Employee Turn-Over EDA and Predictive Models

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

from warnings import filterwarnings
filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('Employee-turnover.csv')
df.head()
```

Out[2]:

	Employee Count	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	...
0	1	1	Sales	Sales Executive	Female	41	Single	College	Life Sciences	Travel_Rarely	...
1	1	2	Research & Development	Research Scientist	Male	49	Married	Below College	Life Sciences	Travel_Frequently	...
2	1	4	Research & Development	Laboratory Technician	Male	37	Single	College	Other	Travel_Rarely	...
3	1	5	Research & Development	Research Scientist	Female	33	Married	Master	Life Sciences	Travel_Frequently	...
4	1	7	Research & Development	Laboratory Technician	Male	27	Married	Below College	Medical	Travel_Rarely	...

5 rows × 29 columns

In [3]:
```
df.shape
```

Out[3]:
```
(1470, 29)
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Employee Count                0
Employee ID                   0
Department                    0
Job Role                      0
Gender                        0
Age                           0
Marital Status                0
Education                     0
Education Field               0
Business Travel               0
Distance From Home (kms)      0
Job Involvement               0
Job Level                     0
Job Satisfaction              0
Monthly Income (USD)          0
Salary Hike (%)               0
Stock Option Level            0
```

```
Over Time                     0
No. of Companies Worked       0
Total Working Years           0
Years At Company              0
Years In Current Role         0
Years Since Last Promotion    0
Years With Curr Manager       0
Environment Satisfaction      0
Training Times Last Year      0
Work Life Balance             0
Relationship Satisfaction     0
Attrition (Yes/No)            0
dtype: int64
```

In [5]:
```
df['Employee Count'].describe()
```

Out[5]:
```
count    1470.0
mean        1.0
std         0.0
min         1.0
25%         1.0
50%         1.0
75%         1.0
max         1.0
Name: Employee Count, dtype: float64
```

In [6]:
```
# We can remove this column since it doesn't help us in any way, values are same for all u
# no deviation and doesn't make sense
df.drop('Employee Count',axis=1,inplace=True)
df
```

Out[6]:

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distanc Fror Hom (km:
0	1	Sales	Sales Executive	Female	41	Single	College	Life Sciences	Travel_Rarely	
1	2	Research & Development	Research Scientist	Male	49	Married	Below College	Life Sciences	Travel_Frequently	
2	4	Research & Development	Laboratory Technician	Male	37	Single	College	Other	Travel_Rarely	
3	5	Research & Development	Research Scientist	Female	33	Married	Master	Life Sciences	Travel_Frequently	
4	7	Research & Development	Laboratory Technician	Male	27	Married	Below College	Medical	Travel_Rarely	
...	...	...	...	...	...	...	...	...	...	
1465	2061	Research & Development	Laboratory Technician	Male	36	Married	College	Medical	Travel_Frequently	2
1466	2062	Research & Development	Healthcare Representative	Male	39	Married	Below College	Medical	Travel_Rarely	
1467	2064	Research & Development	Manufacturing Director	Male	27	Married	Bachelor	Life Sciences	Travel_Rarely	
1468	2065	Sales	Sales Executive	Male	49	Married	Bachelor	Medical	Travel_Frequently	

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distanc Fro Hom (kms
1469	2068	Research & Development	Laboratory Technician	Male	34	Married	Bachelor	Medical	Travel_Rarely	

1470 rows × 28 columns

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 28 columns):
 #   Column                      Non-Null Count  Dtype 
---  ------                      --------------  ----- 
 0   Employee ID                 1470 non-null   int64 
 1   Department                  1470 non-null   object
 2   Job Role                    1470 non-null   object
 3   Gender                      1470 non-null   object
 4   Age                         1470 non-null   int64 
 5   Marital Status              1470 non-null   object
 6   Education                   1470 non-null   object
 7   Education Field             1470 non-null   object
 8   Business Travel             1470 non-null   object
 9   Distance From Home (kms)    1470 non-null   int64 
 10  Job Involvement             1470 non-null   object
 11  Job Level                   1470 non-null   int64 
 12  Job Satisfaction            1470 non-null   object
 13  Monthly Income (USD)        1470 non-null   int64 
 14  Salary Hike (%)             1470 non-null   int64 
 15  Stock Option Level          1470 non-null   int64 
 16  Over Time                   1470 non-null   object
 17  No. of Companies Worked     1470 non-null   int64 
 18  Total Working Years         1470 non-null   int64 
 19  Years At Company            1470 non-null   int64 
 20  Years In Current Role       1470 non-null   int64 
 21  Years Since Last Promotion  1470 non-null   int64 
 22  Years With Curr Manager     1470 non-null   int64 
 23  Environment Satisfaction    1470 non-null   object
 24  Training Times Last Year    1470 non-null   int64 
 25  Work Life Balance           1470 non-null   object
 26  Relationship Satisfaction   1470 non-null   object
 27  Attrition (Yes/No)          1470 non-null   object
dtypes: int64(14), object(14)
memory usage: 321.7+ KB
```

In [8]:

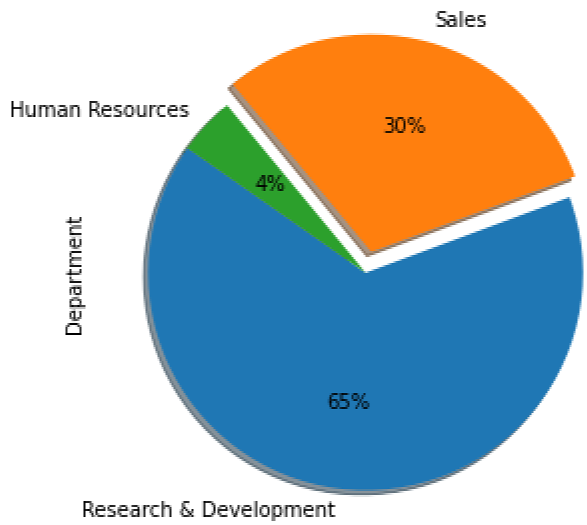
```
df['Attrition'] = df['Attrition (Yes/No)'].apply(lambda x: 1 if x=='Yes' else 0)
df.head()
print(df['Attrition'].value_counts())
print(df['Attrition (Yes/No)'].value_counts())
```

```
0    1233
1     237
Name: Attrition, dtype: int64
No     1233
Yes     237
Name: Attrition (Yes/No), dtype: int64
```

In [9]:

```
#Department Column
plt.figure(figsize=(10,5))
```

```python
df['Department'].value_counts(normalize=True).plot.pie(autopct='%1.f%%',shadow=True,exploc
plt.show()
```



> 1. 65% of employees are from R&D Department
> 2. 30% of employees are from Sales Dept.
> 3. ~5% of employees are from HR Dept.

In [10]:

```python
#Checking Attrition Rate for each category, we can create a function for that.
def calculate_attrition_rate(df,col):
    temp_df = pd.DataFrame(columns=['Category','Attrition Rate'])
    for cat in df[col].unique():
        attrition_count = df[(df[col]==cat) & (df['Attrition']==1)].shape[0]
        total_count = df[df[col]==cat].shape[0]
        temp_df = temp_df.append({'Category':cat,'Attrition Rate':(attrition_count/total_c
    return temp_df.sort_values(by='Attrition Rate',ascending=False)
calculate_attrition_rate(df,'Department')
```

Out[10]:

	Category	Attrition Rate
0	Sales	20.627803
2	Human Resources	19.047619
1	Research & Development	13.839750

In [11]:

```python
#Job Role
df['Job Role'].value_counts()
```

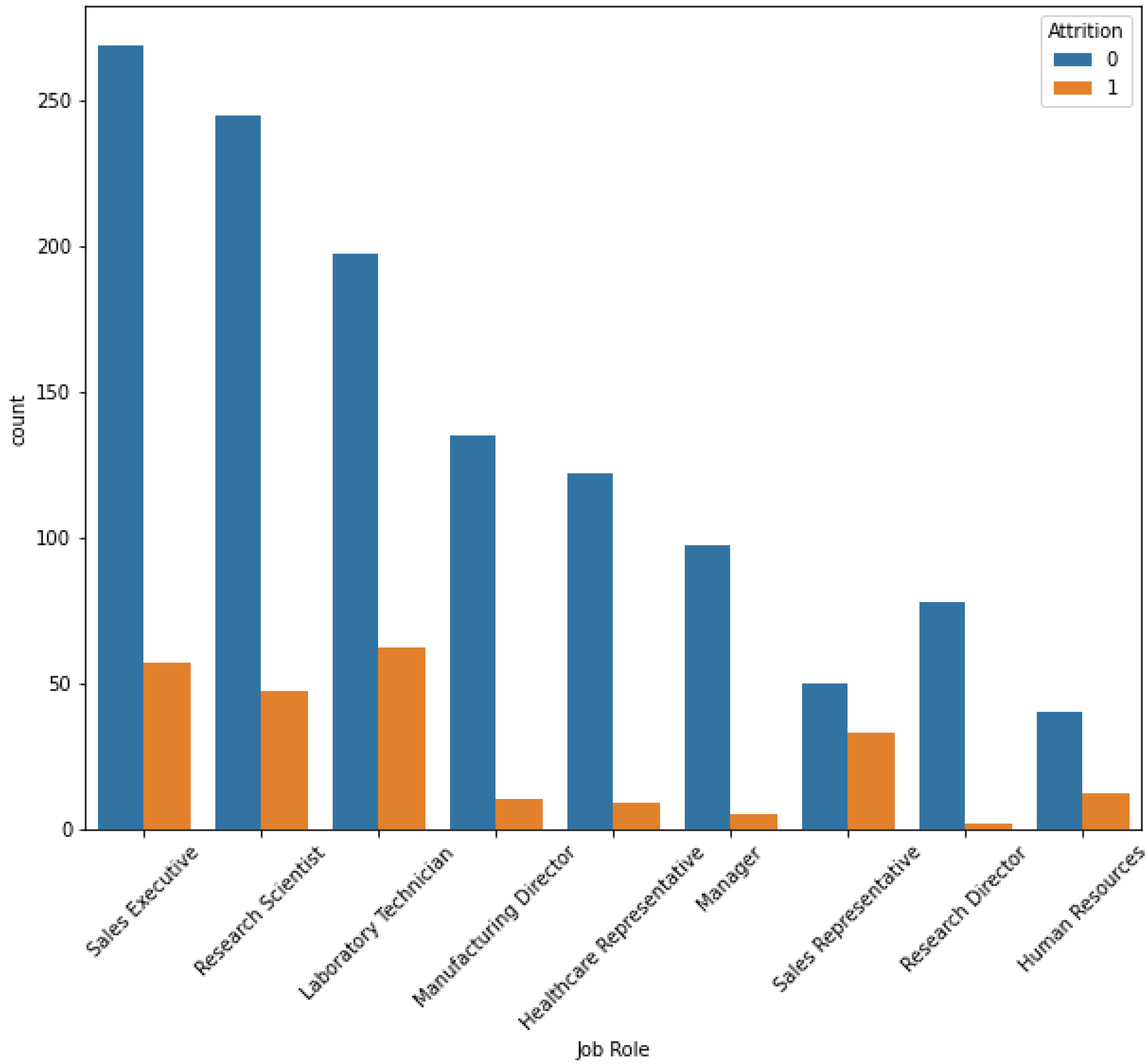
Out[11]:

```
Sales Executive              326
Research Scientist           292
Laboratory Technician        259
Manufacturing Director       145
Healthcare Representative    131
Manager                      102
Sales Representative          83
Research Director             80
Human Resources               52
Name: Job Role, dtype: int64
```

In [12]:

```python
plt.figure(figsize=(10,8))
sns.countplot(x='Job Role',data=df,hue='Attrition')
```

```
plt.xticks(rotation=45)
plt.show()
```



In [13]:

```
calculate_attrition_rate(df,'Job Role')
```

Out[13]:

	Category	Attrition Rate
6	Sales Representative	39.759036
2	Laboratory Technician	23.938224
8	Human Resources	23.076923
0	Sales Executive	17.484663
1	Research Scientist	16.095890
3	Manufacturing Director	6.896552
4	Healthcare Representative	6.870229
5	Manager	4.901961
7	Research Director	2.500000

In [14]:

```
#Check Gender only Male and Female
df['Gender'].value_counts()
```

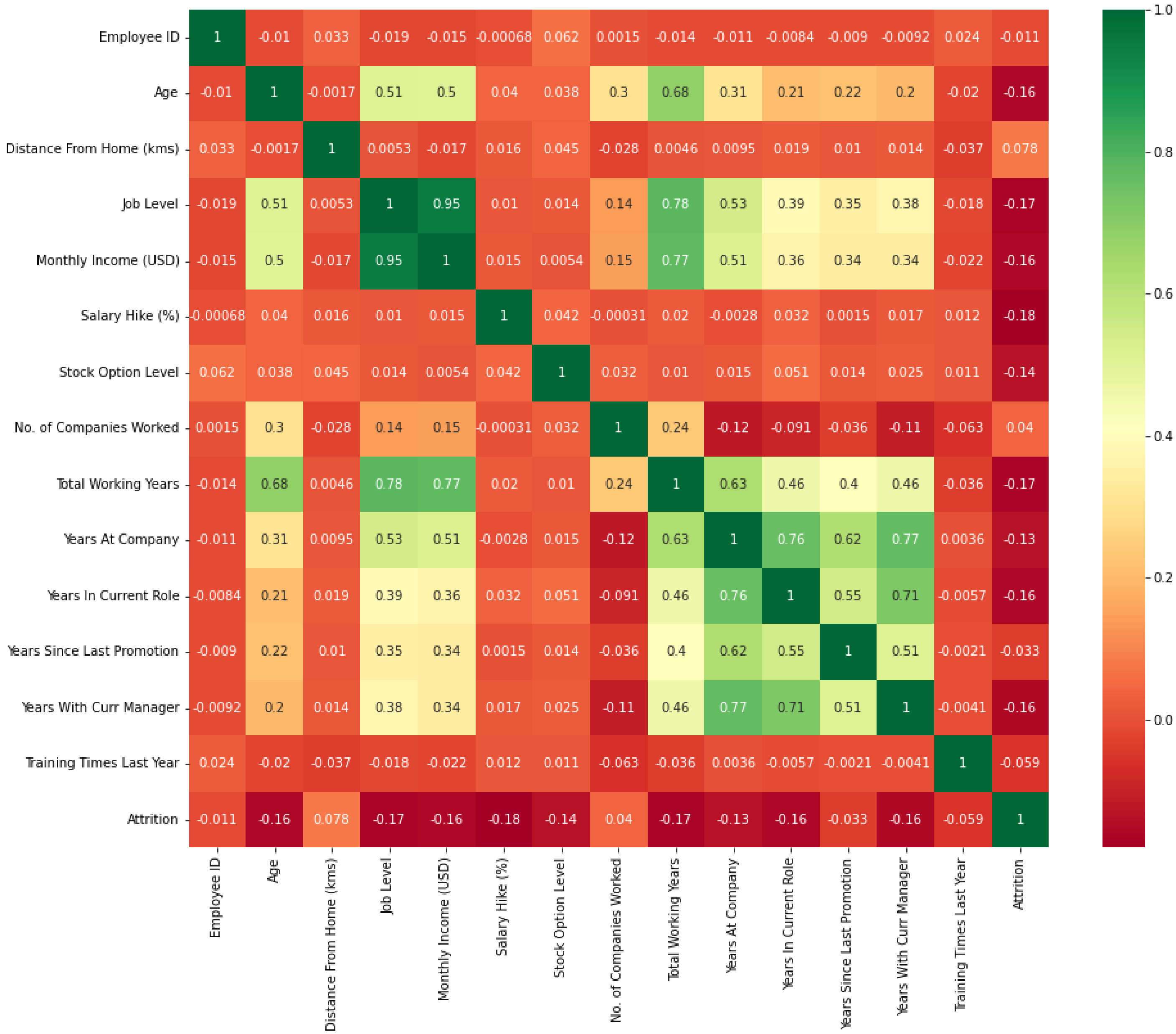
Out[14]:
```
Male      882
Female    588
Name: Gender, dtype: int64
```

In [15]:
```python
calculate_attrition_rate(df,'Gender')
```

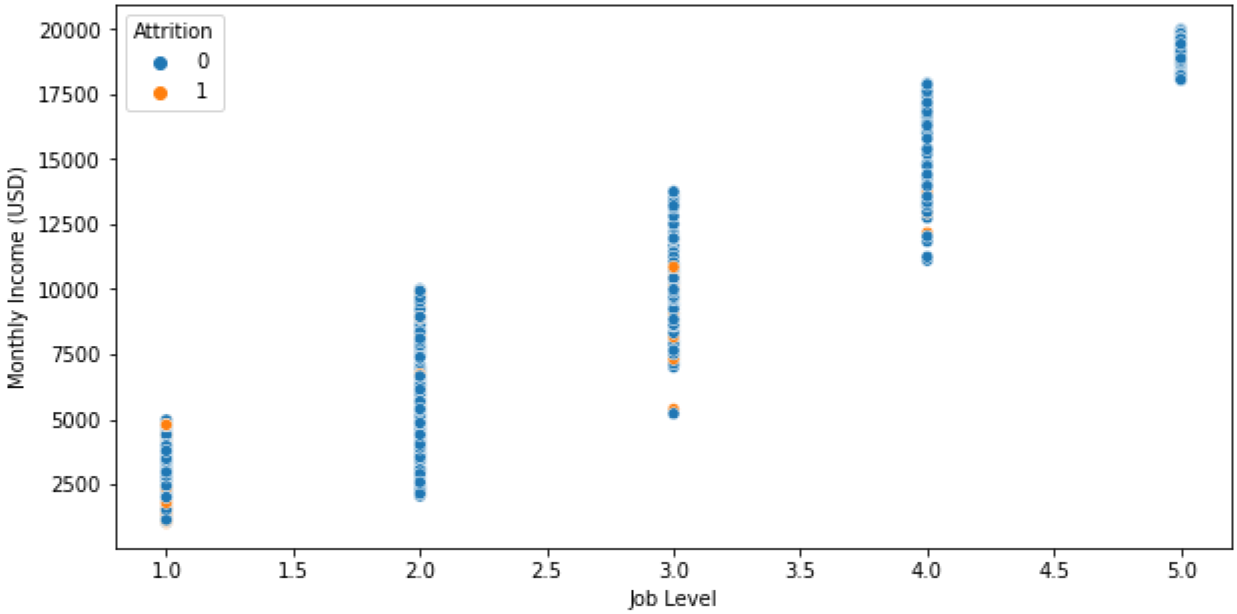
Out[15]:

	Category	Attrition Rate
1	Male	17.006803
0	Female	14.795918

In [16]:
```python
corr = df.corr()
plt.figure(figsize=(15,12))
sns.heatmap(corr,annot=True,cmap='RdYlGn')
plt.show()
```



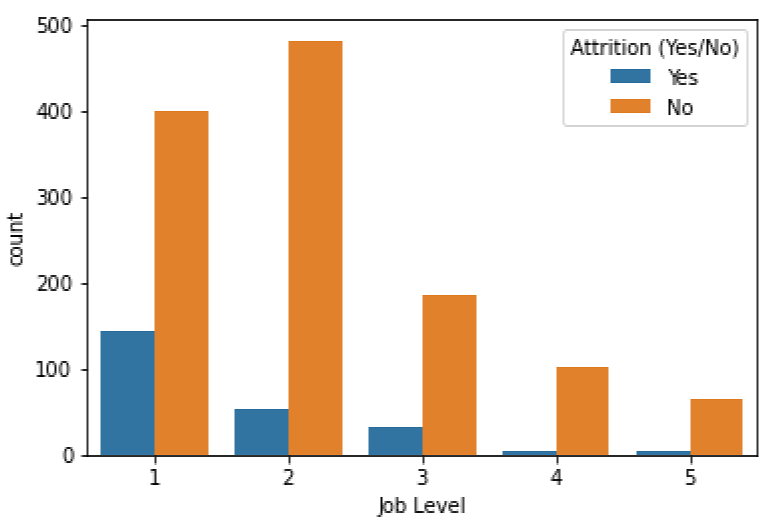
In [17]:
```python
# We will study high correlations > 0.6 just to eliminate similar columns/ remove multi-co
# For example, let's see the columns Monthly Income (USD) and Job Level with pearson coefi
plt.figure(figsize=(10,5))
sns.scatterplot(data=df,x='Job Level',y='Monthly Income (USD)',hue='Attrition')
plt.show()
```



> We can clearly see as Job Level rises, monthly income will rise as well. That's why having both these 2 columns for our model would be harmful hence we should remove 1 of them.

In [18]:
```
sns.countplot(data=df,x='Job Level',hue='Attrition (Yes/No)')
```

Out[18]: <AxesSubplot:xlabel='Job Level', ylabel='count'>



> As job level increases, number of attritions decreases.
> We can also see this from Heatmap that Job level and Attrition have negative correlation.

In [19]:
```
df.head()
```

Out[19]:

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distance From Home (kms)	...
0	1	Sales	Sales Executive	Female	41	Single	College	Life Sciences	Travel_Rarely	1	...
1	2	Research & Development	Research Scientist	Male	49	Married	Below College	Life Sciences	Travel_Frequently	8	...

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distance From Home (kms)	...
2	4	Research & Development	Laboratory Technician	Male	37	Single	College	Other	Travel_Rarely	2	...
3	5	Research & Development	Research Scientist	Female	33	Married	Master	Life Sciences	Travel_Frequently	3	...
4	7	Research & Development	Laboratory Technician	Male	27	Married	Below College	Medical	Travel_Rarely	2	...

5 rows × 29 columns

In [20]:

```
#We can either remove Job Level or Monthly Income (USD) column. I will remove income becau
#better correlation with other independent variables which is required.
#Even removing the total working years as it is highly correlated with job level.
df.drop(columns=['Monthly Income (USD)','Total Working Years'],axis=1,inplace=True)
df.head()
```

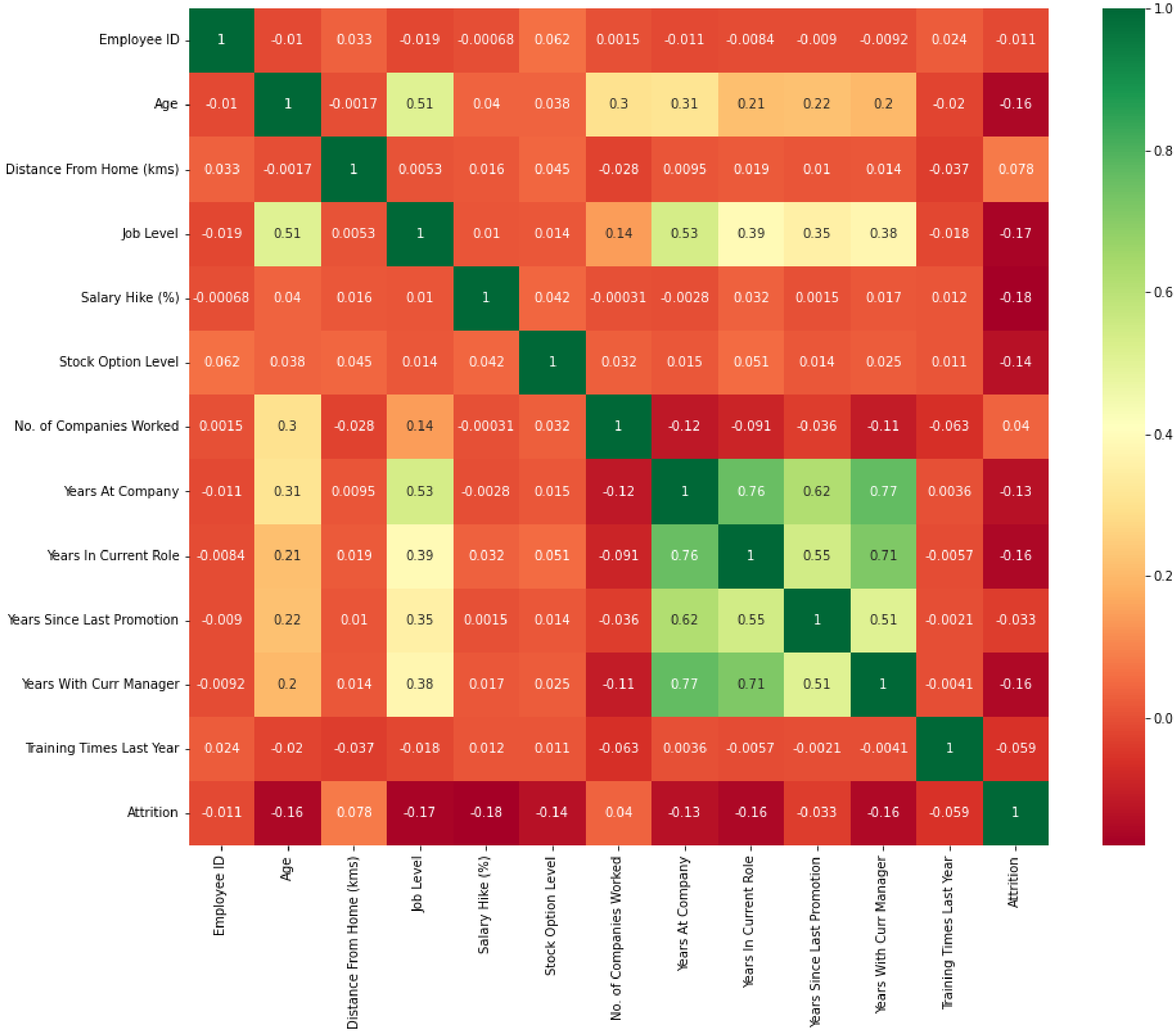
Out[20]:

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distance From Home (kms)	...
0	1	Sales	Sales Executive	Female	41	Single	College	Life Sciences	Travel_Rarely	1	...
1	2	Research & Development	Research Scientist	Male	49	Married	Below College	Life Sciences	Travel_Frequently	8	...
2	4	Research & Development	Laboratory Technician	Male	37	Single	College	Other	Travel_Rarely	2	...
3	5	Research & Development	Research Scientist	Female	33	Married	Master	Life Sciences	Travel_Frequently	3	...
4	7	Research & Development	Laboratory Technician	Male	27	Married	Below College	Medical	Travel_Rarely	2	...

5 rows × 27 columns

In [21]:

```
#Let's see the heatmap once again
corr = df.corr()
plt.figure(figsize=(15,12))
sns.heatmap(corr,annot=True,cmap='RdYlGn')
plt.show()
```



> We see 'Years At Company' also has strong correlations with 'Years with Curr Manager' and 'Years in Current Role'. But I think these columns might be important so we won't remove them.

> Also, we see that Attrition is most negatively correlated with Salary Hike %. It means, more the salary hike, less attrition.

Columns/Features which might be responsible for attrition:

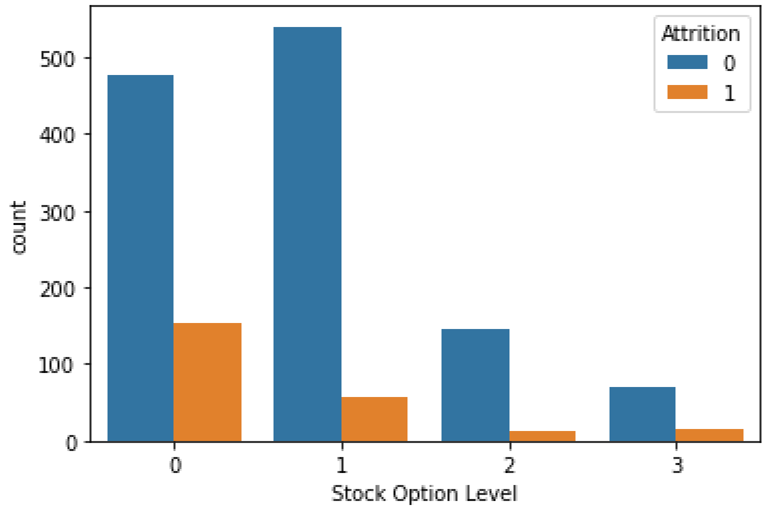
```
1. Salary Hike % <br>
2. Yeas with current manager <br>
3. Years in Current Role <br>
4. Years at a Company <br>
5. Job Level <br>
6. Stock Option Level <br>
7. Age <br>
8. Years Since Last Promotion
```

In [22]:
```
#let's try to understand Stock Option Level
df['Stock Option Level'].value_counts()
```

Out[22]:
```
0    631
1    596
2    158
3     85
Name: Stock Option Level, dtype: int64
```

In [23]:
```
sns.countplot(data=df,x='Stock Option Level',hue='Attrition')
```

Out[23]:
```
<AxesSubplot:xlabel='Stock Option Level', ylabel='count'>
```



In [24]:
```
#Delete Attrition (Yes/No) column since we have our new Attrition column now.
df.drop(columns=['Attrition (Yes/No)'],inplace=True,axis=1)
```

In [25]:
```
df.head()
```

Out[25]:

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distance From Home (kms)	...
0	1	Sales	Sales Executive	Female	41	Single	College	Life Sciences	Travel_Rarely	1	...
1	2	Research & Development	Research Scientist	Male	49	Married	Below College	Life Sciences	Travel_Frequently	8	...
2	4	Research & Development	Laboratory Technician	Male	37	Single	College	Other	Travel_Rarely	2	...
3	5	Research & Development	Research Scientist	Female	33	Married	Master	Life Sciences	Travel_Frequently	3	...
4	7	Research & Development	Laboratory Technician	Male	27	Married	Below College	Medical	Travel_Rarely	2	...

5 rows × 26 columns

Now, let's come to our categorical columns

In [26]:
```
#Create a separate df for categorical columns
cat_df = df.select_dtypes(include='object').copy()
cat_df.head()
```

Out[26]:

	Department	Job Role	Gender	Marital Status	Education	Education Field	Business Travel	Job Involvement	Job Satisfaction	Ove Tim
0	Sales	Sales Executive	Female	Single	College	Life Sciences	Travel_Rarely	High	Very High	Ye
1	Research & Development	Research Scientist	Male	Married	Below College	Life Sciences	Travel_Frequently	Medium	Medium	N
2	Research & Development	Laboratory Technician	Male	Single	College	Other	Travel_Rarely	Medium	High	Ye
3	Research & Development	Research Scientist	Female	Married	Master	Life Sciences	Travel_Frequently	High	High	Ye
4	Research & Development	Laboratory Technician	Male	Married	Below College	Medical	Travel_Rarely	High	Medium	N

In [27]:

```
cat_df['Marital Status'].unique()
```

Out[27]:

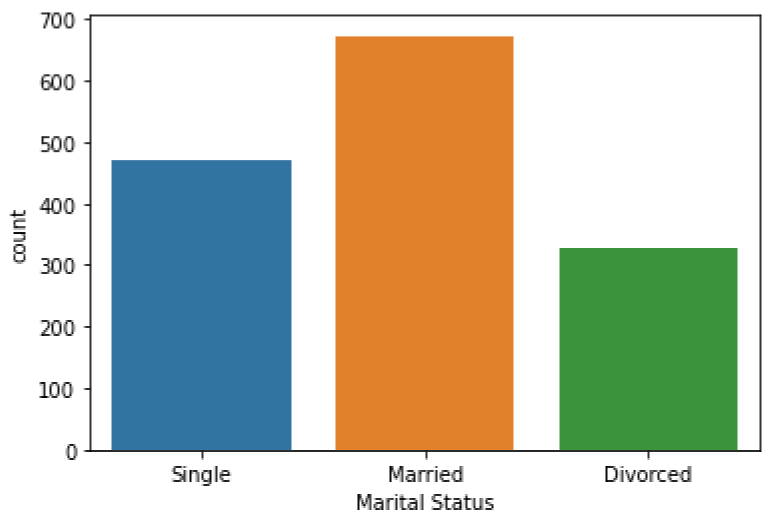
```
array(['Single', 'Married', 'Divorced'], dtype=object)
```

In [28]:

```
sns.countplot(data=cat_df,x='Marital Status')
```

Out[28]:

```
<AxesSubplot:xlabel='Marital Status', ylabel='count'>
```



In [29]:

```
#Let's look at the relationship between MaritaL Status and Attrition
cat_df['Attrition'] = df.loc[:,'Attrition'].copy()
cat_df.head()
```

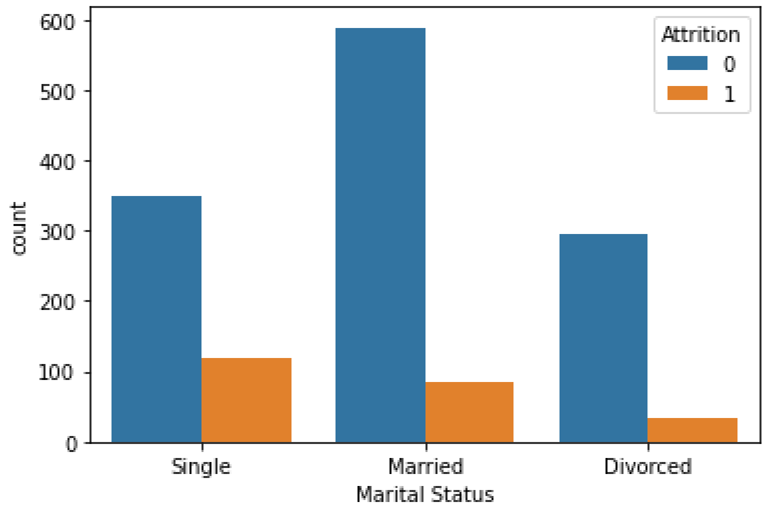
Out[29]:

	Department	Job Role	Gender	Marital Status	Education	Education Field	Business Travel	Job Involvement	Job Satisfaction	Ove Tim
0	Sales	Sales Executive	Female	Single	College	Life Sciences	Travel_Rarely	High	Very High	Ye
1	Research & Development	Research Scientist	Male	Married	Below College	Life Sciences	Travel_Frequently	Medium	Medium	N
2	Research & Development	Laboratory Technician	Male	Single	College	Other	Travel_Rarely	Medium	High	Ye

	Department	Job Role	Gender	Marital Status	Education	Education Field	Business Travel	Job Involvement	Job Satisfaction	Ove Tim
3	Research & Development	Research Scientist	Female	Married	Master	Life Sciences	Travel_Frequently	High	High	Ye
4	Research & Development	Laboratory Technician	Male	Married	Below College	Medical	Travel_Rarely	High	Medium	N

In [30]:

```
sns.countplot(data=cat_df,x='Marital Status',hue='Attrition')
plt.show()
```



In [31]:

```
calculate_attrition_rate(cat_df,'Marital Status')
```

Out[31]:

	Category	Attrition Rate
0	Single	25.531915
1	Married	12.481426
2	Divorced	10.091743

> **Single Employees have the most attrition rate.**
> This could be one of the driving factors for attrition rate.

In [32]:

```
cat_df.columns
```

Out[32]:

```
Index(['Department', 'Job Role', 'Gender', 'Marital Status', 'Education',
       'Education Field', 'Business Travel', 'Job Involvement',
       'Job Satisfaction', 'Over Time', 'Environment Satisfaction',
       'Work Life Balance', 'Relationship Satisfaction', 'Attrition'],
      dtype='object')
```

In [33]:

```
#Education Field
cat_df['Education'].unique()
```

Out[33]:

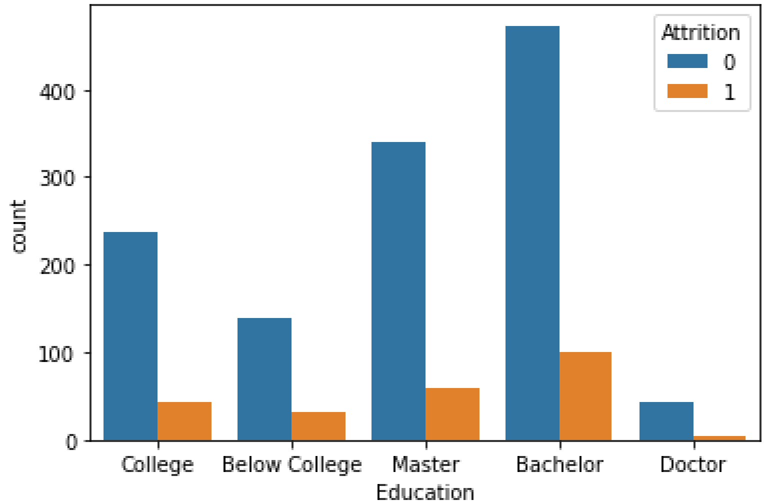
```
array(['College', 'Below College', 'Master', 'Bachelor', 'Doctor'],
      dtype=object)
```

In [34]:

```
cat_df['Education'].value_counts()
```

Out[34]:
```
Bachelor         572
Master           398
College          282
Below College    170
Doctor            48
Name: Education, dtype: int64
```

In [35]:
```
sns.countplot(data=cat_df,x='Education',hue='Attrition')
plt.show()
```



In [36]:
```
calculate_attrition_rate(cat_df,'Education')
```

Out[36]:

	Category	Attrition Rate
1	Below College	18.235294
3	Bachelor	17.307692
0	College	15.602837
2	Master	14.572864
4	Doctor	10.416667

> **Attrition Rate is almost similar among categories of different Education, hence we can drop this column.**

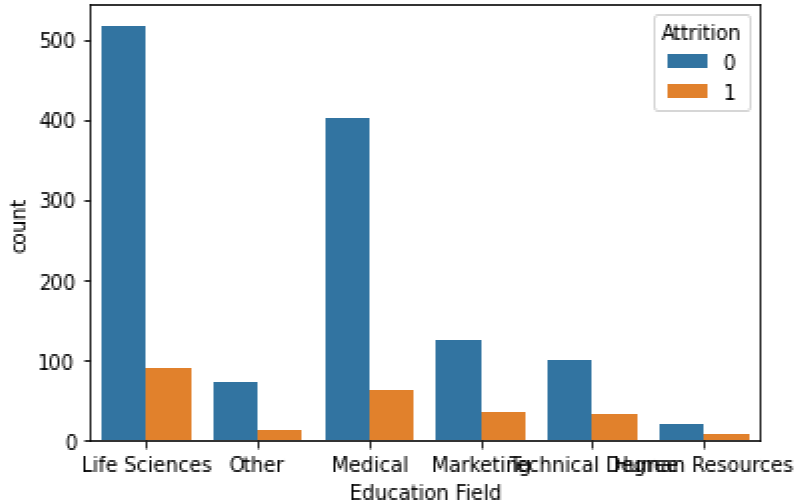
In [37]:
```
calculate_attrition_rate(cat_df,'Education Field')
```

Out[37]:

	Category	Attrition Rate
5	Human Resources	25.925926
4	Technical Degree	24.242424
3	Marketing	22.012579
0	Life Sciences	14.686469
2	Medical	13.577586
1	Other	13.414634

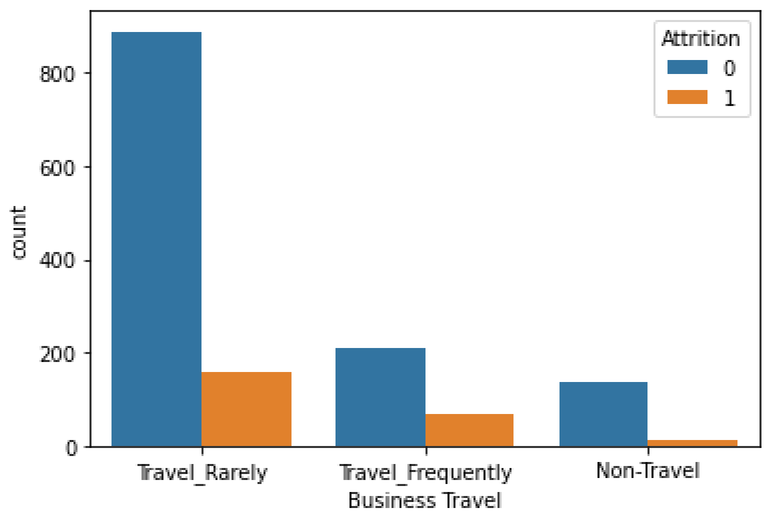
In [38]:

```
sns.countplot(data=cat_df,x='Education Field',hue='Attrition')
plt.show()
```



> **We can delete Education Field column as well**

In [39]:
```
#Checking Business Travel Column. This might be interesting.
sns.countplot(data=cat_df,x='Business Travel',hue='Attrition')
plt.show()
```



In [40]:
```
calculate_attrition_rate(cat_df,'Business Travel')
```

Out[40]:

	Category	Attrition Rate
1	Travel_Frequently	24.909747
0	Travel_Rarely	14.956855
2	Non-Travel	8.000000

Huge Insight:

> 1. People who have to travel frequently have the highest attrition rate.
> 2. People who don't travel have the least attrition rate which is best for organization.

In [41]:
```
cols_list = list(cat_df.columns)
```

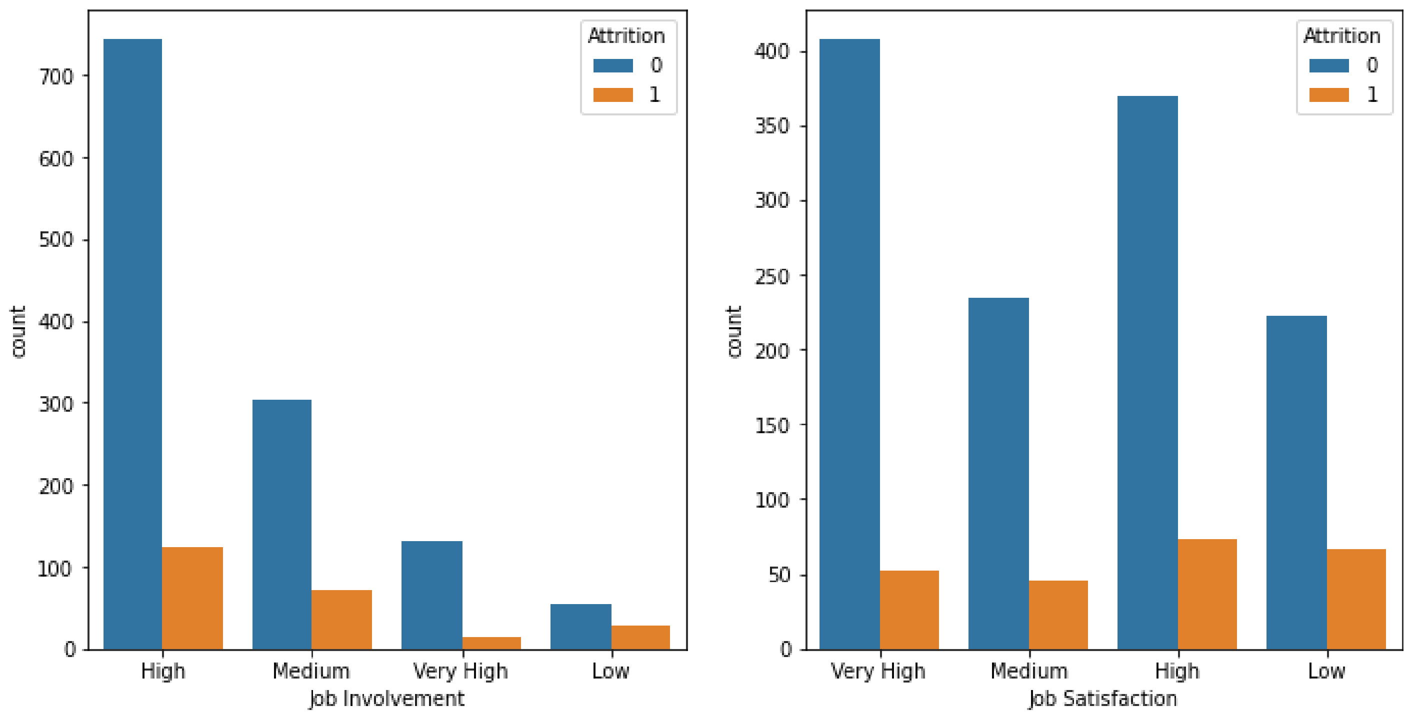
```
cols_list
```

Out[41]:

```
['Department',
 'Job Role',
 'Gender',
 'Marital Status',
 'Education',
 'Education Field',
 'Business Travel',
 'Job Involvement',
 'Job Satisfaction',
 'Over Time',
 'Environment Satisfaction',
 'Work Life Balance',
 'Relationship Satisfaction',
 'Attrition']
```

In [42]:

```
fig,(ax1,ax2) = plt.subplots(1,2,figsize=(12,6))
sns.countplot(data=cat_df,x='Job Involvement',hue='Attrition',ax=ax1)
sns.countplot(data=cat_df,x='Job Satisfaction',hue='Attrition',ax=ax2)
plt.show()
```



In [43]:

```
calculate_attrition_rate(cat_df,'Job Involvement')
```

Out[43]:

	Category	Attrition Rate
3	Low	33.734940
1	Medium	18.933333
0	High	14.400922
2	Very High	9.027778

In [44]:

```
calculate_attrition_rate(cat_df,'Job Satisfaction')
```

Out[44]:

	Category	Attrition Rate

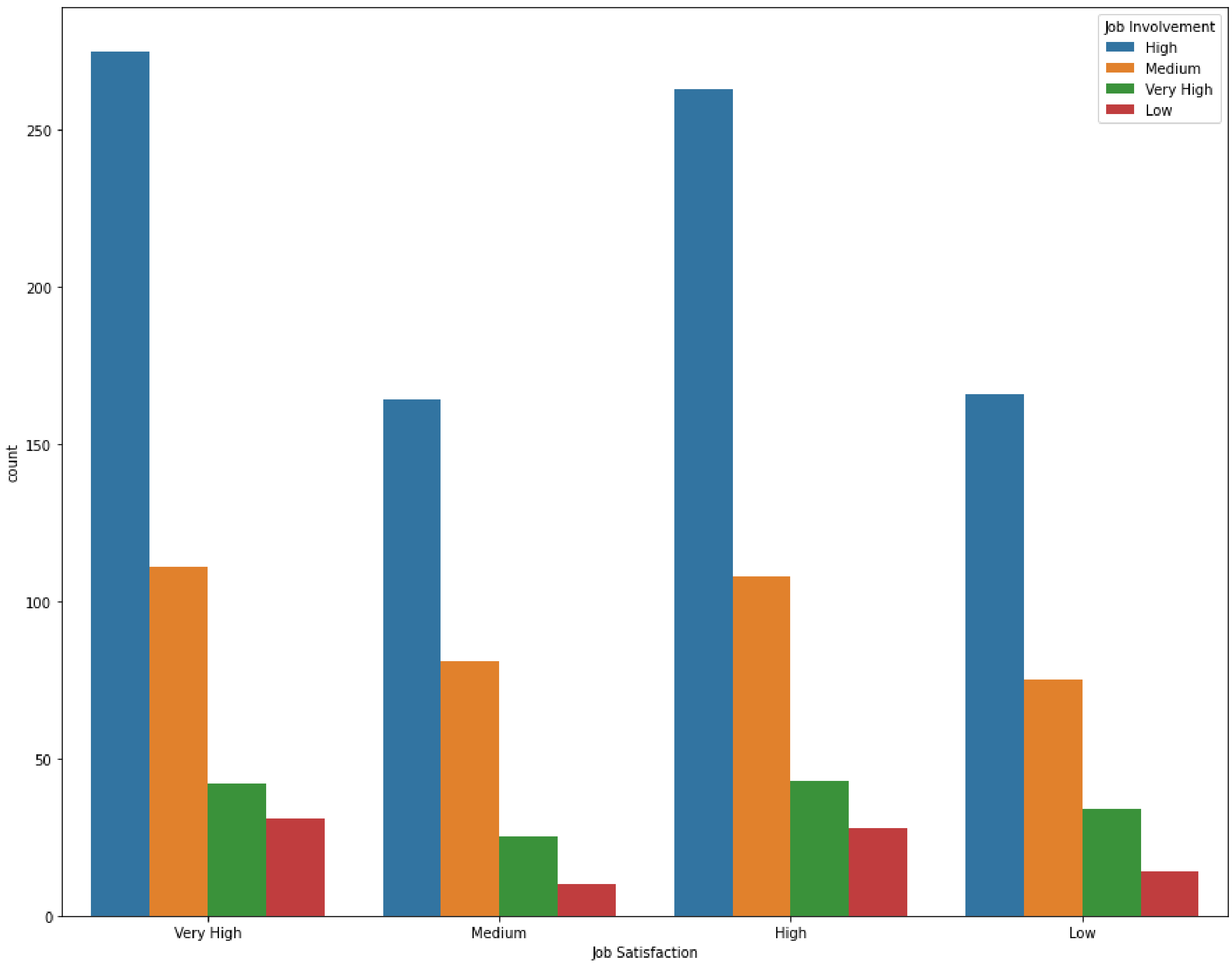
	Category	Attrition Rate
3	Low	22.837370
2	High	16.515837
1	Medium	16.428571
0	Very High	11.328976

Insights:

> 1. Employees like to get involved in their job. As the job involvement decreases, there is huge rise in attrition rate.
> 2. Employees with low job satisfaction have high attrition rate.

In [45]:

```
plt.figure(figsize=(15,12))
sns.countplot(data=cat_df,x='Job Satisfaction',hue='Job Involvement')
plt.show()
```



In [46]:

```
cat_df.head()
```

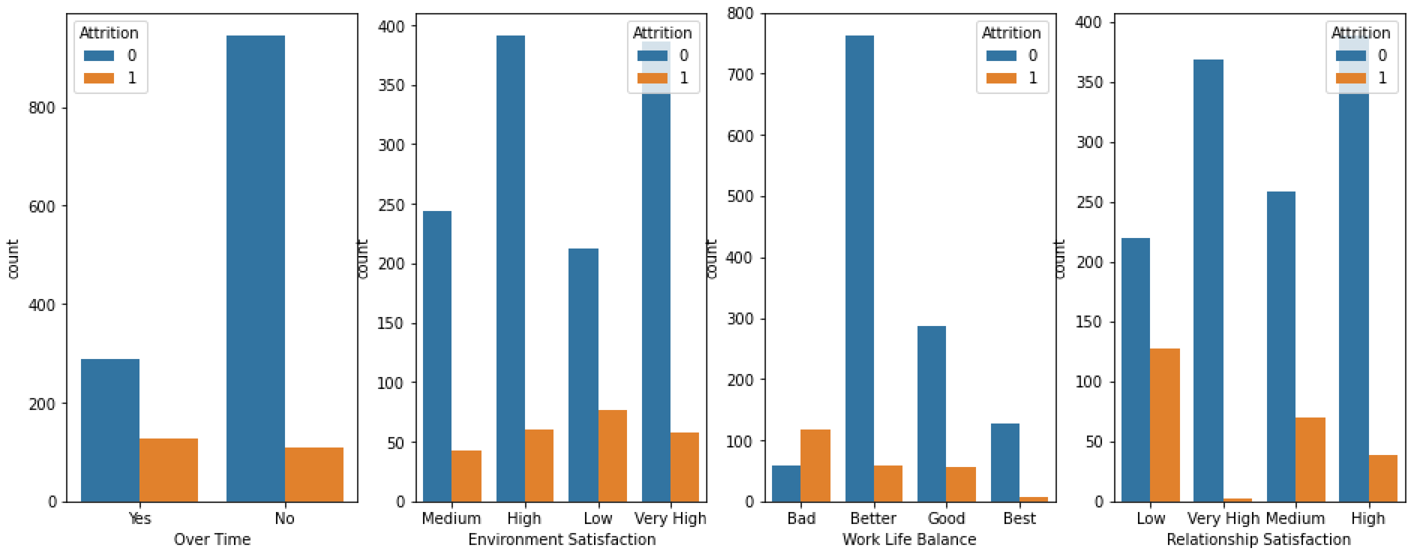
Out[46]:

Department	Job Role	Gender	Marital Status	Education	Education Field	Business Travel	Job Involvement	Job Satisfaction	Ove Tim

	Department	Job Role	Gender	Marital Status	Education	Education Field	Business Travel	Job Involvement	Job Satisfaction	Ove Tim
0	Sales	Sales Executive	Female	Single	College	Life Sciences	Travel_Rarely	High	Very High	Ye
1	Research & Development	Research Scientist	Male	Married	Below College	Life Sciences	Travel_Frequently	Medium	Medium	N
2	Research & Development	Laboratory Technician	Male	Single	College	Other	Travel_Rarely	Medium	High	Ye
3	Research & Development	Research Scientist	Female	Married	Master	Life Sciences	Travel_Frequently	High	High	Ye
4	Research & Development	Laboratory Technician	Male	Married	Below College	Medical	Travel_Rarely	High	Medium	N

In [47]:

```
fig,(ax1,ax2,ax3,ax4) = plt.subplots(1,4,figsize=(16,6))
sns.countplot(data=cat_df,x='Over Time',hue='Attrition',ax=ax1)
sns.countplot(data=cat_df,x='Environment Satisfaction',hue='Attrition',ax=ax2)
sns.countplot(data=cat_df,x='Work Life Balance',hue='Attrition',ax=ax3)
sns.countplot(data=cat_df,x='Relationship Satisfaction',hue='Attrition',ax=ax4)
plt.show()
```



In [48]:

```
calculate_attrition_rate(cat_df,'Over Time')
```

Out[48]:

	Category	Attrition Rate
0	Yes	30.528846
1	No	10.436433

High Attrition Rate when employees have to do Over Time.

In [49]:

```
calculate_attrition_rate(cat_df,'Environment Satisfaction')
```

Out[49]:

	Category	Attrition Rate
2	Low	26.388889
0	Medium	14.982578

	Category	Attrition Rate
1	High	13.303769
3	Very High	13.063063

Employees don't want a very high satisfactory environment but it should be decent enough. A really bad environment could be a driver for attrition rates.

In [50]:
```
calculate_attrition_rate(cat_df,'Work Life Balance')
```

Out[50]:

	Category	Attrition Rate
0	Bad	66.666667
2	Good	16.129032
1	Better	7.073171
3	Best	4.545455

Huge Insight:

> **Bad Work Life Balance literally drives away the employee. Highest Attrition Rate in the data.**

In [51]:
```
calculate_attrition_rate(cat_df,'Relationship Satisfaction')
```

Out[51]:

	Category	Attrition Rate
0	Low	36.705202
2	Medium	21.341463
3	High	8.920188
1	Very High	0.540541

Insights:

> 1. Low relationship satisfaction results in a high attrition rate.
> 2. Very High satisfaction has such low Attrition Rate.

Summary of Insights

1. Data is quite inconsistent because we have around 65% of employee from R&D Department, 30% from Sales and only 5% from HR Department.
2. We could clearly see as Job Level rises, monthly income will rise as well.
That's why having both these 2 columns for our model would be harmful hence we should remove 1 of them.
3. Single Employees have the most attrition rate.
This could be one of the driving factors for attrition rate.
4. Attrition Rate is almost similar among categories of different Education, hence we can drop this column.Similar for Education Field column.
5. People who have to travel frequently have the highest attrition rate
6. People who don't travel have the least attrition rate which is best for organization.
7. Employees like to get involved in their job. As the job involvement decreases, there is huge rise in

attrition rate.
8. Employees with low job satisfaction have high attrition rate.
9. High Attrition Rate when employees have to do Over Time.
10. Employees don't want a very high satisfactory environment but it should be decent enough. A really bad environment could be a driver for attrition rates.
11. Bad Work Life Balance literally drives away the employee. Highest Attrition Rate in the data.
12. Low relationship satisfaction results in a high attrition rate.
Very High satisfaction has such low Attrition Rate.

Key Driver Factors for Modeling

> 1. Salary Hike %
> 2. Years with current manager
> 3. Years in Current Role
> 4. Years at a Company
> 5. Job Level
> 6. Stock Option Level
> 7. Age
> 8. Marital Status
> 9. Business Travel
> 10. Job Satisfaction
> 11. Job Involvement
> 12. Over Time
> 13. Environment Satisfaction
> 14. Work Life Balance
> 15. Relationship Satisfaction
> 16. Department
> 17. Job Role
> 18. Gender
> 19. Years Since Last Promotion

Data Pre-Processing

In [52]:
```
df.head()
```

Out[52]:

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distance From Home (kms)	...
0	1	Sales	Sales Executive	Female	41	Single	College	Life Sciences	Travel_Rarely	1	...
1	2	Research & Development	Research Scientist	Male	49	Married	Below College	Life Sciences	Travel_Frequently	8	...
2	4	Research & Development	Laboratory Technician	Male	37	Single	College	Other	Travel_Rarely	2	...
3	5	Research & Development	Research Scientist	Female	33	Married	Master	Life Sciences	Travel_Frequently	3	...

	Employee ID	Department	Job Role	Gender	Age	Marital Status	Education	Education Field	Business Travel	Distance From Home (kms)	...
4	7	Research & Development	Laboratory Technician	Male	27	Married	Below College	Medical	Travel_Rarely	2	...

5 rows × 26 columns

In [53]:

```
df.select_dtypes(include='object')
```

Out[53]:

	Department	Job Role	Gender	Marital Status	Education	Education Field	Business Travel	Job Involvement	Jo Satisfactio
0	Sales	Sales Executive	Female	Single	College	Life Sciences	Travel_Rarely	High	Very Hig
1	Research & Development	Research Scientist	Male	Married	Below College	Life Sciences	Travel_Frequently	Medium	Mediur
2	Research & Development	Laboratory Technician	Male	Single	College	Other	Travel_Rarely	Medium	Hig
3	Research & Development	Research Scientist	Female	Married	Master	Life Sciences	Travel_Frequently	High	Hig
4	Research & Development	Laboratory Technician	Male	Married	Below College	Medical	Travel_Rarely	High	Mediur
...	...	...	...	...	...	...	...	...	.
1465	Research & Development	Laboratory Technician	Male	Married	College	Medical	Travel_Frequently	Very High	Very Hig
1466	Research & Development	Healthcare Representative	Male	Married	Below College	Medical	Travel_Rarely	Medium	Lo
1467	Research & Development	Manufacturing Director	Male	Married	Bachelor	Life Sciences	Travel_Rarely	Very High	Mediur
1468	Sales	Sales Executive	Male	Married	Bachelor	Medical	Travel_Frequently	Medium	Mediur
1469	Research & Development	Laboratory Technician	Male	Married	Bachelor	Medical	Travel_Rarely	Very High	Hig

1470 rows × 13 columns

In [54]:

```
df.select_dtypes(include='int')
```

Out[54]:

	Employee ID	Age	Distance From Home (kms)	Job Level	Salary Hike (%)	Stock Option Level	No. of Companies Worked	Years At Company	Years In Current Role	Years Since Last Promotion	Years With Curr Manager	Train Tir L Y
0	1	41	1	2	11	0	2	6	4	0	5	
1	2	49	8	2	23	1	1	10	7	1	7	
2	4	37	2	1	15	0	6	0	0	0	0	
3	5	33	3	1	11	0	1	8	7	3	0	

	Employee ID	Age	Distance From Home (kms)	Job Level	Salary Hike (%)	Stock Option Level	No. of Companies Worked	Years At Company	Years In Current Role	Years Since Last Promotion	Years With Curr Manager	Train Tir L Y
4	7	27	2	1	12	1	9	2	2	2	2	
...	...	...	...	...	...	...	...	...	...	...	...	
1465	2061	36	23	2	17	1	4	5	2	0	3	
1466	2062	39	6	3	15	1	4	7	7	1	7	
1467	2064	27	4	2	20	1	1	6	2	0	3	
1468	2065	49	2	2	14	0	2	9	6	0	8	
1469	2068	34	8	2	12	0	2	4	3	1	2	

1470 rows × 13 columns

In [55]:

```
ds = df.loc[:,['Department','Job Role','Gender','Marital Status','Business Travel','Job Ir
            'Age','Job Level','Salary Hike (%)','Stock Option Level','Years At Company','Ye
            'Years With Curr Manager','Attrition']].copy()
ds.head()
```

Out[55]:

	Department	Job Role	Gender	Marital Status	Business Travel	Job Involvement	Job Satisfaction	Over Time	Environment Satisfaction	Wo Li Balan
0	Sales	Sales Executive	Female	Single	Travel_Rarely	High	Very High	Yes	Medium	Ba
1	Research & Development	Research Scientist	Male	Married	Travel_Frequently	Medium	Medium	No	High	Bett
2	Research & Development	Laboratory Technician	Male	Single	Travel_Rarely	Medium	High	Yes	Low	Ba
3	Research & Development	Research Scientist	Female	Married	Travel_Frequently	High	High	Yes	Very High	Bett
4	Research & Development	Laboratory Technician	Male	Married	Travel_Rarely	High	Medium	No	Low	Bett

In [56]:

```
ds.shape
```

Out[56]:

```
(1470, 20)
```

In [57]:

```
#We have reduced the number of columns to 20. Great!
```

Setting Dependent and Independent variables

In [58]:

```
X = ds.iloc[:,:-1].values
y=ds.iloc[:,-1].values
print(X)
print(y)
```

```
[['Sales' 'Sales Executive' 'Female' ... 4 0 5]
```

```
 ['Research & Development' 'Research Scientist' 'Male' ... 7 1 7]
 ['Research & Development' 'Laboratory Technician' 'Male' ... 0 0 0]
 ...
 ['Research & Development' 'Manufacturing Director' 'Male' ... 2 0 3]
 ['Sales' 'Sales Executive' 'Male' ... 6 0 8]
 ['Research & Development' 'Laboratory Technician' 'Male' ... 3 1 2]]
[1 0 1 ... 0 0 0]
```

Encoding the Independent Variables

In [59]:

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
```

In [60]:

```
ct = ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[0,1,2,3,4,5,6,7,8,9,10])]
X = np.array(ct.fit_transform(X))
```

In [61]:

```
print(X)
```

```
[[0.0 0.0 1.0 ... 4 0 5]
 [0.0 1.0 0.0 ... 7 1 7]
 [0.0 1.0 0.0 ... 0 0 0]
 ...
 [0.0 1.0 0.0 ... 2 0 3]
 [0.0 0.0 1.0 ... 6 0 8]
 [0.0 1.0 0.0 ... 3 1 2]]
```

In [62]:

```
X.shape
```

Out[62]:

```
(1470, 50)
```

Splitting dataset into training and test set

In [63]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=0)
```

In [64]:

```
print(X_train[0,42:])
#print(X_train)
```

```
[58 4 13 1 1 0 0 0]
```

In [65]:

```
X_train.shape
```

Out[65]:

```
(1176, 50)
```

In [66]:

```
print(X_test)
```

```
[[0.0 0.0 1.0 ... 3 9 7]
 [0.0 1.0 0.0 ... 3 0 2]
 [0.0 0.0 1.0 ... 2 3 2]
 ...
 [0.0 0.0 1.0 ... 7 7 7]
 [0.0 1.0 0.0 ... 0 0 0]
 [0.0 1.0 0.0 ... 0 0 0]]
```

In [67]:

```
print(y_train)
```

```
[0 0 0 ... 0 0 0]
```

In [68]:

```python
print(y_test)
```

```
[0 0 1 0 1 0 1 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
 0 1 0 0 0 0 0 0 1 0 0 1 1 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0
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 1 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0]
```

Feature Scaling

In [69]:

```python
from sklearn.preprocessing  import StandardScaler
sc = StandardScaler()
#Gives value between -3 to +3
#We do not standardize our dummy variables.
X_train[:,42:] = sc.fit_transform(X_train[:,42:])
X_test[:,42:] = sc.transform(X_test[:,42:])
```

In [70]:

```python
print(X_train[0,42:])
```

```
[2.3389367036100883 1.759027295888783 -0.5394871849927129
 0.22505569171608666 -0.9820078512815037 -1.1568405801129382
 -0.6738150570956313 -1.1504388612192216]
```

In [71]:

```python
print(X_test[0,42:])
```

```
[-0.08886551888941858 0.8545165394544985 -0.256887216372922
 -0.9306888212014588 0.49540097572111685 -0.3303250745158451
 2.132819560889478 0.8143770527966774]
```

Machine Learning Classification Models

> 1. Logistic Regression
> 2. KNN
> 3. SVM
> 4. Kernel SVM
> 5. Naive Bayes
> 6. Decision Tree Classification
> 7. Random Forest Classification

Logistic Regression

In [72]:

```python
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state=0)
classifier.fit(X_train,y_train)
```

Out[72]:

```
LogisticRegression(random_state=0)
```

In [73]:

```python
#### Predicting test results
y_pred = classifier.predict(X_test)
```

```
print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)),1))
```

```
[[0 0]
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```

In [74]:

```
#### Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test,y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[240   5]
 [ 23  26]]
```

Out[74]:

```
0.9047619047619048
```

Logistic Regression Model - 90.5% accuracy.

KNN Classifier

In [75]:

```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=7,metric='minkowski',p=2)
classifier.fit(X_train,y_train)
#Predicting test result
y_pred = classifier.predict(X_test)
#print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)),1))
#### Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test,y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[244   1]
 [ 36  13]]
```

Out[75]: 0.8741496598639455

KNN Classifier Model - 87.4% accuracy.

SVM Classifier

In [76]:

```
from sklearn.svm import SVC
classifier = SVC(kernel = 'rbf', random_state=0)
classifier.fit(X_train,y_train)
#Predicting test result
y_pred = classifier.predict(X_test)
#print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)),1))
#### Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test,y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[241   4]
 [ 30  19]]
```

Out[76]: 0.8843537414965986

SVM Classifier Model - 88.4% accuracy.

Decision Tree Classification

In [77]:

```
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion='entropy',random_state=0)
classifier.fit(X_train,y_train)
#Predicting test result
y_pred = classifier.predict(X_test)
#print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)),1))
#### Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test,y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[224  21]
 [ 22  27]]
```

Out[77]: 0.8537414965986394

Decision Tree Classifier Model - 85.3% accuracy.

In [78]:

```
# Random Forest Classification
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 50,random_state=0)
classifier.fit(X_train,y_train)
#Predicting test result
y_pred = classifier.predict(X_test)
#print(np.concatenate((y_pred.reshape(len(y_pred),1),y_test.reshape(len(y_test),1)),1))
#### Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test,y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[241   4]
 [ 30  19]]
```

Out[78]: 0.8843537414965986

Random Forest Classifier Model - 88.4% accuracy.

Result

We should use Logistic Regression Model (90.5% accuracy) since it gives us more than 90% accurate results.