CS-E4840
Information Visualization
Lecture 10: student presentations
+ recap

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Student presentations

RECAP FROM LAST LECTURE

Dimensionmal reduction

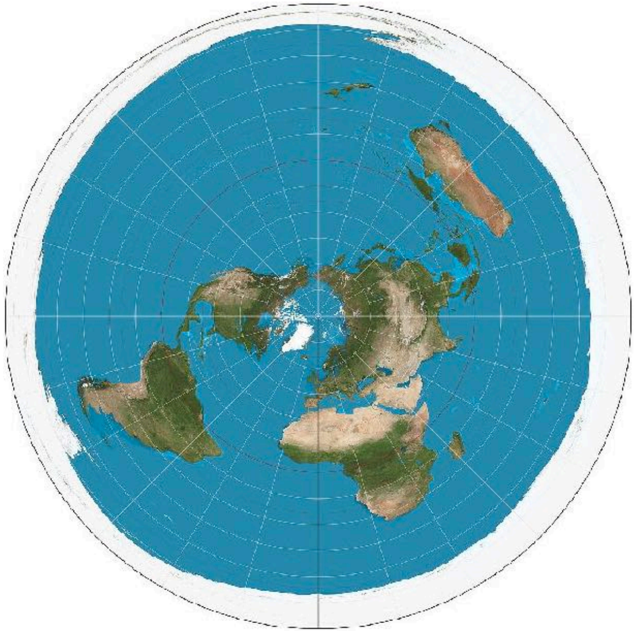
- Multi-Dimensional Scaling (MDS)
- Projection pursuit methods: PCA, ICA
- Graph-based methods: ISOMAP

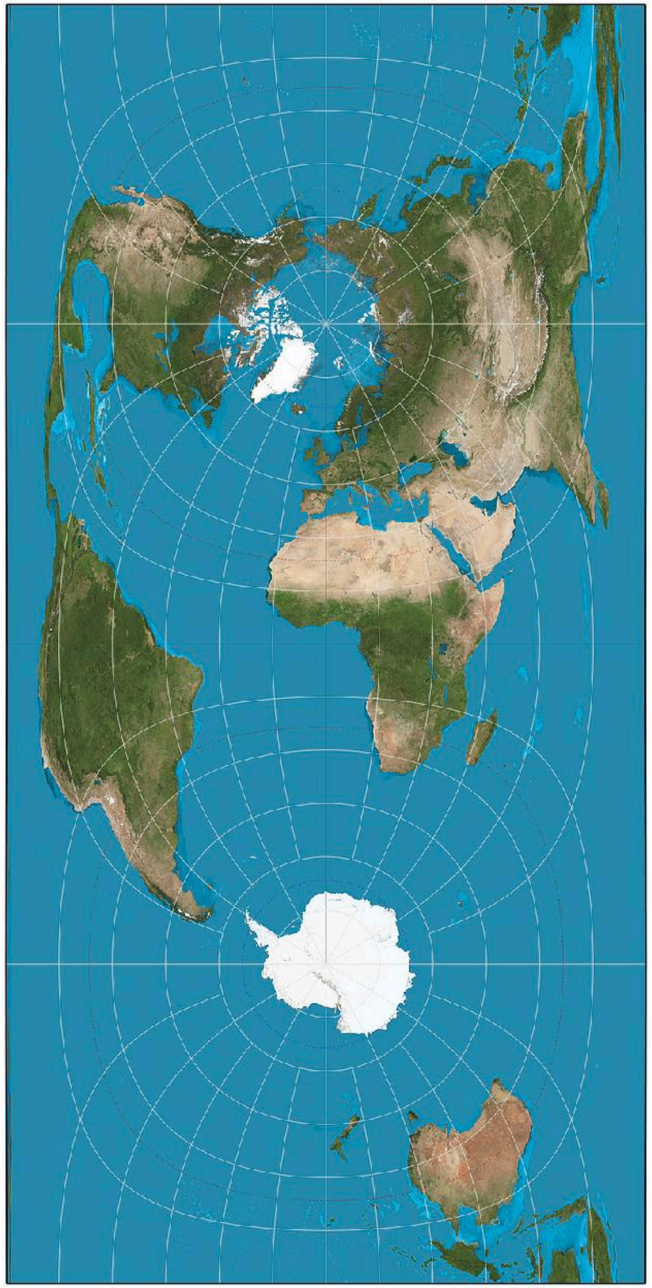
Which properties are important to retain?

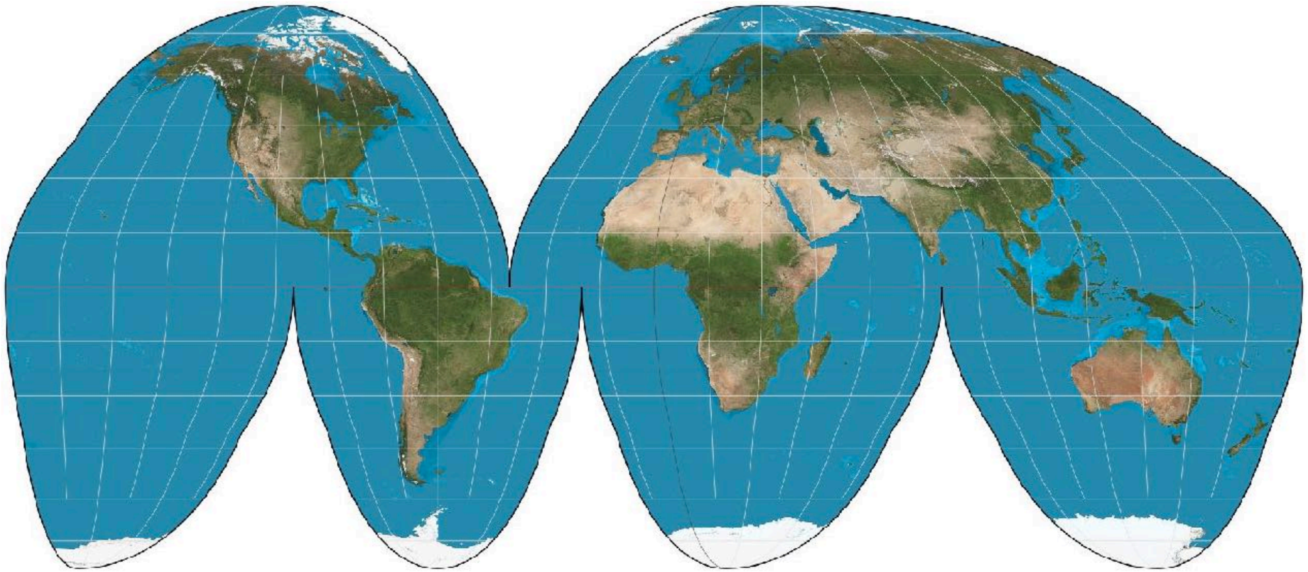
https://en.wikipedia.org/wiki/List_of_map_projections

Select embedding based on:

- long/short distances
- directions
- local shape
- connectivity (topology)
- other…







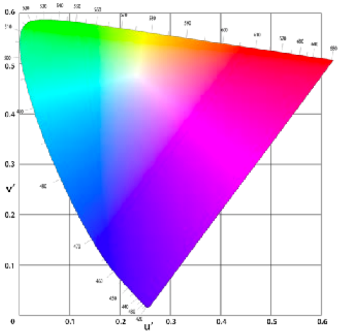
Multidimensional scaling (MDS)

- Formally, an MDS algorithm is given as input the original distances p_{ij} (called ***proximities***) between data points i and j

- MDS algorithm then tries to find a k-dimensional (usually k=2 or k=3) representation X for the points that minimises the error function (called ***stress***, by convention)

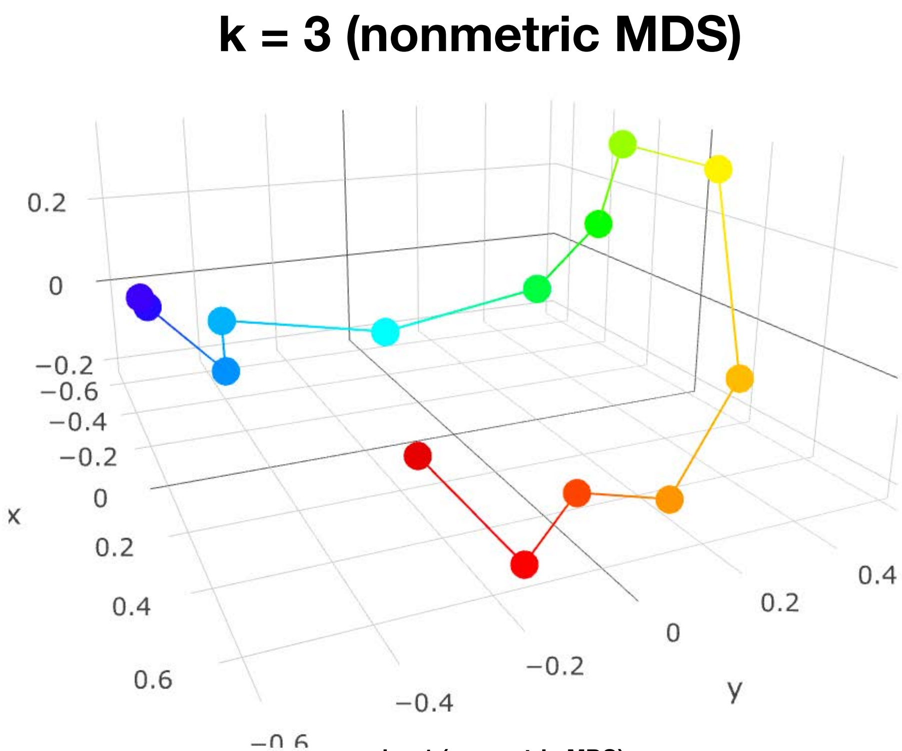
$$\sigma_r = \sum_{i<j} \left(f(p_{ij}) - d_{ij}(X)\right)^2$$

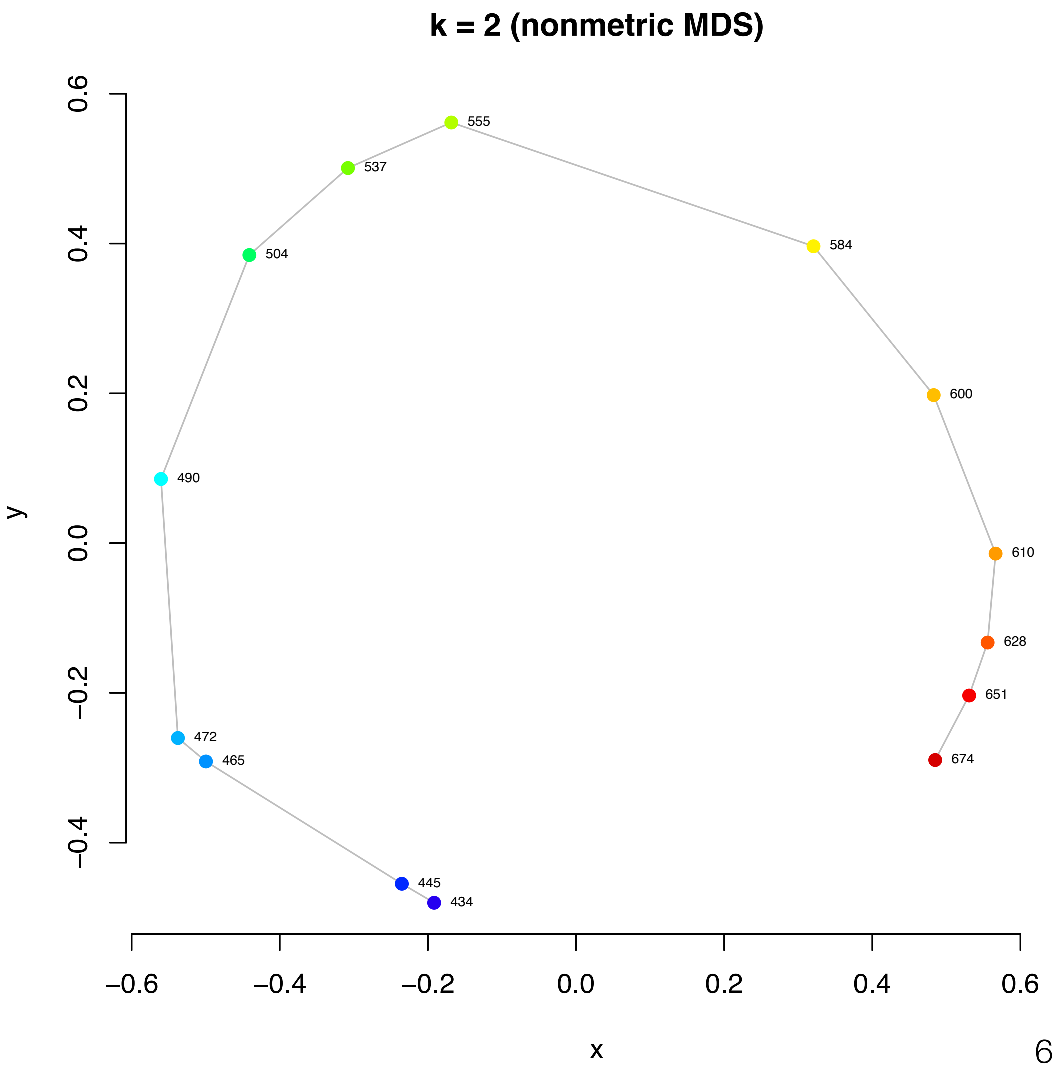
- …where $d_{ij}(X)$ is the Euclidean distance between the data points *i* and *j* in representation X and *f* is a function that defines the MDS model (**metric** vs. **nonmetric**).

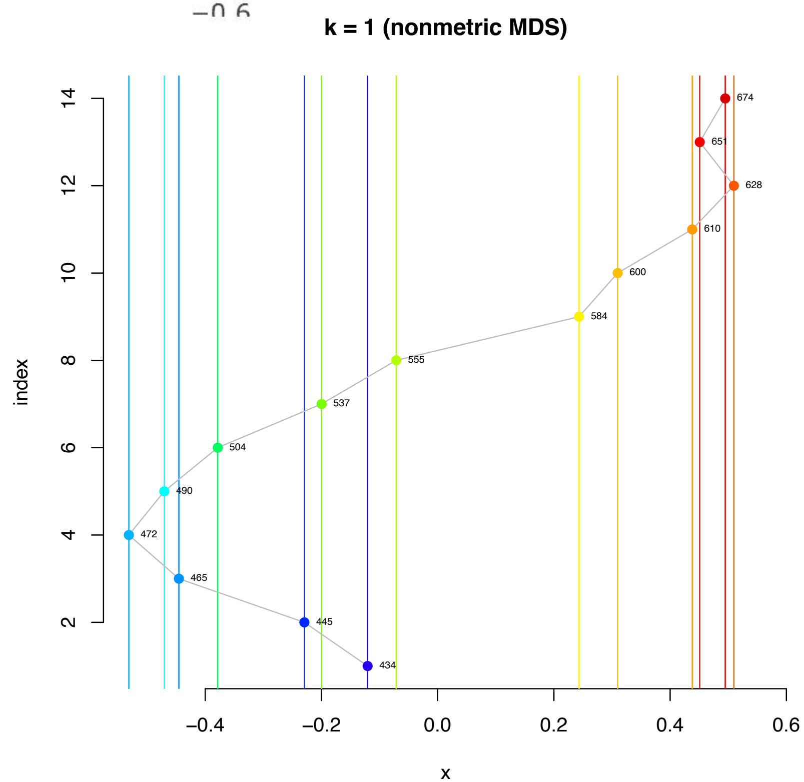


CIELUV

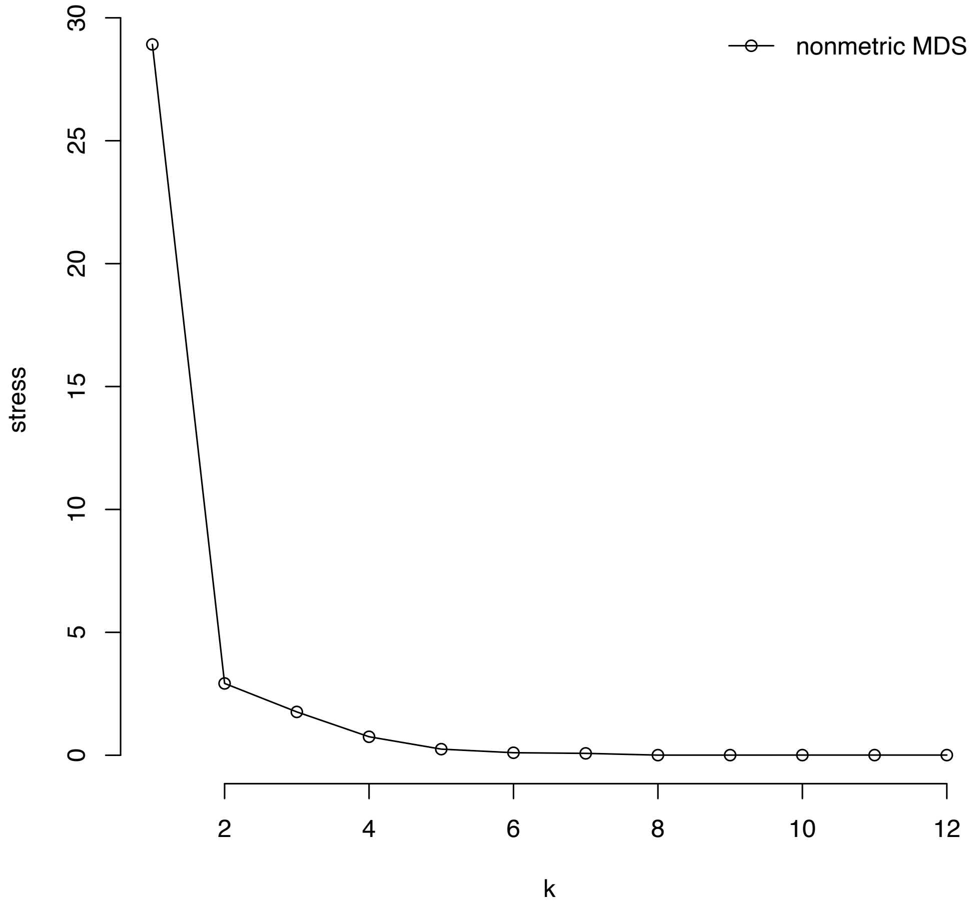
Example: colour

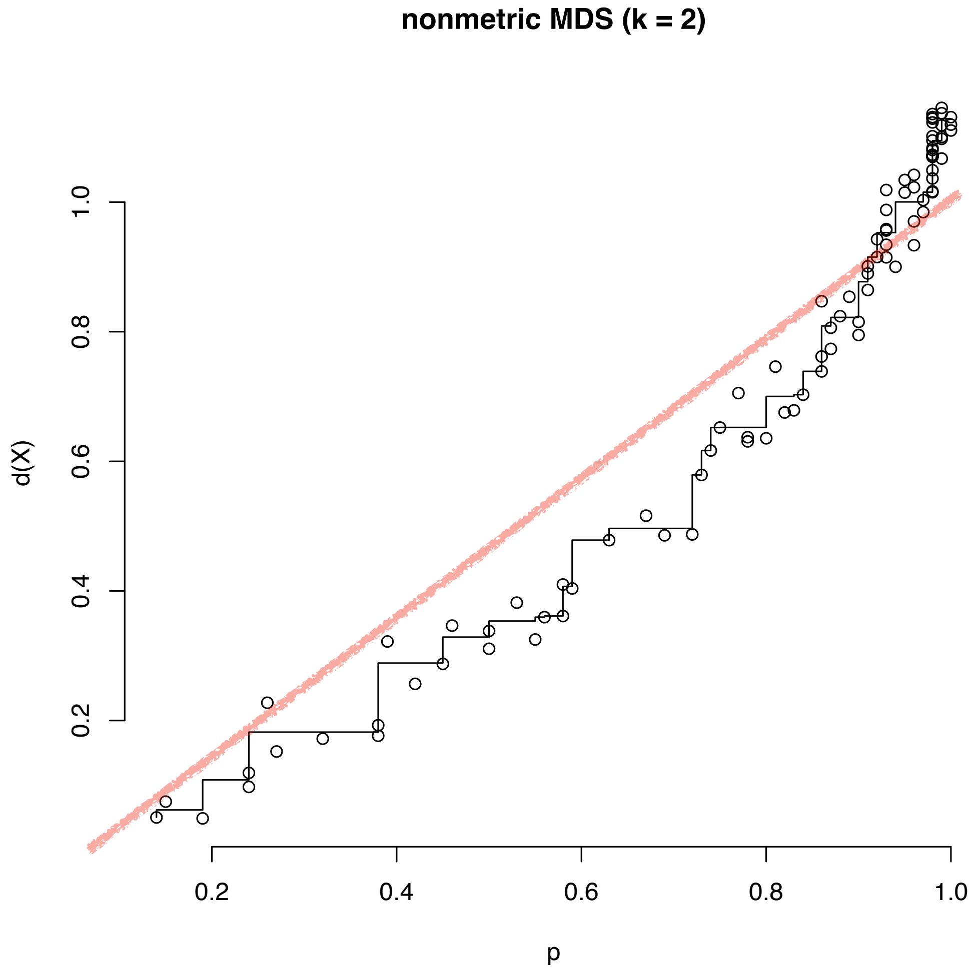






Evaluating the mapping
example: colour





Scree plot gives the stress as a function of k. Here k=1 is too small but k=2 already gives quite a good result.

Shepard plot gives the distances in the embedding as a function of the proximities in the original space.

Evaluating the mapping: Precision and recall

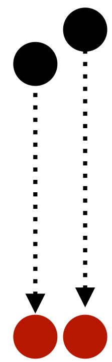
- **Precision:** points nearby in embedding $\Longrightarrow$ also nearby in original space

  proximity in the visualization is truthful

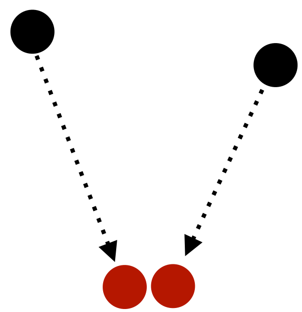
- **Recall:** points nearby in original space $\Longrightarrow$ also nearby in the embedding

  proximities of the original are preserved

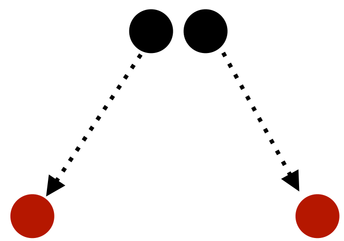
- Projection pursuit methods such as **PCA**:
  - distance in projection is at most the distance in the original space
  - always **good recall,** but possibly **bad precision**



good precision and recall

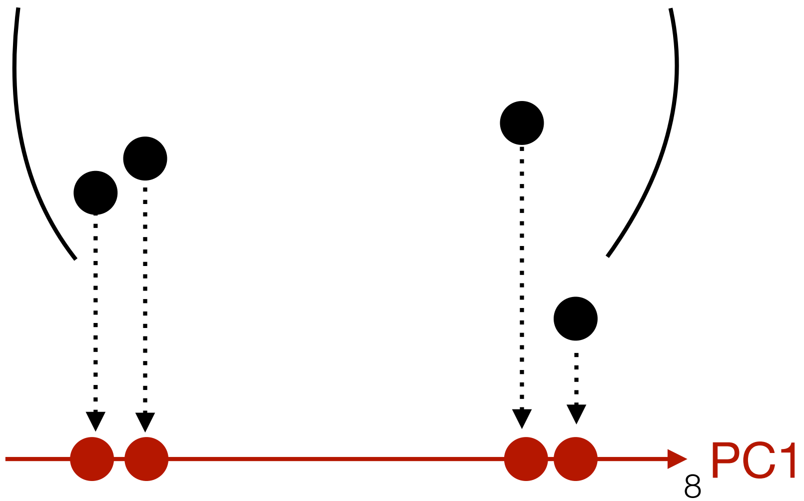


bad precision



bad recall

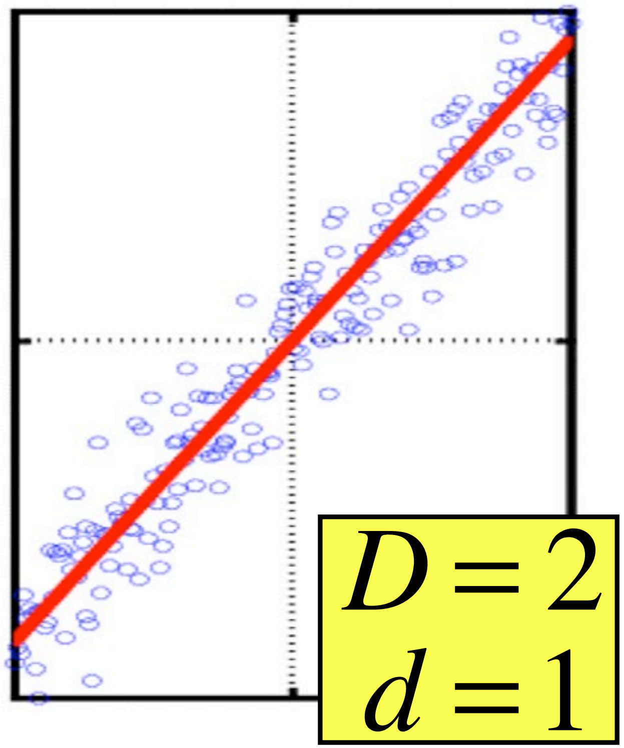
original space

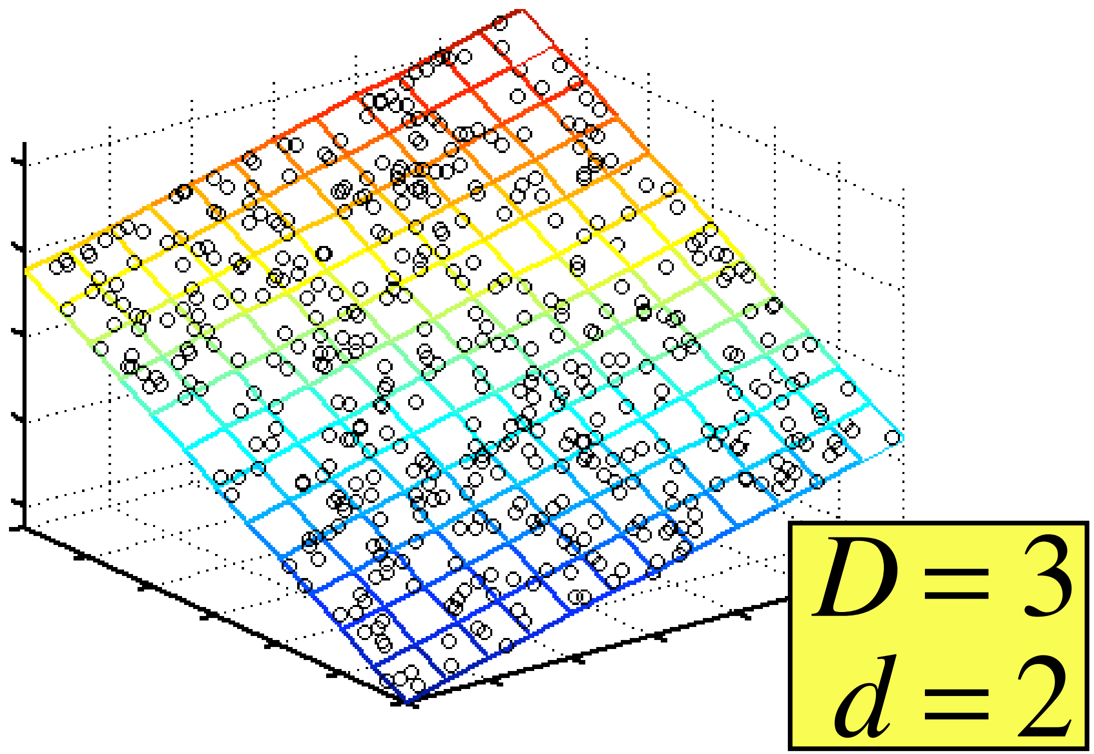


projection

Projection pursuit methods

- MDS (and variants) are based on **distance matrix** between points.
- If data is composed of D-dimensional **vectors** we can try to **find a linear subspace** (dim = d) that maximises some quantity

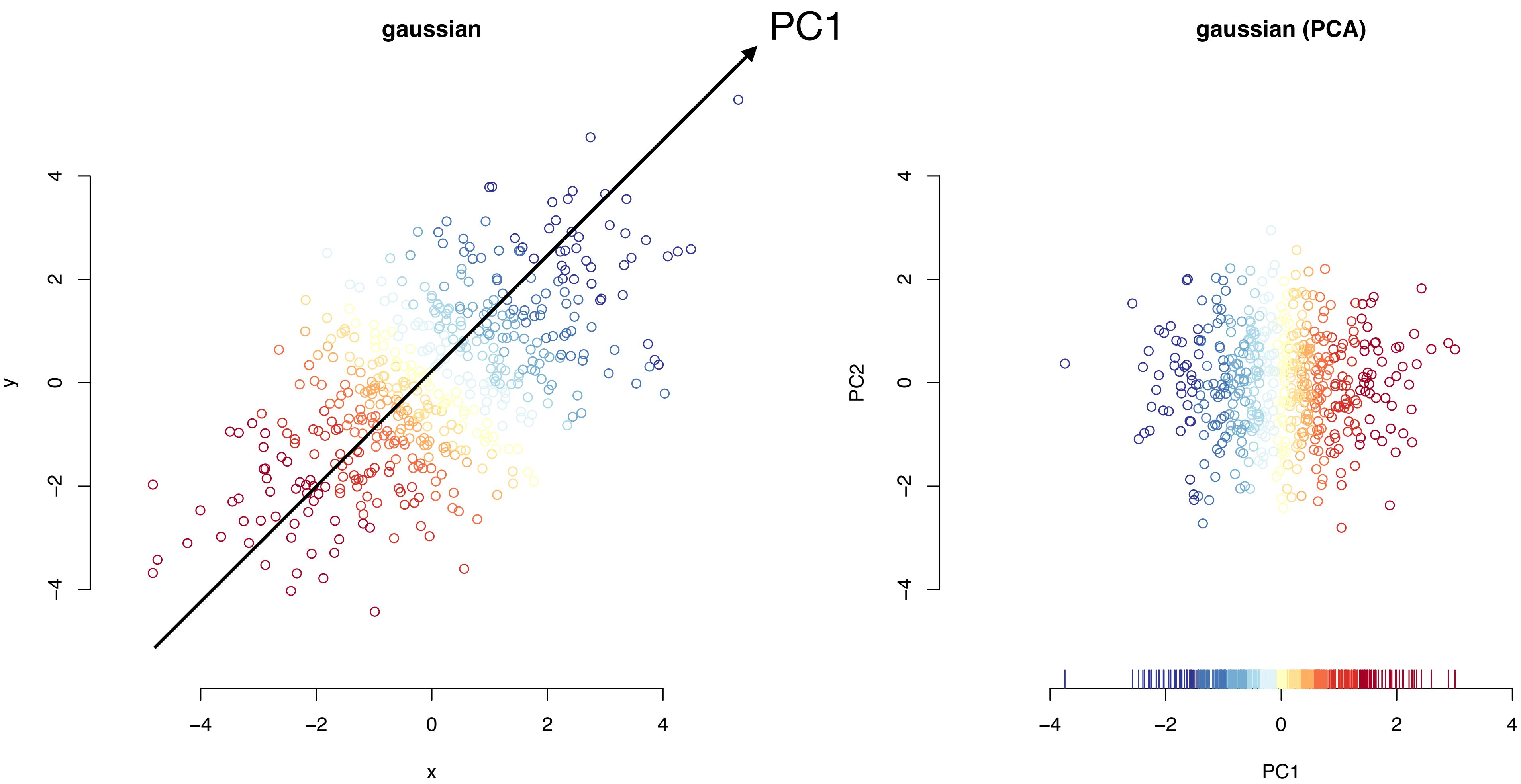




Principal component analysis (PCA)

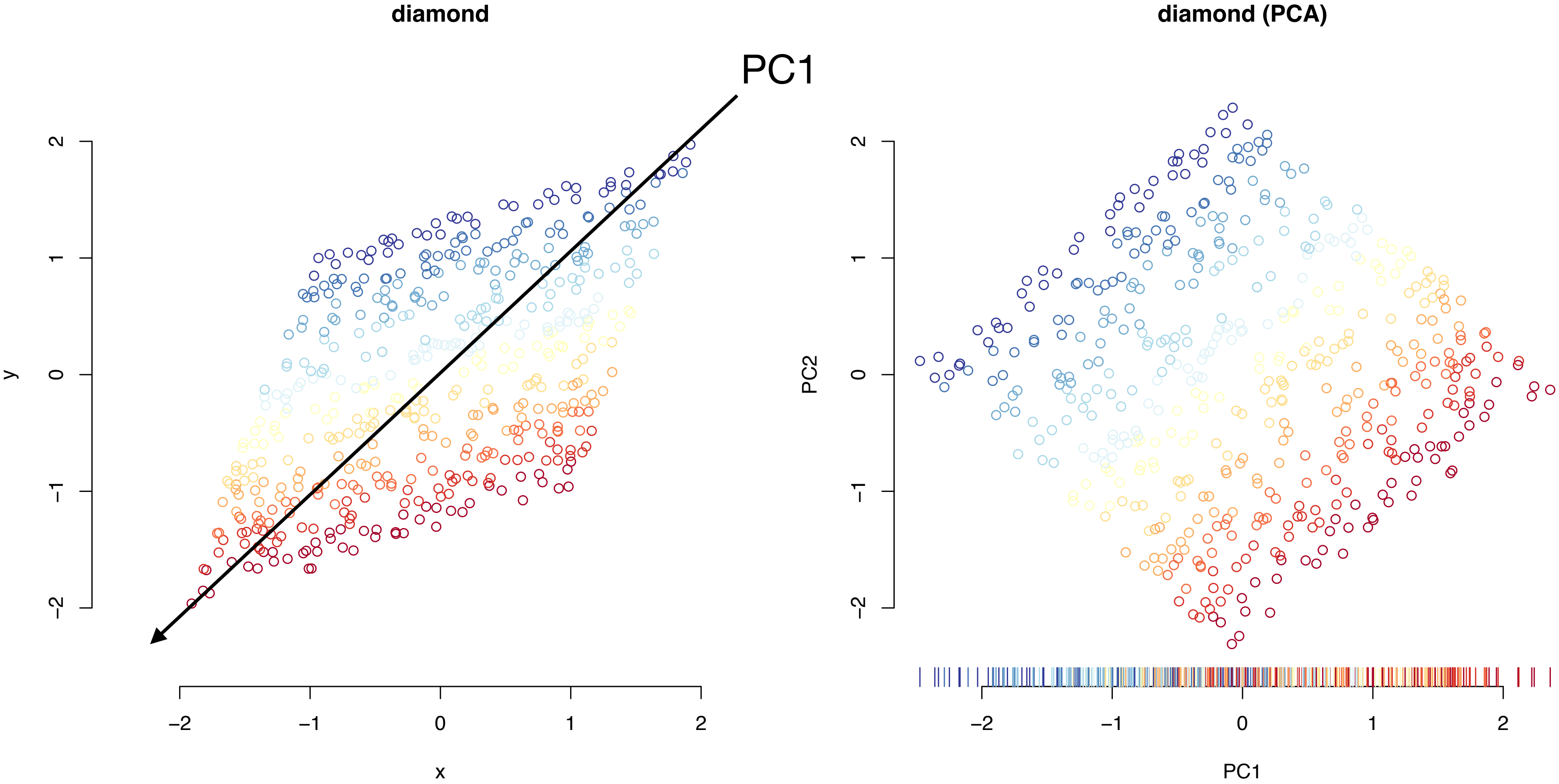
- PCA finds the directions of maximal variance in the data
- Simple and stable method ➡ PCA is usually the first method to try (if it doesn't work, then try something more fancy)
- If you find PCA difficult, this may be helpful :-) https://stats.stackexchange.com/questions/2691/making-sense-of-principal-component-analysis-eigenvectors-eigenvalues

Gaussian data



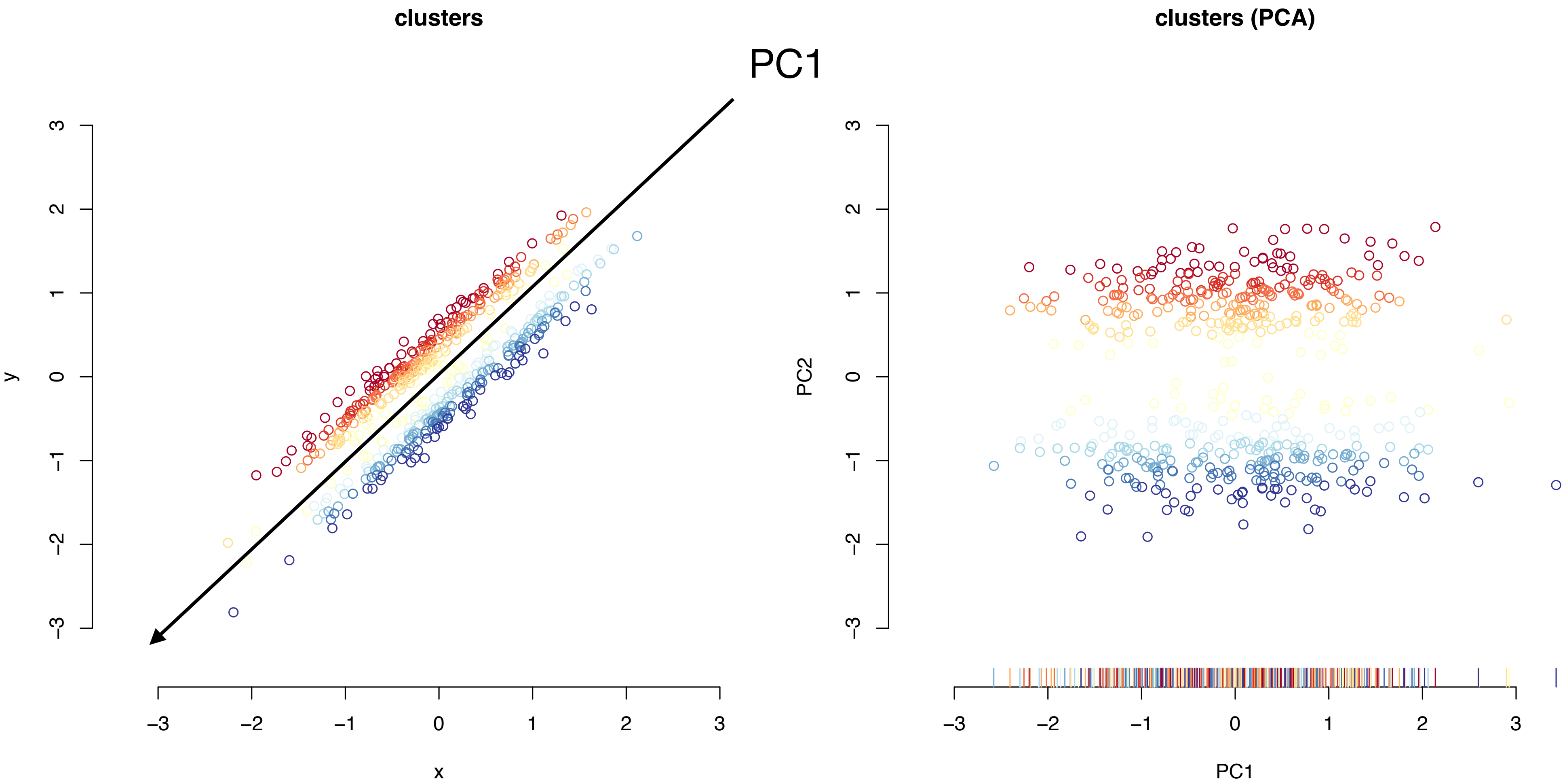
PC1 finds the direction of largest variance.

Diamond shaped data



PC1 misses the square structure.

Two clusters

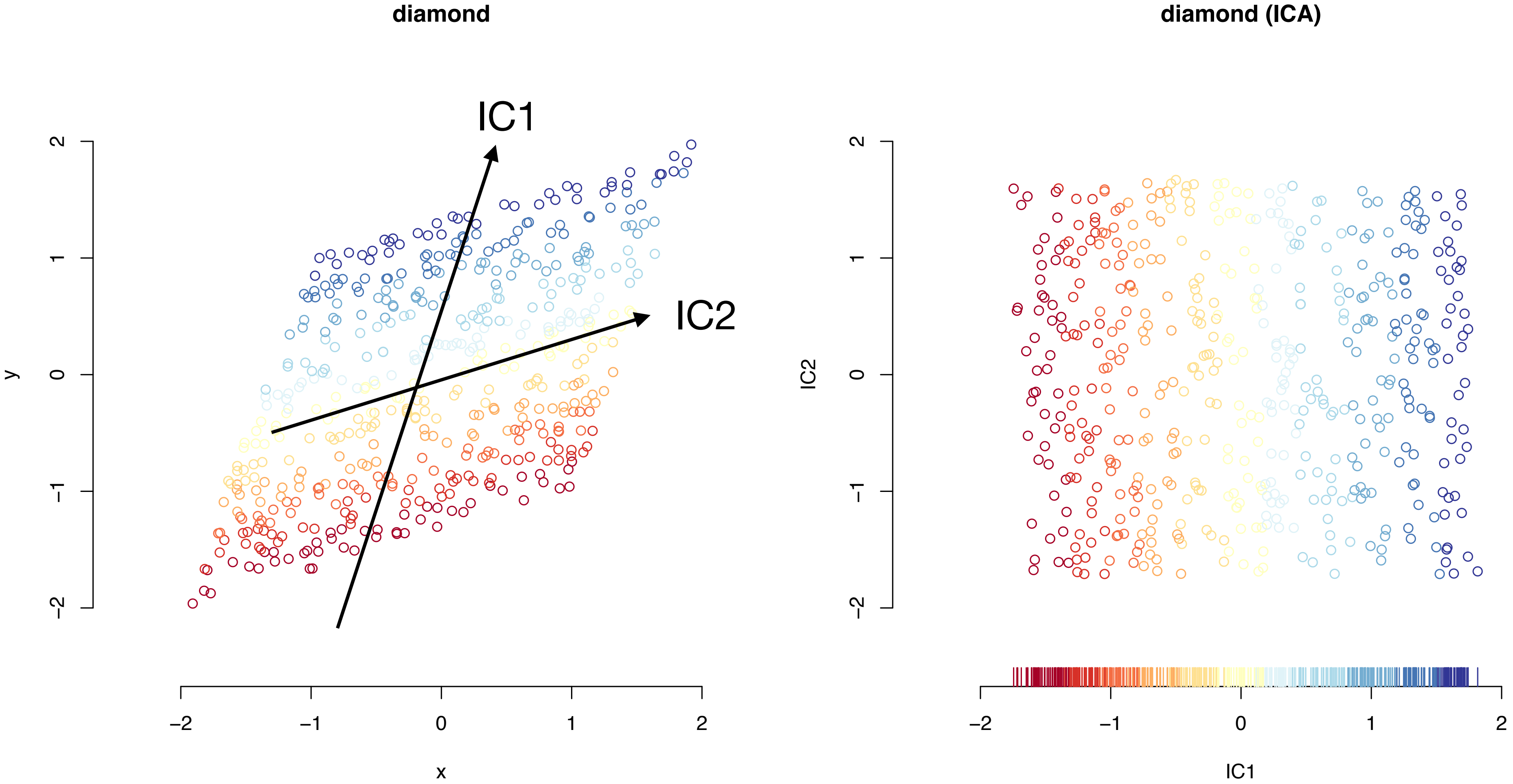


PC1 misses the cluster structure.

Independent component analysis (ICA)

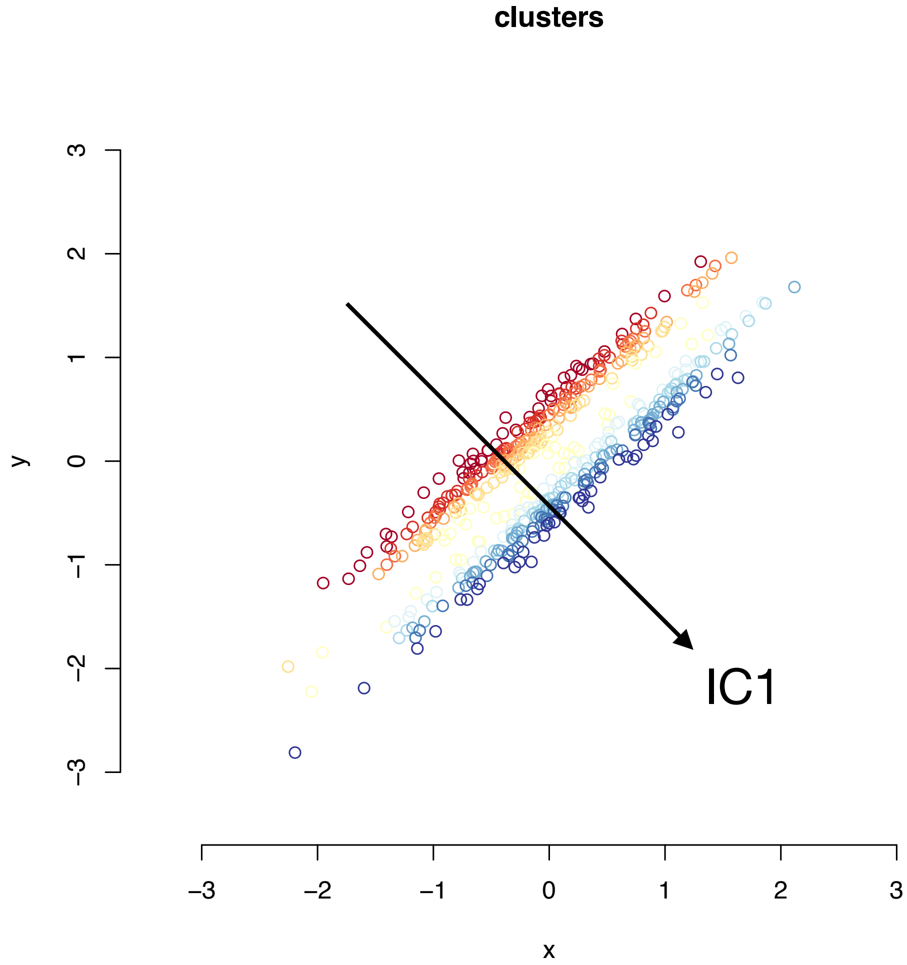
- ICA finds directions of maximal non-Gaussianity
- Often this means data consists of subsets originating from separate independent processes (thus named ICA)
- Directions are not necessarily orthogonal.

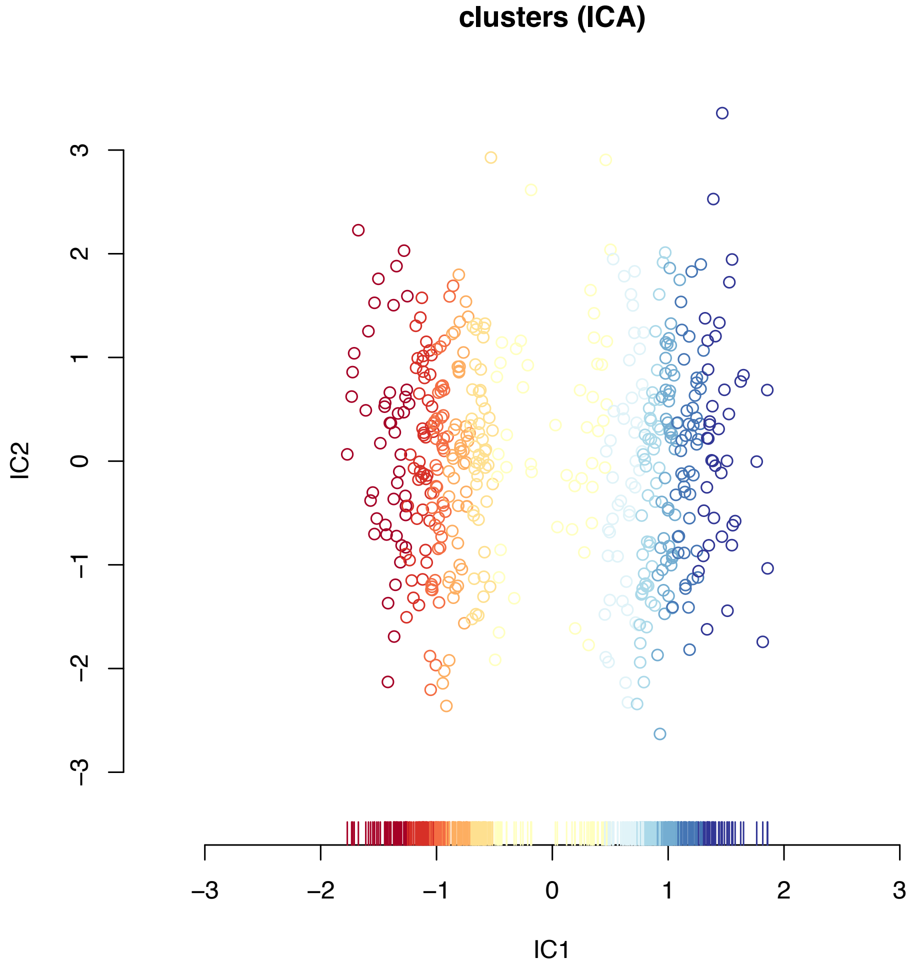
Diamond shaped data



IC1 finds the box in the diamond.

