

Correlation Analysis and Model Testing on HR Dataset

February 8, 2024

0.0.1 About Dataset:

0.0.2 Context:

The data is details of business employees from a company.

0.0.3 Contents:

Employees Personal Details (Age, Marital Status, Distance from home, Educational Background).

Employees Official Details (Hourly Wages, Salary Hike, Overtime, Department, Job-role, Years in current role, Department, Jobrole, Years in current role, Total Working Hours, Training times,etc.).

0.0.4 Problem Statement:

Analyse and visualize the given data.

0.0.5 Import Libraries and Dataset

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

```
[2]: # Import Dataset:
employee_df = pd.read_csv("C:/Users/amitm/Desktop/New folder/Task Impetus/Class/
↳Python/Case Study/Human_Resources.csv")
```

```
[3]: employee_df.head()
```

```
[3]:   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	EmployeeNumber	\
0	1	2	Life Sciences	1	1	
1	8	1	Life Sciences	1	2	
2	2	2	Other	1	4	
3	3	4	Life Sciences	1	5	
4	2	1	Medical	1	7	

	RelationshipSatisfaction	StandardHours	StockOptionLevel	\
0	...	1	80	0
1	...	4	80	1
2	...	2	80	0
3	...	3	80	0
4	...	4	80	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 35 columns]

```
[4]: employee_df.tail()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	\
1465	36	No	Travel_Frequently	884	Research & Development	
1466	39	No	Travel_Rarely	613	Research & Development	
1467	27	No	Travel_Rarely	155	Research & Development	
1468	49	No	Travel_Frequently	1023	Sales	
1469	34	No	Travel_Rarely	628	Research & Development	

	DistanceFromHome	Education	EducationField	EmployeeCount	\
1465	23	2	Medical	1	
1466	6	1	Medical	1	
1467	4	3	Life Sciences	1	
1468	2	3	Medical	1	
1469	8	3	Medical	1	

EmployeeNumber	...	RelationshipSatisfaction	StandardHours	\
----------------	-----	--------------------------	---------------	---

1465	2061	...	3	80
1466	2062	...	1	80
1467	2064	...	2	80
1468	2065	...	4	80
1469	2068	...	1	80

	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	\
1465	1	17	3	
1466	1	9	5	
1467	1	6	0	
1468	0	17	3	
1469	0	6	3	

	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole	\
1465	3	5	2	
1466	3	7	7	
1467	3	6	2	
1468	2	9	6	
1469	4	4	3	

	YearsSinceLastPromotion	YearsWithCurrManager
1465	0	3
1466	1	7
1467	0	3
1468	0	8
1469	1	2

[5 rows x 35 columns]

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

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

```
[6]: employee_df.columns
```

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

```
[7]: # Print Columns:
print(employee_df.columns)
```

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

Describing Data:

```
[8]: 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

```

```
[9]: employee_df[['Age', 'Over18', 'Attrition']]
```

```

[9]:      Age  Over18  Attrition
0      41         Y         Yes
1      49         Y          No
2      37         Y         Yes
3      33         Y          No
4      27         Y          No
...
1465   36         Y          No
1466   39         Y          No
1467   27         Y          No
1468   49         Y          No
1469   34         Y          No

```

```
[1470 rows x 3 columns]
```

```
[10]: employee_df['Over18'].unique()
```

```
[10]: array(['Y'], dtype=object)
```

```
[11]: employee_df['Attrition'].unique()
```

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

```

[12]: # Employees leaving the company:
employee_df[(employee_df['Attrition']=='Yes') & (employee_df['Over18']=='Y')].
    ↪ shape[0]
print("No of Employees leaving company: ", employee_df[np.logical_and(
    ↪ (employee_df['Attrition']=='Yes',
    ↪ employee_df['Over18']=='Y')]).shape[0])
# There are no employees below 18 of age

```

```
No of Employees leaving company: 237
```

```
[13]: # Checking for null values:
employee_df.isnull().sum()
```

```
[13]: 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
```

```
[14]: employee_df[['Attrition', 'OverTime', 'Over18']]
```

```
[14]:   Attrition  OverTime  Over18
0         Yes        Yes      Y
1         No         No      Y
2         Yes        Yes      Y
3         No         Yes      Y
```

4	No	No	Y
...
1465	No	No	Y
1466	No	No	Y
1467	No	Yes	Y
1468	No	No	Y
1469	No	No	Y

[1470 rows x 3 columns]

```
[15]: employee_df.describe().T
```

```
[15]:
```

	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	
Education	1470.0	2.912925	1.024165	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	
EnvironmentSatisfaction	1470.0	2.721769	1.093082	1.0	2.00	
HourlyRate	1470.0	65.891156	20.329428	30.0	48.00	
JobInvolvement	1470.0	2.729932	0.711561	1.0	2.00	
JobLevel	1470.0	2.063946	1.106940	1.0	1.00	
JobSatisfaction	1470.0	2.728571	1.102846	1.0	2.00	
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	
PerformanceRating	1470.0	3.153741	0.360824	3.0	3.00	
RelationshipSatisfaction	1470.0	2.712245	1.081209	1.0	2.00	
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	
WorkLifeBalance	1470.0	2.761224	0.706476	1.0	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
Education	3.0	4.00	5.0
EmployeeCount	1.0	1.00	1.0
EmployeeNumber	1020.5	1555.75	2068.0

EnvironmentSatisfaction	3.0	4.00	4.0
HourlyRate	66.0	83.75	100.0
JobInvolvement	3.0	3.00	4.0
JobLevel	2.0	3.00	5.0
JobSatisfaction	3.0	4.00	4.0
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
PerformanceRating	3.0	3.00	4.0
RelationshipSatisfaction	3.0	4.00	4.0
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
WorkLifeBalance	3.0	3.00	4.0
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

```
[16]: def convertToZeroorOne(x):
      if x=='Yes':
          return 1
      else:
          return 0
```

```
[17]: convertToZeroorOne('Yes')
```

```
[17]: 1
```

```
[18]: employee_df_new=employee_df['Attrition'].apply(convertToZeroorOne)
```

```
[19]: employee_df_new
```

```
[19]: 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
```



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

```
[21]: employee_df.head()
```

```
[21]:   Age  Attrition  BusinessTravel  DailyRate  Department \
0   41         1      Travel_Rarely    1102      Sales
1   49         0  Travel_Frequently     279  Research & Development
2   37         1      Travel_Rarely    1373  Research & Development
3   33         0  Travel_Frequently    1392  Research & Development
4   27         0      Travel_Rarely     591  Research & Development

      DistanceFromHome  Education  EducationField  EmployeeCount  EmployeeNumber \
0                1         2  Life Sciences             1             1
1                8         1  Life Sciences             1             2
2                2         2      Other             1             4
3                3         4  Life Sciences             1             5
4                2         1      Medical             1             7

      ...  RelationshipSatisfaction  StandardHours  StockOptionLevel \
0  ...                1             80             0
1  ...                4             80             1
2  ...                2             80             0
3  ...                3             80             0
4  ...                4             80             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 35 columns]
```

```
[22]: employee_df[['Attrition','OverTime','Over18']]
```

```
[22]:      Attrition  OverTime  Over18
      0          1          1          1
      1          0          0          1
      2          1          1          1
      3          0          1          1
      4          0          0          1
      ...
      1465      0          0          1
      1466      0          0          1
      1467      0          1          1
      1468      0          0          1
      1469      0          0          1
```

[1470 rows x 3 columns]

```
[23]: g=employee_df.groupby(['Age'])
```

```
[24]: type(g)
```

```
[24]: pandas.core.groupby.generic.DataFrameGroupBy
```

```
[25]: g.get_group(30)
```

```
[25]:      Age  Attrition  BusinessTravel  DailyRate  Department \
      7    30          0      Travel_Rarely      1358  Research & Development
      32    30          0      Travel_Rarely      125  Research & Development
      44    30          0  Travel_Frequently      721  Research & Development
      80    30          0      Travel_Rarely      852  Research & Development
      88    30          0      Travel_Rarely      288  Research & Development
      92    30          0      Travel_Rarely     1334                Sales
      120   30          0  Travel_Frequently     1312  Research & Development
      139   30          0      Travel_Rarely     1240                Human Resources
      143   30          0      Travel_Rarely      438  Research & Development
      145   30          0      Travel_Rarely      201  Research & Development
      146   30          0      Travel_Rarely     1427  Research & Development
      167   30          0      Travel_Rarely     1339                Sales
      173   30          0          Non-Travel      111  Research & Development
      211   30          0          Non-Travel      829  Research & Development
      214   30          1      Travel_Rarely     1005  Research & Development
      216   30          1  Travel_Frequently      334                Sales
      324   30          0      Travel_Rarely     1275  Research & Development
      338   30          0      Travel_Rarely      570                Sales
      354   30          0          Non-Travel      641                Sales
      381   30          0      Travel_Rarely      202                Sales
      385   30          1  Travel_Frequently      464  Research & Development
      402   30          0      Travel_Rarely     1082                Sales
      410   30          0      Travel_Rarely      317  Research & Development
```

419	30	0	Non-Travel	1400	Research & Development
423	30	0	Non-Travel	1398	Sales
426	30	0	Non-Travel	1116	Research & Development
437	30	0	Travel_Rarely	413	Sales
480	30	1	Travel_Frequently	448	Sales
501	30	0	Travel_Frequently	160	Research & Development
545	30	0	Travel_Rarely	501	Sales
581	30	0	Travel_Rarely	921	Research & Development
602	30	0	Travel_Rarely	946	Research & Development
623	30	0	Travel_Frequently	1012	Research & Development
702	30	0	Travel_Rarely	231	Sales
720	30	1	Travel_Rarely	138	Research & Development
730	30	0	Travel_Rarely	153	Research & Development
732	30	1	Travel_Frequently	109	Research & Development
782	30	0	Travel_Rarely	1176	Research & Development
844	30	0	Travel_Rarely	852	Sales
865	30	0	Travel_Rarely	1329	Sales
874	30	0	Travel_Rarely	853	Research & Development
886	30	0	Travel_Rarely	1465	Research & Development
931	30	0	Non-Travel	879	Research & Development
941	30	0	Travel_Rarely	1138	Research & Development
948	30	0	Travel_Rarely	634	Research & Development
1013	30	0	Travel_Rarely	855	Sales
1049	30	0	Travel_Rarely	1358	Sales
1052	30	0	Non-Travel	990	Research & Development
1064	30	0	Travel_Rarely	330	Human Resources
1106	30	1	Travel_Rarely	740	Sales
1109	30	0	Travel_Rarely	1288	Sales
1141	30	0	Travel_Rarely	241	Research & Development
1233	30	0	Travel_Rarely	793	Research & Development
1244	30	0	Travel_Frequently	1312	Research & Development
1246	30	1	Travel_Frequently	600	Human Resources
1251	30	0	Travel_Rarely	979	Sales
1259	30	0	Travel_Rarely	305	Research & Development
1296	30	0	Travel_Rarely	1092	Research & Development
1338	30	1	Travel_Rarely	945	Sales
1412	30	0	Travel_Rarely	911	Research & Development

	DistanceFromHome	Education	EducationField	EmployeeCount	\
7	24	1	Life Sciences	1	
32	9	2	Medical	1	
44	1	2	Medical	1	
80	1	1	Life Sciences	1	
88	2	3	Life Sciences	1	
92	4	2	Medical	1	
120	23	3	Life Sciences	1	
139	9	3	Human Resources	1	

143	18	3	Life Sciences	1
145	5	3	Technical Degree	1
146	2	1	Medical	1
167	5	3	Life Sciences	1
173	9	3	Medical	1
211	1	1	Life Sciences	1
214	3	3	Technical Degree	1
216	26	4	Marketing	1
324	28	2	Medical	1
338	5	3	Marketing	1
354	25	2	Technical Degree	1
381	2	1	Technical Degree	1
385	4	3	Technical Degree	1
402	12	3	Technical Degree	1
410	2	3	Life Sciences	1
419	3	3	Life Sciences	1
423	22	4	Other	1
426	2	3	Medical	1
437	7	1	Marketing	1
480	12	4	Life Sciences	1
501	3	3	Medical	1
545	27	5	Marketing	1
581	1	3	Life Sciences	1
602	2	3	Medical	1
623	5	4	Life Sciences	1
702	8	2	Other	1
720	22	3	Life Sciences	1
730	8	2	Life Sciences	1
732	5	3	Medical	1
782	20	3	Other	1
844	10	3	Marketing	1
865	29	4	Life Sciences	1
874	7	4	Life Sciences	1
886	1	3	Medical	1
931	9	2	Medical	1
941	6	3	Technical Degree	1
948	17	4	Medical	1
1013	7	4	Marketing	1
1049	16	1	Life Sciences	1
1052	7	3	Technical Degree	1
1064	1	3	Life Sciences	1
1106	1	3	Life Sciences	1
1109	29	4	Technical Degree	1
1141	7	3	Medical	1
1233	16	1	Life Sciences	1
1244	2	4	Technical Degree	1
1246	8	3	Human Resources	1

1251	15	2	Marketing	1
1259	16	3	Life Sciences	1
1296	10	3	Medical	1
1338	9	3	Medical	1
1412	1	2	Medical	1

	EmployeeNumber	...	RelationshipSatisfaction	StandardHours	\
7	11	...	2	80	
32	41	...	1	80	
44	57	...	4	80	
80	104	...	3	80	
88	117	...	1	80	
92	121	...	2	80	
120	159	...	3	80	
139	184	...	4	80	
143	194	...	3	80	
145	197	...	4	80	
146	198	...	4	80	
167	228	...	3	80	
173	239	...	3	80	
211	292	...	3	80	
214	297	...	3	80	
216	299	...	3	80	
324	441	...	4	80	
338	456	...	3	80	
354	475	...	2	80	
381	508	...	1	80	
385	514	...	3	80	
402	533	...	2	80	
410	548	...	3	80	
419	562	...	3	80	
423	567	...	3	80	
426	571	...	3	80	
437	585	...	1	80	
480	648	...	3	80	
501	680	...	3	80	
545	747	...	4	80	
581	806	...	3	80	
602	833	...	2	80	
623	861	...	2	80	
702	982	...	1	80	
720	1004	...	2	80	
730	1015	...	3	80	
732	1017	...	1	80	
782	1084	...	3	80	
844	1179	...	1	80	
865	1211	...	3	80	

874	1224	...	1	80
886	1241	...	1	80
931	1298	...	3	80
941	1311	...	1	80
948	1321	...	4	80
1013	1428	...	2	80
1049	1479	...	3	80
1052	1482	...	2	80
1064	1499	...	1	80
1106	1562	...	4	80
1109	1568	...	2	80
1141	1609	...	2	80
1233	1729	...	2	80
1244	1745	...	4	80
1246	1747	...	3	80
1251	1754	...	1	80
1259	1763	...	3	80
1296	1816	...	2	80
1338	1876	...	3	80
1412	1989	...	3	80

	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	\
7	1	1	2	
32	0	10	5	
44	0	12	2	
80	2	10	1	
88	3	11	3	
92	3	11	4	
120	3	10	2	
139	0	12	2	
143	0	5	4	
145	1	8	3	
146	0	6	3	
167	1	12	2	
173	2	12	4	
211	0	12	2	
214	0	8	5	
216	0	9	5	
324	2	11	2	
338	3	10	2	
354	1	4	2	
381	1	1	3	
385	0	3	4	
402	0	6	6	
410	0	11	2	
419	1	9	3	
423	0	10	3	

426	0	12	2
437	0	4	3
480	1	1	2
501	1	1	2
545	1	10	2
581	2	7	2
602	0	12	4
623	1	10	3
702	1	10	2
720	0	7	2
730	3	9	4
732	0	4	3
782	1	7	1
844	1	10	3
865	3	8	3
874	3	10	4
886	1	12	2
931	0	10	3
941	1	10	6
948	2	9	2
1013	2	8	3
1049	2	4	2
1052	2	1	2
1064	1	6	3
1106	1	10	4
1109	1	9	3
1141	1	6	3
1233	1	10	2
1244	0	10	2
1246	1	6	0
1251	1	12	2
1259	1	10	3
1296	0	9	3
1338	0	1	3
1412	0	12	6

	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole \
7	3	1	0
32	3	10	0
44	3	12	8
80	2	10	8
88	3	11	10
92	2	11	8
120	2	10	7
139	1	11	9
143	2	5	4
145	3	3	2

146	3	5	3
167	3	10	9
173	3	12	9
211	3	11	8
214	3	5	2
216	2	6	3
324	3	10	8
338	3	10	9
354	4	2	2
381	3	1	0
385	3	1	0
402	3	5	4
410	3	5	4
419	1	5	3
423	3	9	8
426	2	11	7
437	3	3	2
480	4	1	0
501	3	1	0
545	2	8	7
581	3	2	2
602	2	0	0
623	2	5	4
702	4	8	4
720	3	5	2
730	2	8	7
732	3	3	2
782	2	6	2
844	3	10	3
865	3	4	3
874	2	10	7
886	3	11	9
931	3	8	4
941	3	9	2
948	3	9	1
1013	3	3	2
1049	2	2	1
1052	2	1	0
1064	4	5	3
1106	3	10	8
1109	3	4	2
1141	2	6	4
1233	2	10	0
1244	3	9	7
1246	2	4	2
1251	3	7	7
1259	3	7	0

1296	3	7	7
1338	2	1	0
1412	2	12	8

	YearsSinceLastPromotion	YearsWithCurrManager
7	0	0
32	1	8
44	3	7
80	3	0
88	10	8
92	2	7
120	0	9
139	4	7
143	0	4
145	2	2
146	1	2
167	7	4
173	6	10
211	5	8
214	0	4
216	0	1
324	1	9
338	1	2
354	2	2
381	0	0
385	0	0
402	4	4
410	0	2
419	1	4
423	7	8
426	6	7
437	1	2
480	0	0
501	0	0
545	7	7
581	0	2
602	0	0
623	0	3
702	7	7
720	0	1
730	1	7
732	1	2
782	0	2
844	1	4
865	0	3
874	8	9
886	5	7

931	1	7
941	6	7
948	0	8
1013	0	2
1049	2	2
1052	0	0
1064	1	3
1106	6	7
1109	1	3
1141	1	1
1233	0	8
1244	0	7
1246	1	2
1251	1	7
1259	1	7
1296	0	2
1338	0	0
1412	1	7

[60 rows x 35 columns]

```
[26]: employee_df.groupby(['Age', 'Attrition']).agg('count')
```

```
[26]:
```

		BusinessTravel	DailyRate	Department	DistanceFromHome	\
Age	Attrition					
18	0	4	4	4		4
	1	4	4	4		4
19	0	3	3	3		3
	1	6	6	6		6
20	0	5	5	5		5
...		
57	0	4	4	4		4
58	0	9	9	9		9
	1	5	5	5		5
59	0	10	10	10		10
60	0	5	5	5		5

		Education	EducationField	EmployeeCount	EmployeeNumber	\
Age	Attrition					
18	0	4	4	4		4
	1	4	4	4		4
19	0	3	3	3		3
	1	6	6	6		6
20	0	5	5	5		5
...		
57	0	4	4	4		4
58	0	9	9	9		9

	1	5	5	5	5
59	0	10	10	10	10
60	0	5	5	5	5

		EnvironmentSatisfaction	Gender	...	RelationshipSatisfaction	\
Age	Attrition			...		
18	0		4	4	...	4
	1		4	4	...	4
19	0		3	3	...	3
	1		6	6	...	6
20	0		5	5	...	5
...		
57	0		4	4	...	4
58	0		9	9	...	9
	1		5	5	...	5
59	0		10	10	...	10
60	0		5	5	...	5

		StandardHours	StockOptionLevel	TotalWorkingYears	\
Age	Attrition				
18	0	4		4	4
	1	4		4	4
19	0	3		3	3
	1	6		6	6
20	0	5		5	5
...		
57	0	4		4	4
58	0	9		9	9
	1	5		5	5
59	0	10		10	10
60	0	5		5	5

		TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany	\
Age	Attrition				
18	0		4	4	4
	1		4	4	4
19	0		3	3	3
	1		6	6	6
20	0		5	5	5
...		
57	0		4	4	4
58	0		9	9	9
	1		5	5	5
59	0		10	10	10
60	0		5	5	5

YearsInCurrentRole	YearsSinceLastPromotion	\
--------------------	-------------------------	---

Age Attrition

18	0	4	4
	1	4	4
19	0	3	3
	1	6	6
20	0	5	5
...		...	
57	0	4	4
58	0	9	9
	1	5	5
59	0	10	10
60	0	5	5

YearsWithCurrManager

Age Attrition

18	0	4
	1	4
19	0	3
	1	6
20	0	5
...		...
57	0	4
58	0	9
	1	5
59	0	10
60	0	5

[82 rows x 33 columns]

[27]: g.head()

```
[27]:
```

	Age	Attrition	BusinessTravel	DailyRate	Department	\
0	41	1	Travel_Rarely	1102		Sales
1	49	0	Travel_Frequently	279	Research & Development	
2	37	1	Travel_Rarely	1373	Research & Development	
3	33	0	Travel_Frequently	1392	Research & Development	
4	27	0	Travel_Rarely	591	Research & Development	
...
727	18	0	Non-Travel	287	Research & Development	
828	18	1	Non-Travel	247	Research & Development	
879	60	0	Travel_Rarely	696		Sales
1053	57	0	Travel_Rarely	405	Research & Development	
1209	60	0	Travel_Rarely	370	Research & Development	

	DistanceFromHome	Education	EducationField	EmployeeCount	\
0	1	2	Life Sciences	1	
1	8	1	Life Sciences	1	

2	2	2	Other	1
3	3	4	Life Sciences	1
4	2	1	Medical	1
...
727	5	2	Life Sciences	1
828	8	1	Medical	1
879	7	4	Marketing	1
1053	1	2	Life Sciences	1
1209	1	4	Medical	1

	EmployeeNumber	...	RelationshipSatisfaction	StandardHours	\
0	1	...	1	80	
1	2	...	4	80	
2	4	...	2	80	
3	5	...	3	80	
4	7	...	4	80	
...	
727	1012	...	4	80	
828	1156	...	4	80	
879	1233	...	2	80	
1053	1483	...	1	80	
1209	1697	...	3	80	

	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	\
0	0	8	0	
1	1	10	3	
2	0	7	3	
3	0	8	3	
4	1	6	3	
...	
727	0	0	2	
828	0	0	0	
879	1	12	3	
1053	1	13	2	
1209	1	19	2	

	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole	\
0	1	6	4	
1	3	10	7	
2	3	0	0	
3	3	8	7	
4	3	2	2	
...	
727	3	0	0	
828	3	0	0	
879	3	11	7	
1053	2	12	9	

1209	4	1	0
	YearsSinceLastPromotion	YearsWithCurrManager	
0	0	5	
1	1	7	
2	0	0	
3	3	0	
4	2	2	
...	
727	0	0	
828	0	0	
879	1	9	
1053	2	8	
1209	0	0	

[214 rows x 35 columns]

0.0.6 Visualizing Dataset:

```
[28]: # Let's replace the 'Attritition' and 'overtime' column with integers before
      ↪ performing any visualizations
      #employee_df['Attritition'] = employee_df['Attritition'].apply(lambda x: 1 if x ==
      ↪ 'Yes' else 0)
      #employee_df['OverTime'] = employee_df['OverTime'].apply(lambda x: 1 if x ==
      ↪ 'Yes' else 0)
      #employee_df['Over18'] = employee_df['Over18'].apply(lambda x: 1 if x == 'Y'
      ↪ else 0)
```

```
[29]: employee_df.head()
```

```
[29]:   Age  Attrition  BusinessTravel  DailyRate  Department \
0   41         1      Travel_Rarely      1102      Sales
1   49         0  Travel_Frequently       279  Research & Development
2   37         1      Travel_Rarely     1373  Research & Development
3   33         0  Travel_Frequently     1392  Research & Development
4   27         0      Travel_Rarely       591  Research & Development

      DistanceFromHome  Education  EducationField  EmployeeCount  EmployeeNumber \
0                1         2  Life Sciences           1           1
1                8         1  Life Sciences           1           2
2                2         2      Other           1           4
3                3         4  Life Sciences           1           5
4                2         1      Medical           1           7

      ...  RelationshipSatisfaction  StandardHours  StockOptionLevel \
0   ...                1                80                0
1   ...                4                80                1
```

2	...	2	80	0
3	...	3	80	0
4	...	4	80	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 35 columns]

```
[30]: # Drop Employee Count, Standard Hours, Over 18, Employee Number
employee_df.drop(['EmployeeCount', 'StandardHours', 'Over18', 'EmployeeNumber'], axis=1, inplace=True)

[31]: # Check For Missing Values:
sns.heatmap(employee_df.isnull(), yticklabels=False, cbar=False, cmap="Blues")
plt.show()
```

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 -

```
[32]: # Get the list of columns in the DataFrame
columns = employee_df.columns
columns = [col for col in columns if col != 'JobRole']

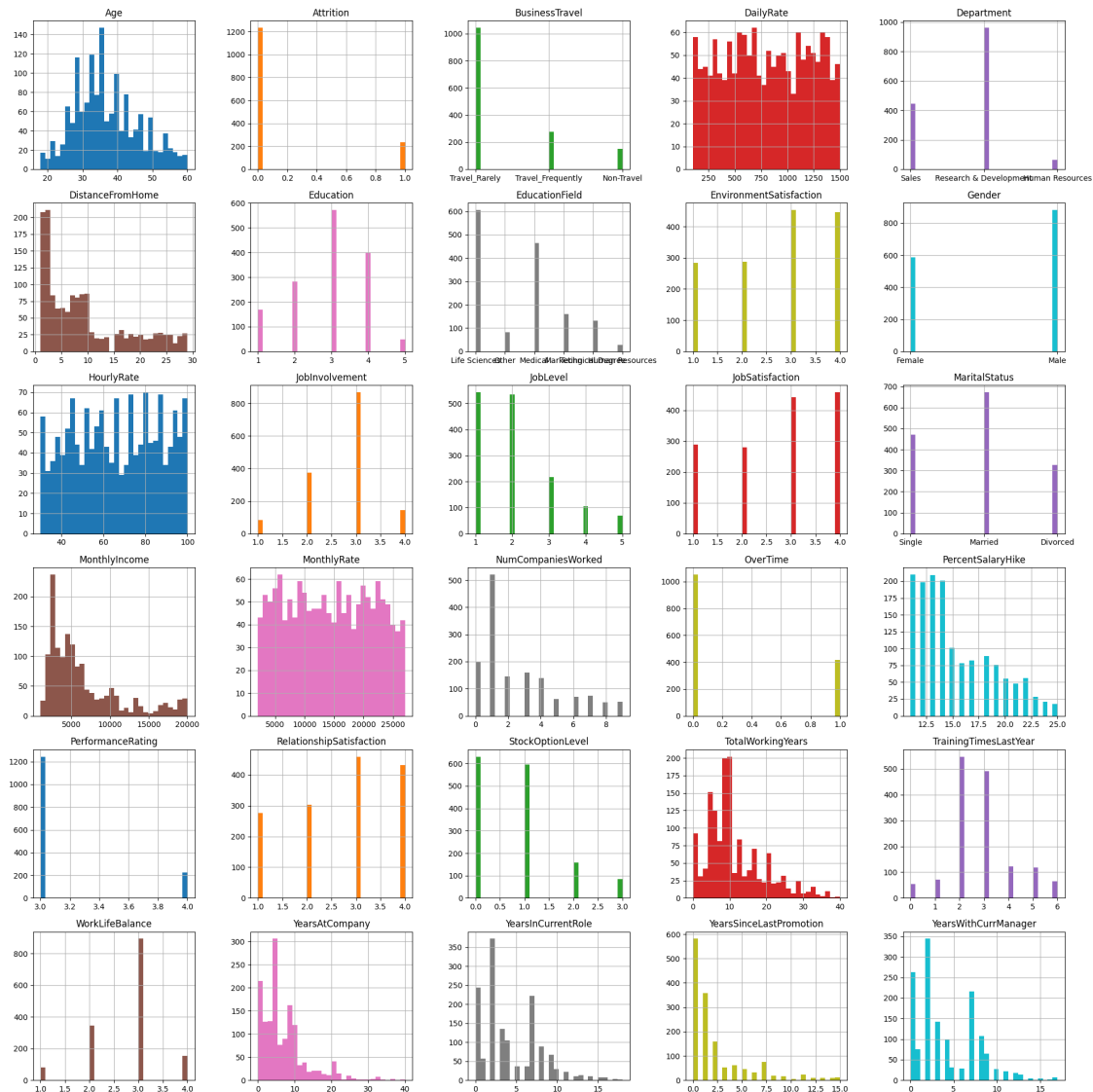
# Calculate the number of rows and columns based on the number of columns in
↳ the DataFrame
num_cols = len(columns)
num_rows = (num_cols + 4) // 5
# Create a figure and axes objects
fig, axes = plt.subplots(nrows=num_rows, ncols=5, figsize=(20, 20))
# Flatten axes if necessary
axes = axes.flatten()
# Plot histograms in a grid layout
```



```

for i, col in enumerate(columns):
    employee_df[col].hist(ax=axes[i], bins=30, color='C{}'.format(i))
    axes[i].set_title(col)
# Remove any empty subplots at the end if the number of columns is not a
multiple of 5
if num_cols % 5 != 0:
    for j in range(num_cols % 5, 5):
        fig.delaxes(axes[-j])
plt.tight_layout()
plt.show()

```



```
[33]: employee_df.head(5)
```

```

[33]:   Age  Attrition    BusinessTravel  DailyRate          Department \
0    41         1      Travel_Rarely      1102             Sales
1    49         0  Travel_Frequently      279  Research & Development
2    37         1      Travel_Rarely     1373  Research & Development
3    33         0  Travel_Frequently     1392  Research & Development
4    27         0      Travel_Rarely      591  Research & Development

      DistanceFromHome  Education  EducationField  EnvironmentSatisfaction \
0                1          2  Life Sciences                2
1                8          1  Life Sciences                3
2                2          2          Other                4
3                3          4  Life Sciences                4
4                2          1          Medical                1

      Gender  ...  PerformanceRating  RelationshipSatisfaction  StockOptionLevel \
0  Female  ...                3                1                0
1   Male  ...                4                4                1
2   Male  ...                3                2                0
3  Female  ...                3                3                0
4   Male  ...                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 31 columns]

```

[34]: # Count the number of employees who stayed and left:
left_df= employee_df[employee_df['Attrition'] == 1]
stayed_df= employee_df[employee_df['Attrition'] == 0]

```

```

[35]: print("Total =", len(employee_df))

print("Number of employees who left the company =", len(left_df))
print("Percentage of employees who left the company =", 1.*len(left_df)/
      ↪len(employee_df)*100.0, "%")

```

```
print("Number of employees who did not leave the company (stayed) =",
      len(stayed_df))
print("Percentage of employees who did not leave the company (stayed) =", 1.
      *len(stayed_df)/len(employee_df)*100.0, "%")
```

Total = 1470

Number of employees who left the company = 237

Percentage of employees who left the company = 16.122448979591837 %

Number of employees who did not leave the company (stayed) = 1233

Percentage of employees who did not leave the company (stayed) =
83.87755102040816 %

```
[36]: # Describing Employees who left:
left_df.describe().T
```

```
[36]:
```

	count	mean	std	min	25%	\
Age	237.0	33.607595	9.689350	18.0	28.0	
Attrition	237.0	1.000000	0.000000	1.0	1.0	
DailyRate	237.0	750.362869	401.899519	103.0	408.0	
DistanceFromHome	237.0	10.632911	8.452525	1.0	3.0	
Education	237.0	2.839662	1.008244	1.0	2.0	
EnvironmentSatisfaction	237.0	2.464135	1.169791	1.0	1.0	
HourlyRate	237.0	65.573840	20.099958	31.0	50.0	
JobInvolvement	237.0	2.518987	0.773405	1.0	2.0	
JobLevel	237.0	1.637131	0.940594	1.0	1.0	
JobSatisfaction	237.0	2.468354	1.118058	1.0	1.0	
MonthlyIncome	237.0	4787.092827	3640.210367	1009.0	2373.0	
MonthlyRate	237.0	14559.308017	7208.153264	2326.0	8870.0	
NumCompaniesWorked	237.0	2.940928	2.678519	0.0	1.0	
OverTime	237.0	0.535865	0.499768	0.0	0.0	
PercentSalaryHike	237.0	15.097046	3.770294	11.0	12.0	
PerformanceRating	237.0	3.156118	0.363735	3.0	3.0	
RelationshipSatisfaction	237.0	2.599156	1.125437	1.0	2.0	
StockOptionLevel	237.0	0.527426	0.856361	0.0	0.0	
TotalWorkingYears	237.0	8.244726	7.169204	0.0	3.0	
TrainingTimesLastYear	237.0	2.624473	1.254784	0.0	2.0	
WorkLifeBalance	237.0	2.658228	0.816453	1.0	2.0	
YearsAtCompany	237.0	5.130802	5.949984	0.0	1.0	
YearsInCurrentRole	237.0	2.902954	3.174827	0.0	0.0	
YearsSinceLastPromotion	237.0	1.945148	3.153077	0.0	0.0	
YearsWithCurrManager	237.0	2.852321	3.143349	0.0	0.0	
	50%	75%	max			
Age	32.0	39.0	58.0			
Attrition	1.0	1.0	1.0			
DailyRate	699.0	1092.0	1496.0			
DistanceFromHome	9.0	17.0	29.0			

Education	3.0	4.0	5.0
EnvironmentSatisfaction	3.0	4.0	4.0
HourlyRate	66.0	84.0	100.0
JobInvolvement	3.0	3.0	4.0
JobLevel	1.0	2.0	5.0
JobSatisfaction	3.0	3.0	4.0
MonthlyIncome	3202.0	5916.0	19859.0
MonthlyRate	14618.0	21081.0	26999.0
NumCompaniesWorked	1.0	5.0	9.0
OverTime	1.0	1.0	1.0
PercentSalaryHike	14.0	17.0	25.0
PerformanceRating	3.0	3.0	4.0
RelationshipSatisfaction	3.0	4.0	4.0
StockOptionLevel	0.0	1.0	3.0
TotalWorkingYears	7.0	10.0	40.0
TrainingTimesLastYear	2.0	3.0	6.0
WorkLifeBalance	3.0	3.0	4.0
YearsAtCompany	3.0	7.0	40.0
YearsInCurrentRole	2.0	4.0	15.0
YearsSinceLastPromotion	1.0	2.0	15.0
YearsWithCurrManager	2.0	5.0	14.0

```
[37]: # Describing Employees who stayed:
      stayed_df.describe().T
```

```
[37]:
```

	count	mean	std	min	25%	\
Age	1233.0	37.561233	8.888360	18.0	31.0	
Attrition	1233.0	0.000000	0.000000	0.0	0.0	
DailyRate	1233.0	812.504461	403.208379	102.0	477.0	
DistanceFromHome	1233.0	8.915653	8.012633	1.0	2.0	
Education	1233.0	2.927007	1.027002	1.0	2.0	
EnvironmentSatisfaction	1233.0	2.771290	1.071132	1.0	2.0	
HourlyRate	1233.0	65.952149	20.380754	30.0	48.0	
JobInvolvement	1233.0	2.770479	0.692050	1.0	2.0	
JobLevel	1233.0	2.145985	1.117933	1.0	1.0	
JobSatisfaction	1233.0	2.778589	1.093277	1.0	2.0	
MonthlyIncome	1233.0	6832.739659	4818.208001	1051.0	3211.0	
MonthlyRate	1233.0	14265.779400	7102.260749	2094.0	7973.0	
NumCompaniesWorked	1233.0	2.645580	2.460090	0.0	1.0	
OverTime	1233.0	0.234388	0.423787	0.0	0.0	
PercentSalaryHike	1233.0	15.231144	3.639511	11.0	12.0	
PerformanceRating	1233.0	3.153285	0.360408	3.0	3.0	
RelationshipSatisfaction	1233.0	2.733982	1.071603	1.0	2.0	
StockOptionLevel	1233.0	0.845093	0.841985	0.0	0.0	
TotalWorkingYears	1233.0	11.862936	7.760719	0.0	6.0	
TrainingTimesLastYear	1233.0	2.832928	1.293585	0.0	2.0	
WorkLifeBalance	1233.0	2.781022	0.681907	1.0	2.0	

YearsAtCompany	1233.0	7.369019	6.096298	0.0	3.0
YearsInCurrentRole	1233.0	4.484185	3.649402	0.0	2.0
YearsSinceLastPromotion	1233.0	2.234388	3.234762	0.0	0.0
YearsWithCurrManager	1233.0	4.367397	3.594116	0.0	2.0

	50%	75%	max
Age	36.0	43.0	60.0
Attrition	0.0	0.0	0.0
DailyRate	817.0	1176.0	1499.0
DistanceFromHome	7.0	13.0	29.0
Education	3.0	4.0	5.0
EnvironmentSatisfaction	3.0	4.0	4.0
HourlyRate	66.0	83.0	100.0
JobInvolvement	3.0	3.0	4.0
JobLevel	2.0	3.0	5.0
JobSatisfaction	3.0	4.0	4.0
MonthlyIncome	5204.0	8834.0	19999.0
MonthlyRate	14120.0	20364.0	26997.0
NumCompaniesWorked	2.0	4.0	9.0
OverTime	0.0	0.0	1.0
PercentSalaryHike	14.0	18.0	25.0
PerformanceRating	3.0	3.0	4.0
RelationshipSatisfaction	3.0	4.0	4.0
StockOptionLevel	1.0	1.0	3.0
TotalWorkingYears	10.0	16.0	38.0
TrainingTimesLastYear	3.0	3.0	6.0
WorkLifeBalance	3.0	3.0	4.0
YearsAtCompany	6.0	10.0	37.0
YearsInCurrentRole	3.0	7.0	18.0
YearsSinceLastPromotion	1.0	3.0	15.0
YearsWithCurrManager	3.0	7.0	17.0

```
[38]: # Correlating Dataset:
numeric_df = employee_df.select_dtypes(include='number')
correlations = numeric_df.corr()
correlations
```

```
[38]:
```

	Age	Attrition	DailyRate	DistanceFromHome	\
Age	1.000000	-0.159205	0.010661	-0.001686	
Attrition	-0.159205	1.000000	-0.056652	0.077924	
DailyRate	0.010661	-0.056652	1.000000	-0.004985	
DistanceFromHome	-0.001686	0.077924	-0.004985	1.000000	
Education	0.208034	-0.031373	-0.016806	0.021042	
EnvironmentSatisfaction	0.010146	-0.103369	0.018355	-0.016075	
HourlyRate	0.024287	-0.006846	0.023381	0.031131	
JobInvolvement	0.029820	-0.130016	0.046135	0.008783	
JobLevel	0.509604	-0.169105	0.002966	0.005303	

JobSatisfaction	-0.004892	-0.103481	0.030571	-0.003669
MonthlyIncome	0.497855	-0.159840	0.007707	-0.017014
MonthlyRate	0.028051	0.015170	-0.032182	0.027473
NumCompaniesWorked	0.299635	0.043494	0.038153	-0.029251
OverTime	0.028062	0.246118	0.009135	0.025514
PercentSalaryHike	0.003634	-0.013478	0.022704	0.040235
PerformanceRating	0.001904	0.002889	0.000473	0.027110
RelationshipSatisfaction	0.053535	-0.045872	0.007846	0.006557
StockOptionLevel	0.037510	-0.137145	0.042143	0.044872
TotalWorkingYears	0.680381	-0.171063	0.014515	0.004628
TrainingTimesLastYear	-0.019621	-0.059478	0.002453	-0.036942
WorkLifeBalance	-0.021490	-0.063939	-0.037848	-0.026556
YearsAtCompany	0.311309	-0.134392	-0.034055	0.009508
YearsInCurrentRole	0.212901	-0.160545	0.009932	0.018845
YearsSinceLastPromotion	0.216513	-0.033019	-0.033229	0.010029
YearsWithCurrManager	0.202089	-0.156199	-0.026363	0.014406

	Education	EnvironmentSatisfaction	HourlyRate	\
Age	0.208034	0.010146	0.024287	
Attrition	-0.031373	-0.103369	-0.006846	
DailyRate	-0.016806	0.018355	0.023381	
DistanceFromHome	0.021042	-0.016075	0.031131	
Education	1.000000	-0.027128	0.016775	
EnvironmentSatisfaction	-0.027128	1.000000	-0.049857	
HourlyRate	0.016775	-0.049857	1.000000	
JobInvolvement	0.042438	-0.008278	0.042861	
JobLevel	0.101589	0.001212	-0.027853	
JobSatisfaction	-0.011296	-0.006784	-0.071335	
MonthlyIncome	0.094961	-0.006259	-0.015794	
MonthlyRate	-0.026084	0.037600	-0.015297	
NumCompaniesWorked	0.126317	0.012594	0.022157	
OverTime	-0.020322	0.070132	-0.007782	
PercentSalaryHike	-0.011111	-0.031701	-0.009062	
PerformanceRating	-0.024539	-0.029548	-0.002172	
RelationshipSatisfaction	-0.009118	0.007665	0.001330	
StockOptionLevel	0.018422	0.003432	0.050263	
TotalWorkingYears	0.148280	-0.002693	-0.002334	
TrainingTimesLastYear	-0.025100	-0.019359	-0.008548	
WorkLifeBalance	0.009819	0.027627	-0.004607	
YearsAtCompany	0.069114	0.001458	-0.019582	
YearsInCurrentRole	0.060236	0.018007	-0.024106	
YearsSinceLastPromotion	0.054254	0.016194	-0.026716	
YearsWithCurrManager	0.069065	-0.004999	-0.020123	

	JobInvolvement	JobLevel	JobSatisfaction	...	\
Age	0.029820	0.509604	-0.004892	...	
Attrition	-0.130016	-0.169105	-0.103481	...	

DailyRate	0.046135	0.002966	0.030571	...
DistanceFromHome	0.008783	0.005303	-0.003669	...
Education	0.042438	0.101589	-0.011296	...
EnvironmentSatisfaction	-0.008278	0.001212	-0.006784	...
HourlyRate	0.042861	-0.027853	-0.071335	...
JobInvolvement	1.000000	-0.012630	-0.021476	...
JobLevel	-0.012630	1.000000	-0.001944	...
JobSatisfaction	-0.021476	-0.001944	1.000000	...
MonthlyIncome	-0.015271	0.950300	-0.007157	...
MonthlyRate	-0.016322	0.039563	0.000644	...
NumCompaniesWorked	0.015012	0.142501	-0.055699	...
OverTime	-0.003507	0.000544	0.024539	...
PercentSalaryHike	-0.017205	-0.034730	0.020002	...
PerformanceRating	-0.029071	-0.021222	0.002297	...
RelationshipSatisfaction	0.034297	0.021642	-0.012454	...
StockOptionLevel	0.021523	0.013984	0.010690	...
TotalWorkingYears	-0.005533	0.782208	-0.020185	...
TrainingTimesLastYear	-0.015338	-0.018191	-0.005779	...
WorkLifeBalance	-0.014617	0.037818	-0.019459	...
YearsAtCompany	-0.021355	0.534739	-0.003803	...
YearsInCurrentRole	0.008717	0.389447	-0.002305	...
YearsSinceLastPromotion	-0.024184	0.353885	-0.018214	...
YearsWithCurrManager	0.025976	0.375281	-0.027656	...

	PerformanceRating	RelationshipSatisfaction	\
Age	0.001904	0.053535	
Attrition	0.002889	-0.045872	
DailyRate	0.000473	0.007846	
DistanceFromHome	0.027110	0.006557	
Education	-0.024539	-0.009118	
EnvironmentSatisfaction	-0.029548	0.007665	
HourlyRate	-0.002172	0.001330	
JobInvolvement	-0.029071	0.034297	
JobLevel	-0.021222	0.021642	
JobSatisfaction	0.002297	-0.012454	
MonthlyIncome	-0.017120	0.025873	
MonthlyRate	-0.009811	-0.004085	
NumCompaniesWorked	-0.014095	0.052733	
OverTime	0.004369	0.048493	
PercentSalaryHike	0.773550	-0.040490	
PerformanceRating	1.000000	-0.031351	
RelationshipSatisfaction	-0.031351	1.000000	
StockOptionLevel	0.003506	-0.045952	
TotalWorkingYears	0.006744	0.024054	
TrainingTimesLastYear	-0.015579	0.002497	
WorkLifeBalance	0.002572	0.019604	
YearsAtCompany	0.003435	0.019367	

YearsInCurrentRole	0.034986	-0.015123
YearsSinceLastPromotion	0.017896	0.033493
YearsWithCurrManager	0.022827	-0.000867

	StockOptionLevel	TotalWorkingYears \
Age	0.037510	0.680381
Attrition	-0.137145	-0.171063
DailyRate	0.042143	0.014515
DistanceFromHome	0.044872	0.004628
Education	0.018422	0.148280
EnvironmentSatisfaction	0.003432	-0.002693
HourlyRate	0.050263	-0.002334
JobInvolvement	0.021523	-0.005533
JobLevel	0.013984	0.782208
JobSatisfaction	0.010690	-0.020185
MonthlyIncome	0.005408	0.772893
MonthlyRate	-0.034323	0.026442
NumCompaniesWorked	0.030075	0.237639
OverTime	-0.000449	0.012754
PercentSalaryHike	0.007528	-0.020608
PerformanceRating	0.003506	0.006744
RelationshipSatisfaction	-0.045952	0.024054
StockOptionLevel	1.000000	0.010136
TotalWorkingYears	0.010136	1.000000
TrainingTimesLastYear	0.011274	-0.035662
WorkLifeBalance	0.004129	0.001008
YearsAtCompany	0.015058	0.628133
YearsInCurrentRole	0.050818	0.460365
YearsSinceLastPromotion	0.014352	0.404858
YearsWithCurrManager	0.024698	0.459188

	TrainingTimesLastYear	WorkLifeBalance \
Age	-0.019621	-0.021490
Attrition	-0.059478	-0.063939
DailyRate	0.002453	-0.037848
DistanceFromHome	-0.036942	-0.026556
Education	-0.025100	0.009819
EnvironmentSatisfaction	-0.019359	0.027627
HourlyRate	-0.008548	-0.004607
JobInvolvement	-0.015338	-0.014617
JobLevel	-0.018191	0.037818
JobSatisfaction	-0.005779	-0.019459
MonthlyIncome	-0.021736	0.030683
MonthlyRate	0.001467	0.007963
NumCompaniesWorked	-0.066054	-0.008366
OverTime	-0.079113	-0.027092
PercentSalaryHike	-0.005221	-0.003280

PerformanceRating	-0.015579	0.002572
RelationshipSatisfaction	0.002497	0.019604
StockOptionLevel	0.011274	0.004129
TotalWorkingYears	-0.035662	0.001008
TrainingTimesLastYear	1.000000	0.028072
WorkLifeBalance	0.028072	1.000000
YearsAtCompany	0.003569	0.012089
YearsInCurrentRole	-0.005738	0.049856
YearsSinceLastPromotion	-0.002067	0.008941
YearsWithCurrManager	-0.004096	0.002759

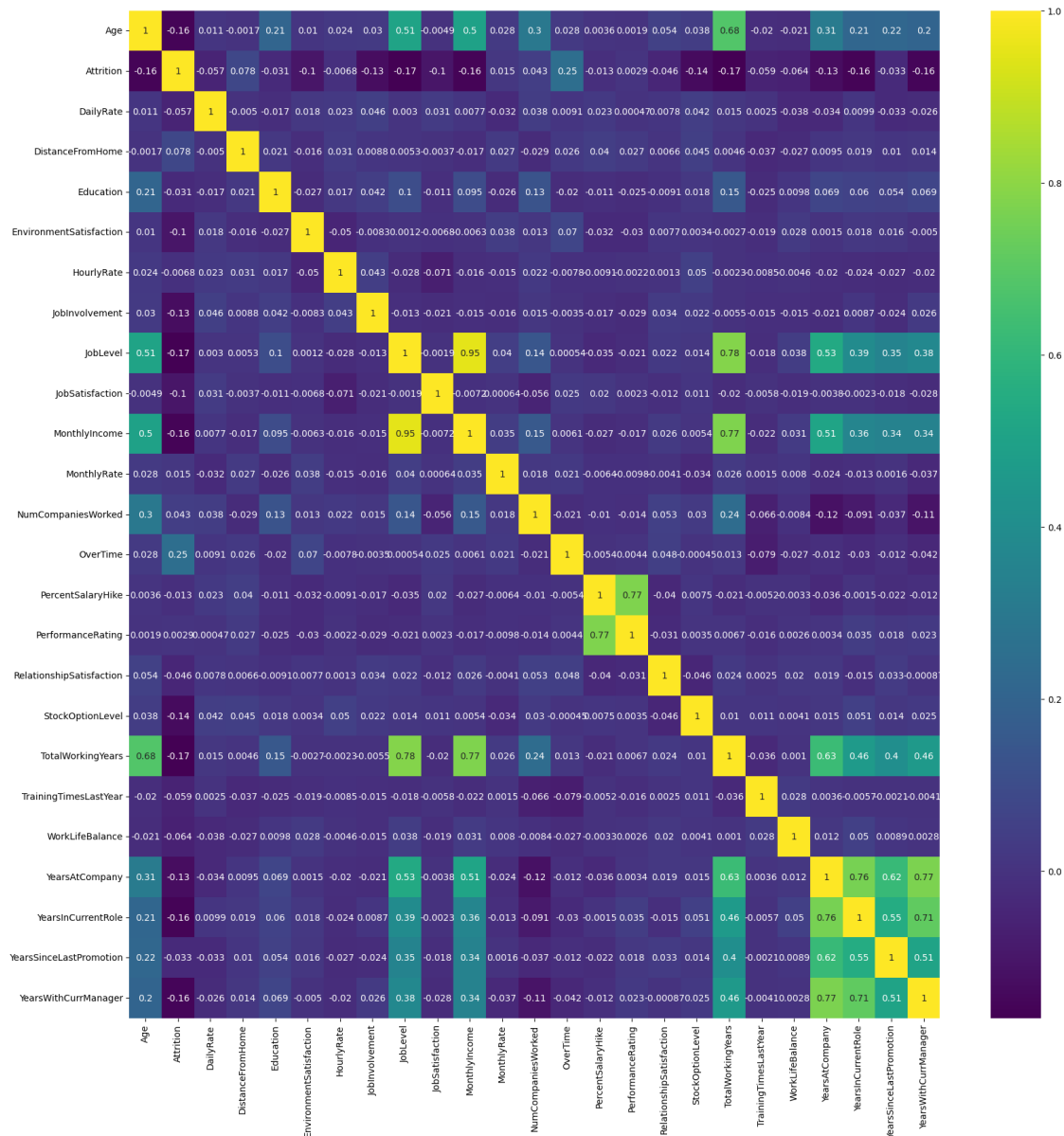
	YearsAtCompany	YearsInCurrentRole \
Age	0.311309	0.212901
Attrition	-0.134392	-0.160545
DailyRate	-0.034055	0.009932
DistanceFromHome	0.009508	0.018845
Education	0.069114	0.060236
EnvironmentSatisfaction	0.001458	0.018007
HourlyRate	-0.019582	-0.024106
JobInvolvement	-0.021355	0.008717
JobLevel	0.534739	0.389447
JobSatisfaction	-0.003803	-0.002305
MonthlyIncome	0.514285	0.363818
MonthlyRate	-0.023655	-0.012815
NumCompaniesWorked	-0.118421	-0.090754
OverTime	-0.011687	-0.029758
PercentSalaryHike	-0.035991	-0.001520
PerformanceRating	0.003435	0.034986
RelationshipSatisfaction	0.019367	-0.015123
StockOptionLevel	0.015058	0.050818
TotalWorkingYears	0.628133	0.460365
TrainingTimesLastYear	0.003569	-0.005738
WorkLifeBalance	0.012089	0.049856
YearsAtCompany	1.000000	0.758754
YearsInCurrentRole	0.758754	1.000000
YearsSinceLastPromotion	0.618409	0.548056
YearsWithCurrManager	0.769212	0.714365

	YearsSinceLastPromotion	YearsWithCurrManager
Age	0.216513	0.202089
Attrition	-0.033019	-0.156199
DailyRate	-0.033229	-0.026363
DistanceFromHome	0.010029	0.014406
Education	0.054254	0.069065
EnvironmentSatisfaction	0.016194	-0.004999
HourlyRate	-0.026716	-0.020123
JobInvolvement	-0.024184	0.025976

JobLevel	0.353885	0.375281
JobSatisfaction	-0.018214	-0.027656
MonthlyIncome	0.344978	0.344079
MonthlyRate	0.001567	-0.036746
NumCompaniesWorked	-0.036814	-0.110319
OverTime	-0.012239	-0.041586
PercentSalaryHike	-0.022154	-0.011985
PerformanceRating	0.017896	0.022827
RelationshipSatisfaction	0.033493	-0.000867
StockOptionLevel	0.014352	0.024698
TotalWorkingYears	0.404858	0.459188
TrainingTimesLastYear	-0.002067	-0.004096
WorkLifeBalance	0.008941	0.002759
YearsAtCompany	0.618409	0.769212
YearsInCurrentRole	0.548056	0.714365
YearsSinceLastPromotion	1.000000	0.510224
YearsWithCurrManager	0.510224	1.000000

[25 rows x 25 columns]

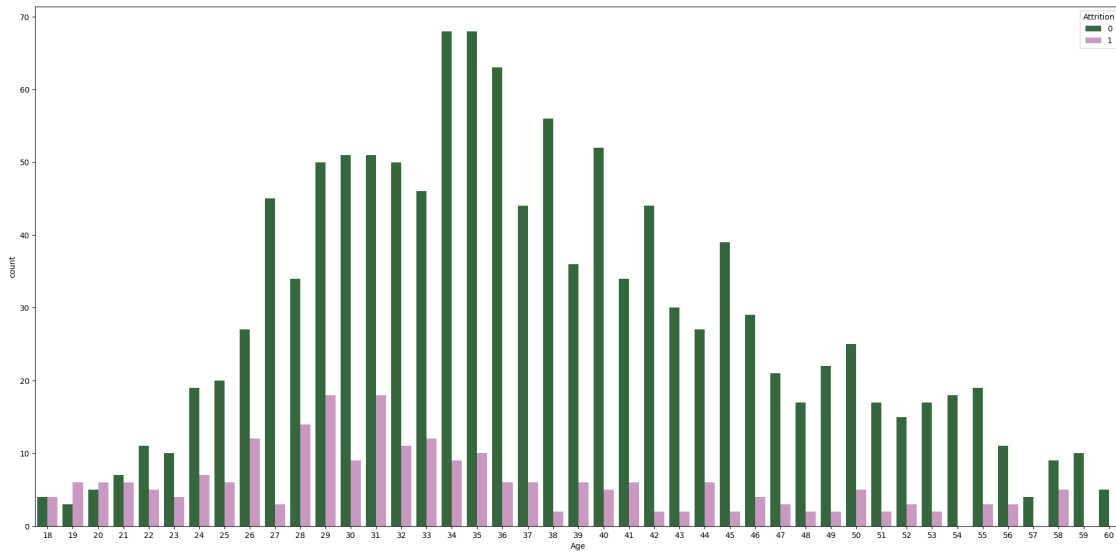
```
[39]: custom_cmap = sns.color_palette("viridis", as_cmap=True)
f, ax = plt.subplots(figsize = (20, 20))
sns.heatmap(correlations, annot = True, cmap=custom_cmap)
plt.show()
```



- Job level is strongly correlated with total working Years
- Monthly income is strongly correlated with Job level
- Monthly income is strongly correlated with total working Years
- Age is strongly correlated with monthly income

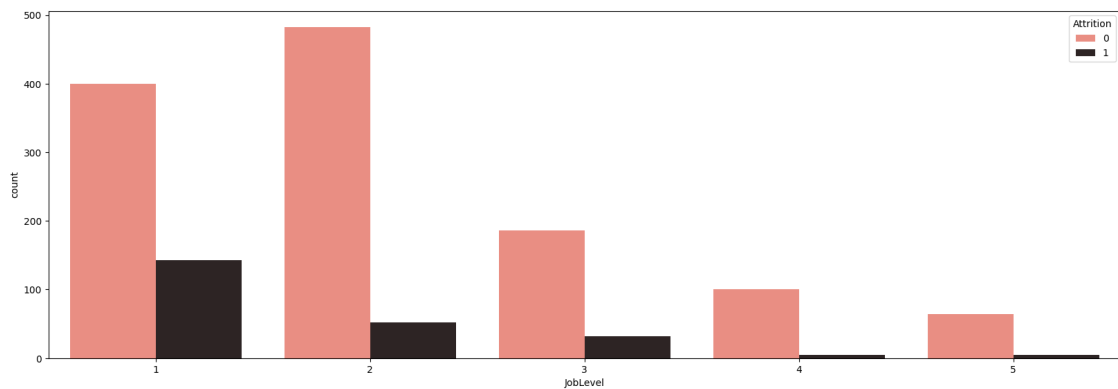
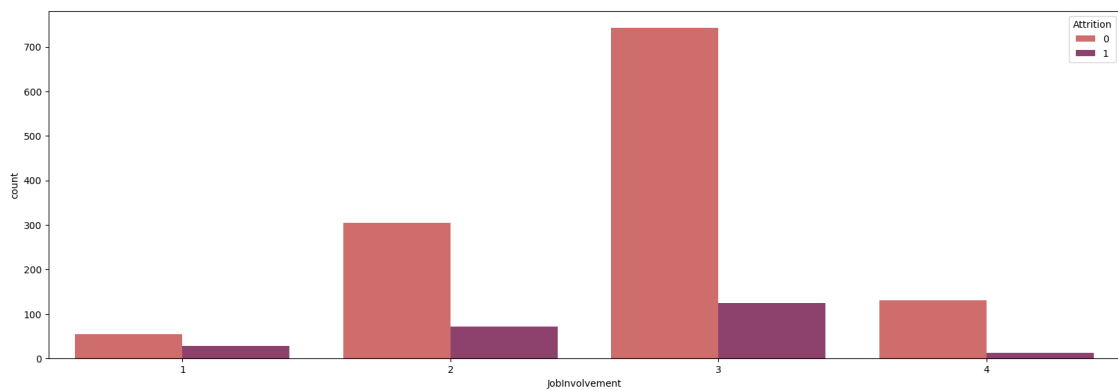
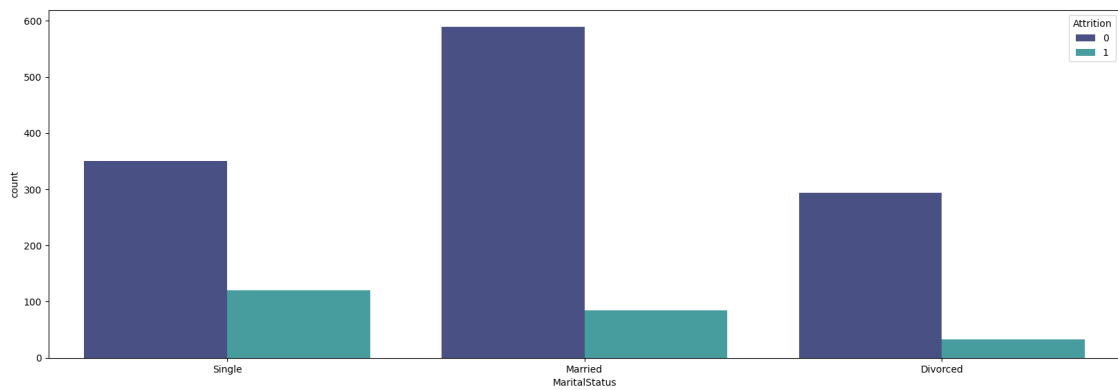
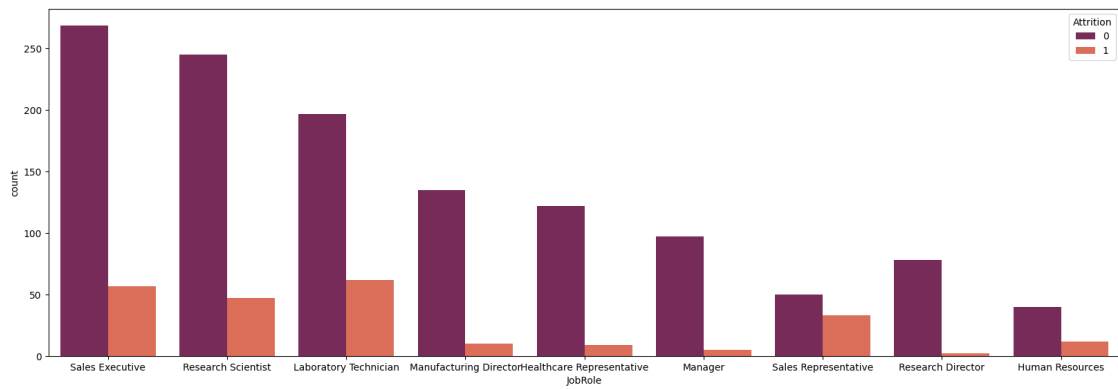
```
[40]: plt.figure(figsize=[25, 12])
sns.countplot(x = 'Age', hue = 'Attrition', data = employee_df,
palette="cubehelix")
```

```
[40]: <Axes: xlabel='Age', ylabel='count'>
```



```
[41]: plt.figure(figsize=[20,30])
plt.subplot(411)
sns.countplot(x = 'JobRole', hue = 'Attrition', data = employee_df,
             palette="rocket")
plt.subplot(412)
sns.countplot(x = 'MaritalStatus', hue = 'Attrition', data = employee_df,
             palette="mako")
plt.subplot(413)
sns.countplot(x = 'JobInvolvement', hue = 'Attrition', data = employee_df,
             palette="flare")
plt.subplot(414)
sns.countplot(x = 'JobLevel', hue = 'Attrition', data = employee_df,
             palette="dark:salmon_r")
```

```
[41]: <Axes: xlabel='JobLevel', ylabel='count'>
```



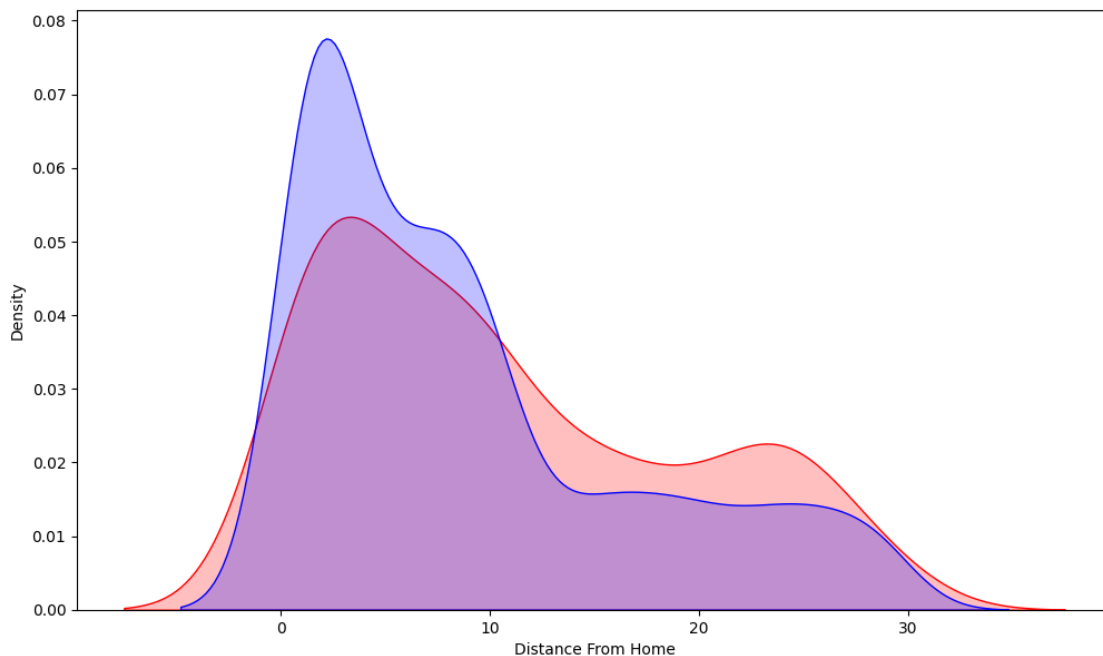
- Single employees tend to leave compared to married and divorced
- Sales Representatives tend to leave compared to any other job
- Less involved employees tend to leave the company
- Less experienced (low job level) tend to leave the company

```
[42]: # KDE (Kernel Density Estimate) is used for visualizing the Probability Density
      ↪ of a continuous variable.
      # KDE describes the probability density at different values in a continuous
      ↪ variable.
      plt.figure(figsize=(12,7))

      sns.kdeplot(left_df['DistanceFromHome'], label = 'Employees who left', fill =
      ↪ True, color = 'red')
      sns.kdeplot(stayed_df['DistanceFromHome'], label = 'Employees who Stayed', fill
      ↪ = True, color = 'blue')

      plt.xlabel('Distance From Home')
```

```
[42]: Text(0.5, 0, 'Distance From Home')
```



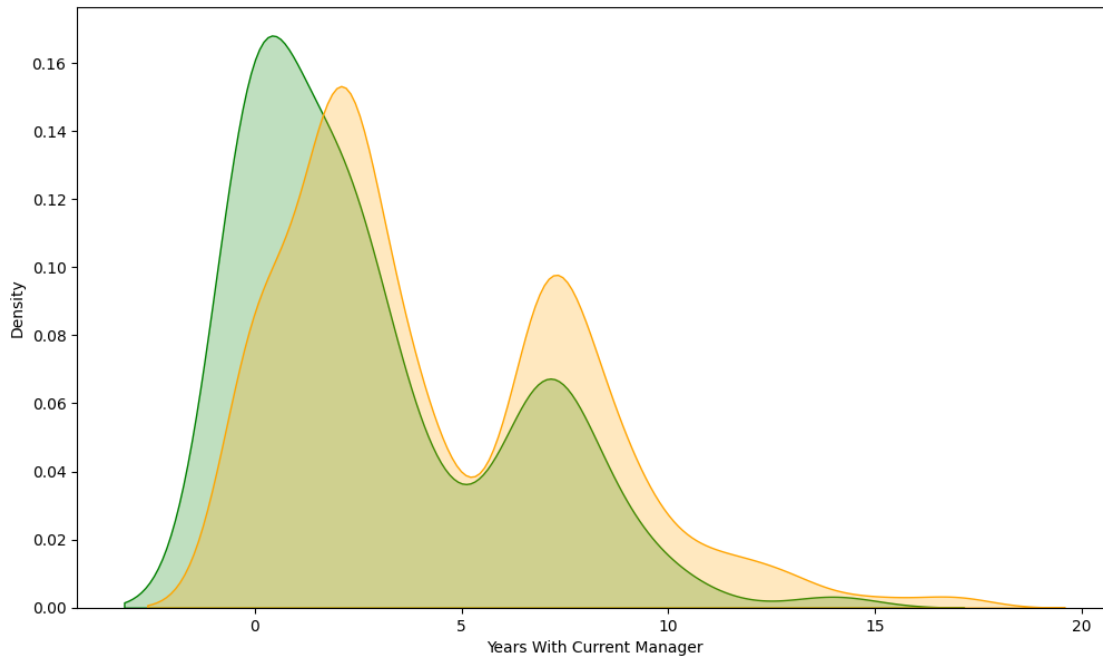
```
[43]: plt.figure(figsize=(12,7))

      sns.kdeplot(left_df['YearsWithCurrManager'], label = 'Employees who left', fill
      ↪ = True, color = 'green')
```

```
sns.kdeplot(stayed_df['YearsWithCurrManager'], label = 'Employees who Stayed',
            fill = True, color = 'orange')

plt.xlabel('Years With Current Manager')
```

[43]: Text(0.5, 0, 'Years With Current Manager')

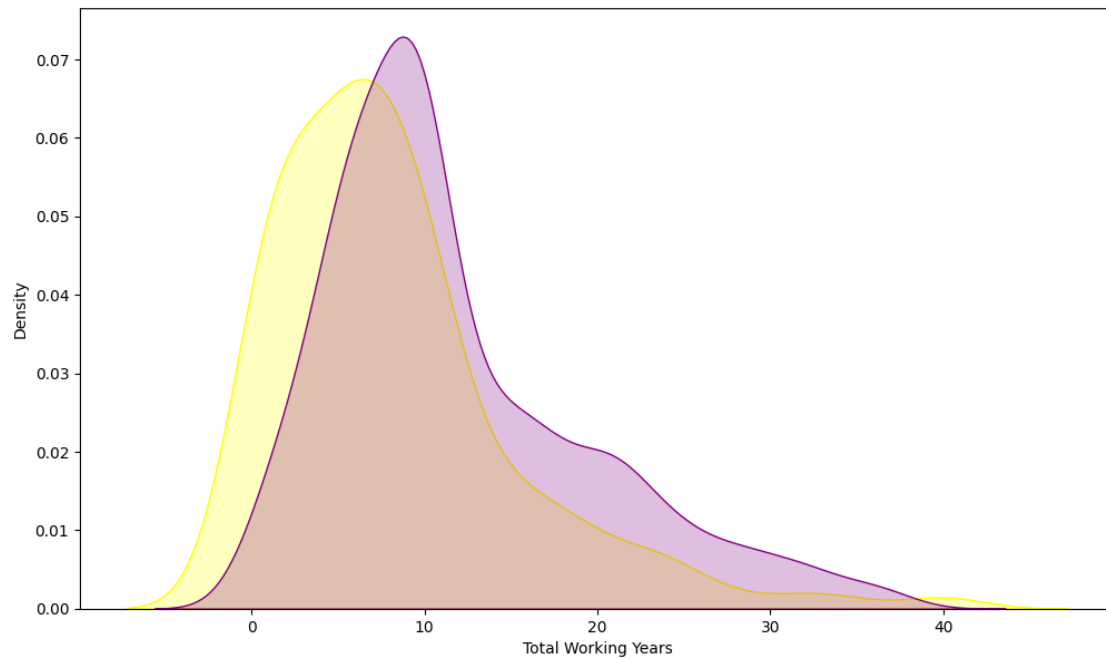


```
[44]: plt.figure(figsize=(12,7))

sns.kdeplot(left_df['TotalWorkingYears'], fill = True, label = 'Employees who
            left', color = 'yellow')
sns.kdeplot(stayed_df['TotalWorkingYears'], fill = True, label = 'Employees who
            Stayed', color = 'purple')

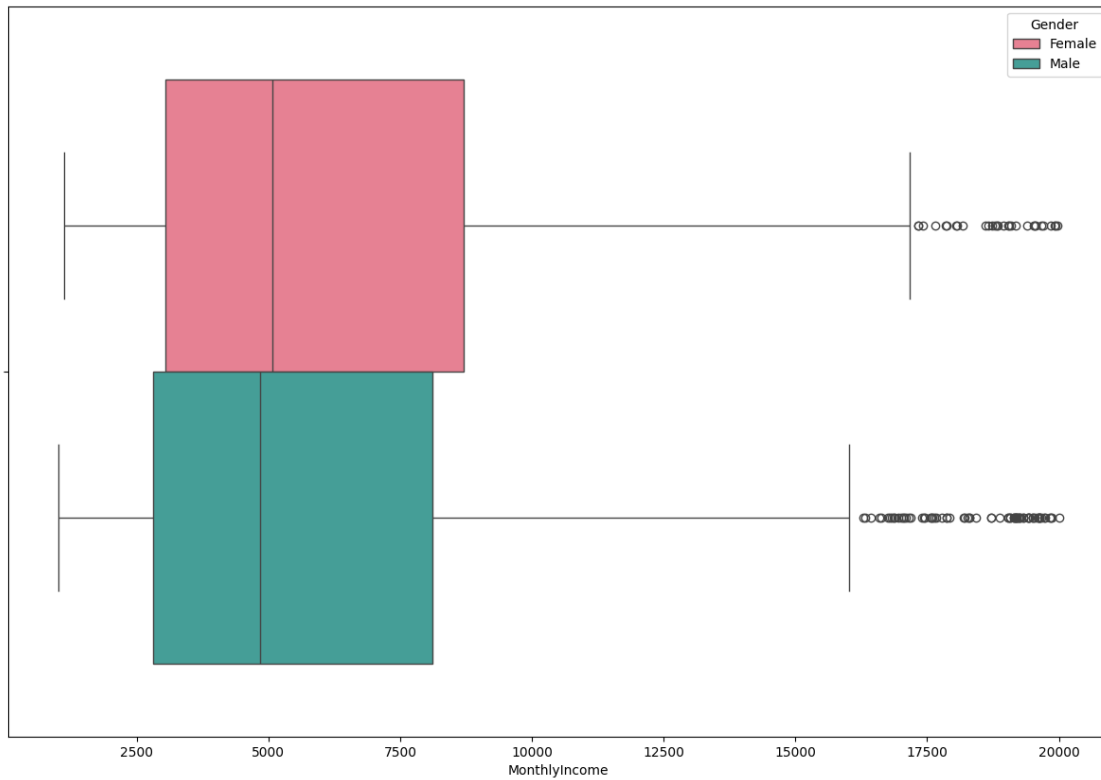
plt.xlabel('Total Working Years')
```

[44]: Text(0.5, 0, 'Total Working Years')



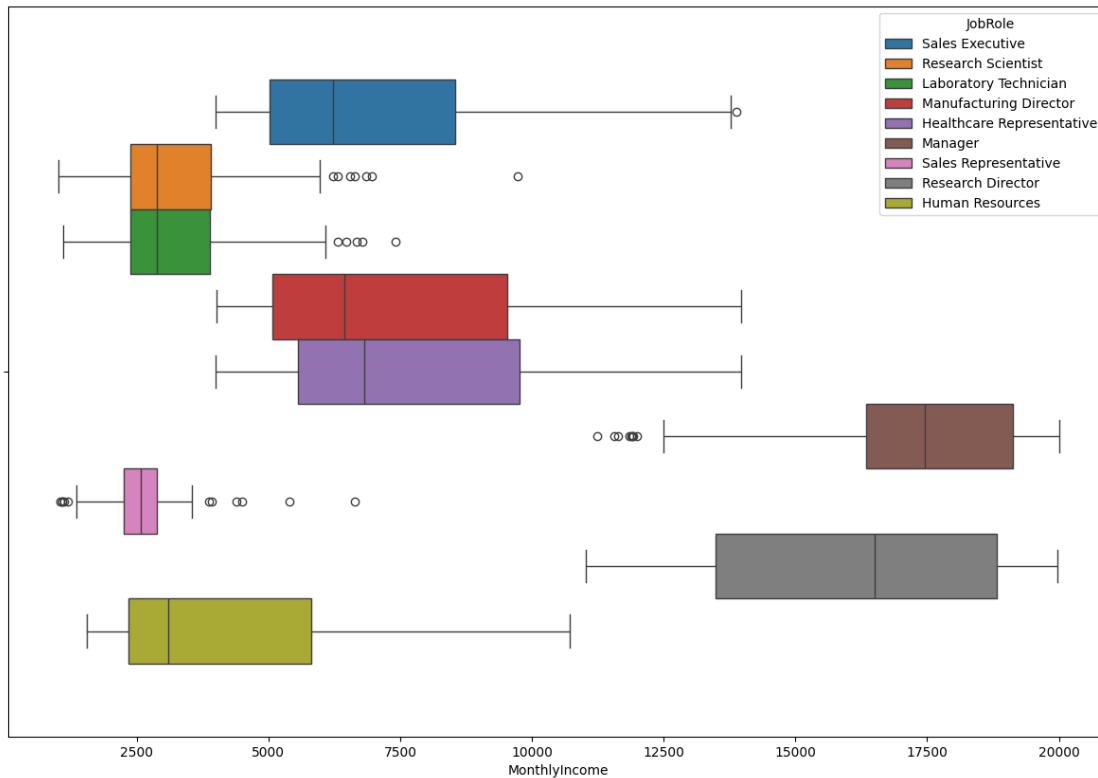
```
[45]: # Let's see the Gender vs. Monthly Income
plt.figure(figsize=(15, 10))
sns.boxplot(x = 'MonthlyIncome', hue= 'Gender', data = employee_df,
            palette='husl')
```

```
[45]: <Axes: xlabel='MonthlyIncome'>
```

```
[46]: # Let's see the monthly income vs. job role
plt.figure(figsize=(15, 10))
sns.boxplot(x= 'MonthlyIncome', hue = 'JobRole', data = employee_df,
            palette="tab10", legend=True)
```

```
[46]: <Axes: xlabel='MonthlyIncome'>
```



0.0.7 Create Testing And Training Dataset:

```
[47]: employee_df.describe(include='object')
```

```
[47]:
```

	BusinessTravel	Department	EducationField	Gender \
count	1470	1470	1470	1470
unique	3	3	6	2
top	Travel_Rarely	Research & Development	Life Sciences	Male
freq	1043	961	606	882

	JobRole	MaritalStatus
count	1470	1470
unique	9	3
top	Sales Executive	Married
freq	326	673

```
[48]: employee_df.head(5)
```

```
[48]:
```

	Age	Attrition	BusinessTravel	DailyRate	Department \
0	41	1	Travel_Rarely	1102	Sales
1	49	0	Travel_Frequently	279	Research & Development
2	37	1	Travel_Rarely	1373	Research & Development

3	33	0	Travel_Frequently	1392	Research & Development
4	27	0	Travel_Rarely	591	Research & Development

	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	\
0	1	2	Life Sciences	2	
1	8	1	Life Sciences	3	
2	2	2	Other	4	
3	3	4	Life Sciences	4	
4	2	1	Medical	1	

	Gender	...	PerformanceRating	RelationshipSatisfaction	StockOptionLevel	\
0	Female	...	3	1	0	
1	Male	...	4	4	1	
2	Male	...	3	2	0	
3	Female	...	3	3	0	
4	Male	...	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 31 columns]

```
[49]: employee_df.shape
```

```
[49]: (1470, 31)
```

```
[50]: employee_df.describe(include='object')
```

```
[50]:
```

	BusinessTravel	Department	EducationField	Gender	\
count	1470	1470	1470	1470	
unique	3	3	6	2	
top	Travel_Rarely	Research & Development	Life Sciences	Male	
freq	1043	961	606	882	

	JobRole	MaritalStatus
count	1470	1470

```

unique          9          3
top    Sales Executive    Married
freq          326        673

```

```
[51]: employee_df['BusinessTravel'].unique()
```

```
[51]: array(['Travel_Rarely', 'Travel_Frequently', 'Non-Travel'], dtype=object)
```

0.0.8 Categorical Column Encoding

```
[52]: # Creating dataset with catgeorial columns:
X_cat = employee_df[['BusinessTravel', 'Department', 'EducationField',
    ↳ 'Gender', 'JobRole', 'MaritalStatus']]
X_cat
```

```
[52]:
```

	BusinessTravel	Department	EducationField	Gender	\
0	Travel_Rarely	Sales	Life Sciences	Female	
1	Travel_Frequently	Research & Development	Life Sciences	Male	
2	Travel_Rarely	Research & Development	Other	Male	
3	Travel_Frequently	Research & Development	Life Sciences	Female	
4	Travel_Rarely	Research & Development	Medical	Male	
...	
1465	Travel_Frequently	Research & Development	Medical	Male	
1466	Travel_Rarely	Research & Development	Medical	Male	
1467	Travel_Rarely	Research & Development	Life Sciences	Male	
1468	Travel_Frequently	Sales	Medical	Male	
1469	Travel_Rarely	Research & Development	Medical	Male	

	JobRole	MaritalStatus
0	Sales Executive	Single
1	Research Scientist	Married
2	Laboratory Technician	Single
3	Research Scientist	Married
4	Laboratory Technician	Married
...
1465	Laboratory Technician	Married
1466	Healthcare Representative	Married
1467	Manufacturing Director	Married
1468	Sales Executive	Married
1469	Laboratory Technician	Married

[1470 rows x 6 columns]

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

onehotencoder = OneHotEncoder()
```

```
X_cat = onehotencoder.fit_transform(X_cat).toarray() #return the valyes in
↪series
type(X_cat)
```

```
[53]: numpy.ndarray
```

```
[54]: X_cat.shape
```

```
[54]: (1470, 26)
```

```
[55]: X_cat = pd.DataFrame(X_cat)
```

```
[56]: X_cat
```

```
[56]:
```

	0	1	2	3	4	5	6	7	8	9	...	16	17	18	\
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	
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	
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	
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	
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	
...
1465	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	1.0	0.0	0.0	
1466	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1467	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	...	0.0	0.0	1.0	
1468	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1469	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	
...
1465	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	1.0	0.0	0.0	
1466	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1467	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	...	0.0	0.0	1.0	
1468	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1469	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	
...
1465	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	1.0	0.0	0.0	
1466	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1467	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	...	0.0	0.0	1.0	
1468	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1469	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	
...
1465	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	1.0	0.0	0.0	
1466	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1467	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	...	0.0	0.0	1.0	
1468	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1469	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	

```
[1470 rows x 26 columns]
```

```
[57]: X_numerical = employee_df[['Age', 'DailyRate', 'DistanceFromHome', 'Education',
↪'EnvironmentSatisfaction', 'HourlyRate',
'JobInvolvement', 'JobLevel',
↪'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate',
```

```

        'NumCompaniesWorked', 'OverTime',␣
↪'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
        'StockOptionLevel',␣
↪'TotalWorkingYears',        'TrainingTimesLastYear',␣
↪'WorkLifeBalance',
        'YearsAtCompany'        , 'YearsInCurrentRole',␣
↪'YearsSinceLastPromotion', 'YearsWithCurrManager']]
X_numerical

```

```

[57]:      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
...  ...      ...      ...      ...      ...
1465   36      884          23           2           3
1466   39      613           6           1           4
1467   27      155           4           3           2
1468   49     1023           2           3           4
1469   34      628           8           3           2

```

```

      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
...      ...      ...      ...      ...      ...
1465        41           4           2           4           2571
1466        42           2           3           1           9991
1467        87           4           2           2           6142
1468        63           2           2           2           5390
1469        82           4           2           3           4404

```

```

      ...  PerformanceRating  RelationshipSatisfaction  StockOptionLevel  \
0      ...           3           1           0
1      ...           4           4           1
2      ...           3           2           0
3      ...           3           3           0
4      ...           3           4           1
...  ...      ...      ...      ...
1465   ...           3           3           1
1466   ...           3           1           1
1467   ...           4           2           1
1468   ...           3           4           0
1469   ...           3           1           0

```

	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	\
0	8	0	1	
1	10	3	3	
2	7	3	3	
3	8	3	3	
4	6	3	3	
...	
1465	17	3	3	
1466	9	5	3	
1467	6	0	3	
1468	17	3	2	
1469	6	3	4	

	YearsAtCompany	YearsInCurrentRole	YearsSinceLastPromotion	\
0	6	4	0	
1	10	7	1	
2	0	0	0	
3	8	7	3	
4	2	2	2	
...	
1465	5	2	0	
1466	7	7	1	
1467	6	2	0	
1468	9	6	0	
1469	4	3	1	

	YearsWithCurrManager
0	5
1	7
2	0
3	0
4	2
...	...
1465	3
1466	7
1467	3
1468	8
1469	2

[1470 rows x 24 columns]

```
[58]: X_all = pd.concat([X_cat, X_numerical], axis = 1)
X_all
```

```
[58]:
```

	0	1	2	3	4	5	6	7	8	9	...	\
0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	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	...
2	0.0	0.0	1.0	0.0	1.0	0.0	0.0	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	...
4	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...
...
1465	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...
1466	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...
1467	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	...
1468	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...
1469	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	...

	PerformanceRating	RelationshipSatisfaction	StockOptionLevel	\
0	3		1	0
1	4		4	1
2	3		2	0
3	3		3	0
4	3		4	1
...
1465	3		3	1
1466	3		1	1
1467	4		2	1
1468	3		4	0
1469	3		1	0

	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	\
0	8	0	1	
1	10	3	3	
2	7	3	3	
3	8	3	3	
4	6	3	3	
...
1465	17	3	3	
1466	9	5	3	
1467	6	0	3	
1468	17	3	2	
1469	6	3	4	

	YearsAtCompany	YearsInCurrentRole	YearsSinceLastPromotion	\
0	6	4	0	
1	10	7	1	
2	0	0	0	
3	8	7	3	
4	2	2	2	
...
1465	5	2	0	
1466	7	7	1	
1467	6	2	0	

1468	9	6	0
1469	4	3	1

	YearsWithCurrManager
0	5
1	7
2	0
3	0
4	2
...	...
1465	3
1466	7
1467	3
1468	8
1469	2

[1470 rows x 50 columns]

0.0.9 Feature Scaling

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

```
X_all.columns = X_all.columns.astype(str)
scaler = MinMaxScaler()
X = scaler.fit_transform(X_all)
```

```
[60]: type(X)
```

```
[60]: numpy.ndarray
```

```
[61]: X
```

```
[61]: 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]])
```

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

```
[62]: 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
```

0.0.10 Model Testing:

```
[63]: # Understanding Logistic Regression, Decision Tree Classifier and Random forest  
      ↳ Classifier :  
  
      from sklearn.model_selection import train_test_split  
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)
```

```
[64]: X_train.shape
```

```
[64]: (1102, 50)
```

```
[65]: X_test.shape
```

```
[65]: (368, 50)
```

```
[66]: # Testing For Logistic Regression:  
      from sklearn.linear_model import LogisticRegression  
      from sklearn.metrics import accuracy_score  
  
      model = LogisticRegression()  
      model.fit(X_train, y_train)  
  
      y_pred = model.predict(X_test)
```

```
[67]: y_pred
```

```
[67]: array([1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,  
        0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,  
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,  
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,  
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0])
```

```

0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
dtype=int64)

```

- Prediction of 0 suggests that the model estimates the probability of the instance belonging to the negative class is greater than 0.5.
- Prediction of 1 suggests that the model estimates the probability of the instance belonging to the positive class is greater than 0.5.

```

[68]: # Testing for Confusion matrix:
from sklearn.metrics import confusion_matrix, classification_report

print("Accuracy of prediction teast: {} %".format( 100 * accuracy_score(y_pred,
↪y_test)))

```

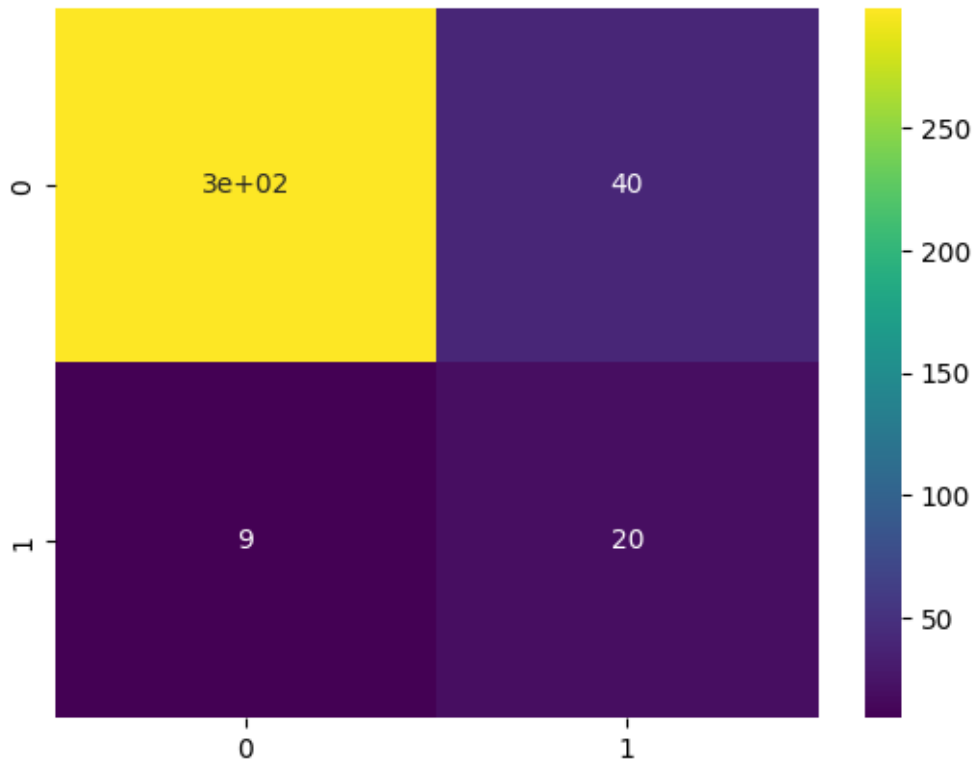
Accuracy of prediction teast: 86.68478260869566 %

```

[69]: # Testing Set Performance
cus_cmap = sns.color_palette("viridis", as_cmap=True)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, cmap=cus_cmap)

```

[69]: <Axes: >



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

	precision	recall	f1-score	support
0	0.88	0.97	0.92	308
1	0.69	0.33	0.45	60
accuracy			0.87	368
macro avg	0.79	0.65	0.69	368
weighted avg	0.85	0.87	0.85	368

- For class 0, F1-score for class 0 is 0.94, reflecting a good balance between precision and recall. With a high support of 311, indicating a large number of instances for class 0, the model's performance on this class seems robust.
- For class 1, F1-score for class 1 is 0.53, indicating a moderate balance between precision and recall. With a support of 57, indicating a smaller number of instances for class 1, the model's performance on this class is less reliable compared to class 0.
- The overall accuracy of the model is 0.89, indicating that it correctly classified approximately 89% .

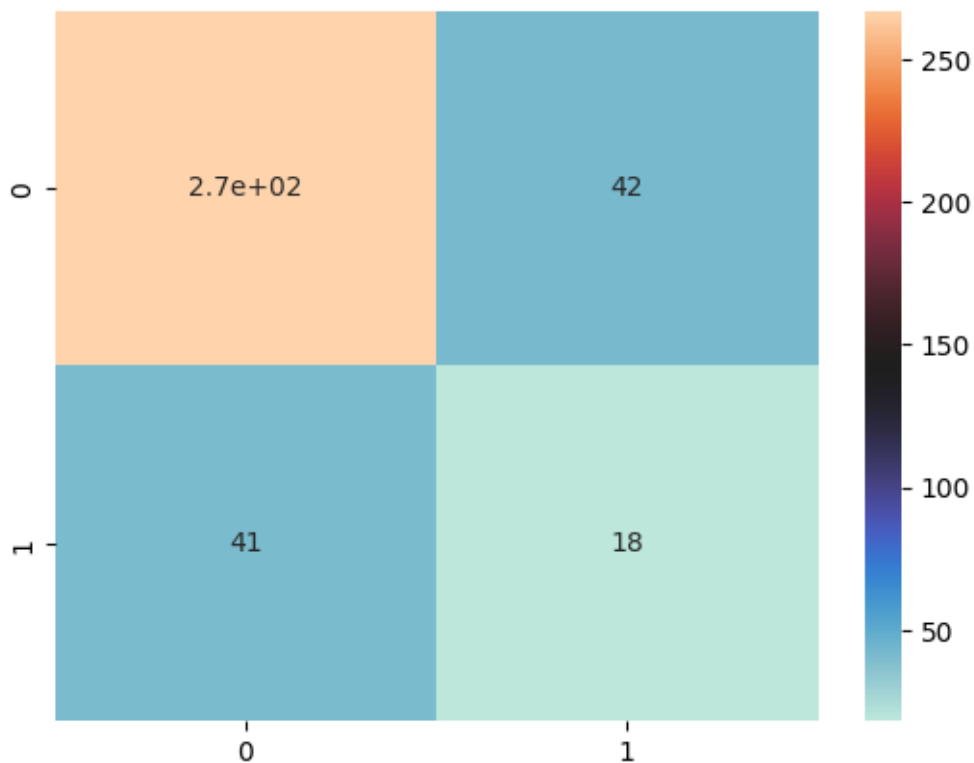
```
[71]: print("Total Record of 1 ",employee_df[employee_df['Attrition']==1].shape[0])
print("Total Record of 0 ",employee_df[employee_df['Attrition']==0].shape[0])
```

Total Record of 1 237
Total Record of 0 1233

```
[72]: # Testing for Decision Tree Classifier:
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
# Testing Set Performance
cus_cmap = sns.color_palette("icefire", as_cmap=True)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, cmap=cus_cmap)
```

[72]: <Axes: >



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

	precision	recall	f1-score	support
0	0.86	0.87	0.87	308
1	0.31	0.30	0.30	60

accuracy			0.77	368
macro avg	0.58	0.58	0.58	368
weighted avg	0.77	0.77	0.77	368

- For class 0, F1-score for class 0 is 0.87, reflecting a good balance between precision and recall. With a support of 311, indicating a large number of instances for class 0, the model's performance on this class seems robust.
- For class 1, F1-score for class 1 is 0.36, indicating a relatively low balance between precision and recall. With a support of 57, indicating a smaller number of instances for class 1, the model's performance on this class is less reliable compared to class 0.
- The overall accuracy of the model is 0.79, indicating that it correctly classified approximately 79%.

```
[74]: # Testing for Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

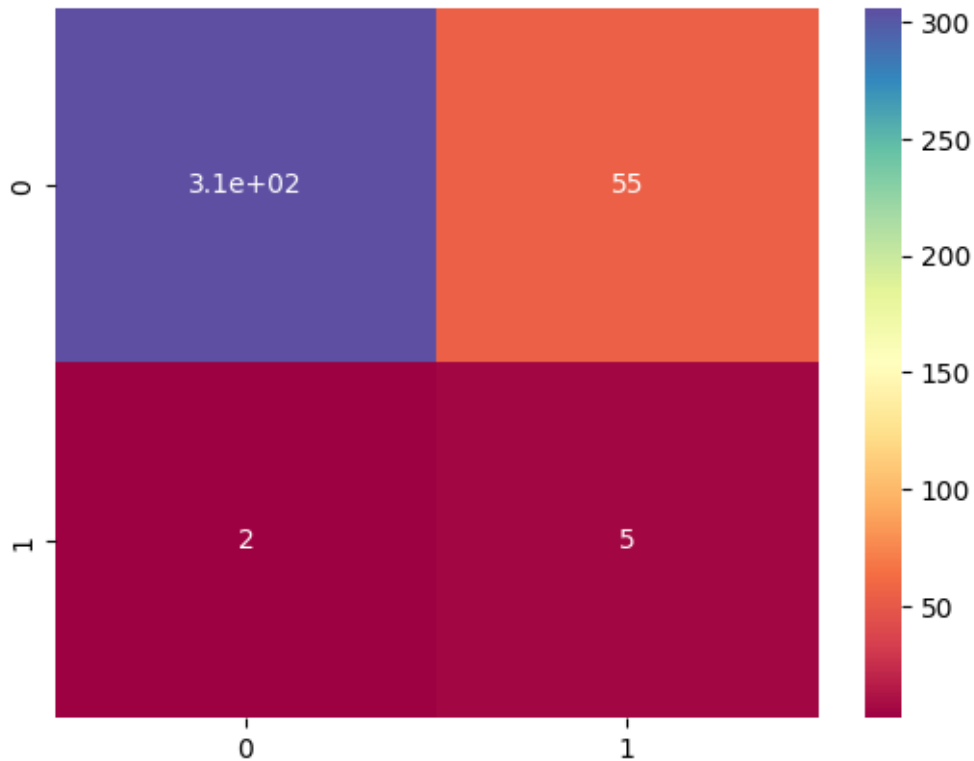
model = RandomForestClassifier()
model.fit(X_train, y_train)
```

```
[74]: RandomForestClassifier()
```

```
[75]: # Testing Set Performance
model=RandomForestClassifier(n_estimators=150,criterion='entropy',random_state=100)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

cus_cmap = sns.color_palette("Spectral", as_cmap=True)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, cmap=cus_cmap)
```

```
[75]: <Axes: >
```



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

	precision	recall	f1-score	support
0	0.85	0.99	0.91	308
1	0.71	0.08	0.15	60
accuracy			0.85	368
macro avg	0.78	0.54	0.53	368
weighted avg	0.83	0.85	0.79	368

- For class 0, F1-score for class 0 is 0.93, reflecting a high balance between precision and recall. With a support of 311, indicating a large number of instances for class 0, the model's performance on this class seems robust.
- For class 1, F1-score for class 1 is 0.35, indicating a relatively low balance between precision and recall. With a support of 57, indicating a smaller number of instances for class 1, the model's performance on this class is less reliable compared to class 0.
- The overall accuracy of the model is 0.88, indicating that it correctly classified approximately 88%

Conclusion For Model Testing:

Logistic Regression:

- Achieves an accuracy of 0.89 with relatively balanced precision and recall for class 0.
- Struggles with recall for class 1, indicating difficulty in correctly identifying instances of that class.

Decision Tree Classifier:

- Shows decent accuracy at 0.79 with better precision and recall for class 0 compared to class 1.
- Struggles with recall for class 1, similar to logistic regression.

Random Forest Classifier:

- Demonstrates the highest accuracy of 0.88 among the three classifiers.
- Shows excellent precision and recall for class 0, but struggles with recall for class 1 similar to the other models.

Overall, while all three classifiers perform well in classifying instances of class 0, they exhibit challenges in correctly identifying instances of class 1, especially in recall. This suggests potential issues related to class imbalance or difficulty in capturing the characteristics of class 1. Further investigation and possibly model tuning, such as adjusting class weights, collecting more data for class 1, or using different feature engineering techniques, may be necessary to improve the performance, particularly for class 1 predictions.