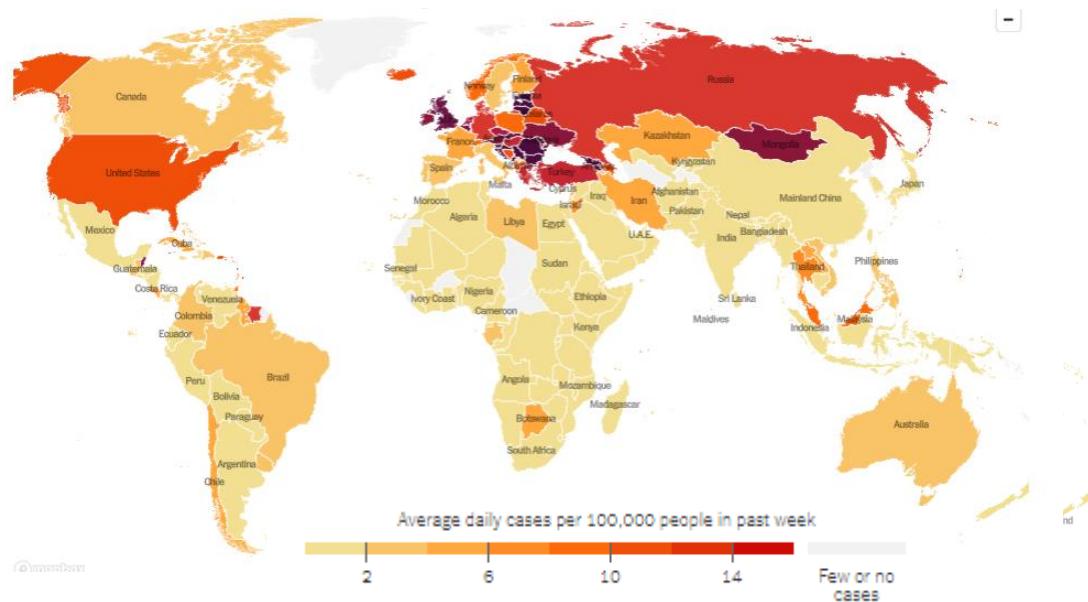
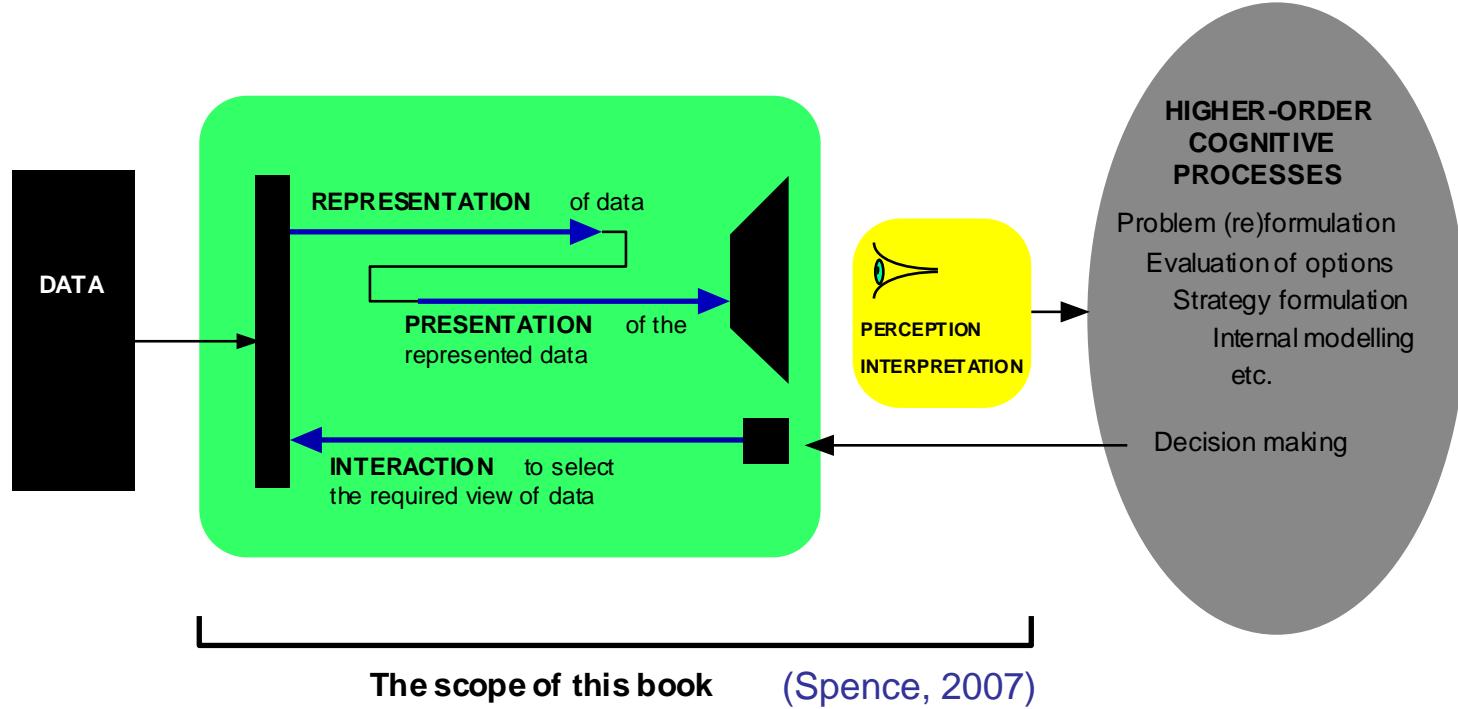




Representation



<https://www.nytimes.com/interactive/2021/world/covid-cases.html>

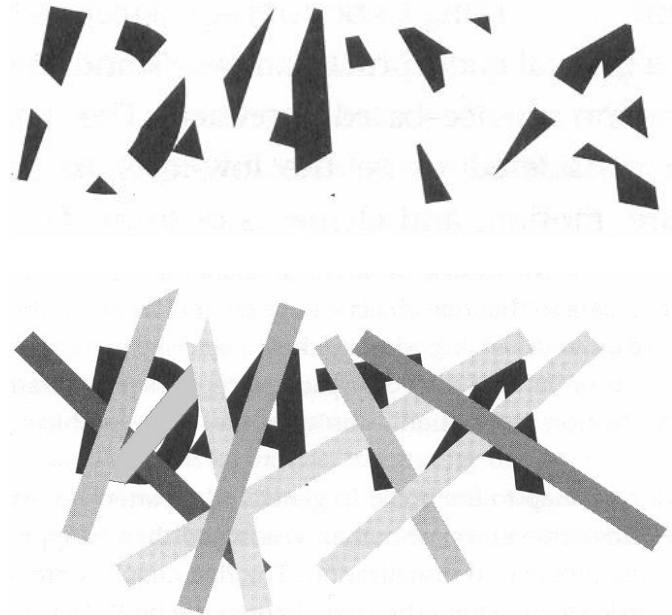


Interaction with data governed by high-order cognitive processes:

- **Representation** (how to code visually the data) ←
- Presentation (what/when/where to show on the screen)
- Interaction (how to let users explore the data)

Remember:

- The Human Visual system is the product of millions of years of evolution
- Although very flexible, it is tuned to data represented in specific ways
- If we understand how its mechanisms work we will be able to produce better results



Pre-attentive attributes can help observers to see before though

Example: Count the number of 7s

6970425934749

3587282949546

4244396854634

2356658789376

6970425934749

3587282949546

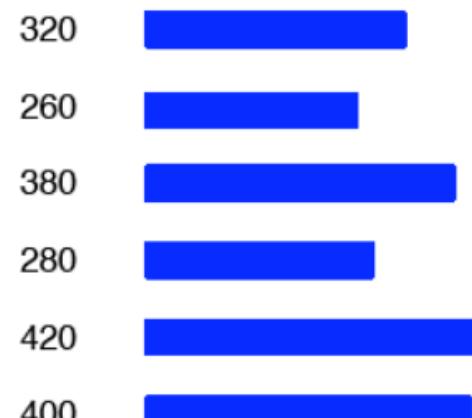
4244396854634

2356658789376

https://www.youtube.com/watch?time_continue=121&v=AiD6etOB6ql

- Visual attributes as **size**, **proximity** are quickly processed by visual perception, **before the cognitive processes** come into play

Example: mapping numerical values to the length of bars:



(Mazza, 2009)

Designing a Visualization

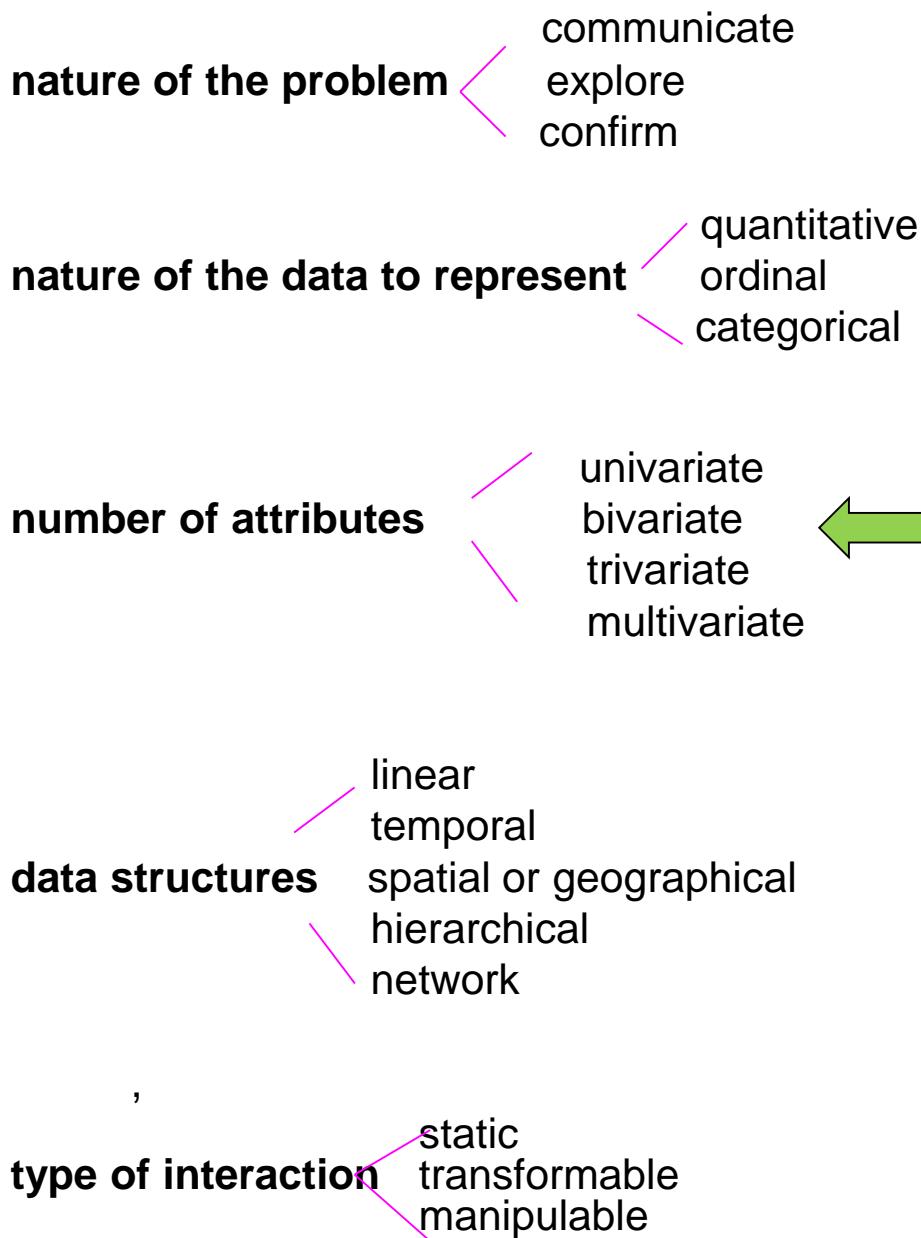
- The process must be preceded by **good design**
- The main problem in designing a visual representation is the choice of mapping, as to:
 - help the user to attain their goals
 - faithfully reproducing the information codified in the data
- The visual representation suitable depends on:
 - the nature of the data and phenomenon
 - the users' tasks and needs (the questions)
 - the user profile and context of use
 - ...

Procedure to follow to create visual representations of abstract data

Taking into consideration **the users' tasks, profile and context of use**:

1. Define the problem and the **users' questions, profile and context of use**
2. Examine the **nature of the phenomenon and data**
3. **Pre-process** the data
4. Determine the **number of attributes**
5. Choose the **visual structures** (how to represent the data)
6. Establish **how and when** to present to the user
and the type of **interaction**

test several ideas and redesign when needed...



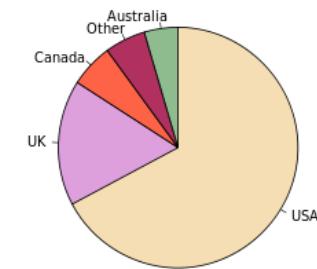
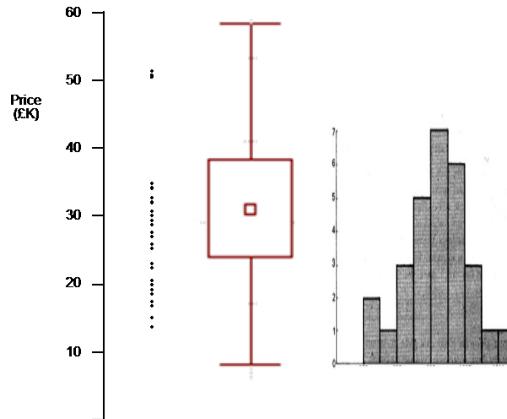
Next: representation methods organized according the n. of attributes

Common Visualization Techniques for univariate, bivariate and trivariate data

Univariate data

- dot plot
- box plot
- bar chart
- histogram
- pie chart

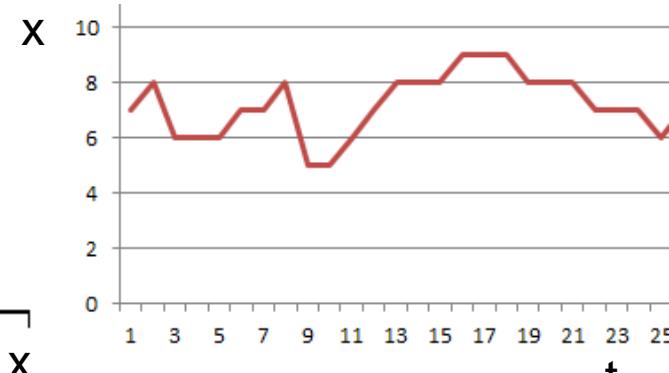
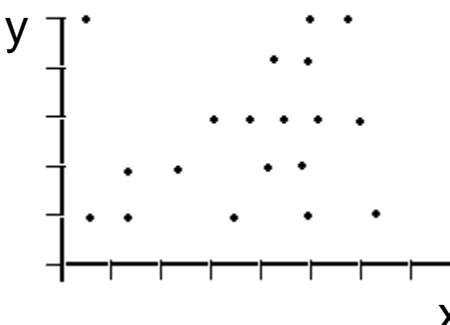
...



Bivariate data

- scatter plot
- line plot
- time series

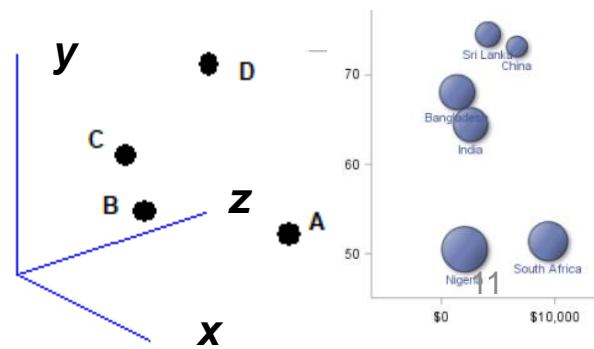
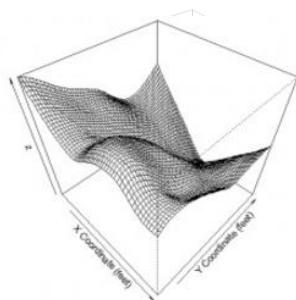
...



Trivariate data

- surface plot
- contour plot
- 3D representation
- bubble plot

...



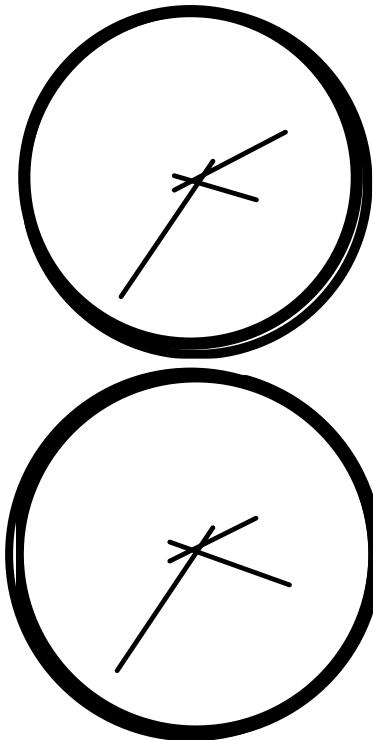
Representing univariate data

- A **single number** can be difficult to represent ensuring a user is made aware of it

Example: the altimeter
(Spence, 2007)



The original type of aircraft altimeter, with usability issues



Two altimeter representations easily assumed to be the same due to change blindness



A more usable solution for altimeter display



**Some more examples
on how humans see...**

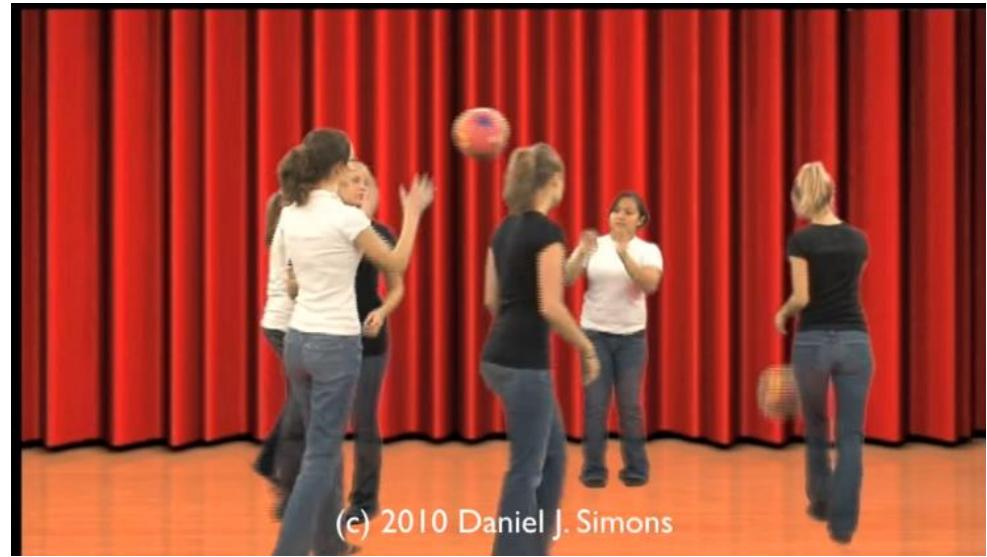
And their limitations...

Example of change blindness
(Spence, 2007)

Example of change blindness
(Spence, 2007)

What is missing now?





(c) 2010 Daniel J. Simons

Inattentional blindness

https://www.youtube.com/watch?v=IGQmdoK_ZfY

Change blindness

http://www.youtube.com/watch?v=vBPG_OBgTWg&feature=related



Representing univariate data (cont.)

- A more common situation consists in representing a **set of values**
- Well established techniques exist
- But new ones can be invented!

Example:

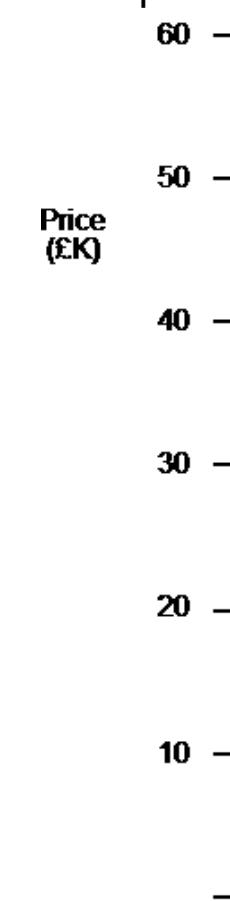


Price for a number of cars:

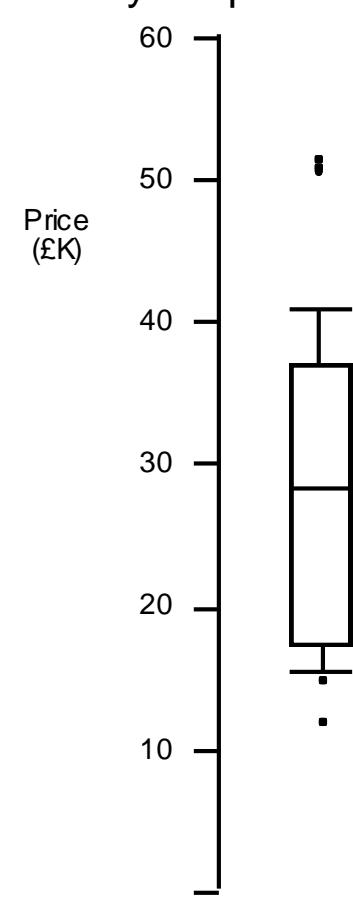
- dots on a linear scale
 - box plot
- (that will answer many questions:
median value, outliers,...)

(Spence, 2007)

Dot plot

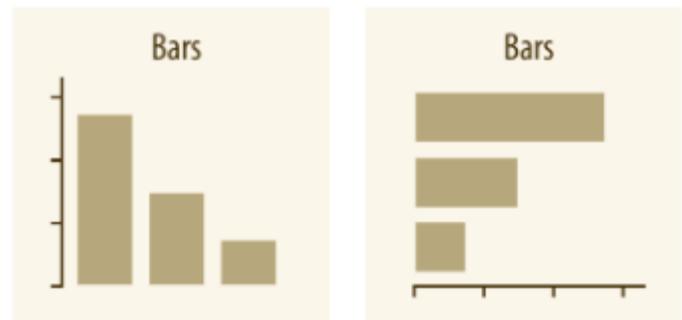
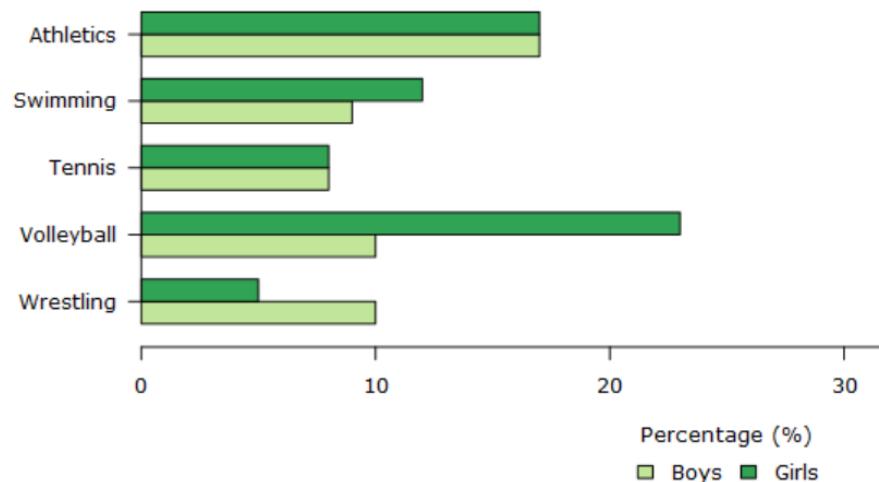


Tukey boxplot

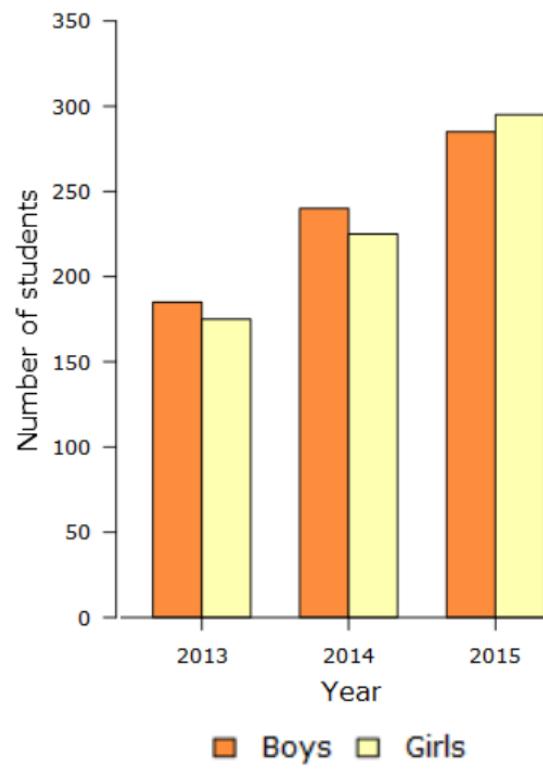


- much of the data is **aggregated**
- precise detail is often not needed
- A **bar chart** is a common way to represent one attribute,
- but we may combine to represent more attributes

Sports practiced by 15-year-old students by gender



(Wilke, 2019)



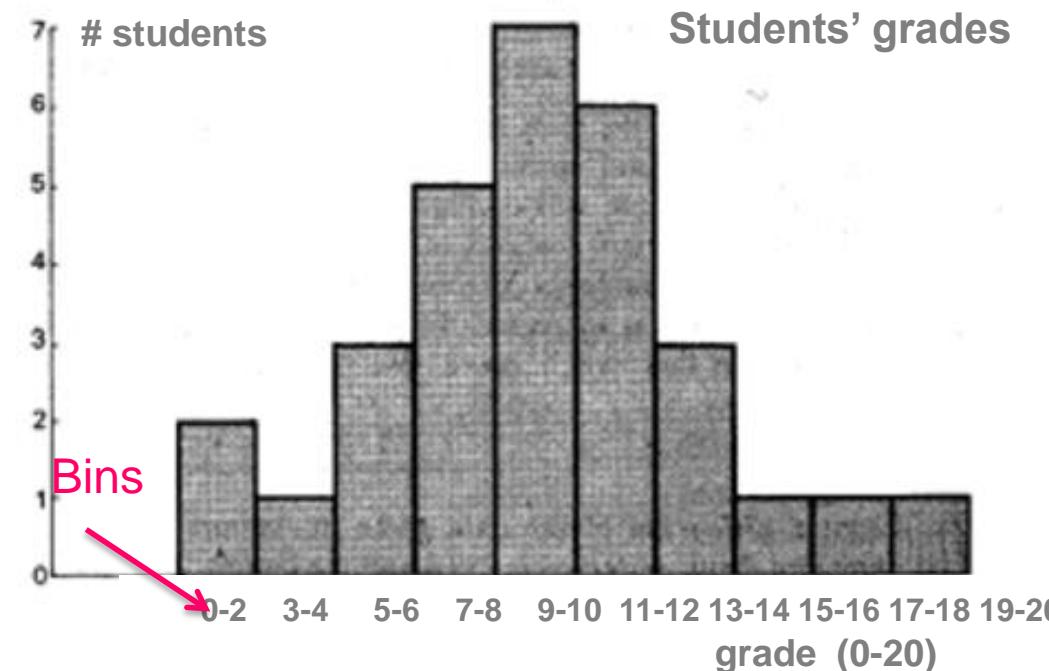
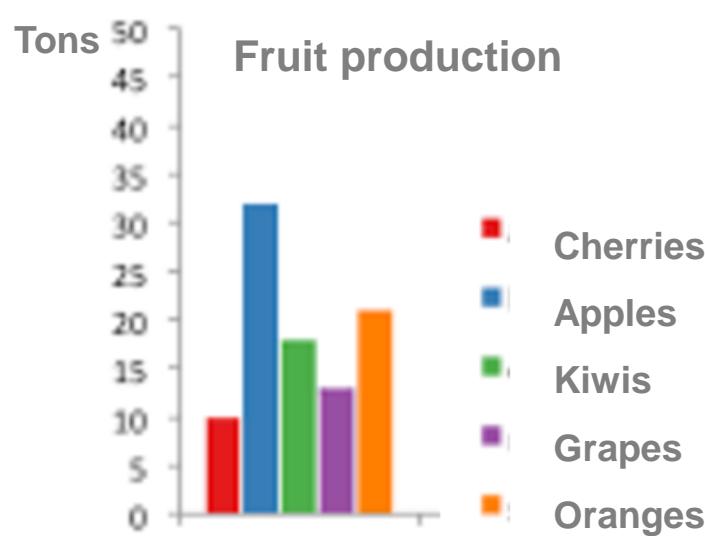
Simple (and common) representations of one attribute data

- Two common techniques not to be confused !

Histogram  represents a distribution of numerical data

Bar chart  represents number of occurrences of categorical/ordinal data

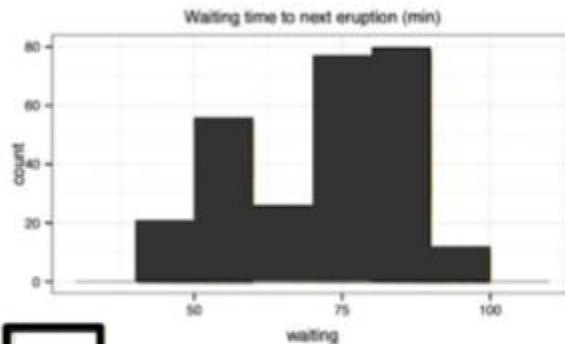
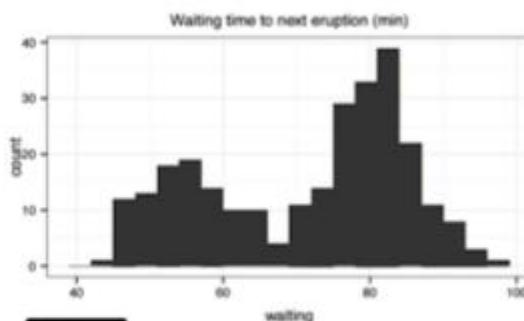
Both represent data by rectangular bars(vertical or horizontal) with length proportional to the values they represent





Histogram Quiz

Given the following plots with different bin widths, Match the description to the plot.



A: good bin width - shows important signal in data (two modes) but not too much noise.

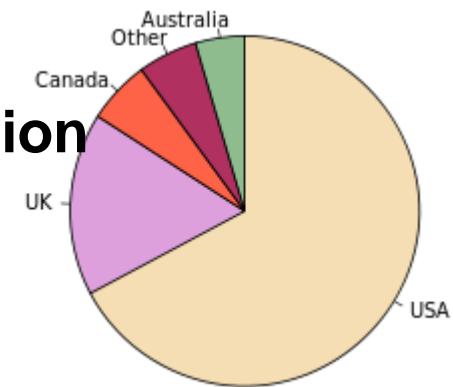
B: bin width is too small
C: bin width is too big

Another simple (and too common) representation

- Pie Chart

Represents numerical proportion, **parts of an whole**

The arc length of each slice (its central angle and area), is proportional to the quantity it represents



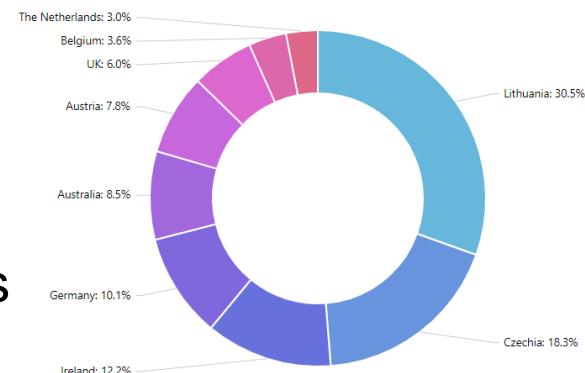
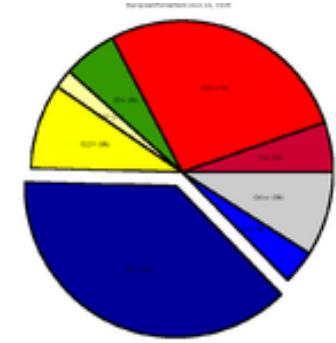
Native English speaking population

Are much controversial:
many experts recommend avoiding them
<http://www.perceptualedge.com/articles/08-21-07.pdf>



It is difficult to compare different sections of a pie chart, or to compare data across different pie charts

Variations of pie charts:

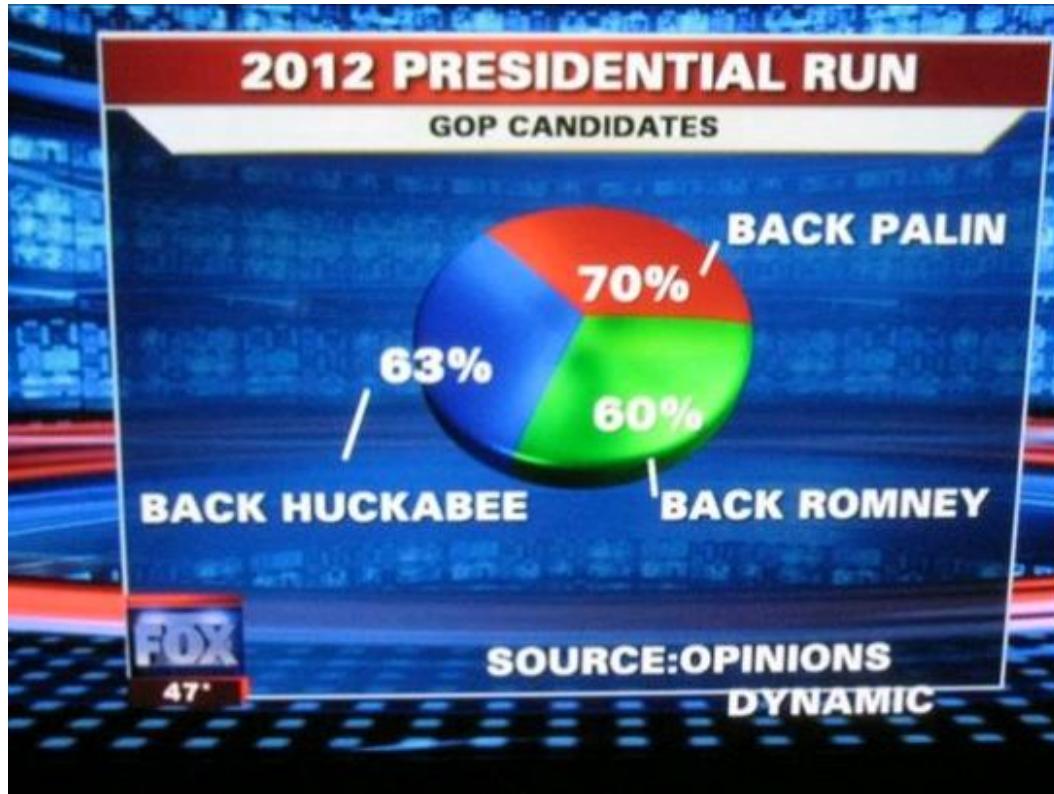


- Simple criteria to determine whether a pie chart is acceptable
- Consider it **only if:**
- **The parts make up a meaningful whole**
- **The parts are mutually exclusive**
- **There are <6 parts and slices have not very different sizes**

If the main purpose is to compare between the parts,
use a different chart!

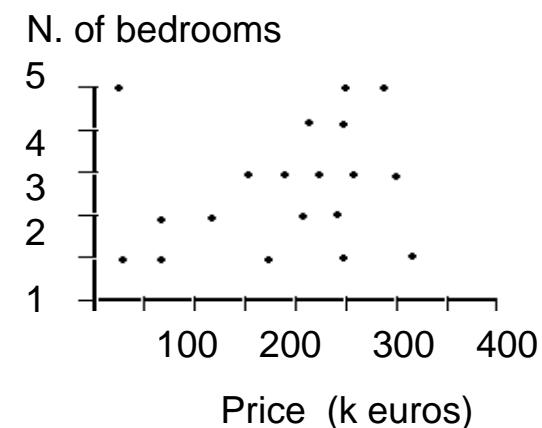
<https://eagereyes.org/techniques/pie-charts>

Prize winning Pie chart!



Representing bivariate data

- The **scatterplot** is a conventional representation



Each observation is represented by a point on a two dimensional space

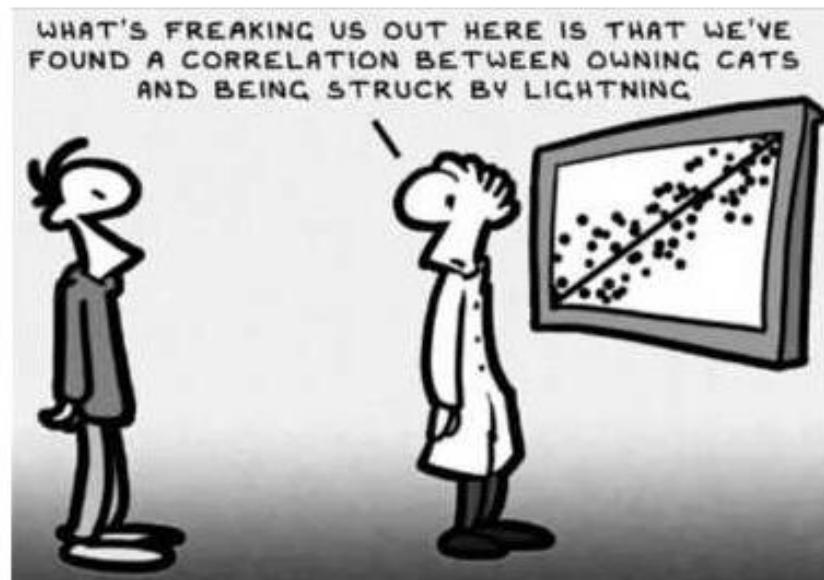
The axes are associated with these two attributes

This representation affords awareness of:

- general trends
- local trade-offs
- outliers



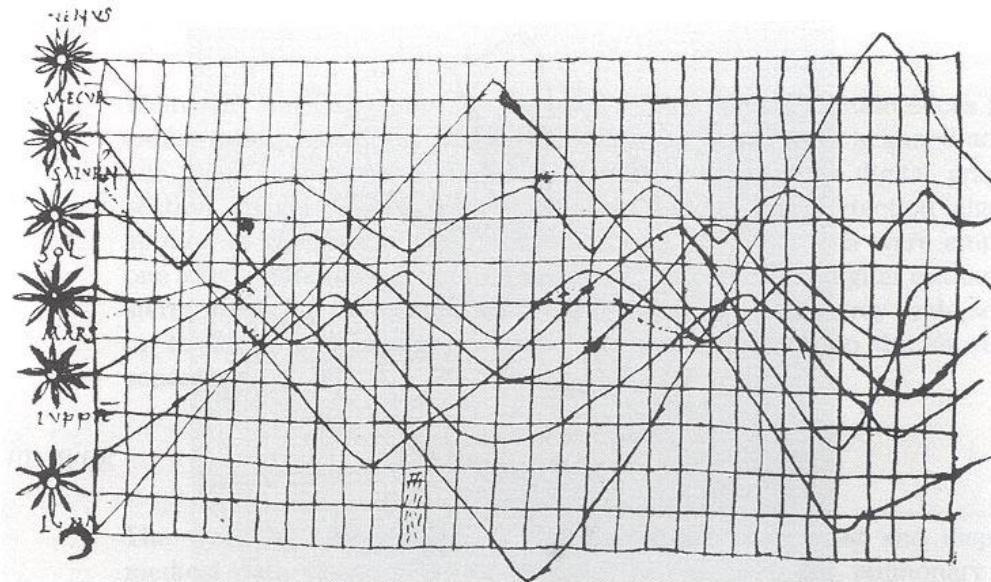
Correlation is not causation



Representing bivariate data

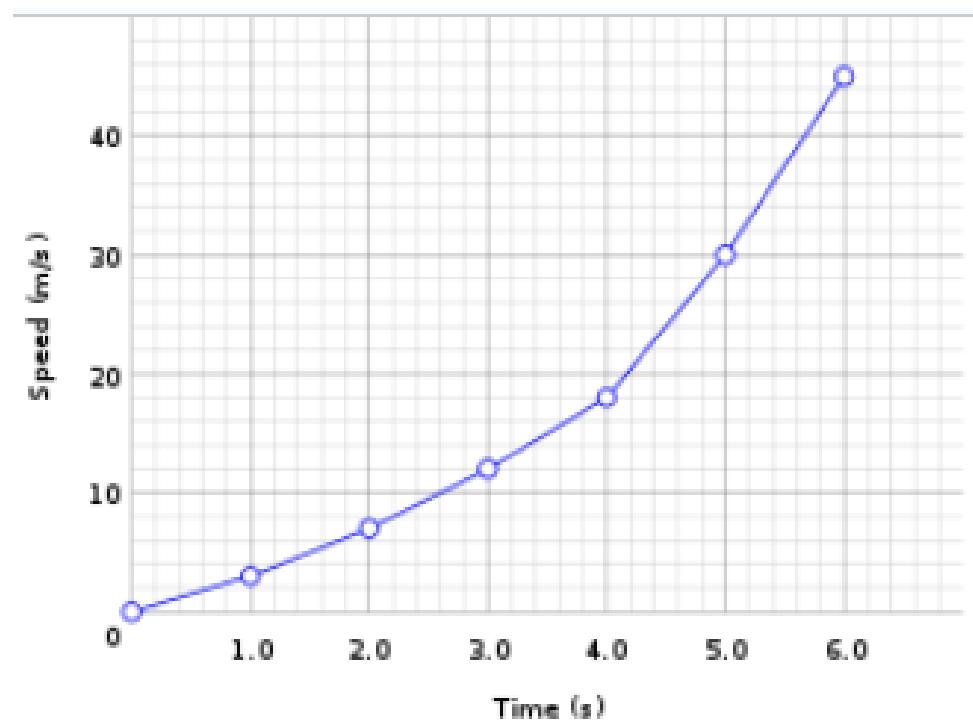
The line chart

One of the oldest known and ubiquitous Visualizations



Inclination of orbits along the time - Xth century (Tufte, 1983)

- A **line chart** or **line plot** or **line graph** or **curve chart** displays information as a series of data points called 'markers' connected by straight line segments
- Basic type of chart common in many fields
- Often used to visualize a trend in data over intervals of time

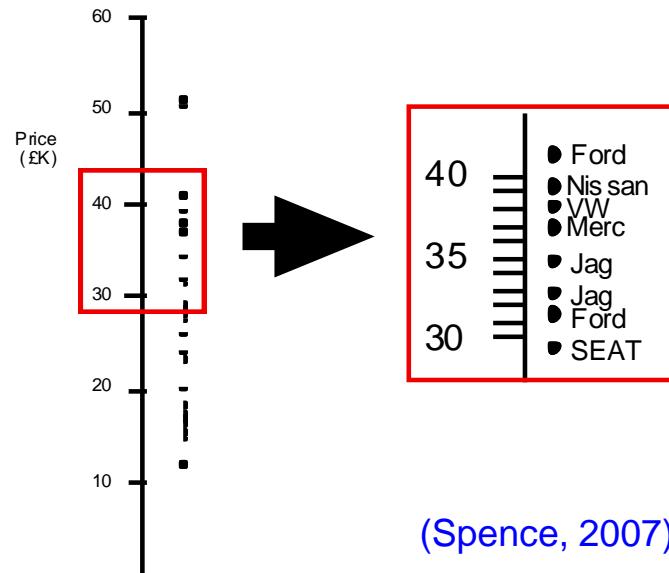


- If one attribute is more important than the other or must be examined first,
- it may be appropriate to employ logical or **semantic zoom**

