

# Fundamentals of AI

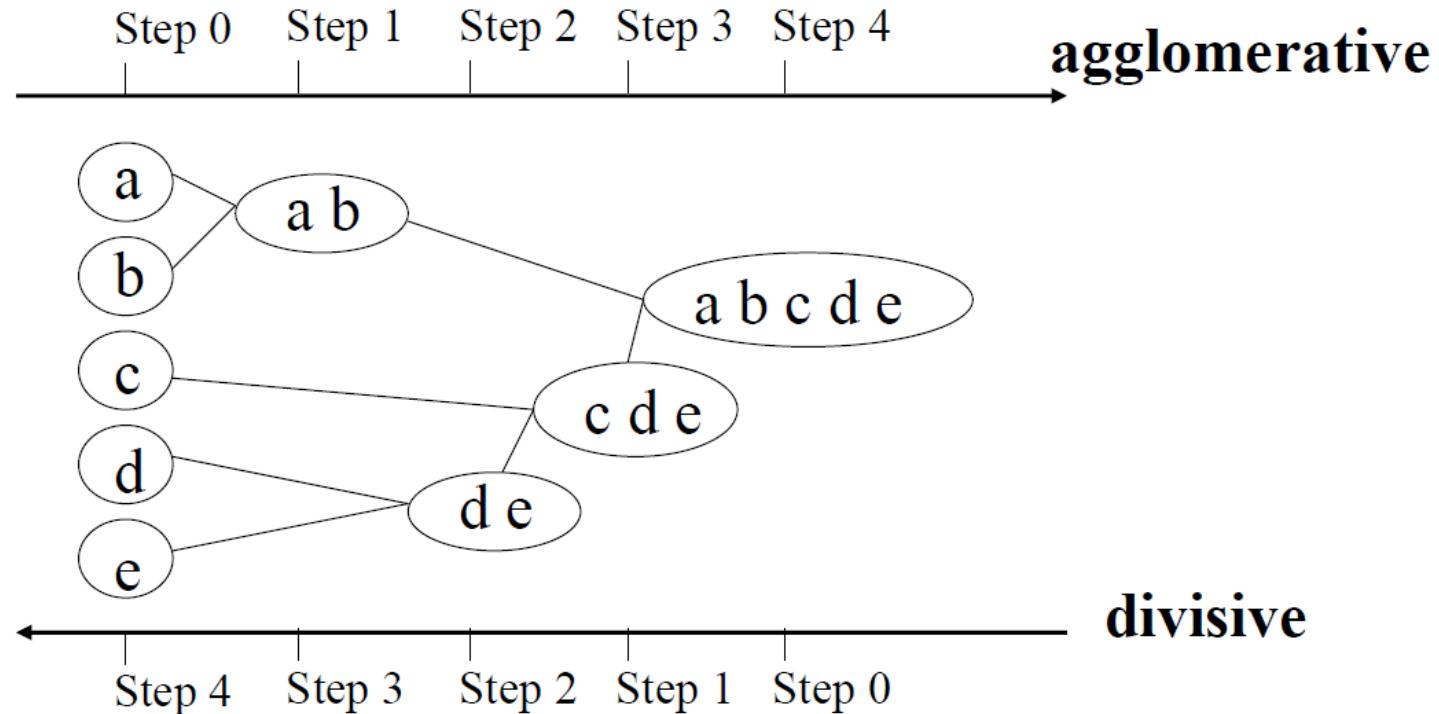
## Clustering

### Hierarchical clustering

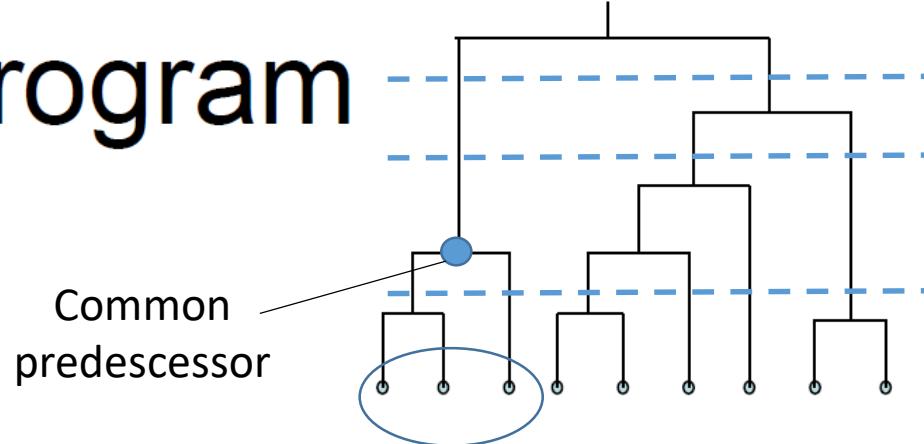
First dendrogram : R. Ling, 1973

