EDA (Algerian Forest Fires Dataset)

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EDA

1. Data Profiling
2. Stastical analysis
3. Graphical Analysis

Dataset: https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++#

Importing all the required libraries

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

warnings.filterwarnings('ignore')
%matplotlib inline

pd.set_option('display.max_columns', 500)
```

1.0 Importing dataset and cleaning data

```
### reading csv file
```

In [133…
```
dataset=pd.read_csv('Algerian_forest_fires_dataset_UPDATE.csv',header=1 )

dataset.iloc[121:].head(4) # index 122, 123 need to be removed from dataset
```

Out[133]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	not fire
122	Sidi-Bel Abbes Region Dataset	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
123	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
124	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fire

1.1 Dropping rows which have no information

In [134…
```
dropping rows having region name and heddersa
dataset.drop(index=[122,123], inplace=True) # droping row 122,123 from dataset
dataset.reset_index(inplace=True)
dataset.drop('index', axis=1, inplace=True)

dataset.iloc[121:].head()
```

Out[134]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	not fire
122	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fire
123	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	not fire
124	03	06	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1	not fire
125	04	06	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1	not fire

1.2 Creating Region feature

In [135…
```
### creating feature called Region 0 for Bejaia region and 1 for Sidi Bel-abbes region
dataset.loc[:122,'Region']=0
dataset.loc[122:, 'Region']=1
```

```
dataset.iloc[120:].head(8)
```

Out[135]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
120	29	09	2012	26	80	16	1.8	47.4	2.9	7.7	0.3	3	0.1	not fire	0.0
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	not fire	0.0
122	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fire	1.0
123	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	not fire	1.0
124	03	06	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1	not fire	1.0
125	04	06	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1	not fire	1.0
126	05	06	2012	32	60	14	0.2	77.1	6	17.6	1.8	6.5	0.9	not fire	1.0
127	06	06	2012	35	54	11	0.1	83.7	8.4	26.3	3.1	9.3	3.1	fire	1.0

1.3 Datatypes and describe

In [136…

```
# here it is visible that all datatypes are in object
dataset.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    object 
 1   month        244 non-null    object 
 2   year         244 non-null    object 
 3   Temperature  244 non-null    object 
 4    RH          244 non-null    object 
 5    Ws          244 non-null    object 
 6   Rain         244 non-null    object 
 7   FFMC         244 non-null    object 
 8   DMC          244 non-null    object 
 9   DC           244 non-null    object 
 10  ISI          244 non-null    object 
 11  BUI          244 non-null    object 
 12  FWI          244 non-null    object 
 13  Classes      243 non-null    object 
 14  Region       244 non-null    float64
dtypes: float64(1), object(14)
memory usage: 28.7+ KB
```

In [214…

```
dataset.describe()
```

Out[214]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	
count	244.000000	244.000000	244.0	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	24
mean	15.754098	7.500000	2012.0	32.172131	61.938525	15.504098	0.760656	77.887705	14.673361	49.288484	4.774180	16.664754	
std	8.825059	1.112961	0.0	3.633843	14.884200	2.810178	1.999406	14.337571	12.368039	47.619393	4.175318	14.204824	
min	1.000000	6.000000	2012.0	22.000000	21.000000	6.000000	0.000000	28.600000	0.700000	6.900000	0.000000	1.100000	
25%	8.000000	7.000000	2012.0	30.000000	52.000000	14.000000	0.000000	72.075000	5.800000	13.275000	1.400000	6.000000	
50%	16.000000	7.500000	2012.0	32.000000	63.000000	15.000000	0.000000	83.500000	11.300000	33.100000	3.500000	12.250000	
75%	23.000000	8.000000	2012.0	35.000000	73.250000	17.000000	0.500000	88.300000	20.750000	68.150000	7.300000	22.525000	1
max	31.000000	9.000000	2012.0	42.000000	90.000000	29.000000	16.800000	96.000000	65.900000	220.400000	19.000000	68.000000	3

1.4 Data Cleaning

In [138…
```
# here it is visible that some columns have spaces in the names like RH, Ws
dataset.columns
```
Out[138]:
```
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes  ', 'Region'],
      dtype='object')
```

In [139…
```
# stripping spaces from column names
dataset.columns= [col_name.strip() for col_name in dataset.columns]
dataset.columns
```
Out[139]:
```
Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'Region'],
      dtype='object')
```

In [141…
```
### converting all feature values to string so that we can do data cleaning as shown below.
dataset=dataset.astype(str)
```

In [142…
```
### somes values in colums also have space
for feature in ['Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes']:
    dataset[feature]= dataset[feature].str.replace(" ","")
```

In [143…
```
### index no 165 for feature name FWI has value fire
dataset[dataset['FWI']== 'fire'].index
```
Out[143]:
```
Int64Index([165], dtype='int64')
```

In [144…
```
### replacing fire value witha float value
dataset.loc[165,'FWI']=' 0.1'
```

In [146…
```
### replacing nan value wit fire to make data equal to the info given in dataset
dataset[dataset['Classes']== 'nan'].index
dataset.loc[165,'Classes']='fire'
```

1.5 Changing datatypes

In [147…
```
### changing datatypes of features to numerical for numerical features as all are in object
```

```
datatype_convert={'day':'int64','month':'int64','year':'int64','Temperature':'int64','RH':'int64', 'Ws':'int64','Rain':'float64',
                  'FFMC':'float64', 'DMC':'float64', 'DC':'float64', 'ISI':'float64', 'BUI':'float64', 'FWI':'float64',
                 'Region':'float64'}

dataset=dataset.astype(datatype_convert)
dataset.dtypes
```

Out[147]:

```
day                 int64
month               int64
year                int64
Temperature         int64
RH                  int64
Ws                  int64
Rain              float64
FFMC              float64
DMC               float64
DC                float64
ISI               float64
BUI               float64
FWI               float64
Classes            object
Region            float64
dtype: object
```

1.6 Info about dataset and its attributes

1. The dataset includes 244 instances that regroup a data 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. 122 instances for each region.
3. The period from June 2012 to September 2012.
4. The dataset includes 11 attribues and 1 output attribue (class)
5. The 244 instances have been classified into fire (138 classes) and notfire (106 classes) classes.

Attributes

1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012)

Weather data observations

1. Temp : 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. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
2. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
3. Drought Code (DC) index from the FWI system: 7 to 220.4
4. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
5. Buildup Index (BUI) index from the FWI system: 1.1 to 68
6. Fire Weather Index (FWI) Index: 0 to 31.1
7. Classes: two classes, namely fire and not fire

In [148…

```
dataset.shape
```

Out[148]:

```
(244, 15)
```

1.7 Checking Null values

In [178…

```
### checking for null values

dataset.isnull().sum()
```

Out[178]:
```
day            0
month          0
year           0
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        0
Region         0
dtype: int64
```

Observation

1. There is no null value in dataset.
2. Total 244 rowws and 15 columns is present.

2.0 Numerical and continuous features

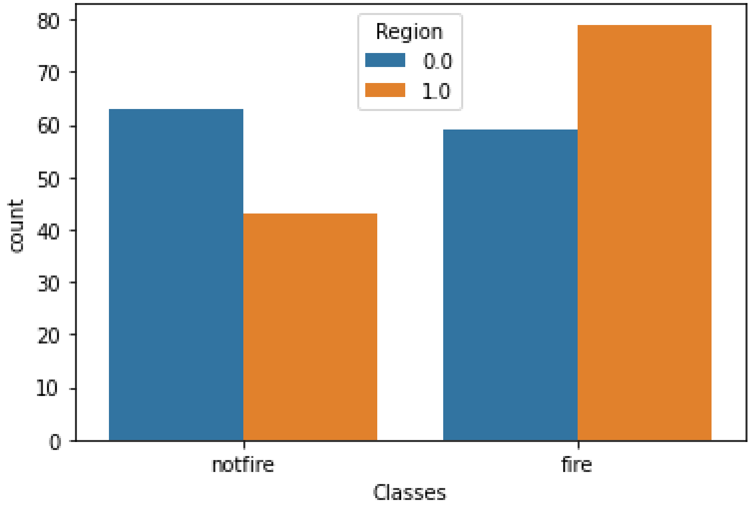
2.1 Categorical Features

In [159…
```
# categorical features
categorical_feature=[feature for feature in dataset.columns if dataset[feature].dtypes=='O']

#getting to know different categories in cateogrical features with its count.
for feature in categorical_feature:
    print(dataset.groupby(feature)['Region'].value_counts())
```

```
Classes  Region
fire     1.0       79
         0.0       59
notfire  0.0       63
         1.0       43
Name: Region, dtype: int64
```

In [166…
```
sns.countplot(data=dataset, x='Classes', hue='Region')
```

Out[166]:
```
<AxesSubplot:xlabel='Classes', ylabel='count'>
```



Observation

1. It is evident that Sidi Bel-abbes region has more occurance of fire than Bejaia region.

2.2 Numerical features

In [175…
```
### Getting list of numerical features
numerical_features=[feature for feature in dataset.columns if dataset[feature].dtypes!='O']
print(numerical_features)
```

```
['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Region']
```

In [177…
```
### Getting uniques values in each numerical features

dataset[numerical_features].nunique()
```

Out[177]:
```
day              31
month             4
year              1
Temperature      19
RH               62
Ws               18
Rain             39
FFMC            173
DMC             166
DC              198
ISI             106
BUI             174
FWI             125
Region            2
dtype: int64
```

2.3 Seggregating discrete and continuous variables

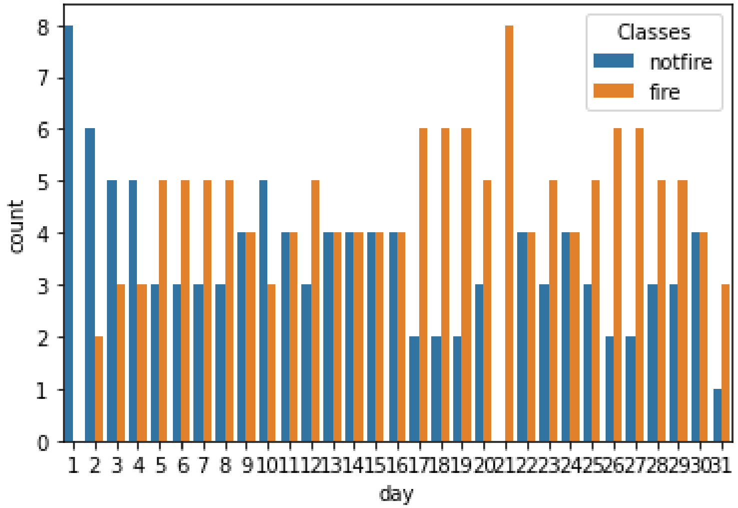
2.3.1 Discrete Numerical Features

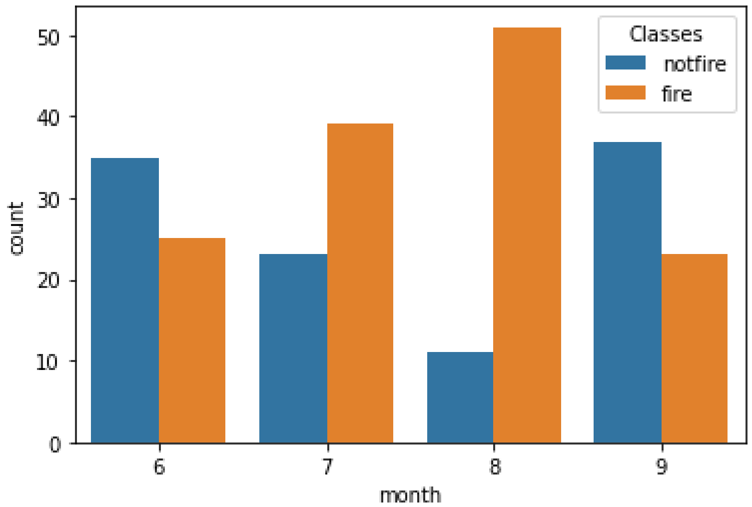
In [184…
```
#here the assumption to consider a feature discrete is that it should have less than 35 unique values otherwise it will be
# considered continuous feature

discrete_features=[feature for feature in numerical_features if len(dataset[feature].unique())<35]
discrete_features
```

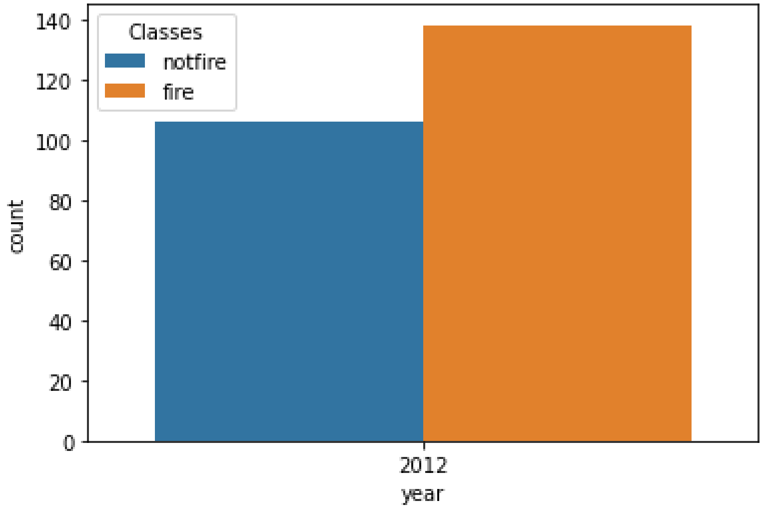
Out[184]:
```
['day', 'month', 'year', 'Temperature', 'Ws', 'Region']
```

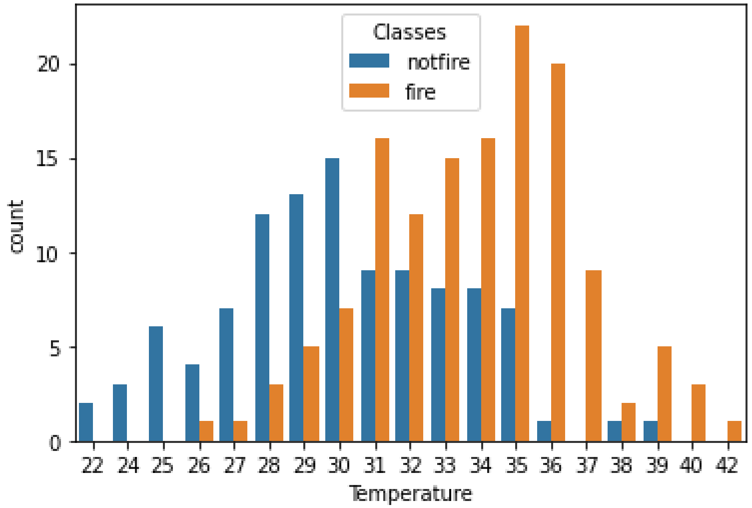
2.3.1.1 Discrete Numerical Feature vs Target Feature

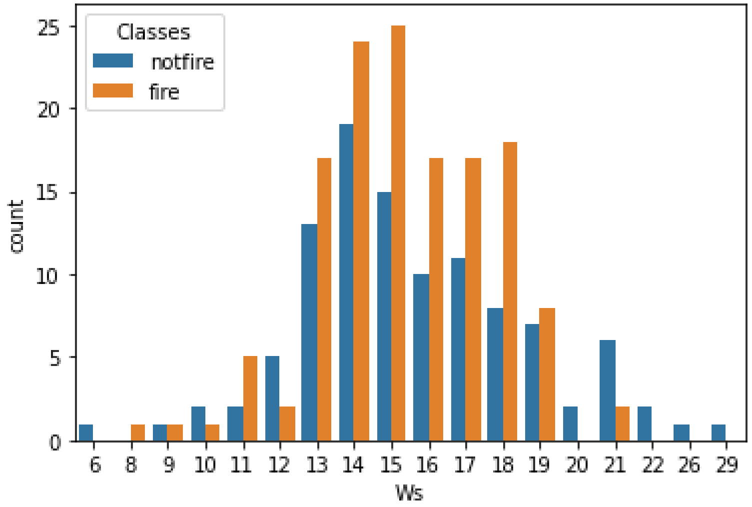
In [189…
```
### this is bivariate analysis between target feature classes and discrete numerical features
### for this we plot count plot
for feature in discrete_features:
    sns.countplot(data=dataset, x=feature, hue='Classes')
    plt.show()
```

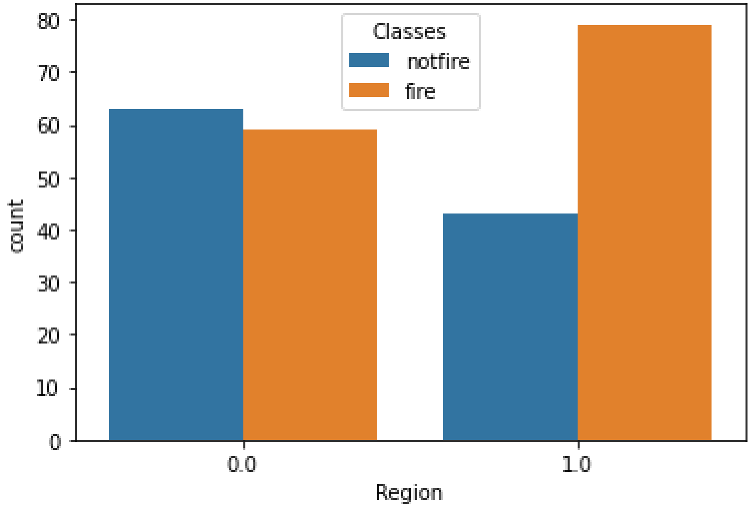

Classes
notfire
fire
count
day
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31
0 1 2 3 4 5 6 7 8


Classes
notfire
fire
count
month
6 7 8 9
0 10 20 30 40 50


Classes
notfire
fire
count
0
20
40
60
80
100
120
140
2012
year


Classes
notfire
fire
count
0
5
10
15
20
22 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 42
Temperature





Observations

1. From day vs Classes plot it is visible that on almost all days the occurance of fire is there, and its count is more than or equal to the count of no fire cases.
2. From month vs Classes plot it is visible that july and august month have more cases of occurance of fire as compared to other two months of june and september where occurance of fire is less as compared to no fire.
3. The month of august has highest no of cases of occurance of fire.

4. Overall cases of occurance of fire is more than the cases of no occurance of fire.
5. From temperature vs Classes plot it is visible that temperature between 30 to 37 degree celcius have most no of cases of occurance of fire.
6. From windspeed vs Classes plot it is visible that for wind speed between 13 to 19 Km/hr range there is most no of occurance of fire.
7. From Region vs Class plot it is visible that in Bejaia region, the no of cases of occurance of fire is less compared to no fire.
8. In Sidi Bel-abbes region the no of cases of occurance of fire is more compared to no fire. Also Overall no of cases of occurance of fire is more in Sidi Bel-abbes region as compared to Bejaia region.

2.3.2 Continuous Numerical Features

In [186…

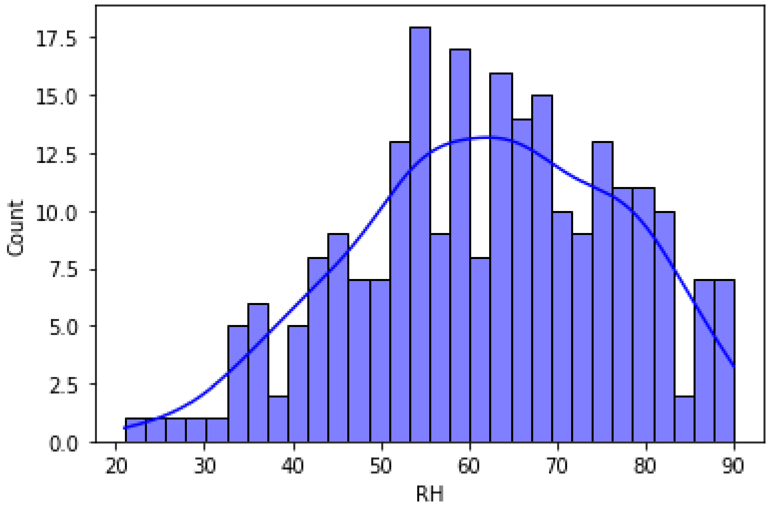
```
continuous_features=[feature for feature in numerical_features if feature not in discrete_features]
print(continuous_features)
```

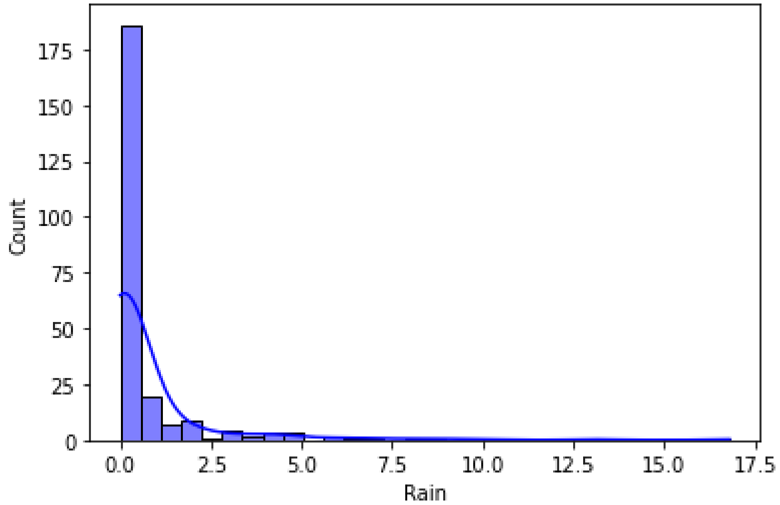
```
['RH', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI']
```

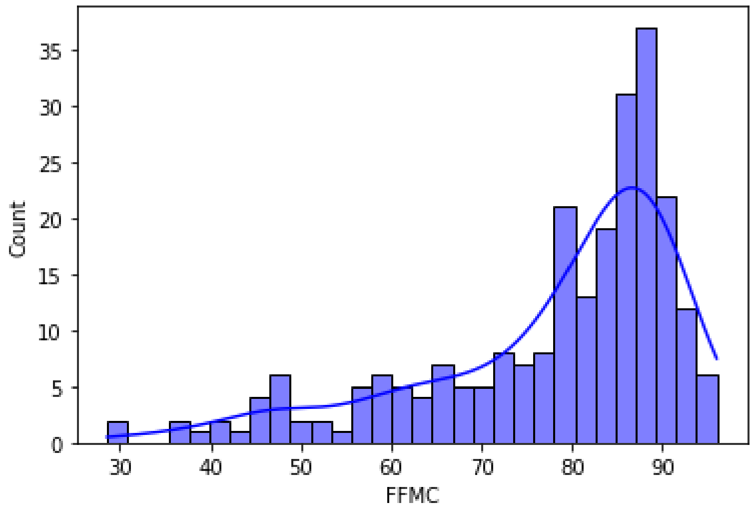
2.3.2.1 Distribution of Continuous Numerical Features

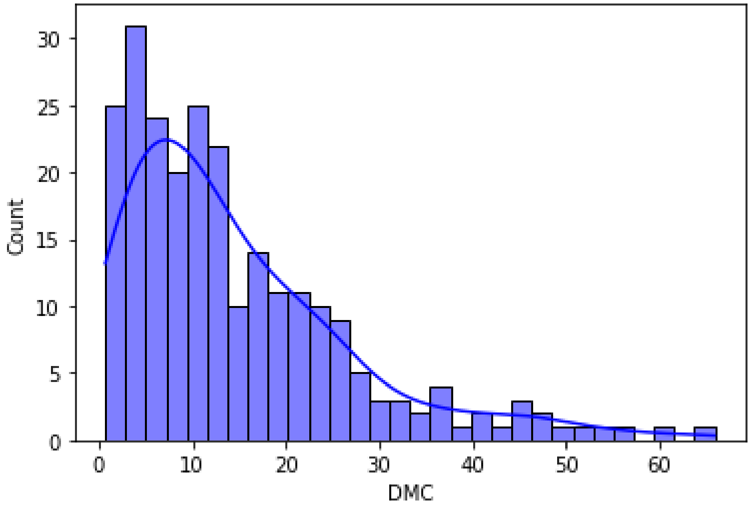
In [227…

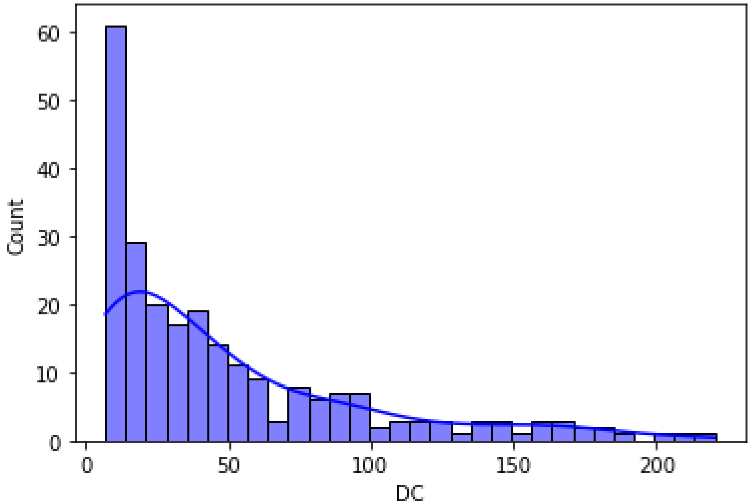
```
### Checking distribution of Continuous numerical features

