## Clustering analysis of gene expression data

Chapter 11 in
Jonathan Pevsner,
Bioinformatics and Functional Genomics,

3<sup>rd</sup> edition

(Chapter 9 in 2<sup>nd</sup> edition)

### Human T cell expression data

- The matrix contains 47 expression samples from Lukk et al,
   Nature Biotechnology 2010
- All samples are from <u>T cells in different individuals</u>
- Only the top 3000 genes with the largest variability were used
- The value is log2 of gene's expression level in a given sample as

measured by the microarray technology

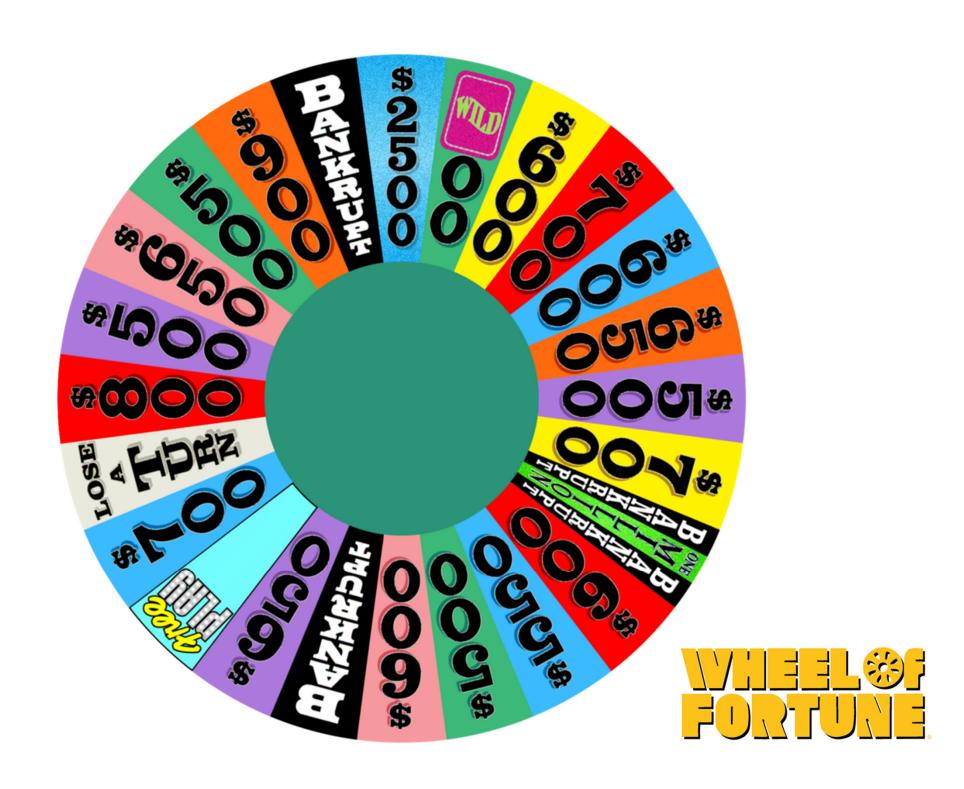
#### A global map of human gene expression

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Although there is only one human genome sequence, different genes are expressed in many different cell types and tissues, as well as in different developmental stages or diseases. The structure of this 'expression space' is still largely unknown, as most transcriptomics experiments focus on sampling small regions. We have constructed a global gene expression map by integrating microarray data from 5,372 human samples representing 369 different cell and tissue types, disease states and cell lines. These have been compiled in an online resource (http://www.ebi.ac.uk/gxa/array/U133A) that allows the user to search for a gene of interest and



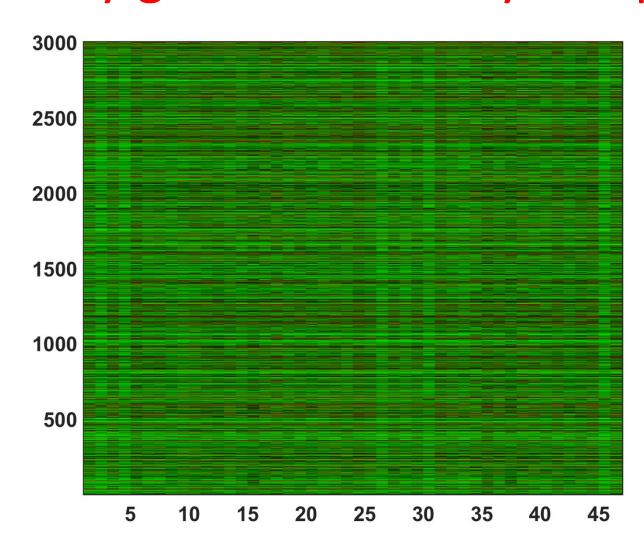
## Correlated pairs plausible biological connection based on short description

```
g1=1994; g2=188; group 1
   g1=2872; g2=1269; group 2
   g1=1321; g2=10; group 3
   g1= 886; g2=819; group 4
   g1=2138; g2=1364; group 5
no obvious biological common function
g1=1+floor(rand.*3000); g2=1+floor(rand.*3000);
disp([g1, g2])
```

#### Matlab exercise

- Every group works with g0=2907; g1=1527; g2=2629; g3=2881; g4=1144; g5=1066;
- Compute Multiple Linear Regression (MLR), where y=exp\_t (g0);
   x1= exp\_t (g1); x2= exp\_t (g2);
- How much better the MLR did compared to the Single Linear Regression (SLR)?
- Continue increasing the number of genes in x until R\_adj starts to decrease

# How to find the entire groups of mutually correlated genes if you have many genes and many samples?



## Clustering to the rescue!

## Clustering is a part of Machine Learning

#### Supervised Learning:

A machine learning technique whereby a system uses a set of human-labelled training examples to learn how to correctly perform a task

Example: a sample of cancer expression profiles each annotated with cancer type

Goal: predict cancer type based on expression pattern

#### Unsupervised Learning (including clustering):

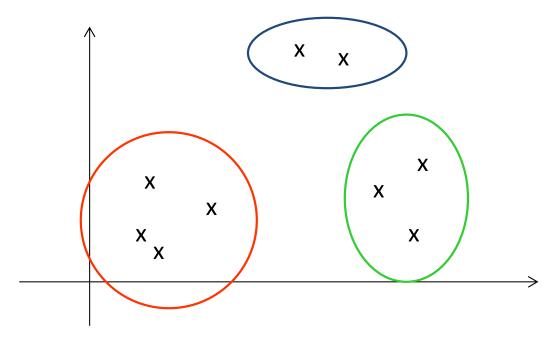
In machine learning, unsupervised learning is a class of problems in which one seeks to determine how the data are organized. One only has unlabeled examples.

Example: a sample of breast cancer expression profiles.

Goal: Identify several different (yet unknown) subtypes with potentially different treatments

### What is clustering?

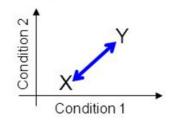
- The goal of clustering is to
  - group data points that are close (or similar) to each other
  - Usually, one needs to identify such groups (or clusters) in an unsupervised manner
  - Sometimes one takes into account prior information (Bayesian methods)
- Need to define some distance d<sub>ij</sub> between objects i and j
- Clustering is easy in 2 dimensions but hard in 3000 dimensions -> need to somehow reduce dimensionality



#### How to define the distance?

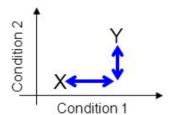
- Euclidean distance:
  - Most commonly used distance
  - Sphere shaped cluster
  - Corresponds to the geometric distance into the multidimensional space

$$d(X,Y) = \sqrt{\sum_{i} (x_i - y_i)^2}$$



- City Block (Manhattan) distance:
  - Sum of differences across dimensions
  - Less sensitive to outliers
  - Diamond shaped clusters

