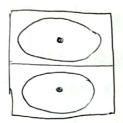
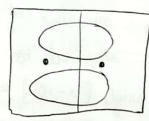


Here the split is made as shown in the figure. Here the distance between the edges of the circles is much less than the radii of the circles. Here the initial centraids are actual data points. Side way centraids have low error of center has higher error.

d) K=2



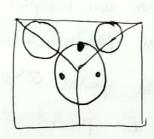
Local minimum



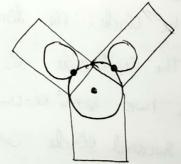
global minimum

There are two possible splits as shown above In the first diagram, the two clusters are only local minimum, in the second case they are global minimum.





Local minimum



global minimum

There are two possible solutions as shown in the figure with load of dobal minimum respectively.

From the global minimum figure - there are Iwo rectangular symmetrical cluster. the third cluster is in the form of a triangle

11) If SSE of an attribute is low for all clusters, then it is a Constant and gives less information when the observations are divided into groups.

H SSE of an attribute is low for just one cluster then it helps in defining the cluster.

If SSE of an attribute is high for all the Clusters then the Corresponding attribute could be a noise

If SSE of an attribute is high for only one Cluster then the attributes with low SSE defines the Cluster. They high SE attribute is not part of defining the cluster.

Per variable SSE can be used to eliminate attributes that have poor classification between the clusters. As mentioned above that if SSE of an attribute is high for all the clusters then it could be a morse and dosent help in defining the cluster.

a) header algorithm is computationally efficient. Than k-mos. Output of a header algorithm is fixed, (ie) it produces same clusters everytime when there is fixed ordering of objects. I means produces different clusters based on the centroid position.

In terms of SSE K means has better accuracy our header algorithm. b) use can use a sample of observations to find the distribution of distance between the points Using this helps to set the value of the threshold. By using different values of thresholds we an get different clusters. P1 P2 P3 P4 P5 Similarity matrix. (6) P1 1 0.1 0.41 0.95 0.35 P2 0.1 1 0.64 0.47 0.98 P3 0.41 0.64 1 0.64 0.85 P4 0.55 0.47 0.44 1 0.76 P5 6.35 0.98 0.85 6.761 Single den kage highest is 0-98 P2-P5 P₁ P₂-P₅ P₃ P4 R-P5 0.35 highest is 0.85 P3 0.41 0.85 Combine P2-Ps-B P4 0.55 0.76 0.44 P, P2-P5-P3 P4 P1 1 (2) highest is 0.76 P2-P3-P3 0.41 Join P2-P5-P3-P4 [0.76] P4 0.55

