

UVA CS 4501 - 001 / 6501 – 007

Introduction to Machine Learning and Data Mining

Lecture 24: Unsupervised Clustering (I)

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11/20/14

Announcements

- HW5:
 - Due on Sunday, Nov 23 midnight
 - 6501: Proposal / Original tex or doc files are needed for the submission
 - 4501: Source code
- HW6
 - Due on Wed, Dec 3rd @ 5pm
 - 11 sample questions for Final exam
 - Both collab submission or handwritten submission are acceptable
- Final exam:
 - In class, 70mins
 - Thursday, Dec 4th @ 3:30pm, the same classroom

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Where are we ? →

major sections of this course

- Regression (supervised)
- Classification (supervised)
 - Feature selection
- Unsupervised models
 - Dimension Reduction (PCA)
 - Clustering (K-means, GMM/EM, Hierarchical)
- Learning theory
- Graphical models

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An unlabeled Dataset X

	X ₁	X ₂	X ₃
s ₁			
s ₂			
s ₃			
s ₄			
s ₅			
s ₆			

a data matrix of n observations on p variables x_1, x_2, \dots, x_p

Unsupervised learning = learning from raw (unlabeled, unannotated, etc) data, as opposed to supervised data where a classification label of examples is given

- Data/points/instances/examples/samples/records: [rows]
- Features/attributes/dimensions/independent variables/covariates/predictors/regressors: [columns]

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Where are we ? →

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Last Lecture Recap

- Dimensionality Reduction (unsupervised) with Principal Components Analysis (PCA)
 - Review of eigenvalue, eigenvector
 - How to project samples into a line capturing the variation of the whole dataset → Eigenvector / Eigenvalue of covariance matrix
 - Another explanation of PCA
 - PCA for dimension reduction
 - Eigenface → PCA for face recognition

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Review: Eigenvalue, e.g.

- Let us take two variables with covariance $c > 0$
 - $\mathbf{C} = \begin{pmatrix} 1 & c \\ c & 1 \end{pmatrix}$ $\mathbf{C} - \lambda \mathbf{I} = \begin{pmatrix} 1-\lambda & c \\ c & 1-\lambda \end{pmatrix}$
- $$\det(\mathbf{C} - \lambda \mathbf{I}) = (1-\lambda)^2 - c^2 = 0$$
- $\mathbf{C}\mathbf{u} = \lambda\mathbf{u}$
 $\mathbf{u} \neq 0$
- Solving this we find $\lambda_1 = 1+c$
 $\lambda_2 = 1-c < \lambda_1$

From Dr. S. Narasimhan

Review: Eigenvector, e.g.

- Any eigenvector \mathbf{U} satisfies the condition

$$\mathbf{C}\mathbf{u} = \lambda\mathbf{u}$$

$$\mathbf{u} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} \quad \mathbf{C}\mathbf{u} = \begin{pmatrix} 1 & c \\ c & 1 \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} a_1 + ca_2 \\ ca_1 + a_2 \end{pmatrix} = \begin{pmatrix} \lambda a_1 \\ \lambda a_2 \end{pmatrix}$$

$$\text{Solving we find } \mathbf{u}_1 = \begin{pmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}, \mathbf{u}_2 = \begin{pmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \end{pmatrix}$$

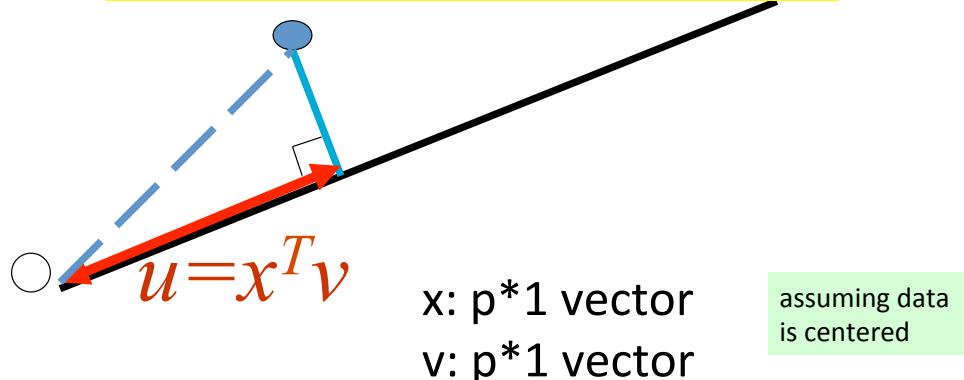
In practice, much more advance methods, e.g. power method

From Dr. S. Narasimhan

Algebraic Interpretation – 1D

- Minimizing sum of squares of distances to the line is the same as **maximizing the sum of squares of the projections on that line**, thanks to Pythagoras.

$$\max(v^T X^T X v), \text{ subject to } v^T v = 1$$



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Algebraic Interpretation – 1D

- Rewriting this: $\max(v^T X^T X v), \text{ subject to } v^T v = 1$

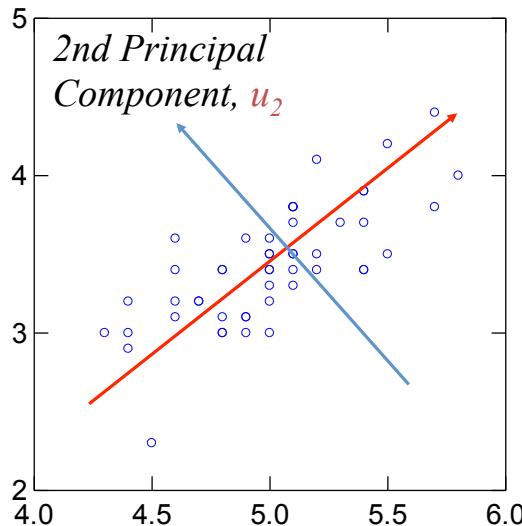
$$v^T X^T X v = \lambda = \lambda v^T v = v^T (\lambda v)$$

$$<=> v^T (X^T X v - \lambda v) = 0$$

- Show that the maximum value of $v^T X^T X v$ is obtained **for those u satisfying $X^T X v = \lambda v$**
- So, λ is the largest eigenvalue of $X^T X$
- So, u is the eigenvector corresponding to λ for $X^T X$

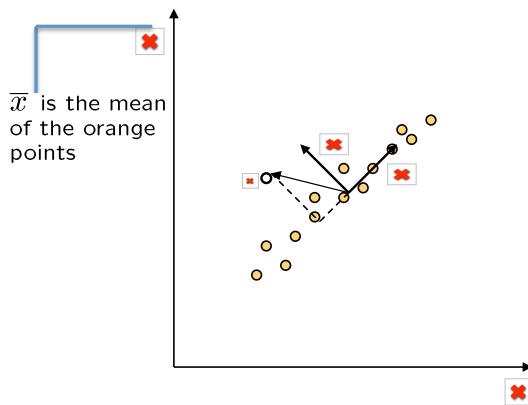
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PCA Eigenvectors → Principal Components



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PCA: *explanation II*



Consider the variation along direction v among all of the orange points:

$$var(v) = \sum_{\text{orange point } x} \|(x - \bar{x})^T \cdot v\|^2$$

$$V(X) = \sum_{v_i} (v_i - \mu)^2 P(X = v_i)$$

$$\begin{aligned} var(v) &= \sum_x \|(x - \bar{x})^T \cdot v\| \\ &= \sum_x v^T (x - \bar{x})(x - \bar{x})^T v \\ &= v^T \left[\sum_x (x - \bar{x})(x - \bar{x})^T \right] v \\ &= v^T A v \quad \text{where } A = \sum_x (x - \bar{x})(x - \bar{x})^T \end{aligned}$$

When for centered data:
 $\max(v^T X^T X v)$,
subject to $v^T v = 1$

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From Dr. S. Narasimhan

Interpretation of PCA

- The new variables (PCs) have a variance equal to their corresponding eigenvalue, since

$$\text{Var}(u_i) = u_i^T X^T X u_i = u_i^T \lambda_i u_i = \lambda_i u_i^T u_i = \lambda_i$$

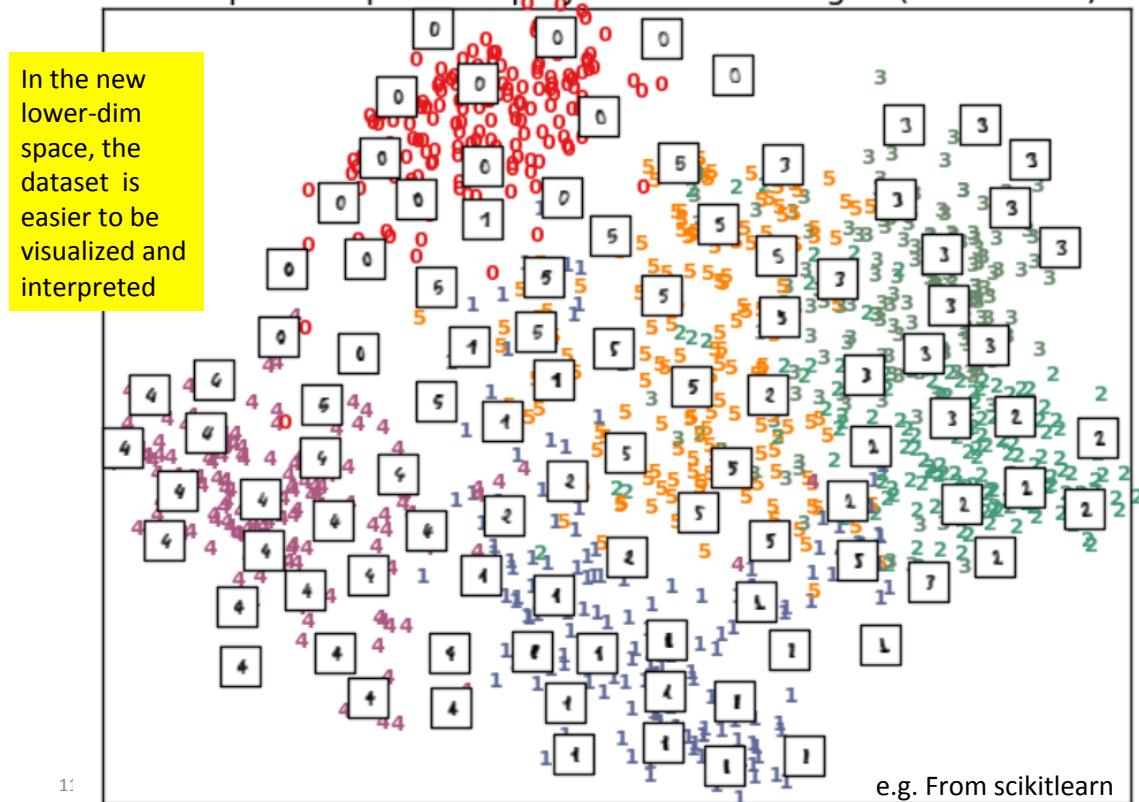
for all $i=1\dots p$

- Small $\lambda_i \Leftrightarrow$ small variance \Leftrightarrow data change little in the direction of component u_i

