APYTHONPROGRAMTOIMPLEMENTADABOOSTING

Ex.No.:8
Date of Submission:11/10/2024

AIM:-

To implement a python program for Ada Boosting.

ALGORITHM:-

Step1: Import the necessary libraries(pandas as pd, numpy as np and plot_decision_regions from mlxtend.plotting)

Step2: Create a dataframe and fill values and labels in the data frame and display it. Step3: Import seaborn as sns and plot a scatter plot with the data frame components as the parameters.

Step4: Add a new component to the data frame called “weights” which equals the inverse of the cumulative dimensions of the data frame and display it.

Step5: Import “DecisionTreeClassifier” from sklearn.tree and create an object.

Step6: Assign the variables “x” and “y” the range of values from the data frame.

Step7: Fit the first tree and then plot the tree using “plot_tree” imported from sklearn.tree.

Step8: Plot the decision regions using the above trained tree as the classifier.

Step9: Introduce a new component in the dataframe called “y_pred” to store the values predicted by the above use decision tree and display the decision tree.

Step10: Create a function which returns half the values of log of (1-error)/(error) and calculate the weight of the decision tree.

Step11: Create a function to update the weights of the instances such that the weight is multiplied by exp(-alpha) if correctly classified and multiplied by exp(alpha) if misclassified. Step12: Create a new component of the data frame called ”updated_weights” and apply the created function on the columns in the data frame and store the resulting values in the new component and display the data frame.

Step13: Add all the values in the “updated_weights” component and add a new component called “normalized_weights” which equals the division of each individual instance value by the sum of values of all instances and display the updated data frame.

Step14: Calculate the sum of the values of the “normalized_values” component and display it.

Step15: Add a new component called “cumsum_upper” the cumulative sum of the ”normalized_weights” values.

Step16: Add another component called “cumsum_lower” which is the difference between the “cumsum_upper” and “normalized_weights” and display all the components of the data frame .

Step17: Follow the above 16 steps two more times for 2 new data frames and 2 new decision trees(second_df,third_df,dt2and dt3 respectively)

Step18: Compare the predicted values of all the decision trees.

Step19: Multiply alpha1, alpha2 and alpha3 by 1 and add all the values.

Step20: Find the sign of the resulting values from the previous step.

Step21: Multiply alpha1 by1, alpha2 and alpha3 by -1 and add the values and find the sign of the resulting value.

IMPLEMENTATION:-

```
import pandas as pd

import numpy as np

from mlxtend.plotting import plot_decision_regions


df = pd.DataFrame()
```

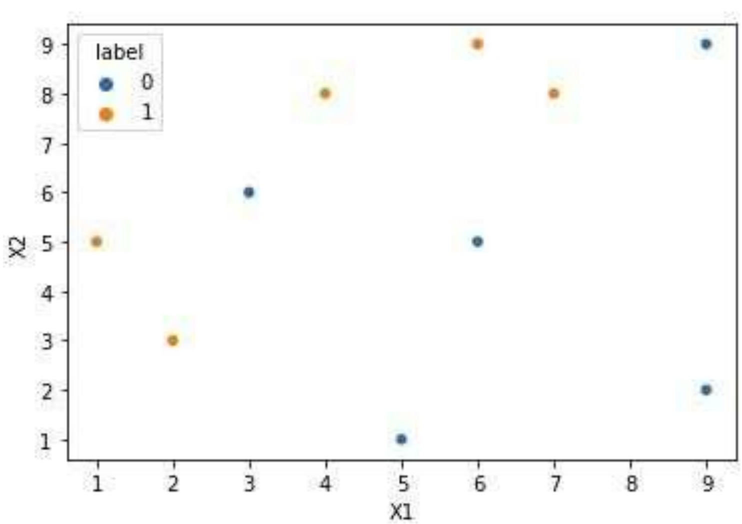
df['X1']=[1,2,3,4,5,6,6,7,9,9] df['X2']=[5,3,6,8,1,9,5,8,9,2]

df['label']=[1,1,0,1,0,1,0,1,0,0] df

	X1	X2	label
0	1	5	1
1	2	3	1
2	3	6	0
3	4	8	1
4	5	1	0
5	6	9	1
6	6	5	0
7	7	8	1
8	9	9	0
9	9	2	0

import seaborn as sns sns.scatterplot(x=df['X1'],y=df['X2'],hue=df['label'])

```
<AxesSubplot:xlabel='X1', ylabel='X2'>
```



df['weights']=1/df.shape[0]
df

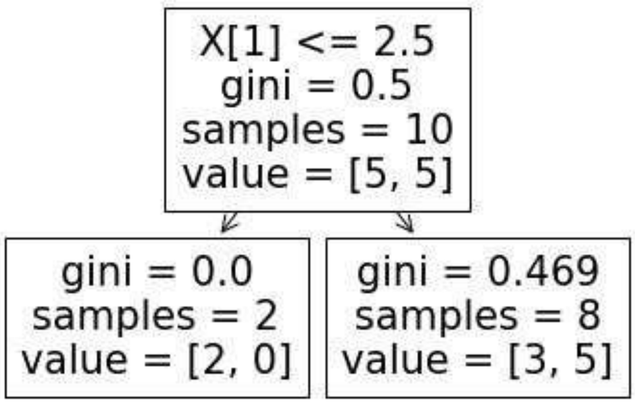
	X1	X2	label	weights
0	1	5	1	0.1
1	2	3	1	0.1
2	3	6	0	0.1
3	4	8	1	0.1
4	5	1	0	0.1
5	6	9	1	0.1
6	6	5	0	0.1
7	7	8	1	0.1
8	9	9	0	0.1
9	9	2	0	0.1

```
from sklearn.tree import DecisionTreeClassifier

dt1 = DecisionTreeClassifier(max_depth=1)

x = df.iloc[:,0:2].values y =

df.iloc[:,2].values

# Step 2 - Train 1st Model dt1.fit(x,y)
```

```
DecisionTreeClassifier(max_depth=1)
```

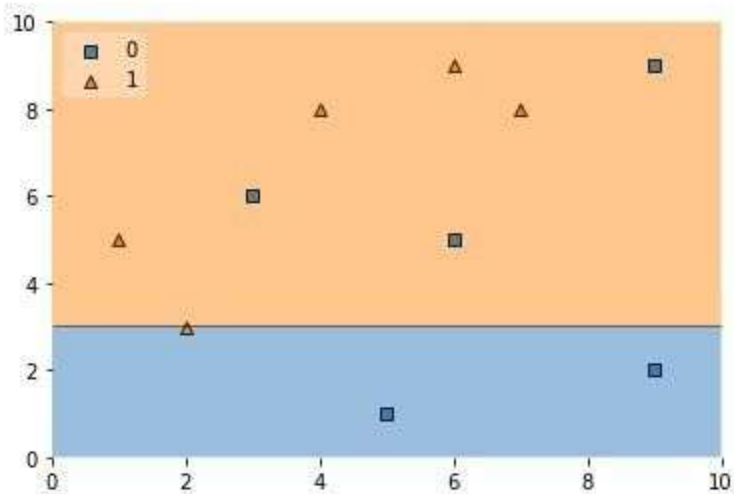
```
from sklearn.tree import plot_tree plot_tree(dt1)
```

```
[Text(0.5, 0.75, 'X[1] <= 2.5\ngini = 0.5\nsamples = 10\nvalue = [5, 5]'),
 Text(0.25, 0.25, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(0.75, 0.25, 'gini = 0.469\nsamples = 8\nvalue = [3, 5]')]
```




```
plot_decision_regions(x,y,clf=dt1,legend=2)
```

```
<AxesSubplot:>
```




```
df['y_pred'] = dt1.predict(x)
df
```

	X1	X2	label	weights	y_pred
0	1	5	1	0.1	1
1	2	3	1	0.1	1
2	3	6	0	0.1	1
3	4	8	1	0.1	1
4	5	1	0	0.1	0
5	6	9	1	0.1	1
6	6	5	0	0.1	1
7	7	8	1	0.1	1
8	9	9	0	0.1	1
9	9	2	0	0.1	0

```
def calculate_model_weight(error):
    return 0.5*np.log((1-error)/(error))
```

```
# Step - 3 Calculate model weight alpha1
= calculate_model_weight(0.3) alpha1
```

```
0.42364893019360184
```

```
# Step -4 Update weights def
update_row_weights(row,alpha=0.423): if row['label']
== row['y_pred']:
        return row['weights']* np.exp(-alpha)
    else: return row['weights']*
        np.exp(alpha)
df['updated_weights'] = df.apply(update_row_weights,axis=1) df
```

	X1	X2	label	weights	y_pred	updated_weights
0	1	5	1	0.1	1	0.065508
1	2	3	1	0.1	1	0.065508
2	3	6	0	0.1	1	0.152653
3	4	8	1	0.1	1	0.065508
4	5	1	0	0.1	0	0.065508
5	6	9	1	0.1	1	0.065508
6	6	5	0	0.1	1	0.152653
7	7	8	1	0.1	1	0.065508
8	9	9	0	0.1	1	0.152653
9	9	2	0	0.1	0	0.065508

```
df['updated_weights'].sum()
```

```
0.9165153319682015
```

```
df['normalized_weights']=df['updated_weights']/df['updated_weights'].sum()
```

```
df
```

	X1	X2	label	weights	y_pred	updated_weights	normalized_weights
0	1	5	1	0.1	1	0.065508	0.071475
1	2	3	1	0.1	1	0.065508	0.071475
2	3	6	0	0.1	1	0.152653	0.166559
3	4	8	1	0.1	1	0.065508	0.071475
4	5	1	0	0.1	0	0.065508	0.071475
5	6	9	1	0.1	1	0.065508	0.071475
6	6	5	0	0.1	1	0.152653	0.166559
7	7	8	1	0.1	1	0.065508	0.071475
8	9	9	0	0.1	1	0.152653	0.166559
9	9	2	0	0.1	0	0.065508	0.071475

```
df['normalized_weights'].sum()
```

```
1.0
```

```
df['cumsum_upper'] = np.cumsum(df['normalized_weights'])
```

```
df['cumsum_lower']=df['cumsum_upper'] - df['normalized_weights']
```

```
df[['X1','X2','label','weights','y_pred','updated_weights','cumsum_lower','cumsum_upper']]
```

	X1	X2	label	weights	y_pred	updated_weights	cumsum_lower	cumsum_upper
0	1	5	1	0.1	1	0.065508	0.000000	0.071475
1	2	3	1	0.1	1	0.065508	0.071475	0.142950
2	3	6	0	0.1	1	0.152653	0.142950	0.309508
3	4	8	1	0.1	1	0.065508	0.309508	0.380983
4	5	1	0	0.1	0	0.065508	0.380983	0.452458
5	6	9	1	0.1	1	0.065508	0.452458	0.523933
6	6	5	0	0.1	1	0.152653	0.523933	0.690492
7	7	8	1	0.1	1	0.065508	0.690492	0.761967
8	9	9	0	0.1	1	0.152653	0.761967	0.928525
9	9	2	0	0.1	0	0.065508	0.928525	1.000000

```
def create_new_dataset(df): indices=
  [] for i in range(df.shape[0]): a =
  np.random.random() for
  index,row in df.iterrows():
        if row['cumsum_upper']>a and a>row['cumsum_lower']:
           indices.append(index)
  return indices

index_values = create_new_dataset(df) index_values
```

```
[6, 6, 0, 6, 7, 5, 1, 8, 4, 6]
```

```
second_df = df.iloc[index_values,[0,1,2,3]]

second_df
```

	X1	X2	label	weights
6	6	5	0	0.1
6	6	5	0	0.1
0	1	5	1	0.1
6	6	5	0	0.1
7	7	8	1	0.1
5	6	9	1	0.1
1	2	3	1	0.1
8	9	9	0	0.1
4	5	1	0	0.1
6	6	5	0	0.1

dt2 = DecisionTreeClassifier(max_depth=1)

x = second_df.iloc[:,0:2].values y =

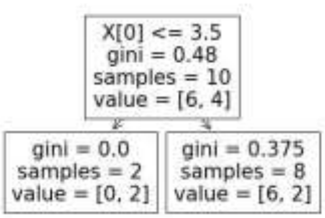
second_df.iloc[:,2].values

dt2.fit(x,y)

```
DecisionTreeClassifier(max_depth=1)
```

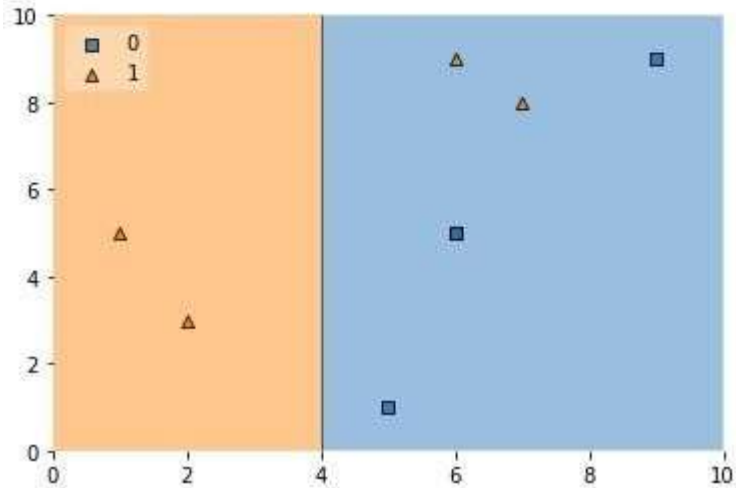
plot_tree(dt2)

```
[Text(0.5, 0.75, 'X[0] <= 3.5\ngini = 0.48\nsamples = 10\nvalue = [6, 4]'),
 Text(0.25, 0.25, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
 Text(0.75, 0.25, 'gini = 0.375\nsamples = 8\nvalue = [6, 2]')]
```



plot_decision_regions(x, y, clf=dt2, legend=2)

<AxesSubplot:>



second_df['y_pred'] = dt2.predict(x)

second_df

	X1	X2	label	weights	y_pred
6	6	5	0	0.1	0
6	6	5	0	0.1	0
0	1	5	1	0.1	1
6	6	5	0	0.1	0
7	7	8	1	0.1	0
5	6	9	1	0.1	0
1	2	3	1	0.1	1
8	9	9	0	0.1	0
4	5	1	0	0.1	0
6	6	5	0	0.1	0

alpha2 = calculate_model_weight(0.1) alpha2

```
1.0986122886681098
```

Step 4 - Update weights def

update_row_weights(row,alpha=1.09): if

row['label'] == row['y_pred']: return

row['weights'] * np.exp(-alpha)

else: return row['weights'] *

np.exp(alpha)

second_df['updated_weights'] = second_df.apply(update_row_weights,axis=1)

second_df

	X1	X2	label	weights	y_pred	updated_weights
6	6	5	0	0.1	0	0.033622
6	6	5	0	0.1	0	0.033622
0	1	5	1	0.1	1	0.033622
6	6	5	0	0.1	0	0.033622
7	7	8	1	0.1	0	0.297427
5	6	9	1	0.1	0	0.297427
1	2	3	1	0.1	1	0.033622
8	9	9	0	0.1	0	0.033622
4	5	1	0	0.1	0	0.033622
6	6	5	0	0.1	0	0.033622

second_df['nomalized_weights'].sum()

```
0.9999999999999999
```

second_df['cumsum_upper'] = np.cumsum(second_df['nomalized_weights'])

second_df['cumsum_lower'] = second_df['cumsum_upper'] - second_df['nomalized_weights']

second_df[['X1','X2','label','weights','y_pred','nomalized_weights','cumsum_lower','cumsum_upp

er']]

	X1	X2	label	weights	y_pred	nomalized_weights	cumsum_lower	cumsum_upper
6	6	5	0	0.1	0	0.038922	0.000000	0.038922
6	6	5	0	0.1	0	0.038922	0.038922	0.077843
0	1	5	1	0.1	1	0.038922	0.077843	0.116765
6	6	5	0	0.1	0	0.038922	0.116765	0.155687
7	7	8	1	0.1	0	0.344313	0.155687	0.500000
5	6	9	1	0.1	0	0.344313	0.500000	0.844313
1	2	3	1	0.1	1	0.038922	0.844313	0.883235
8	9	9	0	0.1	0	0.038922	0.883235	0.922157
4	5	1	0	0.1	0	0.038922	0.922157	0.961078
6	6	5	0	0.1	0	0.038922	0.961078	1.000000

index_values = create_new_dataset(second_df) third_df

= second_df.iloc[index_values,[0,1,2,3]] third_df

	X1	X2	label	weights
1	2	3	1	0.1
6	6	5	0	0.1
5	6	9	1	0.1
1	2	3	1	0.1
5	6	9	1	0.1
8	9	9	0	0.1
8	9	9	0	0.1
8	9	9	0	0.1
5	6	9	1	0.1
8	9	9	0	0.1

dt3 = DecisionTreeClassifier(max_depth=1)

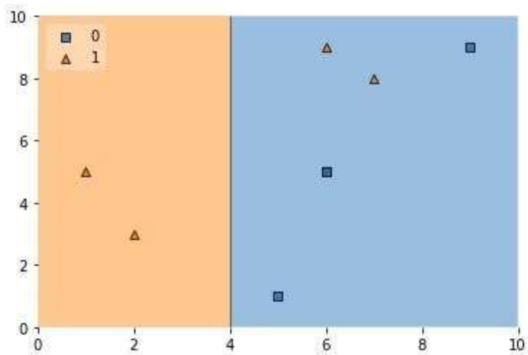
X = second_df.iloc[:,0:2].values y
= second_df.iloc[:,2].values

dt3.fit(X,y)

```
DecisionTreeClassifier(max_depth=1)
```

plot_decision_regions(X, y, clf=dt3, legend=2)

```
&lt;AxesSubplot:&gt;
```



third_df[‘y_pred] = dt3.predict(X)

third_df

alpha3 = calculate_model_weight(0.7) alpha3

```
-0.4236489301936017
```

print(alpha1,alpha2,alpha3)

```
0.42364893019360184 1.0986122886681098 -0.4236489301936017
```

query = np.array([1,5]).reshape(1,2)

dt1.predict(query)

```
array([1])
```

dt2.predict(query)

```
array([1])
```

dt3.predict(query)

```
array([1])
```

alpha1*1 + alpha2*(1) + alpha3*(1)

```
1.09861228866811
```

np.sign(1.09)

```
1.0
```

query = np.array([9,9]).reshape(1,2)

dt1.predict(query)

```
array([1])
```

dt2.predict(query)

```
array([0])
```

dt3.predict(query)

```
array([0])
```

alpha1*(1) + alpha2*(-1) + alpha3*(-1)

```
-0.2513144282809062
```

```
np.sign(-0.25)
```

```
-1.0
```

RESULT:-

Thus the python program to implement Adaboosting has been executed successfully and the results have been verified and analyzed.