IBM Human Resources

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Our Objective is to determine which factors and to what degree each factor is driving employee attrition.

We get the data from IBM Data Science Team Kaggle.com - HR Analytics

All the libraries we used:

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
library(ggplot2)
library(caret)
```

```
## Loading required package: lattice
```

```
library(MASS)
library(tree)
library(knitr)
library(kableExtra)
library(randomForest)
```

```
## randomForest 4.6-12

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
library(gbm)
```

```
## Loading required package: survival

##
## Attaching package: 'survival'

## The following object is masked from 'package:caret':
##
##     cluster

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.3
```

```
library(e1071)
```

Data Cleaning

```
## 'data.frame':    1470 obs. of  35 variables:
```

```
##  $ ï..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
##  $ 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 4 5 7 8 10 11 12 13 ...
##  $ 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 ...
```

```r
# change type chr to factor
attribution$Attrition = as.factor(attribution$Attrition)
attribution$BusinessTravel = as.factor(attribution$BusinessTravel)
attribution$Department = as.factor(attribution$Department)
attribution$EducationField = as.factor(attribution$EducationField)
attribution$Gender = as.factor(attribution$Gender)
attribution$JobRole = as.factor(attribution$JobRole)
attribution$MaritalStatus = as.factor(attribution$MaritalStatus)
attribution$OverTime = as.factor(attribution$OverTime)
```

```r
# check na
any(is.na(attribution))
```

```
## [1] FALSE
```

```r
#remove Over18, EmployeeCount, EmployeeNumber, standard hours
attribution = attribution[ , c(-9,-10,-22, -27)]
```

Visualization

We check correlation here.

As a result:

JobLevel & MonthlyIncome: 0.95

JobLevel & WorkingYears: 0.78

PercentSalaryHike & Performance Rating: 0.77

MonthlyIncome & Working Years: 0.77

YearsatCompany & YearsCurrManager: 0.77

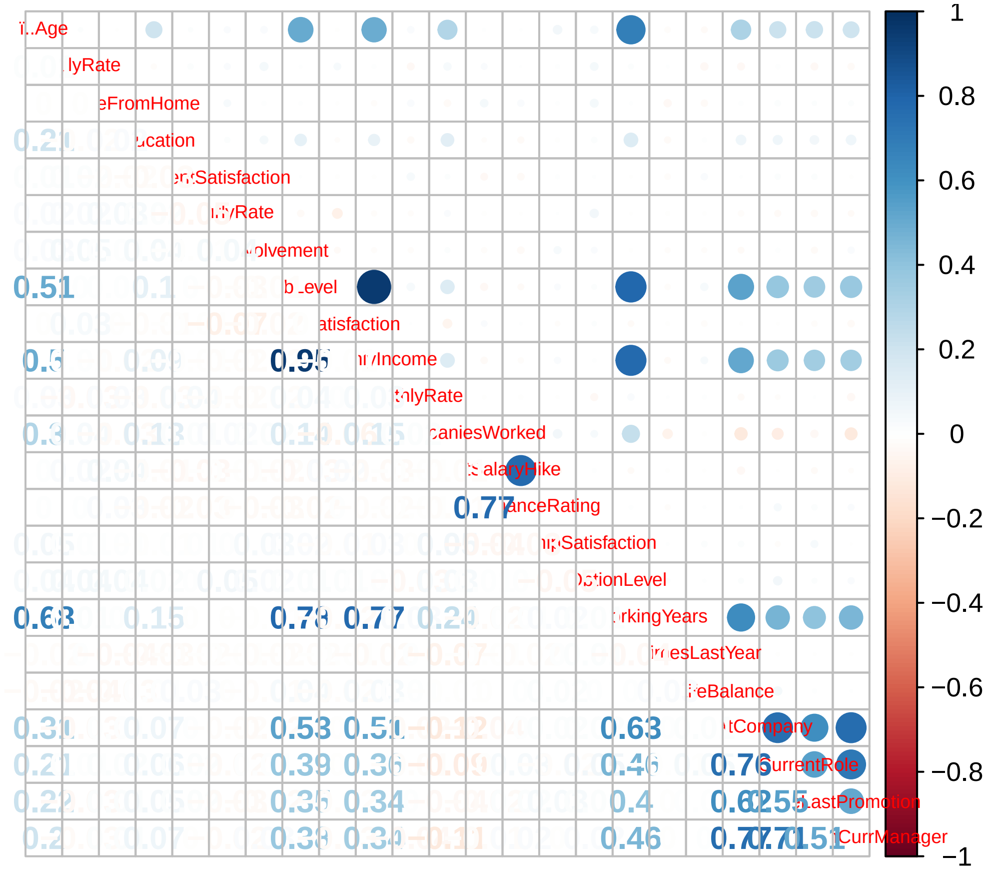
YearsatCompany & YearInCurrentRole: 0.76

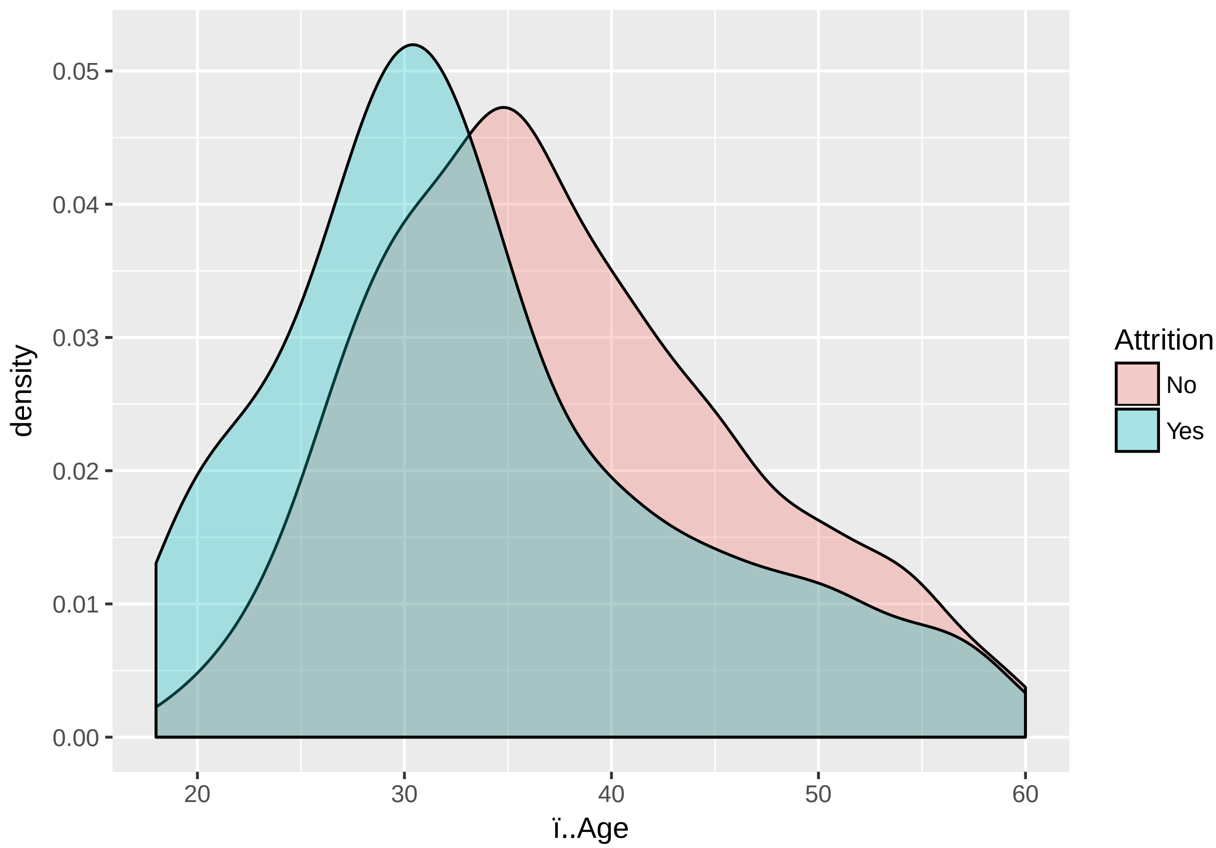
YearInCurrentRole & YearsCurrManager: 0.71

Age & WorkingYears: 0.68

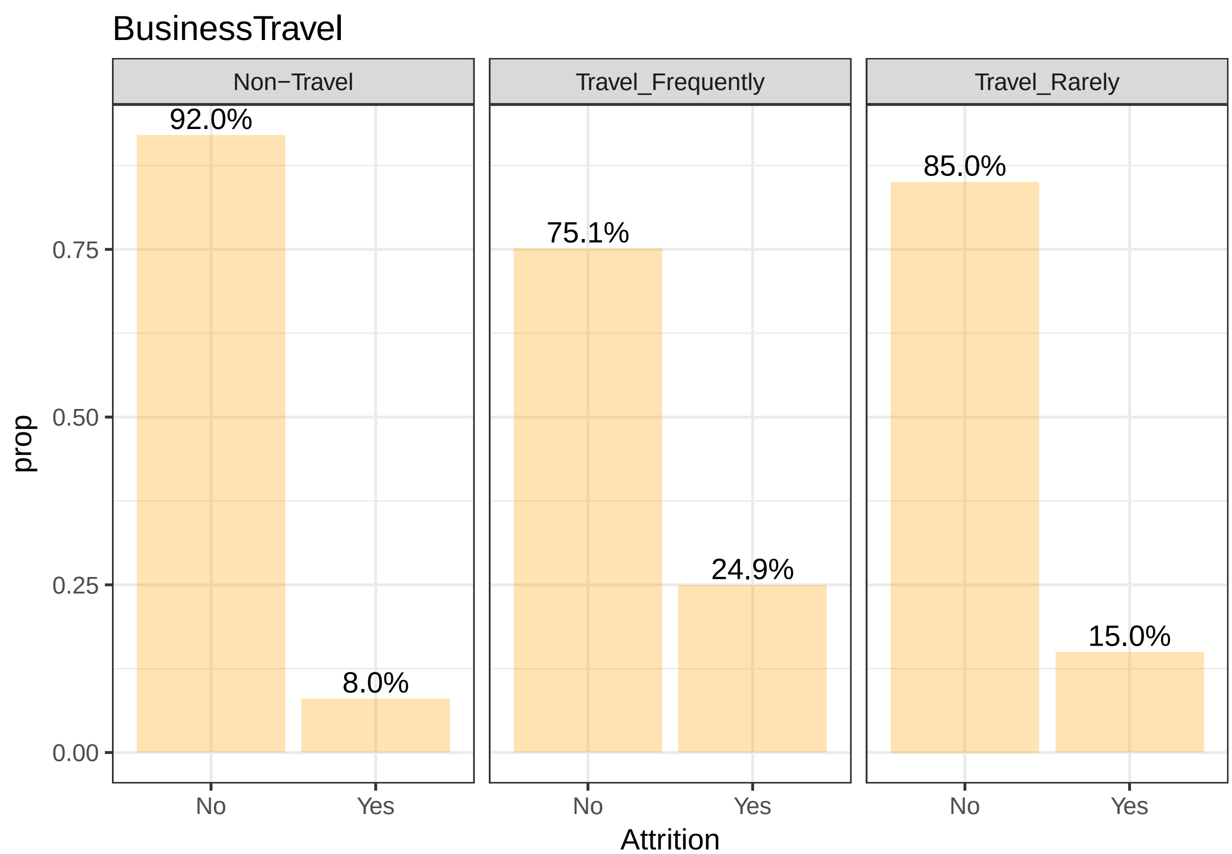
WorkingYears & YearsatCompany: 0.63

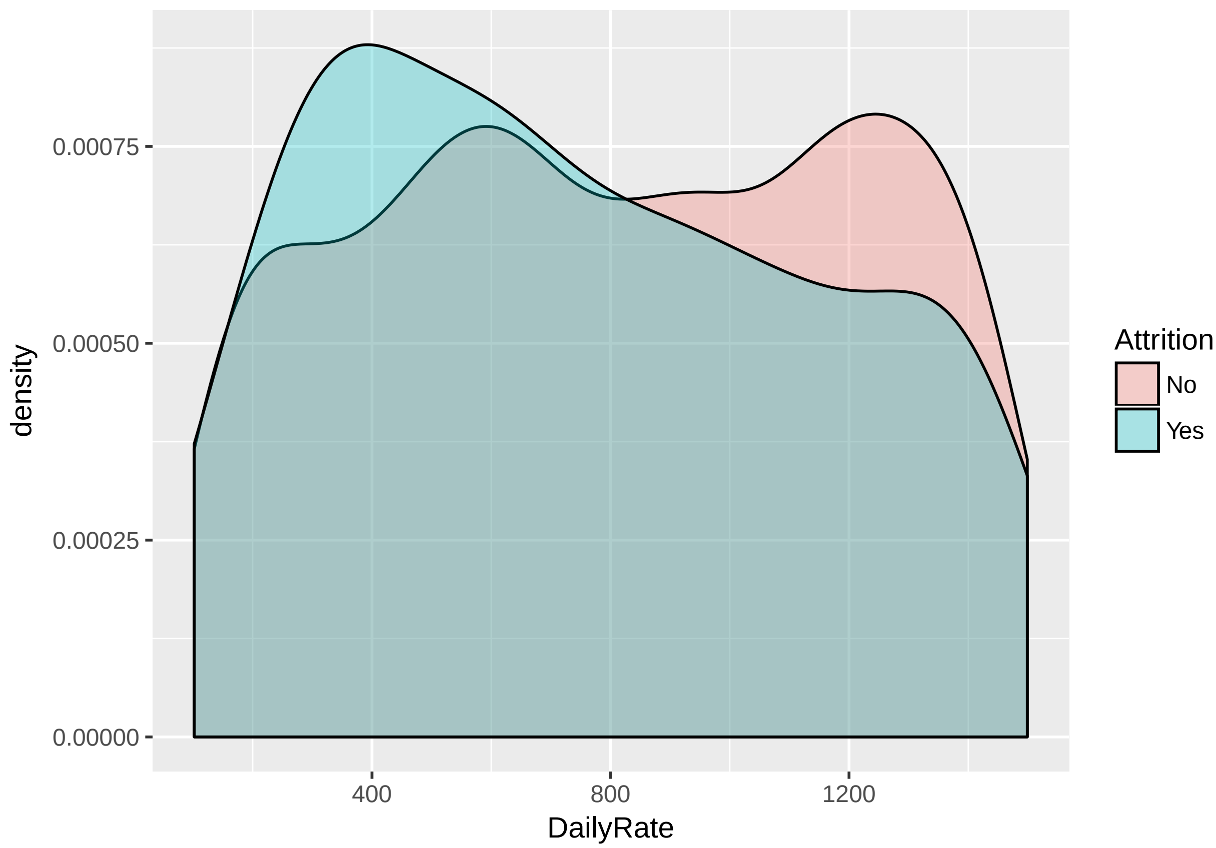
YearsatCompany & YearssinceLastPromotion: 0.62



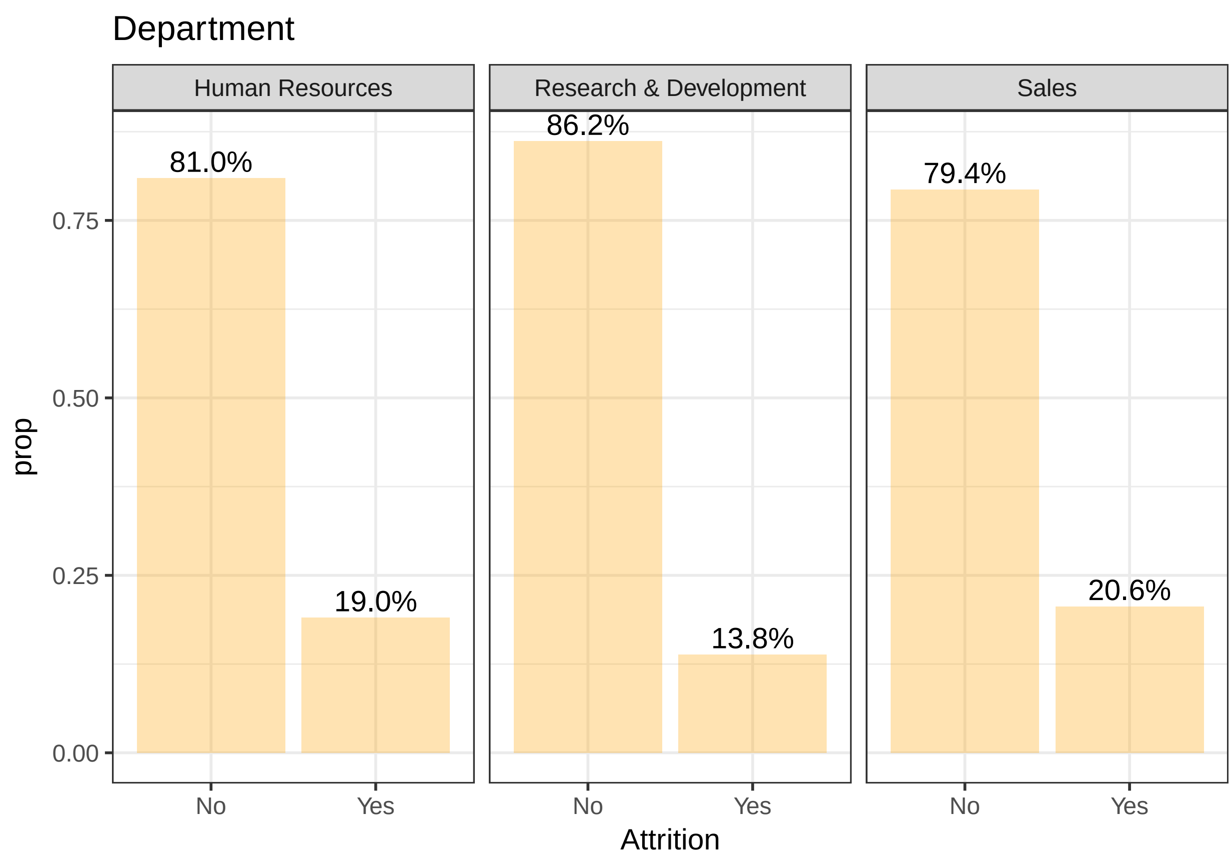


0.05
0.04
0.03
0.02
0.01
0.00
density
20
30
40
50
60
ï..Age
Attrition
No
Yes

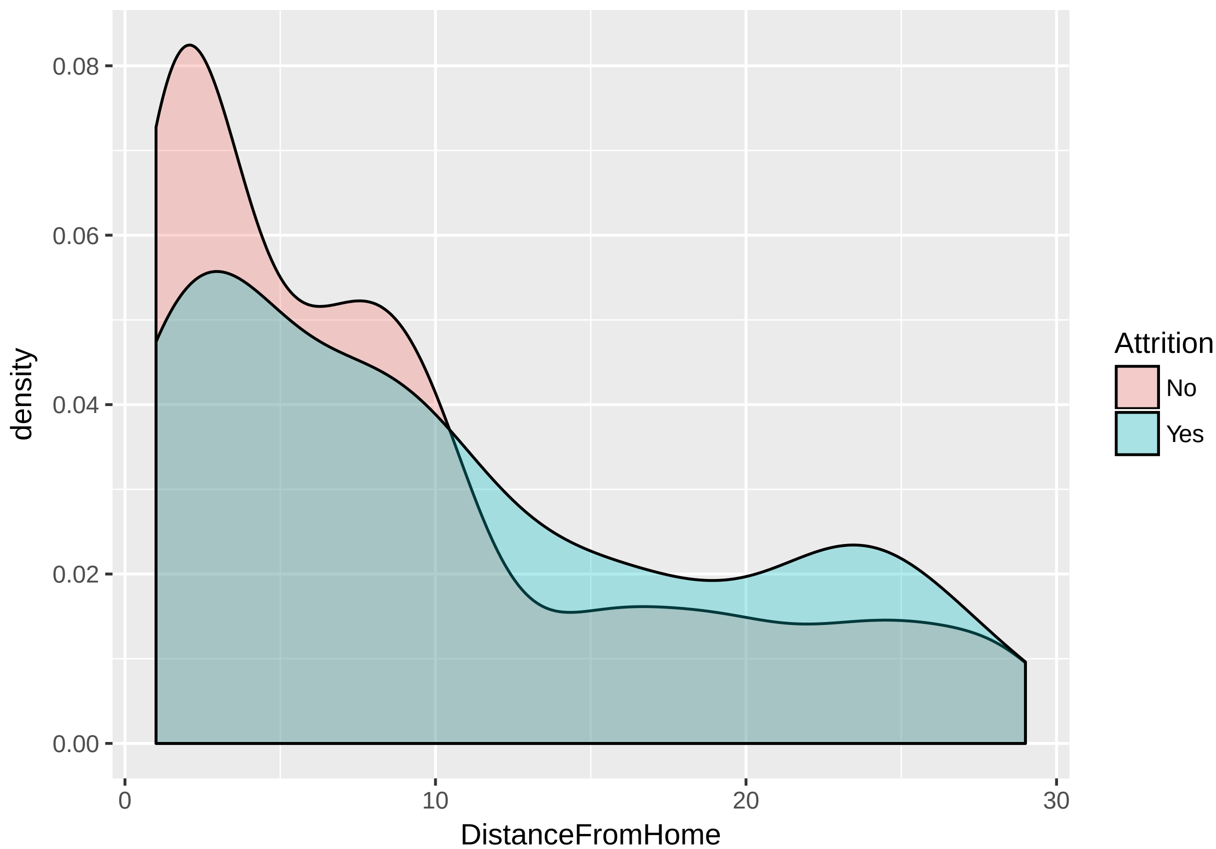

BusinessTravel
Non−Travel
Travel_Frequently
Travel_Rarely
92.0%
8.0%
75.1%
24.9%
85.0%
15.0%
prop
0.00
0.25
0.50
0.75
No
Yes
Attrition

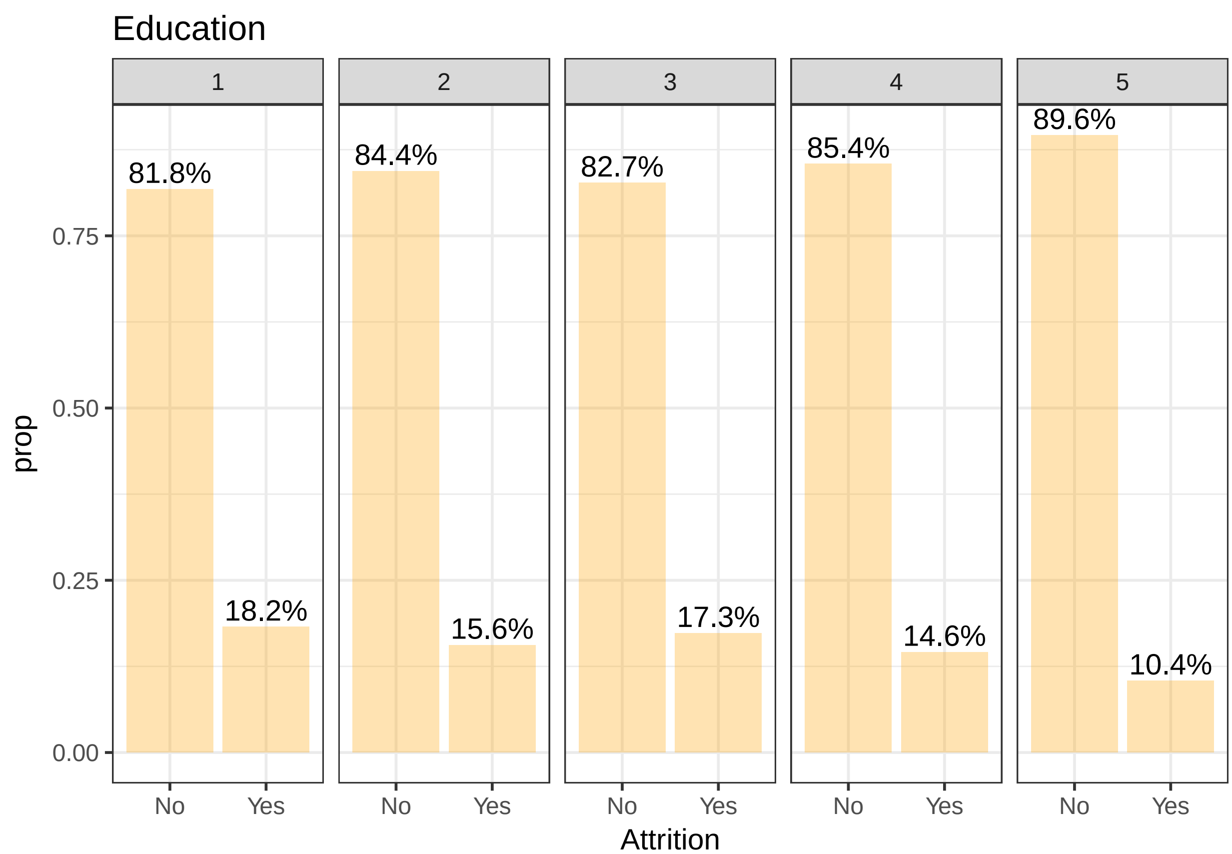


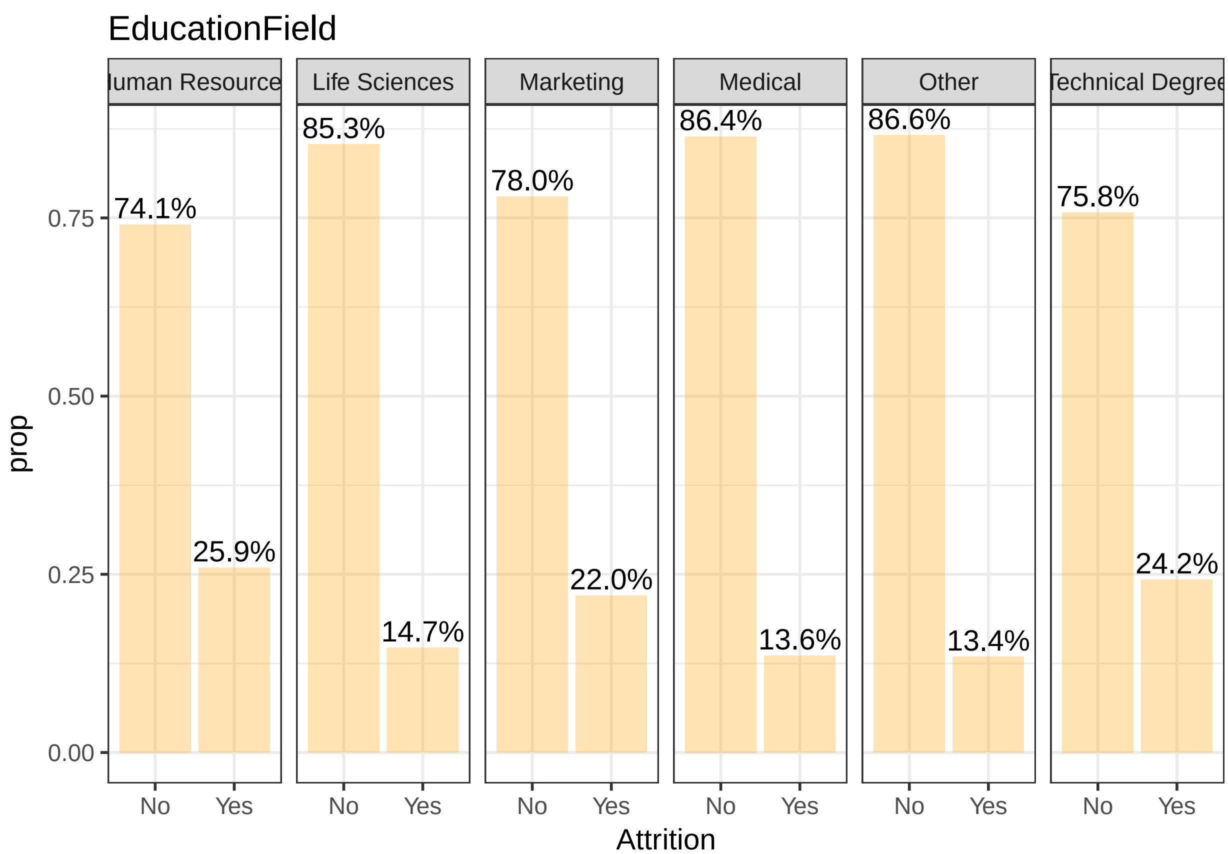
0.00075
0.00050
0.00025
0.00000
density
400
800
1200
DailyRate
Attrition
No
Yes

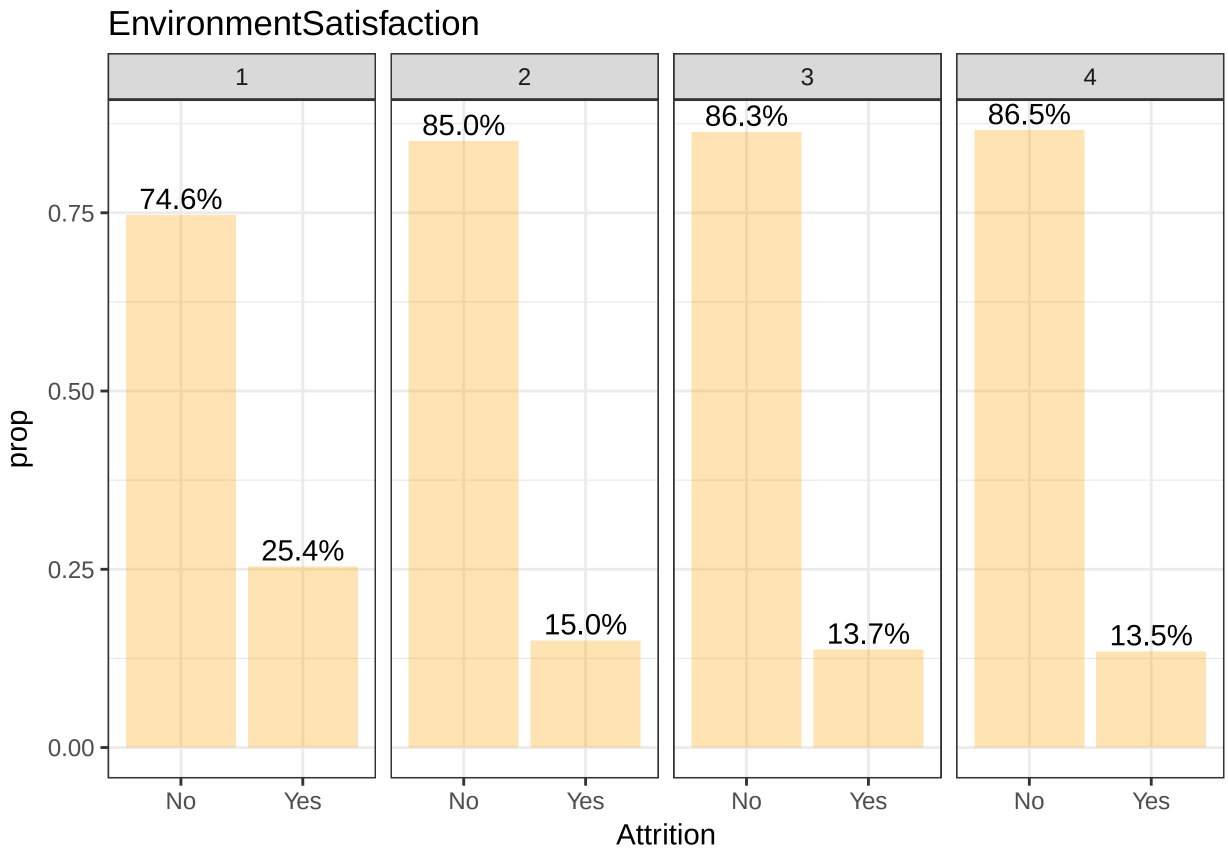


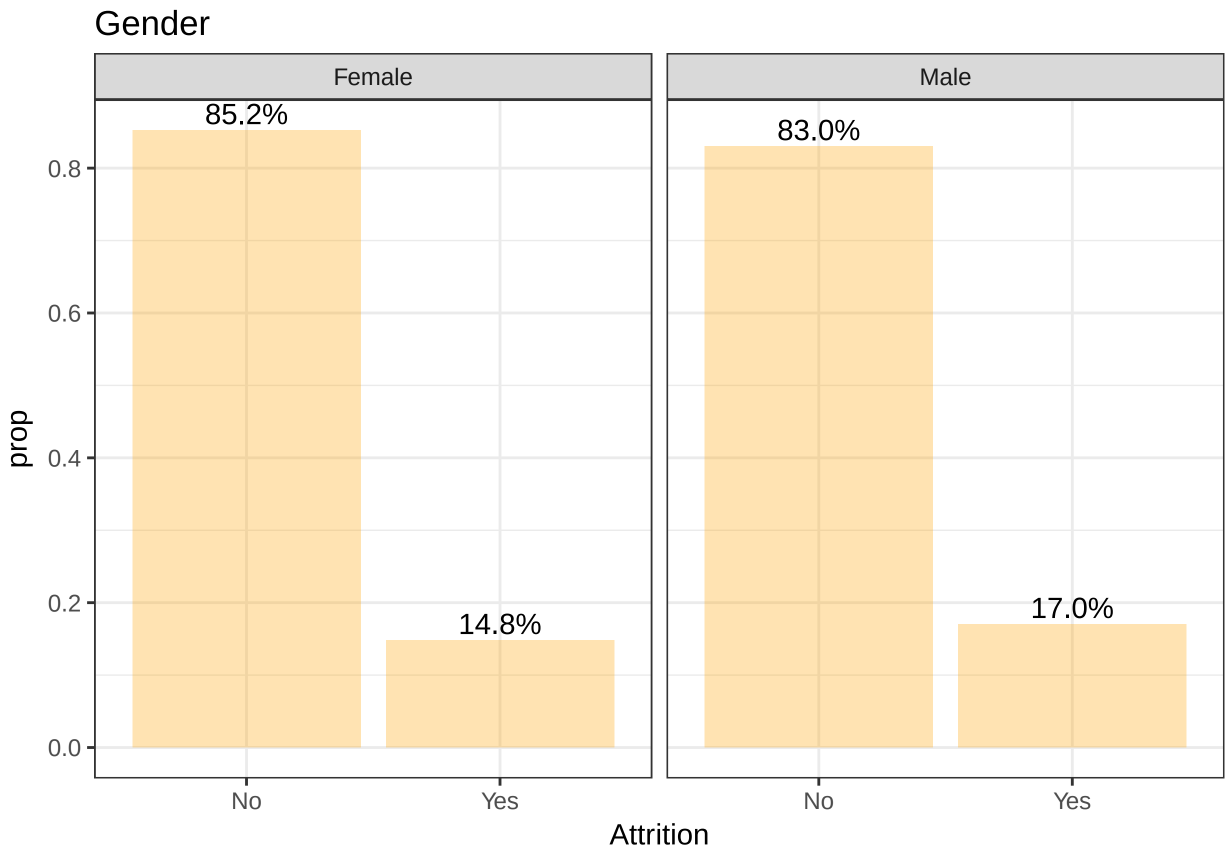
Department
Human Resources
Research & Development
Sales
81.0%
19.0%
86.2%
13.8%
79.4%
20.6%
prop
0.00
0.25
0.50
0.75
No
Yes
Attrition

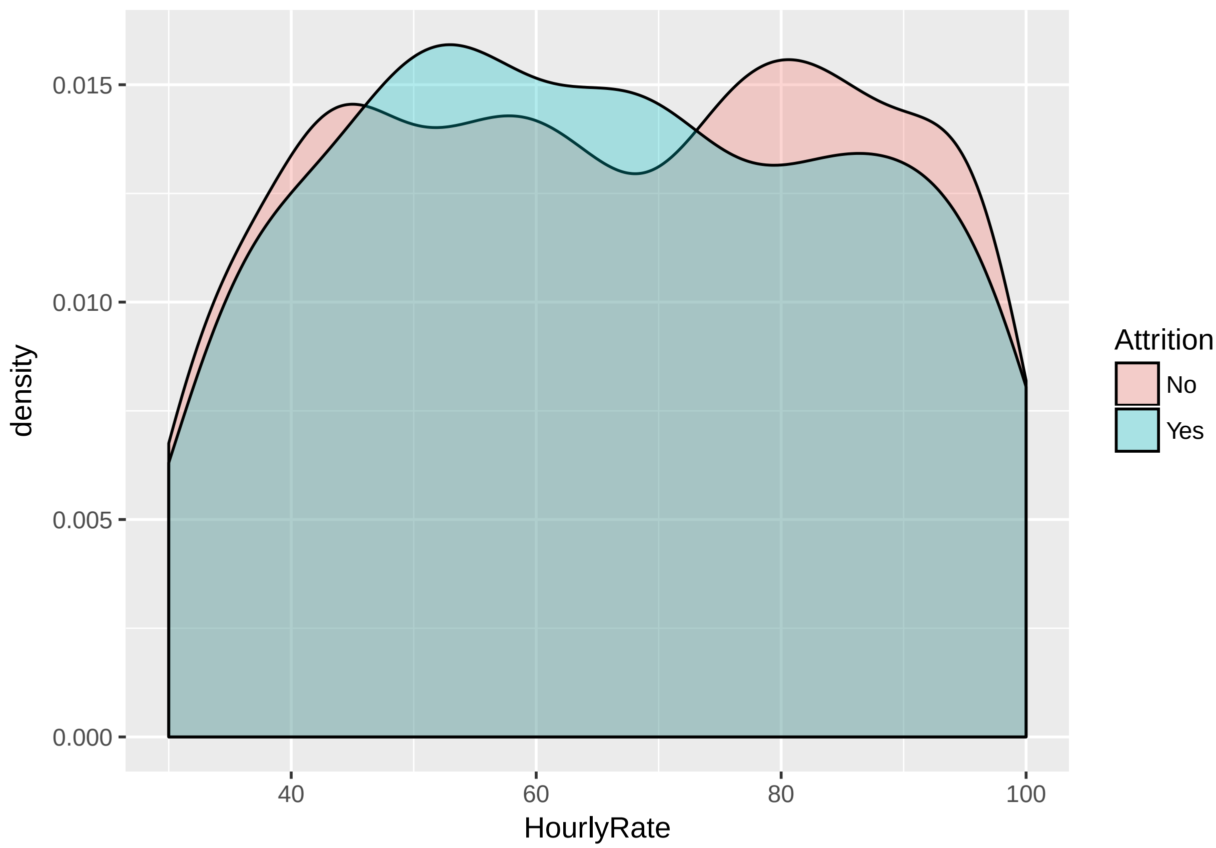

0.08
0.06
0.04
0.02
0.00
density
0
10
20
30
DistanceFromHome
Attrition
No
Yes


Education
1
2
3
4
5
81.8%
18.2%
84.4%
15.6%
82.7%
17.3%
85.4%
14.6%
89.6%
10.4%
0.75
0.50
0.25
0.00
prop
No
Yes
Attrition

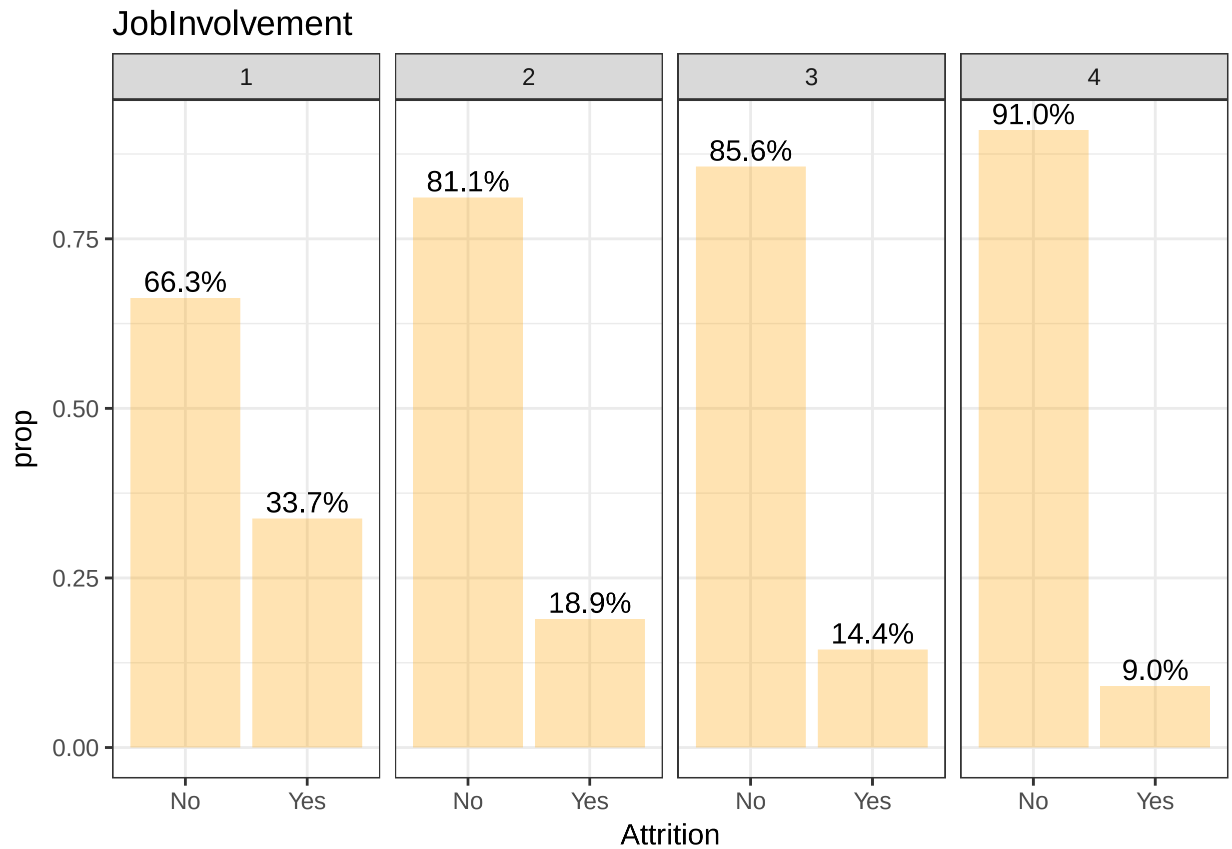

EducationField
Human Resources
Life Sciences
Marketing
Medical
Other
Technical Degree
74.1%
25.9%
85.3%
14.7%
78.0%
22.0%
86.4%
13.6%
86.6%
13.4%
75.8%
24.2%
prop
0.00
0.25
0.50
0.75
No
Yes
Attrition


EnvironmentSatisfaction
1
2
3
4
74.6%
25.4%
85.0%
15.0%
86.3%
13.7%
86.5%
13.5%
0.75
0.50
0.25
0.00
prop
No
Yes
Attrition

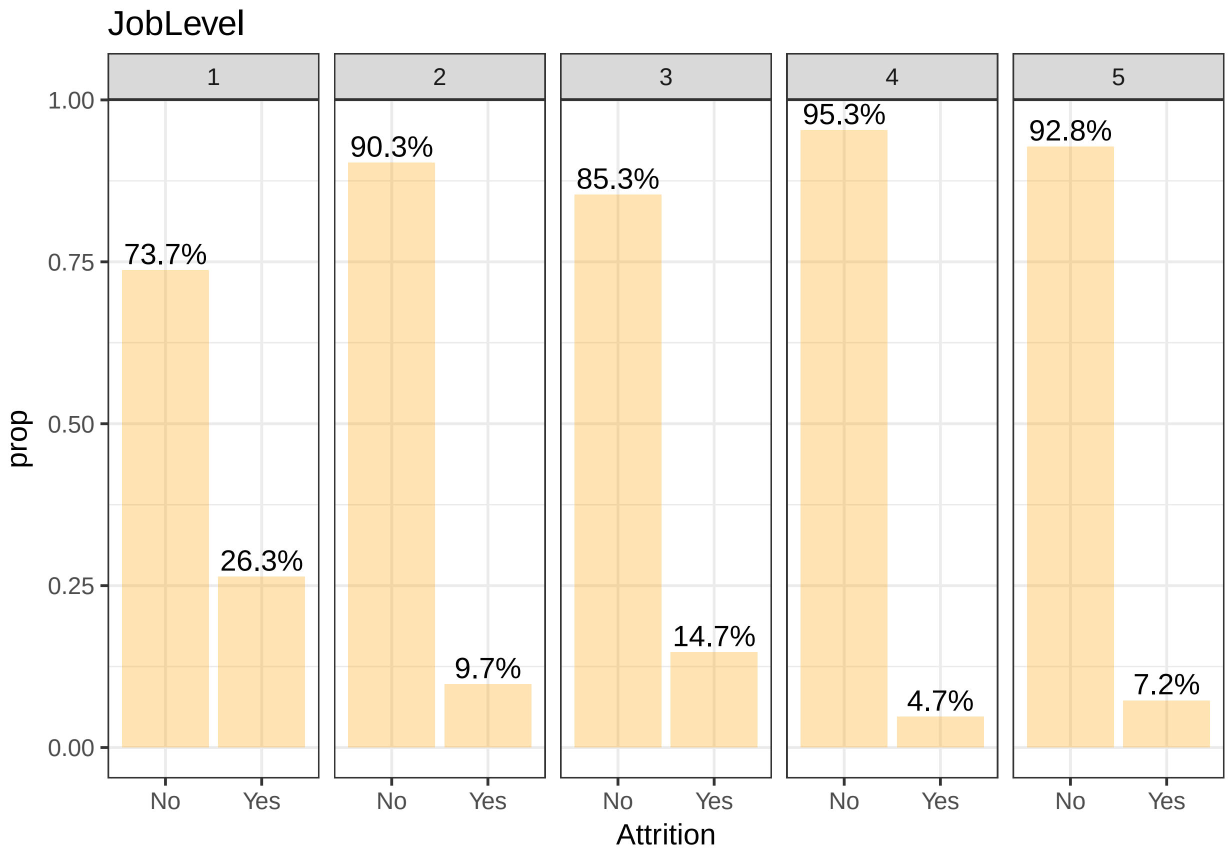

Gender
Female
Male
85.2%
14.8%
83.0%
17.0%
prop
0.0
0.2
0.4
0.6
0.8
No
Yes
No
Yes
Attrition



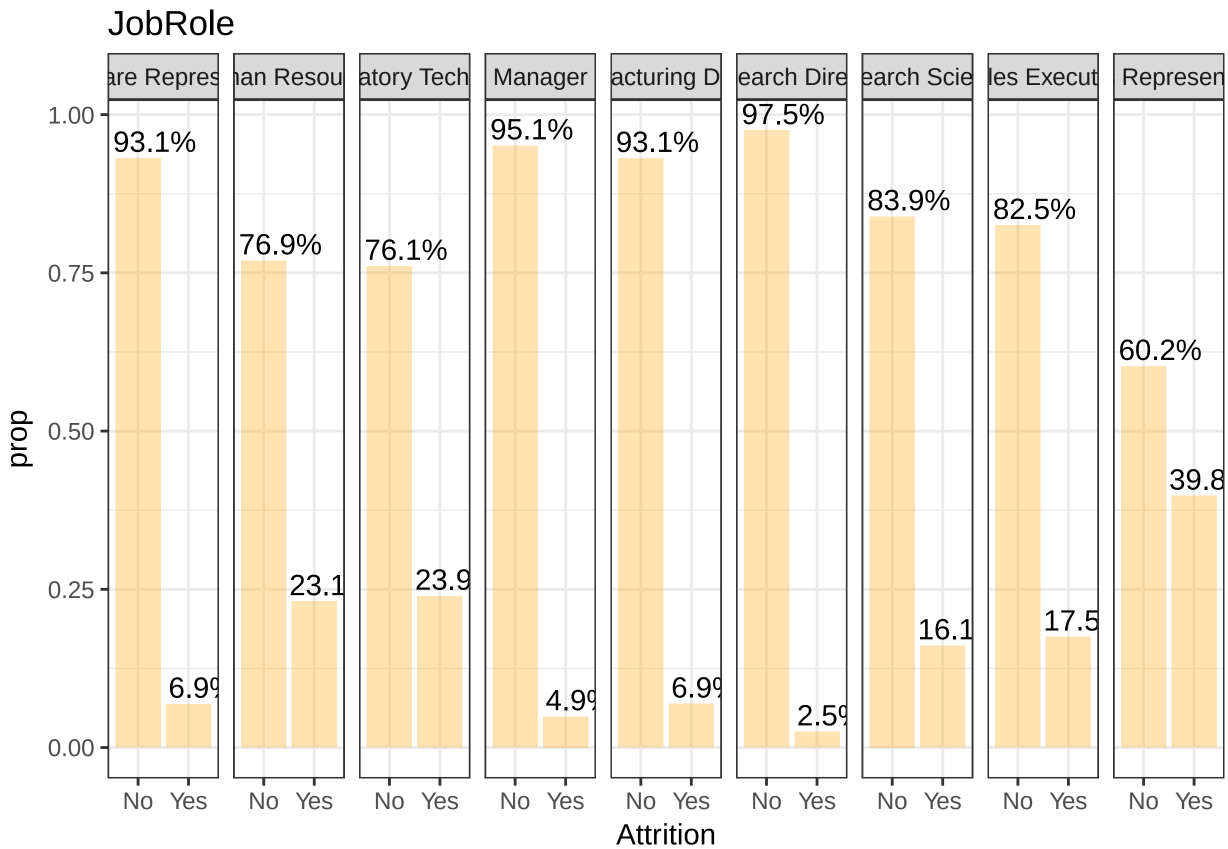
density
0.000
0.005
0.010
0.015
40
60
80
100
HourlyRate
Attrition
No
Yes

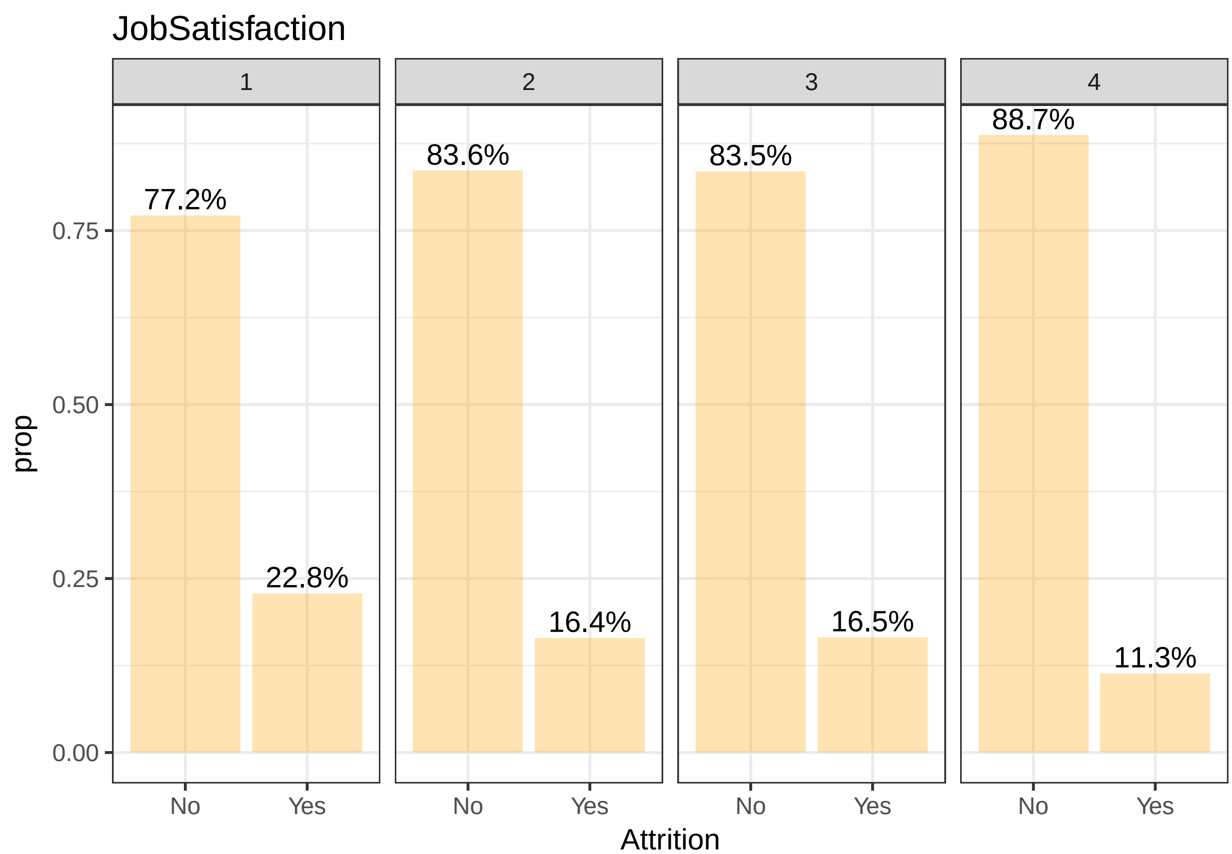


JobInvolvement
1
2
3
4
prop
0.75
0.50
0.25
0.00
66.3%
33.7%
81.1%
18.9%
85.6%
14.4%
91.0%
9.0%
No
Yes
No
Yes
No
Yes
No
Yes
Attrition

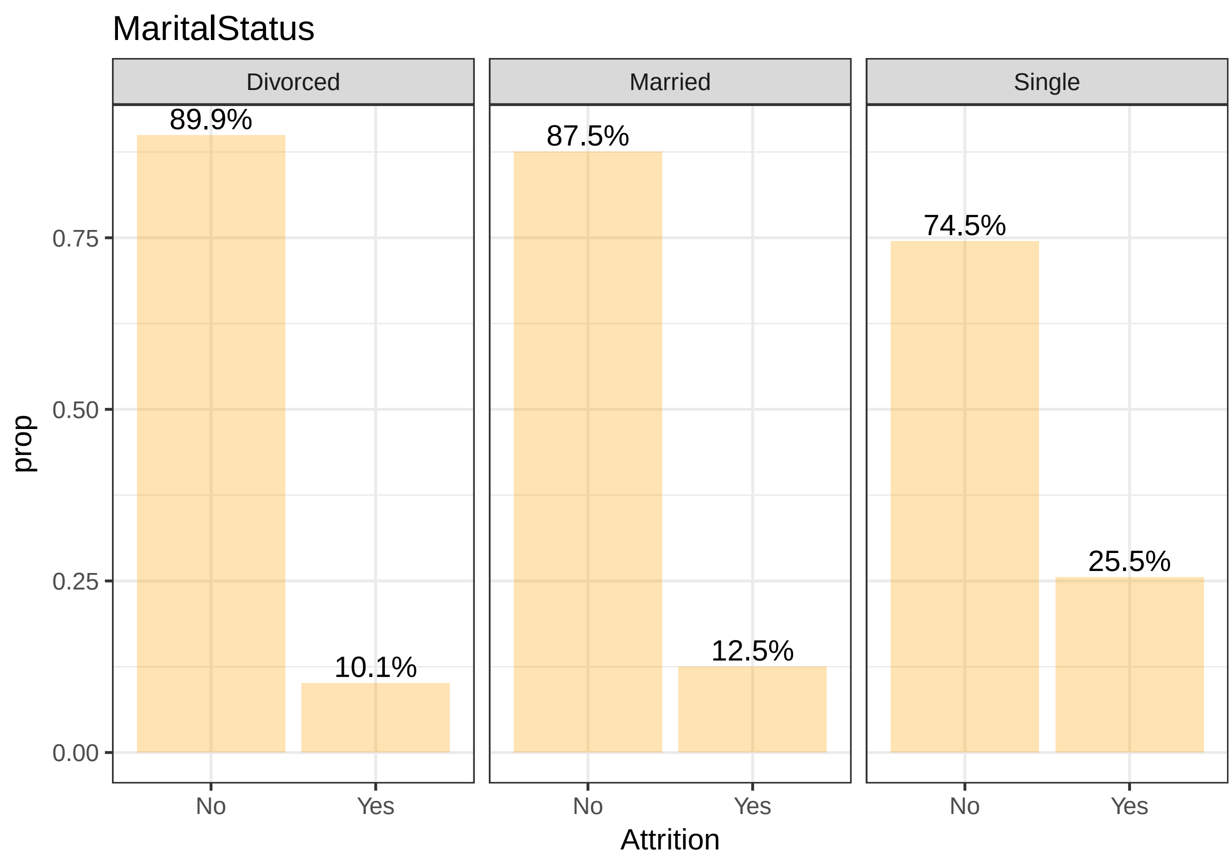


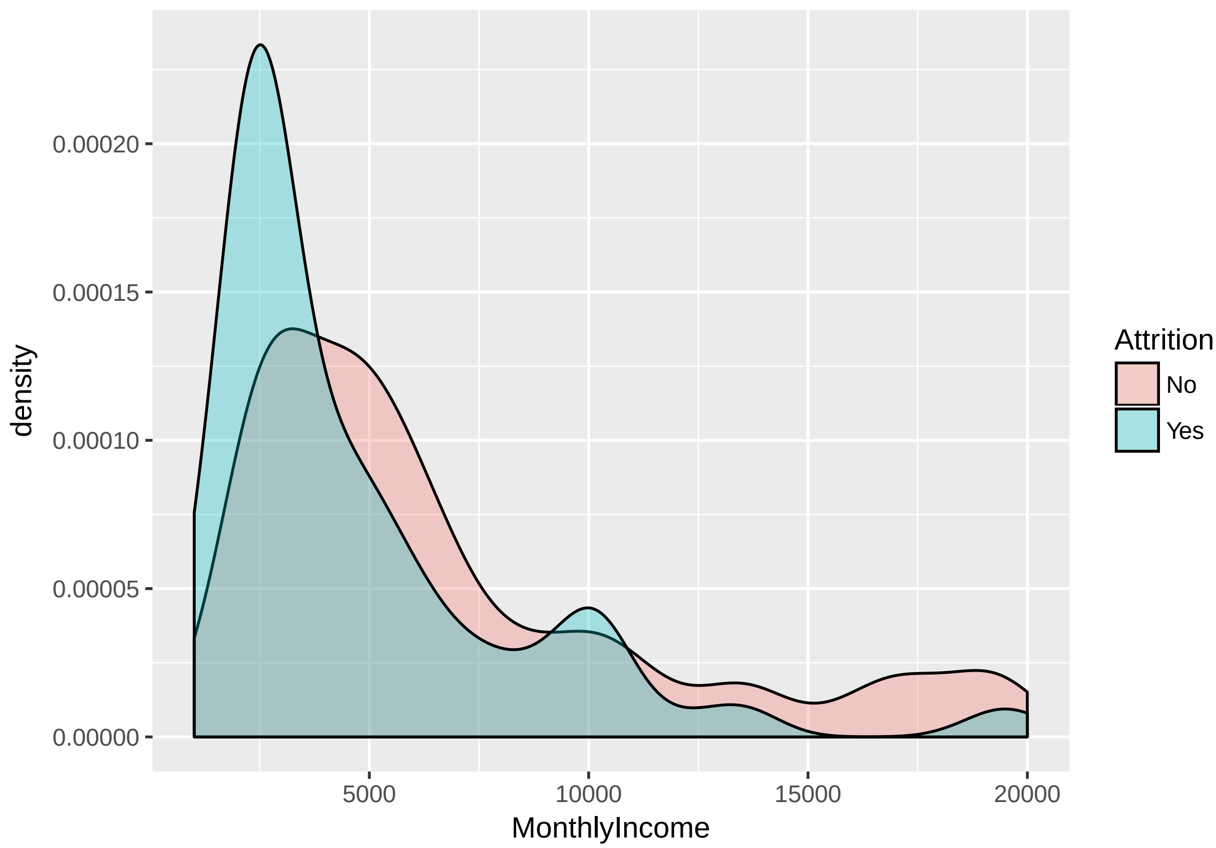
JobLevel
1
2
3
4
5
1.00
0.75
0.50
0.25
0.00
prop
73.7%
26.3%
90.3%
9.7%
85.3%
14.7%
95.3%
4.7%
92.8%
7.2%
No
Yes
No
Yes
No
Yes
No
Yes
No
Yes
Attrition


JobRole
are Repres
nan Resou
atory Tech
Manager
acturing D
earch Dire
earch Scie
les Execut
Represen
93.1%
6.9%
76.9%
23.1
76.1%
23.9
95.1%
4.9%
93.1%
6.9%
97.5%
2.5%
83.9%
16.1
82.5%
17.5
60.2%
39.8
prop
1.00
0.75
0.50
0.25
0.00
No
Yes
Attrition

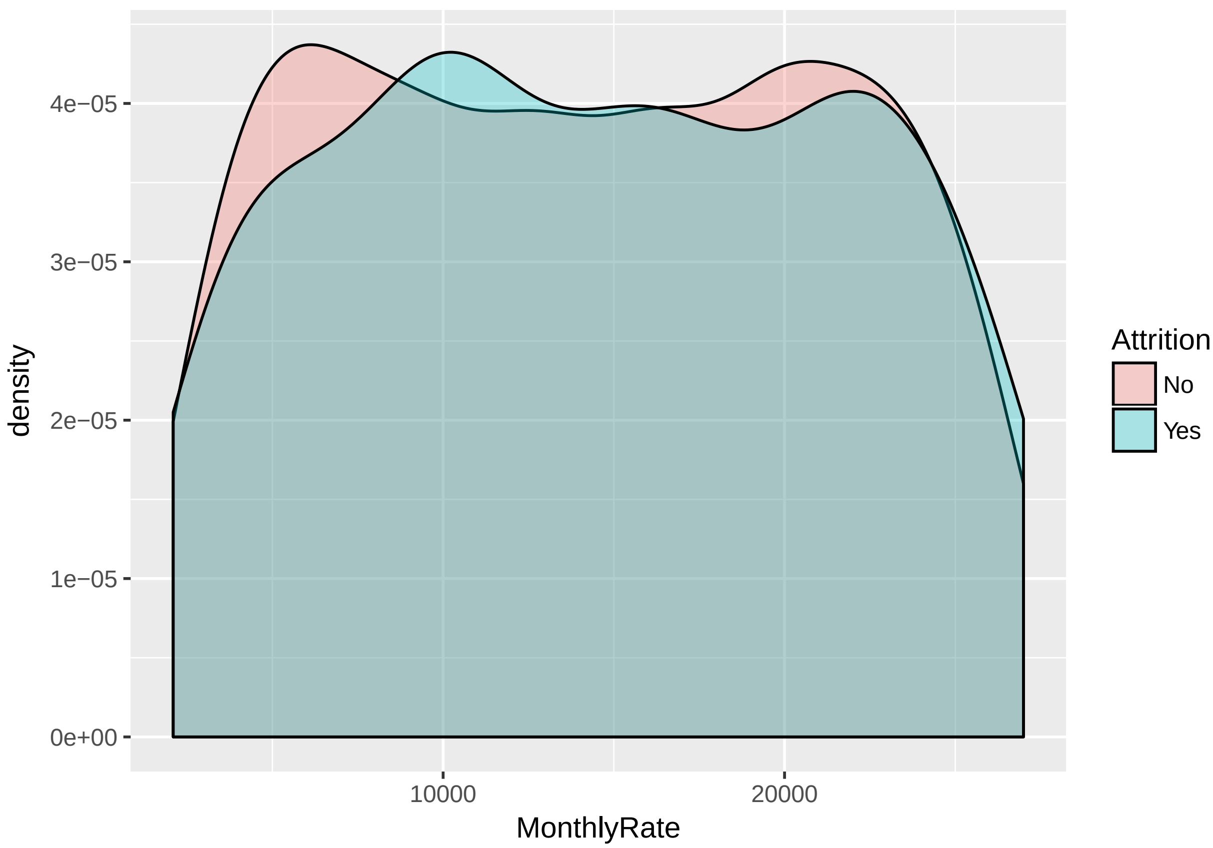


JobSatisfaction
1
2
3
4
77.2%
22.8%
83.6%
16.4%
83.5%
16.5%
88.7%
11.3%
0.75
0.50
0.25
0.00
prop
No
Yes
Attrition

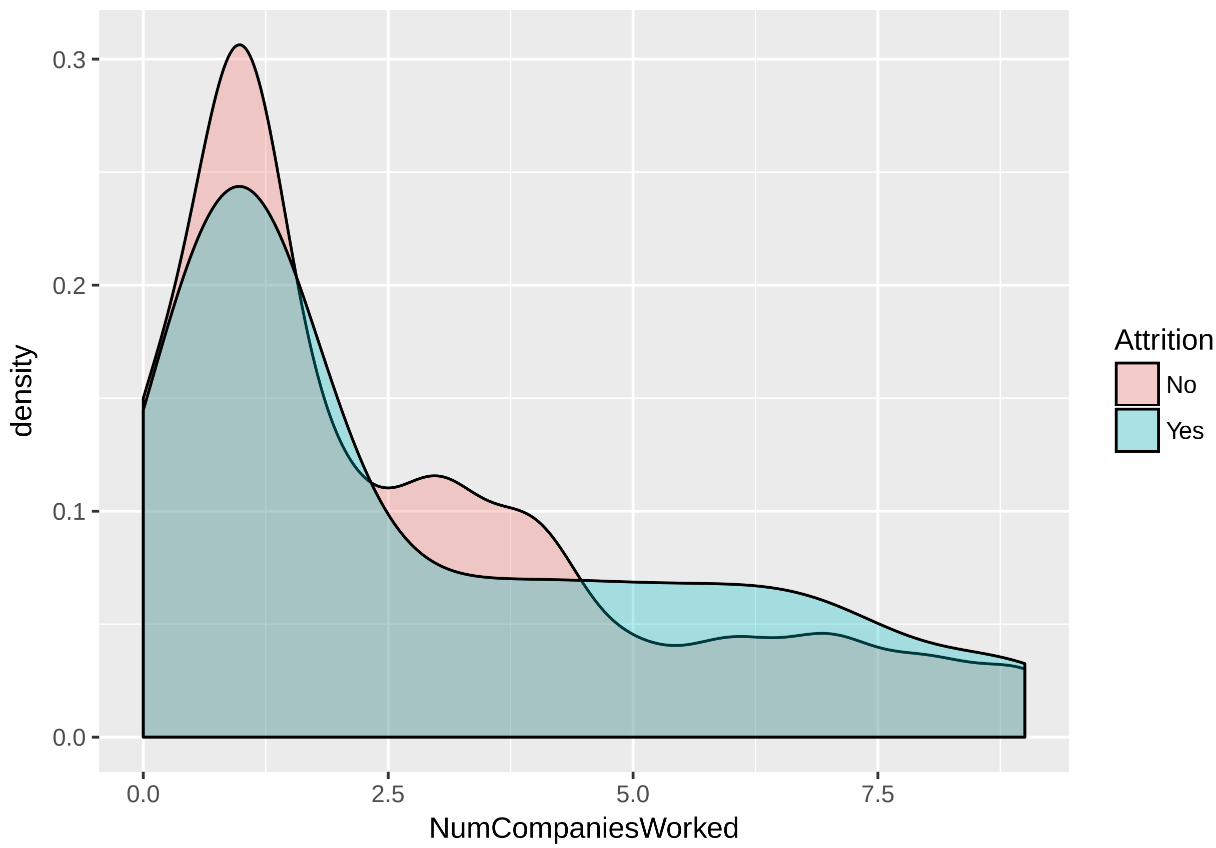

MaritalStatus
Divorced
Married
Single
89.9%
10.1%
87.5%
12.5%
74.5%
25.5%
prop
0.00
0.25
0.50
0.75
No
Yes
No
Yes
No
Yes
Attrition

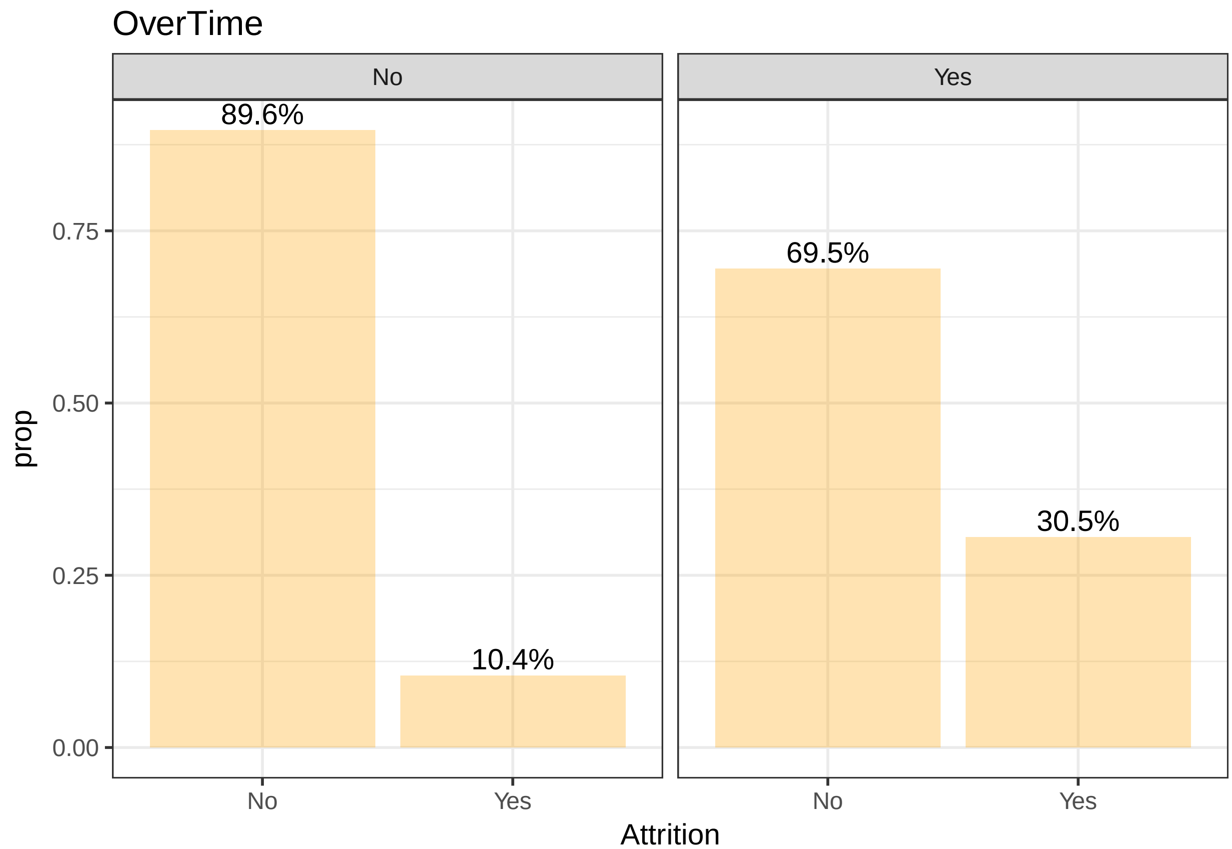


0.00020
0.00015
0.00010
0.00005
0.00000
density
5000
10000
15000
20000
MonthlyIncome
Attrition
No
Yes

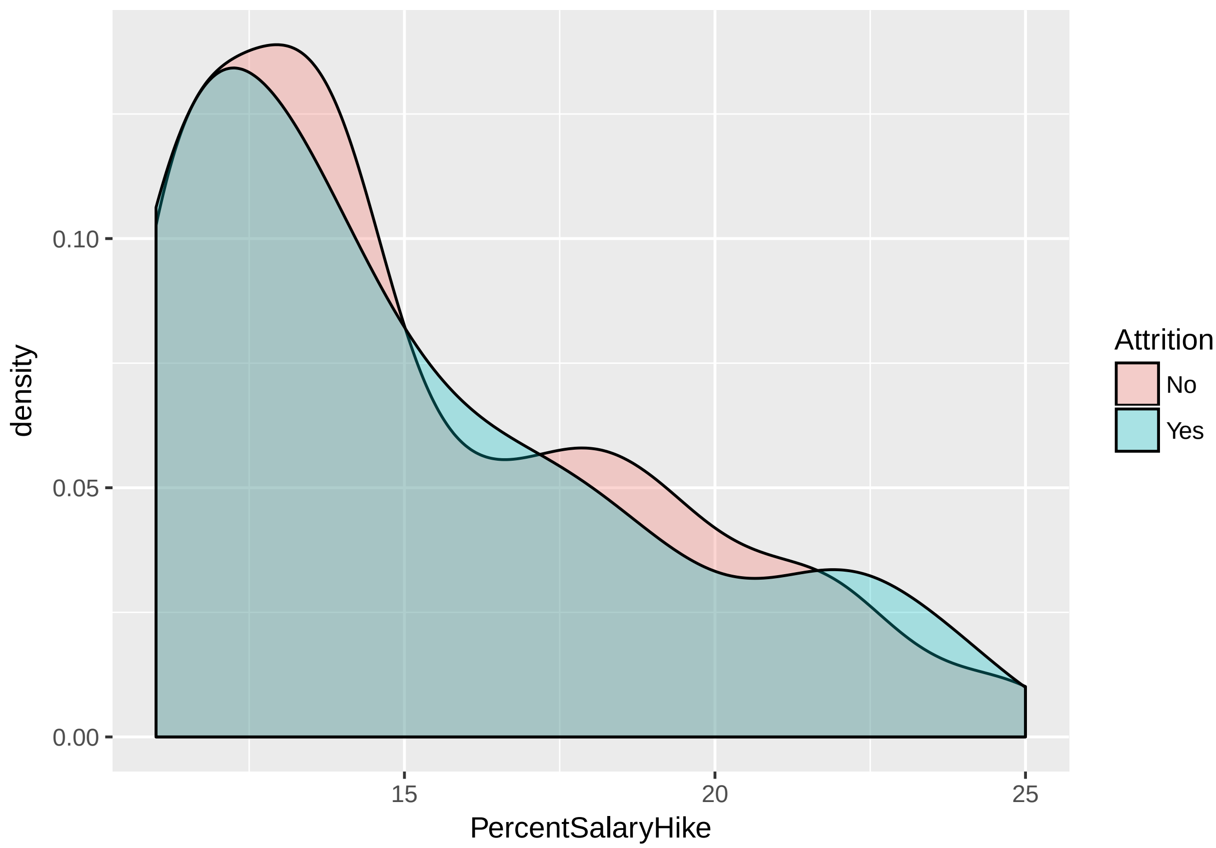


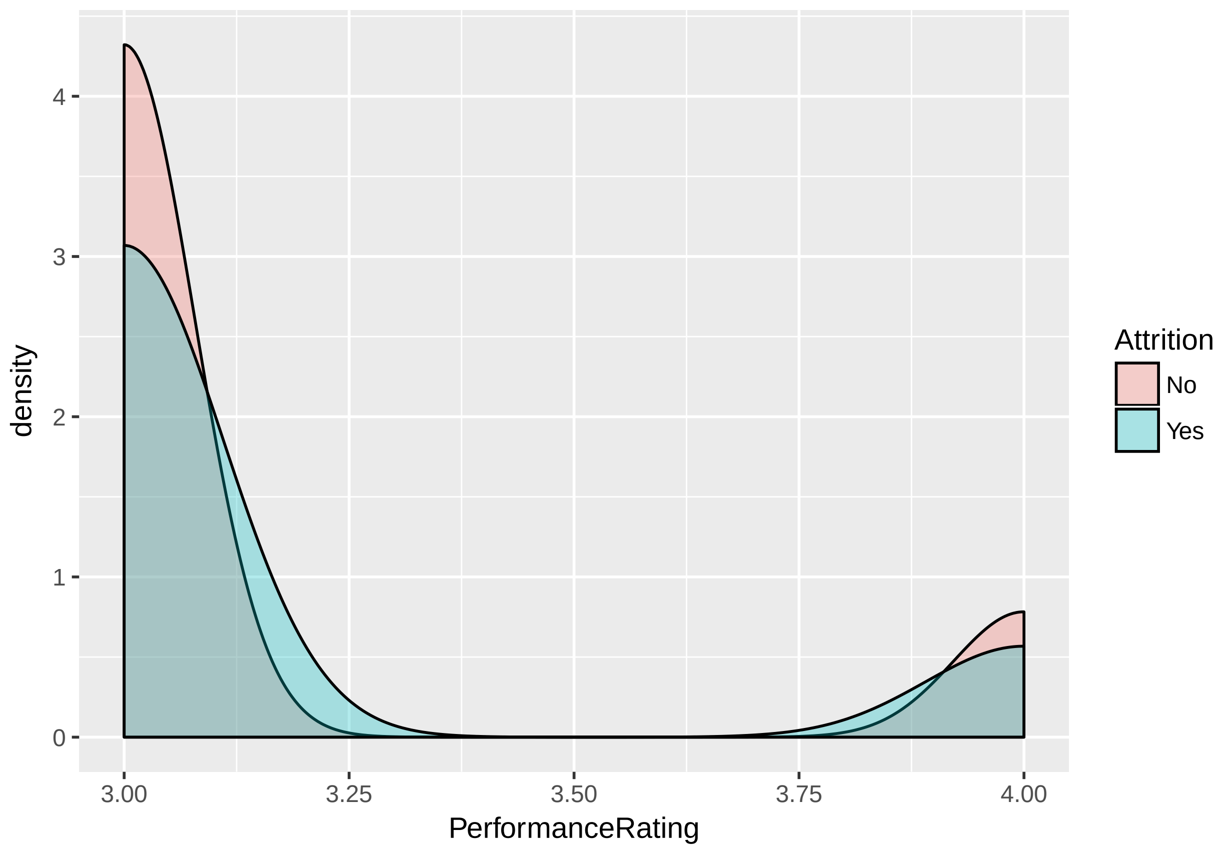
density
4e−05
3e−05
2e−05
1e−05
0e+00
10000
20000
MonthlyRate
Attrition
No
Yes

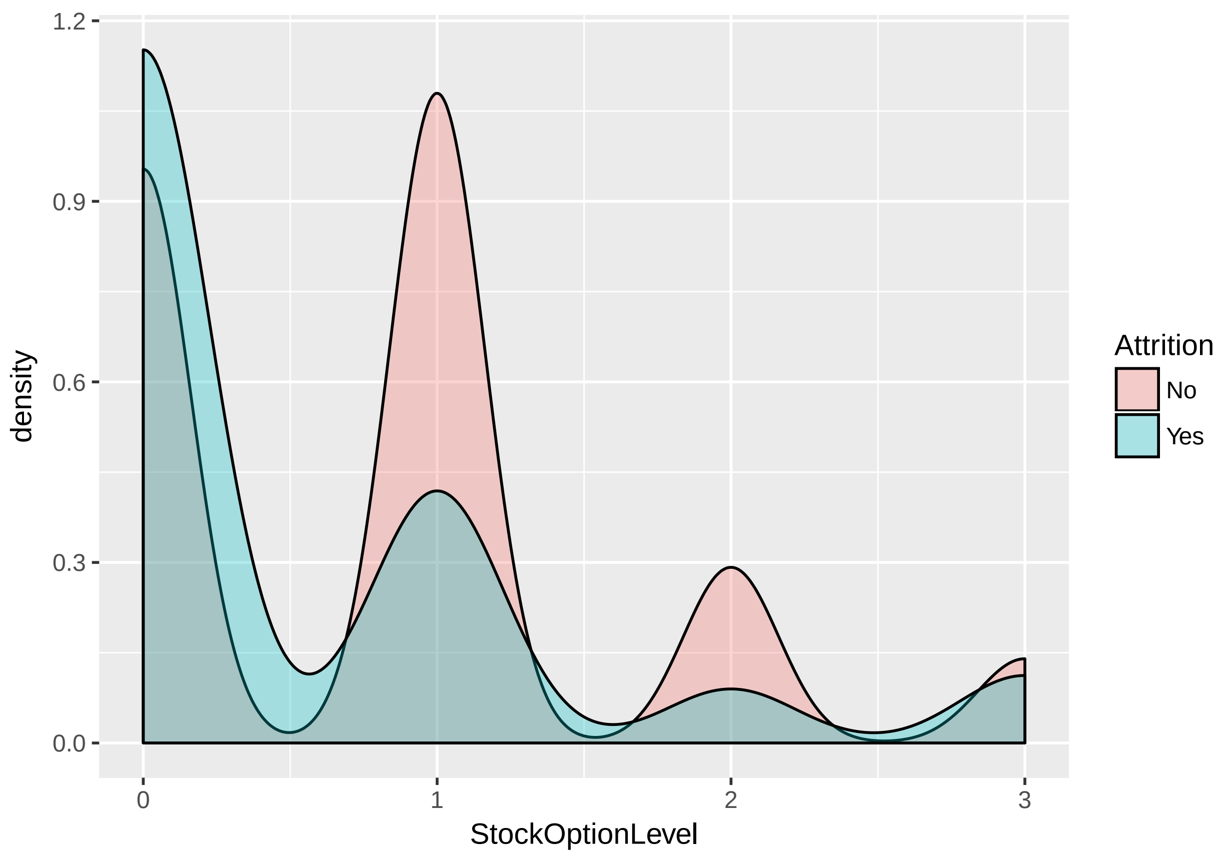

0.3
0.2
0.1
0.0
density
0.0
2.5
5.0
7.5
NumCompaniesWorked
Attrition
No
Yes



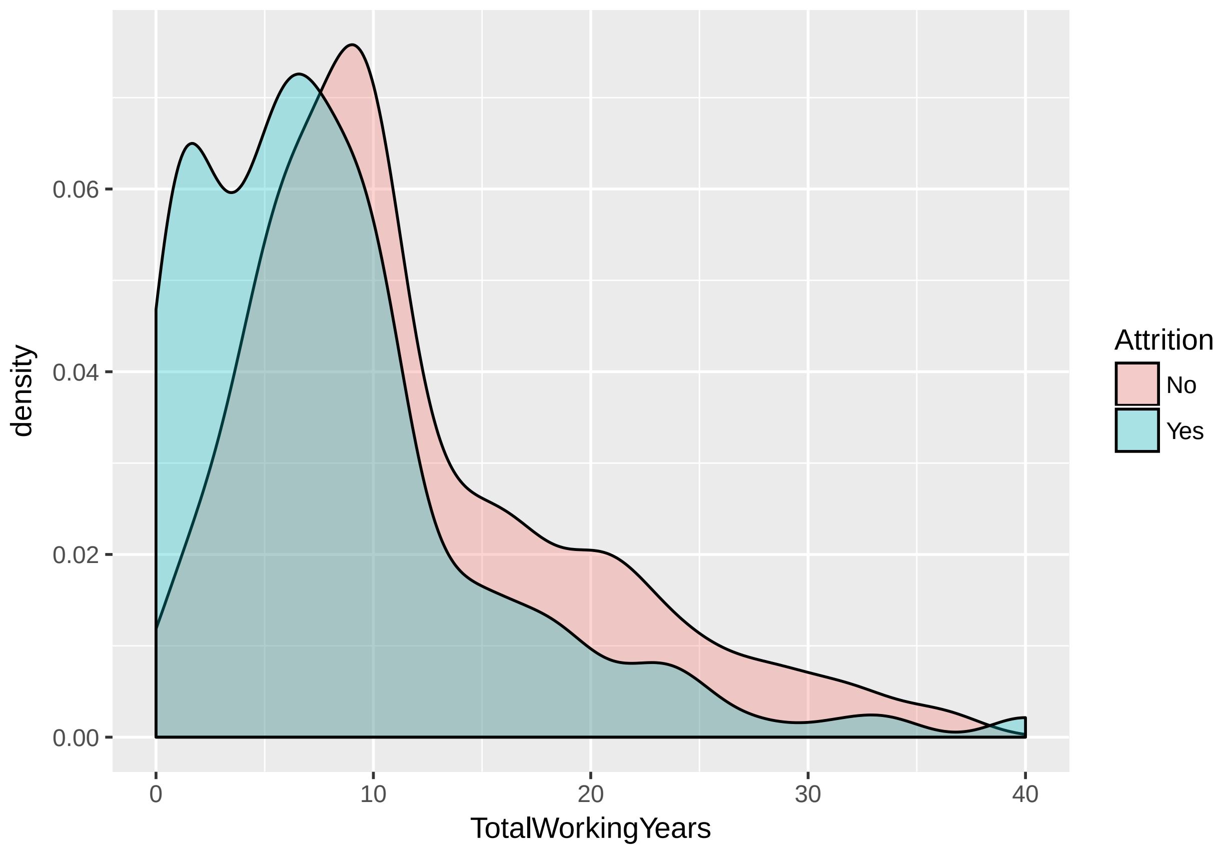
OverTime
No
Yes
89.6%
10.4%
69.5%
30.5%
0.75
0.50
0.25
0.00
prop
No
Yes
No
Yes
Attrition

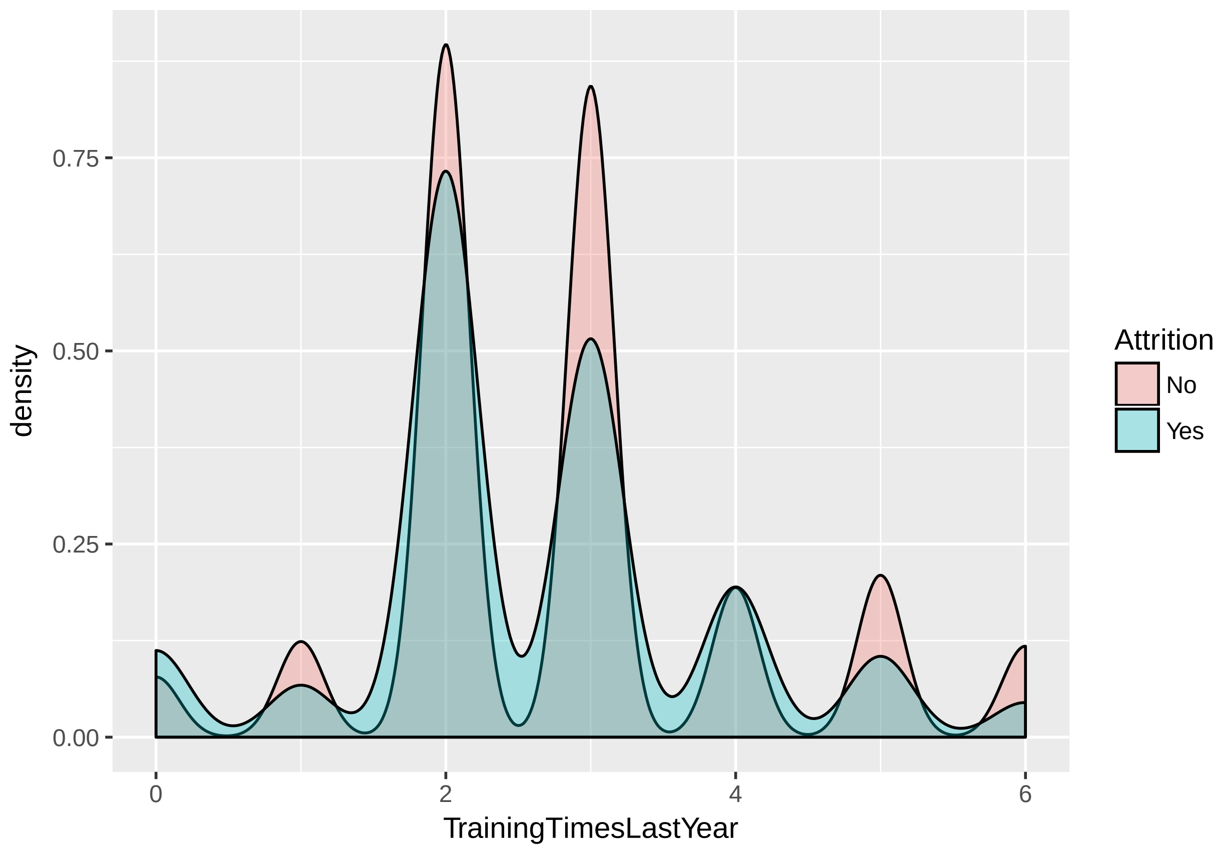

0.10
0.05
0.00
density
15
20
25
PercentSalaryHike
Attrition
No
Yes


4
3
2
1
0
density
3.00
3.25
3.50
3.75
4.00
PerformanceRating
Attrition
No
Yes

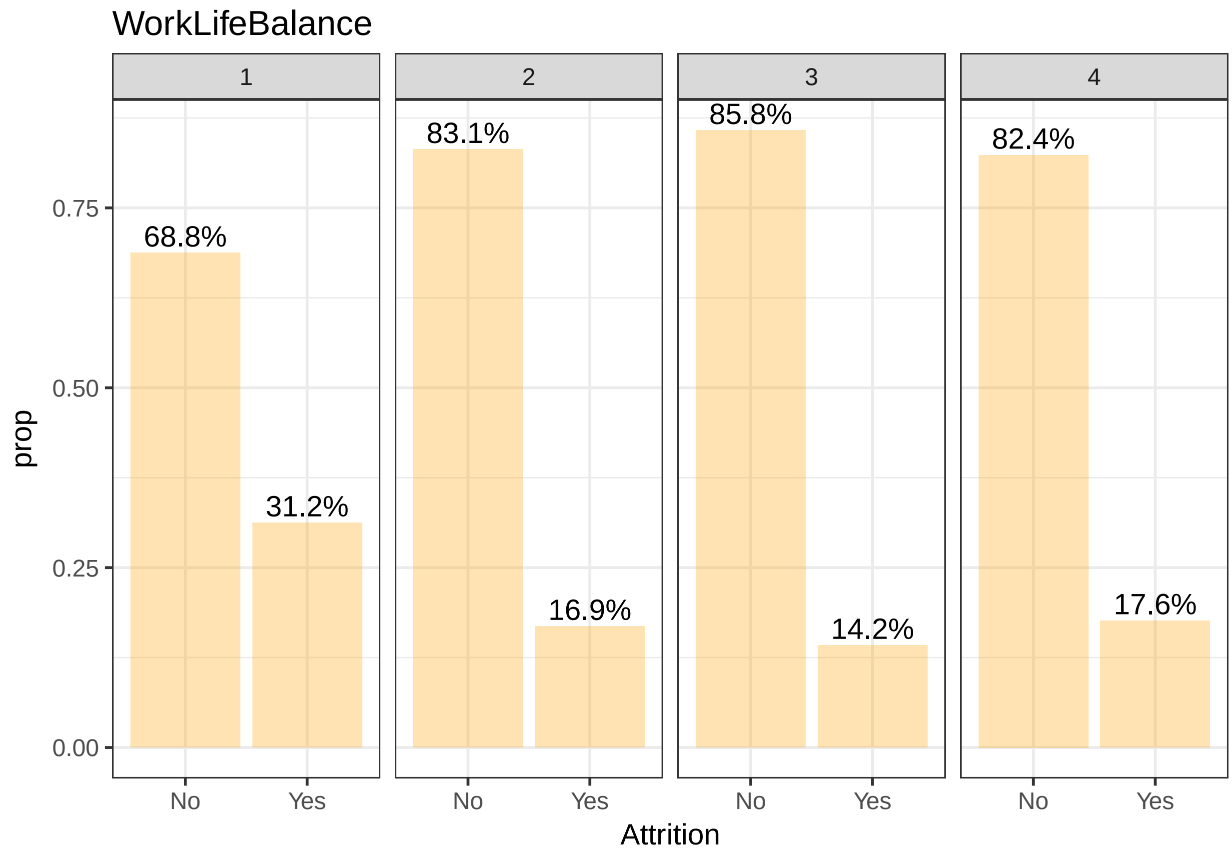


1.2
0.9
0.6
0.3
0.0
density
0
1
2
3
StockOptionLevel
Attrition
No
Yes

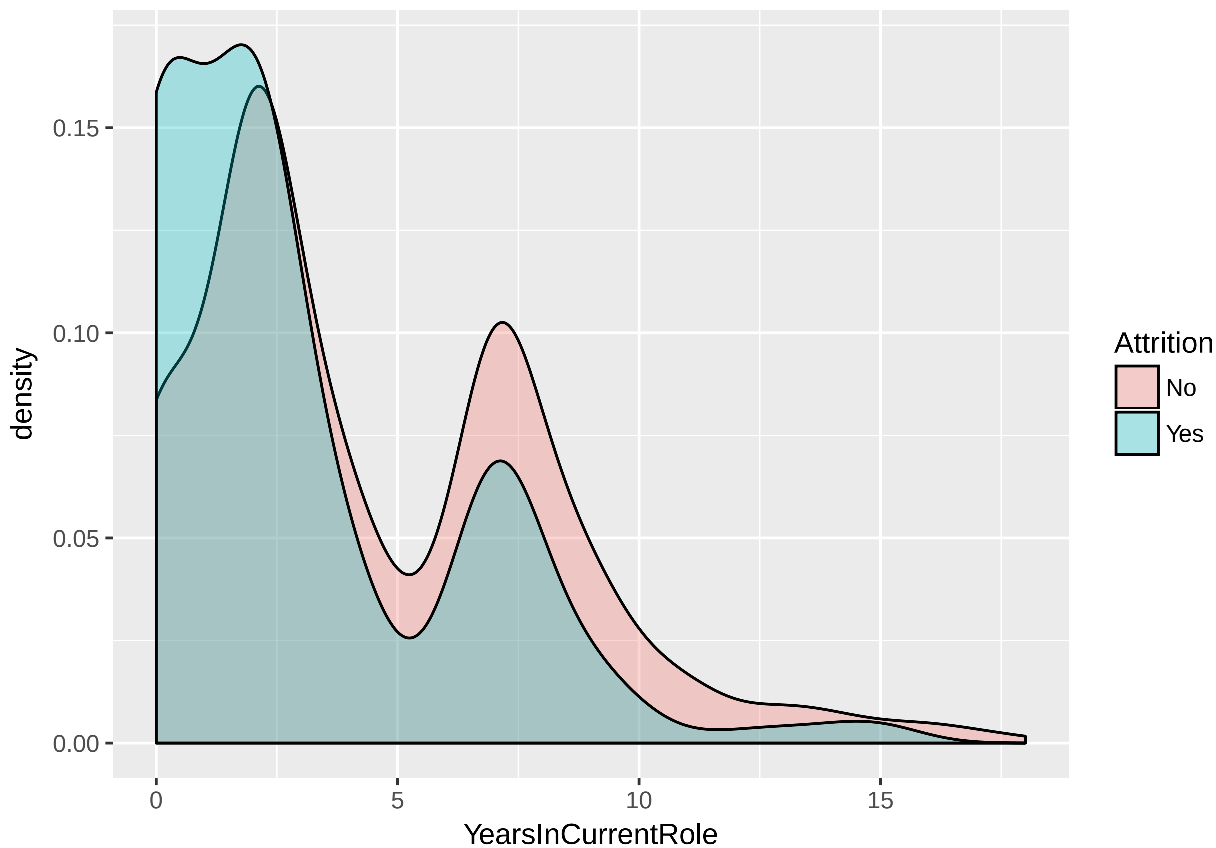

0.06
0.04
0.02
0.00
density
0
10
20
30
40
TotalWorkingYears
Attrition
No
Yes



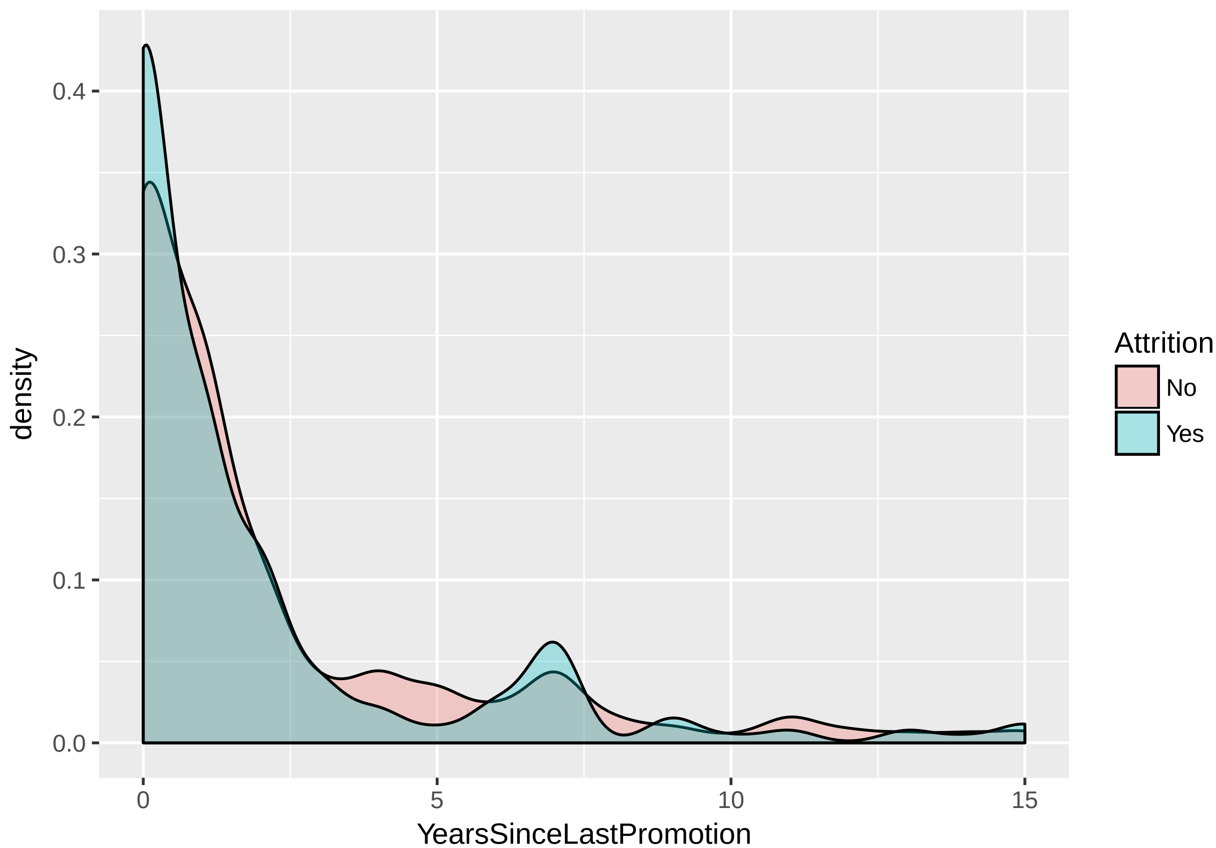
0.75
0.50
0.25
0.00
density
0
2
4
6
TrainingTimesLastYear
Attrition
No
Yes


WorkLifeBalance
1
2
3
4
68.8%
31.2%
83.1%
16.9%
85.8%
14.2%
82.4%
17.6%
prop
0.75
0.50
0.25
0.00
No
Yes
Attrition

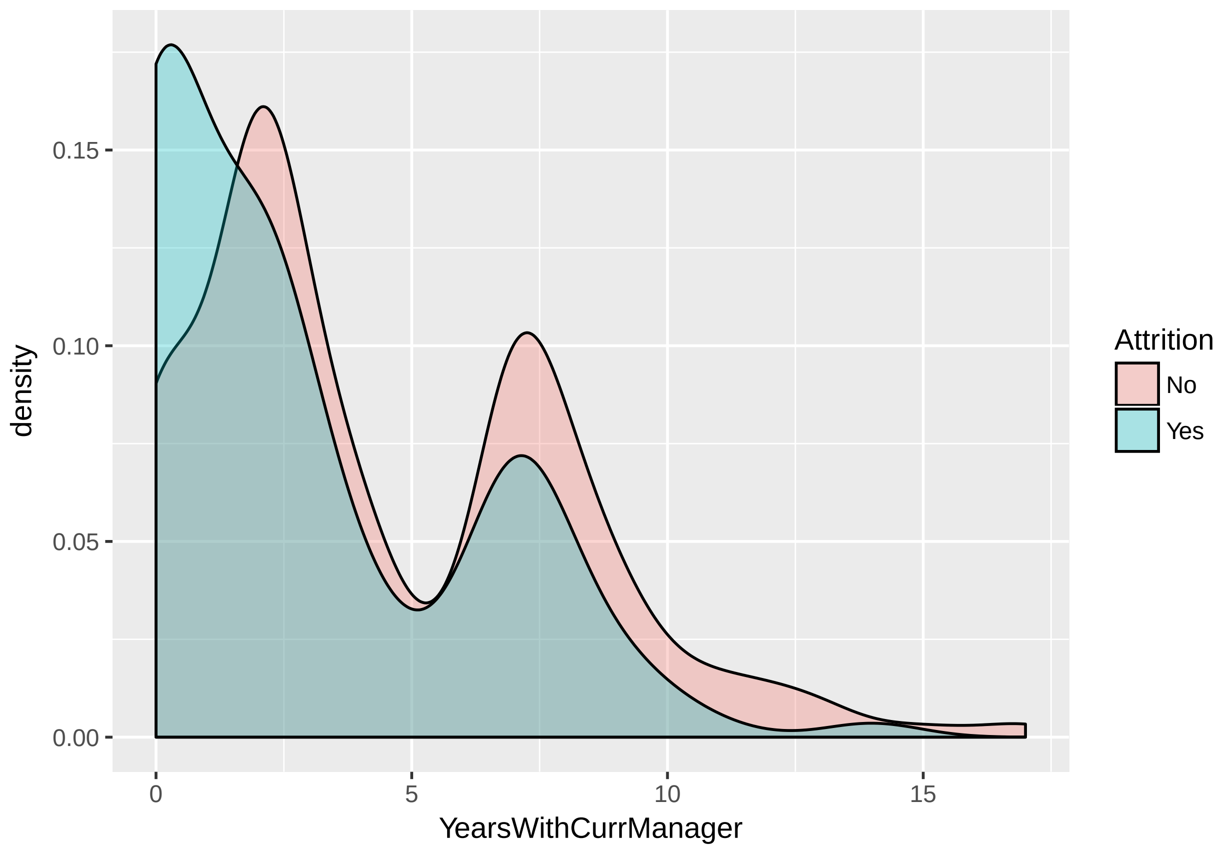
0.10
0.05
0.00
density
0
10
20
30
40
YearsAtCompany
Attrition
No
Yes



density
0.15
0.10
0.05
0.00
0
5
10
15
YearsInCurrentRole
Attrition
No
Yes



0.4
0.3
0.2
0.1
0.0
density
0
5
10
15
YearsSinceLastPromotion
Attrition
No
Yes



Model

We can consider logistic regression, LDA, boosting, tree, random forest, knn.

Note: qda model is not used because of rank deficiency.

For each model, we tested different threshold and pick the one that makes the best prediction.

We use accuracy, percentage of people who leaves / people we predict to leave, and percentage of people leave / people we predict to stay to compare the models because our emphasis on predicting people who intend to leave the company.

```
calc_acc = function(actual, predicted) {
  mean(actual == predicted)
}
# how many people actually leaves when we predicted them to leave
calc_stay = function(TP, FP){
  TP / (TP + FP)
}
calc_leave = function(y, x){
  x / (x + y)
}
```

We use 70% of our dataset as traning data.

```
set.seed(432)
index  = sample(nrow(attribution), size = trunc(0.7 * nrow(attribution)))
```

```
train_data= attribution[index, ]
test_data = attribution[-index, ]
```

Logistic

First, We start with Logistic Regression and we used mixed selection to get 18 important variables. From the model summary, we can see that each variable is significant.

```
set.seed(432)
null = glm(Attrition~1, data=train_data, family="binomial")
log.fit =glm(Attrition~., data=train_data, family="binomial")
regboth = step(null, scope=formula(log.fit), direction="both", trace=0)

log.fit = glm(Attrition ~ OverTime + JobRole + JobInvolvement +
                MaritalStatus + JobSatisfaction + EnvironmentSatisfaction +
                BusinessTravel + DistanceFromHome + YearsInCurrentRole +
                YearsSinceLastPromotion + TrainingTimesLastYear + ï..Age +
                NumCompaniesWorked + RelationshipSatisfaction + WorkLifeBalance +
                YearsWithCurrManager + YearsAtCompany + TotalWorkingYears, data = train_data, family="bi
summary(log.fit)
```

```
##
## Call:
## glm(formula = Attrition ~ OverTime + JobRole + JobInvolvement +
##     MaritalStatus + JobSatisfaction + EnvironmentSatisfaction +
##     BusinessTravel + DistanceFromHome + YearsInCurrentRole +
##     YearsSinceLastPromotion + TrainingTimesLastYear + ï..Age +
##     NumCompaniesWorked + RelationshipSatisfaction + WorkLifeBalance +
##     YearsWithCurrManager + YearsAtCompany + TotalWorkingYears,
##     family = "binomial", data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8729  -0.4979  -0.2467  -0.0899   3.2222
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       0.99979    1.12183   0.891 0.372817
## OverTimeYes                       2.10223    0.23751   8.851  < 2e-16 ***
## JobRoleHuman Resources            1.57058    0.66705   2.355 0.018546 *
## JobRoleLaboratory Technician      1.41633    0.49442   2.865 0.004175 **
## JobRoleManager                    0.48063    0.75034   0.641 0.521816
## JobRoleManufacturing Director    -0.16765    0.63244  -0.265 0.790938
## JobRoleResearch Director         -1.59394    1.21943  -1.307 0.191172
## JobRoleResearch Scientist         0.28258    0.49757   0.568 0.570093
## JobRoleSales Executive            1.11301    0.47592   2.339 0.019353 *
## JobRoleSales Representative       1.92596    0.57585   3.345 0.000824 ***
## JobInvolvement                   -0.61042    0.14931  -4.088 4.35e-05 ***
## MaritalStatusMarried              0.47576    0.31400   1.515 0.129737
## MaritalStatusSingle               1.53499    0.32505   4.722 2.33e-06 ***
## JobSatisfaction                  -0.35508    0.09710  -3.657 0.000255 ***
## EnvironmentSatisfaction          -0.39092    0.09802  -3.988 6.66e-05 ***
## BusinessTravelTravel_Frequently   2.00391    0.54463   3.679 0.000234 ***
## BusinessTravelTravel_Rarely       1.19438    0.50598   2.361 0.018249 *
## DistanceFromHome                  0.05322    0.01290   4.126 3.69e-05 ***
```

```
## YearsInCurrentRole               -0.13467    0.05571  -2.417 0.015642 *
## YearsSinceLastPromotion           0.15101    0.05021   3.007 0.002636 **
## TrainingTimesLastYear            -0.18098    0.08631  -2.097 0.036006 *
## ï..Age                           -0.02984    0.01589  -1.878 0.060378 .
## NumCompaniesWorked                0.18635    0.04520   4.123 3.74e-05 ***
## RelationshipSatisfaction         -0.31144    0.09807  -3.176 0.001494 **
## WorkLifeBalance                  -0.24699    0.15000  -1.647 0.099639 .
## YearsWithCurrManager             -0.12106    0.05813  -2.083 0.037284 *
## YearsAtCompany                    0.06879    0.04816   1.428 0.153218
## TotalWorkingYears                -0.06762    0.03285  -2.059 0.039540 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 896.03  on 1028  degrees of freedom
## Residual deviance: 594.20  on 1001  degrees of freedom
## AIC: 650.2
##
## Number of Fisher Scoring iterations: 7
```

```
log_pred = ifelse(predict(log.fit, newdata = test_data, type = "response") >= 0.7, 'Yes', 'No')
t1 = table(predicted = log_pred, actual = test_data$Attrition)
t1
```

```
##          actual
## predicted  No Yes
##       No  364  55
##       Yes   2  20
```

```
log_accu = calc_acc(actual = test_data$Attrition, predicted = log_pred)
log_stay = calc_stay(t1[2,2], t1[2,1])
log_leave = calc_leave(t1[1,1], t1[1,2])
```

Linear Discriminant Analysis

Then we tried lda and this is how we did varaible selection. We took out variables that have a high correlation which can be found in visualization. Then we tried to take out variables that has little or no relationship with Attrition.

```
set.seed(432)
lda_0 = lda(Attrition~., data = train_data, prior=c(864, 166)/1030)
lda_pred0 = ifelse(predict(lda_0, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
calc_acc(actual = test_data$Attrition,
         predicted = lda_pred0)
```

```
## [1] 0.8707483
```

```
table(predicted = lda_pred0, actual = test_data$Attrition)
```

```
##          actual
## predicted  No Yes
##       No  361  52
##       Yes   5  23
```

```
set.seed(432)
lda_1 = lda(Attrition~.- MonthlyIncome, data = train_data, prior=c(864, 166)/1030)
lda_pred1 = ifelse(predict(lda_1, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
```

```r
calc_acc(actual = test_data$Attrition,
         predicted = lda_pred1)
```

```
## [1] 0.8707483
```

```
##          actual
## predicted  No Yes
##       No  361  52
##       Yes   5  23
```

```r
set.seed(432)
lda_2 = lda(Attrition~.- MonthlyIncome - PerformanceRating, data = train_data, prior=c(864, 166)/1030)
lda_pred2 = ifelse(predict(lda_2, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
calc_acc(actual = test_data$Attrition,
         predicted = lda_pred2)
```

```
## [1] 0.8707483
```

```
##          actual
## predicted  No Yes
##       No  361  52
##       Yes   5  23
```

```r
set.seed(432)
lda_3 = lda(Attrition~.- MonthlyIncome - PerformanceRating - Education, data = train_data, prior=c(864,
lda_pred3 = ifelse(predict(lda_3, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
calc_acc(actual = test_data$Attrition,
         predicted = lda_pred3)
```

```
## [1] 0.8707483
```

```
##          actual
## predicted  No Yes
##       No  361  52
##       Yes   5  23
```

```r
set.seed(432)
lda_4 = lda(Attrition~.- MonthlyIncome - PerformanceRating - Education - Department, data = train_data,
lda_pred4 = ifelse(predict(lda_4, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
calc_acc(actual = test_data$Attrition,
         predicted = lda_pred4)
```

```
## [1] 0.8707483
```

```
##          actual
## predicted  No Yes
##       No  361  52
##       Yes   5  23
```

```r
set.seed(432)
lda_5 = lda(Attrition~.- MonthlyIncome - PerformanceRating - Education - Department - Gender, data = tra
lda_pred5 = ifelse(predict(lda_5, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
calc_acc(actual = test_data$Attrition,
         predicted = lda_pred5)
```

```
## [1] 0.8707483
```

```
##          actual
## predicted  No Yes
```

```
##       No  361  52
##       Yes   5  23
```

```
set.seed(432)
lda_6 = lda(Attrition~.- MonthlyIncome - PerformanceRating - Education - Department - Gender, data = tra
lda_pred6 = ifelse(predict(lda_6, test_data)$posterior[ ,1]>=0.35, 'No', 'Yes')
t2=table(predicted = lda_pred6, actual = test_data$Attrition)
t2
```

```
##          actual
## predicted  No Yes
##       No  361  52
##       Yes   5  23
```

```
lda_accu = calc_acc(actual = test_data$Attrition, predicted = lda_pred6)
lda_stay = calc_stay(t2[2,2], t2[2,1])
lda_leave = calc_leave(t2[1,1], t2[1,2])
```

Decision Tree

```
set.seed(432)
tree_1 = tree(Attrition~., data = train_data)
summary(tree_1)
```

```
##
## Classification tree:
## tree(formula = Attrition ~ ., data = train_data)
## Variables actually used in tree construction:
##  [1] "OverTime"                 "TotalWorkingYears"
##  [3] "HourlyRate"               "JobRole"
##  [5] "StockOptionLevel"         "NumCompaniesWorked"
##  [7] "ï..Age"                   "DistanceFromHome"
##  [9] "RelationshipSatisfaction" "MonthlyIncome"
## [11] "YearsAtCompany"
## Number of terminal nodes:  24
## Residual mean deviance:  0.5095 = 512.1 / 1005
## Misclassification error rate: 0.1079 = 111 / 1029
```

```
tree_pred = ifelse(predict(tree_1, test_data, type="vector")[ ,1] >= 0.65, 'No', 'Yes')
t3 = table(tree_pred, test_data$Attrition)
t3
```

```
##
## tree_pred  No Yes
##       No  315  39
##       Yes  51  36
```

Here we tried to prune the decision tree and we pick best=3 according to the following.

```
set.seed(432)
cv_tree = cv.tree(tree_1, FUN=prune.misclass)
cv_tree
```

```
## $size
##  [1] 24 21 17 16 11  9  8  5  3  1
```

```
##
## $dev
##  [1] 172 172 166 163 163 160 159 155 149 162
##
## $k
##  [1]      -Inf  0.000000  0.750000  1.000000  1.200000  1.500000  2.000000
##  [8]  2.666667  3.500000 10.500000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```
plot(cv_tree$size, cv_tree$dev , type ="b")
plot(cv_tree$k, cv_tree$dev , type ="b")
```

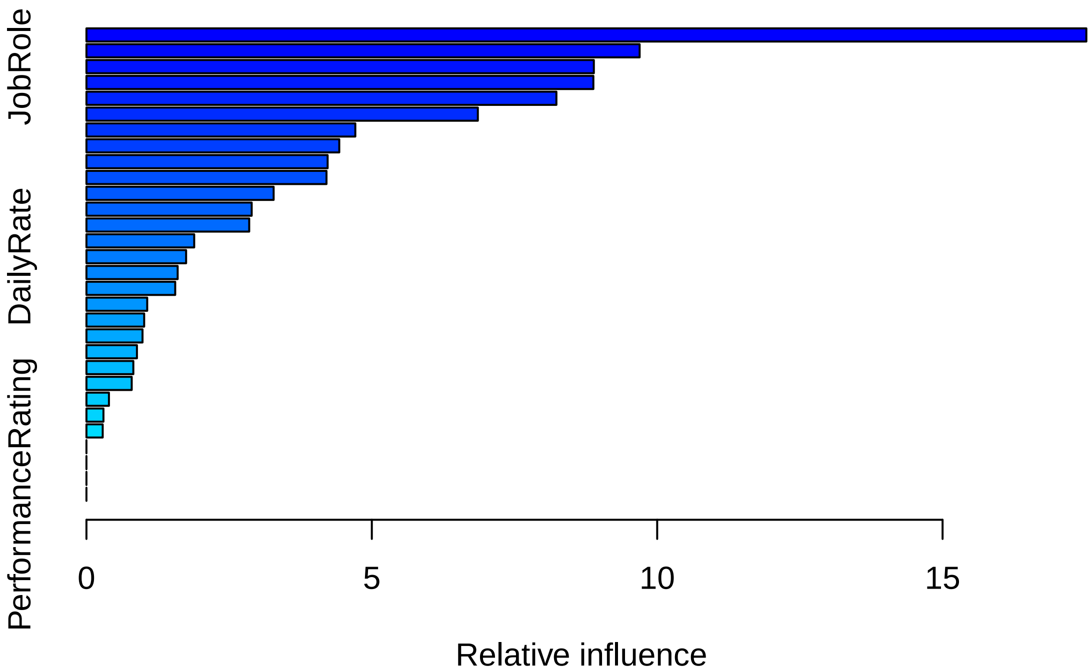
```
set.seed(432)
prune_tree = prune.misclass (tree_1 , best = 3)

tree_pred = ifelse(predict(prune_tree, test_data, type="vector")[ ,1] >= 0.5, 'No', 'Yes')
table(tree_pred, test_data$Attrition)
```

```
##
## tree_pred  No Yes
##       No  357  61
##       Yes   9  14
```

The pruned tree is not good as the original one.

Boosting

```
set.seed(432)
train_data_copy = train_data
train_data_copy$Attrition = ifelse(train_data_copy$Attrition == "No", 0, 1)
boosting_1 = gbm(Attrition~., data=train_data_copy, distribution="bernoulli", n.trees=1000, shrinkage =
summary(boosting_1)
```




```
##                                                   var    rel.inf
## OverTime                                     OverTime 17.5193953
## ï..Age                                         ï..Age  9.6924255
## JobRole                                       JobRole  8.8902645
## TotalWorkingYears                   TotalWorkingYears  8.8817874
## MonthlyIncome                           MonthlyIncome  8.2345343
## StockOptionLevel                     StockOptionLevel  6.8576548
## JobInvolvement                         JobInvolvement  4.7108351
## DistanceFromHome                     DistanceFromHome  4.4297462
## NumCompaniesWorked                 NumCompaniesWorked  4.2260420
## EnvironmentSatisfaction   EnvironmentSatisfaction  4.2057388
## EducationField                         EducationField  3.2797490
## YearsAtCompany                         YearsAtCompany  2.8953101
## RelationshipSatisfaction RelationshipSatisfaction  2.8519677
## WorkLifeBalance                       WorkLifeBalance  1.8881729
## DailyRate                                   DailyRate  1.7463060
## YearsWithCurrManager             YearsWithCurrManager  1.5985834
## BusinessTravel                         BusinessTravel  1.5556085
## JobSatisfaction                       JobSatisfaction  1.0646936
## MonthlyRate                               MonthlyRate  1.0113264
## MaritalStatus                           MaritalStatus  0.9823965
## TrainingTimesLastYear           TrainingTimesLastYear  0.8849912
## HourlyRate                                 HourlyRate  0.8217715
## JobLevel                                     JobLevel  0.7933201
## YearsSinceLastPromotion   YearsSinceLastPromotion  0.3941980
## PercentSalaryHike                   PercentSalaryHike  0.2981278
```

```
## YearsInCurrentRole             YearsInCurrentRole  0.2850534
## Department                             Department  0.0000000
## Education                               Education  0.0000000
## Gender                                     Gender  0.0000000
## PerformanceRating               PerformanceRating  0.0000000
```

```
##          actual
## predicted  No Yes
##       No  350  45
##       Yes  16  30
```

After we adjust the shrinkage and n.minobsinnode.

```
set.seed(432)
boosting_1 = gbm(Attrition~.-PerformanceRating-Gender-Department, data=train_data_copy, distribution="b
boo_pred = ifelse(predict(boosting_1, newdata = test_data, n.trees = 1000, type="response")>0.45, 'Yes'
t6=table(predicted = boo_pred, actual = test_data$Attrition)
t6
```

```
##          actual
## predicted  No Yes
##       No  360  56
##       Yes   6  19
```

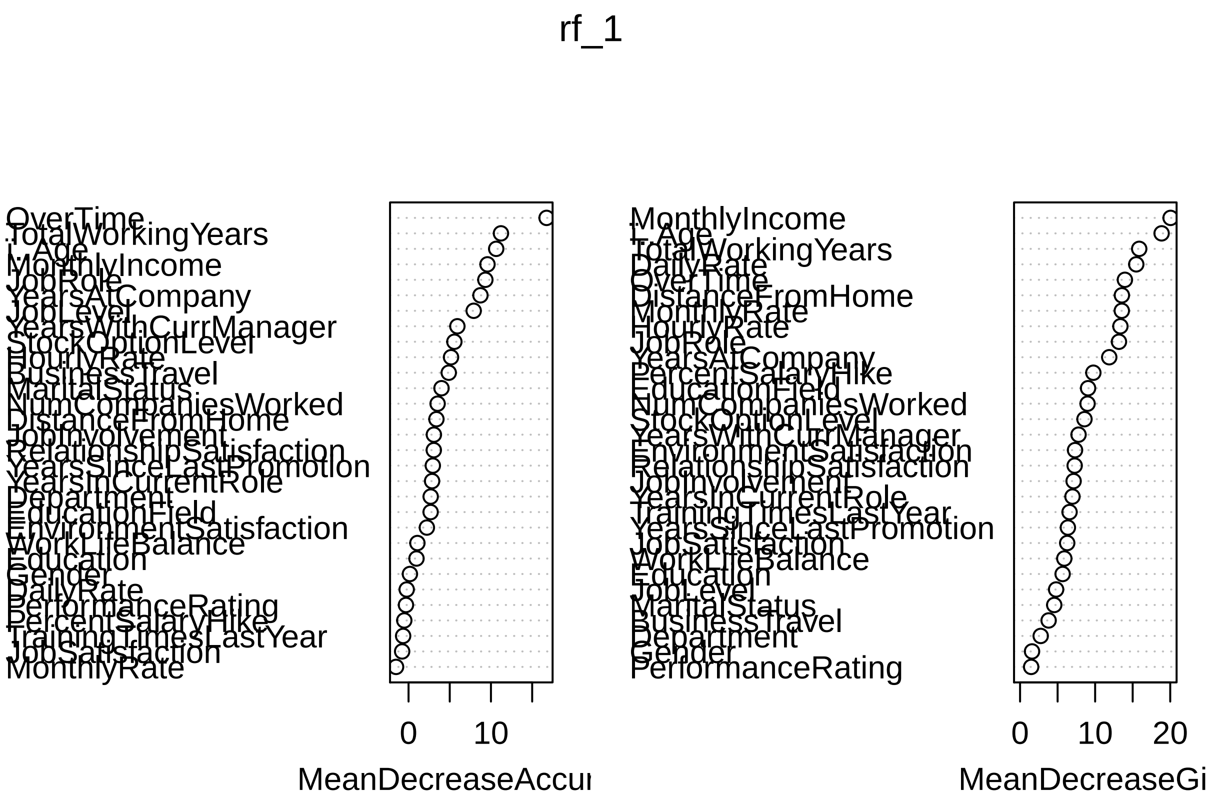
Random Forest

We start by fitting all the variables in the model and then take out the least important variable one by one.

```
set.seed(432)
rf_1 = randomForest(Attrition~., data = train_data, importance=TRUE)
rf_pred = ifelse(predict(rf_1, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  339  41
##     Yes  27  34
```

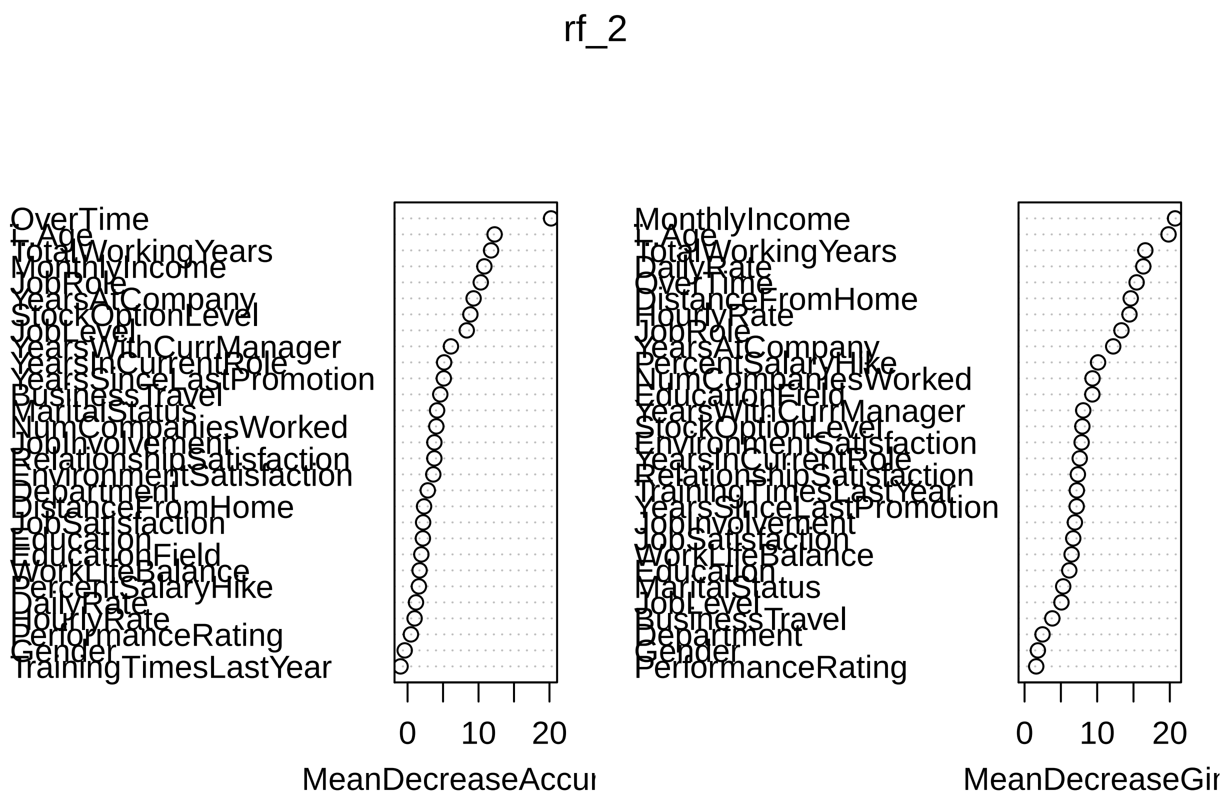
```
varImpPlot(rf_1)
```




```r
set.seed(432)
rf_2 = randomForest(Attrition~.-MonthlyRate, data = train_data, importance=TRUE)
rf_pred = ifelse(predict(rf_2, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  339  41
##     Yes  27  34
```

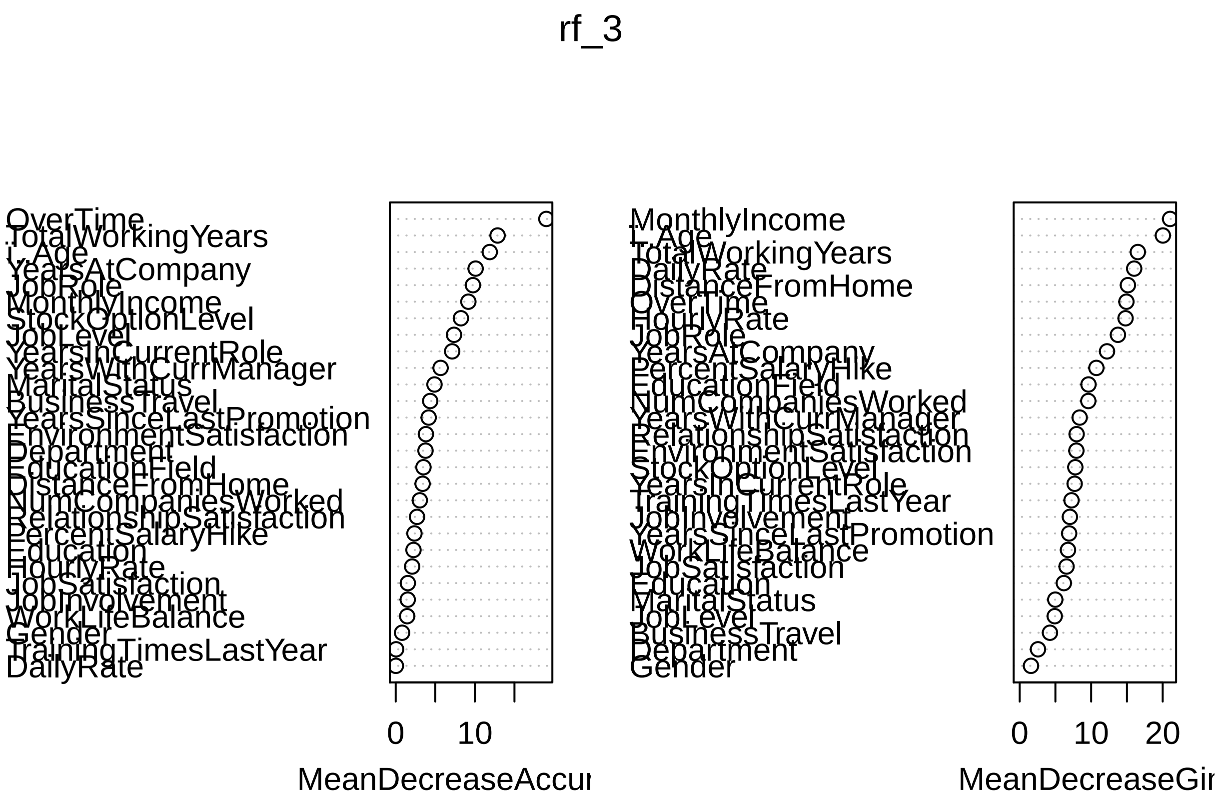
```r
varImpPlot(rf_2)
```




```
set.seed(432)
rf_3 = randomForest(Attrition~.-MonthlyRate - PerformanceRating, data = train_data, importance=TRUE)
rf_pred = ifelse(predict(rf_3, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  338  41
##     Yes  28  34
```

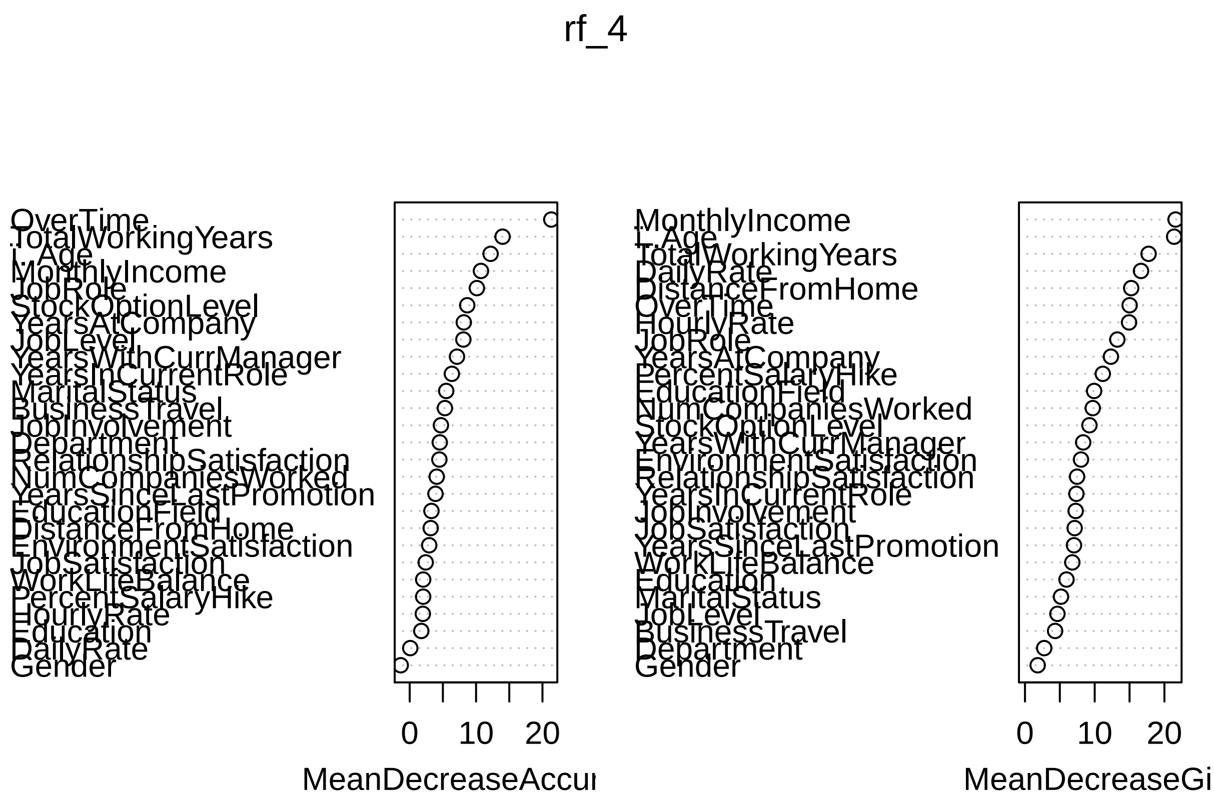
```
varImpPlot(rf_3)
```




```r
set.seed(432)
rf_4 = randomForest(Attrition~.-MonthlyRate - PerformanceRating - TrainingTimesLastYear, data = train_da
rf_pred = ifelse(predict(rf_4, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  337  43
##     Yes  29  32
```

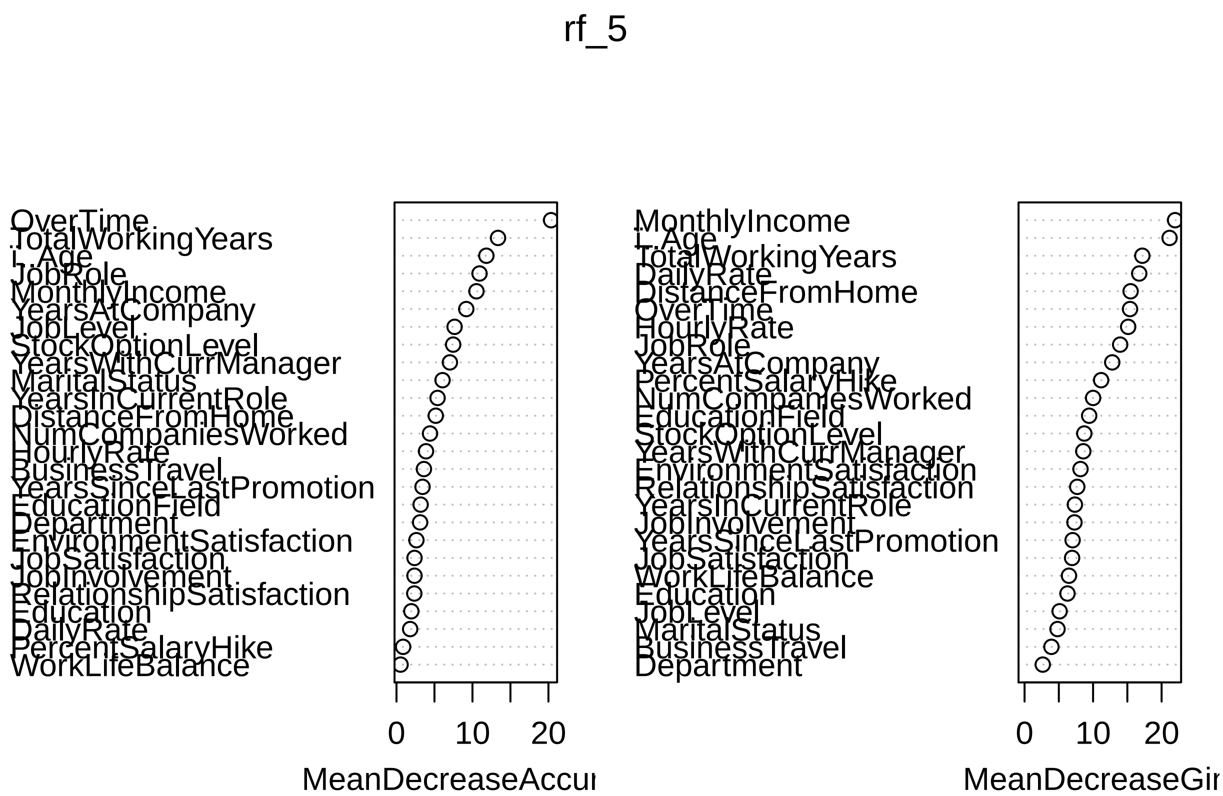
```r
varImpPlot(rf_4)
```




```r
set.seed(432)
rf_5 = randomForest(Attrition~.-MonthlyRate - PerformanceRating - TrainingTimesLastYear - Gender, data =
rf_pred = ifelse(predict(rf_5, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  334  41
##     Yes  32  34
```

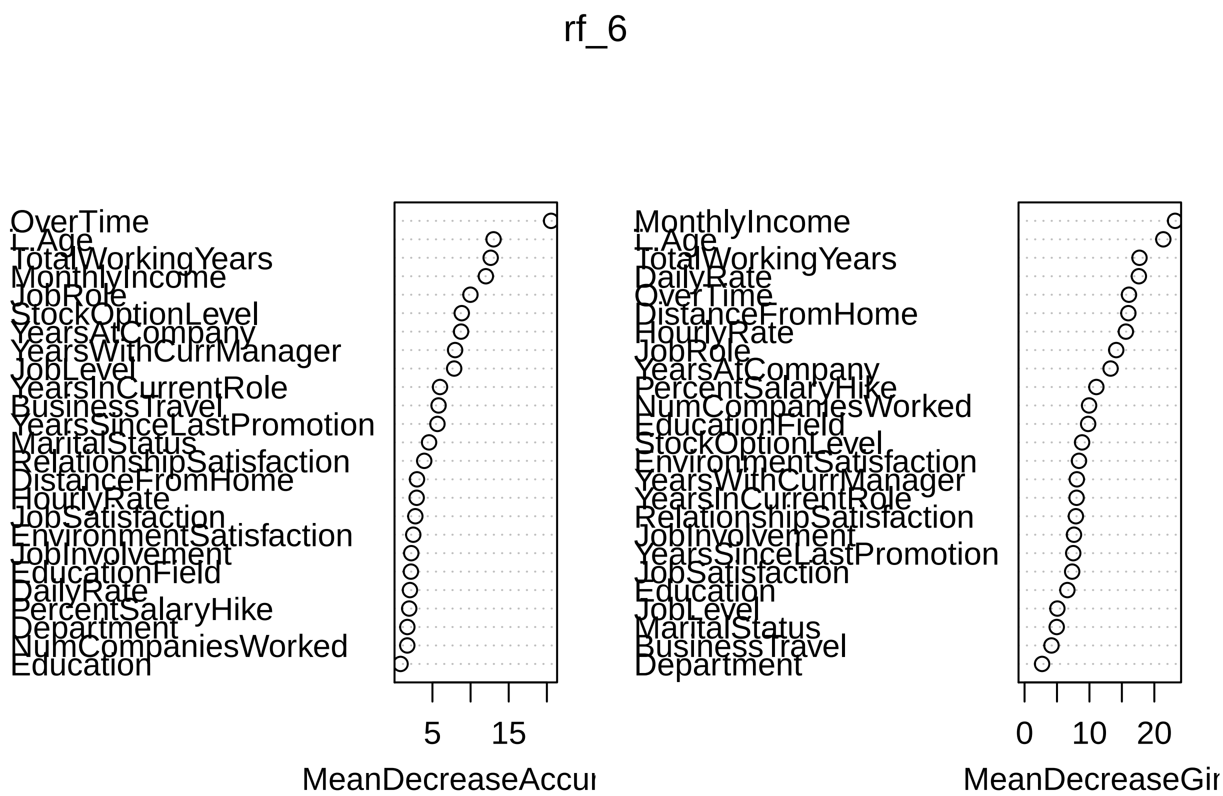
```r
varImpPlot(rf_5)
```




```
set.seed(432)
rf_6 = randomForest(Attrition~.-MonthlyRate  - PerformanceRating - TrainingTimesLastYear - Gender - Wor
rf_pred = ifelse(predict(rf_6, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  336  45
##     Yes  30  30
```

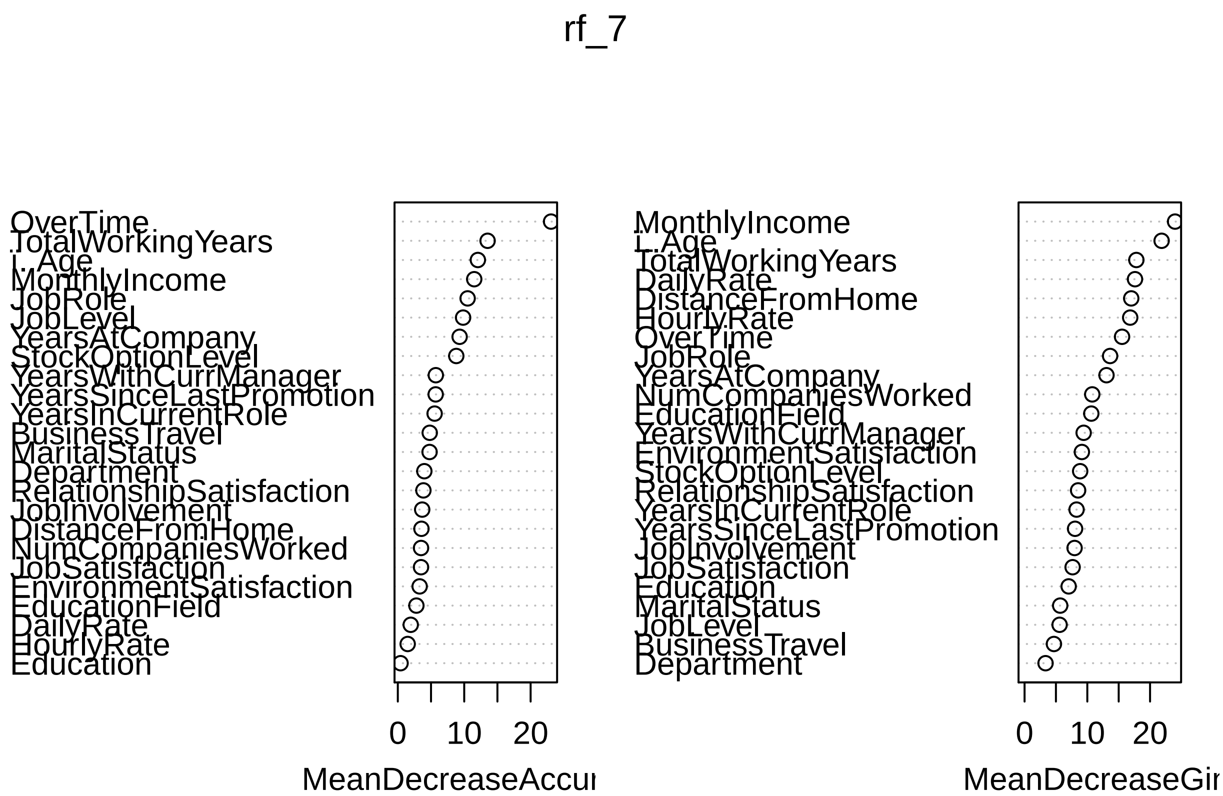
```
varImpPlot(rf_6)
```




```
set.seed(432)
rf_7 = randomForest(Attrition~.-MonthlyRate  - PerformanceRating - TrainingTimesLastYear - Gender - Wor
rf_pred = ifelse(predict(rf_7, newdata = test_data, type = "prob")[ ,1] >= 0.7, 'No', 'Yes')
table(rf_pred, test_data$Attrition)
```

```
##
## rf_pred  No Yes
##     No  332  42
##     Yes  34  33
```

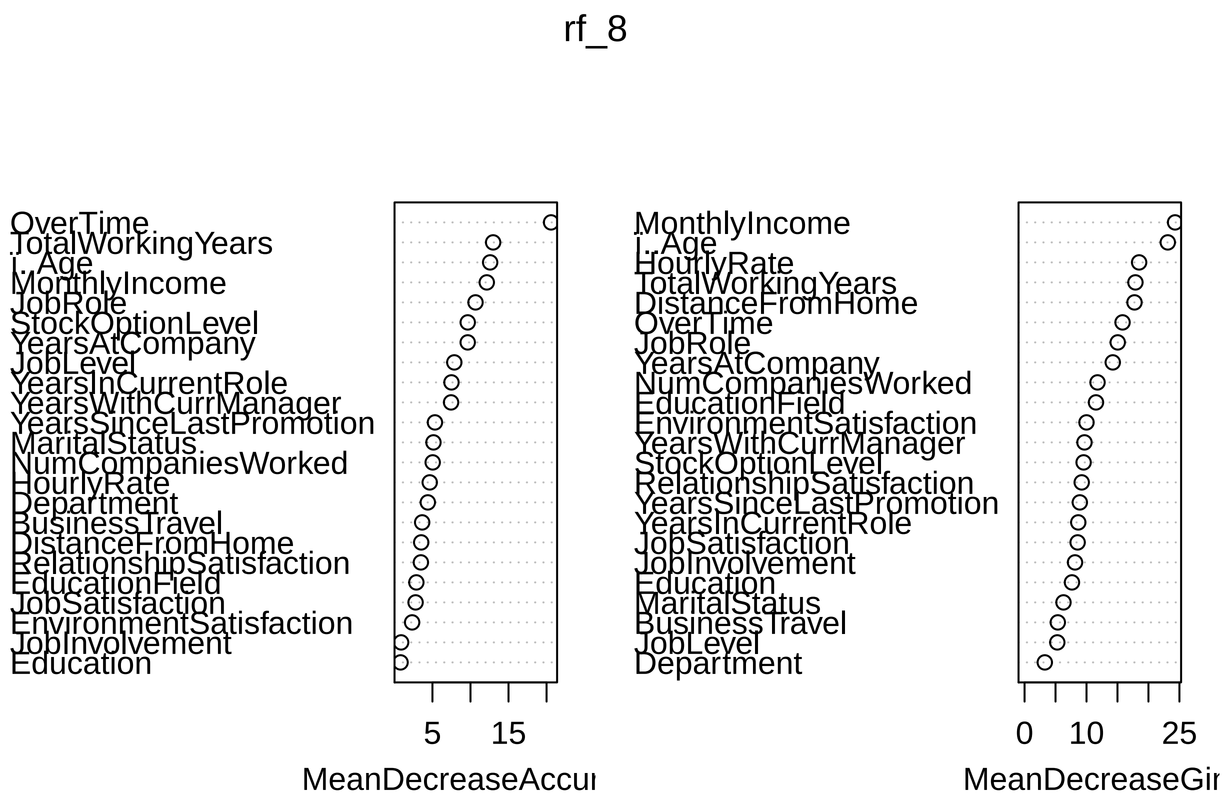
```
varImpPlot(rf_7)
```




```
set.seed(432)
rf_8 = randomForest(Attrition~.-MonthlyRate  - PerformanceRating - TrainingTimesLastYear - Gender - Worl
rf_pred = ifelse(predict(rf_8, newdata = test_data, type = "prob")[ ,1] >= 0.6, 'No', 'Yes')
t4=table(rf_pred, test_data$Attrition)
t4
```

```
##
## rf_pred  No Yes
##     No  357  56
##     Yes   9  19
```

```
varImpPlot(rf_8)
```



knn

We first put all the predictors into the knn model.

```r
set.seed(56)
knnFit <- train(Attrition ~ ., data = train_data, method = "knn", trControl = trainControl(method = "cv
table(predicted = ifelse(predict(knnFit, test_data, type = "prob")[ ,1]>=0.7, 'No', 'Yes'), actual = tes
```

```
##           actual
## predicted  No Yes
##       No  352  58
##       Yes  14  17
```

```r
set.seed(56)
knnFit1 <- train(Attrition ~ .- JobLevel - Gender - DailyRate - Department - PercentSalaryHike - NumComp
knn_pred = ifelse(predict(knnFit1, test_data, type = "prob")[ ,1]>=0.7, 'No', 'Yes')
t5 = table(predicted = ifelse(predict(knnFit1, test_data, type = "prob")[ ,1]>=0.6, 'No', 'Yes'), actual
t5
```

```
##           actual
## predicted  No Yes
##       No  358  59
##       Yes   8  16
```

"The strength of naive Bayes comes from its ability to handle a large number of predictors, p, even with a limited sample size n. Even with the naive independence assumption, naive Bayes works rather well in practice. Also because of this assumption, we can often train naive Bayes where LDA and QDA may be impossible to train because of the large number of parameters relative to the number of observations."

we give naivebayes a try here.

We fit a full model first and then we fit a very simple model with only 5 predictors.

naivebayes

```
set.seed(56)
nb_1 = naiveBayes(Attrition~., data = train_data, prior=c(864, 166)/1030)
nb_pred = ifelse(predict(nb_1, test_data, type = "raw")[ ,1]>=0.1, 'No', 'Yes')
calc_acc(nb_pred, test_data$Attrition)
```

```
## [1] 0.8503401
```

```
t7=table(predicted = nb_pred, actual = test_data$Attrition)
t7
```

```
##          actual
## predicted  No Yes
##       No  356  56
##       Yes  10  19
```

```
nb_accu = calc_acc(actual = test_data$Attrition, predicted = nb_pred)
nb_stay = calc_stay(t7[2,2], t7[2,1])
nb_leave = calc_leave(t7[1,1], t7[1,2])
```

Model Comparison

Model Name	Model Formula	Accuracy	Percentage of people leave if we predict they will leave	Percentage of People leave if we predict they will stay
Logistic Regression	‘Attrition~.-DailyRate-Department-Education-EducationField-Gender-HourlyRate-JobLevel-MonthlyIncome-MonthlyRate-PercentSalaryHike-PerformanceRating-StockOptionLevel‘	0.871	0.909	0.131
Linear Discriminent Analysis	‘Attrition~.-MonthlyIncome - PerformanceRating - Education - Department - Gender‘	0.871	0.821	0.126
Tree	‘Attrition ~ .‘	0.841	0.414	0.110
Random Forest	‘Attrition~.-MonthlyRate - PerformanceRating - TrainingTimesLastYear - Gender - WorkLifeBalance - PercentSalaryHike - DailyRate‘	0.871	0.679	0.136
knn	‘Attrition ~ .-JobLevel - Gender - DailyRate - Department - PercentSalaryHike‘	0.844	0.667	0.141
Boosting	‘Attrition~.-PerformanceRating-Gender-Department‘	0.859	0.760	0.135
Naive Bayes	‘Attrition~.‘	0.850	0.655	0.136