

# Algerian Forest Fire EDA Practical Implementation

## Life cycle of Machine learning Project

- 1 Understanding the Problem Statement
- 2 Data Collection
- 3 Exploratory data analysis
- 4 Data Cleaning
- 5 Data Pre-Processing
- 6 Model Training
- 7 Choose best model

## 1) Problem statement.

- 1 The dataset Comprises of two regions of Algeria, namely the Bejaia region located in the northeast of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria.
- 2
- 3 If User can Predict that Algerian Forest will Catch Fire or Not based on Input Features.
- 4
- 5 Prediction result can be used for Forest Fire Situation Tackers & Make Correct Preventions to Avoid it in future.

## 2) Data Collection.

- 1 The Dataset is collected from Website named, UCI Machine Learning Repository.
- 2
- 3 The data consists of 15 columns and 244 rows.

## Import Data and Required Packages

```
In [ ]: 1 #importing required libraies
        2 import pandas as pd
        3 import numpy as np
        4 import matplotlib.pyplot as plt
        5 import seaborn as sns
        6 import plotly.express as px
        7 import warnings
        8
        9 warnings.importwarnings("ignore")
       10 %matplotlib inline
```

## loading csv dataset as dataframe

In [16]: 1 df = pd.read\_csv(r"C:\Users\user\Downloads\Algerian\_forest\_fires\_dataset\_UPD

## showing top 5 records

In [17]: 1 df.head()

Out[17]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire
4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire

## shape of the dataset

In [19]: 1 df.shape

Out[19]: (246, 14)

## summary of the dataset

In [23]: 1 df.describe()

Out[23]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
count	246	245	245	245	245	245	245	245	245	245	245	245	245	2
unique	33	5	2	20	63	19	40	174	167	199	107	175	128	
top	01	07	2012	35	64	14	0	88.9	7.9	8	1.1	3	0.4	f
freq	8	62	244	29	10	43	133	8	5	5	8	5	12	1

## Check Datatypes in the dataset

In [26]:

```
1 df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246 entries, 0 to 245
Data columns (total 14 columns):
#   Column          Non-Null Count  Dtype
---  -
0   day              246 non-null    object
1   month            245 non-null    object
2   year             245 non-null    object
3   Temperature      245 non-null    object
4   RH               245 non-null    object
5   Ws               245 non-null    object
6   Rain             245 non-null    object
7   FFMC             245 non-null    object
8   DMC              245 non-null    object
9   DC               245 non-null    object
10  ISI              245 non-null    object
11  BUI              245 non-null    object
12  FWI              245 non-null    object
13  Classes          244 non-null    object
dtypes: object(14)
memory usage: 27.0+ KB
```

### 3) DATA Cleaning

#### Removing Unnecessary Rows From Dataset

In [28]:

```
1 df.drop(index=[122,123], inplace=True)
2 df.reset_index(inplace=True)
3 df.drop('index', axis=1, inplace=True)
```

#### Adding New Feature, named 'Region' in a Dataset

In [30]:

```
1 df.loc[:,122, 'region'] = 'bejaia'
2 df.loc[122:, 'region'] = 'Sidi-Bel Abbes'
```

#### Stripping the names of the columns

In [32]:

```
1 df.columns = [i.strip() for i in df.columns]
2 df.columns
```

Out[32]: Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'region'], dtype='object')

#### Stripping the Classes Features data

```
In [34]: 1 df.Classes = df.Classes.str.strip()
          2 df['Classes'].unique()
```

Out[34]: array(['not fire', 'fire', nan], dtype=object)

```
In [35]: 1 df.head()
```

Out[35]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	req
0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	be
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire	be
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	be
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire	be
4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire	be

## Changing The DataTypes of the Columns

```
In [37]: 1 df['day']=df['day'].astype(int)
2 df['month']=df['month'].astype(int)
3 df['year']=df['year'].astype(int)
4 df['Temperature']=df['Temperature'].astype(int)
5 df['RH']=df['RH'].astype(int)
6 df['Rain']=df['Rain'].astype(float)
7 df['FFMC']=df['FFMC'].astype(float)
8 df['DMC']=df['DMC'].astype(float)
9 df['BUI']=df['BUI'].astype(float)
10 df['ISI']=df['ISI'].astype(float)
11 df['Ws']=df['Ws'].astype(float)
12 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 15 columns):
#   Column          Non-Null Count  Dtype
---  -
0   day              244 non-null    int32
1   month            244 non-null    int32
2   year             244 non-null    int32
3   Temperature      244 non-null    int32
4   RH               244 non-null    int32
5   Ws               244 non-null    float64
6   Rain             244 non-null    float64
7   FFMC             244 non-null    float64
8   DMC              244 non-null    float64
9   DC               244 non-null    object
10  ISI              244 non-null    float64
11  BUI              244 non-null    float64
12  FWI              244 non-null    object
13  Classes          243 non-null    object
14  region           244 non-null    object
dtypes: float64(6), int32(5), object(4)
memory usage: 24.0+ KB
```

### Adding New Feature,named 'Date' by Replacing Unnecessary feature like 'day','month','year'

```
In [43]: 1 df["date"] = pd.to_datetime(df[["day","month","year"]])
2 df.drop(["day","month","year"],axis=1,inplace = True)
```

### Showing Updated Dataset after Modification Done.

In [44]: 1 df.head()

Out[44]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	region	date
0	29	57	18.0	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	bejaia	2012-06-01
1	29	61	13.0	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	bejaia	2012-06-02
2	26	82	22.0	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	bejaia	2012-06-03
3	25	89	13.0	2.5	28.6	1.3	6.9	0.0	1.7	0	not fire	bejaia	2012-06-04
4	27	77	16.0	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire	bejaia	2012-06-05

## 4) EXPLORING DATA

### Profile of the Data

#### shape of the dataset

In [46]: 1 df.shape

Out[46]: (244, 13)

### Observation

In this Dataset there are 13 Columns & 244 Rows

#### columns of the dataset

In [48]: 1 df.columns

Out[48]: Index(['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'region', 'date'], dtype='object')

### Check Missing Value in Dataset

```
In [50]: 1 df.isnull().sum()
```

```
Out[50]: Temperature    0
          RH             0
          Ws             0
          Rain           0
          FPMC           0
          DMC            0
          DC             0
          ISI            0
          BUI            0
          FWI            0
          Classes        1
          region         0
          date           0
          dtype: int64
```

## Observation

we got one null value in classes feature

## Handling Categorical Feature Classes

```
In [51]: 1 df['Classes']=df['Classes'].map({'not fire':0,'fire':1})
          2 df.head()
```

```
Out[51]:
```

