Principles of Data Visualization I

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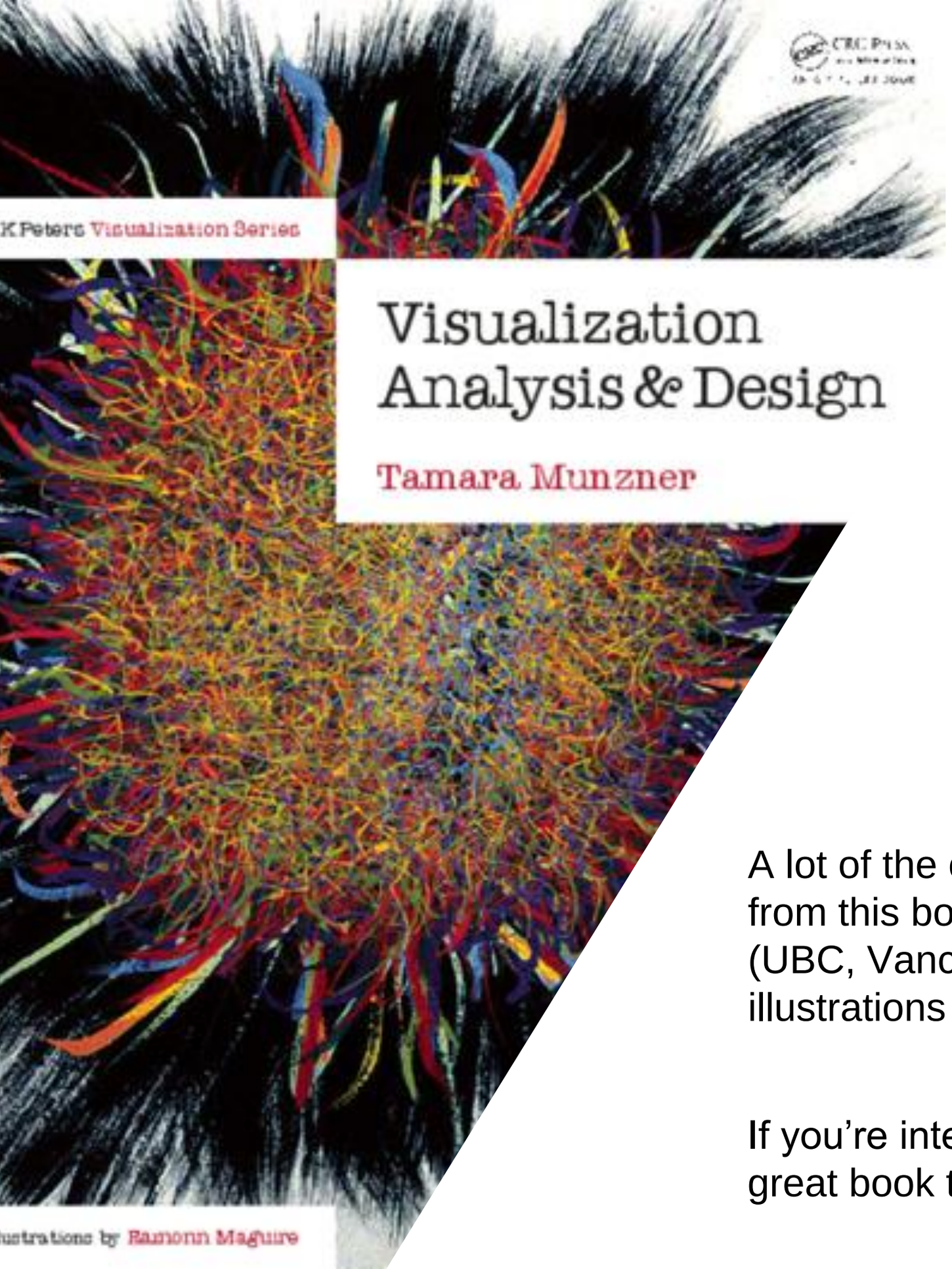
CERN School of Computing, Poland
September 2022



A lot of the content for this introduction comes from this book from Prof. Tamara Munzner (UBC, Vancouver, Canada) which I created the illustrations for.

If you’re interested in learning more, it’s a great book to check out :)

Visualization

The role of visualization systems is to provide visual representations of datasets that help people carry out tasks **more effectively**.

Visualization is suitable when there is a need to augment human capabilities rather than replace people with computational decision-making methods.

Tamara Munzner

A Visualization should:

1. Save time
2. Have a **clear purpose***
3. Include only the **relevant content***
4. **Encodes data/information** appropriately

* from Noel Illinsky, http://complexdiagrams.com/

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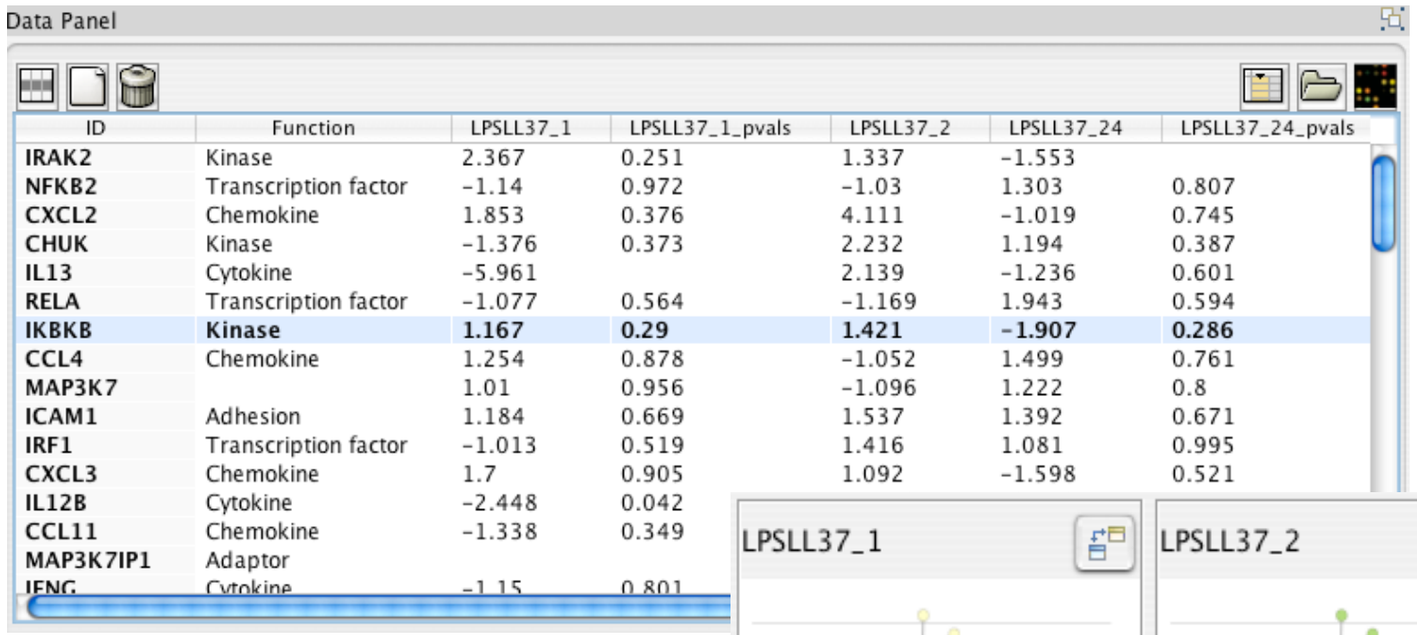
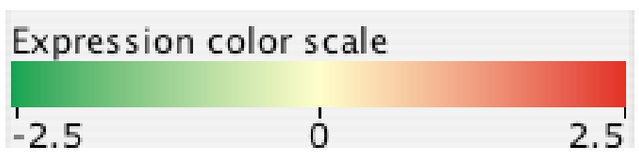
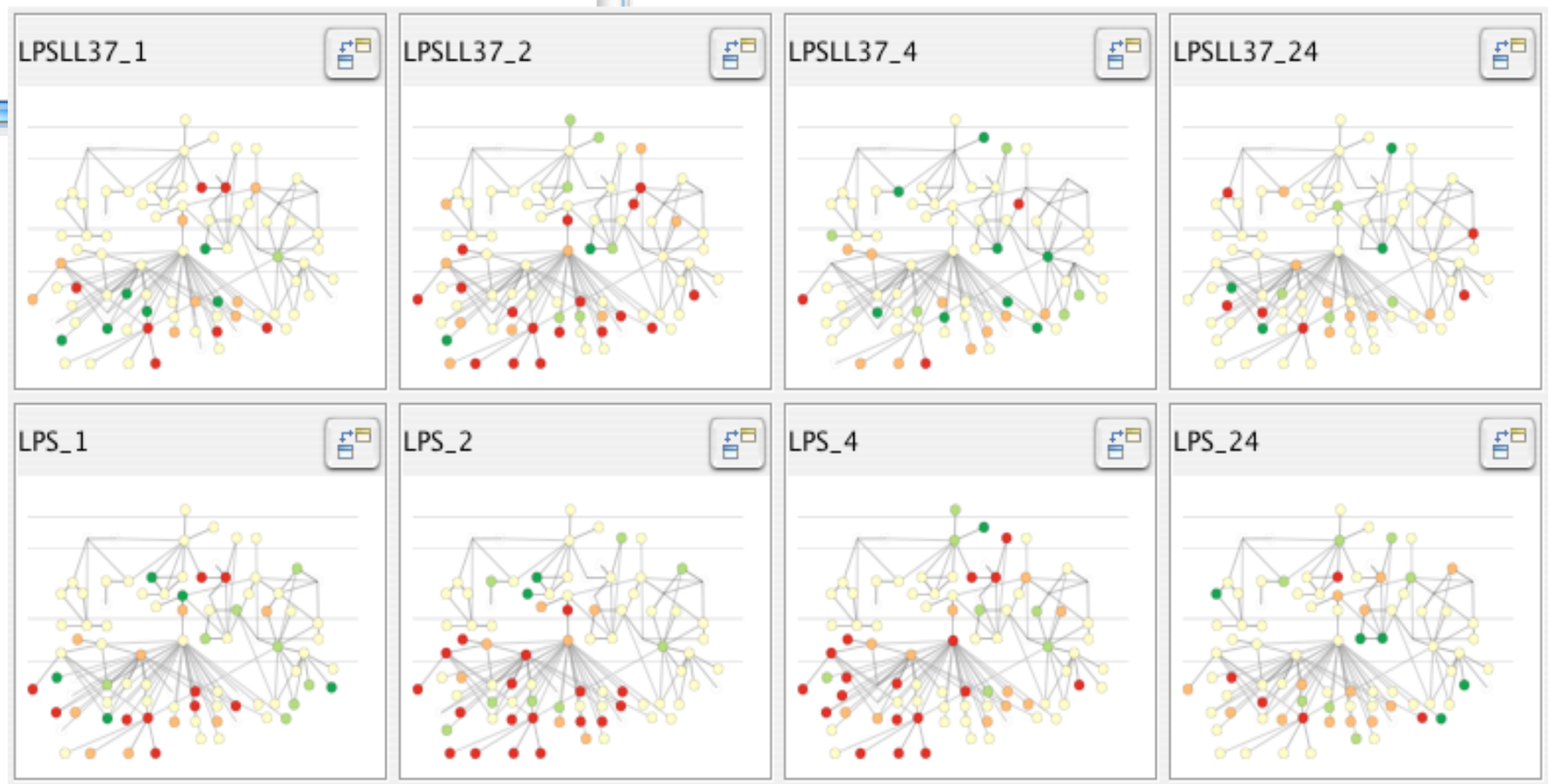




External representation:
replace cognition with perception

Cerebral: Visualizing Multiple Experimental Conditions on a Graph with Biological Context. Barsky, Munzner, Gardy, and Kincaid. IEEE TVCG (Proc. InfoVis) 14(6):1253-1260, 2008.]



What are we visualising?

Major data types & classifications of them

Why are we visualising it?

What is the need for this visualization?

Why do the users need this, and what do they need to be able to do with it?

How can we visualise?

How can we visualize?

The components of a visualization.

Good and bad practices.

What are we visualising?

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What are we visualising?

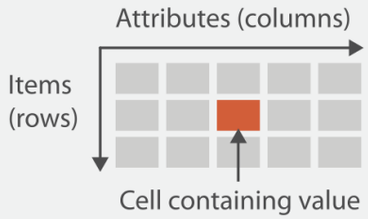
DATA TYPES

- STATIC

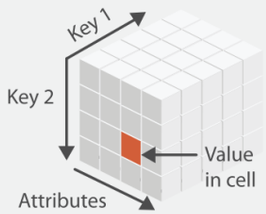
- DYNAMIC

DATASET TYPES

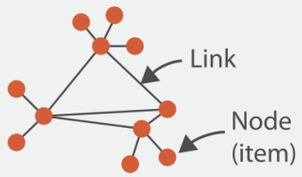
- TABLES



  - Multidimensional Table

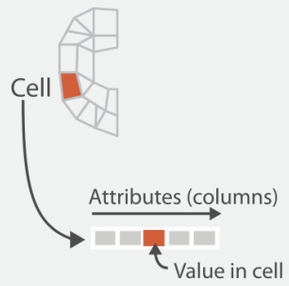


- NETWORKS



  - Trees

- FIELDS (CONTINUOUS)



- GEOMETRY (SPATIAL)

- TEXT
  - Prose Documents
  - Document Collections
  - Log Files
  - Code
  - Multimedia

ATTRIBUTE TYPES

- CATEGORICAL

- ORDERED
  - Ordinal

  - Quantitative

  - Sequential

  - Diverging

  - Cyclic

What are we visualising?

STATIC

For static data, we have fixed scales.

We know our data range,
therefore scales will not change.

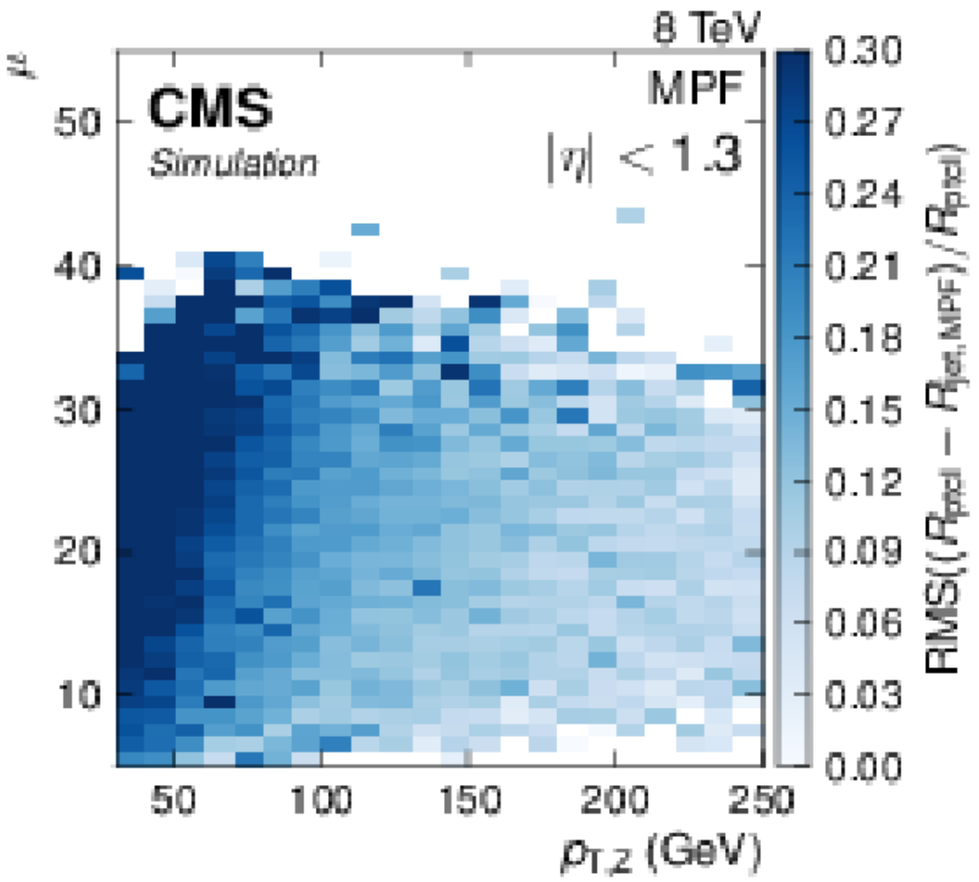
DYNAMIC

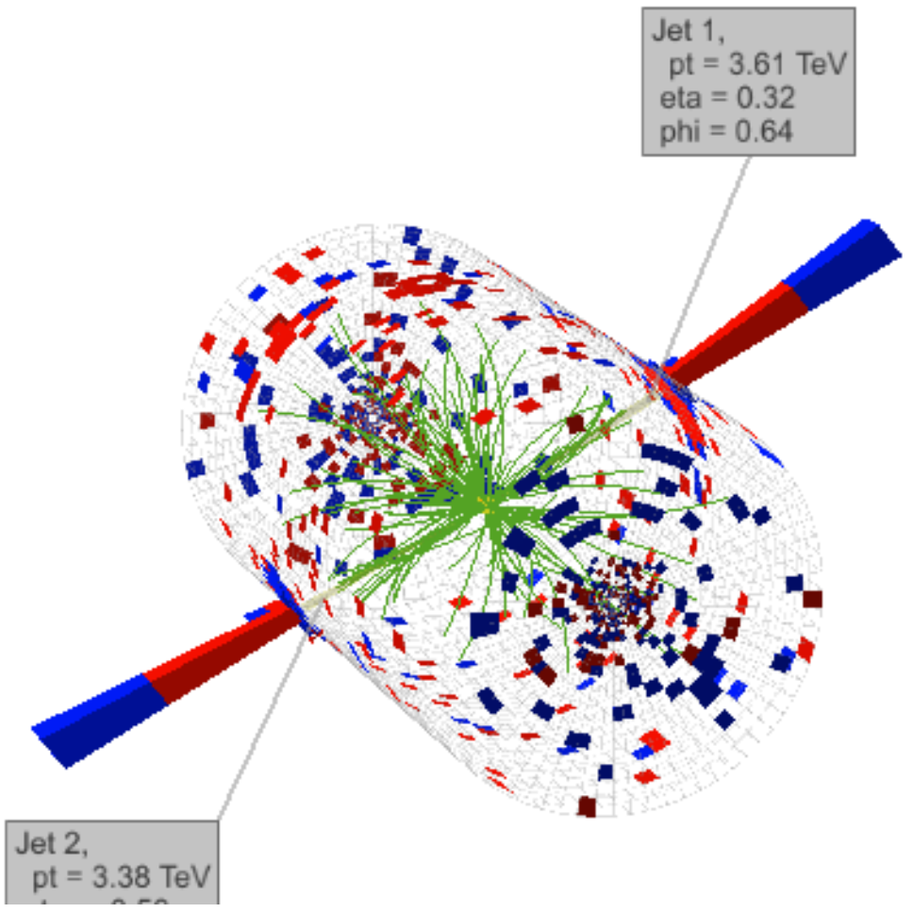
For dynamic data, the observed min and max values can change, therefore scales will change.

This can have big consequences for the readability of our visualization.

What are we visualising?

The branches of data visualization





Information Visualization

Position is derived.
Incl. GeoVis

We decide what is on the X and Y axis, and what we do changes the information we extract.

Scientific Visualization

Position is given.
e.g. detector or medical visualizations

We have the X, Y, and Z coordinates of a cell in ATLAS, we show the energy deposit left here. We don’t choose, the data tells us.

What are we visualising?

Major data types & classifications of them

Why are we visualising it?

What is the need for this visualization?

Why do the users need this, and what do they need to be able to do with it?

How can we visualise?

How can we visualize?

The components of a visualization.

Good and bad practices.

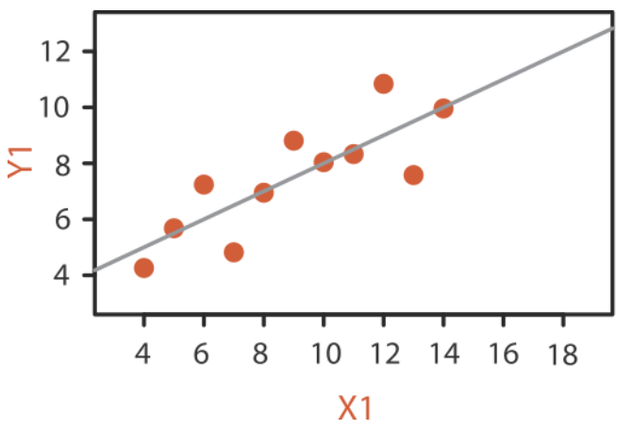
Why are we visualising?

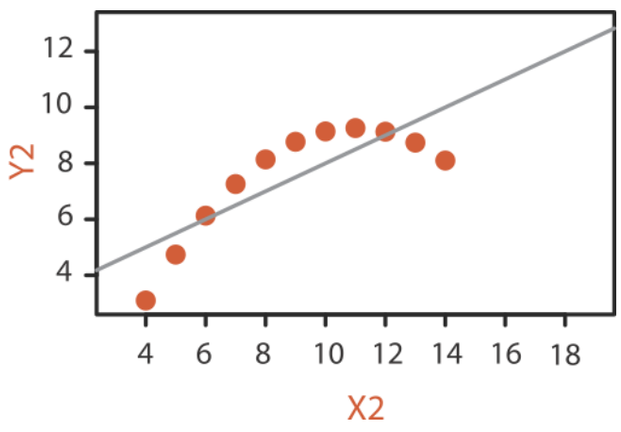
The role of visualisation systems is to provide visual representations of datasets that help people **carry out tasks more effectively.**

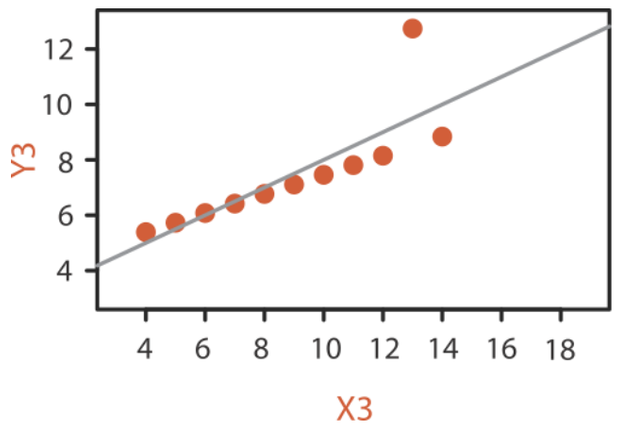
Anscombe's Quartet: Raw Data

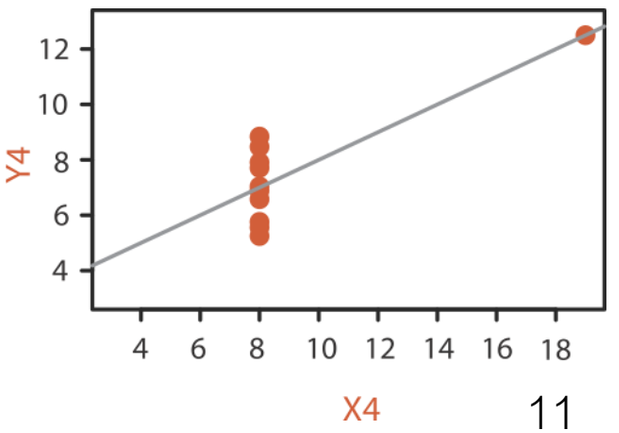
	1		2		3		4	
	X	Y	X	Y	X	Y	X	Y
	10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
	8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
	13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
	9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
	11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
	14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
	6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
	4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
	12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
	7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
	5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89
Mean	9.0	7.5	9.0	7.5	9.0	7.5	9.0	7.5
Variance	10.0	3.75	10.0	3.75	10.0	3.75	10.0	3.75
Correlation	0.816		0.816		0.816		0.816	

The statistics would lead us to believing that everything is the same

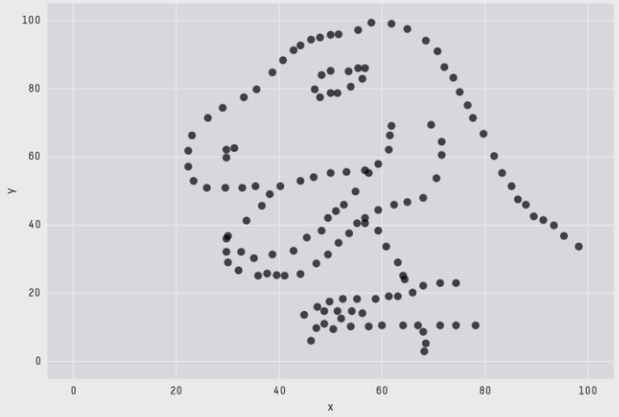




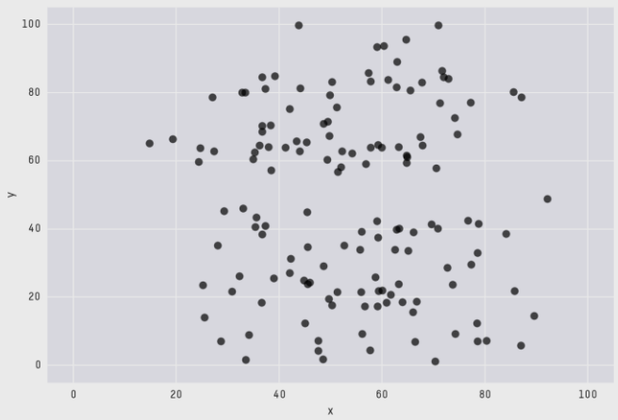


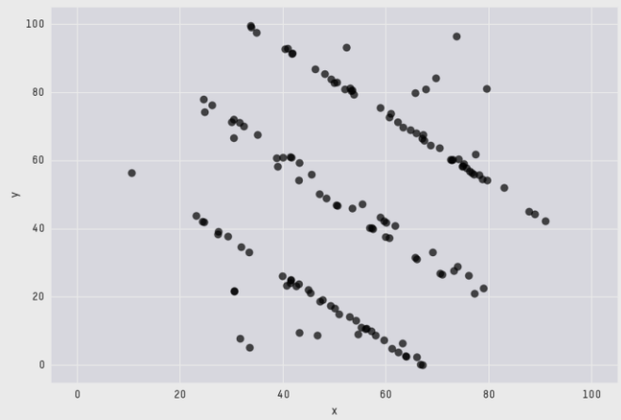


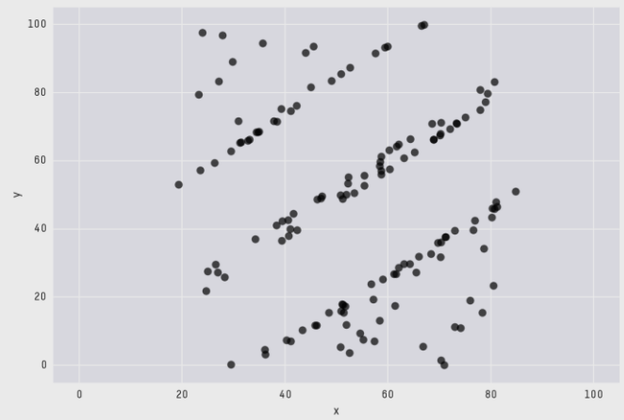
Datasaurus!

