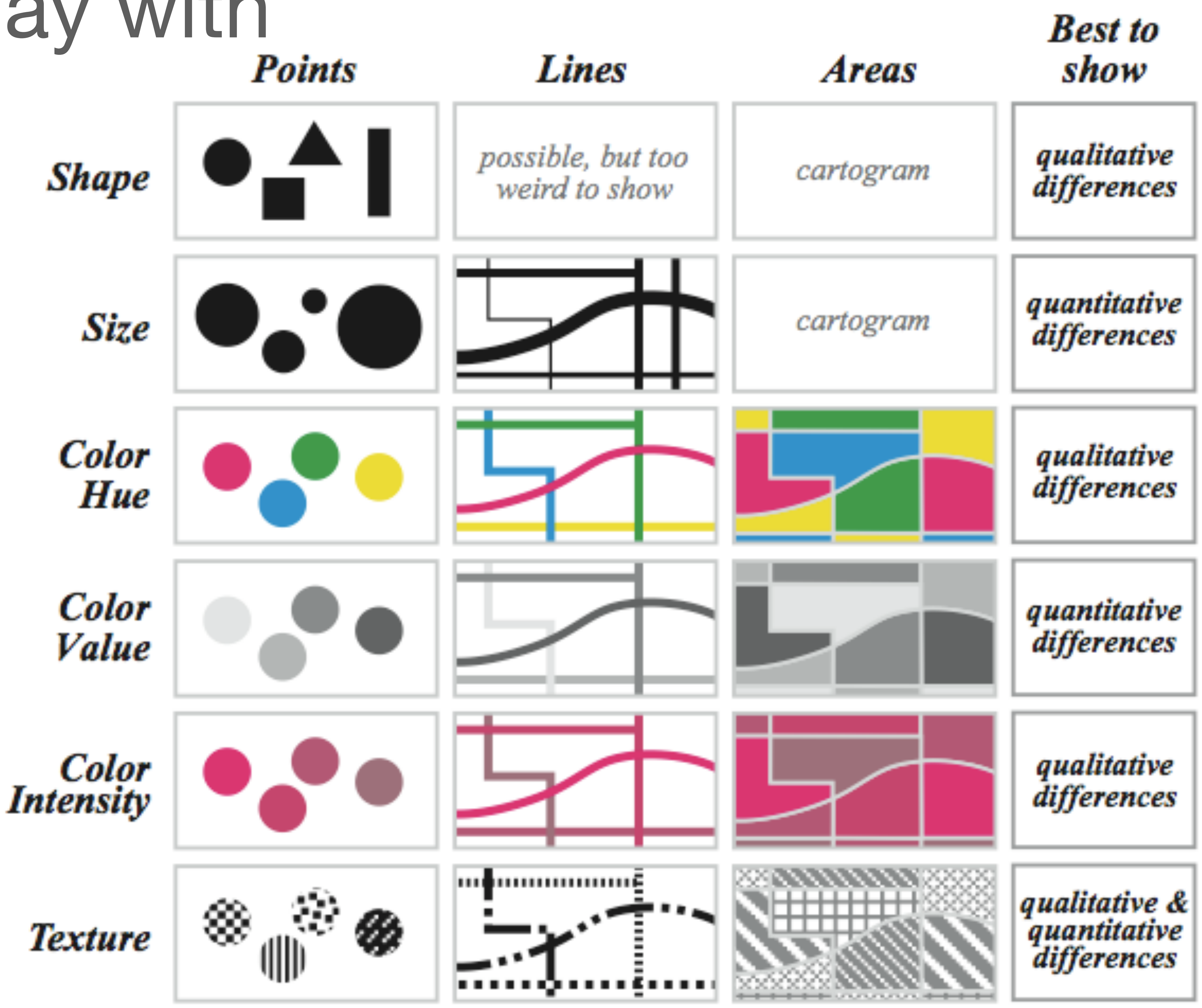
gestalt and perception

“The greatest value of a picture is when it forces us to notice what we never expected to see.”

John Tukey

Flashback

Some (all?) of the visual attributes we have to play with



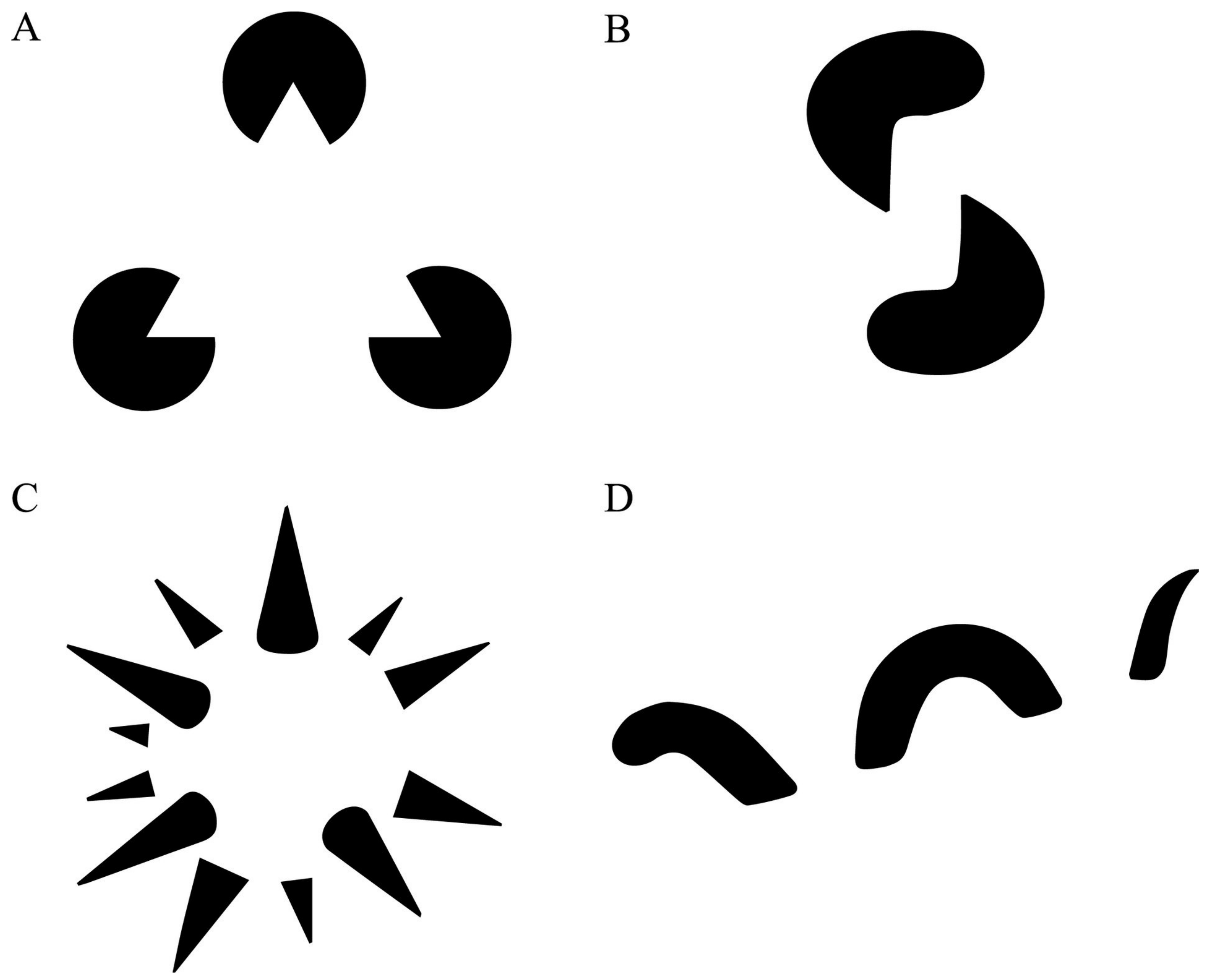
Jacques Bertin, *Semiology of Graphics*. 1967

How does this play out?

The gestalt effect

"The whole is other than
the sum of the parts"
- Kurt Koffka

1. Reification

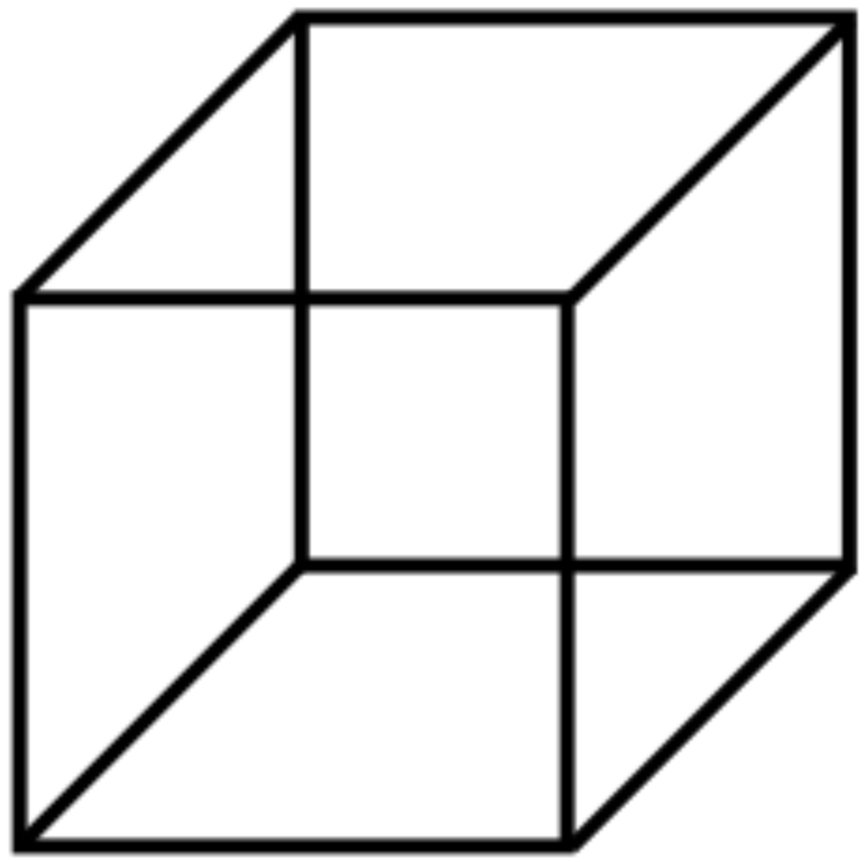


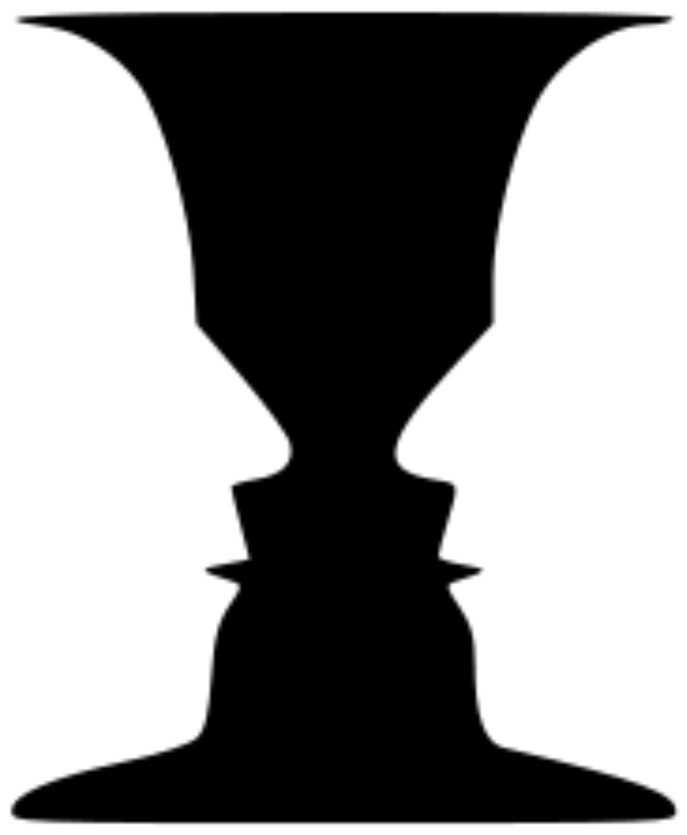
via wikipedia

2. Emergence

Life Magazine: 58;7, 1965-02-19, p 120. Photographer Ronald C Jamesvia Jordan Crouser

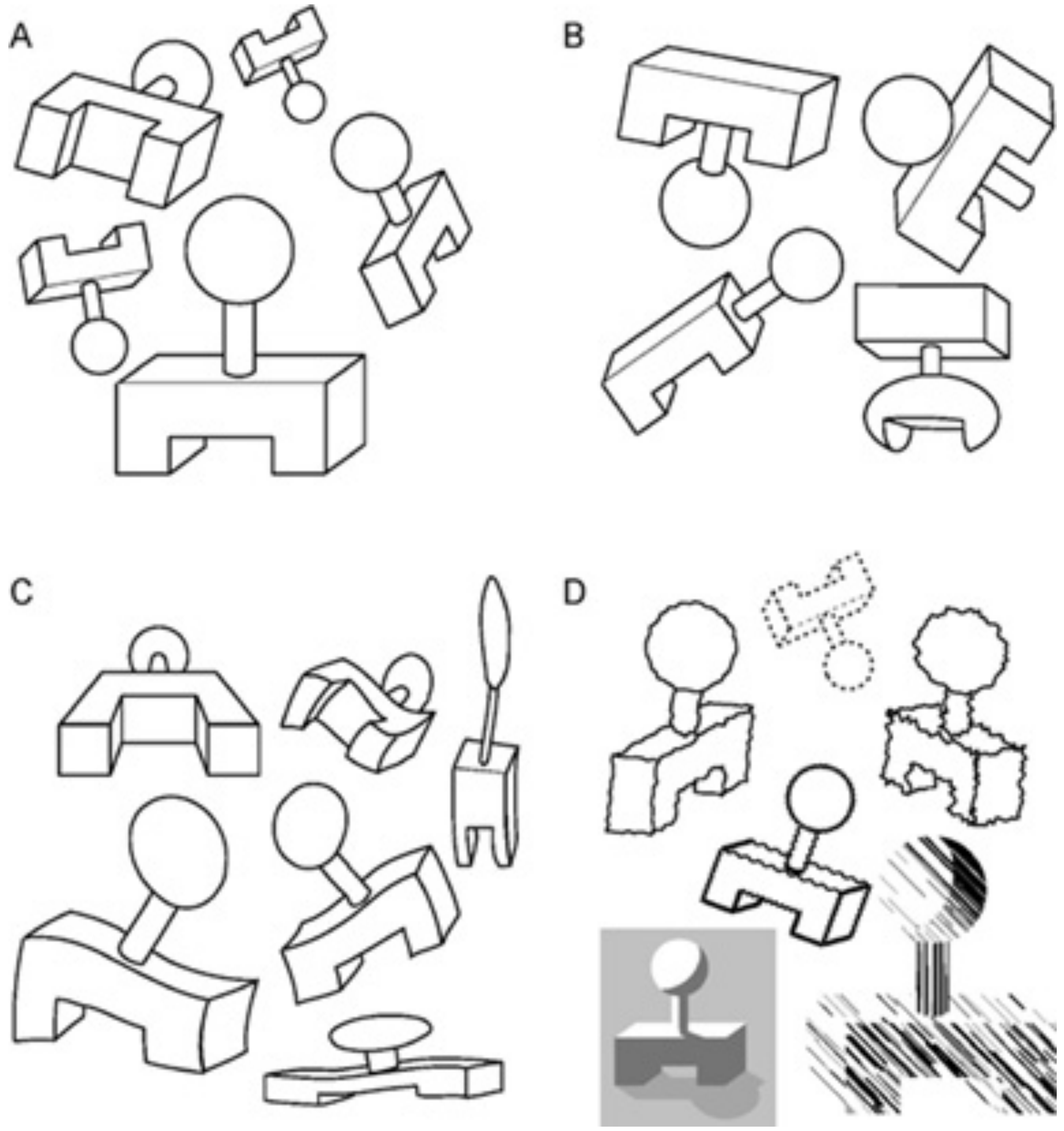
3. Multistability





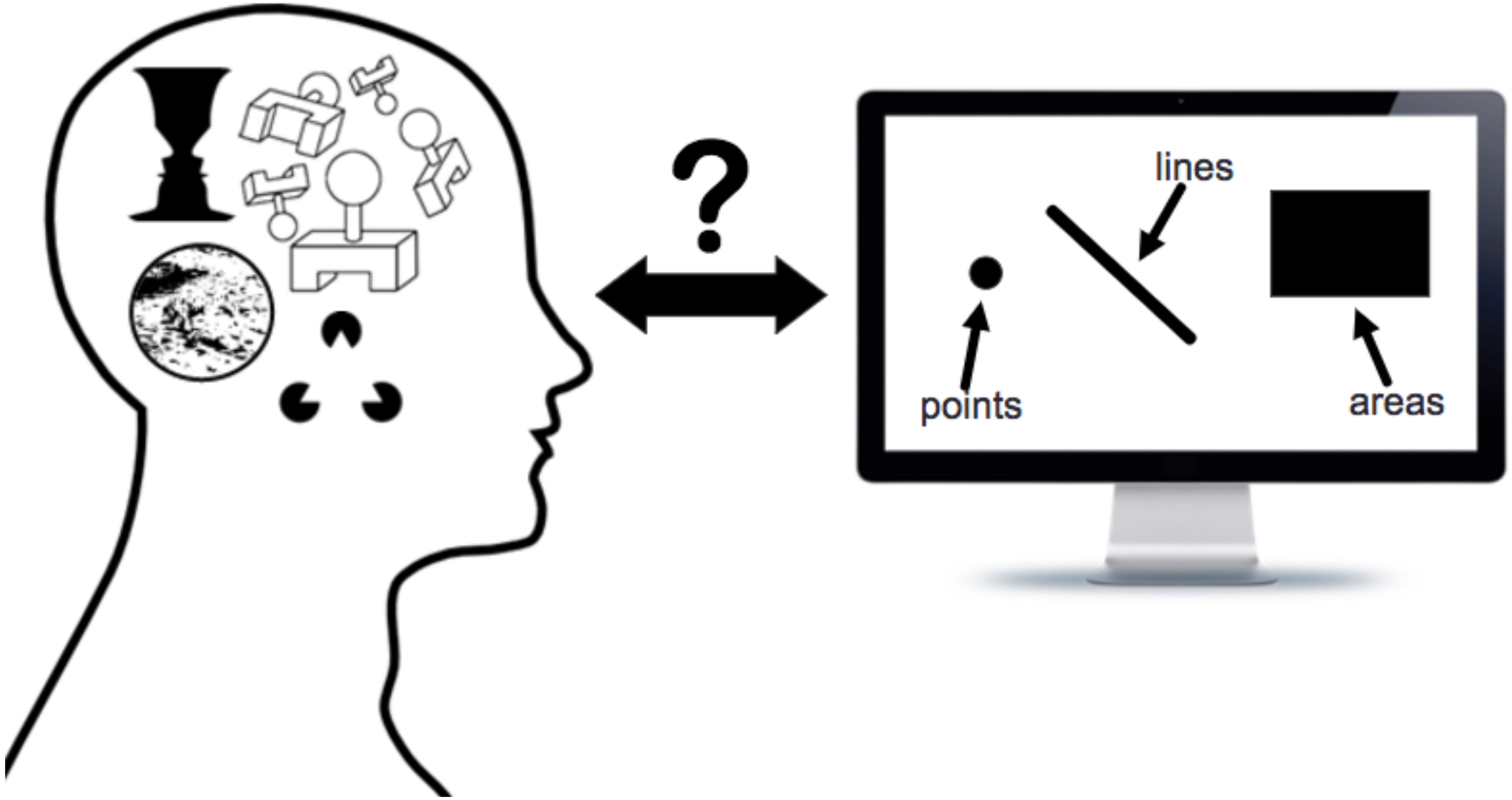
via wikipedia

4. Invariance



via wikipedia

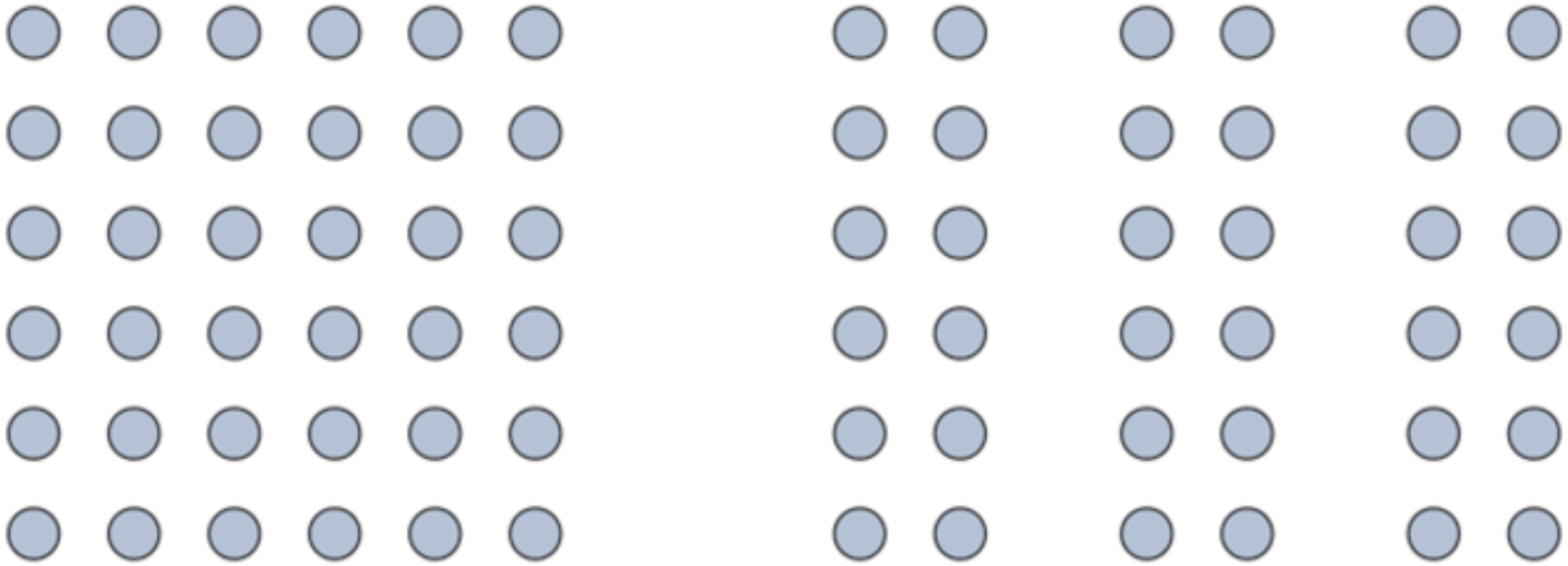
What does this mean for visualization?



via Jordan Crouser

Law of proximity

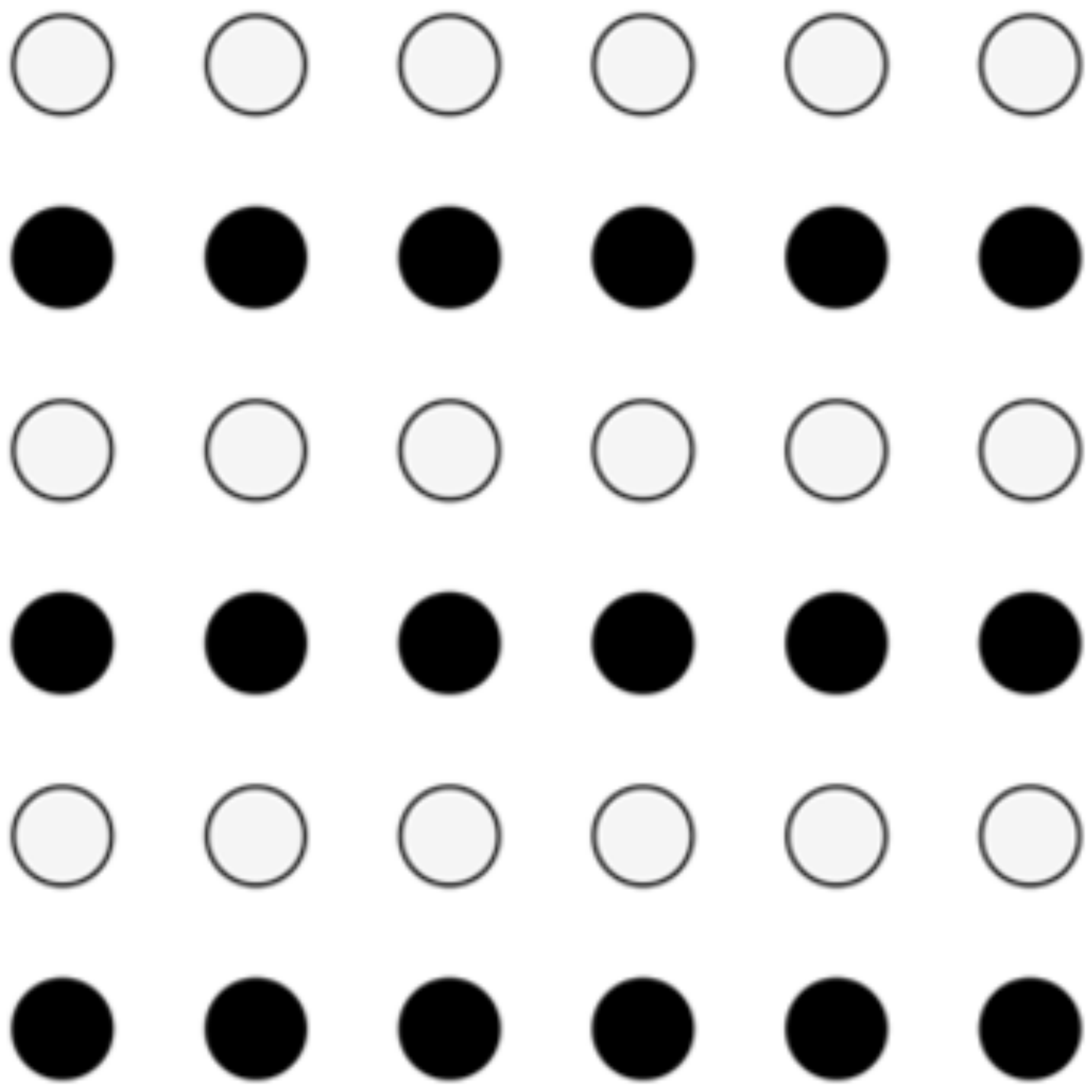
We interpret objects that are close to each other as a group



via Jordan Crouser

Law of similarity

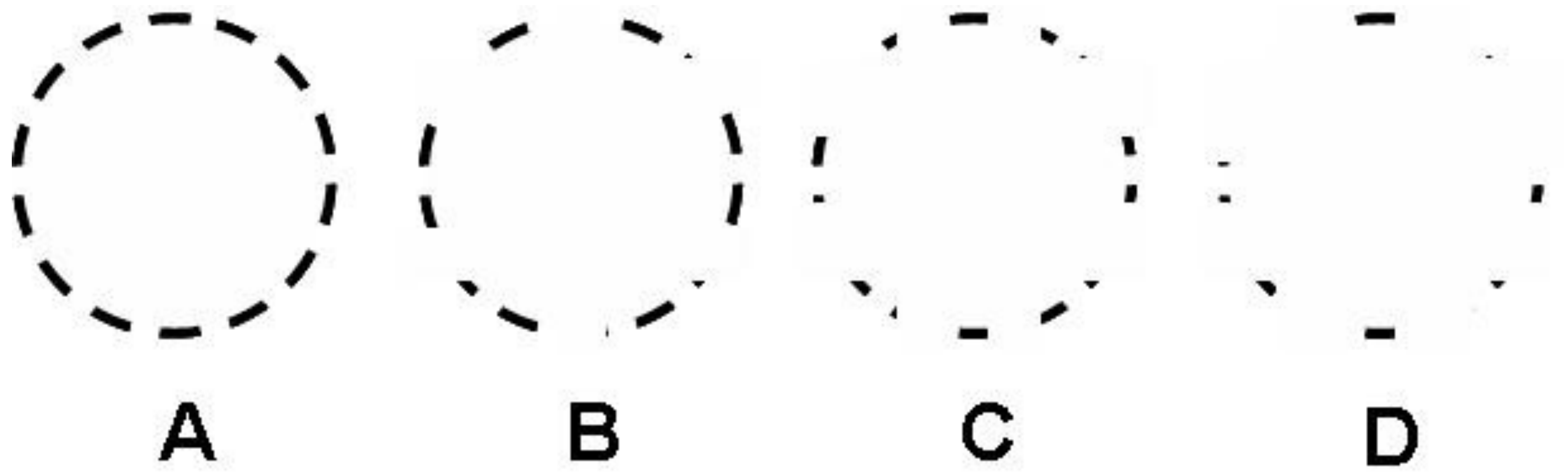
We interpret objects that are visually similar to each other as a group



via Jordan Crouser

Law of closure

When parts of a picture are missing, we fill in the visual gap



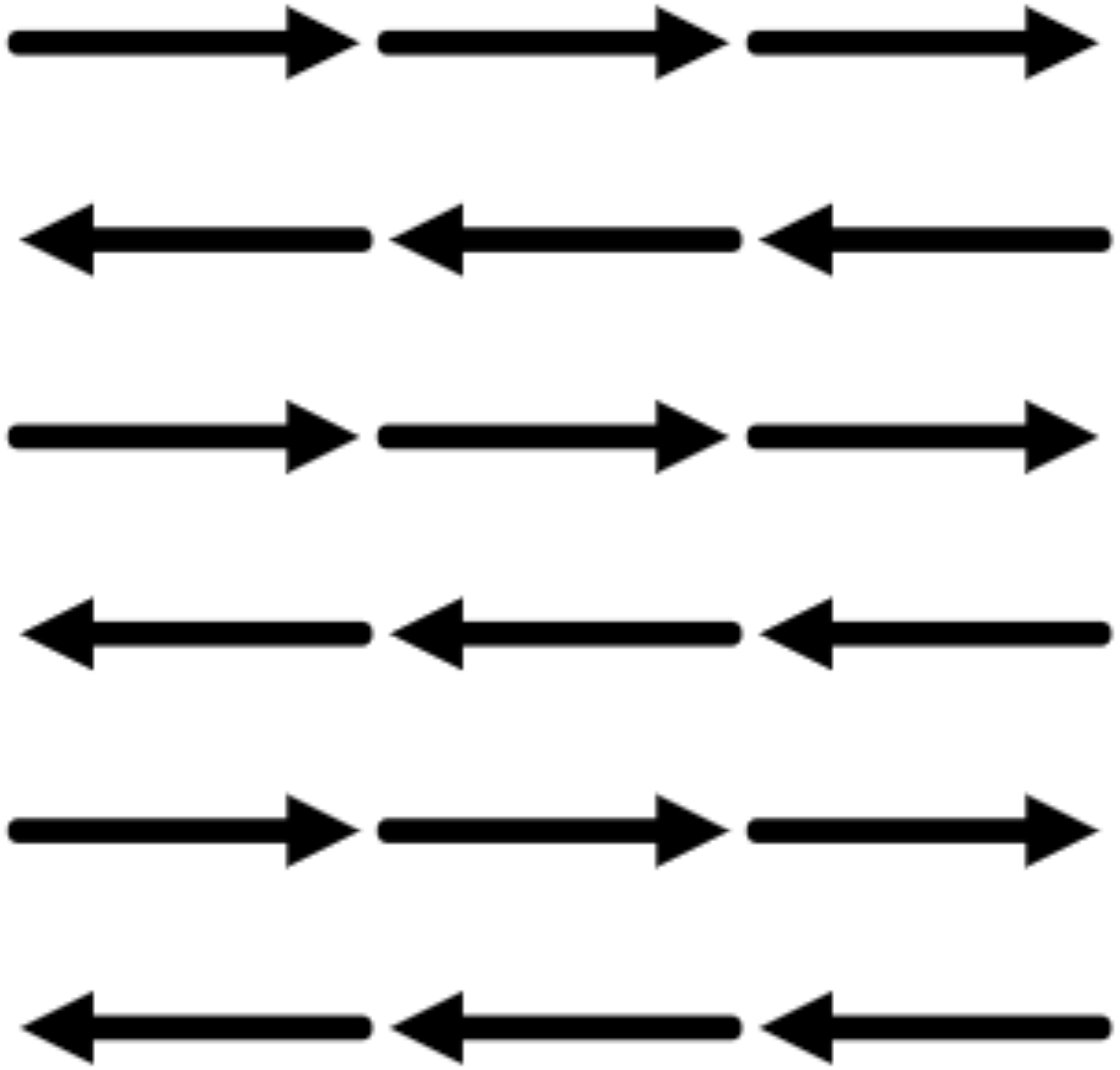
http://changingminds.org/explanations/perception/gestalt/closure.htm

Law of symmetry

We perceive objects as being symmetrical, arranged around a center point

[ ] { } [ ]

Law of common fate

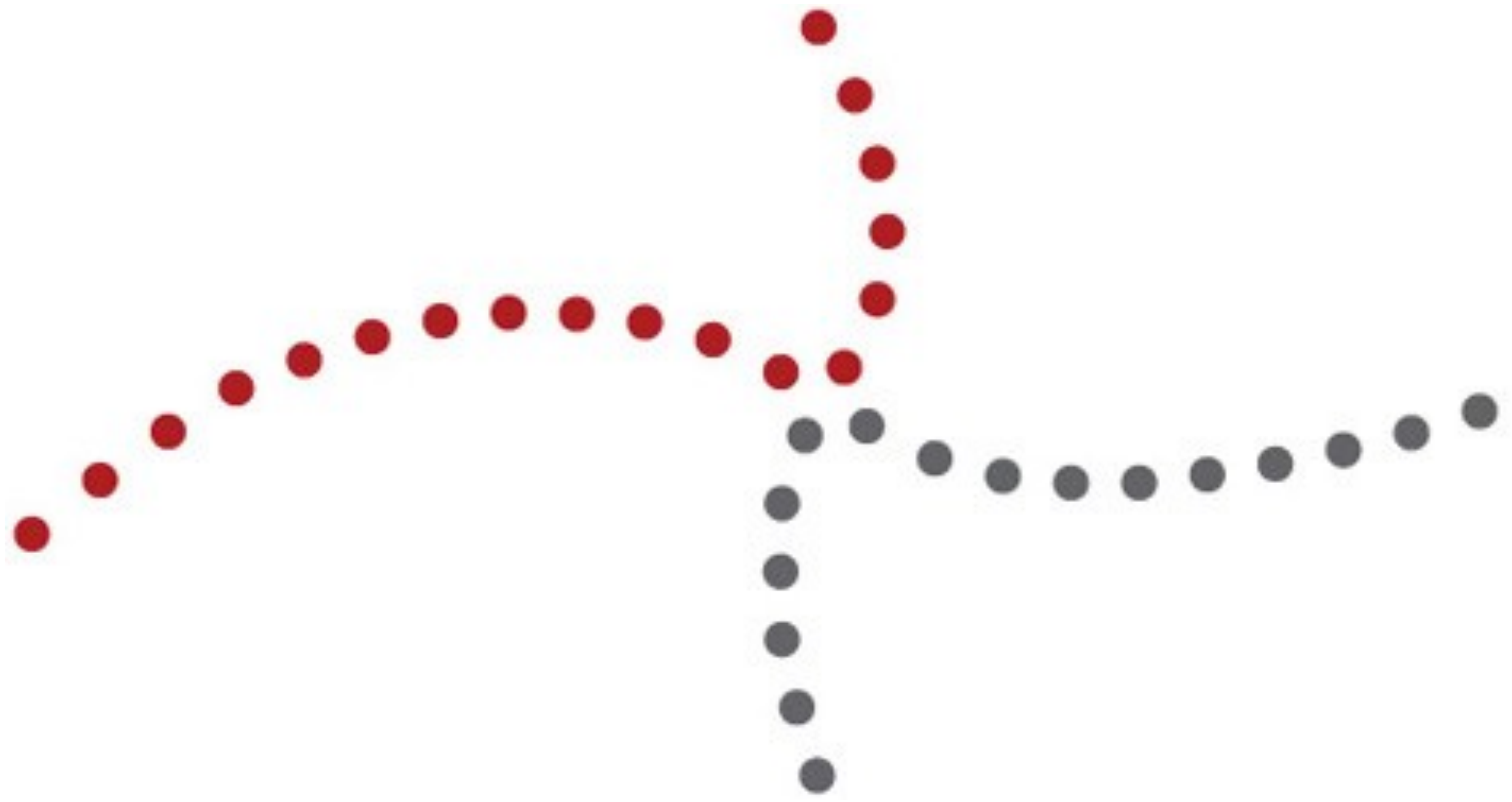


We group objects that we perceive to be moving along the same path

via Jordan Crouser

Law of continuity

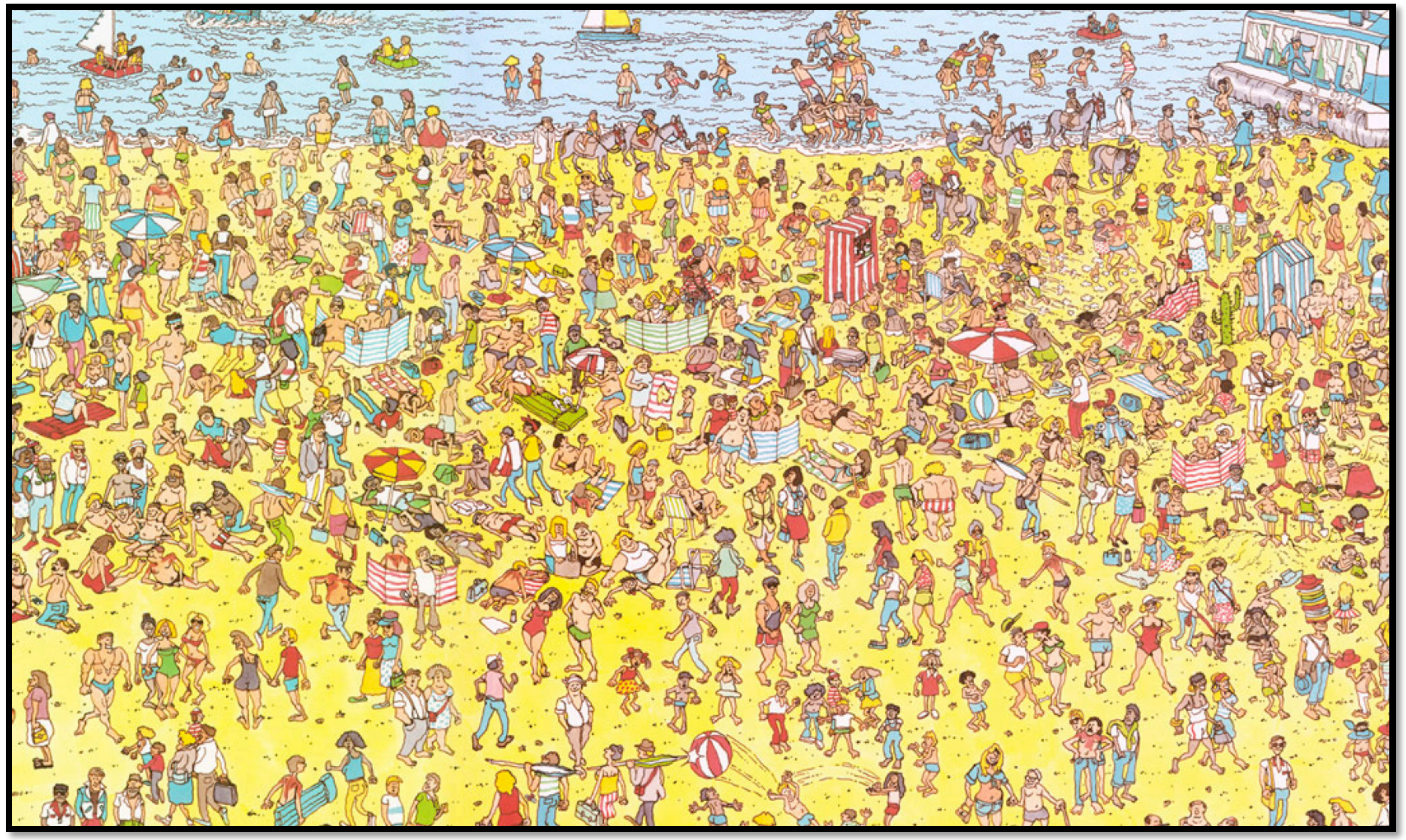
We tend to group objects along the smoothest path



https://psycheleven2015.wordpress.com/category/the-gestalt-psychology/

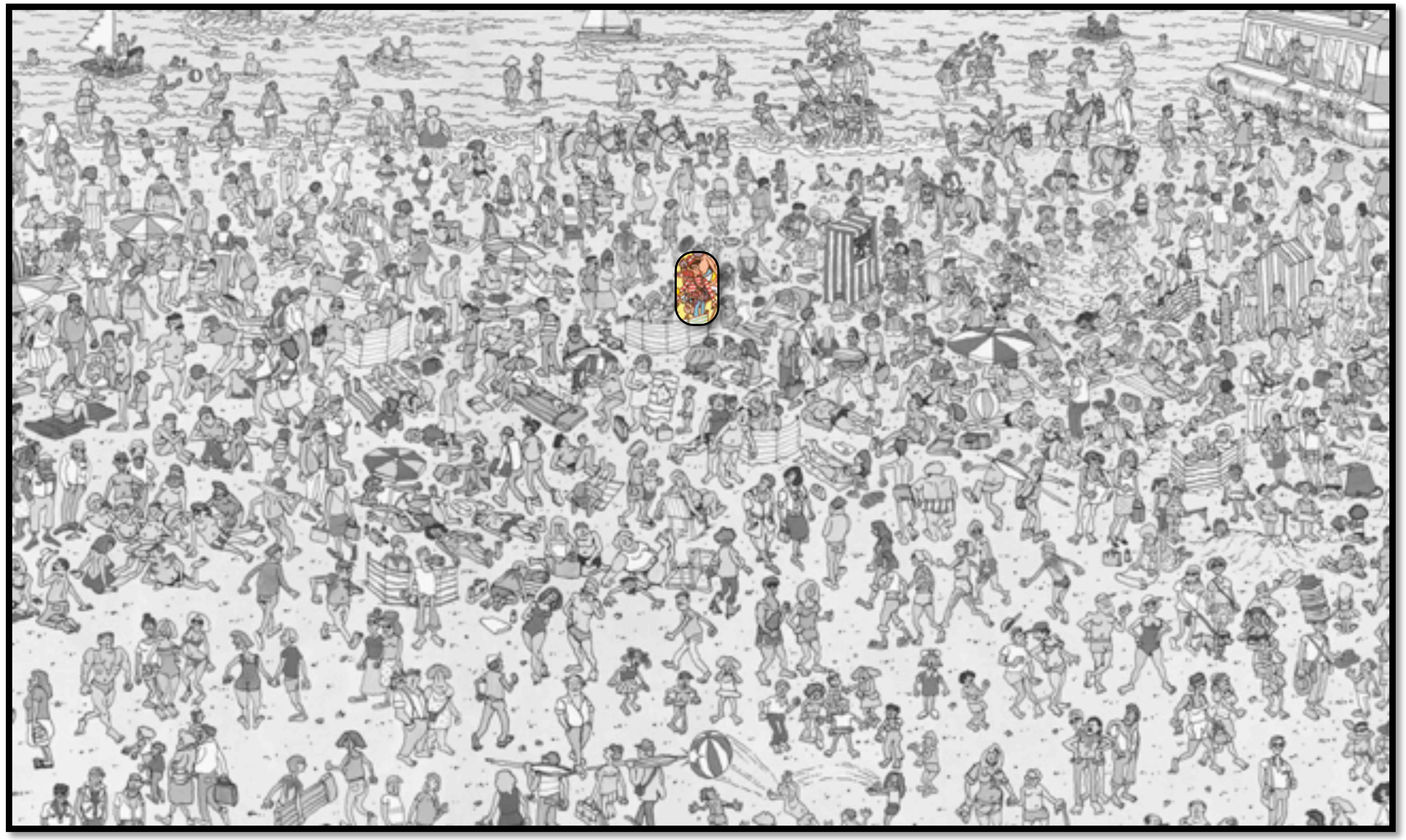
Perception

Some things are processed slowly



via Jordan Crouser

Others are incredibly fast



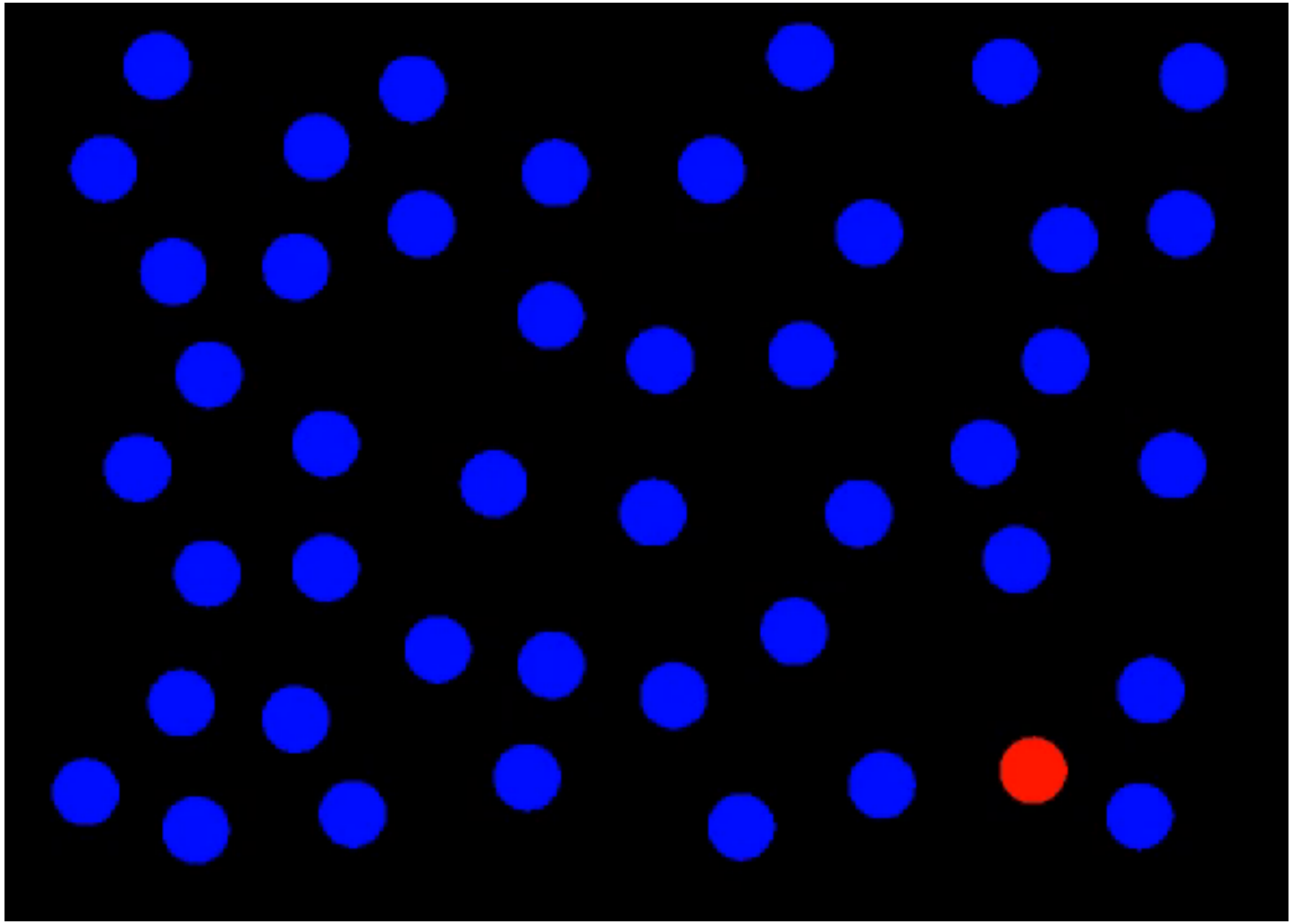
via Jordan Crouser

Fast = “pre-attentive processing”

- Things that happen in <200ms of visual stimulation
- Performed in parallel across the entire visual field

via Jordan Crouser

Get ready



via Jordan Crouser

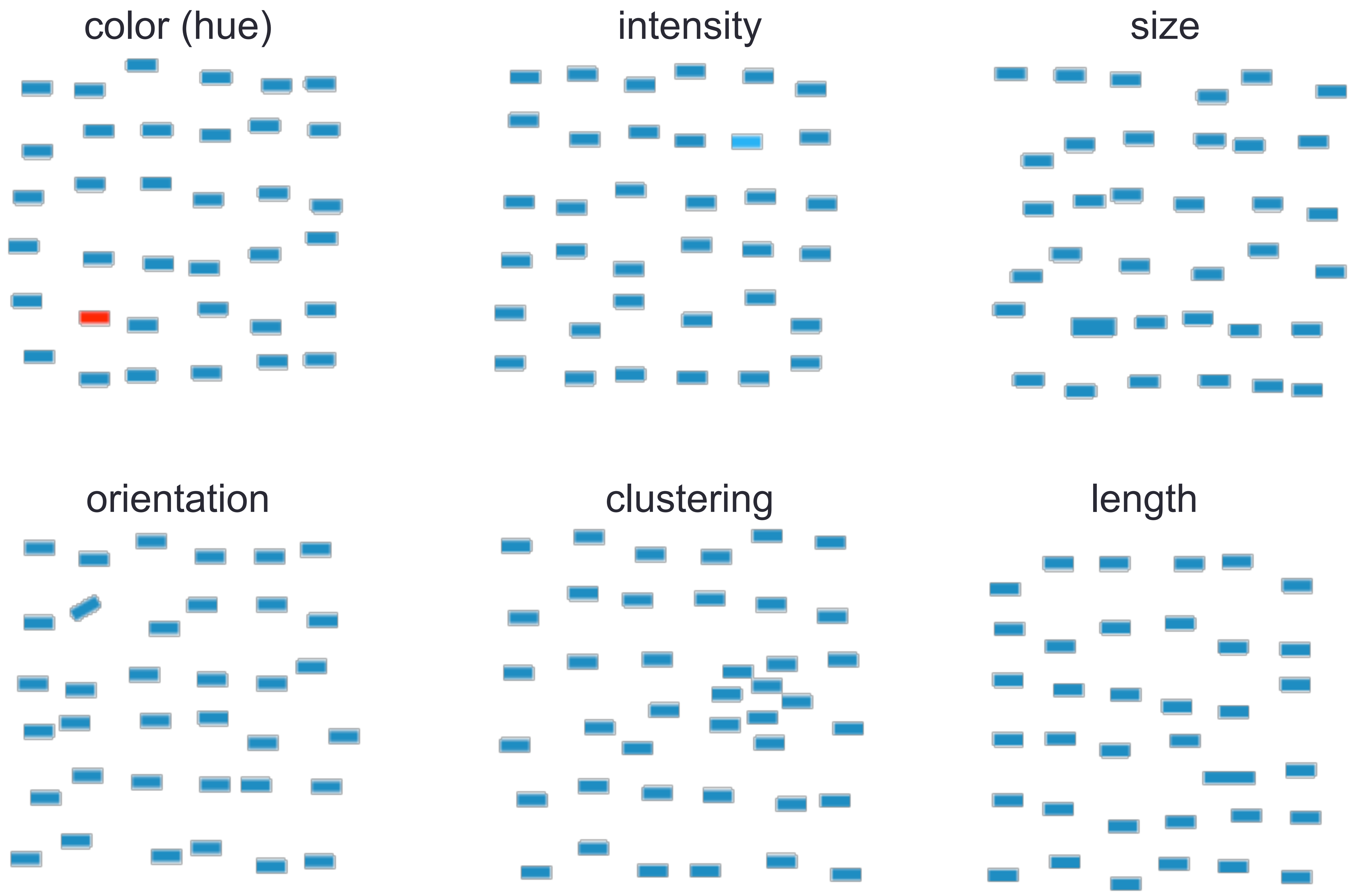
What did you see?

via Jordan Crouser

“An understanding of what is processed pre-attentively is probably the most important contribution that visual science can make to data visualization” (Ware, 2004, p. 19)

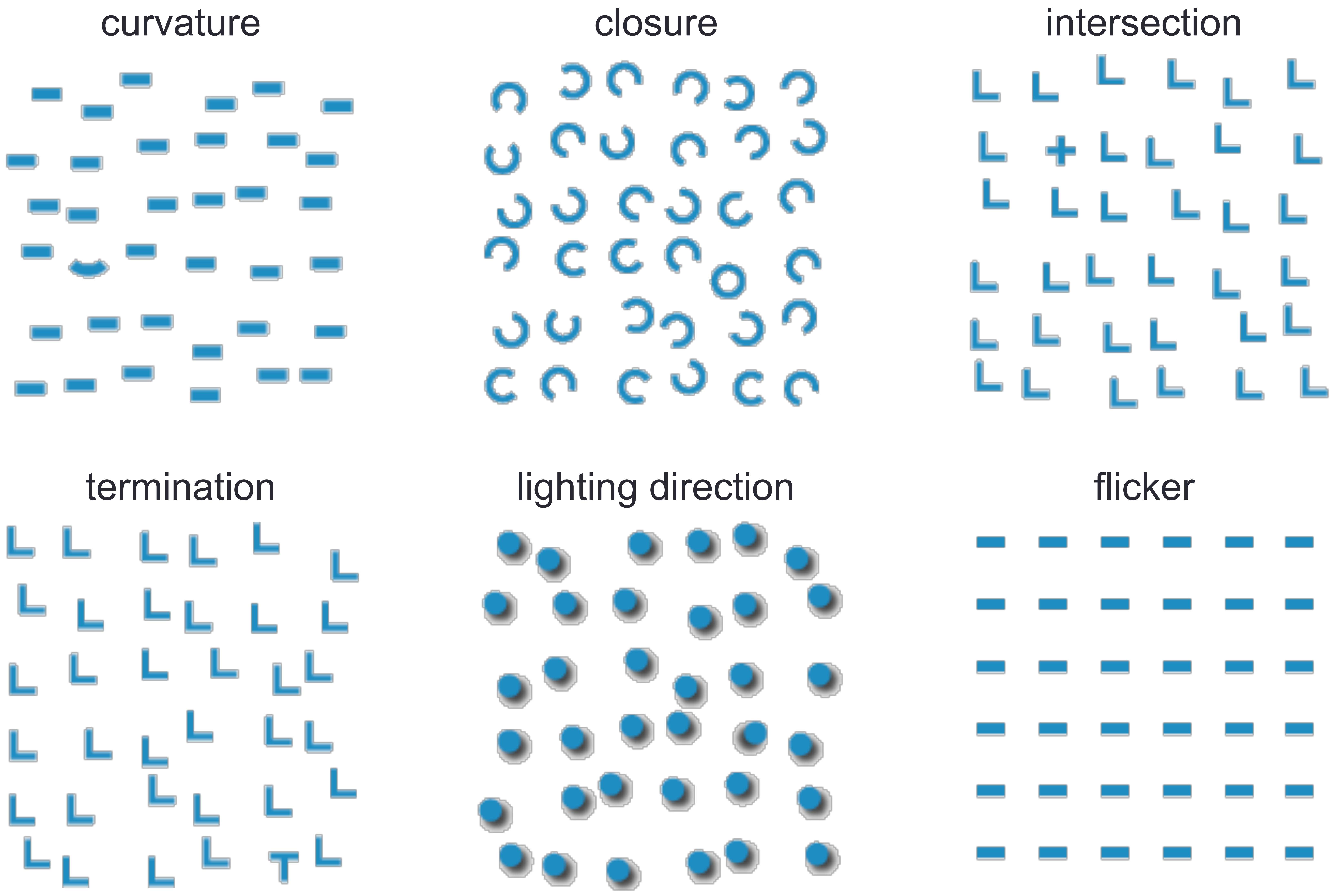
via Jordan Crouser

Pre-attentive features



via Jordan Crouser, and http://www.csc.ncsu.edu/faculty/Healy/PP/

Pre-attentive features



via Jordan Crouser, and http://www.csc.ncsu.edu/faculty/Healy/PP/

Pre-attentive processing facilities:

- Target detection (presence or absence)
- Boundary detection / grouping
- Region tracking
- Counting and estimation

via Jordan Crouser

Attentive counting

1281768756138976546984506985604982826762
9809858458224509856458945098450980943585
9091030209905959595772564675050678904567
8845789809821677654876364908560912949686

How many threes are there?

via Jordan Crouser

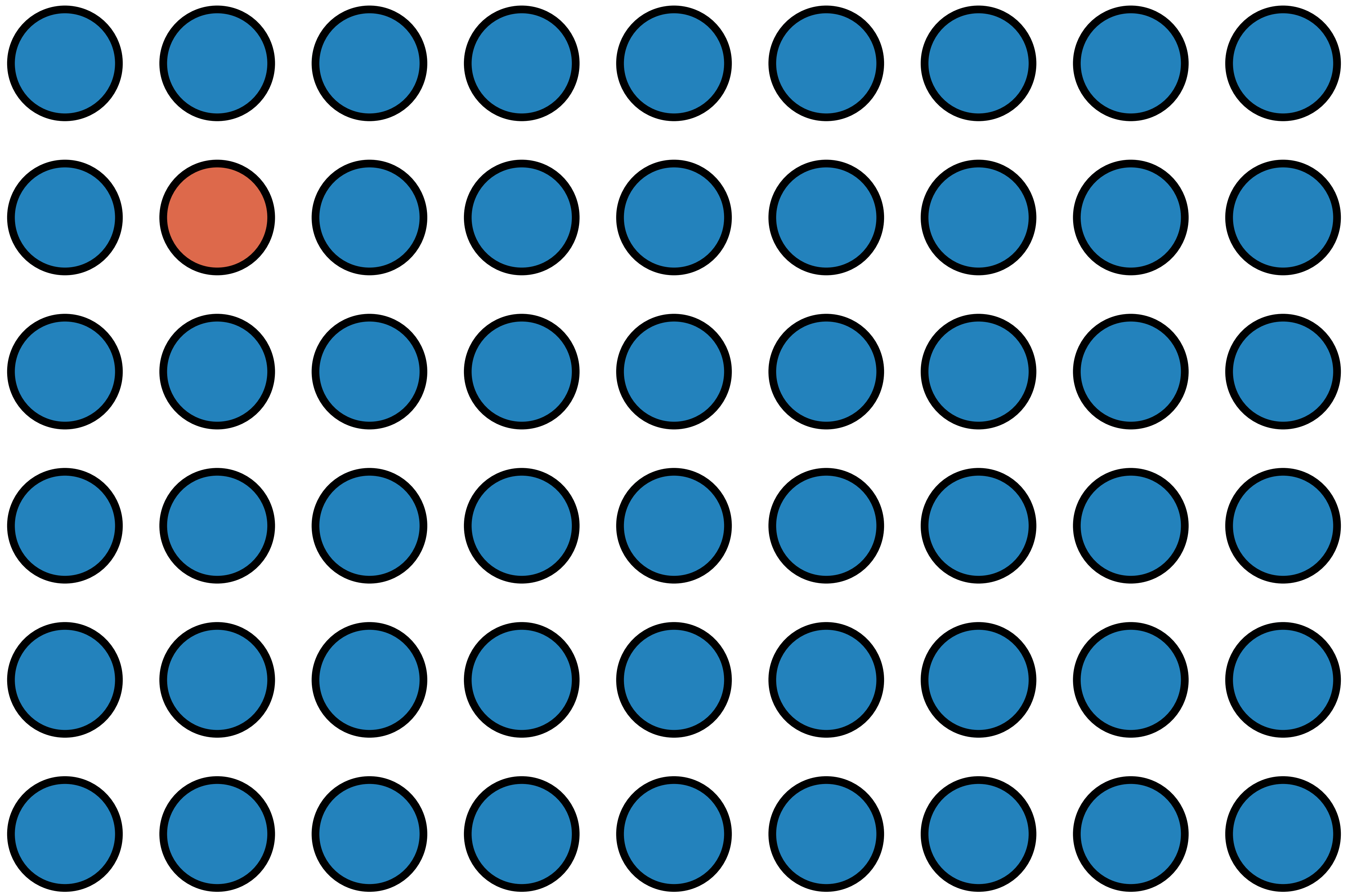
Pre-attentive counting

1281768756138976546984506985604982826762
9809858458224509856458945098450980943585
9091030209905959595772564675050678904567
8845789809821677654876364908560912949686

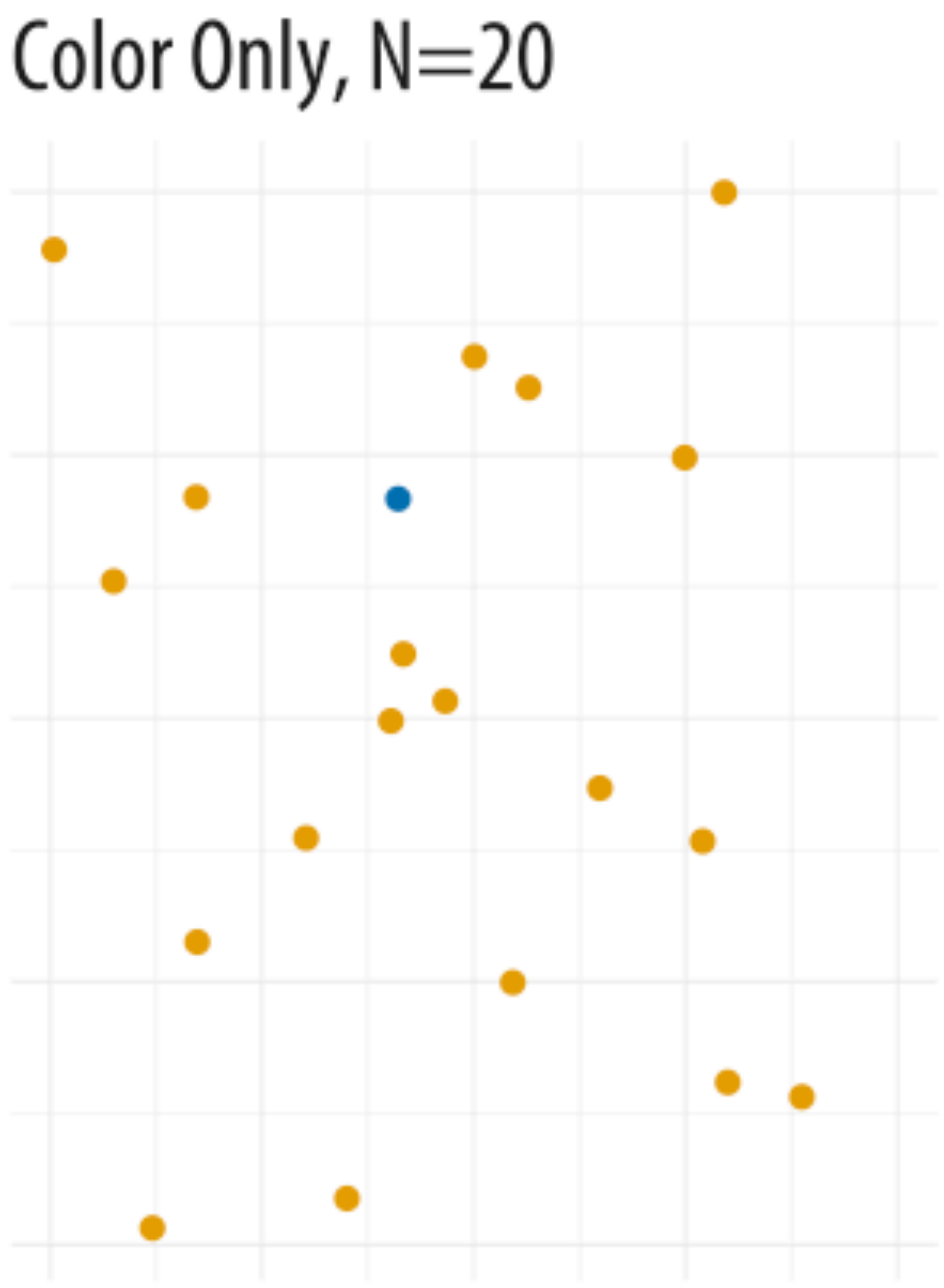
How many threes are there?

via Jordan Crouser

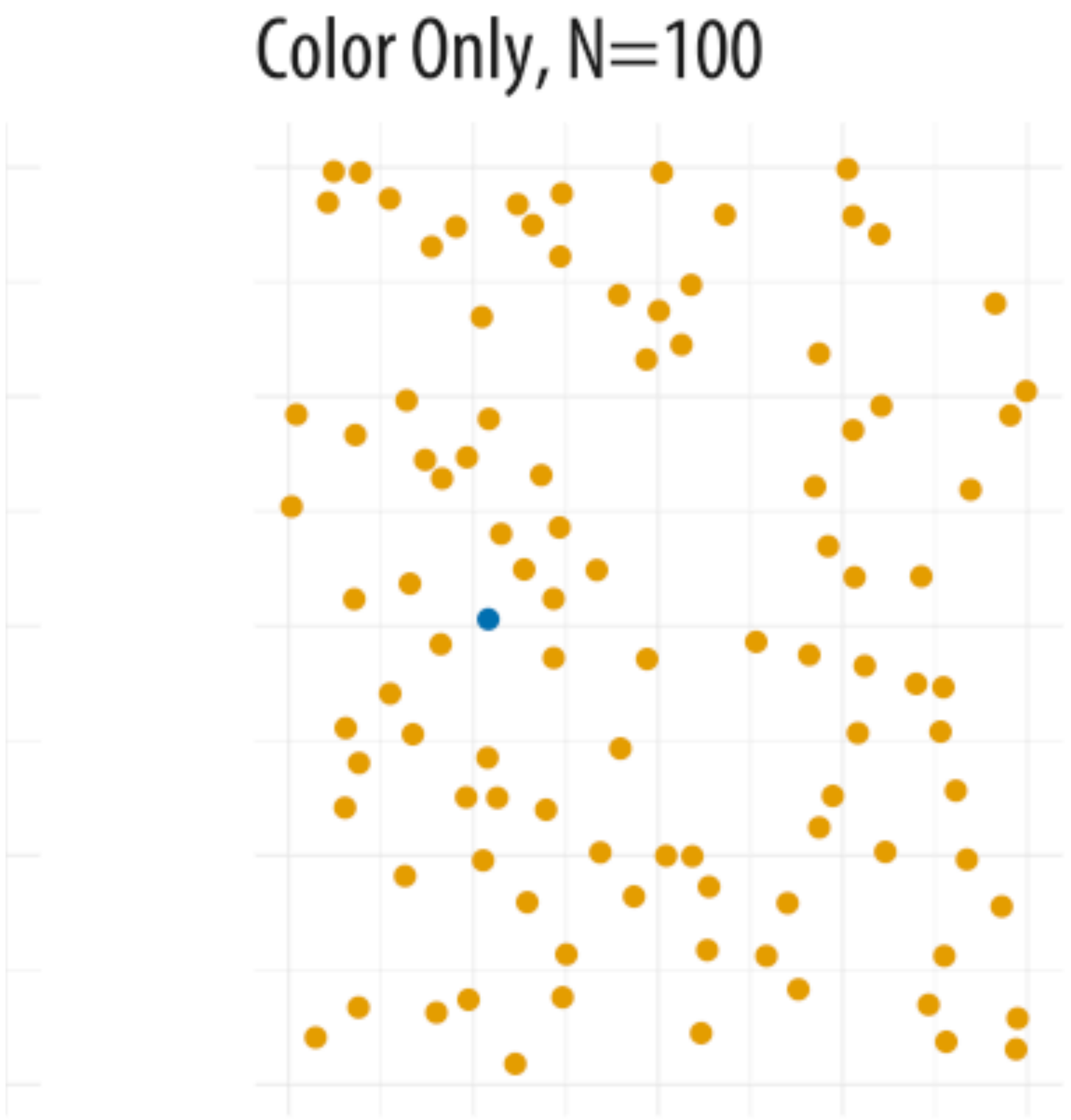
Pre-attentive processing: color (hue)



via Jordan Crouser

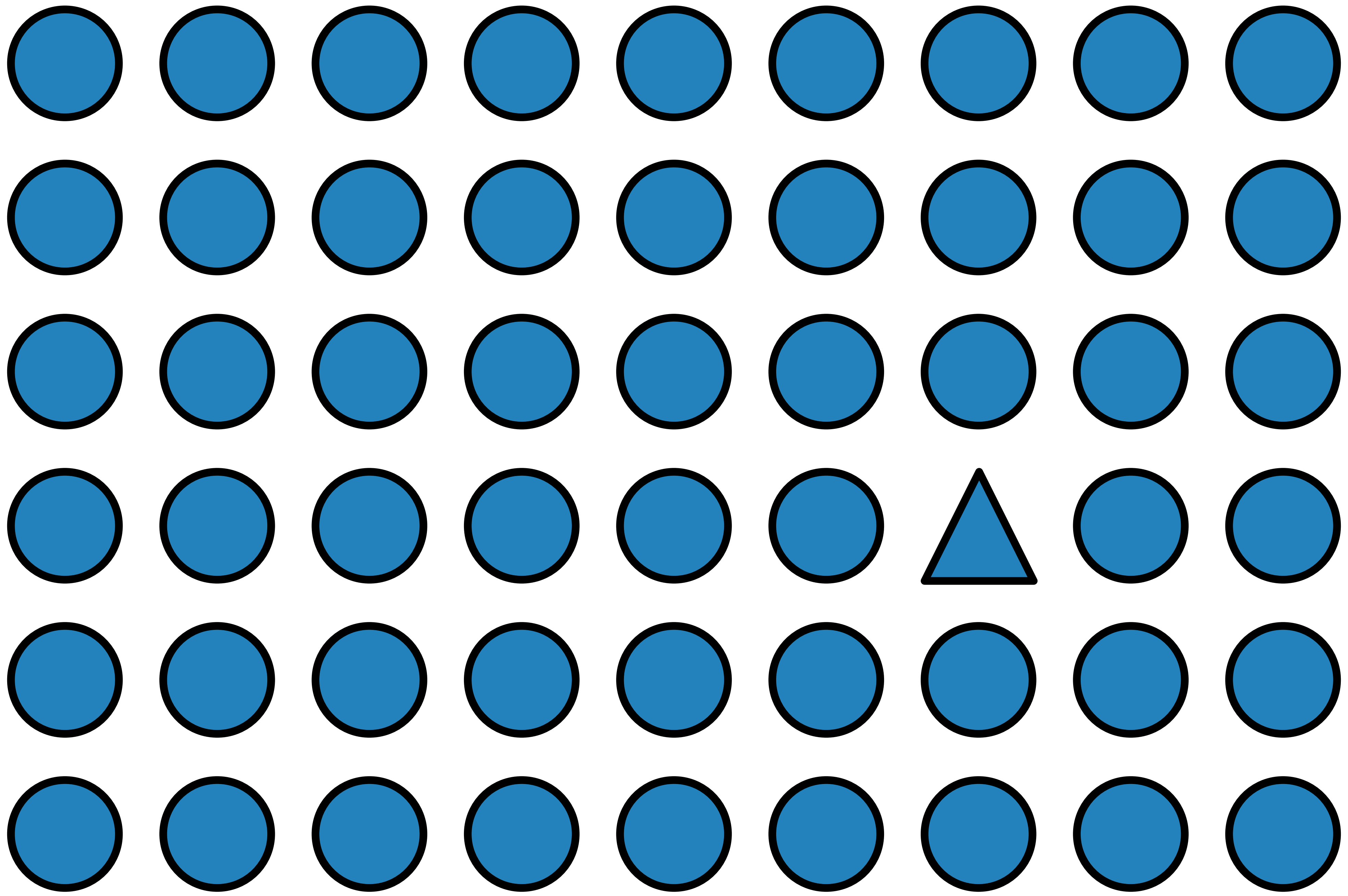


via Kieran Healy's A Practical Introduction to Data Visualization with ggplot2

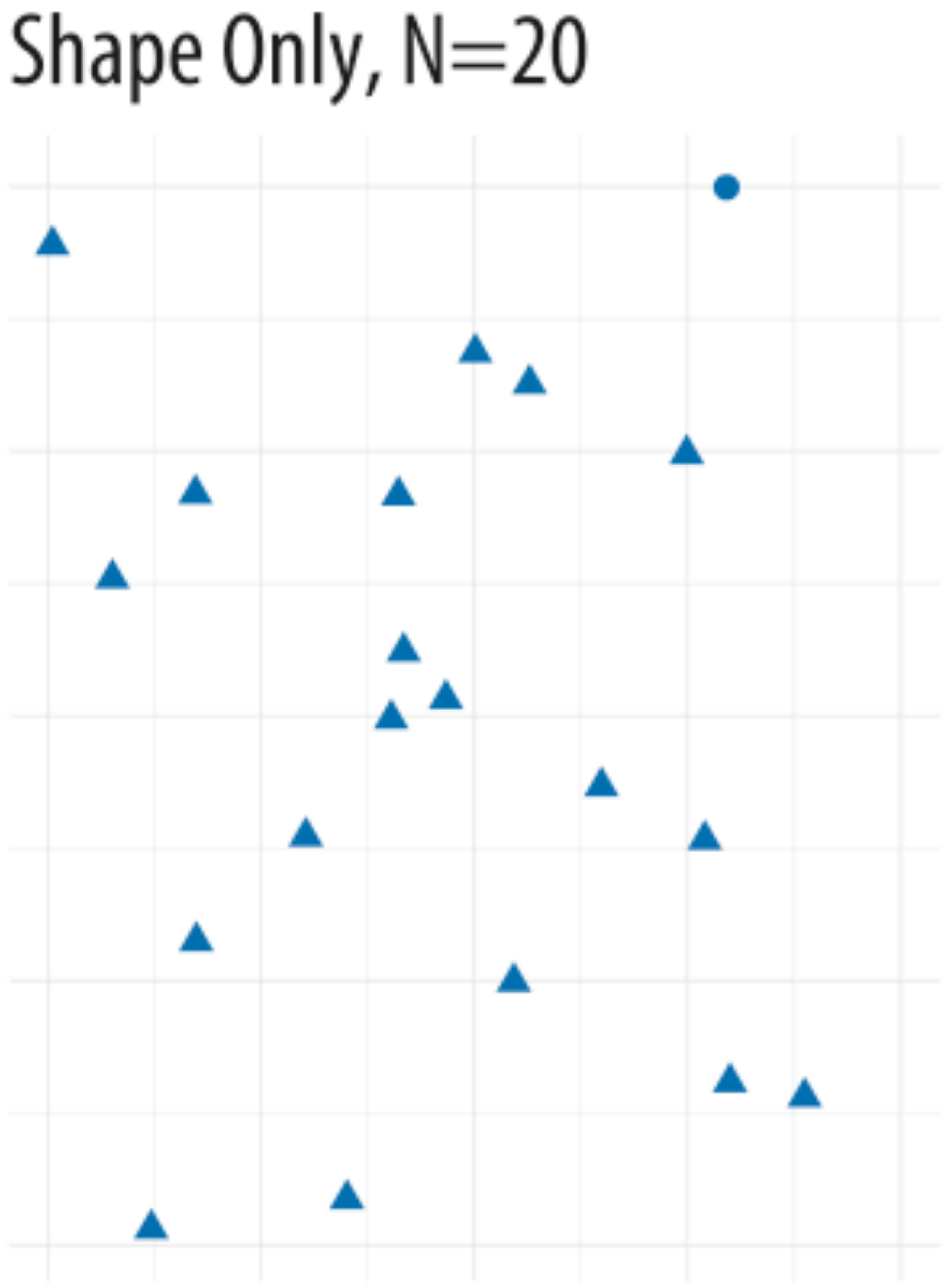


via Kieran Healy's [A Practical Introduction to Data Visualization with ggplot2]

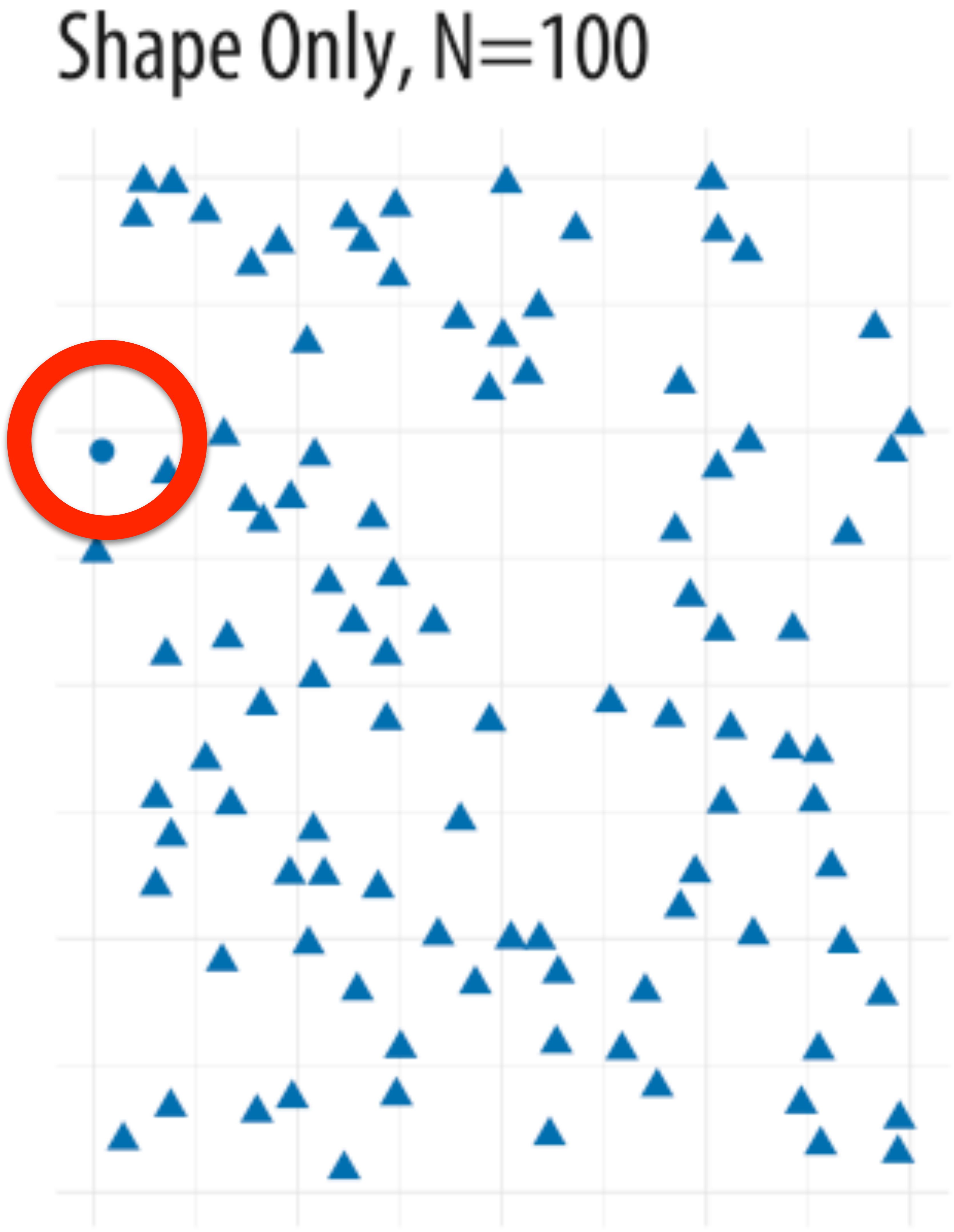
Pre-attentive processing: shape (curvature)



via Jordan Crouser

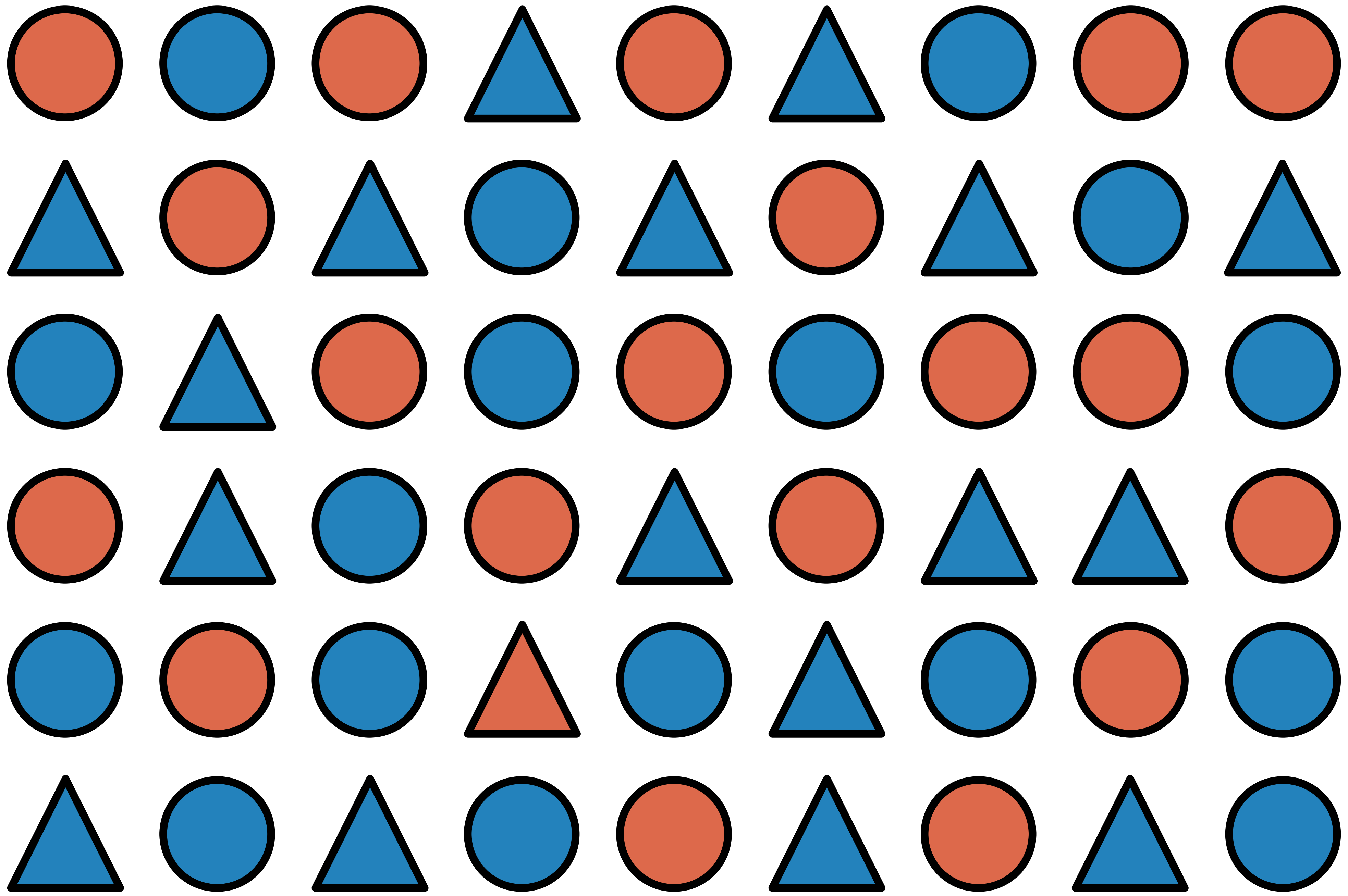


via Kieran Healy's A Practical Introduction to Data Visualization with ggplot2

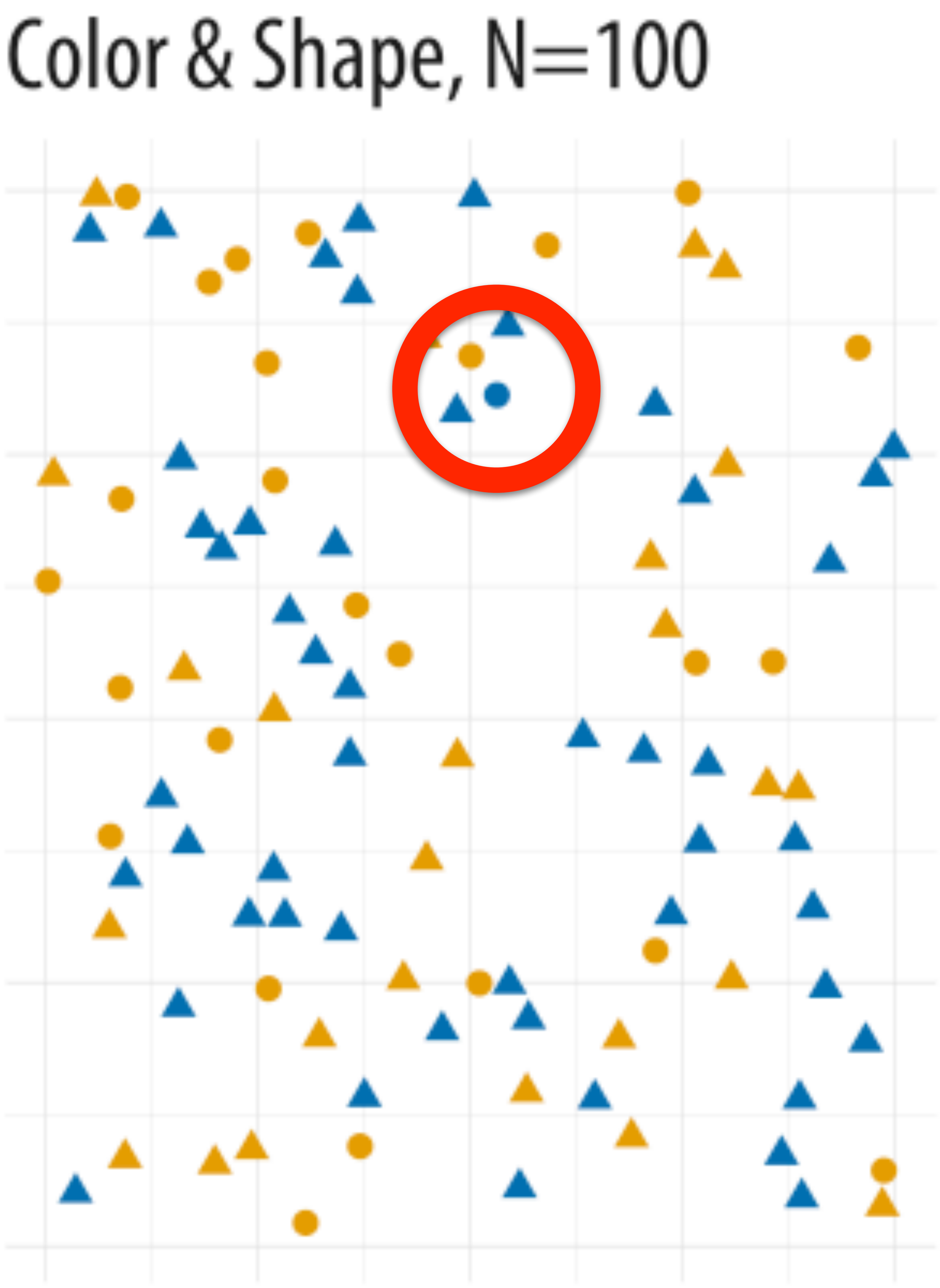


via Kieran Healy's A Practical Introduction to Data Visualization with ggplot2

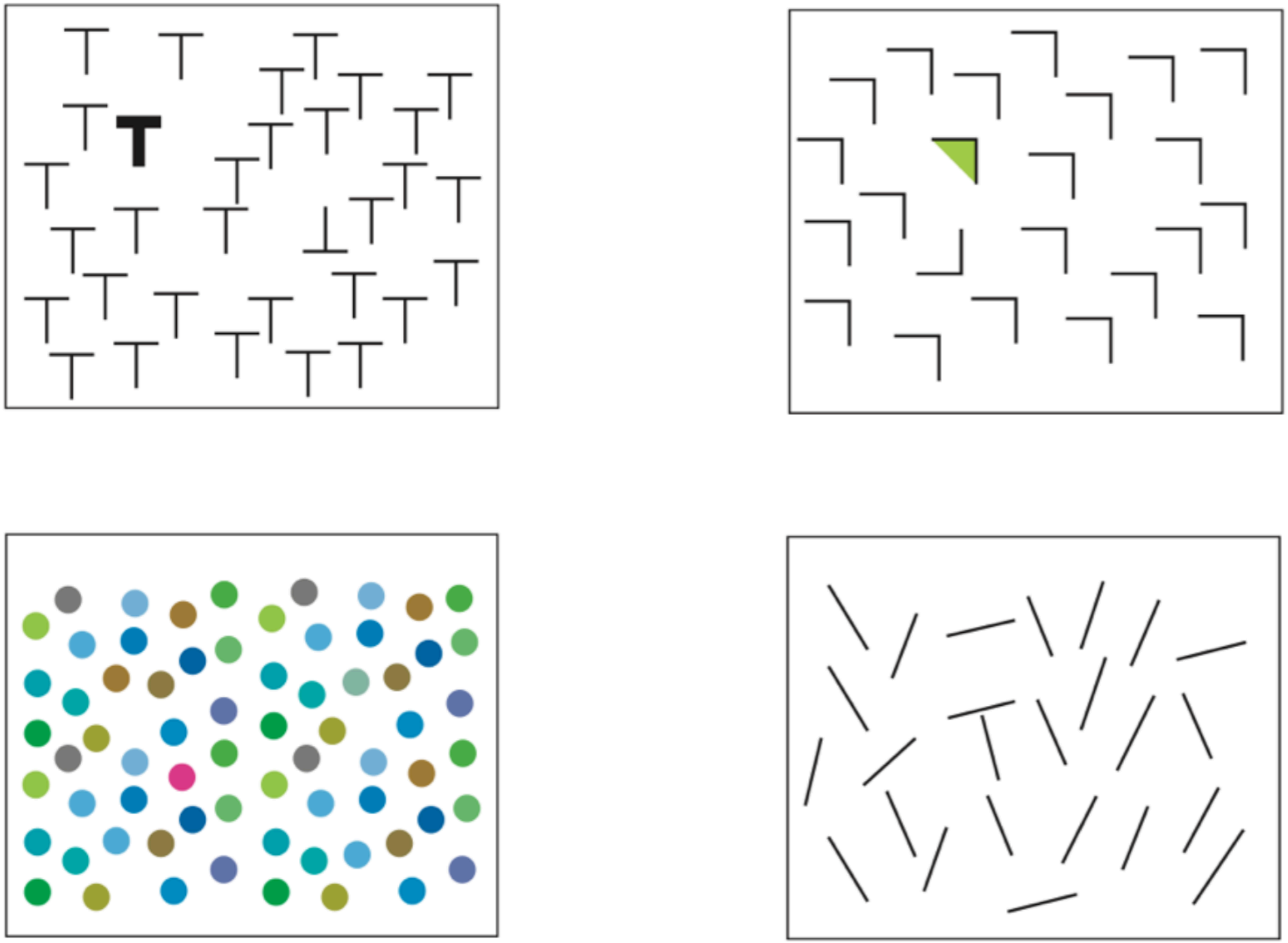
Pre-attentive processing: shape + color?



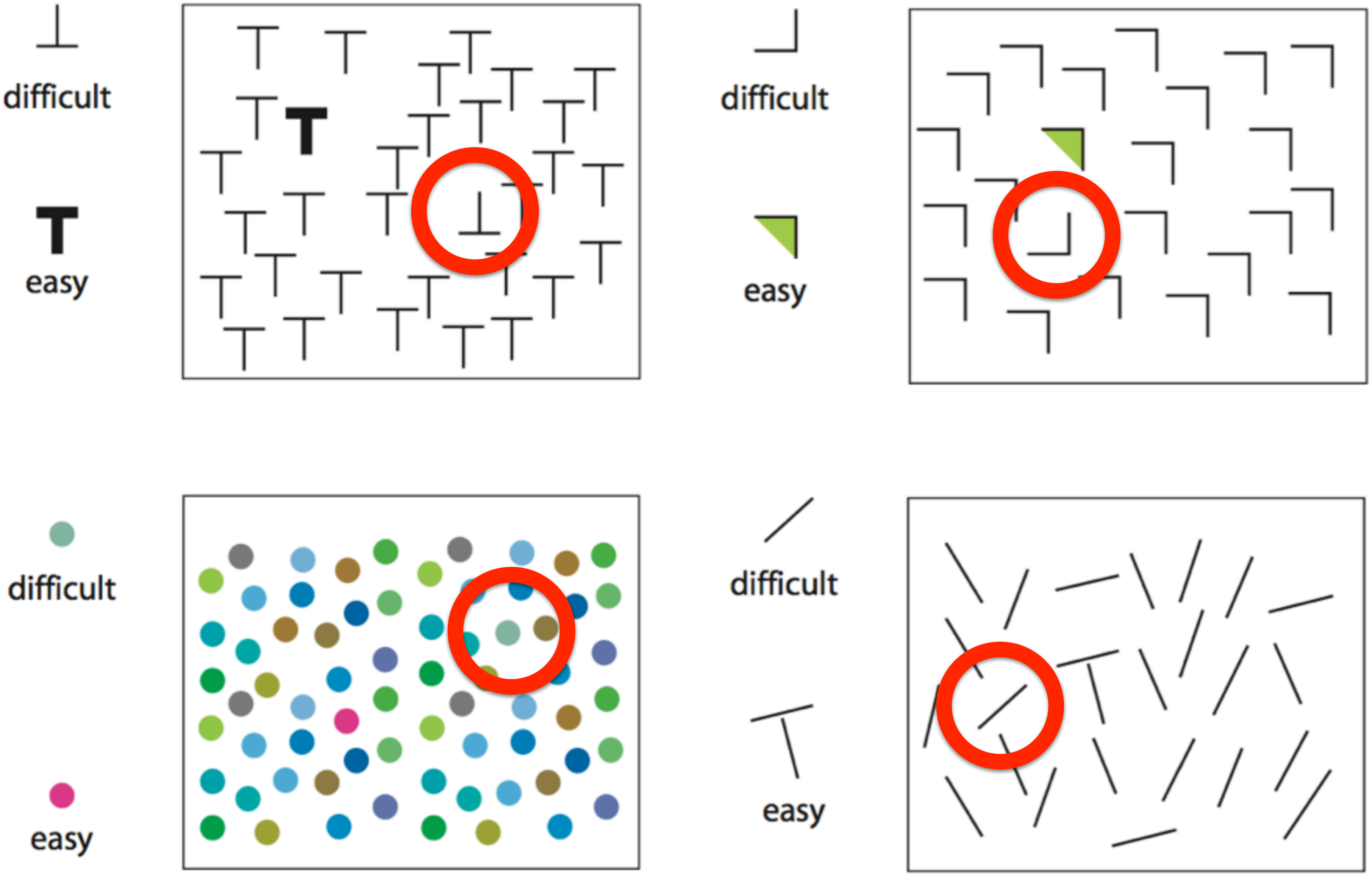
via Jordan Crouser



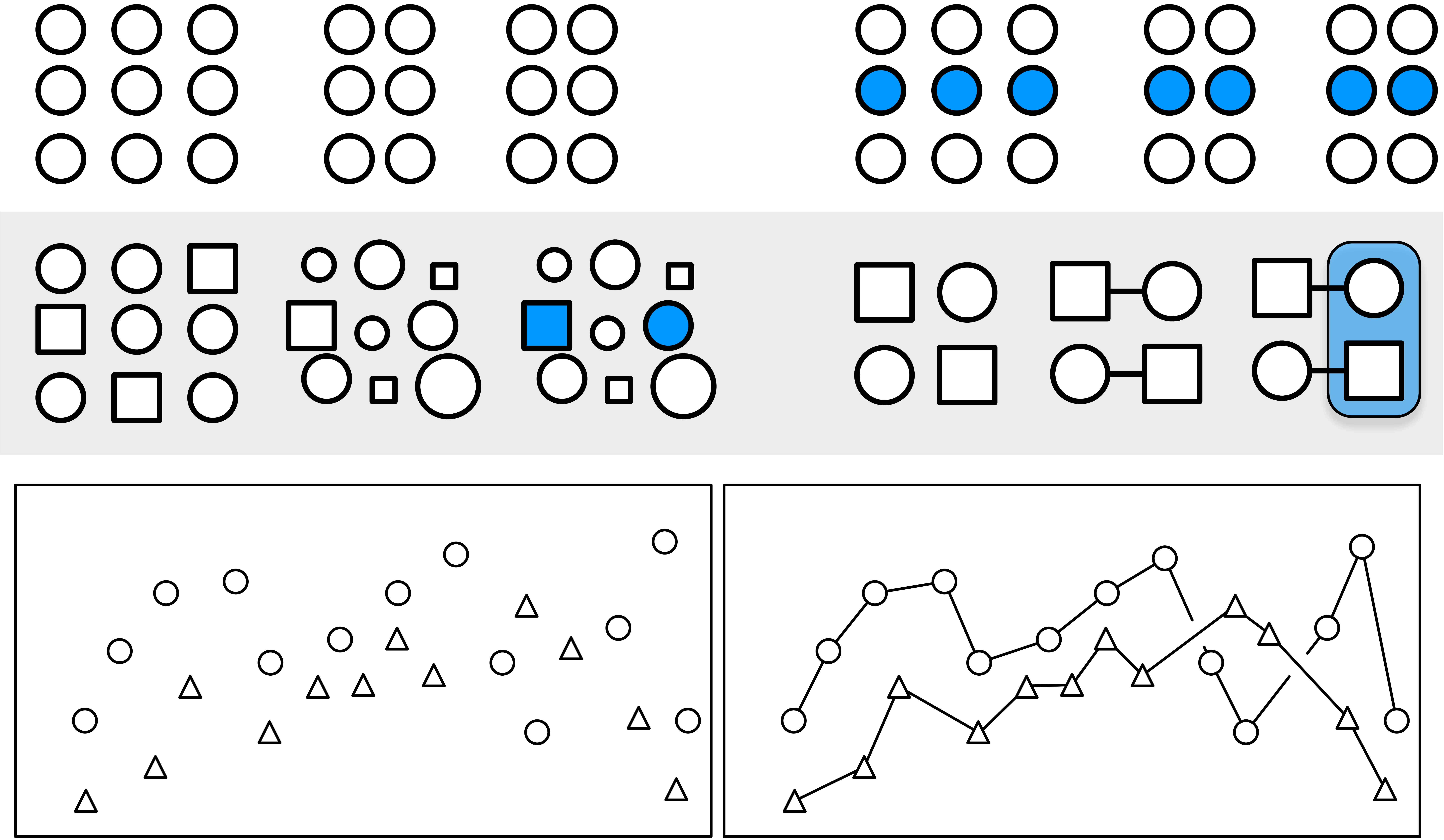
via Kieran Healy's [A Practical Introduction to Data Visualization with ggplot2]



via Kieran Healy's A Practical Introduction to Data Visualization with ggplot2



via Kieran Healy's A Practical Introduction to Data Visualization with ggplot2



via Kieran Healy's A Practical Introduction to Data Visualization with ggplot2

Cleveland and McGill, 1984

The following are the 10 elementary tasks in Figure 1, ordered from most to least accurate:

1. Position along a common scale
2. Positions along nonaligned scales
3. Length, direction, angle
4. Area
5. Volume, curvature
6. Shading, color saturation

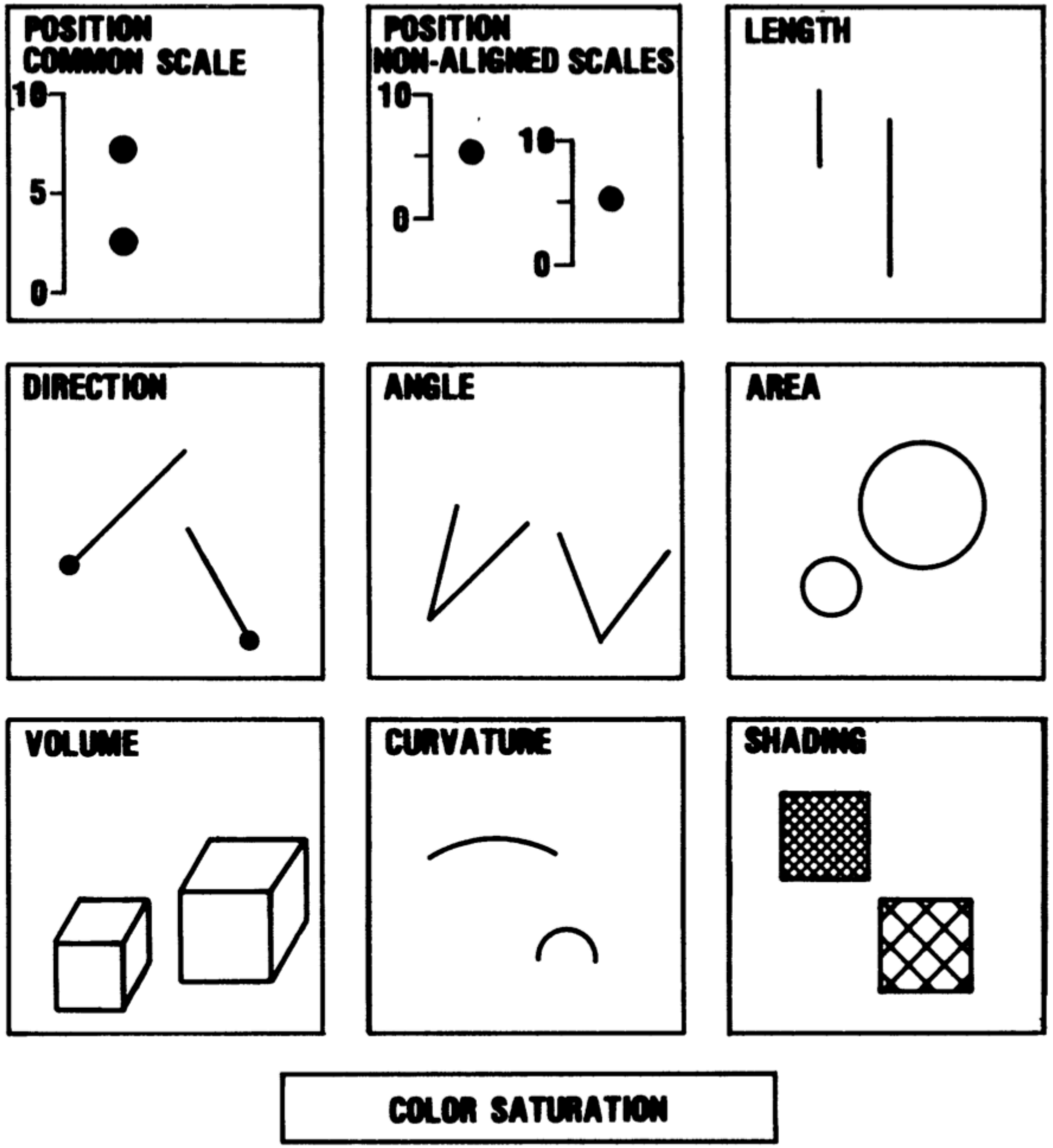


Figure 1. Elementary perceptual tasks.

William Cleveland and Robert McGill. "Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods." Journal of the American Statistical Association, 79(387). 1984.
http://info.slis.indiana.edu/~katy/S637-S11/cleveland84.pdf

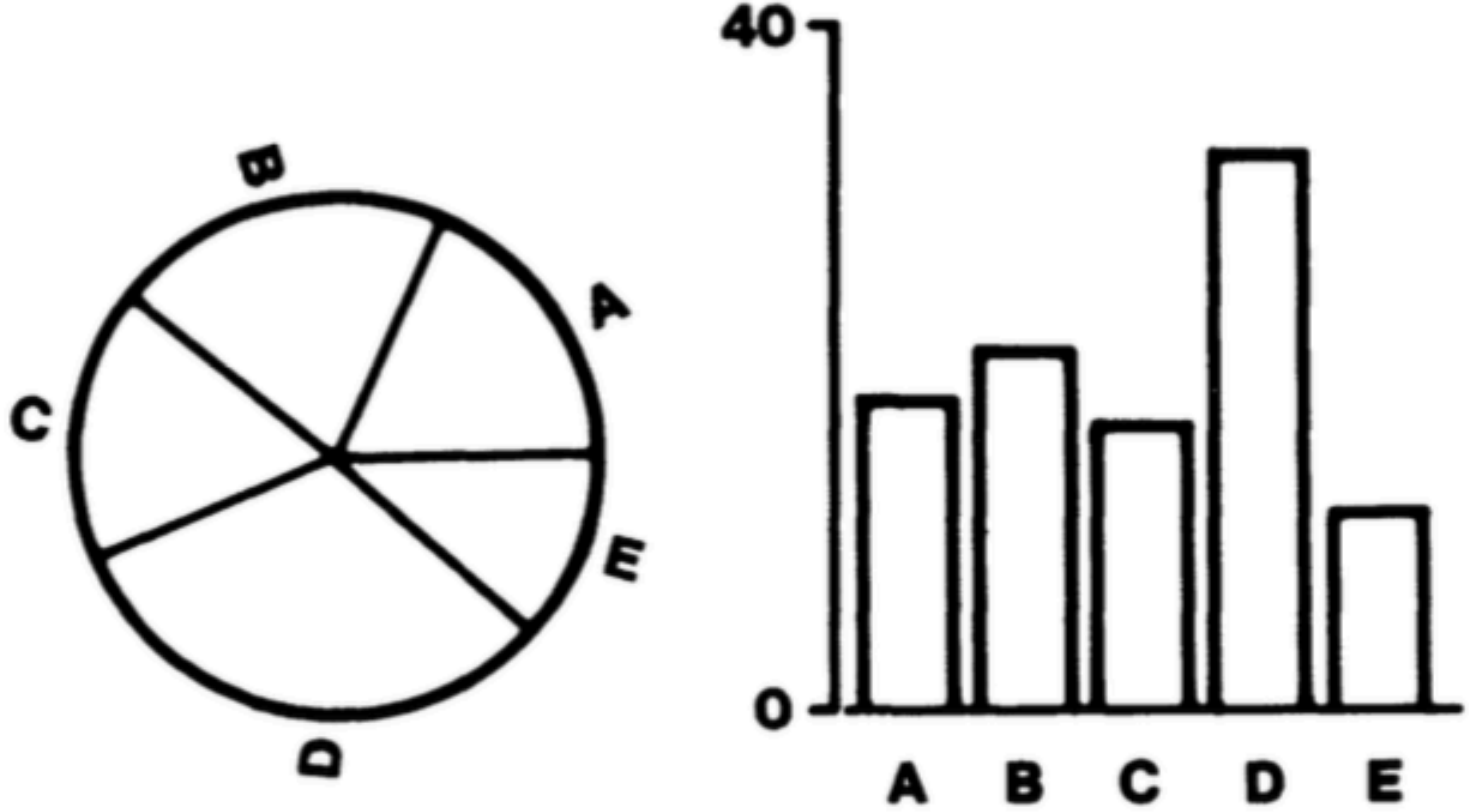


Figure 3. Graphs from position–angle experiment.

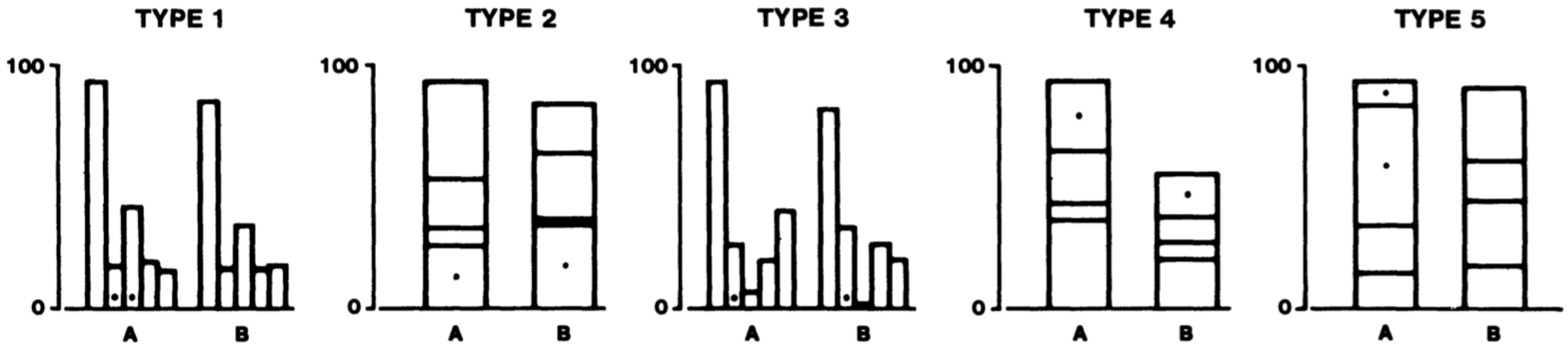
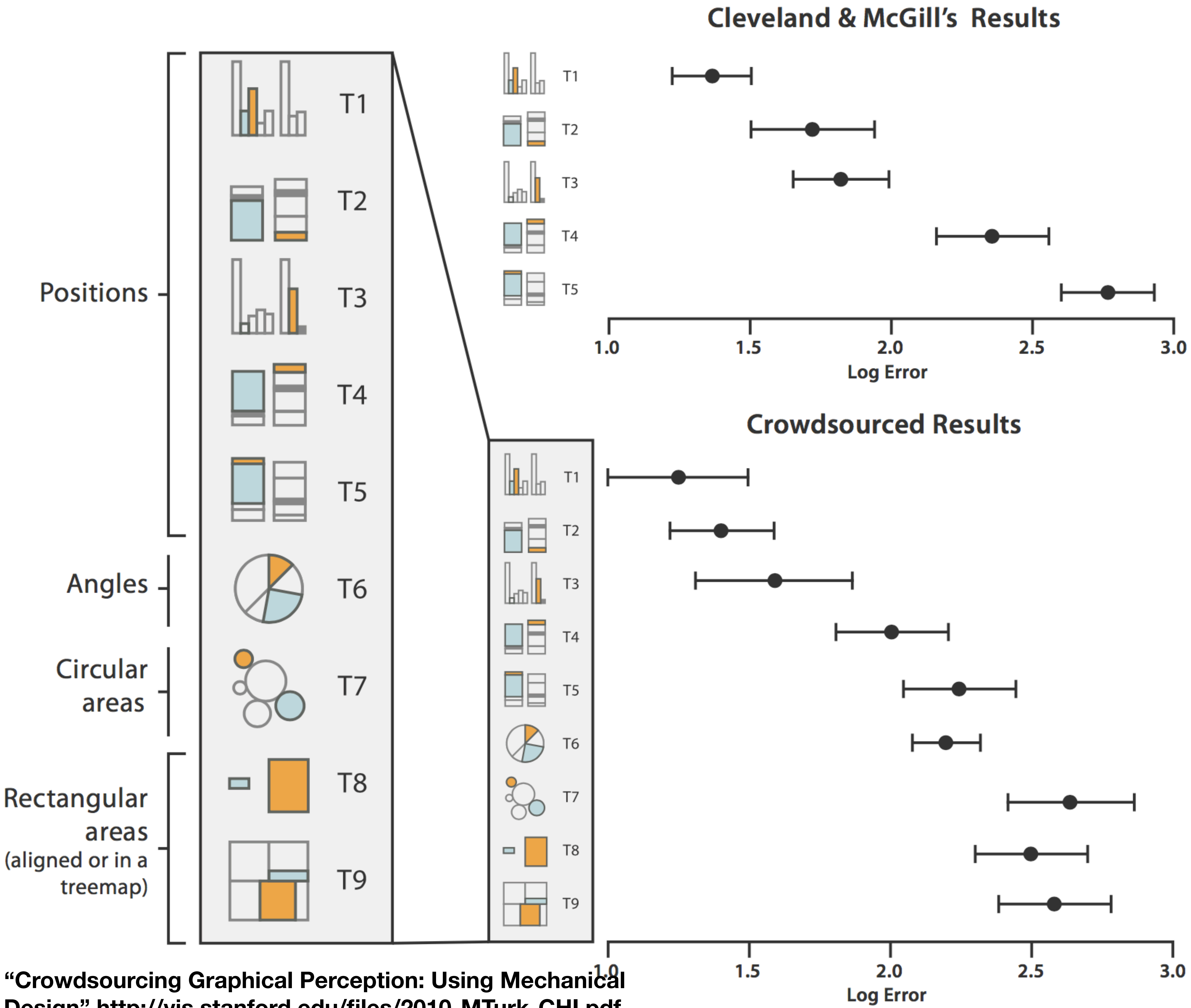


Figure 4. Graphs from position–length experiment.



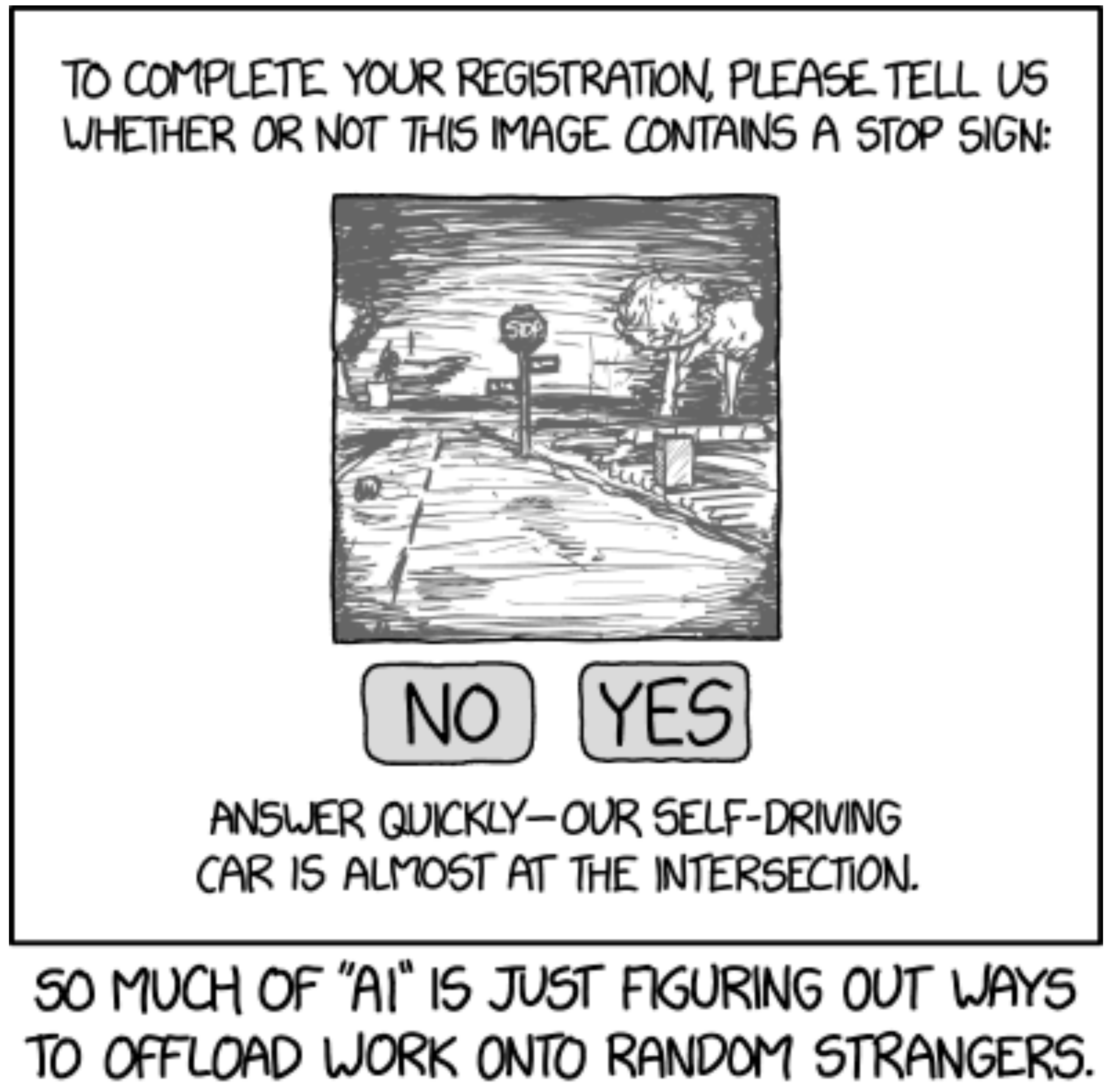
Jeff Heer and Mike Bostock. "Crowdsourcing Graphical Perception: Using Mechanical Turk to Assess Visualization Design" http://vis.stanford.edu/files/2010-MTurk-CHI.pdf

Aside— Amazon Mechanical Turk

- A platform for paying for and providing Human Intelligence Tasks (HITs)

- HITs are things that humans are good at, but computers are not

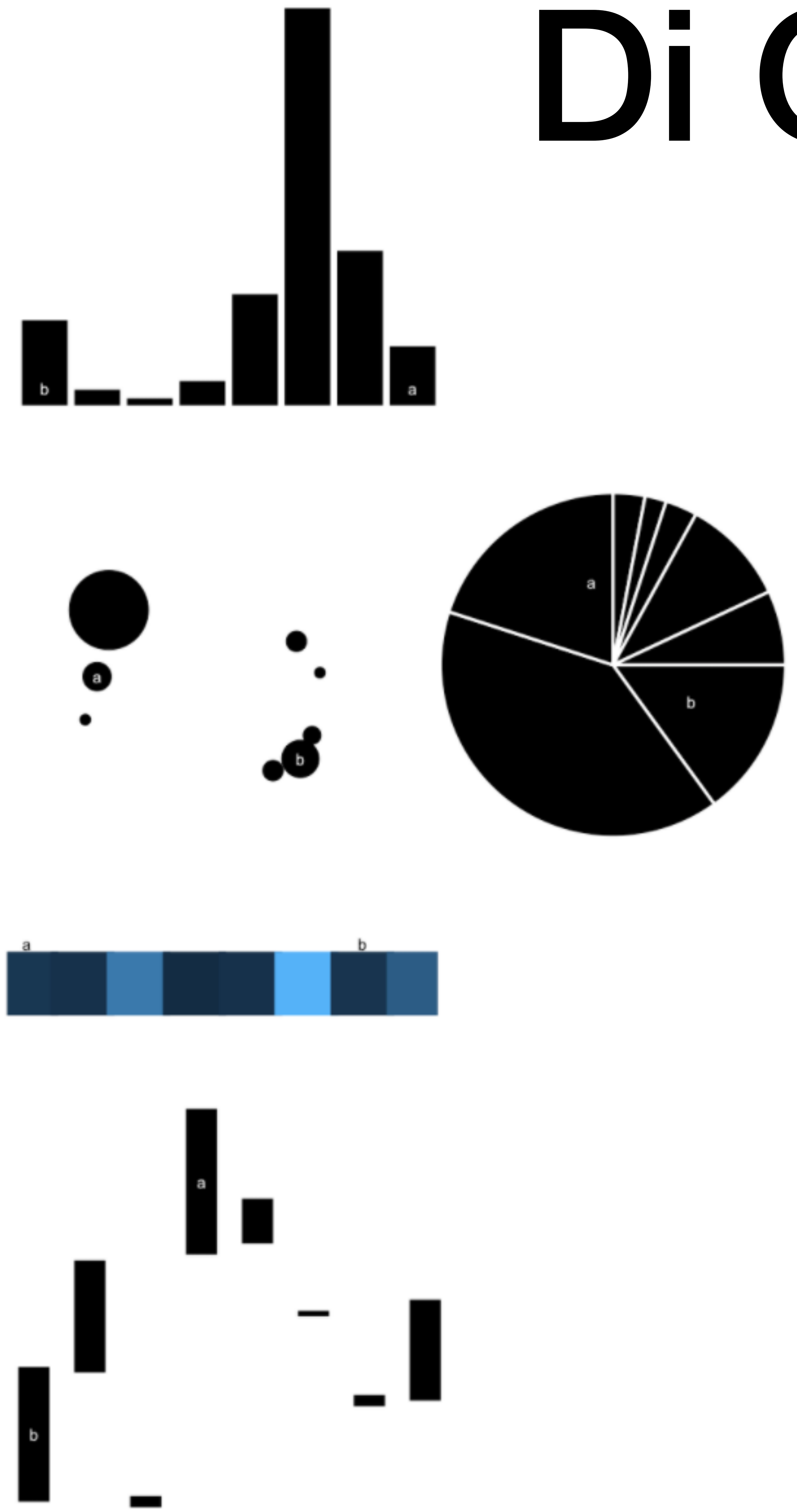
- Now, researchers use it to find study participants



https://www.xkcd.com/1897/

http://knowyourmeme.com/memes/puppy-or-bagel

Di Cook, 2016



This yields a hierarchy:

1. Position along a common scale
2. Angle
3. Area
4. Color hue
5. Position on identical but nonaligned scales

Di Cook. "Modern Crowd-Sourcing and Cleveland-McGill's graphical hierarchy." http://visiphilia.org/2016/08/03/CM-hierarchy 2016.

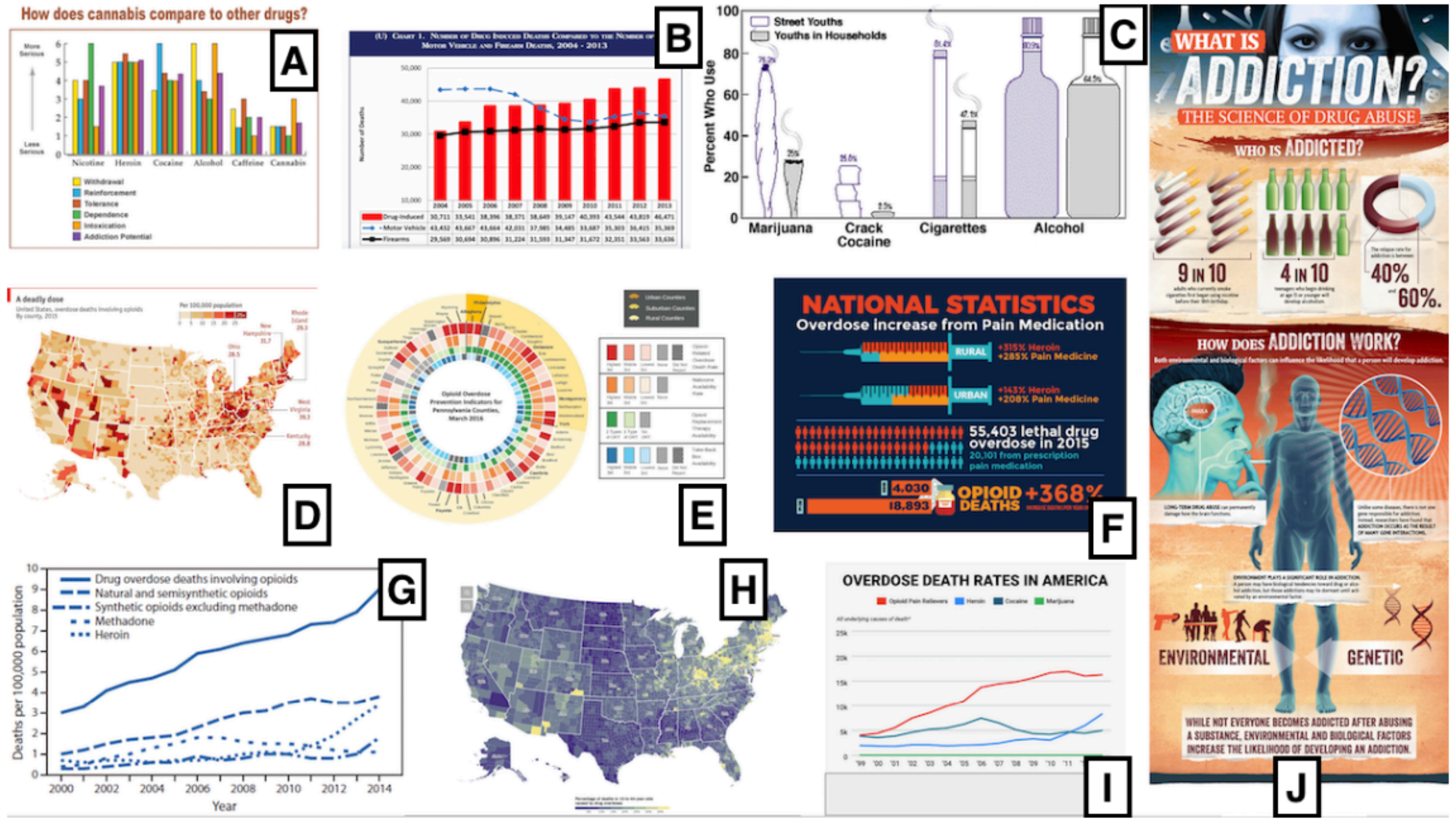


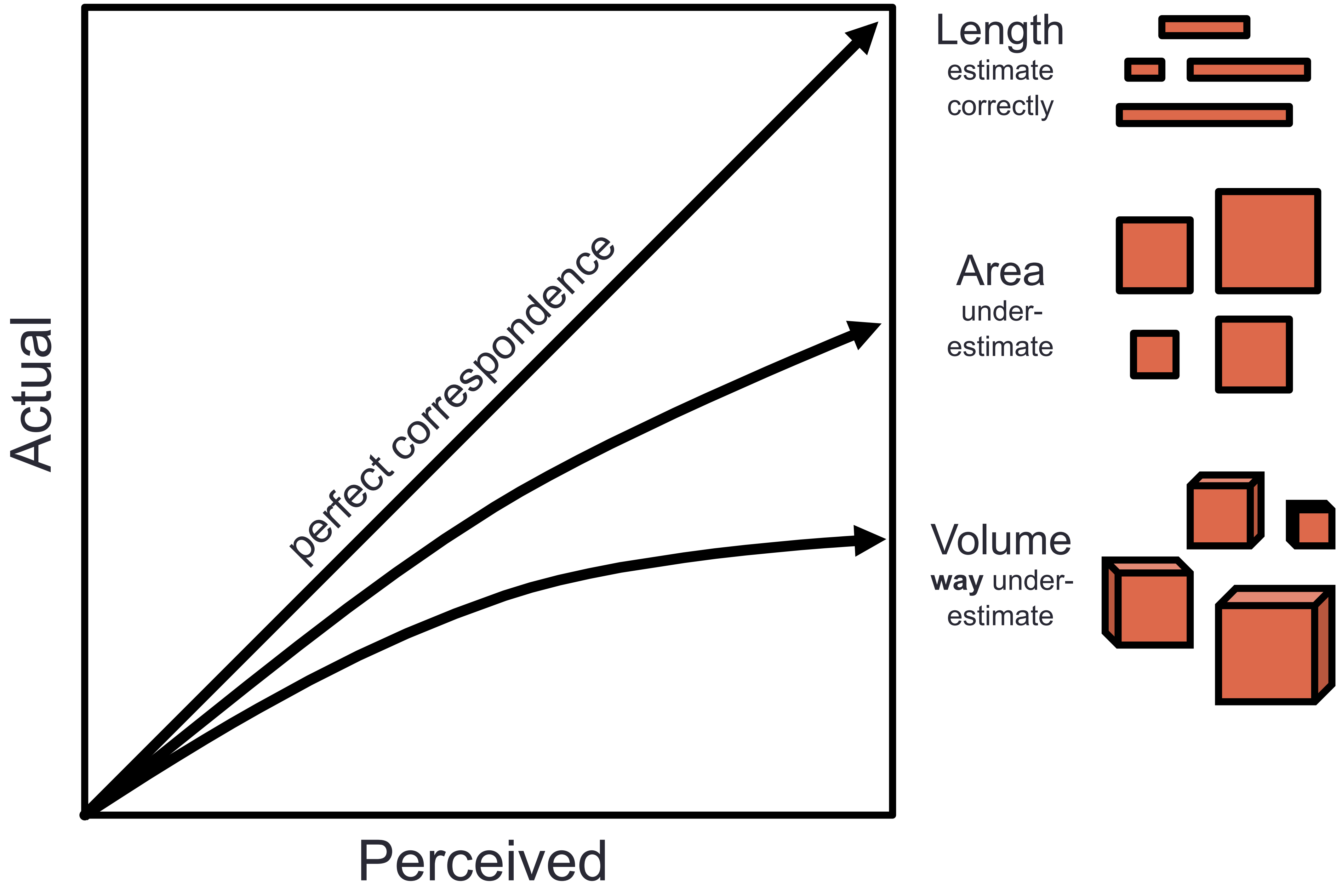
Figure 4: The graphs shown to participants. Each graph was presented on an independent sheet of paper

#	Topic	Type	Found on (Source)	Perceptions (Code Frequency)
A	Severity of cannabis vs. other drugs	Bar	National Institute on Drug Abuse (NIDA)	*Relatable*(4), *Informative*(2)
B	Comparison of drug, vehicle, and firearm deaths over time	Bar / Line	BreitBart	*Confusing*(2), *Informative*(2)
C	Drug use in 'street' youths vs. youths in households	Isotype	National Institute on Drug Abuse (NIDA)	*Simple*(3), *Not trusted*(3), *Clear*(2), *Relatable*(2)
D	Overdose deaths involving opioids by county	Map	The Economist	*Clear*(4), *Attractive*(3), *Confusing*(3), *Cluttered*(3), *Simple*(3), *Relatable*(3)
E	Opioid overdose prevention indicators for PA counties	Heat map	Drexel University	*Cluttered*(8), *Confusing*(8), *Clear*(4), *Colorful*(4), *Informative*(4)
F	Overdose increase from pain medication	Infographic	AgriMed (Medical Cannabis)	*Attractive*(5), *Confusing*(5), *Simple*(4)
G	Drug overdoses over time	Line	National Vital Statistics System (NVSS) - CDC	*Confusing*(6), *Simple*(3), *Cluttered*(2), *Intriguing*(2)
H	Overdose deaths by country (15-to-44-year olds)	Map	The New York Times	*Clear*(4), *Colorful*(3), *Relatable*(3), *Simple*(3)
I	Overdose death rates over time	Line	Business Insider	*Colorful*(16), *Attractive*(6), *Clear*(6), *Simple*(5)
J	The science of drug abuse	Infographic	Alternatives in Treatment (Rehab Center)	*Informative*(4), *Attractive*(3), *Relatable*(3)

Table 1: Graphs were chosen for representing diverse styles and sources. Codes are derived from interviews. When interpreting frequencies, recall that many participants chose to only comment on a select group of graphs

Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural Pennsylvania." Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019.

"Apparent" magnitude



via Jordan Crouser and http://makingmaps.net/2007/08/28/perceptual-scaling-of-map-symbols/

Weber's law

"Simple differential sensitivity is inversely proportional to the size of the components of the difference; relative differential sensitivity remains the same regardless of size."

$$dp = k\frac{dS}{S} \qquad (1)$$

https://en.wikipedia.org/wiki/Weber%E2%80%93Fechner_law

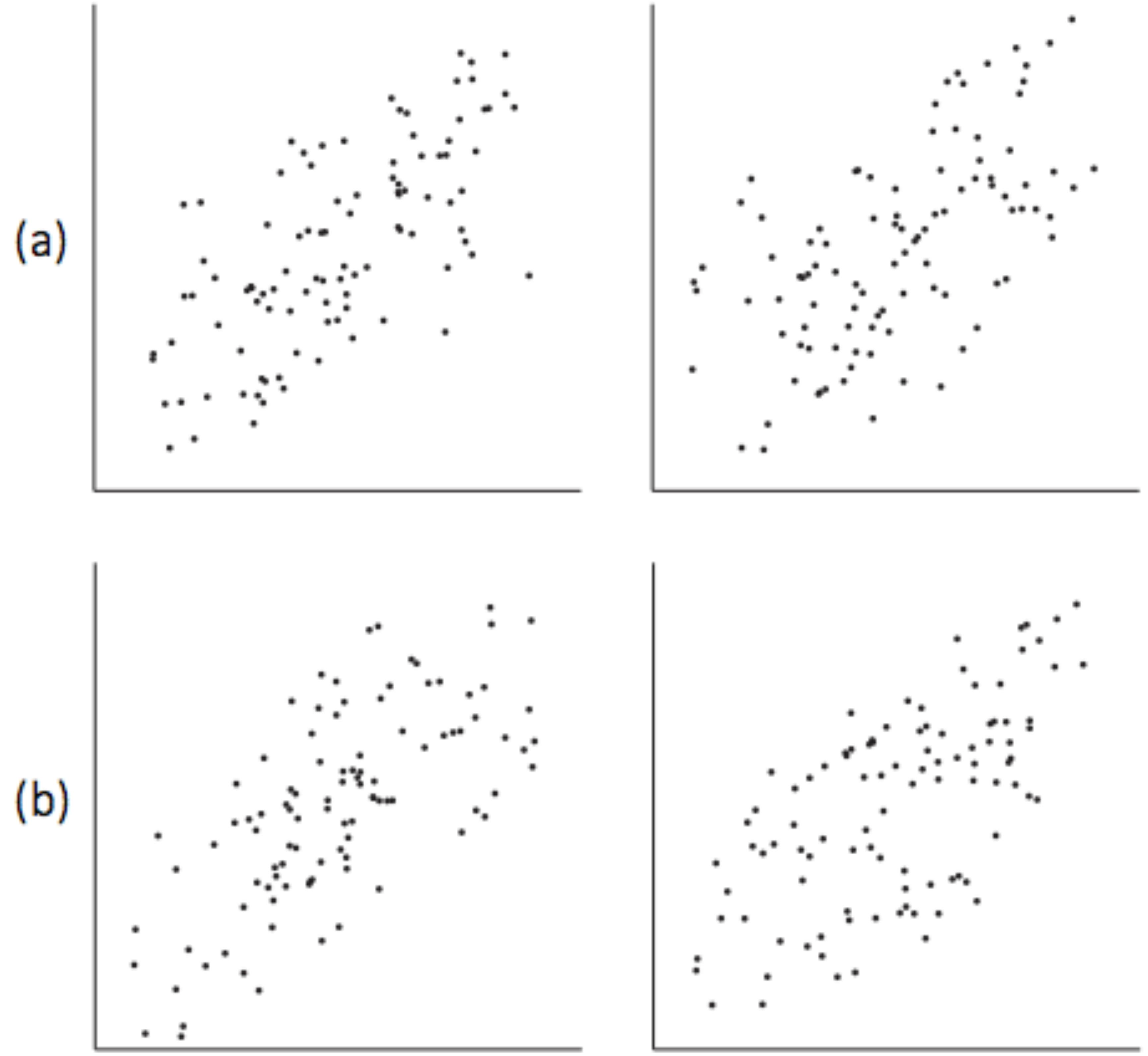
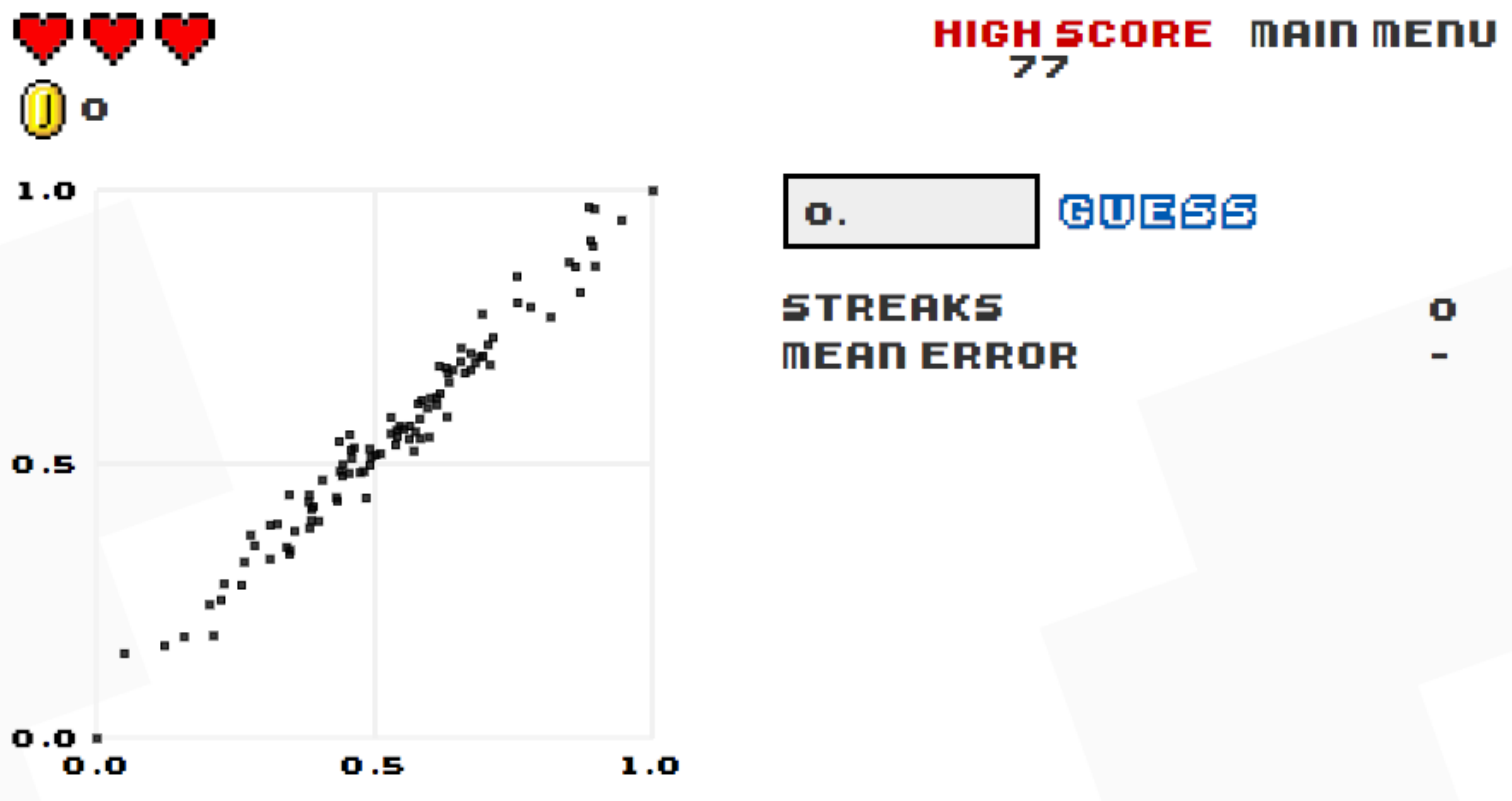


Fig. 1: a) A sample starting comparison from the experiment: $r = 0.7$ on the left and $r = 0.6$ on the right. Participants were asked to choose which of the two appeared to be more highly correlated. b) The staircase procedure hones in on the just-noticeable difference by gradually making comparisons more difficult: $r = 0.7$ on the left and $r = 0.65$ on the right.

Lane Harrison, Fuming Yang, Steven Franconeri, Remco Chang. “Ranking Visualizations of Correlation Using Weber’s Law” 2014. http://vis.cs.ucdavis.edu/vis2014papers/TVCG/papers/1943_20tvcg12-harrison-2346979.pdf



Guess the Correlation. http://guessthecorrelation.com/

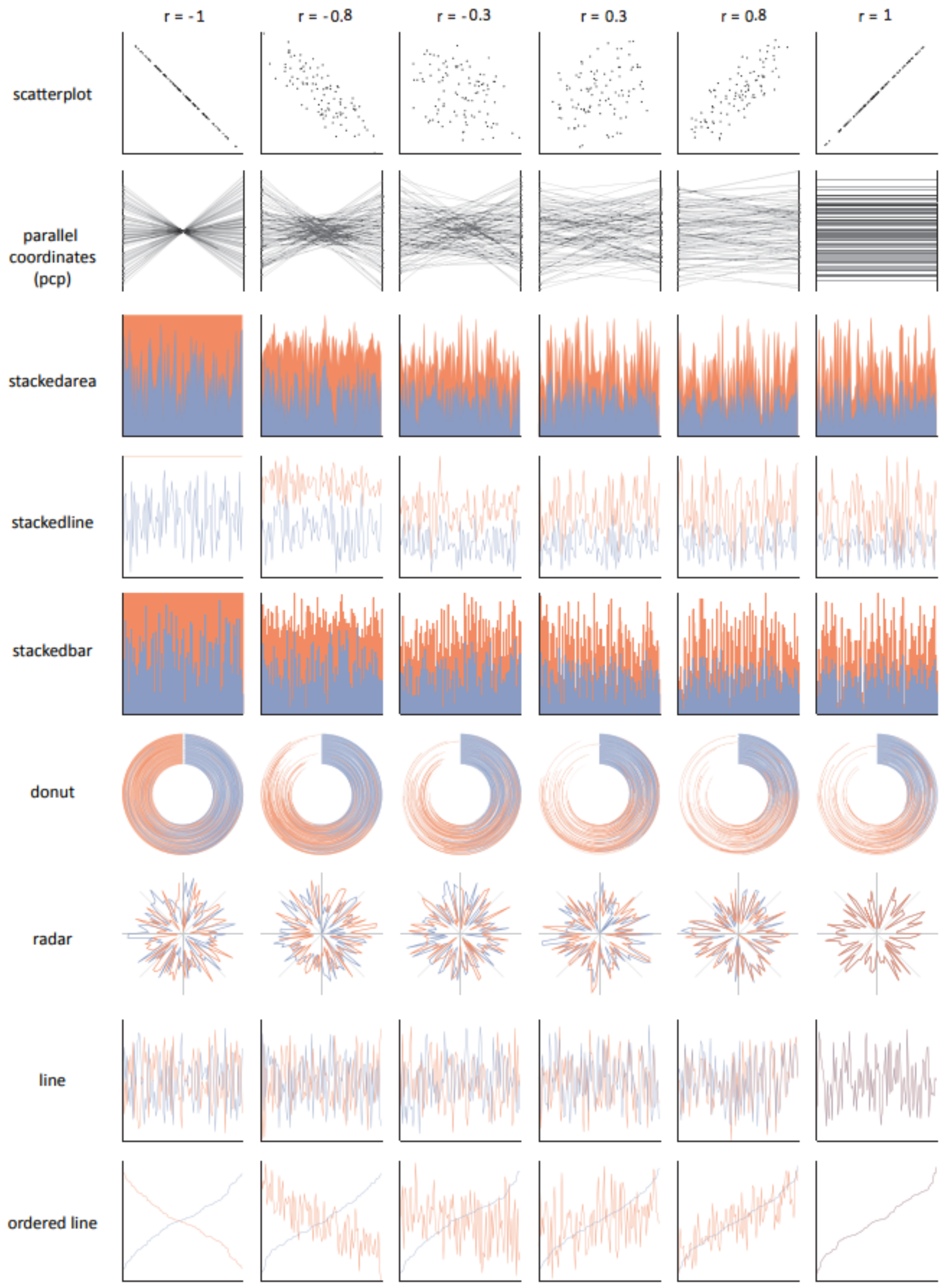
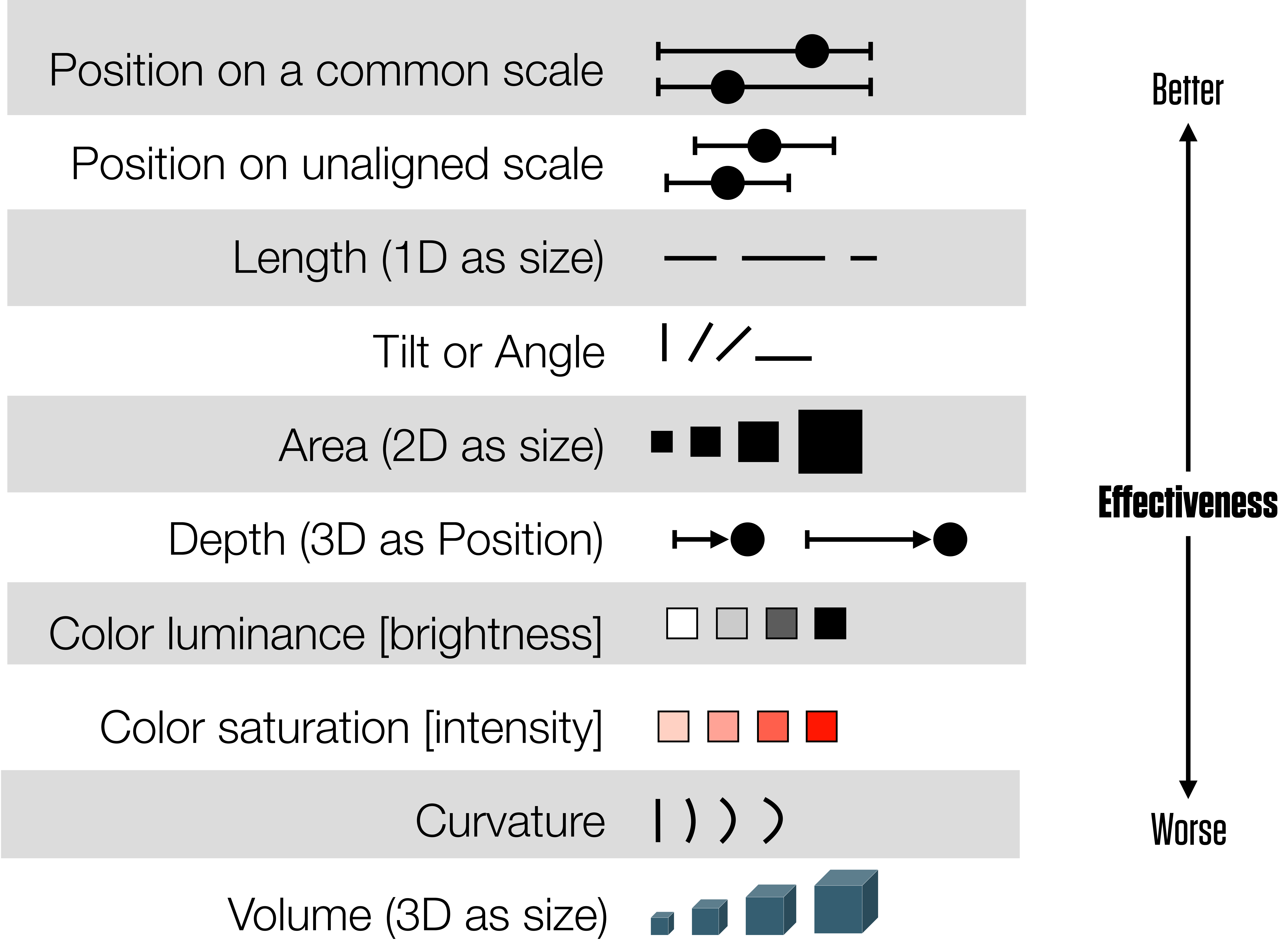


Fig. 3: The nine visualizations tested in our experiment, at several correlation values. Because many of these visualizations appear differently when depicting negatively versus positively correlated data, we test both in our experiment. The visualizations were larger (300×300 pixels) when presented to participants. The color scheme used is colorblind-safe, chosen from ColorBrewer.

Lane Harrison, Fuming Yang, Steven Franconeri, Remco Chang. "Ranking Visualizations of Correlation Using Weber's Law" 2014. http://vis.cs.ucdavis.edu/vis2014papers/TVCG/papers/1943_20tvcg12-harrison-2346979.pdf



See e.g. Munzer (2014)

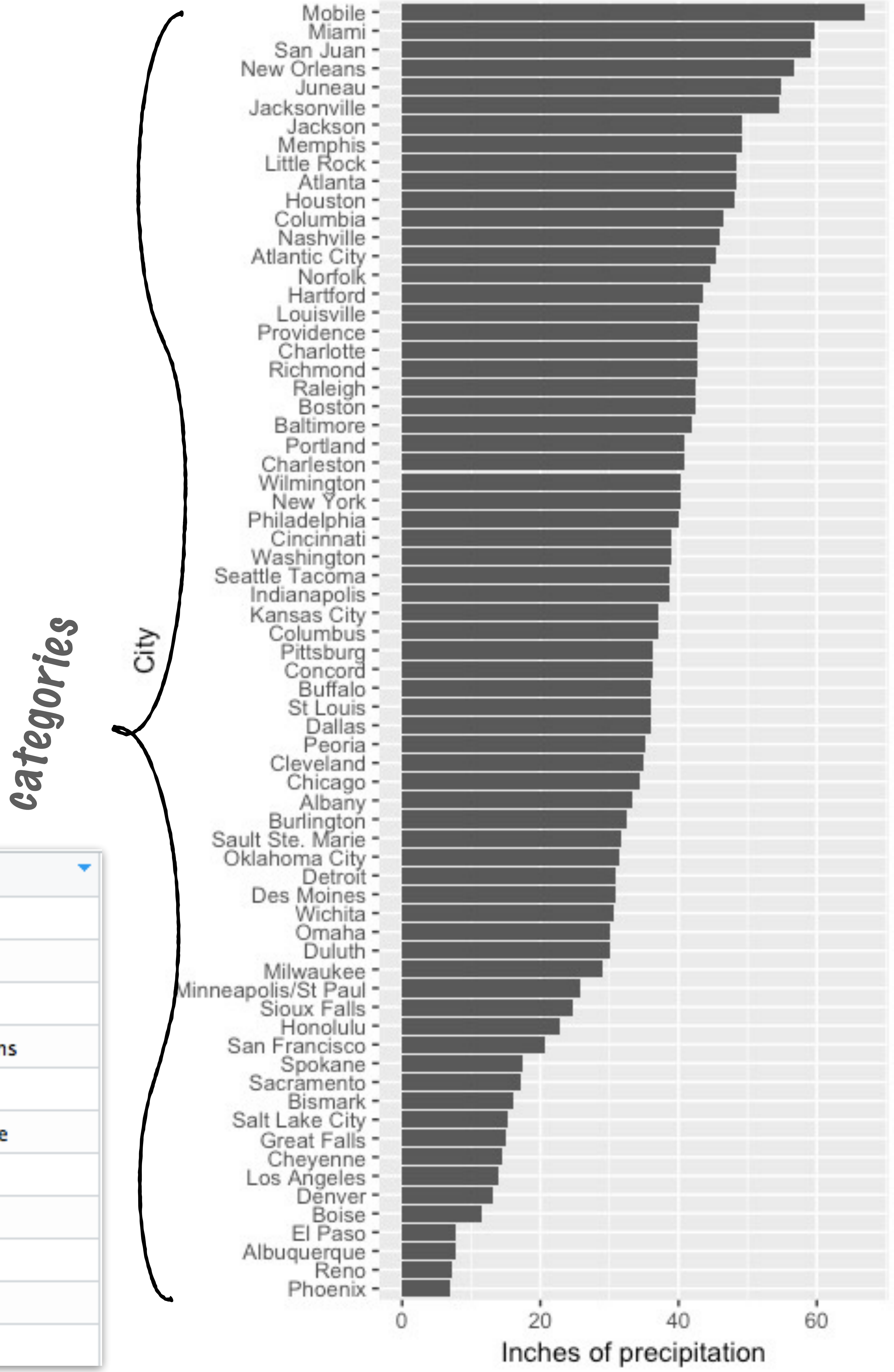
via Kieran Healy's [A Practical Introduction to Data Visualization with ggplot2]

Bar charts and histograms

Bar charts

- A way to visualize one categorical variable
- Uses bars to show comparisons between categories
- Mapping: value of variable to height (or length) of bar

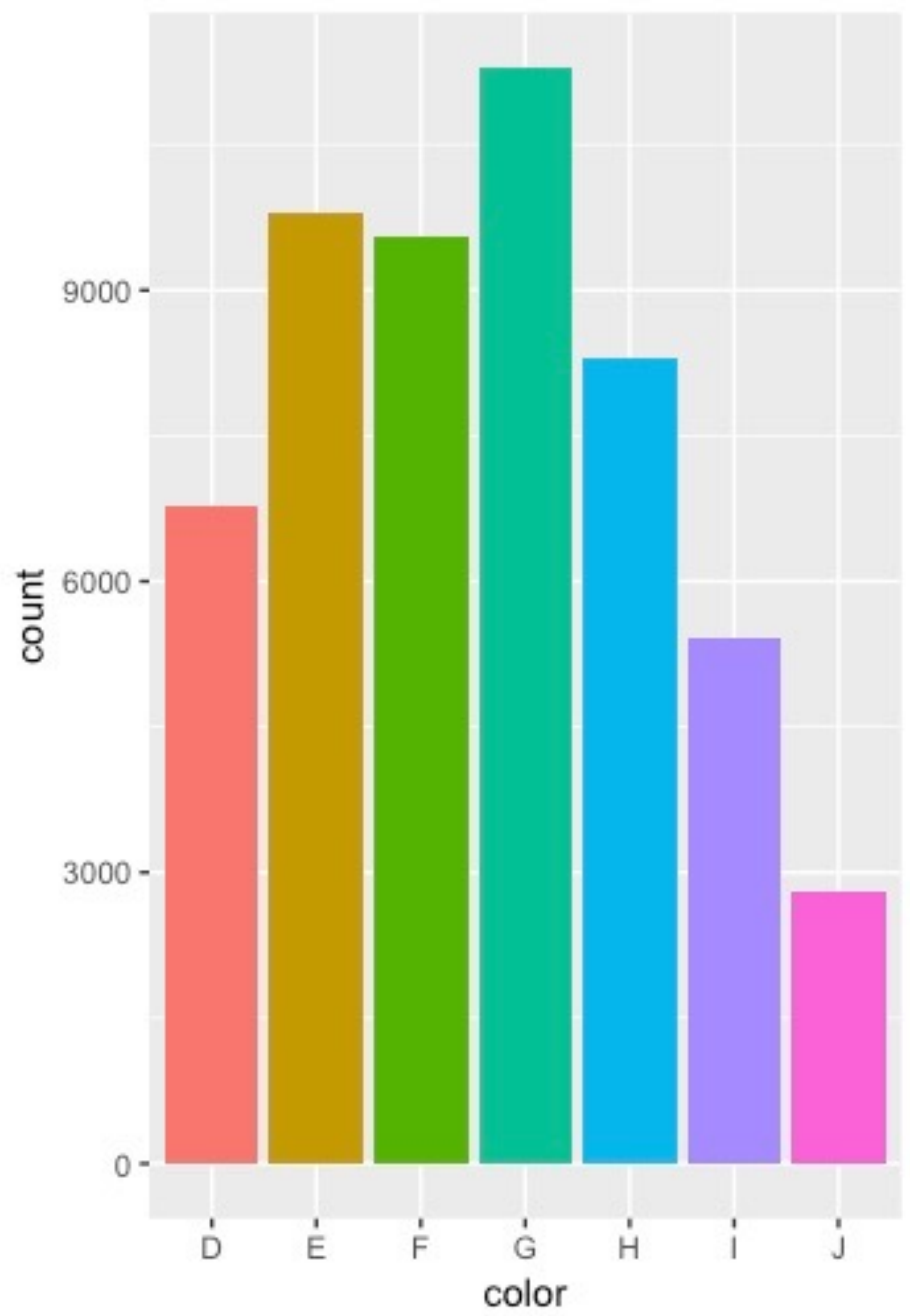
precip	City
67.0	Mobile
59.8	Miami
59.2	San Juan
56.8	New Orleans
54.7	Juneau
54.5	Jacksonville
49.2	Jackson
49.1	Memphis
48.5	Little Rock
48.3	Atlanta
48.2	Houston



Bar charts

- Sometimes, it’s necessary to aggregate first

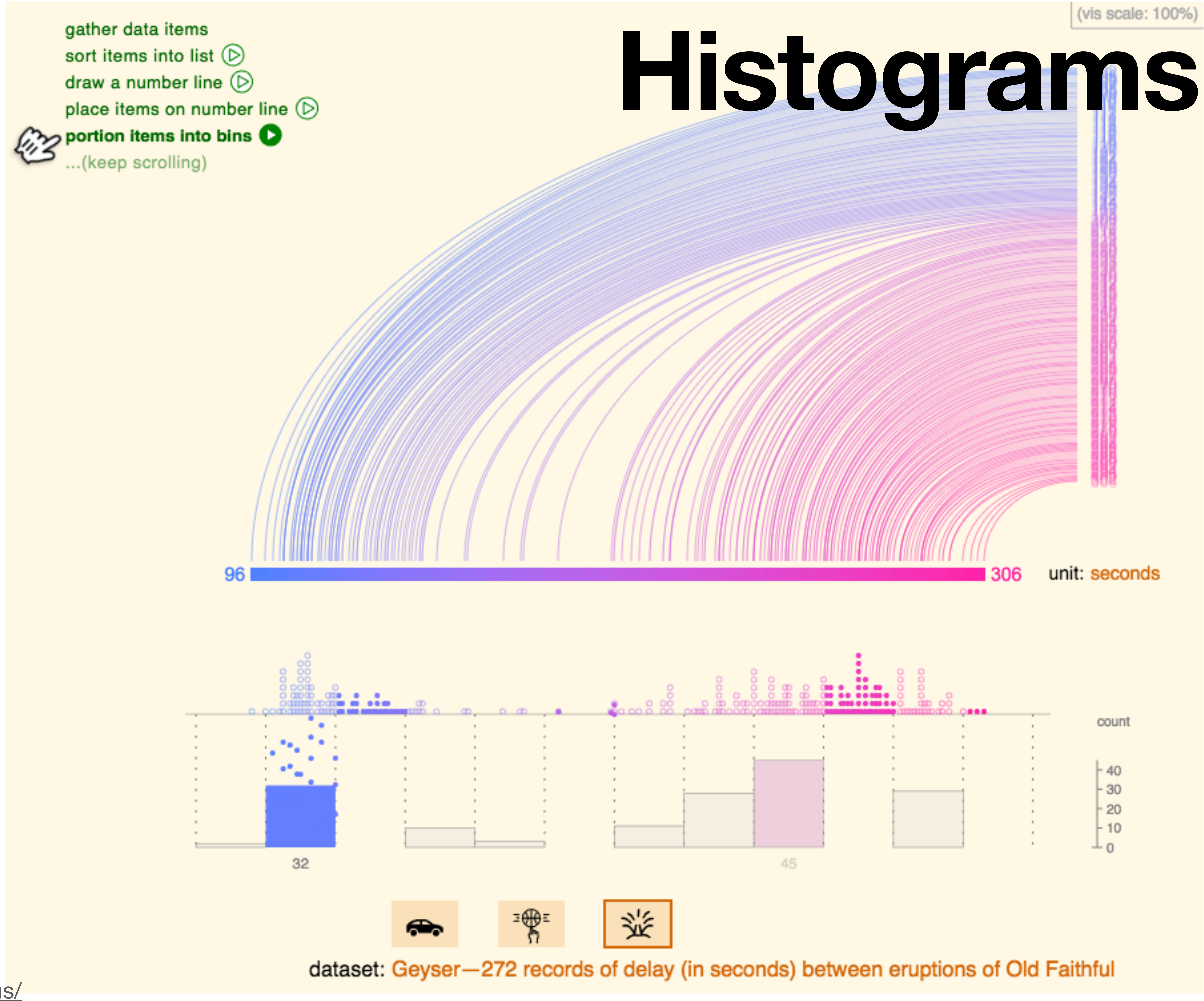
carat	cut	color	clarity	depth	table	price	x	y	z
0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
0.24	Very Good	J	VVS2	62.8	57.0	336	3.94	3.96	2.48
0.24	Very Good	I	VVS1	62.3	57.0	336	3.95	3.98	2.47
0.26	Very Good	H	SI1	61.9	55.0	337	4.07	4.11	2.53
0.22	Fair	E	VS2	65.1	61.0	337	3.87	3.78	2.49
0.23	Very Good	H	VS1	59.4	61.0	338	4.00	4.05	2.39
0.30	Good	J	SI1	64.0	55.0	339	4.25	4.28	2.73



categories

color	total
D	6775
E	9797
F	9542
G	11292
H	8304
I	5422
J	2808

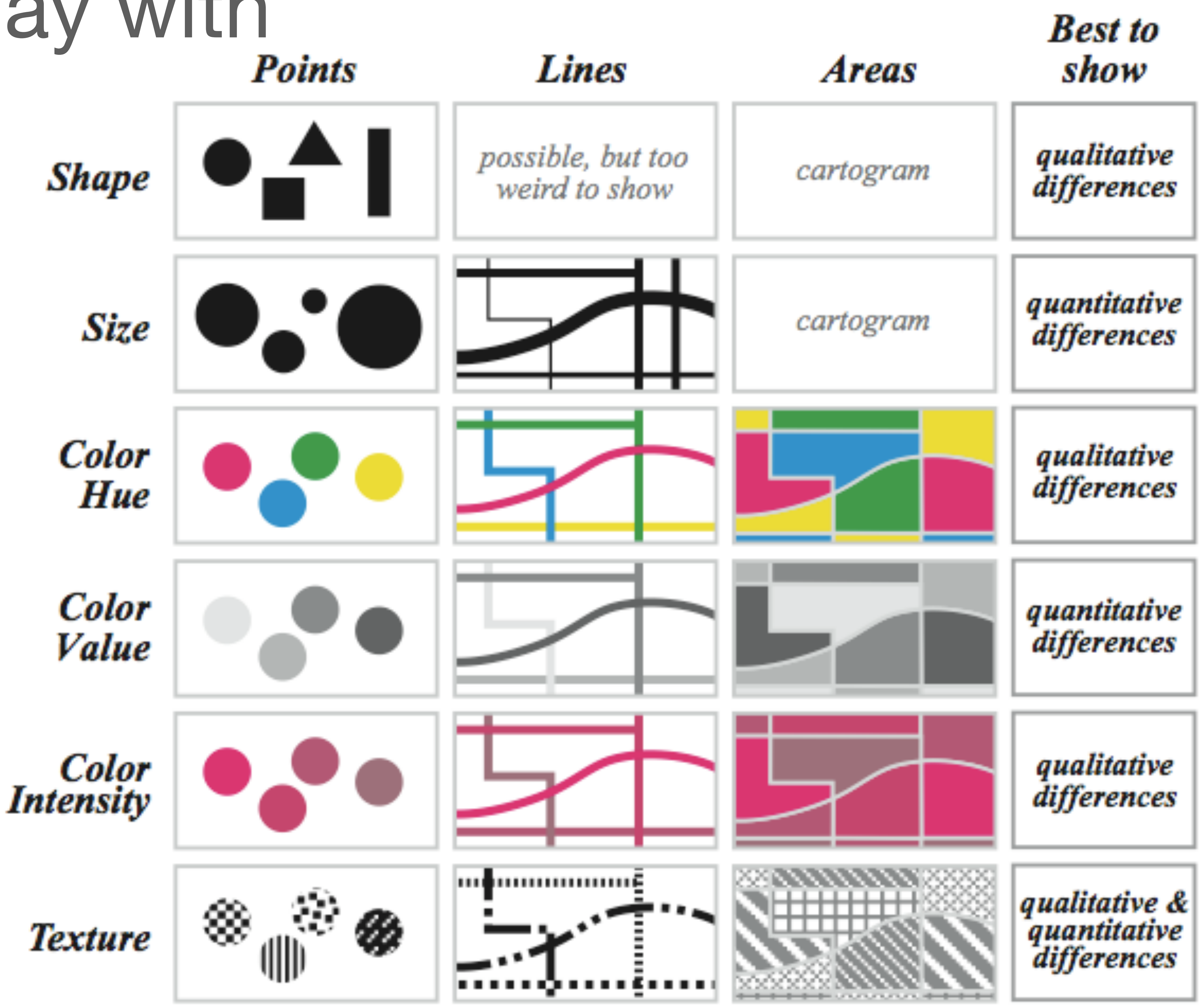
Histograms



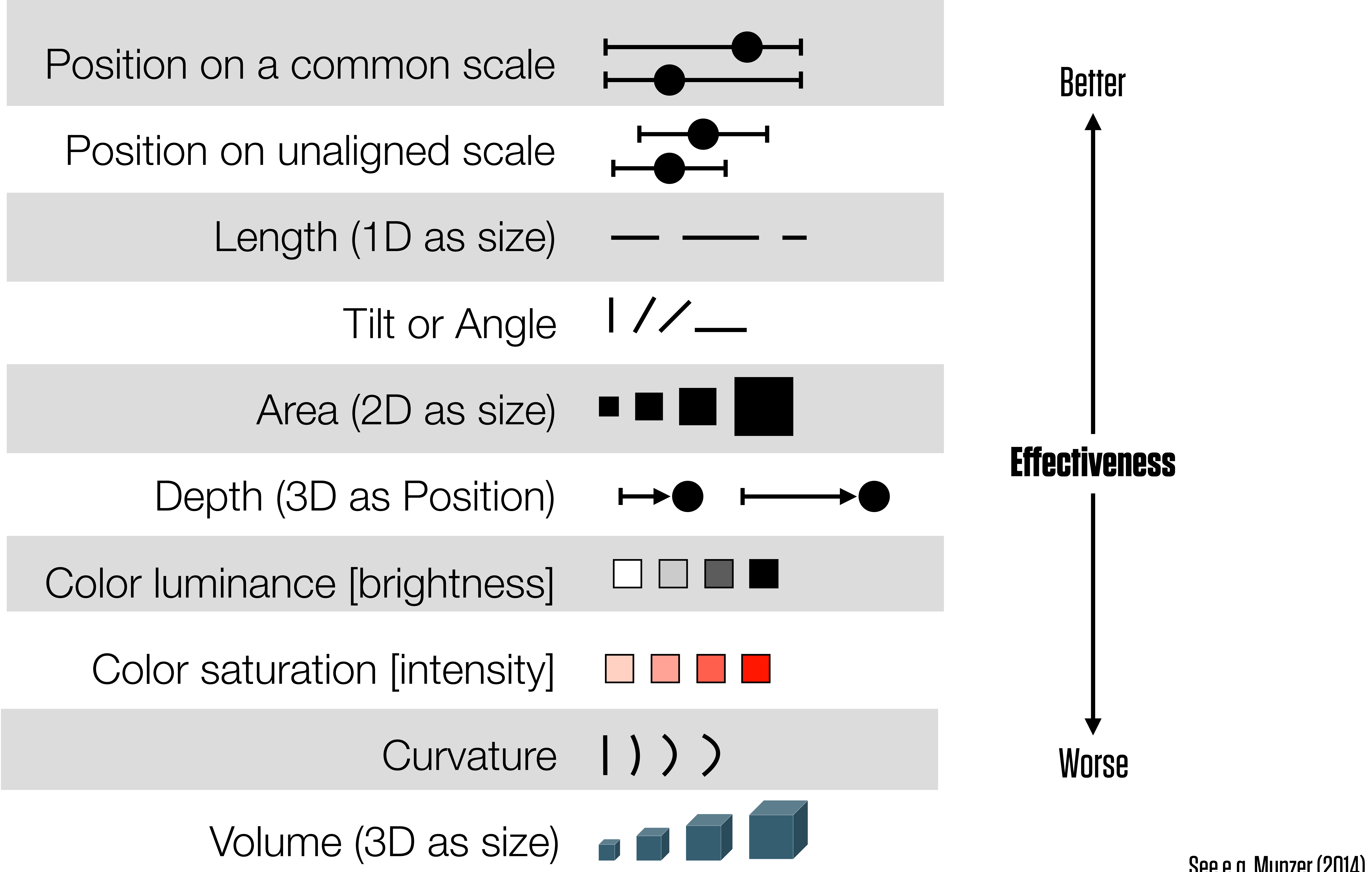
https://tinlizzie.org/histograms/

Flashback

Some (all?) of the visual attributes we have to play with



Jacques Bertin, *Semiology of Graphics*. 1967



via Kieran Healy's [A Practical Introduction to Data Visualization with ggplot2]