Import packages

In [1]:
```
import pandas as pd
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

In [2]:
```
# check data directory
# ls
```

import data into pandas dataframe

In [3]:
```
medical_df = pd.read_csv("project_dataset - project_dataset.csv")
medical_df.head(10)
```

Out[3]:

	EmployeeID	Age	BusinessTravel	MonthlyIncome	JobSatisfaction	Bonus	Department	DistanceFromHome	Education	EducationField	EnvSatisfaction	Gender	JobRole	MaritalStatus	PerformanceRating	TrainingTim
0	1	41	Travel_Rarely	5993	4	17979	Sales	1	2	Life Sciences	2	Female	Sales Executive	Single	3	
1	2	49	Travel_Frequently	5130	2	20520	Research & Development	8	1	Life Sciences	3	Male	Research Scientist	Married	4	
2	4	37	Travel_Rarely	2090	3	6270	Research & Development	2	2	Other	4	Male	Laboratory Technician	Single	3	
3	5	33	Travel_Frequently	2909	3	8727	Research & Development	3	4	Life Sciences	4	Female	Research Scientist	Married	3	
4	7	27	Travel_Rarely	3468	2	10404	Research & Development	2	1	Medical	1	Male	Laboratory Technician	Married	3	
5	8	32	Travel_Frequently	3068	4	9204	Research & Development	2	2	Life Sciences	4	Male	Laboratory Technician	Single	3	
6	10	59	Travel_Rarely	2670	1	10680	Research & Development	3	3	Medical	3	Female	Laboratory Technician	Married	4	
7	11	30	Travel_Rarely	2693	3	10772	Research & Development	24	1	Life Sciences	4	Male	Laboratory Technician	Divorced	4	
8	12	38	Travel_Frequently	9526	3	38104	Research & Development	23	3	Life Sciences	4	Male	Manufacturing Director	Single	4	
9	13	36	Travel_Rarely	5237	3	15711	Research & Development	27	3	Medical	3	Male	Healthcare Representative	Married	3	

In [4]:
```
# make the EmployeeID as the index column
medical_df = medical_df.set_index('EmployeeID')
medical_df
```

Out[4]:

EmployeeID	Age	BusinessTravel	MonthlyIncome	JobSatisfaction	Bonus	Department	DistanceFromHome	Education	EducationField	EnvSatisfaction	Gender	JobRole	MaritalStatus	PerformanceRating	TrainingTimesl
1	41	Travel_Rarely	5993	4	17979	Sales	1	2	Life Sciences	2	Female	Sales Executive	Single	3	
2	49	Travel_Frequently	5130	2	20520	Research & Development	8	1	Life Sciences	3	Male	Research Scientist	Married	4	
4	37	Travel_Rarely	2090	3	6270	Research & Development	2	2	Other	4	Male	Laboratory Technician	Single	3	
5	33	Travel_Frequently	2909	3	8727	Research & Development	3	4	Life Sciences	4	Female	Research Scientist	Married	3	
7	27	Travel_Rarely	3468	2	10404	Research & Development	2	1	Medical	1	Male	Laboratory Technician	Married	3	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2061	36	Travel_Frequently	2571	4	7713	Research & Development	23	2	Medical	3	Male	Laboratory Technician	Married	3	
2062	39	Travel_Rarely	9991	1	29973	Research & Development	6	1	Medical	4	Male	Healthcare Representative	Married	3	
2064	27	Travel_Rarely	6142	2	24568	Research & Development	4	3	Life Sciences	2	Male	Manufacturing Director	Married	4	
2065	49	Travel_Frequently	5390	2	16170	Sales	2	3	Medical	4	Male	Sales Executive	Married	3	
2068	34	Travel_Rarely	4404	3	13212	Research & Development	8	3	Medical	2	Male	Laboratory Technician	Married	3	

1470 rows × 19 columns

Data Preparation

Perform Exploration Data Analysis

- check the data shape
- Check for Null Data
- Check for Duplicates
- Check the data summary statistics
- Check for correlations
- Check for multicolinearity
- Rearranging the columns

In [5]:

```
# check the data shape
medical_df.shape
```

Out[5]:

```
(1470, 19)
```

In [6]:

```
# check for null data
medical_df.isnull().sum()
```

Out[6]:
```
Age                        0
BusinessTravel             0
MonthlyIncome              0
JobSatisfaction            0
Bonus                      0
Department                 0
DistanceFromHome           0
Education                  0
EducationField             0
EnvSatisfaction            0
Gender                     0
JobRole                    0
MaritalStatus              0
PerformanceRating          0
TrainingTimesLastYear      0
YearsAtCompany             0
YearsSinceLastPromotion    0
OverTime                   0
Attrition                  0
dtype: int64
```

In [7]:
```
#check for duplicates
medical_df[medical_df.duplicated(keep=False)]
```

Out[7]:

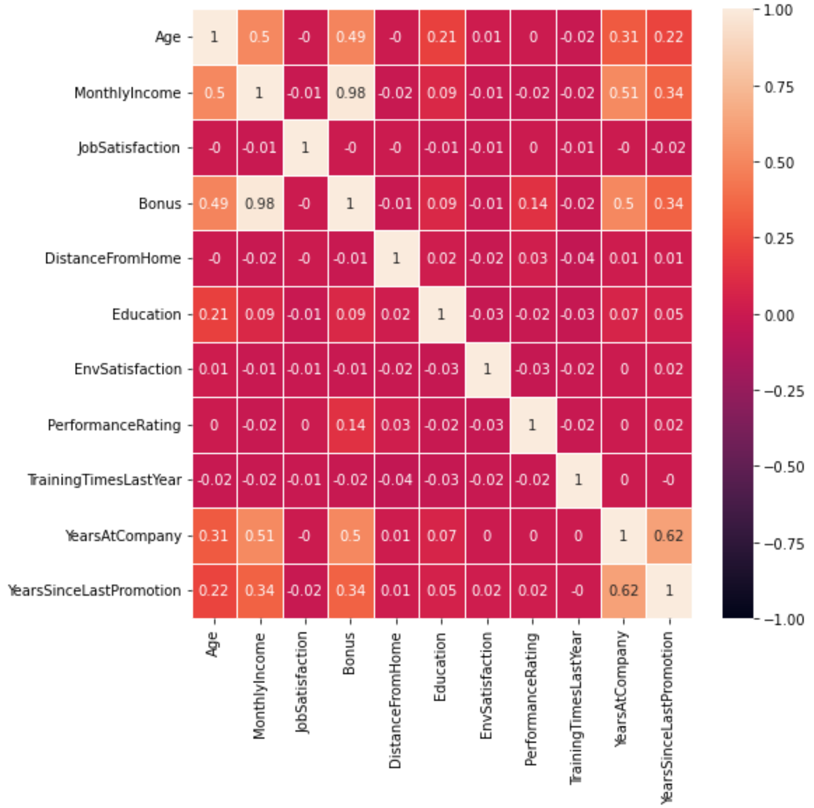
	Age	BusinessTravel	MonthlyIncome	JobSatisfaction	Bonus	Department	DistanceFromHome	Education	EducationField	EnvSatisfaction	Gender	JobRole	MaritalStatus	PerformanceRating	TrainingTimesLastYear
EmployeeID															

In [8]:
```
#check the data summary statistics
medical_df.describe(include='all')
```

Out[8]:

	Age	BusinessTravel	MonthlyIncome	JobSatisfaction	Bonus	Department	DistanceFromHome	Education	EducationField	EnvSatisfaction	Gender	JobRole	MaritalStatus	PerformanceRating	TrainingTi
count	1470.000000	1470	1470.000000	1470.000000	1470.000000	1470	1470.000000	1470.000000	1470	1470.000000	1470	1470	1470	1470.000000	
unique	NaN	3	NaN	NaN	NaN	3	NaN	NaN	6	NaN	2	9	3	NaN	
top	NaN	Travel_Rarely	NaN	NaN	NaN	Research & Development	NaN	NaN	Life Sciences	NaN	Male	Sales Executive	Married	NaN	
freq	NaN	1043	NaN	NaN	NaN	961	NaN	NaN	606	NaN	882	326	673	NaN	
mean	36.923810	NaN	6502.931293	2.728571	20479.501361	NaN	9.192517	2.912925	NaN	2.721769	NaN	NaN	NaN	3.153741	
std	9.135373	NaN	4707.956783	1.102846	15066.272964	NaN	8.106864	1.024165	NaN	1.093082	NaN	NaN	NaN	0.360824	
min	18.000000	NaN	1009.000000	1.000000	3027.000000	NaN	1.000000	1.000000	NaN	1.000000	NaN	NaN	NaN	3.000000	
25%	30.000000	NaN	2911.000000	2.000000	9333.750000	NaN	2.000000	2.000000	NaN	2.000000	NaN	NaN	NaN	3.000000	
50%	36.000000	NaN	4919.000000	3.000000	15484.500000	NaN	7.000000	3.000000	NaN	3.000000	NaN	NaN	NaN	3.000000	
75%	43.000000	NaN	8379.000000	4.000000	26103.750000	NaN	14.000000	4.000000	NaN	4.000000	NaN	NaN	NaN	3.000000	
max	60.000000	NaN	19999.000000	4.000000	79892.000000	NaN	29.000000	5.000000	NaN	4.000000	NaN	NaN	NaN	4.000000	

In [9]:
```
#use heatmap function to understand the data summary better
# use seaborn to visualize the correlation with heatmap
plt.figure(figsize=(8,8))
sns.heatmap(medical_df.corr().round(2),vmin=-1, vmax=1, annot=True,linewidth=.5);
```



In [10]:
```
medical_df.columns
```

Out[10]:
```
Index(['Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'Bonus',
       'Department', 'DistanceFromHome', 'Education', 'EducationField',
       'EnvSatisfaction', 'Gender', 'JobRole', 'MaritalStatus',
       'PerformanceRating', 'TrainingTimesLastYear', 'YearsAtCompany',
       'YearsSinceLastPromotion', 'OverTime', 'Attrition'],
      dtype='object')
```

In [11]:
```
# check for multicolinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
copy_medical = medical_df.copy()
copy_medical['Attrition'] = copy_medical['Attrition'].map({'Yes':1,'No':0})
copy_medical['OverTime'] = copy_medical['OverTime'].map({'Yes':1,'No':0})
copy_medical['MaritalStatus'] = copy_medical['MaritalStatus'].map({'Married':1,'Divorced':2,'Single':3})
copy_medical['BusinessTravel'] = copy_medical['BusinessTravel'].map({'Travel_Rarely':1,'Travel_Frequently':2,'Non-Travel':3})
copy_medical['Gender'] = copy_medical['Gender'].map({'Female':1,'Male':0})

# select certain input variables
copy_medical = copy_medical[['Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'Bonus',
       'DistanceFromHome',
       'EnvSatisfaction', 'Gender', 'MaritalStatus',
       'PerformanceRating', 'TrainingTimesLastYear', 'YearsAtCompany',
       'YearsSinceLastPromotion', 'OverTime', 'Attrition']]

copy_medical
```

Out[11]:

	Age	BusinessTravel	MonthlyIncome	JobSatisfaction	Bonus	DistanceFromHome	EnvSatisfaction	Gender	MaritalStatus	PerformanceRating	TrainingTimesLastYear	YearsAtCompany	YearsSinceLastPromotion	OverT
EmployeeID														
1	41	1	5993	4	17979	1	2	1	3	3	0	6	0	
2	49	2	5130	2	20520	8	3	0	1	4	3	10	1	
4	37	1	2090	3	6270	2	4	0	3	3	3	0	0	
5	33	2	2909	3	8727	3	4	1	1	3	3	8	3	
7	27	1	3468	2	10404	2	1	0	1	3	3	2	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2061	36	2	2571	4	7713	23	3	0	1	3	3	5	0	
2062	39	1	9991	1	29973	6	4	0	1	3	5	7	1	
2064	27	1	6142	2	24568	4	2	0	1	4	0	6	0	
2065	49	2	5390	2	16170	2	4	0	1	3	3	9	0	
2068	34	1	4404	3	13212	8	2	0	1	3	3	4	1	

1470 rows × 15 columns

In [12]:

```
# VIF Dataframe
vif_data = pd.DataFrame()
vif_data['feature'] = copy_medical.columns
vif_data
```

Out[12]:

	feature
0	Age
1	BusinessTravel
2	MonthlyIncome
3	JobSatisfaction
4	Bonus
5	DistanceFromHome
6	EnvSatisfaction
7	Gender
8	MaritalStatus
9	PerformanceRating
10	TrainingTimesLastYear
11	YearsAtCompany
12	YearsSinceLastPromotion
13	OverTime
14	Attrition

In [13]:
```
#calculating VIF for each feature
vif_data['VIF'] = [variance_inflation_factor(copy_medical.values,i) for i in range(len(copy_medical.columns))]
print(vif_data)
```

```
                  feature         VIF
0                     Age   22.295740
1          BusinessTravel    5.312998
2           MonthlyIncome  111.293878
3         JobSatisfaction    7.053365
4                   Bonus  106.448691
5          DistanceFromHome    2.302447
6          EnvSatisfaction    7.161742
7                  Gender    1.678806
8           MaritalStatus    5.674453
9       PerformanceRating   40.294776
10   TrainingTimesLastYear    5.669428
11          YearsAtCompany    4.540620
12  YearsSinceLastPromotion    2.392605
13                OverTime    1.526281
14               Attrition    1.409794
```

In [14]:
```
# copy_medical.columns
```

In [15]:
```
# copy_medical = copy_medical[['Age','DistanceFromHome', 'MonthlyIncome', 'JobSatisfaction','EnvSatisfaction','YearsAtCompany','Gender','OverTime','Attrition']]
```

In [16]:
```
# copy_medical = pd.get_dummies(copy_medical)
# copy_medical
```

In [17]:
```
# plt.figure(figsize=(8,8))
# sns.heatmap(copy_medical.corr().round(2),vmin=-1, vmax=1, annot=True);
```

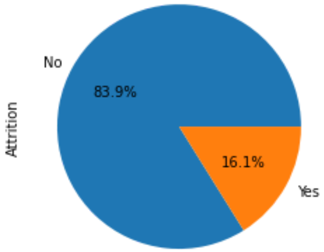
Check for variables that affect the attrition rate

Univariate Analysis

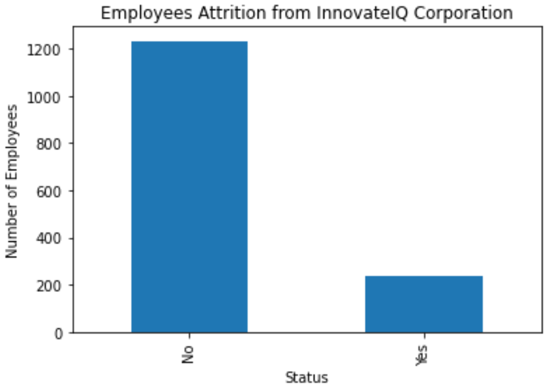
In [18]:
```
# use value count function to find the number of counts of
# attributes within the class
# and use normalize to find the proportion of it
attrition = medical_df['Attrition'].value_counts(normalize=True)*100
attrition
```

Out[18]:
```
No     83.877551
Yes    16.122449
Name: Attrition, dtype: float64
```

In [19]:
```
attrition.plot(kind='pie',autopct='%.1f%%')
plt.show()
```



In [20]:
```
# use graphical to understand the data better
medical_raw_count = medical_df['Attrition'].value_counts()
medical_raw_count.plot(kind='bar')
plt.xlabel('Status')
plt.ylabel('Number of Employees')
plt.title('Employees Attrition from InnovateIQ Corporation')
plt.show()
```



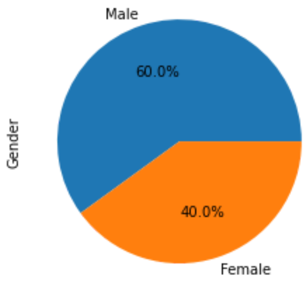
Finding For Attrition:

The data for attrition column shows about 84% of their client are still working in the company.while about 16% has attrited from the medical company.However the class proportion is unbalanced.

In [21]:
```
gender = medical_df['Gender'].value_counts(normalize=True)*100
gender
```

Out[21]:
```
Male      60.0
Female    40.0
Name: Gender, dtype: float64
```

In [22]:
```
gender.plot(kind='pie',autopct='%.1f%%')
plt.show()
```



Finding For Gender:

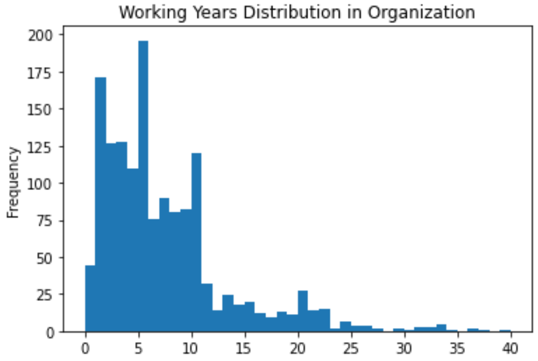
The data for gender column shows that 60% of their employees are male and 40% are female regardless their attrition status

In [23]:
```
years_at_com = medical_df['YearsAtCompany'].describe()
years_at_com
```

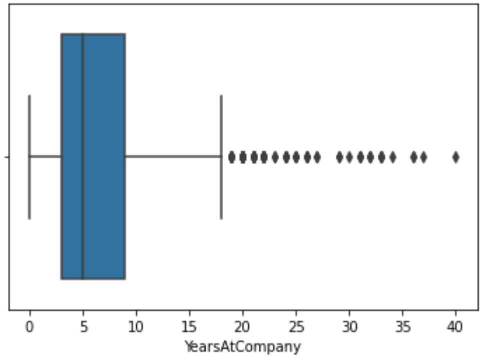
Out[23]:
```
count    1470.000000
mean        7.008163
std         6.126525
min         0.000000
25%         3.000000
50%         5.000000
75%         9.000000
max        40.000000
Name: YearsAtCompany, dtype: float64
```

In [24]:
```
medical_df['YearsAtCompany'].plot(kind='hist',bins=40)
plt.title('Working Years Distribution in Organization')
# check for the skewness and kurtosis
print("Skewness: {:0.3f}".format(medical_df['YearsAtCompany'].skew()))
print("Kurtosis: {:0.3f}".format(medical_df['YearsAtCompany'].kurt()))
```

