

# Gene Expression Data Visualization with R

## Theory Session

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## Main topics

- Principal component analysis (PCA)
  - Dimensionality reduction
  - Grouping by similarity
- Heatmaps
  - Hierarchical clustering
  - Sample correlation / difference
- Mean – variance plots
  - Variance stabilization
- MA plots
  - Visualization of fold changes
  - Fold change shrinkage

# Principal component analysis (PCA)



<https://blog.freepeople.com/2013/02/book-club-meeting-deepest/>

## Principal component analysis (PCA)

- Orthogonal projection of
  - an N-dimensional object viewed from a **random perspective**
  - into an M-dimensional object viewed from **another perspective**
- The projection has the following features
  - First axis (principal component) explains **as much of total variation between data points as possible**
  - Second PC explains **as much of remaining variation as possible**
  - ...
  - M<sup>th</sup> (last) PC explains **the last remaining variation**
  - No axis depends on another
- Total variation is preserved
- No data is created or removed

## Principal component analysis (PCA)

- A gene expression dataset is a multidimensional object
  - $n$  genes in  $m$  samples =  $n \times m$  matrix
  - Every sample can be represented as a point in an  $n$ -dimensional space
  - Coordinates of a point are expression values of all genes

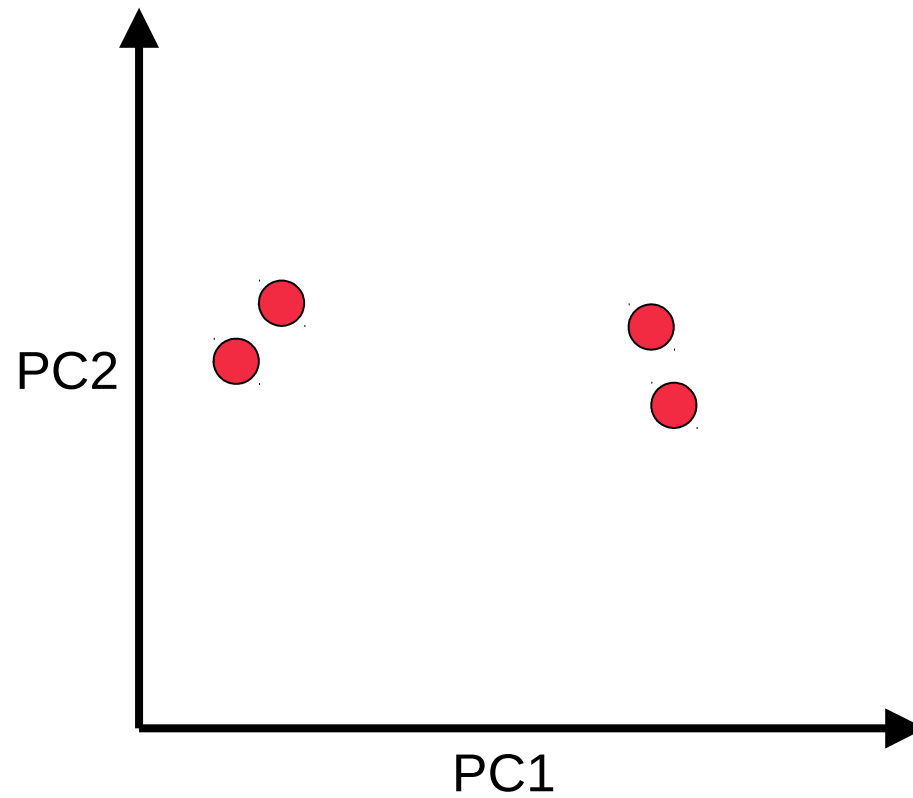
	$S_1$	$S_2$	$S_3$	$S_4$
$G_1$	$E_{11}$	$E_{12}$	$E_{13}$	$E_{14}$
$G_2$	$E_{21}$	$E_{22}$	$E_{23}$	$E_{24}$
...	...	...	...	...
$G_n$	$E_{n1}$	$E_{n2}$	$E_{n3}$	$E_{n4}$

$$S_1 = \langle E_{11}, E_{21}, \dots, E_{n1} \rangle$$

## Principal component analysis (PCA)

- Can you imagine a point in a 5-dimensional space?
  - If yes, I want to talk to you after the seminar ☐
- Solution: Reduce dimensionality
- Based on which criteria?
  - Variation among genes!
  - A unique signature of the sample
- How many dimensions are enough?
  - Usually two, at most 3 (not recommended)

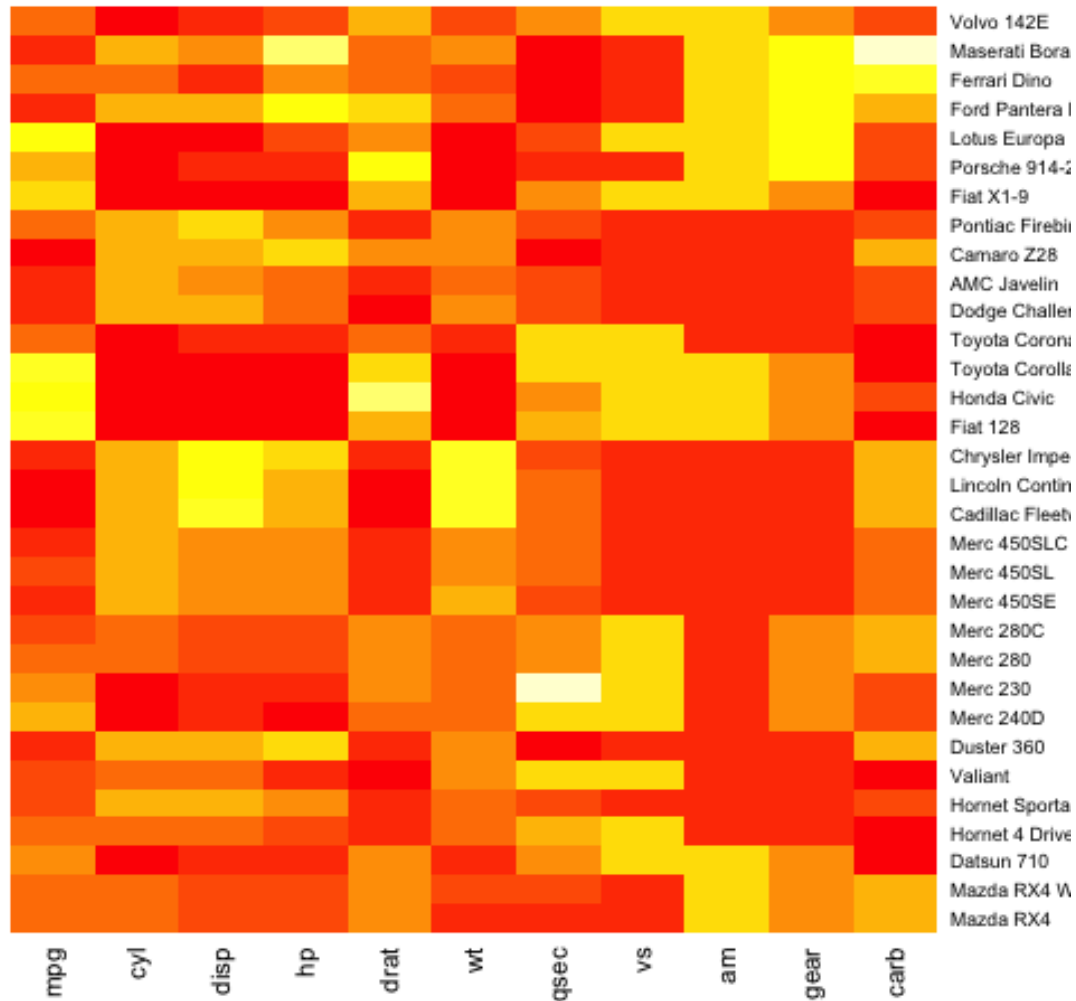
## Principal component analysis (PCA)



Questions?



# Heatmaps



[www.r-graph-gallery.com](http://www.r-graph-gallery.com)

