KOLEJ UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF COMPUTING AND INFORMATION TECHNOLOGY

Assignment

BMCS2114 MACHINE LEARNING

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Student’s name/ ID Number	:	Tan Jie Ying 19WMR03168
Student’s name/ ID Number	:	Andy Chow Sai Kit 19WMR04486
Student’s name/ ID Number	:	Wong Yew Lee 19WMR06837
Student’s name/ ID Number	:	Li Chen Zhen 19WMR06552
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Tutorial Group	:	Group 1
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Rain Prediction in Australia

April 18, 2021

0.1 Title : Rain Prediction in Australia

0.2 Background :

Weather forecasting is the application of science and technology to predict the conditions of the atmosphere for a given location and time. Weather forecasts are made by collecting quantitative data about the current state of the atmosphere at a given place and using meteorology to project how the atmosphere will change. One of the types of weather forecasting is rain forecasting. There are several importance of rain forecasting. The following is a list of various reasons why rain forecasts are important:

1. Helps people prepare for how to dress.
2. Helps people prepare if they need to take extra gear to prepare for the weather.
3. Helps people plan outdoor activities.
4. Helps businesses and people plan for severe weather and other weather hazards.
5. Helps businesses plan for transportation hazards that can result from the weather.

0.3 Problem Statement :

Will it rain tomorrow or later? This is a question which everyone is trying to have an answer to. One of the first things we probably do every morning is look out the window to see what the weather is like. The weather affects us in many ways, it affects us on how we live our life, from agriculture to our outdoor activities. Weather forecasting has been important to everyone for thousands of years, agriculture relies on accurate weather forecasting. Since the late 1930s, observing and forecasting weather requires difficult work which is to send radiosonde balloons up the atmosphere(National Geographic, 2021). Forecasting has always been a tedious job as it requires to observe a few variables such as "humidity", "wind speed", "wind direction" and etc. Such a large number of variables has made human-produced-prediction fairly inaccurate and inefficient. To make the forecasting accurate and efficient, we hope to apply the machine learning algorithms on large datasets, to uncover the hidden pattern within, in order to produce very accurate forecasts. Our proposed model explores the prediction of occurrence of rain the next day using various machine learning models.

0.4 Solution :

In this proposed solution, we explore several machine learning models to predict whether it will rain tomorrow. The following model is being trained and tested using a dataset provided by the

Bureau of Meteorology, Australia. This dataset contains 10 years of daily weather observations from many locations across Australia. We aimed to produce a predictive model which provides fairly accurate predictions with the least amount of training time and human efforts, to maximize the outputs and resources.

0.5 Project Plan

Firstly, the dataset has been obtained from Kaggle, which the datasets was compiled from Bureau of Meteorology Australia. Data understanding and Exploratory Data Analysis will be carried out on the data. Categorical and numerical data is then being identified and explored. Features of the dataset are then being engineered to suit the needs of the solution.

Secondly, the explored and engineered data is then being used for data preprocessing. Datasets were splitted into training and testing sets. Duplication and missing values were being checked. Missing categorical values are being imputed using mode. Missing numerical data is being imputed using median. Outliers are then identified and cleaned, Binary encoding on categorical data is then being performed. Features are then being scaled to map the variables onto the same scale.

Thirdly, 12 baseline models are trained, which includes Logistic Regression, Decision Tree Classifier, K-Neighbors Classifier, MLP Classifier, Gaussian-Naive Bayes, Bernoulli-Naive Bayes, Multinomial Naive Bayes, Support Vector Classifier, SGD Classifier, Random Forest Classifier, Gradient Boosting Classifier and AdaBoost Classifier. Models are being evaluated to extract the metrics of Accuracy, Balanced Accuracy, Precision, Recall, F1 Score, ROC-AUC, PR-AUC, Cohen Kappa Score, Fit Time and Score Time.

Fourthly, Feature Selection such as RFECV and PCA is being performed and evaluation was made on the models after feature selection. The best performing models are being shortlisted by looking at the criteria of 'Balanced Accuracy', 'Time Taken For Training', 'PR-AUC' and 'Cohen's Kappa Score'

Furthermore, 3 models which are Logistic Regression, Support Vector Classifier and Gradient Boosting Classifier were chosen for hyperparameter tuning. 3 Ensemble Models are being created using the combinations of three classifiers, it was tested and results were compared.

Lastly, the 6 models are being tested and evaluated by comparing the learning curve and other metrics before one of the models being concluded.

0.6 Task Allocation

Name	Tasks
Tan Jie Ying	Data Understanding (EDA on Categorical and Numerical Data) + Missing Value Processing + Training Baseline Model
Andy Chow Sai Kit	Data Understanding (Boxplot Visualization) + Outlier Processing + Feature Selection
Wong Yew Lee	Data Understanding (Class Distribution) + Data Encoding + Shortlisting Models + Evaluation
Li Chen Zhen	Data Understanding(Multivariate Analysis) + Feature Scaling + Ensemble Modeling

0.7 Import Libraries and Dataset

[1]:
```
# from google.colab import drive
# drive.mount('/content/drive')
```

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
```

```
warnings.filterwarnings('ignore')

data = pd.read_csv('Weather.csv')

%load_ext autotime
```

```
time: 528 µs (started: 2021-04-18 15:33:58 +08:00)
```

0.8 Data Understanding

This dataset contains about 10 years of daily weather observations from many locations across Australia.

RainTomorrow is the target variable to predict. It means -- did it rain the next day, Yes or No? This column is Yes if the rain for that day was 1mm or more.

The dataset has 23 columns with 12982 rows.

1. Date
   The date of observation
2. Location
   The common name of the location of the weather station
3. MinTemp
   The minimum temperature in degrees celsius
4. MaxTemp
   The maximum temperature in degrees celsius
5. Rainfall
   The amount of rainfall recorded for the day in mm
6. Evaporation
   The so-called Class A pan evaporation (mm) in the 24 hours to 9am
7. Sunshine
   The number of hours of bright sunshine in the day.
8. WindGustDir
   The direction of the strongest wind gust in the 24 hours to midnight
9. WindGustSpeed
   The speed (km/h) of the strongest wind gust in the 24 hours to midnight
10. WindDir9am
    Direction of the wind at 9am
11. WindDir3pm
    Direction of the wind at 3pm
12. WindSpeed9am
    Wind speed (km/hr) averaged over 10 minutes prior to 9am

13. WindSpeed3pm
    Wind speed (km/hr) averaged over 10 minutes prior to 3pm

14. Humidity9am
    Humidity (percent) at 9am

15. Humidity3pm
    Humidity (percent) at 3pm

16. Pressure9am
    Atmospheric pressure (hpa) reduced to mean sea level at 9am

17. Pressure3pm
    Atmospheric pressure (hpa) reduced to mean sea level at 3pm

18. Fraction of sky obscured by cloud at 9am. This is measured in ”oktas”, which are a unit of eigths. It records how many eigths of the sky are obscured by cloud. A 0 measure indicates completely clear sky whilst an 8 indicates that it is completely overcast.

19. Cloud3pm
    Fraction of sky obscured by cloud (in ”oktas”: eighths) at 3pm. See Cload9am for a description of the values

20. Temp9am
    Temperature (degrees C) at 9am

21. Temp3pm
    Temperature (degrees C) at 3pm

22. RainToday
    Boolean: 1 if precipitation (mm) in the 24 hours to 9am exceeds 1mm, otherwise 0

23. RainTomorrow
    The amount of next day rain in mm. Used to create response variable RainTomorrow. A kind of measure of the ”risk”.

0.9 Exploratory Data Analysis

[3]:
```
data.head()
```

[3]:
```
       Date    Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  \
0  1/1/2009  WaggaWagga      9.9     28.4       0.0          9.8      13.5
1  1/2/2009  WaggaWagga      8.9     25.3       0.0         14.8      13.7
2  1/3/2009  WaggaWagga     11.0     30.7       0.0          9.8      13.7
3  1/4/2009  WaggaWagga     14.7     35.2       0.0          9.4      12.1
4  1/5/2009  WaggaWagga     11.8     36.5       0.0         11.6      13.4

  WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  Humidity3pm  \
0         WNW           59.0         NW  …        37.0         24.0
1         WSW           48.0         SW  …        37.0         10.0
2          NE           39.0        ENE  …        43.0         18.0
```

```
3          N          39.0          NE  …        46.0          19.0
4          W          43.0         NNE  …        23.0           5.0

   Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  RainToday  \
0       1005.2       1003.5       1.0       1.0     20.8     27.0         No
1       1013.9       1012.9       1.0       0.0     14.7     23.2         No
2       1017.8       1014.3       0.0       1.0     18.9     28.0         No
3       1014.8       1010.6       1.0       4.0     24.7     33.7         No
4       1013.1       1009.8       1.0       1.0     23.6     34.6         No

   RainTomorrow
0            No
1            No
2            No
3            No
4            No

[5 rows x 23 columns]
```

```
time: 516 ms (started: 2021-04-18 15:33:58 +08:00)
```

[4]:
```
data.shape
```

[4]:
```
(12982, 23)
```

```
time: 11.8 ms (started: 2021-04-18 15:33:58 +08:00)
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12982 entries, 0 to 12981
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           12982 non-null  object
 1   Location       12982 non-null  object
 2   MinTemp        12492 non-null  float64
 3   MaxTemp        12496 non-null  float64
 4   Rainfall       12166 non-null  float64
 5   Evaporation    11186 non-null  float64
 6   Sunshine       10616 non-null  float64
 7   WindGustDir    11563 non-null  object
 8   WindGustSpeed  11565 non-null  float64
 9   WindDir9am     12216 non-null  object
 10  WindDir3pm     12694 non-null  object
 11  WindSpeed9am   12725 non-null  float64
 12  WindSpeed3pm   12733 non-null  float64
 13  Humidity9am    12419 non-null  float64
```

```
 14  Humidity3pm    12470 non-null  float64
 15  Pressure9am    12255 non-null  float64
 16  Pressure3pm    12259 non-null  float64
 17  Cloud9am       10085 non-null  float64
 18  Cloud3pm       9877 non-null   float64
 19  Temp9am        12478 non-null  float64
 20  Temp3pm        12487 non-null  float64
 21  RainToday      12166 non-null  object
 22  RainTomorrow   12166 non-null  object
dtypes: float64(16), object(7)
memory usage: 2.3+ MB
time: 91.5 ms (started: 2021-04-18 15:33:59 +08:00)
```

[6]:
```
data.dtypes
```

[6]:
```
Date               object
Location           object
MinTemp           float64
MaxTemp           float64
Rainfall          float64
Evaporation       float64
Sunshine          float64
WindGustDir        object
WindGustSpeed     float64
WindDir9am         object
WindDir3pm         object
WindSpeed9am      float64
WindSpeed3pm      float64
Humidity9am       float64
Humidity3pm       float64
Pressure9am       float64
Pressure3pm       float64
Cloud9am          float64
Cloud3pm          float64
Temp9am           float64
Temp3pm           float64
RainToday          object
RainTomorrow       object
dtype: object
```

```
time: 27.9 ms (started: 2021-04-18 15:33:59 +08:00)
```

[7]:
```
data.nunique()
```

[7]:
```
Date              3436
Location             4
MinTemp            341
MaxTemp            370
```

```
Rainfall          260
Evaporation       147
Sunshine          142
WindGustDir        16
WindGustSpeed      55
WindDir9am         16
WindDir3pm         16
WindSpeed9am       37
WindSpeed3pm       36
Humidity9am        87
Humidity3pm       100
Pressure9am       441
Pressure3pm       440
Cloud9am           10
Cloud3pm            9
Temp9am           348
Temp3pm           372
RainToday           2
RainTomorrow        2
dtype: int64
```

```
time: 134 ms (started: 2021-04-18 15:33:59 +08:00)
```

[8]:
```
data.describe()
```

[8]:
```
            MinTemp       MaxTemp       Rainfall   Evaporation      Sunshine  \
count  12492.000000  12496.000000  12166.000000  11186.000000  10616.000000
mean      10.722799     21.968214      2.193786      4.903549      7.219621
std        6.302727      6.554904      7.096515      3.389818      3.894060
min       -8.000000      4.100000      0.000000      0.000000      0.000000
25%        6.700000     16.900000      0.000000      2.400000      4.100000
50%       10.900000     21.400000      0.000000      4.100000      8.000000
75%       15.300000     26.300000      0.600000      6.800000     10.300000
max       28.600000     46.400000    119.400000     39.400000     14.100000

       WindGustSpeed  WindSpeed9am  WindSpeed3pm   Humidity9am   Humidity3pm  \
count   11565.000000  12725.000000  12733.000000  12419.000000  12470.000000
mean       41.045828     14.390570     19.236472     69.343023     48.575060
std        14.583387      9.338961      8.936211     16.049204     18.545674
min        11.000000      0.000000      0.000000      9.000000      1.000000
25%        31.000000      7.000000     13.000000     59.000000     35.000000
50%        39.000000     13.000000     19.000000     70.000000     48.000000
75%        50.000000     20.000000     24.000000     81.000000     60.000000
max       122.000000     67.000000     76.000000    100.000000    100.000000

        Pressure9am   Pressure3pm      Cloud9am     Cloud3pm       Temp9am  \
count  12255.000000  12259.000000  10085.000000  9877.000000  12478.000000
```

```
mean     1018.395945   1015.983522        4.494993      4.572542      15.013119
std         7.358022      7.172440        2.855661      2.635960       5.963419
min       986.700000    984.200000        0.000000      0.000000      -1.300000
25%      1013.500000   1011.100000        1.000000      2.000000      10.700000
50%      1018.500000   1016.100000        5.000000      5.000000      14.900000
75%      1023.400000   1020.900000        7.000000      7.000000      19.300000
max      1040.600000   1037.900000        9.000000      8.000000      36.500000

            Temp3pm
count  12487.000000
mean      20.527541
std        6.374995
min        3.700000
25%       15.700000
50%       20.000000
75%       24.800000
max       45.400000

time: 229 ms (started: 2021-04-18 15:33:59 +08:00)
```

0.9.1 Exploring Categorical Variables

[9]:
```
categorical = [var for var in data.columns if data[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',
'WindDir9am', 'WindDir3pm', 'RainToday', 'RainTomorrow']
time: 2.06 ms (started: 2021-04-18 15:33:59 +08:00)
```

[10]:
```
data[categorical].head()
```

[10]:
```
       Date    Location WindGustDir WindDir9am WindDir3pm RainToday  \
0  1/1/2009  WaggaWagga         WNW         NW          W        No
1  1/2/2009  WaggaWagga         WSW         SW         SW        No
2  1/3/2009  WaggaWagga          NE        ENE        NNE        No
3  1/4/2009  WaggaWagga           N         NE         NW        No
4  1/5/2009  WaggaWagga           W        NNE         SW        No

  RainTomorrow
0           No
1           No
```

```
2            No
3            No
4            No

time: 101 ms (started: 2021-04-18 15:33:59 +08:00)
```

Cardinality

The number of labels within a categorical variable is known as cardinality. A high number of labels within a variable is known as high cardinality. High cardinality may pose some serious problems in the machine learning model. So, I will check for high cardinality.

[11]:
```
categorical = [var for var in data.columns if data[var].dtype=='O']

for var in categorical:

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

```
Date  contains  3436  labels
Location  contains  4  labels
WindGustDir  contains  17  labels
WindDir9am  contains  17  labels
WindDir3pm  contains  17  labels
RainToday  contains  3  labels
RainTomorrow  contains  3  labels
time: 121 ms (started: 2021-04-18 15:33:59 +08:00)
```

Summary of categorical variables - There is a date variable - 'Date'. - There are two binary categorical variables - 'RainToday' and 'RainTomorrow'. - The target variable is 'RainTomorrow'. - All categorical variables need to be transformed.

Feature Engineering of Date

[12]:
```
from datetime import datetime

data['Date'] = pd.to_datetime(data['Date'])
data['Day'] = data['Date'].dt.day
data['Month'] = data['Date'].dt.month
data['Year'] = data['Date'].dt.year
data.head()
```

[12]:
```
         Date    Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  \
0  2009-01-01  WaggaWagga      9.9     28.4       0.0          9.8      13.5
1  2009-01-02  WaggaWagga      8.9     25.3       0.0         14.8      13.7
2  2009-01-03  WaggaWagga     11.0     30.7       0.0          9.8      13.7
3  2009-01-04  WaggaWagga     14.7     35.2       0.0          9.4      12.1
4  2009-01-05  WaggaWagga     11.8     36.5       0.0         11.6      13.4

  WindGustDir  WindGustSpeed WindDir9am  … Pressure3pm  Cloud9am  Cloud3pm  \
0         WNW           59.0         NW  …      1003.5       1.0       1.0
```

```
1         WSW           48.0         SW  …      1012.9       1.0       0.0
2          NE           39.0        ENE  …      1014.3       0.0       1.0
3           N           39.0         NE  …      1010.6       1.0       4.0
4           W           43.0        NNE  …      1009.8       1.0       1.0

   Temp9am  Temp3pm  RainToday  RainTomorrow  Day  Month  Year
0     20.8     27.0         No            No    1      1  2009
1     14.7     23.2         No            No    2      1  2009
2     18.9     28.0         No            No    3      1  2009
3     24.7     33.7         No            No    4      1  2009
4     23.6     34.6         No            No    5      1  2009

[5 rows x 26 columns]
```

time: 5.45 s (started: 2021-04-18 15:33:59 +08:00)

[13]:
```python
data  = data.drop(["Date"],axis=1)
data.head()
```

[13]:
```
     Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine WindGustDir  \
0  WaggaWagga      9.9     28.4       0.0          9.8      13.5         WNW
1  WaggaWagga      8.9     25.3       0.0         14.8      13.7         WSW
2  WaggaWagga     11.0     30.7       0.0          9.8      13.7          NE
3  WaggaWagga     14.7     35.2       0.0          9.4      12.1           N
4  WaggaWagga     11.8     36.5       0.0         11.6      13.4           W

   WindGustSpeed WindDir9am WindDir3pm  …  Pressure3pm  Cloud9am  Cloud3pm  \
0           59.0         NW          W  …       1003.5       1.0       1.0
1           48.0         SW         SW  …       1012.9       1.0       0.0
2           39.0        ENE        NNE  …       1014.3       0.0       1.0
3           39.0         NE         NW  …       1010.6       1.0       4.0
4           43.0        NNE         SW  …       1009.8       1.0       1.0

   Temp9am  Temp3pm  RainToday  RainTomorrow  Day  Month  Year
0     20.8     27.0         No            No    1      1  2009
1     14.7     23.2         No            No    2      1  2009
2     18.9     28.0         No            No    3      1  2009
3     24.7     33.7         No            No    4      1  2009
4     23.6     34.6         No            No    5      1  2009

[5 rows x 25 columns]
```

time: 525 ms (started: 2021-04-18 15:34:05 +08:00)

[14]:
```python
#update categorical variable list
categorical = [var for var in data.columns if data[var].dtype=='O']
categorical
```

[14]:
```
['Location',
 'WindGustDir',
 'WindDir9am',
 'WindDir3pm',
 'RainToday',
 'RainTomorrow']
```

```
time: 55.8 ms (started: 2021-04-18 15:34:05 +08:00)
```

0.9.2 Exploring Numerical Variables

[15]:
```python
numerical = [var for var in data.columns if data[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', 'Evaporation',
'Sunshine', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
'Temp3pm', 'Day', 'Month', 'Year']
time: 19.9 ms (started: 2021-04-18 15:34:05 +08:00)
```

[16]:
```python
data[numerical].head()
```

[16]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	\
0	9.9	28.4	0.0	9.8	13.5	59.0	
1	8.9	25.3	0.0	14.8	13.7	48.0	
2	11.0	30.7	0.0	9.8	13.7	39.0	
3	14.7	35.2	0.0	9.4	12.1	39.0	
4	11.8	36.5	0.0	11.6	13.4	43.0	

	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	\
0	7.0	35.0	37.0	24.0	1005.2	
1	22.0	28.0	37.0	10.0	1013.9	
2	26.0	9.0	43.0	18.0	1017.8	
3	17.0	13.0	46.0	19.0	1014.8	
4	7.0	19.0	23.0	5.0	1013.1	

	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm	Day	Month	Year
0	1003.5	1.0	1.0	20.8	27.0	1	1	2009
1	1012.9	1.0	0.0	14.7	23.2	2	1	2009
2	1014.3	0.0	1.0	18.9	28.0	3	1	2009
3	1010.6	1.0	4.0	24.7	33.7	4	1	2009

```
4       1009.8       1.0       1.0     23.6     34.6    5      1  2009
```

```
time: 111 ms (started: 2021-04-18 15:34:06 +08:00)
```

Summary of numerical variables - All of the numerical variables are of continuous type.

[17]:
```
# view summary statistics in numerical variables

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

```
       MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed  \
count  12492.0  12496.0   12166.0      11186.0   10616.0        11565.0
mean      11.0     22.0       2.0          5.0       7.0           41.0
std        6.0      7.0       7.0          3.0       4.0           15.0
min       -8.0      4.0       0.0          0.0       0.0           11.0
25%        7.0     17.0       0.0          2.0       4.0           31.0
50%       11.0     21.0       0.0          4.0       8.0           39.0
75%       15.0     26.0       1.0          7.0      10.0           50.0
max       29.0     46.0     119.0         39.0      14.0          122.0

       WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  \
count       12725.0       12733.0      12419.0      12470.0      12255.0
mean           14.0          19.0         69.0         49.0       1018.0
std             9.0           9.0         16.0         19.0          7.0
min             0.0           0.0          9.0          1.0        987.0
25%             7.0          13.0         59.0         35.0       1014.0
50%            13.0          19.0         70.0         48.0       1018.0
75%            20.0          24.0         81.0         60.0       1023.0
max            67.0          76.0        100.0        100.0       1041.0

       Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm      Day    Month  \
count      12259.0   10085.0    9877.0  12478.0  12487.0  12982.0  12982.0
mean        1016.0       4.0       5.0     15.0     21.0     16.0      6.0
std            7.0       3.0       3.0      6.0      6.0      9.0      3.0
min          984.0       0.0       0.0     -1.0      4.0      1.0      1.0
25%         1011.0       1.0       2.0     11.0     16.0      8.0      3.0
50%         1016.0       5.0       5.0     15.0     20.0     16.0      6.0
75%         1021.0       7.0       7.0     19.0     25.0     23.0      9.0
max         1038.0       9.0       8.0     36.0     45.0     31.0     12.0

          Year
count  12982.0
mean    2012.0
std        3.0
min     2007.0
25%     2010.0
50%     2012.0
75%     2015.0
```

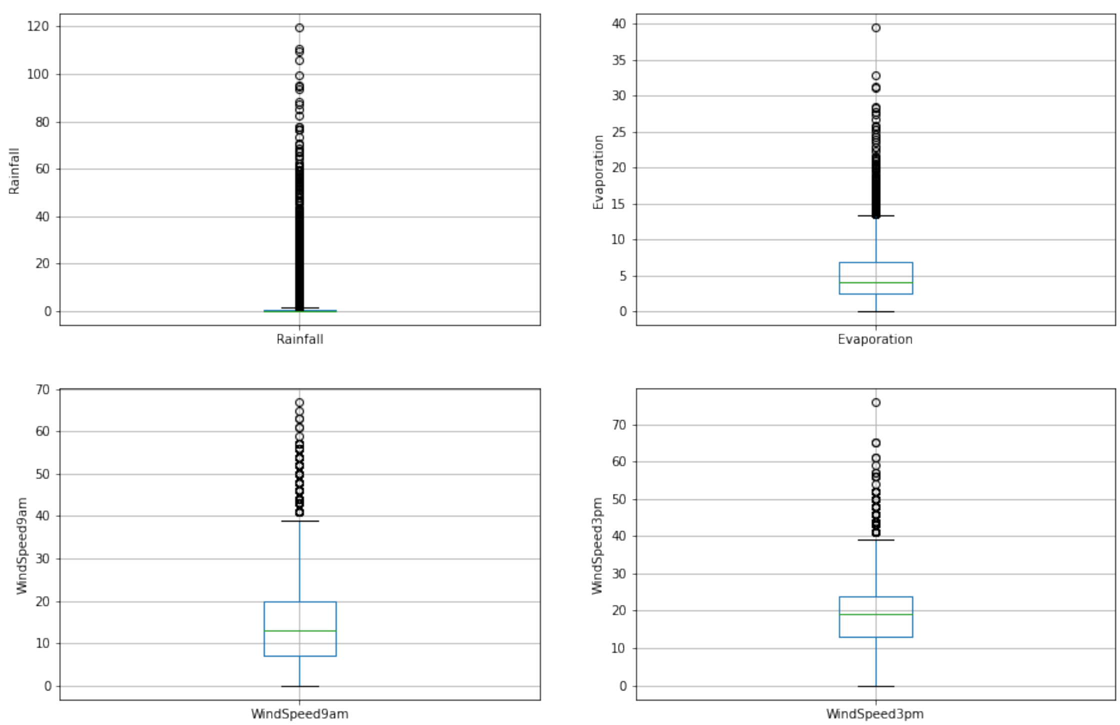
```
max      2017.0   2
time: 152 ms (started: 2021-04-18 15:34:06 +08:00)
```

Boxplot for Outliers

[18]:
```
# draw boxplots to visualize outliers

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


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


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


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

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

# find outliers for Rainfall variable

IQR = data.Rainfall.quantile(0.75) - data.Rainfall.quantile(0.25)
Lower_fence = data.Rainfall.quantile(0.25) - (IQR * 3)
Upper_fence = data.Rainfall.quantile(0.75) + (IQR * 3)
print('Rainfall outliers are values < {lowerboundary} or > {upperboundary}'.
 ↪format(lowerboundary=Lower_fence, upperboundary=Upper_fence))

# find outliers for Evaporation variable

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

```python
# find outliers for WindSpeed9am variable

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

# find outliers for WindSpeed3pm variable

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

```
Rainfall outliers are values < -1.7999999999999998 or > 2.4
Evaporation outliers are values < -10.8 or > 20.0
WindSpeed9am outliers are values < -32.0 or > 59.0
WindSpeed3pm outliers are values < -20.0 or > 57.0
```

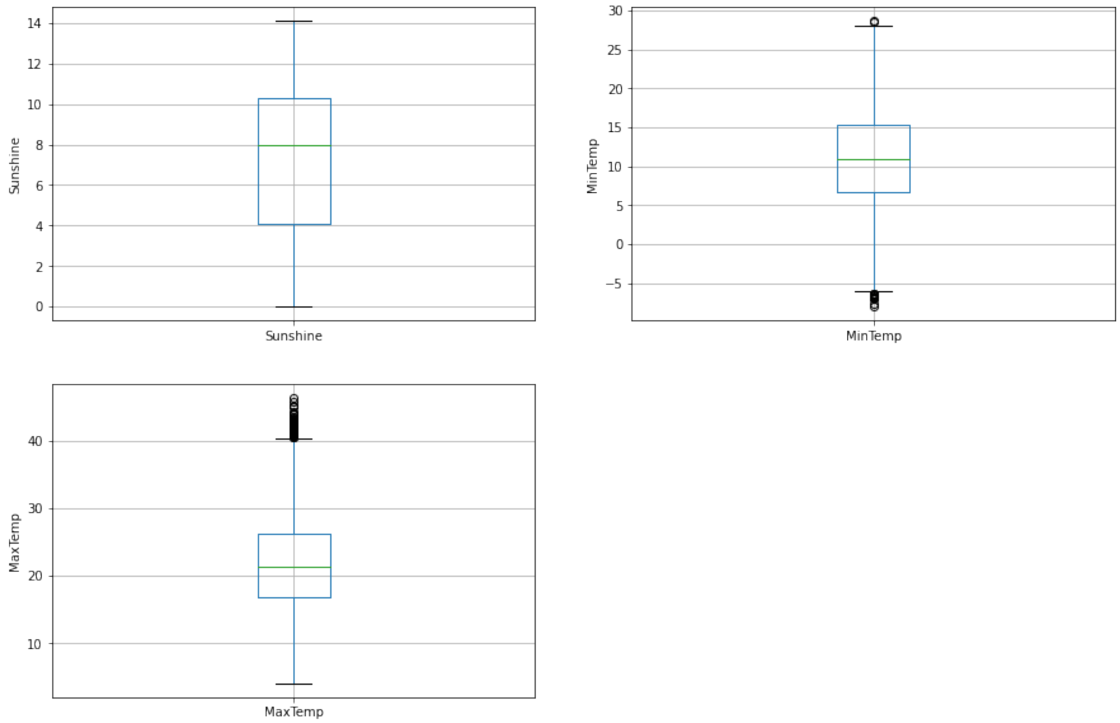



```
time: 6.03 s (started: 2021-04-18 15:34:06 +08:00)
```

[19]:
```
# draw boxplots to visualize outliers

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


plt.subplot(2, 2, 1)
fig = data.boxplot(column='Sunshine')
fig.set_title('')
fig.set_ylabel('Sunshine')


plt.subplot(2, 2, 2)
fig = data.boxplot(column='MinTemp')
fig.set_title('')
fig.set_ylabel('MinTemp')


plt.subplot(2, 2, 3)
fig = data.boxplot(column='MaxTemp')
fig.set_title('')
fig.set_ylabel('MaxTemp')

# find outliers for Sunshine variable

IQR = data.Sunshine.quantile(0.75) - data.Sunshine.quantile(0.25)
Lower_fence = data.Sunshine.quantile(0.25) - (IQR * 3)
Upper_fence = data.Sunshine.quantile(0.75) + (IQR * 3)
print('Sunshine outliers are values < {lowerboundary} or > {upperboundary}'.
 ↪format(lowerboundary=Lower_fence, upperboundary=Upper_fence))

# find outliers for MinTemp variable

IQR = data.MinTemp.quantile(0.75) - data.MinTemp.quantile(0.25)
Lower_fence = data.MinTemp.quantile(0.25) - (IQR * 3)
Upper_fence = data.MinTemp.quantile(0.75) + (IQR * 3)
print('MinTemp outliers are values < {lowerboundary} or > {upperboundary}'.
 ↪format(lowerboundary=Lower_fence, upperboundary=Upper_fence))

# find outliers for MaxTemp variable

IQR = data.MaxTemp.quantile(0.75) - data.MaxTemp.quantile(0.25)
Lower_fence = data.MaxTemp.quantile(0.25) - (IQR * 3)
Upper_fence = data.MaxTemp.quantile(0.75) + (IQR * 3)
print('MaxTemp outliers are values < {lowerboundary} or > {upperboundary}'.
 ↪format(lowerboundary=Lower_fence, upperboundary=Upper_fence))
```

```
Sunshine outliers are values < -14.500000000000002 or > 28.900000000000002
```

```
MinTemp outliers are values < -19.100000000000005 or > 41.10000000000001
MaxTemp outliers are values < -11.300000000000008 or > 54.50000000000001
```



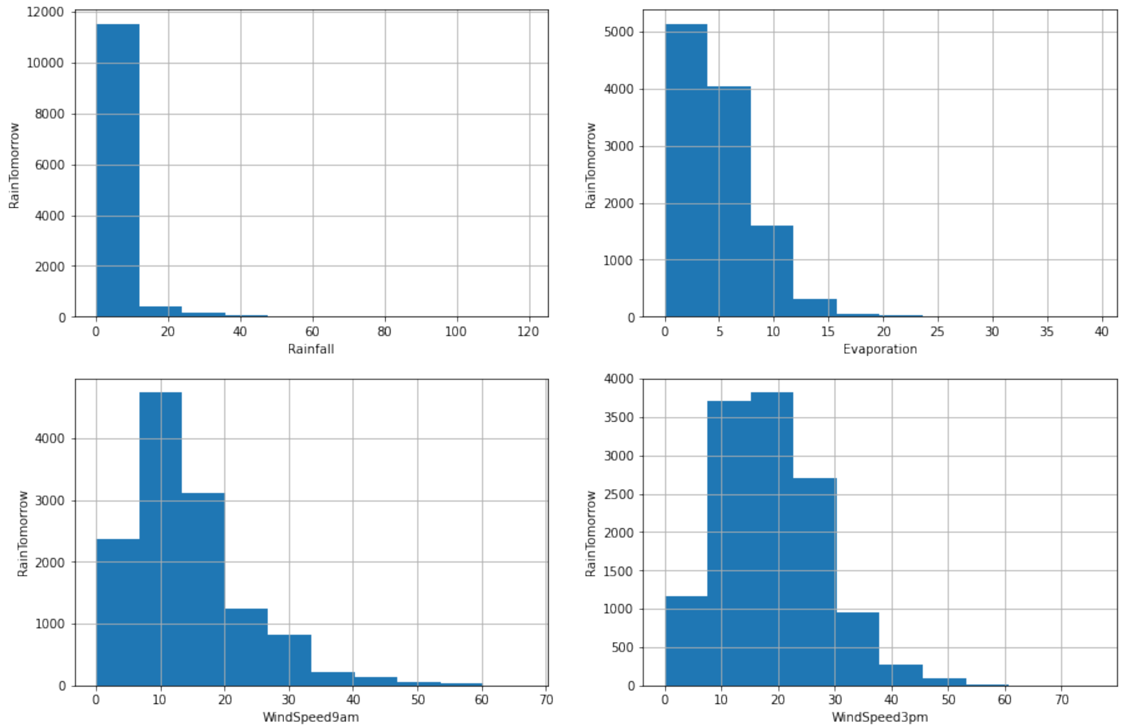

```
time: 4.84 s (started: 2021-04-18 15:34:12 +08:00)
```

[20]:

```
# plot histogram to check distribution

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


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


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


plt.subplot(2, 2, 3)
fig = data.WindSpeed9am.hist(bins=10)
```

```
fig.set_xlabel('WindSpeed9am')
fig.set_ylabel('RainTomorrow')

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

[20]: Text(0, 0.5, 'RainTomorrow')

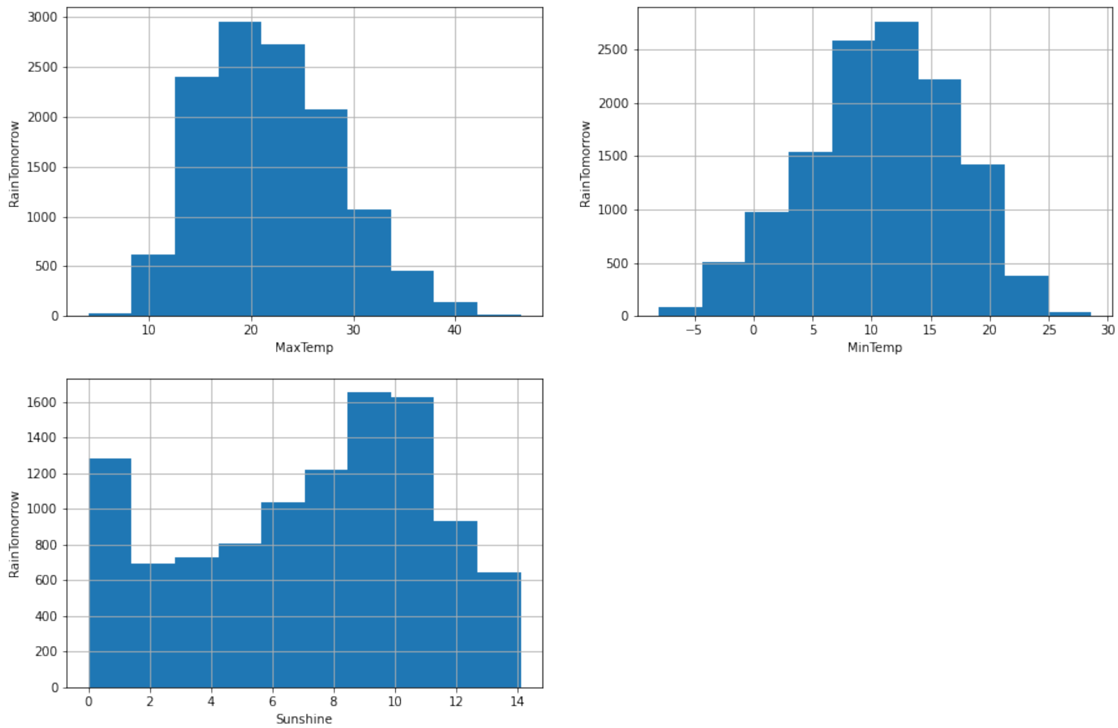


time: 4.78 s (started: 2021-04-18 15:34:17 +08:00)

[21]:
```
# plot histogram to check distribution

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


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

plt.subplot(2, 2, 2)
fig = data.MinTemp.hist(bins=10)
```

```
fig.set_xlabel('MinTemp')
fig.set_ylabel('RainTomorrow')

plt.subplot(2, 2, 3)
fig = data.Sunshine.hist(bins=10)
fig.set_xlabel('Sunshine')
fig.set_ylabel('RainTomorrow')
```

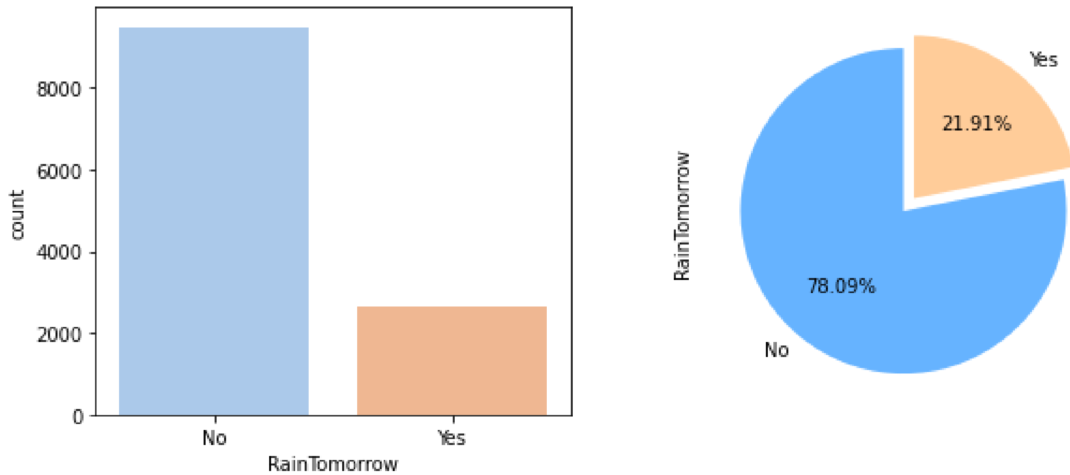
[21]: Text(0, 0.5, 'RainTomorrow')



time: 5.8 s (started: 2021-04-18 15:34:22 +08:00)

0.9.3 Exploring Class Distribution

[22]:
```
fig, ax =plt.subplots(nrows=1,ncols=2, figsize=(10,4))
labels=['No', 'Yes']
sns.countplot(x=data.RainTomorrow, data=data, palette="pastel",ax=ax[0])
data['RainTomorrow'].value_counts().plot.pie(autopct="%1.2f%%", ax=ax[1],␣
↪colors=['#66b3ff','#ffcc99'],
                                    labels=labels, explode = (0, 0.1),␣
↪startangle=90)
plt.show()
```




```
time: 2.75 s (started: 2021-04-18 15:34:28 +08:00)
```

Most of the classes of 'RainTomorrow' is 'No'. Therefore, this dataset is imbalanced.

0.9.4 Exploring Locations

[23]:
```
# print number of labels in Location variable
print('Location contains', len(data.Location.unique()), 'labels')

# check labels in location variable
data.Location.unique()

# check frequency distribution of values in Location variable
data.Location.value_counts()
```

```
Location contains 4 labels
```

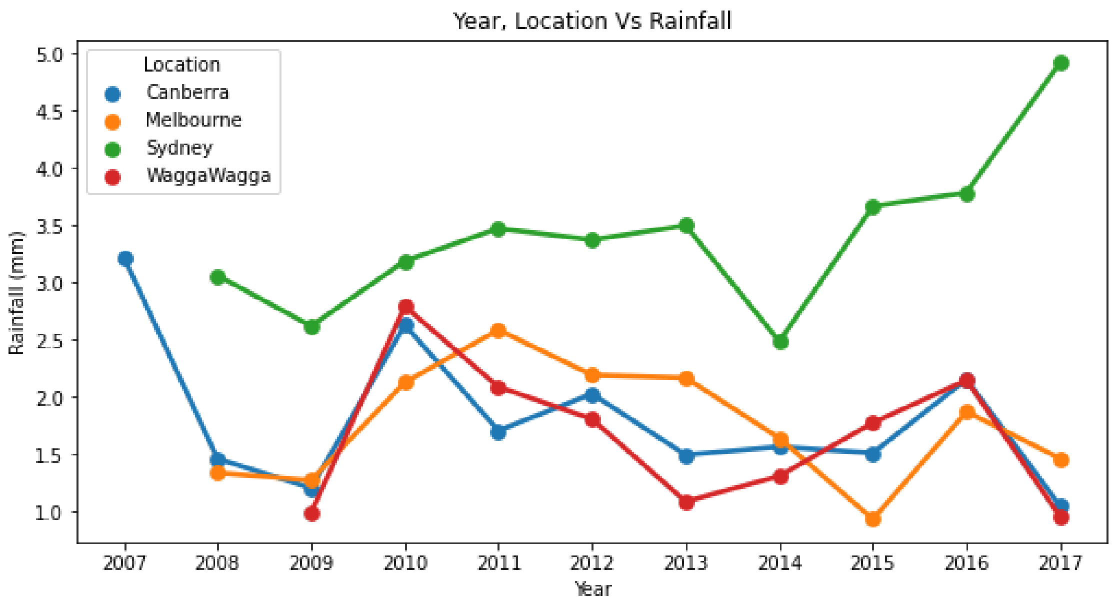
[23]:
```
Canberra      3436
Sydney        3344
Melbourne     3193
WaggaWagga    3009
Name: Location, dtype: int64
```

```
time: 159 ms (started: 2021-04-18 15:34:30 +08:00)
```

[24]:
```
plt.figure(figsize=(10,5))
houragg = pd.DataFrame(data.groupby(['Year','Location'])['Rainfall'].mean()).
↪reset_index()
```

```
sns.
↪pointplot(data=houragg,x=houragg['Year'],y=houragg['Rainfall'],hue=houragg['Location']).
↪set(title='Year, Location Vs Rainfall', ylabel = 'Rainfall (mm)')
```

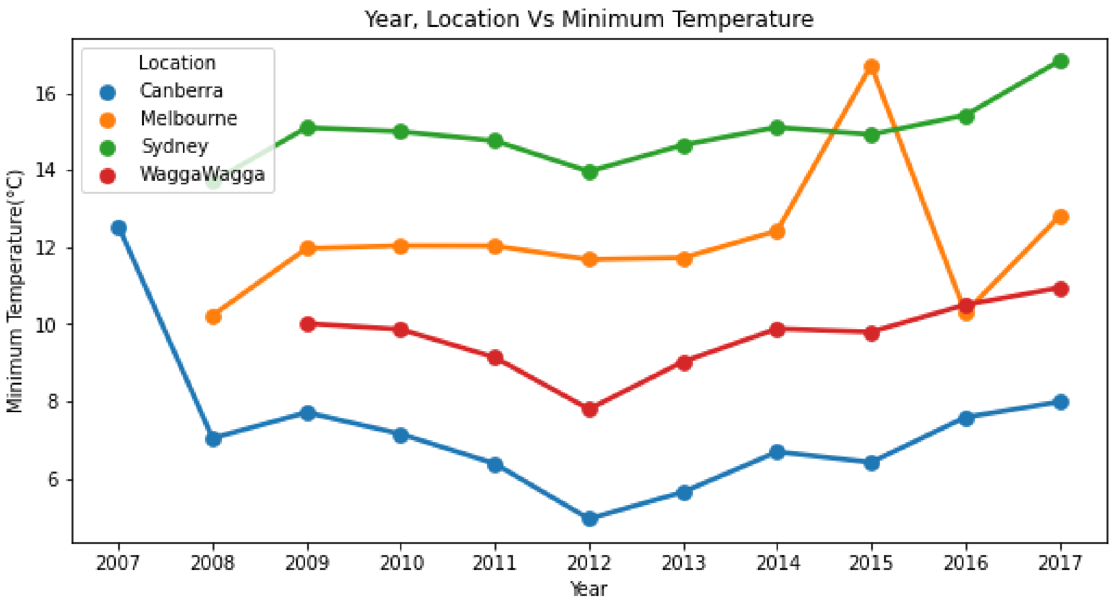
[24]: [Text(0.5, 1.0, 'Year, Location Vs Rainfall'), Text(0, 0.5, 'Rainfall (mm)')]



time: 5.61 s (started: 2021-04-18 15:34:31 +08:00)

[25]:
```
plt.figure(figsize=(10,5))
houragg = pd.DataFrame(data.groupby(['Year','Location'])['MinTemp'].mean()).
↪reset_index()
sns.
↪pointplot(data=houragg,x=houragg['Year'],y=houragg['MinTemp'],hue=houragg['Location']).
↪set(title='Year, Location Vs Minimum Temperature', ylabel = 'Minimum␣
↪Temperature(°C)')
```

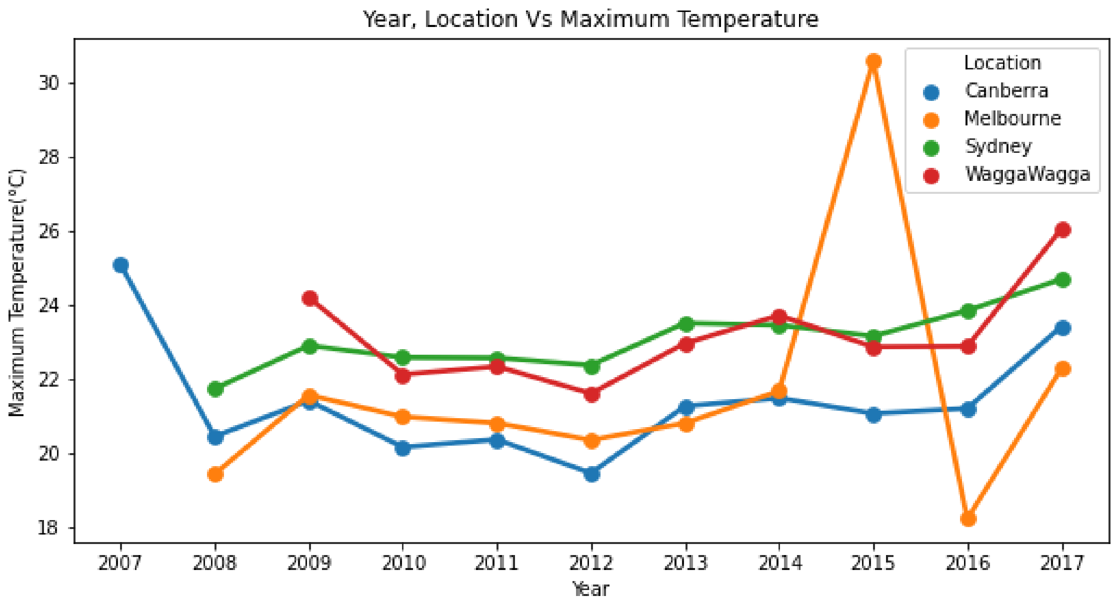
[25]: [Text(0.5, 1.0, 'Year, Location Vs Minimum Temperature'),
Text(0, 0.5, 'Minimum Temperature(°C)')]




```
time: 1.86 s (started: 2021-04-18 15:34:36 +08:00)
```

[26]:
```
plt.figure(figsize=(10,5))
houragg = pd.DataFrame(data.groupby(['Year','Location'])['MaxTemp'].mean()).
 ↪reset_index()
sns.
 ↪pointplot(data=houragg,x=houragg['Year'],y=houragg['MaxTemp'],hue=houragg['Location']).
 ↪set(title='Year, Location Vs Maximum Temperature', ylabel = 'Maximum␣
 ↪Temperature(°C)')
```

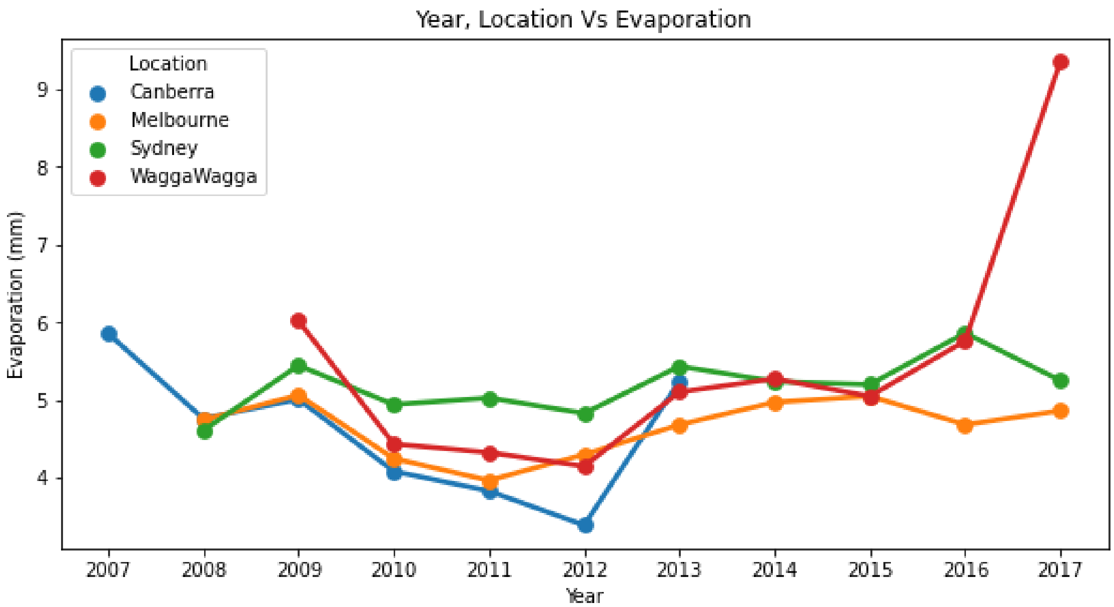
[26]:
```
[Text(0.5, 1.0, 'Year, Location Vs Maximum Temperature'),
 Text(0, 0.5, 'Maximum Temperature(°C)')]
```




```
time: 6.31 s (started: 2021-04-18 15:34:38 +08:00)
```

[27]:
```
plt.figure(figsize=(10,5))
houragg = pd.DataFrame(data.groupby(['Year','Location'])['Evaporation'].mean()).
 ↪reset_index()
sns.
 ↪pointplot(data=houragg,x=houragg['Year'],y=houragg['Evaporation'],hue=houragg['Location']).
 ↪set(title='Year, Location Vs Evaporation', ylabel = 'Evaporation (mm)')
```

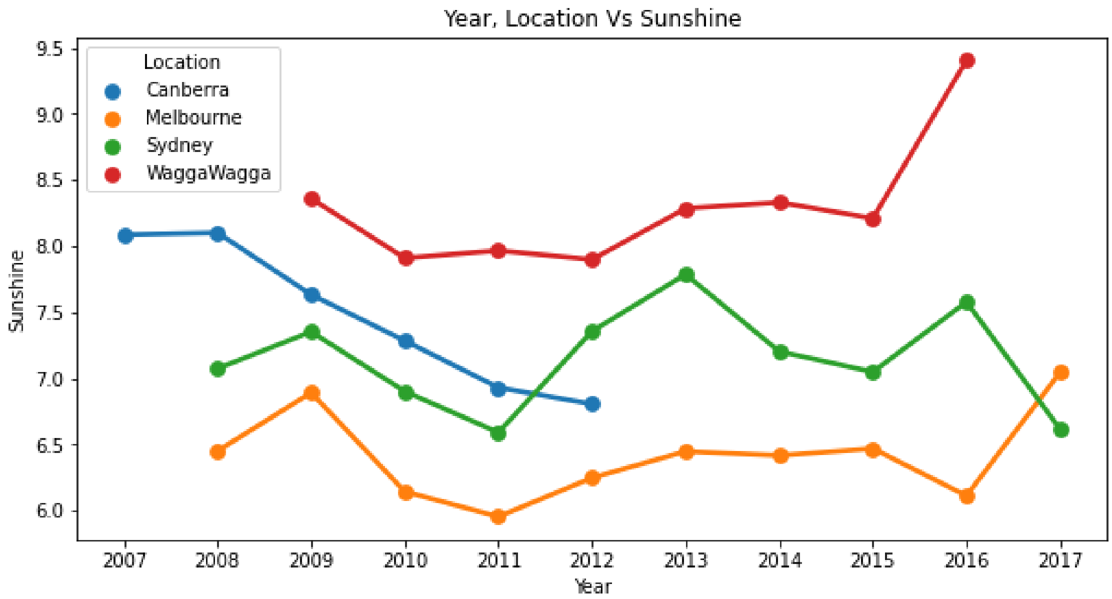
[27]:
```
[Text(0.5, 1.0, 'Year, Location Vs Evaporation'),
 Text(0, 0.5, 'Evaporation (mm)')]
```




```
time: 2.39 s (started: 2021-04-18 15:34:45 +08:00)
```

[28]:
```
plt.figure(figsize=(10,5))
houragg = pd.DataFrame(data.groupby(['Year','Location'])['Sunshine'].mean()).
↪reset_index()
sns.
↪pointplot(data=houragg,x=houragg['Year'],y=houragg['Sunshine'],hue=houragg['Location']).
↪set(title='Year, Location Vs Sunshine')
```

[28]:
```
[Text(0.5, 1.0, 'Year, Location Vs Sunshine')]
```




```
time: 1.67 s (started: 2021-04-18 15:34:47 +08:00)
```

0.9.5 Multivariate Analysis

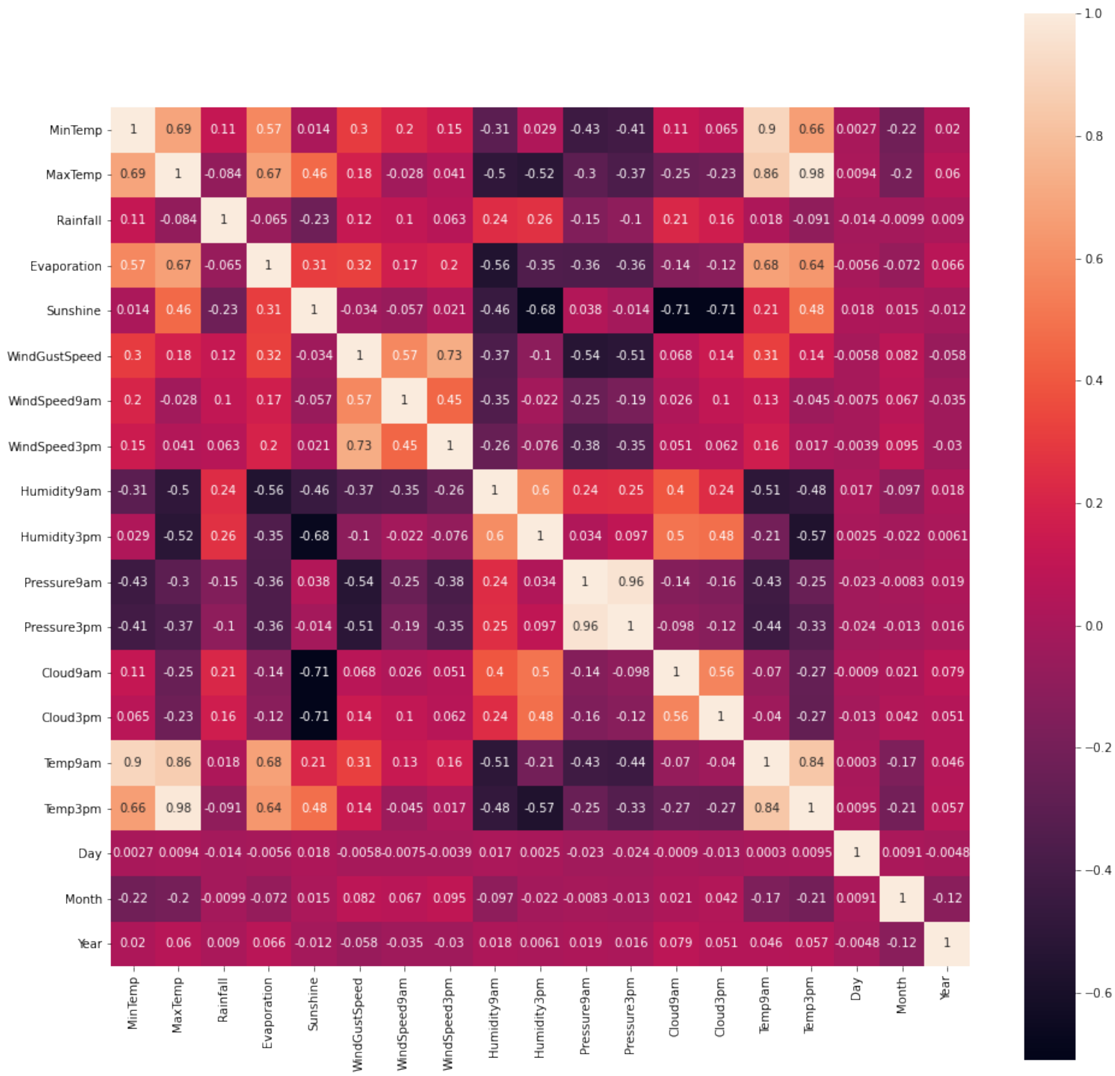
Multivariate means involving multiple dependent variables resulting in one outcome. For example, we cannot predict whether it will rain based on the temperature alone. There are multiple factors like wind direction,wind speed, humidity etc.

Heatmap

A heatmap is a graphical representation of data where values are depicted by color. Heat maps make it easy to visualize complex data and understand it at a glance. In this case, the heat map is used to visualize the correlation between any two variables.

[29]:
```
corrmat = data.corr()
plt.subplots(figsize=(16,16))
sns.heatmap(corrmat,annot=True, square=True)
```

[29]: <AxesSubplot:>




```
time: 15.5 s (started: 2021-04-18 15:34:49 +08:00)
```

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 coeffi-

cient = 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 = 0.86).

[30]:
```
# Calculate the correlation values
feature_cols = [var for var in data.columns if var != 'RainTomorrow']

corr_values = data[feature_cols].corr()

# Simplify by emptying all the data below the diagonal
tril_index = np.tril_indices_from(corr_values)

# Make the unused values NaNs
for coord in zip(*tril_index):
    corr_values.iloc[coord[0], coord[1]] = np.NaN

# Stack the data and convert to a data frame
corr_values = (corr_values.stack().to_frame().reset_index().
 ↪rename(columns={'level_0':'feature1','level_1':'feature2',0:'correlation'}))

# Get the absolute values for sorting
corr_values['abs_correlation'] = corr_values.correlation.abs()

# The most highly correlated values
corr_values.sort_values('correlation', ascending=False).
 ↪query('abs_correlation>0.8')
```

[30]:

	feature1	feature2	correlation	abs_correlation
31	MaxTemp	Temp3pm	0.983102	0.983102
135	Pressure9am	Pressure3pm	0.962644	0.962644
13	MinTemp	Temp9am	0.902728	0.902728
30	MaxTemp	Temp9am	0.863468	0.863468
161	Temp9am	Temp3pm	0.836368	0.836368

```
time: 211 ms (started: 2021-04-18 15:35:04 +08:00)
```

[31]:
```
# Drop columns with correlation higher than 0.95
data = data.drop(['Temp3pm', 'Pressure3pm'], axis=1)
```

```
time: 4.08 ms (started: 2021-04-18 15:35:05 +08:00)
```

[32]:
```
#update numerical variable list
numerical = [var for var in data.columns if data[var].dtype!='O']
numerical
```

[32]:
```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Cloud9am',
 'Cloud3pm',
 'Temp9am',
 'Day',
 'Month',
 'Year']
```

```
time: 139 ms (started: 2021-04-18 15:35:05 +08:00)
```

Pairplot

[33]:
```
#num_var = ['MinTemp', 'MaxTemp', 'Temp9am', 'Temp3pm', 'WindGustSpeed',␣
 ↪'WindSpeed3pm', 'Pressure9am', 'Pressure3pm']
#vars=('MaxTemp','MinTemp','Pressure9am','Pressure3pm', 'Temp9am', 'Temp3pm',␣
 ↪'Evaporation','WindGustSpeed', 'WindSpeed3pm'),
# sns.pairplot(data=data, kind='scatter', diag_kind='hist', hue='RainTomorrow')
# plt.show()
```

```
time: 91.8 ms (started: 2021-04-18 15:35:05 +08:00)
```

0.9.6 Checking for Duplicates

[34]:
```
data.duplicated().sum()
```

[34]:
```
0
```

```
time: 166 ms (started: 2021-04-18 15:35:05 +08:00)
```

0.10 Preparing features and target

[35]:
```
X = data.drop(['RainTomorrow'], axis=1)

y = data['RainTomorrow']
```

time: 30.3 ms (started: 2021-04-18 15:35:05 +08:00)

0.11 Splitting data into training and testing sets

[36]:
```
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,␣
↪random_state = 0)
```

time: 2.27 s (started: 2021-04-18 15:35:05 +08:00)

[37]:
```
X_train.shape, X_test.shape
```

[37]: ((10385, 22), (2597, 22))

time: 2.79 ms (started: 2021-04-18 15:35:07 +08:00)

0.12 Handling Missing Values

0.12.1 Impute Missing Values in Categorical Variables

[38]:
```
categorical_features = [var for var in categorical if var != 'RainTomorrow']
target = 'RainTomorrow'
```

time: 87.4 ms (started: 2021-04-18 15:35:07 +08:00)

[39]:
```
X_train[categorical_features].isnull().sum()
```

[39]:
```
Location          0
WindGustDir    1123
WindDir9am      614
WindDir3pm      221
RainToday       626
dtype: int64
```

time: 104 ms (started: 2021-04-18 15:35:07 +08:00)

[40]:
```
y_train.isnull().sum()
```

[40]: 639

```
time: 91.7 ms (started: 2021-04-18 15:35:08 +08:00)
```

[41]:
```
X_test[categorical_features].isnull().sum()
```

[41]:
```
Location         0
WindGustDir    296
WindDir9am     152
WindDir3pm      67
RainToday      190
dtype: int64
```

```
time: 89.7 ms (started: 2021-04-18 15:35:08 +08:00)
```

[42]:
```
y_test.isnull().sum()
```

[42]:
```
177
```

```
time: 91.5 ms (started: 2021-04-18 15:35:08 +08:00)
```

[43]:
```
cat_missing = data[categorical_features].columns[data[categorical_features].
 ↪isnull().any()].tolist()
cat_missing
```

[43]:
```
['WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

```
time: 103 ms (started: 2021-04-18 15:35:08 +08:00)
```

Replace the missing values of 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday' and 'RainTomorrow' with mode.

Modes of categorical features:

[44]:
```
for m in cat_missing:
  print(m, '\t', X_train[m].mode()[0])
```

```
WindGustDir      N
WindDir9am       W
WindDir3pm       WNW
RainToday        No
time: 86.7 ms (started: 2021-04-18 15:35:08 +08:00)
```

Mode of target:

[45]:
```
y_train.mode()[0]
```

[45]:
```
'No'
```

```
time: 79 ms (started: 2021-04-18 15:35:08 +08:00)
```

[46]:
```
for m in cat_missing:
  X_train[m].fillna(X_train[m].mode()[0], inplace=True)
  X_test[m].fillna(X_train[m].mode()[0], inplace=True)
```

```
time: 104 ms (started: 2021-04-18 15:35:08 +08:00)
```

[47]:
```
y_train.fillna(y_train.mode()[0], inplace=True)
y_test.fillna(y_train.mode()[0], inplace=True)
```

```
time: 58.9 ms (started: 2021-04-18 15:35:08 +08:00)
```

Check whether all missing values for categorical variables have been removed.

[48]:
```
X_train[categorical_features].isnull().sum()
```

[48]:
```
Location       0
WindGustDir    0
WindDir9am     0
WindDir3pm     0
RainToday      0
dtype: int64
```

```
time: 87.7 ms (started: 2021-04-18 15:35:08 +08:00)
```

[49]:
```
y_train.isnull().sum()
```

[49]:
```
0
```

```
time: 48.3 ms (started: 2021-04-18 15:35:09 +08:00)
```

[50]:
```
X_test[categorical_features].isnull().sum()
```

[50]:
```
Location       0
WindGustDir    0
WindDir9am     0
WindDir3pm     0
RainToday      0
dtype: int64
```

```
time: 70.8 ms (started: 2021-04-18 15:35:09 +08:00)
```

[51]:
```
y_test.isnull().sum()
```

[51]:
```
0
```

```
time: 61.5 ms (started: 2021-04-18 15:35:09 +08:00)
```

0.12.2 Impute Missing Values in Numerical Variables

[52]:
```
X_train[numerical].isnull().sum()
```

[52]:
```
MinTemp           381
MaxTemp           378
Rainfall          626
Evaporation      1449
Sunshine         1901
WindGustSpeed    1122
WindSpeed9am      207
WindSpeed3pm      197
Humidity9am       438
Humidity3pm       397
Pressure9am       568
Cloud9am         2282
Cloud3pm         2443
Temp9am           392
Day                 0
Month               0
Year                0
dtype: int64
```

time: 86.3 ms (started: 2021-04-18 15:35:09 +08:00)

[53]:
```
X_test[numerical].isnull().sum()
```

[53]:
```
MinTemp          109
MaxTemp          108
Rainfall         190
Evaporation      347
Sunshine         465
WindGustSpeed    295
WindSpeed9am      50
WindSpeed3pm      52
Humidity9am      125
Humidity3pm      115
Pressure9am      159
Cloud9am         615
Cloud3pm         662
Temp9am          112
Day                0
Month              0
Year               0
dtype: int64
```

time: 75.7 ms (started: 2021-04-18 15:35:09 +08:00)

[54]:
```
num_missing = data[numerical].columns[data[numerical].isnull().any()].tolist()
num_missing
```

[54]:
```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Cloud9am',
 'Cloud3pm',
 'Temp9am']
```

```
time: 85.3 ms (started: 2021-04-18 15:35:09 +08:00)
```

Replace the missing values for the above numerical variables with median.

Medians of numerical variables:

[55]:
```
for m in num_missing:
  print(m, '\t', X_train[m].median())
```

```
MinTemp          10.9
MaxTemp          21.4
Rainfall         0.0
Evaporation      4.0
Sunshine         7.9
WindGustSpeed    39.0
WindSpeed9am     13.0
WindSpeed3pm     19.0
Humidity9am      70.0
Humidity3pm      48.0
Pressure9am      1018.5
Cloud9am         5.0
Cloud3pm         5.0
Temp9am          14.9
time: 121 ms (started: 2021-04-18 15:35:09 +08:00)
```

[56]:
```
for m in num_missing:
  X_train[m].fillna(X_train[m].median(), inplace=True)
  X_test[m].fillna(X_train[m].median(), inplace=True)
```

```
time: 304 ms (started: 2021-04-18 15:35:09 +08:00)
```

Check whether all missing values for numerical variables have been removed.

[57]:
```
X_train[numerical].isnull().sum()
```

[57]:
```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Day              0
Month            0
Year             0
dtype: int64
```

```
time: 98.5 ms (started: 2021-04-18 15:35:10 +08:00)
```

[58]:
```
X_test[numerical].isnull().sum()
```

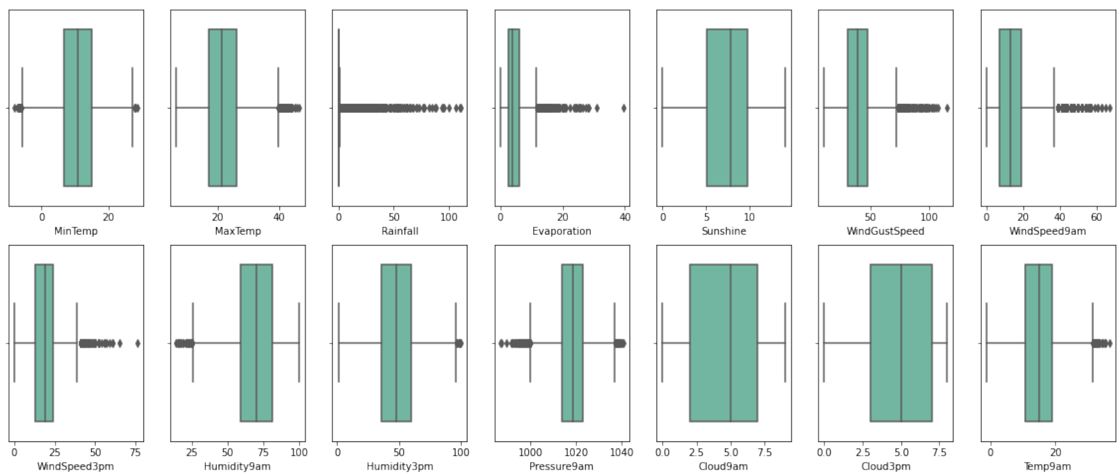
[58]:
```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Day              0
Month            0
Year             0
dtype: int64
```

```
time: 97.5 ms (started: 2021-04-18 15:35:10 +08:00)
```

0.13 Engineering Outliers

Outlier cleaning for training data

[59]:
```
def boxplot_for_outlier(df,columns):
    count = 0
    fig, ax =plt.subplots(nrows=2,ncols=7, figsize=(20,8))
    for i in range(2):
        for j in range(7):
            sns.boxplot(x = df[columns[count]], palette="Set2",ax=ax[i][j])
            count = count+1
boxplot_for_outlier(X_train, numerical)
```



time: 10.2 s (started: 2021-04-18 15:35:10 +08:00)

[60]:
```
lower_and_upper={}
X_train_outlier = X_train.copy()

for col in numerical:
    if(col=="Rainfall"):
        sparse_value = X_train[col].mode()[0]
        nonsparse_data = pd.DataFrame(X_train[X_train[col] !=␣
↪sparse_value][col])
        q1=nonsparse_data[col].describe()[4]
        q3=nonsparse_data[col].describe()[6]
        iqr=q3-q1
        lowerbound = q1 - (1.5*iqr)
        upperbound = q3 + (1.5*iqr)
        lower_and_upper[col]=(lowerbound,upperbound)
        nonsparse_data.loc[(nonsparse_data.loc[:,col]<lowerbound),col] = ␣
↪lowerbound*0.75
```

```
        nonsparse_data.loc[(nonsparse_data.loc[:,col]>upperbound),col] = ␣
↪upperbound*1.25
        X_train_outlier[col][nonsparse_data.index]=nonsparse_data[col]

    else:
        q1=X_train_outlier[col].describe()[4]
        q3=X_train_outlier[col].describe()[6]
        iqr=q3-q1
        lowerbound = q1 - (1.5 * iqr)
        upperbound = q3 + (1.5 * iqr)
        lower_and_upper[col]=(lowerbound,upperbound)
        number_of_outlier = X_train_outlier.loc[(X_train_outlier.loc[:
↪,col]<lowerbound)\
                                                            | (X_train_outlier.
↪loc[:,col]>upperbound)].shape[0]
        if(number_of_outlier>0):
            print(number_of_outlier," outlier values cleared in" ,col)
            X_train_outlier.loc[(X_train_outlier.loc[:,col]<lowerbound),col] = ␣
↪lowerbound*0.75
            X_train_outlier.loc[(X_train_outlier.loc[:,col]>upperbound),col] = ␣
↪upperbound*1.25
```

```
19  outlier values cleared in MinTemp
72  outlier values cleared in MaxTemp
339  outlier values cleared in Evaporation
291  outlier values cleared in WindGustSpeed
228  outlier values cleared in WindSpeed9am
209  outlier values cleared in WindSpeed3pm
65  outlier values cleared in Humidity9am
14  outlier values cleared in Humidity3pm
110  outlier values cleared in Pressure9am
33  outlier values cleared in Temp9am
time: 1.57 s (started: 2021-04-18 15:35:20 +08:00)
```

Outlier cleaning for testing data

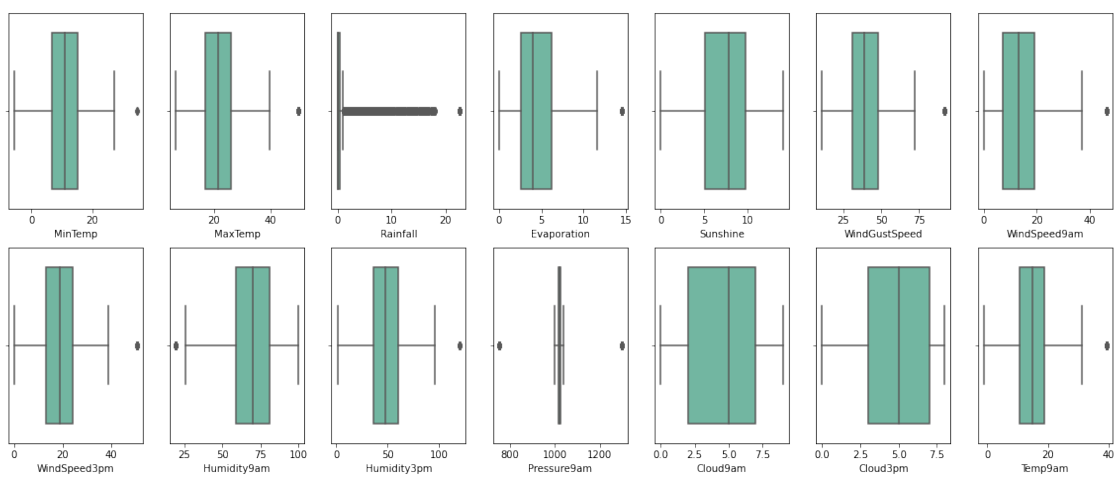
[61]:
```
X_test_outlier = X_test.copy()

for col in numerical:
    if(col =="Rainfall"):
        sparse_value = X_test[col].mode()[0]
        nonsparse_data = pd.DataFrame(X_test[X_test[col] != sparse_value][col])
        nonsparse_data.loc[(nonsparse_data.loc[:
↪,col]<lower_and_upper[col][0]),col] =  lower_and_upper[col][0]*0.75
        nonsparse_data.loc[(nonsparse_data.loc[:
↪,col]>lower_and_upper[col][1]),col] =  lower_and_upper[col][1]*1.25
        X_test_outlier[col][nonsparse_data.index]=nonsparse_data[col]
```

```
    else:

        number_of_outlier_test = X_test_outlier.loc[(X_test_outlier.loc[:
↪,col]<lower_and_upper[col][0]) |\
                                                  (X_test_outlier.loc[:
↪,col]>lower_and_upper[col][1])].shape[0]
        if(number_of_outlier_test>0):
            print(number_of_outlier_test," outlier values cleared in" ,col)
            X_test_outlier.loc[(X_test_outlier.loc[:
↪,col]<lower_and_upper[col][0]),col] =  lower_and_upper[col][0]*0.75
            X_test_outlier.loc[(X_test_outlier.loc[:
↪,col]>lower_and_upper[col][1]),col] =  lower_and_upper[col][1]*1.25
```

```
8  outlier values cleared in MinTemp
16  outlier values cleared in MaxTemp
86  outlier values cleared in Evaporation
61  outlier values cleared in WindGustSpeed
59  outlier values cleared in WindSpeed9am
47  outlier values cleared in WindSpeed3pm
25  outlier values cleared in Humidity9am
5  outlier values cleared in Humidity3pm
27  outlier values cleared in Pressure9am
3  outlier values cleared in Temp9am
time: 438 ms (started: 2021-04-18 15:35:22 +08:00)
```

Visualization after cleaning outliers

[62]:
```
boxplot_for_outlier(X_train_outlier, numerical)
```




```
time: 12.6 s (started: 2021-04-18 15:35:22 +08:00)
```

[63]:
```
X_test[numerical] = X_test_outlier[numerical]
X_train[numerical] = X_train_outlier[numerical]
pd.options.mode.chained_assignment = None
```

time: 42.5 ms (started: 2021-04-18 15:35:35 +08:00)

0.14 Data Encoding

Machine learning models require all input and output variables to be numeric. This means that if the data contains categorical data, then we must encode it to numbers before we can fit and evaluate a model.

0.14.1 Encoding on Binary Data (RainToday)

[64]:
```
#Binary Encoder for RainToday, and RainTomorrow
#Onehotencoding for categorical data

from sklearn import preprocessing
lb = preprocessing.LabelBinarizer()
onehotencoder = preprocessing.OneHotEncoder()

X_train['RainToday'] = lb.fit_transform(X_train['RainToday'])
X_test['RainToday'] = lb.transform(X_test['RainToday'])

y_train = lb.fit_transform(y_train)
y_test = lb.transform(y_test)
```

time: 225 ms (started: 2021-04-18 15:35:35 +08:00)

0.14.2 Encoding on Categorical Data

[65]:
```
# Encoding on train data
X_train['Location'] = pd.Categorical(X_train['Location'])
datasetDummies_Location = pd.get_dummies(X_train['Location'], prefix =␣
↪'Location_encoded')
X_train.drop("Location", axis=1, inplace=True)
X_train = pd.concat([X_train, datasetDummies_Location], axis=1)

X_train['WindGustDir'] = pd.Categorical(X_train['WindGustDir'])
datasetDummies_WindGustDir = pd.get_dummies(X_train['WindGustDir'], prefix =␣
↪'WindGustDir_encoded')
X_train.drop("WindGustDir", axis=1, inplace=True)
X_train = pd.concat([X_train, datasetDummies_WindGustDir], axis=1)

X_train['WindDir9am'] = pd.Categorical(X_train['WindDir9am'])
```

```
datasetDummies_WindDir9am = pd.get_dummies(X_train['WindDir9am'], prefix =␣
↪'WindDir9am_encoded')
X_train.drop("WindDir9am", axis=1, inplace=True)
X_train = pd.concat([X_train, datasetDummies_WindDir9am], axis=1)

X_train['WindDir3pm'] = pd.Categorical(X_train['WindDir3pm'])
datasetDummies_WindDir3pm = pd.get_dummies(X_train['WindDir3pm'], prefix =␣
↪'WindDir3pm_encoded')
X_train.drop("WindDir3pm", axis=1, inplace=True)
X_train = pd.concat([X_train, datasetDummies_WindDir3pm], axis=1)

# Encoding on test data
X_test['Location'] = pd.Categorical(X_test['Location'])
datasetDummies_Location = pd.get_dummies(X_test['Location'], prefix =␣
↪'Location_encoded')
X_test.drop("Location", axis=1, inplace=True)
X_test = pd.concat([X_test, datasetDummies_Location], axis=1)

X_test['WindGustDir'] = pd.Categorical(X_test['WindGustDir'])
datasetDummies_WindGustDir = pd.get_dummies(X_test['WindGustDir'], prefix =␣
↪'WindGustDir_encoded')
X_test.drop("WindGustDir", axis=1, inplace=True)
X_test = pd.concat([X_test, datasetDummies_WindGustDir], axis=1)

X_test['WindDir9am'] = pd.Categorical(X_test['WindDir9am'])
datasetDummies_WindDir9am = pd.get_dummies(X_test['WindDir9am'], prefix =␣
↪'WindDir9am_encoded')
X_test.drop("WindDir9am", axis=1, inplace=True)
X_test = pd.concat([X_test, datasetDummies_WindDir9am], axis=1)

X_test['WindDir3pm'] = pd.Categorical(X_test['WindDir3pm'])
datasetDummies_WindDir3pm = pd.get_dummies(X_test['WindDir3pm'], prefix =␣
↪'WindDir3pm_encoded')
X_test.drop("WindDir3pm", axis=1, inplace=True)
X_test = pd.concat([X_test, datasetDummies_WindDir3pm], axis=1)
```

time: 153 ms (started: 2021-04-18 15:35:35 +08:00)

[66]:
```
X_train.head()
```

[66]:
```
       MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed  \
6353      10.0     28.4       0.6          4.0       7.9           26.0
12621     10.3     11.7       0.0          3.2       0.8           63.0
12189     10.9     21.4       0.0          2.6       0.0           37.0
4779       5.8     27.3       0.0          9.0      10.1           54.0
9098       5.0     14.2       0.0          0.6       4.8           48.0
```

```
       WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  …  \
6353            9.0           9.0         86.0         36.0  …
12621          24.0          24.0         67.0         72.0  …
12189           0.0          13.0         70.0         48.0  …
4779           17.0          33.0         36.0         21.0  …
9098           20.0          19.0         46.0         46.0  …

       WindDir3pm_encoded_NNW  WindDir3pm_encoded_NW  WindDir3pm_encoded_S  \
6353                        0                      0                     0
12621                       0                      0                     0
12189                       0                      0                     0
4779                        0                      0                     0
9098                        0                      0                     0

       WindDir3pm_encoded_SE  WindDir3pm_encoded_SSE  WindDir3pm_encoded_SSW  \
6353                       0                       0                       0
12621                      0                       0                       0
12189                      0                       0                       0
4779                       0                       0                       0
9098                       0                       0                       0

       WindDir3pm_encoded_SW  WindDir3pm_encoded_W  WindDir3pm_encoded_WNW  \
6353                       1                     0                       0
12621                      0                     0                       0
12189                      0                     0                       0
4779                       0                     0                       1
9098                       0                     0                       1

       WindDir3pm_encoded_WSW
6353                        0
12621                       0
12189                       1
4779                        0
9098                        0

[5 rows x 70 columns]
```

```
time: 72.4 ms (started: 2021-04-18 15:35:35 +08:00)
```

[67]:
```
X_test.head()
```

[67]:
```
       MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed  \
10828      7.7     16.3       0.0          3.0       8.4           61.0
9876      14.7     28.2       0.0         10.0       9.1           63.0
2263       1.6     16.5       0.0          0.8       9.0           30.0
11079     15.6     21.9       0.0          8.6       5.6           41.0
12497     10.9     21.4       0.0          6.2       6.3           33.0
```

```
       WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  …  \
10828          20.0          22.0         59.0         33.0  …
9876           35.0          28.0         41.0         13.0  …
2263           15.0          11.0         71.0         46.0  …
11079          15.0          24.0         75.0         71.0  …
12497          19.0          17.0         70.0         48.0  …

       WindDir3pm_encoded_NNW  WindDir3pm_encoded_NW  WindDir3pm_encoded_S  \
10828                       0                      1                     0
9876                        0                      1                     0
2263                        0                      0                     0
11079                       0                      0                     1
12497                       0                      0                     0

       WindDir3pm_encoded_SE  WindDir3pm_encoded_SSE  WindDir3pm_encoded_SSW  \
10828                      0                       0                       0
9876                       0                       0                       0
2263                       0                       0                       0
11079                      0                       0                       0
12497                      0                       1                       0

       WindDir3pm_encoded_SW  WindDir3pm_encoded_W  WindDir3pm_encoded_WNW  \
10828                      0                     0                       0
9876                       0                     0                       0
2263                       0                     0                       0
11079                      0                     0                       0
12497                      0                     0                       0

       WindDir3pm_encoded_WSW
10828                       0
9876                        0
2263                        0
11079                       0
12497                       0

[5 rows x 70 columns]
```

```
time: 120 ms (started: 2021-04-18 15:35:36 +08:00)
```

0.15 Feature Scaling

[68]:
```
X_train.describe()
```

[68]:
```
            MinTemp       MaxTemp      Rainfall   Evaporation      Sunshine  \
count  10385.000000  10385.000000  10385.000000  10385.000000  10385.000000
```

mean	10.701270	21.972874	1.771714	4.755128	7.322985
std	6.176431	6.628597	4.667934	3.076957	3.531044
min	-5.600000	6.600000	0.000000	0.000000	0.000000
25%	6.800000	17.000000	0.000000	2.600000	5.100000
50%	10.900000	21.400000	0.000000	4.000000	7.900000
75%	15.100000	26.100000	0.400000	6.200000	9.800000
max	34.437500	49.687500	22.625000	14.500000	14.100000

	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	\
count	10385.000000	10385.000000	10385.000000	10385.000000	10385.000000	
mean	41.038577	14.378045	19.297412	69.524266	48.676553	
std	14.679347	9.253976	9.174109	15.726469	18.412796	
min	11.000000	0.000000	0.000000	19.500000	1.000000	
25%	31.000000	7.000000	13.000000	59.000000	36.000000	
50%	39.000000	13.000000	19.000000	70.000000	48.000000	
75%	48.000000	19.000000	24.000000	81.000000	60.000000	
max	91.875000	46.250000	50.625000	100.000000	120.000000	

	…	WindDir3pm_encoded_NNW	WindDir3pm_encoded_NW	\
count	…	10385.000000	10385.000000	
mean	…	0.067212	0.077997	
std	…	0.250401	0.268180	
min	…	0.000000	0.000000	
25%	…	0.000000	0.000000	
50%	…	0.000000	0.000000	
75%	…	0.000000	0.000000	
max	…	1.000000	1.000000	

	WindDir3pm_encoded_S	WindDir3pm_encoded_SE	WindDir3pm_encoded_SSE	\
count	10385.000000	10385.000000	10385.000000	
mean	0.083678	0.038421	0.061531	
std	0.276918	0.192219	0.240313	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	

	WindDir3pm_encoded_SSW	WindDir3pm_encoded_SW	WindDir3pm_encoded_W	\
count	10385.000000	10385.000000	10385.000000	
mean	0.050169	0.043524	0.073375	
std	0.218303	0.204044	0.260764	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	

```
       WindDir3pm_encoded_WNW  WindDir3pm_encoded_WSW
count            10385.000000            10385.000000
mean                 0.105537                0.064998
std                  0.307259                0.246533
min                  0.000000                0.000000
25%                  0.000000                0.000000
50%                  0.000000                0.000000
75%                  0.000000                0.000000
max                  1.000000                1.000000

[8 rows x 70 columns]
```

```
time: 1.4 s (started: 2021-04-18 15:35:36 +08:00)
```

[69]:
```
X_test.describe()
```

[69]:
```
           MinTemp      MaxTemp     Rainfall  Evaporation     Sunshine  \
count  2597.000000  2597.000000  2597.000000  2597.000000  2597.000000
mean     10.873729    22.117905     1.563342     4.853831     7.426146
std       6.196932     6.634837     4.332540     3.120053     3.530939
min      -5.500000     4.100000     0.000000     0.000000     0.000000
25%       7.200000    17.200000     0.000000     2.600000     5.400000
50%      10.900000    21.400000     0.000000     4.000000     7.900000
75%      15.100000    26.300000     0.400000     6.600000     9.900000
max      34.437500    49.687500    22.625000    14.500000    14.000000

       WindGustSpeed  WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  \
count    2597.000000   2597.000000   2597.000000  2597.000000  2597.000000
mean       41.300876     14.407682     19.493791    68.696765    48.216018
std        14.190335      9.376890      9.098532    15.754930    17.752599
min        11.000000      0.000000      0.000000    19.500000     5.000000
25%        31.000000      7.000000     13.000000    59.000000    36.000000
50%        39.000000     13.000000     19.000000    70.000000    48.000000
75%        48.000000     19.000000     24.000000    80.000000    59.000000
max        91.875000     46.250000     50.625000   100.000000   120.000000

       …  WindDir3pm_encoded_NNW  WindDir3pm_encoded_NW  \
count  …             2597.000000            2597.000000
mean   …                0.060454               0.075472
std    …                0.238373               0.264202
min    …                0.000000               0.000000
25%    …                0.000000               0.000000
50%    …                0.000000               0.000000
75%    …                0.000000               0.000000
max    …                1.000000               1.000000
```

```
       WindDir3pm_encoded_S  WindDir3pm_encoded_SE  WindDir3pm_encoded_SSE  \
count           2597.000000            2597.000000             2597.000000
mean               0.085868               0.037736                0.061610
std                0.280223               0.190593                0.240491
min                0.000000               0.000000                0.000000
25%                0.000000               0.000000                0.000000
50%                0.000000               0.000000                0.000000
75%                0.000000               0.000000                0.000000
max                1.000000               1.000000                1.000000

       WindDir3pm_encoded_SSW  WindDir3pm_encoded_SW  WindDir3pm_encoded_W  \
count             2597.000000            2597.000000           2597.000000
mean                 0.046592               0.034270              0.073161
std                  0.210804               0.181958              0.260451
min                  0.000000               0.000000              0.000000
25%                  0.000000               0.000000              0.000000
50%                  0.000000               0.000000              0.000000
75%                  0.000000               0.000000              0.000000
max                  1.000000               1.000000              1.000000

       WindDir3pm_encoded_WNW  WindDir3pm_encoded_WSW
count             2597.000000             2597.000000
mean                 0.112822                0.069311
std                  0.316437                0.254031
min                  0.000000                0.000000
25%                  0.000000                0.000000
50%                  0.000000                0.000000
75%                  0.000000                0.000000
max                  1.000000                1.000000

[8 rows x 70 columns]
```

```
time: 994 ms (started: 2021-04-18 15:35:37 +08:00)
```

Feature scaling is for mapping all the feature variables onto the same scale.

[70]:
```
cols = X_train.columns
```

```
time: 514 µs (started: 2021-04-18 15:35:38 +08:00)
```

[71]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)
```

time: 207 ms (started: 2021-04-18 15:35:38 +08:00)

[72]:
```
X_train = pd.DataFrame(X_train, columns=[cols])
```

time: 9.63 ms (started: 2021-04-18 15:35:38 +08:00)

[73]:
```
X_test = pd.DataFrame(X_test, columns=[cols])
```

time: 63.9 ms (started: 2021-04-18 15:35:38 +08:00)

[74]:
```
X_train.describe()
```

[74]:

```
            MinTemp       MaxTemp      Rainfall   Evaporation      Sunshine  \
count  10385.000000  10385.000000  10385.000000  10385.000000  10385.000000
mean       0.407150      0.356783      0.078308      0.327940      0.519361
std        0.154266      0.153840      0.206318      0.212204      0.250429
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.309710      0.241369      0.000000      0.179310      0.361702
50%        0.412114      0.343487      0.000000      0.275862      0.560284
75%        0.517015      0.452567      0.017680      0.427586      0.695035
max        1.000000      1.000000      1.000000      1.000000      1.000000

       WindGustSpeed  WindSpeed9am  WindSpeed3pm   Humidity9am   Humidity3pm  \
count   10385.000000  10385.000000  10385.000000  10385.000000  10385.000000
mean        0.371420      0.310877      0.381183      0.621419      0.400643
std         0.181507      0.200086      0.181217      0.195360      0.154729
min         0.000000      0.000000      0.000000      0.000000      0.000000
25%         0.247295      0.151351      0.256790      0.490683      0.294118
50%         0.346213      0.281081      0.375309      0.627329      0.394958
75%         0.457496      0.410811      0.474074      0.763975      0.495798
max         1.000000      1.000000      1.000000      1.000000      1.000000

       … WindDir3pm_encoded_NNW WindDir3pm_encoded_NW WindDir3pm_encoded_S  \
count  …           10385.000000          10385.000000         10385.000000
mean   …               0.067212              0.077997             0.083678
std    …               0.250401              0.268180             0.276918
min    …               0.000000              0.000000             0.000000
25%    …               0.000000              0.000000             0.000000
50%    …               0.000000              0.000000             0.000000
75%    …               0.000000              0.000000             0.000000
max    …               1.000000              1.000000             1.000000

       WindDir3pm_encoded_SE WindDir3pm_encoded_SSE WindDir3pm_encoded_SSW  \
count           10385.000000           10385.000000           10385.000000
mean                0.038421               0.061531               0.050169
std                 0.192219               0.240313               0.218303
min                 0.000000               0.000000               0.000000
25%                 0.000000               0.000000               0.000000
```

```
50%                  0.000000               0.000000               0.000000
75%                  0.000000               0.000000               0.000000
max                  1.000000               1.000000               1.000000

      WindDir3pm_encoded_SW WindDir3pm_encoded_W WindDir3pm_encoded_WNW  \
count          10385.000000         10385.000000           10385.000000
mean               0.043524             0.073375               0.105537
std                0.204044             0.260764               0.307259
min                0.000000             0.000000               0.000000
25%                0.000000             0.000000               0.000000
50%                0.000000             0.000000               0.000000
75%                0.000000             0.000000               0.000000
max                1.000000             1.000000               1.000000

      WindDir3pm_encoded_WSW
count           10385.000000
mean                0.064998
std                 0.246533
min                 0.000000
25%                 0.000000
50%                 0.000000
75%                 0.000000
max                 1.000000

[8 rows x 70 columns]
```

```
time: 1.63 s (started: 2021-04-18 15:35:39 +08:00)
```

[75]:
```
X_test.describe()
```

[75]:
```
           MinTemp      MaxTemp     Rainfall  Evaporation     Sunshine  \
count  2597.000000  2597.000000  2597.000000  2597.000000  2597.000000
mean      0.411457     0.360149     0.069098     0.334747     0.526677
std       0.154778     0.153985     0.191493     0.215176     0.250421
min       0.002498    -0.058021     0.000000     0.000000     0.000000
25%       0.319700     0.246011     0.000000     0.179310     0.382979
50%       0.412114     0.343487     0.000000     0.275862     0.560284
75%       0.517015     0.457209     0.017680     0.455172     0.702128
max       1.000000     1.000000     1.000000     1.000000     0.992908

      WindGustSpeed WindSpeed9am WindSpeed3pm  Humidity9am  Humidity3pm  …  \
count   2597.000000  2597.000000  2597.000000  2597.000000  2597.000000  …
mean       0.374663     0.311517     0.385063     0.611140     0.396773  …
std        0.175460     0.202744     0.179724     0.195713     0.149182  …
min        0.000000     0.000000     0.000000     0.000000     0.033613  …
25%        0.247295     0.151351     0.256790     0.490683     0.294118  …
50%        0.346213     0.281081     0.375309     0.627329     0.394958  …
```

```
75%        0.457496     0.410811     0.474074     0.751553     0.487395  …
max        1.000000     1.000000     1.000000     1.000000     1.000000  …

      WindDir3pm_encoded_NNW WindDir3pm_encoded_NW WindDir3pm_encoded_S  \
count            2597.000000           2597.000000          2597.000000
mean                0.060454              0.075472             0.085868
std                 0.238373              0.264202             0.280223
min                 0.000000              0.000000             0.000000
25%                 0.000000              0.000000             0.000000
50%                 0.000000              0.000000             0.000000
75%                 0.000000              0.000000             0.000000
max                 1.000000              1.000000             1.000000

      WindDir3pm_encoded_SE WindDir3pm_encoded_SSE WindDir3pm_encoded_SSW  \
count           2597.000000            2597.000000            2597.000000
mean               0.037736               0.061610               0.046592
std                0.190593               0.240491               0.210804
min                0.000000               0.000000               0.000000
25%                0.000000               0.000000               0.000000
50%                0.000000               0.000000               0.000000
75%                0.000000               0.000000               0.000000
max                1.000000               1.000000               1.000000

      WindDir3pm_encoded_SW WindDir3pm_encoded_W WindDir3pm_encoded_WNW  \
count           2597.000000          2597.000000            2597.000000
mean               0.034270             0.073161               0.112822
std                0.181958             0.260451               0.316437
min                0.000000             0.000000               0.000000
25%                0.000000             0.000000               0.000000
50%                0.000000             0.000000               0.000000
75%                0.000000             0.000000               0.000000
max                1.000000             1.000000               1.000000

      WindDir3pm_encoded_WSW
count            2597.000000
mean                0.069311
std                 0.254031
min                 0.000000
25%                 0.000000
50%                 0.000000
75%                 0.000000
max                 1.000000

[8 rows x 70 columns]
```

```
time: 1.43 s (started: 2021-04-18 15:35:40 +08:00)
```

0.16 Training Baseline Models

The performance metrics used to evaluate the models are accuracy, balanced accuracy, precision, recall, F1, PR-AUC, ROC-AUC, Cohen Kappa, Fit Time and Score Time.

[76]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier

from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB

from sklearn.svm import LinearSVC, SVC
from sklearn.linear_model import SGDClassifier

from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier

#from sklearn.metrics import confusion_matrix, classification_report
```

```
time: 286 ms (started: 2021-04-18 15:35:42 +08:00)
```

[77]:
```
from sklearn.model_selection import cross_validate, KFold
from sklearn.metrics import make_scorer, cohen_kappa_score

def evaluate_models(model_list, X_data):

  cv = KFold(n_splits=10, shuffle=True, random_state=42)

  scoring = {'accuracy': 'accuracy',
             'balanced_accuracy': 'balanced_accuracy',
             'precision_macro': 'precision_macro',
             'recall_macro': 'recall_macro',
             'f1_macro': 'f1_macro',
             'average_precision': 'average_precision',
             'roc_auc': 'roc_auc',
             'cohen_kappa': make_scorer(cohen_kappa_score)}

  scores_accuracy = []
  scores_balanced_accuracy = []
  scores_precision = []
  scores_recall = []
  scores_f1 = []
  scores_average_precision = []
  scores_roc_auc = []
  scores_cohen_kappa = []
  fit_time = []
```

```
    score_time = []

    for name, model in model_list:
        score = cross_validate(model, X_data, y_train, cv=cv, scoring=scoring,␣
↪n_jobs=-1, return_train_score=False)
        scores_accuracy.append(score['test_accuracy'].mean())
        scores_balanced_accuracy.append(score['test_balanced_accuracy'].mean())
        scores_precision.append(score['test_precision_macro'].mean())
        scores_recall.append(score['test_recall_macro'].mean())
        scores_f1.append(score['test_f1_macro'].mean())
        scores_average_precision.append(score['test_average_precision'].mean())
        scores_roc_auc.append(score['test_roc_auc'].mean())
        scores_cohen_kappa.append(score['test_cohen_kappa'].mean())
        fit_time.append(score['fit_time'].mean())
        score_time.append(score['score_time'].mean())

    performance = pd.DataFrame({
        'Model': [model[0] for model in model_list],
        'Accuracy': scores_accuracy,
        'Balanced Accuracy': scores_balanced_accuracy,
        'Precision': scores_precision,
        'Recall': scores_recall,
        'F1': scores_f1,
        'PR-AUC': scores_average_precision,
        'ROC-AUC': scores_roc_auc,
        'Cohen Kappa': scores_cohen_kappa,
        'Fit Time': fit_time,
        'Score Time': score_time
    })

    return performance
```

time: 72.8 ms (started: 2021-04-18 15:35:42 +08:00)

[78]:
```
models = []
models.append(("Logistic Regression", LogisticRegression(penalty='l1',␣
↪solver='liblinear', random_state=42)))
models.append(("Decision Tree Classifier",␣
↪DecisionTreeClassifier(criterion='gini', max_depth=None, random_state=42)))
models.append(("K-Nearest Neighbors", KNeighborsClassifier(n_neighbors=3,␣
↪weights='uniform', algorithm='auto')))
models.append(("MLP Classifier", MLPClassifier(activation='relu', alpha=0.0001,␣
↪verbose=0, random_state=42)))
models.append(("Gaussian Naive Bayes", GaussianNB(priors=None,␣
↪var_smoothing=1e-09)))
models.append(("Bernoulli Naive Bayes", BernoulliNB(alpha=1.0, binarize=0.0,␣
↪fit_prior=True, class_prior=None)))
```

```
models.append(("Multinomial Naive Bayes", MultinomialNB(alpha=1.0,␣
 ↪fit_prior=True, class_prior=None)))
models.append(("SVC", SVC(kernel='rbf', random_state=42, probability=True)))
models.append(("SGD Classifier", SGDClassifier(learning_rate = 'optimal',␣
 ↪random_state=42, loss='log')))
models.append(("Random Forest Classifier",␣
 ↪RandomForestClassifier(criterion='gini', random_state=42)))
models.append(("Gradient Boosting Classifier",␣
 ↪GradientBoostingClassifier(learning_rate=0.1, n_estimators=150,␣
 ↪random_state=42)))
models.append(("Ada Boost Classifier", AdaBoostClassifier(n_estimators=60,␣
 ↪learning_rate=1, random_state=42)))
```

```
time: 101 ms (started: 2021-04-18 15:35:42 +08:00)
```

The performance metrics used to evaluate the models are accuracy, balanced accuracy, precision, recall, F1, PR-AUC, ROC-AUC, Cohen Kappa, Fit Time and Score Time.

[79]:
```
pf1 = evaluate_models(models, X_train)
display(pf1)
```

	Model	Accuracy	Balanced Accuracy	Precision	\
0	Logistic Regression	0.854695	0.717491	0.801395	
1	Decision Tree Classifier	0.787192	0.685943	0.679425	
2	K-Nearest Neighbors	0.795570	0.612549	0.674816	
3	MLP Classifier	0.831777	0.718259	0.746049	
4	Gaussian Naive Bayes	0.774197	0.711565	0.677473	
5	Bernoulli Naive Bayes	0.781995	0.633623	0.658170	
6	Multinomial Naive Bayes	0.813192	0.598567	0.735511	
7	SVC	0.857872	0.701601	0.826808	
8	SGD Classifier	0.848436	0.706564	0.799093	
9	Random Forest Classifier	0.854888	0.701413	0.814834	
10	Gradient Boosting Classifier	0.857007	0.720781	0.805794	
11	Ada Boost Classifier	0.851902	0.708613	0.798281	

	Recall	F1	PR-AUC	ROC-AUC	Cohen Kappa	Fit Time	Score Time
0	0.717491	0.745608	0.677692	0.856513	0.495712	15.696754	0.055602
1	0.685943	0.682219	0.352239	0.685943	0.364713	0.907618	0.069158
2	0.612549	0.627623	0.359656	0.687384	0.265685	0.095287	3.635940
3	0.718259	0.729735	0.625403	0.827998	0.460429	74.497700	0.058829
4	0.711565	0.689109	0.496561	0.786164	0.381717	0.278227	0.117762
5	0.633623	0.642711	0.453411	0.706423	0.287612	0.149882	0.110238
6	0.598567	0.614893	0.493658	0.751299	0.257426	0.048542	0.097163
7	0.701601	0.737031	0.691840	0.857510	0.482430	99.203639	0.733149
8	0.706564	0.732583	0.672983	0.853329	0.471682	0.142071	0.010377
9	0.701413	0.734720	0.686875	0.864465	0.477016	1.432706	0.056219
10	0.720781	0.749524	0.692557	0.865345	0.503463	3.414829	0.013336
11	0.708613	0.737532	0.671492	0.852999	0.480463	0.827604	0.043670

```
time: 3min 53s (started: 2021-04-18 15:35:42 +08:00)
```

0.17 Feature Selection

In some cases it is convenient to apply dimensionality reduction to visualize the number of components or elements which could be the best for our model. In this case we apply PCA to discover which ones are the features to obtain an acceptable performance in the model. We tried applying RFECV, but a runtime error was generated as the classifier does not expose "coef_" or "feature_importances_" attributes.

[80]:
```
# from sklearn.feature_selection import RFECV

# X_trainlist = []

# for n in range(len(models)):

#   rfecv = RFECV(estimator=models[n][1], step=1, cv=5, scoring='accuracy')

#   rfecv = rfecv.fit(X_train, y_train)

#   print("Optimal number of features : %d" % rfecv.n_features_)
```

```
time: 187 µs (started: 2021-04-18 15:39:36 +08:00)
```

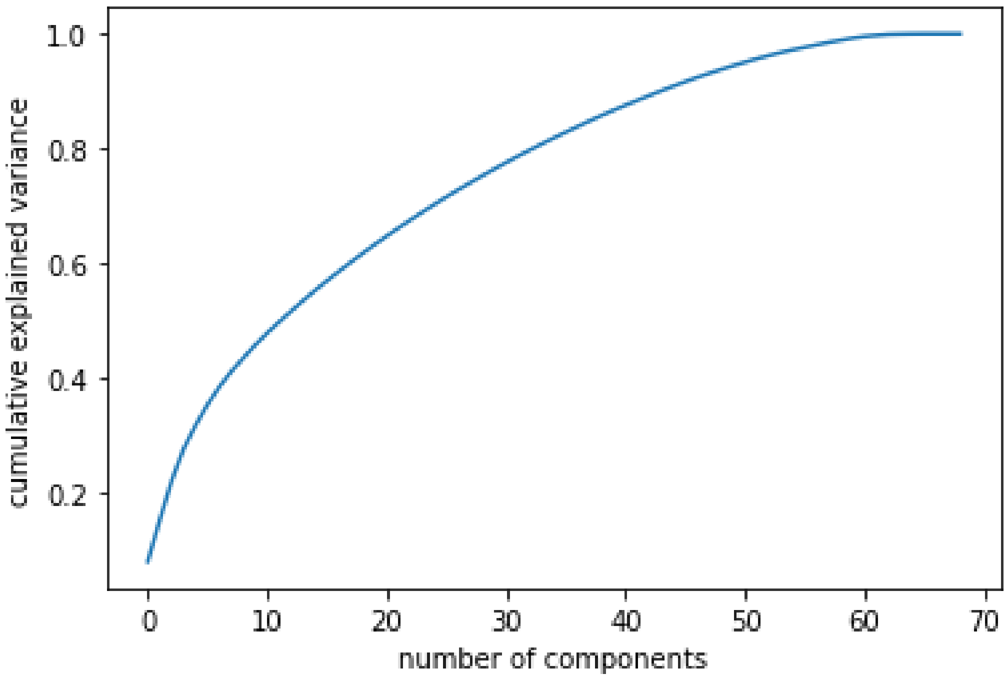
[81]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=69)
X_trainNew = pca.fit_transform(X_train)

print(pd.DataFrame(pca.components_, columns=X_train.columns))
print("\nExplained variance by each component: %s" % pca.
 ↪explained_variance_ratio_)
```

```
         MinTemp       MaxTemp      Rainfall   Evaporation      Sunshine  \
0   7.402732e-02 -3.776100e-02  6.298935e-02 -1.720853e-02 -1.599877e-01
1   9.489682e-02  4.221620e-02  3.234093e-02  3.794741e-02  3.999562e-02
2  -7.305858e-02 -6.761789e-02  5.800507e-02 -8.991682e-02 -6.774770e-02
3   9.243943e-04 -1.032499e-01  2.512354e-01 -1.156510e-01 -2.477098e-01
4  -6.602175e-02 -5.243036e-02  8.787727e-02 -7.788263e-02 -9.889253e-02
..           …            …            …            …            …
64 -6.551599e-01  6.247334e-01 -1.089793e-02  8.943531e-03 -1.936364e-02
65 -4.081812e-01 -3.921915e-01 -2.741965e-03  1.219039e-02  7.398862e-03
66  1.237635e-15  3.913728e-16  1.601116e-16 -5.524108e-16  3.192666e-16
67  0.000000e+00 -1.242812e-16 -7.438993e-17  2.036464e-16 -3.106258e-17
68  0.000000e+00 -6.825008e-18 -5.964708e-18  8.609567e-17 -2.459548e-17

   WindGustSpeed  WindSpeed9am  WindSpeed3pm   Humidity9am   Humidity3pm  …  \
```

```
0   9.142474e-02  1.277490e-01  8.337390e-02  1.840592e-02  8.894472e-02  …
1  -4.345540e-02 -2.342435e-02 -4.500352e-02 -1.897981e-02  2.560757e-02  …
2  -1.414102e-02 -8.255594e-02  2.700178e-03  1.081170e-01  5.350659e-02  …
3  -3.008140e-02 -1.846814e-02 -2.965142e-02  1.823250e-01  1.578927e-01  …
4   3.714652e-02  5.496187e-02  1.006324e-02  5.830001e-02  1.631103e-02  …
..           …             …             …             …             …  …
64 -2.737469e-02  5.820365e-02  2.737428e-02 -5.258702e-02  3.403693e-01  …
65  5.736754e-03  1.509488e-02 -3.092626e-02  1.186595e-01 -1.243731e-01  …
66  1.691486e-16 -1.559871e-16  4.155624e-16 -4.090640e-16  2.451867e-16  …
67 -3.642486e-16  1.208336e-16  2.564372e-16  1.838492e-16  9.184618e-18  …
68 -1.584834e-16 -2.971957e-17 -9.791831e-17 -1.707302e-17  9.344281e-17  …

   WindDir3pm_encoded_NNW WindDir3pm_encoded_NW WindDir3pm_encoded_S  \
0               -0.019460             -0.064158             0.114725
1               -0.080043             -0.084078            -0.047838
2                0.076115              0.093293            -0.057273
3               -0.047526             -0.016641             0.062387
4                0.032797              0.018465            -0.226661
..                    …                     …                    …
64              -0.012078             -0.005955            -0.002058
65               0.004380              0.002135             0.000111
66               0.013203              0.013203             0.013203
67               0.178421              0.178421             0.178421
68              -0.170421             -0.170421            -0.170421

   WindDir3pm_encoded_SE WindDir3pm_encoded_SSE WindDir3pm_encoded_SSW  \
0               0.012087               0.063228               0.031547
1               0.022565               0.007846              -0.008694
2               0.005680              -0.024685              -0.026079
3               0.015559               0.037489               0.056403
4              -0.042771              -0.115014              -0.046718
..                   …                      …                      …
64              0.002205              -0.000261              -0.004467
65             -0.001824              -0.001947              -0.000115
66              0.013203               0.013203               0.013203
67              0.178421               0.178421               0.178421
68             -0.170421              -0.170421              -0.170421

   WindDir3pm_encoded_SW WindDir3pm_encoded_W WindDir3pm_encoded_WNW  \
0              -0.017064            -0.048312              -0.067567
1              -0.015448             0.016207              -0.027219
2              -0.049047            -0.030152               0.164143
3               0.041629             0.039167              -0.069235
4               0.022356             0.068489               0.157282
..                   …                    …                      …
64              0.000780             0.007292               0.008241
65             -0.001187            -0.001891              -0.001895
66              0.013203             0.013203               0.013203
```

```
67             0.178421             0.178421               0.178421
68            -0.170421            -0.170421              -0.170421

   WindDir3pm_encoded_WSW
0                -0.041929
1                 0.000218
2                -0.073577
3                 0.052102
4                 0.060455
..                     …
64                0.008469
65               -0.000901
66                0.013203
67                0.178421
68               -0.170421

[69 rows x 70 columns]

Explained variance by each component: [7.81664546e-02 7.24548640e-02
6.86216060e-02 5.56770156e-02
 4.10863905e-02 3.63466918e-02 3.11697622e-02 2.69140322e-02
 2.32458647e-02 2.29918406e-02 2.05007435e-02 1.94209485e-02
 1.87260173e-02 1.84081823e-02 1.77950082e-02 1.68607166e-02
 1.64615106e-02 1.61533959e-02 1.55334487e-02 1.54258603e-02
 1.47832052e-02 1.44771068e-02 1.39148575e-02 1.37094459e-02
 1.32968872e-02 1.28595851e-02 1.26437580e-02 1.21218731e-02
 1.20742714e-02 1.18608142e-02 1.13901114e-02 1.12280983e-02
 1.08143985e-02 1.06286007e-02 1.03610054e-02 1.01074206e-02
 9.89297747e-03 9.85595983e-03 9.44741239e-03 9.16253192e-03
 8.76803698e-03 8.60788924e-03 8.48894272e-03 8.29919043e-03
 8.01472479e-03 7.80261688e-03 7.46296631e-03 7.03018713e-03
 6.86258137e-03 6.49725498e-03 6.12501248e-03 5.90320916e-03
 5.51106513e-03 5.29577669e-03 4.77124353e-03 4.44828480e-03
 4.25835526e-03 4.20649232e-03 3.82227463e-03 3.64720132e-03
 2.85475176e-03 1.86857615e-03 1.73275568e-03 5.44992474e-04
 4.32141854e-04 1.52800973e-04 1.54156150e-32 3.33308326e-33
 2.06176242e-33]
time: 146 ms (started: 2021-04-18 15:39:36 +08:00)
```

[82]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
plt.show()
```




```
time: 202 ms (started: 2021-04-18 15:39:36 +08:00)
```

[83]:

```
pf2 = evaluate_models(models, X_trainNew)
display(pf2)
```

	Model	Accuracy	Balanced Accuracy	Precision
0	Logistic Regression	0.854117	0.716834	0.800388
1	Decision Tree Classifier	0.766201	0.651211	0.647830
2	K-Nearest Neighbors	0.795570	0.612549	0.674816
3	MLP Classifier	0.836496	0.730010	0.753024
4	Gaussian Naive Bayes	0.819066	0.676119	0.724940
5	Bernoulli Naive Bayes	0.823205	0.622375	0.761138
6	Multinomial Naive Bayes	NaN	NaN	NaN
7	SVC	0.857005	0.703702	0.821177
8	SGD Classifier	0.854599	0.720464	0.799715
9	Random Forest Classifier	0.845643	0.658244	0.830989
10	Gradient Boosting Classifier	0.853347	0.697137	0.813704
11	Ada Boost Classifier	0.839287	0.698478	0.767487

	Recall	F1	PR-AUC	ROC-AUC	Cohen Kappa	Fit Time	Score Time
0	0.716834	0.744632	0.677508	0.856178	0.493837	0.118999	0.007479
1	0.651211	0.649089	0.313830	0.651211	0.298520	1.179182	0.006309
2	0.612549	0.627623	0.359656	0.687384	0.265685	0.011568	0.696651
3	0.730010	0.740025	0.625274	0.822928	0.480631	9.635657	0.008440
4	0.676119	0.693455	0.518883	0.795501	0.390268	0.026141	0.009627

```
5    0.622375  0.645533  0.550620  0.786640     0.312600   0.022242    0.011220
6         NaN       NaN       NaN       NaN          NaN   0.004615    0.000000
7    0.703702  0.737946  0.684492  0.853081     0.483557  45.420653    0.774181
8    0.720464  0.747312  0.675089  0.854417     0.498782   0.124864    0.007342
9    0.658244  0.692410  0.654265  0.838962     0.402656   7.903122    0.051094
10   0.697137  0.730445  0.666709  0.848324     0.469023  28.824953    0.010852
11   0.698478  0.721954  0.627880  0.830257     0.448168   4.795246    0.039359
```

```
time: 1min 50s (started: 2021-04-18 15:39:36 +08:00)
```

0.18 Shortlisting Best Models

To shortlist the best models, we compare the performance of the models based on balanced accuracy, PR-AUC, Cohen's Kappa score and Fit Time.

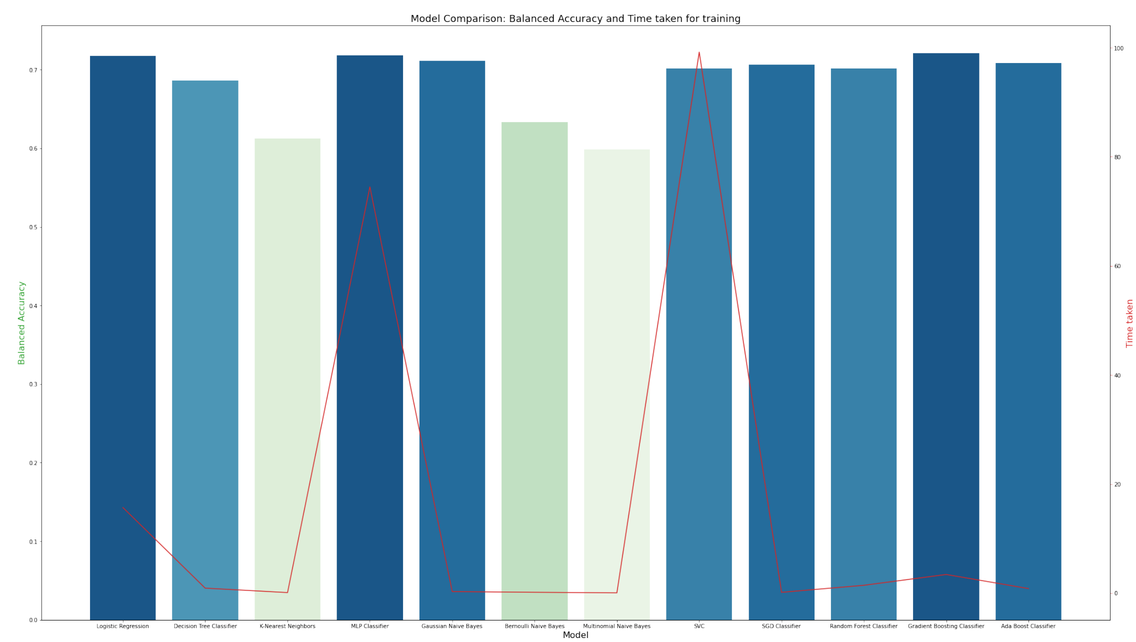
- Balanced Accuracy, PR-AUC, Cohen's Kappa scores are used because they are more appropriate to evaluate the performance of models on an imbalanced dataset.
- Balanced Accuracy shows the average of recall obtained on each class.
- PR-AUC (or average precision score) summarises the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.
- Cohen's Kappa score expresses the level of agreement between two annotators on a classification problem.
- Fit Time is the time taken to train the models.

[84]:
```
def colors_from_values(values, palette_name):
    # normalize the values to range [0, 1]
    normalized = (values - min(values)) / (max(values) - min(values))
    # convert to indices
    indices = np.round(normalized * (len(values) - 1)).astype(np.int32)
    # use the indices to get the colors
    palette = sns.color_palette(palette_name, len(values))
    return np.array(palette).take(indices, axis=0)
```

```
time: 636 µs (started: 2021-04-18 15:41:27 +08:00)
```

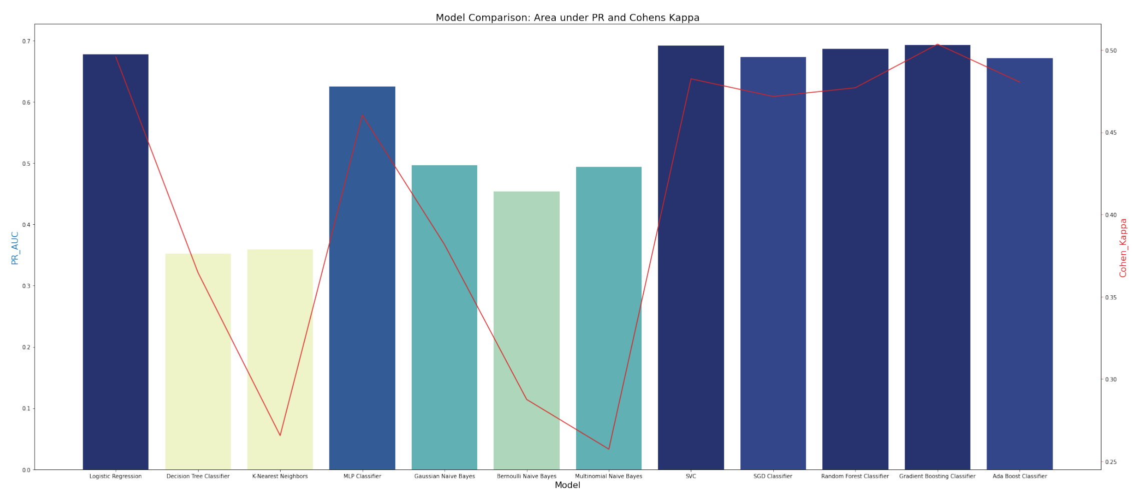
[110]:
```
balanced_accuracy_scores = pf1['Balanced Accuracy']
pr_auc_scores = pf1['PR-AUC']
coh_kap_scores = pf1['Cohen Kappa']
tt = pf1['Fit Time']

model_data = {'Model': ['Logistic Regression','Decision Tree␣
↪Classifier','K-Nearest Neighbors',
                        'MLP Classifier','Gaussian Naive Bayes','Bernoulli␣
↪Naive Bayes',
                        'Multinomial Naive Bayes', 'SVC', 'SGD Classifier',
```

```
                          'Random Forest Classifier', 'Gradient Boosting␣
 ↪Classifier', 'Ada Boost Classifier'],
              'Balanced Accuracy': balanced_accuracy_scores,
              'PR_AUC': pr_auc_scores,
              'Cohen_Kappa': coh_kap_scores,
              'Time taken': tt}
data = pd.DataFrame(model_data)

fig, ax1 = plt.subplots(figsize=(35,20))
ax1.set_title('Model Comparison: Balanced Accuracy and Time taken for␣
 ↪training', fontsize=18)
color = 'tab:green'
ax1.set_xlabel('Model', fontsize=16)
ax1.set_ylabel('Balanced Accuracy', fontsize=16, color=color)
ax2 = sns.barplot(x='Model', y='Balanced Accuracy', data = data,␣
 ↪palette=colors_from_values(data['Balanced Accuracy'], "GnBu"))
ax1.tick_params(axis='y')
ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Time taken', fontsize=16, color=color)
ax2 = sns.lineplot(x='Model', y='Time taken', data = data, sort=False,␣
 ↪color=color)
ax2.tick_params(axis='y', color=color)
```




```
time: 365 ms (started: 2021-04-18 15:57:43 +08:00)
```

[111]:
```
fig, ax3 = plt.subplots(figsize=(35,15))
ax3.set_title('Model Comparison: Area under PR and Cohens Kappa', fontsize=18)
color = 'tab:blue'
ax3.set_xlabel('Model', fontsize=16)
ax3.set_ylabel('PR_AUC', fontsize=16, color=color)
ax4 = sns.barplot(x='Model', y='PR_AUC', data = data,␣
↪palette=colors_from_values(data['PR_AUC'], "YlGnBu"))
ax3.tick_params(axis='y')
ax4 = ax3.twinx()
color = 'tab:red'
ax4.set_ylabel('Cohen_Kappa', fontsize=16, color=color)
ax4 = sns.lineplot(x='Model', y='Cohen_Kappa', data = data, sort=False,␣
↪color=color)
ax4.tick_params(axis='y', color=color)
plt.show()
```




```
time: 406 ms (started: 2021-04-18 15:57:46 +08:00)
```

0.19 Hyperparameter Tuning

[87]:
```
from sklearn.model_selection import RandomizedSearchCV
import pickle

def random_search(models, params, X_train):

  scoring = {'balanced_accuracy': 'balanced_accuracy',
             'average_precision': 'average_precision',
             'cohen_kappa': make_scorer(cohen_kappa_score)}

  best_estimator_list = []
```

```
    best_parameters_list = []

    for (name, model), param in zip(models, params):
        clf = RandomizedSearchCV(estimator=model, param_distributions=param,
                                 n_jobs=-1, refit='cohen_kappa', cv=10,
                                 scoring=scoring, random_state=42)

        search = clf.fit(X_train, y_train)

        # save the model to disk
        filename = name
        outfile = open(filename, 'wb')
        pickle.dump(clf, outfile)
        outfile.close()

        best_estimator_list.append((name, search.best_estimator_))
        best_parameters_list.append(search.best_params_)

    return best_estimator_list, best_parameters_list
```

time: 620 µs (started: 2021-04-18 15:41:28 +08:00)

[88]:
```
models =[]
models.append(("Logistic Regression", LogisticRegression()))
models.append(("Support Vector Classifier", SVC()))
models.append(("Gradient Boosting Classifier", GradientBoostingClassifier()))

params = []
lr_param_grid = {'penalty':['l1', 'l2'],
                 'C':[0.1, 1, 10, 100],
                 'solver':['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
                }
svc_param_grid = {'gamma':[0.5, 1, 2, 10],
                  'C':[0.1, 1, 10, 100],
                  'kernel':['linear', 'rbf', 'poly', 'sigmoid']
                 }
gbc_param_grid = {'loss':['deviance', 'exponential'],
                  'learning_rate':[0.05, 0.1, 0.2],
                  'n_estimators':[50, 100, 150],
                  'criterion':['friedman_mse', 'mse'],
                  'min_samples_split':[0.1, 1, 10],
                  'min_samples_leaf':[0.1, 0.5, 1, 5],
                  'max_depth':[3, 5, 8],
                  'max_features':['log2', 'sqrt']
}
params.append(lr_param_grid)
params.append(svc_param_grid)
```

```
params.append(gbc_param_grid)

best_estimator_list, best_parameters_list = random_search(models, params,␣
↪X_train)
```

time: 4min 1s (started: 2021-04-18 15:41:28 +08:00)

[89]:
```
pd.set_option('display.max_colwidth', None) #remove python output 30 char max

paramdf = pd.DataFrame({
     'Model': [model[0] for model in models],
     'Best Parameters': best_parameters_list,
})

display(paramdf)
```

```
                          Model  \
0           Logistic Regression
1      Support Vector Classifier
2  Gradient Boosting Classifier

                                                                                  ␣
↪                                                                                 ␣
↪          Best Parameters
0                                                                                 ␣
↪                                                              {'solver':␣
↪'liblinear', 'penalty': 'l1', 'C': 1}
1                                                                                 ␣
↪                                                                    {'kernel':␣
↪'linear', 'gamma': 10, 'C': 10}
2  {'n_estimators': 100, 'min_samples_split': 10, 'min_samples_leaf': 5,␣
↪'max_features': 'sqrt', 'max_depth': 8, 'loss': 'exponential', 'learning_rate':
↪ 0.2, 'criterion': 'friedman_mse'}
```

time: 5.14 ms (started: 2021-04-18 15:45:29 +08:00)

[90]:
```
# # load the model from disk
# loaded_model_list=[]
# for model in models:
#   filename = model[0]
#   loaded_model = pickle.load(open(filename, 'rb'))
#   loaded_model_list.append((model[0], loaded_model))

# pf3 = evaluate_models(loaded_model_list, X_train)
```

time: 204 ms (started: 2021-04-18 15:45:29 +08:00)

[91]:
```
pf3 = evaluate_models(best_estimator_list, X_train)
```

time: 17.2 s (started: 2021-04-18 15:45:29 +08:00)

[92]:
```
display(pf3)
```

```
                         Model  Accuracy  Balanced Accuracy  Precision  \
0          Logistic Regression  0.854791           0.717551   0.801637
1     Support Vector Classifier  0.854599           0.704358   0.811781
2  Gradient Boosting Classifier  0.855656           0.723825   0.799625

     Recall        F1    PR-AUC   ROC-AUC  Cohen Kappa   Fit Time  Score Time
0  0.717551  0.745723  0.677712  0.856519     0.495950   1.573660    0.010310
1  0.704358  0.736460  0.675102  0.851341     0.479932  11.875719    0.256398
2  0.723825  0.750471  0.693434  0.864667     0.504591   1.477332    0.016989
```

time: 7.52 ms (started: 2021-04-18 15:45:46 +08:00)

0.20 Ensemble Models

[93]:
```
from sklearn.ensemble import StackingClassifier

def init_stacking():
    level0 = []
    level0.append(('Support Vector Classifier', SVC(kernel='linear', gamma=10,␣
 ↪C=10)))
    level0.append(('Gradient Boosting Classifier',␣
 ↪GradientBoostingClassifier(n_estimators=100, min_samples_split=10,␣
 ↪min_samples_leaf=5,
                                                                               ␣
 ↪max_features='sqrt', max_depth=8, loss='exponential',
                                                                               ␣
 ↪learning_rate= 0.2, criterion='friedman_mse')))
    level1 = LogisticRegression(solver='liblinear', penalty='l1', C= 1)
    model = StackingClassifier(estimators=level0, final_estimator=level1, cv=5,␣
 ↪n_jobs=-1)

    return model

def init_stacking2():
    level0 = []
    level0.append(('Support Vector Classifier', SVC(kernel='linear', gamma=10,␣
 ↪C=10)))
    level0.append(('Logistic ', LogisticRegression(solver='liblinear',␣
 ↪penalty='l1', C= 1)))

    level1 = GradientBoostingClassifier(n_estimators=100, min_samples_split=10,␣
 ↪min_samples_leaf=5,
```

```
↪max_features='sqrt', max_depth=8, loss='exponential',
↪learning_rate= 0.2, criterion='friedman_mse')
    model = StackingClassifier(estimators=level0, final_estimator=level1, cv=5,␣
↪n_jobs=-1)

    return model

def init_stacking3():
    level0 = []
    level0.append(('GBC', GradientBoostingClassifier(n_estimators=100,␣
↪min_samples_split=10, min_samples_leaf=5,
↪max_features='sqrt', max_depth=8, loss='exponential',
↪learning_rate= 0.2, criterion='friedman_mse')))
    level0.append(('Logistic ', LogisticRegression(solver='liblinear',␣
↪penalty='l1', C= 1)))

    level1 = SVC(kernel='linear', gamma=10, C=10)
    model = StackingClassifier(estimators=level0, final_estimator=level1, cv=5,␣
↪n_jobs=-1)

    return model
```

```
time: 77.6 ms (started: 2021-04-18 15:45:46 +08:00)
```

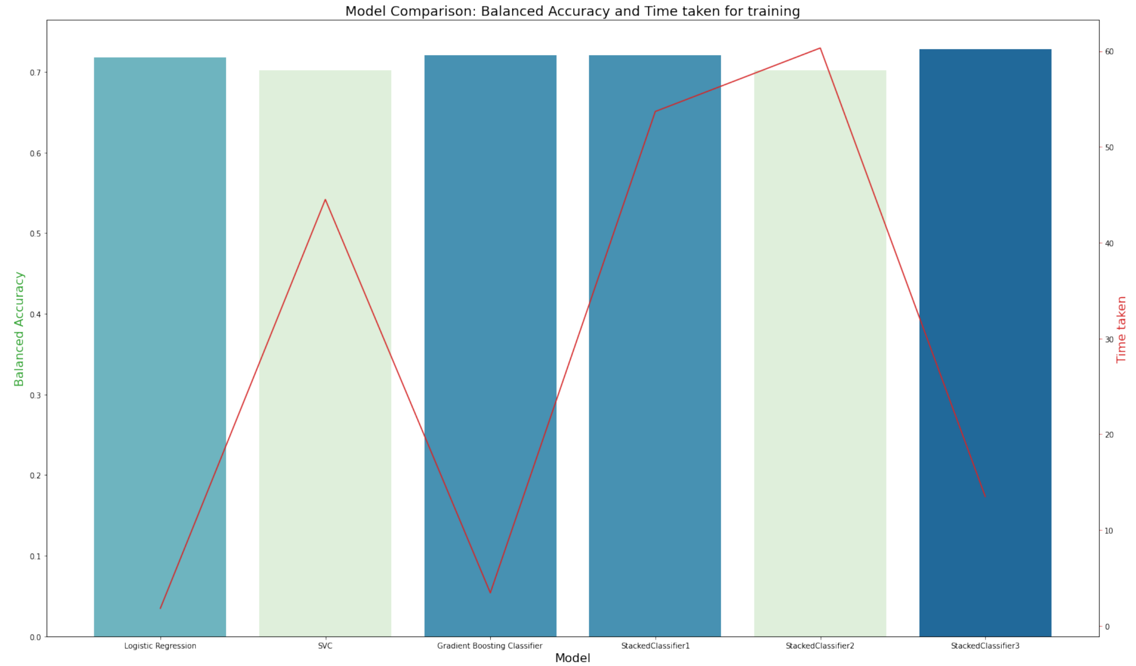
[94]:
```
models=[]
models.append(("Logistic Regression", LogisticRegression(penalty='l1',␣
↪solver='liblinear', random_state=42)))
models.append(("SVC", SVC(kernel='rbf', random_state=42, probability=True)))
models.append(("Gradient Boosting Classifier",␣
↪GradientBoostingClassifier(learning_rate=0.1, n_estimators=150,␣
↪random_state=42)))
models.append(('StackedClassifier1', init_stacking()))
models.append(('StackedClassifier2', init_stacking2()))
models.append(('StackedClassifier3', init_stacking3()))

pf5 = evaluate_models(models, X_train)
display(pf5)
```

```
                        Model  Accuracy  Balanced Accuracy  Precision  \
0         Logistic Regression  0.854695           0.717491   0.801395
1                         SVC  0.857872           0.701601   0.826808
2  Gradient Boosting Classifier  0.857007           0.720781   0.805794
3          StackedClassifier1  0.859028           0.720822   0.813329
```

```
4            StackedClassifier2  0.846991          0.702330   0.787543
5            StackedClassifier3  0.858836          0.727993   0.806997

     Recall        F1    PR-AUC   ROC-AUC  Cohen Kappa   Fit Time  Score Time
0  0.717491  0.745608  0.677692  0.856513     0.495712   1.821607    0.009636
1  0.701601  0.737031  0.691840  0.857510     0.482430  44.514641    0.703556
2  0.720781  0.749524  0.692557  0.865345     0.503463   3.437889    0.012929
3  0.720822  0.751157  0.690893  0.858289     0.507226  53.697808    0.270209
4  0.702330  0.729789  0.643097  0.833593     0.464916  60.327352    0.249652
5  0.727993  0.755611  0.693276  0.867930     0.514899  13.492572    0.110804

time: 3min 7s (started: 2021-04-18 15:45:46 +08:00)
```

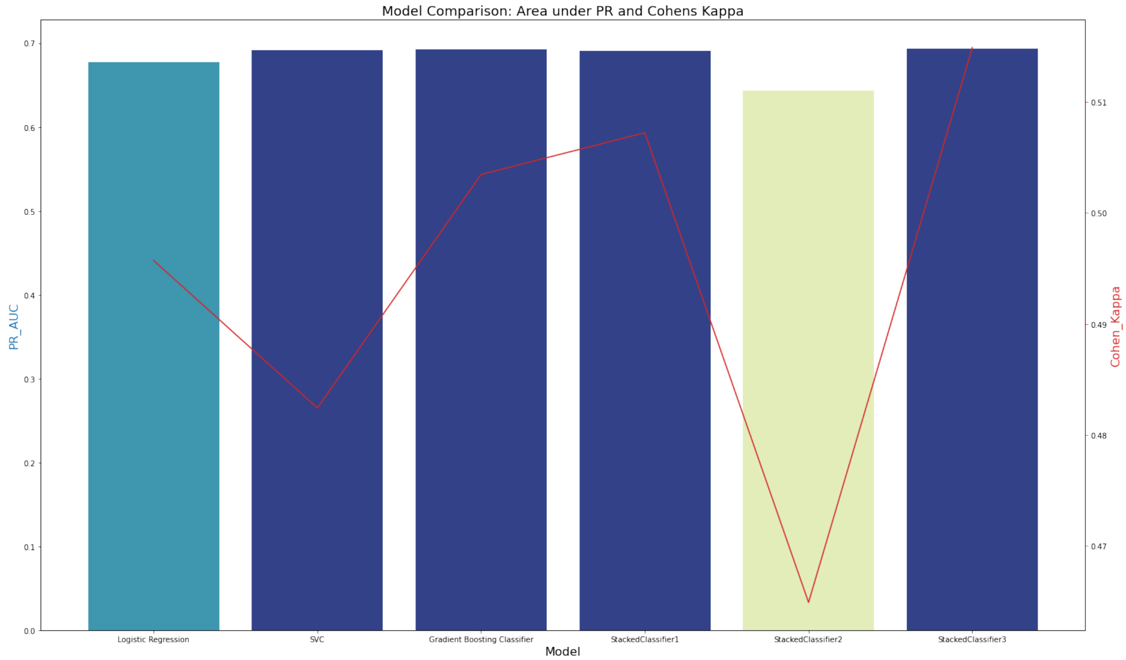
0.21 Model Evaluation

[114]:
```python
balanced_accuracy_scores = pf5['Balanced Accuracy']
pr_auc_scores = pf5['PR-AUC']
coh_kap_scores = pf5['Cohen Kappa']
tt = pf5['Fit Time']

model_data = {'Model': ['Logistic Regression', 'SVC', 'Gradient Boosting␣
 ↪Classifier', 'StackedClassifier1', 'StackedClassifier2',␣
 ↪'StackedClassifier3'],
              'Balanced Accuracy': balanced_accuracy_scores,
              'PR_AUC': pr_auc_scores,
              'Cohen_Kappa': coh_kap_scores,
              'Time taken': tt}
data = pd.DataFrame(model_data)

fig, ax1 = plt.subplots(figsize=(25,15))
ax1.set_title('Model Comparison: Balanced Accuracy and Time taken for␣
 ↪training', fontsize=18)
color = 'tab:green'
ax1.set_xlabel('Model', fontsize=16)
ax1.set_ylabel('Balanced Accuracy', fontsize=16, color=color)
ax2 = sns.barplot(x='Model', y='Balanced Accuracy', data = data,␣
 ↪palette=colors_from_values(data['Balanced Accuracy'], "GnBu"))
ax1.tick_params(axis='y')
ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Time taken', fontsize=16, color=color)
ax2 = sns.lineplot(x='Model', y='Time taken', data = data, sort=False,␣
 ↪color=color)
ax2.tick_params(axis='y', color=color)
```




```
time: 265 ms (started: 2021-04-18 16:01:28 +08:00)
```

```
[113]: fig, ax3 = plt.subplots(figsize=(25,15))
ax3.set_title('Model Comparison: Area under PR and Cohens Kappa', fontsize=18)
color = 'tab:blue'
ax3.set_xlabel('Model', fontsize=16)
ax3.set_ylabel('PR_AUC', fontsize=16, color=color)
ax4 = sns.barplot(x='Model', y='PR_AUC', data = data,␣
 ↪palette=colors_from_values(data['PR_AUC'], "YlGnBu"))
ax3.tick_params(axis='y')
ax4 = ax3.twinx()
color = 'tab:red'
ax4.set_ylabel('Cohen_Kappa', fontsize=16, color=color)
ax4 = sns.lineplot(x='Model', y='Cohen_Kappa', data = data, sort=False,␣
 ↪color=color)
ax4.tick_params(axis='y', color=color)
plt.show()
```




```
time: 237 ms (started: 2021-04-18 16:01:07 +08:00)
```

Learning curve is used to compare the performance of the models on training and testing data over a varying number of training instances.

[95]:
```
y_train = pd.DataFrame(y_train)
y_test = pd.DataFrame(y_test)
X_comb = pd.concat([X_train, X_test], axis=0)
y_comb = pd.concat([y_train, y_test], axis=0)
```

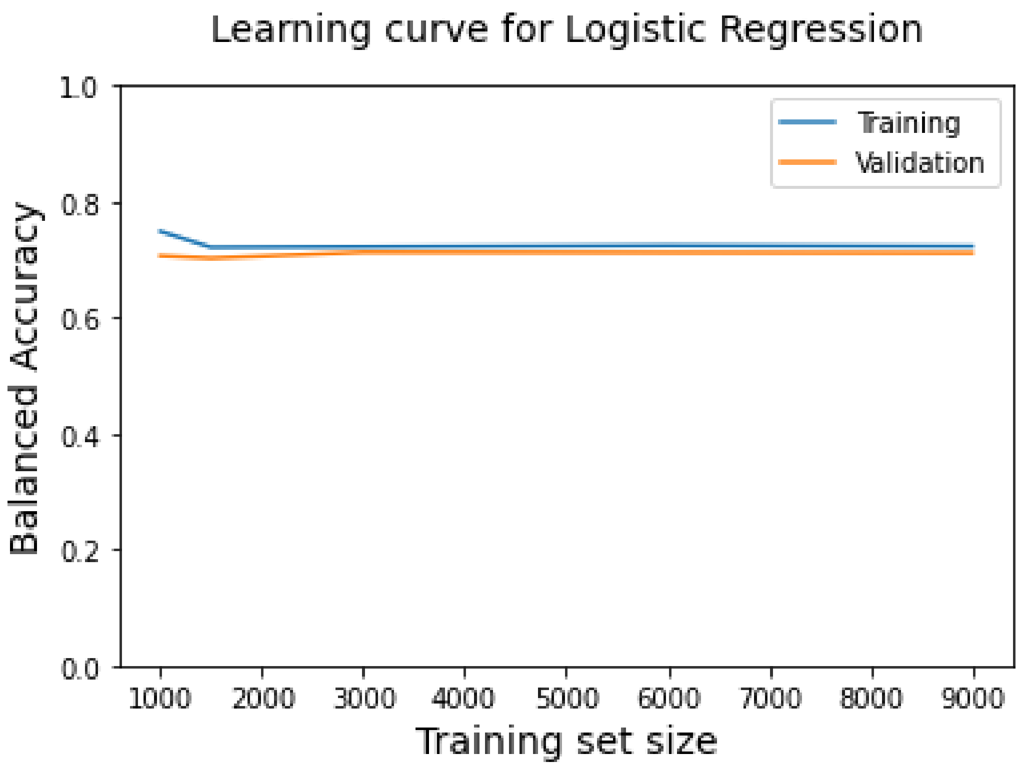
```
time: 5.55 ms (started: 2021-04-18 15:48:54 +08:00)
```

[96]:
```
from sklearn.model_selection import learning_curve

def plot_learning_curve(name, model):

    train_sizes = [1, 1000, 1500, 3000, 6000, 9000]
    train_sizes, train_scores, validation_scores = learning_curve(
        model, X_comb, y_comb, train_sizes = train_sizes,
        cv = 10, n_jobs=-1, scoring = 'balanced_accuracy')

    train_scores_mean = train_scores.mean(axis = 1)
    validation_scores_mean = validation_scores.mean(axis = 1)

    plt.plot(train_sizes, train_scores_mean, label='Training')
    plt.plot(train_sizes, validation_scores_mean, label='Validation')
```

```
    plt.ylabel('Balanced Accuracy', fontsize = 14)
    plt.xlabel('Training set size', fontsize = 14)
    title = 'Learning curve for '+ name
    plt.title(title, fontsize=14, y=1.05)
    plt.legend()
    plt.ylim(0,1.0)
```

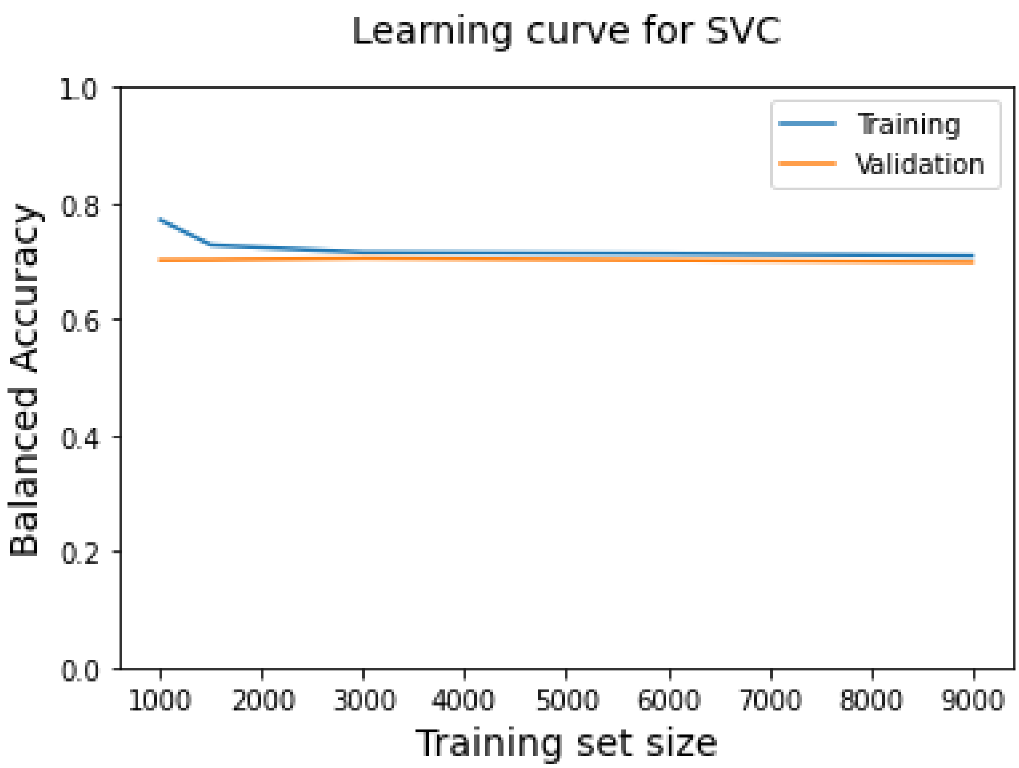
```
time: 51.1 ms (started: 2021-04-18 15:48:54 +08:00)
```

[97]:
```
plot_learning_curve('Logistic Regression', LogisticRegression(penalty='l1',␣
↪solver='liblinear', random_state=42))
```



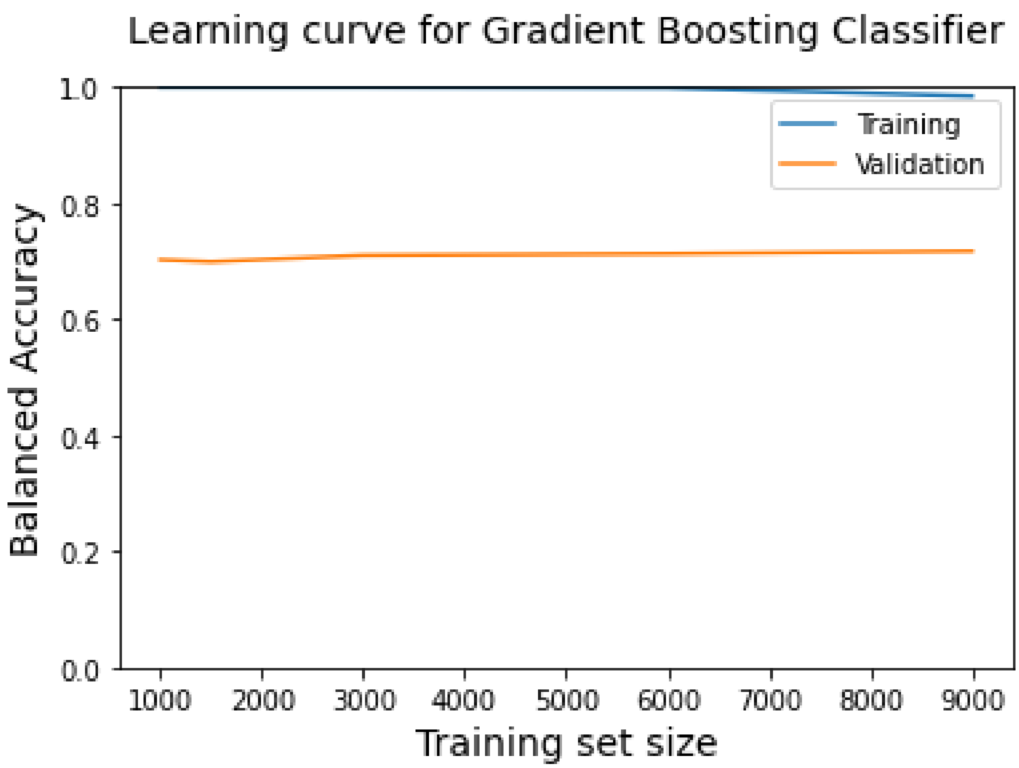

```
time: 3.39 s (started: 2021-04-18 15:48:54 +08:00)
```

[98]:
```
plot_learning_curve('SVC', SVC(kernel='linear', gamma=10, C=10))
```



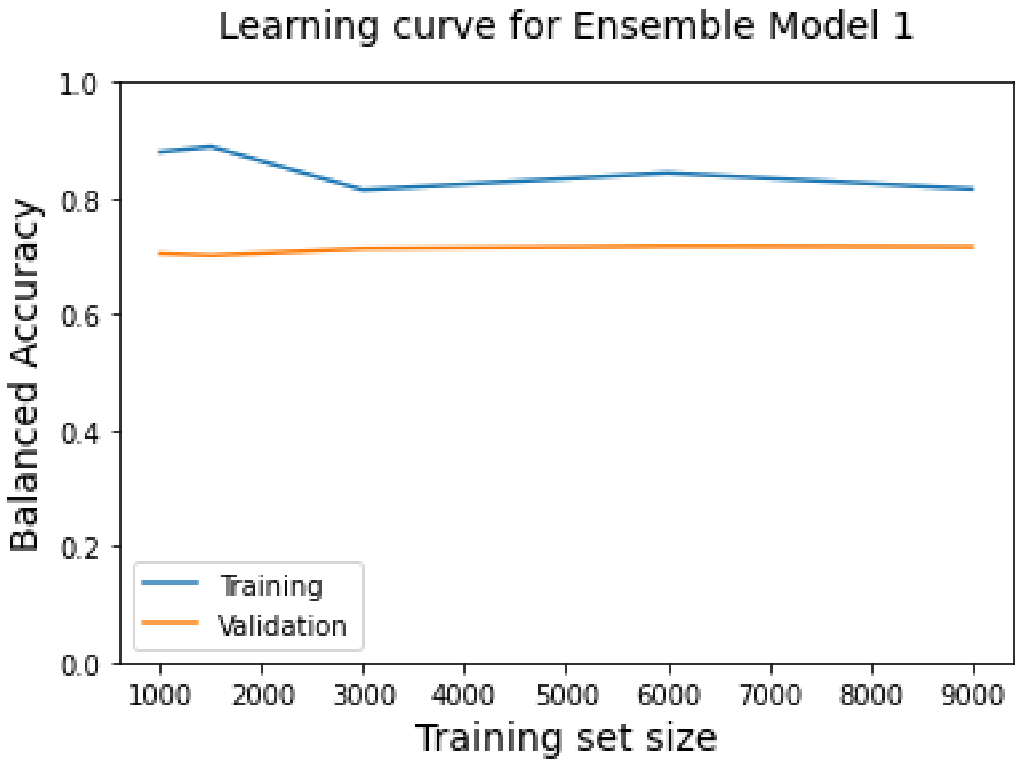

```
time: 21 s (started: 2021-04-18 15:48:57 +08:00)
```

[99]:
```
plot_learning_curve('Gradient Boosting Classifier',␣
↪GradientBoostingClassifier(n_estimators=100, min_samples_split=10,␣
↪min_samples_leaf=5,
                                                                         ␣
↪max_features='sqrt', max_depth=8, loss='exponential',
                                                                         ␣
↪learning_rate= 0.2, criterion='friedman_mse'))
```



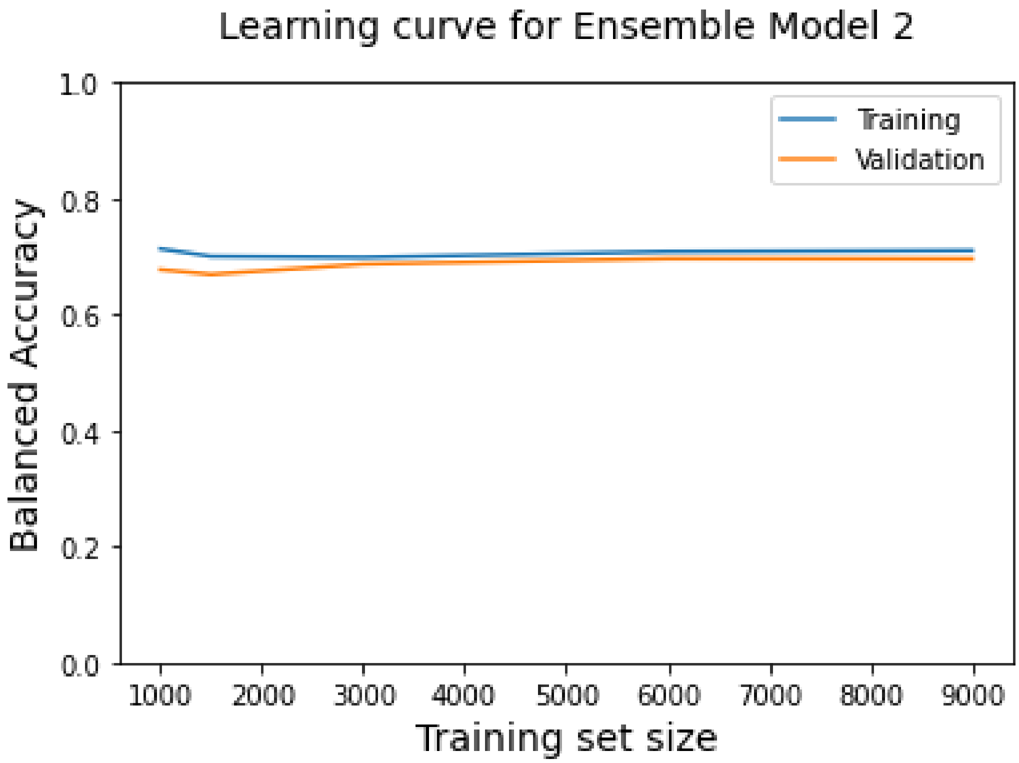
time: 4.24 s (started: 2021-04-18 15:49:18 +08:00)

[100]:
```
plot_learning_curve('Ensemble Model 1', init_stacking())
```



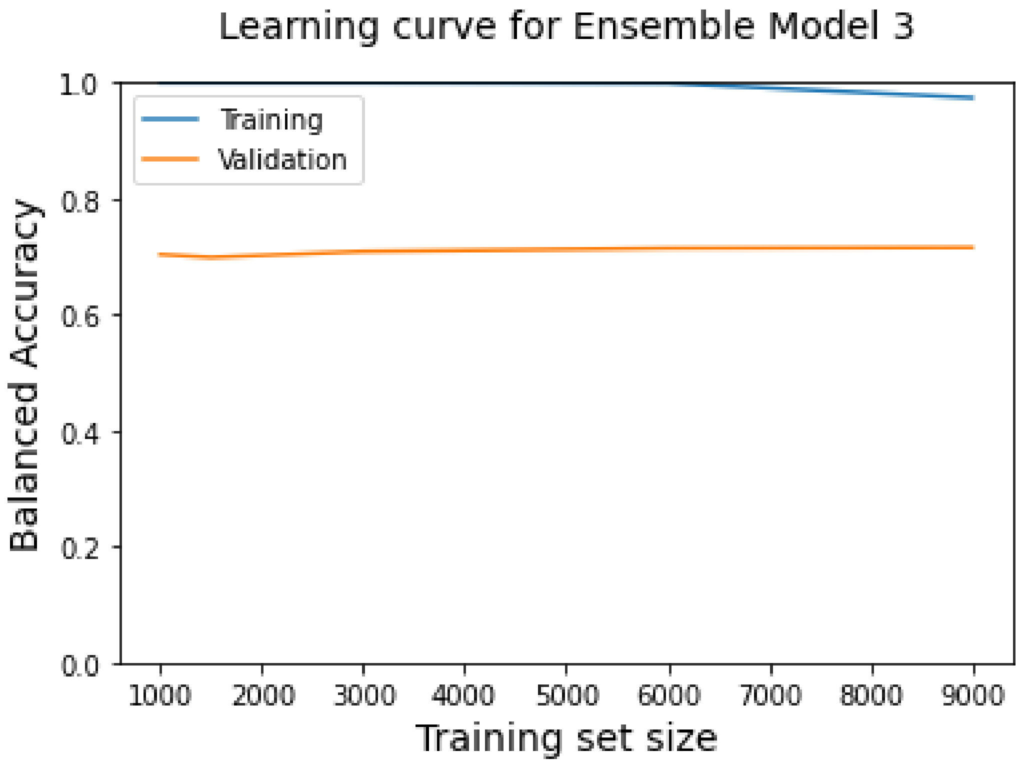

```
time: 1min 23s (started: 2021-04-18 15:49:22 +08:00)
```

[101]:
```
plot_learning_curve('Ensemble Model 2', init_stacking2())
```




```
time: 1min 27s (started: 2021-04-18 15:50:46 +08:00)
```

[102]:
```
plot_learning_curve('Ensemble Model 3', init_stacking3())
```




```
time: 29.2 s (started: 2021-04-18 15:52:14 +08:00)
```

From the Learning Curves, we can conclude that:

- Logistic Regression, SVC and Ensemble Model 2 have minimal overfitting because the validation balanced accuracy scores are only slightly lower than the training balanced accuracy scores.
- Gradient Boosting Classifier, Ensemble Model 1 and Ensemble Model 3 are obviously overfitting because the validation balanced accuracy scores are a lot lower than the training balanced accuracy scores.

1 Conclusion and Results

- By considering the balanced accuracy, Precision-Recall AUC, Cohen's Kappa and Training Time, the best model is Logistic Regression.
- The model has a balanced accuracy of **0.7175, Precision-Recall AUC of 0.6777, Cohen's Kappa score of 0.496 and Training Time of 1.8216s**.
- The model is able to generalise well on the testing data and can predict rain in Australia with an **accuracy of 0.8547**.
- Increasing the size of the training set did not improve the balanced accuracy of the model.

- Feature selection using PCA did not improve the performance of the model.
- Hyperparameter tuning was able to improve the performance of the model.

Future Improvements

We can further improve the performance of the models by - doing non-linear transformation before the model building. - trying other feature selection methods such as SelectPercentile. - comparing performance of models with and without feature scaling and removing outliers.

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Appendix 2

Assessment Rubric

Name(s): Tan Jie Ying, Andy Chow Sai Kit, Wong Yew Lee, Li Chen Zhen Programme: RDS2 Group: 1 Date: 18 April 2021

Project Part A – Shortlist promising models (40%)

No	Item	Criteria: Poor	Criteria: Accomplished	Criteria: Good	Final Marks
1	Problem statement (10)	No or very little discussion on existing problem and the project The proposed project already exists, or with very minor change. No discussion or very little of introduction given to the related system or technology. 0-4	Little discussion on existing problem and introduction of proposed project. Minor ideas are modified from existing system(s). Introduction to the related system is given, but no evaluation provided. 5-7	Good discussion and evaluation of existing problem and the proposed project. Ideas modified from existing system, with some creative ideas are added. Good discussion and evaluation of the related system. 8-10	
2	Programming (20)	The end product fails with many logic errors, many actions lacked exception handling. Solutions are over-simplified. Programming skill needs improvement. Evaluation steps of different models are not automated. 0-7	Major parts are logical, but some steps to complete a specific job may be tedious or unnecessarily complicated. Program algorithm demonstrates acceptable level of complexity. The student is qualified to be a programmer Some evaluation steps are automated. 8-15	Correct and logical flow, exceptions are handled well. Demonstrates appropriate or high level of complex algorithms and programming skills. Almost all evaluation steps are automated. 16-20	
3	degree of completion (10)	Too much still remain to be done. Basic requirements are not fulfilled. The end product produces enormous errors, faults or incorrect results. Limited performance metrics are used. 0-4	All required features present in the interface within the required scope, but some are simplified. Or one or two features are missing. The system is able to run with minor errors. More than 5 performance metrics are shown. 5-7	All required features present in the interface within or beyond the required scope. No bugs apparent during demonstration. More than 8 performance metrics are shown. 8-10	
				Sum of Score	

Project Part B – Fine-tune the system (35%)

No	Item	Criteria: Poor	Criteria: Accomplished	Criteria: Good	Final Marks
1	Model Optimization (10)	The model is not optimized. Default setting is used without any adjustments. 0-4	The model is optimized based on performance metrics. Different parameters are regularized to optimize the model. Ensemble classifier is not attempted. 5-7	The model is optimized based on performance metrics. Different parameters are regularized to optimize the model Ensemble classifier is evaluated. 8-10	
2	system implementation (10)	The end product is produced with different system design or approach, which is not related to the initial proposal. 0-4	The end product conforms to most of the system design, but some are different from the specification. 5-7	The end product fully conforms to the proposed system design. 8-10	
3	Results (Performance measurement) (10)	Analytical methods were missing or inappropriately aligned with data and research design. Results were confusing. 0-4	The analytical methods were identified. Results were presented. All were related to the research question and design. Sufficient metric or measurement is applied. 5-7	Analytical methods and results presentation were sufficient, specific, clear, structured and appropriate based on the research questions and research design. Extra metric or measurement is applied. 8-10	
4	Organization (5)	The structure of the paper was weak. Transition was weak and difficult to understand. 0-2	A workable structure was presented for presenting ideas. Transition was smooth and clear. 3-4	Structure was intuitive and sufficiently inclusive of important information of the research. Transition from one to another was smooth and organized. 5	
				Sum of Score	

Presentation (25%)

No	Item	Criteria			Final Marks
		Poor	Accomplished	Good	
1	Output (10)	Inadequate information/outputs needed are generated. Most of the information/outputs generated are less accurate. Results visualization is overly cluttered or the design seems inappropriate for problem area. Lack of information that are useful for the user 0-4	Adequate information/outputs needed are generated. The information/output generated are accurate but some with errors. Pleasant looking, clean, well-organized results visualization The information displayed are useful for the user, but some details are omitted. 5-7	All the necessary information/outputs are generated. All or most of the information/outputs generated are accurate. Minor errors can be ignored. The results are visually pleasing and appealing. Great use of colors, fonts, graphics and layout. The information displayed are useful to the users and complete with necessary details. 8-10	
2	Presentation (10)	Presentation was unclear. Results were presented without justifications and reasons. Results were not supported with ML concepts and theories. 0-4	Presentation is well organized for the most part, but more clarity with transitions is needed. Answers to the research question and system performances were supported with sufficient ML concepts and theories. 5-7	Presentation was concise and straight to the points. Discussions of the results were presented and illustrated in easily interpretable graphs or charts. The research question and system performance were answered and identified.\ 8-10	
3	Question and answer (5)	The student is unclear about the work produced, sometimes not even knowing where to find the source code. 0-1	The student knows the code whereabouts, but sometimes may not be clear why the work was done in such a way. 2-3	The student is clear about every piece of the work done. 4-5	
				Sum of Score	