

Weather Report of Australia

25/03/2021

Dataset: Australian weather report from 10years.

The task begins with loading the packages and the weatherAUS dataset.

The dataset consists of 145460 rows and 23 columns.

Dataset loaded and NA values removed – currently 56420 rows.

there are total of 3,00,000+ NA values all over the dataset.

```
data <- data[complete.cases(data),]
```

this is the syntax for removing the NA values.

The following are the columns of the dataset:

```
names(data)
```

```
## [1] "Date"           "Location"        "MinTemp"         "MaxTemp"
## [5] "Rainfall"       "Evaporation"     "Sunshine"        "WindGustDir"
## [9] "WindGustSpeed"  "WindDir9am"      "WindDir3pm"      "WindSpeed9am"
## [13] "WindSpeed3pm"   "Humidity9am"     "Humidity3pm"     "Pressure9am"
## [17] "Pressure3pm"    "Cloud9am"        "Cloud3pm"        "Temp9am"
## [21] "Temp3pm"        "RainToday"       "RainTomorrow"
```

Basic statistics of the dataset includes minimum value, maximum value , median , 1st quadrant, 3rd quadrant, length etc;

```
summary(data)
```

```
##      Date           Location           MinTemp           MaxTemp
## Length:56420      Length:56420      Min.   :-6.70      Min.    : 4.10
## Class :character  Class :character  1st Qu.: 8.60      1st Qu.:18.70
## Mode  :character  Mode  :character  Median :13.20     Median :23.90
##                                     Mean   :13.46     Mean   :24.22
##                                     3rd Qu.:18.40     3rd Qu.:29.70
##                                     Max.    :31.40     Max.    :48.10
##      Rainfall       Evaporation       Sunshine       WindGustDir
## Min.   : 0.00      Min.   : 0.000      Min.   : 0.000      Length:56420
## 1st Qu.: 0.00      1st Qu.: 2.800      1st Qu.: 5.000      Class :character
## Median : 0.00      Median : 5.000      Median : 8.600      Mode  :character
```

```
## Mean : 2.13 Mean : 5.503 Mean : 7.736
## 3rd Qu.: 0.60 3rd Qu.: 7.400 3rd Qu.:10.700
## Max. :206.20 Max. :81.200 Max. :14.500
## WindGustSpeed WindDir9am WindDir3pm WindSpeed9am
## Min. : 9.00 Length:56420 Length:56420 Min. : 2.00
## 1st Qu.: 31.00 Class :character Class :character 1st Qu.: 9.00
## Median : 39.00 Mode :character Mode :character Median :15.00
## Mean : 40.88 Mean :15.67
## 3rd Qu.: 48.00 3rd Qu.:20.00
## Max. :124.00 Max. :67.00
## WindSpeed3pm Humidity9am Humidity3pm Pressure9am
## Min. : 2.00 Min. : 0.00 Min. : 0.0 Min. : 980.5
## 1st Qu.:13.00 1st Qu.: 55.00 1st Qu.: 35.0 1st Qu.:1012.7
## Median :19.00 Median : 67.00 Median : 50.0 Median :1017.2
## Mean :19.79 Mean : 65.87 Mean : 49.6 Mean :1017.2
## 3rd Qu.:26.00 3rd Qu.: 79.00 3rd Qu.: 63.0 3rd Qu.:1021.8
## Max. :76.00 Max. :100.00 Max. :100.0 Max. :1040.4
## Pressure3pm Cloud9am Cloud3pm Temp9am
## Min. : 977.1 Min. :0.000 Min. :0.000 Min. : -0.7
## 1st Qu.:1010.1 1st Qu.:1.000 1st Qu.:2.000 1st Qu.:13.1
## Median :1014.7 Median :5.000 Median :5.000 Median :17.8
## Mean :1014.8 Mean :4.242 Mean :4.327 Mean :18.2
## 3rd Qu.:1019.4 3rd Qu.:7.000 3rd Qu.:7.000 3rd Qu.:23.3
## Max. :1038.9 Max. :8.000 Max. :9.000 Max. :39.4
## Temp3pm RainToday RainTomorrow
## Min. : 3.70 Length:56420 Length:56420
## 1st Qu.:17.40 Class :character Class :character
## Median :22.40 Mode :character Mode :character
## Mean :22.71
## 3rd Qu.:27.90
## Max. :46.10
```

str(data)

str() function describes the structure of the dataset.

Below given is the output of the str() function showing the datatypes of the features/columns.

It is a dataframe of 56420 rows and 23 columns.

```
## 'data.frame': 56420 obs. of 23 variables:
```

Date is the char type of variable that needs to be modified into the

Date() type.

```
## $ Date : chr "01-01-2009" "02-01-2009" "04-01-2009" "05-01-2009"
...
## $ Location : chr "Cobar" "Cobar" "Cobar" "Cobar" ...
## $ MinTemp : num 17.9 18.4 19.4 21.9 24.2 27.1 23.3 16.1 19 19.7 ...
```

```
## $ MaxTemp      : num  35.2 28.9 37.6 38.4 41 36.1 34 34.2 35.5 35.5 ...
## $ Rainfall     : num   0 0 0 0 0 0 0 0 0 0 ...
## $ Evaporation  : num  12 14.8 10.8 11.4 11.2 13 9.8 14.6 12 11 ...
## $ Sunshine     : num  12.3 13 10.6 12.2 8.4 0 12.6 13.2 12.3 12.7 ...
## $ WindGustDir  : chr   "SSW" "S" "NNE" "WNW" ...
## $ WindGustSpeed: int   48 37 46 31 35 43 41 37 48 41 ...
## $ WindDir9am   : chr   "ENE" "SSE" "NNE" "WNW" ...
## $ WindDir3pm   : chr   "SW" "SSE" "NNW" "WSW" ...
## $ WindSpeed9am : int    6 19 30 6 17 7 17 15 30 15 ...
## $ WindSpeed3pm : int   20 19 15 6 13 20 19 6 9 17 ...
## $ Humidity9am  : int   20 30 42 37 19 26 33 25 46 61 ...
## $ Humidity3pm  : int   13 8 22 22 15 19 15 9 28 14 ...
## $ Pressure9am  : num  1006 1013 1012 1013 1011 ...
## $ Pressure3pm  : num  1004 1012 1009 1009 1007 ...
## $ Cloud9am     : int    2 1 1 1 1 8 3 1 1 1 ...
## $ Cloud3pm     : int    5 1 6 5 6 8 1 1 5 5 ...
## $ Temp9am      : num  26.6 20.3 28.7 29.1 33.6 30.7 25 20.7 23.4 24 ...
## $ Temp3pm      : num  33.4 27 34.9 35.6 37.6 34.3 31.5 32.8 33.3 33.6 ...
```

These are the very important variables for the project with chr type and to be modified into integer data type.

```
## $ RainToday    : chr   "No" "No" "No" "No" ...
## $ RainTomorrow : chr   "No" "No" "No" "No" ...

data[data$RainToday == "No",]$RainToday <- 0
data[data$RainToday == "Yes",]$RainToday <- 1
data[data$RainTomorrow == "Yes",]$RainTomorrow <- 1
data[data$RainTomorrow == "No",]$RainTomorrow <- 0

data$RainToday <- as.integer(data$RainToday)
data$RainTomorrow <- as.integer(data$RainTomorrow)

datatypes changed!!!
```

```
str(data)
```

```
## $ RainToday    : int   0 0 0 0 0 0 0 0 0 0 ...
## $ RainTomorrow : int   0 0 0 0 0 0 0 0 0 0 ...
```

EXPLORATORY DATA ANALYSIS

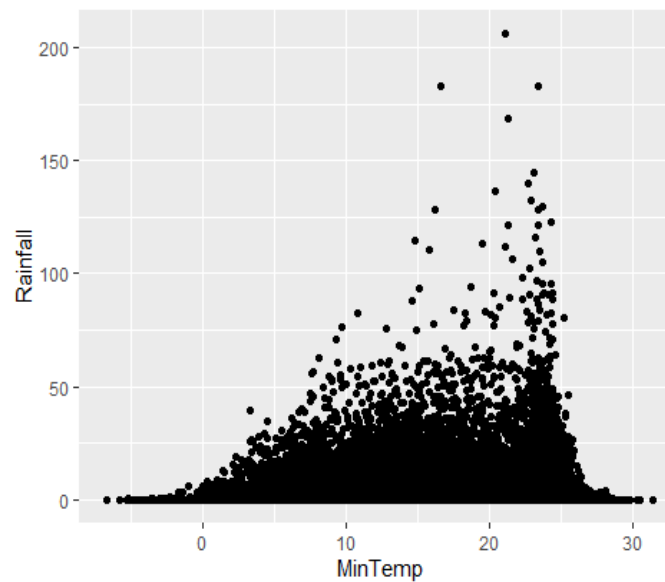
The three ways of looking into the data are

Variables, Variables with respect to location , Variables with respect to time.

These plots are plotted only to what kind of relationship they have with the rainfall parameter...

These doesn't matter when it comes to Raintomorrow (our dependent variable).

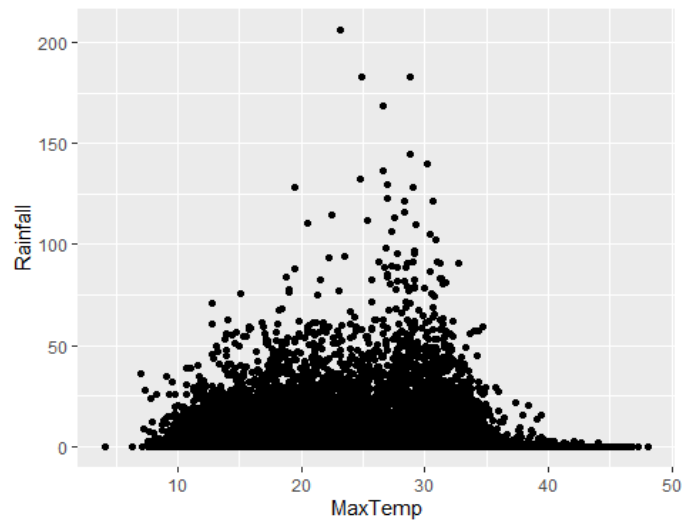
Mintemp vs Rainfall:



Inference from the plot:

The above graph is the overall relationship between the Mintemp variable and the Rainfall variable. From the graph it can be said that there is no positive or negative correlation between the variables. but it seems like the rainfall is more common or there Rainfall generally exists between 0 to 50pts and that increases between 20 to 30 temperatures.

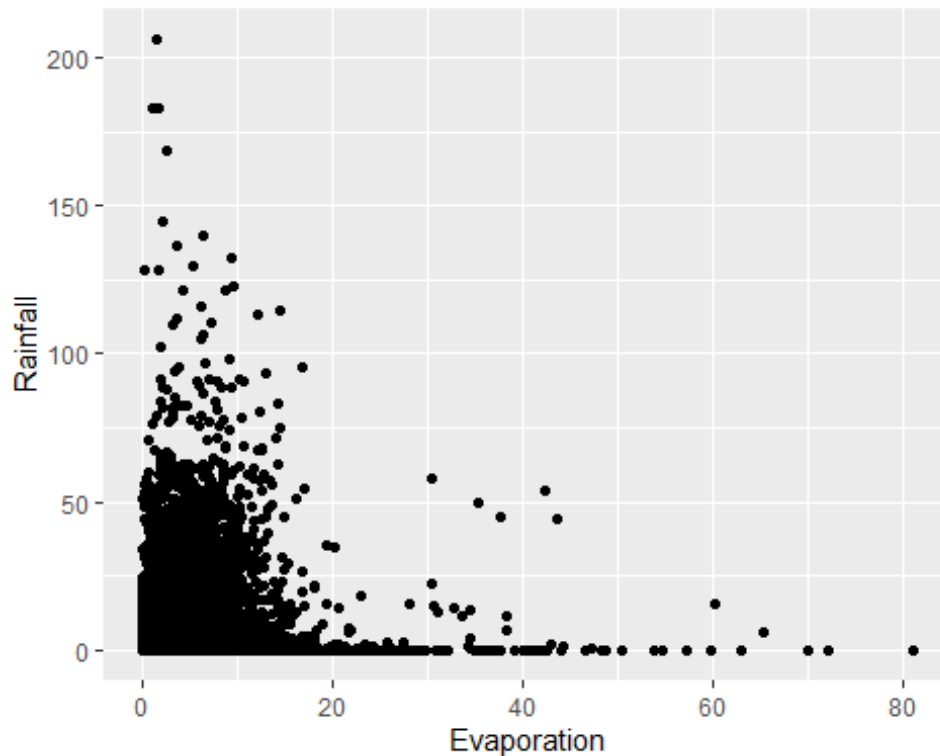
Maxtemp vs Rainfall:



Inference from the plot:

The above graph is the overall relationship between the Maxtemp variable and the Rainfall variable. From the graph it can be said that there is no positive or negative correlation between the variables. The outliers among the data variables seem to have more effect on these plots.

Evaporation vs Rainfall



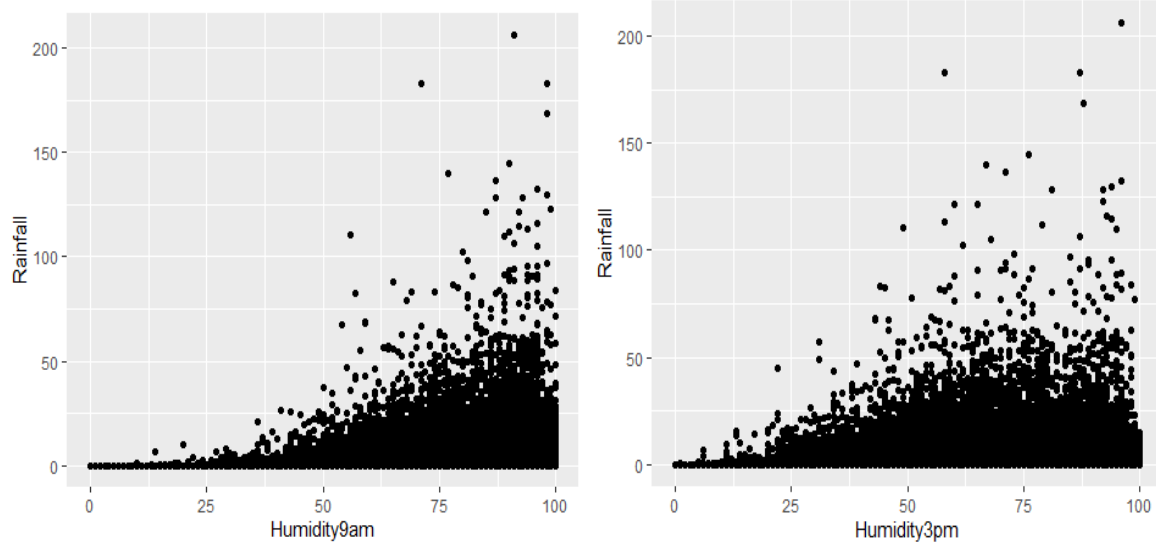
Inference from the plot:

The above graph is the overall relationship between the Evaporation variable and the Rainfall variable. It is seen that the points ranging 0 to 20 of evaporation has more Rainfall rates in Australia.

This dataset is collected all over the Australia and the continent is surrounded by oceans and seas.

That being the case with the lower evaporation rates there is high chance of Rainfall.

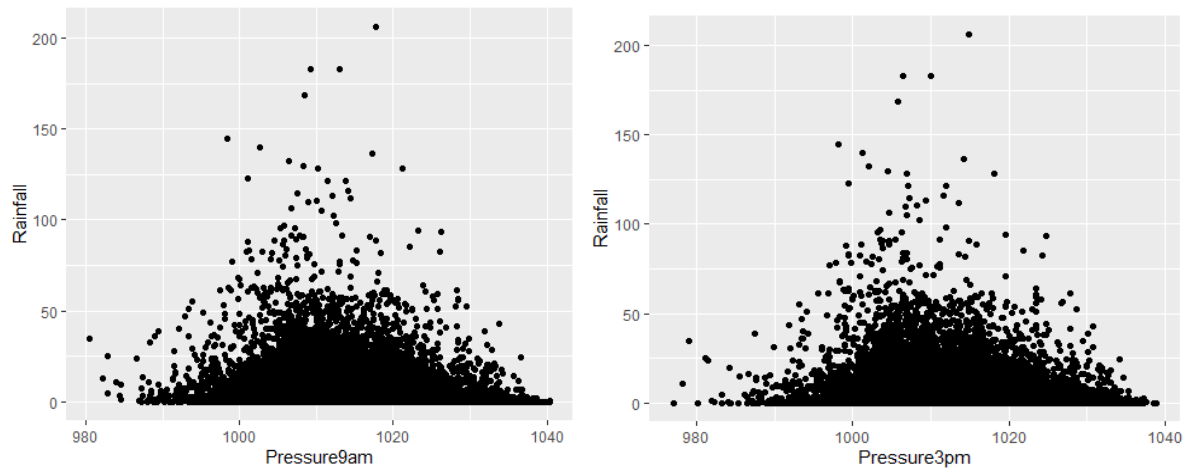
Humidity9am and humidity3pm vs Rainfall



Inference from the plot:

The above graph is the overall relationship between the Mintemp variable and the Rainfall variable. From the graph it can be said that there is no positive or negative correlation between the variables. but it seems like the rainfall is more common or there Rainfall generally exists between 0 to 50pts and that increases between 20 to 30 temperatures.

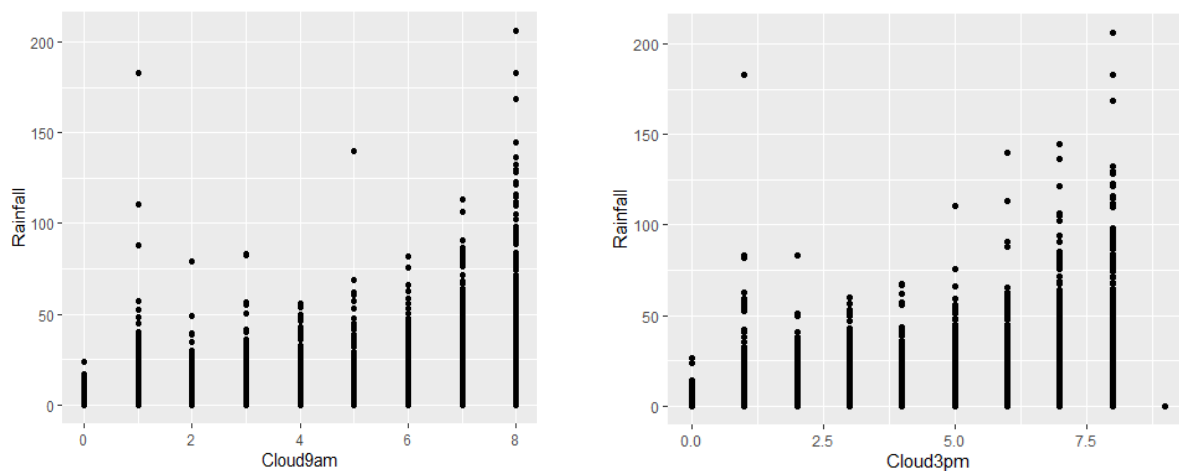
Pressure9am Pressure3pm vs Rainfall



Inference from the plot:

The above graph is the overall relationship between the Pressure variable and the Rainfall variable. Pressure is the very important factor for determining the Rainfall. This graph shows that the pressure and Rainfall relation is constant throughout the day irrespective of timing

cloud9am and cloud3pm vs Rainfall

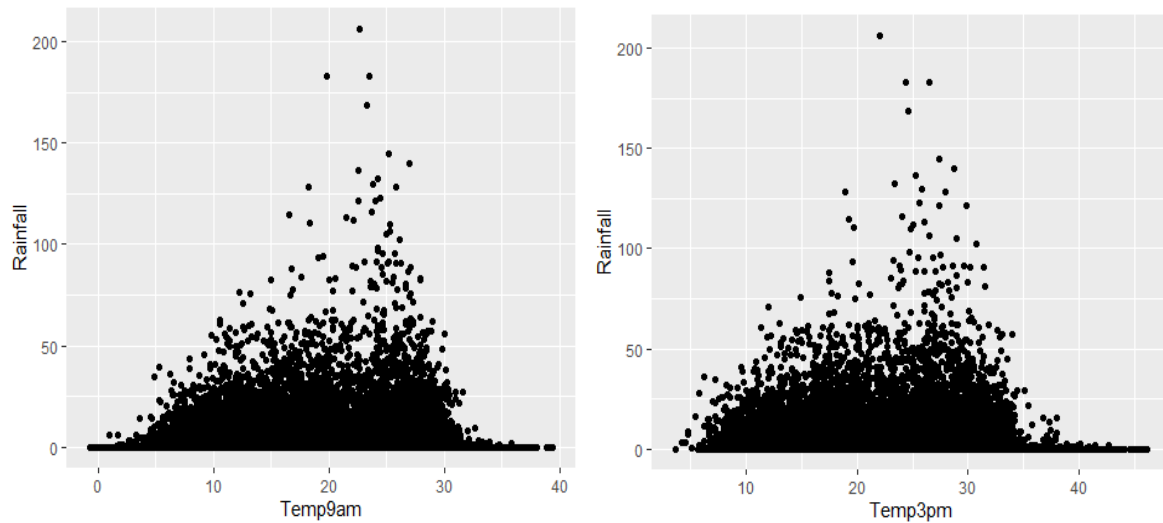


Inference from the plot:

The above graph is the overall relationship between the Cloud variables and the Rainfall variable. From the graphs it can be said that cloud variable with respect to Rainfall variable is a factor variable. It is also seen that clouds at 7.5 and 8 values have much Rainfall rates.

Cloud variable ranges from 0 to 8 in the given dataset.

Temp9am Temp3pm vs Rainfall



Inference from the plot:

The above graph is the overall relationship between the Temperature variables and the Rainfall variable. From the graph it can be said temperature and Rainfall are consistent through the day. On any point of time be it morning or evening the occurrence of Rainfall can be same with respect to Temperature. Outliers are still in our consideration.

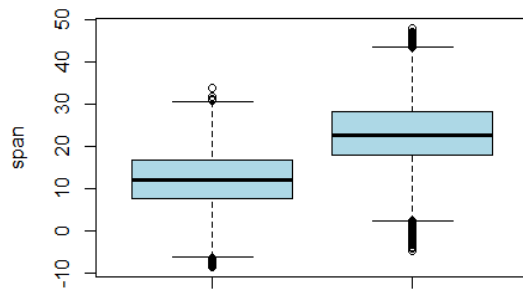
Outliers: Boxplot

boxplots generally helps in extracting the information regarding the span of the data.

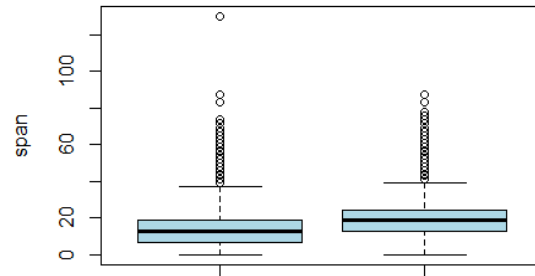
How the data is spanned. Is it skewed or normal etc etc;

In the working of the project the outliers are removed.

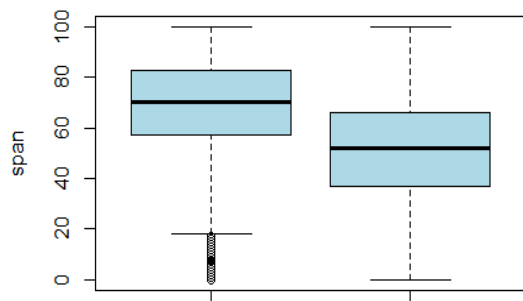
Box plots



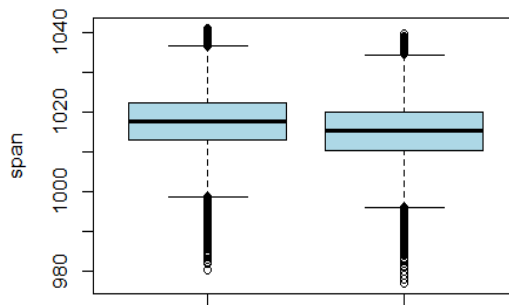
MinTemp and MaxTemp



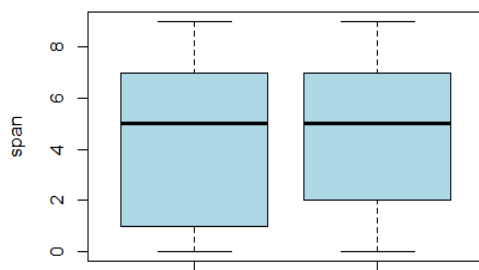
WindSpeed9am and WindSpeed3pm



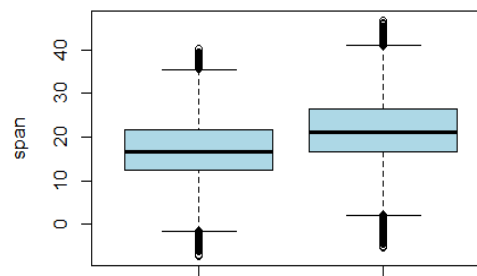
Humidity9am and Humidity3pm



Pressure9am and pressure3pm



Cloud9am and Cloud3pm



temp9am and temp3pm

PREPROCESSING THE DATA... with respect to Locations!

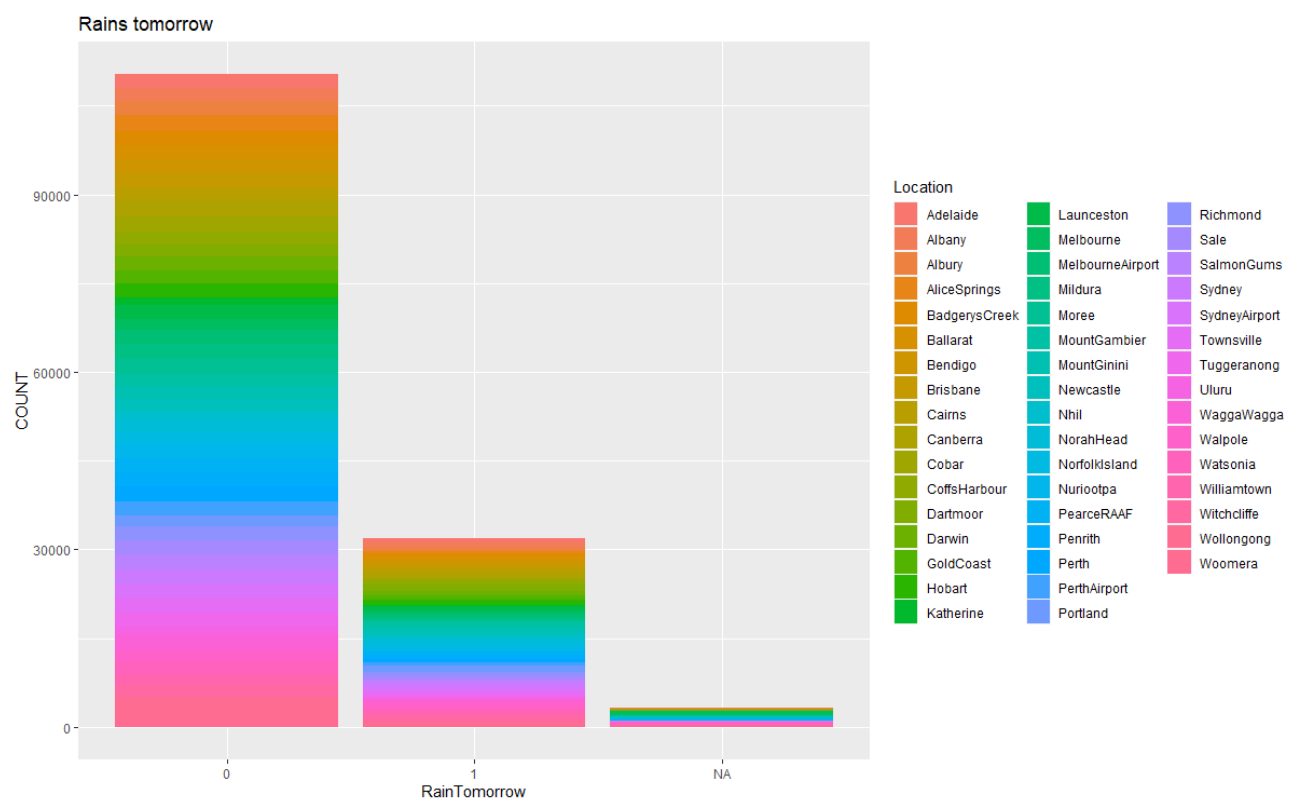
column RainTomorrow and RainToday is in yes/no format

Converting it to 0 or 1

```
data$RainToday<-str_replace_all(data$RainToday,"No","0")
data$RainToday<-str_replace_all(data$RainToday,"Yes","1")
data$RainTomorrow<-str_replace_all(data$RainTomorrow,"No","0")
data$RainTomorrow<-str_replace_all(data$RainTomorrow,"Yes","1")
```

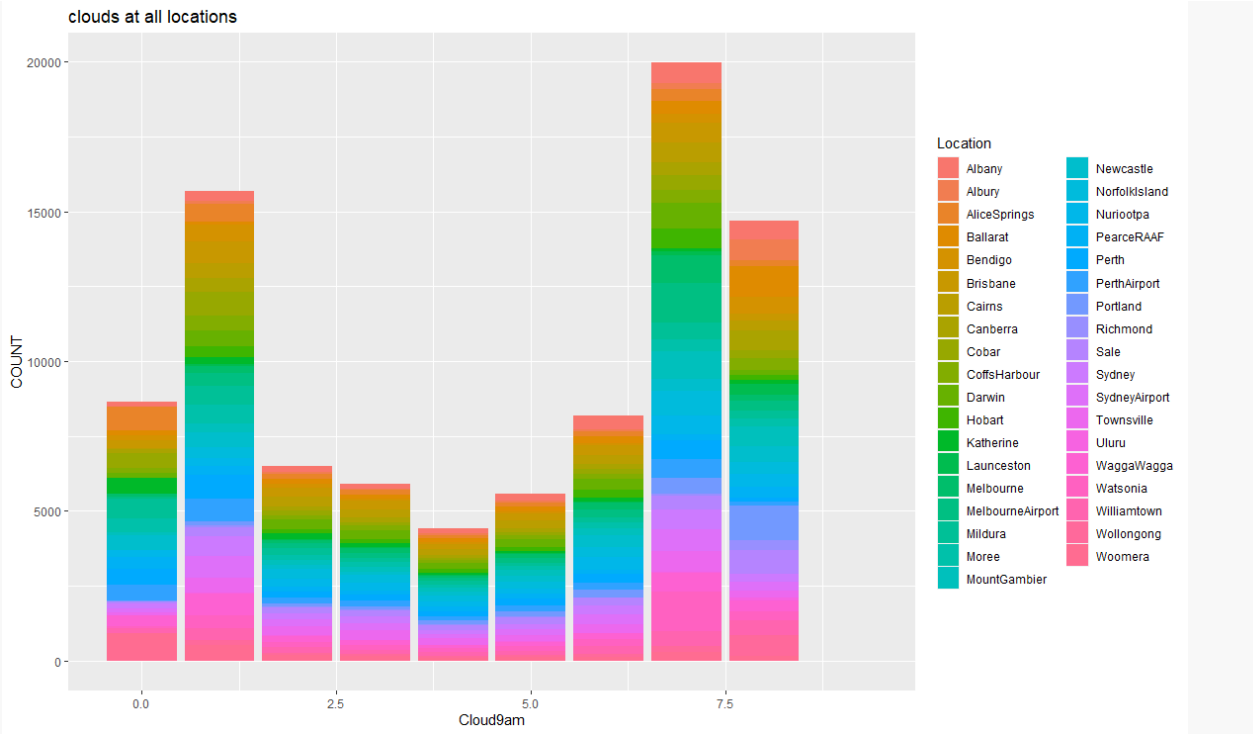
Time for some plots

Raintomorrow values over various locations.

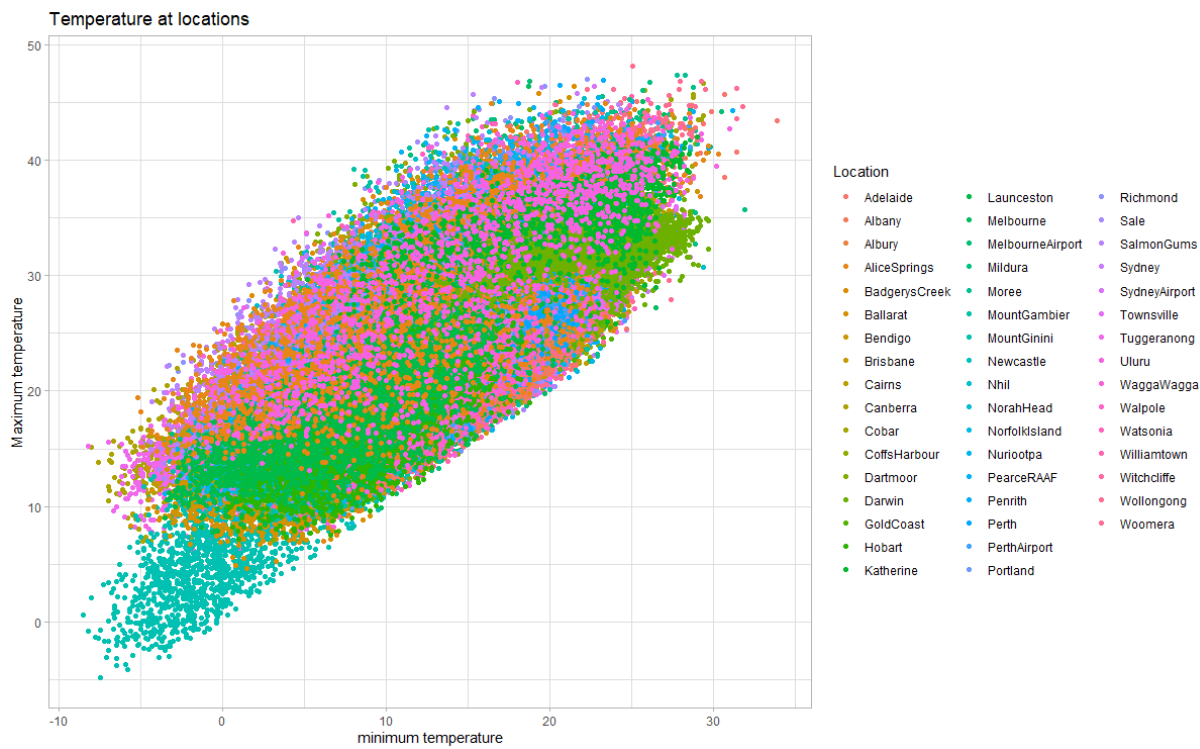


The feature has more number of no-rains (0) than the yes_rains(1).

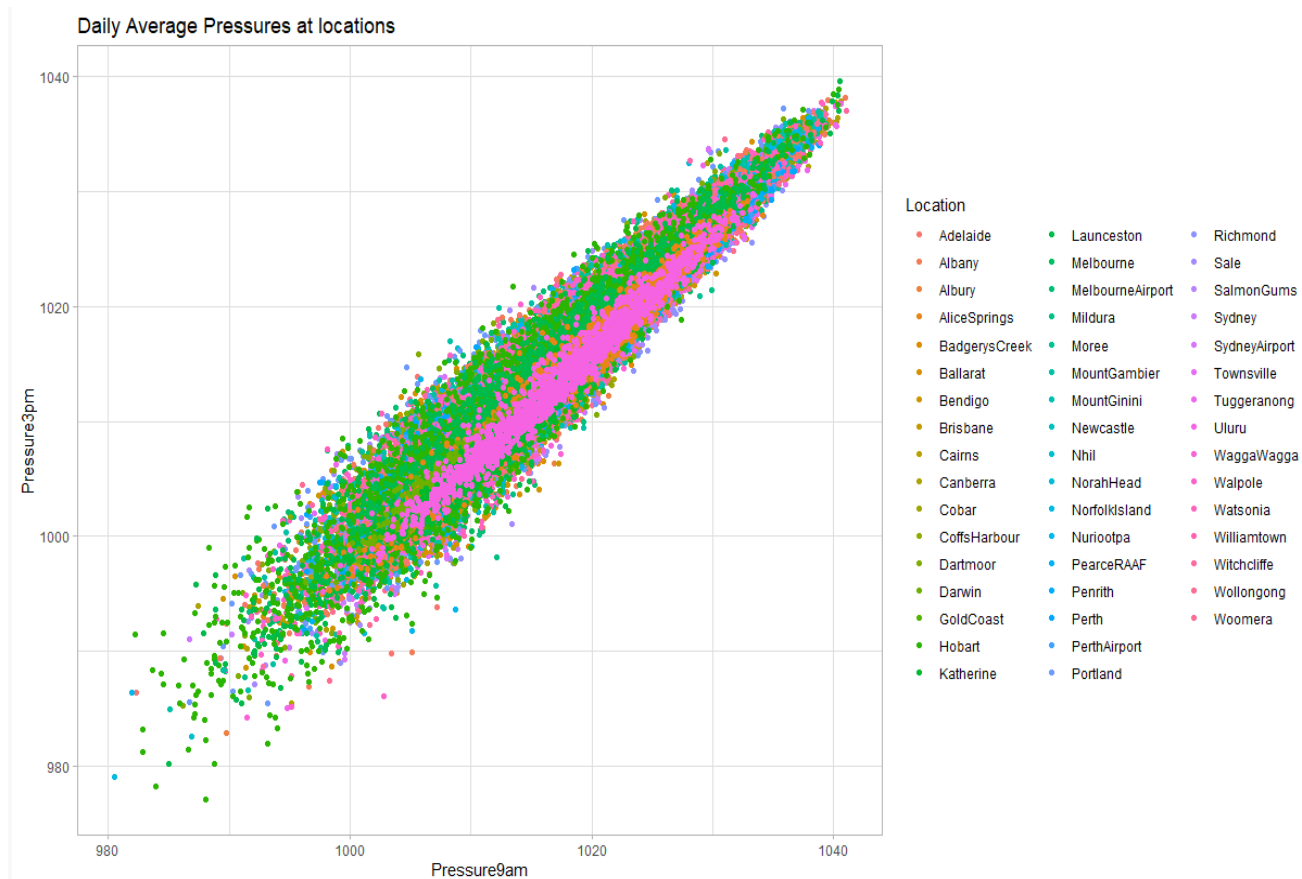
Clouds at various Locations.



Temperatures at different locations



Pressure at different locations



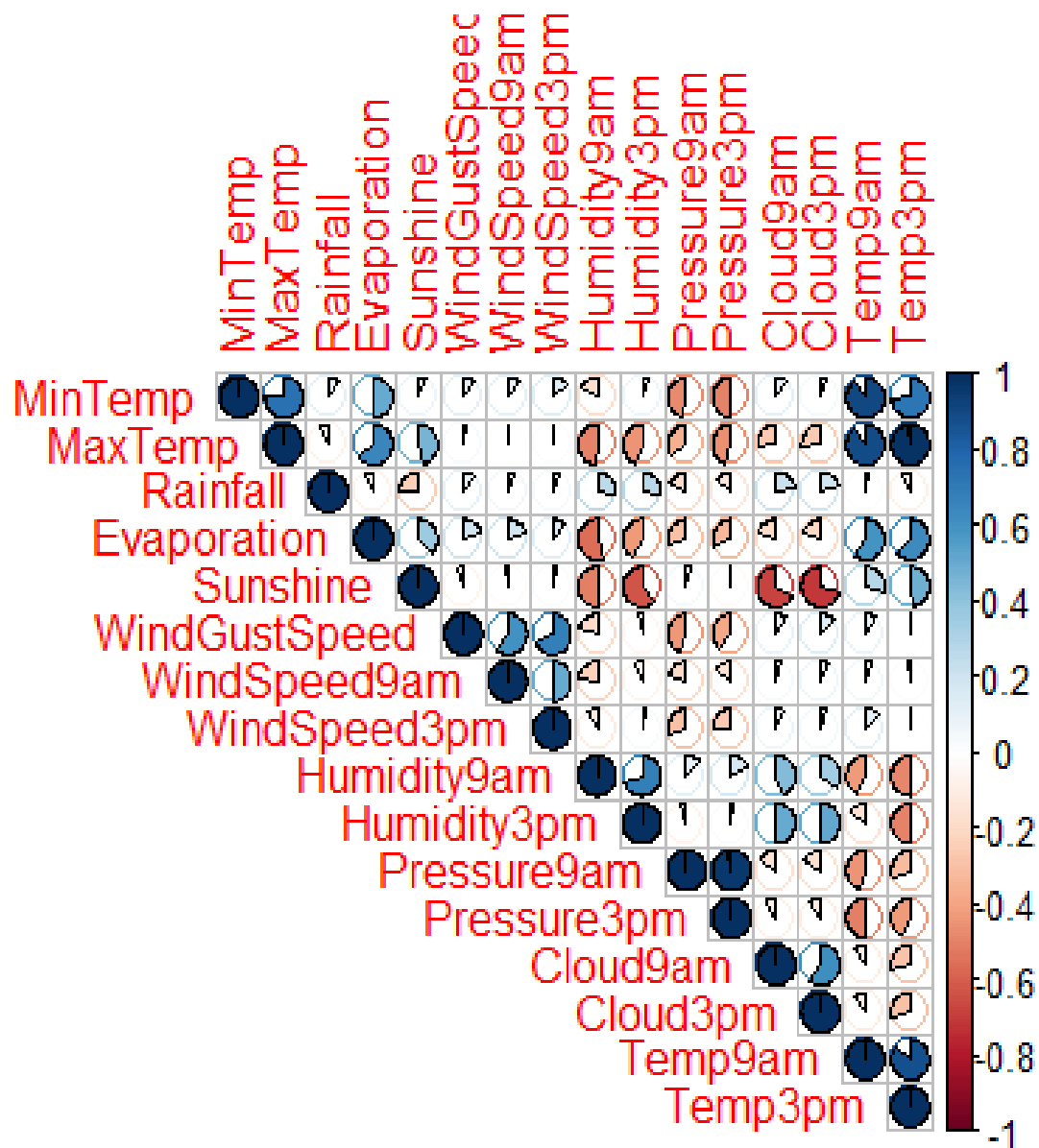
```
data$MinTemp<-as.numeric(data$MinTemp)
data$RainToday<-as.numeric(data$RainToday)
data$RainTomorrow<-as.numeric(data$RainTomorrow)
```

the most important variables/features for this project of predicting the RainTomorrow variable are to be converted into numeric datatype...

Correlation Plot:

For the correlation plot the unnecessary and the categorical variables are removed.

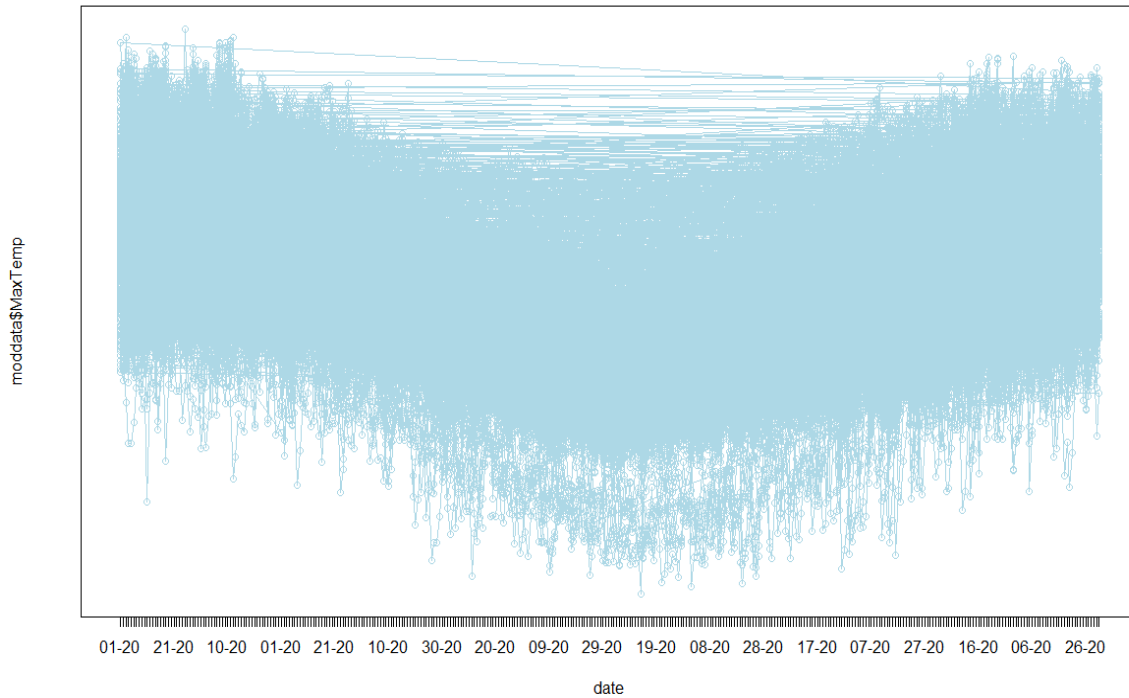
```
corrplot(cor(corrdata),  
  method = "pie",  
  type = "upper" # show only upper side)
```



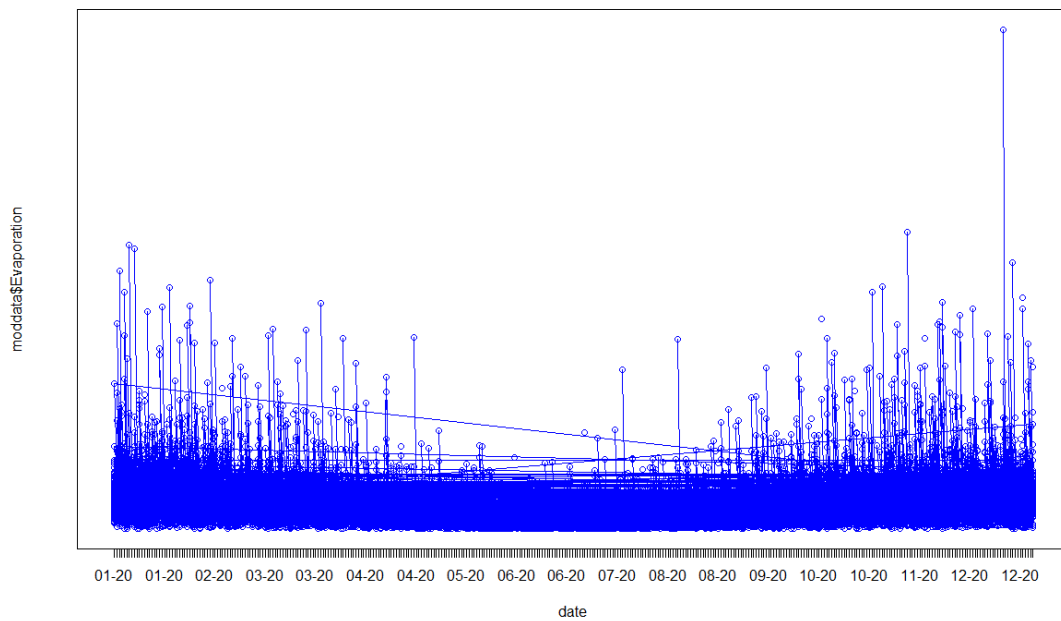
This is the correlation plot that shows the effect of variables on each other by calculating the correlation matrix. Here the unnecessary and categorical variables (date, location, RainToday, RainTomorrow) are ignored!!!

Plots of variables over the years...

Maximum temperatures over the years.



Evaporation over the time



Here we end the exploratory data analysis part and start doing the modelling!!!

Linear Modelling

Linear Regression...

The data now which is being used is not normalized and not scaled data from the weatherAUS dataset.

Here the dataset is splitted into two subsets as traindata and testdata with the ratios of 70% and 30% respectively.

```
smp_size <- floor(0.70 * nrow(data))
```

```
traindata <- data[train_index, ]  
testdata <- data[-train_index, ]
```

Model11: trained using the traindata.

Rainfall ~ MaxTemp+Sunshine+WindSpeed9am+Humidity9am+Humidity3pm+Pressure9am+Pressure3pm

adj.r.squared	sigma	AIC	BIC
<dbl>	<dbl>	<dbl>	<dbl>
0.142	6.	4125883	258913.

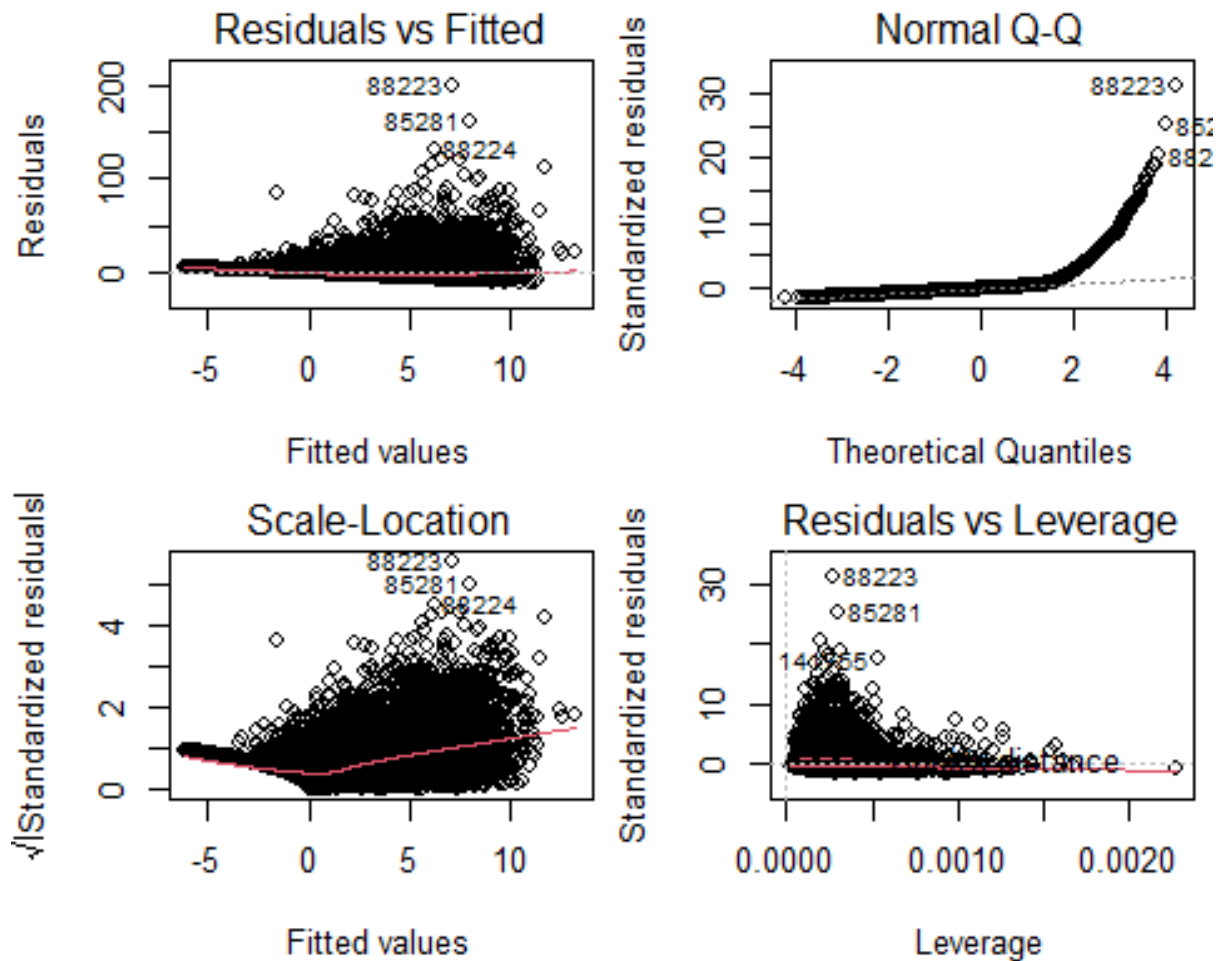
```
summary(model11)
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -10.469  -2.659  -1.000   0.772  199.073
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)  
## (Intercept)  139.065905   5.774541   24.08  <2e-16 ***  
## MaxTemp      0.100559   0.006604   15.23  <2e-16 ***  
## Sunshine     -0.205757   0.011577  -17.77  <2e-16 ***  
## WindSpeed9am  0.058312   0.004215   13.84  <2e-16 ***  
## Humidity9am   0.086976   0.002614   33.27  <2e-16 ***  
## Humidity3pm   0.024303   0.002537    9.58  <2e-16 ***  
## Pressure9am  -0.366662   0.018780  -19.52  <2e-16 ***  
## Pressure3pm   0.224044   0.019453   11.52  <2e-16 ***  
## Multiple R-squared:  0.1425, Adjusted R-squared:  0.1423  
## F-statistic: 937.2 on 7 and 39486 DF,  p-value: < 2.2e-16
```

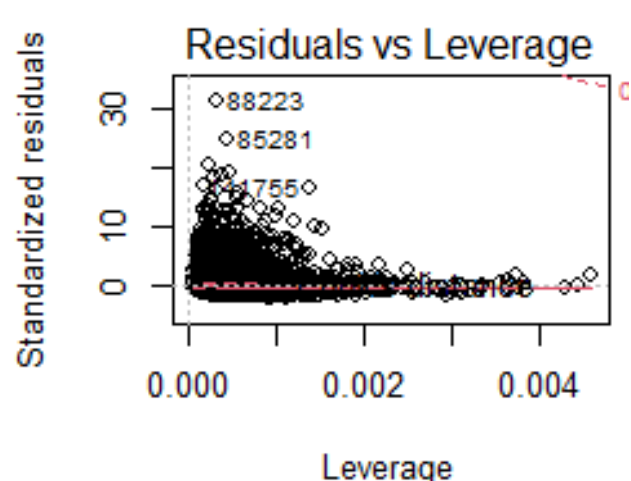
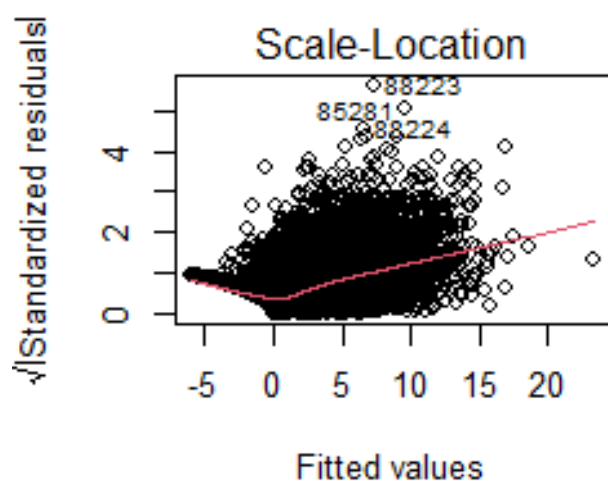
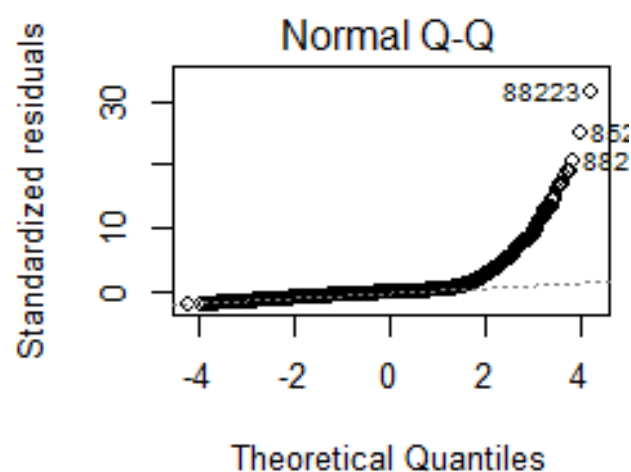
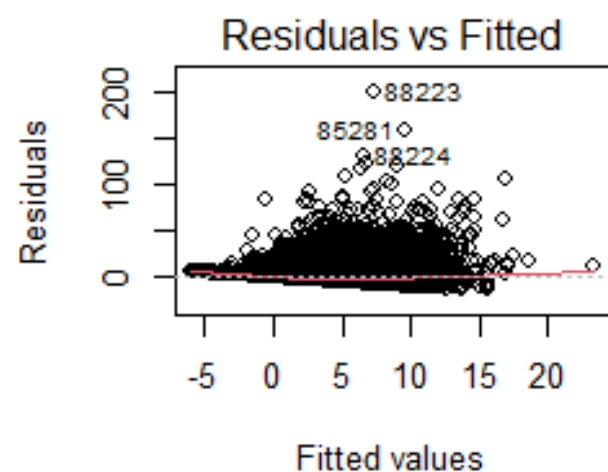



Working on the data that is not normal...

```
model12 <- lm(Rainfall ~ (MaxTemp*Pressure9am)+Sunshine+WindGustSpeed+Humidity
9am+(Humidity3pm*Pressure3pm)+Temp3pm,traindata)
```

```
## adj.r.squared sigma AIC BIC
## <dbl> <dbl> <dbl> <dbl>
## 0.164 6.33 257846. 257949.
```

```
## Residual standard error: 6.33 on 39483 degrees of freedom
## Multiple R-squared: 0.1638, Adjusted R-squared: 0.1636
## F-statistic: 773.5 on 10 and 39483 DF, p-value: < 2.2e-16
```



Logistic Regression...

```
logisticmod <- glm(RainTomorrow ~ Rainfall+RainToday,data=traindata,family =  
"binomial")
```

```
summary(logisticmod)
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -2.8338  -0.5733  -0.5733  -0.5733   1.9427
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -1.722640   0.015884 -108.45  <2e-16 ***  
## Rainfall     0.036910   0.002253   16.39  <2e-16 ***  
## RainToday    1.238666   0.033144   37.37  <2e-16 ***
```

```
##      Null deviance: 41686  on 39493  degrees of freedom
```

```
## Residual deviance: 37931  on 39491  degrees of freedom
```

```
AIC: 37937
```

```
logisticmod2 <- glm(RainTomorrow ~ Rainfall+RainToday+MinTemp+MaxTemp+Sunshin  
e+WindGustSpeed+WindSpeed9am+WindSpeed3pm+Humidity9am+Humidity3pm+Pressure9am  
+Pressure3pm+Cloud3pm+Temp9am+Temp3pm,data=traindata,family = "binomial")  
summary(logisticmod2)
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -3.2087  -0.5120  -0.2831  -0.1268   3.2131
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept)  57.5008364  2.9303688  19.622  < 2e-16 ***  
## Rainfall     0.0115716  0.0025806   4.484  7.33e-06 ***  
## RainToday    0.5000591  0.0430650  11.612  < 2e-16 ***  
## MinTemp      -0.0520319  0.0085910  -6.057  1.39e-09 ***  
## MaxTemp       0.0060878  0.0140848   0.432  0.66558  
## Sunshine     -0.1445786  0.0066074 -21.881  < 2e-16 ***  
## WindGustSpeed 0.0577428  0.0018792  30.728  < 2e-16 ***  
## WindSpeed9am  -0.0145281  0.0025222  -5.760  8.41e-09 ***  
## WindSpeed3pm  -0.0260846  0.0026048 -10.014  < 2e-16 ***  
## Humidity9am   -0.0003748  0.0018320  -0.205  0.83788  
## Humidity3pm   0.0570280  0.0019932  28.611  < 2e-16 ***  
## Pressure9am   0.1365539  0.0095445  14.307  < 2e-16 ***  
## Pressure3pm  -0.1996735  0.0096206 -20.755  < 2e-16 ***  
## Cloud3pm      0.1138662  0.0095843  11.881  < 2e-16 ***  
## Temp9am       0.0358274  0.0130025   2.755  0.00586 **
```

```
## Temp3pm          0.0111949  0.0160324   0.698  0.48501
```

```
##      Null deviance: 41686  on 39493  degrees of freedom
## Residual deviance: 26460  on 39478  degrees of freedom
## AIC: 26492
```

```
logisticmod3 <- glm(RainTomorrow ~ Rainfall+RainToday+MinTemp+Sunshine+WindGustSpeed+WindSpeed9am+WindSpeed3pm+Humidity3pm+Pressure9am+Pressure3pm+Cloud3pm+Temp9am,data=traindata,family = "binomial")
summary(logisticmod3)
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -3.2192  -0.5138  -0.2826  -0.1254   3.2165
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  57.985091   2.907793  19.941  < 2e-16 ***
## Rainfall      0.011852   0.002566   4.620 3.85e-06 ***
## RainToday     0.498220   0.042139  11.823  < 2e-16 ***
## MinTemp      -0.049943   0.007811  -6.394 1.62e-10 ***
## Sunshine     -0.142947   0.006529 -21.893  < 2e-16 ***
## WindGustSpeed  0.057694   0.001831  31.510  < 2e-16 ***
## WindSpeed9am  -0.014933   0.002414  -6.187 6.14e-10 ***
## WindSpeed3pm  -0.026620   0.002553 -10.427  < 2e-16 ***
## Humidity3pm    0.055124   0.001191  46.299  < 2e-16 ***
## Pressure9am    0.143024   0.008667  16.503  < 2e-16 ***
## Pressure3pm   -0.206431   0.008725 -23.659  < 2e-16 ***
## Cloud3pm       0.114420   0.009510  12.031  < 2e-16 ***
## Temp9am       0.048801   0.007874   6.198 5.73e-10 ***
```

```
##      Null deviance: 41686  on 39493  degrees of freedom
## Residual deviance: 26463  on 39481  degrees of freedom
## AIC: 26489
```

the Accuracy:

```
## [1] 0.07313604
```

Confusion Matrix

Confusion Matrix and Statistics

```
##          actual
## Predicted    0    1
##          0 13177  258
##          1 17602  8457
```

```
##          Accuracy : 0.5478
##          95% CI : (0.5429, 0.5527)
```

```
##          Sensitivity : 0.9704
##          Specificity : 0.4281
##          Pos Pred Value : 0.3245
##          Neg Pred Value : 0.9808
##          Prevalence : 0.2207
##          Detection Rate : 0.2141
##          Detection Prevalence : 0.6598
##          Balanced Accuracy : 0.6993
##
##          'Positive' Class : 1
```

LOGISTIC REGRESSION MODEL

Importing the standardized data

After the dataset is normalized it is again written into another csv file named as normaldata which consists of 18 variables.

The dataset is loaded into a dataframe called Rain.

The contents in Rain data frame are splitted into the ratios of 75% and 25% as traindata and testdata respectively.

```
Rain = read.csv("normaldata.csv")
```

Fitting Logistic Regression to the Training set:

```
RainTomorrow ~ WindGustSpeed + Humidity3pm + Pressure3pm
```

the formula used for the fitting the dataset.

```
## Deviance Residuals:
```

```
##      Min      1Q   Median      3Q      Max
## -2.5182 -0.5696 -0.3713 -0.2191  3.0641
```

The deviance residuals are good in this case as they are centered toward 0 (approx).

And also approximately symmetric as Min is -2.5 from 0

Max is +3.0 from 0

```
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.03003    0.01337 -151.87  <2e-16 ***
## WindGustSpeed  0.39822    0.01141  34.90  <2e-16 ***
## Humidity3pm    1.10273    0.01198  92.06  <2e-16 ***
## Pressure3pm   -0.47333    0.01181 -40.09  <2e-16 ***
```

all the pvalues are well below the significance level 0.05 thus the both log(odds) and

log(oddratios) are both statistically significant with decent effect sizes.

```
## Null deviance: 67652  on 73899  degrees of freedom
## Residual deviance: 53351  on 73896  degrees of freedom
```

The null deviance measures the deviance using the intercept and the residual deviance measures the deviance using the independent variables.

In this case, smaller these values better the model.

```
## AIC: 53359
```

here too, smaller the AIC value better the logistic model.

Test data Prediction using the predict function.

The predict function is used to predict the values of testdataset using the model that is trained using the traindata.

The model's true-false matrix.

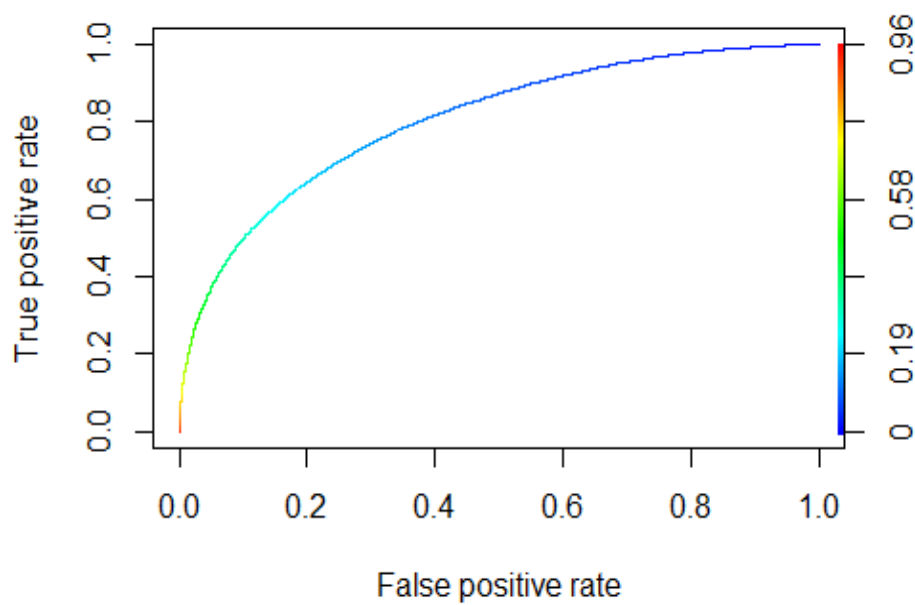
```
##      FALSE  TRUE
## 0 20310  107
## 1  3709  507
```

True positive and False positive Graph:

True positive and False positive Graph:

True positive and False positive Graph:

True positive and False positive Graph:



Performance of the model:

```
## [1] 0.8030272
```

```
anova(model, test = "Chisq")
```

```
## Response variable : RainTomorrow
```

```
## Analysis of Deviance Table
```

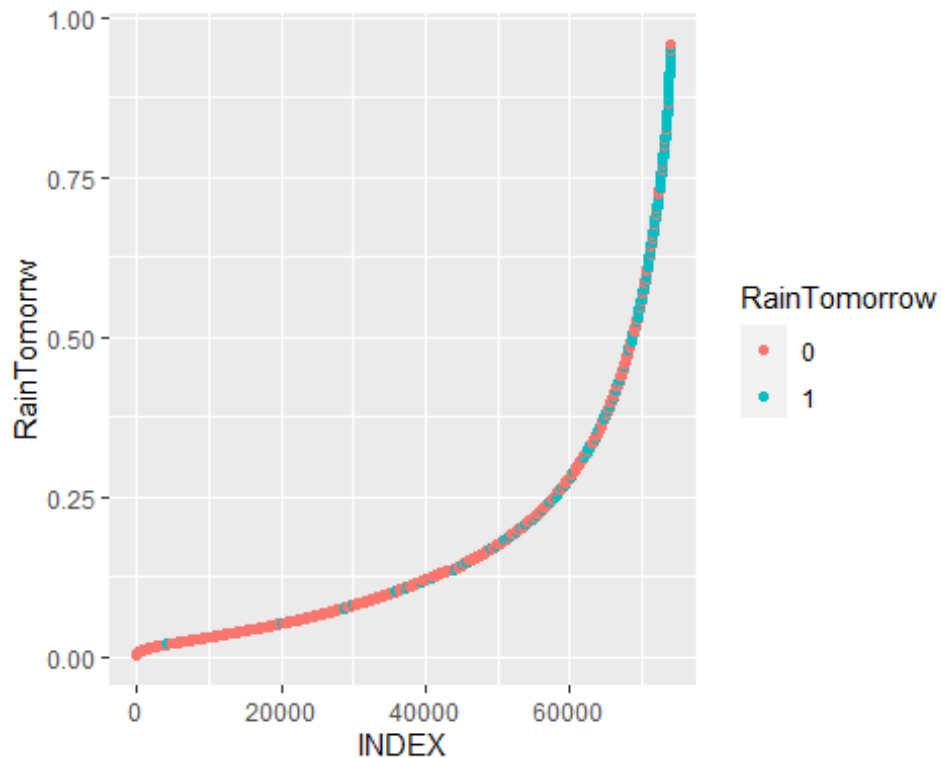
```
## WindGustSpeed  1    1911.3    73898    65741 < 2.2e-16 ***
## Humidity3pm    1   10690.5    73897    55050 < 2.2e-16 ***
## Pressure3pm    1    1698.8    73896    53351 < 2.2e-16 ***
```

```
## Model: binomial
```


Predict function

```
predictdata<-data.frame(ProbRaintomorrow=model$fitted.values,RainTomorrow=trainingdata$RainTomorrow)
```

The graph showing the predictions done by the model for the response variable Raintomorrow.



Raintomorrow is the target variable to be predicted as either 0 or 1.

```
sum(diag(tab))/sum(tab)
```

```
## [1] "accuracytest: 0.844614343707713"
```

Principal Component Analysis

```
eigenvalues: 278.9695328 110.0631689 30.1242673 0.1124081
```

```
eigen vectors[,1]
```

```
-0.008033275 0.049846573 -0.998621870 -0.014322900
```

```
eig_val$eigenvectors[,2]
```

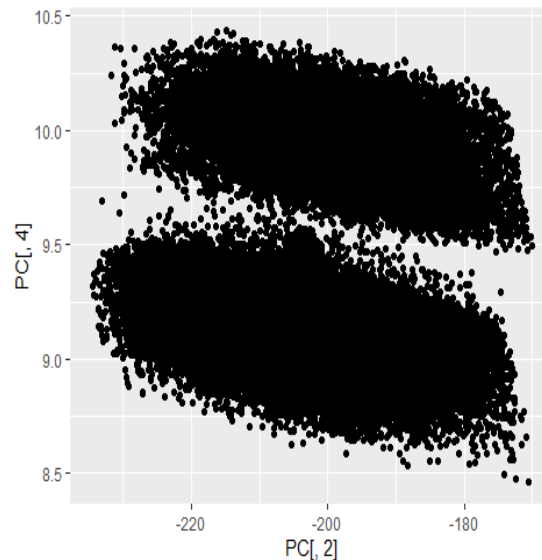
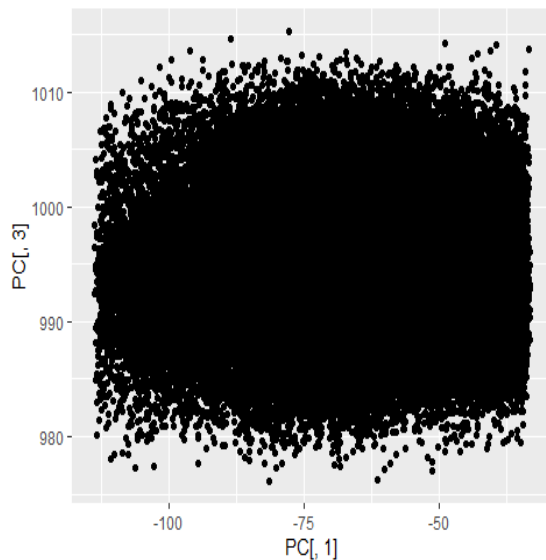
```
0.007368061 0.969554651 0.051767556 -0.239227109
```

```
eig_val$eigenvectors[,3]
```

```
-0.008157726 0.239700164 -0.001893671 0.970810845
```

```
eig_val$eigenvectors[,4]
```

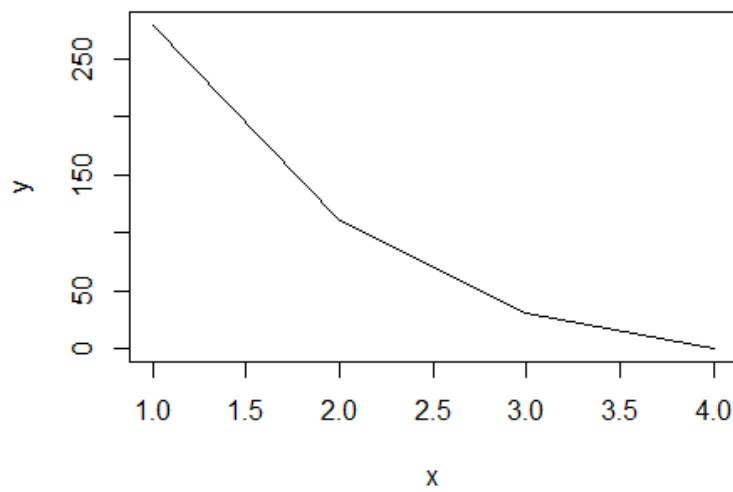
```
0.999907311 -0.004788342 -0.008419859 0.009568076
```



Relation between the principal components:

These are the scatter plots of pc1 with pc3 and Pc2 with pc4. The latter one seems to be negatively correlated. But the 1st seems to be not related to each other.

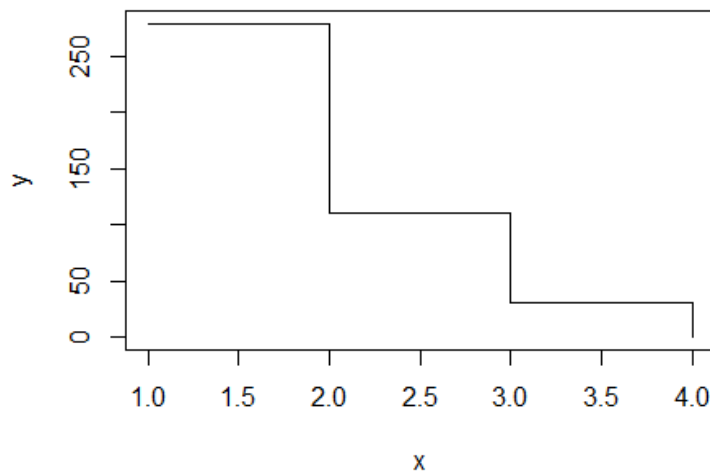
Scree Plot



From Principal component analysis it is Derived that the first three principal components are sufficient to estimate the data.

Screeplot with line

Scree Plot



Screeplot with stepfunction.

$$PC1 = (-0.008)RainTomorrow + (0.049)WindGustSpeed + (-0.998) Humidity3pm + (-0.014)Pressure3pm$$

$$PC2 = (0.007)RainTomorrow + (0.969)WindGustSpeed + (0.051) Humidity3pm + (-0.239)Pressure3pm$$

$$PC3 = (-0.008)RainTomorrow + (0.239)WindGustSpeed + (-0.002) Humidity3pm + (0.970)Pressure3pm$$

$$PC4 = (0.999)RainTomorrow + (-0.004)WindGustSpeed + (-0.008) Humidity3pm + (0.009)Pressure3pm$$

KNN Algorithm

Knn is a machine learning algorithm used for nonparametric and supervised learning models.

Here we chose only 3 variables for modelling and training to predict the target variable RainTomorrow.

```
subset <- dataknn[c('RainTomorrow', 'WindGustSpeed', 'Humidity3pm', 'Pressure3pm')]
```

later the data is normalized using the min-max function.

```
normalize <- function(x) {  
  return ((x - min(x)) / (max(x) - min(x))) }
```

then the dataset is splitted in the ratios of 70% for training and the 30% for testing purposes.

```
nrow(train)  
nrow(test)  
70751  
30322
```

Using the method “ Repeatedcv ” with the function traincontrol() having the parameters Number=10 and repeats=3

Train() for training the traindata set with the method KNN.

The KNN is instance based , non parametric algorithm so it will not have any explicit functionalities such as $y = f(x)$ etc etc.

k-fold cross Validation:

Cross-validation can be used to estimate the test error associated with a learning method in order to evaluate its performance, or to select the appropriate level of flexibility.

Here the k value is selected as a values which is optimal model with the large values

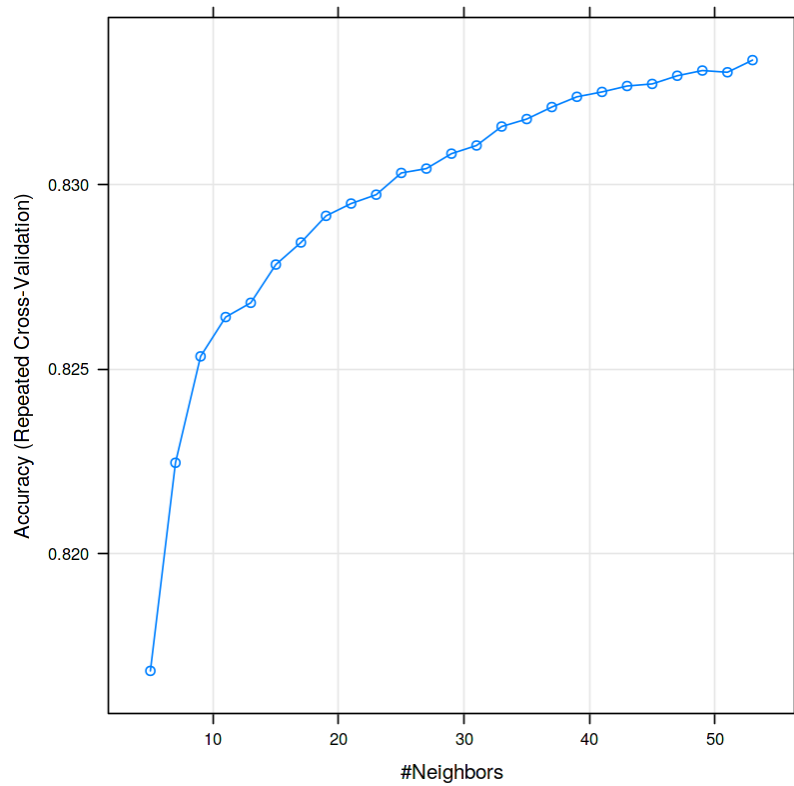
Here the k value is : 53

Finally the accuracy is calculated!!!

k	Accuracy	Kappa
5	0.8168270	0.3036266
7	0.8224666	0.3112242
9	0.8253499	0.3170634
11	0.8264147	0.3166481
13	0.8268010	0.3131528
15	0.8278375	0.3148223
17	0.8284358	0.3139846
19	0.8291567	0.3147686
21	0.8294912	0.3134858
23	0.8297315	0.3128237
25	0.8303204	0.3128565
27	0.8304382	0.3111121
29	0.8308433	0.3107070
31	0.8310648	0.3093233
33	0.8315783	0.3083491
35	0.8317809	0.3066045
37	0.8321060	0.3066131
39	0.8323840	0.3056973
41	0.8325159	0.3050143
43	0.8326761	0.3051338
45	0.8327326	0.3046992
47	0.8329541	0.3045153
49	0.8330954	0.3042392
51	0.8330483	0.3042739
53	0.8333781	0.3055463

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was k = 53.

The Accuracy of the KNN model in predicting the target variable from k= 5 - 53.



Confusion Matrix for the 4 classes of target variable:

Confusion Matrix and Statistics				
Prediction	Reference			
	0	0.2241812	0.224181218484736	1
0	23938	640	7	3581
0.2241812	18	18	0	1
0.224181218484736	0	0	0	0
1	639	55	0	1425

Accuracy : 0.837

95% CI : (0.8328, 0.8412)

Overall statistics of the KNN model:

	Class: 0	Class: 0.2241812	Class: 0.224181218484736	Class: 1
Sensitivity	0.9733	0.0252454	0.0000000	0.28460
Specificity	0.2617	0.9993583	1.0000000	0.97259
Pos Pred Value	0.8499	0.4864865	NaN	0.67249
Neg Pred Value	0.6953	0.9770513	0.9997691	0.87299
Prevalence	0.8111	0.0235143	0.0002309	0.16513
Detection Rate	0.7895	0.0005936	0.0000000	0.04700
Detection Prevalence	0.9289	0.0012202	0.0000000	0.06988
Balanced Accuracy	0.6175	0.5123019	0.5000000	0.62859