3 VISUAL VARIABLES

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VISUAL VARIABLES

SCIENCE

Vol. 103, No. 2684 Friday, June 7, 1946

On the Theory of Scales of Measurement

S. S. Stevens

Director, Psycho-Acoustic Laboratory, Harvard University

FOR SEVEN YEARS A COMMITTEE of the British Association for the Advancement of Science debated the problem of measurement. Appointed in 1932 to represent Section A (Mathematical and Physical Sciences) and Section J (Psychology), the committee was instructed to consider and report upon the possibility of "quantitative estimates of sensory events"—meaning simply: Is it possible to measure human sensation? Deliberation led only to disagreement, mainly about what is meant by the term measurement. An interim report in 1938 found one member complaining that his colleagues by the formal (mathematical) properties of the scales. Furthermore—and this is of great concern to several of the sciences—the statistical manipulations that can legitimately be applied to empirical data depend upon the type of scale against which the data are ordered.

A Classification of Scales of Measurement

Paraphrasing N. R. Campbell (Final Report, p. 340), we may say that measurement, in the broadest sense, is defined as the assignment of numerals to objects or events according to rules. The fact that numerals can be assigned under different rules leads

DATA TYPES

- Nominal (N)
  - Equality relation
  - Apples, bananas, pears,…
- Ordinal (O)
  - Ordering relation
  - Small, medium, large, darker, dark, light,…
- Quantitative (Q)
  - Arithmetic relations
  - 10m, 32 degree, 2 bars,…
- Q-Interval (no reference point)
  - Dates, Location
  - Not directly comparable
  - Distances: A is 3 degree hotter than B
- Q-Ratio (reference point)
  - Length, mass
  - Proportions: A is twice as large as B

DATA TYPES OPERATORS

- Nominal
  - ≠, =
- Ordinal
  - ≠, =, >, <
- Quantitative Interval
  - ≠, =, >, <, +, -
- Quantitative Ratio
  - ≠, =, >, <, +, -, ×, ÷

FROM DATA TO CONCEPTUAL MODEL

- Data Model: low-level representation of data and operations
- Conceptual Model: mental and semantic construction

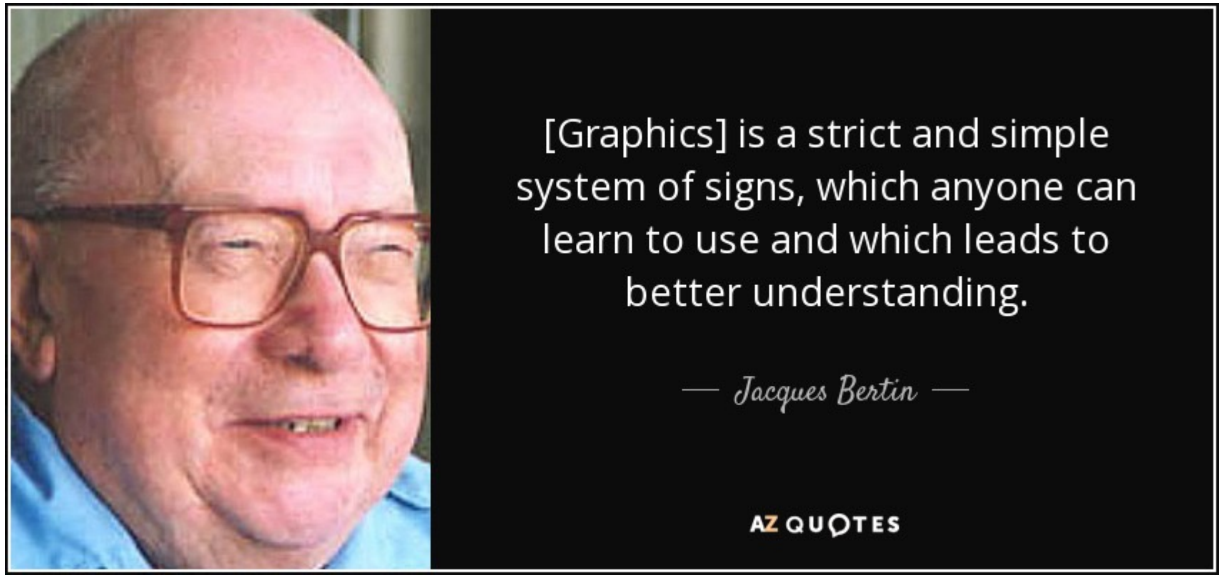
Data	Concept
1D number	Temperature
2D numbers	Geographic Coordinate
3D numbers	Spatio-temporal position

FROM DATA TO CONCEPTUAL MODEL

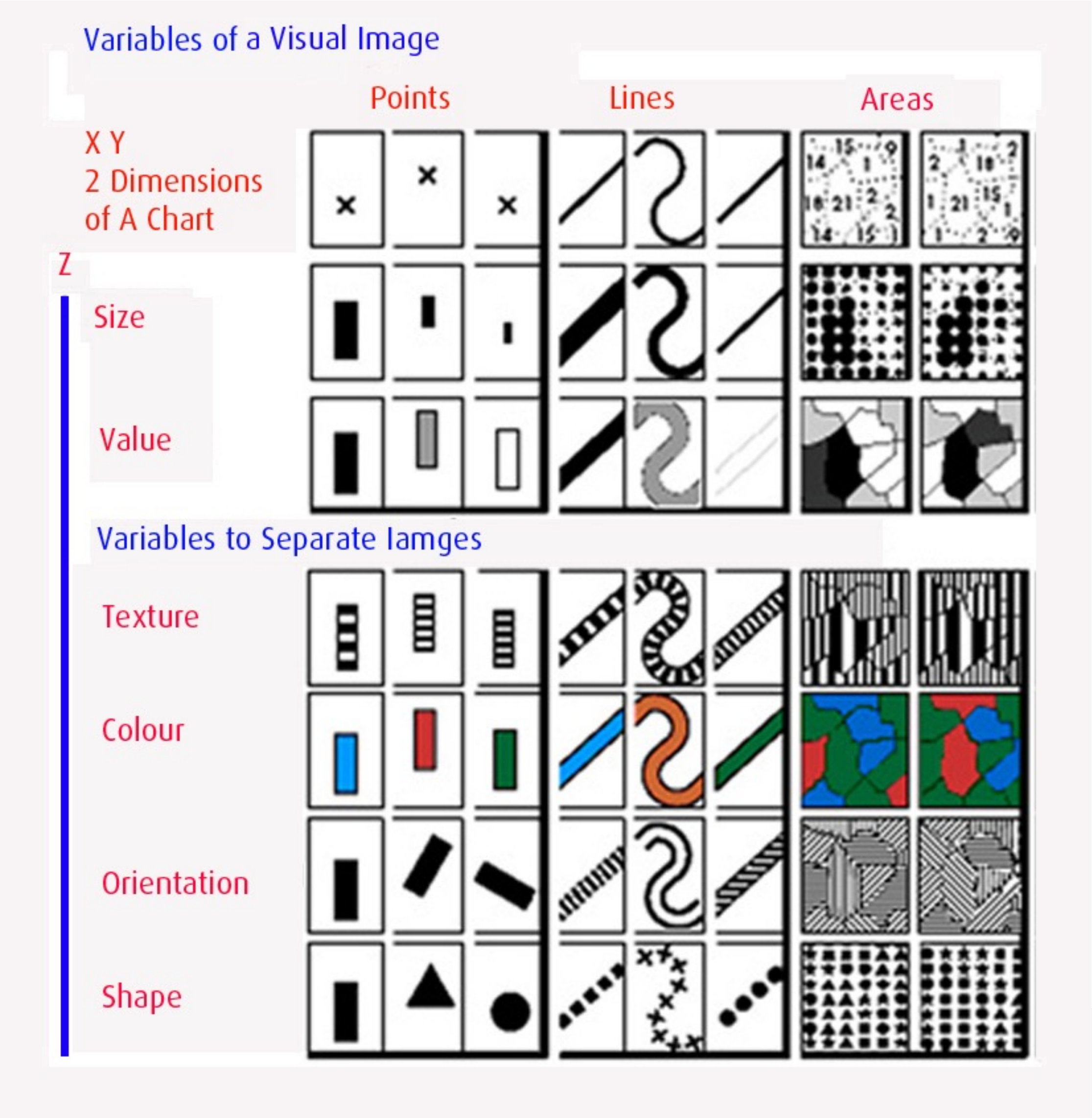
- From data model…
  - 70.8, 27.2, -10.2,…
- … using conceptual model …
  - Temperature
- … to data type
  - Continuous variation
  - Warm, hot, cold
  - Burned vs not burned

VISUAL VARIABLES

- Jacques Bertin (1918-2010), cartographer
- Theoretical principles of visual encodings
- Semiology of Graphics (1967)

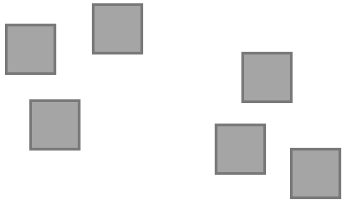


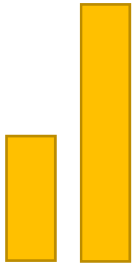
BERTIN'S VISUAL VARIABLES



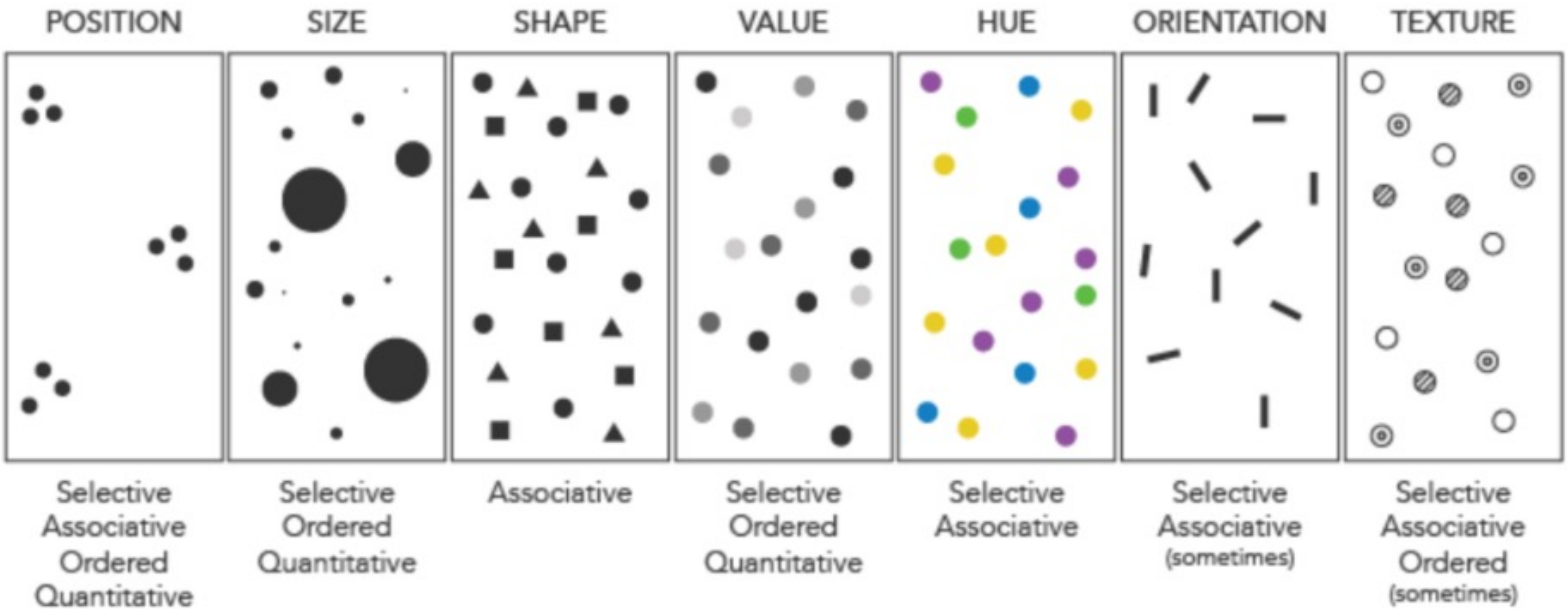
CHARACTERISTICS OF VISUAL VARIABLES

- Selective
  - May I distinguish a symbol from the others
- Associative
  - May I identify groups?
- Quantitative
  - May I quantify the difference of two values?
- Order
  - May I idenfiy an ordering?





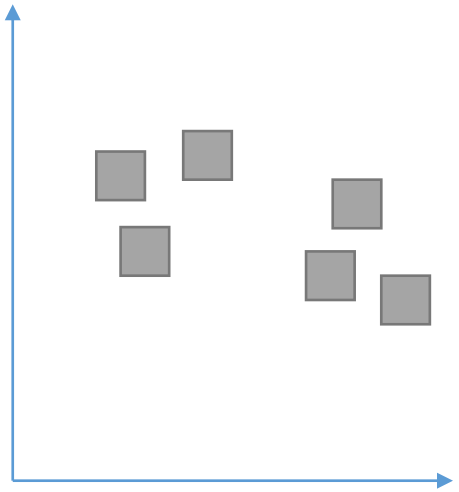
CHARACTERISTICS OF VISUAL VARIABLES



Source: https://www.axismaps.com/guide/general/visual-variables/

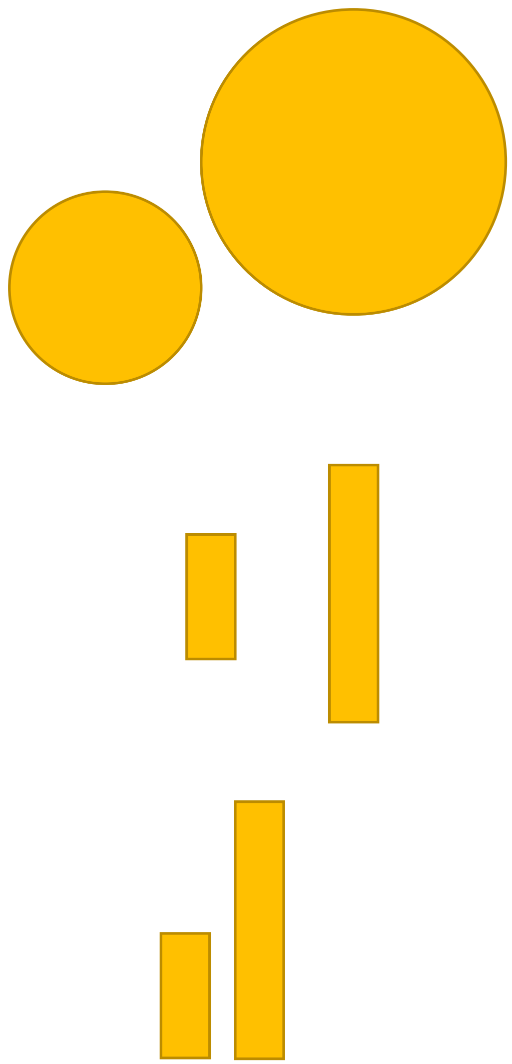
VV: POSITION

- Strongest visual variable
- Compatible for all data types
- Cons:
  - Not always applicable (e.g. nD data)
  - Cluttering



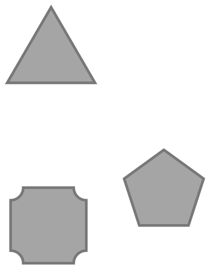
VV: SIZE AND LENGTH

- Easy to compare dimensions
- Grouping
- Estimate differences
  - Quantitative encoding
  - Changes in lengths
  - Worse for change in area



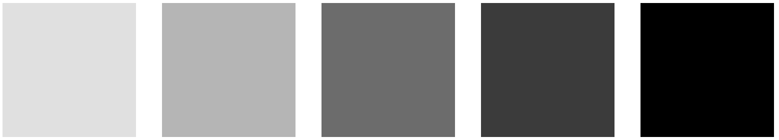
VV: SHAPES

- Strong for nominal encoding
- No ordering
- No grouping



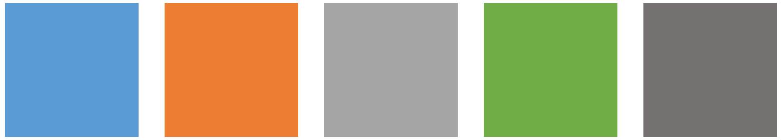
VV: VALUE (INTENSITY)

- Quantitative representation (when size and length are used)
- Limited number of shades
- Support grouping



VV: COLOR (TINT)

- Good for qualitative data
- Limited number of classes (!!!)
- Not good for quantitative data
- Be careful!!



BERTIN VISUAL VARIABLES

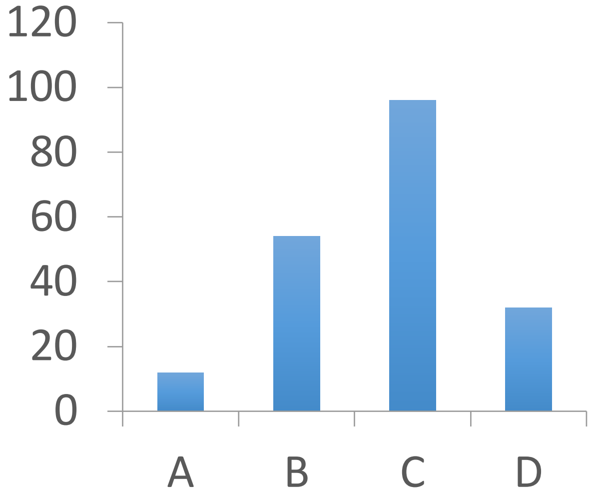
	Nominal	Ordinal	Quantitative
Position	✓	✓	✓
Size	✓	✓	~
Value (intensity)	✓	✓	~
Texture	✓	~	X
Color	✓	X	X
Orientation	✓	X	X
Shape	✓	X	X

VISUAL ENCODING/DECODING

- A graph encode a set of information as a set of graphical attributes
- The observer have to decode the graphical attributes to extract the original information

12 54 96 32
55 68 97 11
01 58 66 15

encode



decode

C>B>D>A

C=100
B=60
A=10
D=38

4 RANKING OF VISUAL VARIABLES

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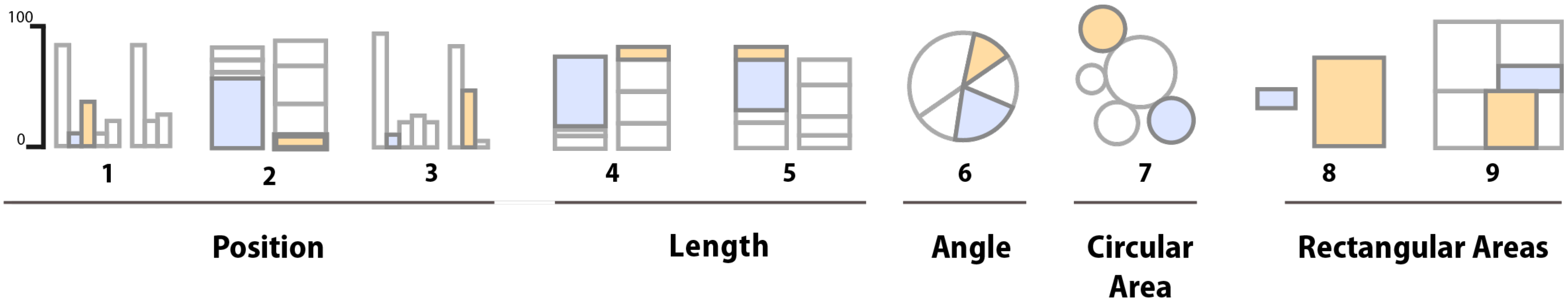
CLEVELAND MCGILL [1984]



EFFECTIVENESS OF VV [MACKINLAY 86]

Quantitative

- Position
- Length
- Angle
- Slope
- Area (size)
- Volume
- Density (value)
- Color sat
- Color Hue
- Texture
- Shape

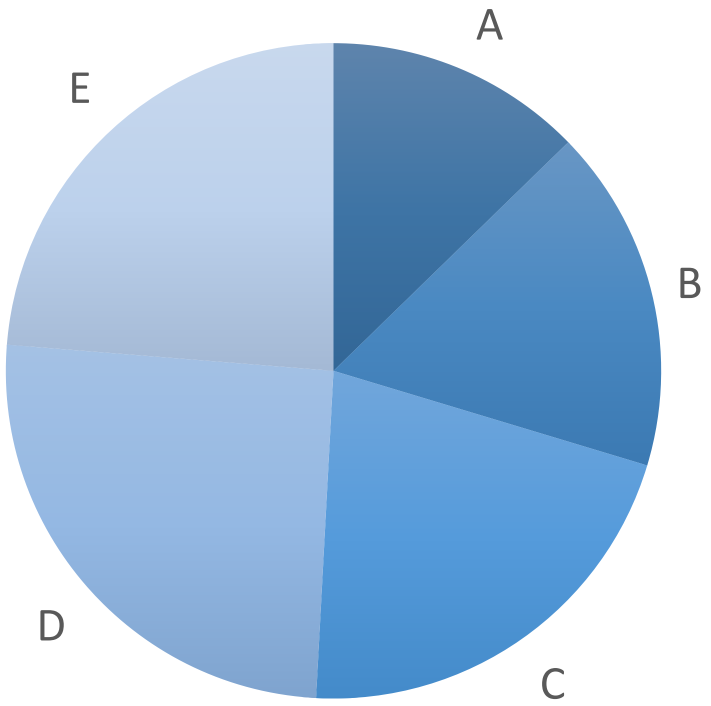
Ordinal

- Position
- Density (value)
- Color sat
- Color Hue
- Texture
- Length
- Angle
- Slope
- Area (size)
- Volume
- Shape

Nominal

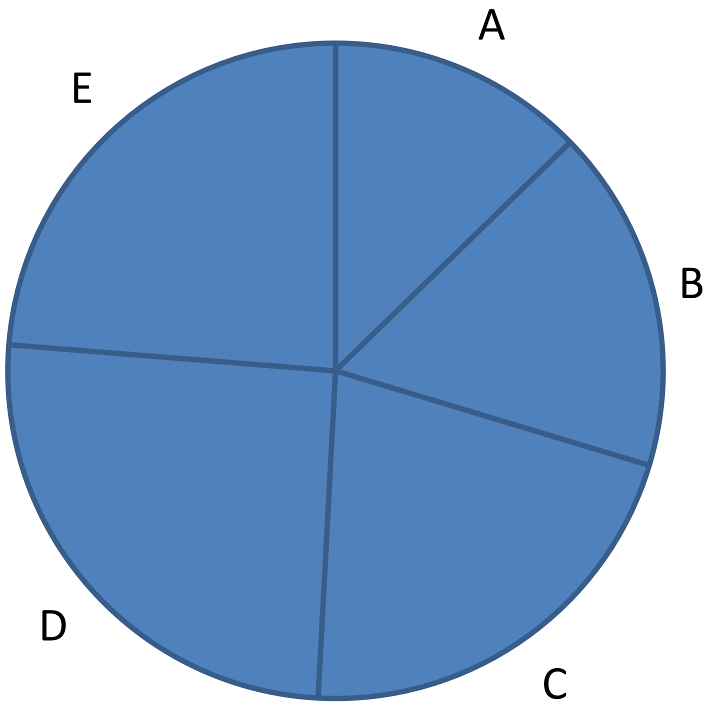
- Position
- Color Hue
- Texture
- Density (value)
- Color sat
- Shape
- Length
- Angle
- Slope
- Area (size)
- Volume

ANGLE DECODING



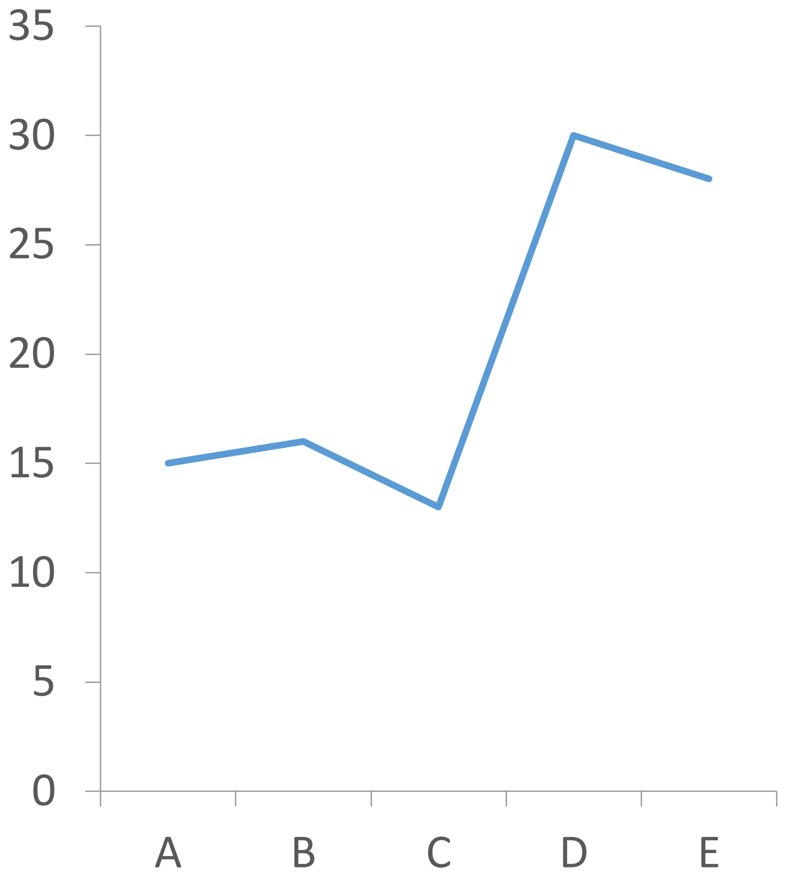
- It is difficult to compare angles
  - Underestimation of acute angles
  - Overestimation of obtuse angles
  - Easier if bisectors are aligned
- Area estimation helps

ANGLE DECODING



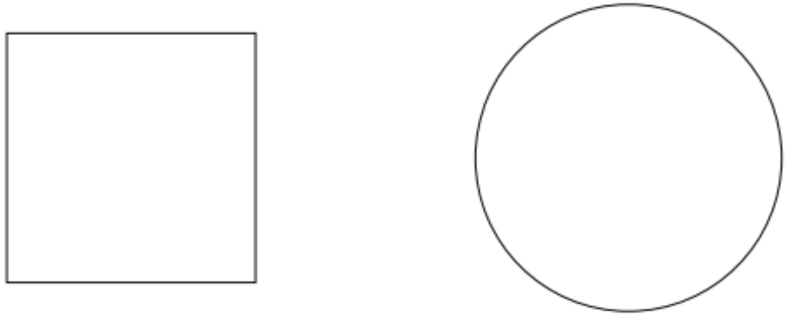
- It is difficult to compare angles
  - Underestimation of acute angles
  - Overestimation of obtuse angles
  - Easier if bisectors are aligned

SLOPES DECODING



- Same difficulties as angles
- Easier task since one branch is aligned with x-axis

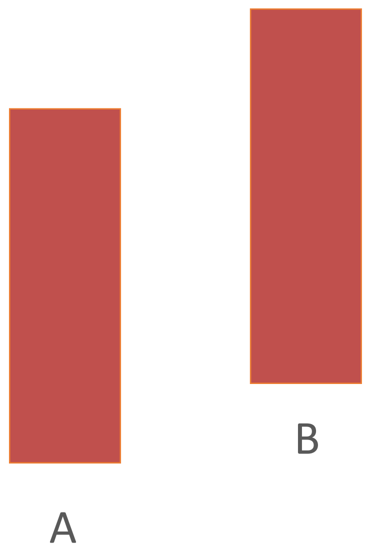
AREA DECODING



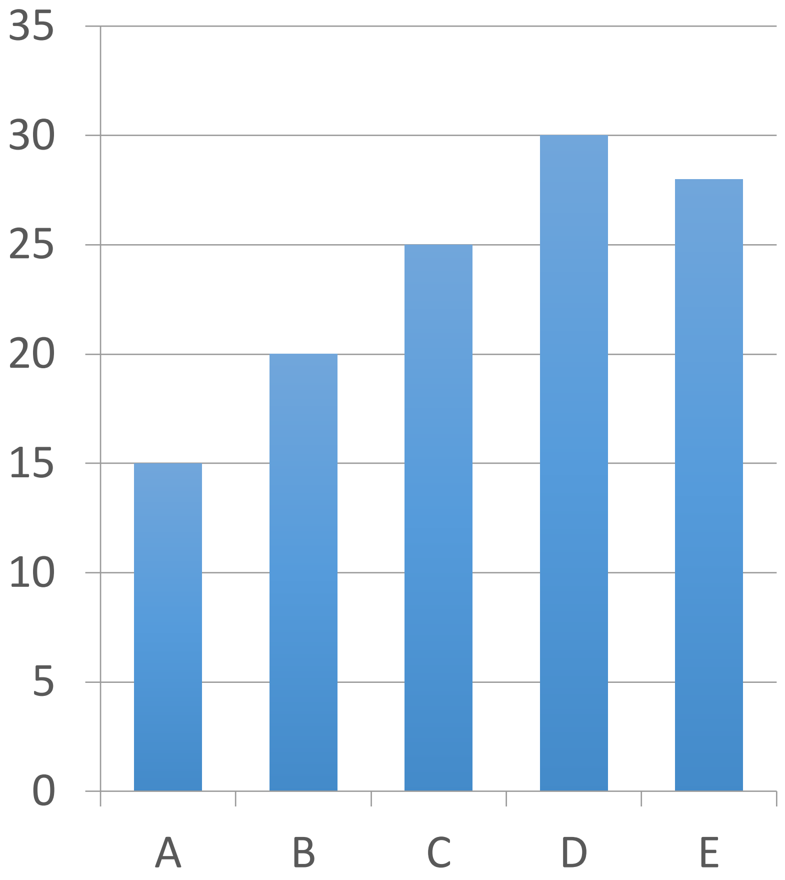
- Area is not well decoded
  - Different regular shapes
  - Irregular shapes
  - Context influences (thin area within compact thick area)

LENGTH DECODING

- Straight forward to endoce numerical values
- Difficulties with relative lengths



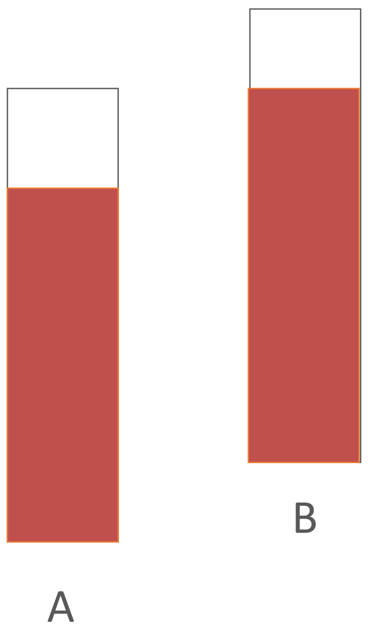
POSITION ON A COMMON SCALE



- Widely used in statistical charts

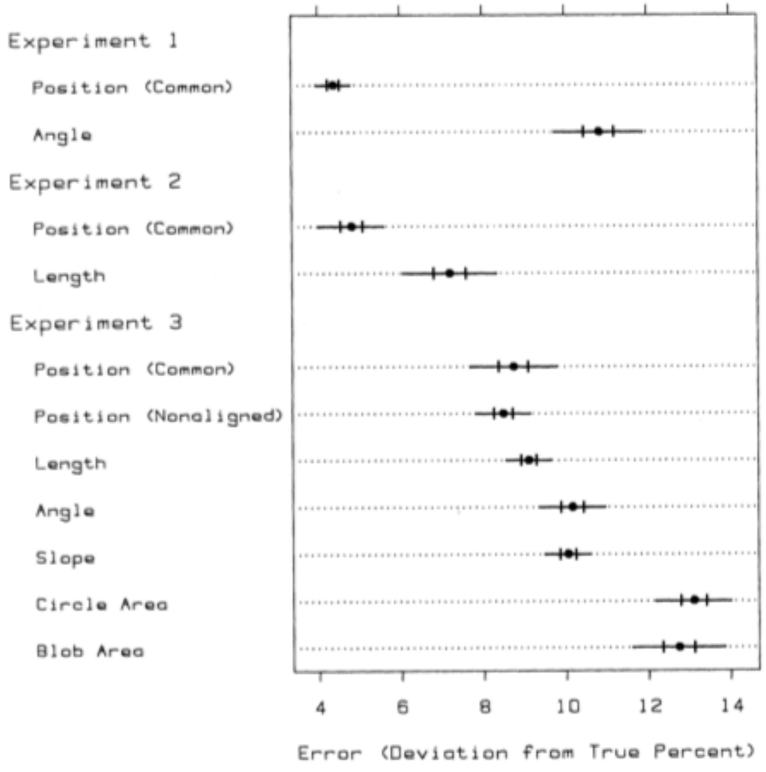
POSITION ON NON-ALIGNED SCALE

- Not as bas as common scale
- Still acceptable



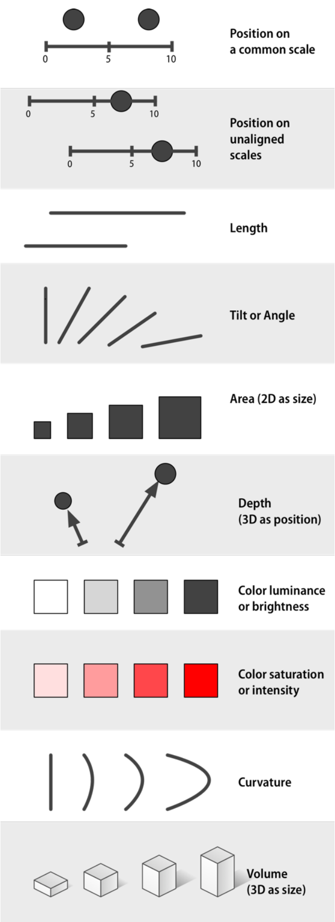
DESIGNING EFFECTIVE VISUALIZATIONS

- If possible, use graphical encoding that are easily decoded
- Graphical Attributes ordered(Cleveland & McGill):
  - Position along a common scale
  - Position on non aligned scales
  - Length
  - Angle and Slope
  - Area
  - Volume, density, color saturation
  - Color Hue

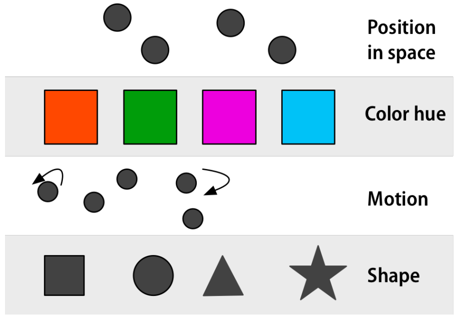


VISUAL VARIABLES

O and Q data types



N data types



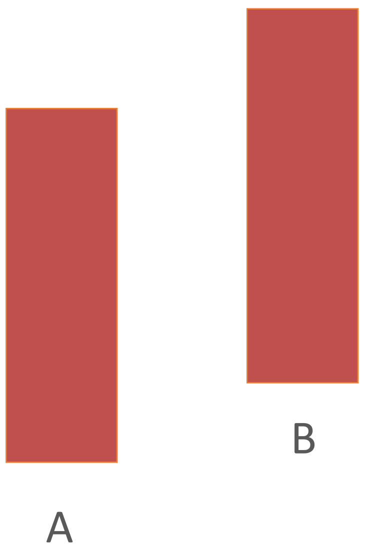
PERCEPTION LAWS

WEBER'S LAW

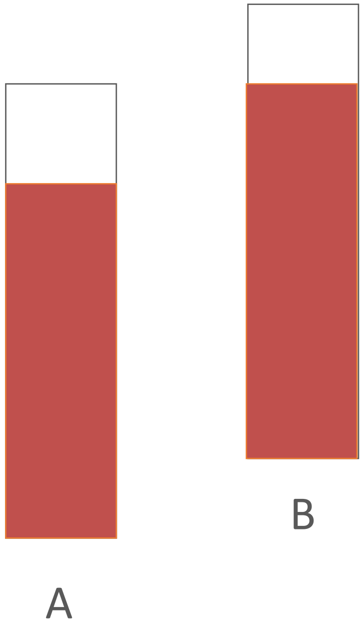
- Just-noticeable difference between two stimuli is proportional to their magnitudes
- Case study on length
  - Given two lines with lengths x and $x+w$
  - If w is small, it is difficult to notice difference between the two lines
  - If w is larger, it is easier to catch the difference
- How large should w be?
  - The probability of detecting the change is proportional to the reltaive value w/x

WEBER'S LAW

- Given values (90, 92)
- Detect with probability of 2/90



- Given values(90,92)
- Detect with probability of 2/10

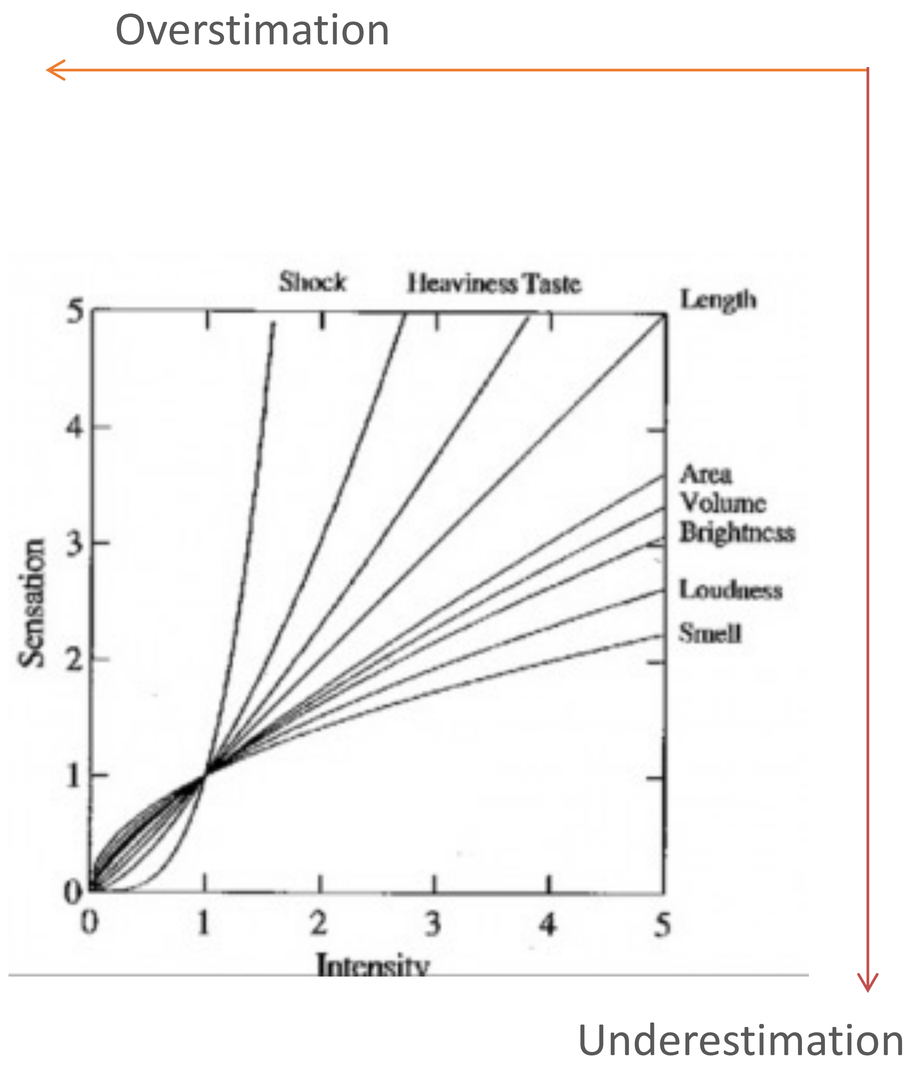


STEVENS' LAW

- Model the relation between a stimulus and its perceived intensity
- Given a stimulus x encoded with a visual attribute
- An observer decode a perceived value $p(x)$
- Stevens' law states that
  - $p(x) = kx^{\beta}$
  - where k is constant and
  - β is a constant that depends on the nature of stimulus

STEVENS' LAW

- Better effectiveness when $p(x) = kx^{\beta}$ is linear
- Linearity depends only on β
- Different visual encodings yields typical ranges for β
  - Lengths: 0.9 – 1.1
  - Area: 0.6 – 0.9
  - Volume: 0.5 – 0.8



WEBER AND STEVENS' LAWS

- Given two values x_1 and x_2
- Let the perceived values be $p(x_1)$ and $p(x_2)$

$$\frac{p(x_1)}{p(x_2)} = \left(\frac{x_1}{x_2}\right)^{\beta}$$

WEBER AND STEVENS' LAWS: AREAS

- For areas β=0.7
- Let x_1=2 and x_2=1
- The perceived difference will be

$$\frac{p(2)}{p(1)} = \left(\frac{2}{1}\right)^{0.7} = 1,6245$$

- For areas β=0.7
- Let x_1=0,5 and x_2=1
- The perceived difference will be

$$\frac{p(\frac{1}{2})}{p(1)} = \left(\frac{1/2}{1}\right)^{0.7} = 0,6155$$

WEBER AND STEVENS' LAWS: AREAS VS LENGTHS

- For areas β=0.7
- Let $x_2=x_1+w$
- The perceived difference will be

$$\left(\frac{x+w}{x}\right)^{0.7} \approx 1+\frac{0.7w}{x}$$

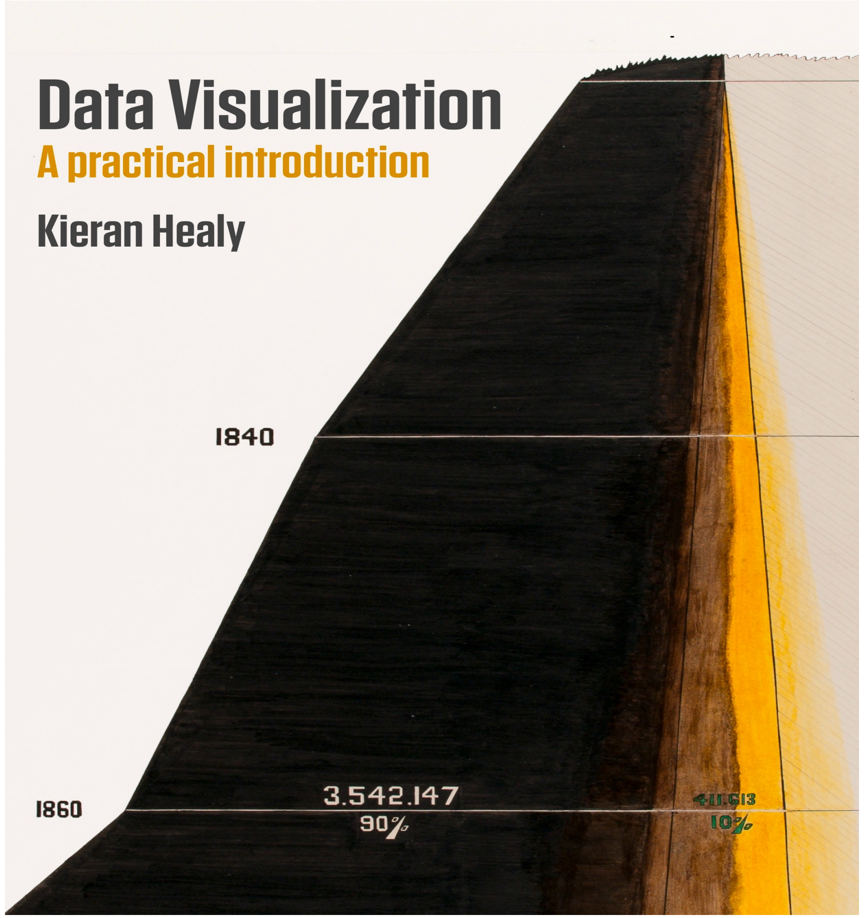
- For lengths β=1
- Let $x_2=x_1+w$
- The perceived difference will be

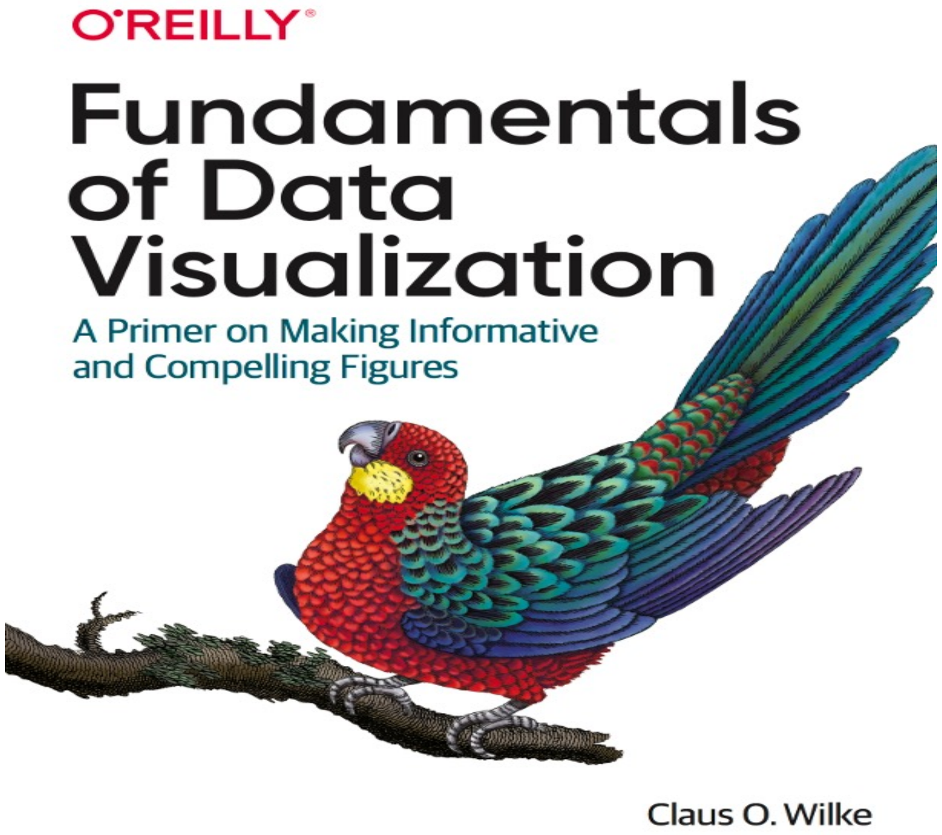
$$\left(\frac{x+w}{x}\right)^{1} = 1+\frac{w}{x}$$

TAKEAWAY MESSAGES

- Data type for entities and relationships
- Visual variables for representation
- Mapping of types to VVs
- Some VVs are more appropriate for specific data types

SUGGESTED READINGS

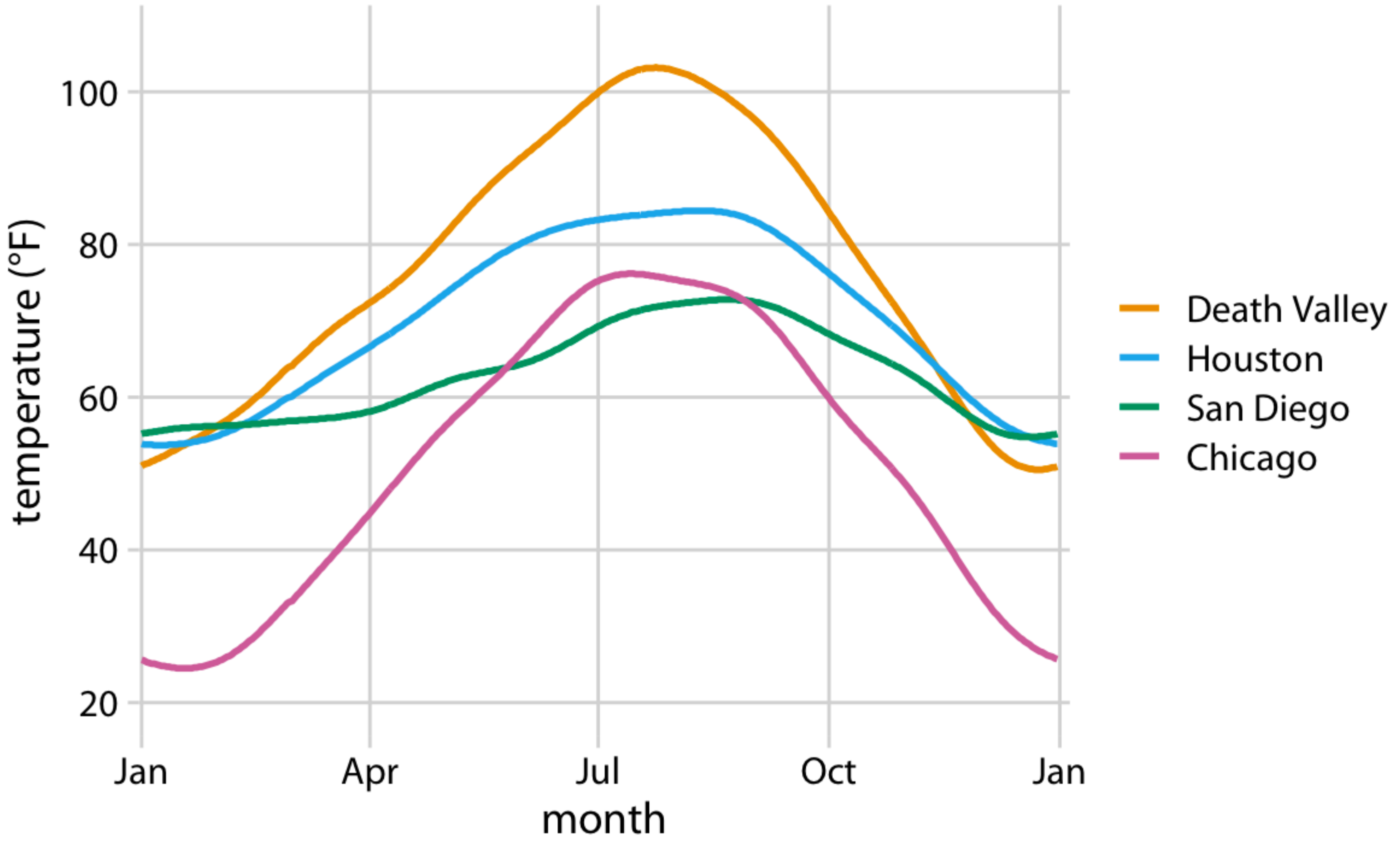




EXAMPLE

Month	Day	Location	Station ID	Temperature
Jan	1	Chicago	USW00014819	25.6
Jan	1	San Diego	USW00093107	55.2
Jan	1	Houston	USW00012918	53.9
Jan	1	Death Valley	USC00042319	51.0
Jan	2	Chicago	USW00014819	25.5
Jan	2	San Diego	USW00093107	55.3
Jan	2	Houston	USW00012918	53.8
Jan	2	Death Valley	USC00042319	51.2
Jan	3	Chicago	USW00014819	25.3
Jan	3	San Diego	USW00093107	55.3
Jan	3	Death Valley	USC00042319	51.3
Jan	3	Houston	USW00012918	53.8

VISUAL SOLUTION (1)



VISUAL SOLUTION (2)