Import libraries

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:
```
a=pd.read_csv("/content/drive/MyDrive/DATASETS/WA_Fn-UseC_-HR-Employee-Attrition.cs
```

In [ ]:
```
a
```

Out[ ]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Ed
0	41	Yes	Travel_Rarely	1102	Sales	1	2	
1	49	No	Travel_Frequently	279	Research & Development	8	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	
4	27	No	Travel_Rarely	591	Research & Development	2	1	
...	...	...	...	...	...	...	...	
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

1470 rows × 35 columns

Read the data types

In [ ]:
```
a.dtypes
```

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

Shape of the dataset

In [ ]:
```
a.shape
```

Out[ ]:
```
(1470, 35)
```

Information about the dataset

In [ ]:
```
a.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
```

Statistics about the dataset

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

Out[ ]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNum
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000

8 rows × 26 columns

Null values identification

In [ ]:

```
a.isnull().any()
```

Out[ ]:

```
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
```

In [ ]:

```
a.isnull().sum()
```

Out[ ]:
```
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
```

In [ ]:
```
# there are no null values
```

Data Visualization

In [ ]:
```
d=a.corr()
d
```

```
<ipython-input-12-385900cf86c7>:1: FutureWarning: The default value of numeric_onl
y in DataFrame.corr is deprecated. In a future version, it will default to False.
Select only valid columns or specify the value of numeric_only to silence this war
ning.
  d=a.corr()
```

Out[ ]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	En
Age	1.000000	0.010661	-0.001686	0.208034	NaN	
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	
Education	0.208034	-0.016806	0.021042	1.000000	NaN	
EmployeeCount	NaN	NaN	NaN	NaN	NaN	
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	
StandardHours	NaN	NaN	NaN	NaN	NaN	
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	

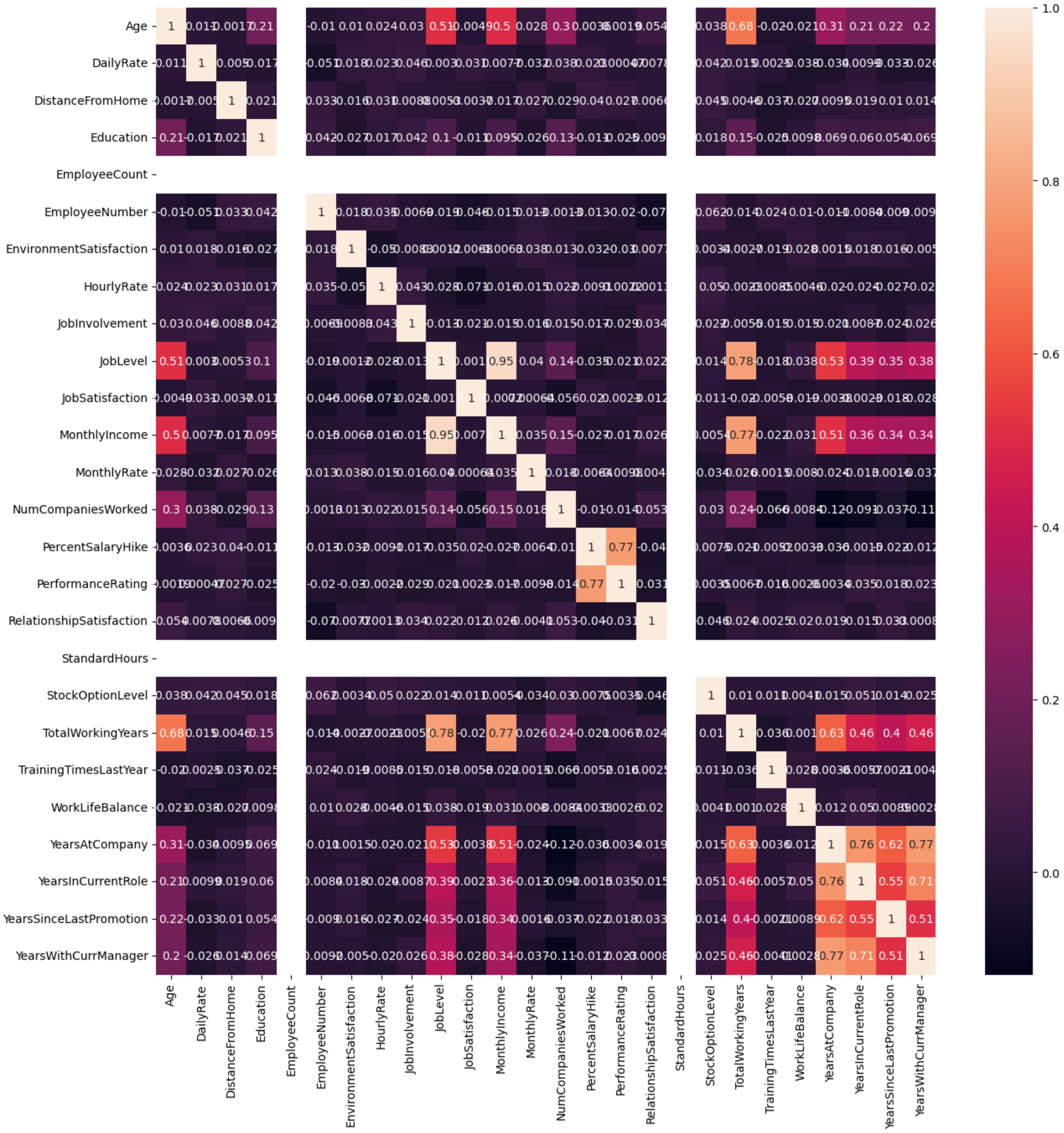
26 rows × 26 columns

In [ ]:

```
plt.subplots(figsize=(15,15))
sns.heatmap(d,annot=True)
```

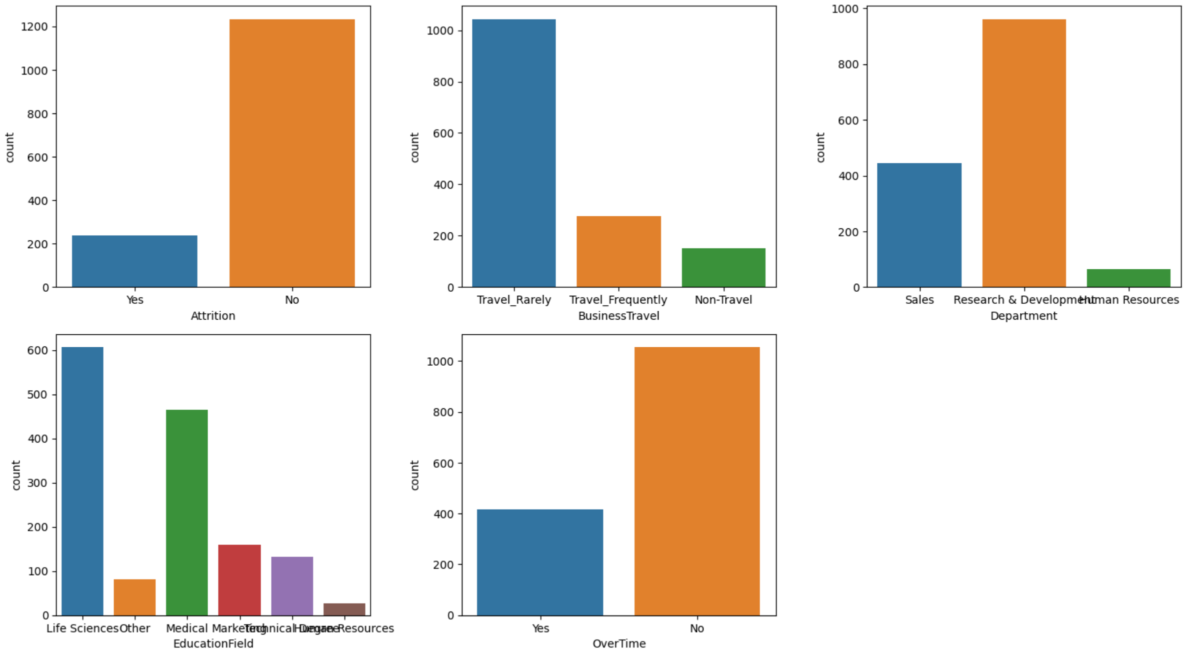
Out[ ]:

```
<Axes: >
```



In [ ]:
```python
f = plt.figure()
f.set_figwidth(15)
f.set_figheight(12)

# Subplot 1
plt.subplot(3, 3, 1)
sns.countplot(x="Attrition", data=a)

# Subplot 2
plt.subplot(3, 3, 2)
sns.countplot(x="BusinessTravel", data=a)

# Subplot 5
plt.subplot(3, 3, 3)
sns.countplot(x="Department", data=a)

# Subplot 8
plt.subplot(3, 3, 4)
sns.countplot(x="EducationField", data=a)

# Subplot 9
plt.subplot(3, 3, 5)
sns.countplot(x="OverTime", data=a)
```

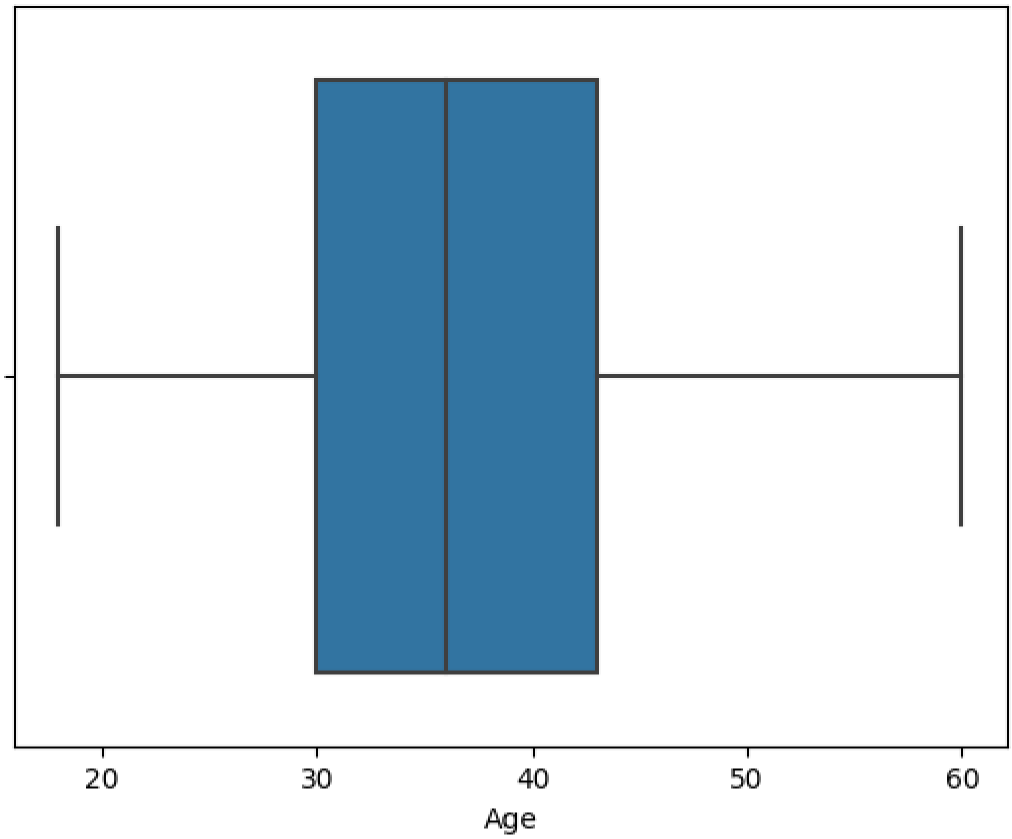
```python
# Adjust layout
plt.tight_layout()

# Show the plots
plt.show()
```



Outlier Detection

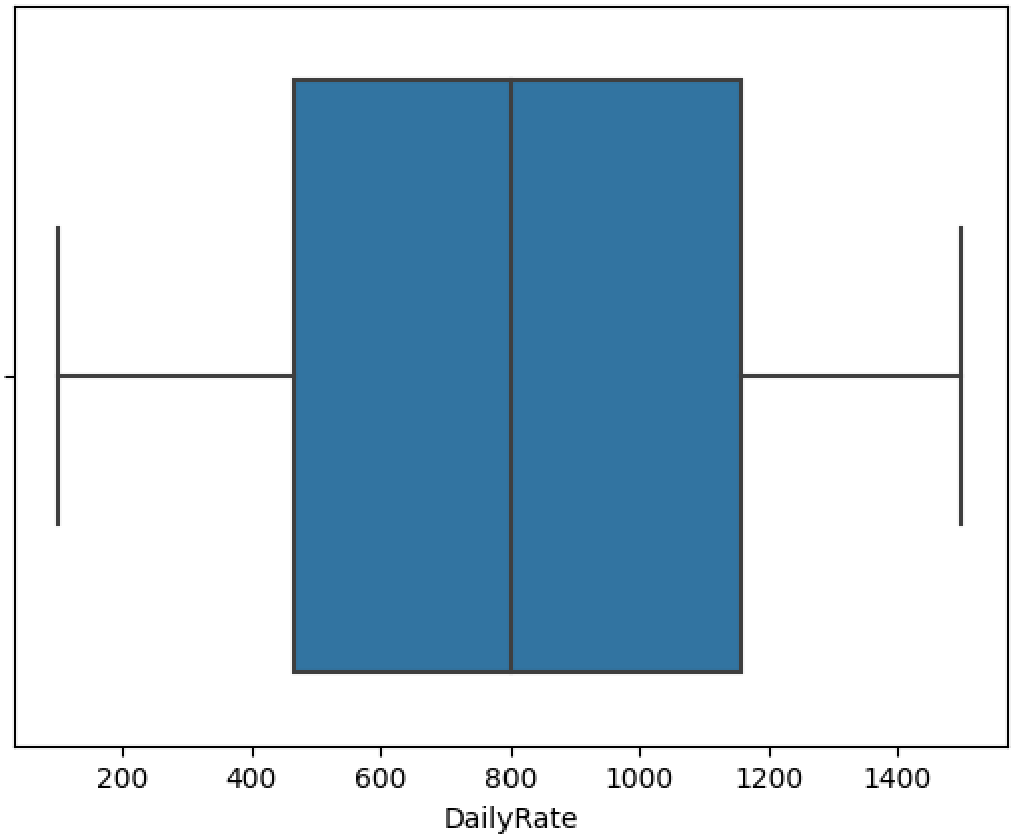
In [ ]:
```python
sns.boxplot(x="Age",data=a)
```

Out[ ]: `<Axes: xlabel='Age'>`



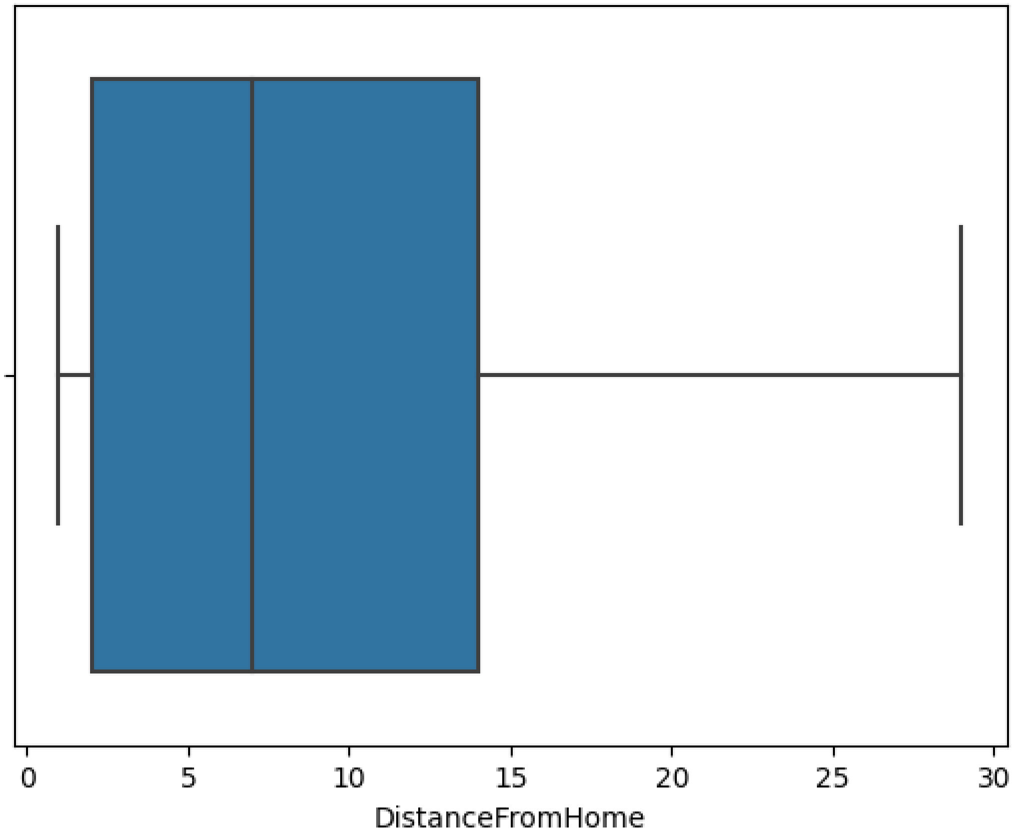
In [ ]:
```python
sns.boxplot(x="DailyRate",data=a)
```

Out[ ]: <Axes: xlabel='DailyRate'>



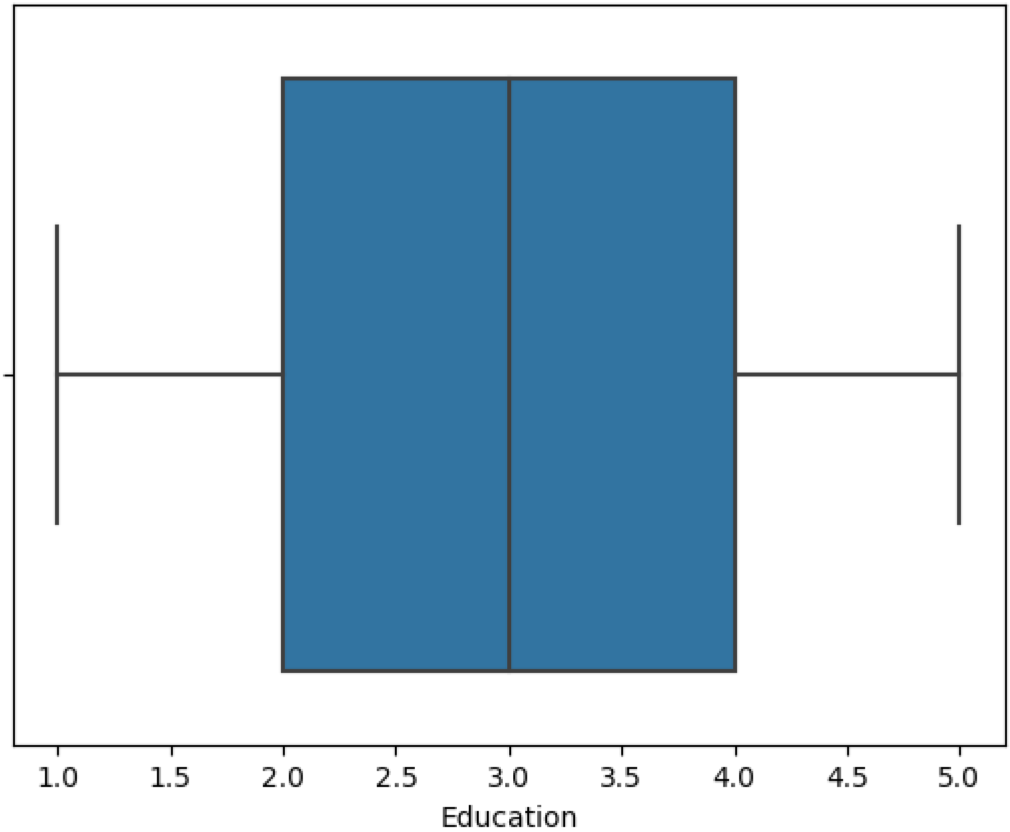
In [ ]:
```
sns.boxplot(x="DistanceFromHome",data=a)
```

