Weather rain project

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github link:

[https://github.com/Salmahalqarni/Weather-rain-project (https://github.com/Salmahalqarni/Weather-rain-project)](https://github.com/Salmahalqarni/Weather-rain-project)

Rains are essential part of our lives. Clouds give the gift of rains to humans. Weather department tries to forecast when will it rain. So, I try to predict whether it will rain in Australia tomorrow or not.

implement Logistic Regression with Python and Scikit-Learn and build a classifier to predict whether or not it will rain tomorrow in Australia. I train a binary classification model using Logistic Regression. I have used the **Rain in Australia** dataset for this project.

The problem statement

Accurate rainfall prediction is crucial for various sectors in Australia, including agriculture, water management, and disaster preparedness. The current weather forecasting methods, while informative, often lack precise predictions for specific locations and timeframes. This leads to uncertainties that can negatively impact decision-making and resource allocation.

Developing a reliable model for predicting rainfall in Australia tomorrow would provide valuable information for individuals and organizations to:

- Plan agricultural activities: Farmers could optimize irrigation schedules and planting times based on anticipated rainfall.
- Manage water resources: Water authorities could adjust reservoir levels and distribution plans to ensure adequate water supply.
- Prepare for potential floods or droughts: Early warnings of potential heavy rainfall or

Objective:

This research aims to develop a robust and accurate machine learning model for predicting rainfall in Australia tomorrow. The model will be trained on historical weather data, including temperature, humidity, wind speed, and cloud cover, along with actual rainfall events. By analyzing these data points, the model will learn to identify patterns and relationships that can predict the probability of rainfall for any given location.

The specific objectives of this research include:

- Collect and pre-process a comprehensive dataset of historical weather data for Australia.
- Explore and analyze the data to identify relevant features and relationships.
- Develop and implement various machine learning algorithms for rainfall prediction.
- Evaluate the performance of each model using metrics like accuracy, precision, recall, and F1-score.
- Optimize the chosen model through hyperparameter tuning.
- Develop a user-friendly interface for the model to facilitate its use by various stakeholders.

Import libraries

The first step in building the model is to import the necessary libraries.

In [1]:
```python


import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# import libraries for plotting
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```python
import warnings

warnings.filterwarnings('ignore')
```

In [3]:
```python
data = 'weatherAUS.csv'

df = pd.read_csv(data)
```

In [4]:
```python
df.shape
```

Out[4]:
```
(142193, 24)
```

In [5]:
```python
df.head()
```

Out[5]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGust
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	

5 rows × 24 columns

In [6]:
```python
col_names = df.columns

col_names
```

Out[6]:
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3p
m',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow'],
      dtype='object')
```

Drop RISK_MM variable

It is given in the dataset description, that we should drop the `RISK_MM` feature variable from the dataset description. So, we should drop it as follows-

In [7]:
```python
df.drop(['RISK_MM'], axis=1, inplace=True)
```

View summary of dataset

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142193 entries, 0 to 142192
Data columns (total 23 columns):
Date             142193 non-null object
Location         142193 non-null object
MinTemp          141556 non-null float64
MaxTemp          141871 non-null float64
Rainfall         140787 non-null float64
Evaporation      81350 non-null float64
Sunshine         74377 non-null float64
WindGustDir      132863 non-null object
WindGustSpeed    132923 non-null float64
WindDir9am       132180 non-null object
WindDir3pm       138415 non-null object
WindSpeed9am     140845 non-null float64
WindSpeed3pm     139563 non-null float64
Humidity9am      140419 non-null float64
Humidity3pm      138583 non-null float64
Pressure9am      128179 non-null float64
Pressure3pm      128212 non-null float64
Cloud9am         88536 non-null float64
Cloud3pm         85099 non-null float64
Temp9am          141289 non-null float64
Temp3pm          139467 non-null float64
RainToday        140787 non-null object
RainTomorrow     142193 non-null object
dtypes: float64(16), object(7)
memory usage: 25.0+ MB
```

Comment

- Categorical variables have data type `object` .
- Numerical variables have data type `float64` .

In [9]:
```
df.describe()
```

Out[9]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed
count	141556.000000	141871.000000	140787.000000	81350.000000	74377.000000	132923.000000
mean	12.186400	23.226784	2.349974	5.469824	7.624853	39.984292
std	6.403283	7.117618	8.465173	4.188537	3.781525	13.588801
min	-8.500000	-4.800000	0.000000	0.000000	0.000000	6.000000
25%	7.600000	17.900000	0.000000	2.600000	4.900000	31.000000
50%	12.000000	22.600000	0.000000	4.800000	8.500000	39.000000
75%	16.800000	28.200000	0.800000	7.400000	10.600000	48.000000
max	33.900000	48.100000	371.000000	145.000000	14.500000	135.000000

Univariate Analysis

Check for missing values

In [10]:
```
df['RainTomorrow'].isnull().sum()
```

Out[10]:
```
0
```

We can see that there are no missing values in the `RainTomorrow` target variable.

View the unique values

In [12]:
```
df['RainTomorrow'].unique()
```

Out[12]:
```
array(['No', 'Yes'], dtype=object)
```

The two unique values are `No` and `Yes` .

View the frequency distribution of values

In [13]:
```
df['RainTomorrow'].value_counts()
```

Out[13]:
```
No     110316
Yes     31877
Name: RainTomorrow, dtype: int64
```

View percentage of frequency distribution of values

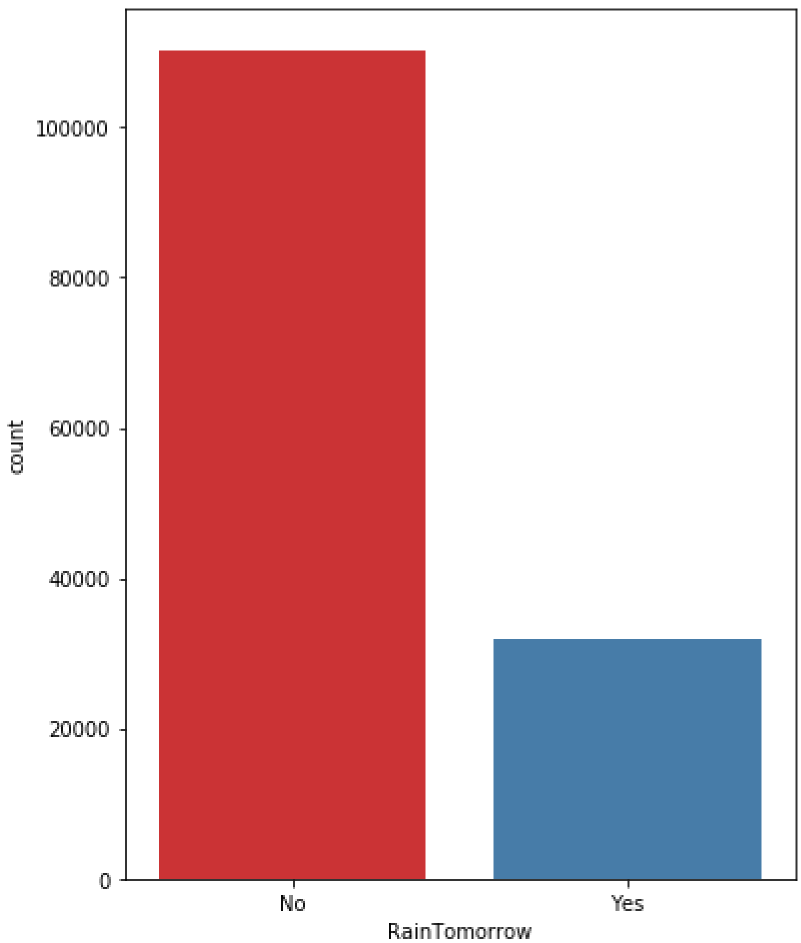
In [14]:
```
df['RainTomorrow'].value_counts()/len(df)
```

Out[14]:
```
No     0.775819
Yes    0.224181
Name: RainTomorrow, dtype: float64
```

Comment

- We can see that out of the total number of `RainTomorrow` values, `No` appears 77.58% times and `Yes` appears 22.42% times.

In [15]:
```
f, ax = plt.subplots(figsize=(6, 8))
ax = sns.countplot(x="RainTomorrow", data=df, palette="Set1")
plt.show()
```

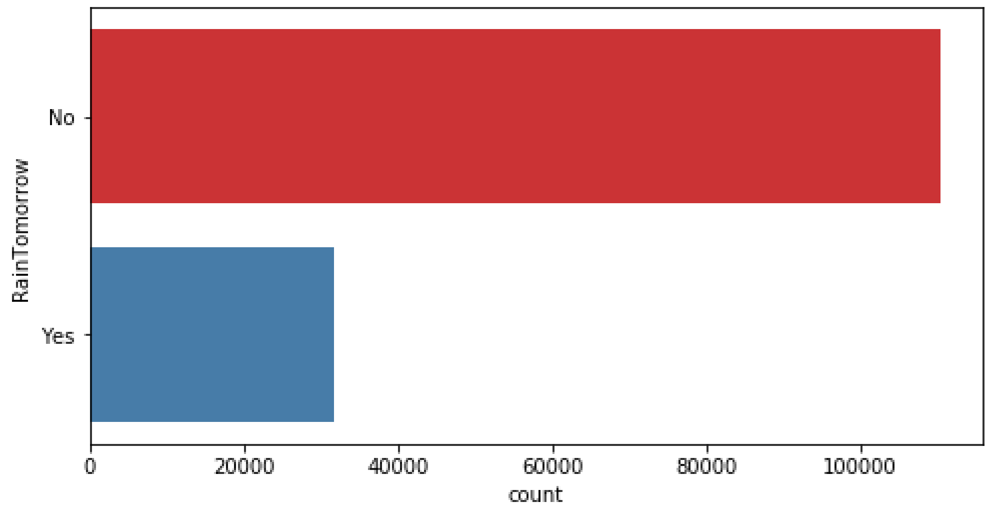


Interpretation

- The above univariate plot confirms our findings that -
    - The `No` variable have 110316 entries, and
    - The `Yes` variable have 31877 entries.

We can plot the bars horizontally as follows :

In [16]:
```python
f, ax = plt.subplots(figsize=(8, 4))
ax = sns.countplot(y="RainTomorrow", data=df, palette="Set1")
plt.show()
```



Bivariate Analysis

Explore Categorical Variables

In [17]:
```python
# find categorical variables

categorical = [var for var in df.columns if df[var].dtype=='O']

print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :', categorical)
```

```
There are 7 categorical variables

The categorical variables are : ['Date', 'Location', 'WindGustDir', 'WindDir9
am', 'WindDir3pm', 'RainToday', 'RainTomorrow']
```

In [18]:
```python
# view the categorical variables

df[categorical].head()
```

Out[18]:

	Date	Location	WindGustDir	WindDir9am	WindDir3pm	RainToday	RainTomorrow
0	2008-12-01	Albury	W	W	WNW	No	No
1	2008-12-02	Albury	WNW	NNW	WSW	No	No
2	2008-12-03	Albury	WSW	W	WSW	No	No
3	2008-12-04	Albury	NE	SE	E	No	No
4	2008-12-05	Albury	W	ENE	NW	No	No

Missing values in categorical variables

In [19]:
```
# check missing values in categorical variables

df[categorical].isnull().sum()
```

Out[19]:
```
Date                0
Location            0
WindGustDir      9330
WindDir9am      10013
WindDir3pm       3778
RainToday        1406
RainTomorrow        0
dtype: int64
```

In [20]:
```
# print categorical variables containing missing values

cat1 = [var for var in categorical if df[var].isnull().sum()!=0]

print(df[cat1].isnull().sum())
```

```
WindGustDir     9330
WindDir9am     10013
WindDir3pm      3778
RainToday       1406
dtype: int64
```

In [23]:
```
# check for cardinality in categorical variables

for var in categorical:

    print(var, ' contains ', len(df[var].unique()), ' labels')
```

```
Date  contains  3436  labels
Location  contains  49  labels
WindGustDir  contains  17  labels
WindDir9am  contains  17  labels
WindDir3pm  contains  17  labels
RainToday  contains  3  labels
RainTomorrow  contains  2  labels
```

Feature Engineering of Date Variable

In [24]:
```
df['Date'].dtypes
```

Out[24]:
```
dtype('O')
```

In [25]:
```
# parse the dates, currently coded as strings, into datetime format

df['Date'] = pd.to_datetime(df['Date'])
```

In [26]:
```python
# extract year from date

df['Year'] = df['Date'].dt.year

df['Year'].head()
```

Out[26]:
```
0    2008
1    2008
2    2008
3    2008
4    2008
Name: Year, dtype: int64
```

In [27]:
```python
# extract month from date

df['Month'] = df['Date'].dt.month

df['Month'].head()
```

Out[27]:
```
0    12
1    12
2    12
3    12
4    12
Name: Month, dtype: int64
```

In [28]:
```python
# extract day from date

df['Day'] = df['Date'].dt.day

df['Day'].head()
```

Out[28]:
```
0    1
1    2
2    3
3    4
4    5
Name: Day, dtype: int64
```

In [30]:
```python
# drop the original Date variable

df.drop('Date', axis=1, inplace = True)
```

In [31]:
```
# preview the dataset again

df.head()
```

Out[31]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0
1	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0
2	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0
3	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0
4	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0

5 rows × 25 columns

In [32]:
```
# find categorical variables

categorical = [var for var in df.columns if df[var].dtype=='O']

print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :', categorical)
```

```
There are 6 categorical variables

The categorical variables are : ['Location', 'WindGustDir', 'WindDir9am', 'Wi
ndDir3pm', 'RainToday', 'RainTomorrow']
```

In [33]:
```
# check for missing values in categorical variables

df[categorical].isnull().sum()
```

Out[33]:
```
Location            0
WindGustDir      9330
WindDir9am      10013
WindDir3pm       3778
RainToday        1406
RainTomorrow        0
dtype: int64
```

Explore Numerical Variables

In [58]:
```
# find numerical variables

numerical = [var for var in df.columns if df[var].dtype!='O']

print('There are {} numerical variables\n'.format(len(numerical)))

print('The numerical variables are :', numerical)
```

```
There are 19 numerical variables

The numerical variables are : ['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporatio
n', 'Sunshine', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9a
m', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Tem
p9am', 'Temp3pm', 'Year', 'Month', 'Day']
```

In [59]:
```
# view the numerical variables

df[numerical].head()
```

Out[59]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSp
0	13.4	22.9	0.6	NaN	NaN	44.0	20.0	
1	7.4	25.1	0.0	NaN	NaN	44.0	4.0	
2	12.9	25.7	0.0	NaN	NaN	46.0	19.0	
3	9.2	28.0	0.0	NaN	NaN	24.0	11.0	
4	17.5	32.3	1.0	NaN	NaN	41.0	7.0	

Missing values in numerical variables

In [60]:
```
# check missing values in numerical variables

df[numerical].isnull().sum()
```

Out[60]:
```
MinTemp            637
MaxTemp            322
Rainfall          1406
Evaporation      60843
Sunshine         67816
WindGustSpeed     9270
WindSpeed9am      1348
WindSpeed3pm      2630
Humidity9am       1774
Humidity3pm       3610
Pressure9am      14014
Pressure3pm      13981
Cloud9am         53657
Cloud3pm         57094
Temp9am            904
Temp3pm           2726
Year                 0
Month                0
Day                  0
dtype: int64
```

We can see that all the 16 numerical variables contain missing values.

Outliers in numerical variables

In [61]:
```
# view summary statistics in numerical variables

print(round(df[numerical].describe()),2)
```

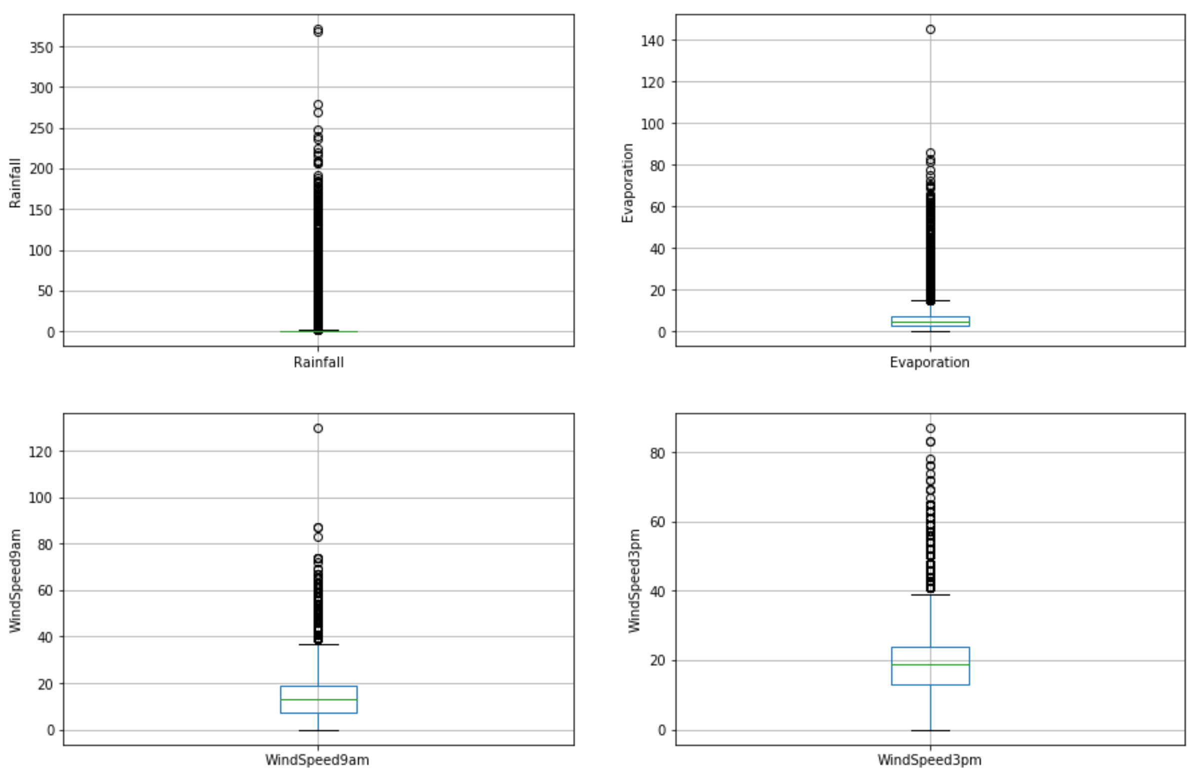
```
        MinTemp   MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed  \
count  141556.0  141871.0  140787.0      81350.0   74377.0       132923.0
mean       12.0      23.0       2.0          5.0       8.0           40.0
std         6.0       7.0       8.0          4.0       4.0           14.0
min        -8.0      -5.0       0.0          0.0       0.0            6.0
25%         8.0      18.0       0.0          3.0       5.0           31.0
50%        12.0      23.0       0.0          5.0       8.0           39.0
75%        17.0      28.0       1.0          7.0      11.0           48.0
max        34.0      48.0     371.0        145.0      14.0          135.0

       WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  \
count      140845.0      139563.0     140419.0     138583.0     128179.0
mean           14.0          19.0         69.0         51.0       1018.0
std             9.0           9.0         19.0         21.0          7.0
min             0.0           0.0          0.0          0.0        980.0
25%             7.0          13.0         57.0         37.0       1013.0
50%            13.0          19.0         70.0         52.0       1018.0
75%            19.0          24.0         83.0         66.0       1022.0
max           130.0          87.0        100.0        100.0       1041.0

       Pressure3pm  Cloud9am  Cloud3pm   Temp9am   Temp3pm      Year  \
count     128212.0   88536.0   85099.0  141289.0  139467.0  142193.0
mean        1015.0       4.0       5.0      17.0      22.0    2013.0
std            7.0       3.0       3.0       6.0       7.0       3.0
min          977.0       0.0       0.0      -7.0      -5.0    2007.0
25%         1010.0       1.0       2.0      12.0      17.0    2011.0
50%         1015.0       5.0       5.0      17.0      21.0    2013.0
75%         1020.0       7.0       7.0      22.0      26.0    2015.0
max         1040.0       9.0       9.0      40.0      47.0    2017.0

          Month       Day
count  142193.0  142193.0
mean        6.0      16.0
std         3.0       9.0
min         1.0       1.0
25%         3.0       8.0
50%         6.0      16.0
75%         9.0      23.0
max        12.0      31.0    2
```

On closer inspection, we can see that the `Rainfall`, `Evaporation`, `WindSpeed9am` and `WindSpeed3pm` columns may contain outliers.

I will draw boxplots to visualise outliers in the above variables.

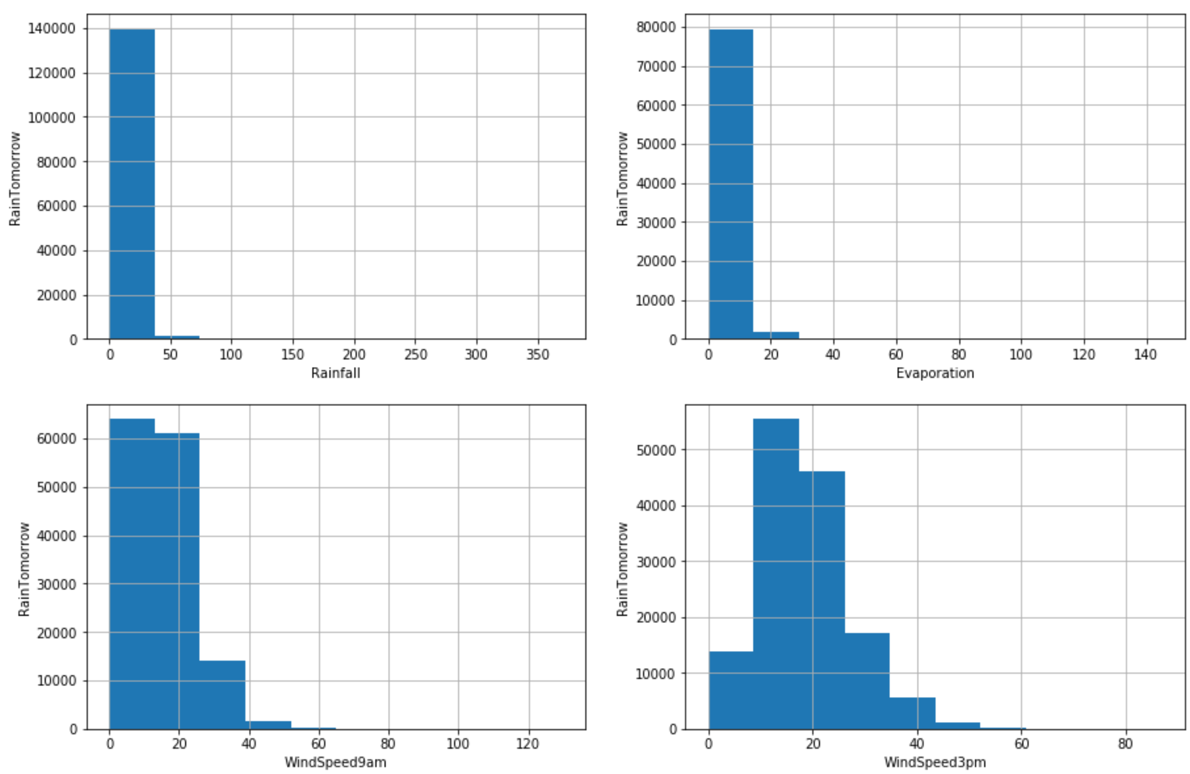
In [62]:
```
# draw boxplots to visualize outliers

plt.figure(figsize=(15,10))


plt.subplot(2, 2, 1)
fig = df.boxplot(column='Rainfall')
fig.set_title('')
fig.set_ylabel('Rainfall')


plt.subplot(2, 2, 2)
fig = df.boxplot(column='Evaporation')
fig.set_title('')
fig.set_ylabel('Evaporation')


plt.subplot(2, 2, 3)
fig = df.boxplot(column='WindSpeed9am')
fig.set_title('')
fig.set_ylabel('WindSpeed9am')


plt.subplot(2, 2, 4)
fig = df.boxplot(column='WindSpeed3pm')
fig.set_title('')
fig.set_ylabel('WindSpeed3pm')
```

Out[62]:
```
Text(0, 0.5, 'WindSpeed3pm')
```



In [63]:
```
# plot histogram to check distribution

plt.figure(figsize=(15,10))


plt.subplot(2, 2, 1)
fig = df.Rainfall.hist(bins=10)
fig.set_xlabel('Rainfall')
fig.set_ylabel('RainTomorrow')


plt.subplot(2, 2, 2)
fig = df.Evaporation.hist(bins=10)
fig.set_xlabel('Evaporation')
fig.set_ylabel('RainTomorrow')


plt.subplot(2, 2, 3)
fig = df.WindSpeed9am.hist(bins=10)
fig.set_xlabel('WindSpeed9am')
fig.set_ylabel('RainTomorrow')


plt.subplot(2, 2, 4)
fig = df.WindSpeed3pm.hist(bins=10)
fig.set_xlabel('WindSpeed3pm')
fig.set_ylabel('RainTomorrow')
```

Out[63]:
```
Text(0, 0.5, 'RainTomorrow')
```



In [64]:
```
# find outliers for Rainfall variable

IQR = df.Rainfall.quantile(0.75) - df.Rainfall.quantile(0.25)
Lower_fence = df.Rainfall.quantile(0.25) - (IQR * 3)
Upper_fence = df.Rainfall.quantile(0.75) + (IQR * 3)
print('Rainfall outliers are values < {lowerboundary} or > {upperboundary}'.for
```

```
Rainfall outliers are values < -2.4000000000000004 or > 3.2
```

For `Rainfall` , the minimum and maximum values are 0.0 and 371.0. So, the outliers are values > 3.2.

In [65]:
```
# find outliers for Evaporation variable

IQR = df.Evaporation.quantile(0.75) - df.Evaporation.quantile(0.25)
Lower_fence = df.Evaporation.quantile(0.25) - (IQR * 3)
Upper_fence = df.Evaporation.quantile(0.75) + (IQR * 3)
print('Evaporation outliers are values < {lowerboundary} or > {upperboundary}'.
```

```
Evaporation outliers are values < -11.800000000000002 or > 21.800000000000004
```

For `Evaporation` , the minimum and maximum values are 0.0 and 145.0. So, the outliers are values > 21.8.

In [66]:
```
# find outliers for WindSpeed9am variable

IQR = df.WindSpeed9am.quantile(0.75) - df.WindSpeed9am.quantile(0.25)
Lower_fence = df.WindSpeed9am.quantile(0.25) - (IQR * 3)
Upper_fence = df.WindSpeed9am.quantile(0.75) + (IQR * 3)
print('WindSpeed9am outliers are values < {lowerboundary} or > {upperboundary}'
```

```
WindSpeed9am outliers are values < -29.0 or > 55.0
```

For `WindSpeed9am` , the minimum and maximum values are 0.0 and 130.0. So, the outliers are values > 55.0.

In [67]:
```
# find outliers for WindSpeed3pm variable

IQR = df.WindSpeed3pm.quantile(0.75) - df.WindSpeed3pm.quantile(0.25)
Lower_fence = df.WindSpeed3pm.quantile(0.25) - (IQR * 3)
Upper_fence = df.WindSpeed3pm.quantile(0.75) + (IQR * 3)
print('WindSpeed3pm outliers are values < {lowerboundary} or > {upperboundary}'
```

```
WindSpeed3pm outliers are values < -20.0 or > 57.0
```

For `WindSpeed3pm` , the minimum and maximum values are 0.0 and 87.0. So, the outliers are values > 57.0.

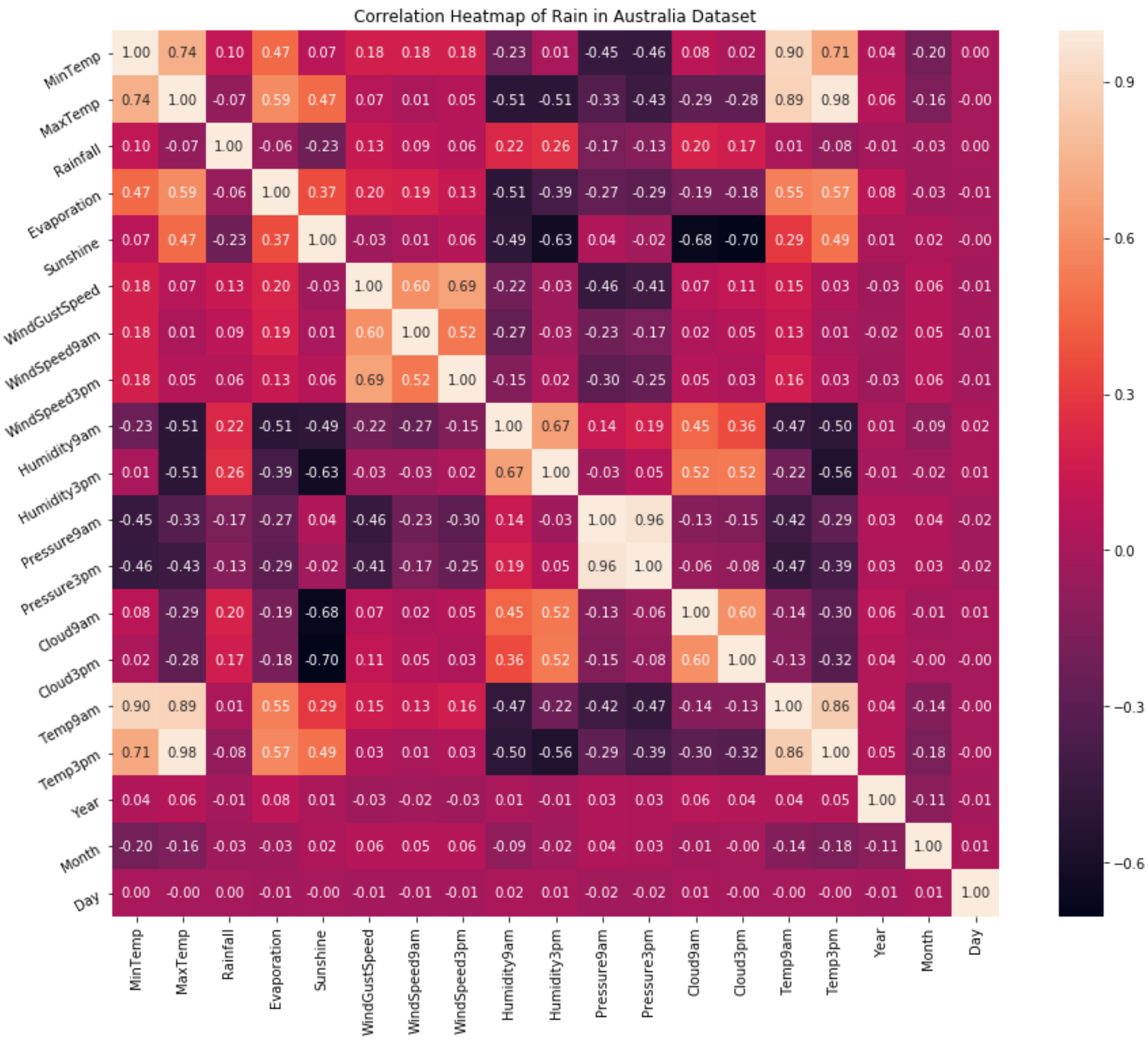
7. Multivariate Analysis

- An important step in EDA is to discover patterns and relationships between variables in the dataset.
- I will use heat map and pair plot to discover the patterns and relationships in the dataset.
- First of all, I will draw a heat map.

In [68]:
```
correlation = df.corr()
```

Heat Map

In [69]:
```
plt.figure(figsize=(16,12))
plt.title('Correlation Heatmap of Rain in Australia Dataset')
ax = sns.heatmap(correlation, square=True, annot=True, fmt='.2f', linecolor='wh
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
ax.set_yticklabels(ax.get_yticklabels(), rotation=30)
plt.show()
```



Interpretation

From the above correlation heat map, we can conclude that :-

- `MinTemp` and `MaxTemp` variables are highly positively correlated (correlation coefficient = 0.74).
- `MinTemp` and `Temp3pm` variables are also highly positively correlated (correlation coefficient = 0.71).
- `MinTemp` and `Temp9am` variables are strongly positively correlated (correlation coefficient = 0.90).

- `MaxTemp` and `Temp9am` variables are strongly positively correlated (correlation coefficient = 0.89).
- `MaxTemp` and `Temp3pm` variables are also strongly positively correlated (correlation coefficient = 0.98).
- `WindGustSpeed` and `WindSpeed3pm` variables are highly positively correlated (correlation coefficient = 0.69).
- `Pressure9am` and `Pressure3pm` variables are strongly positively correlated (correlation coefficient = 0.96).
- `Temp9am` and `Temp3pm` variables are strongly positively correlated (correlation coefficient

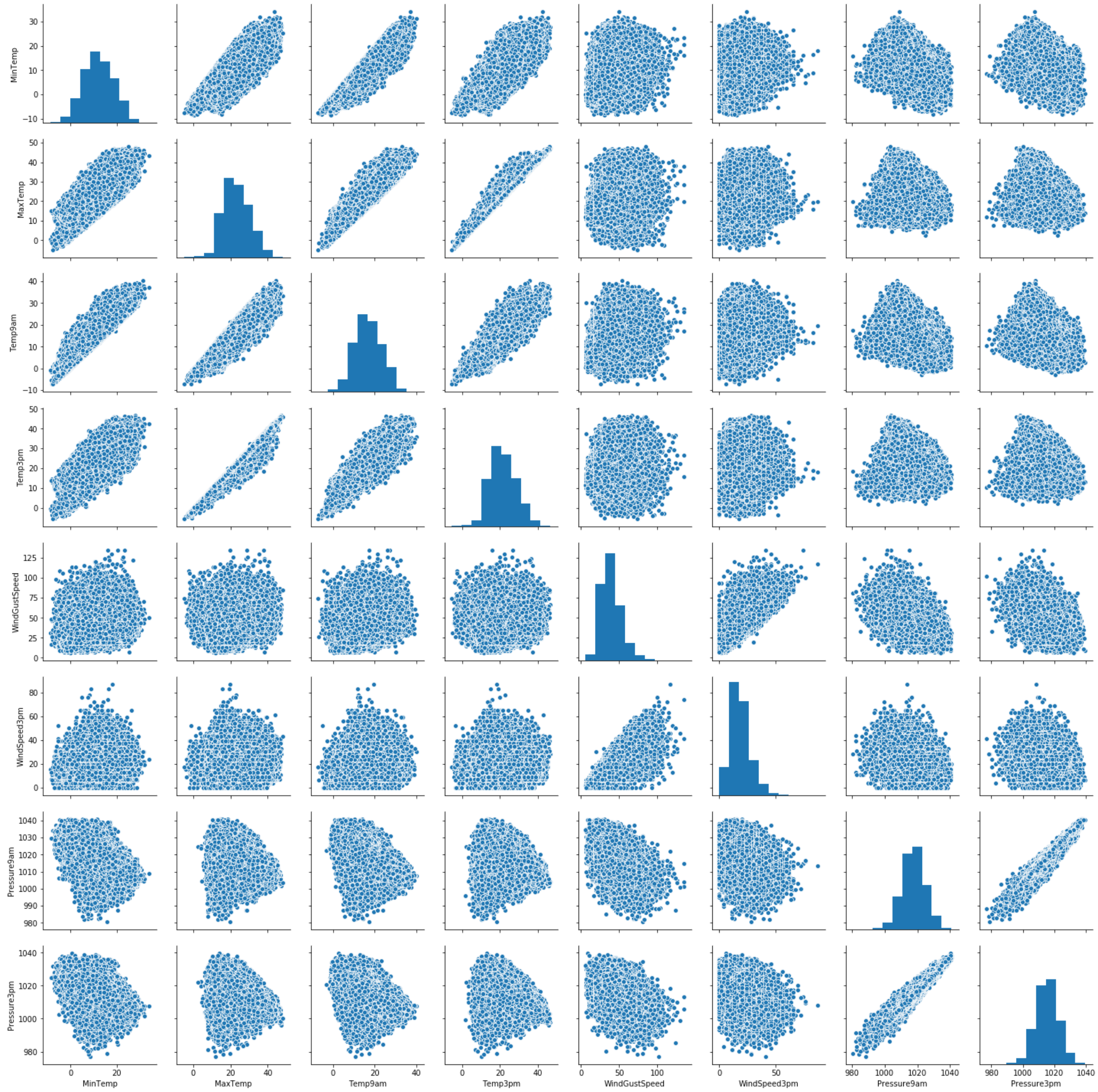
Pair Plot

First of all, I will define extract the variables which are highly positively correlated.

In [70]:
```
num_var = ['MinTemp', 'MaxTemp', 'Temp9am', 'Temp3pm', 'WindGustSpeed', 'WindSp
```

Now, I will draw pairplot to depict relationship between these variables.

In [71]:
```
sns.pairplot(df[num_var], kind='scatter', diag_kind='hist', palette='Rainbow')
plt.show()
```



Interpretation

- I have defined a variable `num_var` which consists of `MinTemp` , `MaxTemp` , `Temp9am` , `Temp3pm` , `WindGustSpeed` , `WindSpeed3pm` , `Pressure9am` and `Pressure3pm` variables.
- The above pair plot shows relationship between these variables.

8. Declare feature vector and target variable

In [72]:
```
X = df.drop(['RainTomorrow'], axis=1)

y = df['RainTomorrow']
```

9. Split data into separate training and test set

In [73]:
```
# split X and y into training and testing sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, ranc
```

In [74]:
```
# check the shape of X_train and X_test

X_train.shape, X_test.shape
```

Out[74]:
```
((113754, 24), (28439, 24))
```

In [76]:
```
# display categorical variables

categorical = [col for col in X_train.columns if X_train[col].dtypes == 'O']

categorical
```

Out[76]:
```
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

In [77]:
```
# display numerical variables

numerical = [col for col in X_train.columns if X_train[col].dtypes != 'O']

numerical
```

Out[77]:
```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Pressure3pm',
 'Cloud9am',
 'Cloud3pm',
 'Temp9am',
 'Temp3pm',
 'Year',
 'Month',
 'Day']
```

Engineering missing values in numerical variables

In [78]:
```
# check missing values in numerical variables in X_train

X_train[numerical].isnull().sum()
```

Out[78]:
```
MinTemp            495
MaxTemp            264
Rainfall          1139
Evaporation      48718
Sunshine         54314
WindGustSpeed     7367
WindSpeed9am      1086
WindSpeed3pm      2094
Humidity9am       1449
Humidity3pm       2890
Pressure9am      11212
Pressure3pm      11186
Cloud9am         43137
Cloud3pm         45768
Temp9am            740
Temp3pm           2171
Year                 0
Month                0
Day                  0
dtype: int64
```

In [79]:
```
# check missing values in numerical variables in X_test

X_test[numerical].isnull().sum()
```

Out[79]:
```
MinTemp            142
MaxTemp             58
Rainfall           267
Evaporation      12125
Sunshine         13502
WindGustSpeed     1903
WindSpeed9am       262
WindSpeed3pm       536
Humidity9am        325
Humidity3pm        720
Pressure9am       2802
Pressure3pm       2795
Cloud9am         10520
Cloud3pm         11326
Temp9am            164
Temp3pm            555
Year                 0
Month                0
Day                  0
dtype: int64
```

In [80]:
```
# print percentage of missing values in the numerical variables in training set

for col in numerical:
    if X_train[col].isnull().mean()>0:
        print(col, round(X_train[col].isnull().mean(),4))
```

```
MinTemp 0.0044
MaxTemp 0.0023
Rainfall 0.01
Evaporation 0.4283
Sunshine 0.4775
WindGustSpeed 0.0648
WindSpeed9am 0.0095
WindSpeed3pm 0.0184
Humidity9am 0.0127
Humidity3pm 0.0254
Pressure9am 0.0986
Pressure3pm 0.0983
Cloud9am 0.3792
Cloud3pm 0.4023
Temp9am 0.0065
Temp3pm 0.0191
```

In [81]:
```
# impute missing values in X_train and X_test with respective column median in

for df1 in [X_train, X_test]:
    for col in numerical:
        col_median=X_train[col].median()
        df1[col].fillna(col_median, inplace=True)
```

In [82]:
```
# check again missing values in numerical variables in X_train

X_train[numerical].isnull().sum()
```

Out[82]:
```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
Year             0
Month            0
Day              0
dtype: int64
```

In [83]:
```
# check missing values in numerical variables in X_test

X_test[numerical].isnull().sum()
```

Out[83]:
```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
Year             0
Month            0
Day              0
dtype: int64
```

Engineering missing values in categorical variables

In [84]:
```
# print percentage of missing values in the categorical variables in training s

X_train[categorical].isnull().mean()
```

Out[84]:
```
Location       0.000000
WindGustDir    0.065114
WindDir9am     0.070134
WindDir3pm     0.026443
RainToday      0.010013
dtype: float64
```

In [85]:
```
# print categorical variables with missing data

for col in categorical:
    if X_train[col].isnull().mean()>0:
        print(col, (X_train[col].isnull().mean()))
```

```
WindGustDir 0.06511419378659213
WindDir9am 0.07013379749283542
WindDir3pm 0.026443026179299188
RainToday 0.01001283471350458
```

In [86]:
```
# impute missing categorical variables with most frequent value

for df2 in [X_train, X_test]:
    df2['WindGustDir'].fillna(X_train['WindGustDir'].mode()[0], inplace=True)
    df2['WindDir9am'].fillna(X_train['WindDir9am'].mode()[0], inplace=True)
    df2['WindDir3pm'].fillna(X_train['WindDir3pm'].mode()[0], inplace=True)
    df2['RainToday'].fillna(X_train['RainToday'].mode()[0], inplace=True)
```

In [87]:
```
# check missing values in categorical variables in X_train

X_train[categorical].isnull().sum()
```

Out[87]:
```
Location       0
WindGustDir    0
WindDir9am     0
WindDir3pm     0
RainToday      0
dtype: int64
```

In [88]:
```
# check missing values in categorical variables in X_test

X_test[categorical].isnull().sum()
```

Out[88]:
```
Location       0
WindGustDir    0
WindDir9am     0
WindDir3pm     0
RainToday      0
dtype: int64
```

As a final check, I will check for missing values in X_train and X_test.

In [89]:
```
# check missing values in X_train

X_train.isnull().sum()
```

Out[89]:
```
Location         0
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustDir      0
WindGustSpeed    0
WindDir9am       0
WindDir3pm       0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
Year             0
Month            0
Day              0
dtype: int64
```

In [90]:
```
# check missing values in X_test

X_test.isnull().sum()
```

Out[90]:
```
Location         0
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustDir      0
WindGustSpeed    0
WindDir9am       0
WindDir3pm       0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
Year             0
Month            0
Day              0
dtype: int64
```

We can see that there are no missing values in X_train and X_test.

Engineering outliers in numerical variables

We have seen that the `Rainfall` , `Evaporation` , `WindSpeed9am` and `WindSpeed3pm` columns contain outliers. I will use top-coding approach to cap maximum values and remove outliers from the above variables.

In [91]:
```
def max_value(df3, variable, top):
    return np.where(df3[variable]>top, top, df3[variable])

for df3 in [X_train, X_test]:
    df3['Rainfall'] = max_value(df3, 'Rainfall', 3.2)
    df3['Evaporation'] = max_value(df3, 'Evaporation', 21.8)
    df3['WindSpeed9am'] = max_value(df3, 'WindSpeed9am', 55)
    df3['WindSpeed3pm'] = max_value(df3, 'WindSpeed3pm', 57)
```

In [92]:
```
X_train.Rainfall.max(), X_test.Rainfall.max()
```

Out[92]:
```
(3.2, 3.2)
```

In [93]:
```
X_train.Evaporation.max(), X_test.Evaporation.max()
```
Out[93]:
```
(21.8, 21.8)
```

In [94]:
```
X_train.WindSpeed9am.max(), X_test.WindSpeed9am.max()
```
Out[94]:
```
(55.0, 55.0)
```

In [95]:
```
X_train.WindSpeed3pm.max(), X_test.WindSpeed3pm.max()
```
Out[95]:
```
(57.0, 57.0)
```

In [96]:
```
X_train[numerical].describe()
```
Out[96]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpee
count	113754.000000	113754.000000	113754.000000	113754.000000	113754.000000	113754.00000
mean	12.193497	23.237216	0.675080	5.151606	8.041154	39.88407
std	6.388279	7.094149	1.183837	2.823707	2.769480	13.11695
min	-8.200000	-4.800000	0.000000	0.000000	0.000000	6.00000
25%	7.600000	18.000000	0.000000	4.000000	8.200000	31.00000
50%	12.000000	22.600000	0.000000	4.800000	8.500000	39.00000
75%	16.800000	28.200000	0.600000	5.400000	8.700000	46.00000
max	33.900000	48.100000	3.200000	21.800000	14.500000	135.00000

We can now see that the outliers in `Rainfall` , `Evaporation` , `WindSpeed9am` and `WindSpeed3pm` columns are capped.

Encode categorical variables

In [97]:
```
# print categorical variables

categorical
```
Out[97]:
```
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

In [98]:
```
X_train[categorical].head()
```

Out[98]:

	Location	WindGustDir	WindDir9am	WindDir3pm	RainToday
110803	Witchcliffe	S	SSE	S	No
87289	Cairns	ENE	SSE	SE	Yes
134949	AliceSprings	E	NE	N	No
85553	Cairns	ESE	SSE	E	No
16110	Newcastle	W	N	SE	No

In [99]:
```
# encode RainToday variable

import category_encoders as ce

encoder = ce.BinaryEncoder(cols=['RainToday'])

X_train = encoder.fit_transform(X_train)

X_test = encoder.transform(X_test)
```

In [100]:
```
X_train.head()
```

Out[100]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGus
110803	Witchcliffe	13.9	22.6	0.2	4.8	8.5	S	
87289	Cairns	22.4	29.4	2.0	6.0	6.3	ENE	
134949	AliceSprings	9.7	36.2	0.0	11.4	12.3	E	
85553	Cairns	20.5	30.1	0.0	8.8	11.1	ESE	
16110	Newcastle	16.8	29.2	0.0	4.8	8.5	W	

5 rows × 25 columns

We can see that two additional variables `RainToday_0` and `RainToday_1` are created from `RainToday` variable.

Now, I will create the `X_train` training set.

In [101]:
```
X_train = pd.concat([X_train[numerical], X_train[['RainToday_0', 'RainToday_1']
                     pd.get_dummies(X_train.Location),
                     pd.get_dummies(X_train.WindGustDir),
                     pd.get_dummies(X_train.WindDir9am),
                     pd.get_dummies(X_train.WindDir3pm)], axis=1)
```

In [102]:
```
X_train.head()
```

Out[102]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	W
110803	13.9	22.6	0.2	4.8	8.5	41.0	20.0	
87289	22.4	29.4	2.0	6.0	6.3	33.0	7.0	
134949	9.7	36.2	0.0	11.4	12.3	31.0	15.0	
85553	20.5	30.1	0.0	8.8	11.1	37.0	22.0	
16110	16.8	29.2	0.0	4.8	8.5	39.0	0.0	

5 rows × 118 columns

Similarly, I will create the `X_test` testing set.

In [103]:
```
X_test = pd.concat([X_test[numerical], X_test[['RainToday_0', 'RainToday_1']],
                     pd.get_dummies(X_test.Location),
                     pd.get_dummies(X_test.WindGustDir),
                     pd.get_dummies(X_test.WindDir9am),
                     pd.get_dummies(X_test.WindDir3pm)], axis=1)
```

In [104]:
```
X_test.head()
```

Out[104]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	W
86232	17.4	29.0	0.0	3.6	11.1	33.0	11.0	
57576	6.8	14.4	0.8	0.8	8.5	46.0	17.0	
124071	10.1	15.4	3.2	4.8	8.5	31.0	13.0	
117955	14.4	33.4	0.0	8.0	11.6	41.0	9.0	
133468	6.8	14.3	3.2	0.2	7.3	28.0	15.0	

5 rows × 118 columns

We now have training and testing set ready for model building. Before that, we should map all the feature variables onto the same scale. It is called `feature scaling`. I will do it as follows.

Feature Scaling

In [105]:
```
X_train.describe()
```

Out[105]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpee
count	113754.000000	113754.000000	113754.000000	113754.000000	113754.000000	113754.00000
mean	12.193497	23.237216	0.675080	5.151606	8.041154	39.88407
std	6.388279	7.094149	1.183837	2.823707	2.769480	13.11695
min	-8.200000	-4.800000	0.000000	0.000000	0.000000	6.00000
25%	7.600000	18.000000	0.000000	4.000000	8.200000	31.00000
50%	12.000000	22.600000	0.000000	4.800000	8.500000	39.00000
75%	16.800000	28.200000	0.600000	5.400000	8.700000	46.00000
max	33.900000	48.100000	3.200000	21.800000	14.500000	135.00000

8 rows × 118 columns

In [106]:
```
cols = X_train.columns
```

In [107]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)
```

In [108]:
```
X_train = pd.DataFrame(X_train, columns=[cols])
```

In [109]:
```
X_test = pd.DataFrame(X_test, columns=[cols])
```

In [110]:
```
X_train.describe()
```

Out[110]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpee
count	113754.000000	113754.000000	113754.000000	113754.000000	113754.000000	113754.00000
mean	0.484406	0.530004	0.210962	0.236312	0.554562	0.26266
std	0.151741	0.134105	0.369949	0.129528	0.190999	0.10168
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	0.375297	0.431002	0.000000	0.183486	0.565517	0.19379
50%	0.479810	0.517958	0.000000	0.220183	0.586207	0.25581
75%	0.593824	0.623819	0.187500	0.247706	0.600000	0.31007
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.00000

8 rows × 118 columns

We now have `X_train` dataset ready to be fed into the Logistic Regression classifier. I will do it as follows.

Model training

In [111]:
```
# train a logistic regression model on the training set
from sklearn.linear_model import LogisticRegression


# instantiate the model
logreg = LogisticRegression(solver='liblinear', random_state=0)


# fit the model
logreg.fit(X_train, y_train)
```

Out[111]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=0, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

Predict results

In [112]:
```
y_pred_test = logreg.predict(X_test)

y_pred_test
```

Out[112]:
```
array(['No', 'No', 'No', ..., 'No', 'No', 'Yes'], dtype=object)
```

In [113]:
```
# probability of getting output as 0 - no rain

logreg.predict_proba(X_test)[:,0]
```

Out[113]:
```
array([0.91381393, 0.83549933, 0.8202694 , ..., 0.97674837, 0.7984706 ,
       0.30735807])
```

In [114]:
```
# probability of getting output as 1 - rain

logreg.predict_proba(X_test)[:,1]
```

Out[114]:
```
array([0.08618607, 0.16450067, 0.1797306 , ..., 0.02325163, 0.2015294 ,
       0.69264193])
```

Check accuracy score

In [115]:
```
from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred_te
```

```
Model accuracy score: 0.8501
```

In [116]:
```
y_pred_train = logreg.predict(X_train)

y_pred_train
```

Out[116]:
```
array(['No', 'No', 'No', ..., 'No', 'No', 'No'], dtype=object)
```

In [117]:
```
print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y
```

```
Training-set accuracy score: 0.8477
```

In [118]:
```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(logreg.score(X_test, y_test)))
```

```
Training set score: 0.8477
Test set score: 0.8501
```

The training-set accuracy score is 0.8476 while the test-set accuracy to be 0.8501. These two values are quite comparable. So, there is no question of overfitting.

In Logistic Regression, we use default value of C = 1. It provides good performance with approximately 85% accuracy on both the training and the test set. But the model performance on both the training and test set are very comparable. It is likely the case of underfitting.

I will increase C and fit a more flexible model.

In [119]:
```
# fit the Logsitic Regression model with C=100

# instantiate the model
logreg100 = LogisticRegression(C=100, solver='liblinear', random_state=0)


# fit the model
logreg100.fit(X_train, y_train)
```

Out[119]:
```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=0, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [120]:
```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg100.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(logreg100.score(X_test, y_test)))
```

```
Training set score: 0.8478
Test set score: 0.8506
```

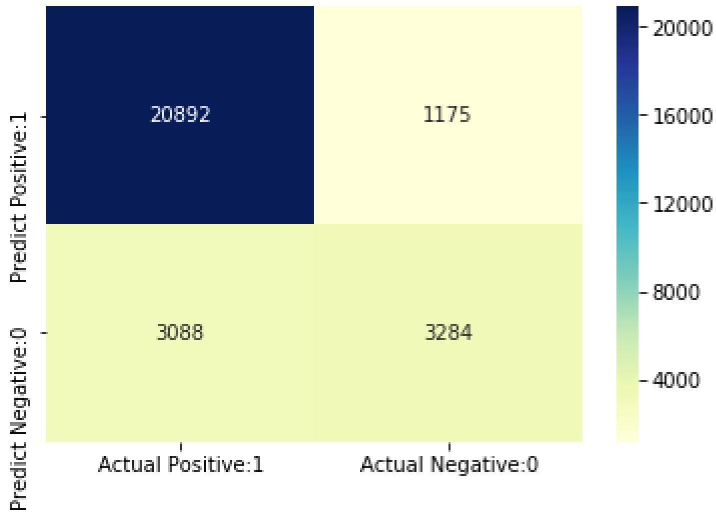
We can see that, C=100 results in higher test set accuracy and also a slightly increased training set accuracy. So, we can conclude that a more complex model should perform better.

In [125]:
```
# Print the Confusion Matrix and slice it into four pieces

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred_test)

print('Confusion matrix\n\n', cm)

print('\nTrue Positives(TP) = ', cm[0,0])

print('\nTrue Negatives(TN) = ', cm[1,1])

print('\nFalse Positives(FP) = ', cm[0,1])

print('\nFalse Negatives(FN) = ', cm[1,0])
```

```
Confusion matrix

 [[20892  1175]
 [ 3088  3284]]

True Positives(TP) =  20892

True Negatives(TN) =  3284

False Positives(FP) =  1175

False Negatives(FN) =  3088
```

In [126]:
```
# visualize confusion matrix with seaborn heatmap

cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive:1', 'Actual Negativ
                                 index=['Predict Positive:1', 'Predict Negative

sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

Out[126]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffa3c199668>



Classification Metrices

In [127]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

          No       0.87      0.95      0.91     22067
         Yes       0.74      0.52      0.61      6372

    accuracy                           0.85     28439
   macro avg       0.80      0.73      0.76     28439
weighted avg       0.84      0.85      0.84     28439
```

Classification Accuracy

In [128]:
```
TP = cm[0,0]
TN = cm[1,1]
FP = cm[0,1]
FN = cm[1,0]
```

In [129]:
```
# print classification accuracy

classification_accuracy = (TP + TN) / float(TP + TN + FP + FN)

print('Classification accuracy : {0:0.4f}'.format(classification_accuracy))
```

```
Classification accuracy : 0.8501
```

Classification Error

In [130]:
```
# print classification error

classification_error = (FP + FN) / float(TP + TN + FP + FN)

print('Classification error : {0:0.4f}'.format(classification_error))
```

```
Classification error : 0.1499
```

In [131]:
```
# print precision score

precision = TP / float(TP + FP)


print('Precision : {0:0.4f}'.format(precision))
```

```
Precision : 0.9468
```

In [132]:
```
recall = TP / float(TP + FN)

print('Recall or Sensitivity : {0:0.4f}'.format(recall))
```

```
Recall or Sensitivity : 0.8712
```

In [133]:
```
true_positive_rate = TP / float(TP + FN)


print('True Positive Rate : {0:0.4f}'.format(true_positive_rate))
```

```
True Positive Rate : 0.8712
```

In [134]:
```
false_positive_rate = FP / float(FP + TN)


print('False Positive Rate : {0:0.4f}'.format(false_positive_rate))
```

```
False Positive Rate : 0.2635
```

Specificity

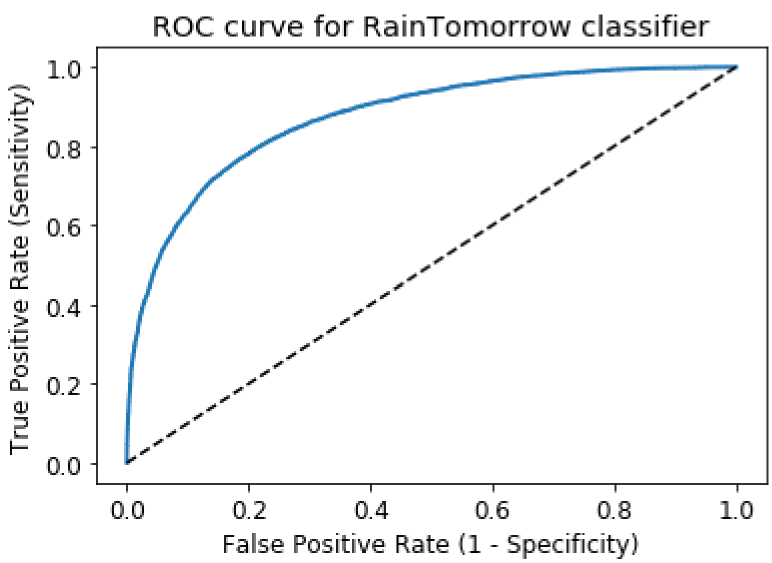
In [135]:
```
specificity = TN / (TN + FP)

print('Specificity : {0:0.4f}'.format(specificity))
```

```
Specificity : 0.7365
```

In [136]:
```
# print the first 10 predicted probabilities of two classes- 0 and 1

y_pred_prob = logreg.predict_proba(X_test)[0:10]

y_pred_prob
```

Out[136]:
```
array([[0.91381393, 0.08618607],
       [0.83549933, 0.16450067],
       [0.8202694 , 0.1797306 ],
       [0.99025597, 0.00974403],
       [0.95726079, 0.04273921],
       [0.97993207, 0.02006793],
       [0.17830442, 0.82169558],
       [0.23461305, 0.76538695],
       [0.9004727 , 0.0995273 ],
       [0.8548867 , 0.1451133 ]])
```

In [142]:
```
# plot ROC Curve

from sklearn.metrics import roc_curve

fpr, tpr, thresholds = roc_curve(y_test, y_pred1, pos_label = 'Yes')

plt.figure(figsize=(6,4))

plt.plot(fpr, tpr, linewidth=2)

plt.plot([0,1], [0,1], 'k--' )

plt.rcParams['font.size'] = 12

plt.title('ROC curve for RainTomorrow classifier')

plt.xlabel('False Positive Rate (1 - Specificity)')

plt.ylabel('True Positive Rate (Sensitivity)')

plt.show()
```



ROC curve help us to choose a threshold level that balances sensitivity and specificity for a particular context.

In [143]:
```
# compute ROC AUC

from sklearn.metrics import roc_auc_score

ROC_AUC = roc_auc_score(y_test, y_pred1)

print('ROC AUC : {:.4f}'.format(ROC_AUC))
```

```
ROC AUC : 0.8729
```

In [144]:
```
# calculate cross-validated ROC AUC

from sklearn.model_selection import cross_val_score

Cross_validated_ROC_AUC = cross_val_score(logreg, X_train, y_train, cv=5, scori

print('Cross validated ROC AUC : {:.4f}'.format(Cross_validated_ROC_AUC))
```

```
Cross validated ROC AUC : 0.8695
```

Conclusion

1. The logistic regression model accuracy score is 0.8501. So, the model does a very good job in predicting whether or not it will rain tomorrow in Australia.
2. Small number of observations predict that there will be rain tomorrow. Majority of observations predict that there will be no rain tomorrow.
3. The model shows no signs of overfitting.
4. Increasing the value of C results in higher test set accuracy and also a slightly increased training set accuracy. So, we can conclude that a more complex model should perform better.
5. Increasing the threshold level results in increased accuracy.
6. ROC AUC of our model approaches towards 1. So, we can conclude that our classifier does a good job in predicting whether it will rain tomorrow or not.
7. Our original model accuracy score is 0.8501 whereas accuracy score after RFECV is 0.8500. So, we can obtain approximately similar accuracy but with reduced set of features.