

## ▼ Import required packages

The dataset was created by IBM employees and was downloaded from Kaggle. The dataset is fiction actually represent any actual IBM employees.

Attrition: It is basically the turnover rate of employees inside an organization.

This can happen for many reasons:

Employees looking for better opportunities. A negative working environment. Bad management Sickr death) Excessive working hours

The objective is to see what influences the attrition

It starts from framing business question t

## ▼ 1. Import required packages

```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
↳ /usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
import pandas.util.testing as tm
```

## ▼ 2. Data Extracting

load the dataset and have clear understanding of the dataset attributes

```
#reading CSV file
df = pd.read_csv('emp_attrition.csv')
```

```
#getting the first rows
```



```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Age                                   1470 non-null   int64
1   Attrition                           1470 non-null   object
2   BusinessTravel                      1470 non-null   object
3   DailyRate                           1470 non-null   int64
4   Department                          1470 non-null   object
5   DistanceFromHome                    1470 non-null   int64
6   Education                           1470 non-null   int64
7   EducationField                      1470 non-null   object
8   EmployeeCount                       1470 non-null   int64
9   EmployeeNumber                      1470 non-null   int64
10  EnvironmentSatisfaction              1470 non-null   int64
11  Gender                              1470 non-null   object
12  HourlyRate                          1470 non-null   int64
13  JobInvolvement                      1470 non-null   int64
14  JobLevel                            1470 non-null   int64
15  JobRole                             1470 non-null   object
16  JobSatisfaction                     1470 non-null   int64
17  MaritalStatus                       1470 non-null   object
18  MonthlyIncome                      1470 non-null   int64
19  MonthlyRate                         1470 non-null   int64
20  NumCompaniesWorked                  1470 non-null   int64
21  Over18                             1470 non-null   object
22  OverTime                           1470 non-null   object
23  PercentSalaryHike                   1470 non-null   int64
24  PerformanceRating                   1470 non-null   int64
25  RelationshipSatisfaction             1470 non-null   int64
26  StandardHours                       1470 non-null   int64
27  StockOptionLevel                    1470 non-null   int64
28  TotalWorkingYears                   1470 non-null   int64
29  TrainingTimesLastYear               1470 non-null   int64
30  WorkLifeBalance                     1470 non-null   int64
31  YearsAtCompany                      1470 non-null   int64
32  YearsInCurrentRole                  1470 non-null   int64
33  YearsSinceLastPromotion              1470 non-null   int64
34  YearsWithCurrManager                 1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
None

```

```

#getting the unique values
print('\nUnique values:')
print(df.nunique())
for col in df.columns:
    print(col, ': ', sorted(df[col].unique()))

```





```

MonthlyRate : [2094, 2097, 2104, 2112, 2122, 2125, 2137, 2227, 2243, 2253, 2261, 2288, 2
NumCompaniesWorked : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
Over18 : ['Y']
OverTime : ['No', 'Yes']
PercentSalaryHike : [11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25]
PerformanceRating : [3, 4]
RelationshipSatisfaction : [1, 2, 3, 4]
StandardHours : [80]
StockOptionLevel : [0, 1, 2, 3]
TotalWorkingYears : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 1
TrainingTimesLastYear : [0, 1, 2, 3, 4, 5, 6]
WorkLifeBalance : [1, 2, 3, 4]
YearsAtCompany : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
YearsInCurrentRole : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18]
YearsSinceLastPromotion : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]
YearsWithCurrManager : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17]

```

\* As we can see “Over18”, “Standard Hours” and “Employee Count” contain the same value which we do not need them in visualizing the dataset

## 2.Data Preparation

### ▾ 2.1 Data Cleaning

find missing data, remove data that will not assist with the visualization in analysis processing

```
df.isnull().sum()
```




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

dtype: int64

```
df.count()
```

```
↳ Age 1470
Attrition 1470
BusinessTravel 1470
DailyRate 1470
Department 1470
DistanceFromHome 1470
Education 1470
EducationField 1470
EmployeeCount 1470
EmployeeNumber 1470
EnvironmentSatisfaction 1470
Gender 1470
HourlyRate 1470
JobInvolvement 1470
JobLevel 1470
JobRole 1470
JobSatisfaction 1470
MaritalStatus 1470
MonthlyIncome 1470
MonthlyRate 1470
NumCompaniesWorked 1470
Over18 1470
OverTime 1470
PercentSalaryHike 1470
PerformanceRating 1470
RelationshipSatisfaction 1470
StandardHours 1470
StockOptionLevel 1470
TotalWorkingYears 1470
TrainingTimesLastYear 1470
WorkLifeBalance 1470
YearsAtCompany 1470
YearsInCurrentRole 1470
YearsSinceLastPromotion 1470
YearsWithCurrManager 1470
dtype: int64
```

```
df.isnull().sum().any()
```

 False

\* This result shows if we have any missing values we used different codes. And as we can see, we have some missing values. Otherwise, we would have done some techniques, like dropping columns or rows, or filling missing values by the mean, backward, or forward values.

## ▼ 2.2 Remove unsupported columns

```
#drop unwanted columns
```

```
df = df.drop(['Over18', 'StandardHours', 'EmployeeCount'], axis=1)
```

```
df.info()
```





```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
```

\* Since "Over18", "Standard Hours" and "Employee Count" has a static variable, we remove of processing the dataframe.

## 2.3 Mapping data

```
6 Education 1470 non-null int64
df.dtypes
```

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

```
df['Attrition'].unique()
```

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

```
#Education map
Attrition_map = {"Yes" : 1, "No": 0}
print(Attrition_map)
df['Attrition']=df['Attrition'].map(Attrition_map)

Education_map = {1:"Below College", 2 : 'College' ,3 : 'Bachelor' , 4 : 'Master', 5 : 'Doctor'
df['Education'] = df['Education'].map(Education_map)

EnvironmentSatisfaction_map = {1 : "Low", 2: "Medium", 3: "High", 4: "Very High"}
df["EnvironmentSatisfaction"] = df["EnvironmentSatisfaction"].map(EnvironmentSatisfaction_map)

JobInvolvement_map = {1 : "Low", 2: "Medium", 3: "High", 4: "Very High"}
df["JobInvolvement"] = df["JobInvolvement"].map(JobInvolvement_map)

JobSatisfaction_map = {1 : "Low", 2: "Medium", 3: "High", 4: "Very High"}
df["JobSatisfaction"] = df["JobSatisfaction"].map(JobSatisfaction_map)

PerformanceRating_map = {1 : "Low", 2: "Medium", 3: "High", 4: "Outstanding"}
df["PerformanceRating"] = df["PerformanceRating"].map(PerformanceRating_map)

RelationshipSatisfaction_map = {1 : "Low", 2: "Medium", 3: "High", 4: "Outstanding"}
df["RelationshipSatisfaction"] = df["RelationshipSatisfaction"].map(RelationshipSatisfaction_map)

WorkLifeBalance_map = {1 : "Low", 2: "Medium", 3: "High", 4: "Outstanding"}
df["WorkLifeBalance"] = df["WorkLifeBalance"].map(WorkLifeBalance_map)
```

```
↳ {'Yes': 1, 'No': 0}
```

```
df['Attrition'].unique()
```

```
↳ array([1, 0])
```

## ▼ 2.4 Grouping / Binning Ages

```
df["Age"].describe()
```

```
↳
```

```

count    1470.000000
mean      36.923810

age_labels = ['18-24', '25-30', '31-35', '36-40', '41-45', '46-50', '51-55', '56-60']
df['age_group'] = pd.cut(df.Age, range(18, 61, 5), right=False, labels=age_labels)

50%      36.000000
df.head(3)

```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education
0	41	1	Travel_Rarely	1102	Sales	1	College
1	49	0	Travel_Frequently	279	Research & Development	8	Below College
2	37	1	Travel_Rarely	1373	Research & Development	2	College

### 3. Exploring statistics on the dataset

#### ▼ 3.1 Descriptive statistic

```
df.describe()
```

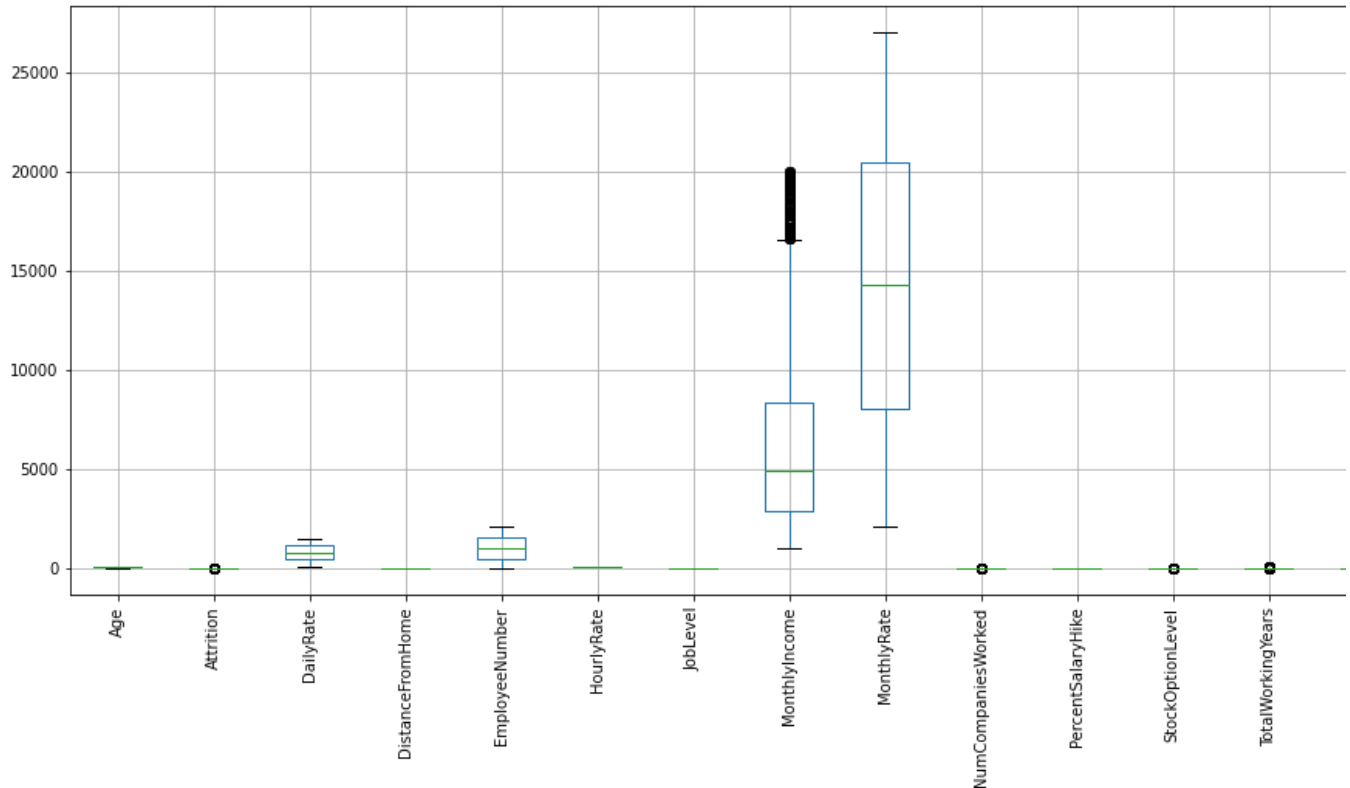
```
↳
```

Age   Attrition   DailyRate   DistanceFromHome   EmployeeNumber   HourlyRate

### ▼ 3.2 Visualizing these statistics using boxplots

```
plt.rcParams["figure.figsize"] = (20,7)
df.boxplot()
plt.xticks(rotation=90)
```

```
↳ (array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
        18]), <a list of 18 Text major ticklabel objects>)
```



```
df["Attrition"].replace("Yes", 1, inplace = True)
df["Attrition"].replace("No", 0, inplace = True)
```

```
df
```

```
↳
```

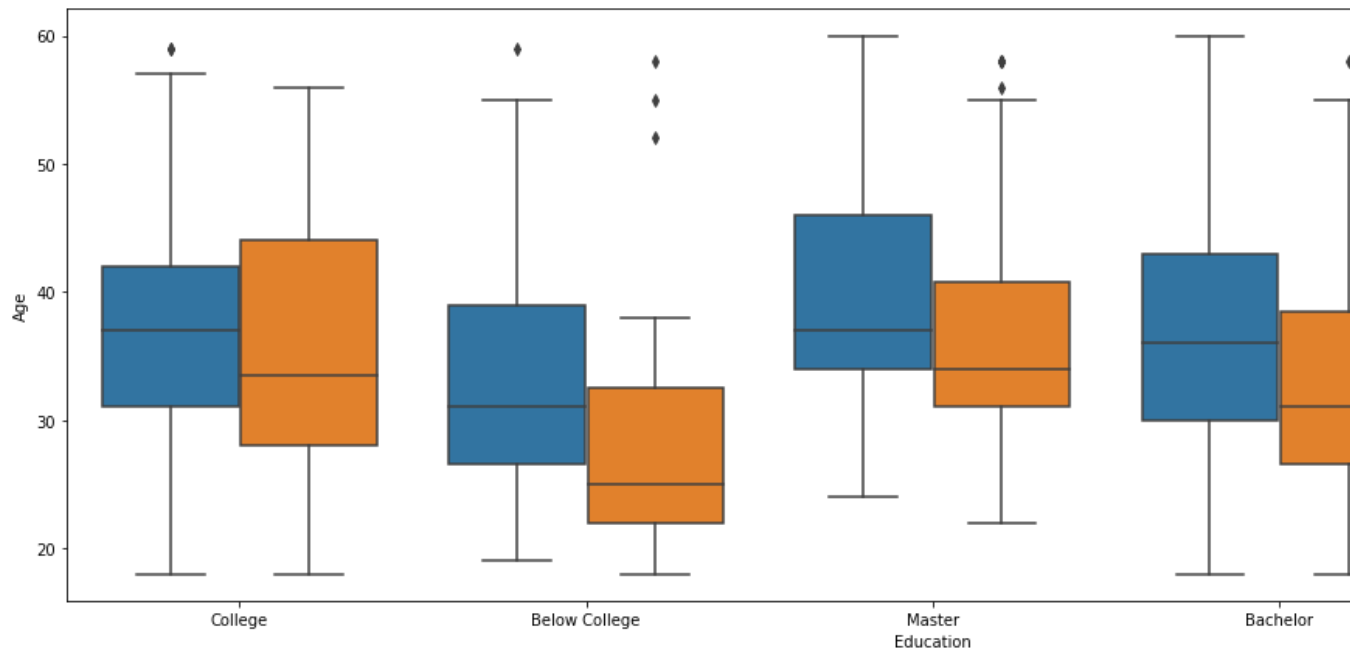
	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Educational
<b>0</b>	41	1	Travel_Rarely	1102	Sales	1	College
<b>1</b>	49	0	Travel_Frequently	279	Research & Development	8	Bel College
<b>2</b>	37	1	Travel_Rarely	1373	Research & Development	2	College
<b>3</b>	33	0	Travel_Frequently	1392	Research & Development	3	Mas
<b>4</b>	27	0	Travel_Rarely	591	Research & Development	2	Bel College
...	...	...	...	...	...	...	
<b>1465</b>	36	0	Travel_Frequently	884	Research & Development	23	College
<b>1466</b>	39	0	Travel_Rarely	613	Research & Development	6	Bel College
<b>1467</b>	27	0	Travel_Rarely	155	Research & Development	4	Bachelor
<b>1468</b>	49	0	Travel_Frequently	1023	Sales	2	Bachelor
<b>1469</b>	34	0	Travel_Rarely	628	Research & Development	8	Bachelor

1470 rows × 33 columns

```
sns.boxplot(x=df['Education'],y=df['Age'],data=df, hue=df["Attrition"])
```



&lt;matplotlib.axes.\_subplots.AxesSubplot at 0x7fe556e09438&gt;



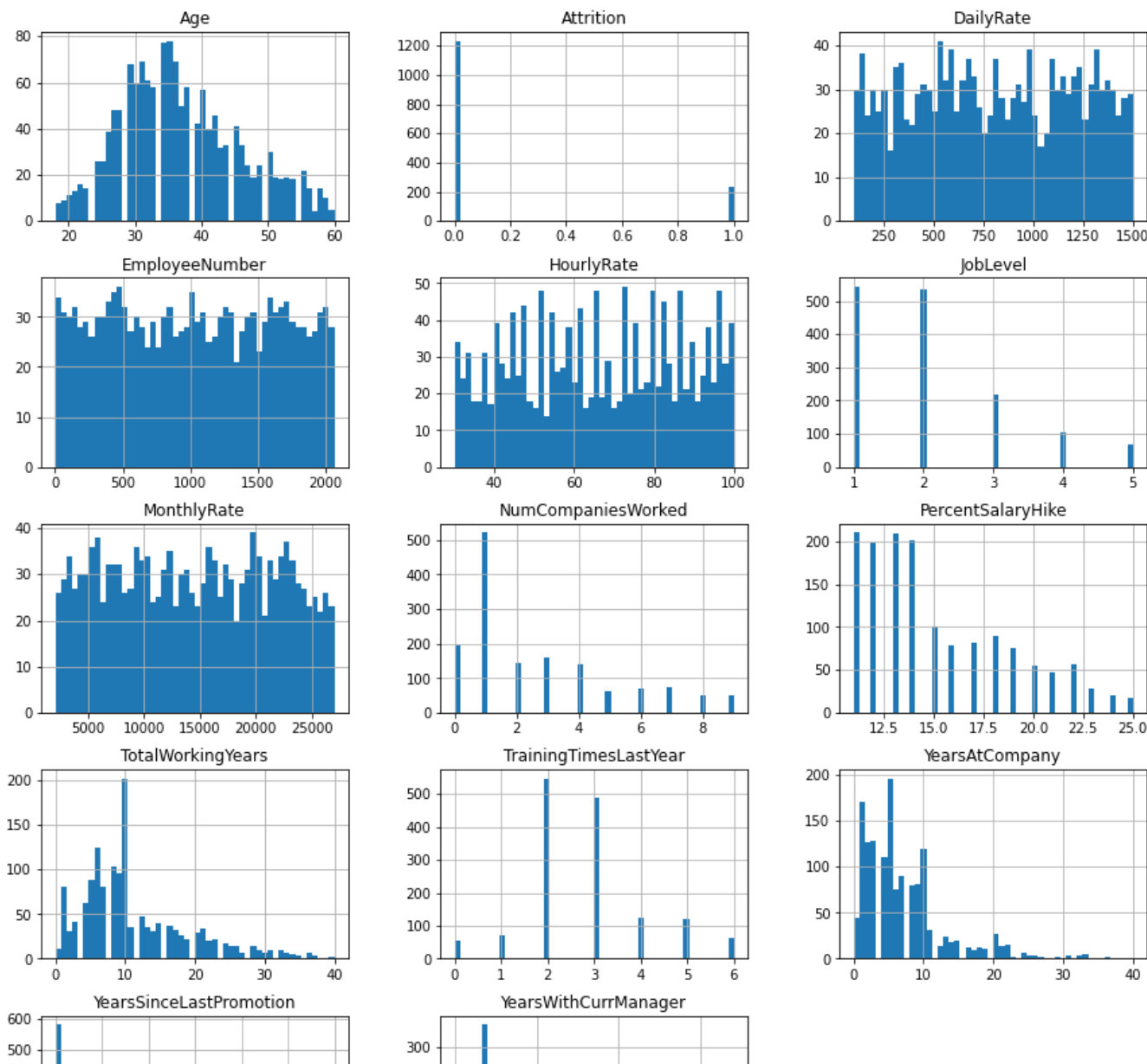
\* It can be observed that the value ranges of columns (**MonthlyIncome**, **MonthlyRate**, **Emp**) are significantly higher than the remaining numeric columns. This can be corrected using normalization.

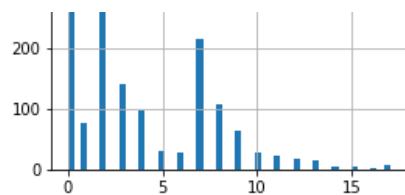
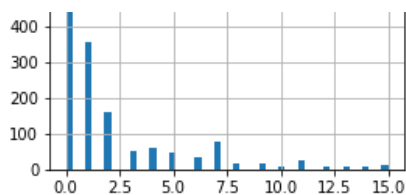
## Visualizing the value distribution for each numeric column in the dataset

```
df.hist(bins=50,figsize=(20,16))
```



```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fe5567b0080>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5567d49b0>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe556787c18>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe55673ee80>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x7fe5566fd128>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5566b4390>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5566645f8>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe556696c88>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x7fe556696cf8>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe556608400>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5565b8780>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe55656ab00>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x7fe55651ce80>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5564de240>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe55650c5c0>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5564bf940>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x7fe556471cc0>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe556431080>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe5563e4400>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x7fe556417780>]],
      dtype=object)
```





## 4. Visualizing the value distributions for the individual variable and exp

### ▼ 4.1 Attrition Rate

```
df.groupby(["Attrition"]).count()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Ed
Attrition							
0	1233	1233	1233	1233	1233	1233	
1	237	237	237	237	237	237	

```
df["Attrition"].value_counts()
```

```
0    1233
1     237
Name: Attrition, dtype: int64
```

```
emp_attrition = df[df["Attrition"] == 1]
emp_attrition = emp_attrition["Attrition"].count()
print ("The total number of employee who suffer from attrition are :", emp_attrition)
```

```
↳ The total number of employee who suffer from attrition are : 237
```

```
emp_no_attrition = df[df["Attrition"] == 0]
emp_no_attrition = emp_no_attrition["Attrition"].count()
print ("The total number of employee who is not suffer from attritionis :", emp_no_attriti
```

```
↳ The total number of employee who is not suffer from attritionis : 1233
```

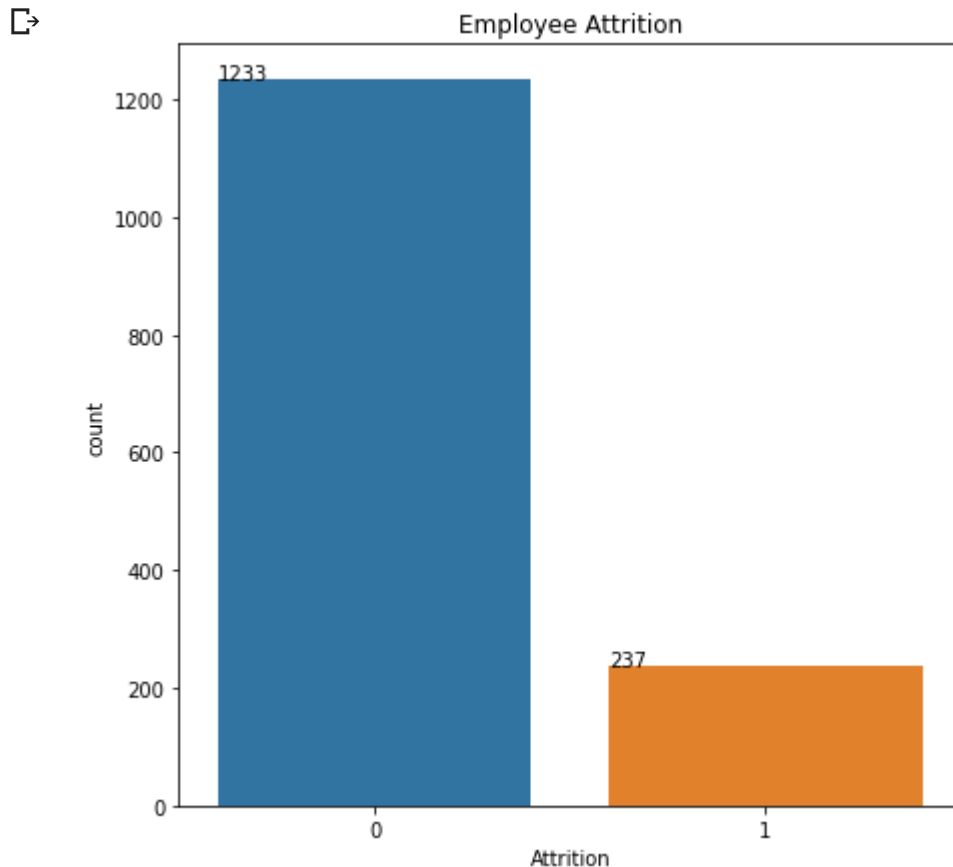
```
# Show the percentage of each unique class label in the target Attrition column
df['Attrition'].value_counts()/len(df['Attrition'])*100
```

```
0    83.877551
1    16.122449
Name: Attrition, dtype: float64
```



```
#Visualize the result
plt.rcParams["figure.figsize"] = (7,7)
ax = sns.countplot(x='Attrition', data=df)
for p in ax.patches:
    ax.annotate('{}' .format(p.get_height()), (p.get_x(), p.get_height()+1))

plt.title("Employee Attrition")
plt.show()
```



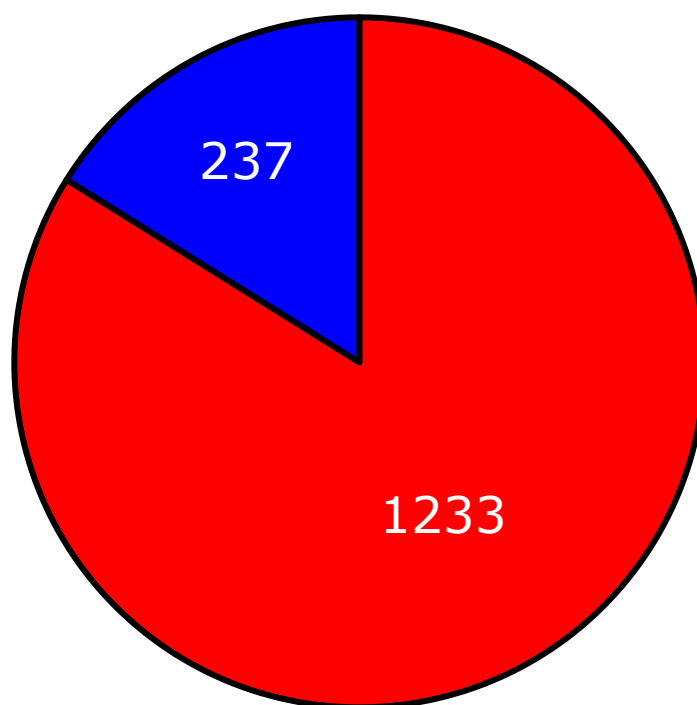
\* The previous percentages show that almost 84% of the employees included in the dataset have attrited. Also, it can be observed that the data is imbalanced between the two class labels (for 'Yes') of the 'Attrition' target column. Thus, there is a need to balance the sampling ratio of a classifier algorithm.

```
#using interactive graph
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
groups = df["Attrition"]
amount = df["Attrition"].value_counts()
colors = ['red', 'blue']
trace = go.Pie(labels=["No", "Yes"], values=amount,
    hoverinfo='label+percent', textinfo='value',
    textfont=dict(size=25),
    marker=dict(colors=colors,
```

```
line=dict(color='#000000', width=3)))
```

```
# print ("it should be the obeset??")
```

```
ipplot([trace])
```



## ▼ 4.2 Finding correlation between variables

```
data_correlation = df.corr()
```

```
plt.rcParams["figure.figsize"] = [20,10]
```

```
sns.heatmap(data_correlation,xticklabels=data_correlation.columns,yticklabels=data_correlat
```

```
print("How can we justify the numbers with boxes?")
```



How can we justify the numbers with boxes?

Age	1	-0.16	0.011	-0.0017	-0.01	0.024	0.51	0.5	0.028	0.3	0.0036	0.038	0.68	-0.02	0
Attrition	-0.16	1	-0.057	0.078	-0.011	-0.0068	-0.17	-0.16	0.015	0.043	-0.013	-0.14	-0.17	-0.059	-0
DailyRate	0.011	-0.057	1	-0.005	-0.051	0.023	0.003	0.0077	-0.032	0.038	0.023	0.042	0.015	0.0025	-0
DistanceFromHome	-0.0017	0.078	-0.005	1	0.033	0.031	0.0053	-0.017	0.027	-0.029	0.04	0.045	0.0046	-0.037	0.0
EmployeeNumber	-0.01	-0.011	-0.051	0.033	1	0.035	-0.019	-0.015	0.013	-0.0013	-0.013	0.062	-0.014	0.024	-0
HourlyRate	0.024	-0.0068	0.023	0.031	0.035	1	-0.028	-0.016	-0.015	0.022	-0.0091	0.05	-0.0023	-0.0085	-0
JobLevel	0.51	-0.17	0.003	0.0053	-0.019	-0.028	1	0.95	0.04	0.14	-0.035	0.014	0.78	-0.018	0
MonthlyIncome	0.5	-0.16	0.0077	-0.017	-0.015	-0.016	0.95	1	0.035	0.15	-0.027	0.0054	0.77	-0.022	0
MonthlyRate	0.028	0.015	-0.032	0.027	0.013	-0.015	0.04	0.035	1	0.018	-0.0064	-0.034	0.026	0.0015	-0
NumCompaniesWorked	0.3	0.043	0.038	-0.029	-0.0013	0.022	0.14	0.15	0.018	1	-0.01	0.03	0.24	-0.066	-0
PercentSalaryHike	0.0036	-0.013	0.023	0.04	-0.013	-0.0091	-0.035	-0.027	-0.0064	-0.01	1	0.0075	-0.021	-0.0052	-0
StockOptionLevel	0.038	-0.14	0.042	0.045	0.062	0.05	0.014	0.0054	-0.034	0.03	0.0075	1	0.01	0.011	0
TotalWorkingYears	0.68	-0.17	0.015	0.0046	-0.014	-0.0023	0.78	0.77	0.026	0.24	-0.021	0.01	1	-0.036	0
TrainingTimesLastYear	-0.02	-0.059	0.0025	-0.037	0.024	-0.0085	-0.018	-0.022	0.0015	-0.066	-0.0052	0.011	-0.036	1	0.0
YearsAtCompany	0.31	-0.13	-0.034	0.0095	-0.011	-0.02	0.53	0.51	-0.024	-0.12	-0.036	0.015	0.63	0.0036	0
YearsInCurrentRole	0.21	-0.16	0.0099	0.019	-0.0084	-0.024	0.39	0.36	-0.013	-0.091	-0.0015	0.051	0.46	-0.0057	0
YearsSinceLastPromotion	0.22	-0.033	-0.033	0.01	-0.009	-0.027	0.35	0.34	0.0016	-0.037	-0.022	0.014	0.4	-0.0021	0
YearsWithCurrManager	0.2	-0.16	-0.026	0.014	-0.0092	-0.02	0.38	0.34	-0.037	-0.11	-0.012	0.025	0.46	-0.0041	0
	Age	Attrition	DailyRate	DistanceFromHome	EmployeeNumber	HourlyRate	JobLevel	MonthlyIncome	MonthlyRate	NumCompaniesWorked	PercentSalaryHike	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	

The correlation analysis shows interesting findings. First, there is a high positive correlation between the "JobLevel" and "MonthlyIncome", which reflects a sort of fairness in promoting and paying people based on their experience level. Second, there was a high positive correlation between "PerformanceRating" and "MonthlyIncome", which again confirms that the increase in salary is based on the increase in the performance level. The "Attrition" column does not have any correlation with the remainder of the numeric columns, which is somehow reasonable to have it increased with the increase in "MonthlyIncome" or "JobLevel" columns.

## ► Normalizing the dataset

before we go in deep in visualize the dataset, it is better to normalize it to avoid differnt variance

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