Example:

Analyzing a list of cars:

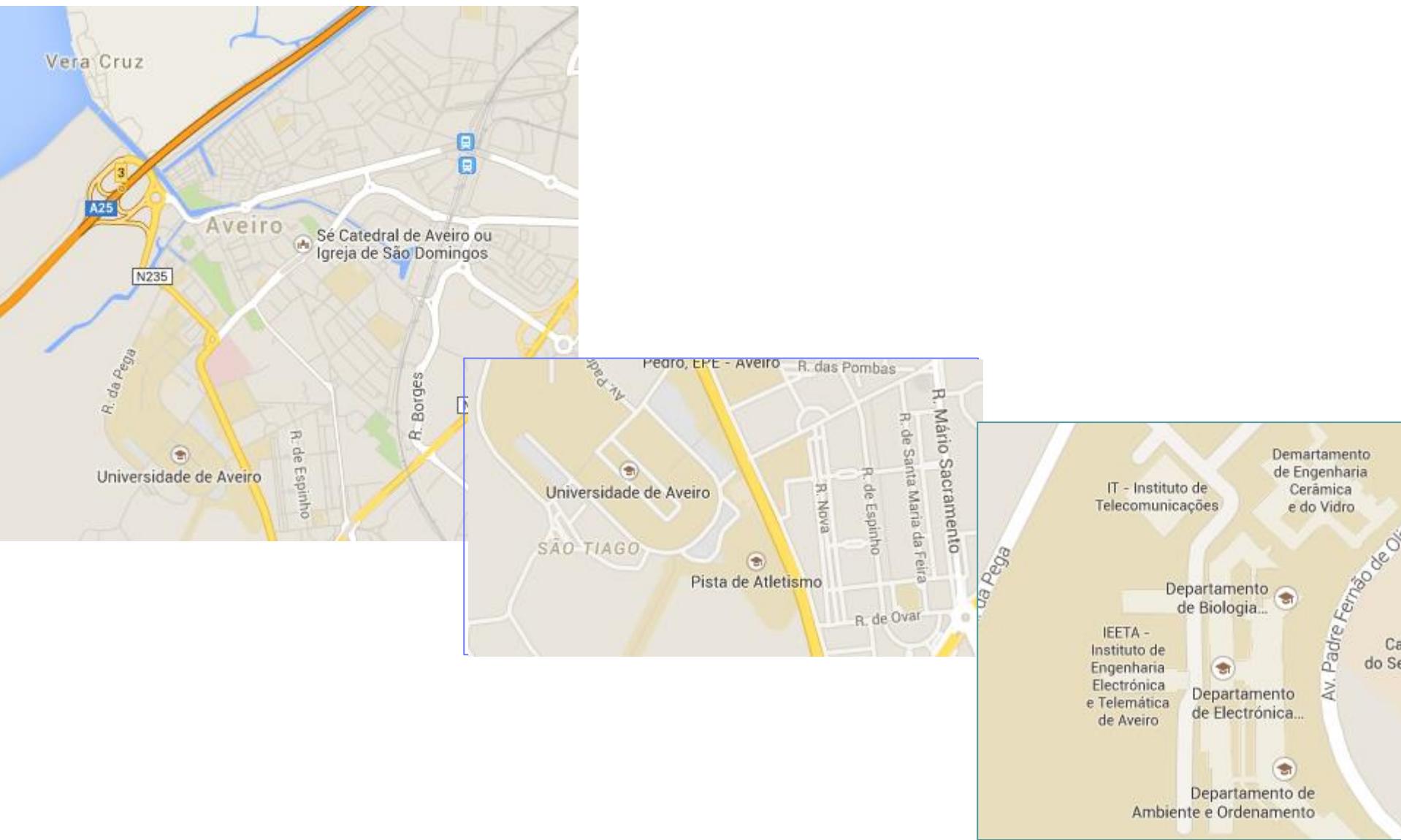
- price is the first attribute to examine
- semantic zoom reveals data about a second attribute



(Spence, 2007)

- This technique is quite general: it can encompass many attributes and many levels of progressive zoom

Example: Zoom in Google Maps

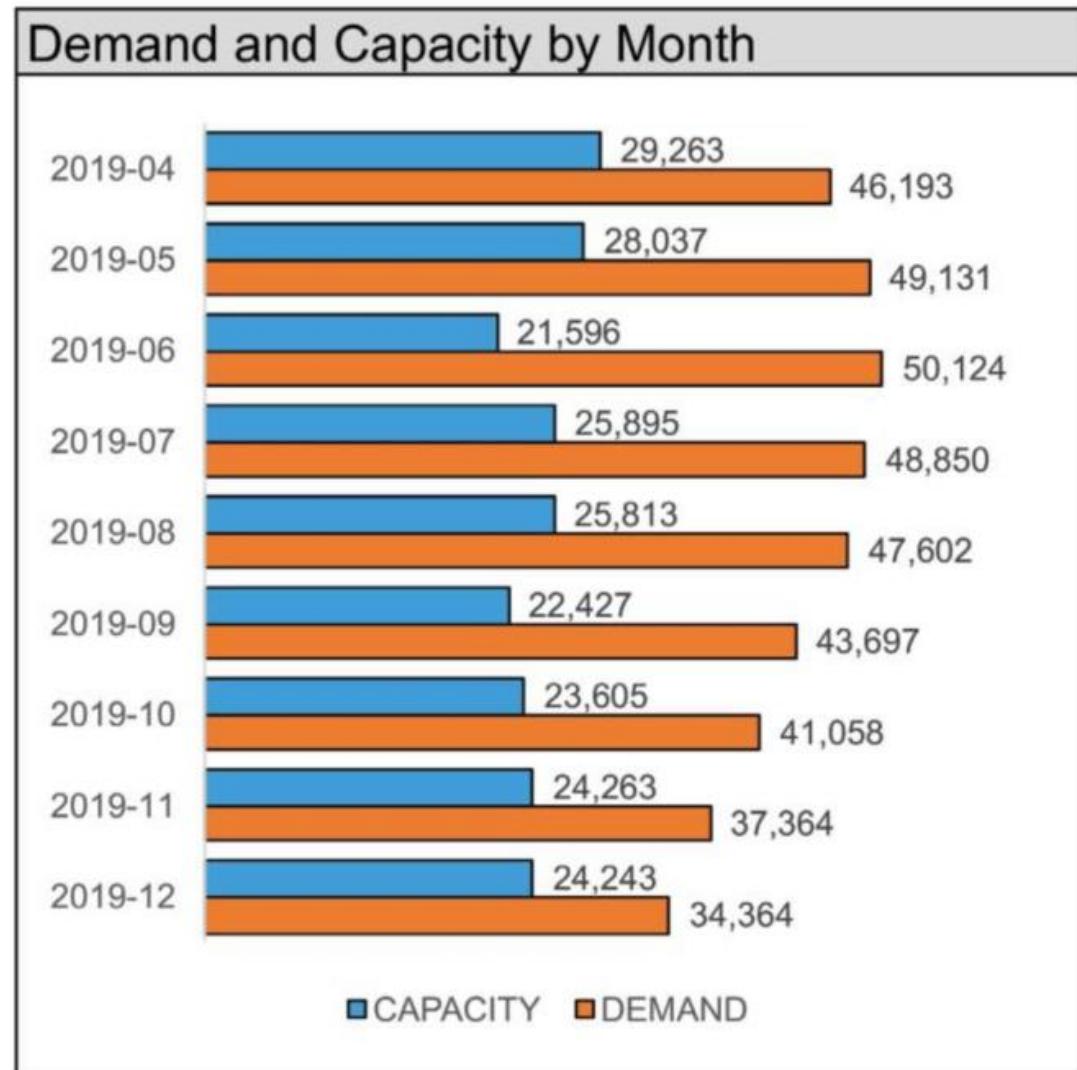


Analyze this visualization

How many attributes?

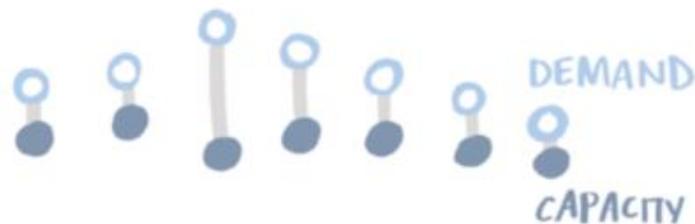
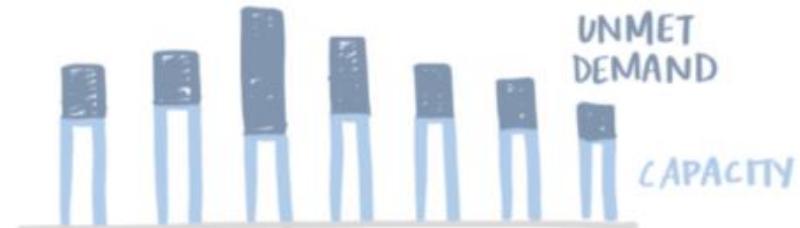
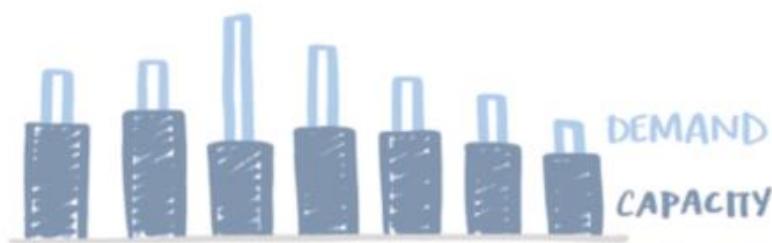
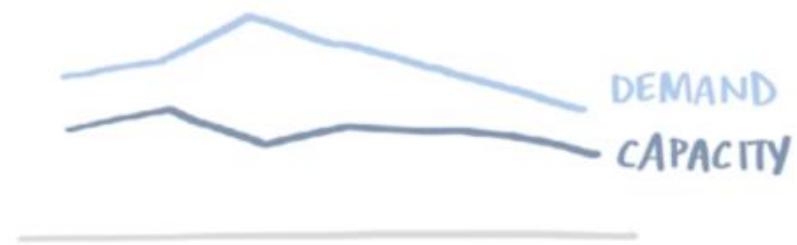
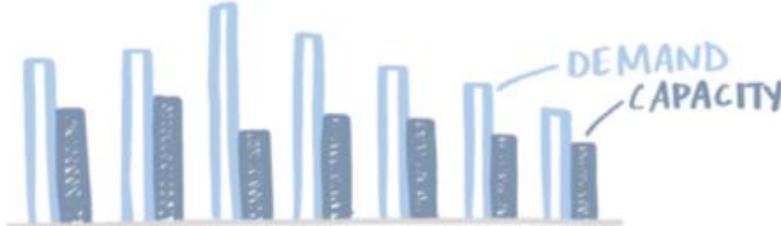
What type of attributes?

Can you think of other ways
of visualizing this dataset?



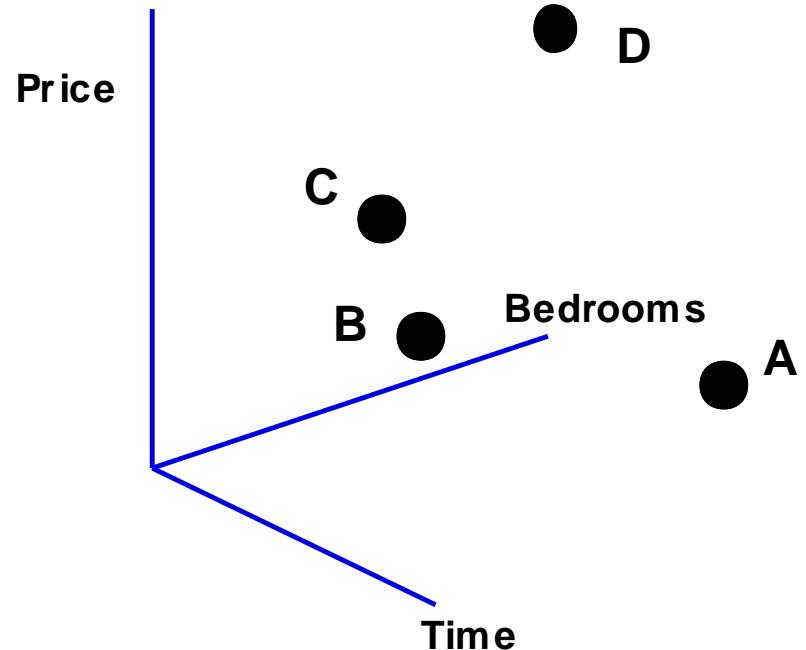
Other possibilities:

what are the advantages/disadvantages of each?



Representing Trivariate data

- Since we live in a 3D world, representing trivariate data as points in a 3D space and displaying a 2D view seems natural
- However, these representations can be **ambiguous**
 - This can be mitigated by interaction, allowing the user to reorient the representation



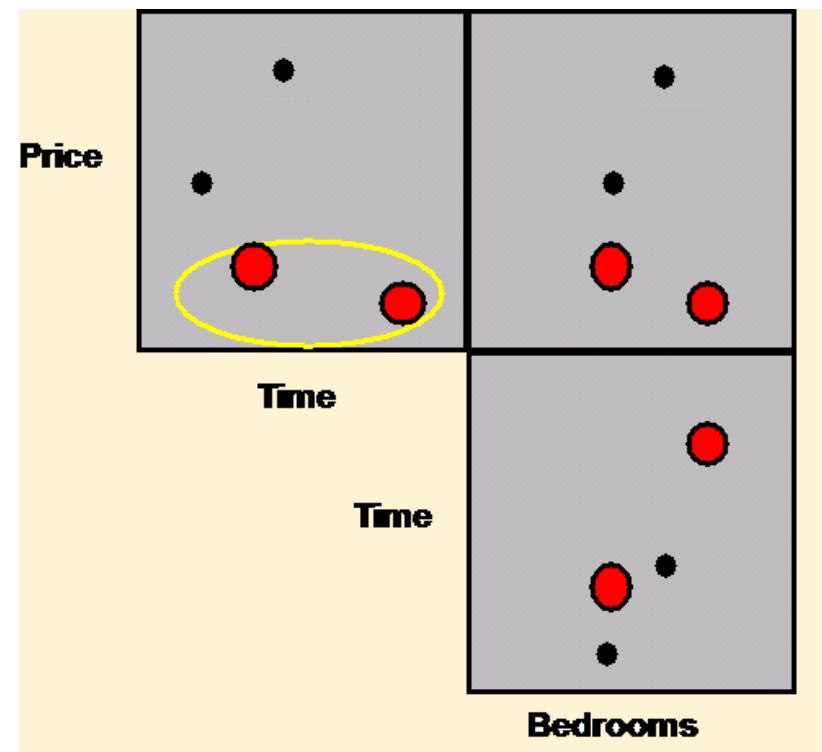
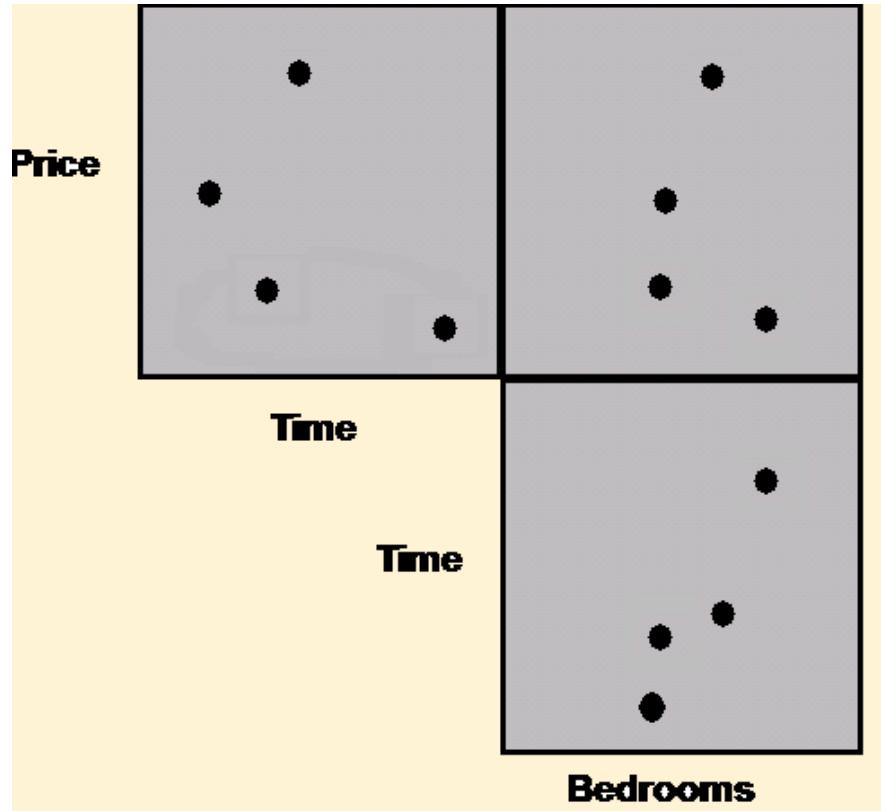
Generally, avoid 3D in InfoVis!

for 3D to be useful, you've got to
be able to move it"

(Spence, 2007)

- Interaction (**brushing**) can help – objects identified in one view are highlighted in the other two planes
- change blindness must be taken into account and ensure that the user notices the highlight in the other two planes

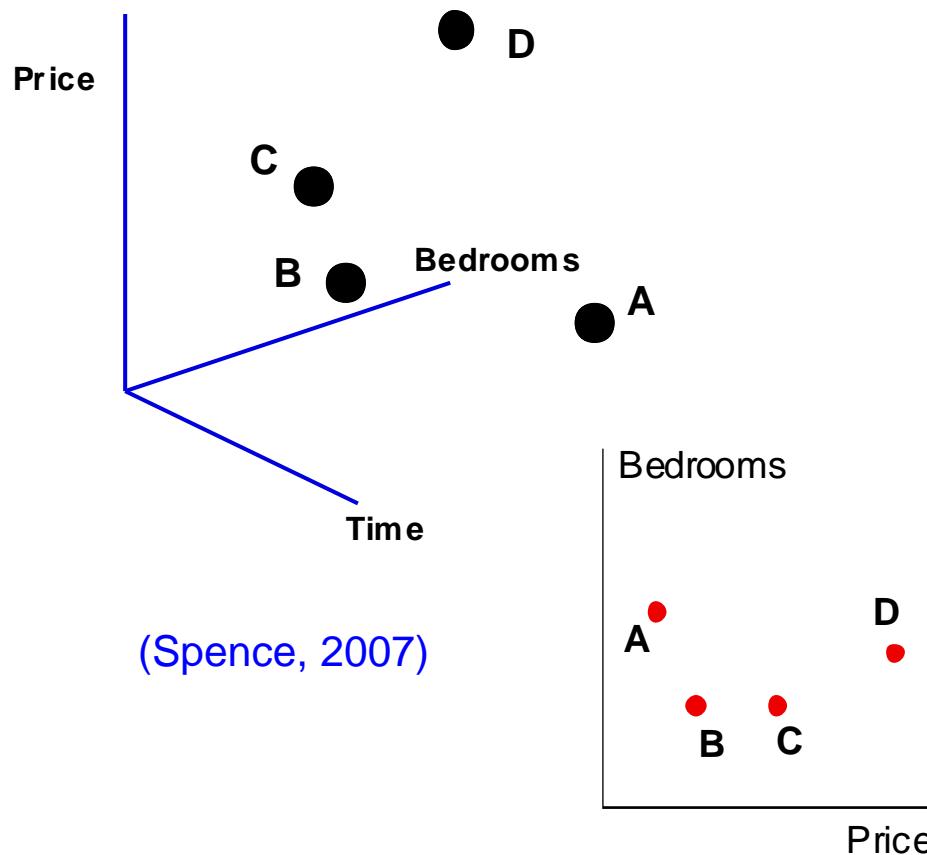
(Spence, 2007)



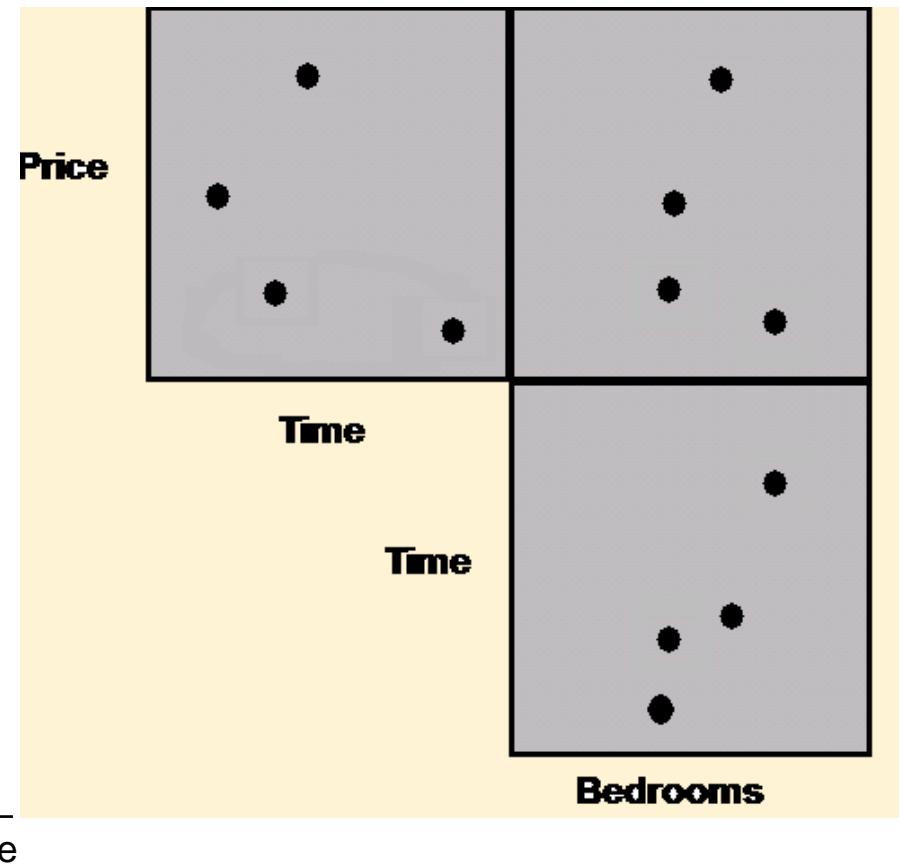
The highlighting of houses in one plane is brushed into the remaining planes.

- An alternative representation for trivariate (and hypervariate) data is a structure formed from the three possible 2D views of the data

Example: houses (price, number of bedrooms, time of journey to work)



Scatterplot matrix

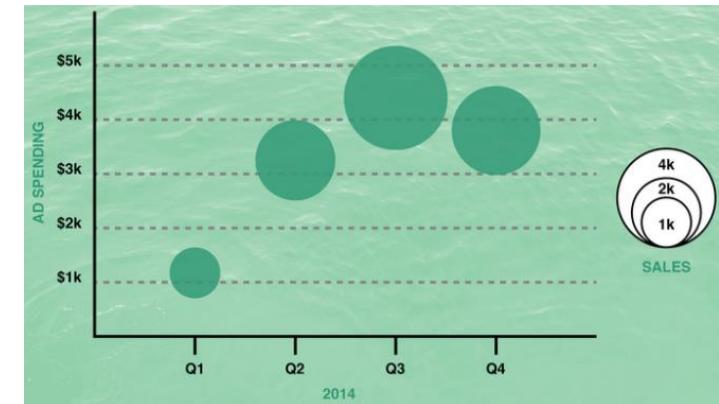


Other Simple (and common) representation of 3D data

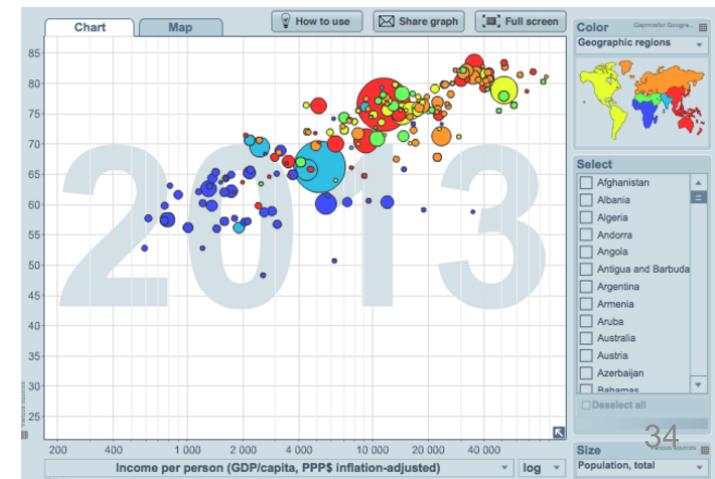
- In a **bubble chart** data are represented as a disk that expresses two of the values through the disk's *xy* location and the third (less accurately) through the size of the disk (radius or area?)



- Mapping the attribute/variable to disk size must be done carefully. The interpretation of may be ambiguous



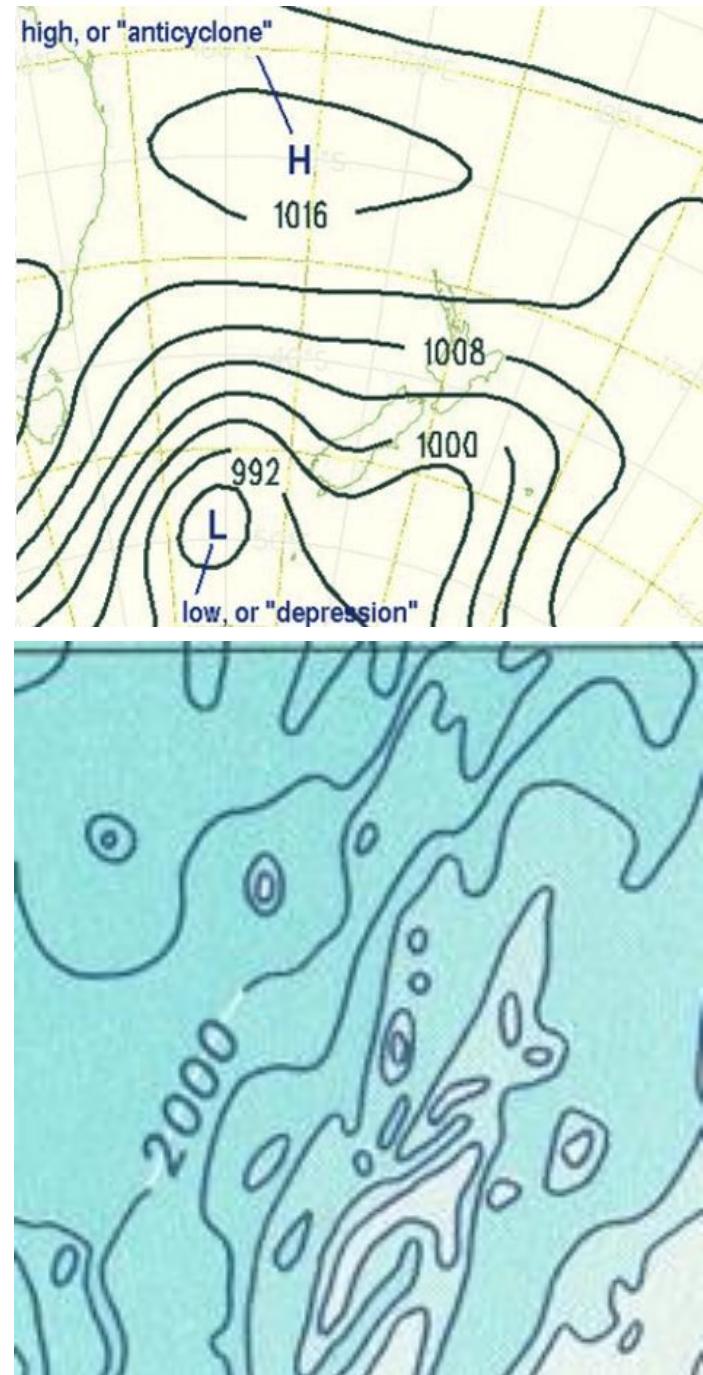
- Representing one more dimension through color



<https://visage.co/data-visualization-101-bubble-charts/>

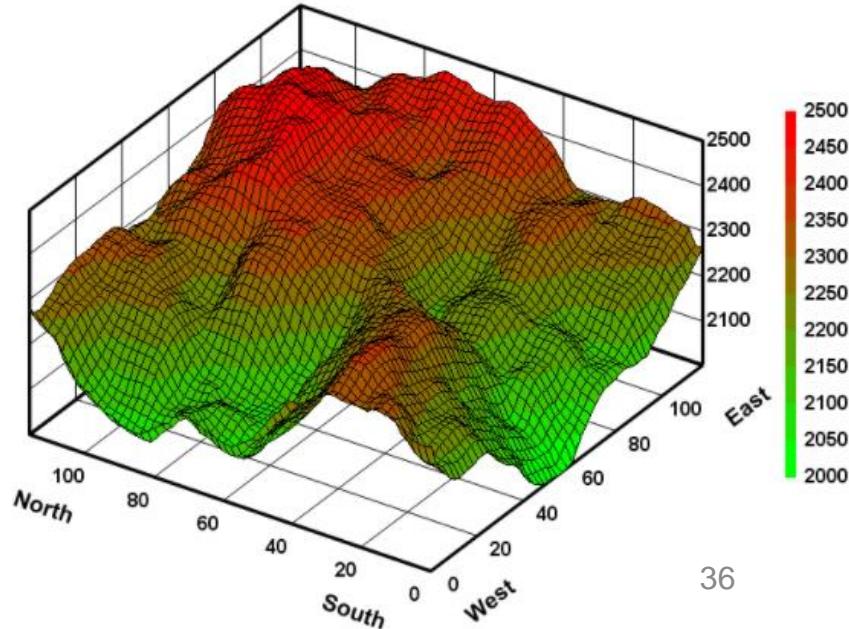
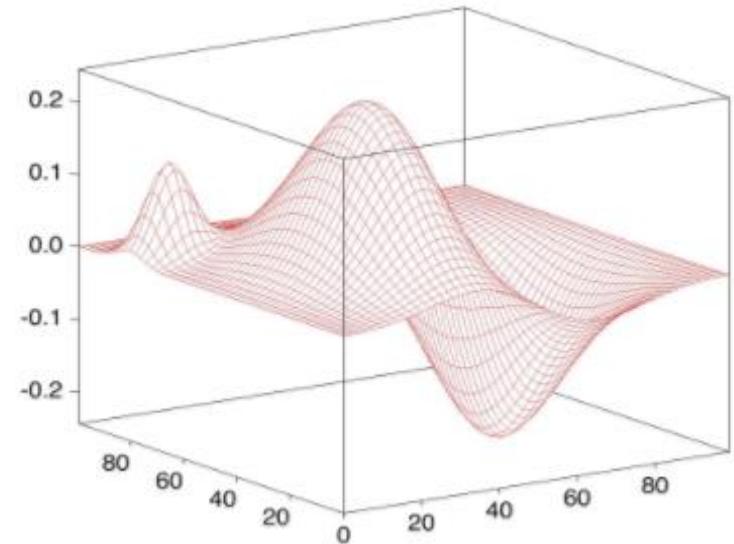
Simple representations of a function (field) of two variables

- Contour plots
- **contour line** (also **isoline**, **isopleth**, or **equipotential curve**) of a function of two variables is a curve along which the **function has a constant value**, so that the curve joins points of equal value.
- Often used in SciVis
- Typical in meteorological charts (isobars and isothermal curves)
- and maps (to represent altitude or depth)

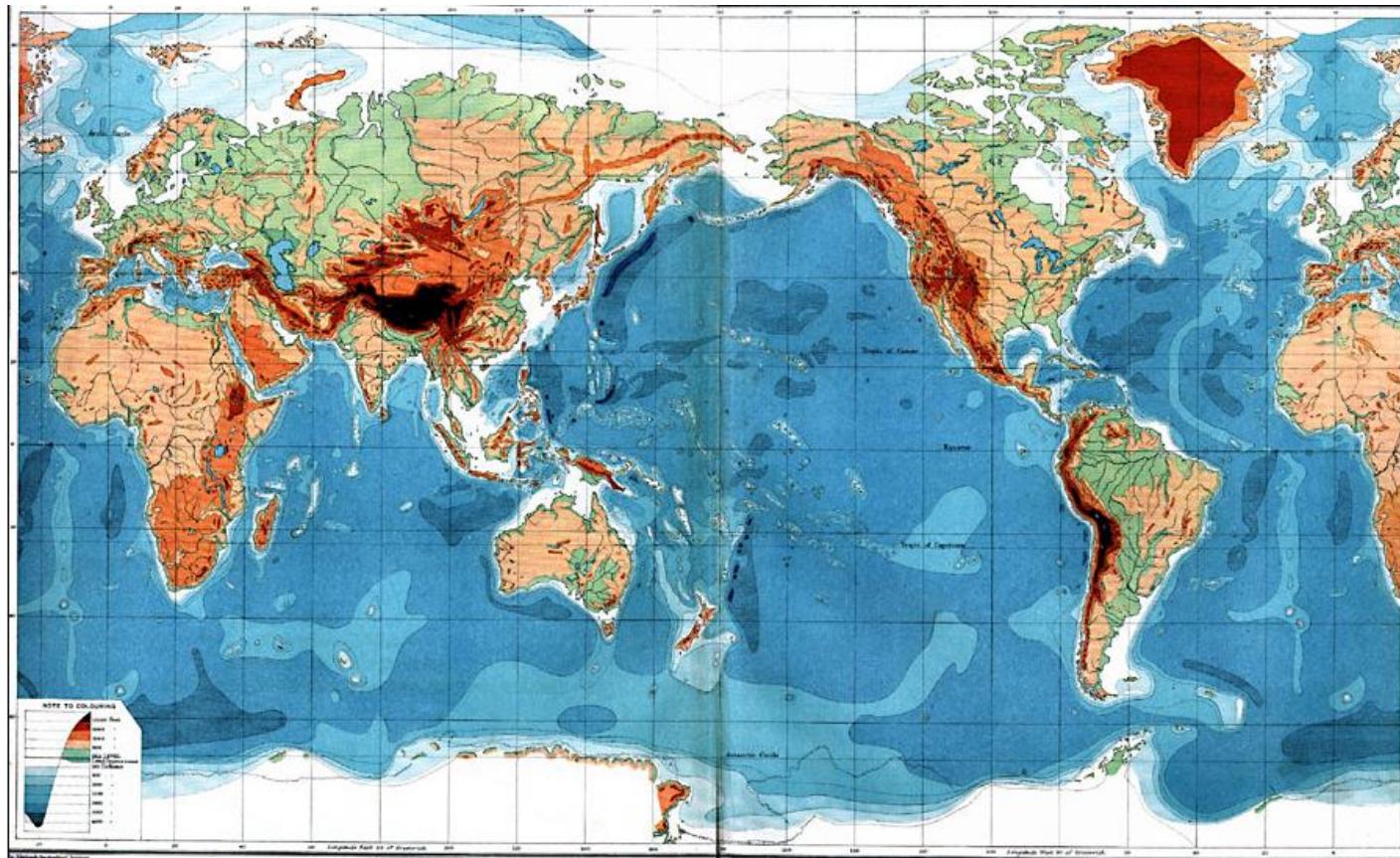


- Surface plots (also often used in SciVis)
- May be combined with color

(preferably in a redundant way and carefully selecting the scale)



A special category of trivariate data: Maps (latitude and longitude + a value)

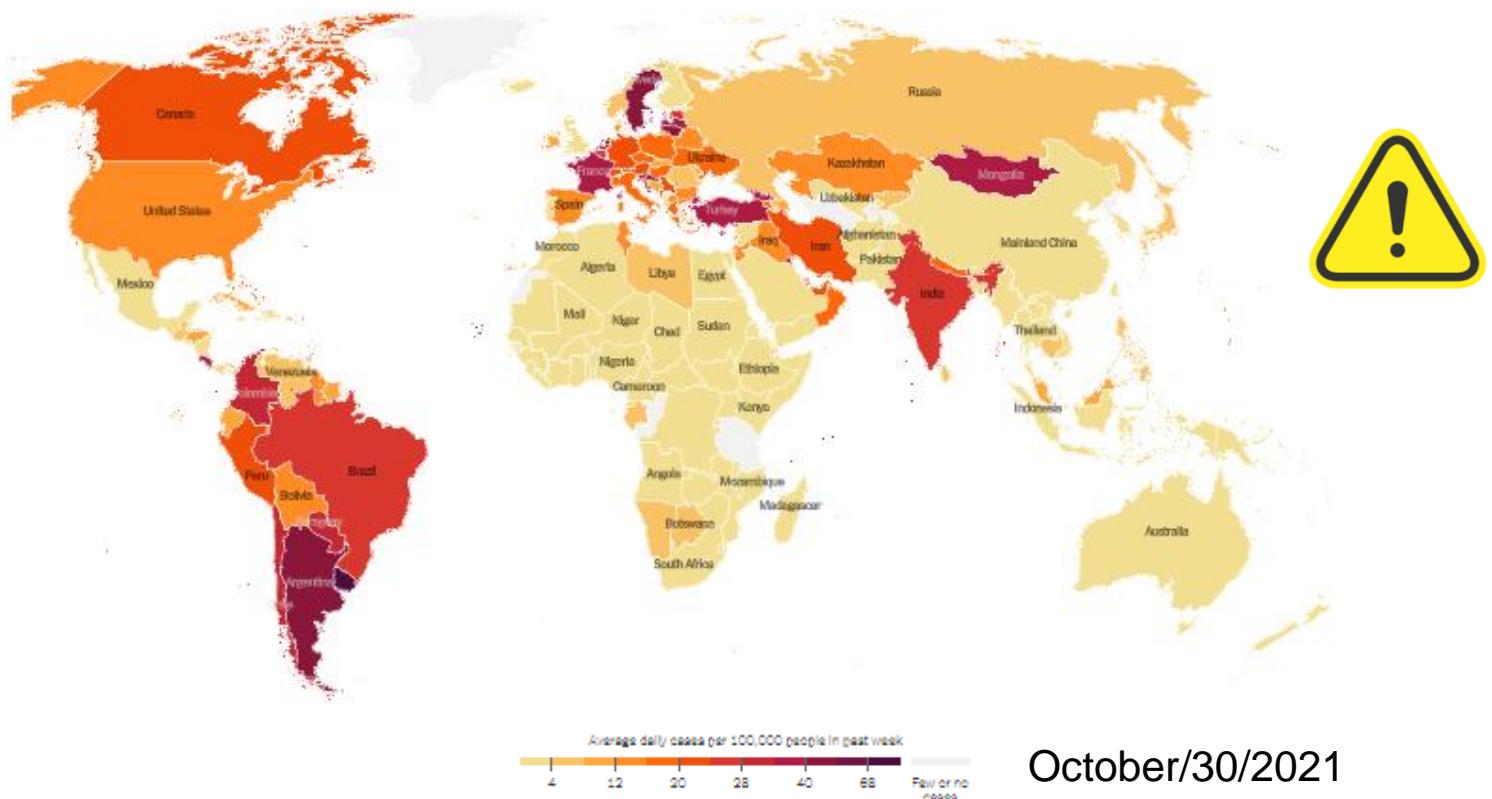


1915 – Orographic Chart of the World

<https://etc.usf.edu/maps/pages/100/167/167.htm>

Choropleth maps - A standard approach to communicating aggregated data by geographical areas using color encoding of the geographic area

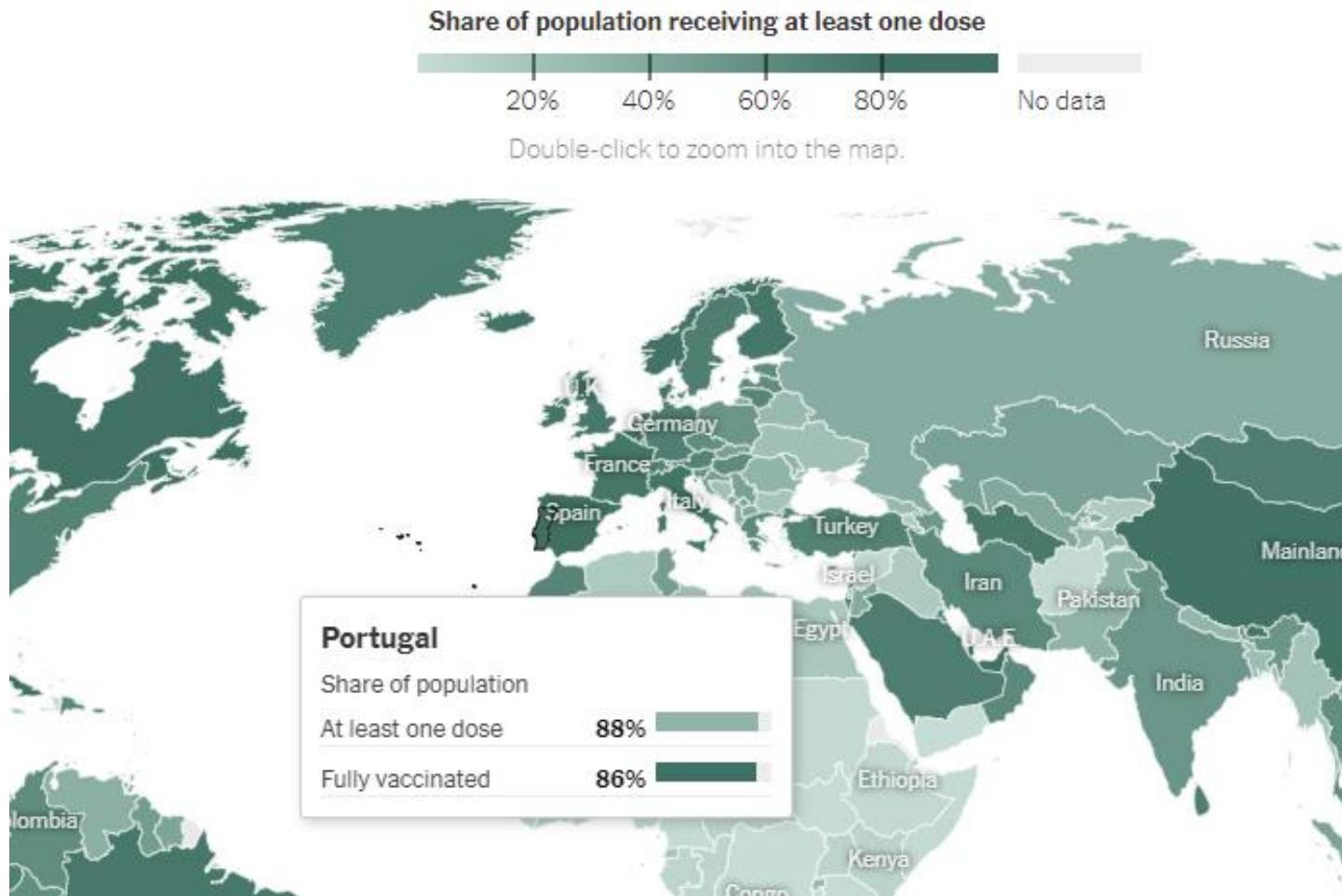
They require some care: what are the possible issues?



<https://www.nytimes.com/interactive/2020/world/coronavirus-maps.html>

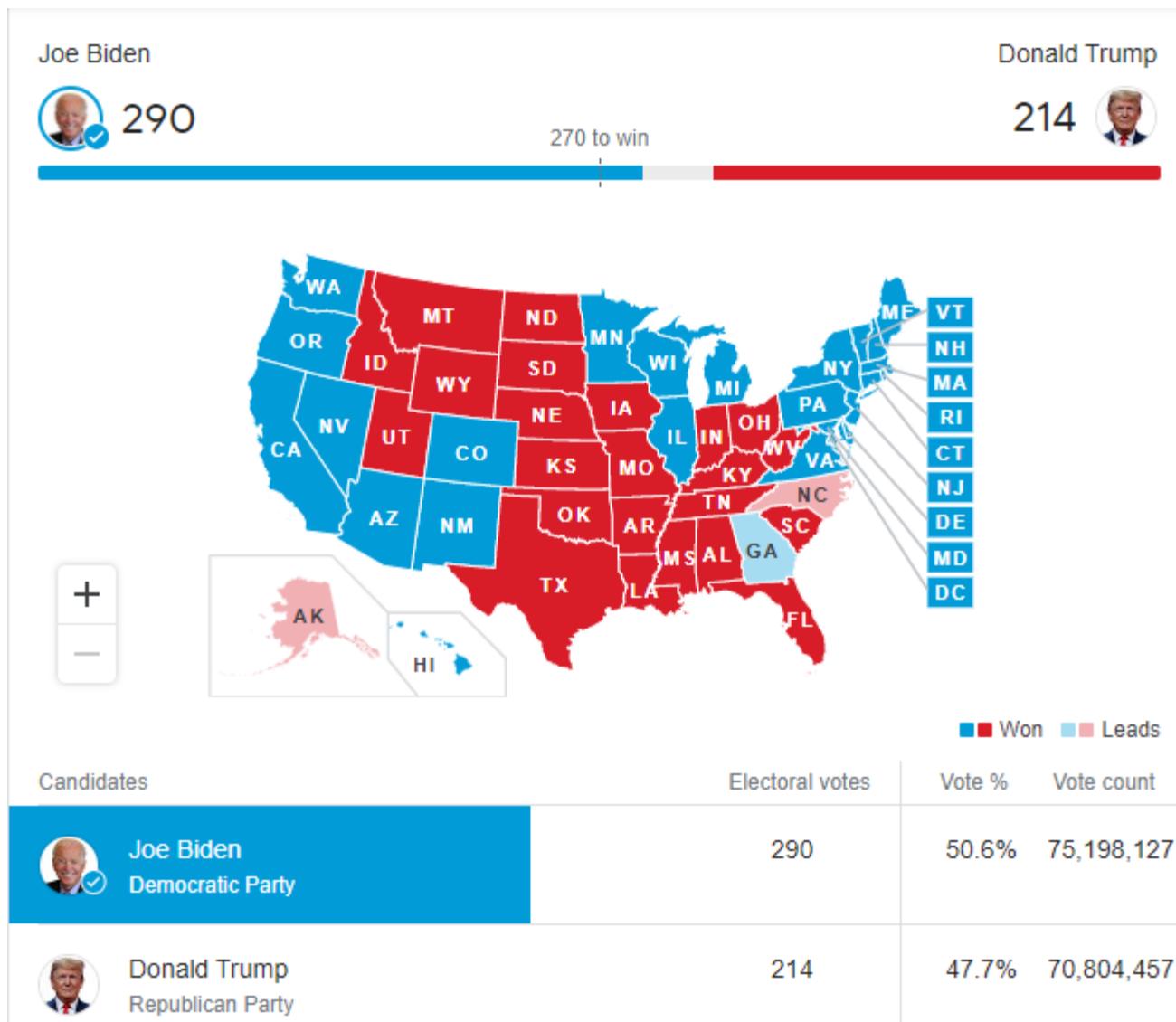
How can these issues be mitigated?

Covid vaccination worldwide (choropleth + details on demand)

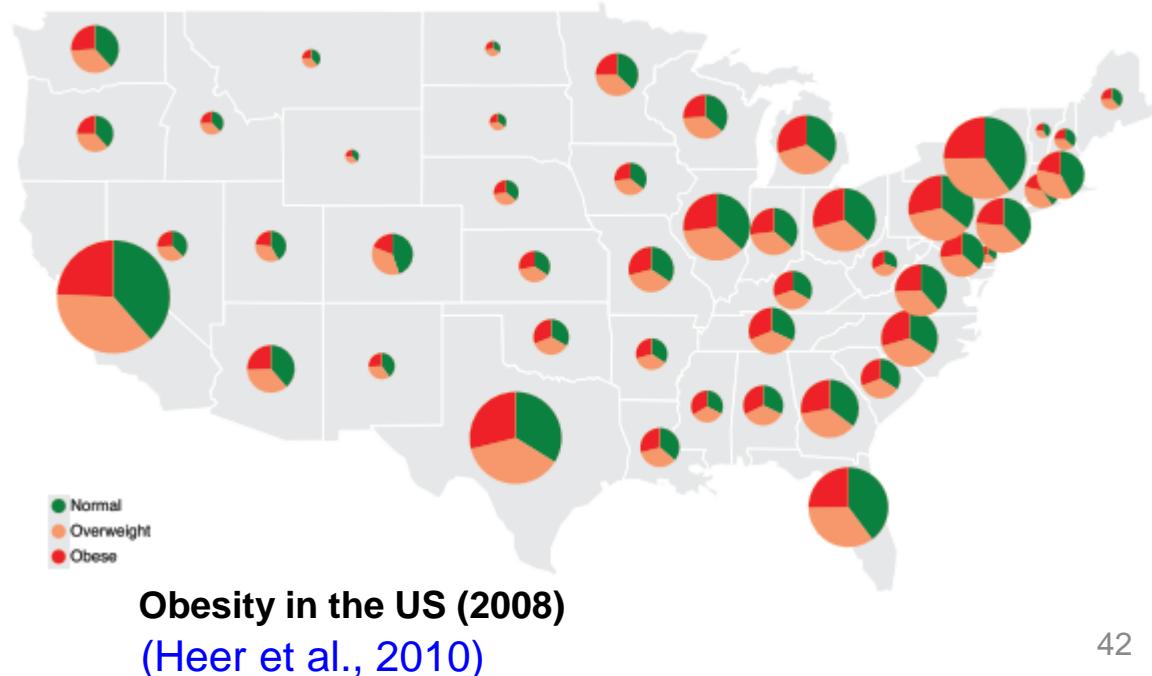


<https://www.nytimes.com/interactive/2021/world/covid-vaccinations-tracker.html>

Visualizations of the US 2020 Election (choropleth + bar)



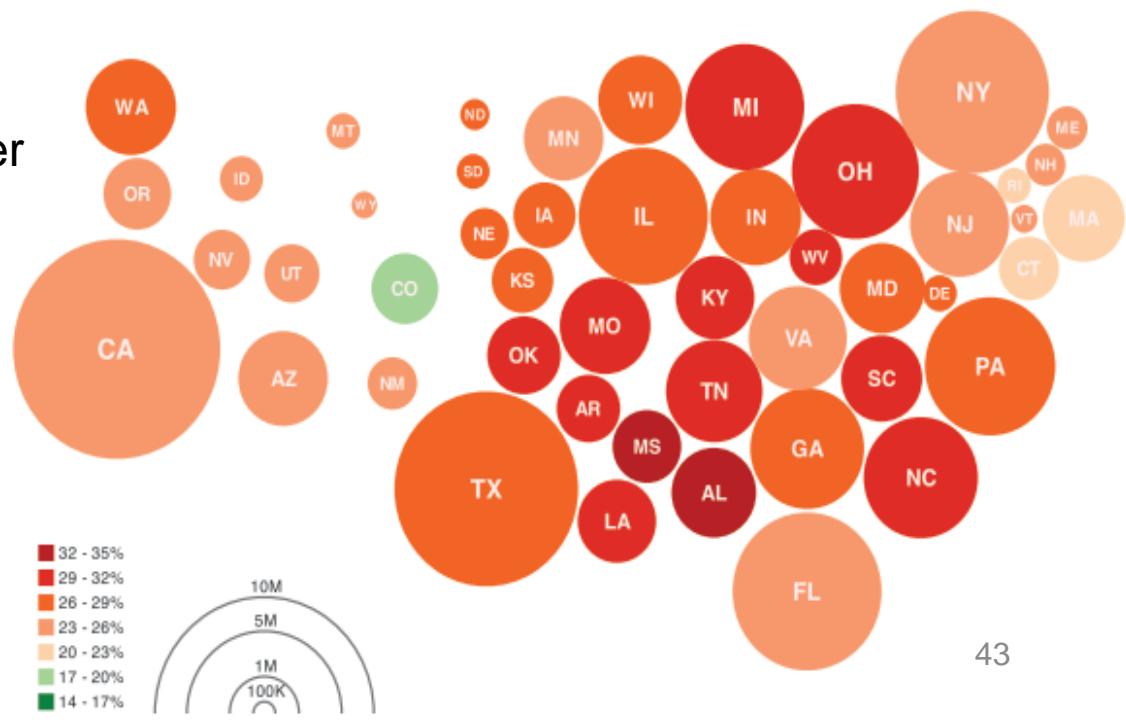
- **Graduated Symbol Maps** are an alternative to the choropleth map;
- Symbols are placed over an underlying map; may show more dimensions
- Avoid confounding geographic area with data values



- **Cartograms** distort the shape of geographic regions so that the area directly encodes a data variable.
- There are several types
- **Dorling cartograms** represent each geographic region with a sized circle placed so as to resemble the true geographic configuration

In these example:

- area encodes the total number of obese people per state
- color encodes percentage of obese population



US Presidential Election 2016

Results mapped at county level showing the candidate with the largest vote share in each area

Overall result:

Trump

60,265,858 votes (47.3%)

290 electoral votes

Clinton

60,839,922 votes (47.8%)

228 electoral votes

Other candidates

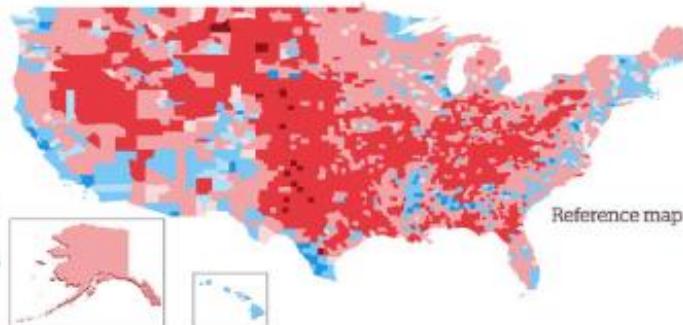
6,226,950 votes (4.9%)

Vote share
of candidate with most votes

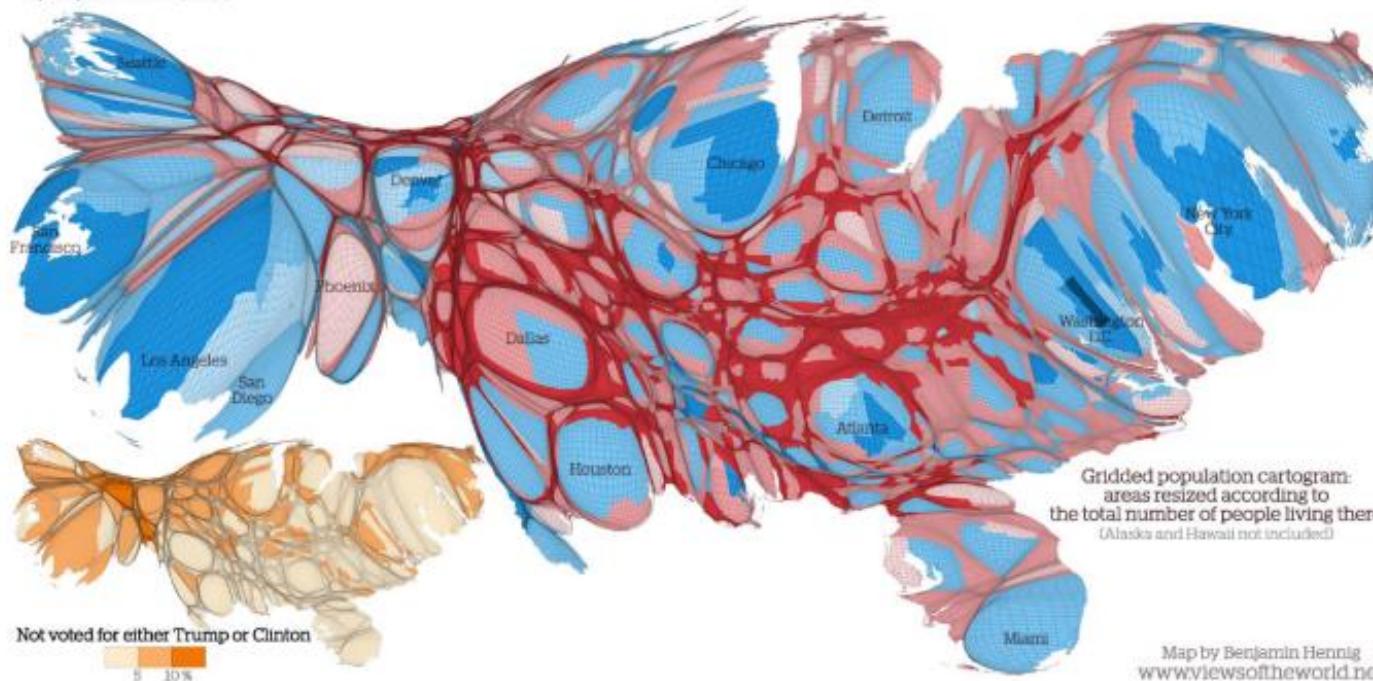
0 50 70 90%

Trump

Clinton



Reference map

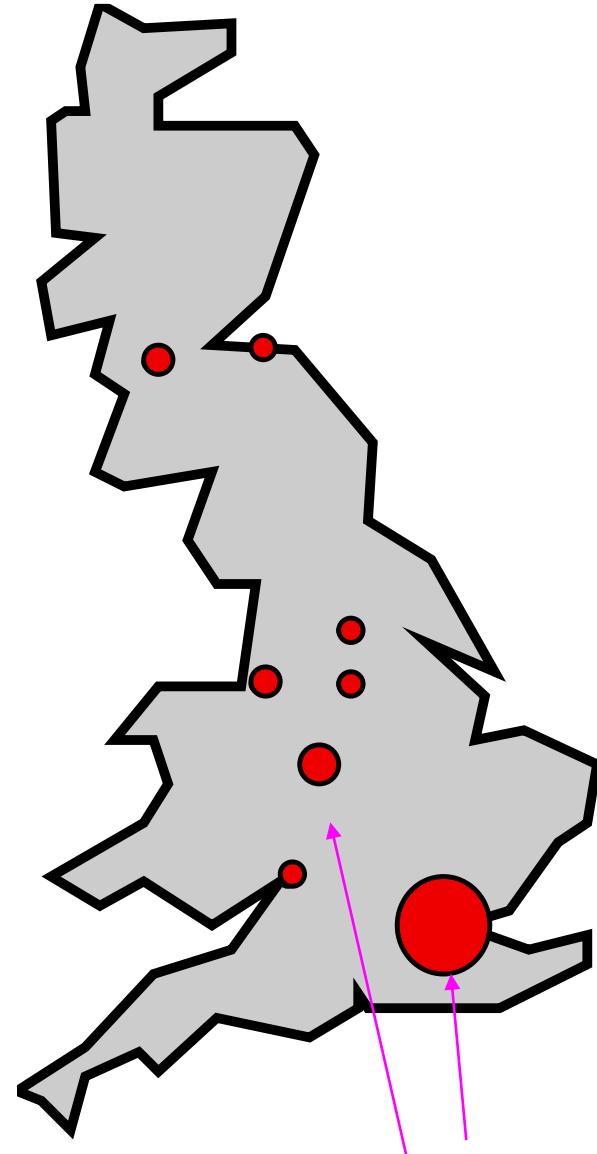


Cartogram showing the 2016 US election results (Click image for larger version)

<https://geographical.co.uk/places/mapping/item/1981-us-election-cartogram-special>

Some more examples on how humans see...

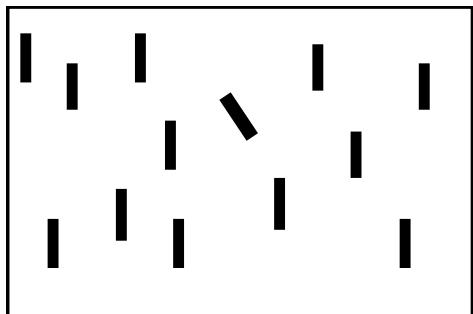
Population of major cities in England, Wales and Scotland. Circle area is proportional to population. ([Spence, 2007](#))



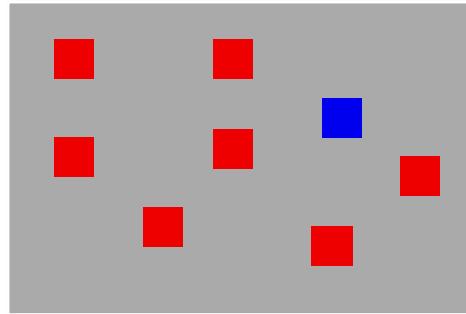
Things that “pop-out”

Pre-attentive processing: Things that “pop out”

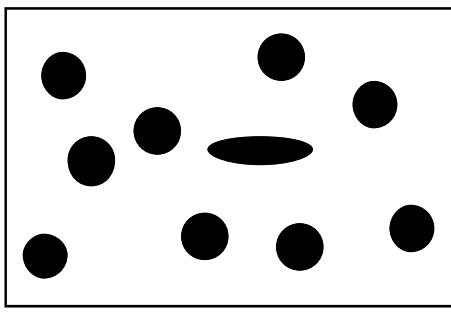
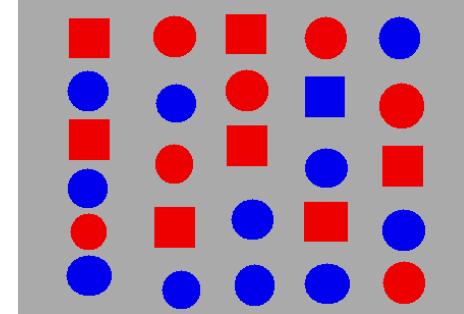
“We can do certain things to symbols to make it much more likely that they will be visually identified even after a very brief exposure” (Ware, 2004)



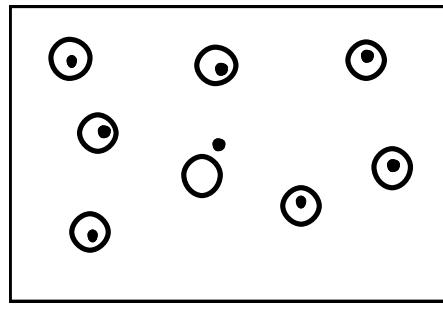
Orientation



Colour



Shape



Enclosure

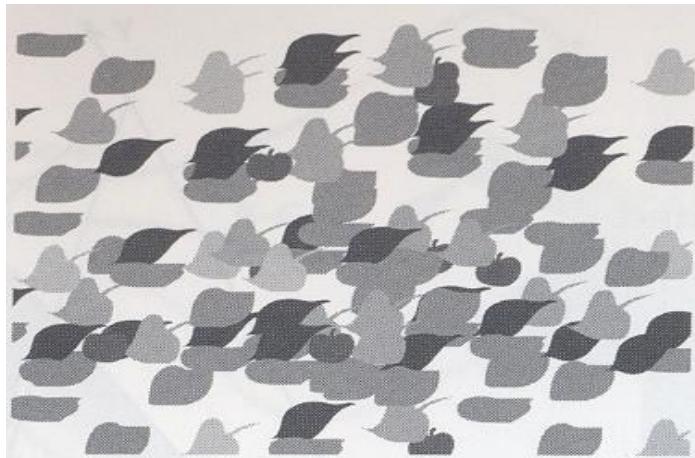
Where is the blue square?

(Spence, 2007)

But we should be careful...

Color is a strong visual cue

- How many cherries?



(Ware, 2004)

Color is a strong visual cue: it may help users perform their tasks

If correctly used

How many cherries?



Color may support users in many tasks!

Or not ...

Using color is complex as color perception is complex...

Color scales

Fundamental use cases for color in visualization:

- distinguish groups of data (qualitative color scales)
- represent data values (sequential color scales)
- Highlight (accent color scales)

The types of colors and the way in which they should be used are quite different
(some examples next)

<https://clauswilke.com/dataviz/>

Qualitative color scales

Okabe Ito



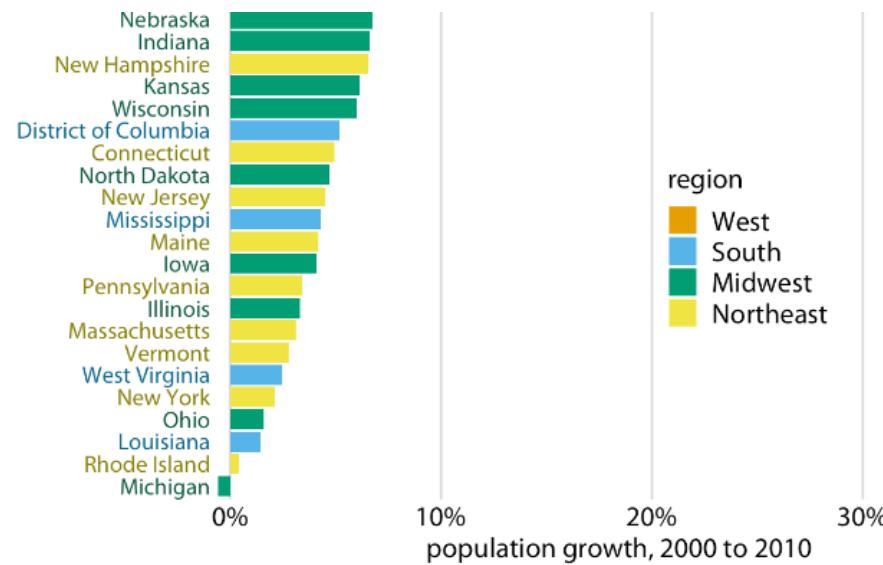
ColorBrewer Dark2



ggplot2 hue



Colors are chosen to be clearly distinct
and not stand out relative to others



<https://clauswilke.com/dataviz/>

Sequential color scales

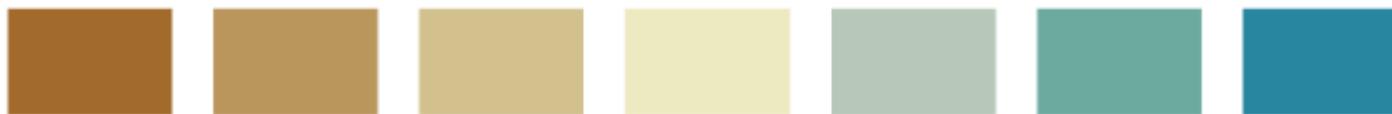
ColorBrewer Blues



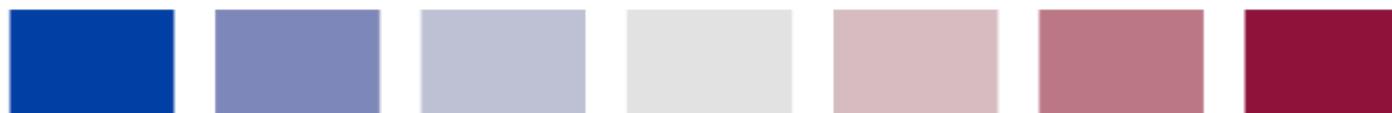
Heat



CARTO Earth



Blue-Red



monochrome

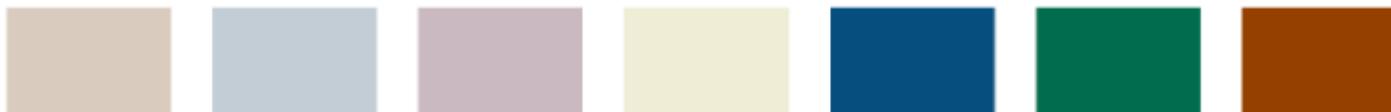


diverging

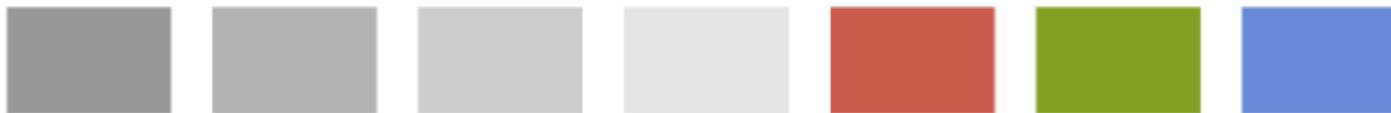
Colors should indicate which values are larger or smaller, and how distant two specific values are from each other, may be monochrome, diverging ...

Accent color scales

Okabe Ito Accent



Grays with accents

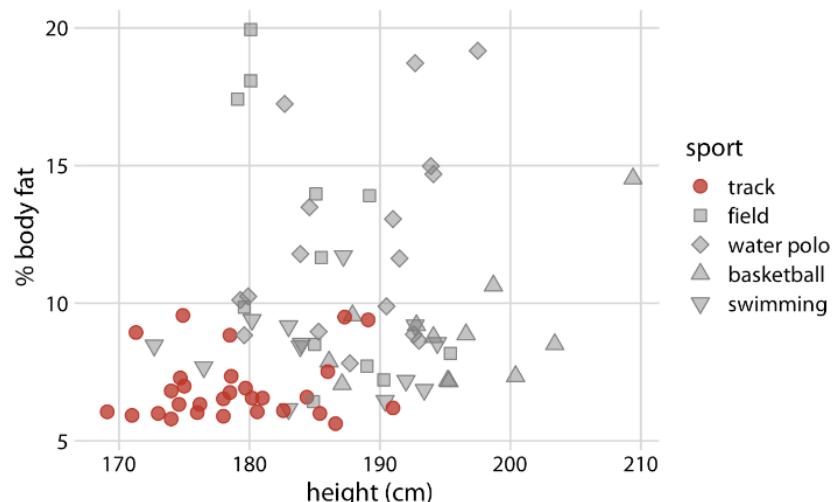


ColorBrewer Accent



These scales contain a set of subdued colors and a matching set of stronger, darker, more saturated colors

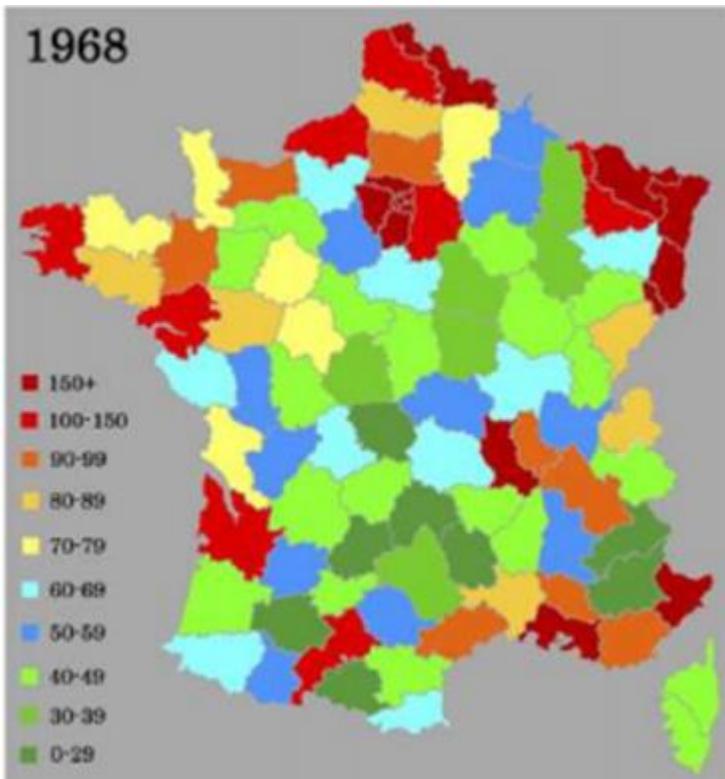
<https://clauswilke.com/dataviz/>



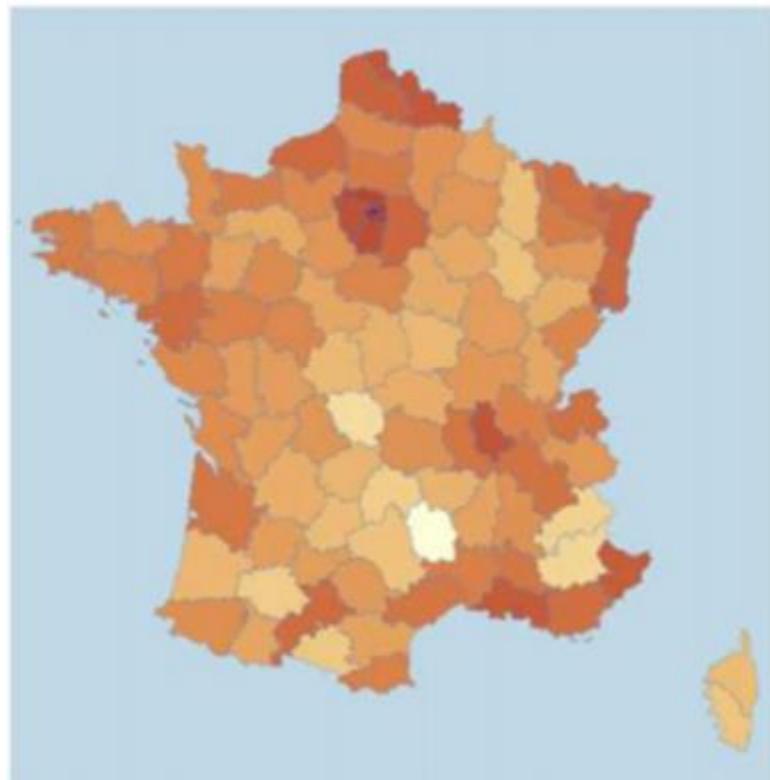


Color may not help or even make it more difficult!

A



B



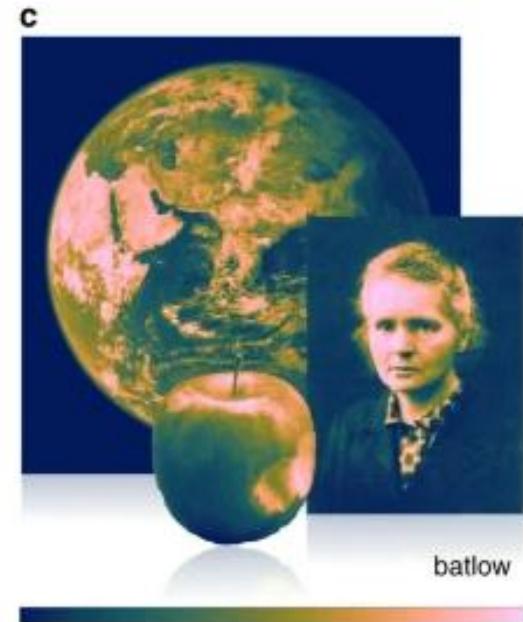
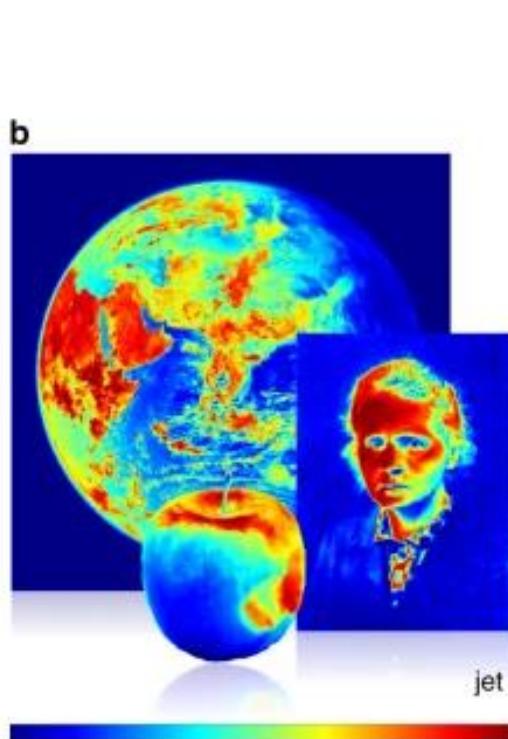
A- no preattentive association that allows efficiently determine the values ([Kirk, 2012](#))

B- a single hue and a sequential color scheme representing values in an immediately understandable way

The misuse of colour in science communication



The superiority of scientifically derived colour maps.



<https://www.nature.com/articles/s41467-020-19160-7>

Remember:

- Not everyone sees color:
- The most common form of color blindness is deutanopia (“daltonism”)
- There are color blindness simulators:
Try this one:

Drag and drop or paste your file in the area below or: [Escolher ficheiro](#) Nenhum ficheiro selecionado

Trichromatic view: Anomalous Trichromacy Dichromatic view: Monochromatic view:

Normal Red-Weak/Protanomaly Red-Blind/Protanopia Monochromacy/Achromatopsia
 Green-Weak/Deutanomaly Green-Blind/Deutanopia Blue Cone Monochromacy
 Blue-Weak/Tritanomaly Blue-Blind/Tritanopia Blue Cone Monochromacy

Use lens to compare with normal view: No Lens Normal Lens Inverse Lens

[Reset View](#)



Zoom, move and lens functionality only with your own images available.

<http://www.color-blindness.com/coblis-color-blindness-simulator>



Normal vision



Deutanopia



Tritanopia
<http://www.colourblindawareness.org/>

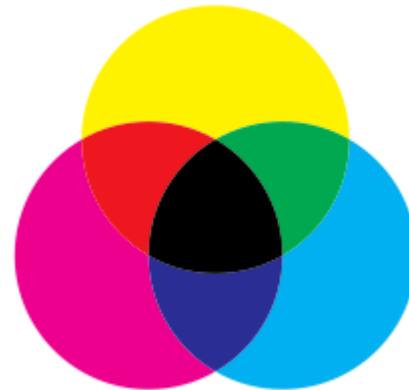
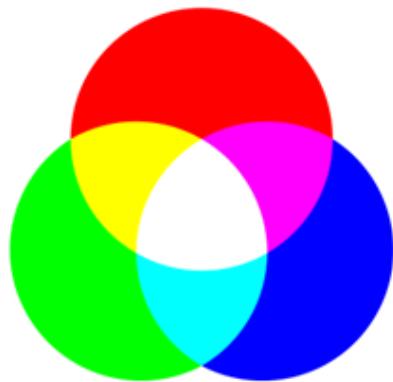
Some rules to use color in visualization

- Make it right is Black and White
- Less is more, or less is better
- Avoid using fully saturated colors in large numbers and in large areas
- Use fully saturated colors only when you want to highlight
- Use blue in larger areas and not in small areas
- Mind colorblindness and use simulators to test your designs
- When adopting color to distinguish, use colors that are easily distinct from each other
- ...

Color models

Are used to measure and produce color

The basic H/W oriented models are RGB (additive) and CMY (subtractive)

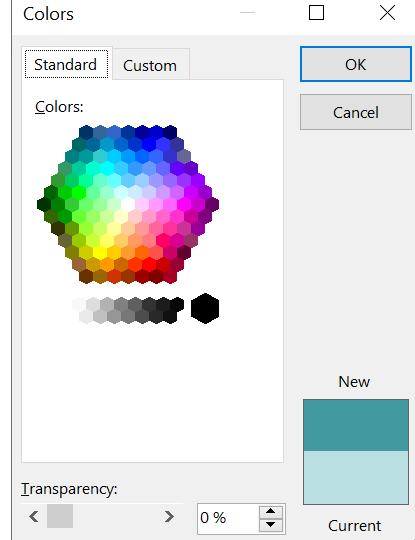


RGB: emitting/screens/projectors

CMYK: reflecting/printers

Are not related to human perception, but to the physical process

Should not be used directly to produce color scales



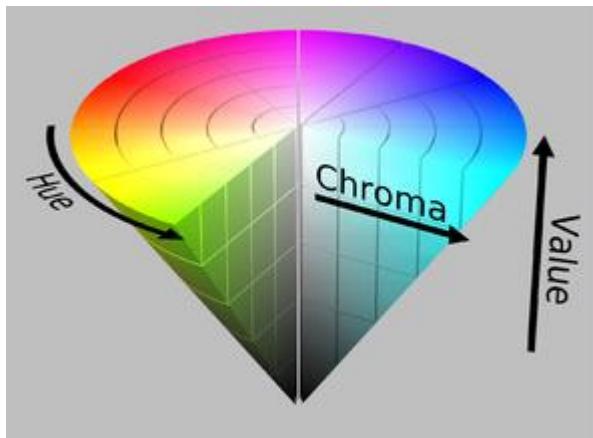
There are color models ([HSV](#) and [HSL](#)) based on perceptual variables:

hue (violet, blue, green, yellow, red ...)

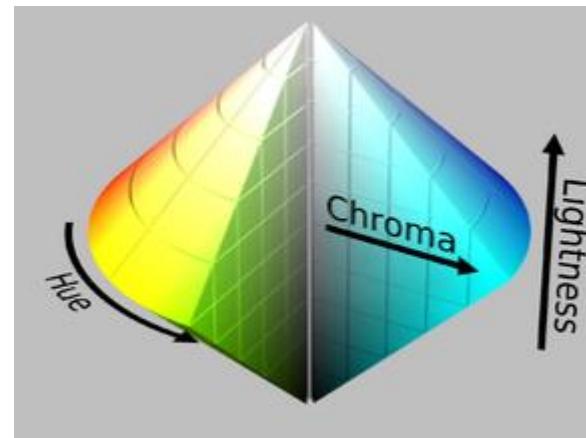
saturation (amount of white)

value/brightness

used when we intuitively describe colors (e.g. light blue or dark green)



HSV



HLS

Are more adequate for users to specify color

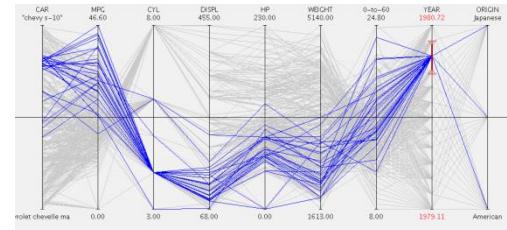
Other models (perceptually corrected) are better to specify quantitative color scales (e.g. L^*, a^*, b^* color model) 59

Representing Hypervariate (or multivariate) data

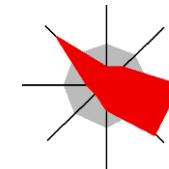
- Many real problems are of high dimensionality
(even after reducing dimensionality...)
- The challenge of representing hypervariate data is substantial and continues to stimulate invention
- Some of the mentioned representation techniques can be scaled to represent hypervariate data (to a limited extent)

Techniques for Hypervariate (or multivariate) data Visualization

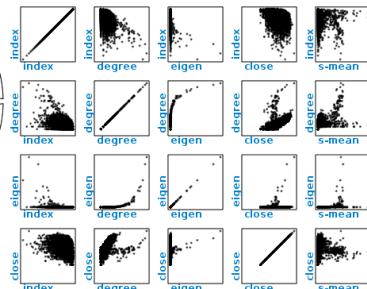
- Coordinate plots parallel coordinate plots



star (radar, or spider) plots



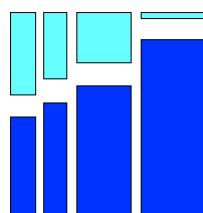
- Scatterplot Matrix



- Maps



- Mosaic Plots



- Icons/glyphs



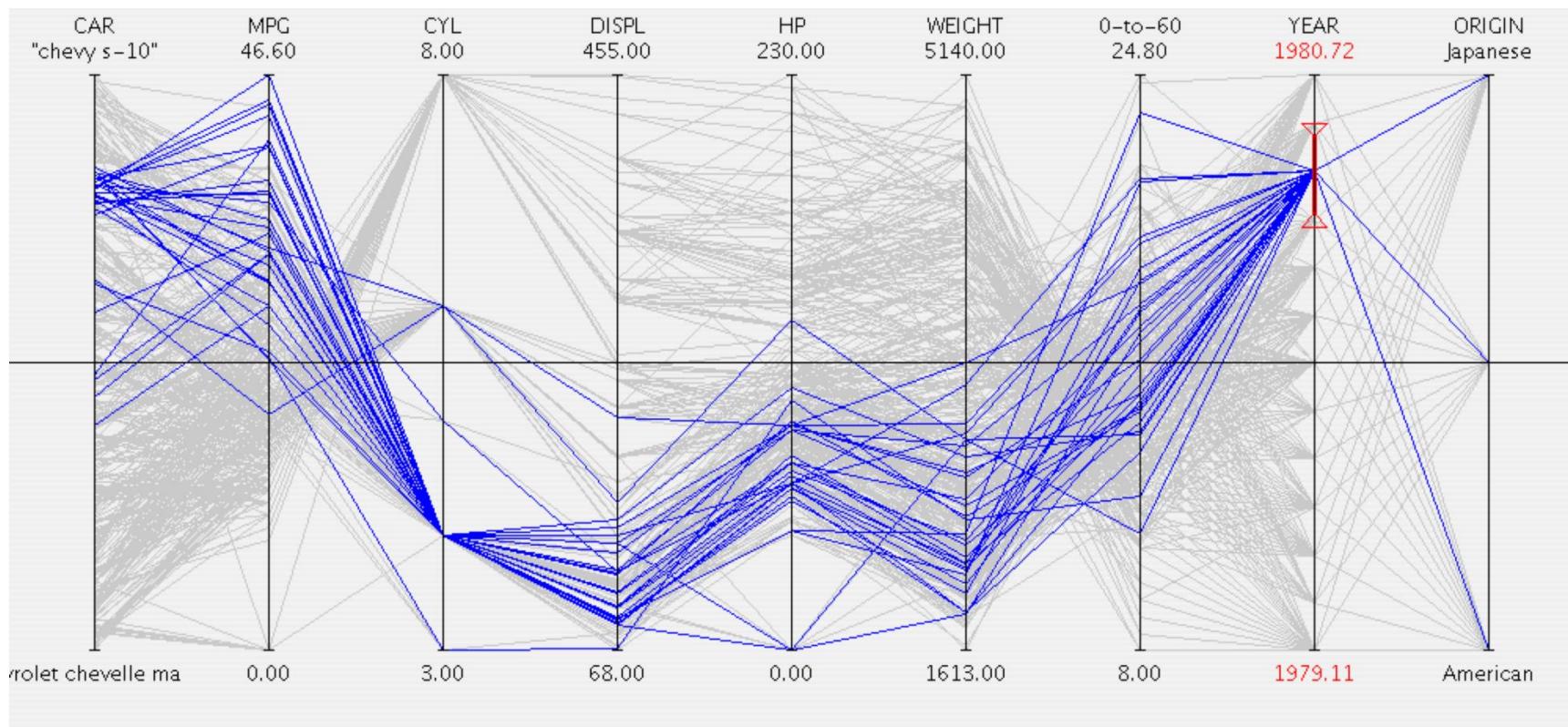
Representing Hypervariate

- **Consider dimensionality reduction!**
 - Several methods can be used (e.g.):
 - Principal Components Analysis
 - t-SNE (t-distributed stochastic neighbor embedding)
- ...

- Parallel coordinates plots are one of the most popular techniques for hypervariate data
- They have a very simple basis

Make	Price (£)	MPG	Rating	Age (yrs)	...
Ford	15,450	31	*****	3	...
Chevy	12,450	27	***	4	...

...

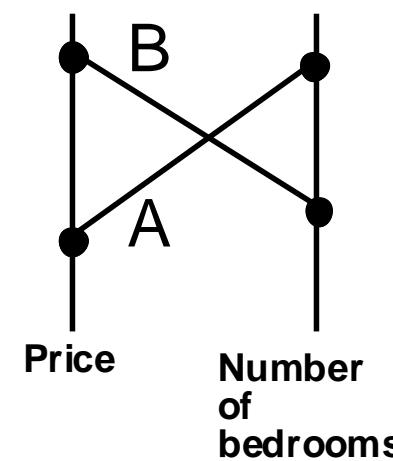
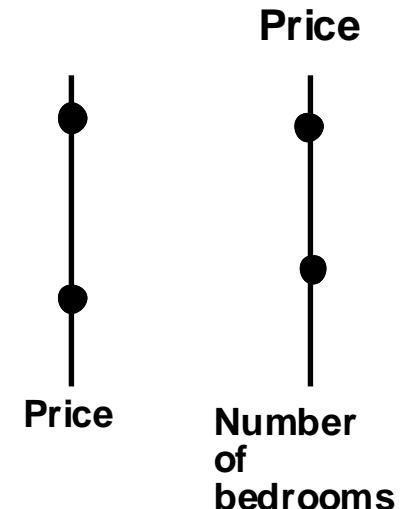
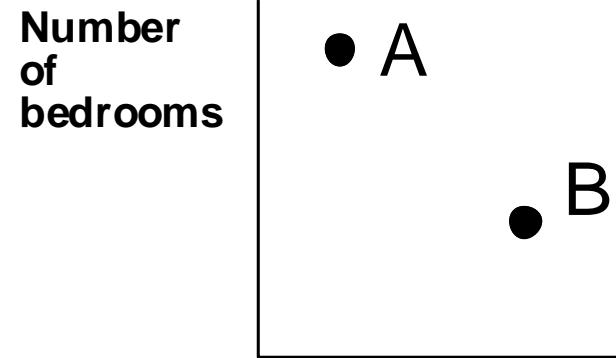


Consider a simple case of bivariate data:

1- A scatterplot represents the price and number of bedrooms associated with two houses

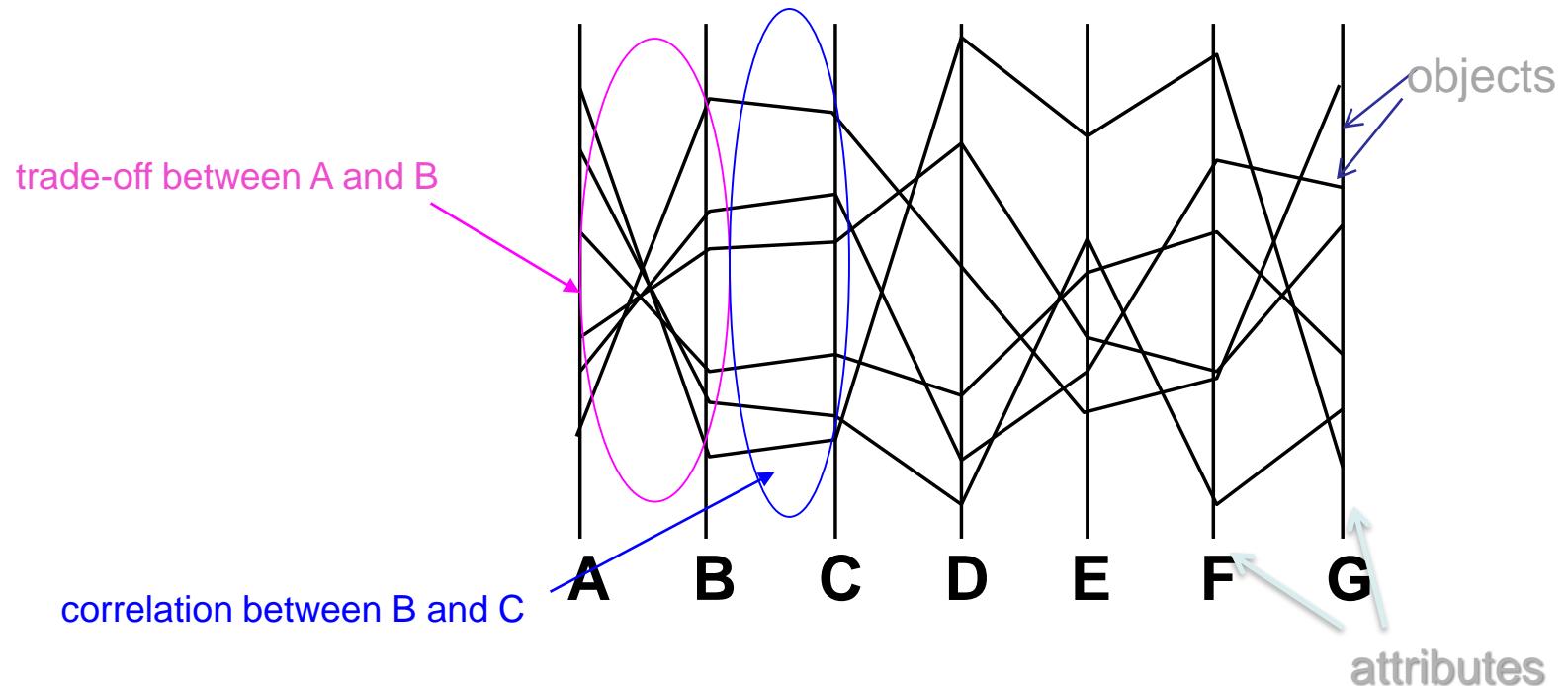
2- the axes are detached and made parallel; each house is represented by a point on each axis

3- To avoid ambiguity the pair of points representing a house are joined and labeled

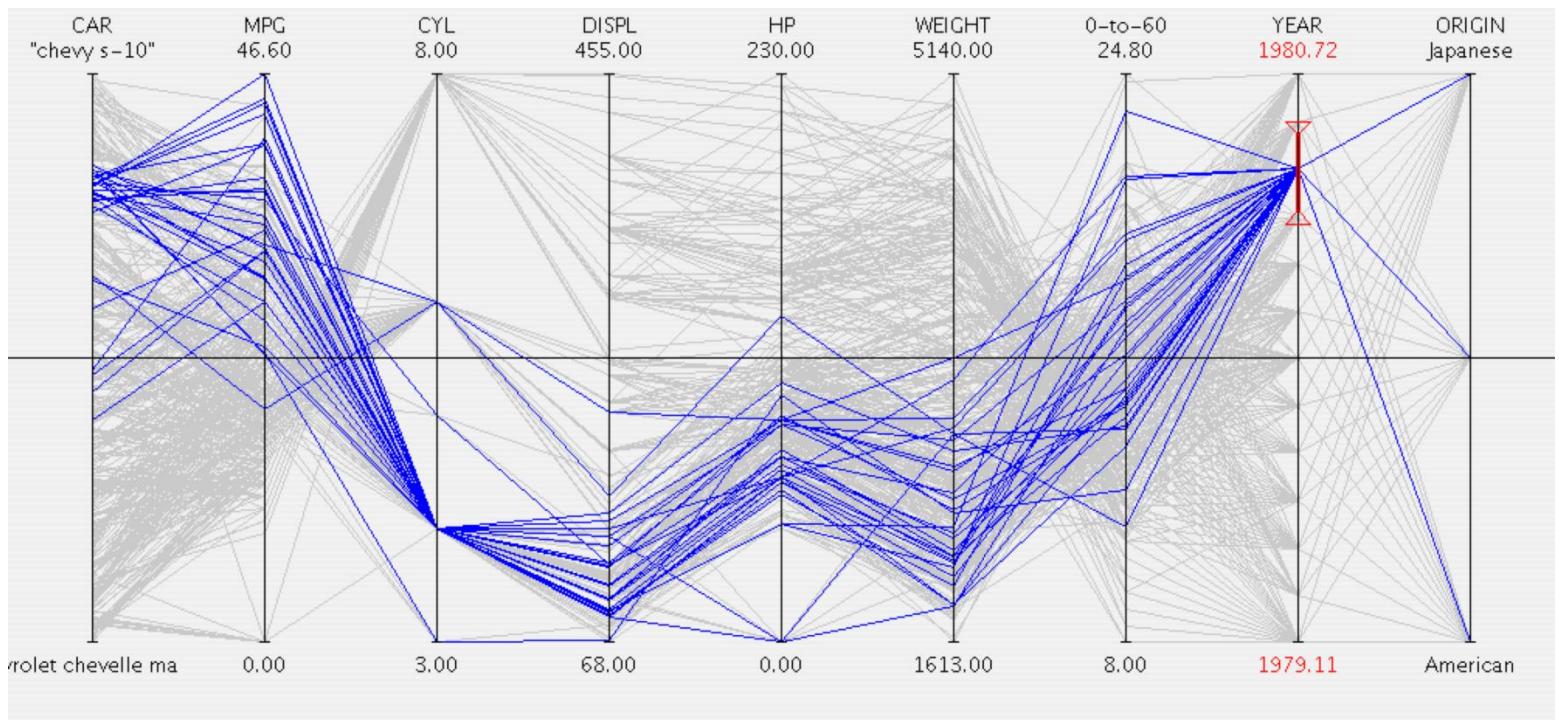


- For objects characterized by many attributes the parallel coordinate plots offer many advantages

A example for six objects, each characterized by seven attributes:

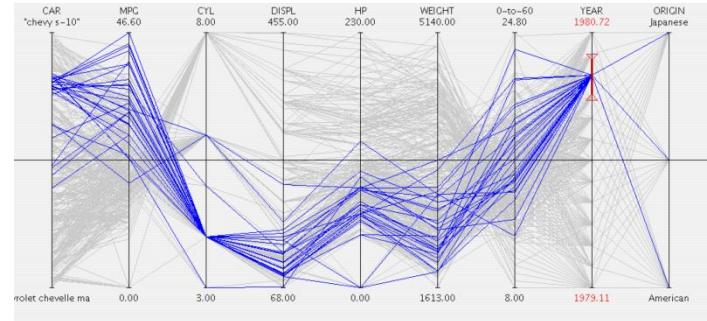


The trade-off between A and B, and the correlation between B and C, are immediately apparent. The trade-off between B and E, and the correlation between C and G, are not.



A parallel coordinate plot representation of a collection of cars, in which a range of the attribute Year has been selected to cause all those cars manufactured during that period to be highlighted.

Properties of parallel coordinate plots:



- Suitable to identify relations between attributes
- Objects are not easily discriminable; each object is represented by a polyline which intersects many others
- They offer attribute visibility (the characteristics of the separate attributes are particularly visible)
- The complexity of parallel coordinate plots (number of axes) is directly proportional to the number of attributes
- All attributes receive uniform treatment

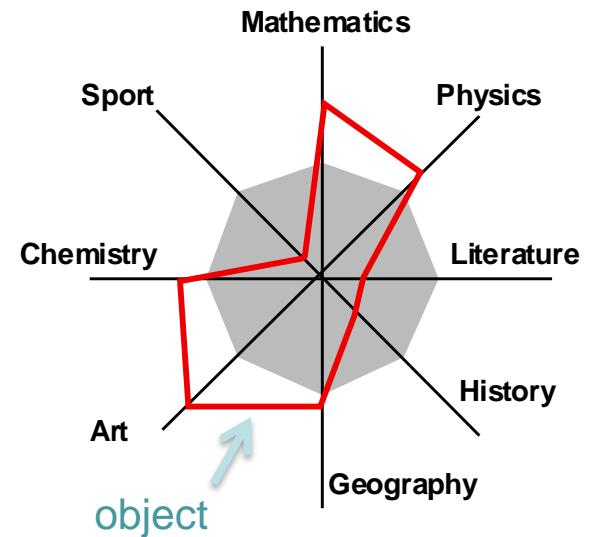
- Star plots have many features in common with parallel coordinate plots

- An attribute value is represented by a point on a coordinate axis

- Attribute axes radiate from a common origin

- For a given object, points are joined by straight lines

- Other useful information such as average values or thresholds can be encoded

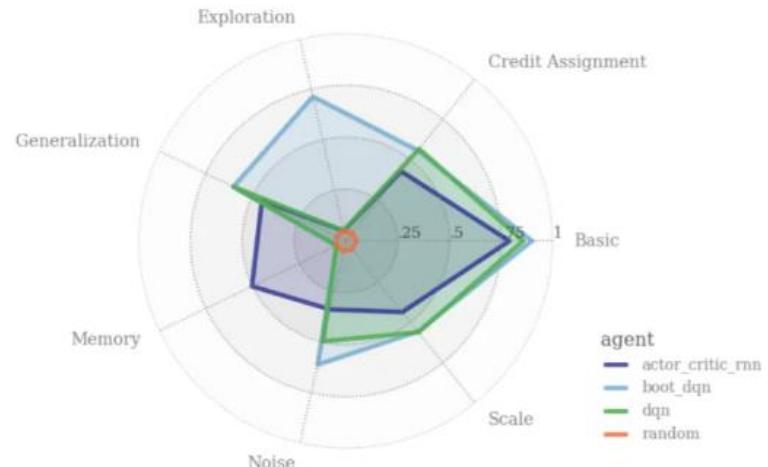


(Spence, 2007)

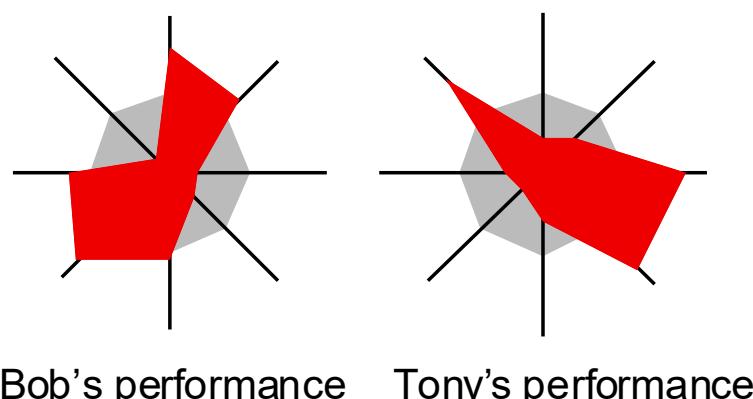
Properties of star plots:

- Their shape can provide a reasonably rapid appreciation of the attributes of the objects
- They offer **object visibility** and are suitable to compare objects

(by visibility it is meant the ability to gain insight pre-attentively; without a great cognitive effort)



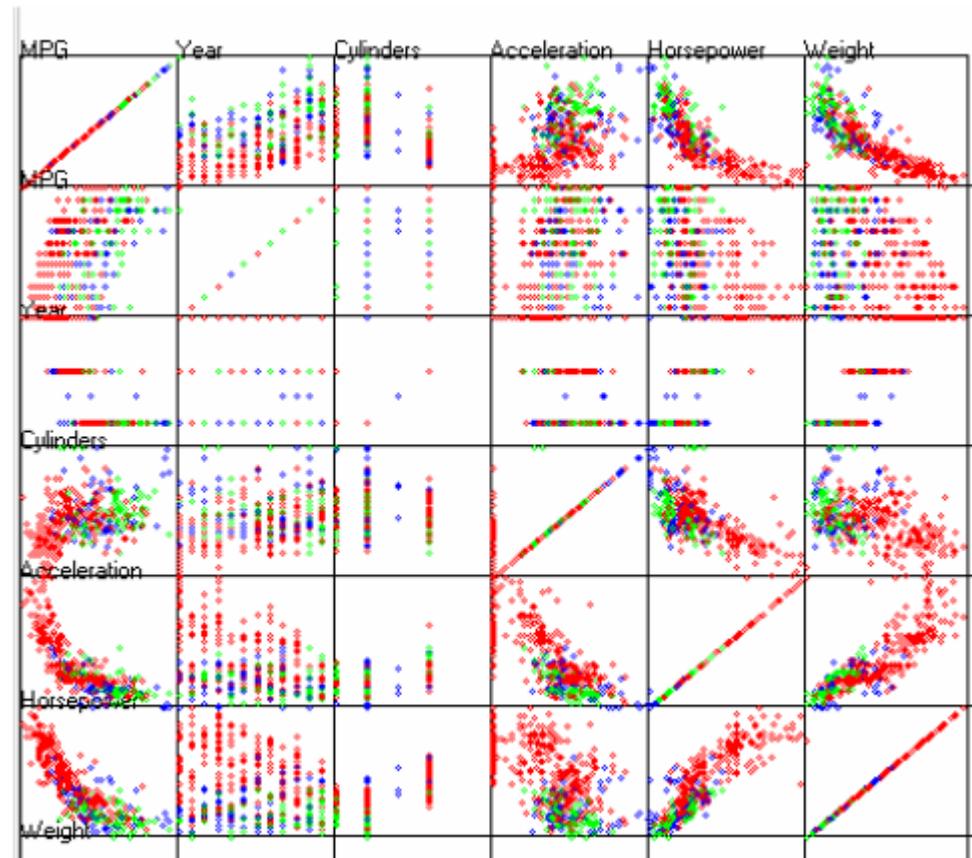
<https://syncedreview.com/2019/08/16/deepmind-bsuite-evaluates-reinforcement-learning-agents/>



- The **scatterplot matrix** (SPLOM) is applicable to higher dimensions
- However, as the number of attributes increase, the number of different pairs of attributes increases rapidly:

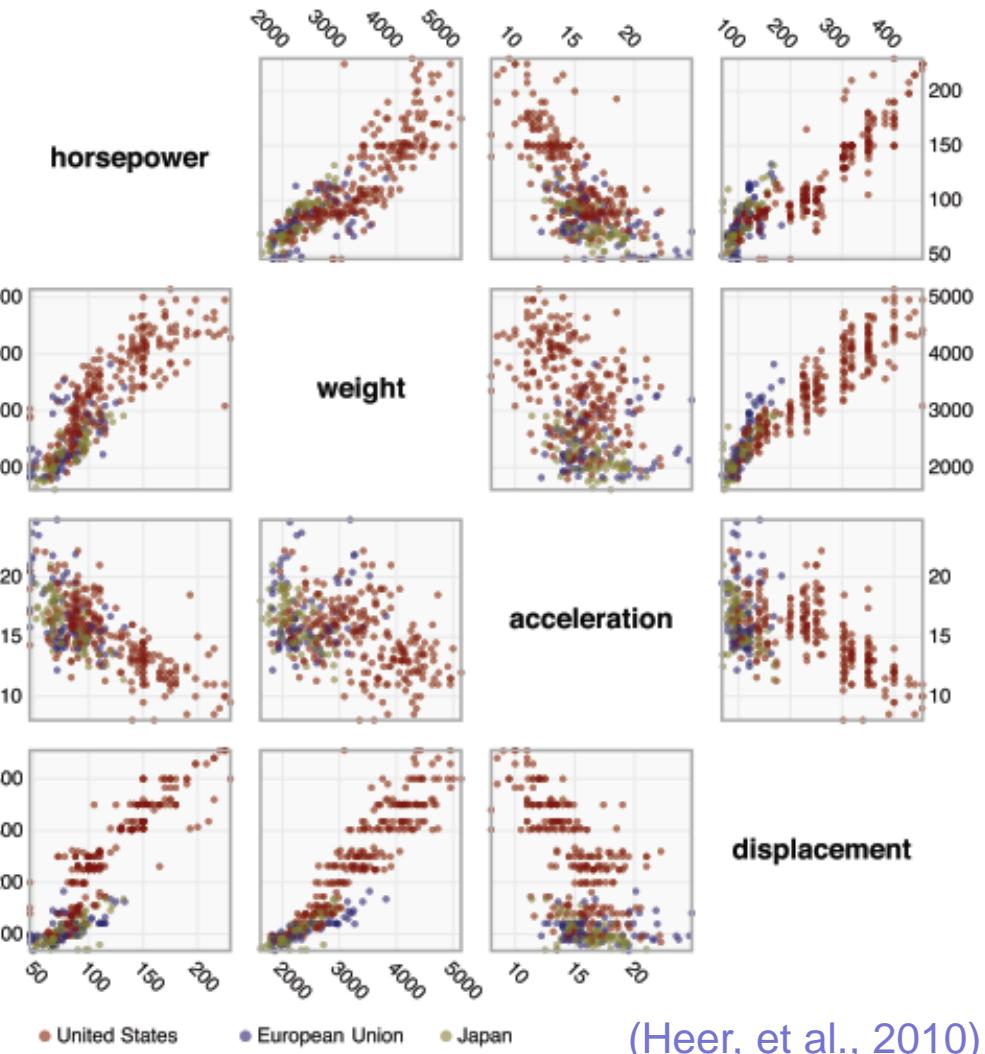
- 2 attributes -> 1 scatterplot
- 3 attributes -> 3 scatterplots
- 4 attributes -> 6 scatterplots

We may try to reduce the number of dimensions keeping the more relevant

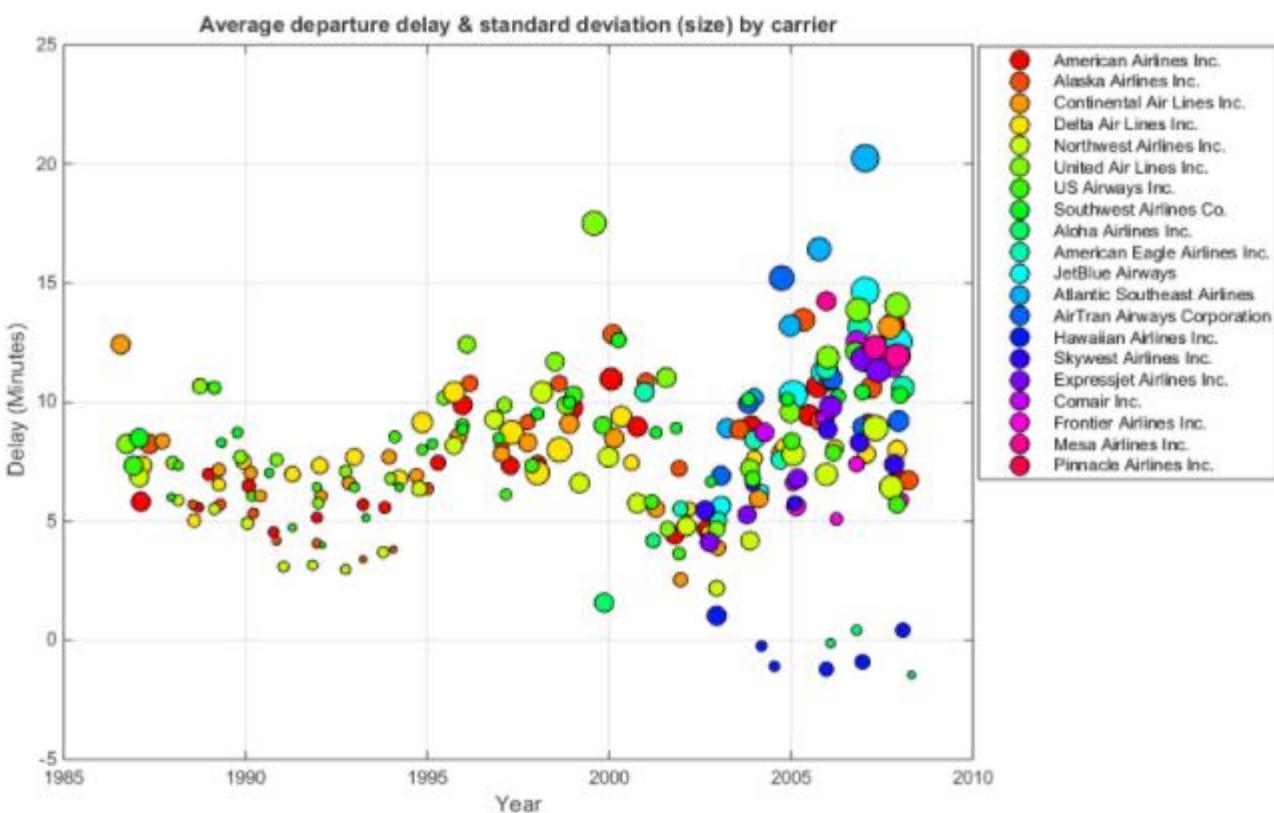
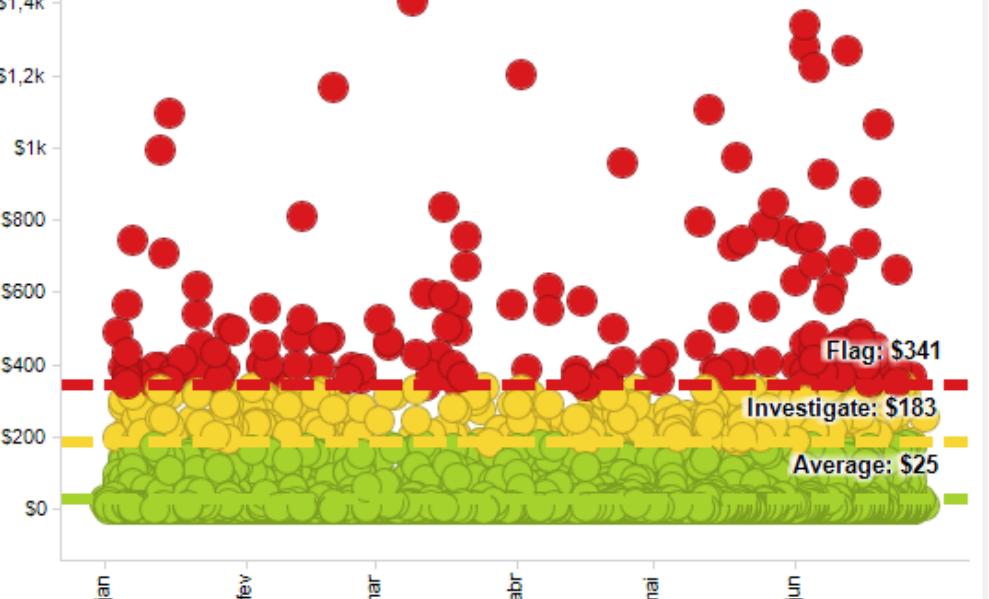


Scatterplot matrix for 6 attributes of a car dataset

- Another example of Scatterplot matrix for a car dataset



- A single scatterplot can be used together with other encoding techniques to represent data of higher dimension



<https://www.mathworks.com/matlabcentral/fileexchange/48005-bubbleplot-multidimensional-scatter-plots>

A scatterplot representing 5 variables

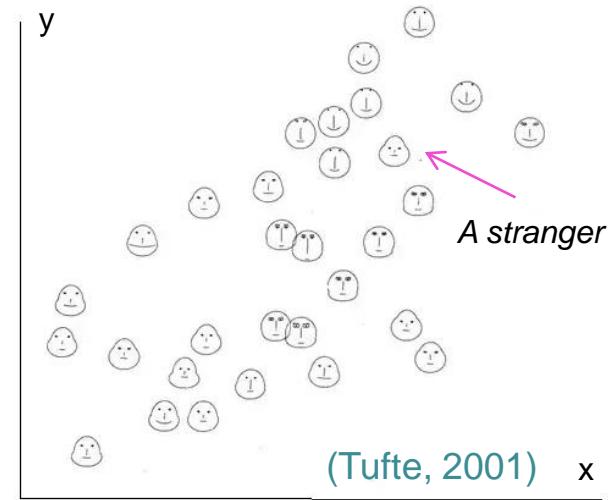
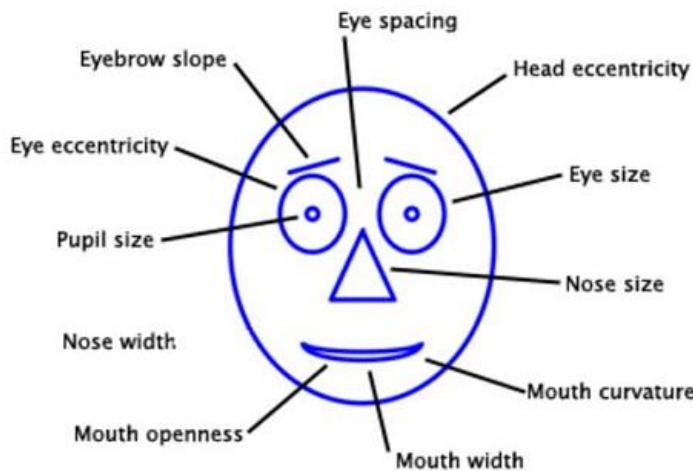
Hans Rosling's 200 Countries, 200 Years, 4 Minutes: 120 000 values

Income (x), Age expectancy (y) , Time (t), Continent (color), Population (size of circle)



<https://www.youtube.com/watch?v=jbkSRLYSoj0>

Icons (aka **glyphs**) represent a number of attributes qualitatively or quantitatively



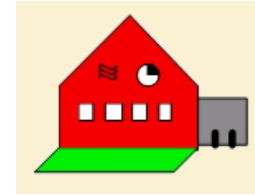
Chernoff Faces allow attribute values to be encoded in the features of cartoon faces

They were originally used to study geological samples, each characterized by 18 attributes

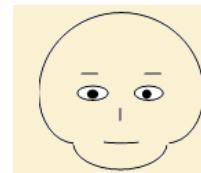
(https://en.wikipedia.org/wiki/Chernoff_face)

- Two examples of metaphorical icons:

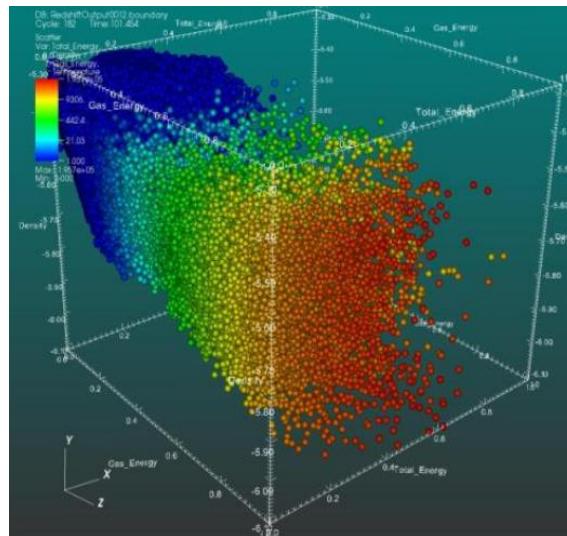
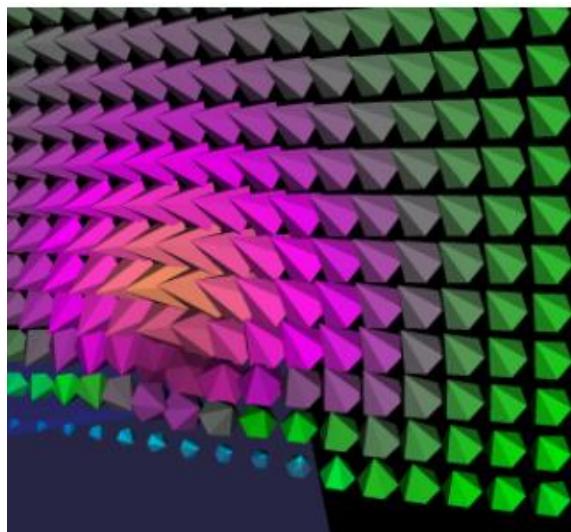
- with direct relation between icon and object (house icon)



- no direct relation between facial features and attributes they represent
(Chernoff faces)

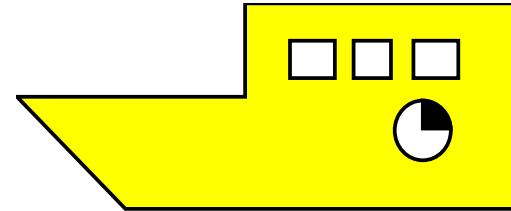
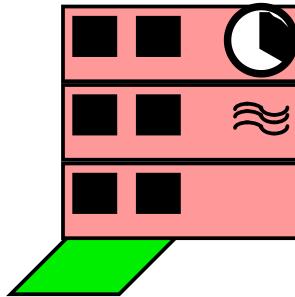
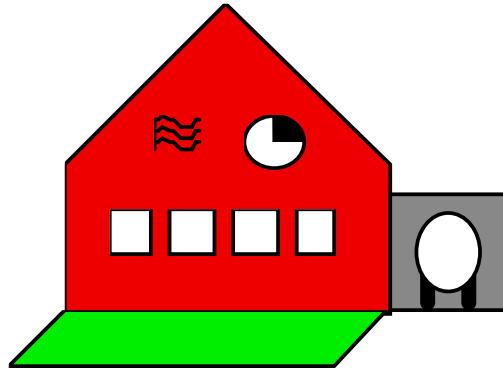


- Examples in SciVis



[https://en.wikipedia.org/wiki/Glyph_\(data_visualization\)](https://en.wikipedia.org/wiki/Glyph_(data_visualization))

Multidimensional icons representing eight attributes of a dwelling



house
£400,000
garage
central heating
four bedrooms
good repair
large garden
Victoria 15 mins

flat
£300,000
no garage
central heating
two bedrooms
poor repair
small garden
Victoria 20 mins

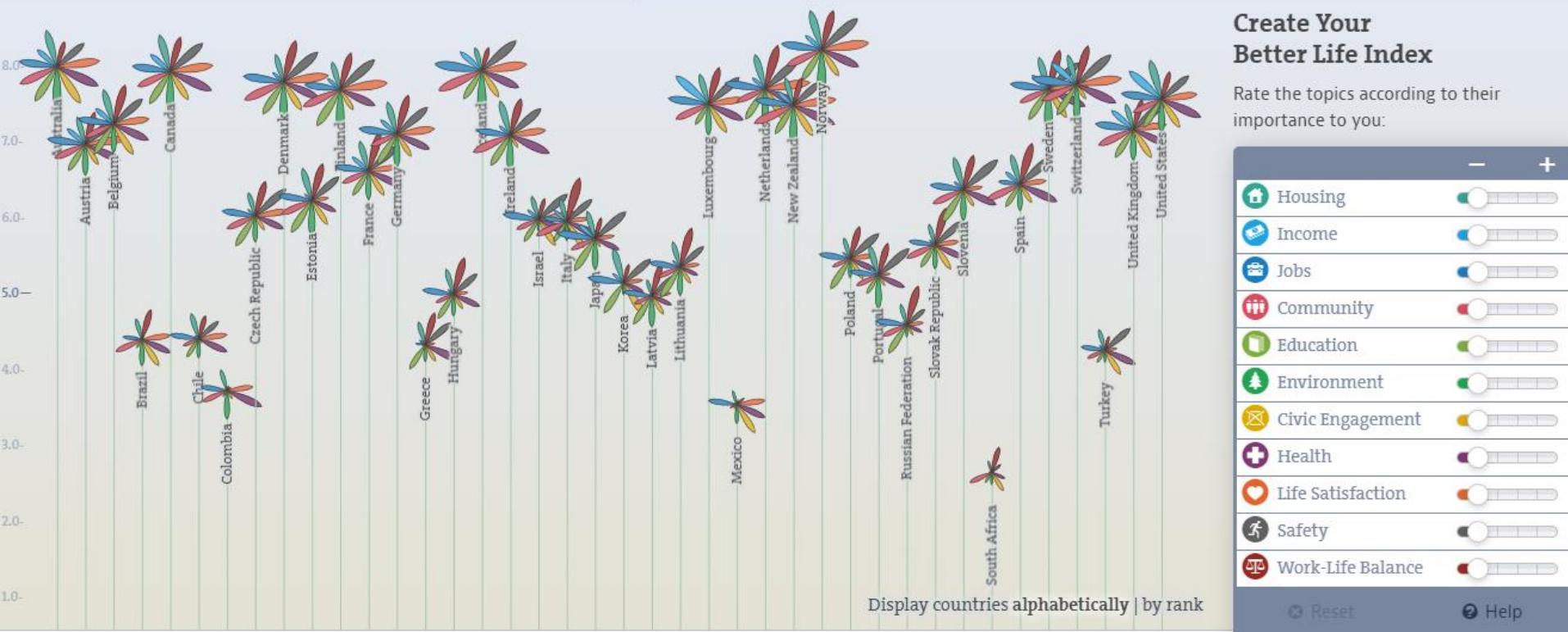
houseboat
£200,000
no garage
no central heating
three bedrooms
good repair
no garden
Victoria 15 mins

Textual descriptions of the dwellings represented by the multidimensional icons
(Spence, 2007)

Glyph chart example:

Based on a shape being the main artifact of representation

The physical properties of the shape represent different categorical variables sized according to the associated quantitative value and distinguished through color

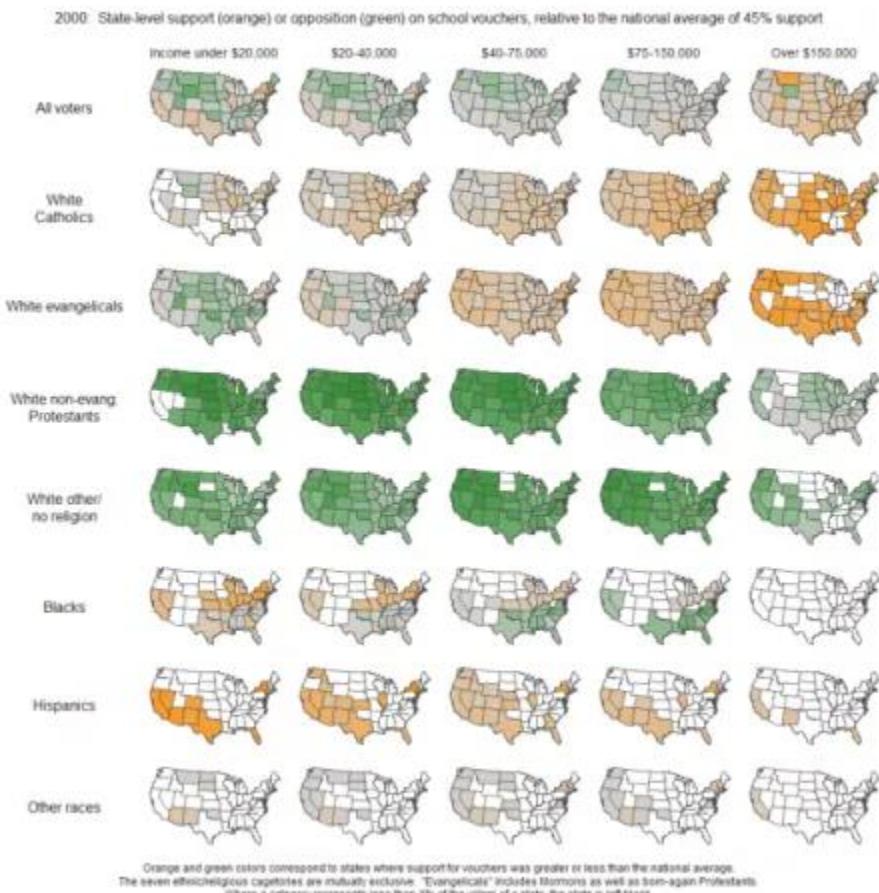


Useful arrangement of several charts

Small multiples:

arrangement approach
that facilitates efficient
and effective
comparisons

(Kirk, 2012)



Dashboards

Visual display summarizing a dataset providing information at-a-glance (e.g. KPIs)

" A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance. " (Few, 2004)

<https://www.nngroup.com/articles/dashboards-preattentive/>

Monitorização Mensal - Todos os Cursos

13,52 13.108

Média N° Alunos

Ano Letivo: 2019
Ano Curricular: Tudo
Mês: fevereiro

Cursos selecionados:

- Procurar
- Selecionar tudo
- Curso 1
- Curso 2
- Curso 3
- Curso 4
- Curso 5

Mais opções de filtragem

Limpar Seleção

Indice Risco

Estudantes por Indicador em Risco

Situação de Prescrição

Estudantes por Situação

Total de 13108 Estudantes

Nome	Curso	Habilaccao	Indice Risco	Programa Tutoria	Situacao Prescricao	Estado Matricula
Aluno 1	Curso 111	Mestrado - 2º Ciclo	1	Não		Activo
Aluno 10	Curso 71	Licenciatura - 1º Ciclo	1	Não	Não Prescrito	Activo
Aluno 100	Curso 30	Mestrado Integrado	2	Não	Não Prescrito	Activo
Aluno 1000	Curso 107	Mestrado - 2º Ciclo	0	Não		Activo

Prototype:
“Portal dos indicadores, UA”

The dashboard displays several key metrics and charts. At the top right, it shows a average of 13,52 students and a total of 13,108 students. On the left, there are dropdown menus for the Academic Year (2019), Curriculum Year (All), and Month (February). Below these are checkboxes for selecting courses and a 'Mais opções de filtragem' (More filtering options) button. A 'Limpar Seleção' (Clear Selection) button is also present.

The central area contains four main sections: 'Indice Risco' (Risk Index) with a value of 6, 'Estudantes por Indicador em Risco' (Students by Risk Indicator) with a bar chart showing counts for Propinas, Sucesso, Asiduidade, Boala, SW5, Nota Ingresso, and SPANE, 'Situação de Prescrição' (Prescription Status) with a bar chart showing counts for Não Prescrito, Em risco de prescrição, Em risco de prescrição, and Prescrito, and 'Estudantes por Situação' (Students by Situation) with a pie chart showing the distribution between Normal and other categories. Below these is a table titled 'Total de 13108 Estudantes' (Total of 13108 Students) with columns for Nome, Curso, Habilaccao, Indice Risco, Programa Tutoria, Situacao Prescricao, and Estado Matricula. The table lists five student entries with their respective details.



Total de 13108 Estudantes

Nome	Curso	Habilitacao	Indice Risco	Programa Tutoria	Situacao Prescricao	Estado Matricula
Aluno 1	Curso 111	Mestrado - 2º Ciclo	1	Não		Activo
Aluno 10	Curso 71	Licenciatura - 1º Ciclo	1	Não	Não Prescrito	Activo
Aluno 100	Curso 30	Mestrado Integrado	2	Não	Não Prescrito	Activo
Aluno 1000	Curso 107	Mestrado - 2º Ciclo	0	Não		Activo

As seen by people with green-blind deutanopia; does it work?

<https://www.color-blindness.com/coblis-color-blindness-simulator/>

Example:

Use visualization techniques to help answer the following questions:

Is there a relation between wanted salary and experience?

How many candidates ask for a salary in [30000, 50000] and in [55000, 75000]?

How many candidates have an advanced level of English?

	Education	Age	Prof. Experience	English	Wanted salary
#	(MSc/PhD)	(years)	(years)	(Bas/Adv)	(\$/year)
1	MSc	22	0	Advanced	36000
2	MSc	23	0	Basic	36000
3	MSc	24	1	Advanced	36000
4	PhD	30	7	Advanced	72000
5	MSc	25	1	Basic	40000
6	PhD	29	5	Advanced	60000
7	MSc	31	7	Advanced	55000
8	MSc	23	0	Advanced	36000
9	MSc	26	2	Intermediate	40000
10	PhD	32	9	Intermediate	65000
11	BSc	30	7	Intermediate	30000
12	PhD	40	17	Advanced	80000
13	MSc	28	4	Advanced	40000

the complete table has many more candidates and attributes, but you may test with these

Bibliography

- Kirk, A., *Data Visualization: a successful design process*, Packt Publishing, 2012
- Kirk, A., *Data Visualization: a handbook for data driven design* *, Sage, 2016
- Mazza, R., *Introduction to Information Visualization*, Springer, 2009
- Munzner, T., *Visualization Analysis and Design* *, A K Peters/CRC Press, 2014
- Spence, R., *Information Visualization, Design for Interaction*, 2nd ed., Prentice Hall, 2007
- Spence, R., *Information Visualization, an Introduction*, 3rd ed., Springer, 2014
- Ware, C., *Information Visualization* *, 3rd ed., Morgan Kaufmann, 2013
- Wilke, C., *Fundamental of Data Visualization*, 2019
- Tufte, E., *The Visual Display of Quantitative Data*, 2nd ed, Graphics Press, 2001
- Books with * and other interesting books at:

<https://learning.oreilly.com/playlists/74bfec5e-4346-48ff-82b4-657fda6922b6>