

# Part 1: Graphical excellence

what is a well-designed presentation

## Graphical excellence

- Graphical excellence is all about the **well-designed** presentation of **interesting** data
  - you need to have good data
  - your (statistical) analysis needs to be solid
  - the plot needs to be well-designed
  - complex ideas communicated with clarity, precision, and efficiency
- Graphical excellence gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space
  - nearly always multivariate, complex data
  - tells the truth about the data
- In summary, graphical excellence is the well-designed presentation of interesting data
  - it is a matter of substance, of statistics, and of design
- Graphical excellence consists of complex ideas communicated with clarity, precision and efficiency or, it should give to the viewer
  - the greatest number of ideas
  - in the shortest time
  - with the least ink
  - in the smallest space

# Goals of visualization

- Presentation (4,000 years)
  - starting point: facts to be presented
  - goal: visualization which makes the facts apparent
  - “You do not really understand something unless you can explain it to your grandmother.” (Albert Einstein ?)
- Confirmative analysis (200 years)
  - starting point: hypothesis about the data
  - goal: confirmation or rejection of the hypothesis
- Explorative analysis ( $\approx$  20 years)
  - starting point: no hypothesis about the data
  - goal: hypothesis about the data

# History of data graphics

- History of graphics
  - maps, time series, narratives of space and time, abstract graphics
- These illustrations serve multiple purposes
  - providing a set of high-quality graphics
  - helping to demonstrate the terminology
  - telling about the history of graphical development
  - seeing how good statistical graphics can be
  - understanding that visual designs that we take for granted sometimes took even thousands of years (!) to be perfected

Lecture 2: Graphical practice

Mar 2, 2023

# Lying with graphics

- It is easy to lie using visualization
- It is important to know how visual quantities are perceived  
(even "technically correct" visualization can be misleading)



## Graphical integrity

- Much of the (first half of) 20th century focused on the question of how charts might fool a viewer
  - the use of graphics for serious data analysis was largely ignored
- Data graphics were meant only for showing the obvious to the ignorant, which led to two fruitless paths
  - the graphics had to be alive, communicatively dynamic, overdecorated, and exaggerated (otherwise, the dullards would fall asleep)
  - the main task of graphical analysis was to detect and denounce deception (because the dullards could not protect themselves)

### Lie Factor

# Lie factor

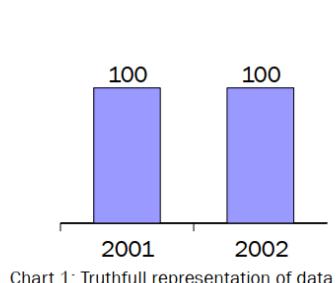


Chart 1: Truthfull representation of data



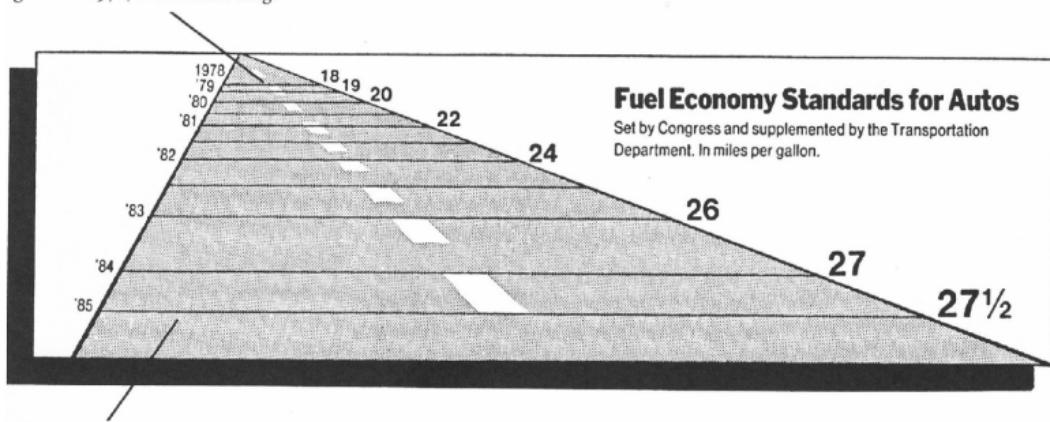
Circulation of periodicals 2003

lie factor =  $\frac{\text{size of effect shown in graphic}}{\text{actual effect in data}}$

## Example: fuel economy standards (1978)

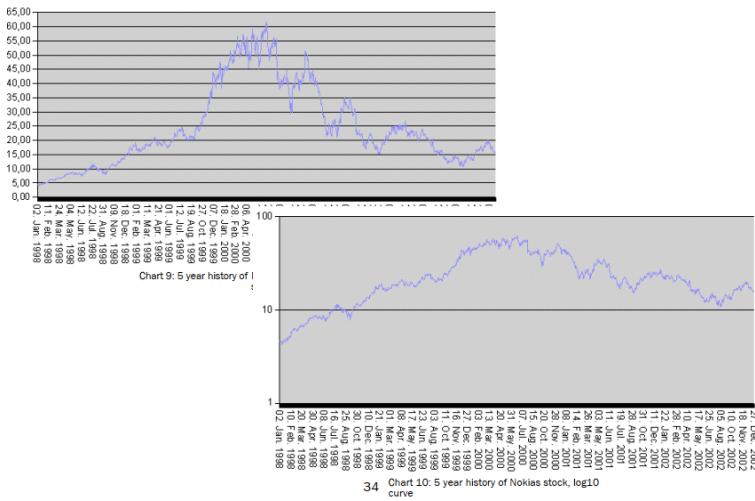
- from 18 mpg (1978) to 27.5 mpg (1985)
- $(27.5-18)/18 = 53\%$  increase in data
- $(5.3-0.6)/0.6 = 783\%$  increase in (perceived?) length
- Lie factor =  $783\% / 53\% = 14.8$

This line, representing 18 miles per gallon in 1978, is 0.6 inches long.



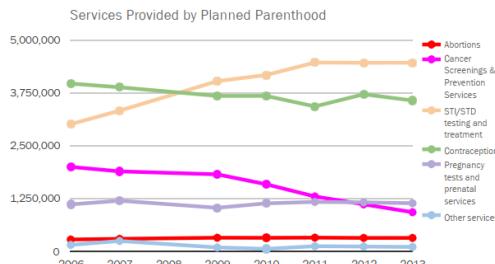
This line, representing 27.5 miles per gallon in 1985, is 5.3 inches long.

# manipulating the axis

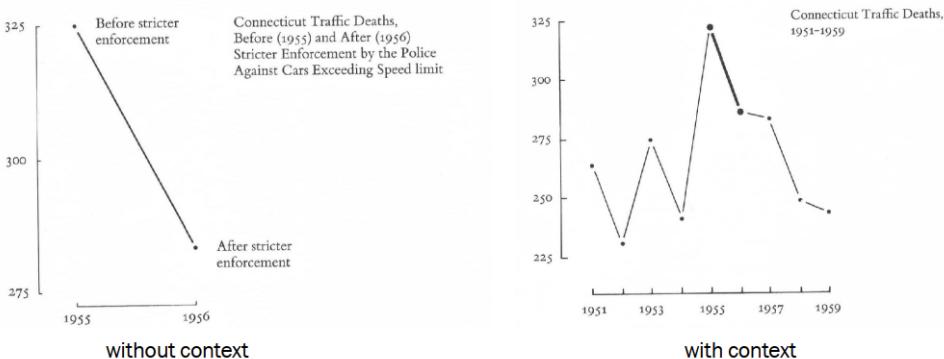


## Example: Planned Parenthood

- same y-axis for all lines
- Missing intermediate points added
- additional context from other spending



## Context matters



# Theory of data graphics

Basic principle:

- Give the viewer the greatest number of ideas (or, most complete understanding)
- ... in the shortest time
- ... using the least amount of ink

By:

- Not wasting space
- Eliminating non-essentials and redundancies
- Making the graphics as easy to read and as simple as possible, while displaying the data fully.

## Tufte's Principles

- Data-ink
- Chartjunk
- Multifunctioning graphical elements
- Data density and small multiples
- Aesthetics and techniques

Data-ink

Chartjunk

Multifunctioning graphical elements

Data density and small multiples

Aesthetics and techniques

<https://medium.com/nightingale/improve-your-visualization-skills-using-tuftes-principles-of-graphical-design-3a0f40a53a2c>

Let us first discuss the reasons for graphical distortions. Tufte explains three different doctrines of inferior graphical work.

**Lack of Quantitative Skills of Professional Artists:** Illustrators having no experience with little experience in statistics often lack competency in analyzing quantitative evidence. They often perceive charts and graphs as “create, concept, and style” rather than aiming to capture the essence of the data. This leads them to focus on “beautifying data” that compromises “statistical integrity”.

**The Doctrine that Statistical Data is Boring:** Designers of inept graphics often treat statistics as “boring” and “tedious”. Because of this misconception, they often unnecessarily inflate the

evidence present in their datasets with decorative styles. Tufte mentioned in his book that the doctrine of boring data also serves political ends to promote certain interests over others (page 80).

**The Doctrine that Graphics are Only for the Unsophisticated Readers:** Illustrators who believe in this doctrine think that readers are not sophisticated enough to understand the complexity of words in the text. This leads them to unnecessarily beautify and animate their graphs to entertain their readers.

## Data-ink

# Data-ink

- Data consists of empty space (white paper) and ink
- Data-ink is the non-erasable and non-redundant core of graphics. Erasing data-ink would reduce the amount of information transmitted by the graphics

$$\text{Data-ink ratio} = \frac{\text{Data-ink}}{\text{Total ink used to print the graphics}}$$

# Maximize data-ink

- It is always a good idea to maximize the data-ink ratio, within reason
- The larger the share of data-ink the better, other matters being equal
  - every bit of ink on a graphic needs a reason
  - nearly always that reason being that the ink presents new information
- Ink that fails to depict statistical information is uninteresting, and often it is also dull

- To increase the proportion of data-ink use two erasing principles
  - erase non data-ink
  - erase redundant data-ink
- Non data-ink is ink that fails to depict information, it has little interest to the viewer
  - sometimes, such non-data-ink clutters up the data
  - sometimes, such non-data-ink helps set the stage
- Redundant data-ink depicts information but it does it showing it over and over

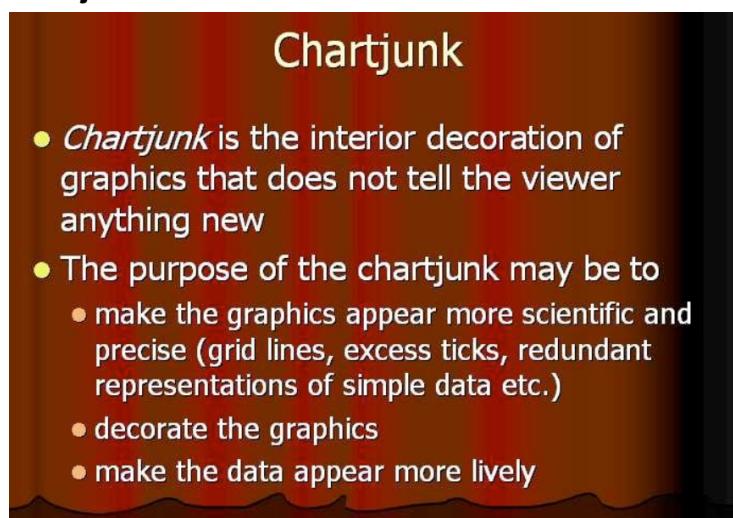
## Lecture 3: Theory of data graphics

Mar 6, 2023

# The five data-ink principles

- Above all **show the data**
- The larger the share of data-ink, the better (all other things being equal): **Maximize the data-ink ratio**, within reason.
- Maximizing the data-ink ratio implies minimizing the amount of non-data ink:
  - **Erase non-data-ink**, within reason.
  - **Erase redundant data-ink**.
- **Revise and edit.**

## Chartjunk



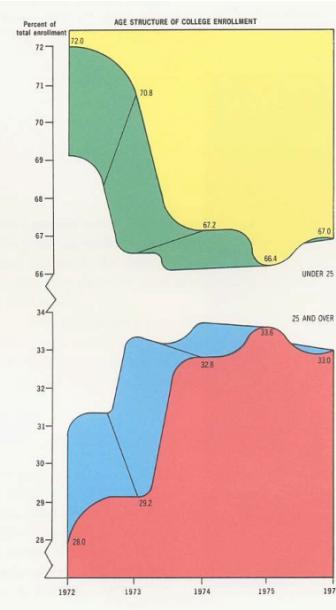
- Ducks (eye candy and self-promoting graphics)
- Vibrations
- Grids

## Self-promoting graphics

The graphics becomes self-promoting when the graphical style takes precedence over data.

American education [T 118].

The above chart could have been represented by a table of five numbers.



44

## Visual stress (vibrations)

- Striped patterns cause visual stress in most people.
- The following combination is most potent:

- about 3 cycles per degree
- flicker rate of about 20 Hz
- large patterns



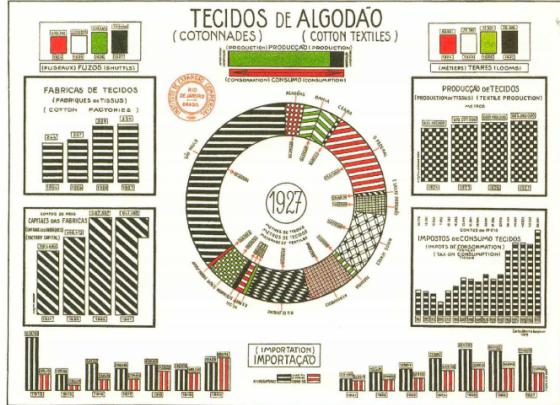
op-art by  
Bridget Riley



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# Moiré effects

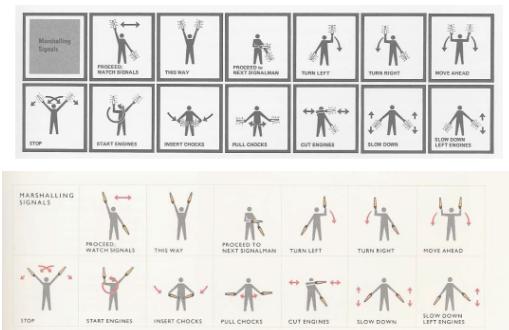
The vibrations caused by repeating lines and optical effects are called Moiré effects.



Instituto de Expansão Commercial, Brazil, 1929 [T 108].

## Grid lines

The grid dominates the graphics. The font is disproportionately weak as compared to the grid. Optical dark spots appear at the intersection of the white grid lines. Redrawing fixes this. The information content is further emphasized by conservative use of color.

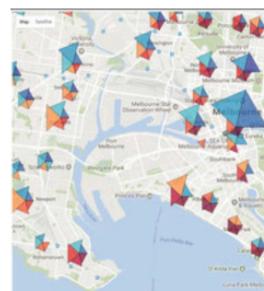


## Multifunctioning graphical elements

# Multifunctioning graphical elements

- A single multifunctioning graphical element can effectively display complex, multivariate data
- Example: a blob on the map specifies not only the geographic coordinates, but also shape of the feature and other properties are specified by color and shading
- Multifunctioning graphical elements will create puzzles, if applied wrongly

glyphs on a map

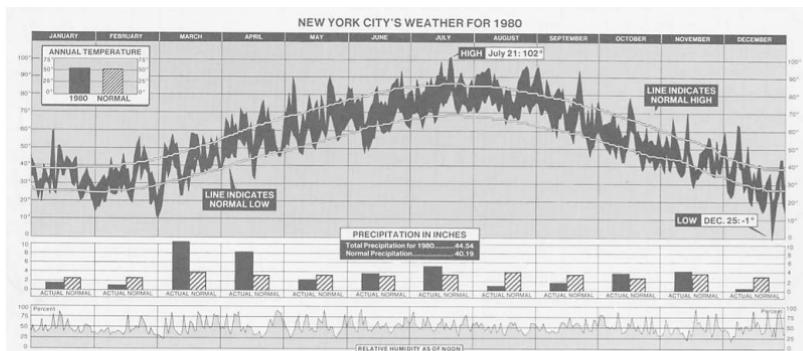


## Data density and small multiples

- In computer graphics, the resolution may be lower due to limitations in hardware (typical monitor at typical distances has a resolution of about 40 cycles per degree, 150 cycles per degree would be optimal)

$$\text{Data density} = \frac{\text{Number of entries in data matrix}}{\text{Area of graphics}}$$

## High data density

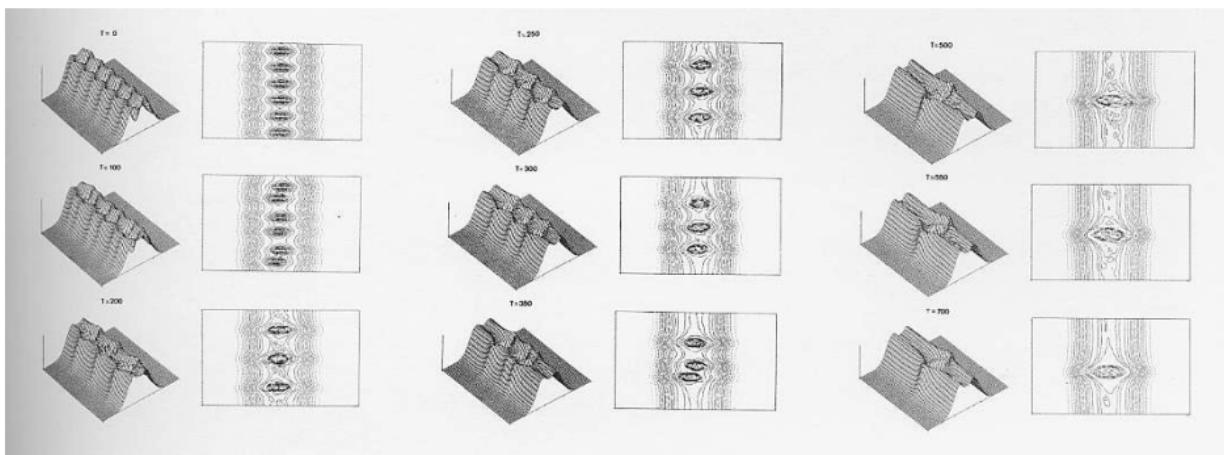


New York Times, 11 January 1981 [T 30].

Data density = 28 numbers per cm<sup>2</sup>.

# Using small multiples to make comparisons

- Comparisons must be positioned within the eye-span for the viewer to make comparisons at glance
  - Show changes in data, not in design.



