Predicting Employee Attrition

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Contents

1 Introduction

Attrition is a terminology in human resources which refers to the employees leaving the company. Attrition is measured by the number of employees are going out of the company either by voluntary resigning or laid off by the company. In general, high attrition is problematic for companies that causes the huge loss. There are many reasons for which the employees leave the company, such as; salary dissatisfaction, no career growth etc. The loss is not only in terms of the money but also the company sometimes loses the skilled employees who are the most valuable assets to the company (Morrison, 2014). If the company can predict the employee attrition (employees which are going to leave the company) in near future, they can also work on retention beforehand and avoid the loss of valuable employee. The prediction of attrition and retention is the part of the HR Analytics. how to retain talent and avoid attrition in the organizations.

In this project, I analyze the IBM Employee Attrition dataset to find the main factors why employees choose to leave and to help the company to predict whether or not a certain employee will leave the company by utilizing machine learning models.

2 Data Acquisition

We used IBM HR Analytics Employee Attrition & Performance dataset from Kaggle. The data is a fictional data set created by IBM data scientists. The data can be reached from this link. The data has 35 columns and 1470 observations and contains numeric and categorical data types. Each row has various attributes from each unique employee such as age, gender, job role, educational field, marital status, monthly income etc.

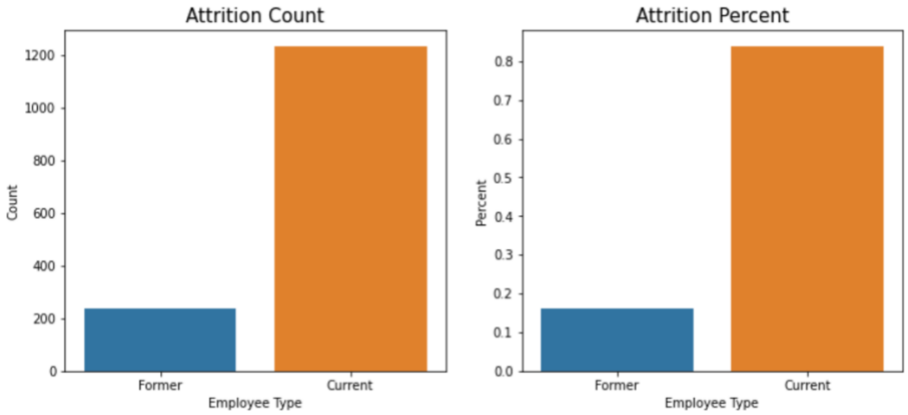
3 Data Cleaning

There are no missing values. Also, there are no duplicated values in the dataset. “Over18”, “EmployeeCount” and “StandardHours” variables are deleted since they contain only one value and there is no variation in these features. “EmployeeNumber” is also deleted because it has all unique numbers like ID (unique indentifier) and it doesn’t generate any value for the model. We count the number of employees who left the company vs who stayed in the company.

4 Exploratory Data Analysis

4.1 Target Variable (Attrition):

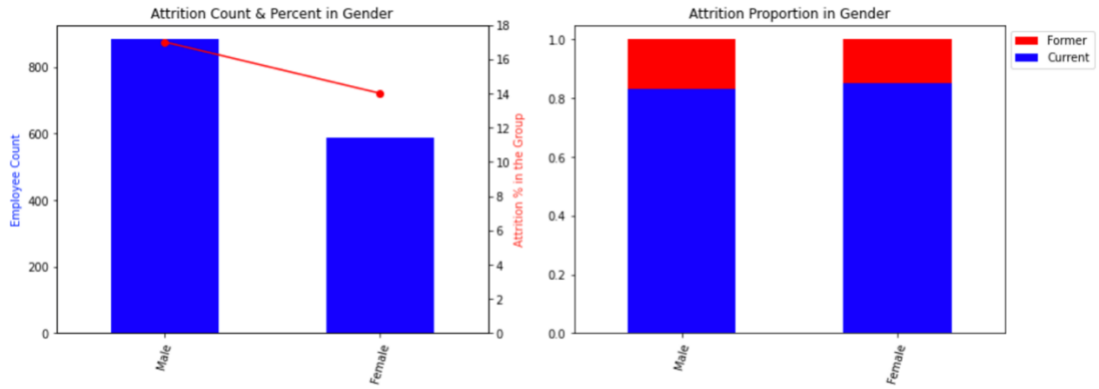
There are 1233 employees who stayed and 237 employees who left the company. As it is shown in the chart below, 16% of the employees left the company which tells us there is quite a large skew in target. Therefore, we have a quite big imbalance in our target variable. We will use an oversampling method known as SMOTE to treat the imbalance in the data.



4.2 Features

4.2.1 Gender:

Gender	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
Male	882	150	17	63
Female	588	87	14	36



According to the table and charts above, we see that the number of male employees is higher than females. Also, the attrition rate in males is higher than females.

4.2.1.1 Hypothesis Testing:

Hypothesis testing is a statistical method that is used in making statistical decisions using experimental data. Hypothesis Testing is basically an assumption that we make about the population parameter.

4.2.1.1.1 Testing Employee Counts in Gender:

There are 558 females and 882 males are in the company. There is a difference between the employee counts. Is the difference significant? Is it too big or not really big? We can find the answer by using Chi Square test. The Chi Square statistics is commonly used for testing relationships between categorical variables. We want to see the difference in numbers between female and male employee categories.

Null Hypothesis:

H_0: There is no difference in the number of males and females in the company.

Alternative Hypothesis:

H_A: There is difference in the number of males and females in the company.

Category	Observed	Expected	Residual = Obsereved - Expected	(Residual)^2	(Residual)^2/Expected	Chi Square Score	Degree of Freedom	P Value
Female	588	735	-147	21609	29.4	58.8	1	< 0.05
Male	882	735	147	21609	29.4			

We used 95% significance level. As in the statistical calculation table above, the p value is less than 0.05. Therefore, we fail reject null hypothesis. We are confident that we can accept that there is no statistically significant difference between the number of males and females.

4.2.1.1.2 Testing Attrition Rates in Gender:

The attrition rate in male is 17% and 14% in female. It is obvious that male attrition is more than female attrition. Is the difference significant? Since we compare the attrition rate and the sample size is greater than 30 it is appropriate to use a two-proportion z-test.

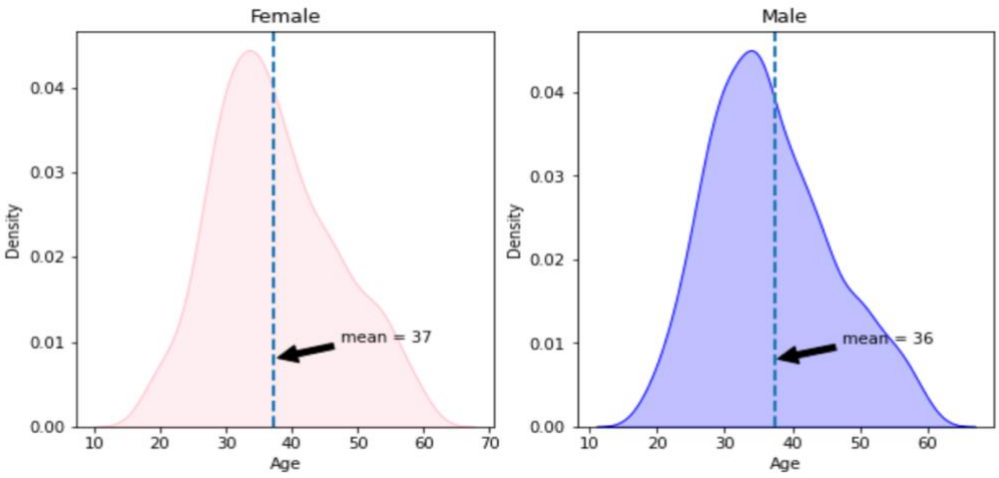
H_0: There is no difference in the attrition rate for male and female employees in the company

H_A: There is a significant difference in the attrition rate for males and female employees in the company.

Category	Observed	Attrition	Proportion	Overall Proportion	Z Score	P Value
Female	588	87	0.147959184	0.16122449	1.129254781	< 0.05
Male	882	150	0.170068027			

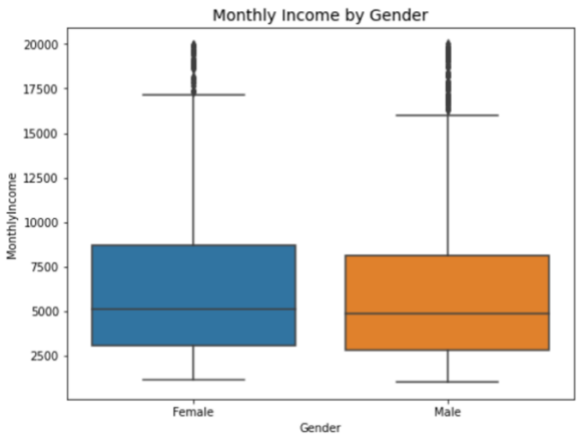
The p-value in the table above is below the significance level (0.05). Therefore, I fail to reject the null hypothesis. I can conclude that there is no significant difference in the attrition rates between female and male employees in the company.

4.2.1.2 Age Distribution by Gender:



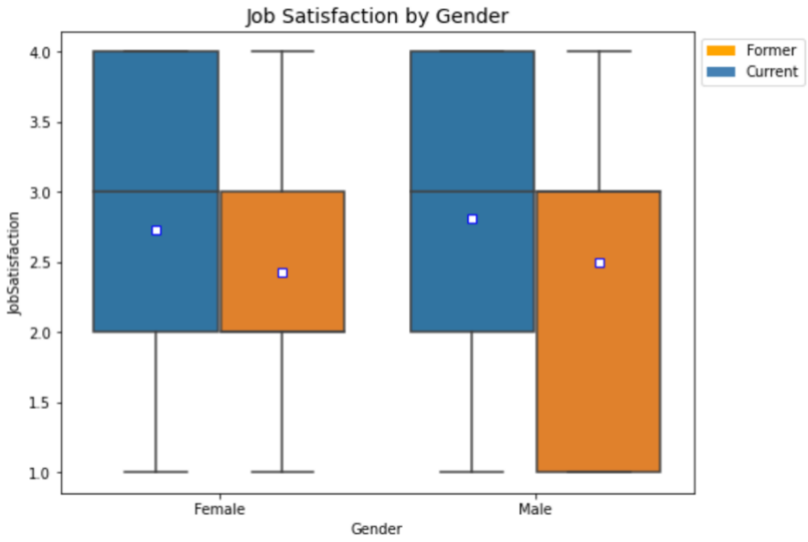
What is the age distribution between males and females? They both have the same distribution as below. The average age of females is 37 and for males is 36.

4.2.1.3 Monthly Income by Gender:



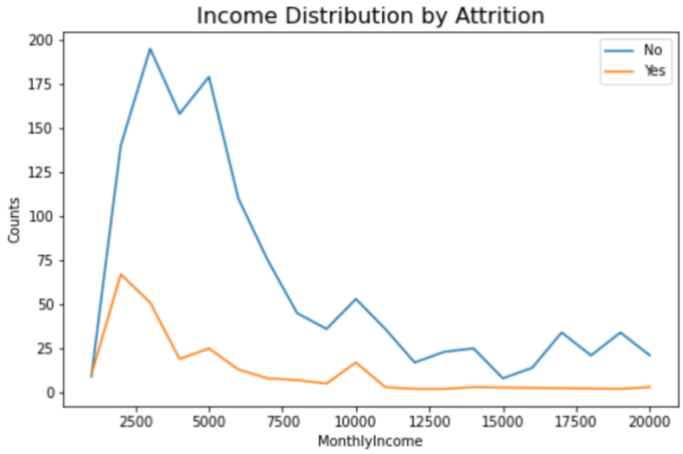
Is there any gender disparity in income? Based on the chart above, it clearly shows that males and females have equal payments on average.

4.2.1.4 Job Satisfaction by Gender:



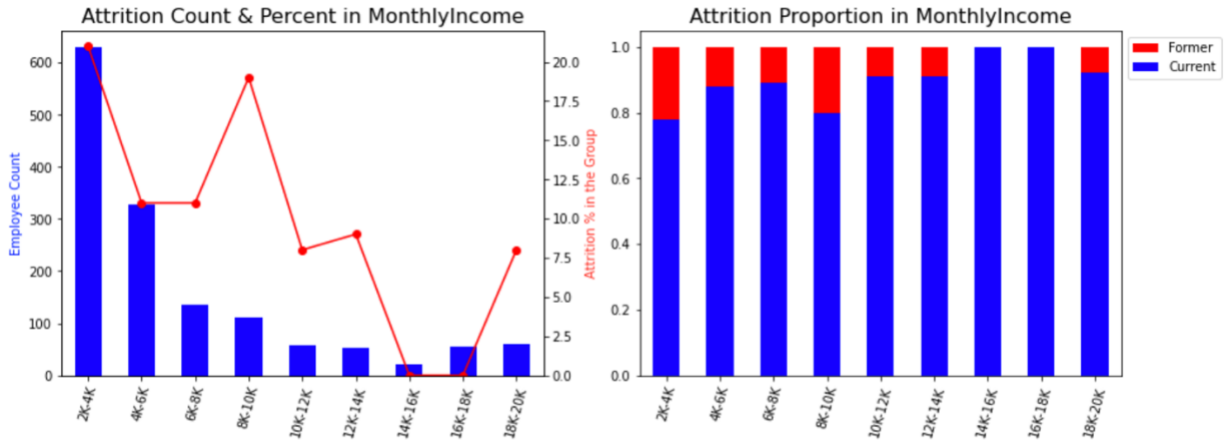
Based on the chart above, it is obvious that job satisfaction is low in males and females who left the company.

4.2.2 Monthly Income:

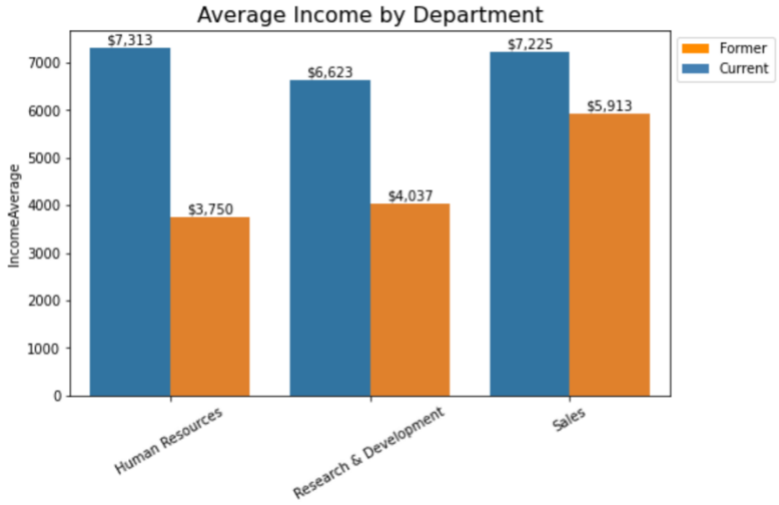


Is income the main factor toward employee attrition? As seen in the chart above, the attrition rate is obviously high at low-income levels, especially for the income levels less than $4,000. The attrition rate decreases after $4,000 but there is a minor spike at around $10,000. Employees at mid-income level tend to go to different company to upgrade salary or to shift toward a better standard of living. When the income is pretty decent, the chances of an employee leaving the company is low as it is seen by the flat line.

	MonthlyIncome	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	2K-4K	630	137	21	57
1	4K-6K	327	38	11	16
2	6K-8K	135	15	11	6
3	8K-10K	111	22	19	9
4	18K-20K	60	5	8	2
5	10K-12K	58	5	8	2
6	16K-18K	55	0	0	0
7	12K-14K	53	5	9	2
8	14K-16K	22	0	0	0

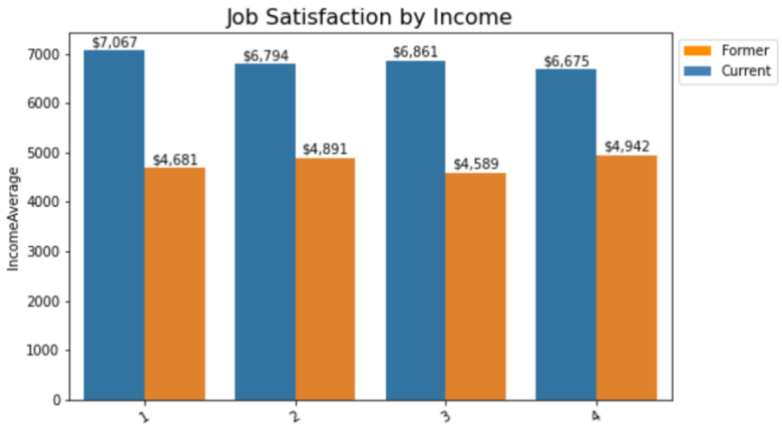


4.2.2.1 Monthly Income by Department:



The attrition rate is high in Sales department despite the high average income compared to other departments.

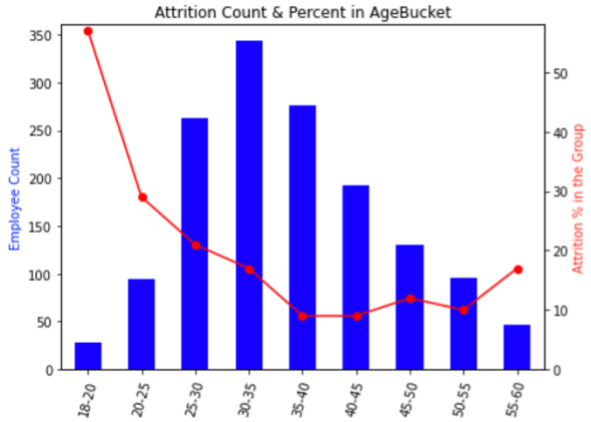
4.2.2.2 Job Satisfaction by Monthly Income:

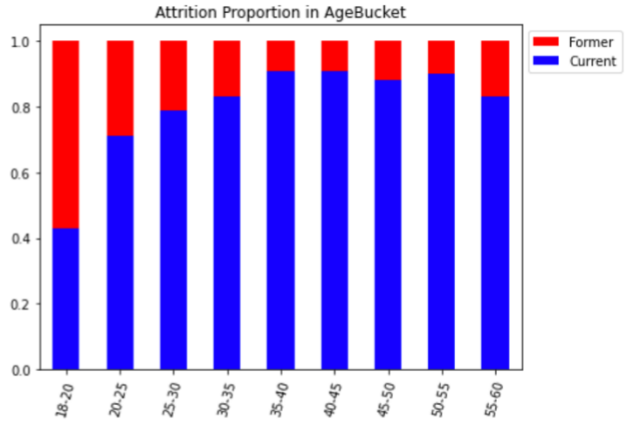


As it is clearly seen in the chart above, employees who left the company have low income in all satisfaction levels.

4.2.3 Age:

	AgeBucket	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	18-20	28	16	57	6
1	20-25	95	28	29	11
2	25-30	263	56	21	23
3	30-35	343	60	17	25
4	35-40	276	25	9	10
5	40-45	192	18	9	7
6	45-50	130	16	12	6
7	50-55	96	10	10	4
8	55-60	47	8	17	3

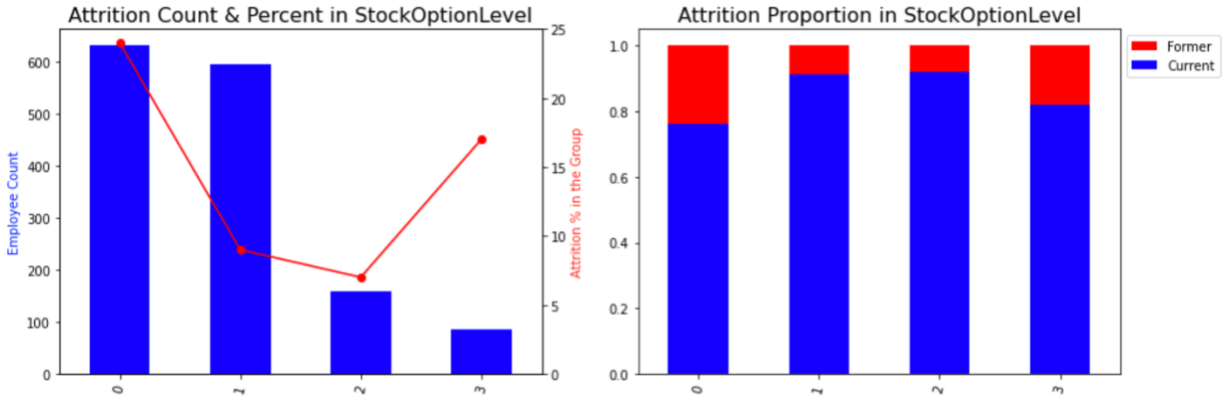




As it is seen in the chart above, the attrition very high for young people who are less than 25. The attrition keeps on failing with increasing age. After around age 35, people prefer stability in their jobs.

4.2.4 Stock Option:

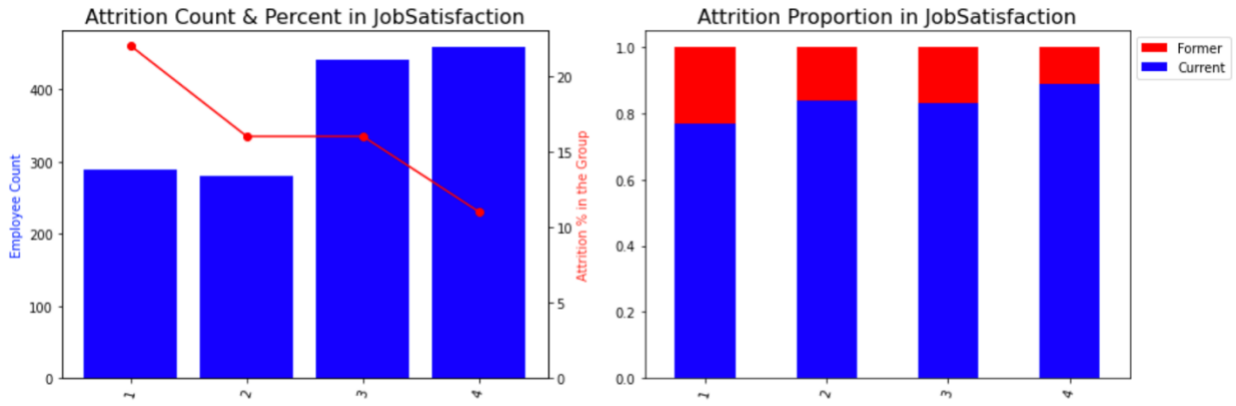
	StockOptionLevel	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	0	631	154	24	64
1	1	596	56	9	23
2	2	158	12	7	5
3	3	85	15	17	6



The tendency of employees to leave the company is high when there is low or no stock options. Since the stocks contributes a huge amount of money, people do not want to lose that opportunity. People tend to leave the company if they are not happy with stock options.

4.2.5 Job Satisfaction:

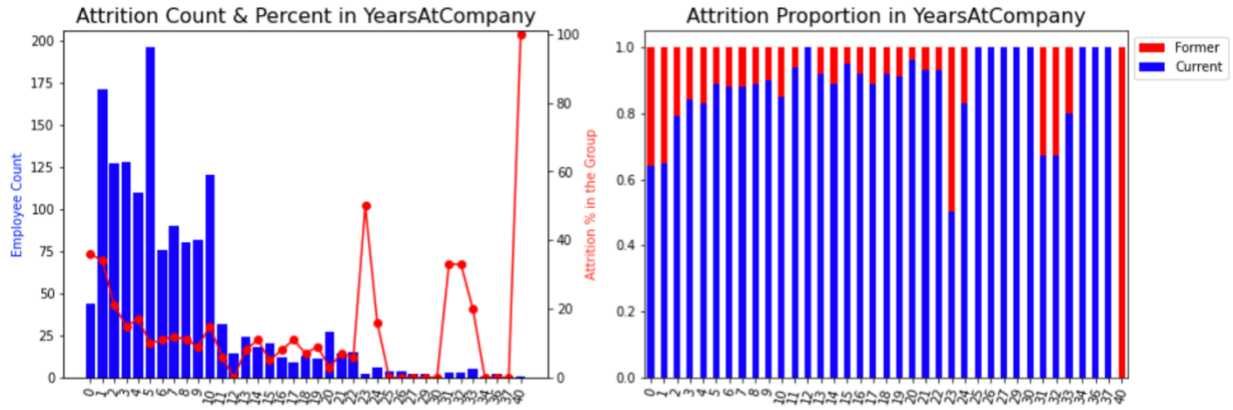
	JobSatisfaction	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	1	289	66	22	27
1	2	280	46	16	19
2	3	442	73	16	30
3	4	459	52	11	21



There are four job satisfaction levels in the data. 1 indicates low satisfaction and 4 indicates high satisfaction. As it is seen in the chart above, employees who have low job satisfaction most likely to leave the company more than employees who have high job satisfaction. The attrition rate in low job satisfaction is 27% and the attrition rate in high job satisfaction is 21%. With an increasing job satisfaction, the attrition rates decrease.

4.2.6 Years at Company:

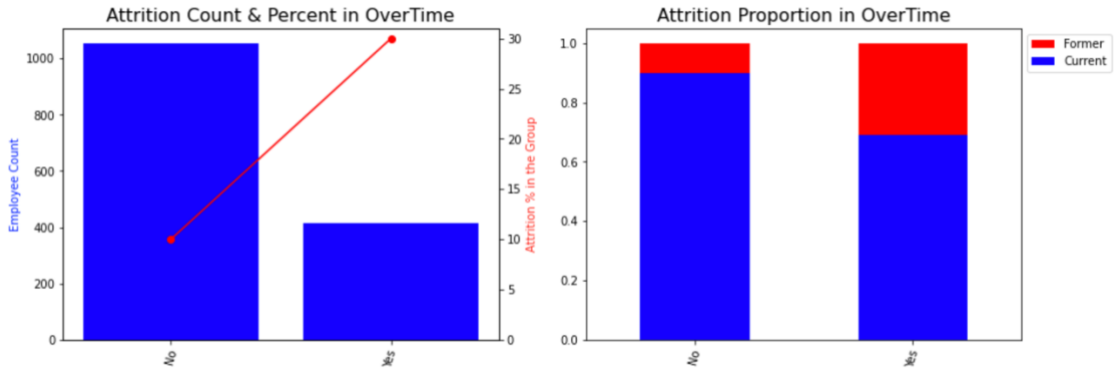
	YearsAtCompany	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	0	44	16	36	6
1	1	171	59	34	24
2	2	127	27	21	11
3	3	128	20	15	8
4	4	110	19	17	8
5	5	196	21	10	8
6	6	76	9	11	3
7	7	90	11	12	4
8	8	80	9	11	3
9	9	82	8	9	3
10	10	120	18	15	7



As it is seen in the chart and table above, employees who have two years or less working experience in the company has the highest attrition percentage. It composes 41% of the total attrition in the company. Employees who are in their initial years have a higher chance of leaving the company. People who have gained working experience tend to stay in the company.

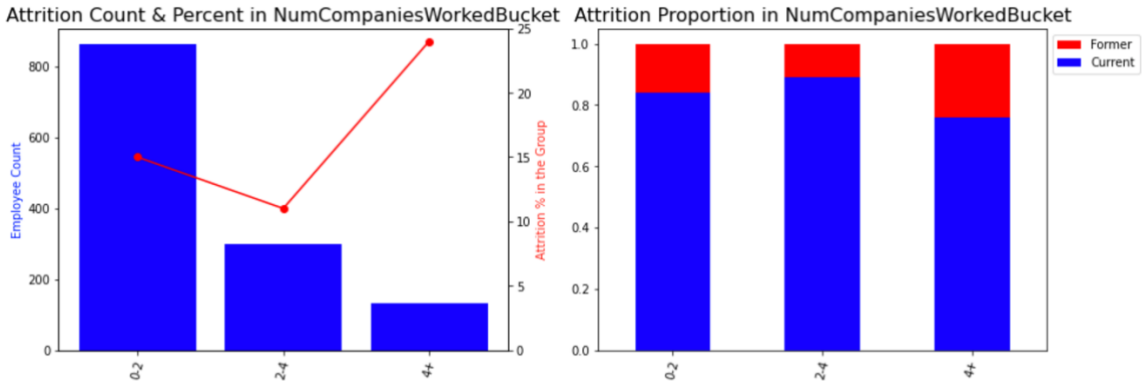
4.2.7 Over Time:

	OverTime	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	No	1054	110	10	46
1	Yes	416	127	30	53



4.2.8 Number of Companies Worked:

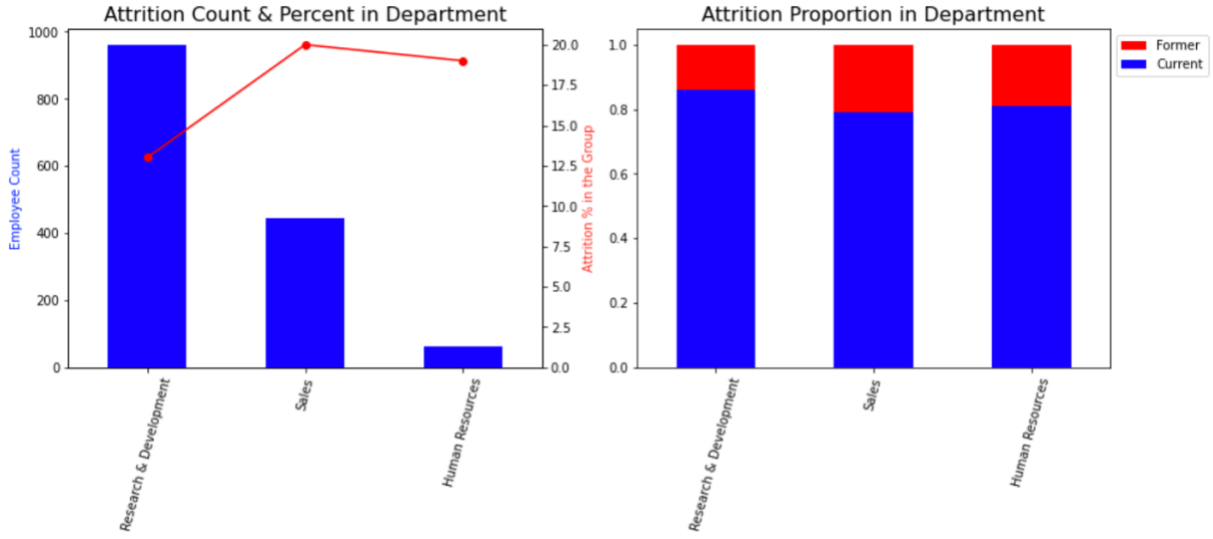
	NumCompaniesWorkedBucket	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	0-2	864	137	15	57
1	2-4	298	33	11	13
2	4+	133	32	24	13



Employees are more likely to leave the company if the number of companies they worked for before this company increases.

4.2.9 Department:

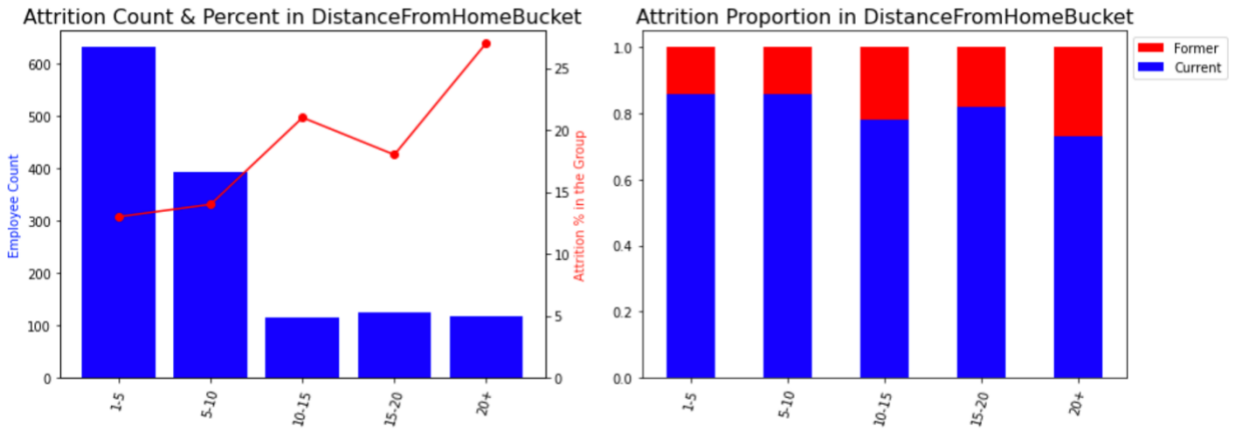
	Department	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	Research & Development	961	133	13	56
1	Sales	446	92	20	38
2	Human Resources	63	12	19	5



There are three departments in the company based on the data. The Sales Department has the highest attrition rates 20% and it is followed by the Human Resource Department which has 19%. Research and Development has the least attrition rates which shows employees prefer stability.

4.2.10 Distance from Home:

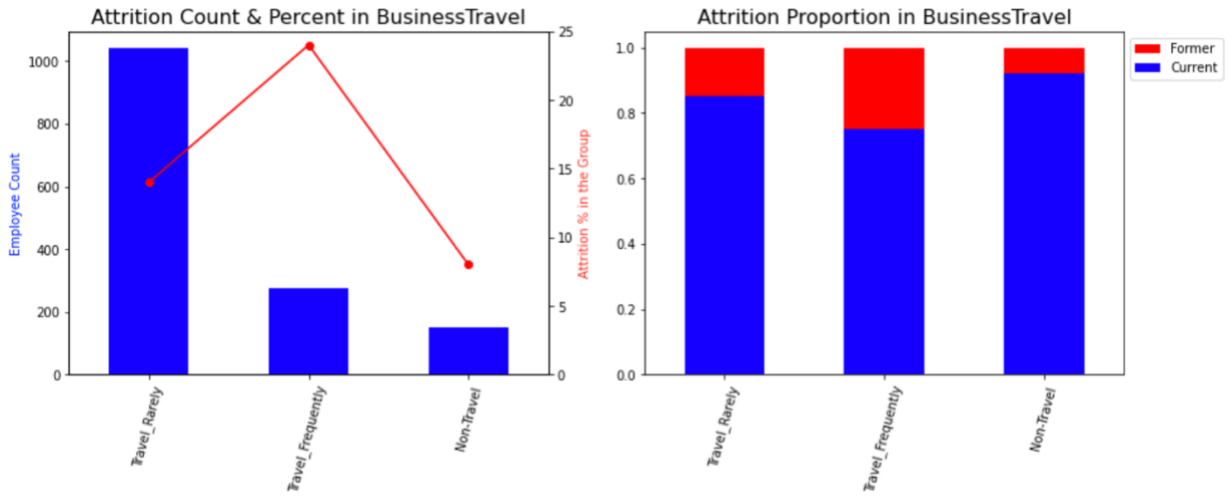
	DistanceFromHomeBucket	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	1-5	632	87	13	36
1	5-10	394	57	14	24
2	10-15	115	25	21	10
3	15-20	125	23	18	9
4	20+	117	32	27	13



How does the distance from home impact attrition? It is clearly shown in the chart that people who live more than 10 miles away from the company are more likely to leave the company. Employees who live more than 10 miles away from the company compose 1/3 of the whole company attrition.

4.2.11 Business Travel:

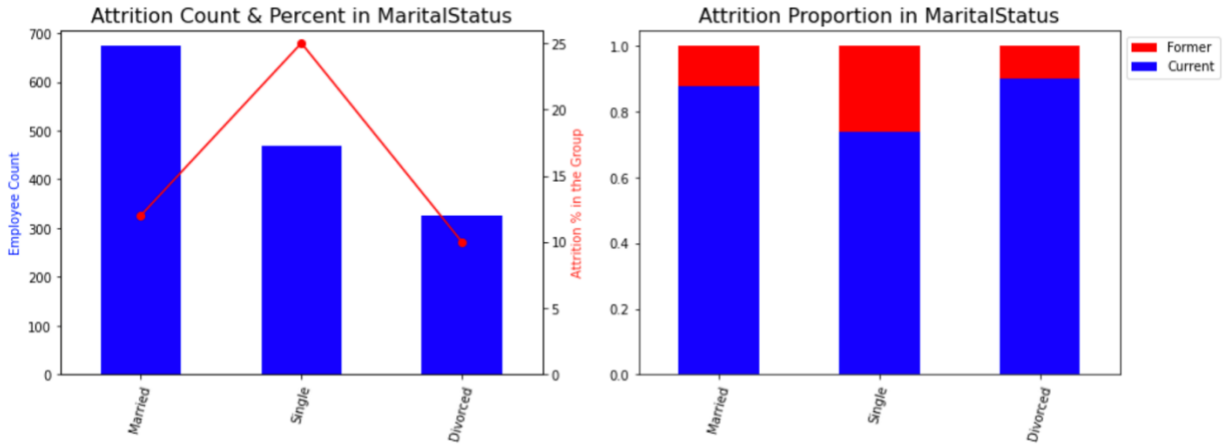
BusinessTravel	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
Non-Travel	150	12	8	5
Travel_Frequently	277	69	24	29
Travel_Rarely	1043	156	14	65



What is the impact of business travel? Employees who travel frequently have the highest attrition rate 24%. Employees who don't travel has the lowest attrition rate in the company 8%. People do not prefer to travel in general.

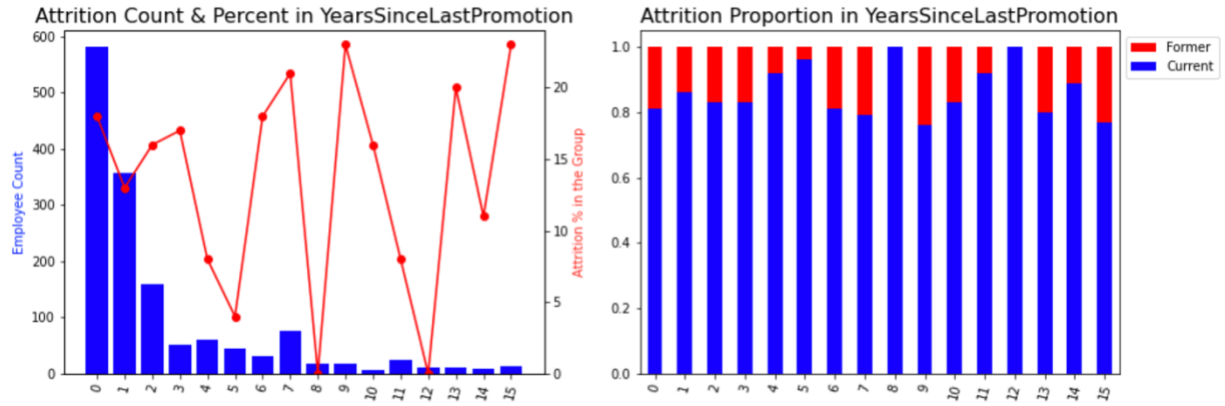
4.2.12 Marital Status:

	MaritalStatus	Employee Count	Attrition Count	Attrition % in the Group	Attrition % in the Company
0	Married	673	84	12	35
1	Single	470	120	25	50
2	Divorced	327	33	10	13



Single employees are more likely to leave the company. They have the highest attrition rate which makes up 50% of all attrition in the company.

4.2.13 Years Since Last Promotion:



There are 1097 employees who have less than 2 years since last promotion and 16% of those employees leave the company. Attrition rate increases if the number of years increases since the last promotion.

5 Data Pre-Processing

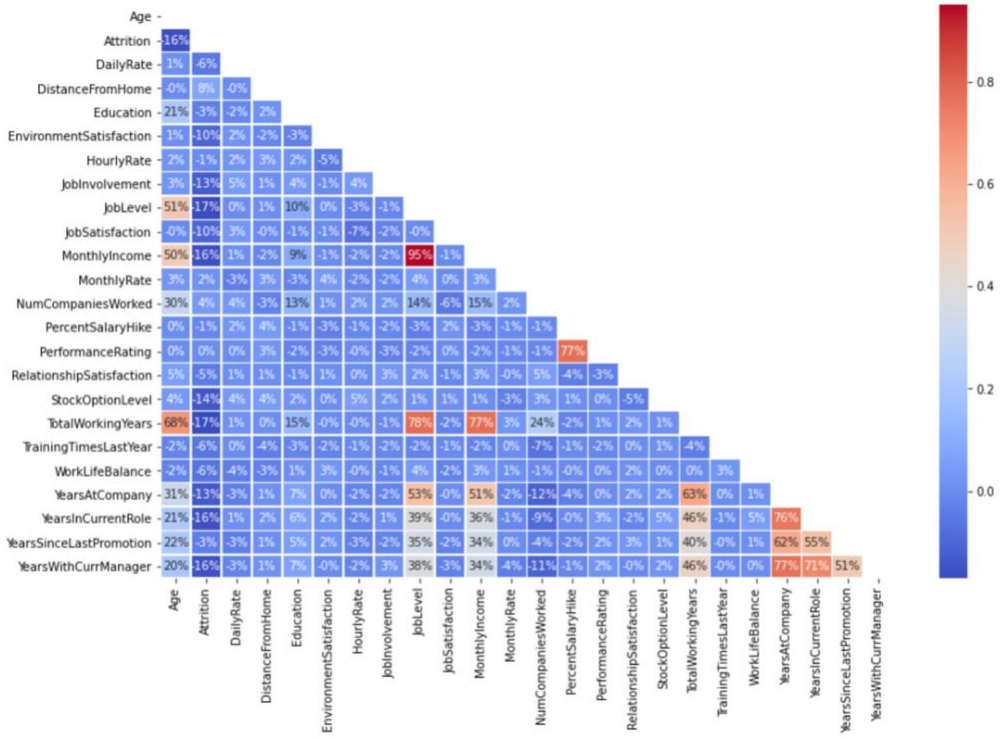
Before running the machine learning algorithms, I will do some pre-processing steps to make the dataset ready for model building.

5.1 Feature Selection

Feature selection is the process of reducing the number of input variables when developing a predictive model. It is desirable to reduce the number of input variables to both reduce the computational cost of modeling and, in some cases, to improve the performance of the model. Adding redundant variables reduces the generalization capability of the model and may also reduce the overall accuracy of a classifier. Furthermore, adding more and more variables to a model increases the overall complexity of the model.

Some features just have one data level that do not contribute anything to our model. EmployeeCount, Over18 and StandardHours, and employee number does not have meaning in analyzing resulting so we also deleted these features.

We built correlation matrix which is a table showing correlation coefficients between variables as in the heat map below. MonthlyIncome and JobLevel variables have strong correlation (95%). Therefore, we can remove JobLevel and keep MontlyIncome in the modeling part based on the results. The rest of the variables have less correlation in general, we will keep all others for now.



5.2 Dummy Variables

We need to convert all the categorical data into numerical data for the Machine Learning model to work. We have used one hot encoding to create dummy variables. The basic strategy is to convert each category value into a new column and assign a 1 or 0 (True/False) value to the column. Dummy coding is a commonly used method for converting a categorical variable into continuous variable.

5.3 Train Test Split

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model. First, we separated features and response variable as X and y. Then, we divided the dataset into the training and test sets. We have used 40% of the data for testing and 60% of the dataset for the training. Splitting our dataset is essential for an unbiased evaluation of prediction performance. We use the training set to build and train the model. Once the model is ready, we will test it on the testing set to see how well it performs.

5.4 Over Sampling Imbalance Data

An imbalanced classification problem is an example of a classification problem where the distribution of examples across the known classes is biased or skewed. Most of the machine learning algorithms used for classification that were designed around the assumption of an equal number of examples for each class. Imbalanced classifications significantly affect the model performance. This will result poor predictive performance, specifically for the minority class. As it is mentioned in the earlier sections, we have imbalanced data with 16% minority class. We have used oversampling method known as the SMOTE (Synthetic Minority Oversampling Technique) which increase the number of observations for the minority class. The SMOTE method randomly creates synthetic instances of the minority class so that the net observations of both the class get balanced out. We balanced only the training dataset and didn't touch the test dataset.

5.5 Feature Scaling

Each feature can have different magnitude and different units. Variables that are measured at different scales do not contribute equally to the model. Some machine learning models are sensitive for scaling and some are not. Since most of the machine learning algorithms use Euclidean distance between two data points in their computation, this is a problem. We used StandardScaler to scale the data. With this scaling method, features will have mean of 0 and a standard deviation of 1. We fit the scaler on the training data and then used it to transform the testing data. This would avoid any data leakage during the model testing process.

5.6. Variance Inflation Factor (VIF)

We will check multicollinearity in this section. Multicollinearity occurs when there are two or more independent variables in a multiple regression model, which have a high correlation among themselves. If there are some features that are highly correlated, we might have difficulty in distinguishing between their individual effects on the dependent variable. We will use Variance Inflation Factor (VIF) method to detect multicollinearity. Generally, a VIF above 10 indicates a high multicollinearity. However, we can keep some important features in the model even though if they have high VIF. We also know from the correlation matrix that JobLelvel has 95% correlation with MonthlyIncome. VIF also shows that they are multicollinear. In this case, we will remove JobLevel based on the table below.

	feature	VIF
0	const	202.093542
1	Age	2.044890
2	DailyRate	1.018198
3	DistanceFromHome	1.015515
4	Education	1.059352
5	EnvironmentSatisfaction	1.010099
6	HourlyRate	1.018318
7	JobInvolvement	1.016316
8	JobLevel	11.205067
9	JobSatisfaction	1.014511
10	MonthlyIncome	10.800070
11	MonthlyRate	1.012282
12	NumCompaniesWorked	1.257737
13	PercentSalaryHike	2.516385
14	PerformanceRating	2.513734
15	RelationshipSatisfaction	1.015771
16	StockOptionLevel	1.017682
17	TotalWorkingYears	4.767796
18	TrainingTimesLastYear	1.009917
19	WorkLifeBalance	1.014884
20	YearsAtCompany	4.587391
21	YearsInCurrentRole	2.718604
22	YearsSinceLastPromotion	1.674278
23	YearsWithCurrManager	2.774587

6 Model Development and Evaluation

6.1 Machine Learning Models

In this part, we build machine learning models to select important features that influence the employee attrition and classify the features to help us understand the main reason why people left the IBM company. We will construct the model to predict the employee attrition according to the given data. Since we have binary response variable in our data, we will use classification models. Our aim is to have a better accuracy of predicting attrition (Attrition = 1) which is “True Positive” in confusion matrix.

We will apply Logistic Regression, Random Forest Classification, KNN Classification, Support Vector Machine Classification, Gradient Boosting Classification and Adaptive Boost Classification algorithms to the IBM Employee Attrition data. Initially, we will apply machine learning algorithms with default parameters. Then, we will try to improve model performance by hyperparameter tuning. Then, we will move the threshold to see any change on the model performance.

6.2 Model Evaluation Metric

Once we built a classification model, we need to evaluate how good the predictions made by that model are. Accuracy can tell us whether a model is being trained correctly and how it may perform generally. However, it does not give detailed information regarding its application to the problem. The problem with using accuracy as our main performance metric is that it does not do well when we have a severe class imbalance. Accuracy is used when the True Positives and True negatives are more important.

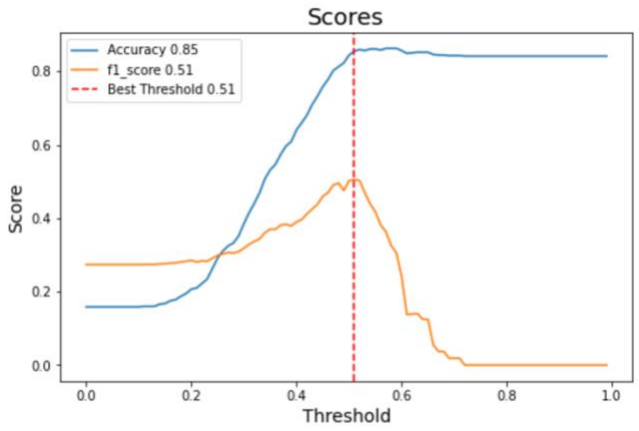
F1 is a harmonic mean of precision and recall. F1-score is used when the False Negatives and False Positives are crucial. A good F1 score means that we have low false positives and low false negatives, so we’re correctly identifying real threats and we are not disturbed by false alerts. Our data is highly imbalanced data. F1-score is a better metric when there are imbalanced classes. Therefore, we will use F1-score to select the best model.

6.3 Model Comparison Table

	default_model	grid_search_model	moved_threshold
Logistic Regression	0.4694	0.5024	0.5052
Random Forest	0.3014	0.4096	0.4889
KNN	0.2818	0.3305	0.3580
SVM	0.3380	0.3920	0.4107
Gradient Boosting	0.4118	0.4118	0.4608
ADA Boosting	0.3700	0.4615	0.4615

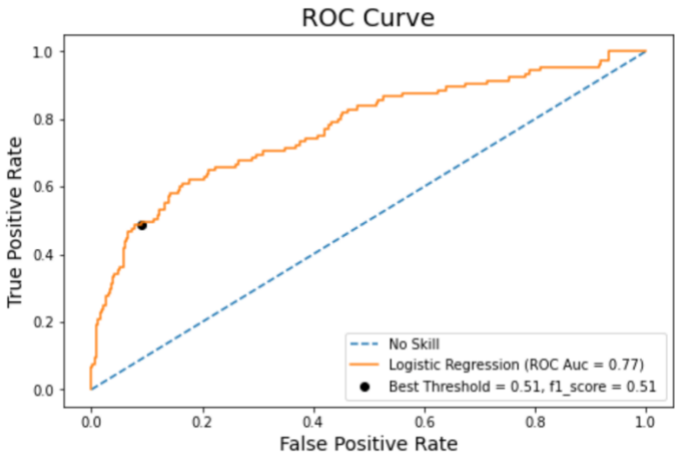
Based on the F1-score of different models, Logistic Regression gives higher F1-score (51%) when we move the threshold. Therefore, we will pick Logistic Regression to understand the factors that are impacting employee attrition.

6.4 Optimum Threshold



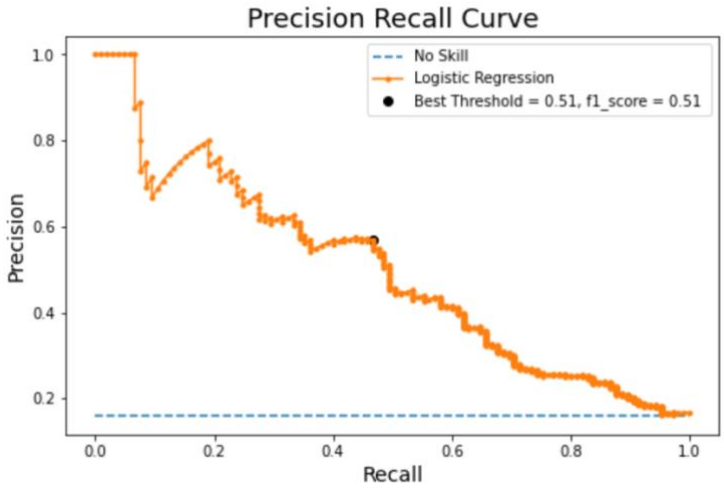
The default threshold for classification algorithms is 0.50. All predicted probabilities that are equal or greater than the threshold is mapped to 1 class and all other values are mapped to 0 class. Based on the chart above, we see that F1-score is having high value when threshold is 0.40. F1-score is decreased if we increase threshold.

6.4 ROC Curve



ROC AUC is a plot of the false positive rate (x-axis) versus the true positive rate (y-axis) for a number of different candidate threshold values between 0 and 1. It is a trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds. The AUC (Area under Curve) is 0.77. The plot shows that we have low False Positives and high True positives.

6.5 Precision Recall Curve



Precision-Recall is a useful measure of successful prediction when the classes are very imbalanced. A high area under the curve represents both high recall and high precision, where high precision relates to a low false positive rate, and high recall relates to a low false negative rate. High scores for both show that the classifier is returning accurate results (high precision), as well as returning a majority of all positive results (high recall).

7 Conclusion

7.1 Important Features

We will use coefficient values to explain the logistic regression model. However, coefficients are not directly related to importance. When a binary outcome variable is modeled using logistic regression, it is assumed that the logit transformation of the outcome variable has a linear relationship with the predictor variables.

$$\text{logit}(p) = \log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \log\left(\frac{P(y=1)}{P(y=0)}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$$

The logit transformation squeezes the output of a linear equation between 0 and 1. We get the odds ratio by taking the exponent of both side of the equation above.

$$\frac{P(y=1)}{1-P(y=1)} = \text{odds} = e^{(\boldsymbol{\beta_0+\beta_1 x_1+\cdots+\beta_n x_n})}$$

Then we compare what happens when we increase one of the feature values by 1. We will look at the ratio of two predictions.

$$\frac{\text{odds}_{x_j+1}}{\text{odds}} = \frac{e^{(\boldsymbol{\beta_0+\beta_1 x_1+\cdots+\beta_j(x_{j+1})+\cdots+\beta_n x_n})}}{e^{(\boldsymbol{\beta_0+\beta_1 x_1+\cdots+\beta_j x_j+\cdots+\beta_n x_n})}}$$

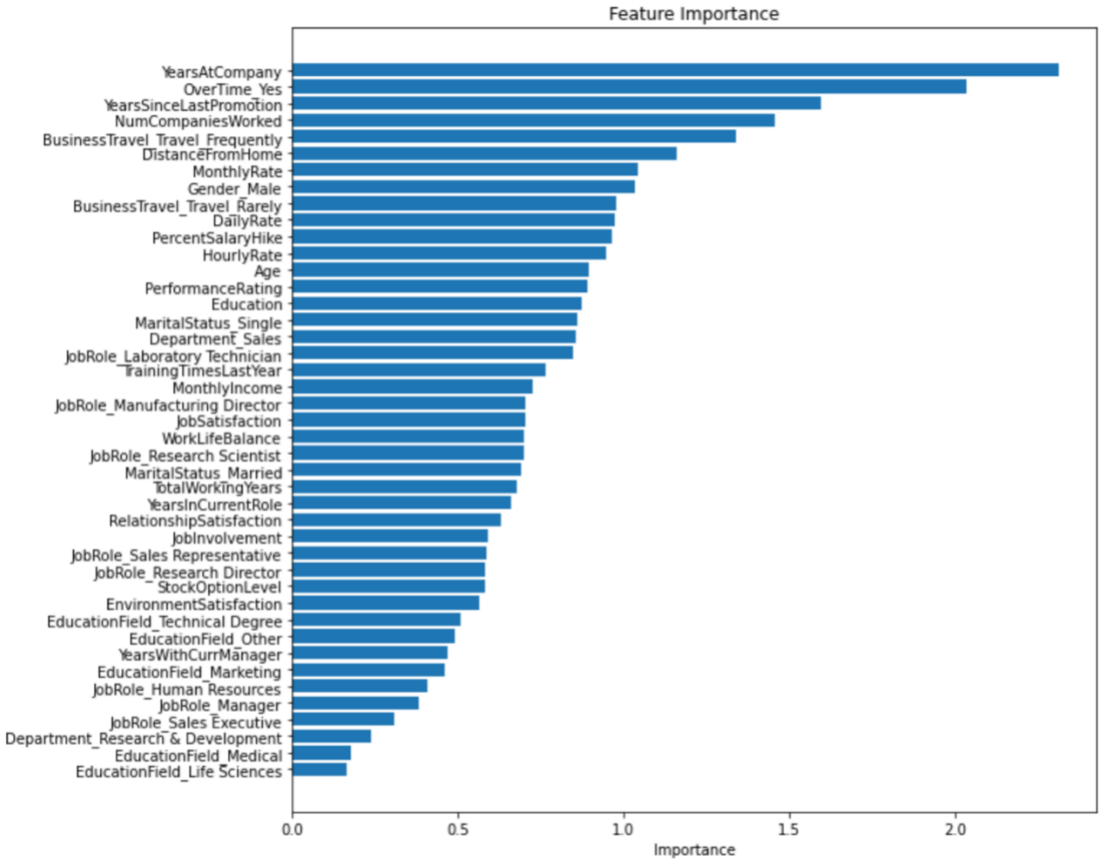
Then we apply this rule:

$$\frac{e^a}{e^b} = e^{(a-b)}$$

And we remove many terms:

$$\frac{\text{odds}_{x_j+1}}{\text{odds}} = e^{(\beta_j(x_j+1)-\beta_j x_j)} = e^{\beta_j}$$

This equation means that a change in a feature by one unit changes the odds ratio by a factor of e^{β_j}. We can apply this rule to the all coefficients to find the feature importance.



As it is seen from the feature importance plot, the strongest feature in employee attrition data is YearsAtCompany. An increase of the YearsAtCompany feature by one unit increases the odds ratio of YearsAtCompany by a factor of 2.3 when all other features remain the same.

7.2 Strong Factors in Employee Attrition:

1 23% of employees have two years or less working experience in the company and 30% of those employees leave the company. The model shows that number of years at company is the strongest factor in attrition. Employees who are in their first years are more likely to leave the company. Employees who have gained working experience prefer to stay in the company. Therefore, the company should understand why their new employees leave the company.

2 28% of employees works over time in the company and 30% of those employees leave the company. The model also shows that over time work is the second strongest factor in attrition. Therefore, the company should understand the reason why they are working overtime. Is it for too high workload or are employees' qualifications not enough to complete the scheduled tasks on time? There might be some other reasons behind that. Our recommendation will be to understand the reason(s) for overtime with detail research and take appropriate measures to reduce the factors behind this attrition factor.

3 There are 1097 employees who have less than 2 years since last promotion and 16% of those employees leave the company. Attrition rate increases if the number of years increases since the last promotion. Because of this reason, the company should review the promotion policy. They can make promotion requirements clear to all employees how and when they can be promoted.

4 9% of employees worked in 4 or more companies before this company and 24% of those employees leave the company. The company should understand why those employees are leaving the company. The company can question the applicants why they want to quit the previous job during interview process. The company can even get in touch with previous company.

5 19% of the employees travels frequently and 70% of those employees leave the company. This is one of the strongest factors in employee attrition. The company should understand if a high number of business travels are really necessary. They can adjust the frequency. If they can't, they can give some extra incentives to motivate those employees.

6 24% of the employees live more than 10 miles away from the company and 22% of those employees leave the company. The company should understand how distance is affecting their work. They can support their employees to move closer areas to the company by providing moving expenses. If they can't move closer due to their mandatory things, the company can adjust their work shift to prevent employees wasting their time from rush hours. The company can enable some days to working from home if they can.

7.3 Next Steps to Improve Model

7.2.1 More Data

In our data, we only have 1470 observations from the company. This is a poor data to create strong model predicting attrition before that happens. Because of this reason, the company should focus on collecting more data to improve predicting power of modeling. They can prepare surveys for the employees who are leaving and for the employees who stay in the company for longer years.

7.2.2 Bootstrap F1 Score

We have highly imbalance data. Therefore, the model score will have high variance. We will bootstrap F1 score. Bootstrapping is a statistical procedure that resamples a single dataset to create many simulated samples. This process allows for the calculation of standard errors, confidence intervals, and hypothesis testing. We will calculate the confidence interval of F1 score to get the stability of results.