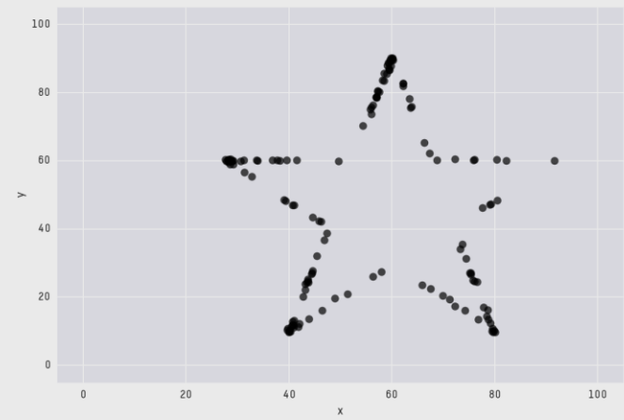


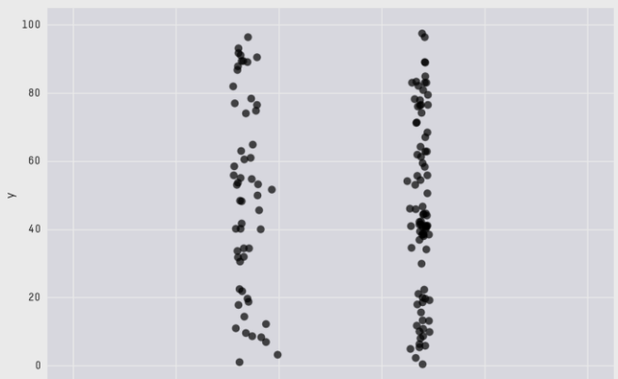
X Mean: 54.26
Y Mean: 47.83
X SD : 16.76
Y SD : 26.93
Corr. : -0.06

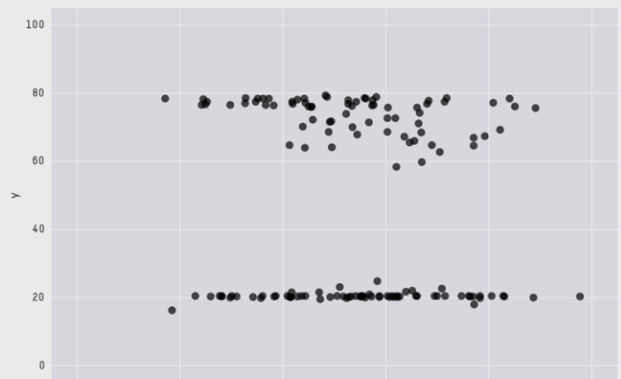


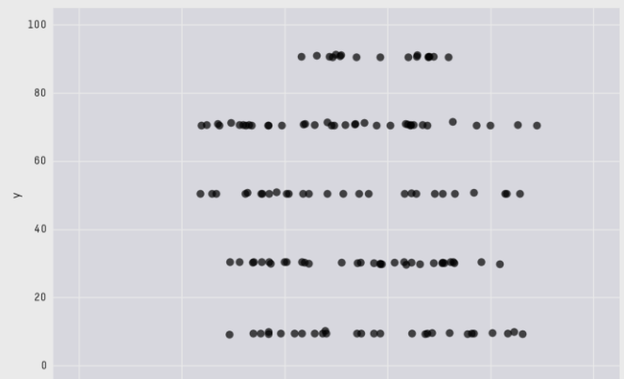


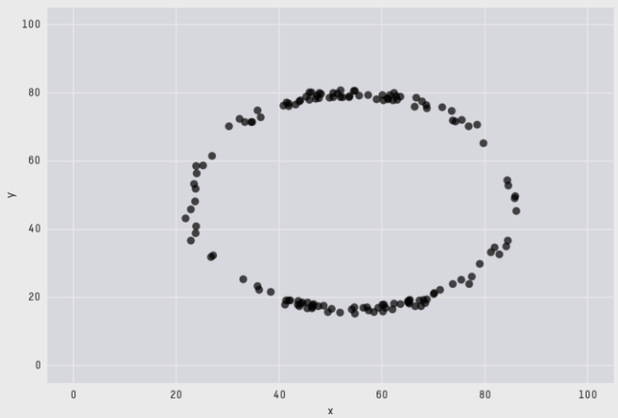


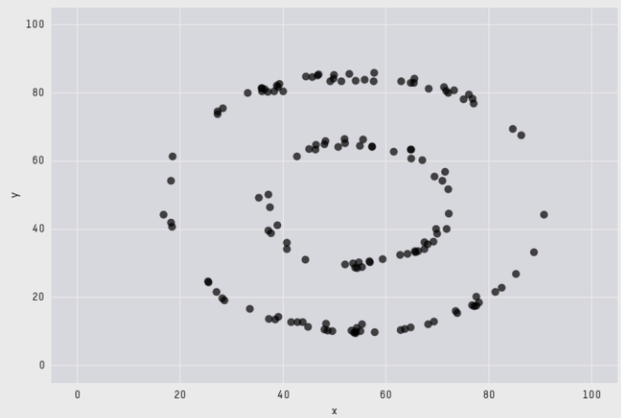


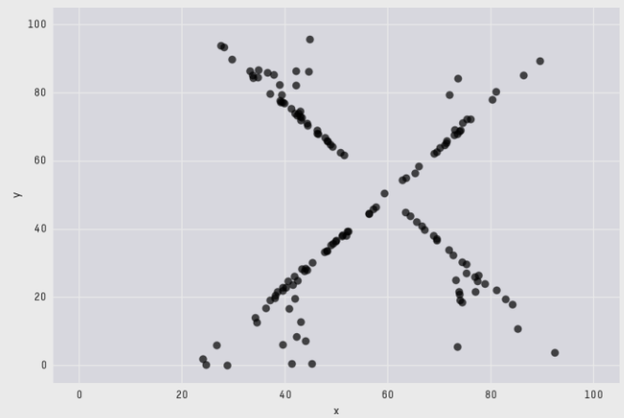


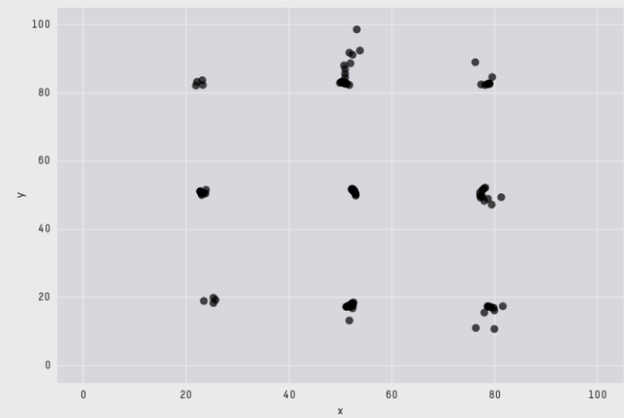












From https://www.autodeskresearch.com/publications/samestats

Why are we visualising?

Every visualisation should be thought of as a product
of what actions the user needs to take to get to their objective (target)

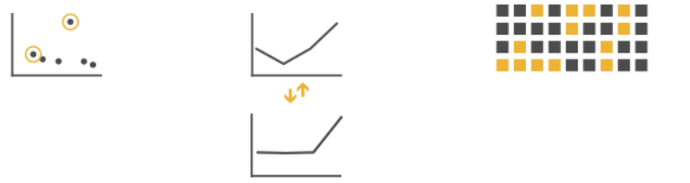
Actions

- Use
  - Consume
    - *Discover*
    - *Present*
    - *Enjoy*
  - Produce
    - *Annotate*
    - *Record*
    - *Derive*

- Search

	Target known	Target unknown
Location known	*Lookup*	*Browse*
Location unknown	*Locate*	*Explore*

- Query
  - Identify
  - Compare
  - Summarise



Always keep in mind why you're doing something. If what you create does not show what you intended, confuses, or misleads, it's time to rethink :)

Why are we visualising?

Given a large matrix, or even a large series of numbers, it’s difficult for humans to ‘see’ patterns in the data.

With a visualisation we want to transition a cognitively demanding task to a perceptual (less demanding) one.

Why are we visualising?

Even in this simple example, it is cognitively demanding to read off all the information.

Category	Sub-Category	Consumer	Corporate	Home Office	Small Business
Furniture	Bookcases	-45.93	-9,300.00	-16,000.00	-7,600.00
	Chairs & Chairmats	42,900.00	41,300.10	41,000.00	25,600.00
	Office Furnishings	12,000.00	27,300.10	42,000.00	18,600.00
	Tables	-12,300.00	-35,400.10	-43,000.00	-8,000.00
Technology	Computer Peripherals	14,100.56	45,300.00	17,000.00	17,300.00
	Copiers & Fax	41,300.00	-28,600.10	29,000.00	68,100.00
	Office Machines	51,400.00	180,300.10	39,000.00	36,500.00
	Comms (Telephones)	49,700.00	120,400.10	86,000.00	-59,800.00

What is the goal of this representation?

Why are we visualising?

We can improve by using ‘pop-out’ to bring attention to negative values.

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Why are we visualising?

Or, adding some additional indicators can provide an idea of intensity.

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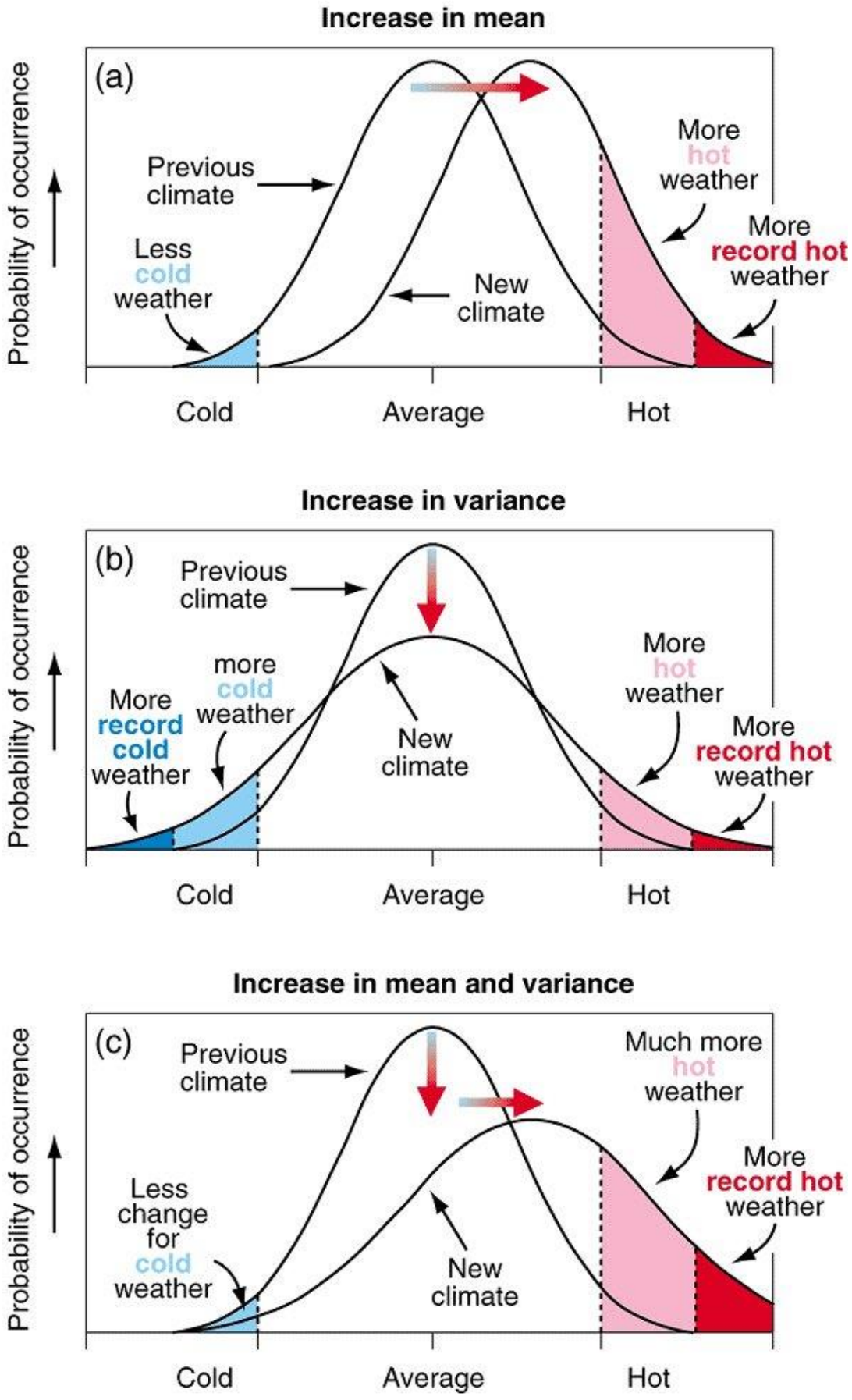
How we present information depends on why we are presenting it…

Why are we visualising?

Sometimes it is to communicate information

We can use visualisation to better communicate concepts that aren't easily explained using text alone.



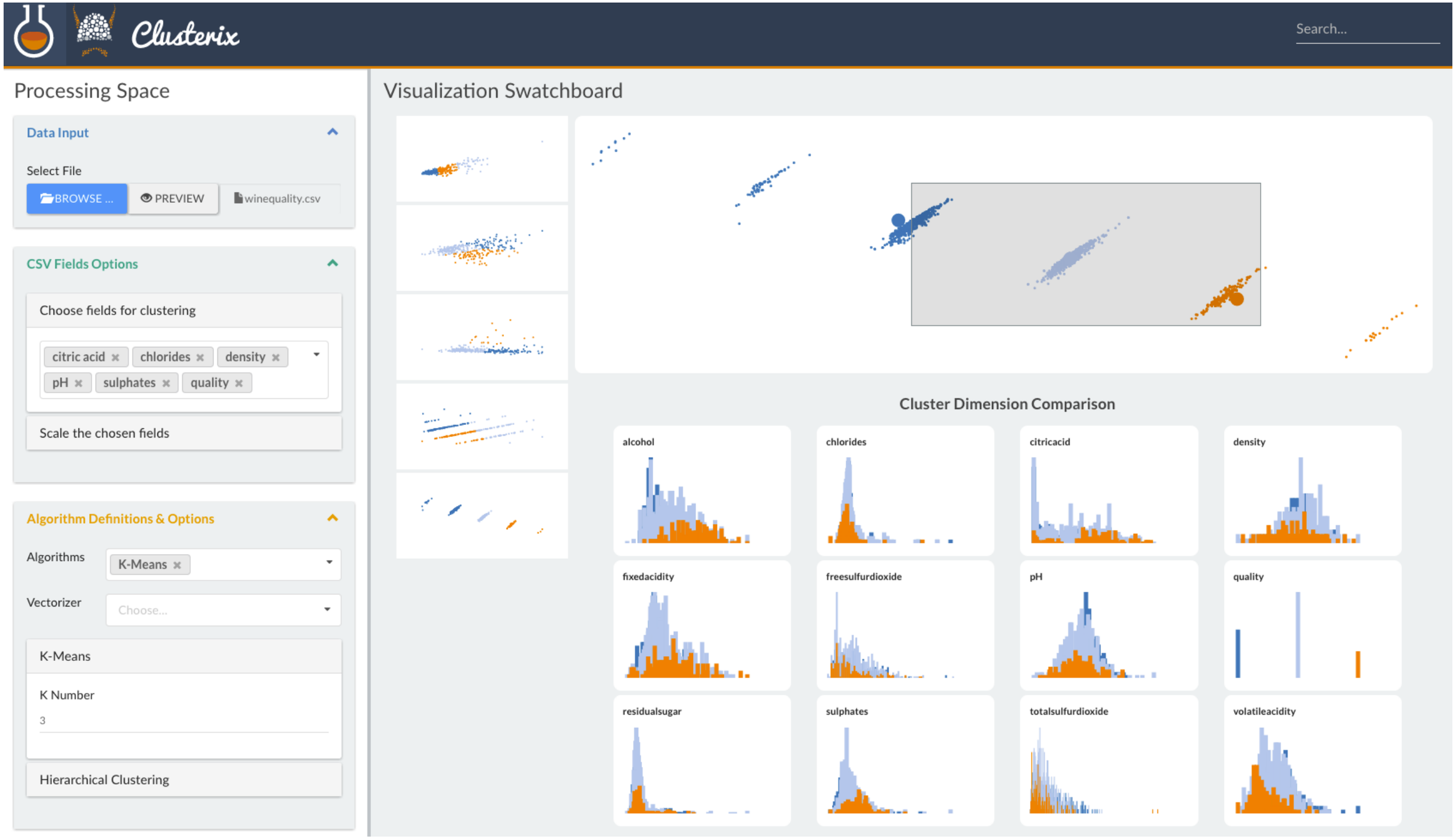
https://www.ipcc.ch/ipccreports/tar/wg1/fig2-32.htm

Sometimes visualization is needed to figure out what the best way to represent a data set can be…combining **analytics**, **visualization**, and **human reasoning**.

This is **visual analytics**.

Why are we visualising?

Discovery and Exploration



Joint Work with Ilias Koutsakis and Gilles Louppe @ CERN

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How can we visualise?

How can we visualize?

The components of a visualization.

Good and bad practices.

How can you encode information optimally?

Encode

Arrange

- Express
- Separate
- Order
- Align
- Use

Map

from qualitative and quantitative attributes

- Color
  - *Hue*
  - *Saturation*
  - *Luminance*
  - *Transparency*
- Region, Texture, Shape, ...
- Motion
  Direction, Rate, Frequency, ...
- Position, Size, Angle, Curvature, ...

Manipulate

- Change
- Select
- Navigate

Facet

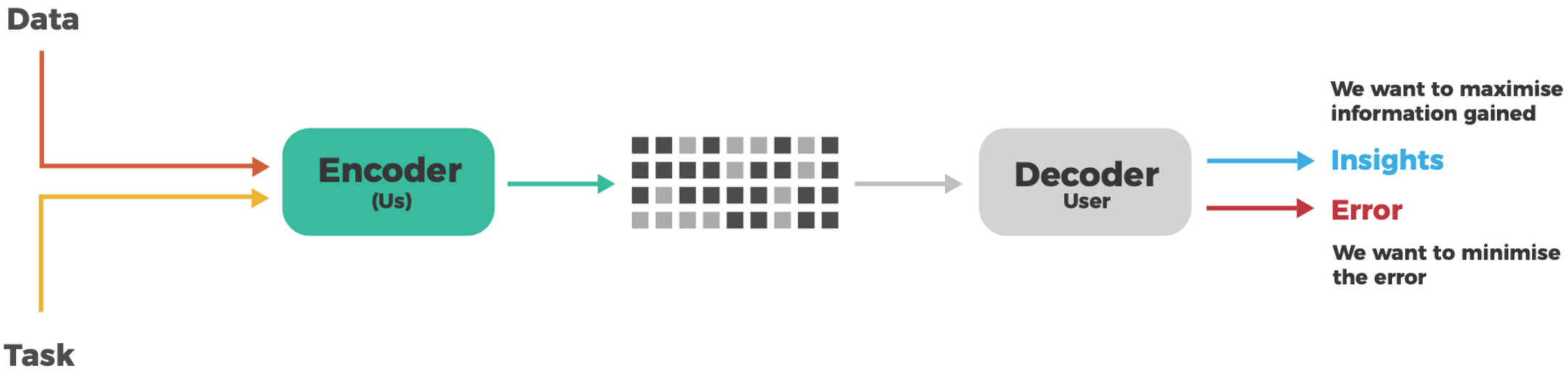
- Juxtapose
- Partition
- Superimpose

Reduce

- Filter
- Aggregate
- Embed

How can you encode information optimally?

If we don’t follow grammatical rules or spell correctly, the meaning of text can be lost.



The same applies for visualisations. We can compose visualisations using a vocabulary (shapes, colour, texture,…), and a grammar. If we learn these, we can do better when it comes to communicating visually.

How can you encode information optimally?

The importance of the error perceived in a visualisation must always be balanced with purpose. Sometimes we don’t need to read off exact values, and perceptual strangeness doesn’t really matter - but sometimes it does.

Roboto Font

x16l52lOlU0

Courier Font

x16I52lOIU0

If this is my password, fine.

If it’s a wifi password for a coffee shop, maybe not.

There is confusion between the upper case i and the lower case L.

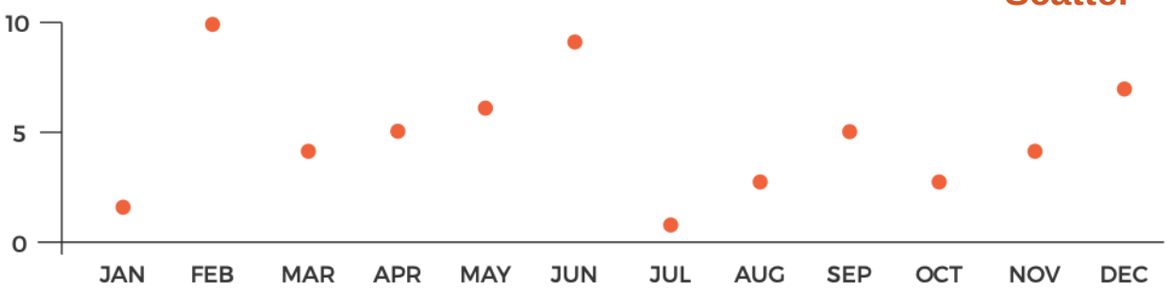
The distance between the characters can cause error in interpretation, causing frustration for users, and in this case, unhappy coffee shop customers.

Graphs are like jokes.
If you have to explain them, they didn’t work.

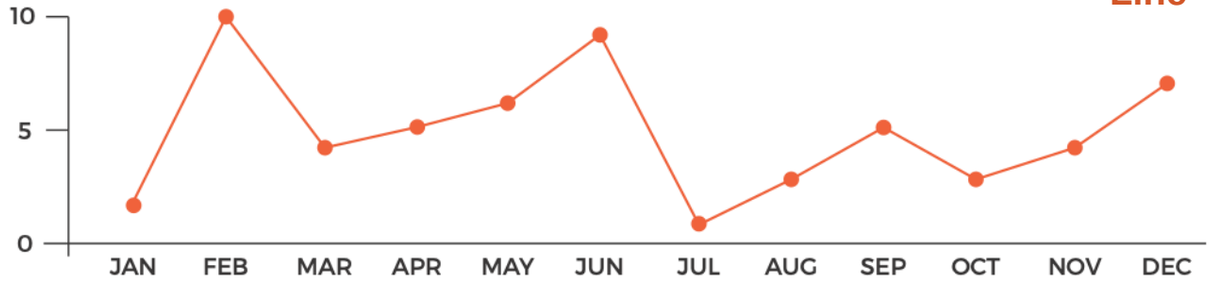
Anon.

JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2	10	4	5	6	9	1	3	5	3	4	7

Scatter

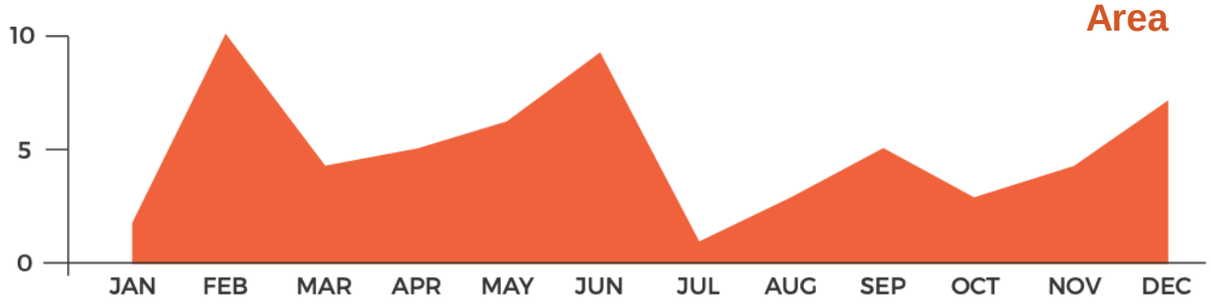


Line



Histogram

Area



Size

Saturation

Size & Saturation

Size, Saturation, & Position

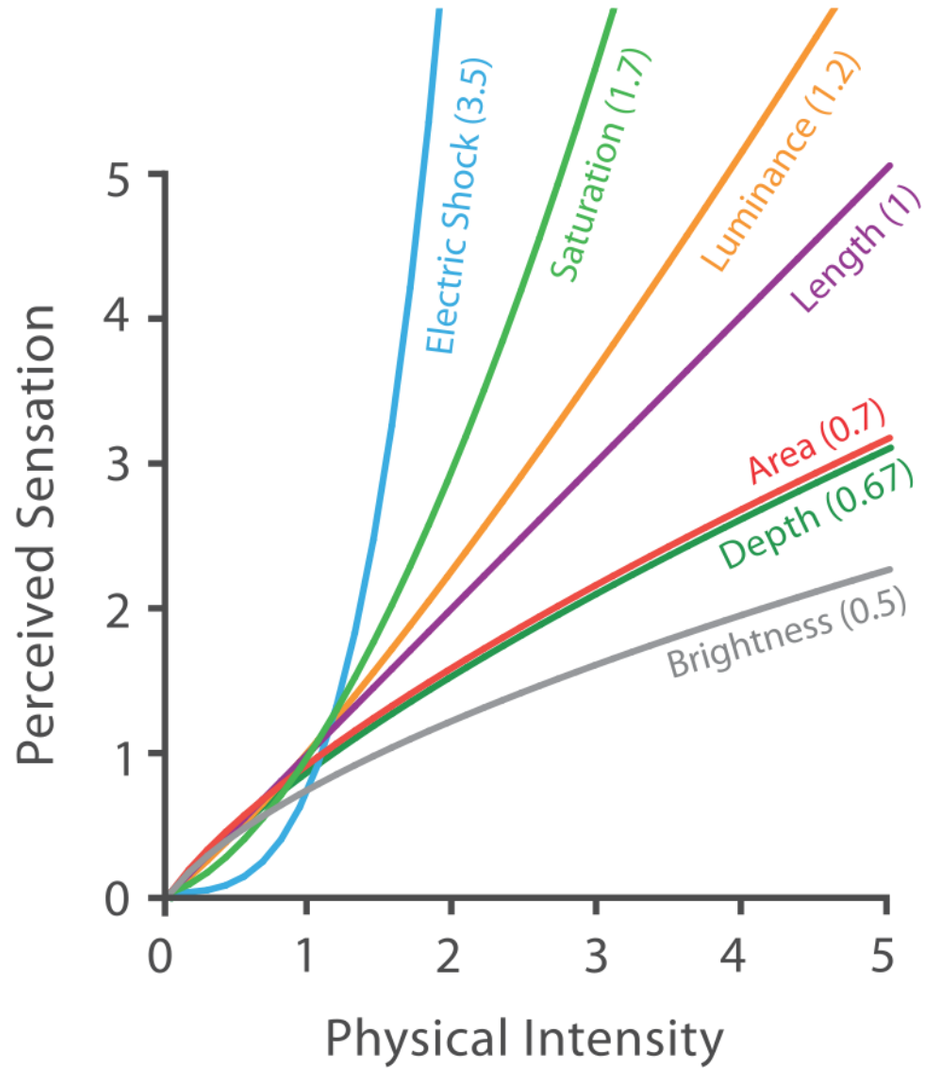
And that’s just a really simple low dimensional example

Moreover, all of these visualizations encode the information, but the decode error (interpreting, comparing, …) for each graph is different

But, why?

Our perception system does not behave linearly.

Some stimuli are perceived less or more than intended.



Steven's Psychophysical Power Law: $S = I^N$

Stevens, 1975

We have to be careful when mapping data to the visual world

Some visual channels are more effective for some data types over others.

Quantitative validated

Cleveland and McGill, 1983
Heer and Bostock, 2010
MacKinley, 1986

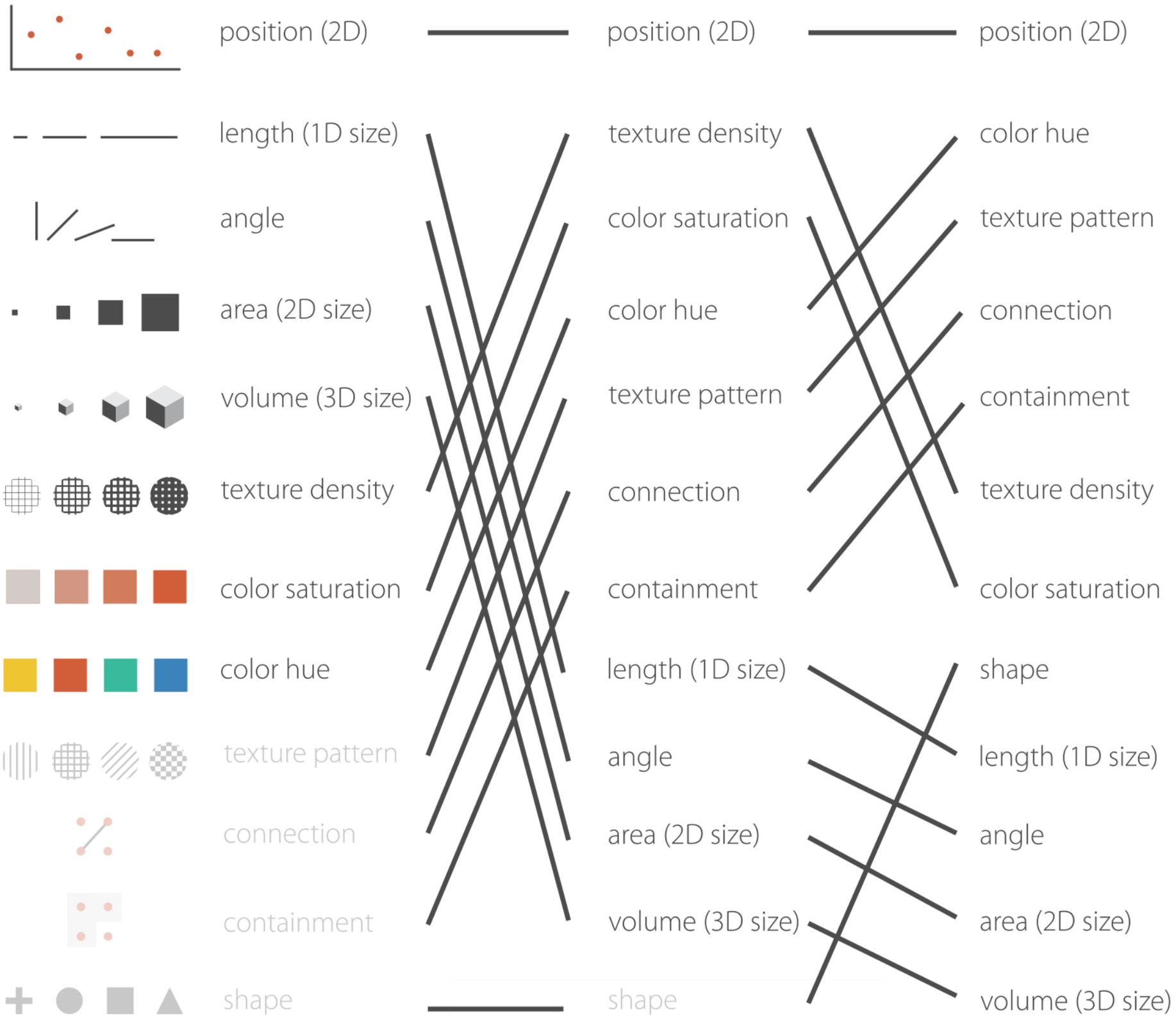
Ordinal not validated

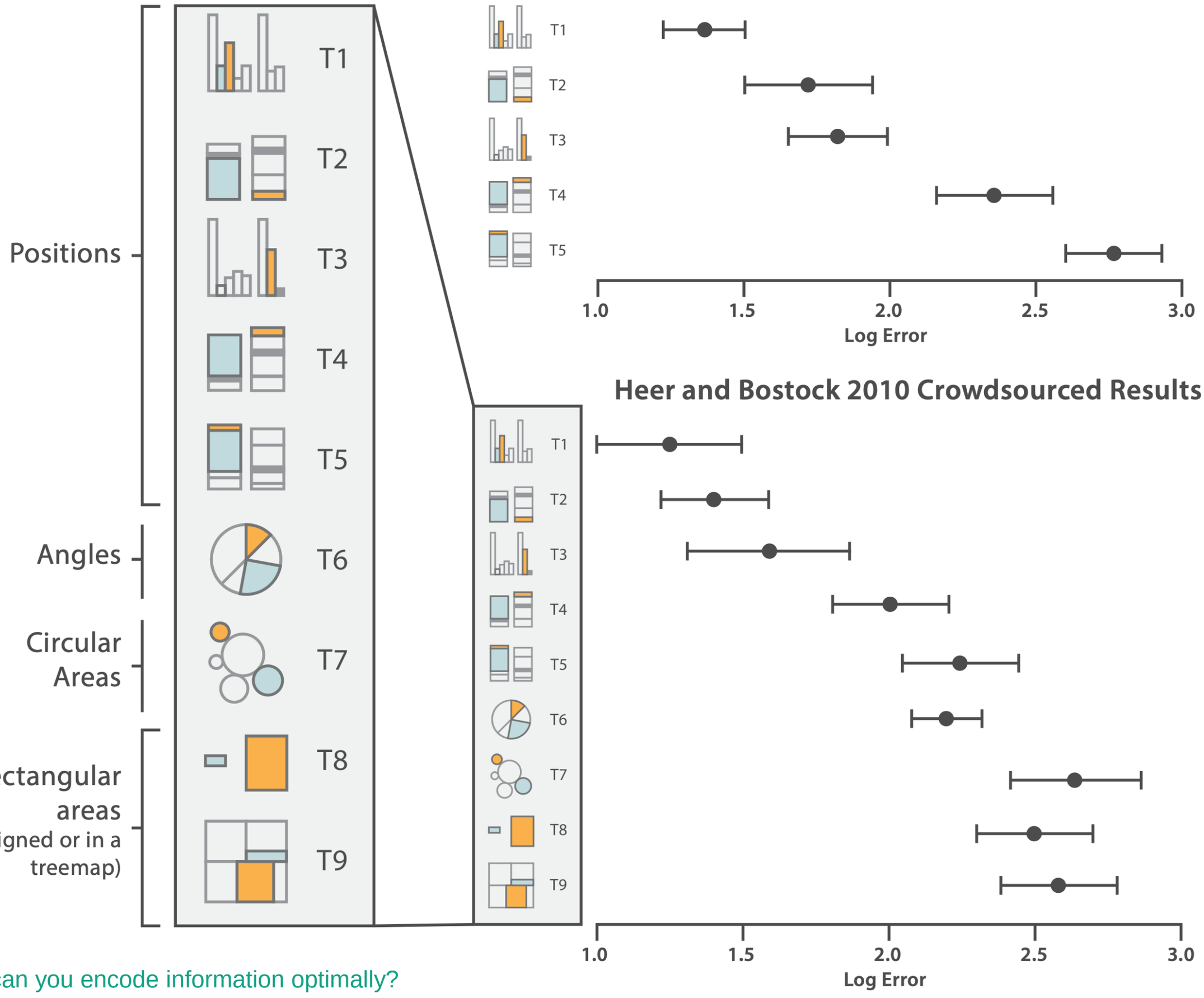
MacKinley, 1986

Categorical not validated

MacKinley, 1986

Suitability of Channel

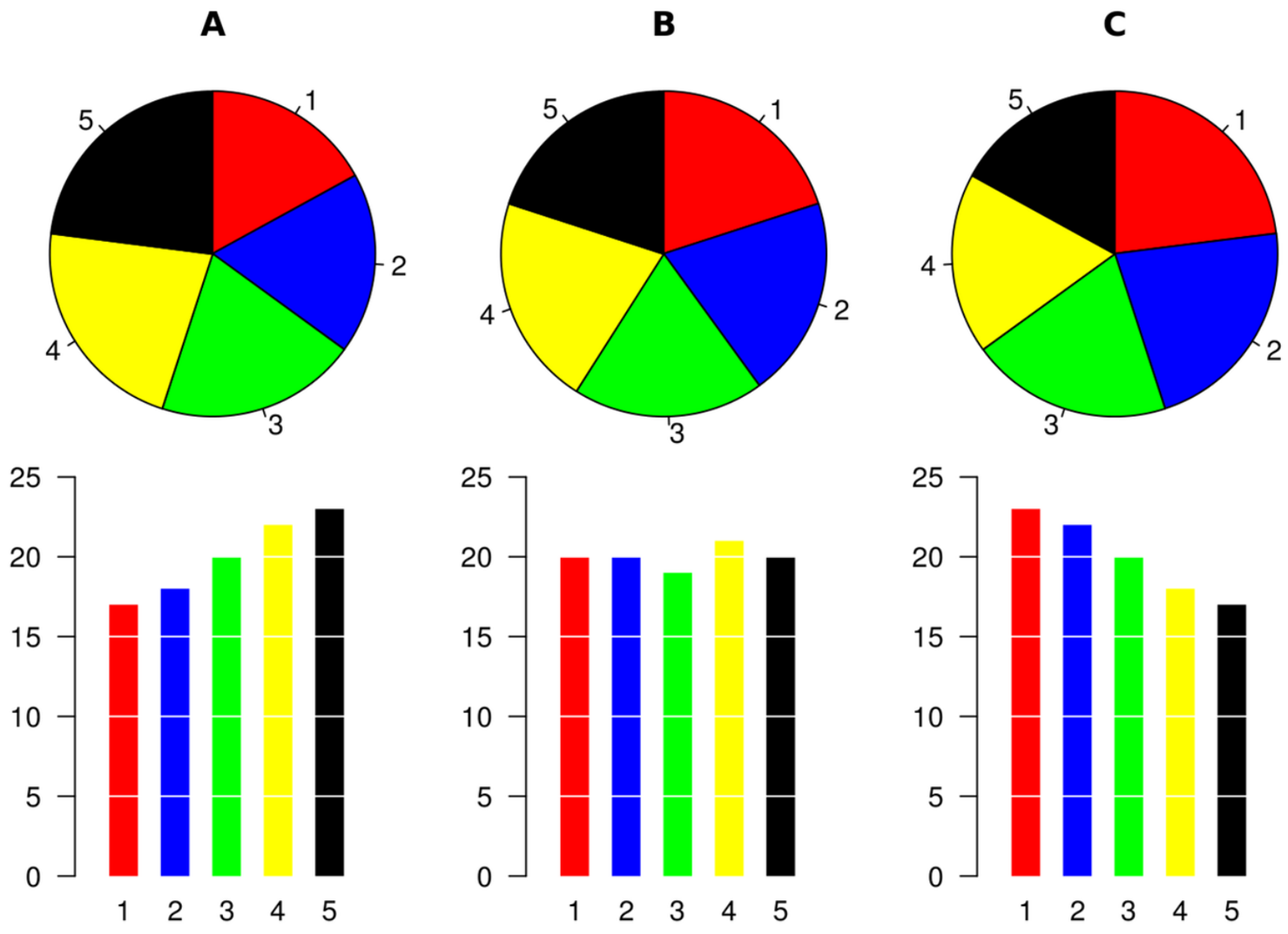




How can you encode information optimally?

T6: Pie charts have also been studied in more detail recently

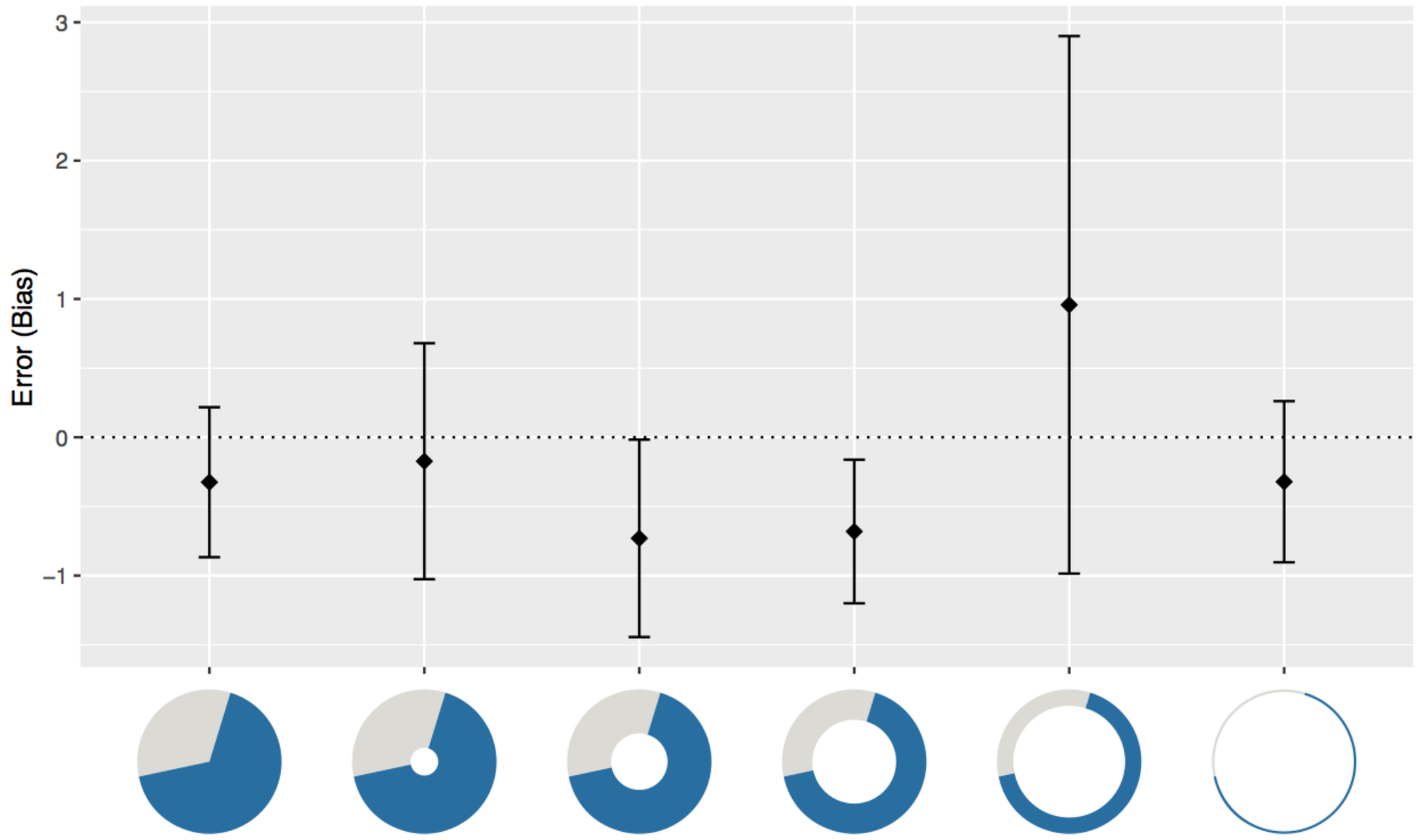
It’s quite clear that bar charts are a more effective visual encoding here than pie charts… our visual system is very good at judging lengths, but not so much at judging angles and areas.



https://commons.wikimedia.org/wiki/File:Piecharts.svg

T6: Pie charts have also been studied in more detail recently

When someone reads or compares values in a pie chart, what are they doing? Comparing angles, areas, length of arc?



Robert Kosara and Drew Skau. 2016. **Judgment error in pie chart variations**. In Proceedings of the Eurographics: Short Papers (EuroVis '16). Eurographics Association, Goslar Germany, Germany, 91-95. DOI: https://doi.org/10.2312/eurovisshort.20161167

Drew Skau and Robert Kosara. 2016. **Arcs, Angles, or Areas: Individual Data Encodings in Pie and Donut Charts**. Comput. Graph. Forum 35, 3 (June 2016), 121-130. DOI: https://doi.org/10.1111/cgf.12888

2012 PRESIDENTIAL RUN

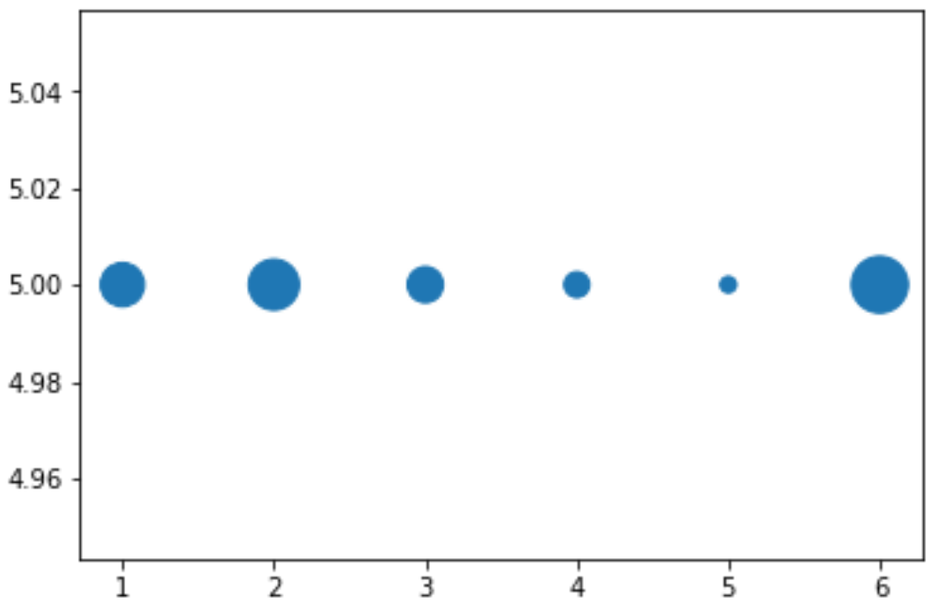
GOP CANDIDATES

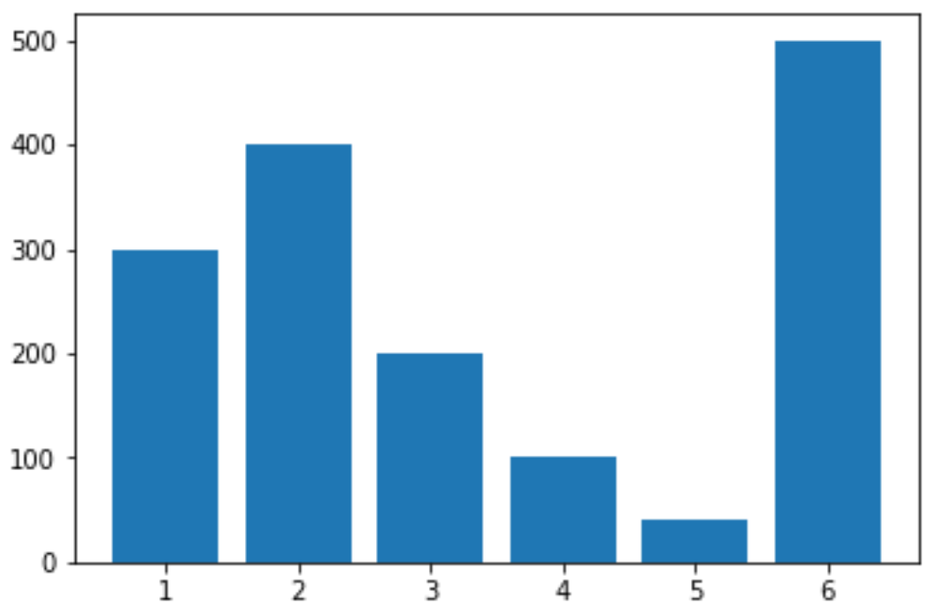
FOX

9:17 PM

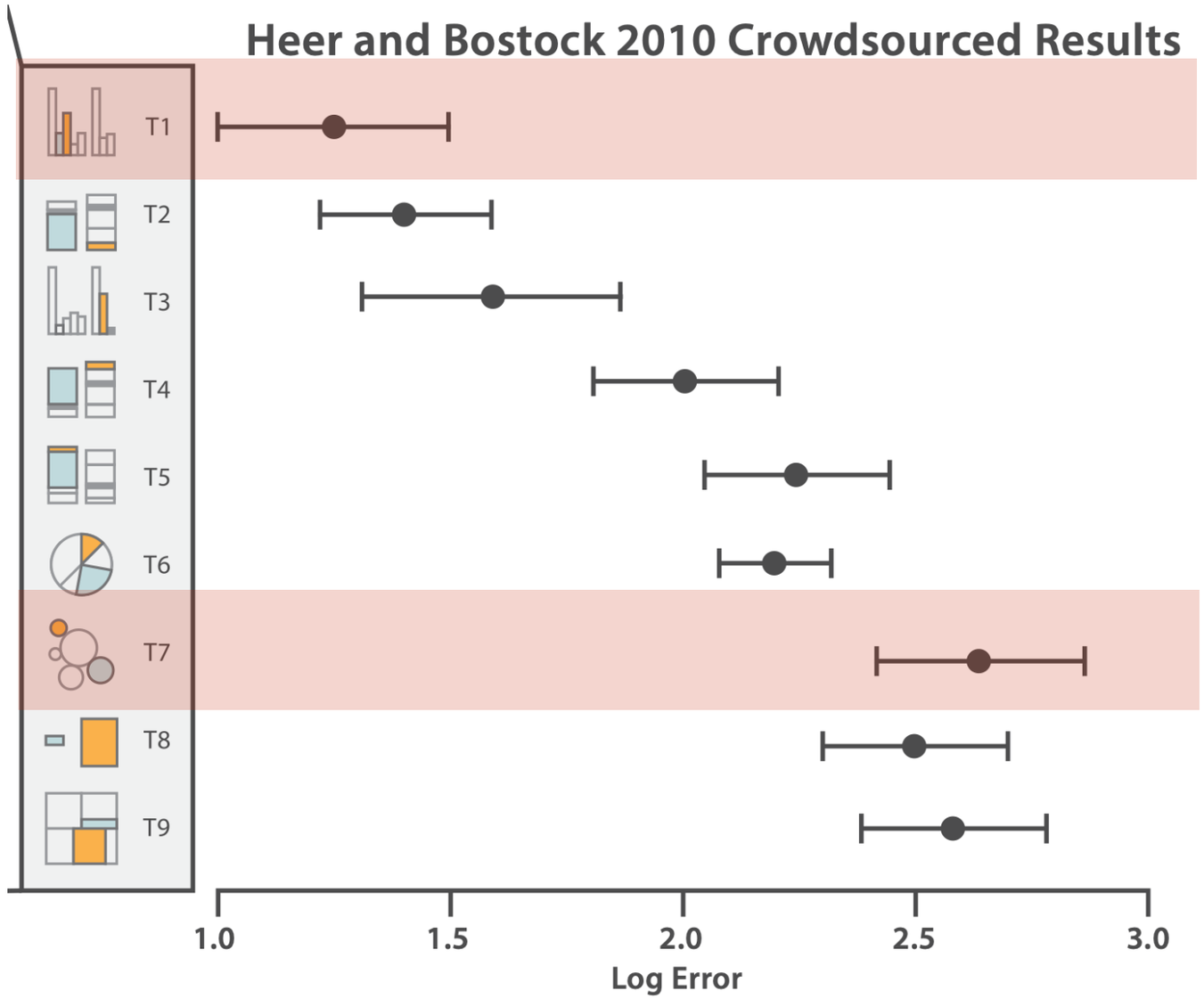
SOURCE:OPINIONS DYNAMIC

T1/T7: Bar charts are better than areas…



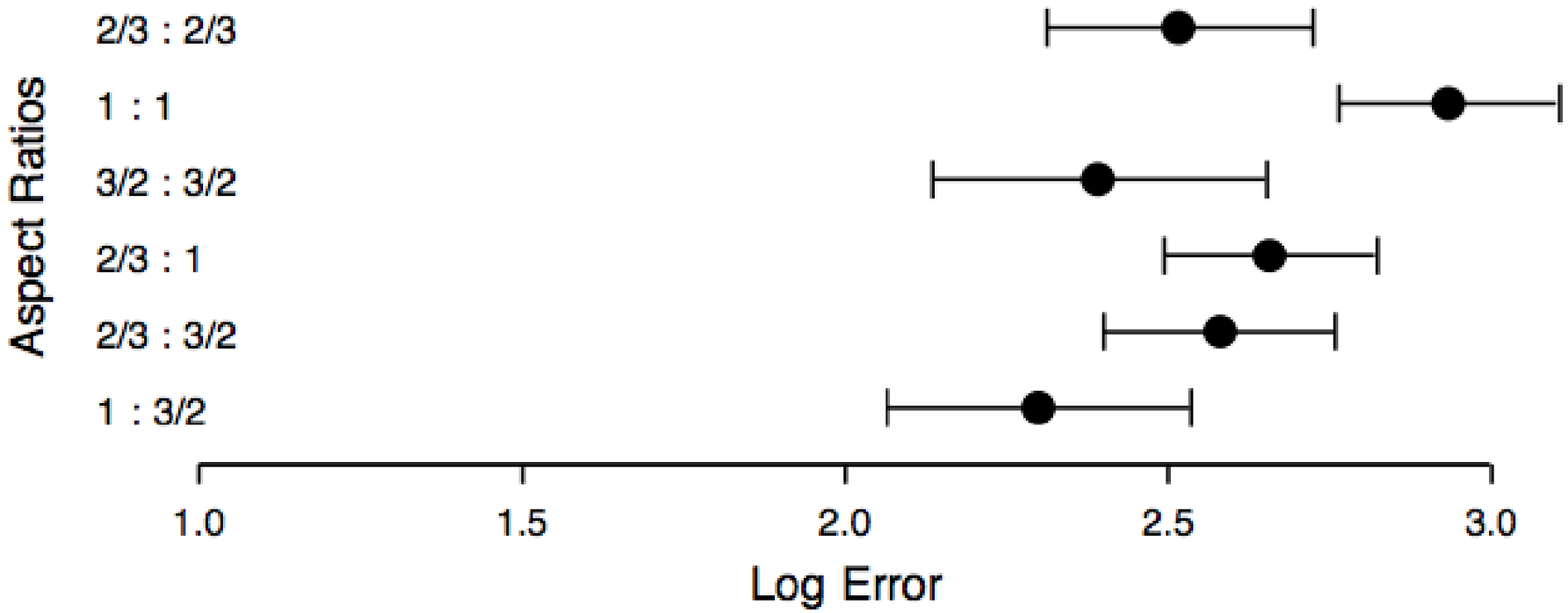


300 400 200 100 40 500



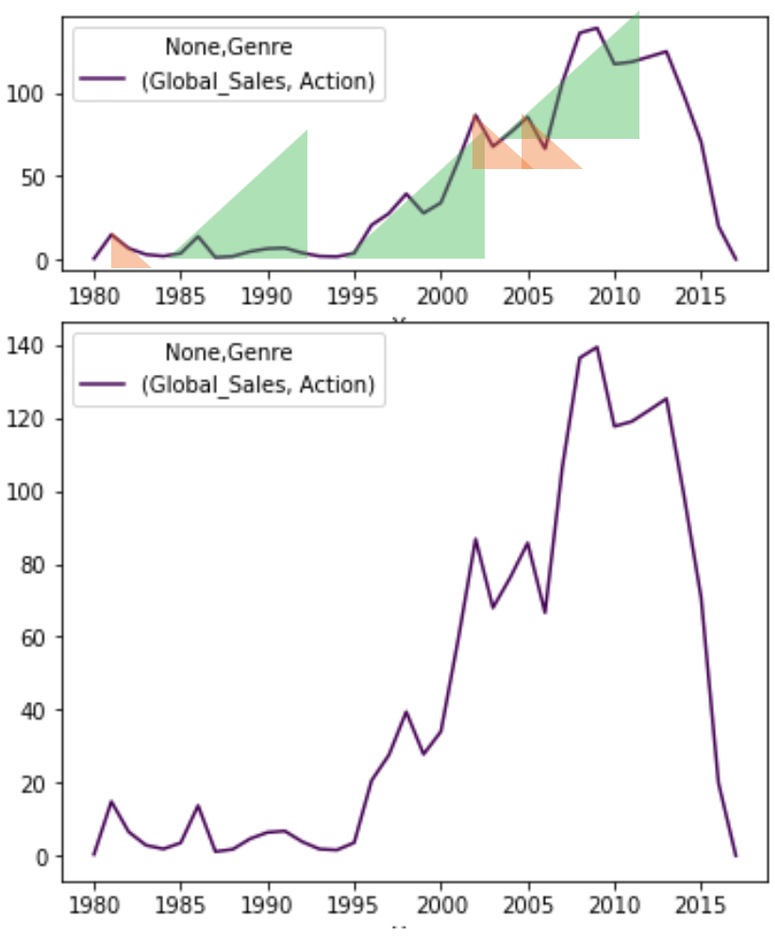
This is exactly the same data, at the right scaling.

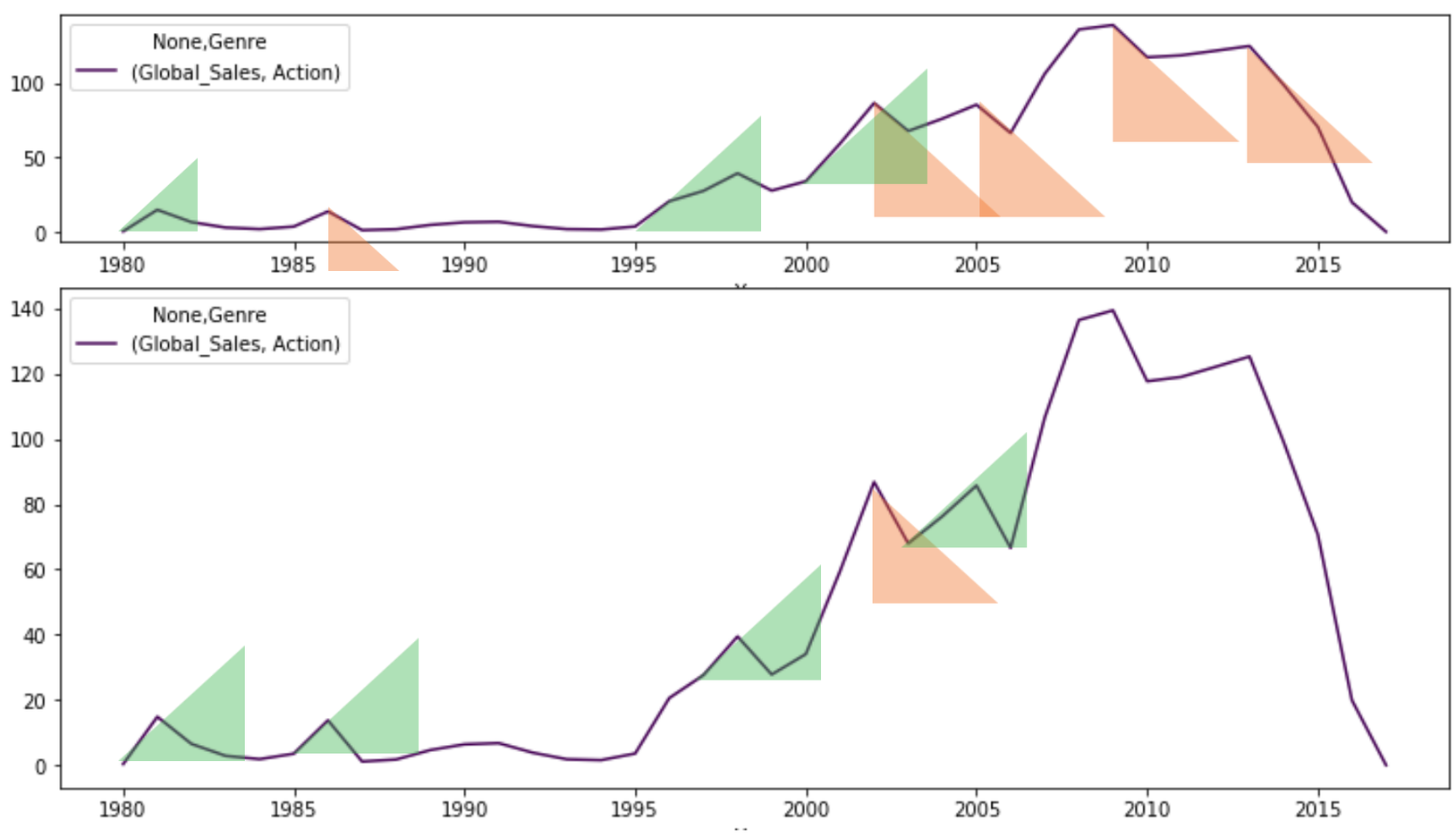
T8/T9: Different aspect ratios for rectangles also result in greater or fewer errors in estimating
errors in interpretation…



Aspect ratio is important!

For line charts there is a basic guideline on optimising plot aspect ratio to have an average angle of 45 degrees from Cleveland et al, 1988.





Although, like most things, not everyone agrees with this guideline.
In this case I think it makes sense, you can decide :)

HOW

We have to be careful when mapping data to the visual world

Some visual channels are more effective for some data types over others.

Some data has a natural mapping that our brains expect given certain types of data

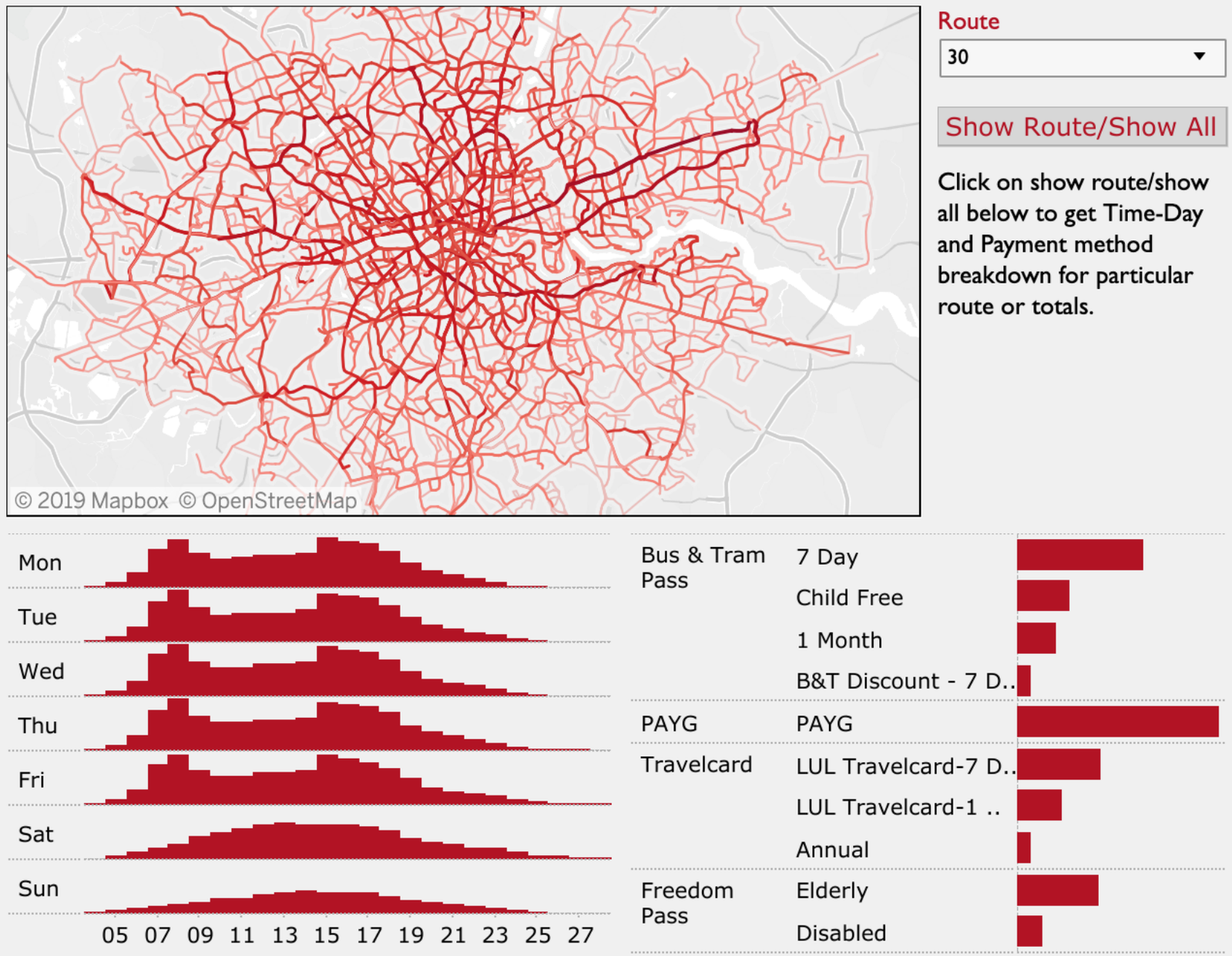
Natural Mappings

Graphical Code		Semantics
Small shapes defined by closed contour, texture, color.		Object, idea, entity, node.
Spatially ordered graphical objects.		Related information or a sequence. In a sequence the left-to-right ordering convention is borrowed from written language (English, French, etc.).
Graphical objects in proximity		Similar concepts
Graphical objects having the same shape color, or texture.		Similar concepts
Size, position or height of graphical object		Size, quantity, importance, 2D location
Shapes connected by contour		Related entities, path between entities.
Thickness of connecting contour		Strength of relationship.
Color and texture of connecting contour		Type of relationship.
Shapes enclosed by a contour, a common texture or color		Contained/related entities.
Nested/partitioned regions		Hierarchical concepts.
Attached shapes		Parts of a conceptual structure.

Locations presented on a map.

Time should be on an X-Axis

Bar charts for comparisons.

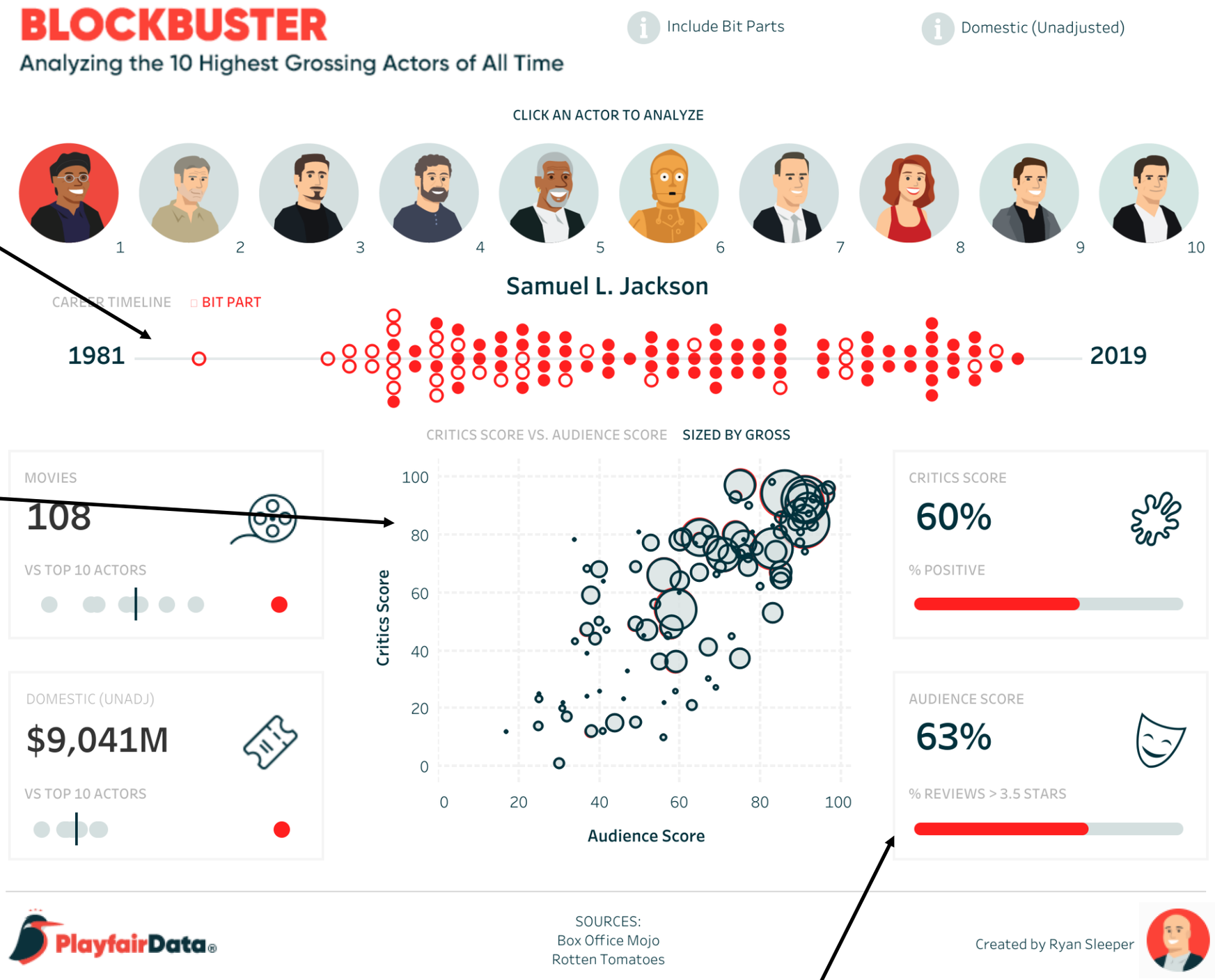


All data sourced from Transport for London (this work is not affiliated to TfL in any way), apart from list of bus routes, which is sourced from londonbusroutes.net. The dataset used is a 5% sample of all Oyster card journeys performed in a week during November 2009 on Bus, Tube, DLR and London Overground. Note that bus routes are based on bus stop locations and are therefore only approximate.

https://public.tableau.com/s/gallery/london-bus-map

Time should be on an X-Axis

Correlations as a scatter plot.



Bar charts for comparisons.

https://public.tableau.com/s/gallery/10-highest-grossing-actors-all-time?tab=featured&type=featured

HOW

We have to be careful when mapping data to the visual world

Some visual channels are more effective for some data types over others.

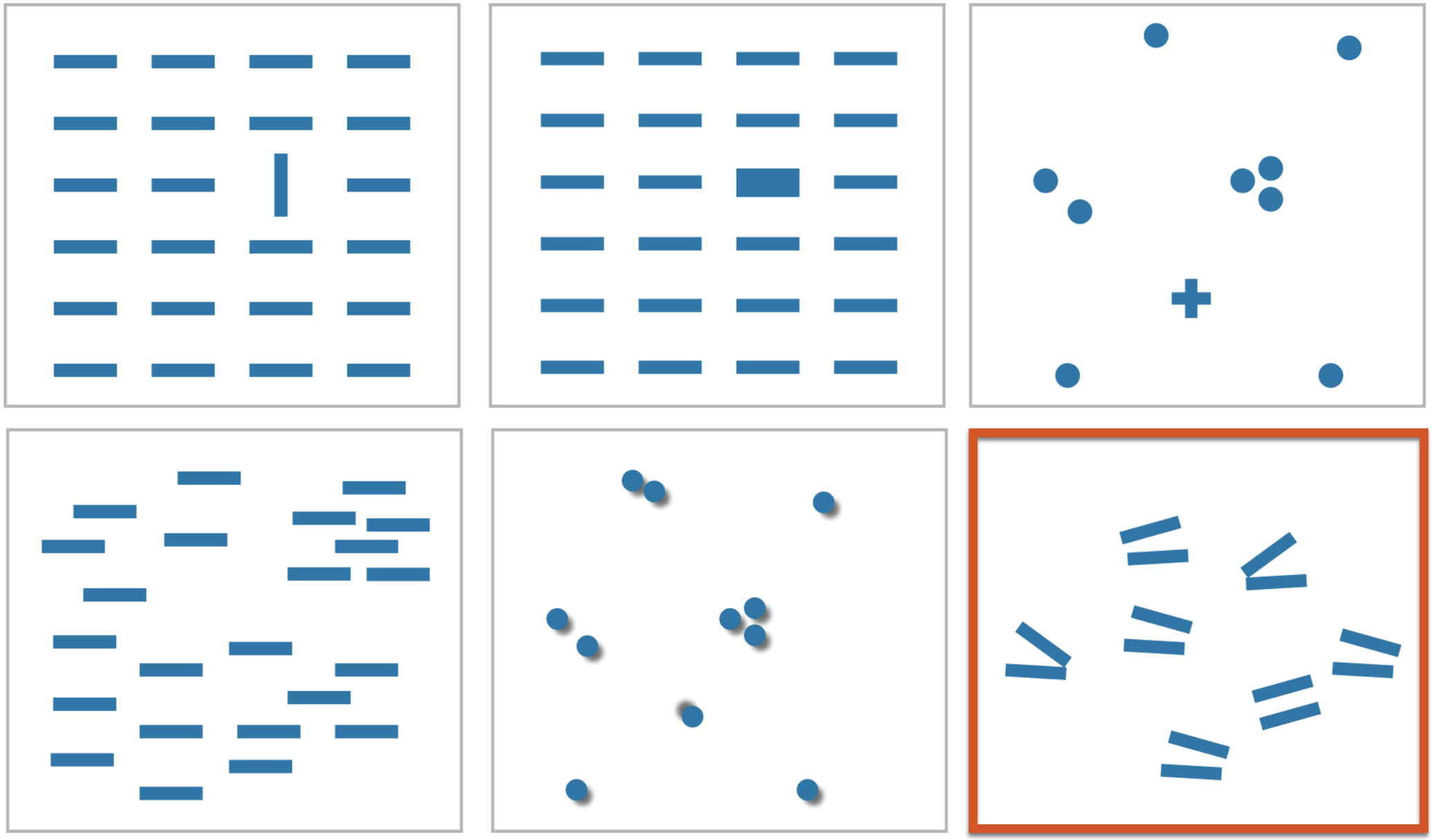
Some data has a natural mapping that our brains expect given certain types of data

There are many intricacies of the visual system that must be considered

The pop-out effect

We pre-attentively process a scene, and some visual elements stand out more than others.

- Parallel processing on many individual channels
  - speed independent of distractor count
  - speed depends on channel and amount of difference from distractors
- Serial search for (almost all) combinations
  - speed depends on number of distractors



Not all exhibit the pop-out effect!

Parallel line pairs do not pop out from tilted pairs…

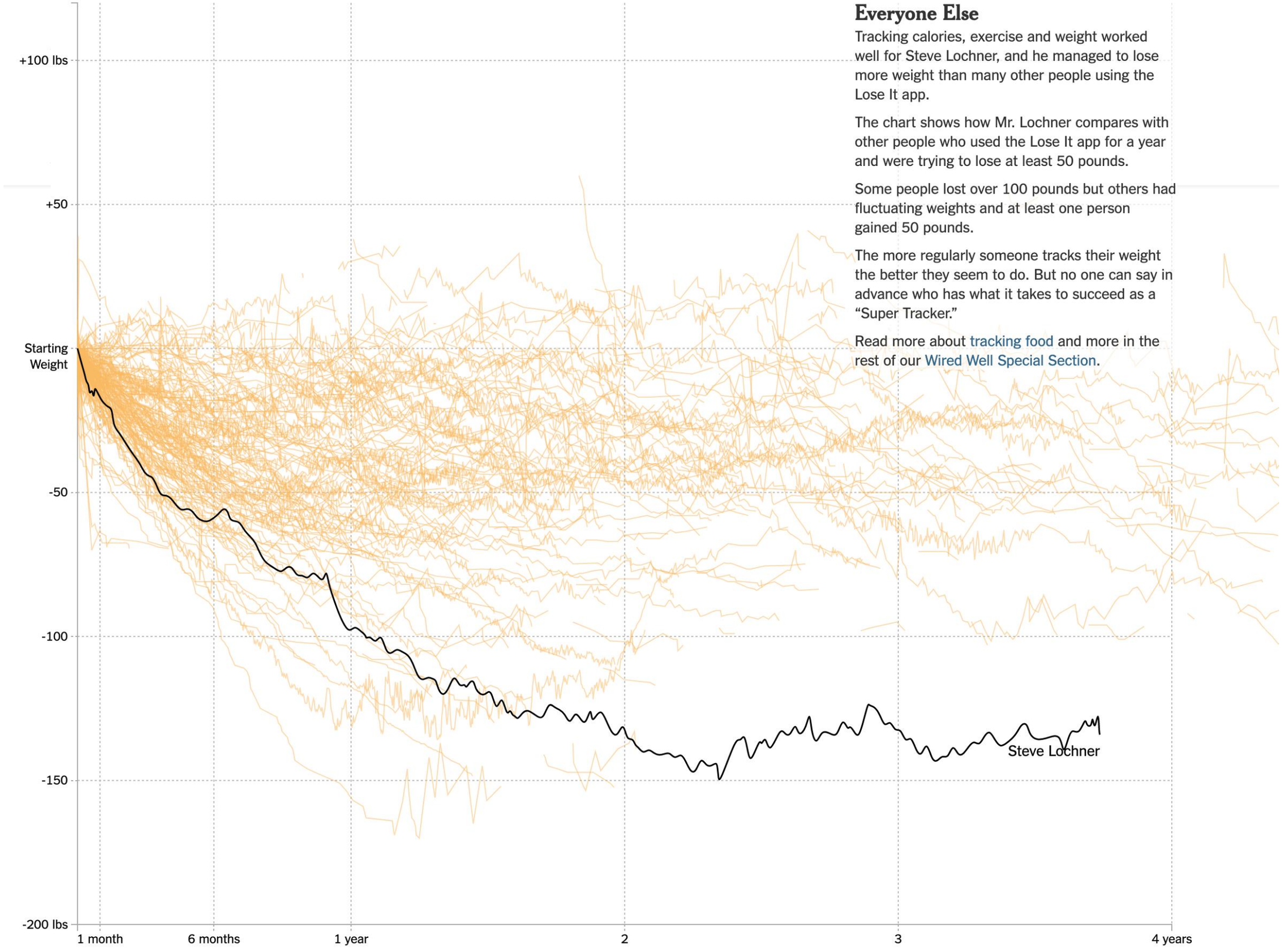
And not all visual channels pop out as quickly as other. E.g. colour is always on top.

The pop-out effect

3 3 0 3 0 1 8 7 6 8 2 1 4 0 3 8 3 7 7 2 0 5 2 3 2 7 0 2 0
7 1 4 6 0 2 1 3 2 7 6 0 2 5 6 3 2 5 7 6 3 3 0 2 0 3 0 7 2
8 7 5 7 2 8 3 8 7 7 8 2 0 7 7 5 2 3 1 1 5 6 3 8 4 7 8 2 0
0 5 0 5 1 6 1 7 5 6 8 0 4 4 6 7 4 7 1 4 0 0 8 4 4 3 0 3 2
2 4 3 1 3 5 4 9 5 0 7 6 0 7 4 3 1 8 2 7 3 4 6 0 2 4 8 2 3
8 6 2 2 6 5 4 6 7 0 7 6 0 0 3 9 0 2 4 7 1 7 2 3 3 5 8 7 0
0 8 4 5 1 3 1 7 6 4 5 4 1 2 4 5 3 3 5 4 9 6 7 7 6 3 4 2 5
4 7 7 0 2 2 0 1 1 7 7 7 0 2 6 6 4 7 5 8 6 1 4 3 7 8 5 4 6
4 3 6 6 4 6 6 2 8 4 8 5 3 7 8 8 1 3 8 5 4 5 7 4 0 3 2 8 4
5 5 0 3 5 3 5 3 8 3 2 3 8 2 3 1 6 2 7 2 4 6 3 6 4 4 3 2 5
4 4 0 2 1 7 2 4 4 7 4 1 9 2 4 5 2 5 0 4 0 0 5 3 6 3 3 6 7
7 4 6 6 8 7 5 7 9 2 0 2 8 8 8 8 3 2 4 2 6 4 0 4 6 3 7 2 1
0 1 7 1 5 9 1 4 2 8 7 3 7 1 4 5 1 8 7 8 0 5 1 7 0 5 8 8 1
2 8 5 2 1 2 8 7 7 6 2 5 6 2 6 4 1 5 1 6 1 2 1 1 0 5 6 4 0
2 1 1 7 7 2 0 0 1 8 7 0 2 9 0 2 8 5 7 8 4 6 0 6 5 0 7 1 2
0 5 2 4 1 5 3 3 1 5 5 1 4 0 1 6 4 3 3 9 8 8 3 4 6 8 4 8 6
7 3 7 5 2 4 0 2 7 6 3 8 5 5 4 5 8 8 7 5 5 6 5 6 7 9 7 7 4
0 3 2 8 1 4 4 6 0 8 2 3 0 1 3 4 6 2 0 5 7 7 3 6 1 8 7 3 5
4 4 8 3 3 3 5 0 1 0 3 8 6 3 2 0 5 0 6 1 3 3 4 3 6 1 5 8 6
1 0 2 2 7 6 3 3 0 8 8 0 3 1 8 8 1 2 1 7 5 2 9 3 5 8 3 2 5

The pop-out effect

3 3 0 3 0 1 8 7 6 8 2 1 4 0 3 8 3 7 7 2 0 5 2 3 2 7 0 2 0
7 1 4 6 0 2 1 3 2 7 6 0 2 5 6 3 2 5 7 6 3 3 0 2 0 3 0 7 2
8 7 5 7 2 8 3 8 7 7 8 2 0 7 7 5 2 3 1 1 5 6 3 8 4 7 8 2 0
0 5 0 5 1 6 1 7 5 6 8 0 4 4 6 7 4 7 1 4 0 0 8 4 4 3 0 3 2
2 4 3 1 3 5 4 **9** 5 0 7 6 0 7 4 3 1 8 2 7 3 4 6 0 2 4 8 2 3
8 6 2 2 6 5 4 6 7 0 7 6 0 0 3 **9** 0 2 4 7 1 7 2 3 3 5 8 7 0
0 8 4 5 1 3 1 7 6 4 5 4 1 2 4 5 3 3 5 4 **9** 6 7 7 6 3 4 2 5
4 7 7 0 2 2 0 1 1 7 7 7 0 2 6 6 4 7 5 8 6 1 4 3 7 8 5 4 6
4 3 6 6 4 6 6 2 8 4 8 5 3 7 8 8 1 3 8 5 4 5 7 4 0 3 2 8 4
5 5 0 3 5 3 5 3 8 3 2 3 8 2 3 1 6 2 7 2 4 6 3 6 4 4 3 2 5
4 4 0 2 1 7 2 4 4 7 4 1 **9** 2 4 5 2 5 0 4 0 0 5 3 6 3 3 6 7
7 4 6 6 8 7 5 7 **9** 2 0 2 8 8 8 8 3 2 4 2 6 4 0 4 6 3 7 2 1
0 1 7 1 5 **9** 1 4 2 8 7 3 7 1 4 5 1 8 7 8 0 5 1 7 0 5 8 8 1
2 8 5 2 1 2 8 7 7 6 2 5 6 2 6 4 1 5 1 6 1 2 1 1 0 5 6 4 0
2 1 1 7 7 2 0 0 1 8 7 0 2 **9** 0 2 8 5 7 8 4 6 0 6 5 0 7 1 2
0 5 2 4 1 5 3 3 1 5 5 1 4 0 1 6 4 3 3 **9** 8 8 3 4 6 8 4 8 6
7 3 7 5 2 4 0 2 7 6 3 8 5 5 4 5 8 8 7 5 5 6 5 6 7 **9** 7 7 4
0 3 2 8 1 4 4 6 0 8 2 3 0 1 3 4 6 2 0 5 7 7 3 6 1 8 7 3 5
4 4 8 3 3 3 5 0 1 0 3 8 6 3 2 0 5 0 6 1 3 3 4 3 6 1 5 8 6
1 0 2 2 7 6 3 3 0 8 8 0 3 1 8 8 1 2 1 7 5 2 **9** 3 5 8 3 2 5



Everyone Else

Tracking calories, exercise and weight worked well for Steve Lochner, and he managed to lose more weight than many other people using the Lose It app.

The chart shows how Mr. Lochner compares with other people who used the Lose It app for a year and were trying to lose at least 50 pounds.

Some people lost over 100 pounds but others had fluctuating weights and at least one person gained 50 pounds.

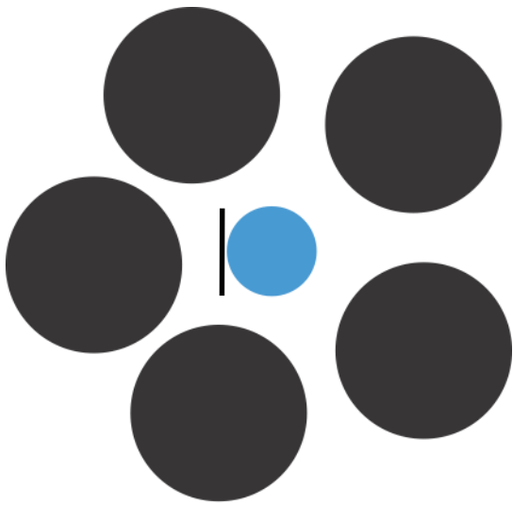
The more regularly someone tracks their weight the better they seem to do. But no one can say in advance who has what it takes to succeed as a "Super Tracker."

Read more about tracking food and more in the rest of our Wired Well Special Section.

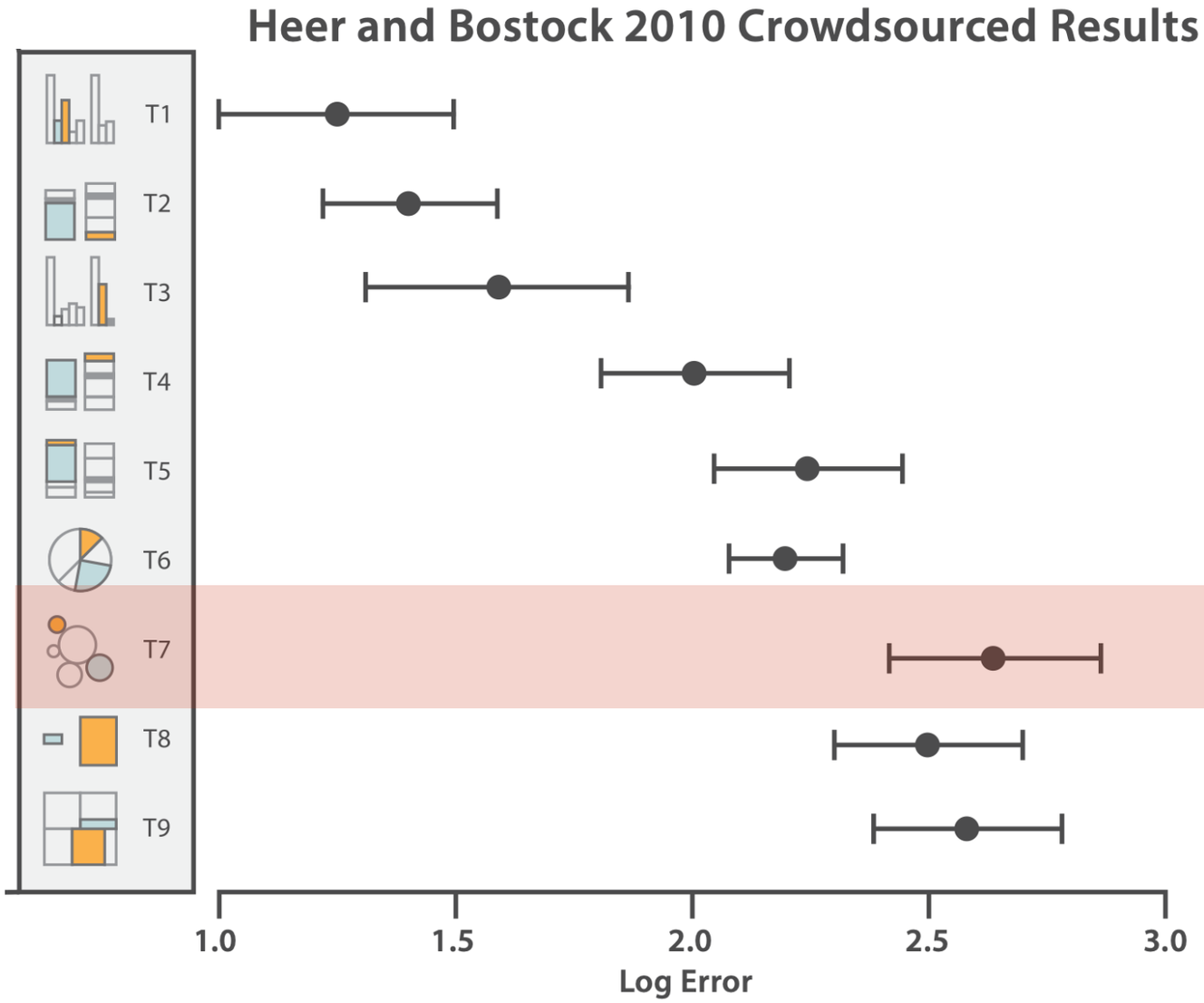
es.com/interactive/2015/11/17/health/wiredwell-food-diary-super-tracker.html - beautiful storytelling using v

Relative Comparison

Relative Comparison



36px

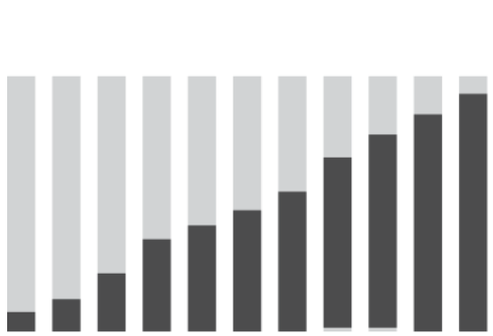


Relative Comparison

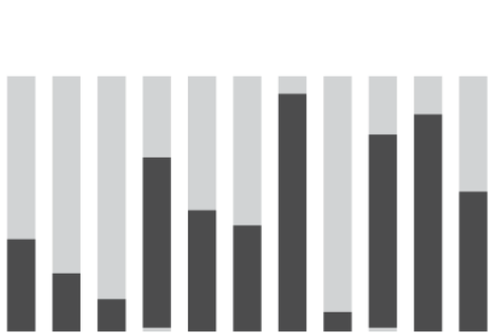
4 values

Unordered

Unaligned

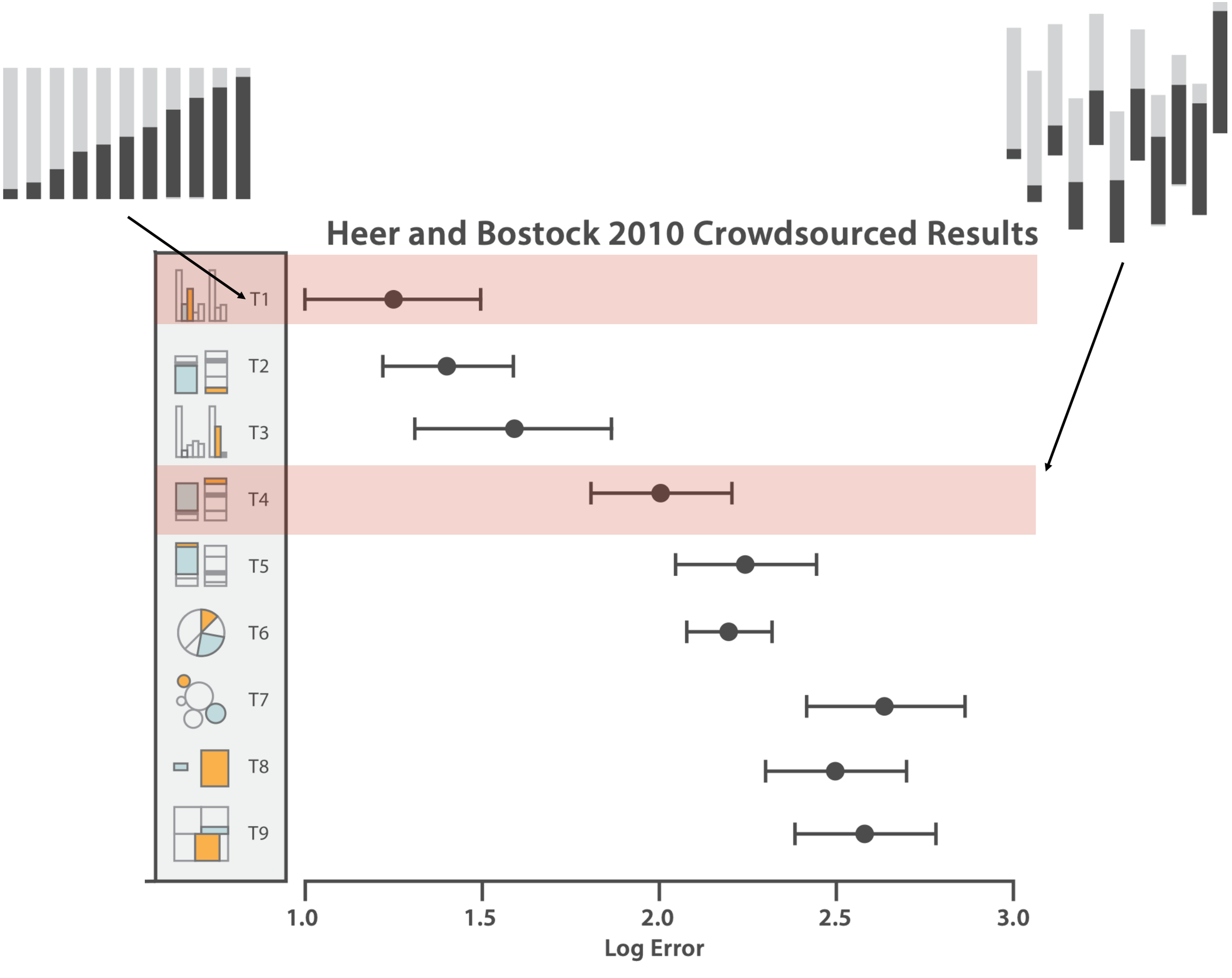


11 values



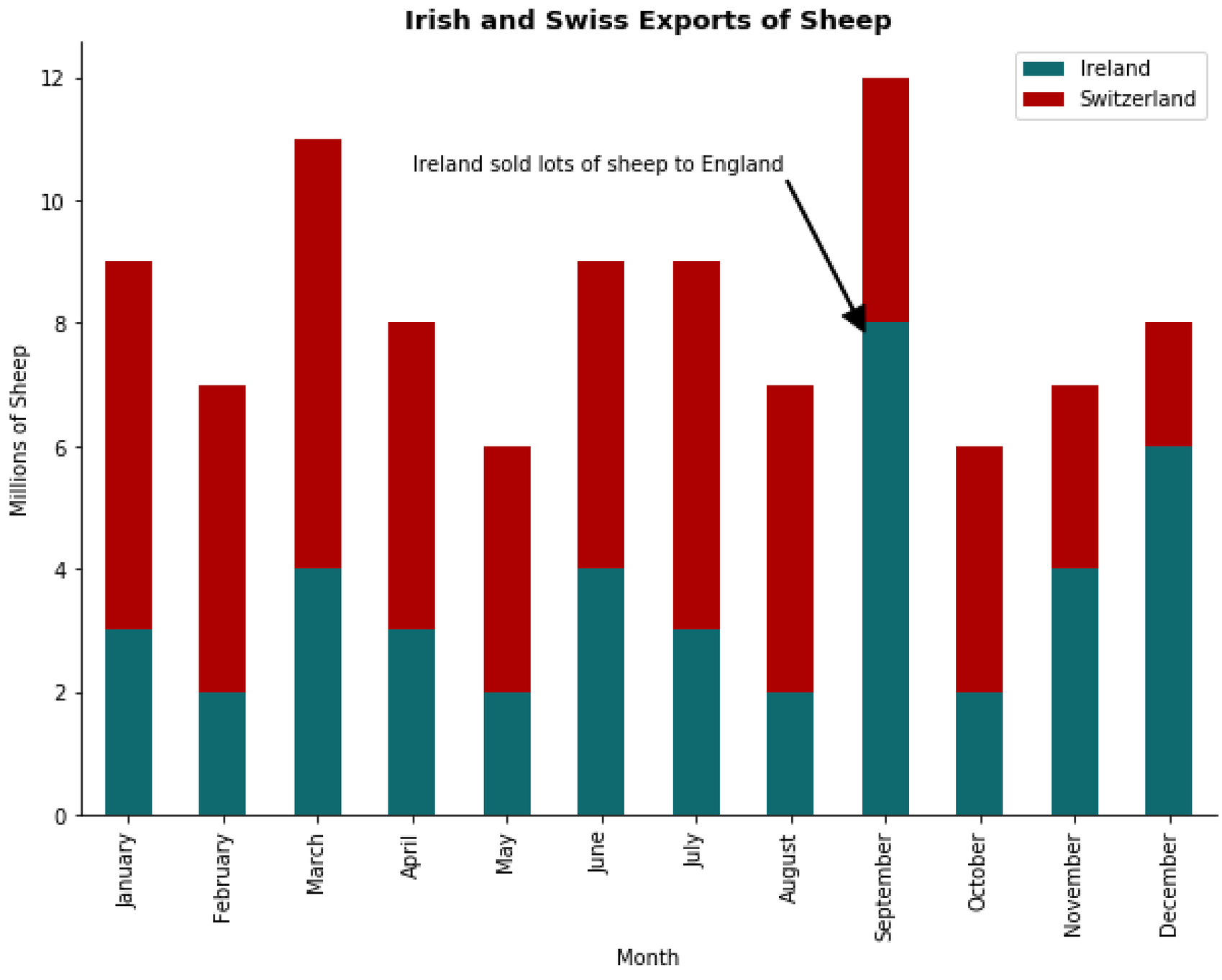
Unordered

Unaligned


Heer and Bostock 2010 Crowdsourced Results
T1
T2
T3
T4
T5
T6
T7
T8
T9
1.0
1.5
2.0
2.5
3.0
Log Error

Relative Comparison

The problems with unaligned areas can be seen in stacked charts. A small number of values is ok, but too many and nothing will be interpretable.



Relative Comparison

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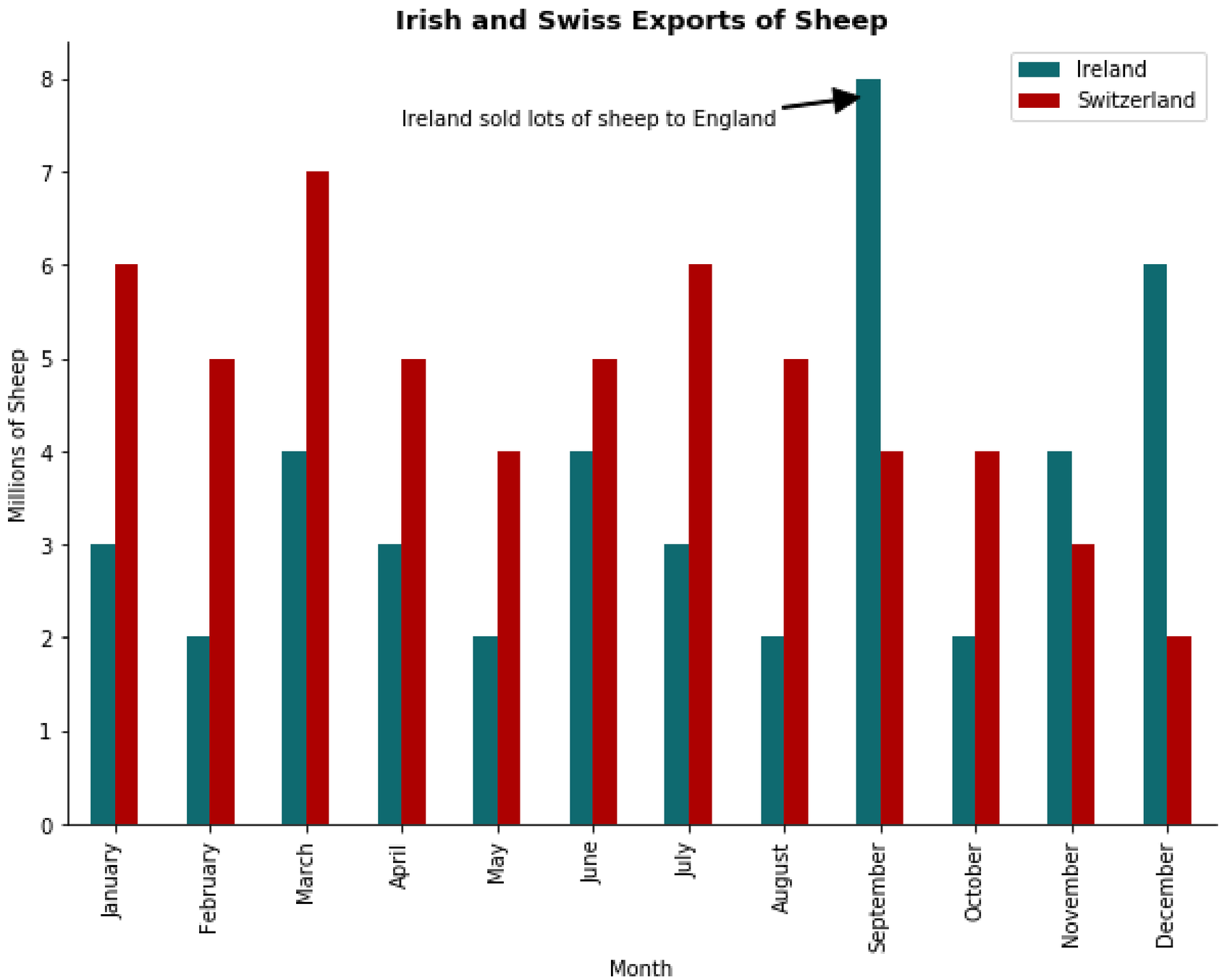
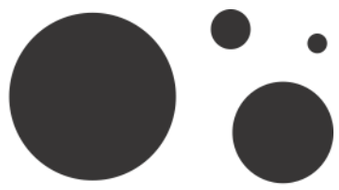


Relative Comparison

4 values

Aligned

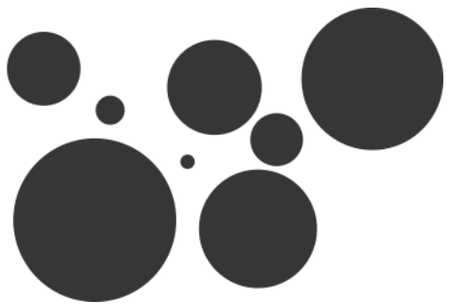
Unordered

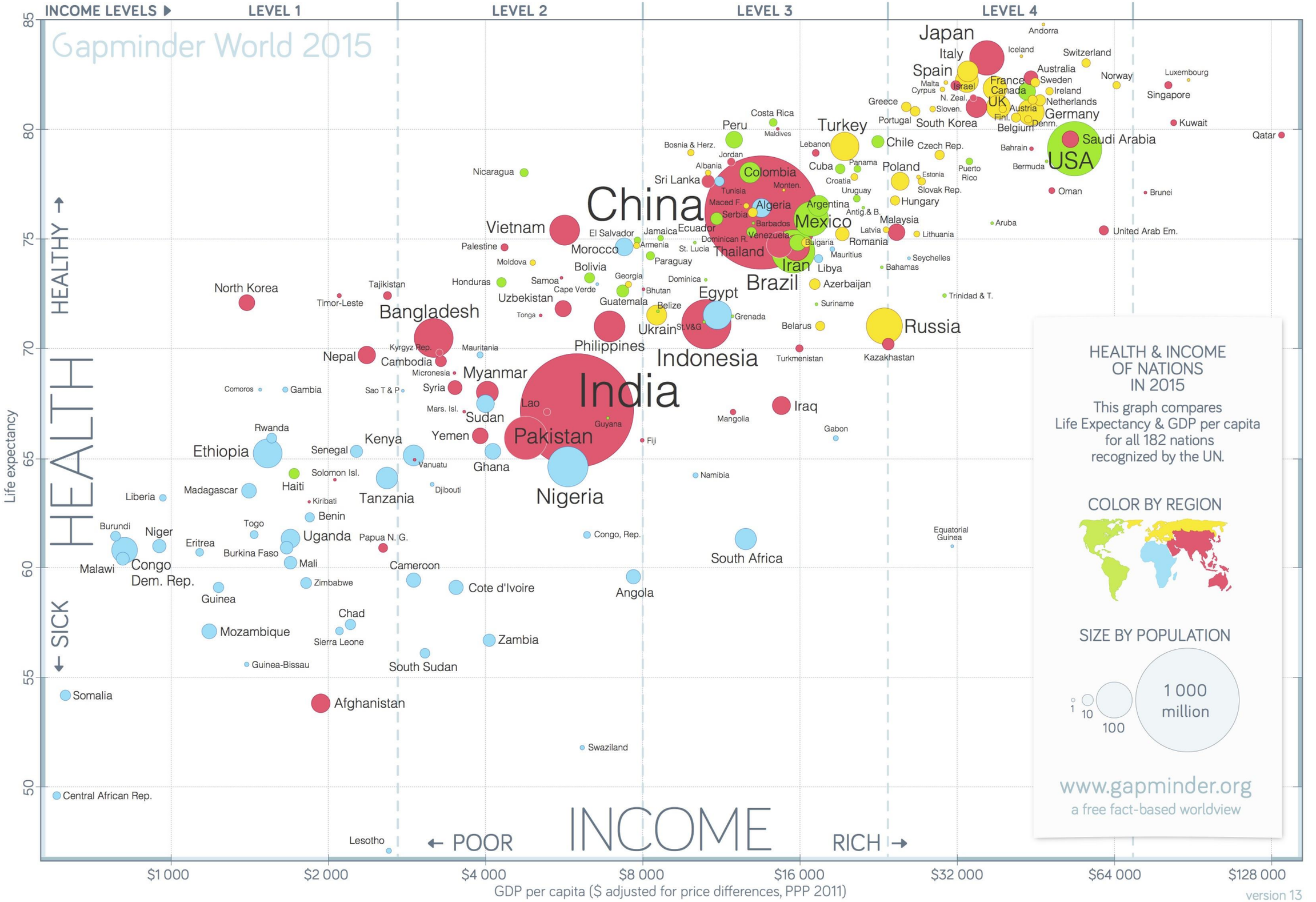


8 values

Aligned

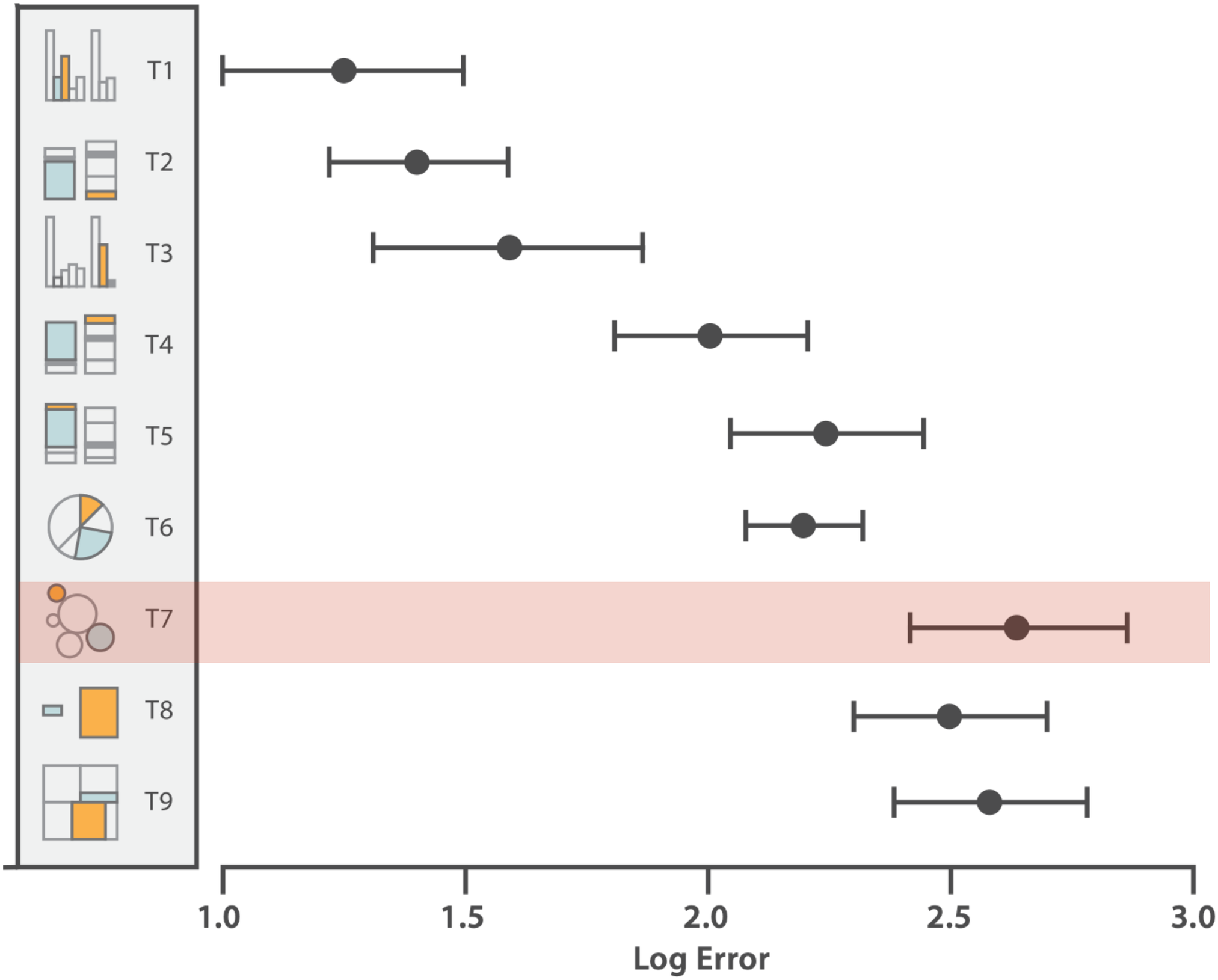
Unordered





The infamous GAP minder chart is subject to such issues with relative comparison.

Heer and Bostock 2010 Crowdsourced Results



Relative Comparison

8 values

20 values

A) Known and Unknown Target Search

Random

Grouped

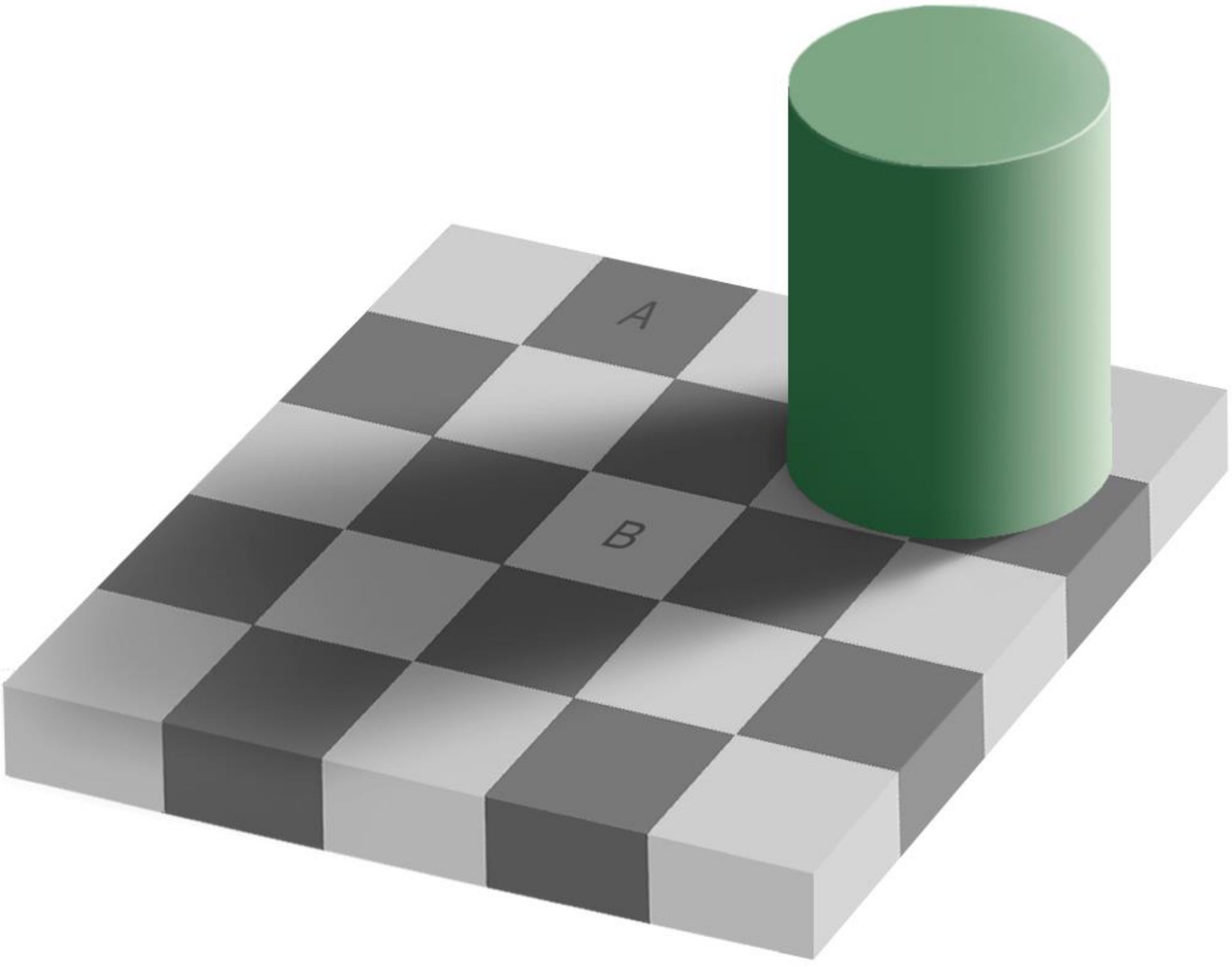
Target shown before hand (**known**) or **not shown** (**unknown**).
The unique colour here is the orange square.

B) Subitizing (how many colours?)

Random

Grouped

Which grid has more colours?


A
B

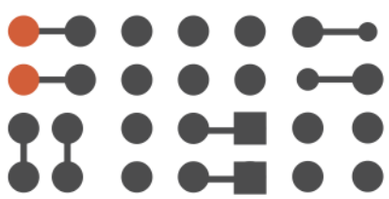
Gestalt Laws

A. Law of Closure

B. Law of Similarity

C. Law of Proximity

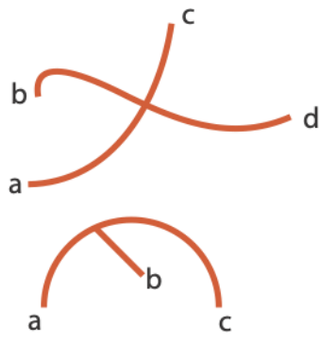
D. Law of Connectedness



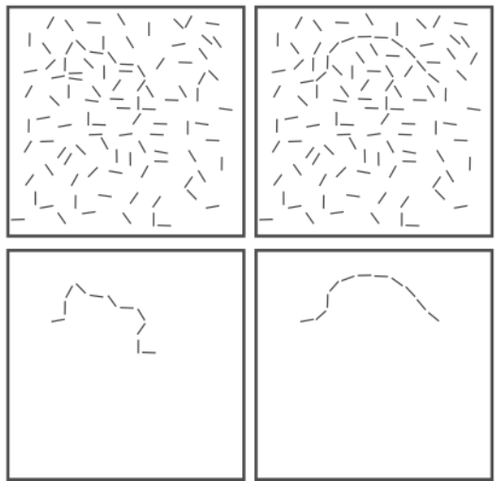
E. Law of Symmetry

[ ] { } ( )

F. Law of Good Continuation



G. Contour Saliency



H. Law of Common Fate

I. Law of Past Experience

J. Law of Pragnanz

K. Figure/Ground

HOW

We have to be careful when mapping data to the visual world

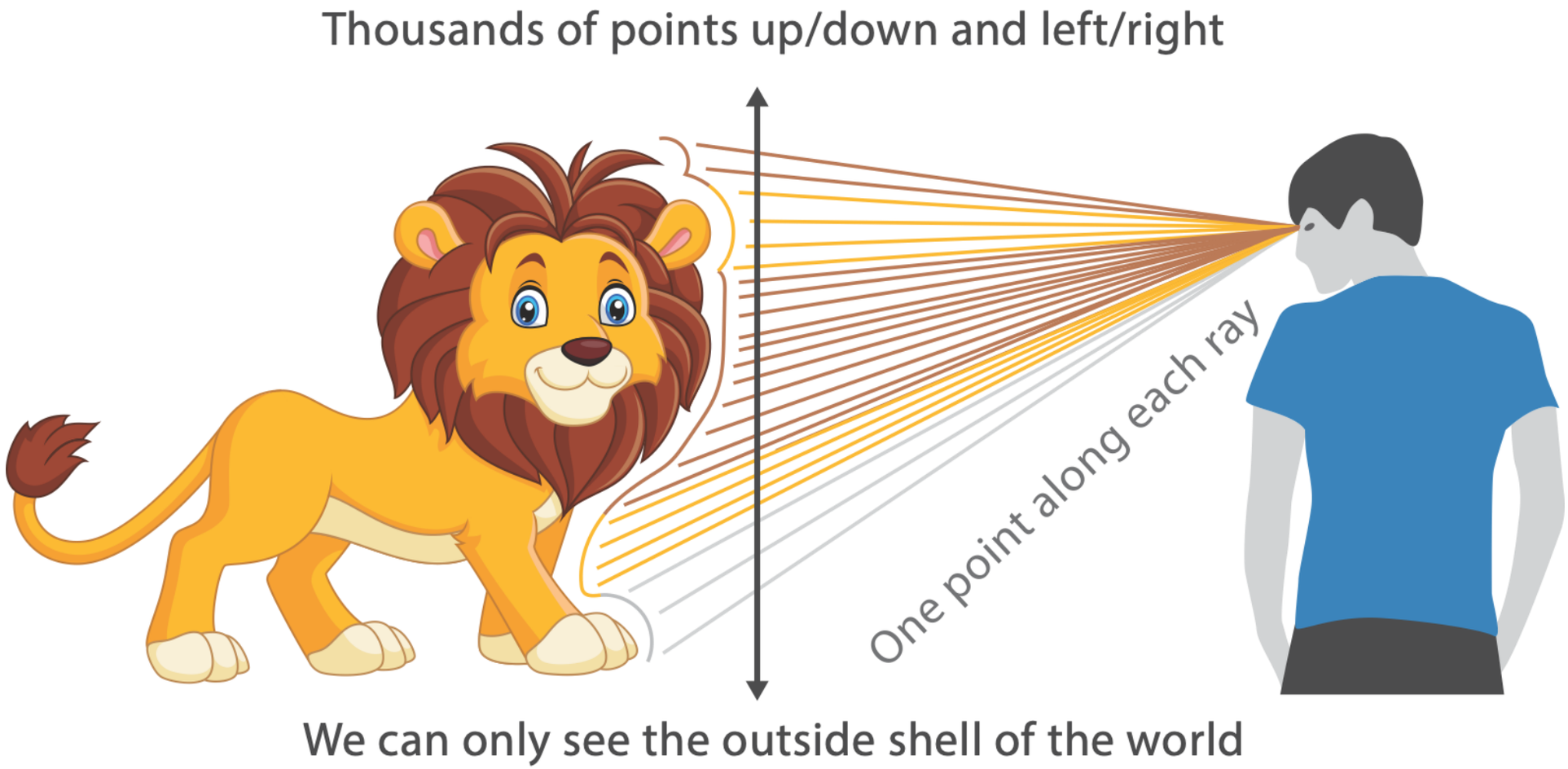
Some visual channels are more effective for some data types over others.

Some data has a natural mapping that our brains expect given certain types of data

There are many visual tricks that can be observed due to how the visual system works

We don’t see in 3D, and we have difficulties interpreting information on the Z-axis.

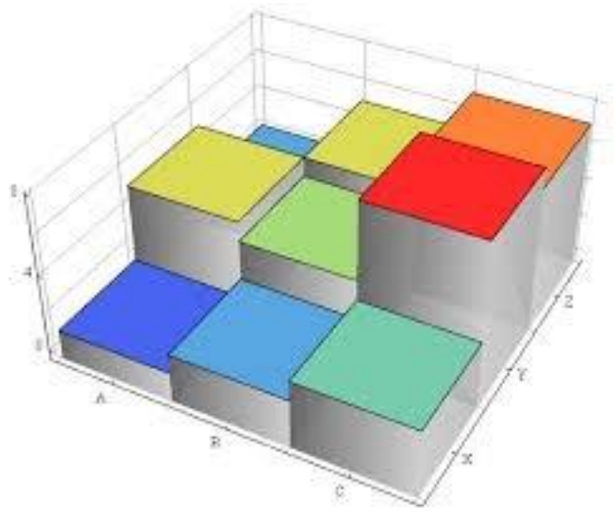
2D always wins…

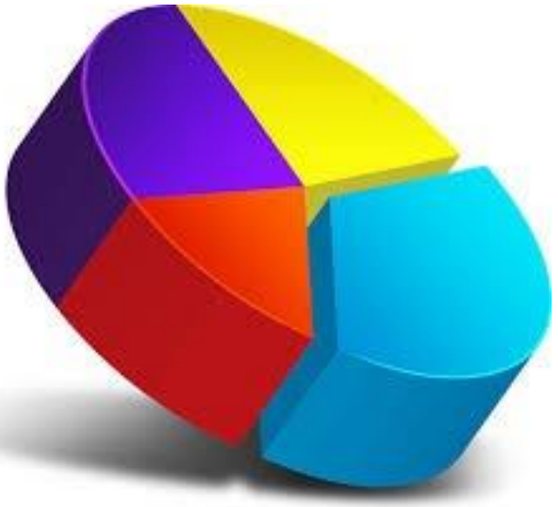


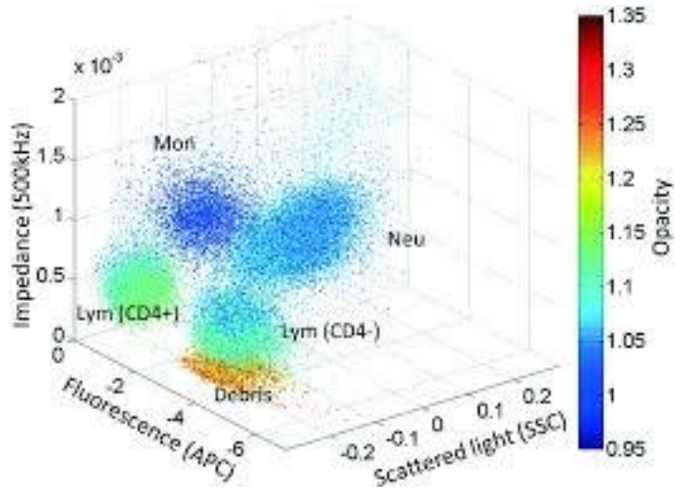
Our visual system is not good at interpreting information on the z-axis.

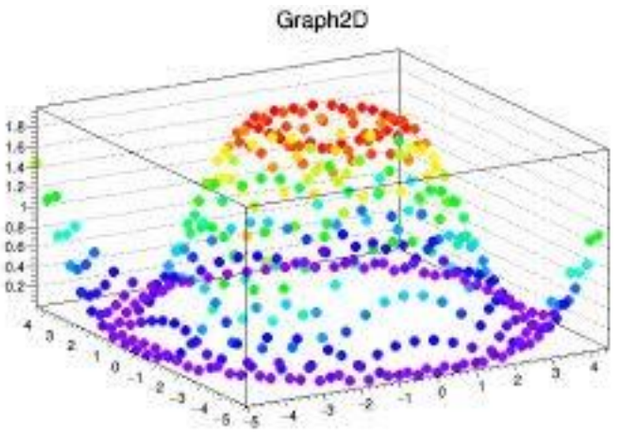
*3D is normally only used for exploration of inherently 3D information, such as medical imaging data…

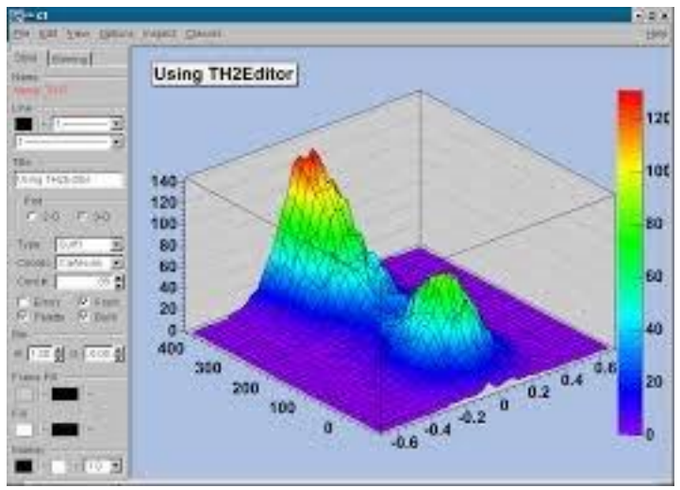
2D always wins…

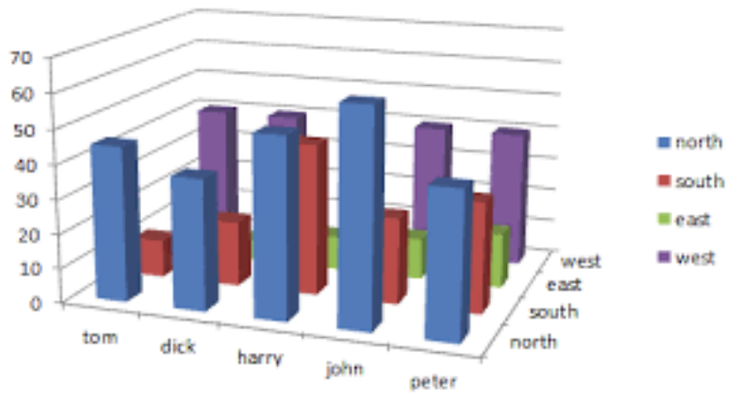






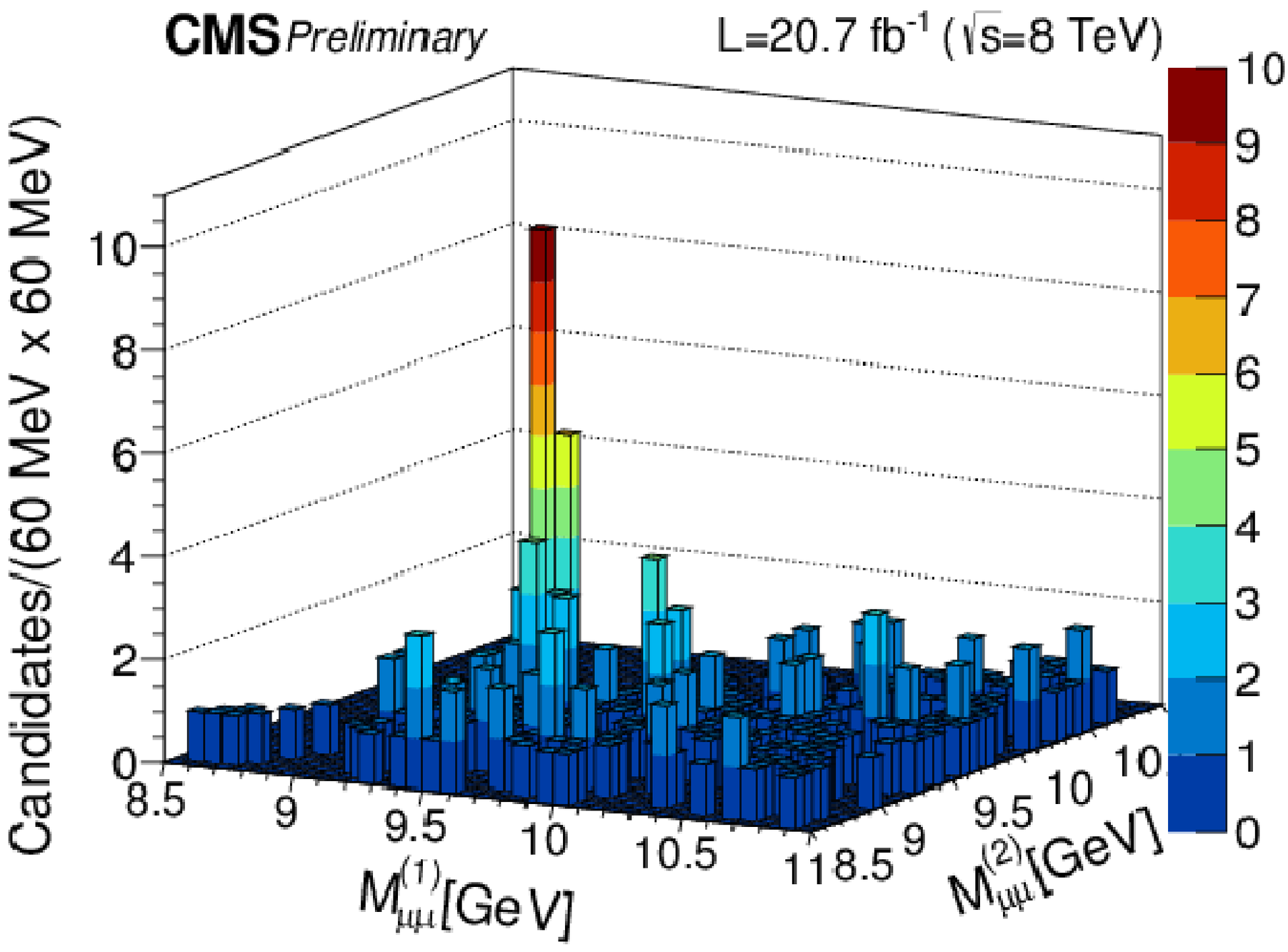






These options, taken randomly from google image searches so how widely 3D is abused in information visualisation. All of these charts are manipulating our perception of the data by using the Z axis to occlude information…it would be avoided in 2D.

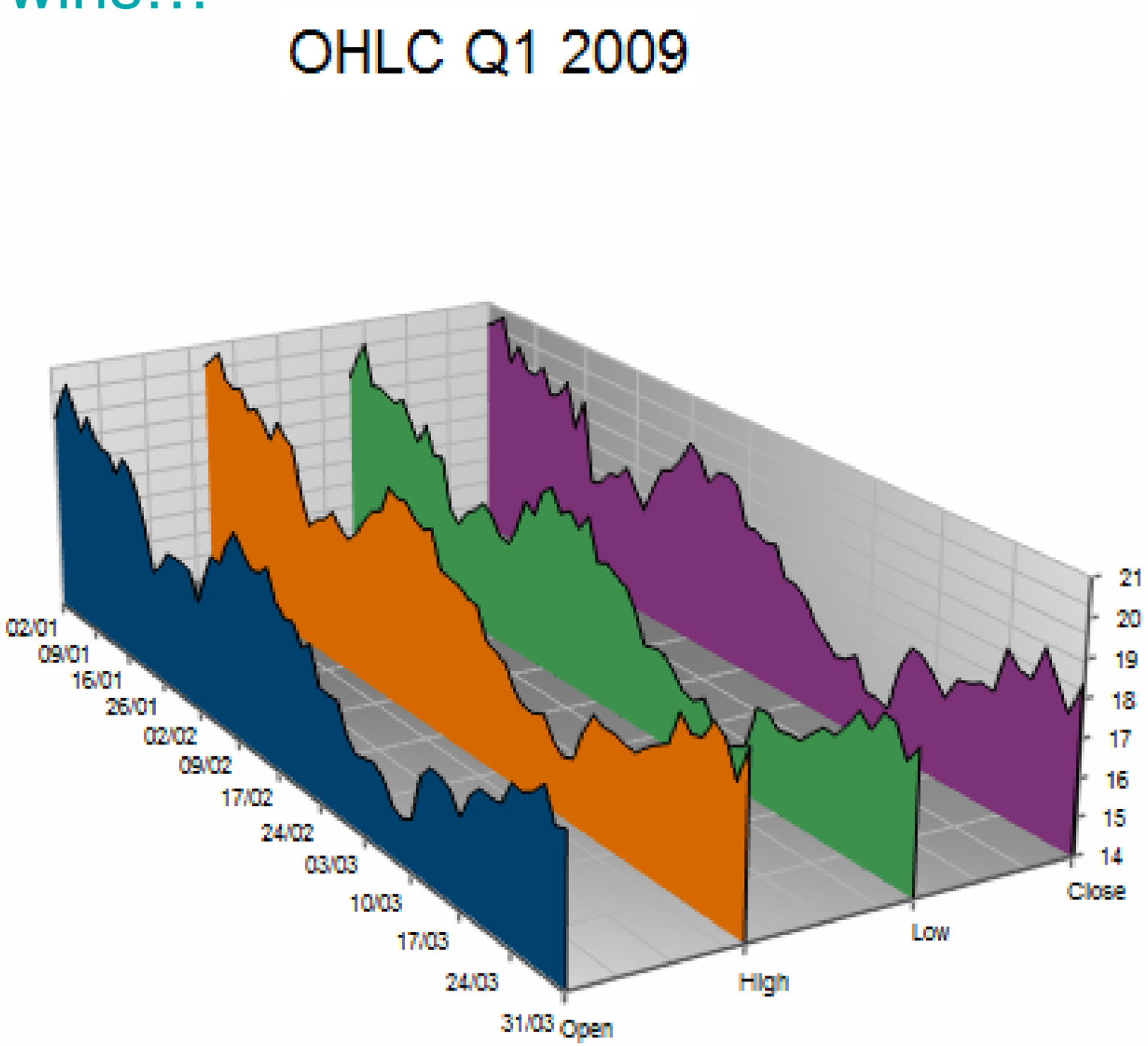
2D always wins…



3D hides information. Is there anything behind the large bars? We'll never know.

http://cms-results.web.cern.ch/cms-results/public-results/preliminary-results/BPH-14-008/index.html

2D always wins…



3D is totally useless in this example. It only makes the nearest points look bigger, and the further away points smaller than they are.

Image from https://www.teraplot.com/financial

HOW

We have to be careful when mapping data to the visual world

Some visual channels are more effective for some data types over others.

Some data has a natural mapping that our brains expect given certain types of data

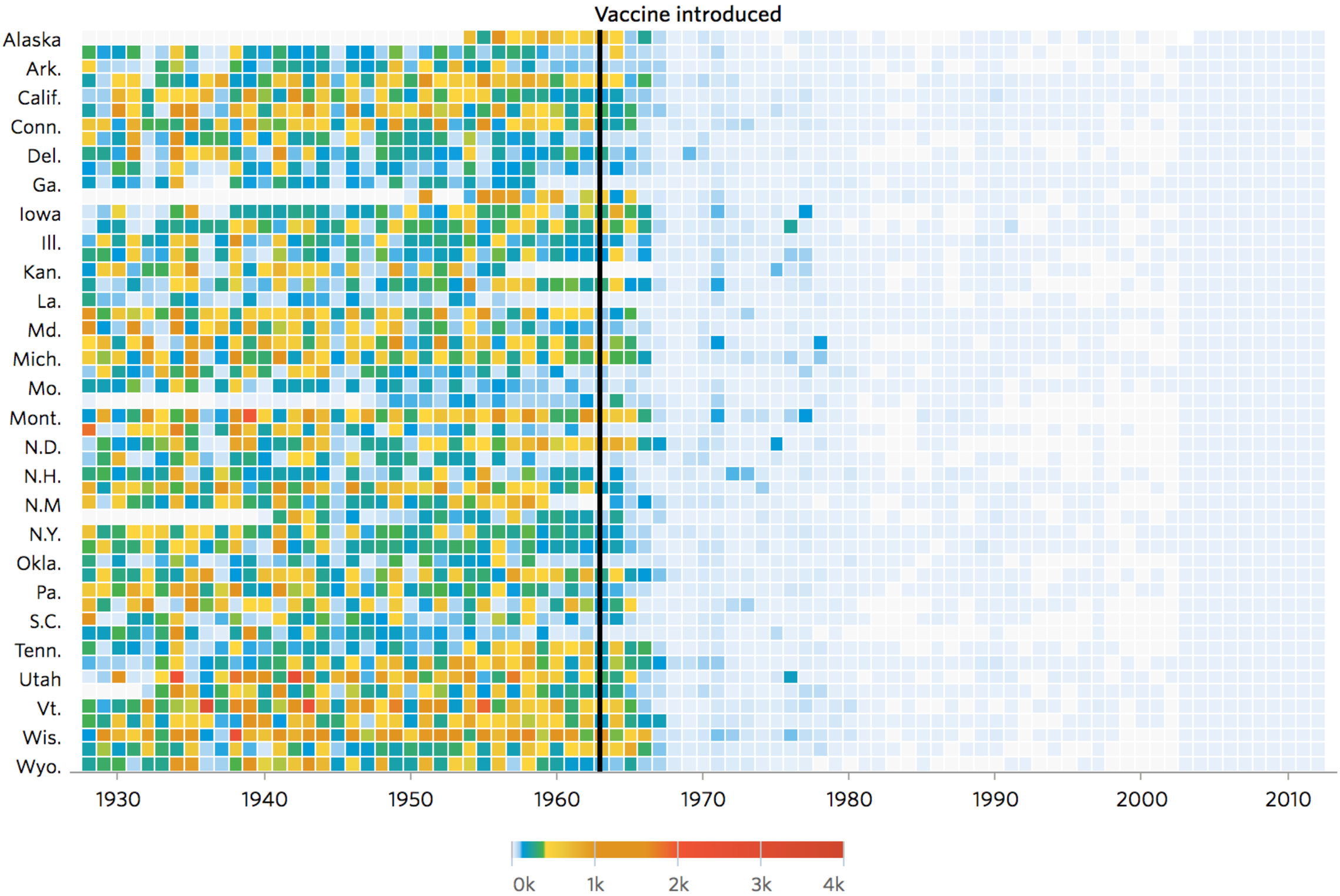
There are many visual tricks that can be observed due to how the visual system works

We don’t see in 3D, and we have difficulties interpreting information on the Z-axis.

Colour

Colour

Measles



http://graphics.wsj.com/infectious-diseases-and-vaccines/

Colour

The simplest, yet most abused of all visual encodings.

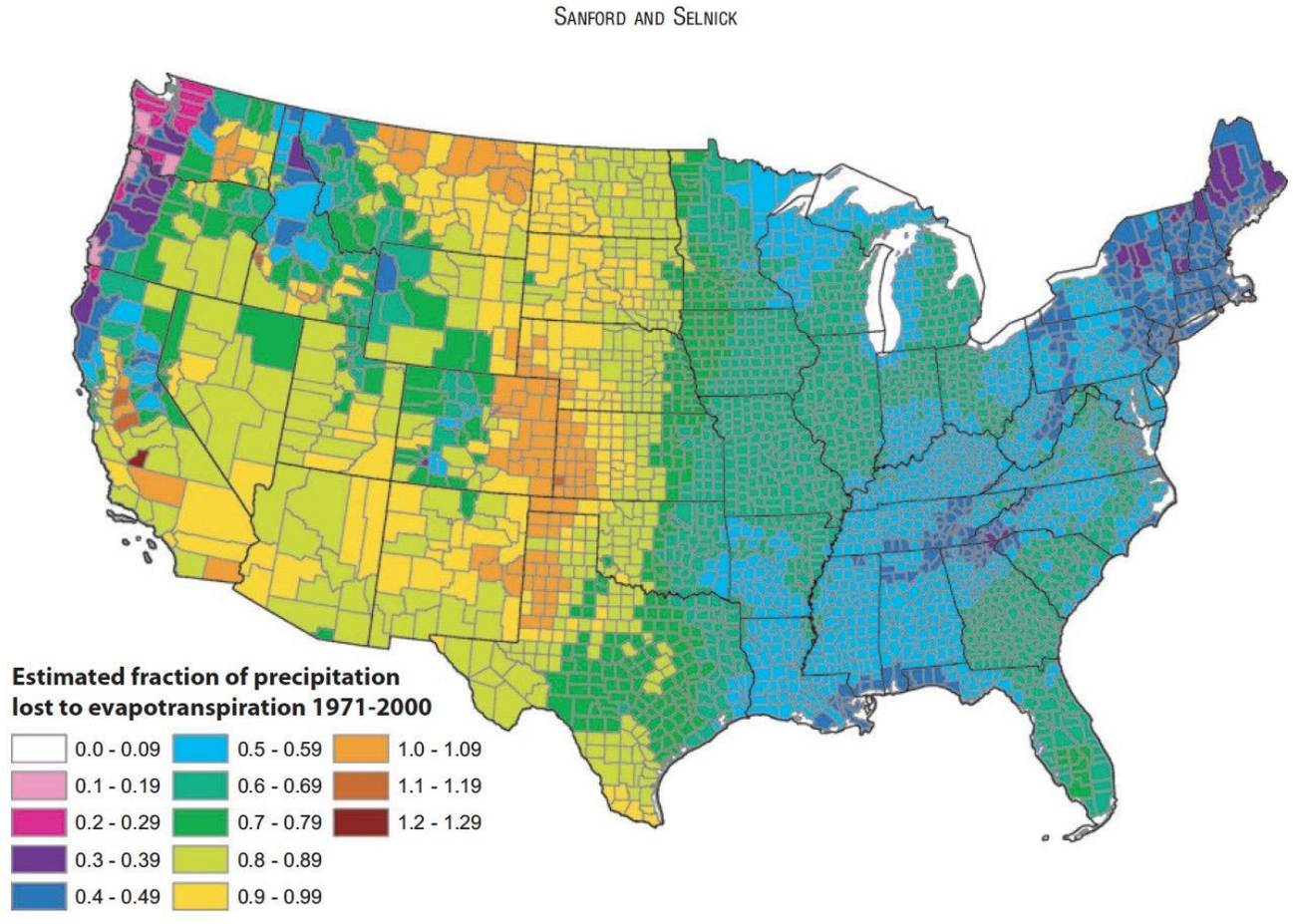
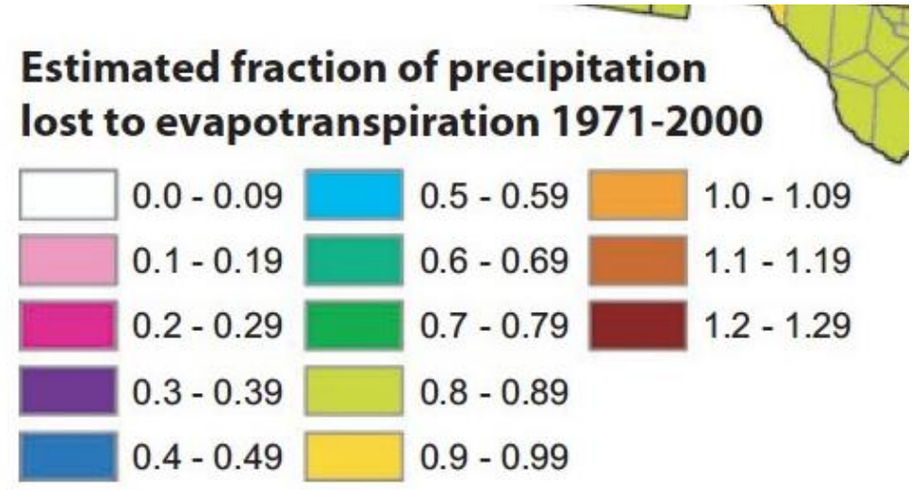


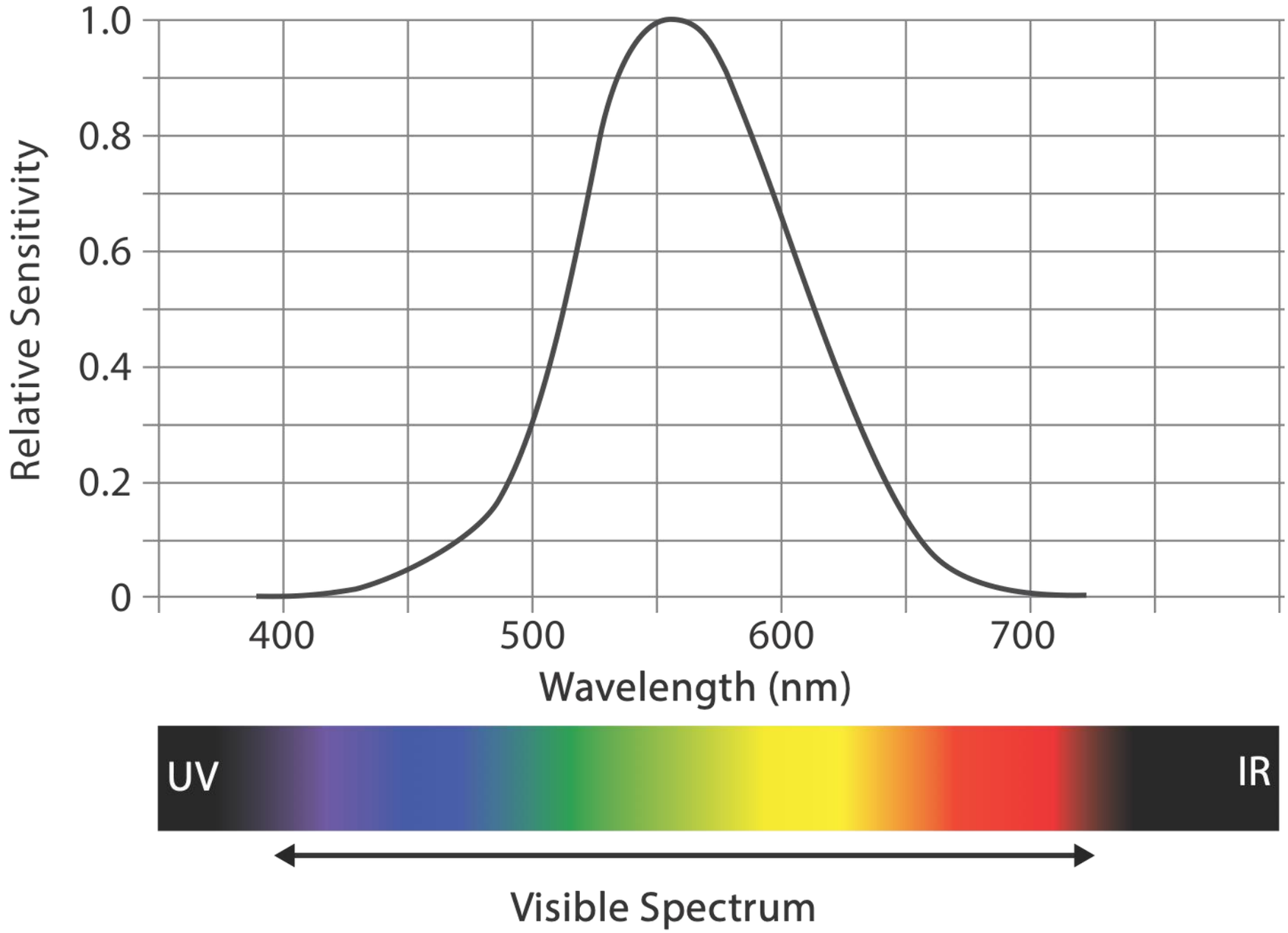
FIGURE 13. Estimated Mean Annual Ratio of Actual Evapotranspiration (ET) to Precipitation (P) for the Conterminous U.S. for the Period 1971-2000. Estimates are based on the regression equation in Table 1 that includes land cover. Calculations of ET/P were made first at the 800-m resolution of the PRISM climate data. The mean values for the counties (shown) were then calculated by averaging the 800-m values within each county. Areas with fractions >1 are agricultural counties that either import surface water or mine deep groundwater.



The problem is that a smooth step in a value does not equate to a smooth colour transition…

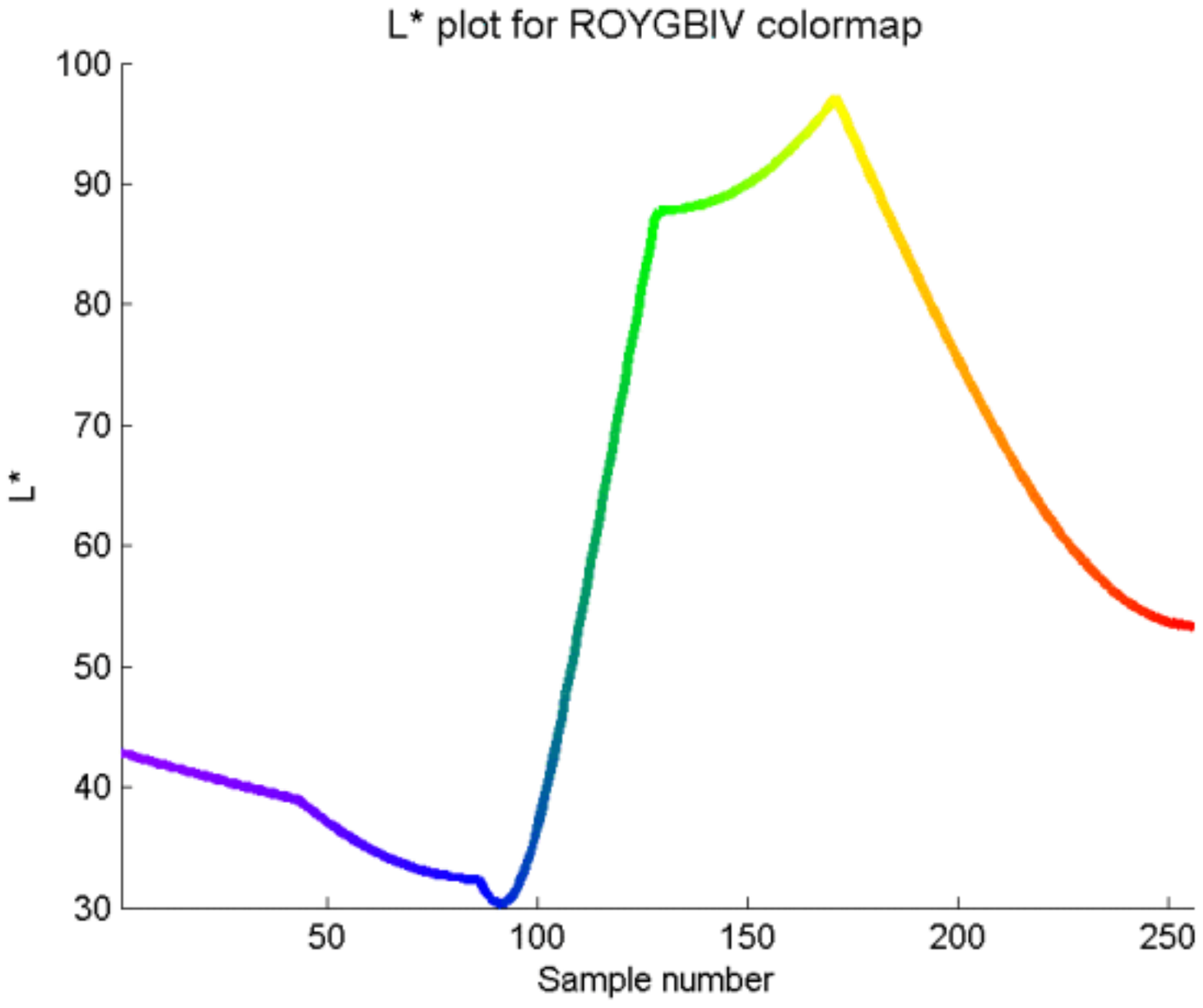
Colour

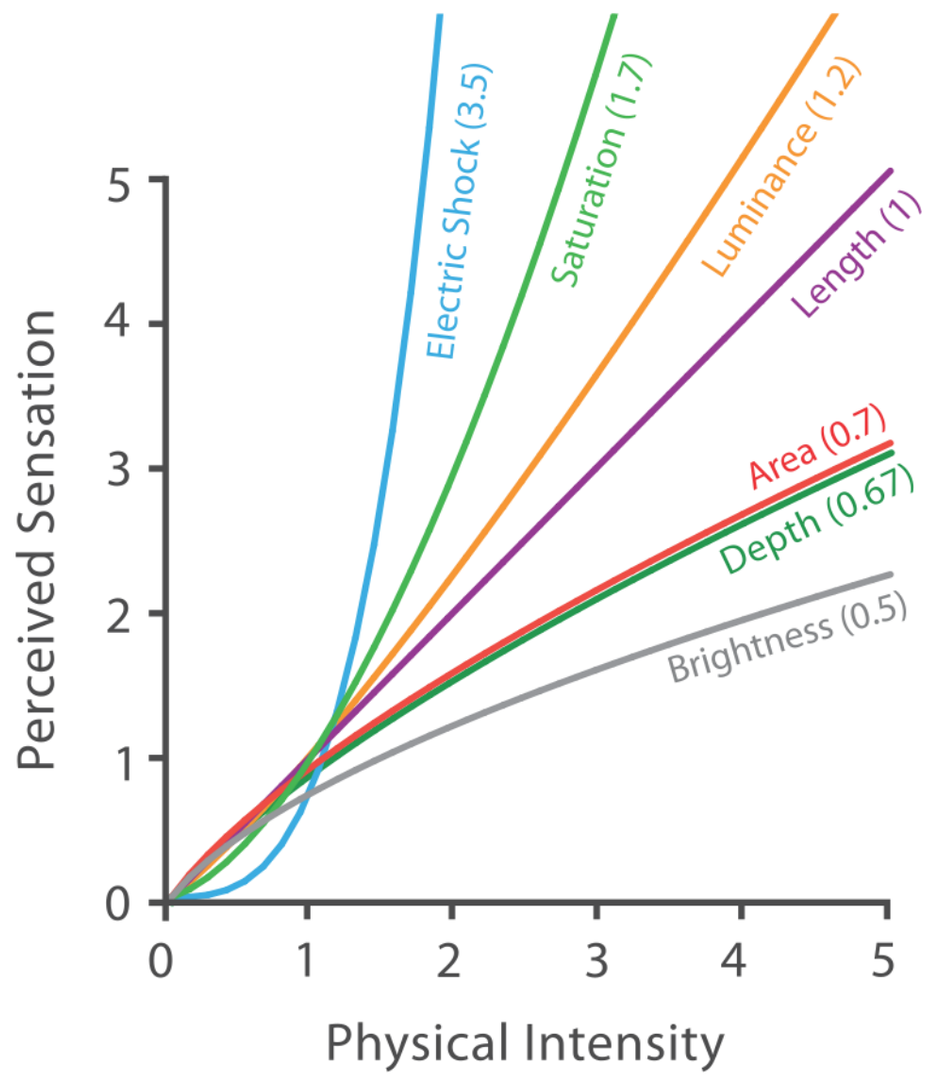
Additionally, colour is not equally binned in reality. We perceive colours differently due to an increased sensitivity to the yellow part of the spectrum…



Colour

Luminosity is also not stable across the colours, meaning some colours will pop out more than others… and not always intentionally.

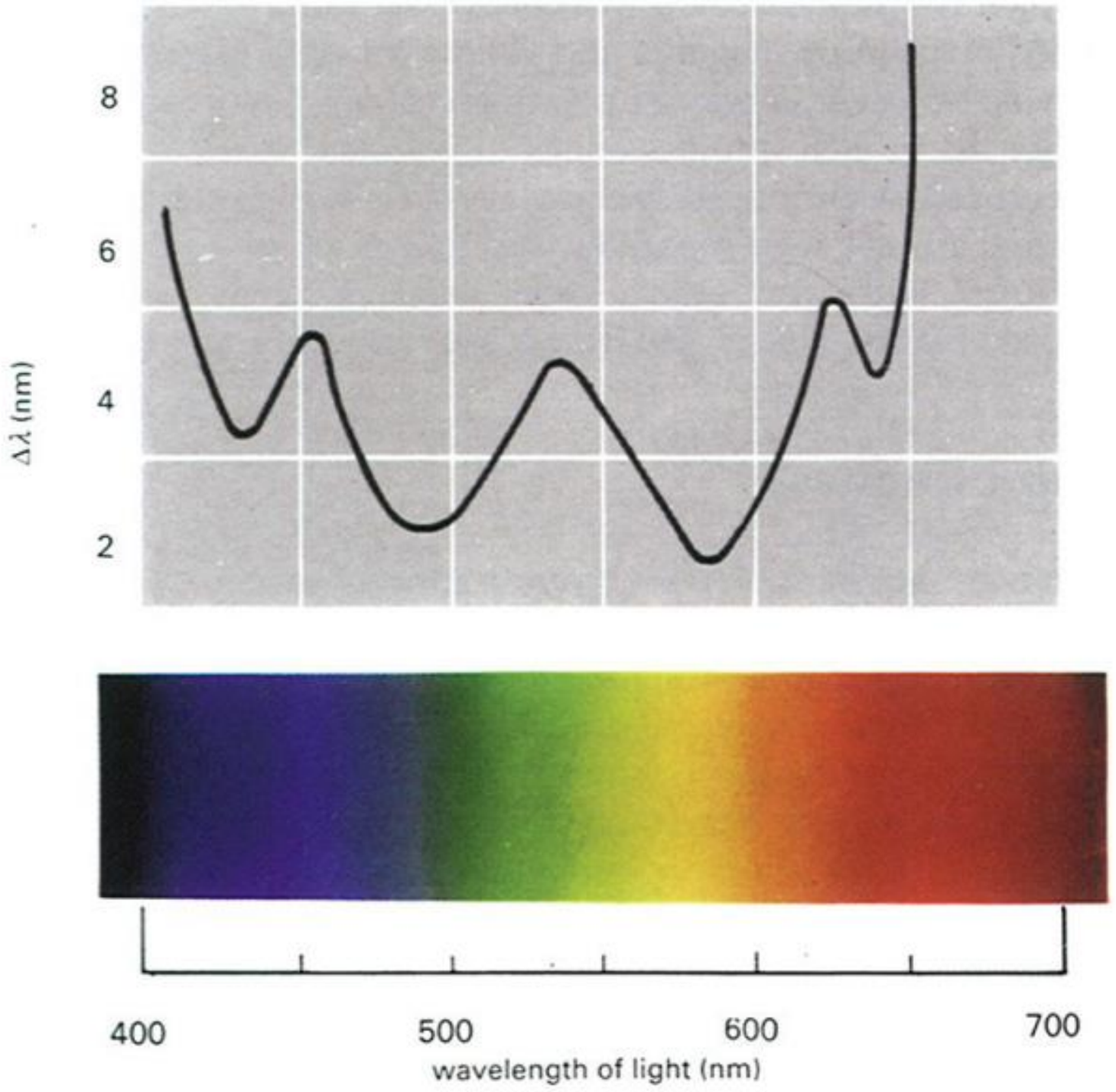




https://mycarta.wordpress.com/2012/10/06/the-rainbow-is-deadlong-live-the-rainbow-part-3/

Colour

And how we perceive changes in hue is also very different.



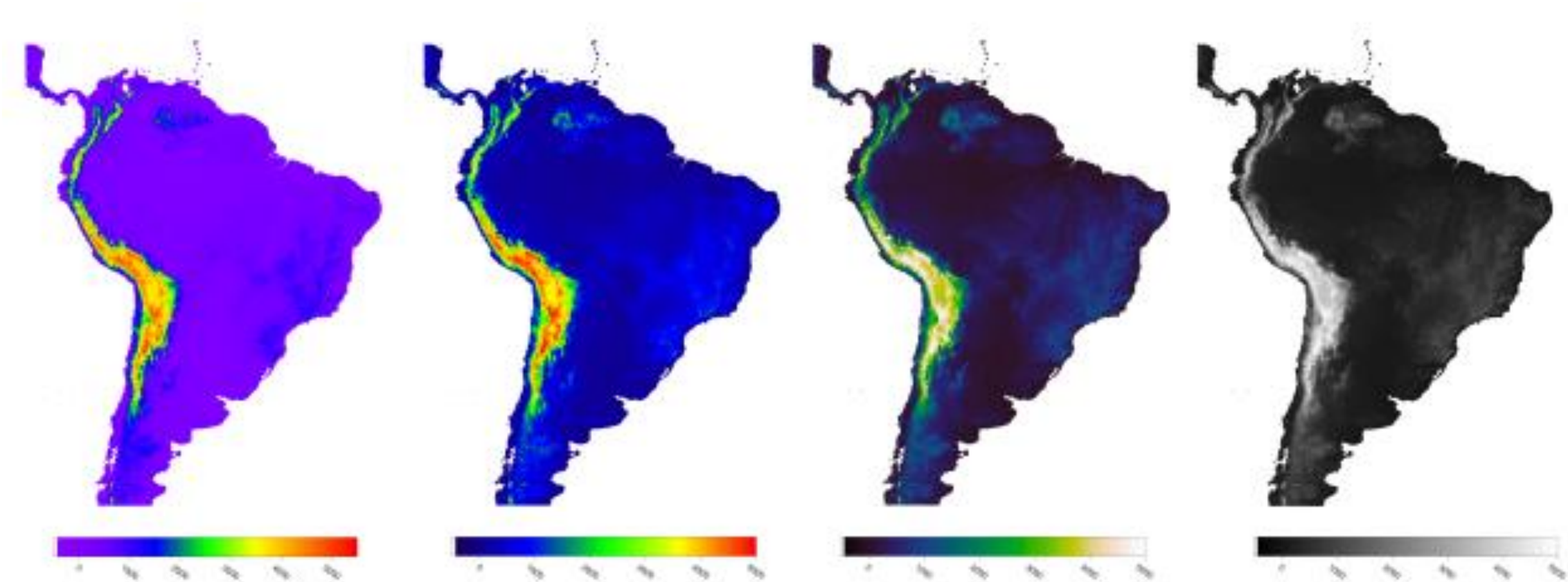
Gregory compared the wavelength of light with the smallest observable difference in hue (expressed as wavelength difference).

As you can see, the line is not flat.

Is there a colour palette for scientific visualisation that works?

Colour

HSL linear L rainbow palette



https://mycarta.wordpress.com/2012/10/06/the-rainbow-is-deadlong-live-the-rainbow-part-3/

nd Creem, S., 2002, Face-based Luminance Matching for Perceptual Colormap Generation, IEEE Proceedings of the co

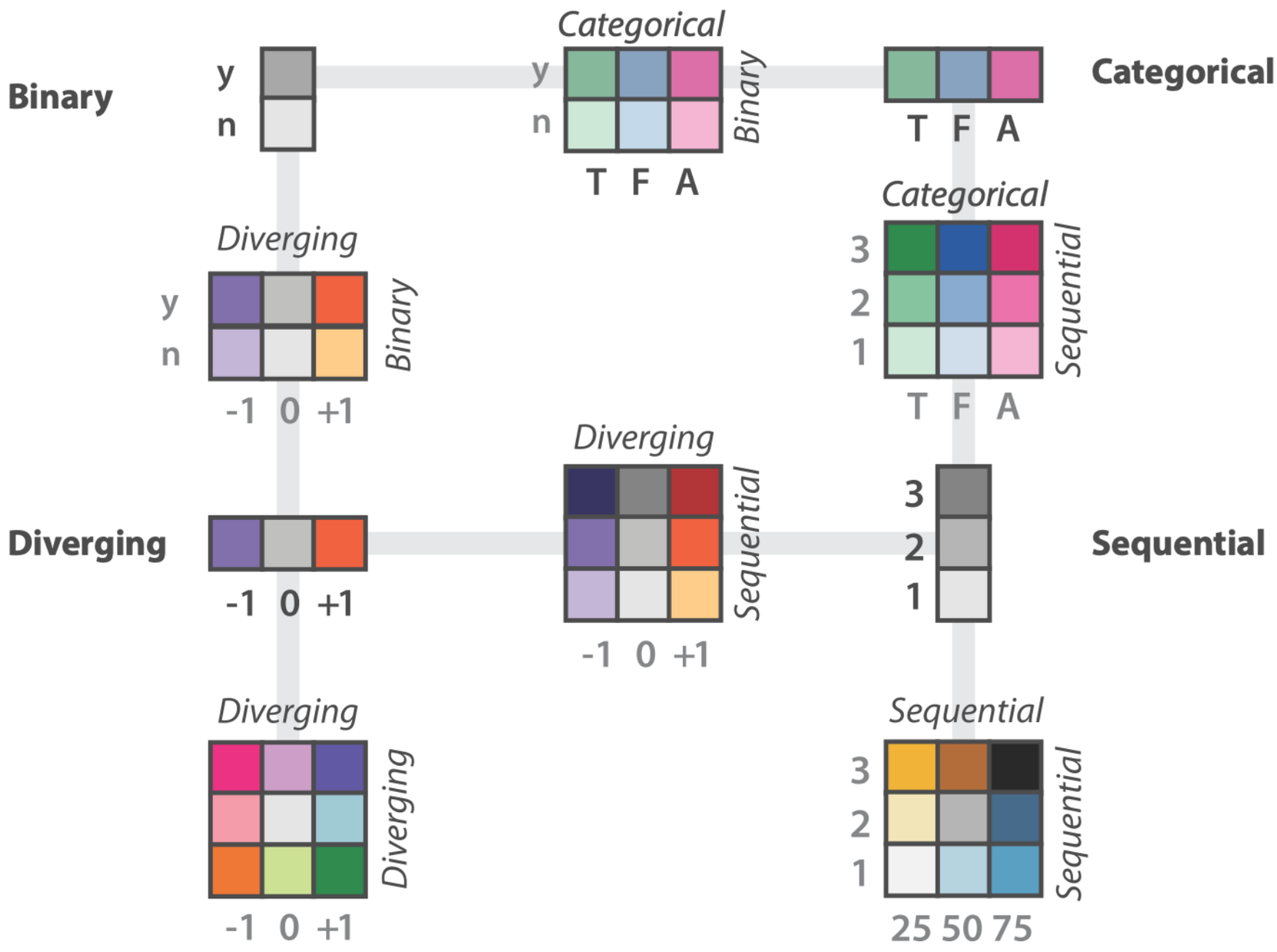
Colour

HSL linear L rainbow palette

These are available in matplotlib and therefore in seaborn, etc, so there’s no excuse :)

Colour

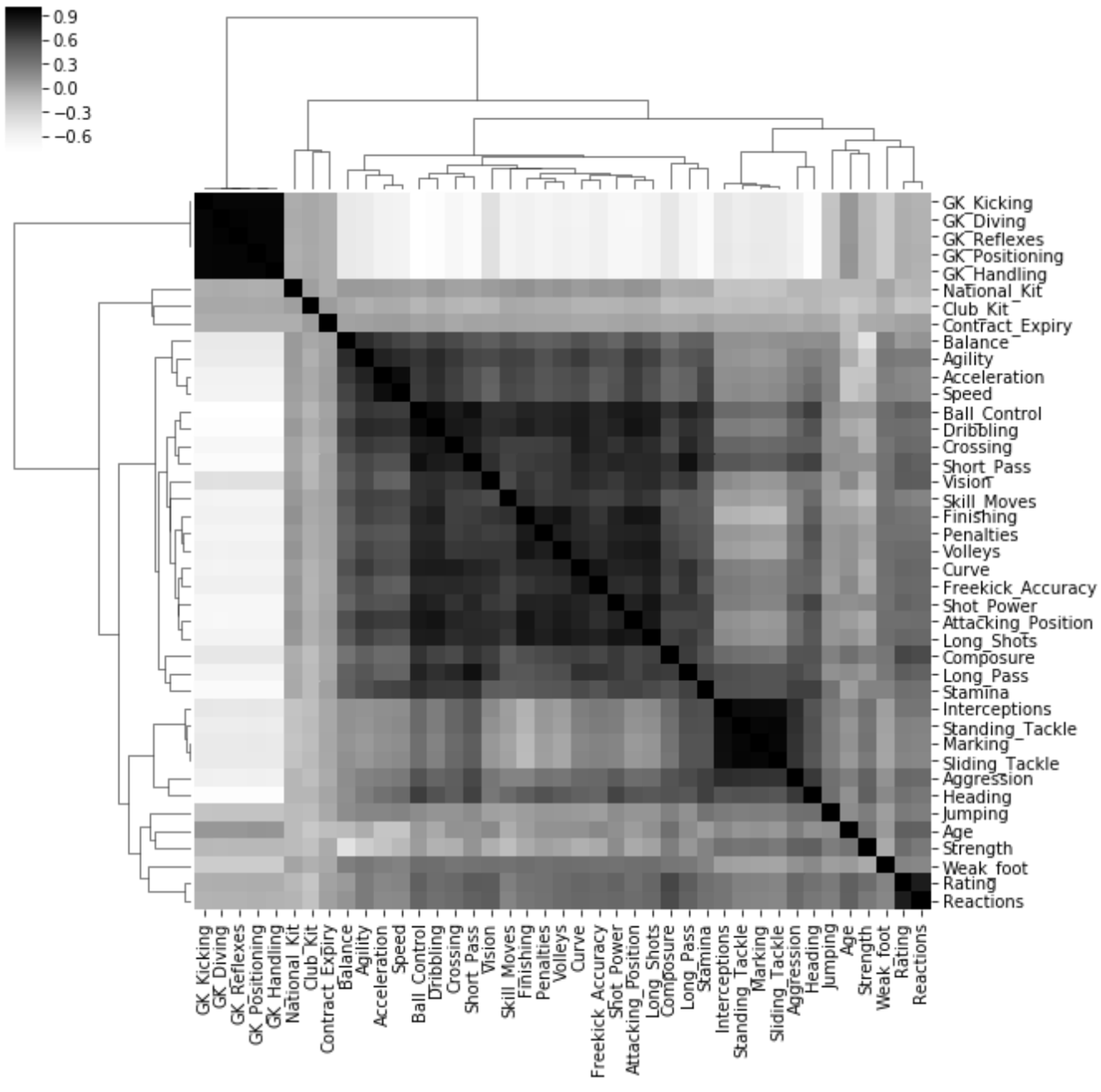
There are also lots of default colour maps that can be applied to particular data types.

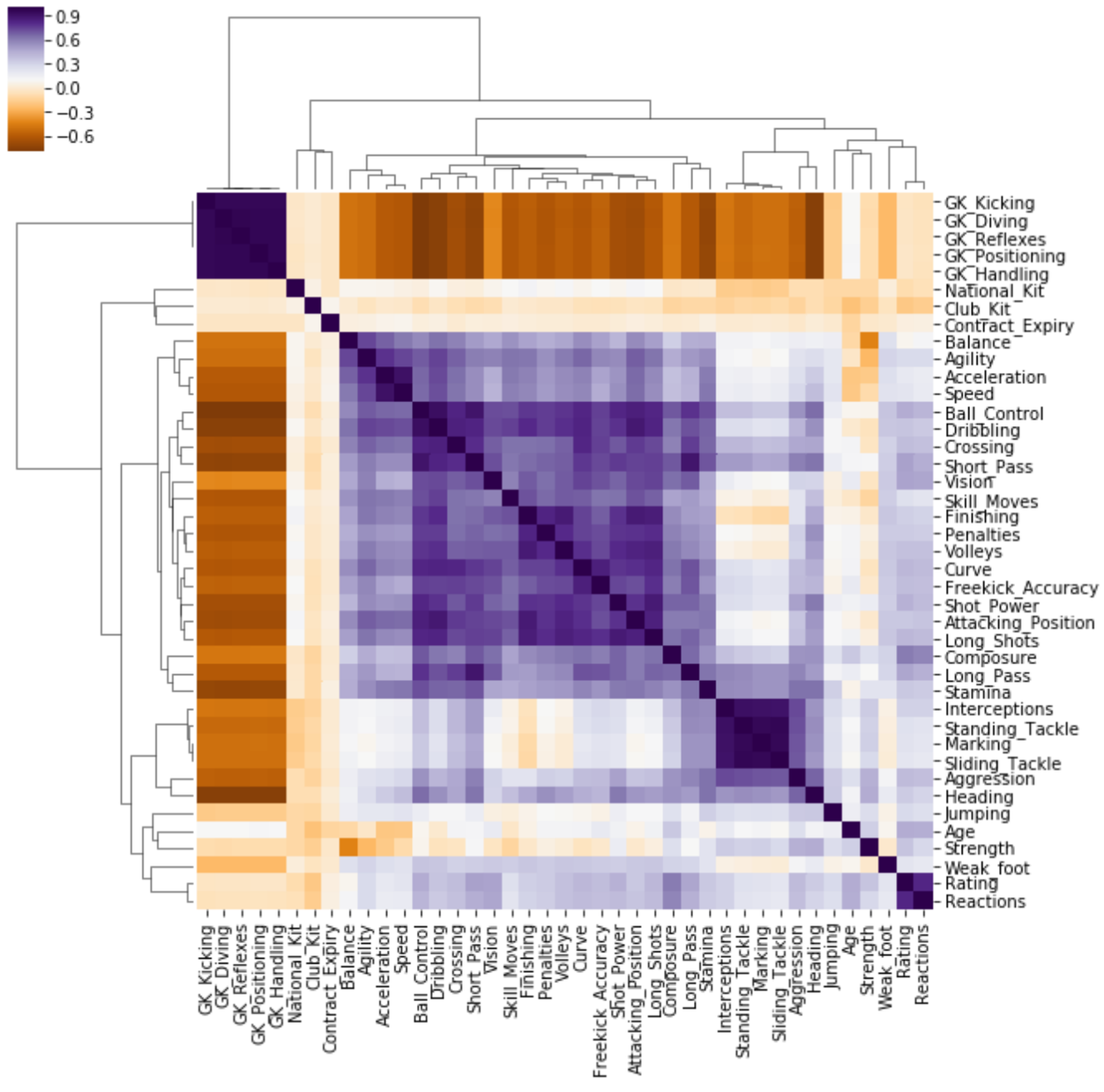


http://colorbrewer2.org/

Color

Here I’m showing the correlation between football player attributes.
Is the choice of colour map helping this comparison?



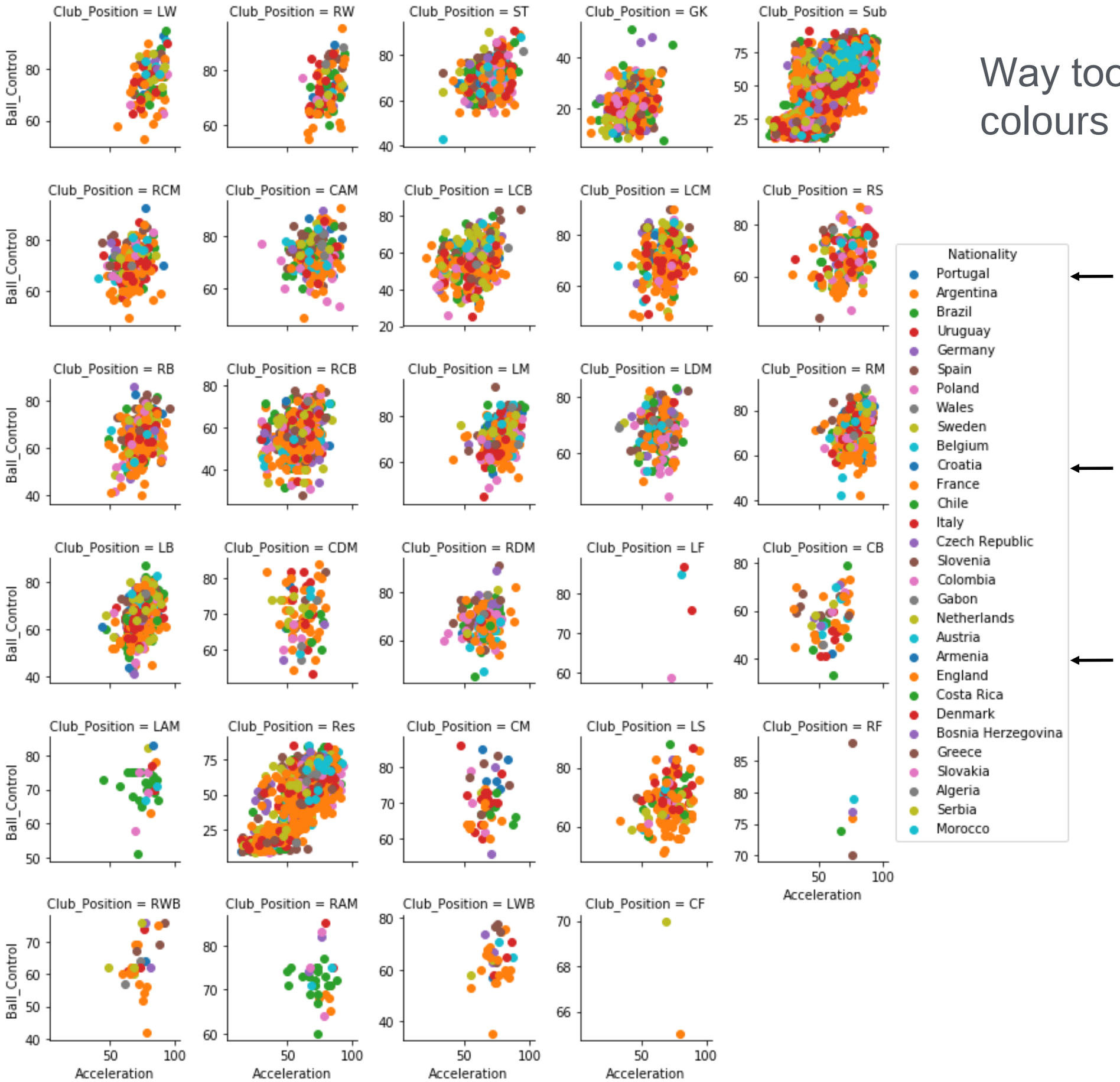



```
import seaborne as sns
sns.clustermap(fifa.corr(), cmap='PuOr')
```

Color

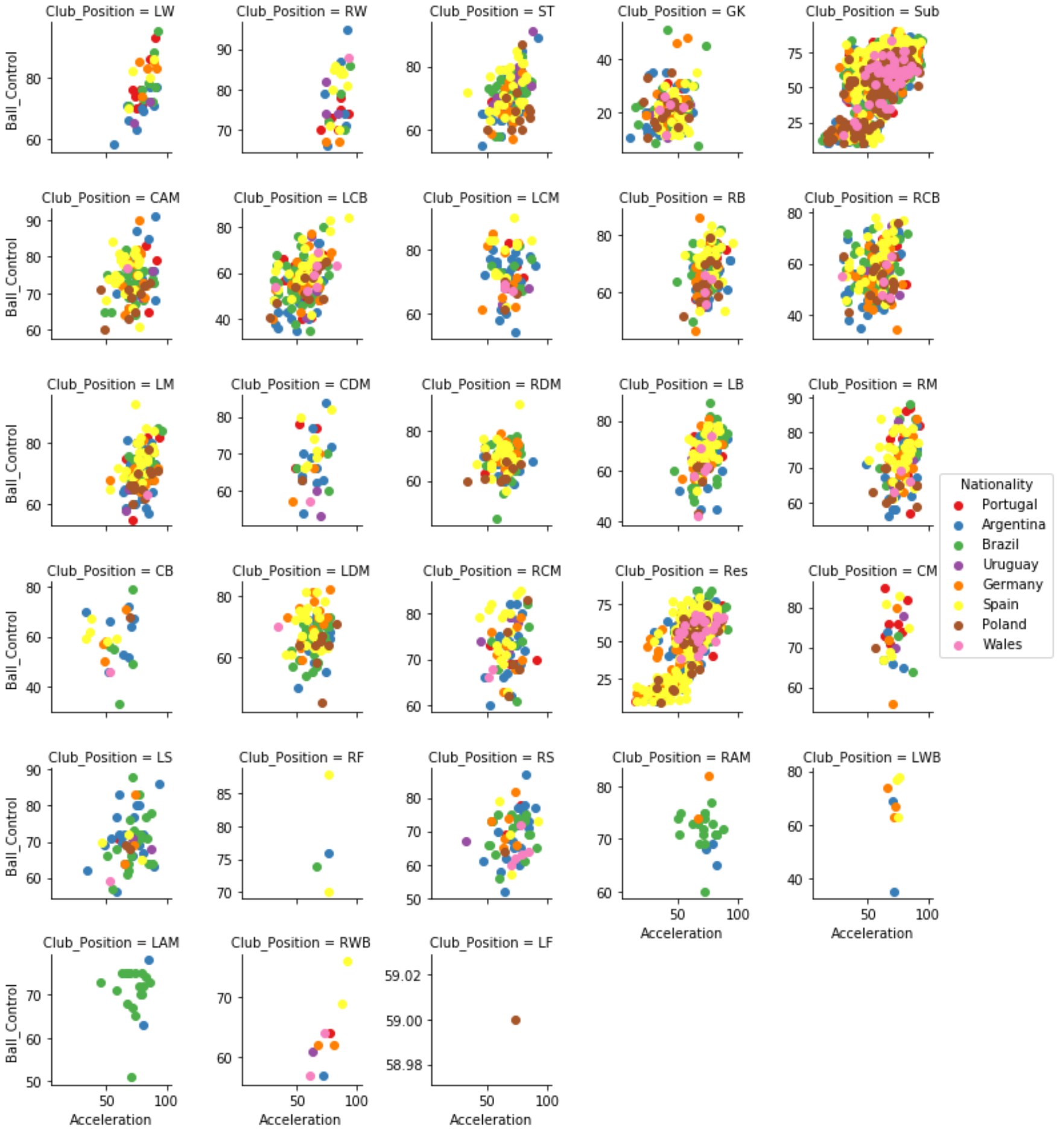
You also don’t want to have too many colours.

Too many colours means that users have to remember what a colour means. So a max of around 8 categories in a plot is recommended, otherwise the ‘distance’ between colours becomes too small.



Way too many…and the colours get reused.

Here 10 colours are being used to represent 29 countries.



Much better

Here 8 colours are being used to represent 8 countries.

Color

Semantic relevance

Or just consistency

When there are many colours for example, we find it difficult to remember abstract associations.

Color

What are semantically resonant colours?

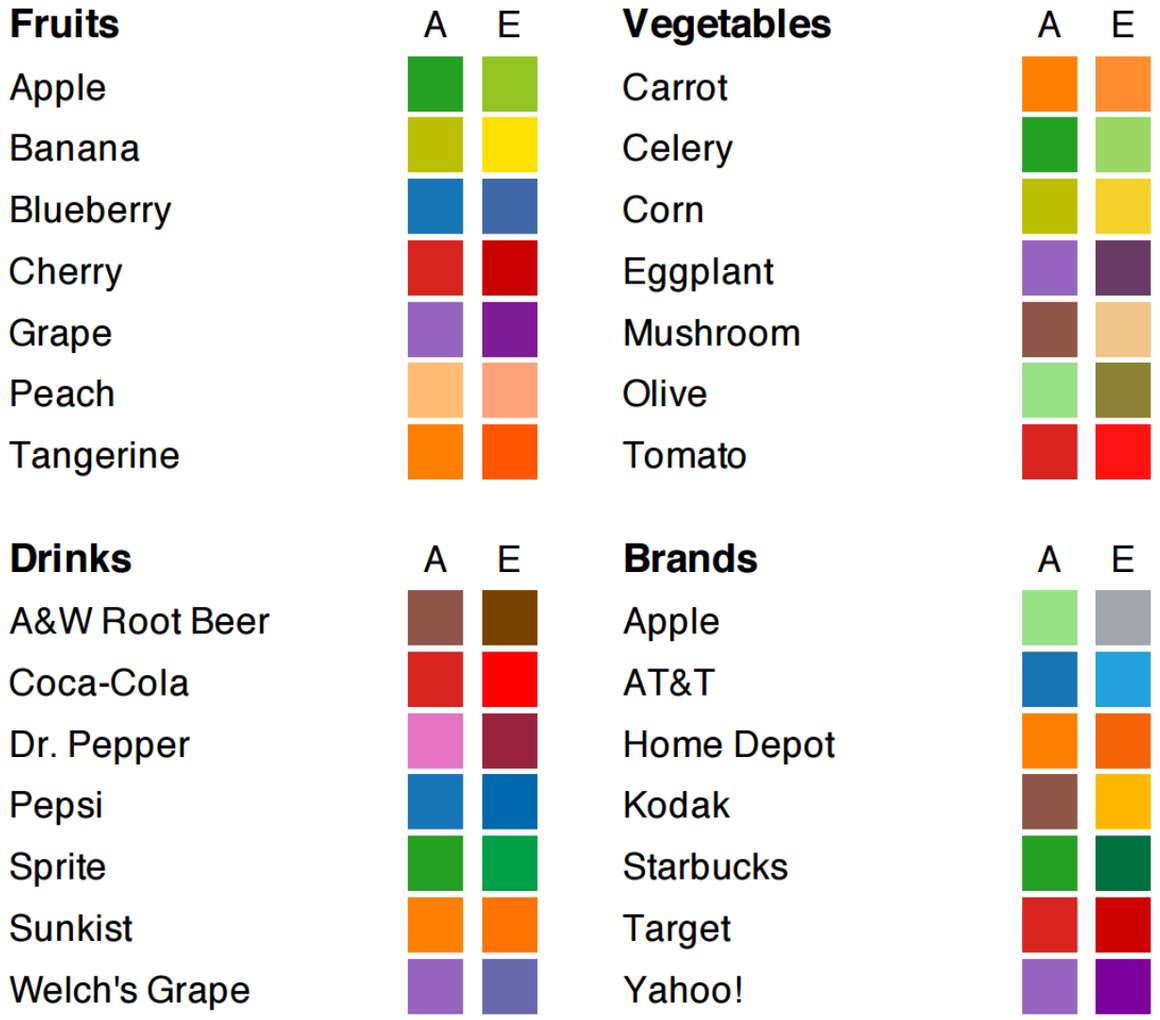
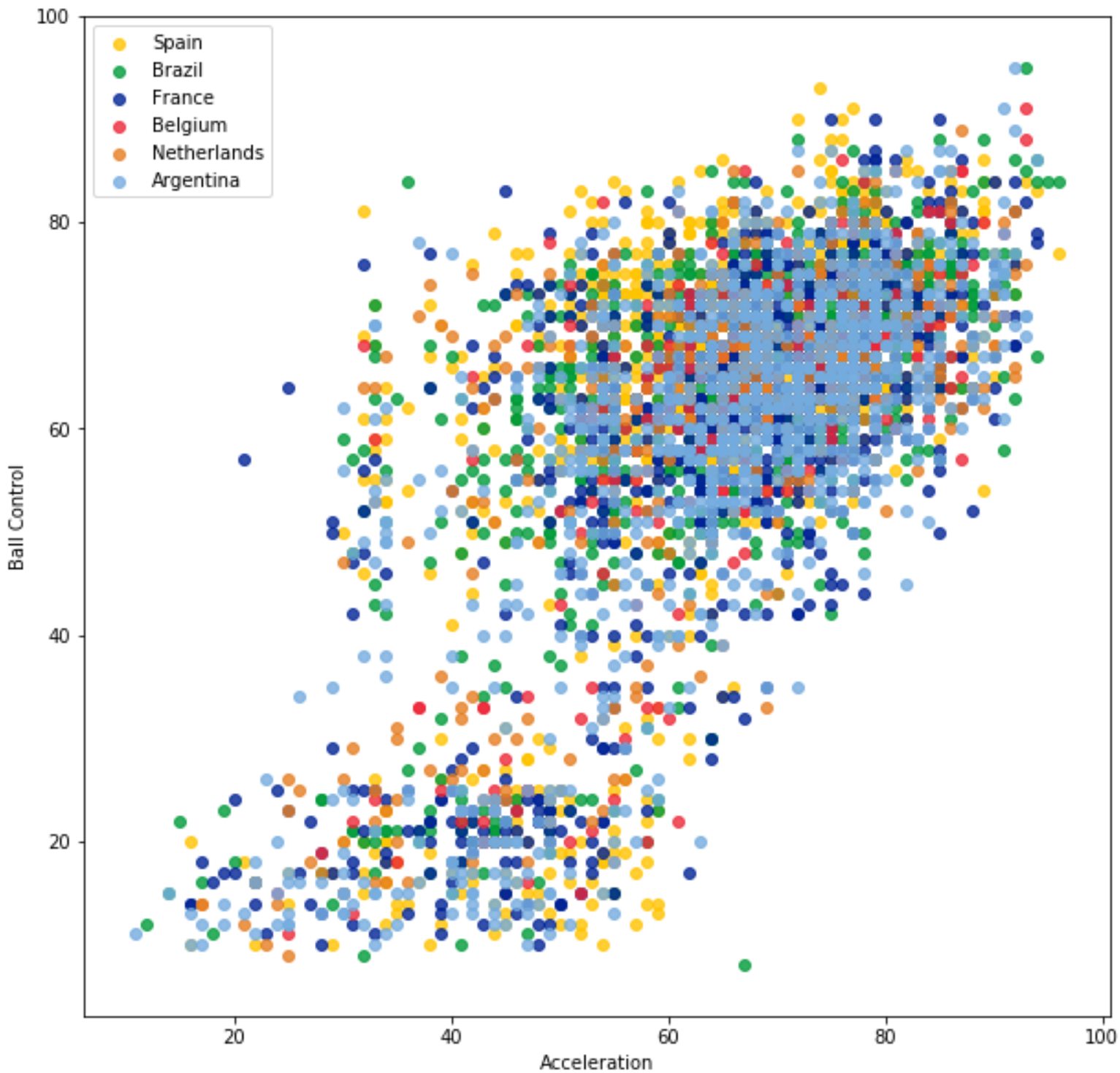


Figure 6: *Color assignments for categorical values in Experiment 1. (A = Algorithm, E = Expert)*

Selecting Semantically-Resonant Colors for Data Visualization
Sharon Lin, Julie Fortuna, Chinmay Kulkarni, Maureen Stone, Jeffrey Heer
Computer Graphics Forum (Proc. EuroVis), 2013

Color

What are semantically resonant colours?



Color

Semantic colouring is a good idea in theory, but there are limited areas where this really works.

But, if you are going to use colour, try to think how you can make it easier for users to decode the colour to the category without constantly having to look up a legend.
That way, the decoding time is less.

Saving time…reducing cognitive load.