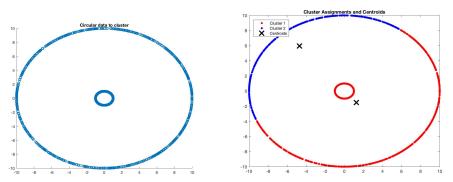
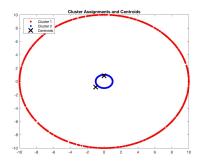
## Question 3

(a) The Original Data and K-means in Cartesian Coordinates

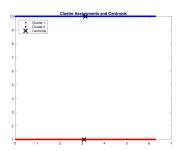


When K = 2, The K-means method in Cartesian Coordinates basically means bisecting all data in Euclidean Space. However, the given data are distributed on two concentric circles, which cannot be bisected by a line in  $R^2$  space.

(b) It is Clearly showed that the data distributed on each circle has been separated into two different clusters.



(c) If we look the data in the polar coordinate space, we can see such polar representation has separate the circle data into linear data. And K-means can easily bisect such data into two clusters in this space.



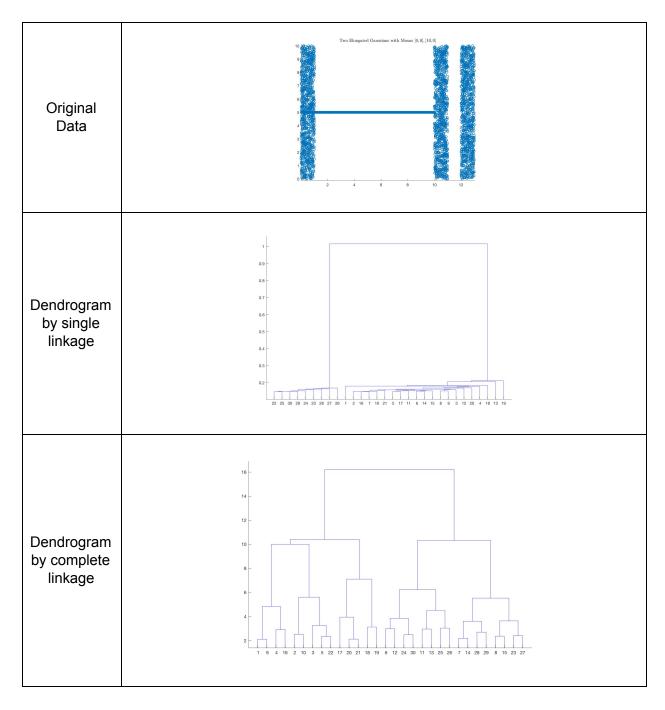
(x-axis is angle and y-axis is radius)

Code to produce k means result for Circular data in terms of Cartesian and Polar Coordinates

```
theta1=2*pi*rand(1000,1);
X1=[cos(theta1),sin(theta1)];
R1=ones(1000,1);
X1_p=[theta1,R1];
theta2=2*pi*rand(1000,1);
X2=10*[cos(theta2),sin(theta2)];
R2=10*ones(1000,1);
X2_p=[theta2,R2];
X=vertcat(X1,X2);
X_p=vertcat(X1_p,X2_p)
close all;
scatter(X(:,1),X(:,2));
title('Circular data to cluster');
[idx,C] = kmeans(X,2,'Display','Iter','Replicates',100);
figure;
plot(X(idx==1,1),X(idx==1,2),'r.','MarkerSize',12)
hold on
plot(X(idx==2,1),X(idx==2,2),'b.','MarkerSize',12)
plot(C(:,1),C(:,2),'kx',...
     'MarkerSize',15,'LineWidth',3)
```

```
legend('Cluster 1','Cluster 2','Centroids',...
       'Location','NW')
title 'Cluster Assignments and Centroids'
hold off
[idx p,C p] = kmeans(X_p,2,'Display','Iter','Replicates',100);
C1_p = [cos(C_p(1,1)), sin(C_p(2,1))];
C2_p=[cos(C_p(1,2)),sin(C_p(2,2))];
figure;
plot(X(idx_p==1,1),X(idx_p==1,2),'r.','MarkerSize',12)
hold on
plot(X(idx_p==2,1),X(idx_p==2,2),'b.','MarkerSize',12)
plot(C1_p,C2_p,'kx',...
     'MarkerSize', 15, 'LineWidth', 3)
legend('Cluster 1','Cluster 2','Centroids',...
       'Location','NW')
title 'Cluster Assignments and Centroids'
hold off
```

## Question 4



For single linkage, the distance between cluster  $X_1$  and  $X_2$ ,  $D(X_1,X_2)=\min D(x_1,x_2)$ , where  $x_1\in X_1,x_2\in X_2$ .

And for complete linkage, the distance between cluster  $X_1$  and  $X_2$ ,  $D(X_1, X_2) = \max D(x_1, x_2)$ , where  $x_1 \in X_1, x_2 \in X_2$ , where the size of the cluster become matter.

Accord the code that generates this dataset (you can see they are from  $S_1, S_2$   $S_3$  and  $S_4$ ), any subclusters from  $S_1, S_2$  or  $S_3$  will merge first, before they merge with any subclusters from  $S_4$ , because you can always find two neighbor subclusters in  $S_1 \cup S_2 \cup S_3$ , who have elements  $D(x_1, x_2) < 1$ . And 1 is the minimum distance between any point in  $S_3$  and any point in  $S_4$ .

```
DistortionMatrix=[1,0;0,10];
S1=rand(1000,2);
S1=S1*DistortionMatrix;

S2=rand(1000,2);
S2=S2*DistortionMatrix;
S2=S2+[10,0];

S3=10*rand(1000,2);
D2Matrix=[1,0;0,0];
S3 = S3*D2Matrix+[0,5]

S4=rand(1000,2);
S4=S4*DistortionMatrix;
S4=S4+[12,0];

X=vertcat(X1,X2,X3,X4);
```

However, the situation is different in complete linkage method. When the subclusters from different regions are <u>sufficiently large</u>, two neighbor subclusters  $S_3$  or  $S_2$  has  $D(X_1, X_2) >> 1$ . Then some subclusters in  $S_3$  may merge with some subcluster in  $S_4$  first, because the distance between  $S_3$  and  $S_4$  is neglectable to the size of such clusters.