CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

Data Visualization

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Indiana University, Bloomington, IN, USA
+ 2018 Humboldt Fellow, TU Dresden, Germany

Guest Lecture in T100 What is Data Science

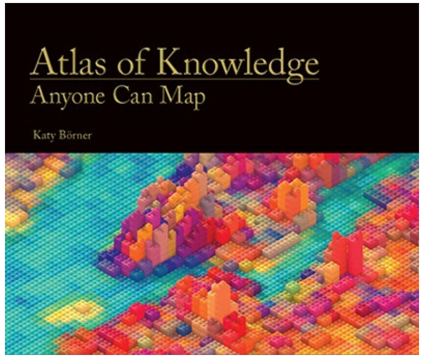
December 7, 2020

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.

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.

Atlas of Forecasts

TOMORROW: Debut 16th iteration of the *Places & Spaces: Mapping Science* exhibit (http://scimaps.org) at The Mill!

Data Visualization Literacy (DVL)

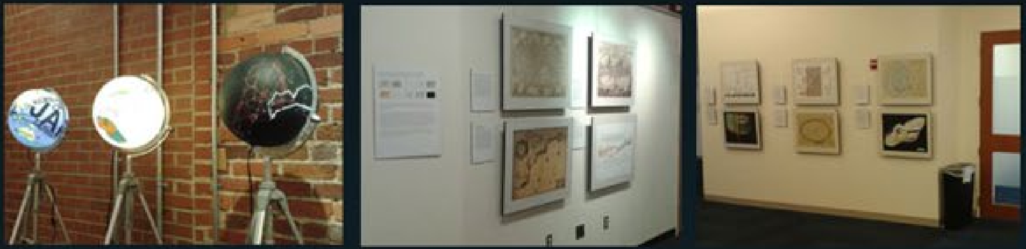
Data visualization literacy (ability to read, make, and explain data visualizations) requires:

- 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.

Oct 1-Nov 3, 2020: Exhibit on display at the Dimension Mill in Bloomington, IN on https://dimensionmill.org

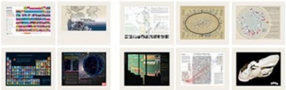
Places & Spaces: Mapping Science Exhibit

1st Decade (2005-2014)

Maps

Iteration I (2005)
The Power of Maps

Iteration II (2006)
The Power of Reference Systems



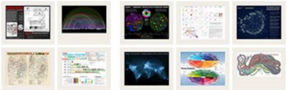
Iteration III (2007)
The Power of Forecasts

Iteration IV (2008)
Science Maps for Economic Decision Makers

Iteration V (2009)
Science Maps for Science Policy Makers

Iteration VI (2010)
Science Maps for Scholars

Iteration VII (2011)
Science Maps as Visual Interfaces to Digital Libraries



Iteration VIII (2012)
Science Maps for Kids

Iteration IX (2013)
Science Maps Showing Trends and Dynamics

Iteration X (2014)
The Future of Science Mapping

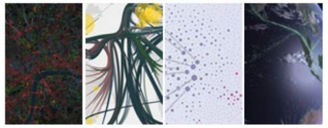
2nd Decade (2015-2024)

Macroscopes

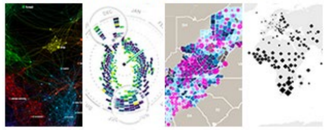
Iteration XI (2015)
Macroscopes for Interacting with Science

Iteration XIII (2017)
Macroscopes for Playing with Scale

Iteration XII (2016)
Macroscopes for Making Sense of Science



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



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.

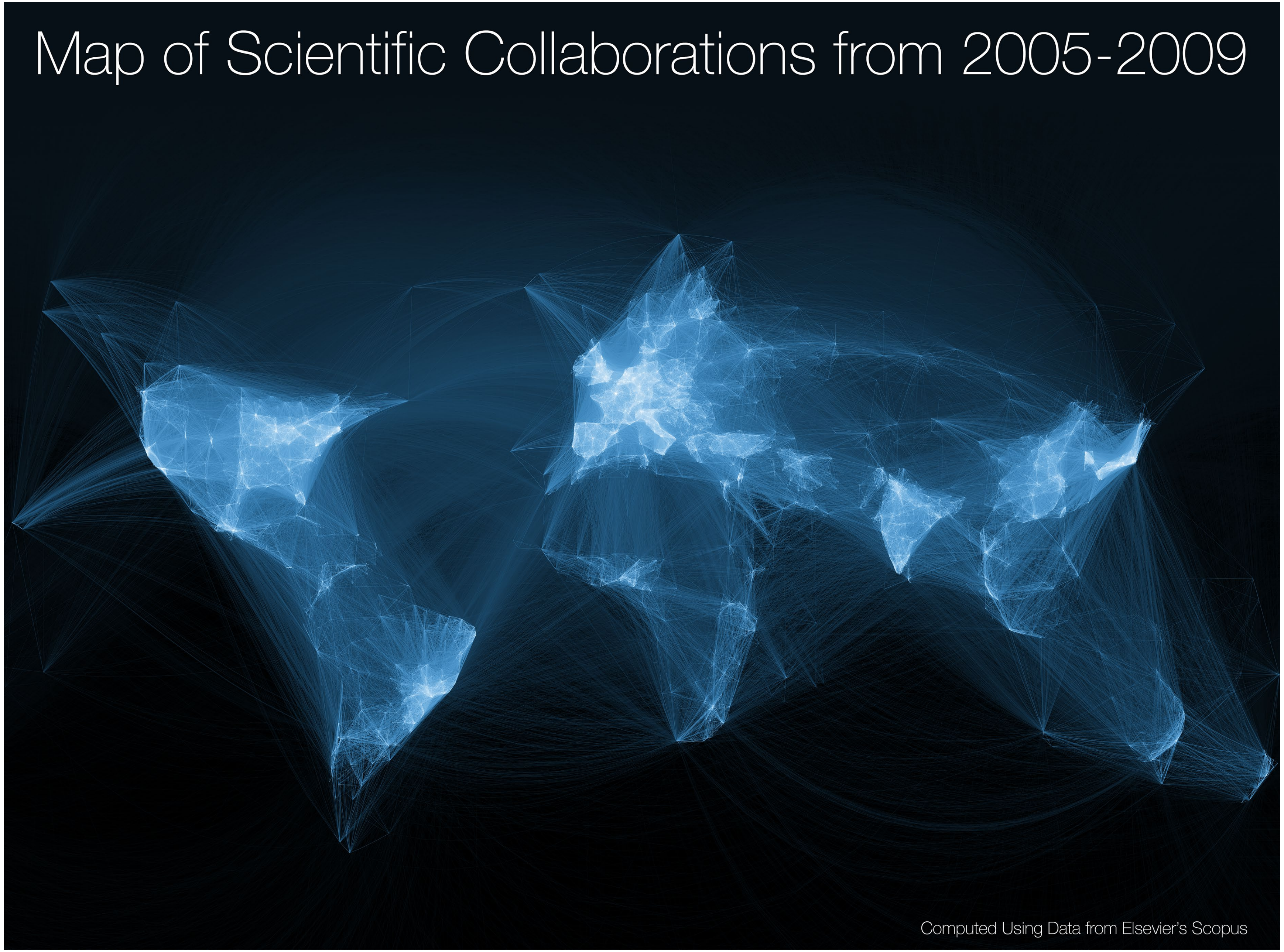
43
MACROSCOPE MAKERS
including one whose job title is "Truth and Beauty Operator."

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



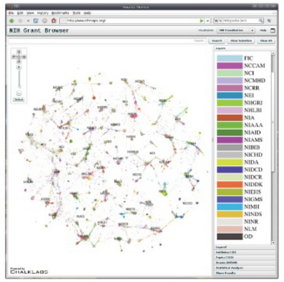
VII.6 Stream of Scientific Collaborations Between World Cities - Olivier H. Beauchesne - 2012

A Topic Map of NIH Grants 2007

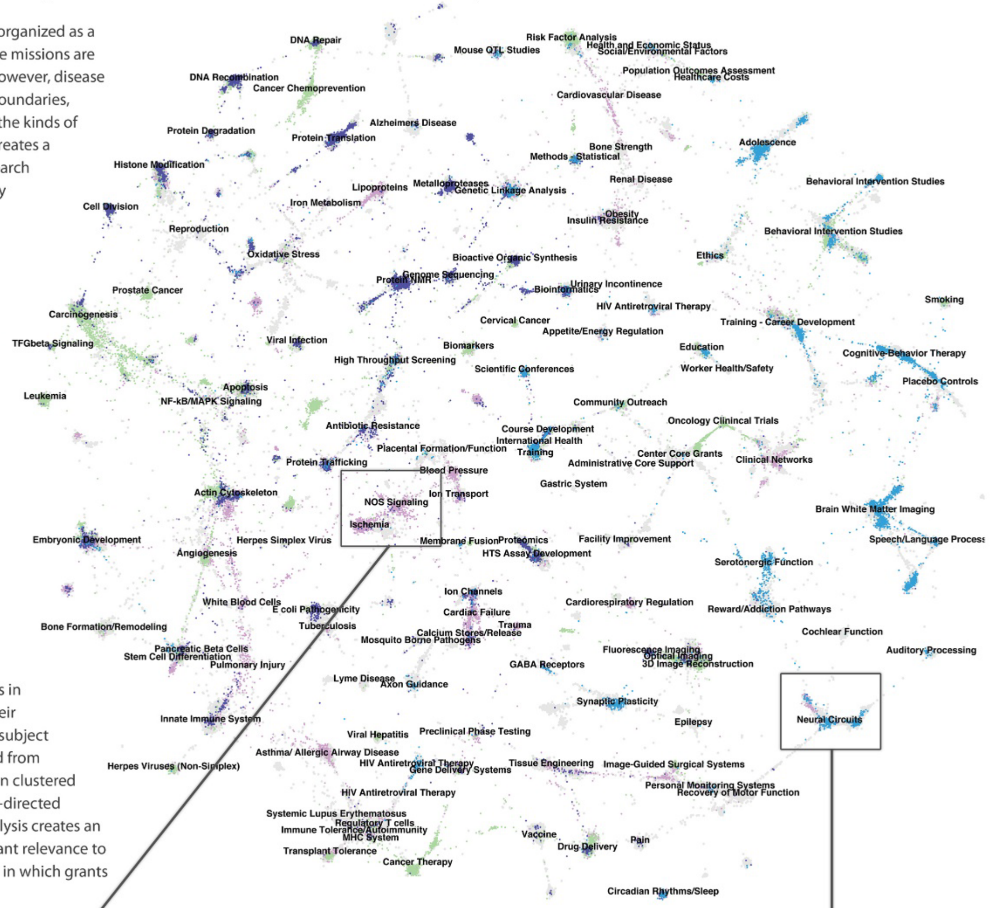
ChalkLabs ISI UCIRVINE

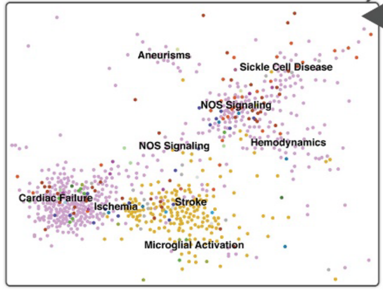
Bruce W. Herr II (Chalklabs & IU), Gully Burns (ISI), David Newman (UCI), Edmund Talley (NIH)

The National Institutes of Health (NIH) is organized as a multitude of Institutes and Centers whose missions are primarily focused on distinct diseases. However, disease etiologies and therapies flout scientific boundaries, and thus there is tremendous overlap in the kinds of research funded by each Institute. This creates a daunting landscape for decisions on research directions, funding allocations, and policy formulations. Shown here is devised an interactive topic map for navigating this landscape, online at www.nihmaps.org. Institute abbreviations can be found at www.nih.gov/icd.



Topic modeling, a statistical technique that automatically learns semantic categories, was applied to assess projects in terms used by researchers to describe their work, without the biases of keywords or subject headings. Grant similarities were derived from their topic mixtures, and grants were then clustered on a two-dimensional map using a force-directed simulated annealing algorithm. This analysis creates an interactive environment for assessing grant relevance to research categories and to NIH Institutes in which grants are localized.



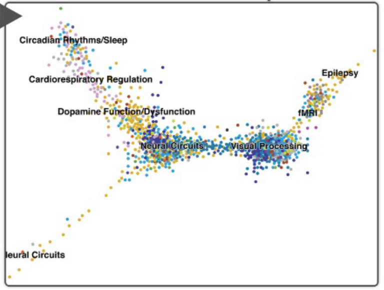


Cardiac Diseases Research

An area of the map focused on cardio-vascular function and dysfunction. Cardiac Failure (primarily funded by NHLBI) is topically clustered next to Stroke (NINDS), since these are the two major medical emergencies associated with ischemia, which results from a re-stricted blood supply. Also localized in this area are grants focused on Nitric Oxide (NOS) Signaling, a major biochem-ical pathway for vasodilation, and grants on Hemodynamics, Sickle Cell Disease, and Aneurysms.

Neural Circuits Research

An area of the map focused on neural circuits, which shows the diversity of topics and NIH Institutes that fund research in this area, such as: Cardiorespiratory Regulation, primarily funded by NHLBI; Visual Processing, primarily funded by NEI; and Epilepsy, primarily funded by NINDS. For color coding, see legend in the upper-left inset.



