(FINAL) MDSD692_PracticumProject_KBeckwith

March 5, 2023

1 Predictive Analytics - Predicting Rainfall

1.0.1 Importing Needed Libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import ExtraTreesRegressor
import pickle
from matplotlib import pyplot
import matplotlib.pyplot as plt
%matplotlib inline
sns.set()
import plotly.express as px


# Ignore harmless warnings
import warnings
warnings.filterwarnings('ignore')
pd.options.display.float_format = '{:.2f}'.format
```

1.0.2 Import the Data

[2]:
```
df_rain = pd.read_csv('weatherAUS.csv')
```

[3]:
```
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
```

[4]:
```
print(df_rain.shape)
```

```
(145460, 23)
```

[5]:
```
df_rain.describe().T
```

[5]:

	count	mean	std	min	25%	50%	75%	max
MinTemp	143975.00	12.19	6.40	-8.50	7.60	12.00	16.90	33.90
MaxTemp	144199.00	23.22	7.12	-4.80	17.90	22.60	28.20	48.10
Rainfall	142199.00	2.36	8.48	0.00	0.00	0.00	0.80	371.00
Evaporation	82670.00	5.47	4.19	0.00	2.60	4.80	7.40	145.00
Sunshine	75625.00	7.61	3.79	0.00	4.80	8.40	10.60	14.50
WindGustSpeed	135197.00	40.04	13.61	6.00	31.00	39.00	48.00	135.00
WindSpeed9am	143693.00	14.04	8.92	0.00	7.00	13.00	19.00	130.00
WindSpeed3pm	142398.00	18.66	8.81	0.00	13.00	19.00	24.00	87.00
Humidity9am	142806.00	68.88	19.03	0.00	57.00	70.00	83.00	100.00
Humidity3pm	140953.00	51.54	20.80	0.00	37.00	52.00	66.00	100.00
Pressure9am	130395.00	1017.65	7.11	980.50	1012.90	1017.60	1022.40	1041.00
Pressure3pm	130432.00	1015.26	7.04	977.10	1010.40	1015.20	1020.00	1039.60
Cloud9am	89572.00	4.45	2.89	0.00	1.00	5.00	7.00	9.00
Cloud3pm	86102.00	4.51	2.72	0.00	2.00	5.00	7.00	9.00
Temp9am	143693.00	16.99	6.49	-7.20	12.30	16.70	21.60	40.20
Temp3pm	141851.00	21.68	6.94	-5.40	16.60	21.10	26.40	46.70

[6]:
```
df_rain.describe(include=[object]).T
```

[6]:

	count	unique	top	freq
Date	145460	3436	2015-01-29	49
Location	145460	49	Canberra	3436
WindGustDir	135134	16	W	9915
WindDir9am	134894	16	N	11758
WindDir3pm	141232	16	SE	10838
RainToday	142199	2	No	110319
RainTomorrow	142193	2	No	110316

1.1 Data Preprocessing

[7]:
```
df_rain.isnull().sum()
```

[7]:
```
Date                 0
Location             0
MinTemp           1485
MaxTemp           1261
Rainfall          3261
Evaporation      62790
Sunshine         69835
WindGustDir      10326
WindGustSpeed    10263
WindDir9am       10566
WindDir3pm        4228
WindSpeed9am      1767
WindSpeed3pm      3062
Humidity9am       2654
Humidity3pm       4507
Pressure9am      15065
Pressure3pm      15028
Cloud9am         55888
Cloud3pm         59358
Temp9am           1767
Temp3pm           3609
RainToday         3261
RainTomorrow      3267
dtype: int64
```

[8]:
```
cat_columns = [column_name for column_name in df_rain.columns if␣
 ↪df_rain[column_name].dtype == 'O']
print('Number of Categorical Features: {}'.format(len(cat_columns)))
print('Categorical Features: ',cat_columns)
```

```
Number of Categorical Features: 7
Categorical Features:  ['Date', 'Location', 'WindGustDir', 'WindDir9am',
'WindDir3pm', 'RainToday', 'RainTomorrow']
```

[9]:
```
num_columns = [column_name for column_name in df_rain.columns if␣
↪df_rain[column_name].dtype != 'O']
print('Number of Numerical Features: {}'.format(len(num_columns)))
print('Numerical Features: ',num_columns)
```

```
Number of Numerical Features: 16
Numerical Features:  ['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation',
'Sunshine', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
'Temp3pm']
```

After taking an initial look at the data, we can see that there are null values in every column except the date and location columns. Above we see the different categorical and the numerical columns.

There are two different types of data in the dataset: object and float.

We will need to handle the missing values before we can do any kind of predictive analytics.

Our target variable is going to be RainTomorrow, so first I will deal with rows missing this value by removing them. Then I will deal with the RainToday null values.

[10]:
```
df_rain.drop(df_rain[df_rain.RainTomorrow.isnull()].index, inplace=True)
df_rain.drop(df_rain[df_rain.RainToday.isnull()].index, inplace=True)
```

[11]:
```
df_rain.isnull().sum()
```

[11]:
```
Date                0
Location            0
MinTemp           468
MaxTemp           307
Rainfall            0
Evaporation     59694
Sunshine        66805
WindGustDir      9163
WindGustSpeed    9105
WindDir9am       9660
WindDir3pm       3670
WindSpeed9am     1055
WindSpeed3pm     2531
Humidity9am      1517
Humidity3pm      3501
Pressure9am     13743
Pressure3pm     13769
Cloud9am        52625
Cloud3pm        56094
Temp9am           656
Temp3pm          2624
RainToday           0
RainTomorrow        0
dtype: int64
```

Great, that took care of the two rain columns.

Now that we've taken care of the rain today and tomorrow columns, we need to focus on the other columns that have null values. I think that we need to fill in the null values with the most common value for each column based on location.

[12]:
```
numerical = list(df_rain.select_dtypes(include = np.number).columns)
```

[13]:
```
for x in numerical:
    r = df_rain.groupby(['Location'])[x].median().fillna(0).reset_index()
    for i in r.Location.unique():
        df_rain.loc[(df_rain.Location == i),[x]] = df_rain.loc[(df_rain.
 ↪Location == i),[x]].fillna(r.loc[r.Location == i, x].item())
```

[14]:
```
df_rain.isnull().sum()
```

[14]:
```
Date                0
Location            0
MinTemp             0
MaxTemp             0
Rainfall            0
Evaporation         0
Sunshine            0
WindGustDir      9163
WindGustSpeed       0
WindDir9am       9660
WindDir3pm       3670
WindSpeed9am        0
WindSpeed3pm        0
Humidity9am         0
Humidity3pm         0
Pressure9am         0
Pressure3pm         0
Cloud9am            0
Cloud3pm            0
Temp9am             0
Temp3pm             0
RainToday           0
RainTomorrow        0
dtype: int64
```

[15]:
```
windgust = pd.crosstab(index = df_rain['Location'], columns =␣
 ↪df_rain['WindGustDir']).unstack().reset_index().rename(columns = {0: 'Freq'})
for i in windgust.Location.unique():
        df_rain.loc[(df_rain.WindGustDir.isnull()) & (df_rain.Location ==␣
 ↪i),'WindGustDir'] = df_rain.loc[df_rain.Location == i,'WindGustDir'].
 ↪value_counts().idxmax()
```

```
df_rain.loc[df_rain['WindGustDir'].isnull(),'WindGustDir'] =␣
↪df_rain['WindGustDir'].value_counts().idxmax()
wind9am = pd.crosstab(index = df_rain['Location'], columns =␣
↪df_rain['WindDir9am']).unstack().reset_index().rename(columns = {0: 'Freq'})
for i in wind9am.Location.unique():
        df_rain.loc[(df_rain.WindDir9am.isnull()) & (df_rain.Location ==␣
↪i),'WindDir9am'] = df_rain.loc[df_rain.Location == i,'WindDir9am'].
↪value_counts().idxmax()
df_rain.loc[df_rain['WindDir9am'].isnull(),'WindDir9am'] =␣
↪df_rain['WindDir9am'].value_counts().idxmax()

wind3pm = pd.crosstab(index = df_rain['Location'], columns =␣
↪df_rain['WindDir3pm']).unstack().reset_index().rename(columns = {0: 'Freq'})
for i in wind9am.Location.unique():
        df_rain.loc[(df_rain.WindDir3pm.isnull()) & (df_rain.Location ==␣
↪i),'WindDir3pm'] = df_rain.loc[df_rain.Location == i,'WindDir3pm'].
↪value_counts().idxmax()
df_rain.loc[df_rain['WindDir3pm'].isnull(),'WindDir3pm'] =␣
↪df_rain['WindDir3pm'].value_counts().idxmax()
```

[16]:
```
df_rain.isnull().sum()
```

[16]:
```
Date             0
Location         0
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustDir      0
WindGustSpeed    0
WindDir9am       0
WindDir3pm       0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
RainTomorrow     0
dtype: int64
```

[17]:
```python
print('Unique Values in Date:', df_rain['Date'].nunique())
print('Unique Values in Location:', df_rain['Location'].nunique())
print('Unique Values in WindGustDir:', df_rain['WindGustDir'].nunique())
print('Unique Values in WindDir9am:', df_rain['WindDir9am'].nunique())
print('Unique Values in WindDir3pm:', df_rain['WindDir3pm'].nunique())
print('Unique Values in RainToday:', df_rain['RainToday'].nunique())
print('Unique Values in RainTomorrow:', df_rain['RainTomorrow'].nunique())
```

```
Unique Values in Date: 3436
Unique Values in Location: 49
Unique Values in WindGustDir: 16
Unique Values in WindDir9am: 16
Unique Values in WindDir3pm: 16
Unique Values in RainToday: 2
Unique Values in RainTomorrow: 2
```

The Date column has many unique values and this might interfere with our modeling so I will feature engineer this column.

[18]:
```python
df_rain['Date'] = pd.to_datetime(df_rain['Date'])
df_rain['Year'] = df_rain['Date'].dt.year.astype('float64')
df_rain['Month'] = df_rain['Date'].dt.month.astype('float64')

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

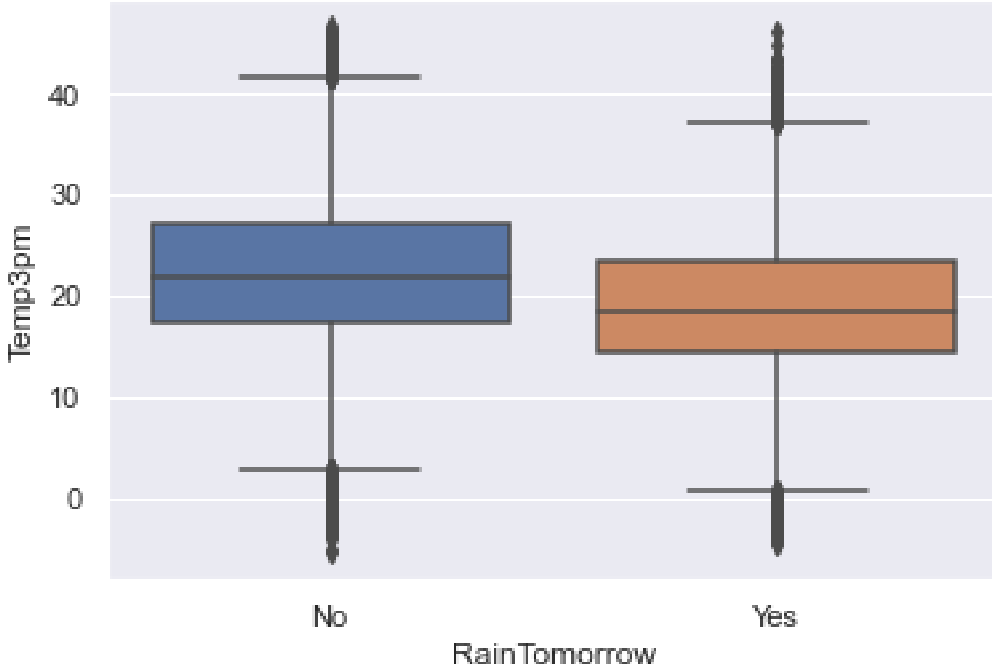
[18]:
```
        Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  \
0         Albury    13.40    22.90      0.60         0.00      0.00
1         Albury     7.40    25.10      0.00         0.00      0.00
2         Albury    12.90    25.70      0.00         0.00      0.00
3         Albury     9.20    28.00      0.00         0.00      0.00
4         Albury    17.50    32.30      1.00         0.00      0.00
…          …       …      …       …        …        …
145454    Uluru     3.50    21.80      0.00         0.00      0.00
145455    Uluru     2.80    23.40      0.00         0.00      0.00
145456    Uluru     3.60    25.30      0.00         0.00      0.00
145457    Uluru     5.40    26.90      0.00         0.00      0.00
145458    Uluru     7.80    27.00      0.00         0.00      0.00

       WindGustDir  WindGustSpeed WindDir9am WindDir3pm  …  Pressure9am  \
0                W          44.00          W        WNW  …      1007.70
1              WNW          44.00        NNW        WSW  …      1010.60
2              WSW          46.00          W        WSW  …      1007.60
3               NE          24.00         SE          E  …      1017.60
4                W          41.00        ENE         NW  …      1010.80
…            …            …        …          …  …          …
145454           E          31.00        ESE          E  …      1024.70
145455           E          31.00         SE        ENE  …      1024.60
```

```
145456         NNW          22.00          SE          N  …       1023.50
145457           N          37.00          SE        WNW  …       1021.00
145458          SE          28.00         SSE          N  …       1019.40

        Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  RainToday  \
0           1007.10      8.00      7.00    16.90    21.80         No
1           1007.80      8.00      7.00    17.20    24.30         No
2           1008.70      8.00      2.00    21.00    23.20         No
3           1012.80      8.00      7.00    18.10    26.50         No
4           1006.00      7.00      8.00    17.80    29.70         No
…                 …         …         …        …        …
145454      1021.20      7.00      5.00     9.40    20.90         No
145455      1020.30      7.00      5.00    10.10    22.40         No
145456      1019.10      7.00      5.00    10.90    24.50         No
145457      1016.80      7.00      5.00    12.50    26.10         No
145458      1016.50      3.00      2.00    15.10    26.00         No

        RainTomorrow    Year  Month
0                 No 2008.00  12.00
1                 No 2008.00  12.00
2                 No 2008.00  12.00
3                 No 2008.00  12.00
4                 No 2008.00  12.00
…                  …       …      …
145454            No 2017.00   6.00
145455            No 2017.00   6.00
145456            No 2017.00   6.00
145457            No 2017.00   6.00
145458            No 2017.00   6.00

[140787 rows x 24 columns]
```

1.1.1 Outlier Detection and Processing

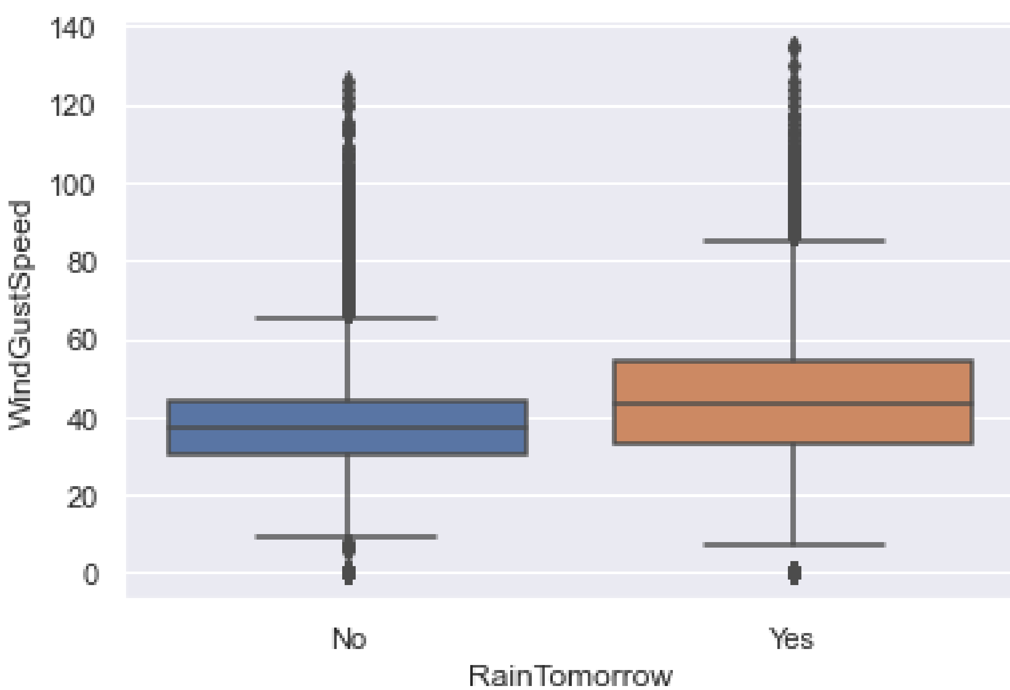
[19]:
```python
sns.boxplot(data = df_rain, x = 'RainTomorrow', y = 'Temp3pm')
```

[19]:
```
<AxesSubplot:xlabel='RainTomorrow', ylabel='Temp3pm'>
```



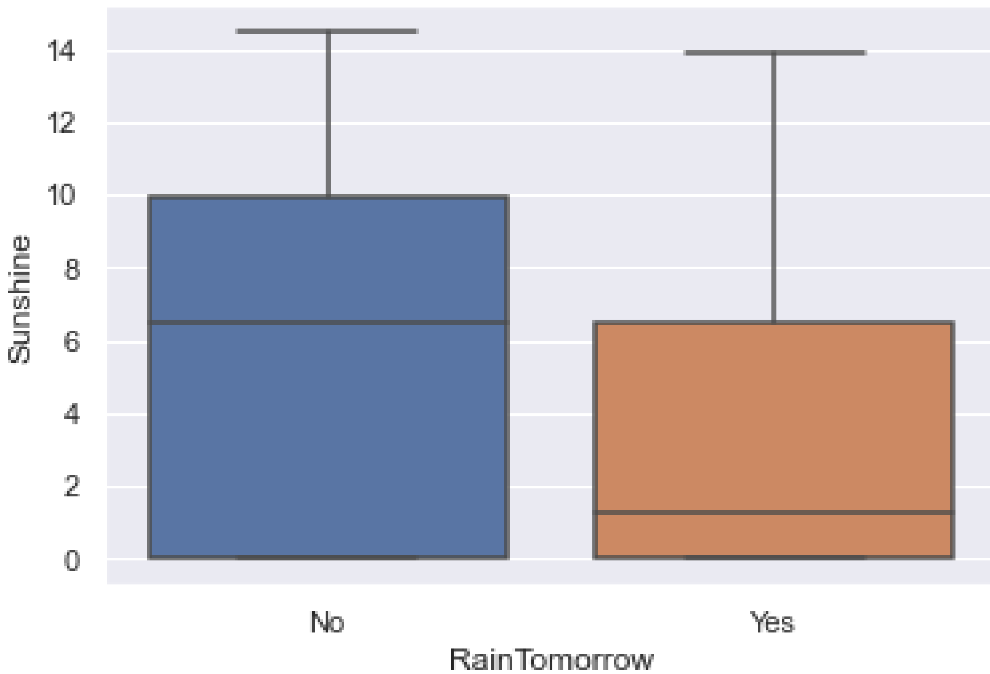
[20]:
```
sns.boxplot(data = df_rain, x = 'RainTomorrow', y = 'WindGustSpeed')
```

[20]: <AxesSubplot:xlabel='RainTomorrow', ylabel='WindGustSpeed'>



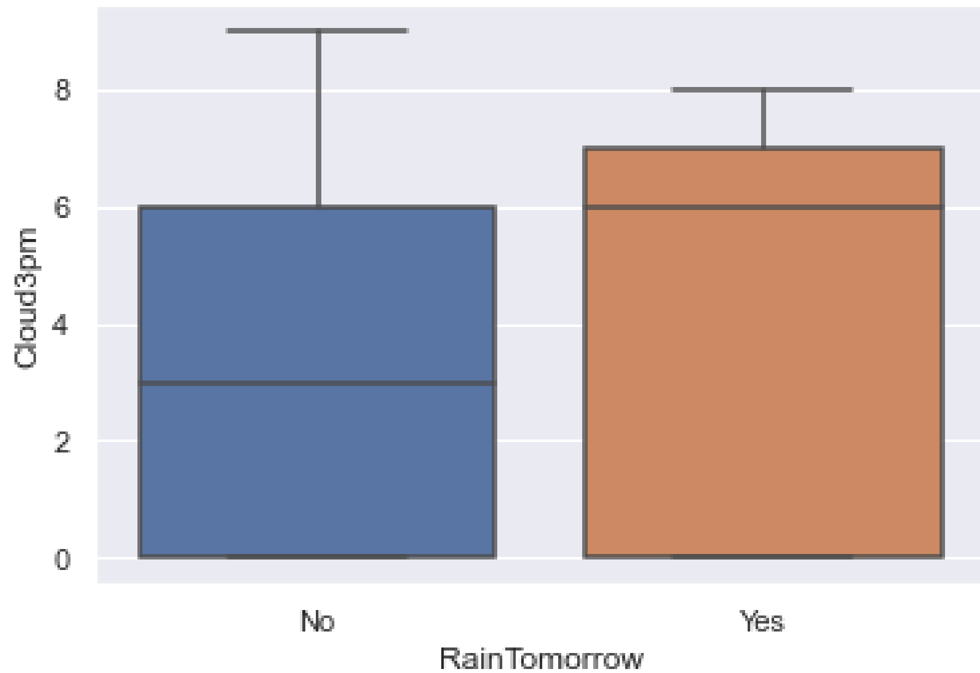
[21]:
```
sns.boxplot(data = df_rain, x = 'RainTomorrow', y = 'Sunshine')
```