Out[ ]: <Axes: xlabel='DistanceFromHome'>



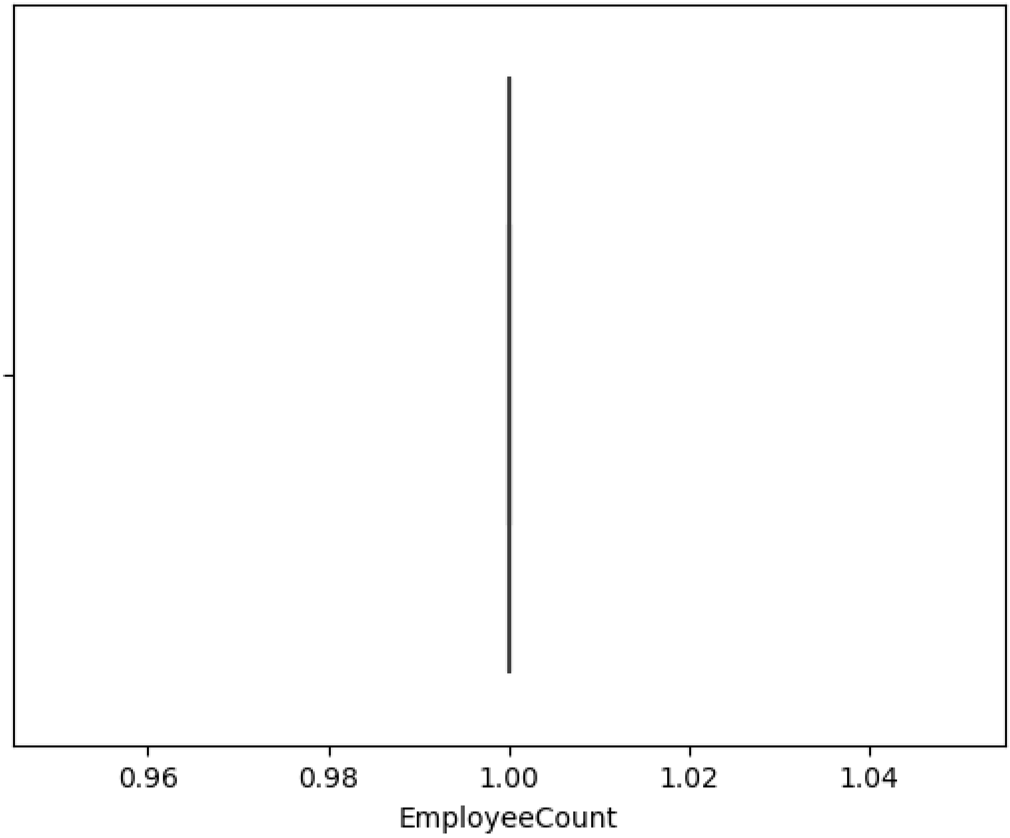
In [ ]:
```
sns.boxplot(x="Education",data=a)
```

Out[ ]: <Axes: xlabel='Education'>



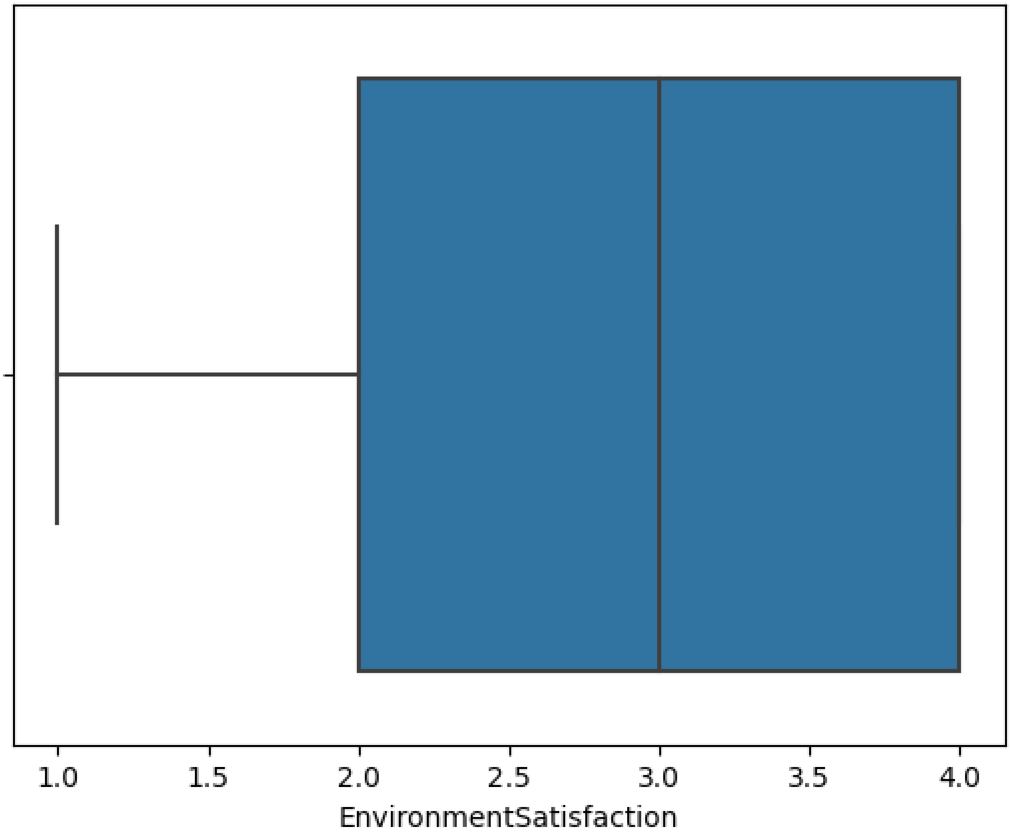
In [ ]:
```
sns.boxplot(x="EmployeeCount",data=a)
```

Out[ ]: <Axes: xlabel='EmployeeCount'>



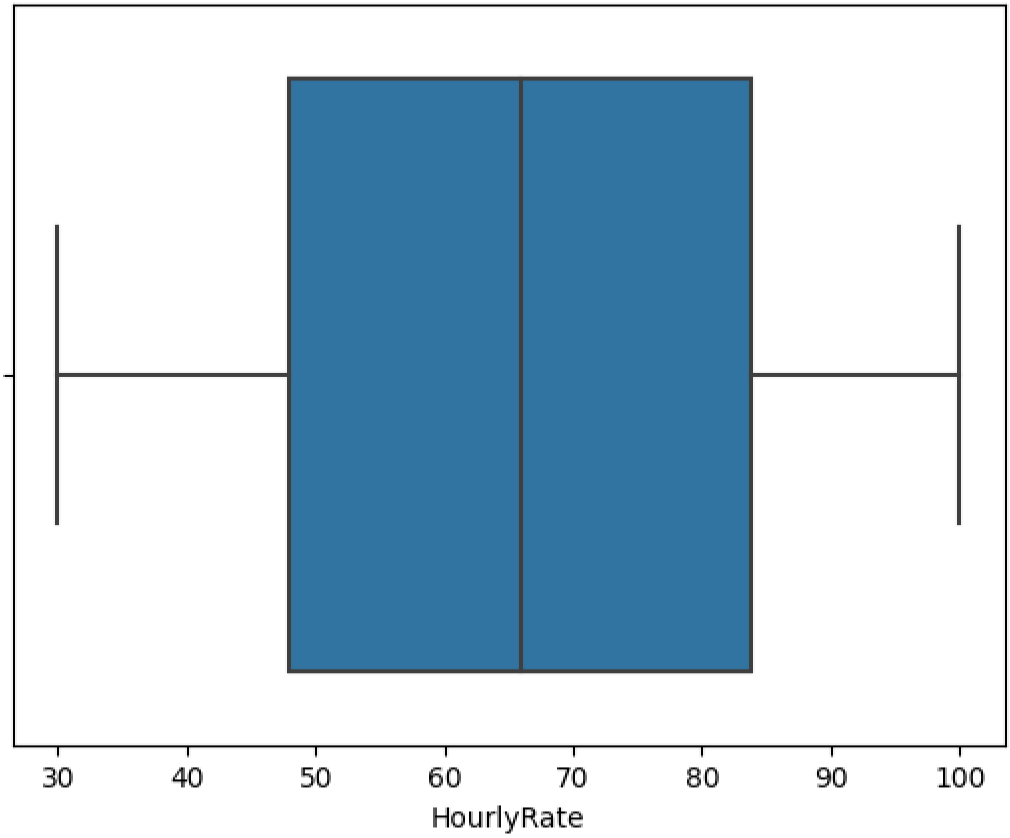
In [ ]:
```
sns.boxplot(x="EnvironmentSatisfaction",data=a)
```

Out[ ]: <Axes: xlabel='EnvironmentSatisfaction'>



In [ ]:
```
sns.boxplot(x="HourlyRate",data=a)
```

Out[ ]: <Axes: xlabel='HourlyRate'>



In [ ]:
```
# there are no outliers , the data is clean
```

Splitting dependent and independent variables

In [ ]:
```
x=a.drop(columns=["Attrition"],axis=1)
x.head()
```

Out[ ]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences
2	37	Travel_Rarely	1373	Research & Development	2	2	Other
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences
4	27	Travel_Rarely	591	Research & Development	2	1	Medical

5 rows × 34 columns

In [ ]:
```
x.shape
```

Out[ ]:
```
(1470, 34)
```

In [ ]:
```
y=a["Attrition"]
y.head()
```

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

In [ ]:
```
y.shape
```

Out[ ]:
```
(1470,)
```

Encoding

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
```

In [ ]:
```
l=LabelEncoder()
```

In [ ]:
```
x["Gender"]=l.fit_transform(x["Gender"])
x['Gender']
```

Out[ ]:
```
0       0
1       1
2       1
3       0
4       1
       ..
1465    1
1466    1
1467    1
1468    1
1469    1
Name: Gender, Length: 1470, dtype: int64
```

In [ ]:
```
x['Gender'].value_counts()
```

Out[ ]:
```
1    882
0    588
Name: Gender, dtype: int64
```

In [ ]:
```
x['Gender'].nunique()
```

Out[ ]:
```
2
```

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

Out[ ]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences
2	37	Travel_Rarely	1373	Research & Development	2	2	Other
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences
4	27	Travel_Rarely	591	Research & Development	2	1	Medical

5 rows × 34 columns

In [ ]:
```
Dept = pd.get_dummies(a, columns=["Department"])
print(Dept)
```

```
      Age Attrition     BusinessTravel  DailyRate  DistanceFromHome  \
0      41       Yes      Travel_Rarely       1102                 1   
1      49        No  Travel_Frequently        279                 8   
2      37       Yes      Travel_Rarely       1373                 2   
3      33        No  Travel_Frequently       1392                 3   
4      27        No      Travel_Rarely        591                 2   
...   ...       ...                ...        ...               ...   
1465   36        No  Travel_Frequently        884                23   
1466   39        No      Travel_Rarely        613                 6   
1467   27        No      Travel_Rarely        155                 4   
1468   49        No  Travel_Frequently       1023                 2   
1469   34        No      Travel_Rarely        628                 8   

      Education EducationField  EmployeeCount  EmployeeNumber  \
0             2  Life Sciences              1               1   
1             1  Life Sciences              1               2   
2             2          Other              1               4   
3             4  Life Sciences              1               5   
4             1        Medical              1               7   
...         ...            ...            ...             ...   
1465          2        Medical              1            2061   
1466          1        Medical              1            2062   
1467          3  Life Sciences              1            2064   
1468          3        Medical              1            2065   
1469          3        Medical              1            2068   

      EnvironmentSatisfaction  ... TotalWorkingYears  TrainingTimesLastYear  \
0                           2  ...                 8                      0   
1                           3  ...                10                      3   
2                           4  ...                 7                      3   
3                           4  ...                 8                      3   
4                           1  ...                 6                      3   
...                       ...  ...               ...                    ...   
1465                        3  ...                17                      3   
1466                        4  ...                 9                      5   
1467                        2  ...                 6                      0   
1468                        4  ...                17                      3   
1469                        2  ...                 6                      3   

      WorkLifeBalance  YearsAtCompany YearsInCurrentRole  \
0                   1               6                  4   
1                   3              10                  7   
2                   3               0                  0   
3                   3               8                  7   
4                   3               2                  2   
...               ...             ...                ...   
1465                3               5                  2   
1466                3               7                  7   
1467                3               6                  2   
1468                2               9                  6   
1469                4               4                  3   

      YearsSinceLastPromotion YearsWithCurrManager  \
0                           0                    5   
1                           1                    7   
2                           0                    0   
3                           3                    0   
4                           2                    2   
...                       ...                  ...   
1465                        0                    3   
1466                        1                    7   
1467                        0                    3   
1468                        0                    8   
1469                        1                    2   
```

```
      Department_Human Resources  Department_Research & Development  \
0                              0                                  0
1                              0                                  1
2                              0                                  1
3                              0                                  1
4                              0                                  1
...                          ...                                ...
1465                           0                                  1
1466                           0                                  1
1467                           0                                  1
1468                           0                                  0
1469                           0                                  1

      Department_Sales
0                    1
1                    0
2                    0
3                    0
4                    0
...                ...
1465                 0
1466                 0
1467                 0
1468                 1
1469                 0

[1470 rows x 37 columns]
```

In [ ]:
```
print(x)
```

```
      Age     BusinessTravel  DailyRate              Department  \
0      41      Travel_Rarely       1102                   Sales
1      49  Travel_Frequently        279  Research & Development
2      37      Travel_Rarely       1373  Research & Development
3      33  Travel_Frequently       1392  Research & Development
4      27      Travel_Rarely        591  Research & Development
...   ...                ...        ...                     ...
1465   36  Travel_Frequently        884  Research & Development
1466   39      Travel_Rarely        613  Research & Development
1467   27      Travel_Rarely        155  Research & Development
1468   49  Travel_Frequently       1023                   Sales
1469   34      Travel_Rarely        628  Research & Development

      DistanceFromHome  Education EducationField  EmployeeCount  \
0                    1          2  Life Sciences              1
1                    8          1  Life Sciences              1
2                    2          2          Other              1
3                    3          4  Life Sciences              1
4                    2          1        Medical              1
...                ...        ...            ...            ...
1465                23          2        Medical              1
1466                 6          1        Medical              1
1467                 4          3  Life Sciences              1
1468                 2          3        Medical              1
1469                 8          3        Medical              1

      EmployeeNumber  EnvironmentSatisfaction  ...  RelationshipSatisfaction  \
0                  1                        2  ...                         1
1                  2                        3  ...                         4
2                  4                        4  ...                         2
3                  5                        4  ...                         3
4                  7                        1  ...                         4
...              ...                      ...  ...                       ...
1465            2061                        3  ...                         3
1466            2062                        4  ...                         1
1467            2064                        2  ...                         2
1468            2065                        4  ...                         4
1469            2068                        2  ...                         1

      StandardHours  StockOptionLevel  TotalWorkingYears  \
0                80                 0                  8
1                80                 1                 10
2                80                 0                  7
3                80                 0                  8
4                80                 1                  6
...             ...               ...                ...
1465             80                 1                 17
1466             80                 1                  9
1467             80                 1                  6
1468             80                 0                 17
1469             80                 0                  6

     TrainingTimesLastYear  WorkLifeBalance YearsAtCompany  \
0                        0                1              6
1                        3                3             10
2                        3                3              0
3                        3                3              8
4                        3                3              2
...                    ...              ...            ...
1465                     3                3              5
1466                     5                3              7
1467                     0                3              6
1468                     3                2              9
1469                     3                4              4
```

```
      YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                      4                        0                     5
1                      7                        1                     7
2                      0                        0                     0
3                      7                        3                     0
4                      2                        2                     2
...                  ...                      ...                   ...
1465                   2                        0                     3
1466                   7                        1                     7
1467                   2                        0                     3
1468                   6                        0                     8
1469                   3                        1                     2

[1470 rows x 34 columns]
```

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

Out[ ]:

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

5 rows × 40 columns

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

Out[ ]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences
2	37	Travel_Rarely	1373	Research & Development	2	2	Other
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences
4	27	Travel_Rarely	591	Research & Development	2	1	Medical

5 rows × 34 columns

In [ ]:
```
Dept=pd.get_dummies(x["Department"],drop_first=True)
Dept
```

Out[ ]:

	Research & Development	Sales
0	0	1
1	1	0
2	1	0
3	1	0
4	1	0
...	...	...
1465	1	0
1466	1	0
1467	1	0
1468	0	1
1469	1	0

1470 rows × 2 columns

In [ ]:
```
x=pd.concat([x,Dept],axis=1)
```

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

Out[ ]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences
2	37	Travel_Rarely	1373	Research & Development	2	2	Other
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences
4	27	Travel_Rarely	591	Research & Development	2	1	Medical

5 rows × 36 columns

Feature Scaling

In [ ]:
```
from sklearn.preprocessing import StandardScaler
```

In [ ]:
```
scaler = StandardScaler()
```

In [ ]:
```
X = a[['Age', 'MonthlyIncome', 'YearsAtCompany', 'JobSatisfaction', 'EnvironmentSat
Y = a['Attrition']
```

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

Out[ ]:

	Age	MonthlyIncome	YearsAtCompany	JobSatisfaction	EnvironmentSatisfaction	YearsWithCurr
0	41	5993	6	4	2	
1	49	5130	10	2	3	
2	37	2090	0	3	4	
3	33	2909	8	3	4	
4	27	3468	2	2	1	

In [ ]:
```
x.tail()
```

Out[ ]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationFie
1465	36	Travel_Frequently	884	Research & Development	23	2	Medic
1466	39	Travel_Rarely	613	Research & Development	6	1	Medic
1467	27	Travel_Rarely	155	Research & Development	4	3	Life Scienc
1468	49	Travel_Frequently	1023	Sales	2	3	Medic
1469	34	Travel_Rarely	628	Research & Development	8	3	Medic

5 rows × 36 columns

In [ ]:
```
x
```

Out[ ]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationFie
0	41	Travel_Rarely	1102	Sales	1	2	Life Scienc
1	49	Travel_Frequently	279	Research & Development	8	1	Life Scienc
2	37	Travel_Rarely	1373	Research & Development	2	2	Oth
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Scienc
4	27	Travel_Rarely	591	Research & Development	2	1	Medic
...	...	...	...	...	...	...	
1465	36	Travel_Frequently	884	Research & Development	23	2	Medic
1466	39	Travel_Rarely	613	Research & Development	6	1	Medic
1467	27	Travel_Rarely	155	Research & Development	4	3	Life Scienc
1468	49	Travel_Frequently	1023	Sales	2	3	Medic
1469	34	Travel_Rarely	628	Research & Development	8	3	Medic

1470 rows × 36 columns

Splitting data into test and train

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_sta
```

In [ ]:
```
X_train,X_test,Y_train,Y_test.shape
```

Out[ ]:
```
(      Age  MonthlyIncome  YearsAtCompany  JobSatisfaction  \
 1097   24           2296               1                1   
 727    18           1051               0                4   
 254    29           6931               3                4   
 1175   39           5295               5                2   
 1341   31           4197              10                3   
 ...   ...            ...             ...              ...   
 1130   35           3407              10                3   
 1294   41           6870               3                2   
 860    22           2853               0                4   
 1459   29           4025               4                2   
 1126   50          19331               1                3   
 
       EnvironmentSatisfaction  YearsWithCurrManager  WorkLifeBalance  
 1097                        3                     0                3  
 727                         2                     0                3  
 254                         4                     2                3  
 1175                        4                     0                3  
 1341                        2                     2                3  
 ...                       ...                   ...              ...  
 1130                        2                     8                2  
 1294                        2                     2                1  
 860                         3                     0                3  
 1459                        4                     3                3  
 1126                        3                     0                3  
 
 [1176 rows x 7 columns],
       Age  MonthlyIncome  YearsAtCompany  JobSatisfaction  \
 1041   28           8463               5                1   
 184    53           4450               4                1   
 1222   24           1555               1                3   
 67     45           9724               1                1   
 220    36           5914              13                2   
 ...   ...            ...             ...              ...   
 567    34           6274               6                4   
 560    34           5121               0                1   
 945    50          16880               3                1   
 522    37           4680               1                4   
 651    47           4537               7                4   
 
       EnvironmentSatisfaction  YearsWithCurrManager  WorkLifeBalance  
 1041                        4                     3                3  
 184                         4                     3                3  
 1222                        4                     0                3  
 67                          2                     0                3  
 220                         4                     7                4  
 ...                       ...                   ...              ...  
 567                         4                     4                3  
 560                         2                     0                3  
 945                         4                     2                3  
 522                         4                     0                3  
 651                         3                     7                3  
 
 [294 rows x 7 columns],
 1097     No
 727      No
 254      No
 1175     No
 1341     No
        ... 
 1130     No
 1294     No
 860     Yes
 1459     No
```

```
1126      No
Name: Attrition, Length: 1176, dtype: object,
(294,))
```

