Logistic Regression

Agenda

In this session, we will cover the following concepts with the help of a business use case:

- EDA (Exploratory Data Analysis)
- Data Cleaning
- Logistic Regression with Sklearn

Use Case: Logistic Regression

Note: At first, with the help of a use case, we are going to perform all the basic steps to reach the training and predicition part.

Problem Statement

One of the aspects Seattle is most notable for, in addition to coffee, grunge, and electronic businesses, is its rains. From January 1, 1948 to December 12, 2017, this dataset provides full records of Seattle's daily rainfall patterns.

Dataset

seattleWeather_1948-2017.csv

Link: https://www.dropbox.com/sh/wn9hcqrcl6oessl/AACVl-_f6Hx1JL0Odltrm6w6a?dl=0

Data Dictionary

Following are the variables with their definition and key:

Variables	Description
DATE	The date of the observation
PRCP	The amount of precipitation, in inches
MAX	The maximum temperature for that day, in degrees Fahrenheit
TMIN	The minimum temperature for that day, in degrees Fahrenheit
RAIN	TRUE if rain was observed on that day, FALSE if it was not

Solution

Import Libraries

- Pandas is a Python library for data manipulation and analysis.
- NumPy is a package that contains a multidimensional array object and several derived ones.
- Matplotlib is a Python visualization package for 2D array plots.
- Seaborn is built on top of matplotlib. It's used for exploratory data analysis and data visualization.
- To work with dates as date objects, use Datetime.

In [1]:
```
#Import the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import time
import datetime
```

Data Acquisition

Before reading data from the CSV file, you need to download the "seattleWeather_1948-2017.csv" dataset from the resource section and upload it to the Lab. We will use the Up arrow icon which is shown on the left side under the View icon. Click on the Up arrow icon and upload the file wherever it is downloaded in your system.

After this, you will see the downloaded file on the left side of your lab with all the .ipynb files.

Loading the dataset

In [3]:
```
data = pd.read_csv('./seattleWeather_1948-2017.csv')
```

Preview the information of first 5 weather conditions

In [4]:
```
data.head()
```

Out[4]:

	DATE	PRCP	TMAX	TMIN	RAIN
0	1948-01-01	0.47	51	42	True
1	1948-01-02	0.59	45	36	True
2	1948-01-03	0.42	45	35	True
3	1948-01-04	0.31	45	34	True
4	1948-01-05	0.17	45	32	True

Preview the information of last 5 weather conditions.

In [5]:
```
data.tail()
```

Out[5]:

	DATE	PRCP	TMAX	TMIN	RAIN
25546	2017-12-10	0.0	49	34	False
25547	2017-12-11	0.0	49	29	False
25548	2017-12-12	0.0	46	32	False
25549	2017-12-13	0.0	48	34	False
25550	2017-12-14	0.0	50	36	False

Check the name of all columns available in dataset

In [6]:
```
#See columns in data
data.columns
```

Out[6]:
```
Index(['DATE', 'PRCP', 'TMAX', 'TMIN', 'RAIN'], dtype='object')
```

A Python data frame's summary statistics are computed and shown using the describe() function.

In [7]:
```
data.describe()
```

Out[7]:

	PRCP	TMAX	TMIN
count	25548.000000	25551.000000	25551.000000
mean	0.106222	59.544206	44.514226
std	0.239031	12.772984	8.892836
min	0.000000	4.000000	0.000000
25%	0.000000	50.000000	38.000000
50%	0.000000	58.000000	45.000000
75%	0.100000	69.000000	52.000000
max	5.020000	103.000000	71.000000

In [9]:
```
data.isna().sum(axis=0)
```

Out[9]:
```
DATE     0
PRCP     3
TMAX     0
TMIN     0
RAIN     3
dtype: int64
```

Finding and Treating Null Values

To make our data trainable, it is important to get rid of the null values.

Following are the techniques used to fix the missing values:

- Substituting the null values with either the median or mean

  Note: Median is preferred, as it is more robust to outliers.

- Dropping the column for the instances where the majority of data is missing

Now, let's deep dive to get specific detail in the missing column.