```
Skewness: 1.765
Kurtosis: 3.936
```



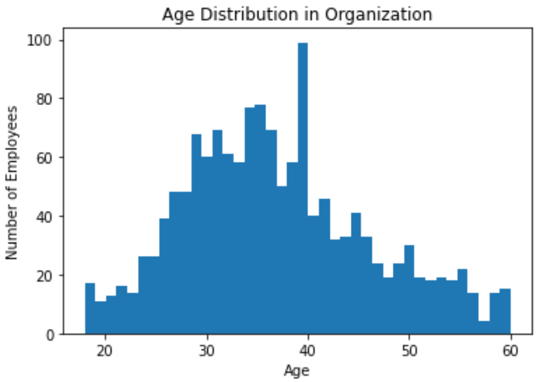
In [25]:
```
sns.boxplot(x='YearsAtCompany',data=medical_df)
plt.show()
```



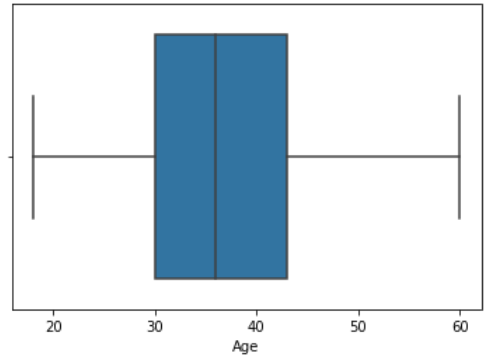
In [26]:
```
medical_df['Age'].describe()
```

Out[26]:
```
count    1470.000000
mean       36.923810
std         9.135373
min        18.000000
25%        30.000000
50%        36.000000
75%        43.000000
max        60.000000
Name: Age, dtype: float64
```

In [27]:
```
medical_df['Age'].plot(kind='hist',bins=40)
plt.xlabel('Age')
plt.ylabel('Number of Employees')
plt.title('Age Distribution in Organization')
plt.show()
```

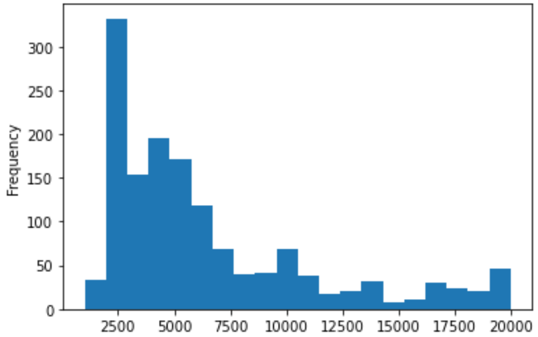


In [28]:
```
sns.boxplot(x='Age',data=medical_df)
plt.show()
```

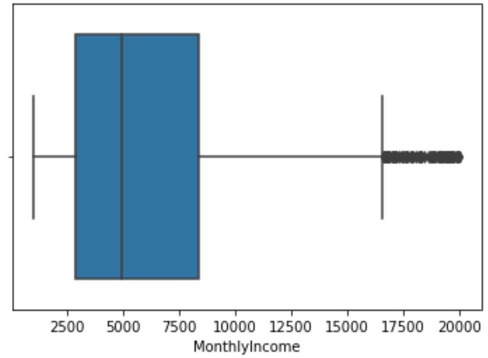


In [29]:
```
medical_df['MonthlyIncome'].plot(kind='hist',bins=20)
```

Out[29]: <AxesSubplot:ylabel='Frequency'>

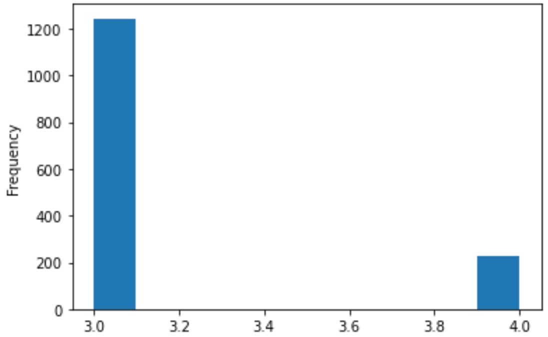


In [30]:
```
sns.boxplot(x='MonthlyIncome',data=medical_df)
plt.show()
```



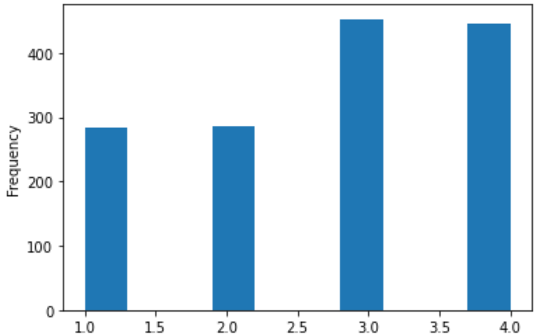
In [31]:
```
medical_df['PerformanceRating'].plot(kind='hist')
```

Out[31]: <AxesSubplot:ylabel='Frequency'>



In [32]:
```
envi = medical_df['EnvSatisfaction'].plot(kind='hist')
envi
```

Out[32]: <AxesSubplot:ylabel='Frequency'>

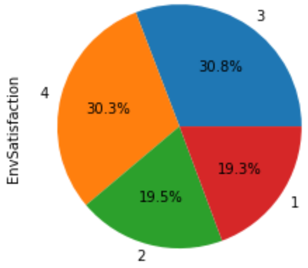


In [33]:
```
envi_prop = medical_df['EnvSatisfaction'].value_counts(normalize=True)*100
envi_prop
```

Out[33]:
```
3    30.816327
4    30.340136
2    19.523810
1    19.319728
Name: EnvSatisfaction, dtype: float64
```

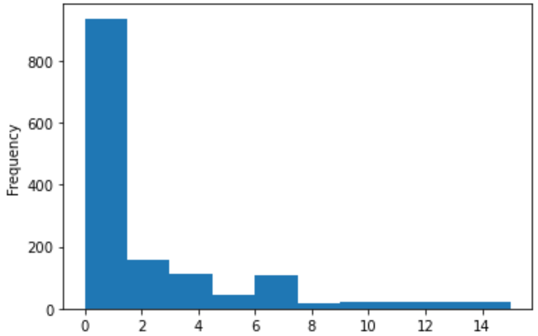
In [34]:
```
envi_prop.plot(kind='pie',autopct='%.1f%%')
```

Out[34]: <AxesSubplot:ylabel='EnvSatisfaction'>

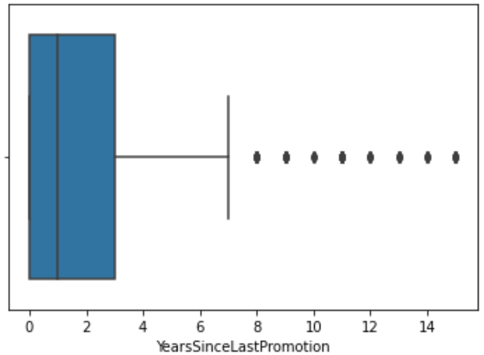


In [35]:
```
promote = medical_df['YearsSinceLastPromotion'].plot(kind='hist')
promote
```

Out[35]:
```
<AxesSubplot:ylabel='Frequency'>
```



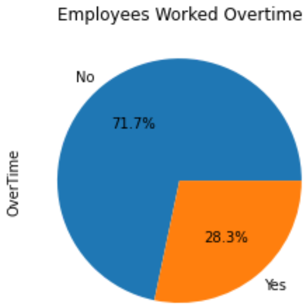
In [36]:
```
sns.boxplot(x='YearsSinceLastPromotion',data=medical_df)
plt.show()
```



In [37]:
```
over_prop = medical_df['OverTime'].value_counts(normalize=True)*100
over_prop
```

Out[37]:
```
No     71.70068
Yes    28.29932
Name: OverTime, dtype: float64
```

In [38]:
```
over_prop.plot(kind='pie',autopct='%.1f%%')
plt.title('Employees Worked Overtime')
plt.show()
```



Multivariate Analysis

Describe the Attrition based on Gender. Compute the attrition rate based on Gender

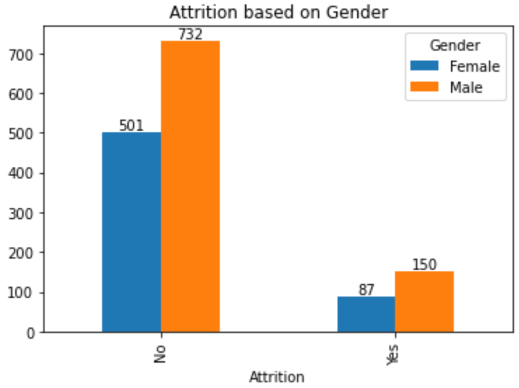
In [39]:
```
round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['Gender'],normalize='index'),2)
```

Out[39]:

Gender	Female	Male
Attrition		
No	0.41	0.59
Yes	0.37	0.63

In [40]:
```
gender = pd.crosstab(index=medical_df['Attrition'],columns=medical_df['Gender'])
ax = gender.plot(kind = 'bar')