National Cancer Institute (NCI)

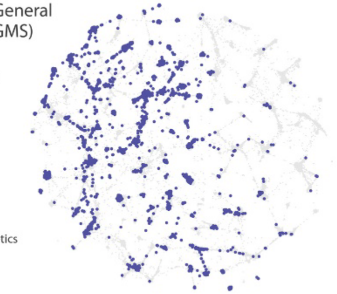
TOP 10 TOPICS

1. Oncology Clinical Trials
2. Cancer Treatment
3. Cancer Therapy
4. Carcinogenesis
5. Risk Factor Analysis
6. Cancer Chemotherapy
7. Metastasis
8. Leukemia
9. Prediction/Prognosis
10. Cancer Chemoprevention

National Institute of General Medical Sciences (NIGMS)

TOP 10 TOPICS

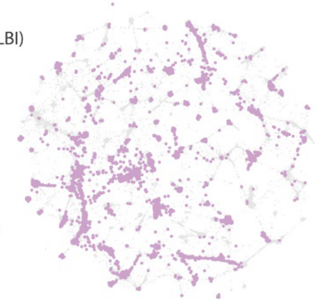
1. Bioactive Organic Synthesis
2. X-ray Crystallography
3. Protein NMR
4. Computational Models
5. Yeast Biology
6. Metalloproteases
7. Enzymatic Mechanisms
8. Protein Complexes
9. Invertebrate/Zebrafish Genetics
10. Cell Division



National Heart, Lung, and Blood Institute (NHLBI)

TOP 10 TOPICS

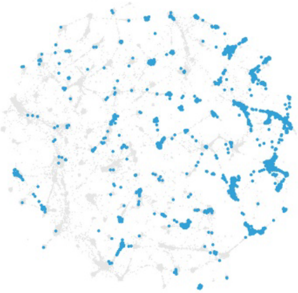
1. Cardiac Failure
2. Pulmonary Injury
3. Genetic Linkage Analysis
4. Cardiovascular Disease
5. Atherosclerosis
6. Hemostasis
7. Blood Pressure
8. Asthma/ Allergic Airway Disease
9. Gene Association
10. Lipoproteins



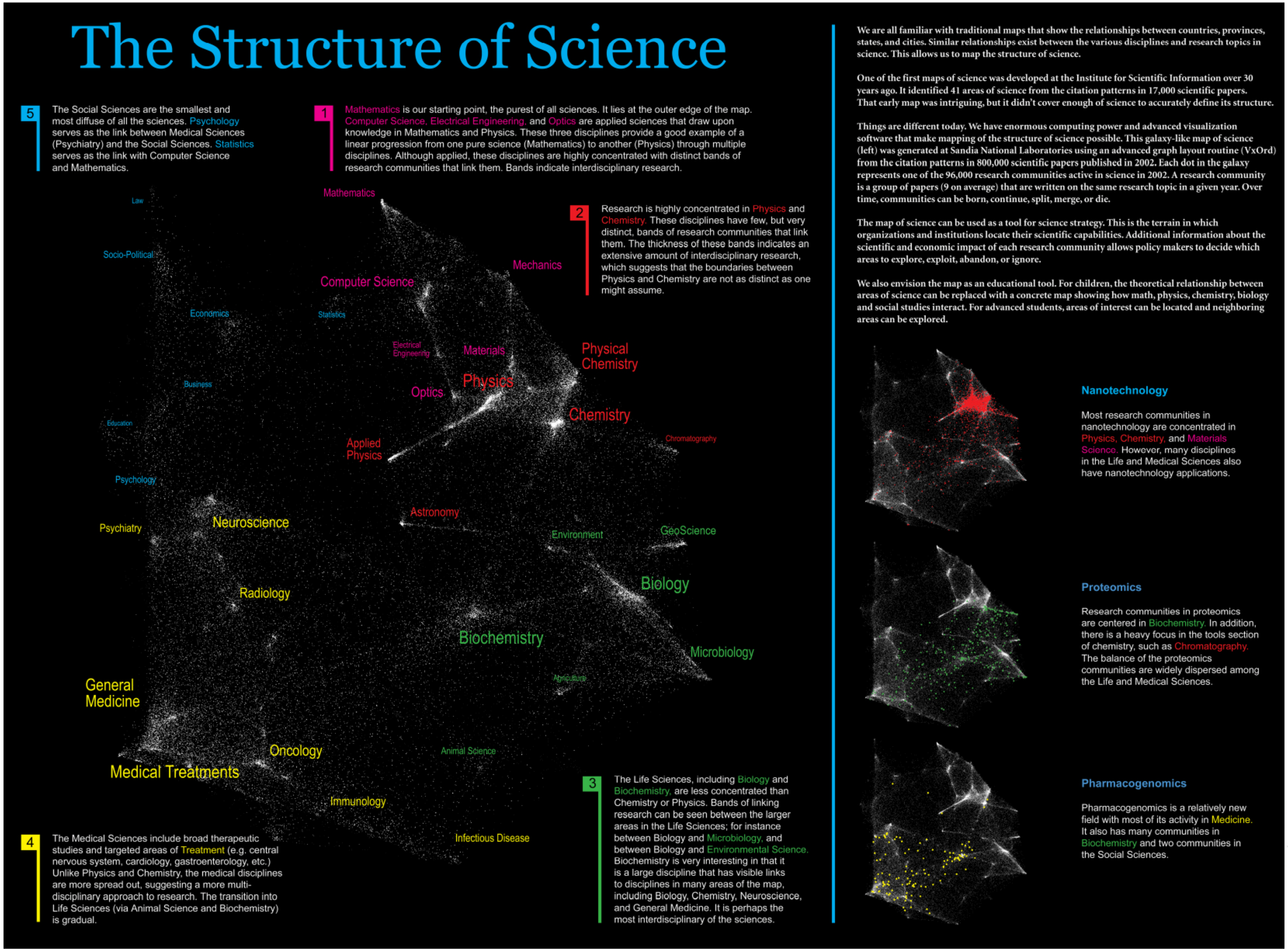
National Institute of Mental Health (NIMH)

TOP 10 TOPICS

1. Mood Disorders
2. Schizophrenia
3. Behavioral Intervention Studies
4. Mental Health
5. Depression
6. Cognitive-Behavior Therapy
7. AIDS Prevention
8. Genetic Linkage Analysis
9. Adolescence
10. Childhood



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

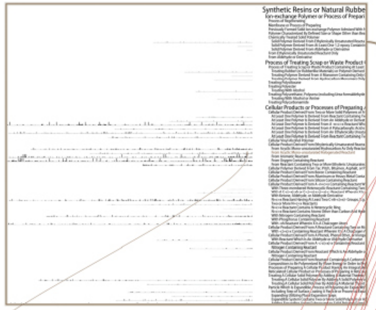
The US Patent Hierarchy

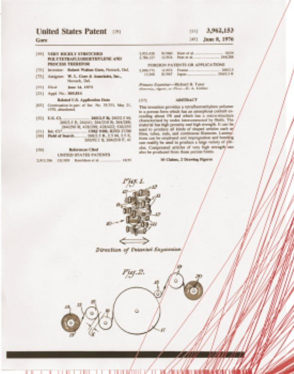
Impact

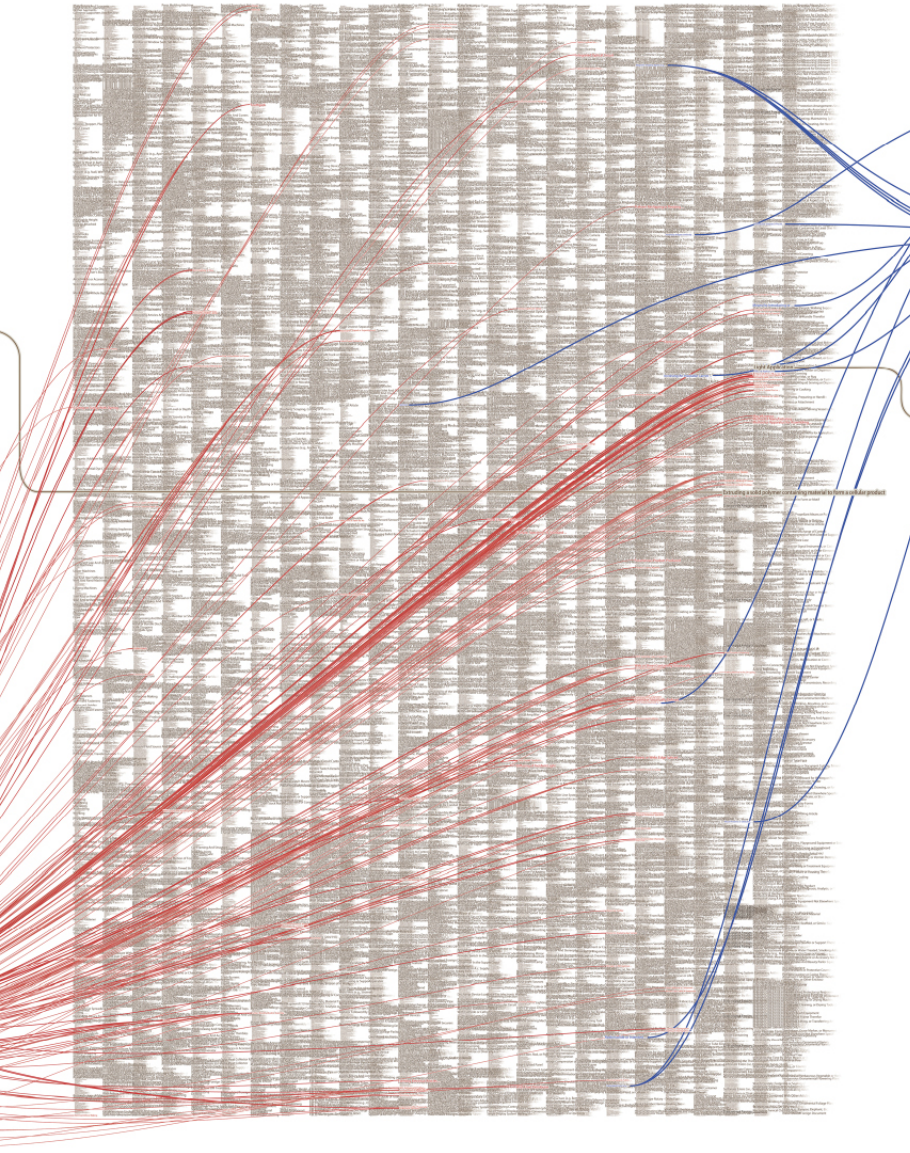
The United States Patent and Trademark Office does scientists and industry a great service by granting patents to protect inventions. Inventions are categorized in a taxonomy that groups patents by industry or use, proximate function, effect or product, and structure. At the time of this writing there are 160,523 categories in a hierarchy that goes 15 levels deep. We display the first three levels (13,529 categories) at right in what might be considered a textual map of inventions.

Patent applications are required to be unique and non-obvious, partially by revealing any previous patents that might be similar in nature or provide a foundation for the current invention. In this way we can trace the impact of a single patent, seeing how many patents and categories it affects.

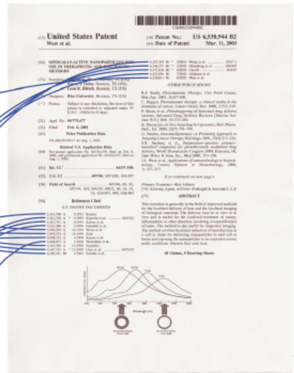
The patent on Goretex—a lightweight, durable synthetic fiber—is an example of one that has had significant impact. The box below enlarges the section of the hierarchy where it is filed, and the red lines (arranged to start along a time line from 1981 to 2006) point to the 130 categories that contain 182 patents, from waterproof clothing to surgical cosmetic implants, that mention Goretex as "prior art."

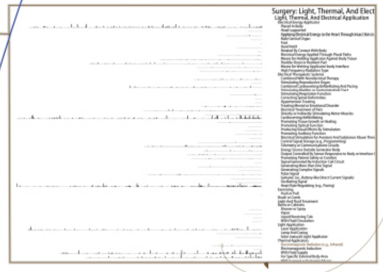






Prior Art





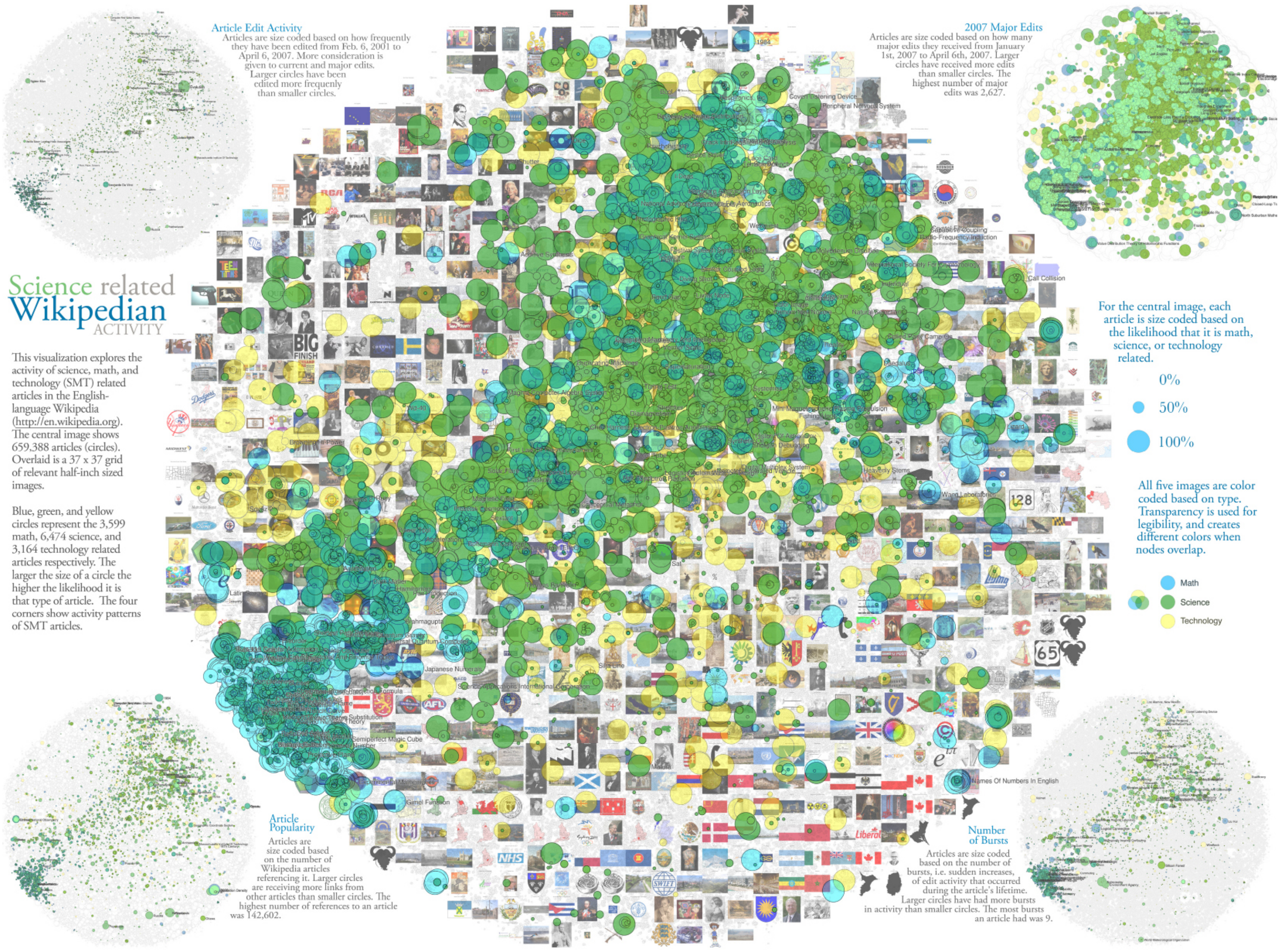
New patents often build on older ideas from many different categories. Here, blue lines originate in the sixteen categories that contain patents cited as prior art for a patent on "gold nanoshells." Gold nanoshells are a new invention: tiny gold spheres (with a diameter ten million times smaller than a human hair) that can be used to make tumors more visible in infra-red scans; they have even helped cause complete remission of tumors in tests with laboratory mice. The blue lines show that widely separated categories provided background for this invention.

Keeping categories understandable is an important part of maintaining any taxonomy, including the patent hierarchy. Categories are easier to understand, search, and maintain if they contain elements that comfortably fit the definition of the category. The box above shows tiny bar charts, part of a *Taxonomy Validator* that reveals whether elements fit their categories. Categories may need to be redefined, and sometimes need to be split when they get too vague or large; a problem shared by many classification systems in this information-rich century. But how can we tell which ones to eliminate, add or revise—or how to revise them—in the complex, abstract sociolinguistic spaces we partition into ontologies?

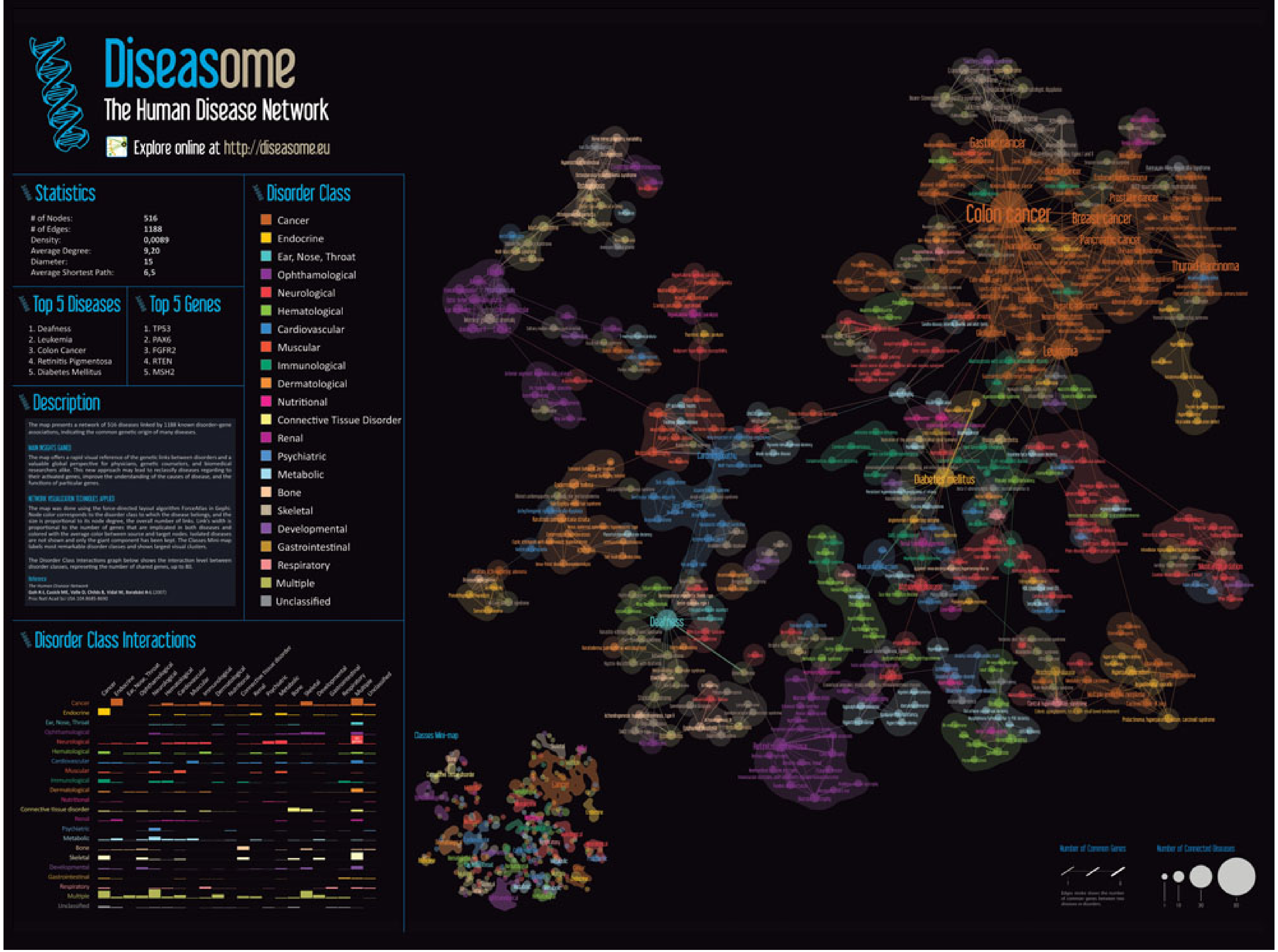
Something as simple as a bar chart helps people see how entities in a category relate to that category. Here, each bar encodes a "distance to prototype": how much each patent differs from an idealized "prototype patent" for that category. A measure like this can be based on statistics, computational linguistics, or even human insight. Thus a category with mostly small bars is a good one, and a generally ragged one needs scrutiny or reorganization; but one that has only two or three tall bars may mean that only those few elements don't belong.

Even simple visuals can make thinking easier by providing better distilled data to the eye: vastly more data than working memory can hold as words. They focus people on exactly the right issues, and support them with the comprehensive overviews they need to make more informed judgements.

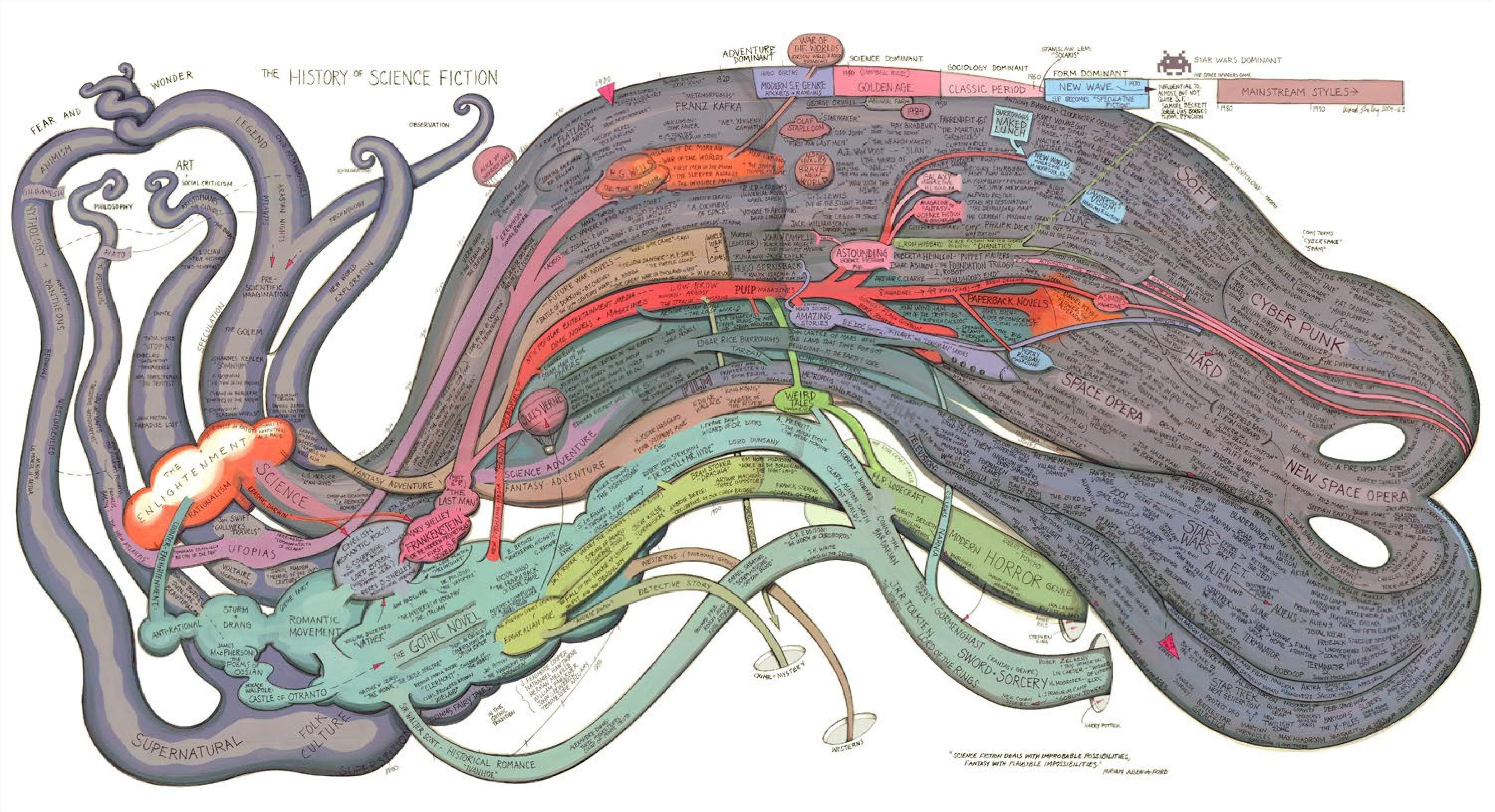
II.8 *Taxonomy Visualization of Patent Data* - Katy Börner, Elisha F. Hardy, Bruce W. Herr II, Todd Holloway, and W. Bradford Paley - 2006



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

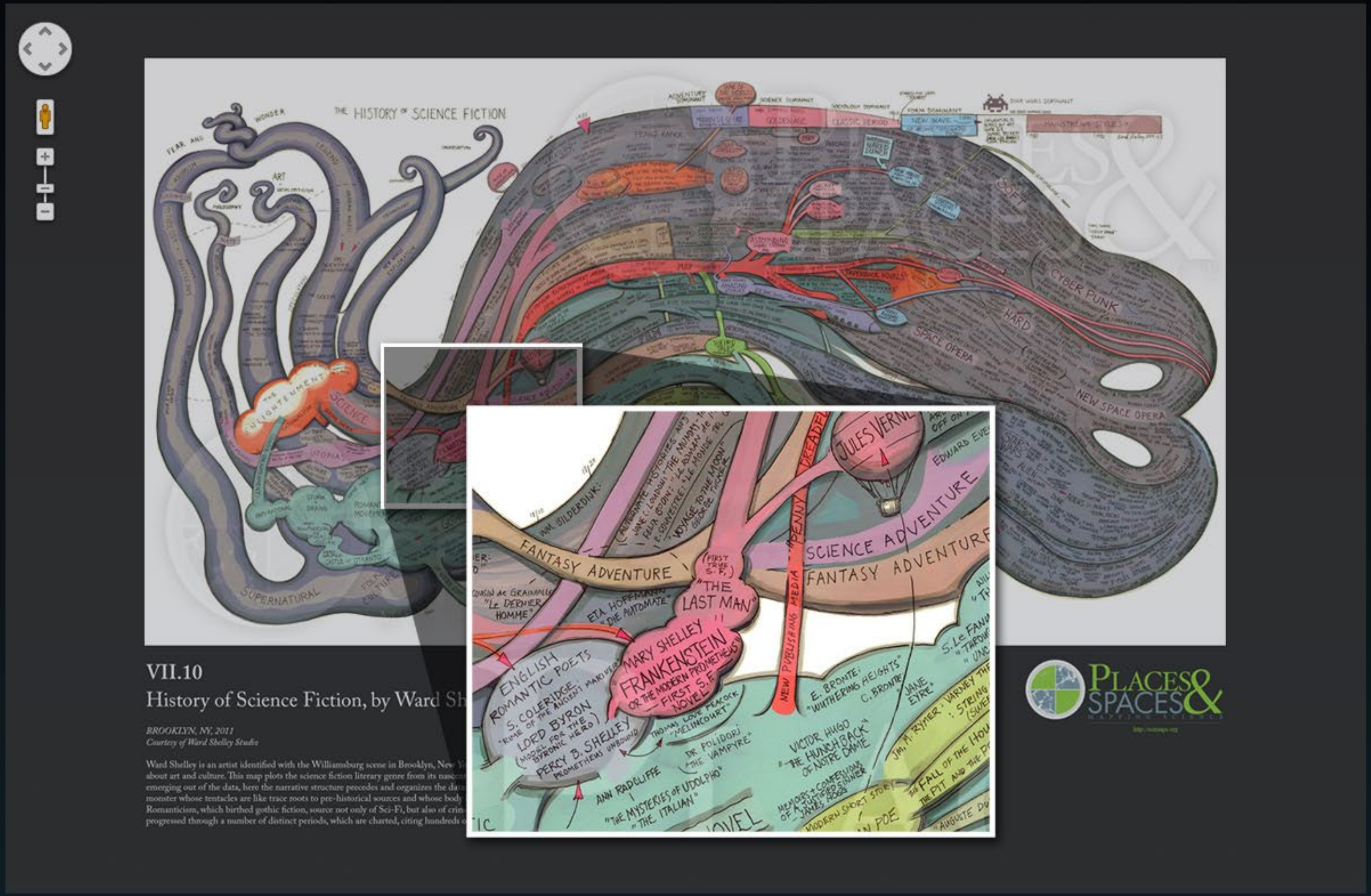


VI.3 *Diseasome: The Human Disease Network* - Mathieu Bastian and Sébastien Heymann - 2009



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!

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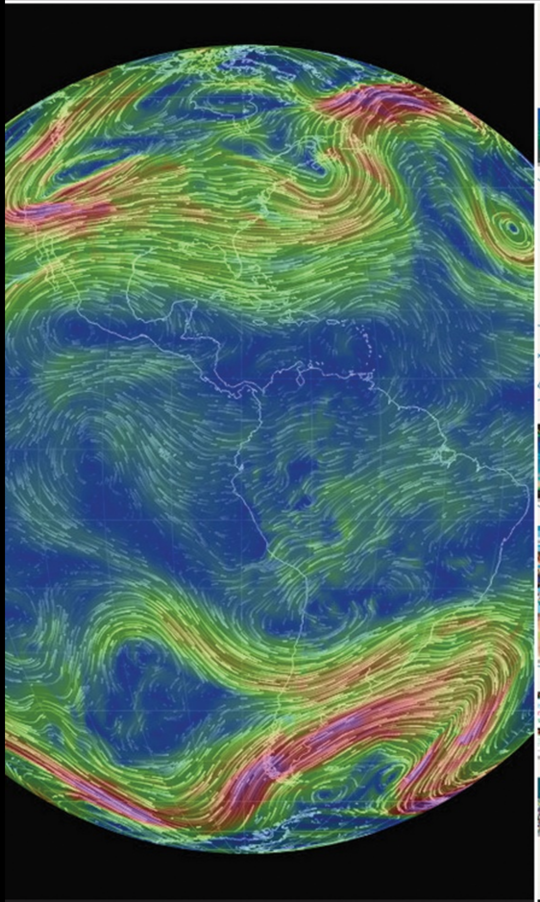
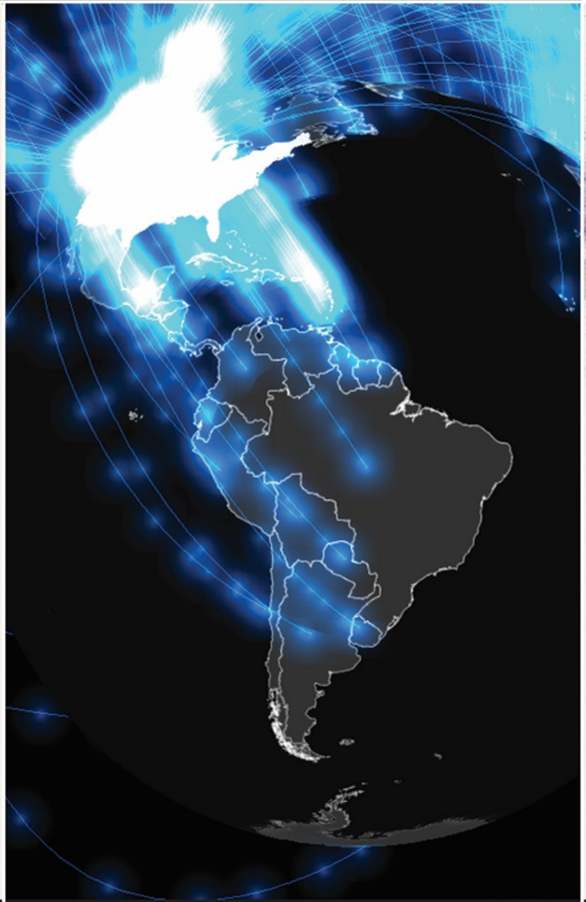


Earth

Weather on a worldwide scale

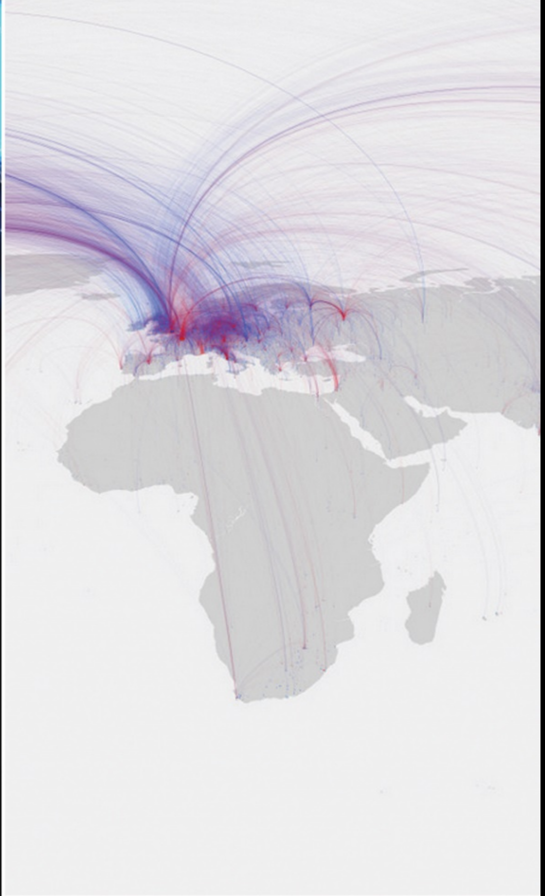
AcademyScope

Exploring the scientific landscape



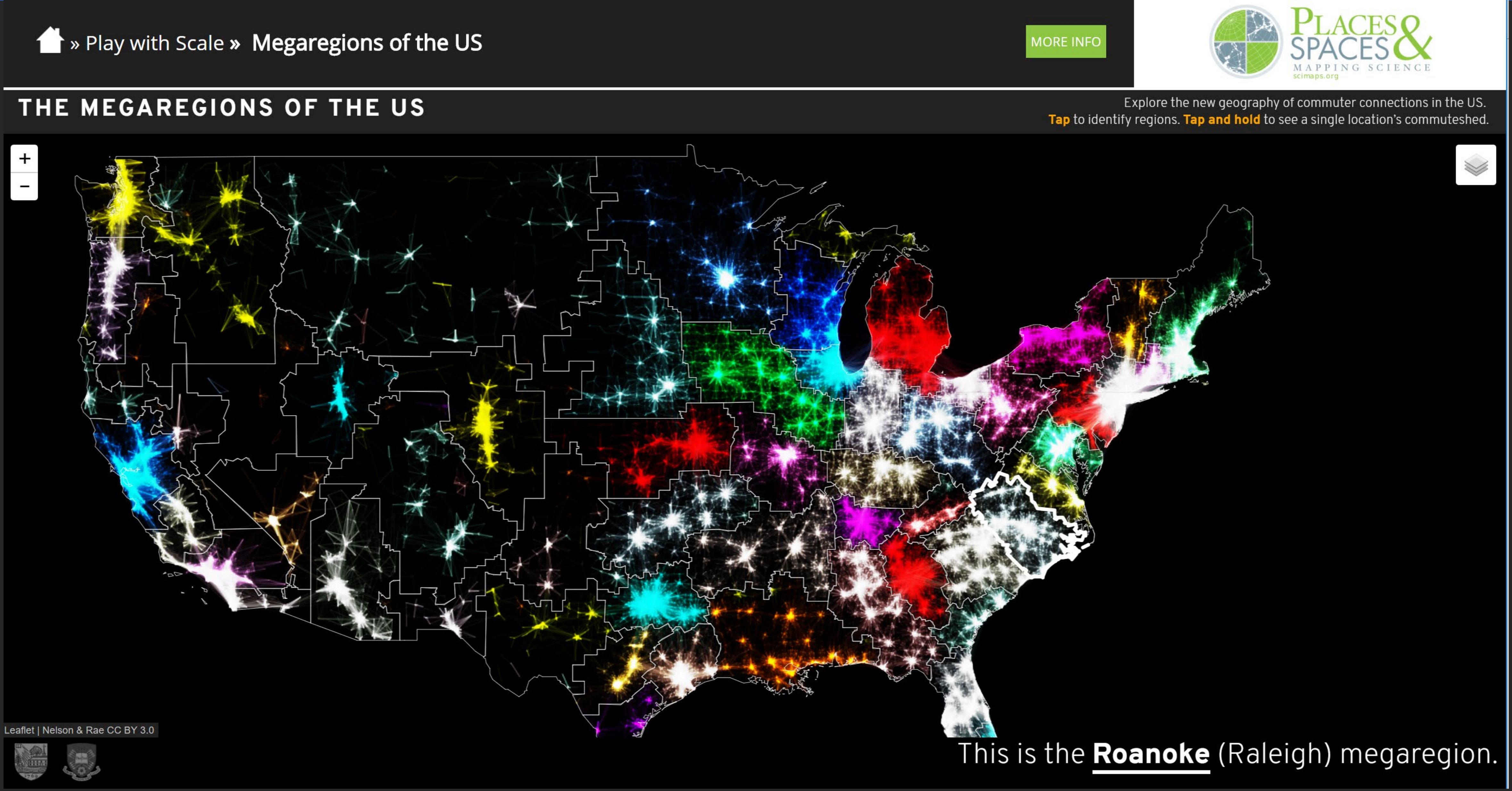
Mapping Global Society

Local news from a global perspective



Charting Culture

2,600 years of human history in 5 minutes

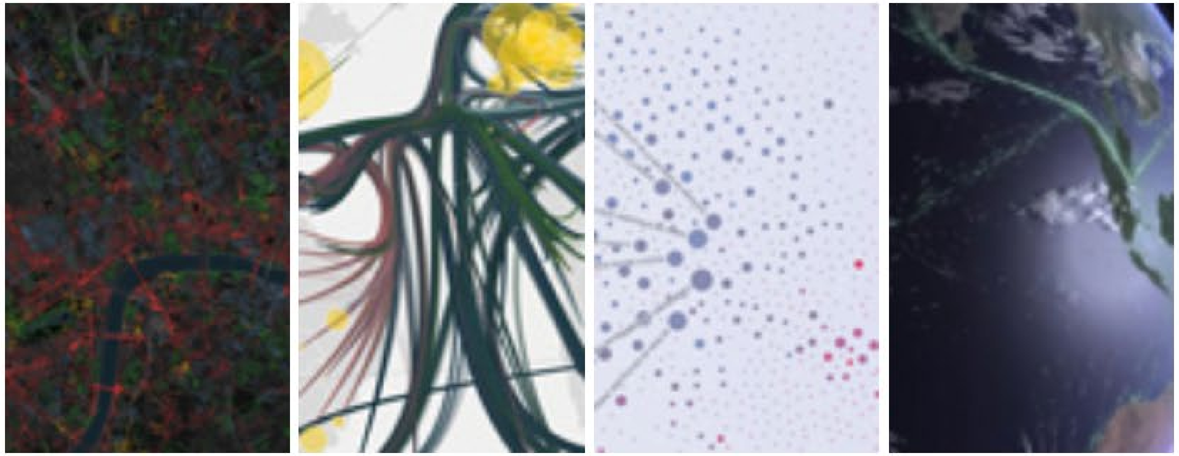


Megaregions of the US –Garrett Dash Nelson and Alasdair Rae – 2016

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)

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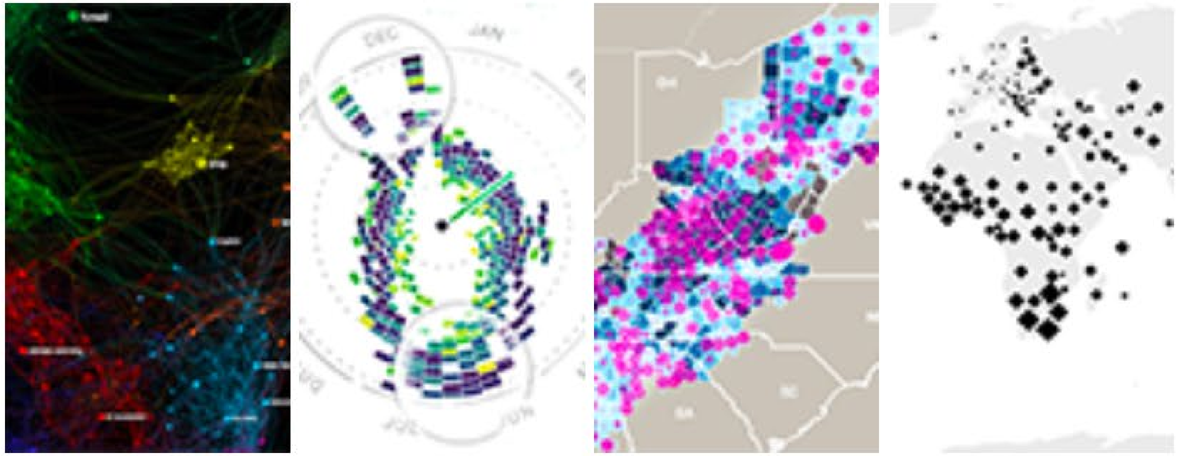
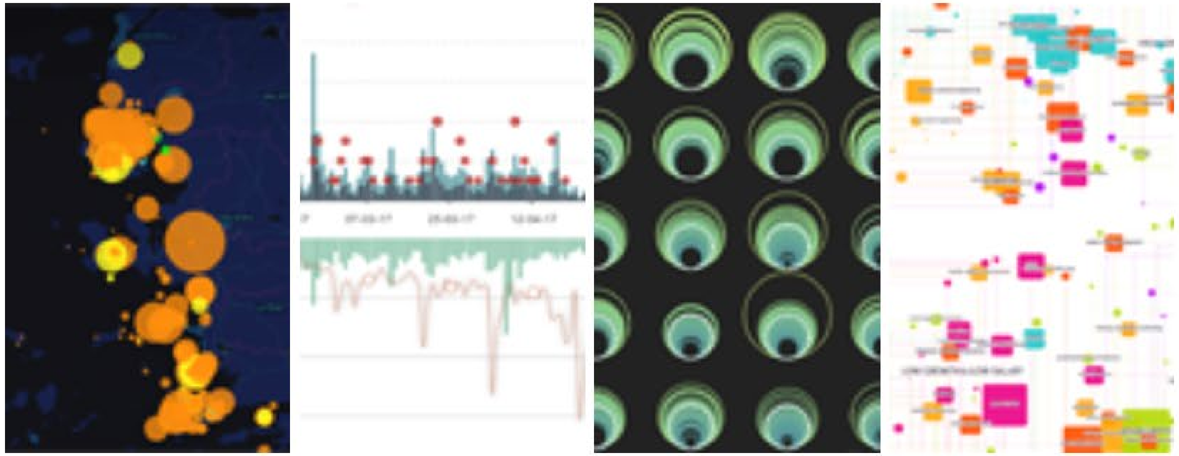


Iteration XV (2019)

Macroscopes for Tracking the Flow of Resources



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.

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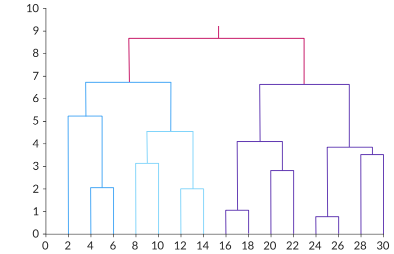
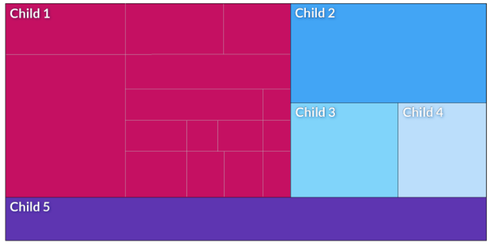
Being able to "read and write" data visualizations is becoming as important as being able to read and write text. Understanding, measuring, and improving data and visualization literacy is important to strategically approach local and global issues.

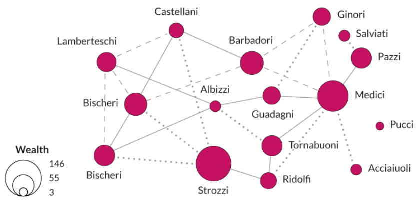
Visualization Frameworks

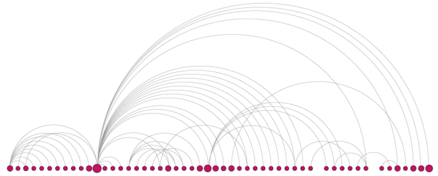
MANY frameworks and taxonomies have been proposed to

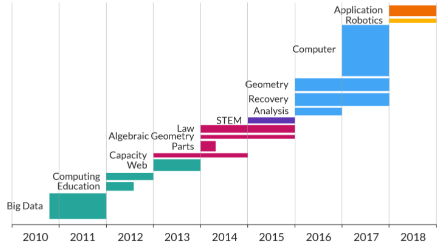
- help organize and manage the evolving zoo of 500+ different data visualization types,
- provide guidance when designing data visualizations, and
- facilitate teaching.

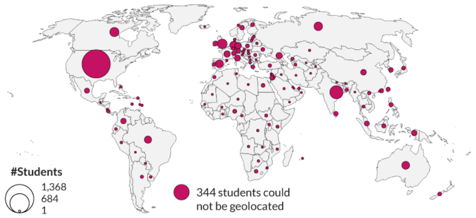


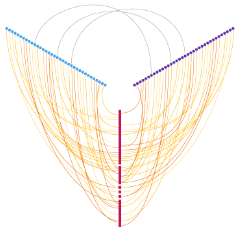


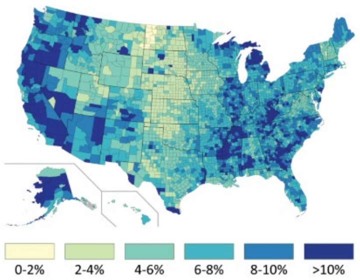


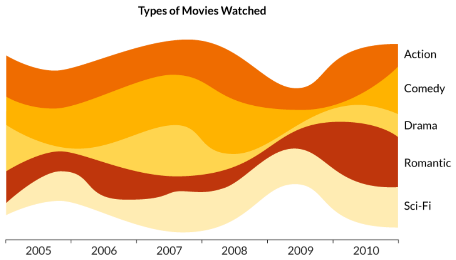








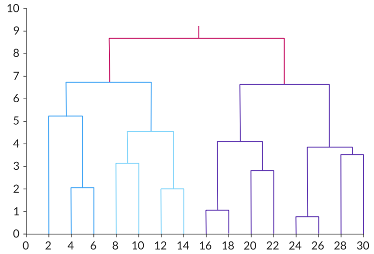


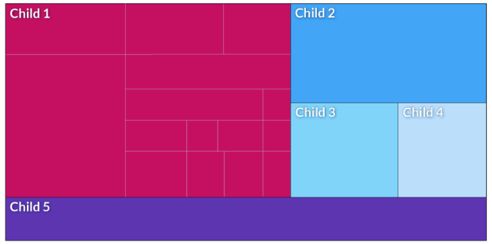


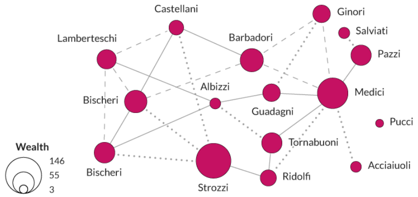
Existing Visualization Frameworks

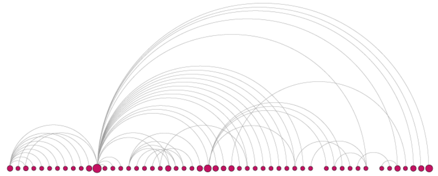
Organize data visualizations by

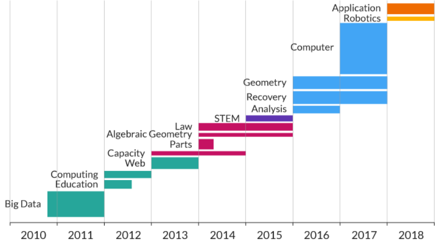
- User insight needs
- User task types
- Data to be visualized
- Data transformations
- Visualization technique
- Visual mapping transformations
- Interaction techniques
- Deployment options
- and other features ...

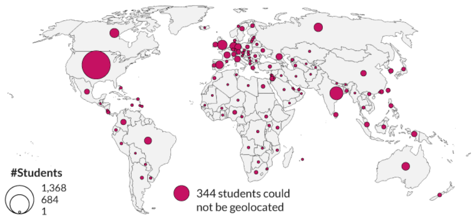


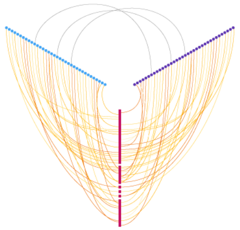


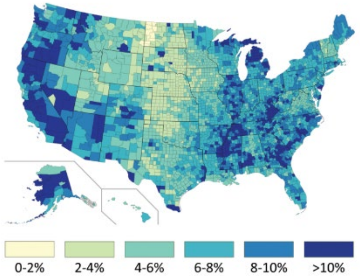


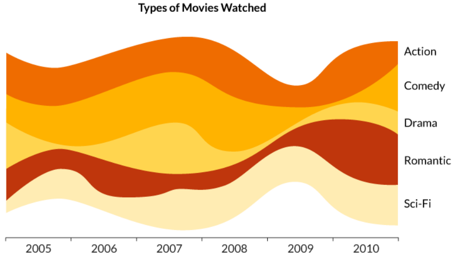












DVL Framework: Desirable Properties

- 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.

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.

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

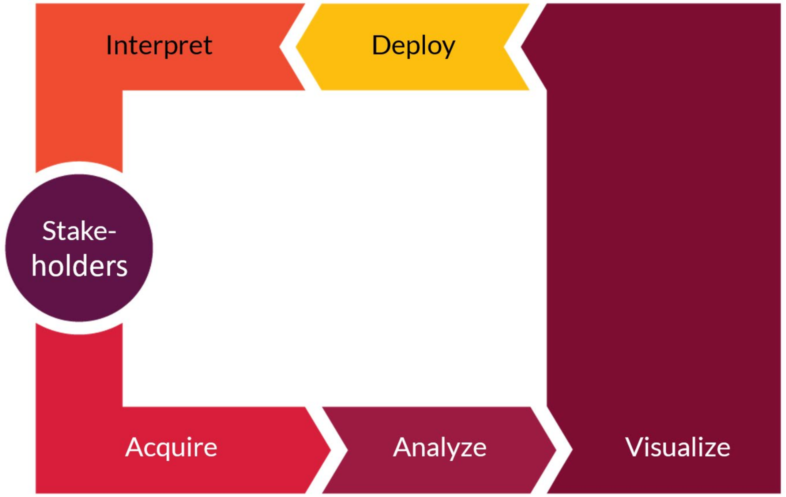
5 **Graphic Symbols**
- geometric symbols
  - point
  - line
  - area
  - surface
  - volume
- linguistic symbols
  - text
  - numerals
  - punctuation marks
- pictorial symbols
  - images
  - icons
  - statistical glyphs

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

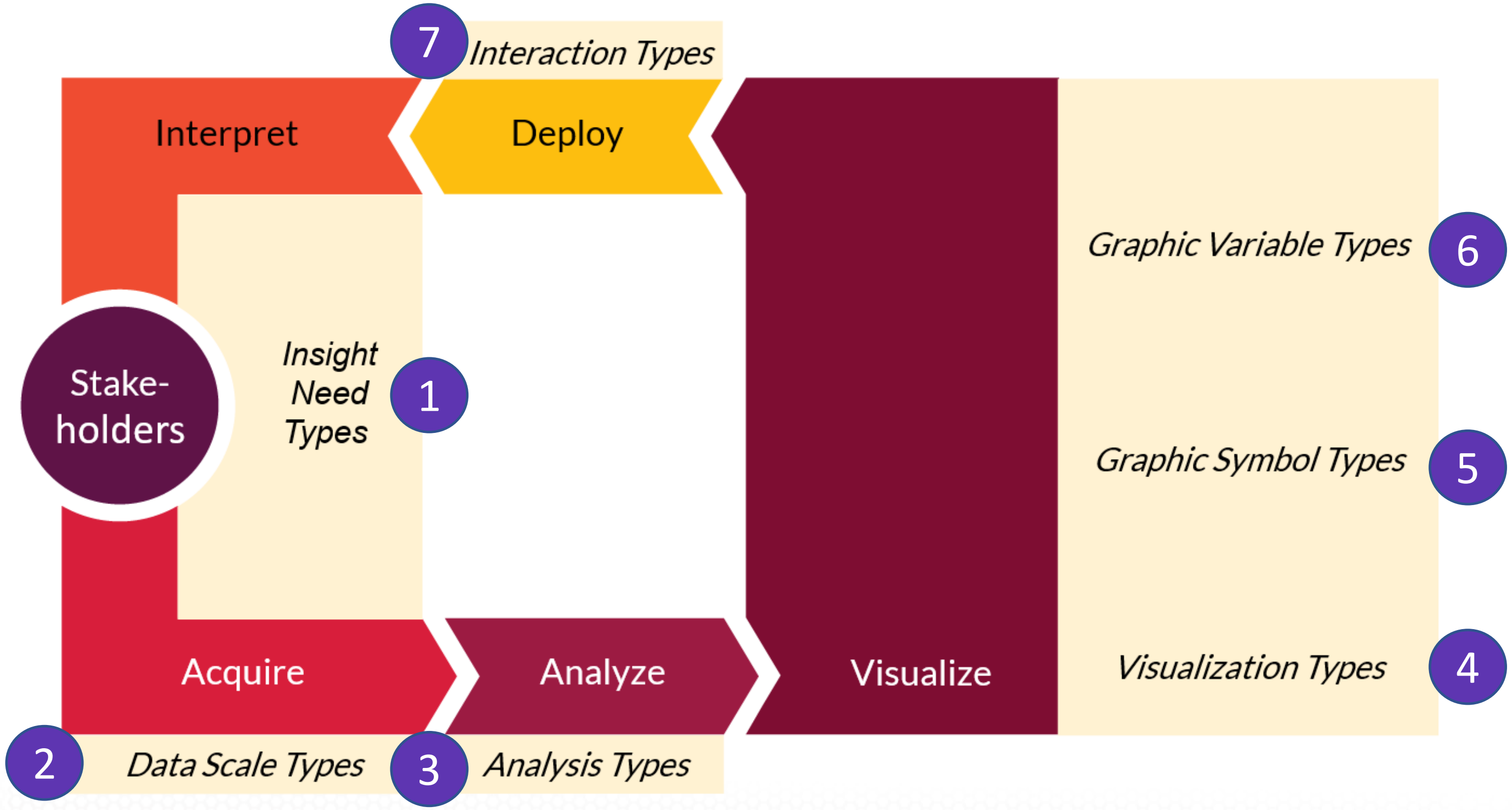
Defines 5 steps required to render data into insights.



Data Visualization Literacy Framework (DVL-FW)

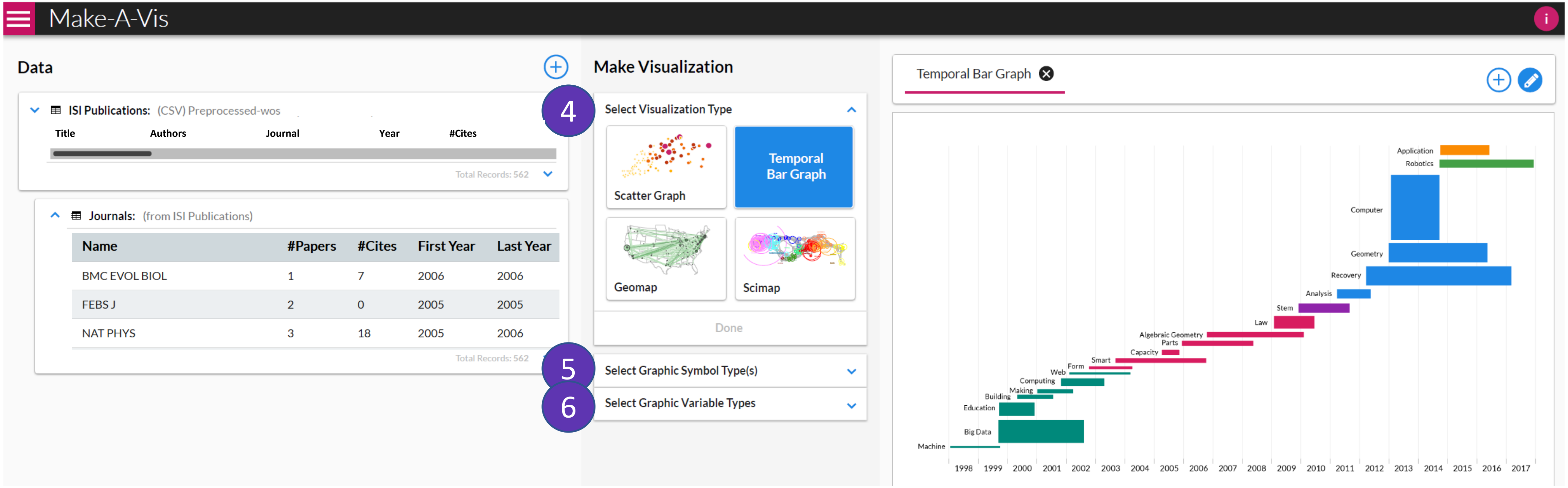
Consists of two parts that are interlinked:

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

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

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

Typology of the Data Visualization Literacy Framework

1

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Börner, Katy. 2015. [Atlas of Knowledge: Anyone Can Map](). Cambridge, MA: The MIT Press. 26-27.

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

Typology of the Data Visualization Literacy Framework

2

Insight Needs
- categorize/cluster
- order/rank/sort
- distributions (also outliers, gaps)
- comparisons
- trends (process and time)
- geospatial
- compositions (also of text)
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Data Scales
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Analyses
- statistical
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- topical
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- history
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- link and brush
- projection
- distortion

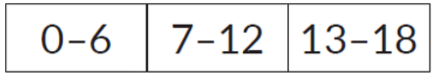
Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 28-29.

Data Scale Types

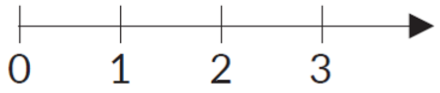
Nominal: A categorical scale, also called a nominal or category scale, is qualitative. Categories are assumed to be non-overlapping.

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

Data Scale Types - Examples

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

Qualitative

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.

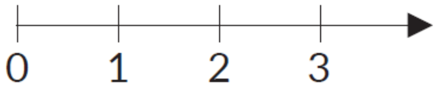
Quantitative

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 - 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	

Qualitative

Quantitative

Typology of the Data Visualization Literacy Framework

3

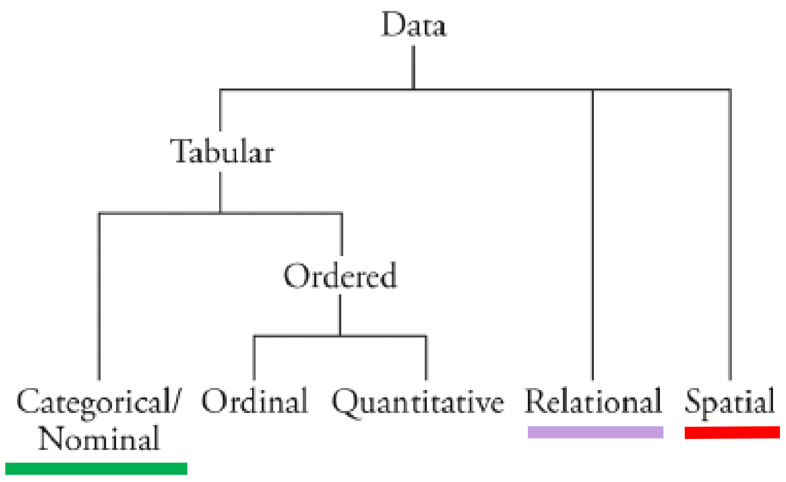
Insight Needs	Data Scales	Analyses	Visualizations	Graphic Symbols	Graphic Variables	Interactions
• categorize/cluster • order/rank/sort • distributions (also outliers, gaps) • comparisons • trends (process and time) • geospatial • compositions (also of text) • correlations/ relationships	• nominal • ordinal • interval • ratio	• statistical • temporal • geospatial • topical • relational	• table • chart • graph • map • tree • network	• geometric symbols point line area surface volume • linguistic symbols text numerals punctuation marks • pictorial symbols images icons statistical glyphs	• spatial position • retinal form color optics motion	• 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

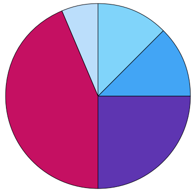
4

Insight Needs	Data Scales	Analyses	Visualizations	Graphic Symbols	Graphic Variables	Interactions
• categorize/cluster	• nominal	• statistical	• table	• geometric symbols	• spatial	• zoom
• order/rank/sort	• ordinal	• temporal	• chart	point	position	• search and locate
• distributions (also outliers, gaps)	• interval	• geospatial	• graph	line	• retinal	• filter
	• ratio	• topical	• map	area	form	• details-on-demand
• comparisons		• relational	• tree	surface	color	• history
• trends (process and time)			• network	volume	optics	• extract
				• linguistic symbols	motion	• link and brush
• geospatial				text		• projection
• compositions (also of text)				numerals		• distortion
				punctuation marks		
• correlations/ relationships				• pictorial symbols		
				images		
				icons		
				statistical glyphs		

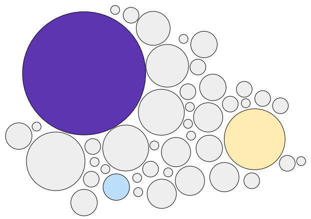
Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 30-31.

Visualization Types

Chart

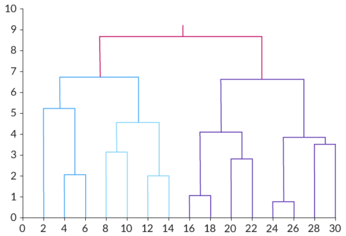


Pie Chart

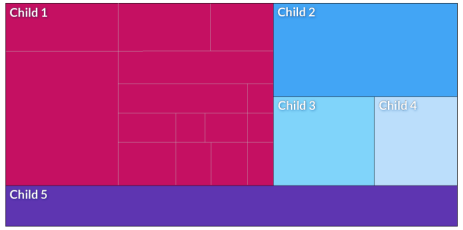


Bubble Chart

Tree

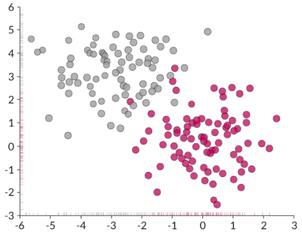


Dendrogram

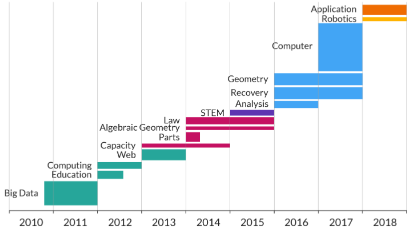


Tree Map

Graph

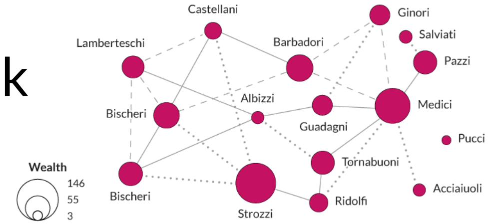


Scatter Graph

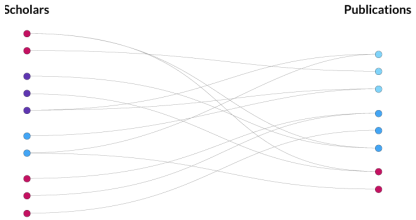


Temporal Bar Graph

Network

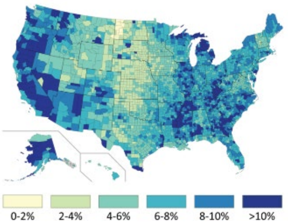


Force-Directed Network Layout

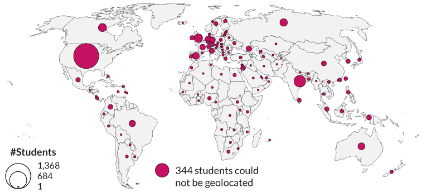


Bimodal Network Layout

Map



Choropleth Map



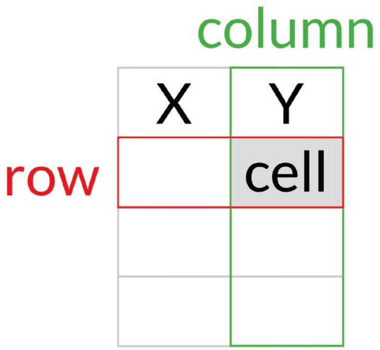
Proportional Symbol Map

Visualize: Reference Systems

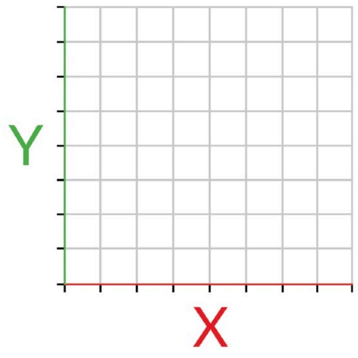
4

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

Table
columns by rows

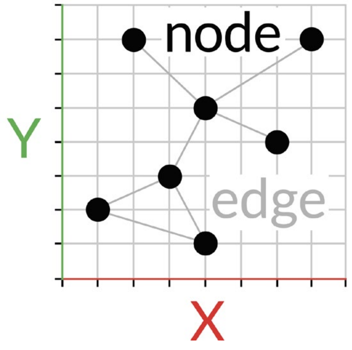


Graph
x-y coordinates

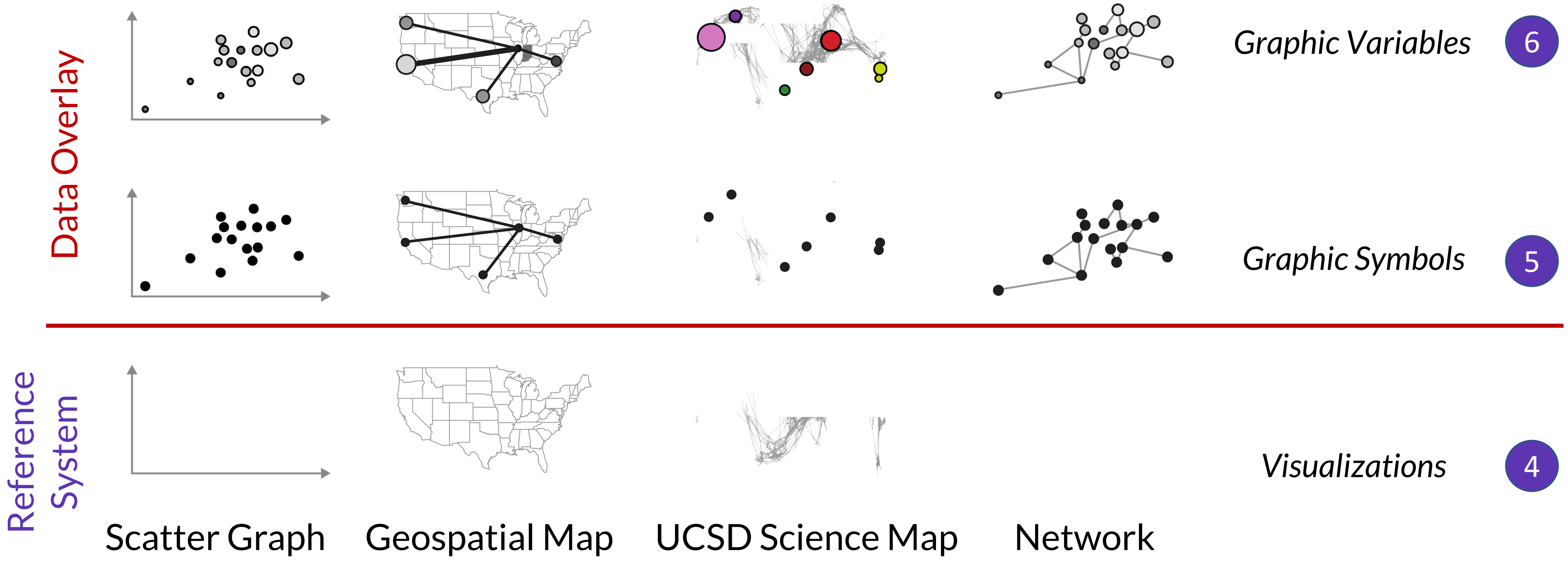


Map
latitude/
longitude

Network
local similarity



Visualize: Reference Systems, Graphic Symbols and Variables



Typology of the Data Visualization Literacy Framework

5

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. 32-33.

