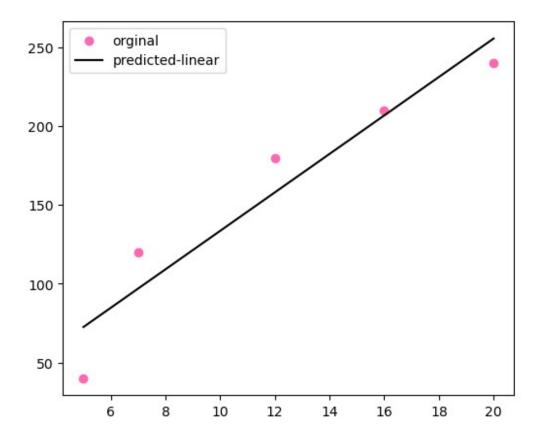
linear regression

- y=a+bx+b1 x1+b2 x2......
- y=>dependent(1) [10]
- x=>independent(0) [20]

```
from sklearn.linear model import LinearRegression
import numpy as np
from sklearn.metrics import
r2_score,mean_absolute_error,mean_squared_error
time=np.array([5,7,12,16,20]).reshape(-1,1)
mass=np.array([40,120,180,210,240])
mymodel=LinearRegression()
mymodel.fit(time,mass)
LinearRegression()
x=int(input("enter the time in minute:"))
result=mymodel.predict([[x]])
print("if the time is",x,"minututes the mass is",result[0],"grams")
enter the time in minute: 41
if the time is 41 minututes the mass is 512.025974025974 grams
mass model=mymodel.predict(time)
print(mass model)
                                         206.83116883 255.662337661
[ 72.54545455 96.96103896 158.
import matplotlib.pyplot as plt
plt.figure(figsize=(6,5))
plt.scatter(time, mass, label='orginal', color='hotpink')
plt.plot(time, mass model, label='predicted-linear', color='k')
plt.legend()
plt.show()
```



Evalution

R-square

lower,the better

```
r2score=r2_score(time, mass_model)
print(r2score)
-816.6925282509699
```

MSE

• LOWER THE BETTER

```
mse=mean_squared_error(time,mass_model)
print(mse)
25184.929870129872
```

MAE

• LOWER THE BETTER

```
mae=mean_absolute_error(time,mass_model)
print(mae)
146.0
```

CASE: Predicating the salary from age, experience, gender, education

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as pt
from sklearn.preprocessing import LabelEncoder
from sklearn.linear model import LinearRegression
from sklearn.metrics import
r2 score, mean absolute error, mean squared error
from sklearn .model selection import train test split
x=pd.read csv(r"C:\Users\DELL\Downloads\Salary EDA.csv")
x.head()
   Age Gender Education Level
                                        Job Title Years of
Experience \
0 32.0
                    Bachelor's Software Engineer
          Male
5.0
1 28.0 Female
                      Master's
                                     Data Analyst
3.0
2 45.0
        Male
                                   Senior Manager
                           PhD
15.0
3 36.0 Female
                    Bachelor's
                                  Sales Associate
7.0
4 36.0 Female
                    Bachelor's Sales Associate
7.0
    Salary
0
   90000.0
1
   65000.0
2
  150000.0
3
   60000.0
4
   60000.0
```

DATA PREPROCESSING

1	28.0	Female	Mas	ter's	Data	Analyst	
3.6	9						
2	45.0	Male		PhD	Senior	Manager	
15.	. 0						
3	36.0	Female	Bache ⁻	lor's	Sales A	ssociate	
7.6	9						
4	36.0	Female	Bache [*]	lor's	Sales A	ssociate	
7.0)						
	Sala	ary Gender	e Edu	cation e			
0	90000	9.Ó	⁻ 1	_0			
1	65000	9.0	0	1			
2	150000		1	2			
3	60000		0	0			
4	60000		0	0			
	2300		<u> </u>				