# Hierarchical Clustering

- Group data objects into a tree of clusters

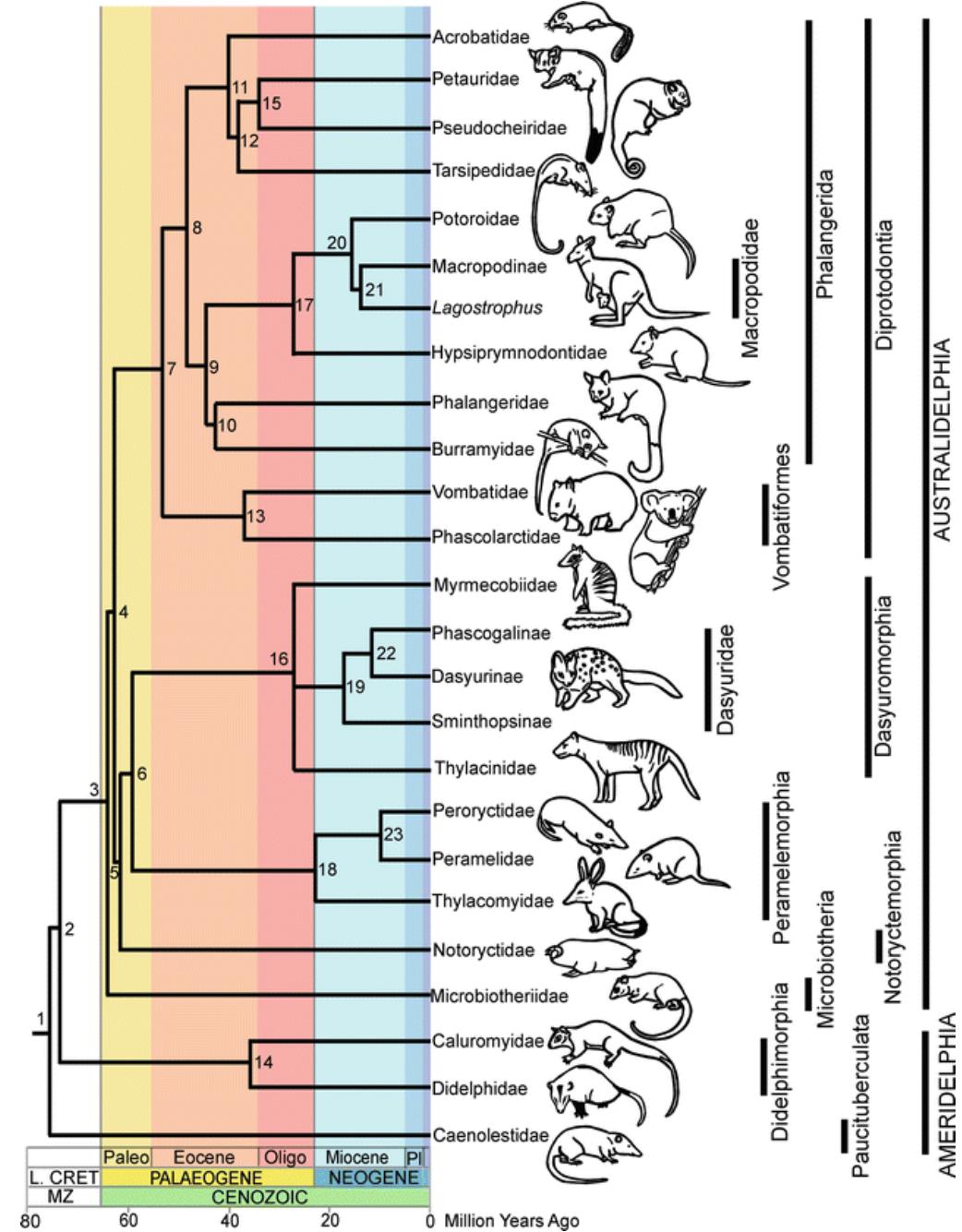


# Dendrogram

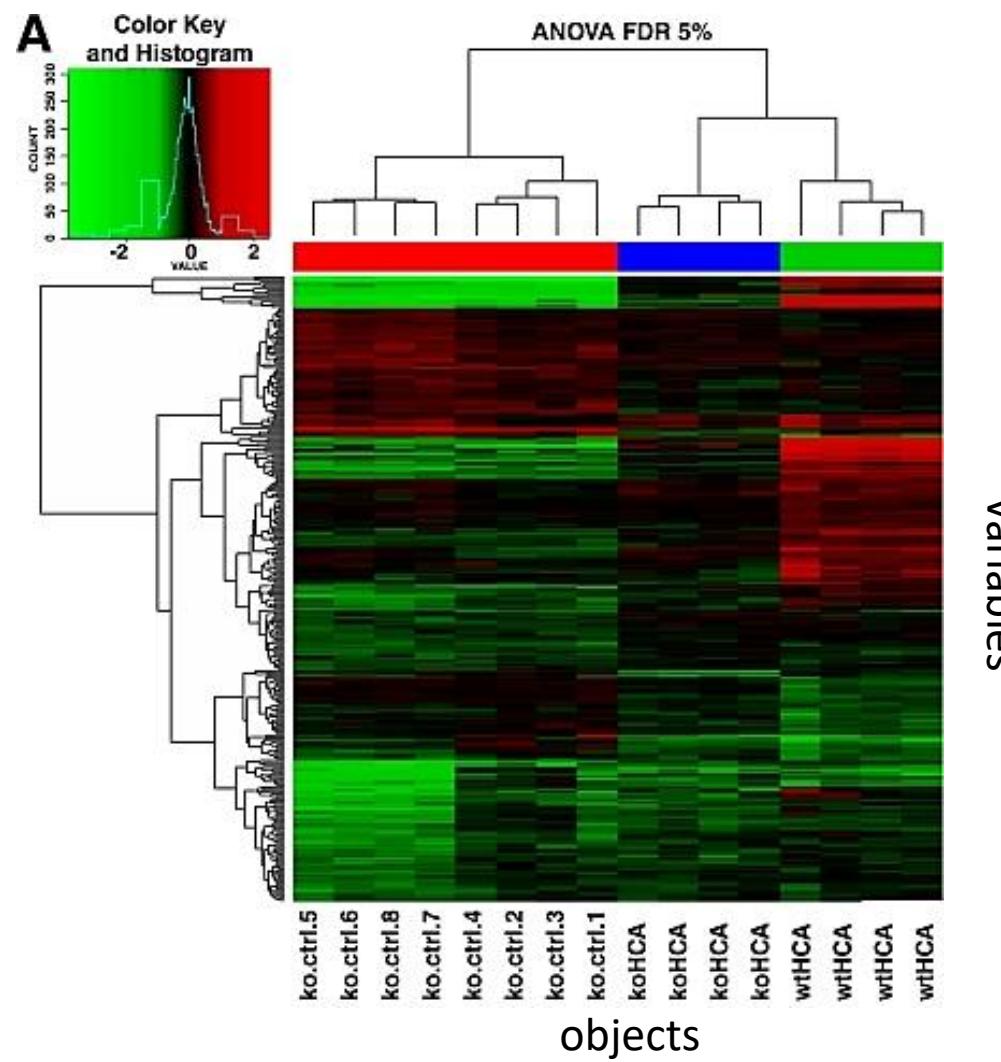


- Show how to merge clusters hierarchically
- Decompose data objects into a multi-level nested partitioning (a tree of clusters)
- A clustering of the data objects: cutting the dendrogram at the desired level
  - Each connected component forms a cluster

# Example of dendrogram: tree of life



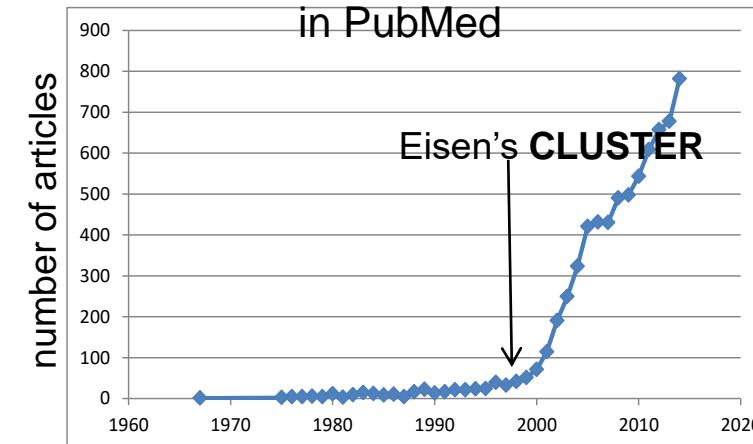
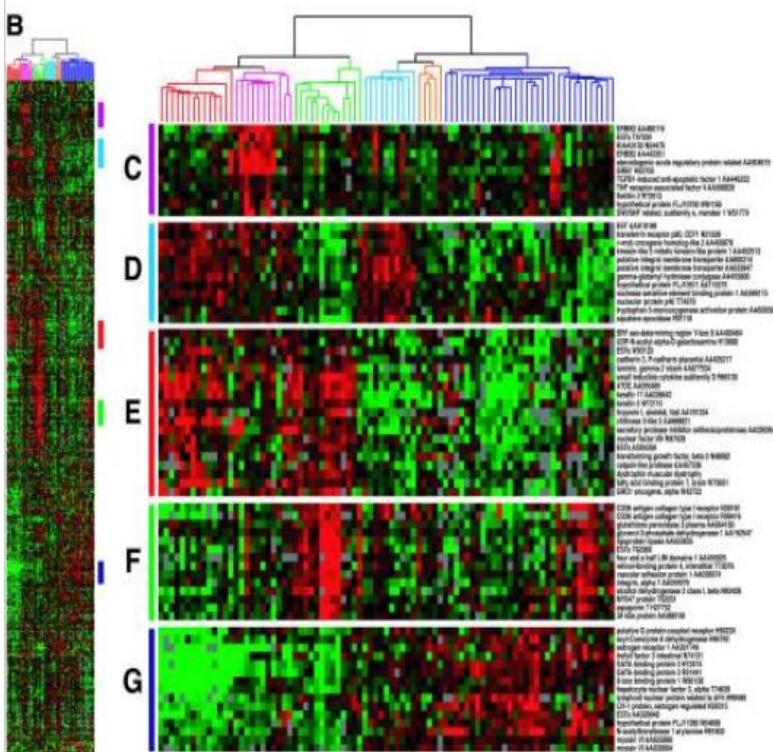
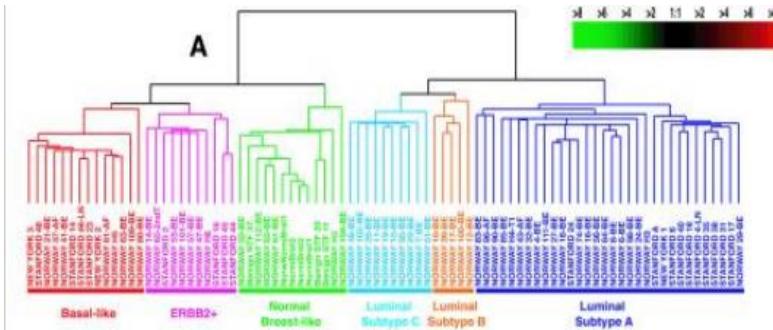
# Heatmap representation of data



Dendrogram + Heatmap =  
killer application in life sciences!\*

\* In 1990-2010s, lost in popularity in the last years

# Hierarchical clustering for studying cancer

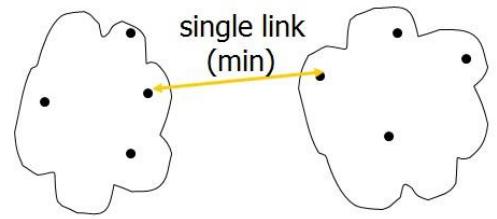


Sorlie, PNAS 2001

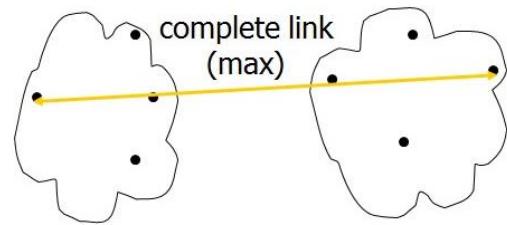
# Agglomerative algorithm(s)

- Initially, each object is a cluster
- Step-by-step **merging of the closest clusters**, until all objects form a single cluster
  - One needs to define:
    - Distance metrics between data points
    - Distance metrics between groups of data points

# Dissimilarity ('distance') between clusters

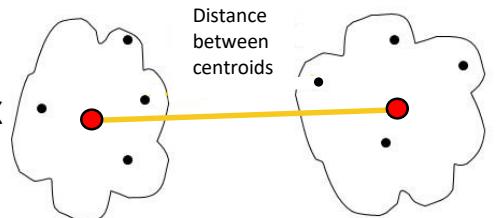


$$d_{\min}(C_i, C_j) = \min_{p \in C_i, q \in C_j} d(p, q)$$

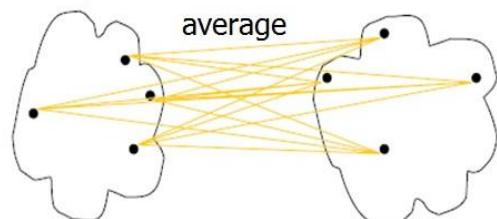


$$d_{\max}(C_i, C_j) = \max_{p \in C_i, q \in C_j} d(p, q)$$

Special case!  
Full data matrix  
is needed!

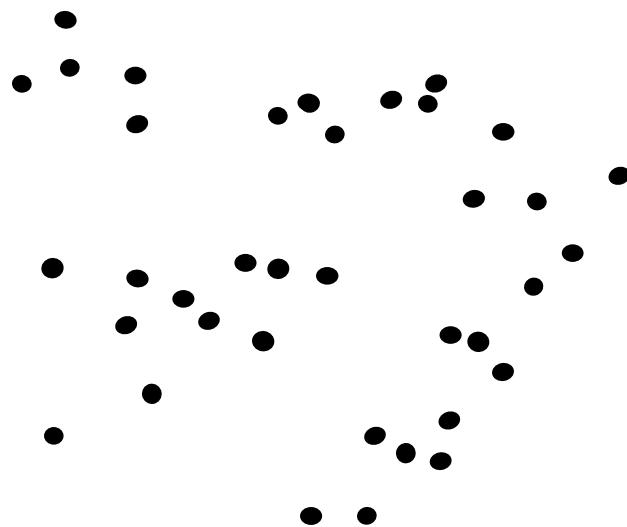


$$d_{\text{mean}}(C_i, C_j) = d(m_i, m_j)$$



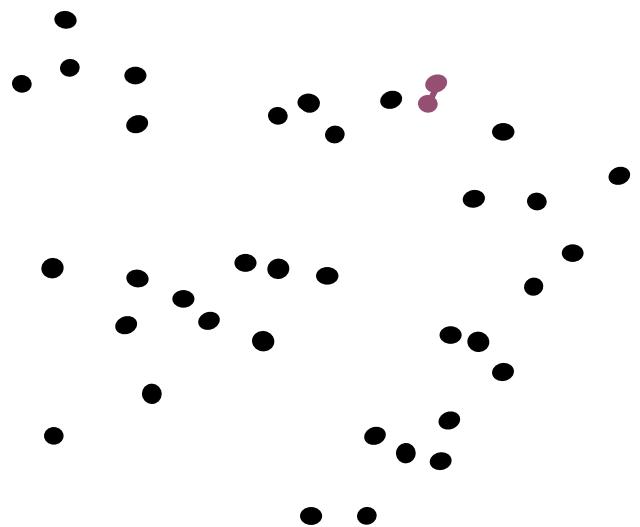
$$d_{\text{avg}}(C_i, C_j) = \frac{1}{n_i n_j} \sum_{p \in C_i} \sum_{q \in C_j} d(p, q)$$

# Example: single linkage, Euclidean distance



1. Say “Every point is its own cluster”

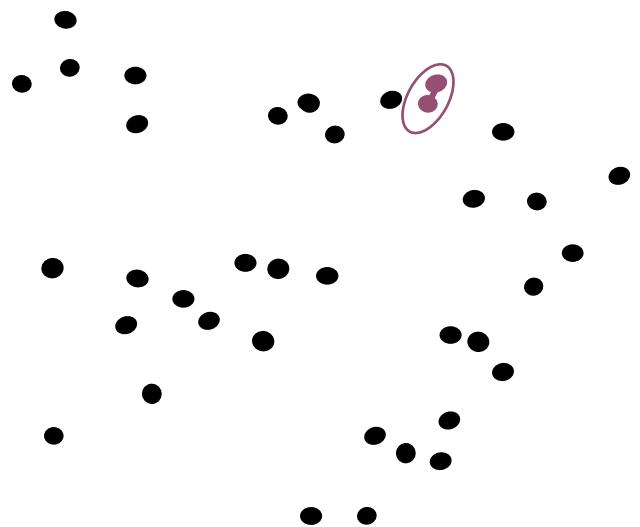
# Example: single linkage, Euclidean distance



1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters



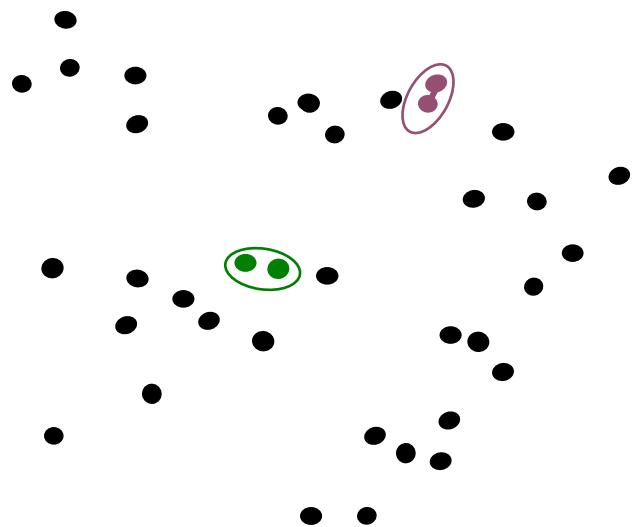
# Example: single linkage, Euclidean distance



1. Say “Every point is its own cluster”
2. Find “most similar” pair of clusters
3. Merge it into a parent cluster



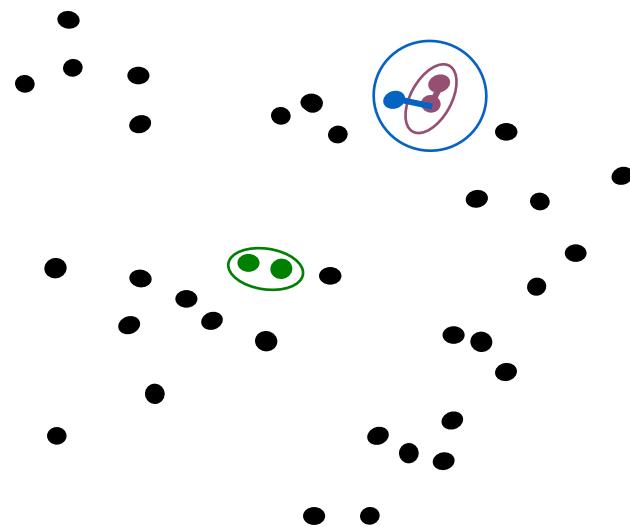
# Example: single linkage, Euclidean distance



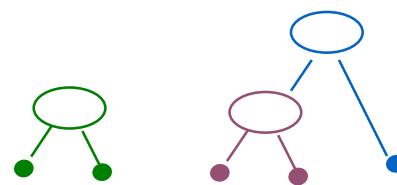
1. Say "Every point is its own cluster"
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3. Merge it into a parent cluster
4. Repeat



# Example: single linkage, Euclidean distance



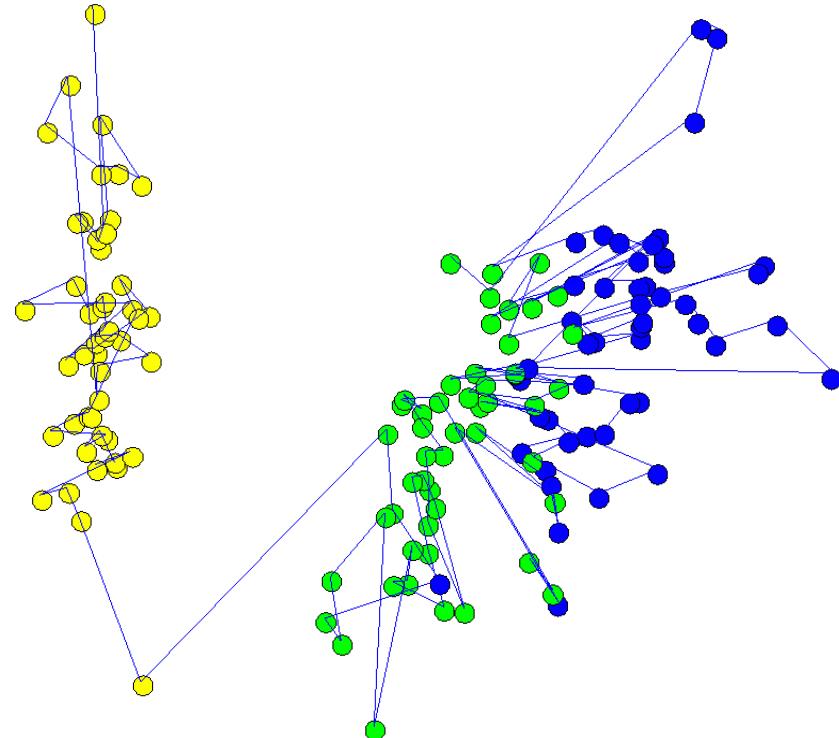
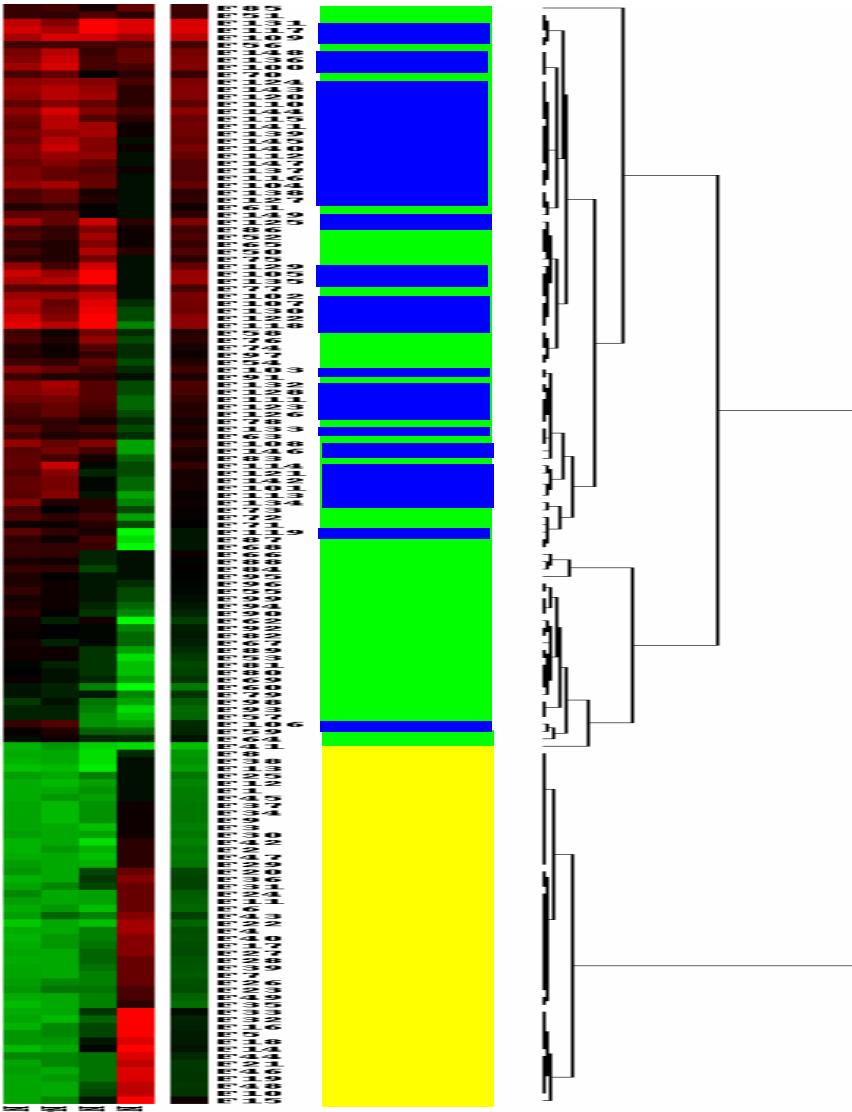
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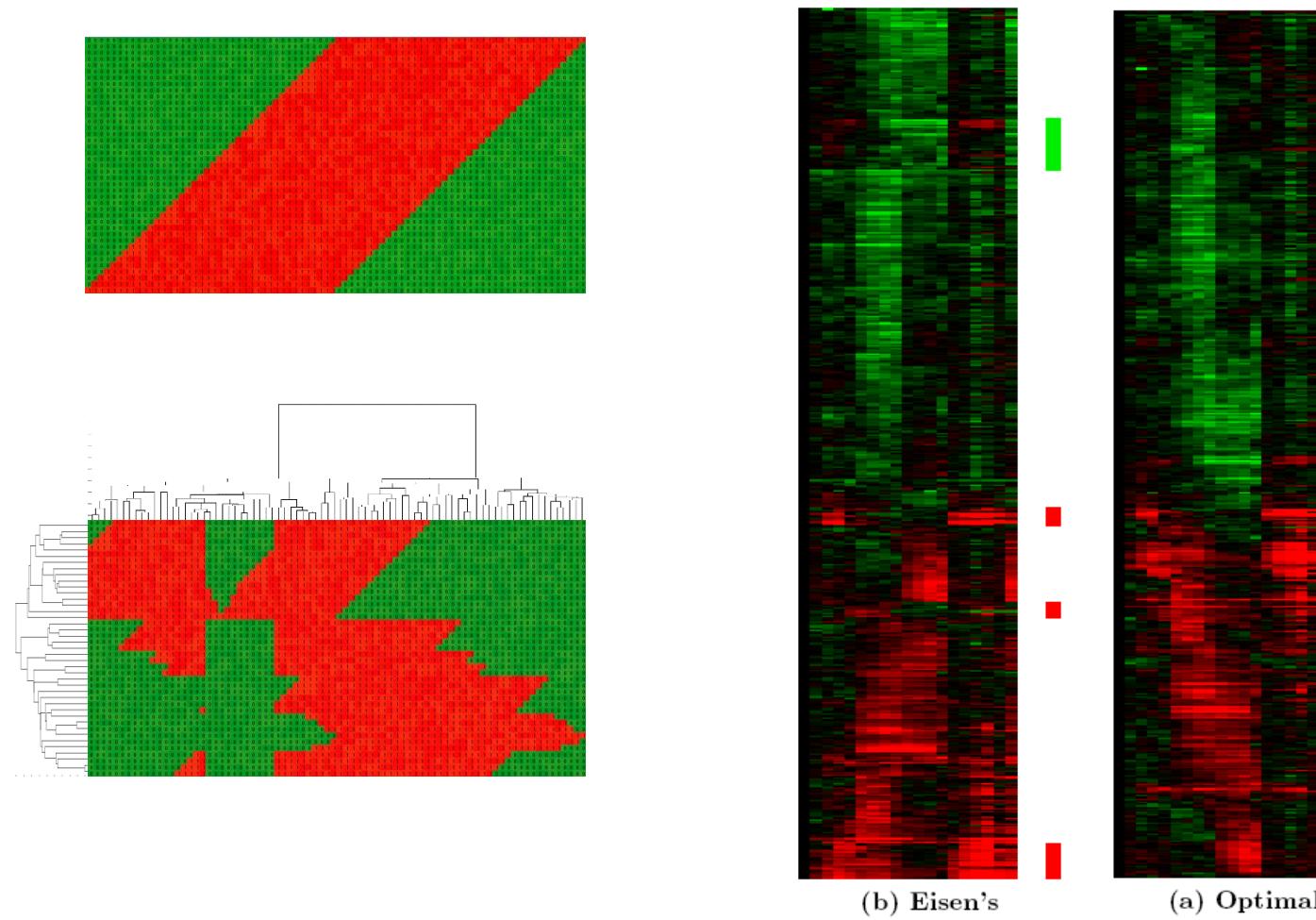
# Pros and cons of hierarchical clustering

- It's nice that you get a hierarchy instead of an amorphous collection of groups
- If you want  $k$  groups, just cut the  $(k-1)$  longest links
- Clusters can have complex shapes
- Can work with any dissimilarity measure
- There's no real statistical or information-theoretic foundation to this
- Do not scale well:  $O(n^2)$  or even  $O(m^2n^2)$
- Uses complete distance matrix – challenge with memory
- Problem with representation of the dendrogram (leaves order)
- Might be unstable

# Problem of leaves ordering is ill-posed



# Hierarchical clustering and dendograms: leaves order



Biedl et al, 2001; Bar-Joseph et al., 2003

# Hierarchical clustering and dendrograms: cluster instability

- Hierarchical clustering results can be very sensitive to a random removal of a small percentage of points

