People Analytics Using R – Employee Churn

Step 1. Define The Goal

My hypothetical company wants to apply data analytics principles and steps to deal with a critical HR issue: employee churn. It realizes that when good people leave, it costs far more to replace them than providing them with some incentives to keep them. So, it would like to be data-driven in the HR decisions it makes with respect to employee retention.

The following questions are among the ones they would like answered:

1. What proportion of our people is leaving?
2. Where is it occurring?
3. How does Age and Length of Service affect termination?
4. What, if anything, else contributes to it?
5. Can we predict future terminations?
6. If so, how well can we predict?

Step 2 – Collect and Manage the Data

Often the data to analyze the problem starts with what is currently readily available. After some initial prototyping of predictive models, ideas surface for additional data collection to further refine the model. Since this is first stab at this, the organization uses only what is readily available.

After consulting with their HRIS staff, they found that they have access to the following information:

- EmployeeID
- Record Date
- Birth Date
- Original Hire Date
- Termination Date (if terminated)

- Age
- Length of Service
- City
- Department
- Job title
- Store Name
- Gender
- termination reason
- termination type (voluntary or involuntary)
- Status Year – year of data
- Status – ACTIVE or TERMINATED during Status year
- Business Unit – either Stores or Head Office

The company found out that they have 10 years of good data – from 2006 to 2015. It wants to use 2006-2014 as training data and use 2015 as the data to test on. The data consists of

- a snapshot of all active employees at the end of each of those years combined with
- terminations that occurred during each of those years.

Therefore, each year will have records that have either a status of 'active' or 'terminated'. Of the above information items listed, the 'STATUS' one is the 'dependent' variable. This is the category to be predicted. The others are independent variables. They are the potential predictors.

First Look at The Data – The Structure

```
# Load an R data frame
> HRChurn <- read.csv("C://Users/alire/Downloads/Datasets-Tutorial-People-Ana
lytics/HRChurn.csv")
> MYdataset <- HRChurn


# Display the internal structure
> str(MYdataset)
```

```
> str(MYdataset)
'data.frame':	49653 obs. of  18 variables:
 $ EmployeeID         : int  1318 1318 1318 1318 1318 1318 1318 1318 1318 1318 ...
 $ recorddate_key     : chr  "12/31/2006 0:00" "12/31/2007 0:00" "12/31/2008 0:00" "12/31/2009 0:00" ...
 $ birthdate_key      : chr  "1954-01-03" "1954-01-03" "1954-01-03" "1954-01-03" ...
 $ orighiredate_key   : chr  "1989-08-28" "1989-08-28" "1989-08-28" "1989-08-28" ...
 $ terminationdate_key: chr  "1900-01-01" "1900-01-01" "1900-01-01" "1900-01-01" ...
 $ age                : int  52 53 54 55 56 57 58 59 60 61 ...
 $ length_of_service  : int  17 18 19 20 21 22 23 24 25 26 ...
 $ city_name          : chr  "Vancouver" "Vancouver" "Vancouver" "Vancouver" ...
 $ department_name    : chr  "Executive" "Executive" "Executive" "Executive" ...
 $ job_title          : chr  "CEO" "CEO" "CEO" "CEO" ...
 $ store_name         : int  35 35 35 35 35 35 35 35 35 35 ...
 $ gender_short       : chr  "M" "M" "M" "M" ...
 $ gender_full        : chr  "Male" "Male" "Male" "Male" ...
 $ termreason_desc    : chr  "Not Applicable" "Not Applicable" "Not Applicable" "Not Applicable" ...
 $ termtype_desc      : chr  "Not Applicable" "Not Applicable" "Not Applicable" "Not Applicable" ...
 $ STATUS_YEAR        : int  2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 ...
 $ STATUS             : chr  "ACTIVE" "ACTIVE" "ACTIVE" "ACTIVE" ...
 $ BUSINESS_UNIT      : chr  "HEADOFFICE" "HEADOFFICE" "HEADOFFICE" "HEADOFFICE" ...
```

```
# opening a spreadsheet-style of dataset

> View(HRChurn)
```

HRChurn

Filter

	EmployeeID	recorddate_key	birthdate_key	orighiredate_key	terminationdate_key	age	length_of_service	city_name
1	1318	12/31/2006 0:00	1954-01-03	1989-08-28	1900-01-01	52	17	Vancouver
2	1318	12/31/2007 0:00	1954-01-03	1989-08-28	1900-01-01	53	18	Vancouver
3	1318	12/31/2008 0:00	1954-01-03	1989-08-28	1900-01-01	54	19	Vancouver
4	1318	12/31/2009 0:00	1954-01-03	1989-08-28	1900-01-01	55	20	Vancouver
5	1318	12/31/2010 0:00	1954-01-03	1989-08-28	1900-01-01	56	21	Vancouver
6	1318	12/31/2011 0:00	1954-01-03	1989-08-28	1900-01-01	57	22	Vancouver
7	1318	12/31/2012 0:00	1954-01-03	1989-08-28	1900-01-01	58	23	Vancouver
8	1318	12/31/2013 0:00	1954-01-03	1989-08-28	1900-01-01	59	24	Vancouver
9	1318	12/31/2014 0:00	1954-01-03	1989-08-28	1900-01-01	60	25	Vancouver
10	1318	12/31/2015 0:00	1954-01-03	1989-08-28	1900-01-01	61	26	Vancouver
11	1319	12/31/2006 0:00	1957-01-03	1989-08-28	1900-01-01	49	17	Vancouver

Showing 1 to 11 of 49,653 entries, 18 total columns

```
# Installing plyr abd dplyr packages

> install.packages("plyr")
> install.packages("dplyr")

> library(plyr)
> library(dplyr)
```

"plyr" is a package that provides a set of tools for splitting, applying, and combining large datasets. It is particularly useful for working with data frames.

"dplyr" is a grammar of data manipulation, providing a consistent set ofverbs

Second Look at The Data – Data Quality

We will now assess data quality, using a few simple descriptive statistics, including the minimum value, mean, and max, and creating a number of counts.

```
# summarizing the values in each column

> summary(HRChurn)
   EmployeeID   recorddate_key     birthdate_key      orighiredate_key   terminationdate_key
 Min.   :1318   Length:49653       Length:49653       Length:49653       Length:49653
 1st Qu.:3360   Class :character   Class :character   Class :character   Class :character
 Median :5031   Mode  :character   Mode  :character   Mode  :character   Mode  :character
 Mean   :4859
 3rd Qu.:6335
 Max.   :8336
      age        length_of_service  city_name          department_name     job_title
 Min.   :19.00   Min.   : 0.00     Length:49653       Length:49653       Length:49653
 1st Qu.:31.00   1st Qu.: 5.00     Class :character   Class :character   Class :character
 Median :42.00   Median :10.00     Mode  :character   Mode  :character   Mode  :character
 Mean   :42.08   Mean   :10.43
 3rd Qu.:53.00   3rd Qu.:15.00
 Max.   :65.00   Max.   :26.00
   store_name   gender_short       gender_full        termreason_desc    termtype_desc
 Min.   : 1.0   Length:49653       Length:49653       Length:49653       Length:49653
 1st Qu.:16.0   Class :character   Class :character   Class :character   Class :character
 Median :28.0   Mode  :character   Mode  :character   Mode  :character   Mode  :character
 Mean   :27.3
 3rd Qu.:42.0
 Max.   :46.0
  STATUS_YEAR      STATUS          BUSINESS_UNIT
 Min.   :2006   Length:49653       Length:49653
 1st Qu.:2008   Class :character   Class :character
 Median :2011   Mode  :character   Mode  :character
 Mean   :2011
 3rd Qu.:2013
 Max.   :2015
```

Third Look at the Data – Generally What Is The Data Telling Us?

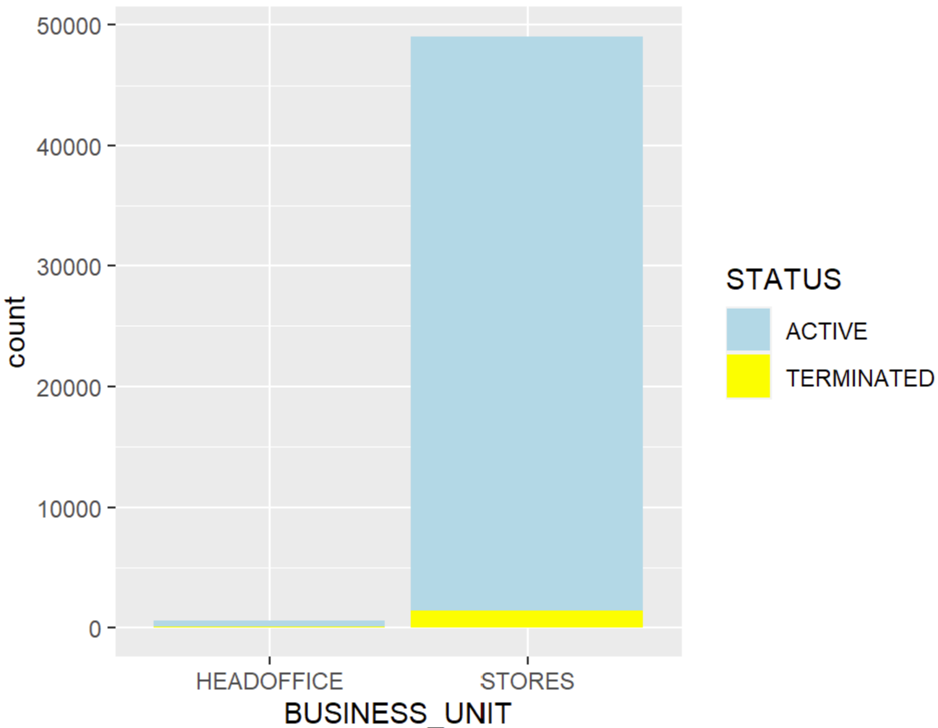
Earlier we had indicated that we had both active records at end of year and terminates during the year for each of 10 years going from 2006 to 2015. To have a population to model from (to differentiate ACTIVES from TERMINATES) we have to include both status types. It's useful then to get a baseline of what percent/proportion the terminates are of the entire population. It also answers our first question. Let's look at that next.

```
> library(dplyr)
> StatusCount <- as.data.frame.matrix(MYdataset %>%
        group_by(STATUS_YEAR) %>%
        select(STATUS) %>%
        table())
> StatusCount$TOTAL <- StatusCount$ACTIVE + StatusCount$TERMINATED
> StatusCount$PercentTerminated <- StatusCount$TERMINATED / (StatusCount$TOTA
L) * 100
> StatusCount
     ACTIVE TERMINATED TOTAL PercentTerminated
2006   4445        134  4579          2.926403
2007   4521        162  4683          3.459321
2008   4603        164  4767          3.440319
2009   4710        142  4852          2.926628
2010   4840        123  4963          2.478340
2011   4972        110  5082          2.164502
2012   5101        130  5231          2.485184
2013   5215        105  5320          1.973684
2014   4962        253  5215          4.851390
2015   4799        162  4961          3.265471
```

```
> mean(StatusCount$PercentTerminated)
[1] 2.997124
```

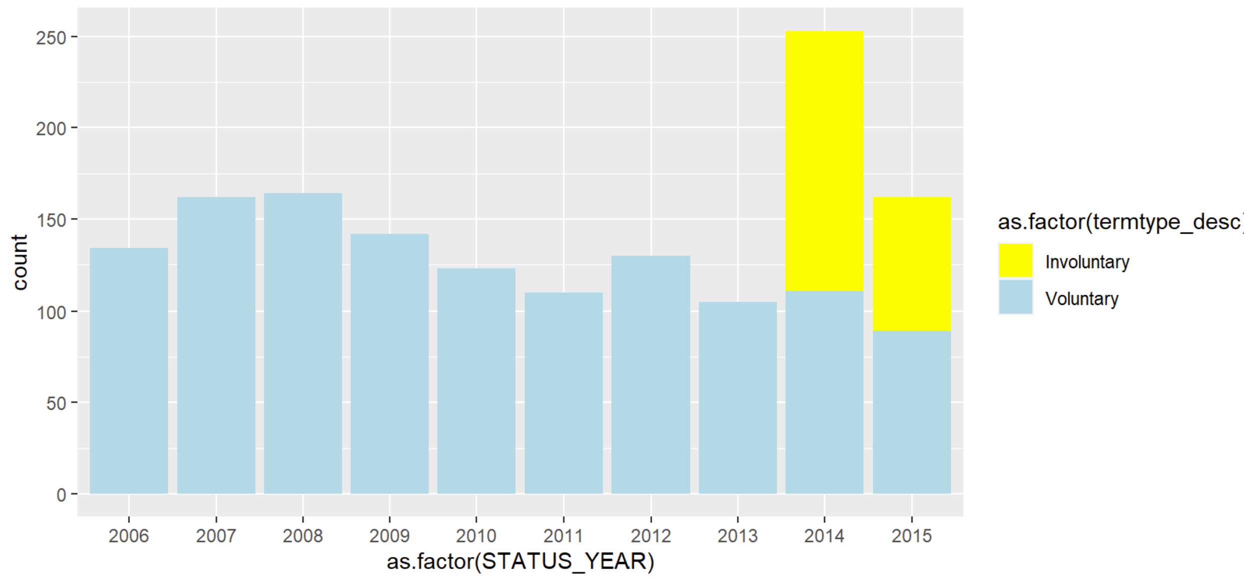
Where are the terminations occurring?

```
Install.Packages("ggplot2")
library(ggplot2)
ggplot(MYdataset, aes(x = BUSINESS_UNIT, fill = STATUS)) +
  geom_bar(position = position_stack()) +
  scale_fill_manual(values = c("ACTIVE" = "lightblue", "TERMINATED" = "yello"
))
```



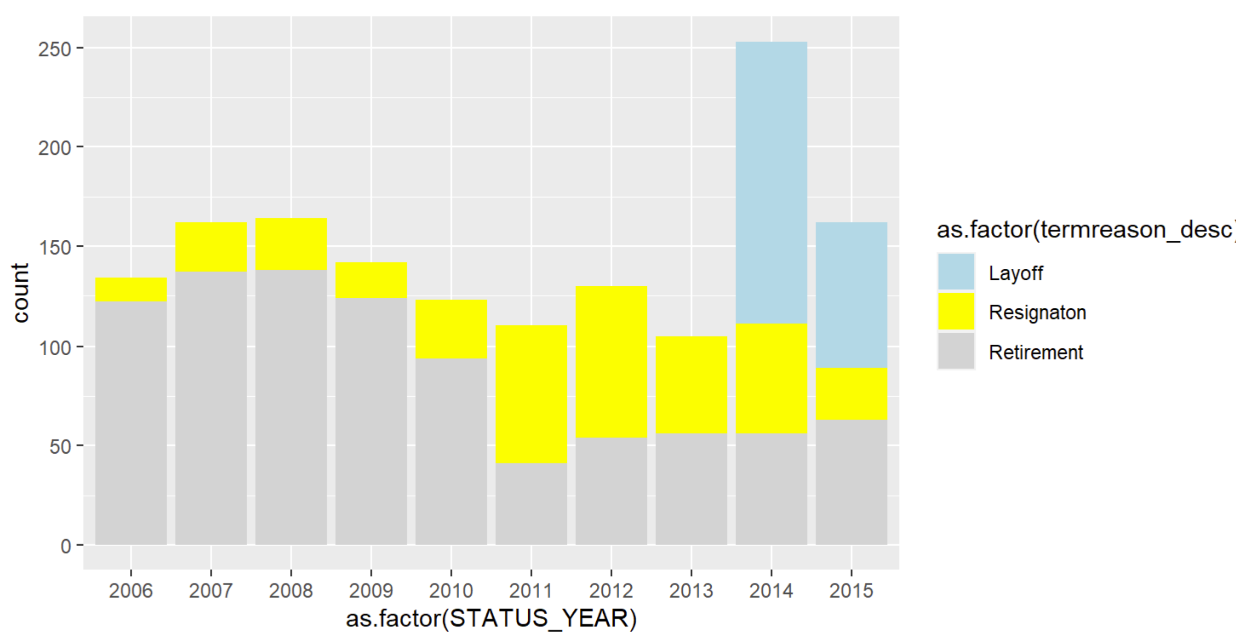
Just Terminates By Termination Type And Status Year

```
library(ggplot2)
ggplot() +
  geom_bar(
    aes(
      y = ..count..,
      x = as.factor(STATUS_YEAR),
      fill = as.factor(termtype_desc)
    ),
    data = TerminatesData,
    position = position_stack()
  ) +
  scale_fill_manual(
    values = c("Voluntary" = "lightblue", "Involuntary" = "yellow"))
```



Just Terminates By Status Year and Termination Reason

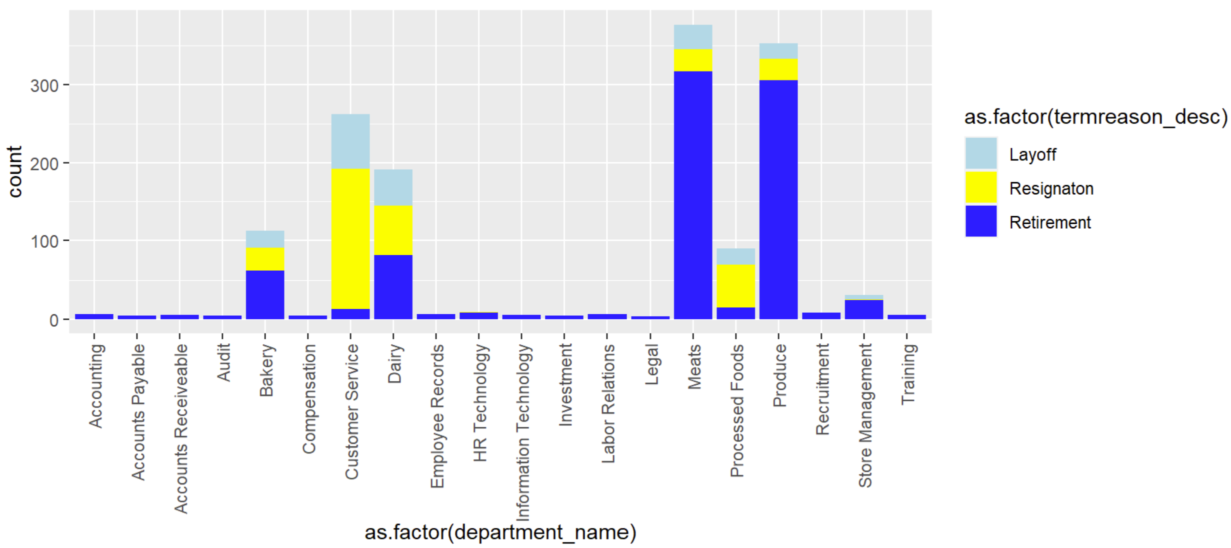
```
library(ggplot2)
ggplot() +
  geom_bar(
    aes(
      y = ..count..,
      x = as.factor(STATUS_YEAR),
      fill = as.factor(termreason_desc)
    ),
    data = TerminatesData,
    position = position_stack()
  ) +
  scale_fill_manual(
    values = c("Layoff" = "lightblue", "Resignaton" = "yellow", "Retirement"
= "lightgray")
  )
```



It seems that there were layoffs in 2014 and 2015 which accounts for the involuntary terminates.

Just Terminates By Termination Reason and Department

```
library(ggplot2)
ggplot() +
  geom_bar(
    aes(
      y = ..count..,
      x = as.factor(department_name),
      fill = as.factor(termreason_desc)
    ),
    data = TerminatesData,
    position = position_stack()
  ) +
  scale_fill_manual(
    values = c("Layoff" = "lightblue", "Resignaton" = "yellow", "Retirement"
= "blue", "Unknown" = "gray")
  ) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5))
```

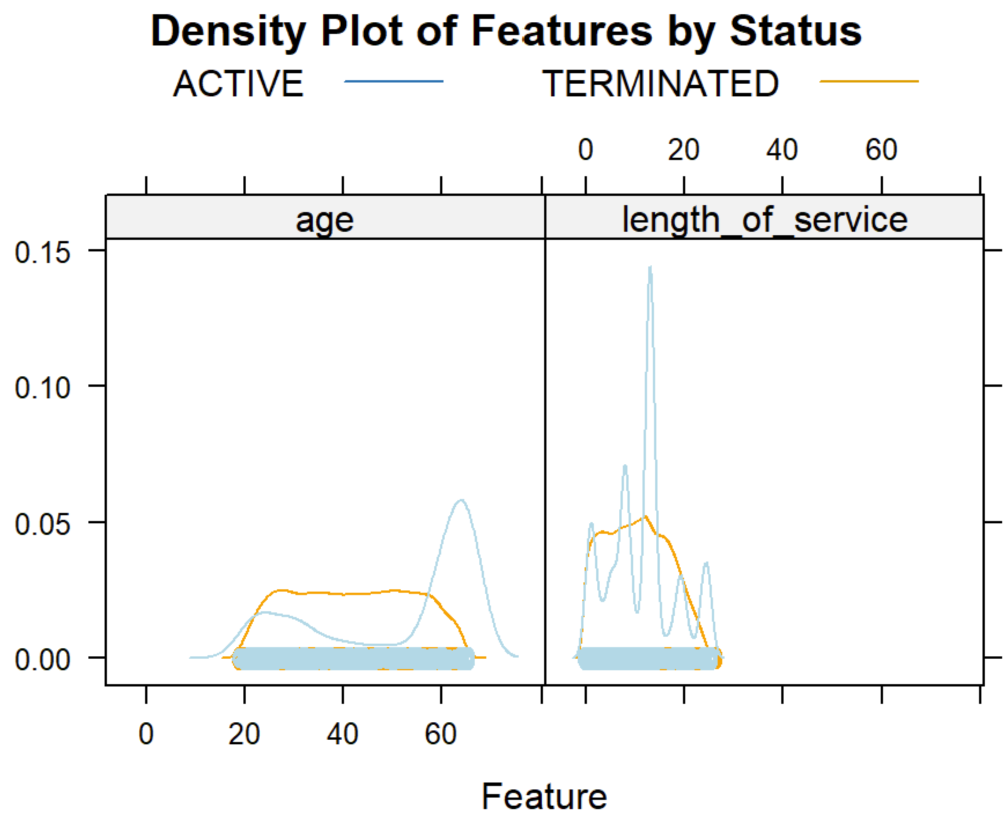


When we look at the terminate by Department, a few things stick out. Customer Service has a much larger proportion of resignation compared to other departments. And retirement, in general, is high in a number of departments.

How does Age and Length of Service affect termination?

```
library(caret)

# Specify the features (columns 6 and 7) and the response variable (STATUS)
features <- MYdataset[, 6:7]
response_variable <- as.factor(MYdataset$STATUS)

# Create a density plot using featurePlot
featurePlot(
  x = features,
  y = response_variable,
  plot = "density",
  auto.key = list(columns = 2),
  main = "Density Plot of Features by Status",
```

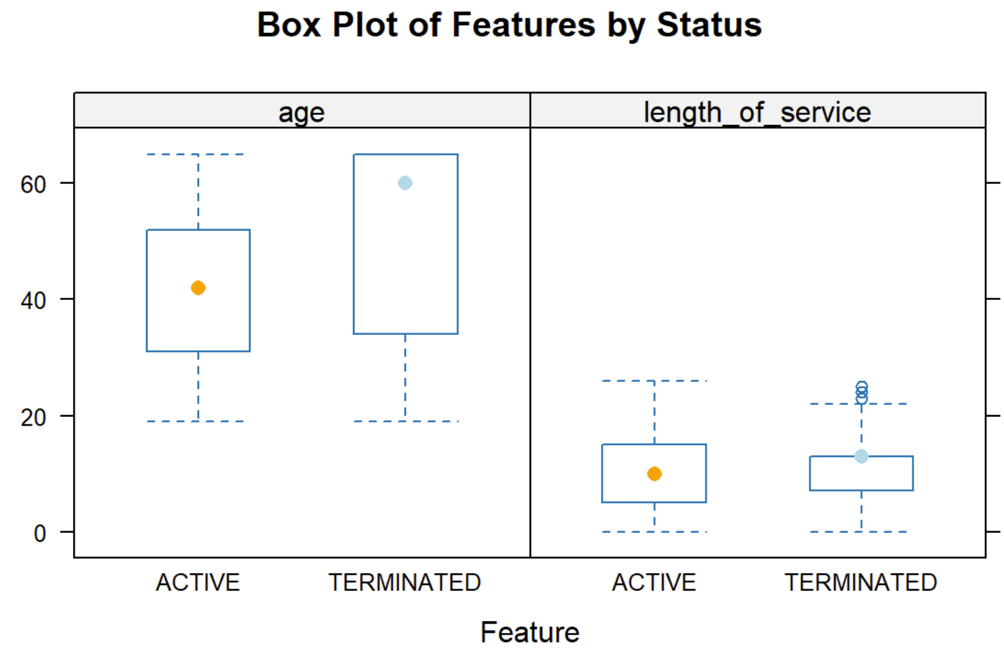
```
  legend.title = "Status",
  legend.labels = c("Active", "Terminated"),
  col = c("orange", "lightblue"))
```



Density plots show some interesting things. For terminates, there is some elevation from 20 to 30 and a spike at 60. For length of service there are 5 spikes. One around 1 year, another one around 5 years, and a big one around 15 years, and a couple at 20 and 25 years.

Age and Length of Service Distributions By Status

```
library(caret)

featurePlot(
  x = MYdataset[, 6:7],
  y = as.factor(MYdataset$STATUS),
  plot = "box",
  auto.key = list(columns = 2),
  col = c("orange", "lightblue"),  # Specify the colors for each status
  main = "Box Plot of Features by Status",
  legend.title = "Status",
  legend.labels = c("Active", "Terminated"))
```



A boxplot analysis shows a high average age for terminates as compared to active. Length of service shows not much difference between active and terminated.

Step 3 – Build The Model

It should be mentioned again that for building models, we never want to use **all** our data to build the model. This can lead to overfitting, where it might be able to predict well on current data that it sees as is built on, but may not predict well on data that it hasn't seen.

We have 10 years of historical data. This is a lot, usually, companies work only with a few years. In our case, we will use the first 9 to train the model, and the 10th year to test it. Moreover, we will use 10 fold cross-validation on the training data as well. So before we actually try out a variety of modeling algorithms, we need to partition the data into training and testing datasets.

Splitting The Data to Train and Test Data

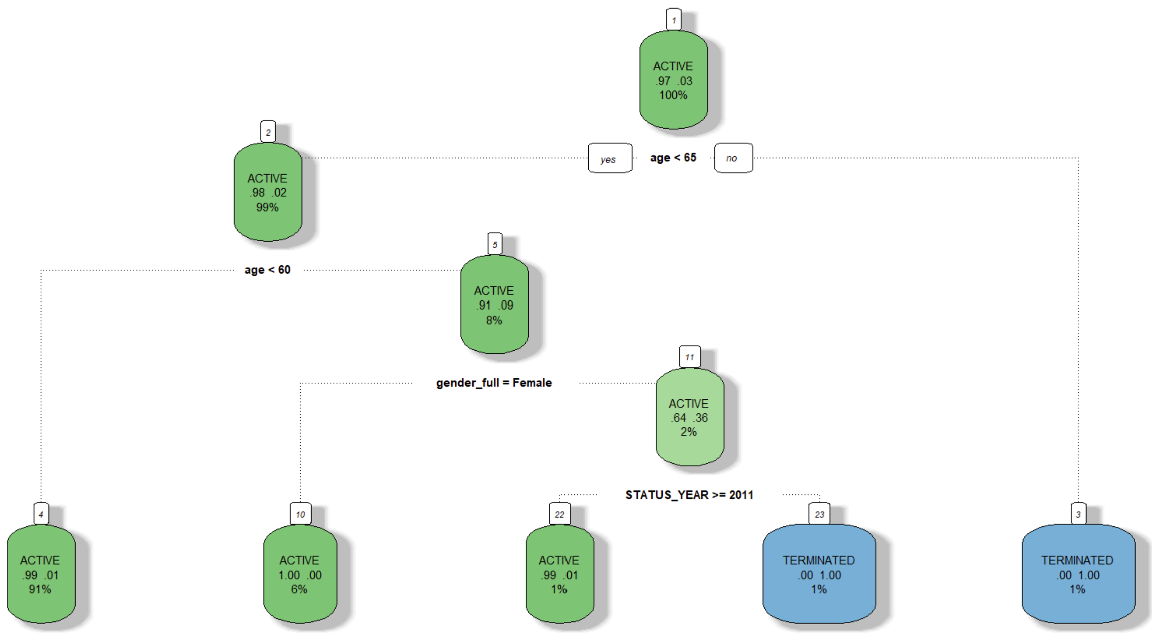
```
library(rattle)
library(magrittr)
# Set a pre-defined value to reset the random seed for repeatability
set.seed(42)
# Load the dataset
MFG10YearTerminationData <- read.csv("C://Users/alire/Downloads/Datasets-Tuto
rial-People-Analytics/HRChurn.csv")
# Create training and testing datasets
MYnobs <- nrow(MFG10YearTerminationData)
MYsample <- subset(MFG10YearTerminationData, STATUS_YEAR <= 2014)
MYvalidate <- NULL
MYtest <- subset(MFG10YearTerminationData, STATUS_YEAR == 2015)

# Variable selections
```

```
MYinput <- c("age", "length_of_service", "gender_full", "STATUS_YEAR", "BUSIN
ESS_UNIT")
MYnumeric <- c("age", "length_of_service", "STATUS_YEAR")
MYcategoric <- c("gender_full", "BUSINESS_UNIT")
MYtarget <- "STATUS"
MYrisk <- NULL
MYident <- "EmployeeID"
MYignore <- c("recorddate_key", "birthdate_key", "orighiredate_key", "termina
tiondate_key", "city_name", "gender_short", "termreason_desc", "termtype_desc
", "department_name", "job_title", "store_name")
MYweights <- NULL
# Create training and testing datasets with selected variables
MYTrainingData <- MYsample[c(MYinput, MYtarget)]
MYTestingData <- MYtest[c(MYinput, MYtarget)]
```

Decision Tree

```
library(rattle)
library(rpart, quietly=TRUE)

# Reset the random number seed to obtain the same results each time.
set.seed(crv$seed)

# Build the Decision Tree model.
MYrpart <- rpart(STATUS ~ .,
                 data = MYTrainingData,
                 method = "class",
                 parms = list(split = "information"),
                 control = rpart.control(usesurrogate = 0, maxsurrogate = 0))

# Generate a textual view of the Decision Tree model.
#print(MYrpart)
#printcp(MYrpart)
#cat("\n")

# Plot the resulting Decision Tree.
fancyRpartPlot(MYrpart, main = "Decision Tree MFG10YearTerminationData $ STAT
US")
```

Decision Tree MFG10YearTerminationData $ STATUS




```
# Rattle timestamp: 2016-03-25 18:50:22 x86_64-w64-mingw32
# Evaluate model performance.
# Generate an Error Matrix for the Decision Tree model.
# Obtain the response from the Decision Tree model.

MYpr <- predict(MYrpart, newdata = MYTestingData[c(MYinput, MYtarget)], type
= "class")

# Generate the confusion matrix showing counts.
conf_matrix <- table(MYTestingData$STATUS, MYpr,
                     dnn = c("Actual", "Predicted"))

# Display the confusion matrix
conf_matrix

            Predicted
Actual       ACTIVE TERMINATED
  ACTIVE       4799          0
  TERMINATED     99         63

# Generate the confusion matrix showing proportions.
pcme <- function(actual, cl) {
  nc <- nrow(cl)
  tbl <- cbind(cl / length(actual),
               Error = sapply(1:nc,
                              function(r) round(sum(cl[r, -r]) / sum(cl[r, ])
, 2)))
  names(attr(tbl, "dimnames")) <- c("Actual", "Predicted")
  return(tbl)
}

# Apply the pcme function to your actual and predicted values
per <- pcme(MYTestingData$STATUS, table(MYTestingData$STATUS, MYpr))
# Display the confusion matrix with proportions
round(per, 2)
```

```
             Predicted
Actual        ACTIVE TERMINATED Error
  ACTIVE        0.97       0.00  0.00
  TERMINATED    0.02       0.01  0.61
```

```
# Calculate the overall error percentage.
> cat(100*round(1-sum(diag(per), na.rm=TRUE), 2))
2

# Calculate the averaged class error percentage.
> cat(100*round(mean(per[,"Error"], na.rm=TRUE), 2))
30
```