PH125.9x Capstone Project - Choose Your Own

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Introduction

The dataset chosen for this project is *Rain in Australia*, which is a publicly available dataset found on the Kaggle website (see https://www.kaggle.com/jsphyg/weather-dataset-rattle-package). The dataset contains daily measurements of various weather variables from weather stations at a number of locations throughout Australia, over a period of several years.

The aim of the project is to fit a machine learning binary classification model to the data that will predict whether or not it will rain on the following day.

The approach adopted was to fit several different classes of model to the data and select the one that gave the best performance. Accuracy was used as the measure of performance.

The models chosen were:

- Generalized Linear Model
- Linear Discriminant Analysis
- Quadratic Discriminant Analysis
- Multi-Layer Perceptron
- k-Nearest Neighbors
- Random Forest

The dataset was cleaned and then split into training and test sets, with the training set used to fit the models and the test set used to assess their performance.

While all of the models chosen gave similar performance, the Random Forest model performed best, with an accuracy of 0.86. Although this appears to be a good result, the model has a sensitivity of only 0.50, which means that it results in as many false negatives as true positives. So if the goal of the model is to correctly predict days on which it will rain (as opposed to whether or not it will rain), the model performs about the same as tossing a coin.

Method

The weather data was downloaded from the Kaggle site in CSV format and saved locally to disk. The CSV file was then loaded into a data frame in memory.

Initial Exploratory Analysis

The structure and dimensions of the data frame are shown below. This shows that the data contains *RainTomorrow*, the variable to be predicted by the model, along with other variables that can potentially be used as inputs to the model. It also shows that the data is a mixture of numeric and character variables, and that there are some missing values.

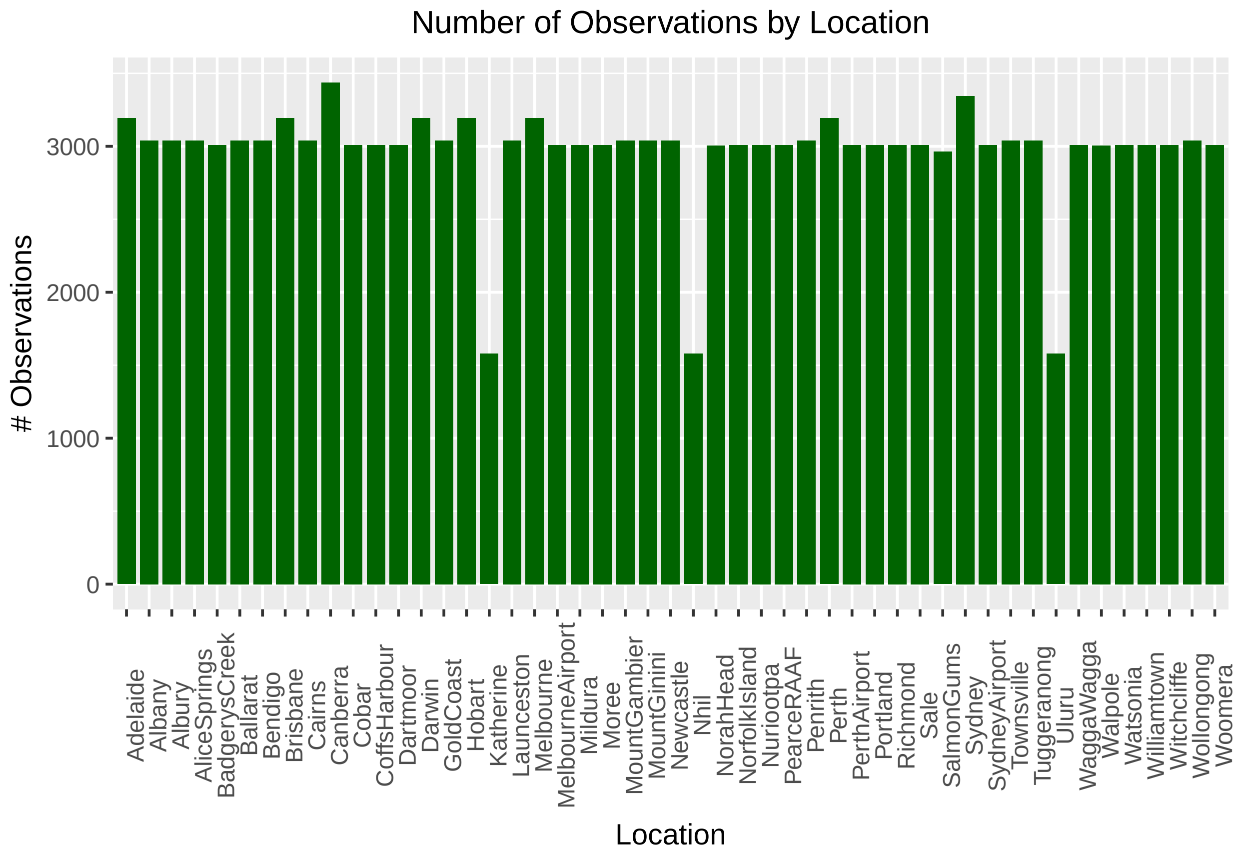
```
## 'data.frame':    145463 obs. of  24 variables:
##  $ Date         : chr  "2008-12-01" "2008-12-02" "2008-12-03" "2008-12-04" ...
##  $ Location     : chr  "Albury" "Albury" "Albury" "Albury" ...
##  $ MinTemp      : num  13.4 7.4 12.9 9.2 17.5 14.6 14.3 7.7 9.7 13.1 ...
##  $ MaxTemp      : num  22.9 25.1 25.7 28 32.3 29.7 25 26.7 31.9 30.1 ...
##  $ Rainfall     : num  0.6 0 0 0 1 0.2 0 0 0 1.4 ...
##  $ Evaporation  : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ Sunshine     : num  NA NA NA NA NA NA NA NA NA NA ...
```

```
##  $ WindGustDir  : chr  "W" "WNW" "WSW" "NE" ...
##  $ WindGustSpeed: int  44 44 46 24 41 56 50 35 80 28 ...
##  $ WindDir9am   : chr  "W" "NNW" "W" "SE" ...
##  $ WindDir3pm   : chr  "WNW" "WSW" "WSW" "E" ...
##  $ WindSpeed9am : int  20 4 19 11 7 19 20 6 7 15 ...
##  $ WindSpeed3pm : int  24 22 26 9 20 24 24 17 28 11 ...
##  $ Humidity9am  : int  71 44 38 45 82 55 49 48 42 58 ...
##  $ Humidity3pm  : int  22 25 30 16 33 23 19 19 9 27 ...
##  $ Pressure9am  : num  1008 1011 1008 1018 1011 ...
##  $ Pressure3pm  : num  1007 1008 1009 1013 1006 ...
##  $ Cloud9am     : int  8 NA NA NA 7 NA 1 NA NA NA ...
##  $ Cloud3pm     : int  NA NA 2 NA 8 NA NA NA NA NA ...
##  $ Temp9am      : num  16.9 17.2 21 18.1 17.8 20.6 18.1 16.3 18.3 20.1 ...
##  $ Temp3pm      : num  21.8 24.3 23.2 26.5 29.7 28.9 24.6 25.5 30.2 28.2 ...
##  $ RainToday    : chr  "No" "No" "No" "No" ...
##  $ RISK_MM      : num  0 0 0 1 0.2 0 0 0 1.4 0 ...
##  $ RainTomorrow : chr  "No" "No" "No" "No" ...
```

The locations at which measurements were recorded and the number of observations at each location are shown in the following table and bar chart.

```
## 
##          Adelaide           Albany           Albury     AliceSprings 
##              3193             3040             3041             3041 
##     BadgerysCreek         Ballarat          Bendigo         Brisbane 
##              3010             3041             3041             3194 
##            Cairns         Canberra            Cobar     CoffsHarbour 
##              3041             3437             3010             3010 
##          Dartmoor           Darwin        GoldCoast           Hobart 
##              3010             3194             3041             3194 
##         Katherine       Launceston        Melbourne MelbourneAirport 
##              1579             3041             3194             3010 
##           Mildura            Moree     MountGambier      MountGinini 
##              3010             3010             3041             3041 
##         Newcastle             Nhil        NorahHead    NorfolkIsland 
##              3041             1579             3005             3010 
##         Nuriootpa       PearceRAAF          Penrith            Perth 
##              3009             3009             3040             3193 
##      PerthAirport         Portland         Richmond             Sale 
##              3009             3010             3010             3010 
##        SalmonGums           Sydney    SydneyAirport       Townsville 
##              2963             3345             3010             3041 
##       Tuggeranong            Uluru       WaggaWagga          Walpole 
##              3040             1579             3010             3006 
##          Watsonia      Williamtown      Witchcliffe       Wollongong 
##              3010             3010             3009             3041 
##           Woomera 
##              3010
```

```
## [1] "Number of locations: 49"
```



This shows that most of the locations have approximately 3000 observations.

The date range of the measurements is a little over 10 years:

```
## [1] "2007-11-01 to 2018-07-30"
```

Checking for Missing Data

Observations containing missing data should be removed (or replaced with estimates) before attempting to fit any models. This section shows the results of checking columns (variables) and rows (observations) for missing data.

Check columns first:

```
##      Sunshine   Evaporation      Cloud3pm      Cloud9am   Pressure9am
##         70820         64800         60416         57043         15354
##   Pressure3pm    WindDir9am   WindGustDir WindGustSpeed    WindDir3pm
##         15349         11029         10730         10667          4576
##   Humidity3pm       Temp3pm  WindSpeed3pm      Rainfall     RainToday
##          4412          3571          3407          3218          3218
##       RISK_MM  RainTomorrow   Humidity9am  WindSpeed9am       Temp9am
##          3217          3217          2579          2081          1751
##       MinTemp       MaxTemp          Date      Location
##          1545          1335             0             0
```

These results show that there are four columns with more than 50000 missing values, substantially more than any of the other columns.

Now check how many rows would remain if these four columns were removed and rows containing any missing values were omitted:

```
## [1] 112658
```

This represents about 77.5% of the observations, which will be regarded as sufficient for fitting and testing models.

Data Cleaning

The operations involved in cleaning the data are:

1. removing the four columns identified above,
2. omitting rows with any remaining missing data,
3. replacing any character data with numeric values, and
4. converting the column to be predicted, *RainTomorrow*, to a factor for classification purposes.

The *Date* column is also to be removed, along with *RISK_MM*, which would give the model an unfair advantage. The reason for not including *RISK_MM* as an input is best explained in the following quote from the creator of the dataset:

> *RISK-MM is the amount of rainfall in millimeters for the next day. It includes all forms of precipitation that reach the ground, such as rain, drizzle, hail and snow. And it was the column that was used to actually determine whether or not it rained to create the binary target. For example, if RISK-MM was greater than 0, then the RainTomorrow target variable is equal to Yes.*

After the above operations had been performed, the resulting dataset had the following dimensions:

```
## [1] "No. of rows (observations): 112658"
```

```
## [1] "No. of columns (variables): 18"
```

Exploratory Analysis of Cleaned Data

The structure of the cleaned data is shown below.

```
## 'data.frame':    112658 obs. of  18 variables:
##  $ Location     : chr  "Albury" "Albury" "Albury" "Albury" ...
##  $ MinTemp      : num  13.4 7.4 12.9 9.2 17.5 14.6 14.3 7.7 9.7 13.1 ...
##  $ MaxTemp      : num  22.9 25.1 25.7 28 32.3 29.7 25 26.7 31.9 30.1 ...
##  $ Rainfall     : num  0.6 0 0 0 1 0.2 0 0 0 1.4 ...
##  $ WindGustDir  : num  14 15 16 5 14 15 14 14 7 14 ...
##  $ WindGustSpeed: int  44 44 46 24 41 56 50 35 80 28 ...
##  $ WindDir9am   : num  14 7 14 10 2 14 13 11 10 9 ...
##  $ WindDir3pm   : num  15 16 16 1 8 14 14 14 8 11 ...
##  $ WindSpeed9am : int  20 4 19 11 7 19 20 6 7 15 ...
##  $ WindSpeed3pm : int  24 22 26 9 20 24 24 17 28 11 ...
##  $ Humidity9am  : int  71 44 38 45 82 55 49 48 42 58 ...
##  $ Humidity3pm  : int  22 25 30 16 33 23 19 19 9 27 ...
##  $ Pressure9am  : num  1008 1011 1008 1018 1011 ...
##  $ Pressure3pm  : num  1007 1008 1009 1013 1006 ...
##  $ Temp9am      : num  16.9 17.2 21 18.1 17.8 20.6 18.1 16.3 18.3 20.1 ...
##  $ Temp3pm      : num  21.8 24.3 23.2 26.5 29.7 28.9 24.6 25.5 30.2 28.2 ...
##  $ RainToday    : num  0 0 0 0 0 0 0 0 0 1 ...
##  $ RainTomorrow : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 2 1 ...
```

Location remains as a character variable, but it will not be used as a variable in fitting the models.

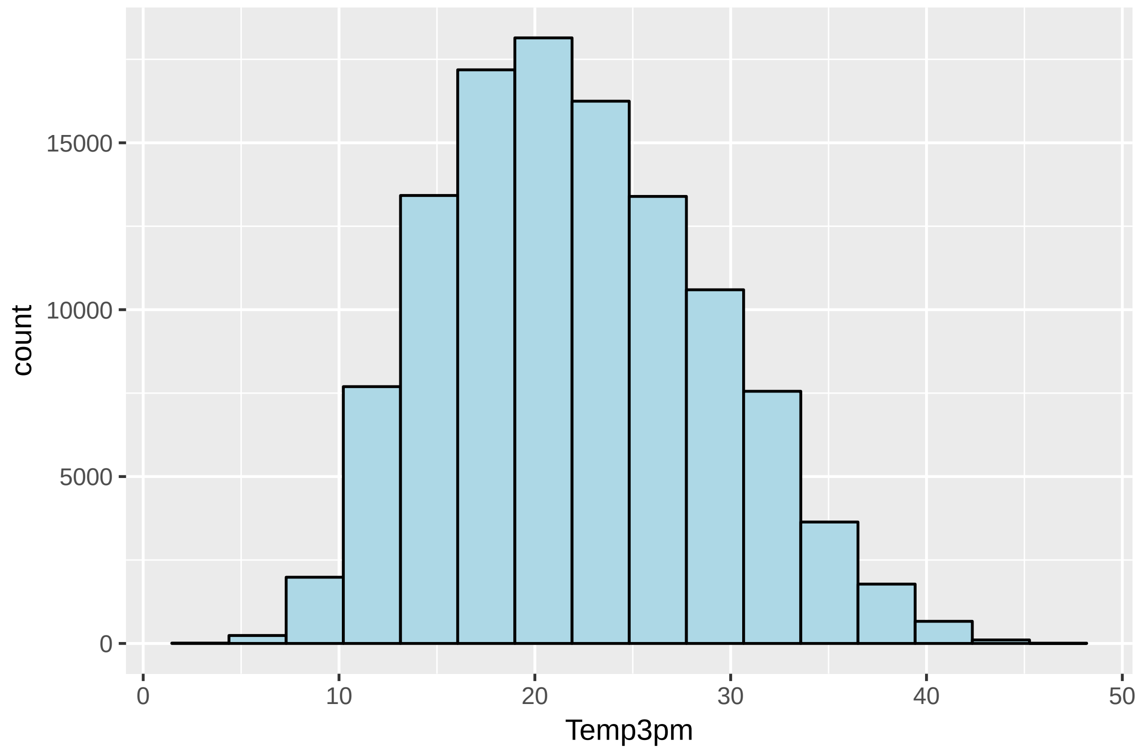
The following table shows summary statistics for each of the variables in the cleaned dataset.

```
##    Location            MinTemp         MaxTemp         Rainfall
##  Length:112658      Min.   :-8.70   Min.   : 2.60   Min.   :  0.000
##  Class :character   1st Qu.: 7.90   1st Qu.:18.20   1st Qu.:  0.000
##  Mode  :character   Median :12.30   Median :23.10   Median :  0.000
##                     Mean   :12.54   Mean   :23.61   Mean   :  2.315
##                     3rd Qu.:17.10   3rd Qu.:28.70   3rd Qu.:  0.600
##                     Max.   :33.90   Max.   :48.10   Max.   :367.600
##   WindGustDir     WindGustSpeed      WindDir9am       WindDir3pm
##  Min.   : 1.000   Min.   :  7.00   Min.   : 1.000   Min.   : 1.000
##  1st Qu.: 4.000   1st Qu.: 31.00   1st Qu.: 4.000   1st Qu.: 5.000
##  Median : 9.000   Median : 39.00   Median : 8.000   Median : 9.000
##  Mean   : 8.713   Mean   : 40.77   Mean   : 8.228   Mean   : 8.756
##  3rd Qu.:13.000   3rd Qu.: 48.00   3rd Qu.:12.000   3rd Qu.:13.000
##  Max.   :16.000   Max.   :135.00   Max.   :16.000   Max.   :16.000
##   WindSpeed9am    WindSpeed3pm    Humidity9am      Humidity3pm
##  Min.   : 2.00   Min.   : 2.00   Min.   :  0.00   Min.   :  0.00
##  1st Qu.: 9.00   1st Qu.:13.00   1st Qu.: 55.00   1st Qu.: 35.00
##  Median :13.00   Median :19.00   Median : 68.00   Median : 51.00
##  Mean   :15.17   Mean   :19.51   Mean   : 67.15   Mean   : 50.27
##  3rd Qu.:20.00   3rd Qu.:24.00   3rd Qu.: 81.00   3rd Qu.: 65.00
##  Max.   :87.00   Max.   :87.00   Max.   :100.00   Max.   :100.00
##   Pressure9am      Pressure3pm        Temp9am          Temp3pm
##  Min.   : 980.5   Min.   : 978.9   Min.   :-3.10   Min.   : 2.30
##  1st Qu.:1012.9   1st Qu.:1010.5   1st Qu.:12.60   1st Qu.:16.90
##  Median :1017.6   Median :1015.1   Median :17.00   Median :21.60
##  Mean   :1017.6   Mean   :1015.2   Mean   :17.37   Mean   :22.08
##  3rd Qu.:1022.4   3rd Qu.:1019.9   3rd Qu.:22.00   3rd Qu.:26.80
##  Max.   :1041.0   Max.   :1039.6   Max.   :40.20   Max.   :46.10
##    RainToday      RainTomorrow
##  Min.   :0.0000   0:88166
##  1st Qu.:0.0000   1:24492
##  Median :0.0000
##  Mean   :0.2204
##  3rd Qu.:0.0000
##  Max.   :1.0000
```