# Graphs and tables

- The data can be shown in
    - sentences,
    - tables or
    - graphics.
  - Tables are the best choice only for presenting for a small collection of numbers

Some Winners and Losers in the Forecasting Game			
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Data Resources: +6.7%			Wharton Economics: Forecasting: 0.0%
Nat. Assn. of Business Economics: +4.5%			Conference Board: 0.7%
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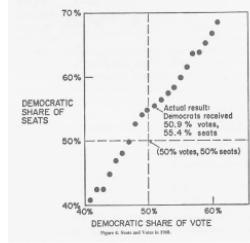
New York Times, 2 January 1979 [T 180]

Nearly 53 % of group A did something compared to 46 % of group B and 57 % of C.	Same using a table:	Better(?) order:												
	<table border="1"> <tr> <td>Group A</td><td>53 %</td></tr> <tr> <td>Group B</td><td>46 %</td></tr> <tr> <td>Group C</td><td>57 %</td></tr> </table>	Group A	53 %	Group B	46 %	Group C	57 %	<table border="1"> <tr> <td>Group B</td><td>46 %</td></tr> <tr> <td>Group A</td><td>53 %</td></tr> <tr> <td>Group C</td><td>57 %</td></tr> </table>	Group B	46 %	Group A	53 %	Group C	57 %
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## Aesthetics and techniques

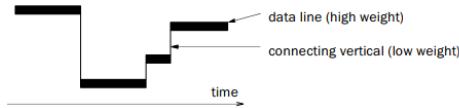
# Line weight and lettering

The weights of the letters should be in proportion to the other visual elements:



E. R. Tufte, 1973 [T 184].

The heavier weight should be given to data measures:

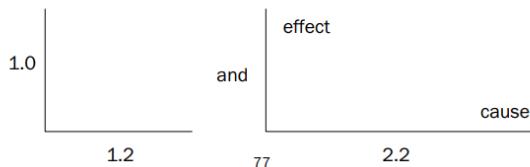


# Proportion of graphics

Graphics should usually have greater length than height:

- Our eye is practiced in detecting deviations from the horizon. Thus, e.g., horizontal time-series are easier to read.
- It is easier to write words and labels horizontally.
- Longer horizontal helps to emphasize the causal variable

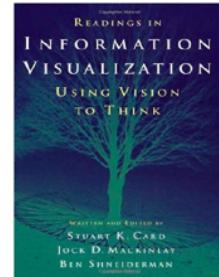
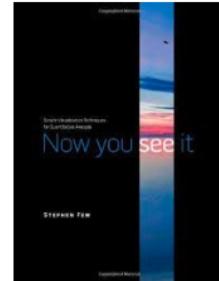
Preferred height/length ratios vary depending on the circumstances; the golden ratio 1:1.618 is a good rule of thumb.



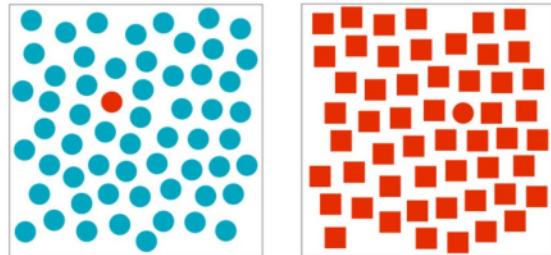
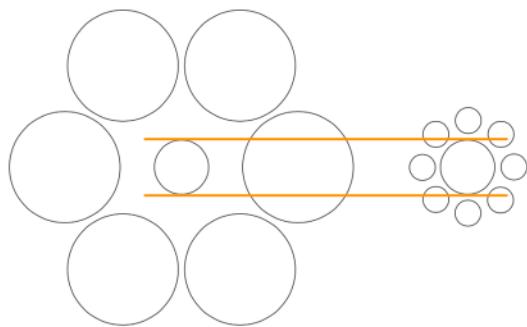
# Presenting statistics: Outline

- Techniques:
  - Bars, boxes, lines, dots
  - multiple plots
  - reference lines and regions
  - rescaling /normalising / re-expressing
  - colors
- Problems:
  - axis ranges
  - use of 3D
  - overplotting
- Scenarios:
  - distribution analysis
  - ranking and part-of-whole analysis
  - time-series
  - high-dimensional data
- Related reading: Few. *Now you see it*. Analytic Press, 2009.
- Older but relevant: Card et al. *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann, 1999.

3



Lecture 5: Human perception  
Mar 13, 2023

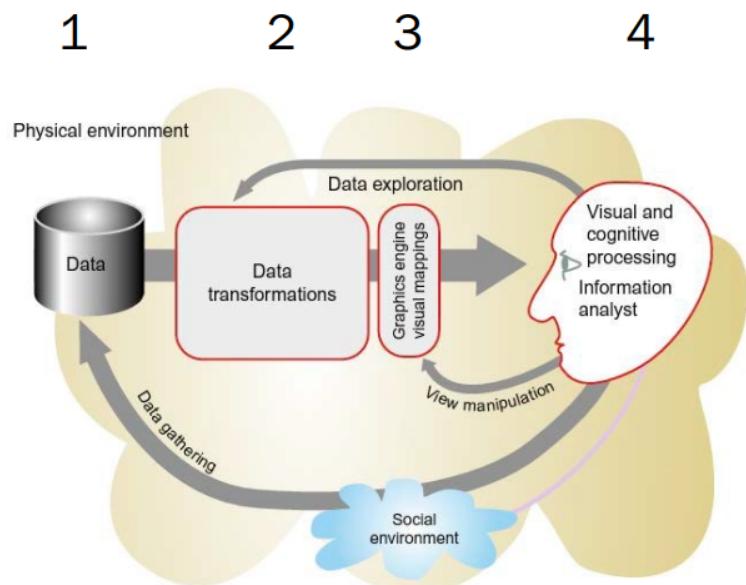


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mttaer waht oreder the ltteers in  
a wrod are, the olny ...

**good**

## The visualization process

1. Data collection and storage
2. Data pre-processing (e.g., data reduction to reveal certain aspects)
3. Selected data mapped into visual representation
4. Human perceptual and cognitive system

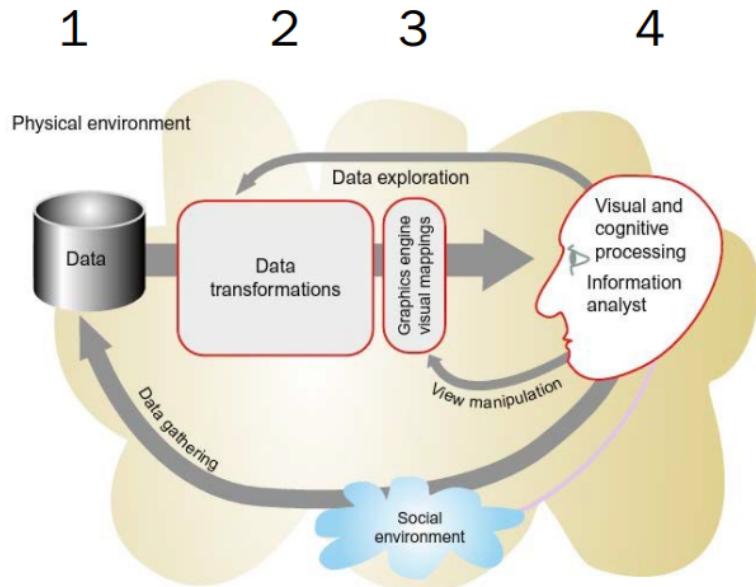


# The visualization process

Thus, in visualization it is important to

encode the data into a visual representation that the human user can easily and correctly understand for timely and optimal decision-making

But, how can we do this best?



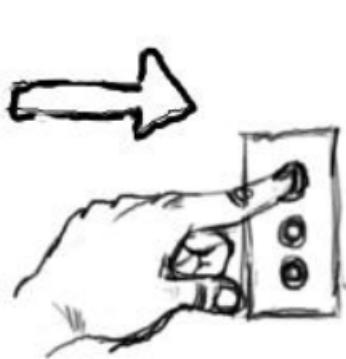
## Sensory vs. arbitrary symbols

- sensory symbols
  - understandable without learning
  - processing is hard-wired and fast
  - resistant to instructional bias
  - cross-cultural
- arbitrary symbols
  - hard to learn and easy to forget (except when overlearned)
  - formally powerful
  - capable of rapid change
  - culture-specific

Gibson Affordance Theory

# Gibson's affordance theory

- We perceive to operate in the environment
- We do not perceive points of light but
  - we perceive possibilities for action in the environment, known as affordances
  - e.g., an open terrain affords walking; a stone on the ground affords tripping while walking
- We perceive affordances directly by the visual system as a whole and
  - not indirectly by the different components and operations in the visual system, as the visual system resonates to respond to properties of the environment
- Influential theory, but it is not to be taken too literally unless we ignore years of vision research (e.g., what we know about colors)



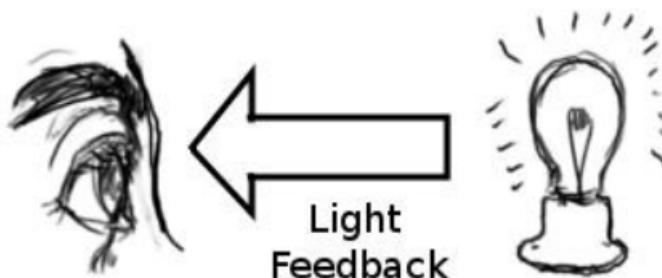
Button - Push



Switch - Flip



Knob - Rotate



# Optics

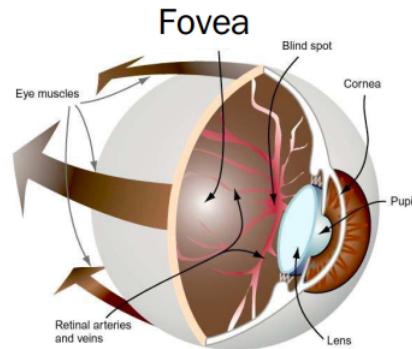
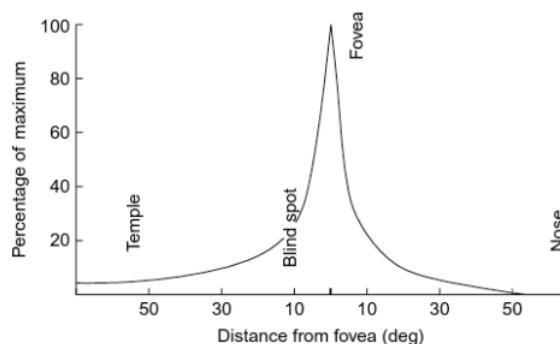
Do not use pure blue text on a black background as the text would be almost unreadable...

...especially if there is white or red nearby to attract the focusing mechanism.

- Do not use pure blue text on a black background, as the text would be almost unreadable
  - especially if there is white or red text nearby to attract the focusing mechanism
- Add red and green to pure blue to alleviate the problem
  - red and green add luminance and so help to perceptually define the colour boundary

## Visual acuities

# Visual acuities



- Visual acuities are measurements of our ability to see detail
  - indicating limits on the information densities, we can perceive
- Acuity is at maximum at the center of the fovea
- Acuity outside of the fovea drops rapidly
  - we can only resolve about 1/10 of the details at 10° from the fovea

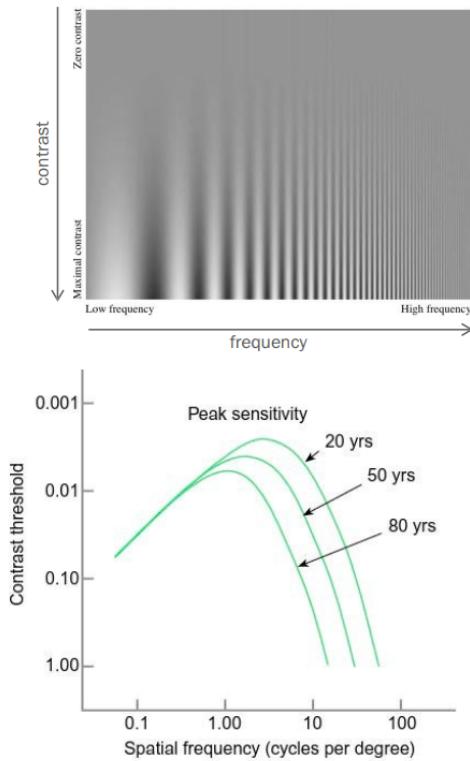
- point acuity ( $1'$ )  
the ability to resolve two distinct point targets

 grating acuity( $1\text{-}2''$ )  
the ability to distinguish a pattern of bright and dark bars  
from a uniform gray patch

 letter acuity ( $5'$ )  
the ability to resolve letters

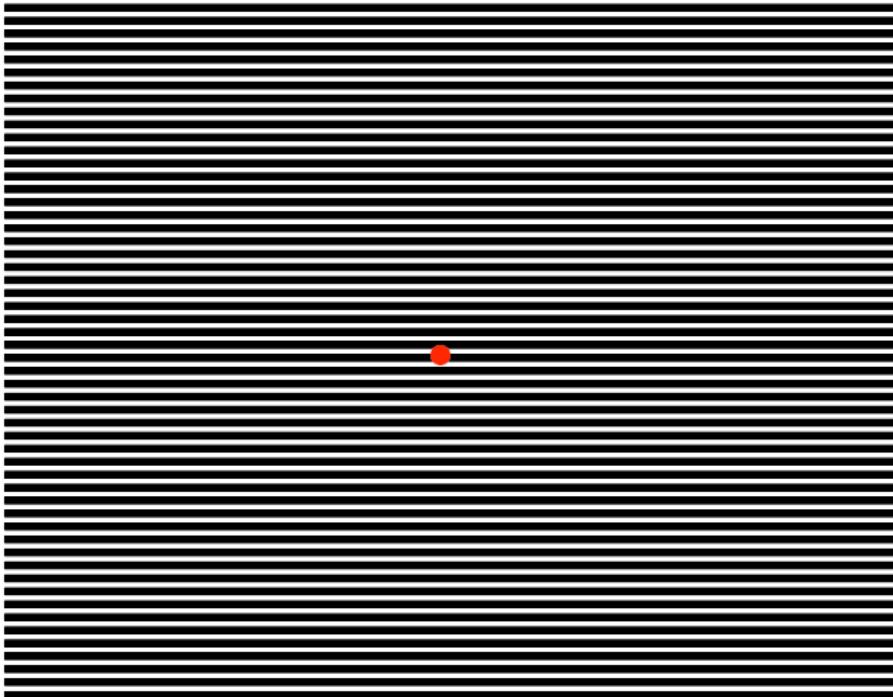
## Contrast sensitivity

- Contrast sensitivity is lowest at high frequencies (zero sensitivity at  $1'$  for young people)
- Lower contrasts can be seen at frequencies of around  $1^\circ$
- Highest contrast sensitivity at about  $20\text{-}30'$  (3-5 cycles/deg)
- Contrast sensitivity falls with age (become less sensitive to patterns below  $1^\circ$ )



# Visual stress

- Striped patterns and flicker cause visual stress
  - most people find them extremely stressful to look at
- Striped patterns and flicker can induce epileptic seizures in susceptible individuals (pattern-induced epilepsy)
- The most potent combination of spatial and temporal frequencies are striped patterns having:
  - spatial frequency of 20'
  - temporal frequency of 20 Hz
  - large overall pattern
- Example on next slide: stop looking at it if you feel ill!

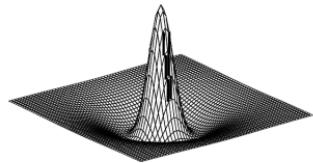


## Difference OF Gaussian (DoG)

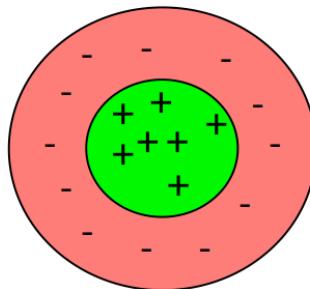
# Difference of Gaussians

- Retinal ganglion cells are organized with circular receptive fields
- When light falls at the center of the receptive field, it emits pulses at increased rate (excitation) 
- When light falls off the center of the receptive field, it emits pulses at a lower rate (lateral inhibition) 
- The receptive fields can be modeled with Difference of Gaussians (DOG) model

$$\text{Response} = K_e e^{-\left(\frac{2r}{a}\right)^2} - K_i e^{-\left(\frac{2r}{b}\right)^2}$$

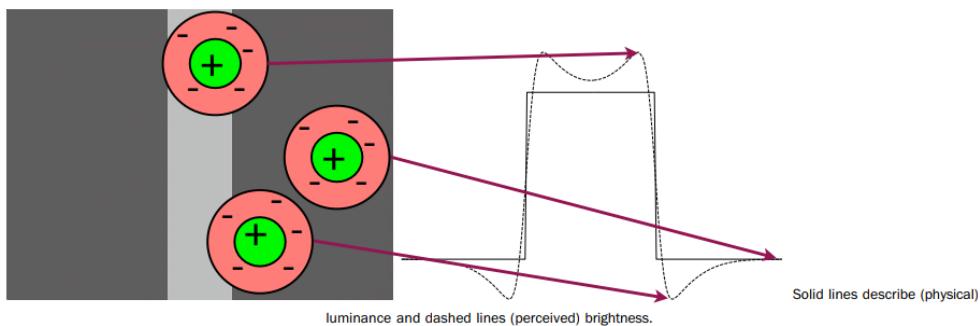


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- The DOG model can be used to explain the difference between *physical luminance* and *perceived brightness*
- Discontinuous lightness profiles generate dark and light bands near the discontinuities (*Chevreul illusion*)
- *Mach bands* appear if there are discontinuities in the first derivative of the lightness profile
- A gray patch placed on a dark background looks brighter than the same patch on a light background

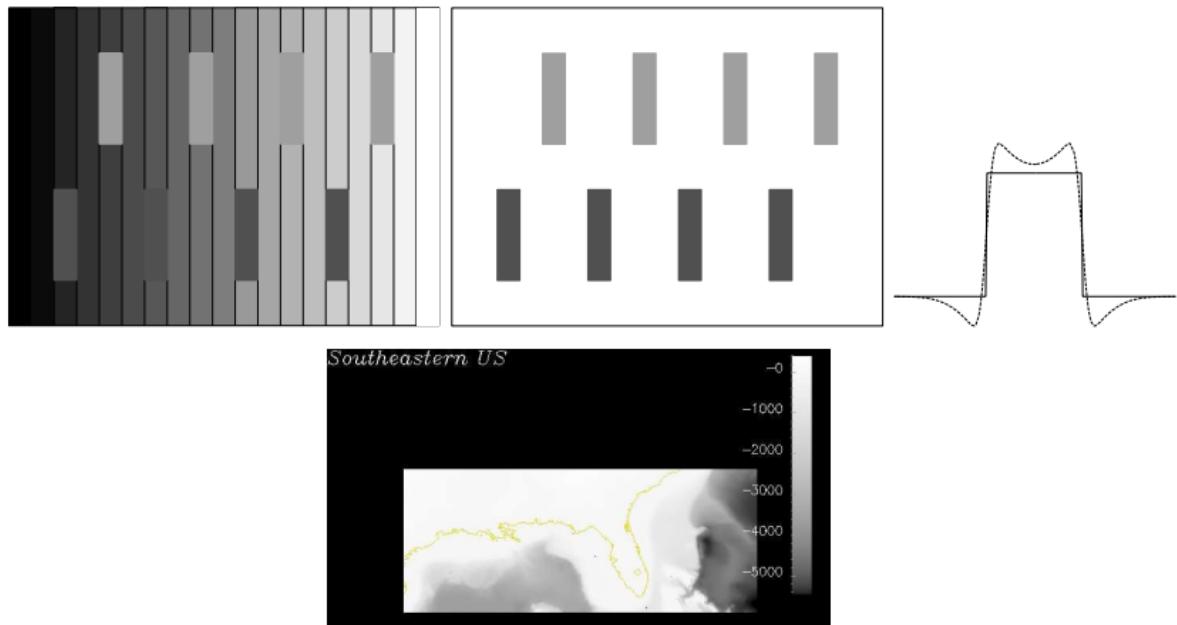
Discontinuous lightness profiles generate dark and light bands near the discontinuities (*Chevreul illusion*)



Simultaneous brightness contrast

## Simultaneous brightness contrast

A gray patch placed on a dark background looks brighter than the same patch on a light background.