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	region	date
0	29	57	18.0	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0.0	bejaia	2012-06-01
1	29	61	13.0	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0.0	bejaia	2012-06-02
2	26	82	22.0	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0.0	bejaia	2012-06-03
3	25	89	13.0	2.5	28.6	1.3	6.9	0.0	1.7	0	0.0	bejaia	2012-06-04
4	27	77	16.0	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0.0	bejaia	2012-06-05

```
In [52]: 1 df['Classes']
```

```
Out[52]: 0    0.0
          1    0.0
          2    0.0
          3    0.0
          4    0.0
          ...
          239  1.0
          240  0.0
          241  0.0
          242  0.0
          243  0.0
          Name: Classes, Length: 244, dtype: float64
```

## Focus on Replacing Null Value

```
In [54]: 1 df['Classes'].mode()[0]
```

```
Out[54]: 1.0
```

```
In [55]: 1 df['Classes']=df['Classes'].fillna(df['Classes'].mode()[0])
```

```
In [56]: 1 df.isnull().sum()
```

```
Out[56]: Temperature    0
          RH            0
          Ws            0
          Rain          0
          FFMC          0
          DMC           0
          DC            0
          ISI           0
          BUI           0
          FWI           0
          Classes       0
          region       0
          date         0
          dtype: int64
```

## Observations

after modification now we have Zero Null Value in dataset

```
In [62]: 1 df["Classes"].unique()
```

```
Out[62]: array([0., 1.])
```

## Check Datatypes in the dataset



In [63]:

```
1 df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 13 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Temperature     244 non-null    int32
1   RH              244 non-null    int32
2   Ws              244 non-null    float64
3   Rain            244 non-null    float64
4   FFMC            244 non-null    float64
5   DMC             244 non-null    float64
6   DC              244 non-null    object
7   ISI             244 non-null    float64
8   BUI             244 non-null    float64
9   FWI             244 non-null    object
10  Classes         244 non-null    float64
11  region          244 non-null    object
12  date            244 non-null    datetime64[ns]
dtypes: datetime64[ns](1), float64(7), int32(2), object(3)
memory usage: 23.0+ KB
```

## observations

- 1 There is total 244 rows and 13 columns.
- 2 There are No Null Value in Dataset
- 3 There is total 4 data types float64, int64, object and datetime64.
- 4 Dtypes Included float64 = 7 Columns, int64 = 2 Columns, object = 3 Columns and datetime64 = 1
- 5 Total Memory Usage is 23.0+ KB

## Checking the usage of the memory by the dataset

In [65]:

```
1 df.memory_usage()
```

Out[65]:

Index	128
Temperature	976
RH	976
Ws	1952
Rain	1952
FFMC	1952
DMC	1952
DC	1952
ISI	1952
BUI	1952
FWI	1952
Classes	1952
region	1952
date	1952

dtype: int64

# Numerical and Categorical Columns

## Numerical dataset

```
In [66]: 1 # 1. Getting Numerical features from dataset
2 # 2. Creating Numerical dataframe
3 numerical_features = [feature for feature in df.columns if df[feature].dtype
4
5 # Print Numerical Features
6 print('We have {} numerical features : {}'.format(len(numerical_features), n
```

We have 10 numerical features : ['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'Classes', 'date']

## Categorical dataset

```
In [71]: 1 # 1. Getting categorical features from dataset
2 # 2. Creating categorical dataframe
3 categorical_features = [feature for feature in df.columns if df[feature].dty
4
5 # Print Numerical Features
6 print('We have {} categorical features : {}'.format(len(categorical_features
```

We have 3 categorical features : ['DC', 'FWI', 'region']

## Feature Information

```
In [72]: 1 df.head()
```

Out[72]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	region	date
0	29	57	18.0	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0.0	bejaia	2012-06-01
1	29	61	13.0	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0.0	bejaia	2012-06-02
2	26	82	22.0	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0.0	bejaia	2012-06-03
3	25	89	13.0	2.5	28.6	1.3	6.9	0.0	1.7	0	0.0	bejaia	2012-06-04
4	27	77	16.0	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0.0	bejaia	2012-06-05

## Weather data observations

```
1 Temperature : temperature noon (temperature max) in Celsius degrees: 22 to 42
2 RH : Relative Humidity in %: 21 to 90
3 Ws :Wind speed in km/h: 6 to 29
4 Rain: total day in mm: 0 to 16.8
```

## FWI Components

- 1 (FFMC) Fine Fuel Moisture Code index from the FWI system: 28.6 to 92.5
- 2 (DMC) Duff Moisture Code index from the FWI system: 1.1 to 65.9
- 3 (DC) Drought Code index from the FWI system: 7 to 220.4
- 4 (ISI) Initial Spread Index from the FWI system: 0 to 18.5
- 5 (BUI) Buildup Index from the FWI system: 1.1 to 68
- 6 (FWI) Fire Weather Index: 0 to 31.1
- 7
- 8 Classes: two classes, namely Fire and not Fire.
- 9
- 10 Region: Two Regions, namely Bejaia Region indicated with 0 and Sidi Bel-Abbes Region indicated with 1.

## DATE Observations (DD/MM/YYYY) :-

Date Displayed in (DD/MM/YYYY) format in dataset

## Univariate Analysis

The term univariate analysis refers to the analysis of one variable prefix  $\text{uni}$  means  $\text{one}$ . The purpose of univariate analysis is to understand the distribution of values for a single variable.

In [75]:

```
1 df.var()
```

C:\Users\user\AppData\Local\Temp\ipykernel\_8576\1568254755.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric\_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction.  
df.var()

```
Out[75]: Temperature    13.204817
RH                    221.539415
Ws                     7.897102
Rain                   3.997623
FFMC                   205.565939
DMC                    152.968382
ISI                    17.433281
BUI                    201.777024
Classes                 0.246711
dtype: float64
```

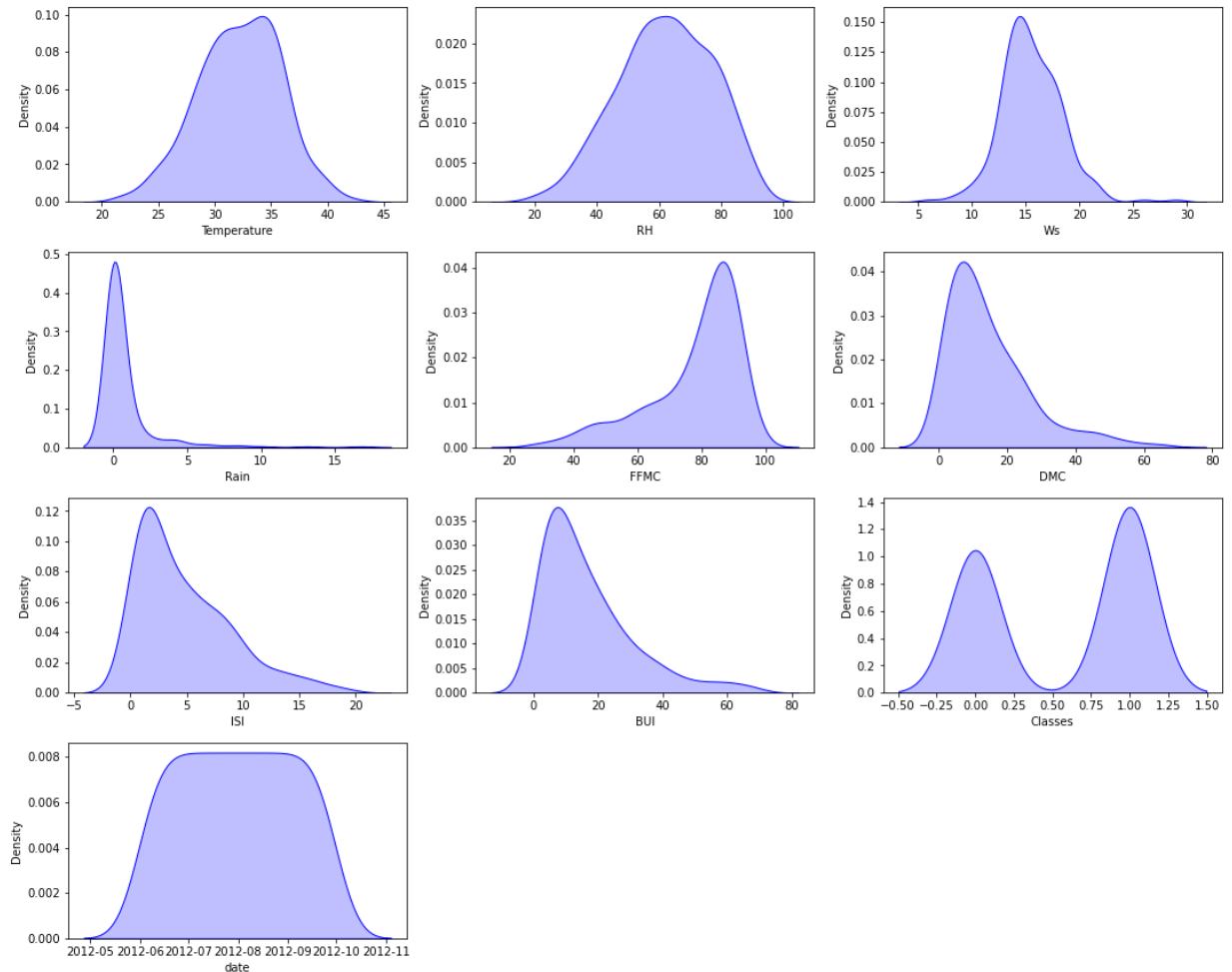
## Numerical Features

```

In [77]: 1 plt.figure(figsize=(15, 15))
2 plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontw
3
4 for i in range(0, len(numerical_features)):
5     plt.subplot(5, 3, i+1)
6     sns.kdeplot(x=df[numerical_features[i]],shade=True, color='b')
7     plt.xlabel(numerical_features[i])
8     plt.tight_layout()

```

**Univariate Analysis of Numerical Features**



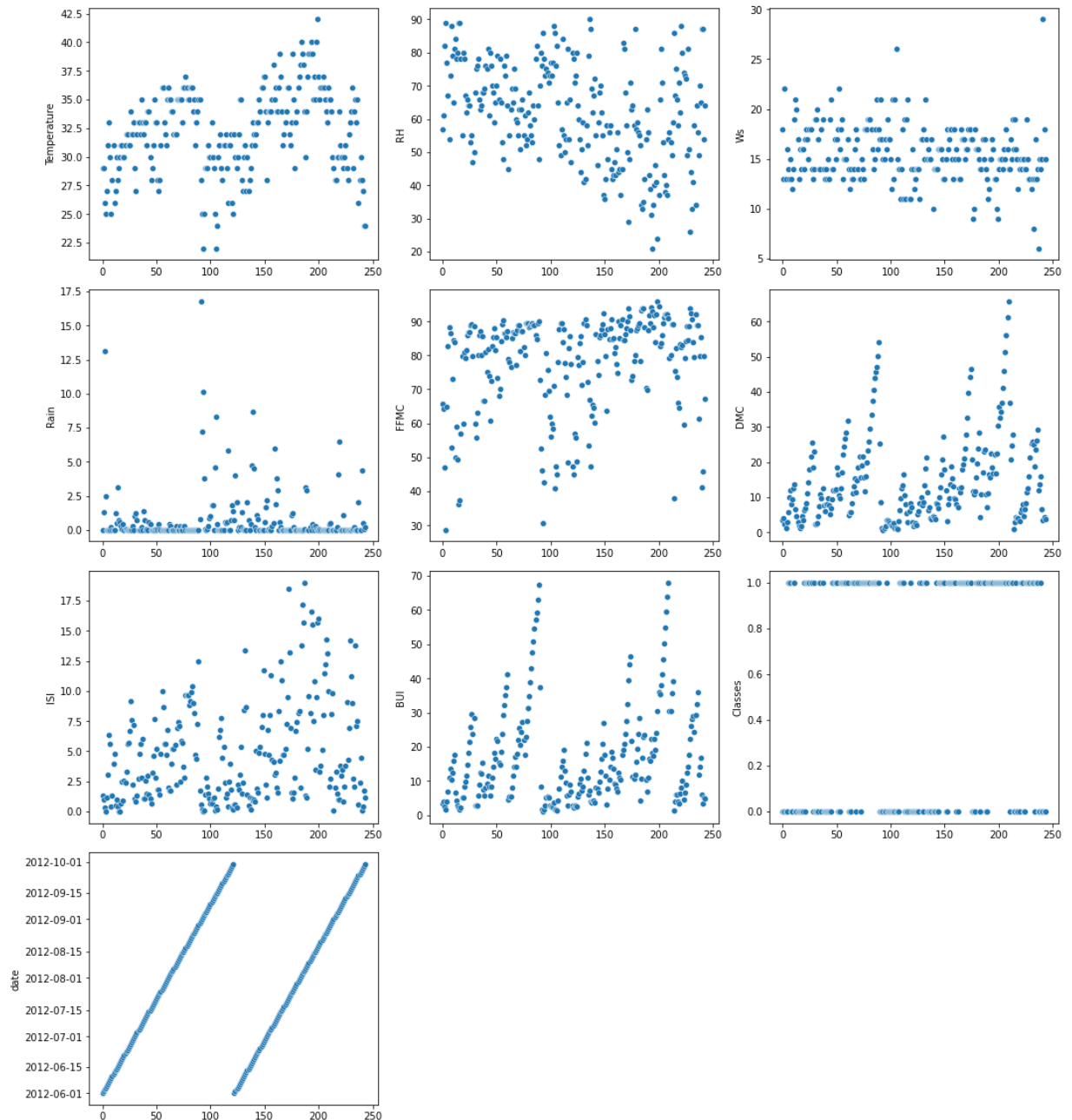
## Observations

- 1 Rain, ISI, BUI, DMC are right skewed and postively skewed.
- 2 FFM is a Left skewed and Negatively skewed.
- 3 Outliers in Rain, ISI, BUI, DMC and FFM