# annotate
ax.bar_label(ax.containers[0], label_type='edge')
ax.bar_label(ax.containers[1], label_type='edge')
plt.title('Attrition based on Gender')
plt.show()
```



In [41]:
```
# test with CHI SQUARE test to check if proportion different for female and male by Attrition status has differently significant
chi,p,dof,exp = stats.chi2_contingency(gender)
print('the chi square test is {}'.format(round(p,3)))
# p > 0.05
#The ratios in our data are the same. Gender isn't a strong determinant of an employee beeing attrited or not
```

```
the chi square test is 0.291
```

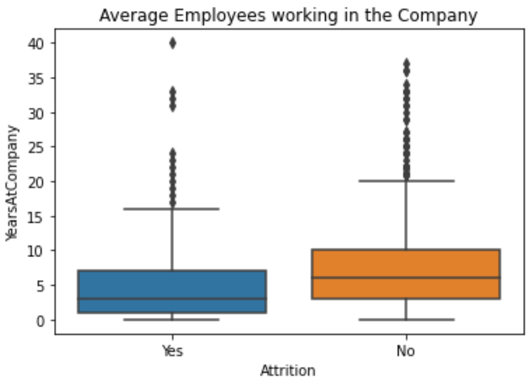
Describe the Attrition based on YearsAtCompany. Compute the attrition rate based on YearsAtCompany

In [42]:
```
mean_years = round(medical_df.groupby('Attrition',as_index=False)['YearsAtCompany'].mean())
mean_years = mean_years.rename(columns={'YearsAtCompany': 'Mean Years working at the Company'})
mean_years
```

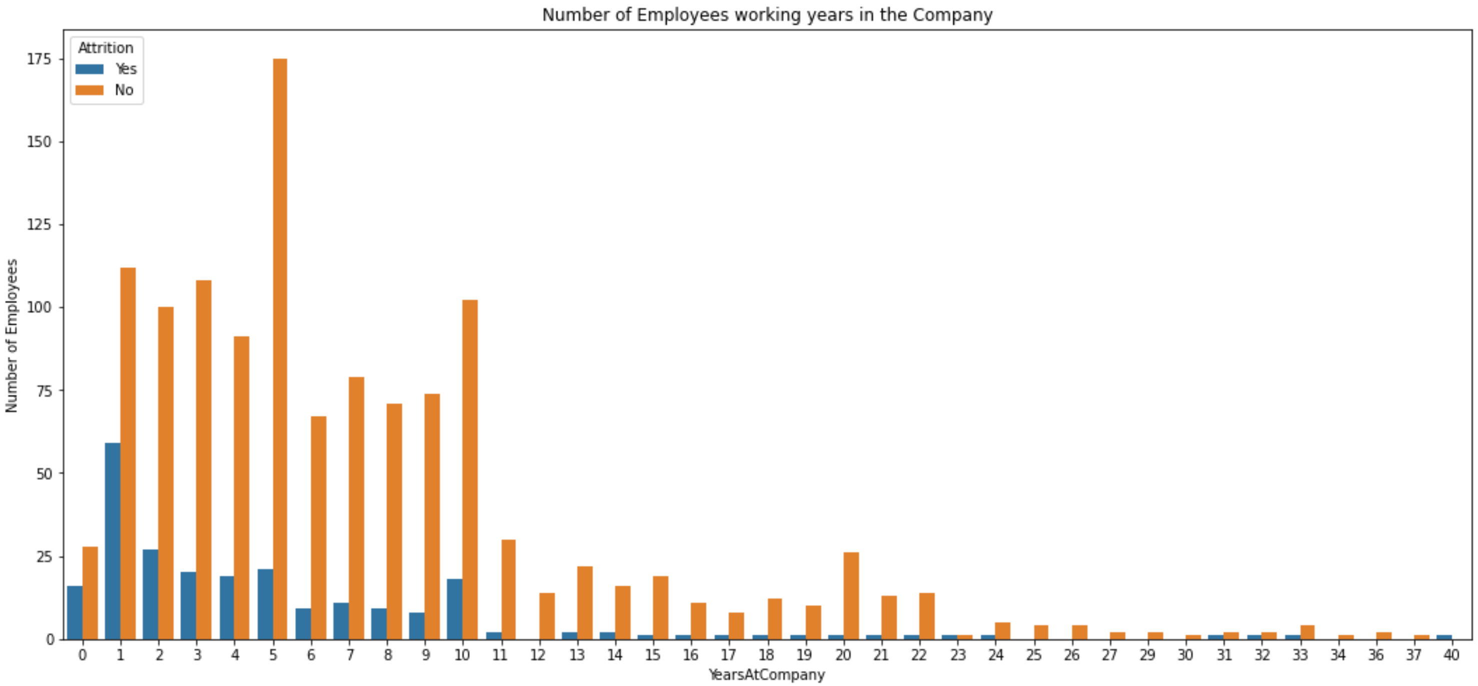
Out[42]:

	Attrition	Mean Years working at the Company
0	No	7.0
1	Yes	5.0

In [43]:
```
sns.boxplot(x ='Attrition', y ='YearsAtCompany', data = medical_df)
plt.title('Average Employees working in the Company')
plt.show()
```



In [44]:
```
fig = plt.figure(figsize=(18,8))
sns.countplot(x='YearsAtCompany',hue = 'Attrition',data = medical_df)
plt.ylabel('Number of Employees')
plt.title('Number of Employees working years in the Company')
plt.show()
```



In [45]:
```
from scipy.stats import levene
from scipy.stats import ttest_ind

print(levene(medical_df['YearsAtCompany'][medical_df['Attrition'] == 'Yes'],
       medical_df['YearsAtCompany'][medical_df['Attrition'] == 'No'], center = 'mean'))

print(ttest_ind(medical_df['YearsAtCompany'][medical_df['Attrition'] == 'Yes'],
       medical_df['YearsAtCompany'][medical_df['Attrition'] == 'No']))

# p < 0.05
# YearsAtCompany is significantly affect the attrition rate
# Employees in their early years of career tend to resign
# a lot more than employees who've worked in the company for  more 7 years
```

```
LeveneResult(statistic=2.5049476586425445, pvalue=0.11370465713766563)
Ttest_indResult(statistic=-5.1963086670254235, pvalue=2.3188716103863033e-07)
```

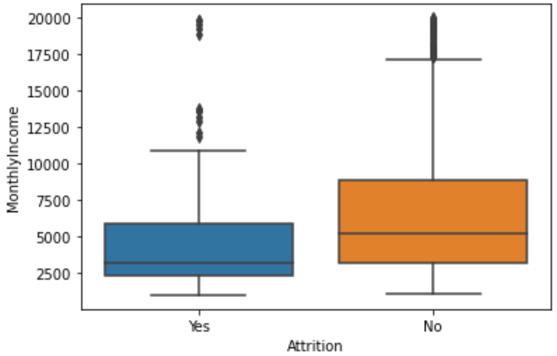
Describe the Attrition based on Income. Compute the attrition rate based on Income

In [46]:
```
mean_income = round(medical_df.groupby('Attrition',as_index=False)['MonthlyIncome'].mean(),2)
mean_income = mean_income.rename(columns={'MonthlyIncome': 'Mean Monthly Income'})
mean_income
```

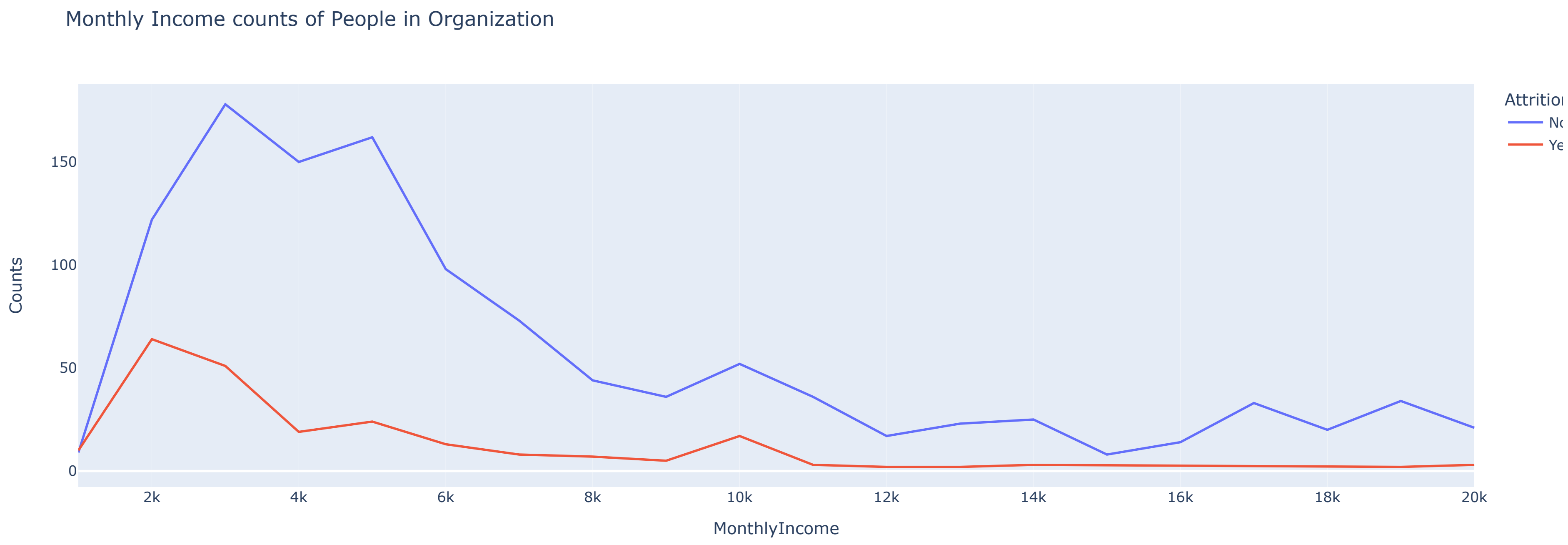
Out[46]:

	Attrition	Mean Monthly Income
0	No	6832.74
1	Yes	4787.09

In [47]:
```
sns.boxplot(x ='Attrition', y ='MonthlyIncome', data = medical_df)
plt.show()
```



In [48]:
```
rate_att=medical_df.groupby(['MonthlyIncome','Attrition']).apply(lambda x:x['MonthlyIncome'].count()).reset_index(name='Counts')
rate_att['MonthlyIncome']=round(rate_att['MonthlyIncome'],-3)
rate_att=rate_att.groupby(['MonthlyIncome','Attrition']).apply(lambda x:x['MonthlyIncome'].count()).reset_index(name='Counts')
fig=px.line(rate_att,x='MonthlyIncome',y='Counts',color='Attrition',title='Monthly Income counts of People in Organization')
fig.show()
```



In [49]:
```
print(levene(medical_df['MonthlyIncome'][medical_df['Attrition'] == 'Yes'],
       medical_df['MonthlyIncome'][medical_df['Attrition'] == 'No'], center = 'mean'))

print(ttest_ind(medical_df['MonthlyIncome'][medical_df['Attrition'] == 'Yes'],
       medical_df['MonthlyIncome'][medical_df['Attrition'] == 'No'], equal_var = False))


# p < 0.05
# Monthly Income is significantly affect the attrition rate
# Higher salary is a usualy motivation to keep working in the same company
```

```
LeveneResult(statistic=26.31302358992364, pvalue=3.29070575711061e-07)
Ttest_indResult(statistic=-7.482621586644742, pvalue=4.433588628286071e-13)
```

Describe the Attrition based on Environment. Compute the attrition rate based on Environment

In [50]:
```
round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['EnvSatisfaction'],normalize='index'),2)
```

Out[50]:

EnvSatisfaction	1	2	3	4
Attrition				
No	0.17	0.20	0.32	0.31
Yes	0.30	0.18	0.26	0.25

In [51]:
```
envi_raw = pd.crosstab(index=medical_df['Attrition'],columns=medical_df['EnvSatisfaction'])
envi_raw
```

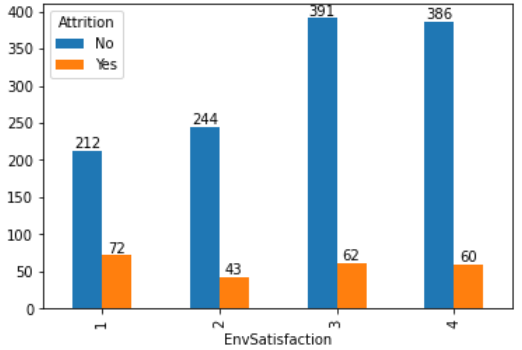
Out[51]:

EnvSatisfaction	1	2	3	4
Attrition				
No	212	244	391	386
Yes	72	43	62	60

In [52]:

```
envi = pd.crosstab(index=medical_df['EnvSatisfaction'],columns=medical_df['Attrition'])
ax = envi.plot(kind = 'bar')

# annotate
ax.bar_label(ax.containers[0], label_type='edge')
ax.bar_label(ax.containers[1], label_type='edge')
plt.show()
```



In [53]:

```
chi,p,dof,exp = stats.chi2_contingency(envi)
print('the chi square test is {}'.format(p))
# 5.1234689062894205e-05 < 0.05
# the satisfaction level from level 1-4, the chances of people leaving the company is slightly decrease.
# There is a change the company to improve and do better to retain the employees
```

```
the chi square test is 5.1234689062894205e-05
```

Describe the Attrition based on Job Satisfaction. Compute the attrition rate based on Job Satisfaction

In [54]:

```
round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['JobSatisfaction'],normalize='index'),2)
```

Out[54]:

JobSatisfaction	1	2	3	4
Attrition				
No	0.18	0.19	0.30	0.33
Yes	0.28	0.19	0.31	0.22

In [55]:

```
satisfaction_raw = round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['JobSatisfaction']),2)
satisfaction_raw
```

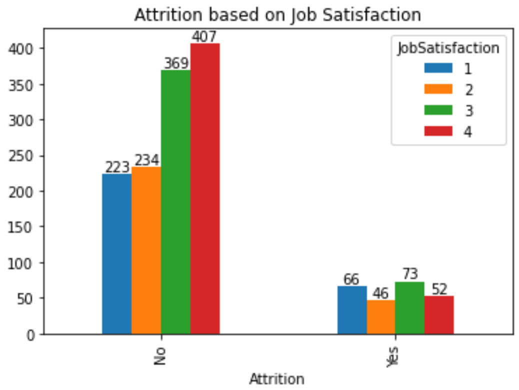
Out[55]:

JobSatisfaction	1	2	3	4
Attrition				
No	223	234	369	407
Yes	66	46	73	52

In [56]:

```
ax = satisfaction_raw.plot(kind = 'bar')

# annotate
ax.bar_label(ax.containers[0], label_type='edge')
ax.bar_label(ax.containers[1], label_type='edge')
ax.bar_label(ax.containers[2], label_type='edge')
ax.bar_label(ax.containers[3], label_type='edge')
plt.title('Attrition based on Job Satisfaction')
plt.show()
```



In [57]:

```
chi,p,dof,exp = stats.chi2_contingency(satisfaction_raw)
print('the chi square test is {}'.format(p))

# 0.0005563004510387556 < 0.05
# the job satisfaction level from level 1-4, affect the attrition rate

# the chances of people leaving the company is slightly decrease.
# There is a change the company to improve and do better to retain the employees
```

```
the chi square test is 0.0005563004510387556
```

Describe the Attrition based on Age. Compute the attrition rate based on Age

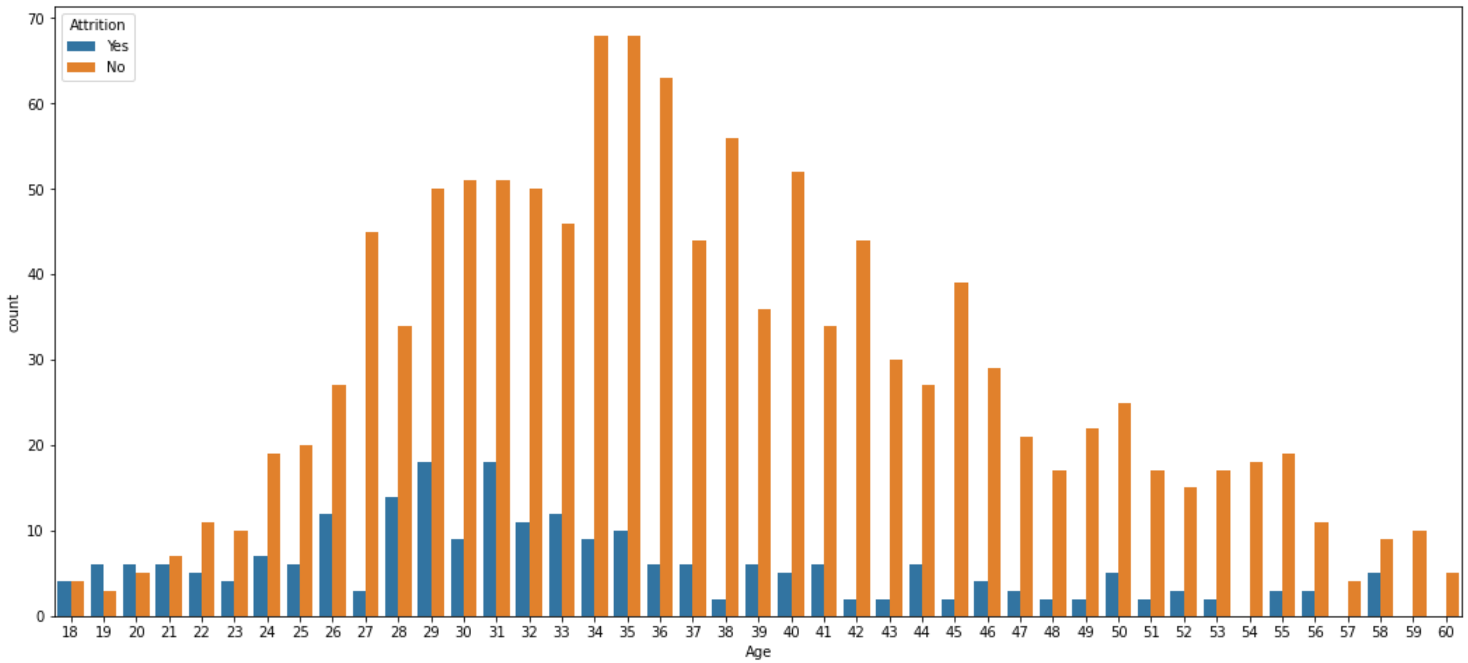
In [58]:

```
mean_age = round(medical_df.groupby('Attrition',as_index=False)['Age'].mean(),1)
mean_age = mean_age.rename(columns={'Age': 'Mean Age'})
mean_age
```

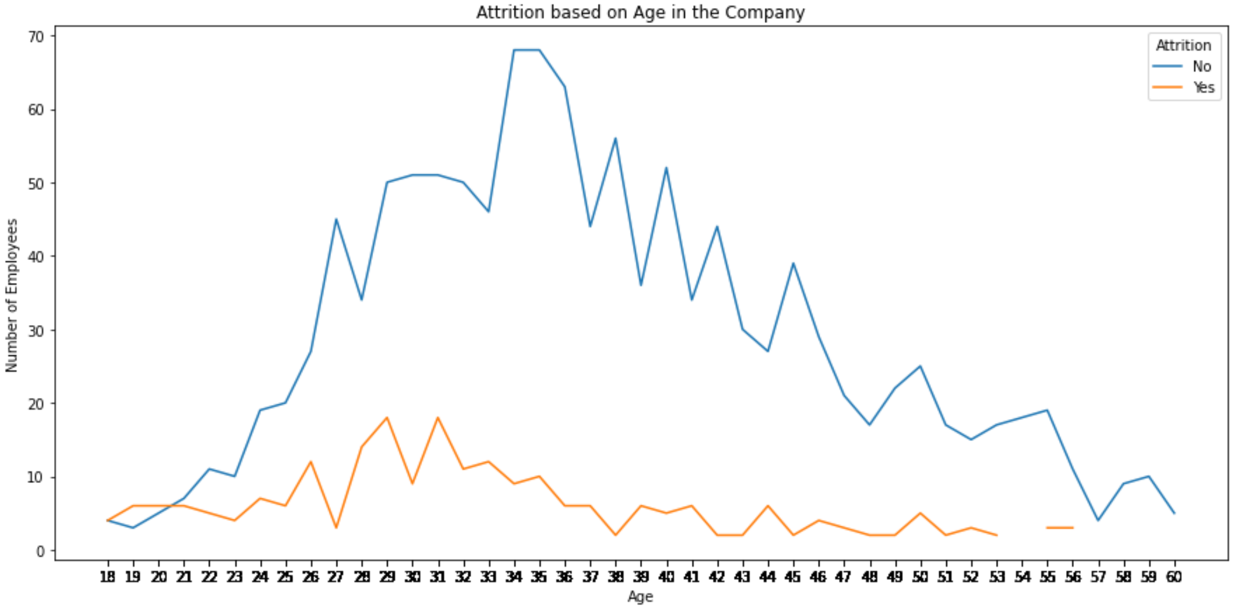
Out[58]:

	Attrition	Mean Age
0	No	37.6
1	Yes	33.6

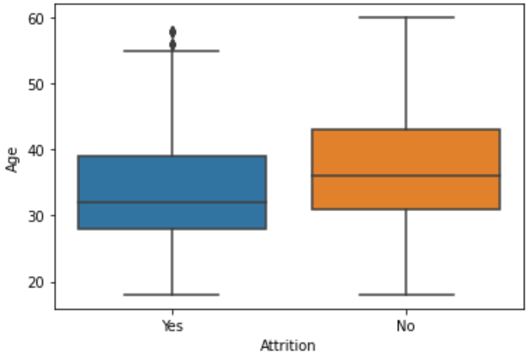
In [59]:
```
fig = plt.figure(figsize=(18,8))
sns.countplot(x='Age',hue = 'Attrition',data = medical_df)
plt.show()
```



In [60]:
```
fig,ax = plt.subplots(figsize=(15,7))
medical_df.groupby(['Age','Attrition']).count()['Gender'].unstack().plot(ax=ax)
ax.set_title('Attrition based on Age in the Company')
# ax.grid()
plt.xticks(medical_df['Age'])
plt.ylabel('Number of Employees')
plt.show()
# the attrition is maximum between the age groups 28-32.
# The attrition rate keeps on falling with increasing age,
# as people look after stability in their jobs at these point of times
```



In [61]:
```
sns.boxplot(x ='Attrition', y ='Age', data = medical_df)
plt.show()
```



In [62]:
```
print(levene(medical_df['Age'][medical_df['Attrition'] == 'Yes'],
       medical_df['Age'][medical_df['Attrition'] == 'No'], center = 'mean'))

print(ttest_ind(medical_df['Age'][medical_df['Attrition'] == 'Yes'],
       medical_df['Age'][medical_df['Attrition'] == 'No']))

# p < 0.05
# Age is significantly affect the attrition rate
# Older people is tend to keep working and stay in the same company
```

```
LeveneResult(statistic=1.1583170677572885, pvalue=0.2819916793250208)
Ttest_indResult(statistic=-6.1786638353072165, pvalue=8.356308021103649e-10)
```

Describe the Attrition based on BusinessTravel. Compute the attrition rate based on BusinessTravel

In [63]:
```
round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['BusinessTravel'],normalize='index'),2)
```

Out[63]:

BusinessTravel	Non-Travel	Travel_Frequently	Travel_Rarely
Attrition			
No	0.11	0.17	0.72
Yes	0.05	0.29	0.66

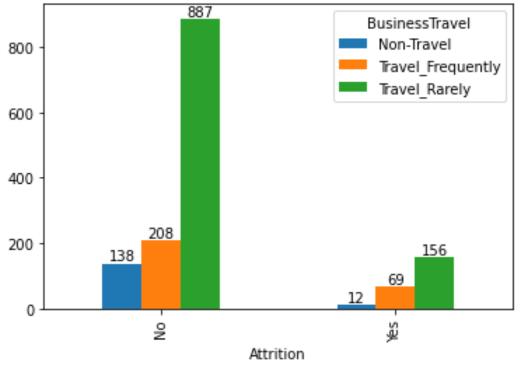
In [64]:
```
travel_raw = round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['BusinessTravel']),2)
travel_raw
```

Out[64]:

BusinessTravel	Non-Travel	Travel_Frequently	Travel_Rarely
Attrition			
No	138	208	887
Yes	12	69	156

In [65]:
```
ax = travel_raw.plot(kind = 'bar')

# annotate
ax.bar_label(ax.containers[0], label_type='edge')
ax.bar_label(ax.containers[1], label_type='edge')
ax.bar_label(ax.containers[2], label_type='edge')
plt.show()
```



In [66]:
```
chi,p,dof,exp = stats.chi2_contingency(travel_raw)
print('the chi square test is {}'.format(p))
# p < 0.05
# BusinessTravel is significantly affect the attrition rate
```

```
the chi square test is 5.608614476449931e-06
```

Describe the Attrition based on Overtime. Compute the attrition rate based on Overtime

In [67]:
```
round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['OverTime'],normalize='index'),2)
```

Out[67]:

OverTime	No	Yes
Attrition		
No	0.77	0.23
Yes	0.46	0.54

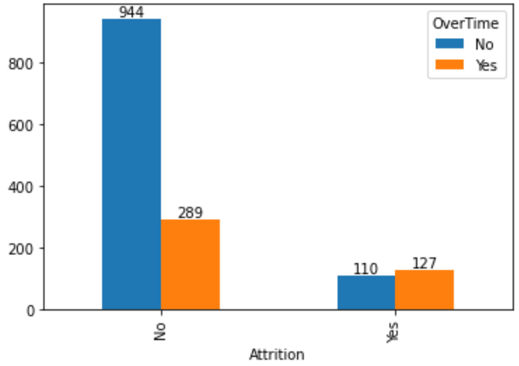
In [68]:
```
over_raw = round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['OverTime']),2)
over_raw
```

Out[68]:

OverTime	No	Yes
Attrition		
No	944	289
Yes	110	127

In [69]:
```
ax = over_raw.plot(kind = 'bar')

