

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
df=pd.read_csv("HR-Employee-Attrition.csv")
df.head(5)
```

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

5 rows × 35 columns

```
In [2]: df.shape
```

```
Out[2]: (1470, 35)
```

```
In [3]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Age              1470 non-null    int64  
 1   Attrition        1470 non-null    object  
 2   BusinessTravel   1470 non-null    object  
 3   DailyRate         1470 non-null    int64  
 4   Department        1470 non-null    object  
 5   DistanceFromHome 1470 non-null    int64  
 6   Education         1470 non-null    int64  
 7   EducationField    1470 non-null    object  
 8   EmployeeCount     1470 non-null    int64  
 9   EmployeeNumber    1470 non-null    int64  
 10  EnvironmentSatisfaction 1470 non-null    int64  
 11  Gender            1470 non-null    object  
 12  HourlyRate        1470 non-null    int64  
 13  JobInvolvement   1470 non-null    int64  
 14  JobLevel          1470 non-null    int64  
 15  JobRole           1470 non-null    object  
 16  JobSatisfaction   1470 non-null    int64  
 17  MaritalStatus     1470 non-null    object  
 18  MonthlyIncome     1470 non-null    int64  
 19  MonthlyRate       1470 non-null    int64  
 20  NumCompaniesWorked 1470 non-null    int64  
 21  Over18            1470 non-null    object  
 22  OverTime          1470 non-null    object  
 23  PercentSalaryHike 1470 non-null    int64  
 24  PerformanceRating 1470 non-null    int64  
 25  RelationshipSatisfaction 1470 non-null    int64  
 26  StandardHours     1470 non-null    int64  
 27  StockOptionLevel   1470 non-null    int64  
 28  TotalWorkingYears 1470 non-null    int64  
 29  TrainingTimesLastYear 1470 non-null    int64  
 30  WorkLifeBalance   1470 non-null    int64  
 31  YearsAtCompany    1470 non-null    int64  
 32  YearsInCurrentRole 1470 non-null    int64  
 33  YearsSinceLastPromotion 1470 non-null    int64  
 34  YearsWithCurrManager 1470 non-null    int64  
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

In [4]: df.describe()

Out[4]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	Employeeel
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024
std	9.135373	403.509100	8.106864	1.024165	0.0	602
min	18.000000	102.000000	1.000000	1.000000	1.0	1
25%	30.000000	465.000000	2.000000	2.000000	1.0	491
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068

8 rows × 26 columns

In [5]: `df.isnull().sum()`

Out[5]:

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

In [6]: `# check no of duplicated row`  
`df.duplicated().sum()`

```
Out[6]: 0
```

```
In [7]: # check missinh value in percentile form  
df.isnull().sum()/len(df)*100
```

```
Out[7]: Age                  0.0  
Attrition              0.0  
BusinessTravel          0.0  
DailyRate                0.0  
Department              0.0  
DistanceFromHome        0.0  
Education                0.0  
EducationField            0.0  
EmployeeCount            0.0  
EmployeeNumber            0.0  
EnvironmentSatisfaction  0.0  
Gender                  0.0  
HourlyRate                0.0  
JobInvolvement            0.0  
JobLevel                  0.0  
JobRole                  0.0  
JobSatisfaction            0.0  
MaritalStatus              0.0  
MonthlyIncome              0.0  
MonthlyRate                0.0  
NumCompaniesWorked        0.0  
Over18                  0.0  
OverTime                  0.0  
PercentSalaryHike          0.0  
PerformanceRating          0.0  
RelationshipSatisfaction  0.0  
StandardHours              0.0  
StockOptionLevel            0.0  
TotalWorkingYears          0.0  
TrainingTimesLastYear      0.0  
WorkLifeBalance            0.0  
YearsAtCompany              0.0  
YearsInCurrentRole          0.0  
YearsSinceLastPromotion     0.0  
YearsWithCurrManager        0.0  
dtype: float64
```

```
In [8]: # check data types  
df.dtypes
```

```
Out[8]: Age           int64
Attrition      object
BusinessTravel   object
DailyRate        int64
Department       object
DistanceFromHome int64
Education         int64
EducationField    object
EmployeeCount     int64
EmployeeNumber    int64
EnvironmentSatisfaction int64
Gender          object
HourlyRate        int64
JobInvolvement    int64
JobLevel          int64
JobRole           object
JobSatisfaction    int64
MaritalStatus     object
MonthlyIncome      int64
MonthlyRate        int64
NumCompaniesWorked int64
Over18            object
OverTime           object
PercentSalaryHike  int64
PerformanceRating  int64
RelationshipSatisfaction int64
StandardHours      int64
StockOptionLevel    int64
TotalWorkingYears   int64
TrainingTimesLastYear int64
WorkLifeBalance     int64
YearsAtCompany      int64
YearsInCurrentRole  int64
YearsSinceLastPromotion int64
YearsWithCurrManager int64
dtype: object
```

## EDA(Exploratory data analysis)

```
In [9]: #Attrition Rate
#Attrition rate: The attrition rate measures the percentage of employees who Left
#company in a given period of time.
df.columns
```

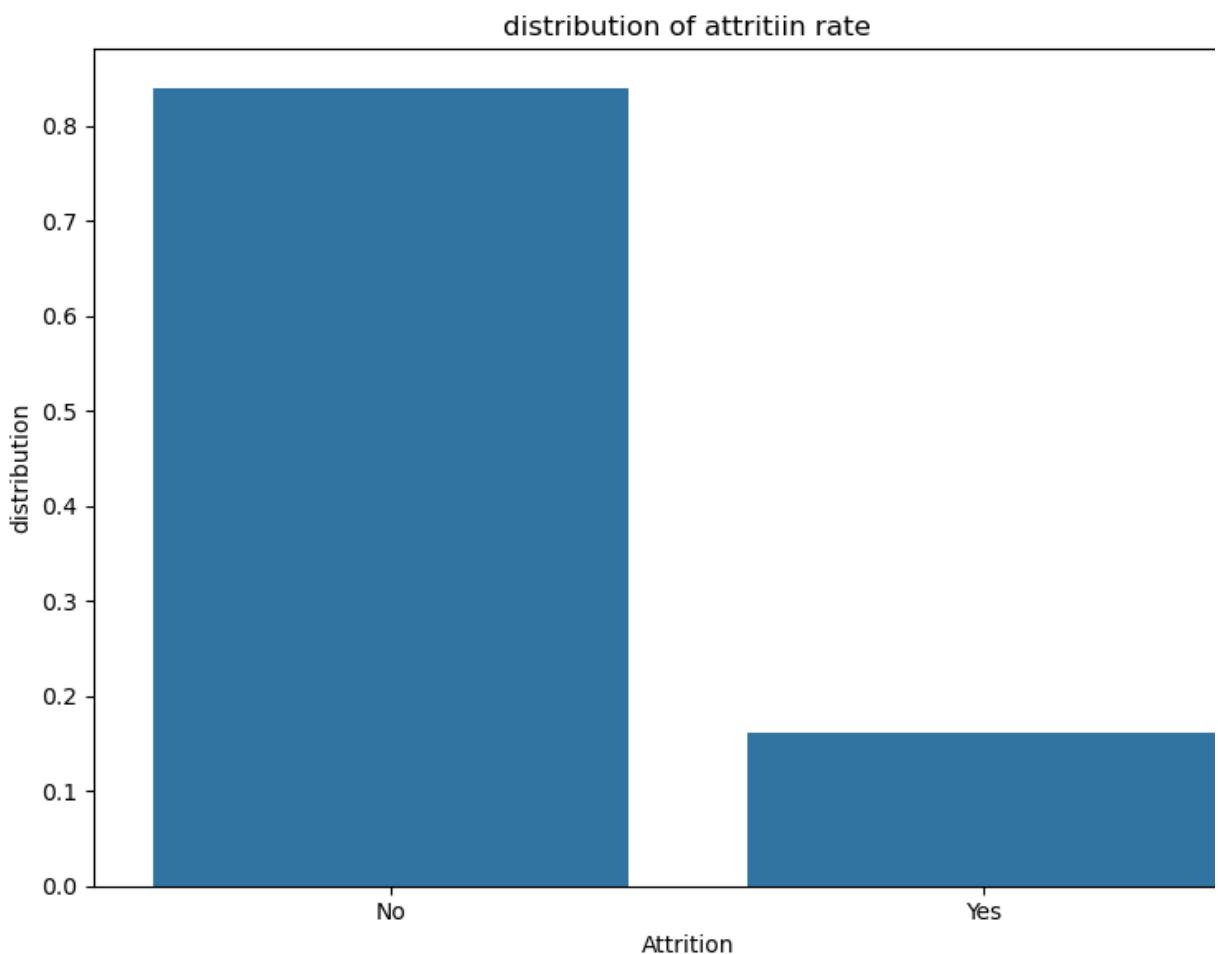
```
Out[9]: Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField', 'EmployeeCount',
       'EmployeeNumber', 'EnvironmentSatisfaction', 'Gender', 'HourlyRate',
       'JobInvolvement', 'JobLevel', 'JobRole', 'JobSatisfaction',
       'MaritalStatus', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
       'Over18', 'OverTime', 'PercentSalaryHike', 'PerformanceRating',
       'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',
       'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance',
       'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
       'YearsWithCurrManager'],
      dtype='object')
```

```
In [10]: df['Attrition'].value_counts(normalize=True)
```

```
Out[10]: Attrition
No      0.838776
Yes     0.161224
Name: proportion, dtype: float64
```

```
In [11]: attrition=df['Attrition'].value_counts(normalize=True)
```

```
In [14]: plt.figure(figsize=(8,6))
sns.barplot(x=attrition.index,y=attrition)
plt.title("distribution of attritiin rate")
plt.xlabel("Attrition")
plt.ylabel("distribution")
plt.tight_layout()
plt.show()
```



```
In [15]: #Average of Tenure
#Average tenure: The average tenure measures the average number of years an
#employee stays with the company before leaving.
df.columns
```

```
Out[15]: 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')
```

```
In [16]: avg_tenure=df['YearsAtCompany'].mean()
```

```
In [17]: print(f"the average tenure of the company is{avg_tenure}")
```