for feature in continuous_features:
    sns.histplot(data=dataset, x=feature,kde=True, bins=30, color='blue')
    plt.show();
```

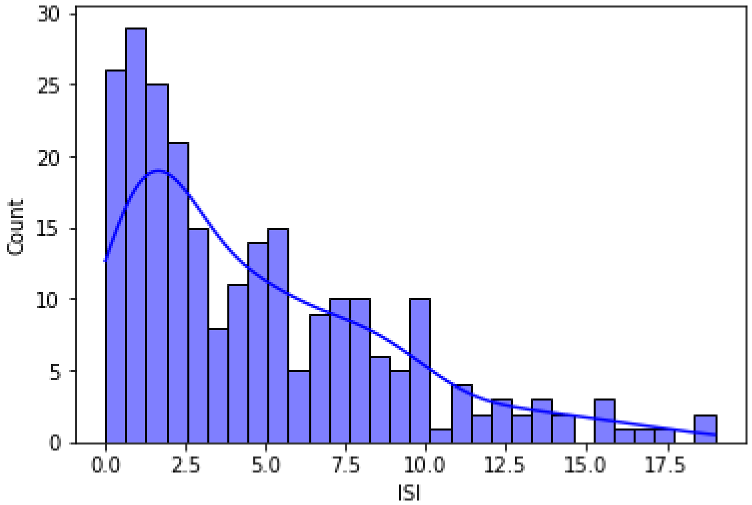


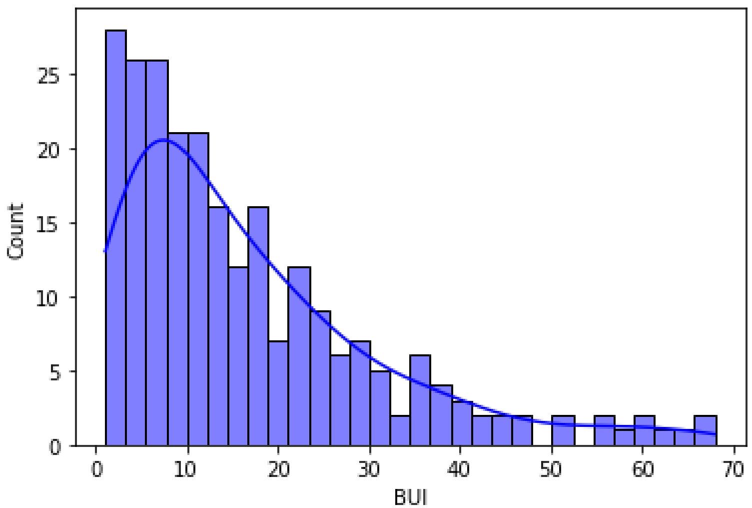

Count
175
150
125
100
75
50
25
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Rain

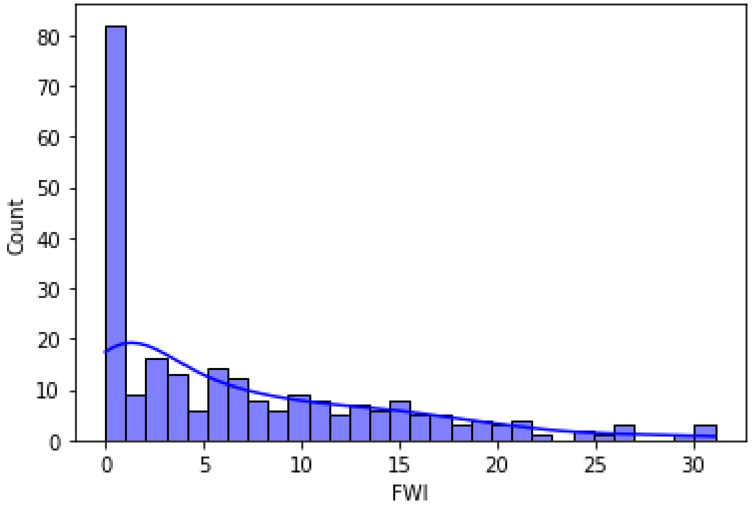

Count
35
30
25
20
15
10
5
0
30
40
50
60
70
80
90
FFMC


Count
DMC
0
10
20
30
40
50
60
5
15
25


Count
DC
0
50
100
150
200
10
20
30
40
60


Count
ISI
0
5
10
15
20
25
30
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Count
BUI
0
5
10
15
20
25
0
10
20
30
40
50
60
70

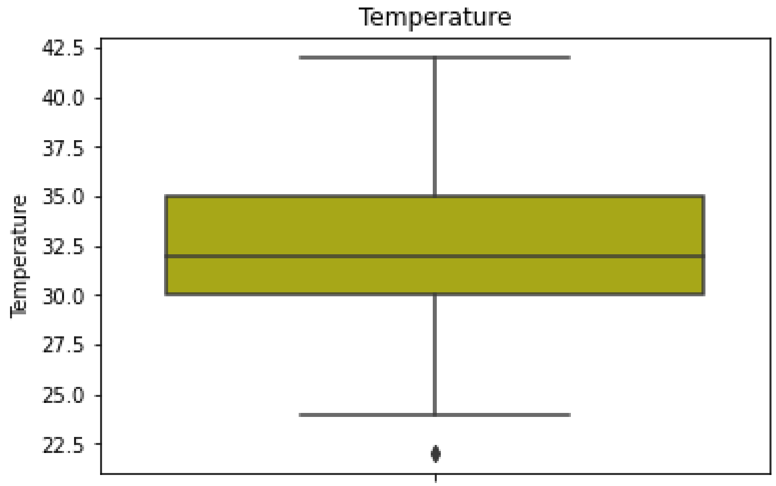


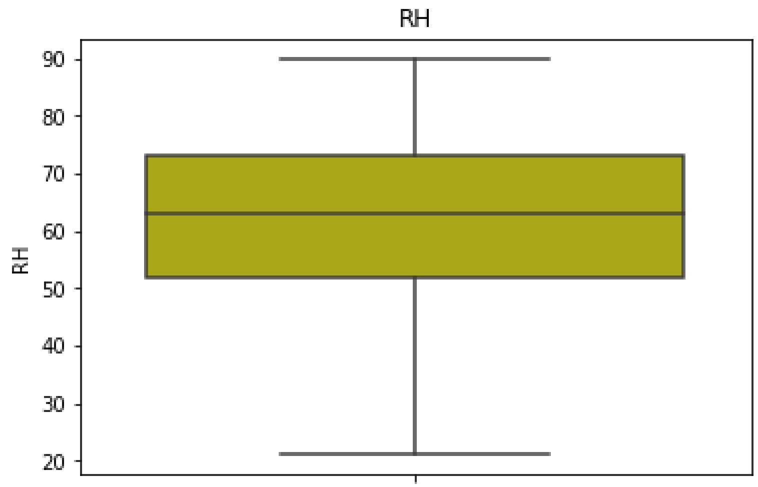
Observations

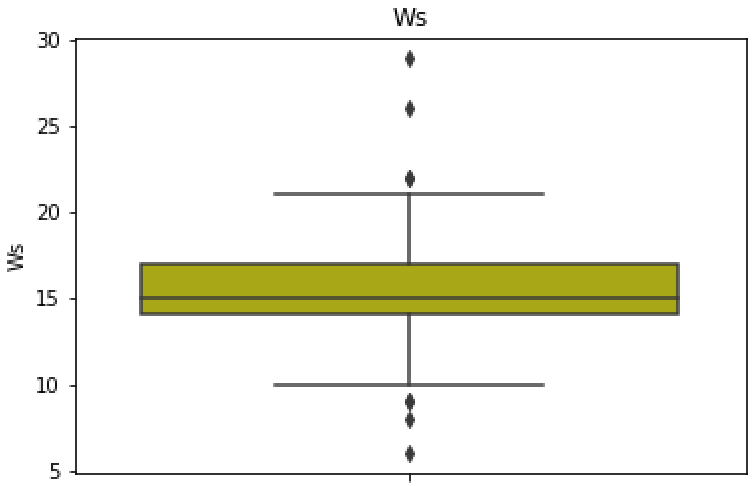
1. Relative humidity is following gaussian distribution.
2. Rain, DMC, DC, ISI, BUI, FWI are following right skewed distribution(Log-Normal distribution).
3. FFMC feature follows left skwed distribution.

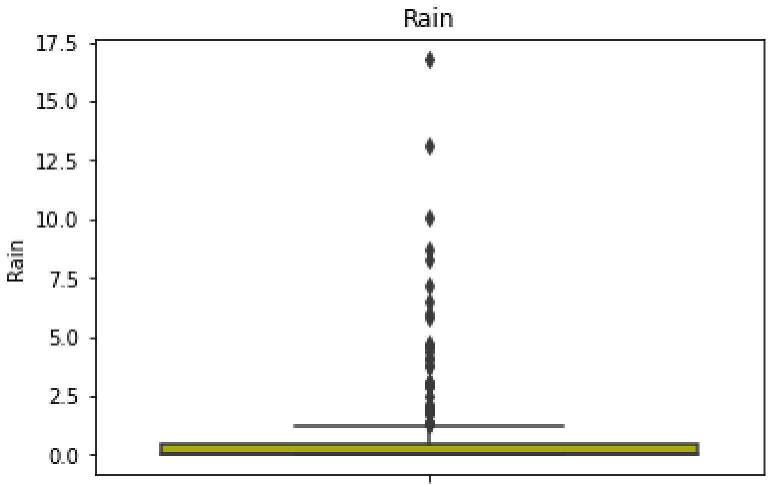
2.4 Checking for outliers

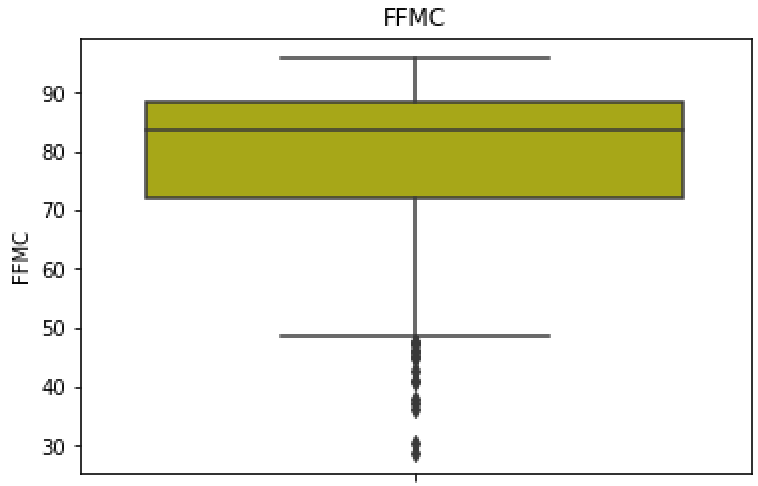
In [225…
```
### excluding 'day', 'month','year', 'Region'.

for feature in [feature for feature in numerical_features if feature not in ['day', 'month','year', 'Region']]:
    sns.boxplot(data=dataset, y= feature, color='y')
    plt.title(feature)
    plt.show();
```

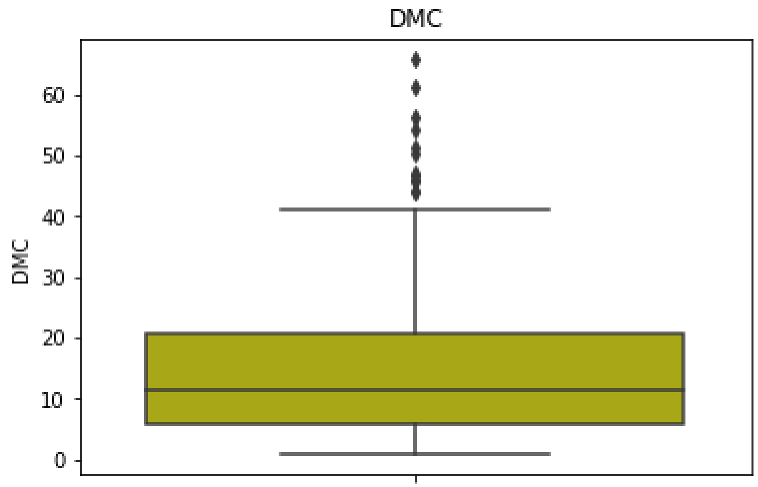

Temperature
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
22.5
Temperature

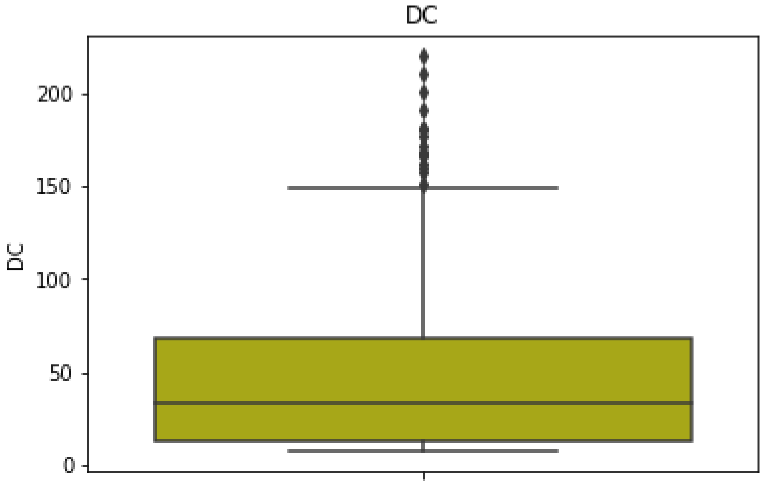

RH
90
80
70
60
50
40
30
20
RH

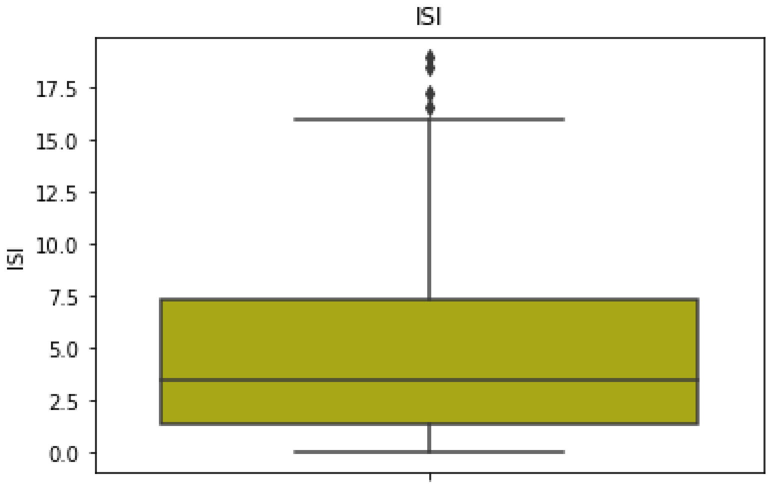

Ws
30
25
20
15
10
5
Ws

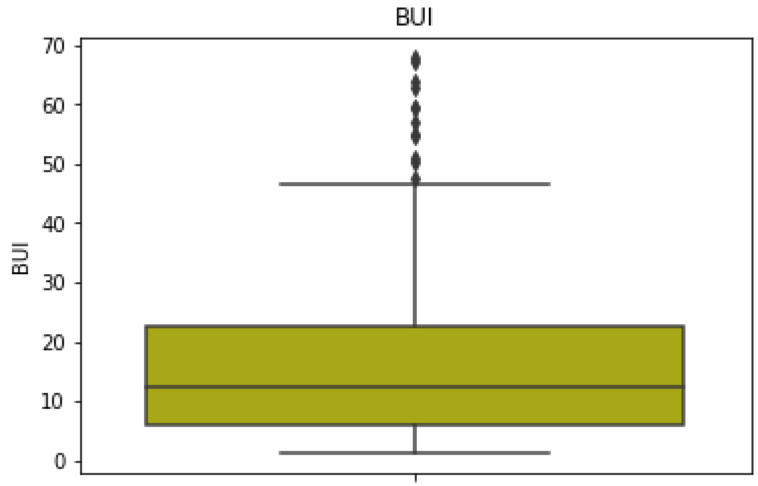

Rain
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
Rain

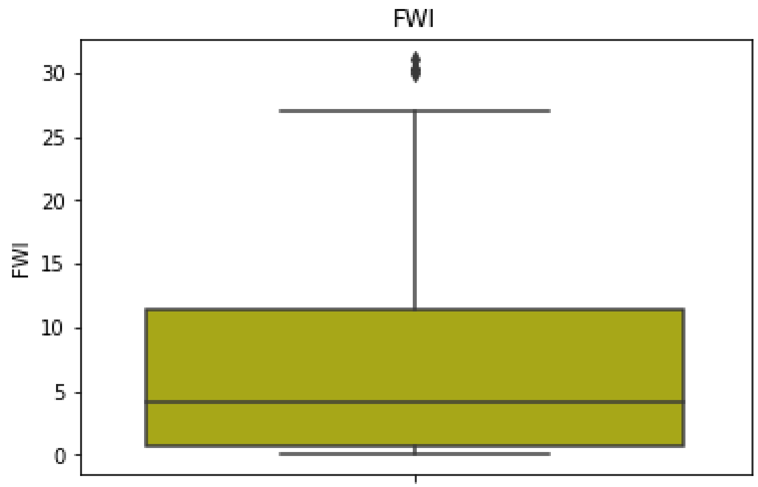

FFMC
FFMC
90
80
70
60
50
40
30


DMC
DMC
60
50
40
30
20
10
0


DC
200
150
100
50
0
DC


ISI
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
ISI





Observations

1. Relative Humidity, RH feature doesnt have outliers.
2. Temperature and FFMC have outliers in lower boundary side.
3. Wind Speed, Ws has outliers on both sides(Upper and lower boundary).
4. Rain, DMC,DC, ISI, BUI and FWI have outilers in upper boundary side.

3.0 Correlation between each Numerical features

In [247…

```
data= round(dataset[[feature for feature in numerical_features if feature not in ['day', 'month','year', 'Region']]].corr(),2)
data
```

Out[247]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI
Temperature	1.00	-0.65	-0.28	-0.33	0.68	0.48	0.37	0.61	0.46	0.56
RH	-0.65	1.00	0.24	0.22	-0.65	-0.41	-0.22	-0.69	-0.35	-0.57
Ws	-0.28	0.24	1.00	0.17	-0.16	-0.00	0.08	0.02	0.03	0.03
Rain	-0.33	0.22	0.17	1.00	-0.54	-0.29	-0.30	-0.35	-0.30	-0.32
FFMC	0.68	-0.65	-0.16	-0.54	1.00	0.60	0.50	0.74	0.59	0.69
DMC	0.48	-0.41	-0.00	-0.29	0.60	1.00	0.88	0.67	0.98	0.87
DC	0.37	-0.22	0.08	-0.30	0.50	0.88	1.00	0.50	0.94	0.74
ISI	0.61	-0.69	0.02	-0.35	0.74	0.67	0.50	1.00	0.64	0.91
BUI	0.46	-0.35	0.03	-0.30	0.59	0.98	0.94	0.64	1.00	0.86
FWI	0.56	-0.57	0.03	-0.32	0.69	0.87	0.74	0.91	0.86	1.00

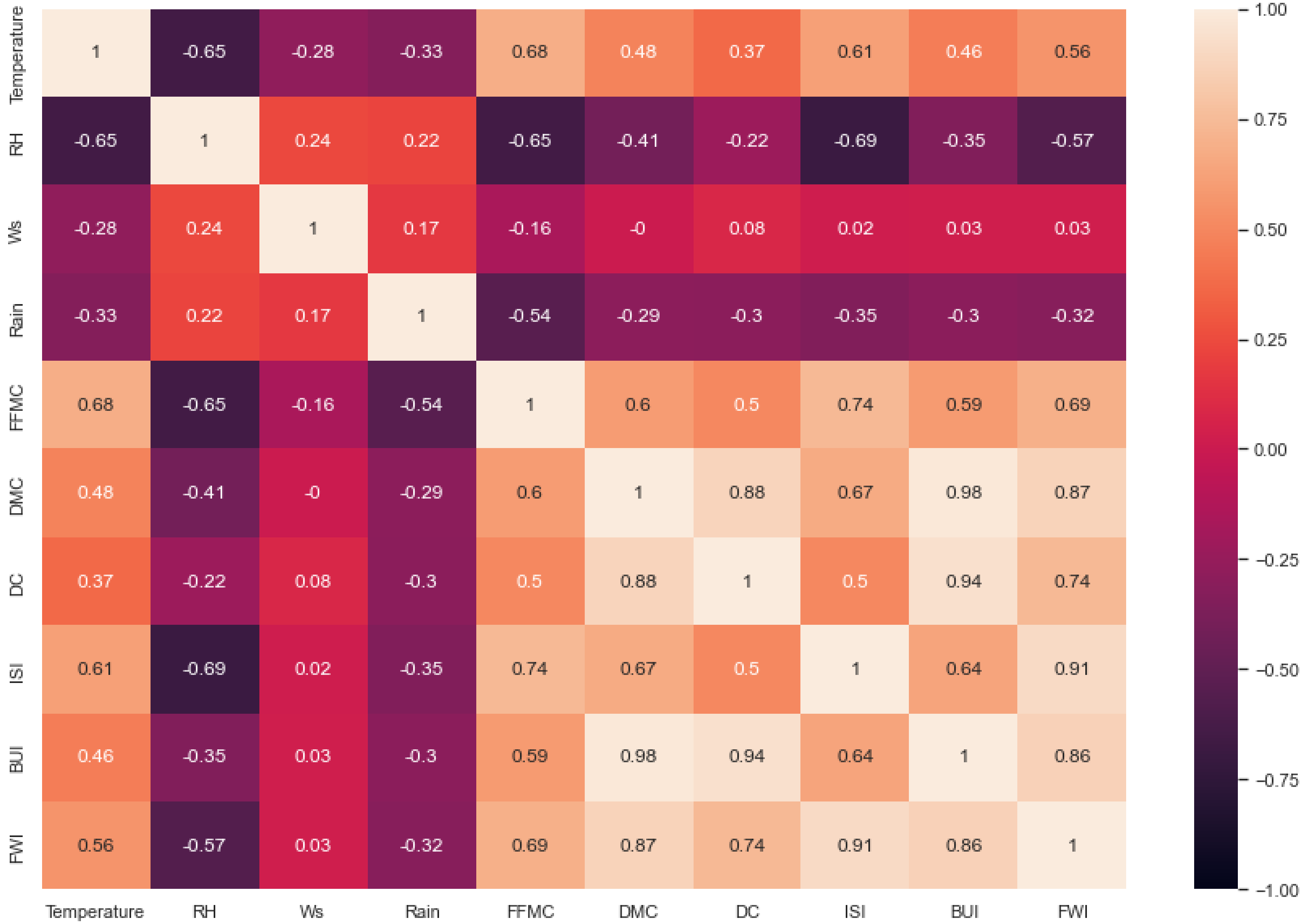
3.1 Heatmap to visualise the Correlation

In [248…

```
### Plotting heatmap for visualising the correlation between features
sns.set(rc={'figure.figsize':(15,10)})
sns.heatmap(data=data, annot=True,  vmin=-1, vmax=1)
```

Out[248]:

```
<AxesSubplot:>
```



	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI
Temperature	1	-0.65	-0.28	-0.33	0.68	0.48	0.37	0.61	0.46	0.56
RH	-0.65	1	0.24	0.22	-0.65	-0.41	-0.22	-0.69	-0.35	-0.57
Ws	-0.28	0.24	1	0.17	-0.16	-0	0.08	0.02	0.03	0.03
Rain	-0.33	0.22	0.17	1	-0.54	-0.29	-0.3	-0.35	-0.3	-0.32
FFMC	0.68	-0.65	-0.16	-0.54	1	0.6	0.5	0.74	0.59	0.69
DMC	0.48	-0.41	-0	-0.29	0.6	1	0.88	0.67	0.98	0.87
DC	0.37	-0.22	0.08	-0.3	0.5	0.88	1	0.5	0.94	0.74
ISI	0.61	-0.69	0.02	-0.35	0.74	0.67	0.5	1	0.64	0.91
BUI	0.46	-0.35	0.03	-0.3	0.59	0.98	0.94	0.64	1	0.86
FWI	0.56	-0.57	0.03	-0.32	0.69	0.87	0.74	0.91	0.86	1

Note (For both positive and negative side)

1. Correlation coefficients between 0.9 and 1.0, very highly correlated.
2. Correlation coefficients between 0.7 and 0.9, highly correlated.
3. Correlation coefficients between 0.5 and 0.7, moderately correlated.

4. Correlation coefficients between 0.3 and 0.5, low correlation.
5. Correlation coefficients less than 0.3, little correlation

Observations

1. Very highly Correlated features: DMC-BUI, DC-BUI, ISI-FWI
2. Highly correlated features: FFMC-ISI, DC-DMC, FWI-DMC, FWI-DC, FWI-BUI

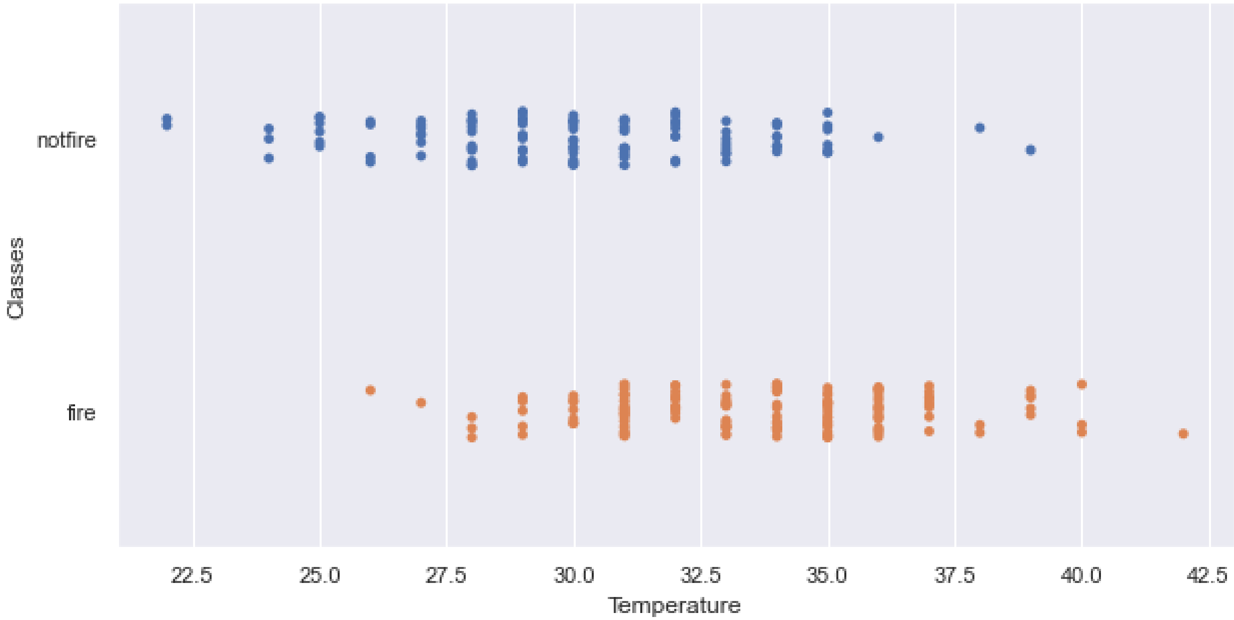
Note: Features with very hihg and high correlation are more linearly dependent and hence have almost the same effect on the dependent variable. So, we can drop one of the two features.

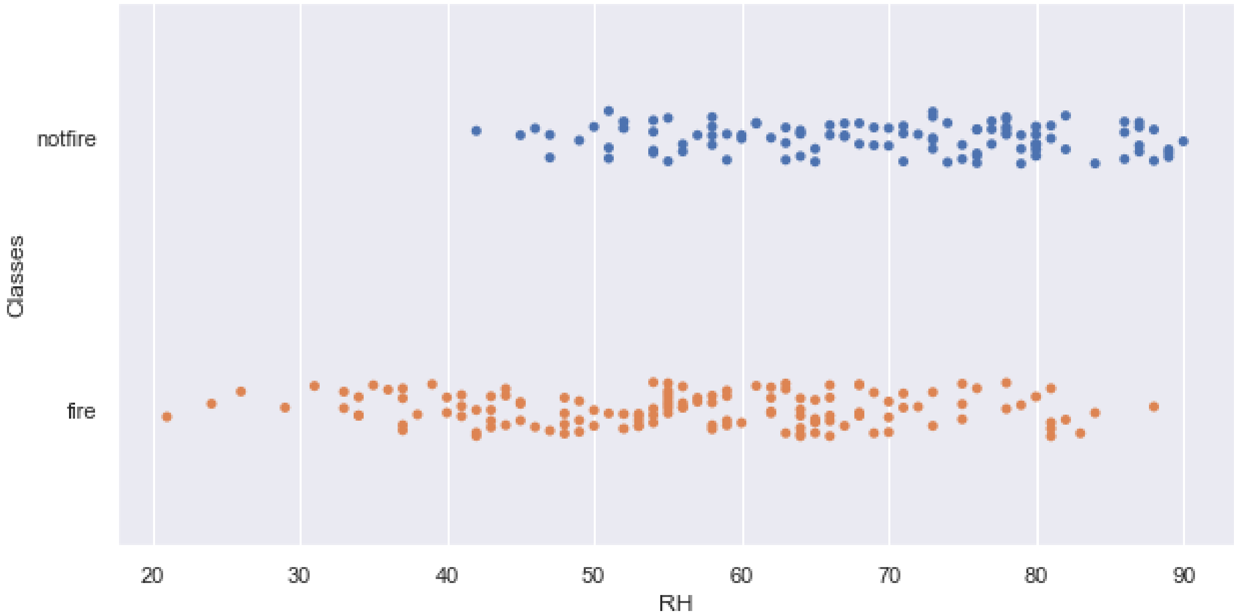
3.2 Relationship between numerical feature and target feature

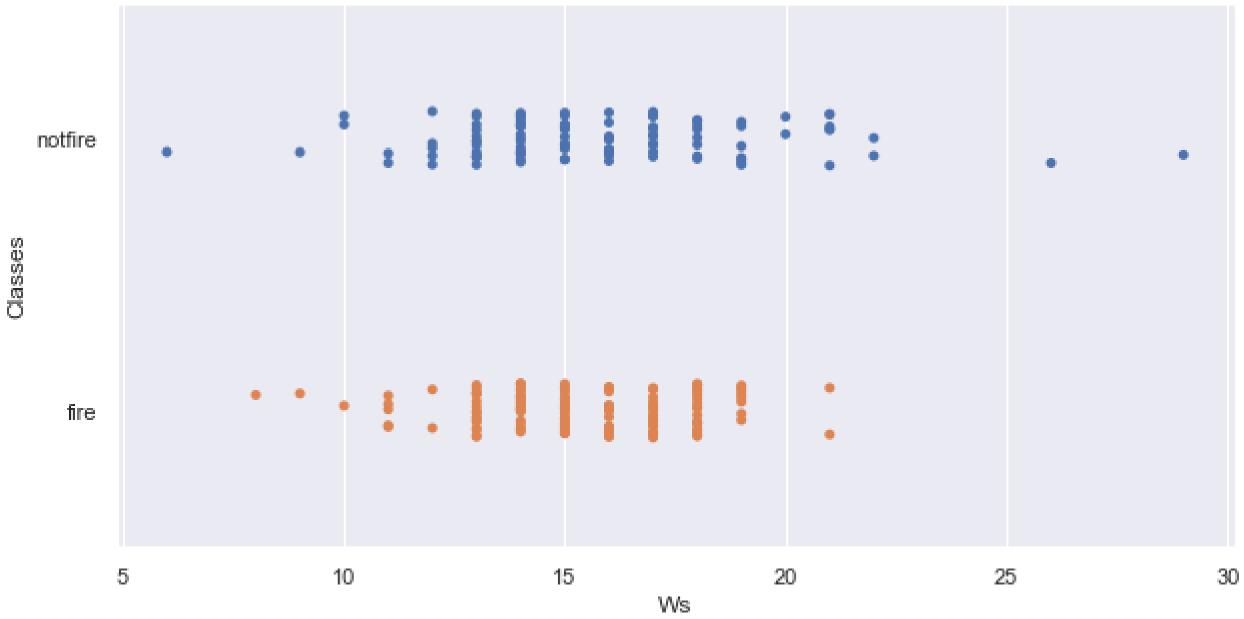
1. strip plot

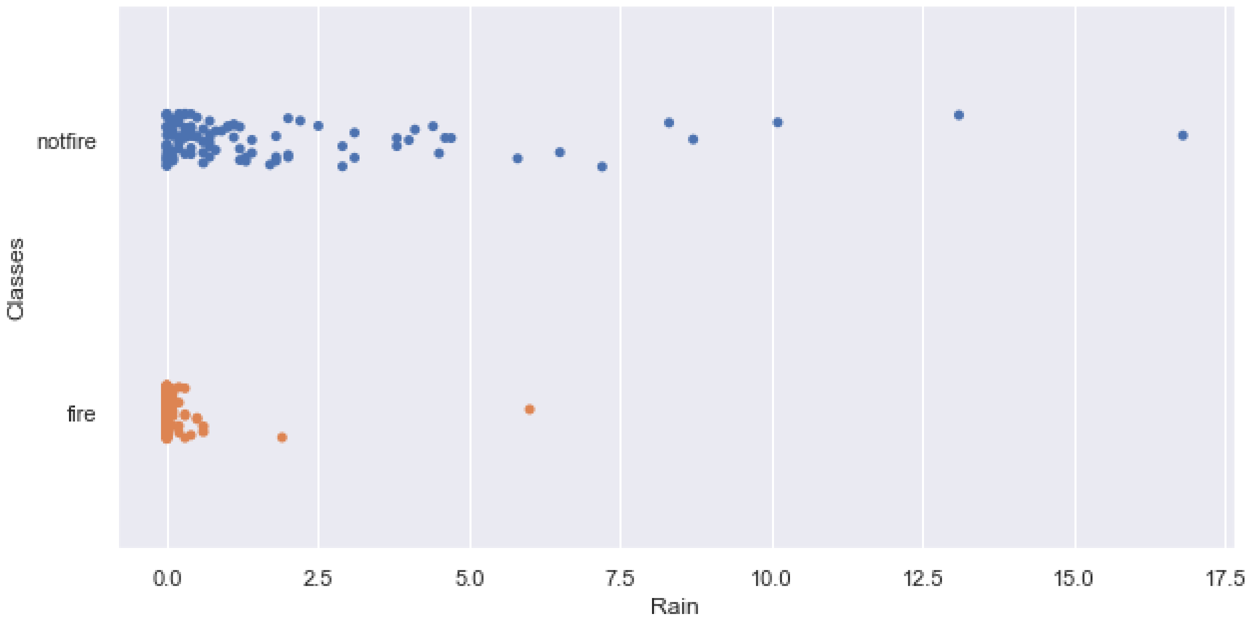
In [255…

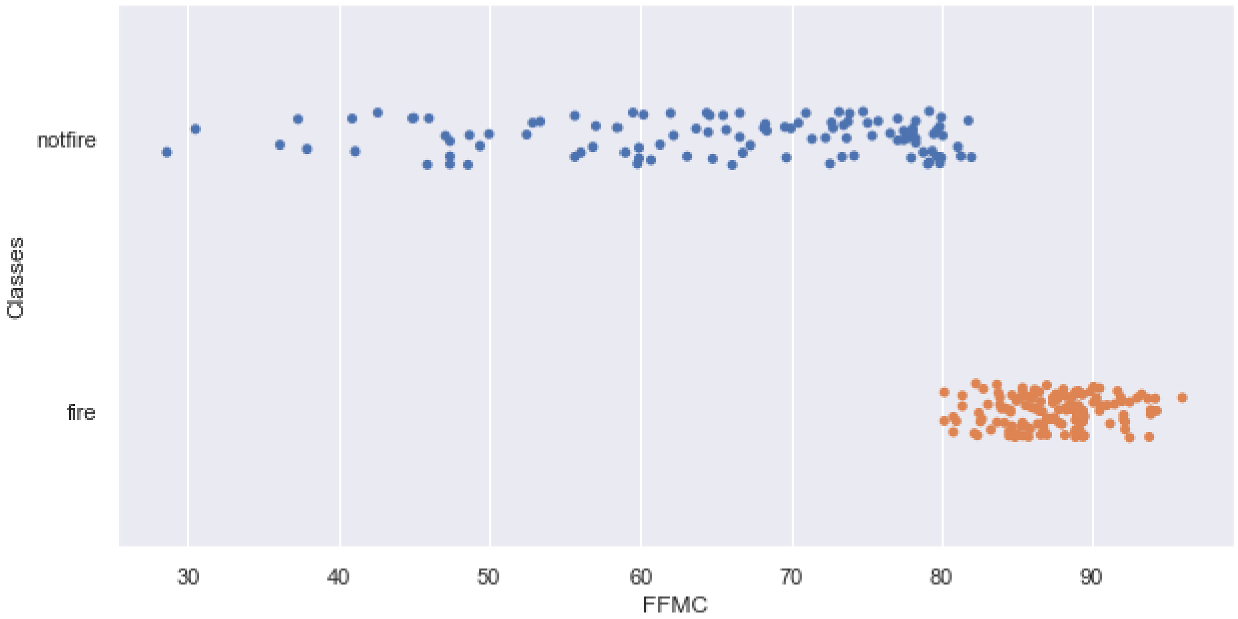
```
num_feature_custom=[feature for feature in numerical_features if feature not in ['day', 'month', 'year', 'Region']]

sns.set(rc={'figure.figsize':(10,5)})
for feature in num_feature_custom:
    sns.stripplot(data=dataset, x=feature, y='Classes')
    plt.show();
```


notfire
fire
Classes
22.5
25.0
27.5
30.0
32.5
35.0
37.5
40.0
42.5
Temperature

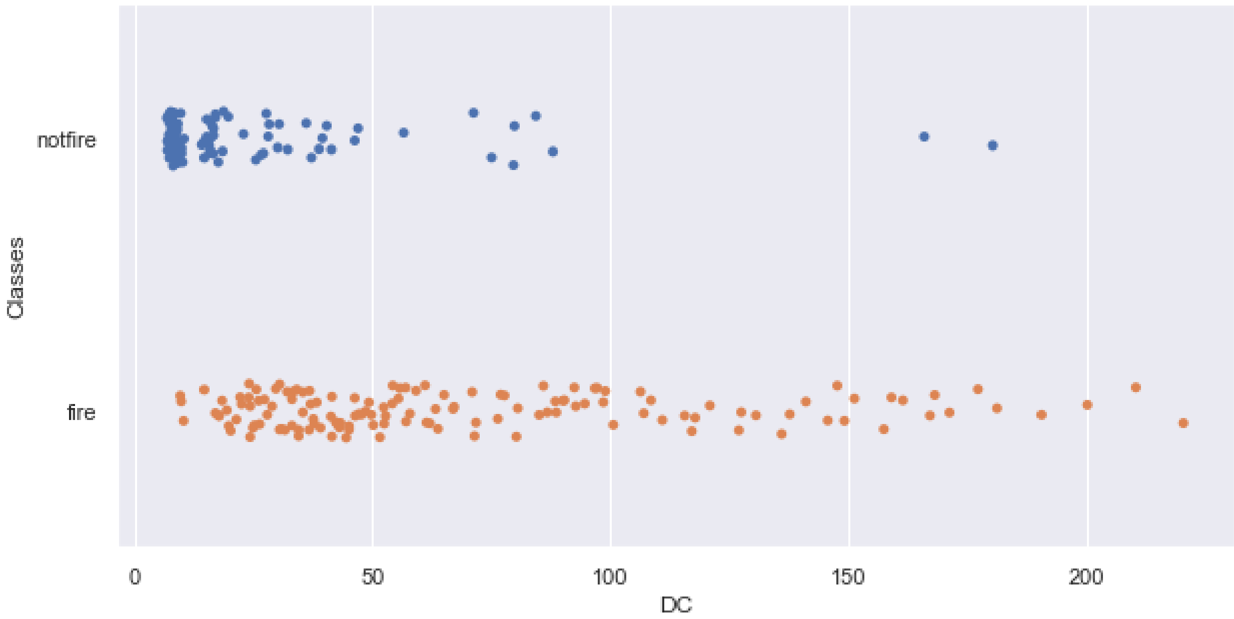

notfire
fire
Classes
20
30
40
50
60
70
80
90
RH

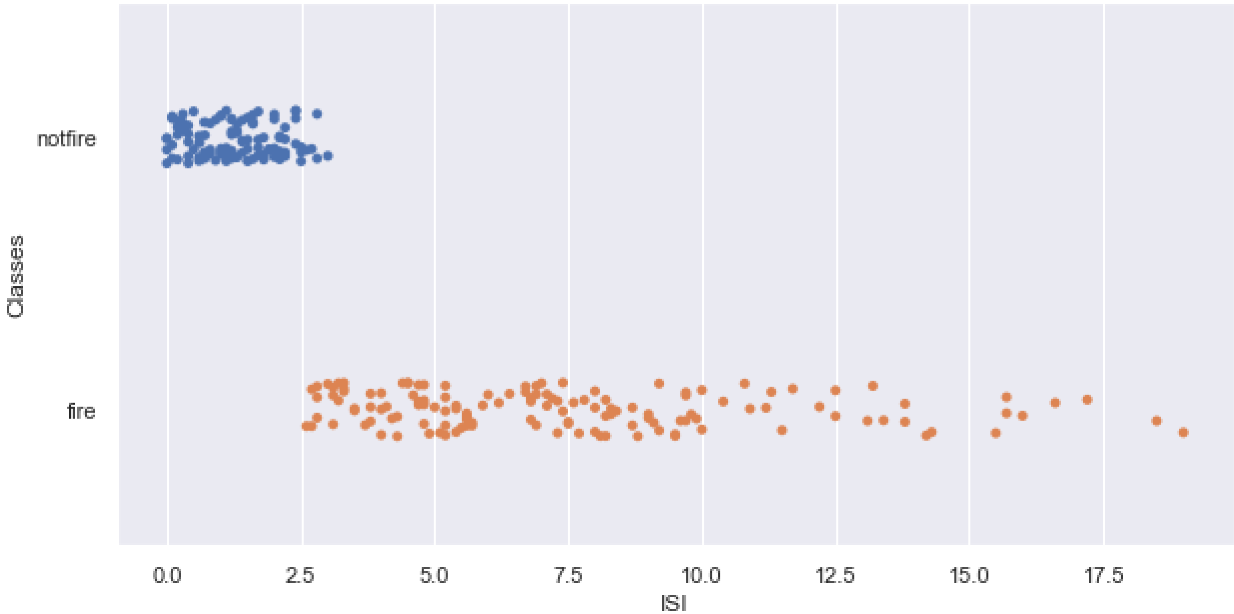

notfire
fire
Classes
5
10
15
20
25
30
Ws

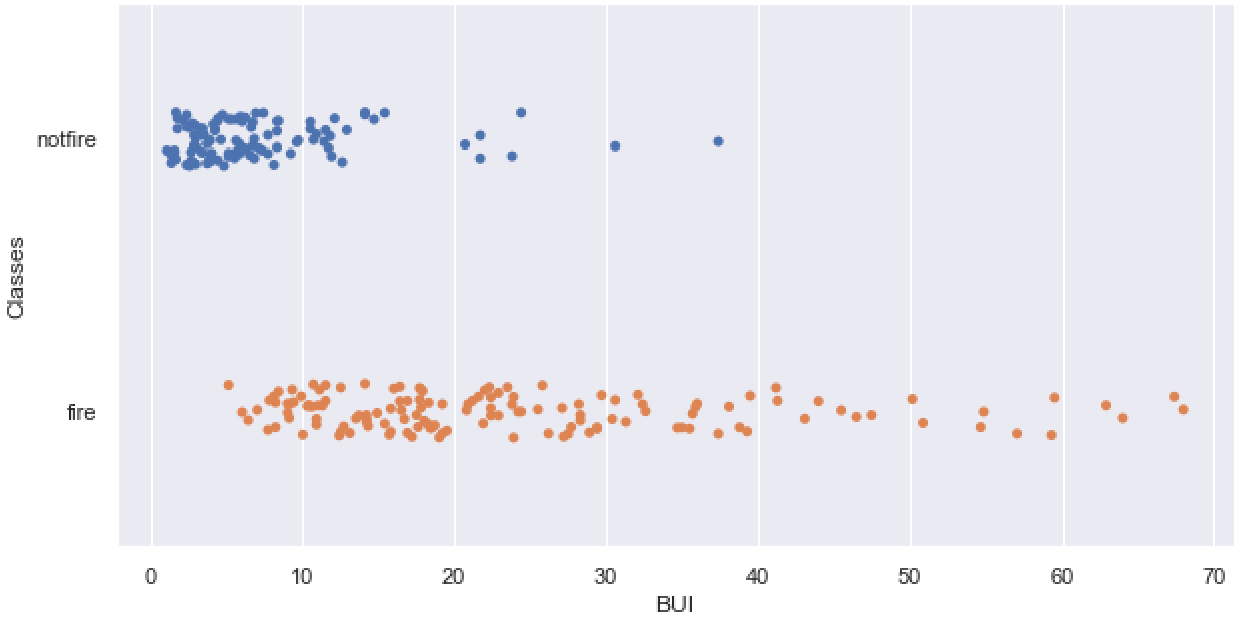

notfire
fire
Classes
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Rain

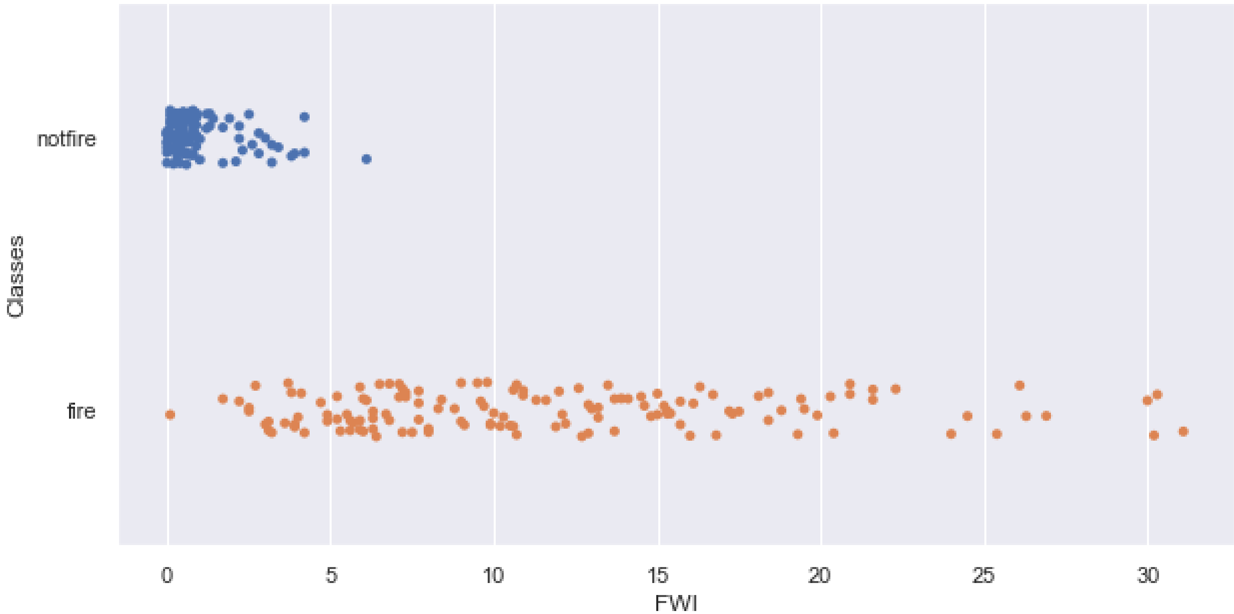

notfire
fire
Classes
30
40
50
60
70
80
90
FFMC


notfire
fire
Classes
0
10
20
30
40
50
60
DMC


notfire
fire
Classes
0
50
100
150
200
DC


notfire
fire
Classes
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
ISI





Observations

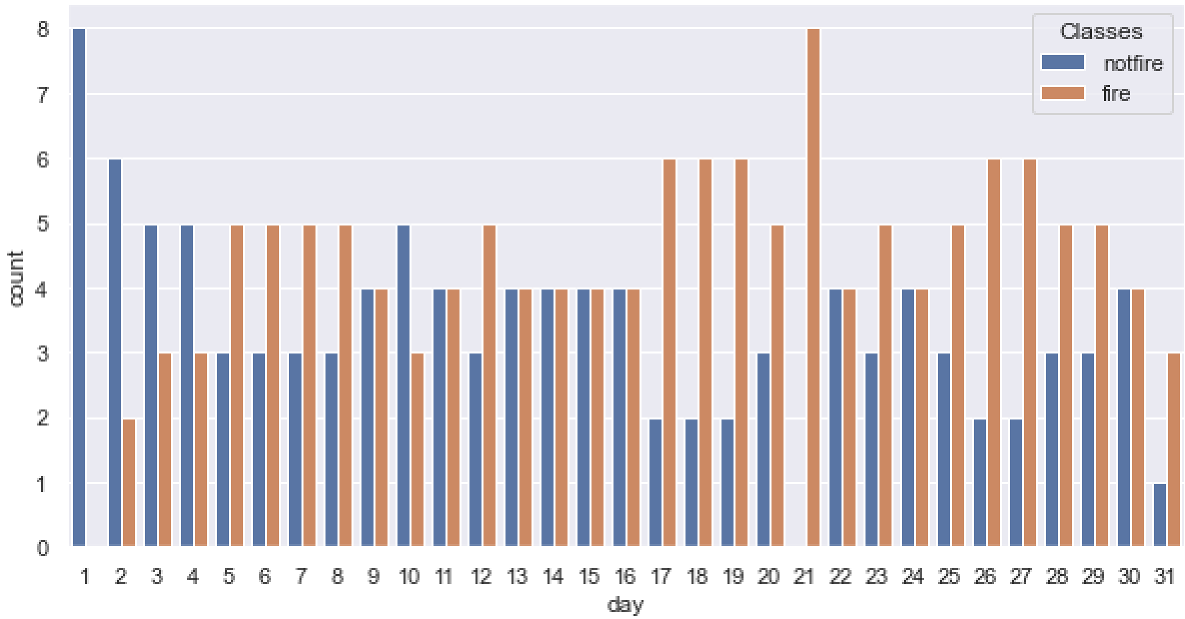
1. It is visible that for temperature between 30 to 37, there is most no of cases of occurance of fire, i.e Hot regions are more prone to forrest fires.
2. For RH 40 to 70 and wind speed between 13 to 19 Km/h, Most no of cases of occurance of fire is reported, i.e dry regions are more prone to forrest fires.
3. Almost all cases of occurance of fire is for region having rain less than 1 mm, i.e dry regions are more prone to forrest fires.
4. For FFMC(Fine Fuel Moisture Code) greater than 80, almost all cases of fire is reported.
5. DMC (Duff Moisture Code) >30 and DC (Drought code) >100, almost all cases of occurance of fire reported, this means drought affected areas are more prone to forrest fires.

4.0 Feature vs target

4.1 day

In [263…
```
sns.countplot(data=dataset, x='day', hue='Classes')
```

Out[263]:
```
<AxesSubplot:xlabel='day', ylabel='count'>
```



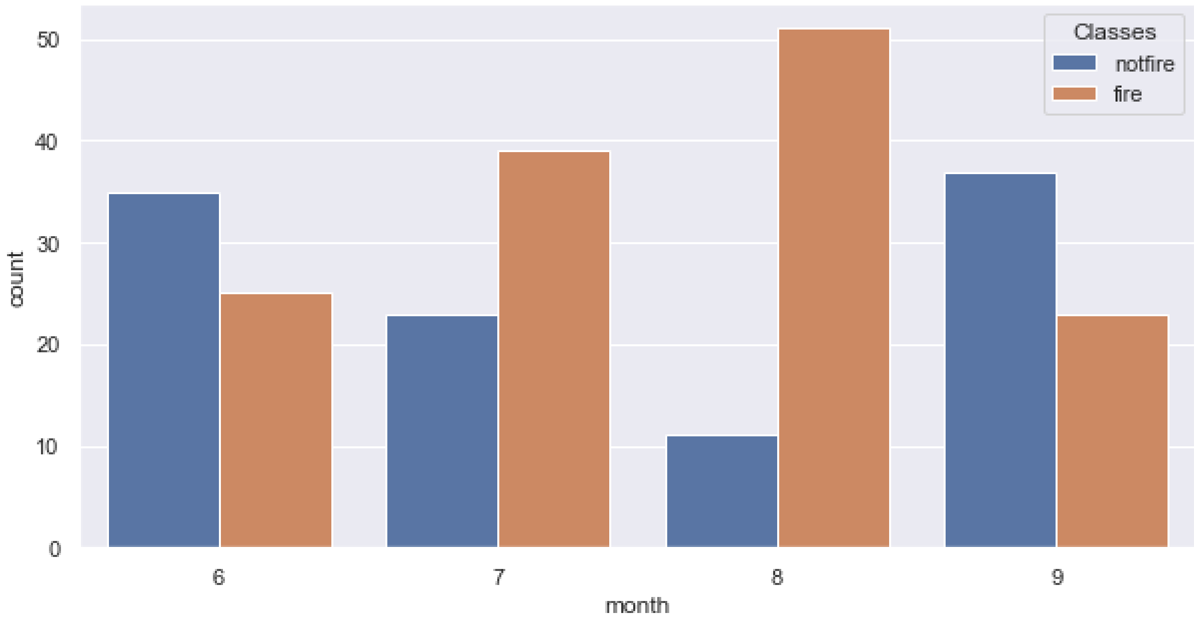
Observation

1. Most no of fires occured on 21st of the month.
2. Least no of fires occured on 2nd of the month.
3. for most days either fire occured was greater than or equal to no fire occured.

4.2 month

In [262…
```
sns.countplot(data=dataset, x='month', hue='Classes')
```

Out[262]:
```
<AxesSubplot:xlabel='month', ylabel='count'>
```



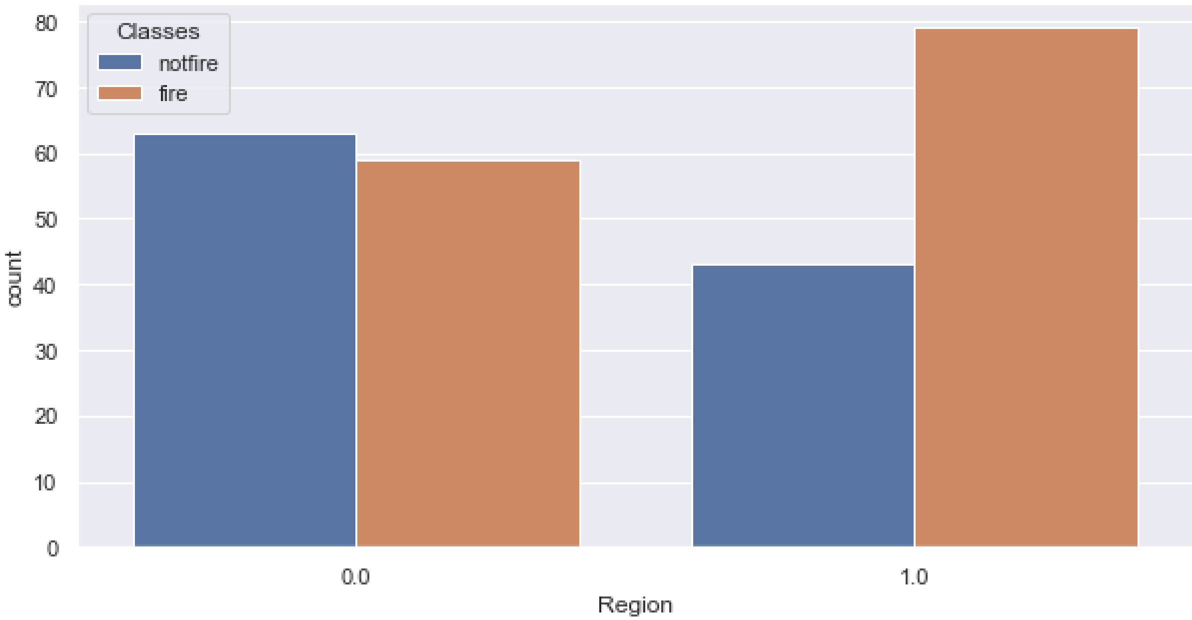
Observations

1. Most no of cases of fire occured are in the month of august and least no of cases of fire occured is in month of september.
2. July and august have more cases of fire as compared to no fire.
3. june and september have more cases of no fire as compared to fire.

4.3 Region

In [265…
```
sns.countplot(data=dataset, x='Region', hue='Classes')
```

Out[265]:
```
<AxesSubplot:xlabel='Region', ylabel='count'>
```



Observations

1. In Bejaia region, the no of cases of occurance of fire is less compared to no of cases of occurance of no fire.
2. In Sidi Bel-abbes region the no of cases of occurance of fire is more compared to no fire.
3. Also Overall no of cases of occurance of fire is more in Sidi Bel-abbes region as compared to Bejaia region.

Final Report

1. Very highly Correlated features: DMC-BUI, DC-BUI, ISI-FWI
2. Highly correlated features: FFMC-ISI, DC-DMC, FWI-DMC, FWI-DC, FWI-BUI

3. Temperature between 30 to 37 degree celcius have most no of cases of occurance of fire.
4. Wind speed between 13 to 19 Km/hr range there is most no of occurance of fire.
5. Almost all cases of occurance of fire is for region having rain less than 1 mm, i.e dry regions are more prone to forrest fires.
6. For FFMC(Fine Fuel Moisture Code) greater than 80, almost all cases of fire is reported.
7. DMC (Duff Moisture Code) >30 and DC (Drought code) >100, almost all cases of occurance of fire reported, this means drought affected areas are more prone to forrest fires.
8. In Bejaia region, the no of cases of occurance of fire is less compared to no of cases of occurance of no fire.
9. In Sidi Bel-abbes region the no of cases of occurance of fire is more compared to no fire.
10. Also Overall no of cases of occurance of fire is more in Sidi Bel-abbes region as compared to Bejaia region.
11. Most no of cases of fire occured are in the month of august and least no of cases of fire occured is in month of september.
12. July and august have more cases of fire as compared to no fire.
13. June and september have more cases of no fire as compared to fire.
14. Relative Humidity, RH feature doesnt have outliers whereas Temperature, FFMC, wind speed, Rain, DMC,DC, ISI, BUI and FWI have outilers.
15. There is no null vales in dataset.

Note: In this EDA i have not used subplots but in comming EDA, i'll use Subplots to better visualise plots.