10/3/2021

Exploratory Data Analysis – Employee attrition

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TABLE OF CONTENTS

DATA SET DESCRIPTION

➔ Brief description of the data set and a summary of its attributes

The data set name is *IBM HR Analytics Employee Attrition and Performance*. This a fictional data set created by IBM data scientists. The data set allow uncovering the factors that lead to employee attrition. The data set is available on KAGGLE: https://www.kaggle.com/pavansubhasht/ibm-hr-analytics-attrition-dataset

The data set has **1470 rows** and **35 columns.**

The column **Attrition** is the target variable

Here is the list of columns:

- Certain **numerical** columns contain **ordinal** data and the meaning of the numerical value is described on the KAGGLE link. I copied the values in the tab below.
- For certain **numerical** data, the unit is unknown and for others like levels, the meaning is unknown as well.
- For **categorical** data, I added, in the tab below, the different values for each categorical features.

Column	Features	Data type	Data type	Values
0	Age	int64	Numerical	In years
1	**Attrition**	object	Categorical	'Yes' 'No'
2	BusinessTravel	object	Categorical	'Travel_Rarely' 'Travel_Frequently' 'Non-Travel'
3	DailyRate	int64	Numerical	In a currency not known
4	Department	object	Categorical	'Sales' 'Research & Development' 'Human Resources'
5	DistanceFromHome	int64	Numerical	In a distance unit not known
6	Education	int64	Ordinal	1 'Below College' 2 'College' 3 'Bachelor' 4 'Master' 5 'Doctor'
7	EducationField	object	Categorical	'Life Sciences' 'Other' 'Medical' 'Marketing' 'Technical Degree' 'Human Resources'
8	EmployeeCount	int64	Numerical	Counter: 1 for each row
9	EmployeeNumber	int64	Numerical	Probably Employee ID

Column	Features	Data type	Data type	Values
10	EnvironmentSatisfaction	int64	Ordinal	1 'Low' 2 'Medium' 3 'High' 4 'Very High'
11	Gender	object	Categorical	'Female' 'Male'
12	HourlyRate	int64	Numerical	In a currency not known
13	JobInvolvement	int64	Ordinal	1 'Low' 2 'Medium' 3 'High' 4 'Very High'
14	JobLevel	int64	Ordinal	From 1 to 5 but the meaning of the level is not known.
15	JobRole	object	Categorical	'Sales Executive' 'Research Scientist' 'Laboratory Technician' 'Manufacturing Director' 'Healthcare Representative' 'Manager' 'Sales Representative' 'Research Director' 'Human Resources'
16	JobSatisfaction	int64	Ordinal	1 'Low' 2 'Medium' 3 'High' 4 'Very High'
17	MaritalStatus	object	Categorical	'Single' 'Married' 'Divorced'
18	MonthlyIncome	int64	Numerical	In a currency not known
19	MonthlyRate	int64	Numerical	In a currency not known
20	NumCompaniesWorked	int64	Numerical	Integer
21	Over18	object	Categorical	Y
22	OverTime	object	Categorical	'Yes' 'No'
23	PercentSalaryHike	int64	Numerical	%
24	PerformanceRating	int64	Ordinal	1 'Low' 2 'Good'

Column	Features	Data type	Data type	Values
				3 'Excellent' 4 'Outstanding'
25	RelationshipSatisfaction	int64	Ordinal	1 'Low' 2 'Medium' 3 'High' 4 'Very High'
26	StandardHours	int64	Numerical	In hours
27	StockOptionLevel	int64	Ordinal	From 0 to 3 but the meaning of the level is not known.
28	TotalWorkingYears	int64	Numerical	In years
29	TrainingTimesLastYear	int64	Numerical	In times
30	WorkLifeBalance	int64	Ordinal	1 'Bad' 2 'Good' 3 'Better' 4 'Best'
31	YearsAtCompany	int64	Numerical	In years
32	YearsInCurrentRole	int64	Numerical	In years
33	YearsSinceLastPromotion	int64	Numerical	In years
34	YearsWithCurrManager	int64	Numerical	In years

INITIAL PLAN FOR DATA EXPLORATION

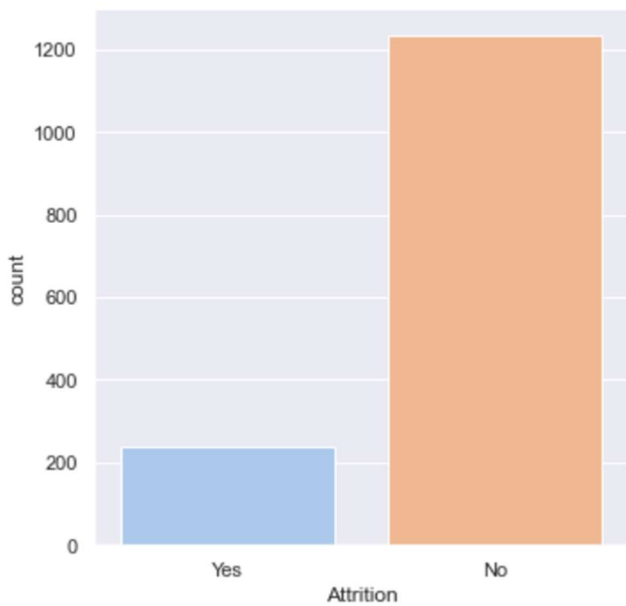
➔ Initial plan for data exploration

Attrition is the target variable and has 2 outcomes:

- **Yes,** the employee leaves the company
- **No,** the employee stays in the company

Thus, the problem is a **binary classification** problem.

Let's see now the distribution between employees who leaves and those who stays in the company:



This distribution is **imbalanced:**

- 237 employee leaves the company (16%)
- 1233 employees stays in the company (84%)

The Plan for data exploration is:

- Analyze target variable
- Describe features statistics
- Analyze relationships between features and target variable
- Analyze relationships between features and other features

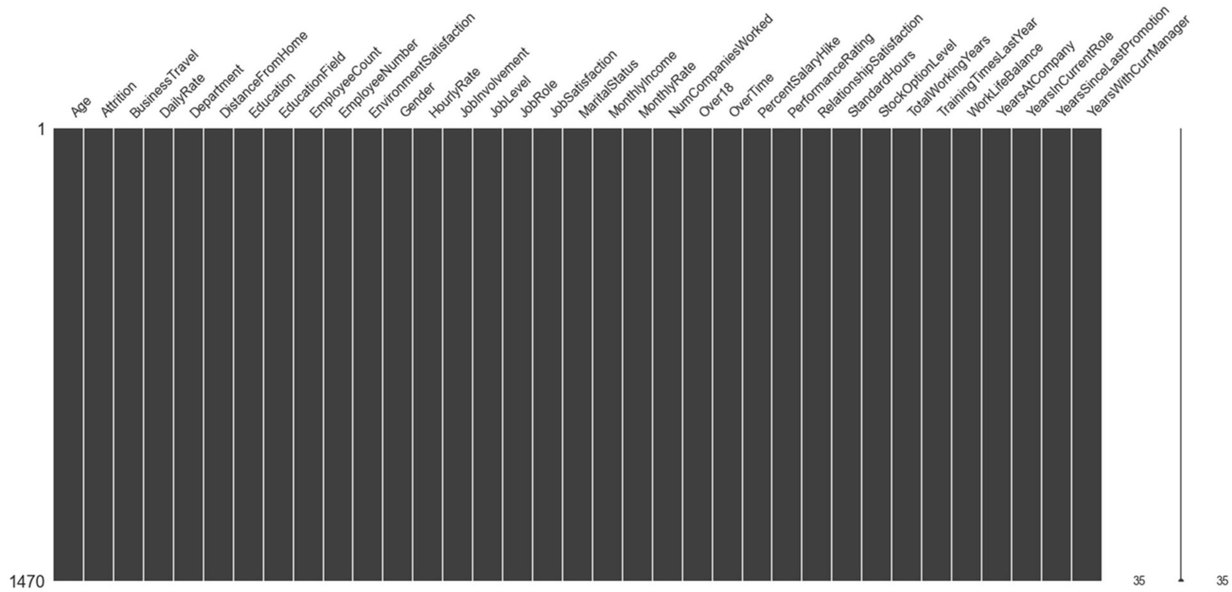
DATA CLEANING AND FEATURE ENGINEERING

➔ Actions taken for data cleaning and feature engineering

MISSING VALUES

In this dataset, there are no missing values.

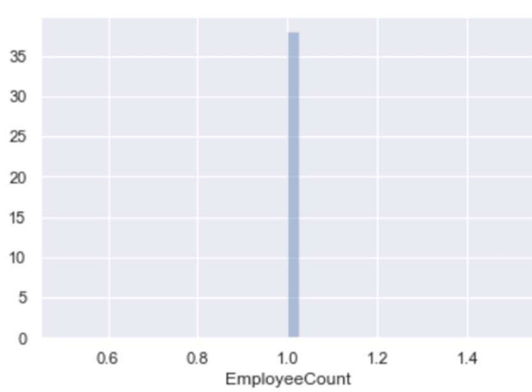
Indeed, there are no blank in the following missing data chart:



UNNECESSARY FEATURES

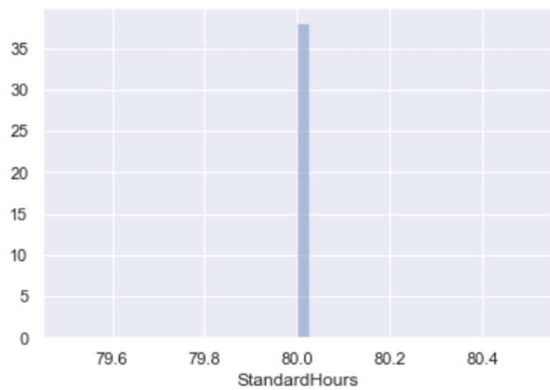
Let's see if the dataset contains unnecessary features.

Here is the distribution of feature **EmployeeCount**:



There is a unique value for all samples (probably an employee counter), so this feature can be removed as it does not bring any valuable information.

It is exactly the same with feature **StandardHours**:



All employees have 80 standard hours, so this feature can be removed as it does not bring any valuable information.

The categorical feature **Over18** has only 1 value: Y for Yes

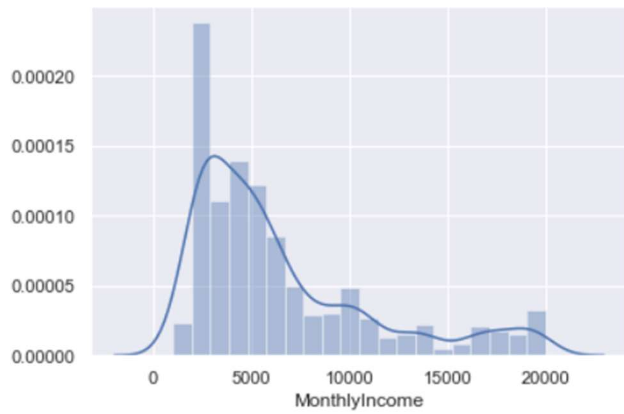
As all employees are other 18 years, this feature can be removed as it does not bring any valuable information.

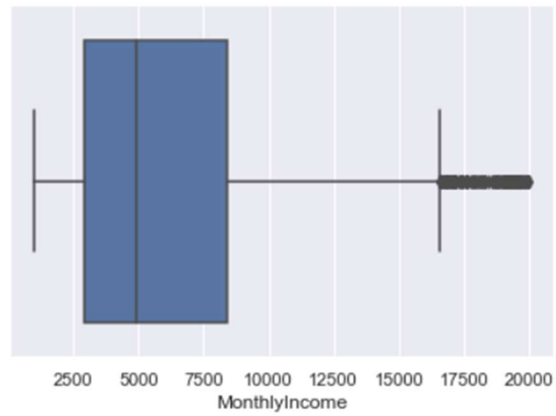
The feature **EmployeeNumber** contain the Employee ID and thus does not bring any valuable information. But, before removing it, it can be interesting to check for duplicates.

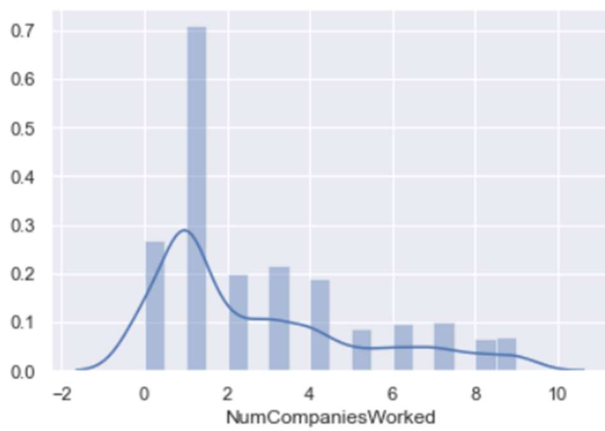
After verification, there are no duplicate on the feature **EmployeeNumber**, so this feature can be removed.

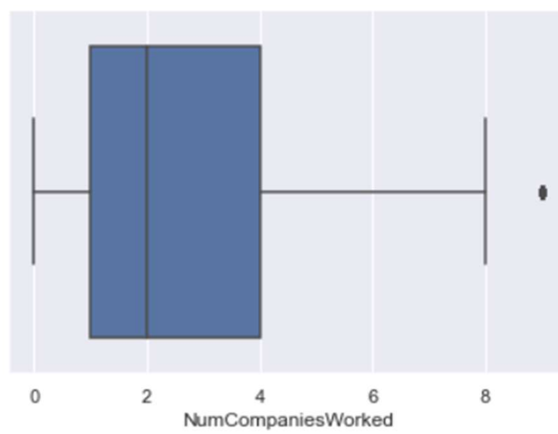
OUTLIERS

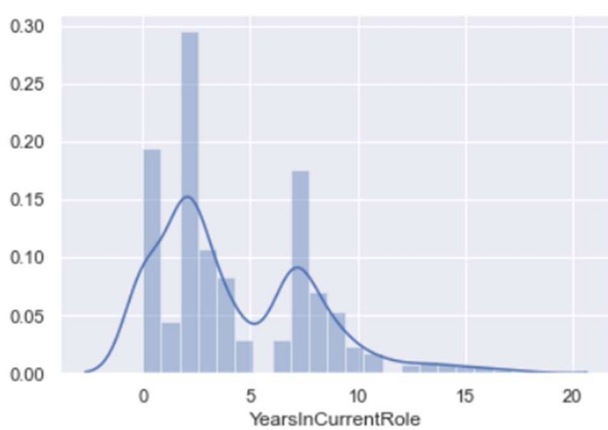
Now, regarding outliers, we have the following features with outliers:

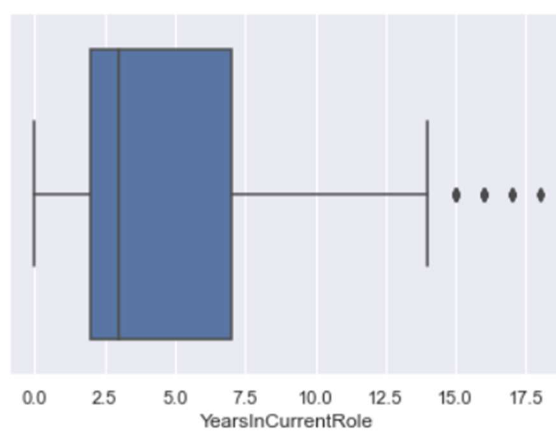


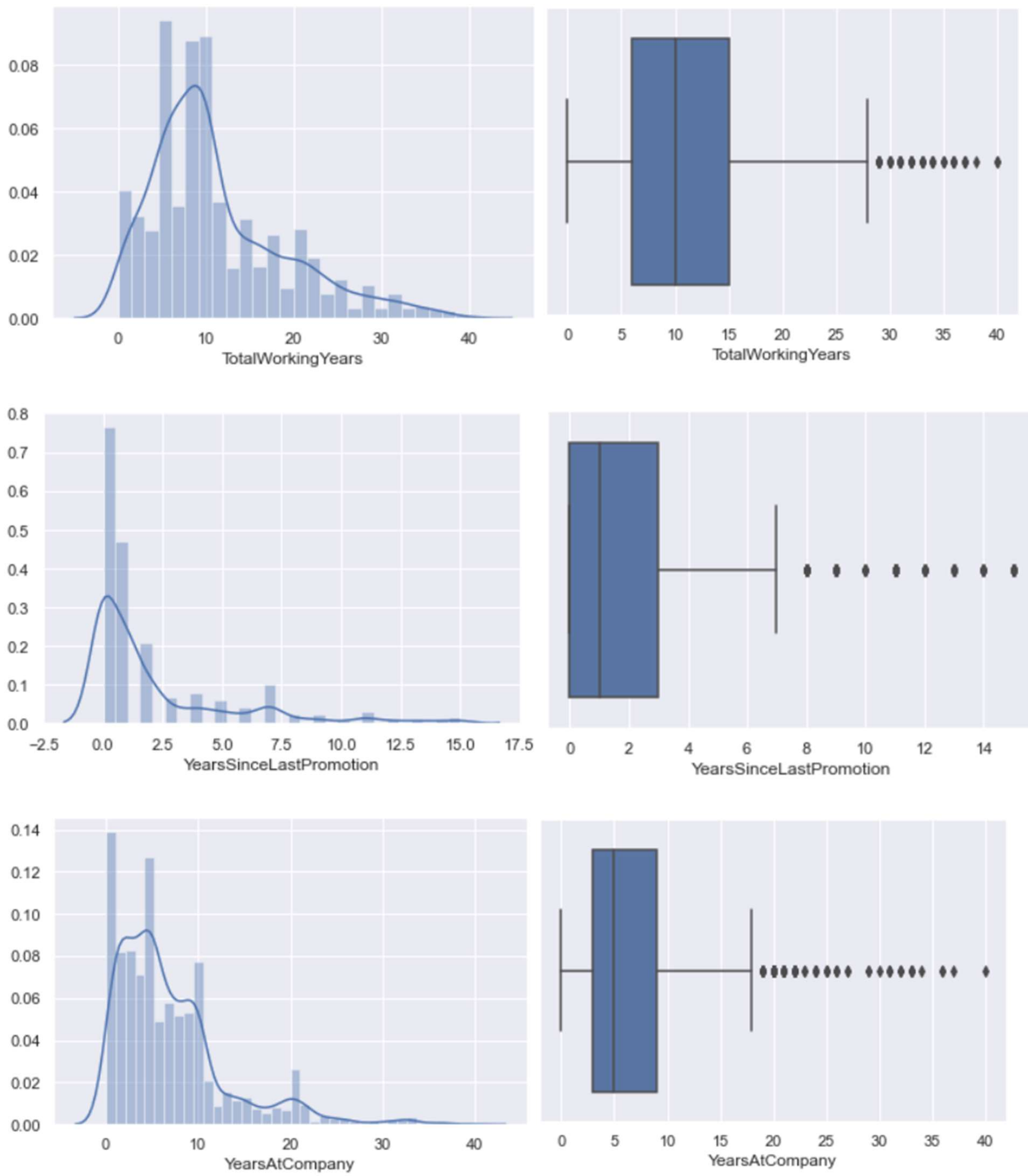












MonthlyIncome, TotalWorkingYears, YearsSinceLastPromotion, YearsAtCompany have a lot of outliers.

At this stage, I keep the outliers with the assumption that I will focus later on models that are resistant to outliers.

FEATURE ENGINEERING

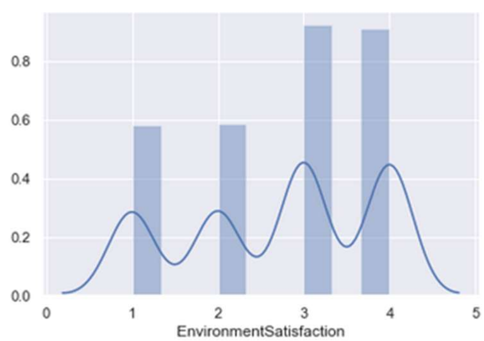
I notice that there are 3 features related to satisfaction:

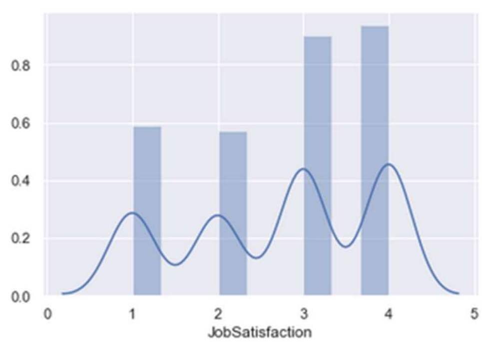
- EnvironmentSatisfaction
- JobSatisfaction
- RelationshipSatisfaction

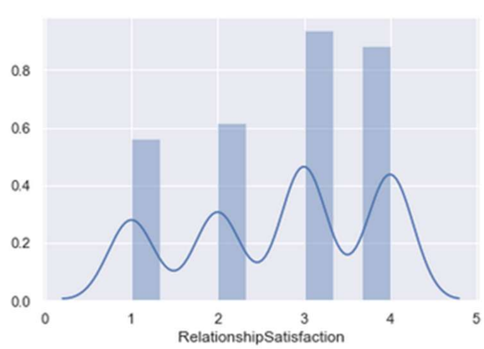
They are all ordinal data with the same possible values:

- 1 - 'Low'
- 2 - 'Medium'
- 3 - 'High'
- 4 - 'Very High'

Here are their distribution:

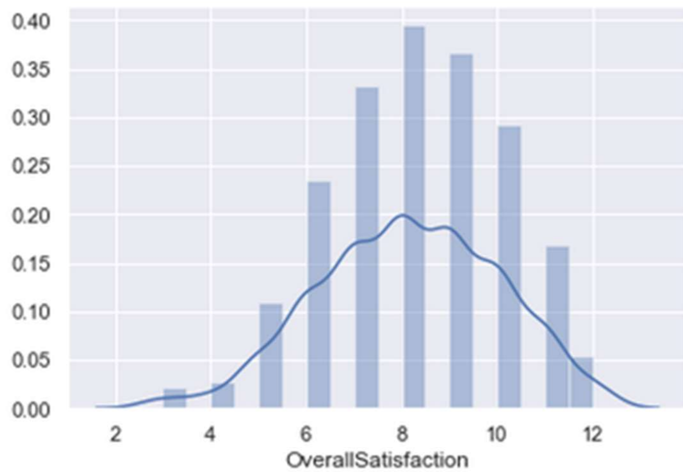






I can group them in a single one, we can name OverallSatisfaction. This new feature will contain the sum of the 3 types of satisfaction.

Here is the distribution of the new feature:



This looks like a nice normal distribution!

I could go deeper in feature engineering by regrouping values with few samples in categorical features.

SCALING

Usually, numerical data of a dataset have different scales.

This is the case here where features **MonthlyIncome** and **MonthlyRate** have a bigger scales than other features:

	mean	std	min	25%	50%	75%	max
Age	36.923810	9.135373	18.000000	30.000000	36.000000	43.000000	60.000000
DailyRate	802.485714	403.509100	102.000000	465.000000	802.000000	1157.000000	1499.000000
DistanceFromHome	9.192517	8.106864	1.000000	2.000000	7.000000	14.000000	29.000000
HourlyRate	65.891156	20.329428	30.000000	48.000000	66.000000	83.750000	100.000000
MonthlyIncome	6502.931293	4707.956783	1009.000000	2911.000000	4919.000000	8379.000000	19999.000000
MonthlyRate	14313.103401	7117.786044	2094.000000	8047.000000	14235.500000	20461.500000	26999.000000
NumCompaniesWorked	2.693197	2.498009	0.000000	1.000000	2.000000	4.000000	9.000000
PercentSalaryHike	15.209524	3.659938	11.000000	12.000000	14.000000	18.000000	25.000000
TotalWorkingYears	11.279592	7.780782	0.000000	6.000000	10.000000	15.000000	40.000000
TrainingTimesLastYear	2.799320	1.289271	0.000000	2.000000	3.000000	3.000000	6.000000
YearsAtCompany	7.008163	6.126525	0.000000	3.000000	5.000000	9.000000	40.000000
YearsInCurrentRole	4.229252	3.623137	0.000000	2.000000	3.000000	7.000000	18.000000
YearsSinceLastPromotion	2.187755	3.222430	0.000000	0.000000	1.000000	3.000000	15.000000
YearsWithCurrManager	4.123129	3.568136	0.000000	2.000000	3.000000	7.000000	17.000000

Later, I will probably evaluate models that require scaled features. So, I will need to proceed to numerical data scaling.

ENCODING

In the dataset, there are categorical data and ordinal data. They need to be encoded before they can be included in certain models.

Categorical data overview before encoding:

	count	unique	top	freq
Attrition	1470	2	No	1233
BusinessTravel	1470	3	Travel_Rarely	1043
Department	1470	3	Research & Development	961
EducationField	1470	6	Life Sciences	606
Gender	1470	2	Male	882
JobRole	1470	9	Sales Executive	326
MaritalStatus	1470	3	Married	673
OverTime	1470	2	No	1054

Ex with the first 5 lines of the dataset:

	Attrition	BusinessTravel	Department	EducationField	Gender	JobRole	MaritalStatus	OverTime
0	Yes	Travel_Rarely	Sales	Life Sciences	Female	Sales Executive	Single	Yes
1	No	Travel_Frequently	Research & Development	Life Sciences	Male	Research Scientist	Married	No
2	Yes	Travel_Rarely	Research & Development	Other	Male	Laboratory Technician	Single	Yes
3	No	Travel_Frequently	Research & Development	Life Sciences	Female	Research Scientist	Married	Yes
4	No	Travel_Rarely	Research & Development	Medical	Male	Laboratory Technician	Married	No

- ➔ I will one hot encode those categorical features

Ordinal data overview before encoding:

	count	mean	std	min	25%	50%	75%	max
Education	1470.0	2.912925	1.024165	1.0	2.0	3.0	4.0	5.0
EnvironmentSatisfaction	1470.0	2.721769	1.093082	1.0	2.0	3.0	4.0	4.0
JobInvolvement	1470.0	2.729932	0.711561	1.0	2.0	3.0	3.0	4.0
JobLevel	1470.0	2.063946	1.106940	1.0	1.0	2.0	3.0	5.0
JobSatisfaction	1470.0	2.728571	1.102846	1.0	2.0	3.0	4.0	4.0
PerformanceRating	1470.0	3.153741	0.360824	3.0	3.0	3.0	3.0	4.0
RelationshipSatisfaction	1470.0	2.712245	1.081209	1.0	2.0	3.0	4.0	4.0
StockOptionLevel	1470.0	0.793878	0.852077	0.0	0.0	1.0	1.0	3.0
WorkLifeBalance	1470.0	2.761224	0.706476	1.0	2.0	3.0	3.0	4.0

- ➔ I will encode these ordinal data with ordinal transformer

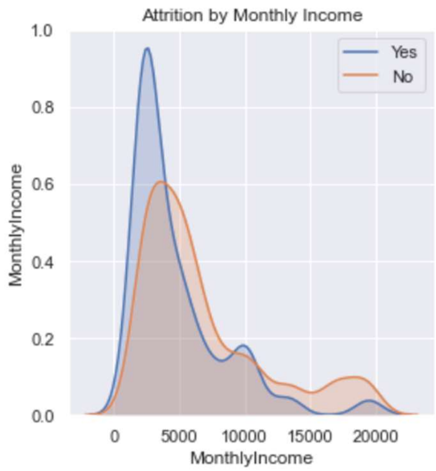
KEY FINDINGS AND INSIGHTS

- ➔ Key Findings and Insights, which synthesizes the results of Exploratory Data Analysis in an insightful and actionable manner

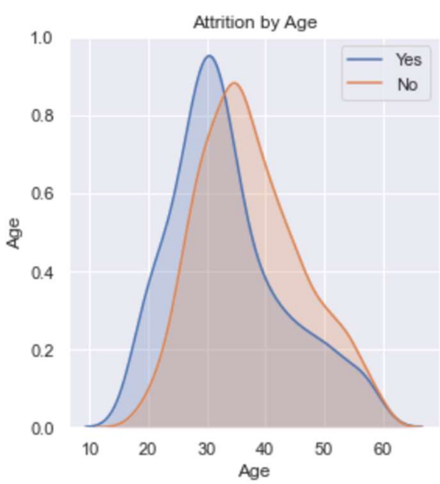
Employees with lower monthly income are more likely to leave the company.

The market is probably more attractive for those employees.

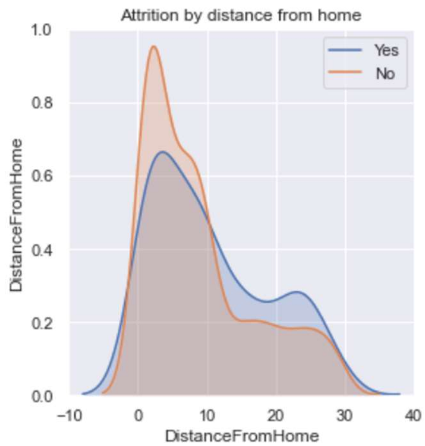
Increasing lowest salaries could reduce attrition.



Young employees are more likely to leave the company. There might be a correlation also with monthly income, to be investigated:



Employees who live next to the company are less likely to leave the company:

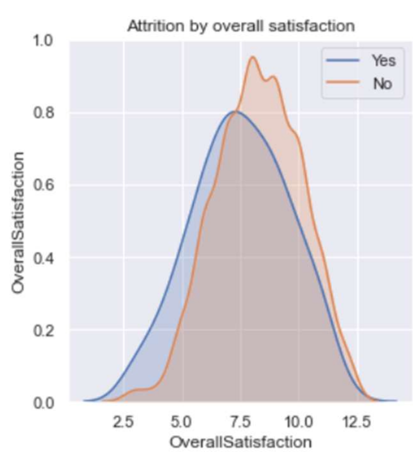


Majority of employees work in the Research & Development Department.

This department has the highest numbers of leavers, probably because it has the higher number of employees.

Actually, employees in Sales and HR are more likely to quit:

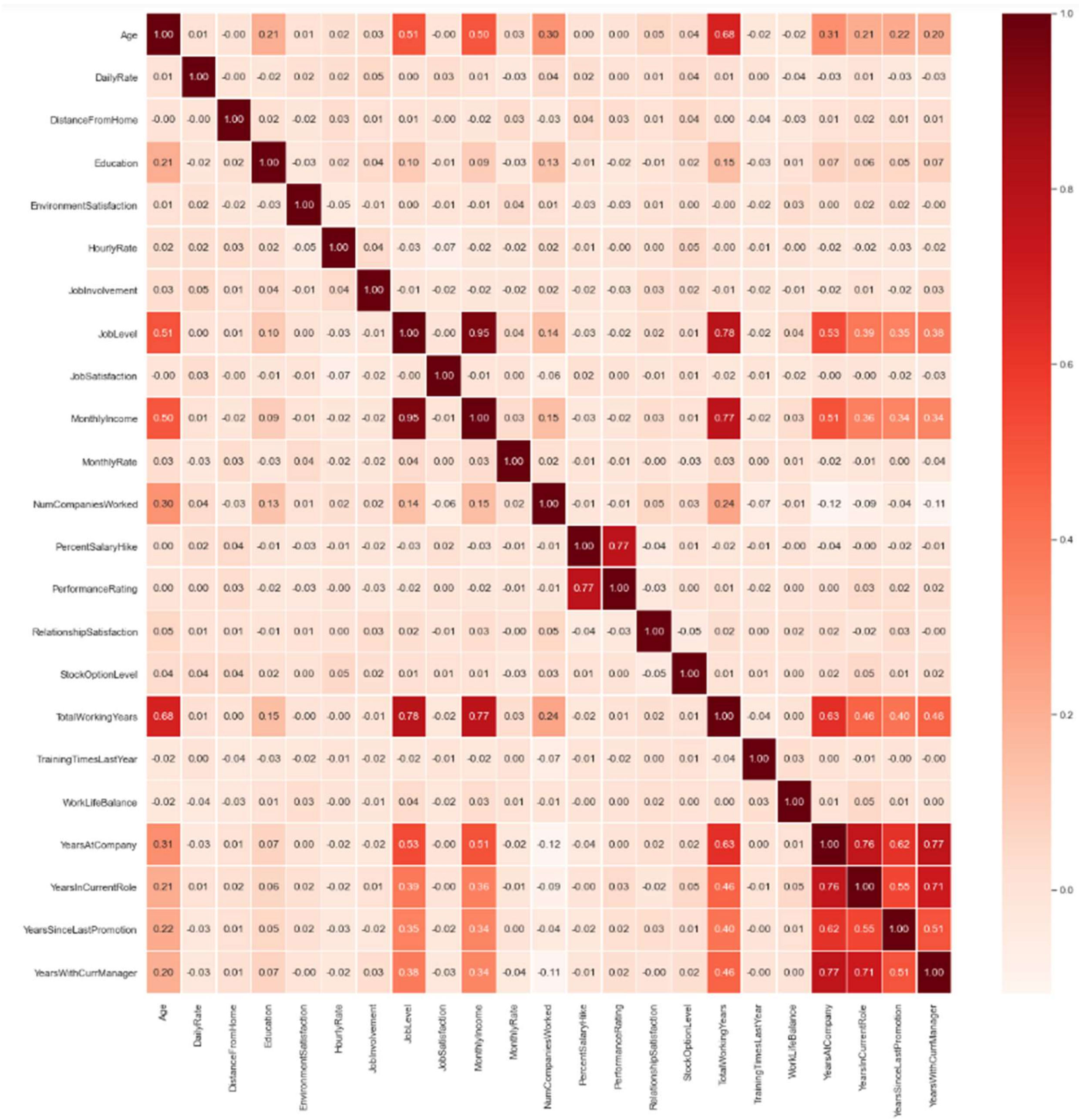
Employees with overall satisfaction (new created feature) are less likely to quit:



From the correlation analysis, we can see that:

- Monthly Income and Job Level are strongly correlated (0,95)
- Total Working Years are significatively correlated with
  - Job Level (0,78)
  - Monthly Income (0,77)
  - Age (0,68)
- Performance Rating and Percentage Salary Hike are significatively correlated (0,77)

There are also a lot of correlation with features linked to years of service as a whole.



- ➔ As we have correlated data, we will probably need later to select the features we keep for models evaluation.

HYPOTHESIS ABOUT THE DATA

- ➔ Formulating at least 3 hypothesis about this data

I formulate the following hypothesis n°1:

Null hypothesis: Group of employees who stays and leaves the company have the same overall satisfaction mean.

Alternative hypothesis: Group of employees who stays and leaves the company do not have the same overall satisfaction mean.

I formulate the following hypothesis n°2:

Null hypothesis: Group of employees who stays and leaves the company have the same monthly income mean.

Alternative hypothesis: Group of employees who stays and leaves the company do not have the same monthly income mean.

I formulate the following hypothesis n°3:

Null hypothesis: Group of employees who stays and leaves the company have the same distance from work.

Alternative hypothesis: Group of employees who stays and leaves the company do not have the same distance from work mean.

SIGNIFICANCE TEST FOR ONE OF THE HYPOTHESES

➔ Conducting a formal significance test for one of the hypotheses and discuss the results

I will proceed to a **two sample T-test,** also known as the independent samples T-test.

This type of statistical test compares two averages (means) and will give us information if these two means are statistically different from each other. The t-test also tells you whether the differences are statistically significant. In other words it lets you know if those differences could have happened by chance.

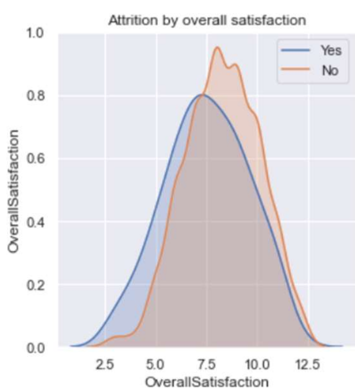
Here are the hypothesis:

<u>Null hypothesis:</u> Group of employees who stays and leaves the company have the same **overall satisfaction** mean.

<u>Alternative hypothesis:</u> Group of employees who stays and leaves the company do not have the same **overall satisfaction** mean.

I will have a look now on the assumptions of this parametric test:

- <u>Assumption 1:</u> Are the two samples independent? Yes, employees who stays and those who leaves are different.
- <u>Assumption 2:</u> Are the data from each of the 2 groups following a normal distribution? Yes



- <u>Assumption 3:</u> Do the two samples have the same variances (Homogeneity of Variance)? Yes

	OverallSatisfaction							
	count	mean	std	min	25%	50%	75%	max
Attrition								
No	1233.0	8.283861	1.824849	3.0	7.0	8.0	10.0	12.0
Yes	237.0	7.531646	2.061566	3.0	6.0	8.0	9.0	12.0

I decide to fix the significance level $\alpha = 5\%$.

The two sample T-test gives a P value = P-value = 1.56e-08

The P-value of the test is less than the significance level alpha (e.g., 0.05). I reject the null hypothesis. This means that I can conclude that average overall satisfaction of leavers is statistically different from the average overall satisfaction of employees who stays in the company.

SUGGESTIONS FOR NEXT STEPS IN ANALYZING THIS DATA

- ➔ Suggestions for next steps in analyzing this data

Continue both the univariate and multivariate analysis.

Think about new features than could be created through feature engineering.

DATA QUALITY

- ➔ A paragraph that summarizes the quality of this data set and a request for additional data if needed

The data set has a good quality level (fictional dataset). There are no missing values. There are quite a lot of features.

From an HR perspective, this dataset could contain the precise date of leaving. Then, it would be possible to run a time series analysis.

In this dataset, we could have had additional data such as absenteeism.

APPENDIX: CODE

The code for this project is available on GITHUB:

https://github.com/Olivier-FONTAINE/IBM-Machine-Learning-professional-certificate/blob/main/01-EDA-Employee%20attrition.ipynb