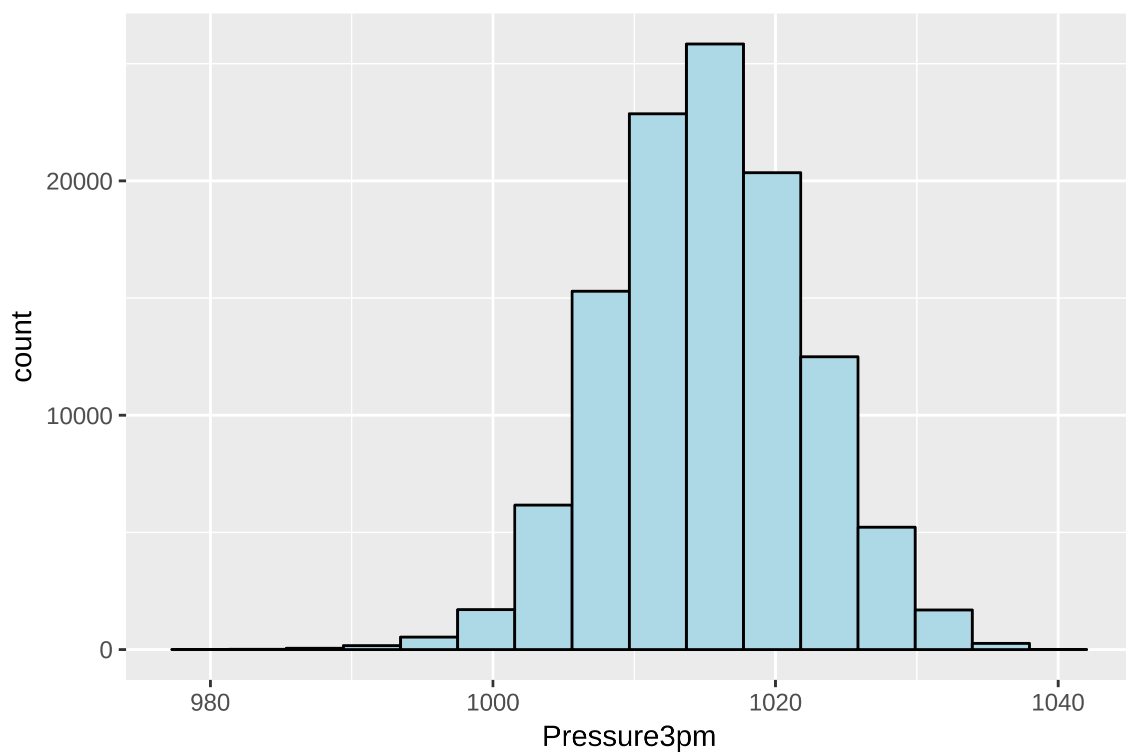
Apart from *Location* and the binary-valued *RainToday* and *RainTomorrow*, most of the variables are fairly symetrically distributed, with their means and medians close in value. The exception is *Rainfall*, which is positively skewed, with a minimum of 0, a median of 0, and a maximum of 367.6.

No attempt was made to detect and remove outliers, although removing them from *Rainfall* may have improved the performance of the models.

Samples of the frequency distributions are shown for two of the variables, *Temp3pm* amd *Pressure3pm*, in the plots below.

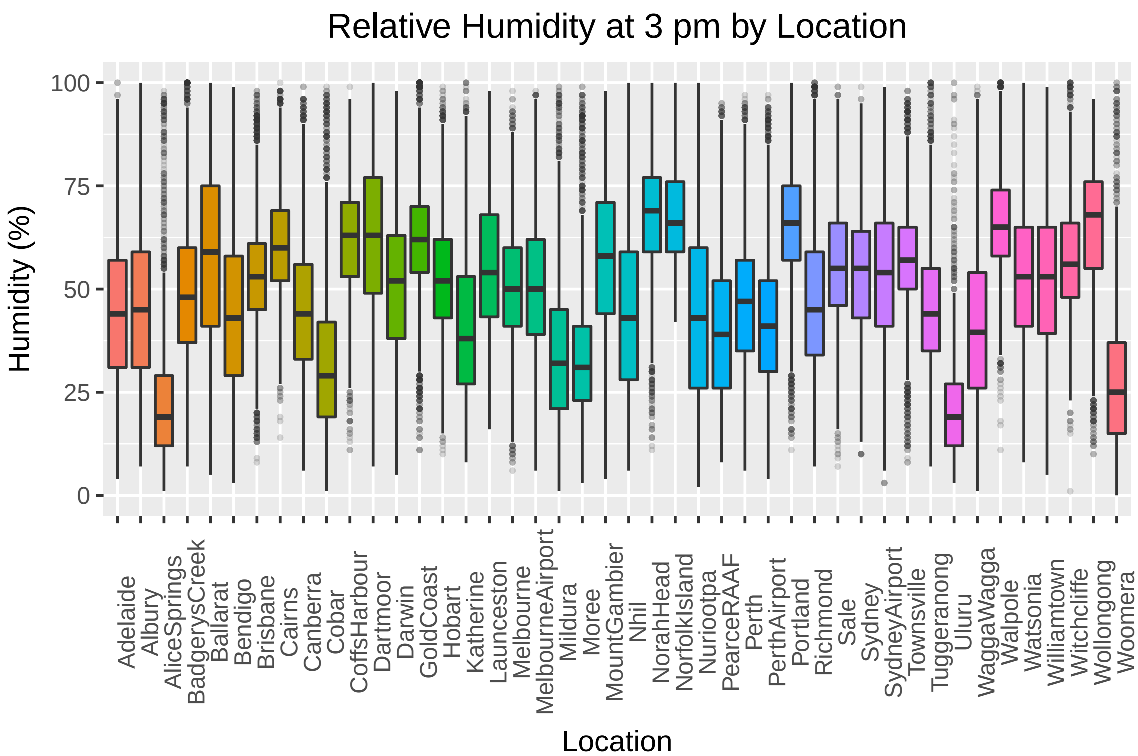


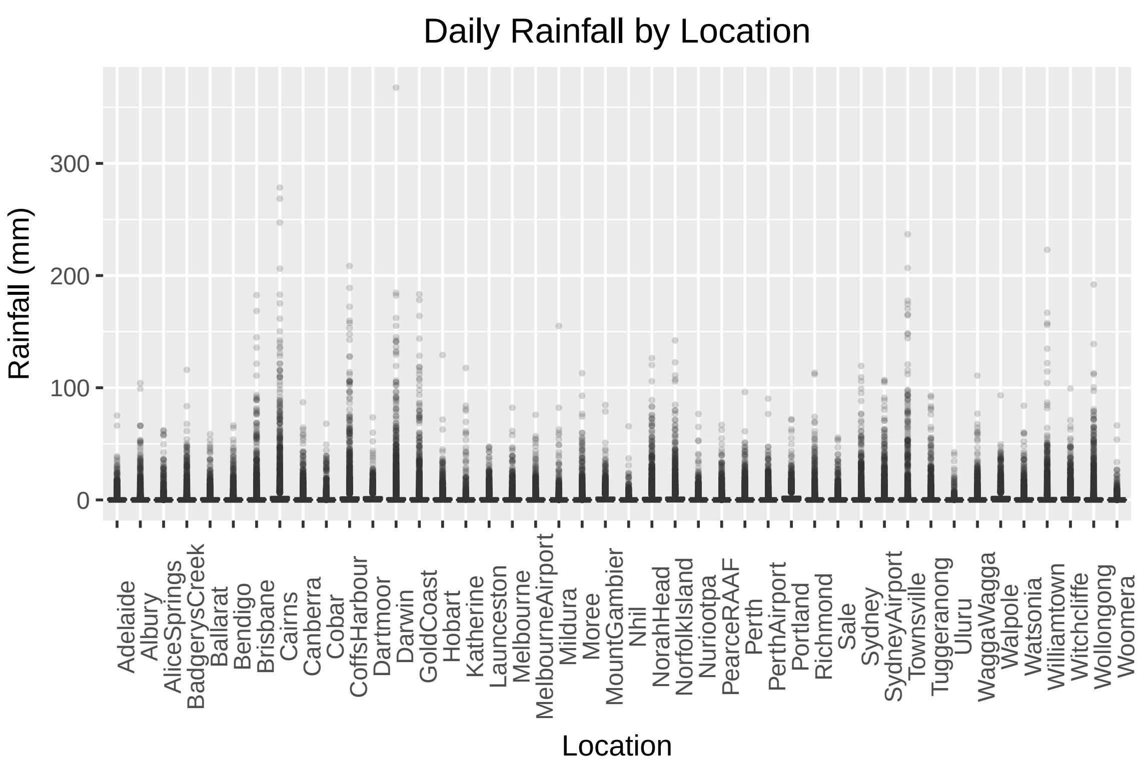
count
15000
10000
5000
0
0
10
20
30
40
50
Temp3pm



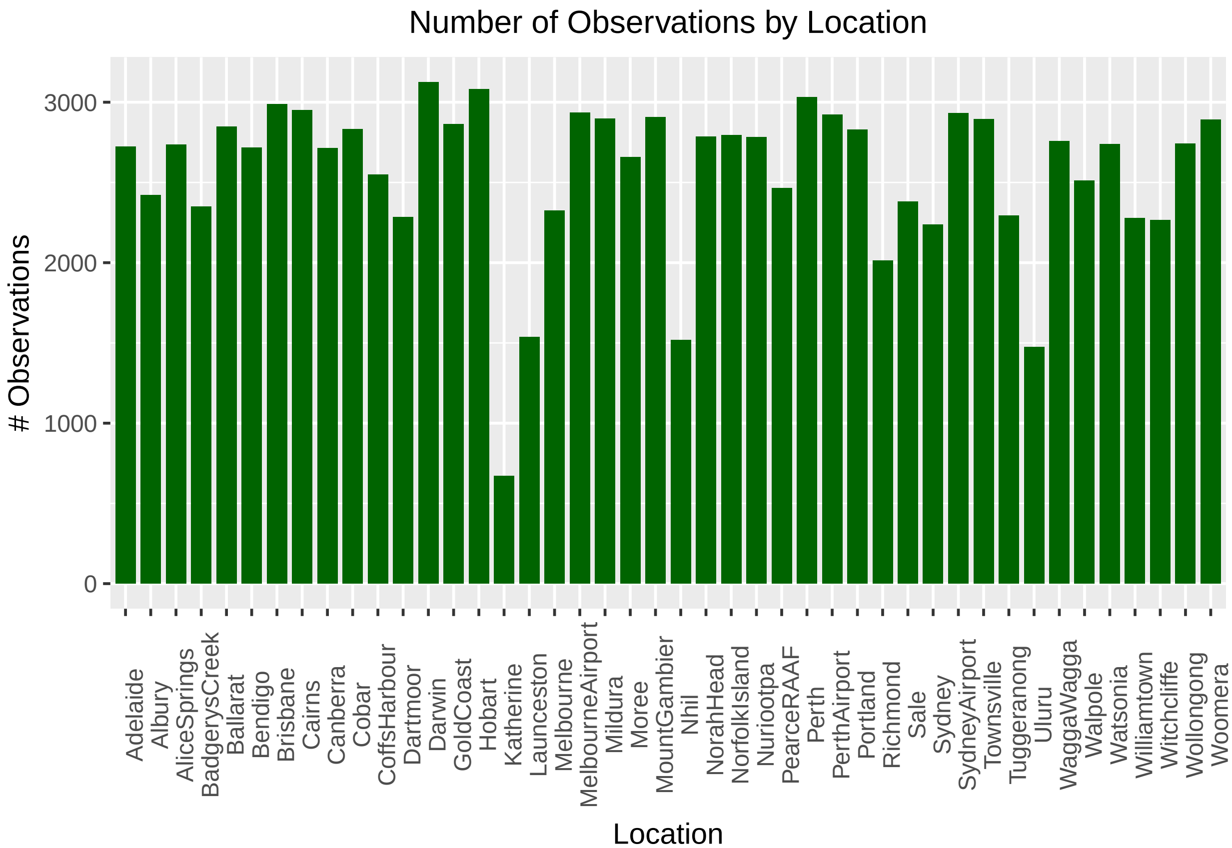
count
20000
10000
0
980
1000
1020
1040
Pressure3pm

While the above plots show distributions over all locations, the following boxplots show how the distribution varies with location. The first plot shows how *Humidity3pm* varies from location to location, in terms of both median value and spread. The second plot shows how *Rainfall* differs from the other variables, with a median value at or near 0 for all locations but quite different ranges of values.





The following plot shows how many observations remain for each location.



It can be seen that there is now more variability in the number of observations across locations, due to each location having a different amount of missing data that has been removed.

It also appears that there are now fewer locations in the plot than there were originally:

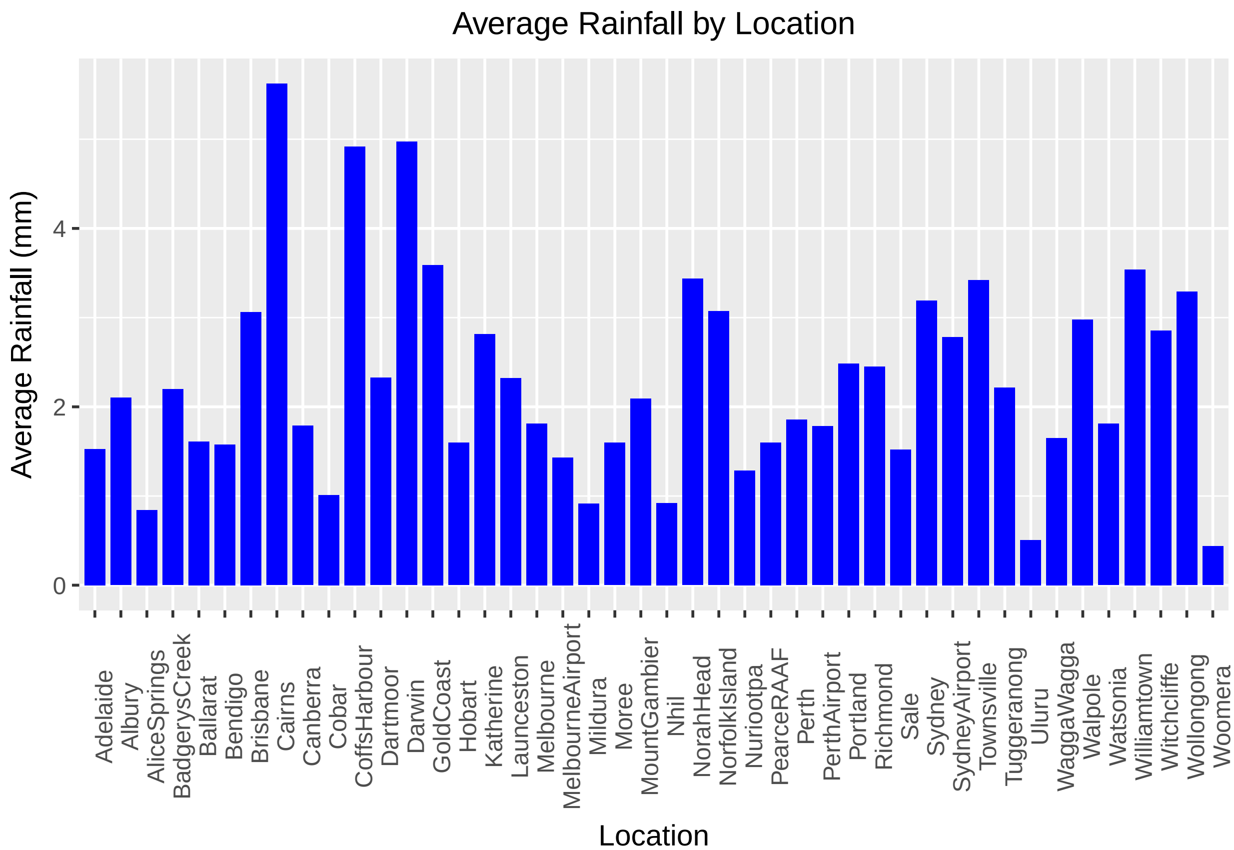
```
## [1] "Number of locations originally: 49"
```

```
## [1] "Number of locations remaining : 44"
```

The reason that some locations are missing from the cleaned data is that these locations did not have any measurements for one or more of the variables.

As the model will be predicting whether or not it will rain, it is worth investigating how rainfall varies across locations, in terms of both average rainfall and days with rain.

The average rainfall for each location, based on the observations in the dataset, is shown in the plot below.



It can be seen from the plot that places like Uluru (Ayres Rock) and Woomera have a very low average rainfall, as expected; while Cairns and Darwin have a much higher average rainfall, also as expected.

The percentage of days with rain at these locations follows a similar trend, as revealed by the following table and plot.

Overall, the number of days without rain is much greater than the number of days with rain.

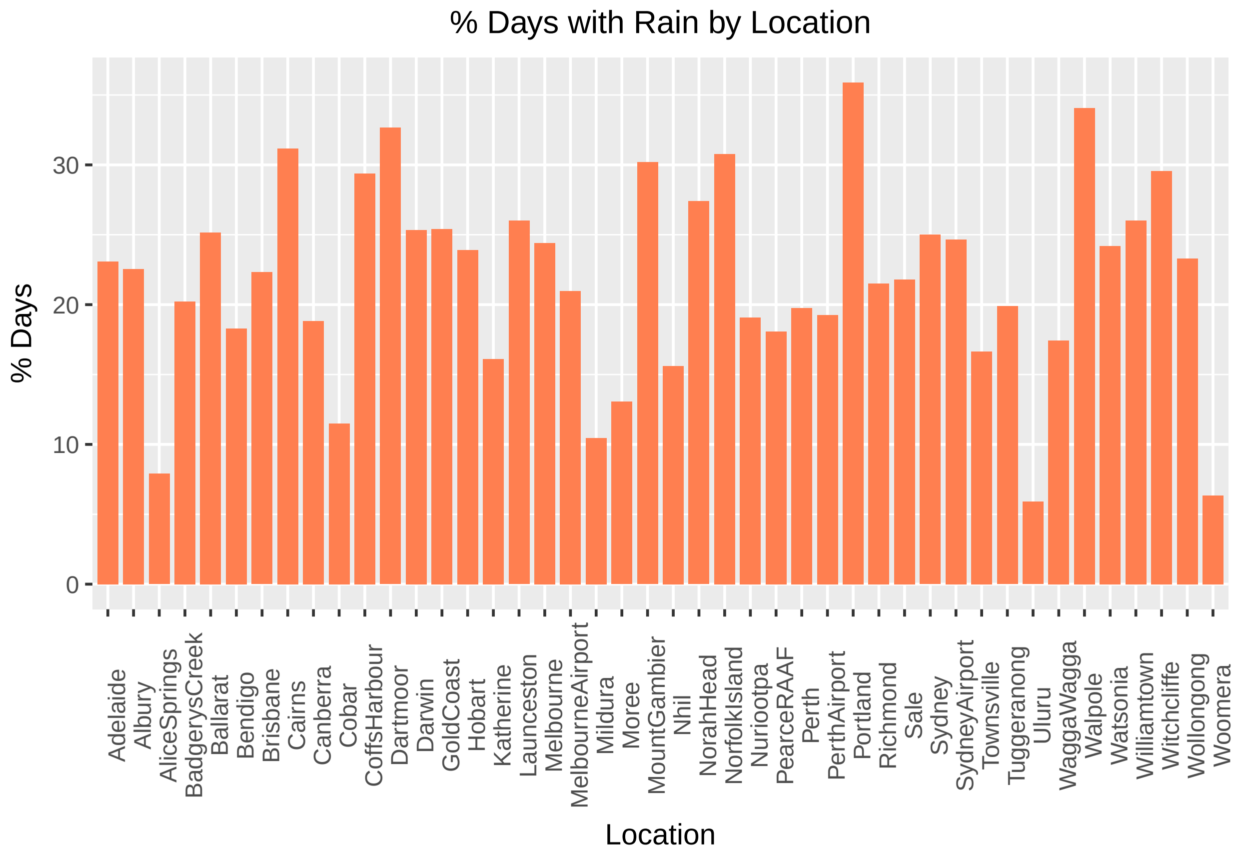
```
##             Location Rainy Days Total Days % Rainy Days
## 1           Adelaide        629       2724         23.1
## 2             Albury        546       2422         22.5
## 3       AliceSprings        216       2735          7.9
## 4      BadgerysCreek        475       2350         20.2
## 5           Ballarat        717       2849         25.2
## 6            Bendigo        497       2718         18.3
## 7           Brisbane        667       2989         22.3
## 8             Cairns        920       2952         31.2
## 9           Canberra        511       2714         18.8
## 10             Cobar        326       2833         11.5
## 11      CoffsHarbour        749       2548         29.4
## 12          Dartmoor        746       2284         32.7
## 13            Darwin        792       3124         25.4
## 14         GoldCoast        728       2864         25.4
## 15            Hobart        737       3082         23.9
```

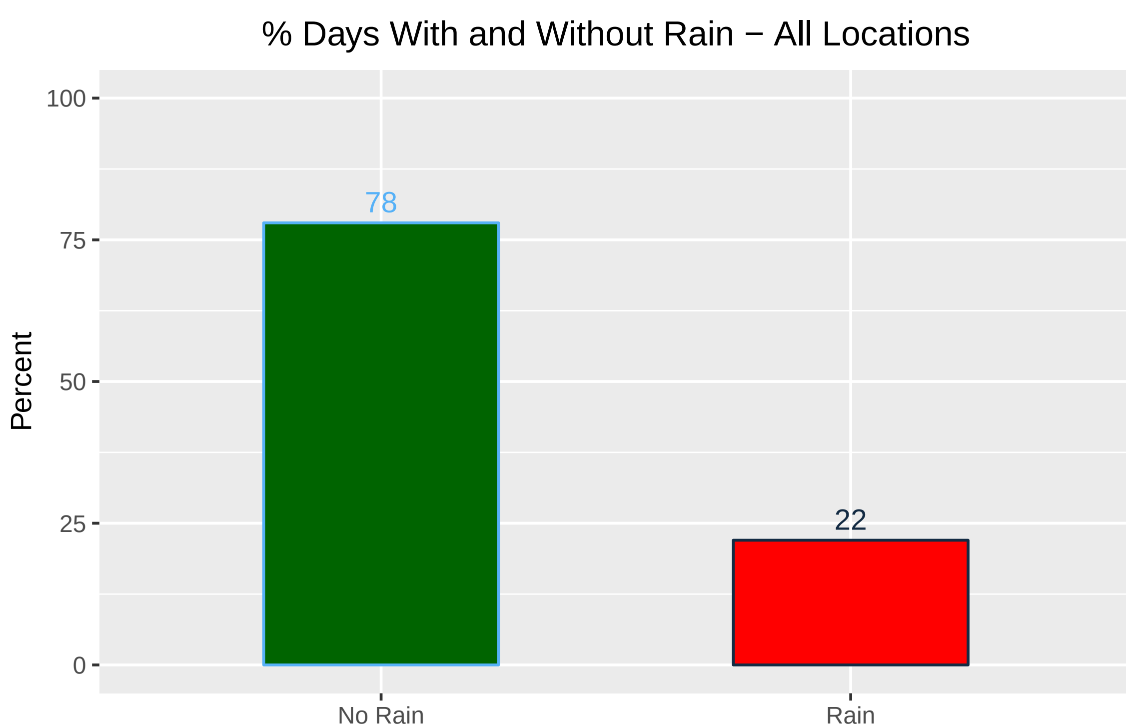
```
## 16        Katherine       108        670          16.1
## 17       Launceston       400       1538          26.0
## 18        Melbourne       567       2323          24.4
## 19 MelbourneAirport       616       2936          21.0
## 20          Mildura       303       2897          10.5
## 21            Moree       347       2659          13.1
## 22     MountGambier       878       2908          30.2
## 23             Nhil       237       1519          15.6
## 24        NorahHead       763       2785          27.4
## 25    NorfolkIsland       860       2795          30.8
## 26        Nuriootpa       531       2783          19.1
## 27       PearceRAAF       446       2466          18.1
## 28            Perth       599       3031          19.8
## 29     PerthAirport       563       2923          19.3
## 30         Portland      1015       2828          35.9
## 31         Richmond       433       2012          21.5
## 32             Sale       519       2382          21.8
## 33           Sydney       559       2236          25.0
## 34    SydneyAirport       723       2933          24.7
## 35       Townsville       482       2894          16.7
## 36      Tuggeranong       456       2293          19.9
## 37            Uluru        87       1475           5.9
## 38       WaggaWagga       481       2758          17.4
## 39          Walpole       855       2510          34.1
## 40         Watsonia       663       2739          24.2
## 41      Williamtown       593       2278          26.0
## 42      Witchcliffe       670       2267          29.6
## 43       Wollongong       639       2742          23.3
## 44          Woomera       183       2890           6.3
```

```
## [1] "Total days in the dataset: 112658"
```

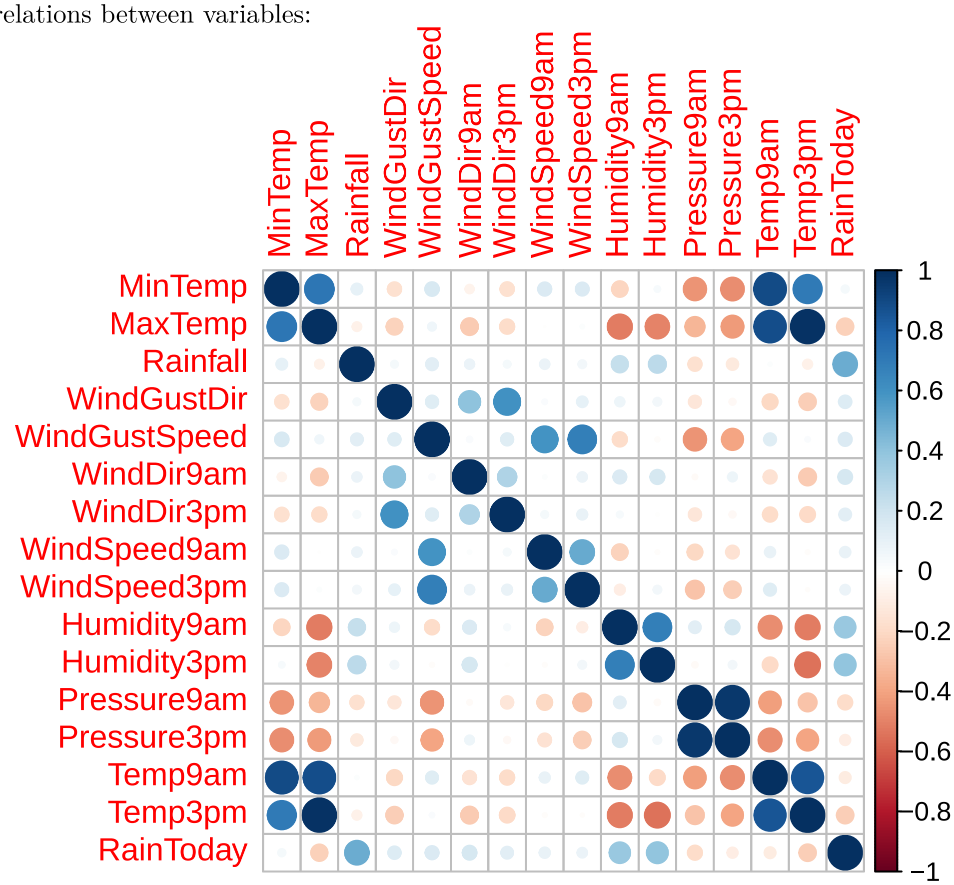
```
## [1] "Number of rainy days:      24832"
```

```
## [1] "Number of fine days:       87826"
```


% Days with Rain by Location
% Days
0
10
20
30
Location
Adelaide
Albury
AliceSprings
BadgerysCreek
Ballarat
Bendigo
Brisbane
Cairns
Canberra
Cobar
CoffsHarbour
Dartmoor
Darwin
GoldCoast
Hobart
Katherine
Launceston
Melbourne
MelbourneAirport
Mildura
Moree
MountGambier
Nhil
NorahHead
NorfolkIsland
Nuriootpa
PearceRAAF
Perth
PerthAirport
Portland
Richmond
Sale
Sydney
SydneyAirport
Townsville
Tuggeranong
Uluru
WaggaWagga
Walpole
Watsonia
Williamtown
Witchcliffe
Wollongong
Woomera


% Days With and Without Rain − All Locations
Percent
0
25
50
75
100
78
22
No Rain
Rain

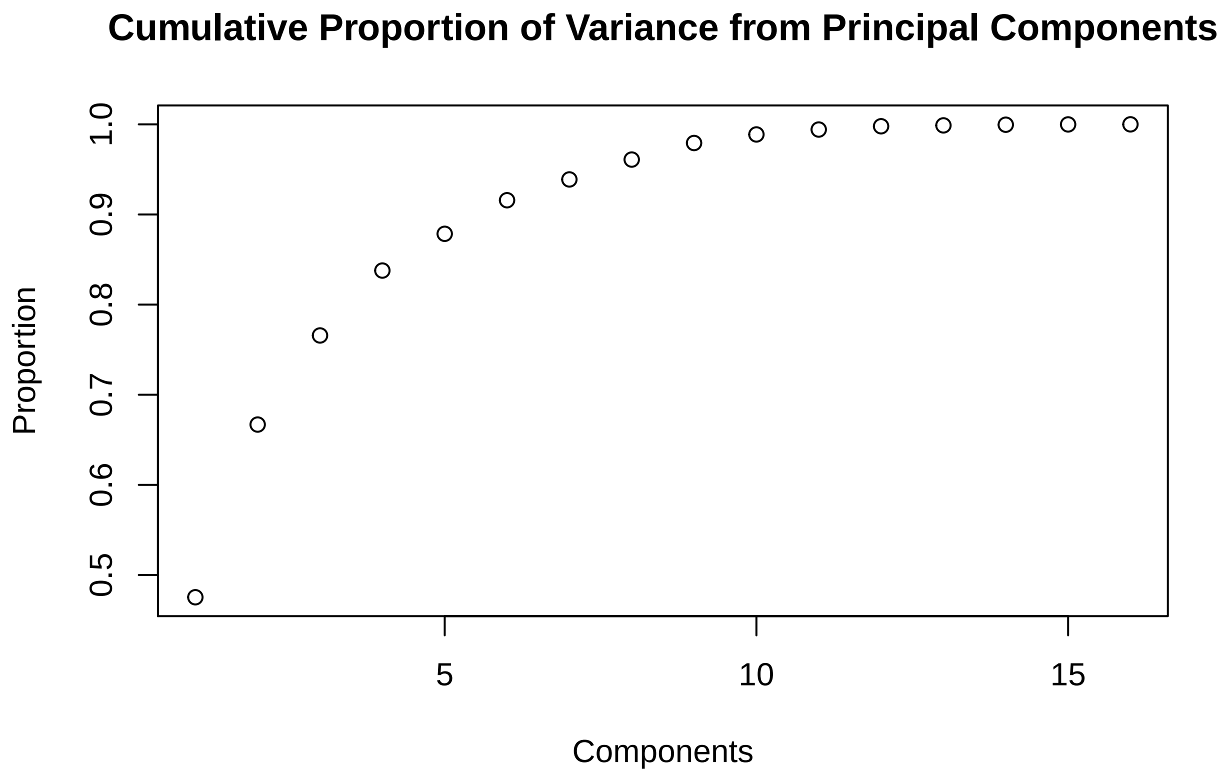
Check for correlations between variables:



The plot shows that there is a strong positive correlation between all the temperature measurements on a given day at a given location. There is also strong positive correlation between the morning and afternoon atmospheric pressure measurements and a slightly weaker correlation between the morning and afternoon humidity measurements. A negative correlation exists between maximum temperature and humidity, and also between minimum temperature and atmospheric pressure.

These correlations suggest that it may be possible to reduce the dimensionality of the data. Principal component analysis indicated that eight principal components are required to explain 95% of the variation in the data - a reduction in the dimensionality of 50%. As the dimensionality is already fairly small and reducing it would probably result in lower prediction accuracy, this was not investigated any further.

```
## Importance of components:
##                            PC1     PC2      PC3      PC4     PC5     PC6
## Standard deviation     26.9110 17.0855 12.27306 10.47337 7.88318 7.53333
## Proportion of Variance  0.4753  0.1916  0.09886  0.07199 0.04079 0.03725
## Cumulative Proportion   0.4753  0.6669  0.76578  0.83777 0.87856 0.91581
##                            PC7     PC8     PC9    PC10    PC11    PC12
## Standard deviation     5.92865 5.79690 5.29169 3.80213 2.88068 2.35244
## Proportion of Variance 0.02307 0.02206 0.01838 0.00949 0.00545 0.00363
## Cumulative Proportion  0.93888 0.96093 0.97931 0.98880 0.99425 0.99788
##                           PC13    PC14    PC15    PC16
## Standard deviation     1.21193 1.06775 0.71920 0.32236
## Proportion of Variance 0.00096 0.00075 0.00034 0.00007
## Cumulative Proportion  0.99884 0.99959 0.99993 1.00000
```



To see whether *RainToday* is a good predictor of *RainTomorrow*, the correlation coefficient for the two variables was calculated:

```
## [1] "Correlation coefficient: 0.33"
```

This value indicates that rain today is a poor predictor of rain tomorrow.

From the above results, it appears that the dataset is now in a suitable form for fitting models.

Choosing and Fitting the Models

The approach adopted was to choose six different classification models, fit a model based on each, and see which model gave the best performance.

The models chosen and the relevant R libraries are shown in the table below.

Model Type	caret Method	Library
Generalized Linear Model	glm	stats (system)
Linear Discriminant Analysis	lda	MASS (system)
Quadratic Discriminant Analysis	qda	MASS (system)
Multi-Layer Perceptron	mlp	RSNNS
k-Nearest Neighbors	knn	class (system)
Random Forest	rf	randomForest

As the functions for training and prediction with these models have different syntax, the *caret* package was chosen so that a uniform syntax could be used. This allows the training of all the models to be performed within a loop, or with a single call to the *lapply()* function.

Prior to fitting the models, the data was standardized so that all values were in the range 0 to 1, and then split into training and test sets:

```
# Scale the data
maxs <- apply(dfWeather[,2:16], 2, max)
mins <- apply(dfWeather[,2:16], 2, min)
dfScaled <- as.data.frame(scale(dfWeather[,2:16], center = mins, scale = maxs-mins))
dfScaled <- cbind(dfScaled, dfWeather[,17:18])

# Create datasets for training and testing
set.seed(1)
test_index <- createDataPartition(y=dfScaled$RainTomorrow, times=1, p=0.2, list=FALSE)
dfTrain <- dfScaled[-test_index,]
dfTest <- dfScaled[test_index,]
rm(dfScaled)
```

The training and predicting could then be performed, and the accuracy determined for each of the models:

```
# Train the models
models <- c("glm", "lda", "qda", "mlp", "knn", "rf")
t0 <- proc.time()
fits <- lapply(models, function(model) {
  caret::train(RainTomorrow ~ ., data = dfTrain, method = model)
})

t1 <- proc.time()
names(fits) <- models

# Perform prediction with each of the models
y_hats <- sapply(fits, function(fit) {
  y_hat <- predict(fit, dfTest)
})
t2 <- proc.time()

# Calculate the accuracy of the models and format as a table
accuracy <- colMeans(y_hats == dfTest$RainTomorrow)
accuracy <- sort(round(accuracy, 4), decreasing = TRUE)
```

```r
accuracy <- cbind(names(accuracy), accuracy)
row.names(accuracy) <- NULL
acc_tbl <- kable(accuracy, col.names = c("Model", "Accuracy"))
```

```
## [1] "Elapsed time for training:   15642 seconds"
```

```
## [1] "Elapsed time for predicting: 34 seconds"
```

Results

All six models were fitted successfully, with accuracies in the range 0.83 to 0.86. The accuracies for each of the models, based on predictions for the test set, are tabulated below.

Model	Accuracy
rf	0.8587
mlp	0.8528
glm	0.8517
lda	0.8503
knn	0.8472
qda	0.8359

The table shows that the Random Forest model gave marginally better performance than the other models. This model was chosen as the one to investigate further.

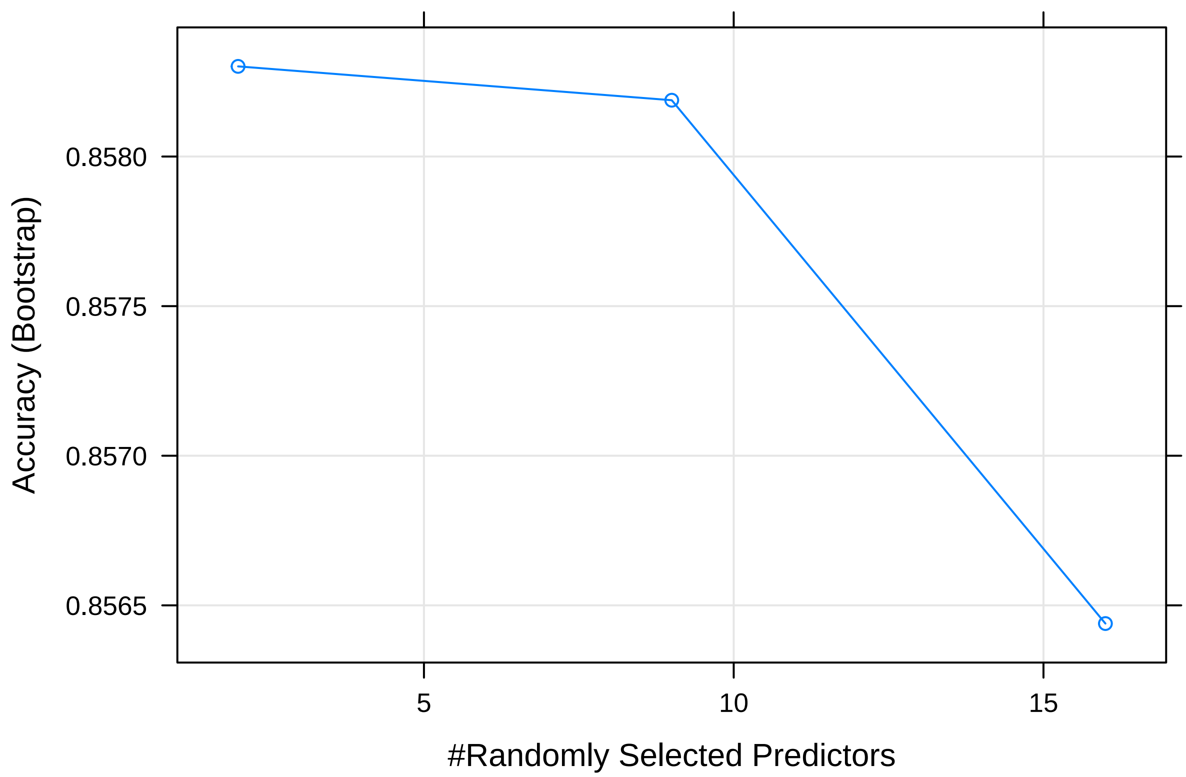
The Variable Importance table below shows which of the input varaibles have the greatest predictive power.

Variable	Importance
Humidity3pm	5533.3762
Pressure3pm	2246.5936
Humidity9am	2237.0872
Pressure9am	2180.1202
WindGustSpeed	2031.0359
Temp3pm	2008.0924
Rainfall	1950.7387
MinTemp	1820.6301
MaxTemp	1790.1789
Temp9am	1712.6539
WindSpeed3pm	1278.1451
WindSpeed9am	1211.3622
WindDir9am	1145.8934
WindDir3pm	1112.7313
WindGustDir	1104.4871
RainToday	914.6302

The table shows that relative humidity and atmospheric pressure on the day are the most important predictors of rain on the following day. It also shows that rain on the day is a poor predictor of rain on the following day, which is consistent with the low correlation between the two that was noted above.

Additional details of the random forest model fitted are presented below.

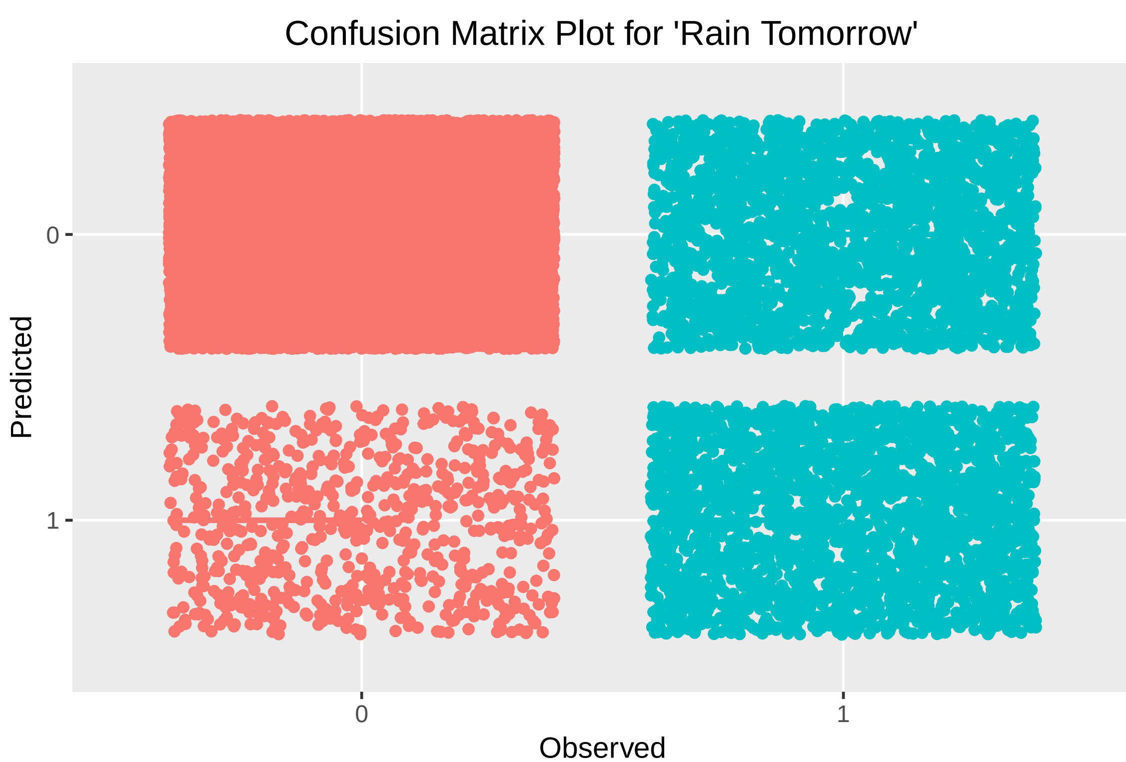
```
## Random Forest
##
## 90125 samples
##    16 predictor
##     2 classes: '0', '1'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 90125, 90125, 90125, 90125, 90125, 90125, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.8583013  0.5251468
##    9    0.8581882  0.5330717
##   16    0.8564392  0.5296578
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```



Although an accuracy of approximately 0.86 was obtained for the test set predictions, the model's ability to predict rain is considerably lower. This can be seen by examining the confusion matrix:

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 16902  2451
##          1   732  2448
##
##                Accuracy : 0.8587
##                  95% CI : (0.8541, 0.8633)
##     No Information Rate : 0.7826
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5247
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.4997
##             Specificity : 0.9585
##          Pos Pred Value : 0.7698
##          Neg Pred Value : 0.8734
##              Prevalence : 0.2174
##          Detection Rate : 0.1086
##    Detection Prevalence : 0.1411
##       Balanced Accuracy : 0.7291
##
##        'Positive' Class : 1
##
```

The confusion matrix shows that the number of false negatives (2451) slightly exceeds the number of true positives (2448). This means that on days that it rained, the model predicted correctly only 50% of the time. This is reflected in the sensitivity value of 0.4997, and can be seen in a visualization of the confusion matrix.



The density of the dots in the two boxes on the right, representing true positives and false negatives, is approximately equal, indicating that on days that it rains the model is just as likely to have predicted that it will be fine.

Conclusion

This project has demonstrated that it is possible to construct models to predict whether or not it will rain tomorrow, based on various weather measurements made today. Six different classification models were fitted, and all had a similar accuracy. A Random Forest model had the highest accuracy, so it was examined in more detail.

The model identified relative humidity and atmospheric pressure on the previous day as the best predictors of whether or not it will rain, and rain on the previous day as the worst.

The results also highlighted the need to consider other model statistics, such as sensitivity and specificity, when assessing the performance of a model. In this case, although the accuracy was fairly high at 0.86, the sensitivity was low, with a value of 0.50. Specificity was good, with a value of 0.96.

The high specificity value means that the false positive rate is low. The low sensitivity value means that the false negative rate is relatively high, so that on days that it rains, there is a 50-50 chance that the model predicted correctly. This is in contrast with the 86% chance that the model makes a correct prediction on average.