[21]: <AxesSubplot:xlabel='RainTomorrow', ylabel='Sunshine'>



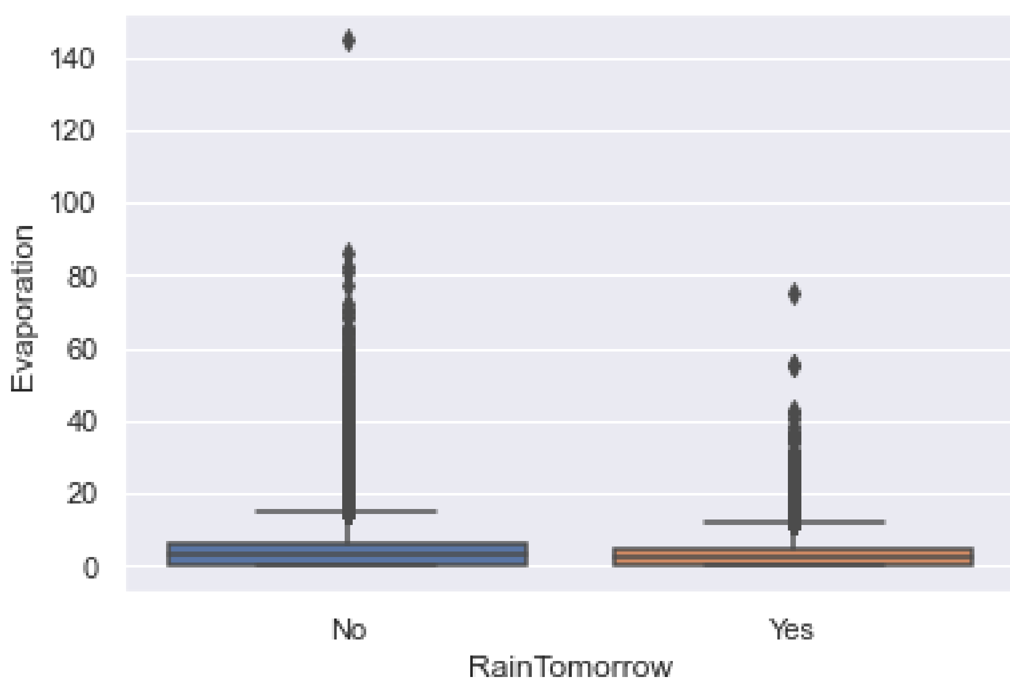
[22]:
```
sns.boxplot(data = df_rain, x='RainTomorrow', y = 'Cloud3pm')
```

[22]: <AxesSubplot:xlabel='RainTomorrow', ylabel='Cloud3pm'>



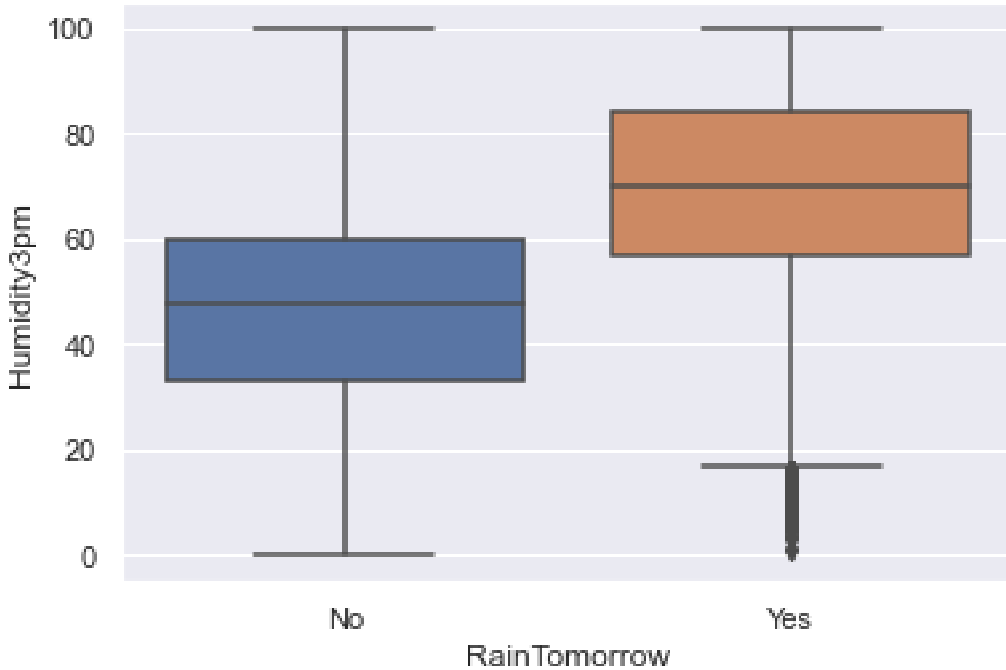

```
[23]: sns.boxplot(data = df_rain, x='RainTomorrow', y = 'Evaporation')
```

[23]: <AxesSubplot:xlabel='RainTomorrow', ylabel='Evaporation'>



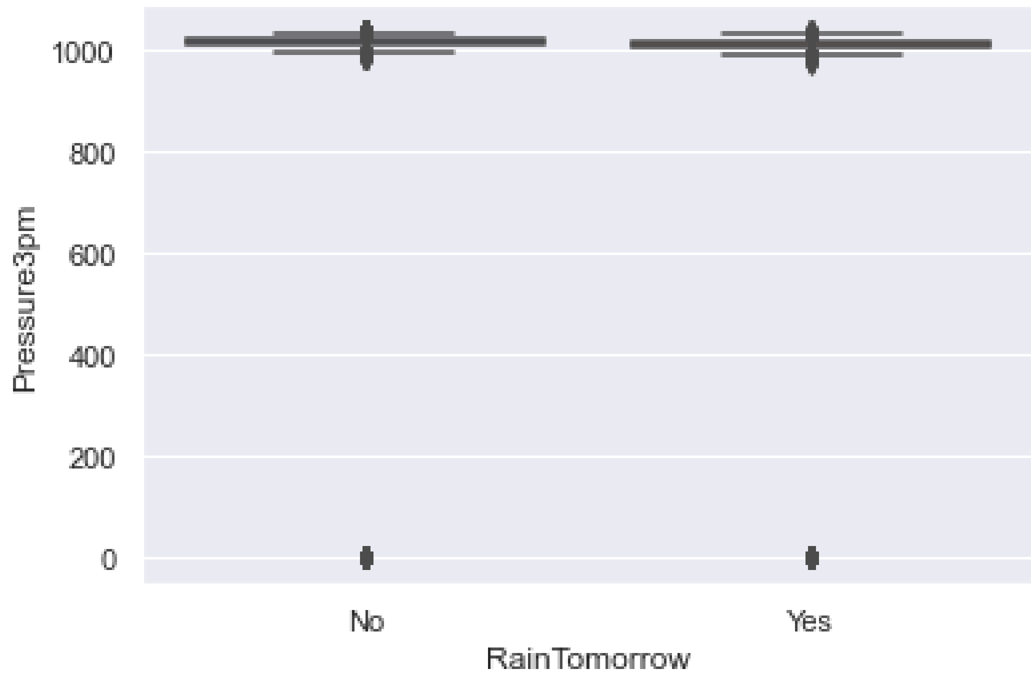
[24]:
```
sns.boxplot(data = df_rain, x='RainTomorrow', y = 'Humidity3pm')
```

[24]: <AxesSubplot:xlabel='RainTomorrow', ylabel='Humidity3pm'>



[25]:
```
sns.boxplot(data = df_rain, x='RainTomorrow', y = 'Pressure3pm')
```

[25]: <AxesSubplot:xlabel='RainTomorrow', ylabel='Pressure3pm'>



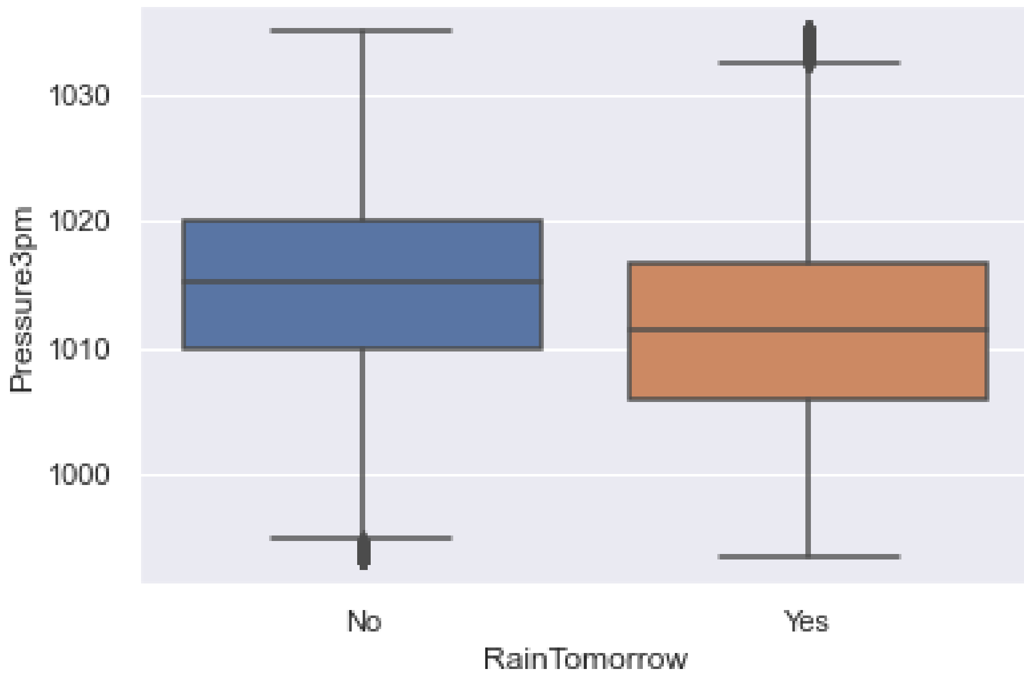
[26]:
```
outliers = ['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'WindGustSpeed',
            'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Pressure9am',␣
 ↪'Pressure3pm', 'Temp9am', 'Temp3pm']
for a in outliers:
    Q1 = df_rain[a].quantile(0.25)
    Q3 = df_rain[a].quantile(0.75)
    IQR = Q3-Q1
    print('Q1: ', Q1)
    print('Q3:', Q3)
    print('IRQ:', IQR)
    Lower_Whisker = Q1-1.5*IQR
    Upper_Whisker = Q3+1.5*IQR
    print('Lower Whisker:', Lower_Whisker, ',', 'Upper Whisker:', Upper_Whisker)
    df_rain.loc[df_rain[a] < Lower_Whisker, a] = Lower_Whisker
    df_rain.loc[df_rain[a] > Upper_Whisker, a] = Upper_Whisker
```

```
Q1:  7.6
Q3: 16.8
IRQ: 9.200000000000001
Lower Whisker: -6.200000000000001 , Upper Whisker: 30.6
Q1:  17.9
Q3: 28.2
IRQ: 10.3
Lower Whisker: 2.4499999999999975 , Upper Whisker: 43.65
Q1:  0.0
```

```
Q3: 0.8
IRQ: 0.8
Lower Whisker: -1.2000000000000002 , Upper Whisker: 2.0
Q1:  0.0
Q3: 5.6
IRQ: 5.6
Lower Whisker: -8.399999999999999 , Upper Whisker: 13.999999999999998
Q1:  30.0
Q3: 46.0
IRQ: 16.0
Lower Whisker: 6.0 , Upper Whisker: 70.0
Q1:  7.0
Q3: 19.0
IRQ: 12.0
Lower Whisker: -11.0 , Upper Whisker: 37.0
Q1:  13.0
Q3: 24.0
IRQ: 11.0
Lower Whisker: -3.5 , Upper Whisker: 40.5
Q1:  57.0
Q3: 83.0
IRQ: 26.0
Lower Whisker: 18.0 , Upper Whisker: 122.0
Q1:  1011.5
Q3: 1021.8
IRQ: 10.299999999999955
Lower Whisker: 996.0500000000001 , Upper Whisker: 1037.25
Q1:  1009.0
Q3: 1019.4
IRQ: 10.399999999999977
Lower Whisker: 993.4000000000001 , Upper Whisker: 1035.0
Q1:  12.2
Q3: 21.5
IRQ: 9.3
Lower Whisker: -1.7500000000000018 , Upper Whisker: 35.45
Q1:  16.7
Q3: 26.4
IRQ: 9.7
Lower Whisker: 2.1500000000000004 , Upper Whisker: 40.949999999999996
```

[27]:
```
#checking that we removed the outliers
sns.boxplot(data = df_rain, x='RainTomorrow', y = 'Pressure3pm')
```

[27]:
```
<AxesSubplot:xlabel='RainTomorrow', ylabel='Pressure3pm'>
```



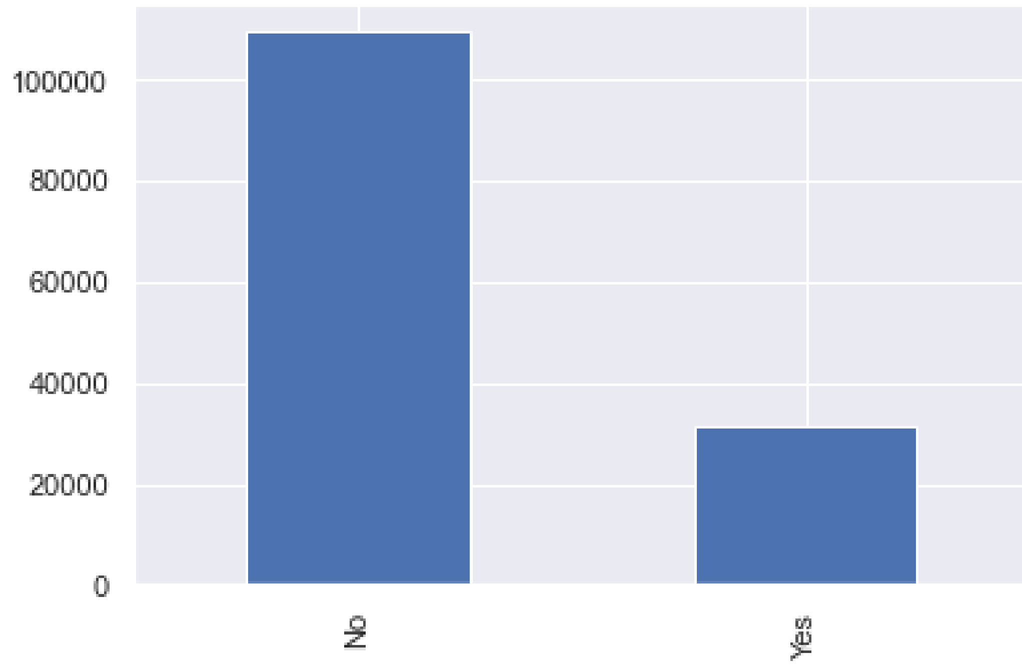
Data preprocessing is completed, I'll now move on to some EDA.

1.2 EDA

The first thing we should look at is the target variable, RainTomorrow.

[28]:
```
df_rain['RainTomorrow'].value_counts().plot(kind='bar')
```

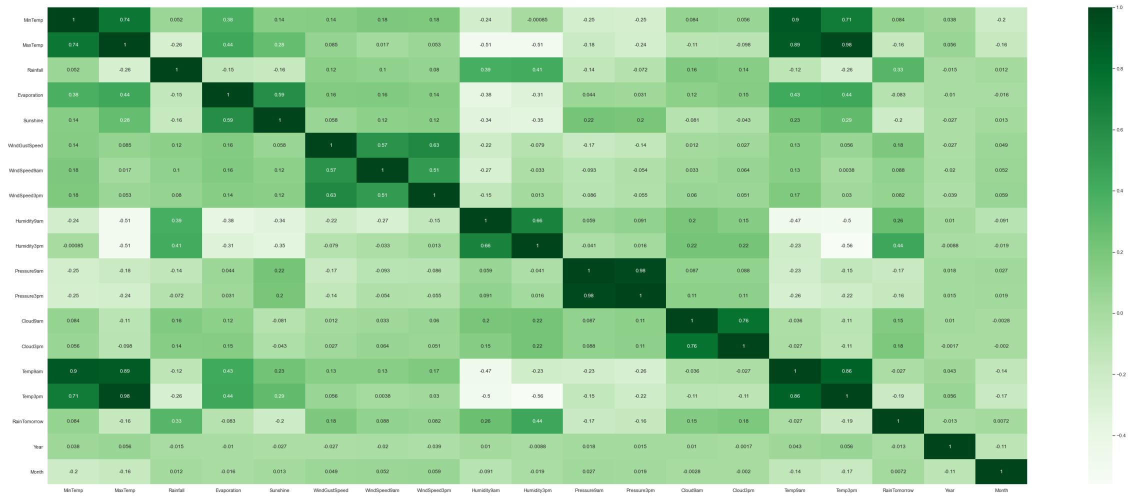
[28]: <AxesSubplot:>



There are substantially more no's than yes's in the dataset. This could effect the performance of my model later on.

[29]:
```
df_rain.RainTomorrow = df_rain.RainTomorrow.map({'No':0, 'Yes':1}).
 ↪astype('float64')
```

[30]:
```
corr = df_rain.corr()
corr.style.background_gradient()

plt.figure(figsize=(50,20))
sns.heatmap(corr,annot=True,cmap='Greens')
plt.savefig('corr.png')
```



There are some variables that look to have a high correlation with our target variable (RainTomorrow).

Negative Correlations:

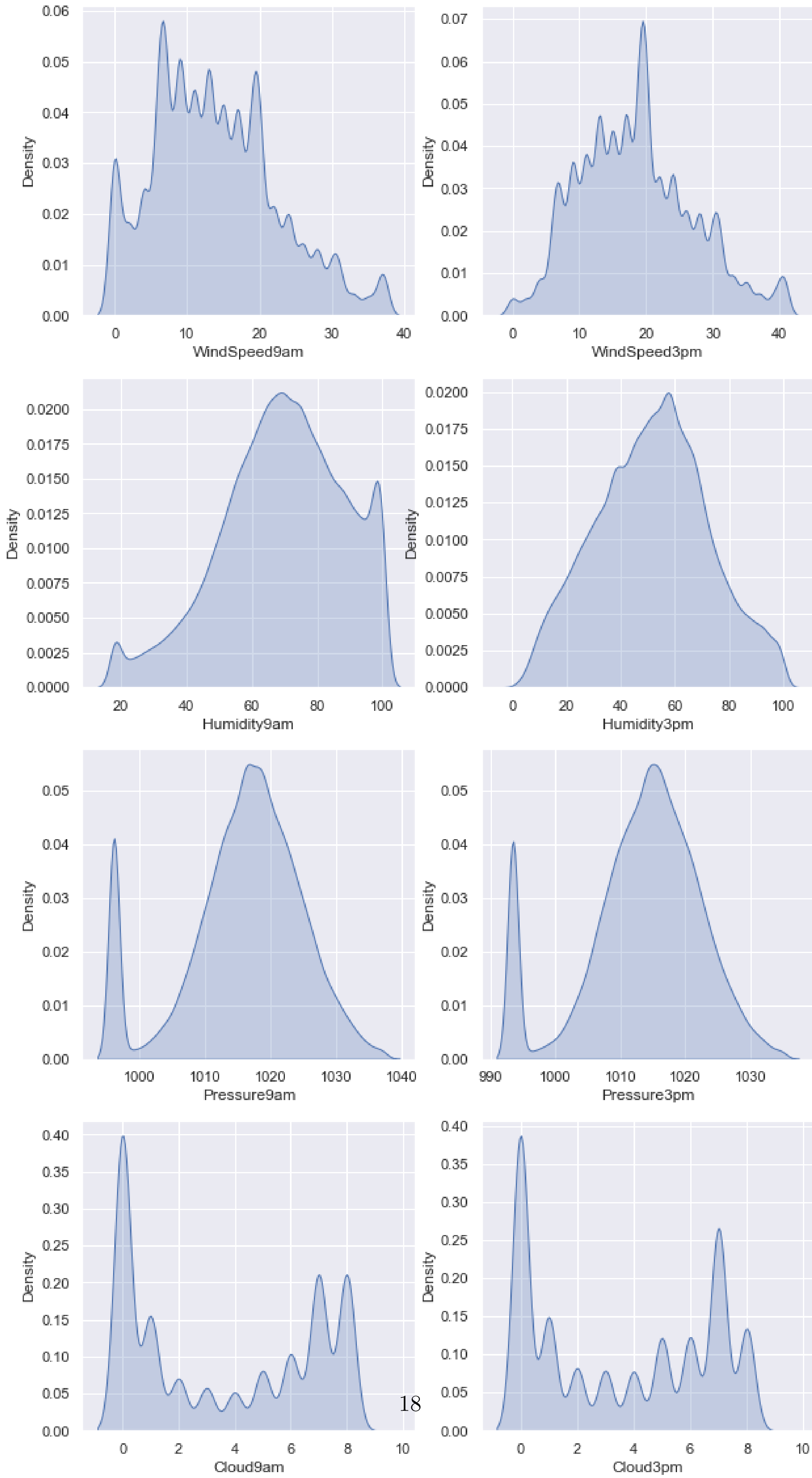
- MaxTemp
- Sunshine
- Pressure
- Temp

Positive Correlations:

- Rainfall
- Humidity
- Cloud

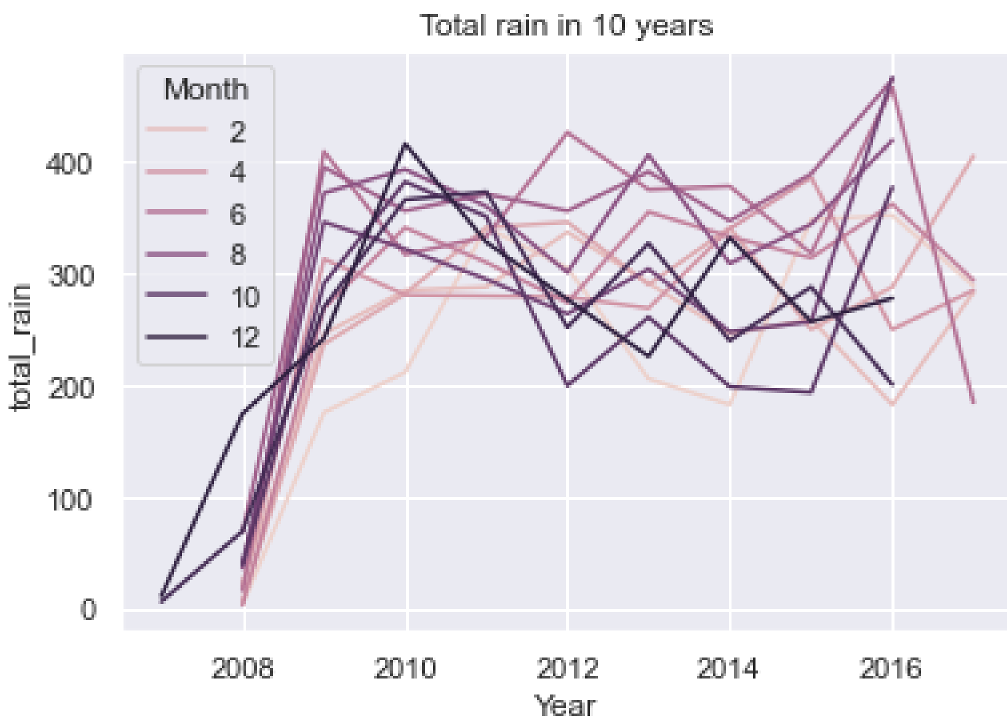
After taking a look at the correlation matrix, let's look at distribution for some of the important variables.

