#### 1 ASSIGNMENT NO: A6

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#### 2 Problem Definition

Implement a simple approach for k-means/k-medoids clustering using C++.

## 3 Learning Objectives:

- 1. To understand the concept of clustering.
- 2. To implement k-means clustering algorithm.

# 4 S/W and H/W requirements:

- 1. Open source 64 bit OS.
- 2. Gedit text editor.
- 3. C++ programming language.
- 4. g++ compiler.

## 5 Theory

#### k-means Clustering:

k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.

The problem is computationally difficult (NP-hard); however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

The algorithm has a loose relationship to the k-nearest neighbor classifier, a popular machine learning technique for classification that is often confused with k-means because of the k in the name. One can apply the 1-nearest neighbor classifier on the cluster centers obtained by k-means to classify new data into

the existing clusters. This is known as nearest centroid classifier or Rocchio algorithm.

Given a set of observations (x1, x2,..., xn), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k (i=n) sets S=S1, S2,..., Sk so as to minimize the within-cluster sum of squares (WCSS) (sum of distance functions of each point in the cluster to the K center). In other words, its objective is to find:

$$rg\min_{\mathbf{S}} \sum_{i=1}^k \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - oldsymbol{\mu}_i 
ight\|^2$$

### Algorithm:

Let X = x1,x2,x3,...,xn be the set of data points and V = v1,v2...,vc be the set of centers.

- 1. Randomly select 'c' cluster centers.
- 2. Calculate the distance between each data point and cluster centers.
- 3. Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.
- 4. Recalculate the new cluster center using:

$$\mathbf{v}_i = (1/c_i) \sum_{j=1}^{c_i} \mathbf{x}_i$$

where, 'ci' represents the number of data points in ith cluster.

- Recalculate the distance between each data point and new obtained cluster centers.
- 6. If no data point was reassigned then stop, otherwise repeat from step 3).

### 6 Related Mathematics

Let S be the solution perspective of the given problem.

The set S is defined as:

 $S = \{ s, e, X, Y, F, DD, NDD | \varnothing_s \}$ 

Where,

s = Start point

s = data set of points i.e. x1,x2,...,xn

e= End point

e= k clusters C1,C2,...,Ck, such that,

C1UC2U...UCk = x1, x2, ..., xn, and

 $C1\cap C2\cap\ldots\cap Ck=\phi$ 

F= Set of main functions

DD= set of deterministic data

NDD= set of non deterministic data

X= Input Set.

 $X = \{ x_1, x_2, ..., x_n, k \}$ 

where,

 $x_i = \text{data points}$ 

k= no. of clusters

 $Y = \{C1, C2, ..., Ck\}$ 

where, Ci = ith cluster.

 $\mathbf{F} = \{f_{choose}, f_{dist}, f_{avg}, f_{assign}\}$ 

 $f_{choose}$ : function to choose random centroids.

 $f_{dist}$ : function to calculate distance of data points from the centroids.

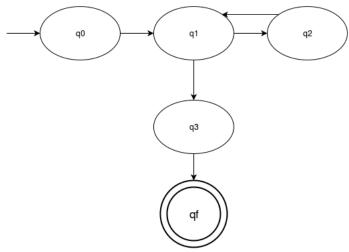
 $f_{average}$ : function to calculate average of all the points in a cluster and update the centroid of that cluster.

 $f_{ack}$ : function to assign a data point to the nearest cluster.

$$DD = \{x_1, x_2, ..., x_n, k\}$$

$$NDD = \{initial centroids\}$$

## 7 State Diagram



q0 = select random centroids

q1 = assign points to clusters

```
q2 = cluster centroid update state q3 = display final clusters state qf = final state
```

## 8 Program

#### PROGRAM

```
filename: a6.cpp
#include<iostream>
#include<stdio.h>
#include<time.h>
#include<stdlib.h>
using namespace std;
class kmeans
{
struct points
 float x;
 float y;
public:
struct points p[8];
struct points c[3];
void input();
int km();
float distance(float a,float b,float x,float y);
int tally[8][10];
int count;
int n;
void kmeans::input()
 p[0].x=2;p[0].y=2;
 p[1].x=1;p[1].y=14;
 p[2].x=10;p[2].y=7;
 p[3].x=1;p[3].y=11;
 p[4].x=3;p[4].y=4;
 p[5].x=11;p[5].y=8;
 p[6].x=4;p[6].y=3;
 p[7].x=12;p[7].y=2;
int i,random=0;
srand(time(NULL));
for(i=0;i<3;i++)
{
```

```
random=(rand())%7;
c[i].x=p[random].x;
c[i].y=p[random].y;
}
float kmeans::distance(float a,float b,float x,float y)
float t1=a-x;
float t2=b-y;
if(t1<0)
t1=-t1;
if(t2<0)
t2=-t2;
return (t1+t2);
int kmeans::km()
int i,j;
float table[8][4];
for(i=0;i<n;i++)
table[i][0]=distance(p[i].x,p[i].y,c[0].x,c[0].y);
table[i][1]=distance(p[i].x,p[i].y,c[1].x,c[1].y);
 table[i][2]=distance(p[i].x,p[i].y,c[2].x,c[2].y);
 if(table[i][0]<=table[i][1] && table[i][0]<=table[i][2])</pre>
 {
 tally[i][count]=0;
 table[i][3]=table[i][0];
 else if(table[i][1]<=table[i][0] && table[i][1]<=table[i][2])</pre>
 tally[i][count]=1;
 table[i][3]=table[i][1];
 else if(table[i][2]<=table[i][0] && table[i][2]<=table[i][1])
 tally[i][count]=2;
 table[i][3]=table[i][2];
}
cout<<"TABLE: "<<count+1<<endl;</pre>
\verb|cout|<<|Centroids are: ("<<c[0].x<<","<<c[0].y<<"), |
("<<c[1].x<<","<<c[1].y<<"), ("<<c[2].x<<","<<c[2].y<<")"<<endl;
cout<<"c1\tc2\tc3\tmin"<<endl;</pre>
cout<<"----"<<endl;
for(i=0;i<n;i++)
{
```

```
for(j=0;j<4;j++)
 cout << table[i][j] << "\t";
cout<<endl;</pre>
}
cout<<"----"<<endl;
float c0=0,c1=0,c2=0,c0x=0,c0y=0,c1x=0,c1y=0,c2x=0,c2y=0;
for(i=0;i<n;i++)</pre>
{
if(tally[i][count]==0)
{
c0x+=p[i].x;
cOy+=p[i].y;
c0++;
}
else if(tally[i][count]==1)
c1x+=p[i].x;
c1y+=p[i].y;
c1++;
else if(tally[i][count]==2)
c2x+=p[i].x;
c2y+=p[i].y;
c2++;
}
}
c[0].x=c0x/c0;
c[0].y=c0y/c0;
c[1].x=c1x/c1;
c[1].y=c1y/c1;
c[2].x=c2x/c2;
c[2].y=c2y/c2;
int flag=0;
if(count!=0)
for(i=0;i<n;i++)</pre>
 if(tally[i][count] == tally[i][count-1])
   flag++;
}
count++;
return flag;
```

```
int main()
kmeans k;
k.input();
n=8;
count=0;
int flag=k.km();
while(flag!=8)
flag=k.km();
if(flag==8)
 cout<<"Centroids found"<<endl;</pre>
for(int i=0;i< n;i++)
{
 for(int j=0;j<count;j++)</pre>
 cout<<tally[i][j]<<" ";
 cout<<endl;</pre>
}
return 0;
OUTPUT
ameeth@ubuntu-16.0.4:~/CL1$ ./a.out
TABLE: 1
Centroids are: (3,4), (1,14), (2,2)
c1 c2 c3 min
3 13 0 0
12 0 13 0
10 16 13 10
9 3 10 3
0 12 3 0
12 16 15 12
2 14 3 2
11 23 10 10
_____
TABLE: 2
Centroids are: (7,5.5), (1,12.5), (7,2)
c1 c2 c3 min
_____
8.5 11.5 5 5
14.5 1.5 18 1.5
4.5 14.5 8 4.5
11.5 1.5 15 1.5
5.5 10.5 6 5.5
6.5 14.5 10 6.5
5.5 12.5 4 4
8.5 21.5 5 5
```

```
TABLE: 3
Centroids are: (8,6.33333), (1,12.5), (6,2.33333)
c1 c2 c3 min
_____
10.3333 11.5 4.33333 4.33333
14.6667 1.5 16.6667 1.5
2.66667 14.5 8.66667 2.66667
11.6667 1.5 13.6667 1.5
7.33333 10.5 4.66667 4.66667
4.66667 14.5 10.6667 4.66667
7.33333 12.5 2.66667 2.66667
8.33333 21.5 6.33333 6.33333
TABLE: 4
Centroids are: (10.5,7.5), (1,12.5), (5.25,2.75)
c1 c2 c3 min
_____
14 11.5 4 4
16 1.5 15.5 1.5
1 14.5 9 1
13 1.5 12.5 1.5
11 10.5 3.5 3.5
1 14.5 11 1
11 12.5 1.5 1.5
7 21.5 7.5 7
______
TABLE: 5
Centroids are: (11,5.66667), (1,12.5), (3,3)
c1 c2 c3 min
_____
12.6667 11.5 2 2
18.3333 1.5 13 1.5
2.33333 14.5 11 2.33333
15.3333 1.5 10 1.5
9.66667 10.5 1 1
2.33333 14.5 13 2.33333
9.66667 12.5 1 1
4.66667 21.5 10 4.66667
_____
Centroids found
2 2 2 2 2
1 1 1 1 1
0 0 0 0 0
1 1 1 1 1
0 0 2 2 2
0 0 0 0
0 2 2 2 2
2 2 2 0 0
ameeth@ubuntu-16.0.4:~/CL1$
```

# 9 Conclusion

Thus we have implemented the Naive Bayes classifier in python using sklearn.