In [1]: # Support vector machines generally deals with the separation between two layers # there is a linear model, non linear model.

## **FOREST FIRE**

```
In [4]: import numpy as np
    import pandas as pd
    from sklearn import preprocessing
    from sklearn import metrics
    import seaborn as sns
    from sklearn.svm import SVC
    from sklearn.model_selection import train_test_split
    from matplotlib import pyplot as plt
    from sklearn.decomposition import PCA
    from mlxtend.plotting import plot_decision_regions
```

In [5]: #classify the Size\_Categorie using SVM

In [6]: # Let us import the dataset
forest\_fire=pd.read\_csv("C:\\Users\\nishi\\Desktop\\Assignments\\Support\_Vector\_N

In [7]: forest\_fire

Out[7]:

|     | month | day | FFMC | DMC   | DC    | ISI  | temp | RH | wind | rain | <br>monthfeb | monthjan | mont |
|-----|-------|-----|------|-------|-------|------|------|----|------|------|--------------|----------|------|
| 0   | mar   | fri | 86.2 | 26.2  | 94.3  | 5.1  | 8.2  | 51 | 6.7  | 0.0  | <br>0        | 0        |      |
| 1   | oct   | tue | 90.6 | 35.4  | 669.1 | 6.7  | 18.0 | 33 | 0.9  | 0.0  | <br>0        | 0        |      |
| 2   | oct   | sat | 90.6 | 43.7  | 686.9 | 6.7  | 14.6 | 33 | 1.3  | 0.0  | <br>0        | 0        |      |
| 3   | mar   | fri | 91.7 | 33.3  | 77.5  | 9.0  | 8.3  | 97 | 4.0  | 0.2  | <br>0        | 0        |      |
| 4   | mar   | sun | 89.3 | 51.3  | 102.2 | 9.6  | 11.4 | 99 | 1.8  | 0.0  | <br>0        | 0        |      |
|     |       |     |      |       |       |      |      |    |      |      | <br>         |          |      |
| 512 | aug   | sun | 81.6 | 56.7  | 665.6 | 1.9  | 27.8 | 32 | 2.7  | 0.0  | <br>0        | 0        |      |
| 513 | aug   | sun | 81.6 | 56.7  | 665.6 | 1.9  | 21.9 | 71 | 5.8  | 0.0  | <br>0        | 0        |      |
| 514 | aug   | sun | 81.6 | 56.7  | 665.6 | 1.9  | 21.2 | 70 | 6.7  | 0.0  | <br>0        | 0        |      |
| 515 | aug   | sat | 94.4 | 146.0 | 614.7 | 11.3 | 25.6 | 42 | 4.0  | 0.0  | <br>0        | 0        |      |
| 516 | nov   | tue | 79.5 | 3.0   | 106.7 | 1.1  | 11.8 | 31 | 4.5  | 0.0  | <br>0        | 0        |      |
|     |       |     |      |       |       |      |      |    |      |      |              |          |      |

517 rows × 31 columns

In [8]: forest\_fire1=forest\_fire.copy()

In [9]: forest fire1.head() Out[9]: day FFMC DMC DC ISI temp RH wind rain ... monthfeb monthjul month 0 0 fri 86.2 26.2 94.3 5.1 8.2 51 6.7 0.0 0 0 mar ... 1 oct tue 90.6 35.4 669.1 6.7 18.0 33 0.9 0.0 ... 0 0 0 2 43.7 686.9 oct sat 90.6 6.7 14.6 33 1.3 0.0 ... 0 0 3 fri 91.7 33.3 77.5 9.0 8.3 97 4.0 0.2 ... 0 0 0 mar 51.3 102.2 9.6 0 0 0 4 89.3 11.4 99 1.8 0.0 ... mar sun 5 rows × 31 columns In [10]: forest\_fire1.iloc[:,0:11] Out[10]: month day **FFMC DMC** DC ISI temp RH wind rain area 0 mar fri 86.2 26.2 94.3 5.1 8.2 51 6.7 0.0 0.00 1 oct tue 90.6 35.4 669.1 6.7 18.0 33 0.9 0.0 0.00 2 90.6 43.7 686.9 14.6 0.00 oct sat 6.7 33 1.3 0.0 3 0.00 mar fri 91.7 33.3 77.5 9.0 8.3 97 4.0 0.2 4 51.3 102.2 9.6 99 0.0 0.00 89.3 11.4 1.8 mar sun ••• ... ... ... ... ... 512 81.6 56.7 665.6 1.9 27.8 32 2.7 0.0 6.44 aug sun 513 81.6 665.6 71 0.0 54.29 aug sun 56.7 1.9 21.9 5.8 514 81.6 665.6 21.2 11.16 56.7 1.9 70 6.7 0.0 aug sun 515 146.0 614.7 25.6 0.0 0.00 94.4 11.3 42 4.0 aug sat 516 nov tue 79.5 3.0 106.7 1.1 11.8 31 4.5 0.0 0.00

517 rows × 11 columns

In [11]: | forest\_fire1.shape

Out[11]: (517, 31)

In [12]: forest\_fire1.describe()

### Out[12]:

|       | FFMC       | DMC        | DC         | ISI        | temp       | RH         | wind       |        |
|-------|------------|------------|------------|------------|------------|------------|------------|--------|
| count | 517.000000 | 517.000000 | 517.000000 | 517.000000 | 517.000000 | 517.000000 | 517.000000 | 517.00 |
| mean  | 90.644681  | 110.872340 | 547.940039 | 9.021663   | 18.889168  | 44.288201  | 4.017602   | 0.02   |
| std   | 5.520111   | 64.046482  | 248.066192 | 4.559477   | 5.806625   | 16.317469  | 1.791653   | 0.29   |
| min   | 18.700000  | 1.100000   | 7.900000   | 0.000000   | 2.200000   | 15.000000  | 0.400000   | 0.00   |
| 25%   | 90.200000  | 68.600000  | 437.700000 | 6.500000   | 15.500000  | 33.000000  | 2.700000   | 0.00   |
| 50%   | 91.600000  | 108.300000 | 664.200000 | 8.400000   | 19.300000  | 42.000000  | 4.000000   | 0.00   |
| 75%   | 92.900000  | 142.400000 | 713.900000 | 10.800000  | 22.800000  | 53.000000  | 4.900000   | 0.00   |
| max   | 96.200000  | 291.300000 | 860.600000 | 56.100000  | 33.300000  | 100.000000 | 9.400000   | 6.40   |