$$d(X,Y) = \sum_{i} |x_i - y_i|$$



The Canberra distance metric is calculated in R by

$$\sum \left(\frac{|x_i-y_i|}{|x_i+y_i|}\right).$$

Correlation coefficient distance

$$d(X,Y) = 1 - \rho(X,Y) = 1 - \frac{Cov(X,Y)}{\sqrt{(Var(X) \cdot Var(Y))}}$$

## Common types of clustering algorithms

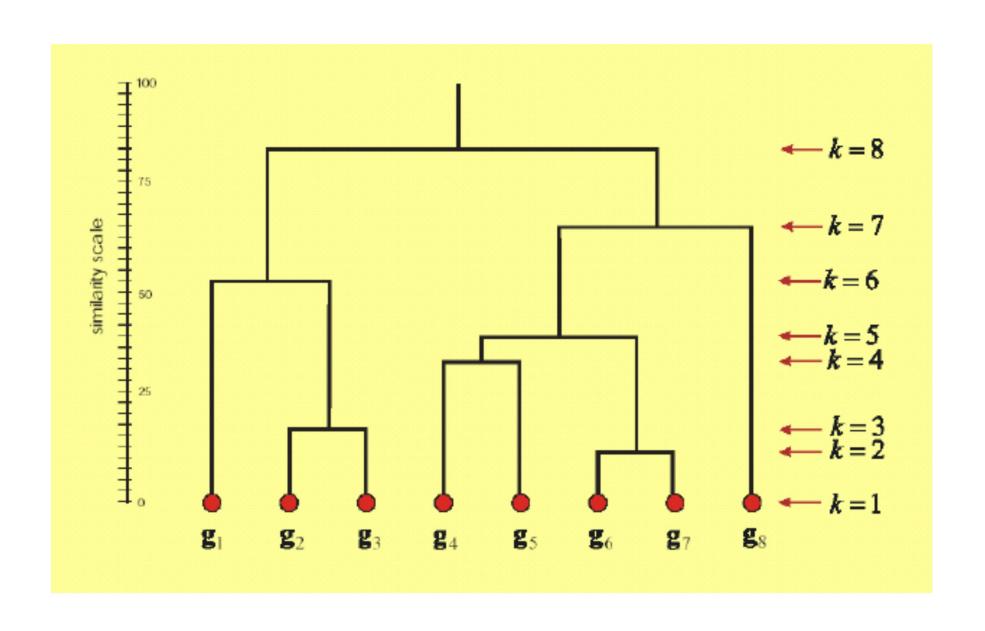
- Hierarchical if one doesn't know in advance the # of clusters
  - Agglomerative: start with N clusters and gradually merge them into 1 cluster
  - Divisive: start with 1 cluster and gradually break it up into N clusters
- Non-hierarchical algorithms
  - K-means clustering:
    - <u>Iteratively</u> apply the following two steps:
    - Calculate the centroid (center of mass) of each cluster
    - Assign each to the cluster to the nearest centroid
  - Principal Component Analysis (PCA)
    - plot pairs of top eigenvectors of the covariance matrix Cov(X<sub>i</sub>, X<sub>i</sub>) and uses visual information to group

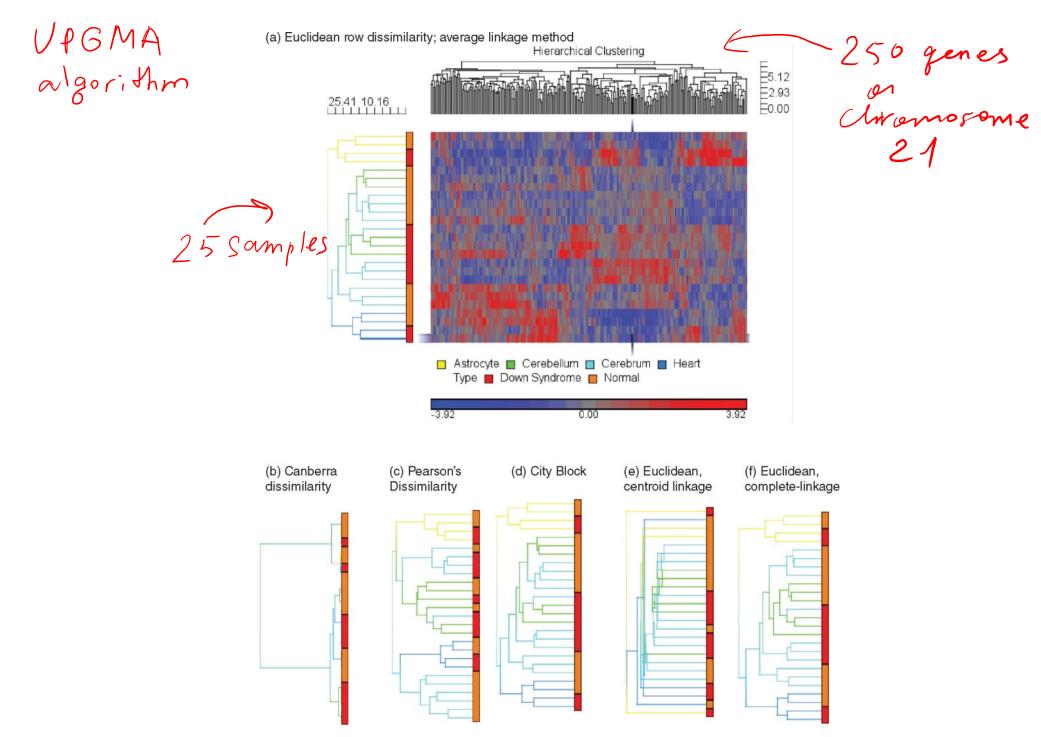
## Hierarchical clustering

#### **UPGMA** algorithm

- Hierarchical agglomerative clustering algorithm
- UPGMA = Unweighted Pair Group Method with Arithmetic mean
- Iterative algorithm:
- Start with a pair with the smallest d(X,Y)
- Cluster these two together and replace it with their arithmetic mean (X+Y)/2
- Recalculate all distances to this new "cluster node"
- Repeat until all nodes are merged

### Output of UPGMA algorithm





**FIGURE 11.16** Hierarchical clustering of 250 chromosome 21 transcripts in 25 samples using Partek software. (a) Hierarchical clustering of microarray data using the default settings of Euclidean dissimilarity for rows (samples) and columns (transcripts). Colors correspond to expression intensity values.



## Clustering Matlab demo

## Choices of distance metrics in clustergram(... 'RowPDistValue' ..., 'ColumnPDistValue' ...,)

Metric	Description	
'euclidean'	Euclidean distance (default).	
'seuclidean'	Standardized Euclidean distance. Each coordinate difference between rows in X is scaled by dividing by the corresponding element of the standard deviation S=nanstd(X). To specify another value for S, use D=pdist(X, 'seuclidean', S).	
'cityblock'	City block metric.	
'minkowski'	Minkowski distance. The default exponent is 2. To specify a different exponent, use $D = pdist(X, 'minkowski', P)$ , where P is a scalar positive value of the exponent.	
'chebychev'	Chebychev distance (maximum coordinate difference).	
'mahalanobis'	Mahalanobis distance, using the sample covariance of X as computed by nancov. To compute the distance with a different covariance, use D = pdist (X, 'mahalanobis', C), where the matrix C is symmetric and positive definite.	
'cosine'	One minus the cosine of the included angle between points (treated as vectors).	
'correlation'	One minus the sample correlation between points (treated as sequences of values).	
'spearman'	One minus the sample Spearman's rank correlation between observations (treated as sequences of values).	
'hamming'	Hamming distance, which is the percentage of coordinates that differ.	
'jaccard'	One minus the Jaccard coefficient, which is the percentage of nonzero coordinates that differ.	
custom distance function	A distance function specified using @: D = pdist(X,@distfun) A distance function must be of form	
	d2 = distfun(XI,XJ)	
	taking as arguments a 1-by- $n$ vector XI, corresponding to a single row of X, and an $m2$ -by- $n$ matrix XJ, corresponding to multiple rows of X. distfun must accept a matrix XJ with an arbitrary number of rows. distfun must return an $m2$ -by-1 vector of distances d2, whose $k$ th element is the distance between XI and XJ( $k$ ,:).	

## Choices of hierarchical clustering algorithm in clustergram(...'linkage',...)

Х		Matrix with two or more rows. The rows represent observations, the columns represent categories or dimensions.		
method	Algorithm for computing distance between clusters.			
	Method	Description		
	'average'	Unweighted average distance (UPGMA)		
	'centroid'	Centroid distance (UPGMC), appropriate for Euclidean distances only		
	'complete'	Furthest distance		
	'median'	Weighted center of mass distance (WPGMC), appropriate for Euclidean distances only		
	'single'	Shortest distance		
	'ward'	Inner squared distance (minimum variance algorithm), appropriate for Euclidean distances only		
	'weighted'	Weighted average distance (WPGMA)		
	Default: 'single	= 1		

#### Clustering group exercise

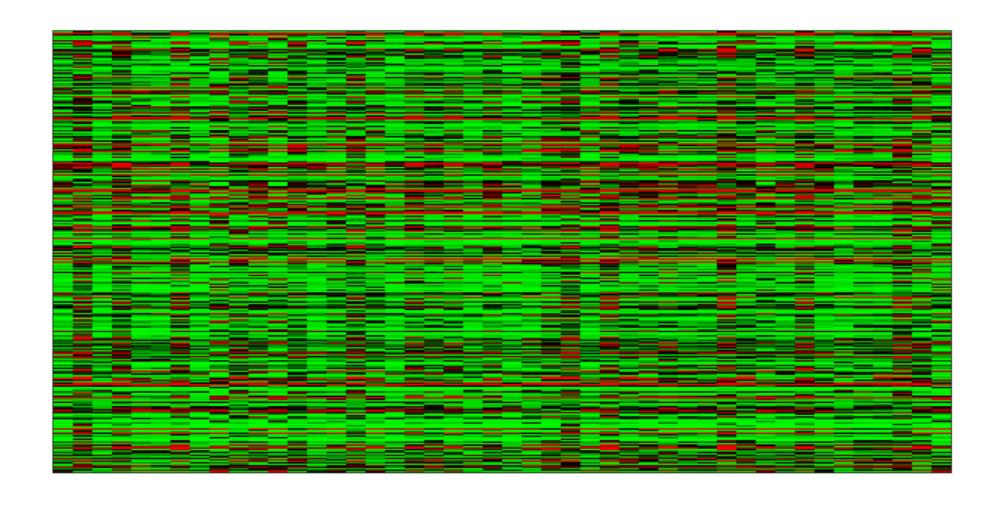
- Each group will analyze a cluster of genes identified in the T cell expression table
- Analyze the table of top 100 genes by variance in 47 samples
- Cluster them using:
  - Group 1: UPGMA = 'linkage', 'average', 'RowPDistValue', 'euclidean',
  - Group 2: 'linkage', 'single', 'RowPDistValue', 'cityblock',
  - Group 3: 'linkage', 'average', 'RowPDistValue', 'correlation',
  - Group 4: UPGMA = 'linkage', 'single', 'RowPDistValue', 'euclidean',
  - Group 5: UPGMA = 'linkage', 'weighted', 'RowPDistValue', 'correlation',
- Use clustergram(..., 'Standardize','Row',
   'linkage', <u>as specified for your group,</u>
   'RowPDistValue' <u>as specified for your group,</u>
  - 'RowLabels', gene names1, 'ColumnLabels', array names)

#### Matlab code

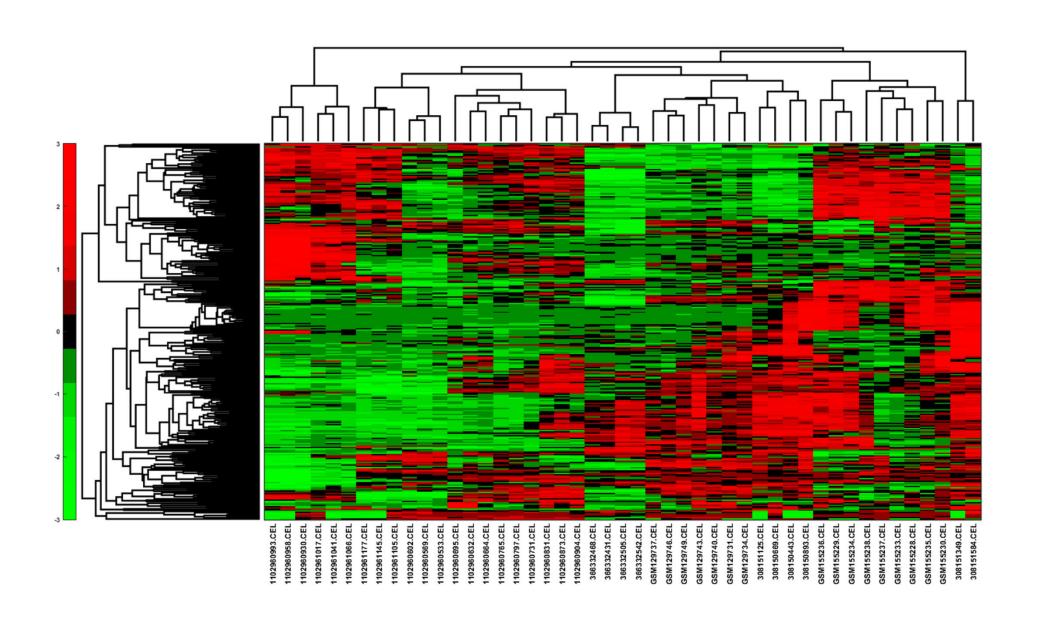
 load expression table.mat gene\_variation=std(exp\_t')'; [a,b]=sort(gene\_variation,'descend'); ngenes=100; exp\_t1=exp\_t(b(1:ngenes),:); gene names1=gene names(b(1:ngenes)); %%% for group 1 CGobj1 = clustergram(exp t1, 'Standardize', 'Row', 'RowLabels', gene\_names1,'ColumnLabels',array\_names) set(CGobj1,'RowLabels',gene\_names1,'ColumnLabels', array\_names,'linkage',

'average','RowPDist','euclidean');

#### Before clustering



#### UPGMA hierarchical clustering, Euclidian distance



#### UPGMA hierarchical clustering, correlation distance

