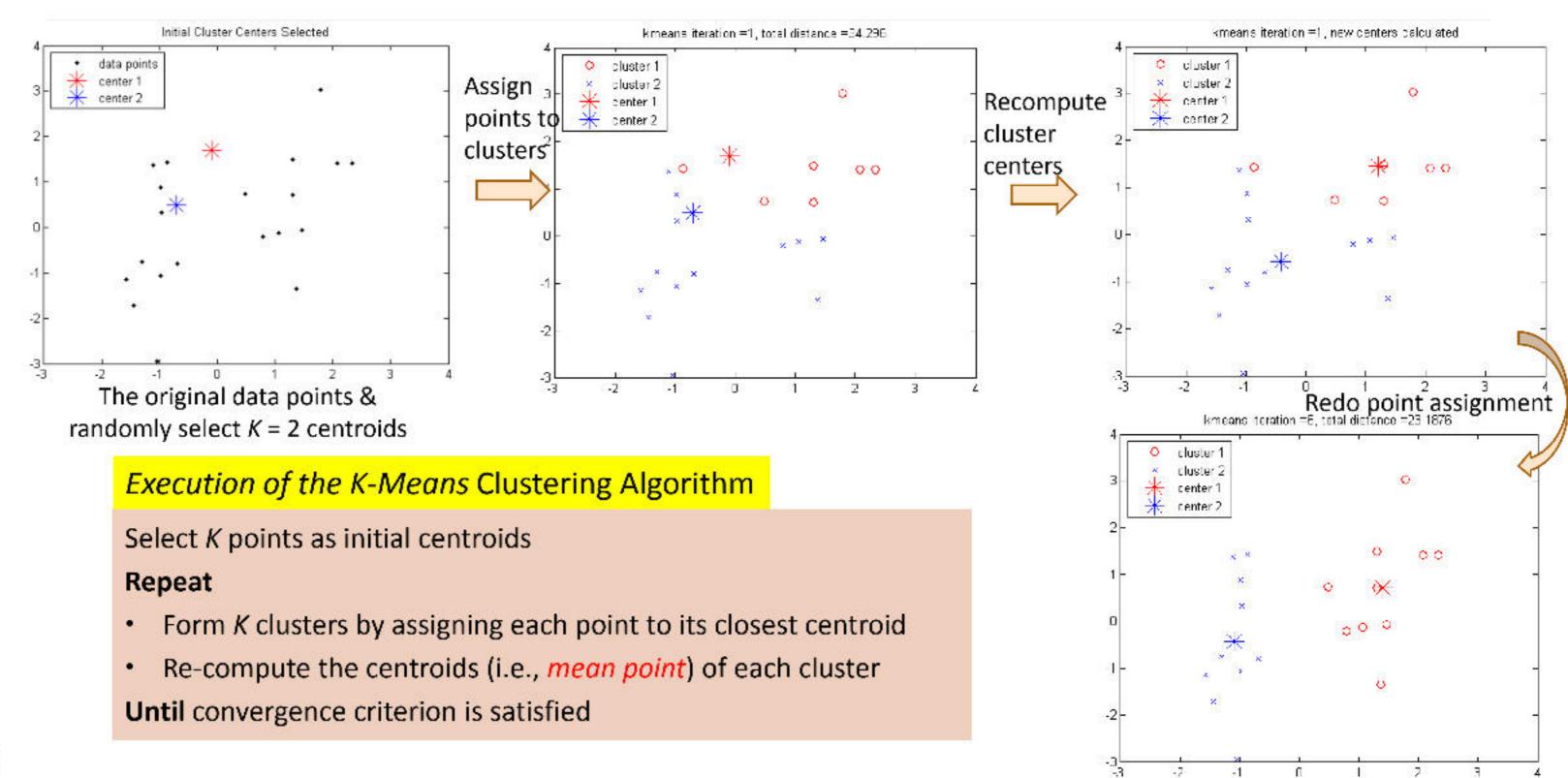


The K-Means Clustering Method

- □ K-Means (MacQueen'67, Lloyd'57/'82)
 □ Each cluster is represented by the center of the cluster
 □ Given K, the number of clusters, the K Means clustering algorithm is outlined.
- □ Given K, the number of clusters, the K-Means clustering algorithm is outlined as follows
 - Select K points as initial centroids
 - Repeat
 - □ Form K clusters by assigning each point to its closest centroid
 - □ Re-compute the centroids (i.e., *mean point*) of each cluster
 - Until convergence criterion is satisfied
- Different kinds of measures can be used
 - ☐ Manhattan distance (L₁ norm), Euclidean distance (L₂ norm), Cosine similarity

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Example: K-Means Clustering



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Discussion on the K-Means Method

- **Efficiency**: O(tKn) where n: # of objects, K: # of clusters, and t: # of iterations ■ Normally, K, t << n; thus, an efficient method</p> K-means clustering often terminates at a local optima Initialization can be important to find high-quality clusters □ **Need to specify** *K*, the *number* of clusters, in advance There are ways to automatically determine the "best" K In practice, one often runs a range of values and selected the "best" K value Sensitive to noisy data and outliers Variations: Using K-medians, K-medoids, etc. K-means is applicable only to objects in a continuous n-dimensional space Using the K-modes for categorical data Not suitable to discover clusters with non-convex shapes
- Using density-based clustering, kernel K-means, etc.

Variations of *K-Means*

There are many variants of the K-Means method, va	rying in different aspects
Choosing better initial centroid estimates	
□ K-means++, Intelligent K-Means, Genetic K-Mean	To be discussed in this lectur
Choosing different representative prototypes for the clusters	
□ K-Medoids, K-Medians, K-Modes	To be discussed in this lecture
Applying feature transformation techniques	
□ Weighted K-Means, Kernel K-Means To be di	scussed in this lecture