ASSIGNMENT-4

Name: Gopu Bala Reshma Sravani

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

```
sns.get_dataset_names ()
```

```
['anagrams',
 'anscombe',
 'attention',
 'brain_networks',
 'car_crashes',
 'diamonds',
 'dots',
 'dowjones',
 'exercise',
 'flights',
 'fmri',
 'geyser',
 'glue',
 'healthexp',
 'iris',
 'mpg',
 'penguins',
 'planets',
 'seaice',
 'taxis',
 'tips',
 'titanic']
```

```
data=pd.read_csv("Employee-Attrition.csv")
```

```
data.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1

```
data.tail()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCoun
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	

5 rows × 35 columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       1470 non-null   int64
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64
 4   Department                1470 non-null   object
```

```
 5   DistanceFromHome          1470 non-null   int64
 6   Education                 1470 non-null   int64
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64
 9   EmployeeNumber            1470 non-null   int64
 10  EnvironmentSatisfaction   1470 non-null   int64
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64
 13  JobInvolvement            1470 non-null   int64
 14  JobLevel                  1470 non-null   int64
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64
 19  MonthlyRate               1470 non-null   int64
 20  NumCompaniesWorked        1470 non-null   int64
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64
 24  PerformanceRating         1470 non-null   int64
 25  RelationshipSatisfaction  1470 non-null   int64
 26  StandardHours             1470 non-null   int64
 27  StockOptionLevel          1470 non-null   int64
 28  TotalWorkingYears         1470 non-null   int64
 29  TrainingTimesLastYear     1470 non-null   int64
 30  WorkLifeBalance           1470 non-null   int64
 31  YearsAtCompany            1470 non-null   int64
 32  YearsInCurrentRole        1470 non-null   int64
 33  YearsSinceLastPromotion   1470 non-null   int64
 34  YearsWithCurrManager      1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

```
data.describe()
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769

Handling the null values

```
data.isnull().any()
```

```
Age                         False
Attrition                   False
BusinessTravel              False
DailyRate                   False
Department                  False
DistanceFromHome            False
Education                   False
EducationField              False
EmployeeCount               False
EmployeeNumber              False
EnvironmentSatisfaction     False
Gender                      False
HourlyRate                  False
JobInvolvement              False
JobLevel                    False
JobRole                     False
JobSatisfaction             False
MaritalStatus               False
MonthlyIncome               False
MonthlyRate                 False
NumCompaniesWorked          False
Over18                      False
OverTime                    False
PercentSalaryHike           False
PerformanceRating           False
RelationshipSatisfaction    False
StandardHours               False
StockOptionLevel            False
TotalWorkingYears           False
TrainingTimesLastYear       False
WorkLifeBalance             False
YearsAtCompany              False
YearsInCurrentRole          False
YearsSinceLastPromotion     False
YearsWithCurrManager        False
dtype: bool
```

```
data.isnull().sum()
```

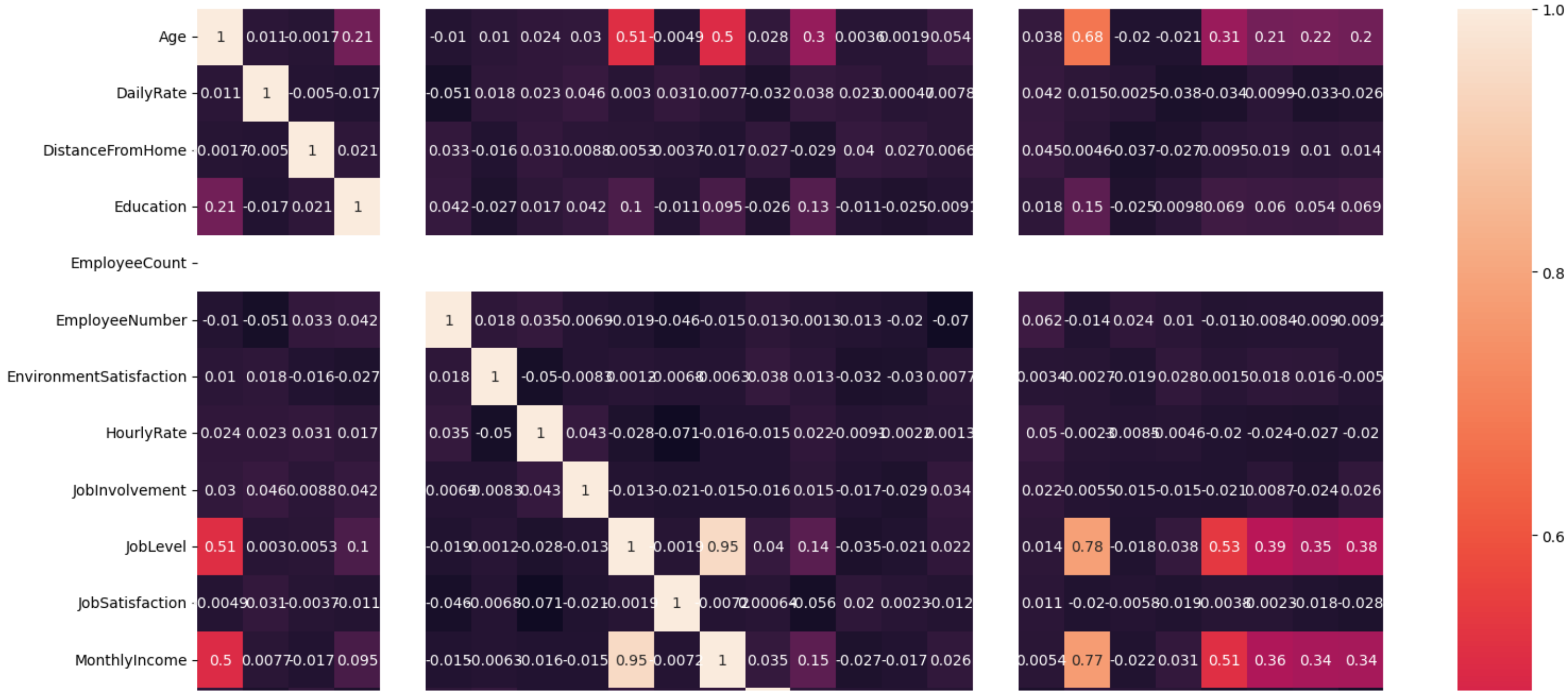
```
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EmployeeNumber              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

```
cor=data.corr()
```

```
<ipython-input-11-410fe4458127>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it w
  cor=data.corr()
```

```
fig=plt.figure(figsize=(18,18))
sns.heatmap(cor,annot=True)
```

```
<Axes: >
```