```
standard=df.copy()
```

```
val=standard.select_dtypes("int64")
```

```
col_names=list(val.columns)
```

```
features = val[col_names]
```

```
scaler = StandardScaler().fit(features.values)
```

```
features = scaler.transform(features.values)
```

```
standard[col_names] = features
```

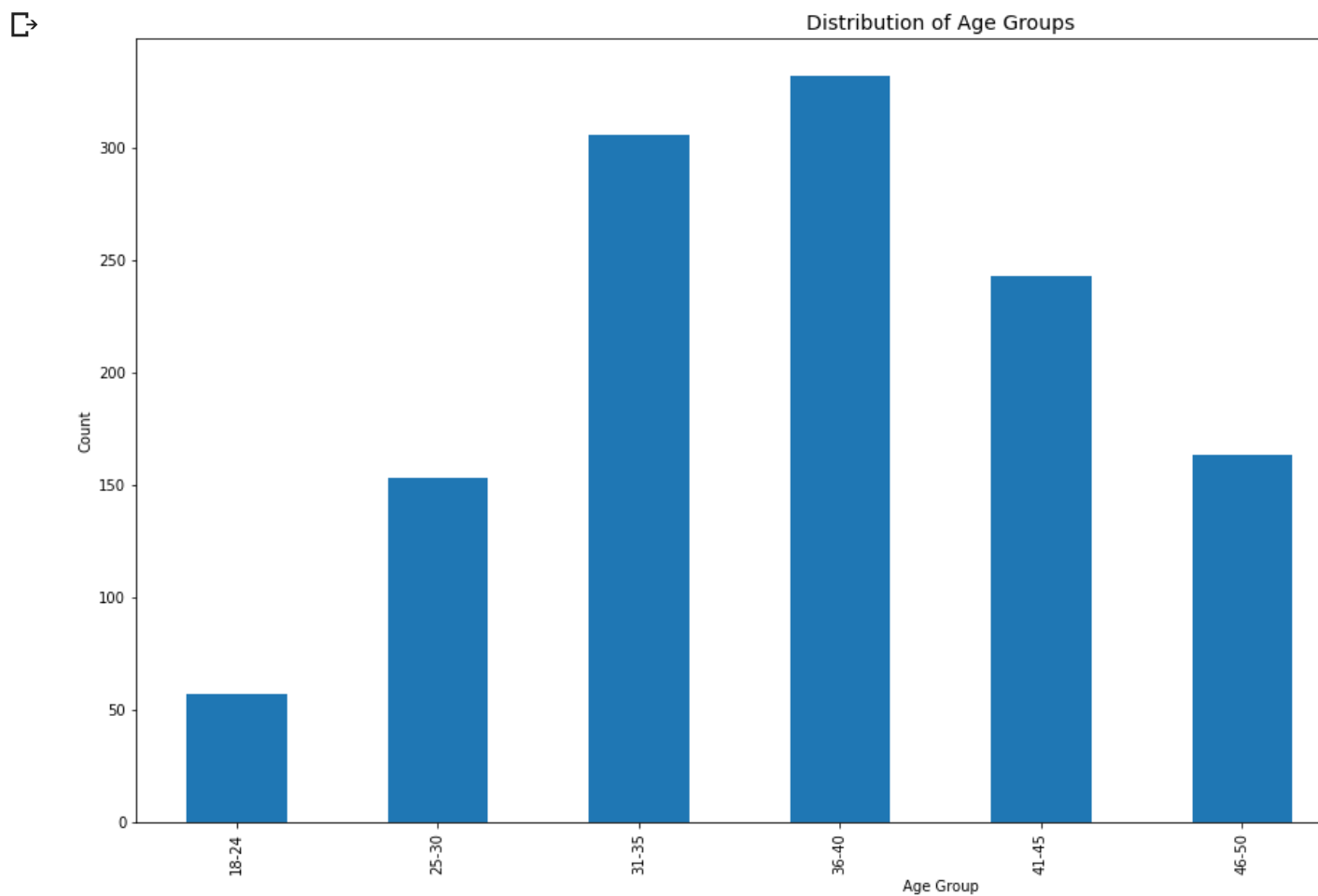
```
standard
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Ec
<b>0</b>	0.446350	2.280906	Travel_Rarely	0.742527	Sales	-1.010909	
<b>1</b>	1.322365	-0.438422	Travel_Frequently	-1.297775	Research & Development	-0.147150	
<b>2</b>	0.008343	2.280906	Travel_Rarely	1.414363	Research & Development	-0.887515	
<b>3</b>	-0.429664	-0.438422	Travel_Frequently	1.461466	Research & Development	-0.764121	
<b>4</b>	-1.086676	-0.438422	Travel_Rarely	-0.524295	Research & Development	-0.887515	
...	...	...	...	...	...	...	
<b>1465</b>	-0.101159	-0.438422	Travel_Frequently	0.202082	Research & Development	1.703764	
<b>1466</b>	0.227347	-0.438422	Travel_Rarely	-0.469754	Research & Development	-0.393938	
<b>1467</b>	-1.086676	-0.438422	Travel_Rarely	-1.605183	Research & Development	-0.640727	
<b>1468</b>	1.322365	-0.438422	Travel_Frequently	0.546677	Sales	-0.887515	
<b>1469</b>	-0.320163	-0.438422	Travel_Rarely	-0.432568	Research & Development	-0.147150	

1470 rows × 33 columns

## ▼ 4.2 Relationship of Age Variable with Attrition

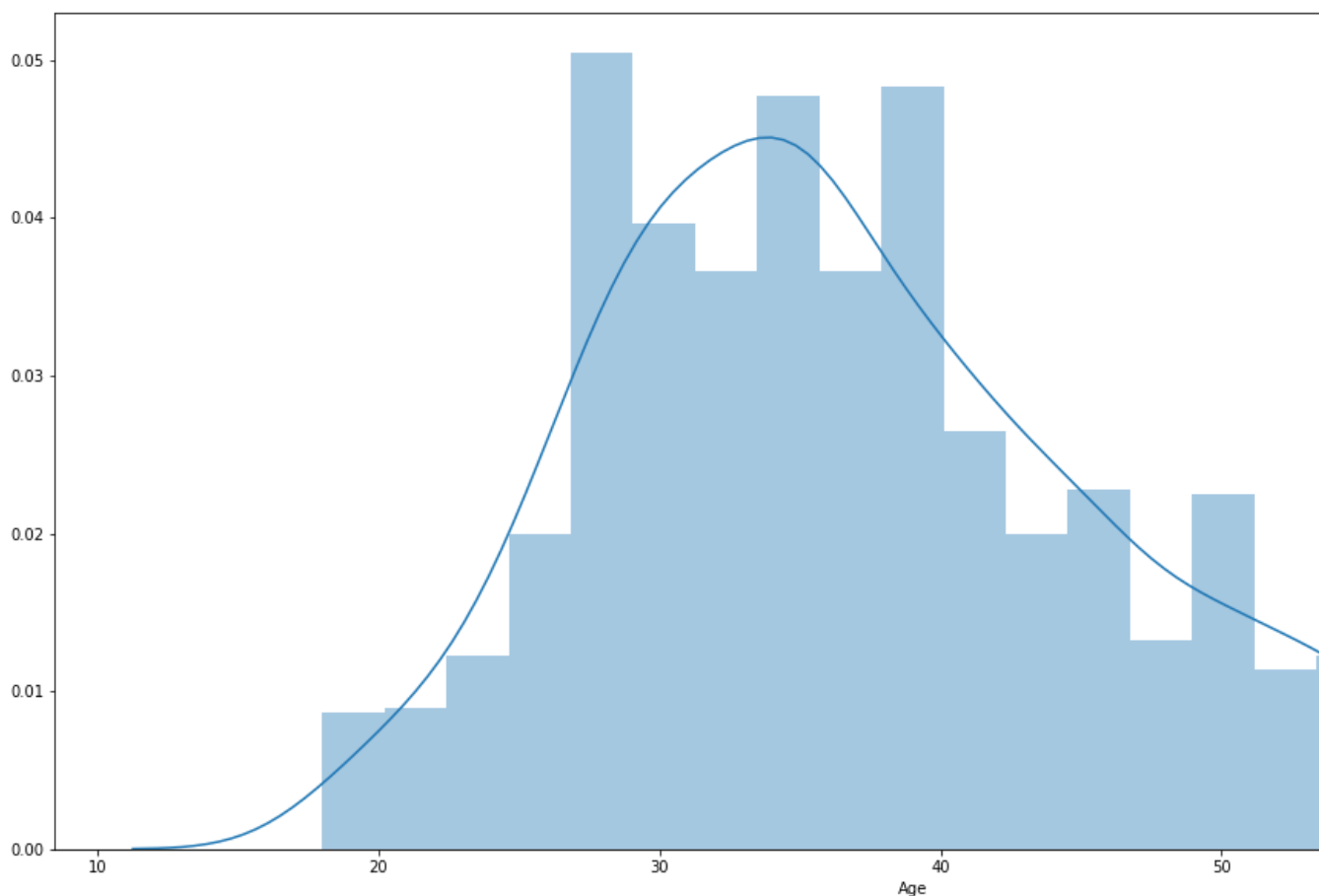
```
df.groupby(['age_group']).size().plot(kind='bar',stacked=True)  
plt.title("Distribution of Age Groups",fontsize=14)  
plt.ylabel('Count')  
plt.xlabel('Age Group');
```



```
sns.distplot(df["Age"])
```



<matplotlib.axes.\_subplots.AxesSubplot at 0x7fe550719cc0>



```
youngest = df['Age'].min()
print(" The youngest employee in the company was in age : ", youngest)
```

☞ The youngest employee in the company was in age : 18

```
oldest = df['Age'].max()
print(" The oldest employee in the company was in age ", oldest)
```

☞ The oldest employee in the company was in age 60

```
#finding out who was the oldest employee
df.loc[oldest,:]
```

☞

```

Age                                     32
Attrition                             0
BusinessTravel                       Travel_Rarely
DailyRate                           427
Department                           Research & Development
DistanceFromHome                     1
Education                             Bachelor
EducationField                       Medical
EmployeeNumber                       78
EnvironmentSatisfaction              Low
Gender                                Male
HourlyRate                           33
JobInvolvement                       High
JobLevel                             2
JobRole                              Manufacturing Director
JobSatisfaction                      Very High
MaritalStatus                        Married
MonthlyIncome                       6162
MonthlyRate                          10877
NumCompaniesWorked                   1
OverTime                             Yes
PercentSalaryHike                    22
PerformanceRating                    Outstanding
RelationshipSatisfaction              Medium
StockOptionLevel                     1
TotalWorkingYears                    9
TrainingTimesLastYear                3
WorkLifeBalance                      High
YearsAtCompany                       9
YearsInCurrentRole                   8
YearsSinceLastPromotion               7
YearsWithCurrManager                  8
age_group                            31-35
Name: 60, dtype: object

```

```

#fining out who was the youngest employee
df[df['Age']==youngest]

```



	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Educational
<b>296</b>	18	1	Travel_Rarely	230	Research & Development	3	Bachelor's
<b>301</b>	18	0	Travel_Rarely	812	Sales	10	Bachelor's
<b>457</b>	18	1	Travel_Frequently	1306	Sales	5	Bachelor's
<b>727</b>	18	0	Non-Travel	287	Research & Development	5	College
<b>828</b>	18	1	Non-Travel	247	Research & Development	8	Bachelor's
<b>972</b>	18	0	Non-Travel	1124	Research & Development	1	Bachelor's
<b>1153</b>	18	1	Travel_Frequently	544	Sales	3	College
<b>1311</b>	18	0	Non-Travel	1431	Research & Development	14	Bachelor's

As we can see from the result above, the oldest employee was in his 60 years old, and he shows not attrition. The youngest employee was in his 18, and he is attrition.

```
positive_attrition_df = df.loc[df['Attrition'] == 1]
negative_attrition_df = df.loc[df['Attrition'] == 0]
```

```
negative_attrition_df.head()
```





	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education
1	49	0	Travel_Frequently	279	Research & Development	8	Below College

```
positive_attrition_df.head()
```



	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education
0	41	1	Travel_Rarely	1102	Sales	1	College
2	37	1	Travel_Rarely	1373	Research & Development	2	College
14	28	1	Travel_Rarely	103	Research & Development	24	Bachelor
21	36	1	Travel_Rarely	1218	Sales	9	Master
24	34	1	Travel_Rarely	699	Research & Development	6	Below College

```
sns.distplot(negative_attrition_df['MonthlyIncome'], label='Negative attrition')
sns.distplot(positive_attrition_df['MonthlyIncome'], label='positive attrition')
plt.legend()
```



<matplotlib.legend.Legend at 0x7fe550975278>

0.00035

type(emp\_attrition)

↳ numpy.int64

from plotly.offline import init\_notebook\_mode, iplot  
import plotly.graph\_objs as go

```
df= df.head(30)
trace1 = go.Bar(
# x = emp_attrition['Age'],
x = df['Age'],
y = df['Age'][df['Attrition']==1],
name= 'Yes')
trace2 = go.Bar(
# x = emp_no_attrition['Age'],
x = df['Age'],
y = df['Age'][df['Attrition']==0],
name= 'No')
data = [trace1, trace2]
layout = go.Layout(barmode='group')
fig = go.Figure(data=data, layout=layout)
iplot(fig, filename='grouped-bar')
```

↳

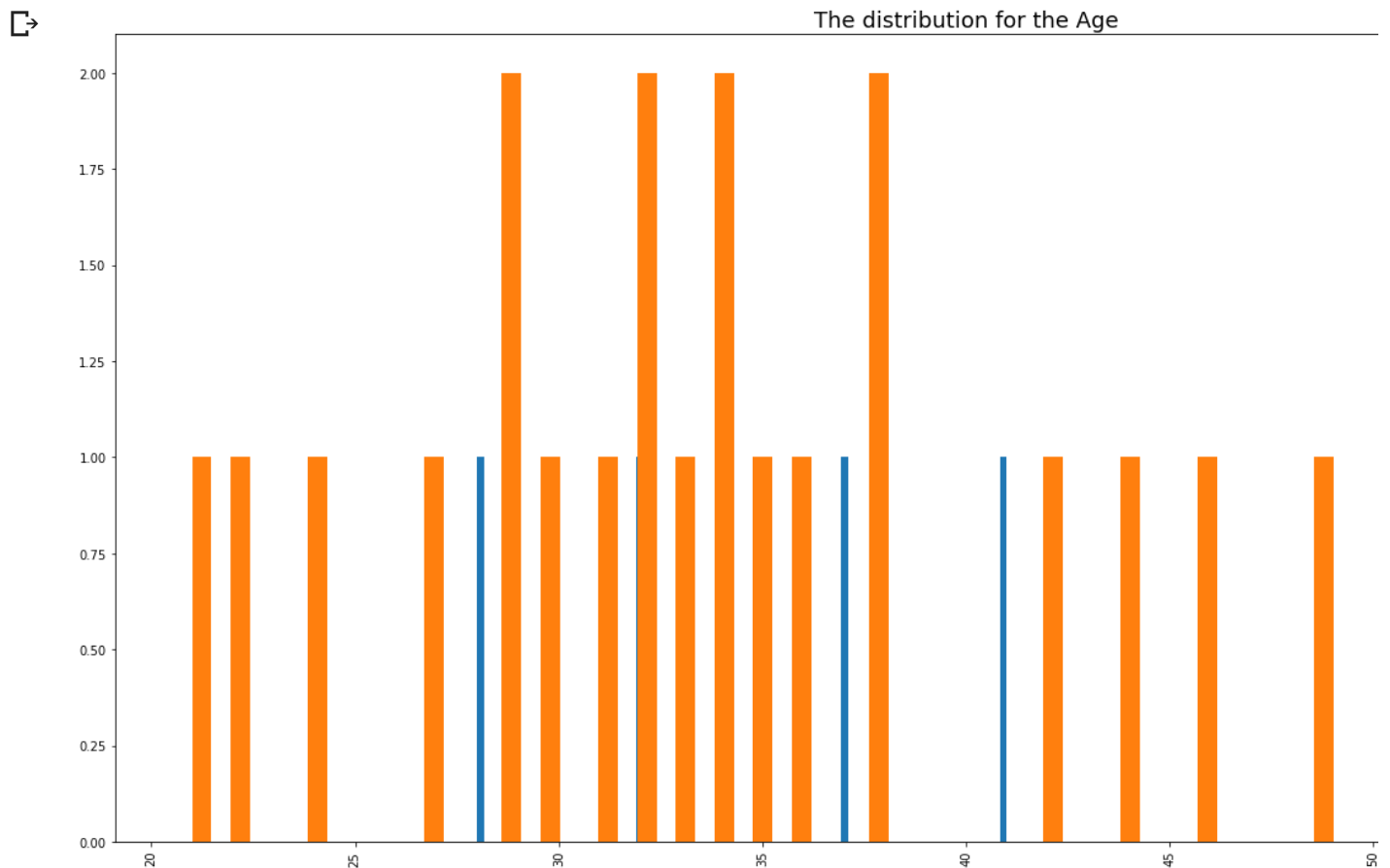
```
plt.hist(df['Age'][df["Attrition"]==1], bins= 80, histtype="bar")
plt.hist(df['Age'][df["Attrition"]==0], bins= 80, histtype="bar")
plt.legend("Age", loc='upper right')
```

```
plt.xlabel= ("Age")
plt.ylabel = ("Frequency")
plt.title('The distribution for the Age', fontsize = 18 )
```

```
plt.xticks(rotation=90)
```

```
plt.tight_layout()
plt.savefig('Age.png', dpi = 300)
```

```
plt.show()
```



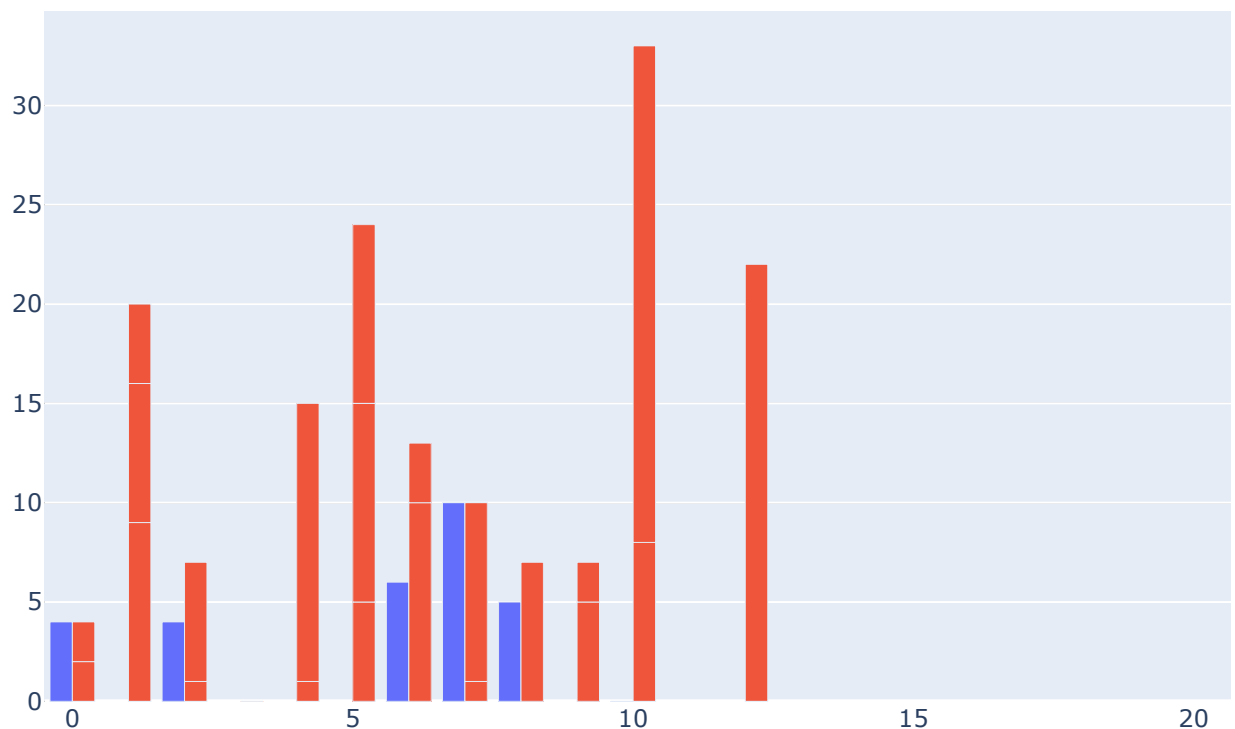
```
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
```

```
df= df.head(30)
```

```

trace1 = go.Bar(
# x = emp_attrition['Age'],
x = df['YearsAtCompany'],
y = df['YearsAtCompany'][df['Attrition']==1],
name= 'Yes')
trace2 = go.Bar(
# x = emp_no_attrition['Age'],
x = df['YearsAtCompany'],
y = df['YearsAtCompany'][df['Attrition']==0],
name= 'No')
data = [trace1, trace2]
layout = go.Layout(barmode='group')
fig = go.Figure(data=data, layout=layout)
iplot(fig, filename='grouped-bar')

```

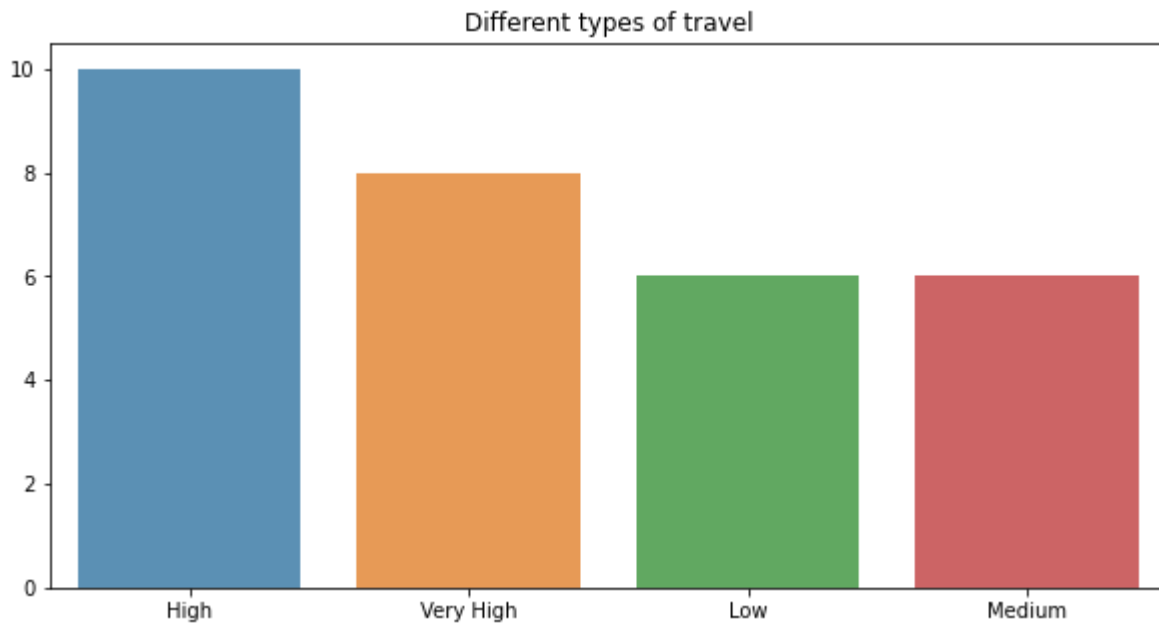


```

job = df['JobSatisfaction'].value_counts()
plt.figure(figsize=(10,5))
sns.barplot(job.index, job.values, alpha=0.8)
plt.title('Different types of travel')
plt.show()

```

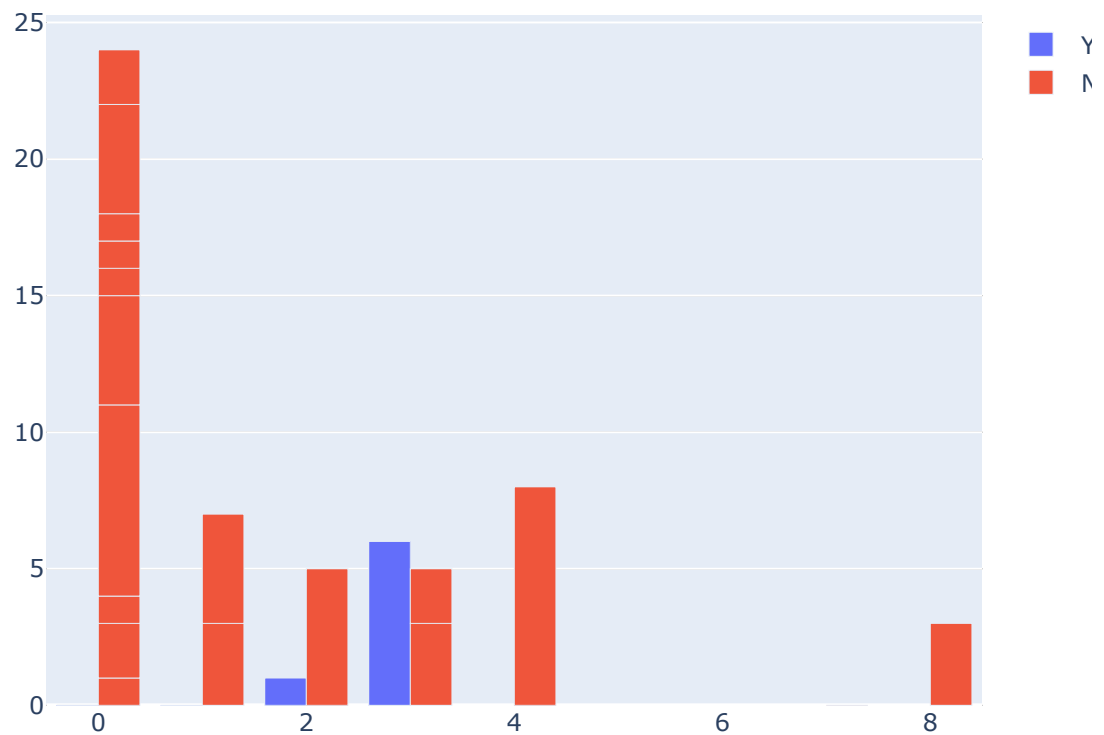




```
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go

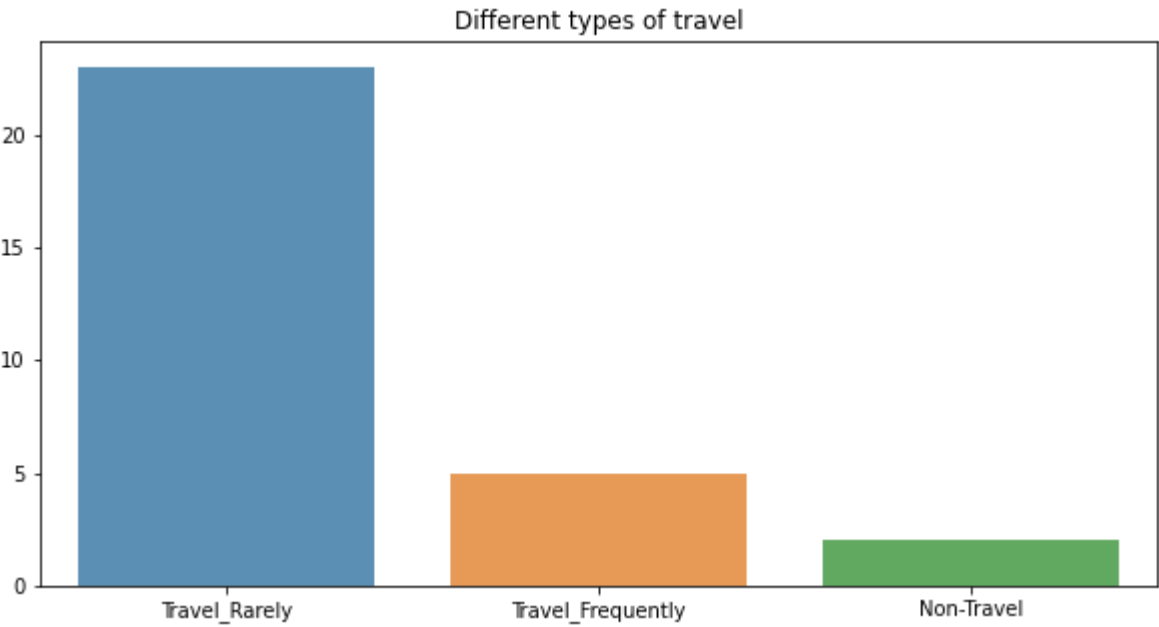
df= df.head(30)
trace1 = go.Bar(
# x = emp_attrition['Age'],
x = df['YearsSinceLastPromotion'],
y = df['YearsSinceLastPromotion'][df['Attrition']==1],
name= 'Yes')
trace2 = go.Bar(
# x = emp_no_attrition['Age'],
x = df['YearsSinceLastPromotion'],
y = df['YearsSinceLastPromotion'][df['Attrition']==0],
name= 'No')
data = [trace1, trace2]
layout = go.Layout(barmode='group')
fig = go.Figure(data=data, layout=layout)
iplot(fig, filename='grouped-bar')
```





```
business = df['BusinessTravel'].value_counts()
plt.figure(figsize=(10,5))
sns.barplot(business.index, business.values, alpha=0.8)
plt.title('Different types of travel')
plt.show()
```





df



	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education
0	41	1	Travel_Rarely	1102	Sales	1	College
1	49	0	Travel_Frequently	279	Research & Development	8	Below College
2	37	1	Travel_Rarely	1373	Research & Development	2	College
3	33	0	Travel_Frequently	1392	Research & Development	3	Master
4	27	0	Travel_Rarely	591	Research & Development	2	Below College
5	32	0	Travel_Frequently	1005	Research & Development	2	College
6	59	0	Travel_Rarely	1324	Research & Development	3	Bachelor
7	30	0	Travel_Rarely	1358	Research & Development	24	Below College
8	38	0	Travel_Frequently	216	Research & Development	23	Bachelor
9	36	0	Travel_Rarely	1299	Research & Development	27	Bachelor
10	35	0	Travel_Rarely	809	Research & Development	16	Bachelor
11	29	0	Travel_Rarely	153	Research & Development	15	College
12	31	0	Travel_Rarely	670	Research & Development	26	Below College
13	34	0	Travel_Rarely	1346	Research & Development	19	College
14	28	1	Travel_Rarely	103	Research & Development	24	Bachelor
15	29	0	Travel_Rarely	1389	Research & Development	21	Master
16	32	0	Travel_Rarely	334	Research & Development	5	College
17	22	0	Non-Travel	1123	Research & Development	16	College
18	53	0	Travel_Rarely	1219	Sales	2	Master
19	38	0	Travel_Rarely	371	Research & Development	2	Bachelor



20	24	0	Non-Travel	673	Research & Development	11	College
21	36	1	Travel_Rarely	1218	Sales	9	Master
22	34	0	Travel_Rarely	419	Research & Development	7	Master
23	21	0	Travel_Rarely	391	Research & Development	15	College
24	34	1	Travel_Rarely	699	Research & Development	6	Below College
25	53	0	Travel_Rarely	1282	Research & Development	5	Bachelor
26	32	1	Travel_Frequently	1125	Research & Development	16	Below College
27	42	0	Travel_Rarely	691	Sales	8	Master
28	44	0	Travel_Rarely	477	Research & Development	7	Master
29	46	0	Travel_Rarely	705	Sales	2	Master

```
!pip install -c plotly chart-studio
```

```
↳ ERROR: Could not open requirements file: [Errno 2] No such file or directory: 'plotly'
```

```
x=['giraffes', 'orangutans', 'monkeys']
y=[12, 18, 29]
zoo=pd.DataFrame(x,columns=['animals'])
zoo['value']=y
zoo
```

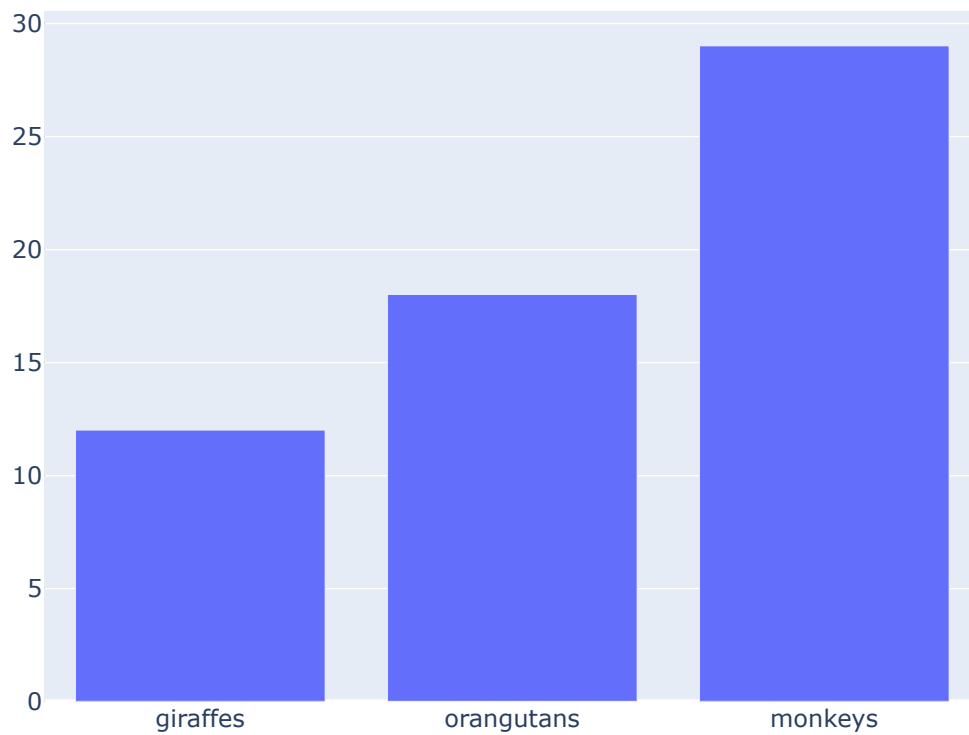
```
↳
```

	animals	value
0	giraffes	12
1	orangutans	18
2	monkeys	29

```
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
```

```
df= df.head(30)
trace4 = go.Bar(
x = zoo['animals'],
```

```
y = zoo['value'],  
name= 'Z00')  
data = [trace4]  
layout = go.Layout(barmode='group')  
fig = go.Figure(data=data, layout=layout)  
iplot(fig, filename='grouped-bar')
```



here i have worked on finding out the no.of animals that were present of a particular type. above i wa two columns - animal name and the value\_count of that spicies and with the help of these plots that i

```
print (df.groupby(['age_group']).Attrition.mean())
```

```
↳ age_group
18-24    0.000
25-30    0.000
31-35    0.250
36-40    0.375
41-45    0.250
46-50    0.000
51-55    0.000
56-60    0.000
Name: Attrition, dtype: float64
```

Here I have tried to find out the mean value of attrition for a particular age group. i.e for eg- 36-40 is t mean attrition means that the avg attrition value for the range is 0.375