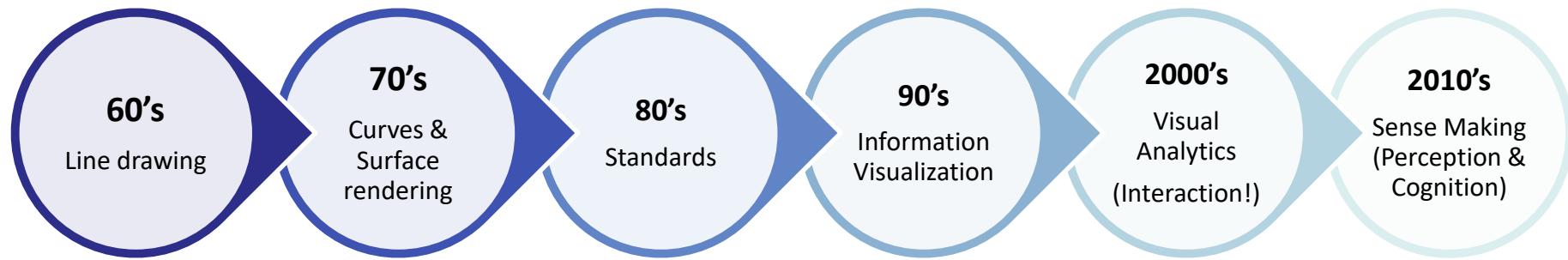


# Biases in Visual Analytics

BAIS 6140 – Information Visualization

L. Miguel Encarnação

# A brief history of Visualization



# What is a bias?

- Bias is a **disproportionate weight** in favor of or against an idea or thing.
- In science and engineering, a bias is a **systematic error**.

*Wikipedia*

# Biases in Data Analysis

Biases can come in at any step along the data analysis pipeline.

Note the general focus on data, not methods!

## Data Source

- **Functional:** biases due to platform affordances and algorithms
- **Normative:** biases due to community norms
- **External:** biases due to phenomena outside social platforms
- **Non-individuals:** e.g., organizations, automated agents

## Data Collection

- **Acquisition:** biases due to, e.g., API limits
- **Querying:** biases due to, e.g., query formulation
- **Filtering:** biases due to removal of data “deemed” irrelevant

## Data Processing

- **Cleaning:** biases due to, e.g., default values
- **Enrichment:** biases from manual or automated annotations
- **Aggregation:** e.g., grouping, organizing, or structuring data

## Data Analysis

- **Qualitative Analyses:** lack generalizability, interpret. biases
- **Descriptive Statistics:** confounding bias, obfuscated measurements
- **Prediction & Inferences:** data representation, perform. variations
- **Observational studies:** peer effects, select. bias, ignorability

## Evaluation

- **Metrics:** e.g., reliability, lack of domain insights
- **Interpretation:** e.g., contextual validity, generalizability
- **Disclaimers:** e.g., lack of negative results and reproducibility

# Biases in Social Data Analysis

## Issues When Working With Social Data.

Organized based on effects and triggers.

### General Challenges

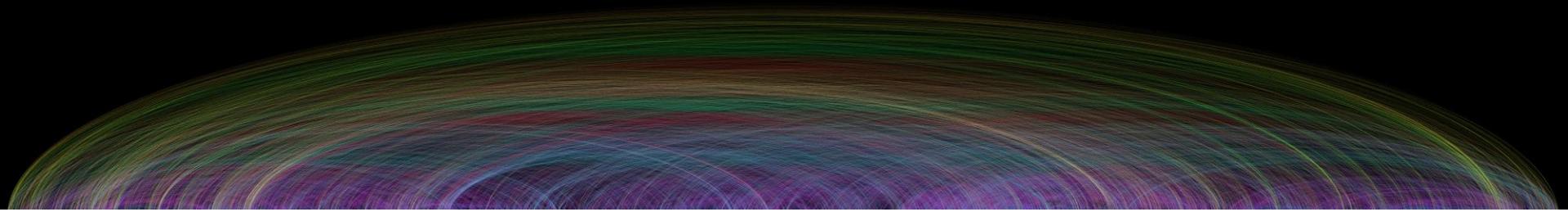
- **Population Biases:** differences in demographics
- **Behavioral Biases:** differences in user behavior
- **Content Biases:** lexical, syntactic, and semantic biases in user content
- **Linking Biases:** differences in network connections, interactions
- **Temporal Biases:** changing biases over time
- **Redundancy:** duplicates, near duplicates

### Challenges During Data Analysis

- **Data Source:** biases at the source of social data
- **Data Collection:** biases due to data collection
- **Data Processing:** biases due to data preprocessing
- **Data Analysis:** validity threats due to methods selection and usage
- **Evaluation:** metrics selection, interpretation pitfalls

### Ethical Boundaries

- **General Concepts and Principles**
- **Individual Autonomy:** ensure informed consent
- **Beneficence and Non-maleficence:** actions are beneficial and do not cause harm
- **Justice:** risks and benefits justly shared



– Benjamin Haydon

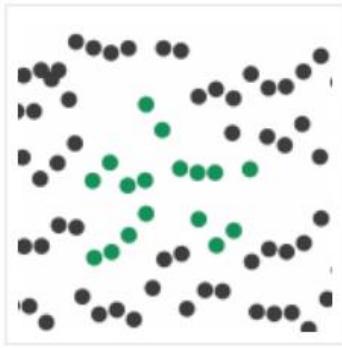
*“FORTUNATELY FOR SERIOUS MINDS, A BIAS  
RECOGNIZED IS A BIAS STERILIZED.”*

# Statistical Bias Types

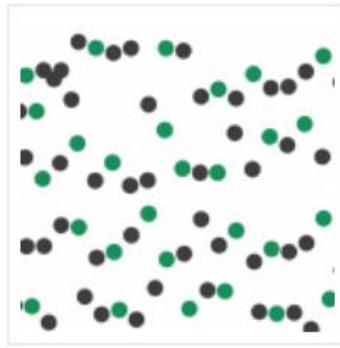
- Selection bias
- Self-selection bias
- Recall bias
- Observer bias
- Survivorship bias
- Omitted variable bias
- Cause-effect bias
- Funding bias
- Cognitive bias

<https://data36.com/statistical-bias-types-explained/>

# Selection Bias



*selection bias*



*proper random sampling*

## Example

- Student experiments

# Self-selection Bias

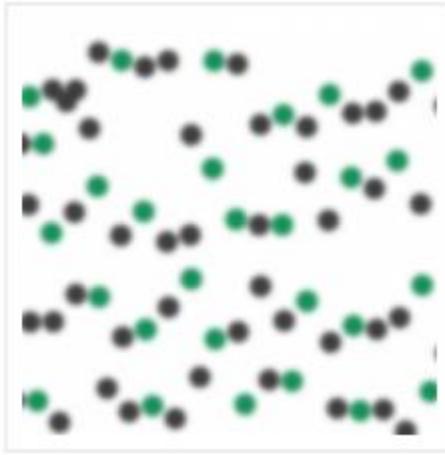


## Example

- Polls

# Recall Bias

## Example



- Nostalgia
  - Good Ol' times
  - Make America Great Again
  - First love

# Observer Bias

## Example

- Conscious & unconscious prejudices

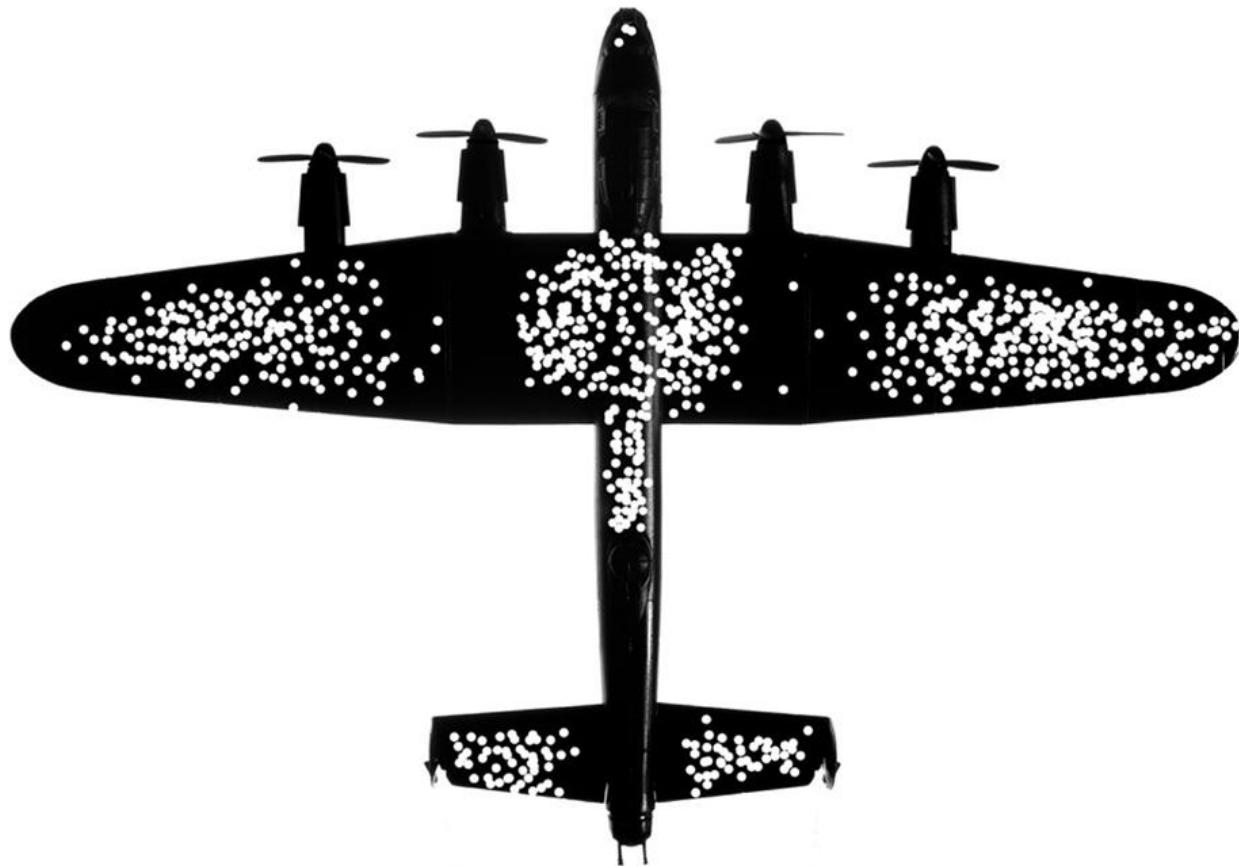
PEANUTS



United Features Syndicate, Inc.

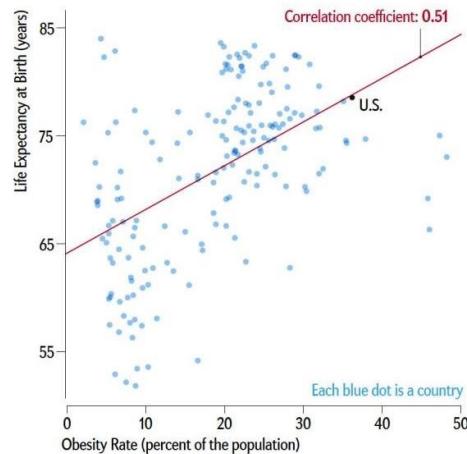
# Survivorship Bias

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



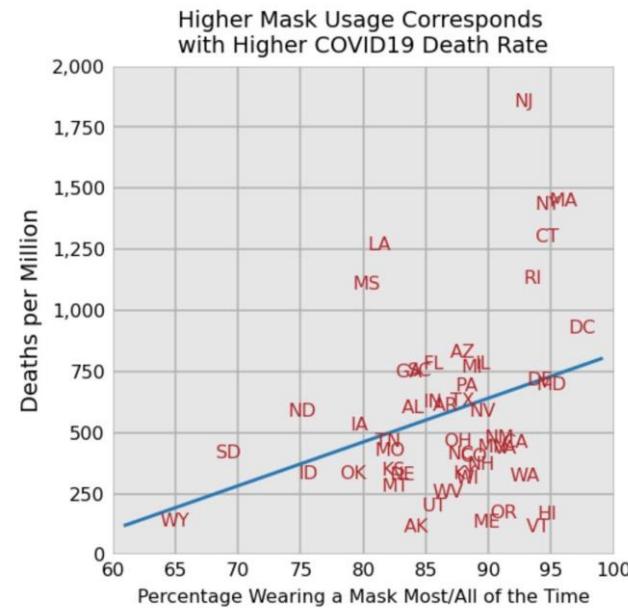
# Omitted Variable Bias

	A and B are positively correlated	A and B are negatively correlated
B has a positive effect on Y	<i>Positive bias</i>	<i>Negative bias</i>
B has a negative effect on Y	<i>Negative bias</i>	<i>Positive bias</i>

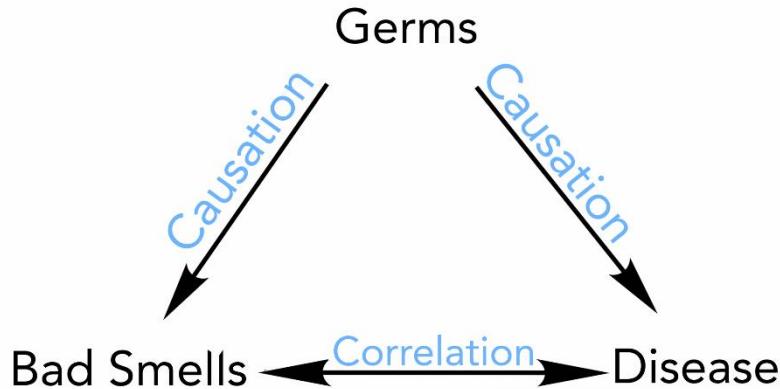


## Example

- Omitting cost of not innovating from innovation risk calculation

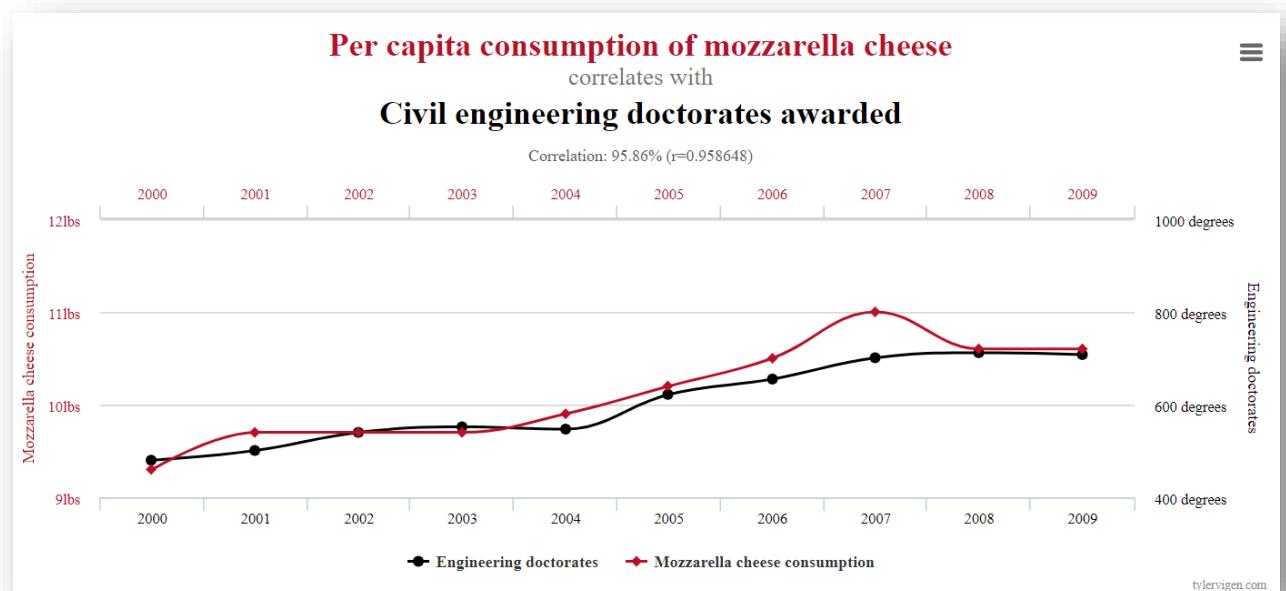


# Cause-Effect Bias



## Example

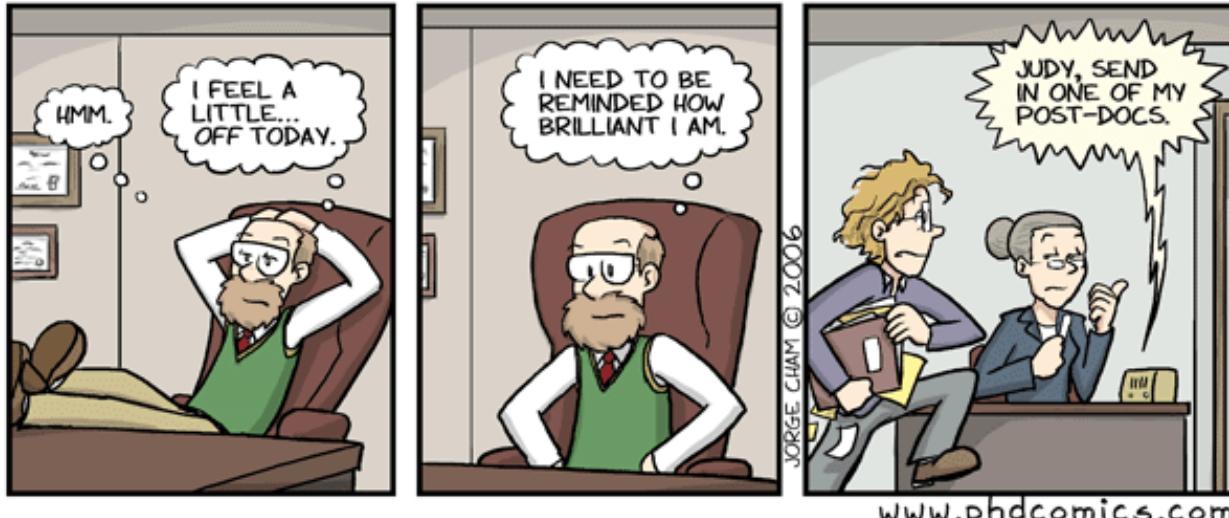
- Increase of autism diagnoses due to vaccinations



# Funding Bias

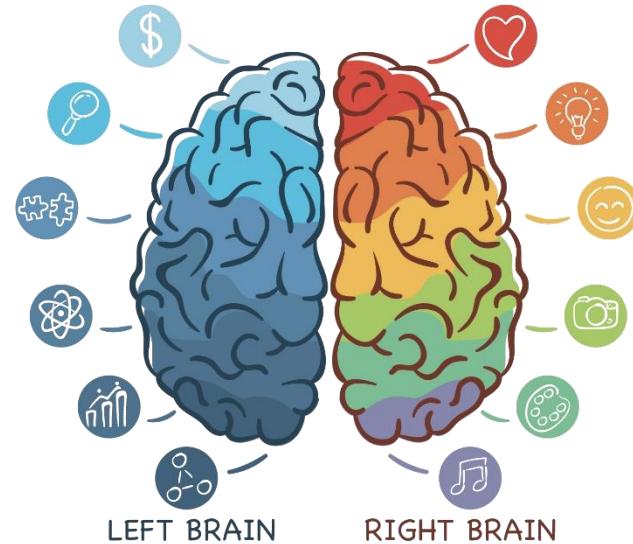
## Examples

- Partisan News
- PhD research
  - also Survivorship Bias once published



# COGNITIVE BIASES

HUMAN BRAIN



# COGNITIVE BIAS CODEX

## What Should We Remember?

We favor simple-looking options and complete information over complex, ambiguous options

To avoid mistakes, we aim to preserve autonomy and group status, and avoid irreversible decisions

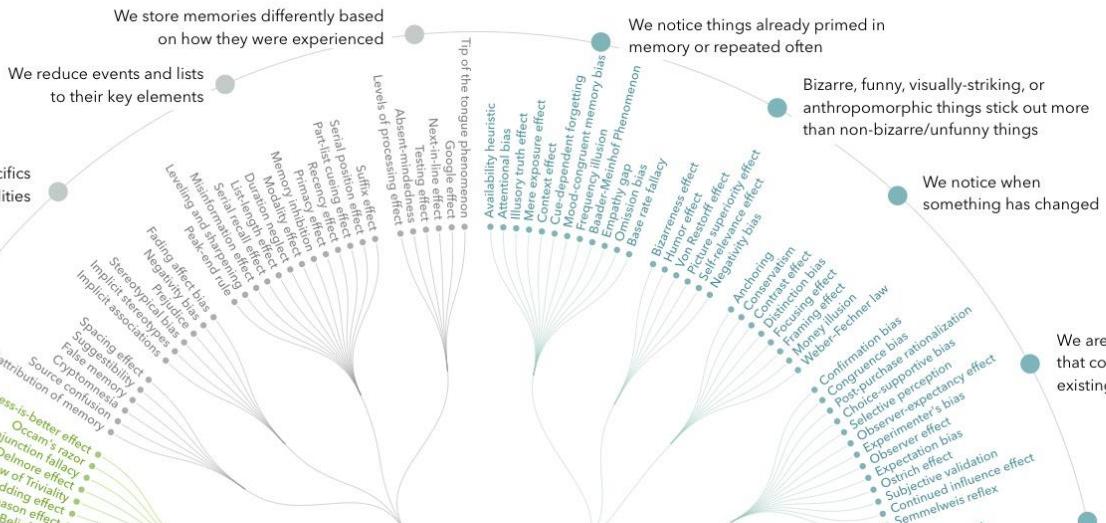
To get things done, we tend to complete things we've invested time & energy in

To stay focused, we favor the immediate, relatable thing in front of us

## Need To Act Fast

To act, we must be confident we can make an impact and feel what we do is important

We project our current mindset and assumptions onto the past and future



## Too Much Information

We notice flaws in others more easily than we notice flaws in ourselves

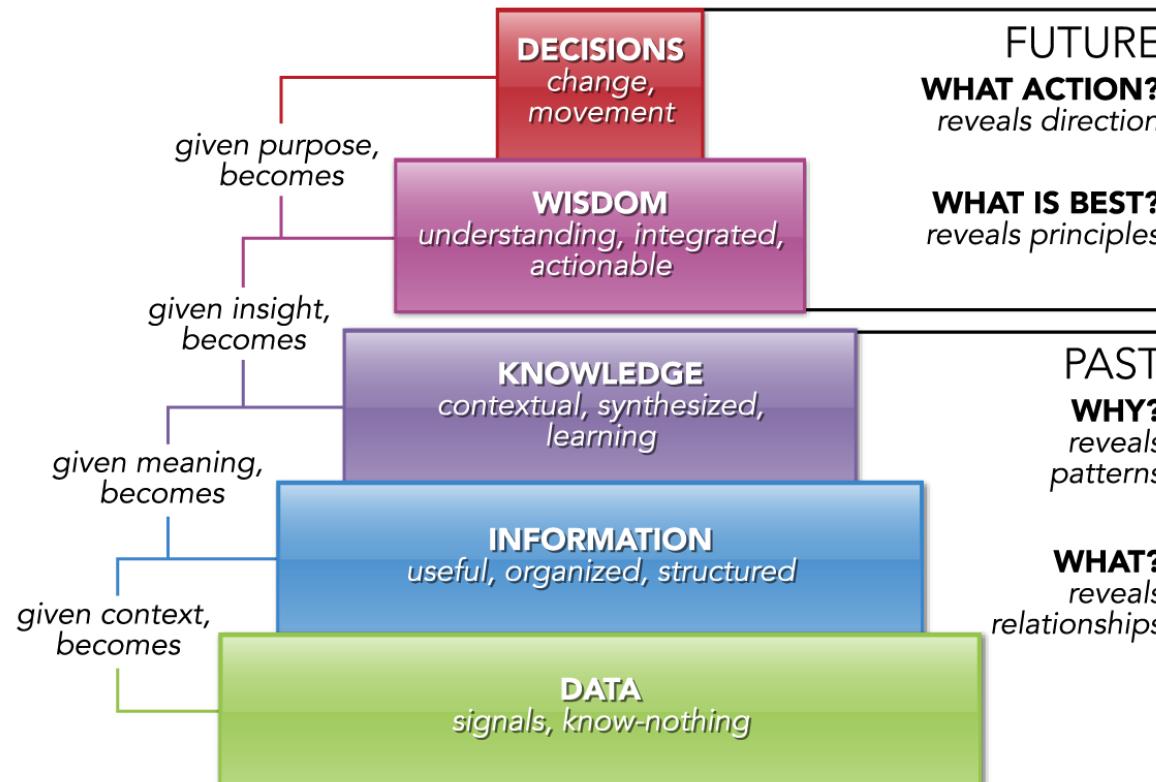
We tend to find stories and patterns even when looking at sparse data

We fill in characteristics from stereotypes, generalities, and prior histories

## Not Enough Meaning

# Recap: Analytic Purposes & Decision Making

DIKW pyramid



# What Should We Remember?

We favor simple-looking options and complete information over

We edit and reinforce some memories after the fact

We discard specifics to form generalities

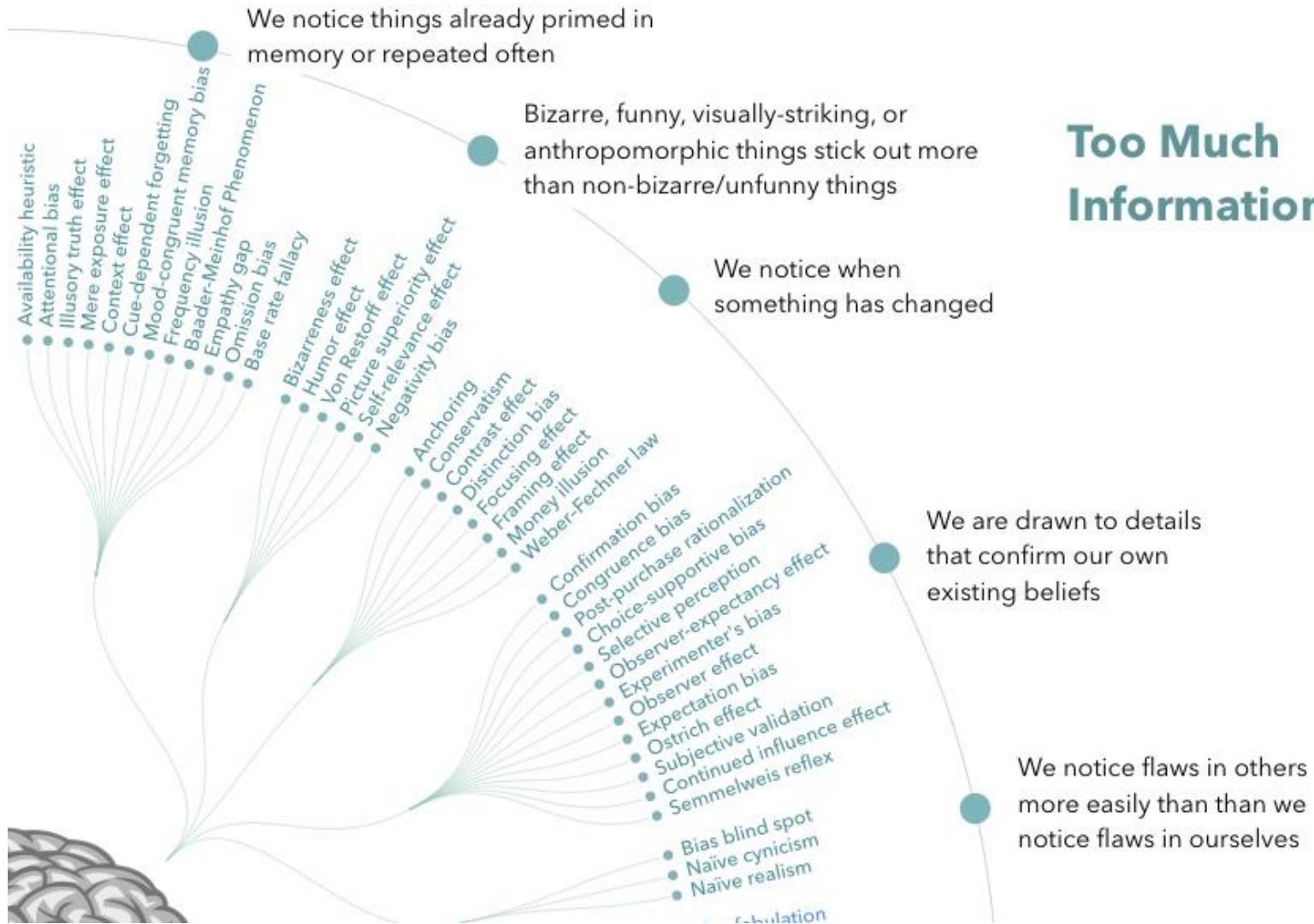
We reduce events and lists to their key elements

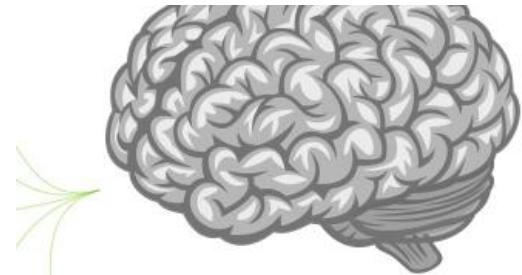
We store memories differently based on how they were experienced

Tip of the tongue phenomenon  
Google effect  
Next-in-line effect  
Testing effect  
Absent-mindedness  
Absent-mindedness  
Levels of processing effect

Suffix effect  
Serial position effect  
Serial position effect  
Part-list cueing effect  
Recency effect  
Primacy effect  
Memory inhibition  
Memory neglect  
Duration effect  
List-length effect  
Serial recall effect  
Misinformation effect  
Misinformation neglect  
Misinformation neglect  
Leveling and sharpening rule  
Misattribution of memory  
Source confusion  
False memory  
Suggestibility  
Spacing effect  
Implicit stereotypes  
Implicit associations  
Stereotypical bias  
Negativity bias  
Prejudice  
Fading affect bias  
Peak-end rule  
Less-is-better effect  
Conjunction fallacy  
Occam's razor

# Too Much Information





mindset and  
st and future

Self-consistency effect  
Restraint bias  
Projection bias  
Pro-innovation bias  
Time-saving bias  
Planning fallacy  
Pessimism bias  
Impact bias  
Declinism  
Moral luck  
Outcome bias  
Hindsight bias  
Rosy retrospection  
Telescoping effect

- Confabulation
- Clustering illusion
- Insensitivity to sample size
- Neglect of probability
- Anecdotal fallacy
- Illusion of validity
- Masked man fallacy
- Recency illusion
- Gambler's fallacy
- Hot-hand fallacy
- Illusory correlation
- Pareidolia
- Anthropomorphism
- Group attribution error
- Ultimate attribution error
- Stereotyping
- Essentialism
- Functional fixedness
- Moral credential effect
- Just-world hypothesis
- Argument from fallacy
- Authority bias
- Bandwagon effect
- Placebo effect
- Out-group homogeneity bias
- In-group bias
- Halo effect
- Cheerleader effect
- Positive effect
- Not invented here
- Reactive devaluation
- Well-traveled road effect
- Mental accounting
- Appeal to probability
- Normalcy bias
- Murphy's Law
- Zero-sum bias
- Survivorship bias
- Subadditivity effect
- Denomination effect
- Magic number 7 $\pm$ 2
- Illusion of transparency
- Curse of knowledge
- Spotlight effect
- Extrinsic incentive error
- Illusion of external agency
- Illusion of asymmetric insight

We think we know what  
other people are thinking

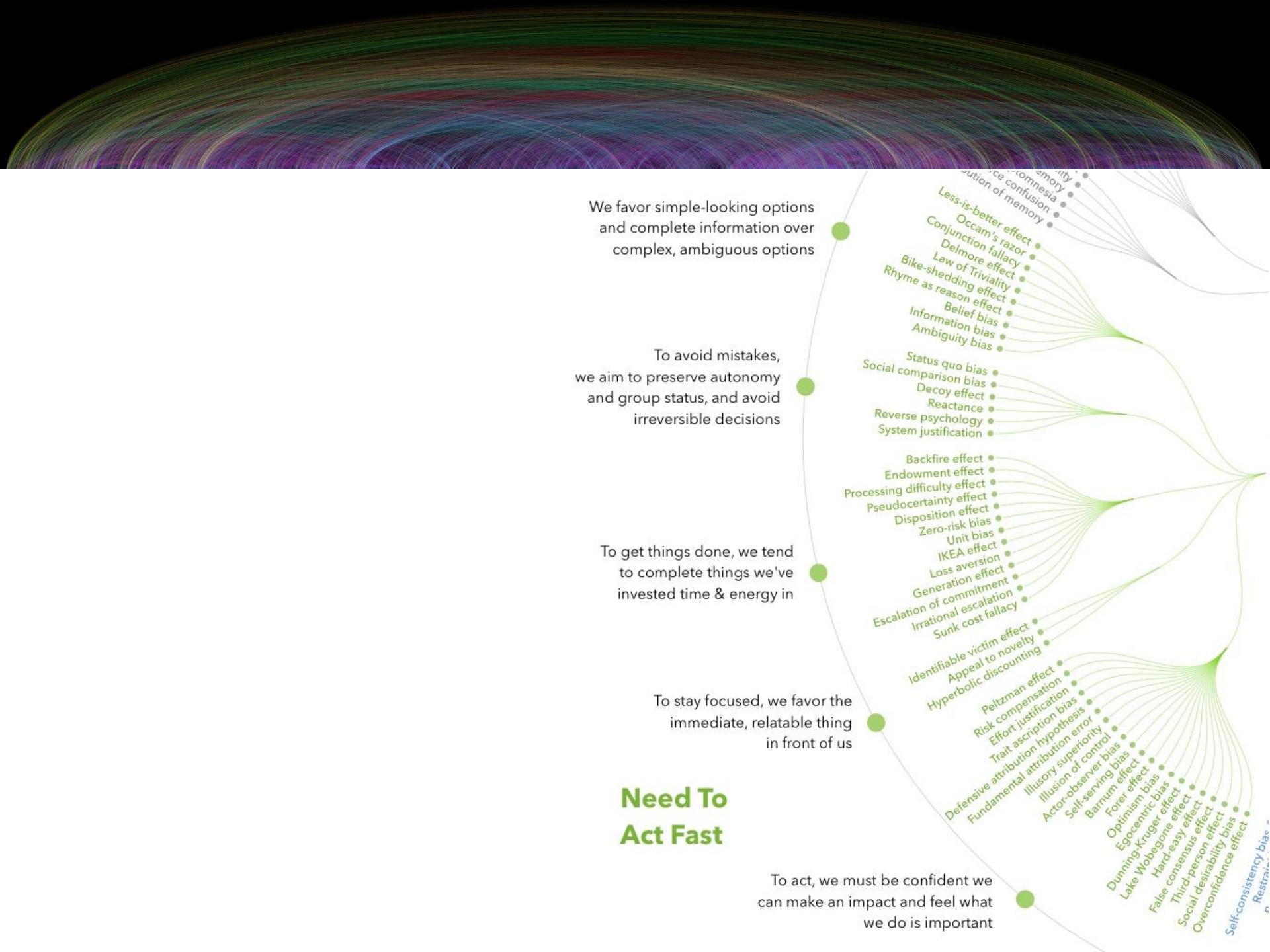
We simplify probabilities and numbers  
to make them easier to think about

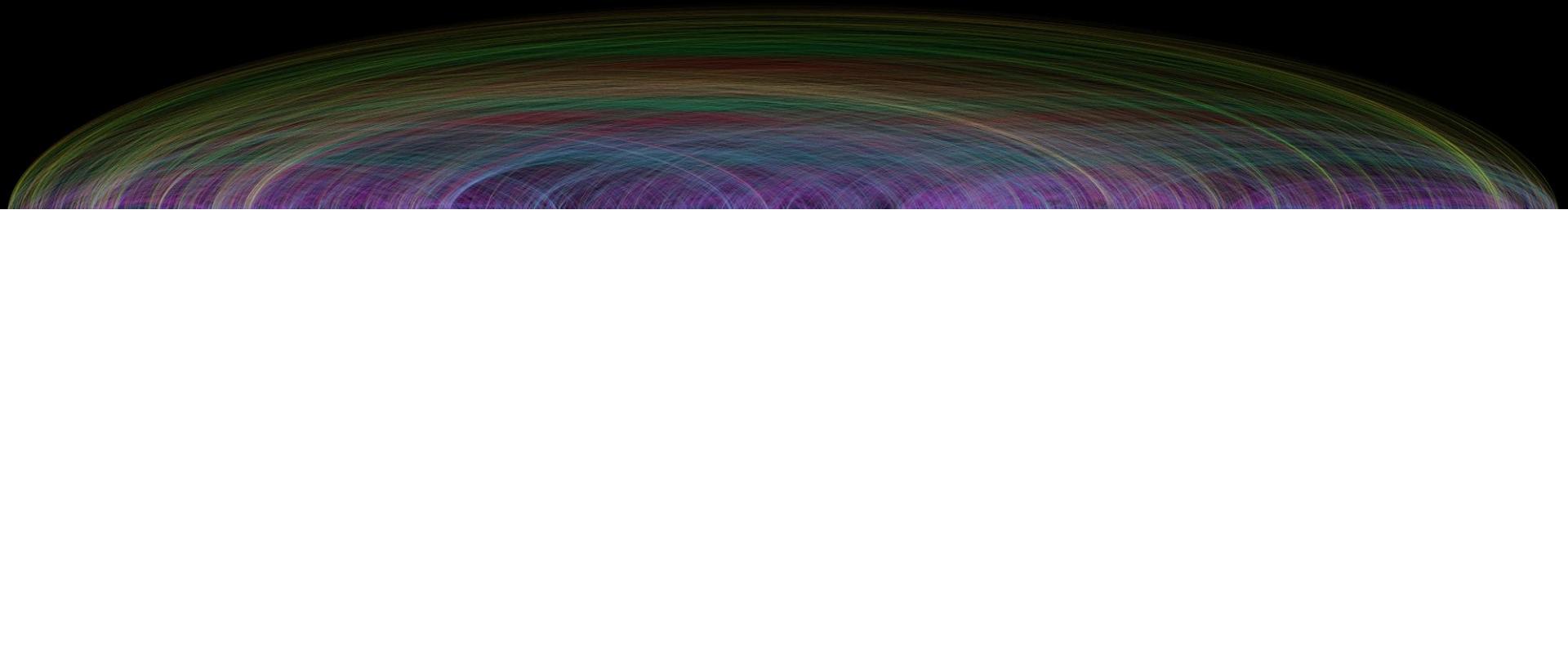
We imagine things and people  
we're familiar with or fond of  
as better

We fill in characteristics from  
stereotypes, generalities,  
and prior histories

We tend to find stories and  
patterns even when looking  
at sparse data

**Not Enough  
Meaning**

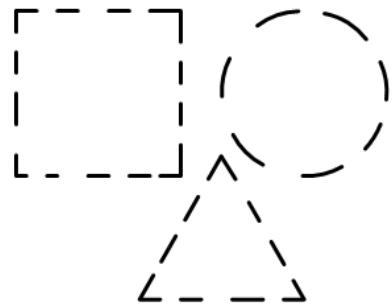




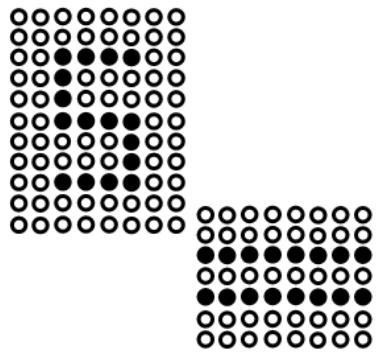
(Nice catalogue at <http://www.psy.ritsumei.ac.jp/~akitaoka/cataloge.html>)

## EXAMPLES OF (VISUAL) BIAS

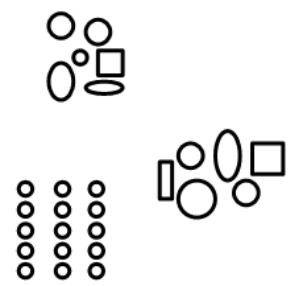
# It starts with Gestalt ...



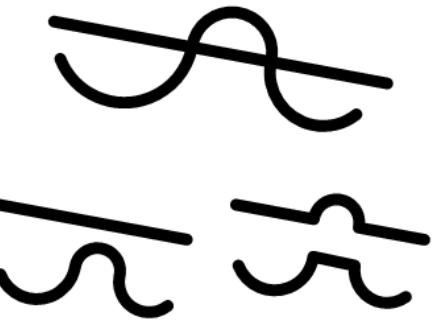
**Closure**



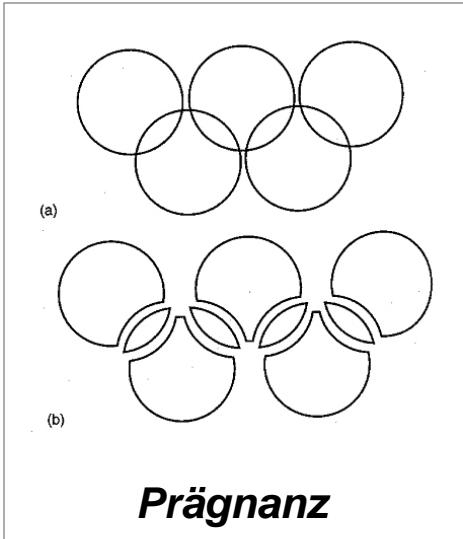
**Similarity**



**Proximity**

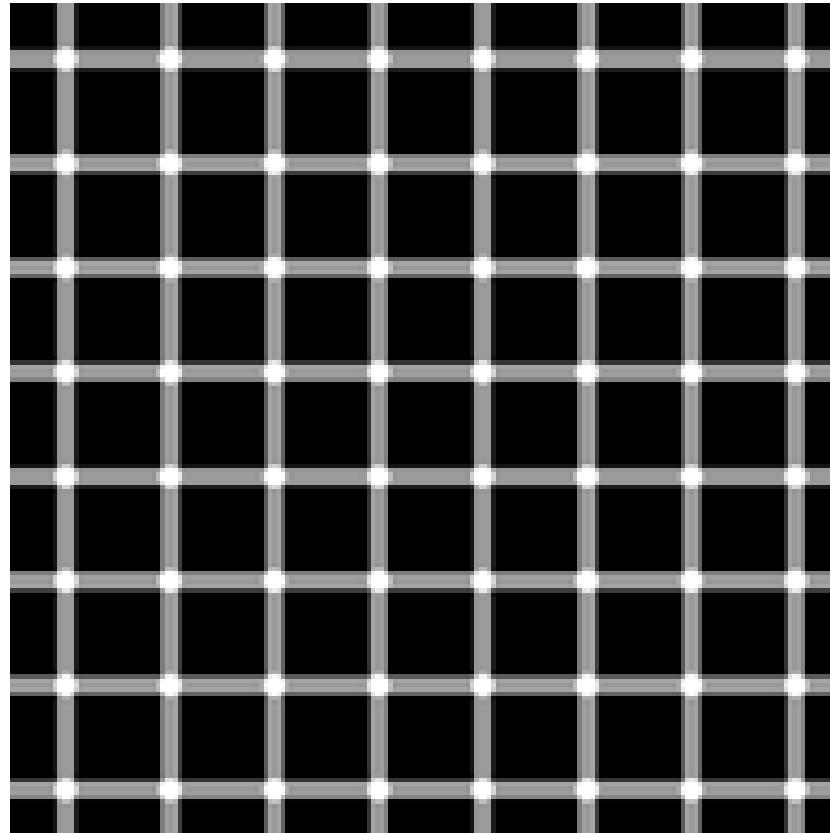


We see this...but not this  
**Continuity**



**Prägnanz**

# Brightness constancy illusion

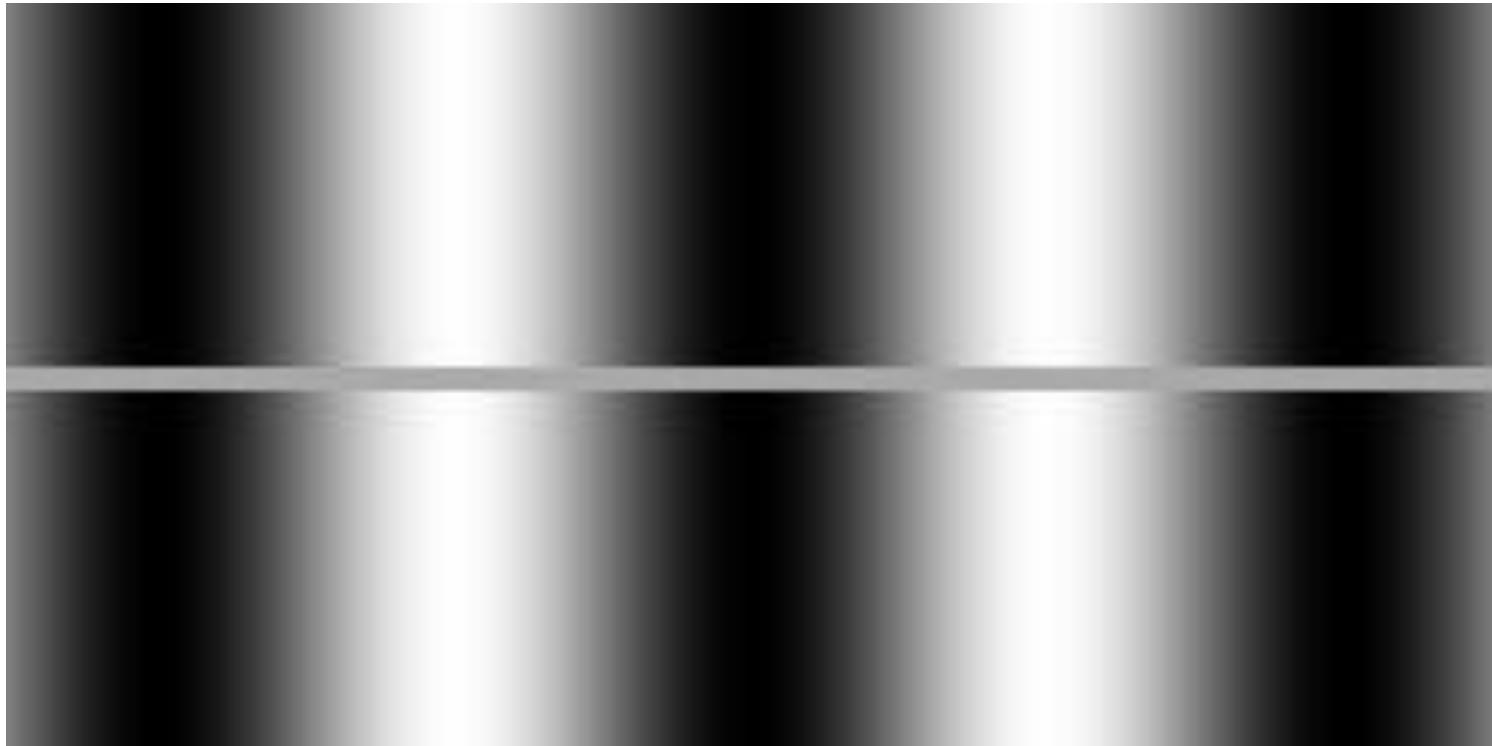


(Scintillating Grid Illusion)

# Brightness constancy illusion



# Brightness constancy illusion



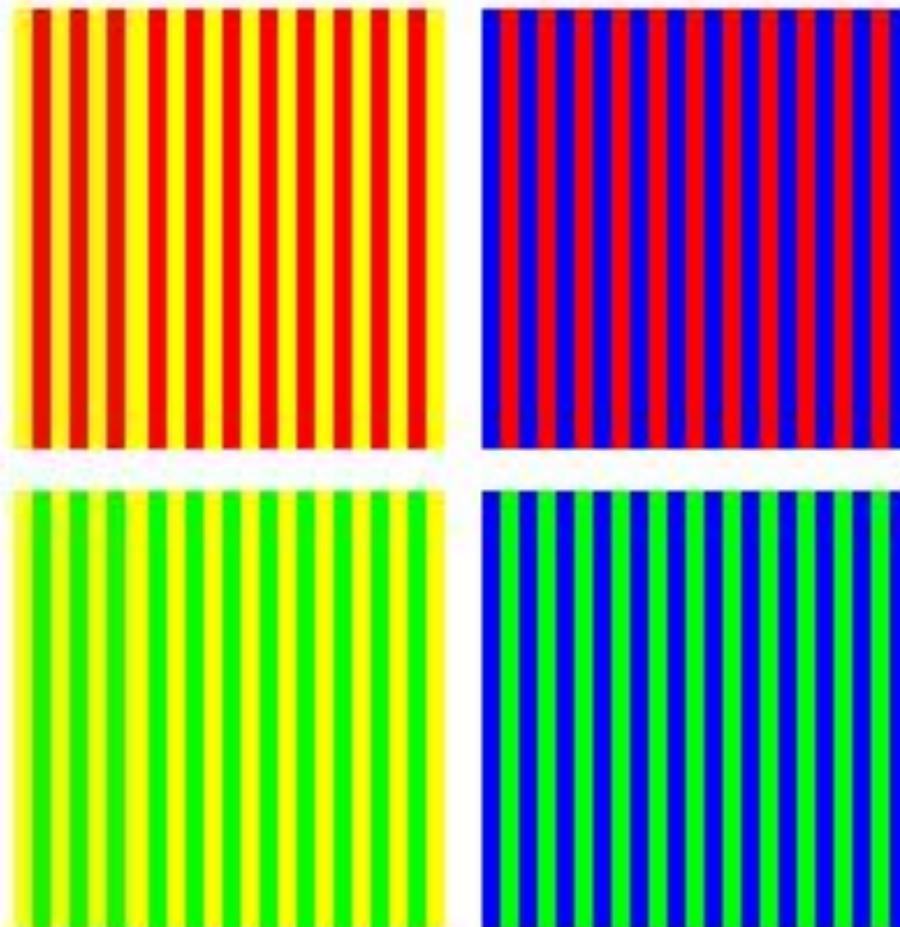


February 27, 2015

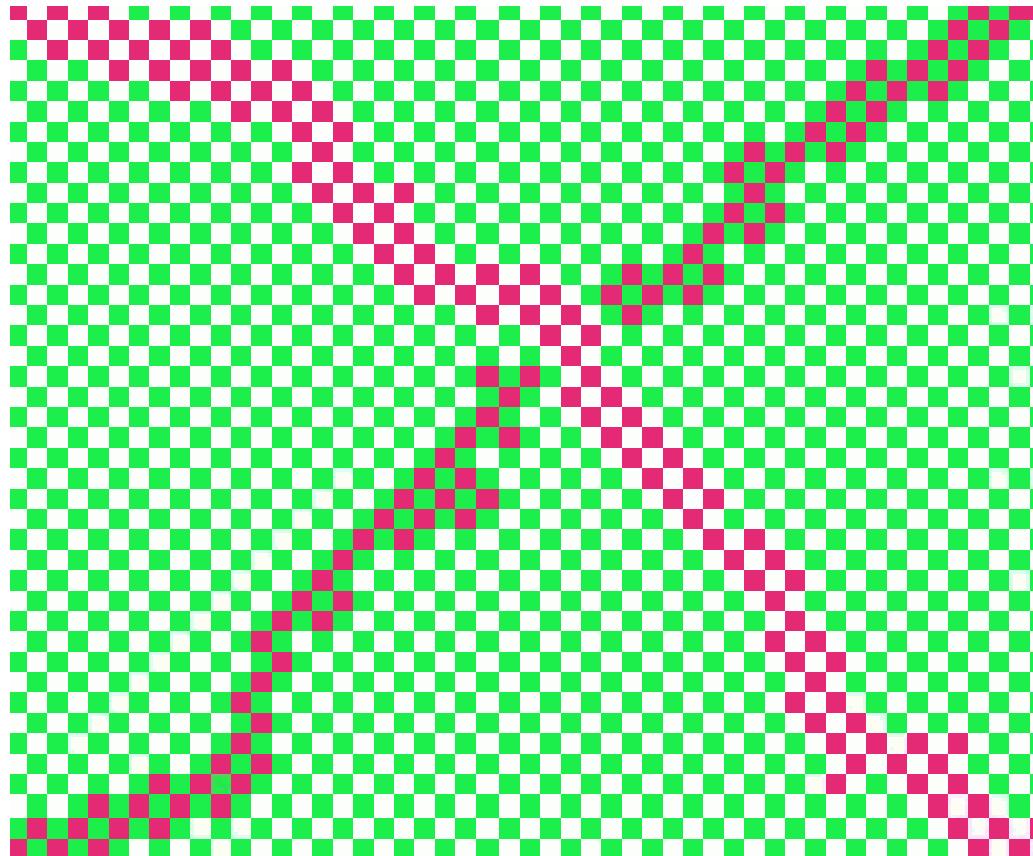
- White/Gold or Black/Blue?



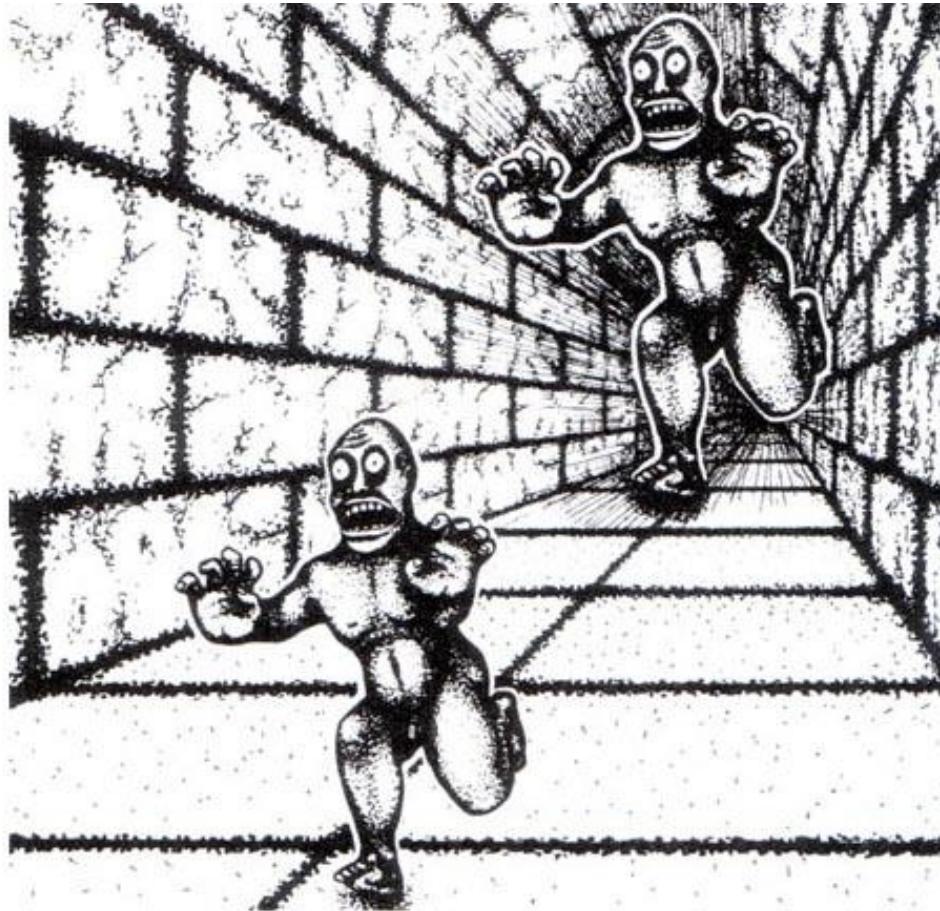
# Color constancy illusion



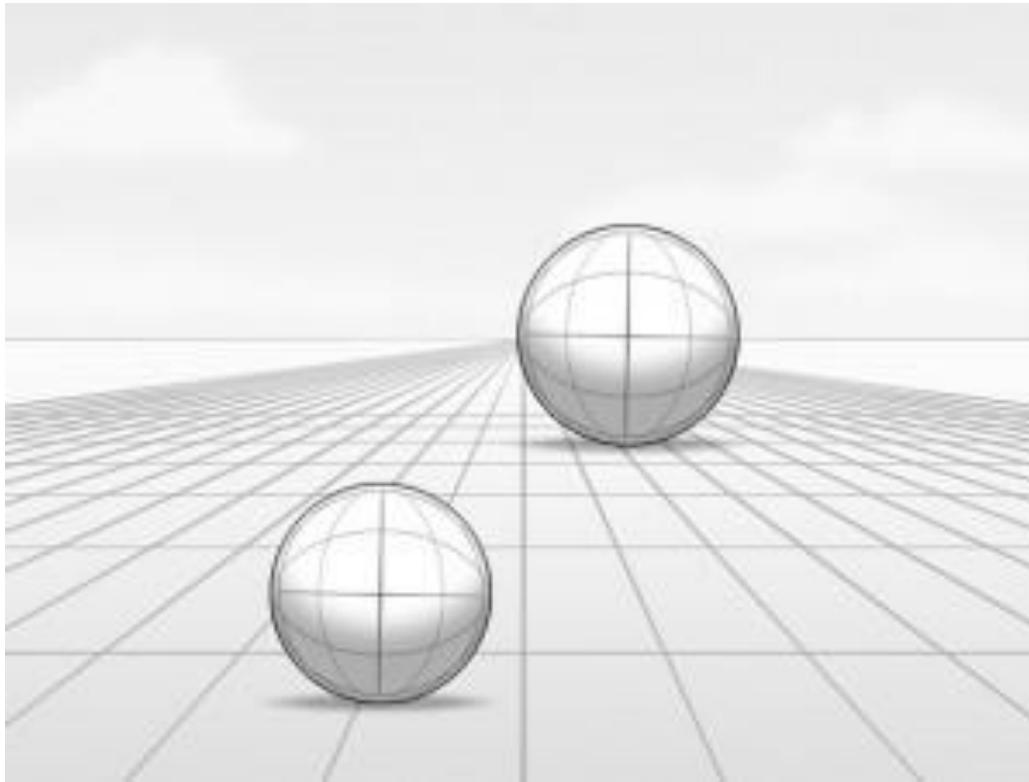
# Color constancy illusion



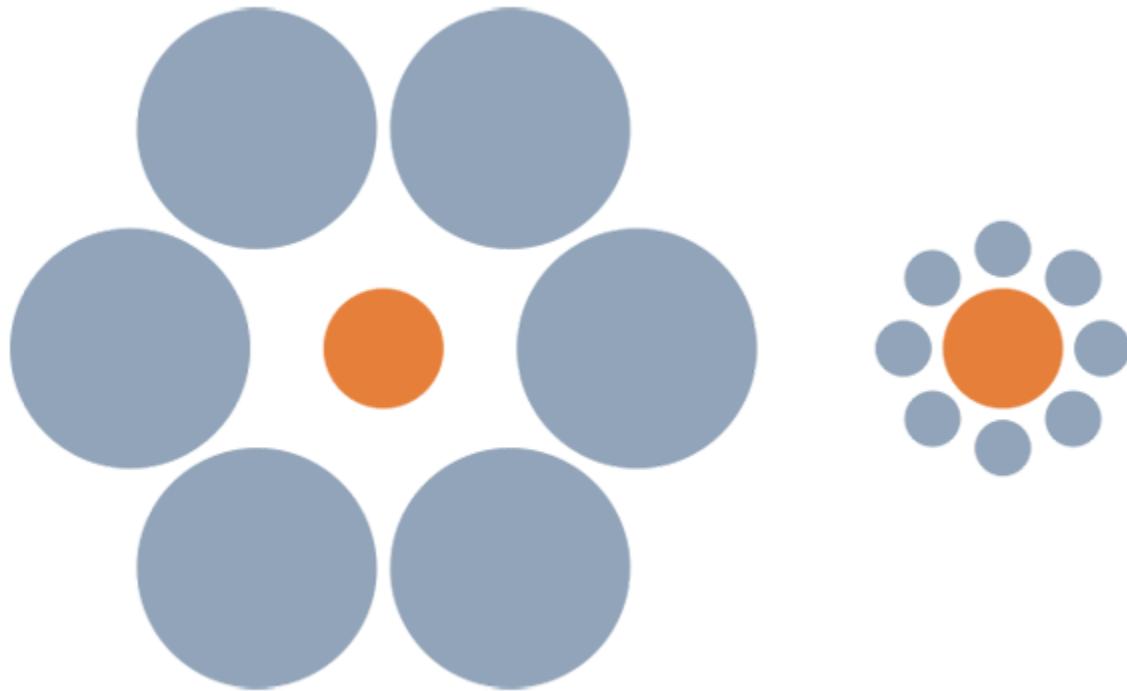
# Size constancy illusion



# Size constancy illusion

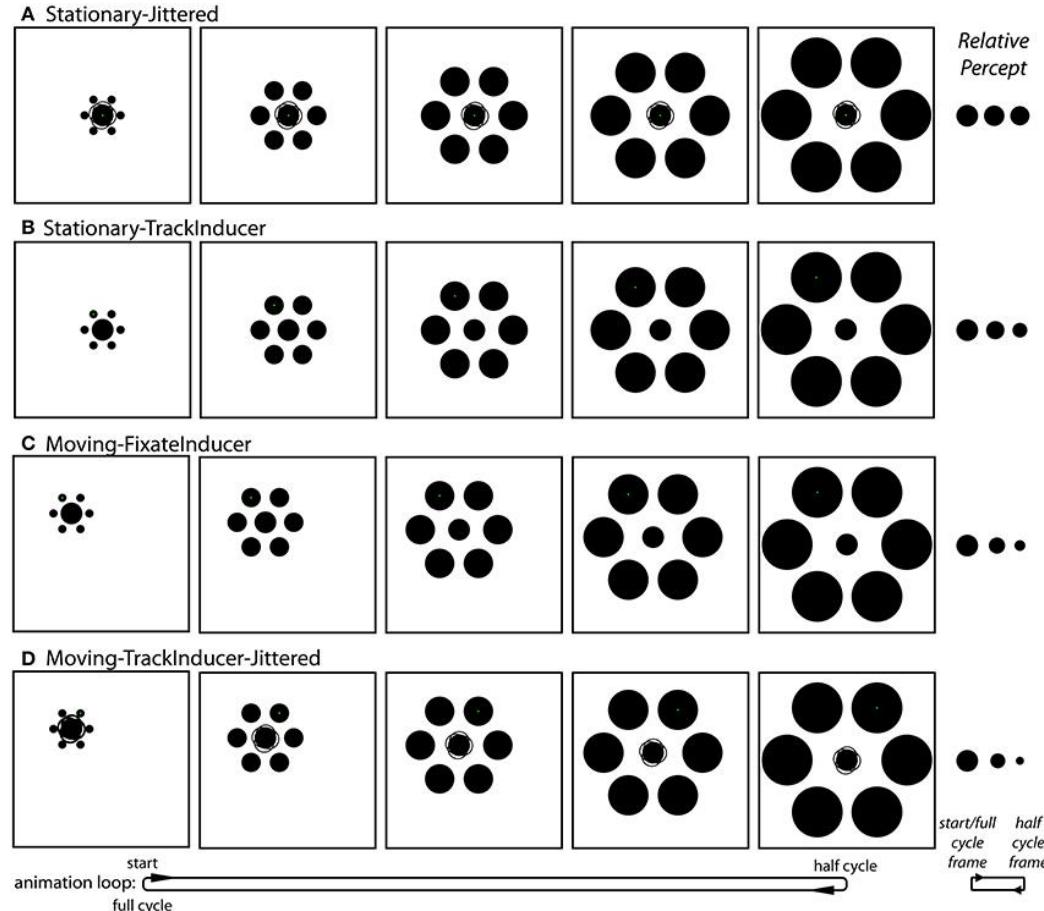


# Size constancy illusion

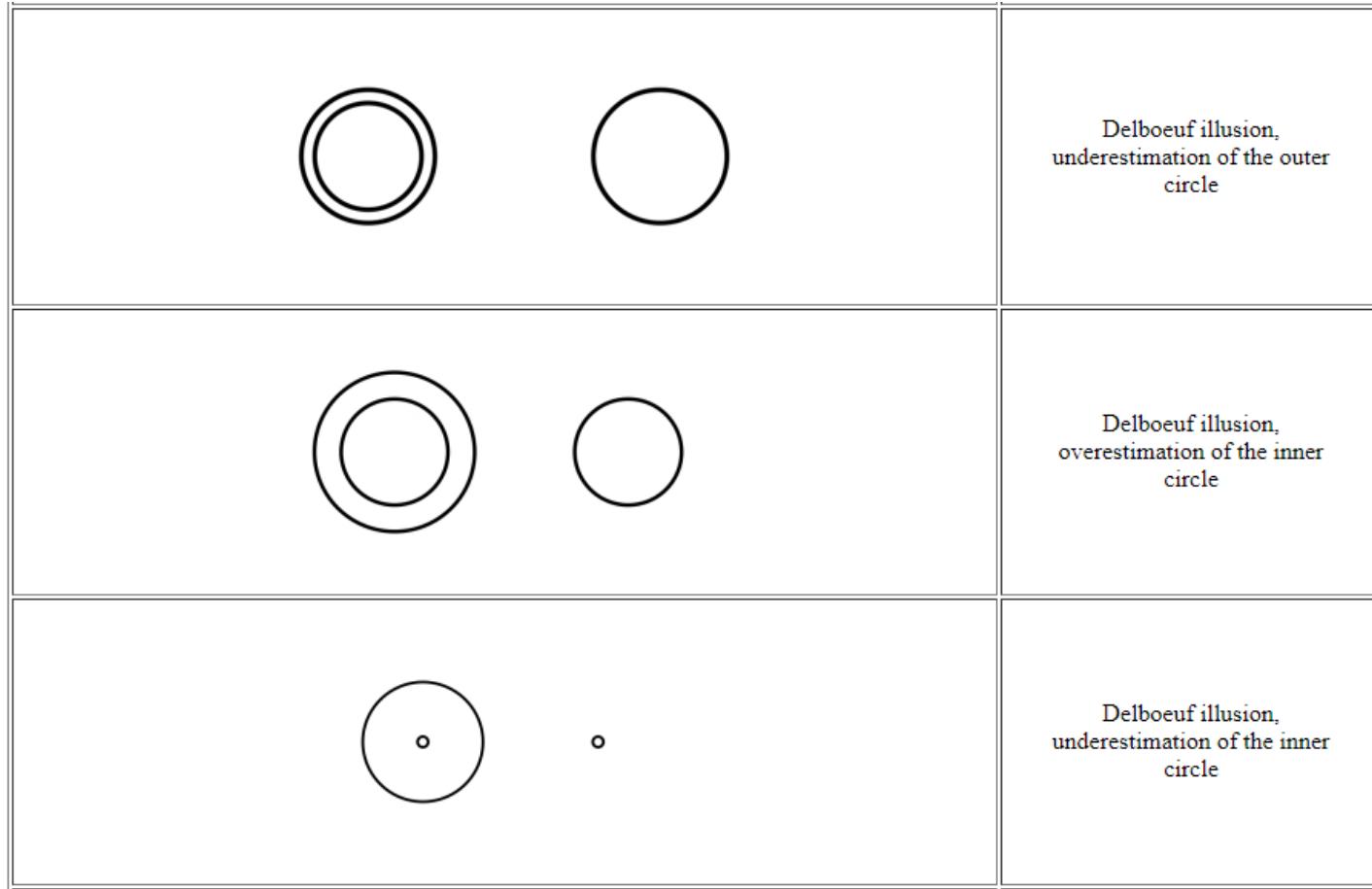


(Ebbinghaus illusion)

# Size constancy illusion



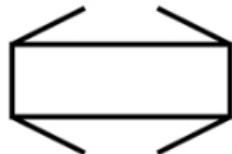
# Size constancy illusion



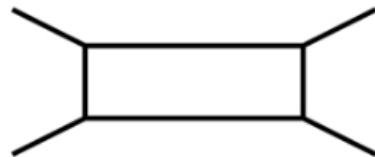
# Size constancy illusion



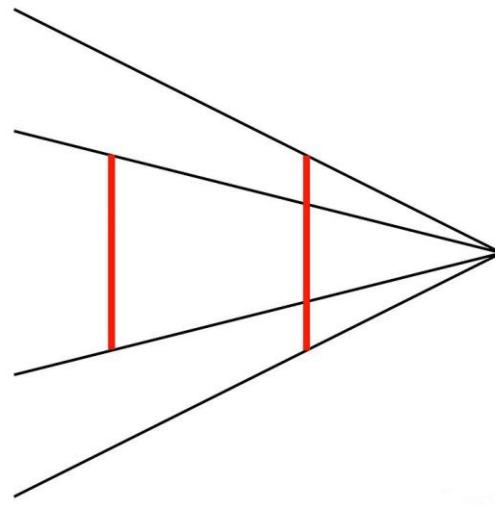
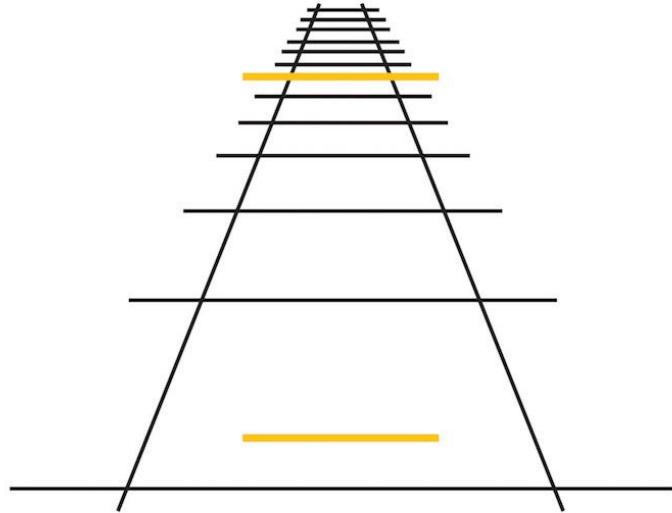
Müller-Lyer illusion



Waite-Massaro illusion

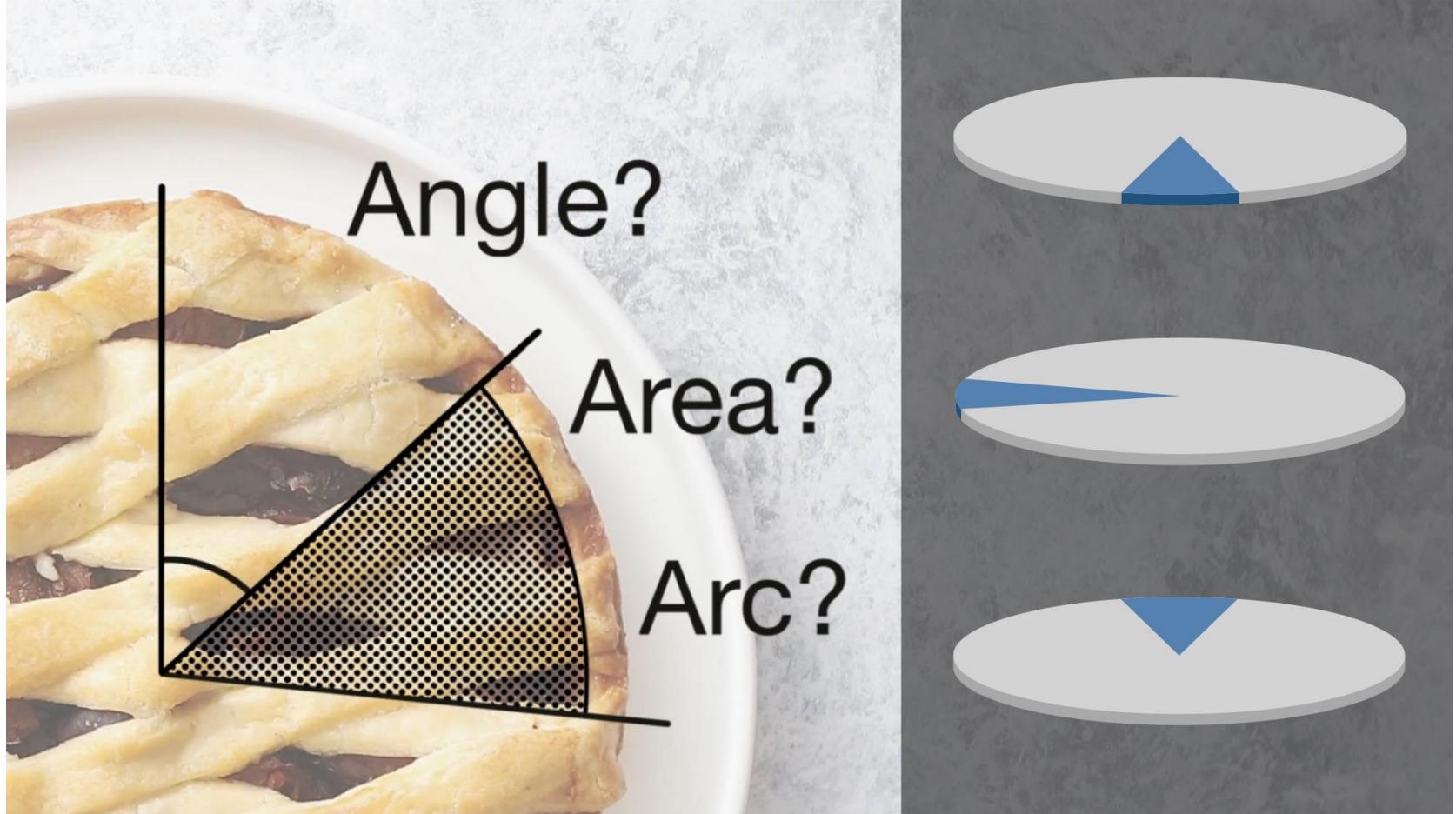


# Size constancy illusion



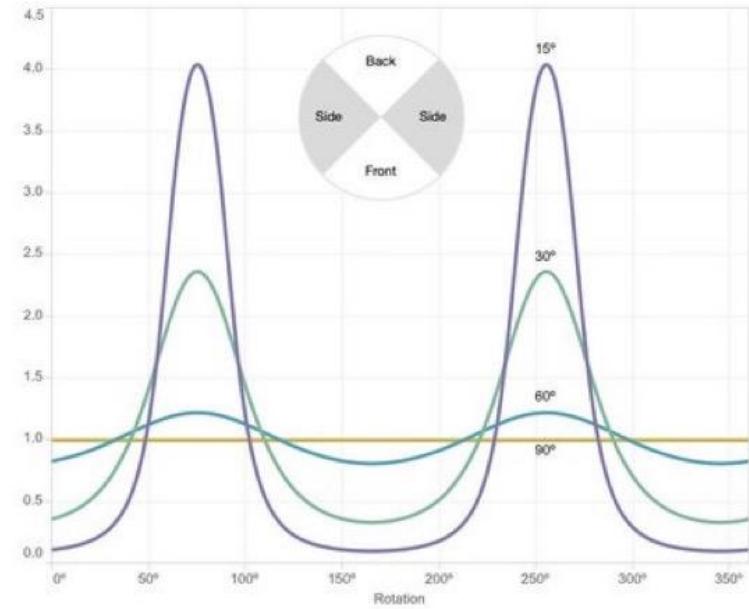
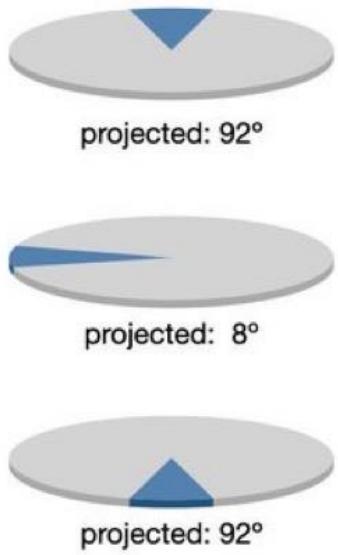
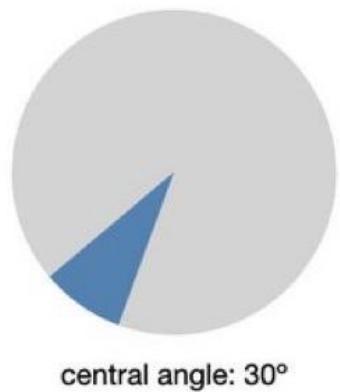
(Ponzo illusion)

# Implications for 3D

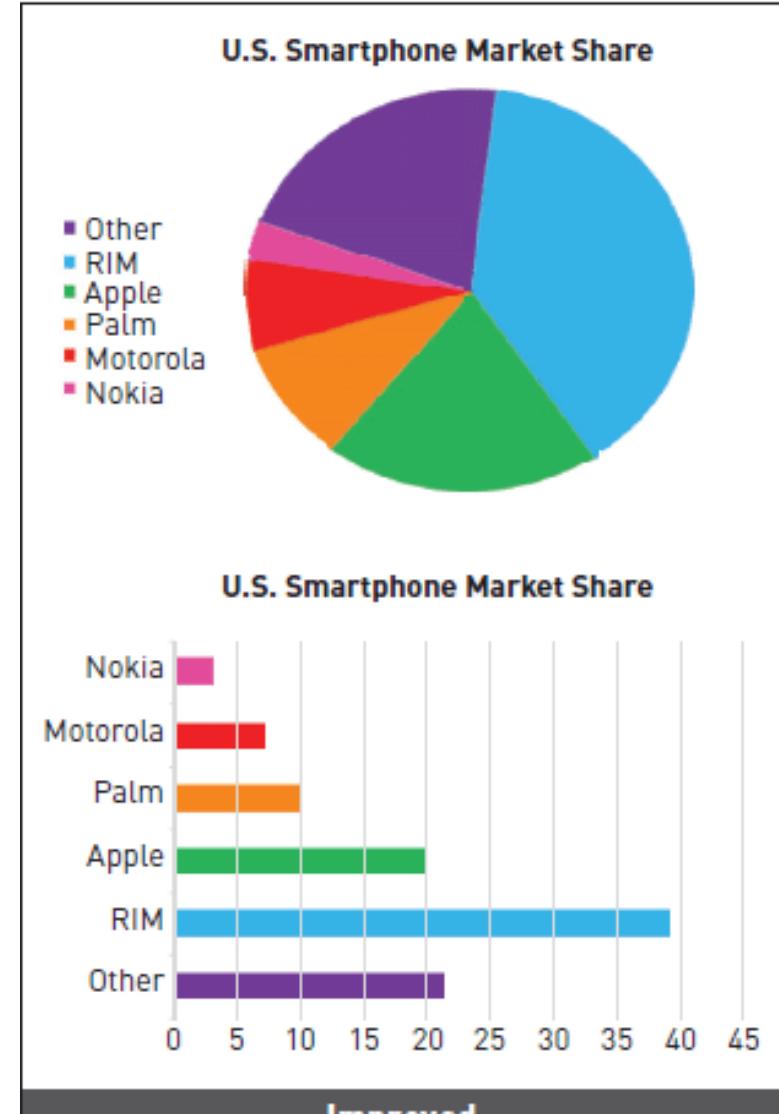


<https://eagereyes.org/blog/2019/eagereyestv-episode-3-3d-pie-charts-for-science>

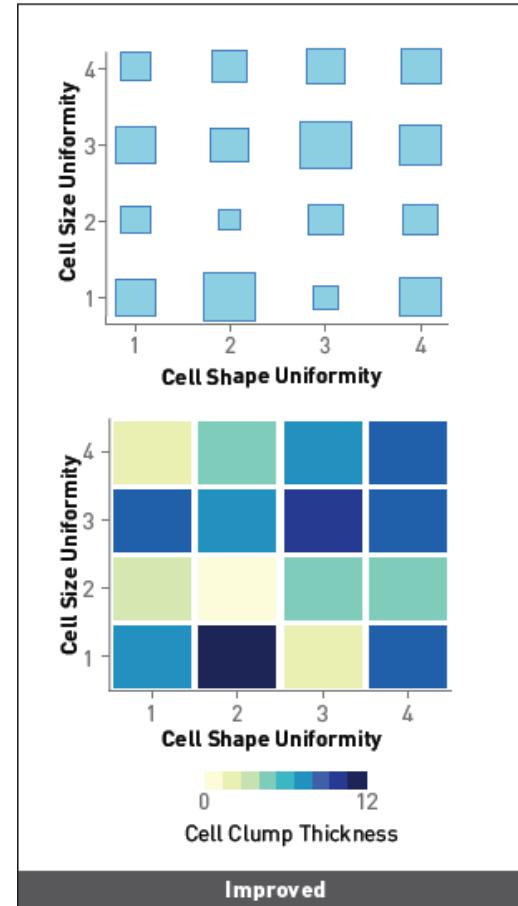
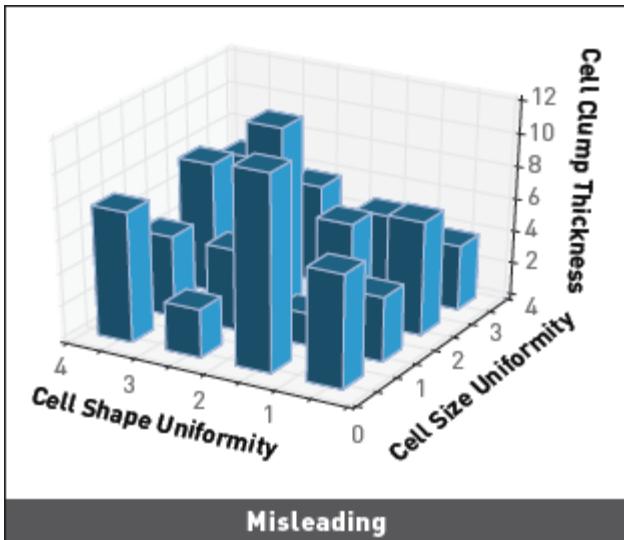
# Implications for 3D



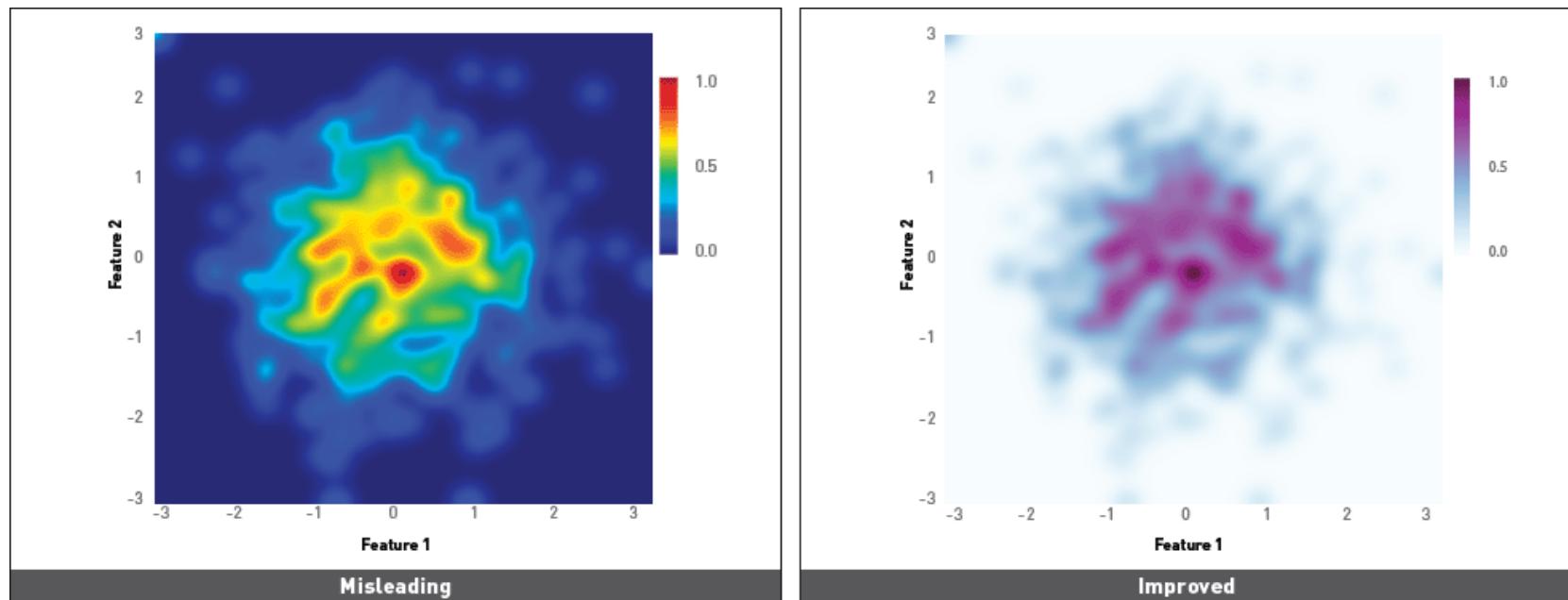
# Implications for 3D



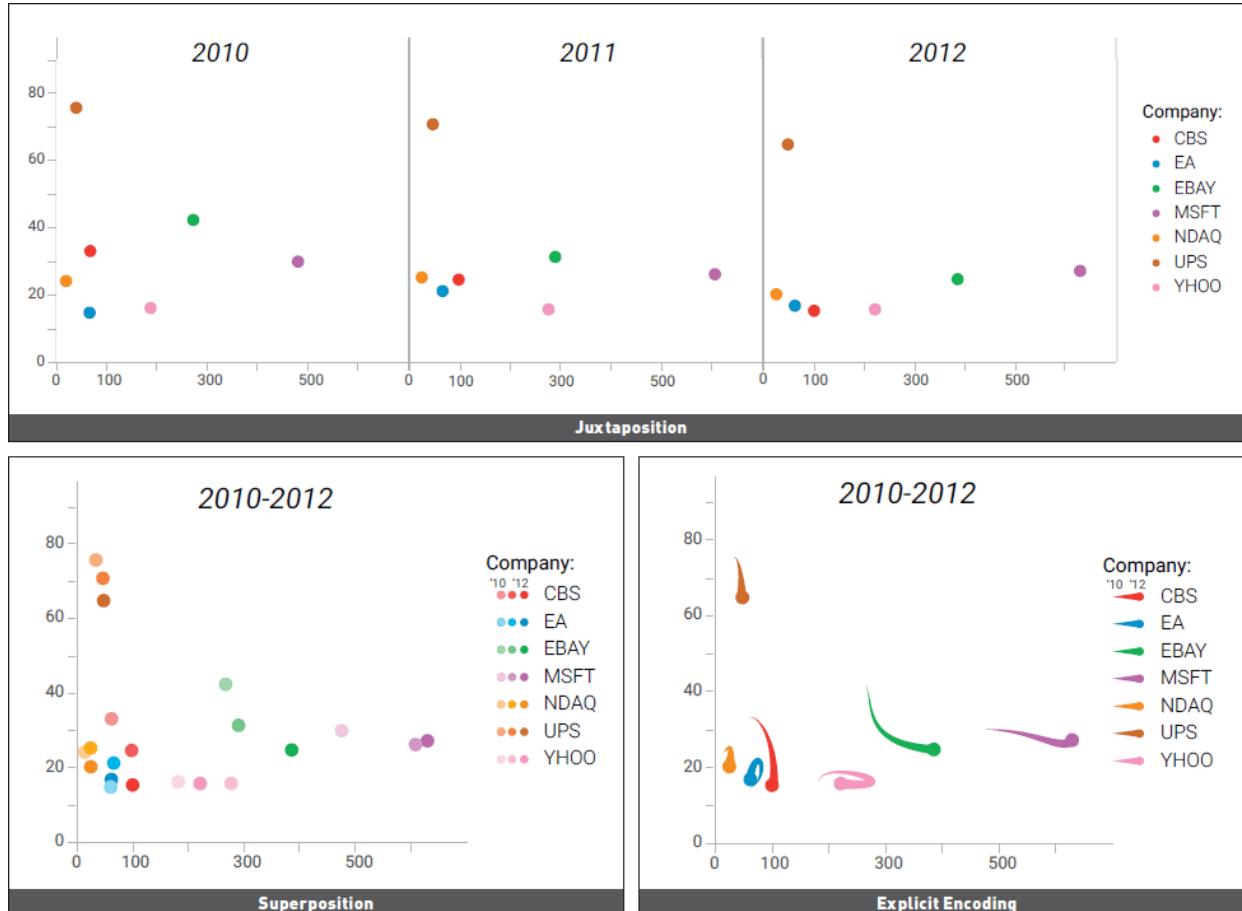
# Implications for 3D



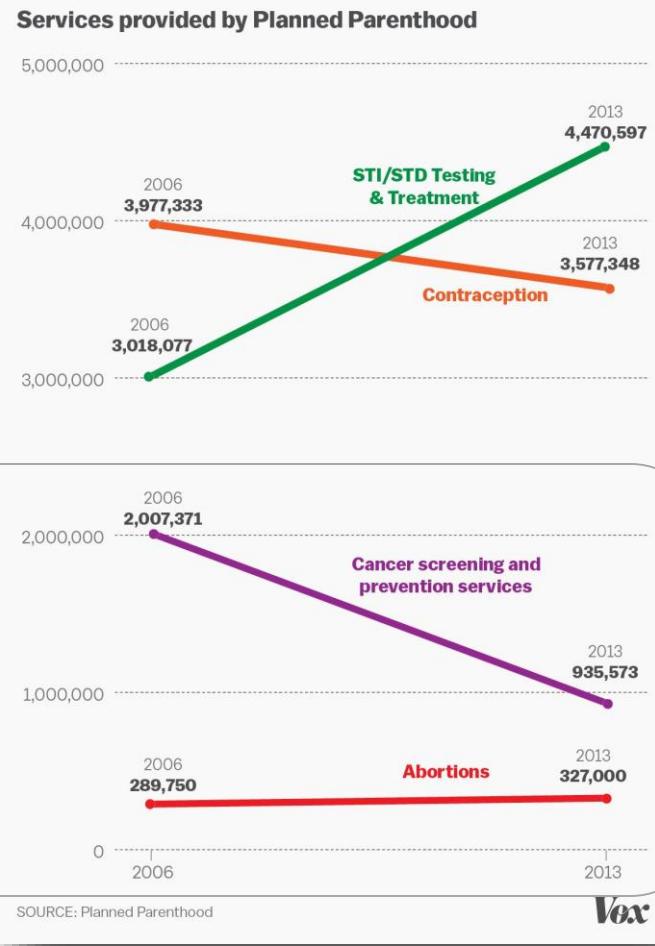
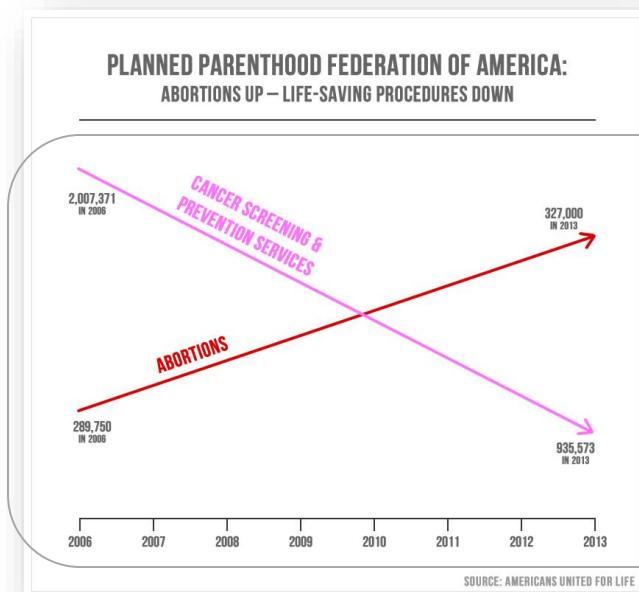
# Rainbow palettes



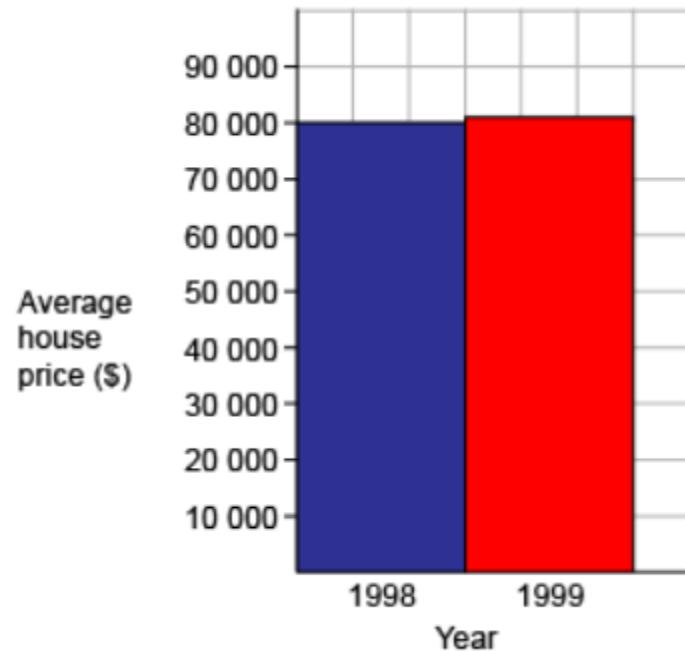
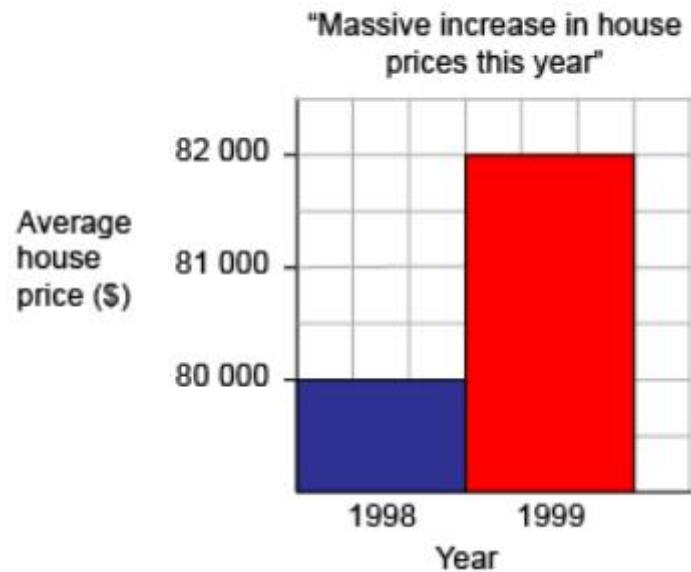
# Animation



# Biased labeling

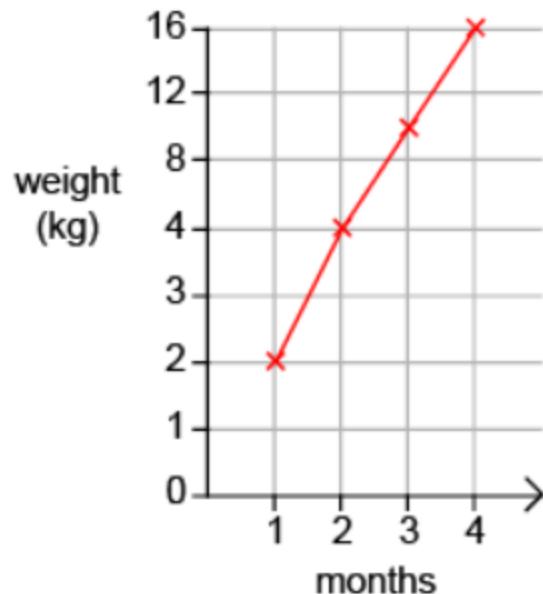


# Truncated axis

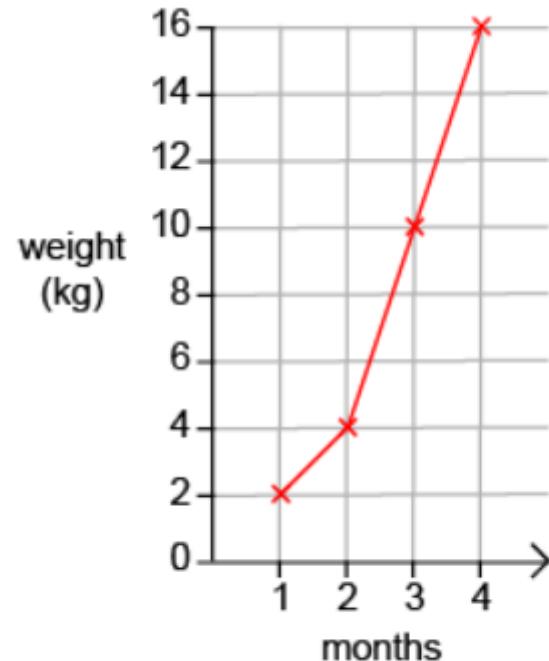


<https://topdrawer.aamt.edu.au/Statistics/Misunderstandings/Misleading-graphs/Misleading-scales>

# Improper intervals/scales



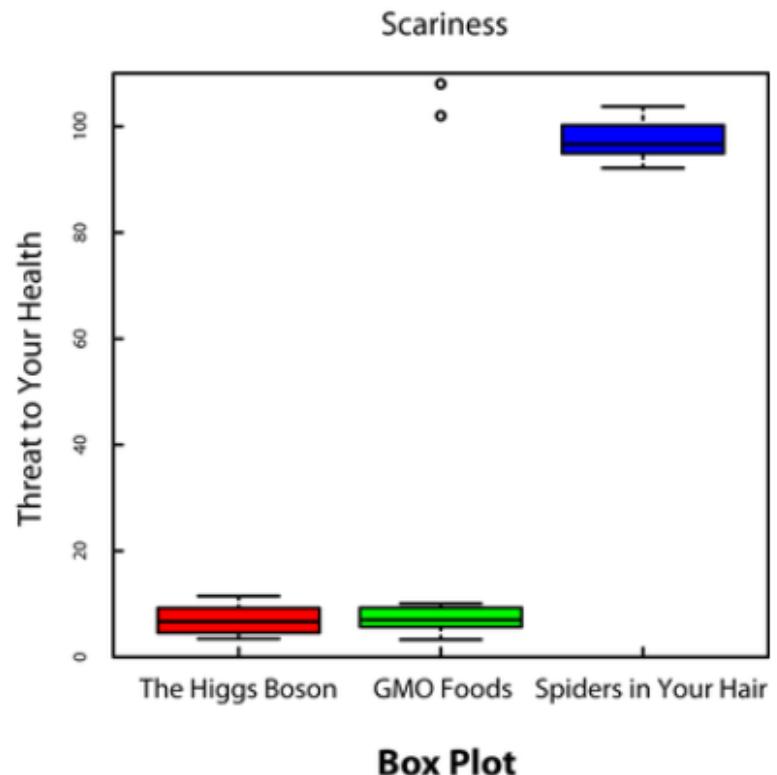
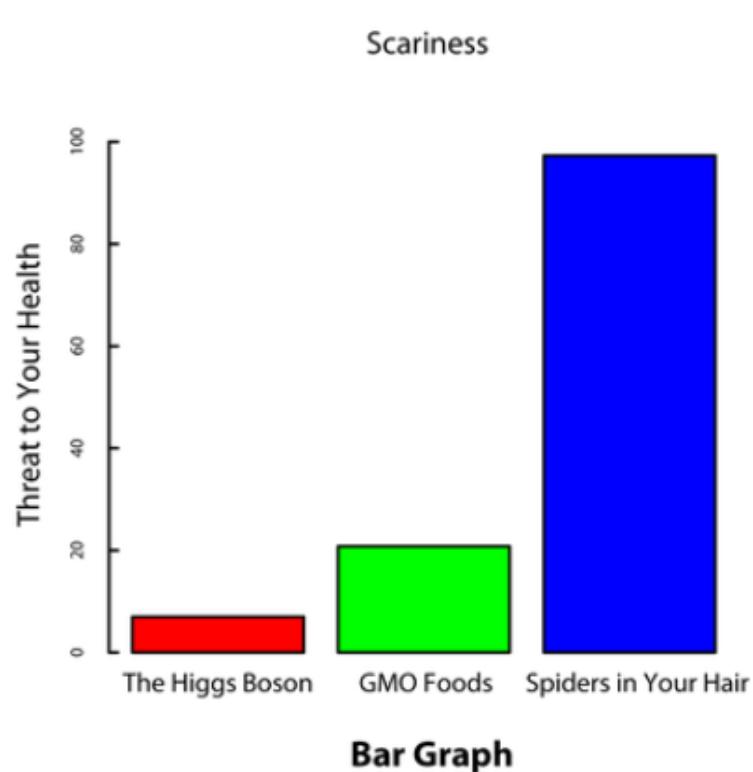
weight of a puppy



weight of a puppy

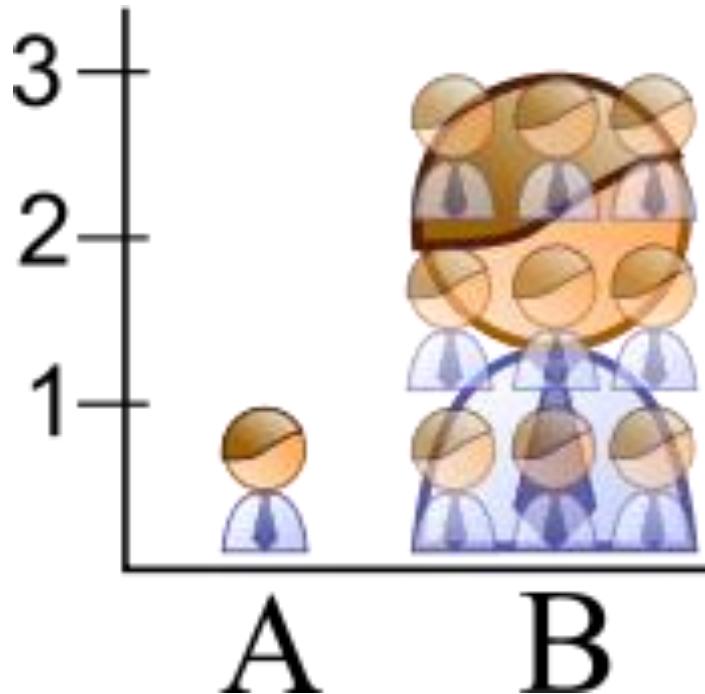
<https://topdrawer.aamt.edu.au/Statistics/Misunderstandings/Misleading-graphs/Misleading-scales>

# Misleading graphs

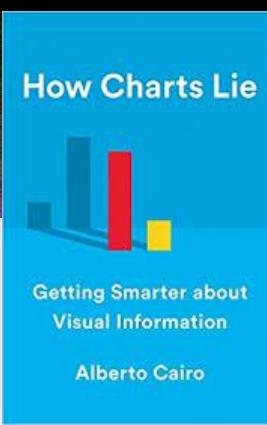
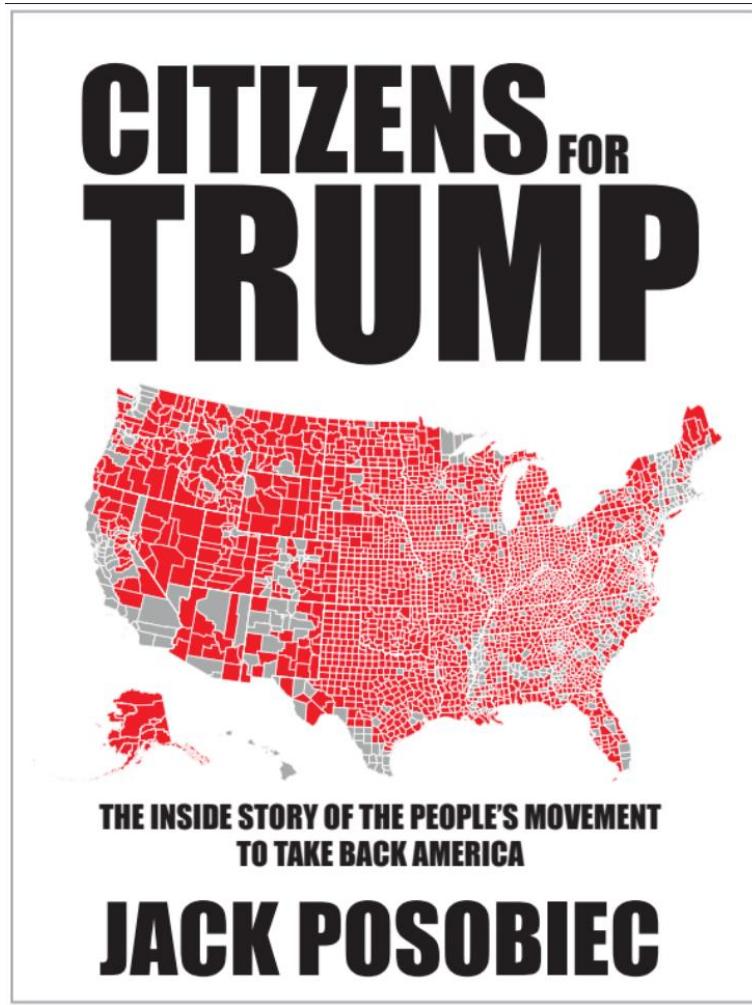


<https://figureoneblog.wordpress.com/2014/03/12/misleading-with-pictures-the-pitfalls-of-data-visualization/>

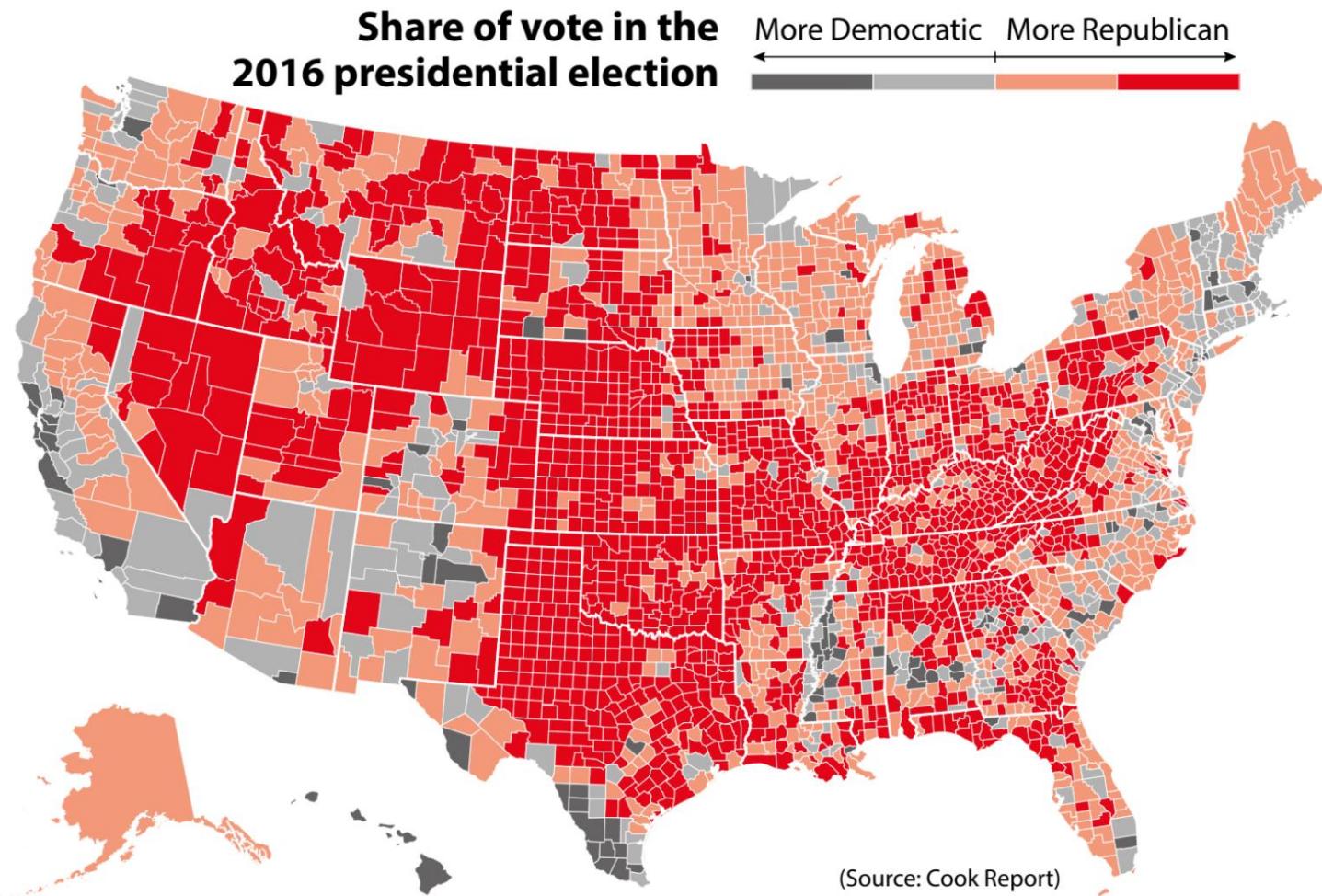
# Misleading pictographs



# Misleading maps

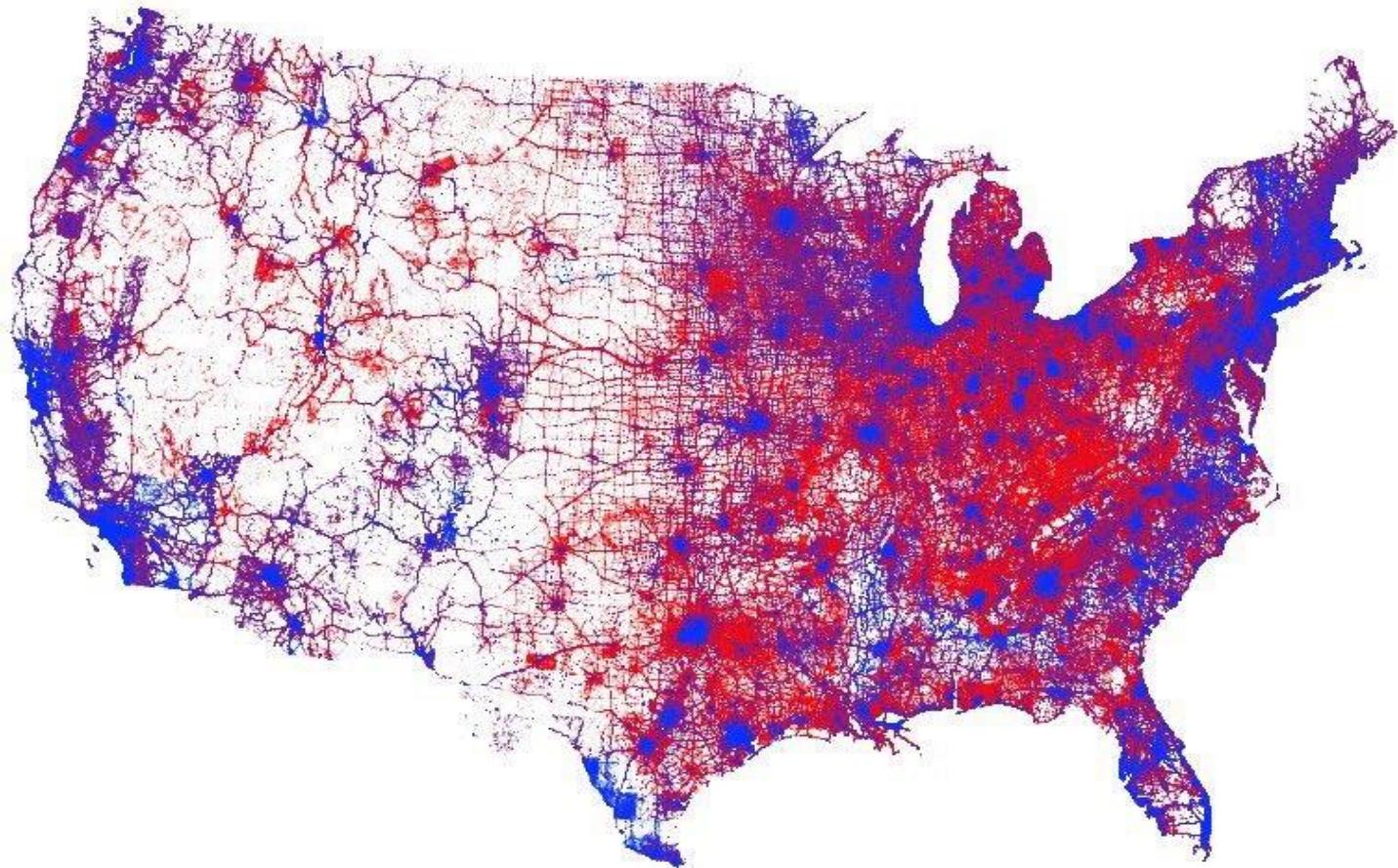


# Misleading maps



# Misleading maps

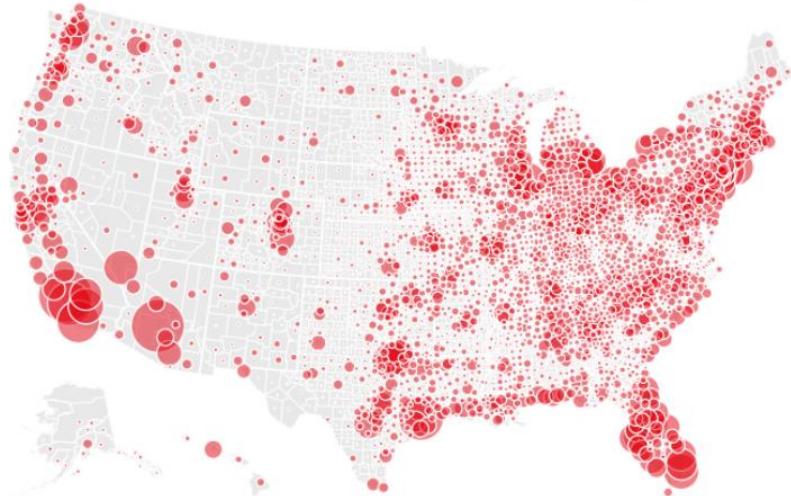
Dasymetric Dot Density



<http://cartonerd.blogspot.com/2018/03/dotty-election-map.html>

# Misleading maps

**Votes for Donald Trump**



**Votes for Hillary Clinton**



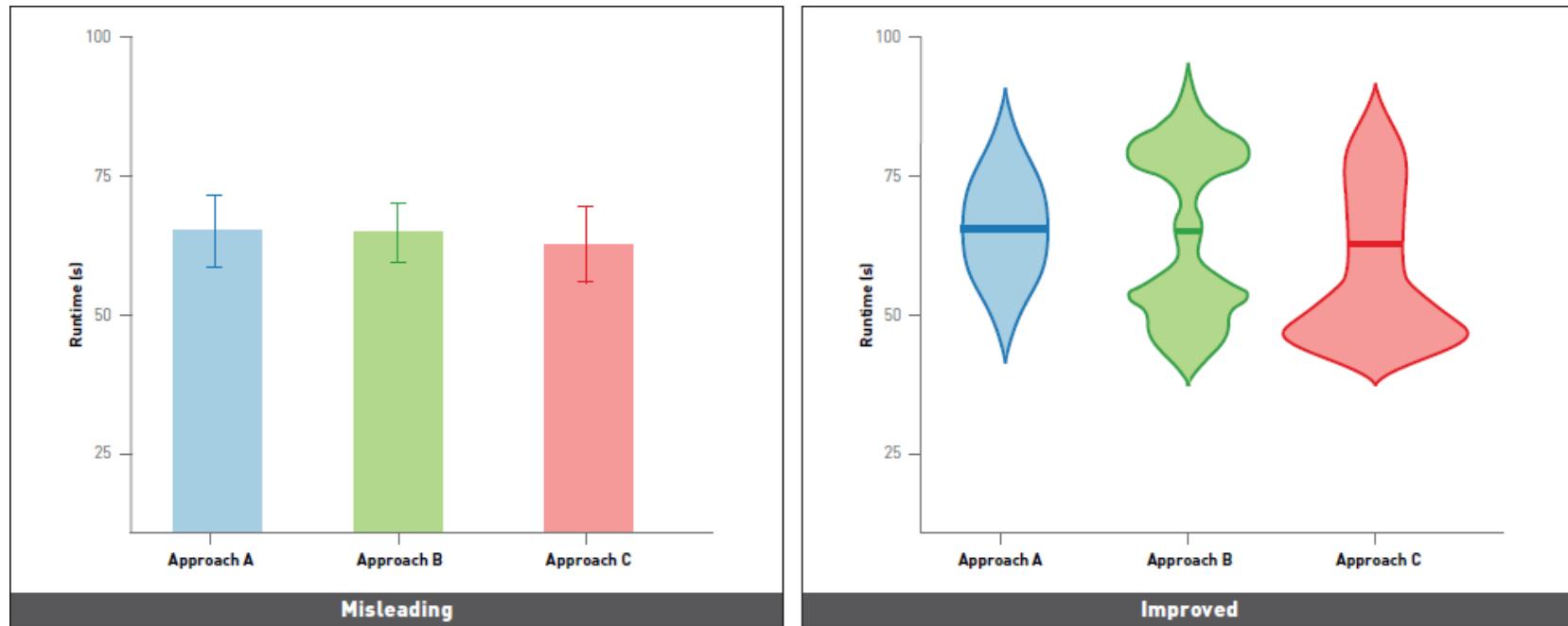
Bubble size is proportional to the number of votes per county

... and much more

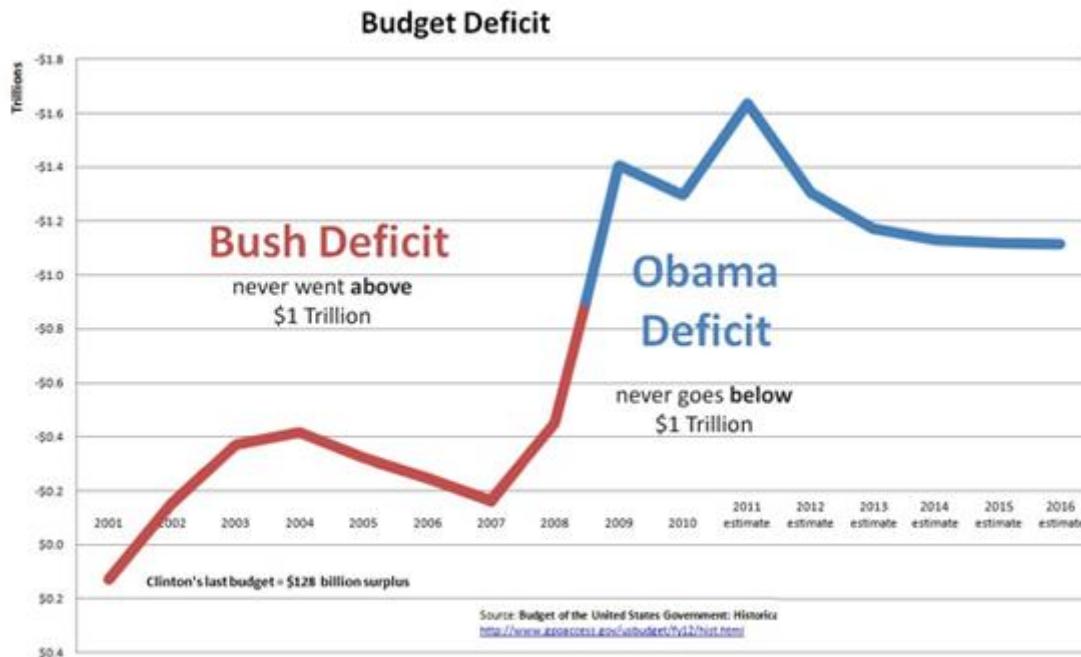


<https://www.nytimes.com/interactive/2020/10/30/opinion/election-results-maps.html>

# Misleading graphs

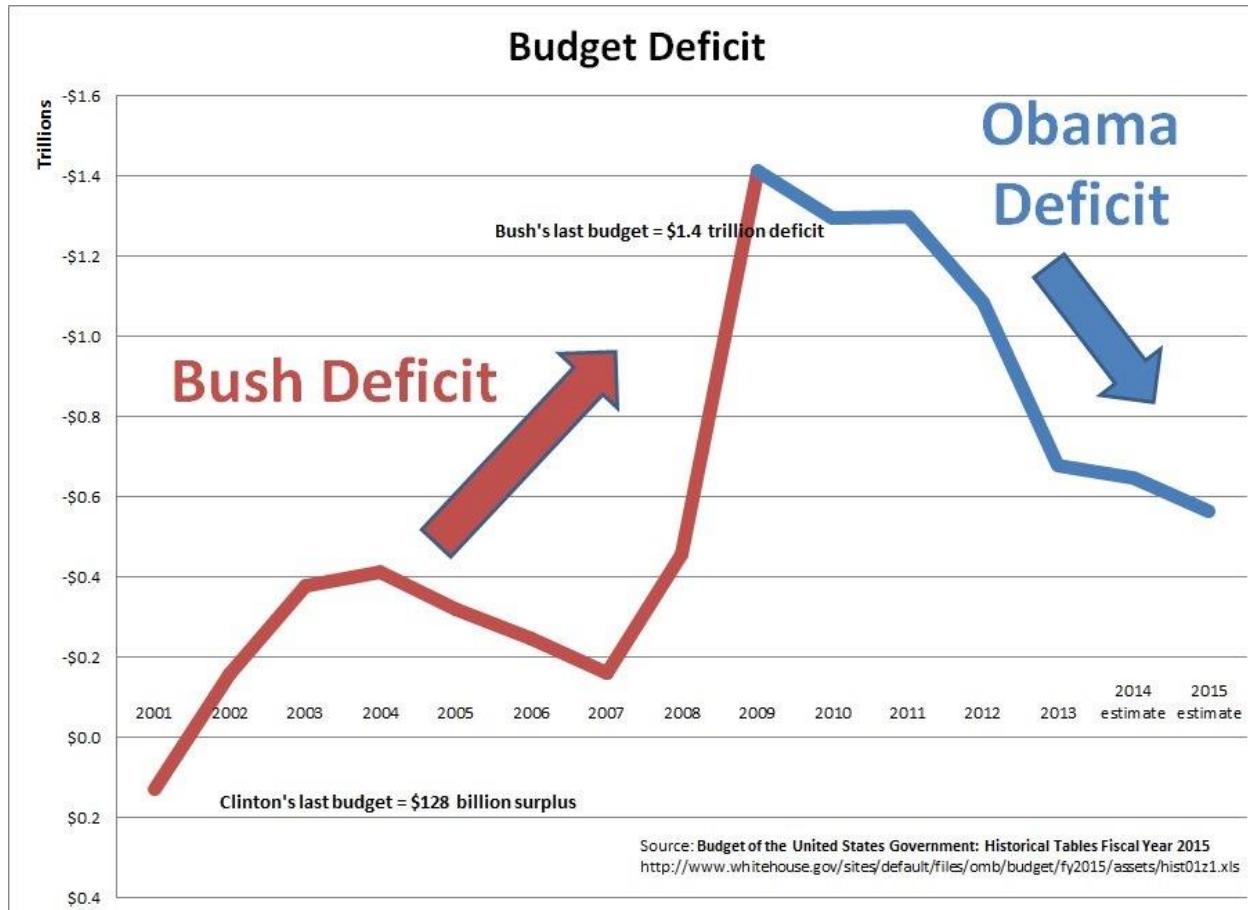


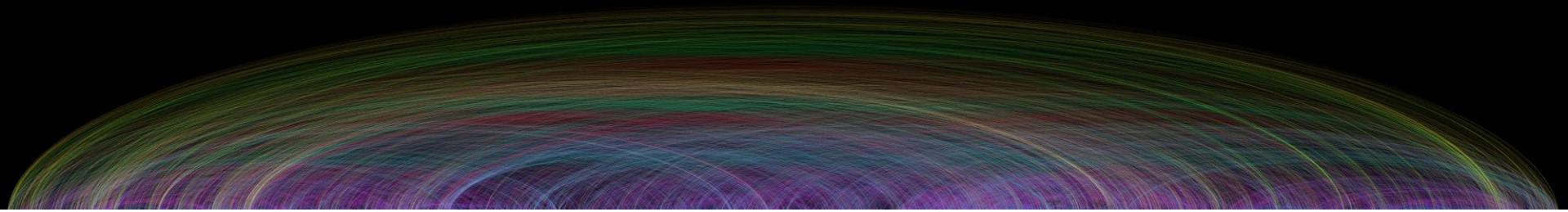
# Cultural Bias



Signal value issues. The red line feels more negative. From <http://www.politicalmathblog.com>

# Cultural Bias



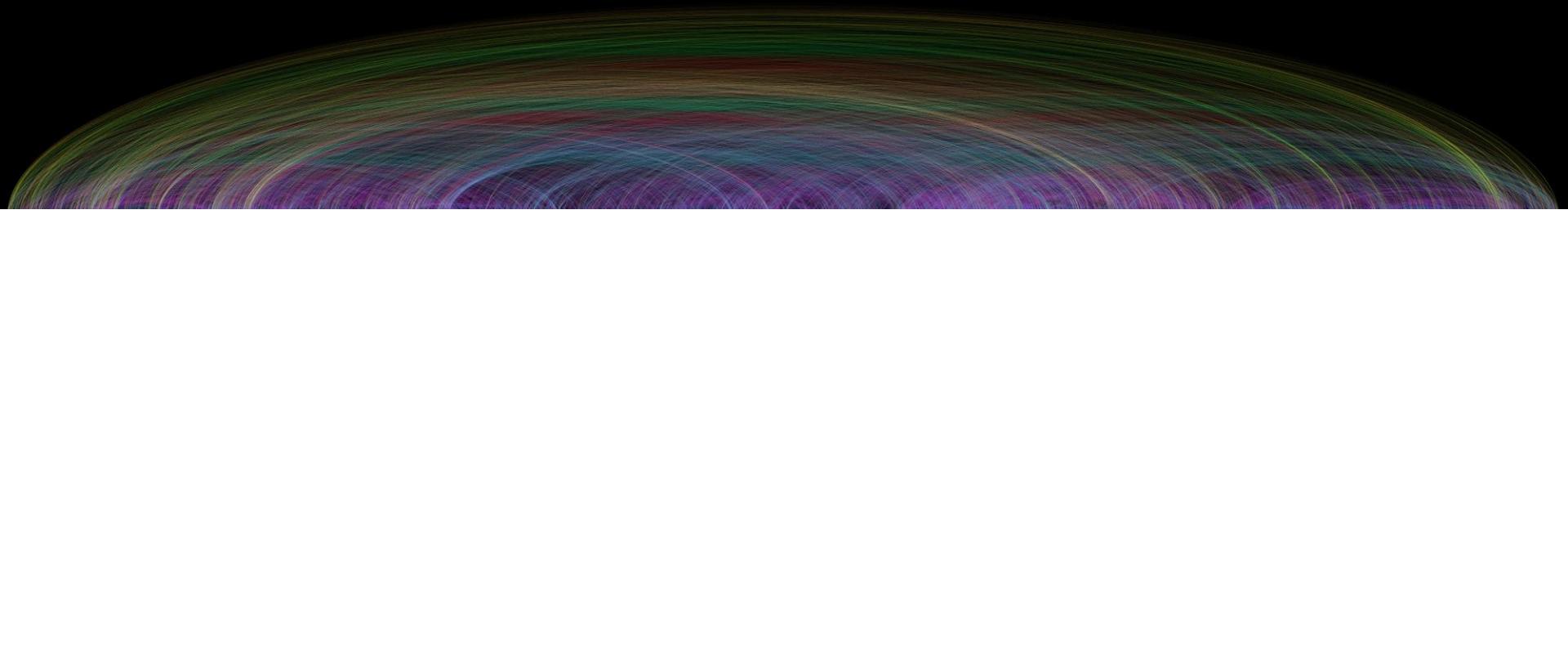


– Benjamin Haydon

*“FORTUNATELY FOR SERIOUS MINDS, A BIAS  
RECOGNIZED IS A BIAS STERILIZED.”*

# Ask yourself

- Why am I seeing what I'm seeing?
- Why am I interpreting it the way I am interpreting it?
- Have I looked at all related data?



Recent Research

# **COGNITIVE BIAS IN INTERACTIVE VISUAL ANALYTICS**

# Cognitive Bias in Interactive Visual Analytics

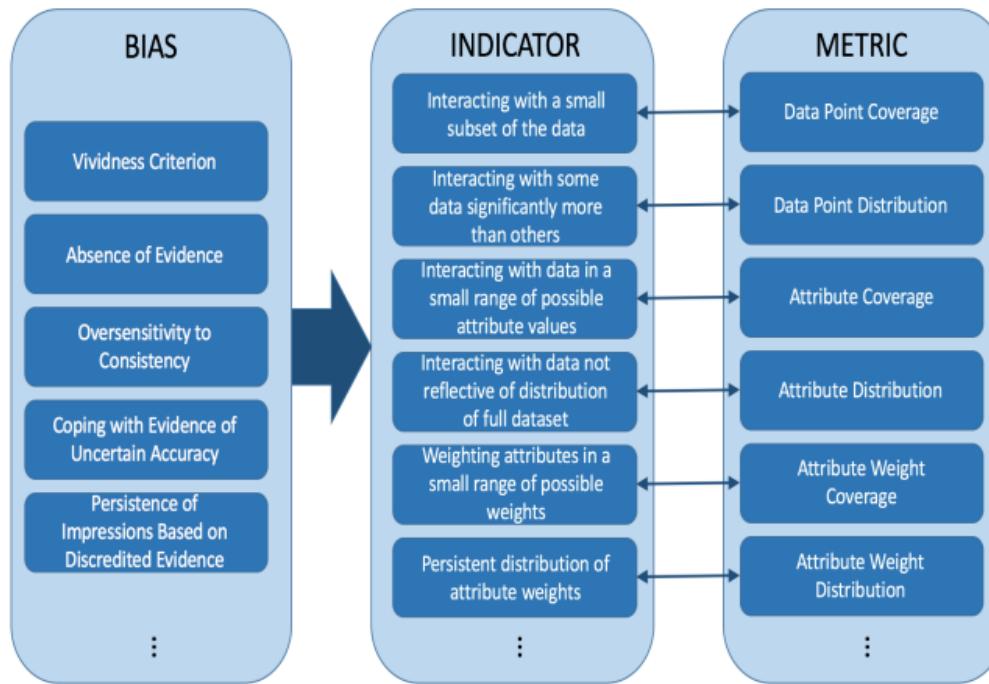


Figure 1: Cognitive biases result in behavioral indicators that are measurable by the proposed metrics. We scope this paper to those indicators and metrics depicted above, but there are numerous other biases, behavioral indicators, and ways to measure those indicators.

Wall et al. (2017), *Warning , Bias May Occur : A Proposed Approach to Detecting Cognitive Bias in Interactive Visual Analytics*, VAST symposium, URL: <https://www.cc.gatech.edu/~ewall9/media/papers/BiasVAST17.pdf>

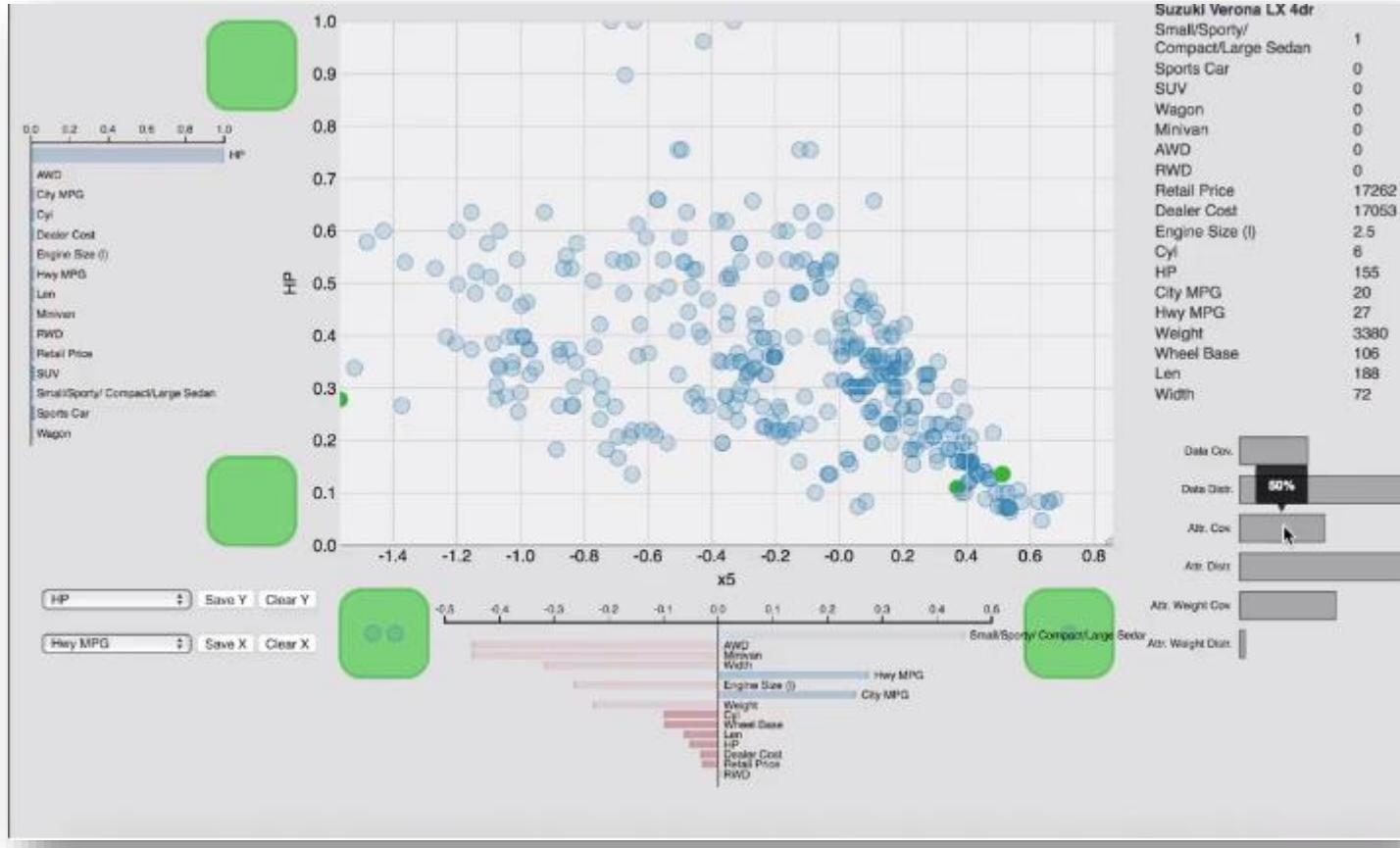
# Cognitive Bias in Interactive Visual Analytics

Bias	Description	Interaction Manifestation
Vividness Criterion	humans rely more heavily on information that is specific or personal than information that is abstract or lacking in detail	e.g., analyst frequently returns to / interacts with data points that are rich in detail
Absence of Evidence	humans tend to focus their attention on the information that is present, ignoring other significant pieces of evidence that may be missing	e.g., analyst filters out a subset of data, forgets about it, and makes future decisions without accounting for the missing data
Oversensitivity to Consistency	humans tend to choose hypotheses that encompass the largest subset of evidence	e.g., analyst interacts almost exclusively with data that supports the largest encompassing hypothesis, dismissing other data
Coping with Evidence of Uncertain Accuracy	humans tend to choose to accept or reject a piece of evidence wholly and seldom account for the probability of its accuracy	e.g., analyst filters out data that supports a seemingly unlikely hypothesis, thus fully rejecting it
Persistence of Impressions Based on Discredited Evidence	humans tend to continue to believe information even after it has been discredited (also known as the <i>continued influence effect</i> )	e.g., analyst continues to interact with data supporting a hypothesis that has been disproved

Table 1: Cognitive biases relevant to intelligence analysis [38] that produce the measurable behavioral indicators we focus on in this paper.

In R. J. Heuer Jr. *Psychology of Intelligence Analysis*. Washington, DC, 1999

# Detecting Cognitive Bias



<https://www.youtube.com/watch?v=W9LWi3oXjM0>

Wall et al. (2017), *Warning , Bias May Occur : A Proposed Approach to Detecting Cognitive Bias in Interactive Visual Analytics, VAST symposium, URL: https://www.cc.gatech.edu/~ewall9/media/papers/BiasVAST17.pdf*