# annotate
ax.bar_label(ax.containers[0], label_type='edge')
ax.bar_label(ax.containers[1], label_type='edge')
plt.show()
```



In [70]:
```
chi,p,dof,exp = stats.chi2_contingency(over_raw)
print('the chi square test is {}'.format(p))
# p < 0.05
# OverTime is significantly affect the attrition rate
```

```
the chi square test is 8.158423721538 32e-21
```

In [71]:
```
# marry_raw = round(pd.crosstab(index=medical_df['Attrition'],columns=medical_df['MaritalStatus']),2)
# marry_raw
```

In [72]:
```
# chi,p,dof,exp = stats.chi2_contingency(marry_raw)
# p
```

In [73]:
```
# rearranging the columns
medical_df.columns
```

```
Out[73]: Index(['Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'Bonus',
       'Department', 'DistanceFromHome', 'Education', 'EducationField',
       'EnvSatisfaction', 'Gender', 'JobRole', 'MaritalStatus',
       'PerformanceRating', 'TrainingTimesLastYear', 'YearsAtCompany',
       'YearsSinceLastPromotion', 'OverTime', 'Attrition'],
      dtype='object')
```

```
In [74]: # medical_df = medical_df[['Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'Bonus',
#          'DistanceFromHome','EnvSatisfaction', 'YearsAtCompany',
#         'YearsSinceLastPromotion', 'OverTime', 'Attrition']]

#logistic - overall 0.86  No       0.86  Yes       0.78
# naive - overall 0.82  No       0.87  Yes       0.41

# medical_df = medical_df[['Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'Bonus',
#         'Department', 'DistanceFromHome',
#         'EnvSatisfaction', 'JobRole',
#         'PerformanceRating', 'TrainingTimesLastYear', 'YearsAtCompany',
#         'YearsSinceLastPromotion', 'OverTime', 'Attrition']]
#logistic -  overall 0.86  No       0.86  Yes       0.86
#naive - overall 0.7 No       0.91 Yes       0.29

# medical_df = medical_df[['Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'DistanceFromHome',
#         'EnvSatisfaction','YearsSinceLastPromotion', 'OverTime', 'Attrition']]

#logistic -  overall 0.85   No 0.85         Yes   0.83
#naive - overall 0.84  No 0.86       Yes  0.47

# medical_df = medical_df[['Age', 'MonthlyIncome',
#         'EnvSatisfaction','YearsSinceLastPromotion', 'OverTime', 'Attrition']]

#logistic -  overall 0.85    No  0.85        Yes 0.75
#naive - overall 0.85   No 0.86       Yes  0.57


# medical_df = medical_df[['JobSatisfaction', 'DistanceFromHome','MaritalStatus', 'OverTime', 'BusinessTravel',
#                           'PerformanceRating', 'TrainingTimesLastYear','Attrition']]

#logistic -  overall 0.84    No 0.85         Yes  0.57
#naive - overall 0.80    No 0.85       Yes 0.23

# 'Age', 'BusinessTravel', 'MonthlyIncome', 'JobSatisfaction', 'Bonus',
#         'DistanceFromHome', 'EnvSatisfaction', 'Gender', 'MaritalStatus',
#         'PerformanceRating', 'TrainingTimesLastYear', 'YearsAtCompany',
#         'YearsSinceLastPromotion', 'OverTime', 'Attrition'

# medical_df = medical_df[['JobSatisfaction','Age','OverTime', 'YearsAtCompany',
#                           'EnvSatisfaction','TrainingTimesLastYear','Attrition']]

#logistic -  overall 0.85    No 0.85         Yes  0.62  f1-score no 0.91 yes 0.19
#naive - overall 0.85     No 0.85      Yes 0.62 f1-score no 0.92 yes 0.23

# medical_df = medical_df[['BusinessTravel', 'JobSatisfaction',
#         'DistanceFromHome', 'EnvSatisfaction', 'Gender', 'MaritalStatus',
#         'TrainingTimesLastYear', 'YearsAtCompany',
#         'YearsSinceLastPromotion', 'OverTime', 'Attrition']]

#logistic -  overall 0.85    No 0.86        Yes  0.67  f1-score no 0.92 yes 0.30
#naive - overall 0.80     No 0.86      Yes 0.33 f1-score no 0.88 yes 0.27

medical_df = medical_df[['Age','BusinessTravel', 'JobSatisfaction',
       'DistanceFromHome', 'EnvSatisfaction', 'Gender', 'MaritalStatus',
       'TrainingTimesLastYear', 'YearsAtCompany',
```

```
      'YearsSinceLastPromotion', 'OverTime', 'Attrition']]

#logistic -  overall 0.87    No 0.87        Yes  0.78 f1-score no 0.9 yes 0.38
#naive - overall 0.82      No 0.87      Yes 0.40  f1-score no 0.9  yes 0.32

# medical_df = medical_df[['MonthlyIncome','BusinessTravel', 'JobSatisfaction',
#        'DistanceFromHome', 'EnvSatisfaction', 'Gender', 'MaritalStatus',
#        'TrainingTimesLastYear', 'YearsAtCompany',
#        'YearsSinceLastPromotion', 'OverTime', 'Attrition']]

#logistic -  overall 0.86    No 0.87        Yes  0.75 f1-score no 0.92 yes 0.33
#naive - overall 0.81       No 0.87       Yes 0.39    f1-score no 0.89   yes 0.33

# medical_df = medical_df[['BusinessTravel', 'JobSatisfaction',
#        'DistanceFromHome', 'EnvSatisfaction', 'Gender', 'MaritalStatus',
#        'TrainingTimesLastYear', 'YearsAtCompany',
#        'YearsSinceLastPromotion', 'OverTime', 'Attrition']]


# medical_df = medical_df[['Age', 'BusinessTravel', 'JobSatisfaction',
#        'Department', 'DistanceFromHome', 'Education', 'EducationField',
#        'EnvSatisfaction', 'Gender', 'JobRole', 'MaritalStatus',
#        'TrainingTimesLastYear', 'YearsAtCompany',
#        'YearsSinceLastPromotion', 'OverTime', 'Attrition']]

medical_df
```

Out[74]:

EmployeeID	Age	BusinessTravel	JobSatisfaction	DistanceFromHome	EnvSatisfaction	Gender	MaritalStatus	TrainingTimesLastYear	YearsAtCompany	YearsSinceLastPromotion	OverTime	Attrition
1	41	Travel_Rarely	4	1	2	Female	Single	0	6	0	Yes	Yes
2	49	Travel_Frequently	2	8	3	Male	Married	3	10	1	No	No
4	37	Travel_Rarely	3	2	4	Male	Single	3	0	0	Yes	Yes
5	33	Travel_Frequently	3	3	4	Female	Married	3	8	3	Yes	No
7	27	Travel_Rarely	2	2	1	Male	Married	3	2	2	No	No
...	...	...	...	...	...	...	...	...	...	...	...	...
2061	36	Travel_Frequently	4	23	3	Male	Married	3	5	0	No	No
2062	39	Travel_Rarely	1	6	4	Male	Married	5	7	1	No	No
2064	27	Travel_Rarely	2	4	2	Male	Married	0	6	0	Yes	No
2065	49	Travel_Frequently	2	2	4	Male	Married	3	9	0	No	No
2068	34	Travel_Rarely	3	8	2	Male	Married	3	4	1	No	No

1470 rows × 12 columns

Assigning X and y variable

In [75]:
```
# Assign X and y values for the partitioning
X = medical_df.iloc[:,:-1]
y = medical_df.iloc[:,-1]
```

In [76]:
```
X
```

Out[76]:

	Age	BusinessTravel	JobSatisfaction	DistanceFromHome	EnvSatisfaction	Gender	MaritalStatus	TrainingTimesLastYear	YearsAtCompany	YearsSinceLastPromotion	OverTime
EmployeeID											
1	41	Travel_Rarely	4	1	2	Female	Single	0	6	0	Yes
2	49	Travel_Frequently	2	8	3	Male	Married	3	10	1	No
4	37	Travel_Rarely	3	2	4	Male	Single	3	0	0	Yes
5	33	Travel_Frequently	3	3	4	Female	Married	3	8	3	Yes
7	27	Travel_Rarely	2	2	1	Male	Married	3	2	2	No
...	...	...	...	...	...	...	...	...	...	...	...
2061	36	Travel_Frequently	4	23	3	Male	Married	3	5	0	No
2062	39	Travel_Rarely	1	6	4	Male	Married	5	7	1	No
2064	27	Travel_Rarely	2	4	2	Male	Married	0	6	0	Yes
2065	49	Travel_Frequently	2	2	4	Male	Married	3	9	0	No
2068	34	Travel_Rarely	3	8	2	Male	Married	3	4	1	No

1470 rows × 11 columns

In [77]:

```
y
```

Out[77]:

```
EmployeeID
1       Yes
2        No
4       Yes
5        No
7        No
       ...
2061     No
2062     No
2064     No
2065     No
2068     No
Name: Attrition, Length: 1470, dtype: object
```

Handling Categorical Data

In [78]:

```
# Only transform the input variable
X = pd.get_dummies(X,drop_first=True)
X.head(5)
```

Out[78]:

	Age	JobSatisfaction	DistanceFromHome	EnvSatisfaction	TrainingTimesLastYear	YearsAtCompany	YearsSinceLastPromotion	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Gender_Male	MaritalStatus_
EmployeeID											
1	41	4	1	2	0	6	0	0	1	0	
2	49	2	8	3	3	10	1	1	0	1	
4	37	3	2	4	3	0	0	0	1	1	
5	33	3	3	4	3	8	3	1	0	0	
7	27	2	2	1	3	2	2	0	1	1	

Partitioning

In [79]:
```
# Partitioning the dataset
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,
                                                    random_state=0, stratify = y) # using test size 0.3
```

In [80]:
```
X_train
```

Out[80]:

	Age	JobSatisfaction	DistanceFromHome	EnvSatisfaction	TrainingTimesLastYear	YearsAtCompany	YearsSinceLastPromotion	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Gender_Male	MaritalStatus_
EmployeeID											
1523	44	1	28	4	1	20	14	0	1	1	
1212	40	2	2	2	2	0	0	1	0	1	
110	34	2	1	1	2	5	1	0	1	1	
615	40	1	28	3	2	1	0	0	0	1	
1161	37	4	25	3	2	6	1	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	
1061	50	3	2	2	2	8	7	0	1	1	
527	25	4	4	2	3	5	1	0	1	0	
602	39	3	8	3	3	8	0	1	0	0	
807	40	2	2	3	2	8	3	1	0	0	
689	37	3	3	3	2	10	7	0	1	1	

1029 rows × 13 columns

In [81]:
```
print(len(X_train),len(X_test))
```

```
1029 441
```

In [82]:
```
X_train
```

Out[82]:

	Age	JobSatisfaction	DistanceFromHome	EnvSatisfaction	TrainingTimesLastYear	YearsAtCompany	YearsSinceLastPromotion	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Gender_Male	MaritalStatus_
EmployeeID											
1523	44	1	28	4	1	20	14	0	1	1	
1212	40	2	2	2	2	0	0	1	0	1	
110	34	2	1	1	2	5	1	0	1	1	
615	40	1	28	3	2	1	0	0	0	1	
1161	37	4	25	3	2	6	1	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	
1061	50	3	2	2	2	8	7	0	1	1	
527	25	4	4	2	3	5	1	0	1	0	
602	39	3	8	3	3	8	0	1	0	0	
807	40	2	2	3	2	8	3	1	0	0	
689	37	3	3	3	2	10	7	0	1	1	

1029 rows × 13 columns

In [83]:
```
y_train
```

Out[83]:
```
EmployeeID
1523    No
1212    No
110     No
615     No
1161    No
        ..
1061    No
527     No
602     No
807     No
689     No
Name: Attrition, Length: 1029, dtype: object
```

Scaling the Data or perform Normalization

In [84]:
```
#Scaling the data
from sklearn.preprocessing import StandardScaler # Zscore normalization

scaler = StandardScaler()
scaler.fit(X_train) # compute the scalar model
X_train = scaler.transform(X_train) # here it will transform the X train into standard data
```

In [85]:
```
X_train
```

Out[85]:
```
array([[ 0.75909679, -1.54871647,  2.3244173 , ...,  1.09485978,
        -0.68097495, -0.63245553],
       [ 0.32796082, -0.64118273, -0.88376782, ...,  1.09485978,
        -0.68097495, -0.63245553],
       [-0.31874314, -0.64118273, -1.00715956, ...,  1.09485978,
        -0.68097495, -0.63245553],
       ...,
       [ 0.22017682,  0.26635101, -0.14341741, ...,  1.09485978,
        -0.68097495, -0.63245553],
       [ 0.32796082, -0.64118273, -0.88376782, ...,  1.09485978,
        -0.68097495, -0.63245553],
       [ 0.00460884,  0.26635101, -0.76037609, ...,  1.09485978,
        -0.68097495, -0.63245553]])
```

In [86]:
```
# x_train_copy = pd.DataFrame(X_train)
# x_train_copy
```

Train the Model using Logistic Regression

In [87]:
```
#Train Logistic Regression Algorithm

#Import LogisticRegression() function
from sklearn.linear_model import LogisticRegression

#Create a Logistic Regression classifier
# random state is 0 because to maintain the data generated value
medical_model = LogisticRegression(random_state=0)

#Train the Logistic Regression algorithm using train set
medical_model.fit(X_train,y_train)
```

Out[87]:
```
▾ LogisticRegression
LogisticRegression(random_state=0)
```

Train the Model using Naive Beyes Thereom

In [88]:
```
# # #Train Naive Beyes Thereom Algorithm
# from sklearn.naive_bayes import GaussianNB

# medical_model = GaussianNB()

# medical_model.fit(X_train,y_train)
```

Apply the model to test set

In [89]:
```
# Apply the model with the test set
#Feature Scaling the Test Set
from sklearn.preprocessing import StandardScaler
X_test = scaler.transform(X_test)
X_test
```

Out[89]:
```
array([[-0.9654471 ,  1.17388475, -0.51359262, ..., -0.91335896,
         1.46848279, -0.63245553],
       [ 0.5435288 , -1.54871647,  0.10336606, ...,  1.09485978,
        -0.68097495, -0.63245553],
       [ 2.48364067,  1.17388475, -0.26680915, ..., -0.91335896,
        -0.68097495,  1.58113883],
       ...,
       [-1.39658307,  0.26635101,  0.10336606, ..., -0.91335896,
        -0.68097495,  1.58113883],
       [ 0.5435288 ,  1.17388475,  1.70745862, ..., -0.91335896,
         1.46848279, -0.63245553],
       [-0.8576631 , -1.54871647, -1.00715956, ...,  1.09485978,
        -0.68097495, -0.63245553]])
```

In [90]:
```
# Apply for Test Set
y_pred=medical_model.predict(X_test)
y_pred
```

Out[90]:
```
array(['No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No',
       'No', 'No'], dtype=object)
```

In [91]:
```
#Dataframe of Predicted Output and Actual Output for Test set
df_validate = pd.DataFrame({'Actual':y_test,'Predicted':y_pred})
```

```
df_validate['Predicted']=df_validate['Predicted']
df_validate.head(5)
```

Out[91]:

	Actual	Predicted
EmployeeID		
916	No	No
1408	No	No
1233	No	No
1640	No	No
1133	No	No

Performance Evaluation

In [92]:
```
# use crosstab to evaluate the categorical
pd.crosstab(y_pred,y_test)
```

Out[92]:

Attrition	No	Yes
row_0		
No	365	53
Yes	5	18

Precision & Sensitivity/Recall Report

- Logistic Regression

In [93]:
```
# Precision & Sensitivity/Recall Report
from sklearn.metrics import classification_report
print(classification_report(y_true=y_test,y_pred=y_pred))
```

```
              precision    recall  f1-score   support

          No       0.87      0.99      0.93       370
         Yes       0.78      0.25      0.38        71

    accuracy                           0.87       441
   macro avg       0.83      0.62      0.65       441
weighted avg       0.86      0.87      0.84       441
```

  - using Age -

Precision & Sensitivity/Recall Report

In [143]:
```
# Precision & Sensitivity/Recall Report
from sklearn.metrics import classification_report
print(classification_report(y_true=y_test,y_pred=y_pred))
```

```
              precision    recall  f1-score   support

          No       0.87      0.99      0.92       370
         Yes       0.75      0.21      0.33        71

    accuracy                           0.86       441
   macro avg       0.81      0.60      0.63       441
weighted avg       0.85      0.86      0.83       441
```

- using Monthly Income -

In [89]:
```
# Precision & Sensitivity/Recall Report
from sklearn.metrics import classification_report
print(classification_report(y_true=y_test,y_pred=y_pred))
```

```
              precision    recall  f1-score   support

          No       0.86      0.98      0.92       370
         Yes       0.67      0.20      0.30        71

    accuracy                           0.85       441
   macro avg       0.77      0.59      0.61       441
weighted avg       0.83      0.85      0.82       441
```

- using Non Monthly Income and Age -

* Naive Beyes

In [89]:
```
# Precision & Sensitivity/Recall Report
from sklearn.metrics import classification_report
print(classification_report(y_true=y_test,y_pred=y_pred))
```

```
              precision    recall  f1-score   support

          No       0.87      0.92      0.90       370
         Yes       0.40      0.27      0.32        71

    accuracy                           0.82       441
   macro avg       0.64      0.60      0.61       441
weighted avg       0.79      0.82      0.80       441
```

- using Age -

In [93]:
```
# Precision & Sensitivity/Recall Report
from sklearn.metrics import classification_report
print(classification_report(y_true=y_test,y_pred=y_pred))
```

```
              precision    recall  f1-score   support

          No       0.87      0.99      0.93       370
         Yes       0.78      0.25      0.38        71

    accuracy                           0.87       441
   macro avg       0.83      0.62      0.65       441
weighted avg       0.86      0.87      0.84       441
```

In [ ]: