IBM HR Employee Attrition Analysis

October 16, 2023

1 IBM HR Analytics Employee Attrition Using Python

1.0.1 Introduction

The IBM HR Attrition Case Study is a fictional dataset which aims to identify important factors that might be influential in determining which employee might leave the firm and who may not.

The Attrition dataset had 1470 observations with 35 variables. Out of the 35 variables, there exists one target variable Attrition with possible outcomes Yes and No. The other 34 variables are independent variables but one, that was, Employee Number which denotes the employee number or the identification number.

Problem Statement

- Attrition is a problem that impacts all businesses, irrespective of geography, industry and size of the company. Employee attrition leads to significant costs for a business, including the cost of business disruption, hiring new staff and training new staff. As such, there is great business interest in understanding the drivers of, and minimizing staff attrition

Objective:

To Minimize the Employees Attrition

[1]:
```
# import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
# Ignore  the warnings
import warnings
warnings.filterwarnings('always')
warnings.filterwarnings('ignore')
```

[3]:
```
# load the dataframe
df = pd.read_csv(r"E:\MeriSkill\Project 3 - HR Analytics\Data P3␣
↪MeriSKILL\HR-Employee-Attrition.csv")
```

[4]:
```
#Data content
styled_df = df.sample(5).style

# Set background color, text color, and border for the entire DataFrame
styled_df.set_properties(**{"background-color": "#7b5973", "color": "#e9c46a",␣
↪"border": "1.5px solid black"})

# Modify the color and background color of the table headers (th)
styled_df.set_table_styles([
    {"selector": "th", "props": [("color", 'white'), ("background-color",␣
↪"#0de601")]}
])
```

[4]:
```
<pandas.io.formats.style.Styler at 0x1f97b691190>
```

1.1 Attribute Information

S.No	Attribute Name	Meaning
1	Age	Employee's age
2	Gender	Employee's Gender
3	BusinessTravel	Frequency of employees' business trips
4	DailyRate	Daily salary rate for employees
5	Department	Office of employees
6	DistanceFromHome	Distance from home in miles to work
7	Education	Level of education achieved by staff
8	EducationField	Employee's field of study
9	EmployeeCount	Total number of employees in the organization
10	EmployeeNumber	A unique identifier for each employee record
11	EnvironmentSatisfaction	Employee satisfaction with their
12	HourlyRate	Hourly rate for employees
13	JobInvolvement	Level of involvement required for the employee's job
14	JobLevel	Employee's level of work
15	JobRole	The role of employees in the organization
16	JobSatisfaction	Employee satisfaction with their work
17	MaritalStatus	Employee's marital status

S.No	Attribute Name	Meaning
18	MonthlyIncome	Employee's monthly income
19	MonthlyRate	Monthly salary rate for employees
20	NumCompaniesWorked	Number of companies the employee worked for
21	Over18	Whether the employee is over 18 years old
22	OverTime	Do employees work overtime
23	PercentSalaryHike	Salary increase rate for employees
24	PerformanceRating	The performance rating of the employee
25	RelationshipSatisfaction	Employee satisfaction with their relationships
26	StandardHours	Standard working hours for employees
27	StockOptionLevel	Employee stock option level
28	TotalWorkingYears	Total number of years the employee has worked
29	TrainingTimesLastYear	Number of times employees were taken to training in the last year
30	WorkLifeBalance	Employees' perception of their work-life balance
31	YearsAtCompany	Number of years employees have been with the company
32	YearsInCurrentRole	Number of years the employee has been in their current role
33	YearsSinceLastPromotion	Number of years since employee's last promotion
34	YearsWithCurrManager	Number of years an employee has been with their current manager
35	Attrition	Does the employee leave the organization

[5]:
```
df.shape
```

[5]: (1470, 35)

1.1.1 Data Pre-processing / Data Cleaning

[6]:
```python
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
```

1.1.2 Checking for Missing Values

[7]:
```python
# Check the data for null values
df.isnull().sum()
```

[7]:
```
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
```

There is no Null Values in the dataframe

1.1.3 Checking for Duplicate Values

[8]:
```python
# Check the data for duplicated values
df.duplicated().sum()
```

[8]:
```
0
```

there is no duplicated values in the dataframe

1.1.4 Checking for Zero Variance Features

[9]:
```python
# Check for Zero variance and Near Zero variance Features
df.var()==0
```

[9]:
```
Age                         False
DailyRate                   False
DistanceFromHome            False
Education                   False
EmployeeCount               False
EmployeeNumber              False
EnvironmentSatisfaction     False
HourlyRate                  False
JobInvolvement              False
JobLevel                    False
JobSatisfaction             False
MonthlyIncome               False
MonthlyRate                 False
NumCompaniesWorked          False
PercentSalaryHike           False
PerformanceRating           False
RelationshipSatisfaction    False
StandardHours                True
StockOptionLevel            False
TotalWorkingYears           False
TrainingTimesLastYear       False
WorkLifeBalance             False
YearsAtCompany              False
YearsInCurrentRole          False
YearsSinceLastPromotion     False
YearsWithCurrManager        False
dtype: bool
```

- Here StandardHours feature has zero vaiance so we can drop this feature
- why because zero variance or near zero variance features doesn't consider for analysis

1.1.5 Numerical Features

[10]:
```
df.select_dtypes(np.number).sample(5).style.
 ↪set_properties(**{'background-color': '#E9F6E2',
                                                          'color':␣
 ↪'black','border-color': '#8b8c8c'})
```

[10]:
```
<pandas.io.formats.style.Styler at 0x1f97b844d90>
```

1.1.6 Inferences:

- some of the numerical features are storing categories labelled in numbers
- so we can replace those labelled numerical values with appropriate categorical values

Labelling Categories in the Numerical features

[11]:
```
df["Education"] = df["Education"].replace({1:"Below College",2:"College",3:
 ↪"Bachelor",4:"Master",5:"Doctor"})
df["EnvironmentSatisfaction"] = df["EnvironmentSatisfaction"].replace({1:
 ↪"Low",2:"Medium",3:"High",4:"Very High"})
df["JobInvolvement"] = df["JobInvolvement"].replace({1:"Low",2:"Medium",3:
 ↪"High",4:"Very High"})
df["JobLevel"] = df["JobLevel"].replace({1:"Entry Level",2:"Junior Level",3:
 ↪"Mid Level",4:"Senior Level",5:"Executive Level"})
df["JobSatisfaction"] = df["JobSatisfaction"].replace({1:"Low",2:"Medium",3:
 ↪"High",4:"Very High"})
df["PerformanceRating"] = df["PerformanceRating"].replace({1:"Low",2:"Good",3:
 ↪"Excellent",4:"Outstanding"})
df["RelationshipSatisfaction"] = df["RelationshipSatisfaction"].replace({1:
 ↪"Low",2:"Medium",3:"High",4:"Very High"})
df["WorkLifeBalance"] = df["WorkLifeBalance"].replace({1:"Bad",2:"Good",3:
 ↪"Better",4:"Best"})
```

[12]:
```
df.head()
```

[12]:
```
   Age Attrition     BusinessTravel  DailyRate              Department  \
0   41       Yes      Travel_Rarely       1102                   Sales
1   49        No  Travel_Frequently        279  Research & Development
2   37       Yes      Travel_Rarely       1373  Research & Development
3   33        No  Travel_Frequently       1392  Research & Development
4   27        No      Travel_Rarely        591  Research & Development

   DistanceFromHome      Education EducationField  EmployeeCount  \
0                 1        College  Life Sciences              1
1                 8  Below College  Life Sciences              1
2                 2        College          Other              1
3                 3         Master  Life Sciences              1
4                 2  Below College        Medical              1
```

```
   EmployeeNumber  … RelationshipSatisfaction StandardHours  \
0               1  …                      Low            80
1               2  …                Very High            80
2               4  …                   Medium            80
3               5  …                     High            80
4               7  …                Very High            80

   StockOptionLevel TotalWorkingYears TrainingTimesLastYear WorkLifeBalance  \
0                 0                 8                     0             Bad
1                 1                10                     3          Better
2                 0                 7                     3          Better
3                 0                 8                     3          Better
4                 1                 6                     3          Better

  YearsAtCompany YearsInCurrentRole  YearsSinceLastPromotion  \
0              6                  4                        0
1             10                  7                        1
2              0                  0                        0
3              8                  7                        3
4              2                  2                        2

   YearsWithCurrManager
0                     5
1                     7
2                     0
3                     0
4                     2

[5 rows x 35 columns]
```

1.1.7 Categorical Features

[13]:
```
df.select_dtypes(include="O").sample(5).style.
↪set_properties(**{'background-color': '#E9F6E2',
                                                            'color':␣
↪'black','border-color': '#8b8c8c'})
```

[13]:
```
<pandas.io.formats.style.Styler at 0x1f97b5335d0>
```

1.1.8 Descriptive Analysis on Numerical Attributes

[14]:
```
df.describe().T
```

[14]:
```
                          count        mean         std    min      25%  \
Age                      1470.0   36.923810    9.135373   18.0    30.00
DailyRate                1470.0  802.485714  403.509100  102.0   465.00
```

DistanceFromHome	1470.0	9.192517	8.106864	1.0	2.00
EmployeeCount	1470.0	1.000000	0.000000	1.0	1.00
EmployeeNumber	1470.0	1024.865306	602.024335	1.0	491.25
HourlyRate	1470.0	65.891156	20.329428	30.0	48.00
MonthlyIncome	1470.0	6502.931293	4707.956783	1009.0	2911.00
MonthlyRate	1470.0	14313.103401	7117.786044	2094.0	8047.00
NumCompaniesWorked	1470.0	2.693197	2.498009	0.0	1.00
PercentSalaryHike	1470.0	15.209524	3.659938	11.0	12.00
StandardHours	1470.0	80.000000	0.000000	80.0	80.00
StockOptionLevel	1470.0	0.793878	0.852077	0.0	0.00
TotalWorkingYears	1470.0	11.279592	7.780782	0.0	6.00
TrainingTimesLastYear	1470.0	2.799320	1.289271	0.0	2.00
YearsAtCompany	1470.0	7.008163	6.126525	0.0	3.00
YearsInCurrentRole	1470.0	4.229252	3.623137	0.0	2.00
YearsSinceLastPromotion	1470.0	2.187755	3.222430	0.0	0.00
YearsWithCurrManager	1470.0	4.123129	3.568136	0.0	2.00

	50%	75%	max
Age	36.0	43.00	60.0
DailyRate	802.0	1157.00	1499.0
DistanceFromHome	7.0	14.00	29.0
EmployeeCount	1.0	1.00	1.0
EmployeeNumber	1020.5	1555.75	2068.0
HourlyRate	66.0	83.75	100.0
MonthlyIncome	4919.0	8379.00	19999.0
MonthlyRate	14235.5	20461.50	26999.0
NumCompaniesWorked	2.0	4.00	9.0
PercentSalaryHike	14.0	18.00	25.0
StandardHours	80.0	80.00	80.0
StockOptionLevel	1.0	1.00	3.0
TotalWorkingYears	10.0	15.00	40.0
TrainingTimesLastYear	3.0	3.00	6.0
YearsAtCompany	5.0	9.00	40.0
YearsInCurrentRole	3.0	7.00	18.0
YearsSinceLastPromotion	1.0	3.00	15.0
YearsWithCurrManager	3.0	7.00	17.0

1.1.9 Inferences:

- (1) The Minimum Age of the employee is 18 and max age is 60
- (2) Employeecount and Standardhours are zero variance features so we can drop those columns
- (3) EmployeeNumber represents a unique value to the each of the employee, which will not provide any meaningfull insights

[15]:
```python
# once againc check for zero variance features
df.var()==0
```

[15]:
```
Age                         False
DailyRate                   False
DistanceFromHome            False
EmployeeCount               False
EmployeeNumber              False
HourlyRate                  False
MonthlyIncome               False
MonthlyRate                 False
NumCompaniesWorked          False
PercentSalaryHike           False
StandardHours                True
StockOptionLevel            False
TotalWorkingYears           False
TrainingTimesLastYear       False
YearsAtCompany              False
YearsInCurrentRole          False
YearsSinceLastPromotion     False
YearsWithCurrManager        False
dtype: bool
```

1.1.10 Drop Redundant Features

[16]:
```python
df.drop(columns =␣
 ↪{'EmployeeCount','EmployeeNumber','Over18','StandardHours'},inplace = True)
df.columns
```

[16]:
```
Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField',
       'EnvironmentSatisfaction', 'Gender', 'HourlyRate', 'JobInvolvement',
       'JobLevel', 'JobRole', 'JobSatisfaction', 'MaritalStatus',
       'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked', 'OverTime',
       'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'YearsWithCurrManager'],
      dtype='object')
```

1.1.11 Descriptive Analysis on Categorical Features

[17]:
```python
df.describe(include ="object").T
```

[17]:
```
                         count unique                  top  freq
Attrition                 1470      2                   No  1233
BusinessTravel            1470      3        Travel_Rarely  1043
```

```
Department                1470      3  Research & Development    961
Education                 1470      5                Bachelor    572
EducationField            1470      6           Life Sciences    606
EnvironmentSatisfaction   1470      4                    High    453
Gender                    1470      2                    Male    882
JobInvolvement            1470      4                    High    868
JobLevel                  1470      5             Entry Level    543
JobRole                   1470      9         Sales Executive    326
JobSatisfaction           1470      4               Very High    459
MaritalStatus             1470      3                 Married    673
OverTime                  1470      2                      No   1054
PerformanceRating         1470      2               Excellent   1244
RelationshipSatisfaction  1470      4                    High    459
WorkLifeBalance           1470      4                  Better    893
```

Inferences:

- All the categorical attributes are having low cardiniality.
- Attrition and OverTime column is highly biased towards No Category.
- Businesstravel Attribute is highly biased towards Travel_Rarely category.
- (Cardinality :categorical features are those that have a large number of unique values)

[ ]:

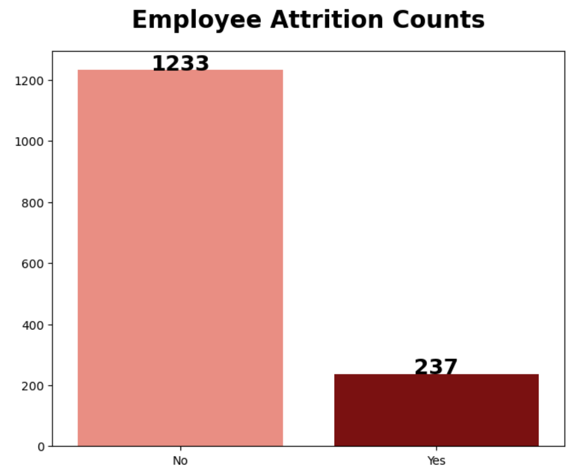
```

```

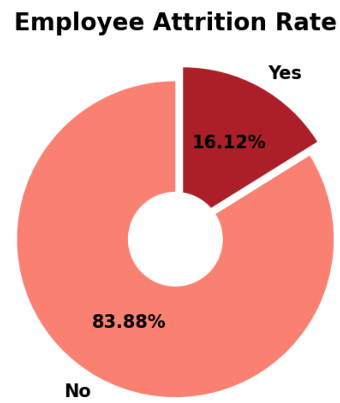
1.1.12 Exploratory Data Analysis

(1) Visualizing the employee Attrition Rate

[18]:

```
#Visualization to show Employee Attrition in Counts.
plt.figure(figsize=(17,6))
plt.subplot(1,2,1)
attrition_rate = df["Attrition"].value_counts()
sns.barplot(x=attrition_rate.index,y=attrition_rate.
 ↪values,palette=["#FA8072","#8B0000"])
plt.title("Employee Attrition Counts",fontweight="black",size=20,pad=20)
for i, v in enumerate(attrition_rate.values):
    plt.text(i, v, v,ha="center", fontweight='black', fontsize=18)

#Visualization to show Employee Attrition in Percentage.
plt.subplot(1,2,2)
plt.pie(attrition_rate, labels=["No","Yes"], autopct="%.2f%%",␣
 ↪textprops={"fontweight":"black","size":15},
        colors = ["#FA8072","#AC1F29"],explode=[0,0.1],startangle=90)
center_circle = plt.Circle((0, 0), 0.3, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)
plt.title("Employee Attrition Rate",fontweight="black",size=20,pad=10)
plt.show()
```





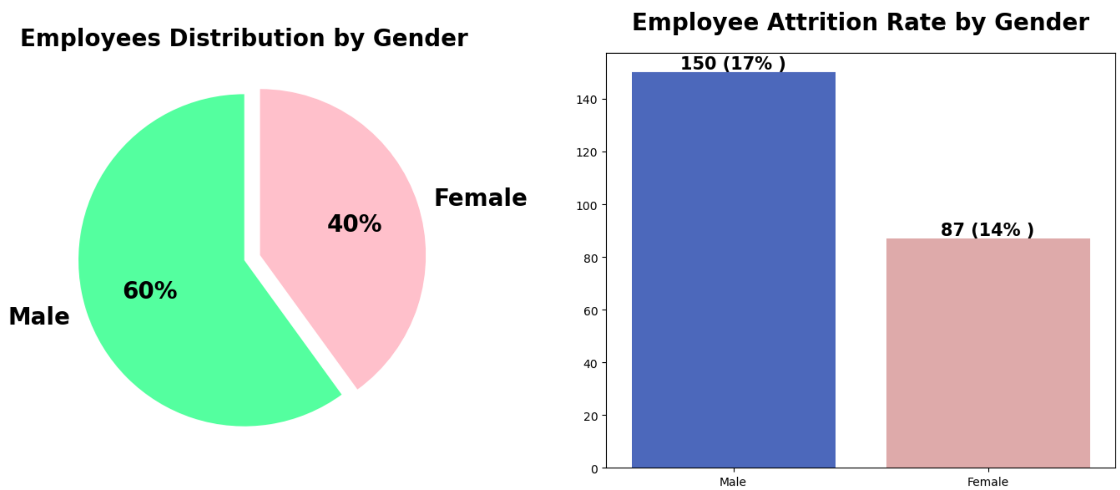
1.1.13 Inferences:

- (1) The employee attrition rate of this organization is 16.12%.
- (2) According to experts in the field of Human Resources, says that the attrition rate 4% to 6% is normal in organization.
- (3) So we can say the attrition rate of the organization is at a dangerous level. Therefore the organization should take measures to reduce the attrition rate

(2) Analyzing the Employee Attrition by Gender

[19]:
```
#Visualization to show Total Employees by Gender.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
gender_attrition = df["Gender"].value_counts()
plt.title("Employees Distribution by Gender",fontweight="black",size=20)
plt.pie(gender_attrition, autopct="%.0f%%",labels=gender_attrition.
 ↪index,textprops=({"fontweight":"black","size":20}),
        explode=[0,0.1],startangle=90,colors= ["#54FF9F","#FFC0CB"])

#Visualization to show Employee Attrition by Gender.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_1 = df["Gender"].value_counts()
value_2 = new_df["Gender"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index, y=value_2.values,palette=["#3A5FCD","#E7A1A1"])
plt.title("Employee Attrition Rate by Gender",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(int(attrition_rate[index]))+"%␣
 ↪)",ha="center",va="bottom",
```

```
                size=15,fontweight="black")
plt.tight_layout()
plt.show()
```

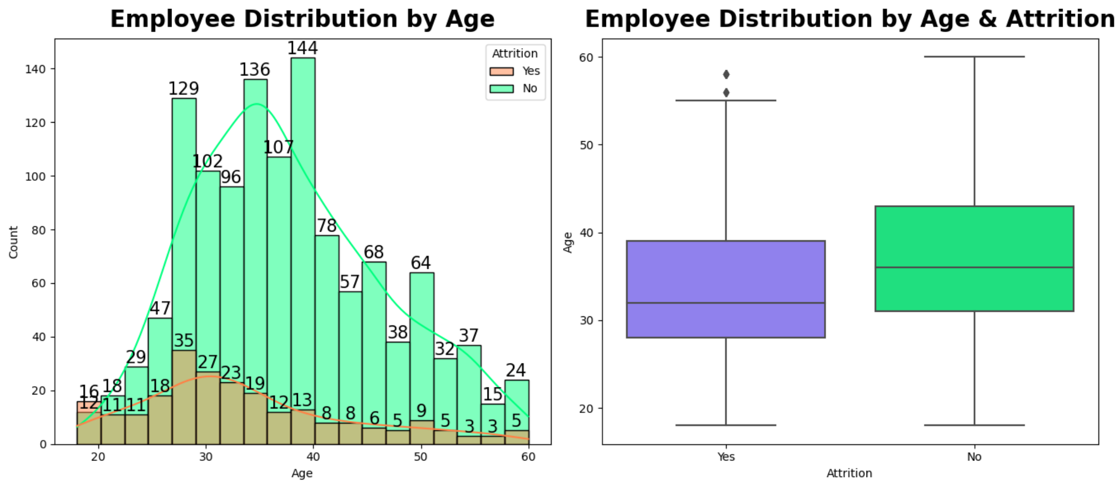


1.1.14 Inferences:

- (1) The No.of Male employees(60%) in the organization is higher than Female Employees(40)%
- (2) Male employees Attrition rate(17%) also higher when compare to the Female Employees(14%)

1.1.15 (3) Analyzing the Employee Attrition by Age

[20]:
```
#Visualization to Employee Distribution by Age.
plt.figure(figsize=(13.5,6))
plt.subplot(1,2,1)
ax = sns.
 ↪histplot(x="Age",hue="Attrition",data=df,kde=True,palette=["#FF8247","#00FF7F"])
for bars in ax.containers:
    ax.bar_label(bars,color = 'black',size = 15)
plt.title("Employee Distribution by Age",fontweight="black",size=20,pad=10)

#Visualization to show Employee Distribution by Age & Attrition.
plt.subplot(1,2,2)
sns.boxplot(x="Attrition",y="Age",data=df,palette=["#836FFF","#00FF7F"])
plt.title("Employee Distribution by Age &␣
 ↪Attrition",fontweight="black",size=20,pad=10)
plt.tight_layout()
plt.show()
```



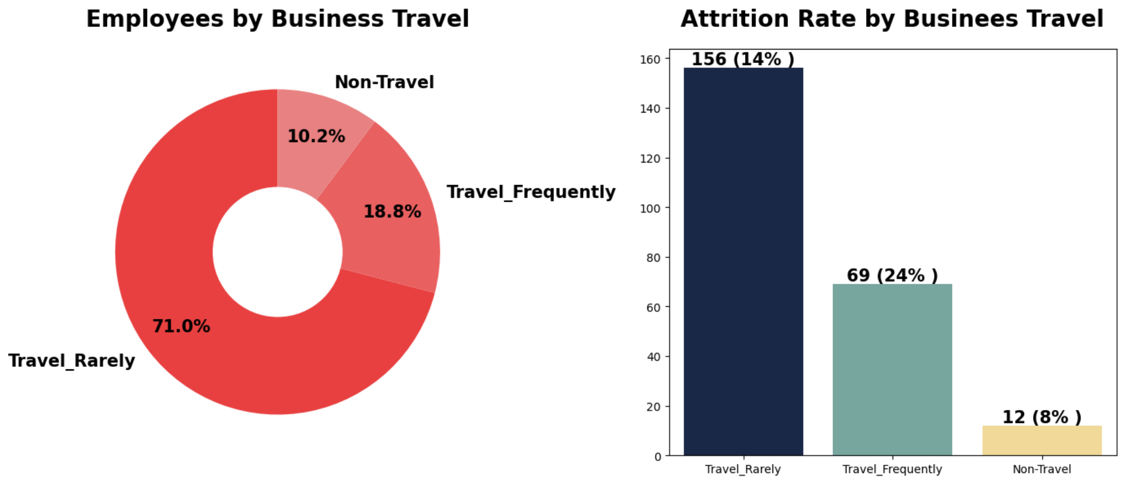
1.1.16 Inferences:

- (1) Most of the employees age is 30 to 40 Range
- (2) we can observe age is inverse proporsnal to attrition because the age is increasing attritionis decreasing
- (3) Younge age employees are leave the company more compared to the elder employees
- (4) According to boxplot, the median age of the attrition employee is less than who are working in the company

1.1.17 (4) Analyzing the Employee Attrition by Business Travel

[21]:
```
#Visualization to show Total Employees by Businees Travel.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["BusinessTravel"].value_counts()
plt.title("Employees by Business Travel", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.75,startangle=90,
        colors=['#E84040', '#E96060', '#E88181'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by Businees Travel.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["BusinessTravel"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
```

```
sns.barplot(x=value_2.index,y=value_2.
 ↪values,palette=["#11264e","#6faea4","#FEE08B"])
plt.title("Attrition Rate by Businees Travel",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(int(attrition_rate[index]))+"%␣
 ↪)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



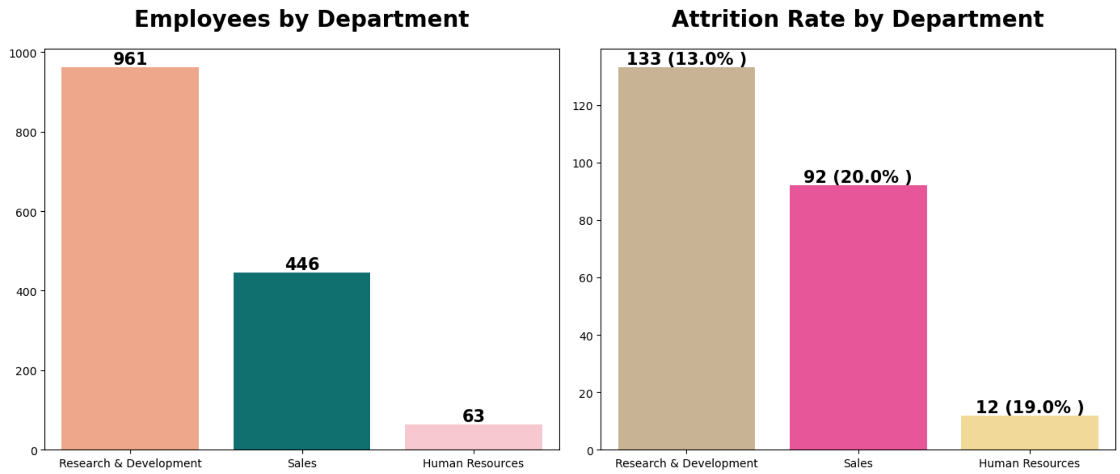
1.1.18 Inferences:

- Most of the employees are Travel_Rarely(71%) and 18% employees Travel_Frequently
- Highest employee attrition can be observed by those employees who Travels Frequently.
- Lowest employee attrition can be observed by those employees who are Non-Travel.

1.1.19 (5) Analyzing the Employee Attrition by Department

[22]:
```
#Visualization to show Total Employees by Department.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["Department"].value_counts()
sns.barplot(x=value_1.index, y=value_1.values,palette = ["#FFA07A", "#008080",␣
 ↪"#FFC0CB"])
plt.title("Employees by Department",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_1.values):
    plt.
 ↪text(index,value,value,ha="center",va="bottom",fontweight="black",size=15,)

#Visualization to show Employee Attrition Rate by Department.
```

```
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["Department"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index, y=value_2.
 ↪values,palette=["#D2B48C","#FF3E96","#FEE08B"])
plt.title("Attrition Rate by Department",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(attrition_rate[index])+"%␣
 ↪)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



1.1.20 Inferences:

- (1) Most of the employees are from Research & Development Department.
- (2) Highest Attrition is in the Sales Department.
- (3) Human Resources Department Attrition rate is also very high.
- (4) Though of highest employees in Research & Development department there is least attrition compared to other departments.

1.1.21 (6) Analyzing the Employee Attrition by DailyRate

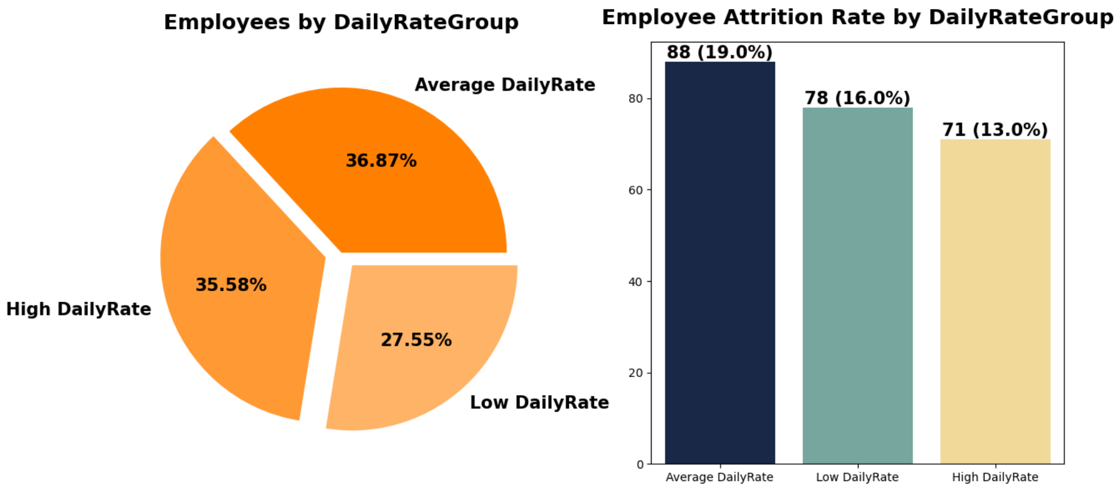
[23]:
```
df["DailyRate"].describe().to_frame().T
```

[23]:

	count	mean	std	min	25%	50%	75%	max
DailyRate	1470.0	802.485714	403.5091	102.0	465.0	802.0	1157.0	1499.0

[24]:
```
# Define the bin edges for the groups
bin_edges = [0, 500, 1000, 1500]

# Define the labels for the groups
bin_labels = ['Low DailyRate', 'Average DailyRate', 'High DailyRate']

# Cut the DailyRate column into groups
df['DailyRateGroup'] = pd.cut(df['DailyRate'], bins=bin_edges,labels=bin_labels)
```

[25]:
```
##Visualization to show Total Employees by DailyRateGroup.
plt.figure(figsize=(13,6))
plt.subplot(1,2,1)
value_1 = df["DailyRateGroup"].value_counts()
plt.pie(value_1.values, labels=value_1.index,autopct="%.
 ↪2f%%",textprops={"fontweight":"black","size":15},
        explode=[0,0.1,0.1],colors= ['#FF8000', '#FF9933', '#FFB366',␣
 ↪'#FFCC99'])
plt.title("Employees by DailyRateGroup",fontweight="black",pad=15,size=18)

#Visualization to show Attrition Rate by DailyRateGroup.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["DailyRateGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(),y= value_2.
 ↪values,palette=["#11264e","#6faea4","#FEE08B"])
plt.title("Employee Attrition Rate by␣
 ↪DailyRateGroup",fontweight="black",pad=15,size=18)
for index,value in enumerate(value_2.values):
    plt.text(index,value, str(value)+"␣
 ↪("+str(attrition_rate[index])+"%)",ha="center",va="bottom",fontweight="black",size=15)

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



1.1.22 Inferences:

- Employees with Average DailyRate & High Daily Rate are approxiamately equal.
- But the attrition rate is very high of employees with average Daily Rate compared to the employees with High DailyRate.
- The attrition rate is also high of employees with low DailyRate.
- Employees which are not getting High Daily Rate are mostly leaving the organization.

1.1.23 (7) Analyzing the Employee Attrition by Distance From Home

[26]:
```
print("Total Unique Values in Attribute is =>",df["DistanceFromHome"].nunique())

df["DistanceFromHome"].describe().to_frame().T
```

```
Total Unique Values in Attribute is => 29
```

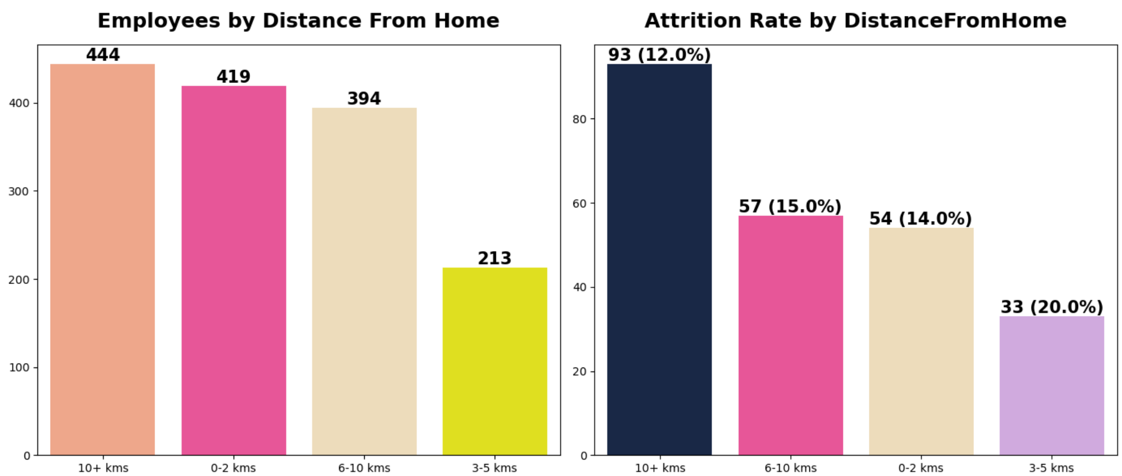
[26]:

	count	mean	std	min	25%	50%	75%	max
DistanceFromHome	1470.0	9.192517	8.106864	1.0	2.0	7.0	14.0	29.0

[27]:
```
# Define the bin edges for the groups
bin_edges = [0,2,5,10,30]

# Define the labels for the groups
bin_labels = ['0-2 kms', '3-5 kms', '6-10 kms',"10+ kms"]

# Cutting the DistanceFromHome column into groups
df['DistanceGroup'] = pd.cut(df['DistanceFromHome'], bins=bin_edges,␣
 ↪labels=bin_labels)
```

[28]:
```
##Visualization to show Total Employees by DistnaceFromHome.
plt.figure(figsize=(14,6))
```

```
plt.subplot(1,2,1)
value_1 = df["DistanceGroup"].value_counts()
sns.barplot(x=value_1.index.tolist(), y=value_1.values,palette = ["#FFA07A",␣
↪"#FF3E96", "#F5DEB3","#FFFF00"])
plt.title("Employees by Distance From Home",fontweight="black",pad=15,size=18)
for index, value in enumerate(value_1.values):
    plt.
↪text(index,value,value,ha="center",va="bottom",fontweight="black",size=15)

#Visualization to show Attrition Rate by DistanceFromHome.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["DistanceGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(),y= value_2.
↪values,palette=["#11264e","#FF3E96","#F5DEB3","#D4A1E7","#FFFF00"])
plt.title("Attrition Rate by␣
↪DistanceFromHome",fontweight="black",pad=15,size=18)
for index,value in enumerate(value_2.values):
    plt.text(index,value, str(value)+"␣
↪("+str(attrition_rate[index])+"%)",ha="center",va="bottom",fontweight="black",size=15)

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

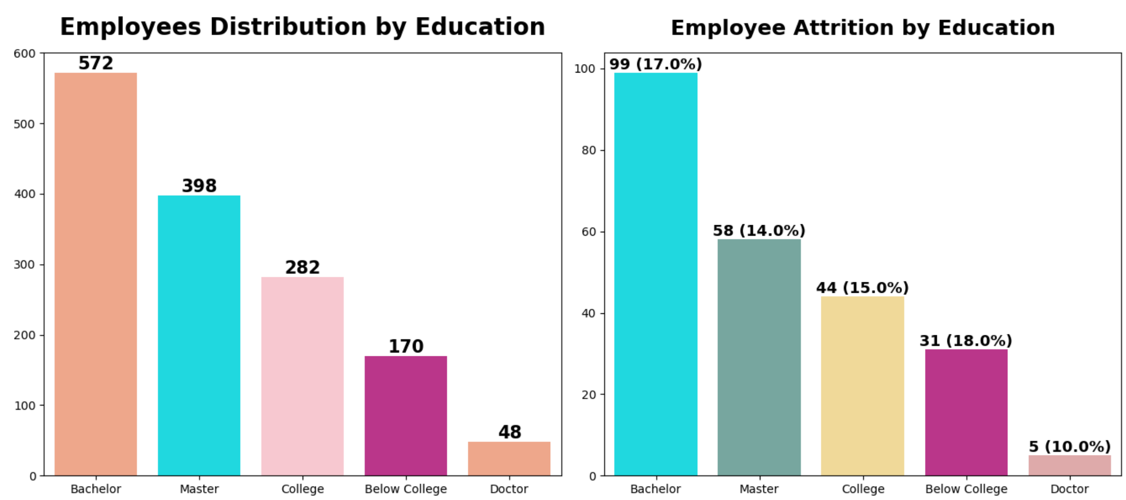


1.1.24 Inferences:

- 1.Most of the employees from the 10+kms distance
- 2.least employees from 3-5kms range
- 3.12% of the employees left from the company whose distnacefromhome is 10+kms

1.1.25 (8) Analyzing the Employee Attrition by Education

[29]:
```python
# Visualization to show Total Employees by Education.
plt.figure(figsize=(13.5,6))
plt.subplot(1,2,1)
value_1 = df["Education"].value_counts()
sns.barplot(x=value_1.index,y=value_1.values,order=value_1.index,palette =␣
 ↪["#FFA07A", "#00F5FF", "#FFC0CB","#D02090"])
plt.title("Employees Distribution by␣
 ↪Education",fontweight="black",size=20,pad=15)
for index,value in enumerate(value_1.values):
    plt.
 ↪text(index,value,value,ha="center",va="bottom",fontweight="black",size=15)

#Visualization to show Employee Attrition by Education.
plt.subplot(1,2,2)
value_2 = new_df["Education"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index,y=value_2.values,order=value_2.
 ↪index,palette=["#00F5FF","#6faea4","#FEE08B","#D02090","#E7A1A1"])
plt.title("Employee Attrition by Education",fontweight="black",size=18,pad=15)
for index,value in enumerate(value_2.values):
    plt.text(index,value,str(value)+"␣
 ↪("+str(attrition_rate[index])+"%)",ha="center",va="bottom",
             fontweight="black",size=13)
plt.tight_layout()
plt.show()
```

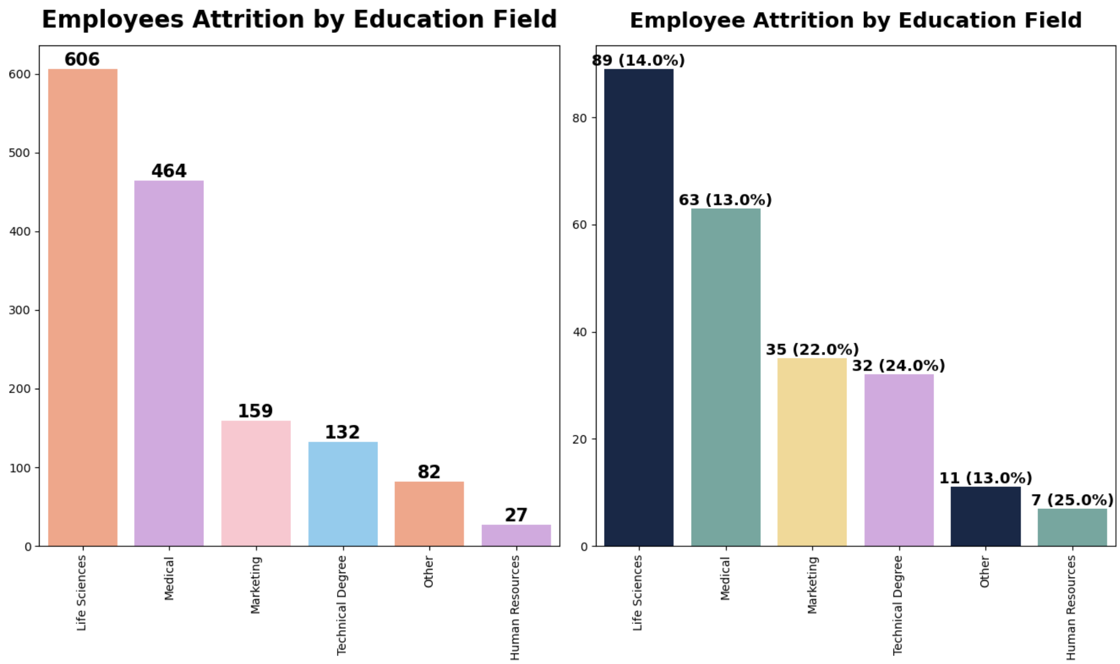


1.1.26 Inferences:

- 1.Most of the employees in the organization have completed Bachelors
- 2.Very few employees in the organization have completed Doctorate degree as their education qualification.
- 3.We can observe a trend of decreasisng in attrition rate as the education qualification increases.

1.1.27 (9) Analyzing the Employee Attrition by Education Field

[30]:
```
#Visualization to show Total Employees by Education Field.
plt.figure(figsize=(13.5,8))
plt.subplot(1,2,1)
value_1 = df["EducationField"].value_counts()
sns.barplot(x=value_1.index, y=value_1.values,order=value_1.index,palette =␣
 ↪["#FFA07A", "#D4A1E7", "#FFC0CB","#87CEFA"])
plt.title("Employees Attrition by Education␣
 ↪Field",fontweight="black",size=20,pad=15)
for index,value in enumerate(value_1.values):
    plt.
 ↪text(index,value,value,ha="center",va="bottom",fontweight="black",size=15)
plt.xticks(rotation=90)

#Visualization to show Employee Attrition by Education Field.
plt.subplot(1,2,2)
value_2 = new_df["EducationField"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index,y=value_2.values,order=value_2.
 ↪index,palette=["#11264e","#6faea4","#FEE08B","#D4A1E7"])
plt.title("Employee Attrition by Education␣
 ↪Field",fontweight="black",size=18,pad=15)
for index,value in enumerate(value_2.values):
    plt.text(index,value,str(value)+"␣
 ↪("+str(attrition_rate[index])+"%)",ha="center",va="bottom",
             fontweight="black",size=13)
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



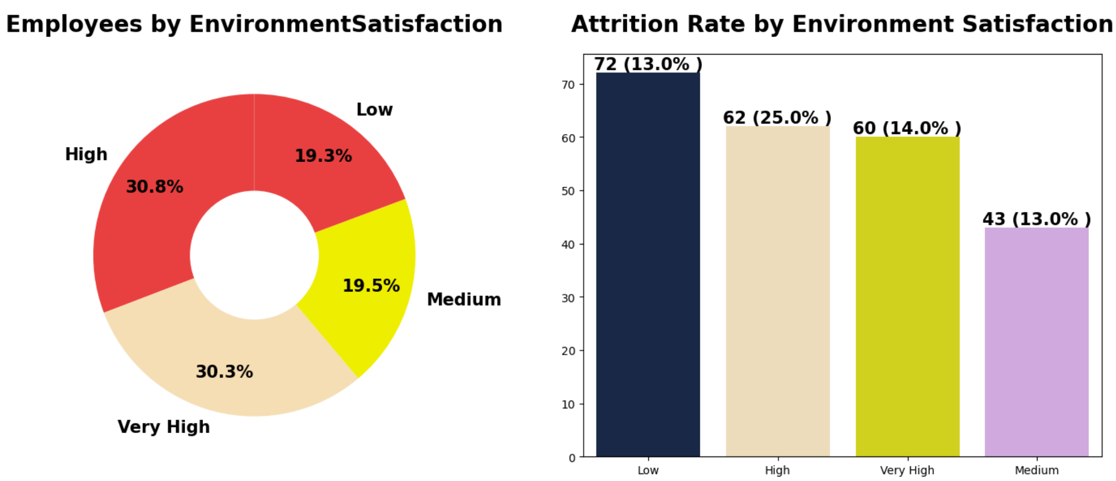
1.1.28 Inferences:

- 1.Most of the employees are either from Life Science or Medical Education Field.
- 2.Very few employees are from Human Resources Education Field.
- 3.Education Fields like Human Resources, Marketing, Technical is having very high attrition rate.
- 4.This may be because of work load becuase there are very few employees in these education fields compared to education field with less attrition rate.

1.1.29 (10) Analyzing the Employee Attrition by Environment Satisfaction

[31]:
```
#Visualization to show Total Employees by EnvironmentSatisfaction.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["EnvironmentSatisfaction"].value_counts()
plt.title("Employees by EnvironmentSatisfaction", fontweight="black", size=20,␣
↪pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=['#E84040', '#F5DEB3', '#EEEE00'],textprops={"fontweight":
↪"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)
```

```
#Visualization to show Attrition Rate by EnvironmentSatisfaction.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["EnvironmentSatisfaction"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index,y=value_2.values,order=value_2.index,palette=["#11264e","#F5DEB3","#EEEE00","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by Environment Satisfaction",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(attrition_rate[index])+"% )",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



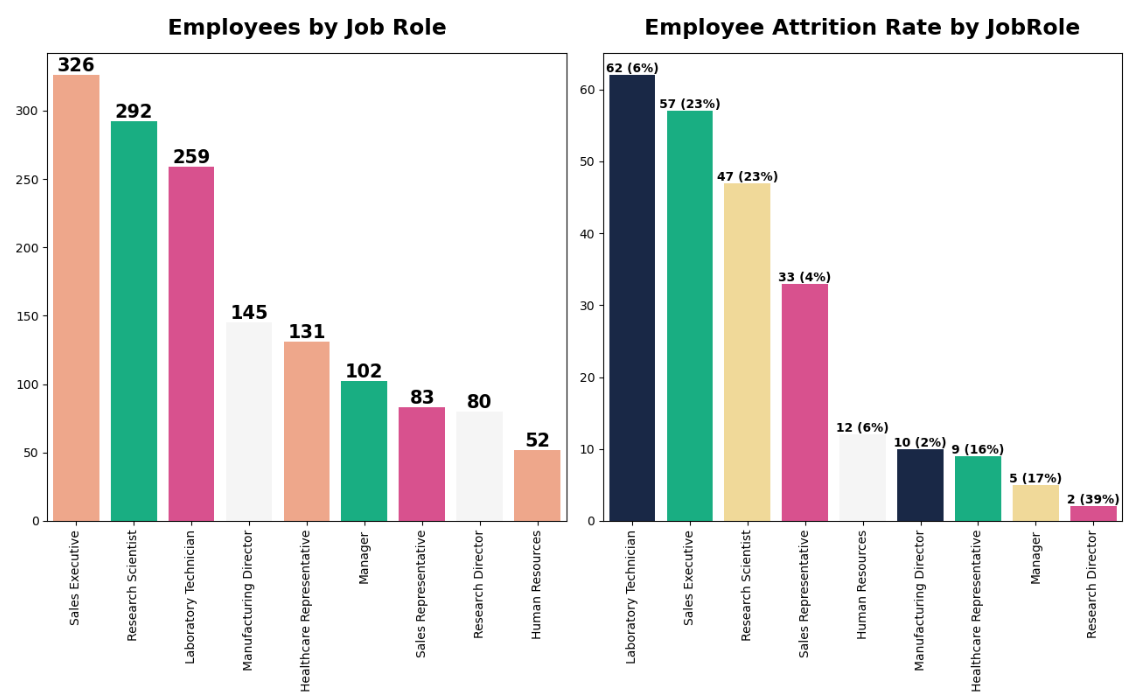
1.1.30 Inferences:

- Most of the employees have rated the organization environment satisfaction High & Very High.
- Though the organization environment satisfaction is high still there's very high attriton in this envirnoment.
- Attrition Rate increases with increase in level of environment satisfication.

1.1.31 (11) Analyzing the Employee Attrition by Job roles

[32]:
```
##Visualization to show Total Employees by JobRole.
plt.figure(figsize=(13,8))
plt.subplot(1,2,1)
value_1 = df["JobRole"].value_counts()
```

```
sns.barplot(x=value_1.index.tolist(), y=value_1.values,palette = ["#FFA07A", "#00C78C", "#EE3A8C","#F5F5F5"])
plt.title("Employees by Job Role",fontweight="black",pad=15,size=18)
plt.xticks(rotation=90)
for index, value in enumerate(value_1.values):
    plt.text(index,value,value,ha="center",va="bottom",fontweight="black",size=15)

#Visualization to show Attrition Rate by JobRole.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["JobRole"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.values,palette=["#11264e","#00C78C","#FEE08B","#EE3A8C","#F5F5F5"])
plt.title("Employee Attrition Rate by JobRole",fontweight="black",pad=15,size=18)
plt.xticks(rotation=90)
for index,value in enumerate(value_2.values):
    plt.text(index,value, str(value)+" ("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             fontweight="black",size=10)
plt.tight_layout()
plt.show()
```

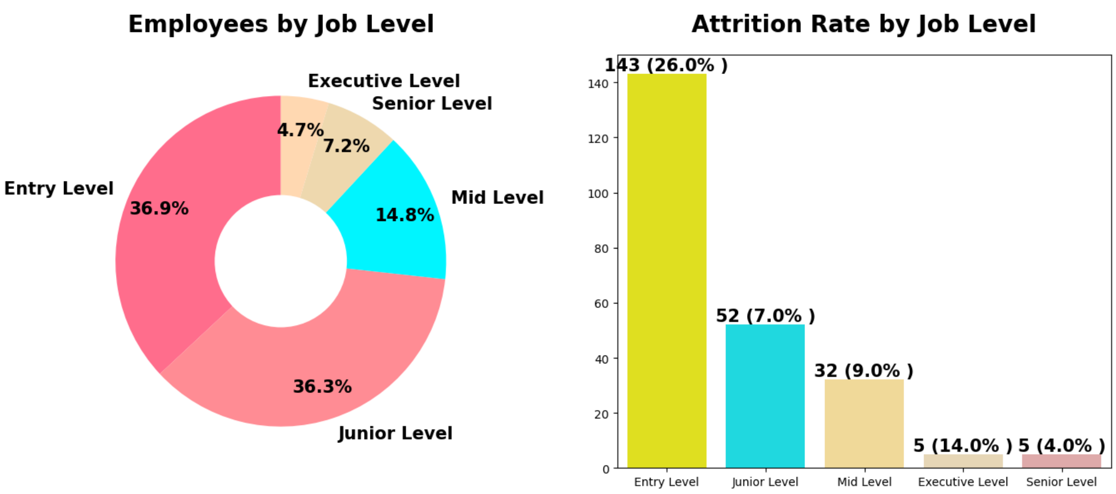


1.1.32 Inferences:

- Most employees is working as Sales executive, Research Scientist or Laboratory Technician in this organization.
- Highest attrition rates are in sector of Research Director, Sales Executive, Research Scientist.

1.1.33 (12) Analyzing the Employee Attrition by Job Level

[33]:
```
#Visualization to show Total Employees by Job Level.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["JobLevel"].value_counts()
plt.title("Employees by Job Level", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪8,startangle=90,
        colors=['#FF6D8C', '#FF8C94', '#00F5FF',␣
↪'#EED8AE',"#FFD8B1"],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by JobLevel.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["JobLevel"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index,y=value_2.values,order=value_2.
↪index,palette=["#FFFF00","#00F5FF","#FEE08B","#EED8AE","#E7A1A1"])
plt.title("Attrition Rate by Job Level",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(attrition_rate[index])+"%␣
↪)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



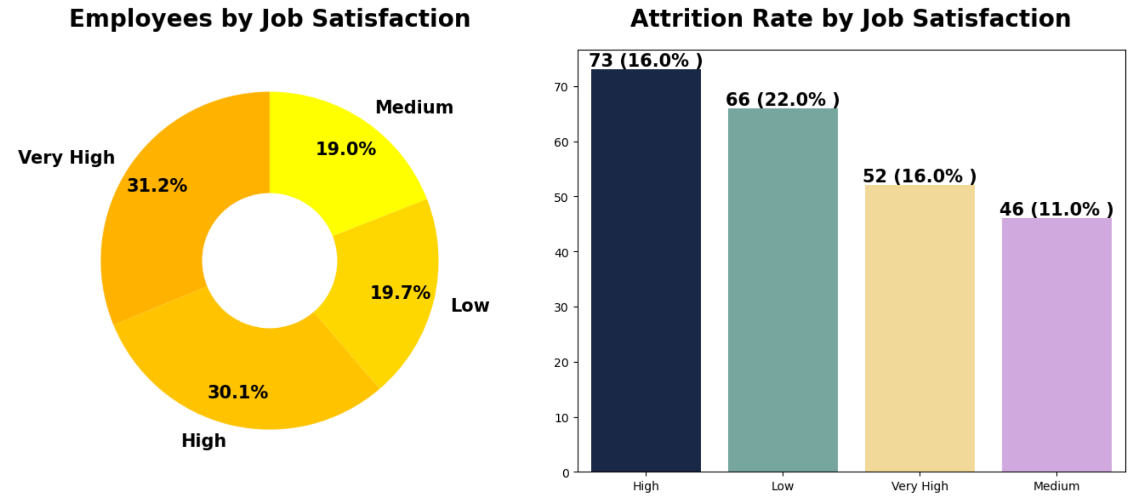
1.1.34 Inferences:

- Most of the employees in the organization are at Entry Level or Junior Level.
- Highest Attrition is at the Entry Level.
- As the level increases the attrition rate decreases.

1.1.35 (13) Analyzing the Employee Attrition by Job Satisfaction

[34]:
```
#Visualization to show Total Employees by Job Satisfaction.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["JobSatisfaction"].value_counts()
plt.title("Employees by Job Satisfaction", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
 ↪8,startangle=90,
        colors=['#FFB300', '#FFC300', '#FFD700',␣
 ↪'#FFFF00'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by Job Satisfaction.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["JobSatisfaction"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index,y=value_2.values,order=value_2.
 ↪index,palette=["#11264e","#6faea4","#FEE08B","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by Job␣
 ↪Satisfaction",fontweight="black",size=20,pad=20)
```

```
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(attrition_rate[index])+"% )",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



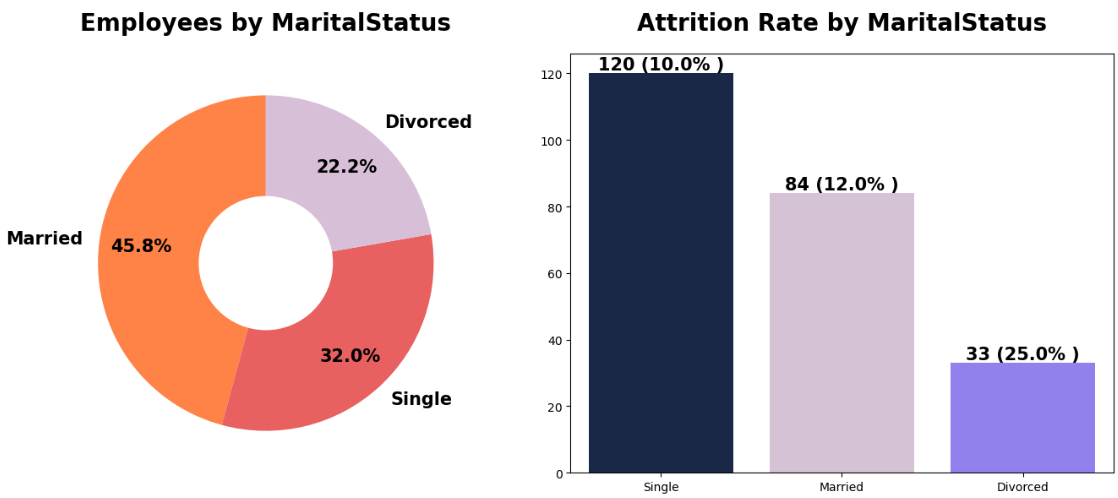
1.1.36 Inferences:

- Most of the employees have rated their job satisfaction as high or very high.
- Employees who rated their job satisfaction low are mostly leaving the organization.
- All the categories in job satisfaction is having high attrition rate.

1.1.37 (14) Analyzing the Employee Attrition by Marital Status

[35]:
```
#Visualization to show Total Employees by MaritalStatus.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["MaritalStatus"].value_counts()
plt.title("Employees by MaritalStatus", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.75,startangle=90,
        colors=['#FF8247', '#E96060', '#D8BFD8', '#836FFF'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by MaritalStatus.
plt.subplot(1,2,2)
```

```
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["MaritalStatus"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index, y=value_2.
 ↪values,palette=["#11264e","#D8BFD8","#836FFF","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by MaritalStatus",
          fontweight="black",
          size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(attrition_rate[index])+"%␣
 ↪)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



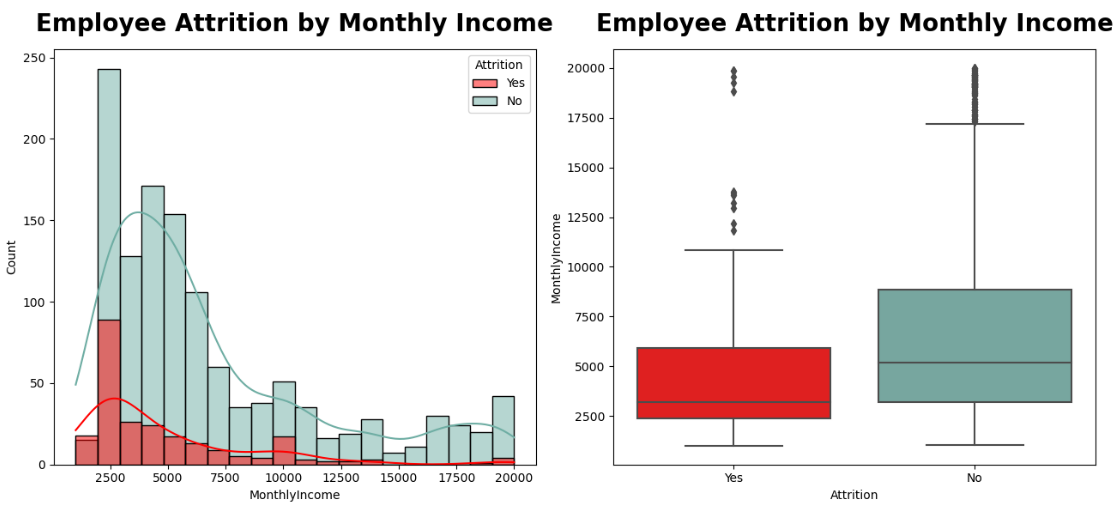
1.1.38 Inferences:

- (1) Most of the employees are Married in the organization.
- (2) The attrition rate is very high of employees who are divorced.
- (3) The attrition rate is low for employees who are single.

1.1.39 (15) Analyzing the Employee Attrition by Monthly Income

[36]:
```
#Visualization to show Employee Distribution by MonthlyIncome.
plt.figure(figsize=(13,6))
plt.subplot(1,2,1)
sns.histplot(x="MonthlyIncome", hue="Attrition", kde=True␣
 ↪,data=df,palette=["#FF0000","#6faea4"])
```

```
plt.title("Employee Attrition by Monthly␣
↪Income",fontweight="black",size=20,pad=15)

#Visualization to show Employee Attrition by Monthly Income.
plt.subplot(1,2,2)
sns.
↪boxplot(x="Attrition",y="MonthlyIncome",data=df,palette=["#FF0000","#6faea4"])
plt.title("Employee Attrition by Monthly␣
↪Income",fontweight="black",size=20,pad=15)
plt.tight_layout()
plt.show()
```



1.1.40 Inferences:

- Most of the employees are getting paid less than 10000 in the organiation.
- The average monthly income of employee who have left is comparatively low with employee who are still working.
- As the Monthly Income increases the attrition decreases.

1.1.41 (16) Analyzing the Employee Attrition by Work Experience

[37]:
```
df["NumCompaniesWorked"].describe().to_frame().T
```

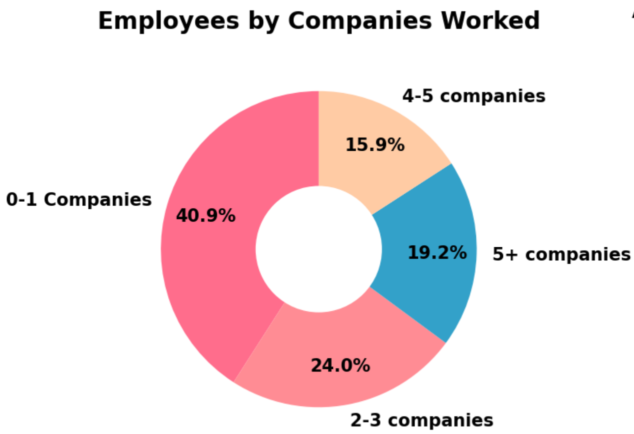
[37]:

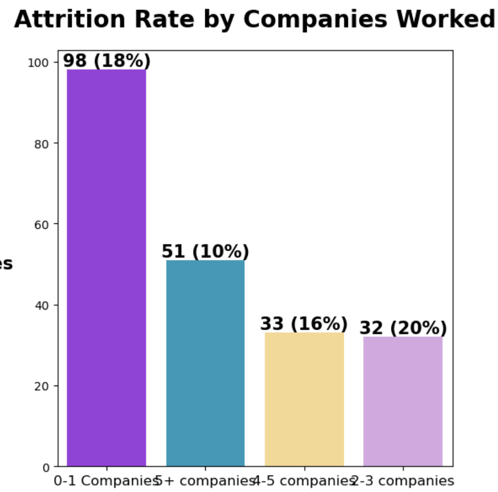
	count	mean	std	min	25%	50%	75%	max
NumCompaniesWorked	1470.0	2.693197	2.498009	0.0	1.0	2.0	4.0	9.0

[38]:
```
# Define the bin edges for the groups
bin_edges = [0, 1, 3, 5, 10]

# Define the labels for the groups
```

```
bin_labels = ['0-1 Companies', '2-3 companies', '4-5 companies', "5+ companies"]

# Cut the DailyRate column into groups
df["NumCompaniesWorkedGroup"] = pd.cut(df['NumCompaniesWorked'],␣
↪bins=bin_edges, labels=bin_labels)
```

[39]:
```
#Visualization to show Total Employees by NumCompaniesWorked.
plt.figure(figsize=(13,6))
plt.subplot(1,2,1)
value_1 = df["NumCompaniesWorkedGroup"].value_counts()
plt.title("Employees by Companies Worked", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=['#FF6D8C', '#FF8C94', '#33A1C9',␣
↪'#FFCBA4'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by NumCompaniesWorked.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["NumCompaniesWorkedGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.
↪values,palette=["#912CEE","#33A1C9","#FEE08B","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by Companies␣
↪Worked",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+"␣
↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.xticks(size=12)
plt.tight_layout()
plt.show()
```





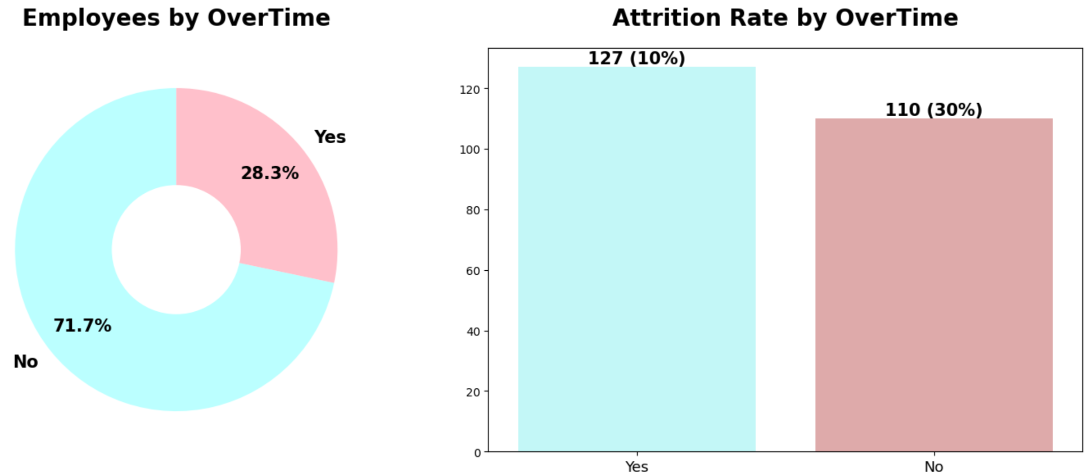
1.1.42 Inferences:

- Most of the employees have worked for less than 2 companies.
- There's a high attrition rate of employees who haved for less than 5 companies.

1.1.43 (17) Analyzing the Employee Attrition by Overtime

[40]:
```
#Visualization to show Total Employees by OverTime.
plt.figure(figsize=(15,6))
plt.subplot(1,2,1)
value_1 = df["OverTime"].value_counts()
plt.title("Employees by OverTime", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
 ↪75,startangle=90,
        colors=["#BBFFFF","#FFC0CB"],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)


#Visualization to show Attrition Rate by OverTime.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["OverTime"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.
 ↪values,palette=["#BBFFFF","#E7A1A1"])
plt.title("Attrition Rate by OverTime",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
```

```
    plt.text(index,value,str(value)+"␣
↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.xticks(size=13)
plt.tight_layout()
plt.show()
```

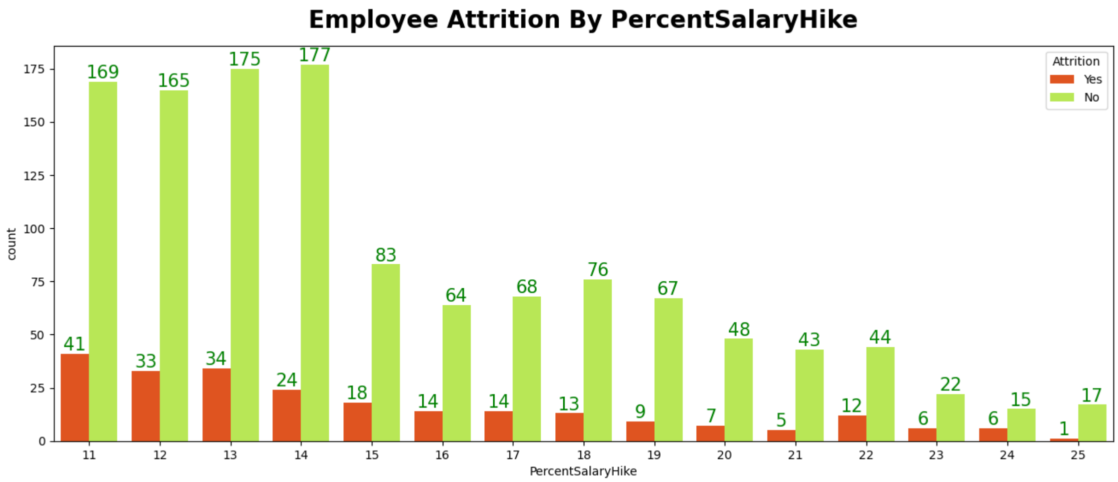


1.1.44 Inferences:

- Most of the employees doesn't work over time
- 10% of the employees left the company who had working overtime

1.1.45 (18) Analyzing the Employee Attrition by SalaryHikek

[41]:
```
#Visualization to show Employee Distribution by Percentage Salary Hike.
plt.figure(figsize=(16,6))
ax=sns.countplot(x="PercentSalaryHike", hue="Attrition", data=df,␣
↪palette=["#FF4500","#C0FF3E"])
for bars in ax.containers:
    ax.bar_label(bars,color = 'green',size = 15)
plt.title("Employee Attrition By␣
↪PercentSalaryHike",fontweight="black",size=20,pad=15)
plt.show()
```



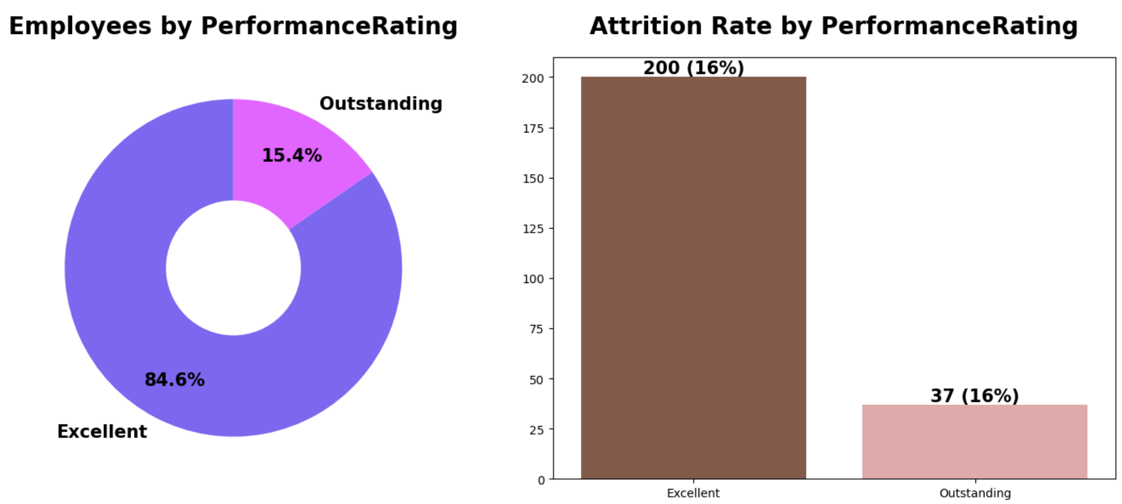
1.1.46 Inferences:

- Less no of employees are getting a high salary hike
- The PercentSalaryHike increases the attrition rate decreases

1.1.47 (19) Analyzing the Employee Attrition by Performance Rating

[42]:
```
#Visualization to show Total Employees by PerformanceRating.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["PerformanceRating"].value_counts()
plt.title("Employees by PerformanceRating", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=["#7B68EE","#E066FF"],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by PerformanceRating.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["PerformanceRating"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(),y= value_2.
↪values,palette=["#8B5742","#E7A1A1"])
plt.title("Attrition Rate by␣
↪PerformanceRating",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
```

```
    plt.text(index,value,str(value)+"␣
↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



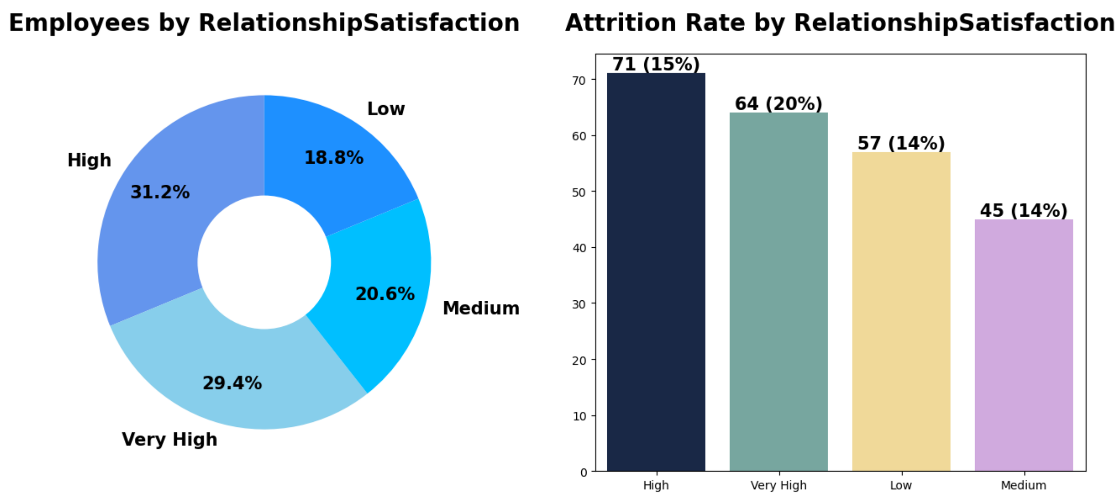
1.1.48 Inferences:

- Most of the employees are having excellent performance rating.
- Both the categories in this field is having same attriton rate.
- That's why we can't generate any meaningful inisghts

1.1.49 (20) Analyzing the Employee Attrition by Relatioship Satisfaction

[43]:
```
#Visualization to show Total Employees by RelationshipSatisfaction.
plt.figure(figsize=(13,6))
plt.subplot(1,2,1)
value_1 = df["RelationshipSatisfaction"].value_counts()
plt.title("Employees by RelationshipSatisfaction", fontweight="black", size=20,␣
↪pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=['#6495ED', '#87CEEB', '#00BFFF',␣
↪'#1E90FF'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by RelationshipSatisfaction.
plt.subplot(1,2,2)
```

```
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["RelationshipSatisfaction"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index, y=value_2.values,order=value_2.index,palette=["#11264e","#6faea4","#FEE08B","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by RelationshipSatisfaction",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



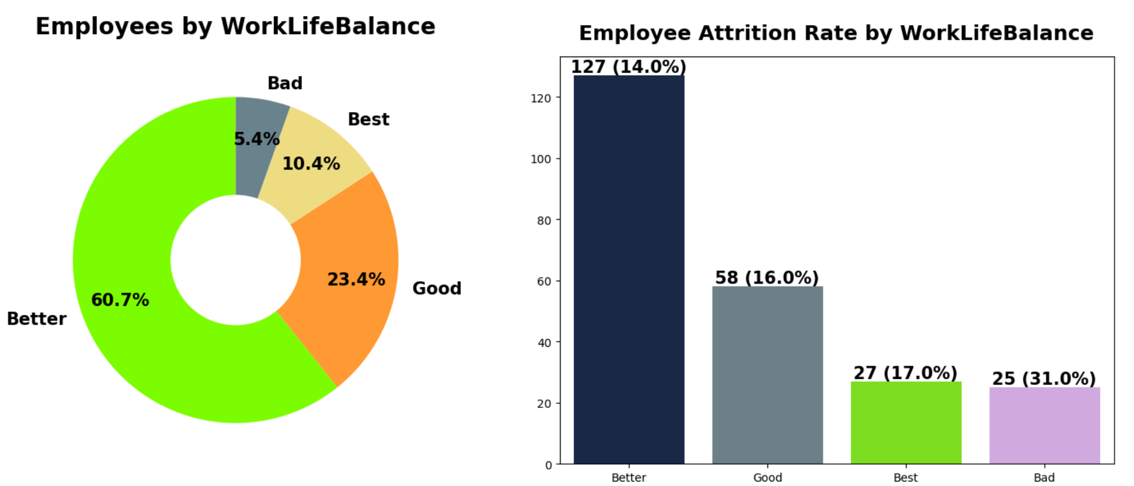
1.1.50 Inferences:

- Most of the employees are having high or very high relationship satisfaction.
- Though the relationship satification is high there's a high attrition rate.
- All the categories in this feature is having a high attriton rate.

1.1.51 (21) Analyzing the Employee Attrition by Work Life Balance

[44]:
```
##Visualization to show Total Employees by WorkLifeBalance.
plt.figure(figsize=(14.5,6))
plt.subplot(1,2,1)
value_1 = df["WorkLifeBalance"].value_counts()
plt.title("Employees by WorkLifeBalance", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.75,startangle=90,
```

```
        colors= ['#7CFC00', '#FF9933', '#EEDC82',␣
↪'#68838B'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by WorkLifeBalance.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["WorkLifeBalance"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index, y=value_2.values,order=value_2.
↪index,palette=["#11264e","#68838B","#7CFC00","#D4A1E7","#E7A1A1"])
plt.title("Employee Attrition Rate by␣
↪WorkLifeBalance",fontweight="black",pad=15,size=18)
for index,value in enumerate(value_2.values):
    plt.text(index,value, str(value)+"␣
↪("+str(attrition_rate[index])+"%)",ha="center",va="bottom",
             fontweight="black",size=15)
plt.tight_layout()
plt.show()
```



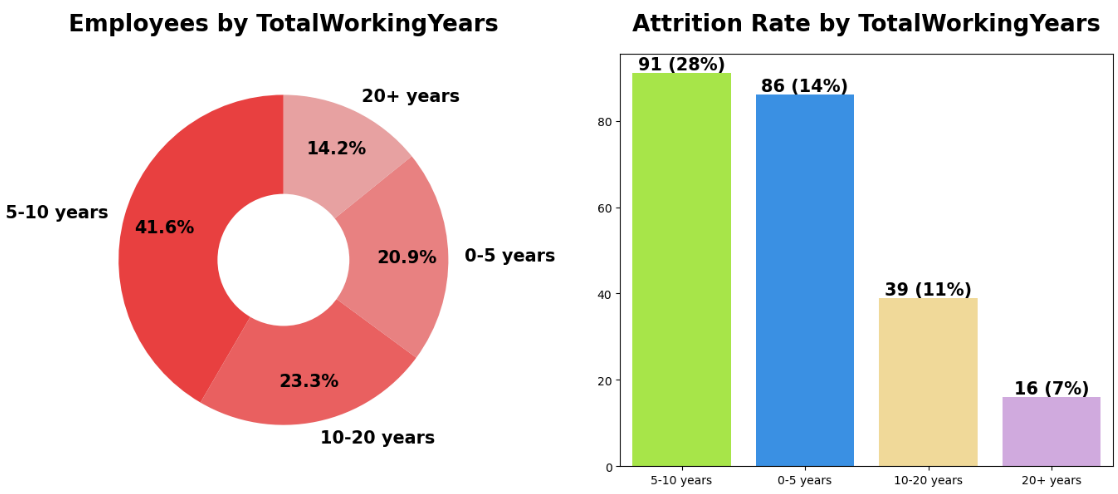
1.1.52 Inferences:

- More than 60% of employees are having a better work life balance.
- Employees with Bad Work Life Balance is having Very High Attrition Rate.
- Other Categories is also having High attriton Rate.

1.1.53 (22) Analyzing the Employee Attrition by Total Working Experience

[45]:
```
# Define the bin edges for the groups
bin_edges = [0, 5, 10, 20, 50]

# Define the labels for the groups
bin_labels = ['0-5 years', '5-10 years', '10-20 years', "20+ years"]

# Cut the DailyRate column into groups
df["TotalWorkingYearsGroup"] = pd.cut(df['TotalWorkingYears'], bins=bin_edges,␣
↪labels=bin_labels)
```

[46]:
```
#Visualization to show Total Employees by TotalWorkingYearsGroup.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["TotalWorkingYearsGroup"].value_counts()
plt.title("Employees by TotalWorkingYears", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=['#E84040', '#E96060', '#E88181',␣
↪'#E7A1A1'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by TotalWorkingYearsGroup.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["TotalWorkingYearsGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.
↪values,palette=["#ADFF2F","#1E90FF","#FEE08B","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by␣
↪TotalWorkingYears",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+"␣
↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



1.1.54 Inferences:

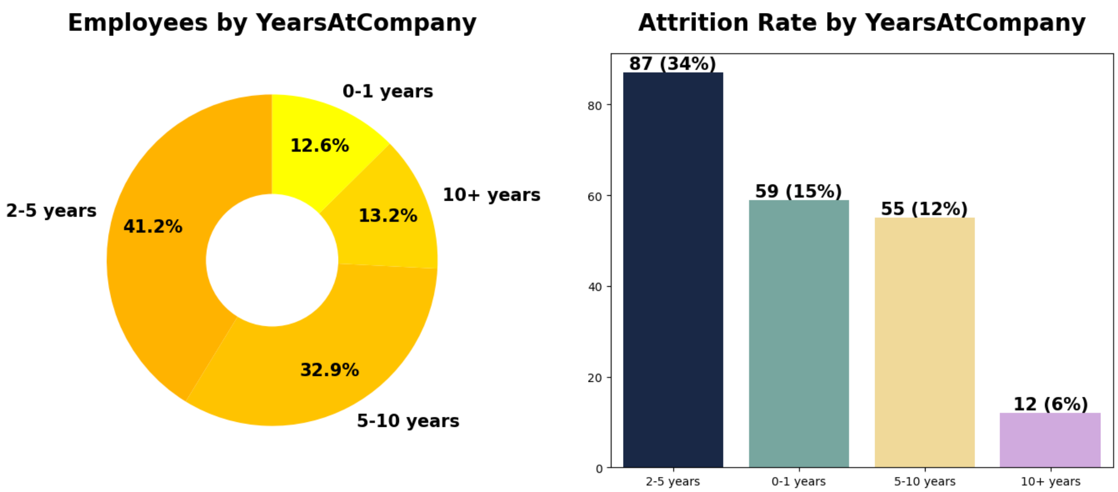
- Most of the employees are having a total of 5 to 10 years of working experience. But their Attrition Rate is also **very high.
- Employee with working experience of less than 10 years are having High Attrition Rate.
- Employee with working experience of more than 10 years are having Less Attrition Rate.

1.1.55 (23) Analyzing the Employee Attrition by YearsAt company

[47]:
```
# Define the bin edges for the groups
bin_edges = [0, 1, 5, 10, 20]

# Define the labels for the groups
bin_labels = ['0-1 years', '2-5 years', '5-10 years', "10+ years"]

# Cut the DailyRate column into groups
df["YearsAtCompanyGroup"] = pd.cut(df['YearsAtCompany'], bins=bin_edges,␣
↪labels=bin_labels)
```

[48]:
```
#Visualization to show Total Employees by YearsAtCompanyGroup.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["YearsAtCompanyGroup"].value_counts()
plt.title("Employees by YearsAtCompany", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=['#FFB300', '#FFC300', '#FFD700',␣
↪'#FFFF00'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
```

```
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by YearsAtCompanyGroup.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["YearsAtCompanyGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.values,palette=["#11264e","#6faea4","#FEE08B","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by YearsAtCompany",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+" ("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



1.1.56 Inferences:

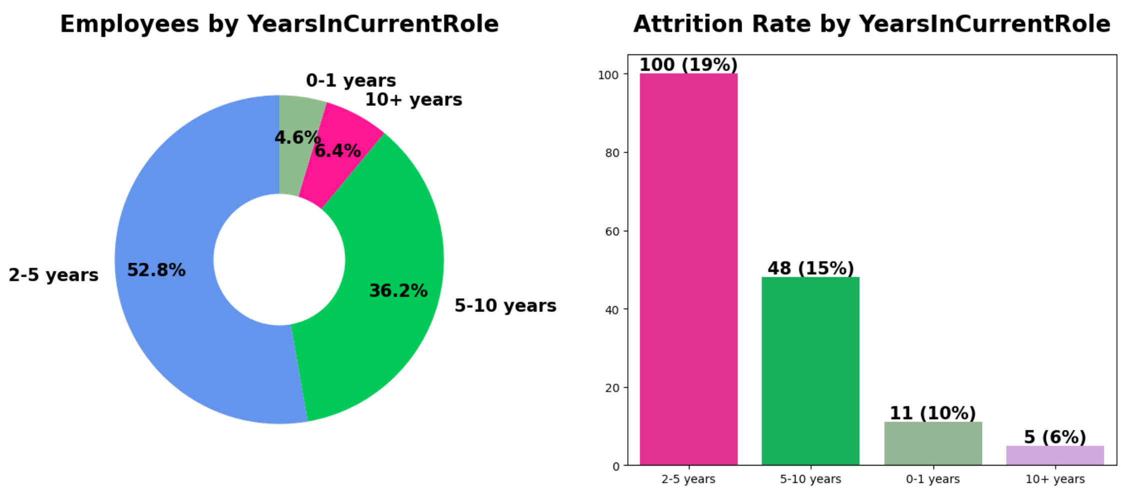
- Most employees has worked for 2 to 10 years in the organization.
- Very few employees has working for less than 1 year or more than 10 years.
- Employee who have worked for 2-5 years are having very high attrition rate.
- Employee who have worked for 10+ years are having low attrition rate.

1.1.57 (24) Analyzing the Employee Attrition by YearsIn Curren Role

[49]:
```
# Define the bin edges for the groups
bin_edges = [0, 1, 5, 10, 20]

# Define the labels for the groups
```

```
bin_labels = ['0-1 years', '2-5 years', '5-10 years', "10+ years"]

# Cut the DailyRate column into groups
df["YearsInCurrentRoleGroup"] = pd.cut(df['YearsInCurrentRole'],␣
↪bins=bin_edges, labels=bin_labels)
```

[50]:
```
#Visualization to show Total Employees by YearsInCurrentRoleGroup.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["YearsInCurrentRoleGroup"].value_counts()
plt.title("Employees by YearsInCurrentRole", fontweight="black", size=20,␣
↪pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors=['#6495ED', '#00C957', '#FF1493',␣
↪'#8FBC8F'],textprops={"fontweight":"black","size":15,"color":"black"})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by YearsInCurrentRoleGroup.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["YearsInCurrentRoleGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.values,palette=␣
↪["#FF1493","#00C957","#8FBC8F","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by␣
↪YearsInCurrentRole",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+"␣
↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



1.1.58 Inferences:

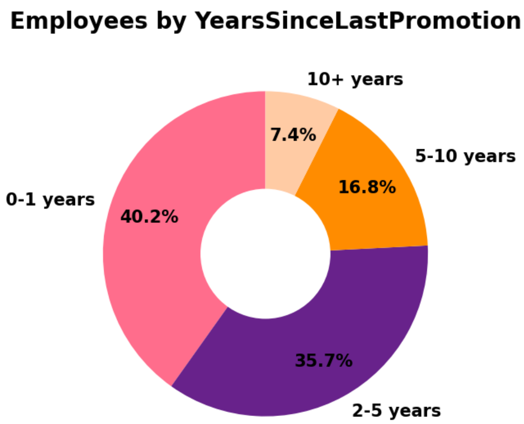
- Most of the employees working in current role from 2 to 5 years
- Only 4.6% employees working less than one year
- Employees who had worked for 10+ years in same role are having high attrition rate

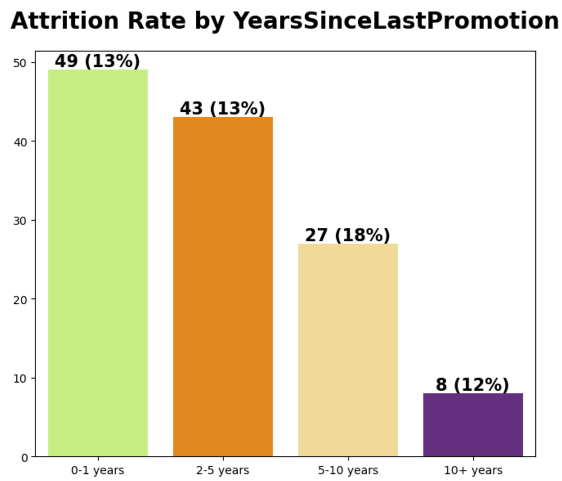
1.1.59 (25) Analyzing the Employee Attrition by Years since last promotion

[51]:
```
# Define the bin edges for the groups
bin_edges = [0, 1, 5, 10, 20]

# Define the labels for the groups
bin_labels = ['0-1 years', '2-5 years', '5-10 years', "10+ years"]

# Cut the DailyRate column into groups
df["YearsSinceLastPromotionGroup"] = pd.cut(df['YearsSinceLastPromotion'], bins=bin_edges, labels=bin_labels)
```

[52]:
```
#Visualization to show Total Employees by YearsSinceLastPromotionGroup.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["YearsSinceLastPromotionGroup"].value_counts()
plt.title("Employees by YearsSinceLastPromotion", fontweight="black", size=20, pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.75,startangle=90,
        colors=['#FF6D8C', '#68228B', '#FF8C00', '#FFCBA4'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
```

```
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by YearsSinceLastPromotionGroup.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["YearsSinceLastPromotionGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.
 ↪values,palette=["#CAFF70","#FF8C00","#FEE08B","#68228B","#E7A1A1"])

plt.title("Attrition Rate by␣
 ↪YearsSinceLastPromotion",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+"␣
 ↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
             size=15,fontweight="black")
plt.tight_layout()
plt.show()
```





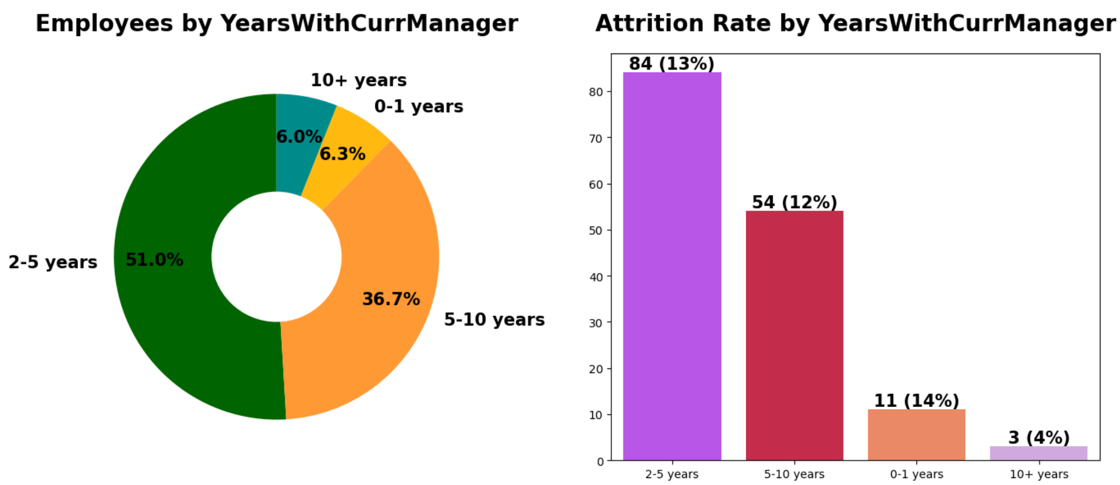
1.1.60 Inferences:

- Almost 36% of employee has not been promoted since 2 to 5 years.
- Almost 8% of employees has not been promoted since 10+ years.
- All the categories in this feature is having high attrition rate specially employee who has not been promoted since 5+ years.

1.1.61 (26) Analyzing the Employee Attrition by Years with current Manager

[53]:
```
# Define the bin edges for the groups
bin_edges = [0, 1, 5, 10, 20]

# Define the labels for the groups
bin_labels = ['0-1 years', '2-5 years', '5-10 years', "10+ years"]

# Cut the DailyRate column into groups
df["YearsWithCurrManagerGroup"] = pd.cut(df['YearsWithCurrManager'],␣
↪bins=bin_edges, labels=bin_labels)
```

[54]:
```
#Visualization to show Total Employees by YearsWithCurrManagerGroup.
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
value_1 = df["YearsWithCurrManagerGroup"].value_counts()
plt.title("Employees by YearsWithCurrManager", fontweight="black", size=20,␣
↪pad=20)
plt.pie(value_1.values, labels=value_1.index, autopct="%.1f%%",pctdistance=0.
↪75,startangle=90,
        colors= ['#006400', '#FF9933', '#FFB90F',␣
↪'#008B8B'],textprops={"fontweight":"black","size":15})
center_circle = plt.Circle((0, 0), 0.4, fc='white')
fig = plt.gcf()
fig.gca().add_artist(center_circle)

#Visualization to show Attrition Rate by YearsWithCurrManagerGroup.
plt.subplot(1,2,2)
new_df = df[df["Attrition"]=="Yes"]
value_2 = new_df["YearsWithCurrManagerGroup"].value_counts()
attrition_rate = np.floor((value_2/value_1)*100).values
sns.barplot(x=value_2.index.tolist(), y=value_2.
↪values,palette=["#BF3EFF","#DC143C","#FF7F50","#D4A1E7","#E7A1A1"])
plt.title("Attrition Rate by␣
↪YearsWithCurrManager",fontweight="black",size=20,pad=20)
for index,value in enumerate(value_2):
    plt.text(index,value,str(value)+"␣
↪("+str(int(attrition_rate[index]))+"%)",ha="center",va="bottom",
                size=15,fontweight="black")
plt.tight_layout()
plt.show()
```



1.1.62 Inferences:

- Most of the employees 2-5 years working with current manager
- 36% employees 5-10 years working with current manager
- Employees who had worked for 10+ years with current manager are having very low attrition rate

[ ]:

```

```

[ ]:

```

```

1.2 Statistical Analysis

1.2.1 (1) Perform ANOVA Test

Analyze the Numerical Features Importance in Employee Attrition

- ANOVA test is used to Analyzing the impact of different numerical features on a response categorical feature
- ANOVA test Returns two statistical values F_Score and P_Value

1.2.2 Importing Statistical Libraries

[55]:

```
# Library to perform Statistical Analysis.
from scipy import stats
from scipy.stats import chi2
from scipy.stats import chi2_contingency

# Library for Ignore the warnings
import warnings
warnings.filterwarnings('always')
warnings.filterwarnings('ignore')
```

[ ]:

```

```

[56]:

```
num_col=df.select_dtypes(np.number).columns
num_col
```

[56]:

```
Index(['Age', 'DailyRate', 'DistanceFromHome', 'HourlyRate', 'MonthlyIncome',
       'MonthlyRate', 'NumCompaniesWorked', 'PercentSalaryHike',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
       'YearsWithCurrManager'],
      dtype='object')
```

[57]:

```
new_df = df.copy()
```

[58]:

```
new_df['Attrition']=new_df['Attrition'].replace({"No":0,"Yes":1})
```

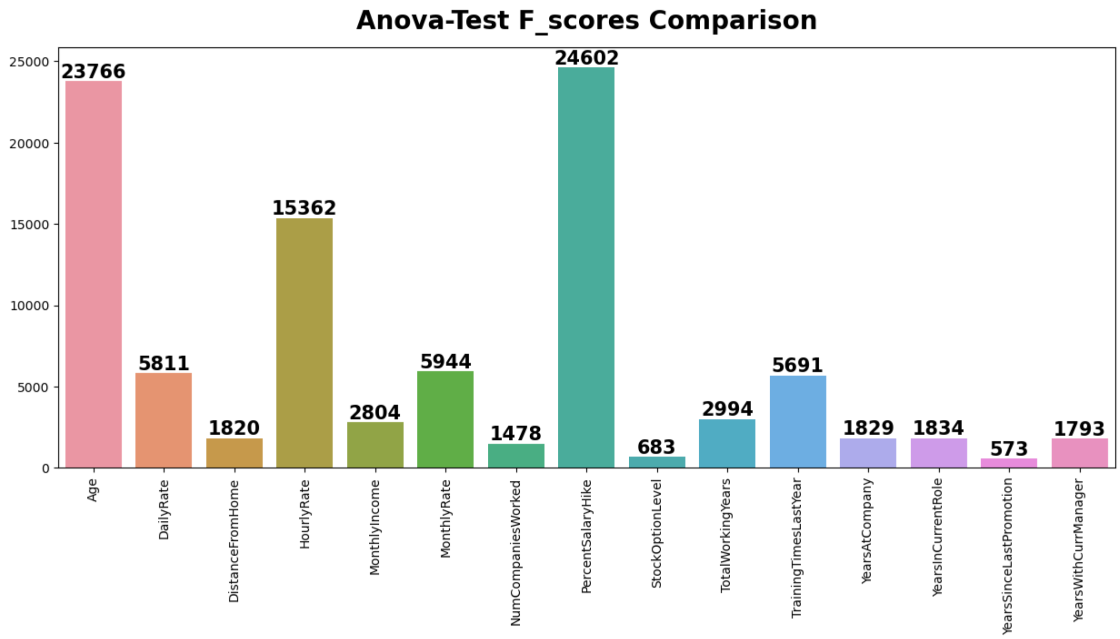
[59]:

```
f_scores = {}
p_values = {}

for column in num_col:
    f_score, p_value = stats.f_oneway(new_df[column],new_df["Attrition"])

    f_scores[column] = f_score
    p_values[column] = p_value
```

1.2.3 Visualize the F_Score and ANOVA Test

[60]:

```
plt.figure(figsize=(15,6))
keys = list(f_scores.keys())
values = list(f_scores.values())

sns.barplot(x=keys, y=values)
plt.title("Anova-Test F_scores Comparison",fontweight="black",size=20,pad=15)
plt.xticks(rotation=90)

for index,value in enumerate(values):
    plt.text(index,value,int(value), ha="center",␣
 ↪va="bottom",fontweight="black",size=15)
plt.show()
```



1.2.4 Comparing F_Score And P_Values of ANOVA

[61]:
```
test_df = pd.DataFrame({"Features":keys,"F_Score":values})
test_df["P_value"] = [format(p, '.20f') for p in list(p_values.values())]
test_df
```

[61]:

	Features	F_Score	P_value
0	Age	23766.934042	0.00000000000000000000
1	DailyRate	5811.796569	0.00000000000000000000
2	DistanceFromHome	1820.614585	0.00000000000000000000
3	HourlyRate	15362.122371	0.00000000000000000000
4	MonthlyIncome	2804.459632	0.00000000000000000000
5	MonthlyRate	5944.089071	0.00000000000000000000
6	NumCompaniesWorked	1478.188633	0.00000000000000000000
7	PercentSalaryHike	24602.507947	0.00000000000000000000
8	StockOptionLevel	683.069576	0.00000000000000000000
9	TotalWorkingYears	2994.906310	0.00000000000000000000
10	TrainingTimesLastYear	5691.401732	0.00000000000000000000
11	YearsAtCompany	1829.442766	0.00000000000000000000
12	YearsInCurrentRole	1834.262264	0.00000000000000000000
13	YearsSinceLastPromotion	573.896430	0.00000000000000000000
14	YearsWithCurrManager	1793.291314	0.00000000000000000000

1.2.5 Inferences:

The following features shows a strong association with attrition, as indicated by their high F-scores and very low p-values.

- Age
- DailyRate
- HourlyRate
- MonthlyIncome
- MonthlyRate
- NumCompaniesWorked
- PercentSalaryHike
- TotalWorkingYears
- TrainingTimesLastYear
- YearsAtCompany
- YearsWithCurrManager

The following features doen't shows significant relationship with attrition because of their moderate F-scores and extremely high p-values.

- DistanceFromHome
- StockOptionLevel
- YearsInCurrentRole
- YearsSinceLastPromotion

It is important for the organization to pay attention to the identified significant features and consider them when implementing strategies to reduce attrition rates

1.2.6 Perform Chi-Square Test

1.2.7 Analyze the Categorical Features Importance in Employee Attrition

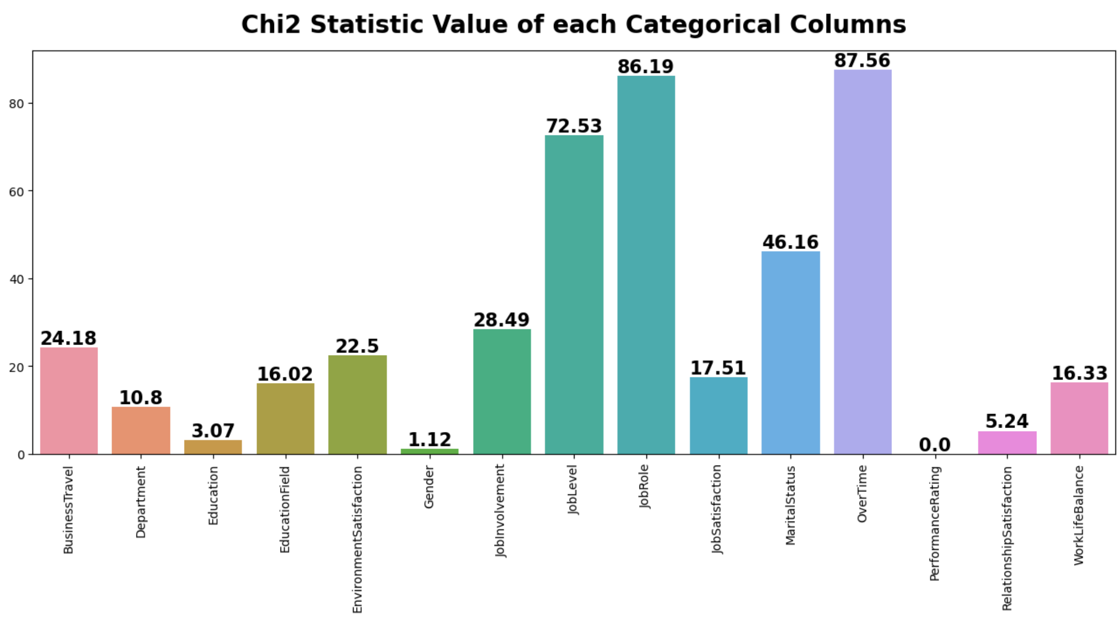
[62]:
```
cat_cols = df.select_dtypes(include="object").columns.tolist()
cat_cols.remove("Attrition")
```

[63]:
```
chi2_statistic = {}
p_values = {}

# Perform chi-square test for each column
for col in cat_cols:
    contingency_table = pd.crosstab(df[col], df['Attrition'])
    chi2, p_value, _, _ = chi2_contingency(contingency_table)
    chi2_statistic[col] = chi2
    p_values[col] = p_value
```

1.2.8 Visualize the Chi-Square Statistics Values of Categorical Features

[64]:
```
columns = list(chi2_statistic.keys())
values = list(chi2_statistic.values())

plt.figure(figsize=(16,6))
sns.barplot(x=columns, y=values)
plt.xticks(rotation=90)
```

```
plt.title("Chi2 Statistic Value of each Categorical␣
↪Columns",fontweight="black",size=20,pad=15)
for index,value in enumerate(values):
    plt.
↪text(index,value,round(value,2),ha="center",va="bottom",fontweight="black",size=15)

plt.show()
```



1.2.9 Compare Chi-Square Statistics And P_values of Chi-Square Test

[65]:
```
test_df = pd.DataFrame({"Features":columns,"Chi_2 Statistic":values})
test_df["P_value"] =  [format(p, '.20f') for p in list(p_values.values())]
test_df
```

[65]:

	Features	Chi_2 Statistic	P_value
0	BusinessTravel	24.182414	0.00000560861447644993
1	Department	10.796007	0.00452560657447963286
2	Education	3.073961	0.54552533765659494414
3	EducationField	16.024674	0.00677398013902521211
4	EnvironmentSatisfaction	22.503881	0.00005123468906289433
5	Gender	1.116967	0.29057244902890855265
6	JobInvolvement	28.492021	0.00000286318063671342
7	JobLevel	72.529013	0.00000000000000663468
8	JobRole	86.190254	0.00000000000000275248
9	JobSatisfaction	17.505077	0.00055630045103875563
10	MaritalStatus	46.163677	0.00000000009455511060

```
11                    OverTime        87.564294  0.00000000000000000001
12           PerformanceRating         0.000155  0.99007454659345761616
13  RelationshipSatisfaction          5.241068  0.15497244371052629197
14             WorkLifeBalance        16.325097  0.00097256988453488236
```

1.2.10 Descriptive Statistics on Categorical Features

The following features showed statistically significant associations with employee attrition:

- Department
- EducationField
- EnvironmentSatisfaction
- JobInvolvement
- JobLevel
- JobRole
- JobSatisfaction
- MaritalStatus
- OverTime
- WorkLifeBalance
- The following features did not show statistically significant associations with attrition.
- Gender
- Education
- PerformanceRating
- RelationshipSatisfaction
- It is important for the organization to pay attention to the identified significant features and consider them when implementing strategies to reduce attrition rates.

[ ]: