

assignment-4

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

```
[4]: df=pd.read_csv("Employee-Attrition.csv")
df.head()
```

```
[4]:   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]

0.1 Data Processing

```
[6]: df.shape
```

```
[6]: (1470, 35)
```

```
[7]: 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

```
[8]: df.describe()
```

```

[8]:
count      Age      DailyRate  DistanceFromHome  Education  EmployeeCount \
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

```

```

count      EmployeeNumber  EnvironmentSatisfaction  HourlyRate  JobInvolvement \
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

```

```

count      JobLevel  ...  RelationshipSatisfaction  StandardHours \
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

```

```

count      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]

```
[10]: corr=dataset.corr(numeric_only = True)
corr
```

```
[10]:
```

	Age	DailyRate	DistanceFromHome	Education	
Age	1.000000	0.010661	-0.001686	0.208034	\
DailyRate	0.010661	1.000000	-0.004985	-0.016806	
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	
Education	0.208034	-0.016806	0.021042	1.000000	
EmployeeCount	NaN	NaN	NaN	NaN	
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	
HourlyRate	0.024287	0.023381	0.031131	0.016775	
JobInvolvement	0.029820	0.046135	0.008783	0.042438	
JobLevel	0.509604	0.002966	0.005303	0.101589	
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	

NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111
PerformanceRating	0.001904	0.000473	0.027110	-0.024539
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118
StandardHours	NaN	NaN	NaN	NaN
StockOptionLevel	0.037510	0.042143	0.044872	0.018422
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065

	EmployeeCount	EmployeeNumber	
Age	NaN	-0.010145	\
DailyRate	NaN	-0.050990	
DistanceFromHome	NaN	0.032916	
Education	NaN	0.042070	
EmployeeCount	NaN	NaN	
EmployeeNumber	NaN	1.000000	
EnvironmentSatisfaction	NaN	0.017621	
HourlyRate	NaN	0.035179	
JobInvolvement	NaN	-0.006888	
JobLevel	NaN	-0.018519	
JobSatisfaction	NaN	-0.046247	
MonthlyIncome	NaN	-0.014829	
MonthlyRate	NaN	0.012648	
NumCompaniesWorked	NaN	-0.001251	
PercentSalaryHike	NaN	-0.012944	
PerformanceRating	NaN	-0.020359	
RelationshipSatisfaction	NaN	-0.069861	
StandardHours	NaN	NaN	
StockOptionLevel	NaN	0.062227	
TotalWorkingYears	NaN	-0.014365	
TrainingTimesLastYear	NaN	0.023603	
WorkLifeBalance	NaN	0.010309	
YearsAtCompany	NaN	-0.011240	
YearsInCurrentRole	NaN	-0.008416	
YearsSinceLastPromotion	NaN	-0.009019	
YearsWithCurrManager	NaN	-0.009197	

	EnvironmentSatisfaction	HourlyRate	JobInvolvement	
Age	0.010146	0.024287	0.029820	\
DailyRate	0.018355	0.023381	0.046135	
DistanceFromHome	-0.016075	0.031131	0.008783	
Education	-0.027128	0.016775	0.042438	

EmployeeCount	NaN	NaN	NaN
EmployeeNumber	0.017621	0.035179	-0.006888
EnvironmentSatisfaction	1.000000	-0.049857	-0.008278
HourlyRate	-0.049857	1.000000	0.042861
JobInvolvement	-0.008278	0.042861	1.000000
JobLevel	0.001212	-0.027853	-0.012630
JobSatisfaction	-0.006784	-0.071335	-0.021476
MonthlyIncome	-0.006259	-0.015794	-0.015271
MonthlyRate	0.037600	-0.015297	-0.016322
NumCompaniesWorked	0.012594	0.022157	0.015012
PercentSalaryHike	-0.031701	-0.009062	-0.017205
PerformanceRating	-0.029548	-0.002172	-0.029071
RelationshipSatisfaction	0.007665	0.001330	0.034297
StandardHours	NaN	NaN	NaN
StockOptionLevel	0.003432	0.050263	0.021523
TotalWorkingYears	-0.002693	-0.002334	-0.005533
TrainingTimesLastYear	-0.019359	-0.008548	-0.015338
WorkLifeBalance	0.027627	-0.004607	-0.014617
YearsAtCompany	0.001458	-0.019582	-0.021355
YearsInCurrentRole	0.018007	-0.024106	0.008717
YearsSinceLastPromotion	0.016194	-0.026716	-0.024184
YearsWithCurrManager	-0.004999	-0.020123	0.025976

	JobLevel	...	RelationshipSatisfaction	
Age	0.509604	...	0.053535	\
DailyRate	0.002966	...	0.007846	
DistanceFromHome	0.005303	...	0.006557	
Education	0.101589	...	-0.009118	
EmployeeCount	NaN	...	NaN	
EmployeeNumber	-0.018519	...	-0.069861	
EnvironmentSatisfaction	0.001212	...	0.007665	
HourlyRate	-0.027853	...	0.001330	
JobInvolvement	-0.012630	...	0.034297	
JobLevel	1.000000	...	0.021642	
JobSatisfaction	-0.001944	...	-0.012454	
MonthlyIncome	0.950300	...	0.025873	
MonthlyRate	0.039563	...	-0.004085	
NumCompaniesWorked	0.142501	...	0.052733	
PercentSalaryHike	-0.034730	...	-0.040490	
PerformanceRating	-0.021222	...	-0.031351	
RelationshipSatisfaction	0.021642	...	1.000000	
StandardHours	NaN	...	NaN	
StockOptionLevel	0.013984	...	-0.045952	
TotalWorkingYears	0.782208	...	0.024054	
TrainingTimesLastYear	-0.018191	...	0.002497	
WorkLifeBalance	0.037818	...	0.019604	
YearsAtCompany	0.534739	...	0.019367	

YearsInCurrentRole	0.389447	...	-0.015123
YearsSinceLastPromotion	0.353885	...	0.033493
YearsWithCurrManager	0.375281	...	-0.000867

	StandardHours	StockOptionLevel	TotalWorkingYears
Age	NaN	0.037510	0.680381 \
DailyRate	NaN	0.042143	0.014515
DistanceFromHome	NaN	0.044872	0.004628
Education	NaN	0.018422	0.148280
EmployeeCount	NaN	NaN	NaN
EmployeeNumber	NaN	0.062227	-0.014365
EnvironmentSatisfaction	NaN	0.003432	-0.002693
HourlyRate	NaN	0.050263	-0.002334
JobInvolvement	NaN	0.021523	-0.005533
JobLevel	NaN	0.013984	0.782208
JobSatisfaction	NaN	0.010690	-0.020185
MonthlyIncome	NaN	0.005408	0.772893
MonthlyRate	NaN	-0.034323	0.026442
NumCompaniesWorked	NaN	0.030075	0.237639
PercentSalaryHike	NaN	0.007528	-0.020608
PerformanceRating	NaN	0.003506	0.006744
RelationshipSatisfaction	NaN	-0.045952	0.024054
StandardHours	NaN	NaN	NaN
StockOptionLevel	NaN	1.000000	0.010136
TotalWorkingYears	NaN	0.010136	1.000000
TrainingTimesLastYear	NaN	0.011274	-0.035662
WorkLifeBalance	NaN	0.004129	0.001008
YearsAtCompany	NaN	0.015058	0.628133
YearsInCurrentRole	NaN	0.050818	0.460365
YearsSinceLastPromotion	NaN	0.014352	0.404858
YearsWithCurrManager	NaN	0.024698	0.459188

	TrainingTimesLastYear	WorkLifeBalance
Age	-0.019621	-0.021490 \
DailyRate	0.002453	-0.037848
DistanceFromHome	-0.036942	-0.026556
Education	-0.025100	0.009819
EmployeeCount	NaN	NaN
EmployeeNumber	0.023603	0.010309
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

PercentSalaryHike	-0.005221	-0.003280
PerformanceRating	-0.015579	0.002572
RelationshipSatisfaction	0.002497	0.019604
StandardHours	NaN	NaN
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 \
DailyRate	-0.034055	0.009932
DistanceFromHome	0.009508	0.018845
Education	0.069114	0.060236
EmployeeCount	NaN	NaN
EmployeeNumber	-0.011240	-0.008416
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
PercentSalaryHike	-0.035991	-0.001520
PerformanceRating	0.003435	0.034986
RelationshipSatisfaction	0.019367	-0.015123
StandardHours	NaN	NaN
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

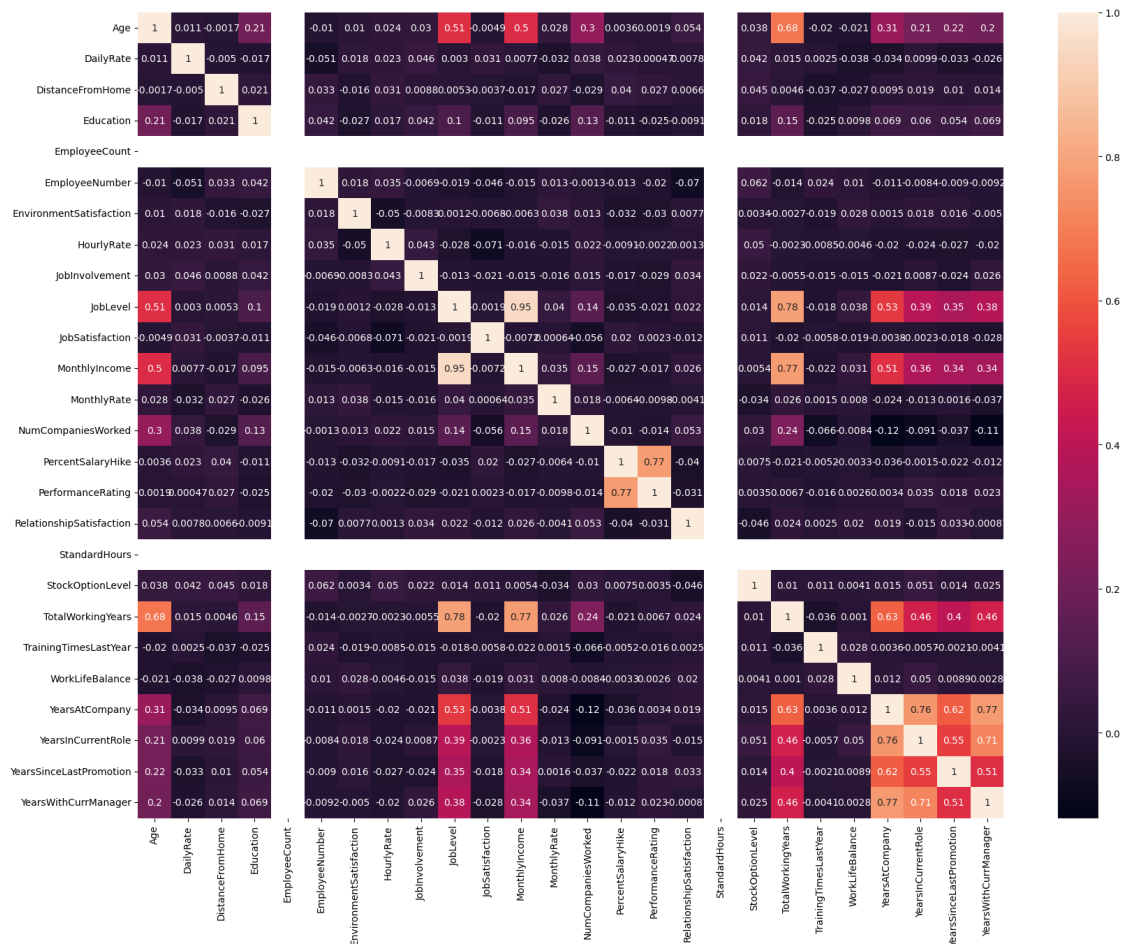
	YearsSinceLastPromotion	YearsWithCurrManager
Age	0.216513	0.202089
DailyRate	-0.033229	-0.026363
DistanceFromHome	0.010029	0.014406
Education	0.054254	0.069065
EmployeeCount	NaN	NaN

EmployeeNumber	-0.009019	-0.009197
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
PercentSalaryHike	-0.022154	-0.011985
PerformanceRating	0.017896	0.022827
RelationshipSatisfaction	0.033493	-0.000867
StandardHours	NaN	NaN
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

[26 rows x 26 columns]

```
[11]: plt.subplots(figsize=(20,15))
      sns.heatmap(corr,annot=True)
```

```
[11]: <Axes: >
```



0.1.1 We can conclude following inferences from above correlation graph.

- jobLevel is highly correlated to MonthlyIncome with value (0.95).
- There is relation between TotalWorkingYears with JobLevel & TotalWorkingYears with MonthlyIncome, value being (0.78).
- The YearsAtCompany is also related with JobLevel and MonthlyIncome, value being (0.53).
- MonthlyIncome is also loosely related to Age with value (0.5).

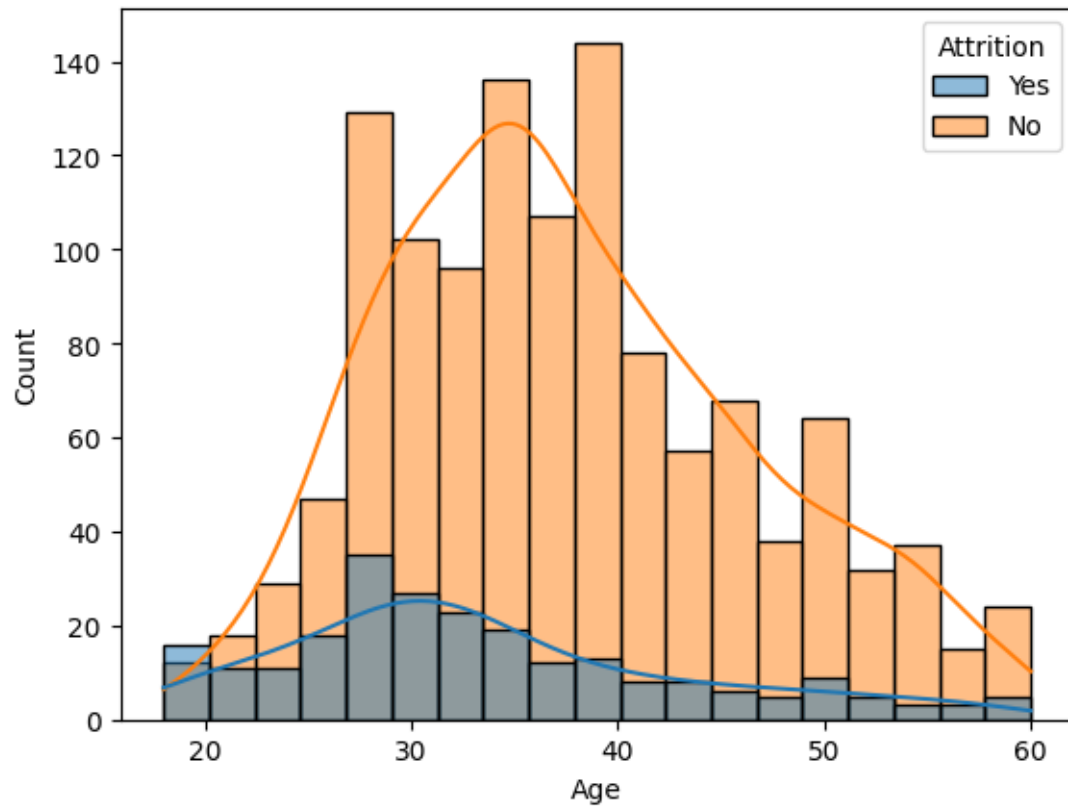
```
[13]: df.Attrition.value_counts()
```

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

```
[14]: #Checking for Null Values.
df.isnull().any()
```

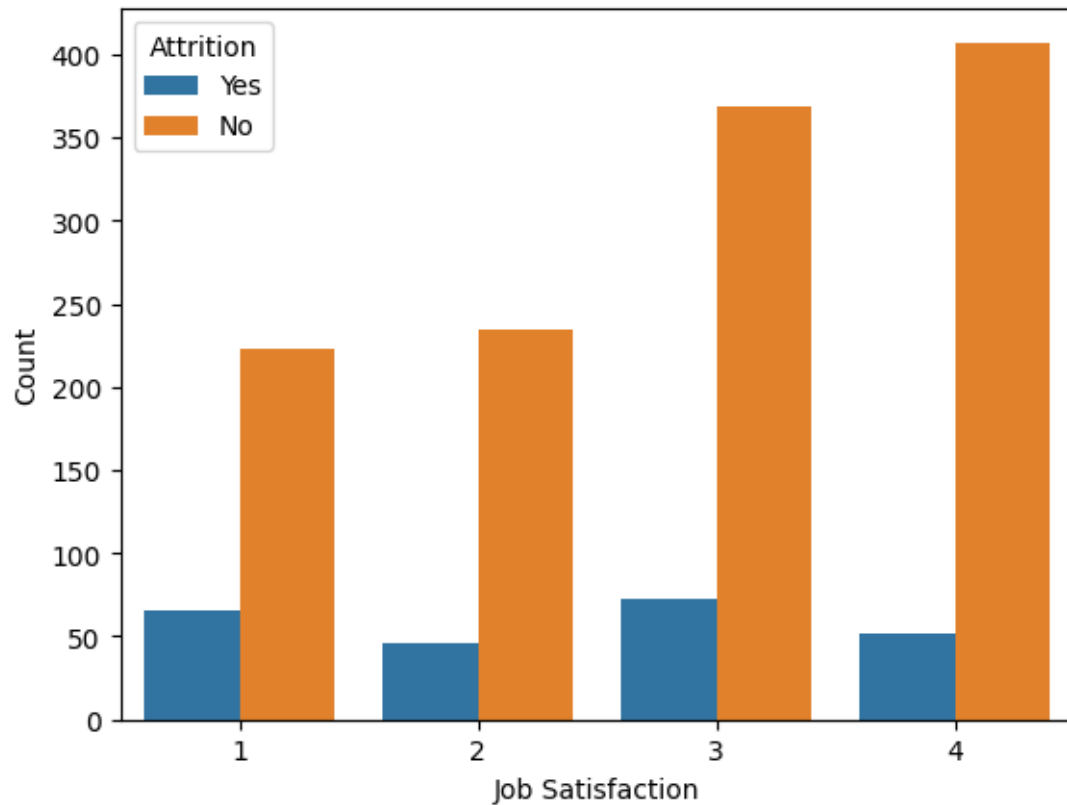
```
[14]: Age False
      Attrition False
      BusinessTravel False
      DailyRate False
      Department False
      DistanceFromHome False
      Education False
      EducationField False
      EmployeeCount False
      EmployeeNumber False
      EnvironmentSatisfaction False
      Gender False
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

```
[15]: # EDA: Distribution of Age to Attrition
      sns.histplot(data=df, x='Age', hue='Attrition', kde=True)
      plt.xlabel('Age')
      plt.ylabel('Count')
      plt.show()
```



Note:- We can plot JobSatisfaction vs Attrition to if satisfied employees are being Attrited too.

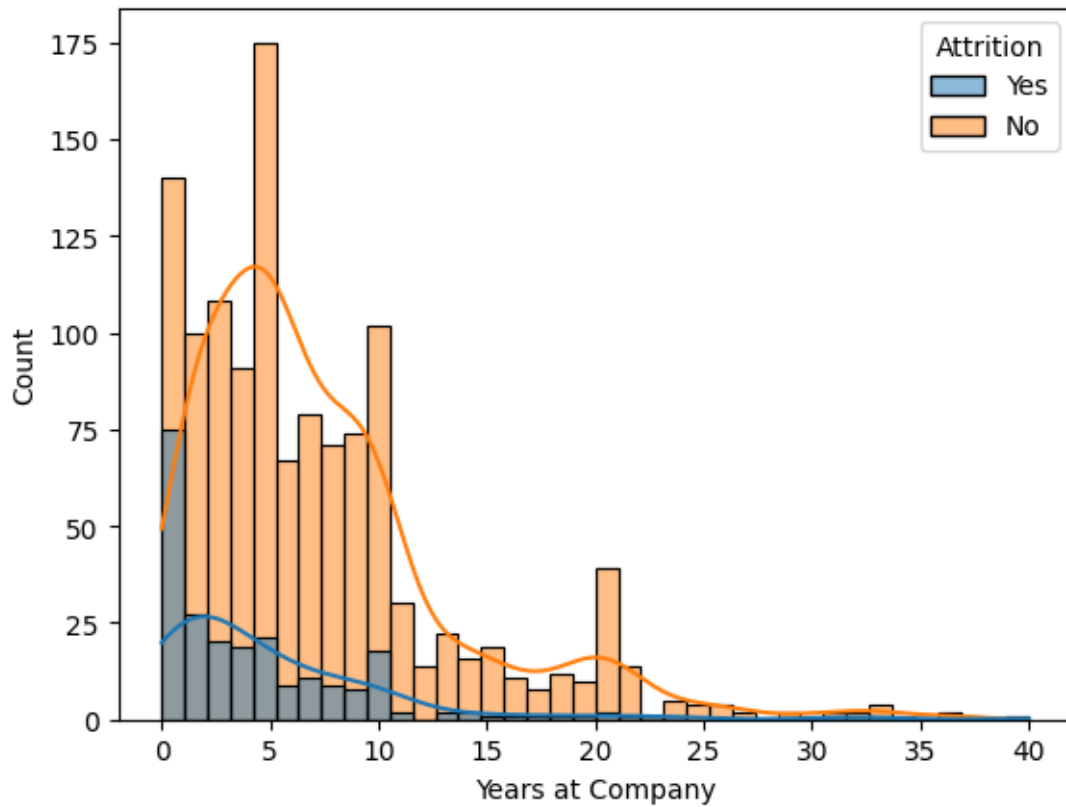
```
[16]: sns.countplot(x='JobSatisfaction', hue='Attrition', data=df)
plt.xlabel('Job Satisfaction')
plt.ylabel('Count')
plt.show()
```



Inference: * There is very loose relation between Attrition and JobSatisfaction. * Higher staisfaction level also triggers Attrition.

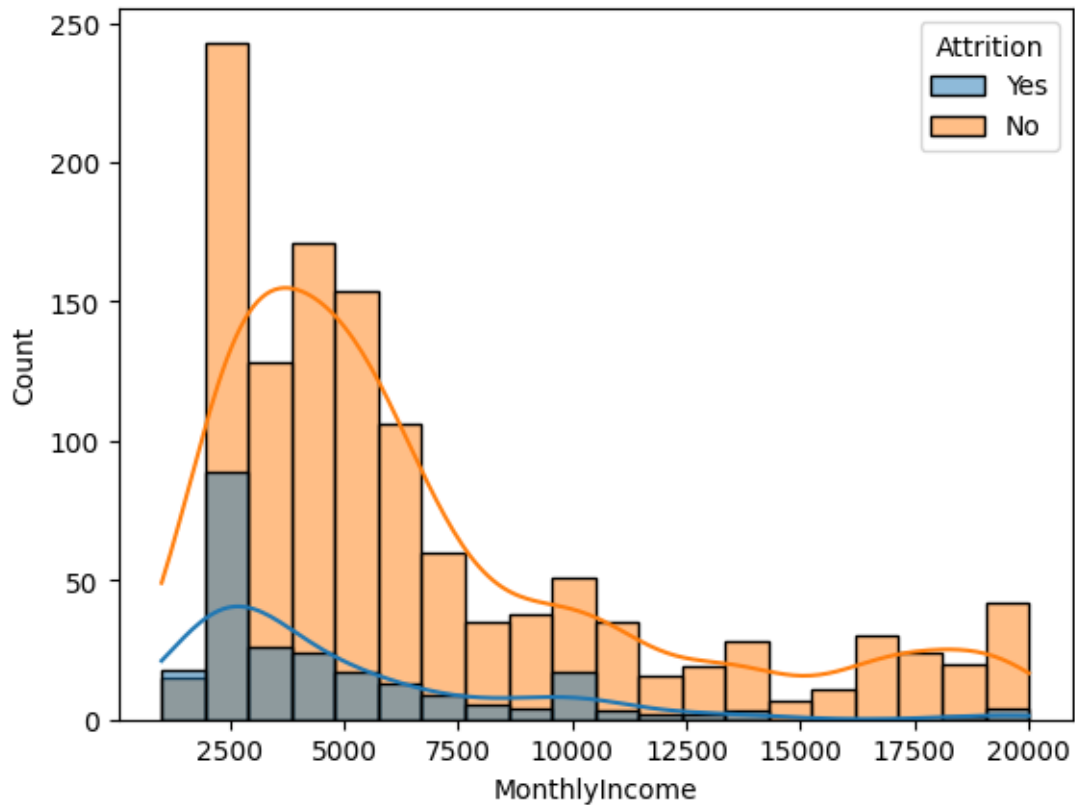
Let's see How YearsAtCompany is related to Attrition.

```
[17]: sns.histplot(data=df, x='YearsAtCompany', hue='Attrition', kde=True)
plt.xlabel('Years at Company')
plt.ylabel('Count')
plt.show()
```



Inferences * The Attrition is more frequent at early stage of the job. * When employee gets more used to work and gain more experiences, inshort Attrition decreases with time spent at company.

```
[18]: # Now, Let's check how "MonthlyIncome" is related to "Attrition".
sns.histplot(data=df, x='MonthlyIncome', hue='Attrition', kde=True)
plt.show()
```



Inferences * The Employees with lower MonthlyIncome is more likely to face Attrition.

```
[27]: # Define the target variable (dependent variable)
y = df['Attrition']

# Define the independent variables (features)
X = df.drop('Attrition', axis=1)
```

```
[28]: # Perform one-hot encoding on categorical columns
X_encoded = pd.get_dummies(df, drop_first=True)
X_encoded.head()
```

```
[28]:   Age  DailyRate  DistanceFromHome  Education  EmployeeCount  EmployeeNumber
0   41     1102             1           2           1           1 \
1   49      279             8           1           1           2
2   37     1373             2           2           1           4
3   33     1392             3           4           1           5
4   27      591             2           1           1           7

   EnvironmentSatisfaction  HourlyRate  JobInvolvement  JobLevel  ...
0                        2           94              3         2  ... \
```

1	3	61	2	2	...
2	4	92	2	1	...
3	4	56	3	1	...
4	1	40	3	1	...

	JobRole_Laboratory Technician	JobRole_Manager
0	False	False \
1	False	False
2	True	False
3	False	False
4	True	False

	JobRole_Manufacturing Director	JobRole_Research Director
0	False	False \
1	False	False
2	False	False
3	False	False
4	False	False

	JobRole_Research Scientist	JobRole_Sales Executive
0	False	True \
1	True	False
2	False	False
3	True	False
4	False	False

	JobRole_Sales Representative	MaritalStatus_Married	MaritalStatus_Single
0	False	False	True \
1	False	True	False
2	False	False	True
3	False	True	False
4	False	True	False

	OverTime_Yes
0	True
1	False
2	True
3	True
4	False

[5 rows x 48 columns]

0.2 Model Building

We'll Follow following below steps to build our model. 1. Make data fit for model. 2. Import the model building Libraries 3. Initializing the model 4. Training and testing the model 5. Evaluation of Model

0.2.1 1. Making data fit for model.

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

# Initialize the scaler
scaler = MinMaxScaler()

# Fit and transform the scaled features
X_scaled = scaler.fit_transform(X_encoded)

# Convert the scaled features back to a DataFrame (optional)
X_scaled_df = pd.DataFrame(X_scaled, columns=X_encoded.columns)

# Check data
X_scaled_df.head()
```

```
[29]:
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	
0	0.547619	0.715820	0.000000	0.25	0.0	\
1	0.738095	0.126700	0.250000	0.00	0.0	
2	0.452381	0.909807	0.035714	0.25	0.0	
3	0.357143	0.923407	0.071429	0.75	0.0	
4	0.214286	0.350036	0.035714	0.00	0.0	

	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	
0	0.000000	0.333333	0.914286	0.666667	\
1	0.000484	0.666667	0.442857	0.333333	
2	0.001451	1.000000	0.885714	0.333333	
3	0.001935	1.000000	0.371429	0.666667	
4	0.002903	0.000000	0.142857	0.666667	

	JobLevel	...	JobRole_Laboratory Technician	JobRole_Manager	
0	0.25	...	0.0	0.0	\
1	0.25	...	0.0	0.0	
2	0.00	...	1.0	0.0	
3	0.00	...	0.0	0.0	
4	0.00	...	1.0	0.0	

	JobRole_Manufacturing Director	JobRole_Research Director	
0	0.0	0.0	\
1	0.0	0.0	
2	0.0	0.0	
3	0.0	0.0	
4	0.0	0.0	

	JobRole_Research Scientist	JobRole_Sales Executive	
0	0.0	1.0	\
1	1.0	0.0	

2	0.0	0.0
3	1.0	0.0
4	0.0	0.0

	JobRole_Sales Representative	MaritalStatus_Married	MaritalStatus_Single
0	0.0	0.0	1.0 \
1	0.0	1.0	0.0
2	0.0	0.0	1.0
3	0.0	1.0	0.0
4	0.0	1.0	0.0

	OverTime_Yes
0	1.0
1	0.0
2	1.0
3	1.0
4	0.0

[5 rows x 48 columns]

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

# Split the data into training and testing sets (e.g., 80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
↪random_state=42)
```

0.2.2 2. Import the model building Libraries

```
[35]: from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

0.2.3 3. Initializing the model

```
[36]: logistic_model = LogisticRegression(random_state=42)
random_forest_model = RandomForestClassifier(random_state=42)
```

0.2.4 4. Training and Testing the Model

```
[37]: # Training and testing the Logistic Regression model
logistic_model.fit(X_train, y_train)
logistic_result = logistic_model.predict(X_test)

# Training and testing the Random Forest model
random_forest_model.fit(X_train, y_train)
random_forest_result = random_forest_model.predict(X_test)
```

0.2.5 5. Evaluation

```
[41]: # Evaluation of Logistic Regression model
logistic_accuracy = accuracy_score(y_test, logistic_result)

print("Logistic Regression Model Accuracy:", logistic_accuracy)
```

Logistic Regression Model Accuracy: 1.0

```
[42]: # Evaluation of Random Forest model
random_forest_accuracy = accuracy_score(y_test, random_forest_result)

print("Random Forest Model Accuracy:", random_forest_accuracy)
```

Random Forest Model Accuracy: 1.0