PCA is useful for finding new, more informative, uncorrelated features; it reduces dimensionality by rejecting low variance features

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Example: Principal Components projection of the digits (time 0.02s)

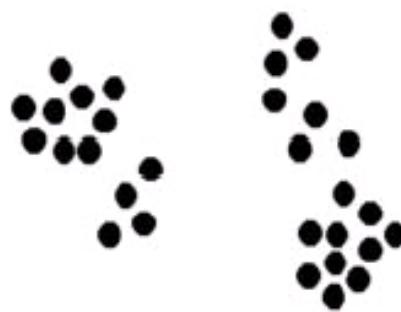


Where are we ? → major sections of this course

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Today: What is clustering?

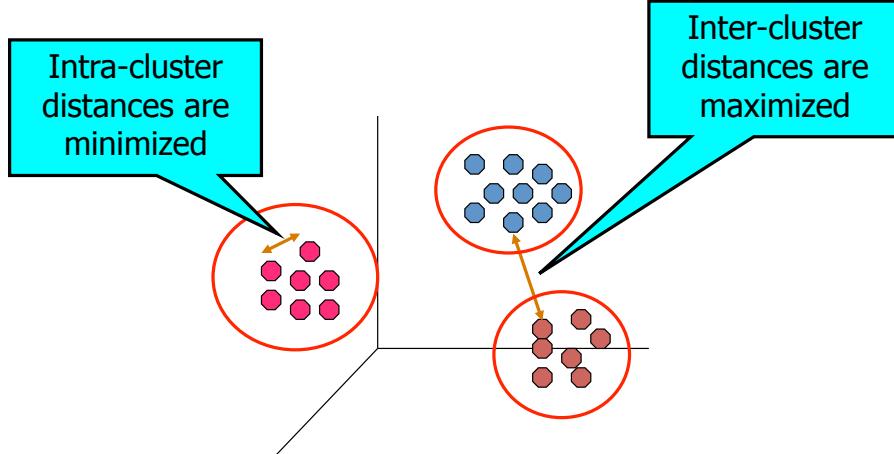


- Are there any “groups”?
- What is each group ?
- How many ?
- How to identify them?

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What is clustering?

- Find groups (clusters) of data points such that data points in a group will be similar (or related) to one another and different from (or unrelated to) the data points in other groups



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What is clustering?

- Clustering: the process of grouping a set of objects into classes of similar objects
 - high intra-class similarity
 - low inter-class similarity
 - It is the commonest form of **unsupervised learning**
- A common and important task that finds many applications in Science, Engineering, information Science, and other places, e.g.
 - Group genes that perform the same function
 - Group individuals that have similar political views
 - Categorize documents of similar topics
 - Identify similar objects from pictures

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Toy Examples

- People



- Images



- Language

Piotr *Pyotr* *Petros* *Pietro* *Pedro* *Pierre* *Piero* *Peter* *Peder* *Peka* *Peadar*

- species



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Issues for clustering

- What is a natural grouping among these objects?
 - Definition of "groupness"
- What makes objects “related”?
 - Definition of "similarity/distance"
- **Representation** for objects
 - Vector space? Normalization?
- **How many** clusters?
 - Fixed a priori?
 - Completely data driven?
 - Avoid “trivial” clusters - too large or small
- Clustering **Algorithms**
 - Partitional algorithms
 - Hierarchical algorithms
- **Formal** foundation and convergence

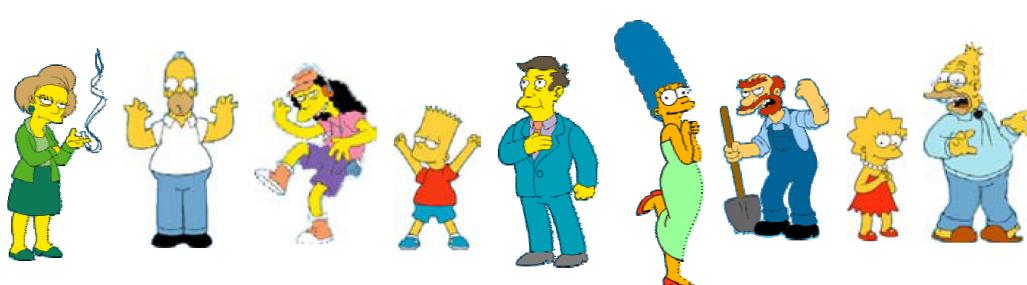
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Today Roadmap: clustering

- Definition of "groupness"
- Definition of "similarity/distance"
- Representation for objects
- How many clusters?
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What is a natural grouping among these objects?



Clustering is subjective



1 Simpson's Family



School Employees

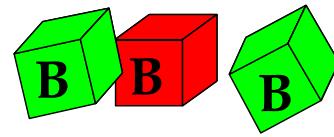
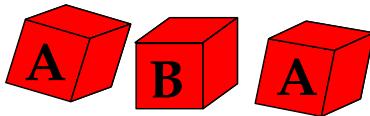


Females

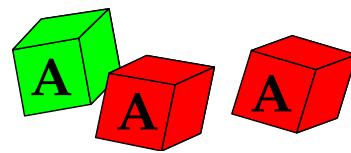
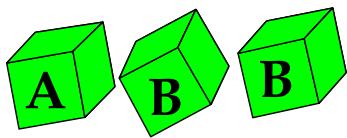


Males

Another example: clustering is subjective



Two possible Solutions...



