Final Project Submission

Please fill out:

- Student name: Justin Grisanti
- Student pace: self-paced
- Scheduled project review date/time: 1/5/2022 @ TBD
- Instructor name: Claude Fried
- Blog post URL: https://justingrisanti.github.io/predicting_rain_patterns_in_australia

Total Time to Run: approx. 27 minutes

Section 1: Business Understanding

The purpose of this section is to define the business problem and understand the stakeholders for the work that I am performing. The Bureau of Meteorology is responsible for predicting weather patterns throughout the entire Australian region. According to their website, their forecast accuracy for rain varies much more than their forecasts for temperature and wind.

According to their analyses, they've underpredicted rainfall each year for the past five years. The goal is to create a classification model that allows the Bureau of Meteorology to improve their predictions of whether or not it will rain the next day. This will allow them to inform the public better so that citizens can prepare accordingly for the possibility of rain.

The stakeholders of this project are the Bureau of Meteorology and citizens of Australia.

The main purpose of this classification model is predictive, meaning that given charactaristics of rain data on a given day, the model should be able to predict whether it will rain the next day or not. My model is not meant to replace the Bureau of Meteorology's current system of predicting rain for the region of Australia, however, it is meant serve as an input to strengthen their predictions and assumptions, and to reduce the risk of failing to predict that it will rain the next day.

Section 2: Data Understanding

After scanning the data, we have weather-related information for a period of 12/1/2008 to 6/25/2017—8 years, 6 months and 24 days worth of data.

As shown below, this data has many different weather-related metrics, such as the wind speed, humidity, pressure, whether it was sunny or cloudy, and temperature. These seem like appropriate parameters to run a classification-based model in order to predict whether or not it will rain the next day, and I do not sense any limitations from this data.

In [1]:

```
# Import Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn import tree
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV, cross_v
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.metrics import accuracy_score
from sklearn.impute import SimpleImputer
from sklearn.metrics import make_scorer, classification_report, log_loss, f
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.base import clone
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
import statsmodels as sm
import sklearn.preprocessing as preprocessing
from scipy import stats
import seaborn as sns
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
# Import data from csv

rain_data = pd.read_csv('data/WeatherAUS.csv')
```

In [3]:

```
rain_data.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
```

Please see the following column descriptions:

> **MinTemp:** The minimum temperature in degrees celsius
>
> **MaxTemp:** The maximum temperature in degrees celsius
>
> **Rainfall:** The amount of rainfall recorded for the day in mm
>
> **Evaporation:** The so-called Class A pan evaporation (mm) in the 24 hours to 9am
>
> **Sunshine:** The number of hours of bright sunshine in the day.
>
> **WindGustDir:** The direction of the strongest wind gust in the 24 hours to midnight
>
> **WindGustSpeed:** The speed (km/h) of the strongest wind gust in the 24 hours to midnight

> **WindDir9am:** Direction of the wind at 9am
>
> **WindDir3pm:** Direction of the wind at 3pm
>
> **WindSpeed9am:** Wind speed (km/hr) averaged over 10 minutes prior to 9am
>
> **WindSpeed3pm:** Wind speed (km/hr) averaged over 10 minutes prior to 3pm
>
> **Humidity9am:** Humidity (percent) at 9am
>
> **Humidity3pm:** Humidity (percent) at 3pm
>
> **Pressure9am:** Atmospheric pressure (hpa) reduced to mean sea level at 9am
>
> **Pressure3pm:** Atmospheric pressure (hpa) reduced to mean sea level at 3pm
>
> **Cloud9am:** Fraction of sky obscured by cloud at 9am. This is measured in "oktas", which are a unit of eigths. It records how many eigths of the sky are obscured by cloud. A 0 measure indicates completely clear sky whilst an 8 indicates that it is completely overcast.
>
> **Cloud3pm:** Fraction of sky obscured by cloud (in "oktas": eighths) at 3pm. See Cload9am for a description of the values
>
> **Temp9am:** Temperature (degrees C) at 9am
>
> **Temp3pm:** Temperature (degrees C) at 3pm
>
> **RainToday:** Boolean: 1 if precipitation (mm) in the 24 hours to 9am exceeds 1mm, otherwise 0
>
> **RainTomorrow:** The amount of next day rain in mm. Used to create response variable RainTomorrow. A kind of measure of the "risk".

In [4]:

```
# To show all columns and rows

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

rain_data.head()
```

Out[4]:

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

In [5]:

```
rain_data[rain_data['RainTomorrow'].isna()].head()
```

Out[5]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	W
14	2008-12-15	Albury	8.4	24.6	0.0	NaN	NaN	NaN	
283	2009-09-10	Albury	2.6	NaN	0.0	NaN	NaN	NaN	
435	2010-02-09	Albury	22.1	35.1	0.0	NaN	NaN	NaN	
437	2010-02-11	Albury	21.5	35.0	0.0	NaN	NaN	NaN	
443	2010-02-17	Albury	15.5	30.6	0.0	NaN	NaN	NaN	

In [6]:

```
rain_data = rain_data.dropna(axis=0, subset = ['RainTomorrow'])
```

In [7]:

```
rain_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 142193 entries, 0 to 145458
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           142193 non-null  object 
 1   Location       142193 non-null  object 
 2   MinTemp        141556 non-null  float64
 3   MaxTemp        141871 non-null  float64
 4   Rainfall       140787 non-null  float64
 5   Evaporation    81350 non-null   float64
 6   Sunshine       74377 non-null   float64
 7   WindGustDir    132863 non-null  object 
 8   WindGustSpeed  132923 non-null  float64
 9   WindDir9am     132180 non-null  object 
 10  WindDir3pm     138415 non-null  object 
 11  WindSpeed9am   140845 non-null  float64
 12  WindSpeed3pm   139563 non-null  float64
 13  Humidity9am    140419 non-null  float64
 14  Humidity3pm    138583 non-null  float64
 15  Pressure9am    128179 non-null  float64
 16  Pressure3pm    128212 non-null  float64
 17  Cloud9am       88536 non-null   float64
 18  Cloud3pm       85099 non-null   float64
 19  Temp9am        141289 non-null  float64
 20  Temp3pm        139467 non-null  float64
 21  RainToday      140787 non-null  object 
 22  RainTomorrow   142193 non-null  object 
dtypes: float64(16), object(7)
memory usage: 26.0+ MB
```

In [8]:

```python
# Separate target variable from data and complete train-test split

y = rain_data['RainTomorrow']
X = rain_data.drop('RainTomorrow', axis=1)

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

In [9]:

```python
# Reset index and drop it

X_train.reset_index(inplace=True)
X_train = X_train.drop(columns=['index'],axis=1)
X_train.head()
```

Out[9]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	W
0	2009-04-12	Woomera	14.9	30.3	0.0	7.4	10.9	S	
1	2014-12-08	Witchcliffe	14.6	21.5	0.2	NaN	NaN	SSE	
2	2015-06-06	SalmonGums	9.0	23.7	0.0	NaN	NaN	W	
3	2014-01-09	Albany	15.3	24.0	0.0	8.2	12.1	NaN	
4	2014-12-14	Mildura	17.3	37.5	0.0	8.6	11.4	N	

In [10]:

```
# Reset index and drop it

X_test.reset_index(inplace=True)
X_test = X_test.drop(columns=['index'],axis=1)
X_test.head()
```

Out[10]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	W
0	2016-06-09	Ballarat	7.1	13.0	8.8	NaN	NaN	N	
1	2009-10-24	Walpole	13.2	18.3	0.0	NaN	NaN	E	
2	2015-09-21	PerthAirport	9.2	22.7	0.0	5.0	11.1	ENE	
3	2011-12-06	Cobar	15.3	26.1	0.0	10.4	NaN	E	
4	2014-03-15	Sale	11.9	31.8	0.0	5.0	4.1	NW	

In [11]:

```
y_train = y_train.replace('Yes', 1.0)
y_train = y_train.replace('No', 0.0)
y_test = y_test.replace('Yes', 1.0)
y_test = y_test.replace('No', 0.0)
```

In [12]:
```
# Inspect Target Variable

y_train.value_counts(normalize=True)
```

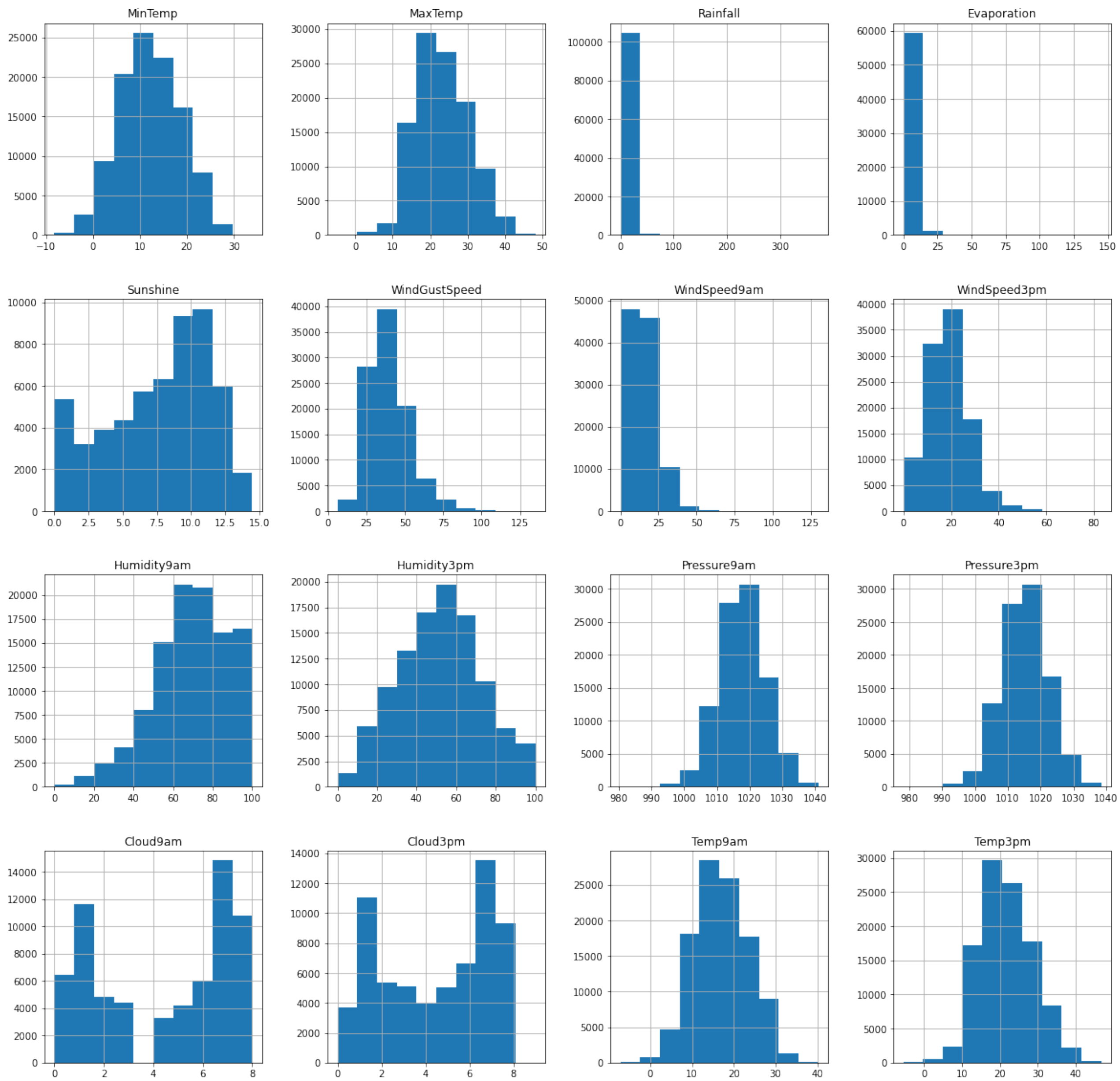
Out[12]:
```
0.0    0.775412
1.0    0.224588
Name: RainTomorrow, dtype: float64
```

In [13]:
```
# Ensure we get a fair spread of data across the country