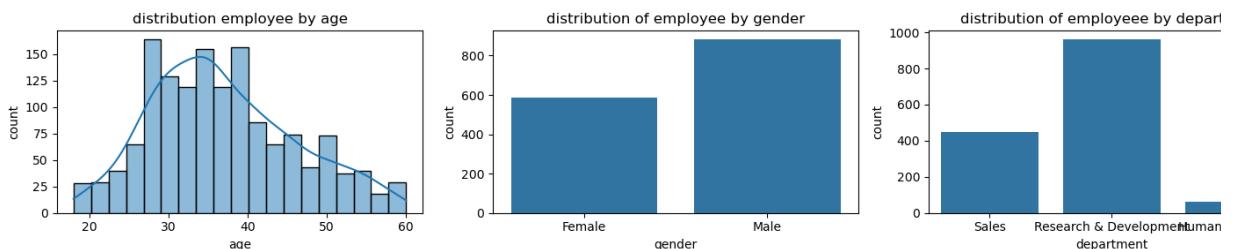
```
the average tenure of the company is7.0081632653061225
```

```
In [22]: # Employee's Demographics
fig,axes=plt.subplots(nrows=1,ncols=3,figsize=(15,3))
df.columns
sns.histplot(data=df,x='Age',kde=True,ax=axes[0])
axes[0].set_title("distribution employee by age")
axes[0].set_xlabel("age")
axes[0].set_ylabel("count")

sns.countplot(data=df,x="Gender",ax=axes[1])
axes[1].set_title("distribution of employee by gender")
axes[1].set_xlabel("gender")
axes[1].set_ylabel("count")

sns.countplot(data=df,x="Department",ax=axes[2])
axes[2].set_title("distribution of employee by department")
axes[2].set_xlabel("department")
axes[2].set_ylabel("count")

plt.tight_layout()
plt.show()
```



```
In [ ]: # from the above visualization we can conclude that
# age:Most of the company's employees are in the 30-35 age group.
# gender:The majority of employees at this company are male.
# department:Most of the company's employees are concentrated in the research and
```

```
In [23]: df_attrition=df[df['Attrition'] == 'Yes']
df_attrition.head(5)
```

Out[23]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Edu
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Li
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
14	28	Yes	Travel_Rarely	103	Research & Development	24	3	Li
21	36	Yes	Travel_Rarely	1218	Sales	9	4	Li
24	34	Yes	Travel_Rarely	699	Research & Development	6	1	

5 rows × 35 columns

In [24]:

```
def NumericalVariables_targetPlots(df,segment_by,target_var = "Attrition"):
    """A function for plotting the distribution of numerical variables and its comparison based on Attrition"""

    fig, ax = plt.subplots(ncols= 2, figsize = (14,6))

    #boxplot for comparison
    sns.boxplot(x = target_var, y = segment_by, data=df, ax=ax[0])
    ax[0].set_title("Comparision of " + segment_by + " vs " + target_var)

    #distribution plot
    ax[1].set_title("Distribution of "+segment_by)
    ax[1].set_ylabel("Frequency")
    sns.distplot(a = df[segment_by], ax=ax[1], kde=False)

    plt.show()
```

In [26]:

```
#Analyzing the daily wage rate vs employee left the company or not

NumericalVariables_targetPlots(df,"DailyRate")
```

