machine_learning_supervised_final_project

February 16, 2023

0.0.1 Import the required modules

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.impute import KNNImputer
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.preprocessing import normalize
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.metrics import confusion_matrix
```

0.1 I. Project Information

This is a project where I will use supervised machine learning to perform binary classification. In this specific case, I chose weather data collected for 10 years from Australia. The goal is to predict whether it will rain tomorrow, based on the weather data from today.

Weather forecasting is a complicated topic, and I was interested in how accurate we can make predictions about tomorrow's weather, solely based on the weather today, without using information about the weather that is happening elsewhere.

Github repository: https://github.com/highdeltav/SupervisedLearning/blob/main/machine_learning_supervised
https://github.com/highdeltav/SupervisedLearning/blob/main/machine_learning_supervised_final_project.pdf

0.2 II. Data Information

This dataset was obtained from Kaggle. I only downloaded the raw dataset, and because of the nature of this assignment, I did not read any of the other code relating to the dataset.

The dataset itself is 10 years worth of weather data from different cities in Australia. The data was gathered from publicly available weather data, produced by the Australian Bureau of Meteorology.

The weather observations were taken twice a day at 9 AM and 3PM. There are also some values that were aggregated over the entire 24 hour day.

The data is tabulated data featuring 14,5460 samples and 23 features. However, because weather data would vary from region to region and station to station, I limited the data that I was using to just the city of Sydney, which has 3,344 observations.

There are features relating to temperature, pressure, cloudiness and rainfall. Most of the features are numerical, however, wind direction is categorical, with 16 different categories, and 'RainToday' and "RainTomorrow' are both binary categories, with a yes/no value.

This is also an unbalanced dataset. Approximately 25 percent of the days have rain, and 75 percent do not.

Citation Young, Joe. *Rain in Australia* [Data set]. https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package?resource=download

[2]:
```
# Read in CSV
df_all =pd.read_csv('rain_aus/weatherAUS.csv')
```

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

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

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

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

   RainTomorrow
0            No
1            No
2            No
3            No
4            No
```

```
[5 rows x 23 columns]
```

[4]:
```python
print(f"Total number of Observations: {len(df_all.index)}" )
print(f"Total number of wind directions: {len(df_all['WindDir9am'].
 ↪value_counts())}")
```

```
Total number of Observations: 145460
Total number of wind directions: 16
```

[5]:
```python
# List features and their types
df_all.dtypes
```

[5]:
```
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
```

[6]:
```python
# Number of observations from each city
df_all['Location'].value_counts()
```

[6]:
```
Canberra            3436
Sydney              3344
Darwin              3193
Melbourne           3193
Brisbane            3193
Adelaide            3193
```

```
Perth               3193
Hobart              3193
Albany              3040
MountGambier        3040
Ballarat            3040
Townsville          3040
GoldCoast           3040
Cairns              3040
Launceston          3040
AliceSprings        3040
Bendigo             3040
Albury              3040
MountGinini         3040
Wollongong          3040
Newcastle           3039
Tuggeranong         3039
Penrith             3039
Woomera             3009
Nuriootpa           3009
Cobar               3009
CoffsHarbour        3009
Moree               3009
Sale                3009
PerthAirport        3009
PearceRAAF          3009
Witchcliffe         3009
BadgerysCreek       3009
Mildura             3009
NorfolkIsland       3009
MelbourneAirport    3009
Richmond            3009
SydneyAirport       3009
WaggaWagga          3009
Williamtown         3009
Dartmoor            3009
Watsonia            3009
Portland            3009
Walpole             3006
NorahHead           3004
SalmonGums          3001
Katherine           1578
Nhil                1578
Uluru               1578
Name: Location, dtype: int64
```

[7]:
```
# Take only the rows from Sydney
df = df_all.loc[df_all['Location']=='Sydney']
```

```python
#df_syd[['month']] = df_syd.Date.dt.month
print(f"Total Number of observations from Sydney: {len(df.index)}")
df.head()
```

```
Total Number of observations from Sydney: 3344
```

[7]:
```
             Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  \
30176  2008-02-01   Sydney     19.5     22.4      15.6          6.2       0.0
30177  2008-02-02   Sydney     19.5     25.6       6.0          3.4       2.7
30178  2008-02-03   Sydney     21.6     24.5       6.6          2.4       0.1
30179  2008-02-04   Sydney     20.2     22.8      18.8          2.2       0.0
30180  2008-02-05   Sydney     19.7     25.7      77.4          NaN       0.0

      WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  Humidity3pm  \
30176         NaN            NaN          S  …        92.0         84.0
30177         NaN            NaN          W  …        83.0         73.0
30178         NaN            NaN        ESE  …        88.0         86.0
30179         NaN            NaN        NNE  …        83.0         90.0
30180         NaN            NaN        NNE  …        88.0         74.0

       Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  \
30176       1017.6       1017.4       8.0       8.0     20.7     20.9
30177       1017.9       1016.4       7.0       7.0     22.4     24.8
30178       1016.7       1015.6       7.0       8.0     23.5     23.0
30179       1014.2       1011.8       8.0       8.0     21.4     20.9
30180       1008.3       1004.8       8.0       8.0     22.5     25.5

       RainToday  RainTomorrow
30176        Yes           Yes
30177        Yes           Yes
30178        Yes           Yes
30179        Yes           Yes
30180        Yes           Yes

[5 rows x 23 columns]
```

[8]:
```python
print(df['Date'].max(), df['Date'].min())
```

```
2017-06-25 2008-02-01
```

[9]:
```python
percentage_of_rainy_days = np.count_nonzero(df['RainTomorrow'])/len(df)
print(f"Percentage of Rainy Days: {percentage_of_rainy_days:.3}")
```

```
Percentage of Rainy Days: 1.0
```

0.3 III. Data Cleaning

After looking at the dtypes of the dataframe, I first noticed that the date was an object, so I converted that to a datetime object. I didn't feel that a specific date would do much good in model, but weather patterns have extreme variations based on time of year, so I extracted just the month, and created a new column for it.

[10]:
```
df.dtypes
```

[10]:
```
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
```

[11]:
```
# Convert date column to a datetime object
pd.to_datetime(df['Date'])
df = df.astype({'Date':'datetime64'})
df.dtypes
```

[11]:
```
Date             datetime64[ns]
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
```

[12]:
```
# Add a month column
df['month'] = df.Date.dt.month
```

The next step I accomplished was for the 'RainToday' and 'RainTomorrow' features, I converted the yes values to 1 and the no values to 0.

[13]:
```
# Convert the boolean, yes/no columns into 1s and 0s
df.loc[df['RainToday']=='Yes', 'RainToday'] = 1
df.loc[df['RainToday']=='No', 'RainToday'] = 0
df.loc[df['RainTomorrow']=='Yes', 'RainTomorrow'] = 1
df.loc[df['RainTomorrow']=='No', 'RainTomorrow'] = 0

# Make the columns numeric
df[['RainToday', 'RainTomorrow']] = df[['RainToday', 'RainTomorrow']].apply(pd.
 ↪to_numeric)
```

once that was done, the next part I undertook in the data cleaning process was to look at null values of the data. The first thing I noticed is that there were null values in the "RainTomorrow" feature. Since that is what we are going to create our predictive models from, I just deleted the rows with null values in that feature.

For all of the other features, except 'Clouds9am', 'Clouds3pm', 'WindGustDir' and 'WindGust-Speed', I decided to take the median value of that feature for that month, since weather patterns do change from month to month, I felt that taking the median from the month would give me a more accurate replacement value.

The wind gust and wind speeds, were a different challenge. There made up a substantial amount of rows, so I was trying to decide whether I should just delete both columns. However, I looked at the minimum value of "gust speed" and it was 17. This caused me to do some more research about how wind gusts are classified. I couldn't find a specific answer for the Australian Bureau of Meteorology, but I did find a definition from the National Weather Service, in the United States. that listed 16 knots as the minimum for a gust, pl. 17 Km/h is about 10 knots. Because of this information, I decided to treat the null gust values, as a zero, instead of dropping the feature all together. I did this because it would appear in this data, the days where there aren't gusts, are not recorded at all, and appear as a null value.

Lastly, I had to deal with the values of cloud cover. These data points felt important to me since we are trying to predict rain, and clouds are and important part of rain. That is a measurement that is taken in eights of the sky covered. Since the dataset shows a min of zero and a max of 8, I decided not to treat this like the wind gusts, because it did appear that they did record both clear days, and overcast days. Because of the importance I placed on this feature, I decided to just delete all of the rows that contained null values for clouds.

Once this was done, the only null values remaining were for 'WindGustDir', and I left them, so they would become their own category, when I changed the categorical values to numerical values.

[ ]:

```

```

[14]:

```
df.isnull().sum()
```

[14]:

```
Date                 0
Location             0
MinTemp              4
MaxTemp              2
Rainfall             7
Evaporation         51
Sunshine            16
WindGustDir       1038
WindGustSpeed     1038
WindDir9am          56
WindDir3pm          33
WindSpeed9am        26
WindSpeed3pm        25
Humidity9am         15
Humidity3pm         13
Pressure9am         21
Pressure3pm         19
Cloud9am           568
Cloud3pm           563
Temp9am              5
Temp3pm              4
RainToday            7
RainTomorrow         7
month                0
dtype: int64
```

[15]:

```
# Drop rows with NA Values

#Drop RainTomorrow, since it is supposed to be truth
df.dropna(subset = 'RainTomorrow', inplace = True)
```

```
df.dropna(subset = 'WindDir9am', inplace = True)
df.dropna(subset = 'WindDir3pm', inplace = True)
df.dropna(subset = 'Cloud9am', inplace = True)
df.dropna(subset = 'Cloud3pm', inplace = True)

# The minnimum for gusts is 17. The NWS in the US only records gusts above 16␣
↪knots.
# Because of that, I am assuming null values, had no wind gusts above that␣
↪threshold, so I am replacing them with 0.
df['WindGustSpeed'].fillna(0, inplace = True)

# Select coulumns to take the median of for NA values. I took the median of the␣
↪values, grouped by month, since the
# median and means would change drastically through the year
columns_to_median = ['MinTemp', 'MaxTemp', 'Rainfall',␣
↪'Evaporation','Sunshine','Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm','Temp9am', 'Temp3pm', 'RainToday']
for col in columns_to_median:
    df[col].fillna(df.groupby(['month'])[col].transform('median'), inplace =␣
↪True)

print(f"Observations remaining: {len(df)}")
df.isnull().sum()
```

```
Observations remaining: 2705
```

[15]:

```
Date               0
Location           0
MinTemp            0
MaxTemp            0
Rainfall           0
Evaporation        0
Sunshine           0
WindGustDir      959
WindGustSpeed      0
WindDir9am         0
WindDir3pm         0
WindSpeed9am       0
WindSpeed3pm       0
Humidity9am        0
Humidity3pm        0
Pressure9am        0
Pressure3pm        0
Cloud9am           0
Cloud3pm           0
Temp9am            0
Temp3pm            0
```

```
RainToday          0
RainTomorrow       0
month              0
dtype: int64
```

I then converted the categorical variables to numbers, so that each different category would be have a different number. This included the null values for WindGustDir.

[16]:
```python
# Chaingning the catagorical features to numbers.
df['WindDir9am'] = df['WindDir9am'].astype('category').cat.codes
df['WindDir3pm'] = df['WindDir3pm'].astype('category').cat.codes

# Chaning WindGustDir to catagories also makes the null values equal to zero,␣
↪which is expected
df['WindGustDir'] = df['WindGustDir'].astype('category').cat.codes
```

[17]:
```python
df.dtypes
```

[17]:
```
Date                 datetime64[ns]
Location                     object
MinTemp                     float64
MaxTemp                     float64
Rainfall                    float64
Evaporation                 float64
Sunshine                    float64
WindGustDir                    int8
WindGustSpeed               float64
WindDir9am                     int8
WindDir3pm                     int8
WindSpeed9am                float64
WindSpeed3pm                float64
Humidity9am                 float64
Humidity3pm                 float64
Pressure9am                 float64
Pressure3pm                 float64
Cloud9am                    float64
Cloud3pm                    float64
Temp9am                     float64
Temp3pm                     float64
RainToday                   float64
RainTomorrow                float64
month                         int64
dtype: object
```

The last step that I took was to remove the date and location features. As previously discussed, since I was only using data from Sydney, that field was now superfluous. As for the date, I had already extracted the value that I needed from it, so the date in its present format would not help in the modeling process.

[18]:
```
# Drops 'Date' and 'Location' because they will not help the machine learning␣
↪modeling
df.drop(['Date', 'Location'], axis = 1, inplace = True)
df.head()
```

[18]:
```
       MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustDir  \
30176     19.5     22.4      15.6          6.2       0.0           -1
30177     19.5     25.6       6.0          3.4       2.7           -1
30178     21.6     24.5       6.6          2.4       0.1           -1
30179     20.2     22.8      18.8          2.2       0.0           -1
30180     19.7     25.7      77.4          6.8       0.0           -1

       WindGustSpeed  WindDir9am  WindDir3pm  WindSpeed9am  …  Humidity3pm  \
30176            0.0           8          11          17.0  …         84.0
30177            0.0          13           0           9.0  …         73.0
30178            0.0           2           2          17.0  …         86.0
30179            0.0           5           0          22.0  …         90.0
30180            0.0           5          13          11.0  …         74.0

       Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  \
30176       1017.6       1017.4       8.0       8.0     20.7     20.9
30177       1017.9       1016.4       7.0       7.0     22.4     24.8
30178       1016.7       1015.6       7.0       8.0     23.5     23.0
30179       1014.2       1011.8       8.0       8.0     21.4     20.9
30180       1008.3       1004.8       8.0       8.0     22.5     25.5

       RainToday  RainTomorrow  month
30176        1.0           1.0      2
30177        1.0           1.0      2
30178        1.0           1.0      2
30179        1.0           1.0      2
30180        1.0           1.0      2

[5 rows x 22 columns]
```

0.4 IV. Exploratory Data Analysis

The first thing that I did was look at the summary values of the different rows. I looked for any values that didn't seem to make sense, especially for the max and min values. I was looking for outliers that might need to be addressed in the data. The data seemed reasonable from this perspective. There were certainly some really hot days, or really windy days, but nothing that didn't seem possible.

Looking at the box plots, rainfall showed significant outliers, but that makes sense in a region where most days it does not rain at all.

Also, looking at the histograms, there didn't seem to be any strange outliers, or distributions that didn't make sense for the data.

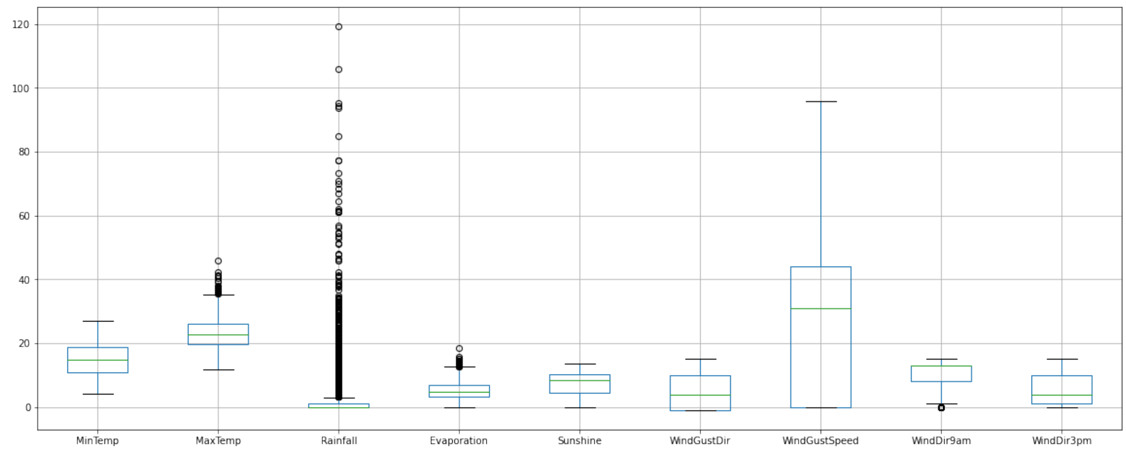
[19]:
```python
with pd.option_context('display.max_columns', 40):
    print(df.describe(include='all'))
```

```
           MinTemp      MaxTemp     Rainfall  Evaporation     Sunshine  \
count  2705.000000  2705.000000  2705.000000  2705.000000  2705.000000
mean     14.772052    23.018743     3.205989     5.213974     7.294584
std       4.546462     4.515104     9.544302     2.788708     3.760587
min       4.300000    11.700000     0.000000     0.000000     0.000000
25%      11.000000    19.600000     0.000000     3.200000     4.500000
50%      14.800000    22.800000     0.000000     4.800000     8.400000
75%      18.700000    26.000000     1.200000     7.000000    10.200000
max      27.100000    45.800000   119.400000    18.400000    13.600000

       WindGustDir  WindGustSpeed   WindDir9am   WindDir3pm  WindSpeed9am  \
count  2705.000000    2705.000000  2705.000000  2705.000000   2705.000000
mean      4.876155      27.027357    10.223290     5.925693     15.112015
std       5.788733      22.570370     4.404775     4.998153      6.914125
min      -1.000000       0.000000     0.000000     0.000000      2.000000
25%      -1.000000       0.000000     8.000000     1.000000     11.000000
50%       4.000000      31.000000    13.000000     4.000000     15.000000
75%      10.000000      44.000000    13.000000    10.000000     20.000000
max      15.000000      96.000000    15.000000    15.000000     54.000000

       WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  Pressure3pm  \
count   2705.000000  2705.000000  2705.000000  2705.000000  2705.000000
mean      19.322366    67.612939    53.984473  1018.453309  1016.069979
std        7.409985    15.271722    16.282516     6.984624     7.019000
min        2.000000    19.000000    10.000000   986.700000   990.300000
25%       15.000000    58.000000    43.000000  1013.900000  1011.300000
50%       19.000000    68.000000    55.000000  1018.700000  1016.400000
75%       24.000000    79.000000    64.000000  1023.200000  1020.900000
max       57.000000   100.000000    96.000000  1039.000000  1036.000000

          Cloud9am     Cloud3pm      Temp9am      Temp3pm    RainToday  \
count  2705.000000  2705.000000  2705.000000  2705.000000  2705.000000
mean      4.159704     4.205545    17.767930    21.548688     0.255453
std       2.751076     2.642655     4.909296     4.305569     0.436196
min       0.000000     0.000000     6.400000    10.200000     0.000000
25%       1.000000     1.000000    13.800000    18.400000     0.000000
50%       4.000000     4.000000    18.000000    21.300000     0.000000
75%       7.000000     7.000000    21.700000    24.500000     1.000000
max       9.000000     8.000000    36.500000    44.700000     1.000000

       RainTomorrow        month
count   2705.000000  2705.000000
mean       0.252865     6.498706
std        0.434735     3.354667
```

```
min        0.000000     1.000000
25%        0.000000     4.000000
50%        0.000000     7.000000
75%        1.000000     9.000000
max        1.000000    12.000000
```

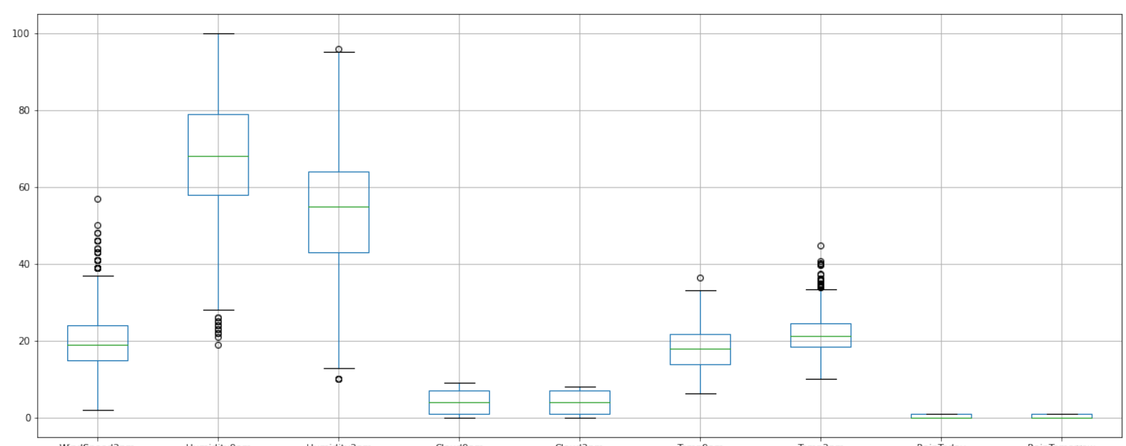
[20]:
```python
plt.rcParams["figure.figsize"] = (20,8)
box_plot_columns = df.columns.tolist()
box_plot_columns.remove('Pressure9am')
box_plot_columns.remove('Pressure3pm')
df.boxplot(column= box_plot_columns[0:9])
```

[20]:
```
<AxesSubplot:>
```



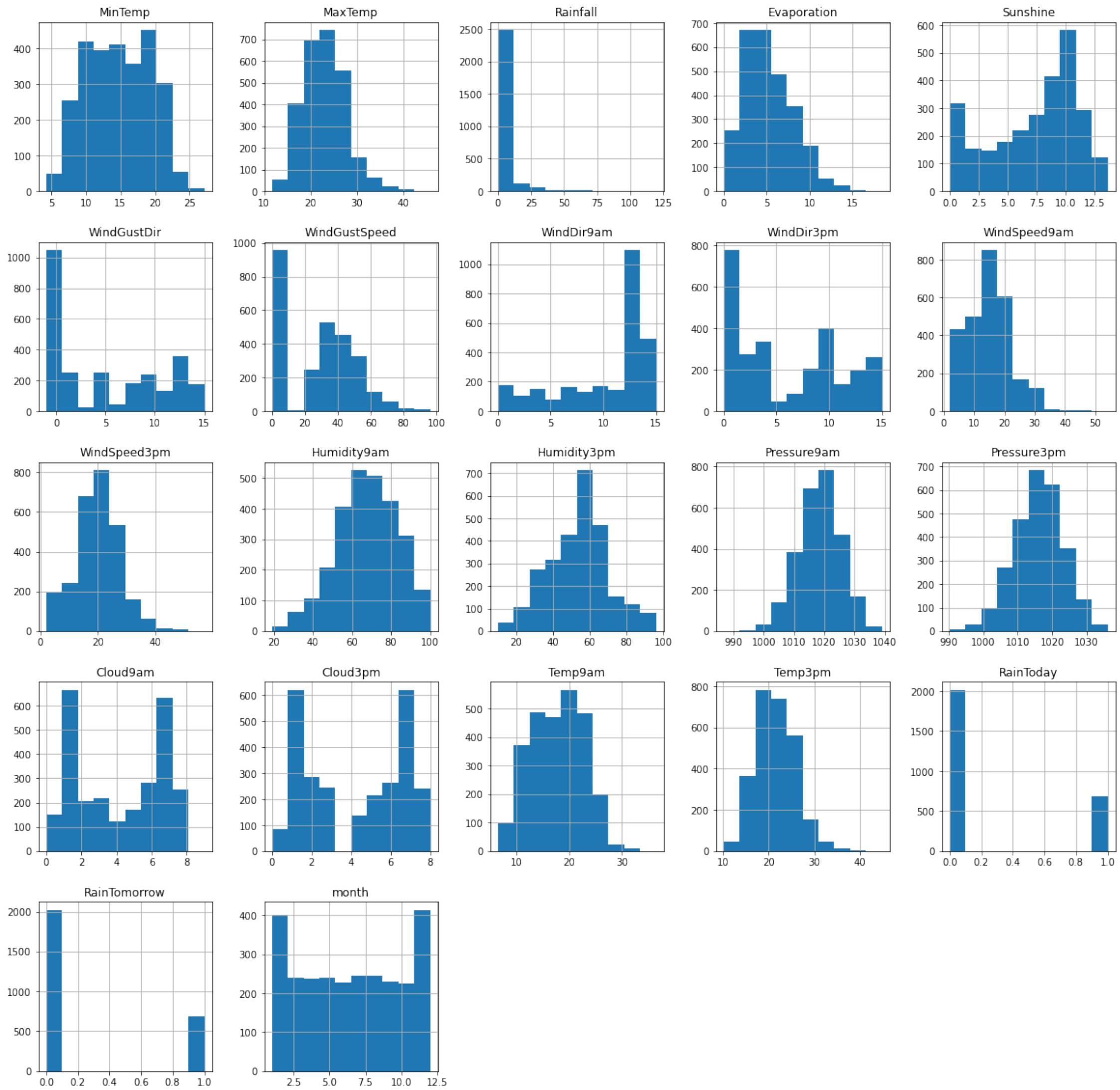
[21]:
```python
df.boxplot(column= box_plot_columns[10:19])
```

[21]:
```
<AxesSubplot:>
```



[22]:
```
plt.rcParams["figure.figsize"] = (20,20)
df.hist()
```

[22]:
```
array([[<AxesSubplot:title={'center':'MinTemp'}>,
        <AxesSubplot:title={'center':'MaxTemp'}>,
        <AxesSubplot:title={'center':'Rainfall'}>,
        <AxesSubplot:title={'center':'Evaporation'}>,
        <AxesSubplot:title={'center':'Sunshine'}>],
       [<AxesSubplot:title={'center':'WindGustDir'}>,
        <AxesSubplot:title={'center':'WindGustSpeed'}>,
        <AxesSubplot:title={'center':'WindDir9am'}>,
        <AxesSubplot:title={'center':'WindDir3pm'}>,
        <AxesSubplot:title={'center':'WindSpeed9am'}>],
       [<AxesSubplot:title={'center':'WindSpeed3pm'}>,
        <AxesSubplot:title={'center':'Humidity9am'}>,
        <AxesSubplot:title={'center':'Humidity3pm'}>,
        <AxesSubplot:title={'center':'Pressure9am'}>,
        <AxesSubplot:title={'center':'Pressure3pm'}>],
       [<AxesSubplot:title={'center':'Cloud9am'}>,
        <AxesSubplot:title={'center':'Cloud3pm'}>,
        <AxesSubplot:title={'center':'Temp9am'}>,
        <AxesSubplot:title={'center':'Temp3pm'}>,
        <AxesSubplot:title={'center':'RainToday'}>],
       [<AxesSubplot:title={'center':'RainTomorrow'}>,
        <AxesSubplot:title={'center':'month'}>, <AxesSubplot:>,
        <AxesSubplot:>, <AxesSubplot:>]], dtype=object)
```



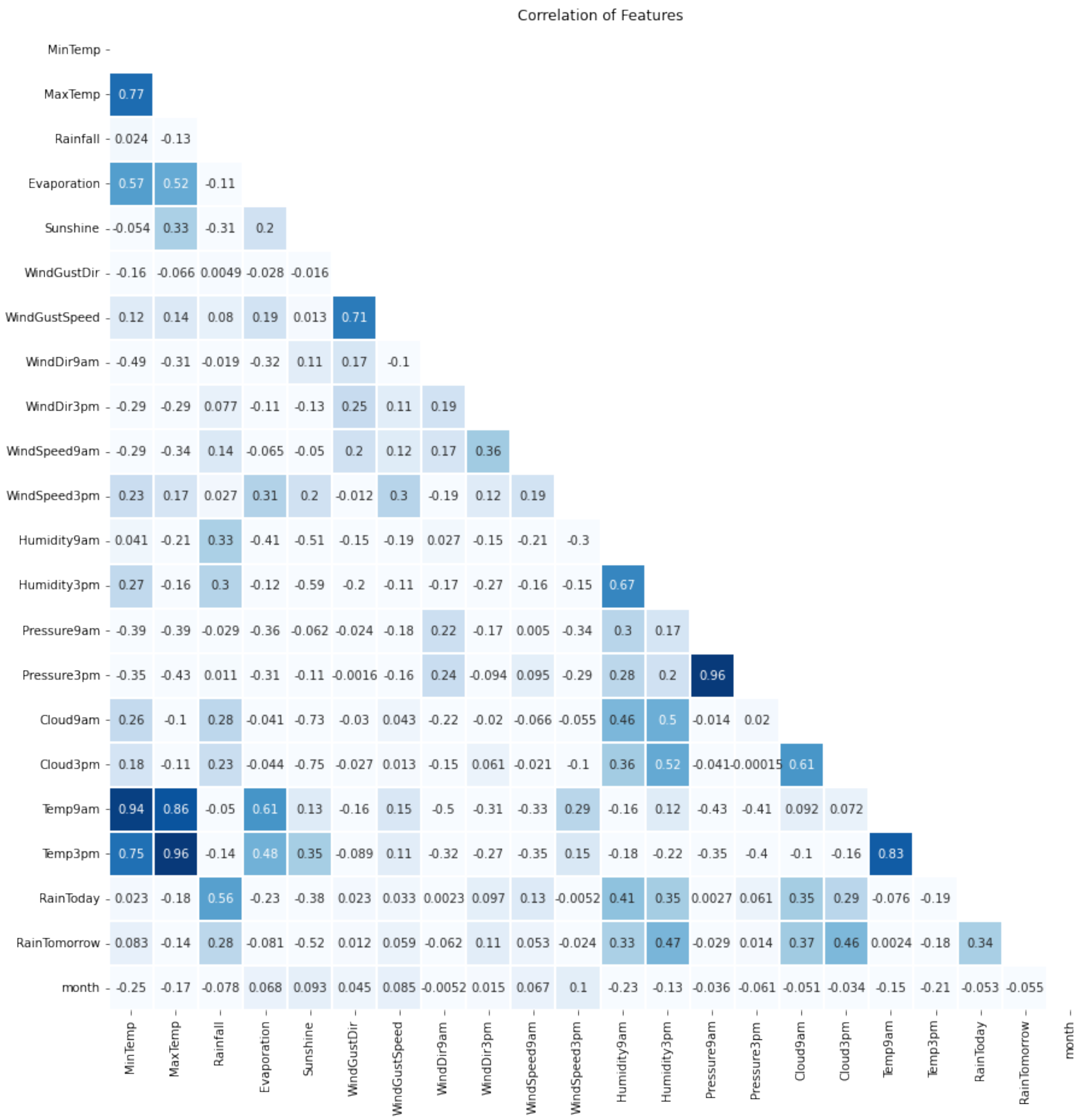
I also created a heatmap to look at the correlation of the different features. There was high correlation between some of the columns. The temperatures taken at 9 AM and 3 PM, where highly correlated with the temperatures max and the min temperatures for the day. I decided to remove the individual temperature readings, and just keep the minimum and the maximum readings.

The two pressure readings were also highly correlated with themselves. Since we are trying to predict rain tomorrow, and pressure is an indicator of the type of weather that is happening, I just kept the afternoon reading, which is closer to the time we are trying to predict.

[23]:
```
corr = df.corr()
mask = mask = np.triu(corr)
plt.rcParams["figure.figsize"] = (15,15)
```

```
ax1 = sns.heatmap(corr, cbar=0, linewidths=2,vmax=1, vmin=0, square=True,␣
 ↪cmap='Blues', annot=True, mask=mask)
plt.title('Correlation of Features')
```

[23]:
```
Text(0.5, 1.0, 'Correlation of Features')
```



Before dropping 'Pressure9am', I did also did some minor feature engineering by adding a column 'PressureChange'. This takes the difference in pressure from the morning pressure observation, and the afternoon pressure reading. I added this feature since pressure change can signal changes in weather.

[24]:
```
# Add Pressure Change
df['PressueChange'] = df['Pressure3pm']-df['Pressure9am']
```

[25]:

```
# Drop the highly correlated features
df_dropped = df.drop(['Pressure9am','Temp9am','Temp3pm'], axis = 1)
```

[26]:

```
df_dropped.describe()
```

[26]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine
count	2705.000000	2705.000000	2705.000000	2705.000000	2705.000000
mean	14.772052	23.018743	3.205989	5.213974	7.294584
std	4.546462	4.515104	9.544302	2.788708	3.760587
min	4.300000	11.700000	0.000000	0.000000	0.000000
25%	11.000000	19.600000	0.000000	3.200000	4.500000
50%	14.800000	22.800000	0.000000	4.800000	8.400000
75%	18.700000	26.000000	1.200000	7.000000	10.200000
max	27.100000	45.800000	119.400000	18.400000	13.600000

	WindGustDir	WindGustSpeed	WindDir9am	WindDir3pm	WindSpeed9am
count	2705.000000	2705.000000	2705.000000	2705.000000	2705.000000
mean	4.876155	27.027357	10.223290	5.925693	15.112015
std	5.788733	22.570370	4.404775	4.998153	6.914125
min	-1.000000	0.000000	0.000000	0.000000	2.000000
25%	-1.000000	0.000000	8.000000	1.000000	11.000000
50%	4.000000	31.000000	13.000000	4.000000	15.000000
75%	10.000000	44.000000	13.000000	10.000000	20.000000
max	15.000000	96.000000	15.000000	15.000000	54.000000

	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure3pm	Cloud9am
count	2705.000000	2705.000000	2705.000000	2705.000000	2705.000000
mean	19.322366	67.612939	53.984473	1016.069979	4.159704
std	7.409985	15.271722	16.282516	7.019000	2.751076
min	2.000000	19.000000	10.000000	990.300000	0.000000
25%	15.000000	58.000000	43.000000	1011.300000	1.000000
50%	19.000000	68.000000	55.000000	1016.400000	4.000000
75%	24.000000	79.000000	64.000000	1020.900000	7.000000
max	57.000000	100.000000	96.000000	1036.000000	9.000000

	Cloud3pm	RainToday	RainTomorrow	month	PressueChange
count	2705.000000	2705.000000	2705.000000	2705.000000	2705.000000
mean	4.205545	0.255453	0.252865	6.498706	-2.383330
std	2.642655	0.436196	0.434735	3.354667	1.965685
min	0.000000	0.000000	0.000000	1.000000	-17.400000
25%	1.000000	0.000000	0.000000	4.000000	-3.600000
50%	4.000000	0.000000	0.000000	7.000000	-2.500000
75%	7.000000	1.000000	1.000000	9.000000	-1.200000
max	8.000000	1.000000	1.000000	12.000000	6.500000

0.5 V. Modeling

My first step in the modeling process was the split the target variable into its own dataframe, and split the data into training and test sets.

[27]:
```
# Create the X and y sets.
y = df_dropped['RainTomorrow']
X = df_dropped.drop('RainTomorrow', axis = 1)
```

[28]:
```
# Split the data into training and test

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)
```

Some of the models I was going to work better with normalized data. With the same train/test split, I also normalized the data.

[29]:
```
X_norm_train = normalize(X_train)
X_norm_test = normalize(X_test)
X_norm = normalize(X)
```

I also created empty lists, so I could graph some comparison of models.

[30]:
```
all_scores = []
all_recall = []
all_precision = []
all_tpr = []
all_fpr = []
all_auc = []
all_models = []
```

0.5.1 KNN Neighbor Model

The first model that I chose to work with was the KNN nearest neighbors mode. I initially tried just the default values, and got a reasonable value, so I then moved on to trying to tune the hyperparameter of number of neighbors. This resulted in a best neighbor score of 25.

[31]:
```
KN_class = KNeighborsClassifier()
KN_model = KN_class.fit(X_norm_train, y_train)
```

[32]:
```
KN_model.score(X_norm_test, y_test)
```

[32]: 0.8040313549832027

[33]:
```
test_neighbors = range(1,50)
grid_kn=GridSearchCV(estimator = KNeighborsClassifier(),
                     cv = 5,
                     param_grid={
                         'n_neighbors': test_neighbors}
```

```
                         ,verbose = 1)
grid_kn.fit(X_norm,y)
```

```
Fitting 5 folds for each of 49 candidates, totalling 245 fits
```

[33]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': range(1, 50)}, verbose=1)
```

[34]:
```
print(grid_kn.best_params_)
print(grid_kn.best_score_)
```

```
{'n_neighbors': 27}
0.8310536044362292
```

[35]:
```
#Create an estimator off of the best estimator from the grid search
KN_best = grid_kn.best_estimator_
fpr, tpr, threshold = metrics.roc_curve(y_test, KN_best.predict_proba(X_test.
 ↪values)[:,1])
all_fpr.append(fpr)
all_tpr.append(tpr)

# Generate statistics about the models
pred = KN_best.predict(X_test.values)
accuracy = metrics.accuracy_score(y_test, pred)
recall = metrics.recall_score(y_test, pred)
precision = metrics.precision_score(y_test, pred)
auc = metrics.auc(fpr, tpr)

#Append scores for final analysis comparison
all_scores.append(accuracy)
all_recall.append(recall)
all_precision.append(precision)
all_auc.append(auc)
all_models.append('KNN')

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
```

```
Accuracy: 0.8253079507278835
Recall: 0.4425531914893617
Precision: 0.8062015503875969
```

0.5.2 Decision Tree Model

I then moved on to try a decision tree model. I first tested it with the default parameters, and then tried to tune max_depth and ccp_alpha. Interestingly, in a basic decision tree model, the most accurate model, that I found, only had a max_depth of 1, with the most important feature being the afternoon humidity. If a model was only going to use one value, this is a logical one for it to use, since rain is moisture in the air, and humidity is a measure of moisture.

[36]:
```
tree_class = DecisionTreeClassifier()
tree_mod = tree_class.fit(X_train, y_train)
```

[37]:
```
tree_mod.score(X_test, y_test)
```

[37]:
```
0.7681970884658454
```

[38]:
```
print(tree_mod.get_depth())
```

```
19
```

[39]:
```
grid_tree=GridSearchCV(estimator = DecisionTreeClassifier(),
                  cv = 5,
                  param_grid={
                      'max_depth': [1,2,3,4,5,7,8,9,10,15,20,50],
                      'ccp_alpha': [0,.01,.02,.03,.04,.05,.06]},
                  verbose =1)
grid_tree.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 84 candidates, totalling 420 fits
```

[39]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'ccp_alpha': [0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06],
                         'max_depth': [1, 2, 3, 4, 5, 7, 8, 9, 10, 15, 20, 50]},
             verbose=1)
```

[40]:
```
print(grid_tree.best_params_)
print(grid_tree.best_score_)
```

```
{'ccp_alpha': 0, 'max_depth': 1}
0.8316926167754897
```

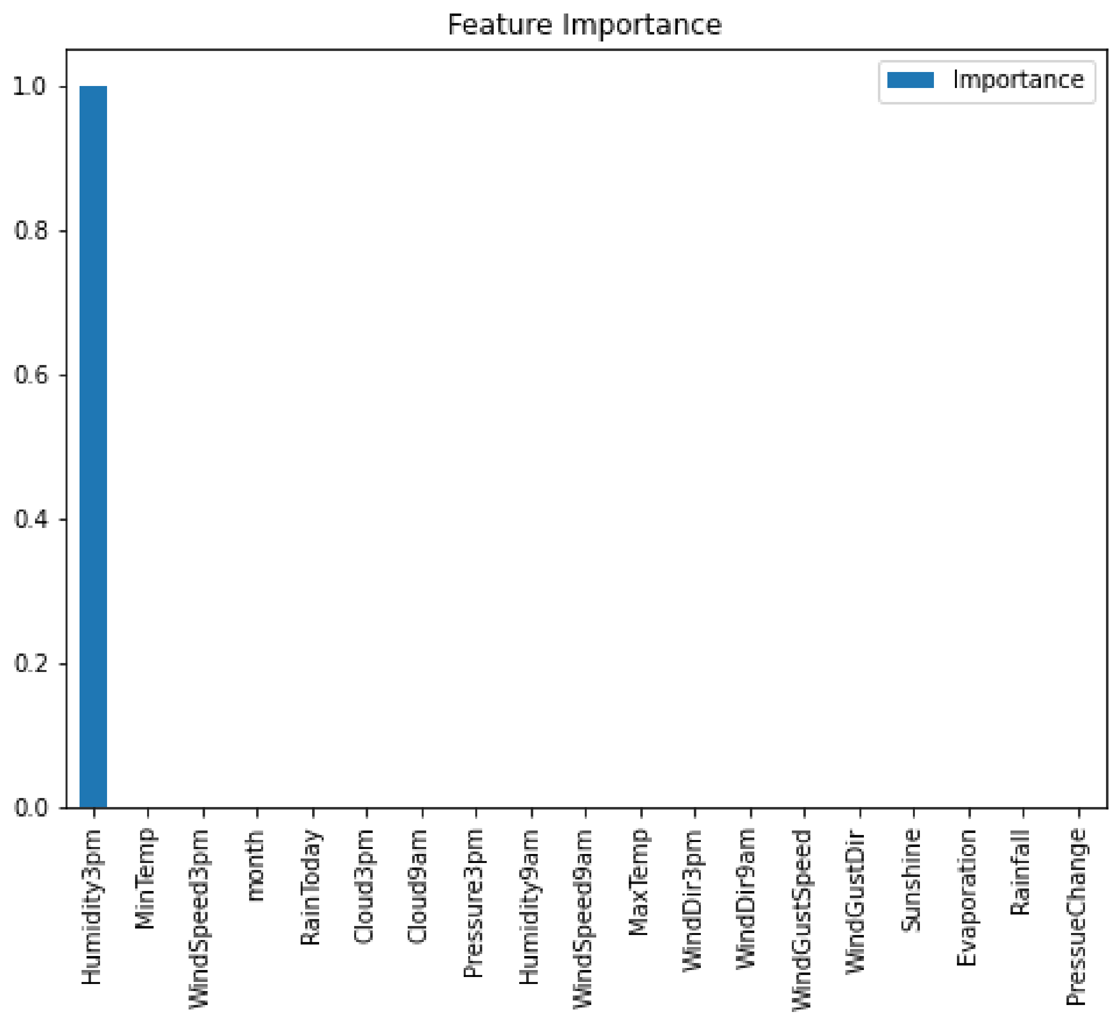
[41]:
```
#Create an estimator off of the best estimator from the grid search
grid_tree_best = grid_tree.best_estimator_
fpr, tpr, threshold = metrics.roc_curve(y_test, grid_tree_best.
 ↪predict_proba(X_test)[:,1])
all_fpr.append(fpr)
all_tpr.append(tpr)

# Generate statistics about the models
```

```
pred = grid_tree_best.predict(X_test)
accuracy = metrics.accuracy_score(y_test, pred)
recall = metrics.recall_score(y_test, pred)
precision = metrics.precision_score(y_test, pred)
auc = metrics.auc(fpr, tpr)

#Append scores for final analysis comparison
all_scores.append(accuracy)
all_recall.append(recall)
all_precision.append(precision)
all_auc.append(auc)
all_models.append('Decision Tree')

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
```

```
Accuracy: 0.812989921612542
Recall: 0.3702127659574468
Precision: 0.8207547169811321
```

[42]:
```
# Plot of feature importance

feat_importances = pd.DataFrame(grid_tree_best.feature_importances_, index=X.
 ↪columns, columns=["Importance"])
feat_importances.sort_values(by='Importance', ascending=False, inplace=True)
feat_importances.plot(kind='bar', figsize=(8,6), title = 'Feature Importance')
```

[42]:
```
<AxesSubplot:title={'center':'Feature Importance'}>
```



0.5.3 AdaBoost Model

I also tried an AdaBoost Model. After an initial test with the default parameters, I also tuned the parameters n-estimators and learning_rate. I initially ran the grid search, and then when I got the answer, I then added some parameters around the best model, so see if I could further fine tune the model. It also showed that afternoon humidity was the most important, but also took into account other variables as well. The pressure change feature that I added, had importance in the model, but it was the least important of the important features that the model used.

[43]:
```
ada_class = AdaBoostClassifier(learning_rate = .5)
ada_model = ada_class.fit(X_train, y_train)
ada_model.score(X_test, y_test)
```

[43]: 0.8085106382978723

[44]:
```
learning_rate = np.logspace(-5,1,11, base = 2)
grid_ada=GridSearchCV(estimator = AdaBoostClassifier(),
                  cv = 5,
                  param_grid={
                      'n_estimators': [1,30,35,40,45,50,55,58,59,60,61,65],
                      'learning_rate': learning_rate},
                      verbose = 1)
grid_ada.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 132 candidates, totalling 660 fits
```

[44]:
```
GridSearchCV(cv=5, estimator=AdaBoostClassifier(),
             param_grid={'learning_rate': array([0.03125   , 0.04736614,
0.07179365, 0.10881882, 0.16493849,
       0.25      , 0.37892914, 0.57434918, 0.87055056, 1.31950791,
       2.        ]),
                         'n_estimators': [1, 30, 35, 40, 45, 50, 55, 58, 59, 60,
                                          61, 65]},
             verbose=1)
```

[45]:
```
print(grid_ada.best_params_)
print(grid_ada.best_score_)
```

```
{'learning_rate': 0.16493848884661177, 'n_estimators': 40}
0.8493447787772249
```

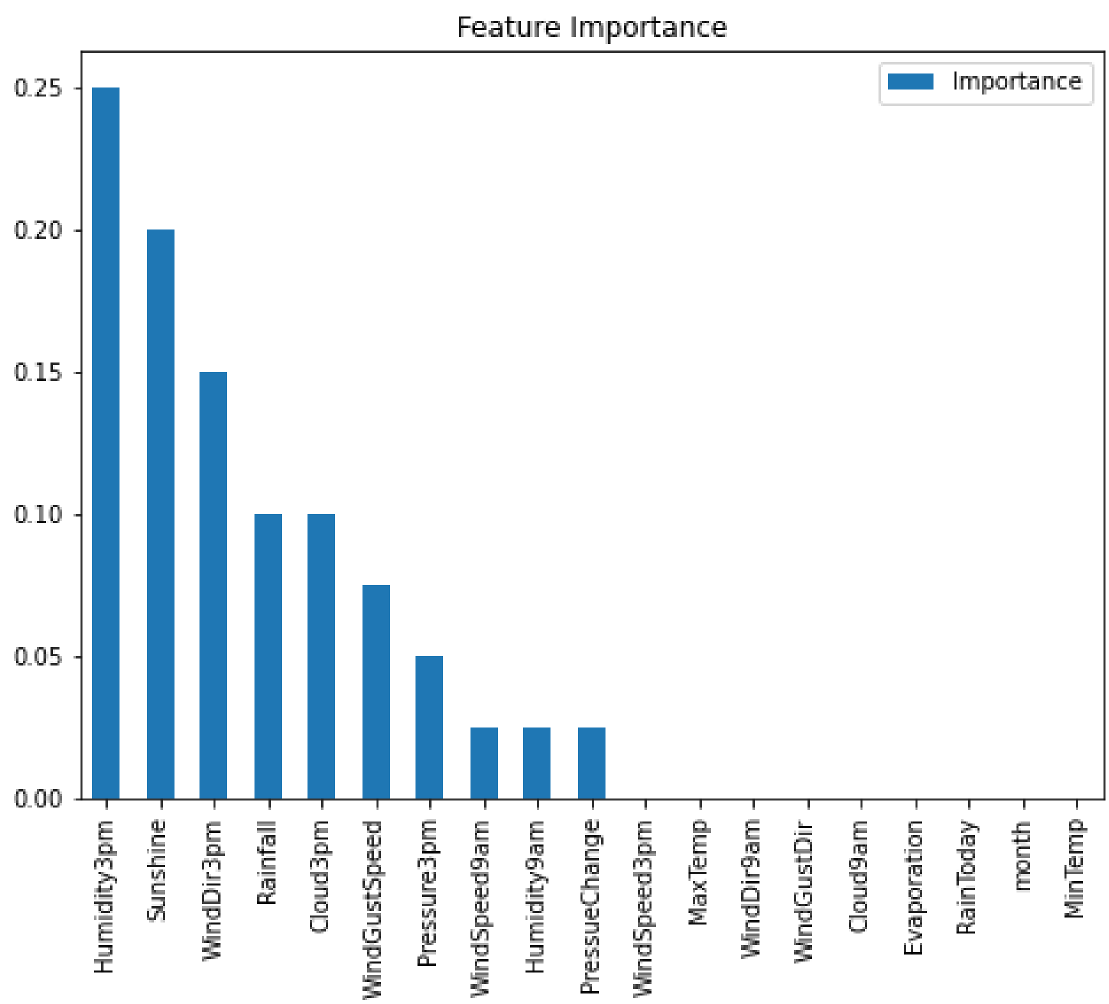
[46]:
```
#Create an estimator off of the best estimator from the grid search
ada_best = grid_ada.best_estimator_
fpr, tpr, threshold = metrics.roc_curve(y_test, ada_best.predict_proba(X_test)[:
 ↪,1])
all_fpr.append(fpr)
all_tpr.append(tpr)

# Generate statistics about the models
pred = ada_best.predict(X_test)
accuracy = metrics.accuracy_score(y_test, pred)
recall = metrics.precision_score(y_test, pred)
precision = metrics.precision_score(y_test, pred)
auc = metrics.auc(fpr, tpr)

#Append scores for final analysis comparison
all_scores.append(accuracy)
all_recall.append(recall)
all_precision.append(precision)
all_auc.append(auc)
all_models.append('AdaBoost')
```

```
print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
```

```
Accuracy: 0.8174692049272116
Recall: 0.7571428571428571
Precision: 0.7571428571428571
```

[47]:
```
# Plot of feature importance

feat_importances = pd.DataFrame(ada_best.feature_importances_, index=X.columns,␣
↪columns=["Importance"])
feat_importances.sort_values(by='Importance', ascending=False, inplace=True)
feat_importances.plot(kind='bar', figsize=(8,6), title = 'Feature Importance')
```

[47]:
```
<AxesSubplot:title={'center':'Feature Importance'}>
```



0.5.4 Random Forest

I also used the same procedure for random forest and tuned the hyperparameters n_estimators and max_features. The random forest did use all of the features, but the afternoon humidity was still the most important feature, but sunshine, was close behind on how important it is in the model.

[48]:
```
rf_class = RandomForestClassifier()
rf_model = rf_class.fit(X_train, y_train)
rf_model.score(X_test, y_test)
```

[48]:
```
0.8230683090705487
```

[49]:
```
grid_rf=GridSearchCV(estimator = RandomForestClassifier(),
                  cv = 5,
                  param_grid={
                      'n_estimators': [25,50,100,140,150,160,200],
                      'max_features' : ['sqrt','log2']},
                      verbose = 1)
grid_rf.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 14 candidates, totalling 70 fits
```

[49]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_features': ['sqrt', 'log2'],
                         'n_estimators': [25, 50, 100, 140, 150, 160, 200]},
             verbose=1)
```

[50]:
```
print(grid_rf.best_params_)
print(grid_rf.best_score_)
```

```
{'max_features': 'sqrt', 'n_estimators': 140}
0.8465884358400683
```

[51]:
```
#Create an estimator off of the best estimator from the grid search
rf_best = grid_rf.best_estimator_
fpr, tpr, threshold = metrics.roc_curve(y_test, rf_best.predict_proba(X_test)[:
 ↪,1])
all_fpr.append(fpr)
all_tpr.append(tpr)

# Generate statistics about the models
pred = rf_best.predict(X_test)
accuracy = metrics.accuracy_score(y_test, pred)
recall = metrics.recall_score(y_test, pred)
precision = metrics.precision_score(y_test, pred)
auc = metrics.auc(fpr, tpr)

#Append scores for final analysis comparison
```

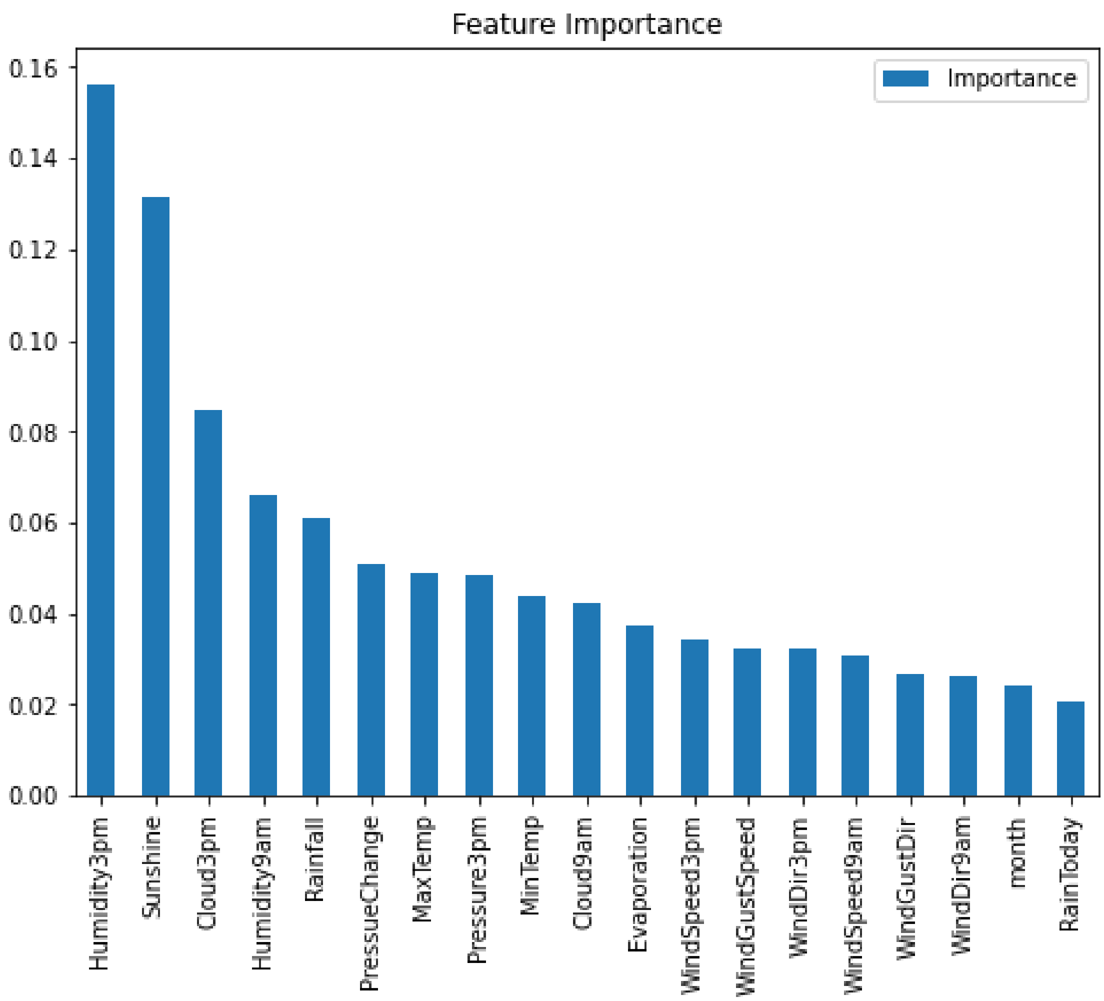
```python
all_scores.append(accuracy)
all_recall.append(recall)
all_precision.append(precision)
all_auc.append(auc)
all_models.append('Random Forest')

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
```

```
Accuracy: 0.8219484882418813
Recall: 0.46382978723404256
Precision: 0.7676056338028169
```

[52]:

```python
# Plot of feature importance

feat_importances = pd.DataFrame(rf_best.feature_importances_, index=X.columns,␣
↪columns=["Importance"])
feat_importances.sort_values(by='Importance', ascending=False, inplace=True)
feat_importances.plot(kind='bar', figsize=(8,6), title = 'Feature Importance')
```

[52]: <AxesSubplot:title={'center':'Feature Importance'}>



0.6 VI. Results and Analysis

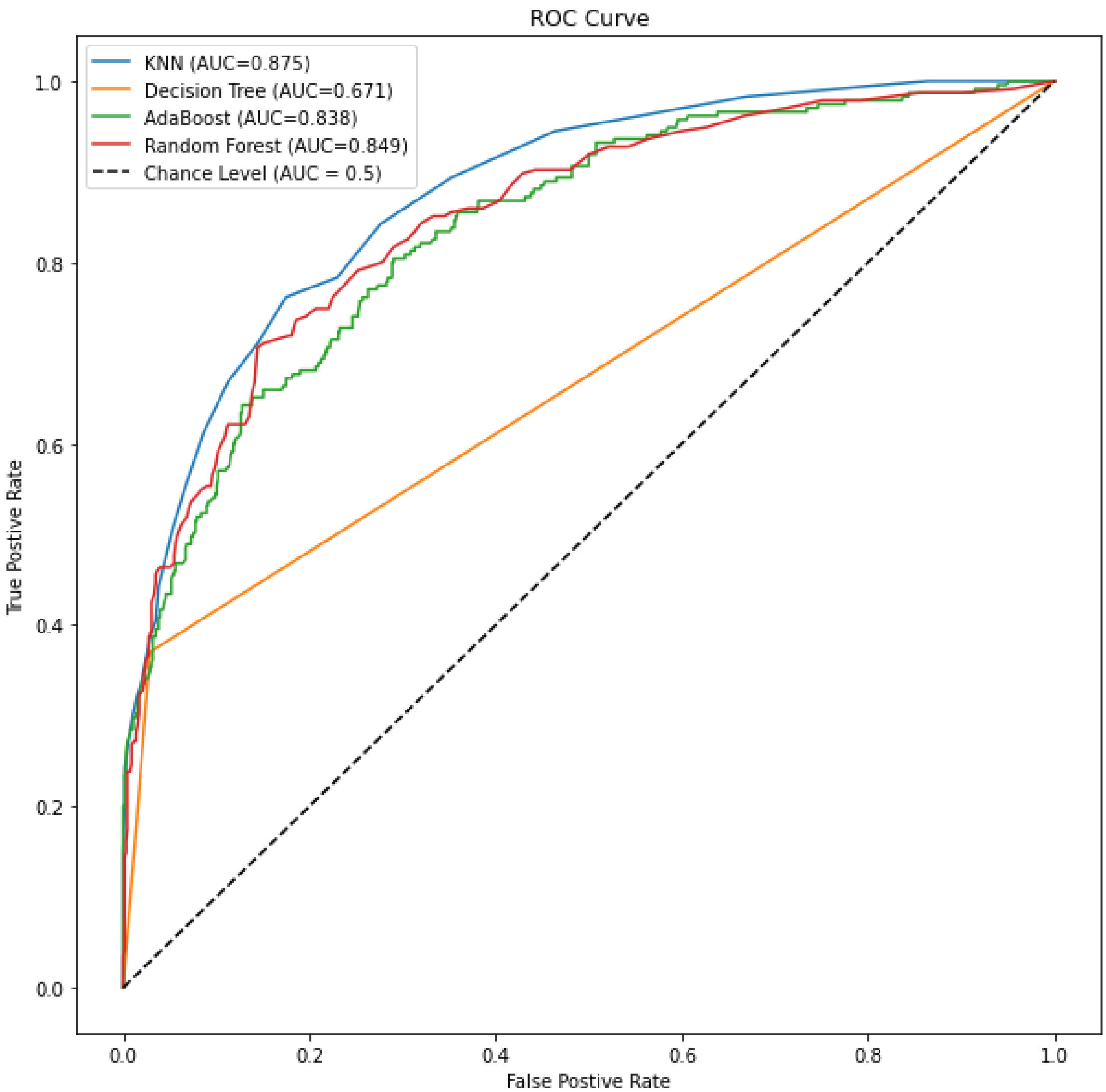
Since this is an unbalanced dataset, it is important to remember that there was only rain the next day on 25 percent of days. This means that you could guess that there no rainy days and you would have an accuracy of 75 percent. Therefore, accuracy should not be the most important metric to look at. All of the models have very similar accuracy, but that is misleading in this case.

Other metrics that can be looked at include, AUC, precision and recall. If we look at AUC, KNN was the hight rated metric, with decision tree coming in a distant last place.

However, if we then look at precision, the basic decision tree appears to be the winner, with KNN almost as good, while AdaBoost and Random Forest, have slightly lower precision scores.

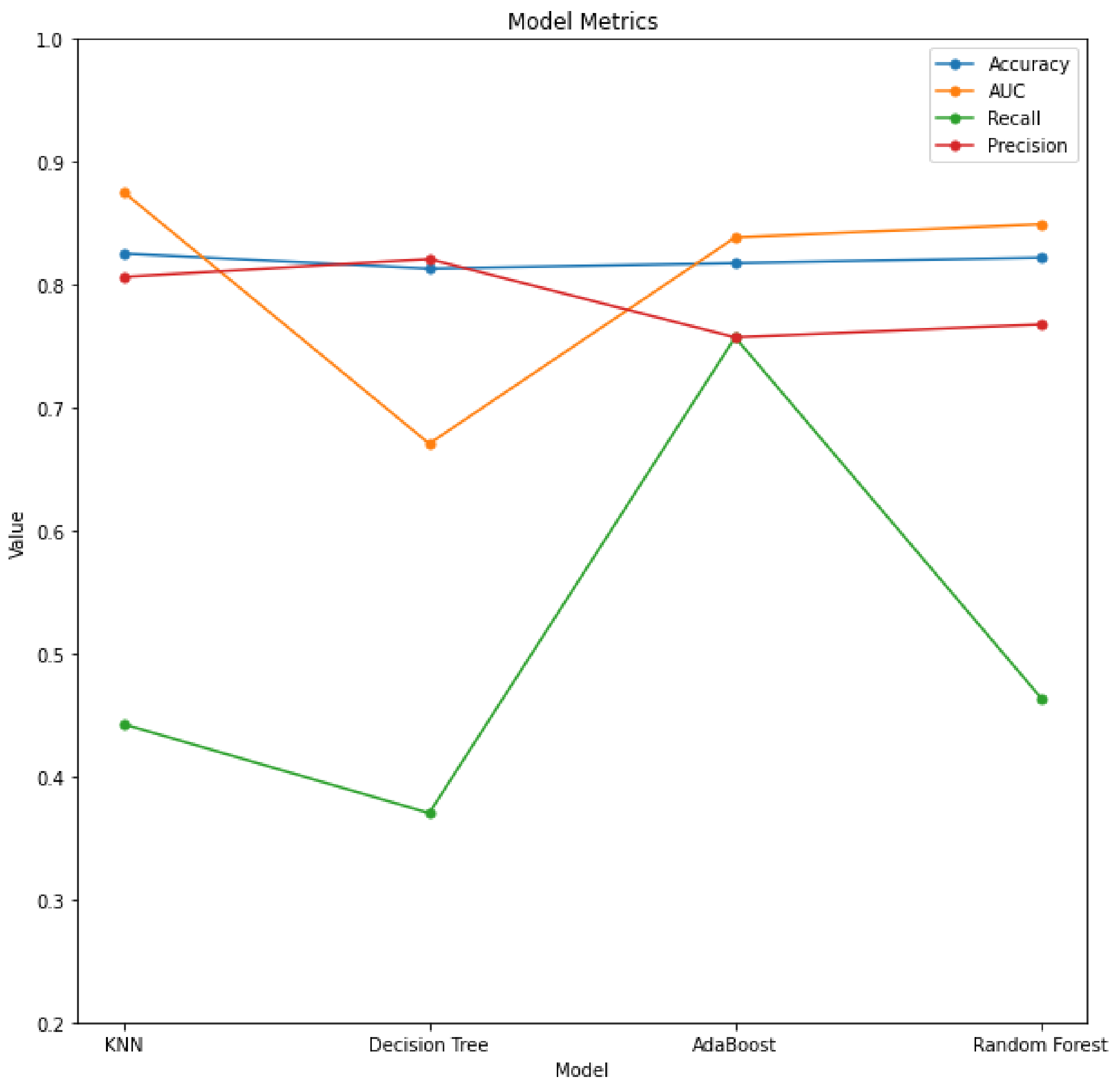
Recall, though, is where things get interesting. Most of the models are absolutely abysmal when it comes to recall. Three of the models had a recall of less than .5. Which means, even though the model tended to be right about its positive predictions, they also predicted that a lot of days would have no rain, when in fact it did rain. The interesting outlier in this case is the AdaBoost model. It had a recall of .75, which is significantly higher than all of the other models. This was made with a slight decrease in precision.

[53]:
```
#ROC Graph
plt.rcParams["figure.figsize"] = (10,10)

#plt.plot(all_fpr,all_tpr, label = 'AUC = %0.2f' % auc, color = 'orange')

for i, tpr in enumerate(all_tpr):
    plt.plot(all_fpr[i],tpr, label = f"{all_models[i]} (AUC={all_auc[i]:.3})")

plt.title('ROC Curve')
plt.ylabel('True Postive Rate')
plt.xlabel('False Postive Rate')
plt.plot([0, 1], [0, 1], "k--", label="Chance Level (AUC = 0.5)")
plt.legend(loc = 'best')
plt.show()
```



[54]:
```
#ROC Graph
plt.rcParams["figure.figsize"] = (10,10)

#plt.plot(all_fpr,all_tpr, label = 'AUC = %0.2f' % auc, color = 'orange')
axes = plt.axes()
axes.set_ylim([0, 1])
axes.set_ylim([.2, 1])
plt.plot(all_models,all_scores, label = 'Accuracy', marker = '.', markersize =␣
↪10)
plt.plot(all_models,all_auc, label = 'AUC', marker = '.', markersize = 10)
plt.plot(all_models,all_recall, label = 'Recall', marker = '.', markersize = 10)
plt.plot(all_models,all_precision, label = 'Precision', marker = '.',␣
↪markersize = 10)
```

```python
plt.title('Model Metrics')
plt.xlabel('Model')
plt.ylabel('Value')



plt.legend()
plt.show()
```



This brings us to the question about what model we should use if we want to predict if it will rain tomorrow, from weather information from today. There isn't one obvious answer. If you want simplicity, you could go with the decision tree model. All one would need to measure the humidity in the afternoon, and you could make a prediction. However, that is certainly not the best solution, if you have access to more sophisticated modeling techniques.

In that case, the choice is between KNN or AdaBoost. In overall performance, the KNN model does seem to be more accurate. But, since it has a lower recall value, it does this at the expense of having many false negatives. AdaBoost does a better job if having a more accurate recall is important. This is at the expense of a slight decrease in the precision of the model.

0.7 VII. Conclusion

One major thing that we can takeaway from this model is that predicting the weather from a single source is difficult. This is using weather data to predict if it will rain the next day with data from the same location. Obviously, models that use a more comprehensive set of data, would yield much better results.

Another takeaway, is how important humidity seems to be in predicting rain in these models. It is so important, that in the decision tree model, it stopped after only on decision, even when attempting to iterate to a higher max depth.

One thing that went wrong is that none of these models work particularly well. While they have fairly high accuracy that isn't abysmal, one has to go back to the fact that only 25 percent of the days had rain to begin with, so if you always guess that it will never rain, then you will end up with a 75 percent accuracy. I think the reason for this is weather isn't only created locally, and 24 hours in the future is a long time to predict whether it will rain, by looking at the current weather at that location. The model could be improved by more feature selection. While I did spend some time on feature selection, there could be more iteration in that regard to see if any features could be added or removed that would give more accurate results.

There are many ways in which we could expand this model testing. It would be interesting to add additional cities near Sydney, and give them a variable of next day rain in Sydney. I think this would enhance the model, and probably make it more accurate.