# Phase2WeatherProject

September 8, 2023

# 1 Weather in Australia

### 1.0.1 We will predict whether there will be rain tomorrow based off the data given.

**Data is consisted of weather information of various cities based in Australia from 2008 - 2012.**

# 2 STEP 1: IMPORTING DATA

Here we will be importing data as well as adding some basic packages to our analysis. We also examine what data we are working with.

[1]:
```
import pandas as pd
pd.options.mode.chained_assignment = None
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import make_classification
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.metrics import confusion_matrix, mean_squared_error,␣
↪mean_absolute_error, r2_score, accuracy_score, classification_report
from sklearn import linear_model, preprocessing
from sklearn.preprocessing import PolynomialFeatures
from statsmodels.stats.outliers_influence import variance_inflation_factor

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_csv("weather in australia.csv")
```

[3]:
```
df
```

[3]:
```
             Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  \
0      2008-12-01   Albury     13.4     22.9       0.6          NaN
1      2008-12-02   Albury      7.4     25.1       0.0          NaN
```

```
2       2008-12-03   Albury     12.9     25.7        0.0          NaN
3       2008-12-04   Albury      9.2     28.0        0.0          NaN
4       2008-12-05   Albury     17.5     32.3        1.0          NaN
…              …      …     …      …        …          …
145455  2017-06-21    Uluru      2.8     23.4        0.0          NaN
145456  2017-06-22    Uluru      3.6     25.3        0.0          NaN
145457  2017-06-23    Uluru      5.4     26.9        0.0          NaN
145458  2017-06-24    Uluru      7.8     27.0        0.0          NaN
145459  2017-06-25    Uluru     14.9      NaN        0.0          NaN

        Sunshine WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  \
0            NaN           W           44.0          W  …        71.0
1            NaN         WNW           44.0        NNW  …        44.0
2            NaN         WSW           46.0          W  …        38.0
3            NaN          NE           24.0         SE  …        45.0
4            NaN           W           41.0        ENE  …        82.0
…          …           …             …         …  …           …
145455       NaN           E           31.0         SE  …        51.0
145456       NaN         NNW           22.0         SE  …        56.0
145457       NaN           N           37.0         SE  …        53.0
145458       NaN          SE           28.0        SSE  …        51.0
145459       NaN         NaN            NaN        ESE  …        62.0

        Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  \
0              22.0       1007.7       1007.1       8.0       NaN     16.9
1              25.0       1010.6       1007.8       NaN       NaN     17.2
2              30.0       1007.6       1008.7       NaN       2.0     21.0
3              16.0       1017.6       1012.8       NaN       NaN     18.1
4              33.0       1010.8       1006.0       7.0       8.0     17.8
…            …          …          …          …        …      …
145455         24.0       1024.6       1020.3       NaN       NaN     10.1
145456         21.0       1023.5       1019.1       NaN       NaN     10.9
145457         24.0       1021.0       1016.8       NaN       NaN     12.5
145458         24.0       1019.4       1016.5       3.0       2.0     15.1
145459         36.0       1020.2       1017.9       8.0       8.0     15.0

        Temp3pm  RainToday  RainTomorrow
0          21.8         No            No
1          24.3         No            No
2          23.2         No            No
3          26.5         No            No
4          29.7         No            No
…        …        …            …
145455     22.4         No            No
145456     24.5         No            No
145457     26.1         No            No
145458     26.0         No            No
```

```
145459     20.9          No            NaN

[145460 rows x 23 columns]
```

# 3 STEP 2: PERORMING INITIAL DATA INSPECTION

We will be checking for… - head - tail - data information - describing the data

[4]:
```python
df.head()
```

[4]:
```
         Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  \
0  2008-12-01   Albury     13.4     22.9       0.6          NaN       NaN
1  2008-12-02   Albury      7.4     25.1       0.0          NaN       NaN
2  2008-12-03   Albury     12.9     25.7       0.0          NaN       NaN
3  2008-12-04   Albury      9.2     28.0       0.0          NaN       NaN
4  2008-12-05   Albury     17.5     32.3       1.0          NaN       NaN

  WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  Humidity3pm  \
0           W           44.0          W  …        71.0         22.0
1         WNW           44.0        NNW  …        44.0         25.0
2         WSW           46.0          W  …        38.0         30.0
3          NE           24.0         SE  …        45.0         16.0
4           W           41.0        ENE  …        82.0         33.0

   Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  RainToday  \
0       1007.7       1007.1       8.0       NaN     16.9     21.8         No
1       1010.6       1007.8       NaN       NaN     17.2     24.3         No
2       1007.6       1008.7       NaN       2.0     21.0     23.2         No
3       1017.6       1012.8       NaN       NaN     18.1     26.5         No
4       1010.8       1006.0       7.0       8.0     17.8     29.7         No

   RainTomorrow
0            No
1            No
2            No
3            No
4            No

[5 rows x 23 columns]
```

Here we see, that we are primarily working with numerical data as well as some categorical data.

[5]:
```python
df.tail()
```

[5]:
```
              Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  \
145455  2017-06-21    Uluru      2.8     23.4       0.0          NaN
```

```
145456  2017-06-22    Uluru      3.6      25.3       0.0           NaN
145457  2017-06-23    Uluru      5.4      26.9       0.0           NaN
145458  2017-06-24    Uluru      7.8      27.0       0.0           NaN
145459  2017-06-25    Uluru     14.9       NaN       0.0           NaN

        Sunshine WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  \
145455       NaN           E           31.0         SE  …        51.0
145456       NaN         NNW           22.0         SE  …        56.0
145457       NaN           N           37.0         SE  …        53.0
145458       NaN          SE           28.0        SSE  …        51.0
145459       NaN         NaN            NaN        ESE  …        62.0

        Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  \
145455         24.0       1024.6       1020.3       NaN       NaN     10.1
145456         21.0       1023.5       1019.1       NaN       NaN     10.9
145457         24.0       1021.0       1016.8       NaN       NaN     12.5
145458         24.0       1019.4       1016.5       3.0       2.0     15.1
145459         36.0       1020.2       1017.9       8.0       8.0     15.0

        Temp3pm  RainToday  RainTomorrow
145455     22.4         No            No
145456     24.5         No            No
145457     26.1         No            No
145458     26.0         No            No
145459     20.9         No           NaN

[5 rows x 23 columns]
```

[6]:
```
df.shape
```

[6]:
```
(145460, 23)
```

There are 145,460 records of weather with 23 columns.

[7]:
```
df.columns
```

[7]:
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RainTomorrow'],
      dtype='object')
```

From the columns seen, we can see that the temperature of the day was calculated twice. The following categories are recorded: - Date - Location - Temperature: MIN/MAX - Rainfall - Evaporation - Sunshine - Wind Gust Direction - Wind Gust Speed - Wind Gust Direction at 9 AM and 3 PM - Wind Speed at 9 AM and 3 PM - Humidity at 9 AM and 3 PM - Pressure at at 9 AM and 3 PM - Cloud at 9 AM and 3 PM - Temperature at 9 AM and 3 PM - If there was rain today - If there will be rain tomorrow.

[8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Date            145460 non-null  object
 1   Location        145460 non-null  object
 2   MinTemp         143975 non-null  float64
 3   MaxTemp         144199 non-null  float64
 4   Rainfall        142199 non-null  float64
 5   Evaporation     82670 non-null   float64
 6   Sunshine        75625 non-null   float64
 7   WindGustDir     135134 non-null  object
 8   WindGustSpeed   135197 non-null  float64
 9   WindDir9am      134894 non-null  object
 10  WindDir3pm      141232 non-null  object
 11  WindSpeed9am    143693 non-null  float64
 12  WindSpeed3pm    142398 non-null  float64
 13  Humidity9am     142806 non-null  float64
 14  Humidity3pm     140953 non-null  float64
 15  Pressure9am     130395 non-null  float64
 16  Pressure3pm     130432 non-null  float64
 17  Cloud9am        89572 non-null   float64
 18  Cloud3pm        86102 non-null   float64
 19  Temp9am         143693 non-null  float64
 20  Temp3pm         141851 non-null  float64
 21  RainToday       142199 non-null  object
 22  RainTomorrow    142193 non-null  object
dtypes: float64(16), object(7)
memory usage: 25.5+ MB
```

Here we see that there are 145,460 records of weather data based in Australia. We have a multitude of categories that happen in every day weather. Here we will see what categories are predictors of rain and if we can predict if it will rain tomorrow.

[9]:
```
df.Location.unique()
```

[9]:
```
array(['Albury', 'BadgerysCreek', 'Cobar', 'CoffsHarbour', 'Moree',
       'Newcastle', 'NorahHead', 'NorfolkIsland', 'Penrith', 'Richmond',
       'Sydney', 'SydneyAirport', 'WaggaWagga', 'Williamtown',
       'Wollongong', 'Canberra', 'Tuggeranong', 'MountGinini', 'Ballarat',
       'Bendigo', 'Sale', 'MelbourneAirport', 'Melbourne', 'Mildura',
       'Nhil', 'Portland', 'Watsonia', 'Dartmoor', 'Brisbane', 'Cairns',
       'GoldCoast', 'Townsville', 'Adelaide', 'MountGambier', 'Nuriootpa',
```

```
'Woomera', 'Albany', 'Witchcliffe', 'PearceRAAF', 'PerthAirport',
'Perth', 'SalmonGums', 'Walpole', 'Hobart', 'Launceston',
'AliceSprings', 'Darwin', 'Katherine', 'Uluru'], dtype=object)
```

Since 'Date' and 'Location' are not directly in relationship to our dependent variable. Many of these cities are spread apart from one another. We will drop them later.

## 3.1 Duplicates

Let's search for duplicates

[10]:
```
df.duplicated().sum()
```

[10]:
```
0
```

[11]:
```
duplicate = df[df.duplicated()]
duplicate
```

[11]:
```
Empty DataFrame
Columns: [Date, Location, MinTemp, MaxTemp, Rainfall, Evaporation, Sunshine,
WindGustDir, WindGustSpeed, WindDir9am, WindDir3pm, WindSpeed9am, WindSpeed3pm,
Humidity9am, Humidity3pm, Pressure9am, Pressure3pm, Cloud9am, Cloud3pm, Temp9am,
Temp3pm, RainToday, RainTomorrow]
Index: []

[0 rows x 23 columns]
```

[12]:
```
df = df.drop_duplicates(keep = 'first')
```

[13]:
```
df.shape
```

[13]:
```
(145460, 23)
```

Here we see that there are no duplicated rows of data.

# 4 STEP 3: MISSING / IRRELEVANT DATA ACROSS DIFFERENT TYPES OF VARIABLES. DATA TREATMENT.

Based off the data given, we can see that the max number of non-null counts can be 145,460 entries. Looking at the data, a lot of the columns are missing little, some or a lot of data.

[14]:
```
mintemp = 143975/145460
maxtemp = 144199/145460
rainfall = 142199/145460
evap = 82670/145460
```

```python
sun = 75625/145460
wgdir = 135134/145460
wgsp = 135197/145460
winddir9= 134894/145460
winddir3= 141232/145460
windsp9= 143693/145460
windsp3= 142398/145460
hum9= 142806/145460
hum3= 140953/145460
pr9= 130395/145460
pr3= 130432/145460
cl9= 89572/145460
cl3= 86102/145460
temp9= 143693/145460
temp3= 141851/145460
print("mintemp:", "%.3f" % mintemp, "%")
print("maxtemp:", "%.3f" % maxtemp, "%")
print("rainfall:", "%.3f" % rainfall, "%")
print("evap:", "%.3f" % evap, "%")
print("sun:", "%.3f" % sun, "%")
print("wgdir:", "%.3f" % wgdir, "%")
print("wgsp:", "%.3f" % wgsp, "%")
print("winddir9:", "%.3f" % winddir9, "%")
print("winddir3:", "%.3f" % winddir3, "%")
print("windsp9:", "%.3f" % windsp9, "%")
print("windsp3:", "%.3f" % windsp3, "%")
print("hum9:", "%.3f" % hum9, "%")
print("hum3:", "%.3f" % hum3, "%")
print("pr9:", "%.3f" % pr9, "%")
print("pr3:", "%.3f" % pr3, "%")
print("cl9:", "%.3f" % cl9, "%")
print("cl3:", "%.3f" % cl3, "%")
print("temp9:", "%.3f" % temp9, "%")
print("temp3:", "%.3f" % temp3, "%")
```

```
mintemp: 0.990 %
maxtemp: 0.991 %
rainfall: 0.978 %
evap: 0.568 %
sun: 0.520 %
wgdir: 0.929 %
wgsp: 0.929 %
winddir9: 0.927 %
winddir3: 0.971 %
windsp9: 0.988 %
windsp3: 0.979 %
hum9: 0.982 %
```

```
hum3: 0.969 %
pr9: 0.896 %
pr3: 0.897 %
cl9: 0.616 %
cl3: 0.592 %
temp9: 0.988 %
temp3: 0.975 %
```

Here we see that Evaporation has 56% of the data, Sunshine has 52%, Cloud9am has 61%, and Cloud3pm 59% and we will be dropping these columns from our dataframes.

[15]:
```
df = df.drop(columns = ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm',␣
↪'Date','Location'], axis =1)
df
```

[15]:
```
        MinTemp  MaxTemp  Rainfall WindGustDir  WindGustSpeed WindDir9am  \
0          13.4     22.9       0.6           W           44.0          W
1           7.4     25.1       0.0         WNW           44.0        NNW
2          12.9     25.7       0.0         WSW           46.0          W
3           9.2     28.0       0.0          NE           24.0         SE
4          17.5     32.3       1.0           W           41.0        ENE
…           …      …       …      …          …        …
145455      2.8     23.4       0.0           E           31.0         SE
145456      3.6     25.3       0.0         NNW           22.0         SE
145457      5.4     26.9       0.0           N           37.0         SE
145458      7.8     27.0       0.0          SE           28.0        SSE
145459     14.9      NaN       0.0         NaN            NaN        ESE

       WindDir3pm  WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  \
0             WNW          20.0          24.0         71.0         22.0
1             WSW           4.0          22.0         44.0         25.0
2             WSW          19.0          26.0         38.0         30.0
3               E          11.0           9.0         45.0         16.0
4              NW           7.0          20.0         82.0         33.0
…          …          …          …          …          …
145455        ENE          13.0          11.0         51.0         24.0
145456          N          13.0           9.0         56.0         21.0
145457        WNW           9.0           9.0         53.0         24.0
145458          N          13.0           7.0         51.0         24.0
145459        ESE          17.0          17.0         62.0         36.0

        Pressure9am  Pressure3pm  Temp9am  Temp3pm RainToday RainTomorrow
0            1007.7       1007.1     16.9     21.8        No           No
1            1010.6       1007.8     17.2     24.3        No           No
2            1007.6       1008.7     21.0     23.2        No           No
3            1017.6       1012.8     18.1     26.5        No           No
4            1010.8       1006.0     17.8     29.7        No           No
…             …          …      …      …       …          …
```

```
145455        1024.6        1020.3      10.1      22.4         No            No
145456        1023.5        1019.1      10.9      24.5         No            No
145457        1021.0        1016.8      12.5      26.1         No            No
145458        1019.4        1016.5      15.1      26.0         No            No
145459        1020.2        1017.9      15.0      20.9         No           NaN

[145460 rows x 17 columns]
```

[16]:
```
df.describe()
```

[16]:
```
             MinTemp        MaxTemp       Rainfall  WindGustSpeed  \
count  143975.000000  144199.000000  142199.000000  135197.000000
mean       12.194034      23.221348       2.360918      40.035230
std         6.398495       7.119049       8.478060      13.607062
min        -8.500000      -4.800000       0.000000       6.000000
25%         7.600000      17.900000       0.000000      31.000000
50%        12.000000      22.600000       0.000000      39.000000
75%        16.900000      28.200000       0.800000      48.000000
max        33.900000      48.100000     371.000000     135.000000

        WindSpeed9am   WindSpeed3pm    Humidity9am    Humidity3pm  \
count  143693.000000  142398.000000  142806.000000  140953.000000
mean       14.043426      18.662657      68.880831      51.539116
std         8.915375       8.809800      19.029164      20.795902
min         0.000000       0.000000       0.000000       0.000000
25%         7.000000      13.000000      57.000000      37.000000
50%        13.000000      19.000000      70.000000      52.000000
75%        19.000000      24.000000      83.000000      66.000000
max       130.000000      87.000000     100.000000     100.000000

        Pressure9am    Pressure3pm        Temp9am       Temp3pm
count  130395.00000  130432.000000  143693.000000  141851.00000
mean     1017.64994    1015.255889      16.990631      21.68339
std         7.10653       7.037414       6.488753       6.93665
min       980.50000     977.100000      -7.200000      -5.40000
25%      1012.90000    1010.400000      12.300000      16.60000
50%      1017.60000    1015.200000      16.700000      21.10000
75%      1022.40000    1020.000000      21.600000      26.40000
max      1041.00000    1039.600000      40.200000      46.70000
```

After describing the data, we see that there are extreme values given in the max values for some columns. For example, the mean of Rainfall is 2.36 and the max is 371.

Below we see the amount of missing values for each column. We will then fill in our missing values with mean for numerical values and mode for categorical values.

[17]:
```
df.isnull().sum()
```

[17]:
```
MinTemp           1485
MaxTemp           1261
Rainfall          3261
WindGustDir      10326
WindGustSpeed    10263
WindDir9am       10566
WindDir3pm        4228
WindSpeed9am      1767
WindSpeed3pm      3062
Humidity9am       2654
Humidity3pm       4507
Pressure9am      15065
Pressure3pm      15028
Temp9am           1767
Temp3pm           3609
RainToday         3261
RainTomorrow      3267
dtype: int64
```

[18]:
```
df['MinTemp'].fillna(df['MinTemp'].mean(), inplace = True)
df['MaxTemp'].fillna(df['MaxTemp'].mean(), inplace = True)
df['Rainfall'].fillna(df['Rainfall'].mean(), inplace = True)
df['WindGustSpeed'].fillna(df['WindGustSpeed'].mean(), inplace = True)
df['WindSpeed9am'].fillna(df['WindSpeed9am'].mean(), inplace = True)
df['WindSpeed3pm'].fillna(df['WindSpeed3pm'].mean(), inplace = True)
df['Humidity9am'].fillna(df['Humidity9am'].mean(), inplace = True)
df['Humidity3pm'].fillna(df['Humidity3pm'].mean(), inplace = True)
df['Pressure9am'].fillna(df['Pressure9am'].mean(), inplace = True)
df['Pressure3pm'].fillna(df['Pressure3pm'].mean(), inplace = True)
df['Temp9am'].fillna(df['Temp9am'].mean(), inplace = True)
df['Temp3pm'].fillna(df['Temp3pm'].mean(), inplace = True)

df['WindGustDir'].fillna(df['WindGustDir'].mode()[0], inplace = True)
df['WindDir9am'].fillna(df['WindDir9am'].mode()[0], inplace = True)
df['WindDir3pm'].fillna(df['WindDir3pm'].mode()[0], inplace = True)
```

Here we have removed all missing values with a mean or mode as a replacement except our RainToday and RainTomorrow columns.

[19]:
```
df.isnull().sum()
```

[19]:
```
MinTemp            0
MaxTemp            0
Rainfall           0
WindGustDir        0
WindGustSpeed      0
WindDir9am         0
```

```
WindDir3pm          0
WindSpeed9am        0
WindSpeed3pm        0
Humidity9am         0
Humidity3pm         0
Pressure9am         0
Pressure3pm         0
Temp9am             0
Temp3pm             0
RainToday        3261
RainTomorrow     3267
dtype: int64
```

# 5 STEP 4: RECORD DELETION

Now, we will delete any records where the response variable y, has missing values or any other values that are not yes or no.

[20]:
```
df.shape
```

[20]:
```
(145460, 17)
```

[21]:
```
df = df.dropna()
```

[22]:
```
df.shape
```

[22]:
```
(140787, 17)
```

[23]:
```
df['RainTomorrow'] = df['RainTomorrow'].replace('Yes', '1')
df['RainTomorrow'] = df['RainTomorrow'].replace('No', '0')
df['RainTomorrow'] = df['RainTomorrow'].astype(str).astype(int)

df['RainToday'] = df['RainToday'].replace('Yes', '1')
df['RainToday'] = df['RainToday'].replace('No', '0')
df['RainToday'] = df['RainToday'].astype(str).astype(int)
```

# 6 STEP 5: CARDINALITY IN CATEGORICAL VARIABLES. ORDINAL OR NOMINAL?

[24]:
```
#le = preprocessing.LabelEncoder()
#df['WindGustDir'] = le.fit_transform(df.WindGustDir.values)
#df['WindDir9am'] = le.fit_transform(df.WindDir9am.values)
#df['WindDir3pm'] = le.fit_transform(df.WindDir3pm.values)
```

```
#columns = df[['WindGustDir', 'WindDir9am', 'WindDir3pm']]
df = pd.get_dummies(df, columns=['WindGustDir', 'WindDir9am', 'WindDir3pm'])
```

[25]:
```
df
```

[25]:
```
        MinTemp  MaxTemp  Rainfall  WindGustSpeed  WindSpeed9am  WindSpeed3pm  \
0          13.4     22.9       0.6           44.0          20.0          24.0
1           7.4     25.1       0.0           44.0           4.0          22.0
2          12.9     25.7       0.0           46.0          19.0          26.0
3           9.2     28.0       0.0           24.0          11.0           9.0
4          17.5     32.3       1.0           41.0           7.0          20.0
…           …        …        …              …             …             …
145454      3.5     21.8       0.0           31.0          15.0          13.0
145455      2.8     23.4       0.0           31.0          13.0          11.0
145456      3.6     25.3       0.0           22.0          13.0           9.0
145457      5.4     26.9       0.0           37.0           9.0           9.0
145458      7.8     27.0       0.0           28.0          13.0           7.0

        Humidity9am  Humidity3pm  Pressure9am  Pressure3pm  …  \
0              71.0         22.0       1007.7       1007.1  …
1              44.0         25.0       1010.6       1007.8  …
2              38.0         30.0       1007.6       1008.7  …
3              45.0         16.0       1017.6       1012.8  …
4              82.0         33.0       1010.8       1006.0  …
…               …            …            …            …  …
145454         59.0         27.0       1024.7       1021.2  …
145455         51.0         24.0       1024.6       1020.3  …
145456         56.0         21.0       1023.5       1019.1  …
145457         53.0         24.0       1021.0       1016.8  …
145458         51.0         24.0       1019.4       1016.5  …

        WindDir3pm_NNW  WindDir3pm_NW  WindDir3pm_S  WindDir3pm_SE  \
0                    0              0             0              0
1                    0              0             0              0
2                    0              0             0              0
3                    0              0             0              0
4                    0              1             0              0
…                  …             …            …             …
145454               0              0             0              0
145455               0              0             0              0
145456               0              0             0              0
145457               0              0             0              0
145458               0              0             0              0

        WindDir3pm_SSE  WindDir3pm_SSW  WindDir3pm_SW  WindDir3pm_W  \
```

```
0                          0            0            0            0
1                          0            0            0            0
2                          0            0            0            0
3                          0            0            0            0
4                          0            0            0            0
…                     …          …          …          …
145454                     0            0            0            0
145455                     0            0            0            0
145456                     0            0            0            0
145457                     0            0            0            0
145458                     0            0            0            0

        WindDir3pm_WNW  WindDir3pm_WSW
0                    1               0
1                    0               1
2                    0               1
3                    0               0
4                    0               0
…                  …             …
145454               0               0
145455               0               0
145456               0               0
145457               1               0
145458               0               0

[140787 rows x 62 columns]
```

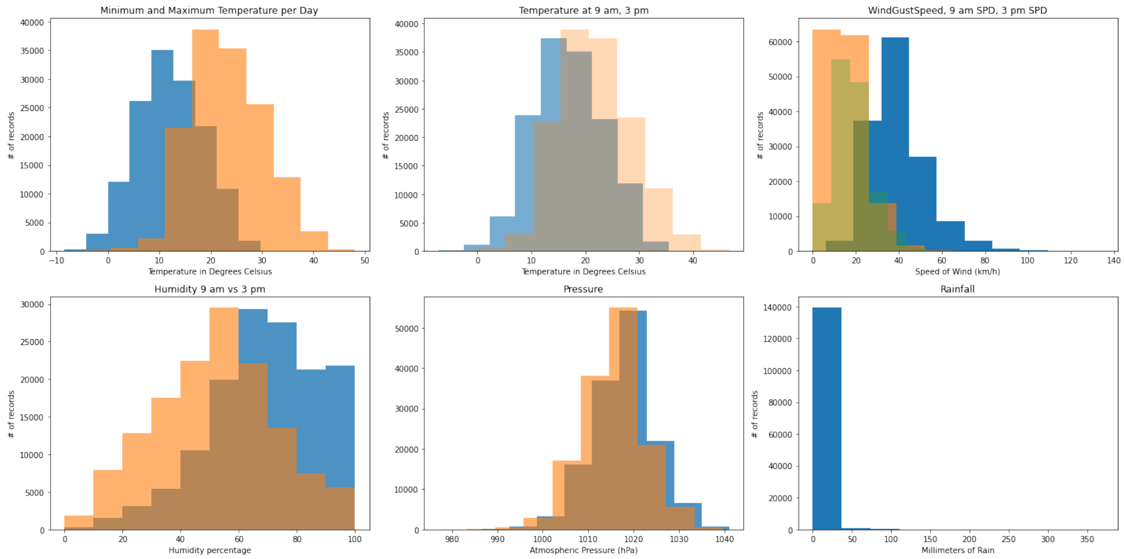
# 7 STEP 6: FINDING OUTLIERS AND THE REMOVAL OF THEM WITH IQR METHOD.

## 7.1 OUTLIERS

We're going to be searching for outliers. In order to do so, we'll be searching through each independent variable to see if outliers are present. We will then remove any entries that have such information.

[26]:
```
fig, ((plt0, plt1, plt2), (plt3,plt4, plt5)) = plt.subplots(nrows=2, ncols=3,␣
 ↪figsize=(20, 10))

plt0.hist(df.MinTemp, alpha=.8)
plt0.hist(df.MaxTemp, alpha=.6)
plt0.set_title('Minimum and Maximum Temperature per Day')
plt0.set_xlabel('Temperature in Degrees Celsius')
plt0.set_ylabel('# of records')
```

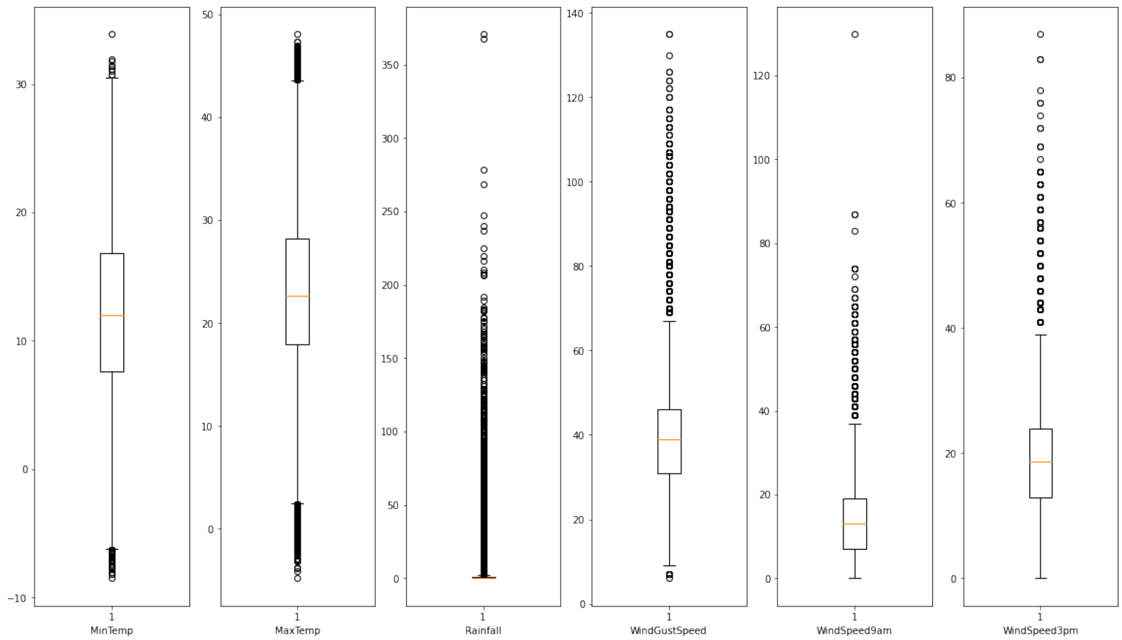
```
plt1.hist(df.Temp9am, alpha=.6)
plt1.hist(df.Temp3pm, alpha=.3)
plt1.set_title('Temperature at 9 am, 3 pm')
plt1.set_xlabel('Temperature in Degrees Celsius')
plt1.set_ylabel('# of records')


plt2.hist(df.WindGustSpeed)
plt2.hist(df.WindSpeed9am, alpha=.6)
plt2.hist(df.WindSpeed3pm, alpha=.3)
plt2.set_title('WindGustSpeed, 9 am SPD, 3 pm SPD')
plt2.set_xlabel('Speed of Wind (km/h)')
plt2.set_ylabel('# of records')

plt3.hist(df.Humidity9am, alpha=.8)
plt3.hist(df.Humidity3pm, alpha=.6)
plt3.set_title('Humidity 9 am vs 3 pm')
plt3.set_xlabel('Humidity percentage')
plt3.set_ylabel('# of records')

plt4.hist(df.Pressure9am, alpha=.8)
plt4.hist(df.Pressure3pm, alpha=.6)
plt4.set_title('Pressure')
plt4.set_xlabel('Atmospheric Pressure (hPa)')
plt5.set_ylabel('# of records')

plt5.hist(df.Rainfall)
plt5.set_title('Rainfall')
plt5.set_xlabel('Millimeters of Rain')
plt5.set_ylabel('# of records')

fig.tight_layout()
plt.show()
```

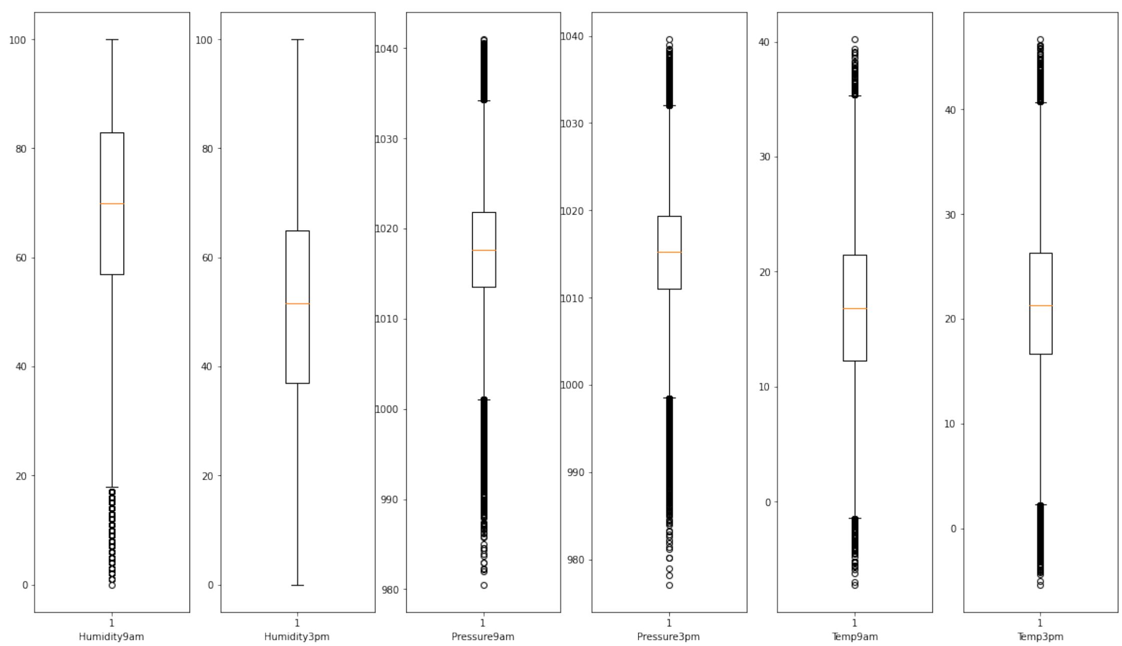



Based off the information given on the histograms, most x variables contain normal distributions with about average looking plots. No real outliers are being shown.

[27]:
```
fig, ((plt6, plt7, plt8, plt9,plt10, plt11), (plt12,plt13, plt14, plt15,plt16,␣
↪plt17)) = plt.subplots(nrows=2, ncols=6, figsize=(20, 25))

plt6.boxplot(df.MinTemp)
plt6.set_xlabel('MinTemp')

plt7.boxplot(df.MaxTemp)
plt7.set_xlabel('MaxTemp')

plt8.boxplot(df.Rainfall)
plt8.set_xlabel('Rainfall')

plt9.boxplot(df.WindGustSpeed)
plt9.set_xlabel('WindGustSpeed')

plt10.boxplot(df.WindSpeed9am)
plt10.set_xlabel('WindSpeed9am')

plt11.boxplot(df.WindSpeed3pm)
plt11.set_xlabel('WindSpeed3pm')

plt12.boxplot(df.Humidity9am)
plt12.set_xlabel('Humidity9am')

plt13.boxplot(df.Humidity3pm)
plt13.set_xlabel('Humidity3pm')
```

```
plt14.boxplot(df.Pressure9am)
plt14.set_xlabel('Pressure9am')

plt15.boxplot(df.Pressure3pm)
plt15.set_xlabel('Pressure3pm')

plt16.boxplot(df.Temp9am)
plt16.set_xlabel('Temp9am')

plt17.boxplot(df.Temp3pm)
plt17.set_xlabel('Temp3pm')


plt.show()
```




Based off the information given, most x variables look like they contain man outliers but none that seem out of the ordinary except WindGustSpeed and Rainfall. Since weather can vary and go beyond the IQR due to seasonality changes, the outliers may be considered potential outliers. Splitting the data into the various seasons will be helpful in creating more in depth analysis for the data. For simplistic terms, we will keep it to overall weather.

[28]:
```
df_cap = df.copy()
```

[29]:

```
df_cap = df_cap.drop(['RainTomorrow'], axis=1)
```

[30]:

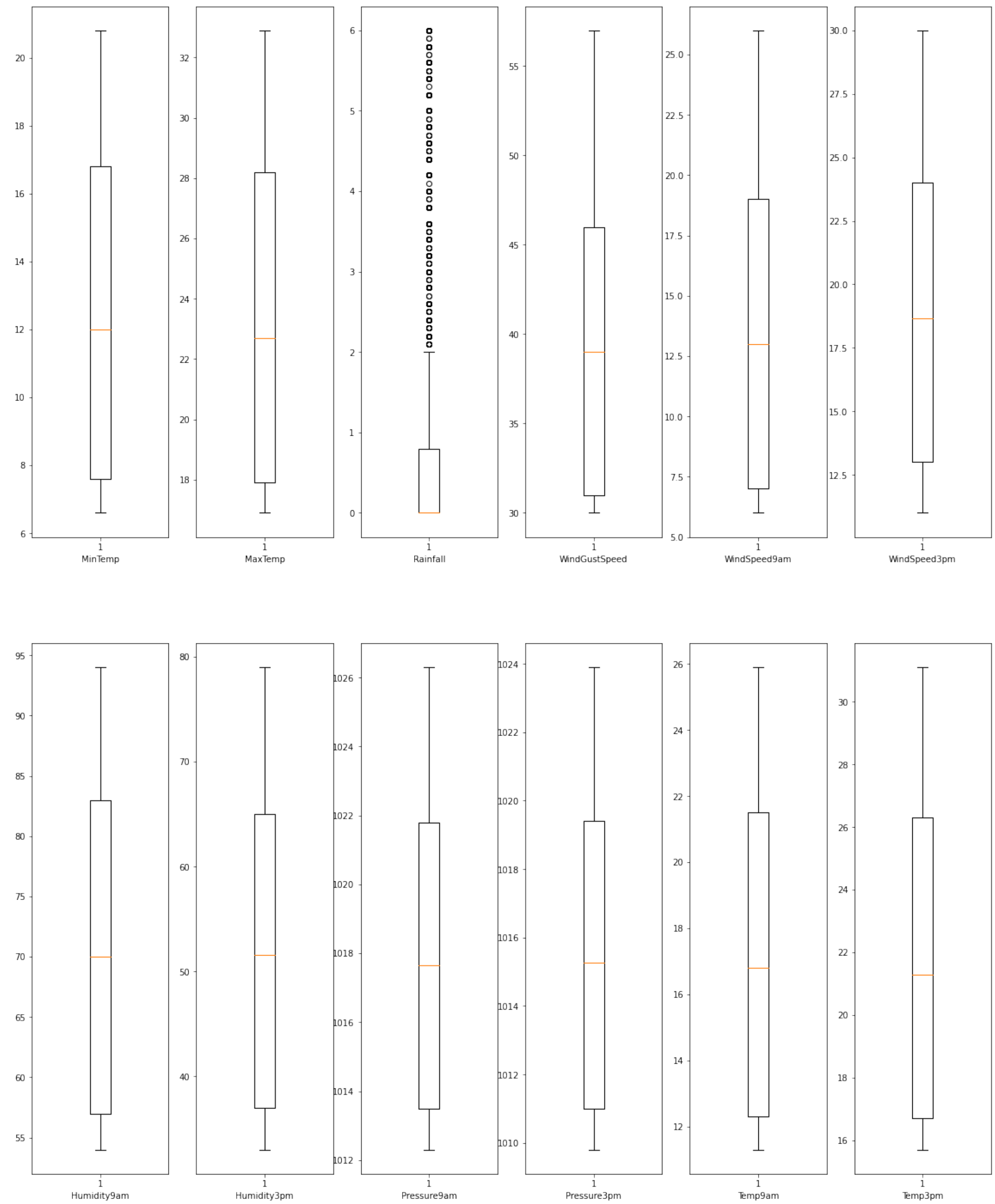
```
def cap_data(df):
    for col in df.columns:
        print("capping the ",col)
        if (((df[col].dtype)=='float64') | ((df[col].dtype)=='int64')):
            percentiles = df[col].quantile([0.20,0.90]).values
            df[col][df[col] <= percentiles[0]] = percentiles[0]
            df[col][df[col] >= percentiles[1]] = percentiles[1]
        else:
            df[col]=df[col]
    return df

final_df=cap_data(df_cap)
```

```
capping the  MinTemp
capping the  MaxTemp
capping the  Rainfall
capping the  WindGustSpeed
capping the  WindSpeed9am
capping the  WindSpeed3pm
capping the  Humidity9am
capping the  Humidity3pm
capping the  Pressure9am
capping the  Pressure3pm
capping the  Temp9am
capping the  Temp3pm
capping the  RainToday
capping the  WindGustDir_E
capping the  WindGustDir_ENE
capping the  WindGustDir_ESE
capping the  WindGustDir_N
capping the  WindGustDir_NE
capping the  WindGustDir_NNE
capping the  WindGustDir_NNW
capping the  WindGustDir_NW
capping the  WindGustDir_S
capping the  WindGustDir_SE
capping the  WindGustDir_SSE
capping the  WindGustDir_SSW
capping the  WindGustDir_SW
capping the  WindGustDir_W
capping the  WindGustDir_WNW
capping the  WindGustDir_WSW
capping the  WindDir9am_E
capping the  WindDir9am_ENE
capping the  WindDir9am_ESE
```

```
capping the  WindDir9am_N
capping the  WindDir9am_NE
capping the  WindDir9am_NNE
capping the  WindDir9am_NNW
capping the  WindDir9am_NW
capping the  WindDir9am_S
capping the  WindDir9am_SE
capping the  WindDir9am_SSE
capping the  WindDir9am_SSW
capping the  WindDir9am_SW
capping the  WindDir9am_W
capping the  WindDir9am_WNW
capping the  WindDir9am_WSW
capping the  WindDir3pm_E
capping the  WindDir3pm_ENE
capping the  WindDir3pm_ESE
capping the  WindDir3pm_N
capping the  WindDir3pm_NE
capping the  WindDir3pm_NNE
capping the  WindDir3pm_NNW
capping the  WindDir3pm_NW
capping the  WindDir3pm_S
capping the  WindDir3pm_SE
capping the  WindDir3pm_SSE
capping the  WindDir3pm_SSW
capping the  WindDir3pm_SW
capping the  WindDir3pm_W
capping the  WindDir3pm_WNW
capping the  WindDir3pm_WSW
```

[31]:
```
fig, ((plt6, plt7, plt8, plt9,plt10, plt11), (plt12,plt13, plt14, plt15,plt16,␣
 ↪plt17)) = plt.subplots(nrows=2, ncols=6, figsize=(20, 25))

plt6.boxplot(final_df.MinTemp)
plt6.set_xlabel('MinTemp')

plt7.boxplot(final_df.MaxTemp)
plt7.set_xlabel('MaxTemp')

plt8.boxplot(final_df.Rainfall)
plt8.set_xlabel('Rainfall')

plt9.boxplot(final_df.WindGustSpeed)
plt9.set_xlabel('WindGustSpeed')

plt10.boxplot(final_df.WindSpeed9am)
plt10.set_xlabel('WindSpeed9am')
```

```
plt11.boxplot(final_df.WindSpeed3pm)
plt11.set_xlabel('WindSpeed3pm')

plt12.boxplot(final_df.Humidity9am)
plt12.set_xlabel('Humidity9am')

plt13.boxplot(final_df.Humidity3pm)
plt13.set_xlabel('Humidity3pm')

plt14.boxplot(final_df.Pressure9am)
plt14.set_xlabel('Pressure9am')

plt15.boxplot(final_df.Pressure3pm)
plt15.set_xlabel('Pressure3pm')

plt16.boxplot(final_df.Temp9am)
plt16.set_xlabel('Temp9am')

plt17.boxplot(final_df.Temp3pm)
plt17.set_xlabel('Temp3pm')


plt.show()
```




After removing the outliers using the IQR method, we can see that our boxplots have had our outliers removed.

[32]:
```
corr = df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

[32]: <pandas.io.formats.style.Styler at 0x7f36a7521190>

Based off of our cleaning methods, Humidity9AM, Humidity3PM, RainToday, Rainfall, and WindGustSpeed are the closest in relation to RainTomorrow

# 8 STEP 7: DATA DISTRIBUTION - USING SMOTE

Based off the variables given, we find that RainToday column has an imbalanced dataset. So we balance it, using the SMOTE method.

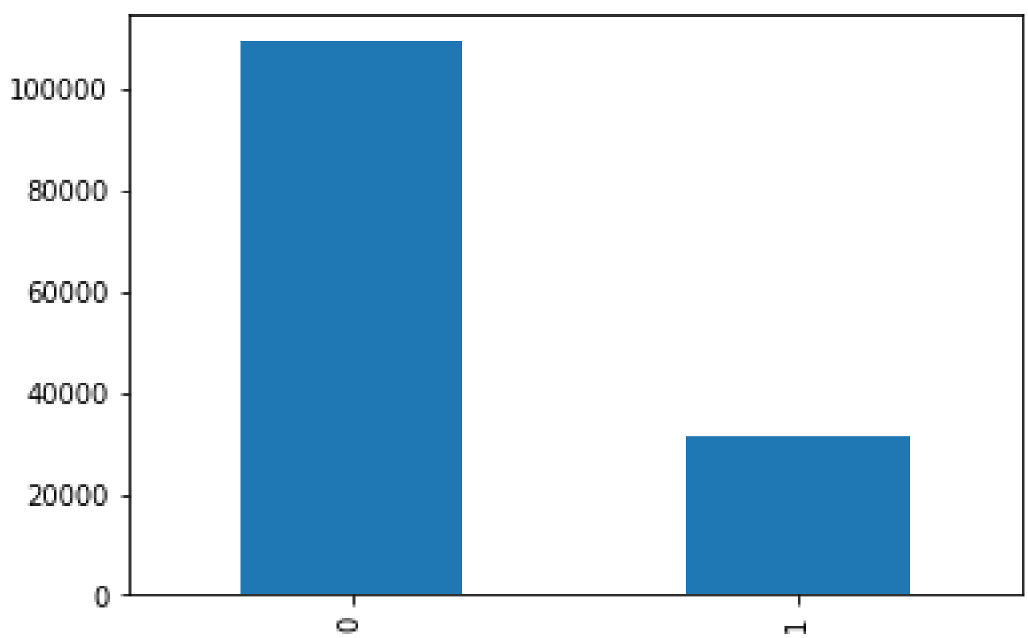
[33]:
```
print(final_df['RainToday'].value_counts())
```

```
0    109332
1     31455
Name: RainToday, dtype: int64
```

[34]:
```
print(final_df['RainToday'].value_counts(normalize=True))

final_df['RainToday'].value_counts().plot(kind='bar')
```

```
0    0.776577
1    0.223423
Name: RainToday, dtype: float64
```

[34]: <AxesSubplot:>



[35]:
```
from imblearn.over_sampling import SMOTE
```

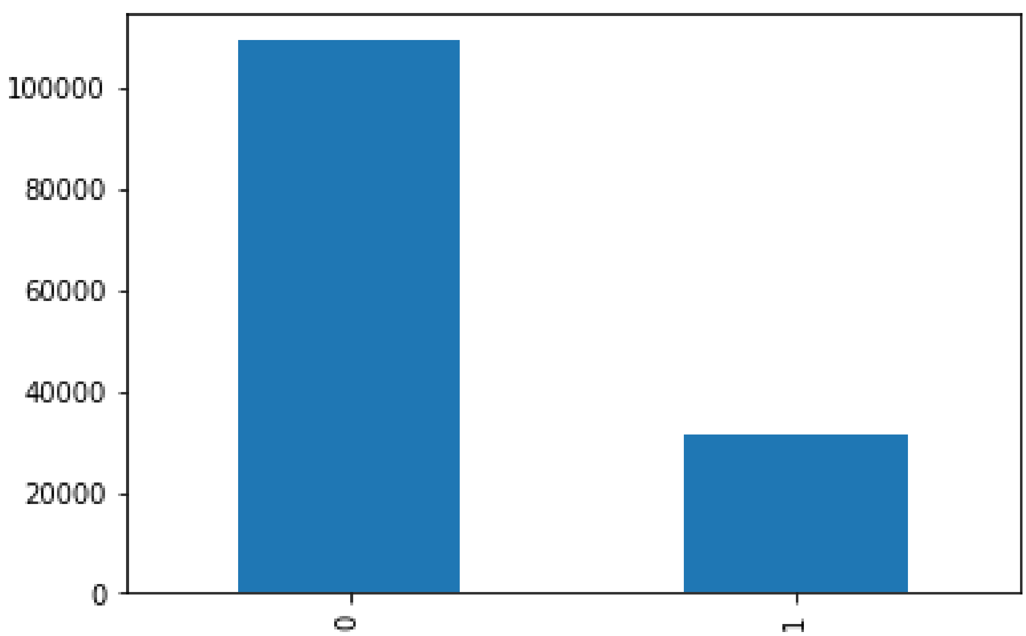
[36]:
```
df_train, df_test = train_test_split(final_df, test_size=0.2,␣
↪stratify=final_df['RainToday'], random_state=888)

features = df_train.drop(columns=['RainToday']).columns

smote = SMOTE(random_state=888)
X_resampled, y_resampled = smote.fit_resample(df_train[features],␣
↪df_train['RainToday'])

y_resampled.value_counts()
```

[36]:
```
1    87465
0    87465
Name: RainToday, dtype: int64
```

[37]:
```
print(final_df['RainToday'].value_counts(normalize=True))

final_df['RainToday'].value_counts().plot(kind='bar')
```

```
0    0.776577
1    0.223423
Name: RainToday, dtype: float64
```

[37]: <AxesSubplot:>



# 9 STEP 8: LOGISTIC REGRESSION AND CLASSIFICATION REPORT

[38]:
```
X = final_df
y = df['RainTomorrow']
```

[39]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,␣
↪random_state =42)
```

[40]:
```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

[40]:
```
LogisticRegression()
```

[41]:
```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.3f}'.
↪format(logreg.score(X_test, y_test)))
```

```
Accuracy of logistic regression classifier on test set: 0.834
```

[42]:
```
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[25865  1522]
 [ 4306  3504]]
```

[43]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.94      0.90     27387
           1       0.70      0.45      0.55      7810

    accuracy                           0.83     35197
   macro avg       0.78      0.70      0.72     35197
weighted avg       0.82      0.83      0.82     35197
```

[44]:
```
logreg.predict(X_test[0:50])
```

[44]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0])
```

# 10 STEP 9: XGBOOST CLASSIFICATION AND COMPARATIVE ANALYSIS WITH LOGREG MODEL

[45]:
```
from xgboost import XGBClassifier
from vecstack import stacking
```

[46]:
```
model = XGBClassifier(random_state=42, n_jobs=-1, learning_rate=0.1,␣
 ↪n_estimators=100, max_depth=5)
```

[47]:
```
model.fit(X_train, y_train)
```

[47]:
```
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=-1, num_parallel_tree=1, random_state=42,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=None)
```

[48]:
```
scores = cross_val_score(model, X_train, y_train, cv=5)
print("Mean cross-validation score: %.3f" % scores.mean())

kfold = KFold(n_splits=10, shuffle=True)
kf_cv_scores = cross_val_score(model, X_train, y_train, cv=kfold )
print("K-fold CV average score: %.3f" % kf_cv_scores.mean())
```

```
Mean cross-validation score: 0.850
K-fold CV average score: 0.850
```

[49]:
```
model.predict(X_test[0:50])
```

[49]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1])
```