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December 13, 2017

Objective of our Analysis:

The goal is to learn more about the factors that lead to particularly damaging forest fires and then building a machine learning model to predict forest fires. The variable of interest is *area* in our analysis.

Approach:

1) EDA: We will first conduct a basic exploratory analysis of the given dataset and determine correlations between area burnt and other parameters(factoring day and month). In our EDA, we will try and determine the strength of correlations between area burnt and other factors we take into consideration (in turn determine whether these factors are responsible for significantly damaging fires), we will then determine whether the strength of observed correlations lets us make a prediction using a linear or polynomial regression model.

2) Building a machine Learning Model: After our EDA, we will try using the Random Forest, SVM Classifier(linear and Kernel) and Gradient Boosting, we will then compare the accuracy of each of these models and make a decision as to which is the Best model to use in our prediction scenario.

Loading Required Libraries

```
library(Hmisc)
library(plyr)
library(dplyr)
library(car)
library(ggplot2)
library(GGally)
library(Hmisc)
library(psych)

df.forest<- read.csv("~/R/R Working Directory/forestfires.csv", header=TRUE,
stringsAsFactors= FALSE)
summary(df.forest)

##        X               Y           month               day
##  Min.   :1.000   Min.   :2.0   Length:517         Length:517
##  1st Qu.:3.000   1st Qu.:4.0   Class :character   Class :character
```

```
##  Median :4.000   Median :4.0   Mode  :character   Mode  :character
##  Mean   :4.669   Mean   :4.3
##  3rd Qu.:7.000   3rd Qu.:5.0
##  Max.   :9.000   Max.   :9.0
##       FFMC            DMC               DC              ISI
##  Min.   :18.70   Min.   :  1.1   Min.   :  7.9   Min.   : 0.000
##  1st Qu.:90.20   1st Qu.: 68.6   1st Qu.:437.7   1st Qu.: 6.500
##  Median :91.60   Median :108.3   Median :664.2   Median : 8.400
##  Mean   :90.64   Mean   :110.9   Mean   :547.9   Mean   : 9.022
##  3rd Qu.:92.90   3rd Qu.:142.4   3rd Qu.:713.9   3rd Qu.:10.800
##  Max.   :96.20   Max.   :291.3   Max.   :860.6   Max.   :56.100
##       temp             RH              wind            rain
##  Min.   : 2.20   Min.   : 15.00   Min.   :0.400   Min.   :0.00000
##  1st Qu.:15.50   1st Qu.: 33.00   1st Qu.:2.700   1st Qu.:0.00000
##  Median :19.30   Median : 42.00   Median :4.000   Median :0.00000
##  Mean   :18.89   Mean   : 44.29   Mean   :4.018   Mean   :0.02166
##  3rd Qu.:22.80   3rd Qu.: 53.00   3rd Qu.:4.900   3rd Qu.:0.00000
##  Max.   :33.30   Max.   :100.00   Max.   :9.400   Max.   :6.40000
##       area
##  Min.   :   0.00
##  1st Qu.:   0.00
##  Median :   0.52
##  Mean   :  12.85
##  3rd Qu.:   6.57
##  Max.   :1090.84
```

Filtering non zero area

```
chce_mod<- subset(df.forest, area!=0)
```

270 observations of non zero areas are affected, we will still consider the 0 area affected Values as occurences

```
str(chce_mod)
```

```
## 'data.frame':    270 obs. of  13 variables:
##  $ X    : int  9 1 2 1 8 1 2 6 5 8 ...
##  $ Y    : int  9 4 5 2 6 2 5 5 4 3 ...
##  $ month: chr  "jul" "sep" "sep" "aug" ...
##  $ day  : chr  "tue" "tue" "mon" "wed" ...
##  $ FFMC : num  85.8 91 90.9 95.5 90.1 90 95.5 95.2 90.1 84.4 ...
##  $ DMC  : num  48.3 129.5 126.5 99.9 108 ...
##  $ DC   : num  313 693 686 513 530 ...
##  $ ISI  : num  3.9 7 7 13.2 12.5 8.7 13.2 10.4 6.2 3.2 ...
##  $ temp : num  18 21.7 21.9 23.3 21.2 16.6 23.8 27.4 13.2 24.2 ...
##  $ RH   : int  42 38 39 31 51 53 32 22 40 28 ...
##  $ wind : num  2.7 2.2 1.8 4.5 8.9 5.4 5.4 4 5.4 3.6 ...
##  $ rain : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ area : num  0.36 0.43 0.47 0.55 0.61 0.71 0.77 0.9 0.95 0.96 ...
```

The mean area burnt taking the entire Data Set into account is 12.84729

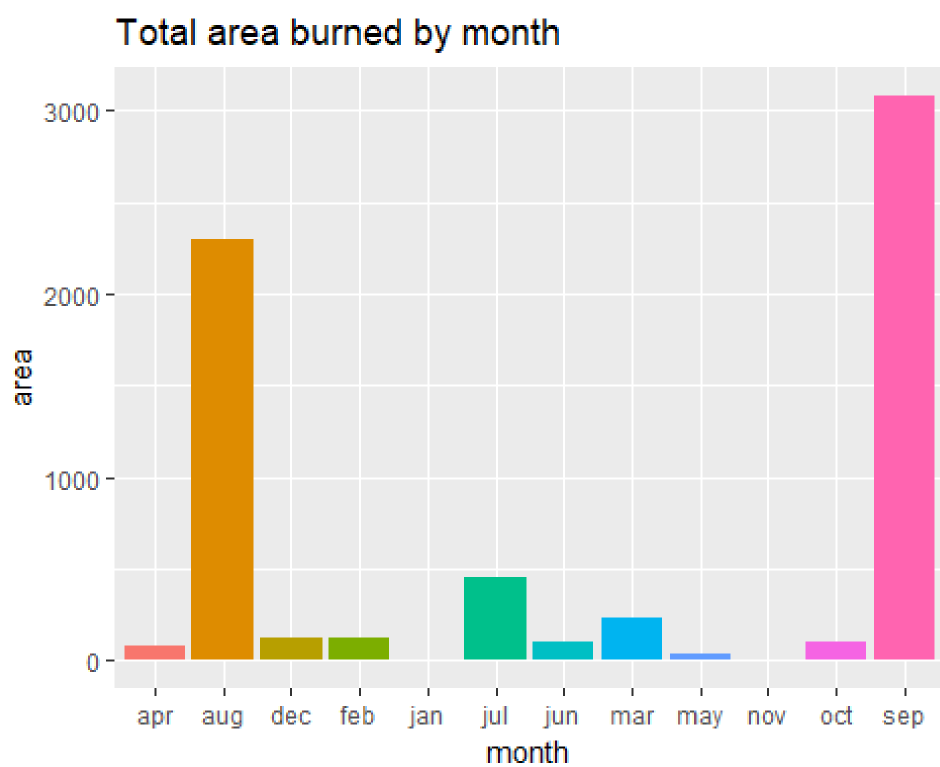
```
mean(df.forest$area)

## [1] 12.84729
```

The mean area burnt taking the Non-Zero affected values of the Data Set into account is 24.60019

```
mean(chce_mod$area)

## [1] 24.60019
```

Area by Month

```
ggplot(data=df.forest, aes(x=month, y=area, fill=month)) +
  geom_bar(stat="identity") +
  guides(fill=FALSE) +
  ggtitle("Total area burned by month")
```




```
library(psych)
Area_df<- aggregate(area~month, data=df.forest,sum)
Area_df
```

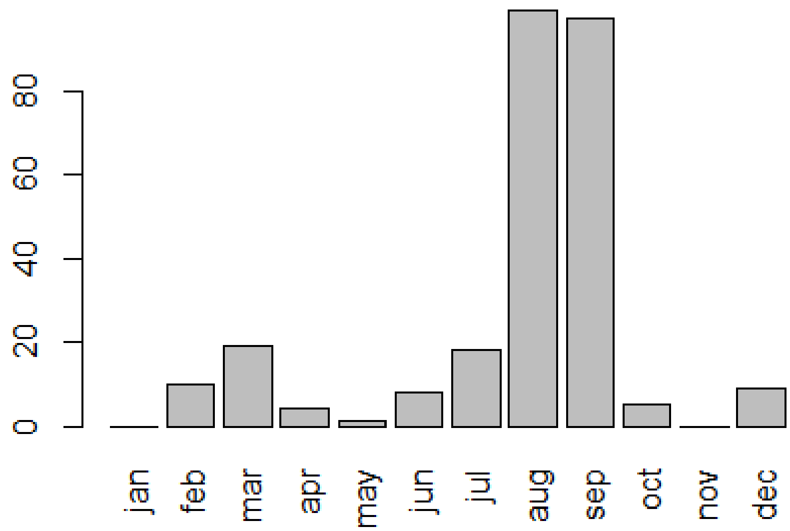
```
##    month    area
## 1    apr   80.02
## 2    aug 2297.99
## 3    dec  119.97
## 4    feb  125.50
## 5    jan    0.00
## 6    jul  459.83
## 7    jun   99.30
## 8    mar  235.26
## 9    may   38.48
## 10   nov    0.00
## 11   oct   99.57
## 12   sep 3086.13
```

Occurence by Month

```
chce<- subset(df.forest, area!=0, month)
count(chce, month)
```

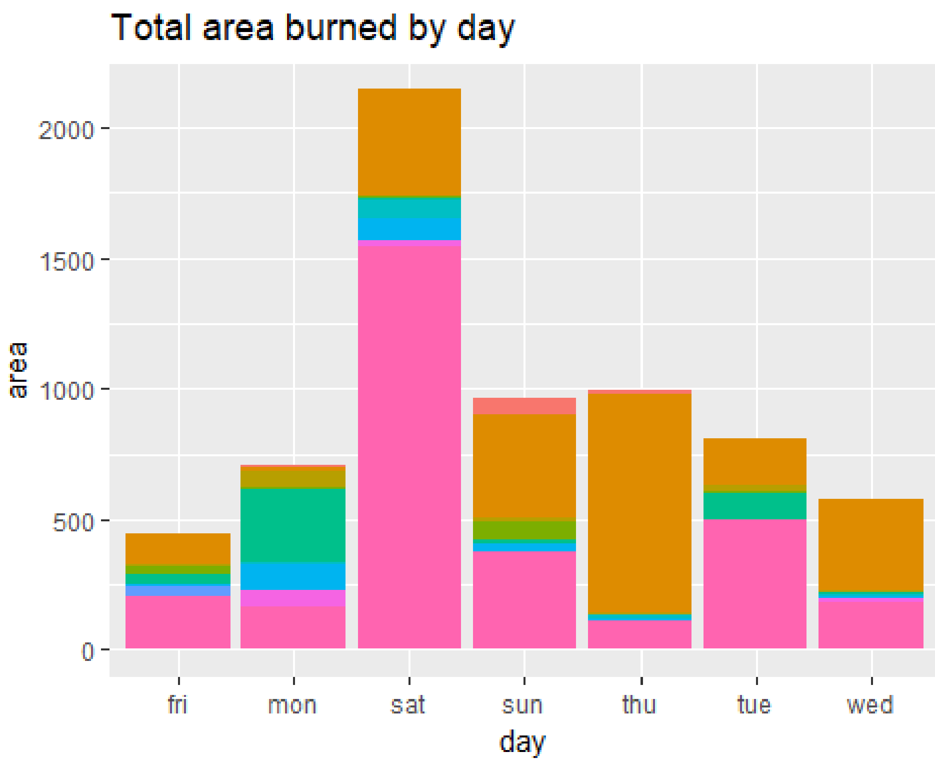
```
## # A tibble: 10 x 2
##    month     n
##    <chr> <int>
##  1   apr     4
##  2   aug    99
##  3   dec     9
##  4   feb    10
##  5   jul    18
##  6   jun     8
##  7   mar    19
##  8   may     1
##  9   oct     5
## 10   sep    97
```

```
discrete_month <- factor(chce$month, levels=c("jan","feb","mar","apr","may","
jun","jul","aug","sep","oct","nov","dec"))
barplot(table(discrete_month),las=3)
```



Area by Day

```
ggplot(data=df.forest, aes(x=day, y=area, fill=month)) +
  geom_bar(stat="identity") +
  guides(fill=FALSE) +
  ggtitle("Total area burned by day")
```




```
day_df<- aggregate(area~day, data=df.forest,sum)
day_df

##   day    area
## 1 fri  447.24
## 2 mon  706.53
## 3 sat 2144.86
## 4 sun  959.93
## 5 thu  997.10
## 6 tue  807.79
## 7 wed  578.60
```

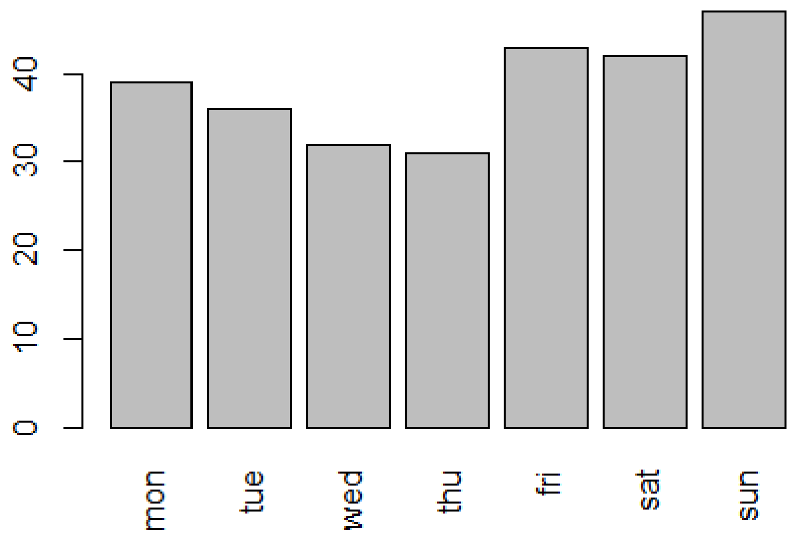
Occurence by Day

Intersting Observation here is that Friday has the Least Total Area Burnt. but the 2nd Highest Occurences

```
chce1<- subset(df.forest, area!=0, day)
count(chce1, day)

## # A tibble: 7 x 2
##     day     n
##   <chr> <int>
## 1   fri    43
## 2   mon    39
## 3   sat    42
```

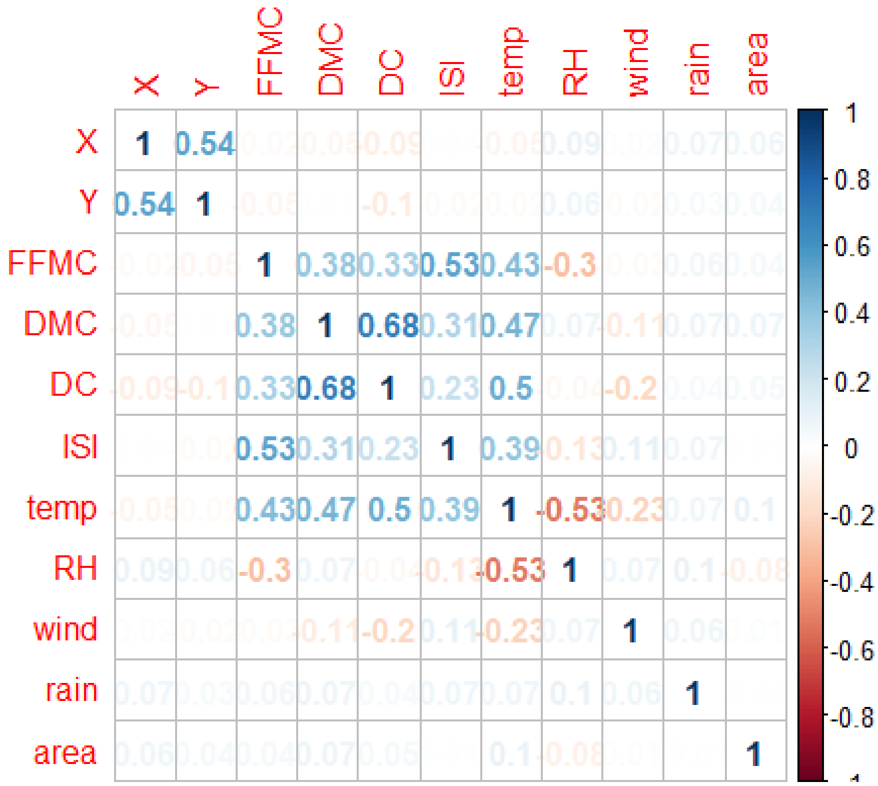
```
## 4    sun     47
## 5    thu     31
## 6    tue     36
## 7    wed     32
```

```
discrete_day <- factor(chce1$day, levels=c("mon","tue","wed","thu","fri","sat
","sun"))
barplot(table(discrete_day), las=3)
```



Subsetting for corplot numeric data entry, running corplot on entire Data Set

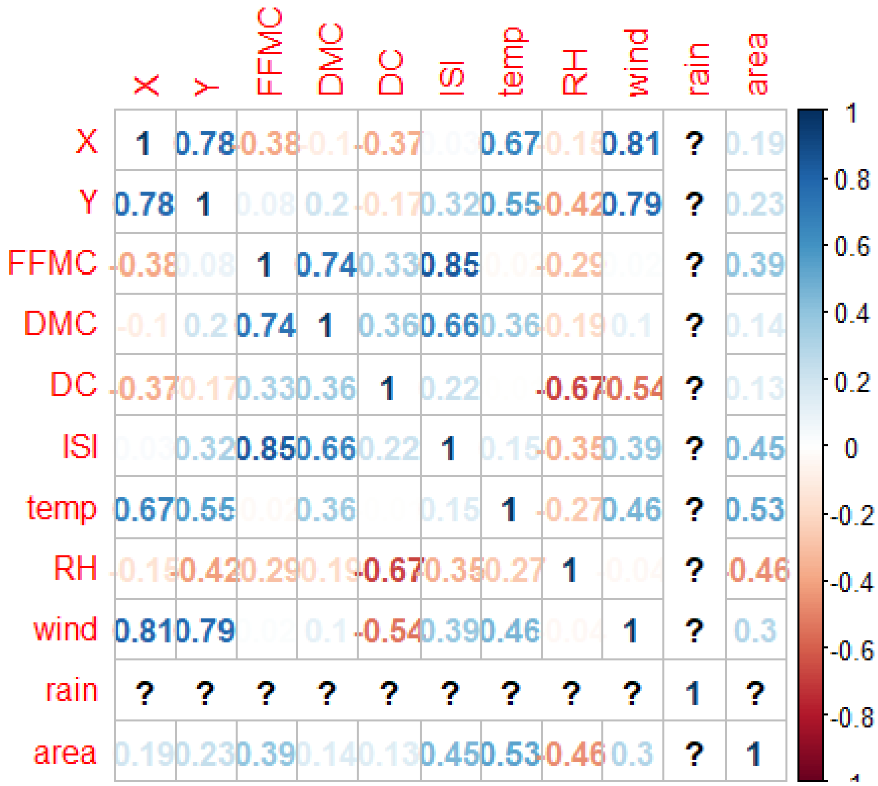
```
df.forest1<- df.forest[c(1,2,5:13)]
library( corrplot)
corrplot(cor(df.forest1[ ,1:11]), method = "number")
```



Subset for top 10 Fire Breakouts

Note: 4 of the Top 10 Fires occured on a Saturday

```
df.forest10<- head(df.forest[order(df.forest$area, decreasing=TRUE), ], 10)
df.forest10

##     X Y month day FFMC   DMC    DC  ISI temp RH wind rain    area
## 239 6 5   sep sat 92.5 121.1 674.4  8.6 25.1 27  4.0    0 1090.84
## 416 8 6   aug thu 94.8 222.4 698.6 13.9 27.5 27  4.9    0  746.28
## 480 7 4   jul mon 89.2 103.9 431.6  6.4 22.6 57  4.9    0  278.53
## 238 1 2   sep tue 91.0 129.5 692.6  7.0 18.8 40  2.2    0  212.88
## 237 2 2   sep sat 92.5 121.1 674.4  8.6 18.2 46  1.8    0  200.94
## 236 8 6   aug sun 91.4 142.4 601.4 10.6 19.6 41  5.8    0  196.48
## 421 8 8   aug wed 91.7 191.4 635.9  7.8 26.2 36  4.5    0  185.76
## 378 2 2   aug sat 93.7 231.1 715.1  8.4 21.9 42  2.2    0  174.63
## 235 4 5   sep sat 92.5 121.1 674.4  8.6 17.7 25  3.1    0  154.88
## 234 9 4   sep tue 84.4  73.4 671.9  3.2 24.3 36  3.1    0  105.66

df.forest10_adjust<- df.forest10[c(1,2,5:13)] ## adjust for corplot entry
corrplot(cor(df.forest10_adjust[ ,1:11]), method = "number")
```



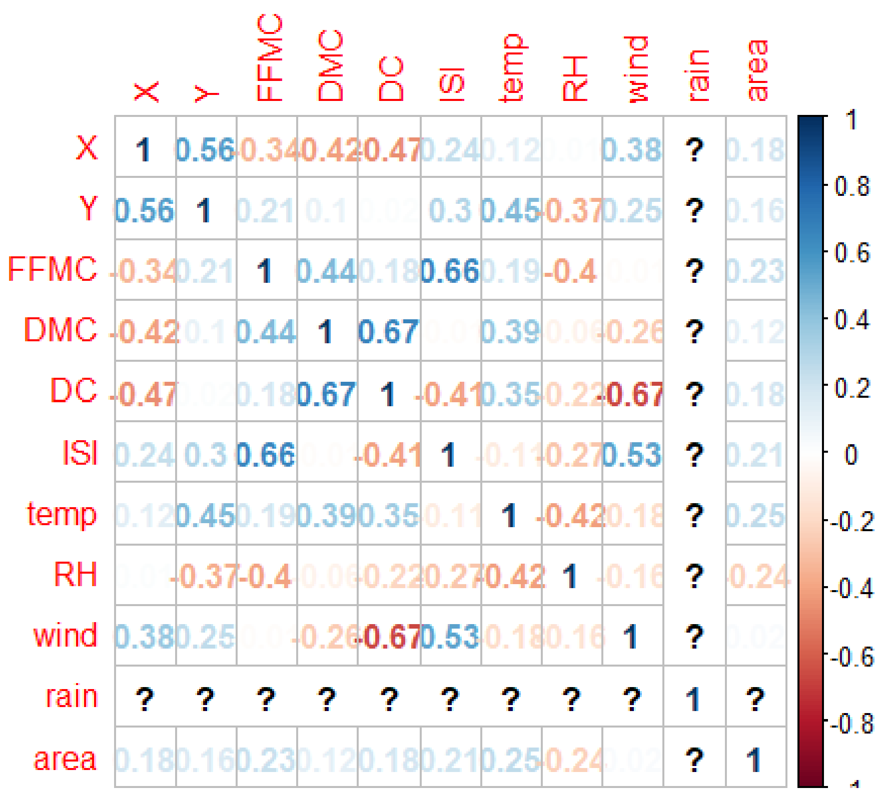

```
count(df.forest10,day)

## # A tibble: 6 x 2
##     day     n
##   <chr> <int>
## 1   mon     1
## 2   sat     4
## 3   sun     1
## 4   thu     1
## 5   tue     2
## 6   wed     1
```

Subset for top 20 Fire Breakouts

```
df.forest20<- head(df.forest[order(df.forest$area, decreasing=TRUE), ], 20)

df.forest20

##      X Y month day FFMC   DMC    DC  ISI temp RH wind rain    area
## 239 6 5   sep sat 92.5 121.1 674.4  8.6 25.1 27  4.0    0 1090.84
## 416 8 6   aug thu 94.8 222.4 698.6 13.9 27.5 27  4.9    0  746.28
## 480 7 4   jul mon 89.2 103.9 431.6  6.4 22.6 57  4.9    0  278.53
## 238 1 2   sep tue 91.0 129.5 692.6  7.0 18.8 40  2.2    0  212.88
## 237 2 2   sep sat 92.5 121.1 674.4  8.6 18.2 46  1.8    0  200.94
## 236 8 6   aug sun 91.4 142.4 601.4 10.6 19.6 41  5.8    0  196.48
## 421 8 8   aug wed 91.7 191.4 635.9  7.8 26.2 36  4.5    0  185.76
```

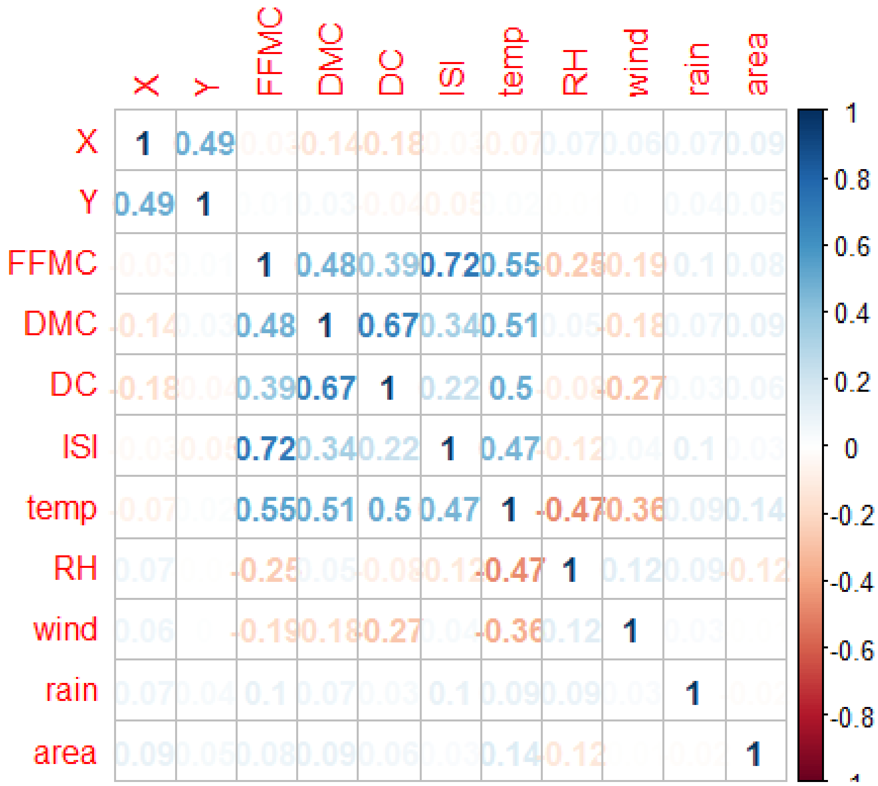
```
## 378 2 2   aug sat 93.7 231.1 715.1  8.4 21.9 42  2.2    0  174.63
## 235 4 5   sep sat 92.5 121.1 674.4  8.6 17.7 25  3.1    0  154.88
## 234 9 4   sep tue 84.4  73.4 671.9  3.2 24.3 36  3.1    0  105.66
## 233 6 4   sep tue 91.0 129.5 692.6  7.0 18.7 43  2.7    0  103.39
## 232 1 5   sep sun 93.5 149.3 728.6  8.1 27.8 27  3.1    0   95.18
## 231 4 4   sep wed 92.9 133.3 699.6  9.2 26.4 21  4.5    0   88.49
## 294 7 6   jul tue 93.1 180.4 430.8 11.0 26.9 28  5.4    0   86.45
## 458 1 4   aug wed 91.7 191.4 635.9  7.8 19.9 50  4.0    0   82.75
## 230 8 6   aug sat 92.2  81.8 480.8 11.9 16.4 43  4.0    0   71.30
## 393 1 3   sep sun 91.0 276.3 825.1  7.1 21.9 43  4.0    0   70.76
## 474 9 4   jun sat 90.5  61.1 252.6  9.4 24.5 50  3.1    0   70.32
## 229 4 6   sep sun 93.5 149.3 728.6  8.1 28.3 26  3.1    0   64.10
## 470 6 3   apr sun 91.0  14.6  25.6 12.3 13.7 33  9.4    0   61.13
```

```
df.forest20_adjust<- df.forest20[c(1,2,5:13)] ## adjust for corplot entry

corrplot(cor(df.forest20_adjust[ ,1:11]), method = "number")
```



Subset for top 200 Fire Breakout

```
df.forest200<- head(df.forest[order(df.forest$area, decreasing=TRUE), ], 200)


df.forest200_adjust<- df.forest200[c(1,2,5:13)] ## adjust for corplot entry

corrplot(cor(df.forest200_adjust[ ,1:11]), method = "number")
```



From above we observe that

1) We notice a decrease in Correlation Coefficient between area and temperature, ISI from the Top 10 (0.53,0.45) to top 20 (0.21,0.25) and negligible in the sample of top 200(approx 0,0.14)

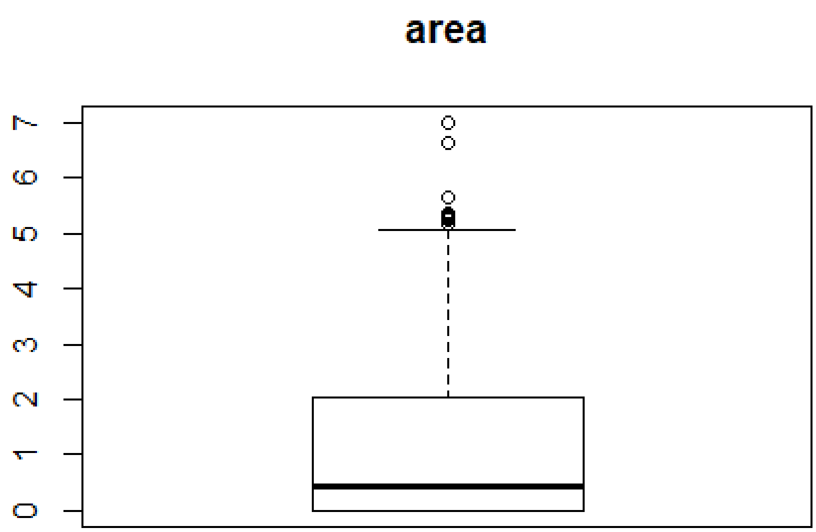
2) We also notice a weak Correlation between Area and every other parameter within the Entire dataset

3) Hence, we decided that neither Ploynomial nor Linear Correlation can be useful to predict in this case

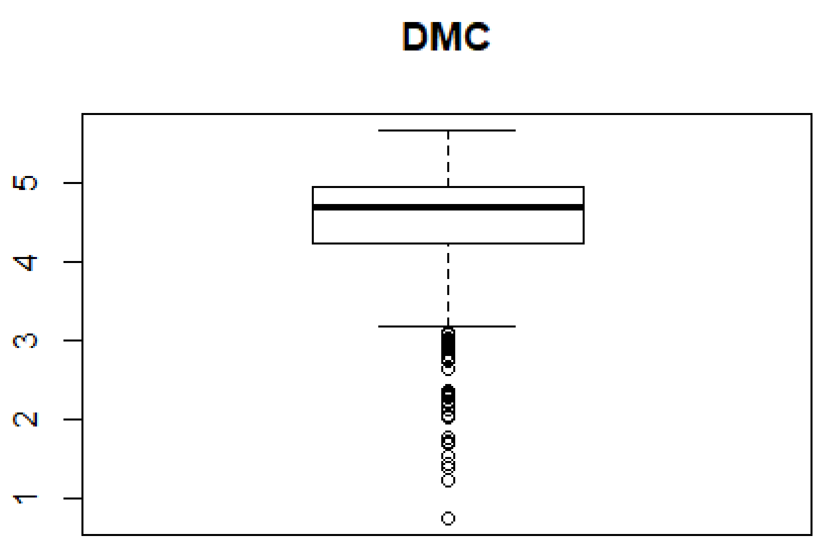
Examining our Data Set for Outliers:

We run Boxplots on all Parameters and determine cases where there is a dense concentration of outliers. Parameters with Considerable Outliers (we find that ISI DMC and area have data with considerable amount of outliers).

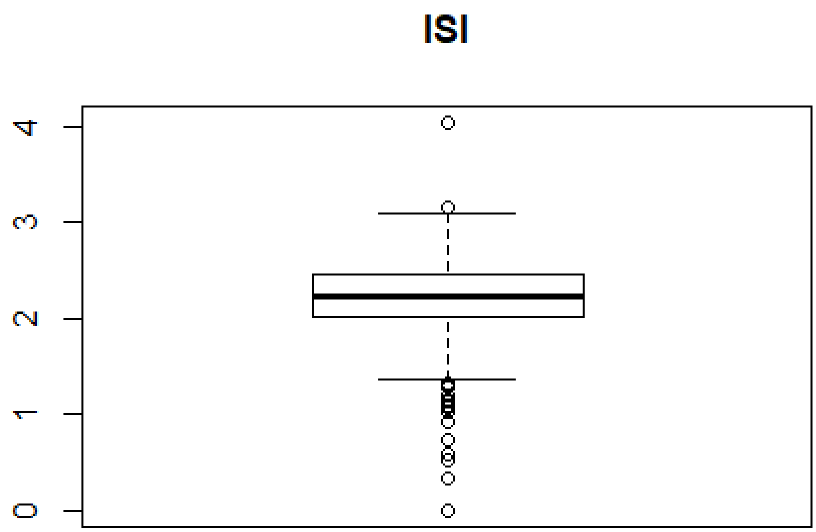
```
boxplot(log((df.forest$area)+1), main='area')
```




```
boxplot(log((df.forest$DMC)+1), main='DMC')
```




```
boxplot(log((df.forest$ISI)+1), main='ISI')
```



Solution for Objective 1: Descriptive Analysis

We categorized the paticularly damaging fires, to be the ones to affect most area (top 10). On observing the correlation matrix for the top 10 fires (refer the corrplot of df.forest10 above) we notice the following correlation coefficients of significance between area and 5 other parametres:

1) ***temprature * (0.53)***
2) ***ISI * (0.45)***
3) ***RH * (-0.46)***
4) ***FFMC * (0.39)***
5) ***Wind * (0.3)***

Note: RH is the only parameter with a negative correlation coefficient that is an increase in RH results a lesser area burnt in the top 10 area burnt data set.

Loading required libraries

```
library(randomForest)
library(corrplot)
library(psych)
library(e1071)
library(caret)
library(ggplot2)
```

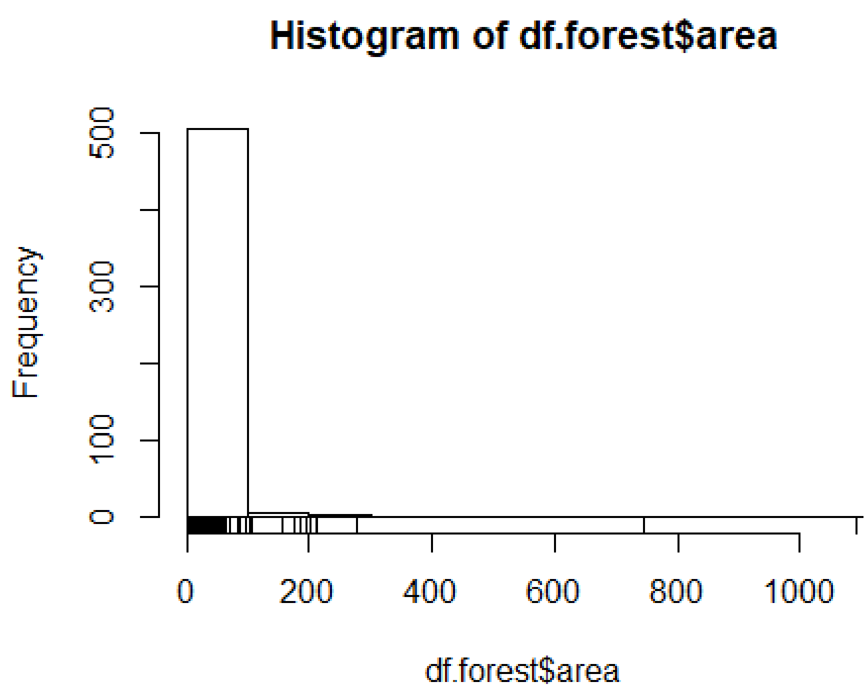
```r
library(gbm)
library(dplyr)
library(kernlab)
library(ROCR)
```

Importing Data

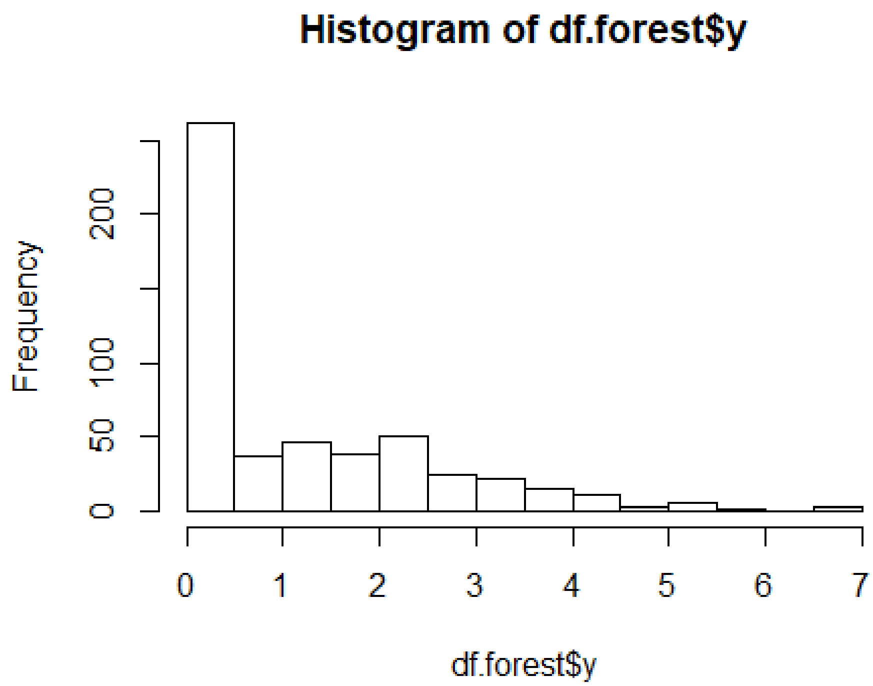
```r
df.forest <- tbl_df(df.forest)
set.seed(1234)
```

Checking skewness by using log transformation

```r
hist(df.forest$area)
rug(df.forest$area)
```




```r
df.forest <- mutate(df.forest, y = log(area + 1))
hist(df.forest$y)
```



Normalize

Subtracting the min value in x and dividing by the range of values in x.

```
normalise <- function(x) {
  return((x - min(x)) / (max(x) - min(x)))
}
df.forest$temp <- normalise(df.forest$temp)
df.forest$rain <- normalise(df.forest$rain)
df.forest$RH <- normalise(df.forest$RH)
df.forest$wind <- normalise(df.forest$wind)
```

Checking the Number of Small and Large fires

```
sum(df.forest$area < 5)

## [1] 366

sum(df.forest$area >= 5)

## [1] 151
```

Creating a new column and add 'small' and 'large' labels for area<5 hectares and area>=5 hectares respectively

```
df.forest$size <- NULL
df.forest$size <- factor(ifelse(df.forest$area < 5, 0, 1),
                         labels = c("small", "large"))
```

Seperating into data into training and testing

```
intrain <- sample(x = nrow(df.forest), size = 400, replace = FALSE)
```

Training Linear SVM Classifier

```
m.lin <- svm(size ~ temp + RH + wind + rain,
             data = df.forest[intrain, ],
             kernel = "linear", C = 1)
m.lin

##
## Call:
## svm(formula = size ~ temp + RH + wind + rain, data = df.forest[intrain,
##     ], kernel = "linear", C = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##       gamma:  0.25
##
## Number of Support Vectors:  253
```

Checking error rate of training model

```
#predict and check accuracy
pred <- predict(m.lin, newdata = df.forest[-intrain, ], type = "response")
table(pred, df.forest[-intrain, "size"][[1]])

##
## pred    small large
##   small    87    30
##   large     0     0

confusionMatrix(table(pred, df.forest[-intrain, "size"][[1]]), positive = "sm
all")

## Confusion Matrix and Statistics
##
##
## pred    small large
```

```
##   small     87     30
##   large      0      0
##
##                Accuracy : 0.7436
##                  95% CI : (0.6546, 0.8198)
##     No Information Rate : 0.7436
##     P-Value [Acc > NIR] : 0.5489
##
##                   Kappa : 0
##  Mcnemar's Test P-Value : 1.192e-07
##
##             Sensitivity : 1.0000
##             Specificity : 0.0000
##          Pos Pred Value : 0.7436
##          Neg Pred Value :    NaN
##              Prevalence : 0.7436
##          Detection Rate : 0.7436
##    Detection Prevalence : 1.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : small
##
```

Training Polynomial SVM Classifier

```
m.poly <- ksvm(size ~ temp + RH + wind + rain,
               data = df.forest[intrain, ],
               kernel = "polydot", C = 1)

##  Setting default kernel parameters

m.poly

## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Polynomial kernel function.
##  Hyperparameters : degree =  1  scale =  1  offset =  1
##
## Number of Support Vectors : 258
##
## Objective Function Value : -240.8177
## Training error : 0.3
```

Training Radial SVM Classifier

```
m.rad <- ksvm(size ~ temp + RH + wind + rain,
              data = df.forest[intrain, ],
```

```
               kernel = "rbfdot", C = 1)
m.rad

## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.691569468125734
##
## Number of Support Vectors : 276
##
## Objective Function Value : -228.0904
## Training error : 0.2725
```

Training Tan SVM Classifier

```
m.tan <- ksvm(size ~ temp + RH + wind + rain,
              data = df.forest[intrain, ],
              kernel = "tanhdot", C = 1)

##  Setting default kernel parameters

m.tan

## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Hyperbolic Tangent kernel function.
##  Hyperparameters : scale =  1  offset =  1
##
## Number of Support Vectors : 196
##
## Objective Function Value : -1911.148
## Training error : 0.4775
```

As lowest error rate amongst the 3 classifiers above is of Radial SVM hence

Predicting using Radial SVM and checking accuracy

```
pred <- predict(m.rad, newdata = df.forest[-intrain, ], type = "response")
table(pred, df.forest[-intrain, "size"][[1]])
```

```
##
## pred    small large
##   small    86    30
##   large     1     0
```

```r
confusionMatrix(table(pred, df.forest[-intrain, "size"][[1]]), positive = "sm
all") # from the caret package, also need e1071 package
```

```
## Confusion Matrix and Statistics
##
##
## pred    small large
##   small    86    30
##   large     1     0
##
##                Accuracy : 0.735
##                  95% CI : (0.6455, 0.8123)
##     No Information Rate : 0.7436
##     P-Value [Acc > NIR] : 0.6304
##
##                   Kappa : -0.0168
##  Mcnemar's Test P-Value : 4.932e-07
##
##             Sensitivity : 0.9885
##             Specificity : 0.0000
##          Pos Pred Value : 0.7414
##          Neg Pred Value : 0.0000
##              Prevalence : 0.7436
##          Detection Rate : 0.7350
##    Detection Prevalence : 0.9915
##       Balanced Accuracy : 0.4943
##
##        'Positive' Class : small
##
```

To build a prediction model, we need to first split the available data into test data and training data.

We will first set aside a dataset of 20 observations, pulled out randomly from the existing data-set. This test data-set will be used to run the final predictive model.

The dataset is also divided into training dataset (60%), which will be used to build the models, and testing dataset, which will be used to test the models.

```
test <- df.forest[rbinom(20, 10, 0.5),]
# Now divide the remaining data into training and testing

intrain <- createDataPartition(df.forest$size, p=0.6, list=FALSE)

train_data <- df.forest[intrain, ]
test_data <- df.forest[-intrain, ]

p <- predict(m.rad , test)
p

##  [1] small small small small small small small small small small small
## [12] small small small small small small small small small
## Levels: small large
```

Test ensemble classifiers - random forest and gradient boosting model

First lets fit random forest classifier and check error rate

```
forest.rf <- randomForest(size ~ temp + RH + wind + rain, data = df.forest[in
train, ], importance=TRUE, ntree=300)
forest.rf

##
## Call:
##  randomForest(formula = size ~ temp + RH + wind + rain, data = df.forest[i
ntrain,      ], importance = TRUE, ntree = 300)
##                Type of random forest: classification
##                      Number of trees: 300
## No. of variables tried at each split: 2
##
##         OOB estimate of  error rate: 36.33%
```

```
## Confusion matrix:
##       small large class.error
## small   183    37   0.1681818
## large    76    15   0.8351648
```

```r
#predict and find accuracy
pred <- predict(forest.rf, newdata = df.forest[-intrain, ], type = "response"
)
confusionMatrix(table(pred, df.forest[-intrain, "size"][[1]]), positive = "sm
all")  # from the caret package, also need e1071 package
```

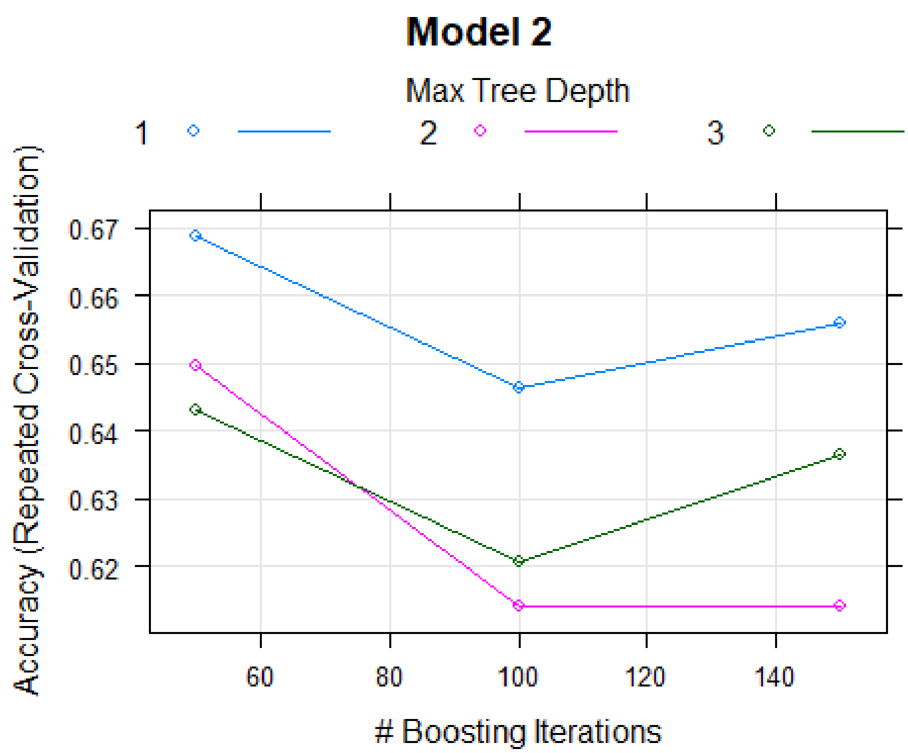
```
## Confusion Matrix and Statistics
## 
## 
## pred    small large
##   small   128    53
##   large    18     7
## 
##                Accuracy : 0.6553
##                  95% CI : (0.5861, 0.72)
##     No Information Rate : 0.7087
##     P-Value [Acc > NIR] : 0.9594
## 
##                   Kappa : -0.008
##  Mcnemar's Test P-Value : 5.459e-05
## 
##             Sensitivity : 0.8767
##             Specificity : 0.1167
##          Pos Pred Value : 0.7072
##          Neg Pred Value : 0.2800
##              Prevalence : 0.7087
##          Detection Rate : 0.6214
##    Detection Prevalence : 0.8786
##       Balanced Accuracy : 0.4967
## 
##        'Positive' Class : small
## 
```

Now using Gradient Boosting Classifier and Checking error rate

```r
fitControl <- trainControl(method = "repeatedcv",
                           number = 3,
                           repeats = 1)
mod_BR <- train(size ~ temp + RH + wind + rain, df.forest[intrain, ], method=
"gbm", trControl=fitControl, verbose = FALSE)
```

Predicting and finding accuracy

```
pred <- predict(mod_BR, newdata = df.forest[-intrain, ])
plot(mod_BR, main = "Model 2")
```




```
confusionMatrix(table(pred, df.forest[-intrain, "size"][[1]]), positive = "sm
all")  # from the caret package,

## Confusion Matrix and Statistics
##
##
## pred    small large
##   small   142    56
##   large     4     4
##
##                Accuracy : 0.7087
##                  95% CI : (0.6416, 0.7698)
##     No Information Rate : 0.7087
##     P-Value [Acc > NIR] : 0.5348
##
##                   Kappa : 0.0527
##  Mcnemar's Test P-Value : 4.577e-11
##
##             Sensitivity : 0.97260
##             Specificity : 0.06667
##          Pos Pred Value : 0.71717
##          Neg Pred Value : 0.50000
```

```
##               Prevalence : 0.70874
##           Detection Rate : 0.68932
##     Detection Prevalence : 0.96117
##        Balanced Accuracy : 0.51963
##
##         'Positive' Class : small
##
```

Solution for Objective 2: Predictive Analysis

We have built 3 models to predict forest fires.

1) Linear SVM Classifier The accuracy rate using Linear SVM Classifier is: 78.6

2) Kernel SVM Classifier In SVM we have used three methods, Polynomial, Radial and Tan. - Using Polynomial SVM we get a Training Error of 0.3 - Using Radial SVM we get a Training Error of 0.27 - Tan SVM we get a Training Error of 0.46 We got the lowest training error rate using Radial SVM hence we have used it.

Using Radial SVM method we get an accuracy of 79.49%

3) Random Forest Classifier The accuracy using Random Forest Classifier is: 67.52%

4) Gradient Boosting Classifier The accuracy using Boosting is: 71.84%

We have compared the performance of 4 methods: Linear SVM, Kernel SVM, Random Forest, Gradient Boosting and finally selected Radial SVM Classifier as our prediction model due its least error rate and highest accuracy. Hence, the proposed model will be considerably suitable for identifying particularly damaging forest fires.