MSDS696 Data Science Practicum II

Topic: Rain Prediction in Australia using Machine Learning with Python

Date: 21AUGUST2022

Author: Olumide Aluko

Purpose: The project aims to use Rain in Australia Dataset from Kaggle. The problem is to predict whether it will rain tomorrow or not given the weather conditions of today. We will be using Decision Tree Classifier.

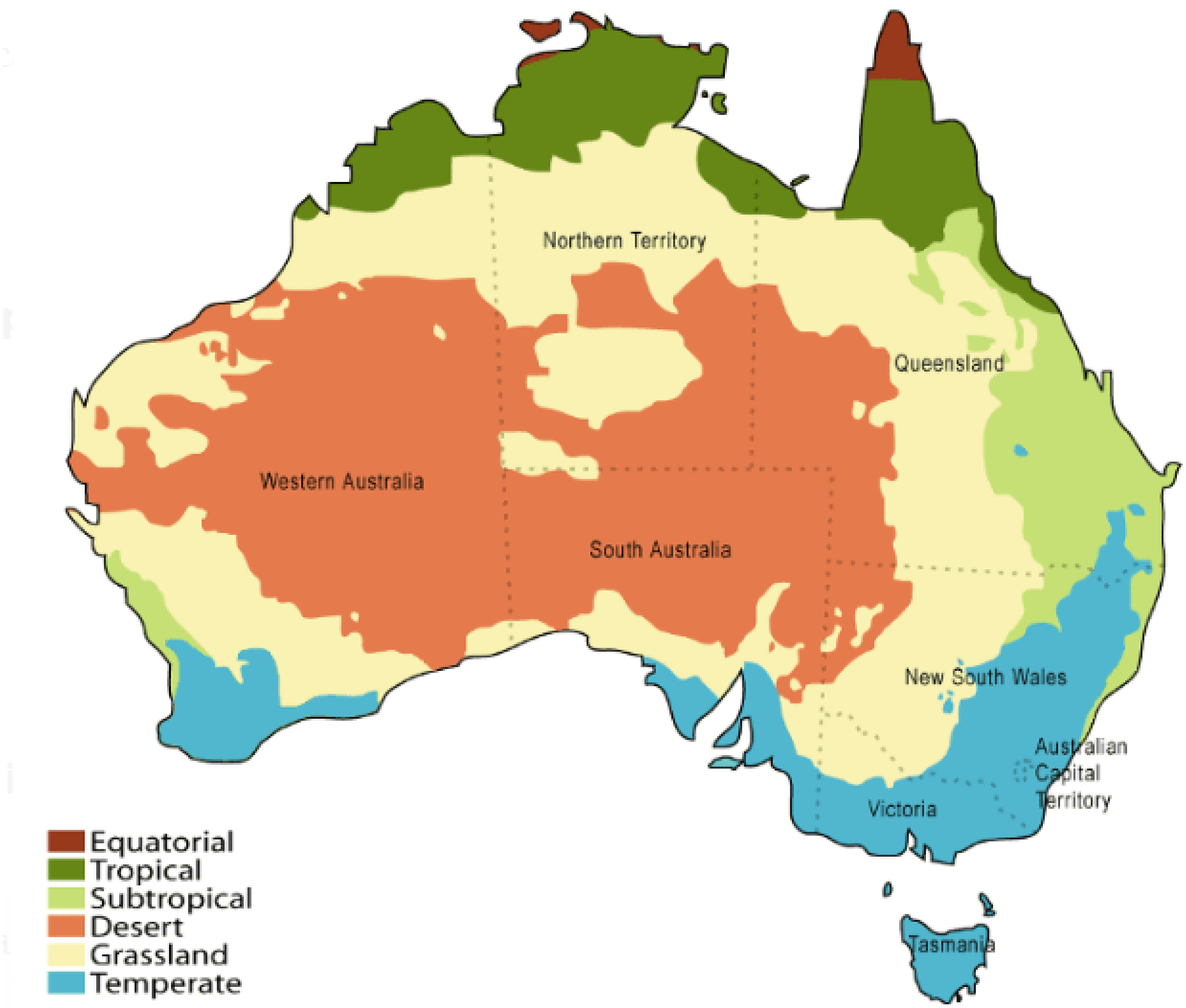


Table of contents:

5. Import Dataset
6. Train, Validation, Test Split
7. Identify Inputs & Target Columns
8. Identify Numerical & Categorical Columns
9. Impute Missing Values
10. Scaling Numerical Columns
11. Encoding Categorical Columns
12. Training & Visualizing Decision Trees
13. Feature Importance
14. Hyperparameter Tuning - To Reduce Overfitting
15. Results and Conclusion

1. Problem Statement:

Predict next-day rain by training classification models on the target variable using the Australia Rainfall data.

Solution: Design a predictive classification model (Decision) using machine learning algorithms to forecast whether or not it will rain tomorrow in Australia.

2. Data Description:

Dataset Source: https://www.kaggle.com/code/ankitjoshi97/rainfall-in-australia-eda-prediction-89-acc/data

The dataset is taken from Kaggle and contains about 10 years of daily weather observations from many locations across Australia.

Dataset Description:

- Number of columns: 23
- Number of rows: 145460
- Number of Independent Columns: 22
- Number of Dependent Column: 1

3. Import Libraries

Let's import the necessary libraries.

In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib
%matplotlib inline
```

```
import os
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.tree import DecisionTreeClassifier, plot_tree, export_text
from sklearn.metrics import accuracy_score, confusion_matrix
import pyarrow as pa
from sklearn.ensemble import RandomForestClassifier
import joblib
# Warnings configuration
# ==============================================================================
import warnings
warnings.filterwarnings('ignore')
```

4. Configurations

Lets set some configurations needed for matplotlib, seaborn and pandas.

In [2]:
```
pd.set_option('display.max_columns', None) #display unlimited columns
pd.set_option('display.max_rows', 150) #display maximum of 150 rows
sns.set_style('darkgrid') #style
matplotlib.rcParams['font.size'] = 14 #font size = 14pt
matplotlib.rcParams['figure.figsize'] = (10, 6) #figure size = (10. 6)
matplotlib.rcParams['figure.facecolor'] = '#00000000' #background color of figure
```

5. Import Dataset

Let's download the dataset and import it using pandas function read_csv().

In [3]:
```
# view data head
df_rain = pd.read_csv('weatherAUS.csv')
df_rain
```

Out[3]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGus
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	
...	...	...	...	...	...	...	...	...	
145455	2017-06-21	Uluru	2.8	23.4	0.0	NaN	NaN	E	

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGus
145456	2017-06-22	Uluru	3.6	25.3	0.0	NaN	NaN	NNW	
145457	2017-06-23	Uluru	5.4	26.9	0.0	NaN	NaN	N	
145458	2017-06-24	Uluru	7.8	27.0	0.0	NaN	NaN	SE	
145459	2017-06-25	Uluru	14.9	NaN	0.0	NaN	NaN	NaN	

145460 rows × 23 columns

In [4]:

```
#print df_rain.head
print(df_rain.head())
```

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

  WindGustDir  WindGustSpeed WindDir9am WindDir3pm  WindSpeed9am  \
0           W           44.0          W        WNW          20.0   
1         WNW           44.0        NNW        WSW           4.0   
2         WSW           46.0          W        WSW          19.0   
3          NE           24.0         SE          E          11.0   
4           W           41.0        ENE         NW           7.0   

   WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  \
0          24.0         71.0         22.0       1007.7       1007.1       8.0   
1          22.0         44.0         25.0       1010.6       1007.8       NaN   
2          26.0         38.0         30.0       1007.6       1008.7       NaN   
3           9.0         45.0         16.0       1017.6       1012.8       NaN   
4          20.0         82.0         33.0       1010.8       1006.0       7.0   

   Cloud3pm  Temp9am  Temp3pm RainToday RainTomorrow  
0       NaN     16.9     21.8        No           No  
1       NaN     17.2     24.3        No           No  
2       2.0     21.0     23.2        No           No  
3       NaN     18.1     26.5        No           No  
4       8.0     17.8     29.7        No           No  
```

Let's look at the info of the dataset,

In [5]:

```
df_rain.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           145460 non-null  object 
 1   Location       145460 non-null  object 
 2   MinTemp        143975 non-null  float64
 3   MaxTemp        144199 non-null  float64
```

```
 4   Rainfall       142199 non-null  float64
 5   Evaporation    82670 non-null   float64
 6   Sunshine       75625 non-null   float64
 7   WindGustDir    135134 non-null  object
 8   WindGustSpeed  135197 non-null  float64
 9   WindDir9am     134894 non-null  object
 10  WindDir3pm     141232 non-null  object
 11  WindSpeed9am   143693 non-null  float64
 12  WindSpeed3pm   142398 non-null  float64
 13  Humidity9am    142806 non-null  float64
 14  Humidity3pm    140953 non-null  float64
 15  Pressure9am    130395 non-null  float64
 16  Pressure3pm    130432 non-null  float64
 17  Cloud9am       89572 non-null   float64
 18  Cloud3pm       86102 non-null   float64
 19  Temp9am        143693 non-null  float64
 20  Temp3pm        141851 non-null  float64
 21  RainToday      142199 non-null  object
 22  RainTomorrow   142193 non-null  object
dtypes: float64(16), object(7)
memory usage: 25.5+ MB
```

There are 145460 samples out of which there are 142193 samples whose 'RainTomorrow' column is non-null. Therefore, we can just remove the rows in which the 'RainTomorrow' column is null since there will be no significant information loss.

In [6]:
```
df_rain.dropna(subset=['RainTomorrow'], inplace=True)
```

Checking the Dimensions of Dataset: The shape property is utilized to detect the dimensions of the dataset.

print(df_rain.shape)

In [7]:
```
# view columns
df_rain.columns
```

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

Summary of a Dataset:

Let’s generate descriptive statistics for the dataset using the function describe() in pandas.

Descriptive Statistics: It is used to summarize and describe the features of data in a meaningful way to extract insights. It uses two types of statistic to describe or summarize data:

Measures of tendency Measures of spread

In [8]:
```
df_rain.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
MinTemp	141556.0	12.186400	6.403283	-8.5	7.6	12.0	16.8	33.9

	count	mean	std	min	25%	50%	75%	max
MaxTemp	141871.0	23.226784	7.117618	-4.8	17.9	22.6	28.2	48.1
Rainfall	140787.0	2.349974	8.465173	0.0	0.0	0.0	0.8	371.0
Evaporation	81350.0	5.469824	4.188537	0.0	2.6	4.8	7.4	145.0
Sunshine	74377.0	7.624853	3.781525	0.0	4.9	8.5	10.6	14.5
WindGustSpeed	132923.0	39.984292	13.588801	6.0	31.0	39.0	48.0	135.0
WindSpeed9am	140845.0	14.001988	8.893337	0.0	7.0	13.0	19.0	130.0
WindSpeed3pm	139563.0	18.637576	8.803345	0.0	13.0	19.0	24.0	87.0
Humidity9am	140419.0	68.843810	19.051293	0.0	57.0	70.0	83.0	100.0
Humidity3pm	138583.0	51.482606	20.797772	0.0	37.0	52.0	66.0	100.0
Pressure9am	128179.0	1017.653758	7.105476	980.5	1012.9	1017.6	1022.4	1041.0
Pressure3pm	128212.0	1015.258204	7.036677	977.1	1010.4	1015.2	1020.0	1039.6
Cloud9am	88536.0	4.437189	2.887016	0.0	1.0	5.0	7.0	9.0
Cloud3pm	85099.0	4.503167	2.720633	0.0	2.0	5.0	7.0	9.0
Temp9am	141289.0	16.987509	6.492838	-7.2	12.3	16.7	21.6	40.2
Temp3pm	139467.0	21.687235	6.937594	-5.4	16.6	21.1	26.4	46.7

From the above descriptive statistics, we can deduce the following:

- The average minimum temperature is 12.19 and average maximum temperature is 23.221 degree Celcius.
- The mean rainfall is 2.35 mm. -The average sunshine recieved is 7.62 hour.
- The average wind gust speed is 40.00 km/hr.
- The minimum temperature recorded is -8.5 degree Celcius and the maximum recorded temperature is 48.1 degree Celcius.
- The minimum rainfall recorded for a particular day is 0 mm and maximum is 371 mm.
- The median evaporation is 4.8 mm
- Temp ranges from -8.5 to 33 with a standard deviation of 6.4 -Hottest day in Australia had 48 degrees
- On average Wind speed remains pretty similar at 9 am and 3 pm.

In [9]:

```
print(df_rain.describe(include=[object]))
```

```
              Date  Location WindGustDir WindDir9am WindDir3pm RainToday  \
count       142193    142193      132863     132180     138415    140787   
unique        3436        49          16         16         16         2   
top     2017-06-09  Canberra           W          N         SE        No   
freq            49      3418        9780      11393      10663    109332   

       RainTomorrow  
count        142193  
unique            2  
top              No  
freq         110316  
```

The statistics displayed for the attributes of 'object' datatype is different from the one displayed for numeric datatypes. Some of the conclusions drawn from the above table are:

- There are total 49 unique locations and 16 unique wind directions.
- RainToday and RainTomorrow attribute has 2 unique values.
- The top location is Canberra occuring 3418 times.

In [10]:

```
df_rain.isnull().sum()
```

Out[10]:

```
Date                0
Location            0
MinTemp           637
MaxTemp           322
Rainfall         1406
Evaporation     60843
Sunshine        67816
WindGustDir      9330
WindGustSpeed    9270
WindDir9am      10013
WindDir3pm       3778
WindSpeed9am     1348
WindSpeed3pm     2630
Humidity9am      1774
Humidity3pm      3610
Pressure9am     14014
Pressure3pm     13981
Cloud9am        53657
Cloud3pm        57094
Temp9am           904
Temp3pm          2726
RainToday        1406
RainTomorrow        0
dtype: int64
```

Observations:-

- Maximum null values are present in Sunshine column followed by Evaporation.
- More than 50,000 null values are present in Cloud9am and Cloud3pm columns.
- Around 13,000 to 14,000 null values are present in Pressure9am and Pressure3pm columns.
- More than 9,000 null values are present in WindGustDir, WindGustSpeed and WindDir9am columns
- There are many columns having more than 1000 null records.

6. Exploratory Data Analysis and Visualization

In [11]:

```
# install required libraries
import plotly.express as px
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
```

```
matplotlib.rcParams['figure.figsize'] = (10, 6)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

Correlations

Let's see if we can pull out some correlations between locations based on temperature and rainfall. We do get ~(4-5) clusters of locations with similar rainfall patterns: Sydney region (Sydney, Penrith, Richmond, etc.), Perth, Central Australia and Southern Australia (Melbourne, Tasmania).

In [12]:

```
# PLot Correlation Matrix

corr = df_rain.corr()
corr.style.background_gradient(cmap='PuBu').set_precision(2)
```

Out[12]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am
MinTemp	1.00	0.74	0.10	0.47	0.07	0.18	0.18
MaxTemp	0.74	1.00	-0.07	0.59	0.47	0.07	0.01
Rainfall	0.10	-0.07	1.00	-0.06	-0.23	0.13	0.09
Evaporation	0.47	0.59	-0.06	1.00	0.37	0.20	0.19
Sunshine	0.07	0.47	-0.23	0.37	1.00	-0.03	0.01
WindGustSpeed	0.18	0.07	0.13	0.20	-0.03	1.00	0.60
WindSpeed9am	0.18	0.01	0.09	0.19	0.01	0.60	1.00
WindSpeed3pm	0.18	0.05	0.06	0.13	0.06	0.69	0.52
Humidity9am	-0.23	-0.51	0.22	-0.51	-0.49	-0.22	-0.27
Humidity3pm	0.01	-0.51	0.26	-0.39	-0.63	-0.03	-0.03
Pressure9am	-0.45	-0.33	-0.17	-0.27	0.04	-0.46	-0.23
Pressure3pm	-0.46	-0.43	-0.13	-0.29	-0.02	-0.41	-0.17
Cloud9am	0.08	-0.29	0.20	-0.19	-0.68	0.07	0.02
Cloud3pm	0.02	-0.28	0.17	-0.18	-0.70	0.11	0.05
Temp9am	0.90	0.89	0.01	0.55	0.29	0.15	0.13
Temp3pm	0.71	0.98	-0.08	0.57	0.49	0.03	0.01

Observation:-

- MaxTemp and Temp3pm have a strong positive correlation of 0.97.
- Pressure9am and Pressure3pm have a strong positive correlation of 0.96.
- MinTemp and Temp9am have a strong positive correlation of 0.90.
- MaxTemp and Temp9am have a strong positive correlation of 0.88.
- Temp9am and Temp3pm have a strong positive correlation of 0.85.
- Humidity and Temperature attributes have a negative correlation of 0.50.

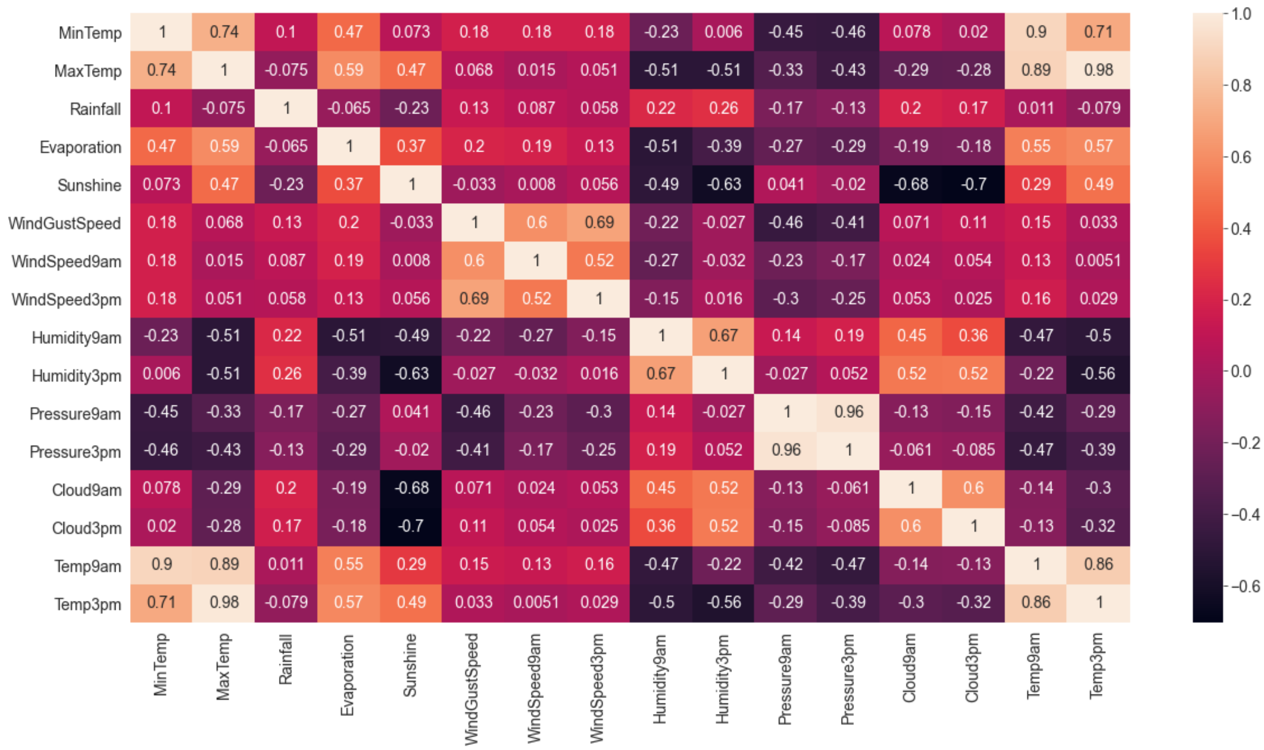
Let us try heatmap of correlation between all features in the dataset

In [13]:

```
plt.figure(figsize = (20,10))
sns.heatmap(df_rain.corr(), annot = True)
```

Out[13]:

```
<AxesSubplot:>
```



From above heatmap of correlation, we can see that there are a few features which are impacting other and can be termed as positively correlated

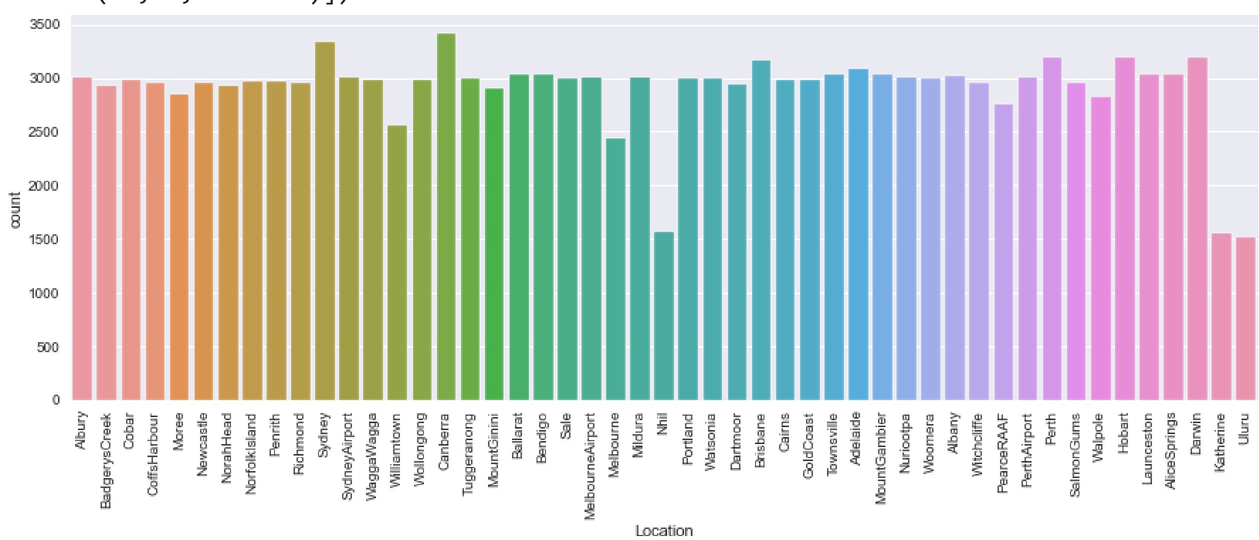
In [14]:

```
plt.style.use('seaborn')

# Distribution of Location

plt.figure(figsize=(15, 5))
sns.countplot(df_rain['Location'])
plt.xticks(rotation=90)
```

Out[14]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48]),
 [Text(0, 0, 'Albury'),
  Text(1, 0, 'BadgerysCreek'),
  Text(2, 0, 'Cobar'),
  Text(3, 0, 'CoffsHarbour'),
  Text(4, 0, 'Moree'),
  Text(5, 0, 'Newcastle'),
  Text(6, 0, 'NorahHead'),
  Text(7, 0, 'NorfolkIsland'),
  Text(8, 0, 'Penrith'),
  Text(9, 0, 'Richmond'),
  Text(10, 0, 'Sydney'),
  Text(11, 0, 'SydneyAirport'),
  Text(12, 0, 'WaggaWagga'),
  Text(13, 0, 'Williamtown'),
```

```
 Text(14, 0, 'Wollongong'),
 Text(15, 0, 'Canberra'),
 Text(16, 0, 'Tuggeranong'),
 Text(17, 0, 'MountGinini'),
 Text(18, 0, 'Ballarat'),
 Text(19, 0, 'Bendigo'),
 Text(20, 0, 'Sale'),
 Text(21, 0, 'MelbourneAirport'),
 Text(22, 0, 'Melbourne'),
 Text(23, 0, 'Mildura'),
 Text(24, 0, 'Nhil'),
 Text(25, 0, 'Portland'),
 Text(26, 0, 'Watsonia'),
 Text(27, 0, 'Dartmoor'),
 Text(28, 0, 'Brisbane'),
 Text(29, 0, 'Cairns'),
 Text(30, 0, 'GoldCoast'),
 Text(31, 0, 'Townsville'),
 Text(32, 0, 'Adelaide'),
 Text(33, 0, 'MountGambier'),
 Text(34, 0, 'Nuriootpa'),
 Text(35, 0, 'Woomera'),
 Text(36, 0, 'Albany'),
 Text(37, 0, 'Witchcliffe'),
 Text(38, 0, 'PearceRAAF'),
 Text(39, 0, 'PerthAirport'),
 Text(40, 0, 'Perth'),
 Text(41, 0, 'SalmonGums'),
 Text(42, 0, 'Walpole'),
 Text(43, 0, 'Hobart'),
 Text(44, 0, 'Launceston'),
 Text(45, 0, 'AliceSprings'),
 Text(46, 0, 'Darwin'),
 Text(47, 0, 'Katherine'),
 Text(48, 0, 'Uluru')])
```



Observation:-

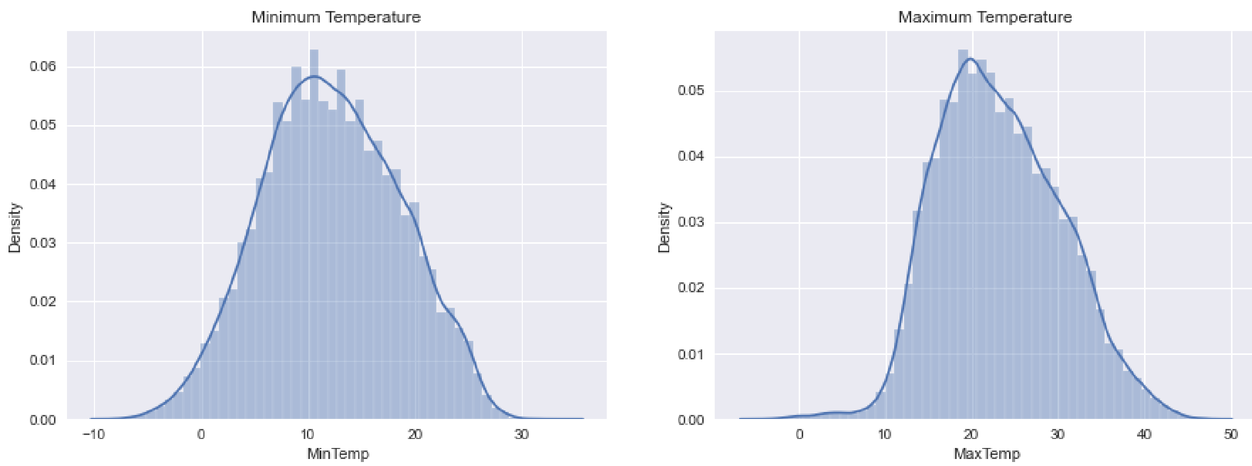
- Most occured location is Canberra followed by Sydney.
- Most of the locations have a frequency near 3000.
- Nhil, Katherine and Uluru have occured the least.

In [15]:

```
# Distribution of MinTemp and MaxTemp
```

```
fig, ax = plt.subplots(1, 2, figsize=(15,5))

# MinTemp
sns.distplot(df_rain['MinTemp'], ax=ax[0])
ax[0].set_title("Minimum Temperature")

# MaxTemp
sns.distplot(df_rain['MaxTemp'], ax=ax[1])
ax[1].set_title("Maximum Temperature")
```

Out[15]: Text(0.5, 1.0, 'Maximum Temperature')



Observation:-

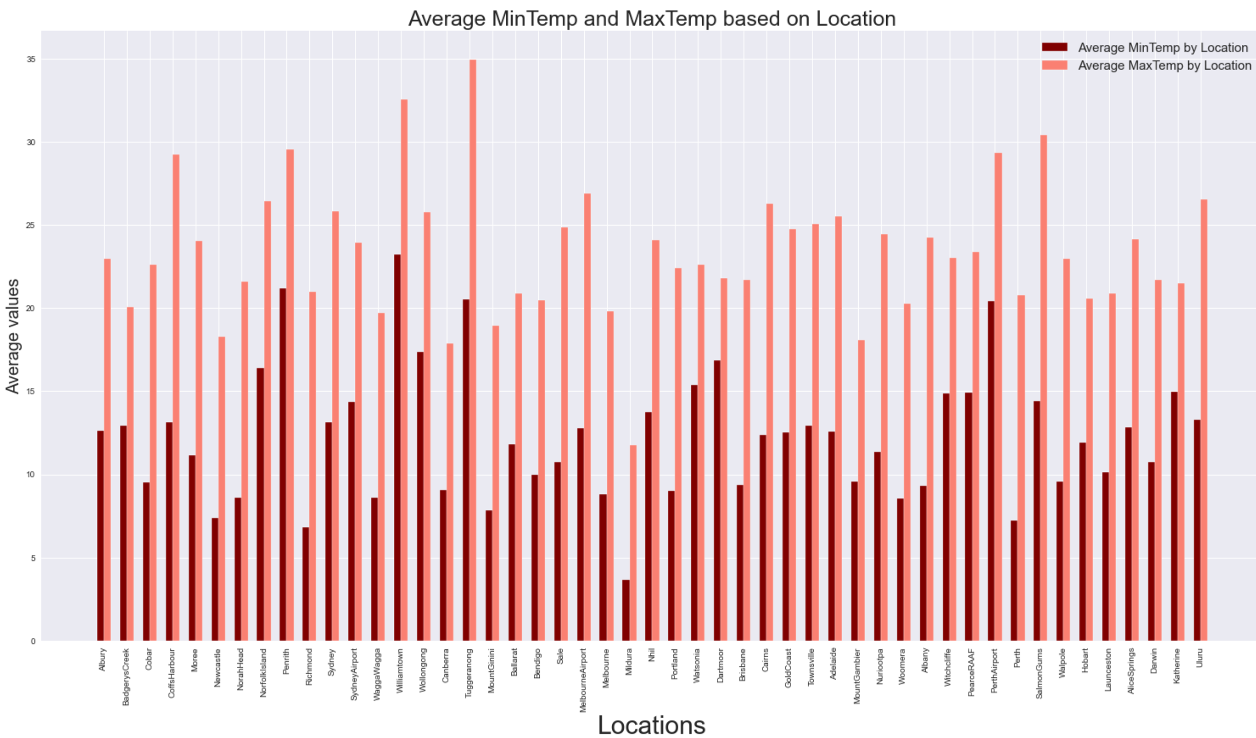
- The Highest concentration of points for minimum temperature is between 10 to 12 degree Celcius.
- The Highest concentration of points for maximum temperature is between 18 to 22 degree Celcius.

In [16]:

```
# MinTemp and MaxTemp of each location

a = df_rain.groupby('Location').agg({'MinTemp':'mean'})
c = df_rain.groupby('Location').agg({'MaxTemp':'mean'})
plt.rcParams["figure.figsize"] = (20,10)

n = df_rain['Location'].nunique()
x = np.arange(n)

loc = df_rain['Location'].unique()

fig = plt.figure()
ax = fig.add_axes([0, 0, 1, 1])

w = 0.3

ax.bar(x-w/2, a[:]['MinTemp'], label='Average MinTemp by Location', color='maroon', wid
ax.bar(x+w/2, c[:]['MaxTemp'], label='Average MaxTemp by Location', color='salmon', wid

ax.set_xticks(x)
ax.set_xticklabels(loc, rotation=90)

plt.xlabel('Locations', fontsize=30)
plt.ylabel('Average values', fontsize=20)
```

```
plt.title('Average MinTemp and MaxTemp based on Location', fontsize=25)
plt.legend(fontsize=15)
```

Out[16]: `<matplotlib.legend.Legend at 0x13a7aff8ac0>`



Observation:-

- The average maximum temperature is above 20 degree Celcius for most locations.
- The average minimum temperature is between 5 and 15 degree Celcius for most locations.

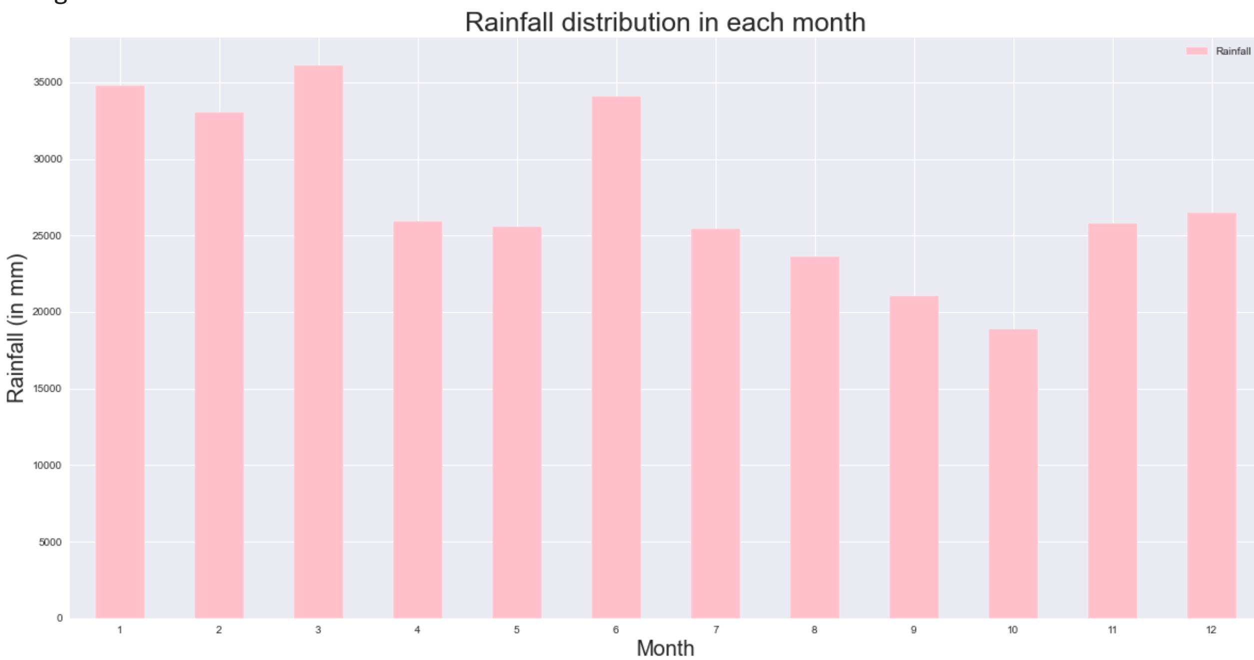
In [17]:

```
# Rainfall distribution in each month

df_rain['Date'] = pd.to_datetime(df_rain['Date'])

# Create a new dataframe rain_df
rainfall =[df_rain['Date'].dt.year, df_rain['Date'].dt.month, df_rain['Rainfall']]
headers = ['Year', 'Month', 'Rainfall']
rain_df = pd.concat(rainfall, axis=1, keys=headers)

plt.figure(figsize=(8,4))
a = rain_df.groupby('Month').agg({'Rainfall':'sum'})
a.plot(kind='bar', color='pink')
plt.title('Rainfall distribution in each month', fontsize=25)
plt.xlabel('Month', fontsize=20)
plt.ylabel('Rainfall (in mm)', fontsize=20)
plt.xticks(rotation=0)
```

Out[17]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11]),
 [Text(0, 0, '1'),
  Text(1, 0, '2'),
  Text(2, 0, '3'),
  Text(3, 0, '4'),
  Text(4, 0, '5'),
  Text(5, 0, '6'),
  Text(6, 0, '7'),
```

```
 Text(7, 0, '8'),
 Text(8, 0, '9'),
 Text(9, 0, '10'),
 Text(10, 0, '11'),
 Text(11, 0, '12')])
<Figure size 576x288 with 0 Axes>
```



Observation:-

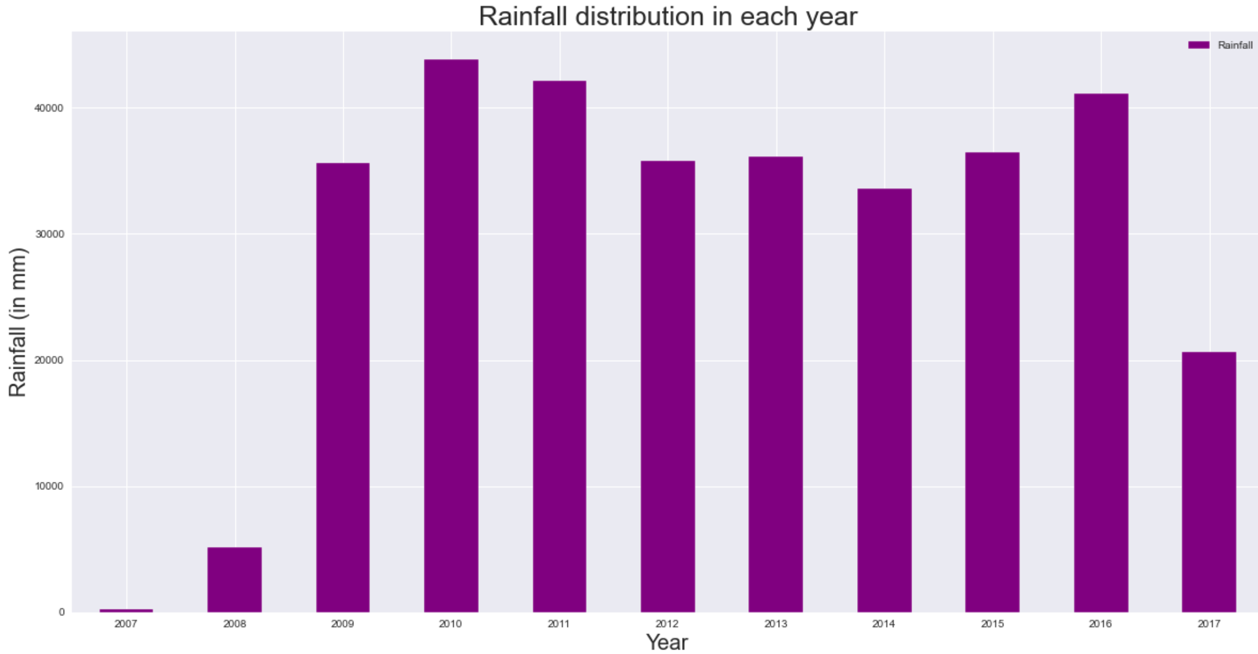
- Maximum rainfall(greater than 35,000 mm) occurs in March.
- January and June also experience high rainfall(nearly 35,000 mm) followed by February.
- Minimum rainfall occurs in October followed by September.

In [18]:

```
# Rainfall distribution in each year

plt.figure(figsize=(8,4))
a = rain_df.groupby('Year').agg({'Rainfall':'sum'})
a.plot(kind='bar', color='purple')
plt.title('Rainfall distribution in each year', fontsize=25)
plt.xlabel('Year', fontsize=20)
plt.ylabel('Rainfall (in mm)', fontsize=20)
plt.xticks(rotation=0)
```

Out[18]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 [Text(0, 0, '2007'),
  Text(1, 0, '2008'),
  Text(2, 0, '2009'),
  Text(3, 0, '2010'),
  Text(4, 0, '2011'),
  Text(5, 0, '2012'),
  Text(6, 0, '2013'),
  Text(7, 0, '2014'),
  Text(8, 0, '2015'),
  Text(9, 0, '2016'),
  Text(10, 0, '2017')])
<Figure size 576x288 with 0 Axes>
```



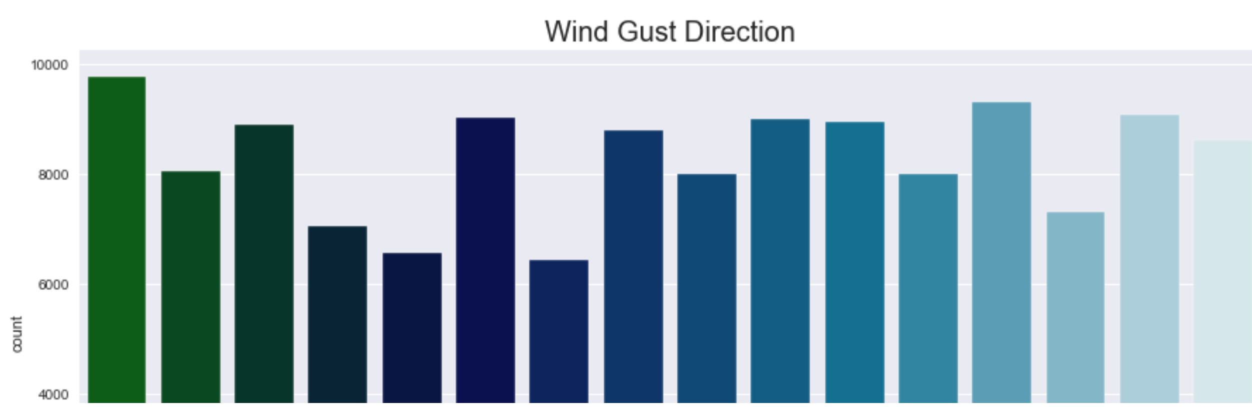
Observation:-

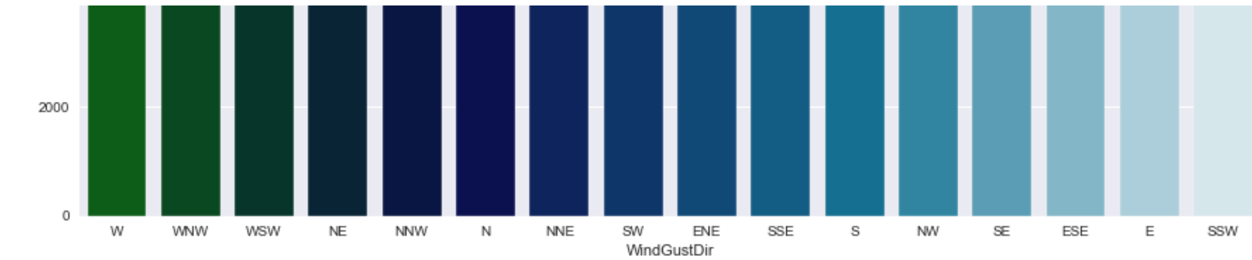
- Maximum rainfall(greater than 40,000 mm) occured in 2010 followed by 2011 and 2016.
- 2009, 2012, 2013, 2014 and 2015 experienced rainfall between 30,000-40,000 mm.
- Least rainfall(less than 200 mm) occured in 2007 followed by 2008 and 2017(greather than 20,000 mm).

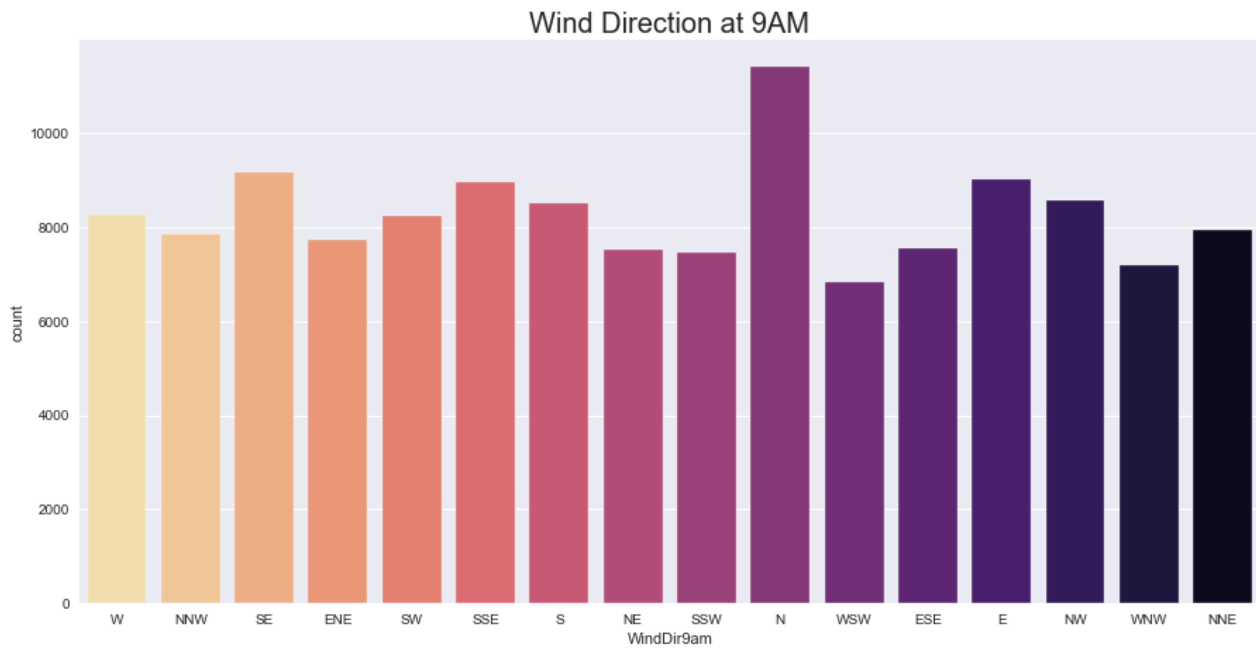
In [19]:

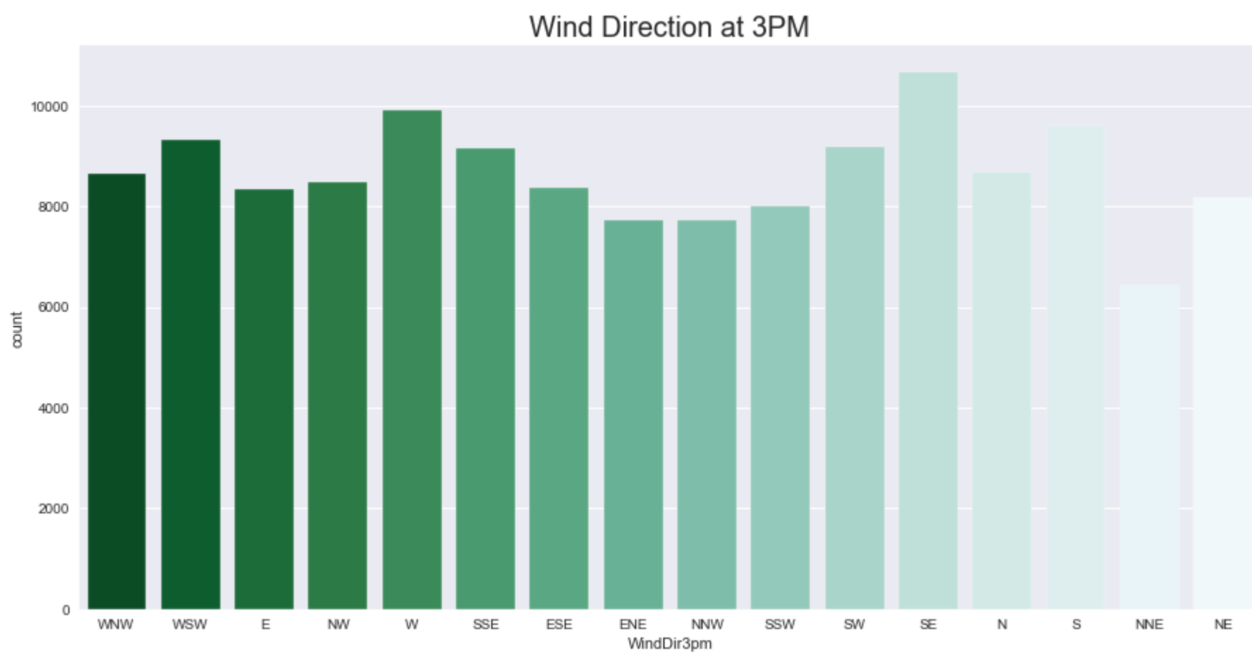
```
# Distribution of WindGustDir, WindDir9am and WindDir3pm

fig, ax = plt.subplots(3, 1, figsize=(15,25))

# WindGustDir
sns.countplot(df_rain['WindGustDir'], palette='ocean', ax=ax[0])
ax[0].set_title("Wind Gust Direction", fontsize=20)

# WindGustDir
sns.countplot(df_rain['WindDir9am'], palette='magma_r', ax=ax[1])
ax[1].set_title("Wind Direction at 9AM", fontsize=20)

# WindGustDir
sns.countplot(df_rain['WindDir3pm'], palette='BuGn_r', ax=ax[2])
ax[2].set_title("Wind Direction at 3PM", fontsize=20)
```

Out[19]: `Text(0.5, 1.0, 'Wind Direction at 3PM')`









Observation:-

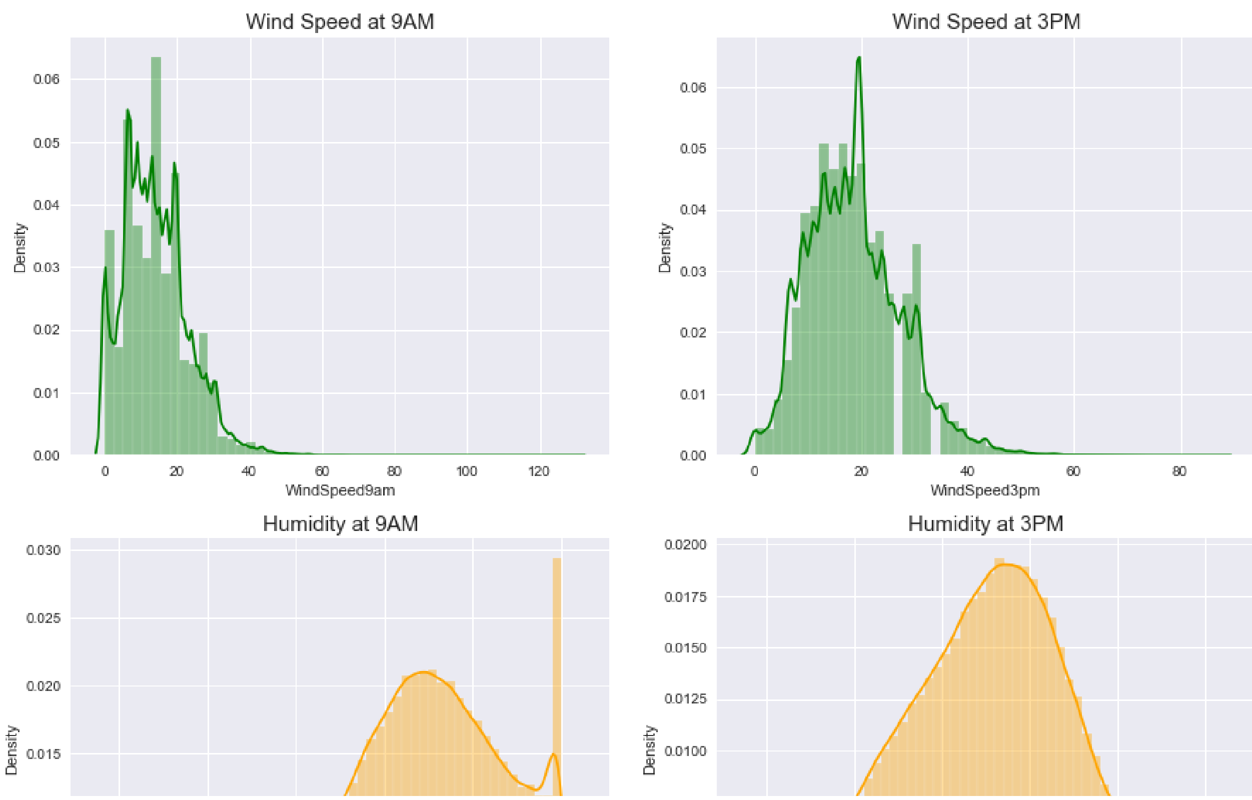
- Wind Gust Direction for maximum records(nearly 17,500) is West.
- Wind Direction at 9AM for maximum records is North followed by North-West and East.
- Wind Direction at 3PM for maximum records is South East.

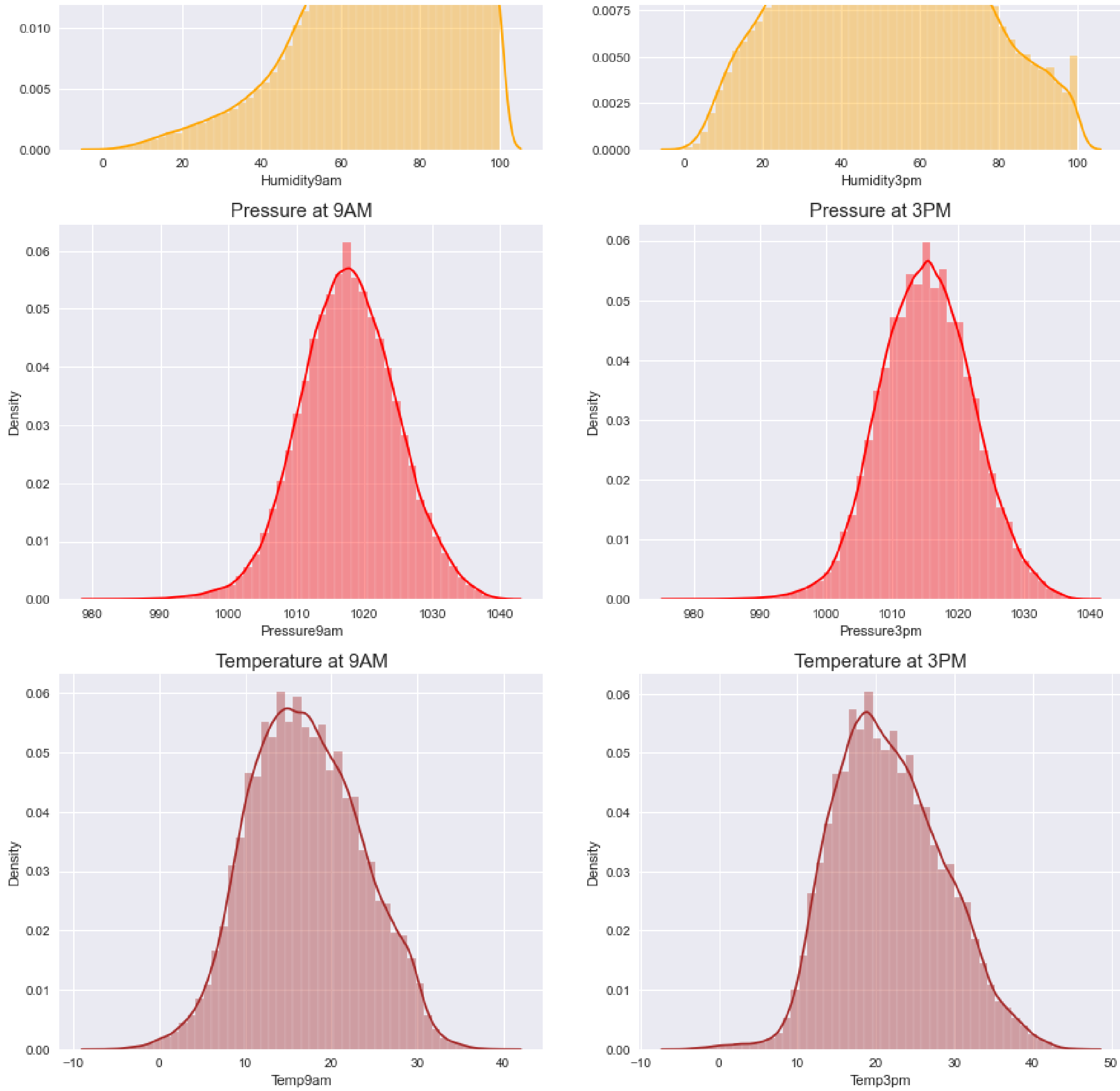
In [20]:

```
# Distribution of WindSpeed9am, WindSpeed3pm, Humidity9am, Humidity3pm, Pressure9am, Pr
```

```python
fig, ax = plt.subplots(4, 2, figsize=(15,25))

# WindSpeed9am
sns.distplot(df_rain['WindSpeed9am'], ax=ax[0,0], color='green')
ax[0,0].set_title("Wind Speed at 9AM", fontsize=15)

# WindSpeed3pm
sns.distplot(df_rain['WindSpeed3pm'], ax=ax[0,1], color='green')
ax[0,1].set_title("Wind Speed at 3PM", fontsize=15)

# Humidity9am
sns.distplot(df_rain['Humidity9am'], ax=ax[1,0], color='orange')
ax[1,0].set_title("Humidity at 9AM", fontsize=15)

# Humidity3pm
sns.distplot(df_rain['Humidity3pm'], ax=ax[1,1], color='orange')
ax[1,1].set_title("Humidity at 3PM", fontsize=15)

# Pressure9am
sns.distplot(df_rain['Pressure9am'], ax=ax[2,0], color='red')
ax[2,0].set_title("Pressure at 9AM", fontsize=15)

# Pressure3pm
sns.distplot(df_rain['Pressure3pm'], ax=ax[2,1], color='red')
ax[2,1].set_title("Pressure at 3PM", fontsize=15)

# Temp9am
sns.distplot(df_rain['Temp9am'], ax=ax[3,0], color='brown')
ax[3,0].set_title("Temperature at 9AM", fontsize=15)

# Temp3pm
sns.distplot(df_rain['Temp3pm'], ax=ax[3,1], color='brown')
ax[3,1].set_title("Temperature at 3PM", fontsize=15)
```

Out[20]: `Text(0.5, 1.0, 'Temperature at 3PM')`





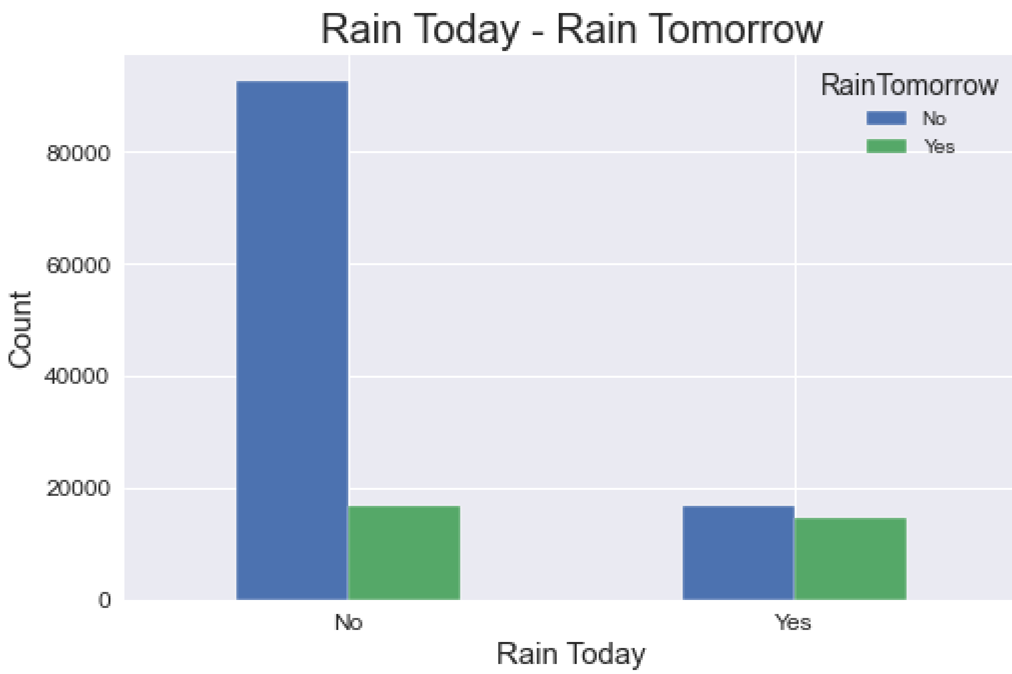
Observation:-

- Maximum wind speed at 9AM ranges from 10 to 20 km/hr whereas at 3PM it ranges from 15 to 22 km/hr.
- Highest concentration of points for humidity at 9AM is between 60-80% whereas at 3PM it's 40-70%.
- Highest concentration of points for pressure at 9AM is between 1015-1018 hpa and at 3PM it's between 1015-1017 hpa.
- Maximum temperature at 9AM is between 16-18 degree Celcius and at 3PM it's between 21-23 degree Celcius.

In [21]:
```
# Analyzing RainToday and RainTomorrow

type_plt = pd.crosstab(df_rain['RainToday'], df_rain['RainTomorrow'])

plt.rcParams["figure.figsize"] = (8,5)

type_plt.plot(kind='bar',stacked=False)
```

```
plt.xlabel('Rain Today', fontsize=15)
plt.ylabel('Count', fontsize=15)
plt.title('Rain Today - Rain Tomorrow', fontsize=20)
plt.xticks(rotation=0, fontsize=12)
plt.yticks(fontsize=12)
```

Out[21]:
```
(array([     0.,  20000.,  40000.,  60000.,  80000., 100000.]),
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```

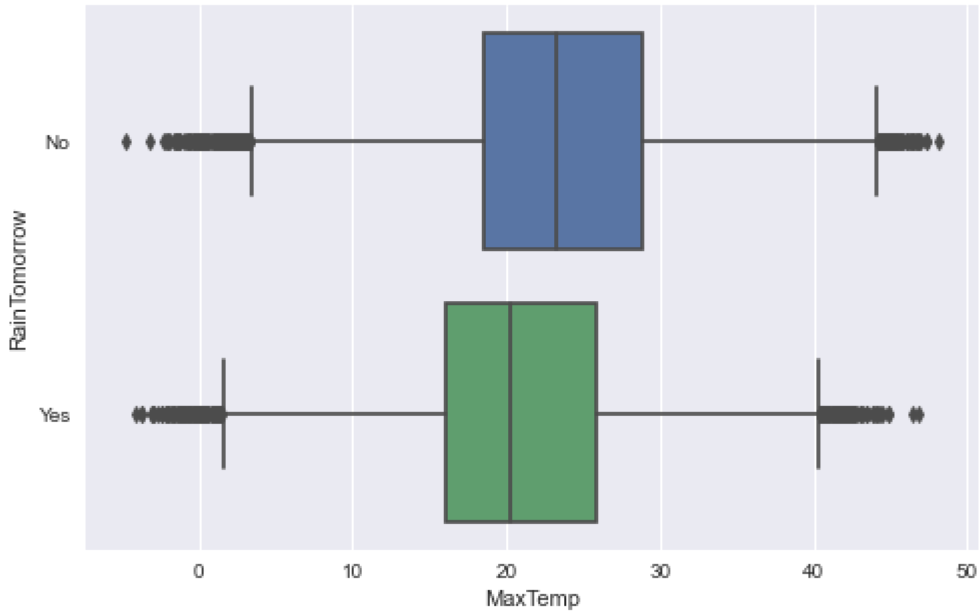


Observation:-

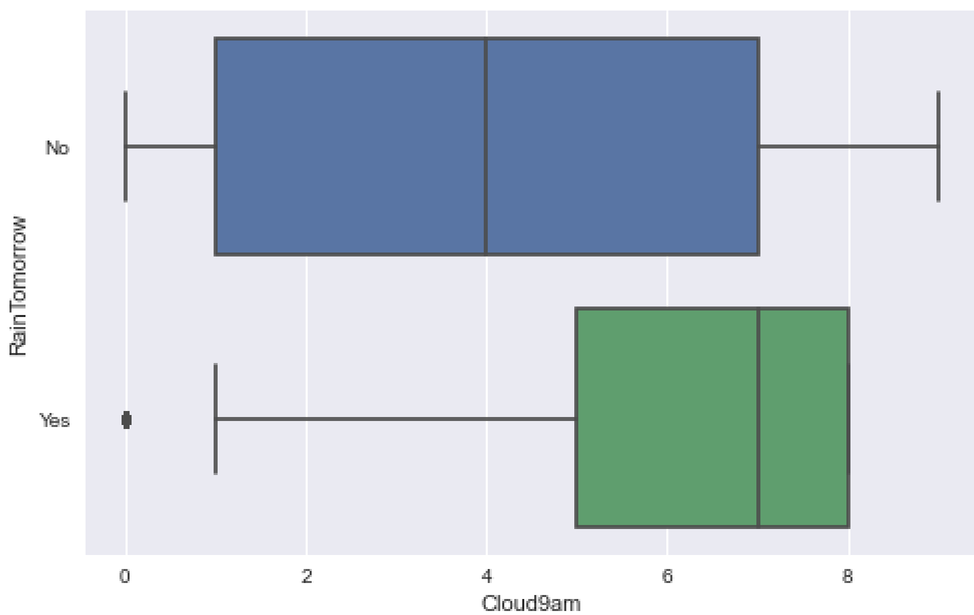
- For maximum records it didn't rain for both days.
- For nearly 20,000 records it didn't rain today but rained tomorrow and rained for both days.
- For nearly 20,000 records it rained today but didn't rain tomorrow.

sns.boxplot(x = "MinTemp", y = "RainTomorrow", data = df_rain, dodge = True);

In [22]:
```
sns.boxplot(x = "MaxTemp", y = "RainTomorrow", data = df_rain, dodge = True);
```

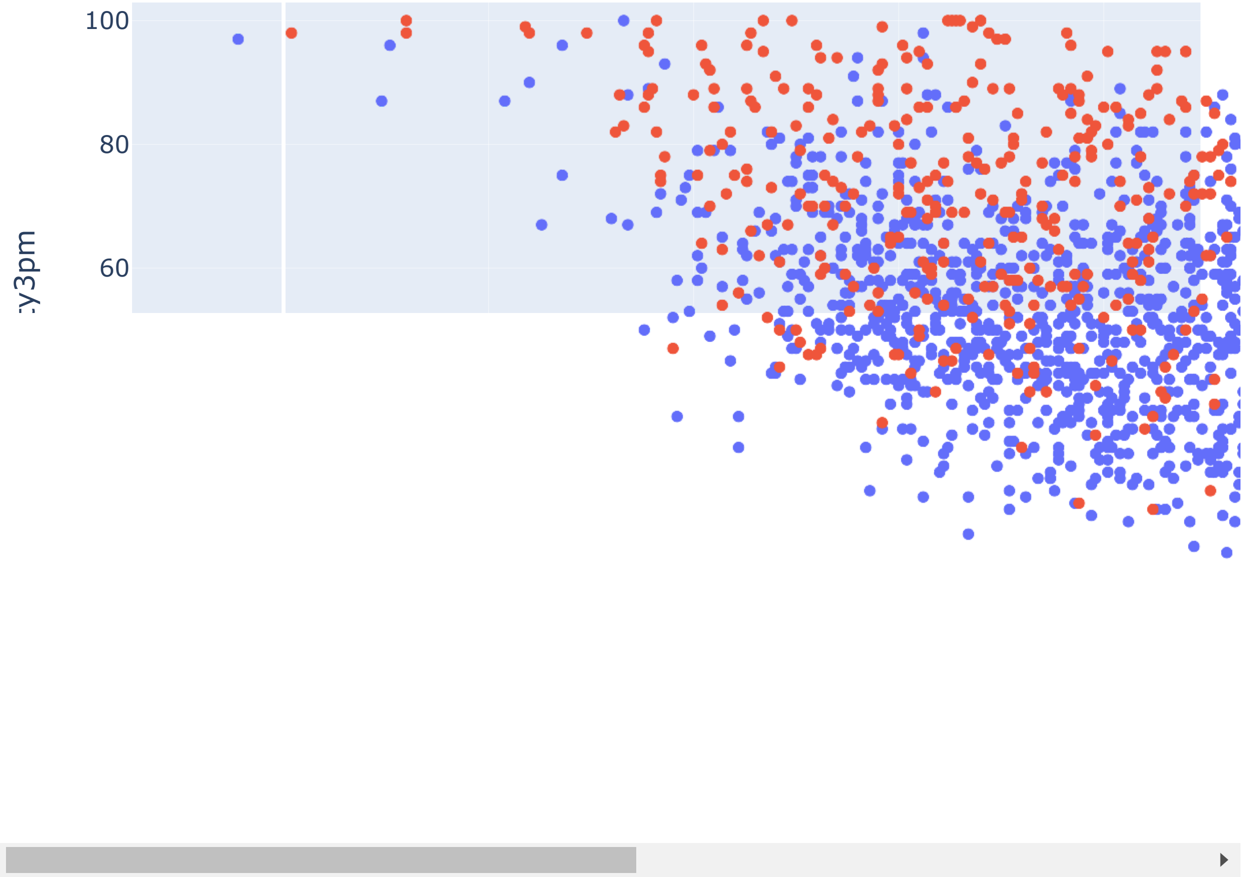


In [23]:
```
sns.boxplot(x = "Cloud9am", y = "RainTomorrow", data = df_rain, dodge = True);
```



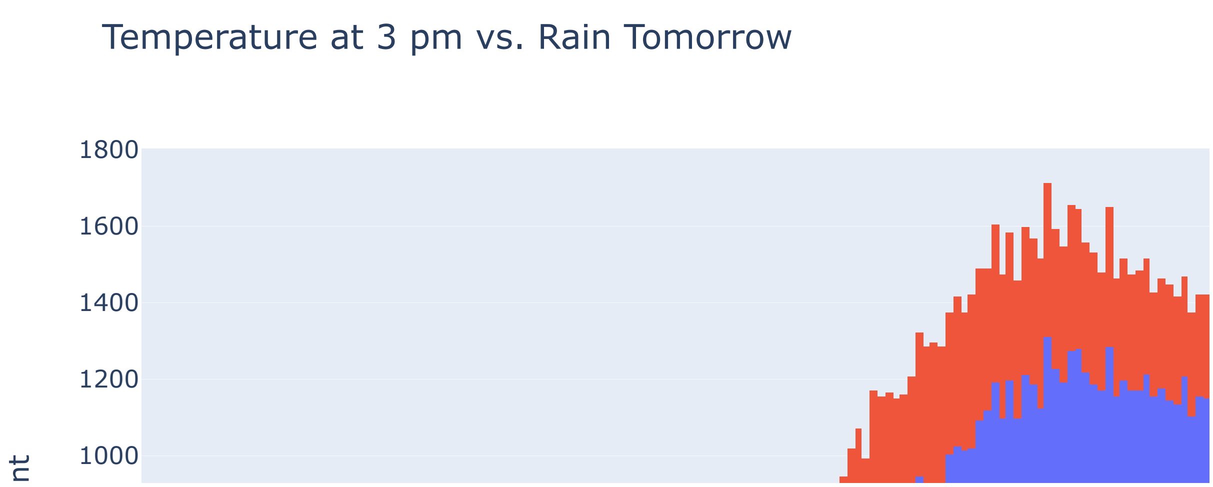
In [24]:
```
#(3 pm) vs. Humidity (3 pm)

px.scatter(df_rain.sample(2000),
           title='Temp (3 pm) vs. Humidity (3 pm)',
           x='Temp3pm',
           y='Humidity3pm',
           color='RainTomorrow')
```

Temp (3 pm) vs. Humidity (3 pm)



From the above graph Raintomorrow with "Yes" has the highest humidity of 100 when Temp3pm is at 20.7 celsius.

In [25]:
```
px.histogram(df_rain,
             x='Temp3pm',
             title='Temperature at 3 pm vs. Rain Tomorrow',
             color='RainTomorrow')
```



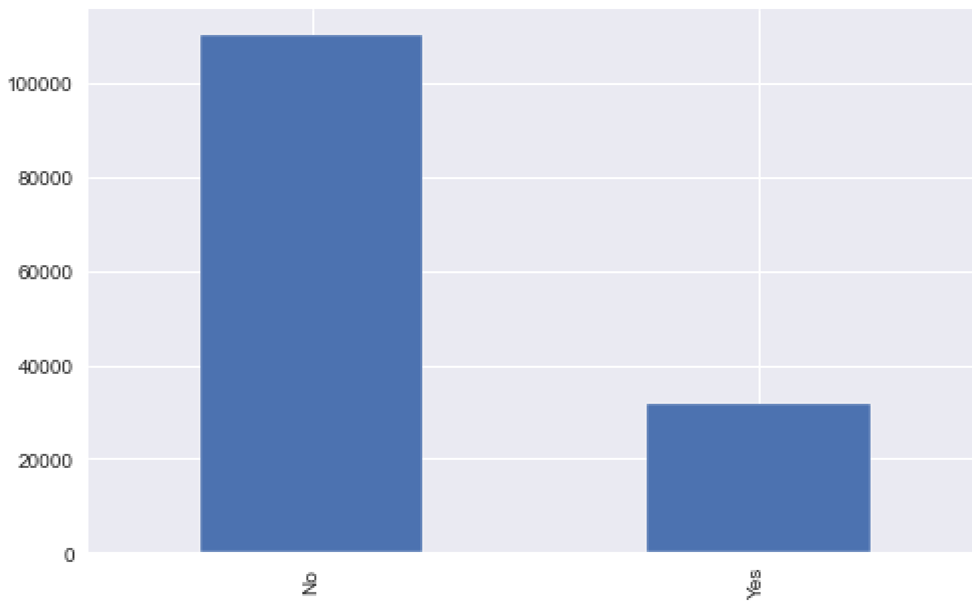
From the above graph Raintomorrow with "No" has the highest count of 1278 when Temp3pm is between (19.2 - 19.3) celsius.

Next, I plotted a count chart of whether it rained the next day.

In [26]:

```
#count chart plot of whether it rained the next day

df_rain['RainTomorrow'].value_counts().plot(kind='bar')
```

Out[26]: `<AxesSubplot:>`



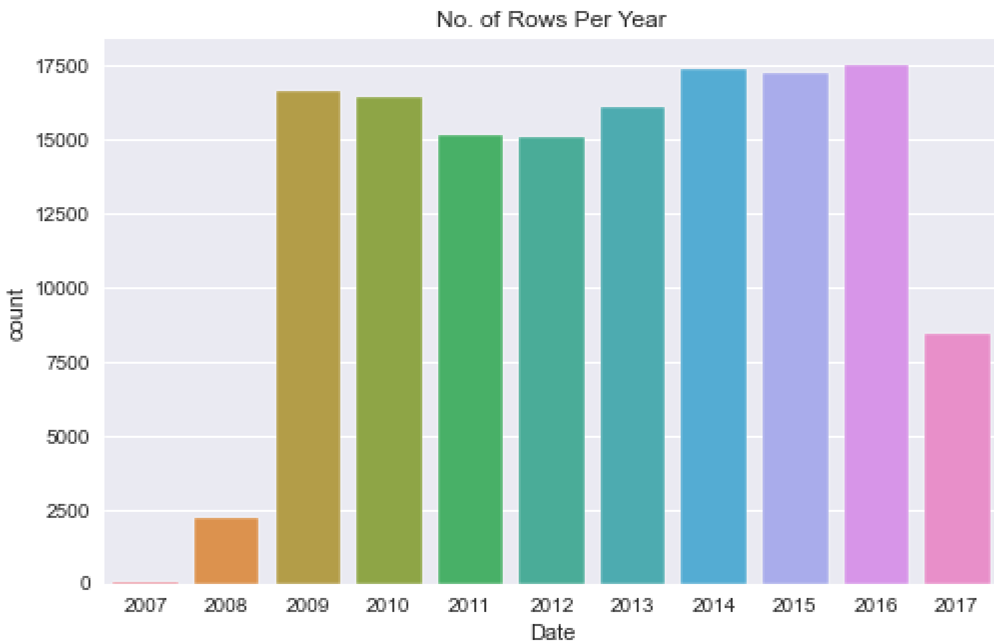
The graph shows that the days of not raining is more than 4 times more than rained in the next. Hence, there is a class imbalance and we have to deal with it. To fight against the class imbalance, we will use here the oversampling of the minority class. Since the size of the dataset is quite small, majority class subsampling wouldn't make much sense here.

7. Train, Validation, Test Split

Lets use time series data, since it is a collection of observations obtained through repeated measurements over time. Plot the points on a graph, and one of your axes would always be time.

The given data is a time-series data and is in chronological form. While working with chronological data, it's often a good concept to separate the training, validation and test sets with time, so that the model is trained on data from the past and evaluated on data from the future.

In [27]:
```
plt.title('No. of Rows Per Year');
sns.countplot(x=pd.to_datetime(df_rain.Date).dt.year);
```



Lets use the data till 2014 for the training set, data from 2015 for the validation set, and the data from 2016 & 2017 for the test set.

To archieve this,

In [28]:
```
year = pd.to_datetime(df_rain.Date).dt.year

train_df = df_rain[year < 2015]
val_df = df_rain[year == 2015]
test_df = df_rain[year > 2015]
```

8. Identify Inputs & Target Columns

The columns other than RainTomorrow are independent columns (input columns) while the RainTomorrow column is dependent column (output columns).

In [29]:
```
input_cols = list(train_df.columns[1:-1])
target_cols = train_df.columns[-1]

input_cols,target_cols
```

Out[29]:
```
(['Location',
  'MinTemp',
  'MaxTemp',
  'Rainfall',
  'Evaporation',
  'Sunshine',
  'WindGustDir',
  'WindGustSpeed',
  'WindDir9am',
  'WindDir3pm',
```

```
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Pressure3pm',
 'Cloud9am',
 'Cloud3pm',
 'Temp9am',
 'Temp3pm',
 'RainToday'],
'RainTomorrow')
```

Identify inputs and outputs

X_train : Training data's inputs Y_train : Training data's output Equally for validation and test data.

In [30]:
```
X_train = train_df[input_cols].copy()
Y_train = train_df[target_cols].copy()

X_val = val_df[input_cols].copy()
Y_val = val_df[target_cols].copy()

X_test = test_df[input_cols].copy()
Y_test = test_df[target_cols].copy()
```

9. Identify Numerical & Categorical Columns

From the information of the dataset shown above, the Dtype column specifies the datatype of the column values. Separate preprocessing steps are to be carried out for categorical data and numerical data. Hence we'll identify the columns which are numerical and which are categorical for preprocessing purposes.

In [31]:
```
print(df_rain.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 142193 entries, 0 to 145458
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Date           142193 non-null  datetime64[ns]
 1   Location       142193 non-null  object
 2   MinTemp        141556 non-null  float64
 3   MaxTemp        141871 non-null  float64
 4   Rainfall       140787 non-null  float64
 5   Evaporation    81350 non-null   float64
 6   Sunshine       74377 non-null   float64
 7   WindGustDir    132863 non-null  object
 8   WindGustSpeed  132923 non-null  float64
 9   WindDir9am     132180 non-null  object
 10  WindDir3pm     138415 non-null  object
 11  WindSpeed9am   140845 non-null  float64
 12  WindSpeed3pm   139563 non-null  float64
 13  Humidity9am    140419 non-null  float64
 14  Humidity3pm    138583 non-null  float64
```

```
 15  Pressure9am    128179 non-null  float64
 16  Pressure3pm    128212 non-null  float64
 17  Cloud9am       88536 non-null   float64
 18  Cloud3pm       85099 non-null   float64
 19  Temp9am        141289 non-null  float64
 20  Temp3pm        139467 non-null  float64
 21  RainToday      140787 non-null  object
 22  RainTomorrow   142193 non-null  object
dtypes: datetime64[ns](1), float64(16), object(6)
memory usage: 30.1+ MB
None
```

Remove rows for which target column is empty

In [32]:
```
numeric_cols = list(X_train.select_dtypes(include=np.number).columns)
categorical_cols = list(X_train.select_dtypes(include='object').columns)

numeric_cols, categorical_cols
```

Out[32]:
```
(['MinTemp',
  'MaxTemp',
  'Rainfall',
  'Evaporation',
  'Sunshine',
  'WindGustSpeed',
  'WindSpeed9am',
  'WindSpeed3pm',
  'Humidity9am',
  'Humidity3pm',
  'Pressure9am',
  'Pressure3pm',
  'Cloud9am',
  'Cloud3pm',
  'Temp9am',
  'Temp3pm'],
 ['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday'])
```

10. Impute Missing Values

As we have discussed already that preprocessing steps are to be done separately for numerical and categorical columns. First, let's impute the numerical columns with mean of the corresponding columns.

Below code displays the counts of null values in numerical columns sorted in descending order.

In [33]:
```
X_train[numeric_cols].isna().sum().sort_values(ascending=False)
```

Out[33]:
```
Sunshine         40696
Evaporation      37110
Cloud3pm         36766
Cloud9am         35764
Pressure9am       9345
Pressure3pm       9309
WindGustSpeed     6902
Humidity9am       1265
Humidity3pm       1186
WindSpeed3pm      1140
WindSpeed9am      1133
```

```
Rainfall         1000
Temp9am           783
Temp3pm           663
MinTemp           434
MaxTemp           198
dtype: int64
```

Below code imputes the numerical columns with their mean respectively.

In [34]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='mean')
imputer.fit(df_rain[numeric_cols])

X_train[numeric_cols] = imputer.transform(X_train[numeric_cols])
X_val[numeric_cols] = imputer.transform(X_val[numeric_cols])
X_test[numeric_cols] = imputer.transform(X_test[numeric_cols])
```

Now, after imputing the null values with mean, the count of null values are:

In [35]:
```
X_train[numeric_cols].isna().sum().sort_values(ascending=False)
```

Out[35]:
```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
dtype: int64
```

In [36]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(df_rain[numeric_cols])

X_train[numeric_cols] = scaler.transform(X_train[numeric_cols])
X_val[numeric_cols] = scaler.transform(X_val[numeric_cols])
X_test[numeric_cols] = scaler.transform(X_test[numeric_cols])
```

11. Scaling Numerical Columns

Let's learn the importance of scaling before proceeding. Feature Scaling is a method to standardize the independent attributes present in the data in a fixed range. It is done during the data pre-processing to handle highly varying magnitudes or values or units. If feature scaling is not done, then a machine learning algorithm tends to weigh greater values, higher and consider smaller values as the lower values, regardless of the unit of the values.

In [37]:
```
scaler = MinMaxScaler()
scaler.fit(df_rain[numeric_cols])

X_train[numeric_cols] = scaler.transform(X_train[numeric_cols])
X_val[numeric_cols] = scaler.transform(X_val[numeric_cols])
X_test[numeric_cols] = scaler.transform(X_test[numeric_cols])
```

12. Encoding Categorical Columns

Let's now learn what is encoding and why it is needed? Encoding categorical data is a process of converting categorical data into integer format so that the data with converted categorical values can be provided to the models to give and improve the predictions.

Every machine learning models learns only from numerical data which is why it is needed to convert the categorical data to integer format during preprocessing.

The categorical columns in our dataset are,

In [38]:
```
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

Out[38]:
```
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

Before encoding the categorical columns one must be sure sure that there are no null values in those columns because those columns will also be encoded which doesn't make sense. Hence, the null values in categorical columns should be imputed before encoding the columns. This is similar to imputing numerical columns followed by scaling them.

Below code displays the count of null values in the categorical columns:

In [39]:
```
X_train[categorical_cols].isna().sum().sort_values(ascending=False)
```

Out[39]:
```
WindDir9am     7323
WindGustDir    6943
WindDir3pm     2030
RainToday      1000
Location          0
dtype: int64
```

Imputing is done by considering mean in numerical columns. But this is not the case for categorical columns. For categorical columns either mode can be considered or some other dummy value can be substituted in place of null values. Here, let's substitue 'Unknown' in place of null values.

This can be archieve as follow:

In [40]:
```
X_train[categorical_cols] = X_train[categorical_cols].fillna('Unknown')
X_val[categorical_cols] = X_val[categorical_cols].fillna('Unknown')
X_test[categorical_cols] = X_val[categorical_cols].fillna('Unknown')
```

Now the counts of null values are:

In [41]:

```
X_train[categorical_cols].isna().sum().sort_values(ascending=False)
```

Out[41]:

```
Location       0
WindGustDir    0
WindDir9am     0
WindDir3pm     0
RainToday      0
dtype: int64
```

After imputing the null values let's perform encoding.

In [42]:

```
encoder = OneHotEncoder(sparse=False, handle_unknown='ignore')
encoder.fit(X_train[categorical_cols])

encoded_cols = list(encoder.get_feature_names(categorical_cols))
encoded_cols
```

Out[42]:

```
['Location_Adelaide',
 'Location_Albany',
 'Location_Albury',
 'Location_AliceSprings',
 'Location_BadgerysCreek',
 'Location_Ballarat',
 'Location_Bendigo',
 'Location_Brisbane',
 'Location_Cairns',
 'Location_Canberra',
 'Location_Cobar',
 'Location_CoffsHarbour',
 'Location_Dartmoor',
 'Location_Darwin',
 'Location_GoldCoast',
 'Location_Hobart',
 'Location_Katherine',
 'Location_Launceston',
 'Location_Melbourne',
 'Location_MelbourneAirport',
 'Location_Mildura',
 'Location_Moree',
 'Location_MountGambier',
 'Location_MountGinini',
 'Location_Newcastle',
 'Location_Nhil',
 'Location_NorahHead',
 'Location_NorfolkIsland',
 'Location_Nuriootpa',
 'Location_PearceRAAF',
 'Location_Penrith',
 'Location_Perth',
 'Location_PerthAirport',
 'Location_Portland',
 'Location_Richmond',
 'Location_Sale',
 'Location_SalmonGums',
 'Location_Sydney',
 'Location_SydneyAirport',
 'Location_Townsville',
 'Location_Tuggeranong',
 'Location_Uluru',
 'Location_WaggaWagga',
 'Location_Walpole',
 'Location_Watsonia',
 'Location_Williamtown',
```

```
 'Location_Witchcliffe',
 'Location_Wollongong',
 'Location_Woomera',
 'WindGustDir_E',
 'WindGustDir_ENE',
 'WindGustDir_ESE',
 'WindGustDir_N',
 'WindGustDir_NE',
 'WindGustDir_NNE',
 'WindGustDir_NNW',
 'WindGustDir_NW',
 'WindGustDir_S',
 'WindGustDir_SE',
 'WindGustDir_SSE',
 'WindGustDir_SSW',
 'WindGustDir_SW',
 'WindGustDir_Unknown',
 'WindGustDir_W',
 'WindGustDir_WNW',
 'WindGustDir_WSW',
 'WindDir9am_E',
 'WindDir9am_ENE',
 'WindDir9am_ESE',
 'WindDir9am_N',
 'WindDir9am_NE',
 'WindDir9am_NNE',
 'WindDir9am_NNW',
 'WindDir9am_NW',
 'WindDir9am_S',
 'WindDir9am_SE',
 'WindDir9am_SSE',
 'WindDir9am_SSW',
 'WindDir9am_SW',
 'WindDir9am_Unknown',
 'WindDir9am_W',
 'WindDir9am_WNW',
 'WindDir9am_WSW',
 'WindDir3pm_E',
 'WindDir3pm_ENE',
 'WindDir3pm_ESE',
 'WindDir3pm_N',
 'WindDir3pm_NE',
 'WindDir3pm_NNE',
 'WindDir3pm_NNW',
 'WindDir3pm_NW',
 'WindDir3pm_S',
 'WindDir3pm_SE',
 'WindDir3pm_SSE',
 'WindDir3pm_SSW',
 'WindDir3pm_SW',
 'WindDir3pm_Unknown',
 'WindDir3pm_W',
 'WindDir3pm_WNW',
 'WindDir3pm_WSW',
 'RainToday_No',
 'RainToday_Unknown',
 'RainToday_Yes']
```

In [43]:

```
X_train[encoded_cols] = encoder.transform(X_train[categorical_cols])
X_val[encoded_cols] = encoder.transform(X_val[categorical_cols])
X_test[encoded_cols] = encoder.transform(X_test[categorical_cols])
```

Let's combine the preprocessed numerical and categorical columns for model training.

In [44]:
```
X_train = X_train[numeric_cols + encoded_cols]
X_val = X_val[numeric_cols + encoded_cols]
X_test = X_test[numeric_cols + encoded_cols]
```

13. Training & Visualizing Decision Trees

A decision tree in machine learning works in the same way, and except that we let the computer figure out the optimal structure & hierarchy of decisions, instead of coming up with criteria manually.

Being a classification task, let's use DecisionTreeClassifier algorithm.

Training

In [45]:
```
model = DecisionTreeClassifier(random_state = 42)
model.fit(X_train, Y_train)
```

Out[45]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

We have trained our classifier with the training data.

Evaluation

To review the training process, let's check how well the model trained with the training data.

In [46]:
```
X_train_pred = model.predict(X_train)
pd.value_counts(X_train_pred)
```

Out[46]:
```
No     76707
Yes    22281
dtype: int64
```

The counts of predicted result shows that our model has predicted more 'No' for the target column RainTomorrow than that of 'Yes'.

Now, let's calculate the accuracy of our model in the training data.

In [47]:
```
train_probs = model.predict_proba(X_train)
print('Training Accuracy :',accuracy_score(X_train_pred,Y_train)*100)
```

```
Training Accuracy : 99.99797955307714
```

Interesting! The training set accuracy is close to 100%. But we can't depend completely on the training set accuracy, we must evaluate the model on the validation set too. This is because our model should be trained in a generalized way i.e, it should be able to predict output which is not present in training data.

In [48]:
```
print('Validation Acuracy :',model.score(X_val,Y_val)*100)
```

```
Validation Acuracy : 79.28152747954267
```

Let's also calculate the percentage of 'Yes' and 'No' in validation data.

In [49]:
```
Y_val.value_counts() / len(Y_val)
```

Out[49]:
```
No     0.788289
Yes    0.211711
Name: RainTomorrow, dtype: float64
```

The above result shows 78.8% 'No' and 21% 'Yes' in validation data. This proves that if it is predicted 'No' for all the validation data, it would still be 78.8% accurate in the result (since there are 78.8% 'No' in the validation data). Hence, our model should remain learning only if it exceeds 78.8% accuracy because even predicting 'No' always using a dumb model gives 78.8% accuracy.

Summary

DecisionTreeClassifier with default parameters

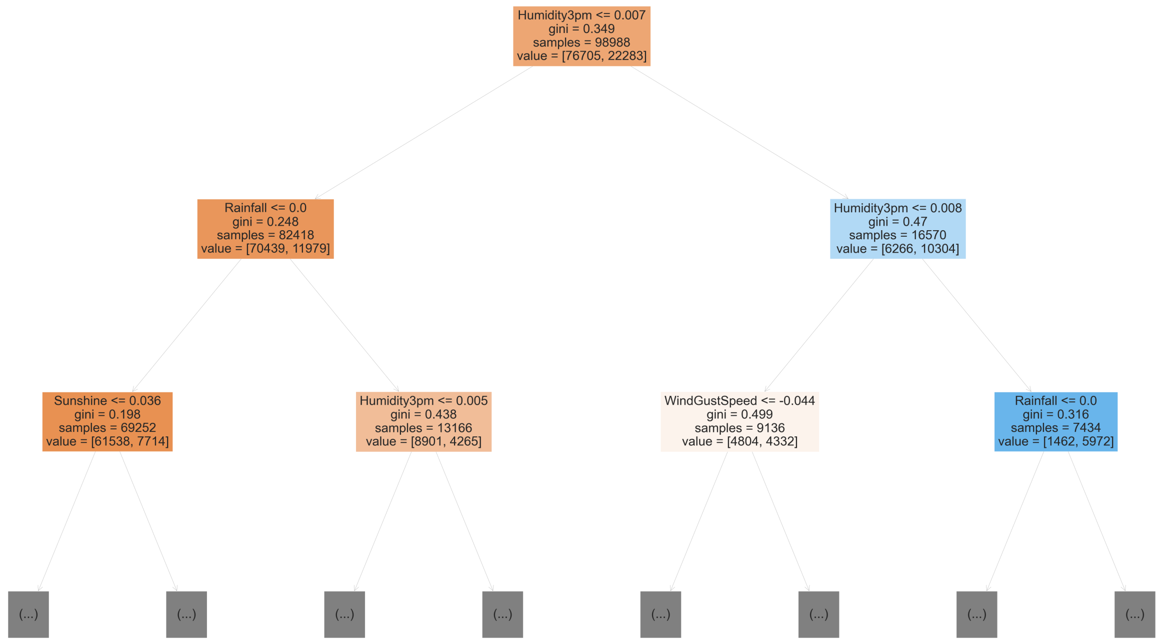
DecisionTreeClassifier with default parameters	
Accuracy of training data	99.99%
Accuracy of test and validation data	79.28%
Max depth of decision tree	48

Table 1 - Performance of DecisionTreeClassifier with default parameters

The above case was an overfitting case as tree used the max depth and memorized the values and failed to predict with low accuracy of 79.28% for test and validation dataset

Visualization of Decision Tree

In [50]:
```
plt.figure(figsize=(80,50))
plot_tree(model, feature_names=X_train.columns, max_depth=2, filled=True);
```



14. Feature Importance

The initial 23 columns or features after encoding became 119 features. Decision Trees can find importance of features by itself. Below are some of the importances of 119 features(total number of features in the training dataset).

In [51]:

```
feature_importance_df = pd.DataFrame({
    'Feature' : X_train.columns,
    'Importance' : model.feature_importances_
}).sort_values(by='Importance', ascending=False)
feature_importance_df
```

Out[51]:

	Feature	Importance
9	Humidity3pm	0.261666
11	Pressure3pm	0.062909
2	Rainfall	0.059698
5	WindGustSpeed	0.055278
4	Sunshine	0.049697
8	Humidity9am	0.039776
0	MinTemp	0.034395
14	Temp9am	0.033930
10	Pressure9am	0.033880
1	MaxTemp	0.032072

	Feature	Importance
15	Temp3pm	0.029998
7	WindSpeed3pm	0.028790
6	WindSpeed9am	0.027729
3	Evaporation	0.024000
13	Cloud3pm	0.018257
12	Cloud9am	0.014163
106	WindDir3pm_NW	0.003952
105	WindDir3pm_NNW	0.003545
85	WindDir9am_N	0.003503
88	WindDir9am_NNW	0.003410
72	WindGustDir_NW	0.003352
68	WindGustDir_N	0.003335
102	WindDir3pm_N	0.003297
107	WindDir3pm_S	0.003246
80	WindGustDir_WNW	0.003168
114	WindDir3pm_WNW	0.003097
109	WindDir3pm_SSE	0.003064
100	WindDir3pm_ENE	0.002913
83	WindDir9am_ENE	0.002812
81	WindGustDir_WSW	0.002796
96	WindDir9am_W	0.002779
74	WindGustDir_SE	0.002776
87	WindDir9am_NNE	0.002774
103	WindDir3pm_NE	0.002763
110	WindDir3pm_SSW	0.002752
89	WindDir9am_NW	0.002721
97	WindDir9am_WNW	0.002701
62	Location_Witchcliffe	0.002675
73	WindGustDir_S	0.002621
79	WindGustDir_W	0.002590
77	WindGustDir_SW	0.002587
115	WindDir3pm_WSW	0.002492
86	WindDir9am_NE	0.002487

	Feature	Importance
101	WindDir3pm_ESE	0.002444
76	WindGustDir_SSW	0.002421
69	WindGustDir_NE	0.002418
91	WindDir9am_SE	0.002416
108	WindDir3pm_SE	0.002366
98	WindDir9am_WSW	0.002345
104	WindDir3pm_NNE	0.002325
16	Location_Adelaide	0.002300
70	WindGustDir_NNE	0.002248
113	WindDir3pm_W	0.002228
94	WindDir9am_SW	0.002225
99	WindDir3pm_E	0.002192
75	WindGustDir_SSE	0.002192
84	WindDir9am_ESE	0.002160
82	WindDir9am_E	0.002157
39	Location_MountGinini	0.002078
118	RainToday_Yes	0.002052
27	Location_CoffsHarbour	0.002050
49	Location_Portland	0.002032
90	WindDir9am_S	0.002015
67	WindGustDir_ESE	0.001982
17	Location_Albany	0.001971
71	WindGustDir_NNW	0.001967
111	WindDir3pm_SW	0.001923
28	Location_Dartmoor	0.001906
92	WindDir9am_SSE	0.001899
93	WindDir9am_SSW	0.001881
63	Location_Wollongong	0.001838
51	Location_Sale	0.001800
23	Location_Brisbane	0.001775
38	Location_MountGambier	0.001727
78	WindGustDir_Unknown	0.001688
25	Location_Canberra	0.001573

	Feature	Importance
59	Location_Walpole	0.001568
61	Location_Williamtown	0.001552
47	Location_Perth	0.001546
65	WindGustDir_E	0.001534
31	Location_Hobart	0.001524
20	Location_BadgerysCreek	0.001514
95	WindDir9am_Unknown	0.001492
44	Location_Nuriootpa	0.001488
34	Location_Melbourne	0.001482
43	Location_NorfolkIsland	0.001475
60	Location_Watsonia	0.001468
66	WindGustDir_ENE	0.001454
42	Location_NorahHead	0.001387
56	Location_Tuggeranong	0.001331
18	Location_Albury	0.001304
54	Location_SydneyAirport	0.001287
53	Location_Sydney	0.001283
58	Location_WaggaWagga	0.001219
24	Location_Cairns	0.001217
21	Location_Ballarat	0.001129
30	Location_GoldCoast	0.001116
112	WindDir3pm_Unknown	0.001094
48	Location_PerthAirport	0.001094
52	Location_SalmonGums	0.000970
35	Location_MelbourneAirport	0.000888
45	Location_PearceRAAF	0.000867
22	Location_Bendigo	0.000867
50	Location_Richmond	0.000852
26	Location_Cobar	0.000843
46	Location_Penrith	0.000834
33	Location_Launceston	0.000830
41	Location_Nhil	0.000764
36	Location_Mildura	0.000762

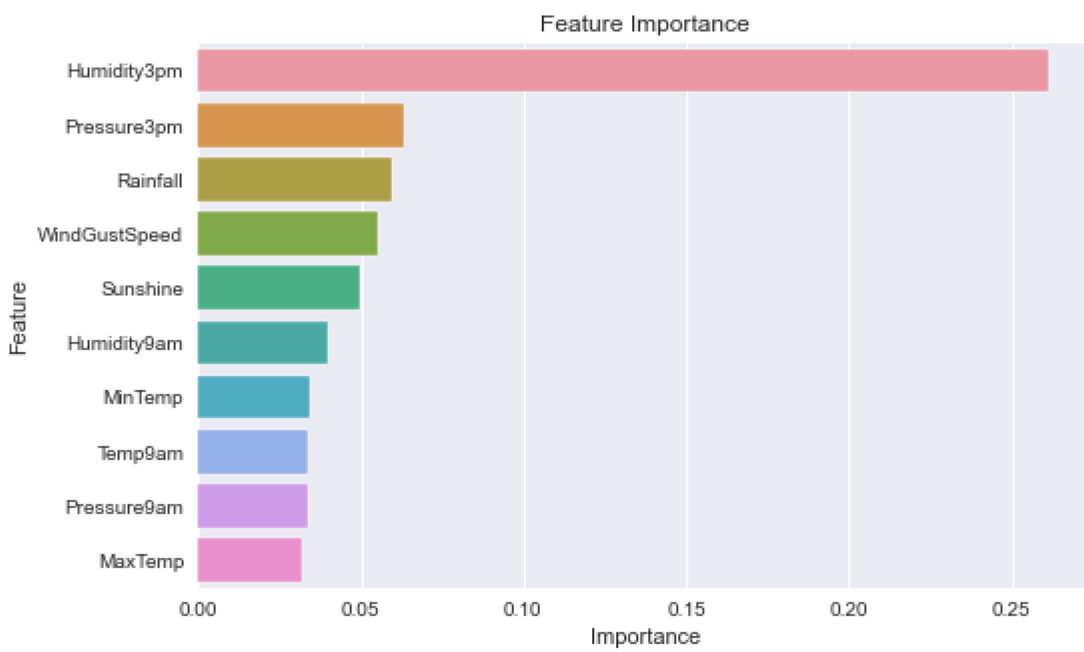
	Feature	Importance
117	RainToday_Unknown	0.000748
19	Location_AliceSprings	0.000705
37	Location_Moree	0.000703
116	RainToday_No	0.000689
32	Location_Katherine	0.000508
40	Location_Newcastle	0.000380
55	Location_Townsville	0.000377
64	Location_Woomera	0.000356
29	Location_Darwin	0.000327
57	Location_Uluru	0.000130

Note: Only some feature importances are displayed but the above code displays for all features.

Let's view importances of top 10 features.

In [52]:

```
plt.title('Feature Importance')
sns.barplot(data = feature_importance_df.head(10), x='Importance', y='Feature');
```



15. Hyperparameter Tuning - To Reduce Overfitting

Now that we found out our model is only marginally better than a dumb model because of overfitting, we should modify some of the parameters of DecisionTreeClassifier to reduce overfitting.

The DecisionTreeClassifier accepts several arguments, some of which can be modified to reduce overfitting.

max_depth max_leaf_nodes By reducing the tree maximum depth can reduce overfitting. Maximum depth (default) is 48 which is reduced to 3 to reduce overfittting as below.

In [53]:
```
model = DecisionTreeClassifier(random_state=42, max_depth=3)
model.fit(X_train, Y_train)

print('Accuracy in Training Dataset :',model.score(X_train, Y_train)*100)
print('Accuracy in Validation Dataset :',model.score(X_val, Y_val)*100)
```

```
Accuracy in Training Dataset : 82.91308037337859
Accuracy in Validation Dataset : 83.34397307178921
```

Hyperparamter tuning

Our model had 100 % training accuracy which means that model is memorising the inputs. Comparing it with validation and test accuracy of approx. 79.28 % we clearly see a case of overfitting. We need to try and make some changes in the parameters of model training to avoid overfitting. One possible way of doing it is to reduce the max depth of the tree. Let us train the model again

In [54]:
```
dt = DecisionTreeClassifier(max_depth = 4, random_state = 42)
dt.fit(X_train, Y_train)
```

Out[54]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=4, random_state=42)
```

Let us score the model on training, validation and test dataset again

In [55]:
```
#Scoring against training dataset
dt.score(X_train, Y_train)
```

Out[55]:
```
0.8342930456216915
```

As we can see the training accuracy is just 83% which means the model is not memorising and overfitting the values. Let us try the same for validation and test dataset

In [56]:
```
#Scoring against validation dataset
dt.score(X_val, Y_val)
```

Out[56]:
```
0.8356450583251117
```

We now have a significantly better performance on training and test dataset Let us get the confusion matrix

In [57]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

In [58]:

```
#Confusion matrix for training data
train_pred = dt.predict(X_train)
matrix_train = confusion_matrix(Y_train, train_pred)
print(matrix_train)

matrix_train = classification_report(Y_train, train_pred)
print(matrix_train)
```

```
[[72602  4103]
 [12300  9983]]
              precision    recall  f1-score   support

          No       0.86      0.95      0.90     76705
         Yes       0.71      0.45      0.55     22283

    accuracy                           0.83     98988
   macro avg       0.78      0.70      0.72     98988
weighted avg       0.82      0.83      0.82     98988
```

In [59]:

```
#Confusion matrix for validation data
validation_pred = dt.predict(X_val)
matrix_validate = confusion_matrix(Y_val, validation_pred)
print(matrix_validate)

matrix_validate = classification_report(Y_val, validation_pred)
print(matrix_validate)
```

```
[[12855   728]
 [ 2104  1544]]
              precision    recall  f1-score   support

          No       0.86      0.95      0.90     13583
         Yes       0.68      0.42      0.52      3648

    accuracy                           0.84     17231
   macro avg       0.77      0.68      0.71     17231
weighted avg       0.82      0.84      0.82     17231
```

In [60]:

```
test_pred = dt.predict(X_test)
matrix_test = confusion_matrix(Y_test, test_pred)
print(matrix_test)

matrix_test = classification_report(Y_test, test_pred)
print(matrix_test)
```

```
[[18875  1153]
 [ 3438  2508]]
              precision    recall  f1-score   support

          No       0.85      0.94      0.89     20028
         Yes       0.69      0.42      0.52      5946

    accuracy                           0.82     25974
   macro avg       0.77      0.68      0.71     25974
weighted avg       0.81      0.82      0.81     25974
```

Tuning max_depth

Since the max_depth value without manual constraint for which our model overfitted is 48. And the max_depth value can't be 0 or lesser. Hence, let's find what the best value of max_depth would be by trial and error method and use the max_depth for which the errors of train and validation dataset is optimal.

In [61]:

```
def max_depth_accuracy1(max_depth_val):
    model = DecisionTreeClassifier(random_state=42, max_depth=max_depth_val)
    model.fit(X_train, Y_train)
    train_accuracy = model.score(X_train, Y_train)*100
    val_accuracy = model.score(X_val, Y_val)*100
    return {'Max_Depth' : max_depth_val, 'Training_Accuracy' : train_accuracy, 'Validat

accuracies_df1 = pd.DataFrame([max_depth_accuracy1(i) for i in range(1,48)])
accuracies_df1
```

Out[61]:

	Max_Depth	Training_Accuracy	Validation_Accuracy
0	1	81.568473	82.206488
1	2	82.045298	82.728803
2	3	82.913080	83.343973
3	4	83.429305	83.564506
4	5	83.932396	84.092624
5	6	84.372853	84.272532
6	7	84.668849	84.533689
7	8	85.219421	84.220301
8	9	85.908393	84.336370
9	10	86.703439	84.237711
10	11	87.675274	84.069410
11	12	88.655191	83.872091
12	13	89.813917	83.460043
13	14	90.997899	83.361384
14	15	92.103083	82.752017
15	16	93.170889	82.450235
16	17	94.161919	82.334165
17	18	95.128702	81.806047
18	19	96.008607	81.306947
19	20	96.777387	81.185073
20	21	97.381501	80.587314
21	22	97.931062	80.593117

	Max_Depth	Training_Accuracy	Validation_Accuracy
22	23	98.352326	80.291335
23	24	98.687720	80.064999
24	25	98.949368	79.948929
25	26	99.164545	79.740003
26	27	99.324161	79.786431
27	28	99.474684	79.542685
28	29	99.570655	79.444025
29	30	99.636320	79.705183
30	31	99.734311	79.316348
31	32	99.813109	79.380187
32	33	99.830282	79.188672
33	34	99.870691	79.246707
34	35	99.911100	79.090012
35	36	99.927264	79.043584
36	37	99.933325	79.258314
37	38	99.960601	79.345366
38	39	99.966663	79.171261
39	40	99.977775	79.385990
40	41	99.987877	79.438222
41	42	99.985857	79.264117
42	43	99.993939	79.327955
43	44	99.995959	79.153851
44	45	99.996969	79.298938
45	46	99.997980	79.159654
46	47	99.997980	79.090012

From the dataframe above, it can be seen that the training accuracy increases with increase in max_depth. Also, it is noted that validation accuracy first increases and then decreases.

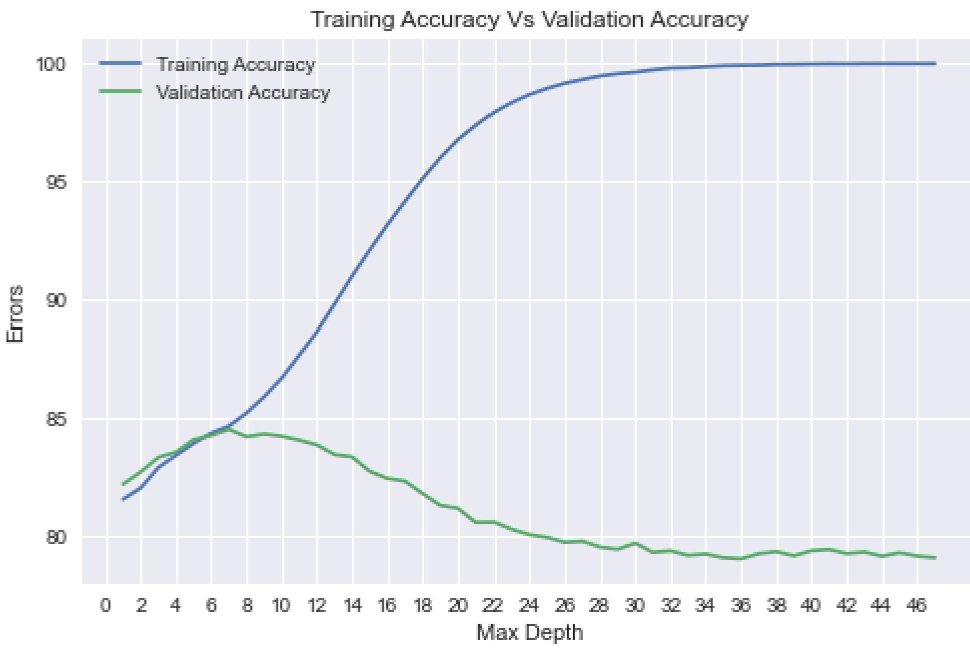
Tuning Graph

Let'us visualise the training accuracy and validation accuracy with different max_depths.

In [62]:

```
plt.title('Training Accuracy Vs Validation Accuracy');
plt.plot(accuracies_df1['Max_Depth'], accuracies_df1['Training_Accuracy']);
plt.plot(accuracies_df1['Max_Depth'], accuracies_df1['Validation_Accuracy']);
plt.legend(['Training Accuracy', 'Validation Accuracy']);
plt.xticks(range(0,48, 2))
```

```
plt.xlabel('Max Depth');
plt.ylabel('Errors');
```



From the graph it can also be seen that training accuracy increases with increase in max_depth while validation accuracy first increases (till max_depth = 7) and then decreases. Hence, optimal max_depth is 7.

Build Decision Tree with max_depth = 7

In [63]:

```
model = DecisionTreeClassifier(random_state=42, max_depth=7)
model.fit(X_train, Y_train)
print('Training Accuracy :', model.score(X_train,Y_train)*100)
print('Validation Accuracy :', model.score(X_val, Y_val)*100)
```

```
Training Accuracy : 84.66884874934335
Validation Accuracy : 84.53368928094713
```

Tuning max_leaf_nodes

Another way to control the size of complexity of a decision tree is to limit the number of leaf nodes. This enables branches of the tree to have varying depths. Let's limit the number of leaf nodes to 128 at maximum.

In [64]:

```
model = DecisionTreeClassifier(max_leaf_nodes=128, random_state=42)
model.fit(X_train, Y_train)
print('Training Accuracy :', model.score(X_train,Y_train)*100)
print('Validation Accuracy :', model.score(X_val, Y_val)*100)
```

```
Training Accuracy : 84.80421869317493
Validation Accuracy : 84.42342290058616
```

Let's see the accuracies when max_leaf_nodes was set to 128 at maximum.

In [65]:

```
accuracies_df1.loc[accuracies_df1['Max_Depth'] == model.tree_.max_depth]
```

Out[65]:

	Max_Depth	Training_Accuracy	Validation_Accuracy
11	12	88.655191	83.872091

Now, let's train our DecisionTreeClassifier with max_leaf_nodes = 128 and max_depth = 6,

In [66]:

```
model = DecisionTreeClassifier(max_leaf_nodes=128, random_state=42, max_depth=6)
```

Let's now use the trial and error method considering the two parameters.

In [67]:

```
def max_depth_accuracy2(max_depth_val):
    model = DecisionTreeClassifier(random_state=42, max_depth=max_depth_val, max_leaf_n
    model.fit(X_train, Y_train)
    train_accuracy = model.score(X_train, Y_train)*100
    val_accuracy = model.score(X_val, Y_val)*100
    return {'Max_Depth' : max_depth_val, 'Training_Accuracy' : train_accuracy, 'Validat
```

In [68]:

```
accuracies_df2 = pd.DataFrame([max_depth_accuracy2(i) for i in range(1,14)])
accuracies_df2
```

Out[68]:

	Max_Depth	Training_Accuracy	Validation_Accuracy
0	1	81.568473	82.206488
1	2	82.045298	82.728803
2	3	82.913080	83.343973
3	4	83.429305	83.564506
4	5	83.932396	84.092624
5	6	84.372853	84.272532
6	7	84.668849	84.533689
7	8	84.904231	84.382798
8	9	84.896149	84.464047
9	10	84.810280	84.464047
10	11	84.813311	84.469851
11	12	84.804219	84.423423
12	13	84.804219	84.423423

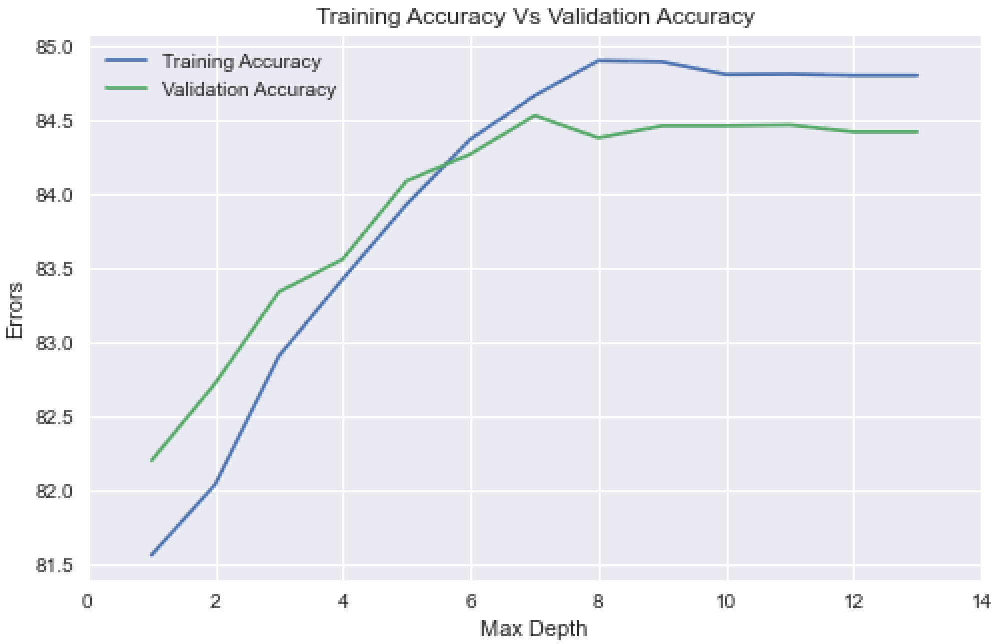
Tuning Graph

Let'us visualise the training accuracy and validation accuracy with different max_depths and max_leaf_nodes = 128.

In [69]:

```
plt.title('Training Accuracy Vs Validation Accuracy');
plt.plot(accuracies_df2['Max_Depth'], accuracies_df2['Training_Accuracy']);
plt.plot(accuracies_df2['Max_Depth'], accuracies_df2['Validation_Accuracy']);
```

```
plt.legend(['Training Accuracy', 'Validation Accuracy']);
plt.xticks(range(0,16, 2))
plt.xlabel('Max Depth');
plt.ylabel('Errors');
```



It seems max_depth = 9 and max_leaf_nodes = 128 is the optimal hyperparameters

Now, let's train our classifier with the best found hyperparameters,

In [70]:
```
model = DecisionTreeClassifier(max_depth=9, max_leaf_nodes=128, random_state=42)
model.fit(X_train, Y_train)
print('Training Accuracy :', model.score(X_train,Y_train)*100)
print('Validation Accuracy :', model.score(X_val, Y_val)*100)
```

```
Training Accuracy : 84.89614902816504
Validation Accuracy : 84.46404735650862
```

DecisionTreeClassifier with max_depth = 9

DecisionTreeClassifier with default parameters	
Accuracy of training data	84.89%
Accuracy of test and validation data	84.50%
Max depth of decision tree	9
Max leaf nodes	128

Table 2 - Performance of model with Hyperparameter tuning

The above performance is considerable better for new predictions as accuracy of training data, test data and validation data is almost the same.

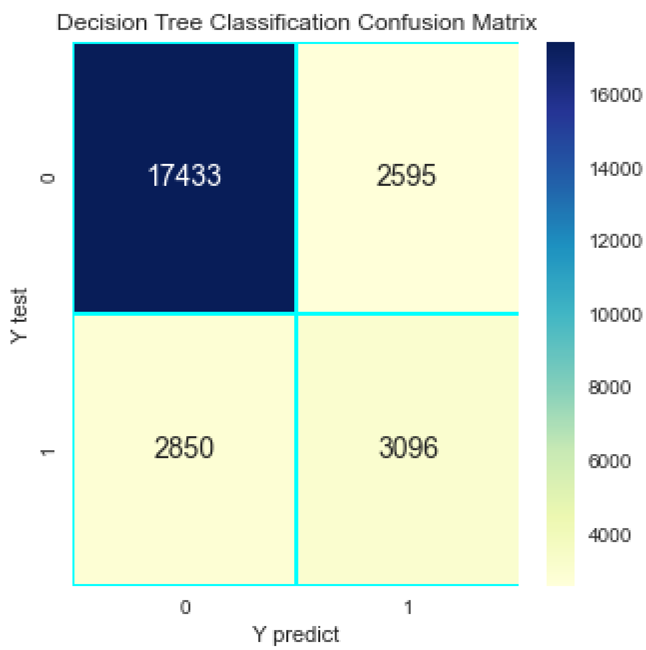
Decision Tree Classification Confusion Matrix

In [71]:
```
from sklearn.tree import DecisionTreeClassifier

# We define the model
dtcla = DecisionTreeClassifier(random_state=9)
```

```
# We train model
dtcla.fit(X_train, Y_train)

# We predict target values
Y_predict4 = dtcla.predict(X_test)
```

In [72]:

```
# The confusion matrix
dtcla_cm = confusion_matrix(Y_test, Y_predict4)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(dtcla_cm, annot=True, linewidth=0.7, linecolor='cyan', fmt='g', ax=ax, cmap
plt.title('Decision Tree Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



In [73]:

```
# Test score
score_dtcla = dtcla.score(X_test, Y_test)
print(score_dtcla)
```

```
0.7903672903672904
```

16. Random Forest Algorithm Training

Ramdom Forest is an ensemble technique where

Multiple DecisionTrees will be trained with different hyperparatmers Outcome of each DecisionTree will be voted / averaged The one with most count in terms of Classifier will be the winner prediction

In [74]:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_jobs = 1, random_state = 42)
```

In [75]:
```
%%time
rfc.fit(X_train, Y_train)
```

```
Wall time: 25 s
```

Out[75]:
```
▾          RandomForestClassifier
RandomForestClassifier(n_jobs=1, random_state=42)
```

Let us now get the score of model for train, test and validation dataset.

In [76]:
```
print("Training accuracy = ", rfc.score(X_train, Y_train) * 100, "%")
```

```
Training accuracy =  99.99595910615429 %
```

In [77]:
```
print("Validation accuracy = ", rfc.score(X_val, Y_val) * 100, "%")
```

```
Validation accuracy =  85.58412164122802 %
```

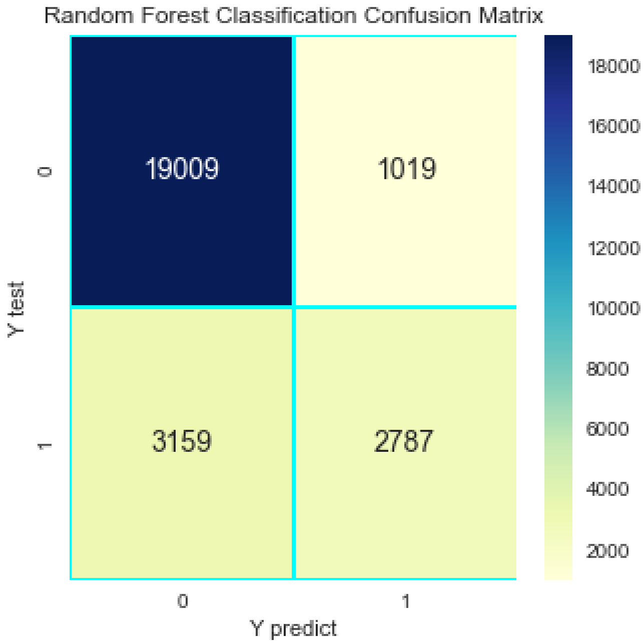
In [78]:
```
print("Test accuracy = ", rfc.score(X_test, Y_test) * 100, "%")
```

```
Test accuracy =  84.00323400323401 %
```

Random Forest Classification Confusion Matrix

In [79]:
```
from sklearn.ensemble import RandomForestClassifier

# We define the model
rfcla = RandomForestClassifier(n_estimators=100,random_state=9,n_jobs=-1)

# We train model
rfcla.fit(X_train, Y_train)

# We predict target values
Y_predict5 = rfcla.predict(X_test)
```

In [80]:
```
# The confusion matrix
rfcla_cm = confusion_matrix(Y_test, Y_predict5)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(rfcla_cm, annot=True, linewidth=0.7, linecolor='cyan', fmt='g', ax=ax, cmap
plt.title('Random Forest Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



From the above confusion matrix, there are 19,009 true negative values, 3,159 false negative values, 1,019 false positive values, and 2,787 true positive values. This illustrate that the best model is the Random Forest model.

In [81]:

```
# Test score
score_rfcla = rfcla.score(X_test, Y_test)
print(score_rfcla)
```

```
0.8391468391468392
```

The notebook also has an implementation of RandomForest with training accuracy 99.99% and a validation accuracy of 85.58%.

Finaly, one can establish that the Random Forest model is better in the sense it yields higher accuracy than other models.

17. Conclusion:

For the decision tree model, the training accuracy is 99.99%, validation accuracy is 79.28% and the percentage of 'No' in validation data is 78.8%. Hence, our model is only marginally better than always predicting "No". This occurs because the training data from which our model learned remains skewed towards 'No'Decision tree overfit.

After an Hyperparamter tuning was applied to make some changes in the parameters of the model training to avoid overfitting. We were able to predict with a training accuracy of 84.89% and validation accuracy of 84.46% using DecisionTree.

Sklearn best understands the value of hyperparameters but it sometimes fail for specific use cases and leave it up to Data scientists to tune the hyperparamters. DecisionTree and RadomForest are always at a risk of overfitting.

Also, the notebook has an implementation of RandomForest with training accuracy 99.99% and a validation accuracy of 85.58%. The Random Forest model has the highest validation accuracy among these two with an approximately 86.0%. From the performance of the two models, Random Forest is greater than Decision Tree.

Finaly, one can establish that the Random Forest model is better in the sense it yields higher accuracy than other models.