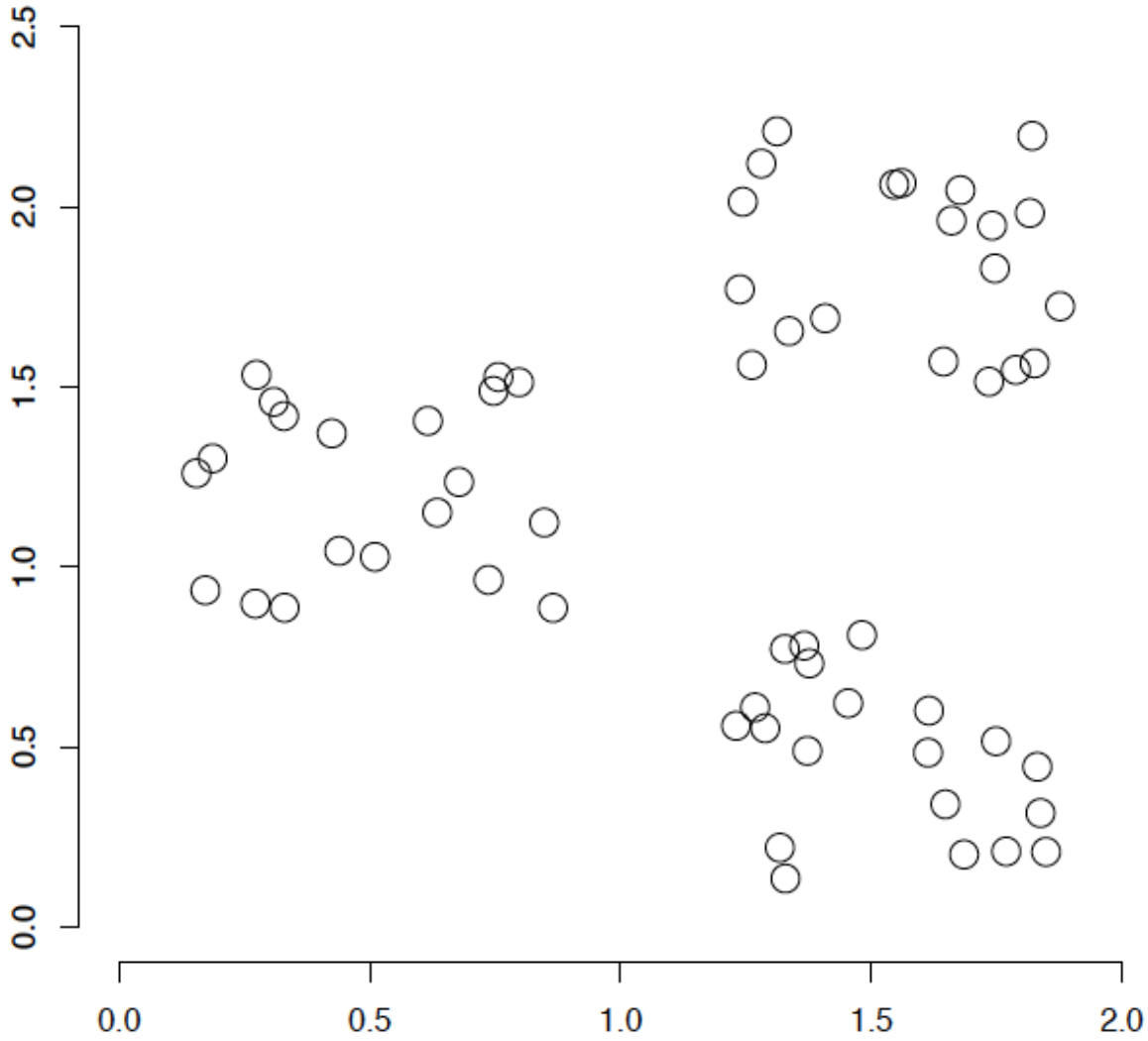
مبانی بازیابی اطلاعات و جستجوی وب

۱۰- خوشه بندی

Original slides by: Pandu Nayak and Prabhakar Raghavan

What is clustering?

- Clustering: the process of grouping a set of objects into classes of similar objects
  - Documents within a cluster should be similar.
  - Documents from different clusters should be dissimilar.
- The commonest form of *unsupervised learning*


0.0
0.5
1.0
1.5
2.0
2.5
0.0
0.5
1.0
1.5
2.0

Applications of clustering in IR

- Whole corpus analysis/navigation
  - Better user interface: search without typing
- For improving recall in search applications
  - Better search results
- For better navigation of search results
  - Effective “user recall” will be higher
- For speeding up vector space retrieval
  - Cluster-based retrieval gives faster search

Issues for clustering

- Representation for clustering
  - Document representation
  - Need a notion of similarity/distance (cosine, Euclidean)
- How many clusters?
  - Fixed a priori?
  - Completely data driven?

Clustering Algorithms

- Flat algorithms
  - Usually start with a random (partial) partitioning
  - Refine it iteratively
    - *K* means clustering
- Hierarchical algorithms
  - Bottom-up, agglomerative
  - (Top-down, divisive)

K-Means

- Assumes documents are real-valued vectors.
- Clusters based on *centroids* (aka the *center of gravity* or mean) of points in a cluster, *c*:

$$\vec{\mu}(c) = \frac{1}{|c|}\sum_{\vec{x}\in c}\vec{x}$$

- Reassignment of instances to clusters is based on distance to the current cluster centroids.
- Minimizing the Cost function:

$$J = \sum_{x} \|x - \mu(c_x)\|^2$$

K-Means Algorithm

Select *K* random docs $\{s_1, s_2, \ldots s_K\}$ as seeds.

Until clustering *converges* (or other stopping criterion):

For each doc d_i:

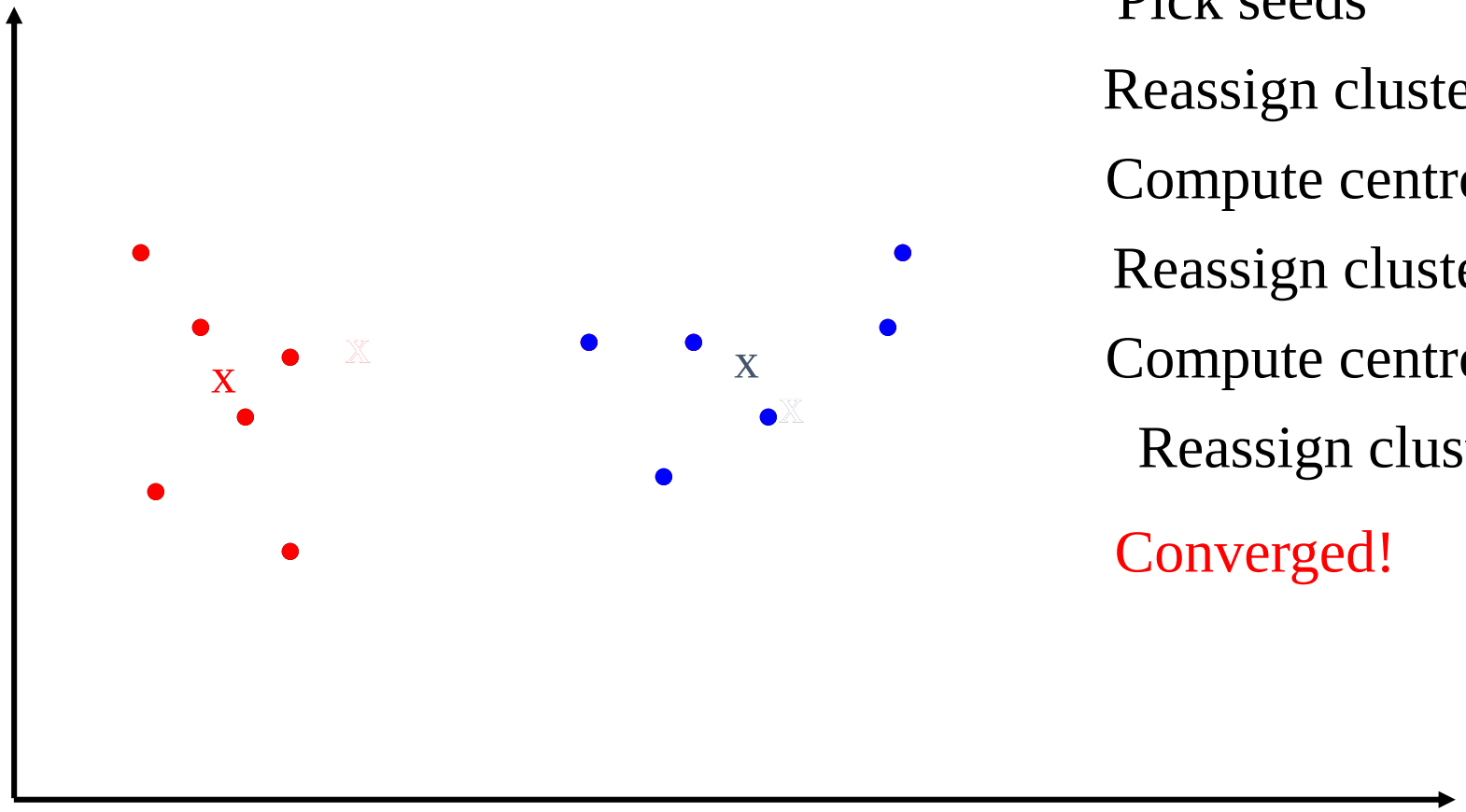
Assign d_i to the cluster c_j such that $dist(x_i, s_j)$ is minimal.

(*Next, update the seeds to the centroid of each cluster*)

For each cluster c_j

$s_j = \mu(c_j)$

K Means Example (*K*=2)



Pick seeds

Reassign clusters

Compute centroids

Reassign clusters

Compute centroids

Reassign clusters

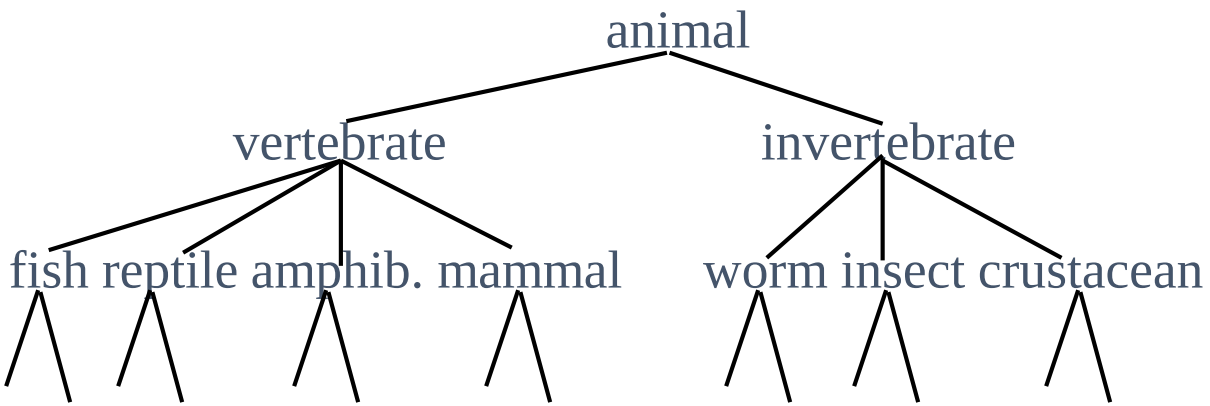
Converged!

Termination conditions

- Several possibilities, e.g.,
  - A fixed number of iterations.
  - Doc partition unchanged.
  - Centroid positions don’t change.

Hierarchical Clustering

- Build a tree-based hierarchical taxonomy (*dendrogram*) from a set of documents.



- Clustering obtained by cutting the dendrogram at a desired level: each connected component forms a cluster.

Hierarchical Agglomerative Clustering (HAC)

- Starts with each doc in a separate cluster
  - then repeatedly joins the *closest pair* of clusters, until there is only one cluster.
- The history of merging forms a binary tree or hierarchy.

Closest pair of clusters

- Many variants to defining closest pair of clusters
- **Single-link**
  - Similarity of the *most* cosine-similar (single-link)
- **Complete-link**
  - Similarity of the "furthest" points, the *least* cosine-similar
- **Centroid**
  - Clusters whose centroids (centers of gravity) are the most cosine-similar
- **Average-link**
  - Average cosine between pairs of elements

What Is A Good Clustering?

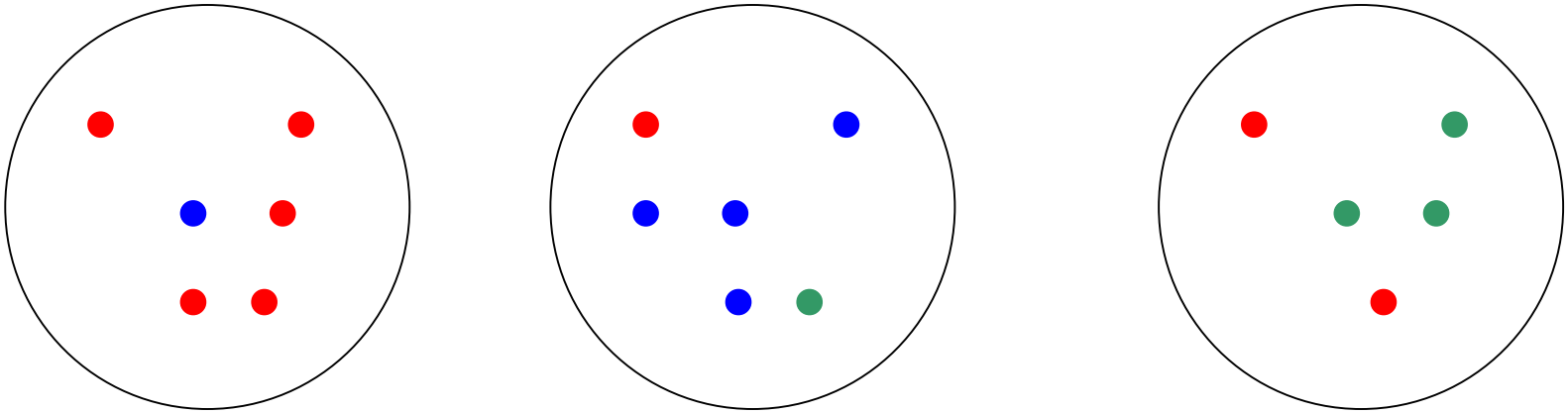
- Internal criterion
- External criterion

External Evaluation of Cluster Quality

- Simple measure: purity, the ratio between the dominant class in the cluster π_i and the size of cluster ω_i

$$Purity(\omega_i) = \frac{1}{n_i} \max_j (n_{ij}) \quad j \in C$$

Purity example



Cluster I Cluster II Cluster III

Cluster I: Purity = 1/6 (max(5, 1, 0)) = 5/6

Cluster II: Purity = 1/6 (max(1, 4, 1)) = 4/6

Cluster III: Purity = 1/5 (max(2, 0, 3)) = 3/5

Rand Index measures between pair decisions. Here RI = 0.68

Number of points	Same Cluster in clustering	Different Clusters in clustering
Same class in ground truth	20	24
Different classes in ground truth	20	72

Rand index and Cluster F-measure

$$RI = \frac{A + D}{A + B + C + D}$$

منابع

- فصل ۱۶ و ۱۷ کتاب An introduction to information retrieval