CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

Data Visualization Literacy

Katy Börner **@katycns**

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Intelligent Systems Engineering & Information Science
Director, Cyberinfrastructure for Network Science Center
School of Informatics, Computing, and Engineering
Indiana University Network Science Institute (IUNI)
Indiana University, Bloomington, IN, USA
+ 2018 Humboldt Fellow, TU Dresden, Germany

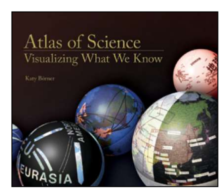
Keynote at IEEE VIS

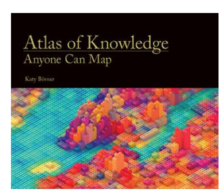
Vancouver, Canada | October 22, 2019

Overview

Theoretical data visualization framework (DVL) meant to empower anyone to systematically render data into insights.

- Börner, Katy, Andreas Bueckle, and Michael Ginda. 2019. Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. *PNAS*, 116 (6) 1857-1864.
- Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press.
- Börner, Katy. 2010. *Atlas of Science: Visualizing What We Know*. Cambridge, MA: The MIT Press.





Atlas of Forecasts

Scaling-Up: Increase global DVL via (in)formal education (AISL, https://ivmooc.cns.iu.edu & https://visanalytics.cns.iu.edu)

Opportunity: The Human BioMolecular Atlas Program (HuBMAP) (https://hubmapconsortium.org)

- Snyder, Michael P., et al. 2019. "Mapping the Human Body at Cellular Resolution -- The NIH Common Fund Human BioMolecular Atlas Program". *Nature*. 574, p. 187-192.

TONIGHT: Debut 15th iteration of the *Places & Spaces: Mapping Science* exhibit (http://scimaps.org).

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Data Visualization Literacy (DVL)

Data visualization literacy (ability to read, make, and explain data visualizations) requires:

- literacy (ability to read and write text in titles, axis labels, legends, etc.),
- visual literacy (ability to find, interpret, evaluate, use, and create images and visual media), and
- mathematical literacy (ability to formulate, employ, and interpret math in a variety of contexts).

Being able to "read and write" data visualizations is becoming as important as being able to read and write text. Understanding, measuring, and improving data and visualization literacy is important to strategically approach local and global issues.

101st Annual Meeting of the Association of American Geographers, Denver, CO.
April 5th - 9th, 2005 (First showing of Places & Spaces)

University of Miami, Miami, FL.
September 4 - December 11, 2014.

Duke University, Durham, NC.
January 12 - April 10, 2015

http://scimaps.org

The David J. Sencer CDC Museum, Atlanta, GA.
January 25 - June 17, 2016.

Places & Spaces: Mapping Science Exhibit

1st Decade (2005-2014)

Maps

2nd Decade (2015-2024)

Macroscopes

100
MAPS
in large format, full color, and high resolution.

248
MAPMAKERS
from fields as disparate as art, urban planning, engineering, and the history of science.

43
MACROSCOPE MAKERS
including one whose job title is "Truth and Beauty Operator."

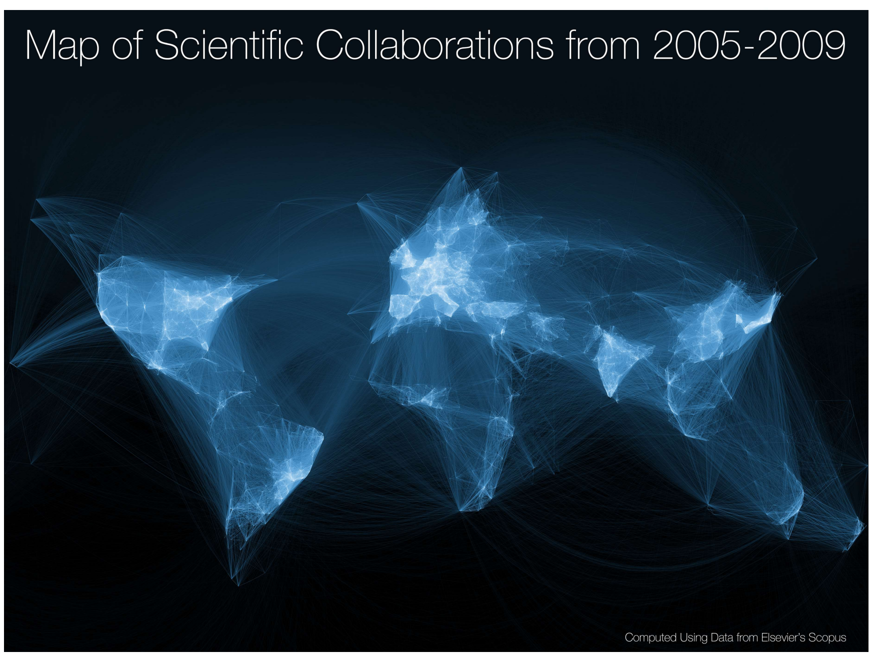
20
MACROSCOPES
for touching all kinds of data.

382
DISPLAY VENUES
from the Cannes Film Festival to the World Economic Forum.

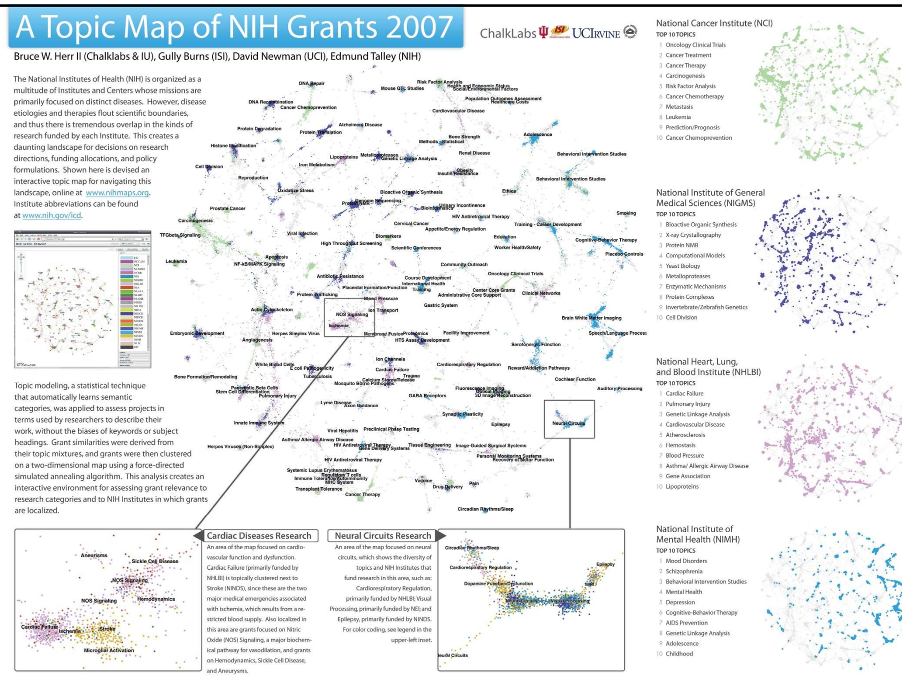
354
PRESS ITEMS
including articles in *Nature*, *Science*, *USA Today*, and *Wired*.

http://scimaps.org

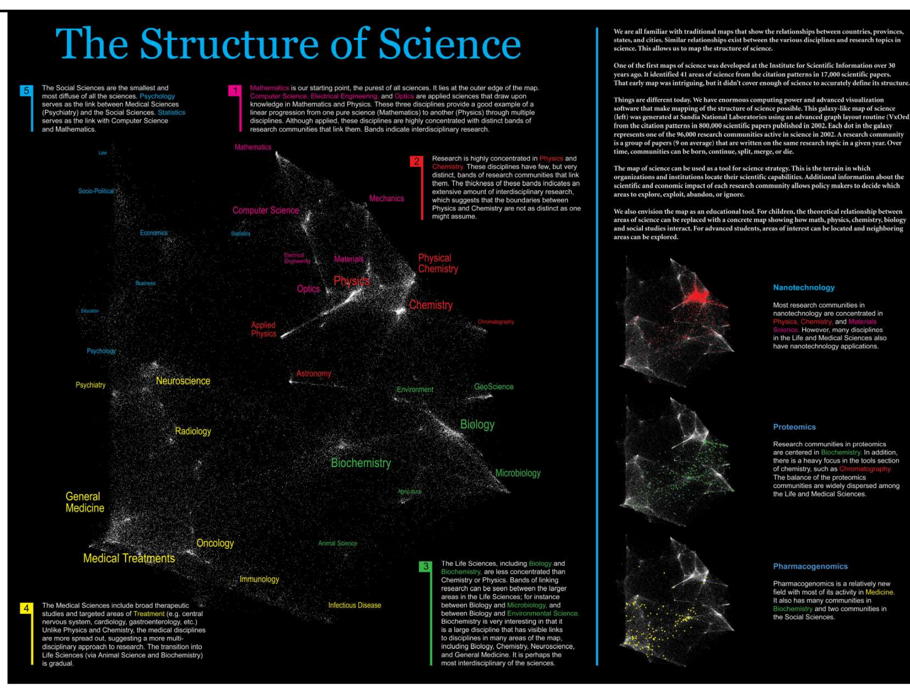
5



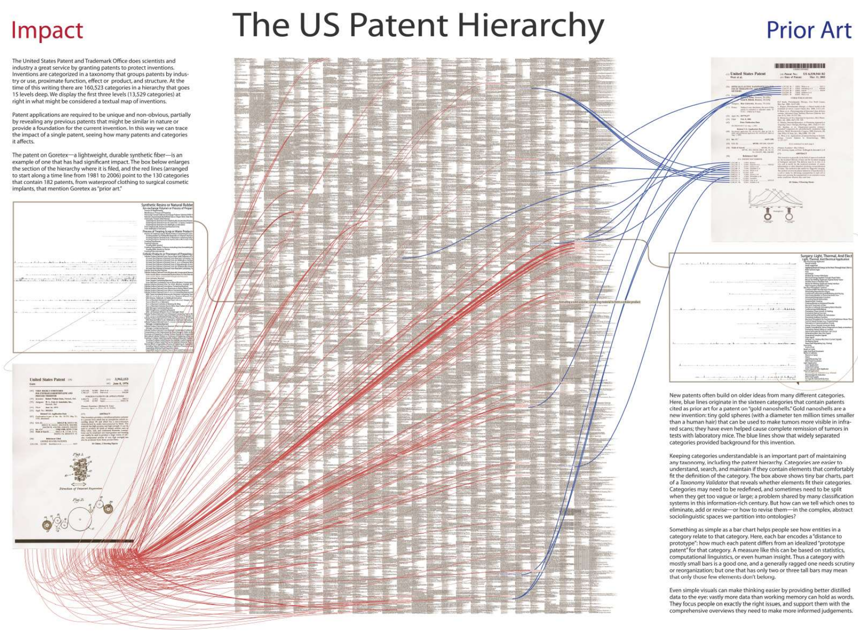
VII.6 Stream of Scientific Collaborations Between World Cities - Olivier H. Beauchesne - 2012



V.7 *A Topic Map of NIH Grants 2007* - Bruce W. Herr II, Gully A.P.C. Burns, David Newman, and Edmund Talley - 2009

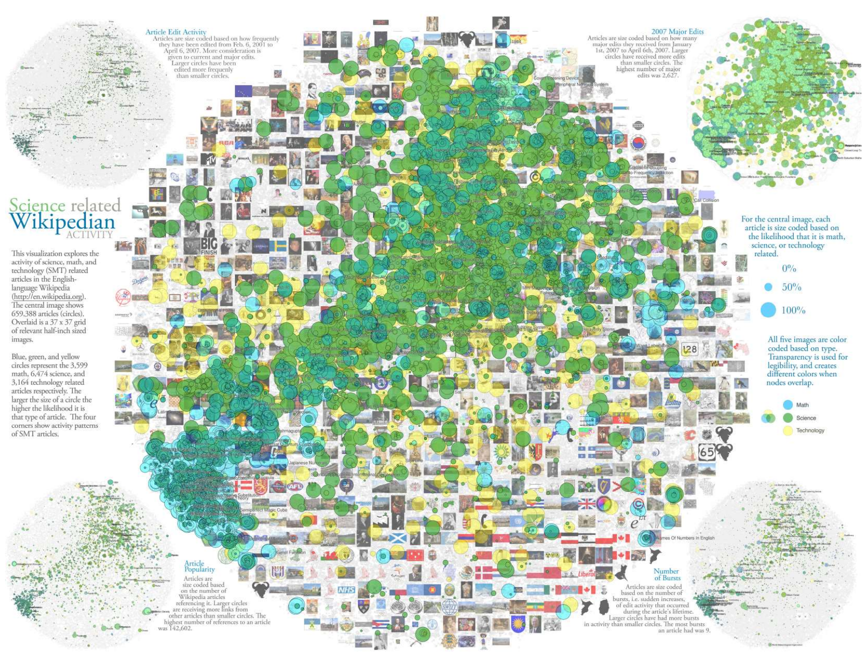


I.10 *The Structure of Science* - Kevin W. Boyack and Richard Klavans - 2005

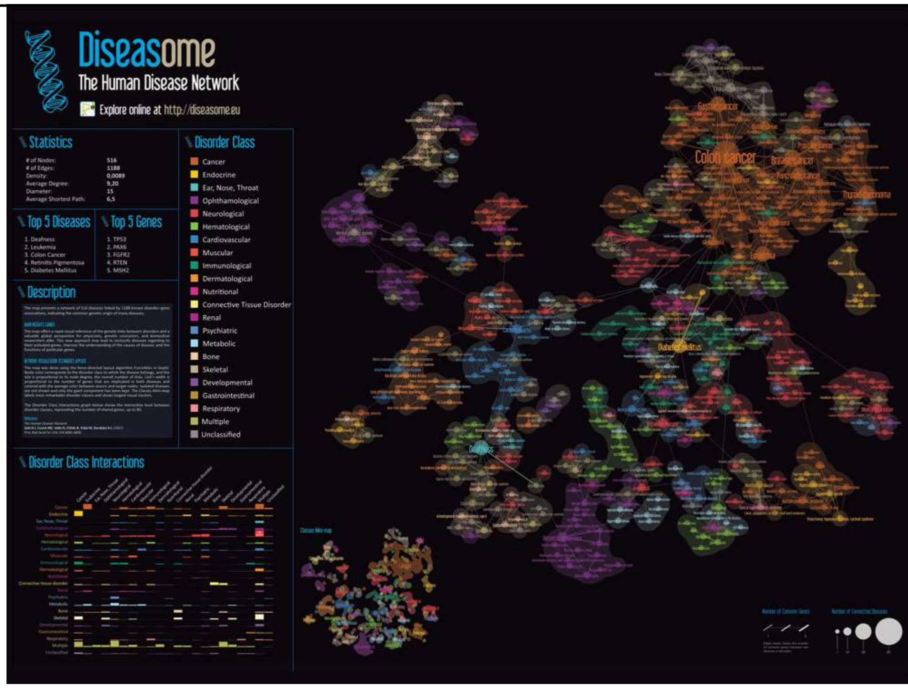


II.8 *Taxonomy Visualization of Patent Data* - Katy Börner, Elisha F. Hardy, Bruce W. Herr II, Todd Holloway, and W. Bradford Paley - 2006

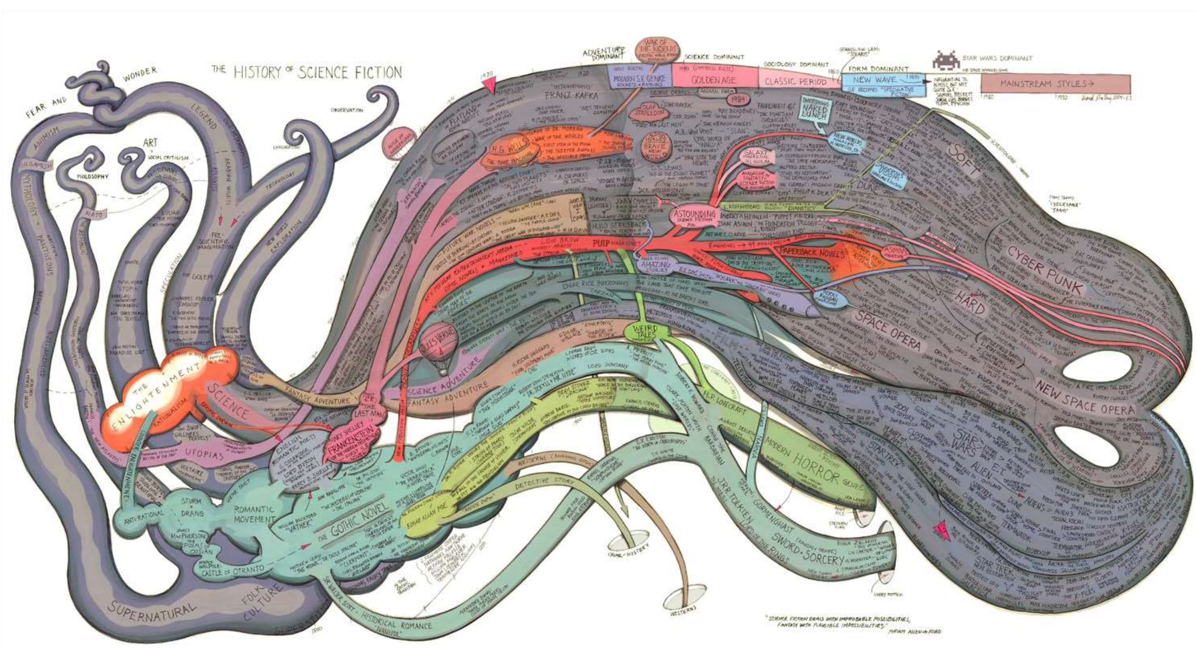
9



III.8 *Science-Related Wikipedian Activity* - Bruce W. Herr II, Todd M. Holloway, Elisha F. Hardy, Katy Börner, and Kevin Boyack - 2007

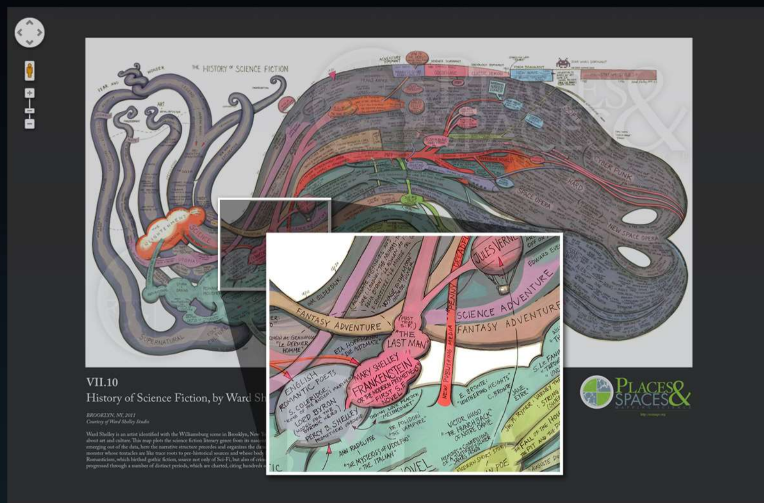


VI.3 *Diseasome: The Human Disease Network* - Mathieu Bastian and Sébastien Heymann - 2009



VII.10 *History of Science Fiction* - Ward Shelley - 2011

Check out our Zoom Maps online!

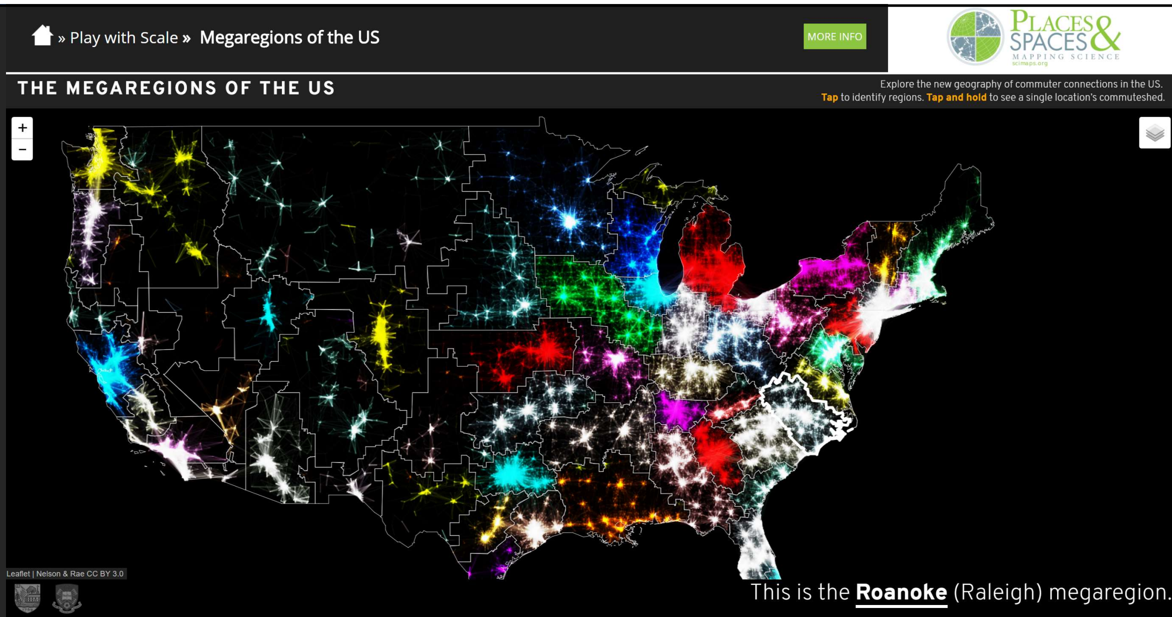


Visit scimaps.org and check out all our maps in stunning detail!

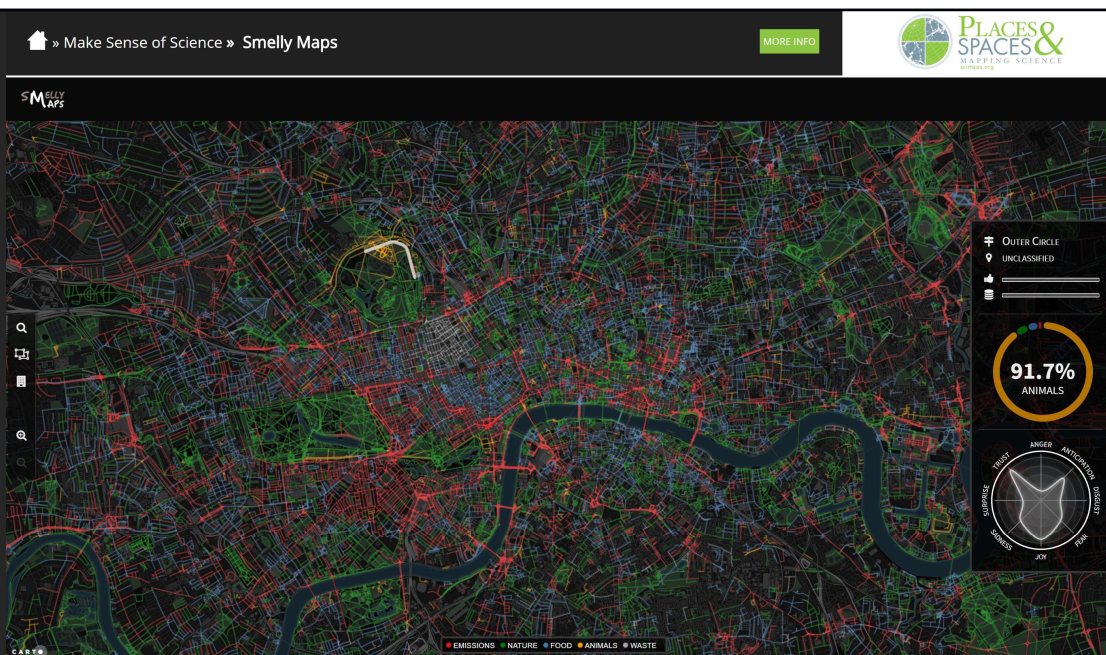
MACROSCOPES FOR INTERACTING WITH SCIENCE

PLACES & SPACES
MAPPING SCIENCE
scimaps.org

Earth	AcademyScope	Mapping Global Society	Charting Culture
Weather on a worldwide scale	*Exploring the scientific landscape*	*Local news from a global perspective*	*2,600 years of human history in 5 minutes*

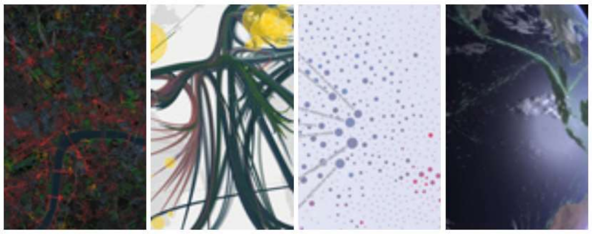


Megaregions of the US –Garrett Dash Nelson and Alasdair Rae – 2016



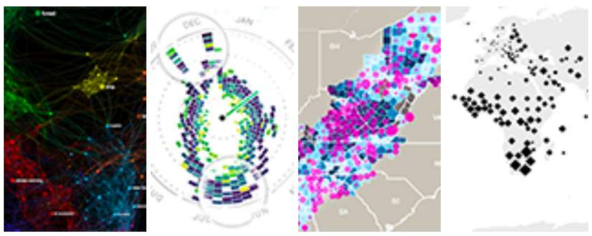
Smelly Maps – Daniele Quercia, Rossano Schifanella, and Luca Maria Aiello – 2015

Iteration XII (2016)
Macroscopes for Making Sense of Science



Iteration XIII (2017)
Macroscopes for Playing with Scale

Iteration XIV (2018)
Macroscopes for Ensuring our Well-being



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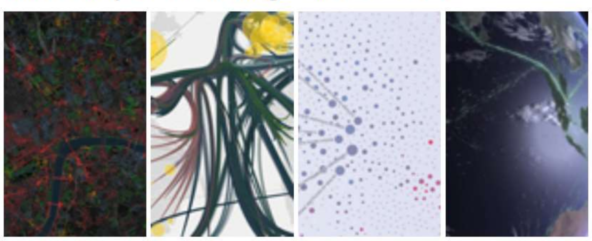
Stop by VISAP in South Foyer tonight
at 6:30pm for a grand tour!
https://visap.net

Iteration XII (2016)
Macroscopes for Making Sense of Science



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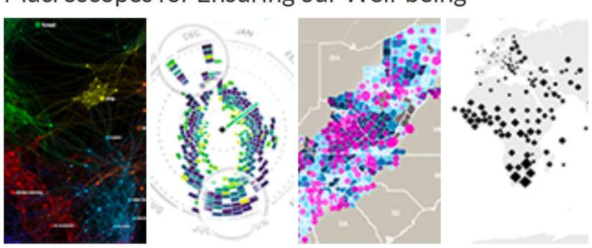
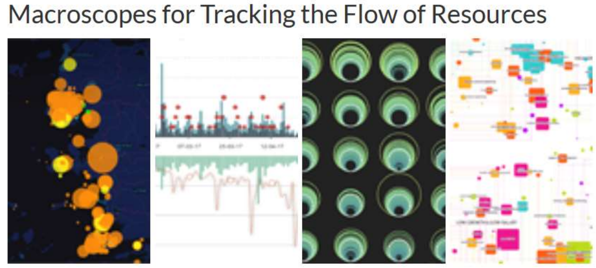


Iteration XV (2019)
Macroscopes for Tracking the Flow of Resources



Government, academic, and industry leaders discussed challenges and opportunities associated with using big data, visual analytics, and computational models in STI decision-making.

Conference slides, recordings, and report are available via http://modsti.cns.iu.edu/report

Arthur M. Sackler COLLOQUIA OF THE NATIONAL ACADEMY OF SCIENCES

Modeling and Visualizing Science and Technology Developments

National Academy of Sciences Sackler Colloquium, December 4-5, 2017, Irvine, CA

Rankings and the Efficiency of Institutions
H. Eugene Stanley | Albert-László Barabási | Lada Adamic | Marta González | Kaye Husbands Fealing | Brian Uzzi | John V. Lombardi

Higher Education and the Science & Technology Job Market
Katy Börner | Wendy L. Martinez | Michael Richey | William Rouse | Stasa Milojevic | Rob Rubin | David Krakauer

Innovation Diffusion and Technology Adoption
William Rouse | Donna Cox | Jeff Alstott | Ben Shneiderman | Rahul C. Basole | Scott Stern | Cesar Hidalgo

Modeling Needs, Infrastructures, Standards
Paul Trunfio | Sallie Keller | Andrew L. Russell | Guru Madhavan | Azer Bestavros | Jason Owen-Smith

nasonline.org/Sackler-Visualizing-Science

Programs > Arthur M. Sackler Colloquia > Completed Colloquia > Modeling and Visualizing Science and Technology Developments   Share

PROGRAMS

- **Sackler Colloquia**
  - About Sackler Colloquia
  - Upcoming Colloquia
  - Completed Colloquia
  - Sackler Lectures
  - Video Gallery
  - Connect with Sackler Colloquia
  - Give to Sackler Colloquia
- **Cultural Programs**
- **Distinctive Voices**
- **Kavli Frontiers of Science**
- **Keck Futures Initiative**
- **LabX**
- **Sackler Forum**
- **Science & Entertainment Exchange**

Arthur M. Sackler COLLOQUIA

Modeling and Visualizing Science and Technology Developments

December 4-5, 2017; Irvine, CA
Organized by Katy Börner, H. Eugene Stanley, William Rouse and Paul Trunfio

Overview

This colloquium was held in Irvine, CA on December 4-5, 2017.

This colloquium brought together researchers and practitioners from multiple disciplines to present, discuss, and advance computational models and visualizations of science and technology (S&T). Existing computational models are being applied by academia, government, and industry to explore questions such as: What jobs will exist in ten years and what career paths lead to success? Which types of institutions will likely be most innovative in the future? How will the higher education cost bubble burst affect these institutions? What funding strategies have the highest return on investment? How will changing demographics, alternative economic growth trajectories, and relationships among nations impact answers to these and other questions? Large-scale datasets (e.g., publications, patents, funding, clinical trials, stock market, social media data) can now be utilized to simulate the structure and evolution of S&T. Advances in computational power have created the possibility of implementing scalable, empirically validated computational models. However, because the databases are massive and multidimensional, both the data and the models tend to exceed human comprehension. How can advances in data visualizations be effectively employed to communicate the data, the models, and the model results to diverse stakeholder groups? Who will be the users of next generation models and visualizations and what decisions will they be addressing.

Videos of the talks are available on the **Sackler YouTube Channel**.

https://www.pnas.org/modeling

Acknowledgments

Exhibit Curators

The exhibit team: Lisel Record, Katy Börner, and Todd Theriault.

http://scimaps.org

Plus, we thank the more than 250 authors of the 100 maps and 16 interactive macroscopes.

Exhibit Advisory Board

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Associate Professor of Geography at San Diego State University, California

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Benjamin Wiederkehr
Founding Partner and Managing Director of Interactive Things in Zürich, Switzerland

Lev Manovich
Professor, The Graduate Center, City University of New York; Director, Software Studies Initiative (big data, digital humanities, visualization)

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Data Visualization Literacy Framework

Börner, Katy, Andreas Bueckle, and Michael Ginda. 2019. Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. *PNAS*, 116 (6) 1857-1864.

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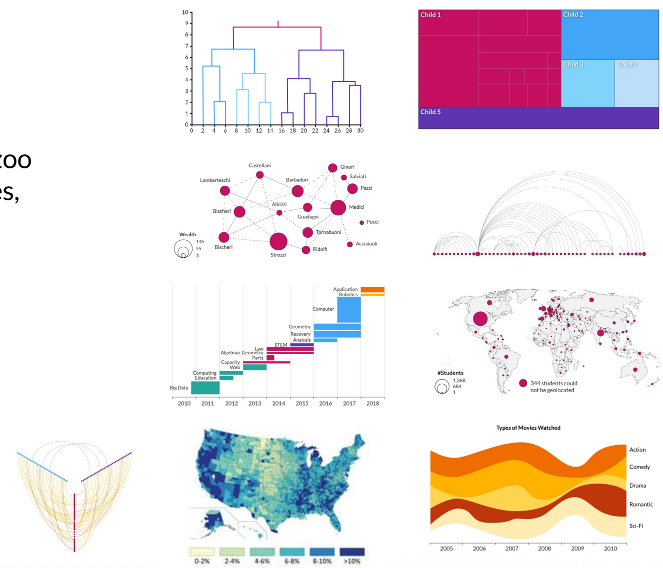
Being able to "read and write" data visualizations is becoming as important as being able to read and write text. Understanding, measuring, and improving data and visualization literacy is important to strategically approach local and global issues.

Visualization Frameworks

MANY frameworks and taxonomies have been proposed to

- help organize and manage the evolving zoo of 500+ different data visualization types,
- provide guidance when designing data visualizations, and
- facilitate teaching.



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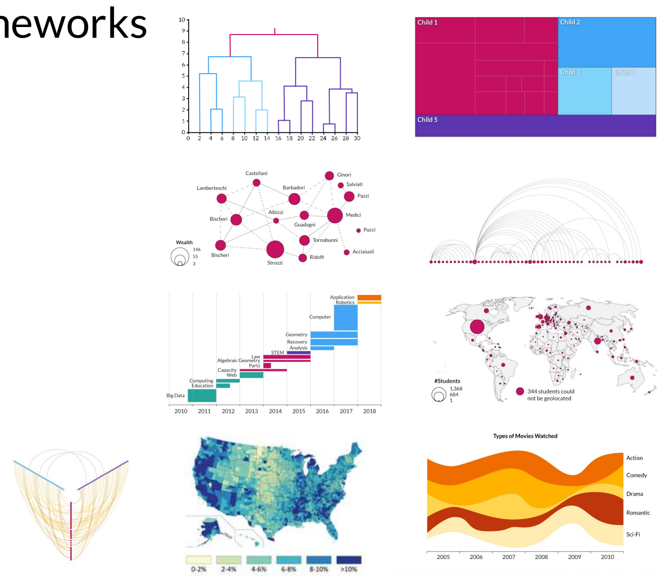
Existing Visualization Frameworks

Organize data visualizations by

- User insight needs
- User task types
- Data to be visualized
- Data transformations
- Visualization technique
- Visual mapping transformations
- Interaction techniques
- Deployment options
- and other features ...



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DVL Framework: Desirable Properties

- Most existing frameworks focus on **READING**. We believe that much expertise is gained from also **CONSTRUCTING** data visualizations.
- Reading and constructing data visualizations needs to take human perception and cognition into account.
- Frameworks should build on and consolidate prior work in cartography, psychology, cognitive science, statistics, scientific visualization, data visualization, learning sciences, etc. in support of a de facto standard.
- Theoretically grounded + practically useful + easy to learn/use.
- Highly modular and extendable.

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DVL Framework: Development Process

- The initial DVL-FW was developed via an extensive literature review.
- The resulting DVL-FW typology, process model, exercises, and assessments were then tested in the *Information Visualization* course taught for more than 17 years at Indiana University. More than 8,500 students enrolled in the IVMOOC version (http://ivmooc.cns.iu.edu) over the last six years.
- The FW was further refined using feedback gained from constructing and interpreting data visualizations for 100+ real-world client projects.
- Data on student engagement, performance, and feedback guided the continuous improvement of the DVL-FW typology, process model, and exercises for defining, teaching, and assessing DVL.
- The DVL-FW used in this course supports the systematic construction and interpretation of data visualizations.

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Data Visualization Literacy Framework (DVL-FW)

Consists of two parts:

DVL Typology
Defines 7 types with 4-17 members each.

1 **Insight Needs**
- categorize/cluster
- order/rank/sort
- distributions (also outliers, gaps)
- comparisons
- trends (process and time)
- geospatial
- compositions (also of text)
- correlations/ relationships

2 **Data Scales**
- nominal
- ordinal
- interval
- ratio

3 **Analyses**
- statistical
- temporal
- geospatial
- topical
- relational

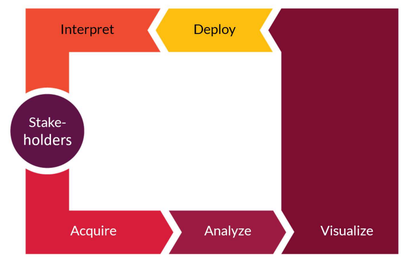
4 **Visualizations**
- table
- chart
- graph
- map
- tree
- network

5 **Graphic Symbols**
- geometric symbols
  point
  line
  area
  surface
  volume
- linguistic symbols
  text
  numerals
  punctuation marks
- pictorial symbols
  images
  icons
  statistical glyphs

6 **Graphic Variables**
- spatial
  position
- retinal
  form
  color
  optics
  motion

7 **Interactions**
- zoom
- search and locate
- filter
- details-on-demand
- history
- extract
- link and brush
- projection
- distortion

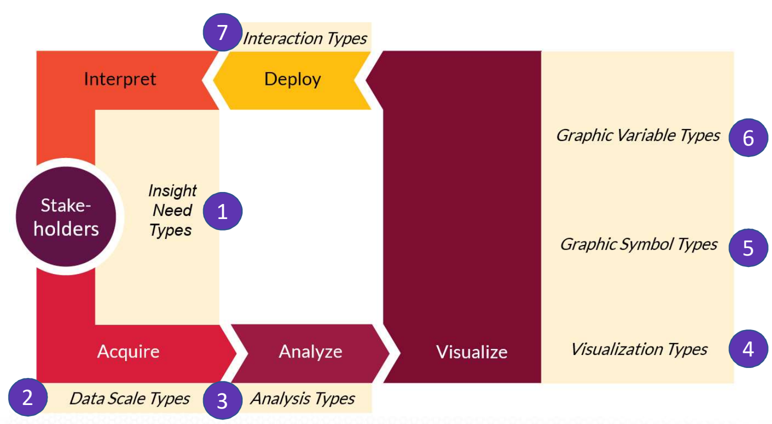
DVL Workflow Process
Defines 5 steps required to render data into insights.



Data Visualization Literacy Framework (DVL-FW)

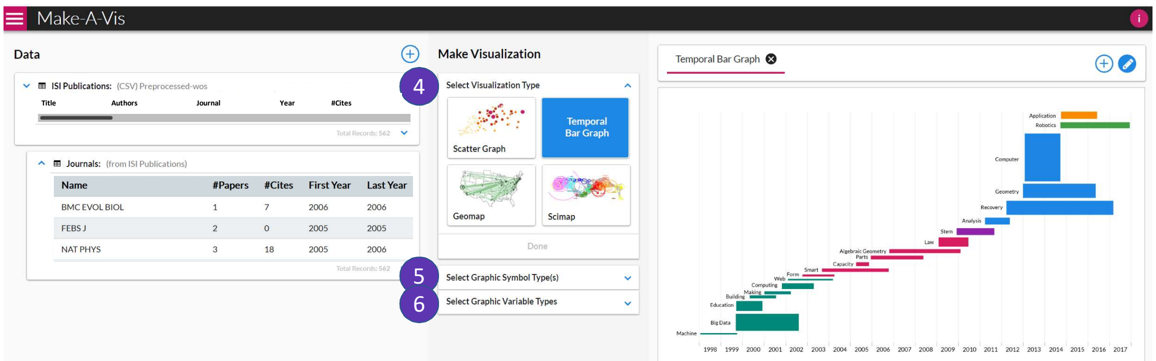
Consists of two parts that are interlinked:

DVL Typology +
DVL Workflow Process



Data Visualization Literacy Framework (DVL-FW)

Implemented in Make-A-Vis (MAV) to support learning via horizontal transfer, scaffolding, hands-on learning, etc.



Typology of the Data Visualization Literacy Framework

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  - line
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  - surface
  - volume
- linguistic symbols
  - text
  - numerals
  - punctuation marks
- pictorial symbols
  - images
  - icons
  - statistical glyphs

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Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 25.

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Bertin, 1967	Wehrend & Lewis, 1996	Few, 2004	Yau, 2011	Rendgen & Wiedemann, 2012	Frankel, 2012	Tool: Many Eyes	Tool: Chart Chooser	Börner, 2014
selection	categorize			category				categorize/ cluster
order	rank	ranking					table	order/rank/ sort
	distribution	distribution					distribution	distributions (also outliers, gaps)
	compare	nominal comparison & deviation	differences		compare and contrast	compare data values	comparison	comparisons
		time series	patterns over time	time	process and time	track rises and falls over time	trend	trends (process and time)
		geospatial	spatial relations	location		generate maps		geospatial
quantity		part-to-whole	proportions		form and structure	see parts of whole, analyze text	composition	compositions (also of text)
association	correlate	correlation	relationships	hierarchy		relations between data points	relationship	correlations/ relationships

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Typology of the Data Visualization Literacy Framework

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Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 28-29.

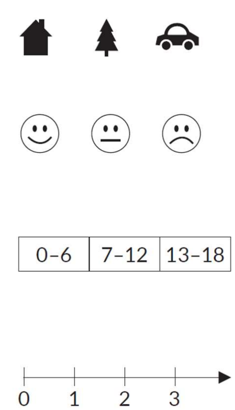
Data Scale Types

Nominal: A categorical scale, also called a nominal or category scale, is qualitative. Categories are assumed to be non-overlapping.

Ordinal: An ordinal scale, also called sequence or ordered, is quantitative. It rank-orders values representing categories based on some intrinsic ranking, but not at measurable intervals.

Interval: An interval scale, also called a value scale, is a quantitative numerical scale of measurement where the distance between any two adjacent values (or intervals) is equal, but the zero point is arbitrary.

Ratio: A ratio scale, also called a proportional scale, is a quantitative numerical scale. It represents values organized as an ordered sequence, with meaningful uniform spacing, and a true zero point.



Data Scale Types - Examples

Nominal: Words or numbers constituting the "categorical" names and descriptions of people, places, things, or events.

Ordinal: Days of the week, degree of satisfaction and preference rating scores (e.g., using a Likert scale), or rankings such as low, medium, high.

Interval: Temperature in degrees or time in hours. Spatial variables such as latitude and longitude are interval.

Ratio: Physical measures such as height, weight, (reaction) time, or intensity of light; number of published papers, co-authors, citations.

Data Scale Types

Stevens, 1946 *Scales of Measurement*	Bertin, 1967 *Level of Organization of the Components*	Harris, 1996 *Classification of Scales*	Munzner, 2011 *Visualization Principles*	Börner, 2014 *Data Scale Types*
nominal	quantitative	category	categorical/nominal	nominal
ordinal	ordered	sequence	ordinal	ordinal
interval	quantitative	quantitative	quantitative	interval
ratio	quantitative	quantitative	quantitative	ratio

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Data Scale Types - Examples

Nominal: Words or numbers constituting the "categorical" names and descriptions of people, places, things, or events.

Qualitative

Quantitative

Ordinal: Days of the week, degree of satisfaction and preference rating scores (e.g., using a Likert scale), or rankings such as low, medium, high.

Interval: Temperature in degrees or time in hours. Spatial variables such as latitude and longitude are interval.

Ratio: Physical measures such as height, weight, (reaction) time, or intensity of light; number of published papers, co-authors, citations.

CNS Cyberinfrastructure for Network Science Center

Data Scale Types - Mathematical Operations

This table shows the logical mathematical operations permissible, the measure of central tendency, and examples for the different data scale types.

Data Scale Types	Logical Mathematical Operations				Measure of Central Tendency	Examples
	= ≠	< >	+ -	x ÷		
Nominal	y				mode	
Ordinal	y	y			median	
Interval	y	y	y		arithmetic mean	0–6 / 7–12 / 13–18
Ratio	y	y	y	y	geometric mean	0 1 2 3

Qualitative

Quantitative

Typology of the Data Visualization Literacy Framework

3

Insight Needs
- categorize/cluster
- order/rank/sort
- distributions (also outliers, gaps)
- comparisons
- trends (process and time)
- geospatial
- compositions (also of text)
- correlations/ relationships

Data Scales
- nominal
- ordinal
- interval
- ratio

Analyses
- statistical
- temporal
- geospatial
- topical
- relational

Visualizations
- table
- chart
- graph
- map
- tree
- network

Graphic Symbols
- geometric symbols
  - point
  - line
  - area
  - surface
  - volume
- linguistic symbols
  - text
  - numerals
  - punctuation marks
- pictorial symbols
  - images
  - icons
  - statistical glyphs

Graphic Variables
- spatial
  - position
- retinal
  - form
  - color
  - optics
  - motion

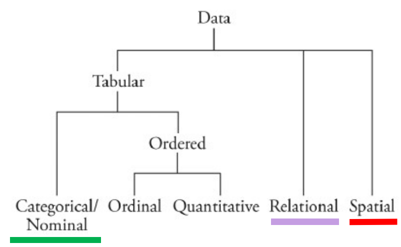
Interactions
- zoom
- search and locate
- filter
- details-on-demand
- history
- extract
- link and brush
- projection
- distortion

Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 25.

Analysis Types

- When: Temporal Data Analysis + Statistical
- Where: Geospatial Data Analysis
- What: Topical Data Analysis
- With Whom: Network Analysis

***Data Hierarchy** by Tamara Munzner distinguishes tabular, relational, and spatial data.*



Typology of the Data Visualization Literacy Framework

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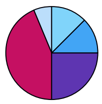
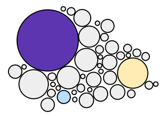
- distortion

Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 30-31.

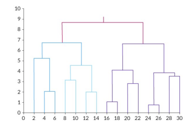
Visualization Types

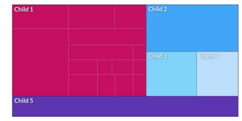
Chart


Pie Chart

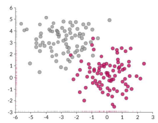

Bubble Chart

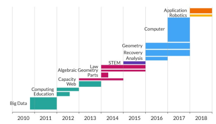
Tree


Dendrogram

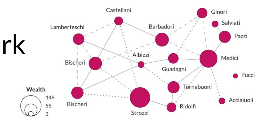

Tree Map

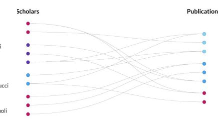
Graph


Scatter Graph


Temporal Bar Graph

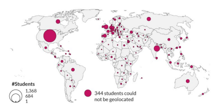
Network


Force-Directed Network Layout


Bimodal Network Layout

Map

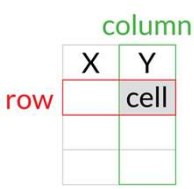

Choropleth Map


Proportional Symbol Map

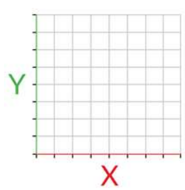
Visualize: Reference Systems

4
Visualization Types
- table
- chart
- graph
- map
- network layout

Table
columns by rows

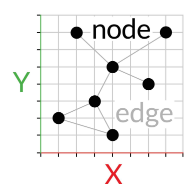


Graph
x-y coordinates

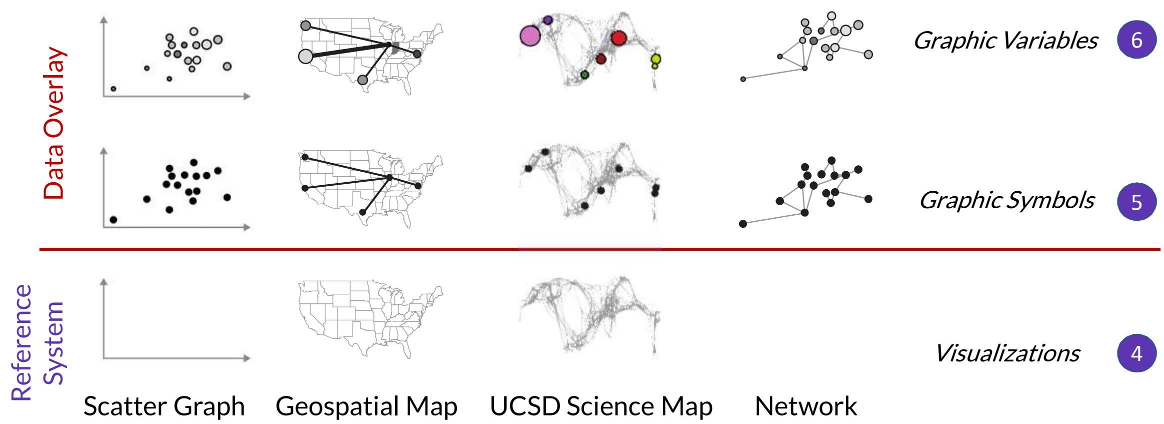


Map
latitude/
longitude

Network
local similarity



Visualize: Reference Systems, Graphic Symbols and Variables



Typology of the Data Visualization Literacy Framework

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Visualizations
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- tree
- network

5

Graphic Symbols
- geometric symbols
  point
  line
  area
  surface
  volume
- linguistic symbols
  text
  numerals
  punctuation marks
- pictorial symbols
  images
  icons
  statistical glyphs

Graphic Variables
- spatial
  position
- retinal
  form
  color
  optics
  motion

Interactions
- zoom
- search and locate
- filter
- details-on-demand
- history
- extract
- link and brush
- projection
- distortion

Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 32-33.

Typology of the Data Visualization Literacy Framework

6

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Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 34-35.

CNS Cyberinfrastructure for Network Science Center

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Graphic Variable Types

Position: x, y; possibly z — Quantitative

Form:
- Size — Quantitative
- Shape — Qualitative
- Rotation (Orientation) — Quantitative

Color:
- Value (Lightness) — Quantitative
- Hue (Tint) — Qualitative
- Saturation (Intensity) — Quantitative

Optics: Blur, Transparency, Shading, Stereoscopic Depth

Texture: Spacing, Granularity, Pattern, Orientation, Gradient

Motion: Speed, Velocity, Rhythm

CNS Cyberinfrastructure for Network Science Center

48

Graphic Variable Types

Position: x, y; possibly z

Form:

- Size
- Shape
- Rotation (Orientation)

Color:

- Value (Lightness)
- Hue (Tint)
- Saturation (Intensity)

Optics: Blur, Transparency, Shading, Stereoscopic Depth

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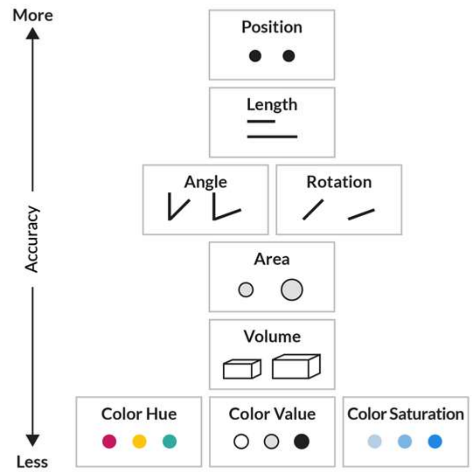
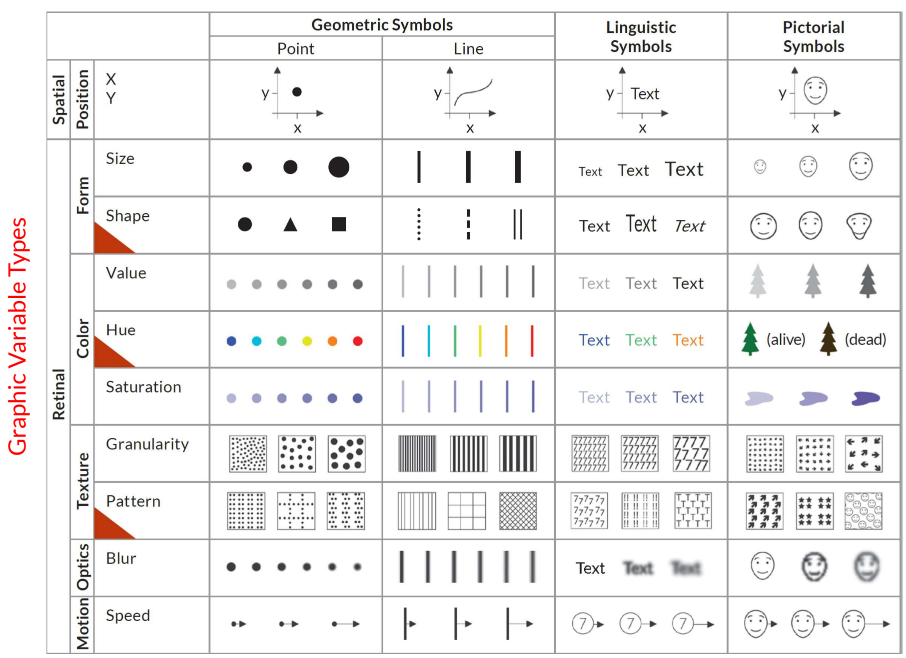


CNS Cyberinfrastructure for Network Science Center

Graphic Symbol Types



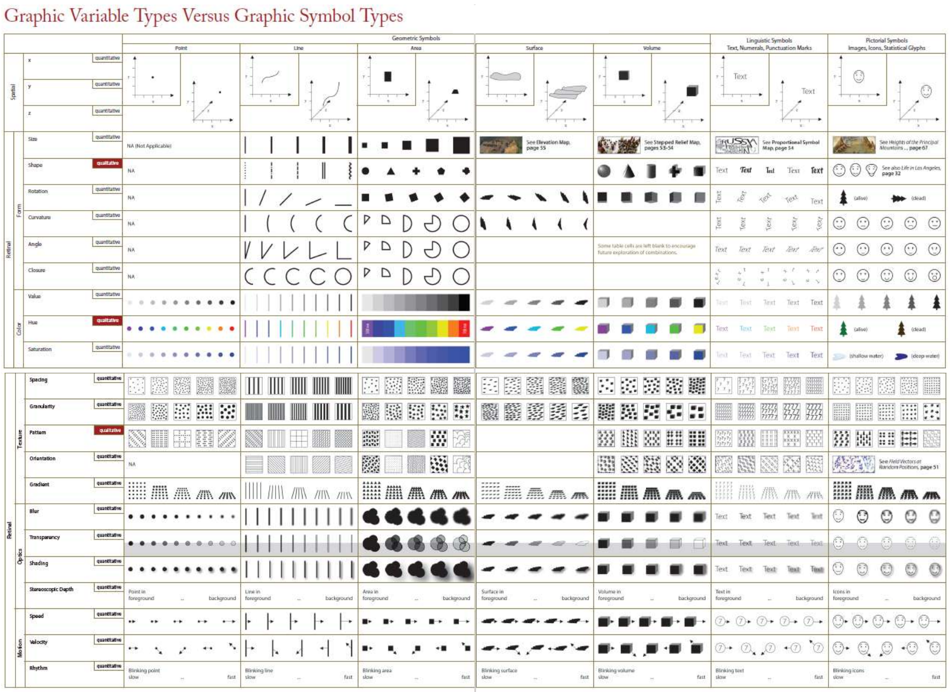
See *Atlas of Knowledge* pages 36-39 for complete table.

Qualitative

Also called:
Categorical Attributes
Identity Channels

Quantitative

Also called:
Ordered Attributes
Magnitude Channels



See *Atlas of Knowledge* pages 36-39 for complete table.

Typology of the Data Visualization Literacy Framework

7

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Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 26, 68-69.

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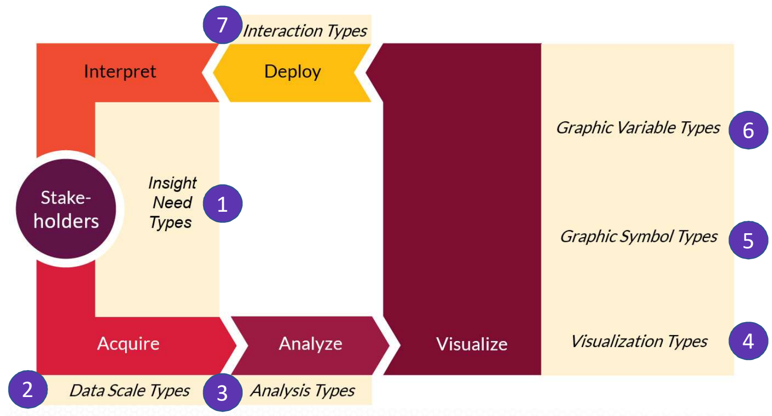
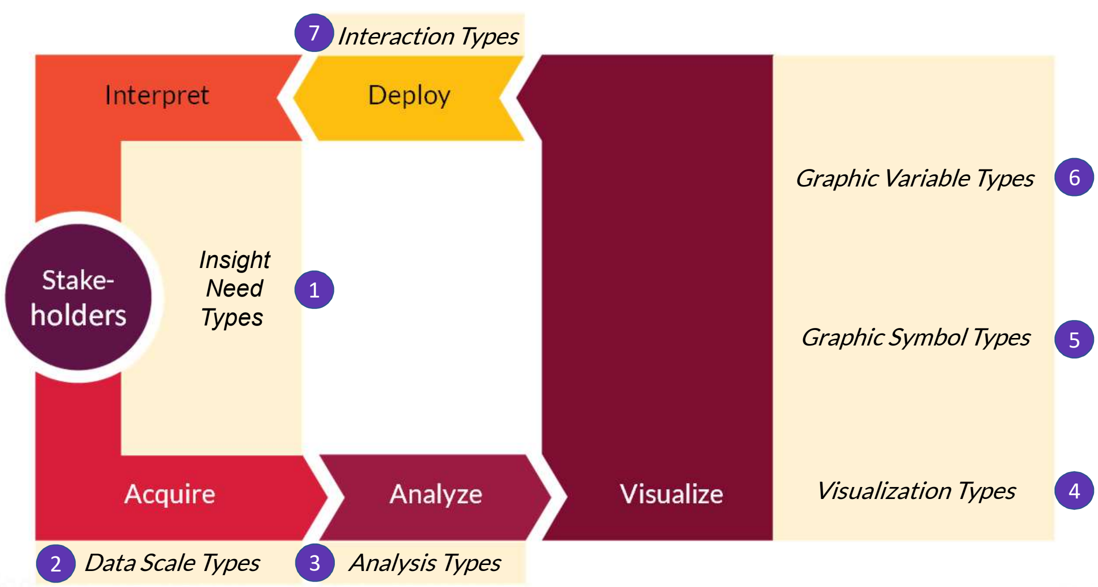
Data Visualization Literacy Framework (DVL-FW)

Consists of two parts that are interlinked:

DVL Typology +
DVL Workflow Process



53



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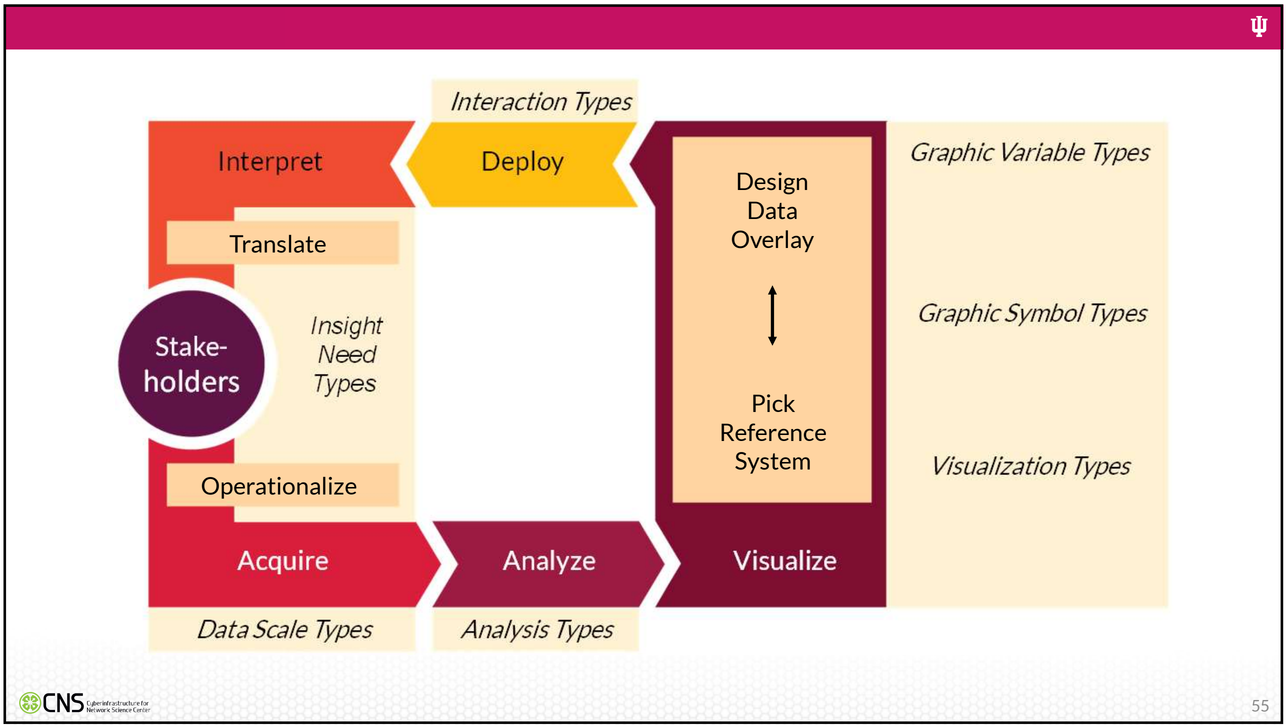
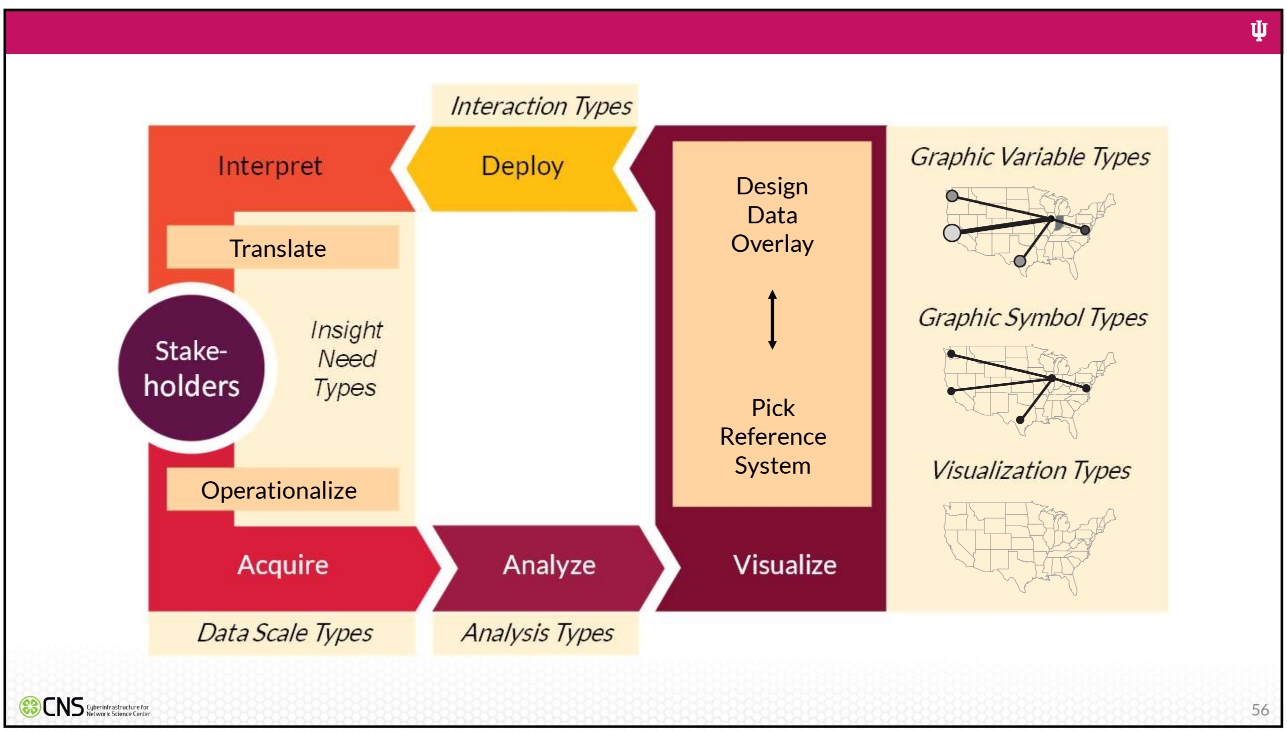

Interaction Types
Interpret
Deploy
Translate
Stake-
holders
Insight
Need
Types
Operationalize
Design
Data
Overlay
Pick
Reference
System
Graphic Variable Types
Graphic Symbol Types
Visualization Types
Acquire
Analyze
Visualize
Data Scale Types
Analysis Types
CNS
55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Types
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Design
Data
Overlay
Pick
Reference
System
Graphic Variable Types
Graphic Symbol Types
Visualization Types
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Data Scale Types
Analysis Types
CNS
56

CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

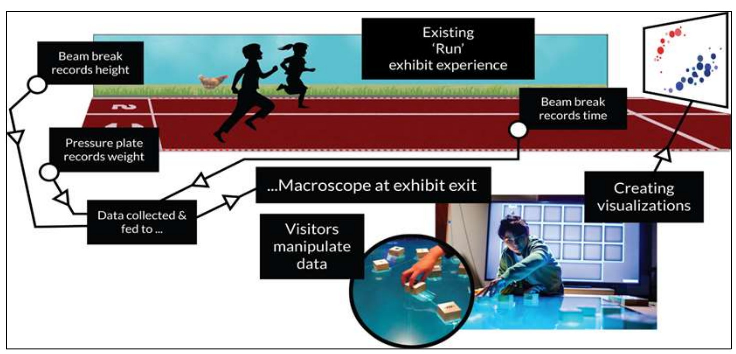
Scaling Up:

Teaching Data Visualization Literacy

MAV in Science Museums

Information Visualization MOOC (IVMOOC) + Visual Analytics Certificate (VAC)

xMacroscopes in Science Museums



Data Visualization Literacy: Research and Tools that Advance Public Understanding of Scientific Data. NSF AISL #1713567

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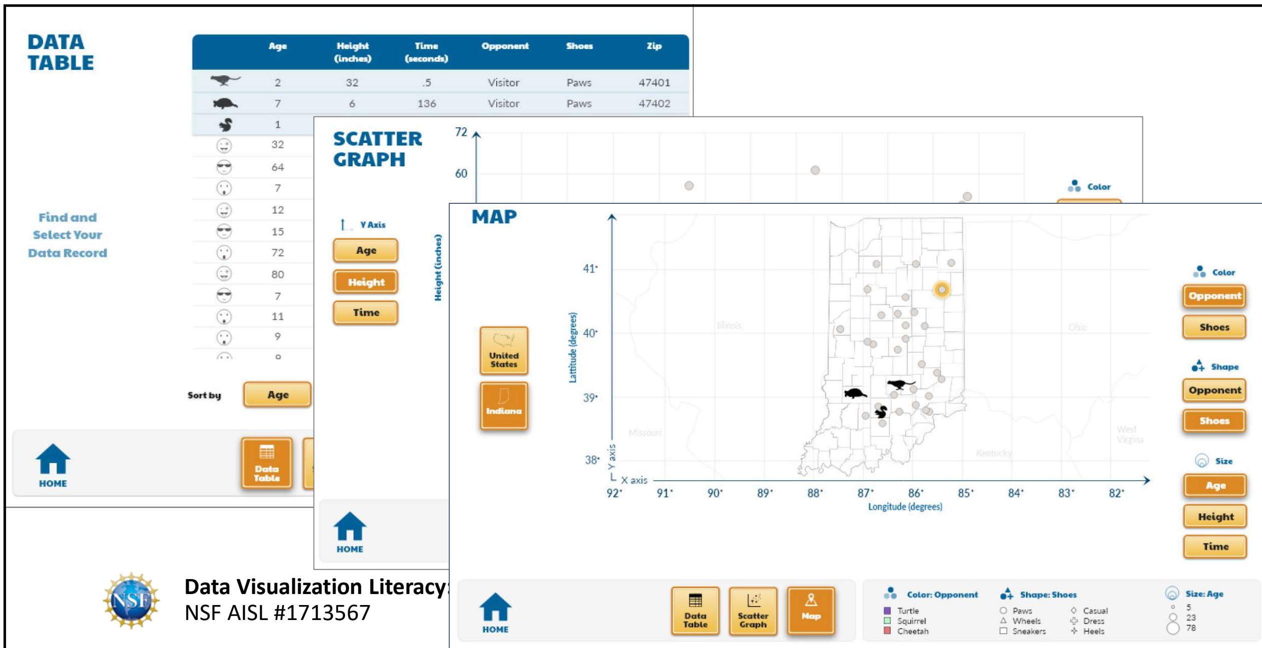

Data Visualization Literacy:
NSF AISL #1713567

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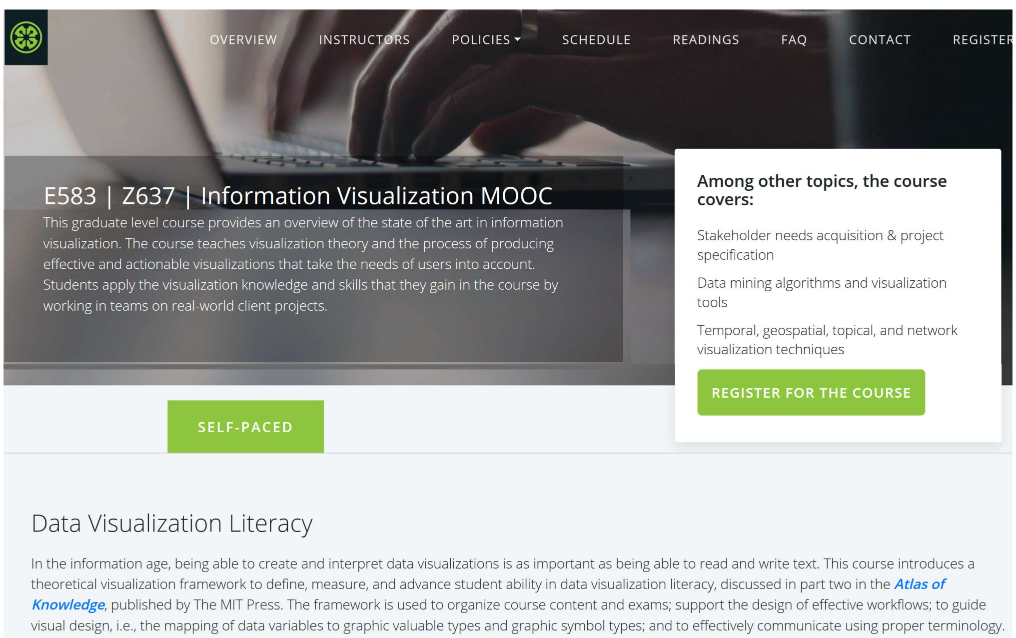
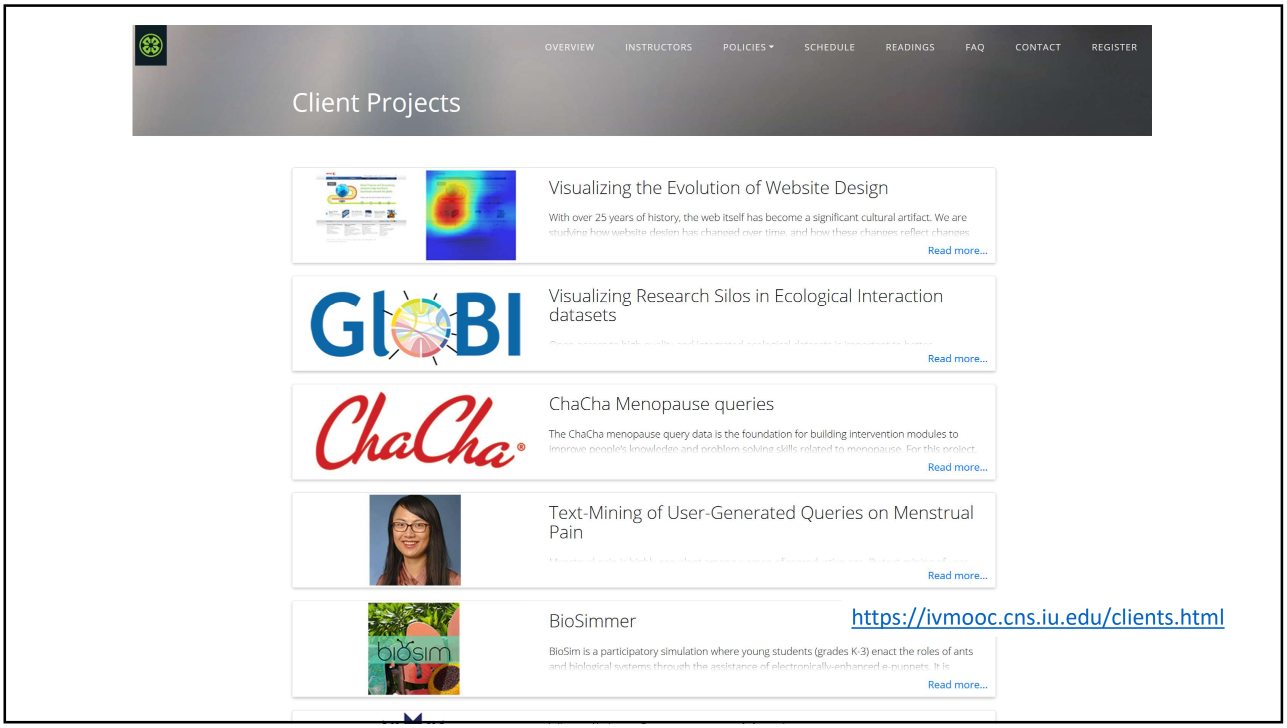
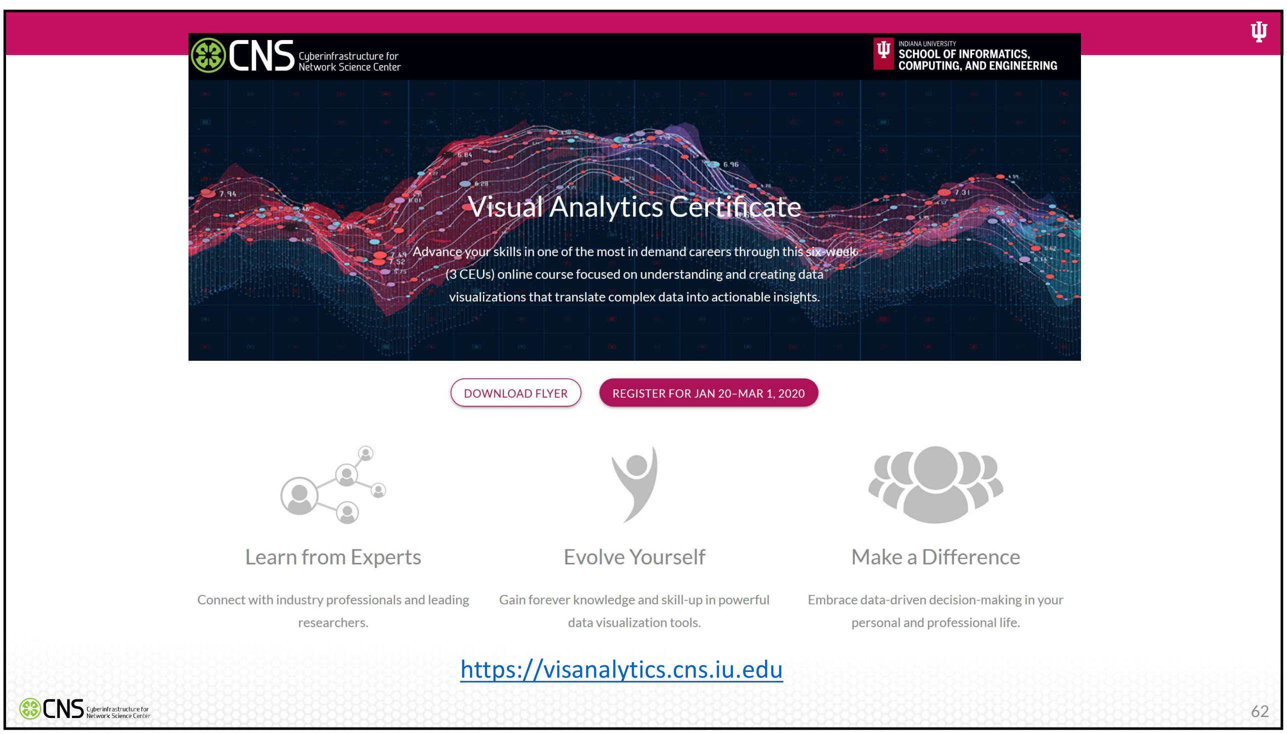


https://ivmooc.cns.iu.edu


OVERVIEW
INSTRUCTORS
POLICIES
SCHEDULE
READINGS
FAQ
CONTACT
REGISTER
Client Projects
Visualizing the Evolution of Website Design
With over 25 years of history, the web itself has become a significant cultural artifact. We are
Read more...
GloBI
Visualizing Research Silos in Ecological Interaction datasets
Read more...
ChaCha
ChaCha Menopause queries
The ChaCha menopause query data is the foundation for building intervention modules to
Read more...
Text-Mining of User-Generated Queries on Menstrual Pain
Read more...
biosim
BioSimmer
BioSim is a participatory simulation where young students (grades K-3) enact the roles of ants
Read more...
https://ivmooc.cns.iu.edu/clients.html


CNS Cyberinfrastructure for Network Science Center
INDIANA UNIVERSITY
SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING
Visual Analytics Certificate
Advance your skills in one of the most in demand careers through this six-week (3 CEUs) online course focused on understanding and creating data visualizations that translate complex data into actionable insights.
DOWNLOAD FLYER
REGISTER FOR JAN 20–MAR 1, 2020
Learn from Experts
Connect with industry professionals and leading researchers.
Evolve Yourself
Gain forever knowledge and skill-up in powerful data visualization tools.
Make a Difference
Embrace data-driven decision-making in your personal and professional life.
https://visanalytics.cns.iu.edu
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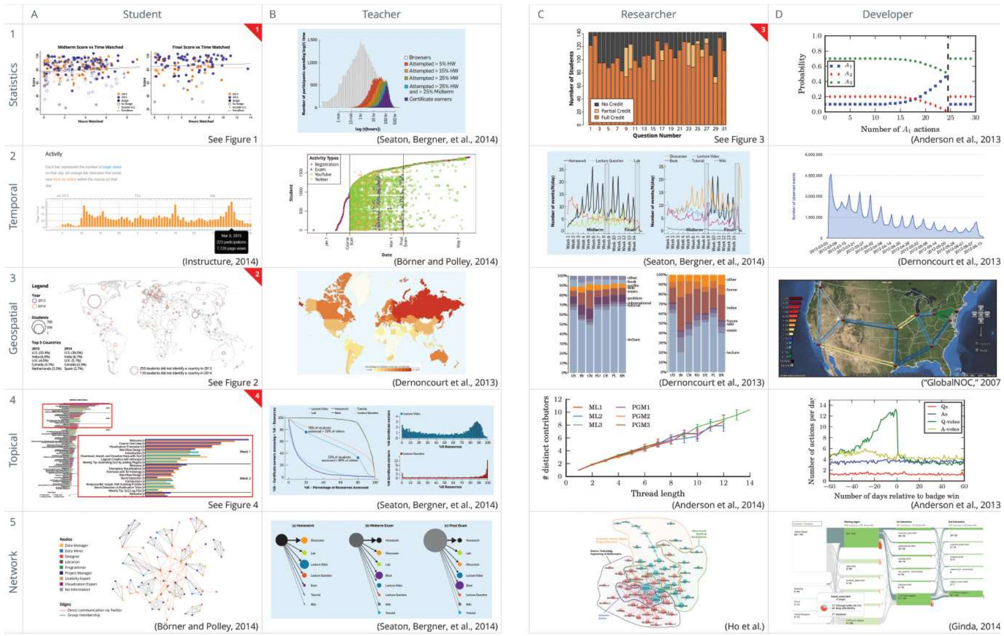

Emmons, Light, and Börner. 2017. "MOOC Visual Analytics: Empowering Teachers, Students, Researchers, and Developers of Massively Open Online Courses". *Journal of the Association for Information Science and Technology.* 68 (10): 2350-2363.

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NSF RAISE: C-Accel Pilot - Track B1: Analytics-Driven Accessible Pathways To Impacts-Validated Education (ADAPTIVE)

Goal: Development of data-driven tools to support the tens of millions of US workers whose jobs are being transformed by Artificial Intelligence (AI) and automation.

The project will demonstrate how labor market and course syllabi data, learning analytics, and insights on transferability of learned skills can be combined and visualized in novel ways to support a learner's decision-making about, sustained engagement in, and application to their job of professional skills acquired through education and job-related training.

Team B-6656: Katy Börner, Indiana University, Ariel Anbar, Arizona State University, Kemi Jona, Northeastern University, Martin Storksdieck and Heather Fischer, Oregon State University

CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

Marvelous Visualization Opportunity:

HuBMAP: Mapping 37 Trillion Cells

Michael P. Snyder, et al. 2019. The human body at cellular resolution: The NIH Human Biomolecular Atlas Program. *Nature*. 574, p. 187-192.
https://www.nature.com/articles/s41586-019-1629-x.pdf

HuBMAP

HuBMAP The Human BioMolecular Atlas Program

https://commonfund.nih.gov/HuBMAP

Vision
Catalyze the development of an open, global framework for comprehensively mapping the human body at cellular resolution.

Goals
1. Accelerate the development of the next generationof tools and techniques for constructing high resolution spatial tissue maps
2. Generate foundational 3D tissue maps
3. Establish an open data platform
4. Coordinate and collaborate with other funding agencies, programs, and the biomedical research community
5. Support projects that demonstrate the value of the resources developed by the program

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The Human Body at Cellular Resolution:
The NIH Human Biomolecular Atlas Program.
Snyder et al. *Nature*. 574, p. 187-192.

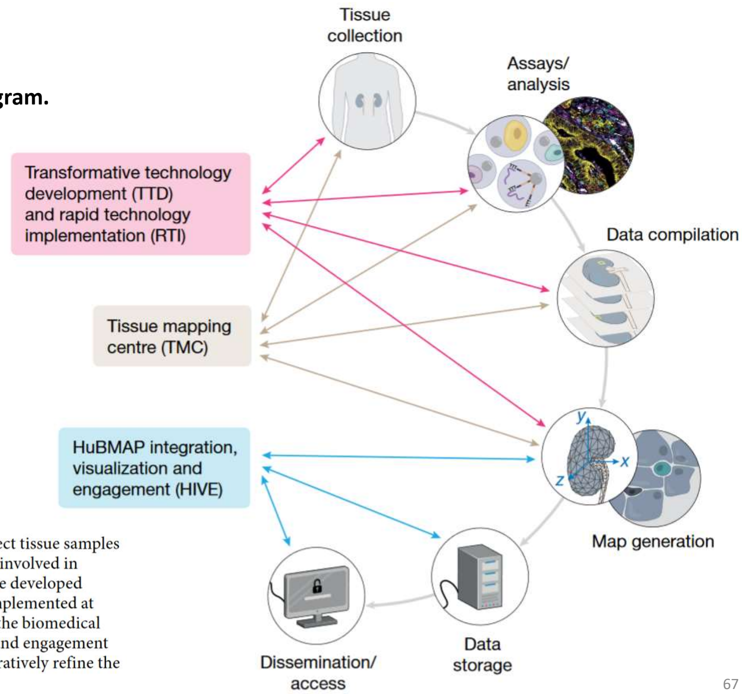

Fig. 1 | The HubMAP consortium. The TMCs will collect tissue samples and generate spatially resolved, single-cell data. Groups involved in TTD and RTI initiatives will develop emerging and more developed technologies, respectively; in later years, these will be implemented at scale. Data from all groups will be rendered useable for the biomedical community by the HuBMAP integration, visualization and engagement (HIVE) teams. The groups will collaborate closely to iteratively refine the atlas as it is gradually realized.

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The Human Body at Cellular Resolution:
The NIH Human Biomolecular Atlas Program.
Snyder et al. *Nature*. 574, p. 187-192.

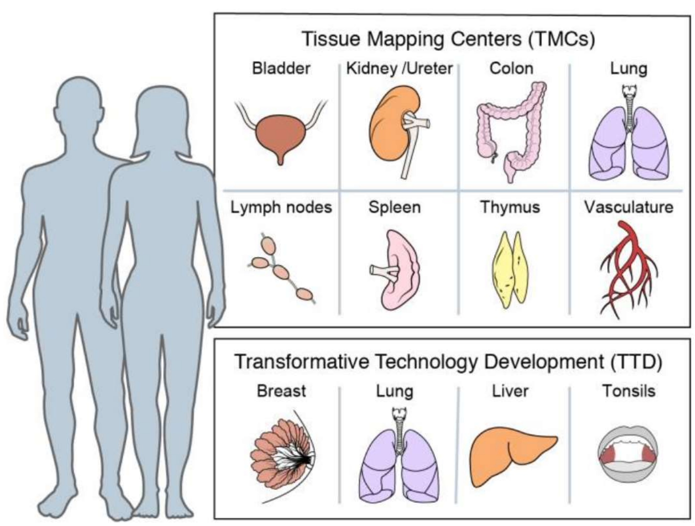

Fig. 2 | Key tissues and organs initially analysed by the consortium. Using innovative, production-grade ('shovel ready') technologies, HuBMAP TMCs will generate data for single-cell, three-dimensional maps of various human tissues. In parallel, TTD projects (and later RTI projects) will refine assays and analysis tools on a largely distinct set of human tissues. Samples from individuals of both sexes and different ages will be studied. The range of tissues will be expanded throughout the program.

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The Human Body at Cellular Resolution: The NIH Human Biomolecular Atlas Program. Snyder et al. *Nature*. 574, p. 187-192.

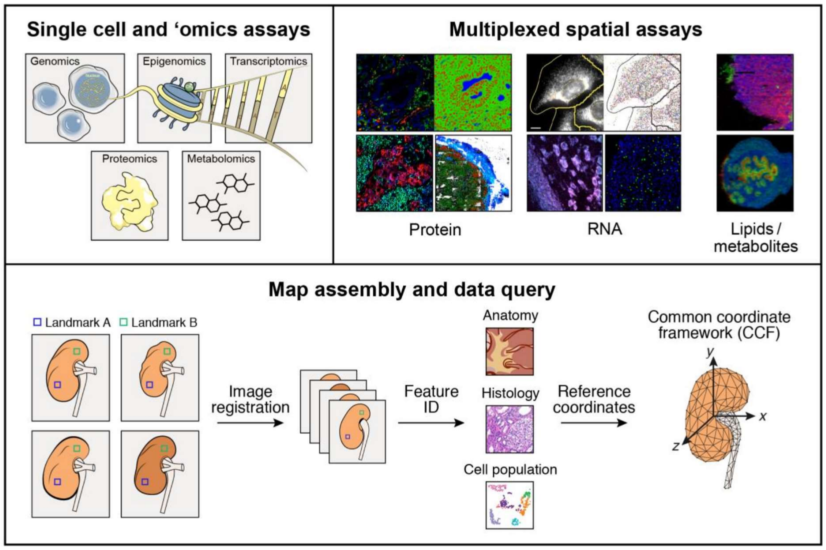
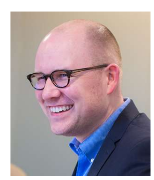


Fig. 3 | Map generation and assembly across cellular and spatial scales. HuBMAP aims to produce an atlas in which users can refer to a histological slide from a specific part of an organ and, in any given cell, understand its contents on multiple ʼomic levels—genomic, epigenomic, transcriptomic, proteomic, and/or metabolomic. To achieve these ends, centres will apply a combination of imaging, ʼomics and mass spectrometry techniques to specimens collected in a reproducible manner from specific sites in the body. These data will be then be integrated to arrive at a high-resolution, high-content three-dimensional map for any given tissue. To ensure inter-individual differences will not be confounded with collection heterogeneity, a robust CCF will be developed.

Acknowledgments



TC-Harvard Team lead by Nils Gehlenborg

https://hubmapconsortium.org

Plus, **patients** that agreed to volunteer healthy tissue and to use their data openly.

MC-IU HIVE Team at IU

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https://cns-nrt.indiana.edu

References

Börner, Katy, Chen, Chaomei, and Boyack, Kevin. (2003). **Visualizing Knowledge Domains.** In Blaise Cronin (Ed.), *ARIST*, Medford, NJ: Information Today, Volume 37, Chapter 5, pp. 179-255. http://ivl.slis.indiana.edu/km/pub/2003-borner-arist.pdf

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