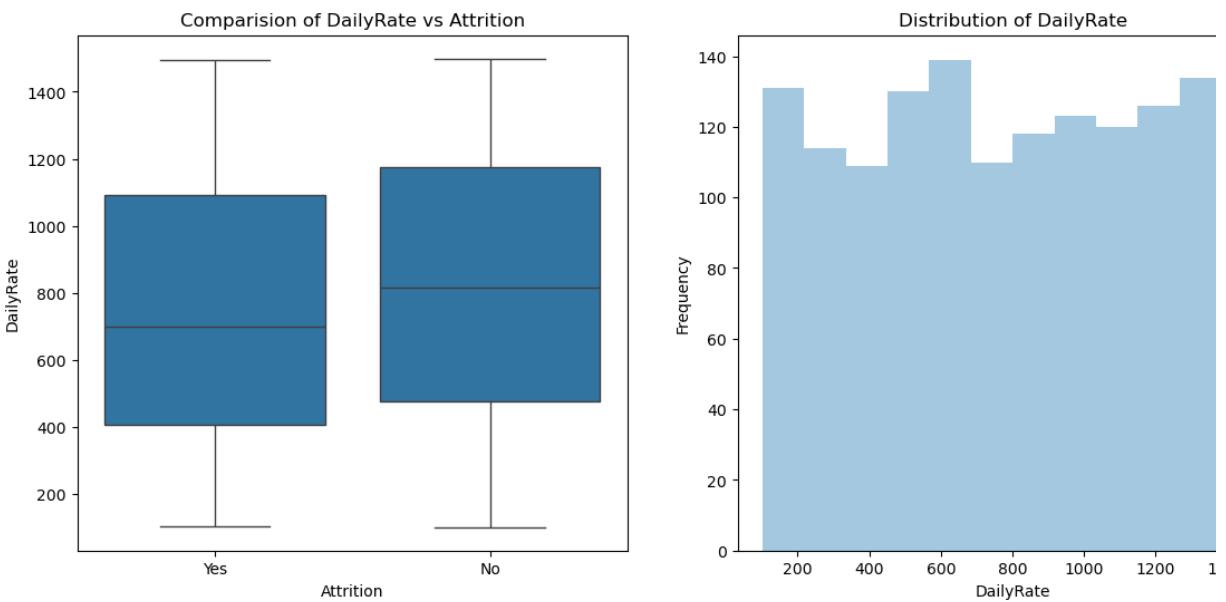
C:\Users\Admin\AppData\Local\Temp\ipykernel\_11348\1104822344.py:13: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

sns.distplot(a = df[segment\_by], ax=ax[1], kde=False)

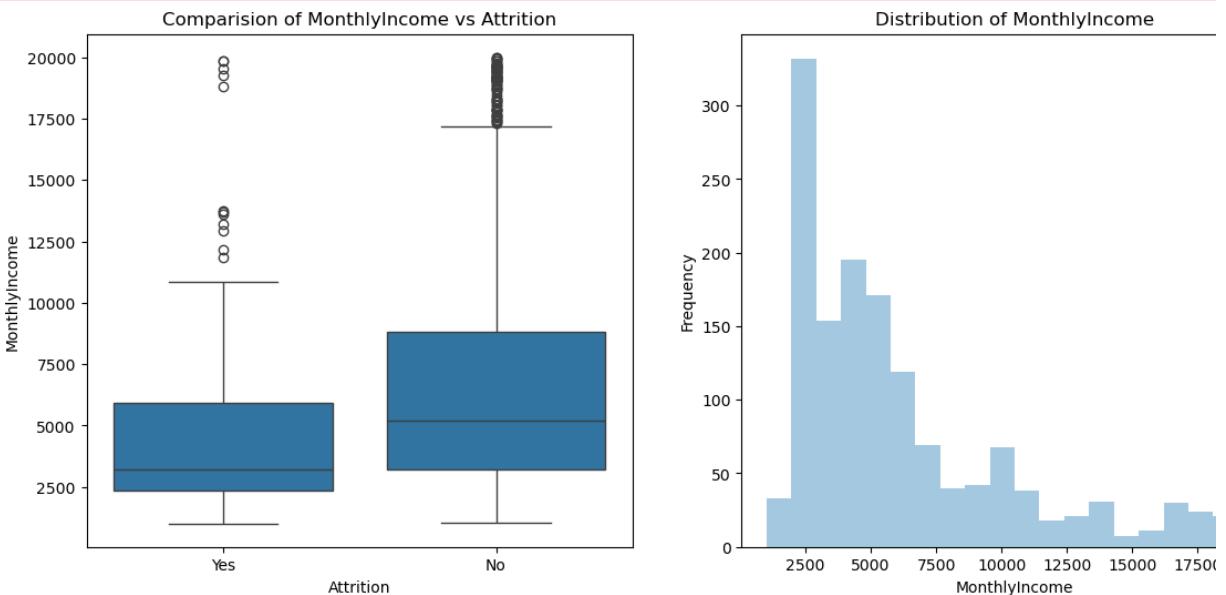


```
In [ ]:
```

```
In [27]: NumericalVariables_targetPlots(df,"MonthlyIncome")
```

