Classification

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CS4375.004 with Karen Mazidi

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Introduction

Linear models for classification are a method that uses a linear function to separate data into different classes. This is done by assigning weight to predictor variables and determining a model that can predict whether a value falls within a threshold or not. The strengths of these linear models are their simplicity and interpretability as they are easy to understand, and use in real world applications. The limitations of this mainly lie in the fact that complex data sets or data sets that use more than two variables will find the data learned from these methods unhelpful.

Getting the File

To run any of the chunks of R script in this file, please insert *weatherAUS.csv (https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package)* into the same folder as this file. You can also find this csv on my Github (https://github.com/Billy-Budd/mensch-maschine/blob/main/blue-monday/weatherAUS.csv) repository. Any other information that pertains to other documents can be found in the read me (https://github.com/Billy-Budd/mensch-maschine#readme). Unfortunately, the prediction function would not work with NA data, so I had to remove it which probably skews the overall results of this. Major sections have headers that are bolded and there are some intermediary sections that just have headers and are not bolded.

```
df <- read.csv("weatherAUS.csv", header = TRUE)
df <- na.omit(df) # remove missing data
```

Creating an 80/20 Split

a. Divide into 80/20 train/test

We set the seed so that our split does not change between runs of the sample() function. We then separate it into a list called train (the 80 split) and test (the 20 split). Output lengths of each split. Also outputs the date of data collection start and end to get a sense of the time period of this data.

```
set.seed(1234)
split <- sample(1:nrow(df), nrow(df)*.8, replace=FALSE) # split the data into 80/20 samples
train <- df[ split, ] # set train as the  80 split
test <- df[ -split, ] # set test as the 20 split

# I used MinTemp here to show observations, but any column header would be acceptable
tmp <- c("Number of observations in train:", length(train$MinTemp),
"Number of observations in test:", length(test$MinTemp),
"Date of data collection start: ", min(df$Date),
"Date of data collection end: ", max(df$Date))
cat(tmp, sep = '\n')
```

```
## Number of observations in train:
## 45136
## Number of observations in test:
## 11284
## Date of data collection start:
## 2007-11-01
## Date of data collection end:
## 2017-06-25
```

Summary Data

b. Use at least 5 R functions for data exploration, using the training data

This is some data from the training data, and below it are some tables that show the frequency of occurrence for some of the variables we will be looking at in our classification data.

```
head(train)
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
104049	2013-05-04	Nuriootpa	10.9	16.2	0.0	2.6	5.2
104142	2013-08-05	Nuriootpa	9.6	18.6	0.8	0.8	9.9
106046	2010-04-29	Woomera	10.4	21.3	0.0	4.6	9.7
46691	2010-11-08	Canberra	9.4	24.2	4.4	5.4	7.5
88792	2013-07-08	Cairns	22.3	27.6	0.2	7.0	8.8
94459	2012-03-23	Townsville	24.0	31.1	0.4	7.0	5.9

6 rows | 1-8 of 24 columns

```
tail(train)
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
65178	2011-10-14	MelbourneAirport	6.8	25.0	0.0	4.0	11.1
139250	2008-11-16	Darwin	25.6	35.0	0.0	7.4	8.7
120115	2016-01-19	PerthAirport	12.8	25.9	0.0	5.2	5.5
106938	2012-11-06	Woomera	14.5	27.1	9.4	11.0	5.4
78695	2010-12-07	Watsonia	19.9	28.4	0.0	6.0	1.0
75329	2009-12-15	Portland	6.8	31.7	0.0	5.4	13.2

6 rows | 1-8 of 24 columns

```
summary(train)
```

```
##      Date             Location            MinTemp         MaxTemp     
##  Length:45136       Length:45136       Min.   :-6.70   Min.   : 6.30  
##  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.   :  0.000   Min.   : 0.000   Min.   : 0.00   Length:45136      
##  1st Qu.:  0.000   1st Qu.: 2.800   1st Qu.: 5.10   Class :character  
##  Median :  0.000   Median : 5.000   Median : 8.60   Mode  :character  
##  Mean   :  2.148   Mean   : 5.511   Mean   : 7.73                     
##  3rd Qu.:  0.600   3rd Qu.: 7.400   3rd Qu.:10.70                     
##  Max.   :206.200   Max.   :72.200   Max.   :14.50                     
##  WindGustSpeed     WindDir9am         WindDir3pm         WindSpeed9am  
##  Min.   :  9.00   Length:45136       Length:45136       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   : 40.87                                         Mean   :15.65  
##  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.   :  0.00   Min.   : 980.5  
##  1st Qu.:13.00   1st Qu.: 55.00   1st Qu.: 35.00   1st Qu.:1012.7  
##  Median :19.00   Median : 67.00   Median : 51.00   Median :1017.2  
##  Mean   :19.77   Mean   : 65.91   Mean   : 49.61   Mean   :1017.2  
##  3rd Qu.:26.00   3rd Qu.: 79.00   3rd Qu.: 63.00   3rd Qu.:1021.8  
##  Max.   :76.00   Max.   :100.00   Max.   :100.00   Max.   :1040.4  
##   Pressure3pm        Cloud9am        Cloud3pm        Temp9am     
##  Min.   : 977.1   Min.   :0.000   Min.   :0.000   Min.   :-0.70  
##  1st Qu.:1010.1   1st Qu.:1.000   1st Qu.:2.000   1st Qu.:13.10  
##  Median :1014.7   Median :5.000   Median :5.000   Median :17.80  
##  Mean   :1014.8   Mean   :4.243   Mean   :4.326   Mean   :18.20  
##  3rd Qu.:1019.4   3rd Qu.:7.000   3rd Qu.:7.000   3rd Qu.:23.23  
##  Max.   :1038.9   Max.   :8.000   Max.   :9.000   Max.   :39.40  
##     Temp3pm       RainToday         RainTomorrow      
##  Min.   : 4.60   Length:45136       Length:45136      
##  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(train)
```

```
## 'data.frame':    45136 obs. of  23 variables:
##  $ Date         : chr  "2013-05-04" "2013-08-05" "2010-04-29" "2010-11-08" ...
##  $ Location     : chr  "Nuriootpa" "Nuriootpa" "Woomera" "Canberra" ...
##  $ MinTemp      : num  10.9 9.6 10.4 9.4 22.3 24 26.1 11.9 12.2 7.3 ...
##  $ MaxTemp      : num  16.2 18.6 21.3 24.2 27.6 31.1 34 15.7 19.9 14.8 ...
##  $ Rainfall     : num  0 0.8 0 4.4 0.2 0.4 0 0 38.6 0.6 ...
##  $ Evaporation  : num  2.6 0.8 4.6 5.4 7 7 7.2 8.2 4.6 4 ...
##  $ Sunshine     : num  5.2 9.9 9.7 7.5 8.8 5.9 11.1 0.4 10.4 7.2 ...
##  $ WindGustDir  : chr  "SE" "NW" "S" "N" ...
##  $ WindGustSpeed: int  43 59 31 50 63 31 37 37 48 67 ...
##  $ WindDir9am   : chr  "E" "NW" "S" "WNW" ...
##  $ WindDir3pm   : chr  "E" "NW" "S" "N" ...
##  $ WindSpeed9am : int  24 20 11 4 39 15 13 13 22 31 ...
##  $ WindSpeed3pm : int  17 33 13 24 48 15 28 17 26 39 ...
##  $ Humidity9am  : int  85 79 65 71 68 72 64 75 72 63 ...
##  $ Humidity3pm  : int  35 55 45 72 57 61 56 68 62 54 ...
##  $ Pressure9am  : num  1026 1016 1027 1017 1020 ...
##  $ Pressure3pm  : num  1024 1010 1024 1016 1018 ...
##  $ Cloud9am     : int  5 4 6 3 5 7 6 7 2 1 ...
##  $ Cloud3pm     : int  7 5 1 5 3 7 2 7 3 7 ...
##  $ Temp9am      : num  13.1 13.3 16.5 18.1 25.3 27.2 31 13.2 15.6 10.4 ...
##  $ Temp3pm      : num  15.8 17.9 20.8 18.9 25.7 30.3 33.2 14.3 19.6 12.5 ...
##  $ RainToday    : chr  "No" "No" "No" "Yes" ...
##  $ RainTomorrow : chr  "No" "No" "No" "Yes" ...
##  - attr(*, "na.action")= 'omit' Named int [1:89040] 1 2 3 4 5 6 7 8 9 10 ...
##   ..- attr(*, "names")= chr [1:89040] "1" "2" "3" "4" ...
```

Wind Gust Direction Frequency:

```
windGustDirFreq <- table(train$WindGustDir)
```

Location Frequency:

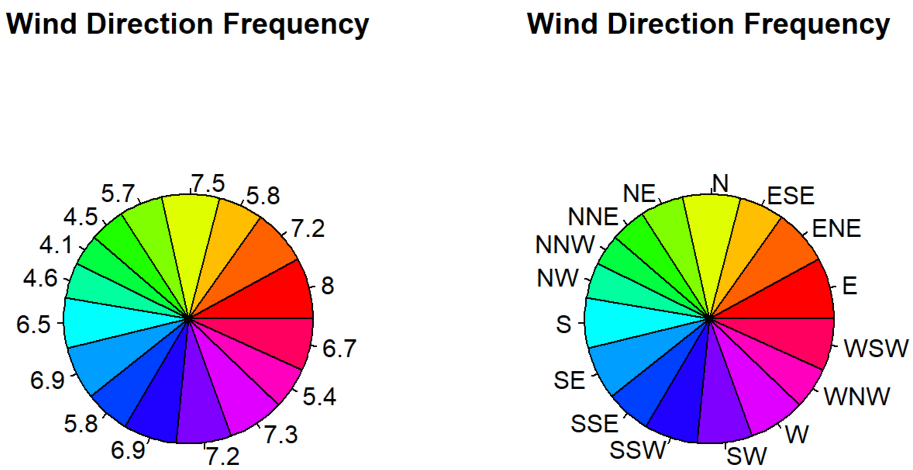
```
locationFreq <- table(train$Location)
```

Simple Graphs

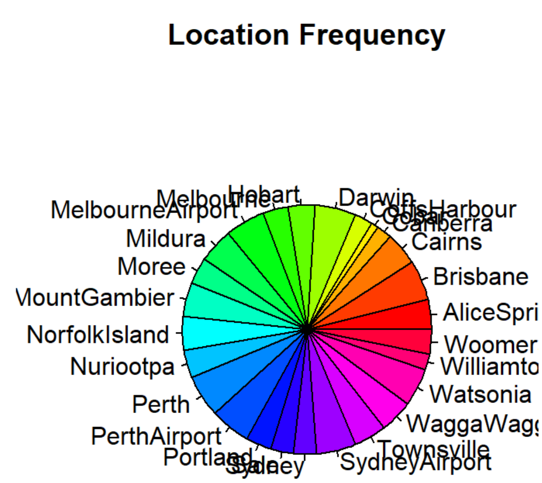
c. Create at least 2 informative graphs, using the training data

These are some simple graphs to just get an idea of what the data looks like. By the looks of these graphs, Pressure at 9AM seems to be a better predictor than maximum temperature at predicting the amount of rainfall in Australia. The graphs were a bit crowded, so I doubled them up to show percentages and what they are. The location frequency pie chart is still difficult to read, so I added a third graph to supplement. The third graph shows the probability of rain tomorrow given there was rain today. This shows that it rains nonsporadically. Given the green on the first day, it is more likely to rain on the second day.

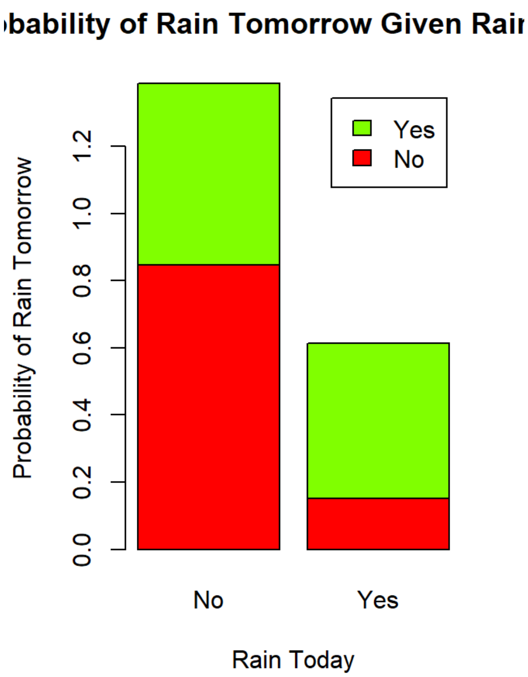
```
par(mfrow=c(1,2)) # output side by side
piepercent1 <- round(100 * windGustDirFreq / sum(windGustDirFreq), 1) # get percents for graph 1
pie(windGustDirFreq, labels = piepercent1, main = "Wind Direction Frequency", col = rainbow(length(windGustDirFreq))) # pe
rcent graph 1
pie(windGustDirFreq, main = "Wind Direction Frequency", col = rainbow(length(windGustDirFreq))) # labeled graph 1
```




```
par(mfrow=c(1,2)) # output side by side
piepercent2 <- round(100 * locationFreq / sum(locationFreq), 1) # get percents for graph 2
pie(locationFreq, labels = piepercent2, main = "Location Frequency", col = rainbow(length(locationFreq))) # percent graph
2
pie(locationFreq, main = "Location Frequency", col = rainbow(length(locationFreq))) # percent graph 2
```




```
tempTable <- prop.table(table(train$RainToday,train$RainTomorrow), margin = 1) # create a table for bar plot
barplot(tempTable, main = "Probability of Rain Tomorrow Given Rain Today", xlab = "Rain Today", ylab = "Probability of Rai
n Tomorrow", legend.text = rownames(tempTable), col = rainbow(length(tempTable))) # create bar plot
```



Creating a Simple Linear Model

d. Build a logistic regression model and output the summary. Write a thorough explanation of the information in the model summary.

The deviance residuals show the difference between the observed and predicted models, and judging that the max difference between 0 and 1 is 1, the prediction is not always correct with a max difference of almost 2 and a minimum difference greater than -1. On the other hand, the median, 1Q, and 3Q are the same so the prediction is often off by the exact same amount which is a neat detail. The coefficients here show the change in the log odds of y for every 1 unit in the predictor change. The p-values are very low, which is a good thing. The null and residual deviance here tells us that the difference is statistically significant.

```
train$RainToday <- ifelse(train$RainToday=="Yes",1,0)
train$RainTomorrow <- ifelse(train$RainTomorrow=="Yes",1,0)
glm1 <- glm(RainTomorrow ~ RainToday, data = train, family = "binomial", maxit = 400) # create logistic regression model
summary(glm1)
```

```
##
## Call:
## glm(formula = RainTomorrow ~ RainToday, family = "binomial",
##     data = train, maxit = 400)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1112  -0.5749  -0.5749  -0.5749   1.9400
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.71661    0.01485 -115.61   <2e-16 ***
## RainToday    1.55884    0.02495   62.48   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 47644  on 45135  degrees of freedom
## Residual deviance: 43791  on 45134  degrees of freedom
## AIC: 43795
##
## Number of Fisher Scoring iterations: 3
```

Naive Bayes

e. Build a naïve Bayes model and output what the model learned. Write a thorough explanation of the data.

I did not include date or wind gust direction as they seem irrelevant to this particular calculation as they are not really dependent on the weather, and the date is unique since it includes the year. This function tells us that the prior probability of predicting rain tomorrow given the the independent variables. Here, we can see that we have a 22.069% of prior probabilities to predict rain tomorrow.

```
library(e1071)
nb1 <- naiveBayes(RainTomorrow~.-Date -WindGustDir -WindDir9am -WindDir3pm, data = train)
nb1
```

```
## 
## Naive Bayes Classifier for Discrete Predictors
## 
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
## 
## A-priori probabilities:
## Y
##         0         1 
## 0.7793114 0.2206886 
## 
## Conditional probabilities:
##    Location
## Y   AliceSprings    Brisbane      Cairns    Canberra       Cobar CoffsHarbour
##   0  0.045657427 0.052508884 0.038152097 0.019388770 0.010689410  0.020810235
##   1  0.014958338 0.052605160 0.060636482 0.018371649 0.005521534  0.034635077
##    Location
## Y        Darwin      Hobart   Melbourne MelbourneAirport     Mildura
##   0 0.050291400 0.034029851 0.031499645      0.050945274 0.051769723
##   1 0.062945487 0.038650738 0.037044473      0.051601245 0.022286919
##    Location
## Y         Moree MountGambier NorfolkIsland   Nuriootpa       Perth PerthAirport
##   0 0.037754087  0.040000000   0.038749112 0.037327647 0.056034115  0.054697939
##   1 0.021584178  0.058628652   0.060837265 0.031723723 0.048790282  0.045678145
##    Location
## Y      Portland        Sale      Sydney SydneyAirport  Townsville  WaggaWagga
##   0 0.025472637 0.030248756 0.029168443   0.049097370 0.046140725 0.045344705
##   1 0.060034133 0.028009236 0.033430378   0.057925911 0.030619416 0.033631162
##    Location
## Y      Watsonia Williamtown     Woomera
##   0 0.046794598 0.020184790 0.037242360
##   1 0.054914165 0.024997490 0.009938761
## 
##    MinTemp
## Y       [,1]     [,2]
##   0 13.16067 6.366739
##   1 14.51064 6.449673
## 
##    MaxTemp
## Y       [,1]     [,2]
##   0 24.76681 6.886300
##   1 22.27322 6.836883
## 
##    Rainfall
## Y       [,1]      [,2]
##   0 1.182877  4.631336
##   1 5.555838 11.725871
## 
##    Evaporation
## Y       [,1]     [,2]
##   0 5.771534 3.820559
##   1 4.590583 3.154288
## 
##    Sunshine
## Y       [,1]     [,2]
##   0 8.629248 3.334472
##   1 4.556510 3.392962
## 
##    WindGustSpeed
## Y       [,1]     [,2]
##   0 39.22724 12.18668
##   1 46.68286 15.47586
## 
##    WindSpeed9am
## Y       [,1]     [,2]
##   0 15.27227 8.077631
```

```
##   1 16.99197 8.979033
##
##    WindSpeed3pm
## Y       [,1]     [,2]
##   0 19.37845 8.269777
##   1 21.15400 9.254369
##
##    Humidity9am
## Y       [,1]     [,2]
##   0 63.24569 18.38337
##   1 75.30931 15.69075
##
##    Humidity3pm
## Y       [,1]     [,2]
##   0 44.71443 17.86888
##   1 66.90674 18.40364
##
##    Pressure9am
## Y       [,1]     [,2]
##   0 1018.186 6.549436
##   1 1013.904 7.061550
##
##    Pressure3pm
## Y       [,1]     [,2]
##   0 1015.648 6.542779
##   1 1011.787 7.102994
##
##    Cloud9am
## Y       [,1]     [,2]
##   0 3.761251 2.770084
##   1 5.943178 2.159871
##
##    Cloud3pm
## Y       [,1]     [,2]
##   0 3.782345 2.579391
##   1 6.243550 1.851493
##
##    Temp9am
## Y       [,1]     [,2]
##   0 18.26153 6.539919
##   1 17.97265 6.568909
##
##    Temp3pm
## Y       [,1]     [,2]
##   0 23.37767 6.706086
##   1 20.34447 6.692738
##
##    RainToday
## Y        [,1]      [,2]
##   0 0.1534897 0.3604640
##   1 0.4629053 0.4986471
```

Classification Models

f. Using these two classification models models, predict and evaluate on the test data using all of the classification metrics discussed in class. Compare the results and indicate why you think these results happened.

```
test$RainToday <- ifelse(test$RainToday=="Yes",1,0)
test$RainTomorrow <- ifelse(test$RainTomorrow=="Yes",1,0)
pred1 <- predict(glm1, newdata = test, type = "response")
acc1 <- mean(pred1)
print(paste("Logistic Accuracy: ", acc1))
```

```
## [1] "Logistic Accuracy:  0.21930869620781"
```