```r
####Setting the directory and loading the dataset into R, verifying that dataset is loaded correctly
library(readr)
X338_cert_proj_datasets_v3_0 <- read_csv("C:/Users/saian/Desktop/edureka/338_cert_proj_datasets_v3.0.csv")
View(X338_cert_proj_datasets_v3_0)
HR_Management<-X338_cert_proj_datasets_v3_0

str(HR_Management)

###Making some changes to the columns
library(plyr)
  HR_Management$salary<- revalue(HR_Management$salary,c("low"=0))
  HR_Management$salary<- revalue(HR_Management$salary,c("medium"=1))
  HR_Management$salary<- revalue(HR_Management$salary,c("high"=2))

  HR_Management$department<- revalue(HR_Management$department,c("hr"=0))
  HR_Management$department<- revalue(HR_Management$department,c("IT"=1))
  HR_Management$department<- revalue(HR_Management$department,c("management"=2))
  HR_Management$department<- revalue(HR_Management$department,c("marketing"=3))
  HR_Management$department<- revalue(HR_Management$department,c("product_mng"=4))
  HR_Management$department<- revalue(HR_Management$department,c("RandD"=5))
  HR_Management$department<- revalue(HR_Management$department,c("sales"=6))
  HR_Management$department<- revalue(HR_Management$department,c("support"=7))
  HR_Management$department<- revalue(HR_Management$department,c("technical"=8))
  HR_Management$department<- revalue(HR_Management$department,c("accounting"=9))

  str(HR_Management)



HR_Management$left<-as.factor(as.integer(HR_Management$left))
HR_Management$salary<-as.factor(as.integer(HR_Management$salary))
HR_Management$department<-as.factor(as.integer(HR_Management$department))

str(HR_Management)

###splitting the data into train and test sets
library(caret)
set.seed(12345)
```

```r
di <- sample(2, nrow(HR_Management), prob = c(0.7,0.3), replace = TRUE)

train <- HR_Management[di==1,]
test <- HR_Management[di==2,]

###using ggplots for visualizations

library(ggplot2)
ggplot(train,aes(left,fill=left))+geom_bar()
prop.table(table(train$left)) #Percentage of left
prop.table(table(train$satisfaction_level))

#Let us look at each variable and see its influence on the churn of the organization

library(ggplot2)
library(grid)
library(gridExtra)
promotion_last_5yearsPlot <- ggplot(train,aes(promotion_last_5years,fill=left))+geom_density()+facet_grid(~left)
time_spend_companyPlot <- ggplot(train,aes(time_spend_company,fill=left))+geom_bar()
salaryPlot <- ggplot(train,aes(salary,left))+geom_point(size=4,alpha = 0.05)
depPlot <- ggplot(train,aes(department,fill = left))+geom_bar()
grid.arrange(promotion_last_5yearsPlot,time_spend_companyPlot,salaryPlot,depPlot,ncol=2,top = "Fig 1")

satisfaction_levelPlot <- ggplot(train,aes(satisfaction_level,fill=left))+geom_bar()
last_evaluationPlot <- ggplot(train,aes(last_evaluation,fill=left))+geom_bar()
number_projectPlot <- ggplot(train,aes(number_project,fill=left))+geom_bar()
average_montly_hoursPlot <- ggplot(train,aes(average_montly_hours,fill=left))+geom_bar()
Work_accidentPlot <- ggplot(train,aes(Work_accident,fill=left))+geom_bar()
grid.arrange(satisfaction_levelPlot,last_evaluationPlot,number_projectPlot,average_montly_hoursPlot,Work_accidentP
lot,ncol=2,top = "Fig 2")

###Binning of Varaibles
##creating average monthly bins
max(train$average_montly_hours)
min(train$average_montly_hours)
```

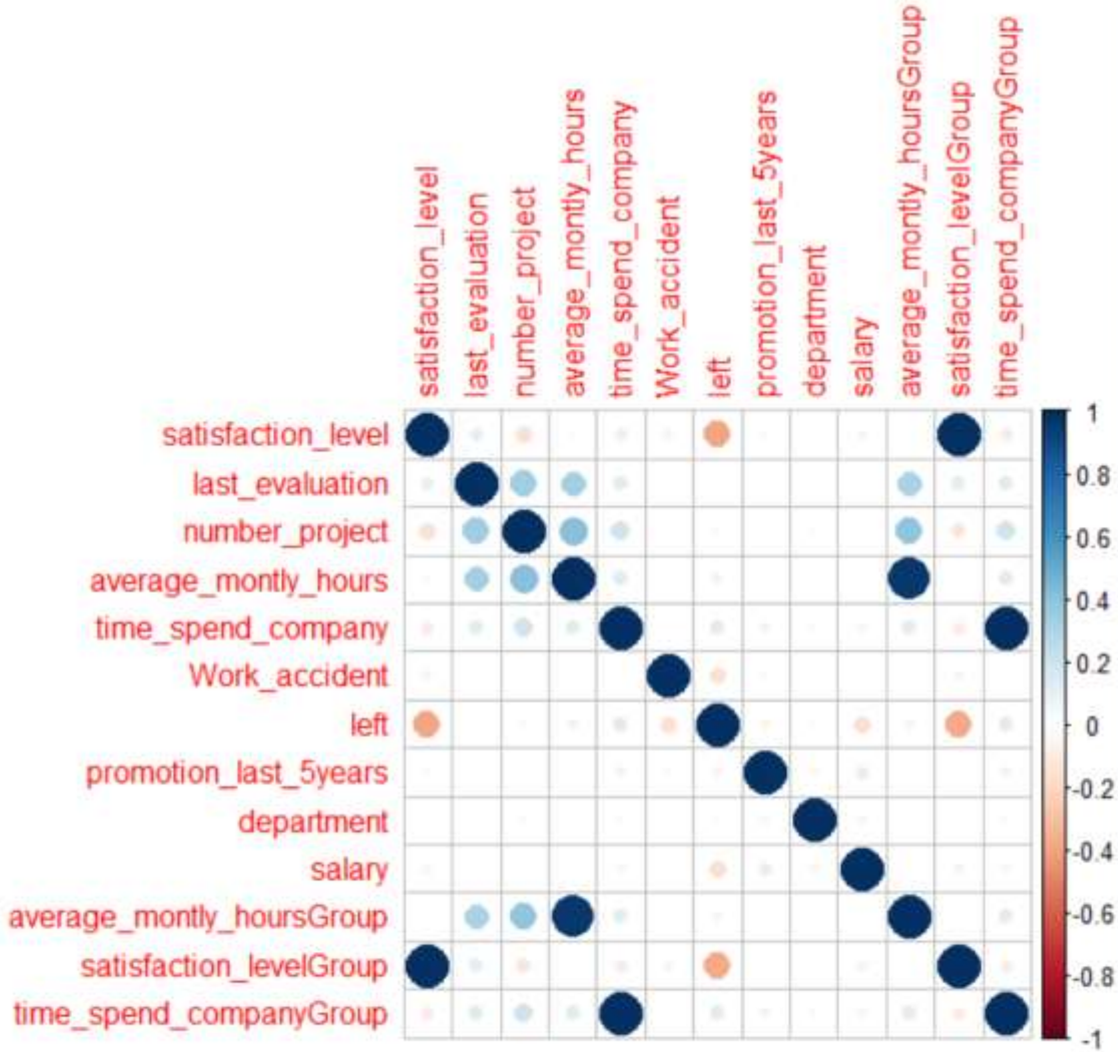
```r
train$average_montly_hoursGroup<-
with(train,ifelse(average_montly_hours>300,7,ifelse(average_montly_hours>250,6,ifelse(average_montly_hours>200,5,ifelse(average_montly_hours>150,4,ifelse(average_montly_hours>100,3,ifelse(average_montly_hours>50,2,1)))))))
test$average_montly_hoursGroup<-
with(test,ifelse(average_montly_hours>300,7,ifelse(average_montly_hours>250,6,ifelse(average_montly_hours>200,5,ifelse(average_montly_hours>150,4,ifelse(average_montly_hours>100,3,ifelse(average_montly_hours>50,2,1)))))))

##creating satisfacting level bins
max(train$satisfaction_level)
min(train$satisfaction_level)
train$satisfaction_levelGroup<-
with(train,ifelse(satisfaction_level>0.9,9,ifelse(satisfaction_level>0.8,8,ifelse(satisfaction_level>0.7,7,ifelse(satisfaction_level>0.6,6,ifelse(satisfaction_level>0.5,5,ifelse(satisfaction_level>0.4,4,ifelse(satisfaction_level>0.3,3,ifelse(satisfaction_level>0.2,2,ifelse(satisfaction_level>0,1))))))))))
test$satisfaction_levelGroup<-
with(test,ifelse(satisfaction_level>0.9,9,ifelse(satisfaction_level>0.8,8,ifelse(satisfaction_level>0.7,7,ifelse(satisfaction_level>0.6,6,ifelse(satisfaction_level>0.5,5,ifelse(satisfaction_level>0.4,4,ifelse(satisfaction_level>0.3,3,ifelse(satisfaction_level>0.2,2,ifelse(satisfaction_level>0,1))))))))))

##creating timespendatcompany level bins
max(train$time_spend_company)
min(train$time_spend_company)
train$time_spend_companyGroup<-
with(train,ifelse(time_spend_company>9,9,ifelse(time_spend_company>8,8,ifelse(time_spend_company>7,7,ifelse(time_spend_company>6,6,ifelse(time_spend_company>5,5,ifelse(time_spend_company>4,4,ifelse(time_spend_company>3,3,ifelse(time_spend_company>2,2,ifelse(time_spend_company>0,1))))))))))
test$time_spend_companyGroup<-
with(test,ifelse(time_spend_company>9,9,ifelse(time_spend_company>8,8,ifelse(time_spend_company>7,7,ifelse(time_spend_company>6,6,ifelse(time_spend_company>5,5,ifelse(time_spend_company>4,4,ifelse(time_spend_company>3,3,ifelse(time_spend_company>2,2,ifelse(time_spend_company>0,1))))))))))

###Correlation of Variables
library(corrplot)
library(psych)

#first make all the variables to numeric or integer to correlate
train$left<-as.numeric(as.factor(train$left))
train$department<-as.numeric(as.factor(train$department))
train$salary<-as.numeric(as.factor(train$salary))
```

```r
train$promotion_last_5years<-as.numeric(as.integer(train$promotion_last_5years))
train$Work_accident<-as.numeric(as.integer(train$Work_accident))
train$time_spend_company<-as.numeric(as.integer(train$time_spend_company))
train$average_montly_hours<-as.numeric(as.integer(train$average_montly_hours))
train$number_project<-as.numeric(as.integer(train$number_project))


test$department<-as.numeric(as.factor(test$department))
test$salary<-as.numeric(as.factor(test$salary))


cor(train) #correlation values between variables

corrplot(cor(train),method = "circle")




##applying Logistic model to see which variables are more significant in churning out employers
model1<-glm(formula = left ~ ., binomial(link="logit"),data =train)
summary(model1)
library(MASS)
exp(cbind(OR=coef(model1),confint(model1)))

###Building models using Decision Tree, Random Forest ,NB and SVM techniques
library(caret)
library(rpart)
library(ROCR)

#####Decision Tree####



DTree_model <-
rpart(left~satisfaction_levelGroup+last_evaluation+number_project+average_montly_hours+time_spend_company+Work_acc
ident, data = train)
```

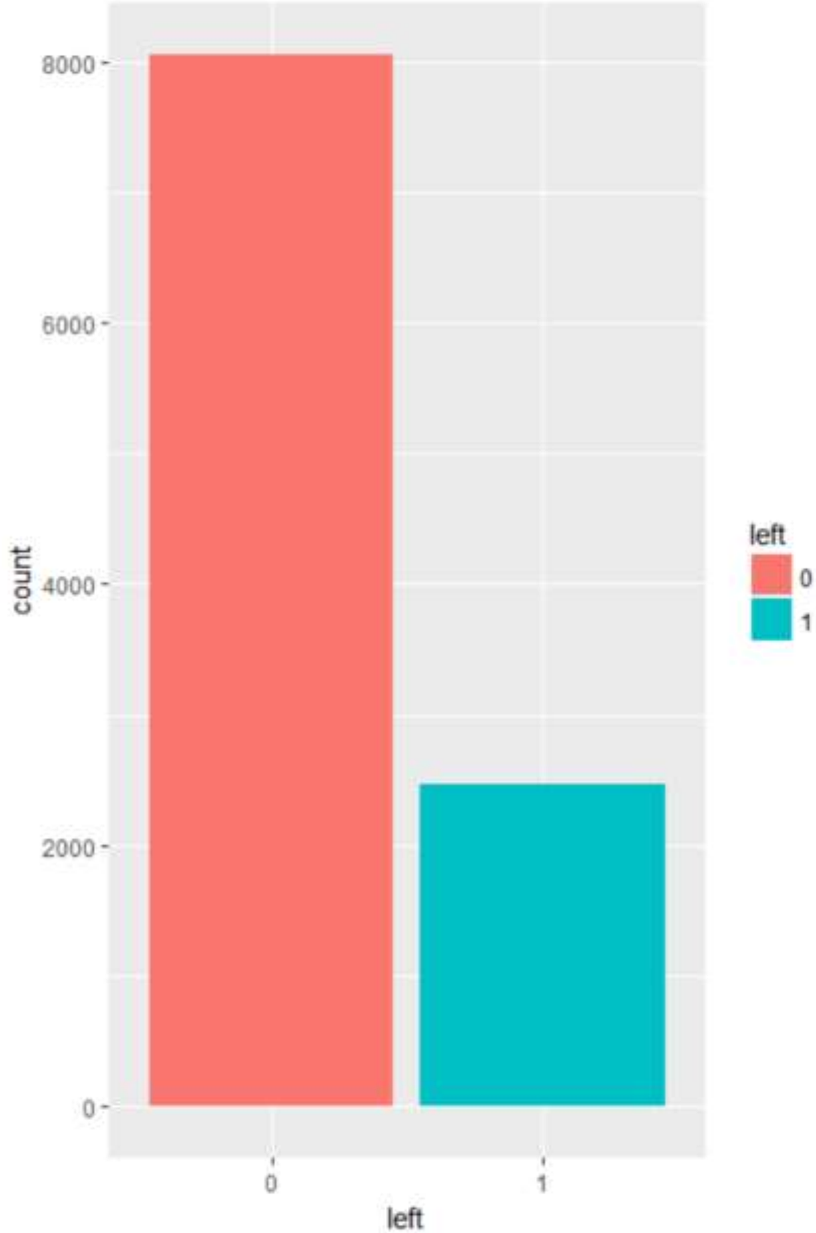
```r
par(mar = rep(2, 4))

plot(DTree_model, margin = 0.1)
text(DTree_model, use.n = TRUE, pretty = TRUE,cex = 0.6)
table(train$left)

pred_DTree_model <- predict (DTree_model, newdata = test)
pred_DTree_model
cm_DTree<-table(pred_DTree_model,test$left)
cm_DTree
accuracy_DTree<-(cm_DTree[1]+cm_DTree[4])/(cm_DTree[1]+cm_DTree[2]+cm_DTree[3]+cm_DTree[4])
accuracy_DTree

confusionMatrix(table(pred_tree, test$left))




####Random Forest#####
library(randomForest)
RF_model <- randomForest(left~., data = train)
RF_model


pred_RF_model <- predict (RF_model, newdata = test, type = "class")

pred_RF_model
cm_RF<-table(pred_RF_model,test$left)
cm_RF
accuracy_RF<-(cm_RF[1]+cm_RF[4])/(cm_RF[1]+cm_RF[2]+cm_RF[3]+cm_RF[4])
accuracy_RF




#####Naive Bayes#####
library(e1071)
```

```
NB_model <-
naiveBayes(left~salary+time_spend_companyGroup+satisfaction_levelGroup+department+average_montly_hoursGroup, data
= train,laplace = laplace)

NB_model

pred_NB_model <- predict (NB_model, newdata = test)

pred_NB_model
cm_NB<-table(pred_NB_model,test$left)
cm
accuracy_NB<-(cm[1]+cm[4])/(cm[1]+cm[2]+cm[3]+cm[4])
accuracy_NB



#####SVM######
library(e1071)

SVM_model <- svm(left~.,data = train,type="C-classification", kernel = "radial", cost = 0.1,
             gamma=c(.5,1,2))


pred_svm <- predict(SVM_model,test, type = "class")
cm_svm<-table(pred_svm,test$left)
cm
accuracy_svm<-(cm[1]+cm[4])/(cm[1]+cm[2]+cm[3]+cm[4])
accuracy_svm
```

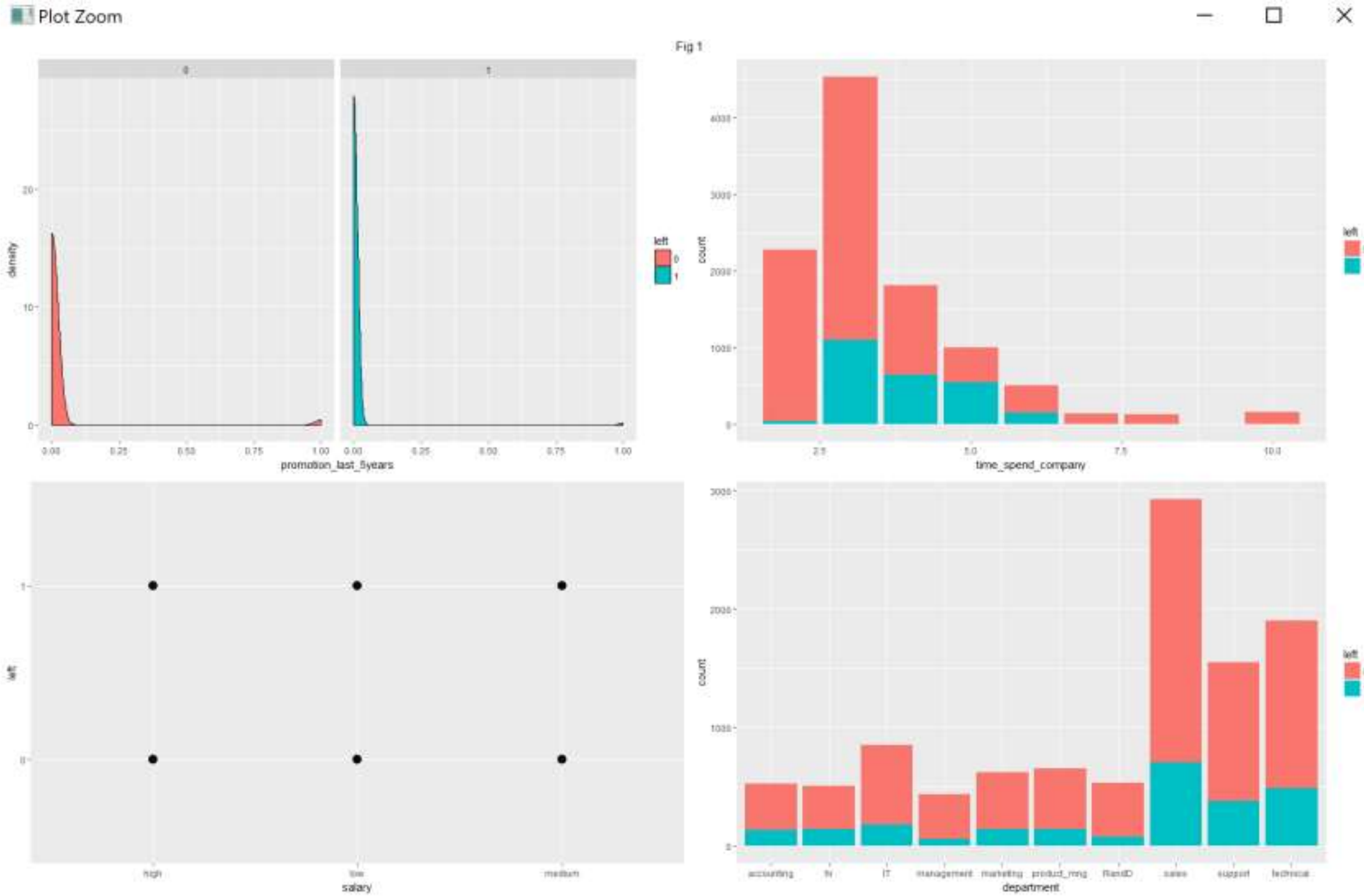
```
> summary(train)
satisfaction_level last_evaluation number_project  average_montly_hours
Min.   :0.0900     Min.   :0.360   Min.   :2.000   Min.   : 96.0
1st Qu.:0.4400     1st Qu.:0.560   1st Qu.:3.000   1st Qu.:156.0
Median :0.6400     Median :0.720   Median :4.000   Median :200.0
Mean   :0.6118     Mean   :0.715   Mean   :3.804   Mean   :201.1
3rd Qu.:0.8100     3rd Qu.:0.870   3rd Qu.:5.000   3rd Qu.:245.0
Max.   :1.0000     Max.   :1.000   Max.   :7.000   Max.   :310.0
time_spend_company Work_accident   left     promotion_last_5years
Min.   : 2.0       Min.   :0.000   0:8056   Min.   :0.00000
1st Qu.: 3.0       1st Qu.:0.000   1:2468   1st Qu.:0.00000
Median : 3.0       Median :0.000            Median :0.00000
Mean   : 3.5       Mean   :0.151            Mean   :0.02147
3rd Qu.: 4.0       3rd Qu.:0.000            3rd Qu.:0.00000
Max.   :10.0       Max.   :1.000            Max.   :1.00000
 department           salary           average_montly_hoursGroup
Length:10524       Length:10524       Min.   :2.000
Class :character   Class :character   1st Qu.:4.000
Mode  :character   Mode  :character   Median :4.000
                                      Mean   :4.515
                                      3rd Qu.:5.000
                                      Max.   :7.000
satisfaction_levelGroup time_spend_companyGroup
Min.   :1.000           Min.   :1.0
1st Qu.:4.000           1st Qu.:2.0
Median :6.000           Median :2.0
Mean   :5.591           Mean   :2.5
3rd Qu.:8.000           3rd Qu.:3.0
Max.   :9.000           Max.   :9.0
>
```


satisfaction_level
last_evaluation
number_project
average_montly_hours
time_spend_company
Work_accident
left
promotion_last_5years
department
salary
average_montly_hoursGroup
satisfaction_levelGroup
time_spend_companyGroup
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

```
> cor(train)
                          satisfaction_level last_evaluation number_project average_montly_hours time_spend_company Work_accident         left promotion_last_5years
satisfaction_level                1.00000000     0.100001484   -0.152795521         -0.026804048       -0.098831159  5.877844e-02 -0.394190480           0.024038008
last_evaluation                   0.10000148     1.000000000    0.349986791          0.330304441        0.135179964 -8.813945e-03  0.004748024          -0.008737904
number_project                   -0.15279552     0.349986791    1.000000000          0.411474375        0.196549960 -9.431695e-03  0.030257097          -0.004647329
average_montly_hours             -0.02680405     0.330304441    0.411474375          1.000000000        0.131026059 -1.388856e-02  0.071158403          -0.003889905
time_spend_company               -0.09883116     0.135179964    0.196549960          0.131026059        1.000000000 -1.456606e-03  0.137620284           0.068879031
Work_accident                     0.05877844    -0.008813945   -0.009431695         -0.013888556       -0.001456606  1.000000e+00 -0.155742958           0.036390198
left                             -0.39419048     0.004748024    0.030257097          0.071158403        0.137620284 -1.557430e-01  1.000000000          -0.060336240
promotion_last_5years             0.02403801    -0.008737904   -0.004647329         -0.003889905        0.068879031  3.639020e-02 -0.060336240           1.000000000
department                       -0.01364294     0.009874083    0.029448950          0.001366705       -0.034399957  6.568128e-05  0.028665569          -0.039917909
salary                            0.05370382    -0.004641392   -0.007444476         -0.005370706        0.041718790  1.150883e-02 -0.166254775           0.106466788
average_montly_hoursGroup        -0.01718891     0.317411487    0.390931909          0.961084820        0.127942423 -1.019747e-02  0.058594583          -0.005117105
satisfaction_levelGroup           0.99244116     0.115030423   -0.130105045         -0.006815489       -0.095253682  5.787055e-02 -0.378168742           0.022814759
time_spend_companyGroup          -0.09883116     0.135179964    0.196549960          0.131026059        1.000000000 -1.456606e-03  0.137620284           0.068879031
                             department       salary average_montly_hoursGroup satisfaction_levelGroup time_spend_companyGroup
satisfaction_level        -1.364294e-02  0.053703817              -0.017188915             0.992441161            -0.098831159
last_evaluation            9.874083e-03 -0.004641392               0.317411487             0.115030423             0.135179964
number_project             2.944895e-02 -0.007444476               0.390931909            -0.130105045             0.196549960
average_montly_hours       1.366705e-03 -0.005370706               0.961084820            -0.006815489             0.131026059
time_spend_company        -3.439996e-02  0.041718790               0.127942423            -0.095253682             1.000000000
Work_accident              6.568128e-05  0.011508831              -0.010197467             0.057870550            -0.001456606
left                       2.866557e-02 -0.166254775               0.058594583            -0.378168742             0.137620284
promotion_last_5years     -3.991791e-02  0.106466788              -0.005117105             0.022814759             0.068879031
department                 1.000000e+00 -0.054699314               0.004476596            -0.013390906            -0.034399957
salary                    -5.469931e-02  1.000000000               0.001460412             0.051095363             0.041718790
average_montly_hoursGroup  4.476596e-03  0.001460412               1.000000000             0.001050063             0.127942423
satisfaction_levelGroup   -1.339091e-02  0.051095363               0.001050063             1.000000000            -0.095253682
time_spend_companyGroup   -3.439996e-02  0.041718790               0.127942423            -0.095253682             1.000000000
```


8000
6000
4000
2000
0
count
0
1
left
left
0
1

```
        0         1
0.7654884 0.2345116
> 
```



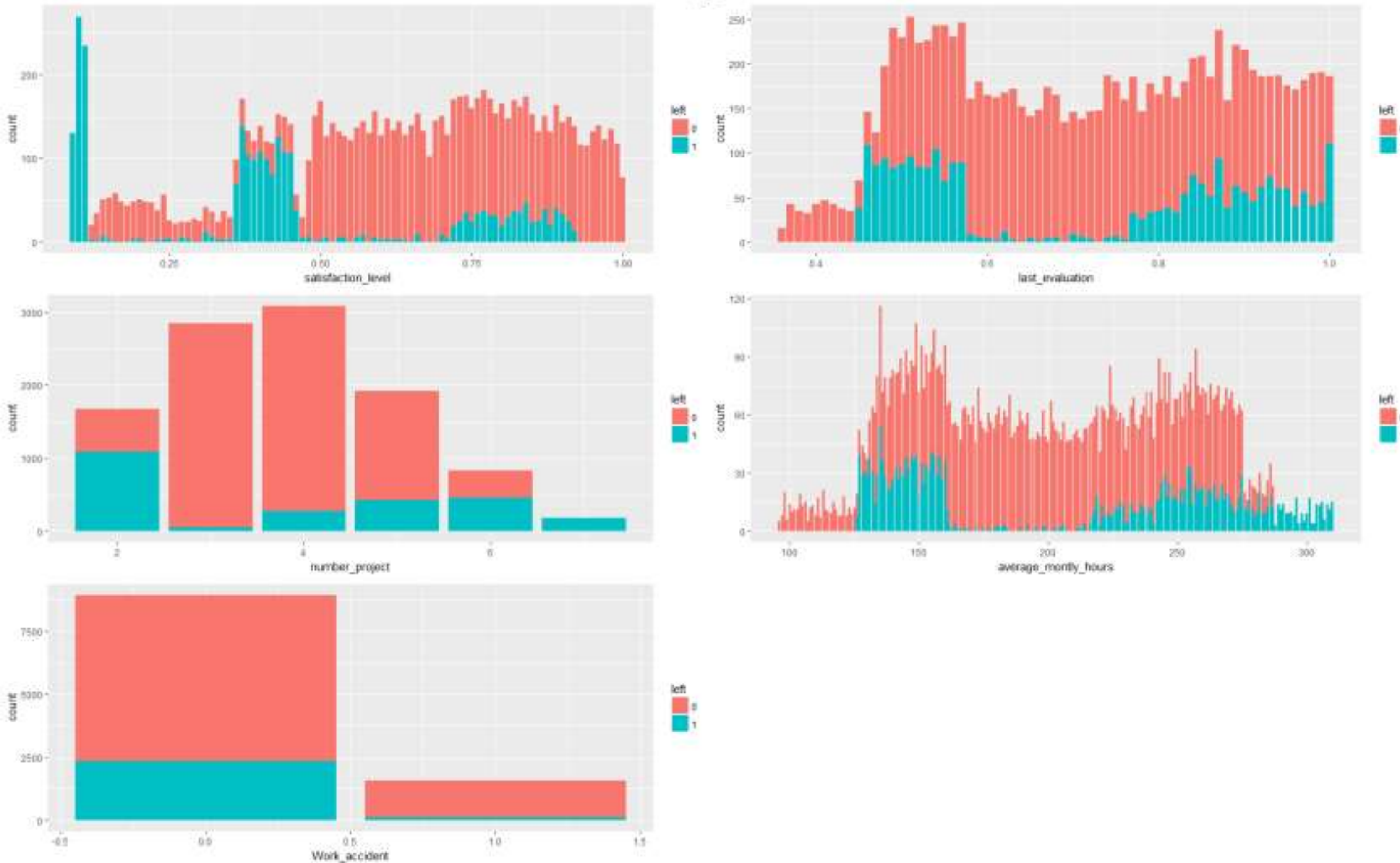
Promotion: Larger proportion of people who have been promoted recently have quit the organization.

Time_spend_company: Larger proportion of new comers are quitting the organization which sidelines the recruitment efforts of the organization.

Salary: We are not able to see any distinguishable feature here

Plot Zoom

Fig 2

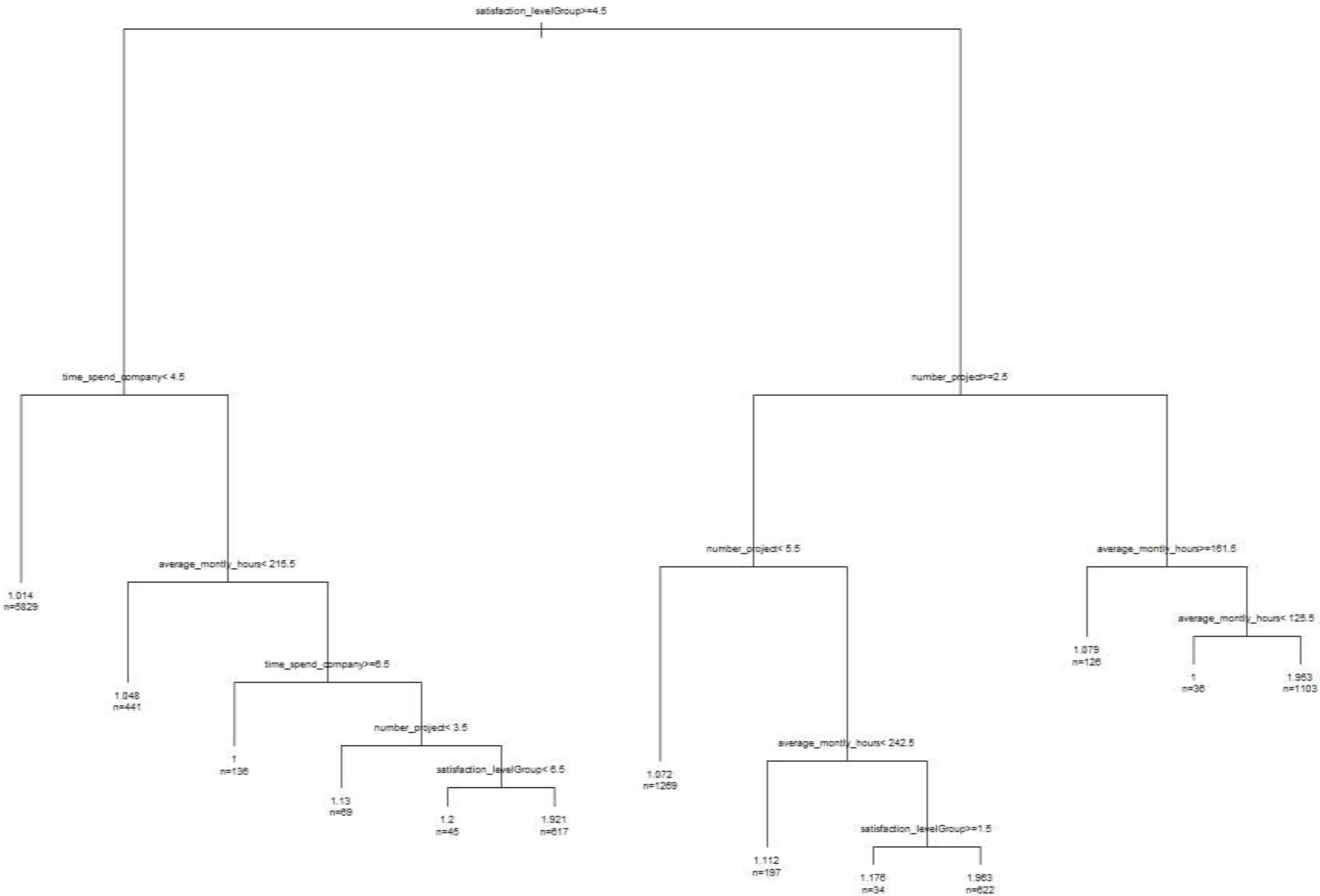


```
Call:
glm(formula = left ~ ., family = binomial(link = "logit"), data = train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-2.1994  -0.6468  -0.3857  -0.1177   3.1549  

Coefficients: (1 not defined because of singularities)
                            Estimate Std. Error z value Pr(>|z|)    
(Intercept)                -0.641264   0.250220  -2.563 0.010383 *  
satisfaction_level        -14.175698   0.913331 -15.521  < 2e-16 ***
last_evaluation             0.617718   0.181328   3.407 0.000658 ***
number_project             -0.347432   0.026245 -13.238  < 2e-16 ***
average_montly_hours        0.006815   0.001945   3.503 0.000460 ***
time_spend_company          0.260763   0.018706  13.940  < 2e-16 ***
Work_accident              -1.513420   0.105344 -14.366  < 2e-16 ***
promotion_last_5years      -1.360504   0.306129  -4.444 8.82e-06 ***
departmenthr                0.090607   0.160443   0.565 0.572256    
departmentIT               -0.255475   0.149594  -1.708 0.087676 .  
departmentmanagement       -0.457203   0.195371  -2.340 0.019274 *  
departmentmarketing        -0.122724   0.159199  -0.771 0.440775    
departmentproduct_mng      -0.183987   0.157303  -1.170 0.242148    
departmentRandD            -0.682667   0.178227  -3.830 0.000128 ***
departmentsales            -0.101533   0.124859  -0.813 0.416112    
departmentsupport           0.002423   0.133301   0.018 0.985499    
departmenttechnical         0.003665   0.129918   0.028 0.977498    
salarylow                   2.057056   0.162425  12.665  < 2e-16 ***
salarymedium                1.479659   0.163326   9.060  < 2e-16 ***
average_montly_hoursGroup  -0.162548   0.089333  -1.820 0.068825 .  
satisfaction_levelGroup     1.023163   0.092337  11.081  < 2e-16 ***
time_spend_companyGroup           NA         NA      NA       NA    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

```
> exp(cbind(OR=coef(model1),confint(model1)))
Waiting for profiling to be done...
                                   OR        2.5 %       97.5 %
(Intercept)              5.266264e-01 3.207391e-01 8.559507e-01
satisfaction_level       6.975457e-07 1.157045e-07 4.153592e-06
last_evaluation          1.854690e+00 1.300424e+00 2.647453e+00
number_project           7.065001e-01 6.709135e-01 7.436245e-01
average_montly_hours     1.006839e+00 1.003010e+00 1.010690e+00
time_spend_company       1.297920e+00 1.251179e+00 1.346403e+00
Work_accident            2.201558e-01 1.783337e-01 2.695925e-01
promotion_last_5years    2.565313e-01 1.351568e-01 4.522753e-01
departmenthr             1.094839e+00 7.994243e-01 1.499818e+00
departmentIT             7.745486e-01 5.779043e-01 1.039058e+00
departmentmanagement     6.330521e-01 4.299490e-01 9.254226e-01
departmentmarketing      8.845077e-01 6.472932e-01 1.208514e+00
departmentproduct_mng    8.319464e-01 6.111184e-01 1.132523e+00
departmentRandD          5.052677e-01 3.553450e-01 7.149887e-01
departmentsales          9.034511e-01 7.085788e-01 1.156260e+00
departmentsupport        1.002426e+00 7.730331e-01 1.303862e+00
departmenttechnical      1.003671e+00 7.792583e-01 1.297047e+00
salarylow                7.822909e+00 5.745844e+00 1.087467e+01
salarymedium             4.391450e+00 3.218966e+00 6.113909e+00
average_montly_hoursGroup 8.499753e-01 7.133831e-01 1.012569e+00
satisfaction_levelGroup  2.781979e+00 2.322393e+00 3.335442e+00
time_spend_companyGroup            NA           NA           NA
>
```

Decision Tree

```
> DTree_model <- rpart(left~., data = train)
> DTree_model
n= 10524

node), split, n, deviance, yval
      * denotes terminal node

 1) root 10524 1889.225000 1.234512
   2) satisfaction_levelGroup>=4.5 7137  622.484500 1.096539
     4) time_spend_company< 4.5 5829   80.846460 1.014068 *
     5) time_spend_company>=4.5 1308  325.311200 1.464067
      10) average_montly_hours< 215.5 441   20.000000 1.047619 *
      11) average_montly_hours>=215.5 867  189.926200 1.675894
        22) time_spend_company>=6.5 136    0.000000 1.000000 *
        23) time_spend_company< 6.5 731  116.238000 1.801642
          46) number_project< 3.5 69    7.826087 1.130435 *
          47) number_project>=3.5 662   74.086100 1.871601
            94) satisfaction_levelGroup< 6.5 45    7.200000 1.200000 *
            95) satisfaction_levelGroup>=6.5 617   45.108590 1.920583 *
   3) satisfaction_levelGroup< 4.5 3387  844.591700 1.525244
     6) number_project>=2.5 2122  475.057500 1.338360
      12) number_project< 5.5 1269   84.474390 1.071710 *
      13) number_project>=5.5 853  166.121900 1.735053
        26) average_montly_hours< 242.5 197   19.543150 1.111675 *
        27) average_montly_hours>=242.5 656   47.035060 1.922256
          54) satisfaction_levelGroup>=1.5 34    4.941176 1.176471 *
          55) satisfaction_levelGroup< 1.5 622   22.149520 1.963023 *
     7) number_project< 2.5 1265  171.102000 1.838735
      14) average_montly_hours>=161.5 126    9.206349 1.079365 *
      15) average_montly_hours< 161.5 1139   81.201050 1.922739
        30) average_montly_hours< 125.5 36    0.000000 1.000000 *
        31) average_montly_hours>=125.5 1103   49.548500 1.952856 *
>
```


satisfaction_levelGroup>=4.5
time_spend_company< 4.5
number_project>=2.5
1.014
n=5829
average_montly_hours< 215.5
1.048
n=441
time_spend_company>=6.5
1
n=136
number_project< 3.5
1.13
n=69
satisfaction_levelGroup< 6.5
1.2
n=45
1.921
n=617
number_project< 5.5
1.072
n=1269
average_montly_hours< 242.5
1.112
n=197
satisfaction_levelGroup>=1.5
1.176
n=34
1.963
n=622
average_montly_hours>=161.5
1.079
n=126
average_montly_hours< 125.5
1
n=36
1.963
n=1103

```
> cm_DTree<-table(pred_DTree_model,test$left)
> cm_DTree

pred_DTree_model       0    1
  1                   12    0
  1.01406759306914 2438   30
  1.0464646464646 5  188    7
  1.0546875           41    4
  1.07171000788022  487   39
  1.07692307692308    60    6
  1.09090909090909    17    2
  1.1116751269035 5   68   12
  1.15151515151515     9    7
  1.91826923076923    20  289
  1.96065873741995    20  467
  1.96308186195827    12  240
> accuracy_DTree<-(cm_DTree[1]+cm_DTree[4])/(cm_DTree[1]+cm_DTree[2]+cm_DTree[3]+cm_DTree[4])
> accuracy_DTree
```

Decision Tree Accuracy 0.780834914611006

Random Forest

```
> RF_model

Call:
 randomForest(formula = left ~ ., data = train)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 4

          Mean of squared residuals: 0.01225822
                    % Var explained: 93.17
```

```
> accuracy_RF<-(cm_RF[1]+cm_RF[4])/(cm_RF[1]+cm_RF[2]+cm_RF[3]+cm_RF[4])
> accuracy_RF
[1] 0.8978102
> 
```

Naïve Bayes

```
> library(e1071)
> NB_model <- naiveBayes(left~., data = train)
>
> NB_model

Naive Bayes Classifier for Discrete Predictors

Call:
naiveBayes.default(x = X, y = Y, laplace = laplace)

A-priori probabilities:
Y
        1         2 
0.7654884 0.2345116 

Conditional probabilities:
   satisfaction_level
Y        [,1]      [,2]
  1 0.6660340 0.2178236
  2 0.4345089 0.2630063

   last_evaluation
Y        [,1]      [,2]
  1 0.7145022 0.1622186
  2 0.7164182 0.1969055

   number_project
Y       [,1]      [,2]
  1 3.783515 0.9790132
  2 3.871556 1.8298391

   average_montly_hours
Y       [,1]     [,2]
  1 199.1574 45.76802
  2 207.5596 61.50919

   time_spend_company
Y       [,1]      [,2]
  1 3.380034 1.5700884
  2 3.864263 0.9734056

   Work_accident
Y         [,1]      [,2]
  1 0.18185204 0.3857465
  2 0.05024311 0.2184905

   promotion_last_5years
Y          [,1]       [,2]
  1 0.026315789 0.16008263
  2 0.005672609 0.07511882

   department
Y       [,1]     [,2]
  1 6.405412 2.495879
  2 6.574959 2.535451

   salary
Y       [,1]      [,2]
```

```
               Accuracy : 0.81
                 95% CI : (0.7728, 0.8435)
    No Information Rate : 0.53
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.6174
Mcnemar's Test P-Value : 0.2183

            Sensitivity : 0.8453
            Specificity : 0.7702
         Pos Pred Value : 0.8058
         Neg Pred Value : 0.8153
             Prevalence : 0.5300
         Detection Rate : 0.4480
   Detection Prevalence : 0.5560
      Balanced Accuracy : 0.8077

       'Positive' Class : Neg
```

__Support Vector Machine__

```
> summary(SVM_model)

Call:
svm(formula = left ~ ., data = train, type = "C-classification",
    kernel = "radial", cost = 0.1, gamma = c(0.5, 1, 2))


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  0.1
      gamma:  0.5 1 2

Number of Support Vectors:  2975

 ( 1041 1934 )


Number of Classes:  2

Levels:
 1 2
```

```
> cm_svm<-table(pred_svm,test$left)
> cm

pred_svm    0    1
       1 3343  162
       2   29  941
> accuracy_svm<-(cm[1]+cm[4])/(cm[1]+cm[2]+cm[3]+cm[4])
> accuracy_svm
[1] 0.9573184
>
```

Summary

From the above example, we can see that Decision Tree and Random Forest can be used for customer churn analysis for this dataset equally fine.

Throughout the analysis, I have learned several important things:

- Features such as satisfaction_level, satisfaction_levelGroup,last_evaluation, number_project, average_monthly_hours,time_spend_company,Work_Accident appear to play a role in customer leaving.
- Out of all the models used, for the employees leaving/churning – the accuracy of SVM model is highest
- SVM>RF>NB>DT