Logistic Regression

Model Building & Import the model building Libraries

In [ ]:
```
from sklearn.linear_model import LogisticRegression
model=LogisticRegression()
```

In [ ]:
```
model.fit(X_train, Y_train)
```

Out[ ]:
```
▾ LogisticRegression
LogisticRegression()
```

In [ ]:
```
pred=model.predict(X_test)
```

In [ ]:
```
pred
```

Out[ ]:
```
array(['No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No'], dtype=object)
```

In [ ]:
```
Y_test
```

Out[ ]:
```
1041      No
184       No
1222     Yes
67        No
220       No
        ...
567       No
560       No
945       No
522       No
651       No
Name: Attrition, Length: 294, dtype: object
```

In [ ]:
```
a
```

Out[ ]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	En
0	41	Yes	Travel_Rarely	1102	Sales	1	2	
1	49	No	Travel_Frequently	279	Research & Development	8	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	
4	27	No	Travel_Rarely	591	Research & Development	2	1	
...	...	...	...	...	...	...	...	
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

1470 rows × 40 columns

Evaluation of classification model

In [ ]:
```
#Accuracy score
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,r
```

In [ ]:
```
accuracy = accuracy_score(Y_test, pred)
```

In [ ]:
```
report = classification_report(Y_test, pred, zero_division=1)
```

In [ ]:
```
print(f'Accuracy: {accuracy}')
print(f'Classification Report:\n{report}')
```

```
Accuracy: 0.8673469387755102
Classification Report:
              precision    recall  f1-score   support

          No       0.87      1.00      0.93       255
         Yes       1.00      0.00      0.00        39

    accuracy                           0.87       294
   macro avg       0.93      0.50      0.46       294
weighted avg       0.88      0.87      0.81       294
```

In [ ]:
```
confusion_matrix(Y_test,pred)
```

Out[ ]:
```
array([[255,   0],
       [ 39,   0]])
```

In [ ]:
```
pd.crosstab(Y_test,pred)
```

Out[ ]:

col_0	No
Attrition	
No	255
Yes	39

Roc-AUC curve

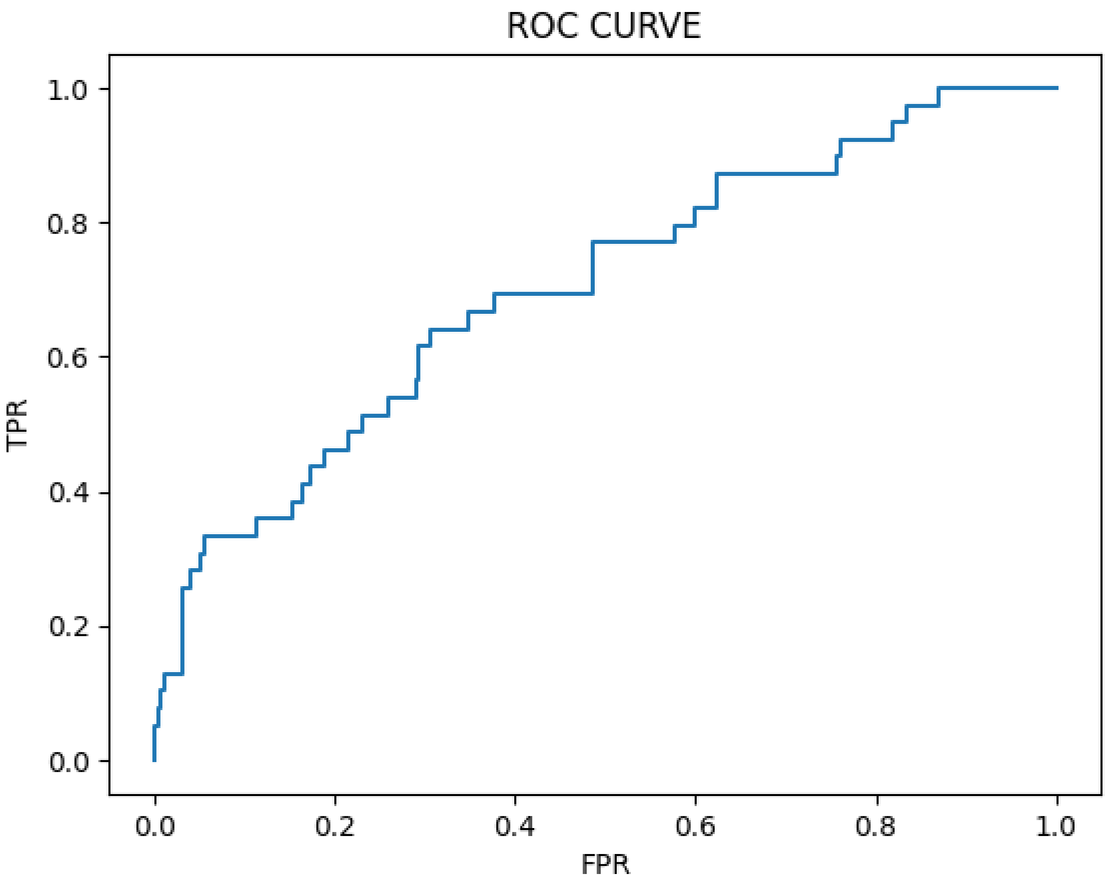
In [ ]:
```
probability=model.predict_proba(X_test)[:,1]
```