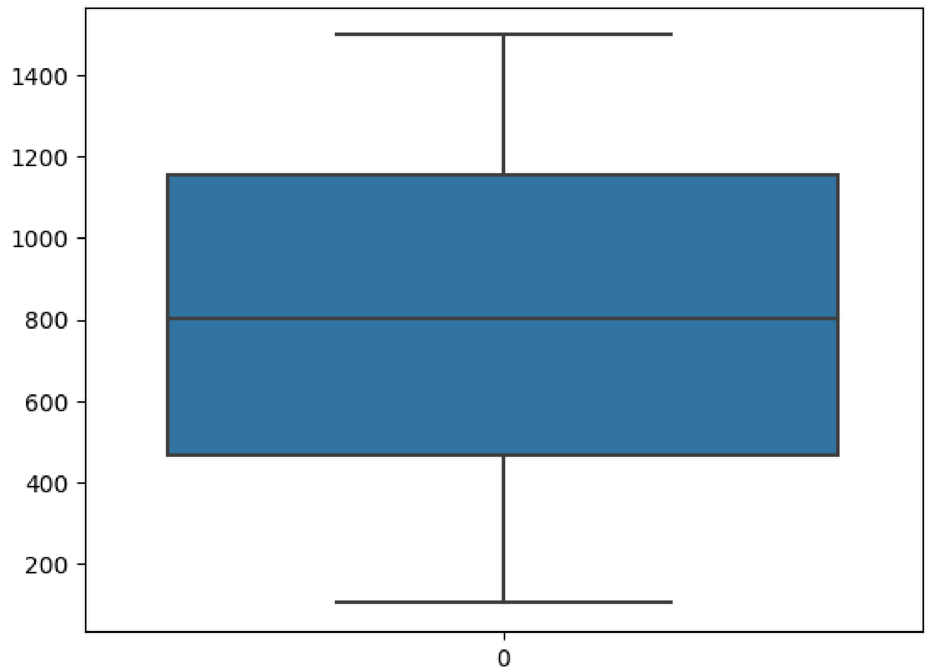
outliers

```
sns.boxplot(data["Age"])
```

<Axes: >


```
sns.boxplot(data["DailyRate"])
```

<Axes: >




```
data.describe()
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	Hour
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.

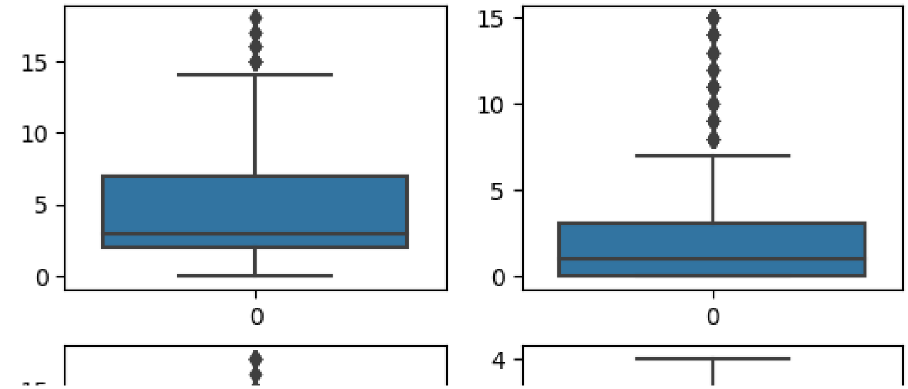
```
data.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	Emplc
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