X_train['Location'].value_counts()
```

Out[13]:
```
Canberra            2578
Sydney              2429
Hobart              2416
Perth               2408
Brisbane            2401
Darwin              2382
Adelaide            2329
Tuggeranong         2298
Mildura             2295
Launceston          2279
Bendigo             2279
PerthAirport        2269
Woomera             2266
Ballarat            2262
Albany              2255
MountGambier        2254
Townsville          2248
CoffsHarbour        2247
MelbourneAirport    2246
Watsonia            2243
Sale                2241
GoldCoast           2240
Witchcliffe         2240
AliceSprings        2237
Portland            2236
NorfolkIsland       2236
WaggaWagga          2236
Cobar               2236
Albury              2234
Penrith             2233
BadgerysCreek       2232
Cairns              2232
Newcastle           2229
Nuriootpa           2224
SydneyAirport       2224
Wollongong          2213
SalmonGums          2206
Richmond            2201
Dartmoor            2200
MountGinini         2192
NorahHead           2179
Moree               2134
Walpole             2133
PearceRAAF          2087
Williamtown         1905
Melbourne           1834
Katherine           1193
Uluru               1138
Nhil                1135
Name: Location, dtype: int64
```

In [14]:

```
# Plot each column in a histogram to see what type of distribution there is
columns_with_nulls = X_train.drop(['Location','Date'], axis=1)
columns_with_nulls.hist(figsize=(20,20))
plt.savefig('Visualizations/ColumnsHist.png', bbox_inches = 'tight')
```



In [15]:

```
X_train.info(1, null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106644 entries, 0 to 106643
Data columns (total 22 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           106644 non-null  object 
 1   Location       106644 non-null  object 
 2   MinTemp        106150 non-null  float64
 3   MaxTemp        106387 non-null  float64
 4   Rainfall       105540 non-null  float64
 5   Evaporation    60909 non-null   float64
 6   Sunshine       55677 non-null   float64
 7   WindGustDir    99665 non-null   object 
 8   WindGustSpeed  99715 non-null   float64
 9   WindDir9am     99120 non-null   object 
 10  WindDir3pm     103822 non-null  object 
 11  WindSpeed9am   105646 non-null  float64
 12  WindSpeed3pm   104681 non-null  float64
 13  Humidity9am    105326 non-null  float64
 14  Humidity3pm    103917 non-null  float64
 15  Pressure9am    96098 non-null   float64
 16  Pressure3pm    96123 non-null   float64
 17  Cloud9am       66285 non-null   float64
 18  Cloud3pm       63757 non-null   float64
 19  Temp9am        105967 non-null  float64
 20  Temp3pm        104579 non-null  float64
 21  RainToday      105540 non-null  object 
dtypes: float64(16), object(6)
memory usage: 17.9+ MB
```

As we can see, Evaporation, Sunshine, and cloud data all have a large amount of nulls. Let's take a deeper look into these variables.

In [16]:

```
X_train.head()
```

Out[16]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	\
0	2009-04-12	Woomera	14.9	30.3	0.0	7.4	10.9	S	
1	2014-12-08	Witchcliffe	14.6	21.5	0.2	NaN	NaN	SSE	
2	2015-06-06	SalmonGums	9.0	23.7	0.0	NaN	NaN	W	
3	2014-01-09	Albany	15.3	24.0	0.0	8.2	12.1	NaN	
4	2014-12-14	Mildura	17.3	37.5	0.0	8.6	11.4	N	

The following code is to create meaningful information about our null values, so that we can impute them in a more educated manner.

In [17]:
```
# Dropping NAs to obtain distribution for data that isn't NA

rain_data_cloud_dropna = X_train.dropna(axis=0, subset=['Cloud3pm','Cloud9a
```

In [18]:
```
# Dropping NAs to obtain distribution for data that isn't NA

rain_data_sunshine_dropna = X_train.dropna(axis=0, subset=['Sunshine'])
```

In [19]:
```
# Checking null sunshine data against rain data to see what the population

rain_data_sunshine_nulls = X_train[X_train['Sunshine'].isna()]
rain_data_sunshine_nulls['RainToday'].value_counts()
```

Out[19]:
```
No     39031
Yes    11143
Name: RainToday, dtype: int64
```

In [20]:
```
# Removing nulls from sunshine data and biforcating the population to get m

sunshine_when_rain = rain_data_sunshine_dropna[rain_data_sunshine_dropna['R
sunshine_no_rain = rain_data_sunshine_dropna[rain_data_sunshine_dropna['Rai
```

In [21]:
```
# Checking evaporation mean when sunshine is greater than zero

evaporation_test = X_train.loc[X_train['Sunshine']>0.0,'Evaporation']
```

In [22]:
```
# Checking the mean of cloud data when it doesn't rain and humidity is high
# (Population is not normal without humidity check)

cloud9_no_rain_lower_humidity = X_train.loc[(rain_data['RainToday']=='No')
cloud9_no_rain_higher_humidity = X_train.loc[(X_train['RainToday']=='No') &
cloud3_no_rain_lower_humidity = X_train.loc[(X_train['RainToday']=='No') &
cloud3_no_rain_higher_humidity = X_train.loc[(X_train['RainToday']=='No') &
```

In [23]:
```
# Checking the mean of cloud data when it does rain

cloud9_rain = X_train.loc[X_train['RainToday']=='Yes','Cloud9am']
cloud3_rain = X_train.loc[X_train['RainToday']=='Yes','Cloud3pm']
```

In [24]:
```
# Checking null data to see how many records have both null cloud data and

test = []

for index in range(0,106643,1):
    if pd.isna(X_train['Cloud3pm'].loc[index]) and pd.isna(X_train['Cloud9a
        if pd.notna(X_train['Sunshine'].loc[index]):
            test.append('Sunshine')
        elif pd.isna(X_train['Sunshine'].loc[index]):
            test.append('Neither')
        else:
            pass
    elif pd.notna(X_train['Cloud3pm'].loc[index]) or pd.notna(X_train['Clou
        if pd.notna(X_train['Sunshine'].loc[index]):
            test.append('Both')
        elif pd.isna(X_train['Sunshine'].loc[index]):
            test.append('Clouds')
        else:
            pass
    else:
        pass
```

In [25]:
```
print("There are " + str(test.count('Sunshine')) + " records of sunshine da
print("There are " + str(test.count('Clouds')) + " records of cloud data wi
print("There are " + str(test.count('Neither')) + " records of neither suns
print("There are " + str(test.count('Both')) + " records of both sunshine a
```

```
There are 5580 records of sunshine data with no cloud data.
There are 19220 records of cloud data with no sunshine data.
There are 31746 records of neither sunshine or cloud data.
There are 50097 records of both sunshine and cloud data.
```

In [26]:
```
test_data = {'Sunshine data with Cloud Nulls': 8258, 'Cloud Data with Sunsh
```

In [27]:
```
# Checking the records to see the relationship between cloud data and sunsh

test2 = []

for index in range(0,106643,1):
    if X_train['Cloud3pm'].loc[index]== 0  or X_train['Cloud9am'].loc[index
        if X_train['Sunshine'].loc[index] != 0:
            test2.append('Sunshine')
        elif X_train['Sunshine'].loc[index]==0:
            test2.append('Neither')
        else:
            pass
    elif X_train['Cloud3pm'].loc[index]!=0 or X_train['Cloud9am'].loc[index
        if X_train['Sunshine'].loc[index]!=0:
            test2.append('Both')
        elif X_train['Sunshine'].loc[index]==0:
            test2.append('Clouds')
        else:
            pass
    else:
        pass
```

In [28]:
```
print("There are " + str(test2.count('Sunshine')) + " records of sunshine d
print("There are " + str(test2.count('Clouds')) + " records of cloud data w
print("There are " + str(test2.count('Neither')) + " records of no sunshine
print("There are " + str(test2.count('Both')) + " records of sunshine and c
```

```
There are 7701 records of sunshine data with 0 cloud coverage.
There are 1712 records of cloud data with 0 sunshine hours.
There are 4 records of no sunshine or cloud coverage.
There are 97226 records of sunshine and cloud coverage.
```

In [29]:
```
test2_data = {'Sunshine with 0 Clouds': 10350, 'Clouds with 0 sunshine': 23
```

In [30]:
```
X_train['RainToday'].value_counts(normalize=True)
```

Out[30]:
```
No     0.775687
Yes    0.224313
Name: RainToday, dtype: float64
```

In [31]:
```
rain_data_today = {'Did Not Rain':113580,'Rained':31880}
```

In [32]:

```
# Create subplot for all of our tests/findings

fig, (ax1, ax2, ax3, ax4, ax5, ax6, ax7, ax8) = plt.subplots(8, 1, figsize=
fig.suptitle('Plots of Cloud data and Sunshine Data')
fig.tight_layout(pad=5.0)

# This is a distribution for sunshine data that eliminates cloud nulls.
ax1.set_title('Chart 1: Dist. of Sunshine Data w/o cloud nulls')
ax1.hist(rain_data_cloud_dropna['Sunshine'])
ax1.set_xlabel('Hours of Sunshine')
ax1.set_ylabel('Sunshine Data')

# This is a distribution for cloud data that eliminates sunshine nulls. It
# hard to impute these values without further biforcation.
ax2.set_title('Chart 2: Dist. of 9am Cloud Data w/o Sunshine nulls')
ax2.hist(rain_data_sunshine_dropna['Cloud9am'])
ax2.set_xlabel('9am Cloud Coverage (0-8)')
ax2.set_ylabel('Cloud Data')

# This is a distribution for cloud data that eliminates sunshine nulls. It
# hard to impute these values without further biforcation.
ax3.set_title('Chart 3: Dist. of 3pm Cloud Data w/o Sunshine nulls')
ax3.hist(rain_data_sunshine_dropna['Cloud3pm'])
ax3.set_xlabel('3pm Cloud Coverage (0-8)')
ax3.set_ylabel('Cloud Data')

# Here we plot the population of nulls and their relationships. Perhaps the
# clouds and sunshine that we can impute. When both records are null, this
ax4.set_title('Chart 4: # of non-nulls by Category (Sunshine vs Cloud Data)
ax4.bar(test_data.keys(),test_data.values())
ax4.set_xlabel('Type')

# Checking the data for zeros.
ax5.set_title('Chart 5: Non-Zero Data by Category')
ax5.bar(test2_data.keys(),test2_data.values())
ax5.set_xlabel('Type')

# Here we find the distribution for days it does rain, and the relevant mea
ax6.set_title('Chart 6: Sunshine Data On Day it Rains')
ax6.hist(sunshine_when_rain['Sunshine'],bins=14)

# Here we find the distribution for days it doesn't rain, and the relevant
ax7.set_title("Chart 7: Sunshine Data On Day it Doesn't Rain")
ax7.hist(sunshine_no_rain['Sunshine'])

# Here is the distribution for evaporation when sunshine is greater than ze
ax8.set_title("Chart 8: Evaporation Data when Sunshine > 0")
ax8.hist(evaporation_test,bins=100)
plt.savefig('Visualizations/Subplot1.png', bbox_inches = 'tight')
plt.show()
```

Plots of Cloud data and Sunshine Data

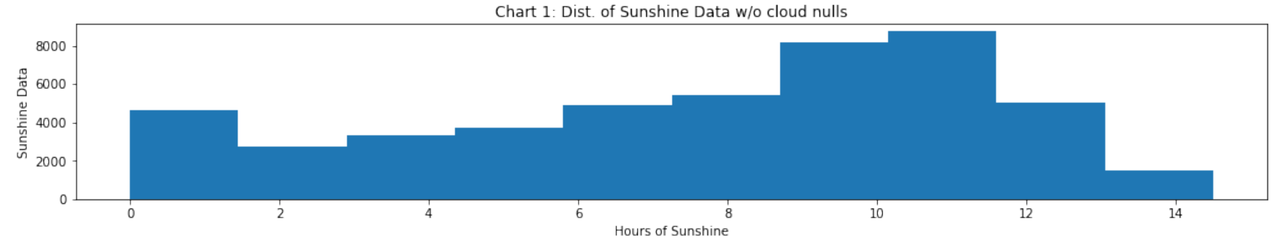


Chart 1: Dist. of Sunshine Data w/o cloud nulls
Sunshine Data
Hours of Sunshine
0
2000
4000
6000
8000
0 2 4 6 8 10 12 14

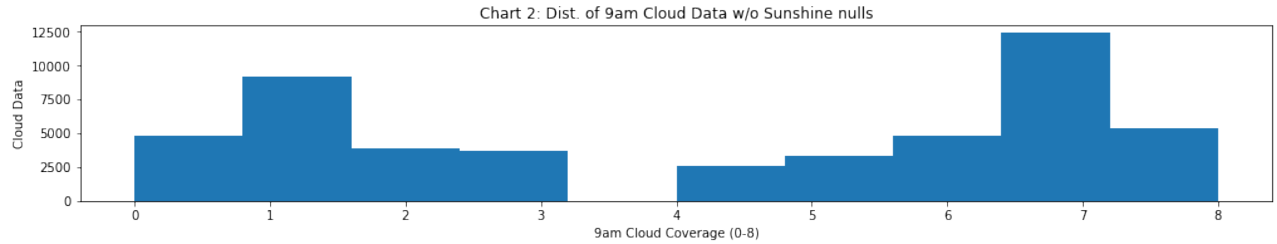


Chart 2: Dist. of 9am Cloud Data w/o Sunshine nulls
Cloud Data
9am Cloud Coverage (0-8)
0
2500
5000
7500
10000
12500
0 1 2 3 4 5 6 7 8

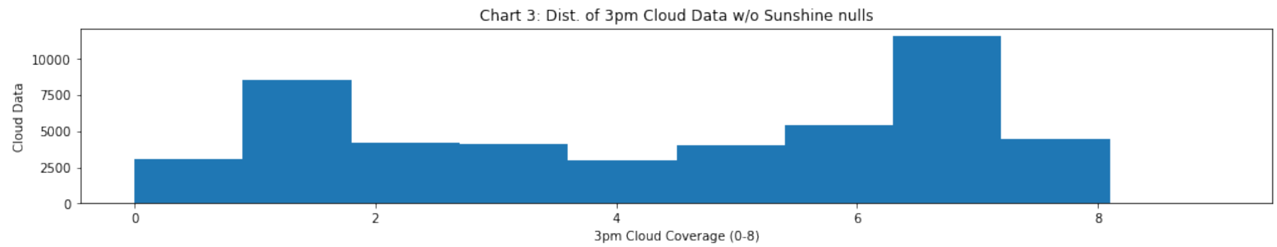


Chart 3: Dist. of 3pm Cloud Data w/o Sunshine nulls
Cloud Data
3pm Cloud Coverage (0-8)
0
2500
5000
7500
10000
0 2 4 6 8

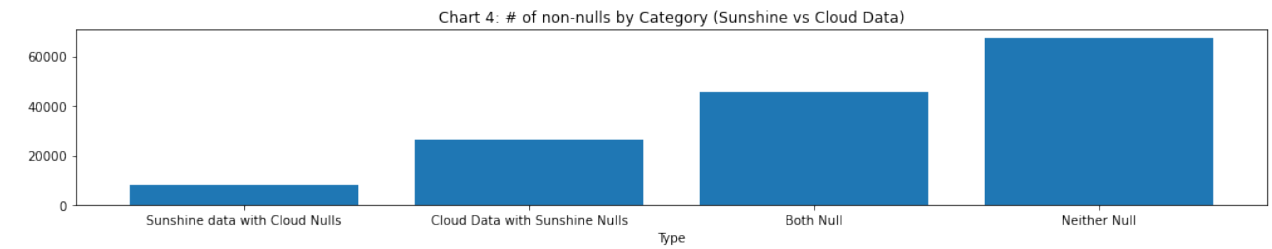


Chart 4: # of non-nulls by Category (Sunshine vs Cloud Data)
0
20000
40000
60000
Sunshine data with Cloud Nulls
Cloud Data with Sunshine Nulls
Both Null
Neither Null
Type

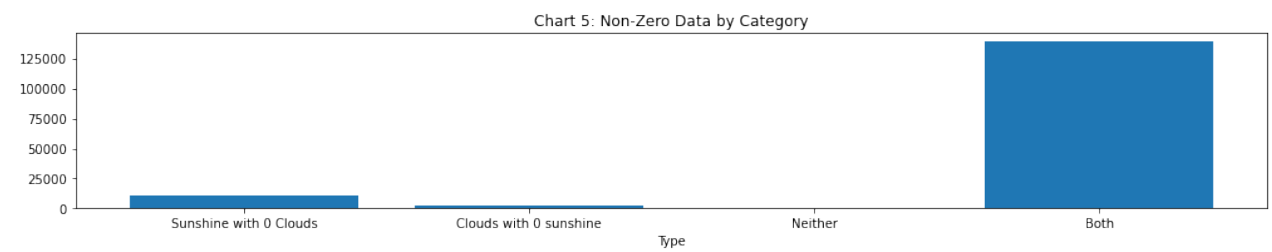


Chart 5: Non-Zero Data by Category
0
25000
50000
75000
100000
125000
Sunshine with 0 Clouds
Clouds with 0 sunshine
Neither
Both
Type

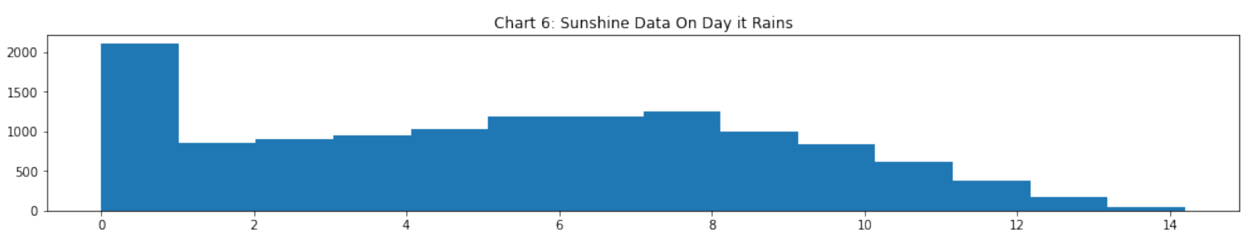


Chart 6: Sunshine Data On Day it Rains
0
500
1000
1500
2000
0 2 4 6 8 10 12 14

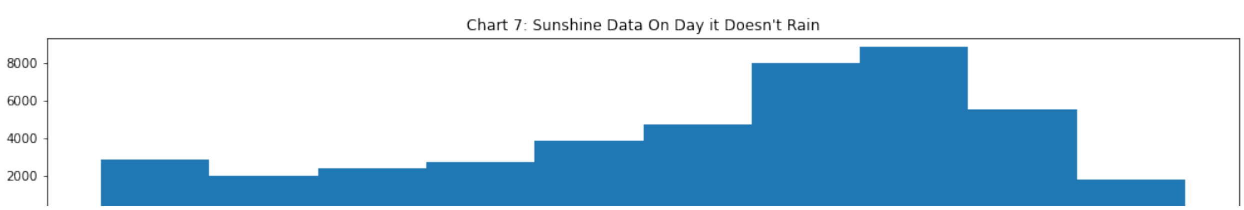
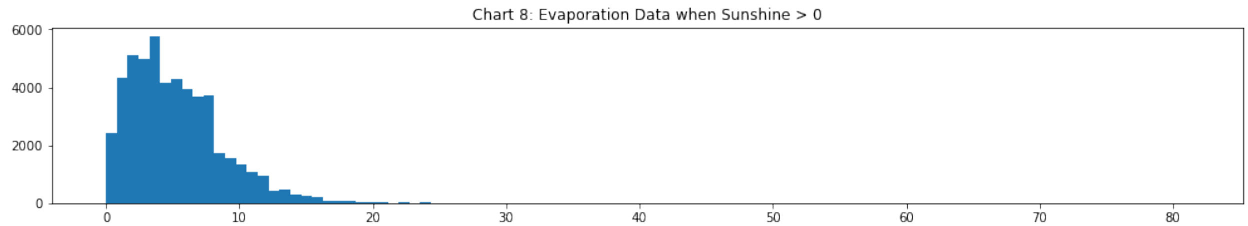


Chart 7: Sunshine Data On Day it Doesn't Rain
2000
4000
6000
8000



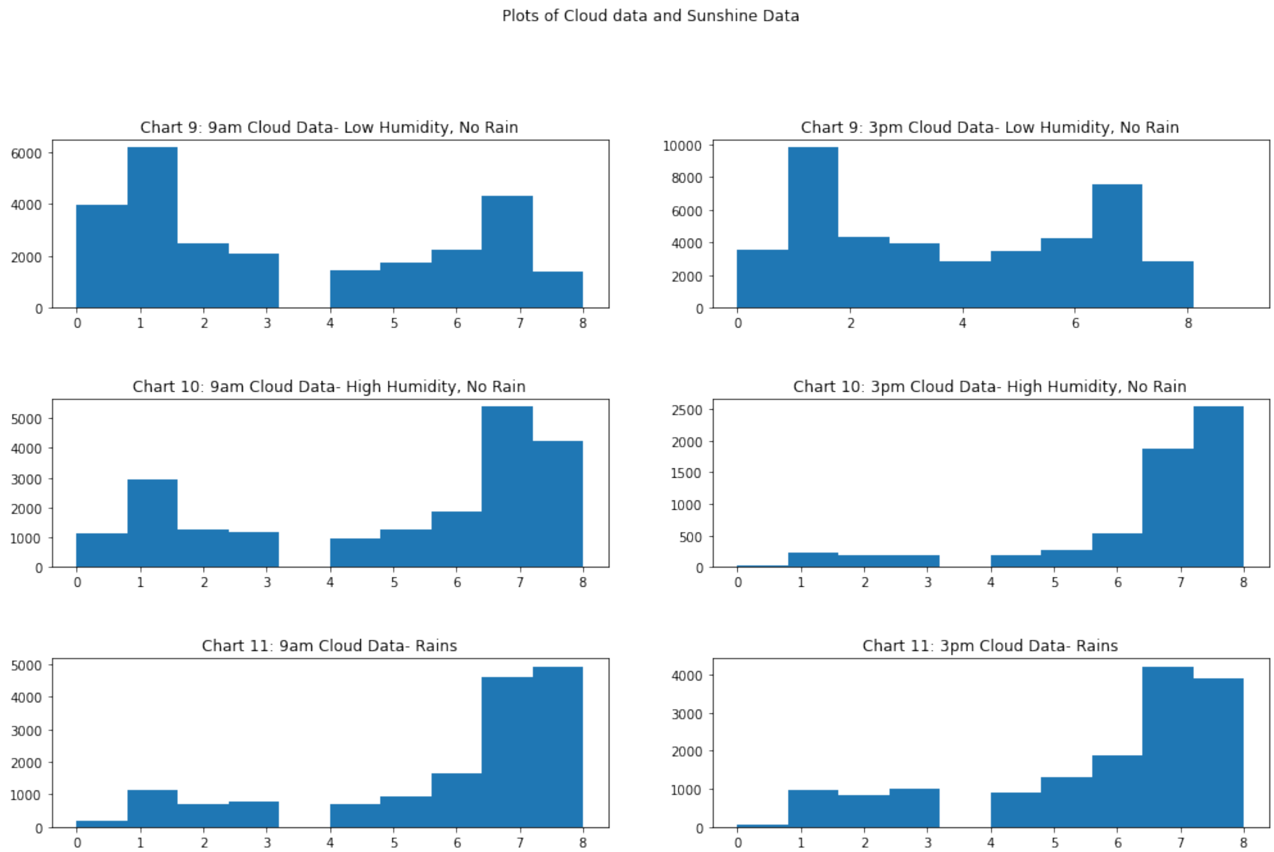
Here are the actionable insights gained from the charts above:

- **Chart 1**: For Sunshine Data overall and with cloud nulls filtered out, it appears to be normally distributed with a slight skew to the left. There are also many zeroes, which can be explained by rainy days.
- **Chart 2 and 3**: For Cloud Data overall and with Sunshine nulls removed, the data appears to be hump shaped, with one large hump at a 1 on the scale, and another large hump at a 7 on the scale.
- **Chart 4**: This chart is designed to look at the overall null population, to further understand what data we will need to impute. For our cloud data with sunshine nulls, I would recommend looking further into the rain data to determine how we should handle imputing sunshine values. For sunshine data with cloud nulls, I will impute based off of both the humps; if it rained, I will use the 7 hump, if it did not rain, I will use the 1 hump. If both are null, I will have to use only rain data to determine how I would like to handle these values.
- **Chart 5**: I made this chart to see situations where there are clouds with 0 sunshine, and sunshine with 0 clouds. These values appear to be minimal.
- **Chart 6 and 7**: I created charts here to see how many hours of sunshine there are when it rains, and when it doesn't rain. This could help us biforcate our population of sunshine data so that I am not imputing the mean onto data that doesn't represent the mean.
- **Chart 8**: This shows evaporation data when Sunshine > 0. We can impute the mean here onto our evaporation nulls.

We need to dive deeper into cloud data in order to figure out how to replace nulls. Please see graphs below for more details about our cloud data:

In [33]:

```
# Now I am going to make a subplot looking into the results of our cloud te

fig, ((ax1, ax4), (ax2, ax5), (ax3, ax6)) = plt.subplots(nrows=3, ncols=2,
fig.suptitle('Plots of Cloud data and Sunshine Data')
fig.tight_layout(pad=5.0)

# This is a graph for our cloud data when there is low humidity and it does
ax1.set_title('Chart 9: 9am Cloud Data- Low Humidity, No Rain')
ax1.hist(cloud9_no_rain_lower_humidity)

# This is a graph for our cloud data when there is high humidity and it doe
ax2.set_title('Chart 10: 9am Cloud Data- High Humidity, No Rain')
ax2.hist(cloud9_no_rain_higher_humidity)

# This is a graph for our cloud data when it does rain.
ax3.set_title('Chart 11: 9am Cloud Data- Rains')
ax3.hist(cloud9_rain)

# This is a graph for our cloud data when there is low humidity and it does
ax4.set_title('Chart 9: 3pm Cloud Data- Low Humidity, No Rain')
ax4.hist(cloud3_no_rain_lower_humidity)

# This is a graph for our cloud data when there is high humidity and it doe
ax5.set_title('Chart 10: 3pm Cloud Data- High Humidity, No Rain')
ax5.hist(cloud3_no_rain_higher_humidity)

# This is a graph for our cloud data when it does rain.
ax6.set_title('Chart 11: 3pm Cloud Data- Rains')
ax6.hist(cloud3_rain)

plt.savefig('Visualizations/Subplot2.png', bbox_inches = 'tight')
```



Let's breakdown our Cloud data:

- **Chart 9**: As we can see here, in our data when it doesn't rain and humidity is less than 70%, our Cloud data has a mean closer to 1. I will fill the nulls meeting this criteria using a lower cloud coverage.
- **Chart 10**: As we can see here, in our data when it doesn't rain and humidity is greater than 70%, our Cloud data has a mean closer to 7 or 8. I will fill the nulls meeting this criteria using a higher cloud coverage.
- **Chart 11**: As we can see here, in our data when it does rain, our Cloud data has a mean closer to 7 or 8. I will fill the nulls meeting this criteria using a higher cloud coverage.

Now that I have an understanding of the data, I will perform the train/test split, and begin imputing these null values.

Section 3: Data Preparation

Before imputing my data, I am going to create numeric columns for our categorical fields using OneHotEncoding.

In [34]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106644 entries, 0 to 106643
Data columns (total 22 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           106644 non-null  object 
 1   Location       106644 non-null  object 
 2   MinTemp        106150 non-null  float64
 3   MaxTemp        106387 non-null  float64
 4   Rainfall       105540 non-null  float64
 5   Evaporation    60909 non-null   float64
 6   Sunshine       55677 non-null   float64
 7   WindGustDir    99665 non-null   object 
 8   WindGustSpeed  99715 non-null   float64
 9   WindDir9am     99120 non-null   object 
 10  WindDir3pm     103822 non-null  object 
 11  WindSpeed9am   105646 non-null  float64
 12  WindSpeed3pm   104681 non-null  float64
 13  Humidity9am    105326 non-null  float64
 14  Humidity3pm    103917 non-null  float64
 15  Pressure9am    96098 non-null   float64
 16  Pressure3pm    96123 non-null   float64
 17  Cloud9am       66285 non-null   float64
 18  Cloud3pm       63757 non-null   float64
 19  Temp9am        105967 non-null  float64
 20  Temp3pm        104579 non-null  float64
 21  RainToday      105540 non-null  object 
dtypes: float64(16), object(6)
memory usage: 17.9+ MB
```

In [35]:
```
X_train = X_train.drop(['Date'],axis=1)
```

In [36]:
```
# Impute sunshine data based off of our findings from above

X_train['Sunshine'] = np.where(((X_train['Sunshine'].isna()) & (X_train['Ra
X_train['Sunshine'] = np.where(((X_train['Sunshine'].isna()) & (X_train['Ra
```

In [37]:
```
X_train['Sunshine'].isna().any()
```

Out[37]:
```
True
```

In [38]:
```
X_train['Sunshine'].value_counts()
```

Out[38]:
```
0.0     1716
10.7     815
```

```
11.0      812
10.5      779
10.8      771
10.3      750
10.2      732
10.9      732
9.8       726
11.1      708
10.6      708
10.4      705
10.0      704
10.1      704
9.2       698
11.2      686
9.9       667
9.5       647
9.4       639
9.6       629
9.7       617
9.3       605
9.0       565
8.8       558
11.3      557
9.1       555
8.4       548
8.9       526
8.7       525
8.2       522
11.4      515
8.0       505
11.6      491
8.3       480
8.6       468
7.2       463
8.5       462
7.8       457
13.0      448
8.1       448
12.0      446
11.7      431
13.1      425
7.3       423
13.2      421
11.5      420
11.9      418
7.7       418
12.7      418
7.6       417
11.8      414
6.8       411
7.1       408
6.9       406
7.5       403
```

```
7.4       401
0.1       399
6.3       398
6.1       396
12.2      394
7.0       388
0.2       388
12.5      383
6.6       380
7.9       370
6.0       366
6.2       366
12.4      365
6.5       364
12.6      363
12.3      359
6.4       356
5.7       356
5.8       353
12.1      353
6.7       343
12.8      342
5.0       340
5.5       339
5.2       337
5.6       325
0.3       325
13.3      319
5.9       317
12.9      316
5.1       310
5.4       310
4.8       307
3.8       301
5.3       300
4.3       295
3.0       295
4.4       293
3.2       292
4.5       291
4.0       291
3.9       291
4.7       290
4.1       285
4.9       279
4.6       273
0.7       263
3.6       262
2.7       255
0.4       253
2.3       252
4.2       251
2.8       245
```

```
1.0      244
3.5      239
1.6      236
2.0      235
2.2      234
2.4      233
1.2      233
2.1      230
0.9      229
3.3      229
13.4     227
0.5      226
0.6      226
2.9      224
1.7      224
0.8      223
3.7      220
1.5      217
1.9      216
2.6      215
1.3      213
1.4      213
3.1      212
1.8      211
2.5      210
3.4      205
1.1      201
13.5     147
13.6     126
13.7      88
13.8      48
13.9      14
14.0      10
14.1       5
14.3       4
14.2       2
14.5       1
Name: Sunshine, dtype: int64
```

In [39]:

```
# Impute zero evaporation when sunshine is zero

X_train['Evaporation'] = np.where(((X_train['Evaporation'].isna()) & (X_tra
```

In [40]:

```
evaporation_test.sum()/len(evaporation_test)
```

Out[40]:

```
5.037441856155372
```

In [41]:
```
# Impute mean evaporation when sunshine is not zero

X_train['Evaporation'] = np.where(((X_train['Evaporation'].isna()) & (X_tra
```

In [42]:
```
X_train['Evaporation'].isna().any()
```

Out[42]:
```
True
```

In [43]:
```
X_train['Evaporation'].value_counts().head()
```

Out[43]:
```
5.0    4186
4.0    2494
8.0    1938
2.2    1567
2.0    1494
Name: Evaporation, dtype: int64
```

In [44]:
```
print(cloud9_no_rain_lower_humidity.value_counts())
print(cloud9_no_rain_higher_humidity.value_counts())
print(cloud9_rain.value_counts())
print(cloud3_no_rain_lower_humidity.value_counts())
print(cloud3_no_rain_higher_humidity.value_counts())
print(cloud3_rain.value_counts())
```

```
1.0    6175
7.0    4297
0.0    3953
2.0    2453
6.0    2237
3.0    2092
5.0    1743
4.0    1422
8.0    1391
Name: Cloud9am, dtype: int64
7.0    5366
8.0    4206
1.0    2952
6.0    1884
5.0    1282
2.0    1261
3.0    1179
0.0    1132
4.0     949
Name: Cloud9am, dtype: int64
8.0    4938
7.0    4617
6.0    1631
1.0    1132
```

```
5.0     955
3.0     794
4.0     710
2.0     691
0.0     174
Name: Cloud9am, dtype: int64
1.0    9839
7.0    7523
2.0    4320
6.0    4268
3.0    3943
0.0    3560
5.0    3474
8.0    2850
4.0    2834
9.0       1
Name: Cloud3pm, dtype: int64
8.0    2529
7.0    1878
6.0     540
5.0     282
1.0     223
4.0     199
3.0     187
2.0     184
0.0      31
Name: Cloud3pm, dtype: int64
7.0    4215
8.0    3907
6.0    1865
5.0    1302
3.0     988
1.0     967
4.0     915
2.0     827
0.0      69
Name: Cloud3pm, dtype: int64
```

In [45]:

```
# Imputing cloud data based on our findings from section 2

X_train['Cloud9am'] = np.where(((X_train['Cloud9am'].isna()) & (X_train['Ra
X_train['Cloud3pm'] = np.where(((X_train['Cloud3pm'].isna()) & (X_train['Ra
X_train['Cloud9am'] = np.where(((X_train['Cloud9am'].isna()) & (X_train['Ra
X_train['Cloud9am'] = np.where(((X_train['Cloud9am'].isna()) & (X_train['Ra
X_train['Cloud3pm'] = np.where(((X_train['Cloud3pm'].isna()) & (X_train['Ra
X_train['Cloud3pm'] = np.where(((X_train['Cloud3pm'].isna()) & (X_train['Ra
```

In [46]:

```
X_train['Cloud9am'].value_counts()
```

Out [46]:

```
7.0    14805
1.0    11618
8.0    10767
0.0     6427
6.0     5999
2.0     4847
3.0     4385
5.0     4177
4.0     3260
Name: Cloud9am, dtype: int64
```

In [47]:

```
X_train['Cloud3pm'].value_counts()
```

Out [47]:

```
7.0    13512
1.0    11081
8.0     9328
6.0     6642
2.0     5346
3.0     5126
5.0     5049
4.0     3952
0.0     3720
9.0        1
Name: Cloud3pm, dtype: int64
```

In [48]:

```
# Imputing remaining columns based on mean, from our charts in section 2

imputer = SimpleImputer(strategy='most_frequent')
imputer = imputer.fit(X_train)
X_train.iloc[:,:] = imputer.transform(X_train)
```

In [49]:

```
categorical_data = X_train[['Location','WindGustDir','WindDir9am','WindDir3

ohe = OneHotEncoder()

# Fit the dummy variables to an array
X = ohe.fit_transform(categorical_data.values).toarray()
y = ohe.get_feature_names()

# To add this back into the original dataframe
dfOneHot = pd.DataFrame(X, columns = y)
X_train = pd.concat([X_train, dfOneHot], axis=1)

# Dropping the base columns, and to avoid multicollinearity, dropping one o
X_train = X_train.drop(['Location','WindGustDir','WindDir9am','WindDir3pm',

# Printing to verify
print(X_train.head())
```

```
   MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed  \
```

```
0     14.9     30.3       0.0           7.4      10.9           33.0
1     14.6     21.5       0.2           5.0       0.0           46.0
2      9.0     23.7       0.0           5.0       0.0           28.0
3     15.3     24.0       0.0           8.2      12.1           35.0
4     17.3     37.5       0.0           8.6      11.4           39.0

   WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  \
0          15.0          11.0         19.0         12.0       1021.1
1          26.0          28.0         65.0         57.0       1012.6
2          11.0          15.0         59.0         45.0       1017.9
3           4.0          15.0         63.0         82.0       1018.1
4           9.0          15.0         26.0         12.0       1009.6

   Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  x0_Adelaide  x0_Albury
\
0       1017.8       1.0       1.0     22.2     29.7          0.0        0.0
1       1013.5       7.0       7.0     17.5     18.6          0.0        0.0
2       1015.1       7.0       7.0     14.6     23.1          0.0        0.0
3       1016.7       3.0       3.0     21.8     21.8          0.0        0.0
4       1006.2       7.0       4.0     23.8     35.7          0.0        0.0

   x0_AliceSprings  x0_BadgerysCreek  x0_Ballarat  x0_Bendigo  x0_Brisbane
\
0              0.0               0.0          0.0         0.0          0.0
1              0.0               0.0          0.0         0.0          0.0
2              0.0               0.0          0.0         0.0          0.0
3              0.0               0.0          0.0         0.0          0.0
4              0.0               0.0          0.0         0.0          0.0

   x0_Cairns  x0_Canberra  x0_Cobar  x0_CoffsHarbour  x0_Dartmoor  x0_Darwin
\
0        0.0          0.0       0.0              0.0          0.0        0.0
1        0.0          0.0       0.0              0.0          0.0        0.0
2        0.0          0.0       0.0              0.0          0.0        0.0
3        0.0          0.0       0.0              0.0          0.0        0.0
4        0.0          0.0       0.0              0.0          0.0        0.0

   x0_GoldCoast  x0_Hobart  x0_Katherine  x0_Launceston  x0_Melbourne  \
0           0.0        0.0           0.0            0.0           0.0
1           0.0        0.0           0.0            0.0           0.0
2           0.0        0.0           0.0            0.0           0.0
3           0.0        0.0           0.0            0.0           0.0
4           0.0        0.0           0.0            0.0           0.0

   x0_MelbourneAirport  x0_Mildura  x0_Moree  x0_MountGambier  x0_MountGinin
i  \
0                  0.0         0.0       0.0              0.0             0.
0
1                  0.0         0.0       0.0              0.0             0.
0
2                  0.0         0.0       0.0              0.0             0.
0
3                  0.0         0.0       0.0              0.0             0.
```

```
0
4                 0.0          1.0       0.0              0.0            0.
0

   x0_Newcastle  x0_Nhil  x0_NorahHead  x0_NorfolkIsland  x0_Nuriootpa  \
0           0.0      0.0           0.0               0.0           0.0
1           0.0      0.0           0.0               0.0           0.0
2           0.0      0.0           0.0               0.0           0.0
3           0.0      0.0           0.0               0.0           0.0
4           0.0      0.0           0.0               0.0           0.0

   x0_PearceRAAF  x0_Perth  x0_PerthAirport  x0_Portland  x0_Richmond  \
0            0.0       0.0              0.0          0.0          0.0
1            0.0       0.0              0.0          0.0          0.0
2            0.0       0.0              0.0          0.0          0.0
3            0.0       0.0              0.0          0.0          0.0
4            0.0       0.0              0.0          0.0          0.0

   x0_Sale  x0_SalmonGums  x0_Sydney  x0_SydneyAirport  x0_Townsville  \
0      0.0            0.0        0.0               0.0            0.0
1      0.0            0.0        0.0               0.0            0.0
2      0.0            1.0        0.0               0.0            0.0
3      0.0            0.0        0.0               0.0            0.0
4      0.0            0.0        0.0               0.0            0.0

   x0_Tuggeranong  x0_Uluru  x0_WaggaWagga  x0_Walpole  x0_Watsonia  \
0             0.0       0.0            0.0         0.0          0.0
1             0.0       0.0            0.0         0.0          0.0
2             0.0       0.0            0.0         0.0          0.0
3             0.0       0.0            0.0         0.0          0.0
4             0.0       0.0            0.0         0.0          0.0

   x0_Williamtown  x0_Witchcliffe  x0_Wollongong  x0_Woomera  x1_E  x1_ENE
\
0             0.0             0.0            0.0         1.0   0.0     0.0
1             0.0             1.0            0.0         0.0   0.0     0.0
2             0.0             0.0            0.0         0.0   0.0     0.0
3             0.0             0.0            0.0         0.0   0.0     0.0
4             0.0             0.0            0.0         0.0   0.0     0.0

   x1_ESE  x1_N  x1_NE  x1_NNW  x1_NW  x1_S  x1_SE  x1_SSE  x1_SSW  x1_SW  \
0     0.0   0.0    0.0     0.0    0.0   1.0    0.0     0.0     0.0    0.0
1     0.0   0.0    0.0     0.0    0.0   0.0    0.0     1.0     0.0    0.0
2     0.0   0.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
3     0.0   0.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
4     0.0   1.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0

   x1_W  x1_WNW  x1_WSW  x2_E  x2_ENE  x2_N  x2_NE  x2_NNE  x2_NNW  x2_NW  \
0   0.0     0.0     0.0   0.0     0.0   0.0    0.0     0.0     0.0    0.0
1   0.0     0.0     0.0   0.0     0.0   0.0    0.0     0.0     0.0    0.0
2   1.0     0.0     0.0   0.0     0.0   0.0    0.0     0.0     0.0    0.0
3   1.0     0.0     0.0   0.0     0.0   0.0    0.0     0.0     0.0    0.0
4   0.0     0.0     0.0   0.0     0.0   0.0    1.0     0.0     0.0    0.0
```

```
   x2_S  x2_SE  x2_SSE  x2_SSW  x2_SW  x2_W  x2_WNW  x2_WSW  x3_E  x3_ESE  \
0   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     0.0
1   1.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     0.0
2   0.0    0.0     0.0     0.0    0.0   0.0     1.0     0.0   0.0     0.0
3   0.0    0.0     0.0     1.0    0.0   0.0     0.0     0.0   0.0     0.0
4   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     0.0

   x3_N  x3_NE  x3_NNE  x3_NNW  x3_NW  x3_S  x3_SE  x3_SSE  x3_SSW  x3_SW  \
0   0.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    1.0
1   0.0    0.0     0.0     0.0    0.0   0.0    0.0     1.0     0.0    0.0
2   0.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
3   0.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     1.0    0.0
4   0.0    0.0     0.0     0.0    1.0   0.0    0.0     0.0     0.0    0.0

   x3_W  x3_WNW  x3_WSW  x4_Yes
0   0.0     0.0     0.0     0.0
1   0.0     0.0     0.0     0.0
2   1.0     0.0     0.0     0.0
3   0.0     0.0     0.0     0.0
4   0.0     0.0     0.0     0.0
```

In [50]:

```
# Imputing remaining columns based on mean, from our charts in section 2

imputer = SimpleImputer(strategy='most_frequent', missing_values=np.nan)
imputer = imputer.fit(X_train)
X_train.iloc[:,:] = imputer.transform(X_train)
```

In [51]:

```
X_train.info(1, null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106644 entries, 0 to 106643
Data columns (total 109 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   MinTemp               106644 non-null  float64
 1   MaxTemp               106644 non-null  float64
 2   Rainfall              106644 non-null  float64
 3   Evaporation           106644 non-null  float64
 4   Sunshine              106644 non-null  float64
 5   WindGustSpeed         106644 non-null  float64
 6   WindSpeed9am          106644 non-null  float64
 7   WindSpeed3pm          106644 non-null  float64
 8   Humidity9am           106644 non-null  float64
 9   Humidity3pm           106644 non-null  float64
 10  Pressure9am           106644 non-null  float64
 11  Pressure3pm           106644 non-null  float64
 12  Cloud9am              106644 non-null  float64
 13  Cloud3pm              106644 non-null  float64
 14  Temp9am               106644 non-null  float64
```

```
 15  Temp3pm             106644 non-null  float64
 16  x0_Adelaide         106644 non-null  float64
 17  x0_Albury           106644 non-null  float64
 18  x0_AliceSprings     106644 non-null  float64
 19  x0_BadgerysCreek    106644 non-null  float64
 20  x0_Ballarat         106644 non-null  float64
 21  x0_Bendigo          106644 non-null  float64
 22  x0_Brisbane         106644 non-null  float64
 23  x0_Cairns           106644 non-null  float64
 24  x0_Canberra         106644 non-null  float64
 25  x0_Cobar            106644 non-null  float64
 26  x0_CoffsHarbour     106644 non-null  float64
 27  x0_Dartmoor         106644 non-null  float64
 28  x0_Darwin           106644 non-null  float64
 29  x0_GoldCoast        106644 non-null  float64
 30  x0_Hobart           106644 non-null  float64
 31  x0_Katherine        106644 non-null  float64
 32  x0_Launceston       106644 non-null  float64
 33  x0_Melbourne        106644 non-null  float64
 34  x0_MelbourneAirport  106644 non-null  float64
 35  x0_Mildura          106644 non-null  float64
 36  x0_Moree            106644 non-null  float64
 37  x0_MountGambier     106644 non-null  float64
 38  x0_MountGinini      106644 non-null  float64
 39  x0_Newcastle        106644 non-null  float64
 40  x0_Nhil             106644 non-null  float64
 41  x0_NorahHead        106644 non-null  float64
 42  x0_NorfolkIsland    106644 non-null  float64
 43  x0_Nuriootpa        106644 non-null  float64
 44  x0_PearceRAAF       106644 non-null  float64
 45  x0_Perth            106644 non-null  float64
 46  x0_PerthAirport     106644 non-null  float64
 47  x0_Portland         106644 non-null  float64
 48  x0_Richmond         106644 non-null  float64
 49  x0_Sale             106644 non-null  float64
 50  x0_SalmonGums       106644 non-null  float64
 51  x0_Sydney           106644 non-null  float64
 52  x0_SydneyAirport    106644 non-null  float64
 53  x0_Townsville       106644 non-null  float64
 54  x0_Tuggeranong      106644 non-null  float64
 55  x0_Uluru            106644 non-null  float64
 56  x0_WaggaWagga       106644 non-null  float64
 57  x0_Walpole          106644 non-null  float64
 58  x0_Watsonia         106644 non-null  float64
 59  x0_Williamtown      106644 non-null  float64
 60  x0_Witchcliffe      106644 non-null  float64
 61  x0_Wollongong       106644 non-null  float64
 62  x0_Woomera          106644 non-null  float64
 63  x1_E                106644 non-null  float64
 64  x1_ENE              106644 non-null  float64
 65  x1_ESE              106644 non-null  float64
 66  x1_N                106644 non-null  float64
 67  x1_NE               106644 non-null  float64
```

```
 68  x1_NNW                 106644 non-null  float64
 69  x1_NW                  106644 non-null  float64
 70  x1_S                   106644 non-null  float64
 71  x1_SE                  106644 non-null  float64
 72  x1_SSE                 106644 non-null  float64
 73  x1_SSW                 106644 non-null  float64
 74  x1_SW                  106644 non-null  float64
 75  x1_W                   106644 non-null  float64
 76  x1_WNW                 106644 non-null  float64
 77  x1_WSW                 106644 non-null  float64
 78  x2_E                   106644 non-null  float64
 79  x2_ENE                 106644 non-null  float64
 80  x2_N                   106644 non-null  float64
 81  x2_NE                  106644 non-null  float64
 82  x2_NNE                 106644 non-null  float64
 83  x2_NNW                 106644 non-null  float64
 84  x2_NW                  106644 non-null  float64
 85  x2_S                   106644 non-null  float64
 86  x2_SE                  106644 non-null  float64
 87  x2_SSE                 106644 non-null  float64
 88  x2_SSW                 106644 non-null  float64
 89  x2_SW                  106644 non-null  float64
 90  x2_W                   106644 non-null  float64
 91  x2_WNW                 106644 non-null  float64
 92  x2_WSW                 106644 non-null  float64
 93  x3_E                   106644 non-null  float64
 94  x3_ESE                 106644 non-null  float64
 95  x3_N                   106644 non-null  float64
 96  x3_NE                  106644 non-null  float64
 97  x3_NNE                 106644 non-null  float64
 98  x3_NNW                 106644 non-null  float64
 99  x3_NW                  106644 non-null  float64
 100 x3_S                   106644 non-null  float64
 101 x3_SE                  106644 non-null  float64
 102 x3_SSE                 106644 non-null  float64
 103 x3_SSW                 106644 non-null  float64
 104 x3_SW                  106644 non-null  float64
 105 x3_W                   106644 non-null  float64
 106 x3_WNW                 106644 non-null  float64
 107 x3_WSW                 106644 non-null  float64
 108 x4_Yes                 106644 non-null  float64
dtypes: float64(109)
memory usage: 88.7 MB
```

In [52]:

```
y_train.count()
```

Out[52]:

```
106644
```

In [53]:

```
X_test.info(1, null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35549 entries, 0 to 35548
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           35549 non-null  object
 1   Location       35549 non-null  object
 2   MinTemp        35406 non-null  float64
 3   MaxTemp        35484 non-null  float64
 4   Rainfall       35247 non-null  float64
 5   Evaporation    20441 non-null  float64
 6   Sunshine       18700 non-null  float64
 7   WindGustDir    33198 non-null  object
 8   WindGustSpeed  33208 non-null  float64
 9   WindDir9am     33060 non-null  object
 10  WindDir3pm     34593 non-null  object
 11  WindSpeed9am   35199 non-null  float64
 12  WindSpeed3pm   34882 non-null  float64
 13  Humidity9am    35093 non-null  float64
 14  Humidity3pm    34666 non-null  float64
 15  Pressure9am    32081 non-null  float64
 16  Pressure3pm    32089 non-null  float64
 17  Cloud9am       22251 non-null  float64
 18  Cloud3pm       21342 non-null  float64
 19  Temp9am        35322 non-null  float64
 20  Temp3pm        34888 non-null  float64
 21  RainToday      35247 non-null  object
dtypes: float64(16), object(6)
memory usage: 6.0+ MB
```

In [54]:

```
X_test.reset_index(inplace=True)
```

In [55]:

```
X_test = X_test.drop(columns=['index'],axis=1)
```

In [56]:

```
# Performing same imputations as train data

X_test['Sunshine'] = np.where(((X_test['Sunshine'].isna()) & (X_test['RainT
X_test['Sunshine'] = np.where(((X_test['Sunshine'].isna()) & (X_test['RainT
X_test['Evaporation'] = np.where(((X_test['Evaporation'].isna()) & (X_test[
X_test['Evaporation'] = np.where(((X_test['Evaporation'].isna()) & (X_test[
X_test['Cloud9am'] = np.where(((X_test['Cloud9am'].isna()) & (X_test['RainT
X_test['Cloud3pm'] = np.where(((X_test['Cloud3pm'].isna()) & (X_test['RainT
X_test['Cloud9am'] = np.where(((X_test['Cloud9am'].isna()) & (X_test['RainT
X_test['Cloud9am'] = np.where(((X_test['Cloud9am'].isna()) & (X_test['RainT
X_test['Cloud3pm'] = np.where(((X_test['Cloud3pm'].isna()) & (X_test['RainT
X_test['Cloud3pm'] = np.where(((X_test['Cloud3pm'].isna()) & (X_test['RainT
```

In [57]:

```
# Performing same imputations as train data

imputer = SimpleImputer(strategy='most_frequent')
imputer = imputer.fit(X_test)
X_test.iloc[:,:] = imputer.transform(X_test)
```

In [58]:

```
categorical_data = X_test[['Location','WindGustDir','WindDir9am','WindDir3p

ohe = OneHotEncoder()

# Fit the dummy variables to an array
X = ohe.fit_transform(categorical_data.values).toarray()
y = ohe.get_feature_names()

# To add this back into the original dataframe
dfOneHot = pd.DataFrame(X, columns = y)
X_test = pd.concat([X_test, dfOneHot], axis=1)

# Dropping the country column
X_test = X_test.drop(['Date','Location','WindGustDir','WindDir9am','WindDir

# Printing to verify
print(X_test.head())
```

```
   MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed  \
0      7.1     13.0       8.8          5.0       0.0           41.0   
1     13.2     18.3       0.0          5.0       0.0           48.0   
2      9.2     22.7       0.0          5.0      11.1           52.0   
3     15.3     26.1       0.0         10.4       0.0           44.0   
4     11.9     31.8       0.0          5.0       4.1           72.0   

   WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  \
0          24.0          22.0        100.0         98.0       1001.7   
1          24.0          20.0         73.0         73.0       1027.6   
2          26.0          20.0         45.0         25.0       1030.1   
3          24.0          19.0         48.0         40.0       1013.2   
4           6.0          19.0         89.0         25.0       1006.7   

   Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  x0_Adelaide  x0_Albury
\
0       1005.4       8.0       8.0      8.6     11.5          0.0        0.0
1       1023.8       7.0       7.0     14.2     17.0          0.0        0.0
2       1025.9       0.0       0.0     15.1     22.5          0.0        0.0
3       1009.8       7.0       7.0     17.5     24.3          0.0        0.0
4       1001.0       7.0       6.0     16.2     27.4          0.0        0.0

   x0_AliceSprings  x0_BadgerysCreek  x0_Ballarat  x0_Bendigo  x0_Brisbane
\
0              0.0               0.0          1.0         0.0          0.0
1              0.0               0.0          0.0         0.0          0.0
```

```
2           0.0               0.0          0.0         0.0          0.0
3           0.0               0.0          0.0         0.0          0.0
4           0.0               0.0          0.0         0.0          0.0

   x0_Cairns  x0_Canberra  x0_Cobar  x0_CoffsHarbour  x0_Dartmoor  x0_Darwin
\
0        0.0          0.0       0.0              0.0          0.0        0.0
1        0.0          0.0       0.0              0.0          0.0        0.0
2        0.0          0.0       0.0              0.0          0.0        0.0
3        0.0          0.0       1.0              0.0          0.0        0.0
4        0.0          0.0       0.0              0.0          0.0        0.0

   x0_GoldCoast  x0_Hobart  x0_Katherine  x0_Launceston  x0_Melbourne  \
0           0.0        0.0           0.0            0.0           0.0
1           0.0        0.0           0.0            0.0           0.0
2           0.0        0.0           0.0            0.0           0.0
3           0.0        0.0           0.0            0.0           0.0
4           0.0        0.0           0.0            0.0           0.0

   x0_MelbourneAirport  x0_Mildura  x0_Moree  x0_MountGambier  x0_MountGinin
i  \
0                  0.0         0.0       0.0              0.0             0.
0
1                  0.0         0.0       0.0              0.0             0.
0
2                  0.0         0.0       0.0              0.0             0.
0
3                  0.0         0.0       0.0              0.0             0.
0
4                  0.0         0.0       0.0              0.0             0.
0

   x0_Newcastle  x0_Nhil  x0_NorahHead  x0_NorfolkIsland  x0_Nuriootpa  \
0           0.0      0.0           0.0               0.0           0.0
1           0.0      0.0           0.0               0.0           0.0
2           0.0      0.0           0.0               0.0           0.0
3           0.0      0.0           0.0               0.0           0.0
4           0.0      0.0           0.0               0.0           0.0

   x0_PearceRAAF  x0_Perth  x0_PerthAirport  x0_Portland  x0_Richmond  \
0            0.0       0.0              0.0          0.0          0.0
1            0.0       0.0              0.0          0.0          0.0
2            0.0       0.0              1.0          0.0          0.0
3            0.0       0.0              0.0          0.0          0.0
4            0.0       0.0              0.0          0.0          0.0

   x0_Sale  x0_SalmonGums  x0_Sydney  x0_SydneyAirport  x0_Townsville  \
0      0.0            0.0        0.0               0.0            0.0
1      0.0            0.0        0.0               0.0            0.0
2      0.0            0.0        0.0               0.0            0.0
3      0.0            0.0        0.0               0.0            0.0
4      1.0            0.0        0.0               0.0            0.0
```

```
   x0_Tuggeranong  x0_Uluru  x0_WaggaWagga  x0_Walpole  x0_Watsonia  \
0             0.0       0.0            0.0         0.0          0.0
1             0.0       0.0            0.0         1.0          0.0
2             0.0       0.0            0.0         0.0          0.0
3             0.0       0.0            0.0         0.0          0.0
4             0.0       0.0            0.0         0.0          0.0

   x0_Williamtown  x0_Witchcliffe  x0_Wollongong  x0_Woomera  x1_E  x1_ENE
\
0             0.0             0.0            0.0         0.0   0.0     0.0
1             0.0             0.0            0.0         0.0   1.0     0.0
2             0.0             0.0            0.0         0.0   0.0     1.0
3             0.0             0.0            0.0         0.0   1.0     0.0
4             0.0             0.0            0.0         0.0   0.0     0.0

   x1_ESE  x1_N  x1_NE  x1_NNW  x1_NW  x1_S  x1_SE  x1_SSE  x1_SSW  x1_SW  \
0     0.0   1.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
1     0.0   0.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
2     0.0   0.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
3     0.0   0.0    0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
4     0.0   0.0    0.0     0.0    1.0   0.0    0.0     0.0     0.0    0.0

   x1_W  x1_WNW  x1_WSW  x2_E  x2_ENE  x2_N  x2_NE  x2_NNE  x2_NNW  x2_NW  \
0   0.0     0.0     0.0   0.0     0.0   1.0    0.0     0.0     0.0    0.0
1   0.0     0.0     0.0   0.0     0.0   0.0    0.0     0.0     0.0    0.0
2   0.0     0.0     0.0   0.0     1.0   0.0    0.0     0.0     0.0    0.0
3   0.0     0.0     0.0   1.0     0.0   0.0    0.0     0.0     0.0    0.0
4   0.0     0.0     0.0   1.0     0.0   0.0    0.0     0.0     0.0    0.0

   x2_S  x2_SE  x2_SSE  x2_SSW  x2_SW  x2_W  x2_WNW  x2_WSW  x3_E  x3_ESE  \
0   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     0.0
1   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     1.0
2   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     1.0
3   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     0.0
4   0.0    0.0     0.0     0.0    0.0   0.0     0.0     0.0   0.0     0.0

   x3_N  x3_NE  x3_NNE  x3_NNW  x3_NW  x3_S  x3_SE  x3_SSE  x3_SSW  x3_SW  \
0   0.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
1   0.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
2   0.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
3   0.0    1.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0
4   1.0    0.0     0.0     0.0    0.0   0.0    0.0     0.0     0.0    0.0

   x3_W  x3_WNW  x3_WSW  x4_Yes
0   0.0     1.0     0.0     1.0
1   0.0     0.0     0.0     0.0
2   0.0     0.0     0.0     0.0
3   0.0     0.0     0.0     0.0
4   0.0     0.0     0.0     0.0
```

In [59]:

```python
X_test.info(1, null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35549 entries, 0 to 35548
Data columns (total 109 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   MinTemp              35549 non-null  float64
 1   MaxTemp              35549 non-null  float64
 2   Rainfall             35549 non-null  float64
 3   Evaporation          35549 non-null  float64
 4   Sunshine             35549 non-null  float64
 5   WindGustSpeed        35549 non-null  float64
 6   WindSpeed9am         35549 non-null  float64
 7   WindSpeed3pm         35549 non-null  float64
 8   Humidity9am          35549 non-null  float64
 9   Humidity3pm          35549 non-null  float64
 10  Pressure9am          35549 non-null  float64
 11  Pressure3pm          35549 non-null  float64
 12  Cloud9am             35549 non-null  float64
 13  Cloud3pm             35549 non-null  float64
 14  Temp9am              35549 non-null  float64
 15  Temp3pm              35549 non-null  float64
 16  x0_Adelaide          35549 non-null  float64
 17  x0_Albury            35549 non-null  float64
 18  x0_AliceSprings      35549 non-null  float64
 19  x0_BadgerysCreek     35549 non-null  float64
 20  x0_Ballarat          35549 non-null  float64
 21  x0_Bendigo           35549 non-null  float64
 22  x0_Brisbane          35549 non-null  float64
 23  x0_Cairns            35549 non-null  float64
 24  x0_Canberra          35549 non-null  float64
 25  x0_Cobar             35549 non-null  float64
 26  x0_CoffsHarbour      35549 non-null  float64
 27  x0_Dartmoor          35549 non-null  float64
 28  x0_Darwin            35549 non-null  float64
 29  x0_GoldCoast         35549 non-null  float64
 30  x0_Hobart            35549 non-null  float64
 31  x0_Katherine         35549 non-null  float64
 32  x0_Launceston        35549 non-null  float64
 33  x0_Melbourne         35549 non-null  float64
 34  x0_MelbourneAirport  35549 non-null  float64
 35  x0_Mildura           35549 non-null  float64
 36  x0_Moree             35549 non-null  float64
 37  x0_MountGambier      35549 non-null  float64
 38  x0_MountGinini       35549 non-null  float64
 39  x0_Newcastle         35549 non-null  float64
 40  x0_Nhil              35549 non-null  float64
 41  x0_NorahHead         35549 non-null  float64
 42  x0_NorfolkIsland     35549 non-null  float64
 43  x0_Nuriootpa         35549 non-null  float64
 44  x0_PearceRAAF        35549 non-null  float64
 45  x0_Perth             35549 non-null  float64
 46  x0_PerthAirport      35549 non-null  float64
 47  x0_Portland          35549 non-null  float64
```

```
 48  x0_Richmond          35549 non-null  float64
 49  x0_Sale              35549 non-null  float64
 50  x0_SalmonGums        35549 non-null  float64
 51  x0_Sydney            35549 non-null  float64
 52  x0_SydneyAirport     35549 non-null  float64
 53  x0_Townsville        35549 non-null  float64
 54  x0_Tuggeranong       35549 non-null  float64
 55  x0_Uluru             35549 non-null  float64
 56  x0_WaggaWagga        35549 non-null  float64
 57  x0_Walpole           35549 non-null  float64
 58  x0_Watsonia          35549 non-null  float64
 59  x0_Williamtown       35549 non-null  float64
 60  x0_Witchcliffe       35549 non-null  float64
 61  x0_Wollongong        35549 non-null  float64
 62  x0_Woomera           35549 non-null  float64
 63  x1_E                 35549 non-null  float64
 64  x1_ENE               35549 non-null  float64
 65  x1_ESE               35549 non-null  float64
 66  x1_N                 35549 non-null  float64
 67  x1_NE                35549 non-null  float64
 68  x1_NNW               35549 non-null  float64
 69  x1_NW                35549 non-null  float64
 70  x1_S                 35549 non-null  float64
 71  x1_SE                35549 non-null  float64
 72  x1_SSE               35549 non-null  float64
 73  x1_SSW               35549 non-null  float64
 74  x1_SW                35549 non-null  float64
 75  x1_W                 35549 non-null  float64
 76  x1_WNW               35549 non-null  float64
 77  x1_WSW               35549 non-null  float64
 78  x2_E                 35549 non-null  float64
 79  x2_ENE               35549 non-null  float64
 80  x2_N                 35549 non-null  float64
 81  x2_NE                35549 non-null  float64
 82  x2_NNE               35549 non-null  float64
 83  x2_NNW               35549 non-null  float64
 84  x2_NW                35549 non-null  float64
 85  x2_S                 35549 non-null  float64
 86  x2_SE                35549 non-null  float64
 87  x2_SSE               35549 non-null  float64
 88  x2_SSW               35549 non-null  float64
 89  x2_SW                35549 non-null  float64
 90  x2_W                 35549 non-null  float64
 91  x2_WNW               35549 non-null  float64
 92  x2_WSW               35549 non-null  float64
 93  x3_E                 35549 non-null  float64
 94  x3_ESE               35549 non-null  float64
 95  x3_N                 35549 non-null  float64
 96  x3_NE                35549 non-null  float64
 97  x3_NNE               35549 non-null  float64
 98  x3_NNW               35549 non-null  float64
 99  x3_NW                35549 non-null  float64
 100 x3_S                 35549 non-null  float64
```

```
 101 x3_SE                   35549 non-null  float64
 102 x3_SSE                  35549 non-null  float64
 103 x3_SSW                  35549 non-null  float64
 104 x3_SW                   35549 non-null  float64
 105 x3_W                    35549 non-null  float64
 106 x3_WNW                  35549 non-null  float64
 107 x3_WSW                  35549 non-null  float64
 108 x4_Yes                  35549 non-null  float64
dtypes: float64(109)
memory usage: 29.6 MB
```

In [60]:

```
y_test.count()
```

Out[60]:

```
35549
```

Section 4: Modeling

To begin, I will build a logistic model. After that, I will be building a kNN model and a decision tree model, and will pick the best model from the three.

The metric I focus on the most will be recall, because if there are false negatives in my model, then it could rain on citizens who expected a dry day. As the Bureau of Meteorology has been underestimating rain over the past five years, we are trying to minimize false negatives as much as possible.

Logistic Regression

In [61]:

```
# Create a Baseline Model

logreg = LogisticRegression()
model_log = logreg.fit(X_train, y_train)
model_log.score(X_test,y_test)
y_pred_lr = model_log.predict(X_test)
```

In [62]:

```
recall_score(y_test,y_pred_lr)
```

Out[62]:

```
0.4690890739338885
```

I will now run various models through a Pipeline to see if I can find a combination of parameters to bring down our performance metric.

In [63]:

```
# Create pipeline

lr_pipeline_1 = Pipeline([('ss', StandardScaler()),
                          ('lr', LogisticRegression())])
```

In [64]:

```
# Create grid using GridSearchCV

lr_grid = [{'lr__random_state':[42],
          'lr__C': [1e-3, 1e-2, 1,1e2,1e3]}]
```

In [65]:

```
# Create grid using GridSearchCV

lr_gridsearch = GridSearchCV(estimator=lr_pipeline_1,
                             param_grid=lr_grid,
                             scoring='recall',
                             cv=3)
```

In [66]:

```
# Re-distributing our population using SMOTE, to account for accuracy bias

smote = SMOTE()
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

In [67]:

```
y_train_resampled.value_counts()
```

Out[67]:

```
1.0    82693
0.0    82693
Name: RainTomorrow, dtype: int64
```

In [68]:

```
# Fit the training data
lr_gridsearch.fit(X_train_resampled, y_train_resampled)
print(lr_gridsearch.score(X_test, y_test))
```

```
0.7721423164269493
```

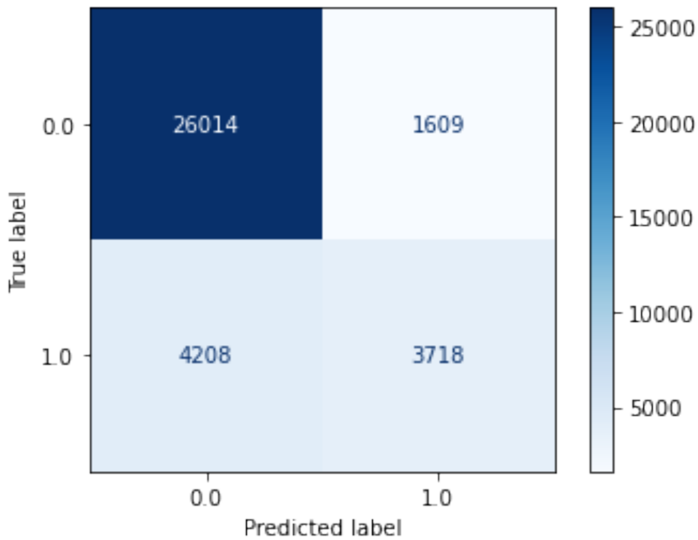
In [69]:

```
# Print best parameters

print(lr_gridsearch.best_params_)
```

```
{'lr__C': 1, 'lr__random_state': 42}
```

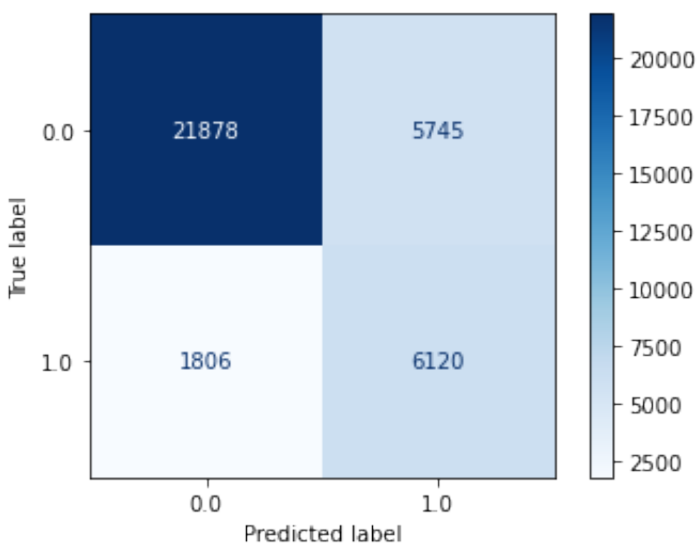
In [70]:

```
# Create confusion matrix for baseline model

plot_confusion_matrix(logreg, X_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.savefig('Visualizations/LogRegBase.png', bbox_inches = 'tight')
plt.show()
```



In [71]:

```
# Create confusion matrix for best model

plot_confusion_matrix(lr_gridsearch, X_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.savefig('Visualizations/LogRegBest.png', bbox_inches = 'tight')
plt.show()
```



k-Nearest Neighbors

In [72]:
```
# Create baseline model

knn_baseline_model = KNeighborsClassifier()
model_knn = knn_baseline_model.fit(X_train, y_train)
model_knn.score(X_test,y_test)
y_pred_knn = model_knn.predict(X_test)
```

In [73]:
```
recall_score(y_test,y_pred_knn)
```

Out[73]:
```
0.5099671965682564
```

Next, I will build a model using Pipeline and kNN to check score using a set of different parameters:

In [74]:
```
# Creating 3 different tests using different parameters

knn_pipeline = Pipeline([('ss', StandardScaler()),
                               ('knn', KNeighborsClassifier())])
```

In [75]:
```
# Create grid using GridSearchCV

knn_grid = [{'knn__n_neighbors':[2,5,7,10]}]
```

In [76]:
```
# Create grid using GridSearchCV

knn_gridsearch = GridSearchCV(estimator=knn_pipeline,
                          param_grid=knn_grid,
                          scoring='recall',
                          cv=3)
```

In [77]:
```
# Fit the training data
knn_gridsearch.fit(X_train_resampled, y_train_resampled)
print(knn_gridsearch.score(X_test, y_test))
```

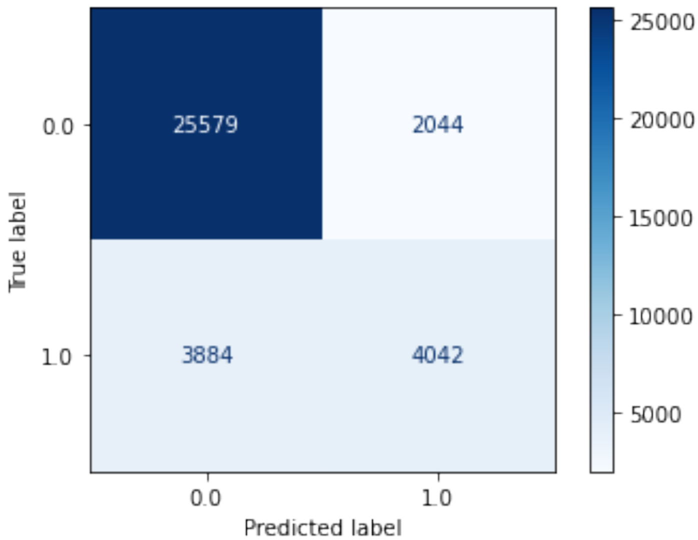
```
0.5547564976028262
```

In [78]:
```
print(knn_gridsearch.best_params_)
```

```
{'knn__n_neighbors': 5}
```

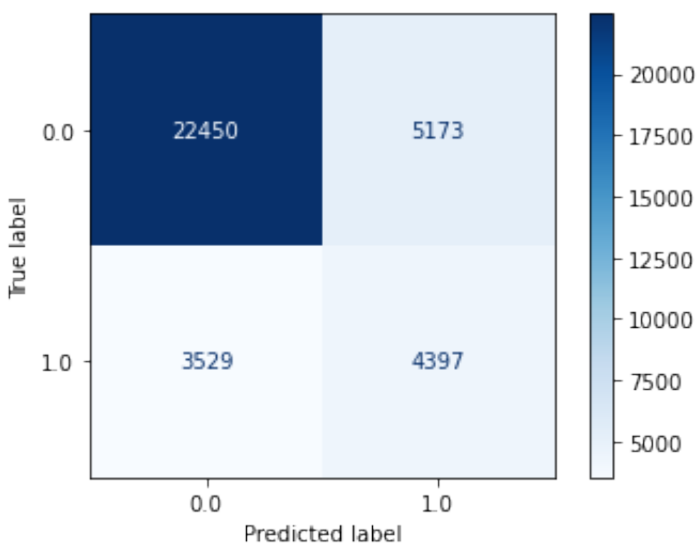
In [79]:

```
# Create confusion matrix for baseline

plot_confusion_matrix(knn_baseline_model, X_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.savefig('Visualizations/KNNbaseline.png', bbox_inches = 'tight')
plt.show()
```



In [80]:

```
# Create confusion matrix for best

plot_confusion_matrix(knn_gridsearch, X_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.savefig('Visualizations/KNNbest.png', bbox_inches = 'tight')
plt.show()
```



As we can see above, our best model seems to cap at a score of around .548. I will now use decision trees and Grid Search CV to see if they generate a stronger model.

Decision Trees

In [81]:
```
# Create a Baseline Model

dt_base = DecisionTreeClassifier()
model_dt = dt_base.fit(X_train, y_train)
model_dt.score(X_test,y_test)
y_pred_dt = model_dt.predict(X_test)
```

In [82]:
```
recall_score(y_test,y_pred_dt)
```

Out[82]: 0.5282614181175876

In [83]:
```
# Create pipeline

dtree_pipeline = Pipeline([('ss', StandardScaler()),
                           ('dt', DecisionTreeClassifier())])
```

In [84]:
```
# Use GridSearchCV to create different models

dt_grid = [{'dt__criterion': ['gini','entropy'],
         'dt__max_leaf_nodes': [5,10,20,None],
         'dt__max_features': ['auto','sqrt','log2', None],
         'dt__random_state':[42]}]
```

In [85]:
```
# Use GridSearchCV to create different models

dt_gridsearch = GridSearchCV(estimator=dtree_pipeline,
                          param_grid=dt_grid,
                          scoring='recall',
                          cv=3)
```

In [86]:
```
# Fit model and print

dt_gridsearch.fit(X_train_resampled, y_train_resampled)
print(dt_gridsearch.score(X_test, y_test))
```

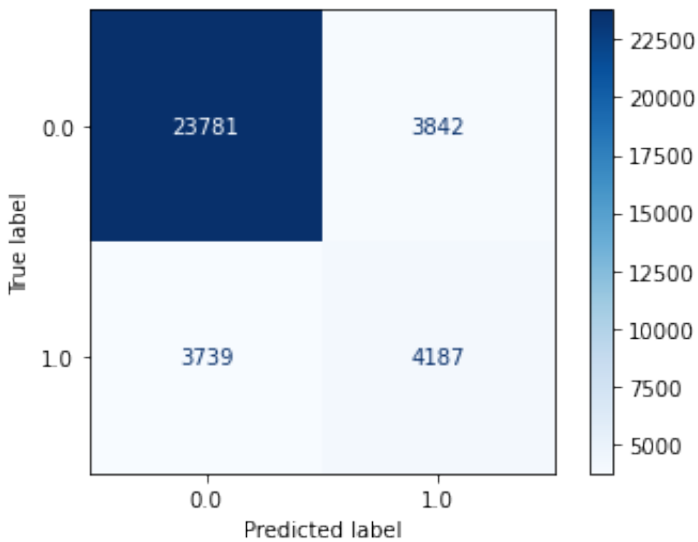
0.7763058289174868

In [87]:
```
print(dt_gridsearch.best_params_)
```

```
{'dt__criterion': 'entropy', 'dt__max_features': None, 'dt__max_leaf_nodes': 5, 'dt__random_state': 42}
```

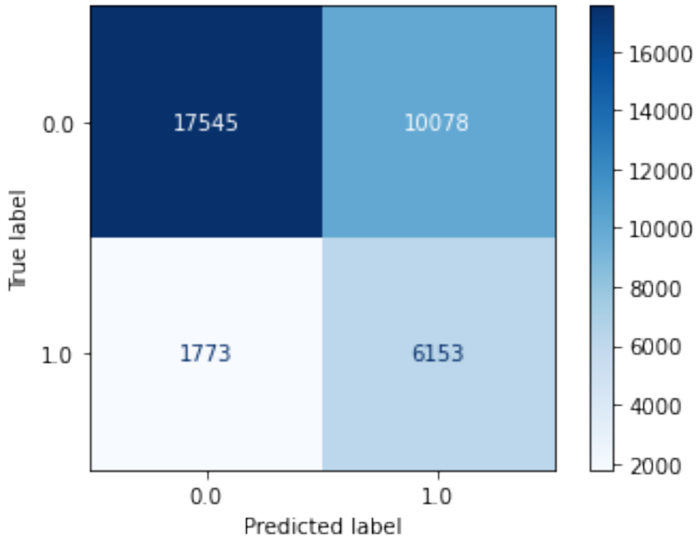
In [88]:

```
# Create confusion matrix for baseline

cm = plot_confusion_matrix(dt_base, X_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.savefig('Visualizations/DT.png', bbox_inches = 'tight')
plt.show()
```



In [89]:

```
# Create confusion matrix for best

plot_confusion_matrix(dt_gridsearch, X_test, y_test,
                      cmap=plt.cm.Blues, values_format = '.5g')
plt.grid(False)
plt.savefig('Visualizations/DT.png', bbox_inches = 'tight')
plt.show()
```



As we can see here, the best decision tree model is slightly worse than the logistic regression model, and better than our best kNN model, at a recall score of .747.

Section 5: Results

Best Model

The logistic regression model is our best model, at a recall of around .771. Now, I will take a look at the remaining metrics.

In [90]:

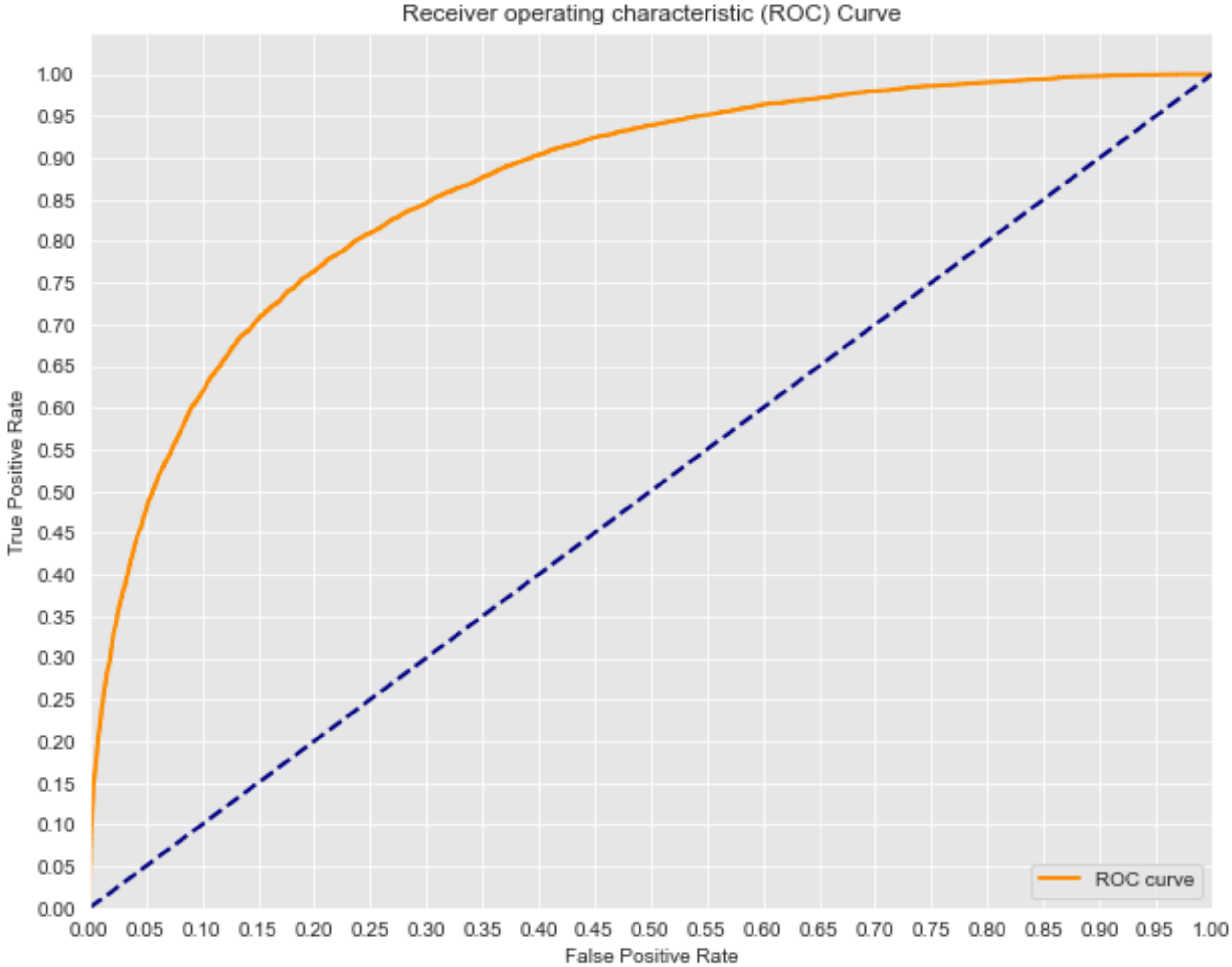
```
# Checking our our train and test data metrics

final_test = lr_gridsearch.predict(X_test)
final_train = lr_gridsearch.predict(X_train_resampled)

print("Training Data Results:\n")
print(classification_report(y_train_resampled, final_train))
print("\nTest Data Results:\n")
print(classification_report(y_test, final_test))
```

```
Training Data Results:

              precision    recall  f1-score   support

         0.0       0.79      0.80      0.79     82693
         1.0       0.80      0.78      0.79     82693

    accuracy                           0.79    165386
   macro avg       0.79      0.79      0.79    165386
weighted avg       0.79      0.79      0.79    165386


Test Data Results:

              precision    recall  f1-score   support

         0.0       0.92      0.79      0.85     27623
         1.0       0.52      0.77      0.62      7926

    accuracy                           0.79     35549
   macro avg       0.72      0.78      0.74     35549
weighted avg       0.83      0.79      0.80     35549
```

In [91]:

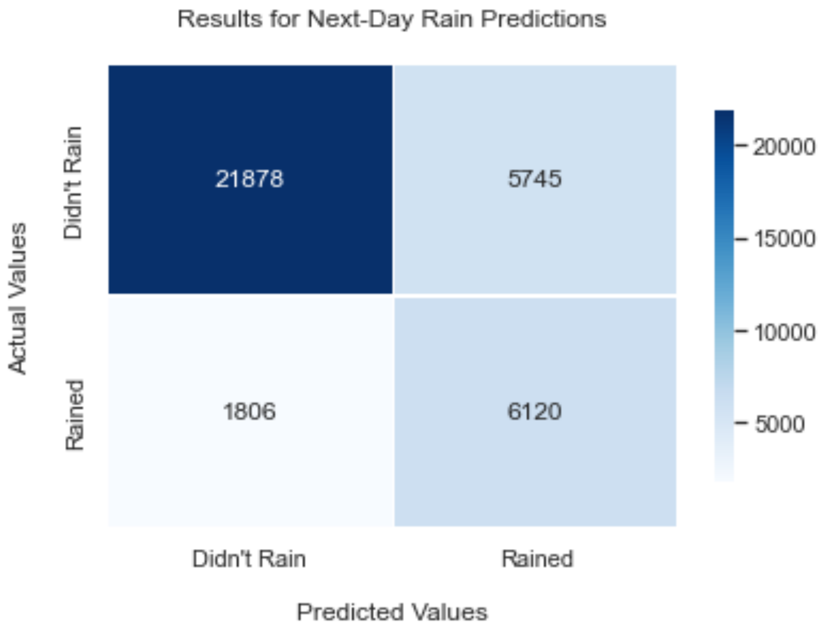
```
# Creating ROC curve to see effectiveness of model.

y_score = lr_gridsearch.decision_function(X_test)

fpr, tpr, thresholds = roc_curve(y_test, y_score)

sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

print('\nAUC: {}'.format(auc(fpr, tpr)))
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.savefig('Visualizations/AUC.png', bbox_inches = 'tight')
plt.show()
```

```
AUC: 0.8653919990407596
```



In [92]:

```
# Create confusion matrix for final model
lrcm = confusion_matrix(y_test, final_test)
sns.set_context("talk")
sns.set_theme(style='darkgrid')
ax = sns.heatmap(lrcm, annot=True, cmap='Blues',fmt = 'g',linewidth=0.3, cb

ax.set_title('Results for Next-Day Rain Predictions\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values\n');

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(["Didn't Rain","Rained"])
ax.yaxis.set_ticklabels(["Didn't Rain","Rained"])
plt.savefig('Visualizations/FinalCM.png', bbox_inches = 'tight')
## Display the visualization of the Confusion Matrix.
plt.show()
```



Accuracy: This model has 79% accuracy, meaning that it correctly determines that it will rain the next day 79% of the time. As True Negatives account for 77% of our test data, there is a lot of bias within this metric. Therefore, it is best to ignore it in our analysis.

Precision: If our model says that it will rain tomorrow, there between a 52% chance that it is a true positive and will actually rain the next day. If our model says it wont rain tomorrow, there is a 92% chance that it won't rain tomorrow. The weighted average precision of our model is 83%. Our model is way better at predicting when it won't rain than when it will. In the future, we should take steps to try to raise precision.

Recall: Our recall score is the most important aspect of this model. For instances when it actually rained the next day, our model correctly classified that it would rain 77% of the time. For instances when it did not rain the next day, our model correctly predicted that it would not rain 79% of the time. The weighted average recall of our model is 79%.

Our AUC Score is .86. That means that our classifiers have an 86% true positive rate.