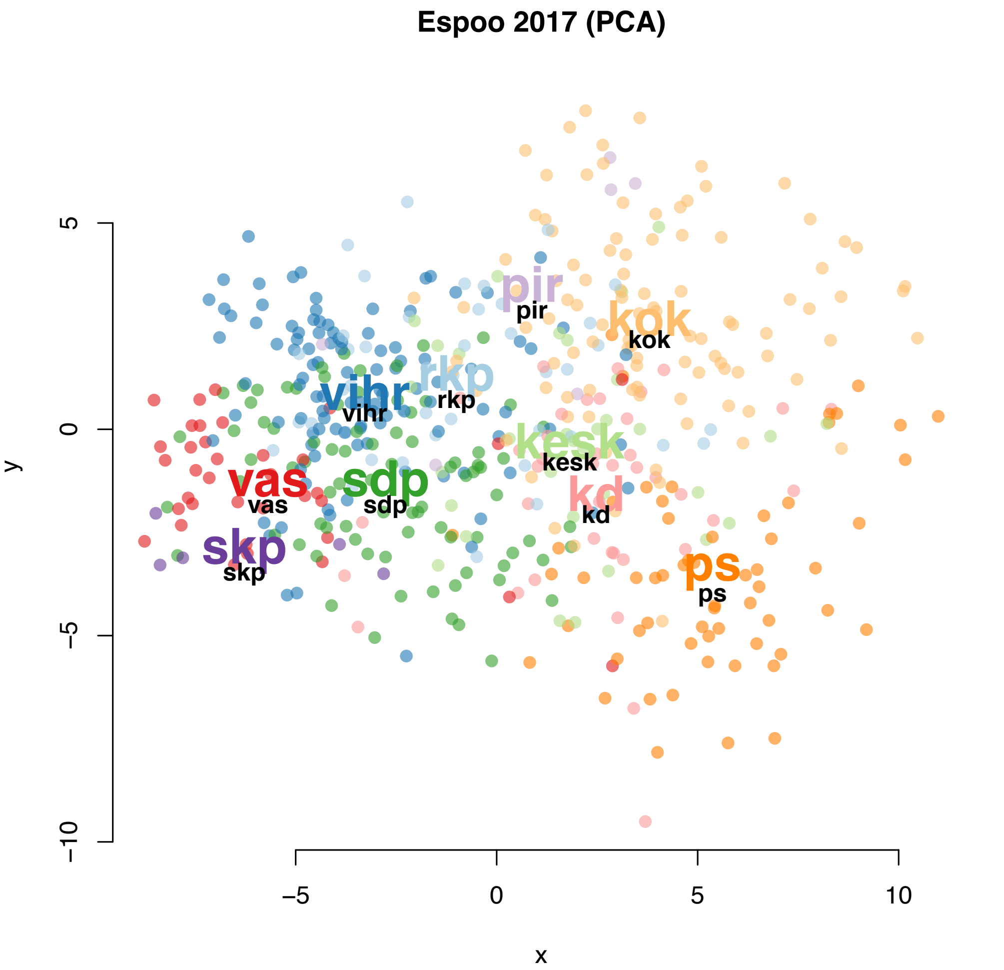
Two clusters

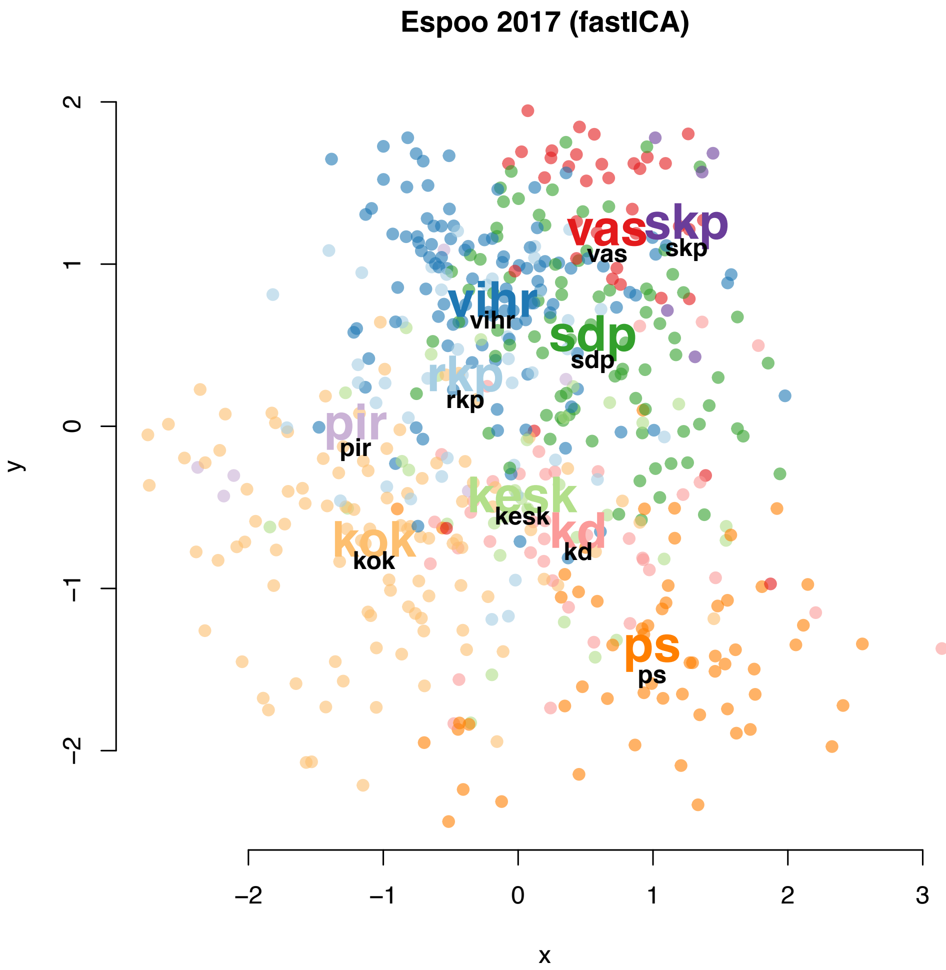




IC1 finds the two clusters.

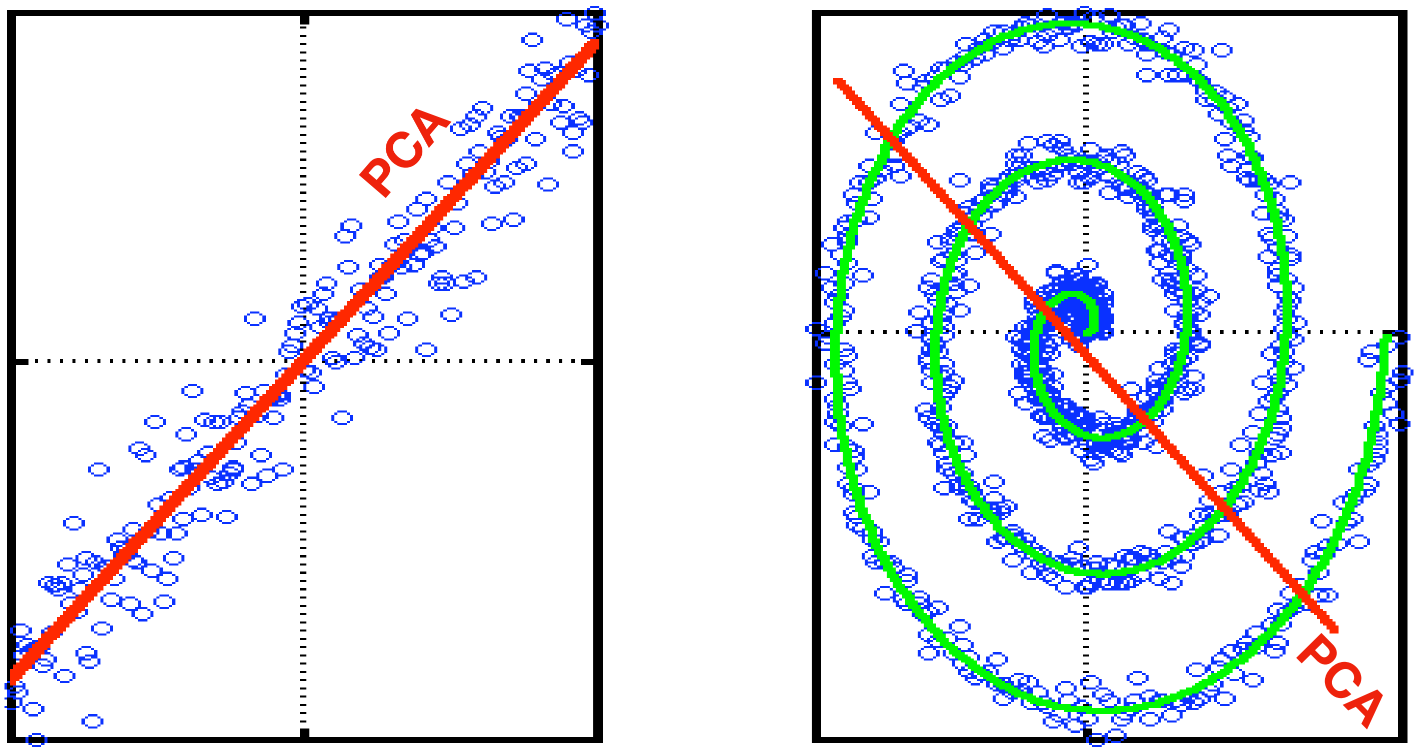
Municipal elections in Espoo in 2017





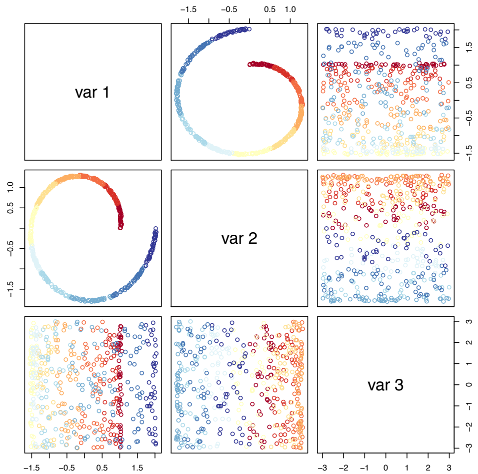
Visualising manifolds

manifold = low-dimensional set (curve, surface, …) in higher-dimensional space



- In an k-manifold each local neighborhoods of points approximately aligns with a k-D linear subspace (hyperplane)

➜ Thus these methods look at local neighborhoods
 (work on a neighborhood graph)

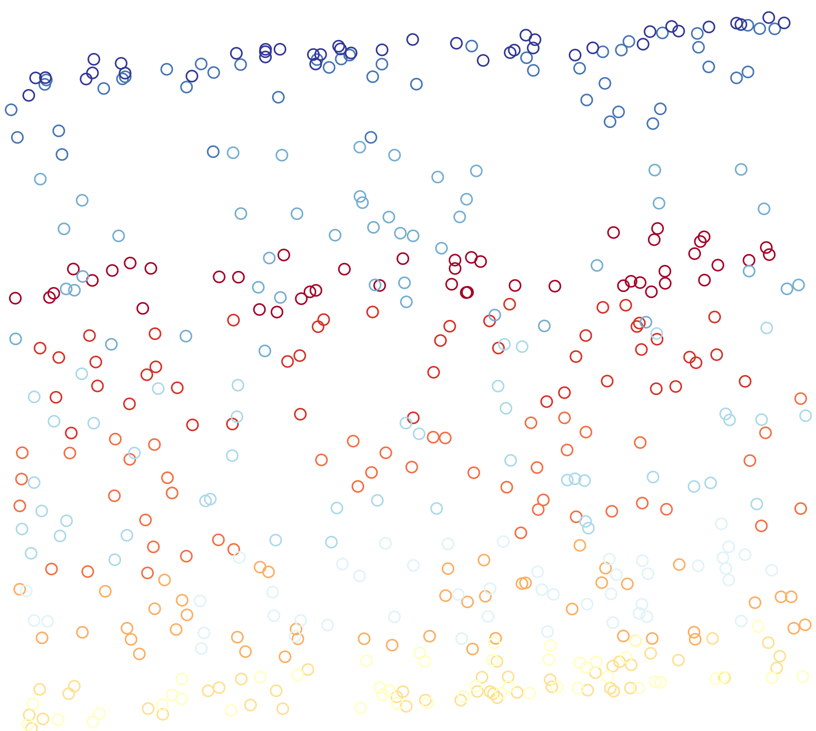


Swiss roll

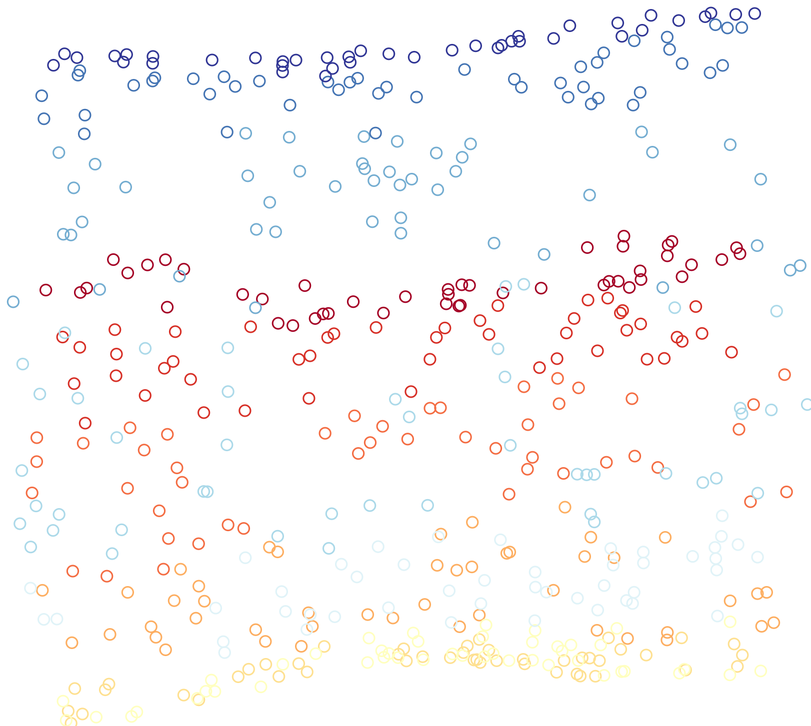
(a curved 2D-manifold in 3D space)

projection methods make a folded mapping!

PCA



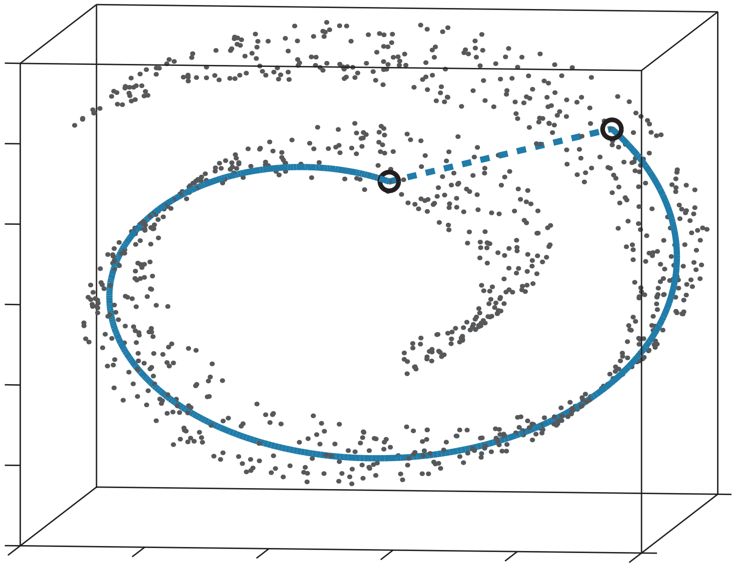
nonmetric MDS

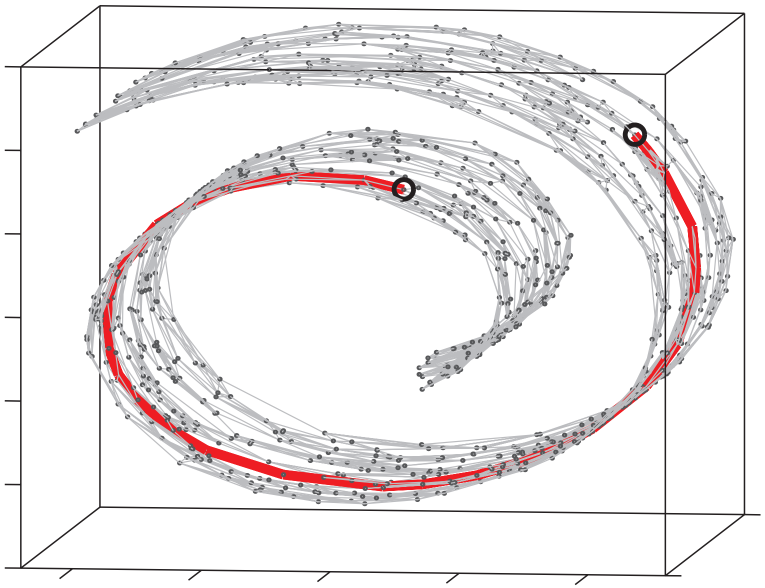


Isometric mapping of data manifolds (ISOMAP)

- Tenenbaum et al. 2000, https://doi.org/10.1126/science.290.5500.2319 See http://web.mit.edu/cocosci/isomap/datasets.html (fig)
- ISOMAP is an example of graph-based methods.
- ISOMAP is a variant of MDS. The difference to MDS is in how the distances (or proximities) are defined.
- ISOMAP first finds **k nearest neighbours** for each data point and constructs a k-nearest-neighbours graph. The distance between two data points (that are not nearest neighbours) is defined as the topological a.k.a. **graph-theoretical distance** (shortest path, i.e. minimum number of links) between the points.
- The resulting distances are fed to the standard linear (metric, because triangle inequality is satisfied) MDS, which finds the actual embedding.

Original data. The graph-distance between two items is shown by solid line, a shortcut is shown by the dotted line.





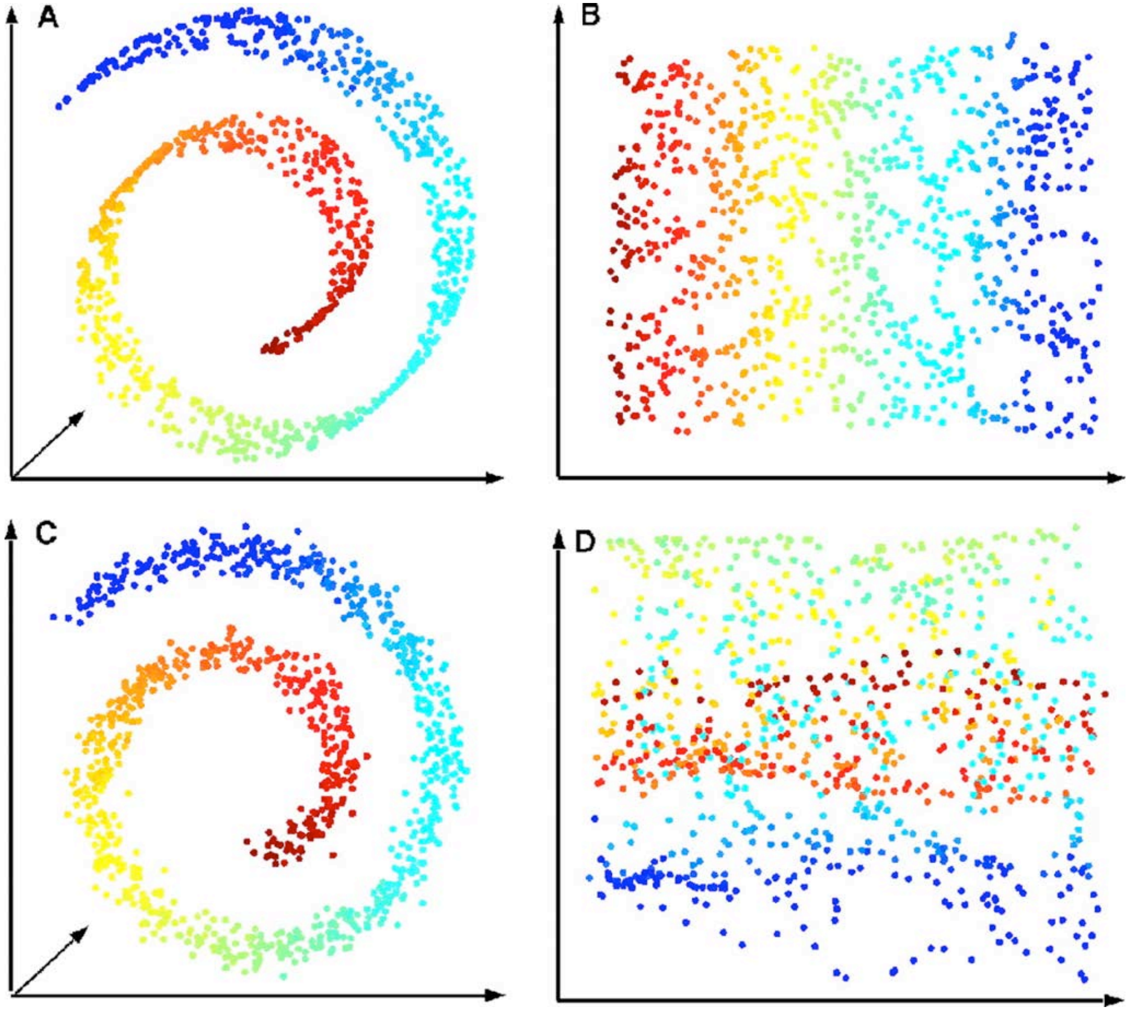
k-nearest neighbours graph used to find the graph-theoretical distances.

Isometric mapping of data manifolds (ISOMAP)

- Assumptions:
  - graph is connected
  - neighbourhood on graph reflects neighbourhoods on manifolds (no "shortcuts")

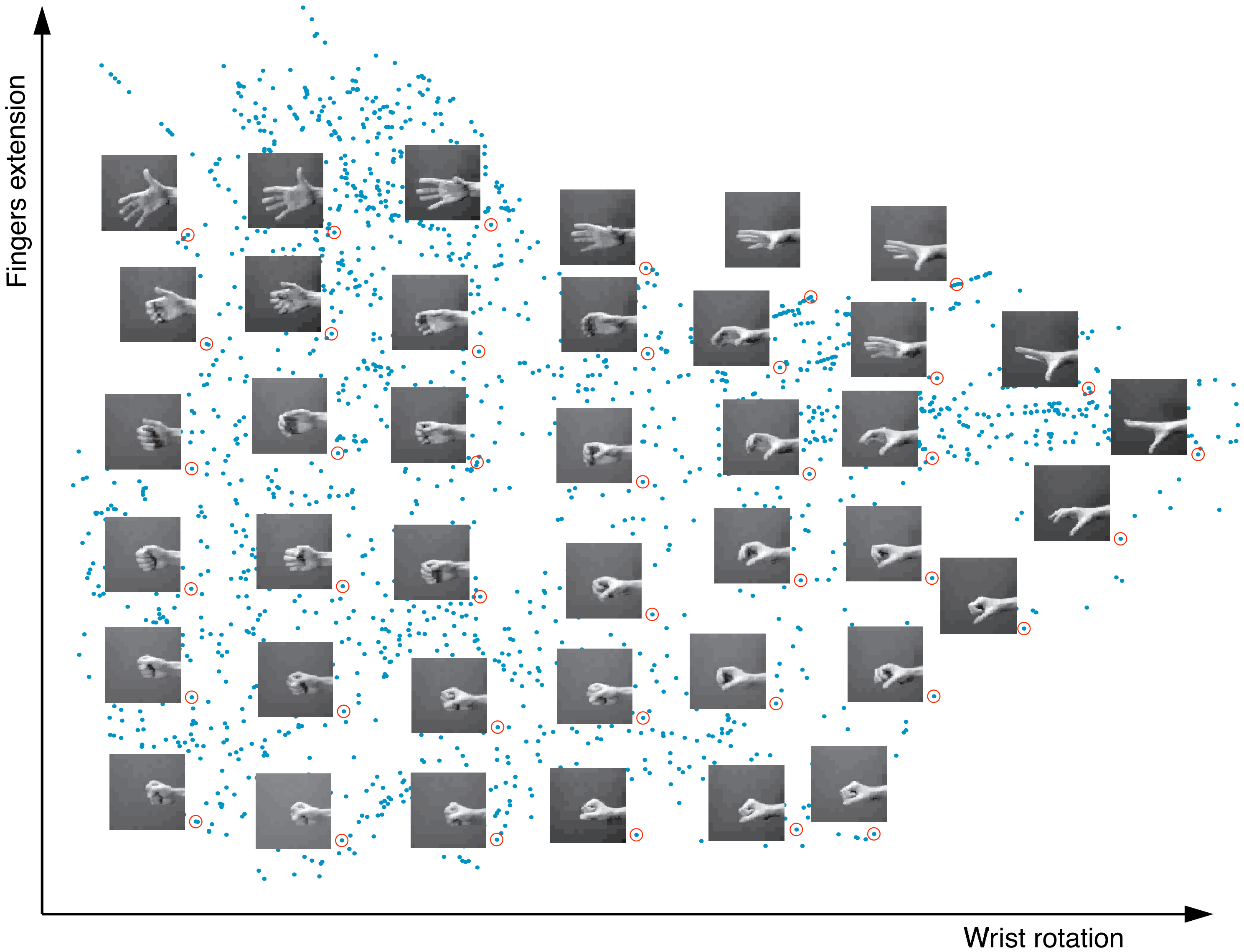
- Weakness (Balasubramian et al.2002, https://doi.org/10.1126/science.295.5552.7a, fig):
  - sensitive to shortcuts (making the algorithm topologically unstable, see the figure right)
- Time complexity ~$O(N^2)$

- Extension: landmark ISOMAP
  - identify subsets of inputs as landmarks, makes the algorithm faster



(A) The "Swiss roll" data used by Tenenbaum et al. (1) to illustrate their algorithm (n = 1000). (B) The two-dimensional (2D) representation computed by the ε−Isomap variant of the Isomap algorithm, with ε = 5. Nearby points in the 2D embedding are also nearby points in the 3D manifold, as desired. (C) Data shown in A, with zero-mean normally distributed noise added to the coordinates of each point, where the standard deviation of the noise was chosen to be 2% of smallest dimension of the bounding box enclosing the data. (D) The Isomap (ε = 5) solution for the noisy data. There are gross "folds" in the embedding, and neither the metric nor the topological structure of the solution in (B) is preserved.

Application case of ISOMAP



ISOMAP (k=6) applied to 2,000 images of a hand in different configurations. The images were generated by making a series of opening and closing movements of the hand at different wrist orientations, designed to give rise to a two-dimensional manifold. The images were treated as 4,096-dimensional (= 64x64 pixels) vectors, with input-space distances defined in the Euclidean metric.