## Scatter plot to see the trends in each numerical column

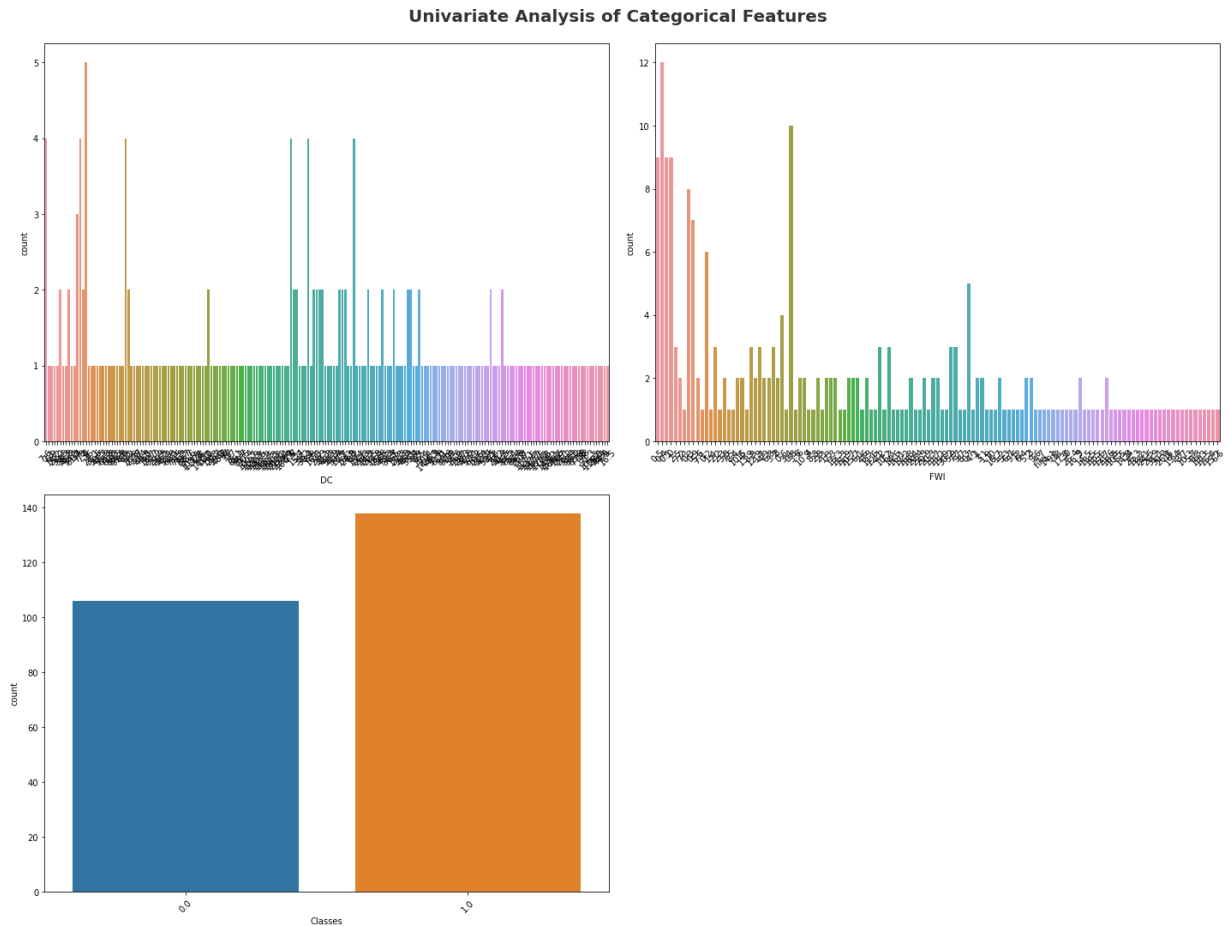
```
In [79]: 1 plt.figure(figsize=(15, 20))
2 plt.suptitle('scatter plot with each numerical feature to explore feature',
3
4 for i in range(0, len(numerical_features)):
5     plt.subplot(5, 3, i+1)
6     sns.scatterplot(y=numerical_features[i], x=df.index, data=df)
7     plt.tight_layout()
```

**scatter plot with each numerical feature to explore feature**



## Categorical Features

```
In [81]: 1 plt.figure(figsize=(20, 15))
2 plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fon
3 cat1 = ['DC', 'FWI', 'Classes']
4 for i in range(0, len(cat1)):
5     plt.subplot(2, 2, i+1)
6     sns.countplot(x=df[cat1[i]])
7     plt.xlabel(cat1[i])
8     plt.xticks(rotation=45)
9     plt.tight_layout()
```



## observations

- 1 Extreme value of Temperature is above 40
- 2 Most of the time RH is above 30
- 3 WS values lie between 10 to 20

```
In [83]: 1 # Bivariate analysis and multivariate analysis
2 # stripplot (categorical vs numerical)
3 # scatterplot / pairplot (numerical vs numerical) (check correlation)
4 # boxplot (outliers)
5 # heatmap (correlation)
6 # lineplot (trend in numerical feature with time)
```

## Multicolleniarity in numerical features

```
In [84]: 1 df.corr()
```

Out[84]:

	Temperature	RH	Ws	Rain	FFMC	DMC	ISI	B
Temperature	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483105	0.607551	0.455504
RH	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405133	-0.690637	-0.348587
Ws	-0.278132	0.236084	1.000000	0.170169	-0.163255	-0.001246	0.015248	0.029756
Rain	-0.326786	0.222968	0.170169	1.000000	-0.544045	-0.288548	-0.347105	-0.299171
FFMC	0.677491	-0.645658	-0.163255	-0.544045	1.000000	0.602391	0.739730	0.589652
DMC	0.483105	-0.405133	-0.001246	-0.288548	0.602391	1.000000	0.674499	0.982073
ISI	0.607551	-0.690637	0.015248	-0.347105	0.739730	0.674499	1.000000	0.635891
BUI	0.455504	-0.348587	0.029756	-0.299171	0.589652	0.982073	0.635891	1.000000
Classes	0.518119	-0.435023	-0.066529	-0.379449	0.770114	0.584188	0.735511	0.583891

```
In [85]: 1 plt.figure(figsize = (15,10))
2         sns.heatmap(df.corr(), cmap="CMRmap", annot=True)
3         plt.show()
```





**observation**

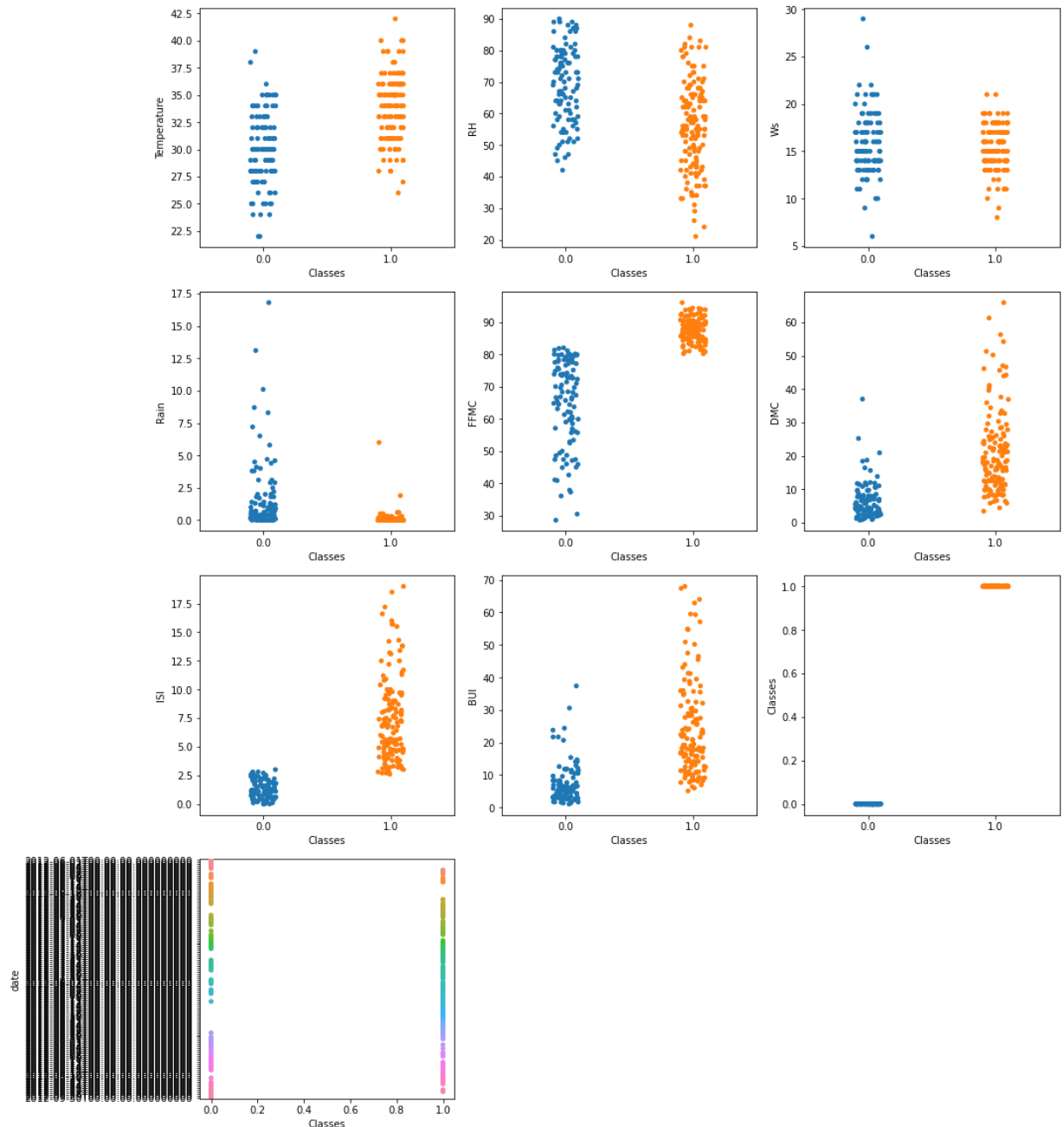
Highly +ve correlated features are DMC and

Highly -ve correlated features are RH and Temp, RH and FFMC, RH and ISI

**strip plot to see the relationship between numerical features and target**

```
In [86]: 1 plt.figure(figsize=(15, 20))
2 plt.suptitle('Strip Plot', fontsize=20, fontweight='bold', alpha=1, y=1)
3
4 for i in range(0, len(numerical_features)):
5     plt.subplot(5, 3, i+1)
6     sns.stripplot(y=numerical_features[i], x='Classes', data=df)
7     plt.tight_layout()
```

Strip Plot



## observation -

Note :- Here 0 = 'not Fire' and 1 = 'Fire'

places with higher temperature has fire

places with lower RH has fire

places with  $ffmc > 80$  has fire

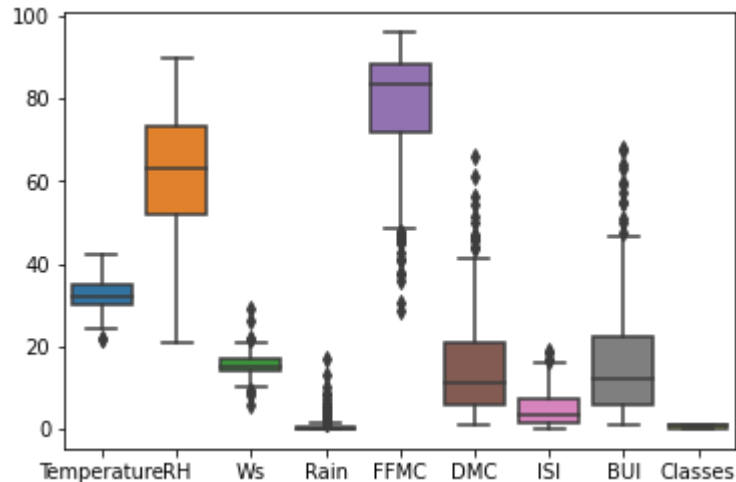
places with  $ISI > 2.5$  has fire

places with  $Rain < 2$  has fire

## Boxplot to find Outliers in the features

```
In [87]: 1 sns.boxplot(data = df,orient="v")
```

```
Out[87]: <AxesSubplot:>
```



## Observation:-

RH, Rain, FFMC, DMC BUI has many outliers

## Statistical Analysis

```
In [88]: 1 df.describe()
```

```
Out[88]:
```

	Temperature	RH	Ws	Rain	FFMC	DMC	ISI	Classes
<b>count</b>	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000
<b>mean</b>	32.172131	61.938525	15.504098	0.760656	77.887705	14.673361	4.774180	16.6
<b>std</b>	3.633843	14.884200	2.810178	1.999406	14.337571	12.368039	4.175318	14.2
<b>min</b>	22.000000	21.000000	6.000000	0.000000	28.600000	0.700000	0.000000	1.1
<b>25%</b>	30.000000	52.000000	14.000000	0.000000	72.075000	5.800000	1.400000	6.0
<b>50%</b>	32.000000	63.000000	15.000000	0.000000	83.500000	11.300000	3.500000	12.2
<b>75%</b>	35.000000	73.250000	17.000000	0.500000	88.300000	20.750000	7.300000	22.5
<b>max</b>	42.000000	90.000000	29.000000	16.800000	96.000000	65.900000	19.000000	68.0

## Observation

df.describe() return all Statistics Summary of Numeric Columns

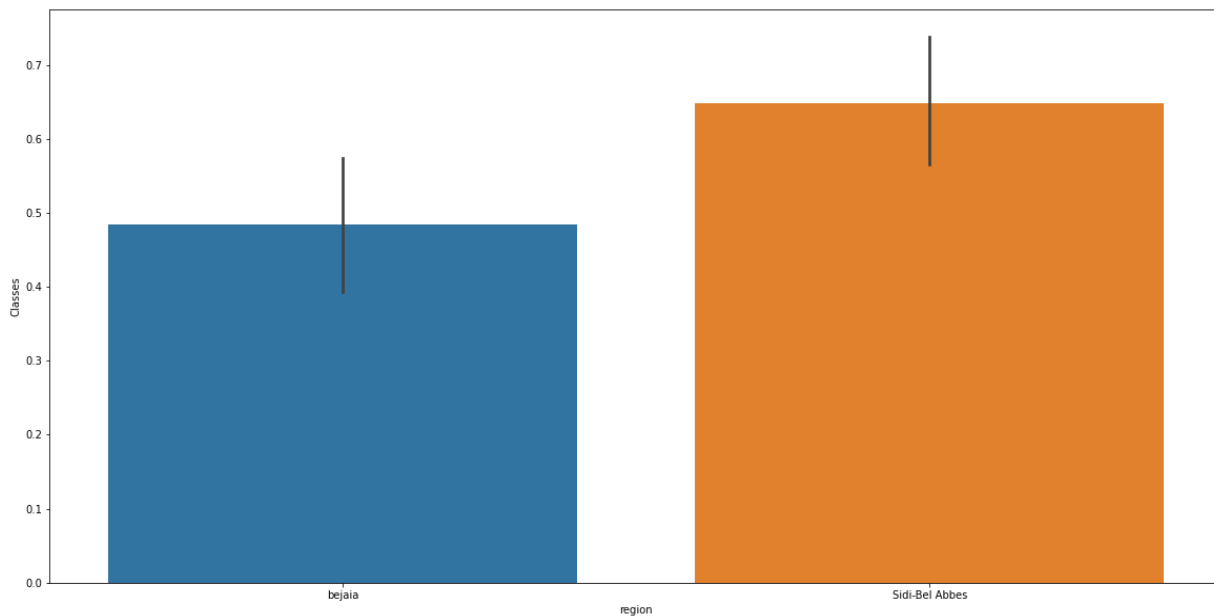
Its Return function like:- count(), mean(), std(), min(), 25%(), 50%(), 75%(), max().

## Graphical Analysis

**Which area has most of the time fire happen ?**

```
In [90]: 1 import matplotlib
          2 matplotlib.rcParams['figure.figsize']=(20,10)
          3
          4 sns.barplot(x="region",y="Classes",data=df)
```

```
Out[90]: <AxesSubplot:xlabel='region', ylabel='Classes'>
```

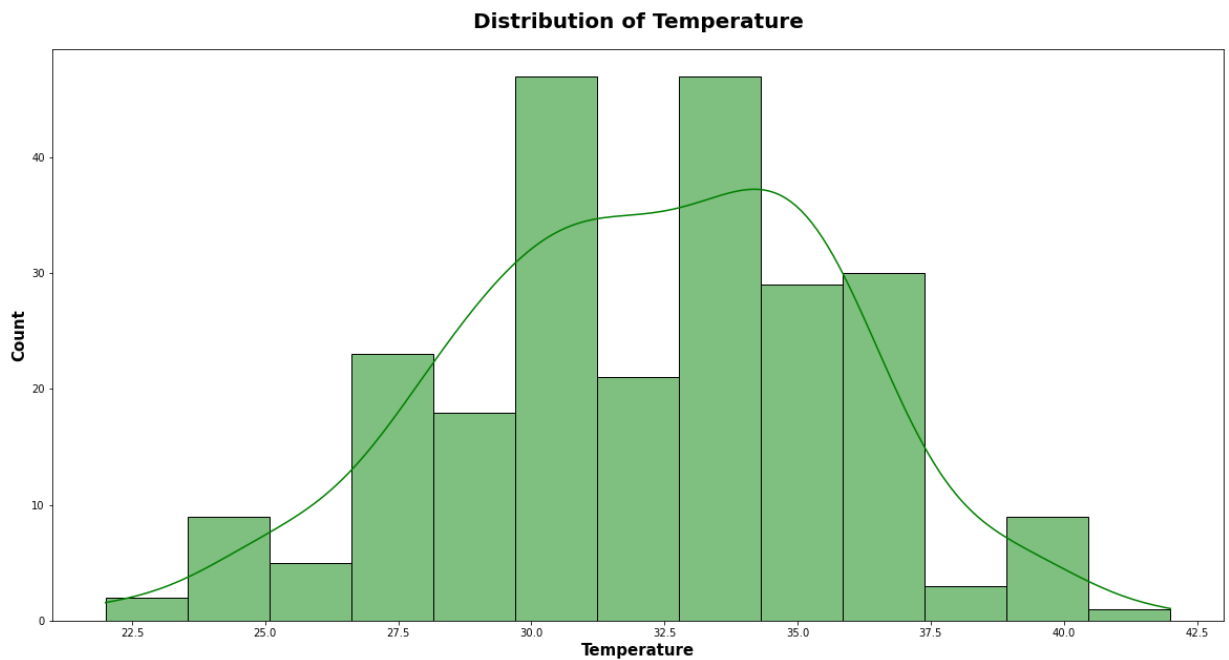


## Observation

Sidi-Bel-Abbes Region has Most of the Time Fire Took Placed.

**Temperature Range which is in most of the places ?**

```
In [91]: 1 plt.subplots(figsize=(20,10))
2 sns.histplot("Distribution of Temperature",x=df.Temperature,color='g',kde=True)
3 plt.title("Distribution of Temperature",weight='bold',fontsize=20,pad=20)
4 plt.xlabel("Temperature",weight='bold',fontsize=15)
5 plt.ylabel("Count",weight='bold',fontsize=15)
6 plt.show()
```



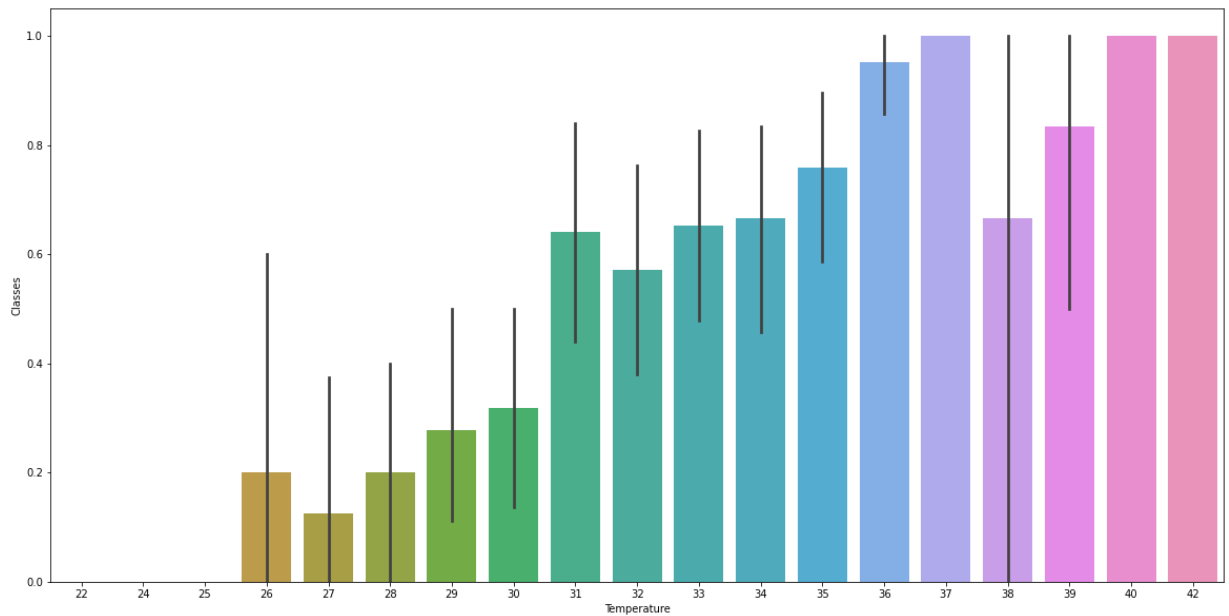
### Observation:-

Temperature occur most of the time in range 32.5 to 35.0

### Highest Temperature attained

```
In [92]: 1 import matplotlib
          2 matplotlib.rcParams['figure.figsize']=(20,10)
          3
          4 sns.barplot(x="Temperature",y="Classes",data=df)
```

Out[92]: <AxesSubplot:xlabel='Temperature', ylabel='Classes'>



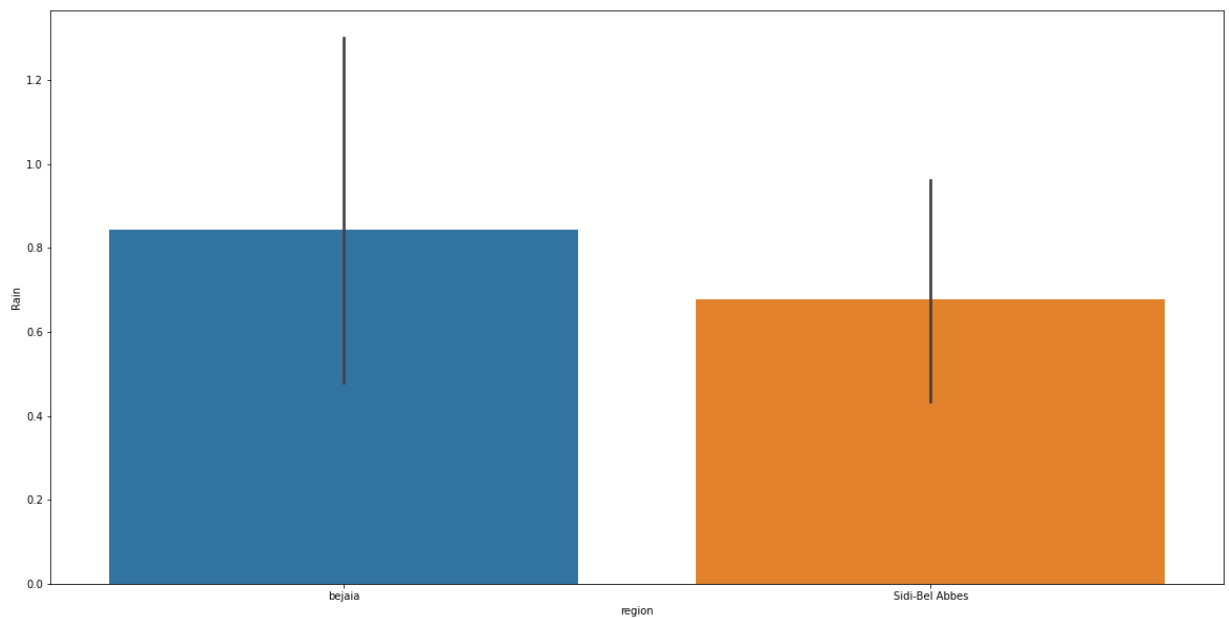
### Observation:-

Highest temperature is 42,40,37

**Which region has most time rain happens**

```
In [93]: 1 import matplotlib
          2 matplotlib.rcParams['figure.figsize']=(20,10)
          3
          4 sns.barplot(x="region",y="Rain",data=df)
```

```
Out[93]: <AxesSubplot:xlabel='region', ylabel='Rain'>
```



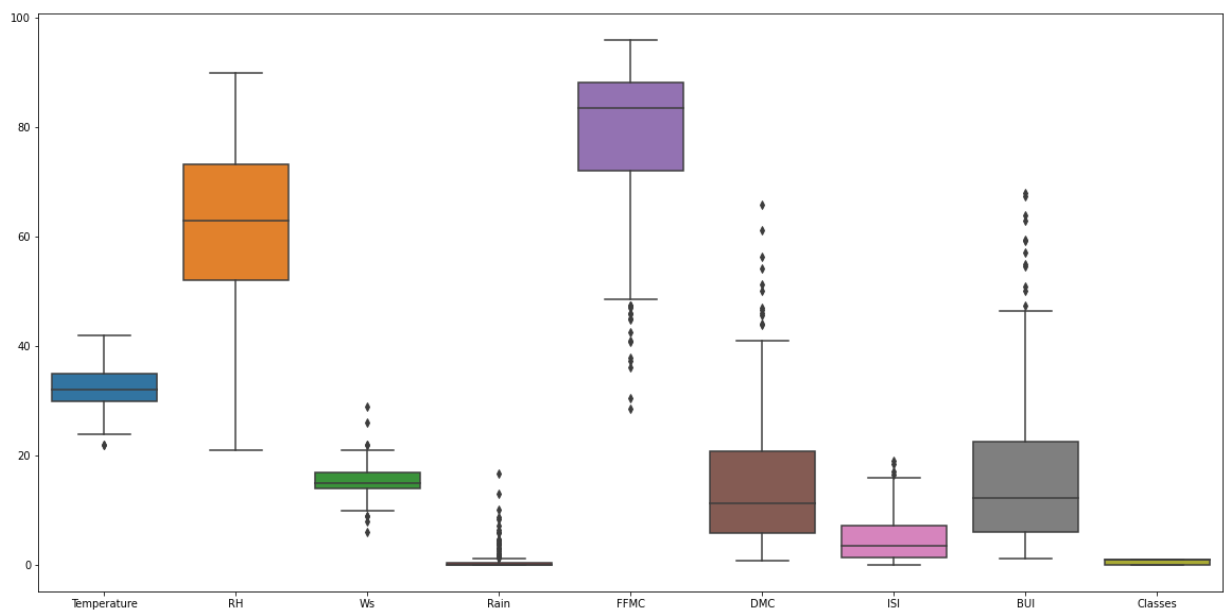
## observation

Bejaia is the region in which most of the time rain happens

## Boxplot to find Outliers in the features

```
In [94]: 1 sns.boxplot(data = df,orient="v")
```

```
Out[94]: <AxesSubplot:>
```



## Observation:-

RH, Rain, FFMC, DMC BUI has many outliers

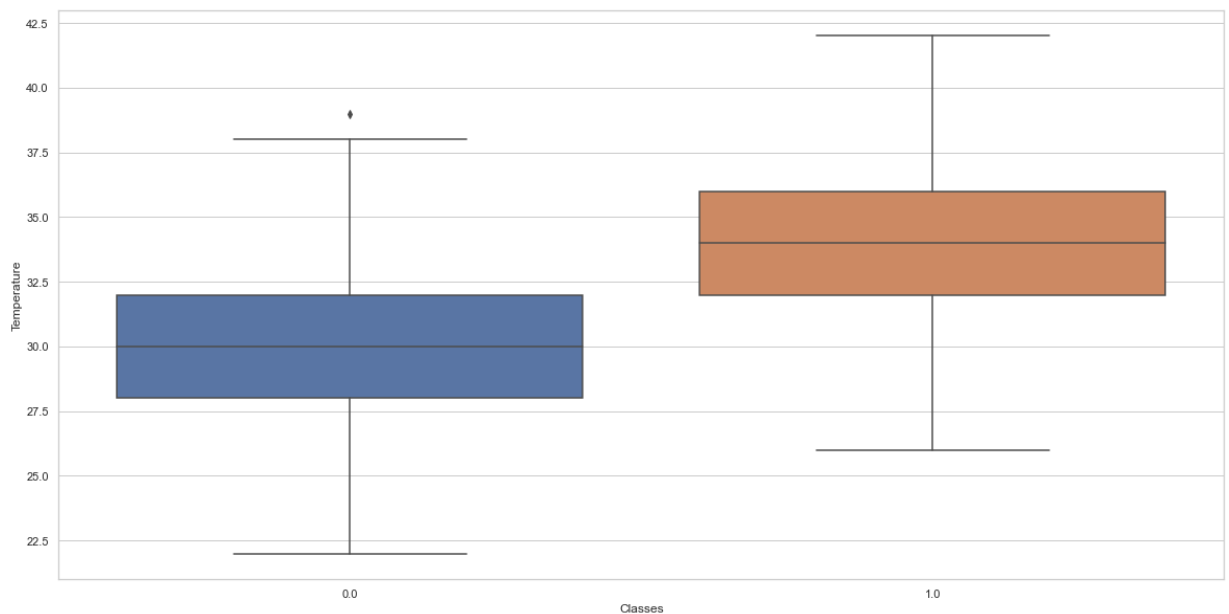
## Boxplot of Class Vs Temperature



In [96]:

```
1 # Python program to illustrate
2 # boxplot using inbuilt data-set
3 # given in seaborn
4
5 # importing the required module
6 import seaborn
7
8 # use to set style of background of plot
9 seaborn.set(style="whitegrid")
10
11 # Loading data-set
12
13 seaborn.boxplot(x = 'Classes', y = 'Temperature', data = df)
```

Out[96]: &lt;AxesSubplot:xlabel='Classes', ylabel='Temperature'&gt;



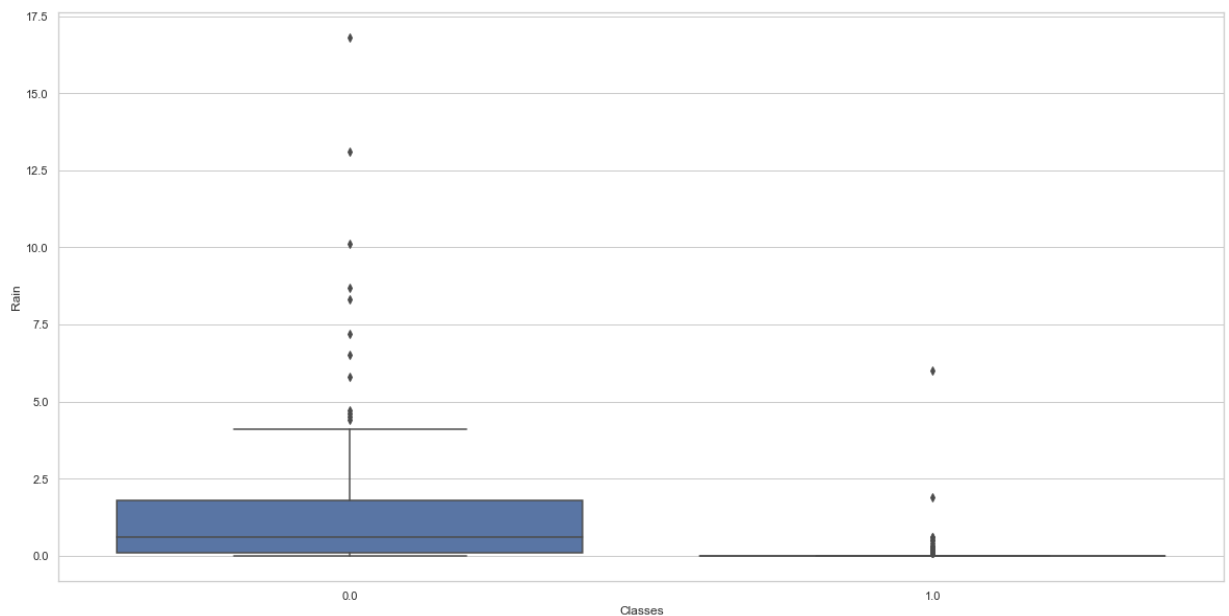
## Observations:-

One day at lower temperature fires occur

## Boxplot of Classes Vs Rain

```
In [97]: 1 # Python program to illustrate
2 # boxplot using inbuilt data-set
3 # given in seaborn
4
5 # importing the required module
6 import seaborn
7
8 # use to set style of background of plot
9 seaborn.set(style="whitegrid")
10
11 # Loading data-set
12
13 seaborn.boxplot(x = 'Classes', y = 'Rain', data = df)
```

Out[97]: <AxesSubplot:xlabel='Classes', ylabel='Rain'>



## Observation:-

In many days after having rain also fire occur