Human Resources. Should we hire new staff?

José Luis Higuera Caraveo

March 02 2022

1 Problem description

Hiring staff can be a very complicated and late task, because depending on the position, candidates are needed who have to meet certain capabilities and cover other skills. Finding the ideal candidate can take a long time, some studies show that this task can last up to 52 days.

Listed below are some points to take into consideration when hiring new employees.

- Hiring and retaining employees are extremely complex tasks within organizations that require capital, time and skills.
- The heads of the Human Resources department dedicate approximately 40% of their working hours to tasks that are related to the hiring and dismissal of employees, tasks that generally do not bring income to the organization.
- Companies can spend between 15% to 20% of the employee's salary to hire a new candidate.
- Depending on the line of business of the organization, in certain jobs, the company has to invest in equipment so that the new employee can work, giving as an example, personal protection equipment, and when an employee decides to leave the position, there is the possibility that this does not return the equipment, so it translates directly into a non-returnable investment for the company.

A database has been generated with information regarding the resignations that have been presented in a company. In order to attack the problem of staff attrition, an analysis is carried out with the aim of predicting which employees are likely to resign their position.

A signal on time can be important for the company to generate solutions to retain the employee and avoid hiring a new one.

Within the set of data provided by the department is information related to the following items: * Labor participation * Education * Work satisfaction * Performance Rating * Satisfaction in relationships * Work-Life Balance

The data to be used for the analysis is Open Database available at: IBM HR Analytics Employee Attrition & Performance.

2 Libraries and analysis of the data set

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
import matplotlib
matplotlib.style.use('ggplot')
```

[3]:
```
# Importing the data
employee_df = pd.read_csv('./Human_Resources.csv')
employee_df.head()
```

[3]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	…	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole	YearsSinceLastPromotion	YearsWithCurrManager
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	…	1	80	0	8	0	1	6	4	0	5
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	…	4	80	1	10	3	3	10	7	1	7
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	…	2	80	0	7	3	3	0	0	0	0
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	…	3	80	0	8	3	3	8	7	3	0
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	…	4	80	1	6	3	3	2	2	2	2

[5 rows x 35 columns]

[32]:
```
# Columns name
columns = employee_df.columns
```

Getting more information to some columns that are difficult to understand. (This information is provided by the Dataset creator).

Education 1. 'Below College' 2. 'College' 3. 'Bachelor' 4. 'Master' 5. 'Doctor'

EnvironmentSatisfaction 1. 'Low' 2. 'Medium' 3. 'High' 4. 'Very High'

JobInvolvement 1. 'Low' 2. 'Medium' 3. 'High' 4. 'Very High'

JobSatisfaction 1. 'Low' 2. 'Medium' 3. 'High' 4. 'Very High'

PerformanceRating 1. 'Low' 2. 'Good' 3. 'Excellent' 4. 'Outstanding'

RelationshipSatisfaction 1. 'Low' 2. 'Medium' 3. 'High' 4. 'Very High'

WorkLifeBalance 1. 'Bad' 2. 'Good' 3. 'Better' 4. 'Best'

We are at face on a dataset with 1470 samples and 35 variables or characteristics.

[5]:
```
employee_df.shape
```

[5]:
```
(1470, 35)
```

Understanding the dataset. Column name, null values and data type for each column.

[6]:
```
employee_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
```

Some statistical information for numerical columns

[7]:
```
employee_df.describe()
```

[7]:

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

	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	\
count	1470.000000	1470.000000	1470.000000	1470.000000	
mean	1024.865306	2.721769	65.891156	2.729932	
std	602.024335	1.093082	20.329428	0.711561	
min	1.000000	1.000000	30.000000	1.000000	
25%	491.250000	2.000000	48.000000	2.000000	
50%	1020.500000	3.000000	66.000000	3.000000	
75%	1555.750000	4.000000	83.750000	3.000000	
max	2068.000000	4.000000	100.000000	4.000000	

	JobLevel	…	RelationshipSatisfaction	StandardHours	\
count	1470.000000	…	1470.000000	1470.0	
mean	2.063946	…	2.712245	80.0	
std	1.106940	…	1.081209	0.0	
min	1.000000	…	1.000000	80.0	
25%	1.000000	…	2.000000	80.0	

```
50%       2.000000  …                 3.000000           80.0
75%       3.000000  …                 4.000000           80.0
max       5.000000  …                 4.000000           80.0

       StockOptionLevel  TotalWorkingYears  TrainingTimesLastYear  \
count       1470.000000        1470.000000            1470.000000
mean           0.793878          11.279592               2.799320
std            0.852077           7.780782               1.289271
min            0.000000           0.000000               0.000000
25%            0.000000           6.000000               2.000000
50%            1.000000          10.000000               3.000000
75%            1.000000          15.000000               3.000000
max            3.000000          40.000000               6.000000

       WorkLifeBalance  YearsAtCompany  YearsInCurrentRole  \
count      1470.000000     1470.000000         1470.000000
mean          2.761224        7.008163            4.229252
std           0.706476        6.126525            3.623137
min           1.000000        0.000000            0.000000
25%           2.000000        3.000000            2.000000
50%           3.000000        5.000000            3.000000
75%           3.000000        9.000000            7.000000
max           4.000000       40.000000           18.000000

       YearsSinceLastPromotion  YearsWithCurrManager
count              1470.000000           1470.000000
mean                  2.187755              4.123129
std                   3.222430              3.568136
min                   0.000000              0.000000
25%                   0.000000              2.000000
50%                   1.000000              3.000000
75%                   3.000000              7.000000
max                  15.000000             17.000000