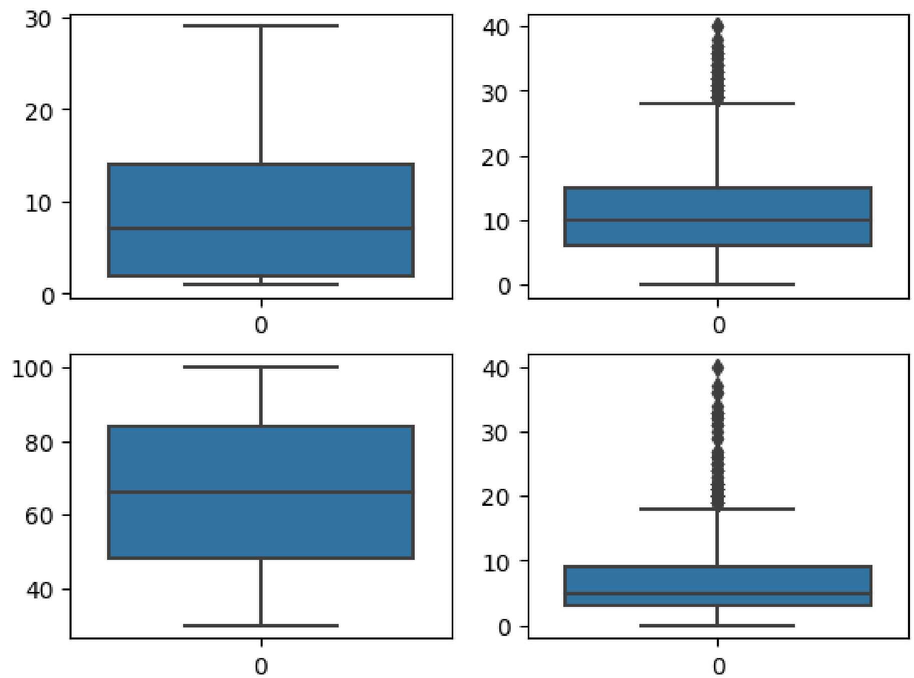
```
fig, axes = plt.subplots(2,2)
sns.boxplot(data=data["YearsInCurrentRole"],ax=axes[0,0])
sns.boxplot(data=data["YearsSinceLastPromotion"],ax=axes[0,1])
sns.boxplot(data=data["YearsWithCurrManager"],ax=axes[1,0])
sns.boxplot(data=data["WorkLifeBalance"],ax=axes[1,1])
```

<Axes: >




```
fig, axes = plt.subplots(2,2)
sns.boxplot(data=data["DistanceFromHome"],ax=axes[0,0])
sns.boxplot(data=data["TotalWorkingYears"],ax=axes[0,1])
sns.boxplot(data=data["HourlyRate"],ax=axes[1,0])
sns.boxplot(data=data["YearsAtCompany"],ax=axes[1,1])
```

<Axes: >

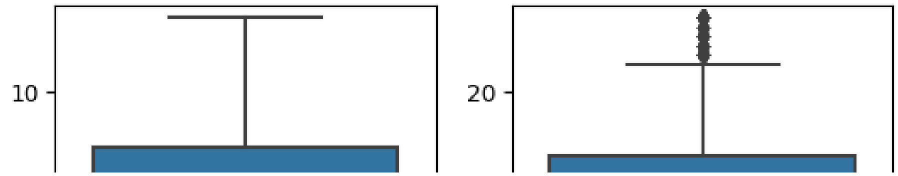


Handling the outliers

```
YearsInCurrentRole_q1 = data.YearsInCurrentRole.quantile(0.25)
YearsInCurrentRole_q3 = data.YearsInCurrentRole.quantile(0.75)
IQR_YearsInCurrentRole=YearsInCurrentRole_q3-YearsInCurrentRole_q1
upperlimit_YearsInCurrentRole=YearsInCurrentRole_q3+1.5*IQR_YearsInCurrentRole
lower_limit_YearsInCurrentRole =YearsInCurrentRole_q1-1.5*IQR_YearsInCurrentRole
median_YearsInCurrentRole=data["YearsInCurrentRole"].median()
data['YearsInCurrentRole'] = np.where(
    (data['YearsInCurrentRole'] > upperlimit_YearsInCurrentRole),
    median_YearsInCurrentRole,
    data['YearsInCurrentRole']
)


YearsSinceLastPromotion_q1 = data.YearsSinceLastPromotion.quantile(0.25)
YearsSinceLastPromotion_q3 = data.YearsSinceLastPromotion.quantile(0.75)
IQR_YearsSinceLastPromotion=YearsSinceLastPromotion_q3-YearsSinceLastPromotion_q1
upperlimit_YearsSinceLastPromotion=YearsSinceLastPromotion_q3+1.5*IQR_YearsSinceLastPromotion
lower_limit_YearsSinceLastPromotion =YearsSinceLastPromotion_q1-1.5*IQR_YearsSinceLastPromotion
median_YearsSinceLastPromotion=data["YearsSinceLastPromotion"].median()
data['YearsSinceLastPromotion'] = np.where(
    (data['YearsSinceLastPromotion'] > upperlimit_YearsSinceLastPromotion),
    median_YearsSinceLastPromotion,
    data['YearsSinceLastPromotion']
)


YearsWithCurrManager_q1 = data.YearsWithCurrManager.quantile(0.25)
YearsWithCurrManager_q3 = data.YearsWithCurrManager.quantile(0.75)
IQR_YearsWithCurrManager=YearsWithCurrManager_q3-YearsWithCurrManager_q1
upperlimit_YearsWithCurrManager=YearsWithCurrManager_q3+1.5*IQR_YearsWithCurrManager
lower_limit_YearsWithCurrManager =YearsWithCurrManager_q1-1.5*IQR_YearsWithCurrManager
median_YearsWithCurrManager=data["YearsWithCurrManager"].median()
data['YearsWithCurrManager'] = np.where(
    (data['YearsWithCurrManager'] > upperlimit_YearsWithCurrManager),
    median_YearsWithCurrManager,
    data['YearsWithCurrManager']
)


TotalWorkingYears_q1 = data.TotalWorkingYears.quantile(0.25)
TotalWorkingYears_q3 = data.TotalWorkingYears.quantile(0.75)
IQR_TotalWorkingYears=TotalWorkingYears_q3-TotalWorkingYears_q1
```

```
upperlimit_TotalWorkingYears=TotalWorkingYears_q3+1.5*IQR_TotalWorkingYears
lower_limit_TotalWorkingYears=TotalWorkingYears_q1-1.5*IQR_TotalWorkingYears
median_TotalWorkingYears=data["TotalWorkingYears"].median()
data['TotalWorkingYears'] = np.where(
    (data['TotalWorkingYears'] > upperlimit_TotalWorkingYears),
    median_TotalWorkingYears,
    data['TotalWorkingYears']
)


YearsAtCompany_q1 = data.YearsAtCompany.quantile(0.25)
YearsAtCompany_q3 = data.YearsAtCompany.quantile(0.75)
IQR_YearsAtCompany=YearsAtCompany_q3-YearsAtCompany_q1
upperlimit_YearsAtCompany=YearsAtCompany_q3+1.5*IQR_YearsAtCompany
lower_limit_YearsAtCompany=YearsAtCompany_q1-1.5*IQR_YearsAtCompany
median_YearsAtCompany=data["YearsAtCompany"].median()
data['YearsAtCompany'] = np.where(
    (data['YearsAtCompany'] > upperlimit_YearsAtCompany),
    median_YearsAtCompany,
    data['YearsAtCompany']
)


fig, axes = plt.subplots(2,2)
sns.boxplot(data=data["YearsWithCurrManager"],ax=axes[0,0])
sns.boxplot(data=data["TotalWorkingYears"],ax=axes[0,1])
sns.boxplot(data=data["YearsSinceLastPromotion"],ax=axes[1,0])
sns.boxplot(data=data["YearsAtCompany"],ax=axes[1,1])
```

```
<Axes: >
```




```
data.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	Emplo
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

```
data.drop("EducationField",axis=1,inplace=True)
```

```
data.head(2)
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Envir
0	41	Yes	Travel_Rarely	1102	Sales	1	2	1	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	1	2	

2 rows × 34 columns

```
data["BusinessTravel"].unique()
```

```
array(['Travel_Rarely', 'Travel_Frequently', 'Non-Travel'], dtype=object)
```