C:\Users\Admin\AppData\Local\Temp\ipykernel\_11348\1104822344.py:13: UserWarning:  
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.  
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).  
For a guide to updating your code to use the new functions, please see  
<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(a = df[segment_by], ax=ax[1], kde=False)
```



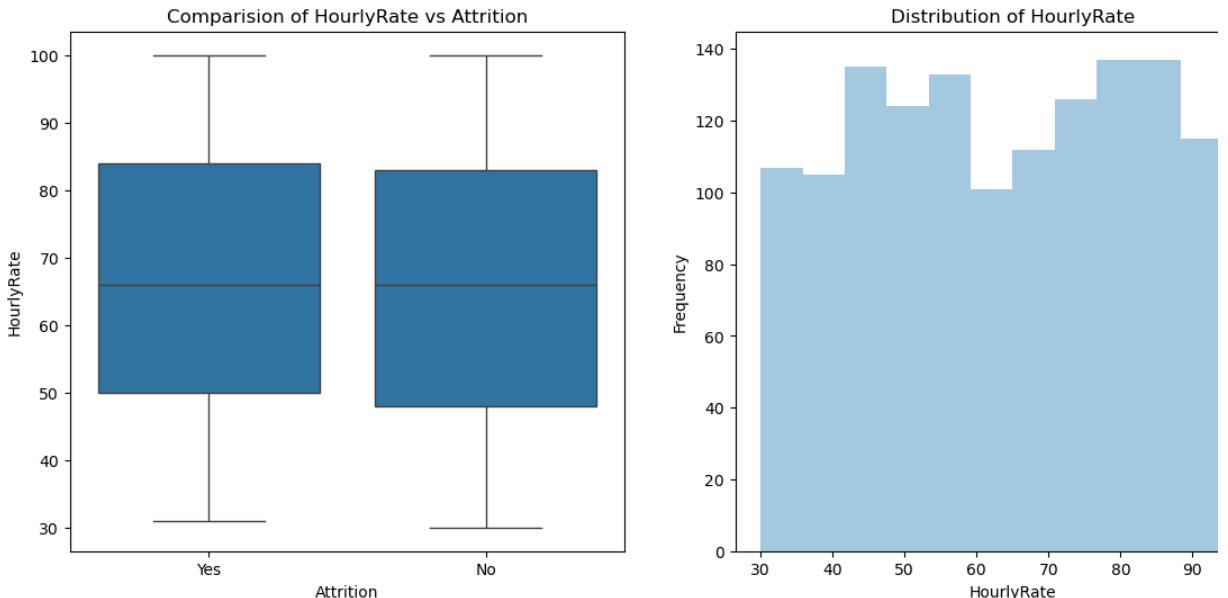
```
In [ ]: #Employee's working with Lower daily rates are more prone to Leave the company t  

#working with higher rates.
```

```
In [28]: NumericalVariables_targetPlots(df,"HourlyRate")
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_11348\1104822344.py:13: UserWarning:  
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.  
Please adapt your code to use either `displot` (a figure-level function with  
similar flexibility) or `histplot` (an axes-level function for histograms).  
For a guide to updating your code to use the new functions, please see  
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

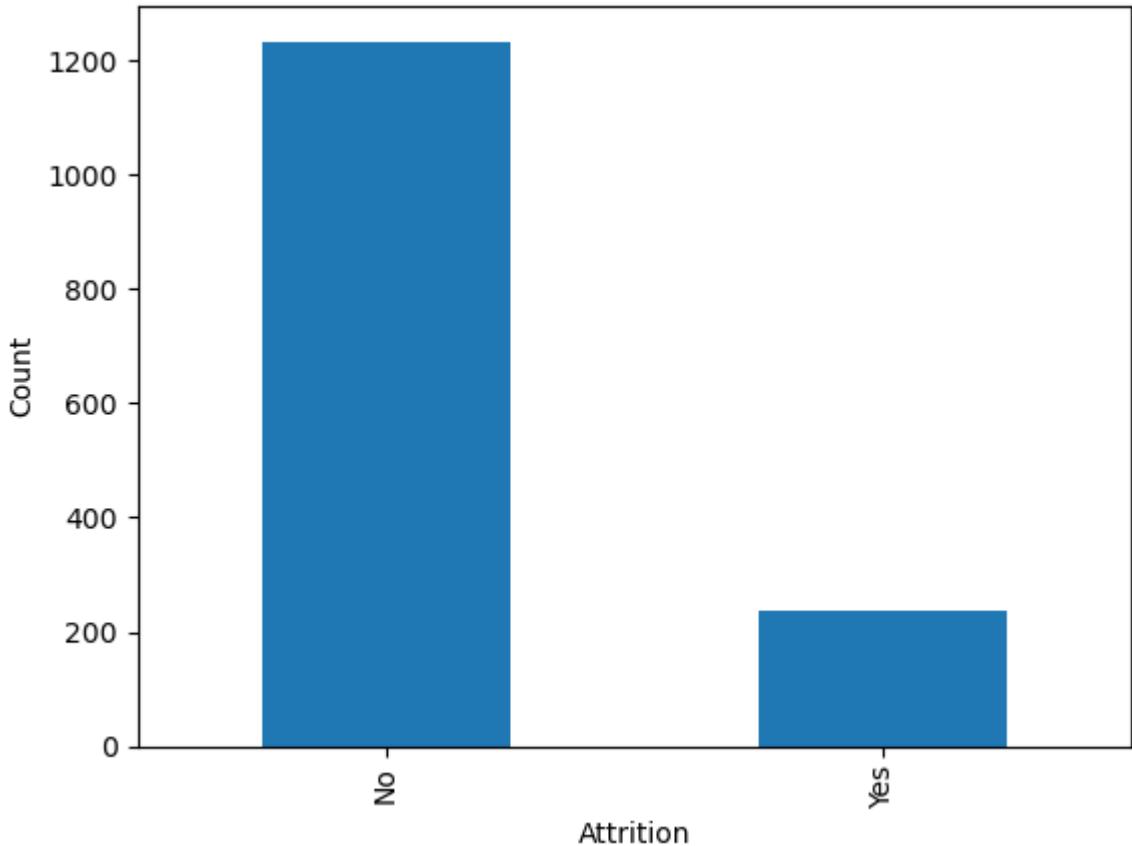
```
sns.distplot(a = df[segment_by], ax=ax[1], kde=False)
```



```
In [ ]: # from the above visualization we have seen that there is no significant difference
```

