# VISUALIZATION

cs2420 | Spring 2015



# administrivia...

-assignment 12 is due Tuesday

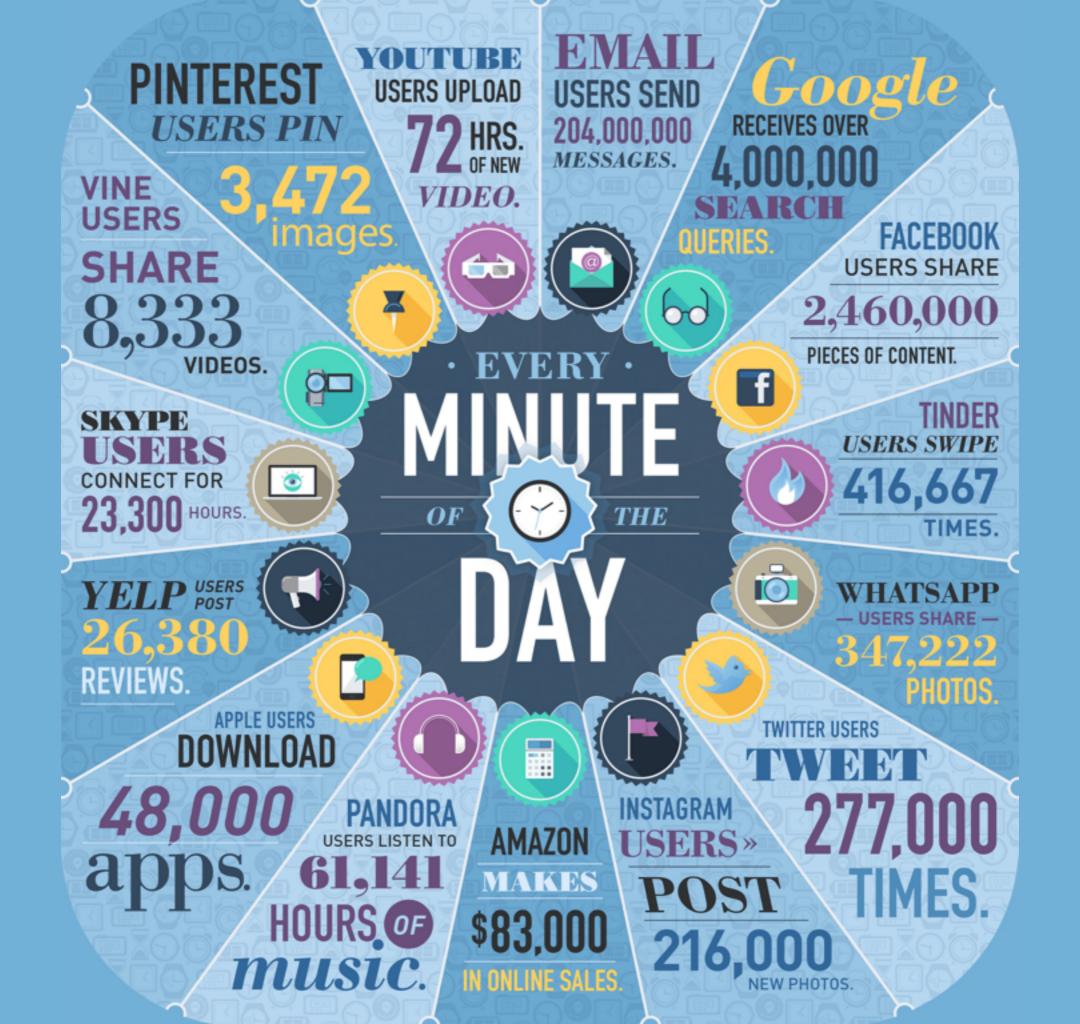
-upcoming lectures



# INDUSTRIAL REVOLUTION OF DATA

Joe Hellerstein, UC Berkley





The ability to take data—to be able to **understand** it, to **process** it, to **extract value** from it, to **visualize** it, to **communicate** it—that's going to be a hugely important skill in the next decades.

Hal Varian, Google's Chief Economist

8:1

1440

25:1

1150

1350

12:1

8:1

1440

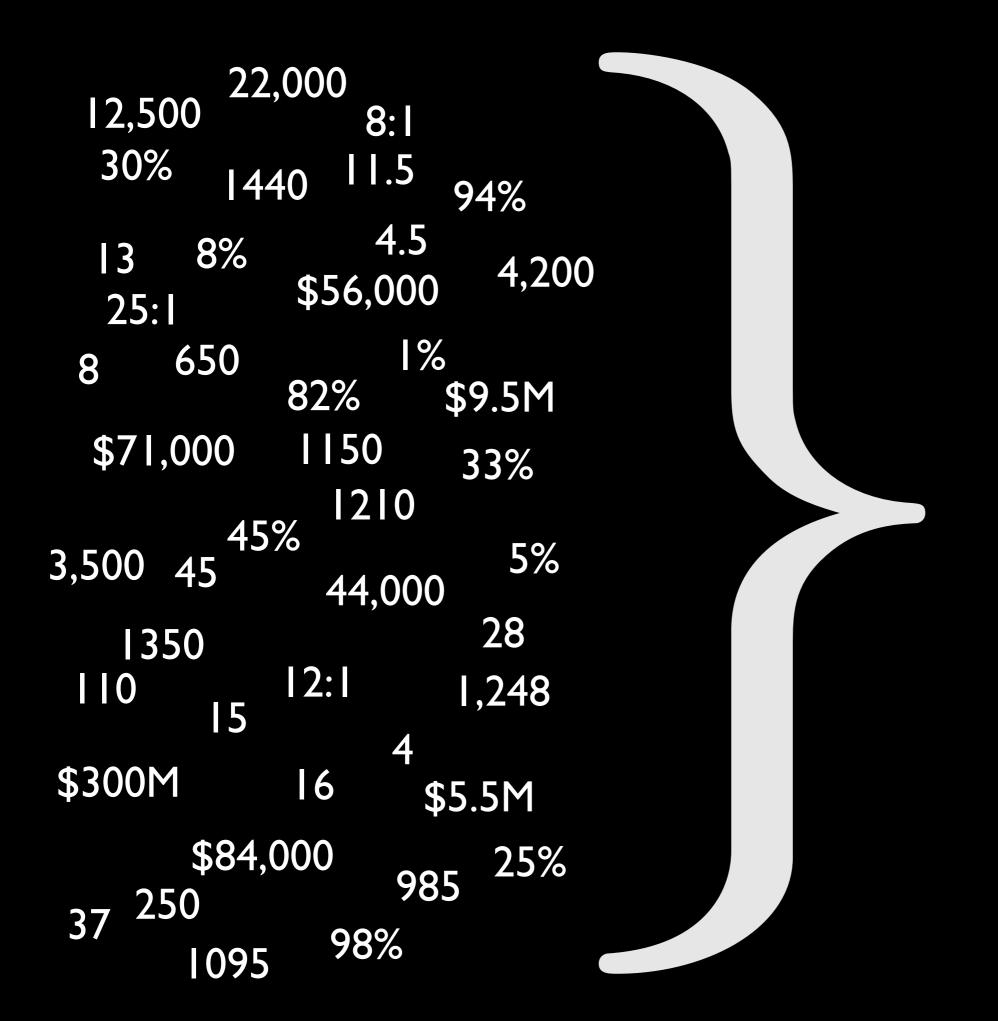
25:1 \$56,000

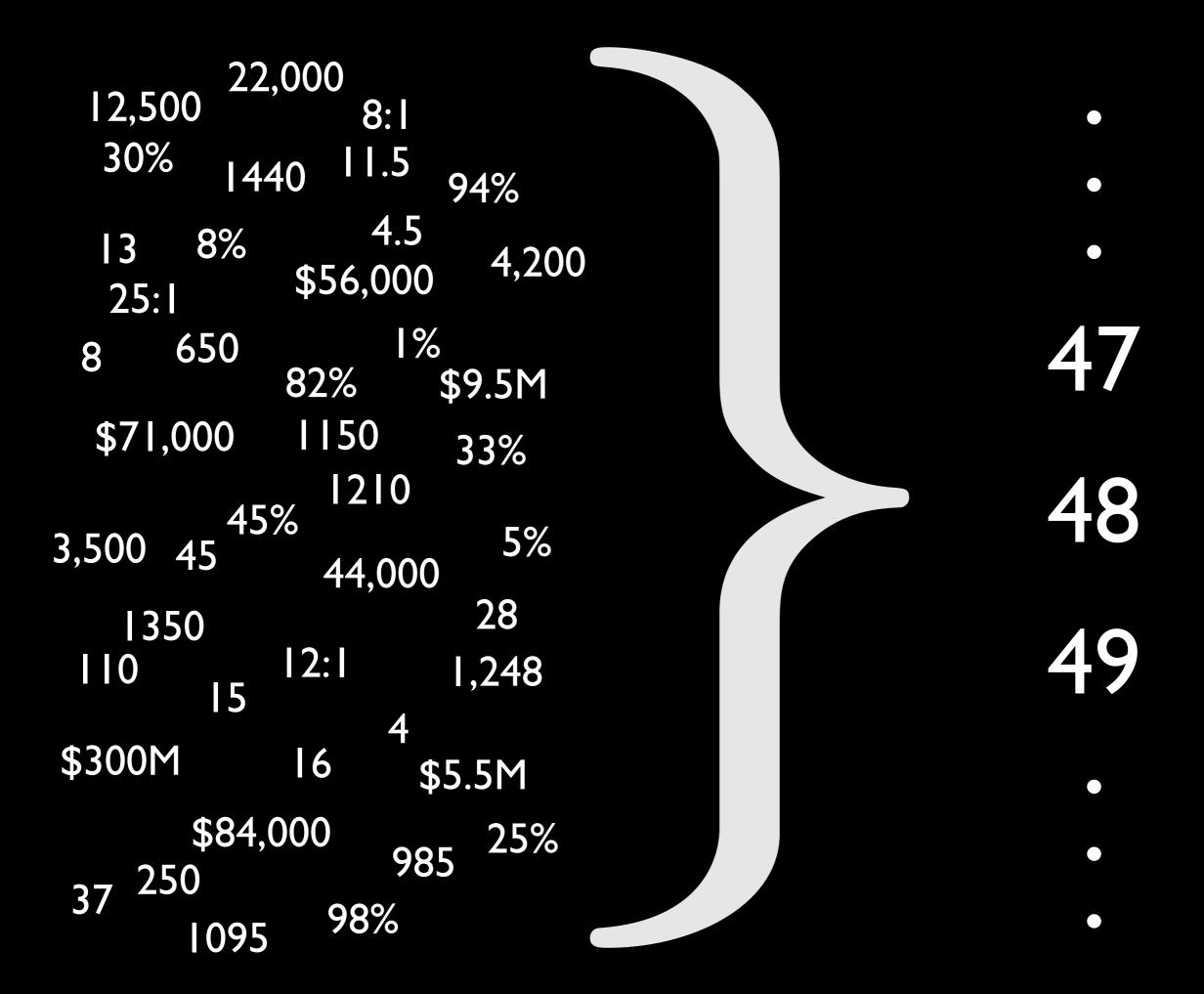
\$71,000 1150

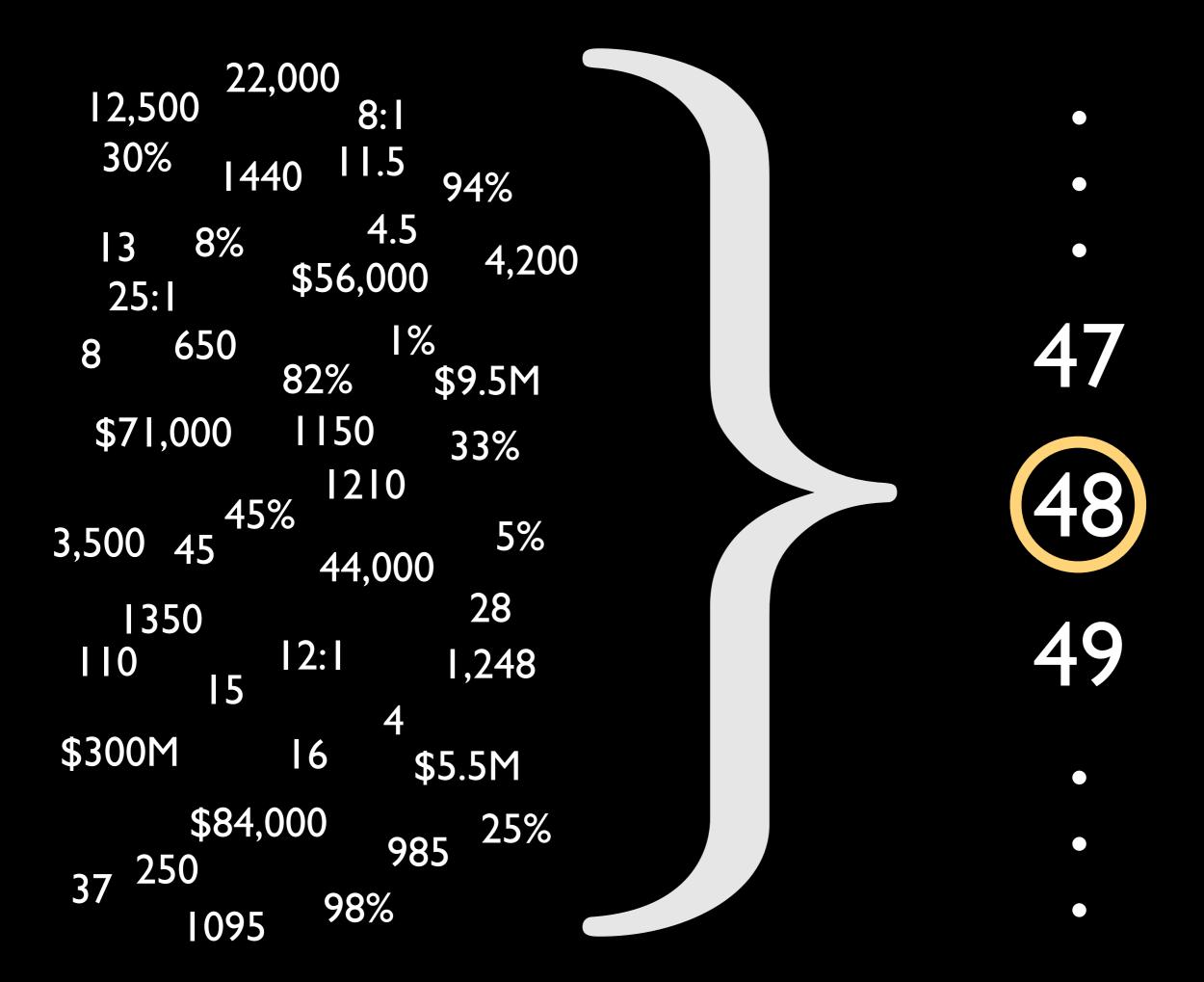
1350

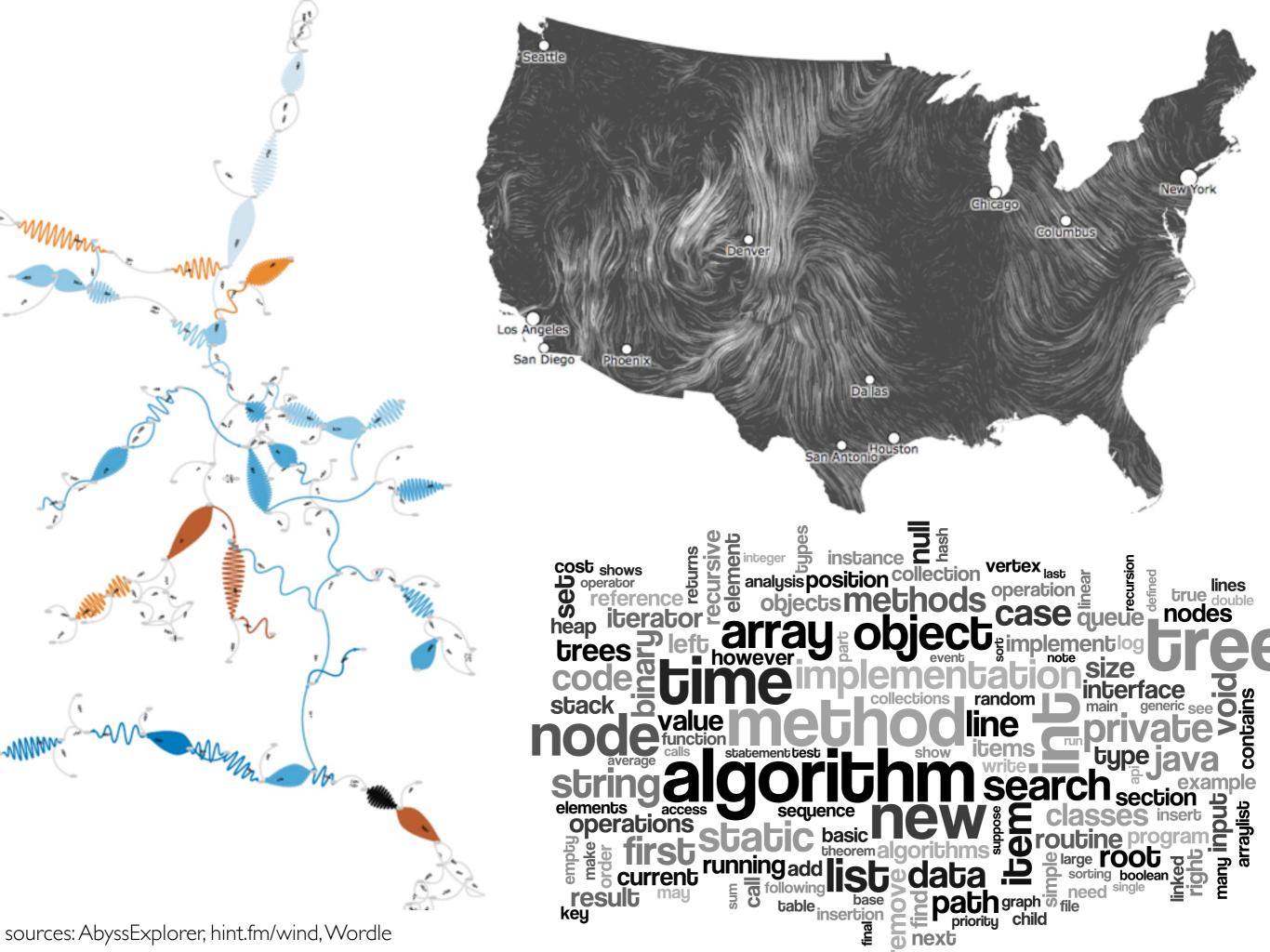
12:1

\$84,000









# visualization uses perception to point out interesting things.

# MTHIVLWYADCEQGHKILKMTWYN ARDCAIREQGHLVKMFPSTWYARN GFPSVCEILQGKMFPSNDRCEQDIFP SGHLMFHKMVPSTWYACEQTWRN

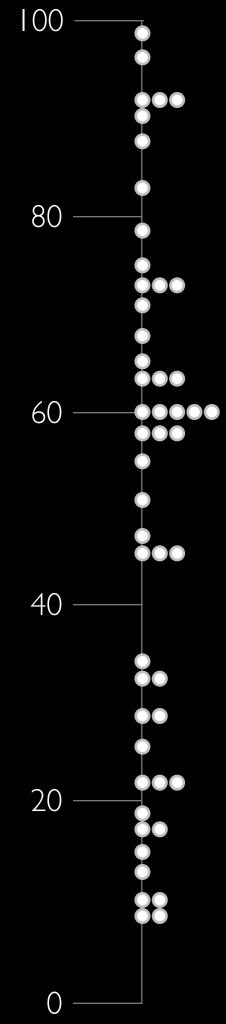
# MTHIVLWYADCEQGHKILKMTWYN ARDCAIREQGHLVKMFPSTWYARN GFPSVCEILQGKMFPSNDRCEQDIFPS GHLMFHKMVPSTWYACEQTWRN

# visualization uses pictures to enhance working memory.

```
60
33
         75
         79
57
    34
18
         92
    51
        13
73
    22
    60
        22
71
     10
         68
     18
         55
73
         29
65
    46
60
    73
        22
    92
46
         97
    58
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88
    92
         60
91
    29
         57
96
     12
         47
```

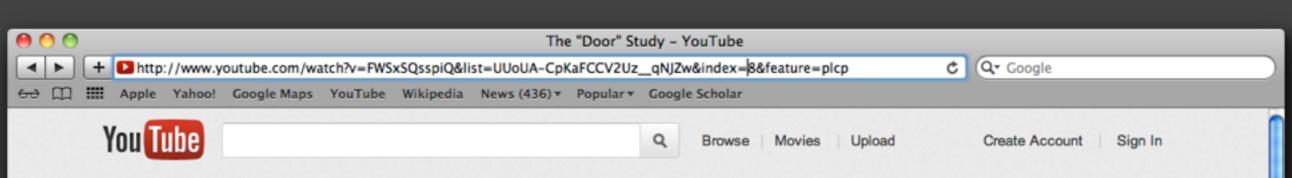
## given these 50 numbers...

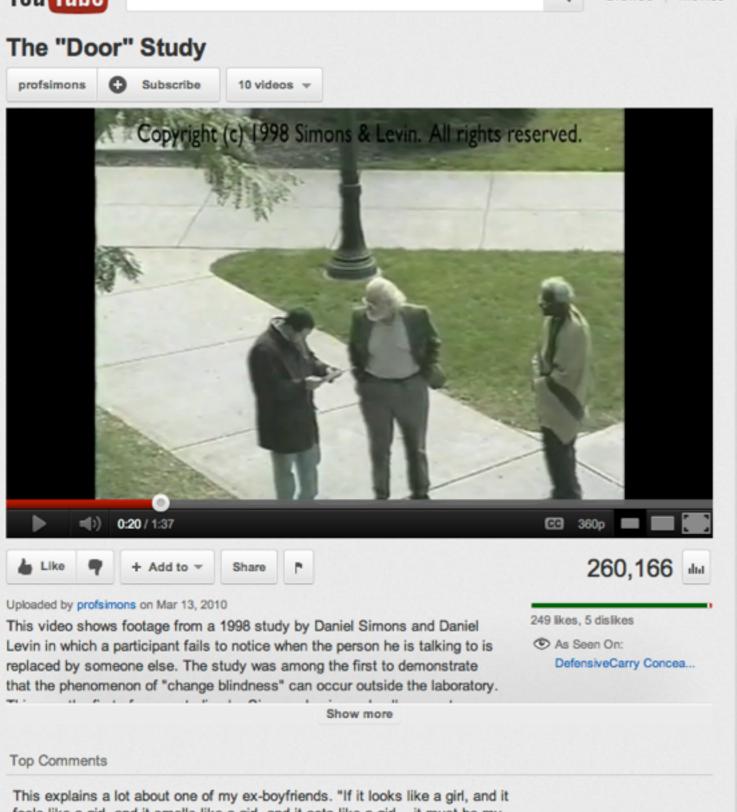
... what number appears most often?



# given these 50 numbers...

... what number appears most often?





feels like a girl, and it smells like a girl, and it acts like a girl... it must be my girlfriend."

ataaah 1 year ago 141 🖒

Change Blindness I 0:22

#### Change Blindness 1

by yeblind 36,759 views

Featured Video

#### Gradual Change Test 1

by profsimons 34,443 views



Change Blindness

by trutapes 25,498 views



Test Your Awareness.....

by beepsquick 43.847 views



Perception of beauty

by andreic27 92,589 views



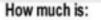
Amazing Fire & Gas Trick!

by brusspup 1,078,932 views



Try To Watch This Without Laughing Or

by 88ownsnascar 2,042,315 views



#### Sociopath Test

75 + 26

by Daanando 213,997 views





**Awareness Test** by JOEKthePANDA

### vi·su·al·i·za·tion

**noun, plural** -s

- I. formation of mental visual images
- 2. the act or process of interpreting in visual terms or of putting into visible form

"Computer-based **visualization** systems provide visual representations of datasets intended to help people carry out tasks more effectively."

Prof. Tamara Munzner

## ANALYZE DATA



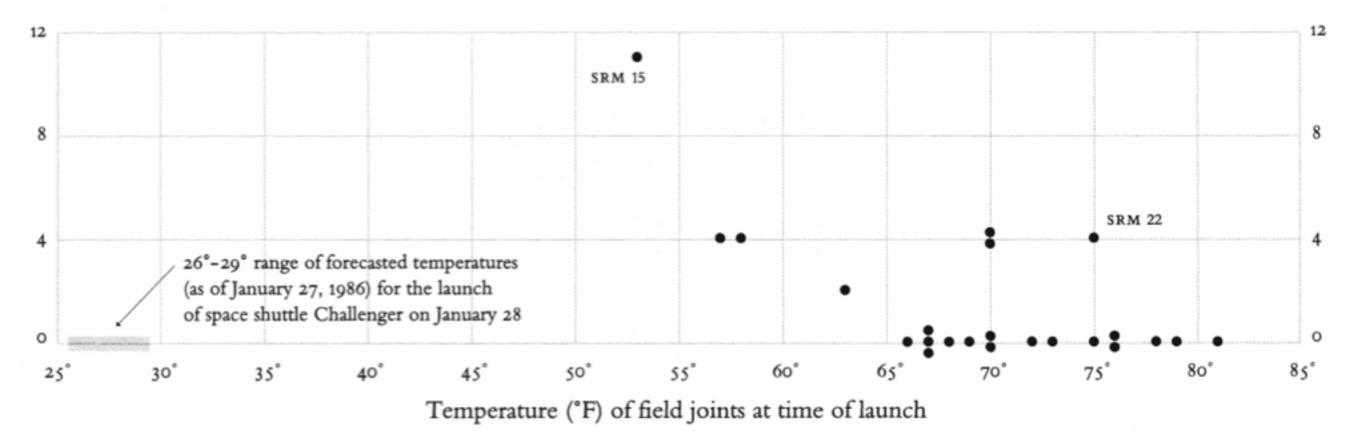
3										
	<b>,</b>		Erosion	ross Sectional Perimeter	View	Length Of	View Total Heat	Clocking	MOTOR	O-RING
6	HET	SRM No.	Depth (in.)	Affected (deg)	Dia. (in.)	Max Erosion (in.)	Affected Length (in.)	(deg)	om-+	47
£ 000	61A LH Center Field** 61A LH CENTER FIELD**  61A LH CENTER FIELD**  61C CH Forward Field**  61C RH Center Field (prim)***  61C RH Center Field (sec)***	22A 22A 15A 15B 15B	None NONE 0.010 0.038	None NONE 154.0 130.0 45.0	0.280 0.280 0.280 0.280 0.280	NONE 4.25 12.50 Hone	None NONE 5.25 58.75 29.50	36°66° 338°-18° 163 354 354	Dm - 2	52
,	410 RH Forward Field	138	None 0.028	110.0	0.280	3.00	Rone	275	Qm - 3	48
	41C LH Aft Field* 418 LH Forward Field	11A 10A	None 0.040	None 217.0	0.280	None 3.00	None 14.50	351	Qm-4	51
1.12	STS-2 RH Aft Field	2B	0.053	116.0	0.280			90		01
									SRM-15	53
*Hot gas path detected in putty. Indication of heat on O-ring, but no damage.  **Soot behind primary O-ring.  ***Soot behind primary O-ring, heat affected secondary O-ring.							5RM-22	75		
	Clocking location of leak o	heck p	ort - 0 deg						SRM-25	29

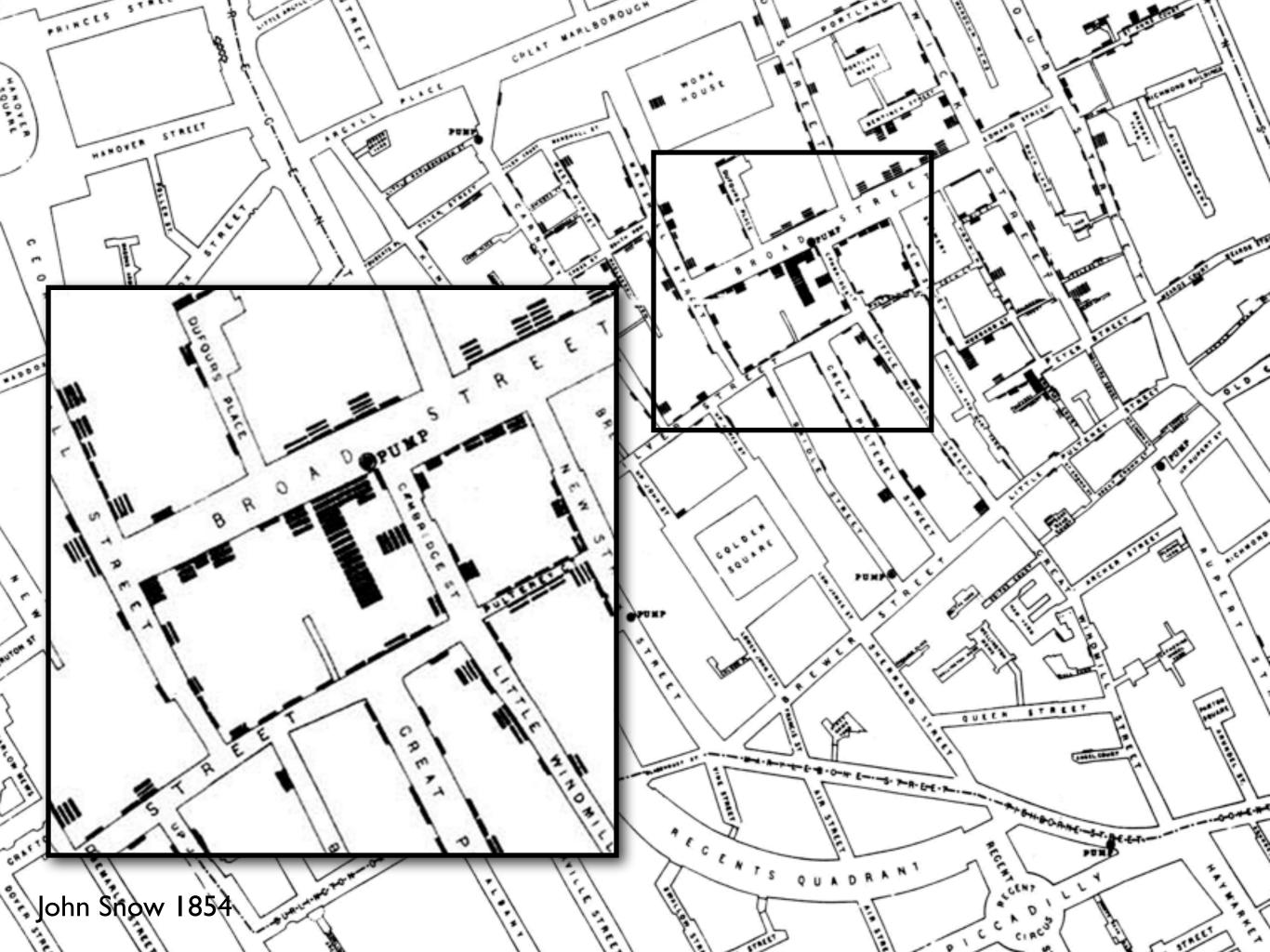
OTHER SRM-15 FIELD JOINTS HAD NO BLOWHOLES IN PUTTY AND NO SOOT NEAR OR BEYOND THE PRIMARY O-RING.

SRM-22 FORWARD FIELD JOINT HAD PUTTY PATH TO PRIMARY O-RING, BUT NO O-RING EROSION AND NO SOOT BLOWBY. OTHER SRM-22 FIELD JOINTS HAD NO BLOWHOLES IN PUTTY.

BLOW BY HISTORY SRM-15 WORST BLOW-BY		HISTORY OF O-RING TEMPERATURES (DEGREES - F)				
0 2 CASE JOINTS (80°), (110°) ARC	MOTOR	_MBT	AMB	O-RING	WIND	
O MUCH WORSE VISUALLY THAN SRM-22	om-+	68	36	47	10 MPH	
	Dm - 2	76	45	52	10 mpH	
SRM 12 BLOW-BY	Qm - 3	72.5	40	48	10 mpH	
0 2 CASE JOINTS (30-40°)	Qm-4	76	48	51	10 mPH	
	SRM-15	52	64	53	10 mpH	
SRM-13A, 15, 16A, 18, 23A 24A	5RM-22	77	78	75	10 MPH	
O NOZZLE BLOW-BY	SRM-25	55	26	29 27	10 MPH 25 MPH	

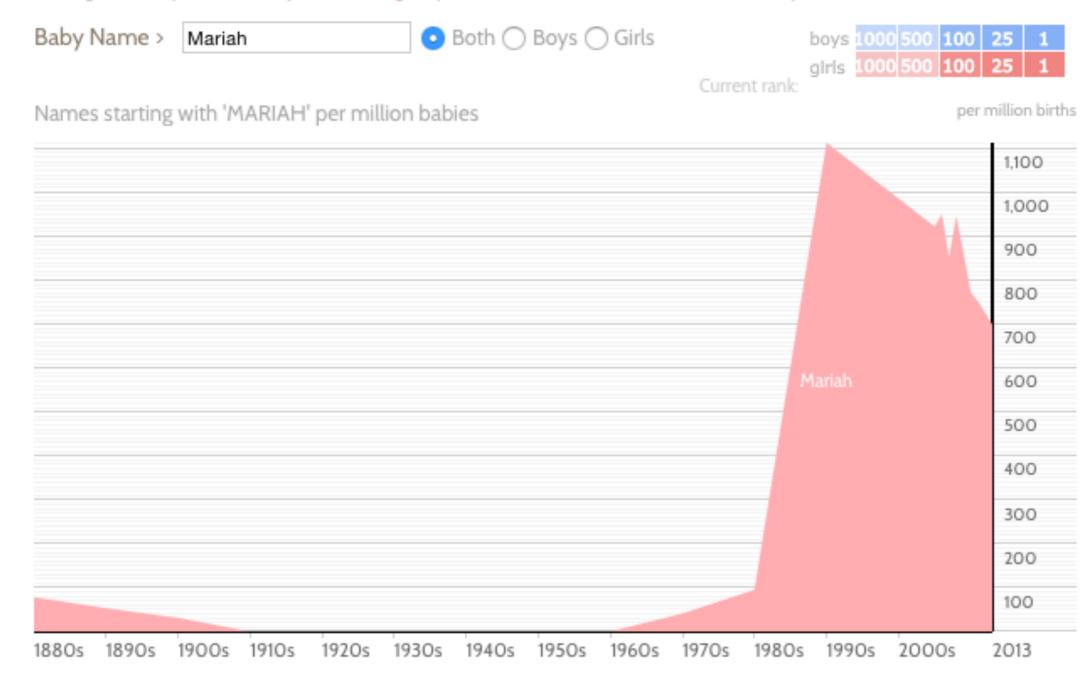
## O-ring damage index, each launch

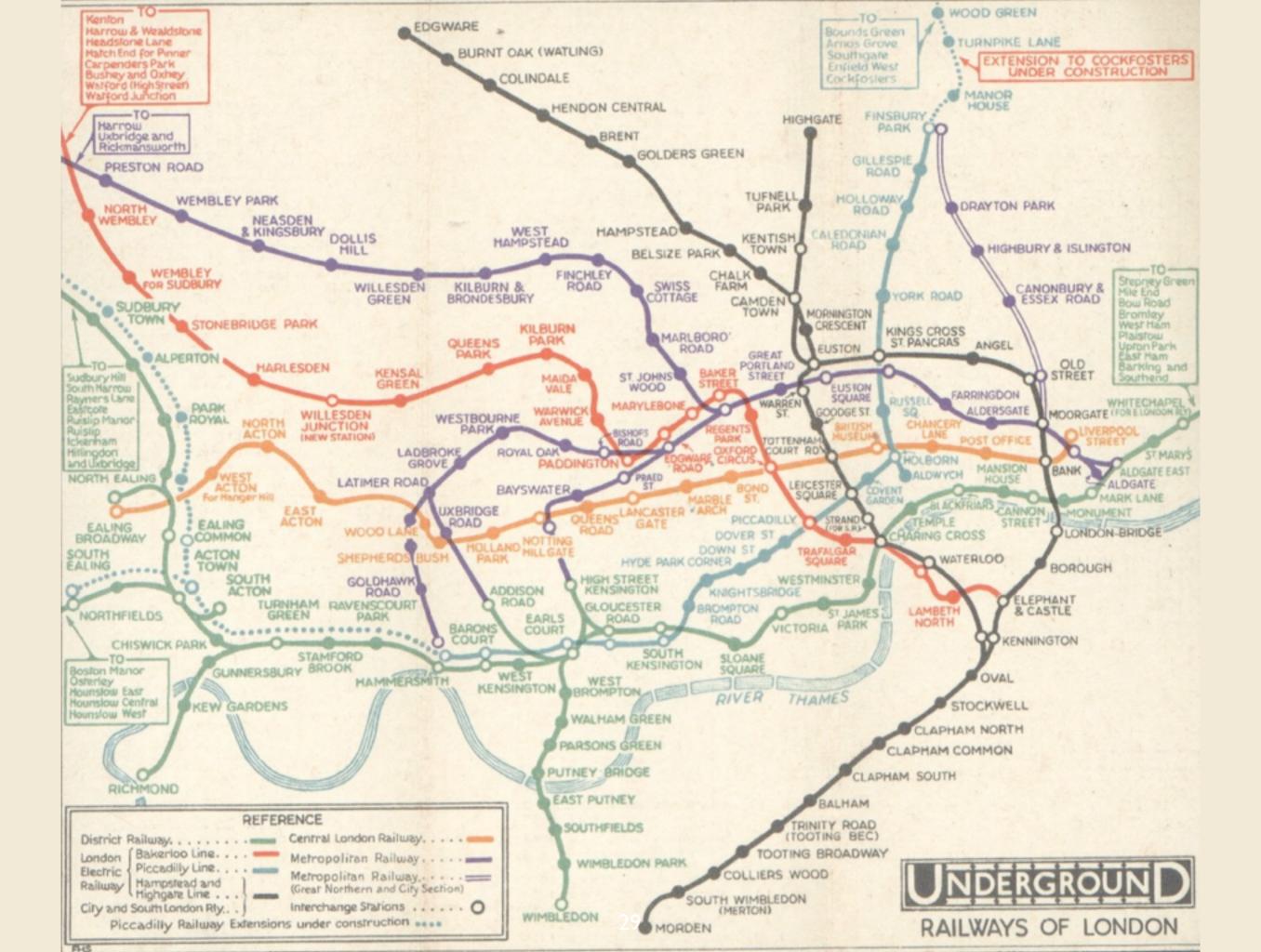


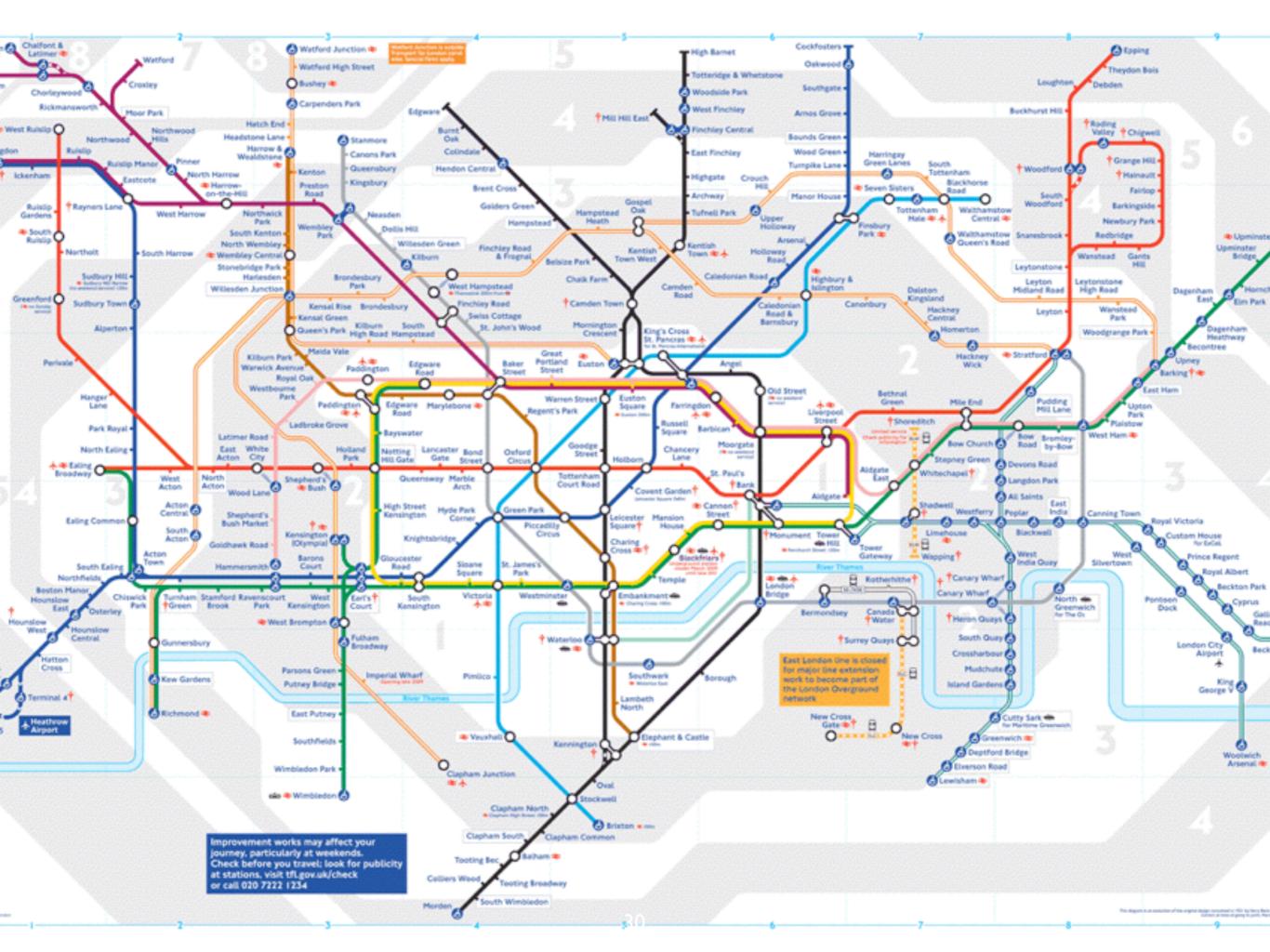


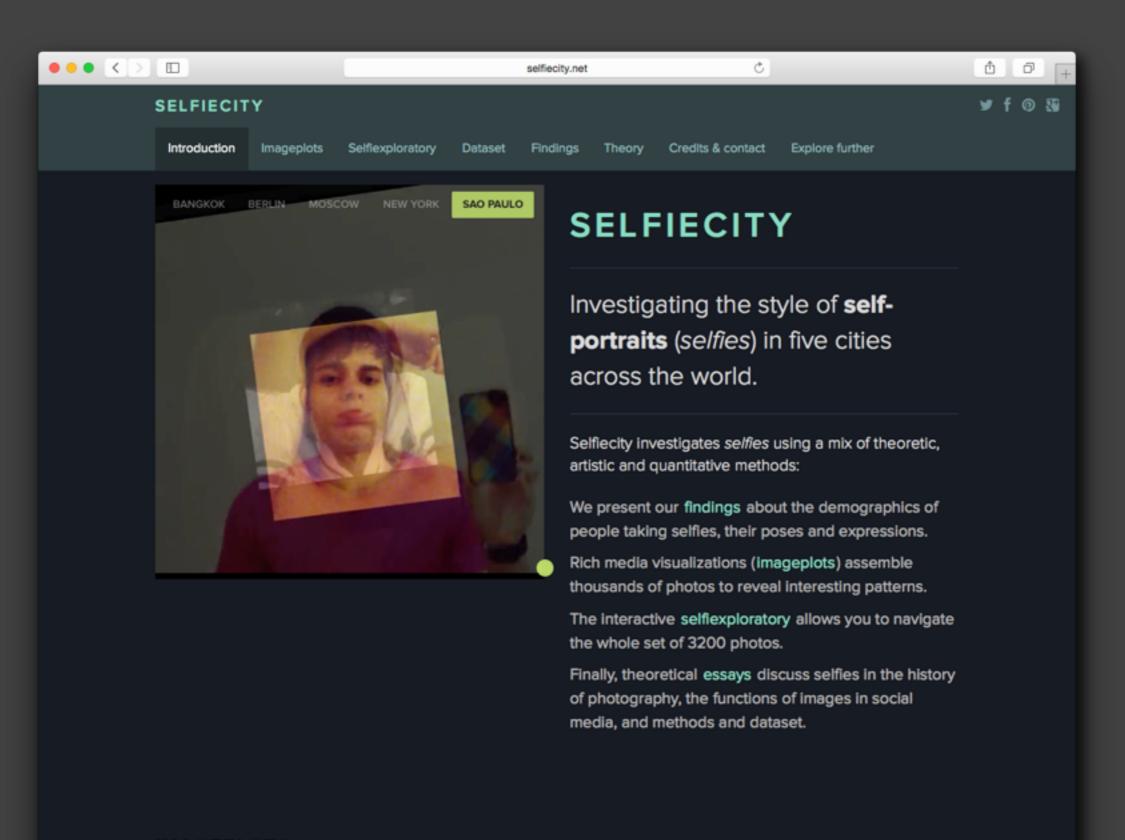
## NameVoyager: Explore baby names and name trends letter by letter

Looking for the perfect baby name? Sign up for free to receive access to our expert tools!









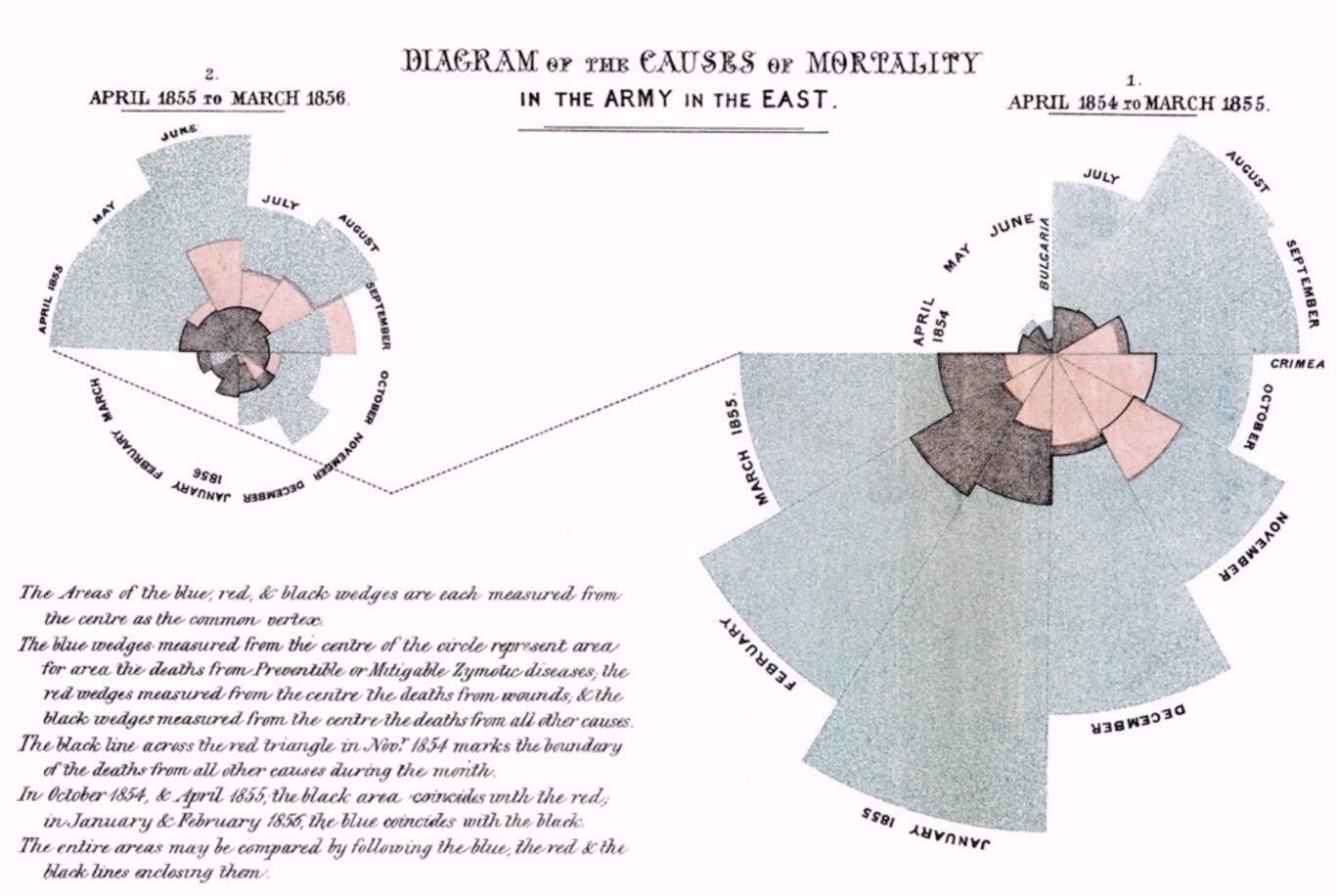
#### **IMAGEPLOTS**

#### POSES

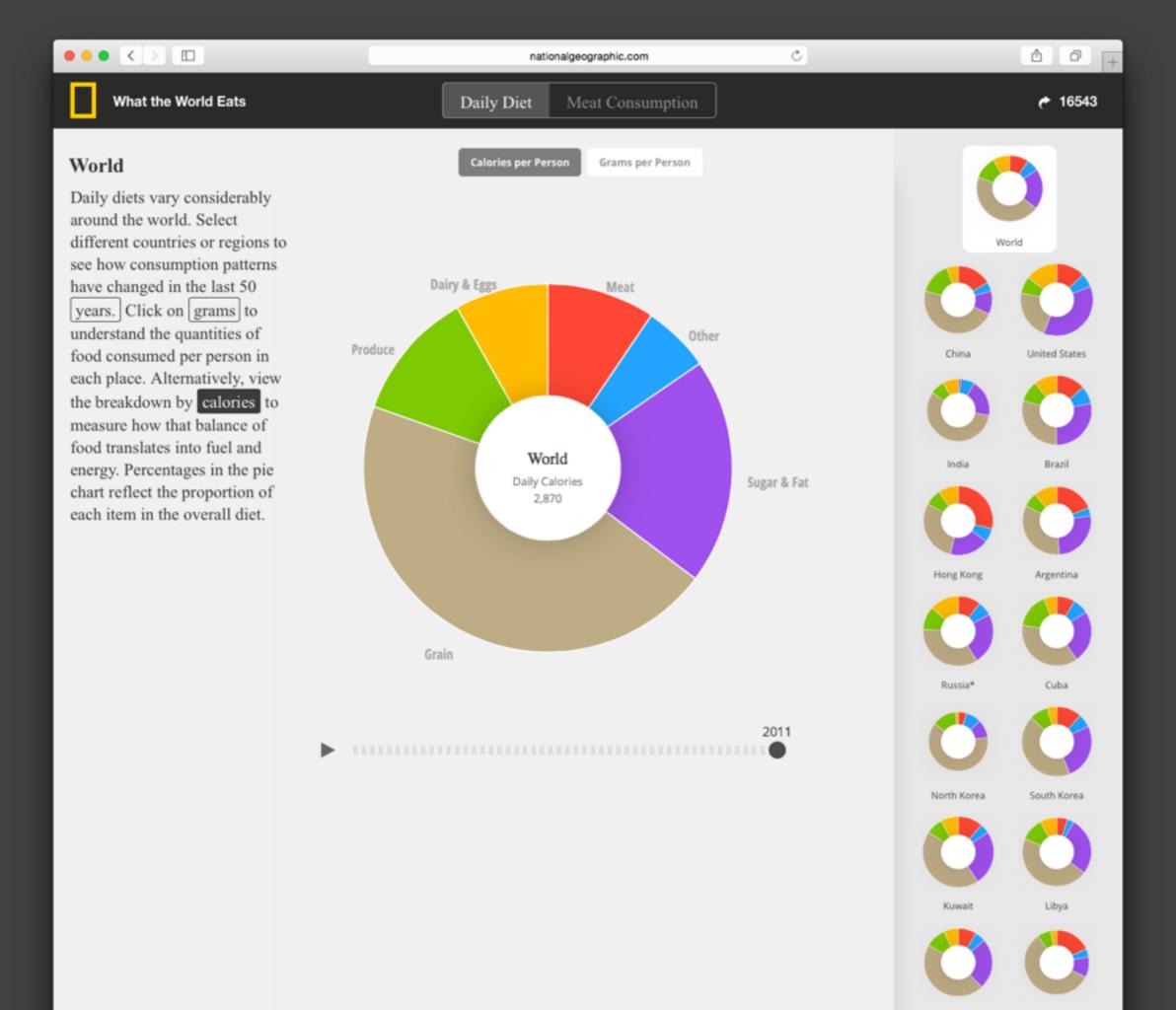
Each city has a different style when it comes to selfies.

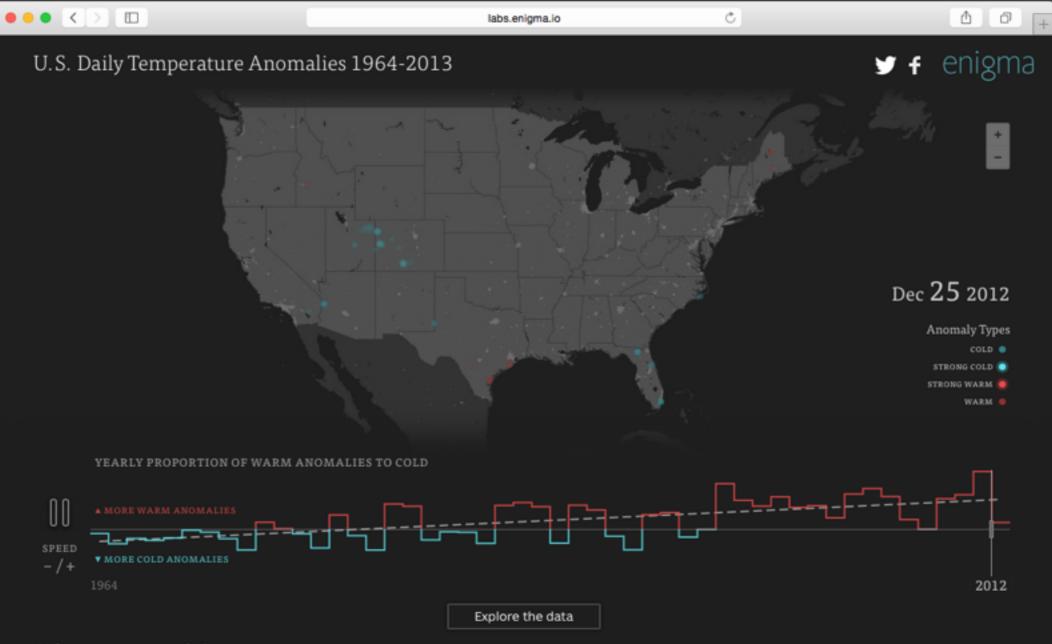


## COMMUNICATE IDEAS



### F. Nightingale 1856





#### What is an anomaly?

Every day, the <u>Global Historical Climatology Network</u> collects temperatures from 90,000 weather stations. Dating back as far as the late 1700's, the records provide an incredible source of insight into our changing climate.

Using this data, we can determine what the weather is normally like for most places on Earth. We can tell you that the average low temperature in New York City on January 11th is 29°F and that the average high temperature in Los Angeles on July 24th is 80°F.

Once we know what temperatures to expect on any given day with a certain degree of confidence, we can sift out the uneventful days, leaving only anomalous weather events.

These criteria enabled us to track the last 50 years of temperature anomalies and categorize them into four types.

**COLD** anomalies occur on days when the daily high or low temperature falls below its expected range.

WARM anomalies occur when the high or low temperature falls above its expected range.

**STRONG** anomalies occur on those rare days when both the daily high and low temperatures fall above (STRONG WARM) or below (STRONG COLD) their expected range.





June 26, 2014 / Mike Bostock

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## Visualizing Algorithms

The power of the unaided mind is highly overrated... The real powers come from devising external aids that enhance cognitive abilities. - Donald Norman

Algorithms are a fascinating use case for visualization. To visualize an algorithm, we don't merely fit data to a chart; there is no primary dataset. Instead there are logical rules that describe behavior. This may be why algorithm visualizations are so unusual, as designers experiment with novel forms to better communicate. This is reason enough to study them.

But algorithms are also a reminder that visualization is more than a tool for finding patterns in data. Visualization leverages the human visual system to augment human intellect: we can use it to better understand these important abstract processes, and perhaps other things, too.

This is an adaption of my talk at Eyeo 2014, A video of the talk is available on Vimeo. (Thanks, Eyeo folks!)

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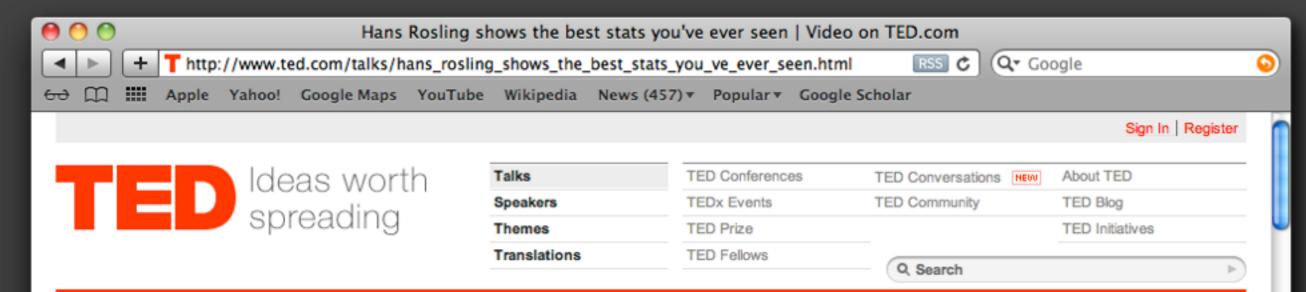
#### Sampling

Before I can explain the first algorithm, I first need to explain the problem it addresses.



Light - electromagnetic radiation - the light emanating from this screen, traveling through the air, focused by your lens and projected onto the retina — is a continuous signal. To be perceived, we must reduce light to discrete impulses by measuring its intensity and frequency distribution at different points in space.

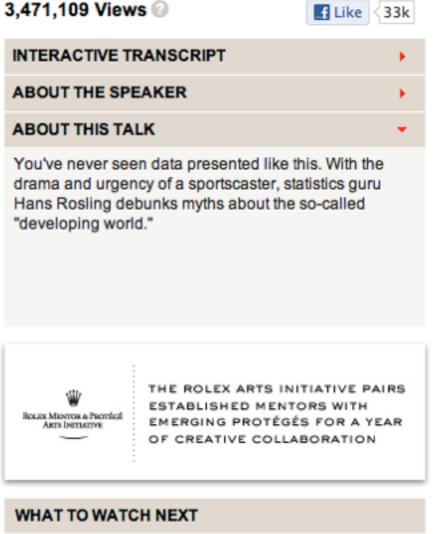
Van Gogh's The Starry Night



#### **TALKS**

#### Hans Rosling shows the best stats you've ever seen





poverty

Hans Rosling's new insights on

Views 1,616,080 | Comments 193

18:57 Posted: Jun 2007

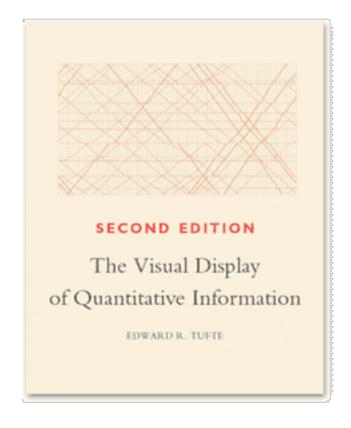
### DESIGN PRINCIPLES

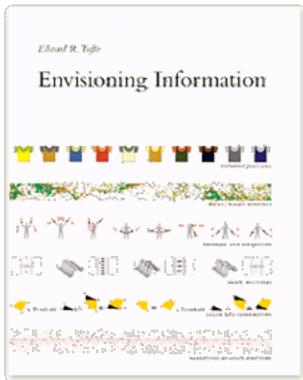
# design excellence

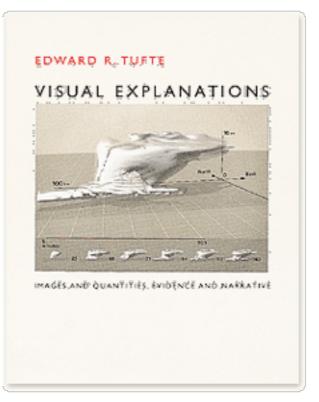
"Well-designed presentations of interesting data are a matter of substance, of statistics,

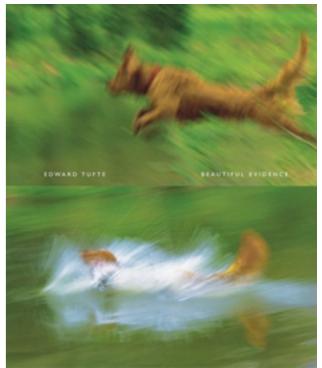
and of design."





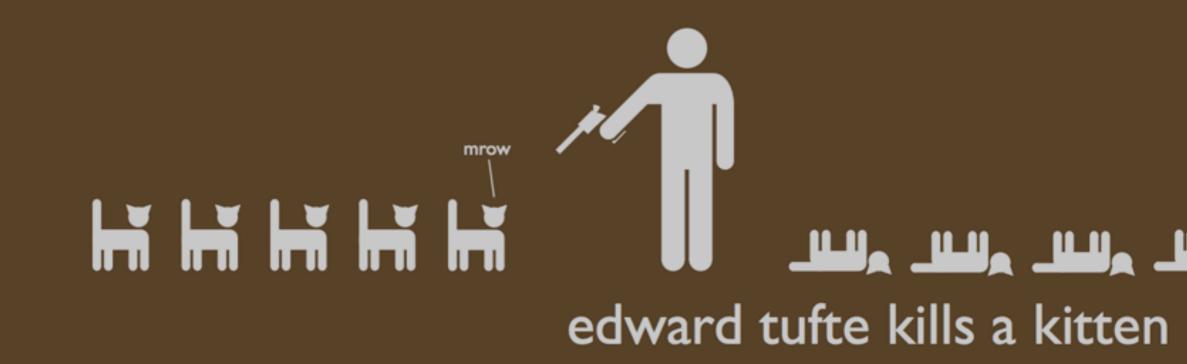




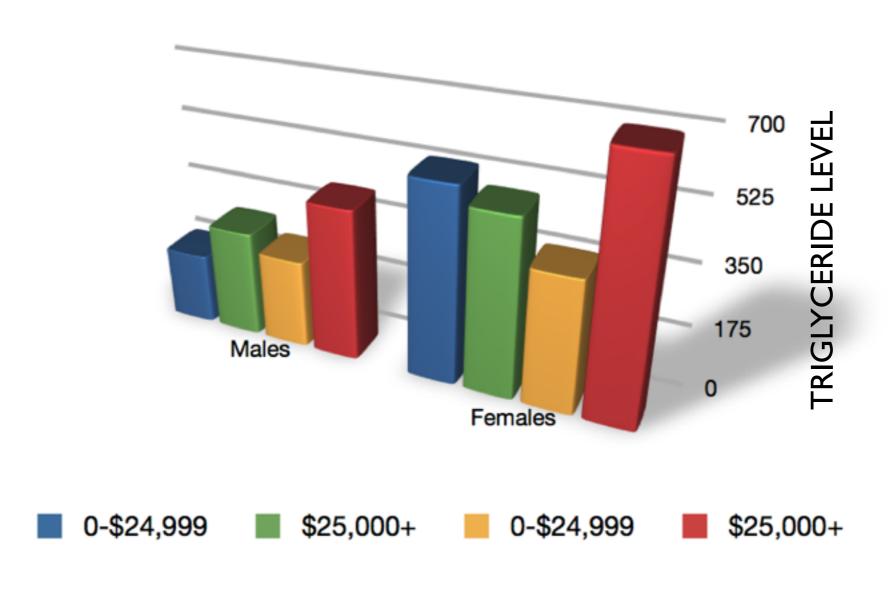


#### every time you make a powerpoint

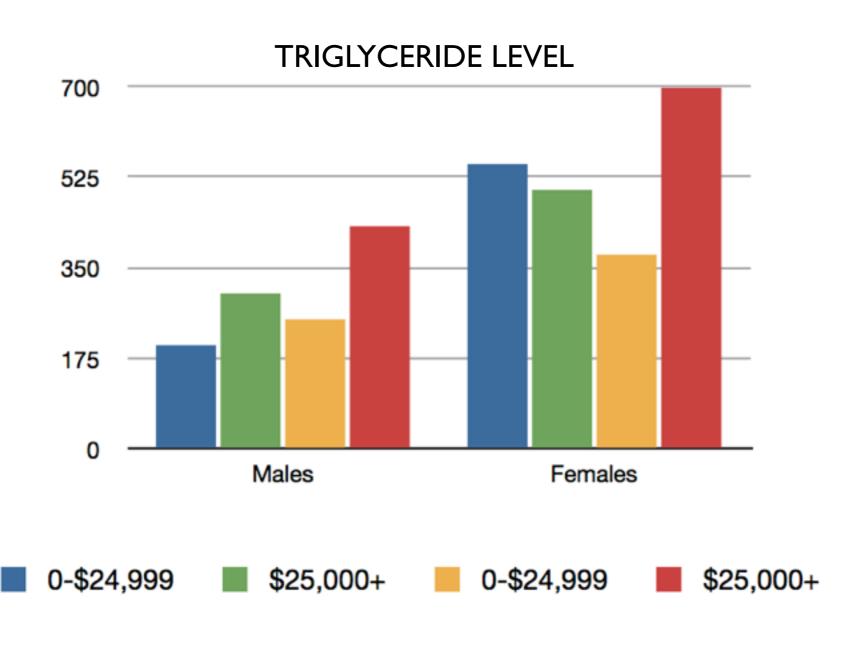




....

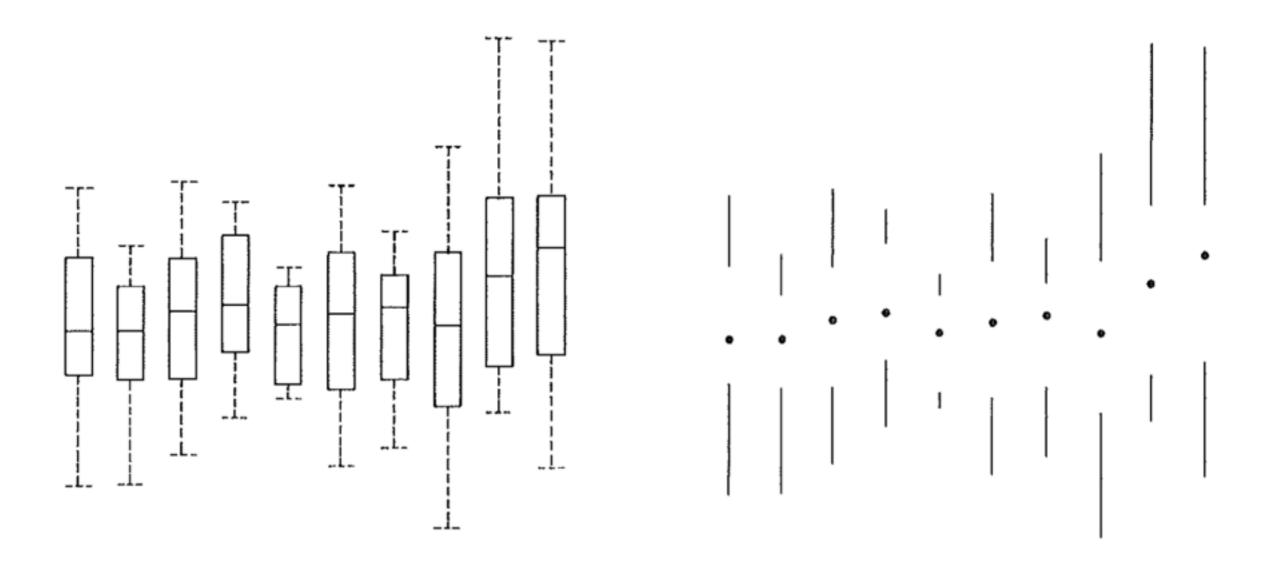


Data-ink Ratio = data-ink total ink used in graphic



Data-ink Ratio =

### data-ink total ink used in graphic



Tufte 2001

Eurographics / IEEE Symposium on Visualization 2011 (EuroVis 2011)
H. Hauser, H. Pfister, and J. J. van Wijk
(Guest Editors)

#### A User Study of Visualization Effectiveness Using EEG and Cognitive Load

E. W. Anderson<sup>1</sup>, K. C. Potter<sup>1</sup>, L. E. Matzen<sup>2</sup>, J. F. Shepherd<sup>2</sup>, G. A. Preston<sup>3</sup>, and C. T. Silva<sup>1</sup>

<sup>1</sup>SCI Institute, University of Utah, USA <sup>2</sup>Sandia National Laboratories, USA <sup>3</sup>Utah State Hospital, USA

#### Abstract

Effectively evaluating visualization techniques is a difficult task often assessed through feedback from user studies and expert evaluations. This work presents an alternative approach to visualization evaluation in which brain

### COUNTER-POINT

This information is processed to provide insight into the cognitive load imposed on the viewer. This paper describes the design of the user study performed, the extraction of cognitive load measures from EEG data, and how those measures are used to quantitatively evaluate the effectiveness of visualizations.

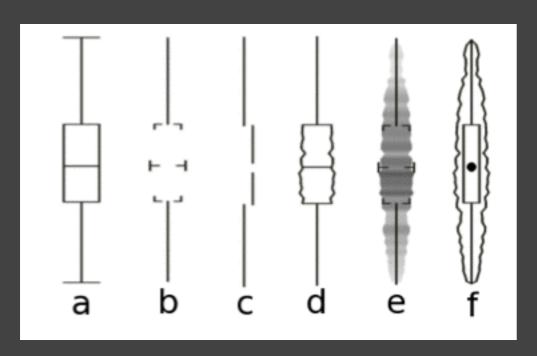
Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: General—Human Factors, Evaluation, Electroencephalography

#### 1. Introduction

Efficient visualizations facilitate the understanding of data

this paper strives to evaluate visualization techniques objectively by using passive, non-invasive monitoring devices to measure the burden placed on a user's cognitive resources.

#### EXPERIMENT

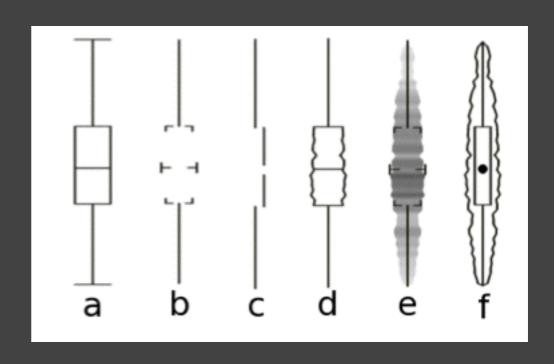


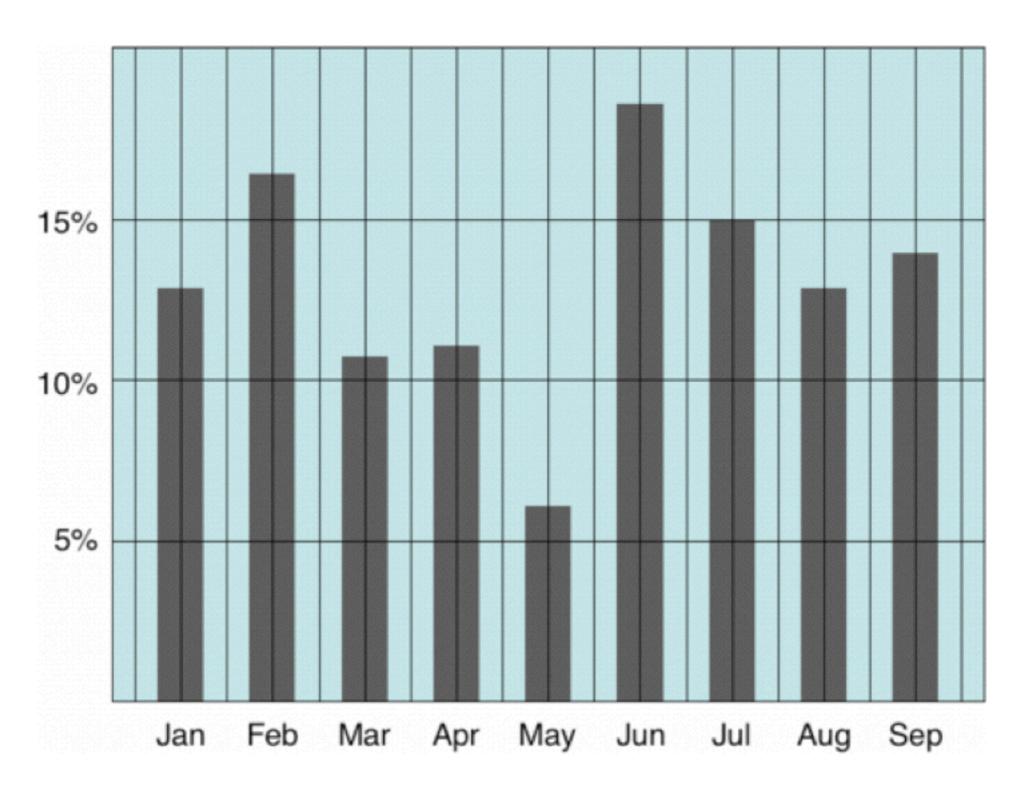


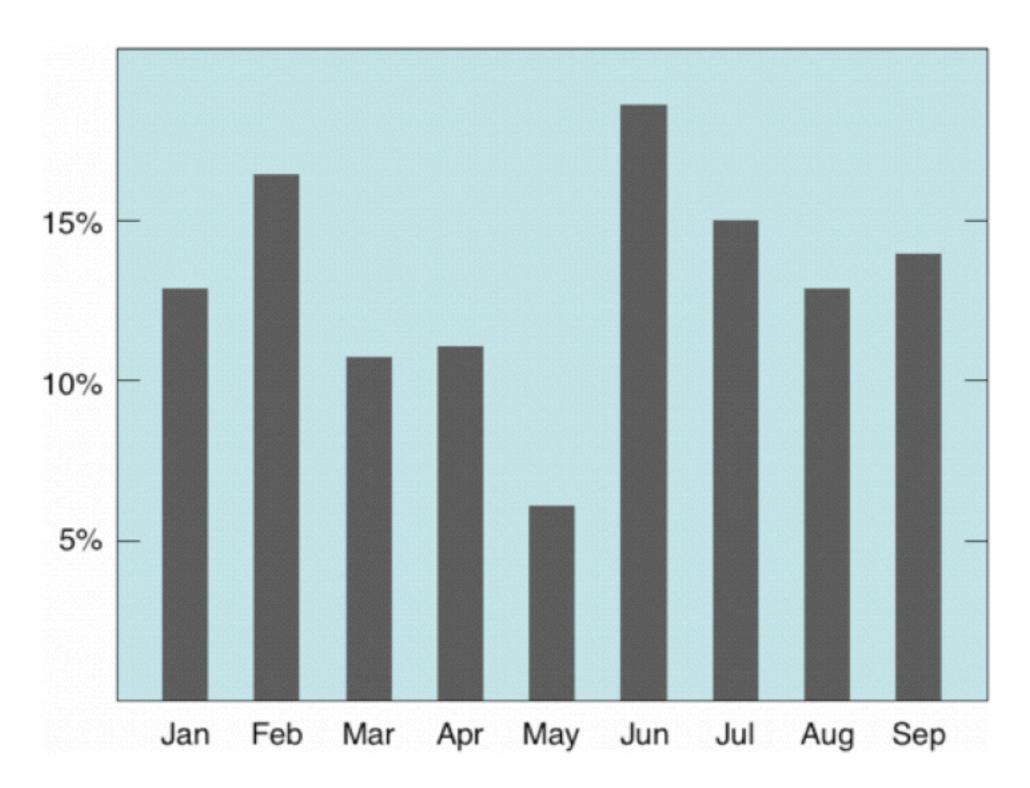
- -asked participants to choose box plot with largest range from a set
- -varied representation
- -measured cognitive load from EEG brain waves

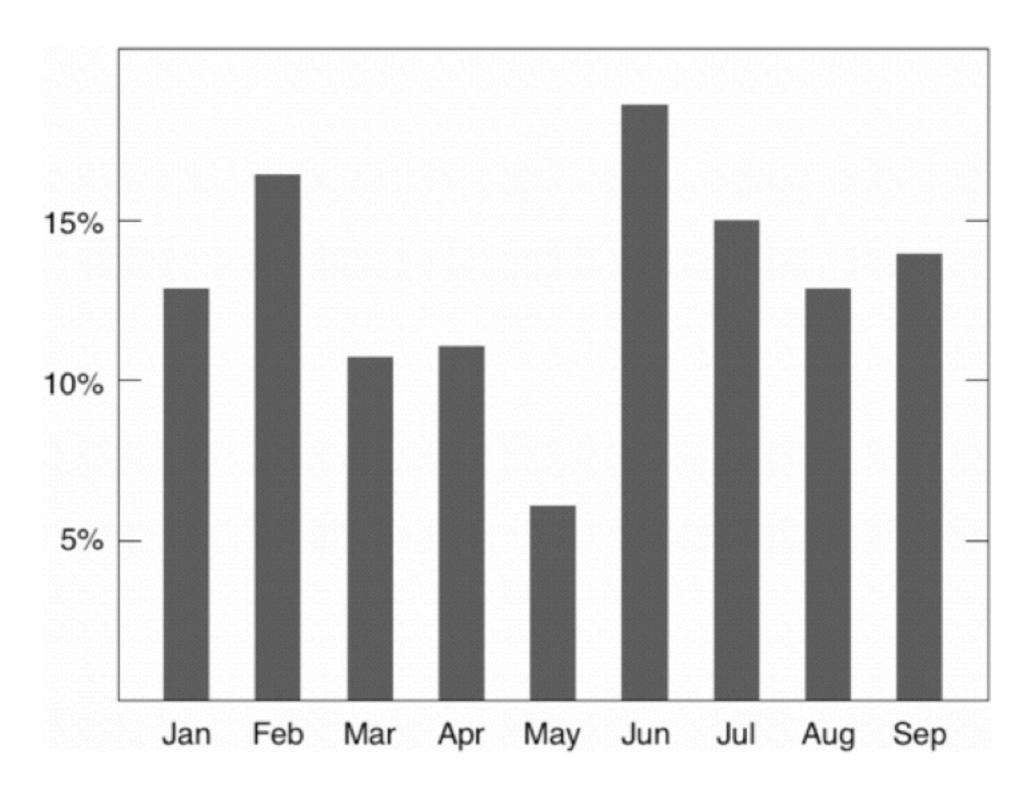
### EXPERIMENTAL RESULTS

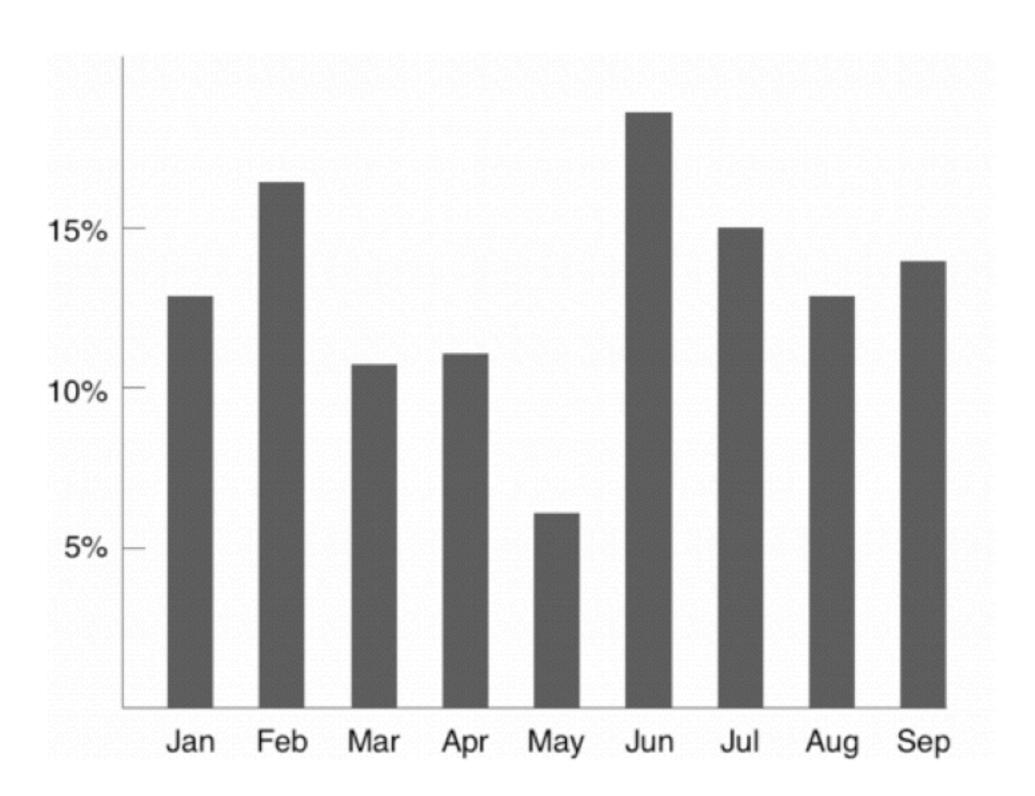
- -paper focused on cognitive load as an evaluation method
- -studies showed that the simplest box plot is hardest to interpret

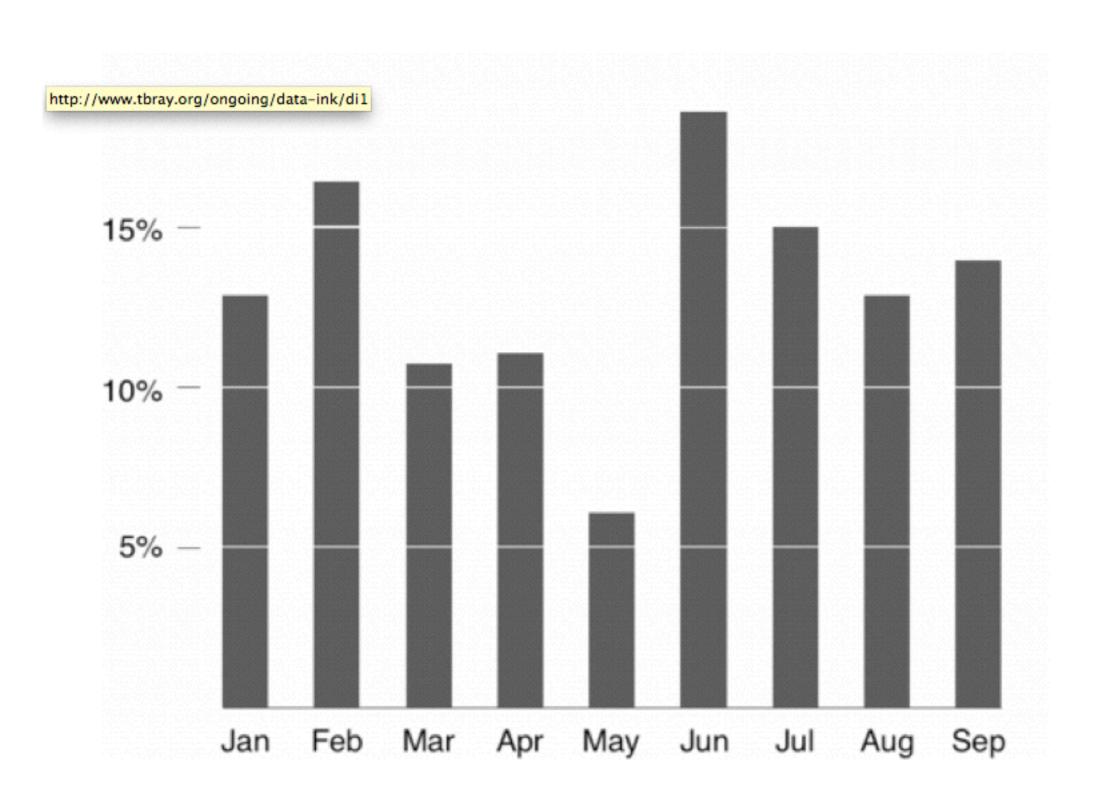


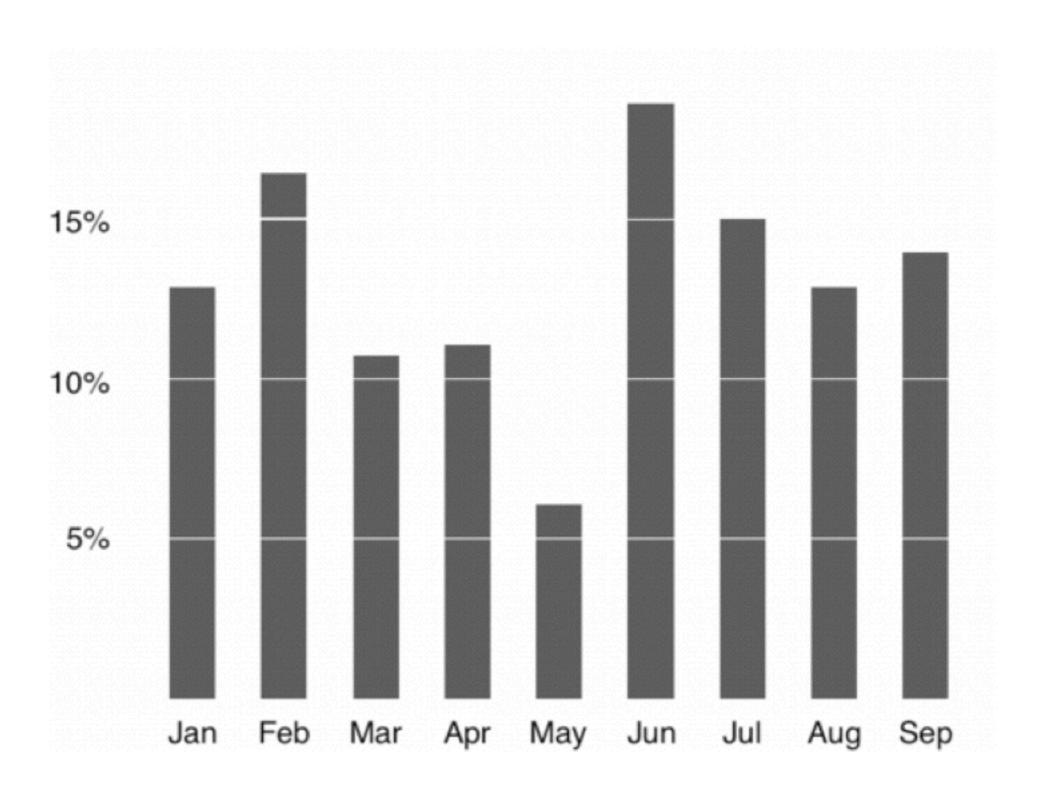




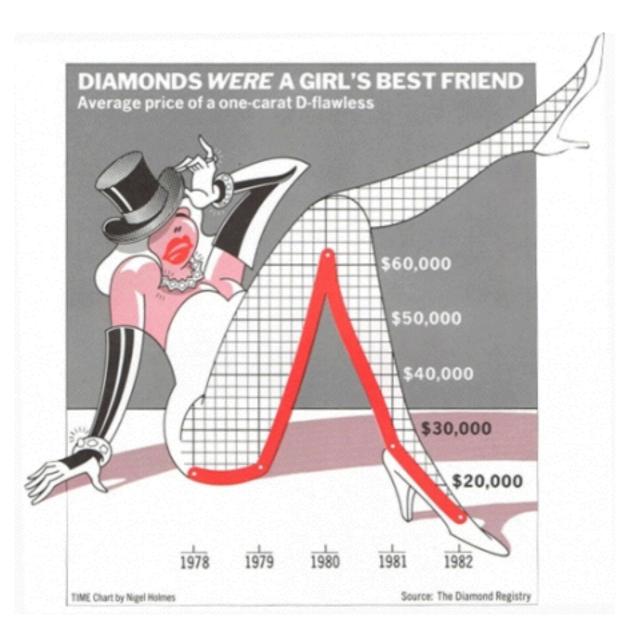


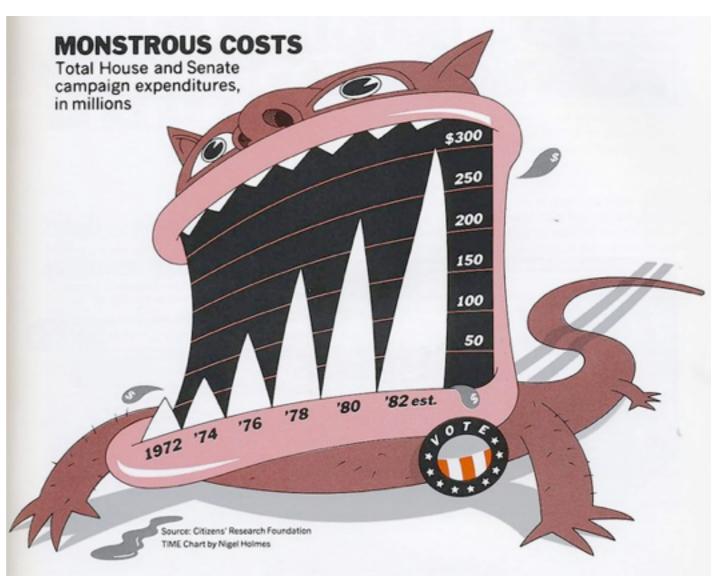






#### redesign exercise ...





#### CHI 2010: Graphs

## Useful Junk? The Effects of Visual Embellishment on Comprehension and Memorability of Charts

Scott Bateman, Regan L. Mandryk, Carl Gutwin, Aaron Genest, David McDine, Christopher Brooks

Department of Computer Science, University of Saskatchewan, Saskatoon, Saskatchewan, Canada scott.bateman@usask.ca, regan@cs.usask.ca, gutwin@cs.usask.ca, aaron.genest@usask.ca, dam085@mail.usask.ca, cab938@mail.usask.ca

#### **ABSTRACT**

Guidelines for designing information charts often state that

Despite these minimalist guidelines, many designers

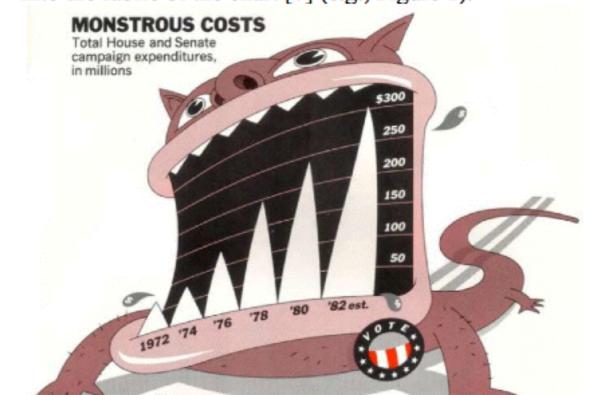
### COUNTER-POINT

presented data in detailed and elaborate imagery, raising the questions of whether this imagery is really as detrimental to understanding as has been proposed, and whether the visual embellishment may have other benefits. To investigate these issues, we conducted an experiment that compared embellished charts with plain ones, and measured both interpretation accuracy and long-term recall. We found that people's accuracy in describing the embellished charts was no worse than for plain charts, and that their recall after a two-to-three-week gap was significantly better. Although we are cautious about recommending that all charts be produced in this style, our results question some of the premises of the minimalist approach to chart design.

#### **Author Keywords**

Charts, information visualization, imagery, memorability.

whose work regularly incorporates strong visual imagery into the fabric of the chart [7] (e.g., Figure 1).



### EXPERIMENTAL QUESTIONS

I) whether visual embellishments do in fact cause comprehension problems

2) whether the embellishments may provide additional information that is valuable for the reader

### EXPERIMENTAL RESULTS

- 1) No significant difference between plain and image charts for interactive interpretation accuracy
- 2) No significant difference in recall accuracy after a five-minute gap
- 3) **Significantly better recall** for Holmes charts of both the chart topic and the details (categories and trend) after long-term gap (2-3 weeks).
- 4) Participants saw value messages in the Holmes charts significantly more often than in the plain charts.
- 5) Participants found the Holmes charts more attractive, most enjoyed them, and found that they were easiest and fastest to remember.

#### What Makes a Visualization Memorable?

Michelle A. Borkin, *Student Member, IEEE*, Azalea A. Vo, Zoya Bylinskii, Phillip Isola, *Student Member, IEEE*, Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister, *Senior Member, IEEE* 

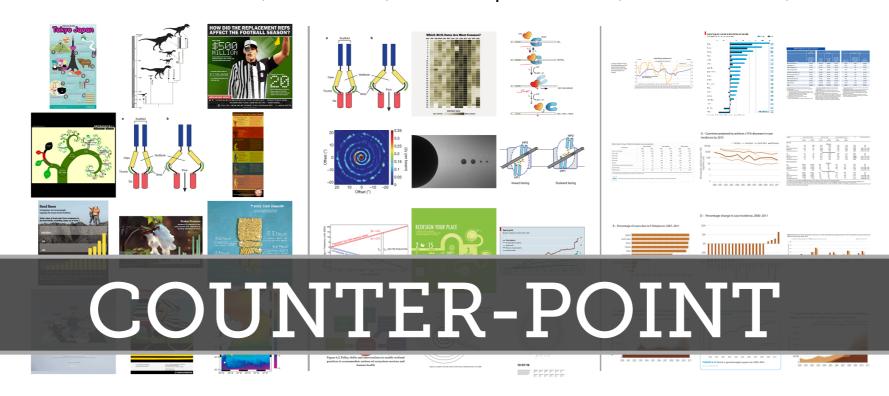


Fig. 1. Left: The top twelve overall most memorable visualizations from our experiment (most to least memorable from top left to bottom right). Middle: The top twelve most memorable visualizations from our experiment when visualizations containing human recognizable cartoons or images are removed (most to least memorable from top left to bottom right). Right: The twelve least memorable visualizations from our experiment (most to least memorable from top left to bottom right).

Abstract—An ongoing debate in the Visualization community concerns the role that visualization types play in data understanding. In human cognition, understanding and memorability are intertwined. As a first step towards being able to ask questions about impact and effectiveness, here we ask: "What makes a visualization memorable?" We ran the largest scale visualization study to date using 2,070 single-panel visualizations, categorized with visualization type (e.g., bar chart, line graph, etc.), collected from news media sites, government reports, scientific journals, and infographic sources. Each visualization was annotated with additional attributes, including ratings for data-ink ratios and visual densities. Using Amazon's Mechanical Turk, we collected memorability scores for hundreds of these visualizations, and discovered that observers are consistent in which visualizations they find memorable and forgettable. We find intuitive results (e.g., attributes like color and the inclusion of a human recognizable object enhance memorability) and less intuitive results (e.g., common graphs are less memorable than unique visualization types). Altogether our findings suggest that quantifying memorability is a general metric of the utility of information, an essential step towards determining how to design effective visualizations.

Index Terms—Visualization taxonomy, information visualization, memorability

### TAKE-AWAY

- I) intuitive findings: color and human recognizable objects enhance memorability
- 2) unintuitive findings: common graphs are less memorable than unique visualization types

take away ...

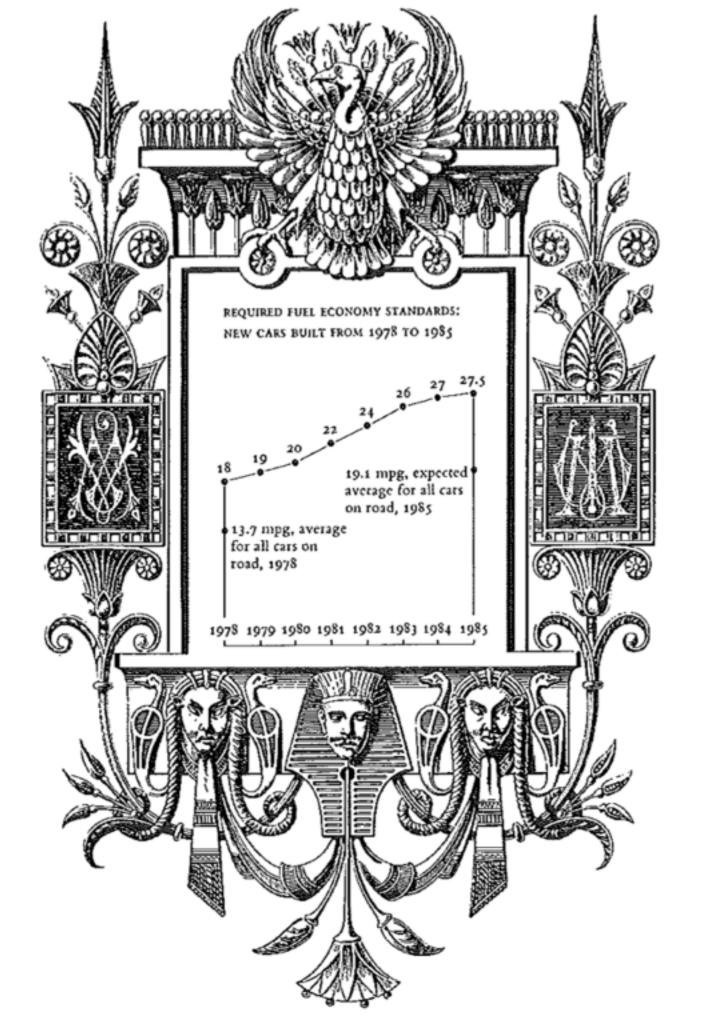
### CHART JUNK? IT DEPENDS

- -persuasion
- -memorability
- -engagement

- -unbiased analysis
- -trustworthiness
- -interpretability
- -space efficiency

PROS

CONS

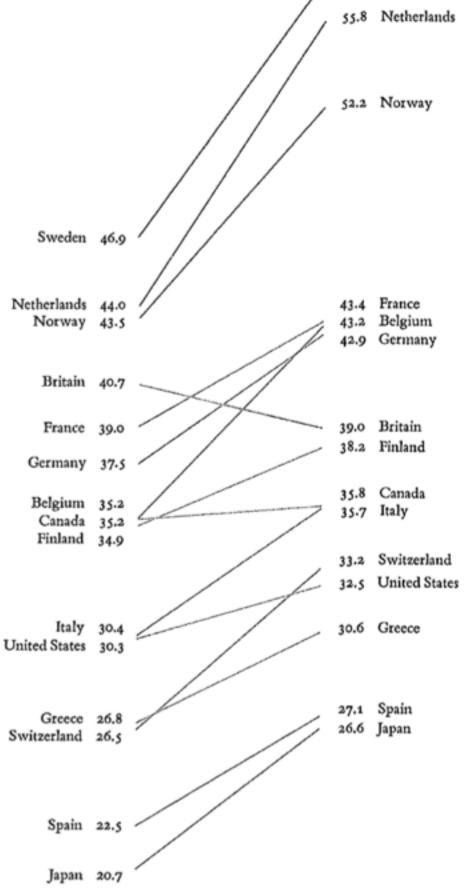




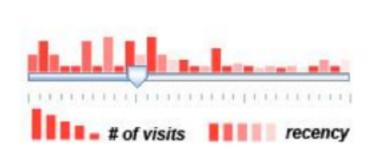
57.4 Sweden

Current Receipts of Government as a Percentage of Gross Domestic Product, 1970 and 1979

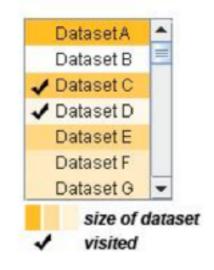
# multifunctioning elements

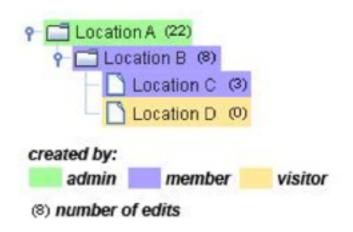


### scented widgets







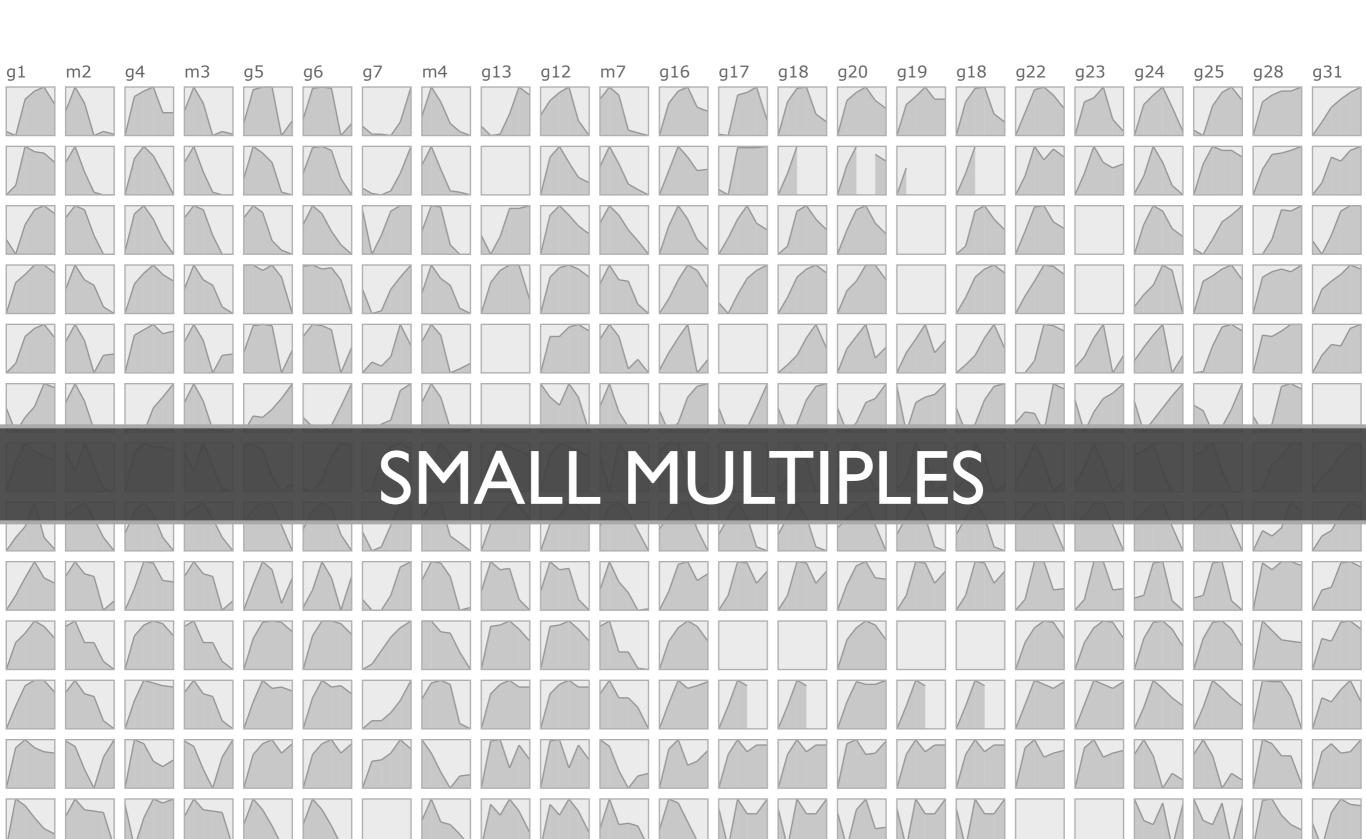


### interactive legend

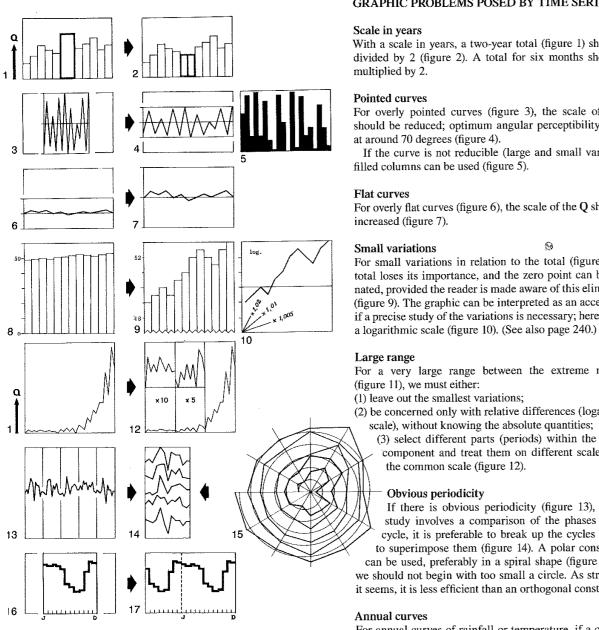


Data Density = number of entries in data array area of data graphic

### SHRINK THE GRAPHICS



### SHRINK THE GRAPHICS



#### GRAPHIC PROBLEMS POSED BY TIME SERIES

#### Scale in years

With a scale in years, a two-year total (figure 1) should be divided by 2 (figure 2). A total for six months should be multiplied by 2.

#### Pointed curves

For overly pointed curves (figure 3), the scale of the 0 should be reduced; optimum angular perceptibility occurs at around 70 degrees (figure 4).

If the curve is not reducible (large and small variations). filled columns can be used (figure 5).

For overly flat curves (figure 6), the scale of the Q should be increased (figure 7).

#### **Small variations**

For small variations in relation to the total (figure 8), the total loses its importance, and the zero point can be eliminated, provided the reader is made aware of this elimination (figure 9). The graphic can be interpreted as an acceleration if a precise study of the variations is necessary; here, we use

#### Large range

For a very large range between the extreme numbers (figure 11), we must either:

- (1) leave out the smallest variations;
- (2) be concerned only with relative differences (logarithmic scale), without knowing the absolute quantities;
  - (3) select different parts (periods) within the ordered component and treat them on different scales above the common scale (figure 12).

#### Obvious periodicity

If there is obvious periodicity (figure 13), and the study involves a comparison of the phases of each cycle, it is preferable to break up the cycles in order to superimpose them (figure 14). A polar construction can be used, preferably in a spiral shape (figure 15), but we should not begin with too small a circle. As striking as it seems, it is less efficient than an orthogonal construction.

#### Annual curves

For annual curves of rainfall or temperature, if a cycle has two phases (figure 17), why depict only one (figure 16)?

#### A contrast

Unlike what we see in figure 18, the pertinent or "new" information must be separated from the background or "reference" information. The background involves: (a) the invariant, highlighted by a heading (Port St. Michel); (b) the highly visible identification of each component (tonnage and dates). The new information (the curve) must stand out from the background (figure 19).

#### Reference points

It is impossible to utilize a graphic such as figure 20, except in a general manner. There is confusion concerning the position of the points, and no potential comparison is possible, as it is in figure 21.

#### Precision reading

A precision reading (utilization on the elementary level, as in figure 24) is difficult in figure 22, which results in a poor reading of the order of the points, and in figure 23, where there is ambiguity concerning the position of the points. On the other hand, figure 22 does favor overall vision (correlation).

Curves accommodate null boxes poorly (figure 25). Columns (figure 26) are preferable.

#### Unknown boxes

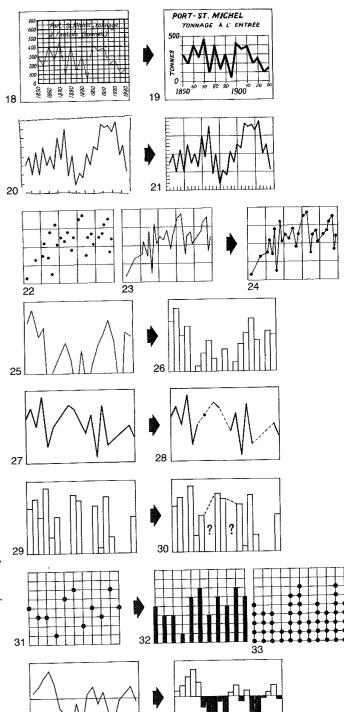
The drawing must indicate the unknowns of the information in an unambiguous way (figures 28 and 30). The reader might interpret figure 27 as a change in the structure of the curve and figure 29 as involving null values.

#### Very small quantities

Except in seeking a correlation (quite improbable here) the number of ships entering into a port is represented better by figure 33 than by figures 31 or 32. The reader can perceive the numerical values at first glance.

#### Positive-negative variation

This is in fact a problem involving three components O, Q, ≠ (+ -), and it must be visually treated as such. Figure 34 can be improved by utilizing a retinal variable (in figure 35 a value difference: black-white) to differentiate the ≠ component and thus highlight positive-negative variation.



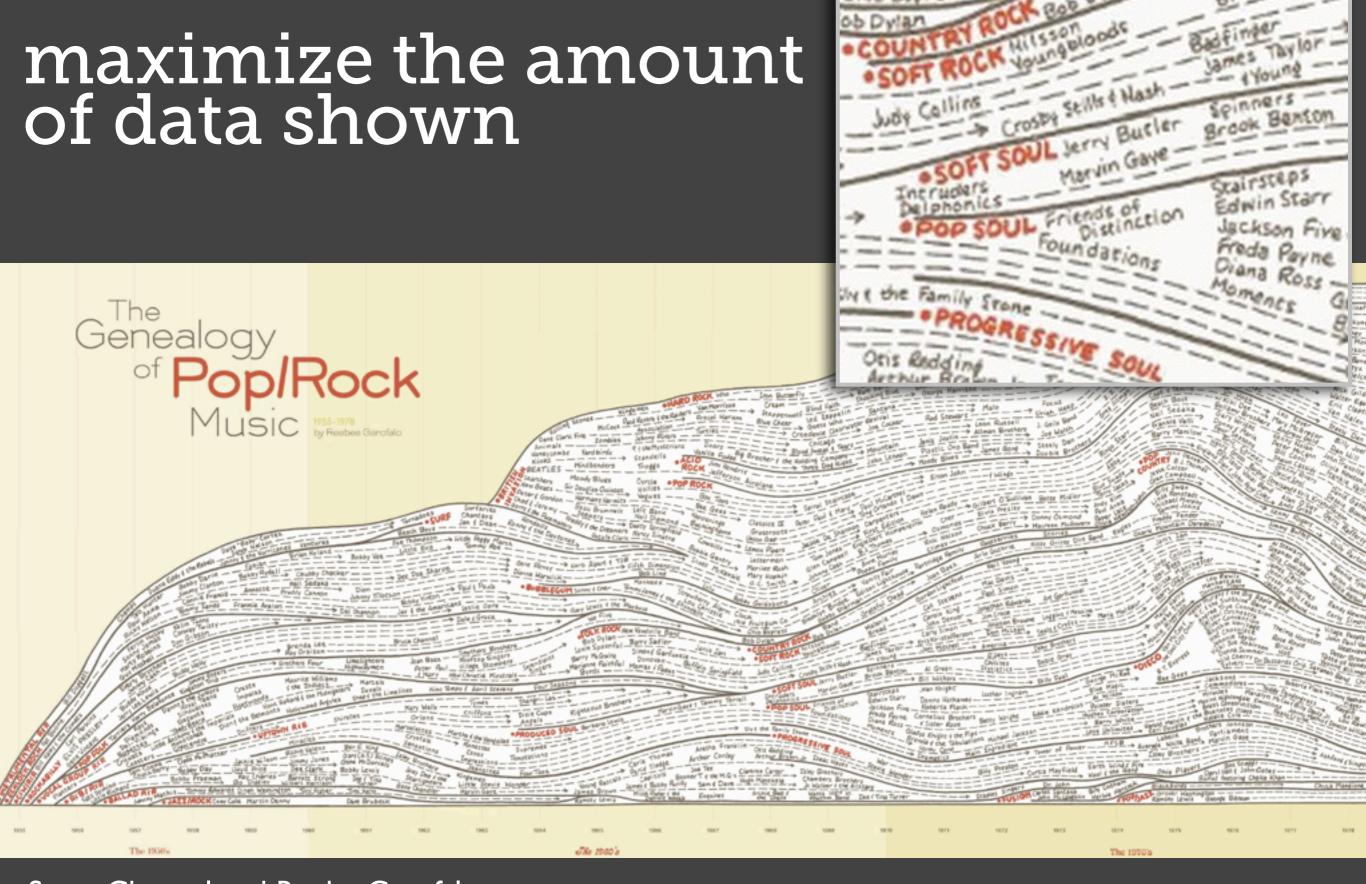
### SHRINK THE GRAPHICS

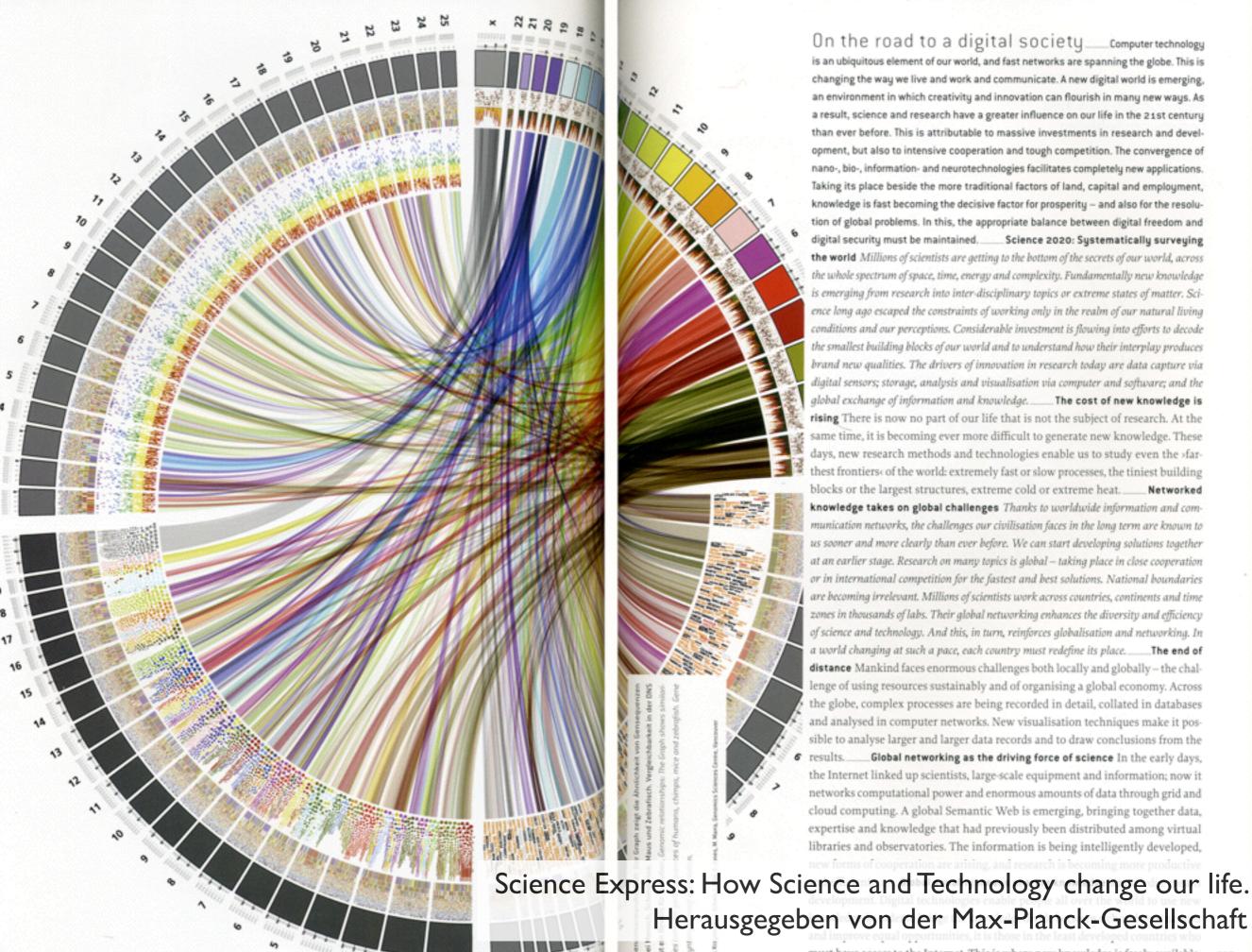
resolving power, the wordlike size of sparklines precludes the overt labels and scaling of conventional statistical displays. Most of our examples have, however, depicted contextual methods for quantifying sparklines: the gray bar for normal limits and the red encoding to link data points in sparklines to exact numbers of glucose 6.6; global scale bars and labels for sparkline clusters; and, probably best of all, surrounding a sparkline with an implicit data-scaling box formed by nearby numbers that label key data points (such as beginning/end, high/low) 1.1025

Production methods Data lines produced by conventional statistical graphics programs must be gathered together, rescaled, and resized into sparklines. Sometimes this can be quickly done by cutting and pasting data lines, then resizing the printed output to sparkline resolutions.

### SPARKLINES

(3) a statistical analysis program to generate hundreds of chartjunk-free sparklines for export into design and layout operations. Once the basic templates for sparklines are worked out, then ongoing production and





### Unseen and Unaware: Implications of Recent Research on Failures of Visual Awareness for Human-Computer Interface Design

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### COUNTER-POINT

#### ABSTRACT

Because computers often rely on visual displays as a way to convey information to a user, recent research suggesting that people have detailed awareness of only a small subset of the visual environment has important implications for human–computer interface design. Equally important to basic limits of awareness is the fact that people often over-predict what they will see and become aware of. Together, basic failures of awareness and people's failure to intuitively understand

# ILLUSIONS OF VISUAL BANDWIDTH

people over-predict what they will see and become aware of

### next time...



A survey of powerful visualization techniques, from the obvious to the obscure.

BY JEFFREY HEER, MICHAEL BOSTOCK, AND VADIM OGIEVETSKY

## A Tour Through the Visualization Zoo

thanks to advances in sensing, networking, and data management, our society is producing digital information at an astonishing rate. According to one estimate, in 2010 alone we will generate 1, 200

#### -homework

-assignment 12 due Tuesday