[8 rows x 26 columns]
```

Before to apply a Machine Learning model it is important to convert the categorical variables into numerical. Will be taken the most important Object data type columns and will be converted into dummies variables.

[8]:
```
employee_df['Attrition'] = employee_df['Attrition'].apply(lambda x: 1 if x ==␣
 ↪'Yes' else 0)
employee_df['Over18'] = employee_df['Over18'].apply(lambda x: 1 if x == 'Y'␣
 ↪else 0)
employee_df['OverTime'] = employee_df['OverTime'].apply(lambda x: 1 if x ==␣
 ↪'Yes' else 0)
```

Checking if the changes have been applied correctly.

[9]:
```
employee_df[['Attrition', 'Over18', 'OverTime']].head()
```

[9]:

	Attrition	Over18	OverTime
0	1	1	1
1	0	1	0
2	1	1	1
3	0	1	1
4	0	1	0

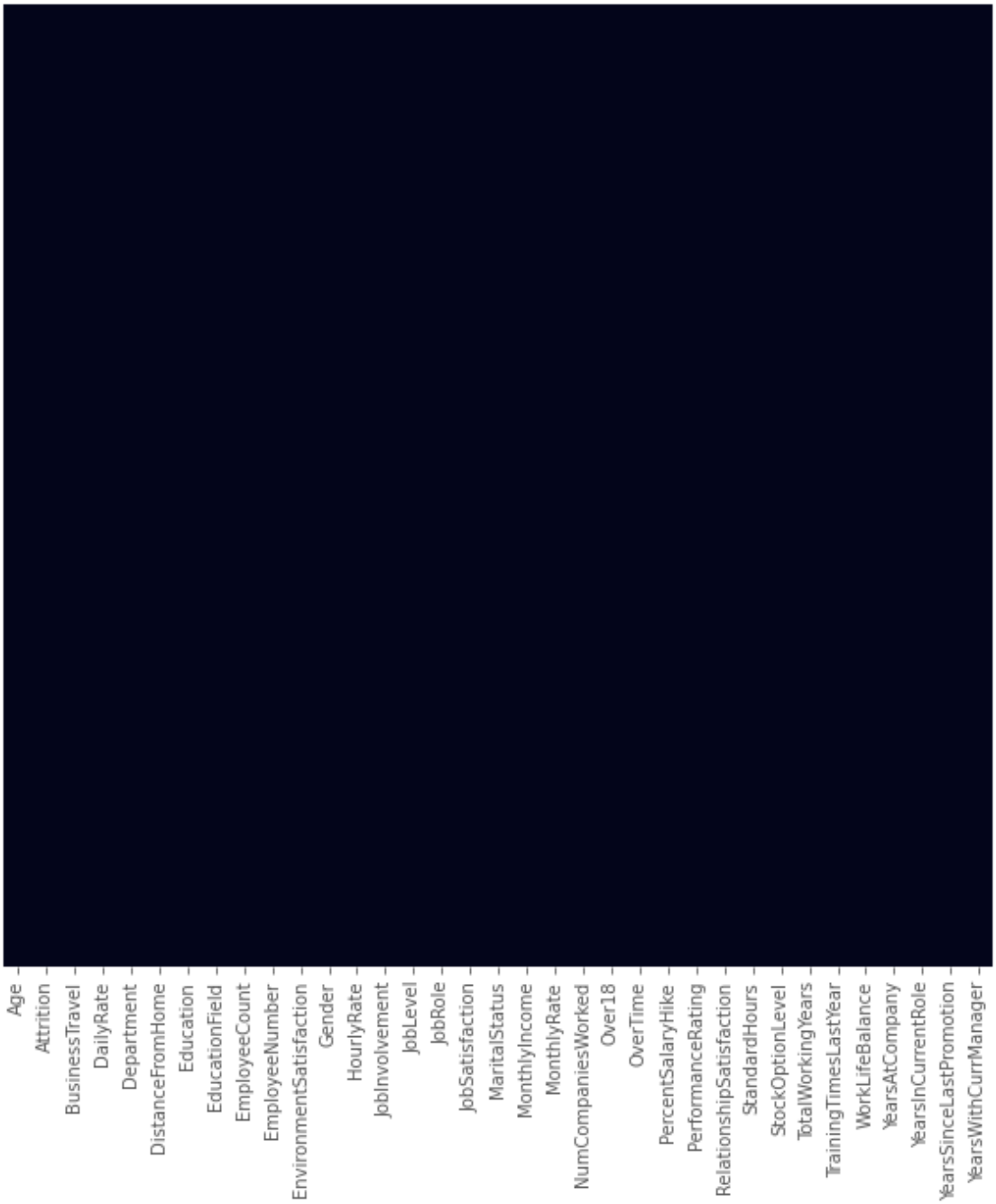
3 Data visualization

3.0.1 Null values

Let's check if there is null data in the dataset.

Will be used the seaborn tool to print a binary heatmap.

[10]:
```
plt.figure(figsize=(10,10))
sns.heatmap(employee_df.isnull(), yticklabels=False, cbar=False)
plt.show()
```



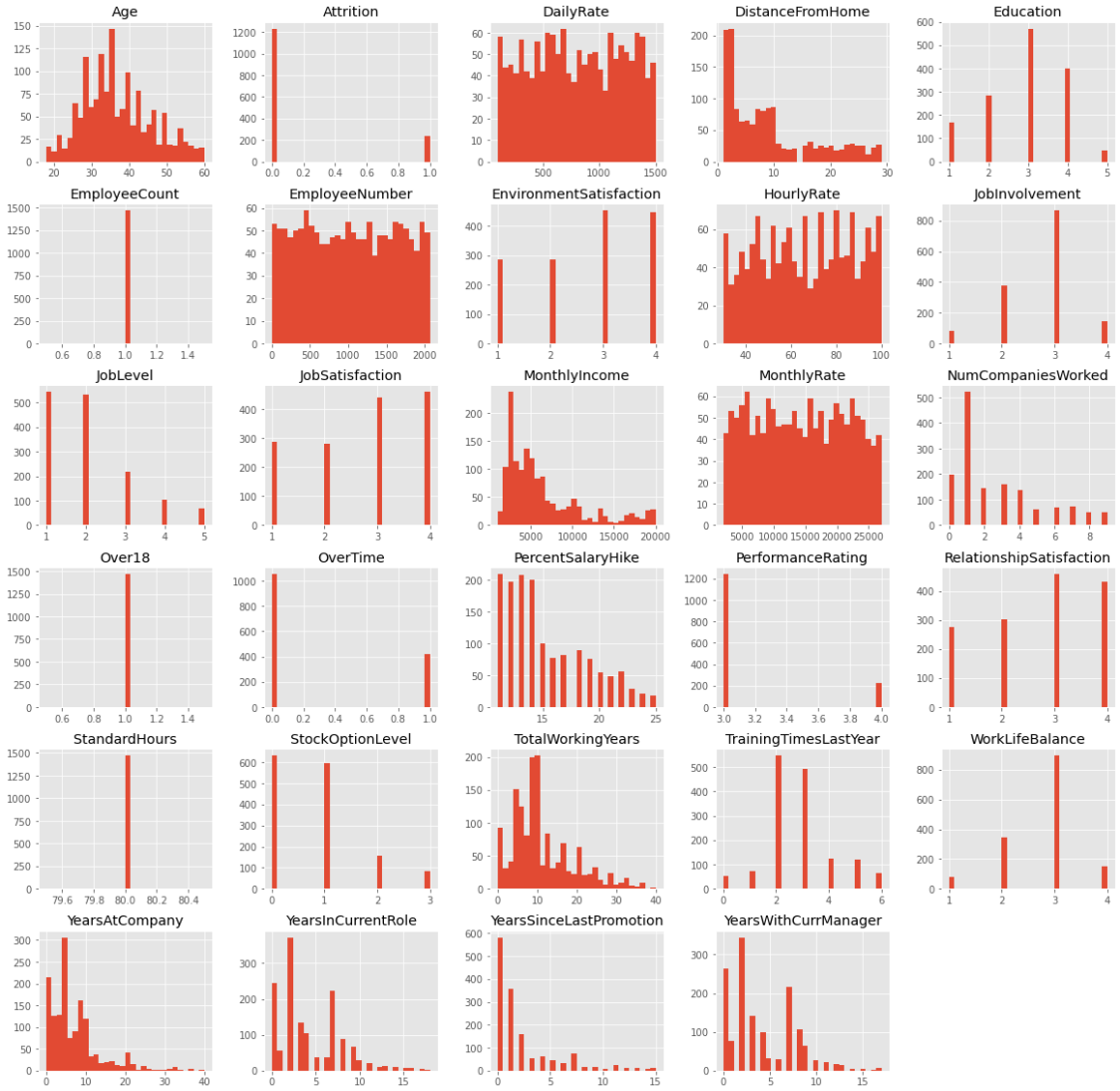
As the graph shows, there is not any null value in the dataset.

3.0.2 Variable distribution

One excellent way to understand a variable is with its histogram. In the next code line will be printed.

[11]:
```
plt.figure()
employee_df.hist(bins = 30, figsize=(20,20))
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



Some important conclusion can be made with the before results. For example, aprox of 80% of the employees are considering not leave the company, the other 20% has left the company.

Now, the goal of the analysis is understand the characteristics of those 20%.

3.0.3 Employees who leave the company vs those who stay.

Deleting variables that do not contribute much to the problem being analyzed.

[12]:
```
employee_df.drop(['EmployeeCount', 'StandardHours', 'Over18', 'EmployeeNumber'],
                 axis=1, inplace=True)
```

Dividing the dataset into the employees that left the company and the other hand with the employees that stay at the company.

[13]:
```
left_df = employee_df[employee_df['Attrition'] == 1]
stayed_df = employee_df[employee_df['Attrition'] == 0]
```

[14]:
```
total_employees = employee_df.shape[0]
total_left = left_df.shape[0]
total_stayed = stayed_df.shape[0]

per_left = round((total_left / total_employees) * 100, 2)
per_estayed = round((total_stayed / total_employees) * 100, 2)

print('Total employees: {}, Total Left: {}, Total Stayed: {}'.
 ↪format(total_employees,

 ↪total_left,

 ↪total_stayed))
print('Persentage Left: {}%, Persentage Stayed: {}%'.format(per_left,␣
 ↪per_estayed))
```

```
Total employees: 1470, Total Left: 237, Total Stayed: 1233
Persentage Left: 16.12%, Persentage Stayed: 83.88%
```

[15]:
```
left_df.describe()
```

[15]:

	Age	Attrition	DailyRate	DistanceFromHome	Education	\
count	237.000000	237.0	237.000000	237.000000	237.000000	
mean	33.607595	1.0	750.362869	10.632911	2.839662	
std	9.689350	0.0	401.899519	8.452525	1.008244	
min	18.000000	1.0	103.000000	1.000000	1.000000	
25%	28.000000	1.0	408.000000	3.000000	2.000000	
50%	32.000000	1.0	699.000000	9.000000	3.000000	
75%	39.000000	1.0	1092.000000	17.000000	4.000000	
max	58.000000	1.0	1496.000000	29.000000	5.000000	

	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	\
count	237.000000	237.000000	237.000000	237.000000	
mean	2.464135	65.573840	2.518987	1.637131	
std	1.169791	20.099958	0.773405	0.940594	
min	1.000000	31.000000	1.000000	1.000000	
25%	1.000000	50.000000	2.000000	1.000000	
50%	3.000000	66.000000	3.000000	1.000000	

```
75%                  4.000000   84.000000        3.000000    2.000000
max                  4.000000  100.000000        4.000000    5.000000

       JobSatisfaction  …  PerformanceRating  RelationshipSatisfaction  \
count       237.000000  …         237.000000                237.000000
mean          2.468354  …           3.156118                  2.599156
std           1.118058  …           0.363735                  1.125437
min           1.000000  …           3.000000                  1.000000
25%           1.000000  …           3.000000                  2.000000
50%           3.000000  …           3.000000                  3.000000
75%           3.000000  …           3.000000                  4.000000
max           4.000000  …           4.000000                  4.000000

       StockOptionLevel  TotalWorkingYears  TrainingTimesLastYear  \
count        237.000000         237.000000             237.000000
mean           0.527426           8.244726               2.624473
std            0.856361           7.169204               1.254784
min            0.000000           0.000000               0.000000
25%            0.000000           3.000000               2.000000
50%            0.000000           7.000000               2.000000
75%            1.000000          10.000000               3.000000
max            3.000000          40.000000               6.000000

       WorkLifeBalance  YearsAtCompany  YearsInCurrentRole  \
count       237.000000      237.000000          237.000000
mean          2.658228        5.130802            2.902954
std           0.816453        5.949984            3.174827
min           1.000000        0.000000            0.000000
25%           2.000000        1.000000            0.000000
50%           3.000000        3.000000            2.000000
75%           3.000000        7.000000            4.000000
max           4.000000       40.000000           15.000000

       YearsSinceLastPromotion  YearsWithCurrManager
count               237.000000            237.000000
mean                  1.945148              2.852321
std                   3.153077              3.143349
min                   0.000000              0.000000
25%                   0.000000              0.000000
50%                   1.000000              2.000000
75%                   2.000000              5.000000
max                  15.000000             14.000000

[8 rows x 25 columns]
```

[16]:
```
stayed_df.describe()
```

[16]:

	Age	Attrition	DailyRate	DistanceFromHome	Education
count	1233.000000	1233.0	1233.000000	1233.000000	1233.000000
mean	37.561233	0.0	812.504461	8.915653	2.927007
std	8.888360	0.0	403.208379	8.012633	1.027002
min	18.000000	0.0	102.000000	1.000000	1.000000
25%	31.000000	0.0	477.000000	2.000000	2.000000
50%	36.000000	0.0	817.000000	7.000000	3.000000
75%	43.000000	0.0	1176.000000	13.000000	4.000000
max	60.000000	0.0	1499.000000	29.000000	5.000000

	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel
count	1233.000000	1233.000000	1233.000000	1233.000000
mean	2.771290	65.952149	2.770479	2.145985
std	1.071132	20.380754	0.692050	1.117933
min	1.000000	30.000000	1.000000	1.000000
25%	2.000000	48.000000	2.000000	1.000000
50%	3.000000	66.000000	3.000000	2.000000
75%	4.000000	83.000000	3.000000	3.000000
max	4.000000	100.000000	4.000000	5.000000

	JobSatisfaction	…	PerformanceRating	RelationshipSatisfaction
count	1233.000000	…	1233.000000	1233.000000
mean	2.778589	…	3.153285	2.733982
std	1.093277	…	0.360408	1.071603
min	1.000000	…	3.000000	1.000000
25%	2.000000	…	3.000000	2.000000
50%	3.000000	…	3.000000	3.000000
75%	4.000000	…	3.000000	4.000000
max	4.000000	…	4.000000	4.000000

	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear
count	1233.000000	1233.000000	1233.000000
mean	0.845093	11.862936	2.832928
std	0.841985	7.760719	1.293585
min	0.000000	0.000000	0.000000
25%	0.000000	6.000000	2.000000
50%	1.000000	10.000000	3.000000
75%	1.000000	16.000000	3.000000
max	3.000000	38.000000	6.000000

	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole
count	1233.000000	1233.000000	1233.000000
mean	2.781022	7.369019	4.484185
std	0.681907	6.096298	3.649402
min	1.000000	0.000000	0.000000
25%	2.000000	3.000000	2.000000
50%	3.000000	6.000000	3.000000

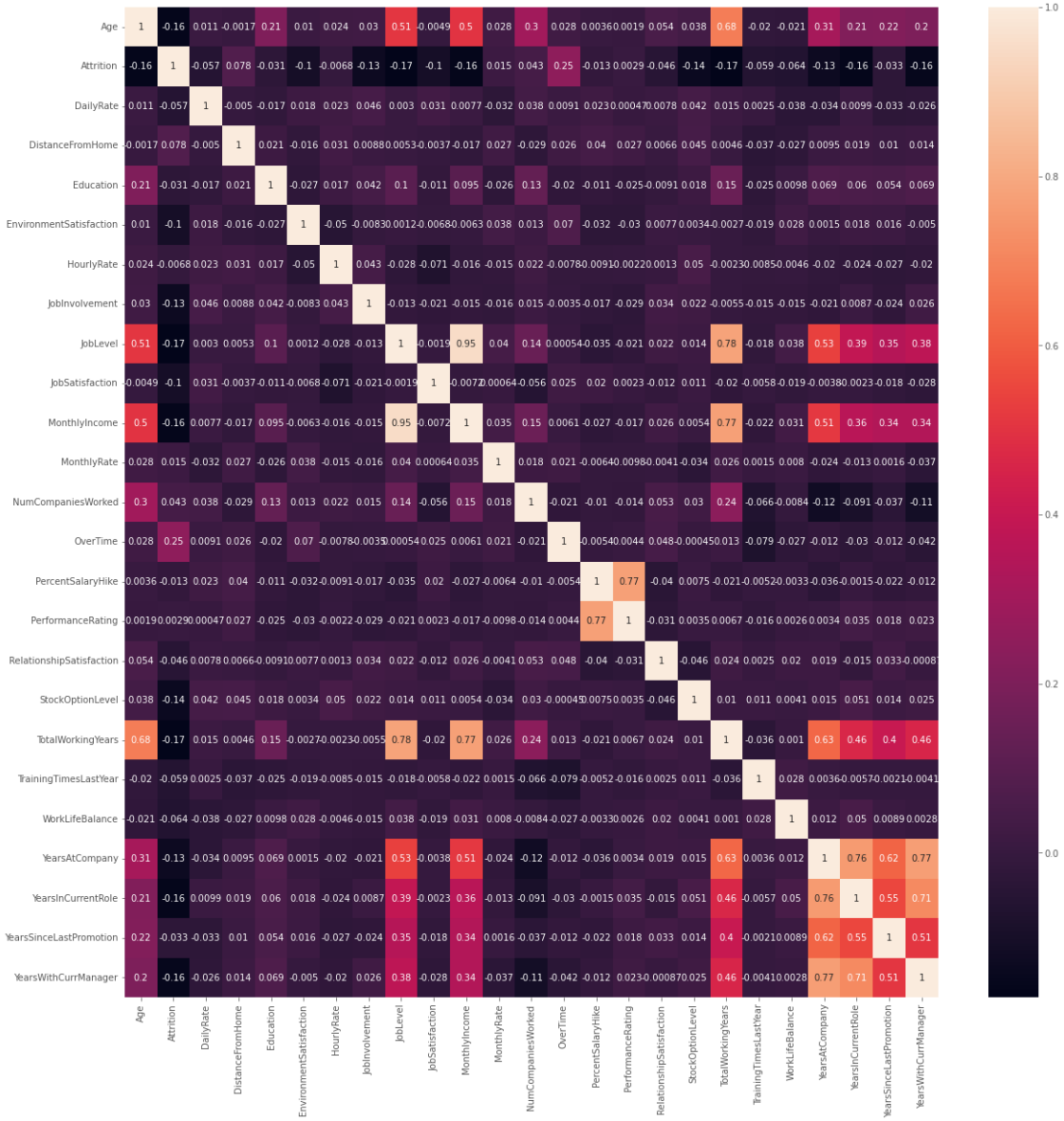
```
75%           3.000000       10.000000            7.000000
max           4.000000       37.000000           18.000000

       YearsSinceLastPromotion  YearsWithCurrManager
count              1233.000000           1233.000000
mean                  2.234388              4.367397
std                   3.234762              3.594116
min                   0.000000              0.000000
25%                   0.000000              2.000000
50%                   1.000000              3.000000
75%                   3.000000              7.000000
max                  15.000000             17.000000

[8 rows x 25 columns]
```

Making an analysis of both datasets to make some conclusion of the data:

- The mean and standard error of the employees who stayed and left are compared.
- 'age': The average age of the employees who stayed is older compared to those who left.
- 'DailyRate': The daily rate of the employees who stayed is higher.
- 'DistanceFromHome': Employees who remain live closer to work.
- 'EnvironmentSatisfaction' & 'JobSatisfaction': Employees who stay are generally more satisfied with their jobs.
- 'StockOptionLevel': Employees who stay have a higher level of stock options.
- 'MonthlyIncome': Employees who stay have a higher monthly Income.

3.0.4 Correlation Matrix

[17]:
```
correlations = employee_df.corr()

plt.figure(figsize=(20,20))
sns.heatmap(correlations, annot=True)
plt.show()
```



Conclusions:

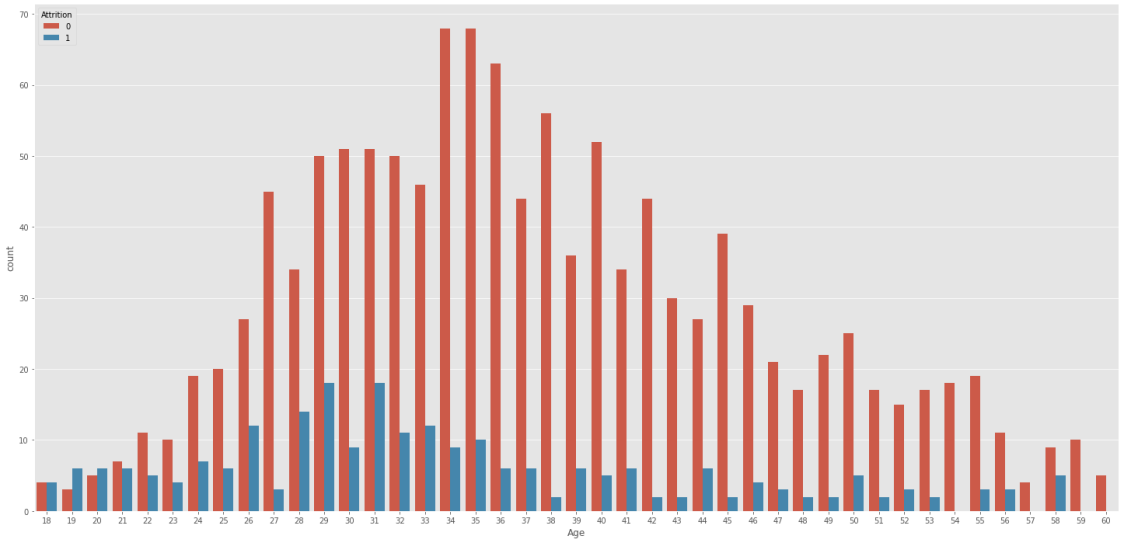
- Job level is highly correlated with the total number of working hours.
- Monthly income is highly correlated with Job level.
- Monthly income is highly correlated with the total number of working hours.
- Age is highly correlated with monthly income.

3.0.5 Distribution

Age vs Attrition

[18]:
```
plt.figure(figsize=(25,12))
sns.countplot(x='Age', hue='Attrition', data=employee_df)
```

```
plt.show()
```

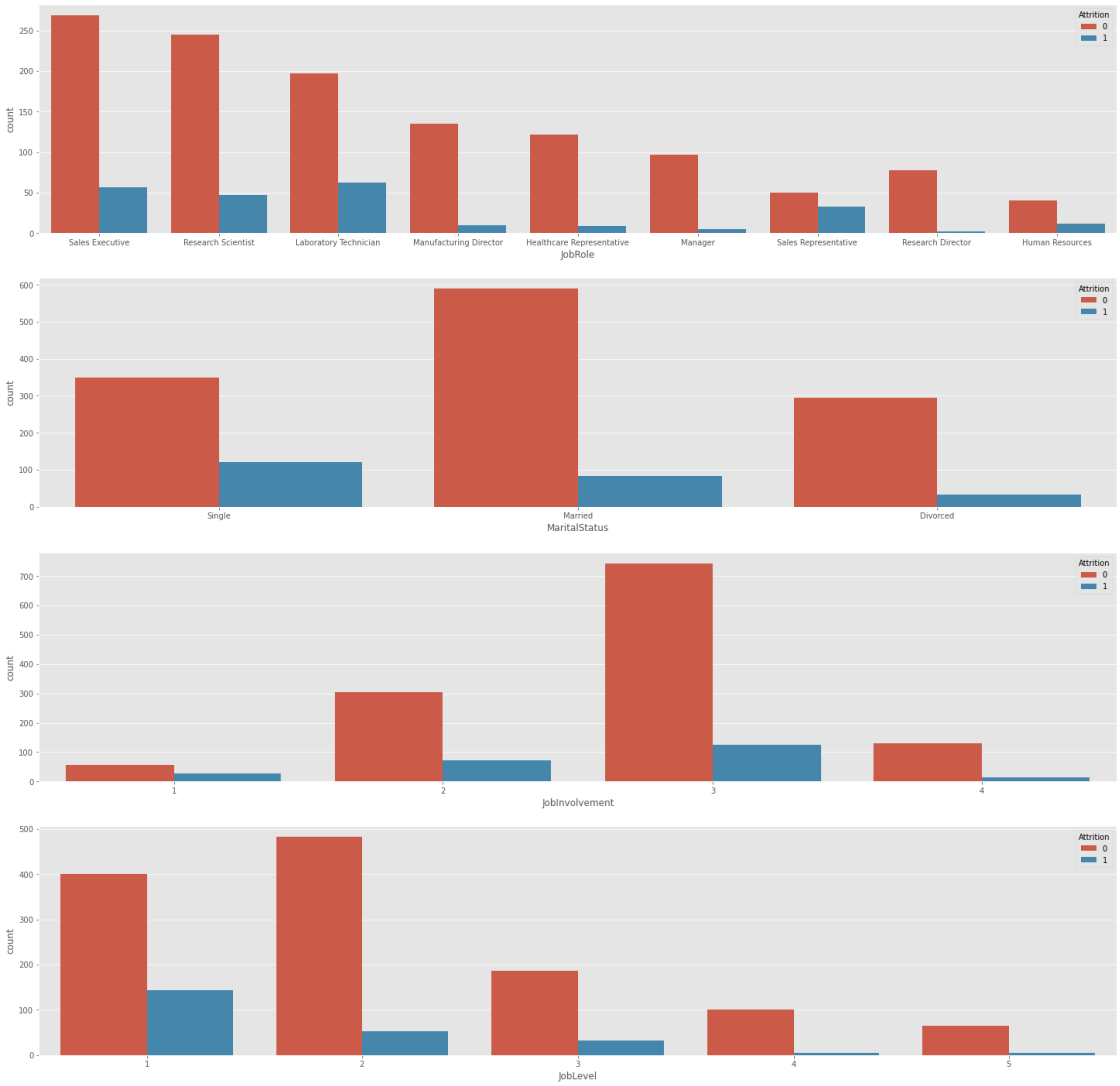


The most employees who leave the company are between the 18 and 37 years old. Once one employee has more than that age, the probability to leave the company decrease.

One factor as the age might be important to determinate if one employee will or not leave the company.

Job Role, Marital Status, Job Involvement and Job Level. More variables could be analyzed to understand the data distribution.

[19]:
```
plt.figure(figsize=(25,25))
plt.subplot(411)
sns.countplot(x='JobRole', hue='Attrition', data=employee_df)
plt.subplot(412)
sns.countplot(x='MaritalStatus', hue='Attrition', data=employee_df)
plt.subplot(413)
sns.countplot(x='JobInvolvement', hue='Attrition', data=employee_df)
plt.subplot(414)
sns.countplot(x='JobLevel', hue='Attrition', data=employee_df)
plt.show()
```



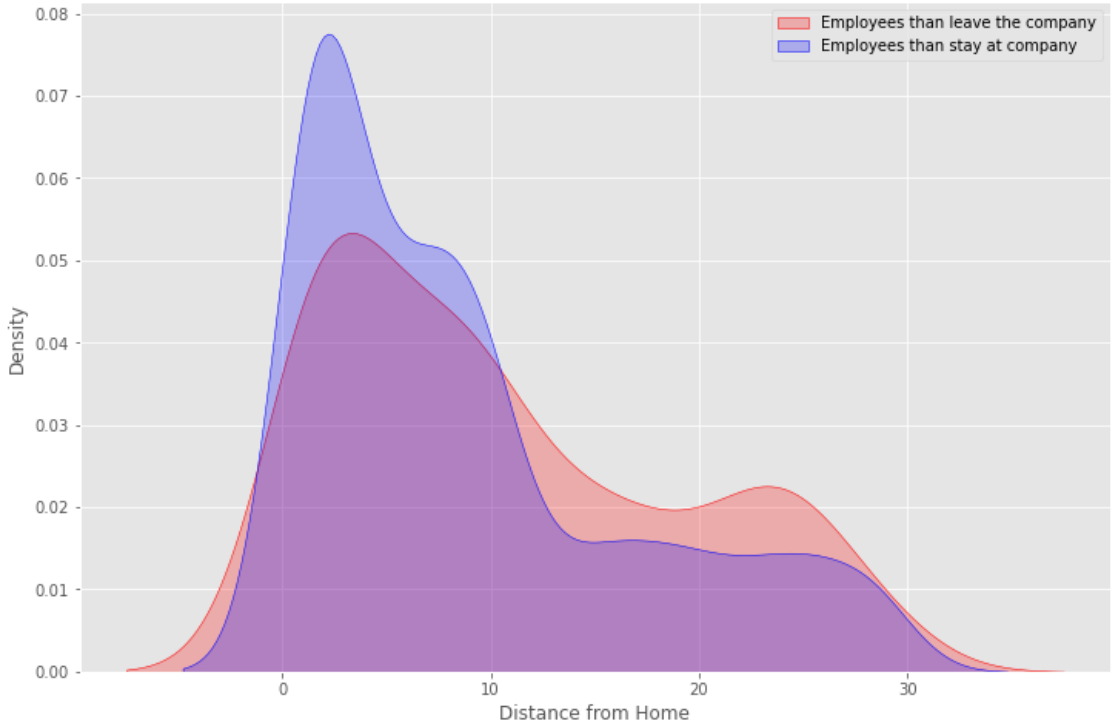
Conclusions: * In sales department exists a high percentage of employees that leave the company, aprox the 40% * The Single employees are more likely to leave the company than the others. * As much as the job involvement is lower is more likely that one employee leaves. * One employee with more Jove level is less likely to leaves the company.

3.0.6 Density Distribution

Distance from Home

[20]:
```
plt.figure(figsize=(12,8))
sns.kdeplot(left_df['DistanceFromHome'], label = 'Employees than leave the␣
↪company',
            shade=True, color='r')
sns.kdeplot(stayed_df['DistanceFromHome'], label = 'Employees than stay at␣
↪company',
```

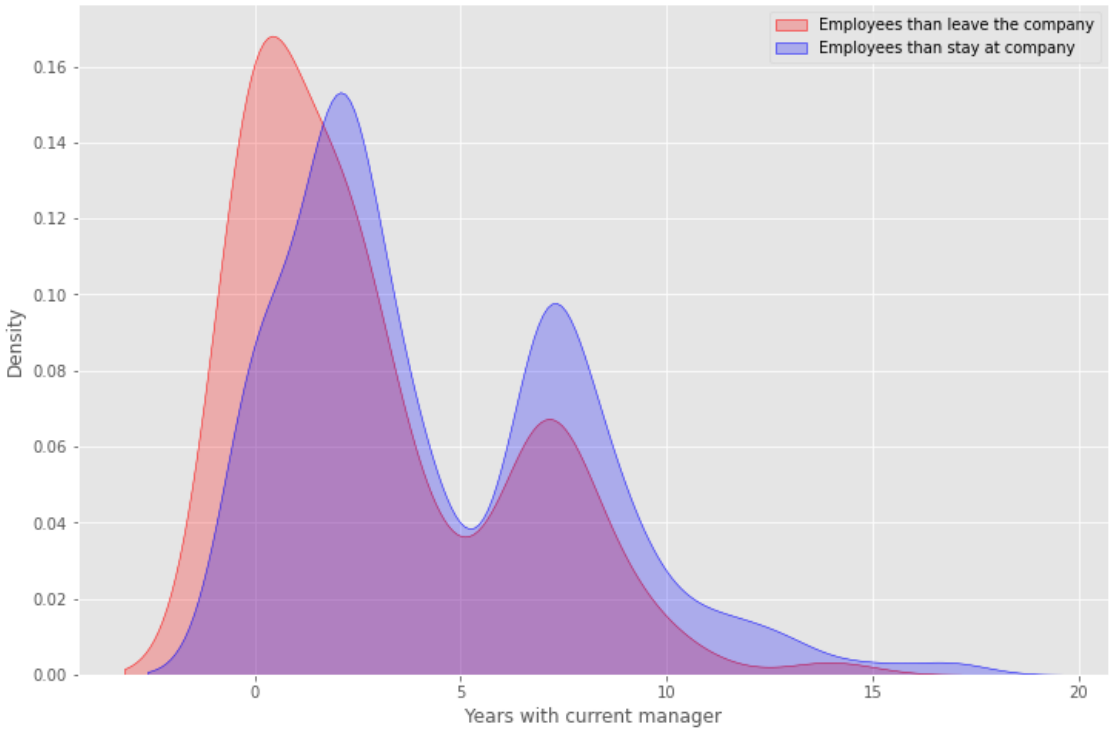
```
            shade=True, color='b')
plt.xlabel('Distance from Home')
plt.legend()
plt.show()
```



In one hand, if the distance is short, the probability of stay is higher, in the other hand, if the distance increase, more than 10 miles, the probability to leave is higher.

Years with current manager

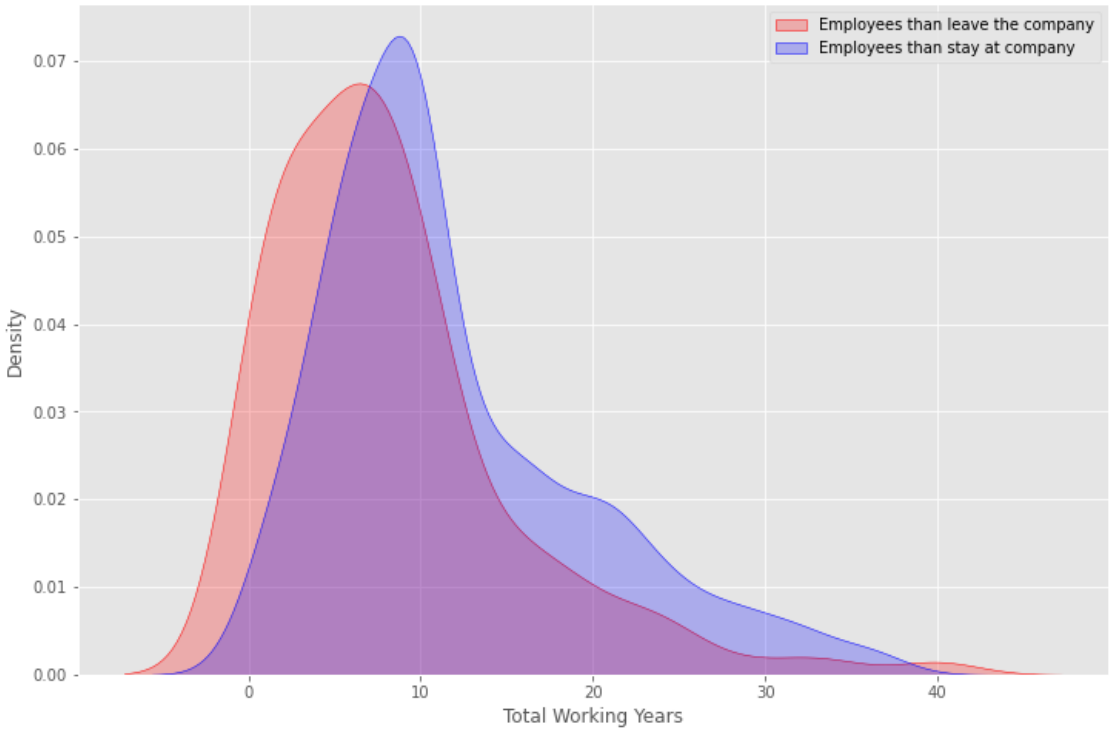
[21]:
```
plt.figure(figsize=(12,8))
sns.kdeplot(left_df['YearsWithCurrManager'], label = 'Employees than leave the␣
↪company',
            shade=True, color='r')
sns.kdeplot(stayed_df['YearsWithCurrManager'], label = 'Employees than stay at␣
↪company',
            shade=True, color='b')
plt.xlabel('Years with current manager')
plt.legend()
plt.show()
```



Once an employee stays approx 1.5 years with the same manager, is more likely to stay at company.

Total working years

[22]:
```
plt.figure(figsize=(12,8))
sns.kdeplot(left_df['TotalWorkingYears'], label = 'Employees than leave the␣
↪company',
            shade=True, color='r')
sns.kdeplot(stayed_df['TotalWorkingYears'], label = 'Employees than stay at␣
↪company',
            shade=True, color='b')
plt.xlabel('Total Working Years')
plt.legend()
plt.show()
```

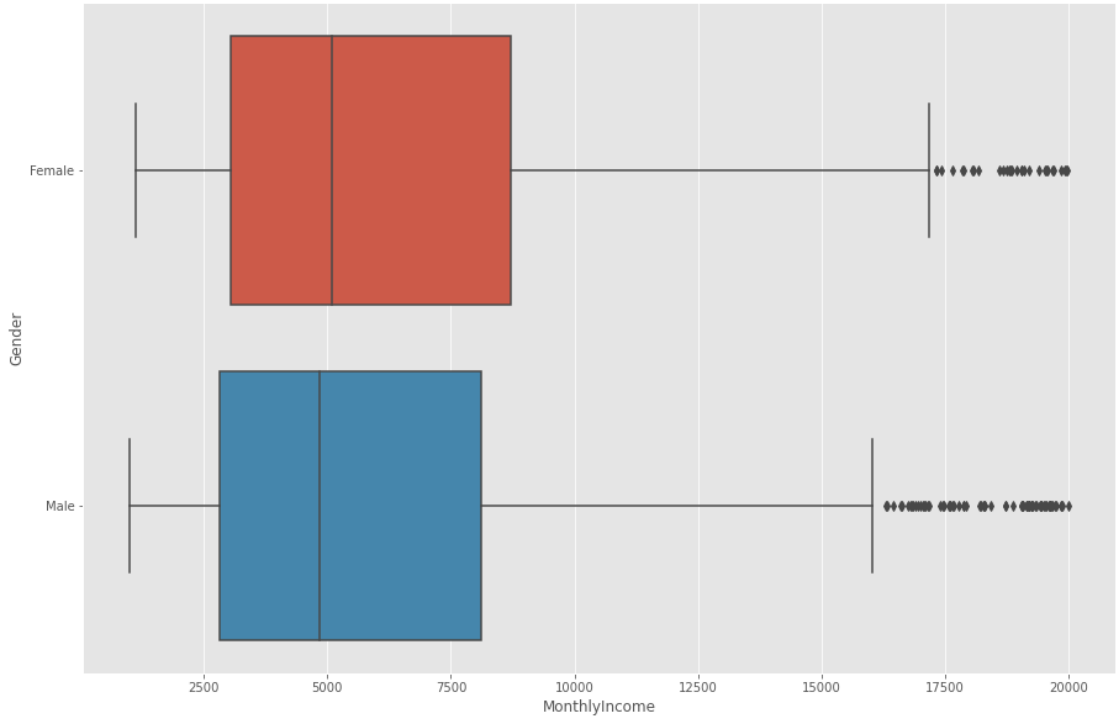


As the time staying at the company is higher, the probability of stay is also high.

