Machine Learning Project 2024

Lucas Jakin   Saša Nanut   Luca Marega

2024-06-04

Table of contents

Predicting next-day rain in Australia

Introduction

As a group we decided to take on the **first project type**. The project focuses on utilizing DM & ML algorithms to address a specific problem chosen from Kaggle.The Goal of the project is to address the classification problem by utilizing more than one classification algorithm, in order to do a systematic experimentation with different algorithms to identify in what they differ and which one is the most effective one for the chosen dataset. We will consider different classification algorithms and make the comparison between three of them, more precisely *Artificial Neural Networks*, *CatBoost* and *Logistic Regression*.

We will divide the work as the following: as a group we will perform a brief analysis of the dataset and make some cleaning of it if needed. Afterwards, each one of us will implement one of the previously mentioned algorithms and then we will compare and interpret the results

About the dataset

The dataset found in Kaggle consists of about 10 years of daily weather observations from numerous locations across Australia.

The problem that is required to be solved from this dataset represents a classification problem, in this case a **binary classification** problem. The objective is to predict whether it will rain tomorrow or not with high accuracy. The dataframe contains 145460 observations (rows) and 23 attributes. The observations are weather conditions of days of a specific region including:

date, location, minimum and maximum temperature, rain fall, humidity and so on.

The most important feature of the dataset is the last column **"RainTomorrow"**, which is the target variable for our ML models that we want to predict.

It has two values:

- Yes –> It will rain tomorrow
- No –> It will not rain tomorrow.

Exploratory Data Analysis

```
library(tidyverse)
library(dplyr)
library(skimr)
library(ggcorrplot)
library(gt)
library(ggplot2)

#use_python("C:\\Python312\python.exe", required = T)
weatherAus <- read.csv("weatherAUS.csv", header = T)
```

Setting up python into Rstudio:

```
# SETTING UP PYTHON ON RSTUDIO
library(reticulate)

virtualenv_create("my-python", python_version = "3.12")
use_virtualenv("my-python", required = TRUE)

#virtualenv_install(envname = "my-python", "matplotlib",ignore_installed = FALSE, pip_opti

#virtualenv_install(envname = "my-python", "catboost",ignore_installed = FALSE, pip_option

#virtualenv_install(envname = "my-python", "numpy",ignore_installed = FALSE, pip_options =

#virtualenv_install(envname = "my-python", "pandas",ignore_installed = FALSE, pip_options

#virtualenv_install(envname = "my-python", "seaborn",ignore_installed = FALSE, pip_options

#virtualenv_install(envname = "my-python", "scikit-learn",ignore_installed = FALSE, pip_op
```

```
#virtualenv_install(envname = "my-python", "tensorflow",ignore_installed = FALSE, pip_opti
```

As we start, we first load the weather data and look at the first rows to identify the features:

```
head(weatherAus) %>% gt()
```

Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGu
2008-12-01	Albury	13.4	22.9	0.6	NA	NA	W	
2008-12-02	Albury	7.4	25.1	0.0	NA	NA	WNW	
2008-12-03	Albury	12.9	25.7	0.0	NA	NA	WSW	
2008-12-04	Albury	9.2	28.0	0.0	NA	NA	NE	
2008-12-05	Albury	17.5	32.3	1.0	NA	NA	W	
2008-12-06	Albury	14.6	29.7	0.2	NA	NA	WNW	

In the next step we check out the summary statistics of the dataset and identify the numerical and categorical attributes:

```
skim(weatherAus)
```

Table 2: Data summary

Name	weatherAus
Number of rows	145460
Number of columns	23
Column type frequency:	
character	7
numeric	16
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
Date	0	1.00	10	10	0	3436	0
Location	0	1.00	4	16	0	49	0
WindGustDir	10326	0.93	1	3	0	16	0
WindDir9am	10566	0.93	1	3	0	16	0
WindDir3pm	4228	0.97	1	3	0	16	0
RainToday	3261	0.98	2	3	0	2	0
RainTomorrow	3267	0.98	2	3	0	2	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
MinTemp	1485	0.99	12.19	6.40	-8.5	7.6	12.0	16.9	33.9	
MaxTemp	1261	0.99	23.22	7.12	-4.8	17.9	22.6	28.2	48.1	
Rainfall	3261	0.98	2.36	8.48	0.0	0.0	0.0	0.8	371.0	
Evaporation	62790	0.57	5.47	4.19	0.0	2.6	4.8	7.4	145.0	
Sunshine	69835	0.52	7.61	3.79	0.0	4.8	8.4	10.6	14.5	
WindGustSpeed	10263	0.93	40.04	13.61	6.0	31.0	39.0	48.0	135.0	
WindSpeed9am	1767	0.99	14.04	8.92	0.0	7.0	13.0	19.0	130.0	
WindSpeed3pm	3062	0.98	18.66	8.81	0.0	13.0	19.0	24.0	87.0	
Humidity9am	2654	0.98	68.88	19.03	0.0	57.0	70.0	83.0	100.0	
Humidity3pm	4507	0.97	51.54	20.80	0.0	37.0	52.0	66.0	100.0	
Pressure9am	15065	0.90	1017.65	7.11	980.5	1012.9	1017.6	1022.4	1041.0	
Pressure3pm	15028	0.90	1015.26	7.04	977.1	1010.4	1015.2	1020.0	1039.6	
Cloud9am	55888	0.62	4.45	2.89	0.0	1.0	5.0	7.0	9.0	
Cloud3pm	59358	0.59	4.51	2.72	0.0	2.0	5.0	7.0	9.0	
Temp9am	1767	0.99	16.99	6.49	-7.2	12.3	16.7	21.6	40.2	
Temp3pm	3609	0.98	21.68	6.94	-5.4	16.6	21.1	26.4	46.7	

As we can see from the figure above, there are 7 **categorical** attributes and 16 **numerical** attributes.
Before taking a deeper look on all other attributes, we first did a brief exploration of the target variable:

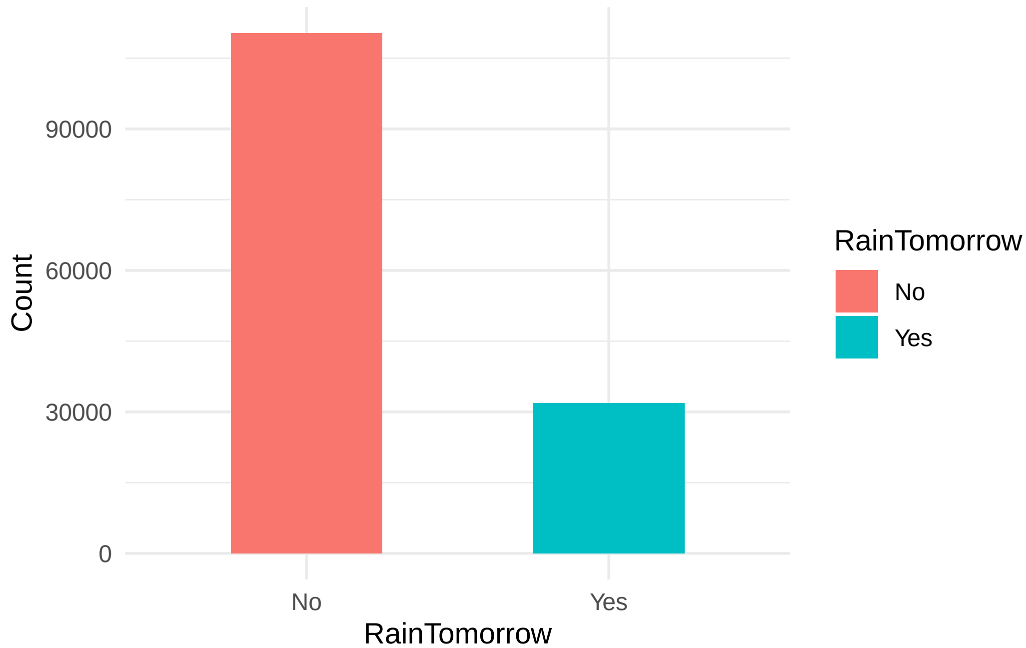
- **MISSING VALUES**

```
missingValues <- sum(is.na(weatherAus$RainTomorrow))
missingValues
```

```
[1] 3267
```

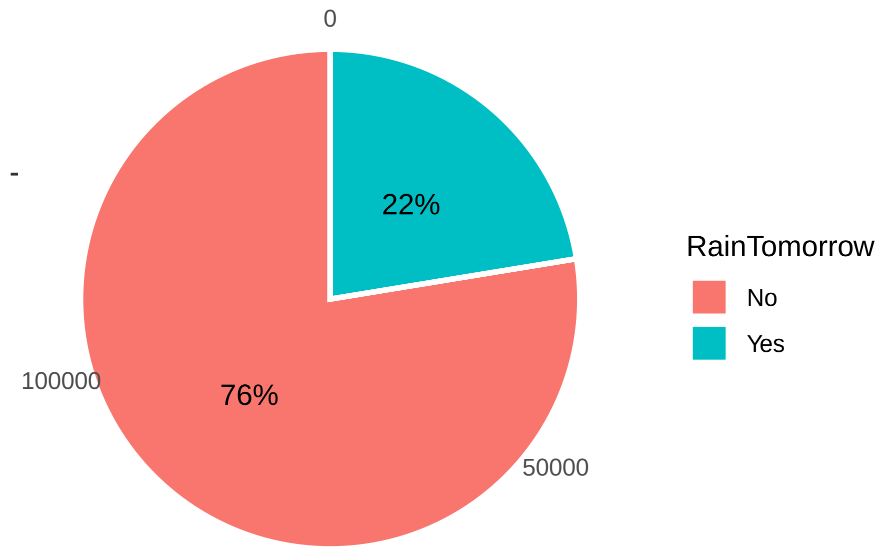
- **FREQUENCY DISTRIBUTION OF VALUES**

```
weatherAus %>% select(RainTomorrow) %>%
count(RainTomorrow) %>% drop_na() %>%
ggplot(., aes(RainTomorrow, n, fill=RainTomorrow)) +
geom_col(width = 0.5)+
labs(x = "RainTomorrow", y = "Count")+
theme_minimal()
```



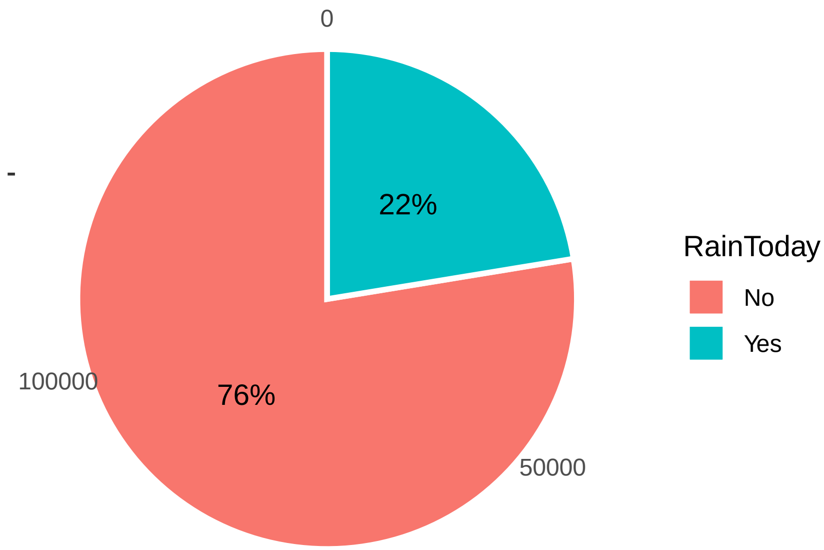
- **RATIO OF FREQUENCY DISTRIBUTION**

```
weatherAus %>% select(RainTomorrow) %>%
count(RainTomorrow) %>% drop_na() %>%
ggplot(., aes(x="", n, fill = RainTomorrow)) +
geom_bar(width = 1, size = 1, color = "white",stat = "identity") + coord_polar("y", star
geom_text(aes(label = paste0(round((n/145460)*100),"%")),
          position = position_stack(vjust = 0.5)) +
theme_classic() +
labs(x = NULL, y = NULL) +
theme(axis.line = element_blank())
```



From the plots drawn above, we can clearly see that RainTomorrow has 2 categories of values: **Yes** and **No**. There are far more NEGATIVE values than POSITIVE. *"No"* and *"Yes"* appears 76% of time and 22% of time respectively after deleting all NA values from the attribute.

```
weatherAus %>% select(RainToday) %>%
count(RainToday) %>% drop_na() %>%
ggplot(., aes(x="", n, fill = RainToday)) +
geom_bar(width = 1, size = 1, color = "white",stat = "identity") + coord_polar("y", star
geom_text(aes(label = paste0(round((n/145460)*100),"%")),
          position = position_stack(vjust = 0.5)) +
theme_classic() +
labs(x = NULL, y = NULL) +
theme(axis.line = element_blank())
```



The variable **RainToday** has a very similar value distribution as the target variable. ...!!!!!!!!!!!!!!!!!!!!!

Categorical values

All together there are 6 categorical features + a Date column. In order to make the information about the date more useful, we decided to extract the year, the month and the day from the date into three separate columns.
This is done here below:

```
weatherAusNew <- weatherAus %>% mutate(
  Year = year(Date),
  Month = month(Date),
  Day = day(Date)
) %>% select(-Date)
as_tibble(weatherAusNew)
```

```
# A tibble: 145,460 x 25
   Location MinTemp MaxTemp Rainfall Evaporation Sunshine WindGustDir
   <chr>      <dbl>   <dbl>    <dbl>       <dbl>    <dbl> <chr>
 1 Albury      13.4    22.9      0.6          NA       NA W
 2 Albury       7.4    25.1      0            NA       NA WNW
 3 Albury      12.9    25.7      0            NA       NA WSW
 4 Albury       9.2    28        0            NA       NA NE
 5 Albury      17.5    32.3      1            NA       NA W
 6 Albury      14.6    29.7      0.2          NA       NA WNW
 7 Albury      14.3    25        0            NA       NA W
 8 Albury       7.7    26.7      0            NA       NA W
 9 Albury       9.7    31.9      0            NA       NA NNW
10 Albury      13.1    30.1      1.4          NA       NA W
# i 145,450 more rows
# i 18 more variables: WindGustSpeed <int>, WindDir9am <chr>, WindDir3pm <chr>,
#   WindSpeed9am <int>, WindSpeed3pm <int>, Humidity9am <int>,
#   Humidity3pm <int>, Pressure9am <dbl>, Pressure3pm <dbl>, Cloud9am <int>,
#   Cloud3pm <int>, Temp9am <dbl>, Temp3pm <dbl>, RainToday <chr>,
#   RainTomorrow <chr>, Year <dbl>, Month <dbl>, Day <int>
```

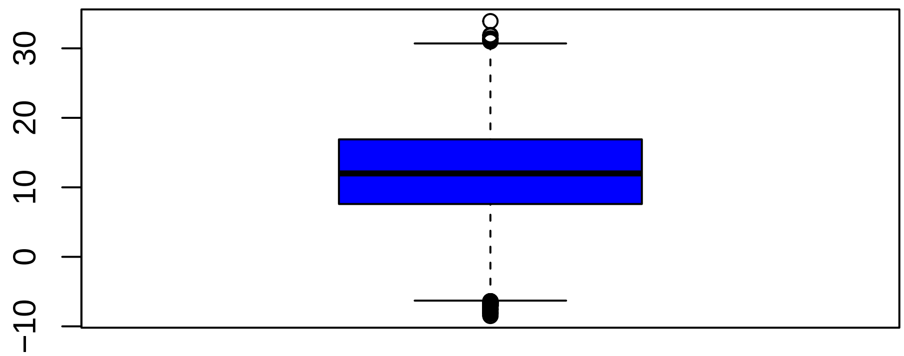
Numerical values

There are 16 numerical attributes in the raw dataset, after adding three columns for year, month and day, there are in total 19 numerical attributes. The main goal when analyzing numerical data is to find the outliers. Outliers are data information that differ significantly from other observations.

The most efficient way to detect outliers is to draw box plots:

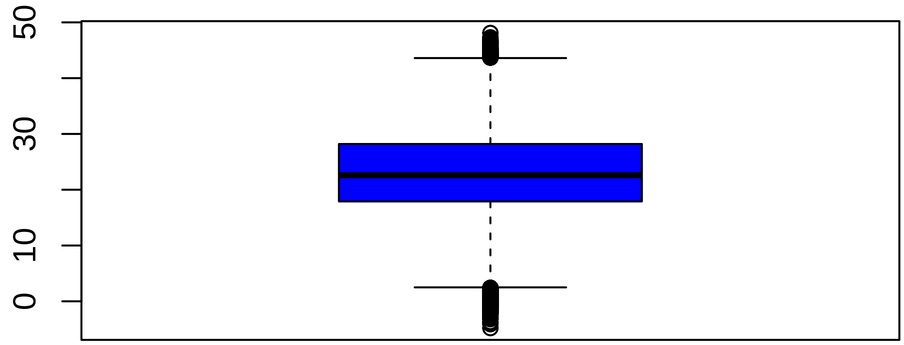
MinTemp

```
boxplot(weatherAusNew$MinTemp, col = "blue", border = "black")
```



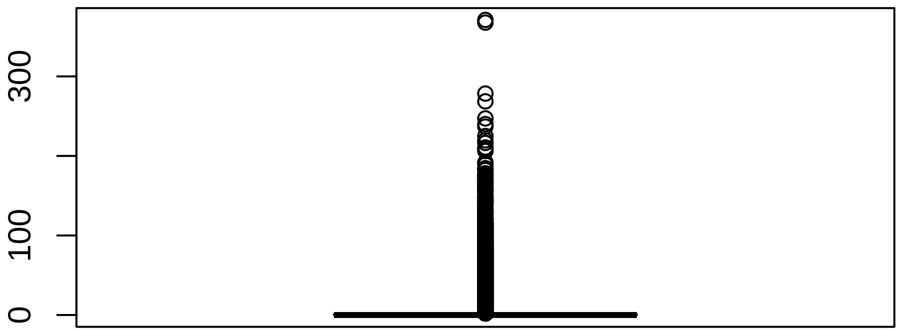
MaxTemp

```r
boxplot(weatherAusNew$MaxTemp, col = "blue", border = "black")
```



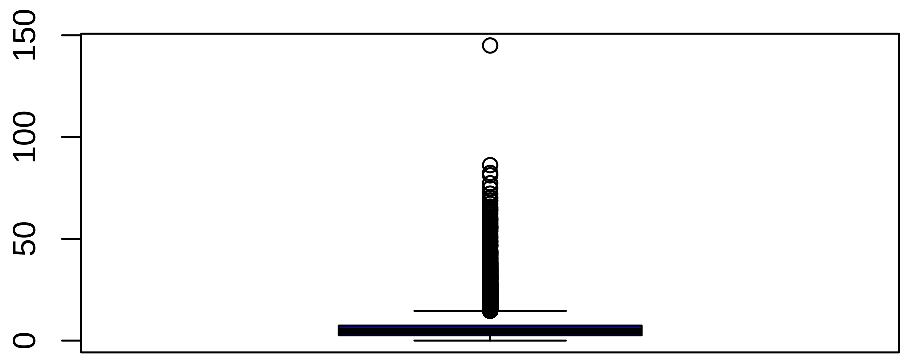
Rainfall

```r
boxplot(weatherAusNew$Rainfall, col = "blue", border = "black")
```



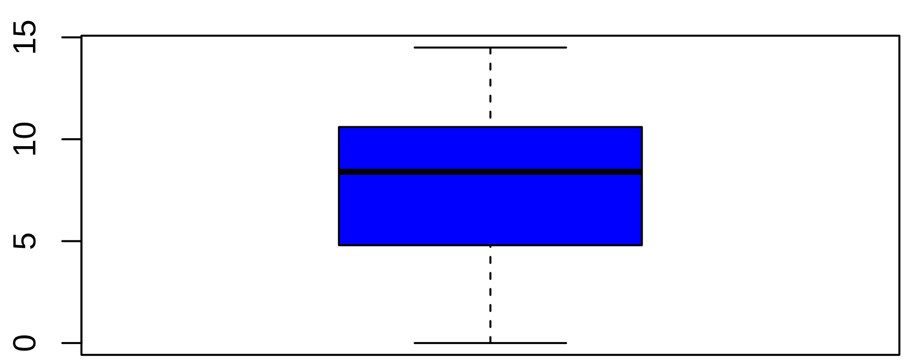
Evaporation

```r
boxplot(weatherAusNew$Evaporation, col = "blue", border = "black")
```



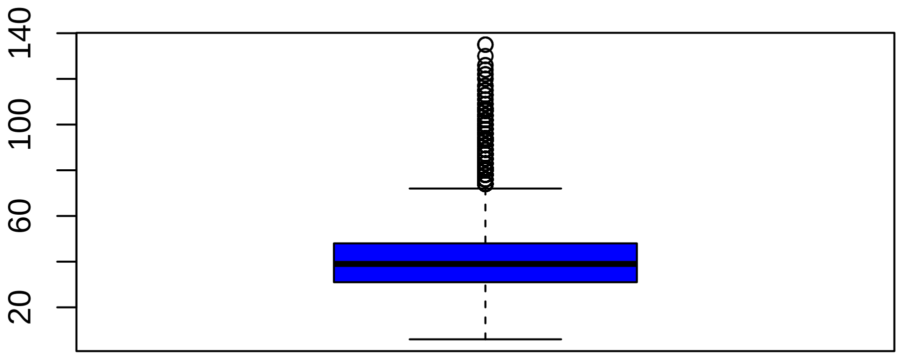
Sunshine

```
boxplot(weatherAusNew$Sunshine, col = "blue", border = "black")
```



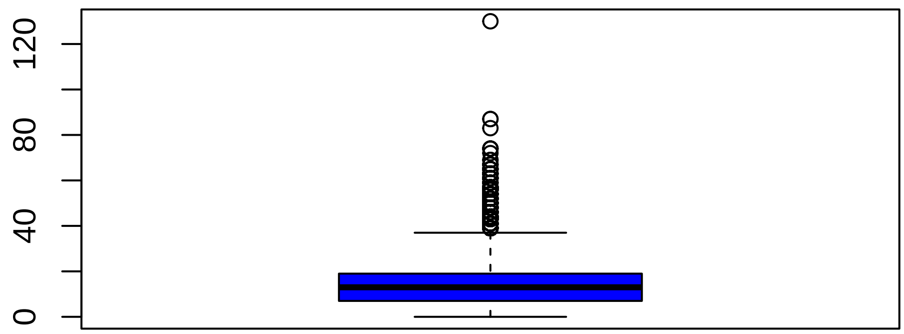
WindGustSpeed

```r
boxplot(weatherAusNew$WindGustSpeed, col = "blue", border = "black")
```



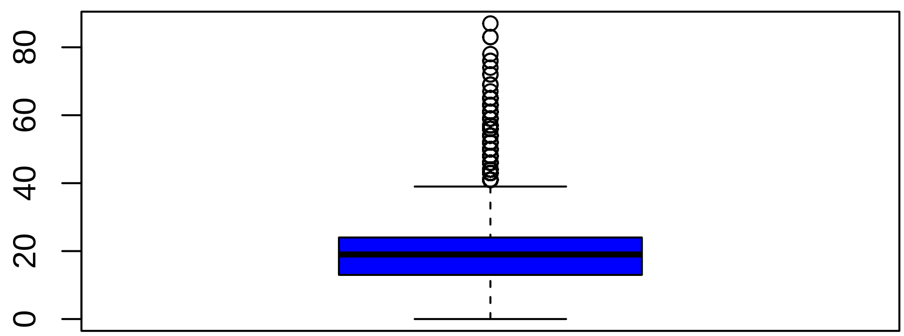
WindSpeed9am

```r
boxplot(weatherAusNew$WindSpeed9am, col = "blue", border = "black")
```



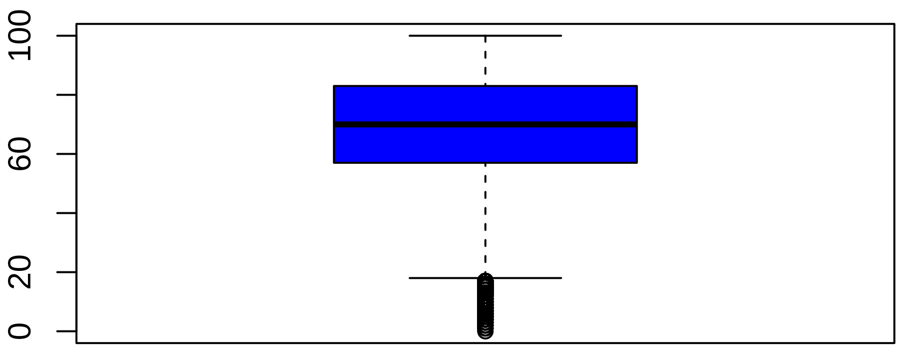
WindSpeed3pm

```
boxplot(weatherAusNew$WindSpeed3pm, col = "blue", border = "black")
```



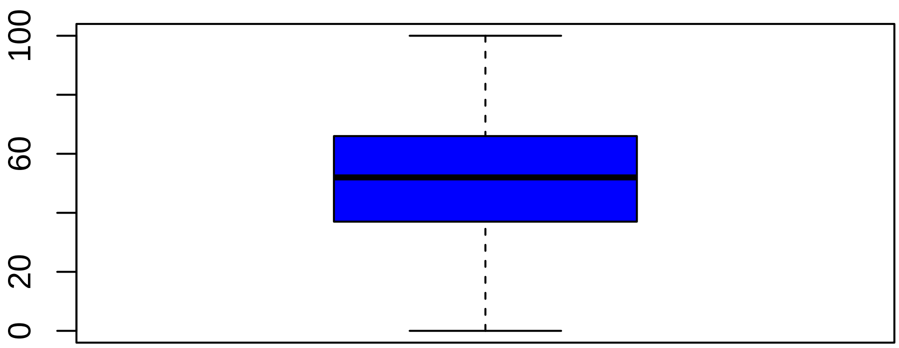
Humidity9am

```r
boxplot(weatherAusNew$Humidity9am, col = "blue", border = "black")
```



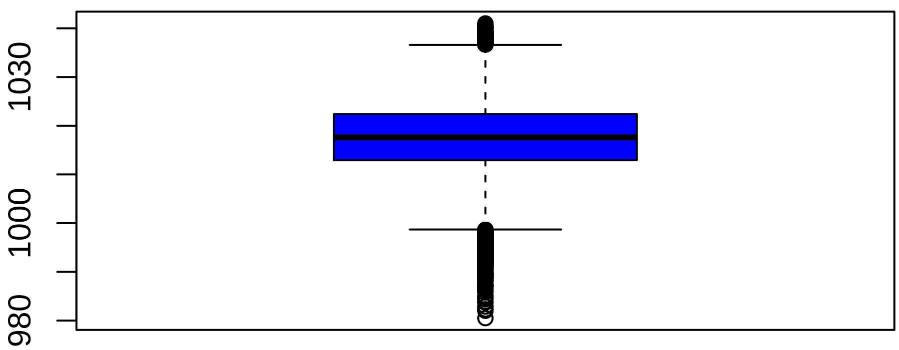
Humidity3pm

```r
boxplot(weatherAusNew$Humidity3pm, col = "blue", border = "black")
```



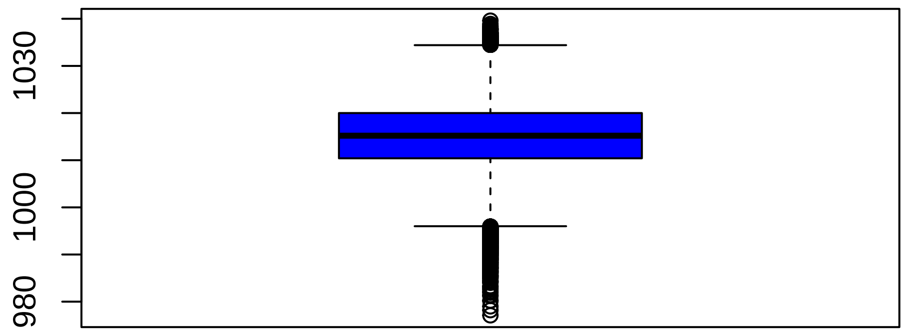
Pressure9am

```
boxplot(weatherAusNew$Pressure9am, col = "blue", border = "black")
```



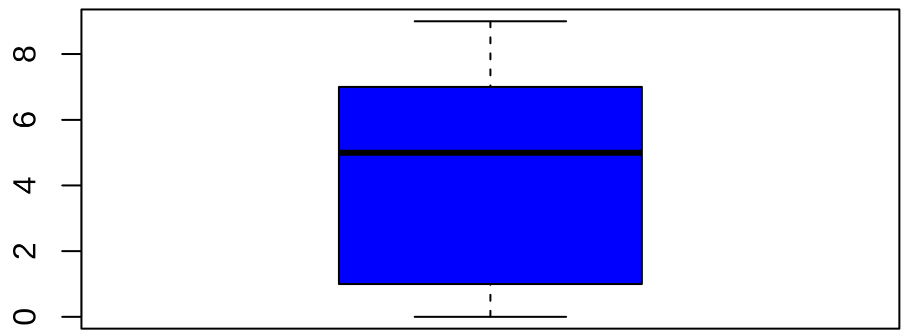
Pressure3pm

```
boxplot(weatherAusNew$Pressure3pm, col = "blue", border = "black")
```



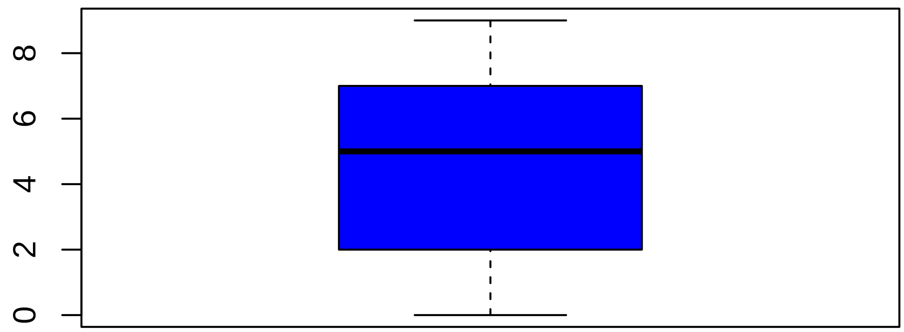
Cloud9am

```
boxplot(weatherAusNew$Cloud9am, col = "blue", border = "black")
```



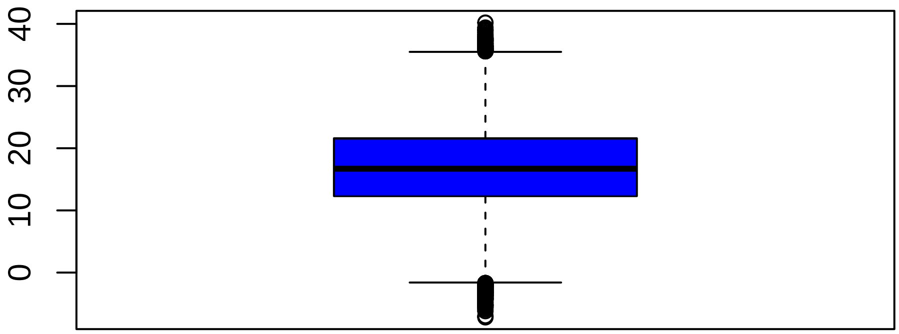
Cloud3pm

```
boxplot(weatherAusNew$Cloud3pm, col = "blue", border = "black")
```



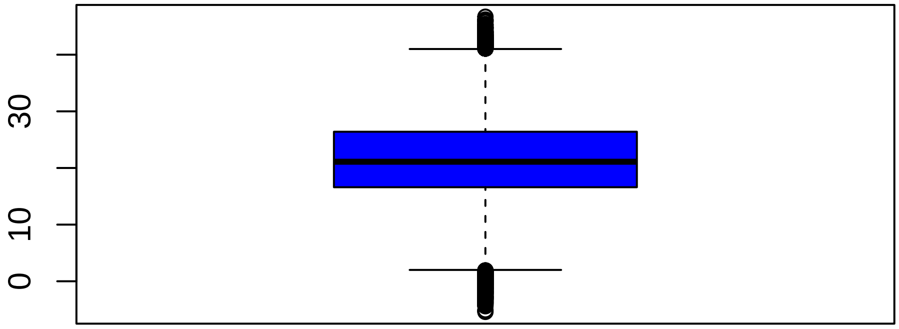
Temp9am

```
boxplot(weatherAusNew$Temp9am, col = "blue", border = "black")
```



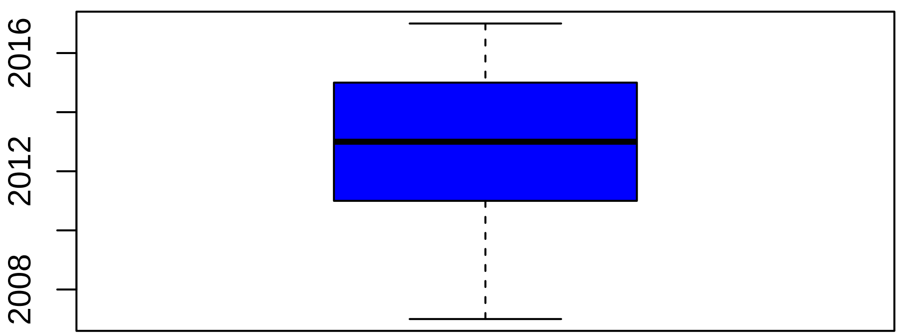
Temp3pm

```
boxplot(weatherAusNew$Temp3pm, col = "blue", border = "black")
```



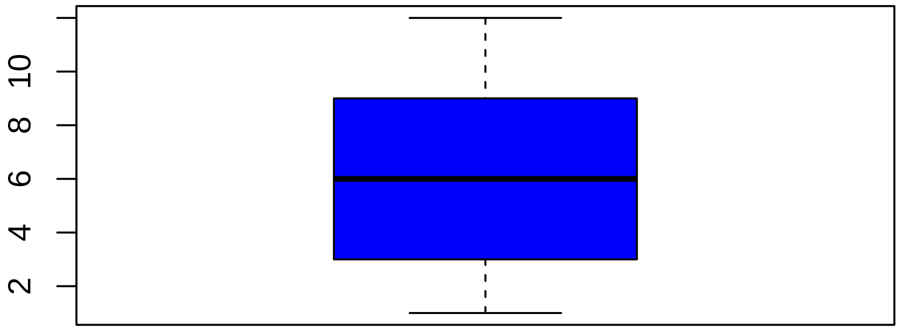
Year

```
boxplot(weatherAusNew$Year, col = "blue", border = "black")
```



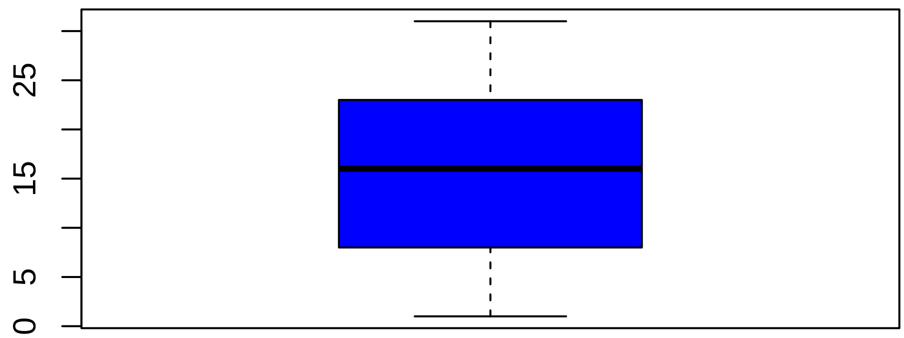
Month

```
boxplot(weatherAusNew$Month, col = "blue", border = "black")
```



Day

```
boxplot(weatherAusNew$Day, col = "blue", border = "black")
```



Multicollinearity

```
weatherAusNew %>% select(where(is.numeric)) %>% model.matrix(~0+.,
              data=.) %>%
    cor(use="pairwise.complete.obs") %>%
    ggcorrplot(show.diag = FALSE, type="full",
               lab=TRUE,legend.title = "Correlation" ,lab_size
               = 2,lab_col = "black" ,ggtheme =
                 ggplot2::theme_gray,
               colors = c("white","green","darkgreen"),
               outline.color = "black")

write.csv(weatherAusNew, file = "weatherNewToPython.csv", row.names = FALSE)
colnames(weatherAusNew)
```

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

```
[25] "Day"
```

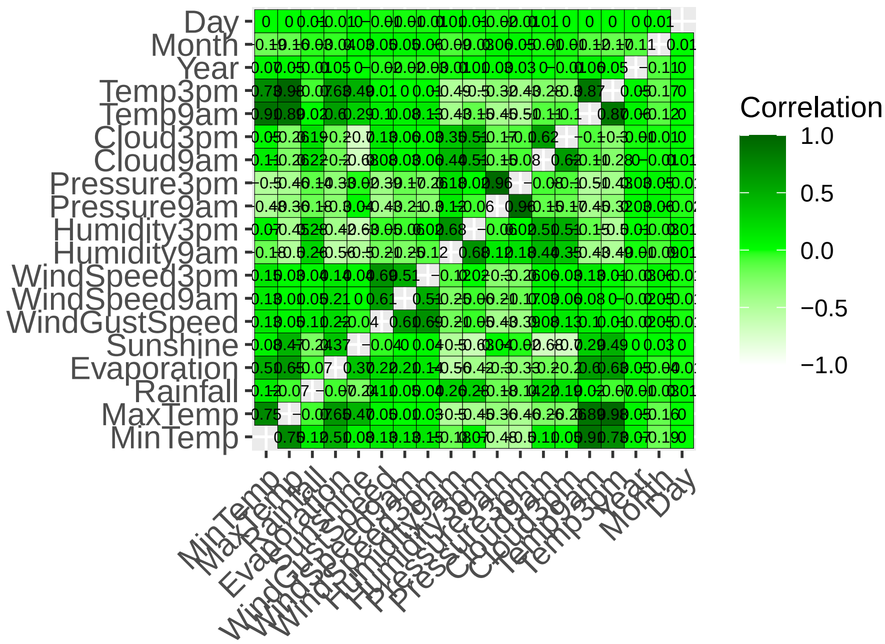


Figure 1: Correlation Heatmap

Outliers & Missing Values

Outliers

After drawing a boxplot for each numerical attribute in the dataset, we compared the mean of each column with the min/max value and we have noticed that that attributes **Rainfall**, **Evaporation**, **WindSpeed9am** and **WindSpeed3pm** might have a large number of outliers as there's a considerable difference between average value and max value. This also can be seen from their plots, as there is a huge amount of points (values) that differ from the average. Outliers can be identified by using some visualization tools as we have seen above, or also with some statistical methods. Once detected, outliers can be addressed by removing them, transforming the data, or using robust models less sensitive to outliers.

When implementing the models, we will split the dataset into training and testing sets. The training set will be used to train machine learning models, allowing the algorithms to learn from the data. The testing set, on the other hand, will be used to evaluate the models' performance on unseen data, ensuring that the models generalize well and provide accurate predictions in real-world scenarios.

Missing Values

Addressing missing values is crucial during data preprocessing. Missing values can result from data entry errors, collection issues, and they can degrade performance. Because of this we are going to impute the missing values at each implementation of the three models. **Missing values in categorical columns** will be filled up using the Python function **mode()** that fills in the cells with the most common/occuring element from all other instances. **Missing values in numerical columns** will be filled up with the median value from all the values of the other instances.

Modeling

After performing the Exploratory Data Analysis, we will proceed to the modeling part. In this phase we will implement three models: **Artificial Neural Network**, **CatBoost**, and **Logistic Regression**.

Till now the analysis was made using code chunks performed in R langauge. For this implementation part the models will be implemented in Python.

Artificial Neural Network

- The ANN model derives from Biological neural networks that have the structure of the human brain. It contains neurons(nodes) interconnected to one another in various layers of the network. It consists of three layers: Input layer, Hidden layers (can be several of them) and Output layer. The input layer accepts inputs in several formats, the hidden layer is in-between the inputs and outputs and performs calculations to find hidden features and patterns. The output layer outputs the results of calculations.

- *ADVANTAGES*
  - **Parallel processing**
  - Information can produce **output** even with **inadequate data**
  - **Success** proportional to **chosen instances**
- *DISADVANTAGES*
  - Depends on **hardware**

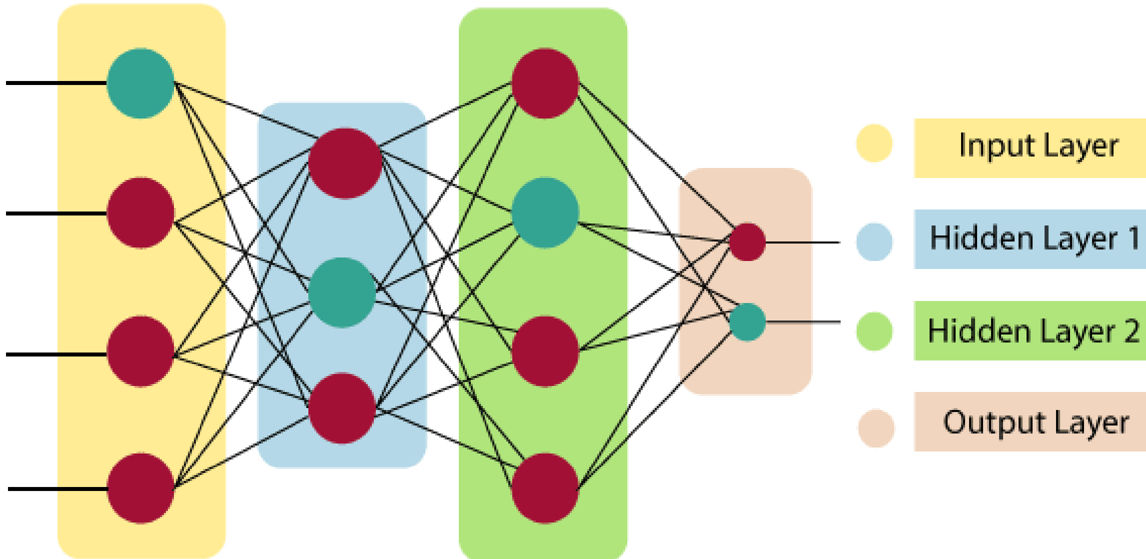


Figure 2: ANN layers

  - ANNs work with **numerical data**
  - Duration of network is **unknown**

- **FUNCTIONING**

  Each input is multiplied by its corresponding weights (strength of interconnections between neurons). All weighted inputs are summarized inside the computing unit. Each neuron has its **bias,** which is added to the weighted sum to make it non-zero, so the total sum of weighted inputs can be from 0 to plus infinity. The maximum value is **benchmarked** to keep the response in the limits. This is performed in *TRANSFER FUNCTIONS.*

  ACTIVATION FUNCTIONS choose whether a node should fire or not. Only those who are *fired* make it to the output layer. Activation functions are distinctive depending on the task that is performed.

- **FEED-BACK**
  - Feed-back networks feed information back to itself

- **FEED-FORWARD**
  - Assessment of ouputs by reviewing its inputs
  - Input –> Neuron layer –> Output

```python
# ANN IMPLEMENTATIONN
import pandas as pd
import numpy as np
import seaborn as sns
from catboost import CatBoostClassifier, Pool
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
from keras.layers import Dense, BatchNormalization, Dropout
from keras.models import Sequential
from keras import callbacks
from keras.optimizers import Adam
from sklearn.preprocessing import LabelEncoder, StandardScaler, OneHotEncoder

df = pd.read_csv('weatherNewToPython.csv')

# Categorical columns
s = (df.dtypes == "object")
cat_cols = list(s[s].index)

print("Categorial variables")
```

```
Categorial variables
```

```python
print(cat_cols)
```

```
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday', 'RainTomorrow']
```

```python
for cols in cat_cols:

    df[cols] = df[cols].fillna(df[cols].mode()[0])
```

```python
# Numerical columns
t = (df.dtypes == "float64")
num_cols = list(t[t].index)

print("Numeric variables:")
```

```
Numeric variables:
```

```python
print(num_cols)
```

```
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpeed', 'WindSpeed9am
```

```python
for cols in num_cols:

    df[cols] = df[cols].fillna(df[cols].median())
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 25 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Location       145460 non-null  object
 1   MinTemp        145460 non-null  float64
 2   MaxTemp        145460 non-null  float64
 3   Rainfall       145460 non-null  float64
 4   Evaporation    145460 non-null  float64
 5   Sunshine       145460 non-null  float64
 6   WindGustDir    145460 non-null  object
 7   WindGustSpeed  145460 non-null  float64
 8   WindDir9am     145460 non-null  object
 9   WindDir3pm     145460 non-null  object
 10  WindSpeed9am   145460 non-null  float64
 11  WindSpeed3pm   145460 non-null  float64
 12  Humidity9am    145460 non-null  float64
 13  Humidity3pm    145460 non-null  float64
 14  Pressure9am    145460 non-null  float64
 15  Pressure3pm    145460 non-null  float64
 16  Cloud9am       145460 non-null  float64
```

```
 17  Cloud3pm       145460 non-null  float64
 18  Temp9am        145460 non-null  float64
 19  Temp3pm        145460 non-null  float64
 20  RainToday      145460 non-null  object
 21  RainTomorrow   145460 non-null  object
 22  Year           145460 non-null  int64
 23  Month          145460 non-null  int64
 24  Day            145460 non-null  int64
dtypes: float64(16), int64(3), object(6)
memory usage: 27.7+ MB
```

```
df.head(10)
```

```
  Location  MinTemp  MaxTemp  Rainfall  ...  RainTomorrow  Year Month  Day
0   Albury     13.4     22.9       0.6  ...            No  2008    12    1
1   Albury      7.4     25.1       0.0  ...            No  2008    12    2
2   Albury     12.9     25.7       0.0  ...            No  2008    12    3
3   Albury      9.2     28.0       0.0  ...            No  2008    12    4
4   Albury     17.5     32.3       1.0  ...            No  2008    12    5
5   Albury     14.6     29.7       0.2  ...            No  2008    12    6
6   Albury     14.3     25.0       0.0  ...            No  2008    12    7
7   Albury      7.7     26.7       0.0  ...            No  2008    12    8
8   Albury      9.7     31.9       0.0  ...           Yes  2008    12    9
9   Albury     13.1     30.1       1.4  ...            No  2008    12   10

[10 rows x 25 columns]
```

```
# Categorical columns of type "object" into "float64"
label_encoder = LabelEncoder()
for cols in cat_cols:
    df[cols] = label_encoder.fit_transform(df[cols])


df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 25 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
```

```
 0   Location       145460 non-null  int32
 1   MinTemp        145460 non-null  float64
 2   MaxTemp        145460 non-null  float64
 3   Rainfall       145460 non-null  float64
 4   Evaporation    145460 non-null  float64
 5   Sunshine       145460 non-null  float64
 6   WindGustDir    145460 non-null  int32
 7   WindGustSpeed  145460 non-null  float64
 8   WindDir9am     145460 non-null  int32
 9   WindDir3pm     145460 non-null  int32
 10  WindSpeed9am   145460 non-null  float64
 11  WindSpeed3pm   145460 non-null  float64
 12  Humidity9am    145460 non-null  float64
 13  Humidity3pm    145460 non-null  float64
 14  Pressure9am    145460 non-null  float64
 15  Pressure3pm    145460 non-null  float64
 16  Cloud9am       145460 non-null  float64
 17  Cloud3pm       145460 non-null  float64
 18  Temp9am        145460 non-null  float64
 19  Temp3pm        145460 non-null  float64
 20  RainToday      145460 non-null  int32
 21  RainTomorrow   145460 non-null  int32
 22  Year           145460 non-null  int64
 23  Month          145460 non-null  int64
 24  Day            145460 non-null  int64
dtypes: float64(16), int32(6), int64(3)
memory usage: 24.4 MB
```

```python
# dropping target and extra columns
features = df.drop(['RainTomorrow', 'Year','Month', 'Day'], axis=1)
target = df['RainTomorrow']

X = features
y = target

# Splitting test and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =

X.shape
```

```
(145460, 21)
```