## building decision treee

```
In [34]: from sklearn.model_selection import train_test_split  
from sklearn.tree import DecisionTreeClassifier  
#to create a confusion matrix  
from sklearn.metrics import confusion_matrix  
from sklearn import metrics  
df.Attrition.value_counts().plot(kind="bar")  
plt.xlabel("Attrition")  
plt.ylabel("Count")  
plt.show()
```



```
In [35]: df["Attrition"].value_counts()
```

```
Out[35]: Attrition
No      1233
Yes     237
Name: count, dtype: int64
```

```
In [36]: #From the Exploratory data analysis, variable that are not significant to attrit
```

```
#EmployeeCount, EmployeeNumber, Gender, HourlyRate, JobLevel, MaritalStatus, Ove
df_new=df.copy()
df_new.head(5)
```

```
Out[36]:   Age Attrition BusinessTravel DailyRate Department DistanceFromHome Education Ec
0    41      Yes  Travel_Rarely     1102        Sales             1         2
1    49      No   Travel_Frequently     279  Research & Development     8         1
2    37      Yes  Travel_Rarely     1373  Research & Development     2         2
3    33      No   Travel_Frequently     1392  Research & Development     3         4
4    27      No  Travel_Rarely      591  Research & Development     2         1
```

5 rows × 35 columns

```
In [15]: df_new.drop(["EmployeeCount", "EmployeeNumber", "Gender", "HourlyRate", "JobLev
```

```
In [16]: df_new.shape
```

```
Out[16]: (1470, 27)
```

```
In [17]: # handling categorical columns  
#Segregate the numerical and Categorical variables  
#Convert Categorical variables to dummy variables
```

```
In [3]: import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns  
df=pd.read_csv("HR-Employee-Attrition.csv")  
  
df_new=df.copy()  
dict(df_new.dtypes)
```

```
Out[3]: {'Age': dtype('int64'),  
'Attrition': dtype('O'),  
'BusinessTravel': dtype('O'),  
'DailyRate': dtype('int64'),  
'Department': dtype('O'),  
'DistanceFromHome': dtype('int64'),  
'Education': dtype('int64'),  
'EducationField': dtype('O'),  
'EmployeeCount': dtype('int64'),  
'EmployeeNumber': dtype('int64'),  
'EnvironmentSatisfaction': dtype('int64'),  
'Gender': dtype('O'),  
'HourlyRate': dtype('int64'),  
'JobInvolvement': dtype('int64'),  
'JobLevel': dtype('int64'),  
'JobRole': dtype('O'),  
'JobSatisfaction': dtype('int64'),  
'MaritalStatus': dtype('O'),  
'MonthlyIncome': dtype('int64'),  
'MonthlyRate': dtype('int64'),  
'NumCompaniesWorked': dtype('int64'),  
'Over18': dtype('O'),  
'OverTime': dtype('O'),  
'PercentSalaryHike': dtype('int64'),  
'PerformanceRating': dtype('int64'),  
'RelationshipSatisfaction': dtype('int64'),  
'StandardHours': dtype('int64'),  
'StockOptionLevel': dtype('int64'),  
'TotalWorkingYears': dtype('int64'),  
'TrainingTimesLastYear': dtype('int64'),  
'WorkLifeBalance': dtype('int64'),  
'YearsAtCompany': dtype('int64'),  
'YearsInCurrentRole': dtype('int64'),  
'YearsSinceLastPromotion': dtype('int64'),  
'YearsWithCurrManager': dtype('int64')}
```

```
In [4]: #segregating the variables based on datatypes  
numeric_variable_names=[key for key in dict(df_new.dtypes)if dict(df_new.dtypes)[key].name=="int64"  
categorical_varibale_name=[key for key in dict(df_new.dtypes)if dict(df_new.dtypes)[key].name=="O"]
```

```
In [5]: numeric_variable_names
```

```
Out[5]: ['Age',
'DailyRate',
'DistanceFromHome',
'Education',
'EmployeeCount',
'EmployeeNumber',
'EnvironmentSatisfaction',
'HourlyRate',
'JobInvolvement',
'JobLevel',
'JobSatisfaction',
'MonthlyIncome',
'MonthlyRate',
'NumCompaniesWorked',
'PercentSalaryHike',
'PerformanceRating',
'RelationshipSatisfaction',
'StandardHours',
'StockOptionLevel',
'TotalWorkingYears',
'TrainingTimesLastYear',
'WorkLifeBalance',
'YearsAtCompany',
'YearsInCurrentRole',
'YearsSinceLastPromotion',
'YearsWithCurrManager']
```

```
In [6]: categorical_varibale_name
```

```
Out[6]: ['Attrition',
'BusinessTravel',
'Department',
'EducationField',
'Gender',
'JobRole',
'MaritalStatus',
'Over18',
'OverTime']
```

```
In [7]: #store the numerical variables data in seperate dataset
df_numeric=df_new[numerical_variable_names]
```

```
In [8]: #store the categorical variables data in seperate dataset
df_categorical=df_new[categorical_varibale_name]
```

```
In [ ]: #dropping the attrition columns
```

```
In [9]: df_categorical.drop(['Attrition'],axis=1,inplace=True)
```

C:\Users\Admin\AppData\Local\Temp\ipykernel\_18784\4285812731.py:1: SettingWithCopyWarning  
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
df\_categorical.drop(['Attrition'],axis=1,inplace=True)

```
In [11]: df_categorical.shape
```

```
Out[11]: (1470, 8)
```

```
In [12]: #converting into dummy variables
```

```
df_categorical=pd.get_dummies(df_categorical)
```

```
In [13]: #Merging the both numerical and categorical data
```

```
df_final_data=pd.concat([df_numeric,df_categorical,df_new[["Attrition"]]],axis=1)
```

```
In [18]: df_final_data.head(5)
```

```
Out[18]:    Age DailyRate DistanceFromHome Education EmployeeCount EmployeeNumber Environm
```

0	41	1102	1	2	1	1
1	49	279	8	1	1	2
2	37	1373	2	2	1	4
3	33	1392	3	4	1	5
4	27	591	2	1	1	7

5 rows × 56 columns

```
In [19]: #final features
```

```
features = list(df_final_data.columns.difference(["Attrition"]))
```

```
In [20]: features
```

```
Out[20]: ['Age',
 'BusinessTravel_Non-Travel',
 'BusinessTravel_Travel_Frequently',
 'BusinessTravel_Travel_Rarely',
 'DailyRate',
 'Department_Human Resources',
 'Department_Research & Development',
 'Department_Sales',
 'DistanceFromHome',
 'Education',
 'EducationField_Human Resources',
 'EducationField_Life Sciences',
 'EducationField_Marketing',
 'EducationField_Medical',
 'EducationField_Other',
 'EducationField_Technical Degree',
 'EmployeeCount',
 'EmployeeNumber',
 'EnvironmentSatisfaction',
 'Gender_Female',
 'Gender_Male',
 'HourlyRate',
 'JobInvolvement',
 'JobLevel',
 'JobRole_Healthcare Representative',
 'JobRole_Human Resources',
 'JobRole_Laboratory Technician',
 'JobRole_Manager',
 'JobRole_Manufacturing Director',
 'JobRole_Research Director',
 'JobRole_Research Scientist',
 'JobRole_Sales Executive',
 'JobRole_Sales Representative',
 'JobSatisfaction',
 'MaritalStatus_Divorced',
 'MaritalStatus_Married',
 'MaritalStatus_Single',
 'MonthlyIncome',
 'MonthlyRate',
 'NumCompaniesWorked',
 'Over18_Y',
 'OverTime_No',
 'OverTime_Yes',
 'PercentSalaryHike',
 'PerformanceRating',
 'RelationshipSatisfaction',
 'StandardHours',
 'StockOptionLevel',
 'TotalWorkingYears',
 'TrainingTimesLastYear',
 'WorkLifeBalance',
 'YearsAtCompany',
 'YearsInCurrentRole',
 'YearsSinceLastPromotion',
 'YearsWithCurrManager']
```

## Separating the Target and the Predictors

In [24]:

```
X=df_final_data[features]
y=df_final_data[["Attrition"]]
```

In [25]: `X.shape`

Out[25]: (1470, 55)

In [23]: `y.shape`

Out[23]: (1470, 1)

```
In [26]: 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,stratify
```

In [27]: `#Checks`

`#Proportion in training data`

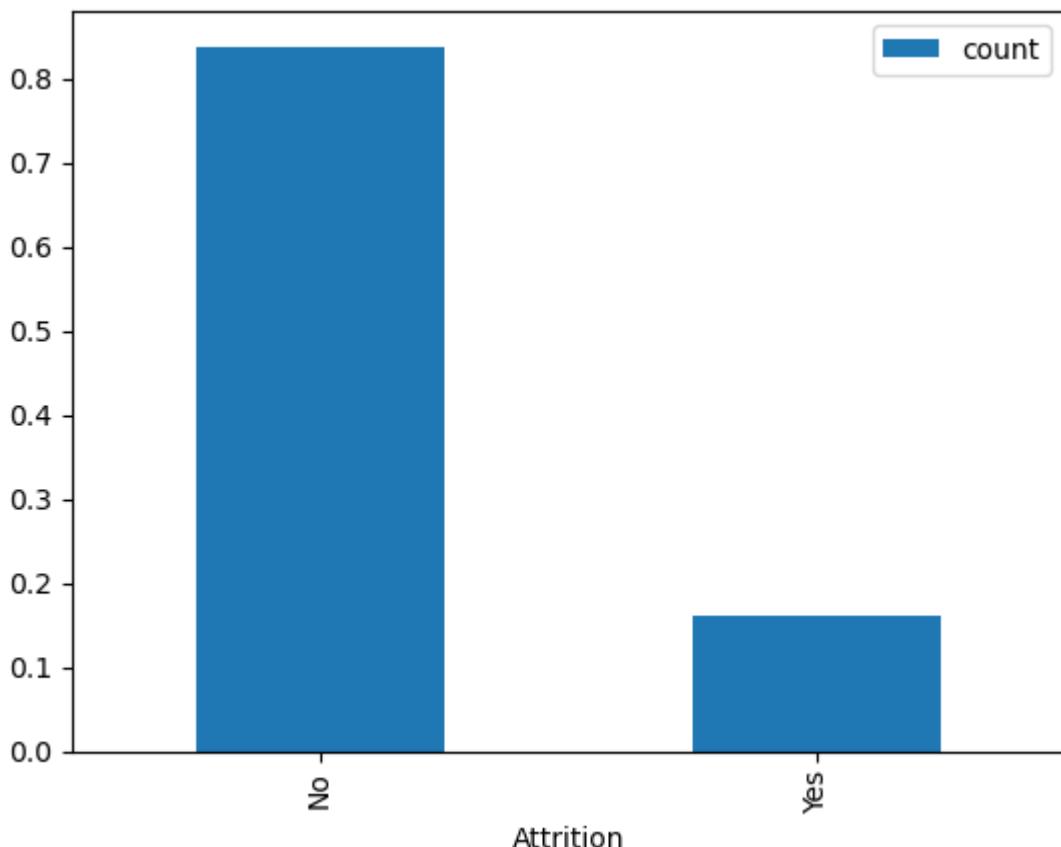
```
y_train.Attrition.value_counts()/len(y_train)
```

Out[27]: Attrition  
No 0.838678  
Yes 0.161322  
Name: count, dtype: float64

In [28]: `#Checks`

`#Proportion in training data`

```
pd.DataFrame(y_train.Attrition.value_counts()/len(y_train)).plot(kind = "bar")
plt.show()
```



In [29]: `#Proportion of test data`

```
y_test.Attrition.value_counts()/len(y_test)
```

```
Out[29]: Attrition
No      0.839002
Yes     0.160998
Name: count, dtype: float64
```

```
In [31]: # Function for creating model pipelines
from sklearn.pipeline import make_pipeline

#function for crossvalidate score
from sklearn.model_selection import cross_validate

#to find the best
from sklearn.model_selection import GridSearchCV
#make a pipeline for decision tree model
from sklearn.tree import DecisionTreeClassifier
pipelines = {
    "clf": make_pipeline(DecisionTreeClassifier(max_depth=3,random_state=100))
}
```

```
In [32]: #Cross Validate
#To check the accuracy of the pipeline
scores = cross_validate(pipelines['clf'], X_train, y_train, return_train_score=True)
```

```
In [33]: scores['test_score'].mean()
```

```
Out[33]: 0.8396590101823348
```

```
In [ ]: #Average accuracy of pipeline with Decision Tree Classifier is 83.48%
```