# CSE4020

# LAB-5

## Experiment 1: Adaboost

# Algorithm:

- 1. First assign weights to all the data records. Weights are equal if it's the first iteration
- 2. Now start creating stumps with each feature and find its Gini index or Gain based on the type of algorithm that is being used (CART or ID3).
- 3. Now calculate the amount of say for each stump
- 4. Now calculate the performance of the stump. Values will be in between 0 and 1, where 0 means horrible.
- 5. Now select the best stump and wrong predictions will be given more weight this time
- 6. Now we need to make a new dataset to see if the errors decreased or not. For this

New sample weight = old weight \* 
$$e^{\pm Amount\ of\ say\ (\alpha)}$$

we will remove the "sample weights" and "new sample weights" column and then based on the "new sample weights" we will divide our data points into buckets.

- 7. Selects random numbers from 0-1. Since incorrectly classified records have higher sample weights, the probability to select those records is very high.
- 8. This will be the new dataset and we will iterate over it till the error reduces.

```
In [2]:
```

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
X = load_iris().data
y = load_iris().target
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, random_s
```

# In [3]:

```
from sklearn.ensemble import AdaBoostClassifier

abclassifier = AdaBoostClassifier(n_estimators=50, learning_rate=1, random_state=2)
model = abclassifier.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

## In [4]:

```
from sklearn.metrics import accuracy_score
print("Accuracy:", accuracy_score(y_test, y_pred))
```

Accuracy: 0.977777777777777

#### In [ ]:

# Experiment 2: K Means Clustering

# Algorithm:

- 1. Select the number K to decide the number of clusters.
- 2. Select random K points or centroids. (It can be other from the input dataset).
- 3. Assign each data point to their closest centroid, which will form the predefined K clusters.
- 4. Calculate the variance and place a new centroid of each cluster.
- 5. Repeat the third steps, which means reassign each datapoint to the new closest centroid of each cluster.
- 6. If any reassignment occurs, then go to step-4 else go to FINISH.

```
In [1]:
from sklearn.datasets import make blobs
import pandas as pd
In [2]:
dataset, classes = make blobs(n samples=300, n features=2, centers=5, cluster std=0.
df = pd.DataFrame(dataset, columns=['X', 'Y'])
df.head(2)
Out[2]:
                 Υ
        X
  1.569719 -0.838530
1 -3.750696 -4.419262
In [3]:
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=5, init='k-means++', random_state=0).fit(df)
In [4]:
print(kmeans.n_iter_) #total number of iterations to convergence
In [5]:
print(kmeans.cluster_centers_) #cluster centers
[[-5.83451299 2.30779804]
 [-1.35495664 -9.43666895]
 [-4.06321324 -4.81843763]
 [ 1.00220205 -1.26008793]
 [-1.56907217 -3.44508562]]
```

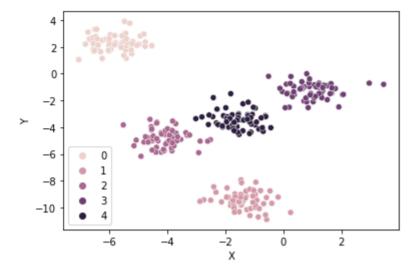
In [6]:

print(kmeans.inertia\_) #defines how well the dataset is clustered

225.49694297568254

# In [7]:

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.scatterplot(data=df, x="X", y="Y", hue=kmeans.labels_)
plt.show()
```



# In [ ]:

# Experiment 3: Agglomerative Clustering

# Algorithm

- 1. Make dataset
- 2. Compute similarity information between every pair of objects in the data set.
- 3. Using linkage function to group objects into hierarchical cluster tree, based on the distance information generated at step 1. Objects/clusters that are in close proximity are linked together using the linkage function.
- 4. Determining where to cut the hierarchical tree into clusters. This creates a partition of the data.

#### In [1]:

```
from sklearn.datasets import make_blobs
import pandas as pd
import numpy as np

dataset, classes = make_blobs(n_samples=300, n_features=2, centers=5, cluster_std=0.
df = pd.DataFrame(dataset, columns=['x1', 'x2'])
X = df.values
x1 = df['x1']
x2 = df['x2']
```

#### In [2]:

```
from sklearn.cluster import AgglomerativeClustering
ac = AgglomerativeClustering(n_clusters=5)
model = ac.fit(X)
```

#### In [3]:

```
print(model.n_clusters)
print(model.n_leaves_)
print(model.n_features_in_)
```

5 300 2

#### In [4]:

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.scatterplot(x1,x2, hue = model.labels_)
```

/Users/sampathroutu/opt/anaconda3/lib/python3.8/site-packages/seaborn/\_decorators.py:36: FutureWarning: Pass the following variables as keyw ord args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

#### Out[4]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f9ee8c5cf40>