splitting the data

```
y=data["Attrition"]
```

```
y.head()
```

```
0    Yes
1     No
2    Yes
3     No
4     No
Name: Attrition, dtype: object
```

```
data.drop("Attrition",axis=1,inplace=True)
```

```
data.head()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSati:
0	41	Travel_Rarely	1102	Sales	1	2	1	1	
1	49	Travel_Frequently	279	Research & Development	8	1	1	2	
2	37	Travel_Rarely	1373	Research & Development	2	2	1	4	
3	33	Travel_Frequently	1392	Research & Development	3	4	1	5	
4	27	Travel_Rarely	591	Research & Development	2	1	1	7	

5 rows × 33 columns

Encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
le=LabelEncoder()
```

```
data["BusinessTravel"]=le.fit_transform(data["BusinessTravel"])
```

```
data["Department"]=le.fit_transform(data["Department"])
```

```
data["Gender"]=le.fit_transform(data["Gender"])
```

```
y=le.fit_transform(y)
```

```
y
```

```
array([1, 0, 1, ..., 0, 0, 0])
```

```
data["JobRole"]=le.fit_transform(data["JobRole"])
```

```
data["Over18"]=le.fit_transform(data["Over18"])
```

```
data["MaritalStatus"]=le.fit_transform(data["MaritalStatus"])
```

```
data["OverTime"]=le.fit_transform(data["OverTime"])
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 33 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       1470 non-null   int64
 1   BusinessTravel            1470 non-null   int64
 2   DailyRate                 1470 non-null   int64
 3   Department                1470 non-null   int64
 4   DistanceFromHome          1470 non-null   int64
 5   Education                 1470 non-null   int64
 6   EmployeeCount             1470 non-null   int64
 7   EmployeeNumber            1470 non-null   int64
 8   EnvironmentSatisfaction   1470 non-null   int64
 9   Gender                    1470 non-null   int64
 10  HourlyRate                1470 non-null   int64
```

```
 11  JobInvolvement            1470 non-null   int64
 12  JobLevel                  1470 non-null   int64
 13  JobRole                   1470 non-null   int64
 14  JobSatisfaction           1470 non-null   int64
 15  MaritalStatus             1470 non-null   int64
 16  MonthlyIncome             1470 non-null   int64
 17  MonthlyRate               1470 non-null   int64
 18  NumCompaniesWorked        1470 non-null   int64
 19  Over18                    1470 non-null   int64
 20  OverTime                  1470 non-null   int64
 21  PercentSalaryHike         1470 non-null   int64
 22  PerformanceRating         1470 non-null   int64
 23  RelationshipSatisfaction  1470 non-null   int64
 24  StandardHours             1470 non-null   int64
 25  StockOptionLevel          1470 non-null   int64
 26  TotalWorkingYears         1470 non-null   float64
 27  TrainingTimesLastYear     1470 non-null   int64
 28  WorkLifeBalance           1470 non-null   int64
 29  YearsAtCompany            1470 non-null   float64
 30  YearsInCurrentRole        1470 non-null   float64
 31  YearsSinceLastPromotion   1470 non-null   float64
 32  YearsWithCurrManager      1470 non-null   float64
dtypes: float64(5), int64(28)
memory usage: 379.1 KB
```

train test split

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(data,y,test_size=0.3,random_state=0)
```

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((1029, 33), (441, 33), (1029,), (441,))
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
```

```
sc=StandardScaler()
```

```
x_train=sc.fit_transform(x_train)
```

```
x_test=sc.fit_transform(x_test)
```

Building the model

Multi-Linear Regression

```
from sklearn.linear_model import LinearRegression
```

```
lr = LinearRegression()
```

```
lr.fit(x_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
lr.coef_  #slope(m)
```

```
array([-3.54940447e-02,  7.88352347e-05, -1.70825038e-02,  3.46389690e-02,
        2.44612841e-02,  3.65668214e-03, -7.25114413e-16, -9.46820520e-03,
       -4.11203734e-02,  1.06338881e-02, -2.97662154e-03, -3.84864283e-02,
       -1.52927977e-02, -1.57839139e-02, -3.67252862e-02,  3.35765928e-02,
       -5.90043558e-03,  5.81099165e-03,  3.78471890e-02,  6.93889390e-18,
        9.55263279e-02, -2.55800078e-02,  2.01844797e-02, -2.64773510e-02,
        2.60208521e-18, -1.79286106e-02, -3.30529386e-02, -1.09247807e-02,
       -3.10631611e-02, -2.47887717e-02, -1.10177742e-02,  2.11897289e-02,
       -6.60823991e-03])
```

```
lr.intercept_  #(c)
```

```
0.16229348882410102
```

```
y_pred = lr.predict(x_test)
```

```
y_pred
```

```
        2.09447907e-01,  4.10525192e-01,  3.33473319e-01,  1.80971041e-01,
        2.76792072e-01,  2.86132531e-01,  2.62476320e-01, -1.83021903e-02,
        2.36094900e-01,  1.54018489e-01,  6.36220924e-02,  6.18224799e-03,
        1.85057193e-02,  7.69476922e-02,  1.34623859e-01,  1.87169316e-01,
        2.36666289e-01, -1.82114662e-01,  2.98547908e-01,  1.73398527e-01,
       -8.87118635e-02,  3.51838607e-02,  1.35598577e-01,  1.70085191e-01,
        1.69932034e-01,  2.29056852e-01,  2.15573570e-01,  1.04403736e-01,
       -8.21467550e-02])
```

```
y_test
```

```
array([0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0])
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
```

```
lg=LogisticRegression()
```

```
lg.fit(x_train,y_train)
```

```
y_pred_lg=lg.predict(x_test)
```

```
y_pred
```

```
array([ 1.30302477e-01,  2.17626230e-01,  3.46282415e-01,  5.41382549e-03,
        4.99292896e-01,  1.01628868e-01,  3.44742777e-01,  1.23994945e-01,
       -1.60694945e-01,  4.02435622e-01,  1.44159172e-01,  2.67416840e-01,
       -4.62559536e-02,  5.58671849e-01,  2.81858700e-01,  1.53537792e-02,
        1.78573363e-01,  2.77532834e-01,  9.37121052e-02,  2.17571624e-01,
        2.65936178e-01,  1.41499184e-02,  8.36251186e-02,  9.58849826e-02,
        5.09869963e-01,  2.94764240e-01,  7.85819529e-02,  1.26647773e-01,
        5.05518902e-01,  8.48456917e-02, -7.97229275e-02,  2.15516993e-02,
        1.08079105e-01,  3.65998400e-01,  1.24517362e-01,  5.13682786e-02,
        1.06749689e-01,  6.07640778e-02,  6.66425313e-02,  4.81312859e-02,
       -1.16761425e-02, -2.97852924e-02,  5.25135582e-02, -1.59076817e-02,
       -1.71522795e-02,  4.17777714e-01,  3.67341564e-01, -2.14569245e-01,
        5.47964121e-01,  4.40723777e-01,  1.96701754e-01,  4.42415223e-01,
        1.45760263e-01,  3.75821843e-01,  4.92762622e-01,  2.95885645e-01,
       -4.62363391e-02,  3.16337190e-01, -7.90813313e-03,  2.52644685e-01,
       -3.18239329e-02,  2.83907645e-01,  9.03615010e-02,  1.26934391e-01,
        3.58670014e-01,  2.40923530e-02,  3.55890111e-01,  1.95961225e-01,
        1.28554515e-01,  1.18806226e-01, -2.86217094e-02,  3.17635336e-01,
        1.08017895e-01,  1.25723940e-01,  2.30183307e-01,  9.84315444e-02,
        9.10911969e-02,  2.72901425e-01,  2.52029723e-01,  4.09210759e-02,
       -9.10277454e-02, -1.08769544e-02,  1.94114970e-01, -2.25933708e-02,
       -1.73984898e-02,  1.15587264e-01,  8.36037575e-02,  2.82744685e-03,
        4.96507732e-02,  2.41862504e-01,  3.14048594e-01,  2.26261102e-01,
        3.30118359e-01,  2.38527777e-01, -2.16338946e-02,  2.26553579e-01,
        3.01400098e-01,  2.98806055e-01,  9.89137248e-02,  8.90108718e-02,
        2.86485256e-01,  5.00403045e-01,  3.03125892e-01, -4.87373316e-03,
        1.71527163e-01, -5.37529492e-03,  2.54338027e-02,  2.15725447e-01,
        6.00786752e-02,  1.64813384e-01,  1.09106397e-01,  1.08287462e-01,
       -3.09499535e-02,  1.96828572e-01,  9.71193504e-02,  3.19061388e-02,
        1.07934574e-01,  2.33635162e-01, -8.52754375e-02, -7.69198906e-02,
        2.00624349e-01,  3.35600477e-02,  1.28249663e-01,  6.03012321e-01,
        5.78155766e-03, -3.07808886e-02, -1.45938525e-01,  2.19398082e-01,
        2.76229397e-01,  1.67698116e-01, -2.88123044e-03,  2.62341213e-01,
        4.41290897e-01,  3.95975088e-01,  1.70004873e-01,  4.18305270e-01,
        4.90462749e-01,  2.02777466e-01,  1.57881421e-01,  3.60759061e-01,
        2.26021266e-01,  1.45366468e-01,  2.13509469e-01,  2.67909863e-01,
        3.12986724e-01, -8.02842312e-04,  1.49216491e-01, -1.34599710e-01,
        2.08537425e-01,  2.79887773e-01,  1.16637429e-01,  2.74165030e-01,
        5.51651427e-02,  3.41585144e-01,  1.70439326e-01, -7.99466715e-06,
       -4.10384806e-02,  1.34296605e-01, -1.03707555e-01, -5.60163735e-02,
        3.36748074e-01, -9.48504896e-02,  2.11704189e-01,  6.18083877e-01,
        2.03467623e-01,  3.04552682e-01,  1.81990599e-01,  1.84838109e-01,
```

```
-3.51278477e-03, -8.95239598e-02,  4.14367926e-02,  1.31087001e-01,
 1.73558095e-01,  1.58265827e-01, -8.67210631e-02,  1.87726385e-01,
 1.99929237e-01,  1.82109241e-01,  1.03646411e-01,  1.91244072e-01,
 2.59558194e-03,  1.94666775e-01, -6.08132432e-02,  5.85376580e-01,
 6.66728668e-02,  4.49620331e-02,  3.30502696e-01,  9.74393000e-02,
 5.51447175e-01,  1.52212203e-01,  3.58819339e-01,  3.66371593e-01,
 2.47091987e-01,  5.86970935e-02,  1.28678988e-01,  2.80584025e-01,
 7.21059443e-02, -8.07006907e-02,  3.39791632e-01,  8.25270203e-02,
 2.20338157e-01,  2.47703594e-01,  4.97067397e-01,  1.36010592e-01,
 2.88153807e-01,  4.61306498e-02,  4.52544344e-01, -8.24037634e-02,
 2.26796295e-01,  1.42129836e-02,  1.62111340e-01,  2.32246950e-01,
 9.12503556e-02,  1.18866795e-01,  2.12735292e-01, -2.69559828e-02,
 4.53611463e-02,  1.09618223e-01,  2.64436901e-02,  2.32180310e-01,
 1.63285101e-01,  2.42669261e-01,  5.44757533e-01,  1.25881866e-01,
 3.69790740e-01, -8.06922880e-02,  1.41602350e-01,  2.86556696e-01,
```

```
y_test
```

```
array([0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0])
```

```
score = lg.score(x_test, y_test)
print(score)
```

```
0.8820861678004536
```

confusion matrix

```
from sklearn import metrics
cm = metrics.confusion_matrix(y_test,y_pred_lg)
print(cm)
```

```
[[366   5]
 [ 47  23]]
```

Ridge and Lasso

```
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
```

```
rg=Ridge()
```

```
parametres={"alpha":[1,2,3,5,10,20,30,40,60,70,80,90]}
ridgecv=GridSearchCV(rg,parametres,scoring="neg_mean_squared_error",cv=5)
ridgecv.fit(x_train,y_train)
```

```
▸ GridSearchCV
▸ estimator: Ridge
  ▸ Ridge
```

```
print(ridgecv.best_params_)
```

```
{'alpha': 90}
```

```
print(ridgecv.best_score_)
```

```
-0.1139062113923418
```

```
y_pred_rg=ridgecv.predict(x_test)
```

```
y_pred_rg
```

```
array([ 1.34413485e-01,  2.22561818e-01,  3.41692977e-01,  3.88209867e-03,
        4.84617338e-01,  1.16361483e-01,  3.30449743e-01,  1.27358807e-01,
```

```
-1.34442619e-01,  3.77692888e-01,  1.33001445e-01,  2.69898751e-01,
-2.54707392e-02,  5.25771894e-01,  2.67543514e-01,  2.78725024e-02,
 1.82233111e-01,  2.78896415e-01,  9.12689699e-02,  2.11494641e-01,
 2.70103341e-01,  8.44922044e-03,  8.74746722e-02,  1.05348798e-01,
 4.87749940e-01,  2.83080512e-01,  8.80556209e-02,  1.23817268e-01,
 4.82185624e-01,  9.34824523e-02, -7.16448509e-02,  4.07003104e-02,
 1.08437994e-01,  3.42151399e-01,  1.22270929e-01,  6.85889862e-02,
 1.06690533e-01,  7.08689637e-02,  7.51570276e-02,  6.05829413e-02,
 1.08782897e-02, -6.91368661e-03,  5.83191600e-02, -1.54680056e-02,
-4.02267475e-03,  4.08010612e-01,  3.43668700e-01, -1.83519405e-01,
 5.29536511e-01,  4.27646098e-01,  1.95234877e-01,  4.25012930e-01,
 1.40754410e-01,  3.52173952e-01,  4.70372694e-01,  2.89240343e-01,
-3.11642726e-02,  3.04206456e-01,  9.89337674e-03,  2.44569884e-01,
-1.40249115e-02,  2.75133912e-01,  8.64669565e-02,  1.24214885e-01,
 3.48994545e-01,  3.41026778e-02,  3.40548051e-01,  1.95847356e-01,
 1.30040885e-01,  1.32259137e-01, -2.34680143e-02,  3.04595468e-01,
 1.12452197e-01,  1.30525275e-01,  2.19329505e-01,  9.44722098e-02,
 9.98185782e-02,  2.60042486e-01,  2.51475715e-01,  4.59039018e-02,
-7.94007856e-02, -7.05812314e-03,  2.04344419e-01, -3.97180151e-03,
-5.91286905e-03,  1.26797761e-01,  8.02495203e-02,  2.55422079e-02,
 4.65384158e-02,  2.32985240e-01,  3.16063931e-01,  2.02833301e-01,
 3.14235904e-01,  2.33427101e-01, -1.42446708e-02,  2.24789285e-01,
 2.94719863e-01,  2.94698323e-01,  1.19907108e-01,  9.47152062e-02,
 2.86026178e-01,  4.75925979e-01,  2.87802013e-01,  6.72561468e-03,
 1.65013565e-01,  1.72887026e-02,  3.34684186e-02,  2.15466121e-01,
 7.50317322e-02,  1.67646673e-01,  1.16585544e-01,  1.07157808e-01,
-1.84689359e-02,  1.86217544e-01,  1.16586463e-01,  4.67201201e-02,
 1.11060472e-01,  2.27053971e-01, -7.00247692e-02, -5.81070776e-02,
 2.03141688e-01,  4.69029664e-02,  1.31525768e-01,  5.66738022e-01,
 2.41883060e-02, -3.41250985e-02, -1.13904557e-01,  2.18572744e-01,
 2.60568042e-01,  1.65533667e-01, -5.94078459e-05,  2.60009384e-01,
 4.20709666e-01,  3.71031267e-01,  1.70250288e-01,  4.03052216e-01,
 4.67312765e-01,  1.98845366e-01,  1.55005619e-01,  3.41505080e-01,
 2.20024496e-01,  1.40989758e-01,  1.97796963e-01,  2.57841889e-01,
 2.99122317e-01,  9.24907038e-03,  1.39162817e-01, -1.13916709e-01,
 1.97670909e-01,  2.70864780e-01,  1.22454317e-01,  2.58893294e-01,
 6.78818374e-02,  3.08485027e-01,  1.49347982e-01,  2.01436659e-02,
-3.30262214e-02,  1.44305312e-01, -8.99199978e-02, -3.74712872e-02,
 3.10198738e-01, -7.96862570e-02,  2.18579680e-01,  5.85363859e-01,
 1.98166099e-01,  3.02558934e-01,  1.82182301e-01,  1.84955080e-01,
 1.83694574e-02, -7.41419216e-02,  4.48013268e-02,  1.38405390e-01,
 1.84013774e-01,  1.60373463e-01, -6.83819091e-02,  2.00146771e-01,
 1.97563797e-01,  1.73505024e-01,  1.01481984e-01,  1.83169586e-01,
 1.99747065e-02,  1.81881922e-01, -5.23948254e-02,  5.46171171e-01,
 6.66114639e-02,  5.88865384e-02,  3.17247692e-01,  9.77721299e-02,
 5.25297461e-01,  1.62566350e-01,  3.51341492e-01,  3.58324715e-01,
 2.37059552e-01,  8.05788438e-02,  1.36041888e-01,  2.66653277e-01,
 7.95513973e-02, -6.96788172e-02,  3.29442074e-01,  8.93231393e-02,
 2.16673846e-01,  2.50725892e-01,  4.72995721e-01,  1.26285837e-01,
 2.72059331e-01,  6.13056795e-02,  4.38912502e-01, -7.79381284e-02,
```

```
       2.09974643e-01,  2.20746796e-02,  1.56186553e-01,  2.26485767e-01,
       9.61150570e-02,  1.27870464e-01,  2.13995902e-01, -9.95070059e-03,
       2.59908614e-02,  1.24499158e-01,  3.31256404e-02,  2.39369272e-01,
       1.48870840e-01,  2.49438253e-01,  5.25239856e-01,  1.25104891e-01,
       3.65711314e-01, -5.96554519e-02,  1.45443911e-01,  2.80327834e-01,
```

```
y_test
```

```
array([0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0])
```

```
from sklearn import metrics
print(metrics.r2_score(y_test,y_pred_rg))
print(metrics.r2_score(y_train,ridgecv.predict(x_train)))
```

```
0.21073458438815906
0.2061567210285109
```

Lasso

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
```

```
la=Ridge()
```

```
parametres={"alpha":[1,2,3,5,10,20,30,40,60,70,80,90]}
ridgecv=GridSearchCV(la,parametres,scoring="neg_mean_squared_error",cv=5)
ridgecv.fit(x_train,y_train)
```

```
▸ GridSearchCV
▸ estimator: Ridge
  ▸ Ridge
```

```
print(ridgecv.best_params_)
```

```
{'alpha': 90}
```

```
print(ridgecv.best_score_)
```

```
-0.1139062113923418
```

```
y_pred_la=ridgecv.predict(x_test)
```

```
y_pred_la
```

```
 1.17416027e-01,  1.20780070e-01,  2.19845528e-01,  3.11363894e-01,
-1.70611843e-01, -6.89093044e-02,  5.87182022e-02,  1.46846582e-02,
 2.07924051e-01,  2.57017951e-01,  2.33929422e-01,  2.81772193e-01,
 2.28214280e-01,  8.56533063e-02,  1.28782763e-01,  6.89964545e-03,
 2.66888647e-01,  1.25060071e-01,  3.71449815e-01,  3.23080605e-01,
 1.80691831e-01,  1.35736688e-01,  3.05937337e-01,  3.02505887e-01,
-1.61842349e-01,  1.22990350e-01,  1.33351902e-02,  3.42072173e-01,
 1.35302335e-01,  3.71921241e-01,  2.43987619e-01, -1.42777272e-01,
 2.54178774e-01, -1.97769860e-01,  3.22194537e-01,  1.46753524e-01,
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```

```
from sklearn import metrics
print(metrics.r2_score(y_test,y_pred_la))
print(metrics.r2_score(y_train,ridgecv.predict(x_train)))
```

```
0.21073458438815906
0.2061567210285109
```