Clustering: Similarity-Based Clustering

CS4780/5780 – Machine Learning
Fall 2013

Thorsten Joachims
Cornell University

Reading: Manning/Raghavan/Schuetze, Chapters 16 (not 16.3) and 17
(http://nlp.stanford.edu/IR-book/)

Outline

- Supervised vs. Unsupervised Learning
- Hierarchical Clustering
  - Hierarchical Agglomerative Clustering (HAC)
- Non-Hierarchical Clustering
  - K-means
  - Mixtures of Gaussians and EM-Algorithm

Supervised Learning vs. Unsupervised Learning

- Supervised Learning
  - Classification: partition examples into groups according to pre-defined categories
  - Regression: assign value to feature vectors
  - Requires labeled data for training
- Unsupervised Learning
  - Clustering: partition examples into groups when no pre-defined categories/classes are available
  - Novelty detection: find changes in data
  - Outlier detection: find unusual events (e.g. hackers)
  - Only instances required, but no labels

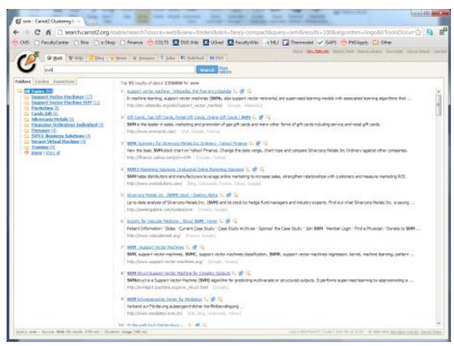
Clustering

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

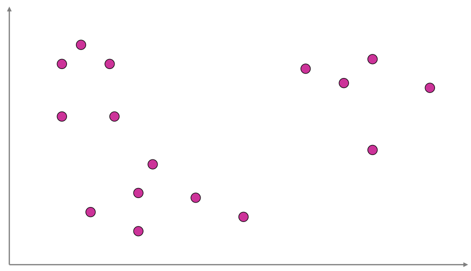
Applications of Clustering

- Cluster retrieved documents
  - to present more organized and understandable results to user → "diversified retrieval"
- Detecting near duplicates
  - Entity resolution
    - E.g. "Thorsten Joachims" == "Thorsten B Joachims"
  - Cheating detection
- Exploratory data analysis
- Automated (or semi-automated) creation of taxonomies
  - e.g. Yahoo, DMOZ
- Compression

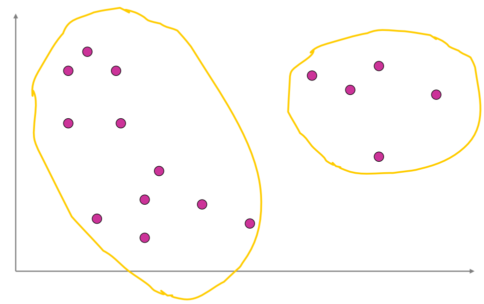
Applications of Clustering



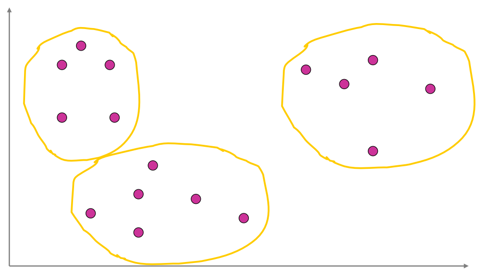
Clustering Example



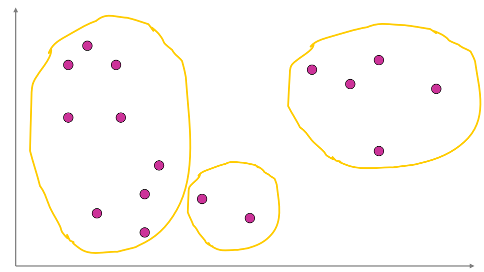
Clustering Example



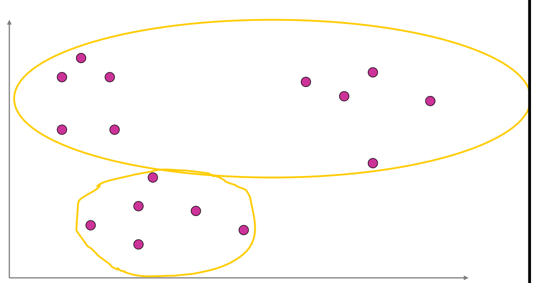
Clustering Example



Clustering Example



Clustering Example



Similarity (Distance) Measures

- Euclidian distance (L_2 norm):

$$L_2(\vec{x}, \vec{x}') = \sqrt{\sum_{i=1}^{N} (x_i - x_i')^2}$$

- L_1 norm:

$$L_1(\vec{x}, \vec{x}') = \sqrt{\sum_{i=1}^{N} |x_i - x_i'|}$$

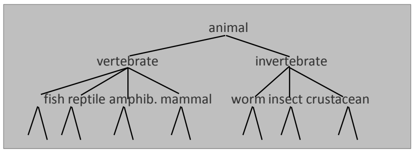
- Cosine similarity:

$$\cos(\vec{x}, \vec{x}') = \frac{\vec{x} * \vec{x}'}{\|\vec{x}\| \, \|\vec{x}'\|}$$

- Kernels

Hierarchical Clustering

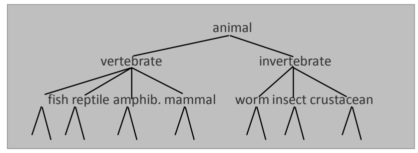
- Build a tree-based hierarchical taxonomy from a set of unlabeled examples.



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

Agglomerative vs. Divisive Clustering

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



Hierarchical Agglomerative Clustering (HAC)

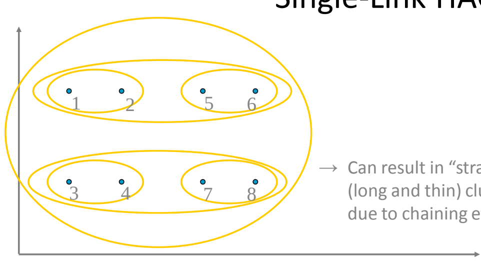
- Assumes a ***similarity function*** for determining the similarity of two clusters.
- Starts with all instances in a separate cluster and then repeatedly joins the two clusters that are most similar until there is only one cluster.
- The history of merging forms a binary tree or hierarchy.
- Basic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

- 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.

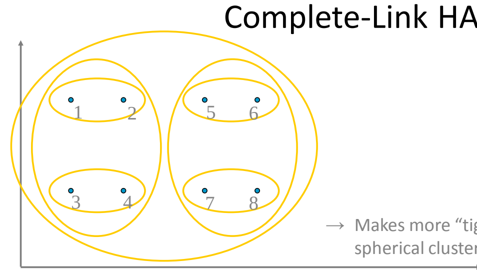
Single-Link HAC



→ Can result in "straggly" (long and thin) clusters due to chaining effect.

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

Complete-Link HAC



→ Makes more "tight," spherical clusters.

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

Computational Complexity of HAC

- In the first iteration, all HAC methods need to compute similarity of all pairs of n individual instances which is $O(n^2)$.
- In each of the subsequent $O(n)$ merging iterations, must find smallest distance pair of clusters → Maintain heap $O(n^2 \log n)$
- In each of the subsequent $O(n)$ merging iterations, it must compute the distance between the most recently created cluster and all other existing clusters. Can this be done in constant time such that $O(n^2 \log n)$ overall?

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:

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

Single-Link Example

	x1	x2	x3	x4	x5
x1	1	0.8	0.2	0.7	0.3
x2	0.8	1	0.1	0.5	0.2
x3	0.2	0.1	1	0.9	0.5
x4	0.7	0.5	0.9	1	0.4
x5	0.3	0.2	0.5	0.4	1

Merge x3,x4
replace with max

	x1	x2	c1	x5
x1	1	0.8	0.7	0.3
x2	0.8	1	0.5	0.2
c1	0.7	0.5	1	0.5
x5	0.3	0.2	0.5	1

Merge x1,x2
replace with max

	c2	c1	x5
c2	1	0.7	0.3
c1	0.7	1	0.5
x5	0.3	0.5	1

Merge c1,c2
replace with max

	c3	x5
c3	1	0.5
x5	0.5	1

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.

Computing Group Average Similarity

- Assume cosine similarity and normalized vectors with unit length.
- Always maintain sum of vectors in each cluster.

$$\vec{s}(c_j) = \sum_{\vec{x} \in c_j} \vec{x}$$

- Compute similarity of clusters in constant time:

$$sim(c_i, c_j) = \frac{(\vec{s}(c_i) + \vec{s}(c_j)) \bullet (\vec{s}(c_i) + \vec{s}(c_j)) - (|c_i| + |c_i|)}{(|c_i| + |c_i|)(|c_i| + |c_i| - 1)}$$

Non-Hierarchical Clustering

- K-means clustering ("hard")
- Mixtures of Gaussians and training via Expectation maximization Algorithm ("soft")

Clustering Criterion

- Evaluation function that assigns a (usually real-valued) value to a clustering
  - Clustering criterion typically function of
    - within-cluster similarity and
    - between-cluster dissimilarity
- Optimization
  - Find clustering that maximizes the criterion
    - Global optimization (often intractable)
    - Greedy search
    - Approximation algorithms

Centroid-Based Clustering

- Assumes instances are real-valued vectors.
- Clusters represented via ***centroids*** (i.e. average of points in a cluster) *c*:

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

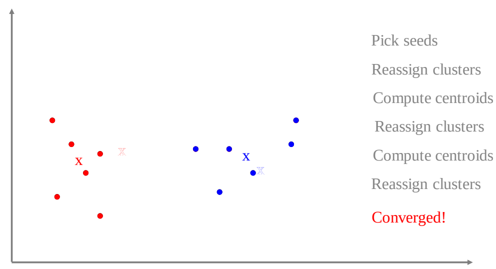
- Reassignment of instances to clusters is based on **distance** to the current cluster centroids.

K-Means Algorithm

- Input: k = number of clusters, distance measure d
- 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 min.
  - For each cluster c_j *//update the centroid of each cluster*
    - $s_j = \mu(c_j)$

K-means Example

(k=2)



Time Complexity

- Assume computing distance between two instances is O(*N*) where *N* is the dimensionality of the vectors.
- Reassigning clusters for *n* points: O(*kn*) distance computations, or O(*knN*).
- Computing centroids: Each instance gets added once to some centroid: O(*nN*).
- Assume these two steps are each done once for *i* iterations: O(*iknN*).
- Linear in all relevant factors, assuming a fixed number of iterations, more efficient than HAC.

Buckshot Algorithm

Problem

- Results can vary based on random seed selection, especially for high-dimensional data.
- Some seeds can result in poor convergence rate, or convergence to sub-optimal clusterings.

Idea: Combine HAC and K-means clustering.

- First randomly take a sample of instances of size
- Run group-average HAC on this sample $n^{1/2}$
- Use the results of HAC as initial seeds for K-means.
- Overall algorithm is efficient and avoids problems of bad seed selection.

Clustering as Prediction

- Setup
  - Learning Task: $P(X)$
  - Training Sample: $S = (\vec{x}_1, \dots, \vec{x}_n)$
  - Hypothesis Space: $H = \{h_1, \dots, h_{|H|}\}$ each describes $P(X|h_i)$ where h_i are parameters
  - Goal: learn which $P(X|h_i)$ produces the data
- What to predict?
  - Predict where new points are going to fall

Gaussian Mixtures and EM

- Gaussian Mixture Models
  - Assume

    $$P(X = \vec{x}|h_i) = \sum_{j=1}^{k} P(X = \vec{x}|Y = j, h_i)P(Y = j)$$

    where $P(X = \vec{x}|Y = j, h) = N(X = \vec{x}|\vec{\mu}_j, \Sigma_j)$
    and $h = (\vec{\mu}_1, \dots, \vec{\mu}_k, \Sigma_1, \dots, \Sigma_k)$.
- EM Algorithm
  - Assume $P(Y)$ and k known and $\Sigma_i = 1$.
  - REPEAT
    - $\vec{\mu}_j = \frac{\sum_{i=1}^{n} P(Y=j|X=\vec{x}_i, \vec{\mu}_j)\vec{x}_i}{\sum_{i=1}^{n} P(Y=j|X=\vec{x}_i, \vec{\mu}_j)}$
    - $P(Y = j|X = \vec{x}_i, \vec{\mu}_j) = \frac{P(X=\vec{x}_i|Y=j, \vec{\mu}_j)P(Y=j)}{\sum_{l=1}^{k} P(X=\vec{x}_i|Y=l, \vec{\mu}_j)P(Y=l)} = \frac{e^{-0.5(\vec{x}_i-\vec{\mu}_j)^2} P(Y=j)}{\sum_{l=1}^{k} e^{-0.5(\vec{x}_i-\vec{\mu}_l)^2} P(Y=l)}$