# DataMiningRajeevMoetwani

#### Problem 1

#### Question a

```
library(tidyverse)
## -- Attaching packages ---
## v ggplot2 3.2.1
                    v purrr
                                 0.3.2
## v tibble 2.1.3
                     v dplyr 0.8.3
## v tidyr 1.0.0 v stringr 1.4.0
## v readr
           1.3.1
                      v forcats 0.4.0
## -- Conflicts -----
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                     masks stats::lag()
library(ggplot2)
library(gridExtra)
## Attaching package: 'gridExtra'
## The following object is masked from 'package:dplyr':
##
##
       combine
forestFires_data <- read.csv("forestfires.csv")</pre>
forestFires_data$month <-</pre>
  forestFires_data$month %>% factor(
   levels = c(
      "jan",
      "feb",
      "mar",
      "apr",
      "may",
      "jun",
      "jul",
      "aug",
      "sep",
      "oct",
      "nov",
      "dec"
   )
  )
temp <- ggplot(forestFires_data, aes(y = area)) +</pre>
  geom_point(aes(x = temp), color = "pink") + ggtitle("Area vs Temperature") +
  xlab("Temperature in Celsius degrees") +
 ylab("Area")
```

month <- ggplot(forestFires\_data, aes(y = area)) +</pre>

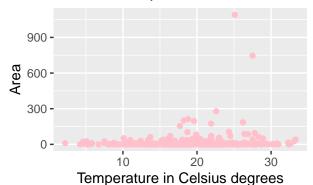
```
geom_point(aes(x = month), color = "green") + ggtitle("Area vs Month") +
    xlab("Month") +
    ylab("")

DC <- ggplot(forestFires_data, aes(y = area)) +
    geom_point(aes(x = DC), color = "blue") + ggtitle("Area vs DC") +
    xlab("DC index") +
    ylab("")

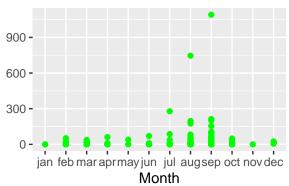
RH <- ggplot(forestFires_data, aes(y = area))+
    geom_point(aes(x = RH), color = "purple") + ggtitle("Area vs RH") +
    xlab("Relative Humidity in %") +
    ylab("")

grid.arrange(temp, month, DC, RH,ncol = 2)</pre>
```

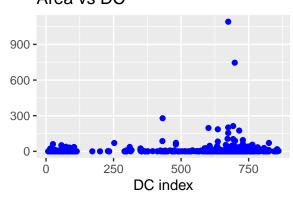
### Area vs Temperature



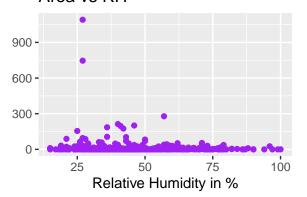
### Area vs Month



### Area vs DC



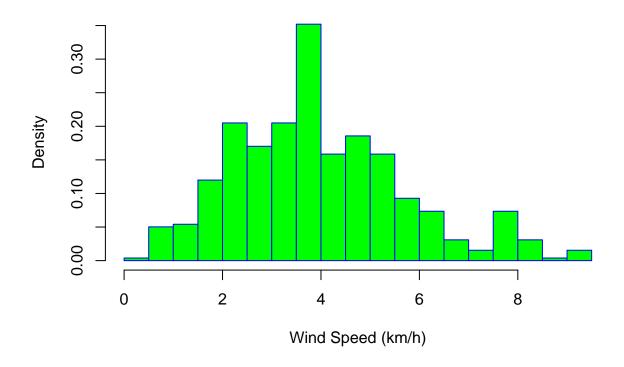
### Area vs RH



#### Question b

```
hist(x = forestFires_data$wind, prob = T,
    main = " Histogram of Wind Speed",
    breaks = 30,
    xlab = "Wind Speed (km/h)",
    col = "green",
    border = "blue")
```

# **Histogram of Wind Speed**



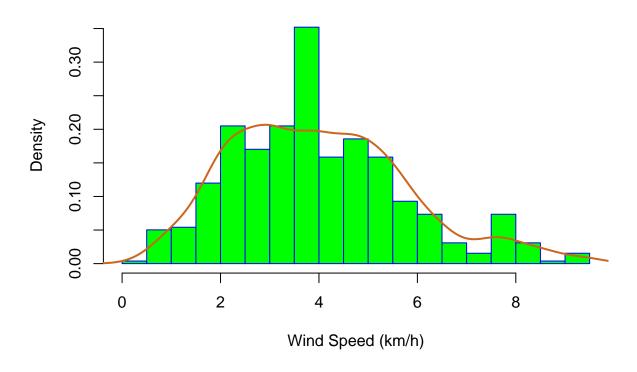
## ${\bf Question}~{\bf c}$

```
summary(forestFires_data$wind)
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.400 2.700 4.000 4.018 4.900 9.400
```

### Question d

```
hist(x = forestFires_data$wind, prob = T,
    main = " Histogram of Wind Speed",
    breaks = 30,
    xlab = "Wind Speed (km/h)",
    col = "green",
    border = "blue")
lines(density(forestFires_data$wind), col = "chocolate3", lwd = 2)
```

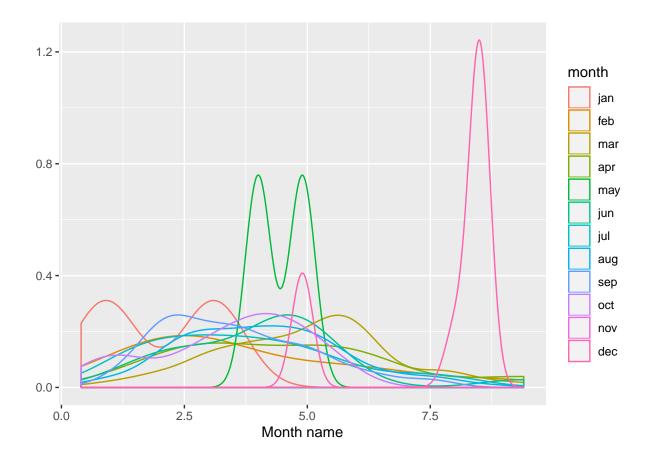
# **Histogram of Wind Speed**



# Question e

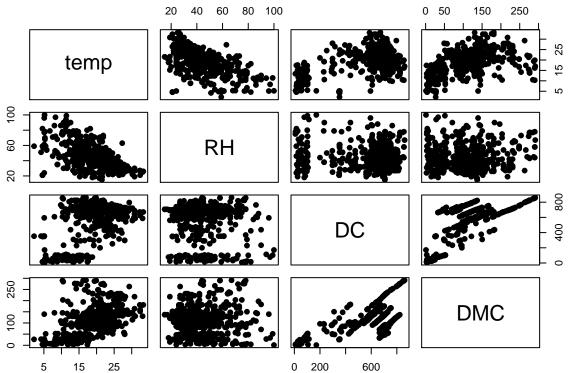
qplot(forestFires\_data\$wind, geom = "density", col = forestFires\_data\$month) + xlab("Month name") + lab

## Warning: Groups with fewer than two data points have been dropped.



# Question f

```
pairs(forestFires_data[,c("temp","RH","DC","DMC")], pch = 19)
```

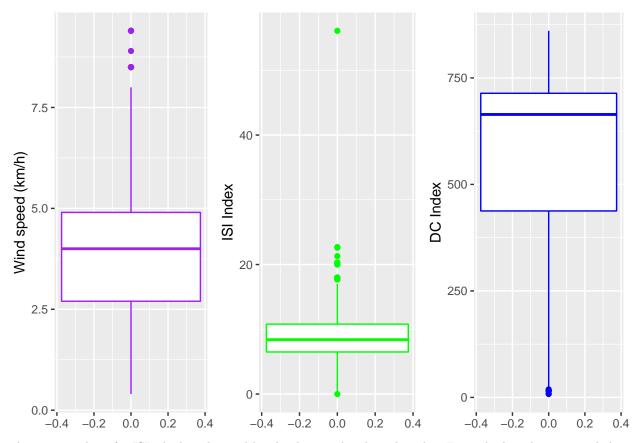


above scatter plot matrix we can clearly see a linear relation between DMC vs DC indexes while higher temperature results in lower  $\rm RH$ 

From the

#### Question g

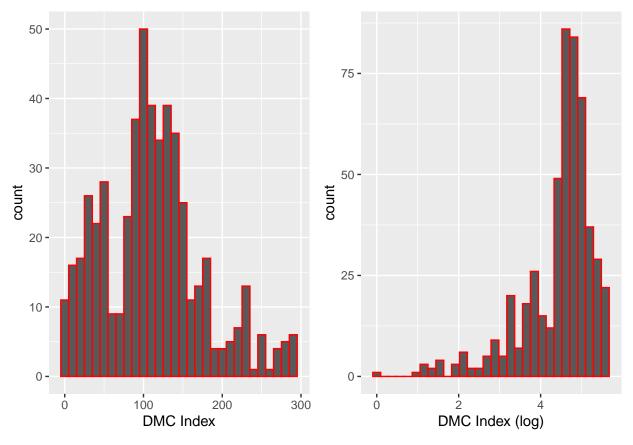
```
wind <- ggplot(forestFires_data)+
  geom_boxplot(aes(y = wind) , color = "purple") + ylab("Wind speed (km/h)")
ISI <- ggplot(forestFires_data)+
  geom_boxplot(aes(y = ISI), color = "green") + ylab("ISI Index")
DC <- ggplot(forestFires_data)+
  geom_boxplot(aes(y = DC), color = "blue") + ylab("DC Index")
grid.arrange(wind, ISI, DC, ncol = 3)</pre>
```



There are outliers for ISI which is denoted by the dots in the above boxplot, From the boxplot we can deduce that the median lies between 2.5 - 5 for wind, for ISI the median lies between 0-20 with the highest outlier above 40, fir DC the median lies between 500 - 750 with outliers near 0.

#### Question h

```
hist_wind <- ggplot(forestFires_data, aes(x = DMC))+
geom_histogram(bins = 30, colour = "red") + xlab("DMC Index")
hist_wind_log <- ggplot(forestFires_data, aes(x = log(DMC)))+
geom_histogram(bins = 30, colour = "red") + xlab("DMC Index (log)")
grid.arrange(hist_wind, hist_wind_log,ncol = 2)
```

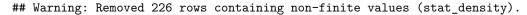


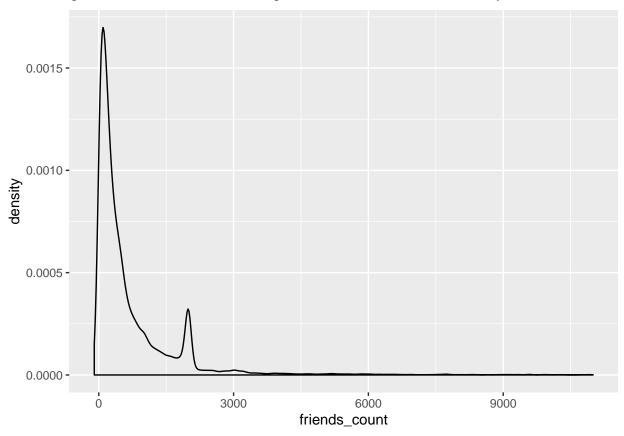
Applying log on the wind prevents spread of the large values in the data and thus results in a much more skewed graph as seen after applying log(DMC)

### Problem 2

### Question a

```
library(tidyverse)
library(ggplot2)
twitter_data <- read_csv("M01_quasi_twitter.csv")</pre>
## Parsed with column specification:
  cols(
##
##
     .default = col_double(),
     screen_name = col_character(),
##
##
     country = col_character(),
##
     location = col_character(),
##
     gender = col_character(),
     race = col_character()
## )
## See spec(...) for full column specifications.
ggplot(twitter_data) +
  geom_density(aes(x = friends_count)) +
  xlim(-100, 11000)
```





#### Question b

```
summary(twitter_data$friends_count)

## Min. 1st Qu. Median Mean 3rd Qu. Max.
## -84 123 324 1058 849 660549
```

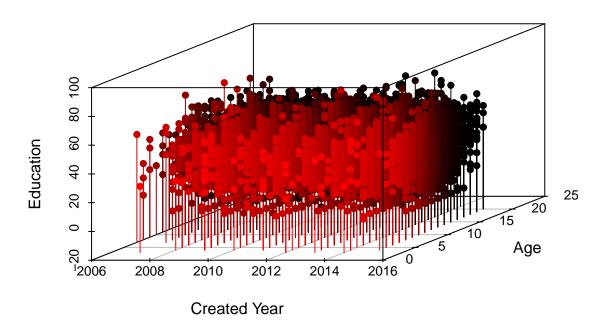
#### Question c

The Data is pretty right skewed with one negative value of -84 and a median of 324. A large number of entries consists of 0 friends which explains the peak at 0 in the above graph. Outliers were removed to depict the distribution amongst the values.

#### Question d

```
library("scatterplot3d")
scatterplot3d(twitter_data$created_at_year,twitter_data$education,twitter_data$age,
main="3D Scatter Plot",highlight.3d = TRUE,xlab='Created Year',ylab='',zlab='Education',type='h',pch=16
dims<-par('usr')
x <- dims[1] + 0.9*diff(dims[1:2])
y <- dims[3] + 0.08*diff(dims[3:4])
text(x,y,expression('Age'),srt=0)</pre>
```

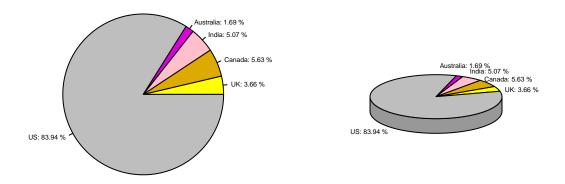
#### 3D Scatter Plot



#### Question e

```
library(tidyverse)
library(plotrix)
tweeter_accounts <-</pre>
  data.frame(
    Country = c('UK', 'Canada', 'India', 'Australia', 'US'),
    number_of_accounts = c(650, 1000, 900, 300, 14900)
  )
tweeter_accounts <-</pre>
  tweeter_accounts %>% mutate(pie_percent =
                                 paste(round(number_of_accounts / sum(tweeter_accounts$number_of_account
  unite(label_names, Country, pie_percent, sep = ": ")
cols <- c("yellow","#ddaa00","pink","#dd00dd","grey")</pre>
par(mfrow = c(1,2))
pie(tweeter_accounts$number_of_accounts, labels = tweeter_accounts$label_names,
    col = cols, radius = 0.9, main = "Simple Pie Chart", cex = 0.4)
pie3D(tweeter_accounts$number_of_accounts,
      radius = 0.9,
      labels = tweeter_accounts$label_names,
      col=cols,
      #shade = 0.6,
      labelcex = 0.4,
      start = 0.25
```

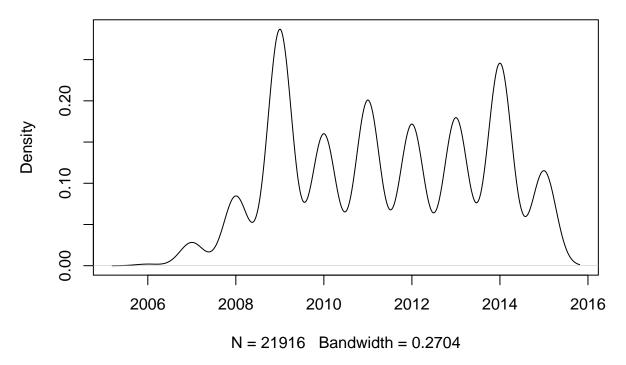
# **Simple Pie Chart**



### Question f

```
density_plot <- density(twitter_data$created_at_year)
plot(density_plot, main = 'Kernel Density plot for Created at year')</pre>
```

# Kernel Density plot for Created at year



From the density plot we can deduce that most of the twitter accounts were created after 2006 and it was which is correctly explained as twitter was invented in 2006, it peaked between 2008-2010 and 2014. It decreased gradually after 2014 which is clearly seen in the above graph.

#### Problem 3

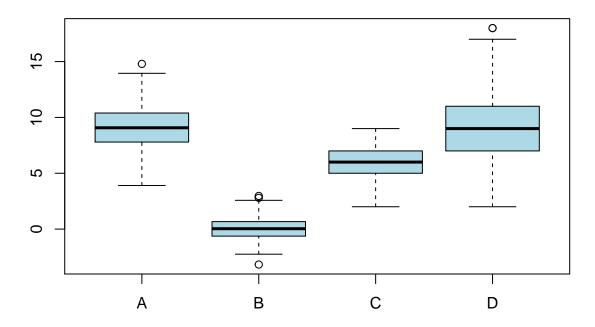
```
library(tidyverse)
library(scatterplot3d)
library(plotrix)
##### Reading the data
pc<-read_csv('raw_data.csv')</pre>
## Parsed with column specification:
## cols(
## A = col_double(),
##
   B = col double(),
   C = col_double(),
##
   D = col_double()
## )
head(pc)
## # A tibble: 6 x 4
                     С
                            D
##
       Α
              В
     <dbl> <dbl> <dbl> <dbl> <
##
## 1 8.26 -0.656
## 2 10.6 -0.716
                     7
                           8
## 3 8.74 0.800
                          5
## 4 6.56 1.58
                   6 10
## 5 9.36 1.03
                     7
                          8
                          12
## 6 9.02 0.720
Question a
##### Using min-max Normalization method
normalize<-function(x){</pre>
  return ((x-min(x))/(max(x)-min(x)))
##### Normalizing data
Ndata<-normalize(pc)
Ndata<-as.data.frame(Ndata)</pre>
head(Ndata)
                      В
                                 С
             Α
## 1 0.5399150 0.1190059 0.4333251 0.5277709
## 2 0.6485377 0.1161841 0.4805480 0.5277709
## 3 0.5629147 0.1877476 0.4805480 0.3861022
```

## 4 0.4595352 0.2247518 0.4333251 0.6222167 ## 5 0.5920942 0.1984951 0.4805480 0.5277709 ## 6 0.5759700 0.1839746 0.4805480 0.7166625

## Question b.

```
#### Box plot for unnormalized data
boxplot(pc[,],main='Box plot for Unnormalized data',col='light blue')
```

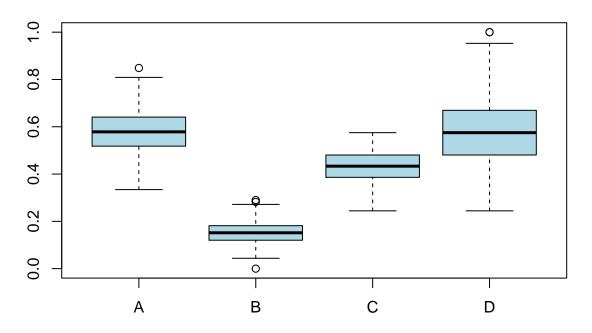
# Box plot for Unnormalized data



# ${\bf Question}~{\bf c}$

```
##### Boxplot for Normalized data
boxplot(Ndata[,],main='Box plot for Normalized data',col='light blue')
```

# **Box plot for Normalized data**



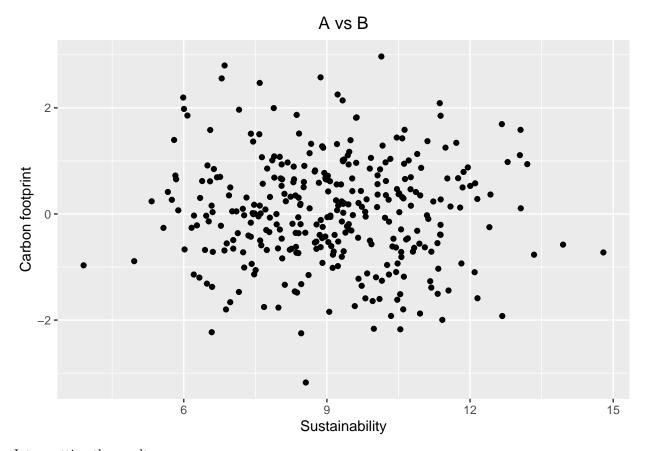
## Question d

Interpreting the results

The difference between two box plot is the range of data points, the normalized data ranges between 0 and 1 for all the variables, while the unnormalized data has different range of data points for all variables. Normalization helps in better visualization of datas and makes optimization algorithm to run faster.

#### Question e.

```
##### Plotting scatter plot
ggplot(pc,aes(x=`A`,y = `B`))+geom_point()+xlab('Sustainability')+ylab('Carbon footprint')+ggtitle('A
```



#### Interpretting the results:

The variables Sustainability and Carbon Footprints(A and B) have no association. The data points are spreaded randomly in the plot indicating there is no correlation between variables.