Lab Report of IBM Employee Retention Data Set

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# Introduction

Companies hire many employees every year. To create a positive working and learning environment, firms invest time and money in trianing the new members and also to get existing employees involved as well. The goal of these programs aim to increase the effectiveness of the employees and in doing so the firm as a whole can have better output in long run.

Human resource analytics (or HR analytics) is an important area in this field and it refers to applying statistical and analytic modelling to understand or extract the insight in hoping of improving employee performance and better return on investment. This is a field of analytics work that is not just gathering data but also to provide insight in each step of the process targeting on making sound decisions about how to improve overall satisfactory for new and existing employees.

## Goal: Employee Attrition

The single most important feature we are interested in is attrition. Attrition in human resources refer to the gradual loss of employees over time. In general relatively high attrition is problematic for companies. Human Resource professionals often asume a leadership role in designing company compensation programs, work culture and motivation systems that help the organization retain top employees.

This is a significant problem because high employee attrition is a huge cost to a firm. Procedures such as job postings, hiring processes, paperwork, and new recruitment training are some of the most expensive costs of losing or replacing employees. On top of these costs, regular employee turnover prevents a firm from increasing its collective knowledge base and experience over time which in most industries can be crucial to the success of a company. Moreover, this also in some way affects customers and revenue streams because some customers prefer to interact with familiar faces. Errors and issues are more likely if you constantly have new workers.

## Data: IBM HR Employee Dataset

To investigate this topic, I use IBM [HR Analytics Employee Attrition and Performance Dataset](https://www.kaggle.com/pavansubhasht/ibm-hr-analytics-attrition-dataset/data). There are total of 1470 samples and 35 features. Among the target, Attrition, there are 237 candidates committed to Yes (i.e. left the company) and the rest 1233 candidates committed to No (i.e. stayed at the company).

# Set Working Directory  
path <- "C:/Users/eagle/OneDrive/HR\_Employee\_Retention\_IBM"  
setwd(paste0(path, "/data"))  
  
# Compile Data  
all <- read.csv("data.csv")  
  
# Define Response  
all$Attrition <- as.numeric(all$Attrition) - 1L  
  
# Define Features (i.e. these are the variables)  
all <- cbind(all$Attrition, all[, -2])  
colnames(all)[1] <- "Attrition"; colnames(all)[2] <- "Age"  
raw\_data <- all  
  
# Convert all features into numerical value  
for (j in 2:ncol(all)) {all[, j] <- as.numeric(all[, j])}  
colnames(all)[1] <- "Attrition"; colnames(all)[2] <- "Age"  
all <- all[, -c(9, 22, 27)] # These variables (EmployeeCount, Over18, StandardHours) are constants so delete them.  
  
# Preview  
print(paste0("The first three rows of the data looks like: ")); all[1:3, ]

## [1] "The first three rows of the data looks like: "

## Attrition Age BusinessTravel DailyRate Department DistanceFromHome  
## 1 1 41 3 1102 3 1  
## 2 0 49 2 279 2 8  
## 3 1 37 3 1373 2 2  
## Education EducationField EmployeeNumber EnvironmentSatisfaction Gender  
## 1 2 2 1 2 1  
## 2 1 2 2 3 2  
## 3 2 5 4 4 2  
## HourlyRate JobInvolvement JobLevel JobRole JobSatisfaction MaritalStatus  
## 1 94 3 2 8 4 3  
## 2 61 2 2 7 2 2  
## 3 92 2 1 3 3 3  
## MonthlyIncome MonthlyRate NumCompaniesWorked OverTime PercentSalaryHike  
## 1 5993 19479 8 2 11  
## 2 5130 24907 1 1 23  
## 3 2090 2396 6 2 15  
## PerformanceRating RelationshipSatisfaction StockOptionLevel  
## 1 3 1 0  
## 2 4 4 1  
## 3 3 2 0  
## TotalWorkingYears TrainingTimesLastYear WorkLifeBalance YearsAtCompany  
## 1 8 0 1 6  
## 2 10 3 3 10  
## 3 7 3 3 0  
## YearsInCurrentRole YearsSinceLastPromotion YearsWithCurrManager  
## 1 4 0 5  
## 2 7 1 7  
## 3 0 0 0

print(paste0("The dimension (row by cols) of the data set is: ")); dim(all)

## [1] "The dimension (row by cols) of the data set is: "

## [1] 1470 32

We can take a look at the list of variables. Variables such as Attrition, BusinessTravel, Department, and so on are discrete. The rest of variables such as DailyRate or EmployeeNumber are considered as continuous.

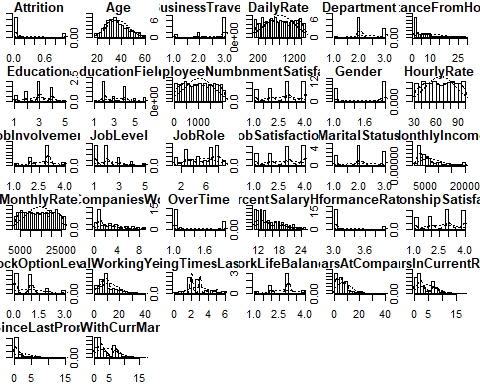
# Check Levels  
levels <- c()  
for (j in 1:ncol(all)) {levels <- c(levels, nrow(plyr::count(all[,j])))}  
levels <- data.frame(cbind(colnames(all), levels))  
colnames(levels) <- c("Variable\_Names","Number\_of\_Levels"); levels

## Variable\_Names Number\_of\_Levels  
## 1 Attrition 2  
## 2 Age 43  
## 3 BusinessTravel 3  
## 4 DailyRate 886  
## 5 Department 3  
## 6 DistanceFromHome 29  
## 7 Education 5  
## 8 EducationField 6  
## 9 EmployeeNumber 1470  
## 10 EnvironmentSatisfaction 4  
## 11 Gender 2  
## 12 HourlyRate 71  
## 13 JobInvolvement 4  
## 14 JobLevel 5  
## 15 JobRole 9  
## 16 JobSatisfaction 4  
## 17 MaritalStatus 3  
## 18 MonthlyIncome 1349  
## 19 MonthlyRate 1427  
## 20 NumCompaniesWorked 10  
## 21 OverTime 2  
## 22 PercentSalaryHike 15  
## 23 PerformanceRating 2  
## 24 RelationshipSatisfaction 4  
## 25 StockOptionLevel 4  
## 26 TotalWorkingYears 40  
## 27 TrainingTimesLastYear 7  
## 28 WorkLifeBalance 4  
## 29 YearsAtCompany 37  
## 30 YearsInCurrentRole 19  
## 31 YearsSinceLastPromotion 16  
## 32 YearsWithCurrManager 18

## EDA: Exploratory Data Analysis

Let us take a look at the distribution matrix of all the variables. We can Age follows a distribution that is similar to normal distribution. However, MonthlyIncome may look more like a Poisson process in the sense that most of the sample falls on the lower end of the distribution.

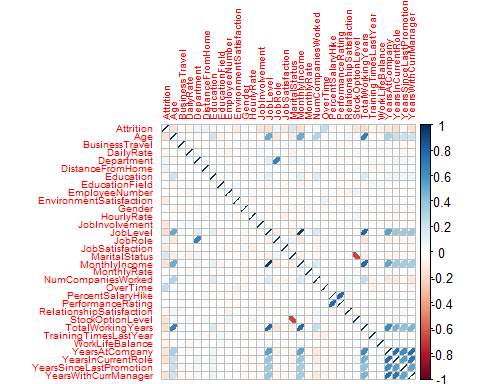
psych::multi.hist(all)



With each distribution in mind, let us also take a look at the correlation plot. For visualization purpose, we align the variables in alphabetical order on both axis. The diagonal is 100% because that is the correlation for each variable and itself. The matrix is symmetric with legend labeled on the right. The legend is color coded from -1 (red) to 1 (blue). Blue means positively correlated while red means negatively correlated. We can see that Education is positively correlated with Age. We can also see that JobLevel is highly correlated Age as well. It is the same with MOnthlyIncome and TotalWorkingYears. Based on the correlation table, I make the following observations:

* Based on correlation, Attrition is associated negatively with Age, JobInvolvement, JobLevel, Jobsatisfaction, MonthlyIncome, StockOptionLevel, TotalWorkingYears, YearsAtCompany, YearsInCurrentCompany, YearsInCurrentRole, and YearsWithCurrManager. However, Attrition is positively associated with MaritalStatus and OverTime.

M <- cor(all); corrplot::corrplot(M, method = "ellipse", tl.cex = 0.6)



* Among those who contribute to Attrition, the highest percentage falls in Life Sciences and the second falls in Medical. In other words, at IBM, the employees that left the firm mostly come from Life Sciences and then perhaps Medical department.

sub\_data <- cbind(raw\_data$Attrition, raw\_data$EducationField); levels(raw\_data$EducationField)

## [1] "Human Resources" "Life Sciences" "Marketing"   
## [4] "Medical" "Other" "Technical Degree"

Pi <- apply(sub\_data,1,paste0,collapse="\_"); plyr::count(Pi)

## x freq  
## 1 0\_1 20  
## 2 0\_2 517  
## 3 0\_3 124  
## 4 0\_4 401  
## 5 0\_5 71  
## 6 0\_6 100  
## 7 1\_1 7  
## 8 1\_2 89  
## 9 1\_3 35  
## 10 1\_4 63  
## 11 1\_5 11  
## 12 1\_6 32

data.frame(EducationField = levels(raw\_data$EducationField),  
 Percentage = round(plyr::count(Pi)[7:12, 2]/sum(plyr::count(Pi)[7:12, 2]),3))

## EducationField Percentage  
## 1 Human Resources 0.030  
## 2 Life Sciences 0.376  
## 3 Marketing 0.148  
## 4 Medical 0.266  
## 5 Other 0.046  
## 6 Technical Degree 0.135

* Based on Age and WorkLifeBalance, we discovered that for those who committed to Attrition age 29 and 31 with WorkLifeBalance to be 3 happened the most frequently, both at 18.6%.

sub\_data <- cbind(raw\_data$Attrition, raw\_data$Age, raw\_data$WorkLifeBalance)  
Pi <- apply(sub\_data,1,paste0,collapse="\_"); # plyr::count(Pi)  
tmp <- plyr::count(Pi)[152:nrow(plyr::count(Pi)), ]  
tmp\_top\_6 <- head(tmp[order(tmp$freq, decreasing = TRUE), ])  
tmp\_top\_6$percent <- round(c(tmp\_top\_6$freq / sum(tmp\_top\_6$freq)), 3)  
data.frame(tmp\_top\_6)

## x freq percent  
## 180 1\_29\_3 8 0.186  
## 187 1\_31\_3 8 0.186  
## 172 1\_26\_3 7 0.163  
## 175 1\_28\_2 7 0.163  
## 195 1\_33\_3 7 0.163  
## 191 1\_32\_3 6 0.140

* For the people who left the firm (committed to Yes to Attrition), the most common JobRole is Laboratory Technician and Sales Representative. From our analysis below, we see that the Laboratory Technician who spent a year at the firm and than left sat on a high of 30.9% among those who committed Yes to Attrition. The second is Sales Representative that stayed at the firm for a year, at 9.1%. The third group of people who stayed at the firm for a year and left are Research Scientist, at a shy of 17.6%. These are the top three demographics that contribute to the Attrition the highest.

sub\_data <- cbind(raw\_data$Attrition, raw\_data$JobRole, raw\_data$YearsAtCompany)  
levels(raw\_data$JobRole)

## [1] "Healthcare Representative" "Human Resources"   
## [3] "Laboratory Technician" "Manager"   
## [5] "Manufacturing Director" "Research Director"   
## [7] "Research Scientist" "Sales Executive"   
## [9] "Sales Representative"

Pi <- apply(sub\_data,1,paste0,collapse="\_")  
tmp <- plyr::count(Pi)[193:nrow(plyr::count(Pi)), ]  
tmp\_top\_6 <- head(tmp[order(tmp$freq, decreasing = TRUE), ])  
tmp\_top\_6$percent <- round(c(tmp\_top\_6$freq / sum(tmp\_top\_6$freq)), 3)  
data.frame(tmp\_top\_6)

## x freq percent  
## 206 1\_3\_1 21 0.309  
## 261 1\_9\_1 13 0.191  
## 230 1\_7\_1 12 0.176  
## 250 1\_8\_2 8 0.118  
## 205 1\_3\_0 7 0.103  
## 209 1\_3\_2 7 0.103

* Moreover, we can look at how JobRole and YearsSinceLastPromotion affect Attrition. From results below, we see that for those who committed to Attrition, the highest group of people are Lab Technician that did not have any promotion. This makese sense as this is correlated with the previous finding. If a person stayed at a firm for a year or less, chances are this person did not receive any promotion before the job ended. The next is Sales Representative who did not receive promotions. The top two groups described about takes up 29.8% and 18.2% of those who committed to Yes to Attrition.

sub\_data <- cbind(raw\_data$Attrition, raw\_data$JobRole, raw\_data$YearsSinceLastPromotion)  
levels(raw\_data$JobRole)

## [1] "Healthcare Representative" "Human Resources"   
## [3] "Laboratory Technician" "Manager"   
## [5] "Manufacturing Director" "Research Director"   
## [7] "Research Scientist" "Sales Executive"   
## [9] "Sales Representative"

Pi <- apply(sub\_data,1,paste0,collapse="\_")  
tmp <- plyr::count(Pi)[111:nrow(plyr::count(Pi)), ]  
tmp\_top\_6 <- head(tmp[order(tmp$freq, decreasing = TRUE), ])  
tmp\_top\_6$percent <- round(c(tmp\_top\_6$freq / sum(tmp\_top\_6$freq)), 3)  
data.frame(tmp\_top\_6)

## x freq percent  
## 121 1\_3\_0 36 0.298  
## 159 1\_9\_0 22 0.182  
## 139 1\_7\_0 20 0.165  
## 122 1\_3\_1 17 0.140  
## 147 1\_8\_0 17 0.140  
## 148 1\_8\_1 9 0.074

# Lab Procedure

The following section we search for an algorithm to further explore our target, Attrition, which is measured by 0 if the employee stays and 1 if the employee leaves.

## Bagging

Consider a regression problem. Suppose we fit a model to our training data , obtaiing the prediction at input . Bootstrap aggregation or bagging averages this prediction over a collection of bootstrap samples, thereby reducing its variance. For each bootstrap sample with ,we fit out model, giving prediction . The baggting estimate is defined by

## Gradient Boosting Machine

To tackle a data set with Gradient Boosting Machine, we first need to define loss function using to predict on the training data, which is

Here the goal is to mimnimize with respect to while can be trained with a sum of trees. Hence, the algorithm has the following objective function

## Naive Bayes

The naive Bayes model assumes given a class , the features are independent:

Then we can derive the following

This has the form of a generalized additive model which can train machine to learn it.

## Linear Model or Least Squares

Linear model is the most common and famous algorithm and remained mainstream of statistics for decades. Given features , we predict the output Attrition using the following model

In this case, we can simply write this as inner product of two matrices, i.e. . We fit this model on training set and find the weights of features by picking coefficients to minimize the following residual sum of squares (RSS)

which is a quadratic function of the parameters and there is always a minimum (the most optimal point).

## Tree-based Algorithm

Random Forest (RF), iterative Random Forest (iRF), and Bayesian Additive Regression Tree (BART) are all tree-based algorithms. To make metters simple, let us use and , any two variables in a given data set, as an example. We split at . Then the region is split at and the region is split at and so on. What this does is to partition into regresions . The corresponding regression model predicts with a constant in region , that is,

# Lab Result

For lab procedure, we use k-fold cross validation to compare the results of handful of algorithms. We cut data set into folds. Iteratively, each fold is used as test and the rest folds as training. We test all folds using all machine learning algorithms. In the end, we average -fold validating or test set average accuracy as final metric for comparisons.

## Important Features

We select features using importance measure based on partitions.

* The first three important variables are EducationField, JobRole, and YearsAtCompany.
* The second two important variables are JobRole, and YearsAtCompany.

selected\_variables <- data.frame(read.csv(paste0(path, "/results/selected\_variables.csv")))[, -1]  
selected\_variables$Variables\_Names <- NA  
for (i in 1:nrow(selected\_variables)) {  
 selected\_variables[i, 3] <- paste0(colnames(all)[c(as.numeric(unlist(strsplit(as.character(selected\_variables[i, 1]), split="\_"))))], collapse = "\_") }  
selected\_variables[1:2, ]

## Top.Module Measure Variables\_Names  
## 1 8\_15\_29 13.86004 EducationField\_JobRole\_YearsAtCompany  
## 2 15\_29 13.30205 JobRole\_YearsAtCompany

## Measurement: AUC

For measurement of Attrition, we use area under curve or AUC which computes the area under curve formed by the axis of recall and precision.

## Result

We present test result in Area-Under-Curve (AUC) for selected machine learning algorithm. The best approach, at 90% accuracy, is to use the following variables and use bagging which is aggregate averages from bootstrap results.

setwd(paste0(path))  
how.many.folds = 5; used\_iscore = "used"  
final\_table <- read.csv(paste0(path, "/results/performance\_5\_fold\_used\_iscore\_top\_7\_var.csv"))[, -1]  
data.frame(final\_table)

## Name Result  
## 1 Bagging 0.904  
## 2 GBM 0.526  
## 3 NB 0.452  
## 4 LM 0.745  
## 5 RF 0.544  
## 6 iRF 0.808  
## 7 BART 0.890

# Summary

This report investigated IBM HR Employee Attrition data set. The analysis extracts insights from data set and conclude the following:

* My analysis identified the following important variables: EducationField, JobRole, and YearsAtCompany.

-For the people who left the firm (committed to Yes to Attrition), the most common JobRole is Laboratory Technician and Sales Representative. From our analysis below, we see that the Laboratory Technician who spent a year at the firm and than left sat on a high of 30.9% among those who committed Yes to Attrition. The second is Sales Representative that stayed at the firm for a year, at 9.1%. The third group of people who stayed at the firm for a year and left are Research Scientist, at a shy of 17.6%. These are the top three demographics that contribute to the Attrition the highest.

* Based on Age and WorkLifeBalance, we discovered that for those who committed to Attrition age 29 and 31 with WorkLifeBalance to be 3 happened the most frequently, both at 18.6%.

We also tested a variety of approaches in machine learning using linear model, naive Bayes, tree-based algorithms and so on. In the end, we propose using bagging algorithm and such algorithm deliver a solution to predict Attrition given candidates information at 90%.