[31]:
```
fig, ax = plt.subplots(4, 2, figsize = (10, 20))
sns.kdeplot(x = df_rain.WindSpeed9am, ax = ax [0, 0], shade = True)
sns.kdeplot(x = df_rain.WindSpeed3pm, ax = ax[0, 1], shade = True)
sns.kdeplot(x = df_rain.Humidity9am, ax = ax[1, 0], shade = True)
sns.kdeplot(x = df_rain.Humidity3pm, ax = ax[1, 1], shade = True)
sns.kdeplot(x = df_rain.Pressure9am, ax = ax[2, 0], shade=True)
sns.kdeplot(x = df_rain.Pressure3pm, ax = ax[2, 1], shade=True)
sns.kdeplot(x = df_rain.Cloud9am, ax = ax[3, 0], shade=True)
sns.kdeplot(x = df_rain.Cloud3pm, ax = ax[3, 1], shade=True);

plt.savefig('dist.png', bbox_inches='tight')
```

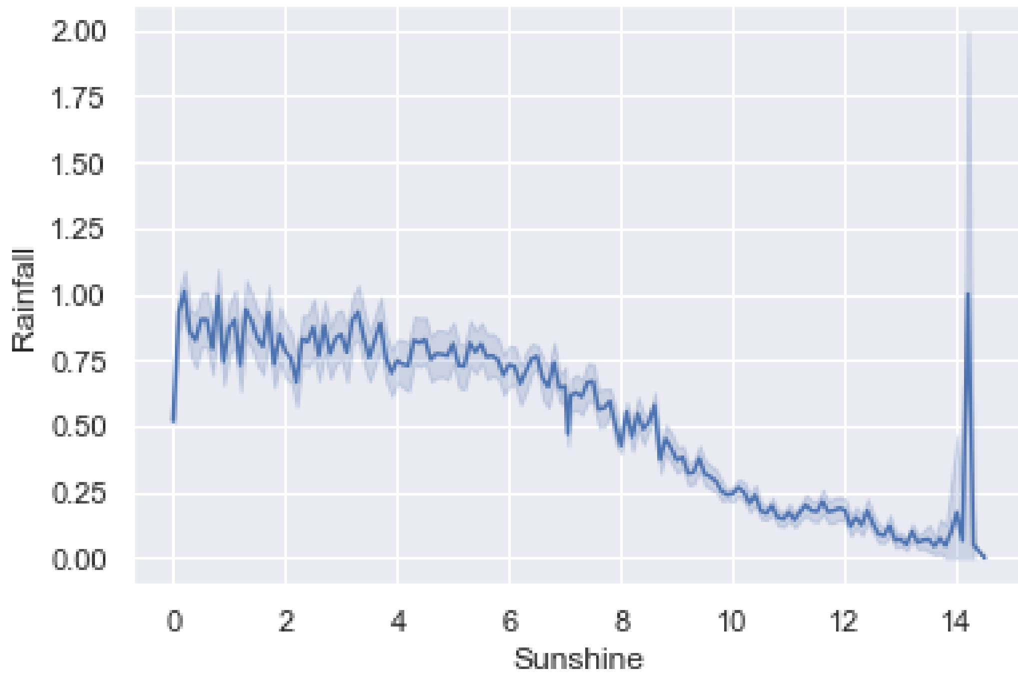

Density
WindSpeed9am
Density
WindSpeed3pm
Density
Humidity9am
Density
Humidity3pm
Density
Pressure9am
Density
Pressure3pm
Density
Cloud9am
Density
Cloud3pm

The distribution is similar between the 9am and 3pm variables for each category (i.e. wind at 9 and 3, pressure at 9 and 3, etc). There's not much variation that can be seen based on the time of day that the variable's value was measured.

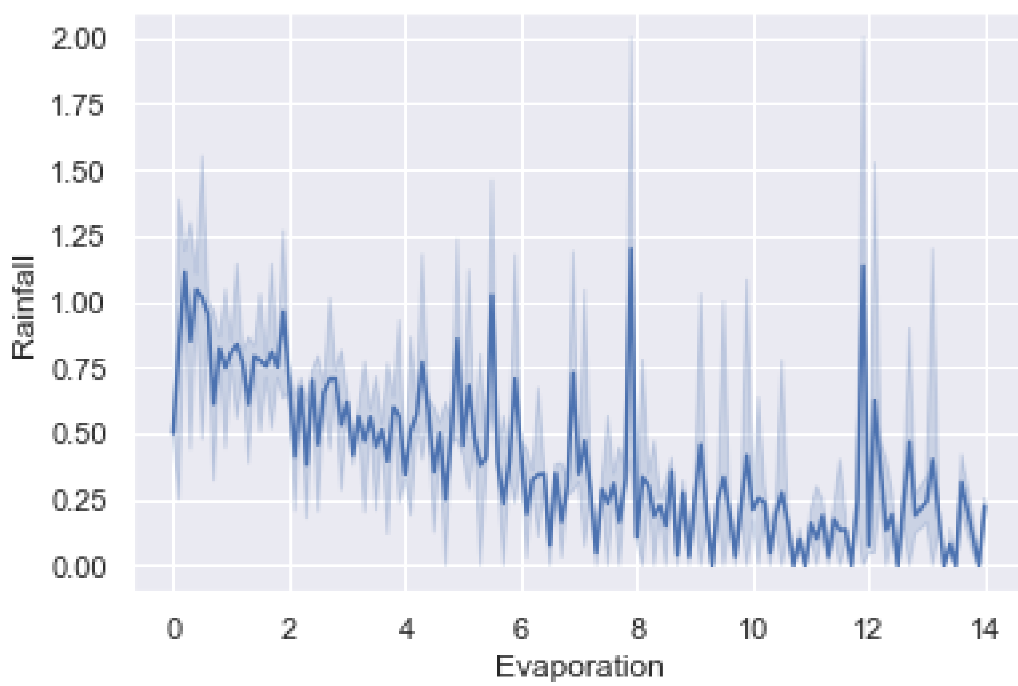
[32]:
```
df_rain['RainToday'] = np.where(df_rain['RainToday'] == 'No', 0, 1)
df_rain['total_rain'] = df_rain['RainToday']
#Total rain month and year
total_rain_year = df_rain.groupby(['Year', 'Month'])['total_rain'].sum().
 ↪reset_index()
fig,ax = plt.subplots()
sns.lineplot(data = total_rain_year, x = 'Year', y = 'total_rain', hue =␣
 ↪'Month').set(title = 'Total rain in 10 years');
```



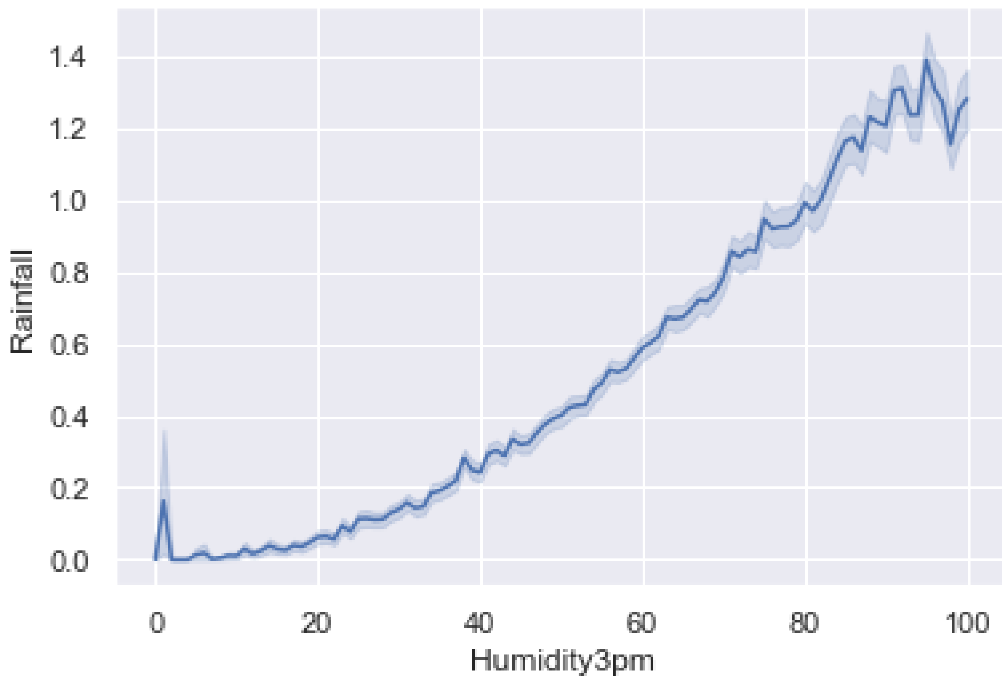
[33]:
```
sns.lineplot(data = df_rain, x = 'Sunshine', y = 'Rainfall');
```



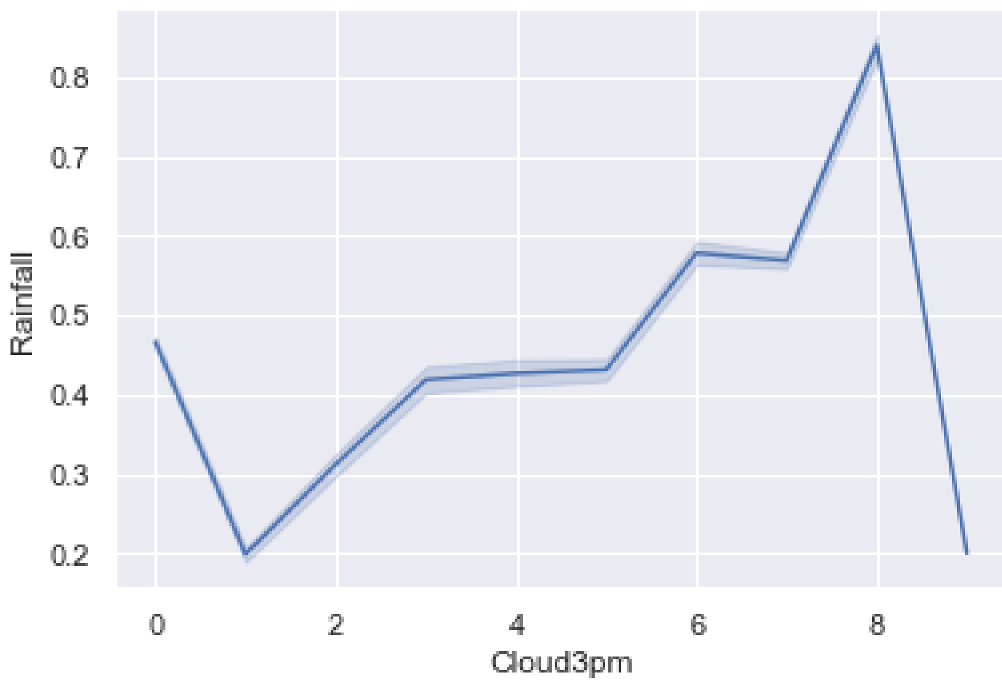
[34]:
```
sns.lineplot(data = df_rain, x = 'Evaporation', y = 'Rainfall');
```



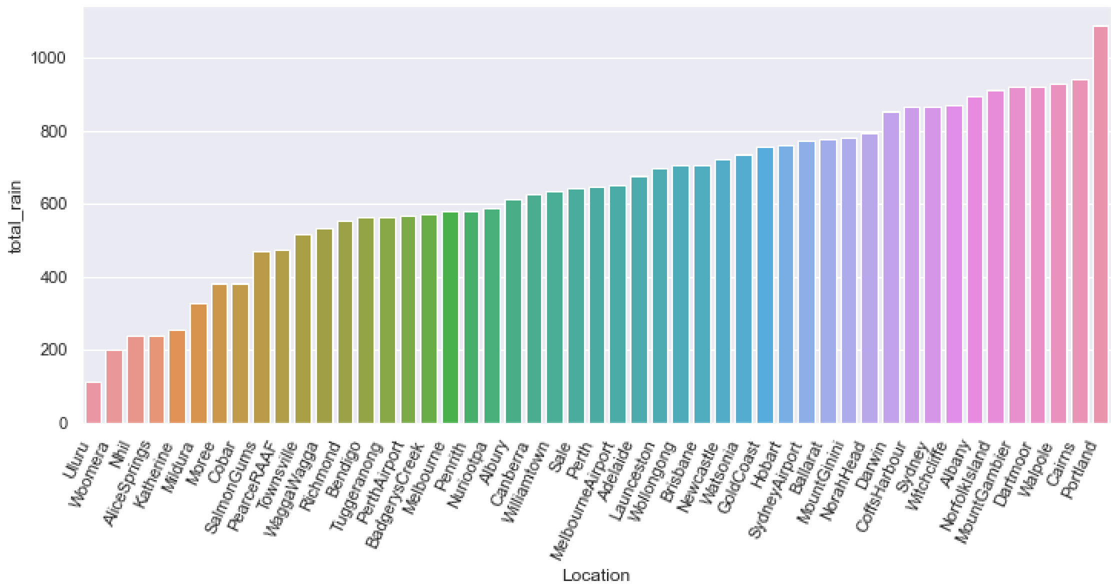
[35]:
```
sns.lineplot(data = df_rain, x = 'Humidity3pm', y = 'Rainfall');
```



[36]:
```
sns.lineplot(data = df_rain, x = 'Cloud3pm', y = 'Rainfall');
```

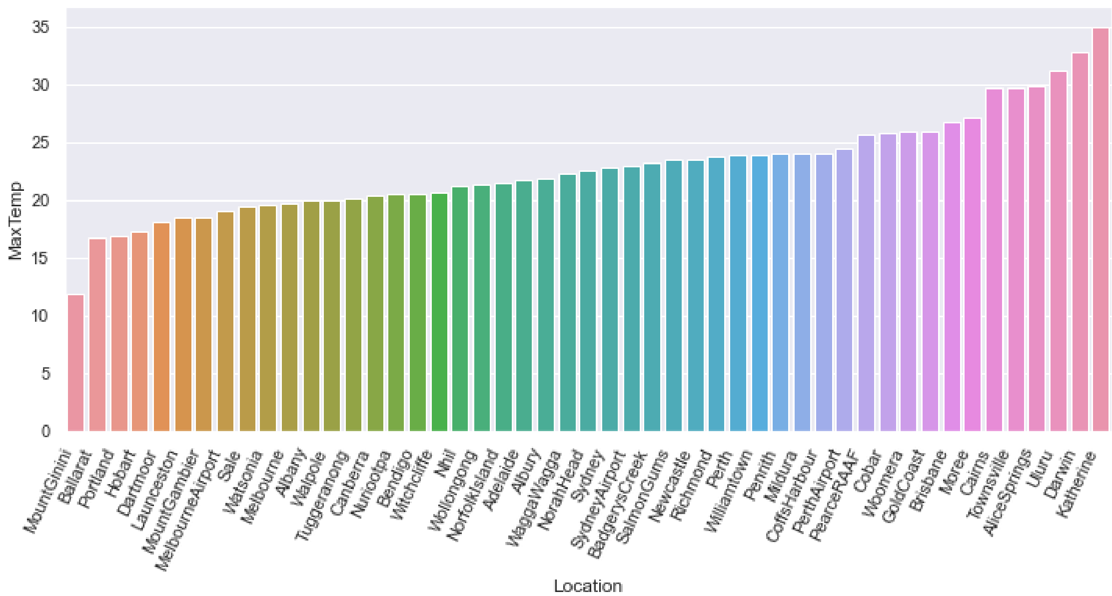


```
[37]: rain_location = df_rain.groupby(['Location'])['total_rain'].sum().reset_index()
plt.figure(figsize = (12, 5))
chart = sns.barplot(data = rain_location, y = 'total_rain', x = 'Location',␣
 ↪order = rain_location.sort_values('total_rain').Location)
chart.set_xticklabels(chart.get_xticklabels(), rotation = 65,␣
 ↪horizontalalignment = 'right', fontweight = 'light');
plt.savefig('location_rain.png', bbox_inches='tight')
```



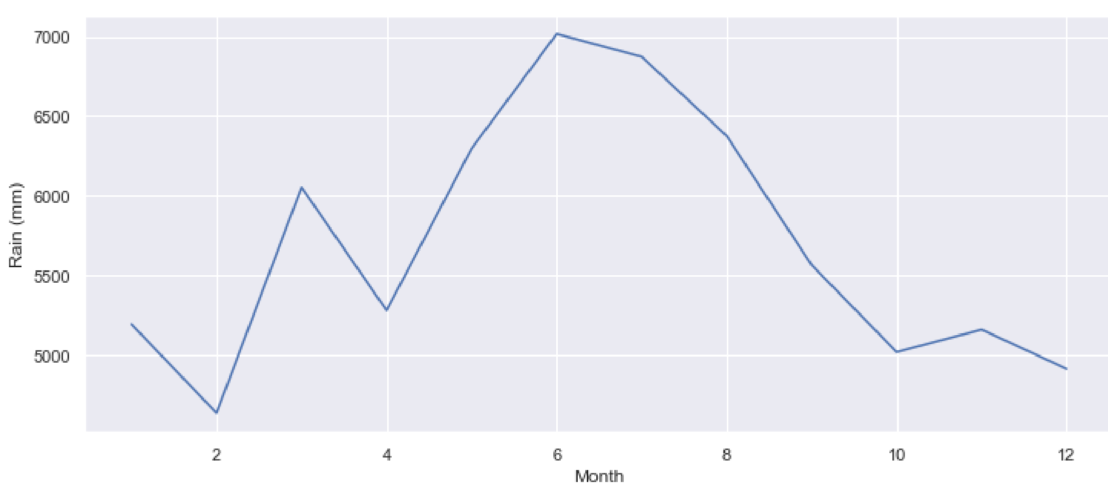
Looking at the above, it looks like the most rain has come from Portland and the least amount has come from Uluru. Let's take a look at the temp by location now.

```
[38]: loc_temp = df_rain.groupby(['Location'])['MaxTemp'].median().reset_index()
plt.figure(figsize = (12, 5))
loc = sns.barplot(data = loc_temp, y = 'MaxTemp', x = 'Location', order =␣
 ↪loc_temp.sort_values('MaxTemp').Location)
loc.set_xticklabels(loc.get_xticklabels(), rotation = 65, horizontalalignment =␣
 ↪'right');
plt.savefig('location_temp.png', bbox_inches='tight')
```



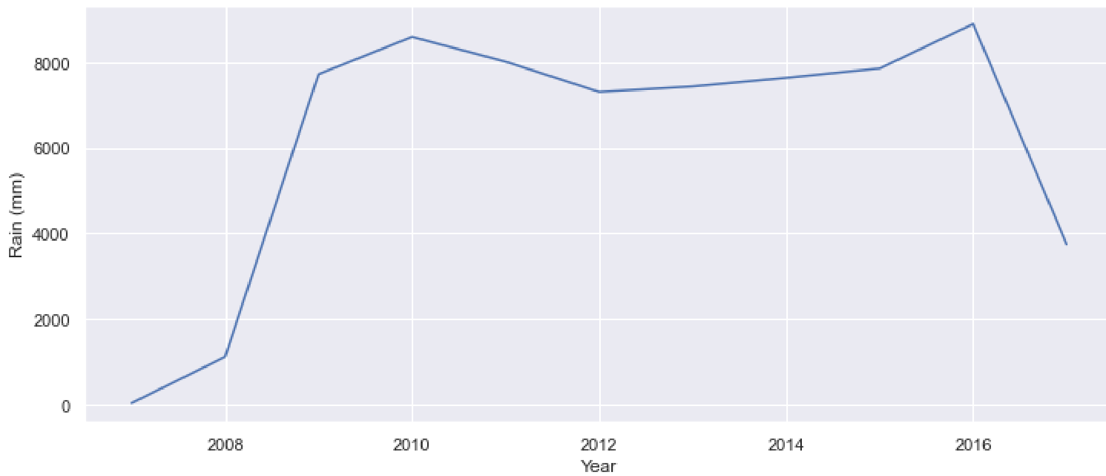
In comparison to the total rainfall by location, the hottest location looks to be Katherine and the coolest location is Mount Ginini. It makes sense that Uluru and Katherine are in the top locations for hottest locations because they are the bottom two locations for total rainfall. Darwin is in the warmest but also in the top 4 for most rainfall, I wonder if humidity has anything to do with this. Let's get the total rainfall for each month.

[39]:
```
fig, (plot1) = plt.subplots(1, figsize = (12, 5))
monthly = df_rain.groupby(['Month'])['Rainfall'].sum().reset_index()
plot1.plot(monthly.Month, monthly.Rainfall)
plot1.set_xlabel('Month')
plot1.set_ylabel('Rain (mm)');
plt.savefig('rain_by_month.png', bbox_inches='tight')
```



The most rainfall occurs in June and the least amount occurs in Feb. Overall the most rain happens in the middle of the year and drops off towards the end and the beginning of the year.

[40]:
```
fig, (plot2) = plt.subplots(1, figsize = (12, 5))
yearly = df_rain.groupby(['Year'])['Rainfall'].sum().reset_index()
plot2.plot(yearly.Year, yearly.Rainfall)
plot2.set_xlabel('Year')
plot2.set_ylabel('Rain (mm)');
plt.savefig('rain_by_year.png', bbox_inches='tight')
```

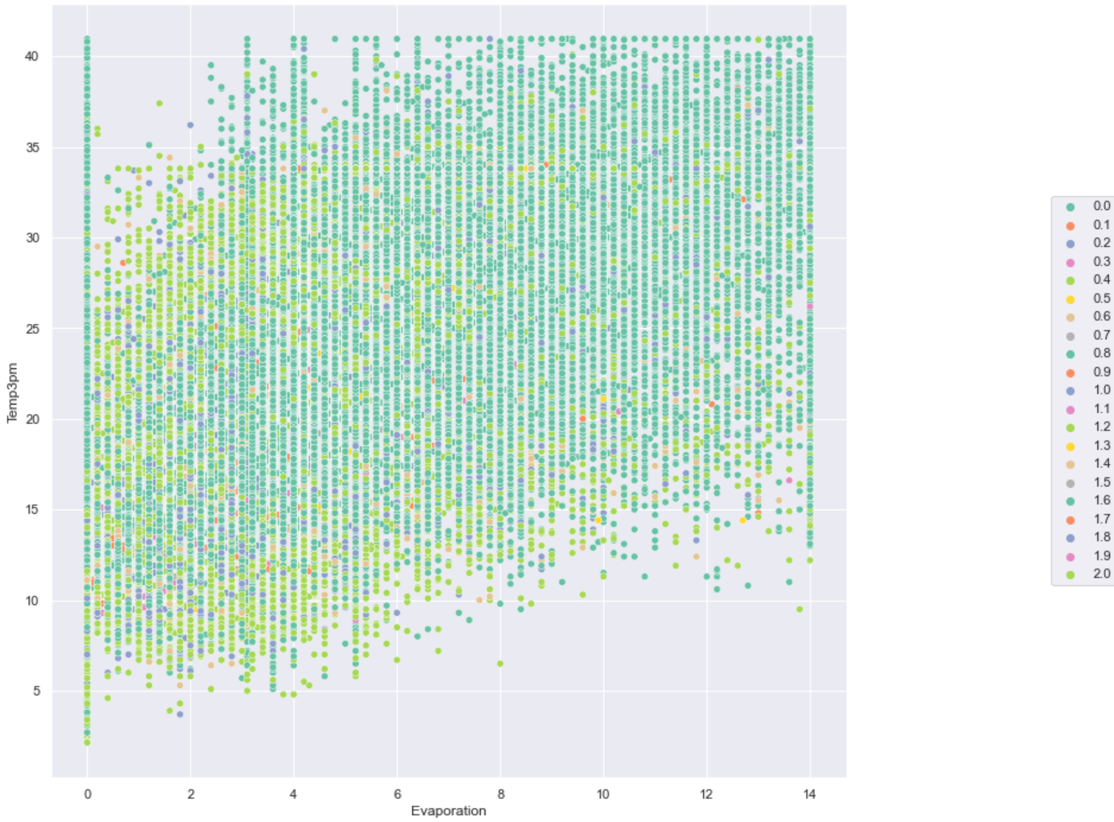


The yearly rainfall increases dramatically in 2009 from 2008 and then drops off again in 2017.

[41]:
```
sns.set(rc = {'figure.figsize':(12,12)})
pop = sns.scatterplot(data = df_rain,x = 'Humidity3pm', y = 'Temp3pm', hue =␣
 ↪'Rainfall', palette = 'Set2')

pop.legend(loc = 'center left', bbox_to_anchor = (1.25, 0.5), ncol = 1)
```

[41]: <matplotlib.legend.Legend at 0x7ff239e4ca30>

[42]:
```
sns.set(rc = {'figure.figsize':(12,12)})
pop = sns.scatterplot(data = df_rain,x = 'Evaporation', y = 'Temp3pm', hue =␣
↪'Rainfall', palette = 'Set2')
pop.legend(loc = 'center left', bbox_to_anchor = (1.25, 0.5), ncol = 1);
```



1.3 Working with Features

1.3.1 Feature Encoding

[43]:
```
def feat_encode(features):
    mapping = {}
    uniqueValues = list(df_rain[features].unique())
    for i in range(len(uniqueValues)):
        mapping[uniqueValues[i]] = i
    return mapping

#replacing the values for binary features
df_rain['RainToday'].replace({'No':0, 'Yes': 1}, inplace = True)
df_rain['RainTomorrow'].replace({'No':0, 'Yes': 1}, inplace = True)

#encoding features that are not bi-variate
df_rain['WindGustDir'].replace(feat_encode('WindGustDir'), inplace = True)
df_rain['WindDir9am'].replace(feat_encode('WindDir9am'),inplace = True)
df_rain['WindDir3pm'].replace(feat_encode('WindDir3pm'),inplace = True)
df_rain['Location'].replace(feat_encode('Location'), inplace = True)
df_rain.RainToday = df_rain.RainToday.astype('float64')
```

```
df_rain.RainTomorrow = df_rain.RainTomorrow.astype('float64')
df_rain.WindGustDir = df_rain.WindGustDir.astype('float64')
df_rain.WindDir9am = df_rain.WindDir9am.astype('float64')
df_rain.WindDir3pm = df_rain.WindDir3pm.astype('float64')
df_rain.Location = df_rain.Location.astype('float64')

df_rain.drop(['total_rain'], axis = 1, inplace = True)
```

[44]:
```
df_rain.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 140787 entries, 0 to 145458
Data columns (total 24 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Location       140787 non-null  float64
 1   MinTemp        140787 non-null  float64
 2   MaxTemp        140787 non-null  float64
 3   Rainfall       140787 non-null  float64
 4   Evaporation    140787 non-null  float64
 5   Sunshine       140787 non-null  float64
 6   WindGustDir    140787 non-null  float64
 7   WindGustSpeed  140787 non-null  float64
 8   WindDir9am     140787 non-null  float64
 9   WindDir3pm     140787 non-null  float64
 10  WindSpeed9am   140787 non-null  float64
 11  WindSpeed3pm   140787 non-null  float64
 12  Humidity9am    140787 non-null  float64
 13  Humidity3pm    140787 non-null  float64
 14  Pressure9am    140787 non-null  float64
 15  Pressure3pm    140787 non-null  float64
 16  Cloud9am       140787 non-null  float64
 17  Cloud3pm       140787 non-null  float64
 18  Temp9am        140787 non-null  float64
 19  Temp3pm        140787 non-null  float64
 20  RainToday      140787 non-null  float64
 21  RainTomorrow   140787 non-null  float64
 22  Year           140787 non-null  float64
 23  Month          140787 non-null  float64
dtypes: float64(24)
memory usage: 30.9 MB
```

Great, now all the variables are numerical.

1.3.2 Defining our features and targets

Independent and Dependent Variables

- X: Independent Features or Input features

- y: Dependent Features or target label

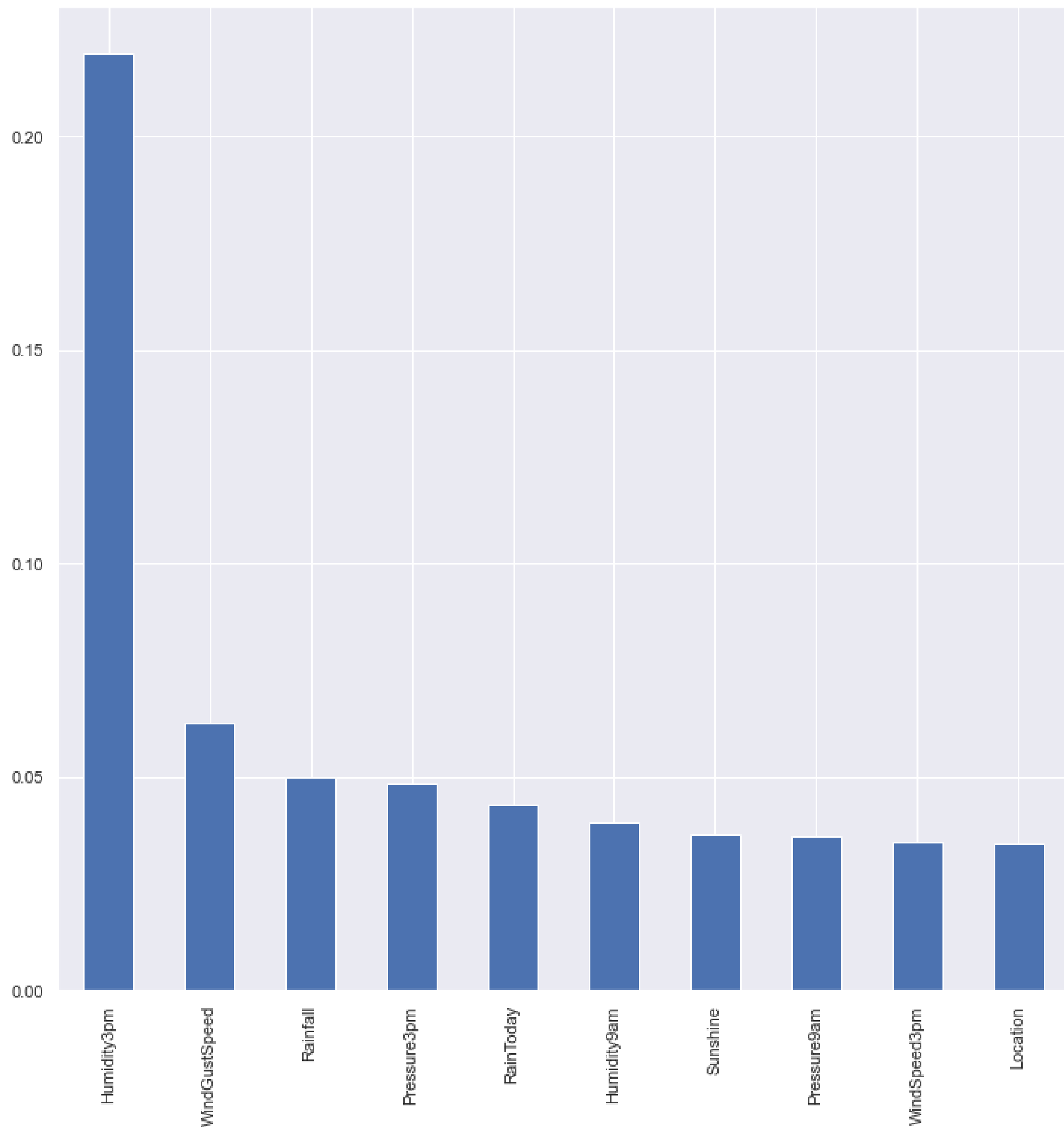
[45]:
```
X = df_rain.drop(['RainTomorrow'],axis=1)
y = df_rain['RainTomorrow']
```

Feature Importance We run the below code to show us the importance of each column and it's relation.

[46]:
```
extraTrees = ExtraTreesRegressor()
extraTrees.fit(X,y)
```

[46]:
```
ExtraTreesRegressor()
```

[47]:
```
importance = pd.Series(extraTrees.feature_importances_, index = X.columns)
importance.nlargest(10).plot(kind = 'bar');
```



This is great information for us, it shows that the measure taken at 3 pm for humidity, will be important in our predictive analytics.

1.3.3 Splitting into Train and Test data

Divide the data into training set and test set randomly with ratio 80:20.

[48]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20,␣
↪random_state = 42)
```

[49]:
```
print(len(X))
print(len(X_train))
```

```
print(len(X_test))
```

```
140787
112629
28158
```

1.4 Finding the Best Model

I will be building and testing multiple models to predict if it will rain tomorrow or not in Australia.

1.4.1 Importing the needed Machine Learning Libraries

[50]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier,␣
↪VotingClassifier,AdaBoostClassifier,GradientBoostingClassifier
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import ConfusionMatrixDisplay, classification_report
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
↪explained_variance_score
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV,␣
↪StratifiedKFold
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
from sklearn.metrics import roc_curve
from confusion_viz import ConfusionViz
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.pipeline import Pipeline
```

1.4.2 Feature Scaling

All features are needing to be standardized because it helps scale the data of each column to a common degree. All features are measured by different units in our dataset so standardization helps by removing the mean and creating a more common measurement.

[51]:
```
scale = StandardScaler()
X_train = scale.fit_transform(X_train)
X_test = scale.transform(X_test)
```

1.4.3 Testing for the Best kfold

[52]:
```
#our base models
models = []
models.append(('LogR', LogisticRegression()))
models.append(('Bagging', BaggingClassifier()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('RFC', RandomForestClassifier()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('ADA', AdaBoostClassifier()))
models.append(('GBM', GradientBoostingClassifier()))
models.append(('ET', ExtraTreesClassifier(n_estimators=15)))

random_state= 30
```

[53]:
```
#accuracy score for basic models where kfold=5
results = []
names = []
for name, model in models:
    kfold = StratifiedKFold(n_splits=5, random_state=random_state, shuffle=True)
    cv_results = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results.append(cv_results)
    names.append(name)
    accuracy = "%s: %f (%f)" %(name, cv_results.mean(), cv_results.std())
    print("Accuracy for Standardized Data - kfold = 5", accuracy)
```

```
Accuracy for Standardized Data - kfold = 5 LogR: 0.842190 (0.001872)
Accuracy for Standardized Data - kfold = 5 Bagging: 0.846256 (0.001565)
Accuracy for Standardized Data - kfold = 5 KNN: 0.833613 (0.000941)
Accuracy for Standardized Data - kfold = 5 RFC: 0.858083 (0.001199)
Accuracy for Standardized Data - kfold = 5 LDA: 0.840911 (0.001541)
Accuracy for Standardized Data - kfold = 5 ADA: 0.845324 (0.002346)
Accuracy for Standardized Data - kfold = 5 GBM: 0.852454 (0.001990)
Accuracy for Standardized Data - kfold = 5 ET: 0.848068 (0.001571)
```

[54]:
```
#accuracy score for basic models where kfold=10
resultsk10 = []
namesk10 = []
for name, model in models:
    kfold10 = StratifiedKFold(n_splits=10, random_state=random_state,␣
 ↪shuffle=True)
    cv_resultsk10 = cross_val_score(model, X_train, y_train, cv=kfold10,␣
 ↪scoring='accuracy')
    resultsk10.append(cv_resultsk10)
    namesk10.append(name)
    accuracyk10 = "%s: %f (%f)" %(name, cv_resultsk10.mean(), cv_resultsk10.
 ↪std())
```

```
    print("Accuracy for Standardized Data - kfold = 10", accuracyk10)
```

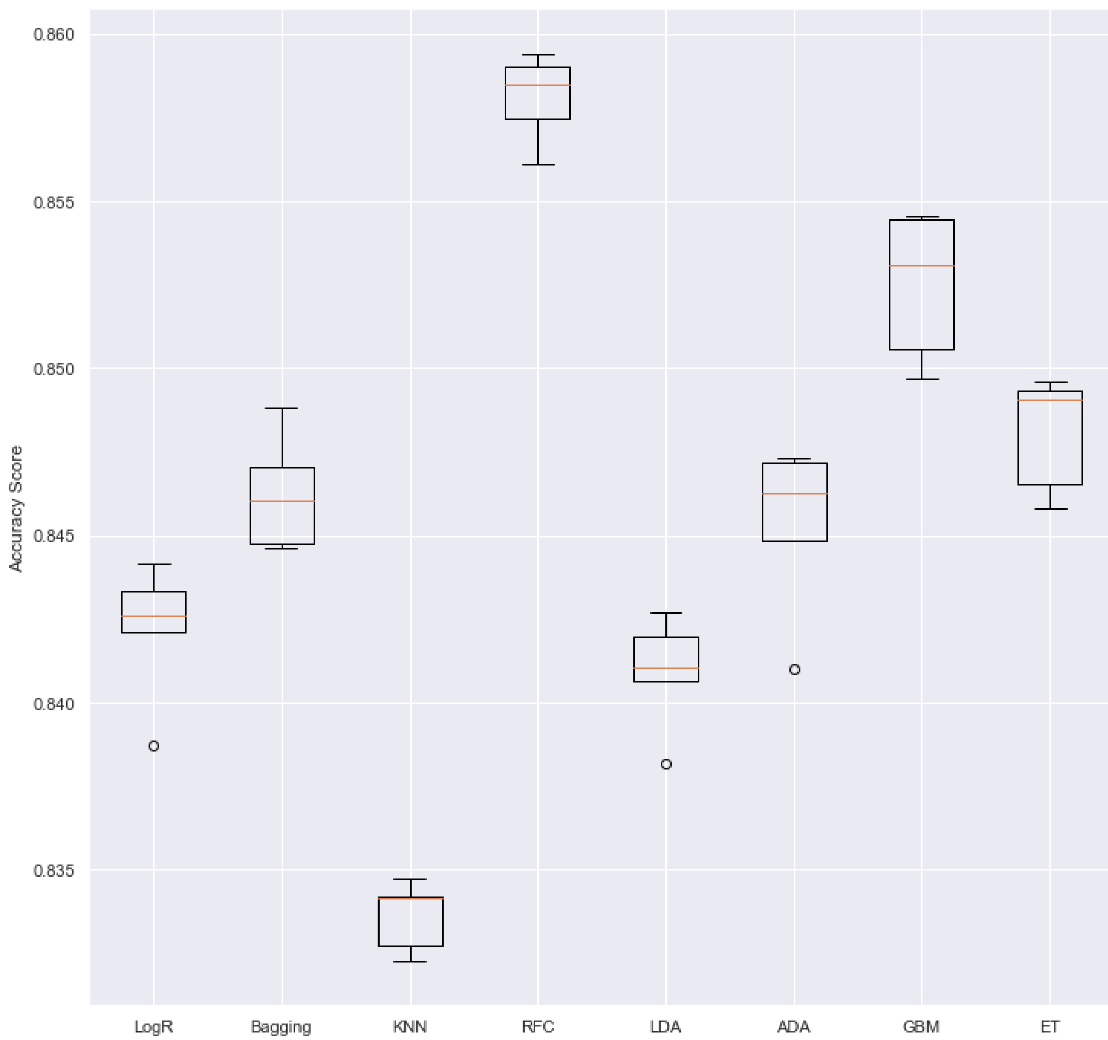
```
Accuracy for Standardized Data - kfold = 10 LogR: 0.842270 (0.003828)
Accuracy for Standardized Data - kfold = 10 Bagging: 0.847446 (0.003501)
Accuracy for Standardized Data - kfold = 10 KNN: 0.834758 (0.002737)
Accuracy for Standardized Data - kfold = 10 RFC: 0.859761 (0.002919)
Accuracy for Standardized Data - kfold = 10 LDA: 0.840769 (0.002707)
Accuracy for Standardized Data - kfold = 10 ADA: 0.845262 (0.003301)
Accuracy for Standardized Data - kfold = 10 GBM: 0.852826 (0.003197)
Accuracy for Standardized Data - kfold = 10 ET: 0.849168 (0.002688)
```

[55]:
```
#accuracy score for basic models where kfold=15
resultsk15 = []
namesk15 = []
for name, model in models:
    kfold15 = StratifiedKFold(n_splits=15, random_state=random_state,␣
 ↪shuffle=True)
    cv_resultsk15 = cross_val_score(model, X_train, y_train, cv=kfold15,␣
 ↪scoring='accuracy')
    resultsk15.append(cv_resultsk15)
    namesk15.append(name)
    accuracyk15 = "%s: %f (%f)" %(name, cv_resultsk15.mean(), cv_resultsk15.
 ↪std())
    print("Accuracy for Standardized Data - kfold = 15", accuracyk15)
```

```
Accuracy for Standardized Data - kfold = 15 LogR: 0.842438 (0.003920)
Accuracy for Standardized Data - kfold = 15 Bagging: 0.847561 (0.002475)
Accuracy for Standardized Data - kfold = 15 KNN: 0.834883 (0.003635)
Accuracy for Standardized Data - kfold = 15 RFC: 0.858971 (0.004552)
Accuracy for Standardized Data - kfold = 15 LDA: 0.840734 (0.003578)
Accuracy for Standardized Data - kfold = 15 ADA: 0.845564 (0.003811)
Accuracy for Standardized Data - kfold = 15 GBM: 0.852960 (0.003663)
Accuracy for Standardized Data - kfold = 15 ET: 0.849346 (0.003296)
```

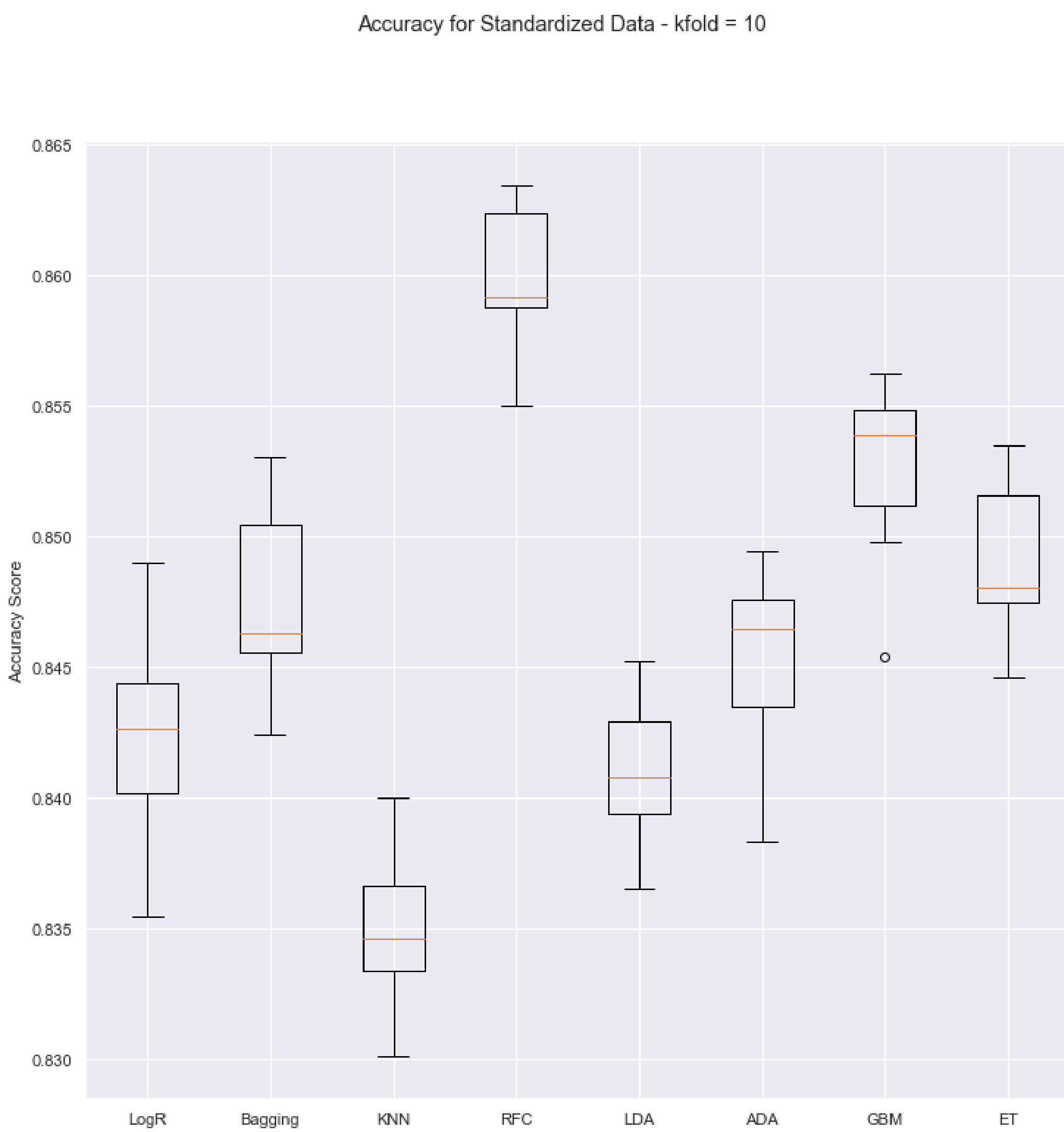
[56]:
```
#compare algorithms at k=5
fig = pyplot.figure()
fig.suptitle('Accuracy for Standardized Data - kfold = 5')
plt.ylabel('Accuracy Score')
ax = fig.add_subplot()
pyplot.boxplot(results)
ax.set_xticklabels(names)
pyplot.show()
```

Accuracy for Standardized Data - kfold = 5

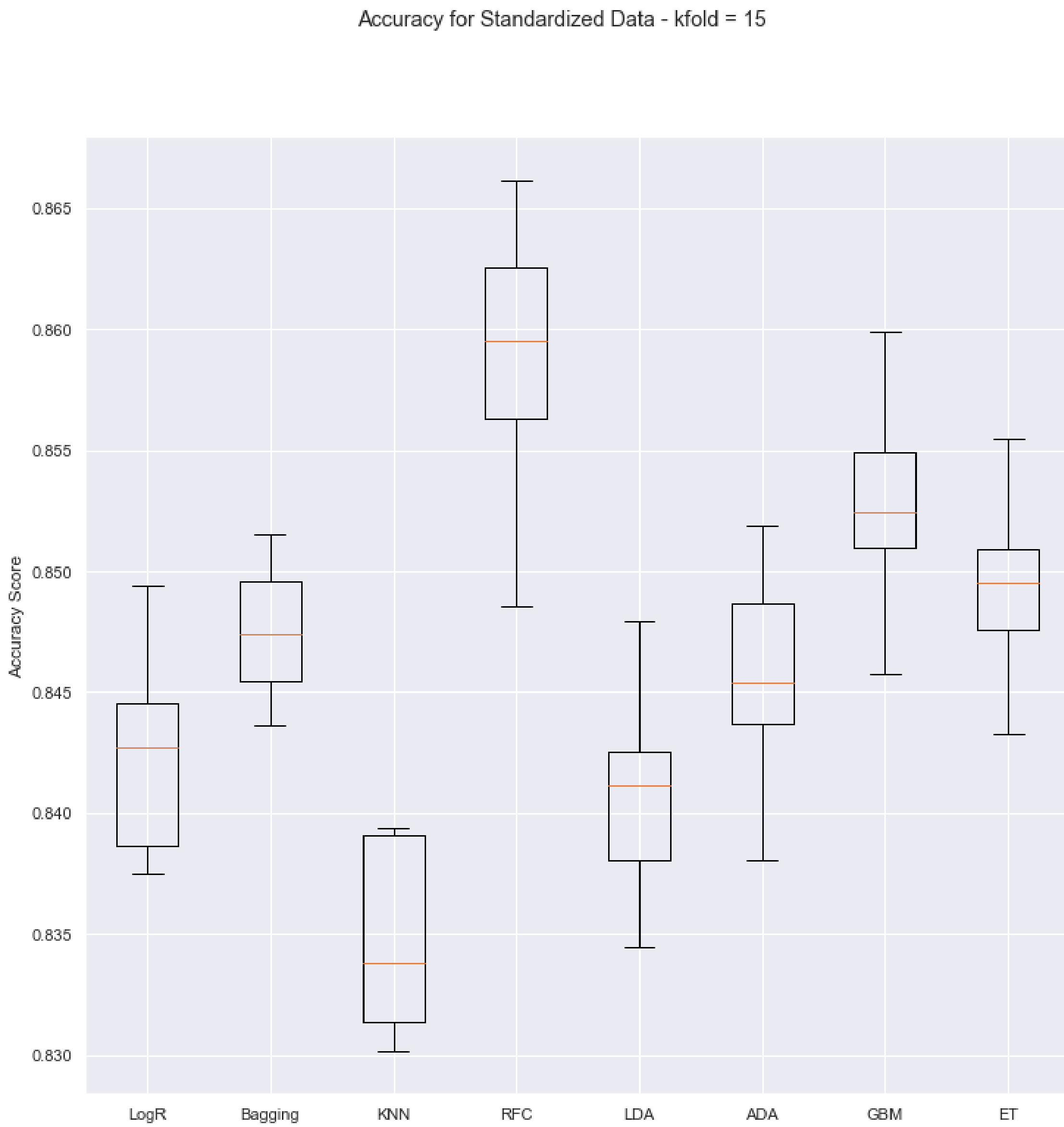


[57]:

```
#compare algorithms at k=10
fig = pyplot.figure()
fig.suptitle('Accuracy for Standardized Data - kfold = 10')
plt.ylabel('Accuracy Score')
ax = fig.add_subplot()
pyplot.boxplot(resultsk10)
ax.set_xticklabels(namesk10)
pyplot.show()
```



[58]:
```
#compare algorithms at k=15
fig = pyplot.figure()
fig.suptitle('Accuracy for Standardized Data - kfold = 15')
plt.ylabel('Accuracy Score')
ax = fig.add_subplot()
pyplot.boxplot(resultsk15)
ax.set_xticklabels(namesk15)
pyplot.show()
```



kfold = 15 returned the best results. We are looking for the closest accuracy score to 1. Random Forest Classifier has the best score across all three kfolds tested. From here our top 3 performing algorithms are Random Forest Classifier, GBM, and ET. Let's see if these continue to be the top three after improving the performance of our models and obtaining the best dataset by using some ensemble methods.

I'm going to run this to check the precision, the closer to 1, the better the precision.

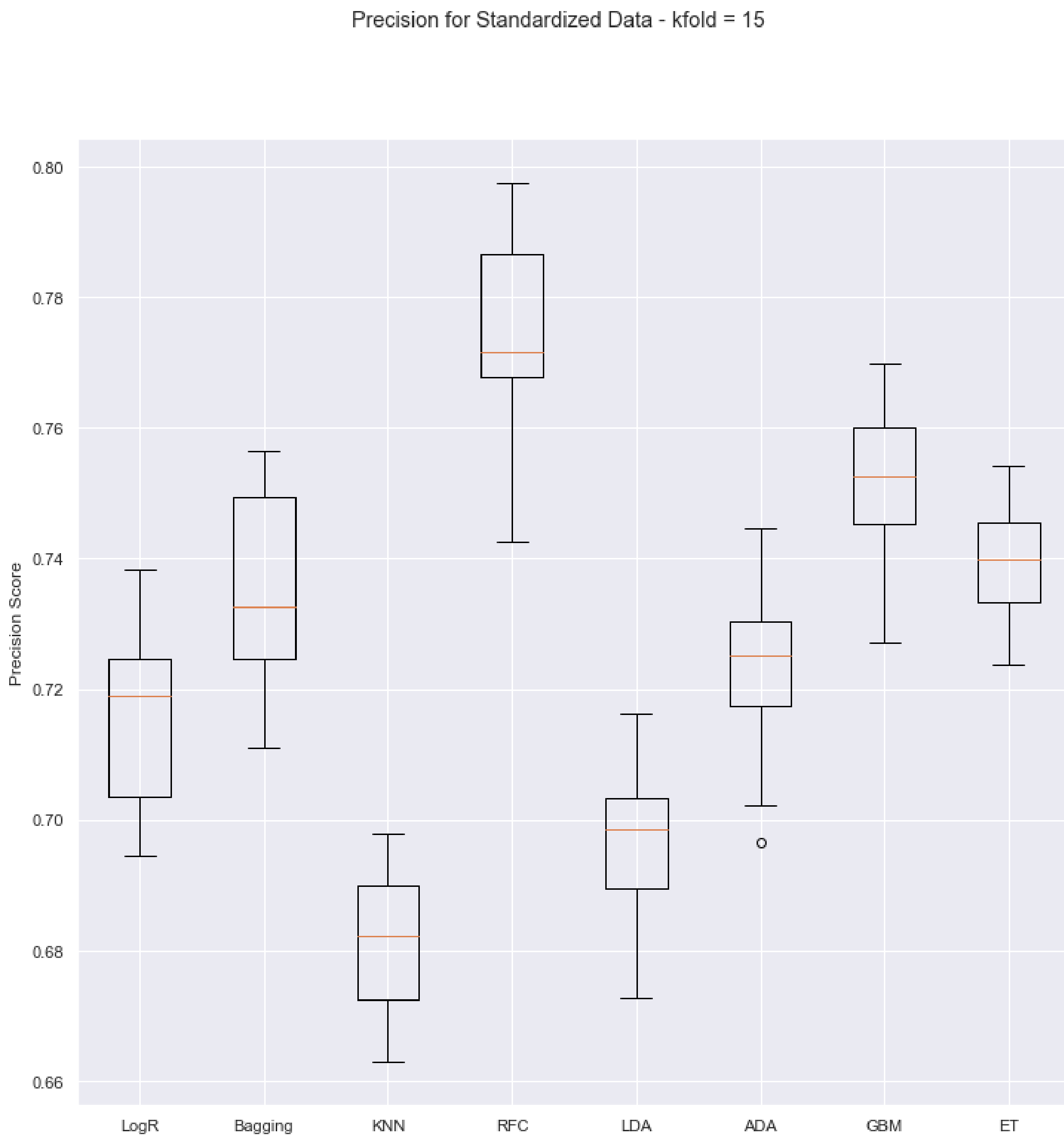
[59]:
```
#precision score for basic models
results2 = []
names2 = []
for name, model in models:
```

```
    kfold2 = StratifiedKFold(n_splits=15, random_state=random_state,␣
↪shuffle=True)
    cv_results2 = cross_val_score(model, X_train, y_train, cv=kfold2,␣
↪scoring='precision')
    results2.append(cv_results2)
    names2.append(name)
    precision = "%s: %f (%f)" %(name, cv_results2.mean(), cv_results2.std())
    print("Precision for Standardized Data - kfold = 15", precision)
```

```
Precision for Standardized Data - kfold = 15 LogR: 0.715482 (0.013739)
Precision for Standardized Data - kfold = 15 Bagging: 0.734768 (0.014177)
Precision for Standardized Data - kfold = 15 KNN: 0.680962 (0.010847)
Precision for Standardized Data - kfold = 15 RFC: 0.775906 (0.014019)
Precision for Standardized Data - kfold = 15 LDA: 0.696033 (0.012369)
Precision for Standardized Data - kfold = 15 ADA: 0.722404 (0.011517)
Precision for Standardized Data - kfold = 15 GBM: 0.751975 (0.011735)
Precision for Standardized Data - kfold = 15 ET: 0.739716 (0.008393)
```

[60]:

```
#compare algorithms
fig = pyplot.figure()
fig.suptitle('Precision for Standardized Data - kfold = 15')
plt.ylabel('Precision Score')
ax = fig.add_subplot()
pyplot.boxplot(results2)
ax.set_xticklabels(names2)
pyplot.show()
```



It looks like the model with the best precision is also Random Forest Classifier. Our other top models are still GBM, and ET, with Bagging Classifier close behind. None of these are very close to having a precision score close to 1 so I will make the testing better by setting a pipeline for each model and scaling the data. This will make the data so it's all treated the same for each algorithm.

1.4.4 Scaling the data

This will standardize the dataset. I will then test for the best model with the optimized data.

[61]:
```
#optimized data with our models where kfold=15
n_jobs=15
```

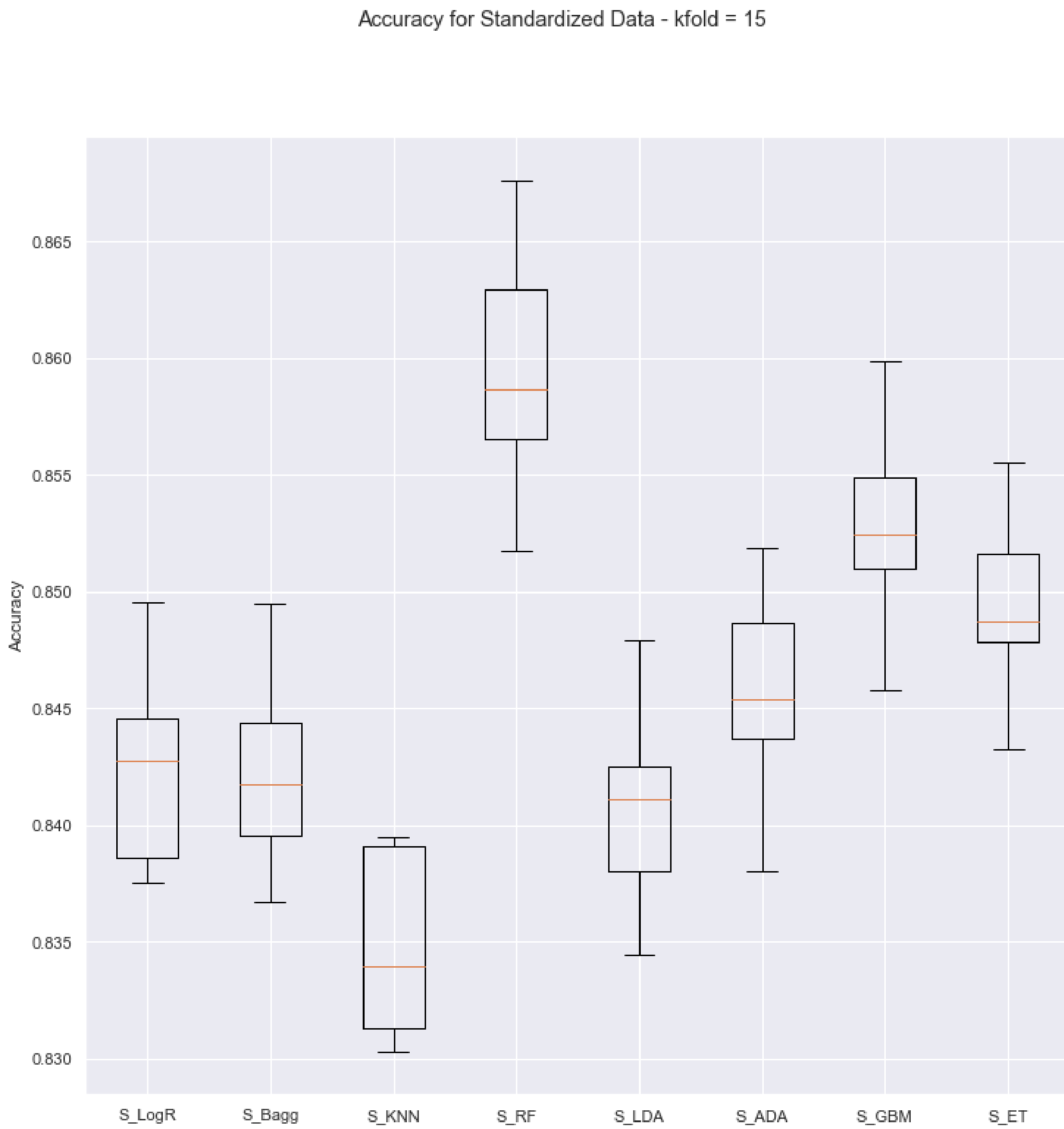
```
pipeline_models=[]
pipeScaled_lr = ('S_LogR', Pipeline([('Scaler', StandardScaler()),
                                       ('LogR',␣
↪LogisticRegression(random_state=random_state, n_jobs=n_jobs,
                                                                           ␣
↪max_iter=500))]))
pipeScaled_bag = ('S_Bagg', Pipeline
                  ([('Scaler', StandardScaler()),('Bagging',
                                                           ␣
↪BaggingClassifier(base_estimator=SGDClassifier
                                                                            ␣
↪(random_state=random_state, n_jobs=n_jobs,
                                                                             ␣
↪max_iter=1500), random_state=random_state,
                                                                            ␣
↪oob_score=True,n_jobs=n_jobs))]))
pipeScaled_knn = ('S_KNN', Pipeline([('Scaler', StandardScaler()),('KNN',␣
↪KNeighborsClassifier(n_jobs=n_jobs))]))

pipeScaled_rf = ('S_RF', Pipeline([('Scaler', StandardScaler()),
                                       ('RFC',␣
↪RandomForestClassifier(random_state=random_state,oob_score=True,
                                                                              ␣
↪n_jobs=n_jobs))]))
pipeScaled_lda = ('S_LDA', Pipeline([('Scaler', StandardScaler()),('LDA',␣
↪LinearDiscriminantAnalysis())]))
pipeScaled_ada = ('S_ADA', Pipeline([('Scaler', StandardScaler()),('ADA',␣
↪AdaBoostClassifier())]))
pipeScaled_gbm = ('S_GBM', Pipeline([('Scaler', StandardScaler()),('GBM',␣
↪GradientBoostingClassifier())]))
pipeScaled_et = ('S_ET', Pipeline([('Scaler', StandardScaler()),('ET',␣
↪ExtraTreesClassifier(n_estimators=15))]))


pipeline_models.append(pipeScaled_lr)
pipeline_models.append(pipeScaled_bag)
pipeline_models.append(pipeScaled_knn)
pipeline_models.append(pipeScaled_rf)
pipeline_models.append(pipeScaled_lda)
pipeline_models.append(pipeScaled_ada)
pipeline_models.append(pipeScaled_gbm)
pipeline_models.append(pipeScaled_et)
```

[62]:
```
#accuracy score of optimized data
results3 = []
names3 = []
```

```python
for name, model in pipeline_models:
    kfold3 = StratifiedKFold(n_splits=n_jobs, random_state=random_state,␣
↪shuffle=True)
    cv_results3 = cross_val_score(model, X_train, y_train, cv=kfold3,␣
↪scoring='accuracy')
    results3.append(cv_results3)
    names3.append(name)
    acc_2 = "%s: %f (%f)" %(name, cv_results3.mean(), cv_results3.std())
    print('Accuracy for Standardized Data - kfold = 15', acc_2)
```

```
Accuracy for Standardized Data - kfold = 15 S_LogR: 0.842430 (0.003944)
Accuracy for Standardized Data - kfold = 15 S_Bagg: 0.842225 (0.003772)
Accuracy for Standardized Data - kfold = 15 S_KNN: 0.834963 (0.003646)
Accuracy for Standardized Data - kfold = 15 S_RF: 0.859557 (0.004512)
Accuracy for Standardized Data - kfold = 15 S_LDA: 0.840734 (0.003578)
Accuracy for Standardized Data - kfold = 15 S_ADA: 0.845564 (0.003811)
Accuracy for Standardized Data - kfold = 15 S_GBM: 0.852960 (0.003663)
Accuracy for Standardized Data - kfold = 15 S_ET: 0.849337 (0.003478)
```

[63]:
```python
#compare algorithms of optimized data
fig = pyplot.figure()
fig.suptitle('Accuracy for Standardized Data - kfold = 15')
plt.ylabel('Accuracy')
ax = fig.add_subplot()
pyplot.boxplot(results3)
ax.set_xticklabels(names3)
pyplot.show()
```



1.4.5 Stacking Ensemble Method

This will standardize the dataset slightly more than the earlier attempt at standardizing the data. We already scaled the data before testing the accuracy and precision of the models so we will try a stacking ensemble method.

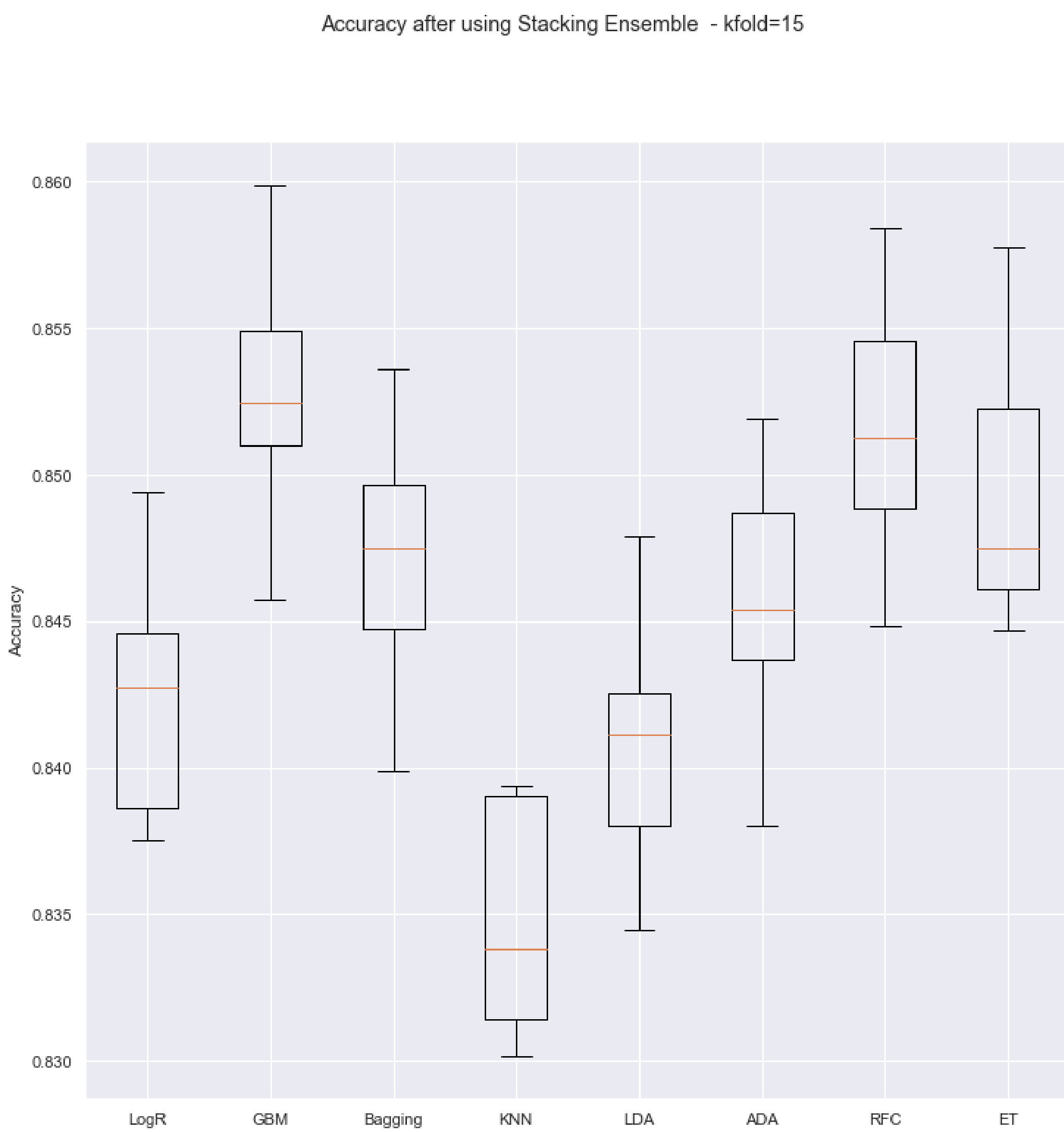
[64]:
```
#basic ensemble models
stacking_model = []

stacking_model.append((('LogR', LogisticRegression())))
stacking_model.append((('GBM', GradientBoostingClassifier())))
```

```
stacking_model.append((('Bagging', BaggingClassifier())))
stacking_model.append((('KNN', KNeighborsClassifier())))
stacking_model.append((('LDA', LinearDiscriminantAnalysis())))
stacking_model.append((('ADA', AdaBoostClassifier())))
stacking_model.append((('RFC', RandomForestClassifier(n_estimators=15))))
stacking_model.append((('ET', ExtraTreesClassifier(n_estimators=15))))
```

[65]:
```
#accuracy scores of ensemble models
results4 = []
names4 = []
for name, model in stacking_model:
    kfold4 = StratifiedKFold(n_splits=n_jobs, random_state=random_state,␣
 ↪shuffle=True)
    cv_results4 = cross_val_score(model, X_train, y_train, cv=kfold4,␣
 ↪scoring='accuracy')
    results4.append(cv_results4)
    names4.append(name)
    cv_results4 = "%s: %f (%f)" %(name, cv_results4.mean(), cv_results4.std())
    print('Accuracy after using Stacking Ensemble - kfold=15', cv_results4)
```

```
Accuracy after using Stacking Ensemble - kfold=15 LogR: 0.842438 (0.003920)
Accuracy after using Stacking Ensemble - kfold=15 GBM: 0.852960 (0.003663)
Accuracy after using Stacking Ensemble - kfold=15 Bagging: 0.847233 (0.003419)
Accuracy after using Stacking Ensemble - kfold=15 KNN: 0.834883 (0.003635)
Accuracy after using Stacking Ensemble - kfold=15 LDA: 0.840734 (0.003578)
Accuracy after using Stacking Ensemble - kfold=15 ADA: 0.845564 (0.003811)
Accuracy after using Stacking Ensemble - kfold=15 RFC: 0.851806 (0.004252)
Accuracy after using Stacking Ensemble - kfold=15 ET: 0.849222 (0.004034)
```

[66]:
```
#compare algorithms
fig = pyplot.figure()
fig.suptitle('Accuracy after using Stacking Ensemble  - kfold=15')
plt.ylabel('Accuracy')
ax = fig.add_subplot()
pyplot.boxplot(results4)
ax.set_xticklabels(names4)
pyplot.show()
```



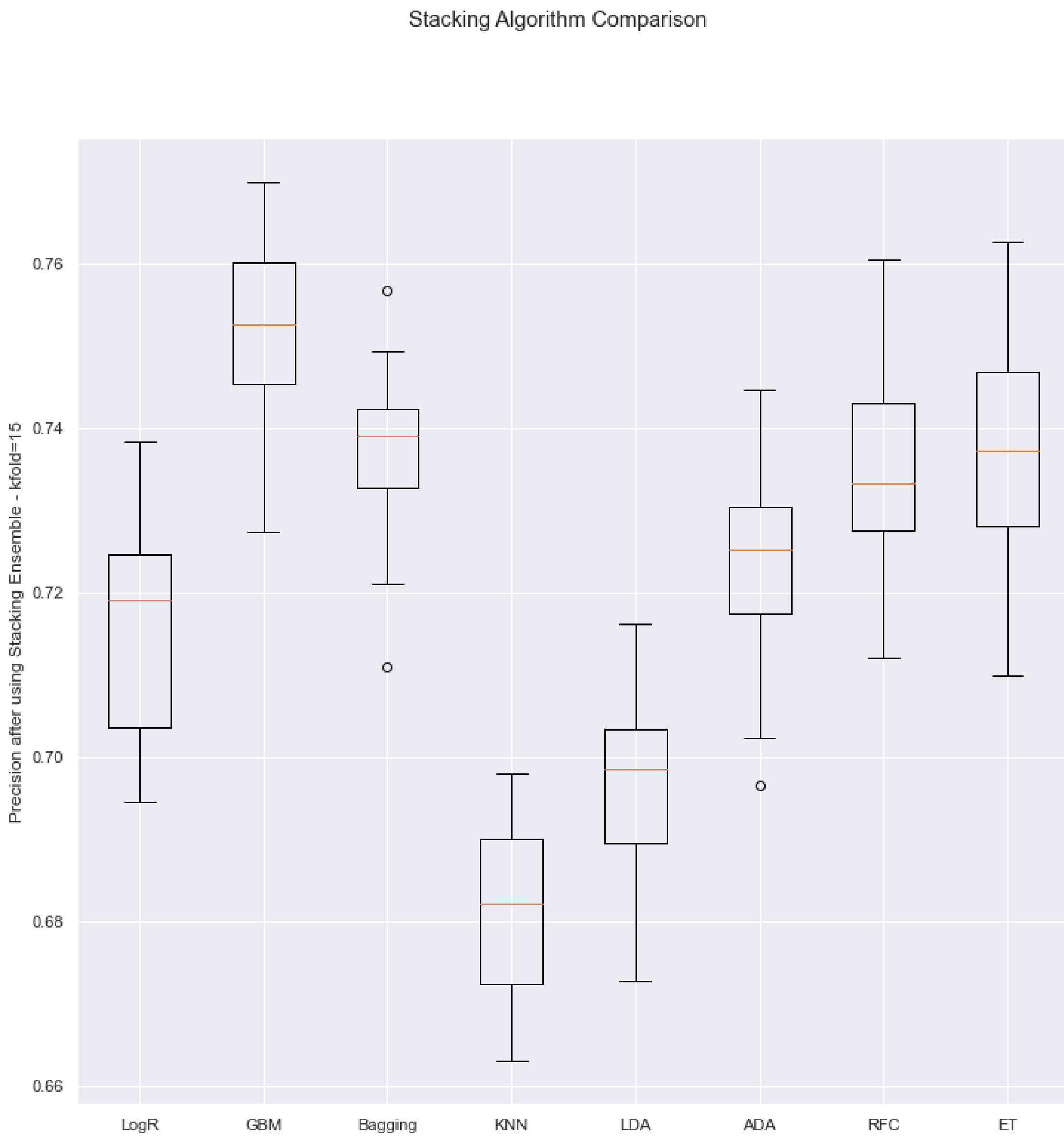
[67]:
```
#precision scores of optimized ensemble models
results5 = []
names5 = []
for name, model in stacking_model:
    kfold5 = StratifiedKFold(n_splits=n_jobs, random_state=random_state,␣
 ↪shuffle=True)
    cv_results5 = cross_val_score(model, X_train, y_train, cv=kfold5,␣
 ↪scoring='precision')
    results5.append(cv_results5)
    names5.append(name)
    cv_results5 = "%s: %f (%f)" %(name, cv_results5.mean(), cv_results5.std())
```

```
    print('Precision after using Stacking Ensemble - kfold=15', cv_results5)
```

```
Precision after using Stacking Ensemble - kfold=15 LogR: 0.715482 (0.013739)
Precision after using Stacking Ensemble - kfold=15 GBM: 0.751975 (0.011735)
Precision after using Stacking Ensemble - kfold=15 Bagging: 0.737222 (0.010788)
Precision after using Stacking Ensemble - kfold=15 KNN: 0.680962 (0.010847)
Precision after using Stacking Ensemble - kfold=15 LDA: 0.696033 (0.012369)
Precision after using Stacking Ensemble - kfold=15 ADA: 0.722404 (0.011517)
Precision after using Stacking Ensemble - kfold=15 RFC: 0.734521 (0.012652)
Precision after using Stacking Ensemble - kfold=15 ET: 0.737128 (0.014738)
```

[68]:

```
#compare algorithms of optimized data
fig = pyplot.figure()
fig.suptitle('Stacking Algorithm Comparison')
plt.ylabel('Precision after using Stacking Ensemble - kfold=15')
ax = fig.add_subplot()
pyplot.boxplot(results5)
ax.set_xticklabels(names5)
pyplot.show()
```



1.4.6 Best Model

From the testing and analysis above, we can see that the best accuracy and precision came when I used a kfold value of 15, and standardized and scaled data. I will test a couple models with this data. The top performing models are Random forest classifier, Gradient Boosting classifier, and the Extra trees classifier.

1.4.7 Model #1 - Random Forest Classifier Model

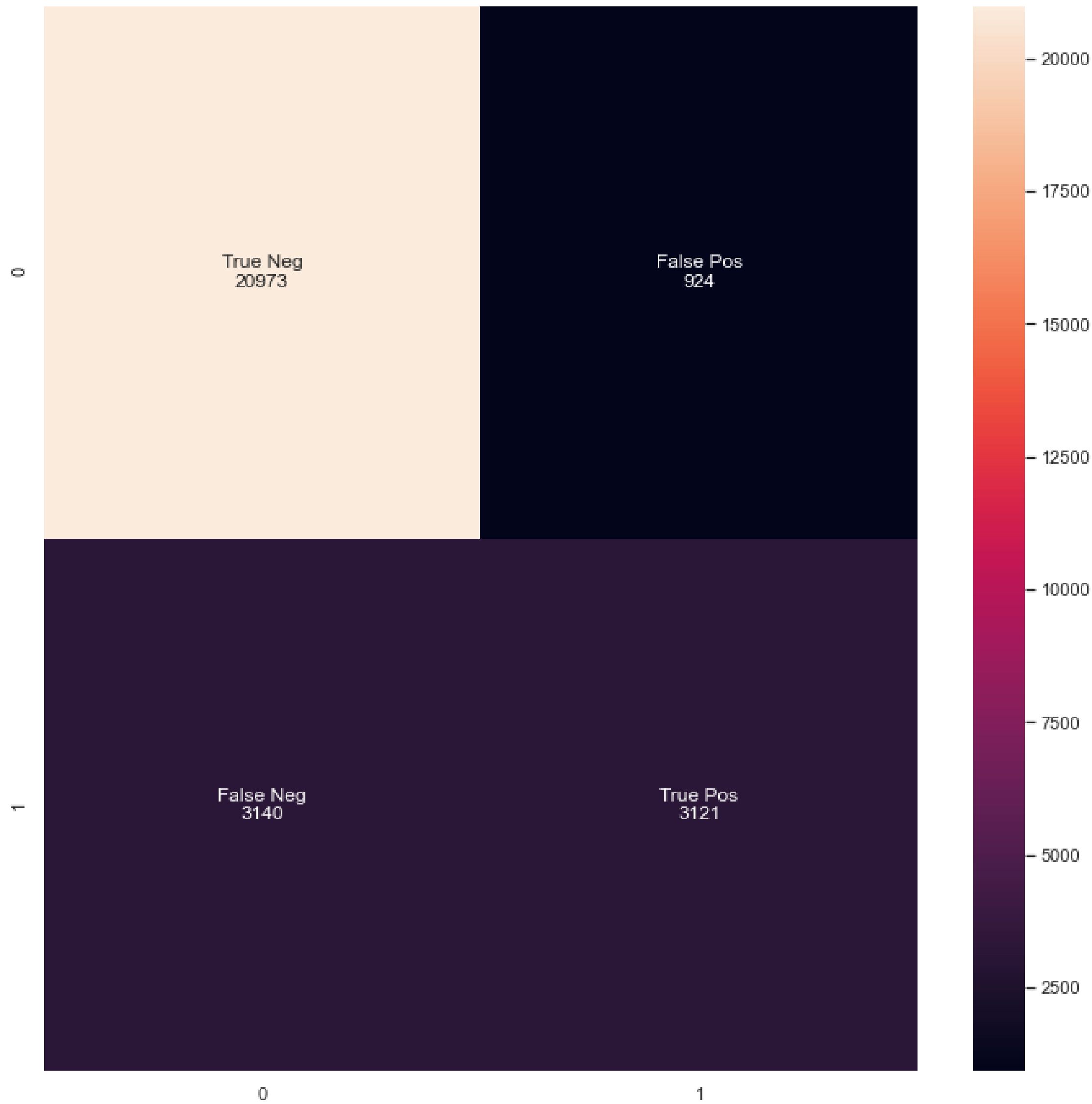
[69]:
```
scale = StandardScaler()
X_train = scale.fit_transform(X_train)
X_test = scale.transform(X_test)


RF = RandomForestClassifier(random_state = random_state, oob_score = True,␣
↪n_jobs = n_jobs).fit(X_train, y_train)
cv = cross_val_score(RF, X_train, y_train, cv = 5)
print("The accuracy of Random Forest using 5-fold test is: ",cv)

#Prediction on test dataset
RF_pred = RF.predict(X_test)
acc = accuracy_score(y_test,RF_pred)
print("The accuracy of Random Forest on test dataset is: ",acc)
```

```
The accuracy of Random Forest using 5-fold test is:  [0.85980645 0.86131581
0.85527835 0.85847465 0.85975583]
The accuracy of Random Forest on test dataset is:  0.855671567582925
```

[70]:
```
print(classification_report(y_test, RF_pred))

RFmatrix = confusion_matrix(y_test, RF_pred)
RFnames = ['True Neg','False Pos','False Neg','True Pos']
RFcounts = ['{0:0.0f}'.format(value) for value in RFmatrix.flatten()]
RFlabels = [f'{v1}\n{v2}' for v1, v2 in
          zip(RFnames, RFcounts)]
RFlabels = np.asarray(RFlabels).reshape(2,2)
sns.heatmap(RFmatrix, annot = RFlabels, fmt='')
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.96      0.91     21897
         1.0       0.77      0.50      0.61      6261

    accuracy                           0.86     28158
   macro avg       0.82      0.73      0.76     28158
weighted avg       0.85      0.86      0.84     28158
```

[70]: <AxesSubplot:>



[71]:
```
print(classification_report(y_test, RF_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.96      0.91     21897
         1.0       0.77      0.50      0.61      6261

    accuracy                           0.86     28158
   macro avg       0.82      0.73      0.76     28158
weighted avg       0.85      0.86      0.84     28158
```

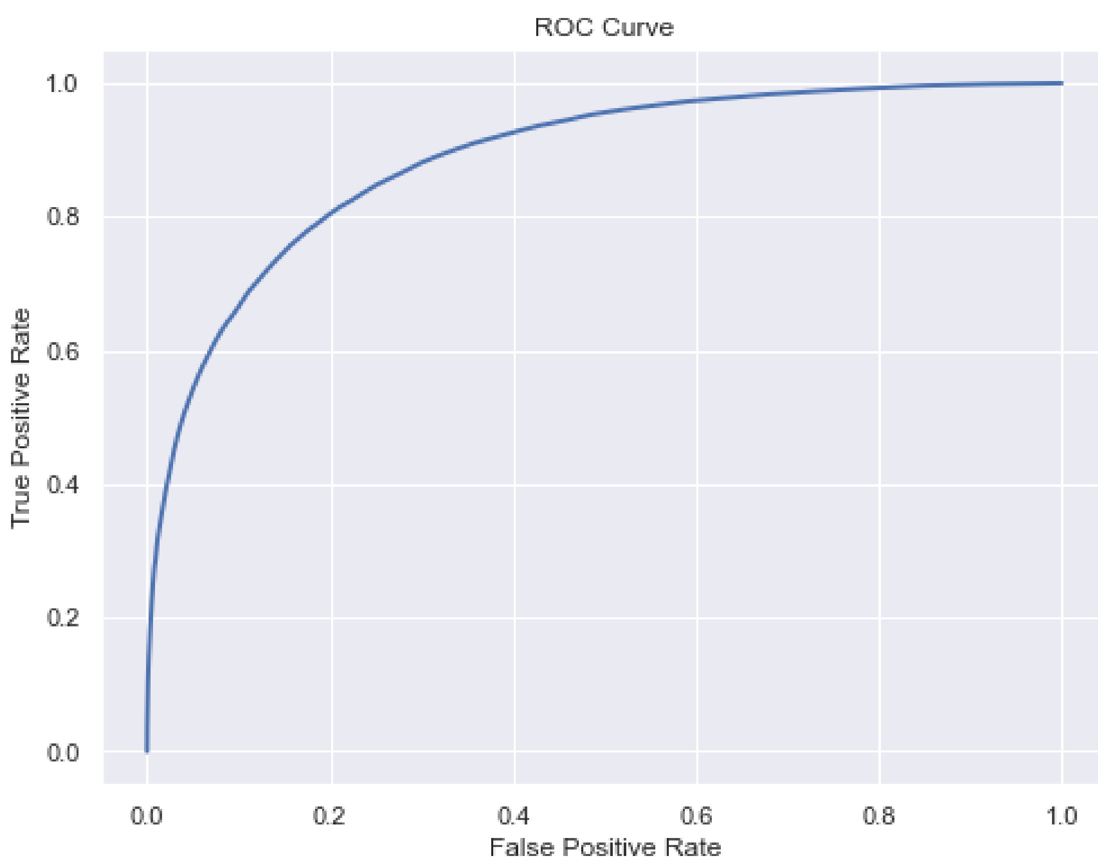
[72]:
```
print(roc_auc_score(y_test, RF_pred))
```

0.7281425545950758

[73]:
```
RF_proba = cross_val_predict(RF, X_train, y_train, cv = 5, method =␣
 ↪'predict_proba')
RF_scores = RF_proba[:, 1]

def ROC_Curve(y_train, RF_scores, label = None):
    fpr, tpr, thresholds = roc_curve(y_train, RF_scores)
    print('AUC Score: {:.2f} '.format(roc_auc_score(y_train, RF_scores)))
    plt.figure(figsize = (8, 6))
    plt.plot(fpr, tpr, linewidth = 2, label = label, color = 'b')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.show()
```

[74]:
```
ROC_Curve(y_train, RF_scores)
```

AUC Score: 0.89



[75]:
```
conf_viz = ConfusionViz()
conf_viz.fit(y_true = y_test, probas_pred = RF_pred)
conf_viz.show()
conf_viz.to_html('RF_confusion_viz.html')
```

1.4.8 Model #2 - Gradient Boosting Classifier Model

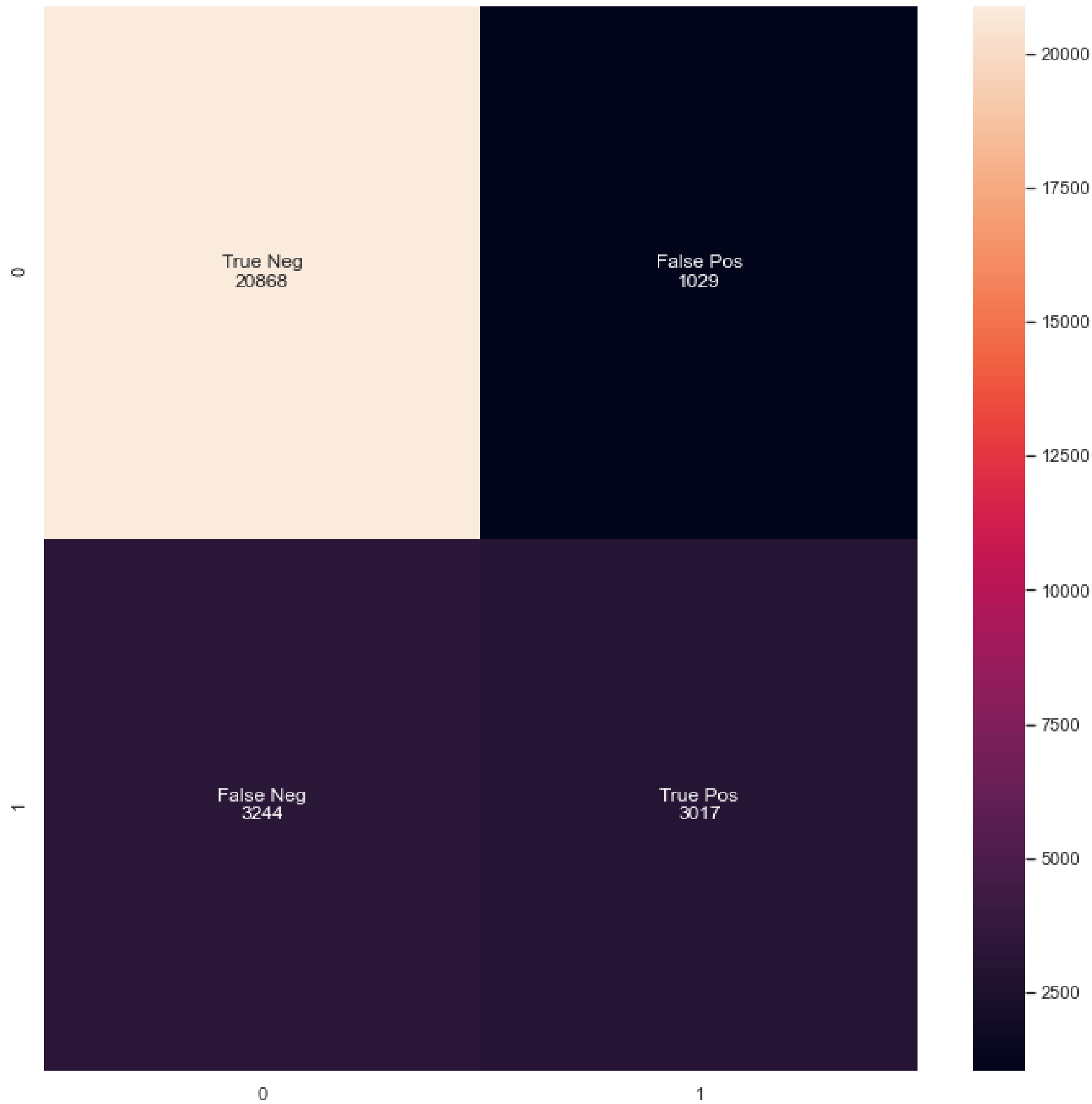
[76]:
```
GB = GradientBoostingClassifier(random_state = random_state).fit(X_train,␣
 ↪y_train)
cv = cross_val_score(GB, X_train, y_train, cv = 5)
print("The accuracy of Gradient Boosting Classifier using 5-fold test is: ",cv)

#Prediction on test dataset
GB_pred = GB.predict(X_test)
acc = accuracy_score(y_test,GB_pred)
print("The accuracy of Gradient Boosting Classifier on test dataset is: ",acc)
```

```
The accuracy of Gradient Boosting Classifier using 5-fold test is:  [0.85412412
0.85589985 0.8478203  0.85381337 0.85283019]
The accuracy of Gradient Boosting Classifier on test dataset is:
0.8482491654236807
```

[77]:
```
print(classification_report(y_test, GB_pred))

GBmatrix = confusion_matrix(y_test, GB_pred)
GBnames = ['True Neg','False Pos','False Neg','True Pos']
GBcounts = ['{0:0.0f}'.format(value) for value in GBmatrix.flatten()]
GBlabels = [f'{v1}\n{v2}' for v1, v2 in
          zip(GBnames, GBcounts)]
GBlabels = np.asarray(GBlabels).reshape(2,2)
sns.heatmap(GBmatrix, annot = GBlabels, fmt='')
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.95      0.91     21897
         1.0       0.75      0.48      0.59      6261

    accuracy                           0.85     28158
   macro avg       0.81      0.72      0.75     28158
weighted avg       0.84      0.85      0.84     28158
```

[77]: <AxesSubplot:>



[78]:
```
print(classification_report(y_test, GB_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.95      0.91     21897
         1.0       0.75      0.48      0.59      6261

    accuracy                           0.85     28158
   macro avg       0.81      0.72      0.75     28158
weighted avg       0.84      0.85      0.84     28158
```

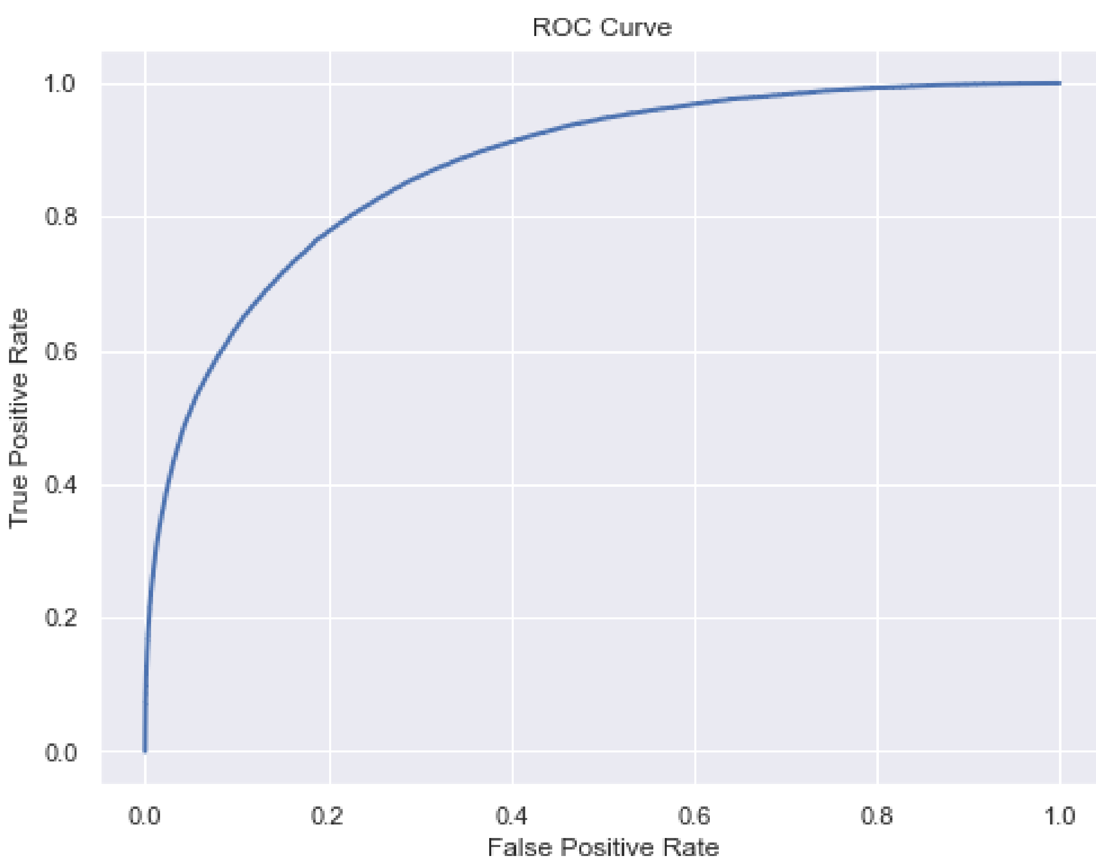
[79]:
```
print(roc_auc_score(y_test, GB_pred))
```

```
0.7174395833575405
```

[80]:
```python
GB_proba = cross_val_predict(GB, X_train, y_train, cv = 5, method =␣
 ↪'predict_proba')
GB_scores = GB_proba[:, 1]

def ROC_Curve(y_train, GB_scores, label = None):
    fpr, tpr, thresholds = roc_curve(y_train, GB_scores)
    print('AUC Score: {:.2f} '.format(roc_auc_score(y_train, GB_scores)))
    plt.figure(figsize = (8, 6))
    plt.plot(fpr, tpr, linewidth = 2, label = label, color = 'b')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.show()
```

[81]:
```python
ROC_Curve(y_train, GB_scores)
```

```
AUC Score: 0.87
```



[82]:
```
conf_viz = ConfusionViz()
conf_viz.fit(y_true = y_test, probas_pred = GB_pred)
conf_viz.show()
conf_viz.to_html('GB_confusion_viz.html')
```

1.4.9 Model #3 - Extra Trees Classifier Model

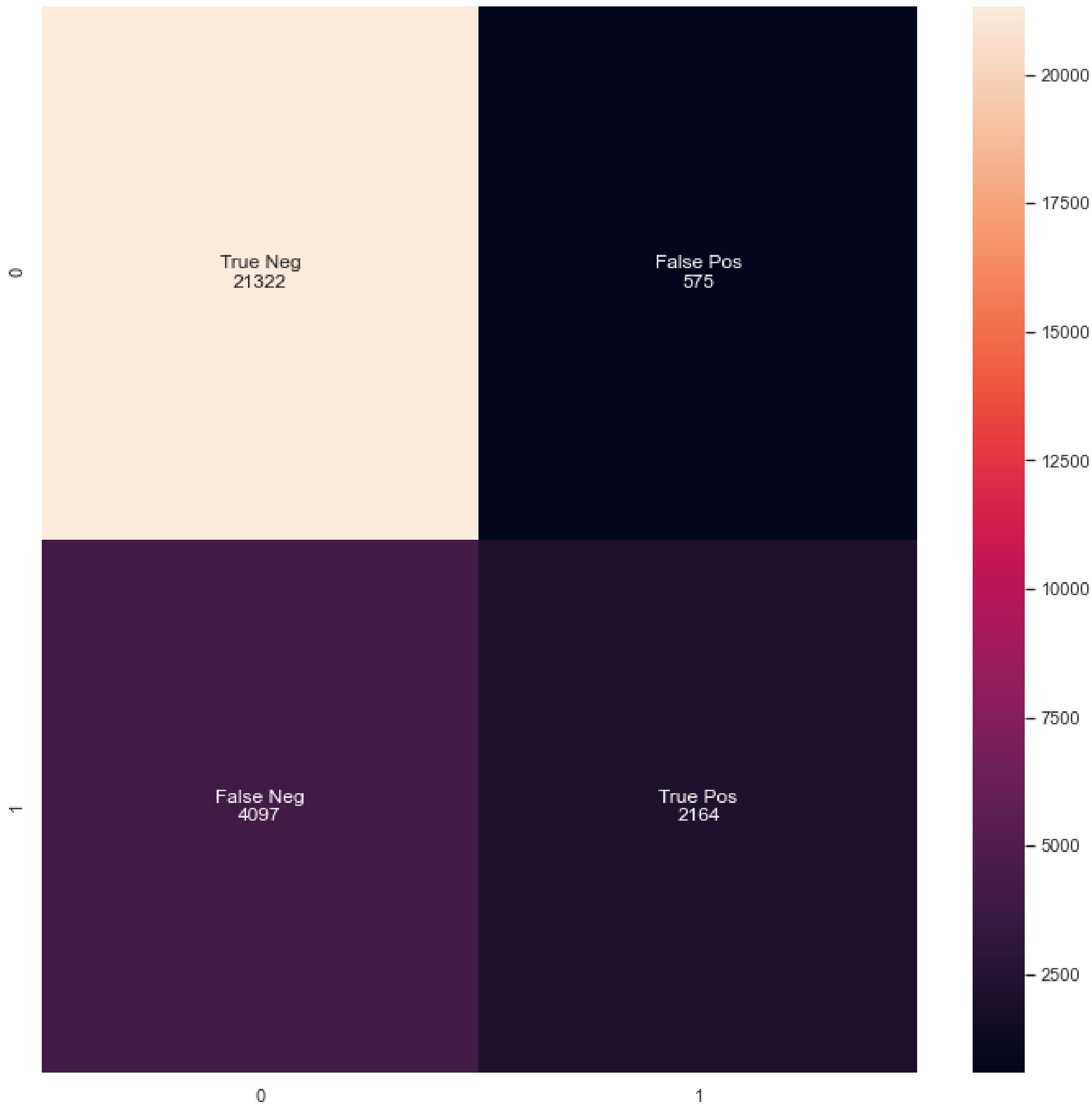
[83]:
```
ET = GradientBoostingClassifier(n_estimators = 15, random_state = random_state).
↪fit(X_train, y_train)
cv = cross_val_score(ET, X_train, y_train, cv = 5)
print("The accuracy of Extra Trees using 5-fold test is: ",cv)

#Prediction on test dataset
ET_pred = ET.predict(X_test)
acc = accuracy_score(y_test,ET_pred)
print("The accuracy of Extra Trees on test dataset is: ",acc)
```

```
The accuracy of Extra Trees using 5-fold test is:  [0.83827577 0.83867531
0.83330374 0.83512386 0.83862375]
The accuracy of Extra Trees on test dataset is:  0.8340791249378507
```

[84]:
```
print(classification_report(y_test, ET_pred))

ETmatrix = confusion_matrix(y_test, ET_pred)
ETnames = ['True Neg','False Pos','False Neg','True Pos']
ETcounts = ['{0:0.0f}'.format(value) for value in ETmatrix.flatten()]
ETlabels = [f'{v1}\n{v2}' for v1, v2 in
          zip(ETnames, ETcounts)]
ETlabels = np.asarray(ETlabels).reshape(2,2)
sns.heatmap(ETmatrix, annot = ETlabels, fmt='')
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.97      0.90     21897
         1.0       0.79      0.35      0.48      6261

    accuracy                           0.83     28158
   macro avg       0.81      0.66      0.69     28158
weighted avg       0.83      0.83      0.81     28158
```

[84]: <AxesSubplot:>



[85]:

```
print(roc_auc_score(y_test, ET_pred))
```

0.659686191650551

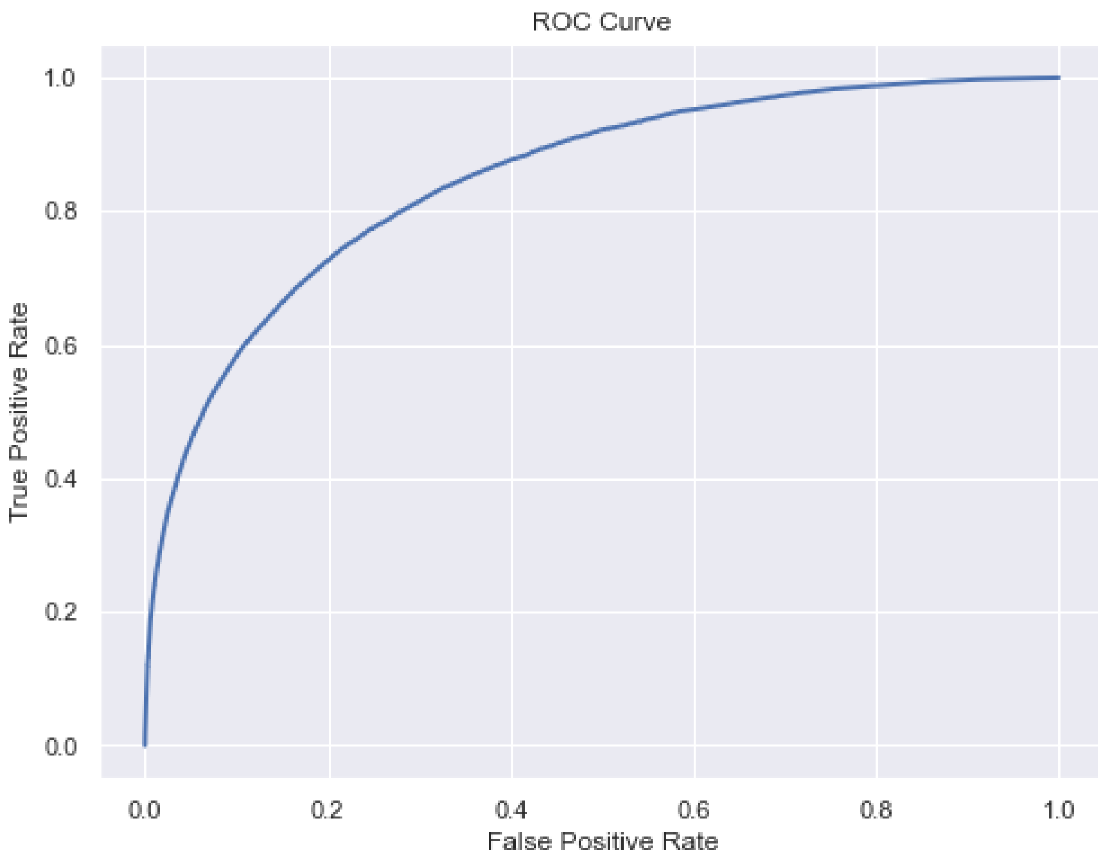
[86]:

```
ET_proba = cross_val_predict(ET, X_train, y_train, cv = 5, method =␣
 ↪'predict_proba')
ET_scores = ET_proba[:, 1]

def ROC_Curve(y_train, ET_scores, label = None):
    fpr, tpr, thresholds = roc_curve(y_train, ET_scores)
    print('AUC Score: {:.2f} '.format(roc_auc_score(y_train, ET_scores)))
    plt.figure(figsize = (8, 6))
    plt.plot(fpr, tpr, linewidth = 2, label = label, color = 'b')
```

```
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.show()
```

[87]:
```
ROC_Curve(y_train, ET_scores)
```

```
AUC Score: 0.85
```



[88]:
```
conf_viz = ConfusionViz()
conf_viz.fit(y_true = y_test, probas_pred = ET_pred)
conf_viz.show()
conf_viz.to_html('ET_confusion_viz.html')
```

The first model tested was random forest classifier with an accuracy score was .86

The second model tested was Gradient Boosting Classifier with an accuracy score of .85

The third model tested was the extra trees classifier model with an accuracy score of .83

We want to look for the model that has the lowest number for false positives and false negatives. A False positive means that it incorrectly predicted that it was going to rain tomorrow and a false negative means it incorrectly predicted if it was not going to rain tomorrow. Since this situation is not a life or death kind of situation, I don't feel like one false prediction is a better outcome than the other. It looks like the random forest classifier has the least number of false negatives and the extra trees classifier has the least number of false positives.

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

2 **NOT USED MODELS

Here's a LogR and KNN model that I built before testing the accuract scores of other models. I decided to leave this in the notebook for reference and to show this work. From this I learned that testing the scores before building and training the models will save time because these two models that I built first did not end up being the best fitting models. I am glad I went back and ran the accuracy and precision scores on 6 other models.

2.0.1 Logistic Regression Model

- Logistic Regression: statistic based algorthm that allows the prediction of probability/classification problems. This will allow us to predict the probability (yes or no) of whether it will rain tomorrow or not.

[89]:

```
LRmodel = LogisticRegression(solver = 'liblinear', random_state = 30).
↪fit(X_train, y_train)
```

[90]:

```
LRpred= LRmodel.predict(X_test)
```

[91]:

```
# Checking for overfitting or underfitting

print('Accuracy score for test Data: ', accuracy_score(y_test, LRpred))
print('Accuracy score for training data: ', LRmodel.score(X_train, y_train))
```

```
Accuracy score for test Data:  0.8392996661694723
Accuracy score for training data:  0.8423674186932317
```

These scores are almost similar so there's not really a worry of under or over fitting.

[92]:

```
print(classification_report(y_test, LRpred))
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.95      0.90     21897
         1.0       0.71      0.47      0.56      6261

    accuracy                           0.84     28158
   macro avg       0.79      0.71      0.73     28158
```

```
weighted avg       0.83      0.84      0.83     28158
```

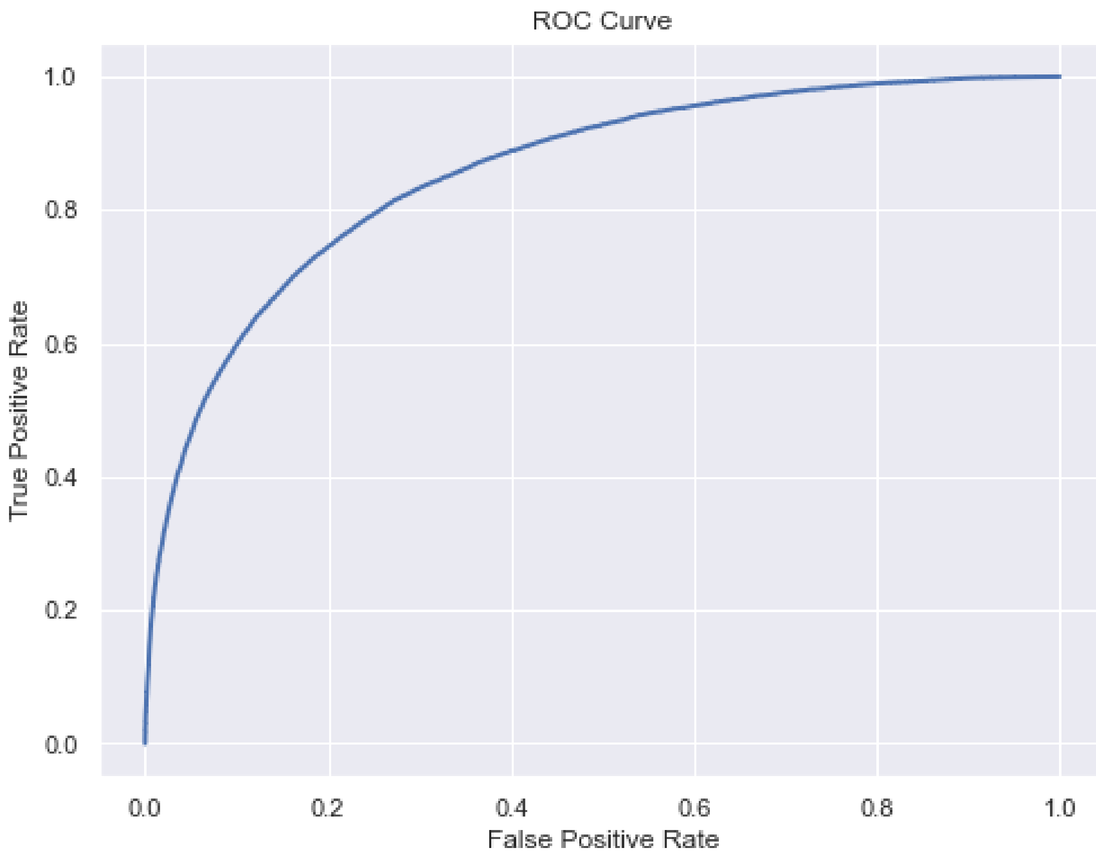
[93]:
```
print(roc_auc_score(y_test, LRpred))
```

```
0.7058117677266693
```

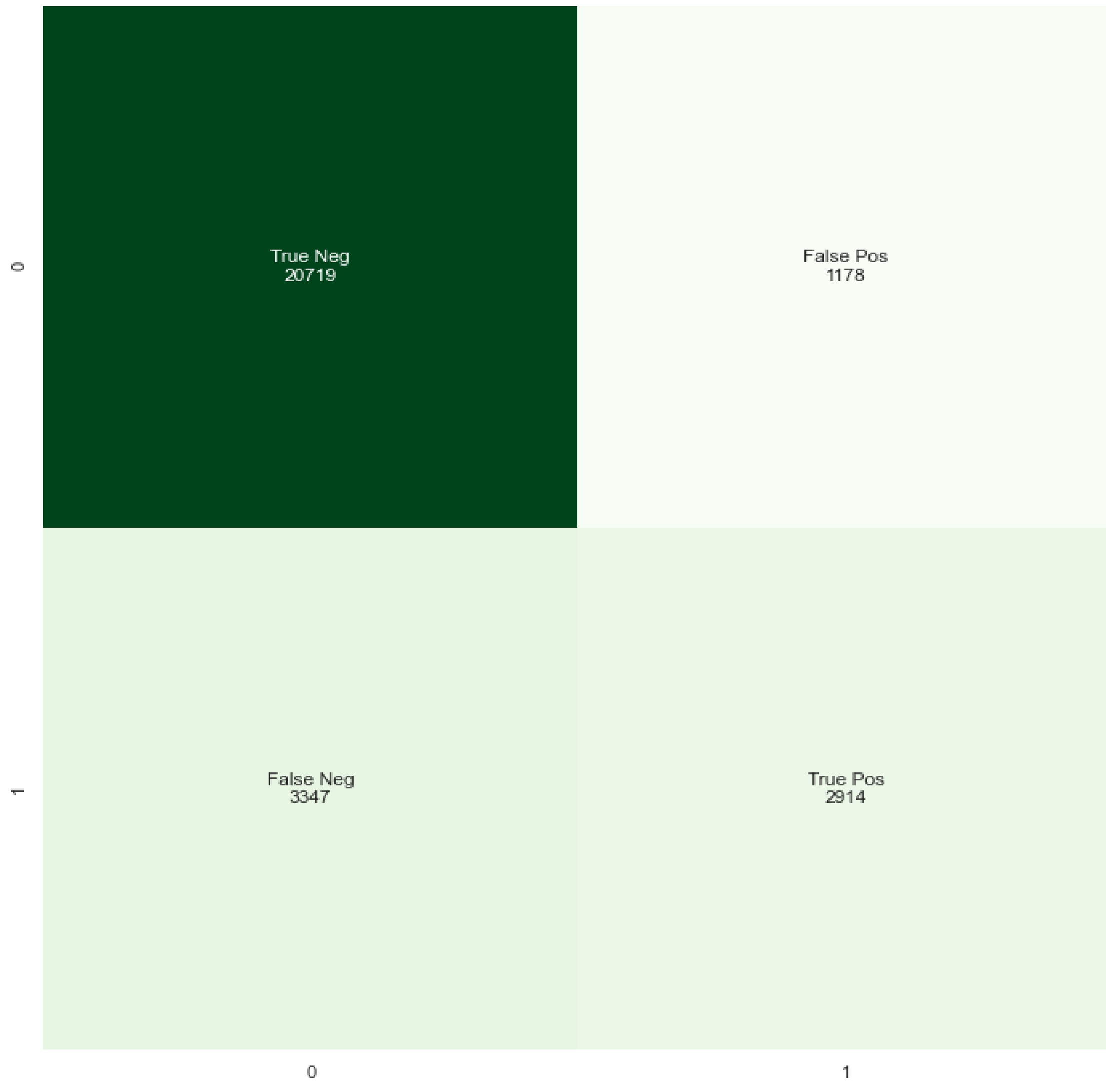
[94]:
```
lr_proba = cross_val_predict(LRmodel, X_train, y_train, cv = 5, method =␣
↪'predict_proba')
lr_scores = lr_proba[:, 1]

def ROC_Curve(y_train, scores, label = None):
    fpr, tpr, thresholds = roc_curve(y_train, scores)
    print('AUC Score: {:.2f} '.format(roc_auc_score(y_train, scores)))

    plt.figure(figsize = (8, 6))
    plt.plot(fpr, tpr, linewidth = 2, label = label, color = 'b')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.show()
```

[95]:
```
ROC_Curve(y_train, lr_scores)
```

```
AUC Score: 0.86
```



[96]:
```
LRmatrix = confusion_matrix(y_test, LRpred)
name = ['True Neg','False Pos','False Neg','True Pos']
count = ['{0:0.0f}'.format(value) for value in
         LRmatrix.flatten()]
labels = [f'{v1}\n{v2}' for v1, v2 in
          zip(name, count)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(LRmatrix, annot= labels, cbar= None, fmt='', cmap='Greens');
```



Logistic Regression Model Analysis The average cross-validation accuracy score of 0.842 is close to the original accuracy score of 0.839. So I don't think we need to try to improve this model with cross validation.

The model does a good job at predicting with qn accuracy score off .84. We don't see any signs of over or underfitting, and cross validation won't improve the model.

However, we do see that there is some imbalance in the dataset. The majority of non rainy days (True Negative) is predicted correctly, with the recall at 95%. But, out of the rainy days (true positive), only half are predicted as rainy, and 47% are predicted as non-rainy day (fales positive).

2.0.2 Model #2 - KNN Model

I will be using classification instead of regression because our target value is binary.

[97]:
```
Kmodel = KNeighborsClassifier(n_neighbors=3, n_jobs=-1).fit(X_train, y_train)
```

[98]:
```
Kpred = Kmodel.predict(X_test)
```

[99]:
```
# Checking for overfitting or underfitting

print('Accuracy score for test Data: ', accuracy_score(y_test, Kpred))
print('Accuracy score for training data: ', Kmodel.score(X_train, y_train))
```

```
Accuracy score for test Data:  0.8267987783223241
Accuracy score for training data:  0.9018547620950199
```

The score on the test data is .83 and the score on the training data is pretty good at .86. There doesn't seem to be any over or under fitting here cause the scores are similar enough.

[100]:
```
print(classification_report(y_test, Kmodel.predict(X_test)))
```

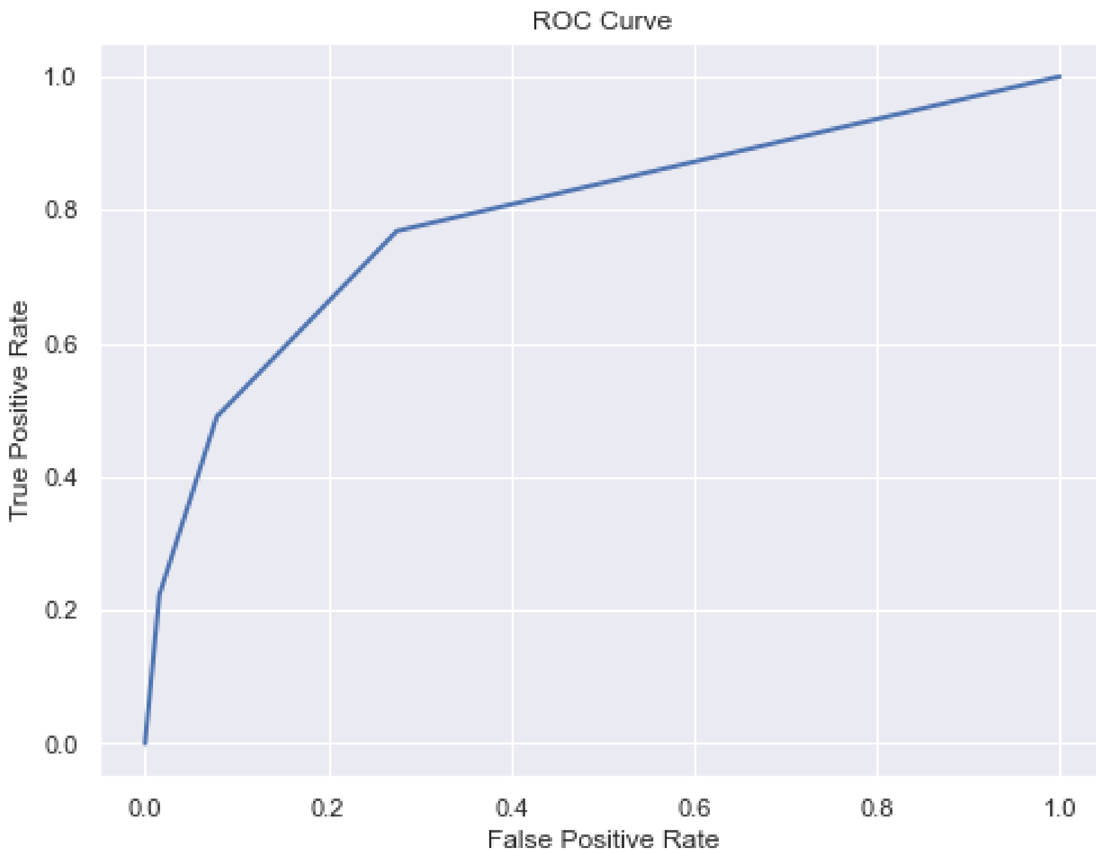
```
              precision    recall  f1-score   support

         0.0       0.86      0.92      0.89     21897
         1.0       0.65      0.48      0.55      6261

    accuracy                           0.83     28158
   macro avg       0.76      0.70      0.72     28158
weighted avg       0.81      0.83      0.82     28158
```

[101]:
```
print(roc_auc_score(y_test, Kpred))
```

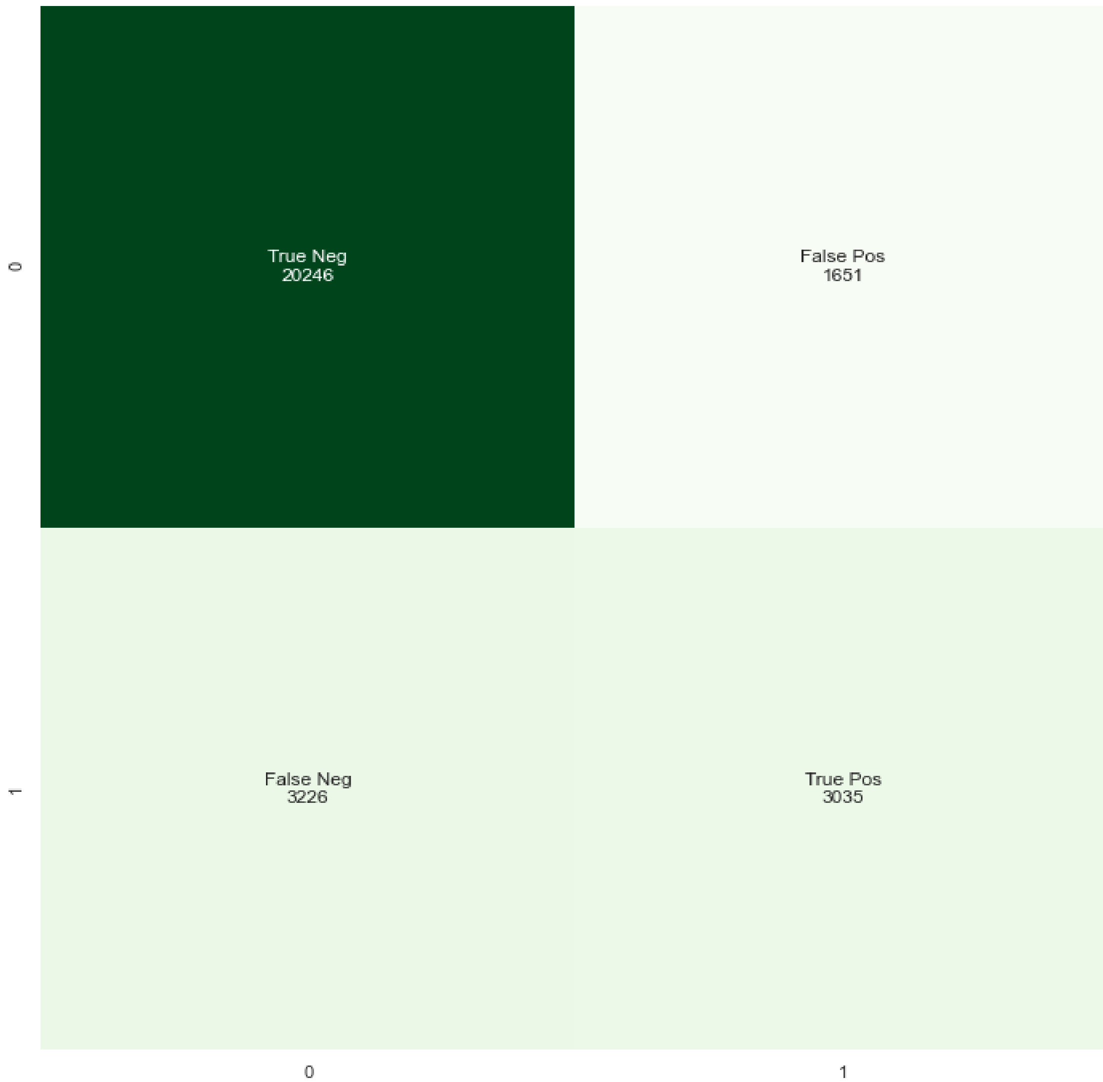
```
0.7046741945711376
```

[102]:
```
Kpredproba = cross_val_predict(Kmodel, X_train, y_train, cv = 5, method =␣
 ↪'predict_proba')
K_scores = Kpredproba[:, 1]

ROC_Curve(y_train, K_scores)
```

```
AUC Score: 0.79
```



[103]:
```
Kmatrix = confusion_matrix(y_test, Kpred)
name = ['True Neg','False Pos','False Neg','True Pos']
count = ['{0:0.0f}'.format(value) for value in
         Kmatrix.flatten()]
labels = [f'{v1}\n{v2}' for v1, v2 in
          zip(name, count)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(Kmatrix, annot= labels, cbar= None, fmt='', cmap='Greens');
```



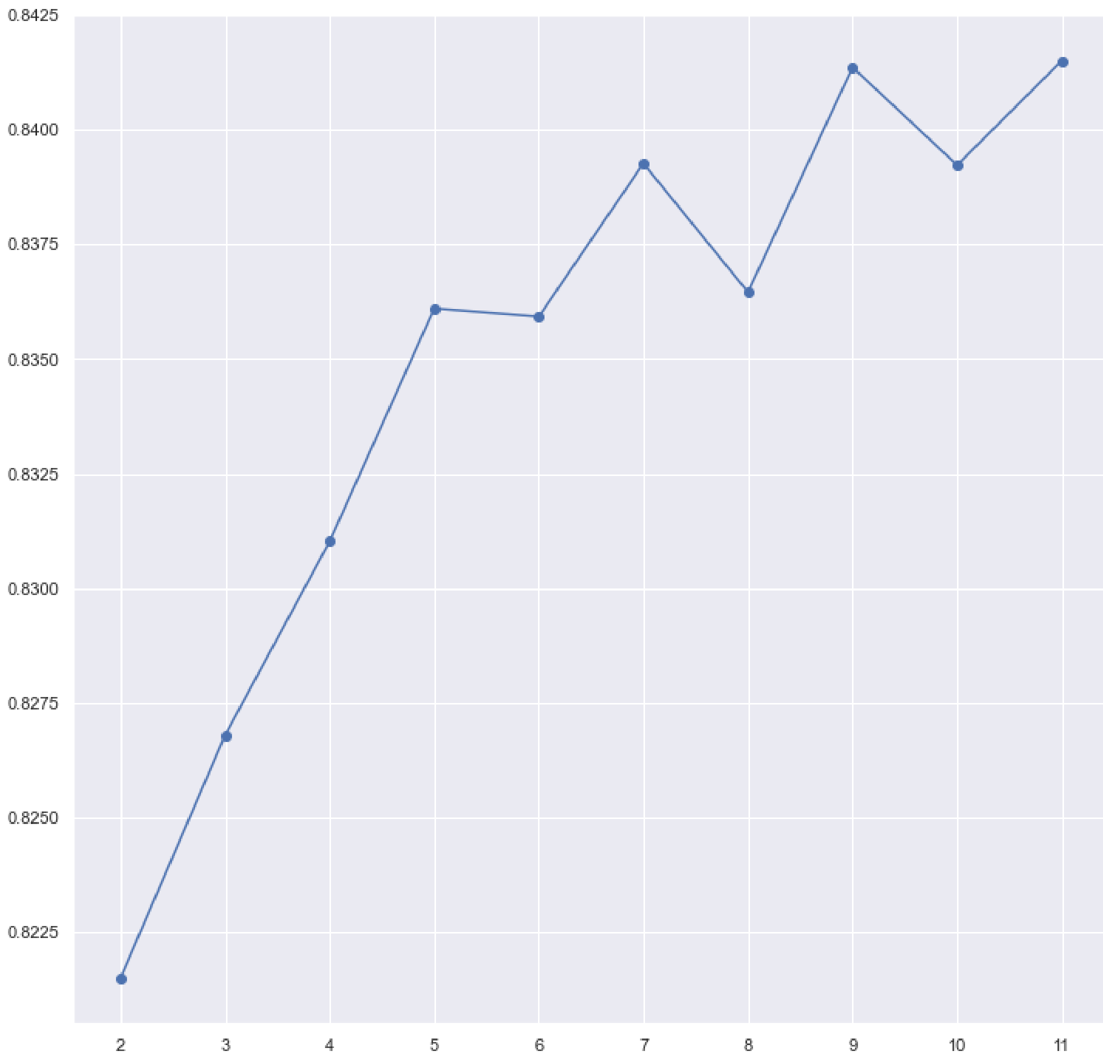
Improving the KNN Model by finding the optimal K-value

[104]:
```
scores = []

for k in range(2, 12):
    print(f'Evaluating {k} clusters')
    Kmodel = KNeighborsClassifier(n_neighbors=k, n_jobs=-1)
    Kmodel.fit(X_train, y_train)
    scores.append(Kmodel.score(X_test, y_test))
```

```
Evaluating 2 clusters
Evaluating 3 clusters
Evaluating 4 clusters
Evaluating 5 clusters
Evaluating 6 clusters
```

```
Evaluating 7 clusters
Evaluating 8 clusters
Evaluating 9 clusters
Evaluating 10 clusters
Evaluating 11 clusters
```

[105]:
```
plt.plot(range(2, 12), scores)
plt.scatter(range(2, 12), scores)
_=plt.xticks(range(2, 12))
```



[106]:
```
max(scores)
```

[106]: 0.8415015270970949

Looks like 9 is an optimal k value. This gives a score of .84 whereas the original model with 3 clusers had a score of .826.

Using the optimal K value

[107]:
```
Kmodel2 = KNeighborsClassifier(n_neighbors = 9).fit(X_train, y_train)
cv = cross_val_score(Kmodel2, X_train, y_train, cv=5)
print("The accuracy of KNN using 5-fold test is: ",cv)
```

```
The accuracy of KNN using 5-fold test is:  [0.84062861 0.84018468 0.83898606
0.84014028 0.84084351]
```

[108]:
```
print(classification_report(y_test, Kmodel2.predict(X_test)))
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.95      0.90     21897
         1.0       0.73      0.46      0.56      6261

    accuracy                           0.84     28158
   macro avg       0.79      0.70      0.73     28158
weighted avg       0.83      0.84      0.83     28158
```

[109]:
```
Kpred2 = Kmodel2.predict(X_test)
print(roc_auc_score(y_test, Kpred2))
```

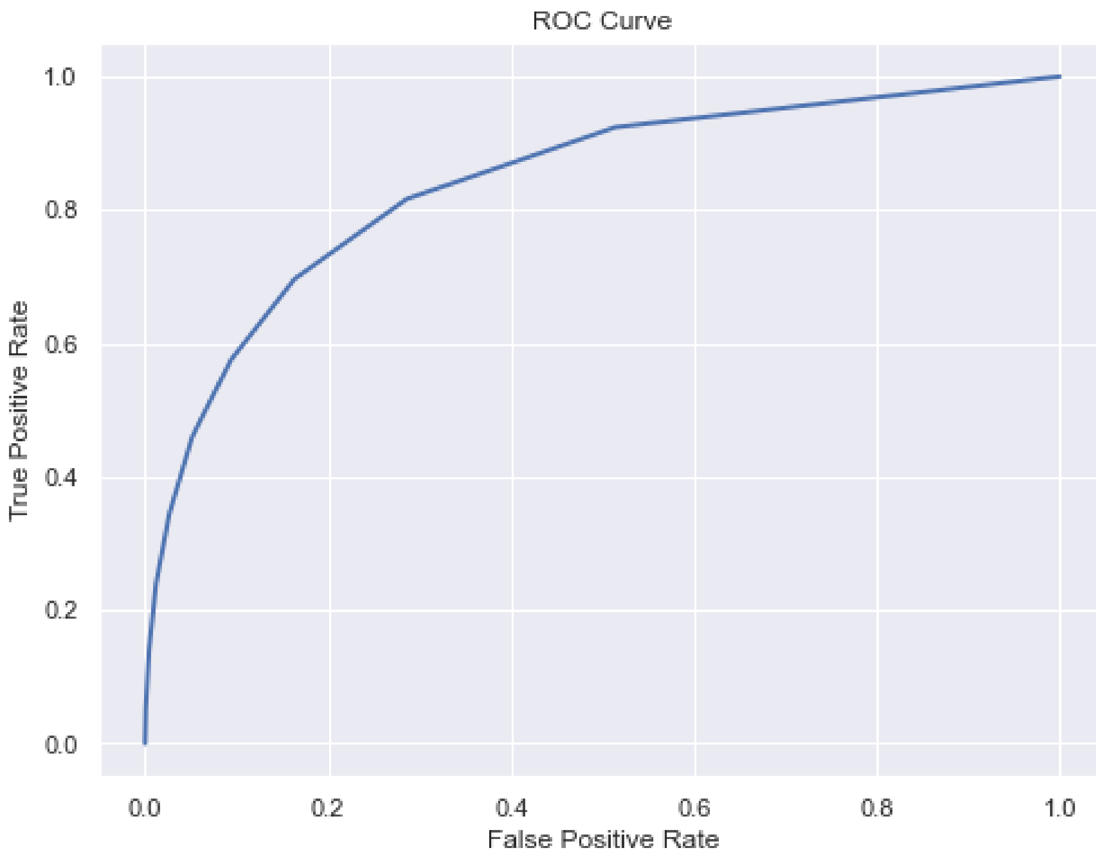
```
0.7045700129492877
```

[110]:
```
Kacc2 = accuracy_score(y_test, Kpred2)
print('Accuracy of KNN test data: ', Kacc2)
```

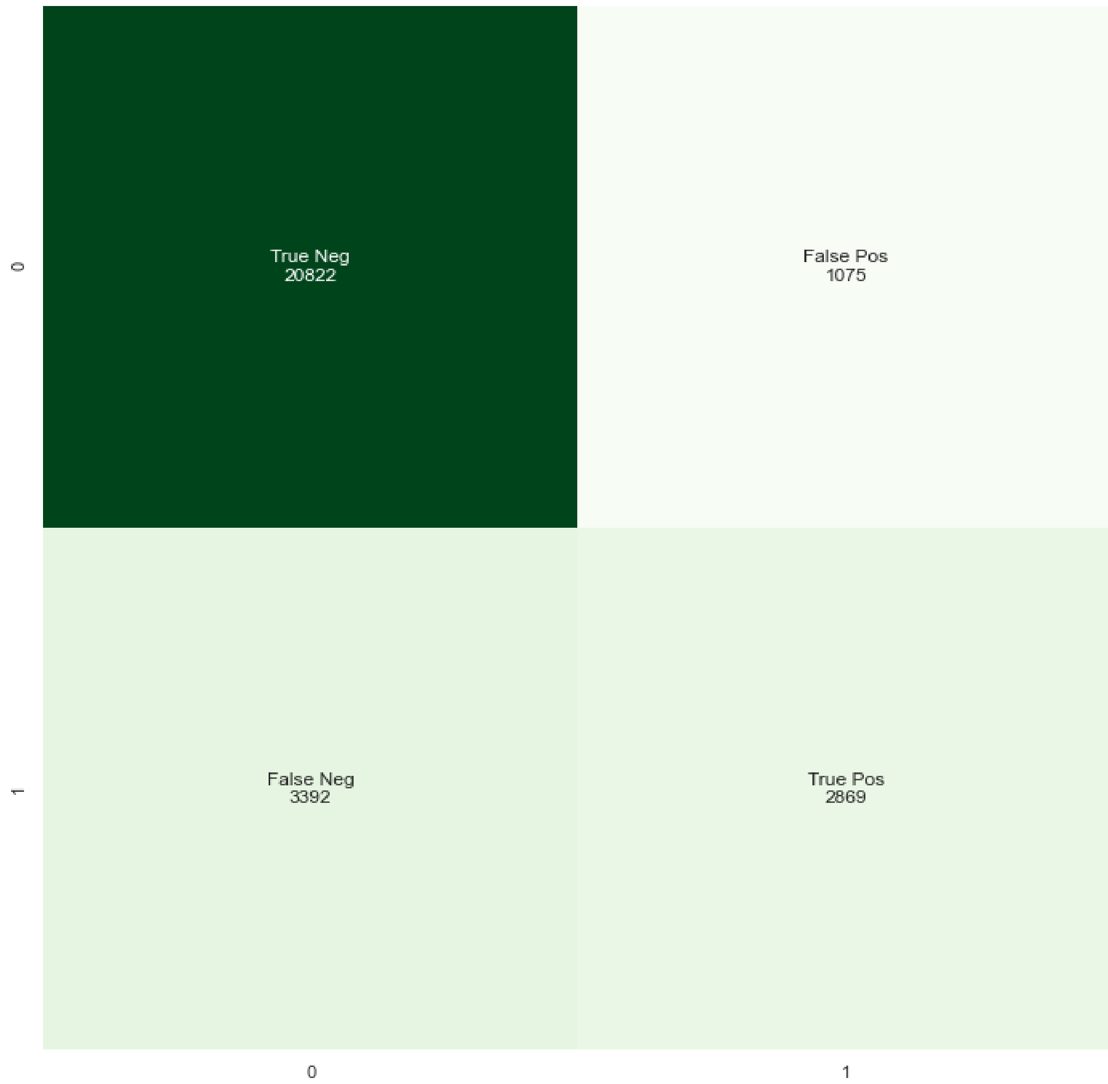
```
Accuracy of KNN test data:  0.8413594715533774
```

[111]:
```
Kpredproba2 = cross_val_predict(Kmodel2, X_train, y_train, cv = 5, method =␣
↪'predict_proba')
K_scores2 = Kpredproba2[:, 1]

ROC_Curve(y_train, K_scores2)
```

```
AUC Score: 0.84
```



[112]:
```
Kmatrix2 = confusion_matrix(y_test, Kpred2)
name = ['True Neg','False Pos','False Neg','True Pos']
count = ['{0:0.0f}'.format(value) for value in
         Kmatrix2.flatten()]
labels = [f'{v1}\n{v2}' for v1, v2 in
          zip(name, count)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(Kmatrix2, annot= labels, cbar= None, fmt='', cmap='Greens');
```



KNN Model Analysis

"From the accuracy and confusion matrix, KNN definitely works more worse than logistic regress

[113]:
```
with open('scaler.pkl', 'wb') as file:
    pickle.dump(scale, file)

with open('logreg.pkl', 'wb') as file:
    pickle.dump(LRmodel, file)
```

[114]:
```
conf_viz = ConfusionViz()
conf_viz.fit(y_true = y_test, probas_pred = LRpred)
conf_viz.show()
conf_viz.to_html('confusion_viz.html')
```