Locally linear embedding (LLE)

- LLE tries to maintain the relationships of nearby points
- Roweis et al. 2000, https://doi.org/10.1126/science.290.5500.2323

- Recipe:
  1. find the set *N(i)*, *k* closest data points to *i*th data point x_i
  2. try to express x_i as a linear combination of its neighbours: find weights minimising

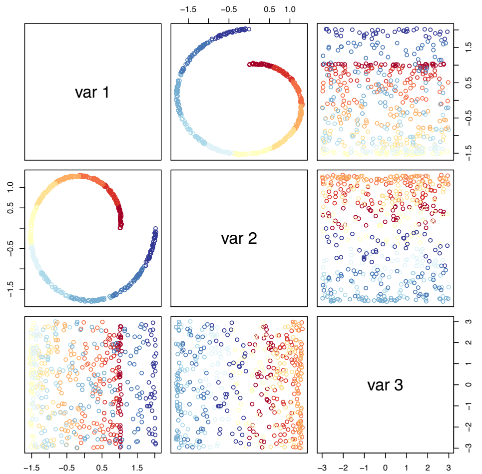
in original space

$$\sum_i \left(x_i - \sum_{j \in N(i)} w_{ij} x_j \right)^2 \quad \text{s.t.} \quad \sum_{j \in N(i)} w_{ij} = 1$$

  3. fix the weights, and find points in plane (y_i are the coordinates in embedding) minimising

in target space

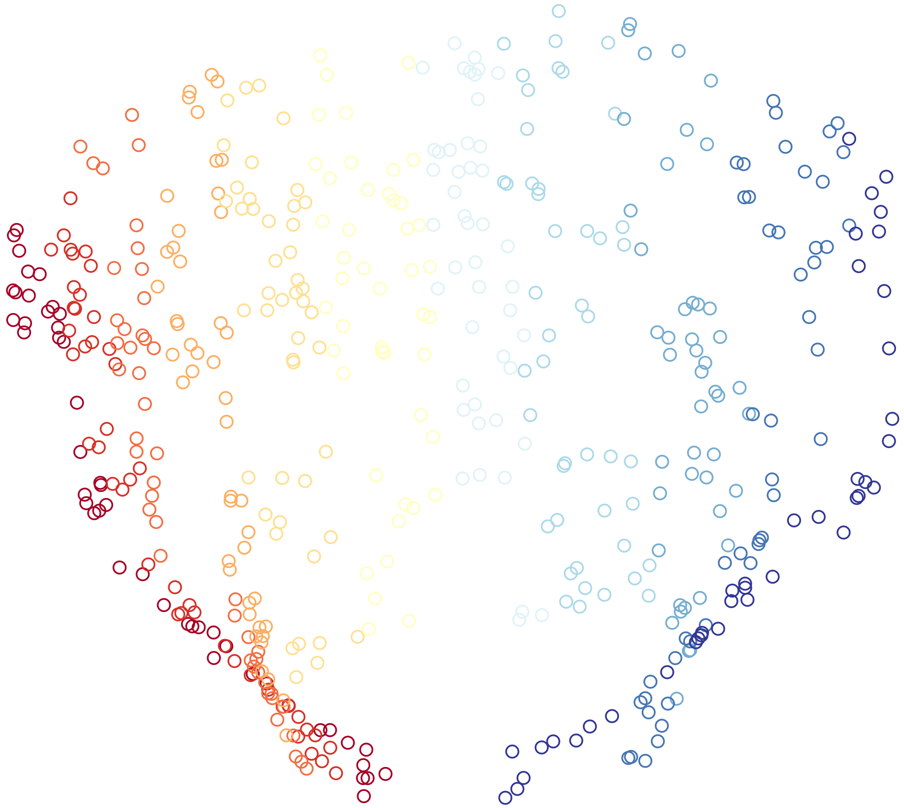
$$\sum_i \left(y_i - \sum_{j \in N(i)} w_{ij} y_j \right)^2$$



Swiss roll

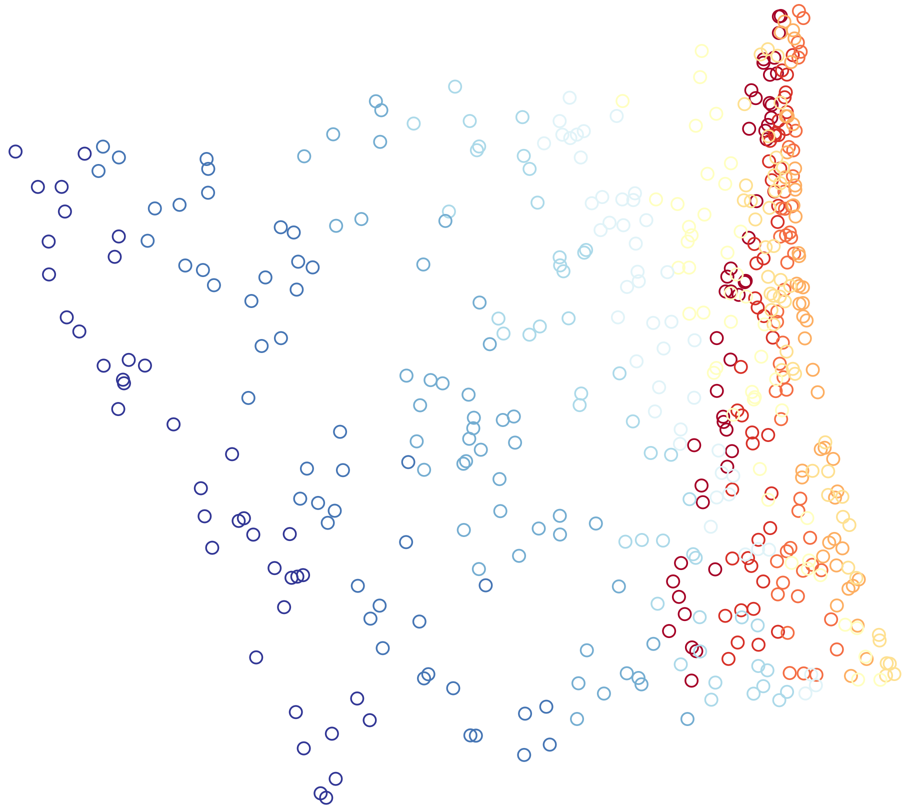
ISOMAP

topological distances

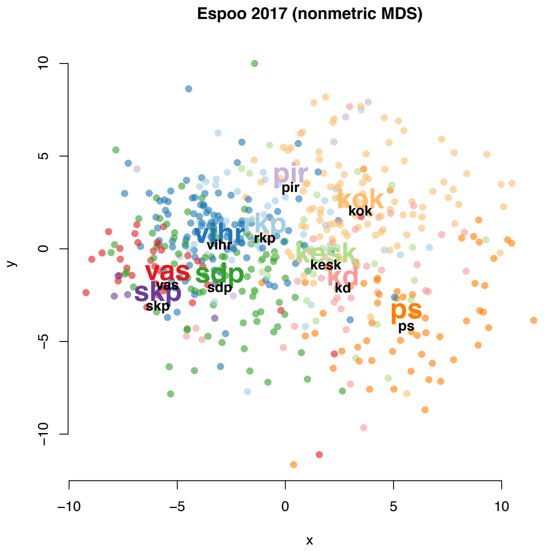


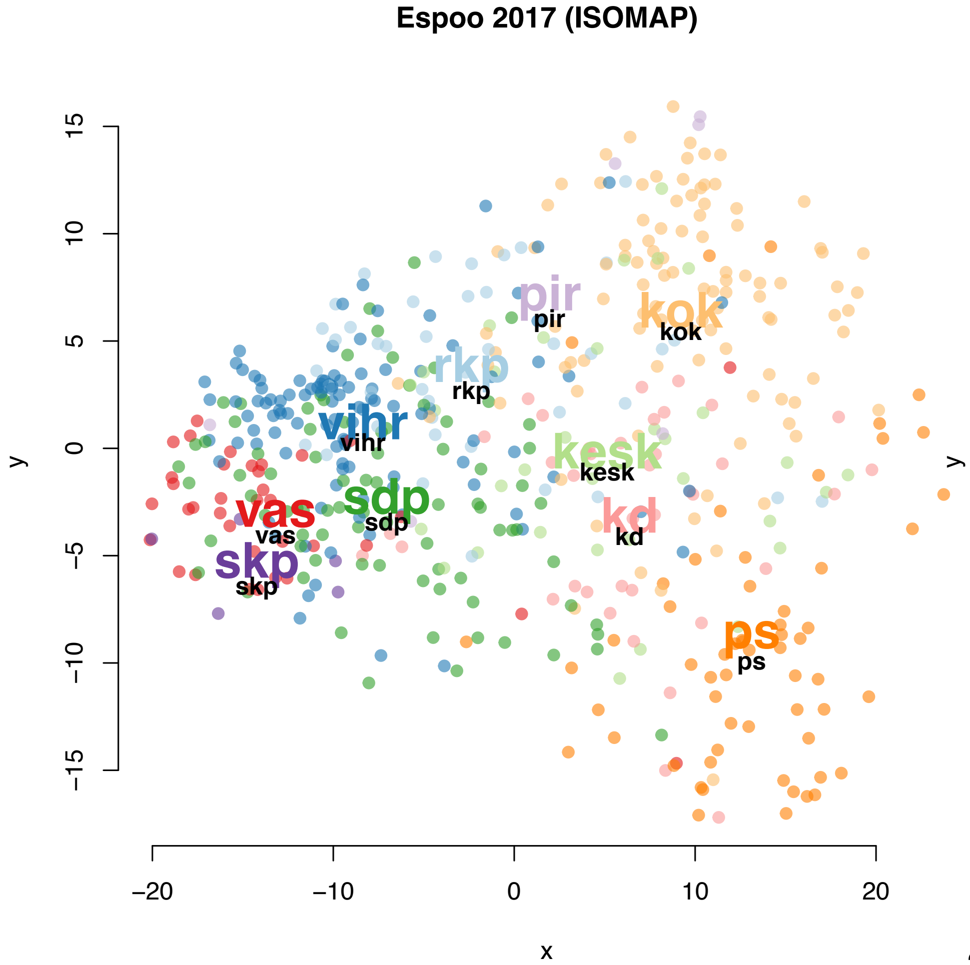
LLE

local metric distances



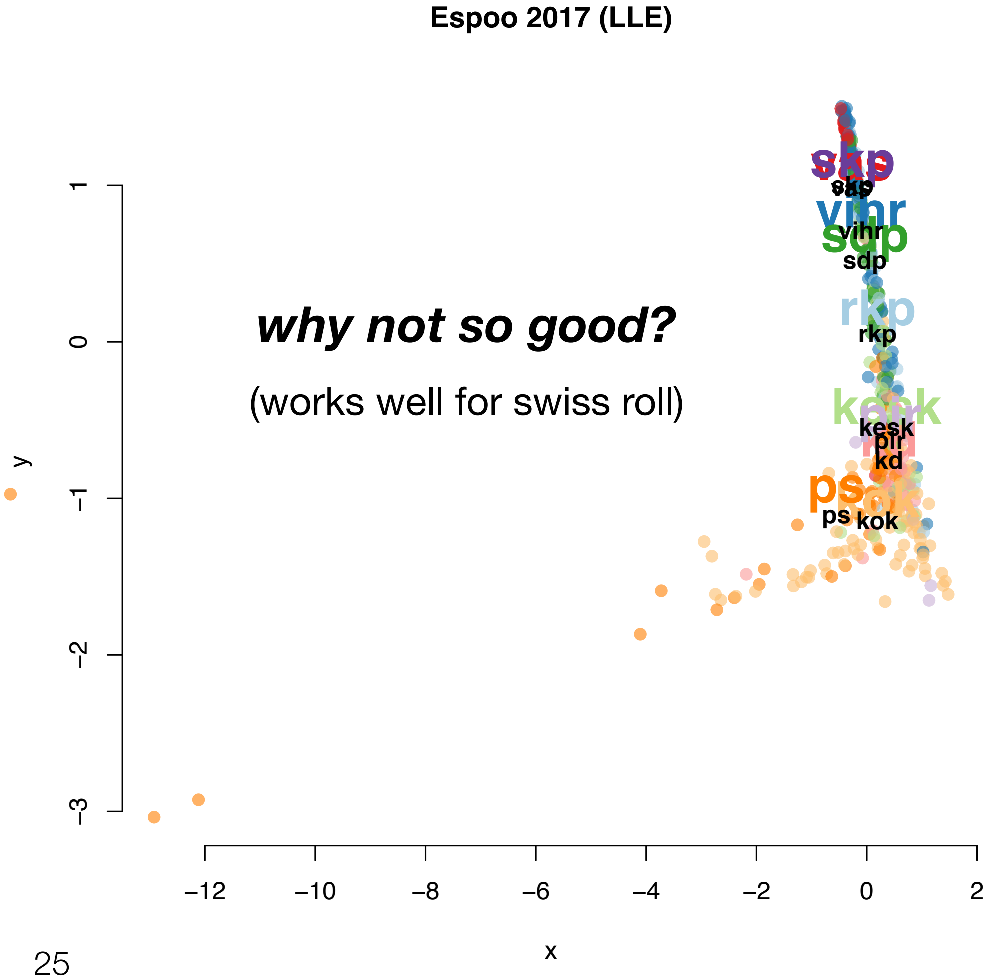
Municipal elections in Espoo in 2017





why not so good?

(works well for swiss roll)



Laplacian eigenmap

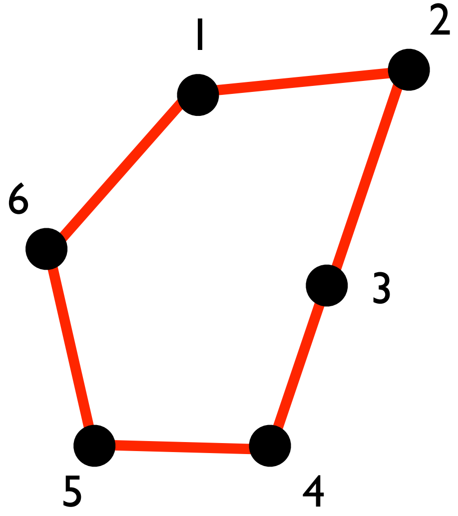
- Eigenmap is a spectral method, like PCA.

- Recipe:
  1. As in ISOMAP, construct k-nearest neighbors graph.
  2. Assign $W_{ij}=1$, if i and j are neighbours, otherwise assign $W_{ij}=0$.
  3. Define diagonal matrix D, $D_{ii}=\sum_j W_{ij}$, and graph Laplacian, $L=D-W$.
  4. The embedding of data points is given by the eigenvectors of L, corresponding to the d smallest non-zero eigenvalues.

- Physical intuition: find lowest frequency vibrational modes of a mass-spring system (mass=nodes, springs=links of the graph).
- Very straightforward to implement, e.g., with R

Laplacian eigenmap

N=6
k=2




```
> L
     [,1] [,2] [,3] [,4] [,5] [,6]
[1,]   -2    1    0    0    0    1
[2,]    1   -2    1    0    0    0
[3,]    0    1   -2    1    0    0
[4,]    0    0    1   -2    1    0
[5,]    0    0    0    1   -2    1
[6,]    1    0    0    0    1   -2
> s <- svd(L)
> s$u
           [,1]          [,2]       [,3]       [,4]          [,5]      [,6]
[1,] -0.4082483 -1.934666e-16 -0.5773503 -0.5773503 -3.951502e-16 0.4082483
[2,]  0.4082483  5.000000e-01  0.2886751 -0.2886751 -5.000000e-01 0.4082483
[3,] -0.4082483 -5.000000e-01  0.2886751  0.2886751 -5.000000e-01 0.4082483
[4,]  0.4082483  4.163336e-16 -0.5773503  0.5773503  2.081668e-16 0.4082483
[5,] -0.4082483  5.000000e-01  0.2886751  0.2886751  5.000000e-01 0.4082483
[6,]  0.4082483 -5.000000e-01  0.2886751 -0.2886751  5.000000e-01 0.4082483
> s$d
[1] 4.000000e+00 3.000000e+00 3.000000e+00 1.000000e+00 1.000000e+00 1.155603e-16
```

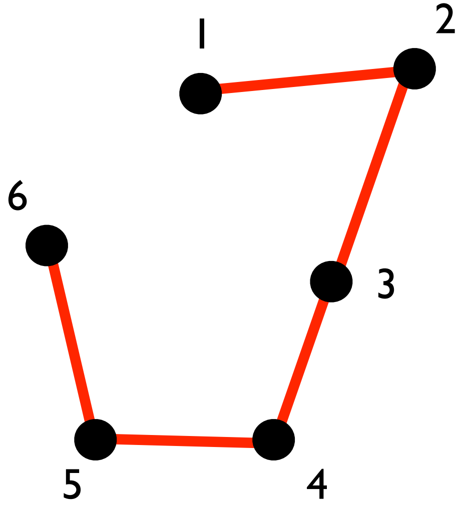
eigenvectors

circular shape

zero eigenvalue

Laplacian eigenmap

N=6
k=1

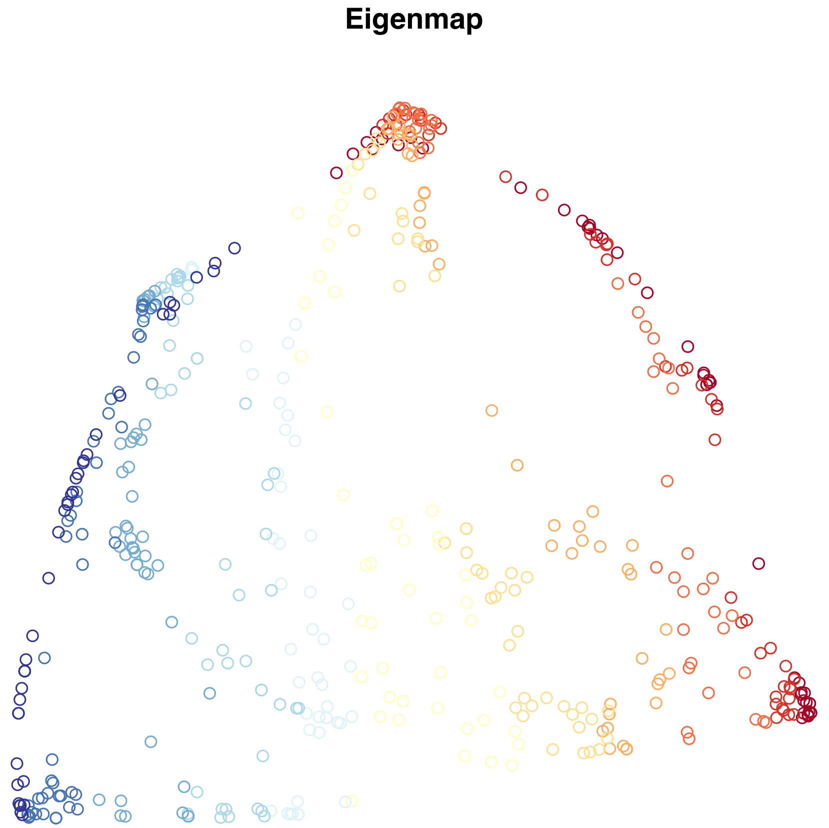


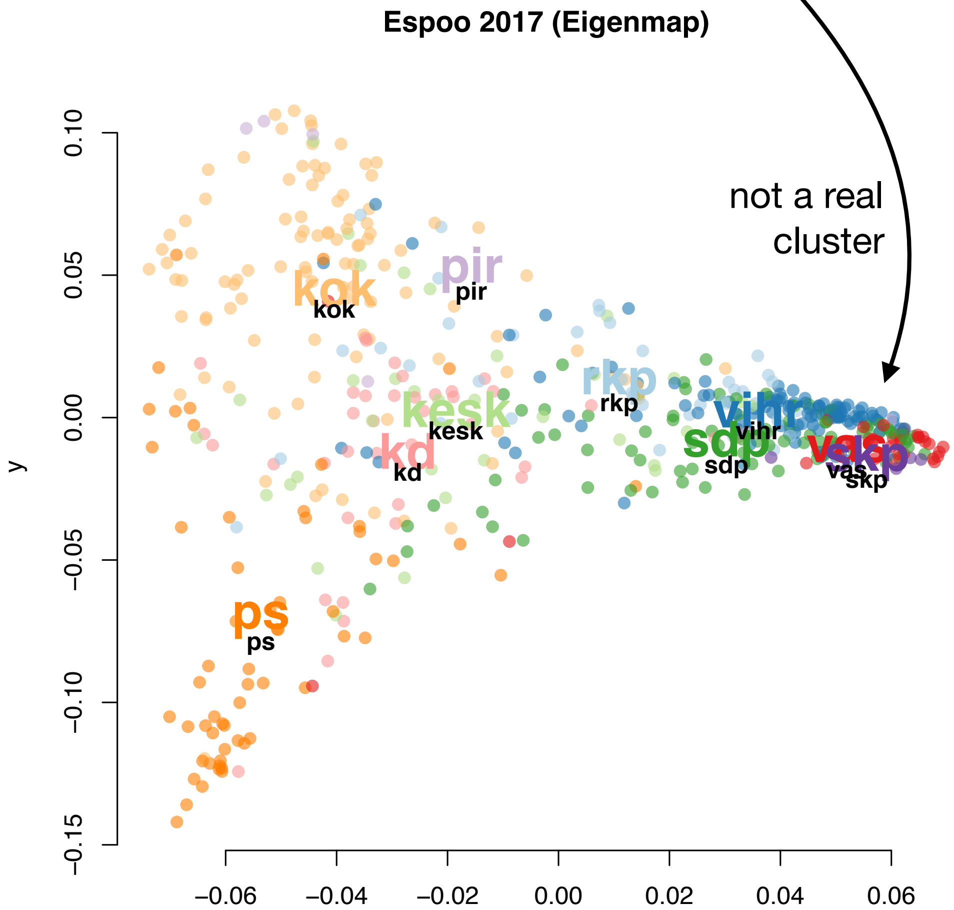

```
> L
     [,1] [,2] [,3] [,4] [,5] [,6]
[1,]   -1    1    0    0    0    0
[2,]    1   -2    1    0    0    0
[3,]    0    1   -2    1    0    0
[4,]    0    0    1   -2    1    0
[5,]    0    0    0    1   -2    1
[6,]    0    0    0    0    1   -1
> s <- svd(L)
> s$u
           [,1]       [,2]       [,3]          [,4]       [,5]      [,6]
[1,] -0.1494292 -0.2886751 -0.4082483  5.000000e-01  0.5576775 0.4082483
[2,]  0.4082483  0.5773503  0.4082483  2.775558e-16  0.4082483 0.4082483
[3,] -0.5576775 -0.2886751  0.4082483 -5.000000e-01  0.1494292 0.4082483
[4,]  0.5576775 -0.2886751 -0.4082483 -5.000000e-01 -0.1494292 0.4082483
[5,] -0.4082483  0.5773503 -0.4082483  8.326673e-17 -0.4082483 0.4082483
[6,]  0.1494292 -0.2886751  0.4082483  5.000000e-01 -0.5576775 0.4082483
> s$d
[1] 3.732051e+00 3.000000e+00 2.000000e+00 1.000000e+00 2.679492e-01 7.510881e-17
```

linear ordering

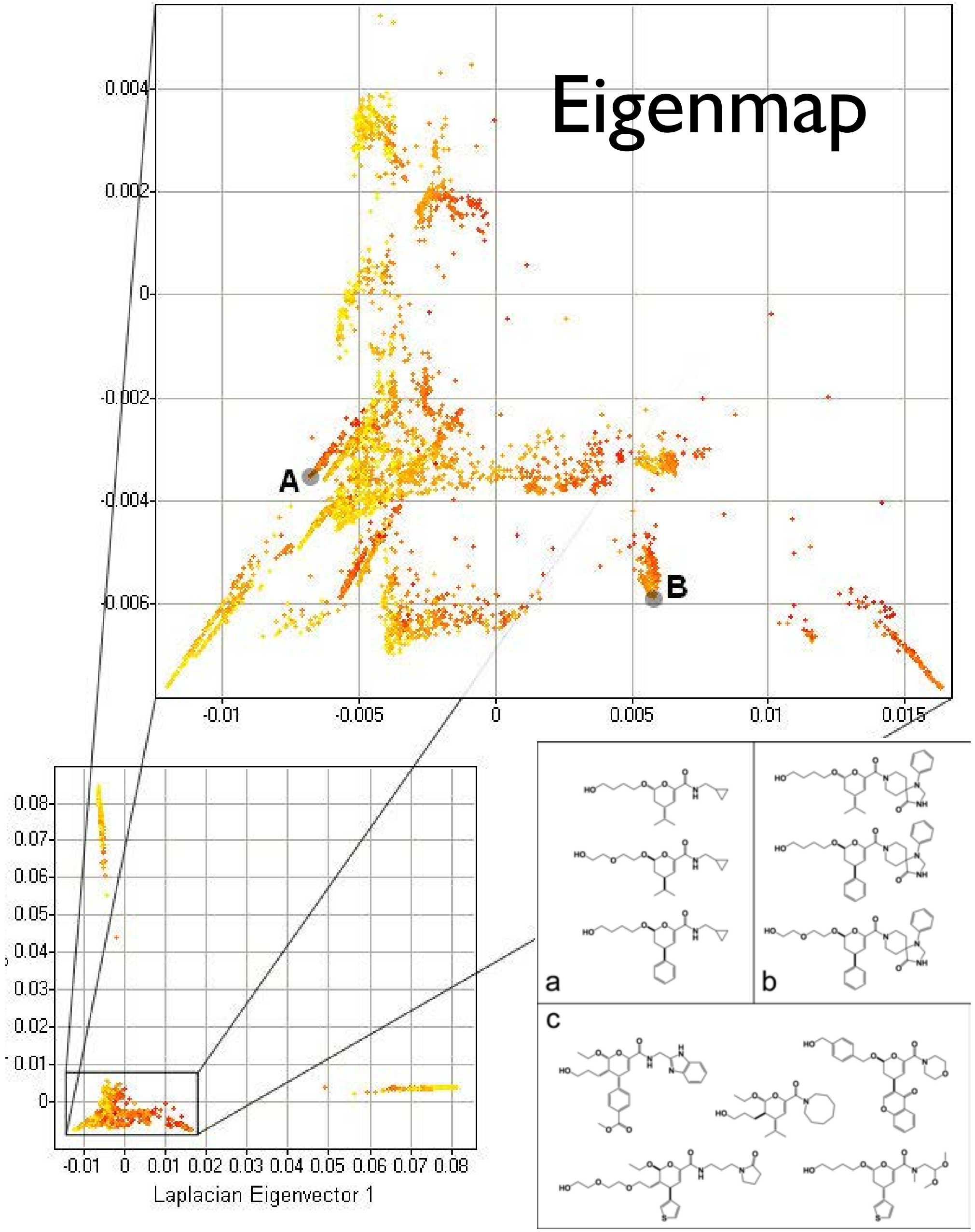
Laplacian eigenmap

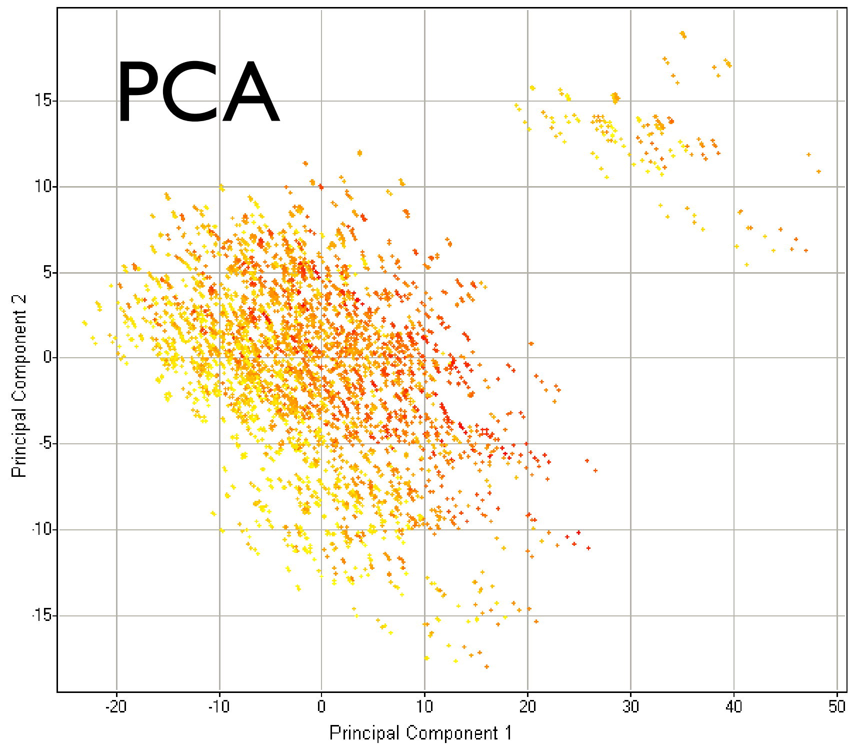
- Eigenmap can be viewed as trying to preserve the expected time a random walk on the neighbourhood graph takes to travel from one point to the other and back. This leads to tendency to magnify some distances (and shrink others), leading to relatively <u>bad precision</u>.





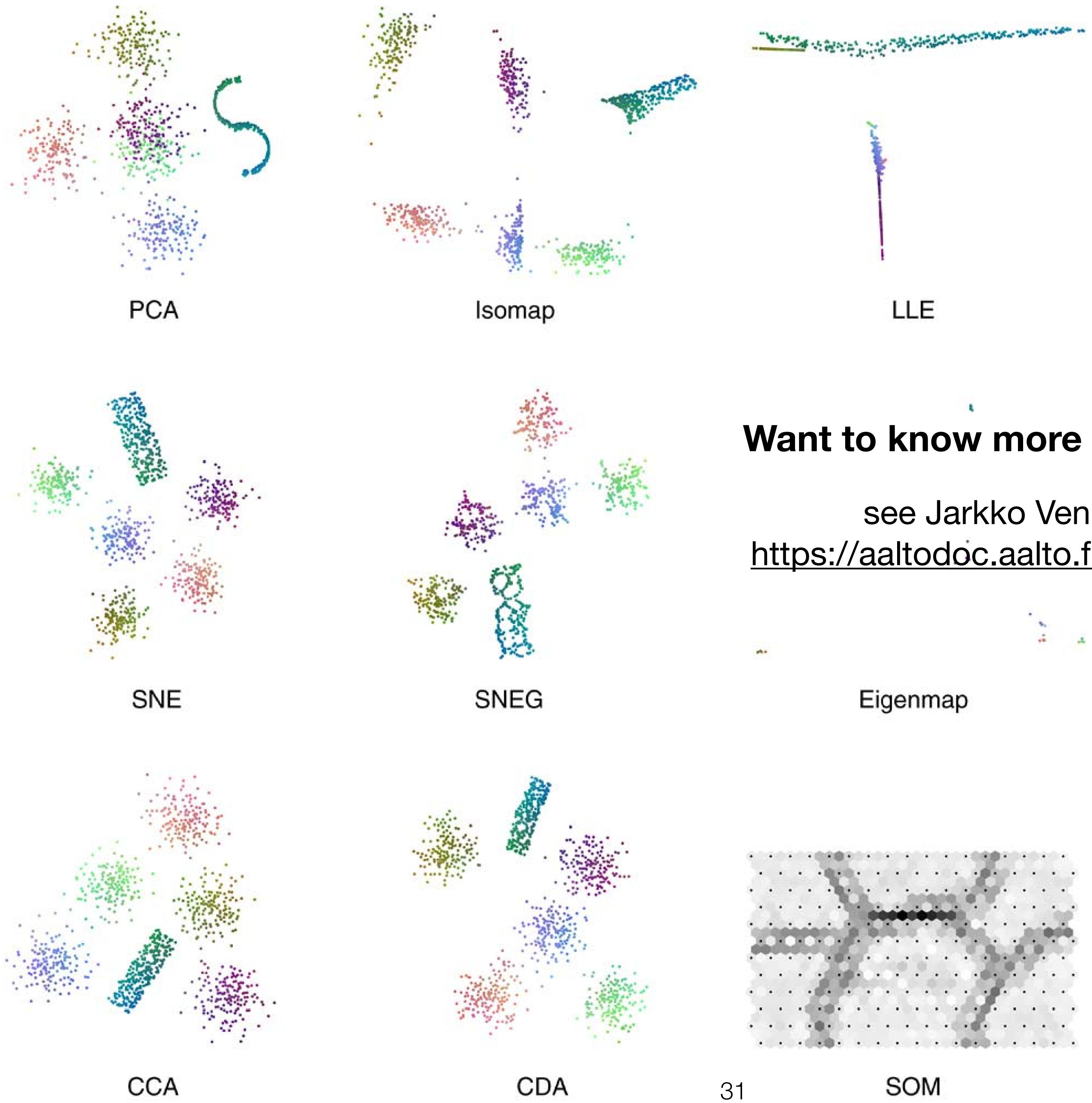
Laplacian eigenmap





Eigenmap (unlike PCA) shows clusters of similar chemical compounds (A&B). The input data is a network of small molecules encoded as molecular descriptors and connected by similarity.

Forman et al. 2005, https://doi.org/10.1186/1471-2105-6-260



Want to know more about these methods?

see Jarkko Venna's PhD thesis at
https://aaltodoc.aalto.fi/handle/123456789/2875

Dimensional reduction: summary

- PCA and MDS variants will struggle with non-linear manifolds
- PCA/Torgerson scaling is a linear projection
- large distances dominate the cost function in MDS methods

- techniques specifically designed to flatten manifolds
  - ISOMAP
  - LLE
  - Laplacian eigenmap
  - and many more exist...

- either redefine the distance or look only at the vicinity of individual points
- practical issues: distortions, may be computationally expensive

How to do these with R ?
Go to http://www.iki.fi/kaip/p/dr2.nb.html

(by Kai Puolamäki)

CS-E4840
Information Visualization
Lecture 10b: other topics

Tassu Takala <tapio.takala@aalto.fi>
8 April 2021

NEW TOPIC

Visualization of networks

Source material

- Tarawneh, Keller, and Ebert:
  A General Introduction To Graph Visualization Techniques
  https://drops.dagstuhl.de/opus/volltexte/2012/3748/pdf/13.pdf

- McGuffin:
  Simple Algorithms for Network Visualization: A Tutorial
  https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6297585

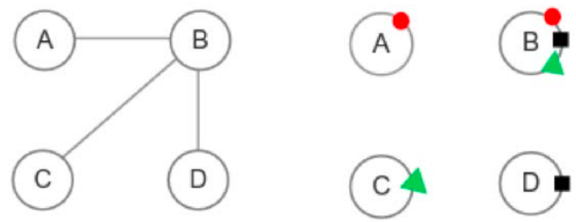
- Freeman:
  Social Network Visualization, Methods of
  https://www.researchgate.net/publication/242008428_Social_Network_Visualization_Methods_of

Basic graph concepts

- Graph (network) = set of nodes (vertices) and
  edges (links, arcs) between them

- Abstract construction, gets meaning by semantic definitions of nodes and edges, e.g.
    - infrastructure (communication, traffic, electricity…)
    - social networks (relations between people)
    - entity-relationship schemas (information systems)
    - ecology (predator-prey relations)
    - etc.

- Most common visualization: circles and lines
    - other principles also exist



(cf. Lecture 5)

Visualisation of graphs

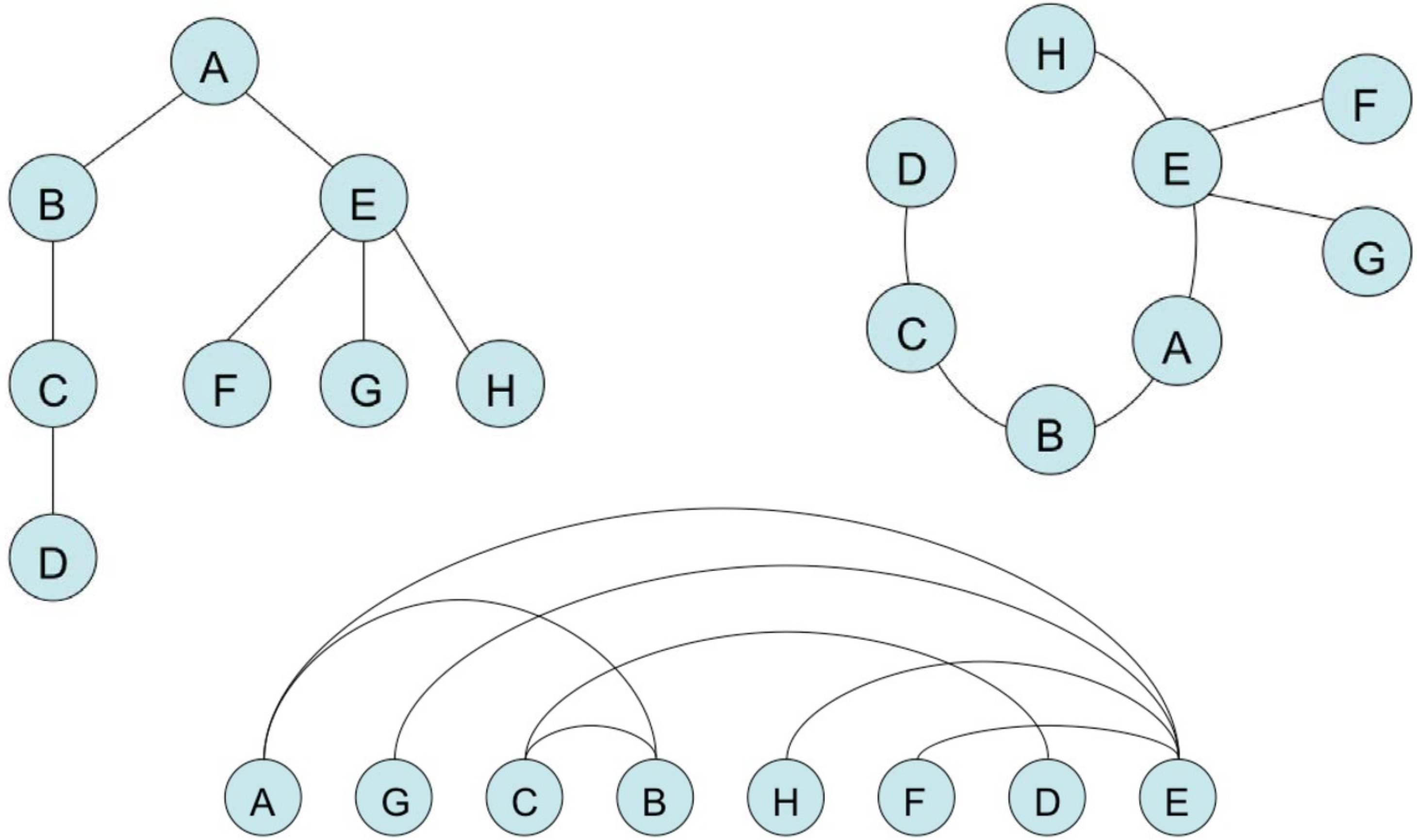
- Abstract graph has no form, but it can be embedded into plane (or 3D space) and made visible

- Properties of good visualisation
  - important elements (nodes, arcs, labes,…) clearly distinguishable
    - space between nodes
    - short arcs, not crossing each other (possible for planar graphs only)
  - semantic information associated to the graph made visible
    - eg. hierarchical levels of an organization
    - interesting parts of a complex network emphasised
  - can be created automatically
  - aesthetical appearance

- Often has to compromise between requirements

**Visualisation greatly determines,
how a graph is semantically interpreted!**

Same tree – different shapes



Visualisation greatly determines,
how a graph is semantically interpreted!

Criteria for visualization

- Nodes and edges should be evenly distributed.
- Edge-crossings should be minimized.
- Depict symmetric sub-graphs in the same way.
- Minimize the edge bending ratio.
- Minimize the edge lengths, which helps readers detecting the relations among different nodes faster.

- In cases where the data is inherently structured distribute the nodes into different layers. This increases the understandability of the underlying graph. For example, in data-flow diagrams it is recommended to separate the graph elements into different layers in a way that the final representation reflects the original semantics.

General layouts

- Spring (force-directed) layout
- Topological Feature-Based Layout
- Tree visualizations (hierarchical, radial, area based …)
- Arc layouts (linear or circular)
- Adjacency matrix

Topological Feature-Based

- Process steps:
  - decomposition phase
  - feature layout phase
  - crossing reduction phase
  - overlap elimination phase

$\left.\begin{array}{l} \text{decomposition phase} \\ \text{feature layout phase} \end{array}\right\}$ based on topological connections (and possibly semantic features) of nodes and subgraphs

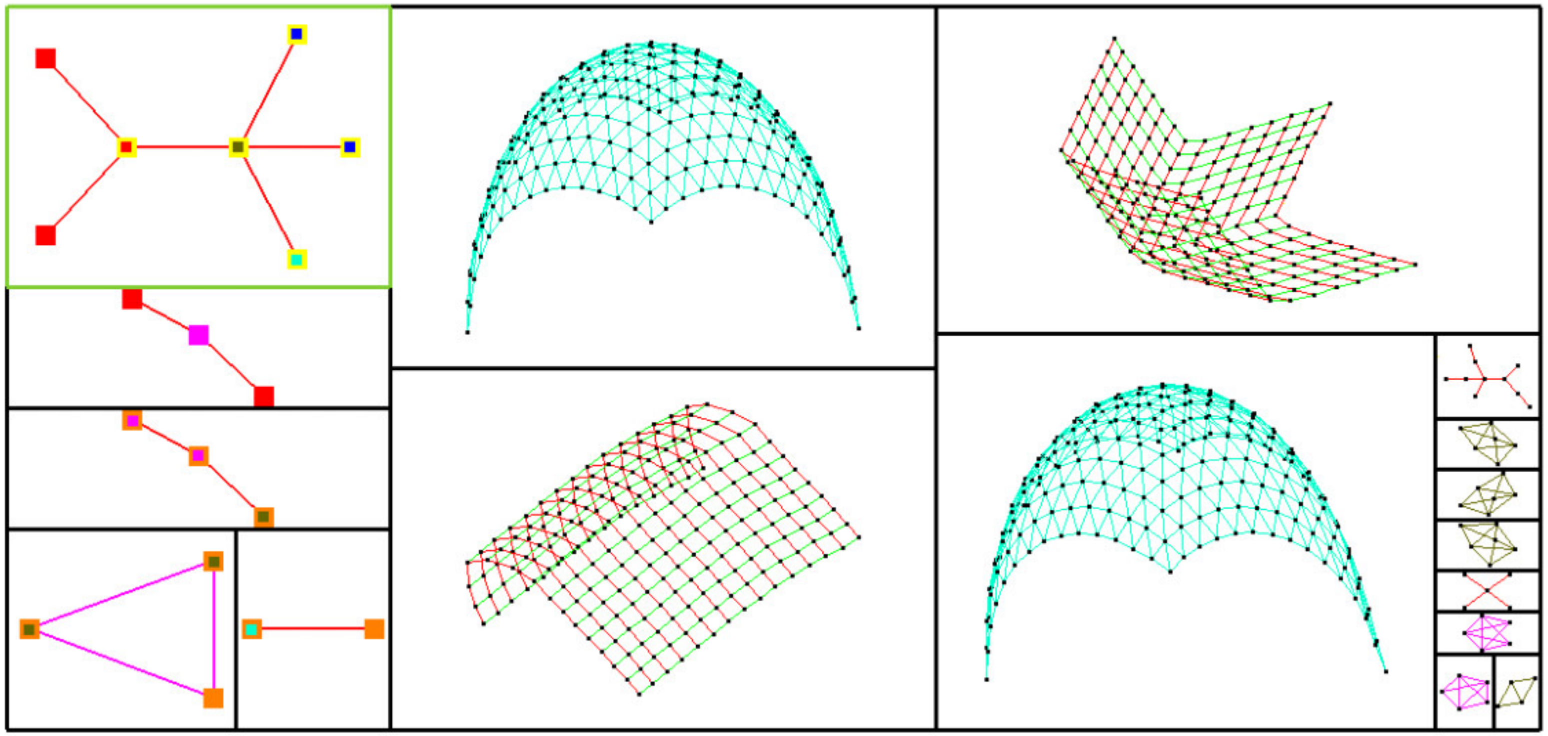
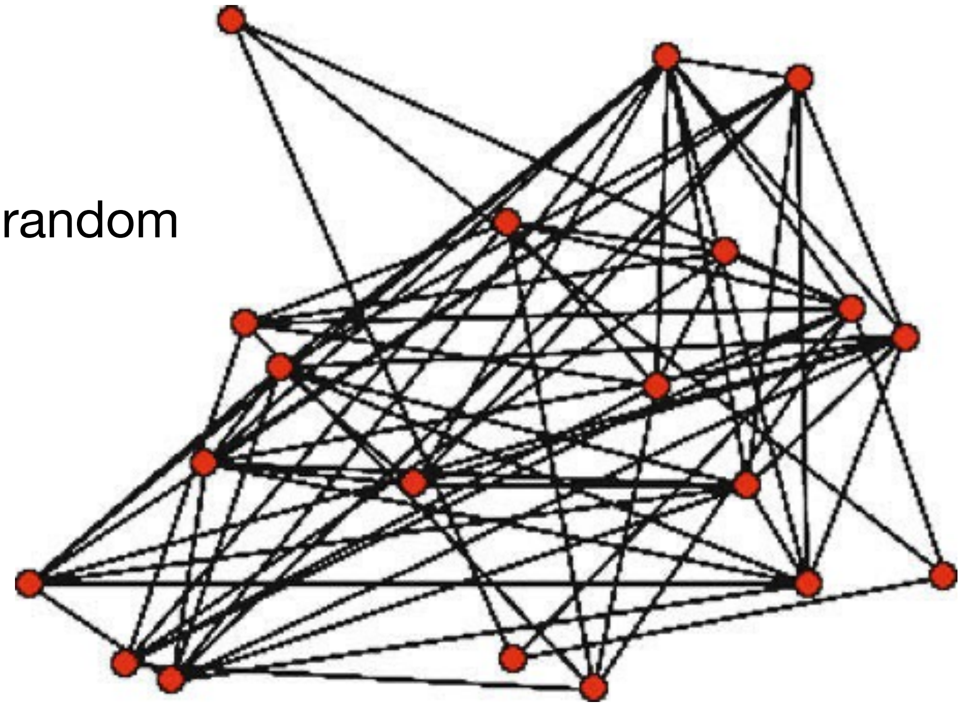


Figure 1 Layout generated by using the TopoLayout algorithm of [20].

Spring layout

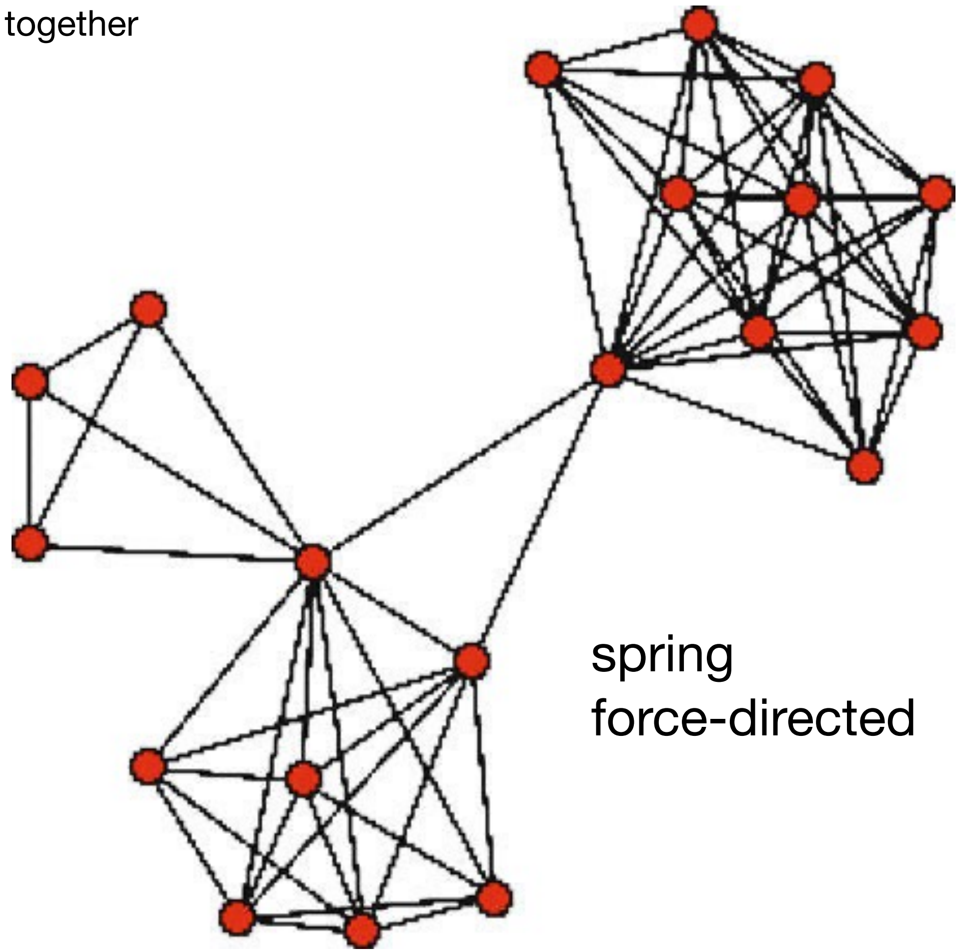
- simulated spring force attached to every edge
- minimize the total tension of the springs
  - tends to make distances equal and clustered nodes together
  - non-predictable (depends on random perturbations)

random



Social Network Visualization, Methods of, Figure 11
Links in the network of a homeless woman I

spring
force-directed



Social Network Visualization, Methods of, Figure 12
Links in the network of a homeless woman II

Example: spring layout

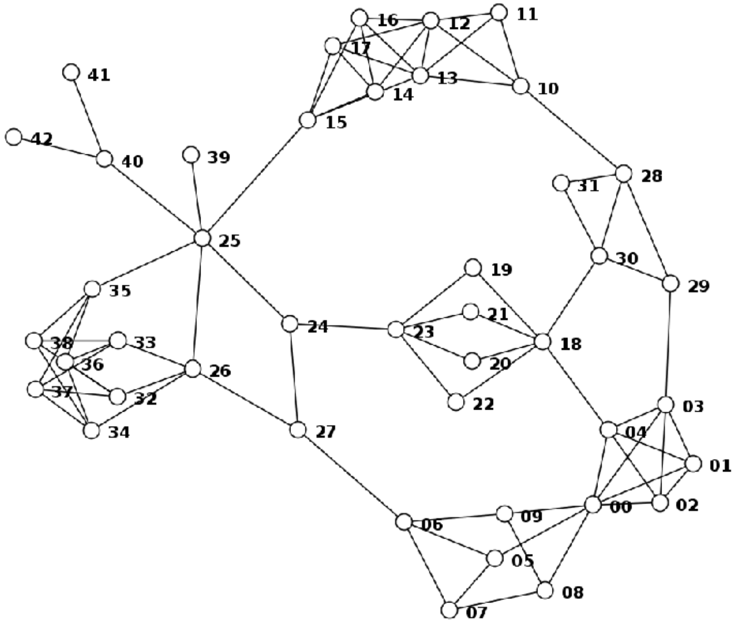
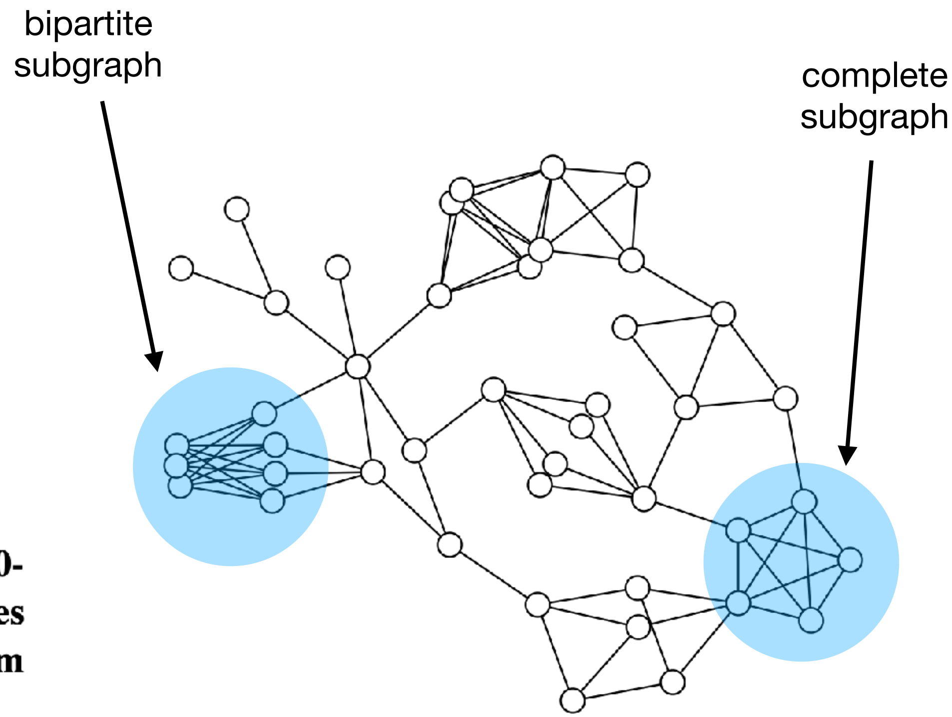
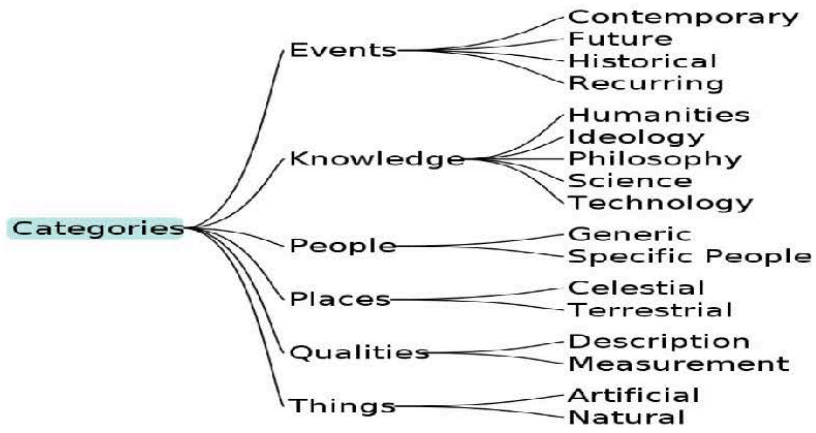


Fig. 1 Force-directed node-link diagrams of a 43-node, 80-edge network. Top: a low spring constant makes the edges more flexible. Bottom: a high spring constant makes them more stiff.

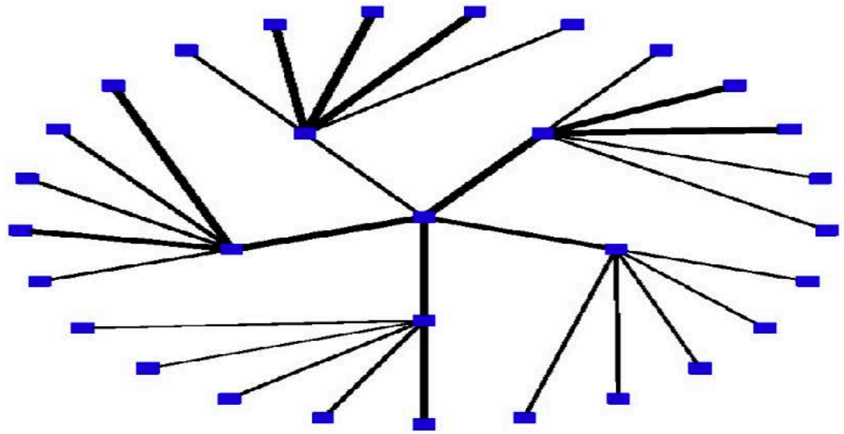
- spring algorithm naturally separates main cluster types



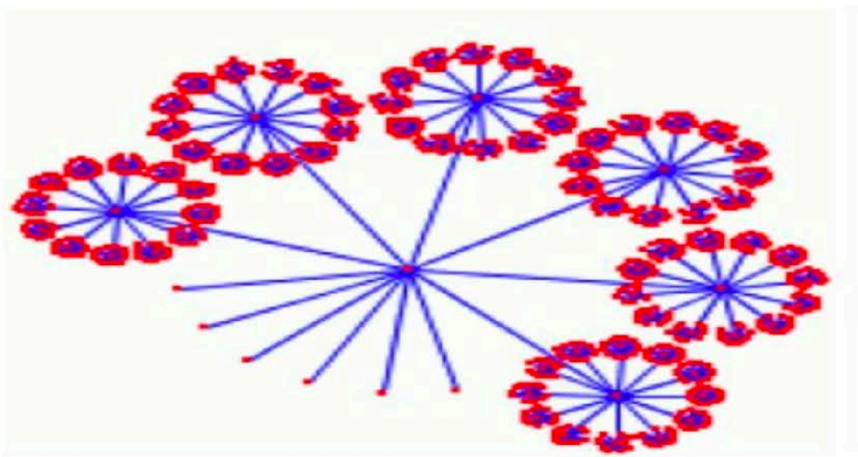
Tree visualization



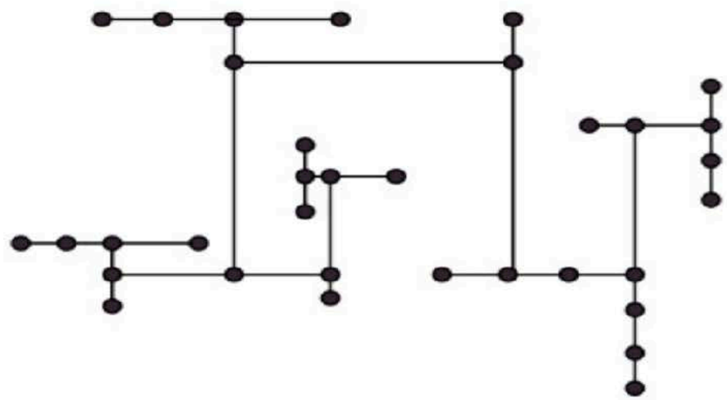
(a) Classical tree layout, produced with [19].



(b) Radial tree layout Example.



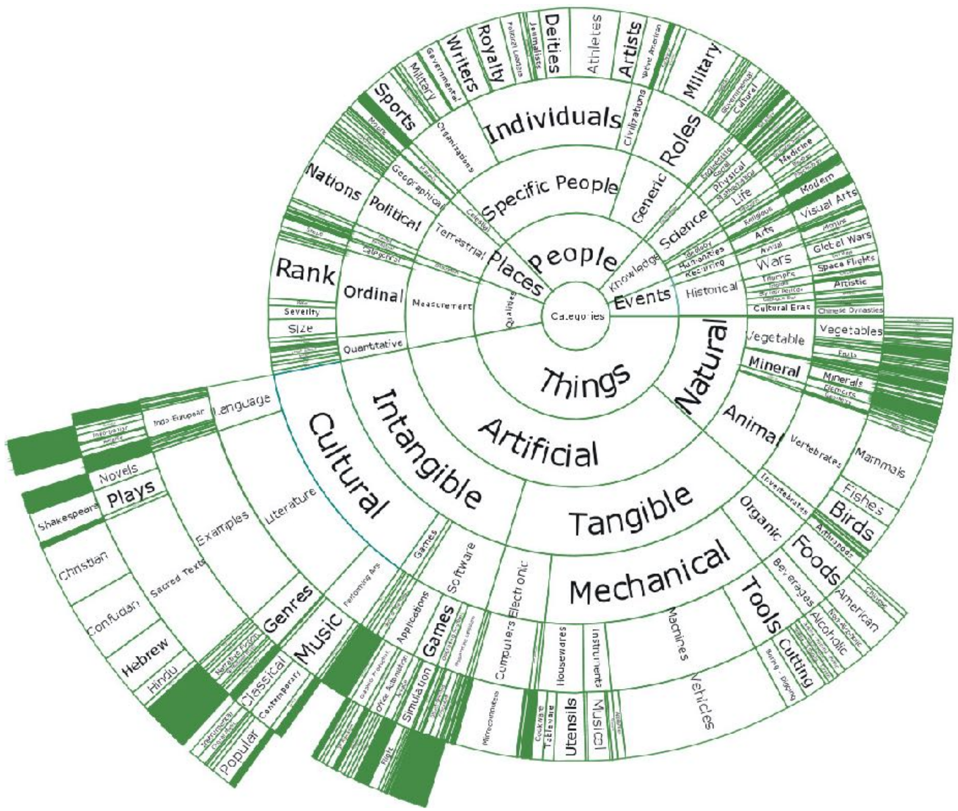
(c) Balloon tree layout: produced by [22].

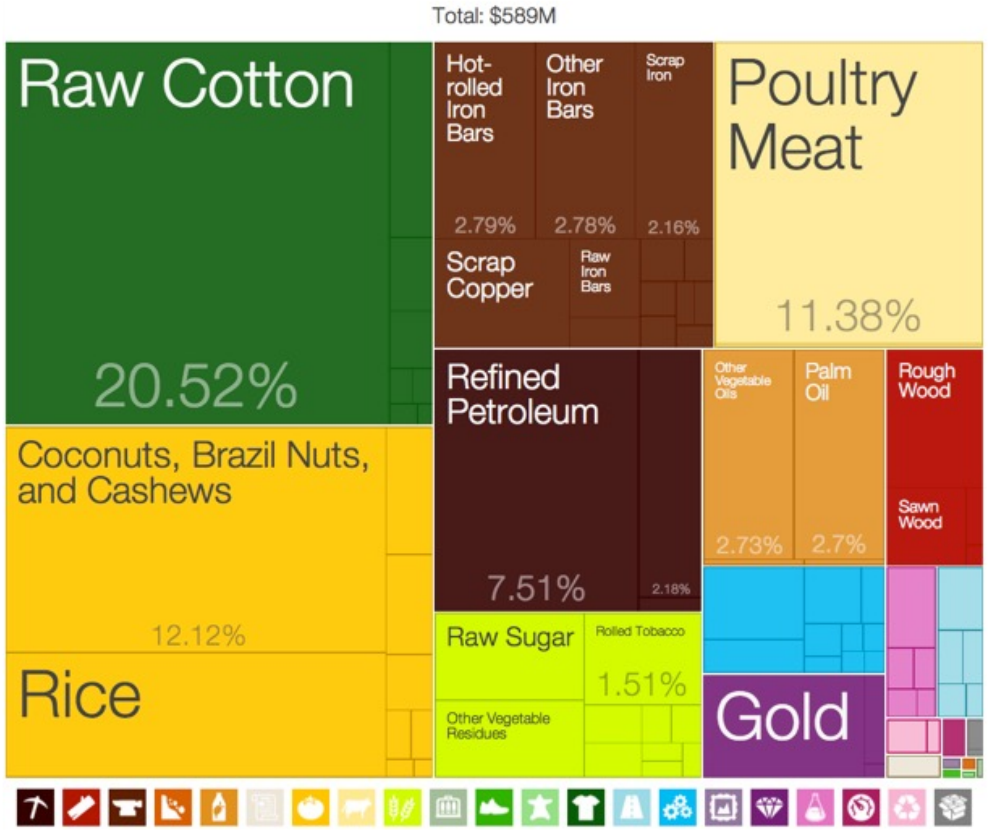


(d) H-Tree layout: produced by [22].

Tree visualization

SunBurst layout





Treemap layout

https://en.wikipedia.org/wiki/Treemapping

Arc layouts

- circular arcs connecting nodes
- ordering of nodes important for reducing complexity

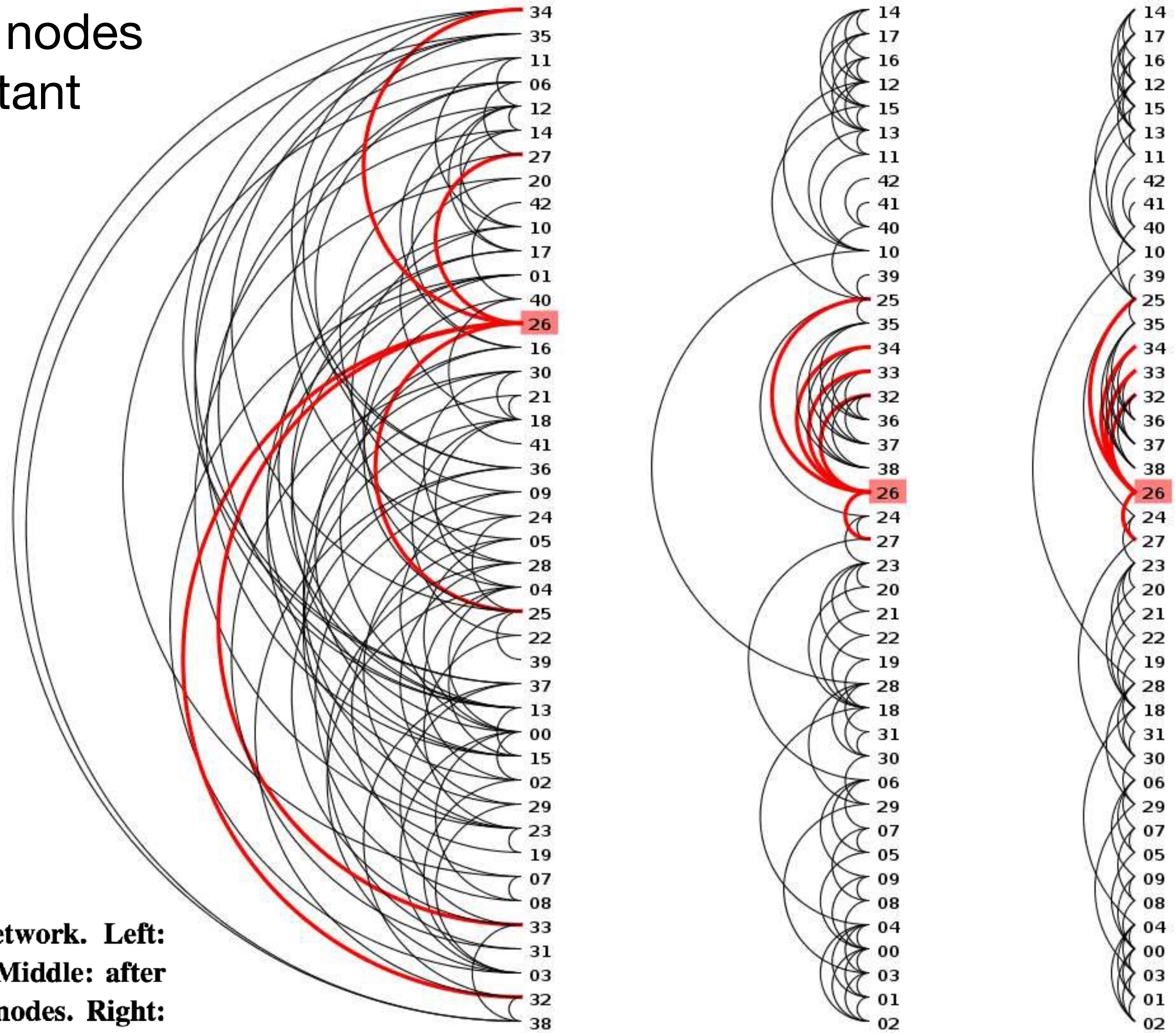
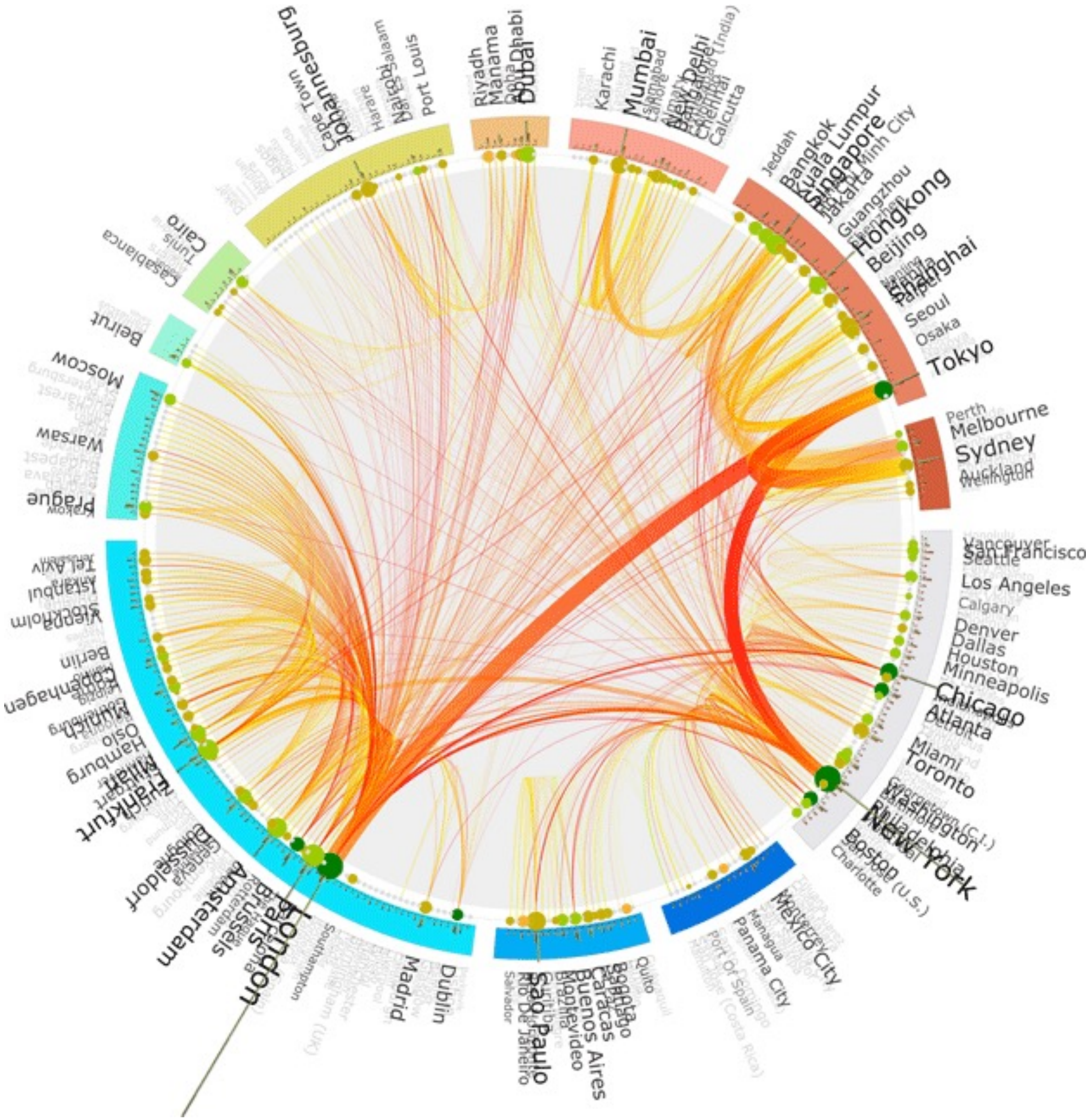


Fig. 3 Arc diagrams of a 43-node, 80-edge network. Left: with a random ordering and 180-degree arcs. Middle: after applying the barycenter heuristic to order the nodes. Right: after changing the angles of the arcs to 100 degrees.

Circular layouts



http://www.lboro.ac.uk/gawc/rb/rb421.html

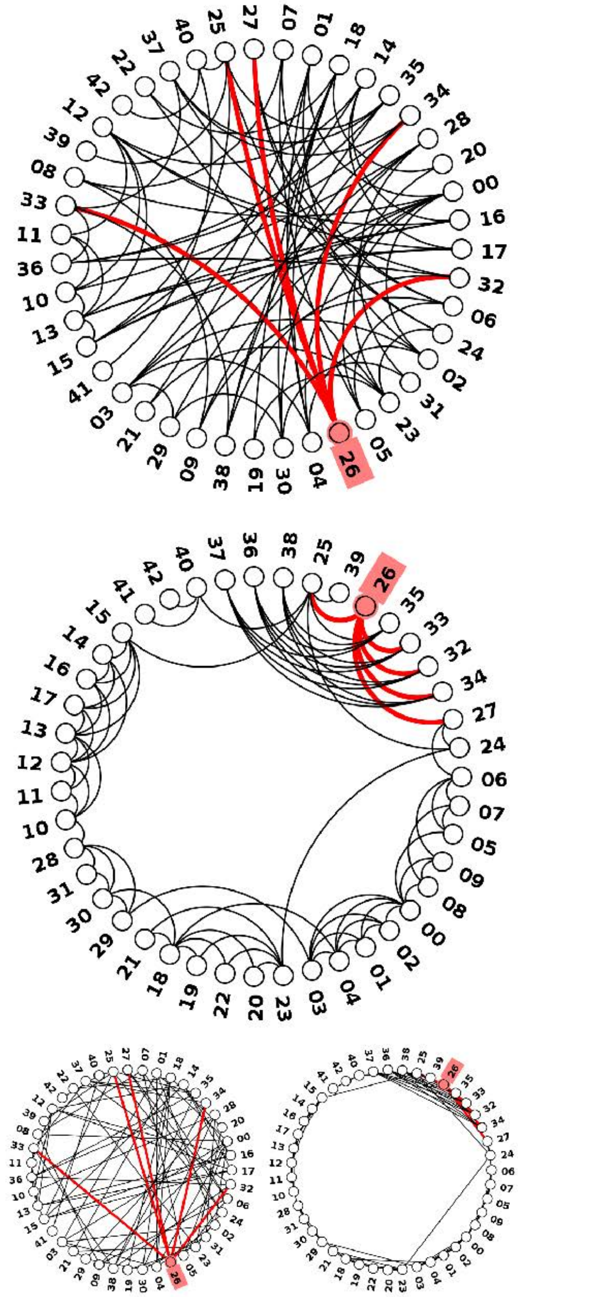


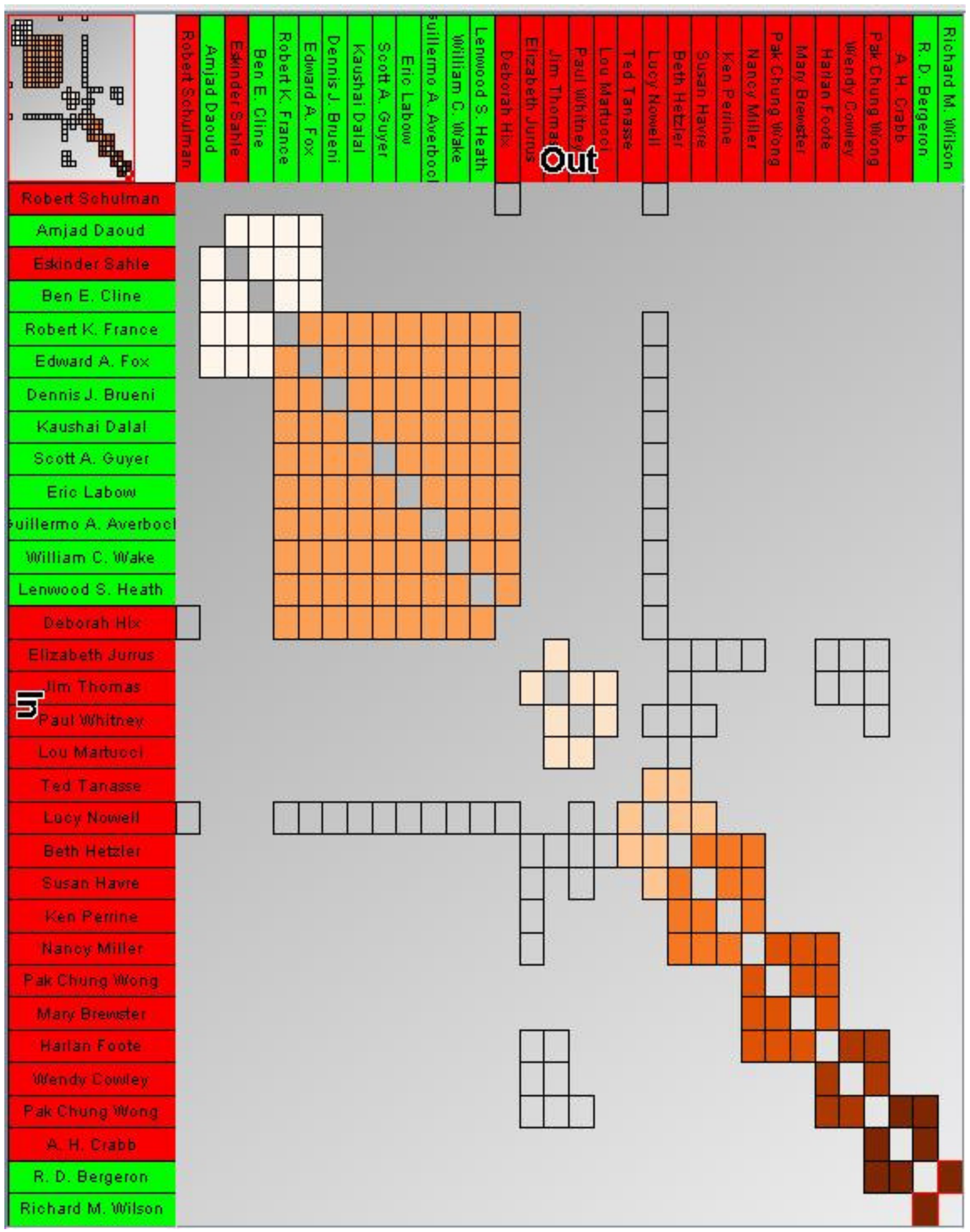
Fig. 8 Circular layouts of a 43-node, 80-edge network, before (top and bottom left) and after (middle and bottom right) barycenter ordering, with curved (top and middle) and straight (bottom) edges.

Matrix visualization

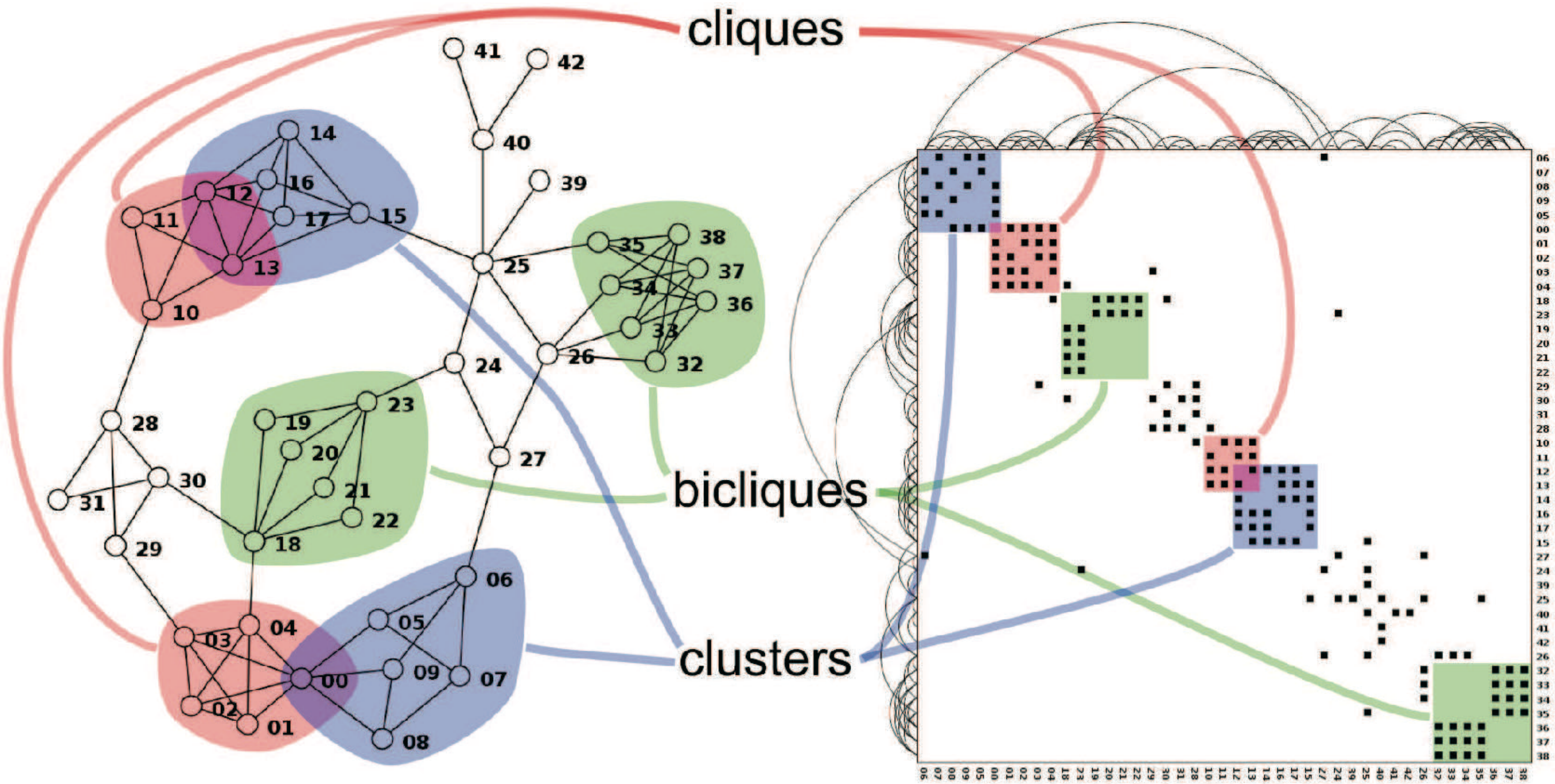
Adjacency matrix

- nodes in rows and columns
- edges (links) in crossings

- ordering of nodes important for visually perceiving the structure



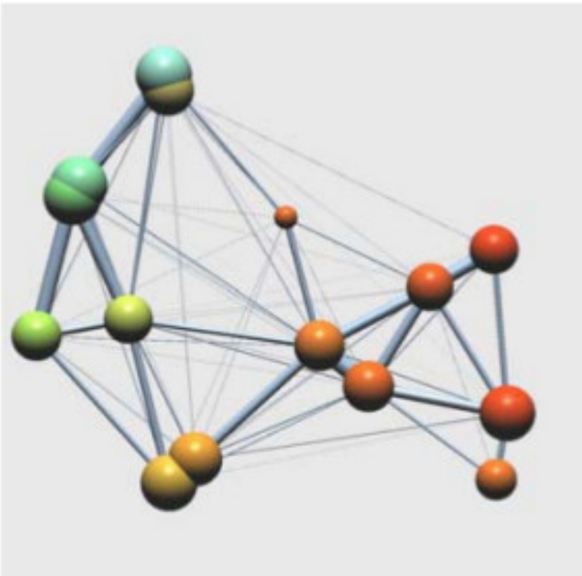
Nodes and Edges Clustering



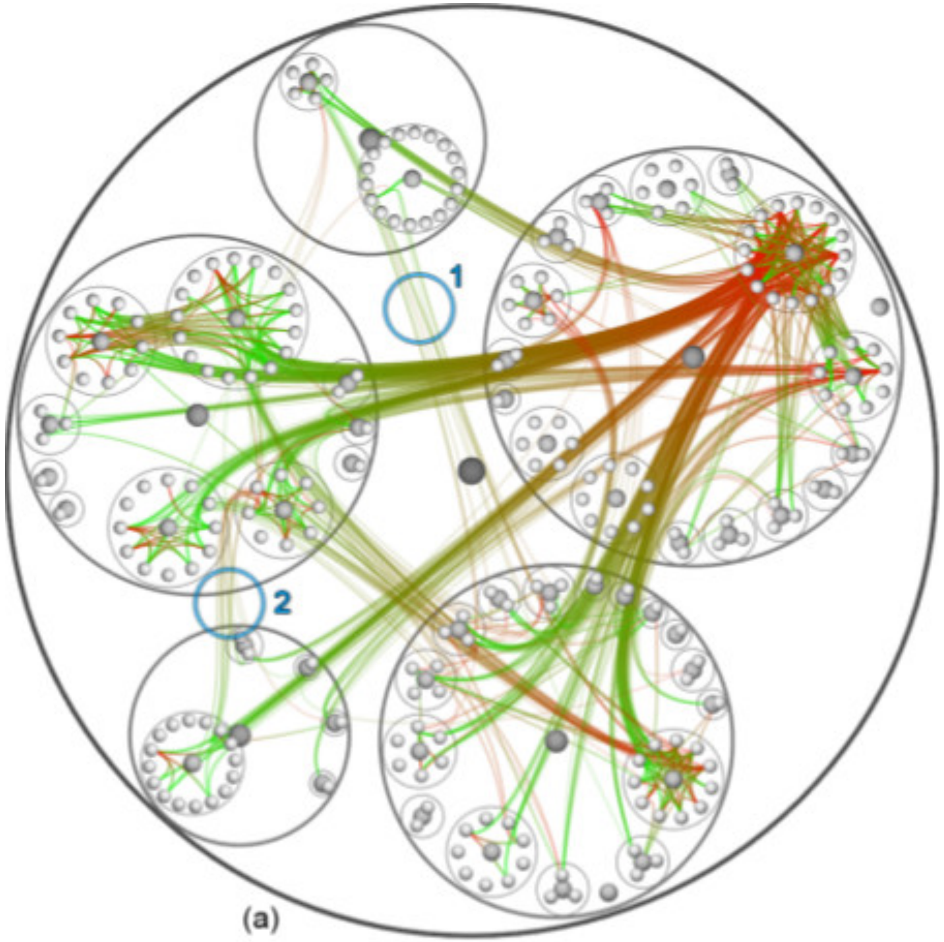
Patterns corresponding to interesting subgraphs appear along the diagonal of an appropriately ordered adjacency matrix

Nodes and Edges Clustering

- If too complex for showing everything:
  - aggregate nodes of an internally well-connected subgraph into a **cluster**
  - represent multiple edges between clusters by a thicker **bundle**



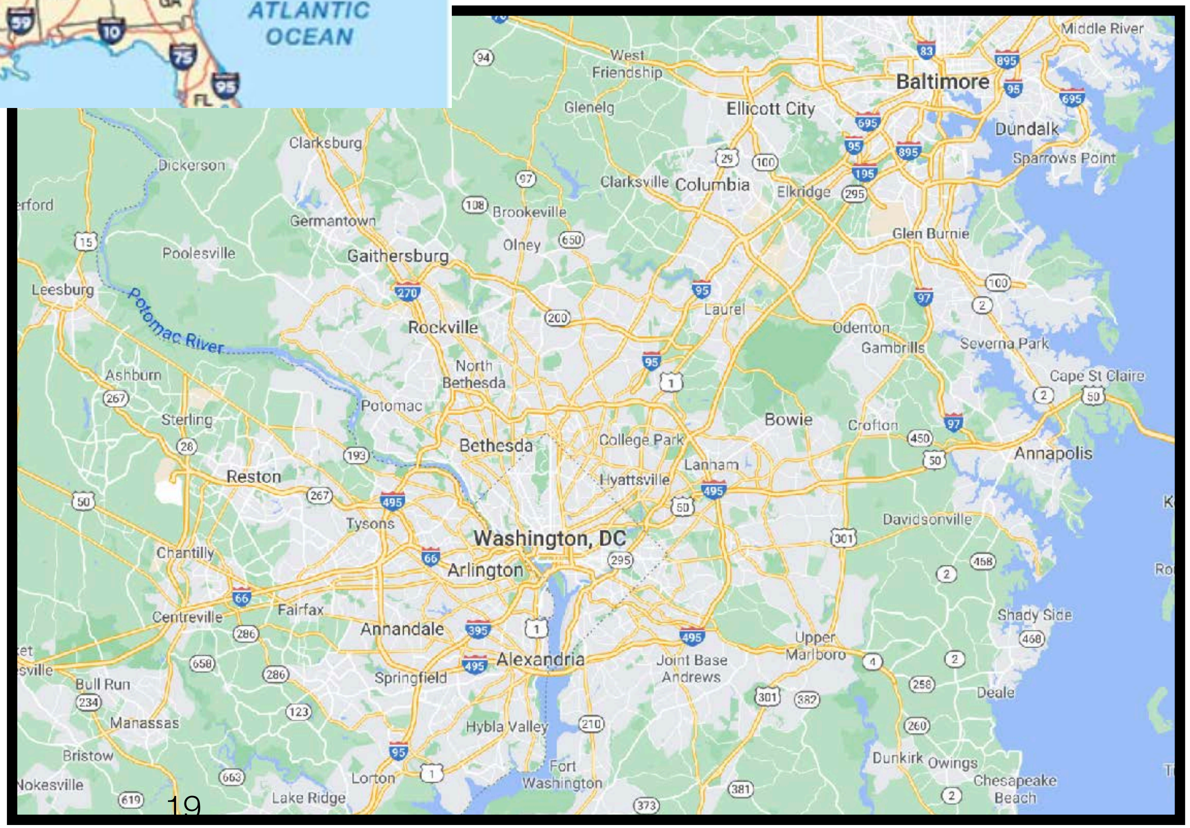
Clustering example



Edge bundling example

…or show only most important elements

…depending on the scale, and
semantic types (weights)
of edges and nodes.



Further sources

- https://flowingdata.com/category/visualization/network-visualization/
- https://cambridge-intelligence.com/keylines/why-visualize-networks/
- http://www.cs.umd.edu/hcil/graphvis/

- and many more...

NEW TOPIC

Avoiding Bullshit

- Misinformation
- Selecting the right data (for visualization)
- How to make conclusions

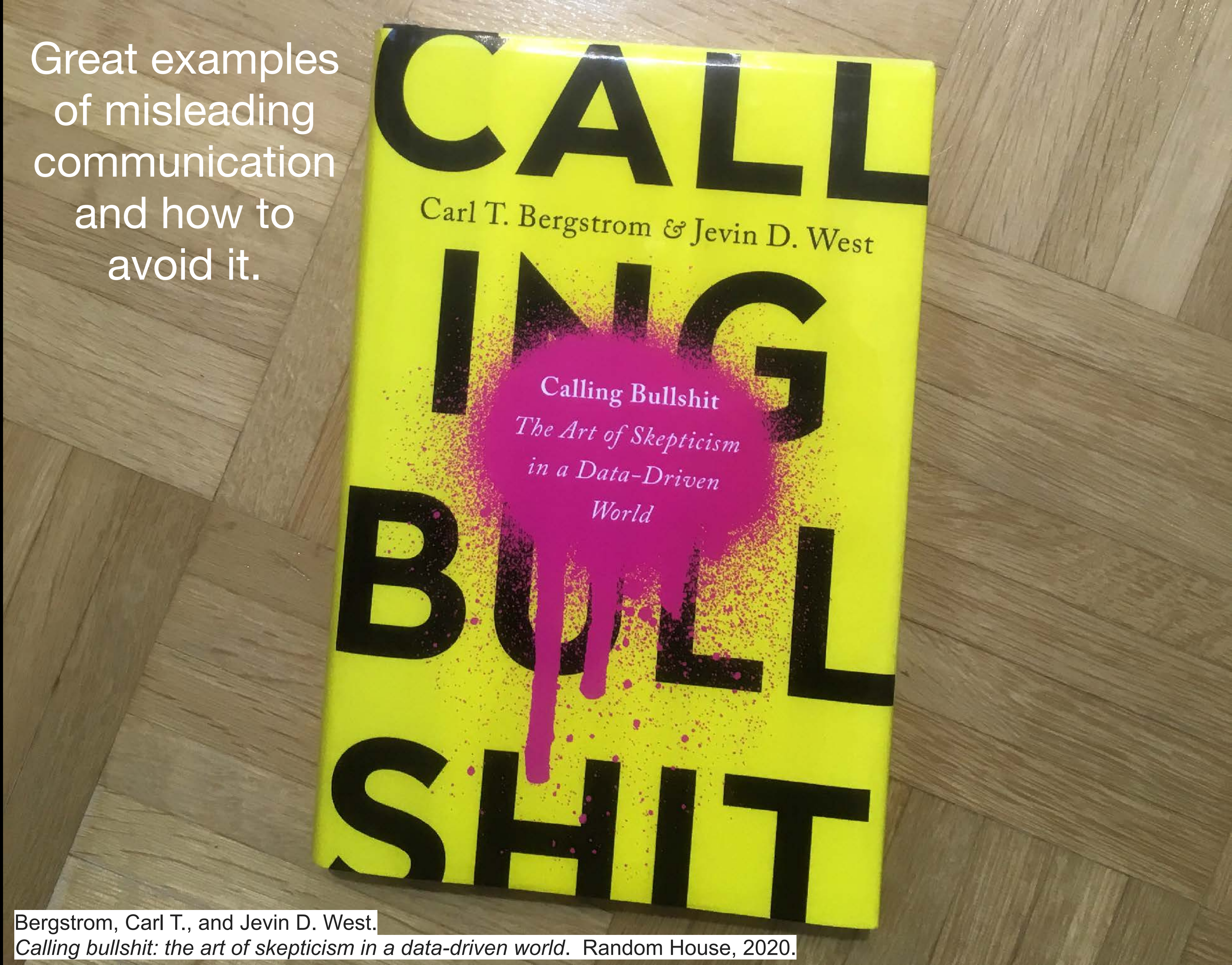
- **Learn to read data (and news) critically**

Source material

- Bergstrom and West
  Calling Bullshit – The Art of Skepticism in a Data_Driven World
  Random House, 2020

- Topics
  - mis- and disinformation
  - causal conclusions from assumptions or inadequate data
  - numbers and mathiness
  - selection bias

Great examples of misleading communication and how to avoid it.



Bergstrom, Carl T., and Jevin D. West.
Calling bullshit: the art of skepticism in a data-driven world. Random House, 2020.

What is "Bullshit" ?

- **Misinformation** = false claims not deliberately designed to deceive
    - headlines made to maximize attraction
        - exaggeration, priority on negative messages (accidents or threats), selecting most shocking/surprising issues for titles, etc.
    - typical in newspapers / news sites
    - fact-checking omitted in the hurry to publish
    - distributed massively in social media

- **Disinformation** = falsehood spread deliberately
    - propaganda to get political/financial gains
    - trolling (aiming at confusion)

- Misleading information = somewhere inbetween
    - giving an impression of something, without saying it straight and clearly
    - typical in advertising: creating a positive atmosphere for the product
    - chart junk: ducks and eye candy
    - accidentally confusing or controversary message

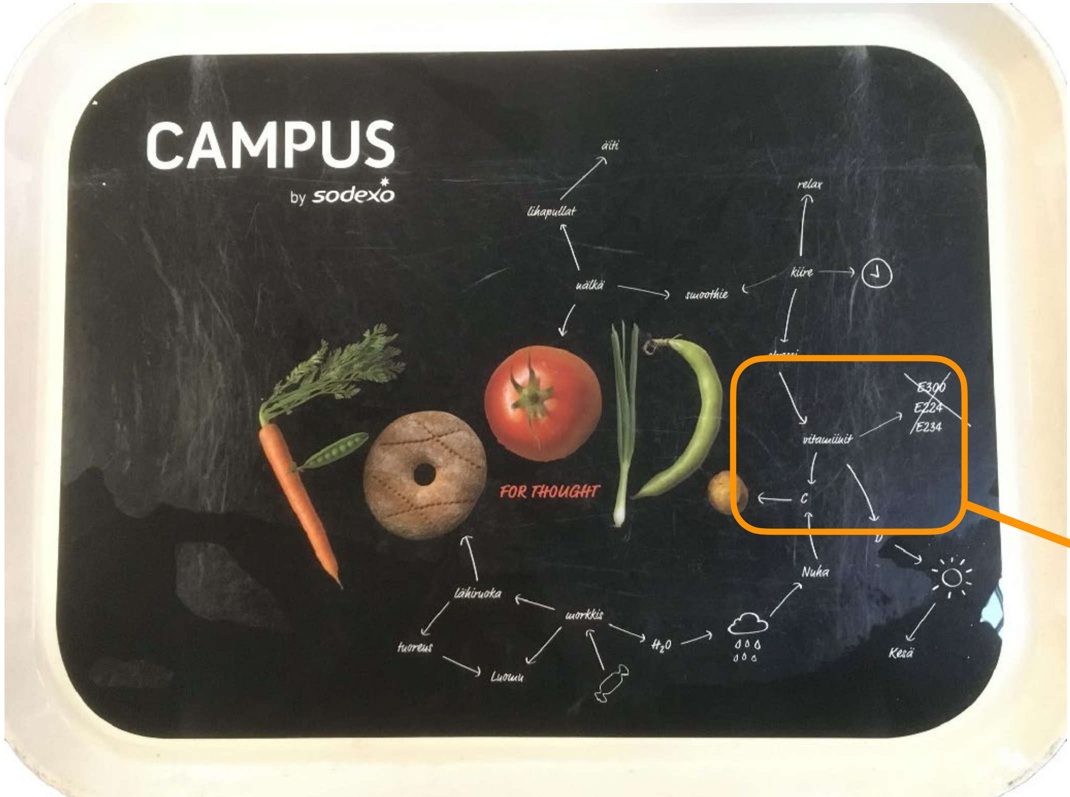
Fake news spread more efficiently

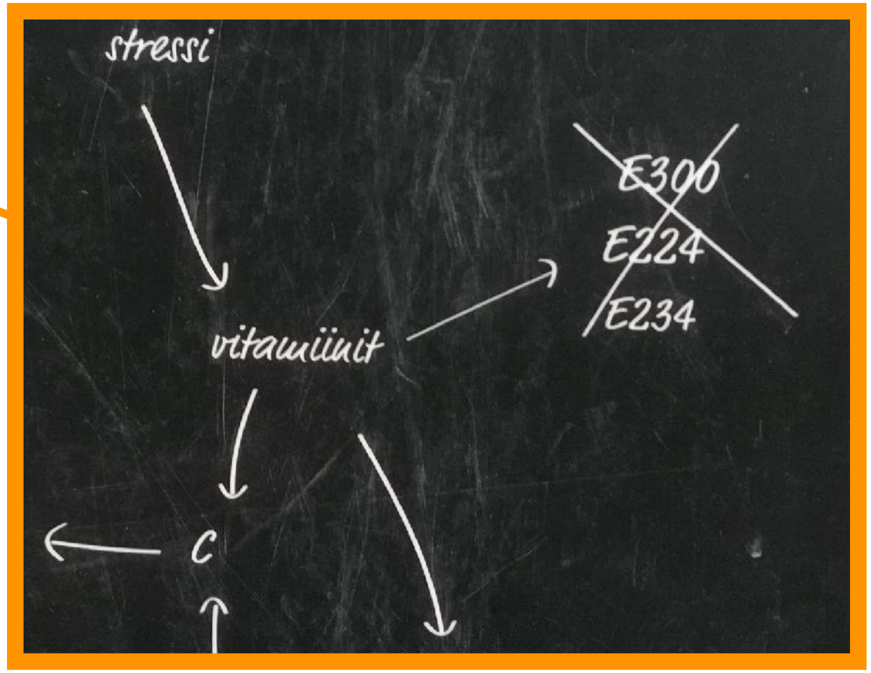
"Falsehood flies, and truth comes limping after it, so that when men come to be undeceived, it is too late; the jest is over, and the tale hath had its effect: like a man, who hath thought of a good repartee when the discourse is changed, or the company parted; or like a physician, who hath found out an infallible medicine, after the patient is dead."

— Jonathan Swift

Accidentally controversary

(see Lecture 2)





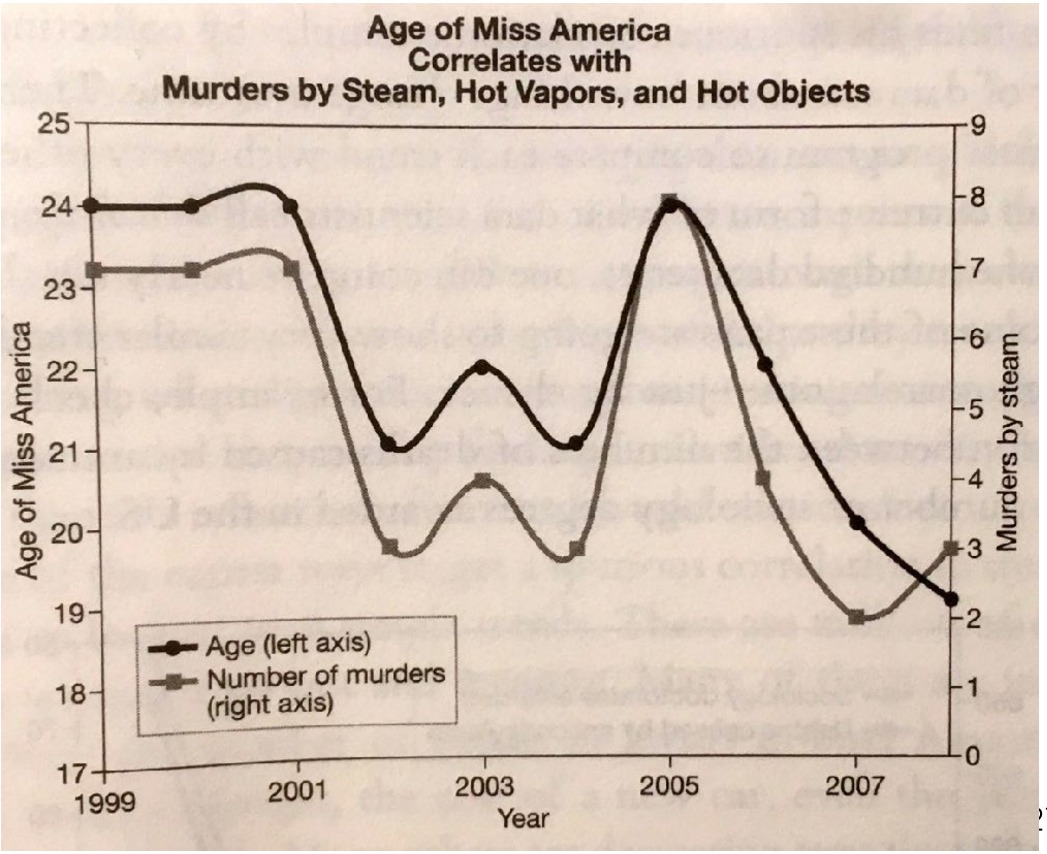
what is E300 ?

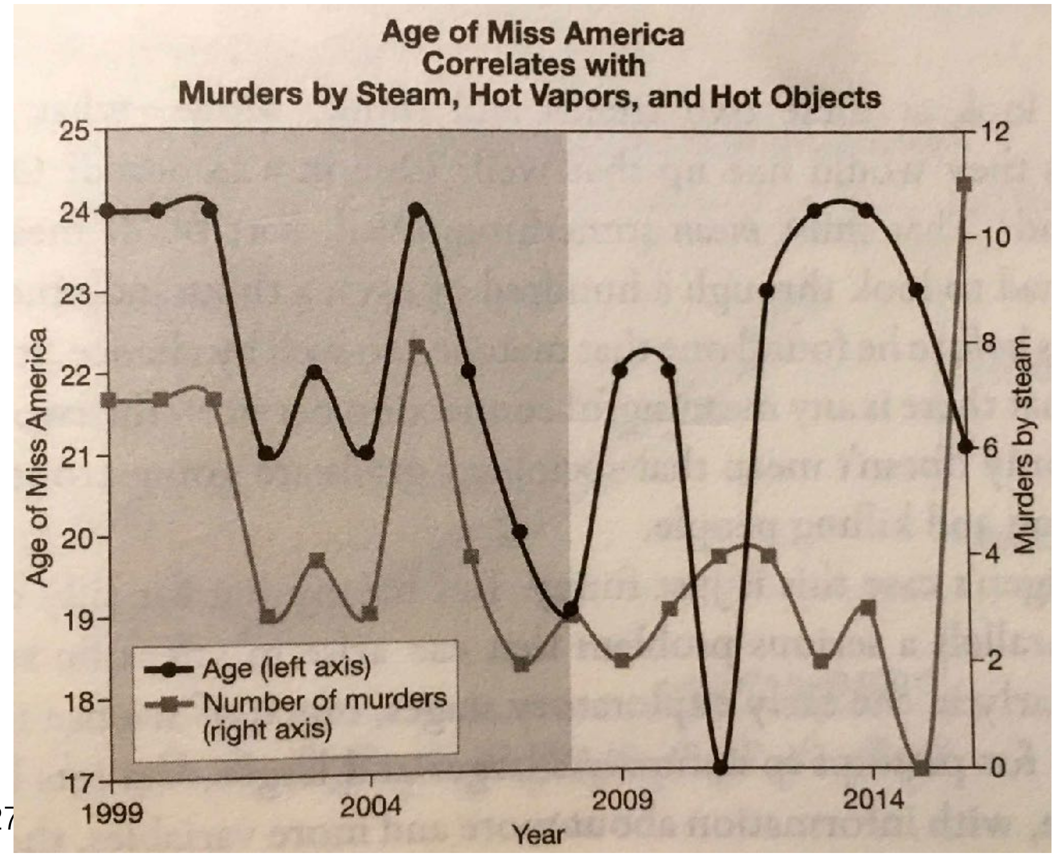
https://en.wikipedia.org/wiki/E_number

Causality

- Making **conclusions from assumptions or inadequate data**

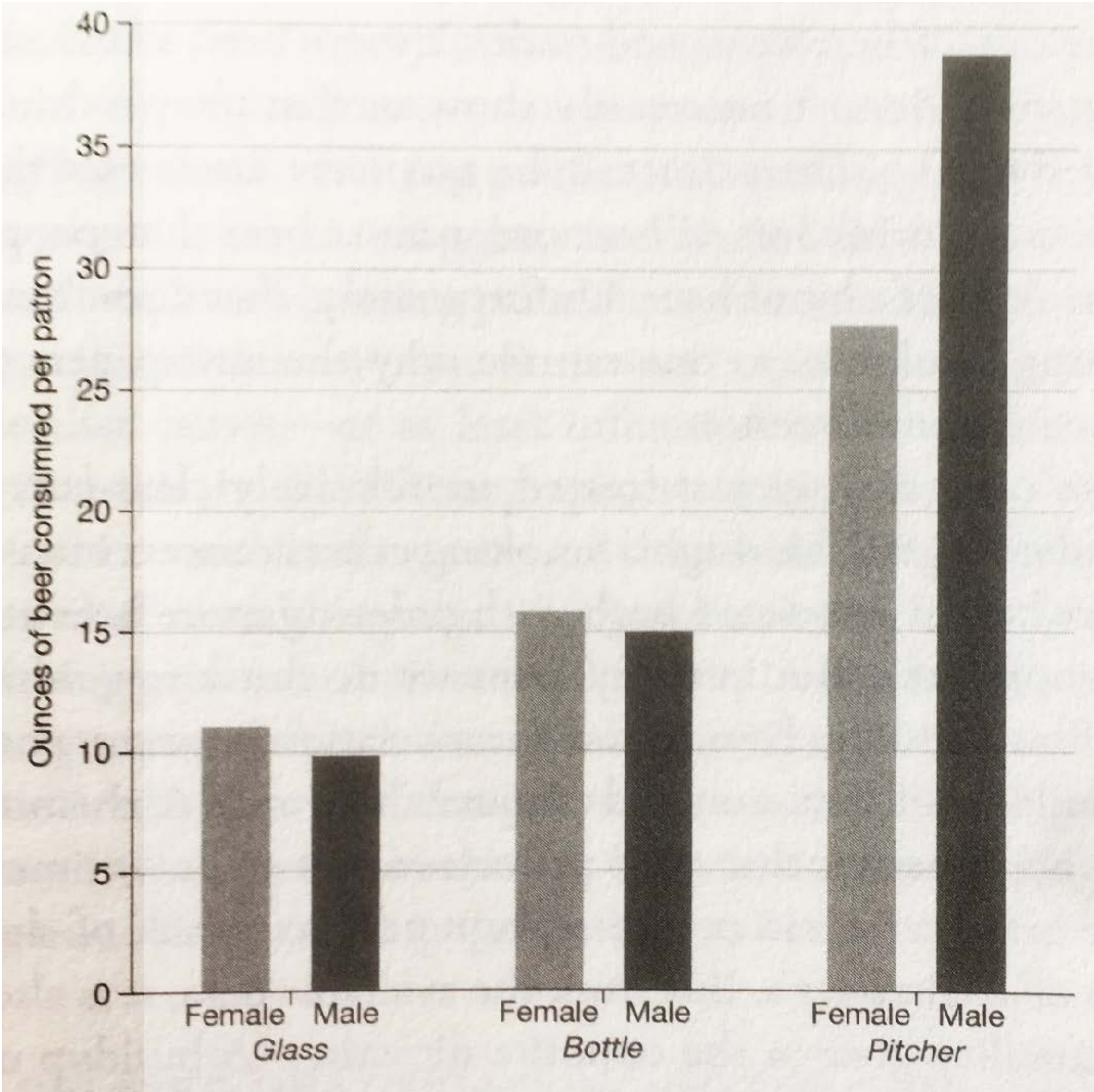
- **Spurious** correlations (cf. Lecture 2)
  http://www.tylervigen.com/spurious-correlations





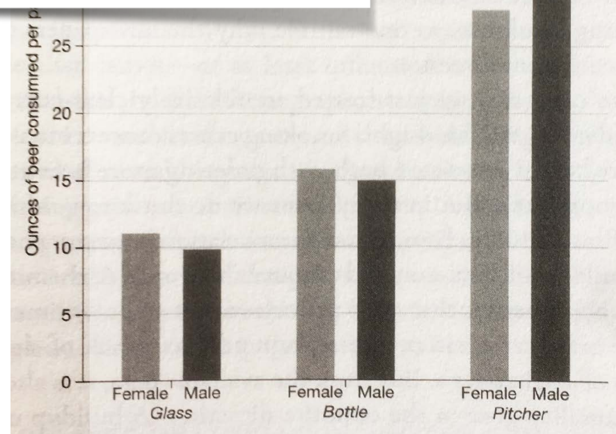
Causality

- What can you tell from this data about overall beer consumption and glass size?



Causality vs. association

Students who drank beer from pitchers drank roughly two to four times as much beer as those who drank their beer by the glass or by the bottle. The original study was careful not to claim a causal relationship.* But the claim evolved as reports of the study filtered through the popular press and into the broader discussion about alcohol abuse on college campuses. "People drink more *when* beer is consumed in pitchers" was taken to mean "People drink more *because* beer is consumed in pitchers." Based on this, people started making prescriptive claims: "We should ban pitchers so that students will drink less."



Coincidence turned into "fact"

- https://www.cdc.gov/mmwr/volumes/69/wr/mm6919e6.htm

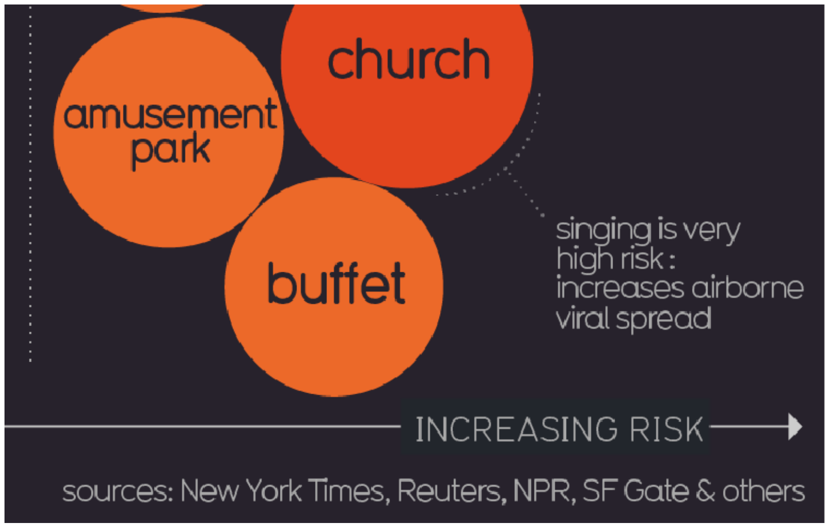
High SARS-CoV-2 Attack Rate Following Exposure at a Choir Practice — Skagit County, Washington, March 2020

- (Choir) singing claimed as significant risk factor, based on just few occasions
- No appropriate consideration for alternative explanations
- No comparison between cases *with vs. without* singing
- Strong assumptions about droplets/aerosols as virus carriers

- But: the rumor was spread out and became a worldwide "scientific fact"

https://informationisbeautiful.net/visualizations/covid-19-coronavirus-infographic-datapack/

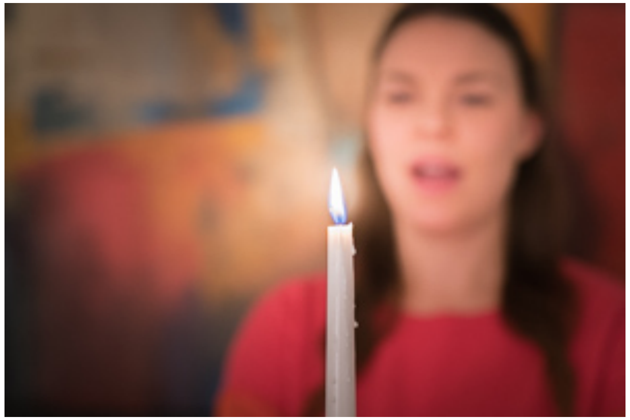
the 'fear factor'



Coincidence turned into "fact"

"Is singing a risk for corona transmission?"
Takala et al. Finnish Medical Journal, 2021

https://www.laakarilehti.fi/ajassa/nakokulmat/onko-laulaminen-koronariski/?public=6636b614b5aedde75a6733887cac3e43



Conclusion in the article:

Available data do not prove singing more dangerous than usual human interaction – at least not at the same decibel level.

- NOTE #1: Cannot make conclusions from **arbitrary coincidental observations without comparative data**
- NOTE #2: Available data does not prove in either direction **"Absense of evidence is not evidence of absense"**
- NOTE #3: Willingness to have answers is not an argument

Numbers and mathiness

- Numeric claims without data

"enough for up to 10 weeks"

Numbers and mathiness

- Numbers with excessive precision
  when presenting experimental results

  - "in the study 3 cases out of 28 were positive".
    – How many percent is that?

    A. 11 %
    B. 10.7 %
    C. 10.71428 %

  - or:
    "the measured mean length was 3.35548 cm (N=202)"
    – with data values 3.12, 3.47, 3.2, … etc.

Numbers and mathiness

- "Mathiness" = Scientific-looking formulas
  - we know only **qualitatively** the effects of different factors
  - no reason to put that in a particular **quantitative** form

Let's begin with an example. The following formula, known as the VMMC Quality Equation, is apparently much discussed in the area of healthcare quality management.

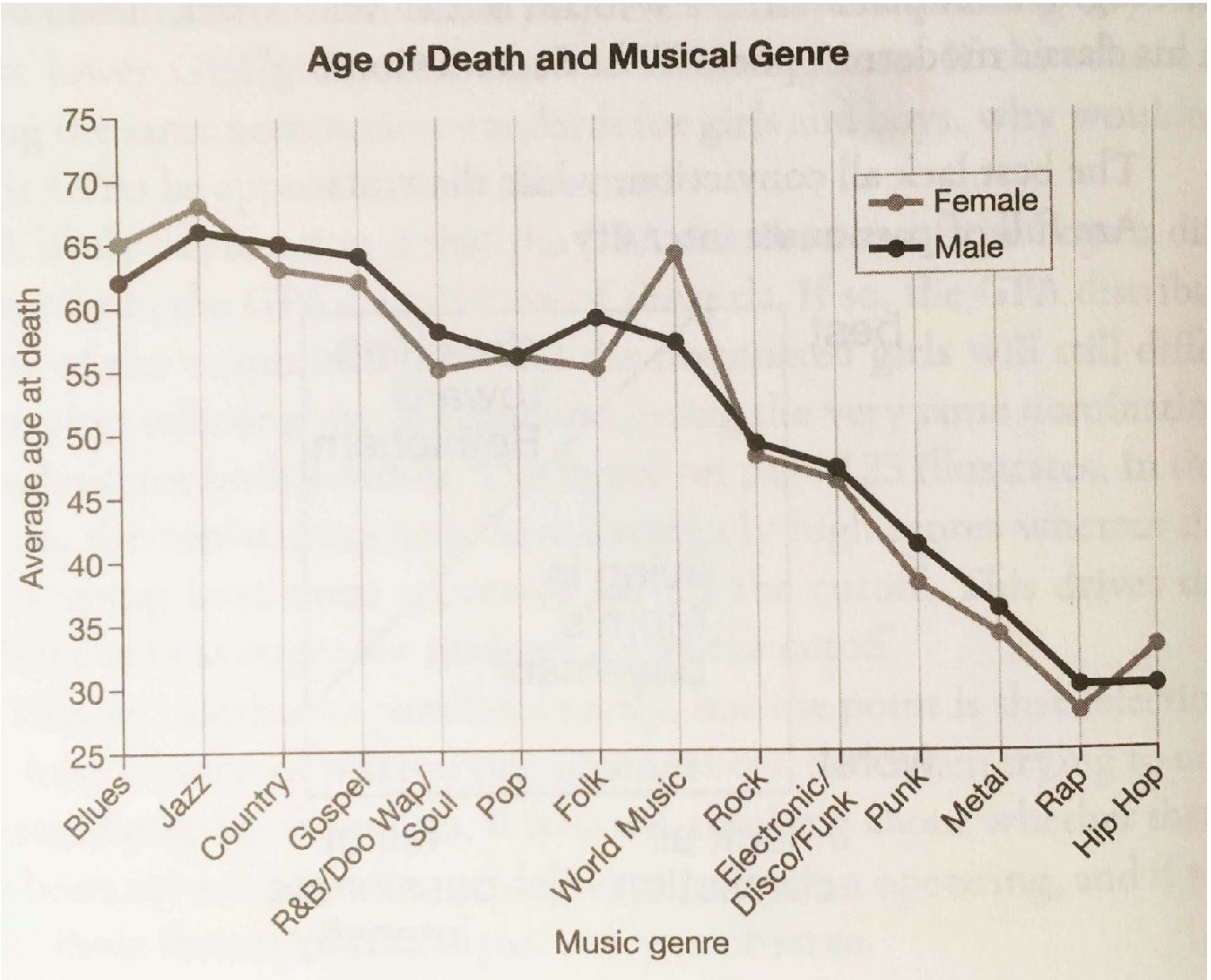
$$Q = A \times \frac{O + S}{W}$$

Q: Quality
A: Appropriateness
O: Outcomes
S: Service
W: Waste

Parameter	Effect on Quality
Appropriateness	+
Outcomes	+
Service	+
Waste	–

All of this is implied by the Quality Equation, but there are many other equations that have the same properties. The formula $Q = S \times \frac{O + A}{W}$ also reflects the qualitative relationship shown in this table, as does $Q = (A + O) \times S - W$. For that matter, so does $Q = \sqrt[W]{A^O + S^O}$. If one is not able to explain why the VMMC Equation is $Q = A \times \frac{O + S}{W}$ and not any of these alternatives, the relationship should not be dignified with an equation in the first place.

Selection bias

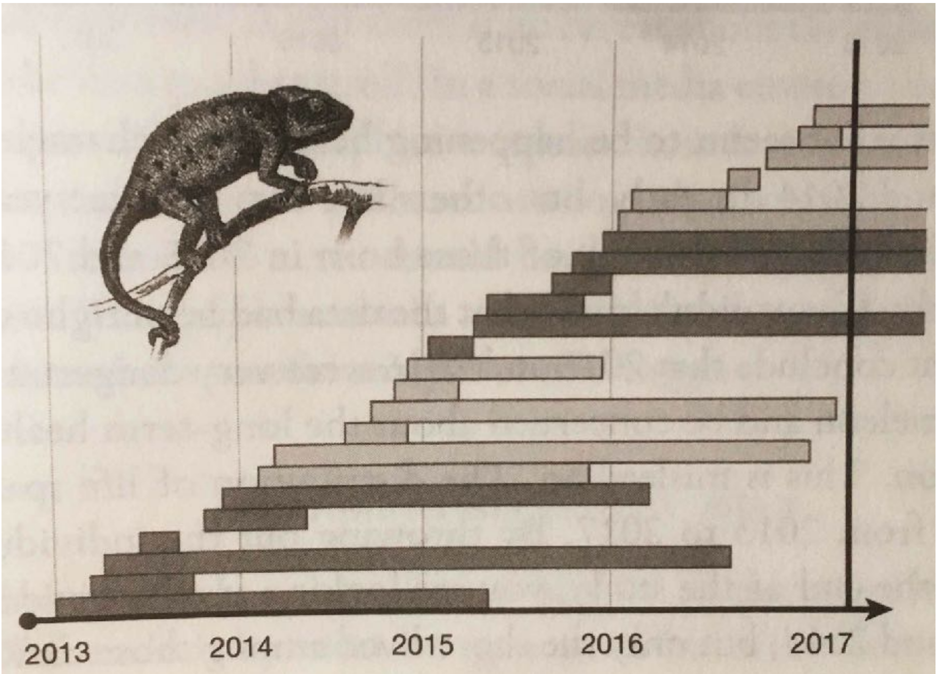


- Is it safer to do jazz than hiphop?

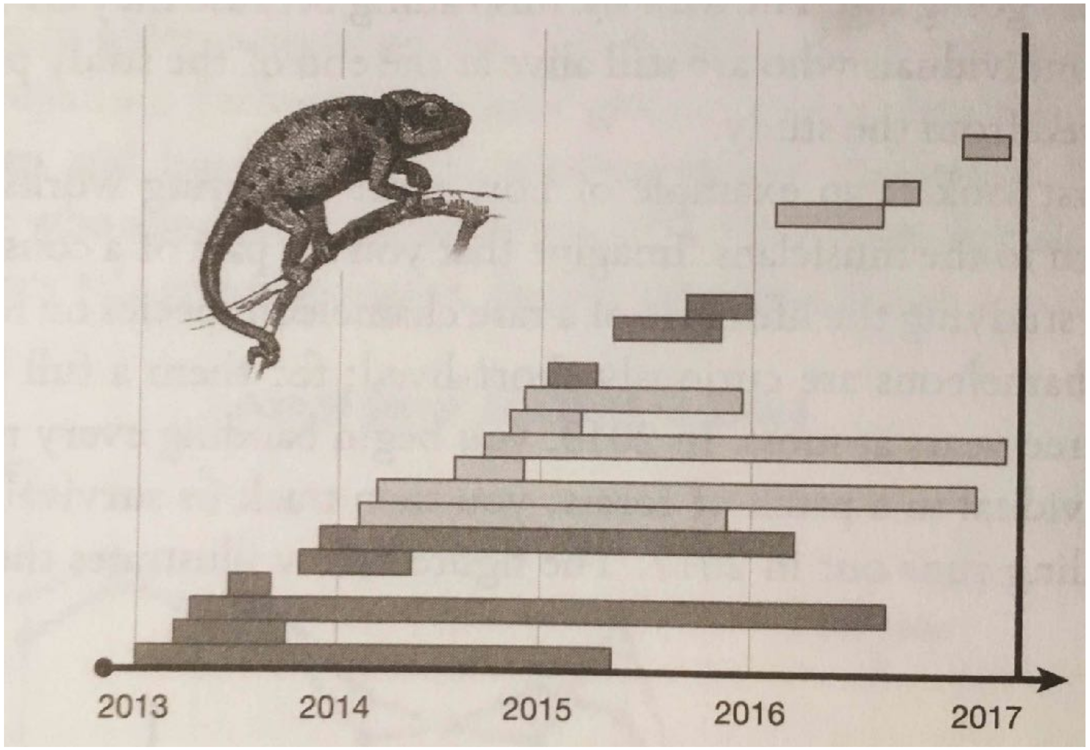
Selection bias

- Taking **data from a non-representative sample**
- "Right-censoring" the data will change the distribution

right-censoring:
neglecting individuals not yet died
before end of study



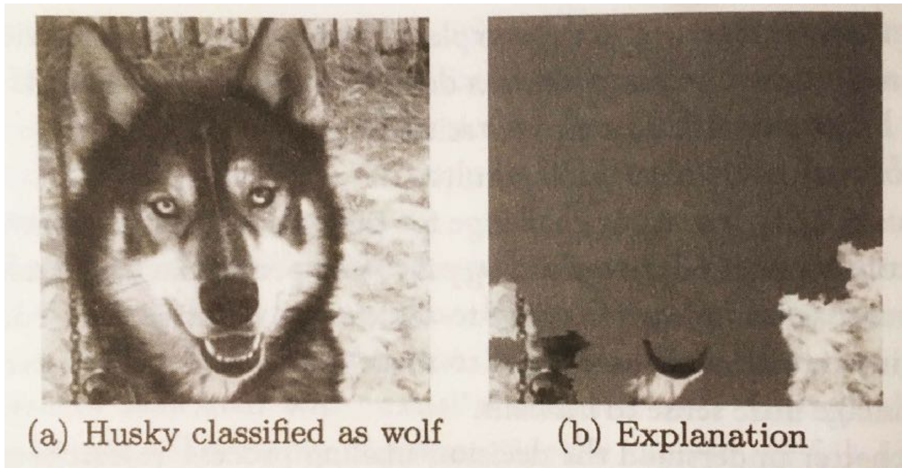
Experimental study about length
of chameleon lifes during 2013-2017



Selection bias in machine learning

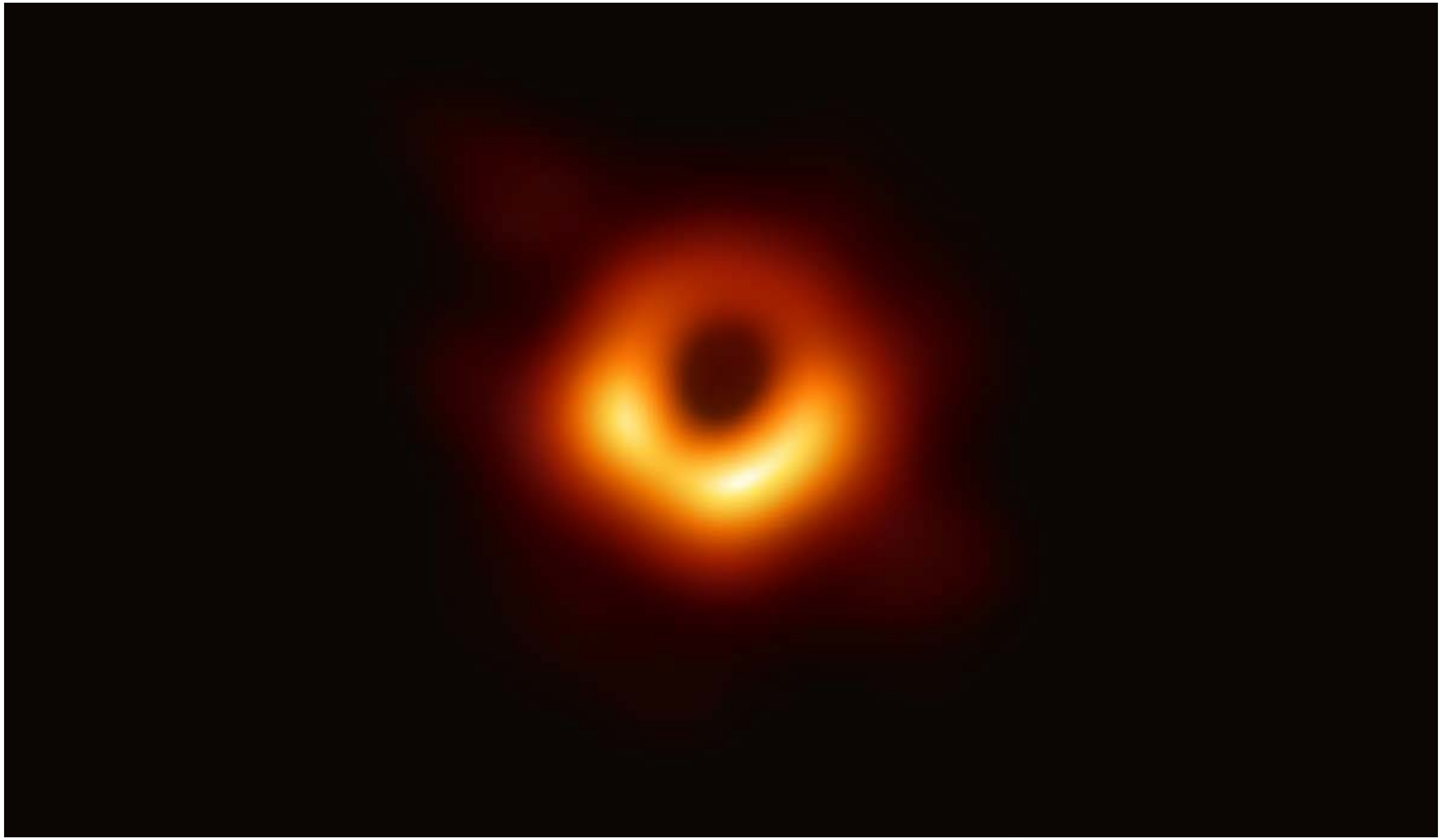
- Can we trust on decisions based on AI algorithms?
- Can we accuse an algorithm for biased results?
  - e.g. classifying dark faces more probably as criminals

- Algorithm **learns** to follow distribution of the **training data**
  - associations in training data are reflected in the results



- Problems with ML
  - non-explainable reasoning
  - over-fitting
  - inadequate training data: "garbage in - garbage out"

"I have a picture to prove it"



Is it a photograph?

Home > News > Science & Astronomy

Eureka! Scientists Photograph a Black Hole for the 1st Time

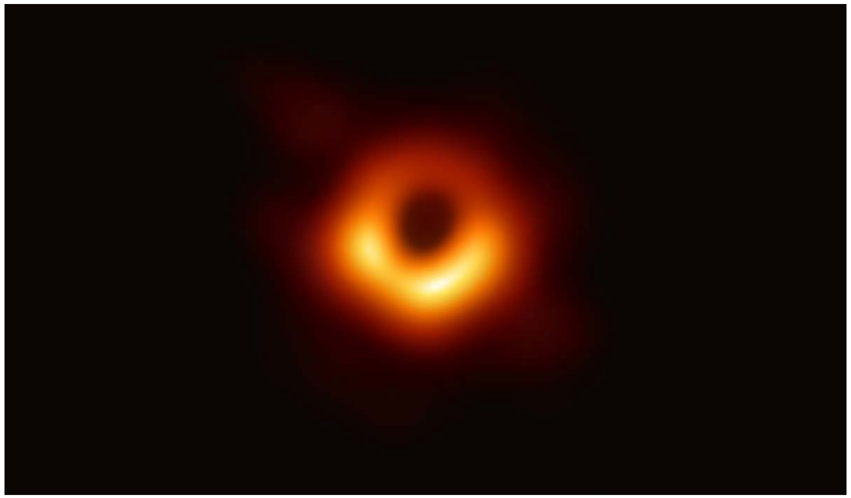
By Mike Wall April 10, 2019

Black holes have finally been dragged out of the shadows.

https://www.space.com/first-black-hole-photo-by-event-horizon-telescope.html

The supermassive black hole at the core of supergiant elliptical galaxy Messier 87, with a mass about 7 billion times that of the Sun,[18] as depicted in the first **false-colour image in radio waves** released by the Event Horizon Telescope (10 April 2019).

https://en.wikipedia.org/wiki/Black_hole



THE END
Thank you!

Give feedback

answer the course feedback survey

survey published automatically to students on
2021-04-09