PROJECT

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CONTENT

# Abstract

Forest fires present severe ecological and socio-economic challenges, necessitating proactive measures for early detection and prevention. In recent years, data science techniques have emerged as invaluable tools in this endeavour, offering sophisticated approaches for forest fire prediction. This project provides an overview of the application of data science in forest fire prediction, and statistical models. We will employ statistical methods to understand the relationship between fire events and potential influencing factors. This may involve the mapping of the fire hotspots and identifying areas with higher fire risk based on environmental conditions. The dataset we have taken is based on environmental conditions, considering data related to a Montesinho natural park..

options(repos = c(CRAN ="https://cran.rstudio.com/"))  
install.packages("dplyr")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'dplyr' successfully unpacked and MD5 sums checked

## Warning: cannot remove prior installation of package 'dplyr'

## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\adith\AppData\Local\R\win-library\4.4\00LOCK\dplyr\libs\x64\dplyr.dll  
## to C:\Users\adith\AppData\Local\R\win-library\4.4\dplyr\libs\x64\dplyr.dll:  
## Permission denied

## Warning: restored 'dplyr'

##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(dplyr)

##   
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':  
##   
## filter, lag

## The following objects are masked from 'package:base':  
##   
## intersect, setdiff, setequal, union

install.packages("ggplot2")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'ggplot2' successfully unpacked and MD5 sums checked  
##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(ggplot2)  
  
install.packages("caret")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'caret' successfully unpacked and MD5 sums checked

## Warning: cannot remove prior installation of package 'caret'

## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\adith\AppData\Local\R\win-library\4.4\00LOCK\caret\libs\x64\caret.dll  
## to C:\Users\adith\AppData\Local\R\win-library\4.4\caret\libs\x64\caret.dll:  
## Permission denied

## Warning: restored 'caret'

##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(caret)

## Loading required package: lattice

install.packages("GGally")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'GGally' successfully unpacked and MD5 sums checked  
##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(GGally)

## Registered S3 method overwritten by 'GGally':  
## method from   
## +.gg ggplot2

install.packages("minpack.lm")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'minpack.lm' successfully unpacked and MD5 sums checked

## Warning: cannot remove prior installation of package 'minpack.lm'

## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\adith\AppData\Local\R\win-library\4.4\00LOCK\minpack.lm\libs\x64\minpack.lm.dll  
## to  
## C:\Users\adith\AppData\Local\R\win-library\4.4\minpack.lm\libs\x64\minpack.lm.dll:  
## Permission denied

## Warning: restored 'minpack.lm'

##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(minpack.lm)  
  
install.packages('e1071')

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'e1071' successfully unpacked and MD5 sums checked

## Warning: cannot remove prior installation of package 'e1071'

## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\adith\AppData\Local\R\win-library\4.4\00LOCK\e1071\libs\x64\e1071.dll  
## to C:\Users\adith\AppData\Local\R\win-library\4.4\e1071\libs\x64\e1071.dll:  
## Permission denied

## Warning: restored 'e1071'

##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(e1071)   
  
install.packages("rpart")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'rpart' successfully unpacked and MD5 sums checked

## Warning: cannot remove prior installation of package 'rpart'

## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\adith\AppData\Local\R\win-library\4.4\00LOCK\rpart\libs\x64\rpart.dll  
## to C:\Users\adith\AppData\Local\R\win-library\4.4\rpart\libs\x64\rpart.dll:  
## Permission denied

## Warning: restored 'rpart'

##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(rpart)  
  
install.packages("rpart.plot")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'rpart.plot' successfully unpacked and MD5 sums checked  
##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(rpart.plot)  
  
install.packages("randomForest")

## Installing package into 'C:/Users/adith/AppData/Local/R/win-library/4.4'  
## (as 'lib' is unspecified)

## package 'randomForest' successfully unpacked and MD5 sums checked

## Warning: cannot remove prior installation of package 'randomForest'

## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\adith\AppData\Local\R\win-library\4.4\00LOCK\randomForest\libs\x64\randomForest.dll  
## to  
## C:\Users\adith\AppData\Local\R\win-library\4.4\randomForest\libs\x64\randomForest.dll:  
## Permission denied

## Warning: restored 'randomForest'

##   
## The downloaded binary packages are in  
## C:\Users\adith\AppData\Local\Temp\RtmpCoyQ6j\downloaded\_packages

library(randomForest)

## randomForest 4.7-1.1

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

##   
## Attaching package: 'randomForest'

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

## The following object is masked from 'package:dplyr':  
##   
## combine

#Reading data  
  
data=file.choose()  
data <- read.csv(data,header=TRUE)  
glimpse(data)

## Rows: 517  
## Columns: 13  
## $ X <int> 7, 7, 7, 8, 8, 8, 8, 8, 8, 7, 7, 7, 6, 6, 6, 6, 5, 8, 6, 6, 6, 5…  
## $ Y <int> 5, 4, 4, 6, 6, 6, 6, 6, 6, 5, 5, 5, 5, 5, 5, 5, 5, 5, 4, 4, 4, 4…  
## $ month <chr> "mar", "oct", "oct", "mar", "mar", "aug", "aug", "aug", "sep", "…  
## $ day <chr> "fri", "tue", "sat", "fri", "sun", "sun", "mon", "mon", "tue", "…  
## $ FFMC <dbl> 86.2, 90.6, 90.6, 91.7, 89.3, 92.3, 92.3, 91.5, 91.0, 92.5, 92.5…  
## $ DMC <dbl> 26.2, 35.4, 43.7, 33.3, 51.3, 85.3, 88.9, 145.4, 129.5, 88.0, 88…  
## $ DC <dbl> 94.3, 669.1, 686.9, 77.5, 102.2, 488.0, 495.6, 608.2, 692.6, 698…  
## $ ISI <dbl> 5.1, 6.7, 6.7, 9.0, 9.6, 14.7, 8.5, 10.7, 7.0, 7.1, 7.1, 22.6, 0…  
## $ temp <dbl> 8.2, 18.0, 14.6, 8.3, 11.4, 22.2, 24.1, 8.0, 13.1, 22.8, 17.8, 1…  
## $ RH <int> 51, 33, 33, 97, 99, 29, 27, 86, 63, 40, 51, 38, 72, 42, 21, 44, …  
## $ wind <dbl> 6.7, 0.9, 1.3, 4.0, 1.8, 5.4, 3.1, 2.2, 5.4, 4.0, 7.2, 4.0, 6.7,…  
## $ rain <dbl> 0.0, 0.0, 0.0, 0.2, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,…  
## $ area <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…

str(data)

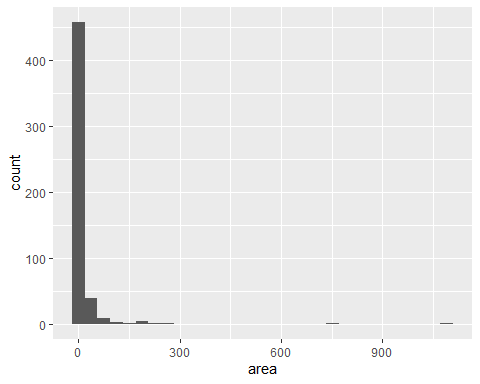
## 'data.frame': 517 obs. of 13 variables:  
## $ X : int 7 7 7 8 8 8 8 8 8 7 ...  
## $ Y : int 5 4 4 6 6 6 6 6 6 5 ...  
## $ month: chr "mar" "oct" "oct" "mar" ...  
## $ day : chr "fri" "tue" "sat" "fri" ...  
## $ FFMC : num 86.2 90.6 90.6 91.7 89.3 92.3 92.3 91.5 91 92.5 ...  
## $ DMC : num 26.2 35.4 43.7 33.3 51.3 ...  
## $ DC : num 94.3 669.1 686.9 77.5 102.2 ...  
## $ ISI : num 5.1 6.7 6.7 9 9.6 14.7 8.5 10.7 7 7.1 ...  
## $ temp : num 8.2 18 14.6 8.3 11.4 22.2 24.1 8 13.1 22.8 ...  
## $ RH : int 51 33 33 97 99 29 27 86 63 40 ...  
## $ wind : num 6.7 0.9 1.3 4 1.8 5.4 3.1 2.2 5.4 4 ...  
## $ rain : num 0 0 0 0.2 0 0 0 0 0 0 ...  
## $ area : num 0 0 0 0 0 0 0 0 0 0 ...

data <- data.frame(data)  
#Exploring the data  
  
colSums(is.na(data))

## X Y month day FFMC DMC DC ISI temp RH wind rain area   
## 0 0 0 0 0 0 0 0 0 0 0 0 0

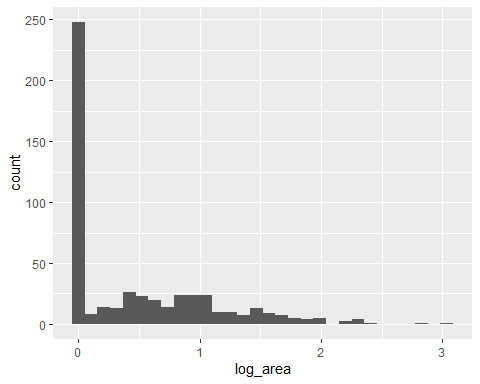
ggplot(data, aes(x = area)) +geom\_histogram()

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



data$log\_area = log10(data$area + 1)  
ggplot(data, aes(x = log\_area)) + geom\_histogram()

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



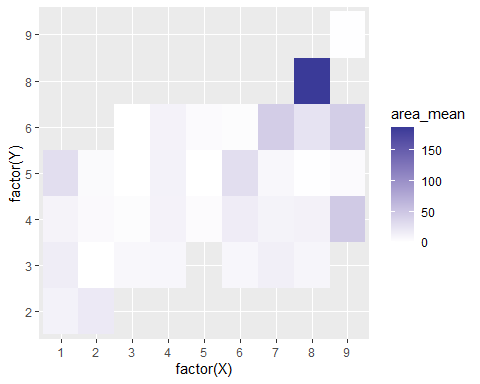
scale\_x\_log10("Burn Area (log10)", breaks = c(1, 10, 100, 1000))

## <ScaleContinuousPosition>  
## Range:   
## Limits: 0 -- 1

burn\_coord = data %>% group\_by(X, Y) %>% summarize(area\_mean = mean(area))

## `summarise()` has grouped output by 'X'. You can override using the `.groups`  
## argument.

ggplot(burn\_coord, aes(x = factor(X), y = factor(Y),  
 fill = area\_mean)) + geom\_tile() + scale\_fill\_gradient2()



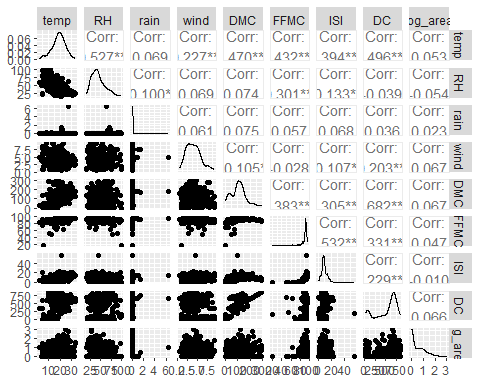
data$month = factor(data$month, levels = c("jan", "feb", "mar", "apr", "may", "jun",   
 "jul", "aug", "sep", "oct", "nov", "dec"))  
  
facet\_wrap(~month)

## <ggproto object: Class FacetWrap, Facet, gg>  
## compute\_layout: function  
## draw\_back: function  
## draw\_front: function  
## draw\_labels: function  
## draw\_panels: function  
## finish\_data: function  
## init\_scales: function  
## map\_data: function  
## params: list  
## setup\_data: function  
## setup\_params: function  
## shrink: TRUE  
## train\_scales: function  
## vars: function  
## super: <ggproto object: Class FacetWrap, Facet, gg>

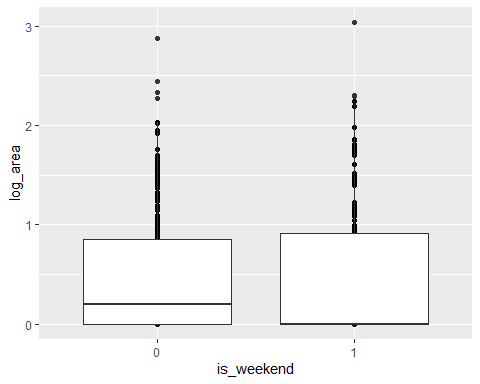
scale\_y\_log10()

## <ScaleContinuousPosition>  
## Range:   
## Limits: 0 -- 1

ggpairs(select(data, temp, RH,rain, wind,DMC,FFMC,ISI,DC, log\_area))



data1 = filter(data, log\_area > 0)  
  
#Classifying records into weekend-records and otherwise  
  
data$is\_weekend = ifelse(data$day %in% c("sat","sun"), 1, 0)  
data$is\_weekend = factor(data$is\_weekend)  
ggplot(data, aes(x = is\_weekend, y = log\_area))+  
geom\_point()+  
geom\_boxplot()



print(nrow(data%>%filter((is\_weekend==1))))

## [1] 179

print(nrow(data%>%filter(is\_weekend==0)))

## [1] 338

IS\_WEEKENDEQUALTOZERO=(data%>%filter(is\_weekend==0))  
print(max(IS\_WEEKENDEQUALTOZERO$log\_area))

## [1] 2.873483

print(min(IS\_WEEKENDEQUALTOZERO$log\_area))

## [1] 0

IS\_WEEKENDEQUALTOONE=(data%>%filter(is\_weekend==1))  
print(max(IS\_WEEKENDEQUALTOONE$log\_area))

## [1] 3.038159

print(min(IS\_WEEKENDEQUALTOONE$log\_area))

## [1] 0

print(quantile(IS\_WEEKENDEQUALTOZERO$log\_area,probs=0.5))

## 50%   
## 0.1985788

print(data$log\_area)

## [1] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [7] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [13] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [19] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [25] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [31] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [37] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [43] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [49] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [55] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [61] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [67] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [73] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [79] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [85] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [91] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [97] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [103] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [109] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [115] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [121] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [127] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [133] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [139] 0.13353891 0.15533604 0.16731733 0.19033170 0.20682588 0.23299611  
## [145] 0.24797327 0.27875360 0.29003461 0.29225607 0.31597035 0.32633586  
## [151] 0.34044411 0.37291200 0.38560627 0.39093511 0.39093511 0.40823997  
## [157] 0.41664051 0.41995575 0.42160393 0.42975228 0.43933269 0.46239800  
## [163] 0.46834733 0.46982202 0.47856650 0.49692965 0.51719590 0.54530712  
## [169] 0.54777471 0.55022835 0.55266822 0.56702637 0.57287160 0.60959441  
## [175] 0.65321251 0.74272513 0.74896286 0.75511227 0.76937733 0.79448805  
## [181] 0.80140371 0.80888587 0.86805636 0.89376176 0.90091307 0.90525605  
## [187] 0.91328390 0.91907809 0.92427929 0.96567197 0.96894968 0.98587536  
## [193] 0.98721923 1.01745073 1.04178732 1.04218159 1.07664044 1.08134731  
## [199] 1.08778142 1.09061071 1.09795107 1.11727130 1.14767632 1.16731733  
## [205] 1.17580163 1.19228861 1.21616590 1.26007139 1.30599588 1.38756778  
## [211] 1.40191725 1.43136376 1.43344979 1.45255306 1.47217115 1.47217115  
## [217] 1.48401496 1.49582175 1.51481329 1.51666756 1.51943419 1.56679091  
## [223] 1.57806588 1.58001211 1.58782317 1.69504366 1.70217195 1.77305469  
## [229] 1.81358099 1.85913830 1.95177451 1.98308477 2.01865890 2.02800158  
## [235] 2.19279040 2.29552312 2.30522235 2.33017018 3.03815900 0.00000000  
## [241] 0.00000000 0.00000000 1.04649516 0.00000000 0.58771097 0.24551267  
## [247] 0.03742650 0.24303805 0.00000000 0.54032947 0.22530928 0.09342169  
## [253] 0.08278537 0.40140054 1.05461305 0.00000000 0.95520654 0.22530928  
## [259] 0.00000000 0.37657696 0.99343623 0.63346846 0.72015930 0.40823997  
## [265] 0.87737135 0.25285303 0.06818586 0.00000000 0.00000000 0.73239376  
## [271] 0.18184359 1.01157044 0.61172331 0.99913054 1.08600371 0.80482068  
## [277] 1.27531135 1.06929801 1.36229394 1.03221570 1.01157044 1.41111442  
## [283] 0.00000000 0.32221929 1.40208935 0.00000000 0.00000000 0.00000000  
## [289] 0.00000000 0.00000000 0.00000000 0.95424251 0.56110138 1.94175981  
## [295] 0.87909588 0.00000000 0.27875360 0.00000000 0.00000000 0.00000000  
## [301] 0.00000000 0.65513843 0.00000000 0.00000000 0.00000000 0.00000000  
## [307] 0.14921911 0.79098848 0.00000000 0.00000000 0.00000000 1.18440749  
## [313] 0.00000000 0.00000000 0.41161971 0.00000000 0.00000000 0.67942790  
## [319] 0.00000000 0.73319727 1.54851226 0.91434316 0.30319606 0.50242712  
## [325] 0.73399929 0.00000000 0.00000000 0.00000000 0.00000000 0.63648790  
## [331] 0.87966921 1.22115332 1.08707121 0.49554434 0.00000000 0.00000000  
## [337] 0.00000000 1.75617952 0.92839585 0.39269695 0.69284692 0.00000000  
## [343] 0.00000000 0.50242712 0.85125835 0.83442070 1.46523409 0.00000000  
## [349] 0.00000000 0.42160393 0.67302091 0.91960102 0.48144263 0.43456890  
## [355] 0.84323278 1.14798532 0.35410844 0.00000000 0.00000000 0.95999484  
## [361] 0.32014629 0.69372695 0.18184359 0.59439255 0.82282165 1.32283927  
## [367] 0.43933269 0.00000000 1.13481437 0.00000000 1.08134731 0.00000000  
## [373] 0.00000000 0.00000000 1.28555731 1.60584354 0.00000000 2.24459870  
## [379] 0.00000000 0.00000000 0.94101424 1.23879856 0.83632412 1.64216763  
## [385] 1.11991541 1.23044892 1.40807029 0.00000000 1.47334096 0.00000000  
## [391] 1.03981055 1.49387611 1.85588243 0.00000000 0.00000000 1.72246939  
## [397] 0.66651798 0.66558099 0.00000000 0.00000000 0.96189547 0.77451697  
## [403] 0.00000000 0.00000000 0.84757266 0.00000000 0.69460520 0.00000000  
## [409] 0.94448267 0.00000000 0.00000000 0.74973632 0.41995575 0.00000000  
## [415] 0.00000000 2.87348336 0.90417437 0.00000000 0.53655844 0.60745502  
## [421] 2.27128387 0.00000000 0.86332286 0.23552845 0.77524626 0.00000000  
## [427] 0.00000000 0.52504481 0.00000000 0.62324929 0.00000000 0.86687781  
## [433] 0.00000000 1.21325205 0.00000000 0.00000000 0.18752072 0.00000000  
## [439] 0.87098881 0.12385164 0.00000000 0.34830486 0.63848926 0.00000000  
## [445] 1.03981055 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [451] 0.87098881 1.02978947 0.00000000 0.00000000 0.00000000 0.00000000  
## [457] 0.00000000 1.92298482 0.63548375 0.46834733 0.00000000 0.00000000  
## [463] 0.67302091 0.80550086 0.49692965 0.89431606 0.62117628 0.81624130  
## [469] 0.88138466 1.79330135 0.00000000 1.59637714 0.46834733 1.85321133  
## [475] 1.04453976 0.62221402 0.44090908 0.92220628 0.50650503 2.44642842  
## [481] 0.57403127 0.00000000 0.35983548 0.00000000 1.43822581 0.48713838  
## [487] 0.47712125 1.24054925 1.67851838 0.00000000 0.00000000 0.00000000  
## [493] 0.00000000 1.64659975 0.98181861 0.00000000 0.57634135 1.19534606  
## [499] 1.61846649 1.07261748 0.00000000 0.00000000 0.00000000 0.46982202  
## [505] 1.70406468 0.83250891 0.00000000 0.00000000 0.00000000 0.50105926  
## [511] 0.15533604 0.00000000 0.87157294 1.74264659 1.08493357 0.00000000  
## [517] 0.00000000

print(quantile(IS\_WEEKENDEQUALTOONE$log\_area,probs=0.5))

## 50%   
## 0

#Extracting records with log\_area>0  
  
print(data$log\_area)

## [1] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [7] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [13] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [19] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [25] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [31] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [37] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [43] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [49] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [55] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [61] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [67] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [73] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [79] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [85] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [91] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [97] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [103] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [109] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [115] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [121] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [127] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [133] 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [139] 0.13353891 0.15533604 0.16731733 0.19033170 0.20682588 0.23299611  
## [145] 0.24797327 0.27875360 0.29003461 0.29225607 0.31597035 0.32633586  
## [151] 0.34044411 0.37291200 0.38560627 0.39093511 0.39093511 0.40823997  
## [157] 0.41664051 0.41995575 0.42160393 0.42975228 0.43933269 0.46239800  
## [163] 0.46834733 0.46982202 0.47856650 0.49692965 0.51719590 0.54530712  
## [169] 0.54777471 0.55022835 0.55266822 0.56702637 0.57287160 0.60959441  
## [175] 0.65321251 0.74272513 0.74896286 0.75511227 0.76937733 0.79448805  
## [181] 0.80140371 0.80888587 0.86805636 0.89376176 0.90091307 0.90525605  
## [187] 0.91328390 0.91907809 0.92427929 0.96567197 0.96894968 0.98587536  
## [193] 0.98721923 1.01745073 1.04178732 1.04218159 1.07664044 1.08134731  
## [199] 1.08778142 1.09061071 1.09795107 1.11727130 1.14767632 1.16731733  
## [205] 1.17580163 1.19228861 1.21616590 1.26007139 1.30599588 1.38756778  
## [211] 1.40191725 1.43136376 1.43344979 1.45255306 1.47217115 1.47217115  
## [217] 1.48401496 1.49582175 1.51481329 1.51666756 1.51943419 1.56679091  
## [223] 1.57806588 1.58001211 1.58782317 1.69504366 1.70217195 1.77305469  
## [229] 1.81358099 1.85913830 1.95177451 1.98308477 2.01865890 2.02800158  
## [235] 2.19279040 2.29552312 2.30522235 2.33017018 3.03815900 0.00000000  
## [241] 0.00000000 0.00000000 1.04649516 0.00000000 0.58771097 0.24551267  
## [247] 0.03742650 0.24303805 0.00000000 0.54032947 0.22530928 0.09342169  
## [253] 0.08278537 0.40140054 1.05461305 0.00000000 0.95520654 0.22530928  
## [259] 0.00000000 0.37657696 0.99343623 0.63346846 0.72015930 0.40823997  
## [265] 0.87737135 0.25285303 0.06818586 0.00000000 0.00000000 0.73239376  
## [271] 0.18184359 1.01157044 0.61172331 0.99913054 1.08600371 0.80482068  
## [277] 1.27531135 1.06929801 1.36229394 1.03221570 1.01157044 1.41111442  
## [283] 0.00000000 0.32221929 1.40208935 0.00000000 0.00000000 0.00000000  
## [289] 0.00000000 0.00000000 0.00000000 0.95424251 0.56110138 1.94175981  
## [295] 0.87909588 0.00000000 0.27875360 0.00000000 0.00000000 0.00000000  
## [301] 0.00000000 0.65513843 0.00000000 0.00000000 0.00000000 0.00000000  
## [307] 0.14921911 0.79098848 0.00000000 0.00000000 0.00000000 1.18440749  
## [313] 0.00000000 0.00000000 0.41161971 0.00000000 0.00000000 0.67942790  
## [319] 0.00000000 0.73319727 1.54851226 0.91434316 0.30319606 0.50242712  
## [325] 0.73399929 0.00000000 0.00000000 0.00000000 0.00000000 0.63648790  
## [331] 0.87966921 1.22115332 1.08707121 0.49554434 0.00000000 0.00000000  
## [337] 0.00000000 1.75617952 0.92839585 0.39269695 0.69284692 0.00000000  
## [343] 0.00000000 0.50242712 0.85125835 0.83442070 1.46523409 0.00000000  
## [349] 0.00000000 0.42160393 0.67302091 0.91960102 0.48144263 0.43456890  
## [355] 0.84323278 1.14798532 0.35410844 0.00000000 0.00000000 0.95999484  
## [361] 0.32014629 0.69372695 0.18184359 0.59439255 0.82282165 1.32283927  
## [367] 0.43933269 0.00000000 1.13481437 0.00000000 1.08134731 0.00000000  
## [373] 0.00000000 0.00000000 1.28555731 1.60584354 0.00000000 2.24459870  
## [379] 0.00000000 0.00000000 0.94101424 1.23879856 0.83632412 1.64216763  
## [385] 1.11991541 1.23044892 1.40807029 0.00000000 1.47334096 0.00000000  
## [391] 1.03981055 1.49387611 1.85588243 0.00000000 0.00000000 1.72246939  
## [397] 0.66651798 0.66558099 0.00000000 0.00000000 0.96189547 0.77451697  
## [403] 0.00000000 0.00000000 0.84757266 0.00000000 0.69460520 0.00000000  
## [409] 0.94448267 0.00000000 0.00000000 0.74973632 0.41995575 0.00000000  
## [415] 0.00000000 2.87348336 0.90417437 0.00000000 0.53655844 0.60745502  
## [421] 2.27128387 0.00000000 0.86332286 0.23552845 0.77524626 0.00000000  
## [427] 0.00000000 0.52504481 0.00000000 0.62324929 0.00000000 0.86687781  
## [433] 0.00000000 1.21325205 0.00000000 0.00000000 0.18752072 0.00000000  
## [439] 0.87098881 0.12385164 0.00000000 0.34830486 0.63848926 0.00000000  
## [445] 1.03981055 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000  
## [451] 0.87098881 1.02978947 0.00000000 0.00000000 0.00000000 0.00000000  
## [457] 0.00000000 1.92298482 0.63548375 0.46834733 0.00000000 0.00000000  
## [463] 0.67302091 0.80550086 0.49692965 0.89431606 0.62117628 0.81624130  
## [469] 0.88138466 1.79330135 0.00000000 1.59637714 0.46834733 1.85321133  
## [475] 1.04453976 0.62221402 0.44090908 0.92220628 0.50650503 2.44642842  
## [481] 0.57403127 0.00000000 0.35983548 0.00000000 1.43822581 0.48713838  
## [487] 0.47712125 1.24054925 1.67851838 0.00000000 0.00000000 0.00000000  
## [493] 0.00000000 1.64659975 0.98181861 0.00000000 0.57634135 1.19534606  
## [499] 1.61846649 1.07261748 0.00000000 0.00000000 0.00000000 0.46982202  
## [505] 1.70406468 0.83250891 0.00000000 0.00000000 0.00000000 0.50105926  
## [511] 0.15533604 0.00000000 0.87157294 1.74264659 1.08493357 0.00000000  
## [517] 0.00000000

max=500  
  
head(data%>% filter(log\_area==0) )

## X Y month day FFMC DMC DC ISI temp RH wind rain area log\_area is\_weekend  
## 1 7 5 mar fri 86.2 26.2 94.3 5.1 8.2 51 6.7 0.0 0 0 0  
## 2 7 4 oct tue 90.6 35.4 669.1 6.7 18.0 33 0.9 0.0 0 0 0  
## 3 7 4 oct sat 90.6 43.7 686.9 6.7 14.6 33 1.3 0.0 0 0 1  
## 4 8 6 mar fri 91.7 33.3 77.5 9.0 8.3 97 4.0 0.2 0 0 0  
## 5 8 6 mar sun 89.3 51.3 102.2 9.6 11.4 99 1.8 0.0 0 0 1  
## 6 8 6 aug sun 92.3 85.3 488.0 14.7 22.2 29 5.4 0.0 0 0 1

d\_areagreaterthanzero=data%>%filter(area>0)  
head(d\_areagreaterthanzero)

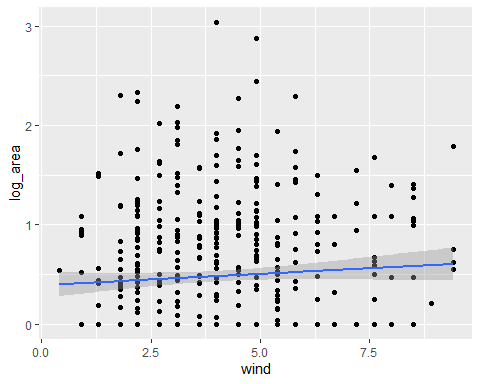
## X Y month day FFMC DMC DC ISI temp RH wind rain area log\_area  
## 1 9 9 jul tue 85.8 48.3 313.4 3.9 18.0 42 2.7 0 0.36 0.1335389  
## 2 1 4 sep tue 91.0 129.5 692.6 7.0 21.7 38 2.2 0 0.43 0.1553360  
## 3 2 5 sep mon 90.9 126.5 686.5 7.0 21.9 39 1.8 0 0.47 0.1673173  
## 4 1 2 aug wed 95.5 99.9 513.3 13.2 23.3 31 4.5 0 0.55 0.1903317  
## 5 8 6 aug fri 90.1 108.0 529.8 12.5 21.2 51 8.9 0 0.61 0.2068259  
## 6 1 2 jul sat 90.0 51.3 296.3 8.7 16.6 53 5.4 0 0.71 0.2329961  
## is\_weekend  
## 1 0  
## 2 0  
## 3 0  
## 4 0  
## 5 0  
## 6 1

print(nrow(d\_areagreaterthanzero%>%filter(wind>6)))

## [1] 37

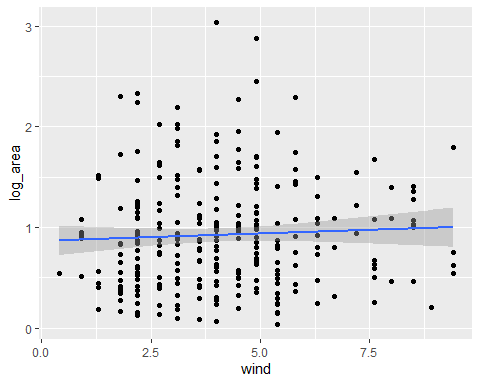
#Plotting attributes against the log\_area attribute  
  
ggplot(data, aes(x = wind, y = log\_area)) + geom\_point() +geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



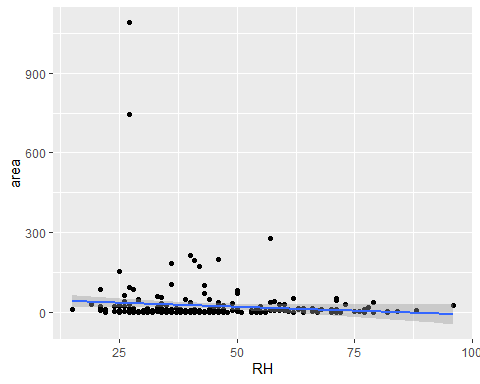
ggplot(d\_areagreaterthanzero, aes(x = wind, y = log\_area)) + geom\_point()+geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



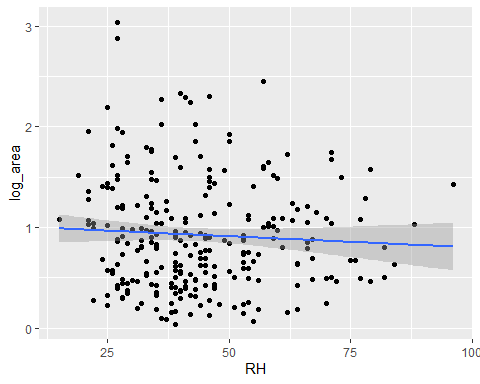
ggplot(d\_areagreaterthanzero, aes(x = RH, y = area)) + geom\_point() + geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



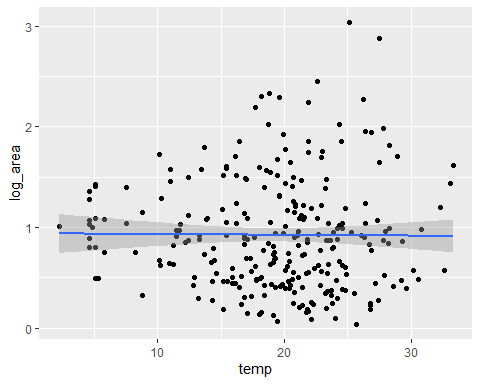
ggplot(d\_areagreaterthanzero, aes(x = RH, y = log\_area)) + geom\_point() + geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



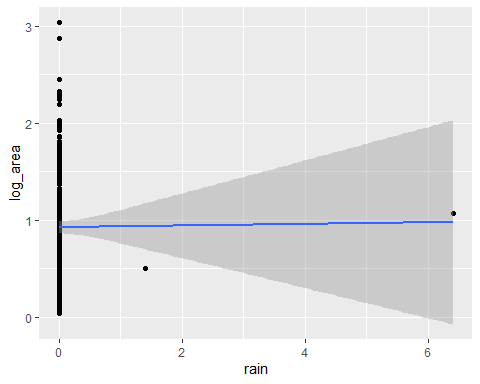
ggplot(d\_areagreaterthanzero, aes(x = temp, y = log\_area)) + geom\_point() +geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



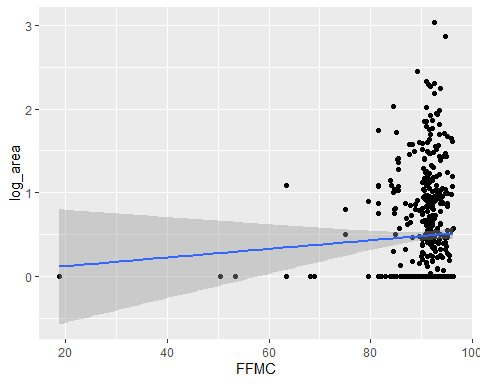
ggplot(d\_areagreaterthanzero, aes(x = rain, y = log\_area)) + geom\_point() +geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



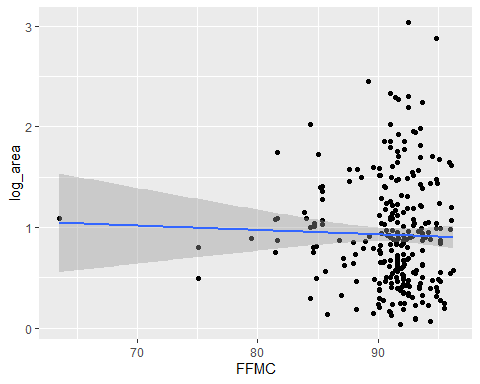
ggplot(data, aes(x = FFMC, y = log\_area)) + geom\_point() +geom\_smooth(method = "lm")

## `geom\_smooth()` using formula = 'y ~ x'



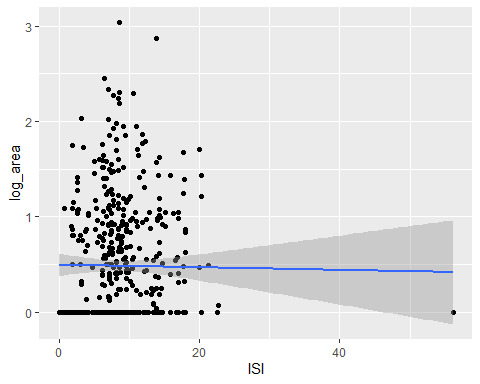
ggplot(d\_areagreaterthanzero,aes(x=FFMC,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'



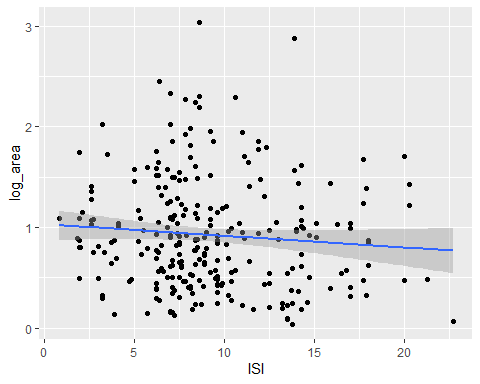
ggplot(data,aes(x=ISI,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'



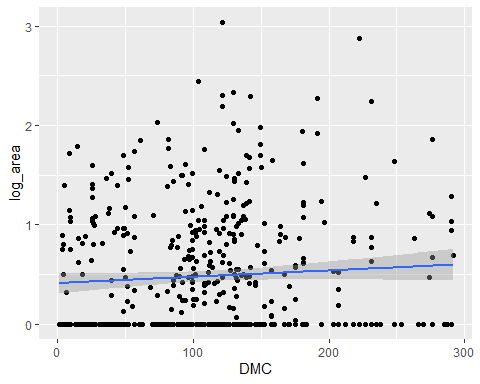
ggplot(d\_areagreaterthanzero,aes(x=ISI,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'



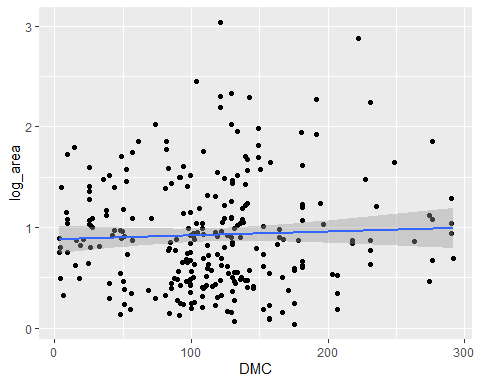
ggplot(data,aes(x=DMC,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'



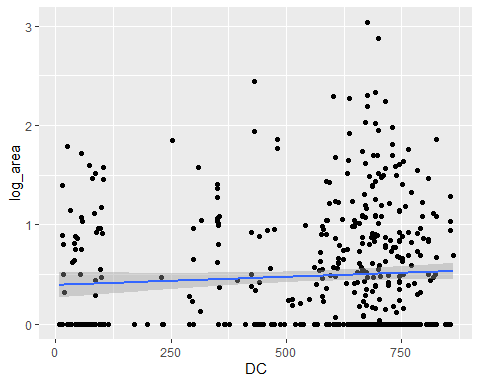
ggplot(d\_areagreaterthanzero,aes(x=DMC,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'



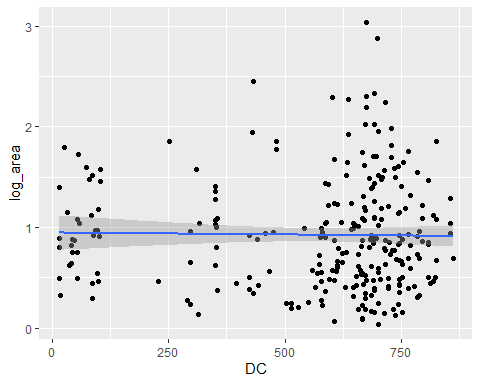
ggplot(data,aes(x=DC,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'

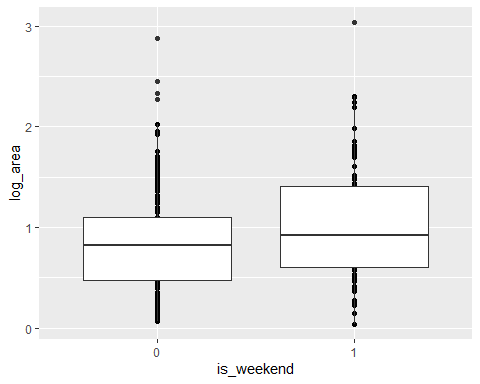


ggplot(d\_areagreaterthanzero,aes(x=DC,y=log\_area))+geom\_point()+geom\_smooth(method="lm")

## `geom\_smooth()` using formula = 'y ~ x'



ggplot(d\_areagreaterthanzero, aes(x = is\_weekend, y = log\_area))+#+geom\_point(aes(col="orange"))+geom\_density()  
 geom\_point()+  
 geom\_boxplot()



#Filtering and selecting is\_weekend for d\_areagreaterthanzero   
  
IS\_WEEKENDEQUALTOZEROaMORE=(d\_areagreaterthanzero%>%filter(is\_weekend==0))  
print(max(IS\_WEEKENDEQUALTOZEROaMORE$log\_area))

## [1] 2.873483

print(min(IS\_WEEKENDEQUALTOZEROaMORE$log\_area))

## [1] 0.06818586

print(nrow(IS\_WEEKENDEQUALTOZEROaMORE))

## [1] 181

IS\_WEEKENDEQUALTOONEaMORE=(d\_areagreaterthanzero%>%filter(is\_weekend==1))  
print(max(IS\_WEEKENDEQUALTOONEaMORE$log\_area))

## [1] 3.038159

print(min(IS\_WEEKENDEQUALTOONEaMORE$log\_area))

## [1] 0.0374265

print(nrow(IS\_WEEKENDEQUALTOONEaMORE))

## [1] 89

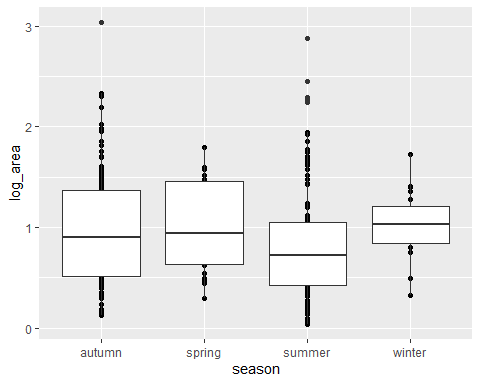
print(nrow(data%>% filter(log\_area==0)) )

## [1] 247

print(length(data$log\_area))

## [1] 517

#Extracting seasons from the data  
  
data$season = 0  
for (i in 1:length(data$month)) {  
 if (data$month[i] %in% c("dec", "jan", "feb")) {  
 data$season[i] = "winter"   
 } else if (data$month[i] %in% c("mar", "apr", "may")) {  
 data$season[i] = "spring"   
 }else if (data$month[i] %in% c("jun", "jul", "aug")) {  
 data$season[i] = "summer"   
 }else data$season[i] = "autumn"  
}  
data$season = as.factor(data$season)  
  
  
  
  
d\_areagreaterthanzero$season = 0  
for (i in 1:length(d\_areagreaterthanzero$month)) {  
 if (d\_areagreaterthanzero$month[i] %in% c("dec", "jan", "feb")) {  
 d\_areagreaterthanzero$season[i] = "winter"   
 } else if (d\_areagreaterthanzero$month[i] %in% c("mar", "apr", "may")) {  
 d\_areagreaterthanzero$season[i] = "spring"   
 }else if (d\_areagreaterthanzero$month[i] %in% c("jun", "jul", "aug")) {  
 d\_areagreaterthanzero$season[i] = "summer"   
 }else d\_areagreaterthanzero$season[i] = "autumn"  
}  
d\_areagreaterthanzero$season = as.factor(d\_areagreaterthanzero$season)  
  
  
#Observing and analysing data based on the season  
  
ggplot(d\_areagreaterthanzero, aes(x = season, y = log\_area)) +  
geom\_point() +  
geom\_boxplot()



print(nrow(d\_areagreaterthanzero%>%filter(season=="autumn")))

## [1] 102

print(nrow(d\_areagreaterthanzero%>%filter(season=="spring")))

## [1] 24

print(nrow(d\_areagreaterthanzero%>%filter(season=="summer")))

## [1] 125

print(nrow(d\_areagreaterthanzero%>%filter(season=="winter")))

## [1] 19

summary(d\_areagreaterthanzero$month)

## jan feb mar apr may jun jul aug sep oct nov dec   
## 0 10 19 4 1 8 18 99 97 5 0 9

length(d\_areagreaterthanzero$month)

## [1] 270

#Encoding attributes and taking a subset of the data  
  
month = model.matrix(~month - 1, data = data)  
day = model.matrix(~day - 1, data = data)  
season\_binary = model.matrix(~season - 1, data = data)  
data = cbind(data, month, day, season\_binary)  
data = select(data, -month, -day, -area)  
head(data)

## X Y FFMC DMC DC ISI temp RH wind rain log\_area is\_weekend season  
## 1 7 5 86.2 26.2 94.3 5.1 8.2 51 6.7 0.0 0 0 spring  
## 2 7 4 90.6 35.4 669.1 6.7 18.0 33 0.9 0.0 0 0 autumn  
## 3 7 4 90.6 43.7 686.9 6.7 14.6 33 1.3 0.0 0 1 autumn  
## 4 8 6 91.7 33.3 77.5 9.0 8.3 97 4.0 0.2 0 0 spring  
## 5 8 6 89.3 51.3 102.2 9.6 11.4 99 1.8 0.0 0 1 spring  
## 6 8 6 92.3 85.3 488.0 14.7 22.2 29 5.4 0.0 0 1 summer  
## monthjan monthfeb monthmar monthapr monthmay monthjun monthjul monthaug  
## 1 0 0 1 0 0 0 0 0  
## 2 0 0 0 0 0 0 0 0  
## 3 0 0 0 0 0 0 0 0  
## 4 0 0 1 0 0 0 0 0  
## 5 0 0 1 0 0 0 0 0  
## 6 0 0 0 0 0 0 0 1  
## monthsep monthoct monthnov monthdec dayfri daymon daysat daysun daythu daytue  
## 1 0 0 0 0 1 0 0 0 0 0  
## 2 0 1 0 0 0 0 0 0 0 1  
## 3 0 1 0 0 0 0 1 0 0 0  
## 4 0 0 0 0 1 0 0 0 0 0  
## 5 0 0 0 0 0 0 0 1 0 0  
## 6 0 0 0 0 0 0 0 1 0 0  
## daywed seasonautumn seasonspring seasonsummer seasonwinter  
## 1 0 0 1 0 0  
## 2 0 1 0 0 0  
## 3 0 1 0 0 0  
## 4 0 0 1 0 0  
## 5 0 0 1 0 0  
## 6 0 0 0 1 0

in\_train = createDataPartition(y = data$log\_area, p = 0.8, list = FALSE)  
head(in\_train)

## Resample1  
## [1,] 1  
## [2,] 2  
## [3,] 3  
## [4,] 5  
## [5,] 6  
## [6,] 7

is(in\_train)

## [1] "matrix" "array" "structure" "vector"

data\_train = data[in\_train, ]  
head(data\_train)

## X Y FFMC DMC DC ISI temp RH wind rain log\_area is\_weekend season  
## 1 7 5 86.2 26.2 94.3 5.1 8.2 51 6.7 0 0 0 spring  
## 2 7 4 90.6 35.4 669.1 6.7 18.0 33 0.9 0 0 0 autumn  
## 3 7 4 90.6 43.7 686.9 6.7 14.6 33 1.3 0 0 1 autumn  
## 5 8 6 89.3 51.3 102.2 9.6 11.4 99 1.8 0 0 1 spring  
## 6 8 6 92.3 85.3 488.0 14.7 22.2 29 5.4 0 0 1 summer  
## 7 8 6 92.3 88.9 495.6 8.5 24.1 27 3.1 0 0 0 summer  
## monthjan monthfeb monthmar monthapr monthmay monthjun monthjul monthaug  
## 1 0 0 1 0 0 0 0 0  
## 2 0 0 0 0 0 0 0 0  
## 3 0 0 0 0 0 0 0 0  
## 5 0 0 1 0 0 0 0 0  
## 6 0 0 0 0 0 0 0 1  
## 7 0 0 0 0 0 0 0 1  
## monthsep monthoct monthnov monthdec dayfri daymon daysat daysun daythu daytue  
## 1 0 0 0 0 1 0 0 0 0 0  
## 2 0 1 0 0 0 0 0 0 0 1  
## 3 0 1 0 0 0 0 1 0 0 0  
## 5 0 0 0 0 0 0 0 1 0 0  
## 6 0 0 0 0 0 0 0 1 0 0  
## 7 0 0 0 0 0 1 0 0 0 0  
## daywed seasonautumn seasonspring seasonsummer seasonwinter  
## 1 0 0 1 0 0  
## 2 0 1 0 0 0  
## 3 0 1 0 0 0  
## 5 0 0 1 0 0  
## 6 0 0 0 1 0  
## 7 0 0 0 1 0

#Defining a function for calculating R-Squared Error  
   
rsquare=function(actual,pred){  
 cor(actual,pred)^2  
}  
  
#Linear Regression Model  
  
model=lm(log\_area~X+Y+temp+rain+RH+wind+FFMC+DMC+DC+ISI,data=data\_train)  
predictions<-predict(model,data\_train)  
  
print(summary(model))

##   
## Call:  
## lm(formula = log\_area ~ X + Y + temp + rain + RH + wind + FFMC +   
## DMC + DC + ISI, data = data\_train)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -0.7508 -0.4743 -0.2384 0.3600 2.4444   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.2371728 0.6695164 0.354 0.723   
## X 0.0247548 0.0159615 1.551 0.122   
## Y -0.0258735 0.0307248 -0.842 0.400   
## temp 0.0023124 0.0082788 0.279 0.780   
## rain 0.0428886 0.0958252 0.448 0.655   
## RH -0.0024180 0.0024878 -0.972 0.332   
## wind 0.0361148 0.0174347 2.071 0.039 \*  
## FFMC 0.0008457 0.0069954 0.121 0.904   
## DMC 0.0008223 0.0007254 1.134 0.258   
## DC 0.0001519 0.0001780 0.853 0.394   
## ISI -0.0093035 0.0078322 -1.188 0.236   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.6134 on 405 degrees of freedom  
## Multiple R-squared: 0.03294, Adjusted R-squared: 0.009062   
## F-statistic: 1.379 on 10 and 405 DF, p-value: 0.1872

print(mean(summary(model)$residuals^2))

## [1] 0.3663421

rsw=rsquare(data\_train$log\_area,predictions)  
print(rsw)

## [1] 0.03293974

#SVMs  
  
classifier = svm(formula = log\_area~X+Y+temp+rain+RH+wind+FFMC+DMC+DC+ISI, data=data\_train)  
  
  
  
pr=predict(classifier,data\_train)   
print(summary(classifier))

##   
## Call:  
## svm(formula = log\_area ~ X + Y + temp + rain + RH + wind + FFMC +   
## DMC + DC + ISI, data = data\_train)  
##   
##   
## Parameters:  
## SVM-Type: eps-regression   
## SVM-Kernel: radial   
## cost: 1   
## gamma: 0.1   
## epsilon: 0.1   
##   
##   
## Number of Support Vectors: 385

print(mean(summary(classifier)$residuals^2))

## [1] 0.3545923

rsw=rsquare(data\_train$log\_area,pr)  
print(rsw)

## [1] 0.1897109

#Classification And Regression Tree  
  
fit.tree=rpart(log\_area~X+Y+temp+rain+RH+wind+FFMC+DMC+DC+ISI,data=data\_train,method='anova')  
  
rpart.plot(fit.tree)  
pr.tree=predict(fit.tree,data\_train)   
print(summary(fit.tree))

## Call:  
## rpart(formula = log\_area ~ X + Y + temp + rain + RH + wind +   
## FFMC + DMC + DC + ISI, data = data\_train, method = "anova")  
## n= 416   
##   
## CP nsplit rel error xerror xstd  
## 1 0.03015137 0 1.0000000 1.005222 0.08621516  
## 2 0.02056083 2 0.9396973 1.047393 0.08611079  
## 3 0.01474319 3 0.9191364 1.134315 0.09546796  
## 4 0.01383139 6 0.8749068 1.218128 0.10159616  
## 5 0.01281886 10 0.8195813 1.235727 0.10388812  
## 6 0.01277636 12 0.7939436 1.240191 0.10417476  
## 7 0.01226747 13 0.7811672 1.240191 0.10417476  
## 8 0.01000000 14 0.7688997 1.264279 0.10406957  
##   
## Variable importance  
## DMC temp RH FFMC wind ISI DC Y X   
## 23 19 14 11 9 9 9 5 1   
##   
## Node number 1: 416 observations, complexity param=0.03015137  
## mean=0.4889403, MSE=0.3788204   
## left son=2 (237 obs) right son=3 (179 obs)  
## Primary splits:  
## DMC < 118.45 to the left, improve=0.02876578, (0 missing)  
## temp < 22.55 to the left, improve=0.02060803, (0 missing)  
## DC < 243.2 to the left, improve=0.01456799, (0 missing)  
## wind < 8.25 to the left, improve=0.01010538, (0 missing)  
## X < 8.5 to the left, improve=0.00905913, (0 missing)  
## Surrogate splits:  
## DC < 560.8 to the left, agree=0.712, adj=0.330, (0 split)  
## FFMC < 92.65 to the left, agree=0.683, adj=0.263, (0 split)  
## temp < 21.45 to the left, agree=0.661, adj=0.212, (0 split)  
## ISI < 6.75 to the left, agree=0.644, adj=0.173, (0 split)  
## X < 1.5 to the right, agree=0.594, adj=0.056, (0 split)  
##   
## Node number 2: 237 observations, complexity param=0.02056083  
## mean=0.3982194, MSE=0.2728236   
## left son=4 (227 obs) right son=5 (10 obs)  
## Primary splits:  
## wind < 8.25 to the left, improve=0.05011144, (0 missing)  
## temp < 5.15 to the right, improve=0.04832537, (0 missing)  
## FFMC < 85.6 to the right, improve=0.03096780, (0 missing)  
## X < 3.5 to the left, improve=0.02042629, (0 missing)  
## RH < 52.5 to the left, improve=0.01908564, (0 missing)  
## Surrogate splits:  
## temp < 4.95 to the right, agree=0.970, adj=0.3, (0 split)  
## RH < 21.5 to the right, agree=0.962, adj=0.1, (0 split)  
##   
## Node number 3: 179 observations, complexity param=0.03015137  
## mean=0.6090567, MSE=0.4938374   
## left son=6 (171 obs) right son=7 (8 obs)  
## Primary splits:  
## DMC < 121.15 to the right, improve=0.05622243, (0 missing)  
## RH < 29.5 to the right, improve=0.02341539, (0 missing)  
## temp < 18.55 to the left, improve=0.01466193, (0 missing)  
## wind < 3.8 to the left, improve=0.01284313, (0 missing)  
## FFMC < 92.45 to the left, improve=0.01265959, (0 missing)  
##   
## Node number 4: 227 observations, complexity param=0.01474319  
## mean=0.3736782, MSE=0.2615864   
## left son=8 (189 obs) right son=9 (38 obs)  
## Primary splits:  
## temp < 22.45 to the left, improve=0.03165827, (0 missing)  
## RH < 52.5 to the left, improve=0.02451269, (0 missing)  
## X < 8.5 to the left, improve=0.02396925, (0 missing)  
## wind < 2.9 to the left, improve=0.01772911, (0 missing)  
## FFMC < 85.5 to the right, improve=0.01256638, (0 missing)  
## Surrogate splits:  
## X < 8.5 to the left, agree=0.841, adj=0.053, (0 split)  
## RH < 23 to the right, agree=0.837, adj=0.026, (0 split)  
##   
## Node number 5: 10 observations  
## mean=0.9553056, MSE=0.2038923   
##   
## Node number 6: 171 observations, complexity param=0.01383139  
## mean=0.5730159, MSE=0.4411308   
## left son=12 (48 obs) right son=13 (123 obs)  
## Primary splits:  
## temp < 18.55 to the left, improve=0.027508930, (0 missing)  
## RH < 29.5 to the right, improve=0.014611260, (0 missing)  
## wind < 3.8 to the left, improve=0.013053820, (0 missing)  
## X < 2.5 to the right, improve=0.011771240, (0 missing)  
## DMC < 141.85 to the right, improve=0.009482026, (0 missing)  
## Surrogate splits:  
## RH < 57 to the right, agree=0.819, adj=0.354, (0 split)  
## FFMC < 91.55 to the left, agree=0.784, adj=0.229, (0 split)  
## DC < 799.6 to the right, agree=0.766, adj=0.167, (0 split)  
## DMC < 236.65 to the right, agree=0.743, adj=0.083, (0 split)  
## wind < 7.4 to the right, agree=0.731, adj=0.042, (0 split)  
##   
## Node number 7: 8 observations  
## mean=1.379428, MSE=0.9992058   
##   
## Node number 8: 189 observations, complexity param=0.01281886  
## mean=0.3328733, MSE=0.2240386   
## left son=16 (131 obs) right son=17 (58 obs)  
## Primary splits:  
## RH < 52.5 to the left, improve=0.04014146, (0 missing)  
## temp < 7.85 to the right, improve=0.02660342, (0 missing)  
## Y < 2.5 to the left, improve=0.02482394, (0 missing)  
## X < 3.5 to the left, improve=0.02463278, (0 missing)  
## DC < 734 to the left, improve=0.02205223, (0 missing)  
## Surrogate splits:  
## temp < 7.1 to the right, agree=0.741, adj=0.155, (0 split)  
## FFMC < 85.15 to the right, agree=0.741, adj=0.155, (0 split)  
## ISI < 2.05 to the right, agree=0.720, adj=0.086, (0 split)  
## DMC < 4.75 to the right, agree=0.709, adj=0.052, (0 split)  
##   
## Node number 9: 38 observations, complexity param=0.01474319  
## mean=0.5766287, MSE=0.3988666   
## left son=18 (11 obs) right son=19 (27 obs)  
## Primary splits:  
## Y < 4.5 to the right, improve=0.15909670, (0 missing)  
## FFMC < 90.65 to the right, improve=0.14854310, (0 missing)  
## RH < 33 to the left, improve=0.10087490, (0 missing)  
## DC < 432.45 to the right, improve=0.10071610, (0 missing)  
## X < 7.5 to the left, improve=0.06974141, (0 missing)  
## Surrogate splits:  
## DMC < 69.7 to the left, agree=0.763, adj=0.182, (0 split)  
## X < 7.5 to the right, agree=0.737, adj=0.091, (0 split)  
## DC < 385.8 to the left, agree=0.737, adj=0.091, (0 split)  
##   
## Node number 12: 48 observations, complexity param=0.01277636  
## mean=0.3966753, MSE=0.2671079   
## left son=24 (14 obs) right son=25 (34 obs)  
## Primary splits:  
## temp < 17.15 to the right, improve=0.15703850, (0 missing)  
## RH < 75.5 to the left, improve=0.13148350, (0 missing)  
## X < 2.5 to the right, improve=0.10742140, (0 missing)  
## FFMC < 90.8 to the right, improve=0.06368219, (0 missing)  
## Y < 4.5 to the right, improve=0.05699593, (0 missing)  
## Surrogate splits:  
## RH < 55 to the left, agree=0.792, adj=0.286, (0 split)  
## FFMC < 92.2 to the right, agree=0.750, adj=0.143, (0 split)  
## ISI < 16.5 to the right, agree=0.729, adj=0.071, (0 split)  
##   
## Node number 13: 123 observations, complexity param=0.01383139  
## mean=0.6418318, MSE=0.4921715   
## left son=26 (116 obs) right son=27 (7 obs)  
## Primary splits:  
## temp < 19 to the right, improve=0.02424690, (0 missing)  
## wind < 1.55 to the left, improve=0.02302072, (0 missing)  
## FFMC < 90.95 to the left, improve=0.01586118, (0 missing)  
## RH < 54.5 to the right, improve=0.01452644, (0 missing)  
## ISI < 7.95 to the right, improve=0.01350571, (0 missing)  
##   
## Node number 16: 131 observations  
## mean=0.2697723, MSE=0.1963303   
##   
## Node number 17: 58 observations, complexity param=0.01281886  
## mean=0.4753946, MSE=0.2573156   
## left son=34 (17 obs) right son=35 (41 obs)  
## Primary splits:  
## RH < 71.5 to the right, improve=0.15682520, (0 missing)  
## Y < 3.5 to the left, improve=0.06309975, (0 missing)  
## DC < 100.55 to the right, improve=0.06178356, (0 missing)  
## ISI < 6.8 to the right, improve=0.05663392, (0 missing)  
## temp < 18.45 to the left, improve=0.04665854, (0 missing)  
## Surrogate splits:  
## FFMC < 78.3 to the left, agree=0.776, adj=0.235, (0 split)  
## DMC < 4.5 to the left, agree=0.759, adj=0.176, (0 split)  
## DC < 34.1 to the left, agree=0.759, adj=0.176, (0 split)  
## ISI < 1.35 to the left, agree=0.759, adj=0.176, (0 split)  
## wind < 6.5 to the right, agree=0.741, adj=0.118, (0 split)  
##   
## Node number 18: 11 observations  
## mean=0.1819625, MSE=0.0838627   
##   
## Node number 19: 27 observations, complexity param=0.01474319  
## mean=0.7374187, MSE=0.4378897   
## left son=38 (16 obs) right son=39 (11 obs)  
## Primary splits:  
## RH < 33.5 to the left, improve=0.22657640, (0 missing)  
## FFMC < 90.8 to the right, improve=0.19116790, (0 missing)  
## DMC < 84.6 to the right, improve=0.17183230, (0 missing)  
## X < 6.5 to the left, improve=0.11528780, (0 missing)  
## ISI < 7.35 to the right, improve=0.09801492, (0 missing)  
## Surrogate splits:  
## FFMC < 91.35 to the right, agree=0.852, adj=0.636, (0 split)  
## ISI < 8.35 to the right, agree=0.815, adj=0.545, (0 split)  
## Y < 3.5 to the left, agree=0.741, adj=0.364, (0 split)  
## temp < 23 to the right, agree=0.741, adj=0.364, (0 split)  
## DC < 440.9 to the right, agree=0.741, adj=0.364, (0 split)  
##   
## Node number 24: 14 observations  
## mean=0.07750548, MSE=0.02958063   
##   
## Node number 25: 34 observations  
## mean=0.5280981, MSE=0.305695   
##   
## Node number 26: 116 observations, complexity param=0.01383139  
## mean=0.6149965, MSE=0.4642892   
## left son=52 (63 obs) right son=53 (53 obs)  
## Primary splits:  
## wind < 3.8 to the left, improve=0.04298472, (0 missing)  
## DMC < 176.75 to the left, improve=0.02727946, (0 missing)  
## RH < 31.5 to the right, improve=0.01901605, (0 missing)  
## Y < 5.5 to the left, improve=0.01766897, (0 missing)  
## FFMC < 90.95 to the left, improve=0.01532300, (0 missing)  
## Surrogate splits:  
## DC < 639.45 to the right, agree=0.698, adj=0.340, (0 split)  
## ISI < 13.75 to the left, agree=0.690, adj=0.321, (0 split)  
## FFMC < 93.45 to the left, agree=0.621, adj=0.170, (0 split)  
## temp < 22.3 to the left, agree=0.603, adj=0.132, (0 split)  
## RH < 61 to the left, agree=0.586, adj=0.094, (0 split)  
##   
## Node number 27: 7 observations  
## mean=1.086531, MSE=0.7445303   
##   
## Node number 34: 17 observations  
## mean=0.1634277, MSE=0.0660605   
##   
## Node number 35: 41 observations, complexity param=0.01226747  
## mean=0.6047467, MSE=0.2795309   
## left son=70 (30 obs) right son=71 (11 obs)  
## Primary splits:  
## FFMC < 87.35 to the right, improve=0.16868170, (0 missing)  
## ISI < 4.45 to the right, improve=0.16270510, (0 missing)  
## DMC < 68.7 to the right, improve=0.11450400, (0 missing)  
## DC < 457.9 to the right, improve=0.09660116, (0 missing)  
## temp < 16.4 to the right, improve=0.09138185, (0 missing)  
## Surrogate splits:  
## ISI < 4.45 to the right, agree=0.976, adj=0.909, (0 split)  
## temp < 10.5 to the right, agree=0.927, adj=0.727, (0 split)  
## DMC < 34.1 to the right, agree=0.927, adj=0.727, (0 split)  
## DC < 75.35 to the right, agree=0.878, adj=0.545, (0 split)  
## RH < 67.5 to the left, agree=0.829, adj=0.364, (0 split)  
##   
## Node number 38: 16 observations  
## mean=0.476247, MSE=0.2455193   
##   
## Node number 39: 11 observations  
## mean=1.117305, MSE=0.4741723   
##   
## Node number 52: 63 observations  
## mean=0.4854222, MSE=0.3349948   
##   
## Node number 53: 53 observations, complexity param=0.01383139  
## mean=0.7690188, MSE=0.5742985   
## left son=106 (44 obs) right son=107 (9 obs)  
## Primary splits:  
## DMC < 186.35 to the left, improve=0.09398630, (0 missing)  
## wind < 5.15 to the right, improve=0.08005902, (0 missing)  
## ISI < 11.8 to the right, improve=0.07594899, (0 missing)  
## Y < 5.5 to the left, improve=0.05491584, (0 missing)  
## RH < 31.5 to the right, improve=0.05358843, (0 missing)  
## Surrogate splits:  
## DC < 707.9 to the left, agree=0.849, adj=0.111, (0 split)  
## ISI < 8.45 to the right, agree=0.849, adj=0.111, (0 split)  
##   
## Node number 70: 30 observations  
## mean=0.4732591, MSE=0.2360809   
##   
## Node number 71: 11 observations  
## mean=0.9633491, MSE=0.2222836   
##   
## Node number 106: 44 observations  
## mean=0.6639447, MSE=0.4388408   
##   
## Node number 107: 9 observations  
## mean=1.282715, MSE=0.9186764   
##   
## n= 416   
##   
## node), split, n, deviance, yval  
## \* denotes terminal node  
##   
## 1) root 416 157.5893000 0.48894030   
## 2) DMC< 118.45 237 64.6591900 0.39821940   
## 4) wind< 8.25 227 59.3801000 0.37367820   
## 8) temp< 22.45 189 42.3433000 0.33287330   
## 16) RH< 52.5 131 25.7192800 0.26977230 \*  
## 17) RH>=52.5 58 14.9243000 0.47539460   
## 34) RH>=71.5 17 1.1230280 0.16342770 \*  
## 35) RH< 71.5 41 11.4607700 0.60474670   
## 70) FFMC>=87.35 30 7.0824270 0.47325910 \*  
## 71) FFMC< 87.35 11 2.4451200 0.96334910 \*  
## 9) temp>=22.45 38 15.1569300 0.57662870   
## 18) Y>=4.5 11 0.9224897 0.18196250 \*  
## 19) Y< 4.5 27 11.8230200 0.73741870   
## 38) RH< 33.5 16 3.9283090 0.47624700 \*  
## 39) RH>=33.5 11 5.2158950 1.11730500 \*  
## 5) wind>=8.25 10 2.0389230 0.95530560 \*  
## 3) DMC>=118.45 179 88.3969000 0.60905670   
## 6) DMC>=121.15 171 75.4333700 0.57301590   
## 12) temp< 18.55 48 12.8211800 0.39667530   
## 24) temp>=17.15 14 0.4141289 0.07750548 \*  
## 25) temp< 17.15 34 10.3936300 0.52809810 \*  
## 13) temp>=18.55 123 60.5371000 0.64183180   
## 26) temp>=19 116 53.8575500 0.61499650   
## 52) wind< 3.8 63 21.1046700 0.48542220 \*  
## 53) wind>=3.8 53 30.4378200 0.76901880   
## 106) DMC< 186.35 44 19.3090000 0.66394470 \*  
## 107) DMC>=186.35 9 8.2680870 1.28271500 \*  
## 27) temp< 19 7 5.2117120 1.08653100 \*  
## 7) DMC< 121.15 8 7.9936460 1.37942800 \*

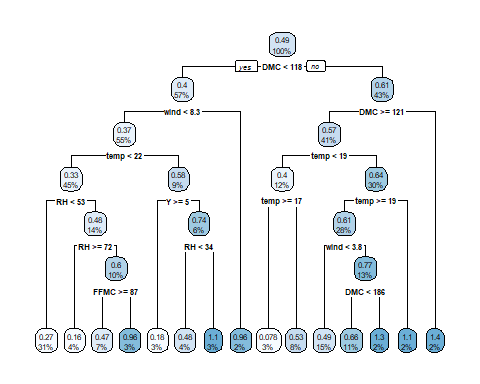
MSE=mean((pr.tree-data\_train$log\_area)^2)  
print(MSE)

## [1] 0.2912749

rsw=rsquare(data\_train$log\_area,pr.tree)  
print(rsw)

## [1] 0.2311003

fit.tree=rpart(log\_area~X+Y+temp+rain+RH+wind+FFMC+DMC+DC+ISI,data\_train)  
rpart.plot(fit.tree)



pr.tree=predict(fit.tree,data\_train)   
print(summary(fit.tree))

## Call:  
## rpart(formula = log\_area ~ X + Y + temp + rain + RH + wind +   
## FFMC + DMC + DC + ISI, data = data\_train)  
## n= 416   
##   
## CP nsplit rel error xerror xstd  
## 1 0.03015137 0 1.0000000 1.003715 0.08616567  
## 2 0.02056083 2 0.9396973 1.039841 0.08662858  
## 3 0.01474319 3 0.9191364 1.073410 0.08428749  
## 4 0.01383139 6 0.8749068 1.129136 0.08860421  
## 5 0.01281886 10 0.8195813 1.207014 0.09600899  
## 6 0.01277636 12 0.7939436 1.218991 0.09670636  
## 7 0.01226747 13 0.7811672 1.238821 0.09728490  
## 8 0.01000000 14 0.7688997 1.266510 0.09939878  
##   
## Variable importance  
## DMC temp RH FFMC wind ISI DC Y X   
## 23 19 14 11 9 9 9 5 1   
##   
## Node number 1: 416 observations, complexity param=0.03015137  
## mean=0.4889403, MSE=0.3788204   
## left son=2 (237 obs) right son=3 (179 obs)  
## Primary splits:  
## DMC < 118.45 to the left, improve=0.02876578, (0 missing)  
## temp < 22.55 to the left, improve=0.02060803, (0 missing)  
## DC < 243.2 to the left, improve=0.01456799, (0 missing)  
## wind < 8.25 to the left, improve=0.01010538, (0 missing)  
## X < 8.5 to the left, improve=0.00905913, (0 missing)  
## Surrogate splits:  
## DC < 560.8 to the left, agree=0.712, adj=0.330, (0 split)  
## FFMC < 92.65 to the left, agree=0.683, adj=0.263, (0 split)  
## temp < 21.45 to the left, agree=0.661, adj=0.212, (0 split)  
## ISI < 6.75 to the left, agree=0.644, adj=0.173, (0 split)  
## X < 1.5 to the right, agree=0.594, adj=0.056, (0 split)  
##   
## Node number 2: 237 observations, complexity param=0.02056083  
## mean=0.3982194, MSE=0.2728236   
## left son=4 (227 obs) right son=5 (10 obs)  
## Primary splits:  
## wind < 8.25 to the left, improve=0.05011144, (0 missing)  
## temp < 5.15 to the right, improve=0.04832537, (0 missing)  
## FFMC < 85.6 to the right, improve=0.03096780, (0 missing)  
## X < 3.5 to the left, improve=0.02042629, (0 missing)  
## RH < 52.5 to the left, improve=0.01908564, (0 missing)  
## Surrogate splits:  
## temp < 4.95 to the right, agree=0.970, adj=0.3, (0 split)  
## RH < 21.5 to the right, agree=0.962, adj=0.1, (0 split)  
##   
## Node number 3: 179 observations, complexity param=0.03015137  
## mean=0.6090567, MSE=0.4938374   
## left son=6 (171 obs) right son=7 (8 obs)  
## Primary splits:  
## DMC < 121.15 to the right, improve=0.05622243, (0 missing)  
## RH < 29.5 to the right, improve=0.02341539, (0 missing)  
## temp < 18.55 to the left, improve=0.01466193, (0 missing)  
## wind < 3.8 to the left, improve=0.01284313, (0 missing)  
## FFMC < 92.45 to the left, improve=0.01265959, (0 missing)  
##   
## Node number 4: 227 observations, complexity param=0.01474319  
## mean=0.3736782, MSE=0.2615864   
## left son=8 (189 obs) right son=9 (38 obs)  
## Primary splits:  
## temp < 22.45 to the left, improve=0.03165827, (0 missing)  
## RH < 52.5 to the left, improve=0.02451269, (0 missing)  
## X < 8.5 to the left, improve=0.02396925, (0 missing)  
## wind < 2.9 to the left, improve=0.01772911, (0 missing)  
## FFMC < 85.5 to the right, improve=0.01256638, (0 missing)  
## Surrogate splits:  
## X < 8.5 to the left, agree=0.841, adj=0.053, (0 split)  
## RH < 23 to the right, agree=0.837, adj=0.026, (0 split)  
##   
## Node number 5: 10 observations  
## mean=0.9553056, MSE=0.2038923   
##   
## Node number 6: 171 observations, complexity param=0.01383139  
## mean=0.5730159, MSE=0.4411308   
## left son=12 (48 obs) right son=13 (123 obs)  
## Primary splits:  
## temp < 18.55 to the left, improve=0.027508930, (0 missing)  
## RH < 29.5 to the right, improve=0.014611260, (0 missing)  
## wind < 3.8 to the left, improve=0.013053820, (0 missing)  
## X < 2.5 to the right, improve=0.011771240, (0 missing)  
## DMC < 141.85 to the right, improve=0.009482026, (0 missing)  
## Surrogate splits:  
## RH < 57 to the right, agree=0.819, adj=0.354, (0 split)  
## FFMC < 91.55 to the left, agree=0.784, adj=0.229, (0 split)  
## DC < 799.6 to the right, agree=0.766, adj=0.167, (0 split)  
## DMC < 236.65 to the right, agree=0.743, adj=0.083, (0 split)  
## wind < 7.4 to the right, agree=0.731, adj=0.042, (0 split)  
##   
## Node number 7: 8 observations  
## mean=1.379428, MSE=0.9992058   
##   
## Node number 8: 189 observations, complexity param=0.01281886  
## mean=0.3328733, MSE=0.2240386   
## left son=16 (131 obs) right son=17 (58 obs)  
## Primary splits:  
## RH < 52.5 to the left, improve=0.04014146, (0 missing)  
## temp < 7.85 to the right, improve=0.02660342, (0 missing)  
## Y < 2.5 to the left, improve=0.02482394, (0 missing)  
## X < 3.5 to the left, improve=0.02463278, (0 missing)  
## DC < 734 to the left, improve=0.02205223, (0 missing)  
## Surrogate splits:  
## temp < 7.1 to the right, agree=0.741, adj=0.155, (0 split)  
## FFMC < 85.15 to the right, agree=0.741, adj=0.155, (0 split)  
## ISI < 2.05 to the right, agree=0.720, adj=0.086, (0 split)  
## DMC < 4.75 to the right, agree=0.709, adj=0.052, (0 split)  
##   
## Node number 9: 38 observations, complexity param=0.01474319  
## mean=0.5766287, MSE=0.3988666   
## left son=18 (11 obs) right son=19 (27 obs)  
## Primary splits:  
## Y < 4.5 to the right, improve=0.15909670, (0 missing)  
## FFMC < 90.65 to the right, improve=0.14854310, (0 missing)  
## RH < 33 to the left, improve=0.10087490, (0 missing)  
## DC < 432.45 to the right, improve=0.10071610, (0 missing)  
## X < 7.5 to the left, improve=0.06974141, (0 missing)  
## Surrogate splits:  
## DMC < 69.7 to the left, agree=0.763, adj=0.182, (0 split)  
## X < 7.5 to the right, agree=0.737, adj=0.091, (0 split)  
## DC < 385.8 to the left, agree=0.737, adj=0.091, (0 split)  
##   
## Node number 12: 48 observations, complexity param=0.01277636  
## mean=0.3966753, MSE=0.2671079   
## left son=24 (14 obs) right son=25 (34 obs)  
## Primary splits:  
## temp < 17.15 to the right, improve=0.15703850, (0 missing)  
## RH < 75.5 to the left, improve=0.13148350, (0 missing)  
## X < 2.5 to the right, improve=0.10742140, (0 missing)  
## FFMC < 90.8 to the right, improve=0.06368219, (0 missing)  
## Y < 4.5 to the right, improve=0.05699593, (0 missing)  
## Surrogate splits:  
## RH < 55 to the left, agree=0.792, adj=0.286, (0 split)  
## FFMC < 92.2 to the right, agree=0.750, adj=0.143, (0 split)  
## ISI < 16.5 to the right, agree=0.729, adj=0.071, (0 split)  
##   
## Node number 13: 123 observations, complexity param=0.01383139  
## mean=0.6418318, MSE=0.4921715   
## left son=26 (116 obs) right son=27 (7 obs)  
## Primary splits:  
## temp < 19 to the right, improve=0.02424690, (0 missing)  
## wind < 1.55 to the left, improve=0.02302072, (0 missing)  
## FFMC < 90.95 to the left, improve=0.01586118, (0 missing)  
## RH < 54.5 to the right, improve=0.01452644, (0 missing)  
## ISI < 7.95 to the right, improve=0.01350571, (0 missing)  
##   
## Node number 16: 131 observations  
## mean=0.2697723, MSE=0.1963303   
##   
## Node number 17: 58 observations, complexity param=0.01281886  
## mean=0.4753946, MSE=0.2573156   
## left son=34 (17 obs) right son=35 (41 obs)  
## Primary splits:  
## RH < 71.5 to the right, improve=0.15682520, (0 missing)  
## Y < 3.5 to the left, improve=0.06309975, (0 missing)  
## DC < 100.55 to the right, improve=0.06178356, (0 missing)  
## ISI < 6.8 to the right, improve=0.05663392, (0 missing)  
## temp < 18.45 to the left, improve=0.04665854, (0 missing)  
## Surrogate splits:  
## FFMC < 78.3 to the left, agree=0.776, adj=0.235, (0 split)  
## DMC < 4.5 to the left, agree=0.759, adj=0.176, (0 split)  
## DC < 34.1 to the left, agree=0.759, adj=0.176, (0 split)  
## ISI < 1.35 to the left, agree=0.759, adj=0.176, (0 split)  
## wind < 6.5 to the right, agree=0.741, adj=0.118, (0 split)  
##   
## Node number 18: 11 observations  
## mean=0.1819625, MSE=0.0838627   
##   
## Node number 19: 27 observations, complexity param=0.01474319  
## mean=0.7374187, MSE=0.4378897   
## left son=38 (16 obs) right son=39 (11 obs)  
## Primary splits:  
## RH < 33.5 to the left, improve=0.22657640, (0 missing)  
## FFMC < 90.8 to the right, improve=0.19116790, (0 missing)  
## DMC < 84.6 to the right, improve=0.17183230, (0 missing)  
## X < 6.5 to the left, improve=0.11528780, (0 missing)  
## ISI < 7.35 to the right, improve=0.09801492, (0 missing)  
## Surrogate splits:  
## FFMC < 91.35 to the right, agree=0.852, adj=0.636, (0 split)  
## ISI < 8.35 to the right, agree=0.815, adj=0.545, (0 split)  
## Y < 3.5 to the left, agree=0.741, adj=0.364, (0 split)  
## temp < 23 to the right, agree=0.741, adj=0.364, (0 split)  
## DC < 440.9 to the right, agree=0.741, adj=0.364, (0 split)  
##   
## Node number 24: 14 observations  
## mean=0.07750548, MSE=0.02958063   
##   
## Node number 25: 34 observations  
## mean=0.5280981, MSE=0.305695   
##   
## Node number 26: 116 observations, complexity param=0.01383139  
## mean=0.6149965, MSE=0.4642892   
## left son=52 (63 obs) right son=53 (53 obs)  
## Primary splits:  
## wind < 3.8 to the left, improve=0.04298472, (0 missing)  
## DMC < 176.75 to the left, improve=0.02727946, (0 missing)  
## RH < 31.5 to the right, improve=0.01901605, (0 missing)  
## Y < 5.5 to the left, improve=0.01766897, (0 missing)  
## FFMC < 90.95 to the left, improve=0.01532300, (0 missing)  
## Surrogate splits:  
## DC < 639.45 to the right, agree=0.698, adj=0.340, (0 split)  
## ISI < 13.75 to the left, agree=0.690, adj=0.321, (0 split)  
## FFMC < 93.45 to the left, agree=0.621, adj=0.170, (0 split)  
## temp < 22.3 to the left, agree=0.603, adj=0.132, (0 split)  
## RH < 61 to the left, agree=0.586, adj=0.094, (0 split)  
##   
## Node number 27: 7 observations  
## mean=1.086531, MSE=0.7445303   
##   
## Node number 34: 17 observations  
## mean=0.1634277, MSE=0.0660605   
##   
## Node number 35: 41 observations, complexity param=0.01226747  
## mean=0.6047467, MSE=0.2795309   
## left son=70 (30 obs) right son=71 (11 obs)  
## Primary splits:  
## FFMC < 87.35 to the right, improve=0.16868170, (0 missing)  
## ISI < 4.45 to the right, improve=0.16270510, (0 missing)  
## DMC < 68.7 to the right, improve=0.11450400, (0 missing)  
## DC < 457.9 to the right, improve=0.09660116, (0 missing)  
## temp < 16.4 to the right, improve=0.09138185, (0 missing)  
## Surrogate splits:  
## ISI < 4.45 to the right, agree=0.976, adj=0.909, (0 split)  
## temp < 10.5 to the right, agree=0.927, adj=0.727, (0 split)  
## DMC < 34.1 to the right, agree=0.927, adj=0.727, (0 split)  
## DC < 75.35 to the right, agree=0.878, adj=0.545, (0 split)  
## RH < 67.5 to the left, agree=0.829, adj=0.364, (0 split)  
##   
## Node number 38: 16 observations  
## mean=0.476247, MSE=0.2455193   
##   
## Node number 39: 11 observations  
## mean=1.117305, MSE=0.4741723   
##   
## Node number 52: 63 observations  
## mean=0.4854222, MSE=0.3349948   
##   
## Node number 53: 53 observations, complexity param=0.01383139  
## mean=0.7690188, MSE=0.5742985   
## left son=106 (44 obs) right son=107 (9 obs)  
## Primary splits:  
## DMC < 186.35 to the left, improve=0.09398630, (0 missing)  
## wind < 5.15 to the right, improve=0.08005902, (0 missing)  
## ISI < 11.8 to the right, improve=0.07594899, (0 missing)  
## Y < 5.5 to the left, improve=0.05491584, (0 missing)  
## RH < 31.5 to the right, improve=0.05358843, (0 missing)  
## Surrogate splits:  
## DC < 707.9 to the left, agree=0.849, adj=0.111, (0 split)  
## ISI < 8.45 to the right, agree=0.849, adj=0.111, (0 split)  
##   
## Node number 70: 30 observations  
## mean=0.4732591, MSE=0.2360809   
##   
## Node number 71: 11 observations  
## mean=0.9633491, MSE=0.2222836   
##   
## Node number 106: 44 observations  
## mean=0.6639447, MSE=0.4388408   
##   
## Node number 107: 9 observations  
## mean=1.282715, MSE=0.9186764   
##   
## n= 416   
##   
## node), split, n, deviance, yval  
## \* denotes terminal node  
##   
## 1) root 416 157.5893000 0.48894030   
## 2) DMC< 118.45 237 64.6591900 0.39821940   
## 4) wind< 8.25 227 59.3801000 0.37367820   
## 8) temp< 22.45 189 42.3433000 0.33287330   
## 16) RH< 52.5 131 25.7192800 0.26977230 \*  
## 17) RH>=52.5 58 14.9243000 0.47539460   
## 34) RH>=71.5 17 1.1230280 0.16342770 \*  
## 35) RH< 71.5 41 11.4607700 0.60474670   
## 70) FFMC>=87.35 30 7.0824270 0.47325910 \*  
## 71) FFMC< 87.35 11 2.4451200 0.96334910 \*  
## 9) temp>=22.45 38 15.1569300 0.57662870   
## 18) Y>=4.5 11 0.9224897 0.18196250 \*  
## 19) Y< 4.5 27 11.8230200 0.73741870   
## 38) RH< 33.5 16 3.9283090 0.47624700 \*  
## 39) RH>=33.5 11 5.2158950 1.11730500 \*  
## 5) wind>=8.25 10 2.0389230 0.95530560 \*  
## 3) DMC>=118.45 179 88.3969000 0.60905670   
## 6) DMC>=121.15 171 75.4333700 0.57301590   
## 12) temp< 18.55 48 12.8211800 0.39667530   
## 24) temp>=17.15 14 0.4141289 0.07750548 \*  
## 25) temp< 17.15 34 10.3936300 0.52809810 \*  
## 13) temp>=18.55 123 60.5371000 0.64183180   
## 26) temp>=19 116 53.8575500 0.61499650   
## 52) wind< 3.8 63 21.1046700 0.48542220 \*  
## 53) wind>=3.8 53 30.4378200 0.76901880   
## 106) DMC< 186.35 44 19.3090000 0.66394470 \*  
## 107) DMC>=186.35 9 8.2680870 1.28271500 \*  
## 27) temp< 19 7 5.2117120 1.08653100 \*  
## 7) DMC< 121.15 8 7.9936460 1.37942800 \*

MSE=mean((pr.tree-data\_train$log\_area)^2)  
print(MSE)

## [1] 0.2912749

rsw=rsquare(data\_train$log\_area,pr.tree)  
print(rsw)

## [1] 0.2311003

rsw=rsquare(data\_train$log\_area,pr)  
print(rsw)

## [1] 0.1897109

#Random Forest  
  
rFModel=randomForest(log\_area~X+Y+temp+rain+RH+wind+FFMC+DMC+DC+ISI,data\_train)  
predictedvalues=predict(rFModel,data\_train)  
print(summary(rFModel))

## Length Class Mode   
## call 3 -none- call   
## type 1 -none- character  
## predicted 416 -none- numeric   
## mse 500 -none- numeric   
## rsq 500 -none- numeric   
## oob.times 416 -none- numeric   
## importance 10 -none- numeric   
## importanceSD 0 -none- NULL   
## localImportance 0 -none- NULL   
## proximity 0 -none- NULL   
## ntree 1 -none- numeric   
## mtry 1 -none- numeric   
## forest 11 -none- list   
## coefs 0 -none- NULL   
## y 416 -none- numeric   
## test 0 -none- NULL   
## inbag 0 -none- NULL   
## terms 3 terms call

MSE=mean((predictedvalues-data\_train$log\_area)^2)  
print(MSE)

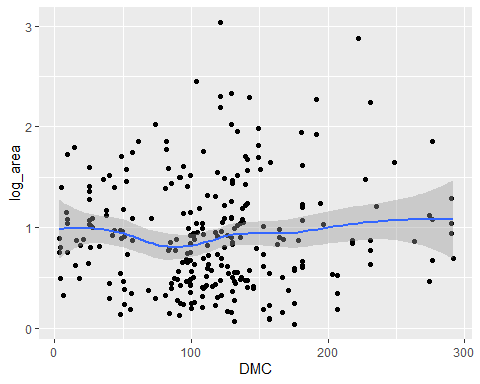
## [1] 0.09360294

rsw=rsquare(data\_train$log\_area,predictedvalues)  
print(rsw)

## [1] 0.9042755

#Loess model  
ggplot(d\_areagreaterthanzero,aes(x=DMC,y=log\_area))+geom\_point()+geom\_smooth(method="loess")

## `geom\_smooth()` using formula = 'y ~ x'



model\_loess=loess(formula=log\_area~FFMC+DMC+DC+ISI,data=d\_areagreaterthanzero)  
  
p=predict(model\_loess,d\_areagreaterthanzero)  
  
print(summary(model\_loess))

## Call:  
## loess(formula = log\_area ~ FFMC + DMC + DC + ISI, data = d\_areagreaterthanzero)  
##   
## Number of Observations: 270   
## Equivalent Number of Parameters: 24.11   
## Residual Standard Error: 0.5666   
## Trace of smoother matrix: 30.41 (exact)  
##   
## Control settings:  
## span : 0.75   
## degree : 2   
## family : gaussian  
## surface : interpolate cell = 0.2  
## normalize: TRUE  
## parametric: FALSE FALSE FALSE FALSE  
## drop.square: FALSE FALSE FALSE FALSE

print(mean(summary(model\_loess)$residuals^2))

## [1] 0.2774175

#Training the models using all predictor variables (including is\_weekend,day and season values)  
  
model=lm(log\_area~X+Y+FFMC+DMC+DC+ISI+temp+RH+wind+rain+is\_weekend+monthjan+monthfeb+monthmar+monthapr+monthmay+monthjun+monthjul+monthaug+monthsep+monthnov+monthdec+daysun+daymon+daytue+daywed+daythu+dayfri+daysat+seasonautumn+seasonspring+seasonsummer+seasonwinter,data=data\_train)  
print(model)

##   
## Call:  
## lm(formula = log\_area ~ X + Y + FFMC + DMC + DC + ISI + temp +   
## RH + wind + rain + is\_weekend + monthjan + monthfeb + monthmar +   
## monthapr + monthmay + monthjun + monthjul + monthaug + monthsep +   
## monthnov + monthdec + daysun + daymon + daytue + daywed +   
## daythu + dayfri + daysat + seasonautumn + seasonspring +   
## seasonsummer + seasonwinter, data = data\_train)  
##   
## Coefficients:  
## (Intercept) X Y FFMC DMC   
## 0.3463300 0.0270437 -0.0372073 0.0019629 0.0022779   
## DC ISI temp RH wind   
## -0.0008202 -0.0060464 0.0176708 0.0005688 0.0290704   
## rain is\_weekend1 monthjan monthfeb monthmar   
## 0.0120756 0.0424702 -0.4011065 -0.3688777 -0.6144571   
## monthapr monthmay monthjun monthjul monthaug   
## -0.3678684 -0.1096880 -0.5397086 -0.4102221 -0.3547009   
## monthsep monthnov monthdec daysun daymon   
## -0.0714129 NA 0.5454392 0.0166133 0.0081763   
## daytue daywed daythu dayfri daysat   
## 0.1309337 0.1007815 0.0194258 NA NA   
## seasonautumn seasonspring seasonsummer seasonwinter   
## NA NA NA NA

print(sample(data,size=20))

## temp seasonspring daysun X Y monthjan monthaug daytue daythu DC RH  
## 1 8.2 1 0 7 5 0 0 0 0 94.3 51  
## 2 18.0 0 0 7 4 0 0 1 0 669.1 33  
## 3 14.6 0 0 7 4 0 0 0 0 686.9 33  
## 4 8.3 1 0 8 6 0 0 0 0 77.5 97  
## 5 11.4 1 1 8 6 0 0 0 0 102.2 99  
## 6 22.2 0 1 8 6 0 1 0 0 488.0 29  
## 7 24.1 0 0 8 6 0 1 0 0 495.6 27  
## 8 8.0 0 0 8 6 0 1 0 0 608.2 86  
## 9 13.1 0 0 8 6 0 0 1 0 692.6 63  
## 10 22.8 0 0 7 5 0 0 0 0 698.6 40  
## 11 17.8 0 0 7 5 0 0 0 0 698.6 51  
## 12 19.3 0 0 7 5 0 0 0 0 713.0 38  
## 13 17.0 0 0 6 5 0 1 0 0 665.3 72  
## 14 21.3 0 0 6 5 0 0 0 0 686.5 42  
## 15 26.4 0 0 6 5 0 0 0 0 699.6 21  
## 16 22.9 0 0 6 5 0 0 0 0 713.9 44  
## 17 15.1 1 0 5 5 0 0 0 0 80.8 27  
## 18 16.7 0 0 8 5 0 0 0 0 664.2 47  
## 19 15.9 1 0 6 4 0 0 0 0 70.8 35  
## 20 9.3 1 0 6 4 0 0 0 0 97.1 44  
## 21 18.3 0 0 6 4 0 0 1 0 692.6 40  
## 22 19.1 0 0 5 4 0 0 0 0 724.3 38  
## 23 21.0 0 1 7 4 0 0 0 0 200.0 44  
## 24 19.5 0 0 7 4 0 1 0 0 537.4 43  
## 25 23.7 0 0 7 4 0 1 0 0 594.2 32  
## 26 16.3 0 1 7 4 0 1 0 0 601.4 60  
## 27 19.0 0 0 7 4 0 0 0 0 668.0 34  
## 28 19.4 0 0 7 4 0 0 0 0 686.5 48  
## 29 30.2 0 0 6 3 0 0 0 0 721.4 24  
## 30 22.8 0 1 6 3 0 0 0 0 728.6 39  
## 31 25.4 0 0 6 3 0 0 0 0 692.3 24  
## 32 11.2 0 0 6 3 0 0 0 0 709.9 78  
## 33 20.6 0 0 6 3 0 0 0 0 706.8 37  
## 34 17.7 0 1 6 3 0 0 0 0 718.3 39  
## 35 21.2 0 0 6 3 0 0 0 0 724.3 32  
## 36 18.2 0 0 6 3 0 0 1 0 730.2 62  
## 37 21.7 0 0 6 3 0 0 1 0 669.1 24  
## 38 11.3 0 0 7 4 0 0 0 0 682.6 60  
## 39 17.8 0 0 7 3 0 0 0 0 686.9 27  
## 40 14.1 1 0 4 4 0 0 1 0 67.6 43  
## 41 23.3 0 0 4 4 0 0 1 0 366.7 37  
## 42 18.4 0 0 4 4 0 1 0 0 624.2 42  
## 43 16.6 0 0 4 4 0 1 1 0 647.1 54  
## 44 19.6 0 0 4 4 0 0 0 0 698.6 48  
## 45 12.9 0 0 4 4 0 0 0 0 735.7 74  
## 46 25.9 0 0 5 6 0 0 0 0 692.3 24  
## 47 14.7 0 0 5 6 0 0 0 0 686.5 70  
## 48 23.0 0 0 6 6 0 0 0 0 442.9 36  
## 49 11.8 1 0 4 4 0 0 0 0 64.7 35  
## 50 11.0 1 0 4 4 0 0 0 0 103.8 46  
## 51 20.8 0 0 4 4 0 0 0 1 706.4 17  
## 52 21.5 0 1 4 3 0 1 0 0 631.2 34  
## 53 20.4 0 0 4 3 0 1 0 0 654.1 42  
## 54 20.4 0 0 4 3 0 1 0 0 654.1 42  
## 55 17.6 0 0 4 3 0 1 0 1 661.3 45  
## 56 27.7 0 0 4 3 0 0 0 1 706.4 24  
## 57 17.8 0 0 4 3 0 0 1 0 730.2 63  
## 58 13.8 0 1 4 3 0 0 0 0 691.8 50  
## 59 13.9 0 0 2 2 0 0 0 0 34.0 40  
## 60 12.3 0 0 2 2 0 0 0 0 43.0 51  
## 61 11.5 1 1 2 2 0 0 0 0 102.2 39  
## 62 5.5 1 1 2 2 0 0 0 0 102.2 59  
## 63 18.8 0 0 2 2 0 1 0 1 466.6 35  
## 64 20.8 0 1 2 2 0 1 0 0 631.2 33  
## 65 23.1 0 0 2 2 0 1 0 0 638.8 31  
## 66 18.6 0 0 2 2 0 1 0 1 661.3 44  
## 67 23.0 0 0 2 2 0 0 0 0 668.0 37  
## 68 19.6 0 0 2 2 0 0 0 0 668.0 33  
## 69 19.6 0 0 2 2 0 0 0 0 668.0 33  
## 70 17.2 1 0 4 5 0 0 0 0 77.5 26  
## 71 15.8 1 0 4 5 0 0 0 0 97.8 27  
## 72 17.7 0 0 4 5 0 0 0 0 692.3 37  
## 73 15.6 1 0 5 4 0 0 0 0 77.5 25  
## 74 17.3 0 0 5 4 0 1 1 0 614.5 43  
## 75 27.6 0 0 5 4 0 0 0 0 713.9 30  
## 76 6.7 0 0 9 9 0 0 0 1 26.6 79  
## 77 15.7 0 0 9 9 0 0 0 0 43.0 43  
## 78 8.3 1 0 1 3 0 0 0 0 103.8 72  
## 79 14.7 0 0 1 2 0 1 0 0 529.8 66  
## 80 21.6 0 0 1 2 0 1 1 0 561.6 19  
## 81 19.5 0 1 1 2 0 1 0 0 601.4 39  
## 82 17.9 0 1 1 2 0 1 0 0 631.2 44  
## 83 18.6 0 0 1 2 0 1 1 0 647.1 51  
## 84 16.6 0 0 1 2 0 1 0 0 654.1 47  
## 85 20.2 0 0 1 2 0 1 0 1 661.3 45  
## 86 21.5 0 0 1 2 0 0 0 1 706.4 15  
## 87 25.4 0 0 1 2 0 0 0 1 706.4 27  
## 88 22.4 0 0 1 2 0 0 0 1 706.4 34  
## 89 25.3 0 1 1 2 0 0 0 0 728.6 36  
## 90 17.4 1 0 6 5 0 0 0 0 80.8 25  
## 91 14.7 0 0 6 5 0 1 0 0 624.2 59  
## 92 17.4 1 0 8 6 0 0 0 0 80.8 24  
## 93 20.8 0 1 8 6 0 1 0 0 488.0 32  
## 94 18.2 0 1 8 6 0 1 0 0 601.4 43  
## 95 23.4 0 0 8 6 0 1 0 0 638.8 22  
## 96 17.8 0 1 4 4 0 0 0 0 704.4 64  
## 97 12.7 0 0 3 4 0 0 0 0 30.2 48  
## 98 17.4 1 0 3 4 0 0 0 0 15.5 24  
## 99 11.6 0 1 3 4 0 1 0 0 601.4 87  
## 100 19.8 0 1 3 4 0 1 0 0 601.4 39  
## 101 19.8 0 1 3 4 0 1 0 0 601.4 39  
## 102 14.4 0 0 3 4 0 1 1 0 614.5 66  
## 103 20.1 0 0 2 4 0 1 1 0 647.1 40  
## 104 24.1 0 0 2 4 0 0 0 0 674.4 29  
## 105 5.3 0 0 2 4 1 0 0 0 9.3 78  
## 106 12.7 1 0 4 5 0 0 0 0 57.3 52  
## 107 18.2 1 0 4 5 0 0 0 1 74.3 29  
## 108 21.4 0 1 4 5 0 1 0 0 631.2 33  
## 109 20.3 0 0 4 5 0 0 0 0 698.6 45  
## 110 17.4 0 0 4 5 0 0 0 0 709.9 56  
## 111 13.7 1 0 4 4 0 0 0 0 57.3 43  
## 112 18.8 1 0 3 4 0 0 0 0 77.5 18  
## 113 22.8 0 1 3 4 0 0 0 0 704.4 39  
## 114 18.9 0 0 3 4 0 0 0 0 724.3 35  
## 115 15.8 1 0 3 4 0 0 1 0 67.6 27  
## 116 15.5 1 0 3 5 0 0 1 0 67.6 27  
## 117 11.6 1 0 3 4 0 0 0 0 80.8 30  
## 118 15.2 1 0 3 4 0 0 0 0 80.8 27  
## 119 10.6 1 0 3 4 0 0 0 0 86.6 30  
## 120 19.6 0 0 3 4 0 1 0 1 466.6 36  
## 121 10.3 0 0 3 4 0 1 0 0 608.2 74  
## 122 17.1 0 0 3 4 0 1 0 0 608.2 43  
## 123 22.5 0 1 3 4 0 0 0 0 680.7 42  
## 124 17.9 0 0 3 4 0 0 1 0 671.9 45  
## 125 19.8 0 0 3 4 0 0 0 0 692.3 50  
## 126 20.6 0 1 3 4 0 0 0 0 691.8 24  
## 127 9.0 1 0 3 5 0 0 0 0 103.8 49  
## 128 17.2 0 0 3 5 0 0 0 0 728.6 43  
## 129 15.9 0 0 3 5 0 0 0 0 673.8 46  
## 130 15.4 0 1 2 5 0 0 0 0 691.8 35  
## 131 15.4 0 0 4 6 0 0 0 0 87.2 40  
## 132 14.0 1 0 4 6 0 0 0 0 64.7 39  
## 133 10.6 1 1 4 6 0 0 0 0 102.2 46  
## 134 17.6 0 0 4 6 0 0 0 1 685.2 42  
## 135 14.9 1 0 3 5 0 0 1 0 67.6 38  
## 136 17.6 0 0 3 5 0 1 0 0 594.2 52  
## 137 17.2 0 1 3 6 0 0 0 0 680.7 58  
## 138 15.6 0 0 3 6 0 0 0 0 686.5 66  
## 139 18.0 0 0 9 9 0 0 1 0 313.4 42  
## 140 21.7 0 0 1 4 0 0 1 0 692.6 38  
## 141 21.9 0 0 2 5 0 0 0 0 686.5 39  
## 142 23.3 0 0 1 2 0 1 0 0 513.3 31  
## 143 21.2 0 0 8 6 0 1 0 0 529.8 51  
## 144 16.6 0 0 1 2 0 0 0 0 296.3 53  
## 145 23.8 0 0 2 5 0 1 0 0 513.3 32  
## 146 27.4 0 0 6 5 0 1 0 1 578.8 22  
## 147 13.2 1 0 5 4 0 0 0 0 86.6 40  
## 148 24.2 0 0 8 3 0 0 1 0 671.9 28  
## 149 17.4 0 0 2 2 0 1 1 0 647.1 43  
## 150 23.7 0 0 8 6 0 0 0 1 685.2 25  
## 151 23.2 0 0 6 5 0 0 0 0 433.3 39  
## 152 24.8 0 1 9 9 0 0 0 0 355.2 29  
## 153 24.6 0 0 3 4 0 0 0 0 424.1 43  
## 154 20.1 0 0 5 4 0 0 0 0 692.3 47  
## 155 29.6 0 0 1 5 0 0 0 0 721.4 27  
## 156 16.4 0 1 7 4 0 1 0 0 647.1 47  
## 157 28.6 0 0 2 4 0 0 0 0 721.4 27  
## 158 18.4 0 0 2 2 0 1 0 0 654.1 45  
## 159 20.5 0 0 2 4 0 1 0 0 654.1 35  
## 160 19.0 0 0 7 4 0 0 0 0 668.0 34  
## 161 16.1 1 0 7 4 0 0 0 0 86.6 29  
## 162 20.3 0 0 6 4 0 1 0 1 578.8 41  
## 163 15.2 1 0 6 3 0 0 0 0 100.4 31  
## 164 17.8 0 0 8 6 0 0 0 0 674.4 56  
## 165 17.8 0 1 8 5 0 0 0 0 704.4 67  
## 166 5.3 1 0 6 5 0 0 0 1 55.0 70  
## 167 16.6 0 0 6 5 0 1 0 0 654.1 47  
## 168 23.4 0 0 6 5 0 1 0 0 570.5 33  
## 169 14.6 1 0 6 5 0 0 0 0 97.8 26  
## 170 20.7 0 0 8 6 0 1 0 1 578.8 45  
## 171 21.9 0 0 5 4 0 0 0 0 699.6 35  
## 172 17.4 0 0 8 6 0 1 0 0 609.6 50  
## 173 20.1 0 1 7 4 0 1 0 0 601.4 39  
## 174 17.7 0 0 4 4 0 0 0 0 686.5 39  
## 175 14.2 0 0 1 4 0 1 0 0 624.2 53  
## 176 20.3 0 0 1 4 0 1 0 0 624.2 39  
## 177 5.8 1 0 6 5 0 0 0 1 55.2 54  
## 178 19.2 0 1 2 5 0 1 0 0 631.2 44  
## 179 18.3 0 0 2 5 0 0 0 0 735.7 45  
## 180 14.4 0 0 8 6 0 1 1 0 614.5 66  
## 181 23.9 0 1 1 3 0 0 0 0 680.7 32  
## 182 19.1 0 0 8 6 0 0 0 0 664.2 32  
## 183 12.4 0 1 5 4 0 0 0 0 48.3 53  
## 184 16.8 0 0 7 4 0 0 0 0 696.1 45  
## 185 20.8 0 0 8 6 0 1 0 0 586.7 34  
## 186 17.6 0 0 2 5 0 0 1 0 692.6 46  
## 187 11.5 1 1 8 6 0 0 0 0 102.2 39  
## 188 21.0 0 0 1 5 0 0 0 0 686.5 42  
## 189 13.3 1 0 6 4 0 0 0 0 89.4 42  
## 190 11.5 1 1 7 4 0 0 0 0 92.4 60  
## 191 11.7 1 0 6 5 0 0 0 0 97.8 33  
## 192 24.2 0 0 2 5 0 1 0 1 578.8 28  
## 193 24.6 0 0 2 2 0 1 1 0 647.1 22  
## 194 24.3 0 0 4 5 0 0 0 0 699.6 25  
## 195 24.6 0 0 2 2 0 1 1 0 647.1 22  
## 196 23.5 0 0 2 5 0 1 0 0 586.7 36  
## 197 5.8 1 0 6 5 0 0 0 1 55.2 54  
## 198 21.5 0 0 4 5 0 0 0 1 706.4 15  
## 199 13.9 0 0 3 4 0 0 1 0 692.6 59  
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## 203 8.8 0 1 7 4 0 0 0 0 32.1 68  
## 204 20.2 0 0 8 6 0 0 0 0 673.8 37  
## 205 15.1 1 0 5 6 0 0 0 0 100.4 64  
## 206 22.1 0 0 4 5 0 0 0 1 706.4 34  
## 207 22.9 0 0 2 2 0 1 0 0 594.2 31  
## 208 20.7 0 0 7 5 0 0 1 0 692.6 37  
## 209 19.6 0 0 6 5 0 0 0 0 668.0 33  
## 210 23.2 0 0 8 3 0 0 0 1 685.2 26  
## 211 18.4 0 0 4 4 0 0 0 0 686.9 25  
## 212 5.1 0 0 7 4 0 1 0 0 594.2 96  
## 213 20.1 0 0 7 4 0 0 0 0 692.3 47  
## 214 11.0 1 0 7 3 0 0 0 0 103.8 46  
## 215 17.0 1 0 4 4 0 0 0 0 80.8 27  
## 216 17.0 1 0 4 4 0 0 0 0 80.8 27  
## 217 16.9 0 1 4 4 0 0 0 0 680.7 60  
## 218 12.4 0 0 1 3 0 0 0 0 709.9 73  
## 219 19.4 0 0 4 5 0 0 0 0 699.6 19  
## 220 15.2 1 0 6 5 0 0 0 0 86.6 27  
## 221 16.2 0 1 8 6 0 1 0 0 631.2 59  
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## 223 11.0 1 0 4 3 0 0 0 0 103.8 46  
## 224 13.4 0 0 2 2 0 0 0 0 309.9 79  
## 225 15.4 0 0 7 4 0 0 0 0 735.7 57  
## 226 22.9 0 1 4 4 0 0 0 0 728.6 39  
## 227 16.1 0 0 7 5 0 0 0 0 696.1 44  
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## 229 28.3 0 1 4 6 0 0 0 0 728.6 26  
## 230 16.4 0 0 8 6 0 1 0 0 480.8 43  
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## 234 24.3 0 0 9 4 0 0 1 0 671.9 36  
## 235 17.7 0 0 4 5 0 0 0 0 674.4 25  
## 236 19.6 0 1 8 6 0 1 0 0 601.4 41  
## 237 18.2 0 0 2 2 0 0 0 0 674.4 46  
## 238 18.8 0 0 1 2 0 0 1 0 692.6 40  
## 239 25.1 0 0 6 5 0 0 0 0 674.4 27  
## 240 13.4 1 1 7 5 0 0 0 0 7.9 75  
## 241 15.2 1 0 6 3 0 0 0 0 43.5 51  
## 242 16.7 1 0 4 4 0 0 0 0 85.3 20  
## 243 15.4 0 1 2 4 0 1 0 0 589.9 66  
## 244 21.9 0 1 7 4 0 1 0 0 700.7 73  
## 245 22.4 0 1 2 4 0 1 0 0 700.7 54  
## 246 26.8 0 1 3 4 0 1 0 0 700.7 38  
## 247 25.7 0 1 5 4 0 1 0 0 700.7 39  
## 248 20.7 0 0 2 4 0 1 0 0 503.6 70  
## 249 28.7 0 0 8 6 0 1 0 0 666.7 28  
## 250 21.7 0 0 3 4 0 1 0 0 666.7 40  
## 251 26.8 0 0 8 5 0 1 0 0 666.7 25  
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## 253 22.1 0 0 6 5 0 1 0 0 666.7 37  
## 254 21.4 0 0 7 4 0 1 0 1 565.5 38  
## 255 18.9 0 0 6 3 0 1 0 1 621.7 41  
## 256 22.3 0 0 2 5 0 1 0 1 694.8 46  
## 257 23.9 0 0 8 6 0 1 0 0 581.1 41  
## 258 21.4 0 0 4 3 0 1 0 0 581.1 44  
## 259 20.6 0 0 3 4 0 1 0 0 692.3 59  
## 260 23.7 0 0 7 4 0 1 0 0 692.3 40  
## 261 28.3 0 0 2 4 0 1 0 0 542.0 32  
## 262 11.2 0 0 3 4 0 1 0 0 573.0 84  
## 263 21.4 0 0 2 4 0 1 0 0 573.0 42  
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## 265 21.8 0 0 4 4 0 1 0 0 684.4 53  
## 266 22.1 0 0 4 4 0 1 1 0 550.3 54  
## 267 19.4 0 0 6 5 0 1 1 0 607.1 55  
## 268 23.7 0 0 2 2 0 1 1 0 658.2 24  
## 269 21.0 0 0 3 4 0 1 1 0 658.2 32  
## 270 19.1 0 0 4 4 0 1 1 0 658.2 53  
## 271 21.8 0 0 2 2 0 1 1 0 658.2 56  
## 272 20.1 0 0 8 6 0 1 1 0 658.2 58  
## 273 20.2 0 0 2 5 0 1 1 0 658.2 47  
## 274 4.8 0 1 4 6 0 0 0 0 353.5 57  
## 275 5.1 0 0 8 6 0 0 0 0 354.6 61  
## 276 5.1 0 0 4 6 0 0 0 1 352.0 61  
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## 278 4.6 0 0 3 4 0 0 0 0 349.7 21  
## 279 4.6 0 0 4 4 0 0 0 0 349.7 21  
## 280 4.6 0 0 4 4 0 0 0 0 349.7 21  
## 281 2.2 0 0 4 6 0 0 0 0 352.6 59  
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## 283 4.2 0 1 6 3 0 0 0 0 353.5 51  
## 284 8.8 0 0 3 4 0 0 0 0 18.7 35  
## 285 7.5 0 0 5 4 0 0 0 0 15.8 46  
## 286 23.4 0 1 2 5 0 0 0 0 411.8 40  
## 287 12.6 0 0 7 6 0 0 0 0 437.7 90  
## 288 22.1 0 0 7 4 0 0 0 0 474.9 49  
## 289 24.2 0 0 7 4 0 0 0 0 474.9 32  
## 290 24.3 0 0 7 4 0 0 0 0 474.9 30  
## 291 18.7 0 0 2 5 0 0 0 0 474.9 53  
## 292 25.3 0 0 9 4 0 0 0 0 474.9 39  
## 293 22.9 0 0 4 5 0 0 0 0 466.3 40  
## 294 26.9 0 0 7 6 0 0 1 0 430.8 28  
## 295 17.1 0 0 8 6 0 0 1 0 440.9 67  
## 296 22.2 0 1 7 5 0 0 0 0 430.8 48  
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## 298 15.4 0 1 8 6 0 0 0 0 290.8 45  
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## 300 10.6 0 0 6 5 0 0 0 0 233.8 90  
## 301 20.7 0 0 6 5 0 0 0 0 298.1 25  
## 302 19.1 0 0 6 5 0 0 0 0 298.1 39  
## 303 19.2 0 0 3 6 0 0 0 0 232.1 38  
## 304 19.2 0 0 3 6 0 0 0 0 232.1 38  
## 305 11.3 1 0 6 5 0 0 0 0 113.8 94  
## 306 19.0 0 1 1 4 0 0 0 0 714.3 52  
## 307 17.1 0 1 7 4 0 0 0 0 714.3 53  
## 308 23.8 0 1 3 4 0 0 0 0 714.3 35  
## 309 16.0 0 1 2 4 0 0 0 0 758.1 45  
## 310 24.9 0 1 2 4 0 0 0 0 758.1 27  
## 311 25.3 0 1 7 4 0 0 0 0 758.1 27  
## 312 24.8 0 1 6 3 0 0 0 0 758.1 28  
## 313 12.2 0 1 2 4 0 0 0 0 706.6 78  
## 314 24.3 0 0 6 5 0 0 0 0 777.1 27  
## 315 19.7 0 0 4 4 0 0 0 0 777.1 41  
## 316 18.5 0 0 3 4 0 0 0 0 817.5 30  
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## 320 21.6 0 0 5 4 0 0 0 1 783.5 28  
## 321 18.9 0 0 6 3 0 0 0 1 783.5 34  
## 322 16.8 0 0 1 4 0 0 0 1 783.5 28  
## 323 16.8 0 0 6 5 0 0 0 1 783.5 28  
## 324 12.9 0 0 3 5 0 0 0 1 822.8 39  
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## 326 24.2 0 0 1 4 0 0 0 0 751.5 27  
## 327 24.1 0 0 5 4 0 0 0 0 751.5 27  
## 328 21.2 0 0 6 5 0 0 0 0 751.5 32  
## 329 19.7 0 0 6 5 0 0 0 0 751.5 35  
## 330 23.5 0 0 4 3 0 0 0 0 751.5 27  
## 331 24.2 0 0 3 3 0 0 0 0 751.5 27  
## 332 21.5 0 0 7 4 0 0 0 0 795.3 28  
## 333 17.1 0 0 4 4 0 0 0 0 795.3 41  
## 334 18.1 0 0 1 4 0 0 0 0 721.1 54  
## 335 18.0 0 0 2 3 0 0 0 0 764.0 51  
## 336 9.8 0 0 4 3 0 0 0 0 764.0 86  
## 337 19.3 0 0 7 4 0 0 0 0 764.0 44  
## 338 23.0 0 0 6 3 0 0 0 0 764.0 34  
## 339 22.7 0 0 8 6 0 0 0 0 764.0 35  
## 340 20.4 0 0 2 4 0 0 0 0 764.0 41  
## 341 19.3 0 0 2 5 0 0 0 0 764.0 44  
## 342 15.7 0 0 8 6 0 0 0 0 770.3 51  
## 343 20.6 0 0 6 3 0 0 0 0 807.1 37  
## 344 15.9 0 0 8 6 0 0 0 0 807.1 51  
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## 350 12.8 0 0 5 4 0 0 0 0 745.3 64  
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## 352 15.4 0 0 4 4 0 0 0 0 745.3 53  
## 353 20.6 0 0 7 4 0 0 0 0 745.3 43  
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## 356 20.8 0 0 4 4 0 0 0 0 745.3 35  
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## 370 13.8 0 1 4 5 0 0 0 0 825.1 77  
## 371 13.8 0 1 7 4 0 0 0 0 825.1 77  
## 372 14.2 0 0 3 4 0 0 0 0 520.5 58  
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## 375 10.3 0 0 6 5 0 0 0 0 855.3 78  
## 376 15.4 0 0 6 5 0 0 0 0 744.4 57  
## 377 21.1 0 0 8 6 0 1 0 0 672.6 54  
## 378 21.9 0 0 2 2 0 1 0 0 715.1 42  
## 379 8.7 1 0 6 5 0 0 0 1 30.6 51  
## 380 5.2 0 1 4 5 1 0 0 0 171.4 100  
## 381 19.3 0 0 5 4 0 0 0 0 458.8 39  
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## 383 28.2 0 0 8 6 0 1 0 0 690.0 29  
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## 385 21.3 0 0 8 4 0 1 0 0 819.1 44  
## 386 20.9 0 1 2 4 0 1 0 0 613.0 50  
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## 388 11.6 1 0 5 5 0 0 0 1 30.6 48  
## 389 23.3 0 0 6 4 0 1 0 0 706.7 34  
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## 397 20.4 0 1 4 3 0 0 0 0 750.5 55  
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## 465 5.1 0 0 6 4 0 0 1 0 16.2 77  
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## 470 13.7 1 1 6 3 0 0 0 0 25.6 33  
## 471 17.6 1 1 5 4 0 0 0 0 25.6 27  
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## monthjun dayfri wind season ISI log\_area monthapr seasonsummer daymon  
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## 373 0 0 0.9 summer 8.1 0.00000000 0 1 0  
## 374 0 0 2.7 summer 13.9 0.00000000 0 1 0  
## 375 0 1 4.0 autumn 7.4 1.28555731 0 0 0  
## 376 0 0 4.9 autumn 8.4 1.60584354 0 0 0  
## 377 0 0 2.2 summer 8.2 0.00000000 0 1 1  
## 378 0 0 2.2 summer 8.4 2.24459870 0 1 0  
## 379 0 0 5.8 spring 8.0 0.00000000 0 0 0  
## 380 0 0 0.9 winter 0.0 0.00000000 0 0 0  
## 381 0 0 7.2 summer 11.9 0.94101424 0 1 0  
## 382 0 0 2.7 summer 6.8 1.23879856 0 1 0  
## 383 0 0 1.8 summer 18.0 0.83632412 0 1 0  
## 384 0 0 2.7 summer 6.3 1.64216763 0 1 0  
## 385 0 0 4.5 summer 7.7 1.11991541 0 1 0  
## 386 0 0 2.2 summer 7.6 1.23044892 0 1 0  
## 387 0 0 5.4 autumn 11.4 1.40807029 0 0 0  
## 388 0 0 5.4 spring 8.0 0.00000000 0 0 0  
## 389 0 1 3.1 summer 12.0 1.47334096 0 1 0  
## 390 0 1 3.1 summer 12.0 0.00000000 0 1 0  
## 391 0 0 6.3 winter 4.1 1.03981055 0 0 1  
## 392 0 1 2.7 autumn 7.2 1.49387611 0 0 0  
## 393 0 0 4.0 autumn 7.1 1.85588243 0 0 0  
## 394 0 0 7.6 spring 11.4 0.00000000 0 0 0  
## 395 0 0 1.8 winter 2.2 0.00000000 0 0 1  
## 396 0 0 1.8 winter 3.5 1.72246939 0 0 0  
## 397 0 0 4.9 autumn 11.4 0.66651798 0 0 0  
## 398 0 0 3.6 summer 7.6 0.66558099 0 1 0  
## 399 0 0 3.1 summer 8.4 0.00000000 0 1 0  
## 400 1 0 4.5 summer 14.0 0.00000000 0 1 0  
## 401 1 0 4.5 summer 14.0 0.96189547 0 1 0  
## 402 0 0 4.0 autumn 8.3 0.77451697 0 0 0  
## 403 0 1 4.0 summer 12.0 0.00000000 0 1 0  
## 404 0 0 3.6 summer 6.8 0.00000000 0 1 0  
## 405 0 0 2.2 autumn 3.7 0.84757266 0 0 0  
## 406 0 0 2.2 summer 9.5 0.00000000 0 1 0  
## 407 0 0 4.9 autumn 4.0 0.69460520 0 0 0  
## 408 0 0 4.0 winter 2.9 0.00000000 0 0 0  
## 409 0 1 3.1 autumn 7.4 0.94448267 0 0 0  
## 410 0 0 5.4 summer 12.1 0.00000000 0 1 0  
## 411 0 1 2.7 winter 2.7 0.00000000 0 0 0  
## 412 0 1 9.4 winter 3.3 0.74973632 0 0 0  
## 413 0 0 4.5 summer 9.8 0.41995575 0 1 1  
## 414 0 0 3.6 summer 8.4 0.00000000 0 1 0  
## 415 0 0 4.0 summer 10.1 0.00000000 0 1 0  
## 416 0 0 4.9 summer 13.9 2.87348336 0 1 0  
## 417 0 0 3.1 summer 8.9 0.90417437 0 1 0  
## 418 0 0 5.8 spring 9.9 0.00000000 0 0 0  
## 419 0 0 5.4 summer 8.1 0.53655844 0 1 0  
## 420 0 0 4.0 summer 7.6 0.60745502 0 1 0  
## 421 0 0 4.5 summer 7.8 2.27128387 0 1 0  
## 422 0 0 4.5 summer 18.0 0.00000000 0 1 0  
## 423 0 0 3.6 summer 5.2 0.86332286 0 1 0  
## 424 0 0 4.0 autumn 8.4 0.23552845 0 0 0  
## 425 0 0 3.6 summer 8.4 0.77524626 0 1 0  
## 426 0 0 2.2 summer 6.3 0.00000000 0 1 0  
## 427 0 0 2.2 summer 6.3 0.00000000 0 1 0  
## 428 0 0 2.2 summer 8.2 0.52504481 0 1 1  
## 429 0 0 5.8 summer 13.9 0.00000000 0 1 0  
## 430 0 0 4.0 summer 7.6 0.62324929 0 1 0  
## 431 0 0 3.6 autumn 6.8 0.00000000 0 0 0  
## 432 0 0 4.0 summer 9.6 0.86687781 0 1 0  
## 433 0 0 6.7 summer 13.9 0.00000000 0 1 0  
## 434 0 0 4.9 summer 10.1 1.21325205 0 1 0  
## 435 0 1 3.6 summer 5.5 0.00000000 0 1 0  
## 436 0 0 1.8 summer 5.6 0.00000000 0 1 0  
## 437 0 0 1.3 summer 8.2 0.18752072 0 1 1  
## 438 0 0 2.7 summer 9.7 0.00000000 0 1 0  
## 439 0 0 4.0 summer 8.4 0.87098881 0 1 0  
## 440 0 1 2.2 autumn 7.2 0.12385164 0 0 0  
## 441 0 1 3.6 autumn 7.4 0.00000000 0 0 0  
## 442 0 0 1.8 summer 8.2 0.34830486 0 1 1  
## 443 0 0 3.1 spring 3.7 0.63848926 1 0 1  
## 444 0 1 8.0 summer 16.8 0.00000000 0 1 0  
## 445 0 1 3.6 autumn 7.4 1.03981055 0 0 0  
## 446 0 0 4.5 summer 10.7 0.00000000 0 1 0  
## 447 0 0 2.2 summer 8.1 0.00000000 0 1 0  
## 448 0 0 8.0 spring 9.9 0.00000000 0 0 0  
## 449 0 0 4.0 autumn 10.1 0.00000000 0 0 0  
## 450 0 0 4.9 summer 7.6 0.00000000 0 1 0  
## 451 0 0 5.4 summer 18.0 0.87098881 0 1 0  
## 452 0 1 4.9 summer 16.3 1.02978947 0 1 0  
## 453 0 0 4.0 summer 7.5 0.00000000 0 1 1  
## 454 0 0 3.1 summer 5.6 0.00000000 0 1 0  
## 455 0 0 3.1 summer 6.3 0.00000000 0 1 0  
## 456 0 0 2.7 summer 16.7 0.00000000 0 1 1  
## 457 0 0 2.7 summer 6.3 0.00000000 0 1 0  
## 458 0 0 4.0 summer 7.8 1.92298482 0 1 0  
## 459 0 0 4.9 summer 8.4 0.63548375 0 1 0  
## 460 0 0 8.0 summer 7.7 0.46834733 0 1 0  
## 461 0 0 4.9 summer 8.4 0.00000000 0 1 0  
## 462 0 0 4.9 summer 8.4 0.00000000 0 1 0  
## 463 0 0 7.6 autumn 7.1 0.67302091 0 0 0  
## 464 0 0 6.3 winter 1.9 0.80550086 0 0 0  
## 465 0 0 5.4 winter 1.9 0.49692965 0 0 0  
## 466 0 0 0.9 winter 1.8 0.89431606 0 0 0  
## 467 0 0 5.8 spring 7.1 0.62117628 0 0 1  
## 468 0 0 5.4 spring 7.3 0.81624130 0 0 0  
## 469 0 0 3.6 spring 8.5 0.88138466 0 0 0  
## 470 0 0 9.4 spring 12.3 1.79330135 1 0 0  
## 471 0 0 5.8 spring 12.3 0.00000000 1 0 0  
## 472 0 1 4.0 spring 5.7 1.59637714 0 0 0  
## 473 1 0 4.0 summer 4.7 0.46834733 0 1 1  
## 474 1 0 3.1 summer 9.4 1.85321133 0 1 0  
## 475 1 0 2.7 summer 10.8 1.04453976 0 1 0  
## 476 1 0 9.4 summer 18.0 0.62221402 0 1 0  
## 477 0 0 1.3 summer 9.9 0.44090908 0 1 0  
## 478 0 0 4.0 summer 14.7 0.92220628 0 1 0  
## 479 0 0 4.5 summer 14.7 0.50650503 0 1 0  
## 480 0 0 4.9 summer 6.4 2.44642842 0 1 1  
## 481 0 0 4.5 summer 9.5 0.57403127 0 1 0  
## 482 0 0 4.9 summer 9.5 0.00000000 0 1 0  
## 483 0 0 5.8 summer 14.1 0.35983548 0 1 0  
## 484 0 0 5.4 summer 14.1 0.00000000 0 1 0  
## 485 0 0 4.0 summer 14.1 1.43822581 0 1 0  
## 486 0 0 3.6 summer 21.3 0.48713838 0 1 1  
## 487 0 0 6.3 summer 17.7 0.47712125 0 1 0  
## 488 0 0 3.6 summer 17.7 1.24054925 0 1 0  
## 489 0 0 7.6 summer 17.7 1.67851838 0 1 0  
## 490 0 0 1.3 summer 17.7 0.00000000 0 1 0  
## 491 0 0 4.0 summer 17.7 0.00000000 0 1 0  
## 492 0 0 4.5 summer 13.8 0.00000000 0 1 0  
## 493 0 1 2.2 summer 11.3 0.00000000 0 1 0  
## 494 0 1 4.5 summer 11.3 1.64659975 0 1 0  
## 495 0 0 4.9 summer 14.0 0.98181861 0 1 0  
## 496 0 0 2.2 summer 16.8 0.00000000 0 1 1  
## 497 0 0 3.1 summer 16.8 0.57634135 0 1 1  
## 498 0 0 2.2 summer 14.3 1.19534606 0 1 0  
## 499 0 0 2.7 summer 14.3 1.61846649 0 1 0  
## 500 0 0 4.9 summer 14.3 1.07261748 0 1 0  
## 501 0 0 4.9 summer 14.3 0.00000000 0 1 0  
## 502 0 0 4.9 summer 14.3 0.00000000 0 1 0  
## 503 0 0 4.9 summer 14.3 0.00000000 0 1 0  
## 504 0 0 4.9 summer 20.0 0.46982202 0 1 0  
## 505 0 0 4.9 summer 20.0 1.70406468 0 1 0  
## 506 0 0 1.8 summer 10.1 0.83250891 0 1 0  
## 507 0 1 8.5 summer 7.1 0.00000000 0 1 0  
## 508 0 1 3.6 summer 7.1 0.00000000 0 1 0  
## 509 0 1 3.6 summer 7.1 0.00000000 0 1 0  
## 510 0 1 7.6 summer 7.1 0.50105926 0 1 0  
## 511 0 1 5.4 summer 7.1 0.15533604 0 1 0  
## 512 0 0 2.7 summer 1.9 0.00000000 0 1 0  
## 513 0 0 2.7 summer 1.9 0.87157294 0 1 0  
## 514 0 0 5.8 summer 1.9 1.74264659 0 1 0  
## 515 0 0 6.7 summer 1.9 1.08493357 0 1 0  
## 516 0 0 4.0 summer 11.3 0.00000000 0 1 0  
## 517 0 0 4.5 autumn 1.1 0.00000000 0 0 0

predictions <- predict(model,data\_train)  
print(predictions)

## 1 2 3 5 6   
## 2.245248e-01 5.498930e-01 4.172835e-01 2.444213e-01 4.959109e-01   
## 7 8 9 10 11   
## 4.500334e-01 1.944010e-01 6.864527e-01 6.286623e-01 6.395904e-01   
## 12 13 15 17 19   
## 4.270211e-01 2.393626e-01 8.177307e-01 3.108054e-01 4.057253e-01   
## 21 22 23 24 25   
## 7.070954e-01 4.163850e-01 3.343290e-01 5.636163e-01 5.711311e-01   
## 26 27 28 29 31   
## 5.167352e-01 6.673410e-01 5.926449e-01 8.676769e-01 6.076642e-01   
## 32 33 36 38 39   
## 5.547580e-01 4.808186e-01 6.682298e-01 4.362910e-01 5.861146e-01   
## 40 43 44 45 46   
## 3.273117e-01 3.621565e-01 4.949507e-01 4.722937e-01 5.902437e-01   
## 47 48 49 50 51   
## 4.604658e-01 2.973533e-01 1.278956e-01 2.640349e-01 5.280887e-01   
## 52 53 54 56 57   
## 3.585904e-01 4.553078e-01 4.553078e-01 7.173694e-01 6.192710e-01   
## 59 61 63 68 69   
## 5.361434e-01 3.149085e-01 4.100898e-01 6.049424e-01 6.311058e-01   
## 70 71 72 73 74   
## 2.414243e-01 3.027463e-01 3.504915e-01 3.291599e-01 5.213231e-01   
## 75 76 77 78 79   
## 6.390449e-01 2.712473e-01 4.107310e-01 1.086986e-01 2.327817e-01   
## 80 81 82 83 84   
## 6.141988e-01 4.996524e-01 2.567396e-01 3.629117e-01 2.307973e-01   
## 85 86 88 89 90   
## 3.107329e-01 5.209758e-01 5.854783e-01 7.358555e-01 3.628192e-01   
## 91 92 93 94 96   
## 3.042326e-01 3.511956e-01 4.990416e-01 4.787341e-01 4.563680e-01   
## 97 98 100 102 103   
## 3.986945e-01 3.087116e-01 4.584632e-01 4.552361e-01 3.212550e-01   
## 106 107 108 109 110   
## 2.402576e-01 2.447117e-01 3.080033e-01 4.800348e-01 4.593464e-01   
## 111 113 114 115 116   
## 2.754812e-01 5.703201e-01 3.570569e-01 4.636524e-01 3.833524e-01   
## 117 118 119 120 121   
## 2.599472e-01 2.811571e-01 1.517808e-01 3.250977e-01 1.674141e-01   
## 122 123 124 125 127   
## 3.629679e-01 6.990975e-01 5.325759e-01 4.574849e-01 6.149524e-02   
## 128 130 131 132 133   
## 4.655506e-01 2.587043e-01 3.847115e-01 1.324235e-01 1.820814e-01   
## 135 136 137 138 139   
## 2.743533e-01 3.293331e-01 4.209400e-01 4.054716e-01 3.938223e-01   
## 140 141 142 143 144   
## 6.162846e-01 4.738120e-01 5.194007e-01 5.598234e-01 4.095490e-01   
## 146 147 149 150 151   
## 5.494913e-01 2.981990e-01 4.281549e-01 5.492333e-01 2.836788e-01   
## 152 153 154 155 156   
## 4.206472e-01 3.305042e-01 5.006320e-01 6.491477e-01 2.447331e-01   
## 158 159 160 161 163   
## 3.670009e-01 3.356352e-01 6.673410e-01 3.304130e-01 5.207627e-01   
## 165 166 167 168 169   
## 5.552054e-01 1.366717e-01 2.543941e-01 5.419725e-01 3.873868e-01   
## 170 171 173 174 175   
## 4.087330e-01 6.778489e-01 5.719394e-01 5.025175e-01 7.769139e-02   
## 176 177 179 180 181   
## 2.676382e-01 3.950332e-01 3.814359e-01 5.160402e-01 7.390600e-01   
## 183 184 185 187 190   
## 4.788643e-01 5.006591e-01 4.349692e-01 3.283418e-01 3.542787e-01   
## 191 192 193 195 196   
## 1.831429e-01 3.503912e-01 4.794849e-01 4.794849e-01 3.732980e-01   
## 197 198 199 200 201   
## 3.950332e-01 4.904852e-01 6.636734e-01 4.493582e-01 5.744663e-01   
## 204 205 206 207 208   
## 5.783274e-01 2.682838e-01 5.380583e-01 5.363201e-01 7.231002e-01   
## 209 210 212 213 215   
## 6.276589e-01 6.642167e-01 2.788577e-01 5.547194e-01 3.400083e-01   
## 217 219 220 221 222   
## 5.182346e-01 5.457848e-01 2.491207e-01 3.018717e-01 5.035894e-01   
## 223 224 225 226 227   
## 3.012421e-01 5.225500e-01 5.763041e-01 7.396601e-01 4.359783e-01   
## 231 233 234 235 236   
## 8.008506e-01 7.158701e-01 8.028121e-01 5.088947e-01 5.284989e-01   
## 237 238 239 240 241   
## 5.494178e-01 6.405915e-01 7.210470e-01 5.125461e-01 6.592404e-01   
## 242 243 244 245 246   
## 4.665298e-01 2.835627e-01 6.735915e-01 5.243253e-01 5.822282e-01   
## 247 248 249 250 252   
## 5.912832e-01 3.857462e-01 5.996702e-01 3.551342e-01 5.700033e-01   
## 253 254 255 256 258   
## 4.974453e-01 4.467163e-01 4.554621e-01 1.626312e-01 4.210526e-01   
## 259 262 263 265 266   
## 3.089480e-01 3.025902e-01 3.010821e-01 3.833712e-01 6.011572e-01   
## 267 269 270 272 273   
## 4.390526e-01 4.363221e-01 4.301080e-01 5.367100e-01 3.926299e-01   
## 274 276 277 278 280   
## 1.096683e+00 9.887721e-01 1.122554e+00 1.095510e+00 1.122554e+00   
## 281 282 284 285 286   
## 9.046534e-01 1.272734e+00 4.269914e-01 4.824524e-01 6.413725e-01   
## 287 288 289 290 291   
## 6.616550e-01 4.891550e-01 4.904307e-01 4.910602e-01 2.327602e-01   
## 292 294 295 296 297   
## 5.417743e-01 8.551722e-01 4.755009e-01 5.001775e-01 3.144226e-01   
## 298 299 300 301 302   
## 3.245928e-01 5.432731e-01 2.146729e-01 4.135920e-01 4.078171e-01   
## 303 305 306 307 308   
## 3.160883e-01 7.672522e-01 3.885811e-01 6.108631e-01 5.585173e-01   
## 309 310 311 312 314   
## 3.406084e-01 4.992682e-01 6.560904e-01 6.318240e-01 6.931487e-01   
## 315 316 317 318 319   
## 5.128278e-01 5.022382e-01 4.694425e-01 4.910889e-01 4.967958e-01   
## 320 321 322 323 324   
## 6.267168e-01 6.728328e-01 3.668601e-01 4.648715e-01 2.919393e-01   
## 325 328 329 330 331   
## 2.623006e-01 4.972025e-01 4.607746e-01 6.076551e-01 5.668176e-01   
## 332 333 334 335 337   
## 6.431896e-01 4.248394e-01 3.336250e-01 4.922010e-01 5.161776e-01   
## 340 341 342 343 345   
## 3.870622e-01 3.437516e-01 4.102981e-01 5.397254e-01 4.979043e-01   
## 346 347 349 350 351   
## 4.428131e-01 3.901596e-01 4.148577e-01 3.654777e-01 3.240234e-01   
## 352 353 354 355 356   
## 4.566113e-01 5.454526e-01 5.074278e-01 4.751611e-01 5.010966e-01   
## 359 360 361 363 364   
## 5.244049e-01 3.621828e-01 4.141895e-01 3.385811e-01 5.411741e-01   
## 365 367 368 369 370   
## 6.170319e-01 5.260431e-01 4.762950e-01 4.921104e-01 8.530369e-01   
## 371 373 374 375 378   
## 9.713753e-01 2.748893e-01 4.941728e-01 6.853568e-01 5.616187e-01   
## 379 380 381 382 384   
## 2.268907e-01 -4.857226e-16 5.622168e-01 4.564056e-01 5.941886e-01   
## 386 387 388 389 391   
## 4.617177e-01 5.319847e-01 2.377577e-01 5.772036e-01 4.974555e-01   
## 393 394 395 396 397   
## 8.654609e-01 3.959827e-01 2.704689e-01 3.442583e-01 5.781663e-01   
## 398 399 401 402 404   
## 5.595440e-01 6.257335e-01 5.767613e-01 5.013648e-01 5.601764e-01   
## 405 406 408 409 410   
## 4.980544e-01 7.274621e-01 4.577244e-01 8.298209e-01 4.912464e-01   
## 411 412 414 416 417   
## 5.123108e-01 5.838759e-01 7.003135e-01 6.835420e-01 7.243892e-01   
## 418 419 420 421 423   
## 3.746707e-01 6.262820e-01 5.377901e-01 6.726135e-01 7.156194e-01   
## 424 425 426 427 429   
## 5.029011e-01 6.978477e-01 5.362717e-01 5.497050e-01 6.130306e-01   
## 430 431 432 433 434   
## 6.030573e-01 9.004326e-01 5.320038e-01 6.785107e-01 5.703626e-01   
## 435 436 437 438 439   
## 4.861768e-01 3.769414e-01 5.752308e-01 4.623886e-01 5.386208e-01   
## 440 441 443 444 445   
## 3.558132e-01 7.767738e-01 4.547658e-01 3.858418e-01 6.584354e-01   
## 446 447 448 452 453   
## 6.282542e-01 5.176602e-01 3.143715e-01 2.651687e-01 5.839038e-01   
## 454 455 456 457 458   
## 4.506099e-01 4.514493e-01 2.826318e-01 4.109497e-01 5.142385e-01   
## 459 460 461 462 463   
## 6.130434e-01 7.070750e-01 4.879882e-01 6.130434e-01 8.209137e-01   
## 465 467 468 469 470   
## 5.453814e-01 2.230898e-01 2.845179e-01 2.216235e-01 7.388233e-01   
## 471 472 473 474 475   
## 6.354221e-01 8.291250e-01 5.094494e-01 5.479462e-01 4.814374e-01   
## 476 477 478 479 480   
## 4.563058e-01 4.804367e-01 5.733380e-01 5.132435e-01 5.780448e-01   
## 482 484 485 486 487   
## 5.674671e-01 6.802288e-01 5.504462e-01 4.436086e-01 6.470422e-01   
## 488 489 490 491 492   
## 6.040757e-01 5.906637e-01 3.911786e-01 5.985820e-01 6.246365e-01   
## 493 494 495 496 497   
## 5.190253e-01 5.004379e-01 6.268438e-01 3.931953e-01 5.471135e-01   
## 498 499 500 501 503   
## 6.691045e-01 7.446657e-01 8.279690e-01 6.505962e-01 5.983771e-01   
## 504 505 506 507 508   
## 4.900479e-01 5.754726e-01 3.864567e-01 4.583581e-01 3.811046e-01   
## 509 511 512 513 514   
## 4.284754e-01 3.802787e-01 3.653566e-01 3.670971e-01 2.838462e-01   
## 515   
## 4.322899e-01

accuracy <- mean(predictions == data\_train$log\_area)  
print(summary(model))

##   
## Call:  
## lm(formula = log\_area ~ X + Y + FFMC + DMC + DC + ISI + temp +   
## RH + wind + rain + is\_weekend + monthjan + monthfeb + monthmar +   
## monthapr + monthmay + monthjun + monthjul + monthaug + monthsep +   
## monthnov + monthdec + daysun + daymon + daytue + daywed +   
## daythu + dayfri + daysat + seasonautumn + seasonspring +   
## seasonsummer + seasonwinter, data = data\_train)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -0.9004 -0.4584 -0.2052 0.3708 2.3171   
##   
## Coefficients: (7 not defined because of singularities)  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.3463300 1.0976408 0.316 0.7525   
## X 0.0270437 0.0163841 1.651 0.0996 .  
## Y -0.0372073 0.0312072 -1.192 0.2339   
## FFMC 0.0019629 0.0102001 0.192 0.8475   
## DMC 0.0022779 0.0009239 2.466 0.0141 \*  
## DC -0.0008202 0.0006249 -1.313 0.1901   
## ISI -0.0060464 0.0087832 -0.688 0.4916   
## temp 0.0176708 0.0108898 1.623 0.1055   
## RH 0.0005688 0.0030466 0.187 0.8520   
## wind 0.0290704 0.0183688 1.583 0.1143   
## rain 0.0120756 0.0973777 0.124 0.9014   
## is\_weekend1 0.0424702 0.1088631 0.390 0.6967   
## monthjan -0.4011065 1.0003722 -0.401 0.6887   
## monthfeb -0.3688777 0.4754140 -0.776 0.4383   
## monthmar -0.6144571 0.4445389 -1.382 0.1677   
## monthapr -0.3678684 0.4977298 -0.739 0.4603   
## monthmay -0.1096880 0.6116264 -0.179 0.8578   
## monthjun -0.5397086 0.3877830 -1.392 0.1648   
## monthjul -0.4102221 0.3225654 -1.272 0.2042   
## monthaug -0.3547009 0.2629916 -1.349 0.1782   
## monthsep -0.0714129 0.2348547 -0.304 0.7612   
## monthnov NA NA NA NA   
## monthdec 0.5454392 0.4062269 1.343 0.1802   
## daysun 0.0166133 0.1061570 0.156 0.8757   
## daymon 0.0081763 0.1138367 0.072 0.9428   
## daytue 0.1309337 0.1140599 1.148 0.2517   
## daywed 0.1007815 0.1233093 0.817 0.4143   
## daythu 0.0194258 0.1153059 0.168 0.8663   
## dayfri NA NA NA NA   
## daysat NA NA NA NA   
## seasonautumn NA NA NA NA   
## seasonspring NA NA NA NA   
## seasonsummer NA NA NA NA   
## seasonwinter NA NA NA NA   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.6106 on 389 degrees of freedom  
## Multiple R-squared: 0.07981, Adjusted R-squared: 0.01831   
## F-statistic: 1.298 on 26 and 389 DF, p-value: 0.1524

cat("Accuracy:", accuracy, "\n")

## Accuracy: 0

print(mean(summary(model)$residuals^2))

## [1] 0.3485858

# Introduction

Forest fires are a common occurrence worldwide due to climate change, which results in severe economic losses and ecological destruction. Forest fires can be natural or man-made forest fires and summer forest fires caused by debris and other biomes, as well as human negligence. Even though, wildfires can benefit local vegetation, animals, and ecosystems, but they can also cause major damage to property and human life. In recent years, the frequency of forest fire accidents has been continuously increasing. Hence, there has been a rise in interest of implementing systems for automated observation and detection of forest fires, as a means of protecting forests from destruction.

There are a number of conventional and cutting-edge fire and smoke detection techniques that have been proposed to reduce damage brought on by fire disasters. Sensor-based and vision-based smoke detection systems have garnered a lot of interest in the research community among these techniques. Based on sensor types and applications, the fire detection technique is split into five basic groups: smoke-sensitive, light-sensitive, gas-sensitive, temperature-sensitive, and composite . Temperature and smoke sensors are frequently used for this purpose. The sensor-based approach has significant limitations in terms of detection range and detection speed. Since fire spreads quickly, it is important to keep the delay as short as possible. Then, as video surveillance technology came up, researchers gathered fire images and used their color characteristics to look for fires. Orange or yellow flames moving side to side are the most common visual representations of fire in videos and images. Soot or burnt particles can be seen in smoke as a blend of white, gray, and black plumes. Smoke detection in videos and images has its own set of difficulties. To be effective, a system must be able to find the difference between images that truly contain the fire and those that appear to have flames but are not. False alarm rates are higher when using simple color features for fire detection .

In this project,however, we will create Regression models to predict the initiation of forest fires (potentially, before they are brought about) .

# METHODOLOGY

## Data Collection:

The dataset has been taken from the “Forest Fires Data Set” by ‘Ahiale Darlington’, which is actually taken from the “UC Irvine Machine Learning Repository” . The characteristics of the dataset, including variables recorded(like.,month day temp humidity wind rainfall, etc). There is no need for pre-processing being done explicitly, as there are no null values in the data and is ready for analysis.

## Exploratory Data Analysis:

We have used ‘ggplot2’ from R packages, for visualizations and ‘dplyr’ for data manipulation.

In order to visualise the park, in terms of fire susceptibility, a heat map was generated using the ggplot() and geom\_tile() layers. Most of the attribute’s values in the data seemed to overlap and skewed towards their minimal values,including the “area” attribute, which consists of values that are very close to zero, the most.

## Feature Engineering:

Since the “area” attribute’s values were very close to zero and overlapped,they might not be differentiated that well. Hence, we have considered a new attribute ,taking the logarithm of the “area” attribute (calling it “log\_area”).

We performed in-max scaling to Scale numerical features to a range between 0 and 1 (which did not show much of an effect on the data, due to it already being preprocessed, in one form.)

We have considered the “day” attribute values and generated a new attribute called the “is\_weekend”, that would have a value of 1 , if the day was either a “Saturday” or “Sunday”, and a value of 0, otherwise. Also, we have extracted the season from the data to capture seasonal patterns in forest fires and also determined whether forest fires are more prevalent on certain days from the dataset. (We had categorize dates into seasons - spring,summer,fall,winter - based on the month.)

## Model Selection and Training:

We have used a linear regression model for forest fire prediction , to begin with. We use a caret package to train a linear regression model using the method argument the formula used for the regression model is ” log\_area - X+Y+temp+RH+wind+rain+FFMC+DMC+DC+ISI”.

Then, we have used an SVM model with a radial kernel, to obtain a predictive model, using the same formula (oweing to the non-linearity in the data).

We have also decided to use a Decision Tree model and a Random Forest model as well, oweing to the number of attributes in the data.

## Model Evaluation:

Assess the performance of the trained models using various evaluation metrics such as Mean Squared Error and R-Squared Error. Resampling methods such as cross-validation can also be used/performed. Both caret and stats packages offer comprehensive tools for linear regression modelling and evaluation in R, allowing to choose the one that best fits the task’s purpose.

## Implementation:

We used the train() function from the caret package to train a linear regression model. Apart from that, we have also used the lm() function from the minpack package, to create a linear model.

We subsequently used the svm() function from the e1071 library.

Then, we used the rpart() function from the rpart library, to create a CART (Classification and Regression Tree, a type of decision tree ).

Finally, we used the randomForest() function from the randomForest library, to build a Random Forest, for the data.

Data can be given to these models for prediction, through the predict() function; and the varous parameters/coefficients of the models can be displayed using the summary() function.

## Validation and Sensitivity Analysis:

Validation and sensitivity analysis are crucial steps in assessing the robustness and generalizability of a linear regression model trained on the forest fires dataset.Used cross-validation to validate the performance of the linear regression model on unseen data.

## Ethical Considerations:

We must ensure that the analysis and any resulting actions or recommendations prioritize environmental conservation and sustainability. It has to be entailed that there are limitations and uncertainties associated with predictive models, because they deal with data that might not be fully furnished , and even if it is, these models deal with predicting values associated with events that are not entirely certain.Therefore, embracing a culture of continuous learning and improvement in forest fire management and analysis, would lead to ideas being formulated and executed actively and sensibly. Staying informed about emerging research, best practices, and technological advancements in the field, and being open to adapting approaches based on new evidence and insights, would lead to finding better and implementing ways or actions or policies to deal with forest fires. Model Selection and Training:} We have used a linear regression model for forest fire prediction , to begin with. We use a caret package to train a linear regression model using the method argument the formula used for the regression model is ” log\_area - X+Y+temp+RH+wind+rain+FFMC+DMC+DC+ISI”.

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# RESULTS

We generated the correlations between various attributes, so as to better understand the relationships between them and how they affect forest fires ## The various models that were considered gave the following performance when trained on a subset of the data.

# CONCLUSION AND FUTURE SCOPE

## CONCLUSION

Seasonal Variations: The analysis revealed distinct seasonal patterns in forest fires, with the majority of incidents occurring during the summer and autumn months.

Weather Factors: Variables such as temperature, relative humidity, wind speed, and rainfall demonstrated significant associations with the severity of forest fires.

Moisture: Variables such as the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DC) , Drought Code (DC) and Initial Spread Index (ISI) from the FWI System , indicated that the presence of moisture in the soil ( in the upper layers of the soil , the lower layers of the soil and amidst/amongst litter) affects the spread of forest fires. Thus,dry leaves,animal and plant wastes and plastic alongside other forms of litter contribute to the spread of forest fires. (Though , logically, an increase in moisture leads to a decrease in the area burnt, the correlations in the data seem to suggest that log\_area values increase with an increase in moisture contents.)

Geospatial Distribution: Mapping the average burn area across different geographical coordinates highlighted region(s) with higher fire susceptibility.

Modeling: Various machine learning models were trained and evaluated to predict forest fire severity, with the Random Forests model performing better than the linear regression , decision trees and SVM models, on the basis of the Mean Square Errors given by them.

## FUTURE SCOPE

Data Augmentation: Incorporating additional datasets, such as satellite imagery or historical fire records, could enhance the accuracy and robustness of the analysis.

Feature Engineering: Exploring advanced feature engineering techniques and incorporating domain-specific knowledge may lead to better models.

Model Optimization: Further fine-tuning and optimization of machine learning models, including hyperparameter tuning and ensemble methods, could improve predictive performance.

Spatial Analysis: Conducting more detailed spatial analysis, including hotspot detection and spatial autocorrelation, may provide deeper insights into the spatial distribution of forest fires.

Real-time Monitoring: Developing a real-time monitoring system using IoT devices or remote sensing technology could aid in early detection and rapid response to forest fire incidents.