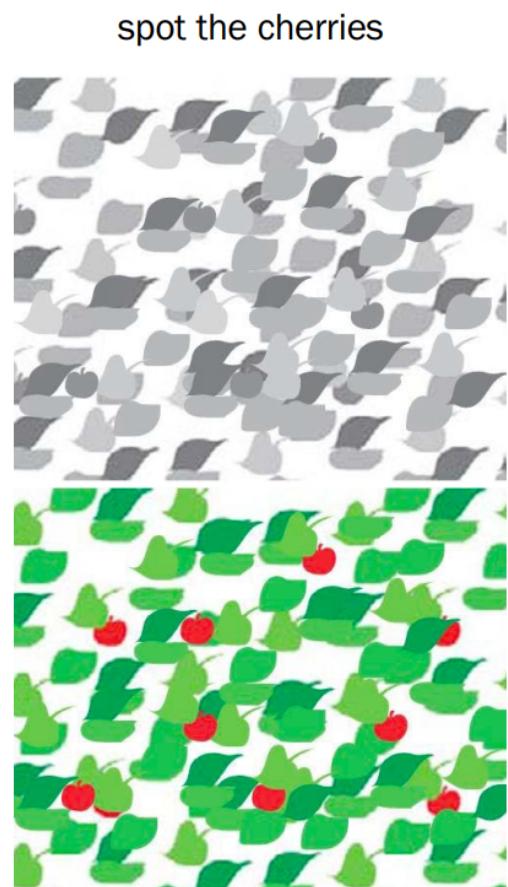
Lecture 6: Colors

Mar 16, 2023

- Human visual system is adapted to illumination levels of six orders of magnitude. The absolute illumination levels are essentially ignored.
- The lightness perception is extremely relative.
  - ...due to adaptation & lateral inhibition
  - physical luminance and perceived brightness can be quite different
- Some design principles:
  - gray scale is bad at encoding absolute values, good at encoding relative values and shapes
  - if outline of the shapes of objects is important:
    - background should have maximal contrast with foreground objects
  - if it is important to see variations in grayscale:
    - background should have minimal contrast with foreground objects

## Why colors?

- Color breaks camouflage
  - some things differ visually from their surroundings only by their color
  - e.g., with color we can easily see the cherries hidden in the leaves
- Color tells us about material properties of objects
  - e.g., which fruit are ripe? Which food has gone bad?
- Color is an attribute of an object that helps us distinguish it from others
  - good for labelling and categorising, but poor for displaying shape, detail or spatial layout

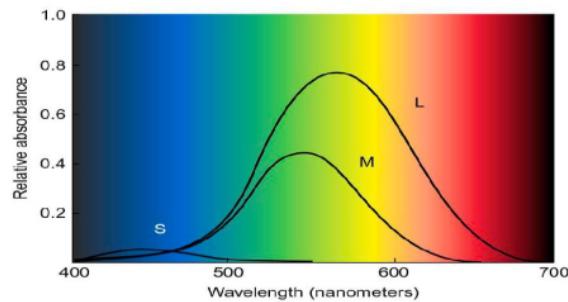
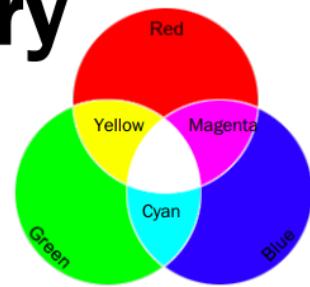


# Color in visualisation

- One of the most (academically) studied topics
- Practical implications in visualisation:
  - basics of color perception
  - opponent process theory
  - two chromatic channels (red-green & yellow-blue) and luminance channel (color is a 2D thing!)
  - how to design color scales to encode information
    - only limited number of identifiable colors
    - perceived difference of colors
  - contrast effects etc. apply also in color perception
  - no physical device can reproduce all perceived colors (gamut)

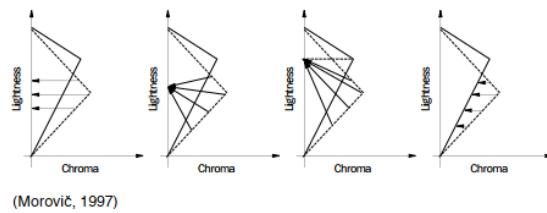
# Trichromacy theory

- The human eye has 3 distinct color receptors, called cones (chicken have 12!)
  - Red (sensitive to long-wavelength light) L
  - Green (sensitive to medium-wavelength light) M
  - Blue (sensitive to short-wavelength light) S
- Red, green, blue = primary colors of light (light primaries, additive primaries)
- Cyan, magenta, yellow = secondary colors (light secondaries, subtractive primaries),
  - produced as equal mixtures of two additive primaries
  - print: absorbing a primary color from white
- Human color vision is fundamentally 3-dimensional
  - color space is an arrangement of colors in a 3d space and
  - any color we perceive can be represented as a mixture of the 3 primaries



# Gamut

- Any physical device with finite number of primary colors can present only a subset of perceivable colors
- Gamut = set of colors that a device can reproduce
- Gamut mapping is needed for devices with different gamuts



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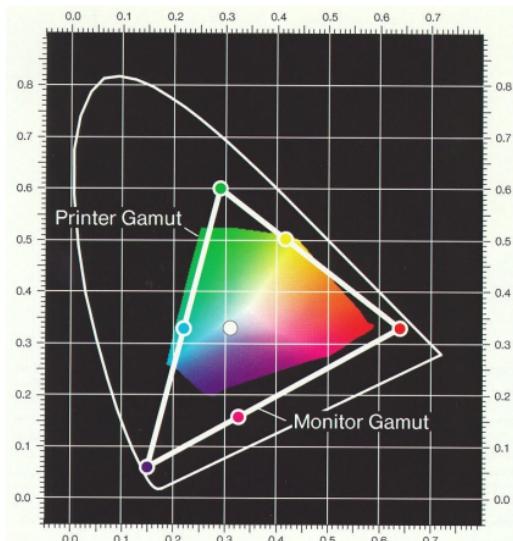
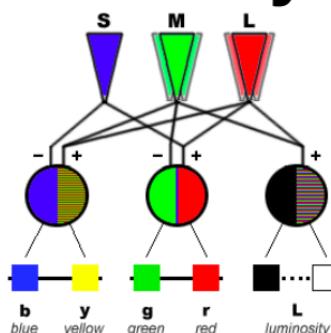
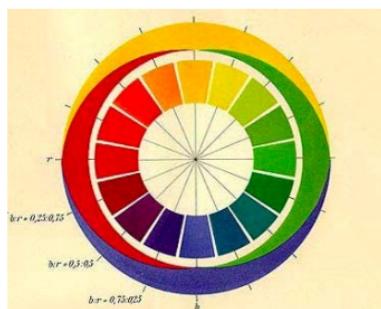


Fig. 8. Gamuts of the Cromalin proof and a typical color monitor overlaid on the CIE chromaticity diagram. The horseshoe shaped plot is the spectrum locus; that is, its interior contains all observable colors represented as chromaticity coordinates.

Stone et al. Color Gamut Mapping and the Printing of Digital Color Images. ACM Transactions on Graphics, 7(4): 249-292, 1988.

## Opponent color theory

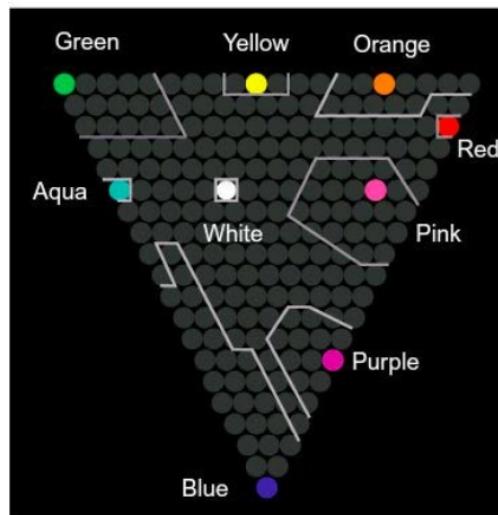
# Opponent color theory



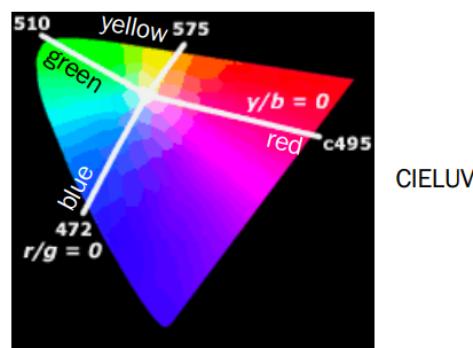
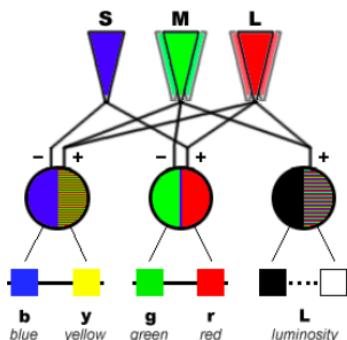
<https://www.handprint.com/HP/WCL/color2.html>

- There are 6 elementary colors. These colors are arranged perceptually as opponent pairs along 3 axes (Hering 1920):
  - black-white, red-green, and yellow-blue
  - Cone signals are transformed into 3 distinct channels:
    - black-white (luminance), red-green, and yellow-blue
- Theory predicts that people will never use “reddish green” or “yellowish blue”
- People tend to divide colors to a few basic categories
- The closer the color is to the “pure color”, the easier it is to remember

- People tend to divide colors to a few basic categories
- The closer the color is to the “pure color”, the easier it is to remember
- The results of an experiment in which subjects were asked to name 210 colors produced on a computer monitor.
- Outlined regions show the colors that were given the same name with over 75% reliability



## Color blindness



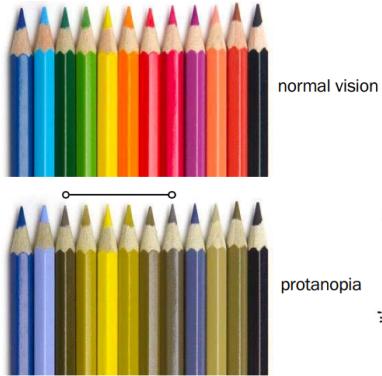
- c. 8% of males and c. 0.5% of females suffer from pure dichromacy or anomalous trichromacy
- The most common form is to have the light response of M (green) and/or L (red) cones to shift toward the other, which reduces range of trichromatic perception and can have variable effects on color vision (anomalous trichromacy)
- [Errata: minor adjustments to prevalence percentages in slides 37-41 pursuant to <https://www.ncbi.nlm.nih.gov/books/NBK11538/> ]

<https://www.handprint.com/HP/WCL/color2.html>

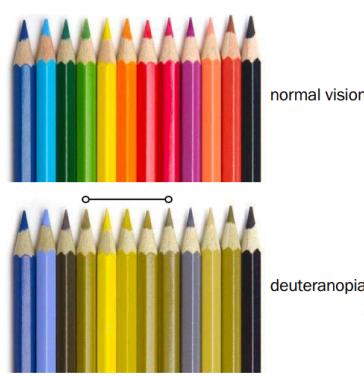
19

- Pure dichromacy is due to lack of one type of cones
  - L (long-wave, red)  
→ protanopia
  - M (mid-wave, green)  
→ deutanopia, or
  - S (short-wave, blue)  
→ tritanopia

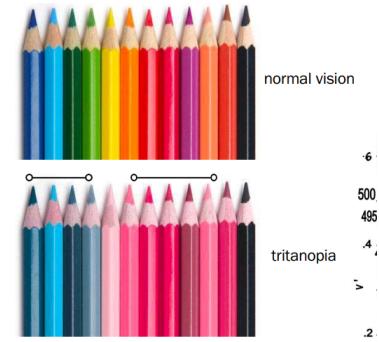
red-green confusion  
blue-yellow confusion



- Protanopia, lack of **L cones**
- ~ 1% males and ~ 0.01% females
- cannot distinguish red from green

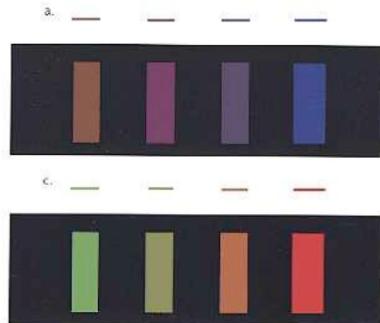


- Deutanopia, lack of **M cones**
- ~ 1.5% males and c. 0.01% females
- cannot distinguish red from green



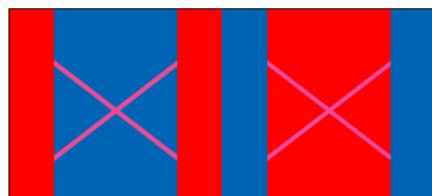
- Tritanopia, lack of **S cones**
- Less than 0.01%
- cannot distinguish blue from green, yellow from violet

## Small field color blindness



- Size of color patches affects the perception of color differences
- For very small patches inability to distinguish color differences occurs (small field color blindness)

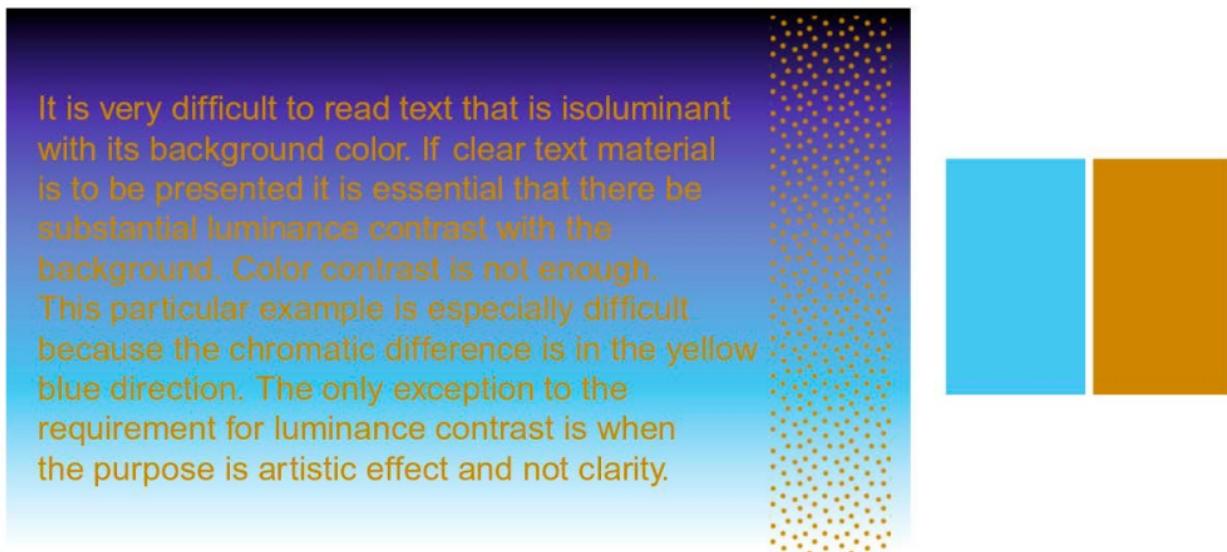
## Color contrast



- The Xs are of the same color on both sides, but they are perceived differently depending on the background
- Chromatic contrast can distort reading from color-coded maps
- Message: relative color is often more important than absolute color (as with grayscale!)

# Color vs. luminance

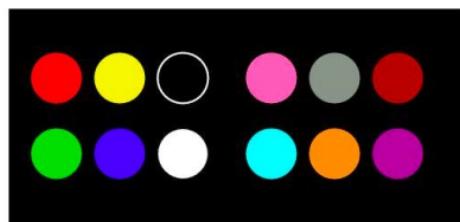
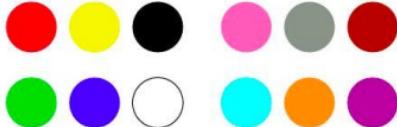
- Color channels have less spatial resolution than luminance channel
- Perception of shape or motion is due to mainly luminance channel
- Color channels are therefore better for labelling than data values



## Color for labelling

# Color for labelling

- For nominal data (e.g., colored symbols represent companies from different sectors) ensure the following when choosing colors for labels:
  - distinctness
  - unique hues
  - contrast with background
  - color blindness (avoid red-green distinctions)
  - number (5-10 colors can be rapidly distinguished)
  - field size
  - convention (in west: red = danger, hot; green = good, go, etc)



# Color scales

- Some differences are not perceived by color blind (avoid red-green channel!)
  - Perceptually ordered channels are in general formed from the six color opponent channels. Other ordering include cold-hot, dark-light.
  - Level of detail: luminance (e.g., grayscale) shows highest level of detail.
  - Perceptually constant steps: Uniform color spaces (e.g., CIELUV) can be used to construct scales with perceptually constant steps
  - Reading values from the scale: minimise contrast effects by cycling through many colors
    - you can even follow a spiral in color space
  - Misclassification of data: color category boundaries may cause misclassification of data
- 
- Spectrum (rainbow) scale
    - perceptually very non-uniform and not ordered
    - can create “false contours”
    - good for reading values back from the a scale
    - should not be used if the shape of the data is important
  - Grayscale
    - not good for reading back values
    - shows detail and shape of the data well



# Color scales

	grayscale	spectrum	
Shows detail	+++	--	?
Perceptually constant steps	++	--	?
Reading values from a scale	--	+	?
Show true shape	+++	--	?
Ordering is shown well	++	--	?
Good for labeling	--	++	?
Color-blind safe	+++	-	?
Shows zero point	--	--	?
...	?	?	?