In [ ]:
```
probability
```

```
Out[ ]: array([0.14873939, 0.17373604, 0.25084589, 0.1865791 , 0.11911736,
       0.14963007, 0.15969356, 0.20644099, 0.08193936, 0.18537088,
       0.16096129, 0.02189805, 0.15660552, 0.11782876, 0.18248771,
       0.13287268, 0.14334387, 0.0892007 , 0.06858367, 0.05708061,
       0.1753651 , 0.14395111, 0.10012064, 0.15057687, 0.2329628 ,
       0.03338823, 0.27116899, 0.15771847, 0.18762417, 0.10029771,
       0.10548668, 0.15048832, 0.12644386, 0.14778903, 0.2030313 ,
       0.06737083, 0.04935137, 0.35253675, 0.19926437, 0.23846212,
       0.08198467, 0.28864726, 0.23955634, 0.19282515, 0.22246873,
       0.11288909, 0.17545014, 0.24051176, 0.14059822, 0.32377579,
       0.08977525, 0.15148043, 0.01896052, 0.14635136, 0.20158982,
       0.10191406, 0.10573264, 0.08537077, 0.1631479 , 0.12443613,
       0.10510977, 0.33623452, 0.11027653, 0.05493965, 0.28005007,
       0.18450873, 0.12499531, 0.17197795, 0.17873294, 0.06110176,
       0.18127058, 0.08791989, 0.15005295, 0.15959692, 0.19866202,
       0.07388538, 0.19341696, 0.19100387, 0.08712656, 0.08033949,
       0.02928375, 0.13253218, 0.05956382, 0.16844953, 0.08753921,
       0.17957672, 0.12899389, 0.16872069, 0.16947305, 0.12397644,
       0.1099147 , 0.24576674, 0.07821105, 0.2716565 , 0.12140547,
       0.06524951, 0.1337184 , 0.14536957, 0.18726004, 0.10915274,
       0.04570312, 0.10169758, 0.07390408, 0.22704117, 0.07208355,
       0.08035364, 0.18593691, 0.16647288, 0.10818369, 0.05315879,
       0.17696614, 0.18973955, 0.22476227, 0.17342537, 0.21403334,
       0.16943373, 0.16771766, 0.09747364, 0.11387728, 0.2559594 ,
       0.32393512, 0.08431327, 0.13118746, 0.10751731, 0.09837008,
       0.25991497, 0.18954525, 0.11954205, 0.10534474, 0.09694665,
       0.07268098, 0.30507638, 0.06501248, 0.14080365, 0.1255734 ,
       0.11537899, 0.23299235, 0.17264787, 0.24765337, 0.06927027,
       0.21512755, 0.09901074, 0.16646941, 0.08047622, 0.03233445,
       0.15363939, 0.14131117, 0.25851265, 0.26761484, 0.1665985 ,
       0.10685997, 0.11549038, 0.19827264, 0.19076354, 0.13247131,
       0.26173972, 0.17180386, 0.21324175, 0.04115976, 0.15054569,
       0.16012435, 0.09434315, 0.09921354, 0.22000675, 0.06421677,
       0.16643204, 0.12016002, 0.14827189, 0.08450615, 0.05725373,
       0.12102272, 0.02681568, 0.18300015, 0.21076054, 0.11715199,
       0.16127828, 0.18483891, 0.09043029, 0.14086669, 0.20253644,
       0.0594472 , 0.10383826, 0.01617733, 0.15428555, 0.08595314,
       0.22434066, 0.11577713, 0.07998958, 0.07811109, 0.12006351,
       0.12845942, 0.14824842, 0.10405812, 0.19816497, 0.1162661 ,
       0.21477996, 0.24395257, 0.04972863, 0.2156586 , 0.16831872,
       0.17867722, 0.15398516, 0.21871738, 0.03416769, 0.07072713,
       0.22242289, 0.10244091, 0.10919764, 0.12517809, 0.0706504 ,
       0.07399615, 0.24438034, 0.17159597, 0.17617076, 0.10663942,
       0.13898632, 0.15178097, 0.10545546, 0.2723432 , 0.07462743,
       0.23465253, 0.26405405, 0.10124306, 0.3028089 , 0.12410107,
       0.1909214 , 0.20302625, 0.13276688, 0.0401135 , 0.18943046,
       0.23129363, 0.25951761, 0.08630086, 0.21347439, 0.20469075,
       0.13330949, 0.08581729, 0.10996842, 0.06690194, 0.04616928,
       0.18853288, 0.11542819, 0.21231547, 0.03597583, 0.07176025,
       0.17130681, 0.11593175, 0.23407496, 0.1533375 , 0.09696206,
       0.16256038, 0.06366454, 0.04689748, 0.0855508 , 0.23703024,
       0.07106702, 0.18067446, 0.2069784 , 0.22648723, 0.02715875,
       0.17170263, 0.14167865, 0.276632  , 0.10463943, 0.12037205,
       0.21133882, 0.02933273, 0.0973697 , 0.23466029, 0.23184945,
       0.1882965 , 0.04906958, 0.19036583, 0.1399965 , 0.11412922,
       0.22223015, 0.12517666, 0.24824295, 0.07113102, 0.07508479,
       0.14609486, 0.15491467, 0.18318556, 0.09382192, 0.04811606,
       0.20893659, 0.20088061, 0.23217748, 0.10747859, 0.11268901,
       0.25784861, 0.07464244, 0.1744561 , 0.09272658])
```

In [ ]:
```
from sklearn.preprocessing import LabelBinarizer
lb = LabelBinarizer()
Y_test_bin = lb.fit_transform(Y_test)
fpr, tpr, thresholds = roc_curve(Y_test_bin, probability)
```

In [ ]:
```
plt.plot(fpr,tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC CURVE')
plt.show()
```



Decision Tree

In [ ]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
```

In [ ]:
```
dt_model = DecisionTreeClassifier(random_state=50)
```

In [ ]:
```
dt_model.fit(X_train, Y_train)
```

Out[ ]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=50)
```

In [ ]:
```
dt_predictions = dt_model.predict(X_test)
```

In [ ]:
```
dt_accuracy = accuracy_score(Y_test, dt_predictions)
```

In [ ]:
```
dt_report = classification_report(Y_test, dt_predictions)
```

In [ ]:
```
print(f'Decision Tree Accuracy: {dt_accuracy}')
```

```
Decision Tree Accuracy: 0.7789115646258503
```

In [ ]:
```
print(f'Decision Tree Classification Report:\n{dt_report}')
```

```
Decision Tree Classification Report:
              precision    recall  f1-score   support

          No       0.90      0.84      0.87       255
         Yes       0.28      0.41      0.33        39

    accuracy                           0.78       294
   macro avg       0.59      0.62      0.60       294
weighted avg       0.82      0.78      0.80       294
```

Random Forest Classifier

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [ ]:
```
rf_model = RandomForestClassifier(random_state=50)
```

In [ ]:
```
rf_model.fit(X_train, Y_train)
```

Out[ ]:
```
RandomForestClassifier
RandomForestClassifier(random_state=50)
```

In [ ]:
```
rf_predictions = rf_model.predict(X_test)
```

In [ ]:
```
rf_accuracy = accuracy_score(Y_test, rf_predictions)
```

In [ ]:
```
rf_report = classification_report(Y_test, rf_predictions)
```

In [ ]:
```
print(f'Random Forest Accuracy: {rf_accuracy}')
```

```
Random Forest Accuracy: 0.8435374149659864
```

In [ ]:
```
print(f'Random Forest Classification Report:\n{rf_report}')
```

```
Random Forest Classification Report:
              precision    recall  f1-score   support

          No       0.88      0.95      0.91       255
         Yes       0.33      0.18      0.23        39

    accuracy                           0.84       294
   macro avg       0.61      0.56      0.57       294
weighted avg       0.81      0.84      0.82       294
```