3.0.7 Box Plots

Gender vs Monthly Income

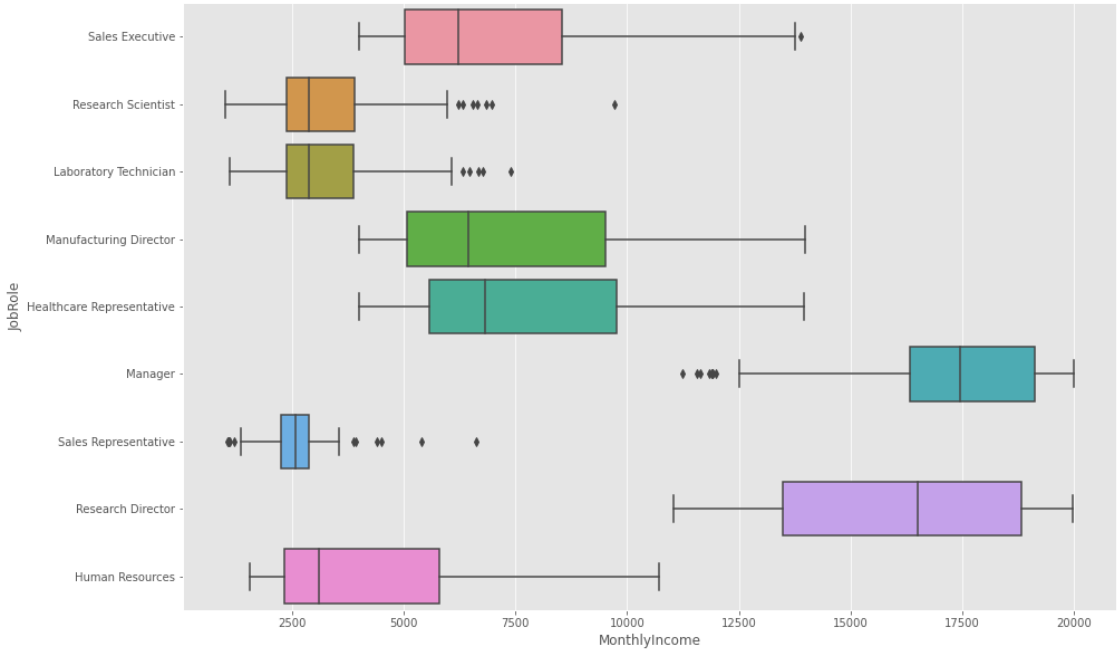
[23]:
```
plt.figure(figsize=(15,10))
sns.boxplot(x='MonthlyIncome', y='Gender', data=employee_df)
plt.show()
```



There is not discrimination due the gender of the employee, in the plot can be ilustrate that the mean salary for gender is almos the same, in fact, the mean salary of the female are a bit higher as the male.

Monthly Income vs Job Role

[24]:
```
plt.figure(figsize=(15,10))
sns.boxplot(x='MonthlyIncome', y='JobRole', data=employee_df)
plt.show()
```



In the previous plot are more interesting information: * The employees with highest salary are those are managers or research directors. * The sales representative, research scientist and laboratory technician are the lowest payed.

4 Data Cleaning, Training and Testing datasets

4.0.1 Working with categorical variables

[25]:
```
cat_cols = ['BusinessTravel', 'Department', 'EducationField', 'Gender',␣
↪'JobRole', 'MaritalStatus']
x_cat = employee_df[cat_cols]
```

[26]:
```
x_cat.head()
```

[26]:

	BusinessTravel	Department	EducationField	Gender	JobRole	MaritalStatus
0	Travel_Rarely	Sales	Life Sciences	Female	Sales Executive	Single
1	Travel_Frequently	Research & Development	Life Sciences	Male	Research Scientist	Married
2	Travel_Rarely	Research & Development	Other	Male	Laboratory Technician	Single
3	Travel_Frequently	Research & Development	Life Sciences	Female	Research Scientist	Married
4	Travel_Rarely	Research & Development	Medical	Male		

```
4  Laboratory Technician       Married
```

[27]:
```
from sklearn.preprocessing import OneHotEncoder
```

[28]:
```
onehotencoder = OneHotEncoder()
x_cat = onehotencoder.fit_transform(x_cat).toarray()
```

[29]:
```
x_cat.shape
```

[29]:
```
(1470, 26)
```

[30]:
```
x_cat = pd.DataFrame(x_cat)
x_cat.head()
```

[30]:

	0	1	2	3	4	5	6	7	8	9	…	16	17	18	19	\
0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	…	0.0	0.0	0.0	0.0	
1	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	…	0.0	0.0	0.0	0.0	
2	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	…	1.0	0.0	0.0	0.0	
3	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	…	0.0	0.0	0.0	0.0	
4	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	…	1.0	0.0	0.0	0.0	

	20	21	22	23	24	25
0	0.0	1.0	0.0	0.0	0.0	1.0
1	1.0	0.0	0.0	0.0	1.0	0.0
2	0.0	0.0	0.0	0.0	0.0	1.0
3	1.0	0.0	0.0	0.0	1.0	0.0
4	0.0	0.0	0.0	0.0	1.0	0.0

[5 rows x 26 columns]

4.0.2 Working with Numerical variables

[33]:
```
num_cols = [col for col in columns if col not in cat_cols if col != 'Attrition']
x_num = employee_df[num_cols]
```

[34]:
```
x_num.head()
```

[34]:

	Age	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	\
0	41	1102	1	2	2	
1	49	279	8	1	3	
2	37	1373	2	2	4	
3	33	1392	3	4	4	
4	27	591	2	1	1	

	HourlyRate	JobInvolvement	JobLevel	JobSatisfaction	MonthlyIncome	…	\
0	94	3	2	4	5993	…	
1	61	2	2	2	5130	…	

```
2          92               2         1                3           2090  …
3          56               3         1                3           2909  …
4          40               3         1                2           3468  …

   PerformanceRating  RelationshipSatisfaction  StockOptionLevel  \
0                  3                         1                 0
1                  4                         4                 1
2                  3                         2                 0
3                  3                         3                 0
4                  3                         4                 1

   TotalWorkingYears  TrainingTimesLastYear  WorkLifeBalance  YearsAtCompany  \
0                  8                      0                1               6
1                 10                      3                3              10
2                  7                      3                3               0
3                  8                      3                3               8
4                  6                      3                3               2

   YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                   4                        0                     5
1                   7                        1                     7
2                   0                        0                     0
3                   7                        3                     0
4                   2                        2                     2

[5 rows x 24 columns]
```

4.0.3 Joining all variables

[35]:
```
x_all = pd.concat([x_cat, x_num], axis=1)
x_all.head()
```

[35]:
```
     0    1    2    3    4    5    6    7    8    9  …  PerformanceRating  \
0  0.0  0.0  1.0  0.0  0.0  1.0  0.0  1.0  0.0  0.0  …                  3
1  0.0  1.0  0.0  0.0  1.0  0.0  0.0  1.0  0.0  0.0  …                  4
2  0.0  0.0  1.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  …                  3
3  0.0  1.0  0.0  0.0  1.0  0.0  0.0  1.0  0.0  0.0  …                  3
4  0.0  0.0  1.0  0.0  1.0  0.0  0.0  0.0  0.0  1.0  …                  3

   RelationshipSatisfaction  StockOptionLevel  TotalWorkingYears  \
0                         1                 0                  8
1                         4                 1                 10
2                         2                 0                  7
3                         3                 0                  8
4                         4                 1                  6

   TrainingTimesLastYear  WorkLifeBalance  YearsAtCompany  YearsInCurrentRole  \
```

```
0                       0                       1                       6                       4
1                       3                       3                      10                       7
2                       3                       3                       0                       0
3                       3                       3                       8                       7
4                       3                       3                       2                       2

   YearsSinceLastPromotion  YearsWithCurrManager
0                        0                     5
1                        1                     7
2                        0                     0
3                        3                     0
4                        2                     2

[5 rows x 50 columns]
```

4.0.4 Min-Max Scaler

[36]:
```
from sklearn.preprocessing import MinMaxScaler
```

[37]:
```
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x_all)
x_scaled
```

[37]:
```
array([[0.        , 0.        , 1.        , …, 0.22222222, 0.        ,
        0.29411765],
       [0.        , 1.        , 0.        , …, 0.38888889, 0.06666667,
        0.41176471],
       [0.        , 0.        , 1.        , …, 0.        , 0.        ,
        0.        ],
       …,
       [0.        , 0.        , 1.        , …, 0.11111111, 0.        ,
        0.17647059],
       [0.        , 1.        , 0.        , …, 0.33333333, 0.        ,
        0.47058824],
       [0.        , 0.        , 1.        , …, 0.16666667, 0.06666667,
        0.11764706]])
```

4.0.5 Predicted variable

[38]:
```
y = employee_df['Attrition']
y
```

[38]:
```
0       1
1       0
2       1
3       0
4       0
```

```
       ..
1465    0
1466    0
1467    0
1468    0
1469    0
Name: Attrition, Length: 1470, dtype: int64
```

5 Train and evaluate the Model

5.1 Logistic Regression

Dividing the data between training set and testing set

[39]:
```
from sklearn.model_selection import train_test_split
```

[40]:
```
x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.25)
```

[41]:
```
x_train.shape
```

[41]:
```
(1102, 50)
```

[42]:
```
x_test.shape
```

[42]:
```
(368, 50)
```

Training the model

[43]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

[44]:
```
model = LogisticRegression()
model.fit(x_train, y_train)

y_pred = model.predict(x_test)
```

Evaluating the model

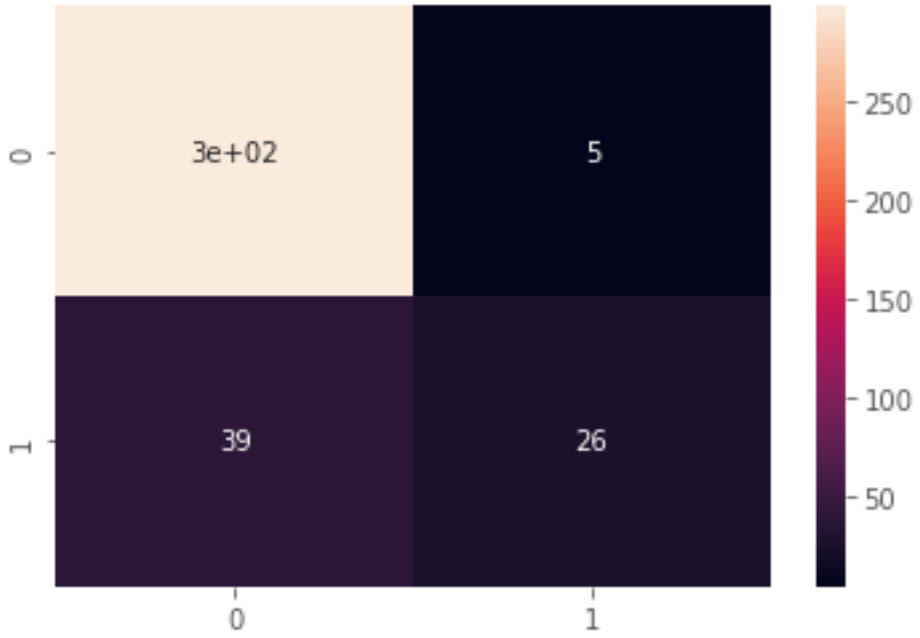
[45]:
```
from sklearn.metrics import confusion_matrix, classification_report
```

[46]:
```
print('Accuracy: {}'.format(100 * accuracy_score(y_pred, y_test)))
```

```
Accuracy: 88.04347826086956
```

The model has an 88.04% of accuracy, that means that the model can predict correctly on the 88.04% if one employee has left the company or has stayed.

[47]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
plt.show()
```



[48]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.98      0.93       303
           1       0.84      0.40      0.54        65

    accuracy                           0.88       368
   macro avg       0.86      0.69      0.74       368
weighted avg       0.88      0.88      0.86       368
```

5.2 Random Forest

[49]:
```
from sklearn.ensemble import RandomForestClassifier
```

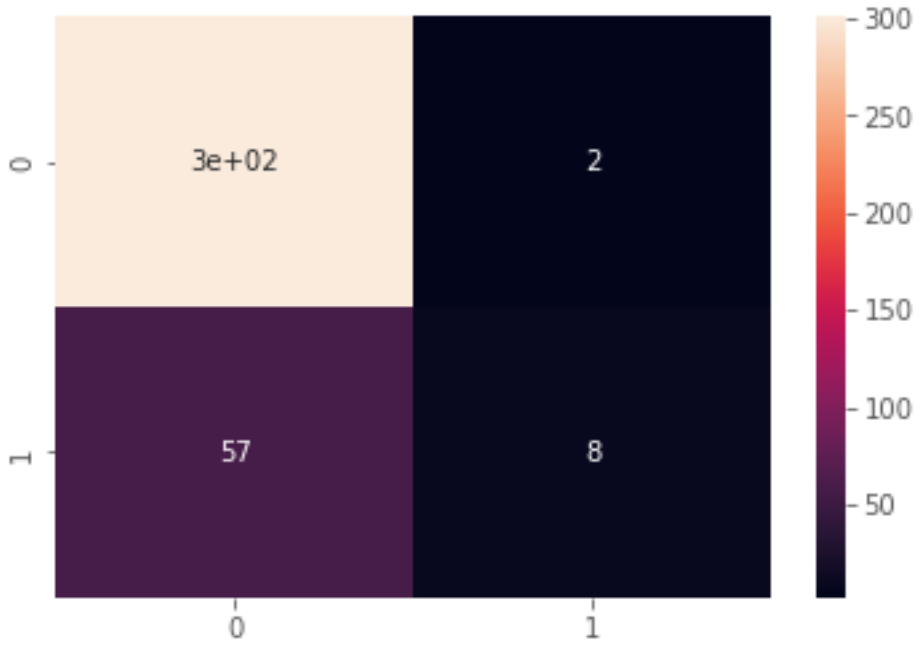
[50]:
```
model = RandomForestClassifier()
model.fit(x_train, y_train)

y_pred = model.predict(x_test)
```

[51]:
```
print('Accuracy: {}'.format(100 * accuracy_score(y_pred, y_test)))
```

```
Accuracy: 83.96739130434783
```

The random forest algorithm is a good choice, we have an accuracy of 83.9%, a little lower than the logistic regression.

[52]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
plt.show()
```



[53]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.99      0.91       303
           1       0.80      0.12      0.21        65

    accuracy                           0.84       368
   macro avg       0.82      0.56      0.56       368
weighted avg       0.83      0.84      0.79       368
```

5.3 Deep Learning

[54]:
```
import tensorflow as tf
```

Training the model

[55]:
```
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Dense(units = 500, activation='relu',␣
 ↪input_shape=(50,)))
model.add(tf.keras.layers.Dense(units = 500, activation='relu'))
model.add(tf.keras.layers.Dense(units = 500, activation='relu'))
model.add(tf.keras.layers.Dense(units = 1, activation='sigmoid'))

model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])

hist = model.fit(x_train, y_train, epochs=30, batch_size=64, verbose=2)
```

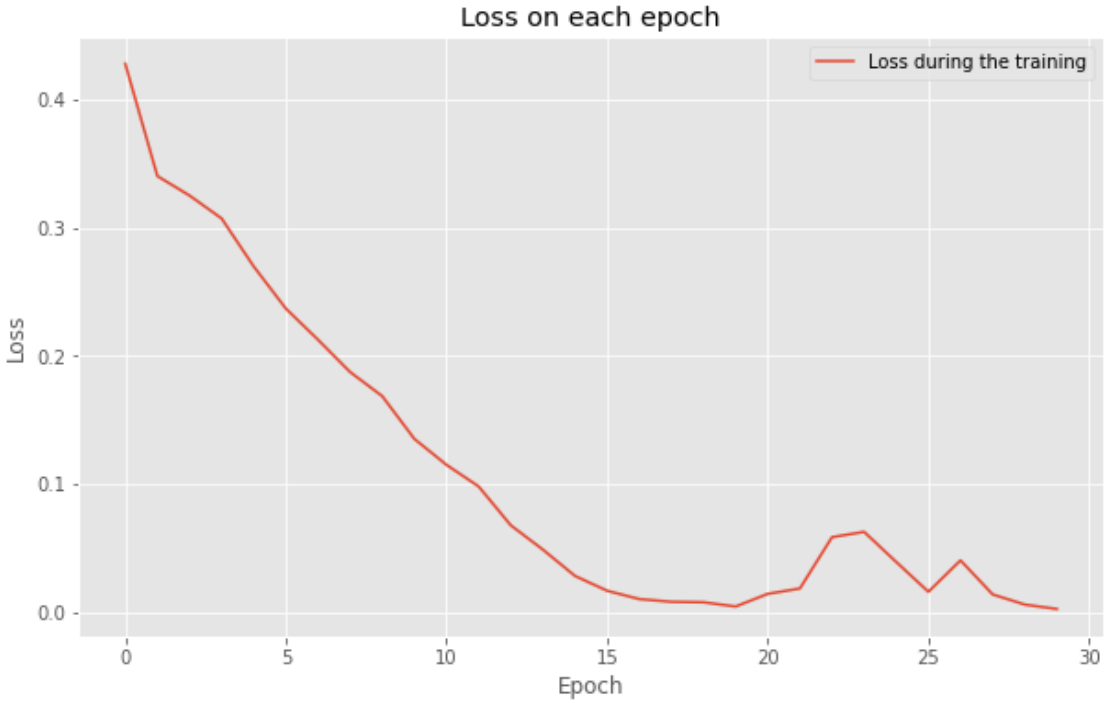
```
2022-03-19 08:07:02.189144: I tensorflow/compiler/jit/xla_cpu_device.cc:41] Not
creating XLA devices, tf_xla_enable_xla_devices not set
2022-03-19 08:07:02.189603: I tensorflow/core/platform/cpu_feature_guard.cc:142]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2022-03-19 08:07:02.192517: I
tensorflow/core/common_runtime/process_util.cc:146] Creating new thread pool
with default inter op setting: 2. Tune using inter_op_parallelism_threads for
best performance.
2022-03-19 08:07:02.361876: I
tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:116] None of the MLIR
optimization passes are enabled (registered 2)
2022-03-19 08:07:02.362716: I
tensorflow/core/platform/profile_utils/cpu_utils.cc:112] CPU Frequency:
2400005000 Hz

Epoch 1/30
18/18 - 2s - loss: 0.4278 - accuracy: 0.8430
Epoch 2/30
18/18 - 0s - loss: 0.3401 - accuracy: 0.8548
Epoch 3/30
18/18 - 0s - loss: 0.3249 - accuracy: 0.8739
Epoch 4/30
18/18 - 0s - loss: 0.3070 - accuracy: 0.8757
Epoch 5/30
18/18 - 0s - loss: 0.2695 - accuracy: 0.9020
Epoch 6/30
18/18 - 0s - loss: 0.2367 - accuracy: 0.9056
Epoch 7/30
18/18 - 0s - loss: 0.2124 - accuracy: 0.9201
Epoch 8/30
18/18 - 0s - loss: 0.1872 - accuracy: 0.9374
Epoch 9/30
```

```
18/18 - 0s - loss: 0.1684 - accuracy: 0.9392
Epoch 10/30
18/18 - 0s - loss: 0.1350 - accuracy: 0.9555
Epoch 11/30
18/18 - 0s - loss: 0.1148 - accuracy: 0.9574
Epoch 12/30
18/18 - 0s - loss: 0.0979 - accuracy: 0.9646
Epoch 13/30
18/18 - 0s - loss: 0.0676 - accuracy: 0.9791
Epoch 14/30
18/18 - 0s - loss: 0.0486 - accuracy: 0.9882
Epoch 15/30
18/18 - 0s - loss: 0.0281 - accuracy: 0.9918
Epoch 16/30
18/18 - 0s - loss: 0.0165 - accuracy: 0.9955
Epoch 17/30
18/18 - 0s - loss: 0.0100 - accuracy: 0.9973
Epoch 18/30
18/18 - 0s - loss: 0.0079 - accuracy: 0.9991
Epoch 19/30
18/18 - 0s - loss: 0.0076 - accuracy: 0.9982
Epoch 20/30
18/18 - 0s - loss: 0.0043 - accuracy: 0.9991
Epoch 21/30
18/18 - 0s - loss: 0.0141 - accuracy: 0.9946
Epoch 22/30
18/18 - 0s - loss: 0.0183 - accuracy: 0.9927
Epoch 23/30
18/18 - 0s - loss: 0.0584 - accuracy: 0.9809
Epoch 24/30
18/18 - 0s - loss: 0.0625 - accuracy: 0.9782
Epoch 25/30
18/18 - 0s - loss: 0.0390 - accuracy: 0.9882
Epoch 26/30
18/18 - 0s - loss: 0.0157 - accuracy: 0.9946
Epoch 27/30
18/18 - 0s - loss: 0.0402 - accuracy: 0.9855
Epoch 28/30
18/18 - 1s - loss: 0.0137 - accuracy: 0.9964
Epoch 29/30
18/18 - 1s - loss: 0.0057 - accuracy: 0.9991
Epoch 30/30
18/18 - 0s - loss: 0.0023 - accuracy: 1.0000
```

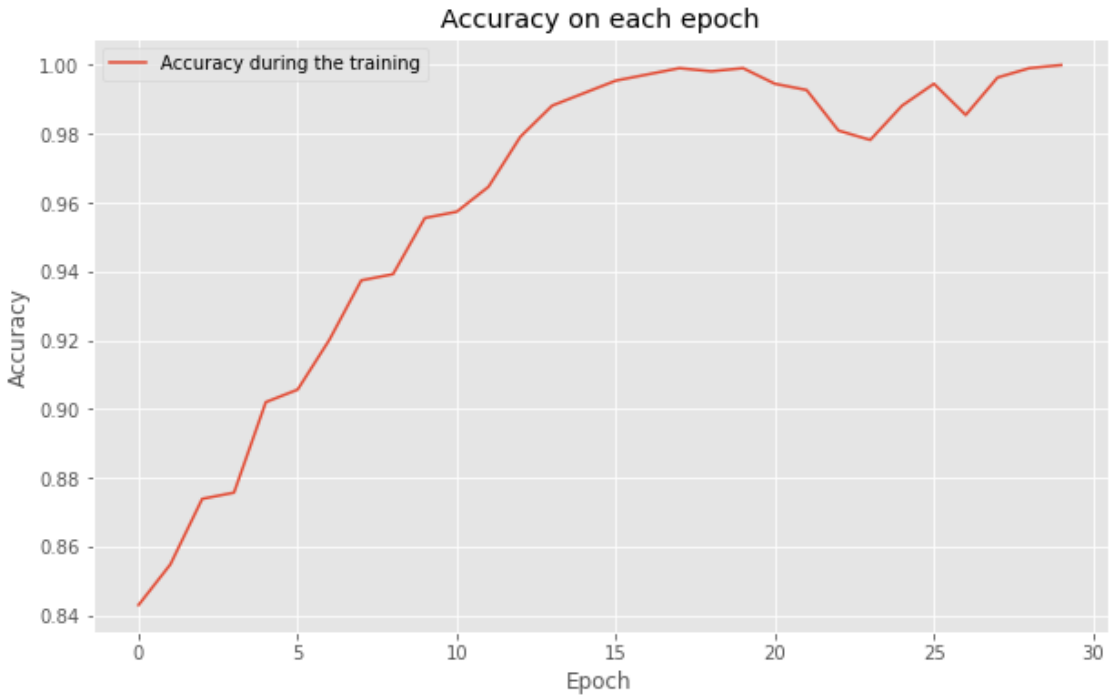
Undestanding the loss and the accuracy on each epoch of the training.

[57]:
```
plt.figure(figsize=(10,6))
plt.plot(hist.history['loss'])
```

```
plt.title('Loss on each epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Loss during the training'])
plt.show()
```



[58]:
```
plt.figure(figsize=(10,6))
plt.plot(hist.history['accuracy'])
plt.title('Accuracy on each epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Accuracy during the training'])
plt.show()
```



The Loss is 0 almost aprox on the 25 epochs and so on, at the same time, the accuracy is almost 100%. It is not exactly a good model, maybe, the model is overfitting the data, to verify this, it is necessary evaluate the model.

Evaluating the model

[59]:
```
y_pred = model.predict(x_test)
```

Due to the results that it is getting from the neural net is a probability, it is important to transform those probabilities into 0 or 1, in order to evaluate the model correctly.

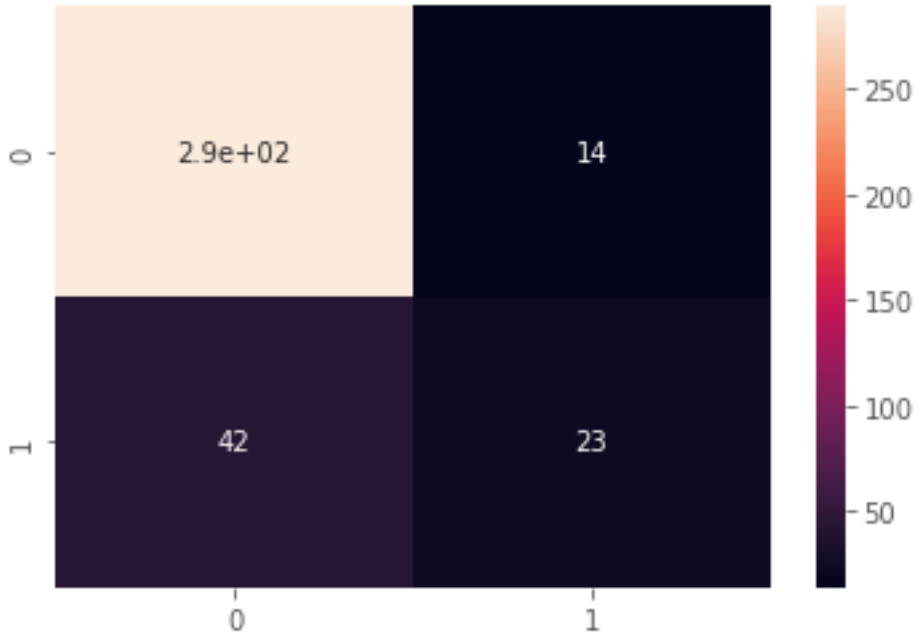
[60]:
```
y_pred = [0 if pred < 0.5 else 1 for pred in y_pred]
```

[61]:
```
print('Accuracy: {}'.format(100 * accuracy_score(y_pred, y_test)))
```

```
Accuracy: 84.78260869565217
```

As we can see, we have and 84.78% of accuracy when the predictions are made with new data.

[62]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
plt.show()
```



[63]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.95      0.91       303
           1       0.62      0.35      0.45        65

    accuracy                           0.85       368
   macro avg       0.75      0.65      0.68       368
weighted avg       0.83      0.85      0.83       368
```

Conclusions

- The best model is the logistic regression model, with 88.04% accuracy when evaluating the test data.
- The neural network, upon reaching a certain number of epochs, learns the data, when evaluated we have a low precision which means that we have an algorithm with overfitting.
- The model to be implemented will be the logistic regression, this to solve the problem. In the future, the neural network can be improved to avoid overfitting by applying regularizations.