Today Roadmap: clustering

- Definition of "groupness"
- ➡ ▪ Definition of "similarity/distance"
 - Representation for objects
 - How many clusters?
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What is Similarity?



Hard to define!
But we know it
when we see it

- The real meaning of similarity is a philosophical question. We will take a more pragmatic approach
- Depends on representation and algorithm. For many rep./alg., easier to think in terms of a distance (rather than similarity) between vectors.

What properties should a distance measure have?

- $D(A,B) = D(B,A)$ *Symmetry*
- $D(A,A) = 0$ *Constancy of Self-Similarity*
- $D(A,B) = 0 \text{ IIf } A = B$ *Positivity Separation*
- $D(A,B) \leq D(A,C) + D(C,B)$ *Triangular Inequality*

Intuitions behind desirable properties of distance measure

- $D(A,B) = D(B,A)$ *Symmetry*
– Otherwise you could claim "Alex looks like Bob, but Bob looks nothing like Alex"
- $D(A,A) = 0$ *Constancy of Self-Similarity*
– Otherwise you could claim "Alex looks more like Bob, than Bob does"
- $D(A,B) = 0$ IIf $A = B$ *Positivity Separation*
– Otherwise there are objects in your world that are different, but you cannot tell apart.
- $D(A,B) \leq D(A,C) + D(C,B)$ *Triangular Inequality*
– Otherwise you could claim "Alex is very like Bob, and Alex is very like Carl, but Bob is very unlike Carl"

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Distance Measures: Minkowski Metric

- Suppose two object x and y both have p features

$$x = (x_1, x_2, \dots, x_p)$$

$$y = (y_1, y_2, \dots, y_p)$$
- The Minkowski metric is defined by

$$d(x,y) = \sqrt[p]{\sum_{i=1}^p |x_i - y_i|^r}$$
- Most Common Minkowski Metrics

1, $r=2$ (Euclidean distance)

$$d(x,y) = \sqrt{2} \sqrt{\sum_{i=1}^p |x_i - y_i|^2}$$

2, $r=1$ (Manhattan distance)

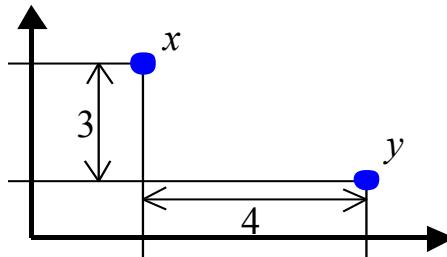
$$d(x,y) = \sum_{i=1}^p |x_i - y_i|$$

3, $r=+\infty$ ("sup" distance)

$$d(x,y) = \max_{1 \leq i \leq p} |x_i - y_i|$$

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An Example



1: Euclidean distance: $\sqrt{4^2 + 3^2} = 5.$

2: Manhattan distance: $4 + 3 = 7.$

3: "sup" distance: $\max\{4, 3\} = 4.$

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Hamming distance: binary features

- Manhattan distance is called *Hamming distance* when all features are **binary**.

$$d(x, y) = \sum_{i=1}^p |x_i - y_i|$$

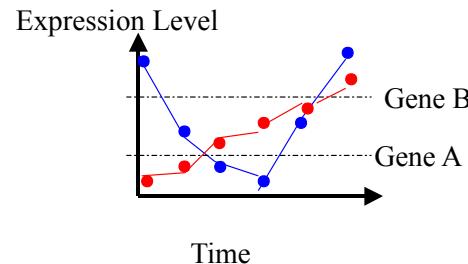
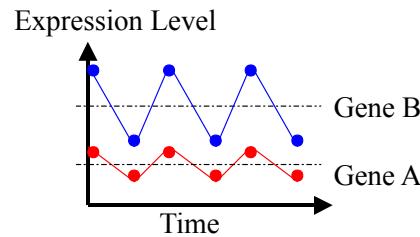
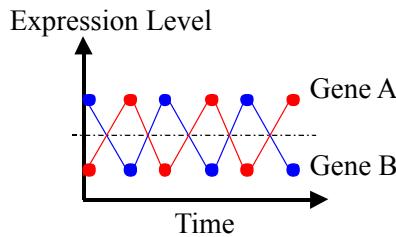
– E.g., Gene Expression Levels Under 17 Conditions (1-High, 0-Low)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
GeneA	0	1	1	0	0	1	0	0	1	0	0	1	1	1	0	0	1
GeneB	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1	1

Hamming Distance: #(01) + #(10) = 4 + 1 = 5.

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Similarity Measures: Correlation Coefficient



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Similarity Measures: Correlation Coefficient

- Pearson correlation coefficient

$$s(x, y) = \frac{\sum_{i=1}^p (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^p (x_i - \bar{x})^2 \times \sum_{i=1}^p (y_i - \bar{y})^2}}$$

where $\bar{x} = \frac{1}{p} \sum_{i=1}^p x_i$ and $\bar{y} = \frac{1}{p} \sum_{i=1}^p y_i$.

- Measuring the linear **correlation** between two sequences, x and y ,
- giving a value between $+1$ and -1 inclusive, where 1 is total positive **correlation**, 0 is no **correlation**, and -1 is total negative **correlation**.

$$|s(x, y)| \leq 1$$

unit independent

- Special case: cosine distance

$$s(x, y) = \frac{x \cdot y}{|x| \cdot |y|}$$

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Edit Distance:

A generic technique for measuring similarity

- To measure the similarity between two objects, transform one of the objects into the other, and **measure how much effort it took**. The measure of effort becomes the distance measure.

The distance between Patty and Selma.

Change dress color, 1 point
 Change earring shape, 1 point
 Change hair part, 1 point

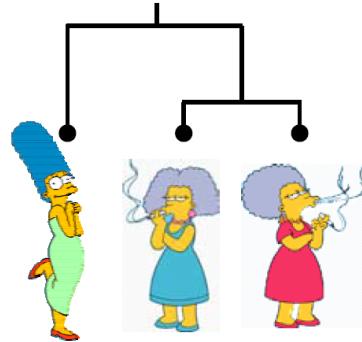
$$D(\text{Patty}, \text{Selma}) = 3$$

The distance between Marge and Selma.

Change dress color, 1 point
 Add earrings, 1 point
 Decrease height, 1 point
 Take up smoking, 1 point
 Lose weight, 1 point

$$D(\text{Marge}, \text{Selma}) = 5$$

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This is called the Edit distance or the Transformation distance

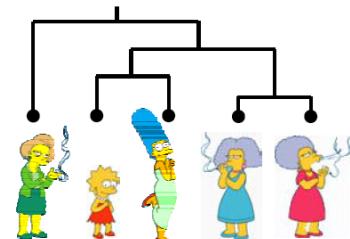
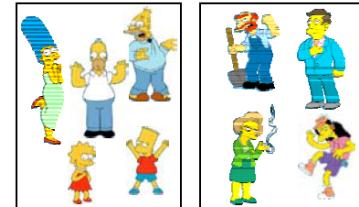
Today Roadmap: clustering

- Definition of "groupness"
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- Representation for objects
- How many clusters?
- ➡ ▪ Clustering Algorithms
 - Partitional algorithms
 - Hierarchical algorithms
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Clustering Algorithms

- Partitional algorithms
 - Usually start with a random (partial) partitioning
 - Refine it iteratively
 - K means clustering
 - Mixture-Model based clustering

- Hierarchical algorithms
 - Bottom-up, agglomerative
 - Top-down, divisive



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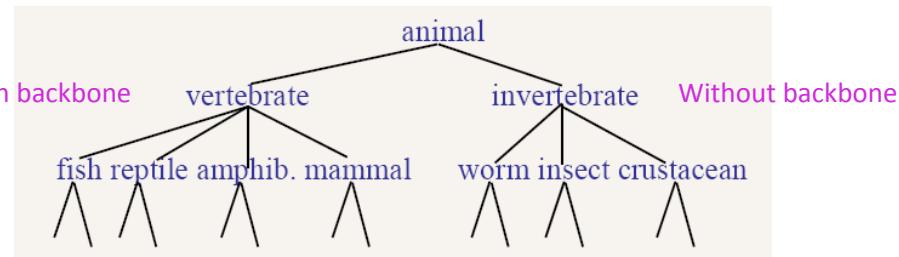
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Hierarchical Clustering

- Build a tree-based hierarchical taxonomy (**dendrogram**) from a set of objects, e.g. organisms, documents.



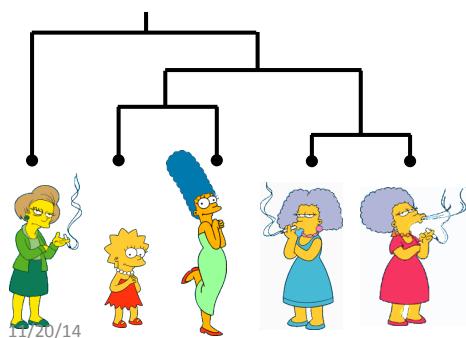
- Note that hierarchies are commonly used to organize information, for example in a web portal.
 - Yahoo! hierarchy is manually created, we will focus on **automatic creation of hierarchies in data mining**.

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(How-to) Hierarchical Clustering

The number of dendograms with n leafs
 $= (2n - 3)! / [(2^{(n-2)}) (n - 2)!]$

Number of Leafs	Number of Possible Dendograms
2	1
3	3
4	15
5	105
...	...
10	34,459,425



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Bottom-Up (agglomerative):

Starting with each item in its own cluster, find the best pair to merge into a new cluster. Repeat until all clusters are fused together.



Clustering: the process of grouping a set of objects into classes of similar objects →

high intra-class similarity
low inter-class similarity

We begin with a distance matrix which contains the distances between every pair of objects in our database.

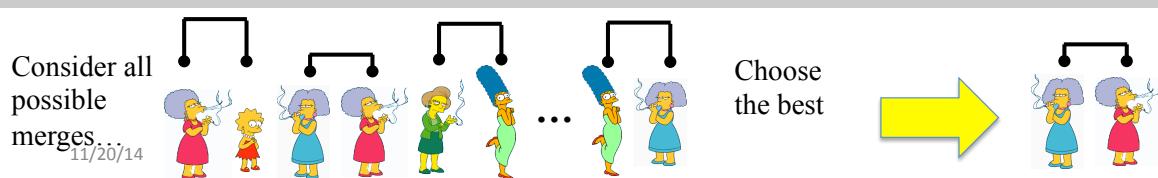
$$D(\text{Marge, Lisa}) = 8$$

$$D(\text{Marge, Marge}) = 1$$

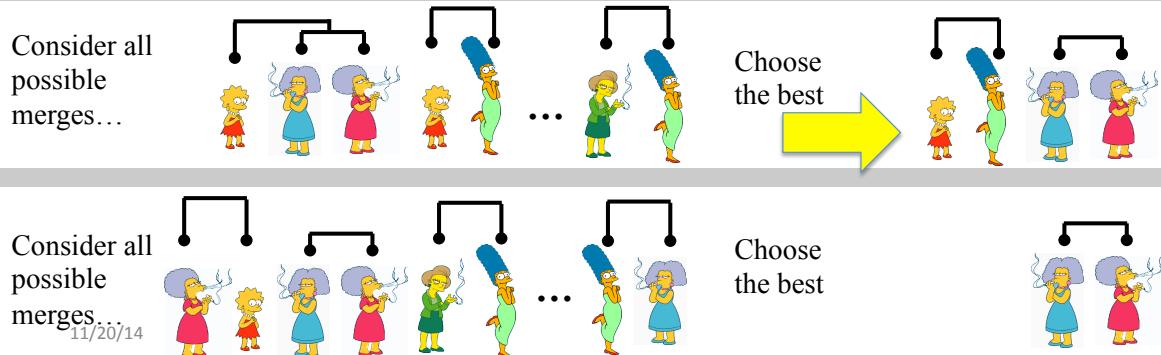
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0	8	8	7	7
	0	2	4	4
		0	3	3
			0	1
				0

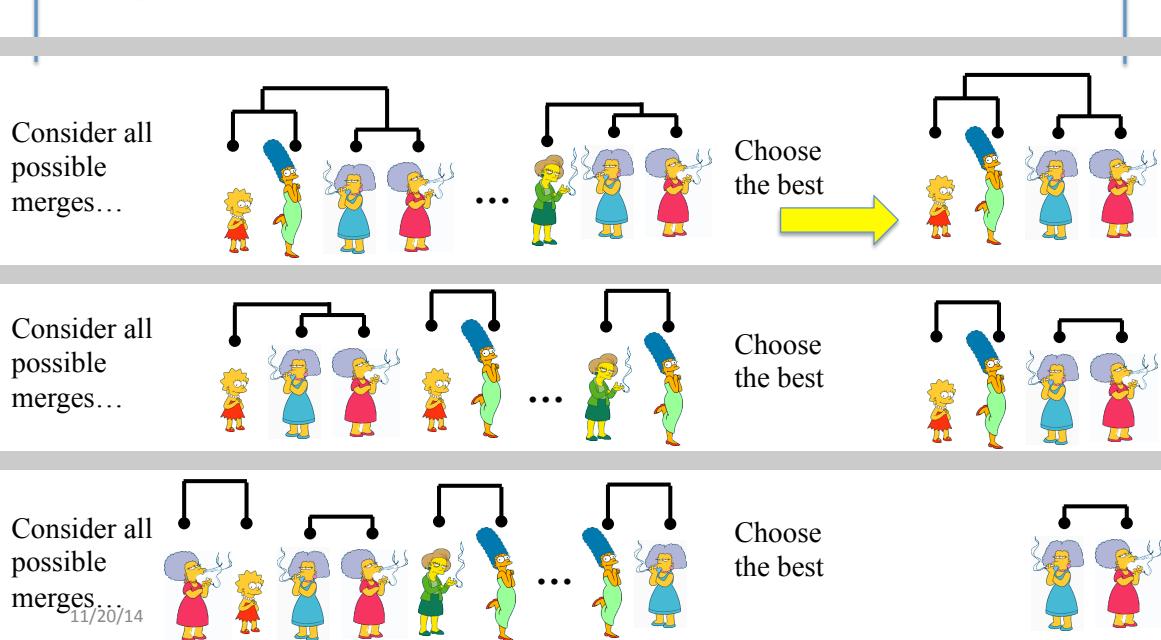
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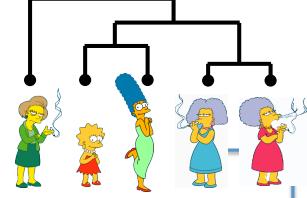


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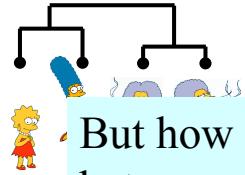


Bottom-Up (agglomerative): Starting with each item in its own cluster, find the best pair to merge into a new cluster. Repeat until all clusters are fused together.

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Consider all possible merges...



Choose

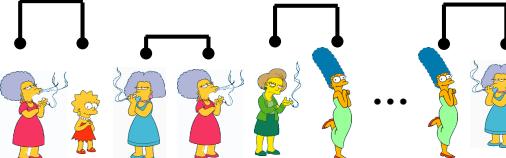
But how do we compute distances between clusters rather than objects?

Consider all possible merges...



the best

Consider all possible merges
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Choose the best



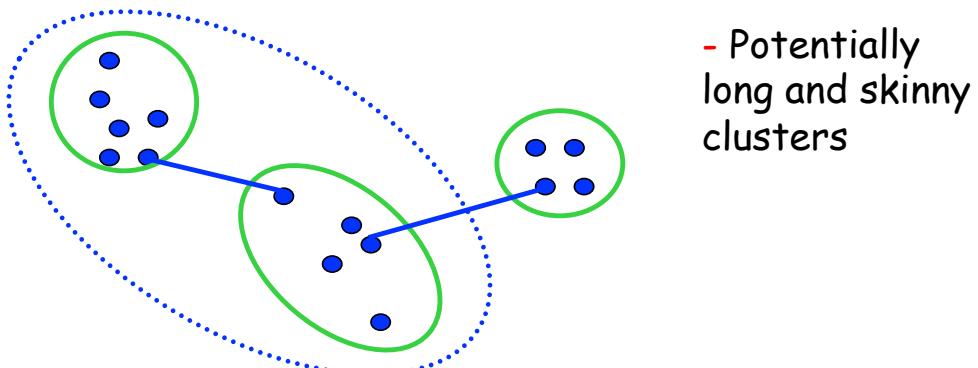
How to decide the distances between clusters ?

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- Single-Link
 - Nearest Neighbor: their closest members.
- Complete-Link
 - Furthest Neighbor: their furthest members.
- Average:
 - average of all cross-cluster pairs.

Computing distance between clusters: Single Link

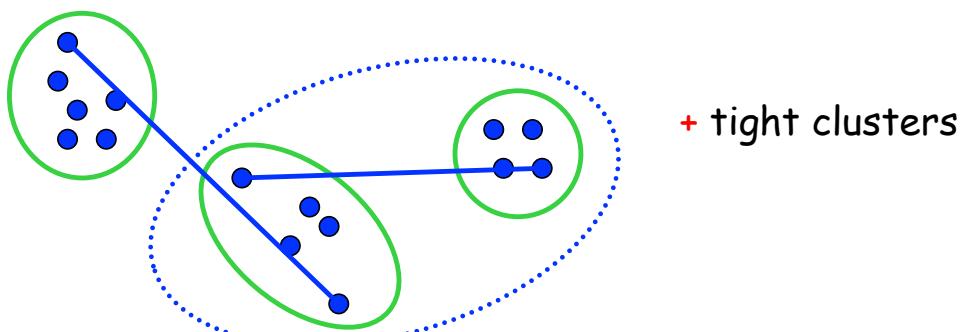
- cluster distance = distance of two **closest** members in each class



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Computing distance between clusters: Complete Link

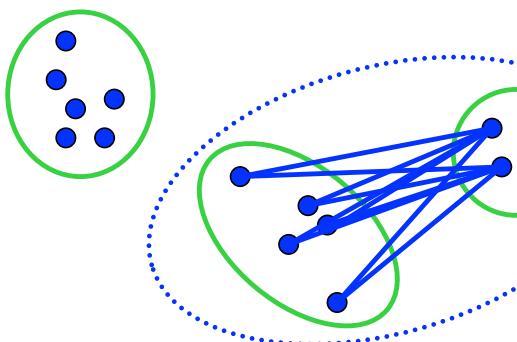
- cluster distance = distance of two farthest members



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Computing distance between clusters: Average Link

- cluster distance = **average distance** of all pairs

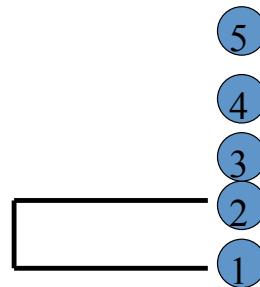


the most widely used measure
Robust against noise

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Example: single link

	1	2	3	4	5
1	0				
2	2	0			
3	6	3	0		
4	10	9	7	0	
5	9	8	5	4	0



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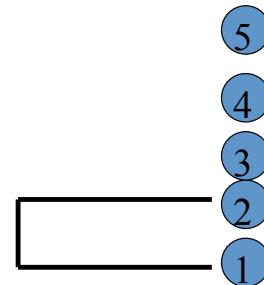
Example: single link

$$\begin{array}{ccccc}
 & 1 & 2 & 3 & 4 & 5 \\
 \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \left[\begin{array}{ccccc} 0 & & & & \\ 2 & 0 & & & \\ 6 & 3 & 0 & & \\ 10 & 9 & 7 & 0 & \\ 9 & 8 & 5 & 4 & 0 \end{array} \right] & \xrightarrow{\hspace{1cm}} & \left[\begin{array}{ccccc} (1,2) & 3 & 4 & 5 \\ (1,2) & 0 & & \\ 3 & 3 & 0 & \\ 4 & 9 & 7 & 0 \\ 5 & 8 & 5 & 4 & 0 \end{array} \right]
 \end{array}$$

$$d_{(1,2),3} = \min\{ d_{1,3}, d_{2,3} \} = \min\{ 6, 3 \} = 3$$

$$d_{(1,2),4} = \min\{ d_{1,4}, d_{2,4} \} = \min\{ 10, 9 \} = 9$$

$$d_{(1,2),5} = \min\{ d_{1,5}, d_{2,5} \} = \min\{ 9, 8 \} = 8$$



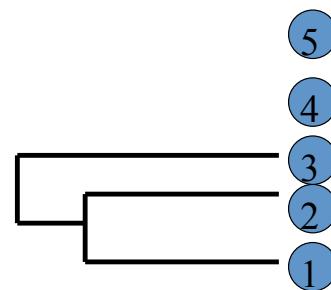
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Example: single link

$$\begin{array}{ccccc}
 & 1 & 2 & 3 & 4 & 5 \\
 \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \left[\begin{array}{ccccc} 0 & & & & \\ 2 & 0 & & & \\ 6 & 3 & 0 & & \\ 10 & 9 & 7 & 0 & \\ 9 & 8 & 5 & 4 & 0 \end{array} \right] & \xrightarrow{\hspace{1cm}} & \left[\begin{array}{ccccc} (1,2) & 3 & 4 & 5 \\ (1,2) & 0 & & \\ 3 & 3 & 0 & \\ 4 & 9 & 7 & 0 \\ 5 & 8 & 5 & 4 & 0 \end{array} \right] & \xrightarrow{\hspace{1cm}} \left[\begin{array}{ccccc} (1,2,3) & 4 & 5 \\ (1,2,3) & 0 & & \\ 4 & 7 & 0 & \\ 5 & 5 & 4 & 0 \end{array} \right]
 \end{array}$$

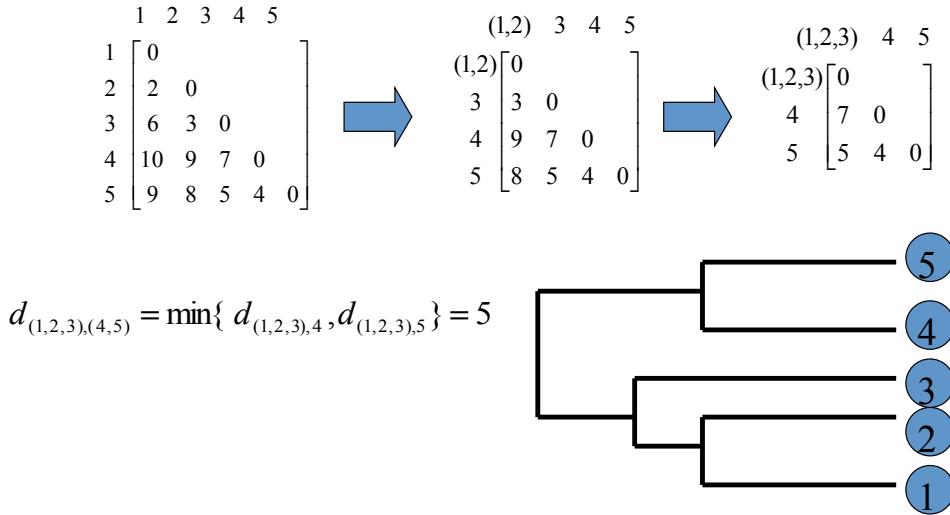
$$d_{(1,2,3),4} = \min\{ d_{(1,2),4}, d_{3,4} \} = \min\{ 9, 7 \} = 7$$

$$d_{(1,2,3),5} = \min\{ d_{(1,2),5}, d_{3,5} \} = \min\{ 8, 5 \} = 5$$



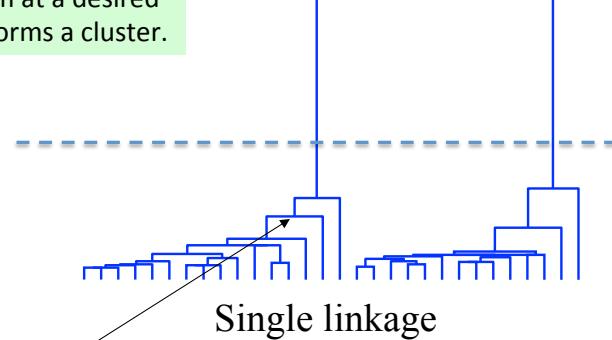
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Example: single link

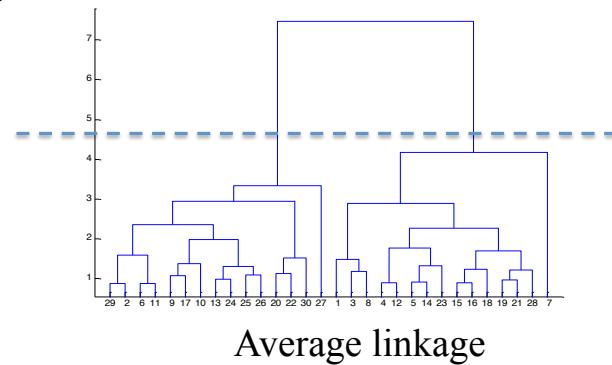


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Partitions by cutting the dendrogram at a desired level: each connected component forms a cluster.



Height represents
distance between
objects / clusters



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Hierarchical Clustering

- **Bottom-Up** Agglomerative Clustering
 - Starts with each object 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 (dendrogram)

- **Top-Down divisive**
 - Starting with all the data in a single cluster,
 - Consider every possible way to divide the cluster into two. Choose the best division
 - And recursively operate on both sides.

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Computational Complexity

- 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 $n-2$ merging iterations, compute the distance between the most recently created cluster and all other existing clusters.
- In order to maintain an overall $O(n^2)$ performance, computing similarity to each other cluster must be done in constant time.
- Else $O(n^2 \log n)$ or $O(n^3)$ if done naively

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Summary of Hierarchical Clustering Methods

- No need to specify the number of clusters in advance.
- Hierarchical structure maps nicely onto human intuition for some domains
- They do not scale well: time complexity of at least $O(n^2)$, where n is the number of total objects.
- Like any heuristic search algorithms, local optima are a problem.
- Interpretation of results is (very) subjective.

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References

- ❑ Hastie, Trevor, et al. *The elements of statistical learning*. Vol. 2. No. 1. New York: Springer, 2009.
- ❑ Big thanks to Prof. Eric Xing @ CMU for allowing me to reuse some of his slides
- ❑ Big thanks to Prof. Ziv Bar-Joseph @ CMU for allowing me to reuse some of his slides

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