8 rows × 28 columns

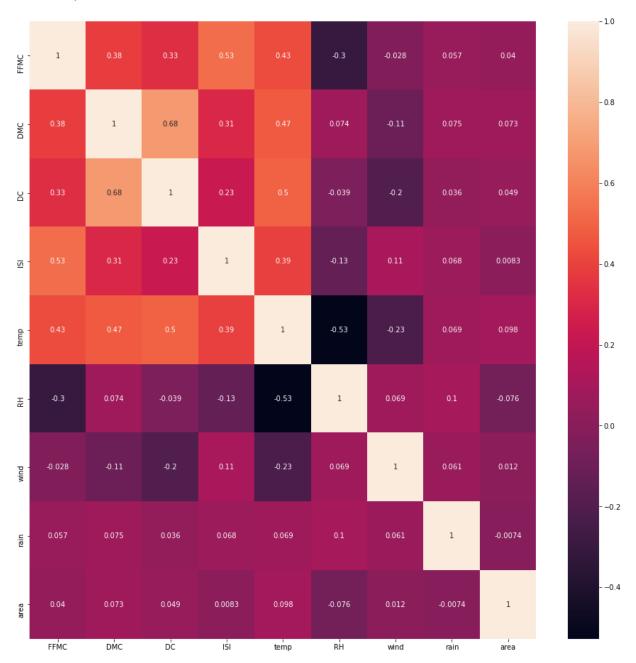
4

•

```
In [13]: forest_fire1.isnull().sum()
Out[13]: month
                            0
                            0
          day
          FFMC
                            0
          DMC
                            0
          DC
                            0
          ISI
                            0
                            0
          temp
          RH
                            0
          wind
                            0
          rain
                            0
                            0
          area
          dayfri
                            0
                            0
          daymon
                            0
          daysat
                            0
          daysun
                            0
          daythu
          daytue
                            0
          daywed
                            0
                            0
          monthapr
          monthaug
                            0
          monthdec
                            0
                            0
          monthfeb
          monthjan
                            0
                            0
          monthjul
          monthjun
                            0
                            0
          monthmar
          monthmay
                            0
          monthnov
                            0
                            0
          monthoct
                            0
          monthsep
          size_category
                            0
          dtype: int64
In [14]: # Correlation
          corr=forest_fire1.iloc[:,0:11].corr()
```

In [15]: plt.figure(figsize=(16,16))
sns.heatmap(corr,annot=True)

#### Out[15]: <AxesSubplot:>

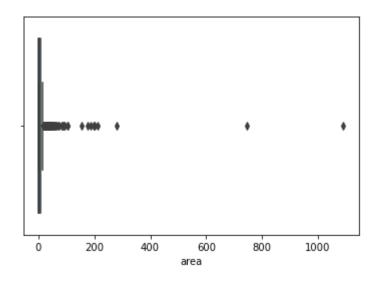


## **Outlier Check**

```
In [16]: outL=sns.boxplot(forest_fire1['area'])
```

C:\Users\nishi\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWar ning: Pass the following variable as a keyword arg: x. From version 0.12, the o nly valid positional argument will be `data`, and passing other arguments witho ut an explicit keyword will result in an error or misinterpretation.

warnings.warn(

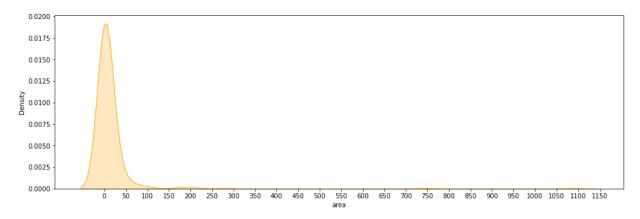


We find 3 Outliers in the data.

```
In [17]: plt.rcParams["figure.figsize"] = 9,5
In [18]: data=forest_fire1['area']
         print(data)
          0
                  0.00
          1
                  0.00
          2
                  0.00
          3
                  0.00
          4
                  0.00
                 . . .
          512
                  6.44
          513
                 54.29
          514
                 11.16
          515
                  0.00
                  0.00
          516
          Name: area, Length: 517, dtype: float64
```

```
In [33]: plt.figure(figsize=(16,5))
    print("Skew: {}".format(forest_fire1['area'].skew()))
    print("Kurtosis: {}".format(forest_fire1['area'].kurtosis()))
    outL= sns.kdeplot(forest_fire1['area'],color='orange',shade='True')
    plt.xticks([i for i in range(0,1200,50)])
    plt.show()
```

Skew: 12.846933533934868 Kurtosis: 194.1407210942299



The plot above is skewed to the right and has a high kurtosis value. We observe that most of the forest fire area lies in less than 150 hectares.

```
In [34]: dfa = forest_fire1[forest_fire1.columns[0:10]]
month_column = dfa.select_dtypes(include='object').columns.tolist()
```

```
In [35]: plt.figure(figsize=(16,10))
           for i,col in enumerate(month_column,1):
                plt.subplot(2,2,i)
                sns.countplot(data=dfa,y=col)
                plt.subplot(2,2,i+2)
                forest_fire1[col].value_counts(normalize=True).plot.bar()
                plt.ylabel(col)
                plt.xlabel('% distribution per category')
           plt.tight_layout()
           plt.show()
             aug
             sep
                                                            g sun
             dec
                                                                                    count
             0.35
                                                             0.175
             0.30
                                                             0.150
             0.25
                                                             0.125
           fj 0.20
                                                            æ 0.100
             0.15
                                                             0.075
             0.10
                                                             0.050
             0.05
                                                             0.025
```

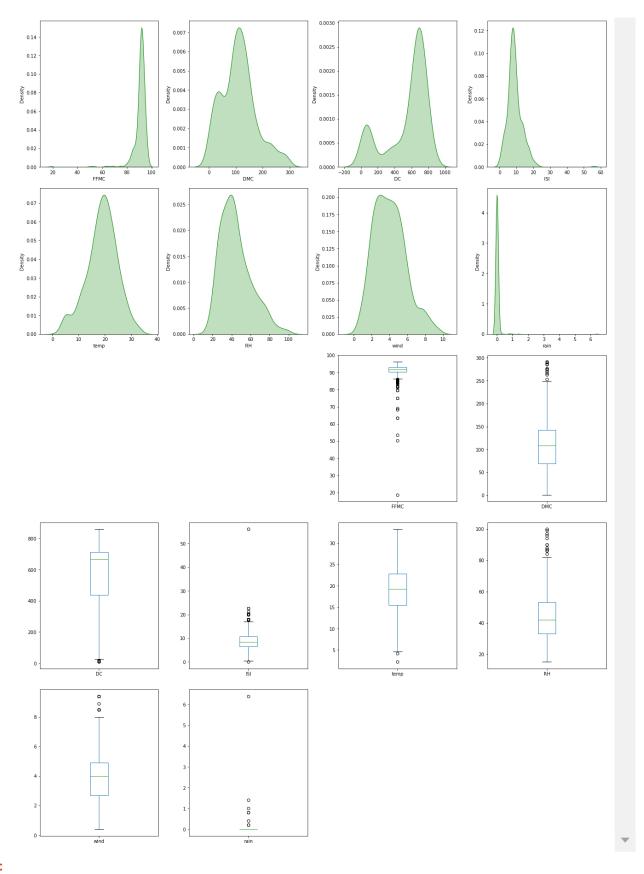
We can conclude that majority of the fires occur in the month of august and september. When we talk about the days the major cases occurr on friday, saturday and sunday.

Sun

```
In [36]: num_columns = dfa.select_dtypes(exclude='object').columns.tolist()
```

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Out[37]:

|          | FFMC      | DMC      | DC        | ISI       | temp      | RH       | wind     | rain       |
|----------|-----------|----------|-----------|-----------|-----------|----------|----------|------------|
| skewness | -6.575606 | 0.547498 | -1.100445 | 2.536325  | -0.331172 | 0.862904 | 0.571001 | 19.816344  |
| kurtosis | 67.066041 | 0.204822 | -0.245244 | 21.458037 | 0.136166  | 0.438183 | 0.054324 | 421.295964 |

#### **SVM**

```
In [38]: X = forest_fire1.iloc[:,2:30]
y = forest_fire1.iloc[:,30]

In [39]: mapping = {'small': 1, 'large': 2}

In [40]: y = y.replace(mapping)

In [41]: x_train,x_test,y_train,y_test = train_test_split(X,y,test_size = 0.20, stratify = 0.20)
```

## Linear

```
In [45]: model_linear = SVC(kernel = "linear")
model_linear.fit(x_train,y_train)
pred_test_linear = model_linear.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, pred_test_linear))
```

Accuracy: 0.9711538461538461

## **Poly**

```
In [46]: model_poly = SVC(kernel = "poly")
model_poly.fit(x_train,y_train)
pred_test_poly = model_poly.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, pred_test_poly))
```

Accuracy: 0.7403846153846154

#### **RBF**

```
In [48]: model_rbf = SVC(kernel = "rbf")
model_rbf.fit(x_train,y_train)
pred_test_rbf = model_rbf.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, pred_test_rbf))
```

Accuracy: 0.7403846153846154

# **Sigmoid**

```
In [49]: model_sigmoid = SVC(kernel = "sigmoid")
model_sigmoid.fit(x_train,y_train)
pred_test_sigmoid = model_sigmoid.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, pred_test_sigmoid))
```

Accuracy: 0.7019230769230769

## **CONCLUSION**

The linear model gives us the best accuracy compared to poly, rbf and sigmoid model.