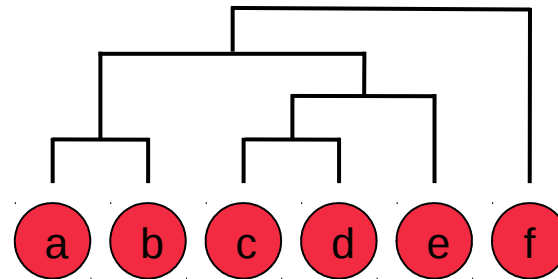
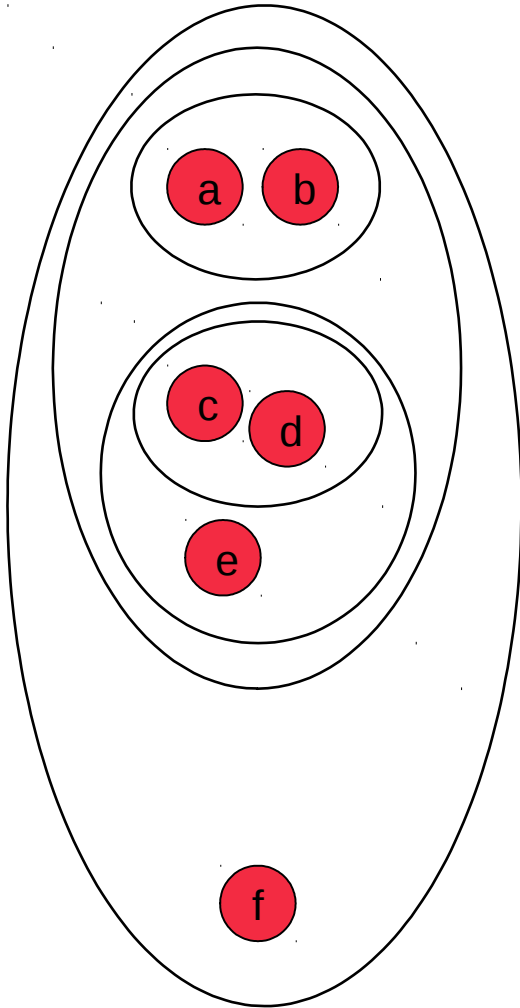
# Heatmaps

- A method to visualize 3-dimensional data on a 2-dimensional space
- Takes advantage of human color perception
  - Dimension 1: x-axis
  - Dimension 2: y-axis
  - Dimension 3: color
- Extra information can be encoded via grouping
- Grouping on which criteria?
  - Similarity / dissimilarity (hierarchical clustering)

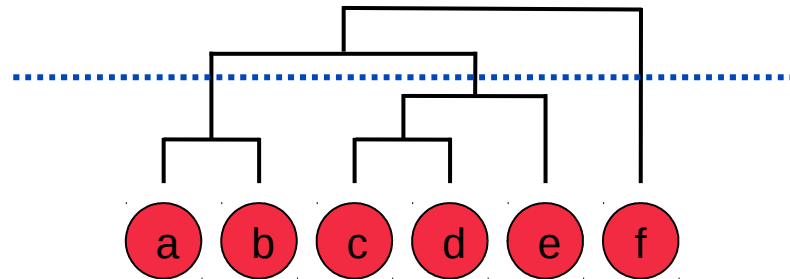
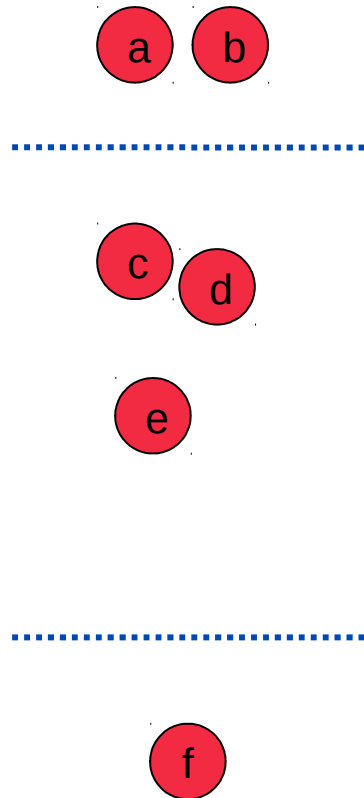
# Heatmaps

- What does hierarchical clustering do?
- First calculate a distance matrix
  - Remember, every sample / gene is a point in a multidimensional space
  - There always exists a line segment that connects two points!
  - The length of that segment is (an Euclidean) distance!
  - A distance matrix is half of a square matrix. Think why!
- Iterate over samples / genes and group them based on distances
  - The result is a tree-like structure called a **dendrogram**

## Hierarchical clustering

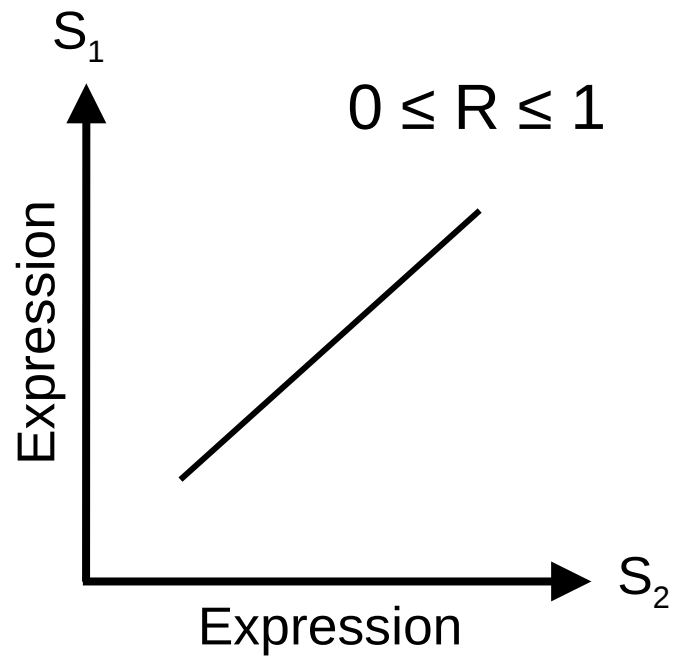


# Hierarchical clustering



## Correlation

- Correlation matrix instead of distance matrix
  - Based on correlation coefficient
  - Easier to interpret



Questions?

## Logarithmic transformation

- Hierarchical clustering and PCA are sensitive to data distribution
- It's best when the data is:
  - Normally distributed
  - Homoskedastic (variance is stable)
- Gene expression data is naturally skewed
  - A lot of low-expression genes, few high-expression genes
  - A logarithmic transformation helps to normalize the data

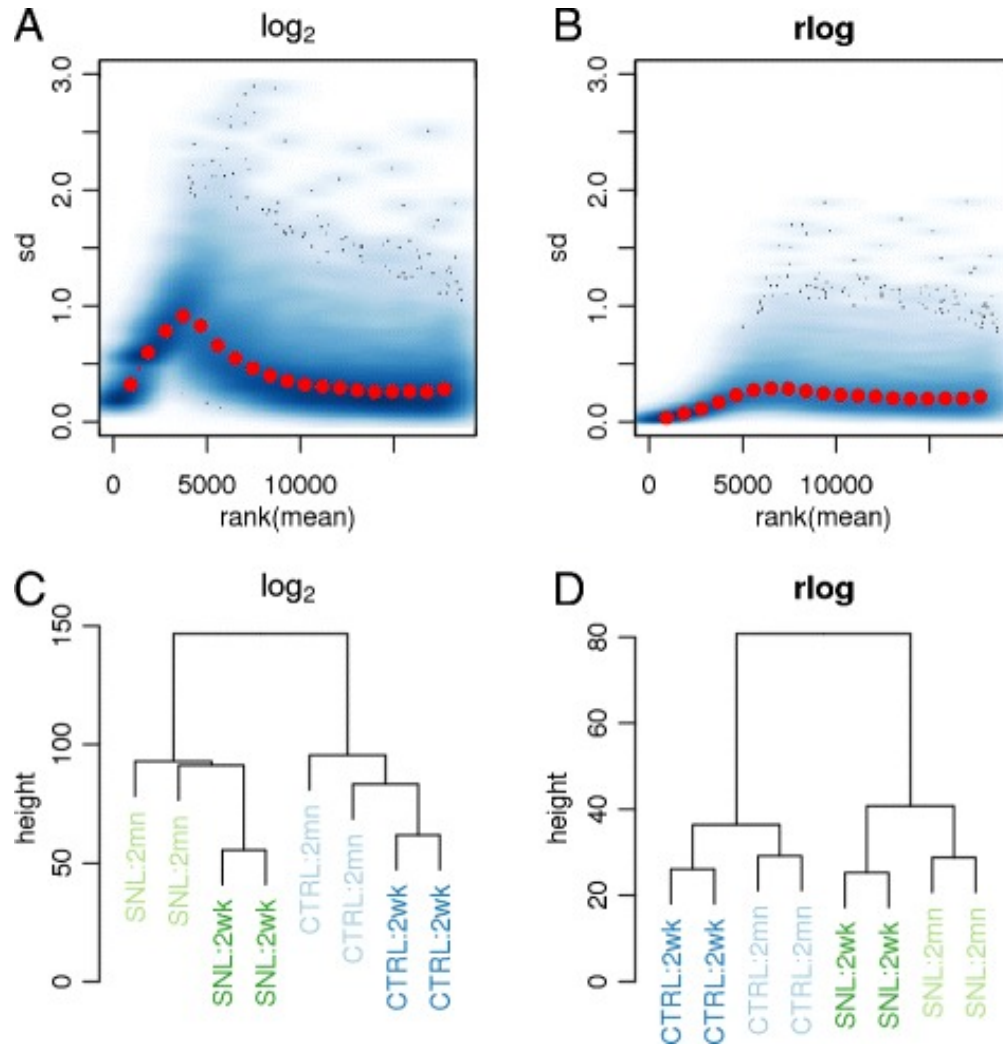


## Variance stabilization

- Log transformation affects the variance of small numbers more than big numbers
  - Set 1: 5, 6, 7
  - Set 2: 5005, 5006, 5007

		Set 1	Set 2
Original	Mean	6	5006
	SD	1	1
log2	Mean	2.571	12.289
	SD	0.2430	0.0003

## Mean-variance plots



Love et al. 2014

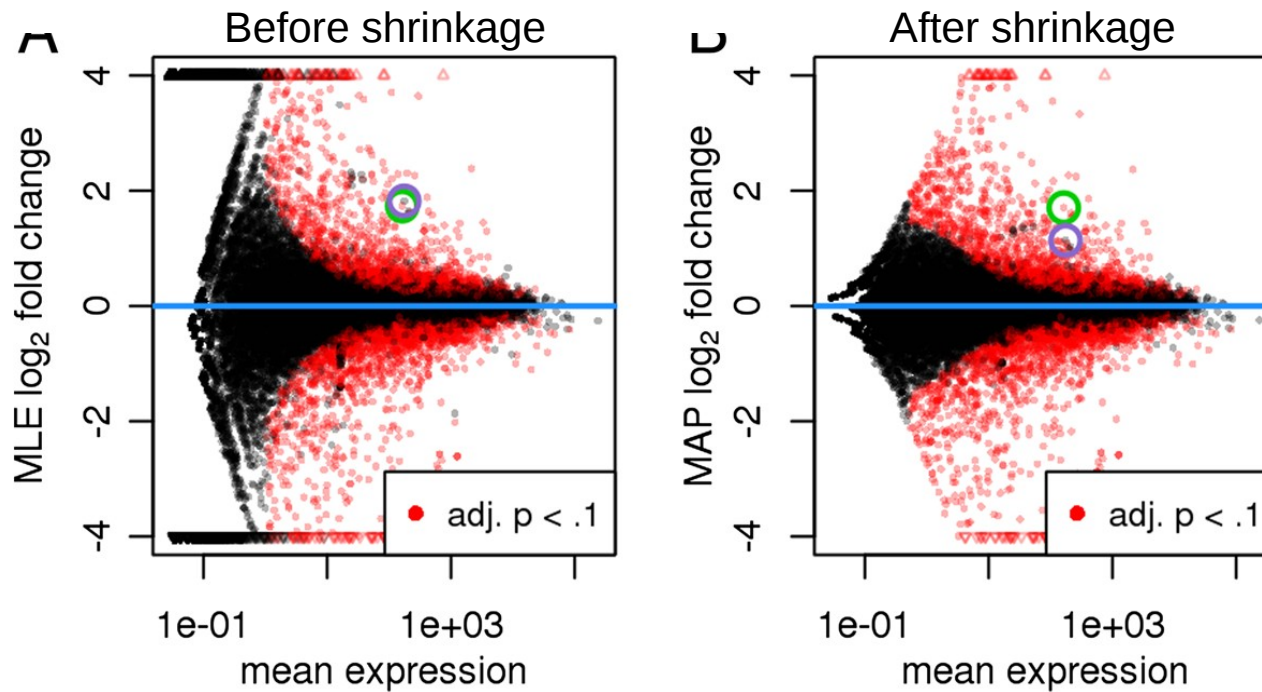
Questions?

## MA Plots

- Why do we do differential gene expression analysis?
  - To find out up- or downregulated genes in a **test sample compared to a control sample**
- M represents log fold change (LFC)
  - $LFC_i = \log_2 \frac{E_{i,test}}{E_{i,control}}$ 
    - :  $LFC \geq 0 \Rightarrow$  Upregulation
    - :  $LFC \leq 0 \Rightarrow$  Downregulations
    - :  $LFC \equiv 0 \Rightarrow$  No difference
  - : Associated with an adjusted p-value
- A represents average gene expression across samples
  - An approximation of abundance level

## LFC shrinkage

- Similar to variance stabilization, more complicated
- Aims to remove very high/low LFCs observed in low counts



Love et al. 2014

Questions?