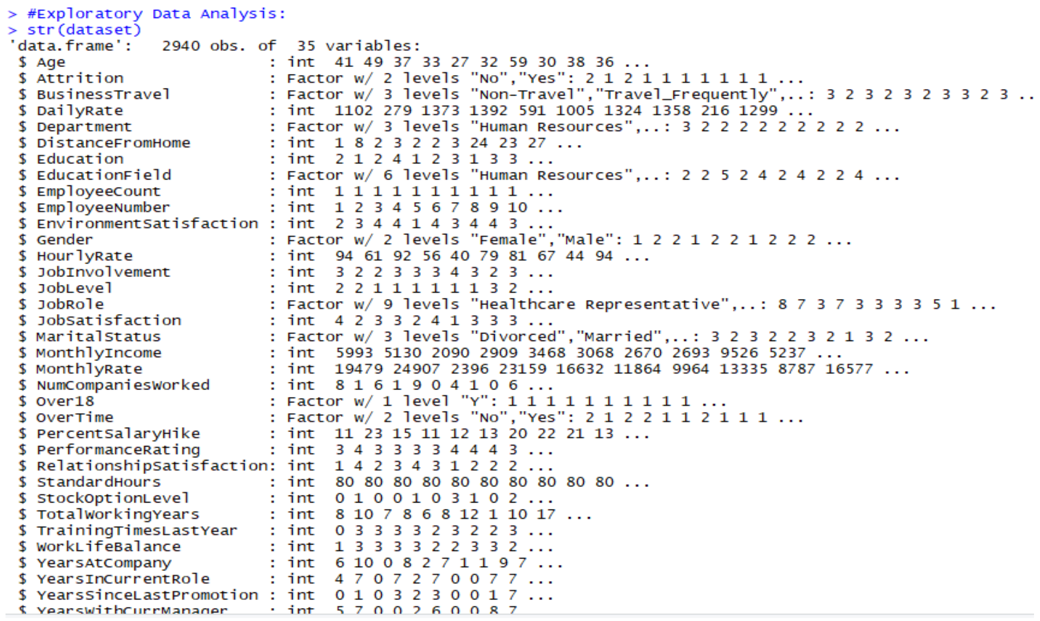
DATA MINING

Data Import (Target variable is "Attrition" column):

The data has been imported from"HR_Employee_Attrition_Data.csv" .

Perform Exploratory Data Analysis:

1.Structure of the dataset:



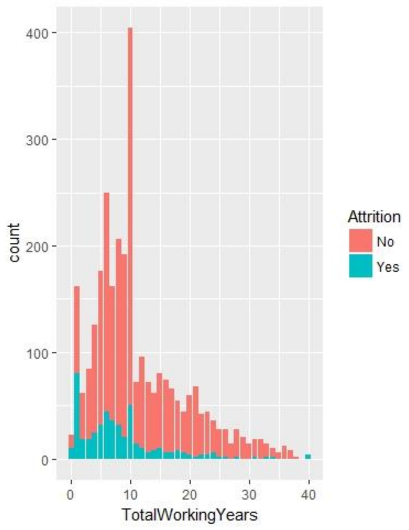
```
> #Exploratory Data Analysis:
> str(dataset)
'data.frame':	2940 obs. of  35 variables:
 $ Age                     : int  41 49 37 33 27 32 59 30 38 36 ...
 $ Attrition               : Factor w/ 2 levels "No","Yes": 2 1 2 1 1 1 1 1 1 1 ...
 $ BusinessTravel          : Factor w/ 3 levels "Non-Travel","Travel_Frequently",..: 3 2 3 2 3 2 3 3 2 3 ..
 $ DailyRate               : int  1102 279 1373 1392 591 1005 1324 1358 216 1299 ...
 $ Department              : Factor w/ 3 levels "Human Resources",..: 3 2 2 2 2 2 2 2 2 2 ...
 $ DistanceFromHome        : int  1 8 2 3 2 2 3 24 23 27 ...
 $ Education               : int  2 1 2 4 1 2 3 1 3 3 ...
 $ EducationField          : Factor w/ 6 levels "Human Resources",..: 2 2 5 2 4 2 4 2 2 4 ...
 $ EmployeeCount           : int  1 1 1 1 1 1 1 1 1 1 ...
 $ EmployeeNumber          : int  1 2 3 4 5 6 7 8 9 10 ...
 $ EnvironmentSatisfaction : int  2 3 4 4 1 4 3 4 4 3 ...
 $ Gender                  : Factor w/ 2 levels "Female","Male": 1 2 2 1 2 2 1 2 2 2 ...
 $ HourlyRate              : int  94 61 92 56 40 79 81 67 44 94 ...
 $ JobInvolvement          : int  3 2 2 3 3 3 4 3 2 3 ...
 $ JobLevel                : int  2 2 1 1 1 1 1 1 3 2 ...
 $ JobRole                 : Factor w/ 9 levels "Healthcare Representative",..: 8 7 3 7 3 3 3 3 5 1 ...
 $ JobSatisfaction         : int  4 2 3 3 2 4 1 3 3 3 ...
 $ MaritalStatus           : Factor w/ 3 levels "Divorced","Married",..: 3 2 3 2 2 3 2 1 3 2 ...
 $ MonthlyIncome           : int  5993 5130 2090 2909 3468 3068 2670 2693 9526 5237 ...
 $ MonthlyRate             : int  19479 24907 2396 23159 16632 11864 9964 13335 8787 16577 ...
 $ NumCompaniesWorked      : int  8 1 6 1 9 0 4 1 0 6 ...
 $ Over18                  : Factor w/ 1 level "Y": 1 1 1 1 1 1 1 1 1 1 ...
 $ OverTime                : Factor w/ 2 levels "No","Yes": 2 1 2 2 1 1 2 1 1 1 ...
 $ PercentSalaryHike       : int  11 23 15 11 12 13 20 22 21 13 ...
 $ PerformanceRating       : int  3 4 3 3 3 3 4 4 4 3 ...
 $ RelationshipSatisfaction: int  1 4 2 3 4 3 1 2 2 2 ...
 $ StandardHours           : int  80 80 80 80 80 80 80 80 80 80 ...
 $ StockOptionLevel        : int  0 1 0 0 1 0 3 1 0 2 ...
 $ TotalWorkingYears       : int  8 10 7 8 6 8 12 1 10 17 ...
 $ TrainingTimesLastYear   : int  0 3 3 3 3 2 3 2 2 3 ...
 $ WorkLifeBalance         : int  1 3 3 3 3 2 2 3 3 2 ...
 $ YearsAtCompany          : int  6 10 0 8 2 7 1 1 9 7 ...
 $ YearsInCurrentRole      : int  4 7 0 7 2 7 0 0 7 7 ...
 $ YearsSinceLastPromotion : int  0 1 0 3 2 3 0 0 1 7 ...
 $ YearsWithCurrManager    : int  5 7 0 0 2 6 0 0 8 7
```

2 .Descriptive Statistical Measures: Using summary (dataset)

3. Plots:

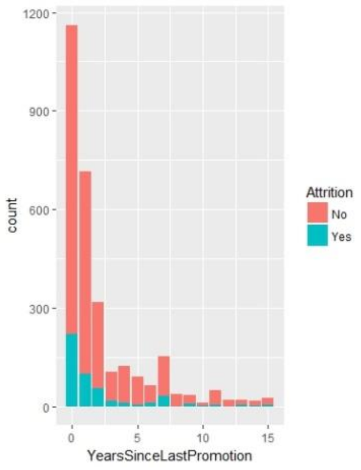
(i) Attrition:

The ratio of people in the company to people leaving the company is 1:5



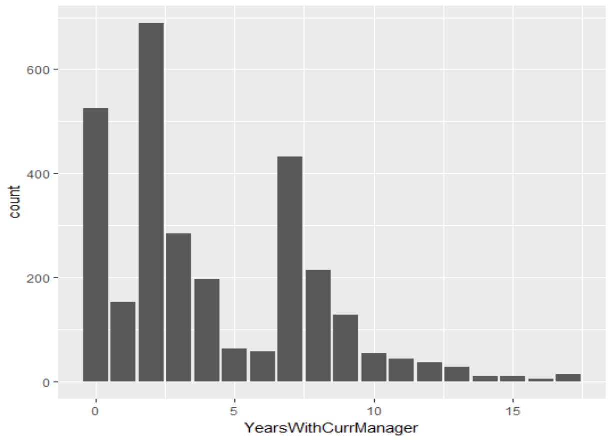
(ii) Yearssincelastpromotion vs Attrition:

People recently promoted quit the company more than the ones not promoted.



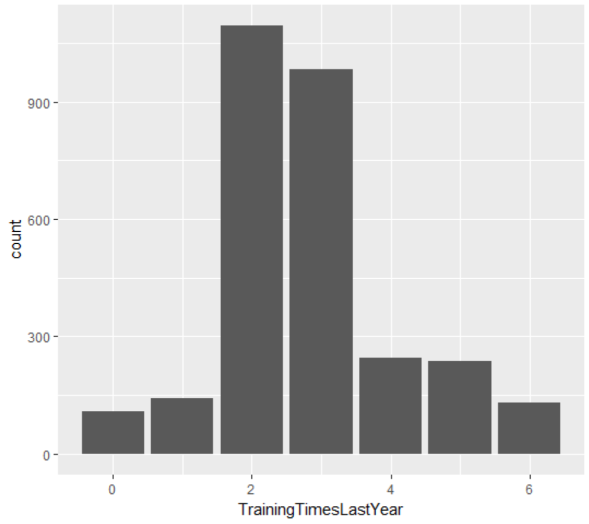
(iii) YearsWithCurrentManager vs Attrition:

As the number of years with Current Manager Increases, Attrition decreases



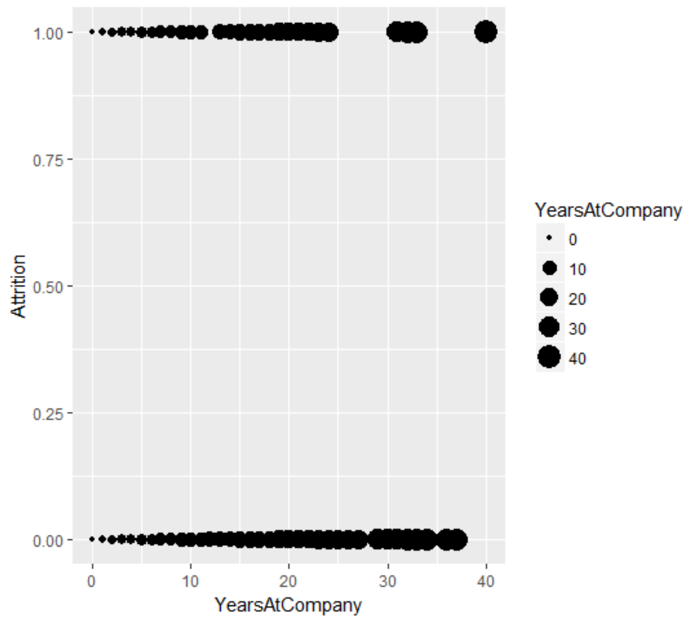
(iv) TrainingTimeLastYear vs Attrition:

Attrition seen in employees trained between 2-4times last year.



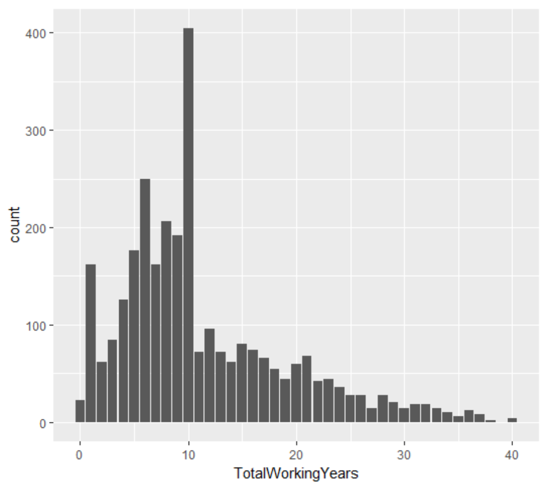
(v) YearsatCompany vs Attrition:

People with less no of years tend to quit the company more.



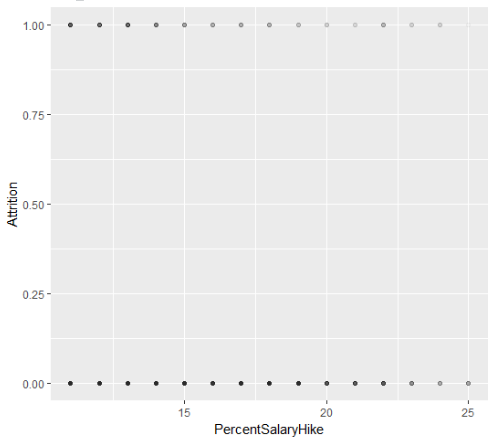
(vi) Total Working Years vs Attrition:

People with less Experience are leaving the job more.



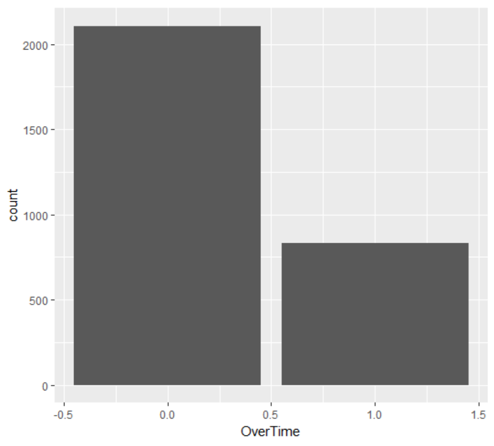
(vii) Present Salary Hike vs Attrition

People with Less Percent Hike leave the company.



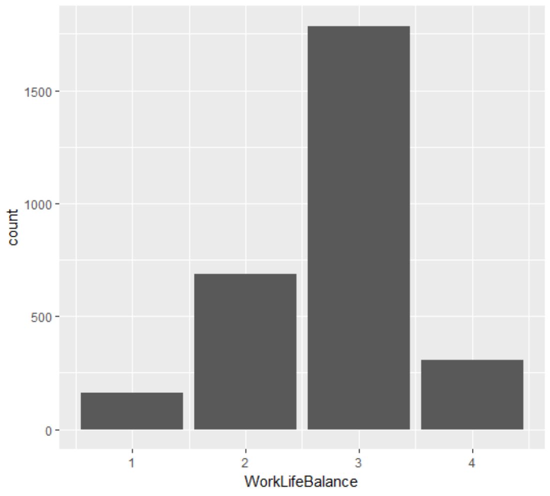
(viii) OverTime vs Attrition

Male employees working overtime leave the company more



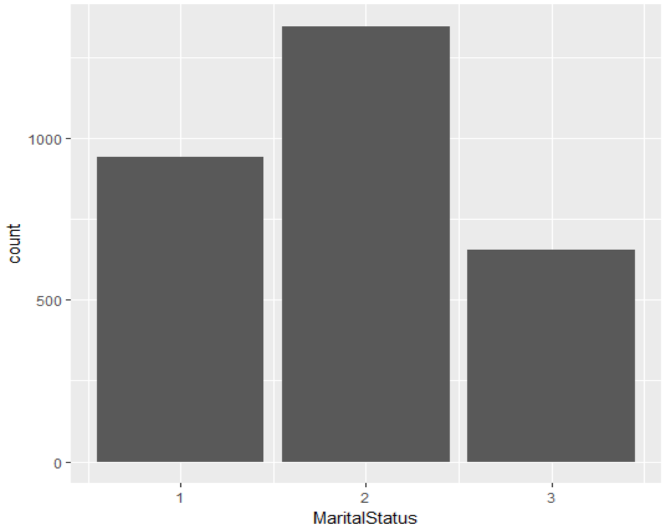
(ix) WorkLifeBalance vs Attrition:

People with better work life balance may tend to quit more.



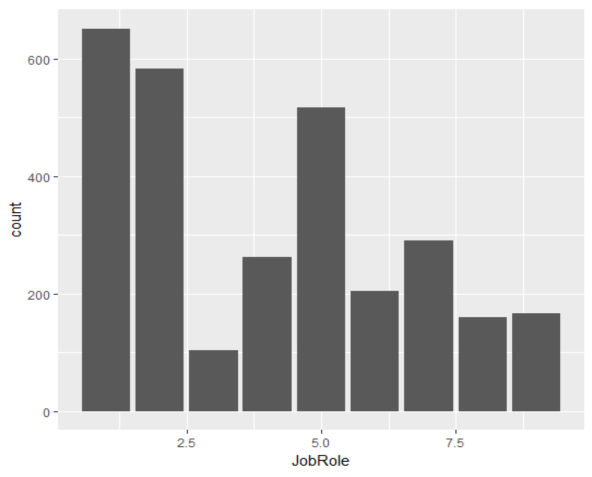
(x) Marital Status vs Attrition:

Attrition highest in Employees who are single, medium in Employees who are married and least in Divorced Employees



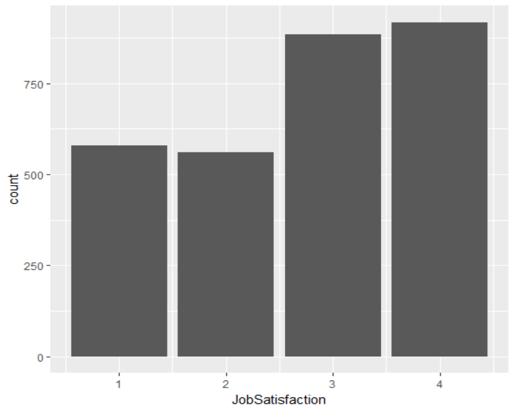
(xi) JobRole vs Attrition:

People leaving the company are highly involved in their jobs.



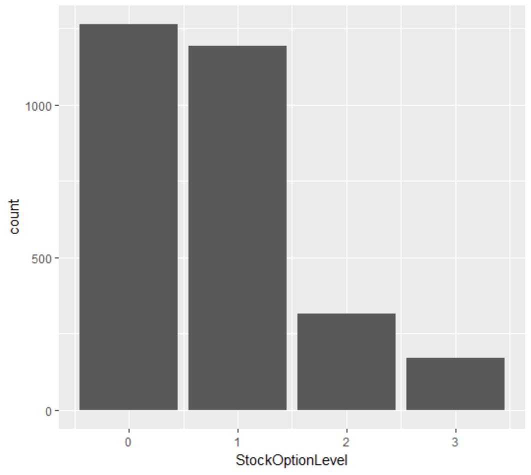
(xii) JobSatisfaction vs Attrition:

Low JobSatisfaction results in people leaving the company.



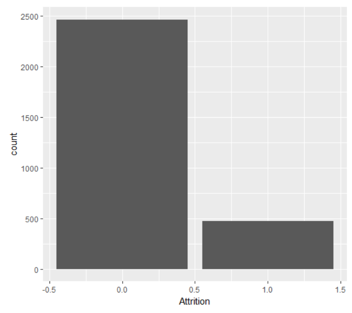
(xiii) StockOptionLevels vs Attrition:

Attrition high in people with No or Less Stock Options



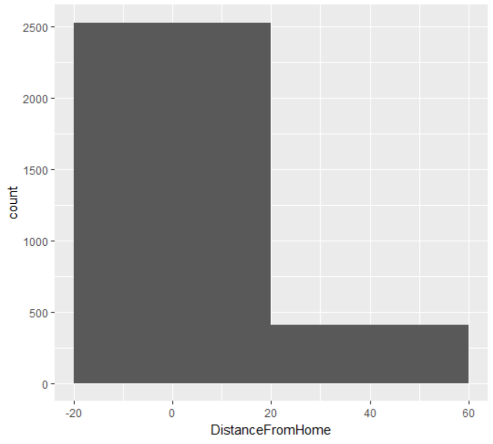
(xiv) Gender vs Attrition

More in Male employees



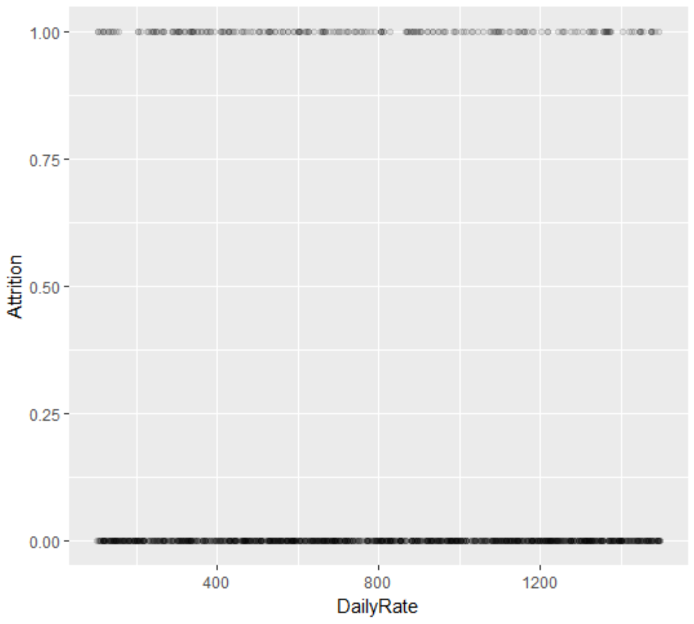
(xv) DistanceFromHome vs Attrition

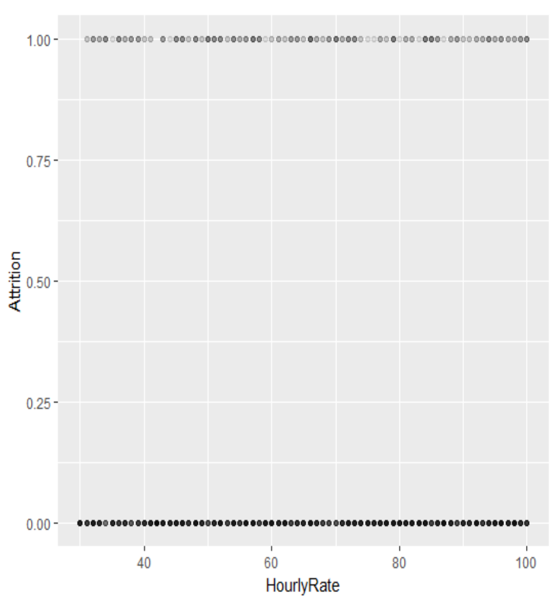
People living in shorter distances from office leave more.

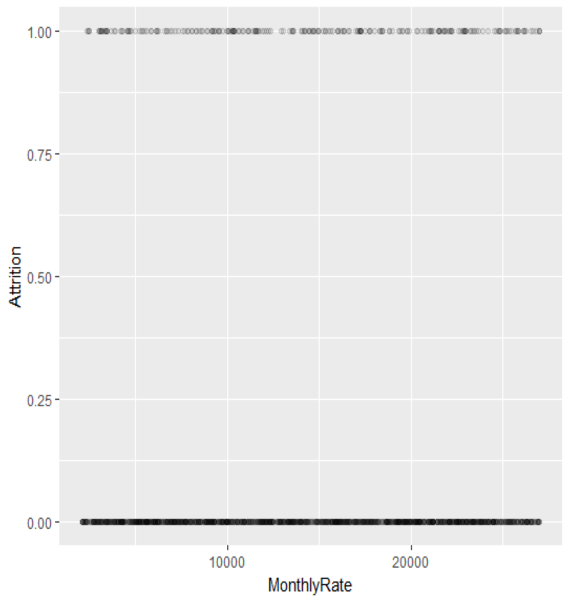


(xvi) Hourly, Daily & Monthly Rates vs Attrition:

These factors do not influence the attrition.

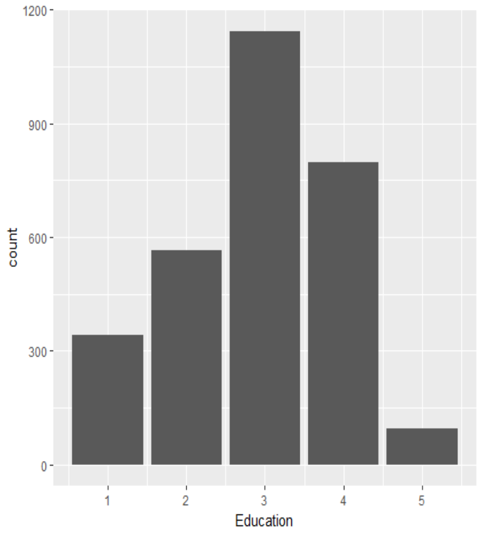


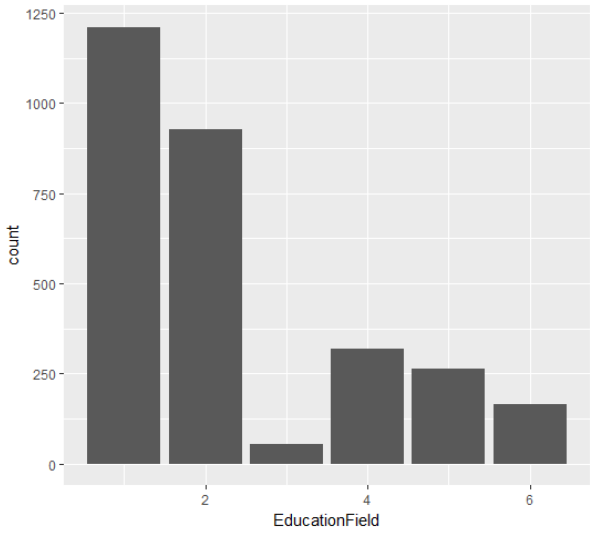




(xvii) Education Field, Education vs Attrition

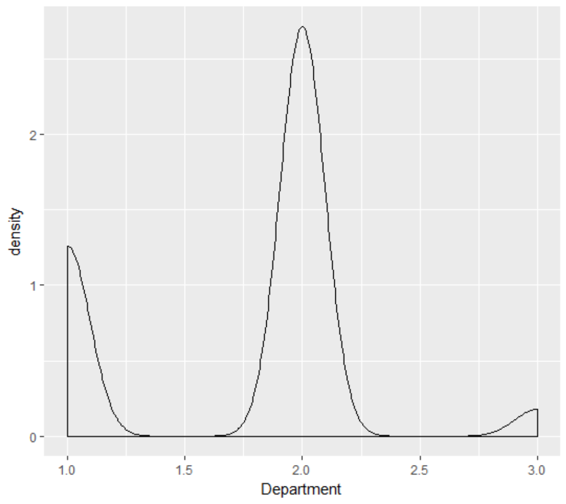
Attrition seems to be higher in Bachelors, Life Sciences and Medical





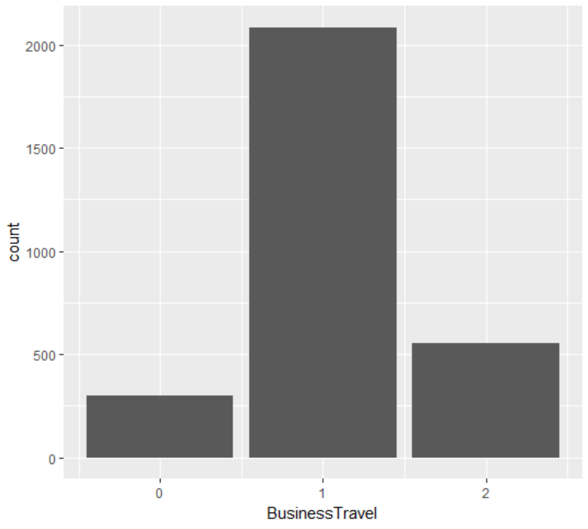
(xviii) Department vs Attrition

People from Reasearch&Development and Sales tend to quit more compared to HR



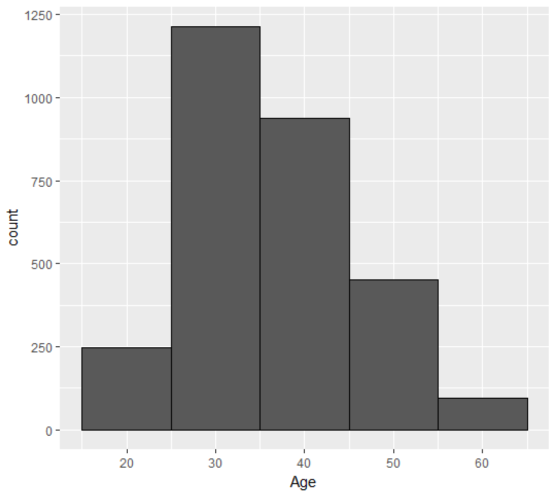
(xix) Business Travel vs Attrition

Attrition is directly proportional to Travel among the employees.



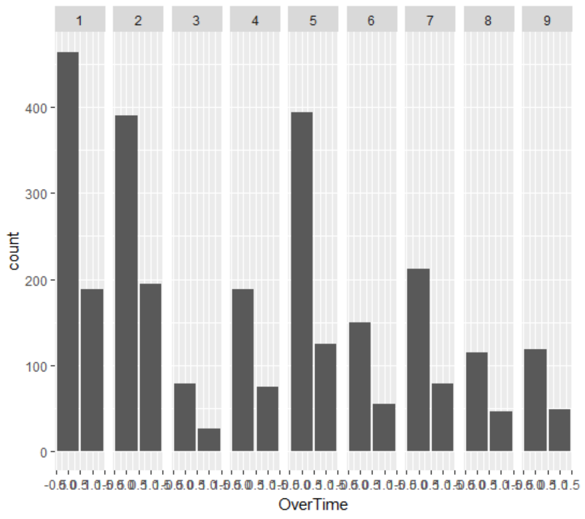
(xx) Age vs Attrition:

Employees around 30years leave the company more



(xxi) Others:

High Attrition among Sales Representatives and Lab Technicians who work Overtime.



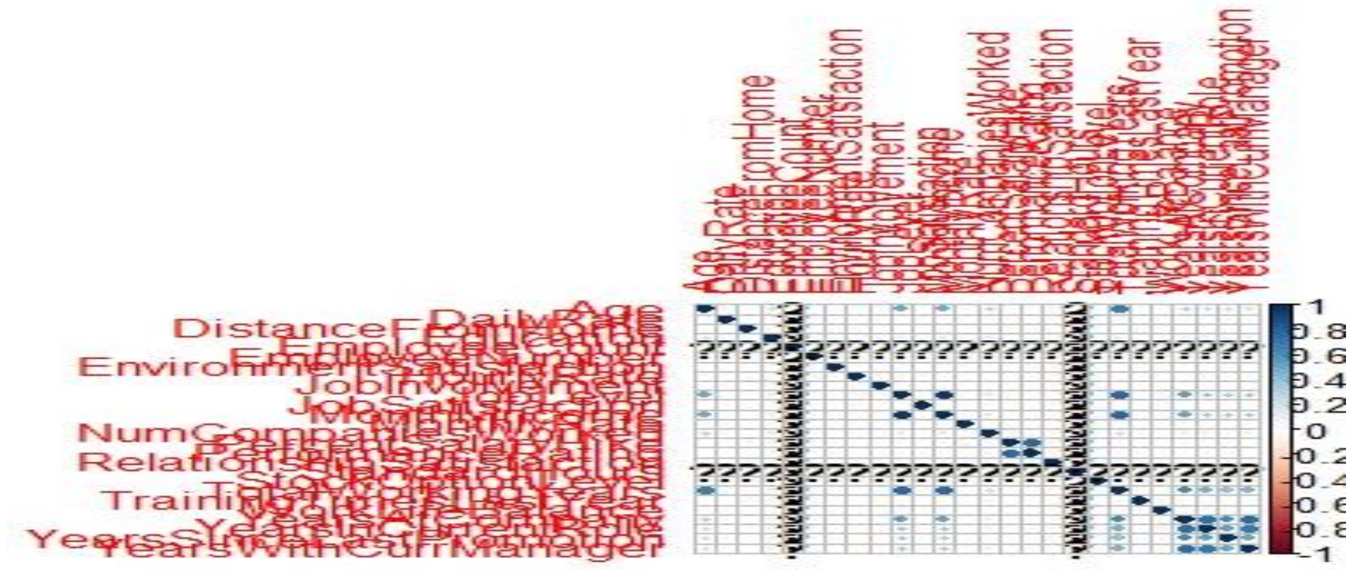
Identify columns which are of no use. Drop those columns:

We have identified columns which need to be dropped in the following ways:

1. **Correlated Variables**: Since we have many independent variables, it is obvious that we will also have correlated variables, which we identified using corrplot function.

From the Correlation plot, we have dropped the following variables:

a) YearsAtCompany
b) YearsInCurrentRole
c) YearsSinceLastPromotion
d) Monthly Income
e) Performance Rating



2. **Redundant/Least Importance variables**: We have dropped the following variables based on intuition and confirmed the same using Boruta .

Employee Count and Employee Number fields do not carry any useful information:

f) Employee Count
g) Employee Number
h) Over18 - Over18 field can be calculated from the Age column:
i) Standard Hours - Standard Hours is same across all the columns:

Boruta output:

Employee Count	0.000000	0.000000	0.000000	0.0000	0.0000	Rejected
Employee Number	-5.177087	-4.938704	-6.649008	-4.0351	0.000	Rejected
Over18	0.0000	0.000000	0.000000	0.0000	0.000000	Rejected
Standard Hours	0.0000	0.000000	0.0000	0.0000	0.00000	Rejected

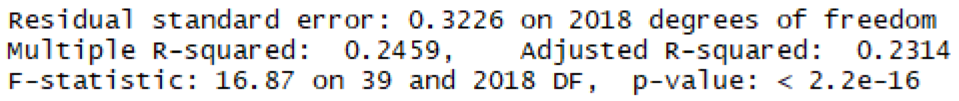
Split the data in Dev & Hold Out sample (70:30):
The imported data after dropping of redundant and correlated variables has been split into training and test sets using sample. Split on Attrition variable with split ratio=0.7 from "caTools" package.
All the models have been trained on training set and validated on test set.
The Target variable has been encoded as Yes-1 No-0.

Write Hypothesis and validate the Hypothesis:

H0: Attrition (dependent variable) is not affected by other independent variables.
H1: Attrition (dependent variable) is affected by other independent variables.

F-Statistic is ***significant*** and hence we **reject Null Hypothesis** and ***accept Alternative Hypothesis.*** i.e. Dependent variable Attrition is affected by the given independent variables.

Output:

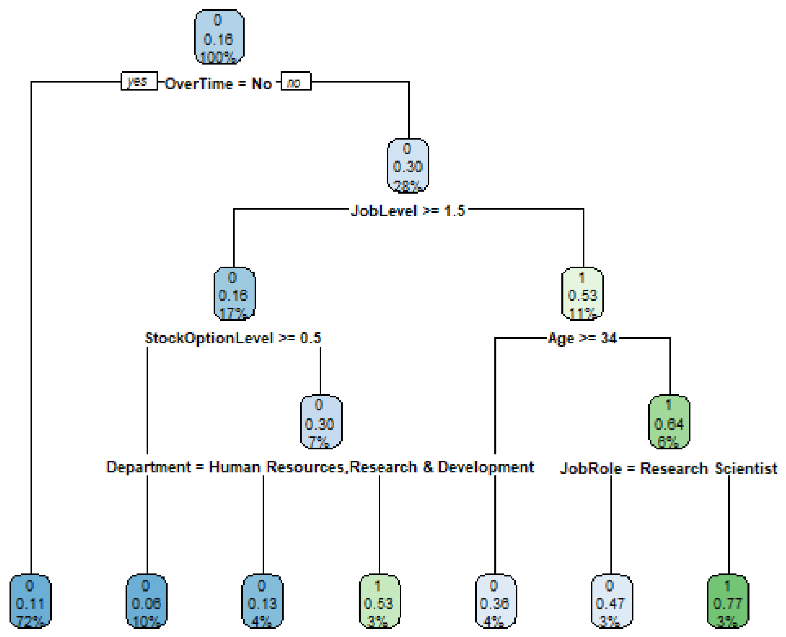


```
Residual standard error: 0.3226 on 2018 degrees of freedom
Multiple R-squared:  0.2459,    Adjusted R-squared:  0.2314
F-statistic: 16.87 on 39 and 2018 DF,  p-value: < 2.2e-16
```

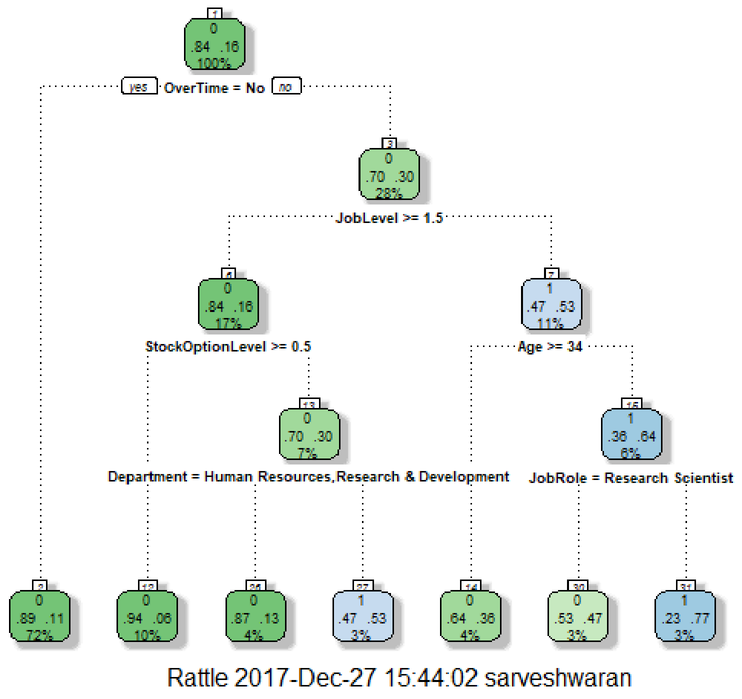
CART Model:
We have built a classification CART model with parameters:

minsplit = 100; the minimum number of observations that must exist in a node in order for a split to be attempted.
minbucket = 10; the minimum number of observations in any terminal node (leaf node)
xval = 10,no of cross validations and to avoid Over-fitting
cp = 0 so that the cross-validated error rate is minimum

rplot:



Fancy r-plot:



```
> printcp(destree)

Classification tree:
rpart(formula = training_set$Attrition ~ ., data = training_set[,
    2:26], method = "class", control = ctrl)

Variables actually used in tree construction:
[1] Age              Department       JobLevel         JobRole          OverTime
[6] StockOptionLevel

Root node error: 332/2058 = 0.16132167

n= 2058

           CP nsplit  rel error     xerror        xstd
1 0.0361445783      0 1.00000000 1.00000000 0.050260716
2 0.0090361446      3 0.89156627 0.94578313 0.049133454
3 0.0045180723      4 0.88253012 1.02108434 0.050684716
4 0.0000000000      6 0.87349398 1.03313253 0.050923513
```

Validate CART Model:

Confusion Matrix:

	0	1
0	722	18
1	108	34

Summary of CART model:

Confusion Matrix outcomes - CART	
Accuracy=(TP+TN)/total	0.857142857
Misclassification Rate or error rate =(FP+FN)/total	0.142857143
Sensitivity or recall or True Positive Rate = TP/actual yes	0.23943662
False Positive Rate = FP/actual no	0.024324324
Specificity = TN/actual no	0.975675676
Precision = TP/predicted yes	0.653846154
Prevalence = actual yes/total	0.160997732

Accuracy = 85.71% on testing set.

Neural Networks:

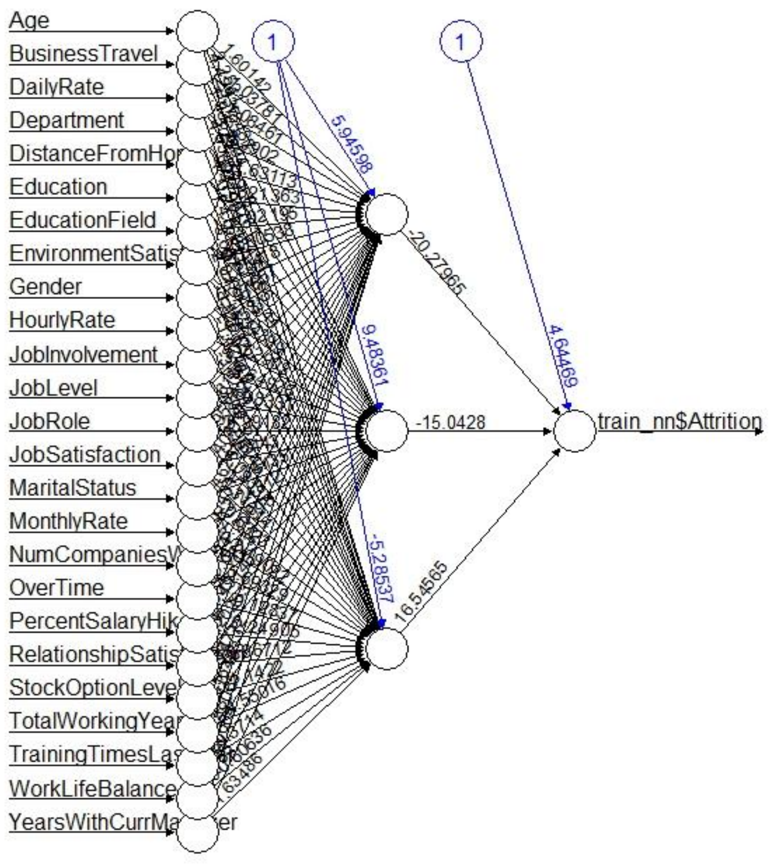
Dataset been reordered as-Attrition followed by all numeric fields and categorical fields for easier cleaning of data for model building.
All the categorical variables have been encoded as factors and all the variables are scaled to ensure easier and faster computations

1. **Neural Network 1: Using Neural Net**

Attrition (Dependent variable) is compared to all Independent Variables .

Parameters considered:

- 2 hidden layers.
- Threshold set to 0.1
- Stepmax: 2000.



g) Validate NN model on Hold Out. If need be improvise:

Threshold = 0.5, if predicted value is above 0.5 encoded as 1 else 0.

Confusion matrix of Neural Network:

	0	0
0	681	59
1	113	29

Summary of Confusion Matrix:

Confusion Matrix outcomes - Neural Network	
Accuracy=(TP+TN)/total	0.804988662
Misclassification Rate or error rate =(FP+FN)/total	0.195011338
Sensitivity or recall or True Positive Rate = TP/actual yes	0.204225352
False Positive Rate = FP/actual no	0.07972973
Specificity = TN/actual no	0.92027027
Precision = TP/predicted yes	0.329545455
Prevalence = actual yes/total	0.160997732

Accuracy Rate: 80.49% on test set using Neural Net.

On Improvising the Model using ***h2o.deeplearning:***

Parameters:2hidden layers with 13 neurons each over 100 epochs.

Confusion Matrix for h2o Neural Network:

	0	0
0	707	33
1	55	87

Summary of Neural Network (h2o) model:

Confusion Matrix outcomes - H2O Neural Network	
Accuracy=(TP+TN)/total	0.900226757
Misclassification Rate or error rate =(FP+FN)/total	0.099773243
Sensitivity or recall or True Positive Rate = TP/actual yes	0.612676056
False Positive Rate = FP/actual no	0.044594595
Specificity = TN/actual no	0.955405405
Precision = TP/predicted yes	0.725
Prevalence = actual yes/total	0.160997732

Accuracy = 90.02% has been achieved on test set using h2o

Reasons for improved accuracy:

1. Runs an instance of a computer system which will help the model learn efficiently along with lot of options.
2. Parameter tuning.

j) Compare NN with CART:

Comparing Improvised Neural Network with the CART model:

Confusion Matrix	CART	h20 - Neural Network
Accuracy=(TP+TN)/total	0.857143	0.900226757
Misclassification Rate or error rate =(FP+FN)/total	0.142857	0.099773243
Sensitivity or recall or True Positive Rate = TP/actual yes	0.239437	0.612676056
False Positive Rate = FP/actual no	0.024324	0.044594595
Specificity = TN/actual no	0.975676	0.955405405
Precision = TP/predicted yes	0.653846	0.725
Prevalence = actual yes/total	0.160998	0.160997732

k) Combine NN and CART into Ensemble Model:

1) Using XGBoost:

Confusion matrix:

	Prediction		
		0	1
Actual	0	731	9
	1	79	63

Summary of XGBOOST:

Confusion Matrix outcomes – XgBoost	
Accuracy=(TP+TN)/total	0.900226757
Misclassification Rate or error rate =(FP+FN)/total	0.099773243
Sensitivity or recall or True Positive Rate = TP/actual yes	0.443661972
False Positive Rate = FP/actual no	0.012162162
Specificity = TN/actual no	0.987837838
Precision = TP/predicted yes	0.875
Prevalence = actual yes/total	0.160997732

Reasons for High Accuracy:

1. Parallel Processing
2. Automatic tree pruning and built in classification.

2) Averaging:

Formula: Taking the average of probabilities of the CART and Neural Network 1:

Confusion Matrix:

Predicted Values			
		0	1
Actual Values	0	493	247
	1	96	46

Summary of Averaging:

Confusion Matrix outcomes Average of all models	
Accuracy=(TP+TN)/total	0.611111111
Misclassification Rate or error rate =(FP+FN)/total	0.388888889
Sensitivity or recall or True Positive Rate = TP/actual yes	0.323943662
False Positive Rate = FP/actual no	0.333783784
Specificity = TN/actual no	0.666216216
Precision = TP/predicted yes	0.156996587
Prevalence = actual yes/total	0.160997732

3.Random Forest:

Formula:

```
tclassifier <- tuneRF(x = training_set[, 2:26],
                y=training_set$Attrition, mtryStart = 3, ntreeTry=100,
stepFactor = 1.5, improve = 0.0001, trace=TRUE, plot = TRUE, doBest = TRUE,
                nodesize = 10, importance=TRUE)

rantree = randomForest(x = training_set[, 2:26], y = training_set$Attrition,
                 ntree = 100, nodesize = 10, mtry=13, importance = TRUE)
```

We give the Optimal mtry value = 13

Confusion matrix:

Prediction			
		0	1
Actual	0	732	8
	1	38	104

Summary of Random Forest:

Confusion Matrix outcomes - Random Forest	
Accuracy=(TP+TN)/total	0.947845805
Misclassification Rate or error rate =(FP+FN)/total	0.052154195
Sensitivity or recall or True Positive Rate = TP/actual yes	0.732394366
False Positive Rate = FP/actual no	0.010810811
Specificity = TN/actual no	0.989189189
Precision = TP/predicted yes	0.928571429
Prevalence = actual yes/total	0.160997732

Accuracy = 94.78% on running it in test set.

Conclusion: Random forest and XGBoost models are performing better than CART and Neural Network models.