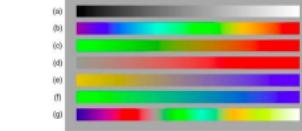
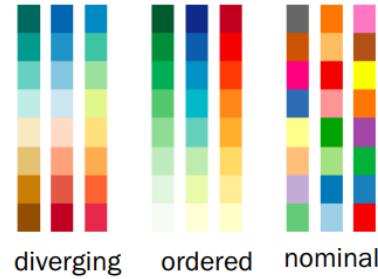


Figure 4.27 Seven different color sequences: (a) Grayscale. (b) Spectrum approximation. (c) Red-green. (d) Saturation. (e, f) Two sequences that will be perceived by people suffering from the most common forms of color blindness. (g) Sequence of colors in which each color is lighter than the previous one.

# Color scales

Some hints on selecting suitable color scale:

- **Nominal** (values have no order):
  - Same as using color for labeling. Colors should be as distinctive as possible.
- **Ordinal sequence** (values have order):
  - Colors should have perceptually the same ordering as the scale. Use luminance channel (if possible) as well as colors.
- **Ratio sequence** (values have order, there is a true zero, and values can be negative)
  - Use diverging sequences: zero has a neutral color (gray or white). Opposite ends use opponent colors.
- **Interval sequence** (difference between two values is what matters)
  - Colors changes should perceptually reflect the differences in the data. The scale should be based on a uniform color space, or clearly defined (discretized) color steps should be used. Adding a contour map is a good option here.
- **Reading the actual value from data is important**
  - Difficult task due to contrast issues. Consider cycling through many colors. Use the luminance channel to indicate order.



## Lecture 7: Human perception, cognitive aspects

### Mar 20, 2023

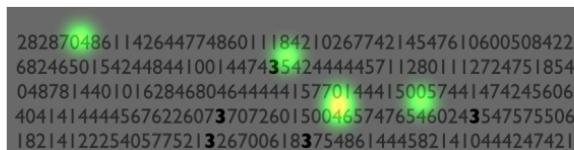
#### Visual channel

## Visual channels

- The previous properties are processed separately, in parallel on different channels,
  - Color, form (orientation and size), motion
- The information expressed in one channel (e.g., the color of a symbol) does not interfere (much) with the information expressed in another channel (e.g., the orientation of a symbol), and properties on different channels (e.g., color and orientation) are visually distinct
- Different visual channels should be used to display aspects of data

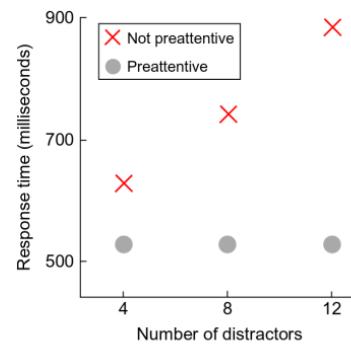
#### Pre-attentiveness

## Pre-attentive processing



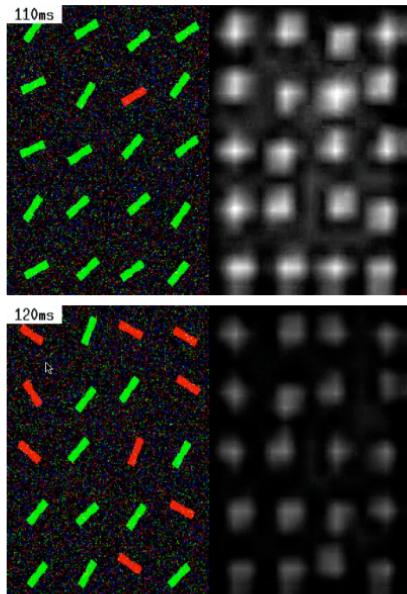
2828704861142644774860111842026774214547610600508422  
6824650154244844100144743542444457112801112724751854  
048781440101628468046444415770144150057441474245606  
40414144445676226073707260150046574765460243547575506  
182141225405775213267006183754861445821410444247421

- Some visual objects are processed pre-attentively, before the conscious attention
- Pre-attentive features "pop out"
- Pre-attentive processing speed is independent of the number of distractors
- Processing speed of non-pre-attentive features is slower and the speed decreases as the number of distractors increases (i.e., you must go through all numbers to find 3s)



## Some of the pre-attentive pop-up explained

- The model reproduces some of the pre-attentive pop-out phenomena (Itti, Koch 2000)
- Search-time of a pop-out task is independent of the number of distractors (pre-attentive search)
- Search-time of conjunction tasks increases linearly with the number of distractors (conjunction searches are usually non-pre-attentive). (Why?)

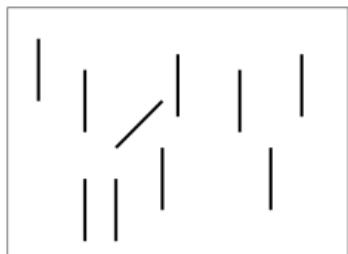


31

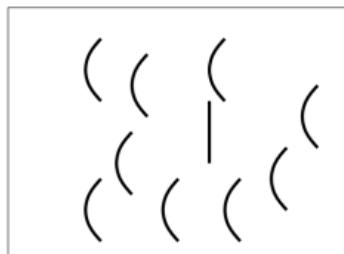
Saliency map on the right.

- **Form** (Line orientation, length, width and collinearity, size, curvature, spatial grouping, added marks, numerosity [up to four])

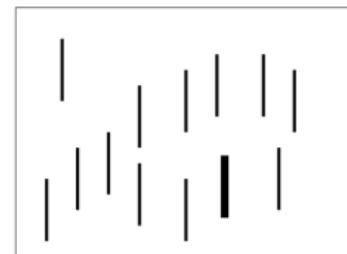
Orientation



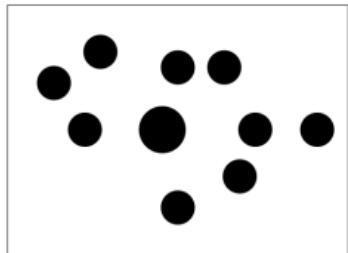
Curved/straight



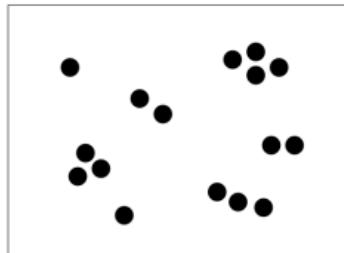
Line width



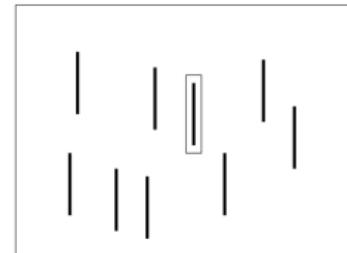
Size



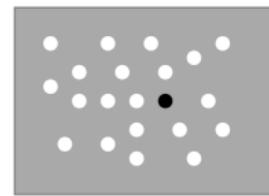
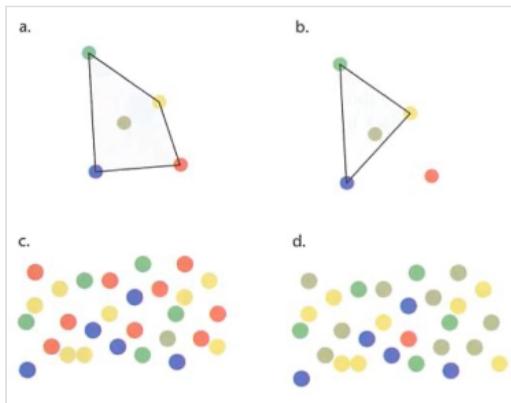
Number



Addition



- **Color** (hue, intensity [if outside CIE convex defined by other colors])



- **Motion** (flicker, direction of motion)
- **Spatial position** (2D position, stereoscopic depth, convex/concave form from shading)



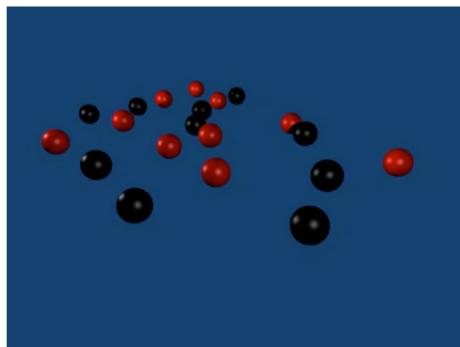
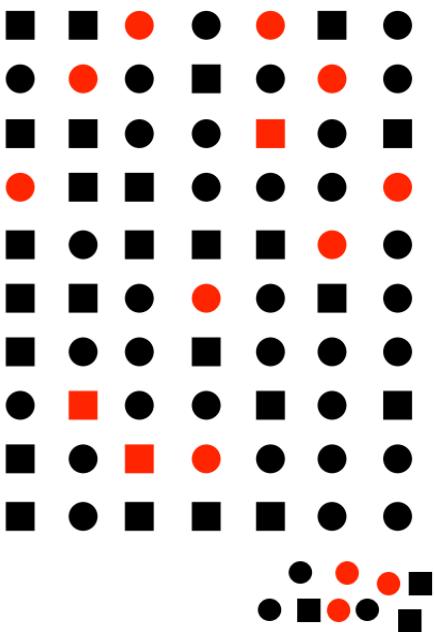
- Try to find the right-slanted line on the right
- Pre-attentive symbols become less distinct as the variety of distractors increases
- For maximum pop-out, a symbol should be the only object in a display that is distinctive on a particular feature channel
  - e.g., it might be the only item that is colored in a display where everything else is black and white



# Conjunction searches

- **Conjunction search** is a visual search that involves searching a specific conjunction of several (2 or more) visual attributes
- Conjunction searches are usually not pre-attentive, even if the individual features are
- Examples:
  - “Find red and square objects” is not pre-attentive search (conjunction search)
  - “Find red objects” is pre-attentive search
  - “Find square objects” is pre-attentive search

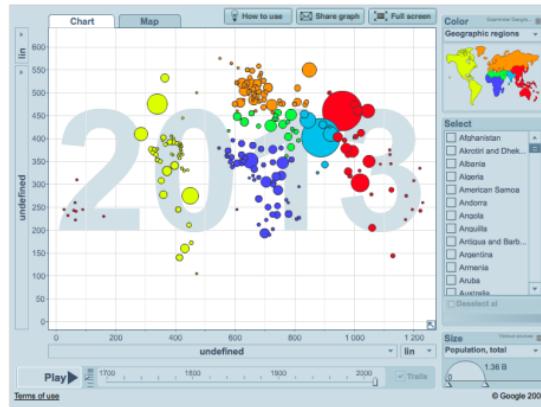
How many red squares?



## Glyph design

# Glyph design

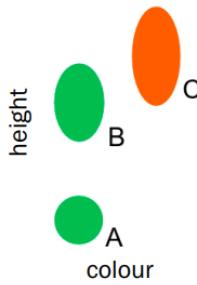
- Glyphs are symbols used to represent multivariate data
- A single glyph corresponds to one sample in a data set
- Data values are mapped to the visual properties of the glyph
- How to design a glyph so that the data values can be perceived pre-attentively?



[www.gapminder.org](http://www.gapminder.org)

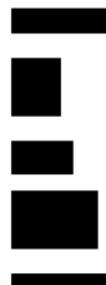
## Integral and separable dimensions

Which two glyphs go best together  
(restricted classification task)?

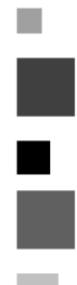


**separable features** are perceived independently of each other (e.g., size and color)

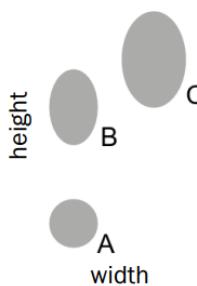
Height and random width



Size and random gray scale



Find this high rectangle.

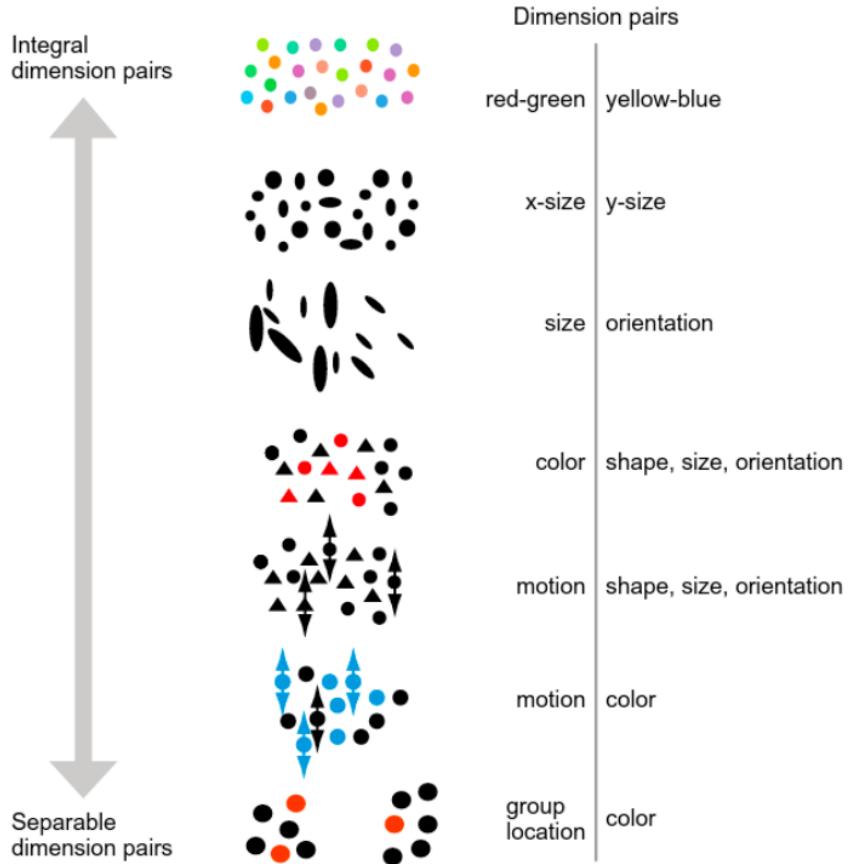


**integral features** are perceived holistically (e.g., a width and height)

Integral

Separable

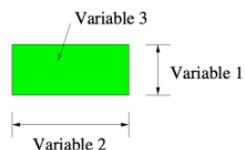
Speeded classification task faster for separable features. **Use separable dimensions to encode different variables in glyphs!**



## Glyph design: some rules of thumb

- All channels are not independent
  - try to use separable channels
  - in practice the number of channels to be used at once is limited
- If we want pre-attentive processing, we typically have 4-8 resolvable steps in each dimension (e.g., the number of size steps we can easily distinguish is ~4)

Visual variable	Dimensionality
Spatial position	3 (X, Y, Z)
Color of glyph	3
Shape	2-3?
Orientation	(1-)3
Surface texture	3
Motion coding	2-3?
Blink coding	1



- Certain visual features “pop out” (pre-attentive features)
- Data variables should (usually) be mapped to pre-attentive features (they are processed fast)
- Restrictions (if you want pre-attentive design):
  - conjunction searches are usually not pre-attentive
  - one can effectively display only limited number of visual variables, with limited accuracy
  - integral visual dimensions interfere with each other: you should use separable dimensions instead

**Gestalt's laws** translate directly into design principles of visual displays. In the simplest terms, gestalt theory is based on the idea that the human brain will attempt to simplify and organize complex images or designs that consist of many elements, by subconsciously arranging the parts into an organized system that creates a whole, rather than just a series of disparate elements. Our brains are built to see structure and patterns in order for us to better understand the environment that we're living in.

Referenced links:

[https://www.toptal.com/designers/ui/gestalt-principles-of-design#:~:text=There%20are%20six%20individual%20principles.order%20\(also%20called%20prägnanz\).](https://www.toptal.com/designers/ui/gestalt-principles-of-design#:~:text=There%20are%20six%20individual%20principles.order%20(also%20called%20prägnanz).)  
<http://andyrutledge.com/gestalt-principles-1-figure-ground-relationship.html>  
<http://andyrutledge.com/gestalt-principles-2-similarity.html>  
<http://andyrutledge.com/gestalt-principles-3.html>  
<http://andyrutledge.com/common-fate.html>  
<http://andyrutledge.com/closure.html>

Gestalt theory principles are an important set of ideas for any designer to learn, and their implementation can greatly improve not just the aesthetics of a design, but also its functionality and user-friendliness.

The laws are:

### **Similarity**

Things that are similar are perceived to be more related than things that are dissimilar.

### **Good Continuation**

Elements arranged on a line or curve are perceived to be more related than elements not on the line or curve.

### **Proximity**

Things that are close to one another are perceived to be more related than things that are spaced farther apart.

### **Symmetry and Order (Pragnanz)**

Humans tend to interpret ambiguous or complex images as simple and complete.

### **Closure**

When looking at a complex arrangement of individual elements, humans tend to first look for a single, recognizable pattern.

### **Figure/ground**

Elements are perceived as either figures (distinct elements of focus) or ground (the background or landscape on which the figures rest).

### **Common Fate**

Humans tend to perceive elements moving in the same direction as being more related than elements that are stationary or that move in different directions.

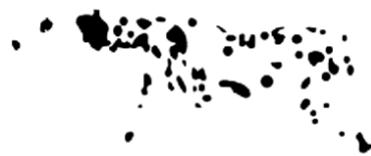
### **Uniform Connectedness**

Elements that share uniform visual characteristics are perceived as being more related than elements with disparate visual characteristics.

- Animation and perception of shapes

## **Animation and perception of shape**

- Gestalt laws also work for animated images: structures and patterns are seen from partial data (as with static images)
- Mystery lights in the dark:



- There is a specific area in human brain for detecting biological motion

- **Causality**



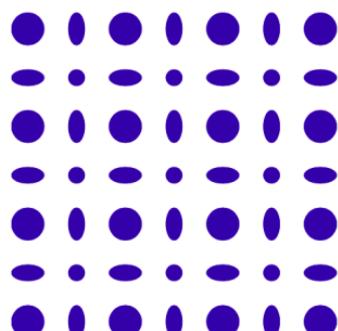
## Causality

- *Launching*: an object is perceived to set another into motion
- Perception of launching requires precise timing (delays less than 0.07-0.16 s)
- Already infants can perceive causal relations, such as launching

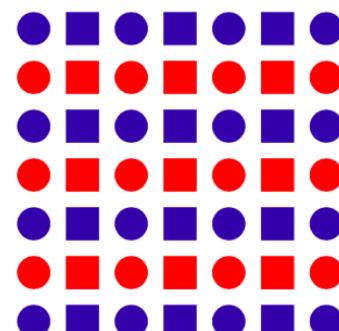


## Similarity

- Similar objects appear to be grouped together
- When designing a grid layout of a data set, code rows and/or columns using low-level visual channel properties, such as colour and texture

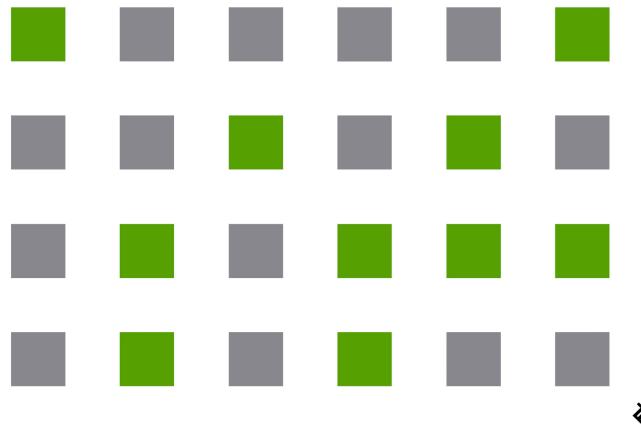


integral dimensions  
emphasize overall pattern



separable dimensions  
segment rows and columns

It's human nature to group similar things together. In gestalt, similar elements are visually grouped, regardless of their proximity to each other. They can be grouped by color, shape, or size. Similarity can be used to tie together elements that might not be right next to each other in a design.



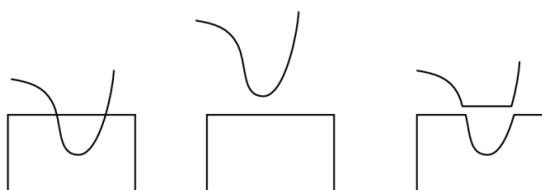
Of course, you can make things dissimilar if you want to make them stand out from the crowd. It's why buttons for calls to action are often designed in a different color than the rest of a page—so they stand out and draw the visitor's attention to the desired action.

In UX design, using similarity makes it clear to your visitors which items are alike. For example, in a features list using repetitive design elements (such as an icon accompanied by 3-4 lines of text), the similarity principle would make it easy to scan through them. In contrast, changing the design elements for features you want to highlight makes them stand out and gives them more importance in the visitor's perception.

Even things as simple as making sure that links throughout a design are formatted in the same way relies on the principle of similarity in the way your visitors will perceive the organization and structure of your site.

## Continuation

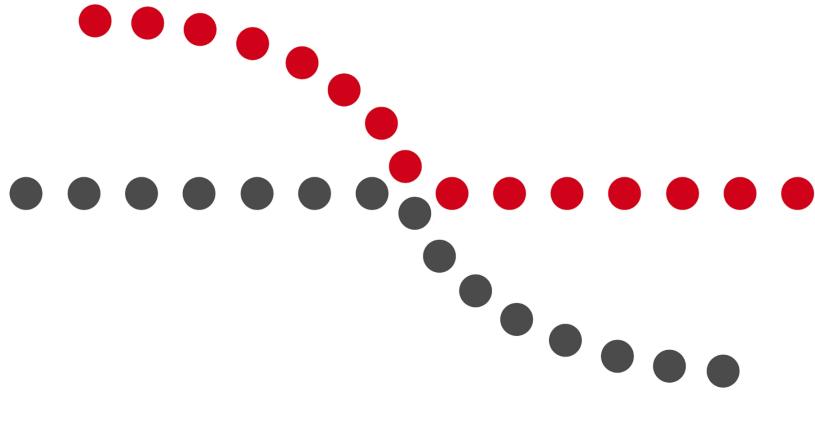
- Visual complete objects are more likely to be constructed from visual elements that are smooth and continuous, rather than ones that contain abrupt changes in direction



The pattern on the left is perceived as a curve overlapping a rectangle (centre) rather than 2 irregular shapes touching (right).

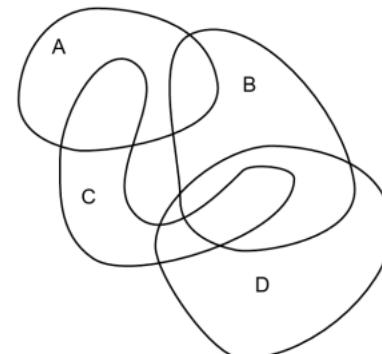
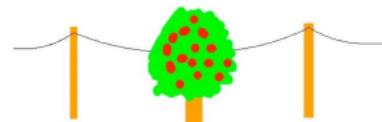
The law of continuity posits that the human eye will follow the smoothest path when viewing lines, regardless of how the lines were actually drawn. This continuation can be a valuable tool when the goal is to guide a visitor's eye in a certain direction. They will follow the simplest path on the page, so make sure the most vital parts they should see fall within that path.

Since the eye naturally follows a line, placing items in a series in a line will naturally draw the eye from one item to the next. Horizontal sliders are one such example, as are related product listings on sites like Amazon.



## Closure

- A closed contour tends to be seen as an object
- There is a perceptual tendency to close contours that have gaps in them
- When a closed contour is seen, there is a very strong perceptual tendency of dividing space into a region enclosed by the contour (a common region) and a region outside the contour
- In window-based interface strong framing effects inhibit between-window comparisons: related items should not reside in separate windows



Closure is one of the coolest gestalt design principles and one I already touched on at the beginning of this piece. It's the idea that your brain will fill in the missing parts of a design or image to create a whole.

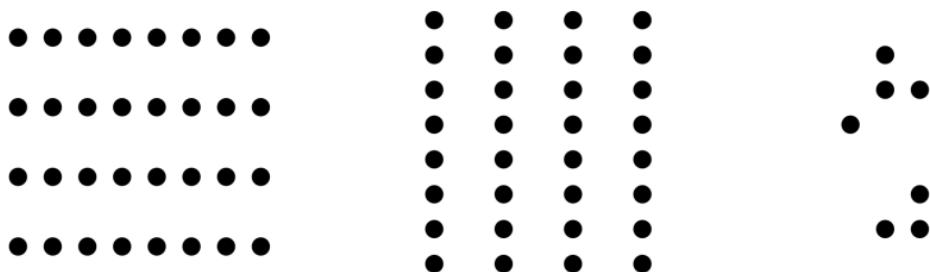
In its simplest form, the principle of closure allows your eye to follow something like a dotted line to its end. But more complex applications are often seen in logos, like that for the World Wildlife Fund. Large chunks of the outline for the panda are missing, but your brain has no problem filling in the missing sections to see the whole animal.



Another very important example of closure at work in UX and UI design is when you show a partial image fading off the user's screen in order to show them that there is more to be found if they swipe left or right. Without a partial image, i.e., if only full images are shown, the brain doesn't immediately interpret that there might be more to be seen, and therefore your user is less likely to scroll (since closure is already apparent).

## Proximity

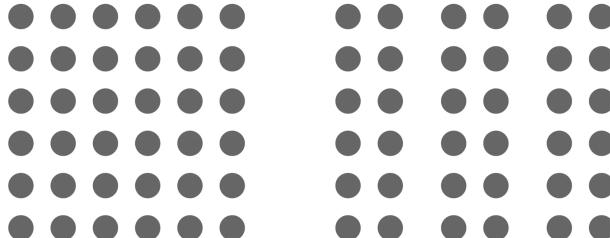
- Things that are near to each other appear to be grouped together
- Proximity is one of the most powerful gestalt laws
- Place the data elements into proximity to emphasise connections between them



Proximity refers to how close elements are to one another. The strongest proximity relationships are those between overlapping subjects, but just grouping objects into a single area can also have a strong proximity effect.

The opposite is also true, of course. By putting space between elements, you can add separation even when their other characteristics are the same.

Take this group of circles, for example:



MM DD YY      use the first date of operation in VVA. (Required. If unknown, please estimate.)

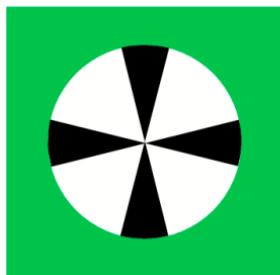
<b>c.</b> _____	Is this location inside city limits? <input type="checkbox"/> Yes <input type="checkbox"/> No		
<small>* Primary Business Name/Trade Name</small>			
<b>d.</b> _____	<small>* Business Street Address (if different than mailing) Do not use PO Box or PMB</small>		
<small>* Business Mailing Address (Street or PO Box, Suite No. do not use building name)</small>	City	State	Zip code
<small>Business Telephone Number</small>	City	State	Zip code
<b>e.</b> ( ) _____	Fax Number	<small>E-Mail Address</small>	
<b>f.</b> <small>List all owners &amp; spouses: Sole proprietor, partners, officers, or LLC members. (Attach additional pages if needed.)</small>			

>

In UX design, proximity is most often used in order to get users to group certain things together without the use of things like hard borders. By utilizing gestalt grouping principles and putting like things closer together, with space in between each group, the viewer will immediately pick up on the organization and structure you want them to perceive.

## Figure/Ground

- Smaller components tend to be perceived as an object
- Groupings perceived as overlapping objects



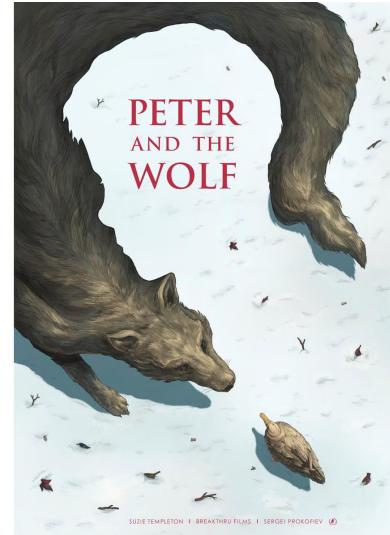
black propeller on  
white background



Rubin's reversible  
face-vase figure  
(multistability) Ware 2013

The figure/ground principle is similar to the closure principle in that it takes advantage of the way the brain processes negative space. You've probably seen examples of this principle floating around in memes on social media, or as part of logos (like the FedEx logo)

Your brain will distinguish between the objects it considers to be in the foreground of an image (the figure, or focal point) and the background (the area on which the figures rest). Where things get interesting is when the foreground and background actually contain two distinct images

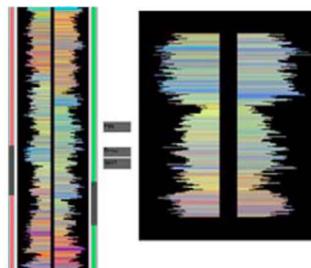
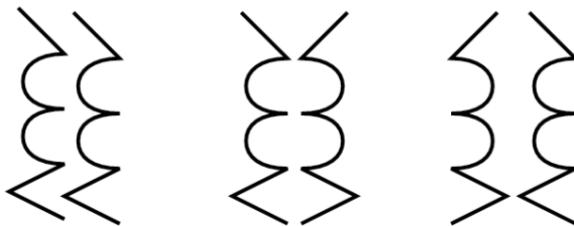


In general terms, your brain will interpret the larger area of an image as the ground and the smaller as the figure. As shown in the image above, though, you can see that lighter and darker colors can influence what is viewed as the figure and what is viewed as the ground.

The figure/ground principle can be very handy when product designers want to highlight a focal point, particularly when it is active or in use—for example, when a modal window pops up and the rest of the site fades into the background, or when a search bar is clicked on and the contrast is increased between it and the rest of the site.

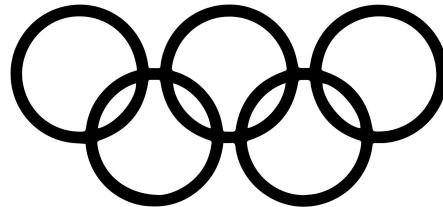
## Symmetry and Order

- Symmetrically arranged pairs of lines are perceived together
- Use symmetry to make pattern comparisons easier
- Symmetrical relations should be arranged on horizontal or vertical axes (as symmetries are more easily perceived), unless a framing pattern is used

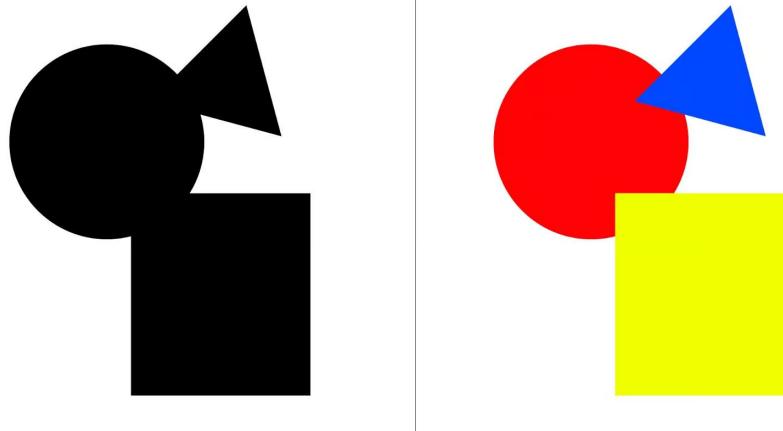


Ware 2013

The law of symmetry and order is also known as *prägnanz*, the German word for “good figure.” What this principle says is that your brain will perceive ambiguous shapes in as simple a manner as possible. For example, a monochrome version of the Olympic logo is seen as a series of overlapping circles rather than a collection of curved lines.



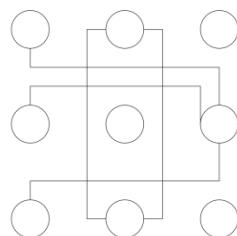
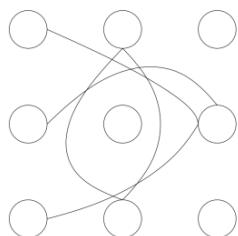
Here's another good example of the gestalt design principle “*prägnanz*”:



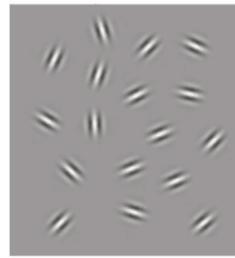
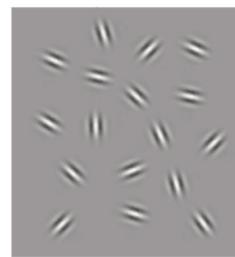
Your brain will interpret the image on the left as a rectangle, circle, and triangle, even when the outlines of each are incomplete because those are simpler shapes than the overall image.

## Uniform Connectedness

- Connectedness is one of the most powerful grouping principles
- It is easier to perceive connections when contours run smoothly
- In networks, lines connecting nodes should be smooth and continuous, so they are easier to follow



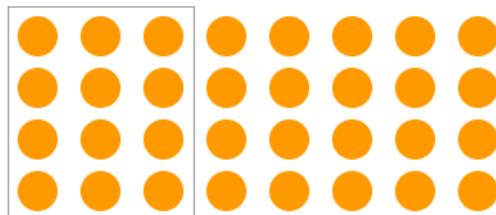
follow the path:



The principle of uniform connectedness is the strongest of the Gestalt Principles concerned with relatedness. It refers to the fact that elements that are connected by uniform visual properties are perceived as being more related than elements that are not connected. As with the principle of proximity, uniform connectedness causes us to perceive groups or chunks rather than unrelated, individual things.

In practice, uniform connectedness is quite simple: draw a box around a group of elements and you've indicated that they're related. Alternately, you can draw connecting lines (or arrows or some other tangible connecting reference) from one element to the next for the same effect. For instance:

*Here, even though the spacing and color is consistent within this collection of elements, those inside of the connecting lines are perceived to be more related than the rest:*



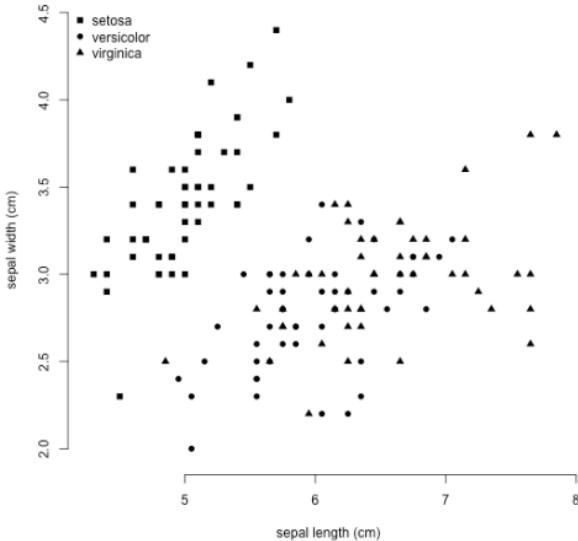
*...as are the ones connected by lines:*



In web design, it is common to employ uniform connectedness to show context. Tabbed navigation is a prime example of this principle. When you have two visually and proximally distinct elements (navigation link – and – page copy), the easiest way to show related context is to enclose disparate elements, like this:

## Common Fate

- Relative motion is an extremely efficient method of showing patterns from data
- Data points oscillate around center point
  - Variables: frequency, phase, amplitude of motion
  - Phase is the most effective variable



While common fate was not originally included in gestalt theory, it has since been added. In UX design, its usefulness can't be overlooked. This principle states that people will group together things that point to or are moving in the same direction.

In nature, we see this in things like flocks of birds or schools of fish. They are made up of a bunch of individual elements, but because they move seemingly as one, our brains group them together and consider them a single stimulus.



This is very useful in UX as animated effects become more prevalent in modern design. Note that elements don't actually have to be moving in order to benefit from this principle, but they do have to give the impression of motion.

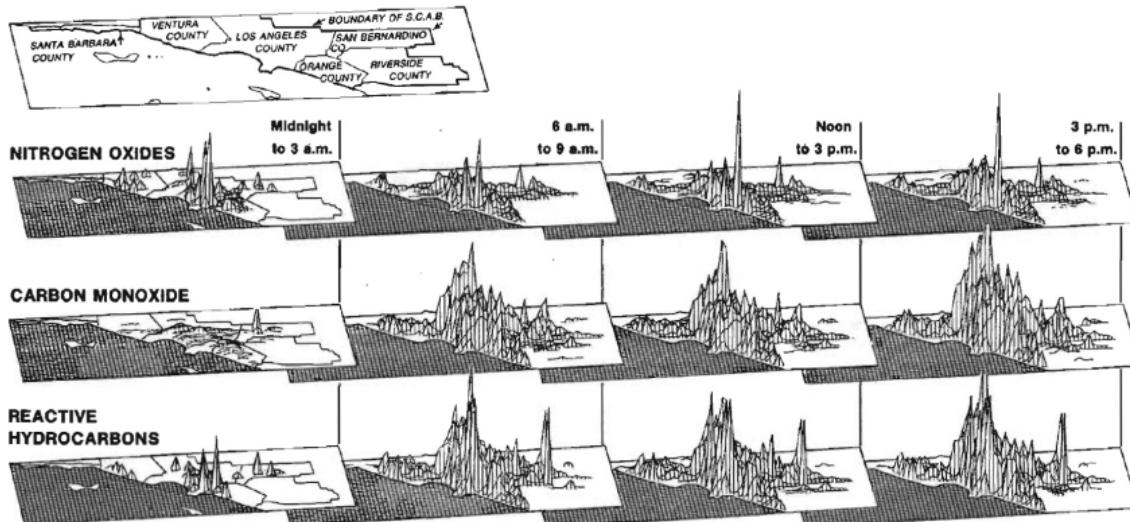
## Gestalt Principles in UX Design

As with any psychological principle, learning to incorporate the visual perception principles of gestalt into your design work can greatly improve the user experience. Understanding how the human brain works and then exploiting a person's natural tendencies creates a more seamless interaction that makes a user feel comfortable on a website, even if it's their first visit.

Gestalt laws are relatively easy to incorporate into just about any design and can quickly elevate a design that seems haphazard or like it's fighting for a user's attention to one that offers a seamless, natural interaction that guides users toward the action you want them to take.

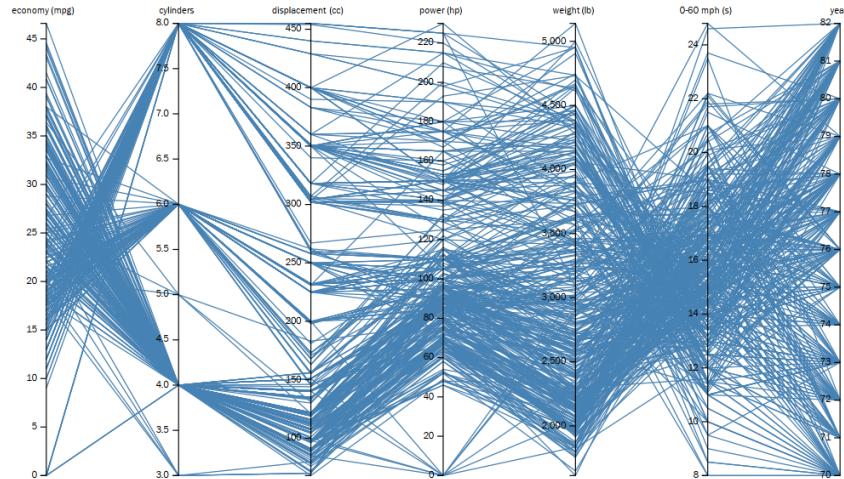
Gestalt laws in action:

## Small multiples (trellis)



- Symmetry?
- Proximity

# Parallel coordinates



Lecture 8: Interactive visualization

Mar 23, 2023

# Exploring information space: navigation + focus&context

- Focus+context problem: how to find details from a larger context in information space. Or, how to *navigate efficiently* in abstract spaces.
- There are several visual techniques to help this (providing user overview, position and landmarks):
  - **Elision techniques.** Part of the structure are hidden until they are needed.
  - **Distortion techniques.** Magnify regions of interest, decrease space of irrelevant regions.
  - **Rapid zooming techniques.** User zooms in and out of regions of interest.
  - **Multiple windows.** Some windows show overview and others content.
  - **Micro-macro readings.** A high-resolution static visualisation supports focus+context.

Lecture 9: Dimensionality reduction  
Mar 27, 2023

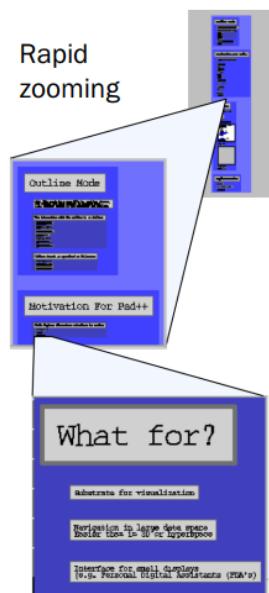
## Big data: too much for one view?



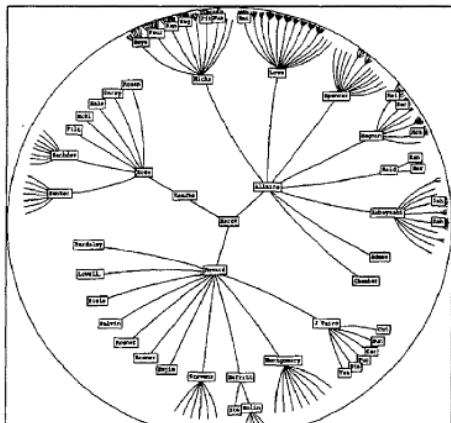
- Dynamic visualization
  - interactive navigation in information space
  - show only a selection of data at a time
- Algorithmic data mining
  - clustering and aggregation
  - dimensionality reduction

# Techniques

## Rapid zooming



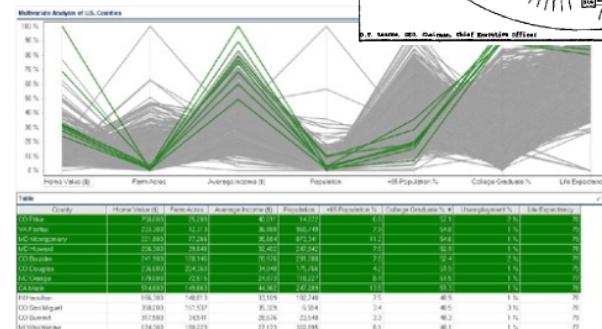
## Distortion



## Elision



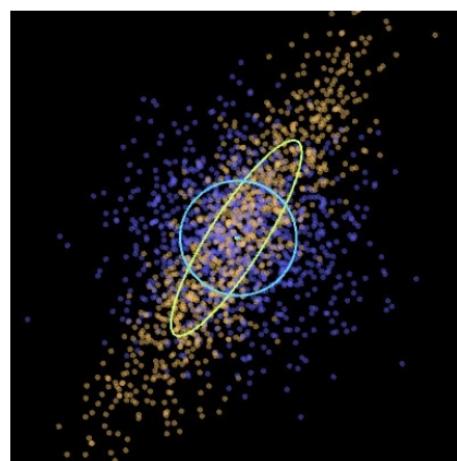
## Micro-macro readings



## Multiple windows

# Clustering and aggregation

- General idea: represent a subset of data by a simpler shape (a glyph)
    - elision technique
  - Example: a normal (= Gaussian) distribution shown by its mean and STD ellipse (analogously with a boxplot)
  - Level-Of-Detail (LOD): show a shape in simplified form, depending on the scale of presentation
    - e.g. cities on a map



## Dimensionality Reduction

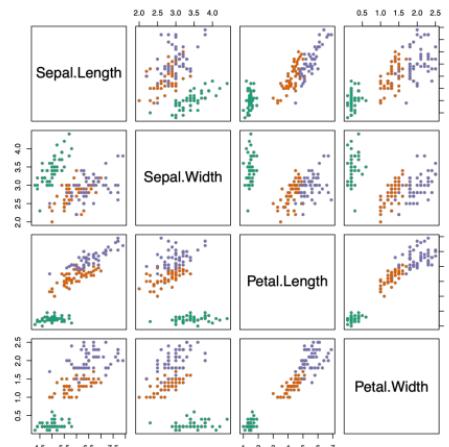
# Dimensionality reduction

- Assume your **data points** are  $m$ -dimensional, i.e. each item is defined by  $m$  measurable properties
- Assume dimensionality  $m$  is so large that a data point cannot be visualized by "traditional" methods
- *Problem statement:* Given a dimensionality  $k$  (typically  $k=2$  or  $k=3$ ), find an embedding  $X$  of data points into  $k$ -D space (=locations of data points) such that some properties in the embedding match the original as well as possible.
- The property to retain can be e.g. distances  $d_{ij}(X)$  between corresponding points, directional angles, local shapes, etc.

## Simple projections

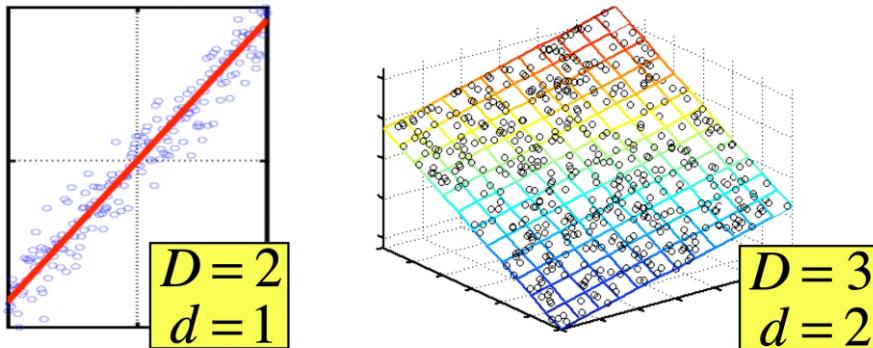
- Assume the data is composed of **vectors** in  $m$ -D space.
- Simple **orthogonal** projection takes 2 (or 3) of the original dimensions and neglects others.
- Example:

What if none of these reveals the true shape of the data set?



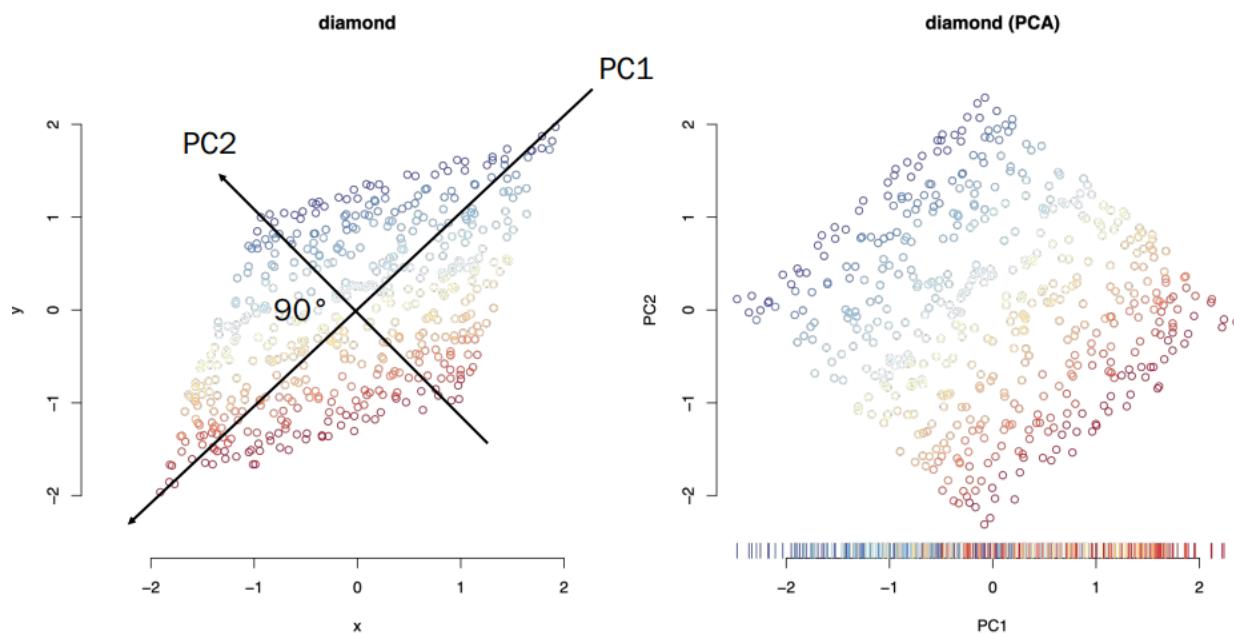
## PCA

# Principal component analysis (PCA)

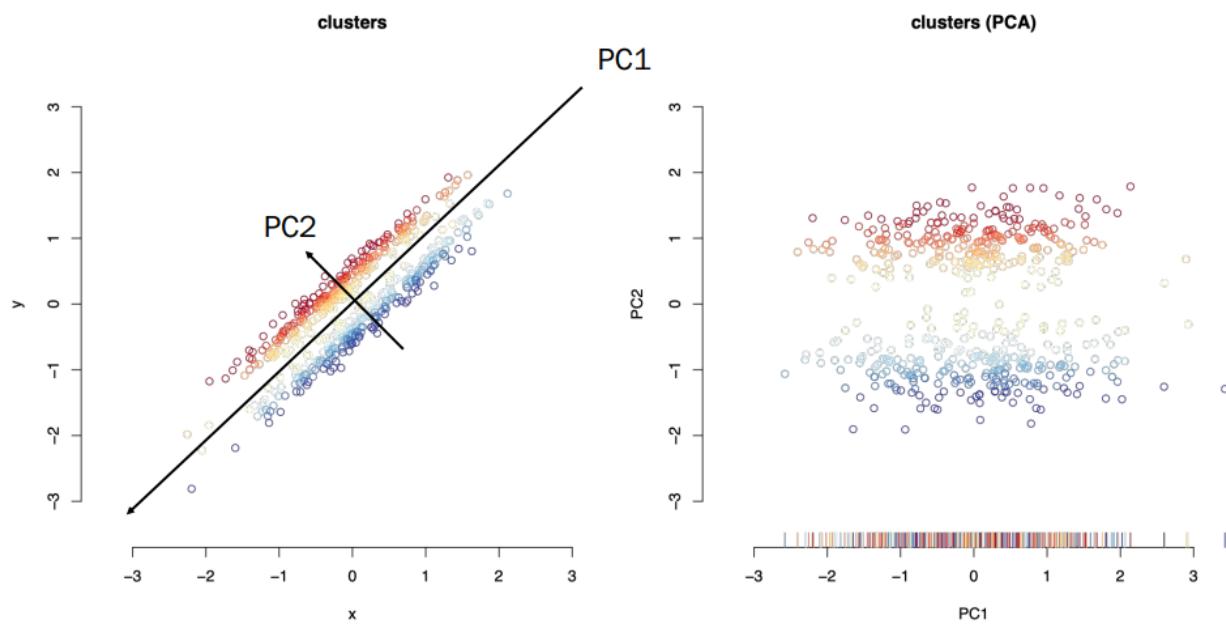


- Basic idea: rotate the space such that the data becomes maximally aligned with the coordinate axes.  
Then take an orthogonal projection.
- The **principal component analysis** (PCA) finds the eigenvalues and -vectors of a matrix
- PCA is an example of the projection pursuit methods. It tries to find a linear subspace that has **maximal variance**.
- Thus, the interesting quality in PCA is variance (distance).
- PCA assumes that the data points are vectors in a high-dimensional Euclidean space,
- The data points are projected to  $d$ -dimensional Euclidean subspace ( $d \ll D$ ) of the original space.
- The projection to  $d$ -dimensional subspace is linear,  
 $y_i = Ax_i$ , where  $e_\alpha$  are orthogonal unit vectors.  $A = \sum_{\alpha=1}^d e_\alpha e_\alpha^T$
- Goal: nearby points remain nearby, distant points remain distant.

# Diamond shaped data



PC1 misses the square structure.

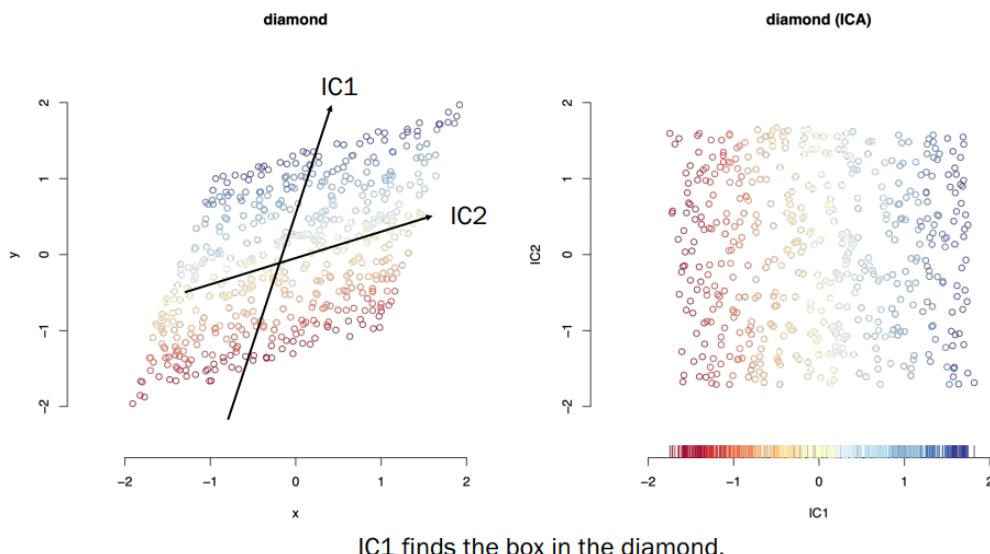


PC1 misses the cluster structure.

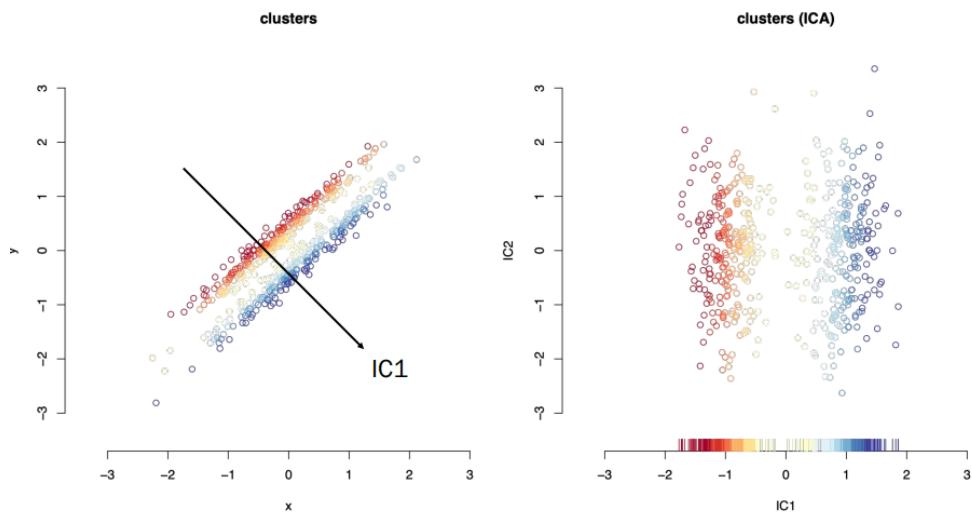
## IDC (Independent component analysis)

# Independent component analysis (ICA)

- Goal: function  $f$  is a measure of non-Gaussianity. Non-Gaussian directions are usually most independent.
- Hence, ICA finds separate processes. Directions are not necessarily orthogonal.
- ICA is unstable and may end up to a local minimum.
- There are robust libraries to compute ICA: use the libraries!



IC1 finds the box in the diamond.



IC1 finds the two clusters.

## Nonlinear methods

# Non-linear methods

- *Problem statement:* Given a dimensionality  $k$  (typically  $k=2$  or  $k=3$ ), find an embedding  $X$  of data points into  $k$ -dimensional space (=locations of data points) such that some properties in the embedding match the original as well as possible.
- Assume that we can define *proximity*  $p_{ij}$  (= *meaningful distance*) between data points  $i$  and  $j$ 
  - note: for  $N$  points there are  $N(N-1)/2$  pairwise distances
- Instead of linear projection, try to find a mapping, such that distances  $d_{ij}(X)$  between corresponding points match.
  - only mutual distances (or similarities) matter, the original points may or may not be located in any dimensional vector space
- What does "as well as possible" mean?
  - Long distances?
  - Short distances?
  - Neighbourhood relations?
  - maintain correct (visual perception of) relations between nodes
- All embeddings have to make compromises. We will now study embeddings that **preserve long distances**.
  - Metric multidimensional scaling (MDS)
  - Nonmetric MDS
  - Sammon mapping
  - (also PCA and ICA have this property)
- The alternative is to preserve short distances (=neighborhoods), leading to manifold embeddings (later)

# 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 minimizes the error function (called *stress*, by convention)

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

- ...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 (next slide).

\*) NOTE: only pairwise distances given as input, no coordinate system (the spectral wavelength is not utilized)

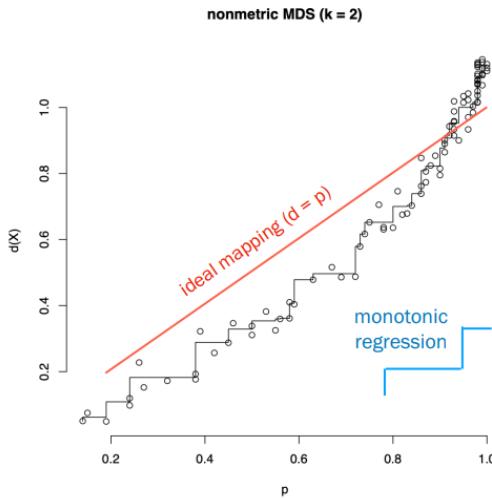
- The choice of  $f$  defines the MDS model. For example:
  - $f(p_{ij}) = p_{ij}$  - absolute MDS (linear model)
  - $f(p_{ij}) = b p_{ij}$  - ratio MDS (linear model)
  - $f(p_{ij}) = a + b p_{ij}$  - interval MDS (linear model)
  - $f(p_{ij}) = a + b \log p_{ij}$  - useful in psychology (logarithmic)
  - $f(p_{ij})$  can be any monotonically increasing function (ordinal or **nonmetric MDS**)
    - this would be the most important special case of MDS
- The parameters of  $f$  (such as  $a$  and  $b$  above) are optimised at the same time as the representation  $X$  (i.e., the locations of the projected points)

## Shepard plot

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

Shepard diagram: "A plot of two measurements of the distances between objects. One measurement is the true distance, and the other measurement is the apparent distance in some representation of the objects. For example, the apparent distance between objects in a photograph (two dimensions) and the real three-dimensional distance. The diagram is used in multidimensional scaling to assess the extent of any distortion. Zero distortion would correspond to a set of collinear points."

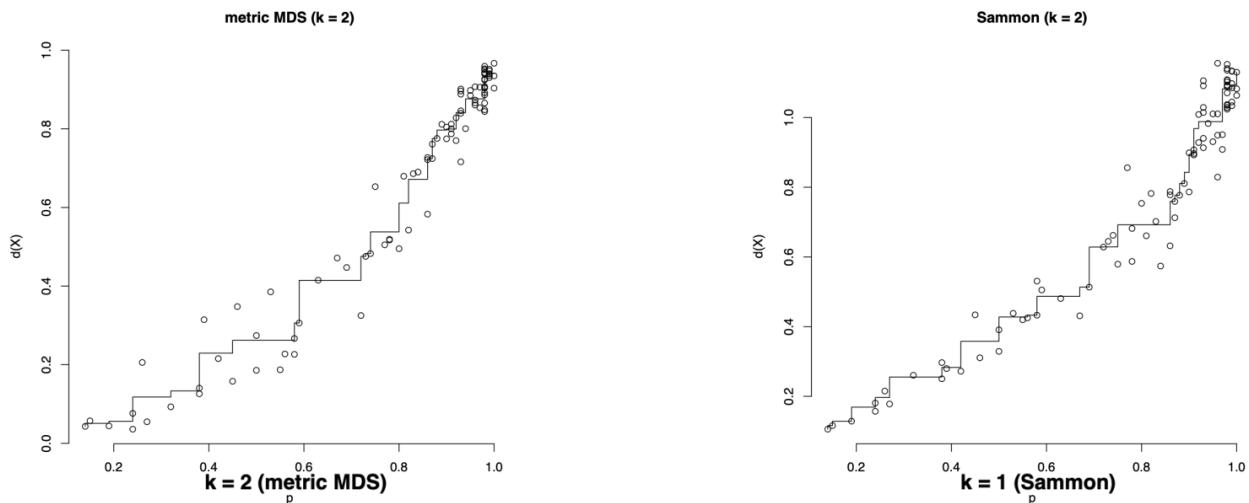
[oxfordreference.com](http://oxfordreference.com)



## Sammon

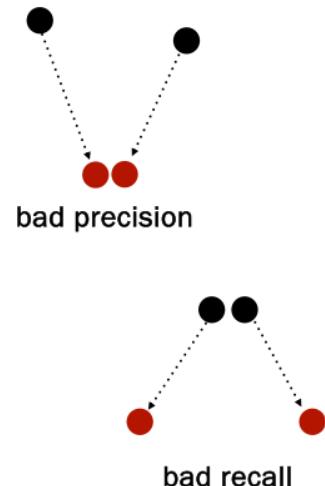
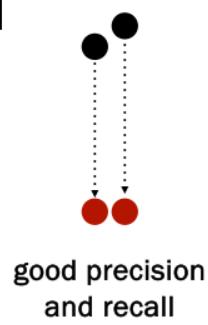
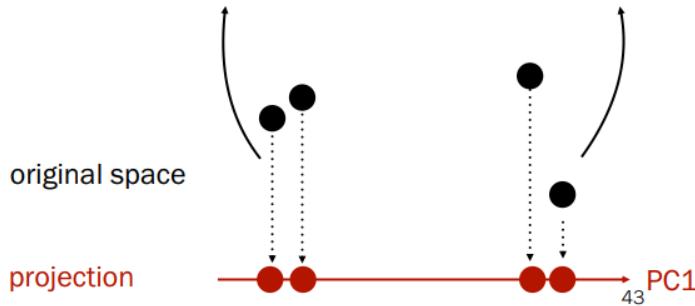
### Classical MDS and Sammon mapping

- **Sammon mapping:** given a distance  $p_{ij}$  find a representation  $X$  that minimises
 
$$E = \sum_{i < j} \frac{(d_{ij}(X) - p_{ij})^2}{p_{ij}}$$
- As compared to MDS Sammon mapping should be more accurate for shorter distances but less accurate for longer (why?)
- Like in nonmetric MDS, solution is found by gradient descent, which may end up in a local minimum
- Classical MDS is an instance of metric MDS
  - a.k.a. Principal Coordinates Analysis (PCoA), Torgerson Scaling, or Torgerson–Gower scaling.



# Precision and recall

- Precision: if the points are nearby in embedding they are nearby in the original space  
*proximity in the visualization is truthful*
- Recall: if the points are nearby in the original space they are nearby in the embedding  
*proximities of the original are preserved*
- Projection pursuit methods such as PCA:
  - the distance between the points in projection is at most the distance in the original space
  - always good recall, but possibly bad precision

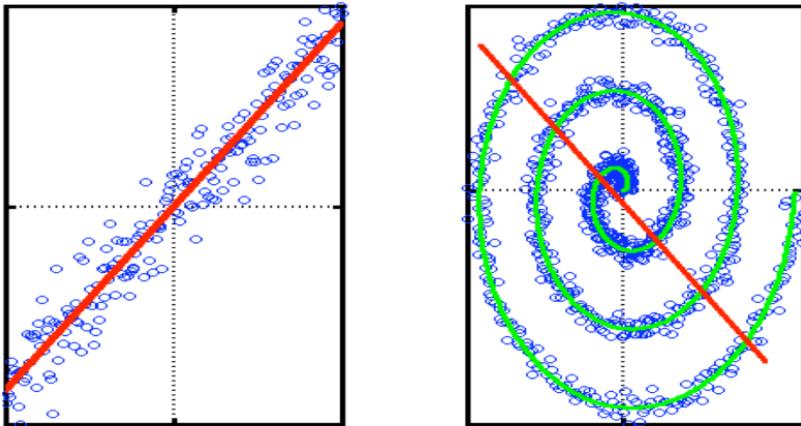


## Performance of MDS

- Relatively better recall, worse precision
- MDS algorithms typically have running times of the order  $O(N^2)$ , where  $N$  is the number of data items.
- This is not very good:  $N=1,000$  data items are ok, but  $N=1,000,000$  is getting slow.
- Some solutions: use landmark points (i.e., use MDS only on a subset of data points and place the remaining points according to those, use MDS on cluster centroids etc.), use some other algorithm or modification of MDS.
- MDS is not guaranteed to find the global optimum of the stress (cost) function, nor it is guaranteed to converge to the same solution at each run (many of the MDS algorithms are quite good and reliable, though)

# Visualising manifolds

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



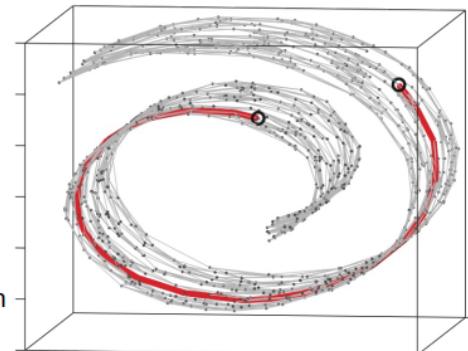
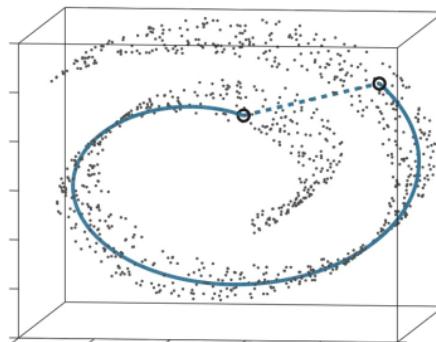
- The first principal component is given by the red line. The green line on the right gives the “correct” non-linear dimension (which PCA is of course unable to find).

## ISOMAP

### Isometric mapping of data manifolds (ISOMAP)

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

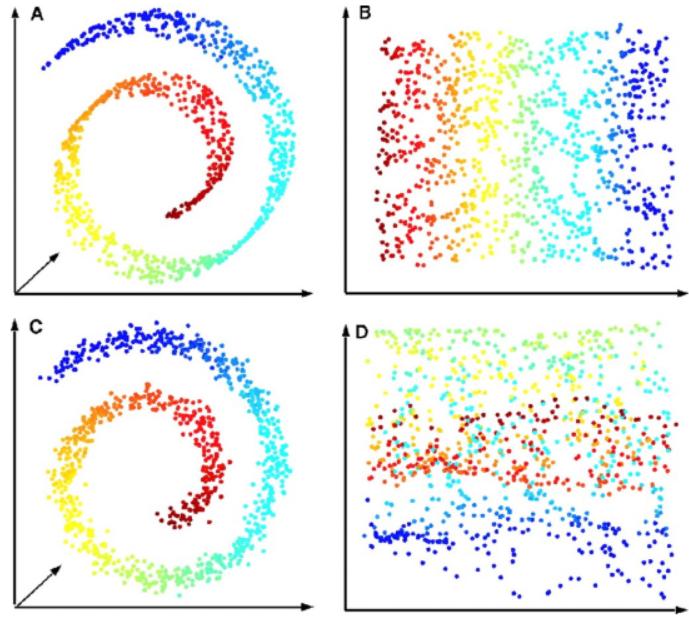
- Tenenbaum et al. 2000,  
<https://doi.org/10.1126/science.290.5500.2319> See  
<http://web.mit.edu/cocosci/isomap/datasets.html> (fig)
- ISOMAP is an example of graph-based methods.
- ISOMAP is a variant of MDS. The difference to MDS is in how the distances (or proximities) are defined.
- ISOMAP first 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.



*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  $\sim O(N^2)$
- Extension: landmark ISOMAP
  - identify subsets of inputs as landmarks, makes the algorithm faster

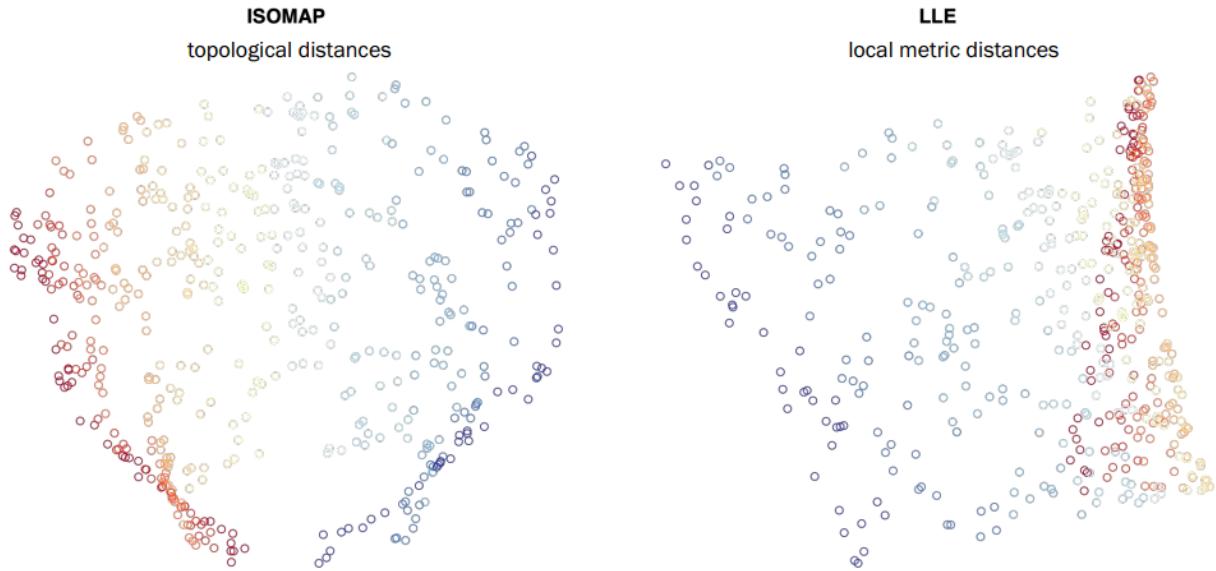


(A) The “Swiss roll” data used by Tenenbaum et al. (1) to illustrate their algorithm ( $n = 1000$ ). (B) The two-dimensional (2D) representation computed by the  $\epsilon$ -Isomap variant of the Isomap algorithm, with  $\epsilon = 5$ . Nearby points in the 2D embedding are also nearby points in the 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 ( $\epsilon = 5$ ) 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.

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# Locally linear embedding (LLE)

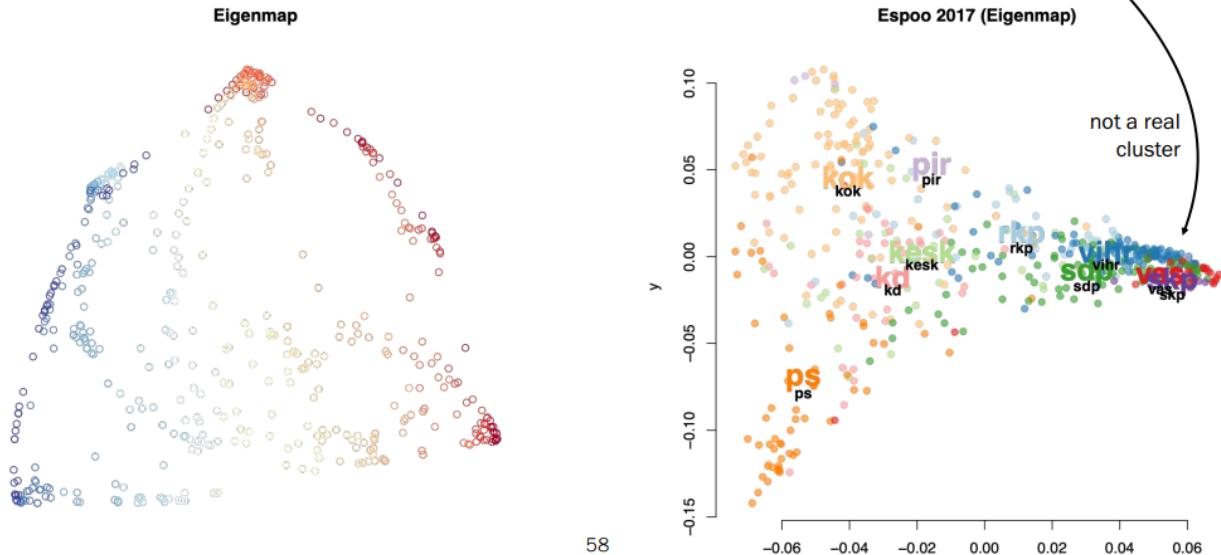
- LLE tries to maintain the relationships of nearby points
- Roweis et al. 2000, <https://doi.org/10.1126/science.290.5500.2323>
- Recipe:
  1. find the set  $N(i)$ ,  $k$  closest data points to  $i$ th data point  $x_i$
  2. try to express  $x_i$  as a linear combination of its neighbours: find weights 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 
$$\sum_i \left( y_i - \sum_{j \in N(i)} w_{ij} y_j \right)^2$$



# Laplacian eigenmap

- Eigenmap is a spectral method, like PCA.
- Recipe:
  1. As in ISOMAP, construct  $k$ -nearest neighbors graph.
  2. Assign  $A_{ij} = 1$ , if  $i$  and  $j$  are neighbors, otherwise assign  $A_{ij} = 0$ .
  3. Define diagonal matrix  $D$ ,  $D_{ii} = \sum_j A_{ij}$ , and graph Laplacian,  $L = A - D$ .
  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

- 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 bad precision.



- 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
  - local multidimensional scaling
  - many more exist...
- either redefine the distance or look only at the vicinity of individual points
- practical issues: distortions, may be computationally expensive

Lecture 10: Other topics  
Mar 30, 2023

# Visualization of networks

Graph visualization

## Visualisation of graphs

- Abstract graph has no form, but it can be embedded into plane (or 3D space) and made visible
- Properties of good visualization
  - important elements (nodes, arcs, labels,...) clearly distinguishable
    - space between nodes
    - short arcs, not crossing each other (possible for planar graphs only)
  - semantic information associated to the graph made visible
    - E.g., hierarchical levels of an organization
    - interesting parts of a complex network emphasized
  - can be created automatically
  - aesthetical appearance
- Often has to compromise between requirements

Visualization greatly determines, how a graph is interpreted!

Criteria for visualization

## 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.

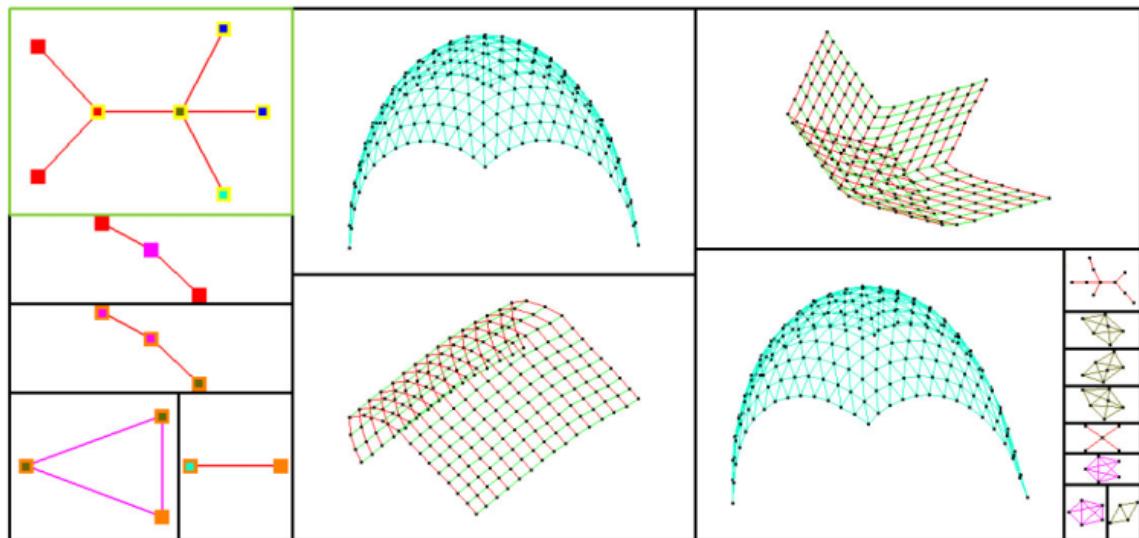
## General layout

# 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

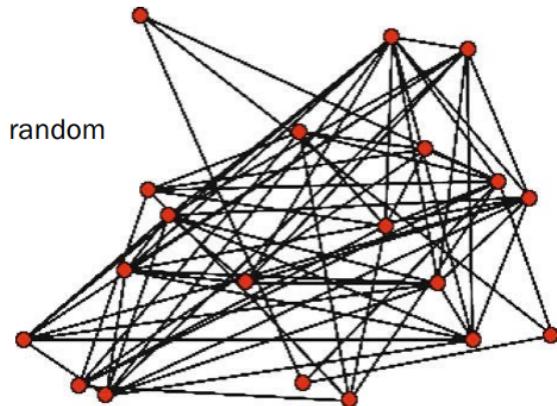
- Process steps:
    - decomposition phase
    - feature layout phase
    - crossing reduction phase
    - overlap elimination phase
- } based on topological connections (and possibly semantic features) of nodes and subgraphs



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

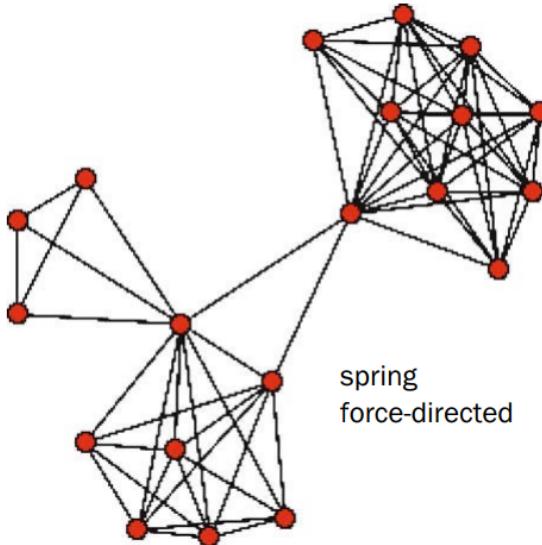
# Spring layout

- 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)



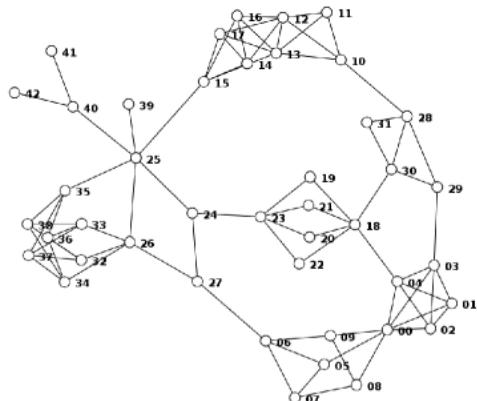
Social Network Visualization, Methods of, Figure 11  
Links in the network of a homeless woman I

10



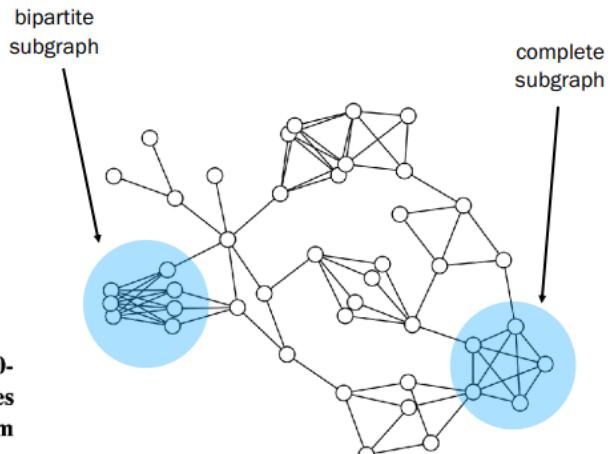
spring  
force-directed

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

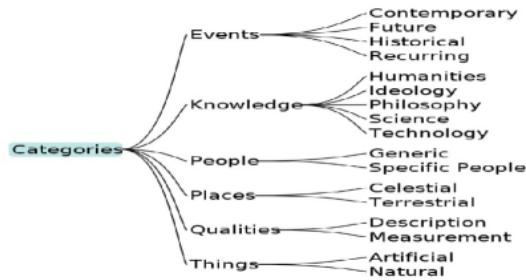


**Fig. 1** Force-directed node-link diagrams of a 43-node, 80-edge network. Top: a low spring constant makes the edges more flexible. Bottom: a high spring constant makes them more stiff.

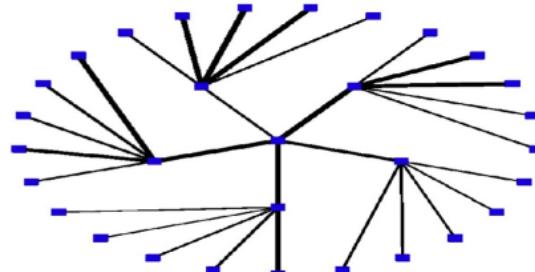
- spring algorithm naturally separates main cluster types



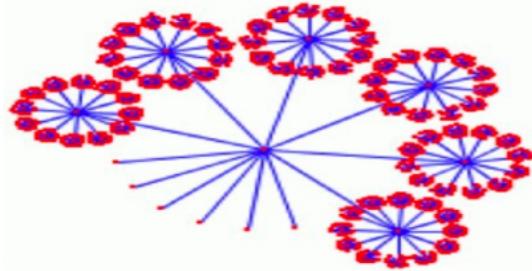
# Tree visualization



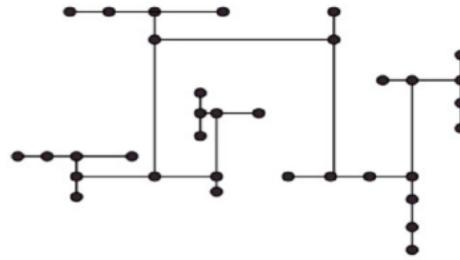
(a) Classical tree layout, produced with [19].



(b) Radial tree layout Example.

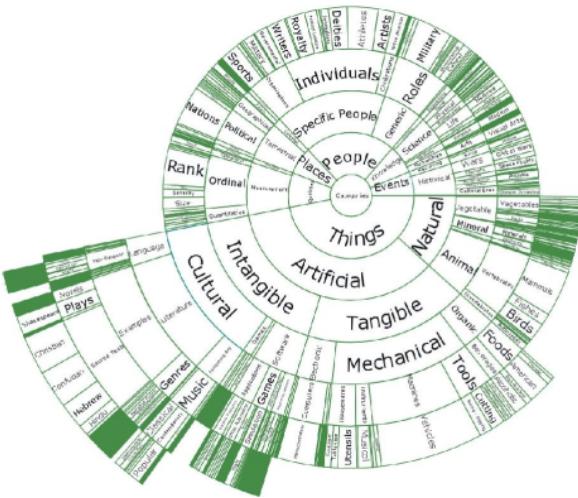


(c) Balloon tree layout: produced by [22].



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

SunBurst layout



Treemap layout

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

# Arc layouts

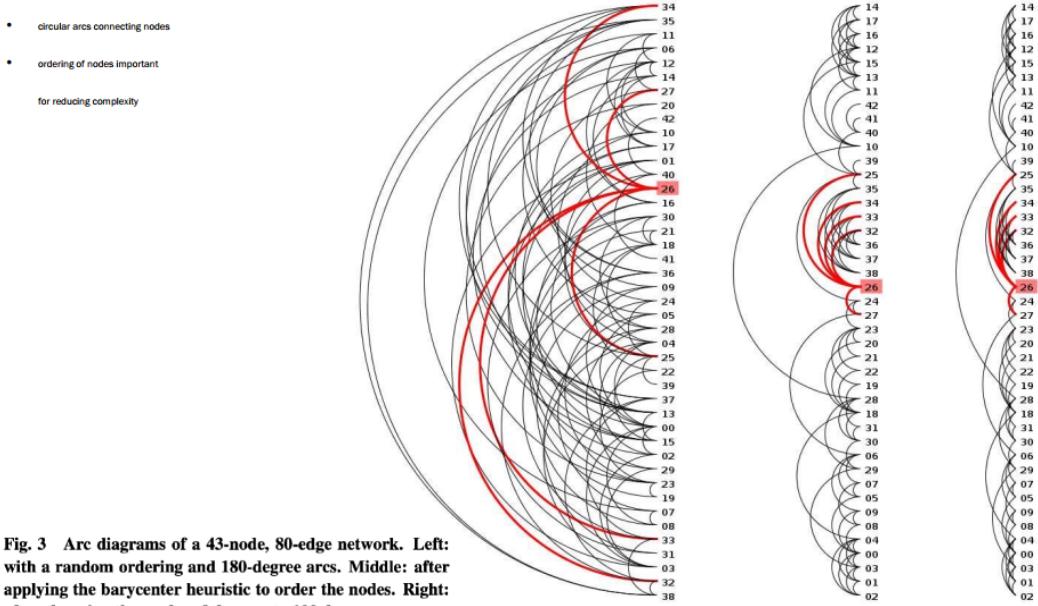


Fig. 3 Arc diagrams of a 43-node, 80-edge network. Left: with a random ordering and 180-degree arcs. Middle: after applying the barycenter heuristic to order the nodes. Right: after changing the angles of the arcs to 100 degrees.

# Circular layouts

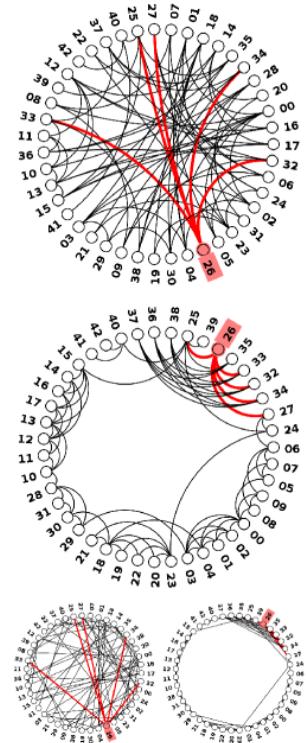
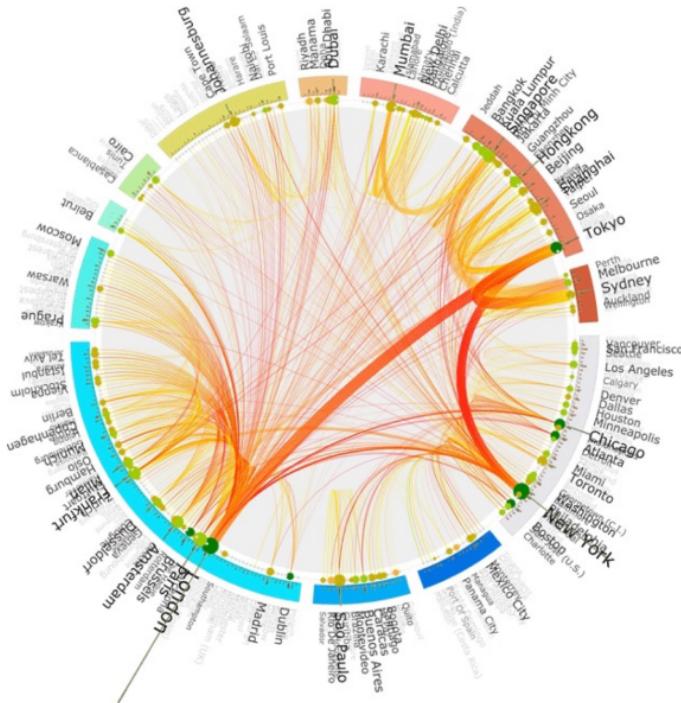
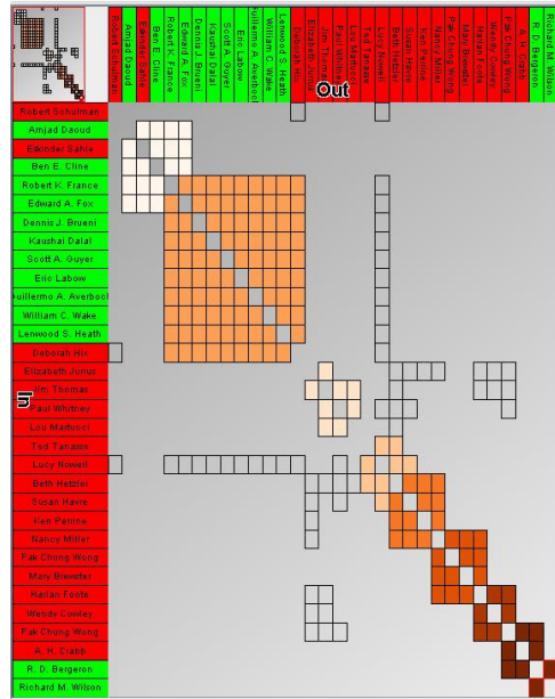


Fig. 8 Circular layouts of a 43-node, 80-edge network, before (top and bottom left) and after (middle and bottom right) barycenter ordering, with curved (top and middle) and straight (bottom) edges.

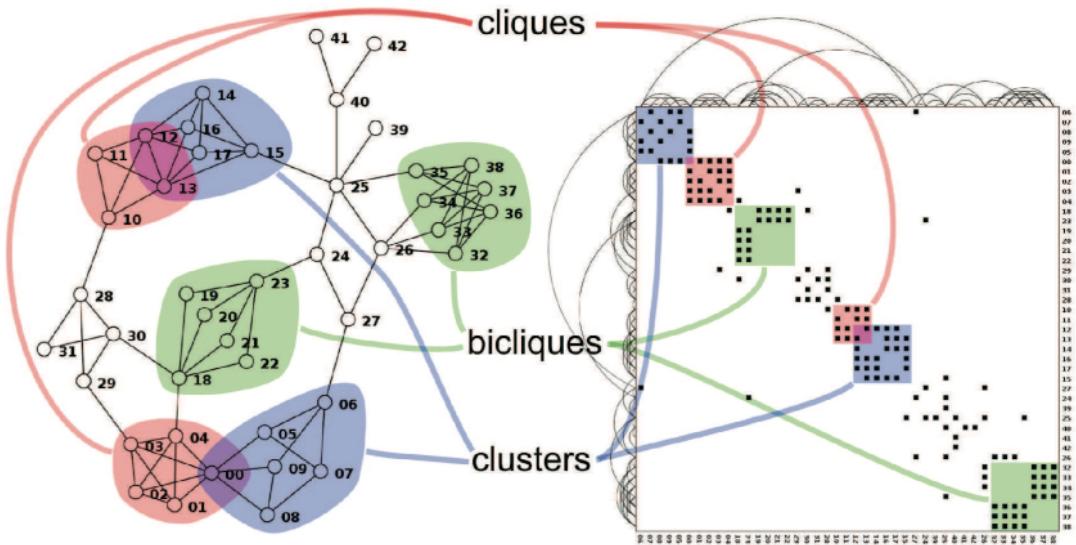
# Matrix visualization

Adjacency matrix

- nodes in rows and columns
- edges (links) in crossings
- ordering of nodes important for visually perceiving the structure



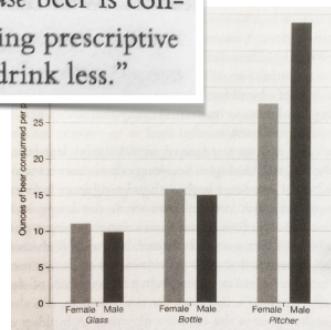
## Nodes and Edges Clustering



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

# 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.”



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## 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"