In [10]:
```
#Finding rows having null values in the 'PRCP' columns
data[pd.isnull(data['PRCP'])]
```

Out[10]:

	DATE	PRCP	TMAX	TMIN	RAIN
18415	1998-06-02	NaN	72	52	NaN
18416	1998-06-03	NaN	66	51	NaN
21067	2005-09-05	NaN	70	52	NaN

There are **three rows** in **'PRCP'** column which have null values

In [11]:
```
#Finding rows having null values in the 'RAIN' columns
data[pd.isnull(data['RAIN'])]
```

Out[11]:

	DATE	PRCP	TMAX	TMIN	RAIN
18415	1998-06-02	NaN	72	52	NaN
18416	1998-06-03	NaN	66	51	NaN
21067	2005-09-05	NaN	70	52	NaN

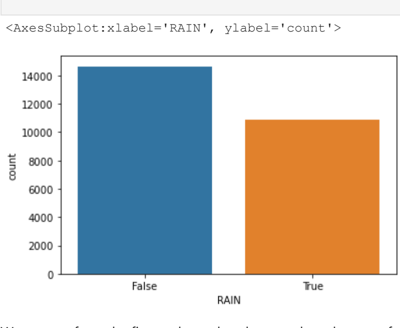
There are **three rows** in **'RAIN'** column which have null values

We learned from the above code that there is a missed value for the 9/5/2005 date column for PRCP and RAIN.

Plot graph to determine the chances of rain

In [12]:
```
sns.countplot(data=data, x='RAIN')
```

Out[12]:
```
<AxesSubplot:xlabel='RAIN', ylabel='count'>
```



We can see from the figure above that there are less chances of rain. So, in the missing information, we can just insert "False".

In [13]:
```
#It is safer to insert a mean value in the PRCP column instead of dropping one row.
data['PRCP'].mean()
```

Out[13]:
```
0.10622162204477956
```

Custom function to determine the chances of 'RAIN'

In [14]:
```
def RAIN_INSERTION(cols):
    RAIN=cols[0]
    if pd.isnull(RAIN):
        return 'False'
    else:
        return RAIN
```

Custom function to determine the amount of 'Precipitation'

In [15]:
```
def PRCP_INSERTION(col):
    PRCP=col[0]
    if pd.isnull(PRCP):
        return data['PRCP'].mean()
    else:
        return PRCP
```

In [16]:
```
#Applying function to determine the chances of rain
data['RAIN']=data[['RAIN']].apply(RAIN_INSERTION,axis=1)
```

In [17]:
```
##Applying function to determine the chances of rain
data['PRCP']=data[['PRCP']].apply(PRCP_INSERTION,axis=1)
```

Now, let's check if the function worked or not.

In [18]:
```
data[pd.isnull(data['RAIN'])]
```

Out[18]:

DATE	PRCP	TMAX	TMIN	RAIN

In [19]:
```
data[pd.isnull(data['PRCP'])]
```

Out[19]:

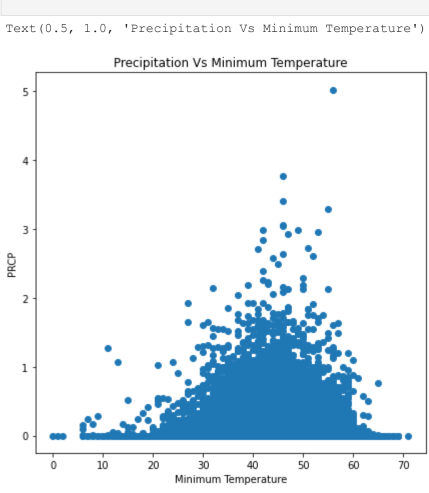
DATE	PRCP	TMAX	TMIN	RAIN

Exploratory Data Analysis

Plot graph to determine the correlation between Precipitation and Minimum Temperature

In [20]:
```
#First explore data for Temperature and Percipitation
plt.figure(figsize=(7,7))
plt.scatter(x='TMIN',y='PRCP',data=data)
plt.xlabel('Minimum Temperature')
plt.ylabel('PRCP')
plt.title('Precipitation Vs Minimum Temperature')
```

Out[20]:
```
Text(0.5, 1.0, 'Precipitation Vs Minimum Temperature')
```

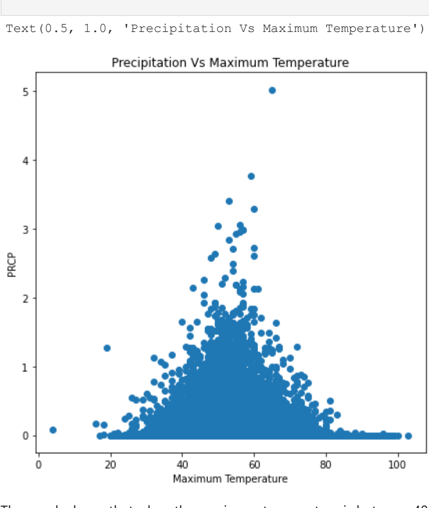


The graph shows that when the minimum temperature is between 30 and 60 degrees, the amount of precipitation increases

Plot graph to determine the correlation between Precipitation and Maximum Temperature

In [21]:
```
plt.figure(figsize=(7,7))
plt.scatter(x='TMAX',y='PRCP',data=data)
plt.xlabel('Maximum Temperature')
plt.ylabel('PRCP')
plt.title('Precipitation Vs Maximum Temperature')
```

Out[21]:
```
Text(0.5, 1.0, 'Precipitation Vs Maximum Temperature')
```



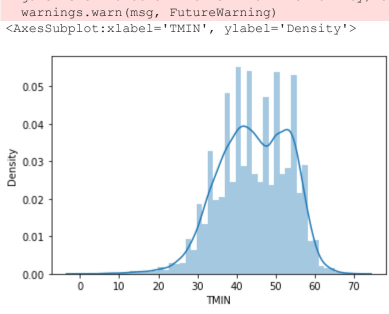
The graph shows that when the maximum temperature is between 40 and 80 degrees, the amount of precipitation increases.

Plot graph to determine the overall distribution of minimum temperature

In [22]:
```
#Plotting Distribution Plot
sns.distplot(data['TMIN'])
```

```
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[22]:
```
<AxesSubplot:xlabel='TMIN', ylabel='Density'>
```



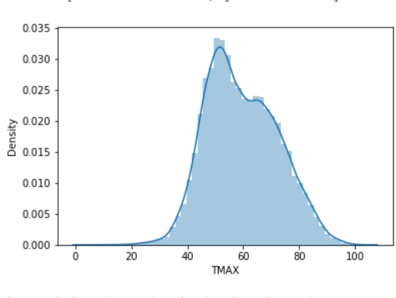
The graph shows increasing density when the minimum temperature is between 30 to 60 degrees.

Plot graph to determine the overall distribution of maximum temperature

In [24]:
```
#Plotting Distribution Plot
sns.distplot(data['TMAX'])
```

```
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[24]:
```
<AxesSubplot:xlabel='TMAX', ylabel='Density'>
```

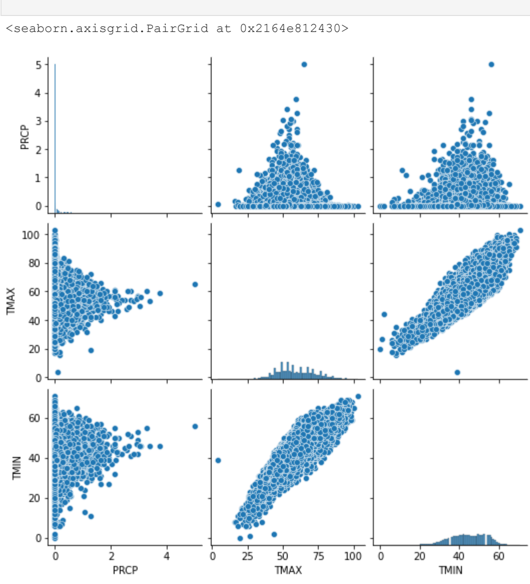


The graph shows increasing density when the maximum temperature is between 40 to 60 degrees.

Plot graph to determine pairwise relationship between precipitation, maximum temperature, and minimum temperature

In [25]:
```
#Plotting pairplot
sns.pairplot(data=data)
```

Out[25]:
```
<seaborn.axisgrid.PairGrid at 0x2164e812430>
```



The graph shows relationship between amount of precipitation, maximum, and minimum temperature.

Plot graph to determine the outliers in precipitation, maximum temperature, and minimum temperature

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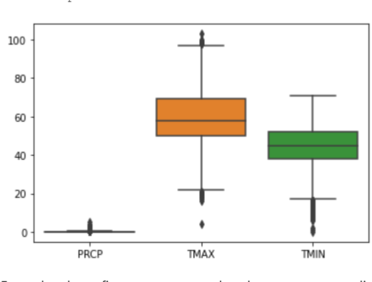
In [26]:
```
#Plotting boxplot
sns.boxplot(data=data)
```

Out[26]:
```
<AxesSubplot:>
```



From the above figure, we can say that there are some outliers.

Outlier Treatment

Let's remove the outliers from the data.

In [27]:
```
#Dropping the outliers from TMIN column
data=data.drop(data[data['TMIN']<17 ].index)
```

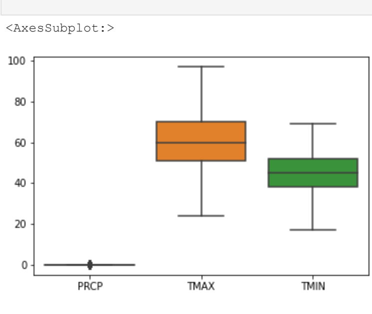
In [28]:
```
#Dropping the outliers from TMAX columns i.e. the value more than 100
data=data.drop(data[(data['TMAX']>97.5) | (data['TMAX']< 21.5)].index)
```

In [29]:
```
#Dropping the outliers from PRCP columns i.e. the value more than 0.275
data=data.drop(data[(data['PRCP']>0.25) | (data['PRCP']< -0.15) ].index)
```

Let's check whether the outliers are removed or not.

In [31]:
```
sns.boxplot(data=data)
```

Out[31]:
```
<AxesSubplot:>
```

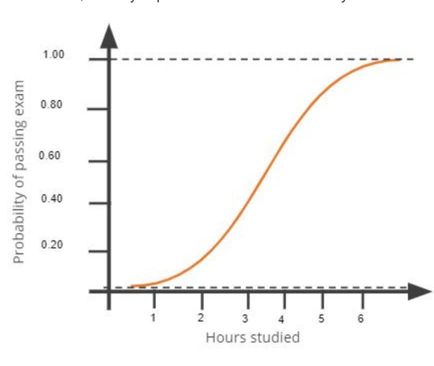


Logistic Regression

Logistic Regression is widely used to predict binary outcomes for a given set of independent variables.

This is true in a case where the dependent variable's outcome is discrete such as $y \in \{0, 1\}$.

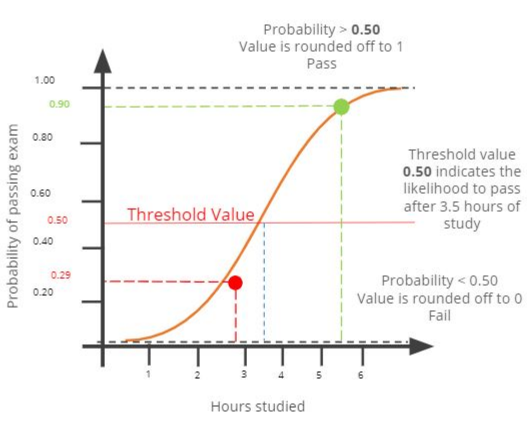
In other words, a binary dependent variable can have only two values such as 0 or 1, win or lose, pass or fail, or healthy or sick.



Understanding the Maximum Likelihood Estimation

- Unlike Linear Regression (and its Normal Equation solution), there is no closed form solution for finding optimal weights of Logistic Regression.
- Instead, we must solve this with maximum likelihood estimation (a probability model to detect maximum likelihood of something happening).
- The probability distribution of output y is restricted to 1 or 0. This is called as the sigmoid probability (σ).

  Note: If σ (θTx) > 0.5, set y = 1, else set y = 0



Logistic Regression Equation and Sigmoid Probability

1. The Logistic regression equation is derived from the straight line equation:

Equation of a straight line

Y = bx1 + cx2 + D → Range is from – (infinity) to (infinity)

Deducing the logistic regression equation from straight line equation

Y = bx1 + cx2 + D → In logistic equation, Y can be only from 0 to 1

Transform it to get the range

$\frac{Y}{1-Y}$ Y= 0 then 0; Y= 1 then infinity → Now, the range is between 0 to infinity

Transform it further to get range: (infinity) to (infinity)

$\log\left[\frac{Y}{1-Y}\right] \Rightarrow$ Y = bx1 + cx2 + D → **Final Logistic Regression Equation**

1. Sigmoid Probability:

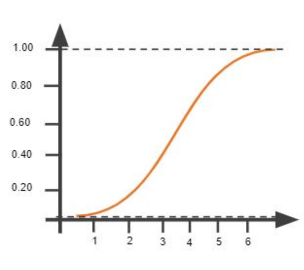
The probability in the logistic regression is represented by the Sigmoid function (logistic function or the S-curve).

$$S(t) = \frac{1}{1+e^{-t}}$$

The sigmoid function gives an 'S' shaped curve.

This curve has a finite limit that is Y can only be 0 or 1

0 as x approaches to $-\infty$
1 as x approaches to $+\infty$



Importing Logistic Regression Model

In [32]:
```
#Importing Logistic Regression model
from sklearn.linear_model import LogisticRegression
```

In [33]:
```
lr= LogisticRegression()
```

In [34]:
```
#Importing "train_test-split" function to test the model
from sklearn.model_selection import train_test_split
```

In [35]:
```
X=data.drop(['RAIN','DATE'],axis=1)
y=data['RAIN']
y=y.astype('str')
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

In [36]:
```
#Fit the model in train and test data
lr.fit(X_train,y_train).score(X_train,y_train)
```

Out[36]:
```
0.915889070146819
```

The accuracy score is 91%. It means the model is predicting fairly well.

In [37]:
```
#Now fitting the model in test set
prediction=lr.predict(X_test)
```

In [38]:
```
#Printing first 5 rows after fitting the model in test set
print (X_test.head())
```

```
       PRCP  TMAX  TMIN
3704   0.20    56    44
7292   0.00    36    31
17243  0.25    57    48
4957   0.00    69    54
19810  0.00    52    42
```

Note: In this topic, we saw the use of the logistic regression methods, but in the next topic we will be working on "Classification".

In [ ]: