project-hr-employee-attrition-data

November 21, 2023

[1]: pip install Pillow

Defaulting to user installation because normal site-packages is not writeable Requirement already satisfied: Pillow in c:\programdata\anaconda3\lib\site-packages (9.4.0)

Note: you may need to restart the kernel to use updated packages.

```
[3]: from IPython.display import Image, display

# Specify the path to your image file
image_path = r"C:\Users\jangi\Downloads\HR_Employee_Attrition_iamge.png"

# Display the image
display(Image(filename=image_path))
```

= eqtble





0.1 HR Employee Attrition Data Analysis

0.2 Objective

• The aim of this dataset is to build a model that can predict the attrition of the employees based on employee factors.

Import the Modules

0.2.1 EDA and Preprocessing

0.2.2 Machine Learning Algorithms

- Logistic Regression
- Random Forest
- Decision Tree

0.3 Read the CSV File

```
[4]: df = pd.read_csv(r"C:\Users\jangi\Downloads\HR_Employee_Attrition_Data.csv")
    df.head()
[5]:
                          BusinessTravel
                                                                  Department
        Age Attrition
                                          DailyRate
         41
                  Yes
                           Travel_Rarely
                                                1102
                                                                        Sales
     0
                       Travel_Frequently
                                                      Research & Development
     1
         49
                                                 279
                   No
     2
         37
                  Yes
                           Travel_Rarely
                                                1373
                                                      Research & Development
                       Travel_Frequently
     3
         33
                   No
                                                1392
                                                      Research & Development
         27
                   No
                           Travel_Rarely
                                                 591
                                                      Research & Development
        DistanceFromHome
                          Education EducationField
                                                     EmployeeCount
                                                                    EmployeeNumber
     0
                       1
                                  2 Life Sciences
                                                                                  1
                       8
                                  1 Life Sciences
                                                                                  2
     1
                                                                  1
                       2
     2
                                  2
                                              Other
                                                                                  3
```

3 4	3 2	4 1	Life Sciences Medical		4 5	
0 1	RelationshipSat	1 4	80 80		0 1	
2 3 4	 	2 3 4	80 80 80		0 0 1	
0 1 2 3 4	TotalWorkingYears 8 10 7 8 6	Training!	FimesLastYear V 0 3 3 3 3	NorkLifeBalance 1 3 3 3 3	YearsAtCompany \ 6 10 0 8 2	
0 1 2 3 4	YearsInCurrentRole 4 7 0 7 2	YearsSind	ceLastPromotion (1 (3) L) 3	anager 5 7 0 0 2	
[5 rows x 35 columns] 0.4 Basic information						
: df	. shape					
: (2940, 35)						
: df	.info()					

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2940 entries, 0 to 2939
Data columns (total 35 columns):

[4]

[4]

[5]

#	Column	Non-Null Count	Dtype
0	Age	2940 non-null	int64
1	Attrition	2940 non-null	object
2	BusinessTravel	2940 non-null	object
3	DailyRate	2940 non-null	int64
4	Department	2940 non-null	object
5	DistanceFromHome	2940 non-null	int64
6	Education	2940 non-null	int64
7	EducationField	2940 non-null	object

8	EmployeeCount	2940	non-null	int64
9	EmployeeNumber	2940	non-null	int64
10	EnvironmentSatisfaction	2940	non-null	int64
11	Gender	2940	non-null	object
12	HourlyRate	2940	non-null	int64
13	JobInvolvement	2940	non-null	int64
14	JobLevel	2940	non-null	int64
15	JobRole	2940	non-null	object
16	JobSatisfaction	2940	non-null	int64
17	MaritalStatus	2940	non-null	object
18	MonthlyIncome	2940	non-null	int64
19	MonthlyRate	2940	non-null	int64
20	NumCompaniesWorked	2940	non-null	int64
21	Over18	2940	non-null	object
22	OverTime	2940	non-null	object
23	PercentSalaryHike	2940	non-null	int64
24	PerformanceRating	2940	non-null	int64
25	${\tt RelationshipSatisfaction}$	2940	non-null	int64
26	StandardHours	2940	non-null	int64
27	StockOptionLevel	2940	non-null	int64
28	${\tt TotalWorkingYears}$	2940	non-null	int64
29	${\tt Training Times Last Year}$	2940	non-null	int64
30	WorkLifeBalance	2940	non-null	int64
31	YearsAtCompany	2940	non-null	int64
32	YearsInCurrentRole	2940	non-null	int64
33	${\tt YearsSinceLastPromotion}$	2940	non-null	int64
34	YearsWithCurrManager	2940	non-null	int64

dtypes: int64(26), object(9)
memory usage: 804.0+ KB

[6]: df.describe()

[6]:		Age	${ t DailyRate}$	DistanceFromHo	me Educati	on EmployeeCoun	t \
	count	2940.000000	2940.000000	2940.0000	00 2940.0000	00 2940.	0
	mean	36.923810	802.485714	9.1925	17 2.9129	25 1.	0
	std	9.133819	403.440447	8.1054	85 1.0239	91 0.	0
	min	18.000000	102.000000	1.0000	00 1.0000	00 1.	0
	25%	30.000000	465.000000	2.0000	00 2.0000	00 1.	0
	50%	36.000000	802.000000	7.0000	00 3.0000	00 1.	0
	75%	43.000000	1157.000000	14.0000	00 4.0000	00 1.	0
	max	60.000000	1499.000000	29.0000	00 5.0000	00 1.	0
		EmployeeNumb	er Environme	ntSatisfaction	HourlyRate	JobInvolvement	\
	count	2940.0000	00	2940.000000	2940.000000	2940.000000	
	mean	1470.5000	00	2.721769	65.891156	2.729932	
	std	848.8492	21	1.092896	20.325969	0.711440	
	min	1.0000	00	1.000000	30.000000	1.000000	

0.5%	725 750000	0	000000	48 00000		0 000000
25%	735.750000		.000000	48.000000		2.000000
50%	1470.500000		.000000	66.000000		3.000000
75%	2205.250000		.000000	84.000000		3.000000
max	2940.000000	4	.000000	100.000000)	4.000000
	JobLevel … F	RelationshipSati	sfaction	StandardHo	ours \	
count	2940.000000	_	0.000000		0.0	
mean	2.063946		2.712245	8	80.0	
std	1.106752		1.081025		0.0	
min	1.000000		1.000000	8	30.0	
25%	1.000000		2.000000	8	30.0	
50%	2.000000	,	3.000000	8	30.0	
75%	3.000000		4.000000		30.0	
max	5.000000		4.000000		30.0	
	${\tt StockOptionLevel}$	${\tt TotalWorkingYe}$	ars Trai	ningTimesLa	stYear	\
count	2940.000000	2940.000	000	2940.	000000	
mean	0.793878	11.279	592	2.	799320	
std	0.851932	7.779	458	1.	289051	
min	0.000000	0.000	000	0.	000000	
25%	0.000000	6.000	000	2.	000000	
50%	1.000000	10.000	000	3.	000000	
75%	1.000000	15.000	000	3.	000000	
max	3.000000	40.000	000	6.	000000	
					,	
	WorkLifeBalance	YearsAtCompany		urrentRole	\	
count	2940.000000	2940.000000	2	940.000000		
mean	2.761224	7.008163		4.229252		
std	0.706356	6.125483		3.622521		
min	1.000000	0.000000		0.000000		
25%	2.000000	3.000000		2.000000		
50%	3.000000	5.000000		3.000000		
75%	3.000000	9.000000		7.000000		
max	4.000000	40.000000		18.000000		
	YearsSinceLastPro	omotion VearsWi	thCurrMan	ager		
count		.000000	2940.00	•		
mean		. 187755		3129		
std	3.221882			7529		
min		.000000		0000		
25%		.000000		0000		
50%		.000000		0000		
75%		.000000		0000		
max		.000000	17.00			
max	10.		11.00	5500		

[8 rows x 26 columns]

[7]: df.isna().sum() 0 [7]: Age Attrition 0 BusinessTravel 0 DailyRate 0 Department 0 DistanceFromHome 0 Education 0 EducationField 0 0 EmployeeCount EmployeeNumber 0 EnvironmentSatisfaction 0 Gender 0 HourlyRate 0 JobInvolvement 0 JobLevel 0 JobRole 0 JobSatisfaction 0 0 MaritalStatus 0 MonthlyIncome 0 MonthlyRate NumCompaniesWorked 0 Over18 0 OverTime 0 0 PercentSalaryHike 0 PerformanceRating RelationshipSatisfaction 0 StandardHours 0 StockOptionLevel 0 TotalWorkingYears 0 TrainingTimesLastYear 0 WorkLifeBalance 0 YearsAtCompany 0 YearsInCurrentRole 0 0 YearsSinceLastPromotion

0

[8]: df.duplicated()

dtype: int64

YearsWithCurrManager

[8]: 0 False
1 False
2 False
3 False
4 False

2935 False
2936 False
2937 False
2938 False
2939 False
Length: 2940, dtype: bool

0.5 EDA & PreProcessing

```
[263]: df.describe().T.style.background_gradient(cmap = 'Reds')
[263]: <pandas.io.formats.style.Styler at 0x24edc099ab0>
[10]: pip install dataprep
      Defaulting to user installation because normal site-packages is not writeable
      Requirement already satisfied: dataprep in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (0.4.5)
      Requirement already satisfied: wordcloud<2.0,>=1.8 in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
      (1.9.2)
      Requirement already satisfied: nltk<4.0.0,>=3.6.7 in
      c:\programdata\anaconda3\lib\site-packages (from dataprep) (3.7)
      Requirement already satisfied: rapidfuzz<3.0.0,>=2.1.2 in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
      (2.15.2)
      Requirement already satisfied: numpy<2.0,>=1.21 in
      c:\programdata\anaconda3\lib\site-packages (from dataprep) (1.23.5)
      Requirement already satisfied: dask[array,dataframe,delayed]>=2022.3.0 in
      c:\programdata\anaconda3\lib\site-packages (from dataprep) (2022.7.0)
      Requirement already satisfied: jinja2<3.1,>=3.0 in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
      Requirement already satisfied: ipywidgets<8.0,>=7.5 in
      c:\programdata\anaconda3\lib\site-packages (from dataprep) (7.6.5)
      Requirement already satisfied: bokeh<3,>=2 in c:\programdata\anaconda3\lib\site-
      packages (from dataprep) (2.4.3)
      Requirement already satisfied: pydot<2.0.0,>=1.4.2 in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
      (1.4.2)
      Requirement already satisfied: python-crfsuite==0.9.8 in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
      (0.9.8)
      Requirement already satisfied: varname<0.9.0,>=0.8.1 in
      c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
      (0.8.3)
      Requirement already satisfied: tqdm<5.0,>=4.48 in
```

```
c:\programdata\anaconda3\lib\site-packages (from dataprep) (4.64.1)
Requirement already satisfied: sqlalchemy==1.3.24 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
(1.3.24)
Requirement already satisfied: python-stdnum<2.0,>=1.16 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
Requirement already satisfied: aiohttp<4.0,>=3.6 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
(3.8.6)
Requirement already satisfied: metaphone<0.7,>=0.6 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
(0.6)
Requirement already satisfied: pydantic<2.0,>=1.6 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
(1.10.13)
Requirement already satisfied: pandas<2.0,>=1.1 in
c:\programdata\anaconda3\lib\site-packages (from dataprep) (1.5.3)
Requirement already satisfied: jsonpath-ng<2.0,>=1.5 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
Requirement already satisfied: flask cors<4.0.0,>=3.0.10 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
(3.0.10)
Requirement already satisfied: regex<2022.0.0,>=2021.8.3 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from dataprep)
(2021.11.10)
Requirement already satisfied: scipy<2.0,>=1.8 in
c:\programdata\anaconda3\lib\site-packages (from dataprep) (1.10.0)
Requirement already satisfied: flask<3,>=2 in c:\programdata\anaconda3\lib\site-
packages (from dataprep) (2.2.2)
Requirement already satisfied: async-timeout<5.0,>=4.0.0a3 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from
aiohttp<4.0,>=3.6->dataprep) (4.0.3)
Requirement already satisfied: multidict<7.0,>=4.5 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from
aiohttp<4.0,>=3.6->dataprep) (6.0.4)
Requirement already satisfied: aiosignal>=1.1.2 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from
aiohttp<4.0,>=3.6->dataprep) (1.3.1)
Requirement already satisfied: frozenlist>=1.1.1 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from
aiohttp<4.0,>=3.6->dataprep) (1.4.0)
Requirement already satisfied: attrs>=17.3.0 in
c:\programdata\anaconda3\lib\site-packages (from aiohttp<4.0,>=3.6->dataprep)
Requirement already satisfied: yarl<2.0,>=1.0 in
c:\users\jangi\appdata\roaming\python\python310\site-packages (from
```

```
aiohttp<4.0,>=3.6->dataprep) (1.9.2)
Requirement already satisfied: charset-normalizer<4.0,>=2.0 in
c:\programdata\anaconda3\lib\site-packages (from aiohttp<4.0,>=3.6->dataprep)
(2.0.4)
Requirement already satisfied: tornado>=5.1 in
c:\programdata\anaconda3\lib\site-packages (from bokeh<3,>=2->dataprep) (6.1)
Requirement already satisfied: pillow>=7.1.0 in
c:\programdata\anaconda3\lib\site-packages (from bokeh<3,>=2->dataprep) (9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
c:\programdata\anaconda3\lib\site-packages (from bokeh<3,>=2->dataprep) (6.0)
Requirement already satisfied: typing-extensions>=3.10.0 in
c:\programdata\anaconda3\lib\site-packages (from bokeh<3,>=2->dataprep) (4.4.0)
Requirement already satisfied: packaging>=16.8 in
c:\programdata\anaconda3\lib\site-packages (from bokeh<3,>=2->dataprep) (22.0)
Requirement already satisfied: fsspec>=0.6.0 in
c:\programdata\anaconda3\lib\site-packages (from
dask[array,dataframe,delayed]>=2022.3.0->dataprep) (2022.11.0)
Requirement already satisfied: partd>=0.3.10 in
c:\programdata\anaconda3\lib\site-packages (from
dask[array,dataframe,delayed]>=2022.3.0->dataprep) (1.2.0)
Requirement already satisfied: cloudpickle>=1.1.1 in
c:\programdata\anaconda3\lib\site-packages (from
dask[array,dataframe,delayed]>=2022.3.0->dataprep) (2.0.0)
Requirement already satisfied: toolz>=0.8.2 in
c:\programdata\anaconda3\lib\site-packages (from
dask[array,dataframe,delayed]>=2022.3.0->dataprep) (0.12.0)
Requirement already satisfied: itsdangerous>=2.0 in
c:\programdata\anaconda3\lib\site-packages (from flask<3,>=2->dataprep) (2.0.1)
Requirement already satisfied: click>=8.0 in c:\programdata\anaconda3\lib\site-
packages (from flask<3,>=2->dataprep) (8.0.4)
Requirement already satisfied: Werkzeug>=2.2.2 in
c:\programdata\anaconda3\lib\site-packages (from flask<3,>=2->dataprep) (2.2.2)
Requirement already satisfied: Six in c:\programdata\anaconda3\lib\site-packages
(from flask_cors<4.0.0,>=3.0.10->dataprep) (1.16.0)
Requirement already satisfied: ipykernel>=4.5.1 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
Requirement already satisfied: ipython-genutils~=0.2.0 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
(0.2.0)
Requirement already satisfied: nbformat>=4.2.0 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
Requirement already satisfied: ipython>=4.0.0 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
Requirement already satisfied: widgetsnbextension~=3.5.0 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
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(3.5.2)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
Requirement already satisfied: traitlets>=4.3.1 in
c:\programdata\anaconda3\lib\site-packages (from ipywidgets<8.0,>=7.5->dataprep)
Requirement already satisfied: MarkupSafe>=2.0 in
c:\programdata\anaconda3\lib\site-packages (from jinja2<3.1,>=3.0->dataprep)
(2.1.1)
Requirement already satisfied: ply in c:\programdata\anaconda3\lib\site-packages
(from jsonpath-ng<2.0,>=1.5->dataprep) (3.11)
Requirement already satisfied: joblib in c:\programdata\anaconda3\lib\site-
packages (from nltk<4.0.0,>=3.6.7->dataprep) (1.1.1)
Requirement already satisfied: python-dateutil>=2.8.1 in
c:\programdata\anaconda3\lib\site-packages (from pandas<2.0,>=1.1->dataprep)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
c:\programdata\anaconda3\lib\site-packages (from pandas<2.0,>=1.1->dataprep)
(2022.7)
Requirement already satisfied: pyparsing>=2.1.4 in
c:\programdata\anaconda3\lib\site-packages (from pydot<2.0.0,>=1.4.2->dataprep)
Requirement already satisfied: colorama in c:\programdata\anaconda3\lib\site-
packages (from tqdm<5.0,>=4.48->dataprep) (0.4.6)
Requirement already satisfied: pure_eval<1.0.0 in
c:\programdata\anaconda3\lib\site-packages (from
varname<0.9.0,>=0.8.1->dataprep) (0.2.2)
Requirement already satisfied: asttokens<3.0.0,>=2.0.0 in
c:\programdata\anaconda3\lib\site-packages (from
varname<0.9.0,>=0.8.1->dataprep) (2.0.5)
Requirement already satisfied: executing<0.9.0,>=0.8.3 in
c:\programdata\anaconda3\lib\site-packages (from
varname<0.9.0,>=0.8.1->dataprep) (0.8.3)
Requirement already satisfied: matplotlib in c:\programdata\anaconda3\lib\site-
packages (from wordcloud<2.0,>=1.8->dataprep) (3.7.0)
Requirement already satisfied: nest-asyncio in
c:\programdata\anaconda3\lib\site-packages (from
ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (1.5.6)
Requirement already satisfied: pyzmq>=17 in c:\programdata\anaconda3\lib\site-
packages (from ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (23.2.0)
Requirement already satisfied: comm>=0.1.1 in c:\programdata\anaconda3\lib\site-
packages (from ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (0.1.2)
Requirement already satisfied: debugpy>=1.0 in
c:\programdata\anaconda3\lib\site-packages (from
ipykernel >= 4.5.1 - ipywidgets < 8.0, >= 7.5 - ipywidgets < 8.0, >= 7.5 - ipywidgets < 8.0, >= 7.5 - ipywidgets < 9.0, ipywidg
Requirement already satisfied: psutil in c:\programdata\anaconda3\lib\site-
packages (from ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (5.9.0)
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Requirement already satisfied: jupyter-client>=6.1.12 in
c:\programdata\anaconda3\lib\site-packages (from
ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (7.3.4)
Requirement already satisfied: matplotlib-inline>=0.1 in
c:\programdata\anaconda3\lib\site-packages (from
ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (0.1.6)
Requirement already satisfied: pickleshare in c:\programdata\anaconda3\lib\site-
packages (from ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (0.7.5)
Requirement already satisfied: prompt-toolkit<3.1.0,>=3.0.30 in
c:\programdata\anaconda3\lib\site-packages (from
ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (3.0.36)
Requirement already satisfied: jedi>=0.16 in c:\programdata\anaconda3\lib\site-
packages (from ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (0.18.1)
Requirement already satisfied: pygments>=2.4.0 in
c:\programdata\anaconda3\lib\site-packages (from
ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (2.11.2)
Requirement already satisfied: backcall in c:\programdata\anaconda3\lib\site-
packages (from ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (0.2.0)
Requirement already satisfied: stack-data in c:\programdata\anaconda3\lib\site-
packages (from ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (0.2.0)
Requirement already satisfied: decorator in c:\programdata\anaconda3\lib\site-
packages (from ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (5.1.1)
Requirement already satisfied: fastjsonschema in
c:\programdata\anaconda3\lib\site-packages (from
nbformat>=4.2.0->ipywidgets<8.0,>=7.5->dataprep) (2.16.2)
Requirement already satisfied: jupyter-core in
c:\programdata\anaconda3\lib\site-packages (from
nbformat>=4.2.0->ipywidgets<8.0,>=7.5->dataprep) (5.2.0)
Requirement already satisfied: jsonschema>=2.6 in
c:\programdata\anaconda3\lib\site-packages (from
nbformat>=4.2.0->ipywidgets<8.0,>=7.5->dataprep) (4.17.3)
Requirement already satisfied: locket in c:\programdata\anaconda3\lib\site-
packages (from partd>=0.3.10->dask[array,dataframe,delayed]>=2022.3.0->dataprep)
(1.0.0)
Requirement already satisfied: notebook>=4.4.1 in
c:\programdata\anaconda3\lib\site-packages (from
widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (6.5.2)
Requirement already satisfied: idna>=2.0 in c:\programdata\anaconda3\lib\site-
packages (from yarl<2.0,>=1.0->aiohttp<4.0,>=3.6->dataprep) (3.4)
Requirement already satisfied: cycler>=0.10 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib->wordcloud<2.0,>=1.8->dataprep) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib->wordcloud<2.0,>=1.8->dataprep) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib->wordcloud<2.0,>=1.8->dataprep) (1.4.4)
```

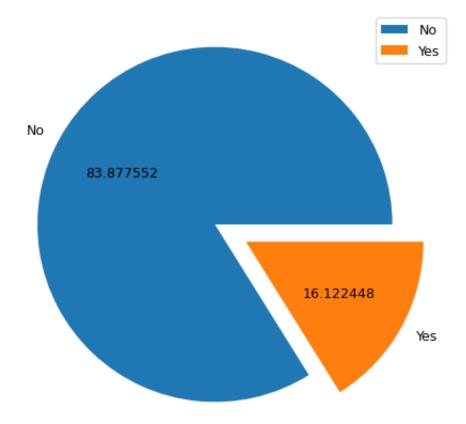
```
Requirement already satisfied: contourpy>=1.0.1 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib->wordcloud<2.0,>=1.8->dataprep) (1.0.5)
Requirement already satisfied: parso<0.9.0,>=0.8.0 in
c:\programdata\anaconda3\lib\site-packages (from
jedi>=0.16->ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (0.8.3)
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in
c:\programdata\anaconda3\lib\site-packages (from
jsonschema \ge 2.6 - nbformat \ge 4.2.0 - ipywidgets < 8.0, > = 7.5 - dataprep) (0.18.0)
Requirement already satisfied: entrypoints in c:\programdata\anaconda3\lib\site-
packages (from jupyter-
client>=6.1.12->ipykernel>=4.5.1->ipywidgets<8.0,>=7.5->dataprep) (0.4)
Requirement already satisfied: platformdirs>=2.5 in
c:\programdata\anaconda3\lib\site-packages (from jupyter-
core->nbformat>=4.2.0->ipywidgets<8.0,>=7.5->dataprep) (2.5.2)
Requirement already satisfied: pywin32>=1.0 in
c:\programdata\anaconda3\lib\site-packages (from jupyter-
core->nbformat>=4.2.0->ipywidgets<8.0,>=7.5->dataprep) (305.1)
Requirement already satisfied: Send2Trash>=1.8.0 in
c:\programdata\anaconda3\lib\site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
(1.8.0)
Requirement already satisfied: nbclassic>=0.4.7 in
c:\programdata\anaconda3\lib\site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
(0.5.2)
Requirement already satisfied: terminado>=0.8.3 in
c:\programdata\anaconda3\lib\site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
(0.17.1)
Requirement already satisfied: nbconvert>=5 in
c:\programdata\anaconda3\lib\site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
(6.5.4)
Requirement already satisfied: argon2-cffi in c:\programdata\anaconda3\lib\site-
packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
Requirement already satisfied: prometheus-client in
c:\programdata\anaconda3\lib\site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
(0.14.1)
Requirement already satisfied: wcwidth in c:\programdata\anaconda3\lib\site-
packages (from prompt-
toolkit<3.1.0,>=3.0.30->ipython>=4.0.0->ipywidgets<8.0,>=7.5->dataprep) (0.2.5)
Requirement already satisfied: notebook-shim>=0.1.0 in
c:\programdata\anaconda3\lib\site-packages (from nbclassic>=0.4.7->notebook>=4.4
.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (0.2.2)
```

```
Requirement already satisfied: jupyter-server>=1.8 in
c:\programdata\anaconda3\lib\site-packages (from nbclassic>=0.4.7->notebook>=4.4
.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (1.23.4)
Requirement already satisfied: bleach in c:\programdata\anaconda3\lib\site-
packages (from nbconvert>=5->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidg
ets<8.0,>=7.5->dataprep) (4.1.0)
Requirement already satisfied: lxml in c:\programdata\anaconda3\lib\site-
packages (from nbconvert>=5->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidg
ets<8.0,>=7.5->dataprep) (4.9.1)
Requirement already satisfied: jupyterlab-pygments in
c:\programdata\anaconda3\lib\site-packages (from nbconvert>=5->notebook>=4.4.1->
widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (0.1.2)
Requirement already satisfied: defusedxml in c:\programdata\anaconda3\lib\site-
packages (from nbconvert>=5->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidg
ets<8.0,>=7.5->dataprep) (0.7.1)
Requirement already satisfied: beautifulsoup4 in
widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (4.11.1)
Requirement already satisfied: nbclient>=0.5.0 in
c:\programdata\anaconda3\lib\site-packages (from nbconvert>=5->notebook>=4.4.1->
widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (0.5.13)
Requirement already satisfied: tinycss2 in c:\programdata\anaconda3\lib\site-
packages (from nbconvert>=5->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidg
ets<8.0,>=7.5->dataprep) (1.2.1)
Requirement already satisfied: mistune<2,>=0.8.1 in
c:\programdata\anaconda3\lib\site-packages (from nbconvert>=5->notebook>=4.4.1->
widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (0.8.4)
Requirement already satisfied: pandocfilters>=1.4.1 in
c:\programdata\anaconda3\lib\site-packages (from nbconvert>=5->notebook>=4.4.1->
widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (1.5.0)
Requirement already satisfied: pywinpty>=1.1.0 in
c:\programdata\anaconda3\lib\site-packages (from terminado>=0.8.3->notebook>=4.4
.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (2.0.10)
Requirement already satisfied: argon2-cffi-bindings in
c:\programdata\anaconda3\lib\site-packages (from argon2-cffi->notebook>=4.4.1->w
idgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (21.2.0)
Requirement already satisfied: websocket-client in
c:\programdata\anaconda3\lib\site-packages (from jupyter-server>=1.8->nbclassic>
=0.4.7->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->datapr
ep) (0.58.0)
Requirement already satisfied: anyio<4,>=3.1.0 in
c:\programdata\anaconda3\lib\site-packages (from jupyter-server>=1.8->nbclassic>
= 0.4.7 - \verb|\noindent = 3.5.0 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - \verb|\noindent = 3.5.0| > ipywidgets < 8.0, > = 7.5 - > ipywidgets < 8.0, > = 7.5 - > ipywidgets < 8.0, > = 7.5 - > ipywidgets < 8.0, > ipywidgets < 8.0, > ipywidgets < 8.0, > ipy
ep) (3.5.0)
Requirement already satisfied: cffi>=1.0.1 in c:\programdata\anaconda3\lib\site-
packages (from argon2-cffi-bindings->argon2-cffi->notebook>=4.4.1->widgetsnbexte
nsion~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (1.15.1)
Requirement already satisfied: soupsieve>1.2 in
```

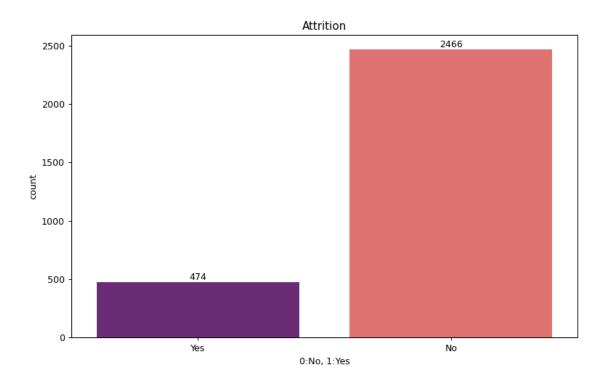
```
otebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep)
      (2.3.2.post1)
      Requirement already satisfied: webencodings in
      c:\programdata\anaconda3\lib\site-packages (from bleach->nbconvert>=5->notebook>
      =4.4.1->widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (0.5.1)
      Requirement already satisfied: sniffio>=1.1 in
      c:\programdata\anaconda3\lib\site-packages (from anyio<4,>=3.1.0->jupyter-server
      >=1.8->nbclassic>=0.4.7->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets<
      8.0,>=7.5->dataprep) (1.2.0)
      Requirement already satisfied: pycparser in c:\programdata\anaconda3\lib\site-
      packages (from cffi>=1.0.1->argon2-cffi-bindings->argon2-cffi->notebook>=4.4.1->
      widgetsnbextension~=3.5.0->ipywidgets<8.0,>=7.5->dataprep) (2.21)
      Note: you may need to restart the kernel to use updated packages.
[264]: from dataprep.eda import create_report
       report = create_report(df, title= 'Data Report')
       report
        0%1
                     | 0/4747 [00:00<?, ?it/s]
[264]:
[76]: df.columns
[76]: Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
              'DistanceFromHome', 'Education', 'EducationField', 'EmployeeCount',
              'EmployeeNumber', 'EnvironmentSatisfaction', 'Gender', 'HourlyRate',
              'JobInvolvement', 'JobLevel', 'JobRole', 'JobSatisfaction',
              'MaritalStatus', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
              'Over18', 'OverTime', 'PercentSalaryHike', 'PerformanceRating',
              'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',
              'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance',
              'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
              'YearsWithCurrManager'],
             dtype='object')
[79]: categorical_col = df.select_dtypes(include = ['object']).columns
       numerical_col = df.select_dtypes(exclude = ['object']).columns
[80]: df['Gender'].replace(['F'],'Female', inplace = True)
       df['MaritalStatus'].replace(['M'],'Married', inplace = True)
[81]: plt.figure(figsize = (10,6), dpi = 90)
       plt.pie(df['Attrition'].value_counts(), labels = df['Attrition'].value_counts().
        ⇒index,
               autopct = \frac{\%2f}{}, explode = (0.1,0.1)
```

c:\programdata\anaconda3\lib\site-packages (from beautifulsoup4->nbconvert>=5->n

```
plt.legend()
plt.show()
```

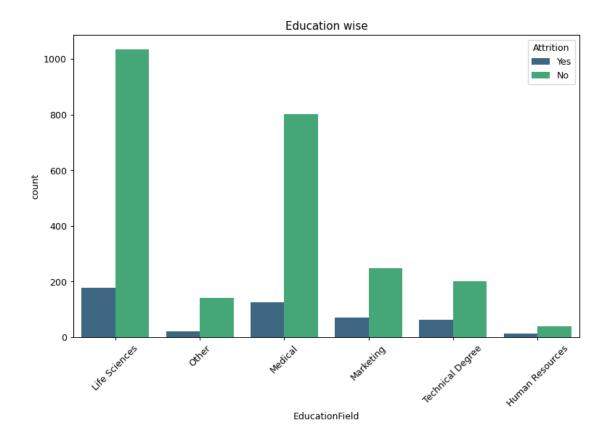


```
[14]: plt.figure(figsize = (10,6), dpi = 90)
ax = sns.countplot(x = "Attrition", data = df , palette='magma')
plt.title('Attrition')
plt.xlabel('0:No, 1:Yes')
for i in ax.containers:
    ax.bar_label(i)
```

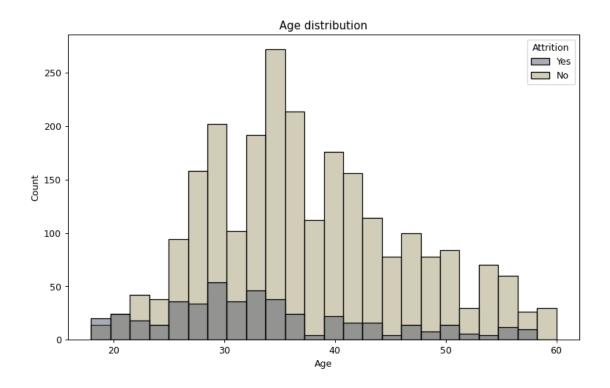


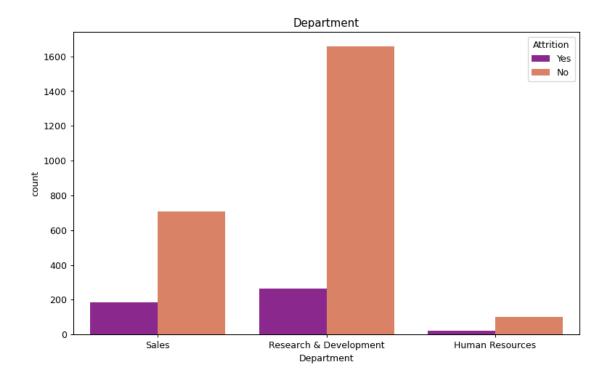
```
[15]: plt.figure(figsize = (10,6), dpi = 90)
sns.countplot(x = "EducationField", hue='Attrition', data = df,

→palette='viridis')
plt.title('Education wise')
plt.xticks(rotation=45)
plt.show()
```



```
[16]: plt.figure(figsize = (10,6), dpi = 90)
sns.histplot(x = "Age", hue='Attrition', data = df, palette='cividis')
plt.title('Age distribution')
plt.show()
```





Using categorical units to plot a list of strings that are all parsable as floats or dates. If these strings should be plotted as numbers, cast to the appropriate data type before plotting.

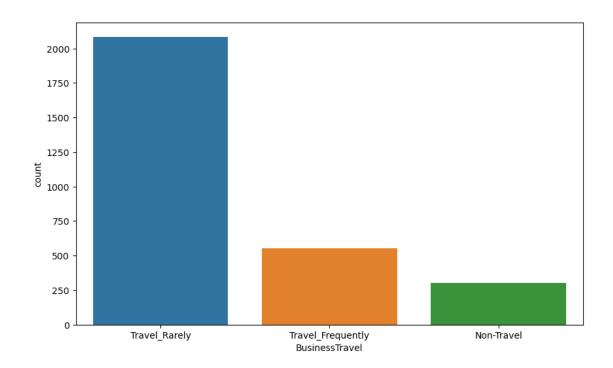
Using categorical units to plot a list of strings that are all parsable as floats or dates. If these strings should be plotted as numbers, cast to the appropriate data type before plotting.

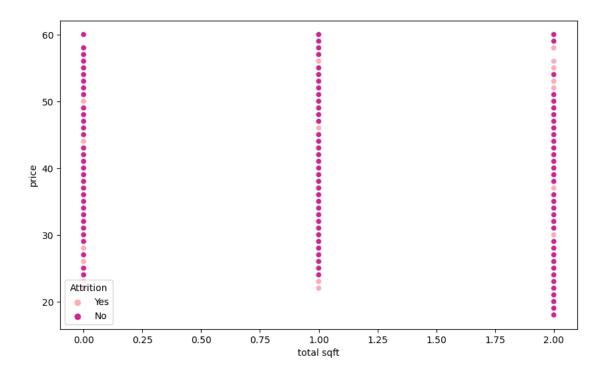


```
[266]: plt.figure(figsize = (10,6))
    print(df['BusinessTravel'].value_counts())
    sns.countplot(x = "BusinessTravel", data = df)
    plt.show()
```

Travel_Rarely 2086
Travel_Frequently 554
Non-Travel 300

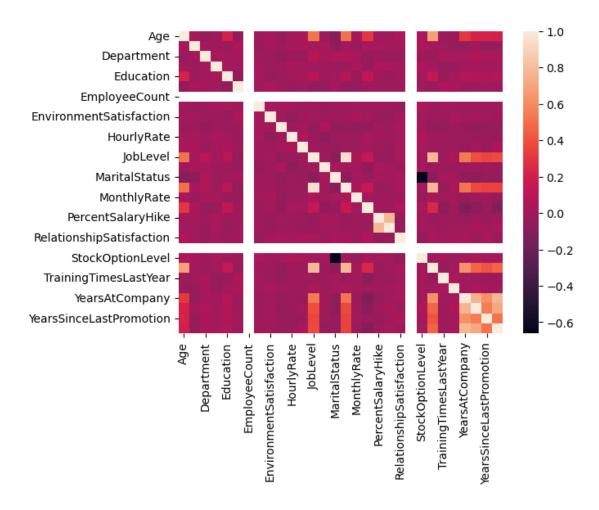
Name: BusinessTravel, dtype: int64





[268]: sns.heatmap(df.corr())

[268]: <Axes: >



0.6 Check the Outliers

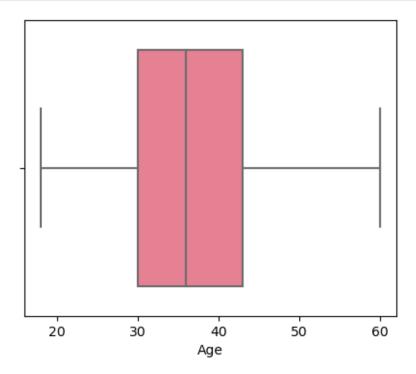
- A few data points that are significently different from the rest of the data points
- if any data points is far from the mean values can be treated as outliers
- outliers are only checked for numerical values
- to detect outliers we used boxplots

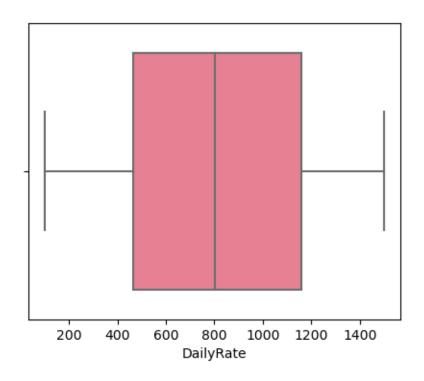
[72]: df.columns

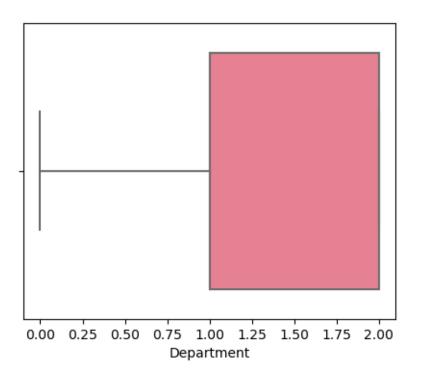
```
'YearsWithCurrManager'],
dtype='object')
```

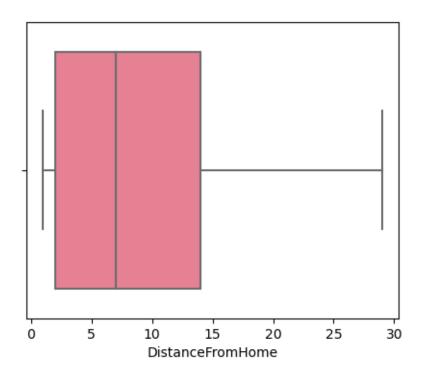
```
[269]: def boxplots(col):
    plt.figure(figsize =(5,4))
        sns.boxplot(df, x=col, palette = 'husl')
        plt.show()

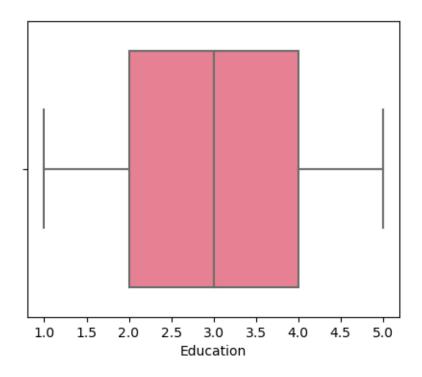
for i in list(df.select_dtypes(exclude=['object']).columns)[0:]:
        boxplots(i)
```

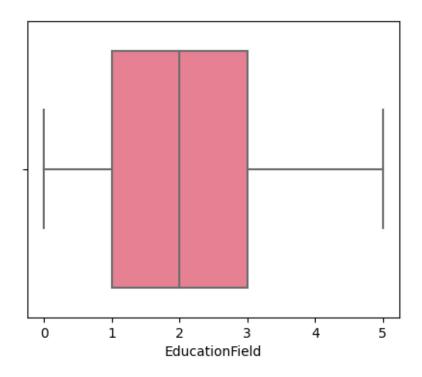


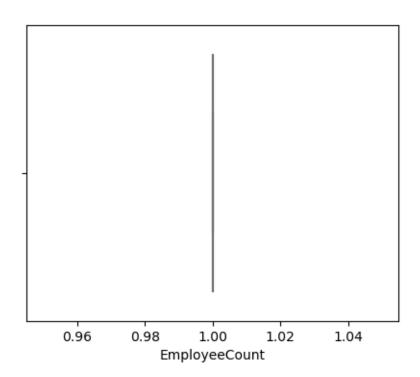


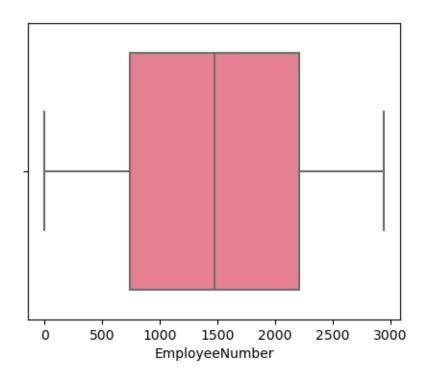


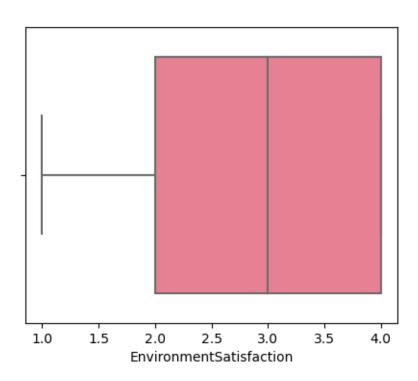


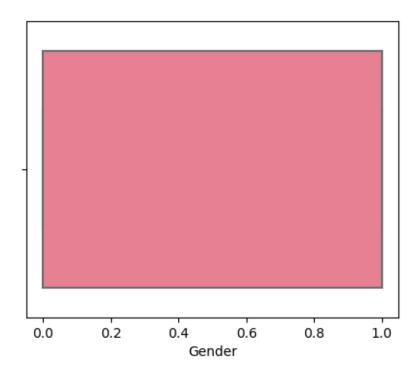


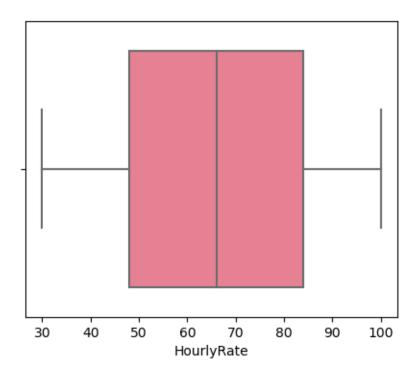


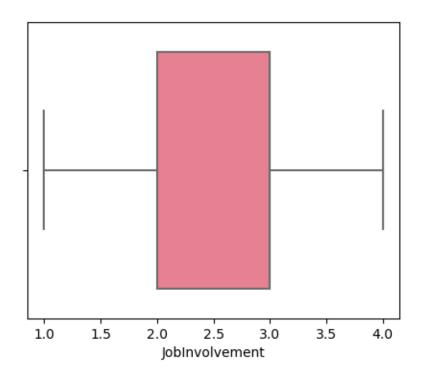


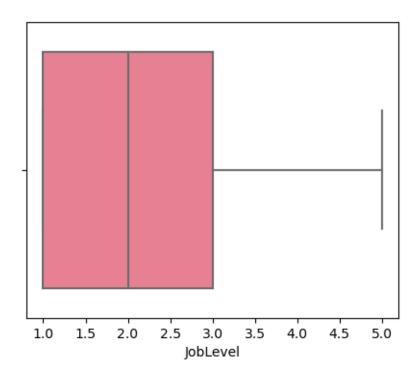


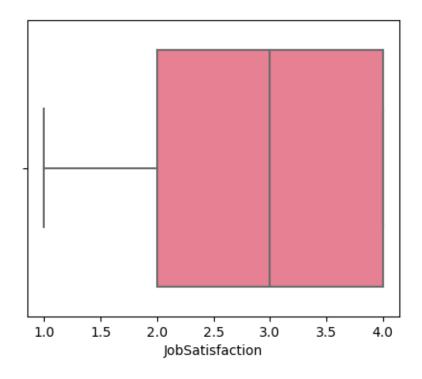


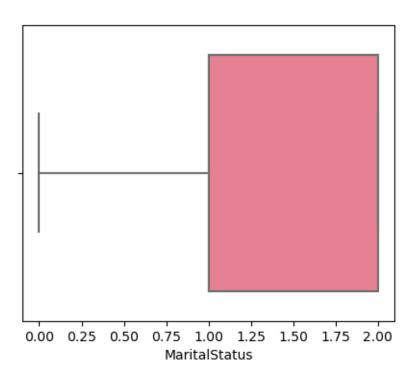


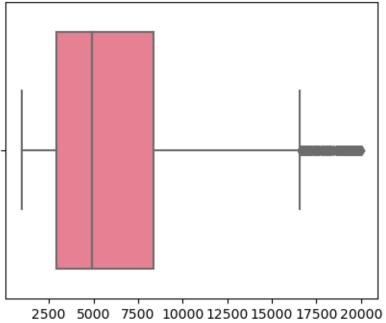




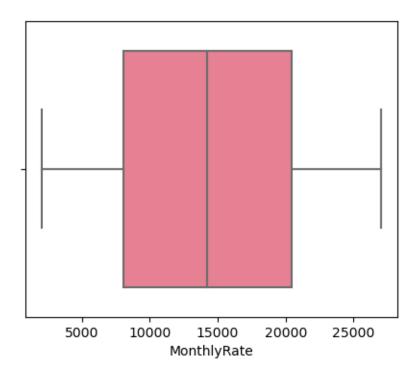


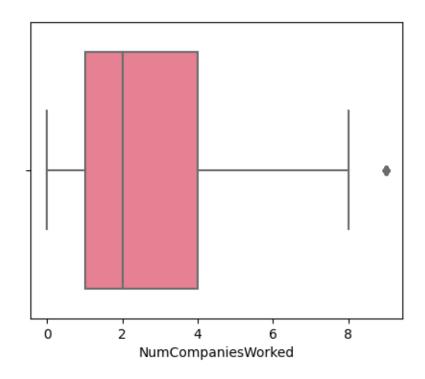


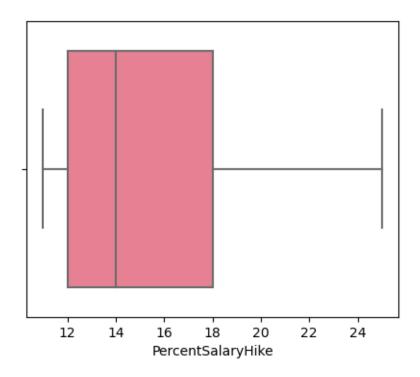


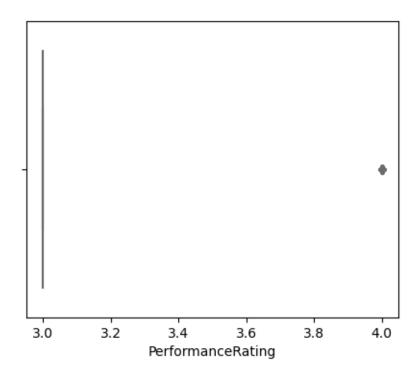


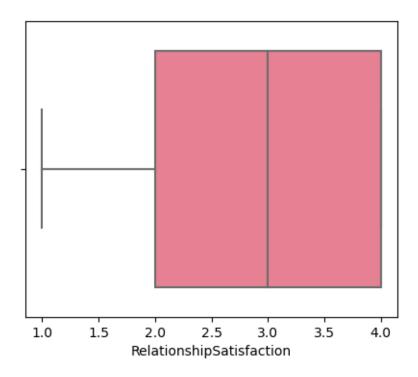
MonthlyIncome

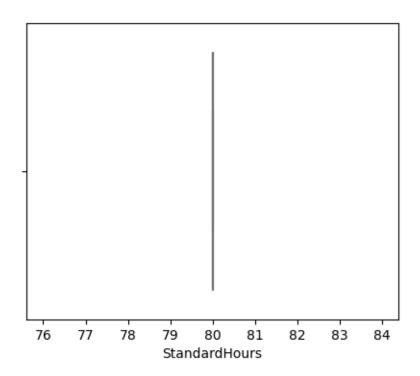


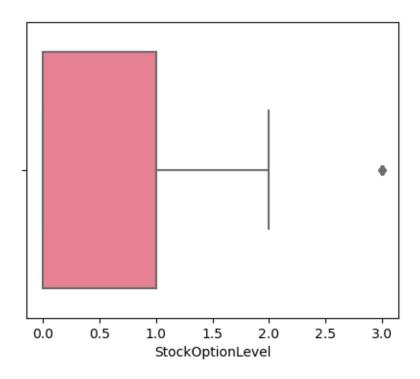


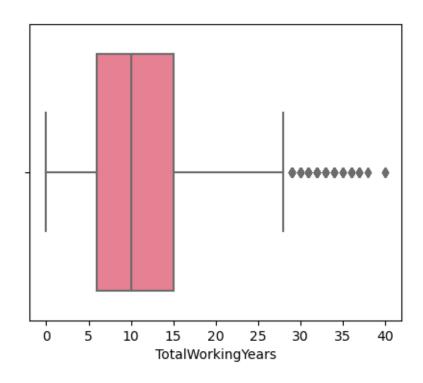


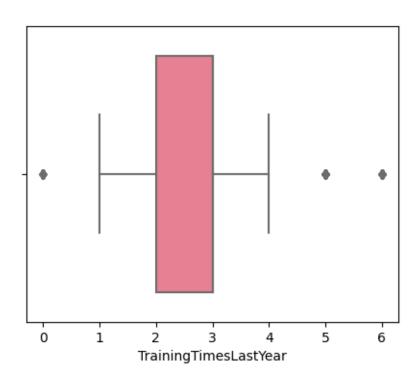


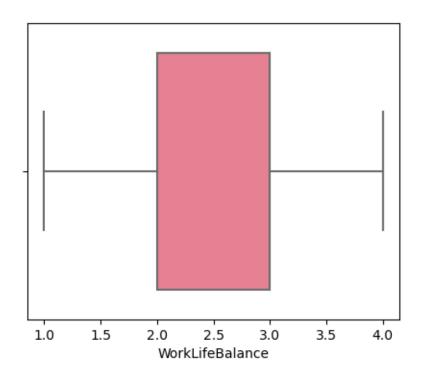


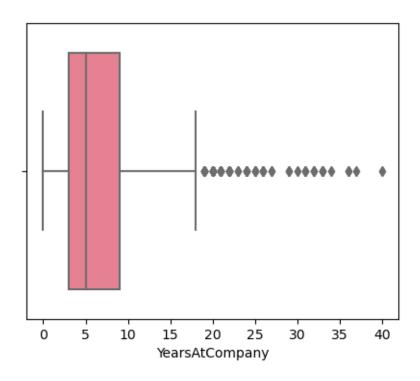


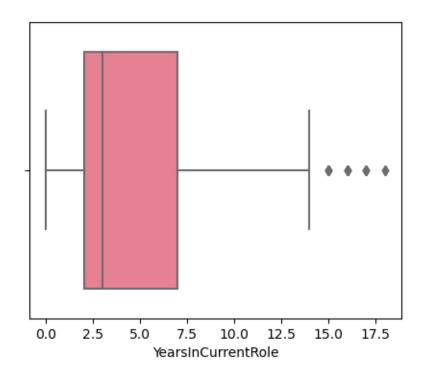


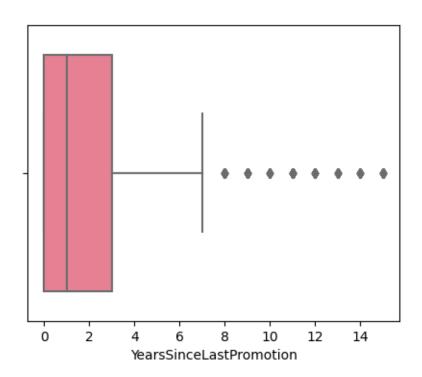


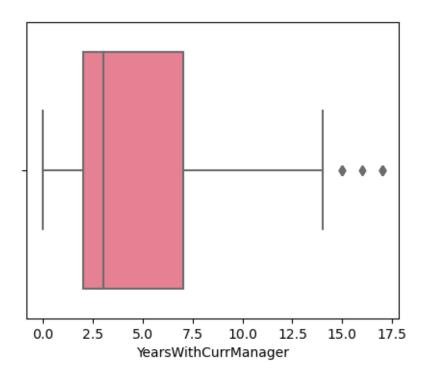












[270]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2940 entries, 0 to 2939
Data columns (total 35 columns):

#	Column	Non-Null Count	Dtype
0	Age	2940 non-null	int64
1	Attrition	2940 non-null	object
2	BusinessTravel	2940 non-null	object
3	DailyRate	2940 non-null	int64
4	Department	2940 non-null	int64
5	DistanceFromHome	2940 non-null	int64
6	Education	2940 non-null	int64
7	EducationField	2940 non-null	int64
8	EmployeeCount	2940 non-null	int64
9	EmployeeNumber	2940 non-null	int64
10	EnvironmentSatisfaction	2940 non-null	int64
11	Gender	2940 non-null	int64
12	HourlyRate	2940 non-null	int64
13	JobInvolvement	2940 non-null	int64
14	JobLevel	2940 non-null	int64
15	JobRole	2940 non-null	object
16	JobSatisfaction	2940 non-null	int64
17	MaritalStatus	2940 non-null	int64

18	MonthlyIncome	2940	non-null	int64
19	MonthlyRate	2940	non-null	int64
20	NumCompaniesWorked	2940	non-null	int64
21	Over18	2940	non-null	object
22	OverTime	2940	non-null	object
23	${\tt PercentSalaryHike}$	2940	non-null	int64
24	PerformanceRating	2940	non-null	int64
25	${\tt RelationshipSatisfaction}$	2940	non-null	int64
26	StandardHours	2940	non-null	int64
27	StockOptionLevel	2940	non-null	int64
28	${ t TotalWorking Years}$	2940	non-null	int64
29	${\tt Training Times Last Year}$	2940	non-null	int64
30	WorkLifeBalance	2940	non-null	int64
31	YearsAtCompany	2940	non-null	int64
32	YearsInCurrentRole	2940	non-null	int64
33	${\tt YearsSinceLastPromotion}$	2940	non-null	int64
34	${\tt YearsWithCurrManager}$	2940	non-null	int64
dt.vn	es: int64(30), object(5)			

dtypes: int64(30), object(5)
memory usage: 804.0+ KB

[271]: df.describe(include='object').T

[271]:		count	unique	top	freq
	Attrition	2940	2	No	2466
	${\tt BusinessTravel}$	2940	3	Travel_Rarely	2086
	JobRole	2940	9	Sales Executive	652
	Over18	2940	1	Y	2940
	OverTime	2940	2	No	2108

[272]: df.describe(include='int').T

[272]:	count	mean	std	min	25%	\
Age	2940.0	36.923810	9.133819	18.0	30.00	
DailyRate	2940.0	802.485714	403.440447	102.0	465.00	
Department	2940.0	1.260544	0.527703	0.0	1.00	
DistanceFromHome	2940.0	9.192517	8.105485	1.0	2.00	
Education	2940.0	2.912925	1.023991	1.0	2.00	
EducationField	2940.0	2.247619	1.331143	0.0	1.00	
EmployeeCount	2940.0	1.000000	0.000000	1.0	1.00	
EmployeeNumber	2940.0	1470.500000	848.849221	1.0	735.75	
${\tt EnvironmentSatisfaction}$	2940.0	2.721769	1.092896	1.0	2.00	
Gender	2940.0	0.600000	0.489981	0.0	0.00	
HourlyRate	2940.0	65.891156	20.325969	30.0	48.00	
JobInvolvement	2940.0	2.729932	0.711440	1.0	2.00	
JobLevel	2940.0	2.063946	1.106752	1.0	1.00	
${ t JobSatisfaction}$	2940.0	2.728571	1.102658	1.0	2.00	
MaritalStatus	2940.0	1.097279	0.729997	0.0	1.00	

2940.0	6502.93129	93 470	7.155770	1009.0	2911.00
2940.0	14313.10340	01 711	6.575021	2094.0	8045.00
2940.0				0.0	1.00
				11.0	12.00
	3.15374	41	0.360762	3.0	3.00
2940.0				1.0	2.00
2940.0					80.00
					0.00
					6.00
					2.00
					2.00
					3.00
					2.00
					0.00
2940.0	4.12312	29	3.567529	0.0	2.00
50%	75%	m a	v		
3.0	4.00	4.	0		
1.0	1.00	1.	0		
66.0	84.00	100.	0		
3.0	3.00	4.	0		
2.0	3.00	5.	0		
3.0	4.00	4.	0		
1.0	2.00	2.	0		
4919.0	8380.00	19999.	0		
14235.5	20462.00	26999.	0		
2.0	4.00	9.	0		
14.0	18.00	25.	0		
3.0	3.00	4.	0		
3.0	4.00	4.	0		
80.0	80.00	80.	0		
1.0	1.00	3.	0		
10.0	15.00	40.	0		
3.0	3.00				
3.0	3.00				
5.0	9.00				
3.0	7.00				
1.0	3.00				
3.0	7.00	17.	0		
	2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 2940.0 36.0 802.0 1.0 7.0 3.0 2.0 1.0 1470.5 3.0 1.0 66.0 3.0 2.0 1.0 14235.5 2.0 14.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3	2940.0 14313.10344 2940.0 2.69318 2940.0 3.15374 2940.0 2.71224 2940.0 80.0000 2940.0 0.7938 2940.0 2.7993 2940.0 2.7612 2940.0 2.7612 2940.0 2.1877 2940.0 2.1877 2940.0 2.1877 2940.0 2.1877 2940.0 2.1877 2940.0 2.1877 2940.0 2.1877 2940.0 3.00 4.00 4.202 2940.0 2.1877 2940.0 2.1877 2940.0 3.00 4.00 3.00 3.0 4.00 1.0 2.00 7.0 14.00 3.0 4.00 1.0 1.00 1470.5 2205.25 3.0 4.00 1.0 3.00 3.0 3.00 <tr< td=""><td>2940.0 14313.103401 711 2940.0 2.693197 2940.0 15.209524 2940.0 3.153741 2940.0 2.712245 2940.0 80.000000 2940.0 0.793878 2940.0 11.279592 2940.0 2.761224 2940.0 7.008163 2940.0 4.229252 2940.0 2.187755 2940.0 4.123129 50% 75% max 36.0 43.00 60. 802.0 1157.00 1499. 1.0 2.00 2. 7.0 14.00 29. 3.0 4.00 5. 2.0 3.00 5. 1.0 1.00 1. 1470.5 2205.25 2940. 3.0 4.00 4. 1.0 1.00 1. 66.0 84.00 100. 3.0 3.00 4. 2.0 3.00 5. 3.0 4.00 4. 1.0 1.00 1. 66.0 84.00 100. 3.0 3.00 4. 2.0 3.00 5. 3.0 4.00 4. 1.0 1.00 1. 4919.0 8380.00 19999. 14235.5 20462.00 26999. 2.0 4.00 9. 14.0 18.00 25. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 9. 14.0 18.00 25. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6.</td><td>2940.0 14313.103401 7116.575021 2940.0 2.693197 2.497584 2940.0 15.209524 3.659315 2940.0 3.153741 0.360762 2940.0 80.000000 0.000000 2940.0 80.000000 0.000000 2940.0 0.793878 0.851932 2940.0 2.799320 1.289051 2940.0 2.761224 0.706356 2940.0 7.008163 6.125483 2940.0 7.008163 6.125483 2940.0 4.229252 3.622521 2940.0 4.229252 3.622521 2940.0 4.123129 3.567529 50% 75% max 36.0 43.00 60.0 802.0 1157.00 1499.0 1.0 2.00 2.0 7.0 14.00 29.0 3.0 4.00 5.0 2.0 3.00 5.0 3.0 4.00 4.0 1.0<td>2940.0 14313.103401 7116.575021 2094.0 2940.0 2.693197 2.497584 0.0 2940.0 15.209524 3.659315 11.0 2940.0 3.153741 0.360762 3.0 2940.0 80.000000 0.000000 80.0 2940.0 0.793878 0.851932 0.0 2940.0 11.279592 7.779458 0.0 2940.0 2.799320 1.289051 0.0 2940.0 2.799320 1.289051 0.0 2940.0 2.761224 0.706356 1.0 2940.0 2.761224 0.706356 1.0 2940.0 7.008163 6.125483 0.0 2940.0 4.229252 3.622521 0.0 2940.0 4.23129 3.567529 0.0 50% 75% max 36.0 43.00 60.0 802.0 1157.00 1499.0 1.0 1.00 1.0 1470.5 2205.25</td></td></tr<>	2940.0 14313.103401 711 2940.0 2.693197 2940.0 15.209524 2940.0 3.153741 2940.0 2.712245 2940.0 80.000000 2940.0 0.793878 2940.0 11.279592 2940.0 2.761224 2940.0 7.008163 2940.0 4.229252 2940.0 2.187755 2940.0 4.123129 50% 75% max 36.0 43.00 60. 802.0 1157.00 1499. 1.0 2.00 2. 7.0 14.00 29. 3.0 4.00 5. 2.0 3.00 5. 1.0 1.00 1. 1470.5 2205.25 2940. 3.0 4.00 4. 1.0 1.00 1. 66.0 84.00 100. 3.0 3.00 4. 2.0 3.00 5. 3.0 4.00 4. 1.0 1.00 1. 66.0 84.00 100. 3.0 3.00 4. 2.0 3.00 5. 3.0 4.00 4. 1.0 1.00 1. 4919.0 8380.00 19999. 14235.5 20462.00 26999. 2.0 4.00 9. 14.0 18.00 25. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 4. 3.0 3.00 4.00 9. 14.0 18.00 25. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6. 3.0 3.00 4.00 3.0 3.00 6.	2940.0 14313.103401 7116.575021 2940.0 2.693197 2.497584 2940.0 15.209524 3.659315 2940.0 3.153741 0.360762 2940.0 80.000000 0.000000 2940.0 80.000000 0.000000 2940.0 0.793878 0.851932 2940.0 2.799320 1.289051 2940.0 2.761224 0.706356 2940.0 7.008163 6.125483 2940.0 7.008163 6.125483 2940.0 4.229252 3.622521 2940.0 4.229252 3.622521 2940.0 4.123129 3.567529 50% 75% max 36.0 43.00 60.0 802.0 1157.00 1499.0 1.0 2.00 2.0 7.0 14.00 29.0 3.0 4.00 5.0 2.0 3.00 5.0 3.0 4.00 4.0 1.0 <td>2940.0 14313.103401 7116.575021 2094.0 2940.0 2.693197 2.497584 0.0 2940.0 15.209524 3.659315 11.0 2940.0 3.153741 0.360762 3.0 2940.0 80.000000 0.000000 80.0 2940.0 0.793878 0.851932 0.0 2940.0 11.279592 7.779458 0.0 2940.0 2.799320 1.289051 0.0 2940.0 2.799320 1.289051 0.0 2940.0 2.761224 0.706356 1.0 2940.0 2.761224 0.706356 1.0 2940.0 7.008163 6.125483 0.0 2940.0 4.229252 3.622521 0.0 2940.0 4.23129 3.567529 0.0 50% 75% max 36.0 43.00 60.0 802.0 1157.00 1499.0 1.0 1.00 1.0 1470.5 2205.25</td>	2940.0 14313.103401 7116.575021 2094.0 2940.0 2.693197 2.497584 0.0 2940.0 15.209524 3.659315 11.0 2940.0 3.153741 0.360762 3.0 2940.0 80.000000 0.000000 80.0 2940.0 0.793878 0.851932 0.0 2940.0 11.279592 7.779458 0.0 2940.0 2.799320 1.289051 0.0 2940.0 2.799320 1.289051 0.0 2940.0 2.761224 0.706356 1.0 2940.0 2.761224 0.706356 1.0 2940.0 7.008163 6.125483 0.0 2940.0 4.229252 3.622521 0.0 2940.0 4.23129 3.567529 0.0 50% 75% max 36.0 43.00 60.0 802.0 1157.00 1499.0 1.0 1.00 1.0 1470.5 2205.25

0.7 Fix outlier or Remove outlier

0.8 IQR Method -

• we can cap the value between the upper bound and lower bound

```
[273]: def outlier(data):
           q1 = data.quantile(0.25)
           q3 = data.quantile(0.75)
           iqr = q3 - q1
           upper_bound = q3 + 1.5 * iqr
           lower_bound = q1 - 1.5 * iqr
           return data.clip(upper_bound,lower_bound)
[274]: df.head()
[274]:
          Age Attrition
                              BusinessTravel DailyRate
                                                          Department
                                                                        DistanceFromHome
           41
                     Yes
                               Travel_Rarely
                                                    1102
                                                                     2
       0
                                                                                        1
           49
                          Travel_Frequently
                                                     279
                                                                                        8
       1
                      No
                                                                     1
       2
           37
                     Yes
                               Travel_Rarely
                                                    1373
                                                                     1
                                                                                        2
       3
                          Travel_Frequently
                                                                                        3
           33
                      No
                                                    1392
                                                                     1
           27
                               Travel_Rarely
                                                                                        2
                      No
                                                     591
                                                                     1
          Education EducationField EmployeeCount EmployeeNumber
       0
                   2
                                    1
                                                                      1
       1
                   1
                                    1
                                                    1
                                                                      2
       2
                   2
                                    4
                                                    1
                                                                      3
       3
                   4
                                                                      4
                   1
       4
                                    3
                                                                      5
          RelationshipSatisfaction StandardHours
                                                      StockOptionLevel
       0
                                                  80
                                   1
                                   4
       1
                                                  80
                                                                       1
       2
                                   2
                                                  80
                                                                       0
       3
                                   3
                                                  80
                                                                       0
       4
                                   4
                                                  80
          TotalWorkingYears
                              TrainingTimesLastYear WorkLifeBalance YearsAtCompany
       0
                           8
                                                                      1
                                                                                       6
                           10
       1
                                                    3
                                                                     3
                                                                                      10
       2
                           7
                                                    3
                                                                     3
                                                                                       0
                           8
                                                    3
                                                                     3
                                                                                       8
       3
       4
                           6
                                                                      3
                                                                                       2
          YearsInCurrentRole YearsSinceLastPromotion YearsWithCurrManager
       0
                             4
                                                       0
                                                                               5
                             7
                                                                               7
       1
                                                       1
       2
                             0
                                                       0
                                                                               0
```

```
      3
      7
      3
      0

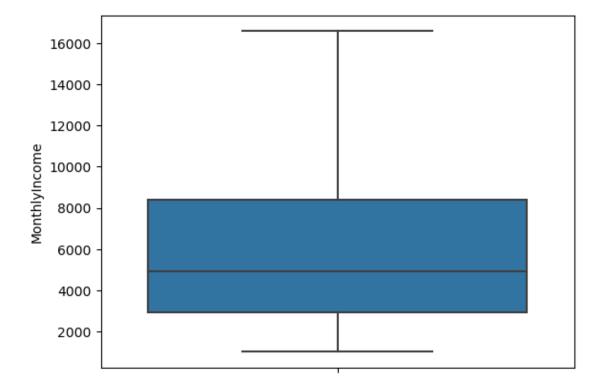
      4
      2
      2
      2
```

[5 rows x 35 columns]

```
[275]: df["MonthlyIncome"] = outlier(df.MonthlyIncome)
```

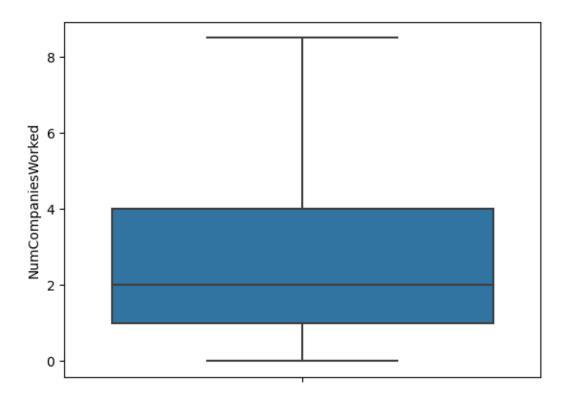
```
[276]: sns.boxplot(y="MonthlyIncome", data=df)
```

[276]: <Axes: ylabel='MonthlyIncome'>



```
[277]: df["NumCompaniesWorked"] = outlier(df.NumCompaniesWorked)
[278]: sns.boxplot(y="NumCompaniesWorked" , data=df )
```

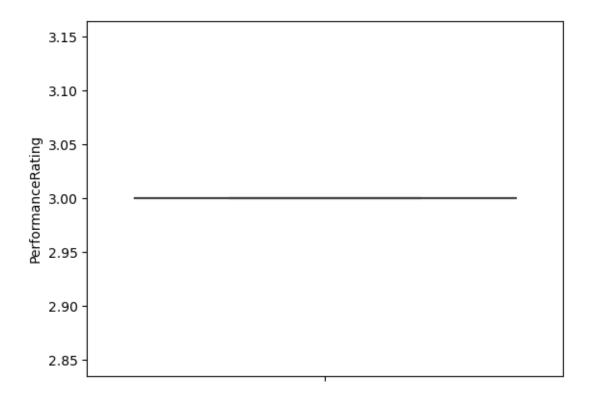
[278]: <Axes: ylabel='NumCompaniesWorked'>



```
[279]: df["PerformanceRating"] = outlier(df.PerformanceRating)

[280]: sns.boxplot(y="PerformanceRating" , data=df )

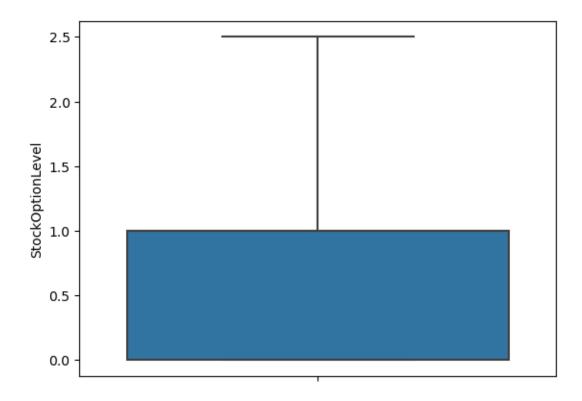
[280]: <Axes: ylabel='PerformanceRating'>
```



```
[281]: df["StockOptionLevel"] = outlier(df.StockOptionLevel)

[282]: sns.boxplot(y="StockOptionLevel" , data=df )

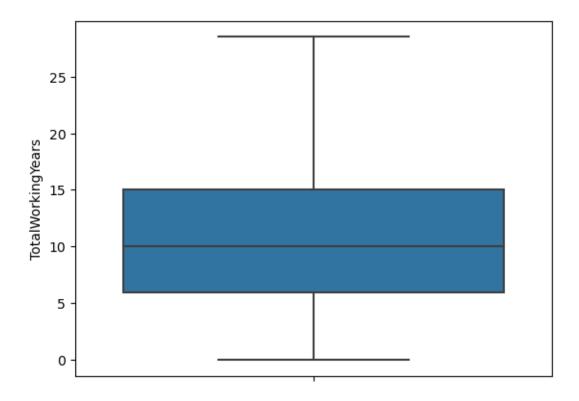
[282]: <Axes: ylabel='StockOptionLevel'>
```



```
[283]: df["TotalWorkingYears"] = outlier(df.TotalWorkingYears)

[284]: sns.boxplot(y="TotalWorkingYears" , data=df )

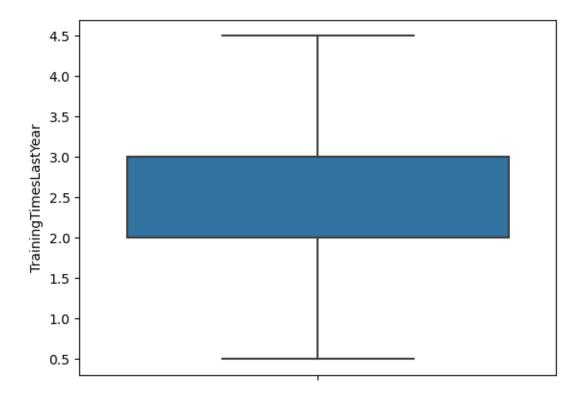
[284]: <Axes: ylabel='TotalWorkingYears'>
```



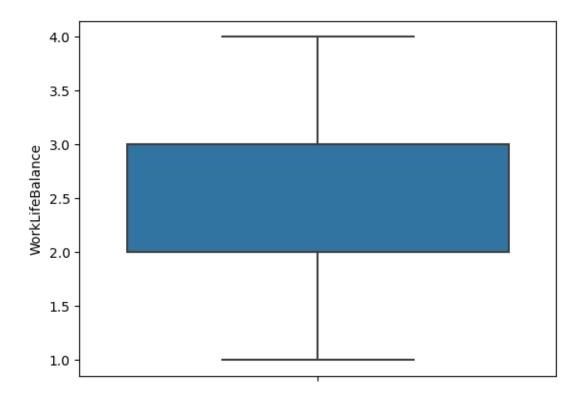
```
[285]: df["TrainingTimesLastYear"] = outlier(df.TrainingTimesLastYear)

[286]: sns.boxplot(y="TrainingTimesLastYear" , data=df )

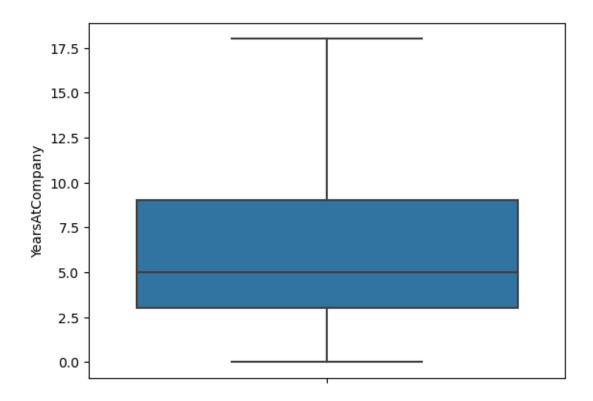
[286]: <Axes: ylabel='TrainingTimesLastYear'>
```



```
[287]: df["WorkLifeBalance"] = outlier(df.WorkLifeBalance)
[288]: sns.boxplot(y="WorkLifeBalance", data=df)
[288]: <Axes: ylabel='WorkLifeBalance'>
```



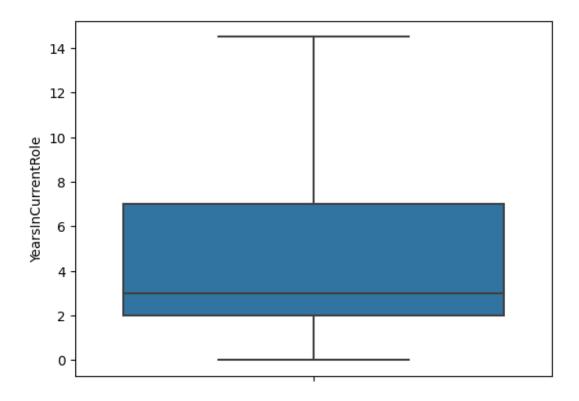
```
[289]: df["YearsAtCompany"] = outlier(df.YearsAtCompany)
[290]: sns.boxplot(y="YearsAtCompany" , data=df )
[290]: <Axes: ylabel='YearsAtCompany'>
```



```
[291]: df["YearsInCurrentRole"] = outlier(df.YearsInCurrentRole)

[292]: sns.boxplot(y="YearsInCurrentRole" , data=df )

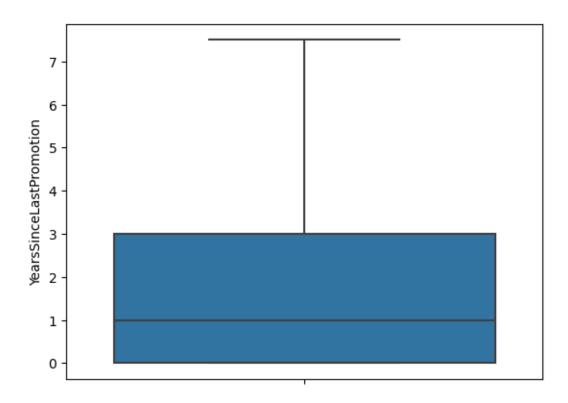
[292]: <Axes: ylabel='YearsInCurrentRole'>
```



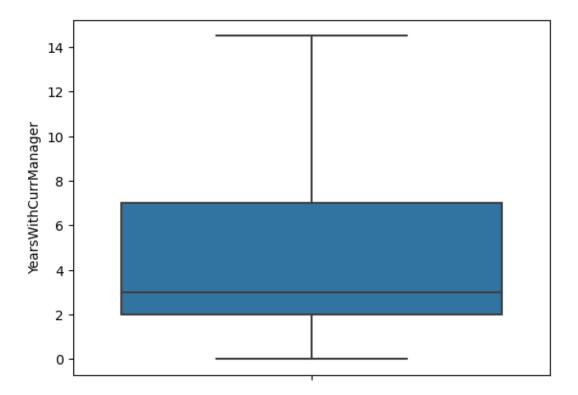
```
[293]: df["YearsSinceLastPromotion"] = outlier(df.YearsSinceLastPromotion)

[294]: sns.boxplot(y="YearsSinceLastPromotion" , data=df )

[294]: <Axes: ylabel='YearsSinceLastPromotion'>
```



```
[295]: df["YearsWithCurrManager"] = outlier(df.YearsWithCurrManager)
[296]: sns.boxplot(y="YearsWithCurrManager", data=df)
[296]: <Axes: ylabel='YearsWithCurrManager'>
```



0.9 Models Buildings:

- logistic Regression
- Random Forest
- Decision Tree

```
[11]: correlations = df.corr()
    correlations
```

[11]:		Age	${ t DailyRate}$	${\tt DistanceFromHome}$	Education	\
	Age	1.000000	0.010661	-0.001686	0.208034	
	DailyRate	0.010661	1.000000	-0.004985	-0.016806	
	DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	
	Education	0.208034	-0.016806	0.021042	1.000000	
	EmployeeCount	NaN	NaN	NaN	NaN	
	EmployeeNumber	-0.005175	-0.025742	0.016464	0.020950	
	EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	
	HourlyRate	0.024287	0.023381	0.031131	0.016775	
	JobInvolvement	0.029820	0.046135	0.008783	0.042438	
	JobLevel	0.509604	0.002966	0.005303	0.101589	
	JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	
	MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	
	MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	

NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111
PerformanceRating	0.001904	0.000473	0.027110	-0.024539
${\tt RelationshipSatisfaction}$	0.053535	0.007846	0.006557	-0.009118
StandardHours	NaN	NaN	NaN	NaN
StockOptionLevel	0.037510	0.042143	0.044872	0.018422
${ t TotalWorking Years}$	0.680381	0.014515	0.004628	0.148280
${\tt TrainingTimesLastYear}$	-0.019621	0.002453	-0.036942	-0.025100
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236
${\tt YearsSinceLastPromotion}$	0.216513	-0.033229	0.010029	0.054254
${\tt YearsWithCurrManager}$	0.202089	-0.026363	0.014406	0.069065

	EmployeeCount	EmployeeNumber	\
Age	NaN	-0.005175	
DailyRate	NaN	-0.025742	
DistanceFromHome	NaN	0.016464	
Education	NaN	0.020950	
EmployeeCount	NaN	NaN	
EmployeeNumber	NaN	1.000000	
EnvironmentSatisfaction	NaN	0.008712	
HourlyRate	NaN	0.017377	
JobInvolvement	NaN	-0.003552	
JobLevel	NaN	-0.009020	
JobSatisfaction	NaN	-0.022970	
MonthlyIncome	NaN	-0.007188	
MonthlyRate	NaN	0.006177	
NumCompaniesWorked	NaN	-0.000345	
PercentSalaryHike	NaN	-0.006685	
PerformanceRating	NaN	-0.010338	
${\tt RelationshipSatisfaction}$	NaN	-0.034827	
StandardHours	NaN	NaN	
StockOptionLevel	NaN	0.031226	
TotalWorkingYears	NaN	-0.007047	
${\tt TrainingTimesLastYear}$	NaN	0.011953	
WorkLifeBalance	NaN	0.005370	
YearsAtCompany	NaN	-0.005779	
YearsInCurrentRole	NaN	-0.004427	
${\tt YearsSinceLastPromotion}$	NaN	-0.004575	
${\tt YearsWithCurrManager}$	NaN	-0.004716	

	EnvironmentSatisfaction	${ t HourlyRate}$	${ t JobInvolvement}$	\
Age	0.010146	0.024287	0.029820	
DailyRate	0.018355	0.023381	0.046135	
DistanceFromHome	-0.016075	0.031131	0.008783	
Education	-0.027128	0.016775	0.042438	

EmployeeCount		NaN	NaN	NaN
EmployeeNumber		0.008712	0.017377	-0.003552
${\tt EnvironmentSatisfaction}$		1.000000	-0.049857	-0.008278
HourlyRate		-0.049857	1.000000	0.042861
JobInvolvement		-0.008278	0.042861	1.000000
JobLevel		0.001212	-0.027853	-0.012630
JobSatisfaction		-0.006784	-0.071335	-0.021476
MonthlyIncome		-0.006259	-0.015794	-0.015271
${ t MonthlyRate}$		0.037600	-0.015297	-0.016322
NumCompaniesWorked		0.012594	0.022157	0.015012
${\tt PercentSalaryHike}$		-0.031701	-0.009062	-0.017205
PerformanceRating		-0.029548	-0.002172	-0.029071
${\tt RelationshipSatisfaction}$		0.007665	0.001330	0.034297
StandardHours		NaN	NaN	NaN
StockOptionLevel		0.003432	0.050263	0.021523
${ t TotalWorking Years}$		-0.002693	-0.002334	-0.005533
${\tt Training Times Last Year}$		-0.019359	-0.008548	-0.015338
WorkLifeBalance		0.027627	-0.004607	-0.014617
YearsAtCompany		0.001458	-0.019582	-0.021355
YearsInCurrentRole		0.018007	-0.024106	0.008717
${\tt YearsSinceLastPromotion}$		0.016194	-0.026716	-0.024184
YearsWithCurrManager		-0.004999	-0.020123	0.025976
-				
	JobLevel	 Relationship	pSatisfaction	\
Age	JobLevel 0.509604	 Relationshi	pSatisfaction 0.053535	\
Age DailyRate		Relationship		\
_	0.509604	 Relationship	0.053535	\
DailyRate	0.509604 0.002966	 Relationship	0.053535 0.007846	\
DailyRate DistanceFromHome	0.509604 0.002966 0.005303	 Relationship	0.053535 0.007846 0.006557	\
DailyRate DistanceFromHome Education	0.509604 0.002966 0.005303 0.101589	 Relationship	0.053535 0.007846 0.006557 -0.009118	\
DailyRate DistanceFromHome Education EmployeeCount	0.509604 0.002966 0.005303 0.101589 NaN	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber	0.509604 0.002966 0.005303 0.101589 NaN -0.009020	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.0000000	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730	 Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike PerformanceRating	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730 -0.021222	Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490 -0.031351	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730	Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730 -0.021222 0.021642 NaN	Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490 -0.031351 1.000000 NaN	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours StockOptionLevel	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730 -0.021222 0.021642 NaN 0.013984	Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490 -0.031351 1.000000 NaN -0.045952	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours StockOptionLevel TotalWorkingYears	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730 -0.021222 0.021642 NaN 0.013984 0.782208	Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490 -0.031351 1.000000 NaN -0.045952 0.024054	
DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate JobInvolvement JobLevel JobSatisfaction MonthlyIncome MonthlyRate NumCompaniesWorked PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours StockOptionLevel	0.509604 0.002966 0.005303 0.101589 NaN -0.009020 0.001212 -0.027853 -0.012630 1.000000 -0.001944 0.950300 0.039563 0.142501 -0.034730 -0.021222 0.021642 NaN 0.013984	Relationship	0.053535 0.007846 0.006557 -0.009118 NaN -0.034827 0.007665 0.001330 0.034297 0.021642 -0.012454 0.025873 -0.004085 0.052733 -0.040490 -0.031351 1.000000 NaN -0.045952	

0.019367

0.534739 ...

YearsAtCompany

YearsInCurrentRole	0.389447		-0.015123
${\tt YearsSinceLastPromotion}$	0.353885	•••	0.033493
YearsWithCurrManager	0.375281	•••	-0.000867

	StandardHours	StockOptionLevel	${\tt TotalWorkingYears}$	١
Age	NaN	0.037510	0.680381	
DailyRate	NaN	0.042143	0.014515	
DistanceFromHome	NaN	0.044872	0.004628	
Education	NaN	0.018422	0.148280	
EmployeeCount	NaN	NaN	NaN	
EmployeeNumber	NaN	0.031226	-0.007047	
${\tt EnvironmentSatisfaction}$	NaN	0.003432	-0.002693	
HourlyRate	NaN	0.050263	-0.002334	
JobInvolvement	NaN	0.021523	-0.005533	
JobLevel	NaN	0.013984	0.782208	
JobSatisfaction	NaN	0.010690	-0.020185	
MonthlyIncome	NaN	0.005408	0.772893	
MonthlyRate	NaN	-0.034323	0.026442	
${\tt NumCompaniesWorked}$	NaN	0.030075	0.237639	
${\tt PercentSalaryHike}$	NaN	0.007528	-0.020608	
PerformanceRating	NaN	0.003506	0.006744	
${\tt RelationshipSatisfaction}$	NaN	-0.045952	0.024054	
StandardHours	NaN	NaN	NaN	
StockOptionLevel	NaN	1.000000	0.010136	
${ t TotalWorking Years}$	NaN	0.010136	1.000000	
${\tt Training Times Last Year}$	NaN	0.011274	-0.035662	
WorkLifeBalance	NaN	0.004129	0.001008	
YearsAtCompany	NaN	0.015058	0.628133	
YearsInCurrentRole	NaN	0.050818	0.460365	
${\tt YearsSinceLastPromotion}$	NaN	0.014352	0.404858	
${\tt YearsWithCurrManager}$	NaN	0.024698	0.459188	

	${\tt TrainingTimesLastYear}$	${\tt WorkLifeBalance}$	\
Age	-0.019621	-0.021490	
DailyRate	0.002453	-0.037848	
DistanceFromHome	-0.036942	-0.026556	
Education	-0.025100	0.009819	
EmployeeCount	NaN	NaN	
EmployeeNumber	0.011953	0.005370	
EnvironmentSatisfaction	-0.019359	0.027627	
HourlyRate	-0.008548	-0.004607	
JobInvolvement	-0.015338	-0.014617	
JobLevel	-0.018191	0.037818	
JobSatisfaction	-0.005779	-0.019459	
MonthlyIncome	-0.021736	0.030683	
MonthlyRate	0.001467	0.007963	
NumCompaniesWorked	-0.066054	-0.008366	

PercentSalaryHike	-0.005221	-0.003280
PerformanceRating	-0.015579	0.002572
RelationshipSatisfaction	0.002497	0.019604
StandardHours	NaN	NaN
StockOptionLevel	0.011274	0.004129
TotalWorkingYears	-0.035662	0.001008
TrainingTimesLastYear	1.000000	0.028072
WorkLifeBalance	0.028072	1.000000
YearsAtCompany	0.003569	0.012089
YearsInCurrentRole	-0.005738	0.049856
${\tt YearsSinceLastPromotion}$	-0.002067	0.008941
YearsWithCurrManager	-0.004096	0.002759

	${\tt YearsAtCompany}$	YearsInCurrentRole	\
Age	0.311309	0.212901	
DailyRate	-0.034055	0.009932	
DistanceFromHome	0.009508	0.018845	
Education	0.069114	0.060236	
EmployeeCount	NaN	NaN	
EmployeeNumber	-0.005779	-0.004427	
${\tt EnvironmentSatisfaction}$	0.001458	0.018007	
HourlyRate	-0.019582	-0.024106	
JobInvolvement	-0.021355	0.008717	
JobLevel	0.534739	0.389447	
JobSatisfaction	-0.003803	-0.002305	
MonthlyIncome	0.514285	0.363818	
MonthlyRate	-0.023655	-0.012815	
NumCompaniesWorked	-0.118421	-0.090754	
PercentSalaryHike	-0.035991	-0.001520	
PerformanceRating	0.003435	0.034986	
${\tt RelationshipSatisfaction}$	0.019367	-0.015123	
StandardHours	NaN	NaN	
StockOptionLevel	0.015058	0.050818	
${\tt TotalWorkingYears}$	0.628133	0.460365	
${\tt Training Times Last Year}$	0.003569	-0.005738	
WorkLifeBalance	0.012089	0.049856	
YearsAtCompany	1.000000	0.758754	
YearsInCurrentRole	0.758754	1.000000	
${\tt YearsSinceLastPromotion}$	0.618409	0.548056	
${\tt YearsWithCurrManager}$	0.769212	0.714365	

	YearsSinceLastPromotion	YearsWithCurrManager
Age	0.216513	0.202089
DailyRate	-0.033229	-0.026363
DistanceFromHome	0.010029	0.014406
Education	0.054254	0.069065
EmployeeCount	NaN	NaN

EmployeeNumber	-0.004575	-0.004716
EnvironmentSatisfaction	0.016194	-0.004999
HourlyRate	-0.026716	-0.020123
JobInvolvement	-0.024184	0.025976
JobLevel	0.353885	0.375281
JobSatisfaction	-0.018214	-0.027656
MonthlyIncome	0.344978	0.344079
MonthlyRate	0.001567	-0.036746
NumCompaniesWorked	-0.036814	-0.110319
PercentSalaryHike	-0.022154	-0.011985
PerformanceRating	0.017896	0.022827
RelationshipSatisfaction	0.033493	-0.000867
StandardHours	NaN	NaN
StockOptionLevel	0.014352	0.024698
TotalWorkingYears	0.404858	0.459188
${\tt TrainingTimesLastYear}$	-0.002067	-0.004096
WorkLifeBalance	0.008941	0.002759
YearsAtCompany	0.618409	0.769212
YearsInCurrentRole	0.548056	0.714365
${\tt YearsSinceLastPromotion}$	1.000000	0.510224
${\tt YearsWithCurrManager}$	0.510224	1.000000

[26 rows x 26 columns]

0.10 Model-1: Logistic Regression Algorthim

						_		C				
[12]:	df	.head	d()									
[12]:		Age	Attrition		Busines	sTı	ravel	DailyRate	e D	epartment	\	
	0	41	Yes		Travel	_Ra	arely	1102	2	Sales		
	1	49	No	Tra	vel_Fre	que	ently	279	Research & De	velopment		
	2	37	Yes		Travel	_Ra	arely	1373	Research & De	velopment		
	3	33	No	Tra	vel_Fre	que	ently	1392	Research & De	velopment		
	4	27	No		Travel	_Ra	arely	591	. Research & De	velopment		
	0 1 2 3	Dist	tanceFromHo	ome 1 8 2 3	Educati	on 2 1 2 4	Life Life	tionField Sciences Sciences Other Sciences	EmployeeCount 1 1 1	EmployeeNu	mber 1 2 3	\
	4			2		1	гте	Medical	1		5	
	0 1 2 3	I	Relationshi	.pSat	isfacti	on 1 4 2	Standa	ardHours 80 80 80 80	StockOptionLeve	1 \ 0 1 0 0		

```
4 ...
                                4
                                            80
                                                              1
        TotalWorkingYears
                         TrainingTimesLastYear WorkLifeBalance YearsAtCompany
     0
     1
                      10
                                            3
                                                           3
                                                                         10
                                            3
                                                           3
     2
                       7
                                                                          0
                       8
                                            3
                                                           3
                                                                          8
     3
     4
                       6
                                                           3
                                                                          2
                                            3
       YearsInCurrentRole
                         YearsSinceLastPromotion
                                                YearsWithCurrManager
     0
     1
                                              1
                                                                   7
     2
                       0
                                              0
                                                                   0
     3
                       7
                                              3
                                                                   0
                                              2
                                                                   2
     [5 rows x 35 columns]
[13]: df['Gender'].replace(['F'],'Female', inplace = True)
     df['MaritalStatus'].replace(['M'],'Married', inplace = True)
[14]: from sklearn.preprocessing import LabelEncoder
     le = LabelEncoder()
     df['Department'] = le.fit_transform(df['Department'])
     df['EducationField'] = le.fit transform(df['EducationField'])
     df['Gender'] = le.fit_transform(df['Gender'])
     df['MaritalStatus'] = le.fit_transform(df['MaritalStatus'])
     0.11 Data(Train-Test) Split
[15]: x=df.drop(['Gender','Attrition','JobRole','Over18',__
      y=df[['Gender']]
[16]: x.head(2)
[16]:
        Age DailyRate Department DistanceFromHome Education EducationField \
         41
                 1102
                               2
                                                1
                                                          2
     0
                  279
     1
         49
                               1
                                                8
                                                          1
                                                                         1
        EmployeeCount EmployeeNumber EnvironmentSatisfaction HourlyRate ... \
                                                                    94 ...
     0
                                                         2
                                  1
     1
                   1
                                                         3
                                                                    61 ...
```

```
0
                          80
                                      0
                 1
1
                 4
                          80
                                      1
  0
           10
                           3
                                      3
                                                10
1
  YearsInCurrentRole YearsSinceLastPromotion YearsWithCurrManager
0
                                           5
             7
                                           7
1
                             1
[2 rows x 29 columns]
```

[17]: x.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2940 entries, 0 to 2939
Data columns (total 29 columns):

#	Column	Non-Null Count	Dtype
0	Age	2940 non-null	 int64
1	DailyRate	2940 non-null	int64
2	Department	2940 non-null	
3	DistanceFromHome	2940 non-null	int64
4	Education	2940 non-null	int64
5	EducationField	2940 non-null	int32
6	EmployeeCount	2940 non-null	int64
7	EmployeeNumber	2940 non-null	int64
8	EnvironmentSatisfaction	2940 non-null	int64
9	HourlyRate	2940 non-null	int64
10	JobInvolvement	2940 non-null	int64
11	JobLevel	2940 non-null	int64
12	JobSatisfaction	2940 non-null	int64
13	MaritalStatus	2940 non-null	int32
14	MonthlyIncome	2940 non-null	int64
15	MonthlyRate	2940 non-null	int64
16	${\tt NumCompaniesWorked}$	2940 non-null	int64
17	${\tt PercentSalaryHike}$	2940 non-null	int64
18	PerformanceRating	2940 non-null	int64
19	${\tt RelationshipSatisfaction}$	2940 non-null	int64
20	StandardHours	2940 non-null	int64
21	StockOptionLevel	2940 non-null	int64
22	${ t TotalWorking Years}$	2940 non-null	int64
23	${\tt Training Times Last Year}$	2940 non-null	int64
24	WorkLifeBalance	2940 non-null	int64
25	YearsAtCompany	2940 non-null	int64
26	YearsInCurrentRole	2940 non-null	int64

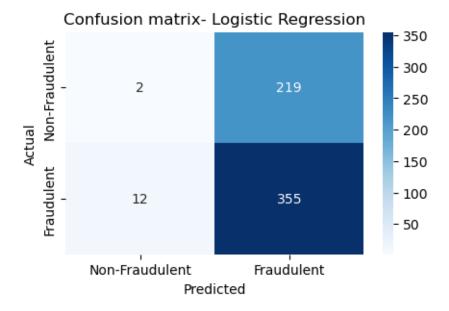
```
27 YearsSinceLastPromotion
                                    2940 non-null
                                                    int64
      28 YearsWithCurrManager
                                    2940 non-null
                                                    int64
     dtypes: int32(3), int64(26)
     memory usage: 631.8 KB
[18]: y.head(2)
[18]:
        Gender
      0
      1
              1
[19]: 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_state=0)
[20]: x_train.shape , x_test.shape
[20]: ((2352, 29), (588, 29))
[21]: y_train.shape , y_test.shape
[21]: ((2352, 1), (588, 1))
     0.12 Logistic Regression Method
[22]: from sklearn.linear_model import LogisticRegression
      logit = LogisticRegression(random_state= 100)
      logit.fit(x train, y train)
[22]: LogisticRegression(random_state=100)
     0.13 Prediction
[23]: y_pred_train_log = logit.predict(x_train)
      y_pred_test_log = logit.predict(x_test)
     0.14 Evaluate test data Accuracy
[24]: from sklearn.metrics import confusion_matrix, classification_report,
      →accuracy_score
      accuracy_log_test=accuracy_score(y_test,y_pred_test_log)
      print('Logistic regression Test accuracy:', accuracy_score(y_test,_
       →y_pred_test_log))
```

Logistic regression Test accuracy: 0.6071428571428571

0.15 Evaluate train data Accuracy

Logistic regression Train accuracy: 0.594812925170068

0.16 Confusion Martrix - Logistic Regression



0.17 AUC (Area under the curve) & ROC (Receiver operating characteristics)

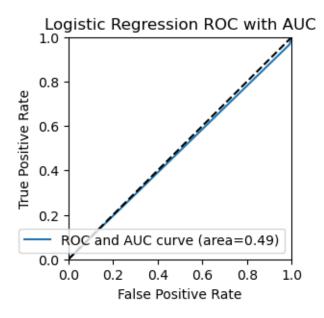
- It is one of the most important evaluation metrics for checking classification model's performance
- It is also written as AUROC (Area Under the Receiver Operating Characteristics)
- ROC is a probability curve and AUC represents the degree or measure of separability.

• It tells how much the model is capable of distinguishing between classes.

```
[26]: from sklearn.metrics import roc_auc_score
logit_roc_auc = roc_auc_score(y_test, y_pred_test_log)
print(logit_roc_auc)
```

0.48817611303586617

```
[27]: from sklearn.metrics import roc_curve
      fpr, tpr, thresholds = roc_curve(y_test, y_pred_test_log)
      display(fpr[:10])
      display(tpr[:10])
      display(thresholds[:10])
     array([0.
                      , 0.99095023, 1.
                                               ])
     array([0.
                      , 0.96730245, 1.
                                               ])
     array([2, 1, 0])
[28]: plt.figure(figsize=(3,3))
      plt.plot(fpr, tpr, label="ROC and AUC curve (area=%0.2f)" % logit_roc_auc)
      plt.plot([0,1],[0,1], 'k--')
      plt.xlim([0.0,1.0])
      plt.ylim([0.0,1.0])
      plt.xlabel('False Positive Rate')
      plt.ylabel('True Positive Rate')
      plt.title("Logistic Regression ROC with AUC")
      plt.legend(loc='lower right')
      plt.show()
```



0.18 Model-2: Random Forest Algorithm

0.18.1 Feature Scaling

```
[29]: x.info()
```

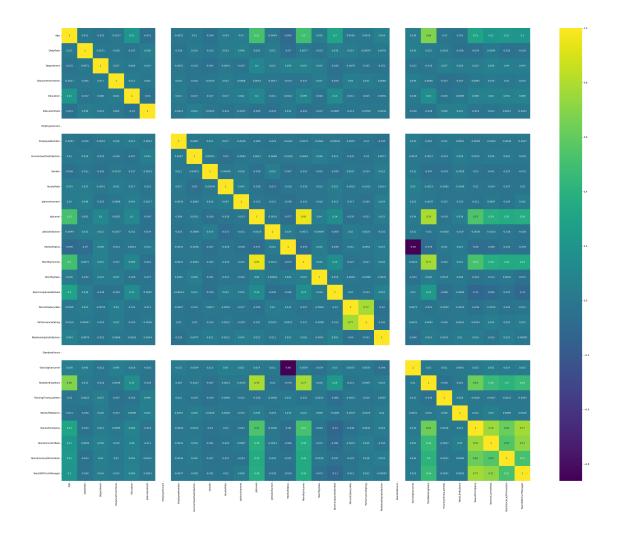
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2940 entries, 0 to 2939
Data columns (total 29 columns):

#	Column	Non-Null Count	Dtype
0	Age	2940 non-null	int64
1	DailyRate	2940 non-null	int64
2	Department	2940 non-null	int32
3	DistanceFromHome	2940 non-null	int64
4	Education	2940 non-null	int64
5	EducationField	2940 non-null	int32
6	EmployeeCount	2940 non-null	int64
7	EmployeeNumber	2940 non-null	int64
8	EnvironmentSatisfaction	2940 non-null	int64
9	HourlyRate	2940 non-null	int64
10	JobInvolvement	2940 non-null	int64
11	JobLevel	2940 non-null	int64
12	JobSatisfaction	2940 non-null	int64
13	MaritalStatus	2940 non-null	int32
14	MonthlyIncome	2940 non-null	int64
15	MonthlyRate	2940 non-null	int64
16	NumCompaniesWorked	2940 non-null	int64
17	PercentSalaryHike	2940 non-null	int64
18	PerformanceRating	2940 non-null	int64
19	${\tt RelationshipSatisfaction}$	2940 non-null	int64
20	StandardHours	2940 non-null	int64
21	StockOptionLevel	2940 non-null	int64
22	${ t TotalWorking Years}$	2940 non-null	int64
23	${\tt Training Times Last Year}$	2940 non-null	int64
24	WorkLifeBalance	2940 non-null	int64
25	YearsAtCompany	2940 non-null	int64
26	YearsInCurrentRole	2940 non-null	int64
27	${\tt YearsSinceLastPromotion}$	2940 non-null	int64
28	YearsWithCurrManager	2940 non-null	int64
dtyp	es: int32(3), int64(26)		

dtypes: int32(3), int64(26) memory usage: 631.8 KB

```
[30]: from sklearn.preprocessing import StandardScaler sc=StandardScaler()
```

```
x1=sc.fit_transform(x)
      pd.DataFrame(x1).head(2)
[30]:
                                    2
                                               3
      0 0.446350 0.742527 1.401512 -1.010909 -0.891688 -0.937414 0.0 -1.731462
      1 \quad 1.322365 \quad -1.297775 \quad -0.493817 \quad -0.147150 \quad -1.868426 \quad -0.937414 \quad 0.0 \quad -1.730284
               8
                          9
                                        19
                                             20
                                                       21
                                                                  22
                                                                             23 \
      0 -0.660531 1.383138 ... -1.584178 0.0 -0.932014 -0.421642 -2.171982
      1 0.254625 -0.240677 ... 1.191438 0.0 0.241988 -0.164511 0.155707
                          25
                                    26
      0 -2.493820 -0.164613 -0.063296 -0.679146 0.245834
      1 0.338096 0.488508 0.764998 -0.368715 0.806541
      [2 rows x 29 columns]
     0.18.2 Check Balance Data
[31]: y.value_counts()
[31]: Gender
      1
                1764
      0
                1176
      dtype: int64
     0.18.3 Conculsion - Data is Imbalaced
[33]: # Done Under Sampling to balaced the data
      import imblearn
      from imblearn.under_sampling import RandomUnderSampler
      ros = RandomUnderSampler()
      x_un,y_un = ros.fit_resample(x1,y)
      print(x_un.shape,y_un.shape,y.shape)
      (2352, 29) (2352, 1) (2940, 1)
[34]: y_un.value_counts()
[34]: Gender
      0
                1176
      1
                1176
      dtype: int64
[41]: plt.figure(figsize = (45, 35))
      sns.heatmap(df.corr(), annot = True, cmap = 'viridis')
      plt.show()
```



0.19 Model Building

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

rf = RandomForestClassifier(n_estimators = 200, oob_score = False)

rf.fit(x_train,y_train)
```

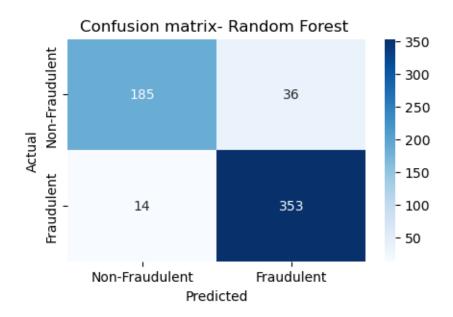
[43]: RandomForestClassifier(n_estimators=200)

0.20 Prediction

```
[44]: y_pred_train_rf = rf.predict(x_train)
y_pred_test_rf = rf.predict(x_test)
```

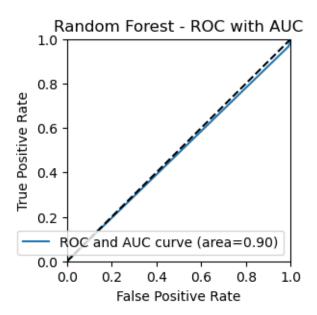
0.21 Evaluate

```
[45]: accuracy_rf_test = accuracy_score(y_test,y_pred_test_rf)
      accuracy_rf_train = accuracy_score(y_train,y_pred_train_rf)
      print('Random Forest - Train accuracy:', accuracy_score(y_train,_
       →y_pred_train_rf))
      print('----'*10)
      print('Random Forest - Test accuracy:', accuracy_score(y_test, y_pred_test_rf))
     Random Forest - Train accuracy: 1.0
     Random Forest - Test accuracy: 0.9149659863945578
     0.22 Confusion Matrix
[46]: print(confusion_matrix(y_test,y_pred_test_rf))
     [[185 36]
      [ 14 353]]
[47]: print(confusion_matrix(y_train,y_pred_train_rf))
     [[ 955
               0]
        0 1397]]
      Γ
[53]: print('Random Forest Train data accuracy')
      acc = accuracy_score (y_train, y_pred_train_rf)
      print('Accuracy score is', acc)
     Random Forest Train data accuracy
     Accuracy score is 1.0
[55]: Labels = ['Non-Fraudulent', 'Fraudulent']
      plt.figure(figsize = (5,3))
      sns.heatmap(confusion_matrix(y_test,y_pred_test_rf), xticklabels = Labels,
                  yticklabels = Labels, cmap = 'Blues', annot = True, fmt = 'g')
      plt.title("Confusion matrix- Random Forest ")
      plt.ylabel('Actual')
      plt.xlabel('Predicted')
      plt.show()
```



```
[56]: rf_roc_auc = roc_auc_score(y_test, y_pred_test_rf)
    print(rf_roc_auc)
    plt.figure(figsize = (3,3))
    plt.plot(fpr, tpr, label = "ROC and AUC curve (area=%0.2f)" % rf_roc_auc)
    plt.plot([0,1],[0,1], 'k--')
    plt.xlim([0.0,1.0])
    plt.ylim([0.0,1.0])
    plt.ylim([0.0,1.0])
    plt.ylabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title("Random Forest - ROC with AUC")
    plt.legend(loc = 'lower right')
    plt.show()
```

0.8994784667168062



0.22.1 Cross validation because of underfitting issue

```
[57]: from sklearn.model_selection import cross_val_score
    train_accuracy_rf = cross_val_score(rf, x_train, y_train, cv = 10)
    crossval_train_rf = train_accuracy_rf.mean()
    test_accuracy_rf = cross_val_score(rf, x_test, y_test, cv = 10)
    crossval_test_rf = test_accuracy_rf.mean()

    print('Random forest after Cross validation Train accuracy:', crossval_train_rf)
    print('-----'*10)
    print('Random forest after Cross validation Test accuracy:', crossval_test_rf)
```

0.23 Model-3: Decision Tree

• A decision tree uses the tree representation to solve the problem in which each leaf node corresponds to a class label and attributes are represented on the internal node of the tree.

0.24 Model building

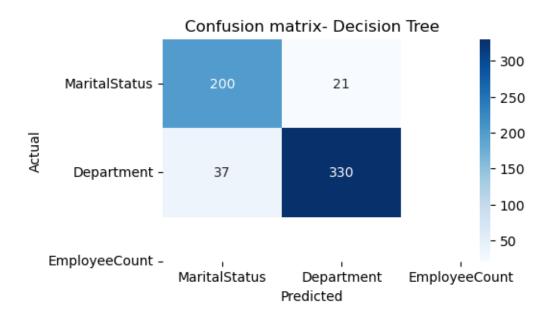
```
[58]: from sklearn.tree import DecisionTreeClassifier,plot_tree
dtree = DecisionTreeClassifier()
dtree.fit(x_train,y_train)
```

```
[58]: DecisionTreeClassifier()
```

0.25 Prediction

```
[60]: y_pred_train_dtree = dtree.predict(x_train)
y_pred_test_dtree = dtree.predict(x_test)
```

0.26 Evaluate



0.26.1 Using Post prunning method to handle overfitting problem

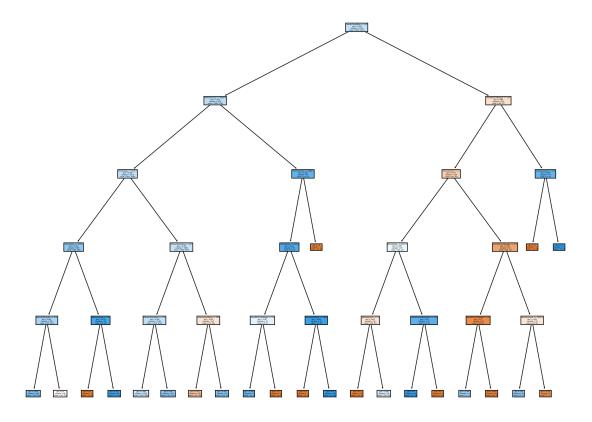
```
def dtree_model(model):
    model_preds = model.predict(x_test)
    print(classification_report(y_test,model_preds))
    print('\n')
    plt.figure(figsize = (15,12), dpi = 150)
    plot_tree(model, filled = True, feature_names = x.columns)
plt.show()
```

```
[67]: # max depth at 5
prunned_dtree = DecisionTreeClassifier(max_depth = 5)
prunned_dtree.fit(x_train,y_train)
```

[67]: DecisionTreeClassifier(max_depth=5)

[68]: dtree_model(prunned_dtree)

	precision	recall	f1-score	support
0	0.55	0.16	0.25	221
1	0.65	0.92	0.76	367
			0.00	F00
accuracy macro avg	0.60	0.54	0.63 0.50	588 588
weighted avg	0.61	0.63	0.57	588



0.26.2 Prediction

```
[73]: y_pred_prunned_train = prunned_dtree.predict(x_train)
y_pred_prunned_test = prunned_dtree.predict(x_test)
```

0.26.3 Evaluate

Decision Tree post prunning- Train accuracy: 0.6326530612244898

Decision Tree post prunning- Test accuracy: 0.6343537414965986

[]: