable:	sales	**R-squared:**	0.612
Model:	OLS	**Adj. R-squared:**	0.610
Method:	Least Squares	**F-statistic:**	312.1
Date:	Sat, 27 Jun 2020	**Prob (F-statistic):**	1.47e-42
Time:	14:35:20	**Log-Likelihood:**	-519.05
No. Observations:	200	**AIC:**	1042.
Df Residuals:	198	**BIC:**	1049.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	7.0326	0.458	15.360	0.000	6.130	7.935
TV	0.0475	0.003	17.668	0.000	0.042	0.053

Omnibus:	0.531	**Durbin-Watson:**	1.935
Prob(Omnibus):	0.767	**Jarque-Bera (JB):**	0.669
Skew:	-0.089	**Prob(JB):**	0.716
Kurtosis:	2.779	**Cond. No.**	338.

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

Another method

In [5]:
```
import statsmodels.formula.api as smf
lm = smf.ols("sales ~ TV", df)
model = lm.fit()
model.summary()
```

Out[5]:

OLS Regression Results

Dep. Variable:	sales	**R-squared:**	0.612
Model:	OLS	**Adj. R-squared:**	0.610
Method:	Least Squares	**F-statistic:**	312.1
Date:	Sat, 04 Jul 2020	**Prob (F-statistic):**	1.47e-42
Time:	12:45:26	**Log-Likelihood:**	-519.05
No. Observations:	200	**AIC:**	1042.
Df Residuals:	198	**BIC:**	1049.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	7.0326	0.458	15.360	0.000	6.130	7.935

TV	0.0475	0.003	17.668	0.000	0.042	0.053

Omnibus:	0.531	**Durbin-Watson:**	1.935
Prob(Omnibus):	0.767	**Jarque-Bera (JB):**	0.669
Skew:	-0.089	**Prob(JB):**	0.716
Kurtosis:	2.779	**Cond. No.**	338.

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

In [43]:
```
model.conf_int()
```

Out[43]:

	0	1
Intercept	6.129719	7.935468
TV	0.042231	0.052843

In [44]:
```
model.f_pvalue
```

Out[44]:
```
1.4673897001947095e-42
```

In [45]:
```
print("f_pvalue:", "%.4f"% model.fvalue)
```

```
f_pvalue: 312.1450
```

In [46]:
```
print("t_pvalue:", "%.4f"% model.tvalues[0:1])
```

```
t_pvalue: 15.3603
```

In [47]:
```
model.mse_model
```

Out[47]:
```
3314.6181668686486
```

In [48]:
```
model.rsquared_adj
```

Out[48]:
```
0.6099148238341623
```

In [49]:
```
model.fittedvalues[0:5
]
```

Out[49]:
```
0    17.970775
1     9.147974
2     7.850224
3    14.234395
4    15.627218
dtype: float64
```

In [29]:
```
import seaborn as sns
y[0:5]
```

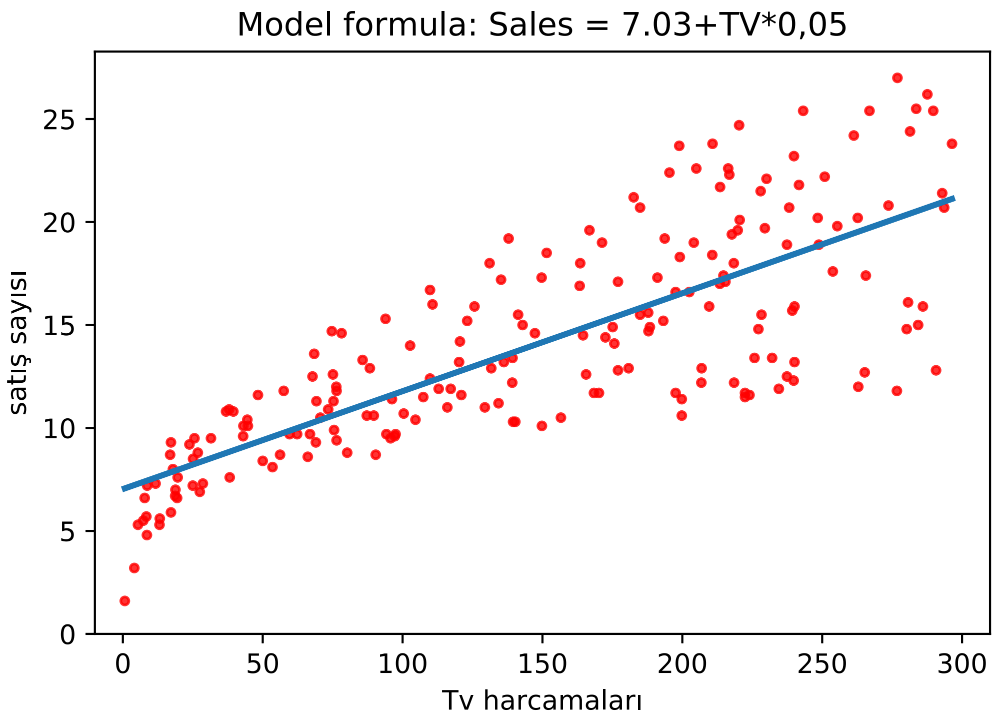
Out[29]:
```
0    22.1
1    10.4
2     9.3
3    18.5
4    12.9
Name: sales, dtype: float64
```

In [50]:
```
print("sales = "+ str("%.2f"% model.params[0])+"+TV"+"*"+ str("%.2f"%model.params[1]))
```

```
sales = 7.03+TV*0.05
```

In [16]:
```
 g = sns.regplot(df["TV"], df["sales"], ci =None, scatter_kws={"color":"r","s":9})
 g.set_title("Model formula: Sales = 7.03+TV*0,05")
 g.set_ylabel("satış sayısı")
 g.set_xlabel("Tv harcamaları")
 plt.xlim(-10,310)
 plt.ylim(bottom = 0)
```

Out[16]:
```
(0, 28.278347130242828)
```



In [9]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [8]:
```
from sklearn.linear_model import LinearRegression
```

In [10]:
```
X=df[["TV"]]
```

In [11]:
```
y=df["sales"]
reg = LinearRegression()
model = reg.fit(X,y)
model.intercept_
model.coef_
```

Out[11]:
```
array([0.04753664])
```

In [61]:
```
model.score(X,y)
```
Out[61]:
```
0.611875050850071
```

Prediction

In [12]:
```
X=df[["TV"]]
y=df["sales"]
reg = LinearRegression()
model = reg.fit(X,y)
```

In [75]:
```
model.predict([[30]])
```
Out[75]:
```
array([8.45869276])
```

In [13]:
```
k_t = pd.DataFrame({"real_y": y[0:10],
                    "predicted_y": reg.predict(X)[0:10]})
```

In [66]:
```
k_t["hata"] = k_t["gercek_y"]-k_t["tahmin_y"]
```

In [14]:
```
k_t
```
Out[14]:

	real_y	predicted_y
0	22.1	17.970775
1	10.4	9.147974
2	9.3	7.850224
3	18.5	14.234395
4	12.9	15.627218
5	7.2	7.446162
6	11.8	9.765950

	real_y	predicted_y
7	13.2	12.746498
8	4.8	7.441409
9	10.6	16.530414

In [68]:
```
k_t["hata_kare"] = k_t["hata"]**2
```

In [69]:
```
k_t
```

Out[69]:

	gercek_y	tahmin_y	hata	hata_kare
0	22.1	17.970775	4.129225	17.050503
1	10.4	9.147974	1.252026	1.567569
2	9.3	7.850224	1.449776	2.101851
3	18.5	14.234395	4.265605	18.195390
4	12.9	15.627218	-2.727218	7.437719
5	7.2	7.446162	-0.246162	0.060596
6	11.8	9.765950	2.034050	4.137358
7	13.2	12.746498	0.453502	0.205664
8	4.8	7.441409	-2.641409	6.977040
9	10.6	16.530414	-5.930414	35.169814

In [70]:
```
np.sum(k_t["hata_kare"])
```

Out[70]: 92.90350329638103

In [82]:
```
X = df.drop("sales", axis = 1)
y = df["sales"]
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.
30,
```

```
                                                    train_size =
0.70, random_state =0)
```

In [83]:

```
training = df.copy()
```

In [84]:

```
lm = sm.OLS(y_train,X_train)
```

In [86]:

```
model = lm.fit()
model.summary()
```

Out[86]:

OLS Regression Results

Dep. Variable:	sales	**R-squared (uncentered):**	0.984
Model:	OLS	**Adj. R-squared (uncentered):**	0.984
Method:	Least Squares	**F-statistic:**	2862.
Date:	Sat, 27 Jun 2020	**Prob (F-statistic):**	2.50e-123
Time:	16:40:24	**Log-Likelihood:**	-289.37
No. Observations:	140	**AIC:**	584.7
Df Residuals:	137	**BIC:**	593.6
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
TV	0.0520	0.002	33.691	0.000	0.049	0.055
radio	0.2321	0.010	22.911	0.000	0.212	0.252
newspaper	0.0188	0.008	2.371	0.019	0.003	0.034

Omnibus:	1.996	**Durbin-Watson:**	1.890
Prob(Omnibus):	0.369	**Jarque-Bera (JB):**	1.965
Skew:	0.284	**Prob(JB):**	0.374

Kurtosis:	2.878	**Cond. No.**	12.3

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

In [ ]:
```
### Scikit-learn model
```

In [87]:
```
lm = LinearRegression()
model = lm.fit(X_train, y_train)
```

In [88]:
```
model.intercept_
```

Out[88]:
```
2.880255286331323
```

In [89]:
```
model.coef_
```

Out[89]:
```
array([0.04391531, 0.20027962, 0.00184368])
```

In [93]:
```
rmse = np.sqrt(mean_squared_error(y_train,model.predict(X_train)))## ha
ta oranı
```

In [94]:
```
rmse
```

Out[94]:
```
1.5768437866753109
```

In [97]:
```
cross_val_score(model,X,y, cv = 10, scoring = "r2").mean()
```

Out[97]:
```
0.8853562237979616
```

In [101]:
```
np.sqrt(-cross_val_score(model,X_train,y_train, cv = 10, scoring = "neg
_mean_squared_error")).mean() ##validating and real result
```

Out[101]:
```
1.59979865949965
```

PLC

In [136]:
```
hit = pd.read_csv("hitters.csv")
```

In [137]:
```
df1 = hit.copy()
```

In [138]:
```
df1 = df1.dropna()
df1.head()
```

Out[138]:

	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun	CRuns	CRBI	CWal
1	315	81	7	24	38	39	14	3449	835	69	321	414	3
2	479	130	18	66	72	76	3	1624	457	63	224	266	2
3	496	141	20	65	78	37	11	5628	1575	225	828	838	3
4	321	87	10	39	42	30	2	396	101	12	48	46	
5	594	169	4	74	51	35	11	4408	1133	19	501	336	1

In [139]:
```
dms = pd.get_dummies(df1[["League", "Division","NewLeague"]])
dms.head()
```

Out[139]:

	League_A	League_N	Division_E	Division_W	NewLeague_A	NewLeague_N
1	0	1	0	1	0	1
2	1	0	0	1	1	0
3	0	1	1	0	0	1
4	0	1	1	0	0	1
5	1	0	0	1	1	0

In [140]:
```
y = df1["Salary"]
```

In [141]:
```
X_ = df1.drop(["Salary","League","Division","NewLeague"],axis =1).astyp
e("float64") #we removed dependent and categoric variables from dataset
```

In [142]:
```
X = pd.concat([X_,dms[["League_N","Division_W","NewLeague_N"]]], axis =
 1)
```

In [143]:
```
X
```

Out[143]:

	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun	CRuns	CRBI
1	315.0	81.0	7.0	24.0	38.0	39.0	14.0	3449.0	835.0	69.0	321.0	414.0
2	479.0	130.0	18.0	66.0	72.0	76.0	3.0	1624.0	457.0	63.0	224.0	266.0
3	496.0	141.0	20.0	65.0	78.0	37.0	11.0	5628.0	1575.0	225.0	828.0	838.0
4	321.0	87.0	10.0	39.0	42.0	30.0	2.0	396.0	101.0	12.0	48.0	46.0
5	594.0	169.0	4.0	74.0	51.0	35.0	11.0	4408.0	1133.0	19.0	501.0	336.0
...	...	...	...	...	...	...	...	...	...	...	...	...
317	497.0	127.0	7.0	65.0	48.0	37.0	5.0	2703.0	806.0	32.0	379.0	311.0
318	492.0	136.0	5.0	76.0	50.0	94.0	12.0	5511.0	1511.0	39.0	897.0	451.0
319	475.0	126.0	3.0	61.0	43.0	52.0	6.0	1700.0	433.0	7.0	217.0	93.0
320	573.0	144.0	9.0	85.0	60.0	78.0	8.0	3198.0	857.0	97.0	470.0	420.0
321	631.0	170.0	9.0	77.0	44.0	31.0	11.0	4908.0	1457.0	30.0	775.0	357.0

263 rows × 19 columns

In [144]:
```
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size =0.25,
                                                    random_state = 42)
```

In [145]:
```
print("X_train", X_train.shape)
print("y_train", y_train.shape)
```

```python
print("X_test",X_test.shape)
print("y_test",y_test.shape)

training = df.copy()

print("training", training.shape)
```

```
X_train (197, 19)
y_train (197,)
X_test (66, 19)
y_test (66,)
training (200, 4)
```

In [146]:
```python
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale
pca= PCA()
```

In [147]:
```python
X_reducen_train = pca.fit_transform(scale(X_train))
```

In [148]:
```python
 np.cumsum(np.round(pca.explained_variance_ratio_,decimals = 4)*100)[0:
100]
```

Out[148]:
```
array([38.18, 59.88, 70.88, 78.88, 84.18, 88.45, 92.05, 94.86, 96.34,
       97.28, 98.01, 98.68, 99.18, 99.49, 99.74, 99.9 , 99.96, 99.98,
       99.99])
```

In [149]:
```python
lm = LinearRegression()
```

In [150]:
```python
pcr_model = lm.fit(X_reducen_train,y_train)
```

In [151]:
```python
pcr_model.intercept_
```

Out[151]:
```
543.4834416243655
```

In [154]:
```python
y_pred = pcr_model.predict(X_reducen_train)
```

In [156]:
```
y_pred[0:5]
```

Out[156]:
```
array([377.44484744, 802.19452124, 495.60987745, 112.53177731,
       426.21613066])
```

In [158]:
```
np.sqrt(mean_squared_error(y_train, y_pred))
```

Out[158]:
```
289.3292825564976
```

In [15]:
```
! jupyter nbconvert --to html MachineLearning1.ipynb
```

```
[NbConvertApp] Converting notebook MachineLearning1.ipynb to html
[NbConvertApp] Writing 685549 bytes to MachineLearning1.html
```

In [ ]:

In [ ]: