

Good for Scientists Bad for Society What happens when our charts don't change our minds?



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What is the story we tell each other about information visualization?

seeing the invisible







Matejka and Fitzmaurice. Same Stats, Different Graphs: Generating Datasets with Varied Appearance and Identical Statistics through Simulated Annealing. ACM CHI 2017

revealing patterns we live with



THE RACIAL DOT MAP

DISPLAYS 308,745,538 INDIVIDUAL DOTS, ONE FOR EACH PERSON AT THE LOCATION THEY WERE ENUMERATED DURING THI

2010 DECENNIAL CENSUS

EACH DOT IS COLOR-CODED BY RACE AND ETHNICITY: BLUE: NON-HISPANIC WHITE; GREEN: AFRICAN-AMERICAN;





CREATED BY DUSTIN A. CABLE JULY 2013

Each of the 308 million dots in this map are too small to discern individually. Therefore, the "smudges" you see are actually aggregations of many individual dots. Because of this, the dots often blend together to create different shades of purple, teal and other color This effect can therefore be a measure of racial integration in a particular area.



revealing patterns we live with

3



communicate to everyone

New reported cases



Updated Jan. 18, 2022

• About 150,000 coronavirus patients are

Account ~





Why doesn't our data promote more positive change?

https://www.fastcompany.com/90367577/this-is-one-of-the-simplest-and-best-climate-change-graphics-weve-ever-seen



visual estimation of the 1:7 Caveats for the visual encoding in ratio is noisier toward bottom each row

For each visualization, statistics are available quickly

0 : 98 98 ab a b

even when the nonzero base is marked, as in the examples at left.

Length

Highest



Stacked bar: Bars on baseline are position-coded = more precise perception.



The black & dark gray bars have the same value differences among them, but the differences are only visible across the black bars.





But beware: if the number is actually mapped to Length, the gray circles ~1:2.5 ratio.



Angle



The difference is larger for the lighter segments compared with the darker ones, right? That is an illusion—the differences are identical.

Franconeri, Steven L., Lace M. Padilla, Priti Shah, Jeffrey M. Zacks, and Jessica Hullman. "The science of visual data communication: What Intworks." Psychological Science in the Public Interest 22, no. 3 (2021): 110-161.













isolating pairs with "larger second values" is tough... So quide viewers to the right comparisons



arisons by adding





EFFCENCY evaluation, timelines UNVERSALTY principles, presentation

NPARTALTY objective, unbiased

EFFICIENCY CARE

Scheuerman, Morgan Klaus, Alex Hanna, and Emily Denton. "Do datasets have politics? Disciplinary values in computer vision dataset development." **Proceedings of the ACM on Human-Computer Interaction CSCW (2021): 1-37.**



UNIVERSALITY CONTEXTUALITY **IMPARTIALITY POSITIONALITY**



What does visualization evaluation capture?

There is a newly discovered disease, Disease X, which is transmitted by a bacterial infection found in the population. There is a test to detect whether or not a person has the disease, but it is not perfect. Here is some information about the current research on Disease X and efforts to test for the infection that causes it.

Ottley, Alvitta, Evan M. Peck, Lane T. Harrison, Daniel Afergan, Caroline Ziemkiewicz, Holly A. Taylor, Paul KJ Han, and Remco Chang. "Improving Bayesian reasoning: the effects of phrasing, visualization, and spatial ability." IEEE transactions on visualization and computer graphics 22, no. 1 (2016): 529-538.



There is a total of 1000 people in the population. Out of the 1000 people in the population, 10 people actually have the disease. Out of these 10 people, 8 will receive a positive test result and 2 will receive a negative test result. On the other hand, 990 people do not have the disease (that is, they are perfectly healthy). Out of these 990 people, 95 will receive a positive test result and 895 will receive a negative test result.

Imagine 1000 people are tested for the disease. (a) How many people will test positive? ____ (b) Of those who test positive, how many will actually have the disease? ____

Ottley, Alvitta, Evan M. Peck, Lane T. Harrison, Daniel Afergan, Caroline Ziemkiewicz, Holly A. Taylor, Paul KJ Han, and Remco Chang. "Improving Bayesian reasoning: the effects of phrasing, visualization, and spatial ability." IEEE transactions on visualization and computer graphics 22, no. 1 (2016): 529-538.

~1 out of 4 people answered these questions correctly





Structured-Text

There is a total of 100 people in the population.

Out of the 100 people in the population,

6 people actually have the disease. Out of these 6 people,

4 will receive a positive test result and

2 will receive a negative test result.

On the other hand, 94 people do not have the disease (i.e., they are

perfectly healthy). Out of these 94 people,

16 will receive a positive test result and

78 will receive a negative test result.

Another way to think about this is...

Out of the 100 people in the population,

20 people will test positive. Out of these 20 people,

4 will actually have the disease and

16 will not have the disease (i.e., they are perfectly healthy).

On the other hand, 80 people will test negative. Out of these 80 people,

2 will actually have the disease and

78 will not have the disease (i.e., they are perfectly healthy).

Ottley, Alvitta, Evan M. Peck, Lane T. Harrison, Daniel Afergan, Caroline Ziemkiewicz, Holly A. Taylor, Paul KJ Han, and Remco Chang. "Improving Bayesian reasoning: the effects of phrasing, visualization, and spatial ability." IEEE transactions on visualization and computer graphics 22, no. 1 (2016): 529-538.

77%

74%



Storyboarding There is a total of 100 people in the population.

Population Out of the 100 people in the population, 6 people actually have the disease.

Have Disease

Population

Out of these 6 people, 4 will receive a positive test result and 2 will receive a negative test result.

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49%

On the other hand, 94 people do not have the disease (i.e., they are perfectly healthy).

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Population

Out of these 94 people, 16 will receive a positive test result and 78 will receive a negative test result.



377 participants on MTurk



Paper folding as a proxy for spatial ability

IowIow

R. B. Ekstrom, J. W. French, H. H. Harman, and D. Dermen. Manual for kit of factorreferenced cognitive tests. Princeton, NJ: Educational Testing Service, 1976







74% 50%

77%

Population Structured Transf There is a t In our efficiency-informed study Out of

Test Positive

Ot. perfectly healthy). Out of these 94 people, 16 will receive a positive test result and 78 will receive a negative test result.

Another way to think about this is...

6

Have Disease

Out of the 100 people in the population,

20 people will test positive. Out of these 20 people,

4 will actually have the disease and

16 will not have the disease (i.e., they are perfectly healthy). On the other hand, 80 people will test negative. Out of these 80

people,

2 will actually have the disease and

78 will not have the disease (i.e., they are perfectly healthy).

Ottley, Alvitta, Evan M. Peck, Lane T. Harrison, Daniel Afergan, Caroline Ziemkiewicz, Holly A. Taylor, Paul KJ Han, and Remco Chang. "Improving Bayesian reasoning: the effects of phrasing, visualization, and spatial ability." IEEE transactions on visualization and computer graphics 22, no. 1 (2016): 529-538.

Do Not Have Disease



Storyboarding

There is a total of 100 people in the population



Out of the 100 people in the population, 6 people actually have the disease. Have Disease

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Population

Have Disease

Out of these 6 people, 4 will receive a positive test result and 2 will receive a negative test result.

designs, who are we missing?



ot have the disease (i.e., they are perfectly

Do Not Have Disease

Population

Out of these 94 people, 16 will receive a positive test result and 78 will receive a negative test result.





Interaction techniques to improve public engagement on the web

Hindsight: personal interaction history



Feng, Mi, Cheng Deng, Evan M. Peck, and Lane Harrison. "Hindsight: Encouraging exploration through direct encoding of personal interaction history." IEEE transactions on visualization and computer graphics 23, no. 1 (2016): 351-360.





Feng, Mi, Cheng Deng, Evan M. Peck, and Lane Harrison. "The effects of adding search functionality to interactive visualizations on the web." In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, pp. 1-13. 2018.



Capturing the impact of interaction

interaction history



impact of search



Feng, Mi, Cheng Deng, Evan M. Peck, and Lane Harrison. "Hindsight: Encouraging exploration through direct encoding of personal interaction history." IEEE transactions on visualization and computer graphics 23, no. 1 (2016): 351-360.

Feng, Mi, Cheng Deng, Evan M. Peck, and Lane Harrison. "The effects of adding search functionality to interactive visualizations on the web." In **Proceedings of the 2018 CHI Conference on Human Factors in Computing** Systems, pp. 1-13. 2018.

... more metrics!



Metrics for Individual Cases SearchinVis - 255Charts (Dataset Naming: STUDY - EXPERIMENT) Baseline Map showing % of visits Participants who explored the same number of visited elements (25 elements) (each circle is an element in the vis): with lower, medium, and higher exploration uniqueness (EU); • EU = 1.4 . EU = 0.9EU = 2.0۲ . 8 . • • at the periphery, which are also 8.5 user A user B Participants who explored for similar amount of time, with lower, medium, and higher exploration pacing (EP, user D EP = 0.06 userE *EP* = 0.12 ∥ user F EP = 0.17 are marked as gray.) HindSight - 255Charts Baseline map showing % of visits Participants who have the same number of visited elements (22 elements). (each circle is an element in the vis) with lower (left), medium (middle), and higher (right) exploration uniqueness (EU, EU = 0.7EU = 1.2 EU = 1.7 Participants with lower EP • • tend to explore with lower ٠ paces, and focus on individual . elements for longer time, while those with higher EP rapid paces. user G user H Participants who explored for similar amount of time, with lower, medium, and higher exploration pacing (EP user J EP = 0.04 user K FP = 0.10 user L EP = 0.15 Experimental Group Metrics for Experiment Analyses (The error bars repre sent 95% Confidence Intervals. p < 0.5 *, p < 0.1 **, p < 0.001 ***) Control Group SearchinVis - 255Charts SearchinVis - Boardrooms HindSight - 255Charts HindSight - Metafilter number of visited elements** number of visited elements number of visited elements number of visited elements ------0-------10 0.0 12.5 25.0 37.5 50.0 10 30 4 8 20 exploration time** exploration time exploration time exploration time 50 100 150 -----+----------100 200 300 400 125 250 375 100 200 300 bias (data point coverage)** bias (data point coverage) bias (data point coverage) bias (data point coverage) 0.00 0.25 0.50 0.75 0.00 0.25 0.50 0.75 0.00 0.25 0.50 0.75 0.00 0.25 0.50 0.75 1.0 bias (data point distribution)*** bias (data point distribution) bias (data point distribution)* bias (data point distribution) ____ ------0-0.25 0.50 0.75 0.00 0.25 0.50 0.75 0.00 0.25 0.50 0.75 0.25 0.50 0.00 exploration uniqueness* exploration uniqueness*** exploration uniqueness exploration uniqueness* -----------------0.8 1.1 0.4 0.5 0.6 0.7 exploration pacing*** exploration pacing exploration pacing exploration pacing -----0.00 0.03 0.06 0.09 0.000 - 0.025 0.050 0.075 0.100 0.00 --- 0.03 ___ 0.06 0.09 0.00 0.03 0.06 0.09 0.12

Feng, Mi, Evan M. Peck, and Lane Harrison. "Patterns and Pace: **Quantifying Diverse Exploration Behavior with Visualizations on the** Web" IEEE TVCG: Transactions on Visualization and Computer Graphics (InfoVis 2018)

. Both exploration uniqueness and exploration pacing metrics

can capture different aspects of user explorations.

number of visited elements have a explore the vis in lower paces.

The metric bias (data point coverage) and bias (data point distribution)

The metrics exploration time and

moderate correlation.

have a strong correlation

The exploration pacing metric

reveals that those participants in

to others.

the experimental group tend to

Metric Correlation and Independence

SearchinVis - 255Charts (positive / negative correlations)

number of visited elements

bias (data point coverage)

bias (data point distribution)

exploration uniqueness 02 0

exploration pacing 🔤 🔹

exploration time

The exploration uniqueness metric reveals that those participants in the experimental group tend to have a more unique exploration compared

tend to explore the vis in

(The timelines represent the participants' interaction logs. The moments visiting an element

frequently visited by others, while those with higher EU tend to explore the middle (rarely-visited) parts of the vis.

Participants with lower FU tend to focus on the elements



The interaction wasn't nearly as interesting as our relationship to the data.

And the evaluation wasn't capturing it







Hollis Winchendon Pepperell Andove Lowe Groton Chel Athol Greenfield Fitchburg Gardner Billerica Leominster Boxboroug Clinton Hudsor Amherst Holden Marlboroug Worcester ramingha Vestborough South Hadle Spencer Holliston Northbridge Charlton Springfield Oxford Uxbridg Southbridge Foxborough Woonsocket Somers Stafford Hollow Enfield Burrillville Cumberland Granby Attebor Windsor Locks Williamsport Lock Haven DuBois Parker New Castle Lewisburg Punxsutawney State Colleg Lower Burrell Altoona Pittsburgh Newpor ollidaysburg Harrisburg Ligonier Washington Mount Pleasant Somerset Chambersburg Uniontown Waynesburg Gettysburg Hanover



Do you think we see the world the same way?

Should we expect that people see charts the same way?





We interviewed 42 community members about charts & graphs

Where

farmers market construction site staff @ university

Who



Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019. Best Paper Award





Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019. Best Paper Award





Rank them





In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019. Best Paper Award







Data is Personal

People prioritized charts in which they could make personal connections.

We found more than 20 instances in which people made person connections with the data.

Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019. Best Paper Award



"Information about alcohol. I'm dealing with a functioning alcoholic... well, was a functioning alcoholic. The most important person in my life is an alcoholic. Right now, that's important to me."

Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019. Best Paper Award

Data is Personal

People prioritized charts in which they could make **personal connections.**



"As for some of the [other graphs I ranked high], I unfortunately know quite a few people who happen to have an issue with opioids... and it's something you consider... are you going to see that person tomorrow or not?"

W

Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019. Best Paper Award

Data is Personal

People prioritized charts in which they could make **personal connections.**





A deadly dose



I don't read this newspaper. Even if I did like this picture, I still won't buy the newspaper because I don't live in New York; The Sunbury paper – that's close to here. Then I would read it.. I still won't read that one. -55-64 year old

Visualization mantra: Overview first, Zoom and filter, Details on demand (Shneiderman 1996)

It's just a little more congested... trying to pinpoint where in a state I would be - 45-54 year old

I like them less. It's the whole country; it's so huge. You naturally look at your state. It's too busy. - 65-74 year old



The cost of ignoring local context in our design?

RISING AND FALLING NEW CORONAVIRUS CASES



Fortune

day with more than 2 positive cases

COVID-19 hot spots



Mayo Clinic

Graphs at a moment in which my county in central PA had yet to record a



Sources: Census Bureau; Federal Communications Commission; Georgia Broadband Program; University of Georgia's Carl Vinson Institute of Government

Our visualizations fail to contextualize within our data definitions

At least 1 location with 25 Mbps download speeds and upload speeds of 3Mbps

https://www.washingtonpost.com/technology/ 2021/12/14/bidens-ambitious-broadband-funding-haskey-impediment-an-outdated-map-who-needs-it/





Sources: Census Bureau; Federal Communications Commission; Georgia Broadband Program; University of Georgia's Carl Vinson Institute of Government

My father's childhood home. It has never had stable broadband connectivity. It is in an area defined as broadband coverage







How COVID dashboards load on a phone with 3G



In-progress work - Katrina Wilson, Reva Sharma, Jaehoon Pyon, Evan M. Peck

Who do we design for when we design on the web?



In-progress work - Katrina Wilson, Reva Sharma, Jaehoon Pyon, Evan M. Peck

Why does our research about novices in visualization often fail? general public non-experts

80% of papers rely on implicit definitions for novices (often ambiguous)

Implicitly...

A novice is most likely to be young A novice is most likely to be a university student A novice is most likely to be a US resident A novice is most likely to lack traditional STEM expertise

Burns, Alyxander, Christiana Lee, Ria Chawla, Evan M. Peck, and Narges Mahyar. "Who Do We Mean When We Talk About Visualization **Novices?**" **Best Paper Award ACM CHI 2023**

Rank them

Reveal sources

Rerank

26 out of 42 didn't change any rankings...

... and people who were less educated were less likely to change their rankings

Rank them

Reveal sources

Rerank

13 out of 28 didn't change any rankings...

... and we saw no characteristics that correlated with this decision

"information is information"

• (among more than a dozen with similar sentiments)

IMPARTIALITY POSITIONALITY

Rationale from person who did not change their rankings in our study

Exploiting perceived impartiality of data

Invisibility of political decisions

Same graph, almost-identical data, ~1 week apart

https://www.nytimes.com/interactive/2020/us/covid-19-vaccine-doses.html

Once trust is lost, the graphs don't matter

"I **don't trust** things if I don't know where it comes from"

"I would **never trust** something from a drug company or Breitbart, and I would always trust something from the CDC or NIH"

"I don't trust the CDC. I believe they hide stuff"

"It's hard to trust a lot of information because you could put anything on anything"

Peck, Evan M., Sofia E. Ayuso, and Omar El-Etr. "Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-12. 2019.

It's not just data literacy

"anti-mask groups are critical about the data sources used to make visualizations in data-driven stories."

"For these users, understanding how and why metrics" come to be is crucial to understanding whether the pandemic is as bad as the news makes it out to be... many of these anti-mask groups implored their opponents to simply follow the data, as sound data (and their visualizations) are crucial to making informed decisions."

Lee, Crystal, Tanya Yang, Gabrielle D. Inchoco, Graham M. Jones, and Arvind Satyanarayan. "Viral Visualizations: How Coronavirus Skeptics Use Orthodox Data **Practices to Promote Unorthodox Science Online.**" In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, pp. 1-18. 2021.

Public visualization needs to learn from (some of) ML's wrestling with data processes, not just models

Sambasivan, Nithya, Shivani Kapania, Hannah Highfill, Diana Akrong, Praveen Paritosh, and Lora M. Aroyo. ""Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI." In proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, pp. 1-15. 2021.

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- Interacting with physical world brittleness
- Inadequate application-domain expertise
- Conflicting reward systems
- Poor cross-organizational documentation
- Impacts of cascades
- ---> Abandon / re-start process

value-centered

Slide modified from Colin Gray's talk on Dark Patterns, Ethical Engagement, & the Potential for Action

Processes over Principles

generic capitalist design asshole design dark patterns

evil

value-centered

Slide modified from Colin Gray's talk on Dark Patterns, Ethical Engagement, & the Potential for Action

Processes over Principles

Designers only see humans as consumers of data

generic capitalist design

Designers coerce users through deliberate data manipulation

asshole design

dark patterns

Designers try to reduce users' agency & value by constrain access to data or views of data

evil

What might it look like to explore design spaces and design processes that reprioritize our values in human-data interaction?

Joe's Pond Ice Out Winners

Year	Winner	Town and State	Date	Time
1988	Edward Bird	West Danville, VT	4/26/88	12:31 p.m.
1989	Bob Kerschner	Sun City, FL	5/5/89	9:05 a.m.
1990	John Reilly	Barre, VT	4/26/90	9:40 a.m.
1991	Scott Lazare	Lido Beach, NJ	4/22/91	4:16 a.m.
1992	Charese McSheffrey	Barre, VT	5/6/92	1:19 p.m.
1993	Ray Strousos	Barre, VT	4/29/93	1:38 p.m.
1994	Jerome Bolkum	Barre, VT	5/4/94	12:12 p.m.
1995	Tom Buzzi	Kent, OH	4/23/95	2:50 p.m.
1996	Nancy Potter	Plainfield, VT	5/1/96	11:29 p.m.
1997	Ralph Bissell	Walden, VT	5/1/97	7:43 a.m.
1998	Andre Jenny	Montpelier, VT	4/16/98	6:41 p.m.
1999	Gilles Moreau	East Barre, VT	4/26/99	2:37 a.m.
2000	Tammy Hatch	West Danville, VT	4/30/00	6:19 a.m.
2001	Kay Scott	St. Johnsbury, VT	5/4/01	1:44 a.m.
2002	N. Mason Jeff Temple Stephen Bean Charlene Zabek	Various	4/18/02	4:18 p.m.
2003	Brodie Frazier	East Montpelier, VT	4/28/03	9:45 a.m.
2004	Janet & Richard Hazen	South Hero, VT	4/21/04	3:25 p.m.
2005	G.D. Lanois	Bonita Springs, FL	4/21/05	2:50 p.m.
2006	Pam Desrochers Frenchie Cutting Lucille Dente	St. Johnsbury, VT Swanton, VT Barre, VT	04/16/06	3:20 p.m.
2007	Dr. Bob Marshall	Montpelier, VT	5/1/07	4:45 p.m.
2008	Janet Egizi Roxanne Gorham Joe Kelly Don Rogers	St. Johnsbury, VT Lyndonville, VT Barre, VT Swartz Creek, MI	4/25/08	5:25 p.m.
2009	Ash Desmond	Richmond, VT	4/20/09	10:21 p.m.
2010	Bill Barber	St Johnsbury, VT	4/05/10	2:46 p.m.
2011	Karen Brouillette	Websterville, VT	4/27/11	10:17 p.m.
2012	Judy Lavely	Danville, VT	4/8/12	5:25 p.m.
2013	Gary Clark	Barre, VT	4/24/13	8:46 a.m.
2014	Kelsey Phillips Bill Brochu	Iowa City, IA Springfield, MA	4/29/14	10:06 a.m.
2015	Mary Numa	West Haven, CT	4/29/15	6:14 p.m.
2016	Pamela Swift	Barre, VT	4/12/16	5:04 p.m.
2017	Emily Wiggett	North Danville, VT	4/23/17	4:32 p.m.
2018	Michael S. Cody	Barre, VT	5/4/18	11:27 a.m.
2019	Robynn L. Albert	Essex Junction, VT	4/25/19	5:39 a.m.
2020	Angela Buttura Nancy Durand	Essex Junction, VT Hardwick, VT	4/15/20	6:07 a.m.

Ice out contests at Joe's Pond in rural Vermont

Joe's Pond Ice Out Winners

Year	Winner	Town and State	Date	Time
1988	Edward Bird	West Danville, VT	4/26/88	12:31 p.m.
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1993	Ray Strousos	Barre, VT	4/29/93	1:38 p.m.
1994	Jerome Bolkum	Barre, VT	5/4/94	12:12 p.m.
1995	Tom Buzzi	Kent, OH	4/23/95	2:50 p.m.
1996	Nancy Potter	Plainfield, VT	5/1/96	11:29 p.m.
1997	Ralph Bissell	Walden, VT	5/1/97	7:43 a.m.
1998	Andre Jenny	Montpelier, VT	4/16/98	6:41 p.m.
1999	Gilles Moreau	East Barre, VT	4/26/99	2:37 a.m.
2000	Tammy Hatch	West Danville, VT	4/30/00	6:19 a.m.
2001	Kay Scott	St. Johnsbury, VT	5/4/01	1:44 a.m.
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2013	Gary Clark	Barre, VT	4/24/13	8:46 a.m.
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2019	Robynn L. Albert	Essex Junction, VT	4/25/19	5:39 a.m.
2020	Angela Buttura Nancy Durand	Essex Junction, VT Hardwick, VT	4/15/20	6:07 a.m.

Ice-out events recorded for over 150 years in ponds and lakes across New England

SLOW LONG LOCAL

EFFICIENCY CARE UNIVERSALITY CONTEXTUALITY IMPARTIALITY POSITIONALITY

Joe's Pond Ice Out Crew Connects Block To Clock caledonianrecord.com

IMPRECISE PHYSICAL VISIBLE

What do data visualizations look like when they are local and participatory vs. universal and designer-centered?

What does it mean when visualizations are long, slow, and personal vs. fast, shortlived, and universal?

What should information visualization focus on?

- ... interrogating our data processes not just our visual designs
- ... including people as participants not just as consumers
- ... creating visualizations for communities not just universal outlets
- ... making visible our framing and bias not just assuming objectivity (It's not possible!)

Evan M. Peck

Associate Professor of Information Science University of Colorado Boulder

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