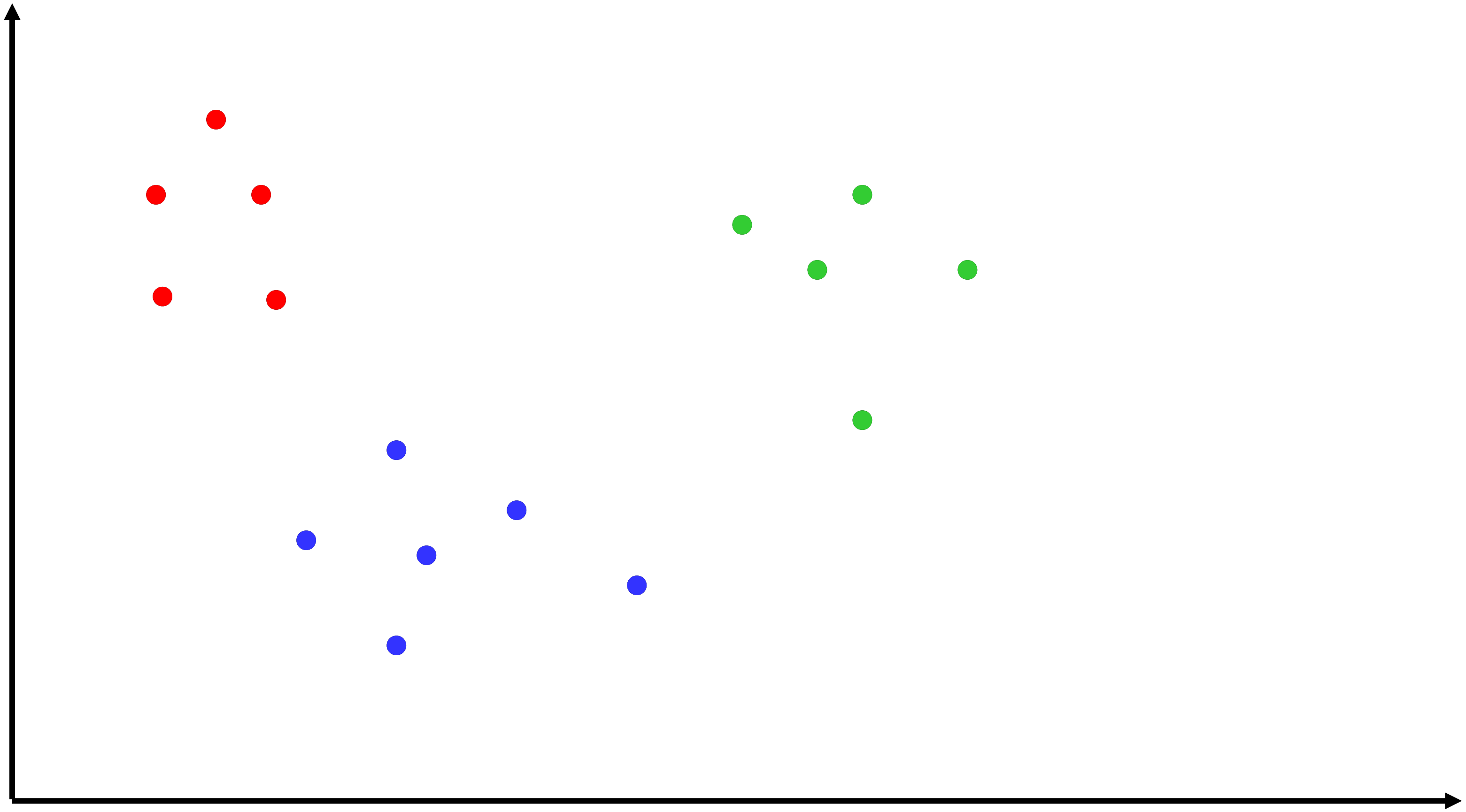
Text Clustering

Clustering

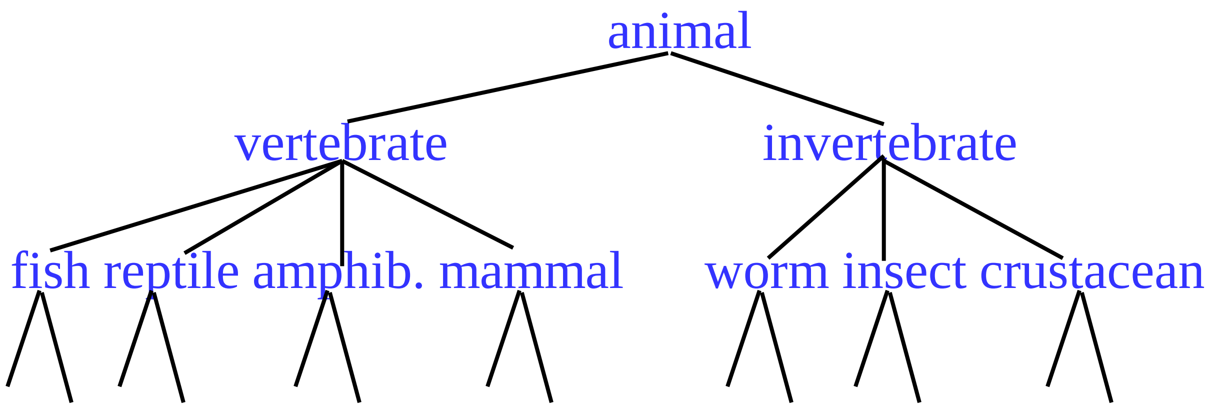
- Partition unlabeled examples into disjoint subsets of *clusters*, such that:
  - Examples within a cluster are very similar
  - Examples in different clusters are very different
- Discover new categories in an *unsupervised* manner (no sample category labels provided).

Clustering Example



Hierarchical Clustering

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



- Recursive application of a standard clustering algorithm can produce a hierarchical clustering.

Aglommerative vs. Divisive Clustering

- *Aglommerative* (*bottom-up*) methods start with each example in its own cluster and iteratively combine them to form larger and larger clusters.
- *Divisive* (*partitional*, *top-down*) separate all examples immediately into clusters.

Direct Clustering Method

- *Direct clustering* methods require a specification of the number of clusters, *k*, desired.
- A *clustering evaluation function* assigns a real-value quality measure to a clustering.
- The number of clusters can be determined automatically by explicitly generating clusterings for multiple values of *k* and choosing the best result according to a clustering evaluation function.

Hierarchical Agglomerative Clustering (HAC)

- Assumes a *similarity function* for determining the similarity of two instances.
- Starts with all instances in a separate cluster and then repeatedly joins the two clusters that are most similar until there is only one cluster.
- The history of merging forms a binary tree or hierarchy.

HAC Algorithm

Start with all instances in their own cluster.
Until there is only one cluster:

Among the current clusters, determine the two clusters, c_i and c_j, that are most similar.

Replace c_i and c_j with a single cluster $c_i \cup c_j$

Cluster Similarity

- Assume a similarity function that determines the similarity of two instances: $sim(x,y)$.
  - Cosine similarity of document vectors.
- How to compute similarity of two clusters each possibly containing multiple instances?
  - Single Link: Similarity of two most similar members.
  - Complete Link: Similarity of two least similar members.
  - Group Average: Average similarity between members.

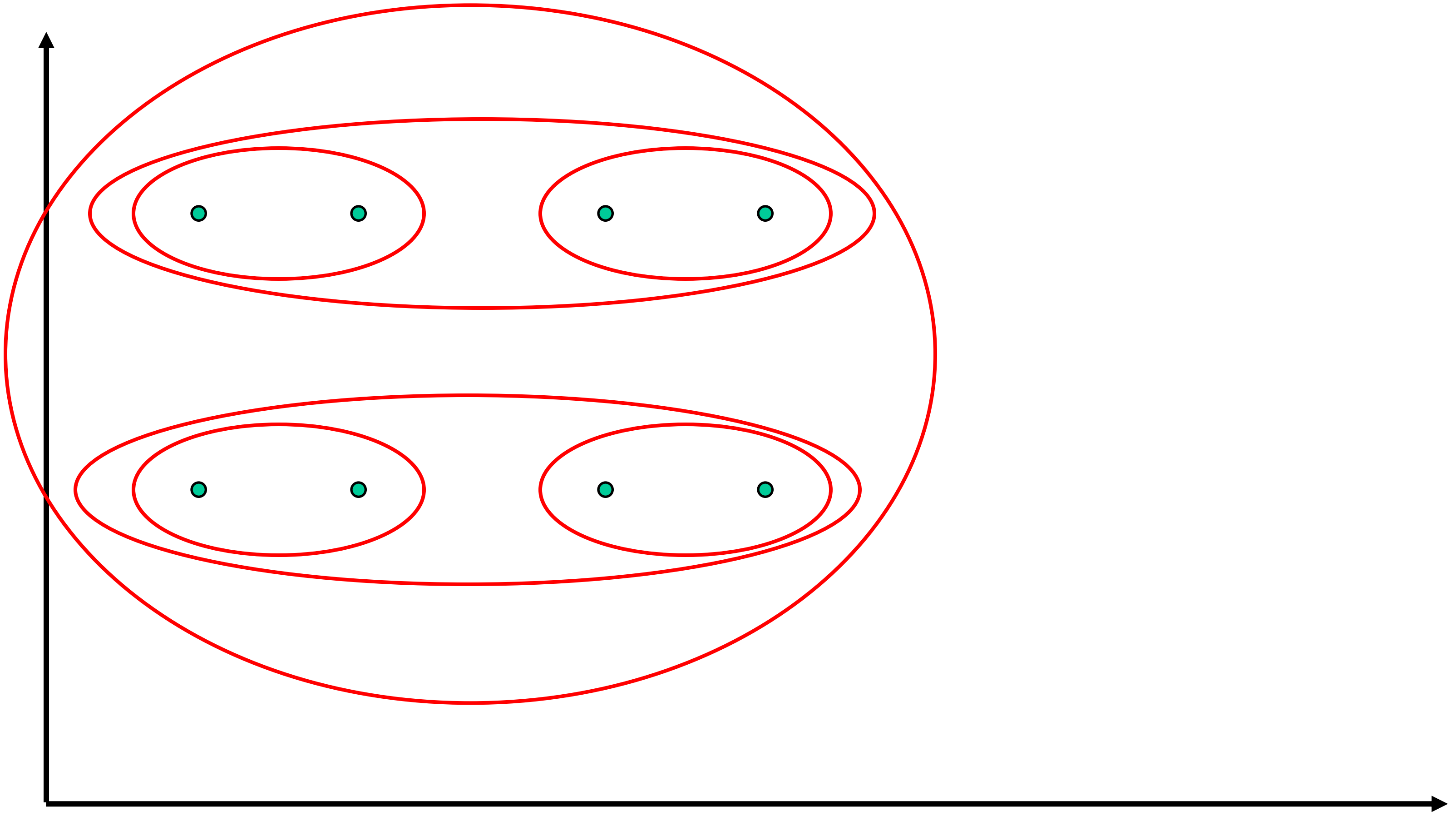
Single Link Agglomerative Clustering

- Use maximum similarity of pairs:

$$sim(c_i, c_j) = \max_{x \in c_i, y \in c_j} sim(x, y)$$

- Can result in "straggly" (long and thin) clusters due to *chaining effect*.
  - Appropriate in some domains, such as clustering islands.

Single Link Example



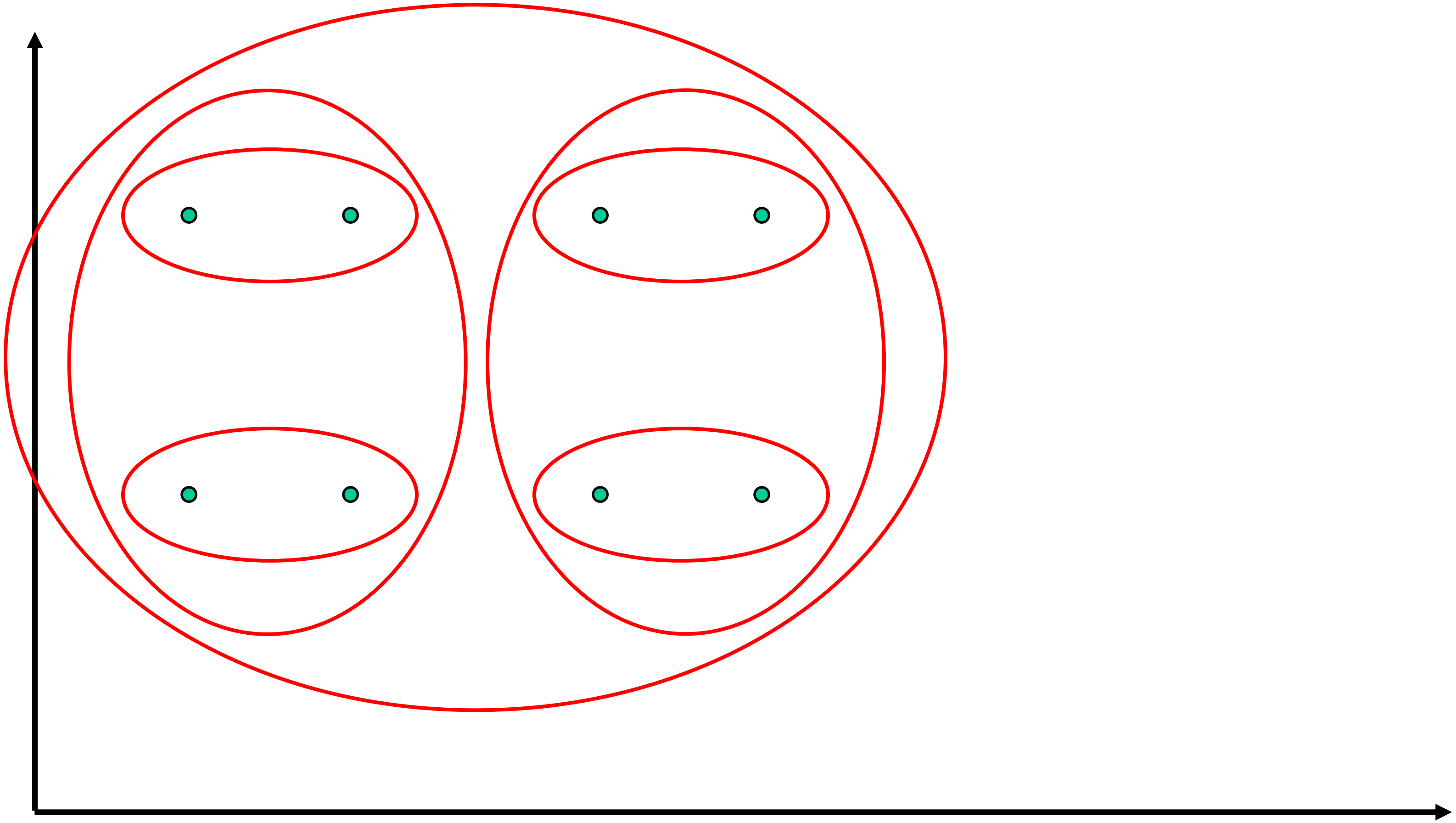
Complete Link Agglomerative Clustering

- Use minimum similarity of pairs:

$$sim(c_i, c_j) = \min_{x \in c_i, y \in c_j} sim(x, y)$$

- Makes more "tight," spherical clusters that are typically preferable.

Complete Link Example



Computing Cluster Similarity

- After merging c_i and c_j, the similarity of the resulting cluster to any other cluster, c_k, can be computed by:
  - Single Link:

$$sim((c_i \cup c_j), c_k) = \max(sim(c_i, c_k), sim(c_j, c_k))$$

  - Complete Link:

$$sim((c_i \cup c_j), c_k) = \min(sim(c_i, c_k), sim(c_j, c_k))$$

Group Average Agglomerative Clustering

- Use average similarity across all pairs within the merged cluster to measure the similarity of two clusters.

$$sim(c_i, c_j) = \frac{1}{|c_i \cup c_j|(|c_i \cup c_j| - 1)} \sum_{\vec{x} \in (c_i \cup c_j)} \sum_{\vec{y} \in (c_i \cup c_j): \vec{y} \neq \vec{x}} sim(\vec{x}, \vec{y})$$

- Compromise between single and complete link.

Non-Hierarchical Clustering

- Typically must provide the number of desired clusters, *k*.
- Randomly choose *k* instances as *seeds*, one per cluster.
- Form initial clusters based on these seeds.
- Iterate, repeatedly reallocating instances to different clusters to improve the overall clustering.
- Stop when clustering converges or after a fixed number of iterations.

K-Means

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

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

- Reassignment of instances to clusters is based on distance to the current cluster centroids.

Distance Metrics

- Euclidian distance (L_2 norm):

$$L_2(\vec{x}, \vec{y}) = \sum_{i=1}^{m} (x_i - y_i)^2$$

- L_1 norm:

$$L_1(\vec{x}, \vec{y}) = \sum_{i=1}^{m} \left| x_i - y_i \right|$$

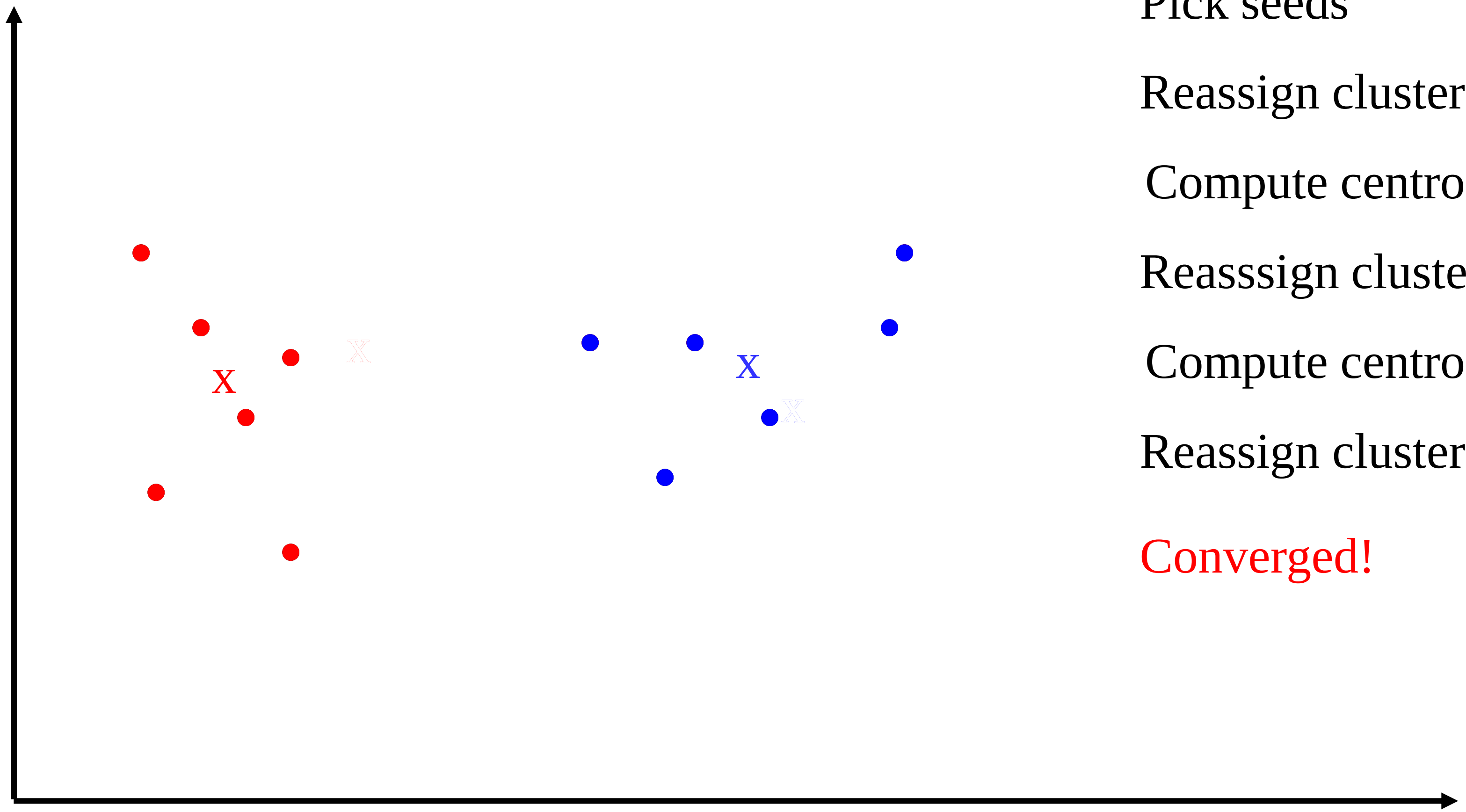
- Cosine Similarity (transform to a distance by subtracting from 1):

$$1 - \frac{\vec{x} \bullet \vec{y}}{|\vec{x}| \cdot |\vec{y}|}$$

K-Means Algorithm

Let d be the distance measure between instances.
Select k random instances $\{s_1, s_2, \ldots s_k\}$ as seeds.
Until clustering converges or other stopping criterion:
    For each instance x_i:
        Assign x_i to the cluster c_j such that $d(x_i, s_j)$ is minimal.
    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

Reasssign clusters

Compute centroids

Reassign clusters

Converged!

Seed Choice

- Results can vary based on random seed selection.
- Some seeds can result in poor convergence rate, or convergence to sub-optimal clusterings.
- Select good seeds using a heuristic or the results of another method.

Text Clustering

- HAC and K-Means have been applied to text in a straightforward way.
- Typically use ***normalized***, TF/IDF-weighted vectors and cosine similarity.
- Optimize computations for sparse vectors.
- Applications:
  - During retrieval, add other documents in the same cluster as the initial retrieved documents to improve recall.
  - Clustering of results of retrieval to present more organized results to the user (à la Northernlight folders).
  - Automated production of hierarchical taxonomies of documents for browsing purposes (à la Yahoo & DMOZ).

Soft Clustering

- Clustering typically assumes that each instance is given a “hard” assignment to exactly one cluster.
- Does not allow uncertainty in class membership or for an instance to belong to more than one cluster.
- *Soft clustering* gives probabilities that an instance belongs to each of a set of clusters.
- Each instance is assigned a probability distribution across a set of discovered categories (probabilities of all categories must sum to 1).

Exercise (exam preparation :-)

Cluster to following documents using K-means with K=2 and cosine similarity.

- Doc1: “go monster go”
- Doc2: “go karting”
- Doc3: “karting monster”
- Doc4: “monster monster”

Assume Doc1 and Doc3 are chosen as initial seeds. Use tf (no idf). Show the clusters and their centroids for each iteration. The algorithm should converge after 2 iterations.