Typology of the Data Visualization Literacy Framework

6

Insight Needs	Data Scales	Analyses	Visualizations	Graphic Symbols	Graphic Variables	Interactions
• categorize/cluster	• nominal	• statistical	• table	• geometric symbols	• spatial	• zoom
• order/rank/sort	• ordinal	• temporal	• chart	point	position	• search and locate
• distributions (also outliers, gaps)	• interval	• geospatial	• graph	line	• retinal	• filter
	• ratio	• topical	• map	area	form	• details-on-demand
• comparisons		• relational	• tree	surface	color	• history
• trends (process and time)			• network	volume	optics	• extract
				• linguistic symbols	motion	• link and brush
• geospatial				text		• projection
• compositions (also of text)				numerals		• distortion
				punctuation marks		
• correlations/ relationships				• pictorial symbols		
				images		
				icons		
				statistical glyphs		

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

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

Graphic Variable Types

Position: x, y; possibly z

Form:

- Size
- Shape
- Rotation (Orientation)

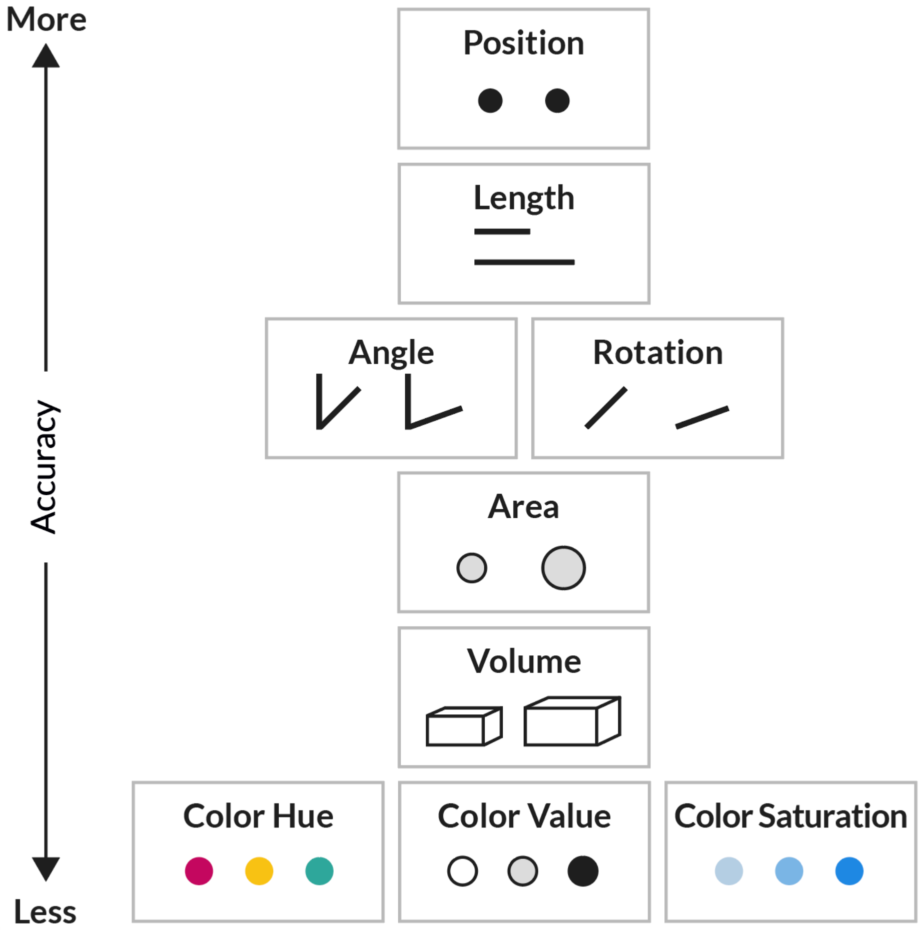
Color:

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

Optics: Blur, Transparency, Shading, Stereoscopic Depth

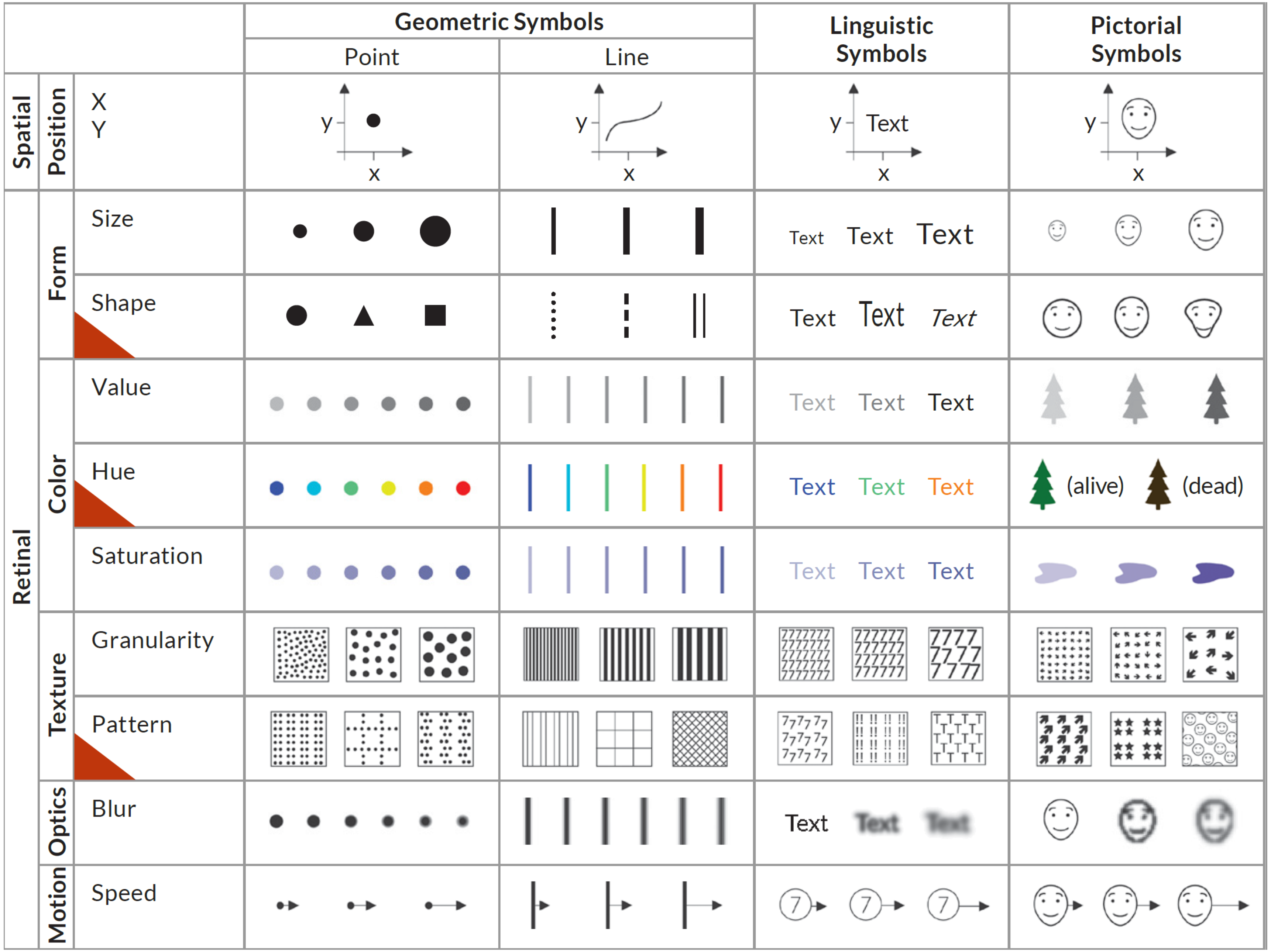
Texture: Spacing, Granularity, Pattern, Orientation, Gradient

Motion: Speed, Velocity, Rhythm



Graphic Symbol Types

Graphic Variable Types



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

Qualitative

Also called:

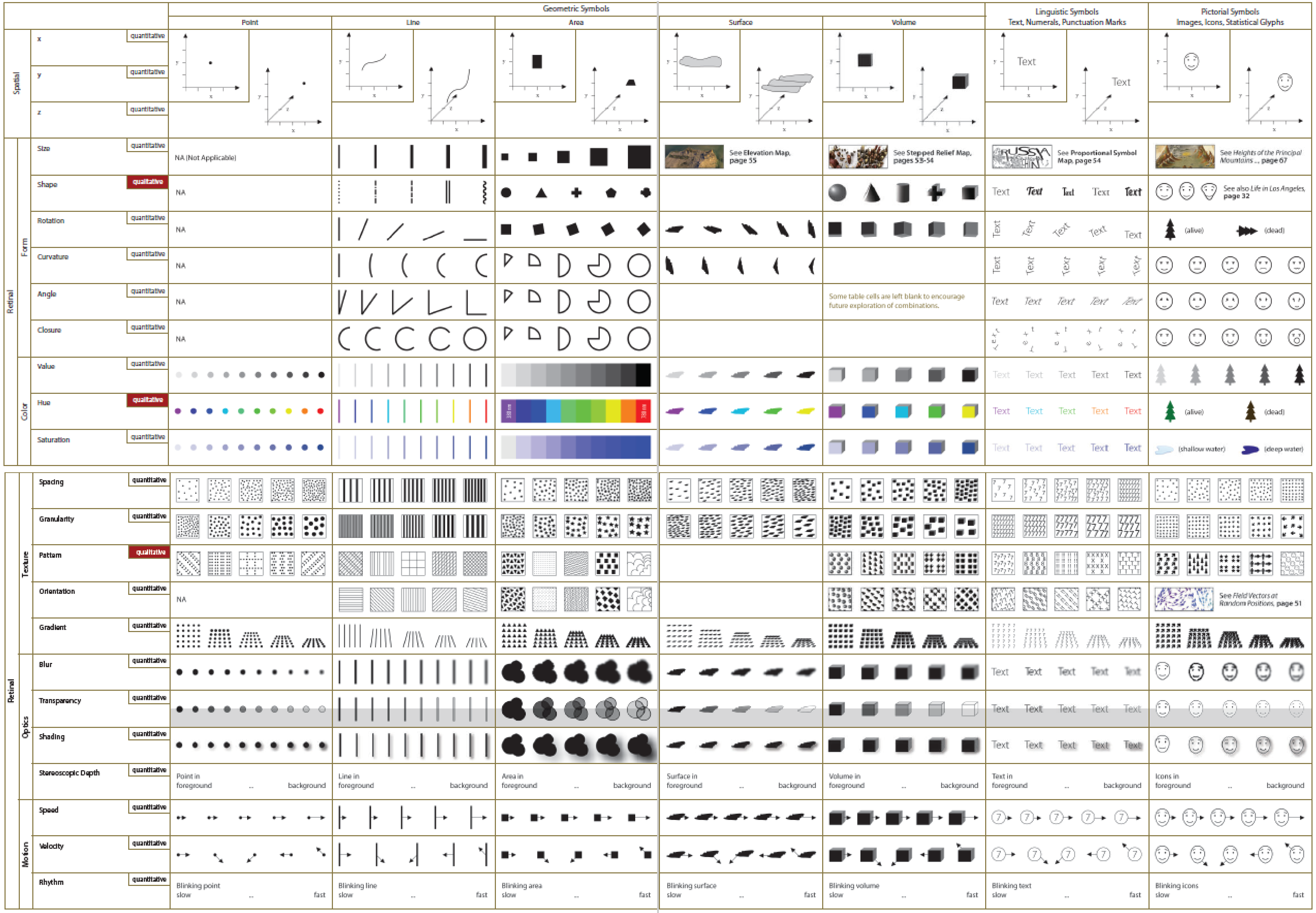
Categorical Attributes
Identity Channels

Quantitative

Also called:

Ordered Attributes
Magnitude Channels

Graphic Variable Types Versus Graphic Symbol Types



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

Typology of the Data Visualization Literacy Framework

7

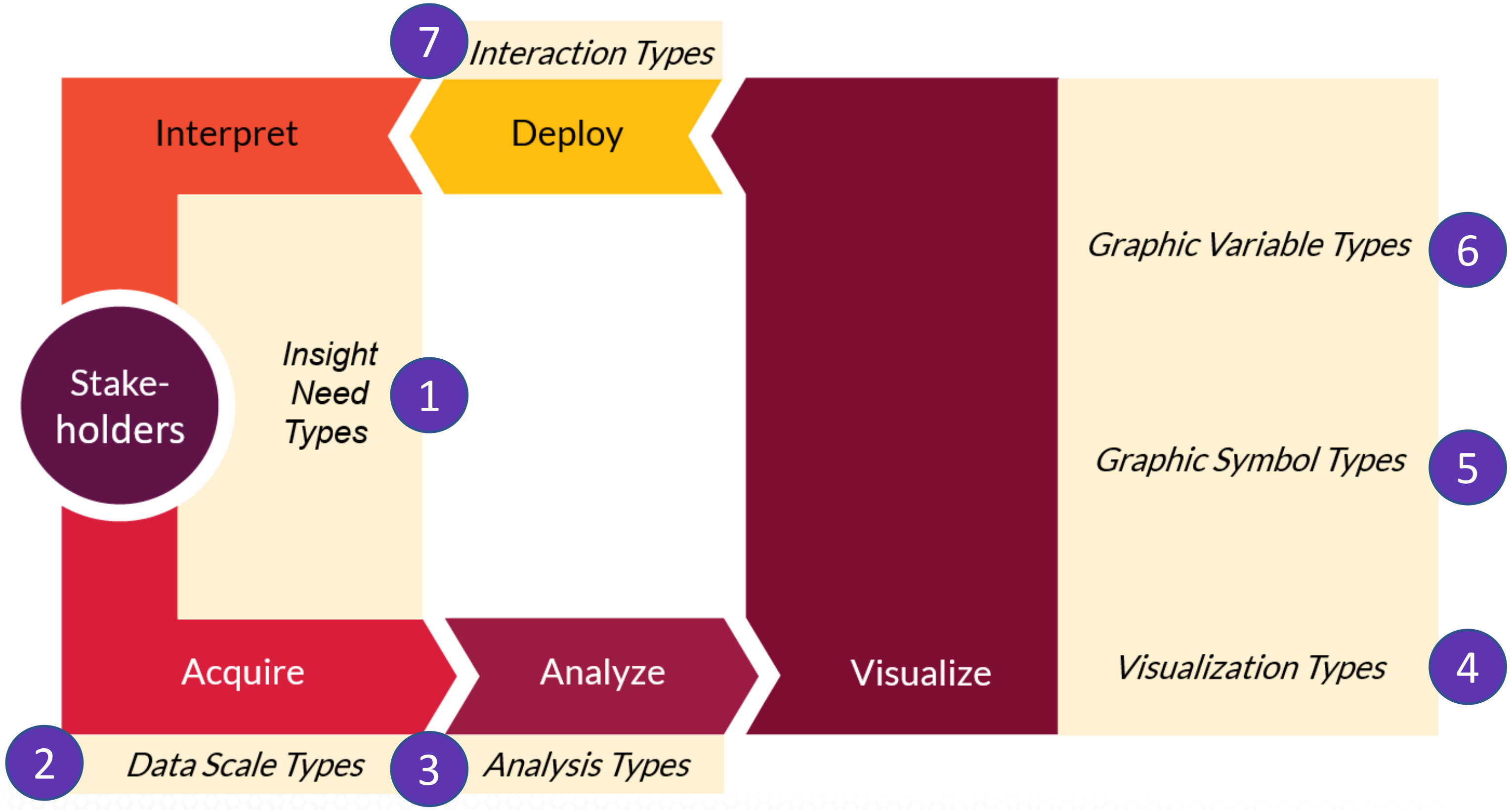
Insight Needs	Data Scales	Analyses	Visualizations	Graphic Symbols	Graphic Variables	Interactions
• categorize/cluster	• nominal	• statistical	• table	• geometric symbols	• spatial	• zoom
• order/rank/sort	• ordinal	• temporal	• chart	point	position	• search and locate
• distributions (also outliers, gaps)	• interval	• geospatial	• graph	line	• retinal	• filter
	• ratio	• topical	• map	area	form	• details-on-demand
• comparisons		• relational	• tree	surface	color	• history
• trends (process and time)			• network	volume	optics	• extract
				• linguistic symbols	motion	• link and brush
• geospatial				text		• projection
• compositions (also of text)				numerals		• distortion
				punctuation marks		
• correlations/ relationships				• pictorial symbols		
				images		
				icons		
				statistical glyphs		

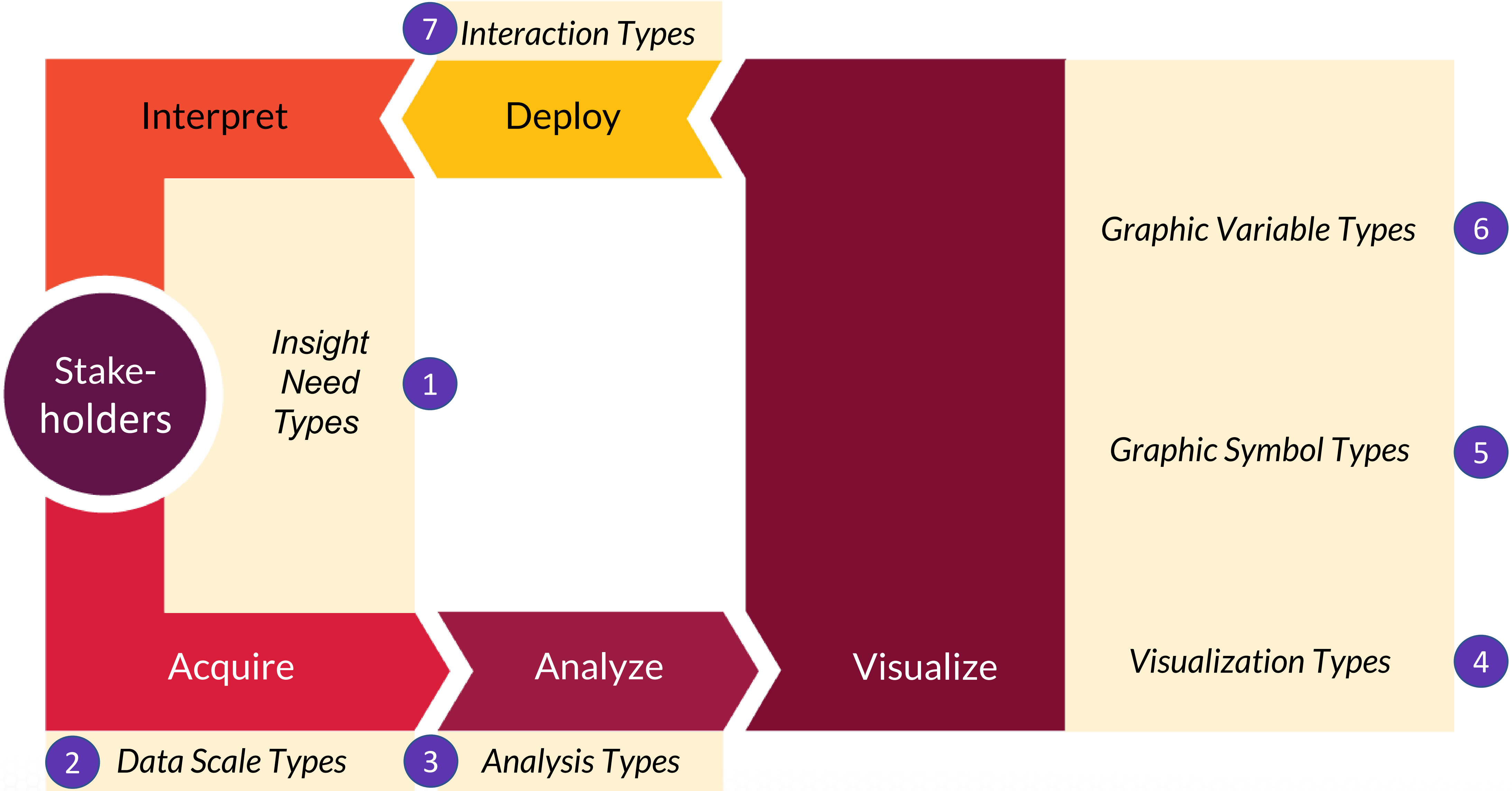
Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 26, 68-69.

Data Visualization Literacy Framework (DVL-FW)

Consists of two parts that are interlinked:

DVL Typology +
DVL Workflow Process




7 Interaction Types
Interpret
Deploy
Stake-
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Insight
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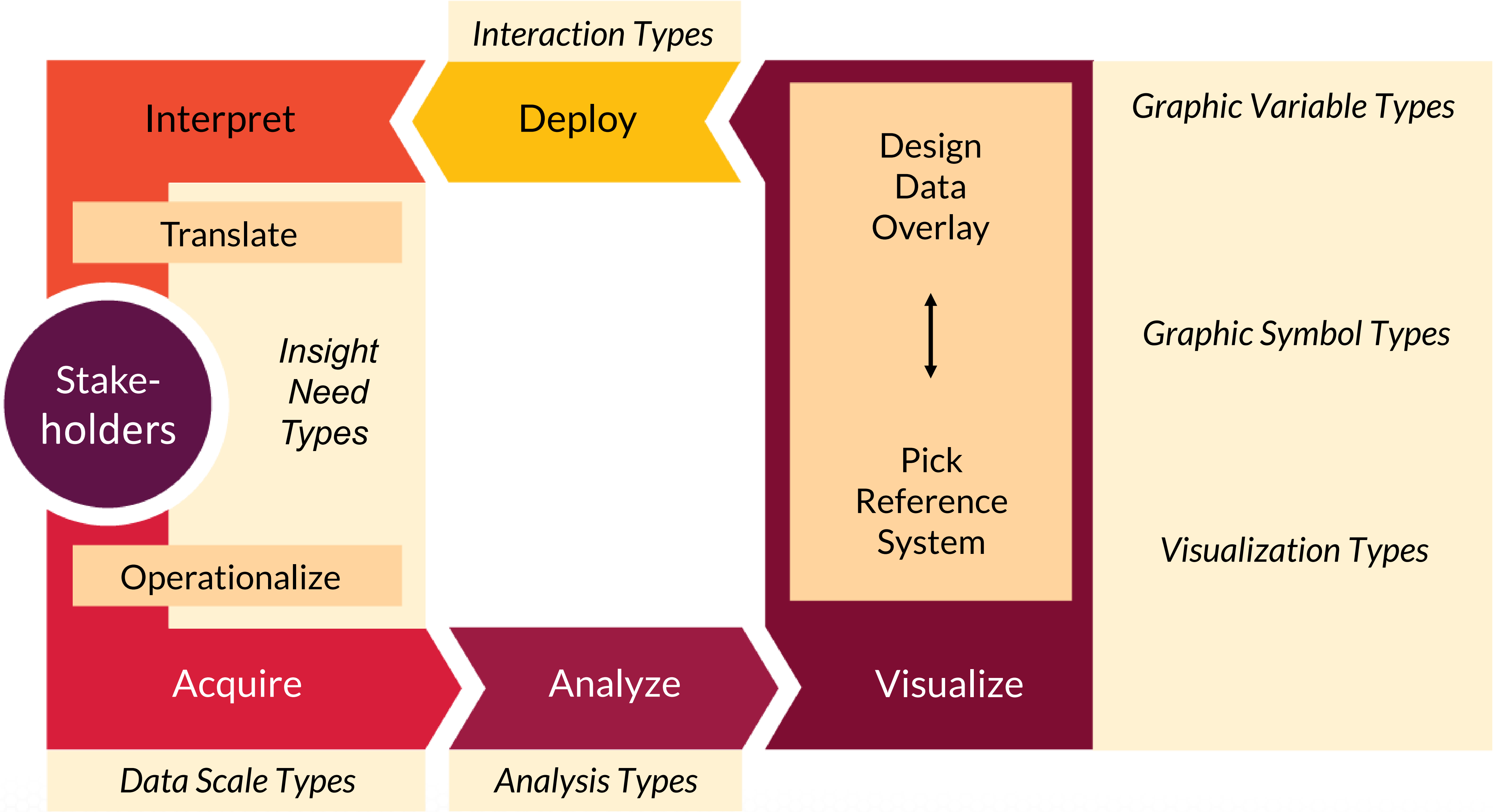
Graphic Variable Types
6
Graphic Symbol Types
5
Acquire
Analyze
Visualize
Visualization Types
4
2 Data Scale Types
3 Analysis Types


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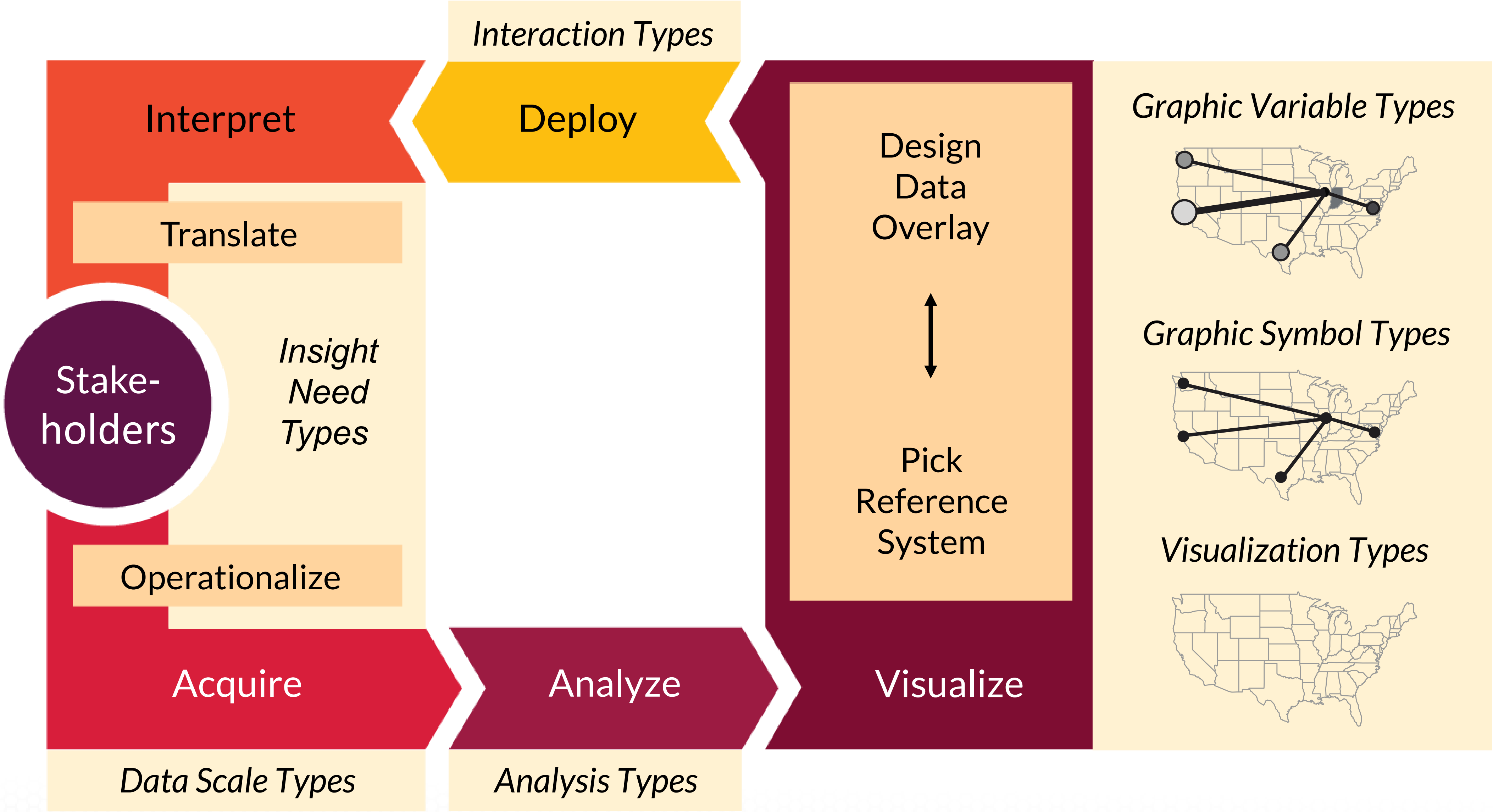
Interaction Types
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Translate
Stake-holders
Insight Need Types
Operationalize
Design Data Overlay
Pick Reference System
Graphic Variable Types
Graphic Symbol Types
Visualization Types
Acquire
Analyze
Visualize
Data Scale Types
Analysis Types

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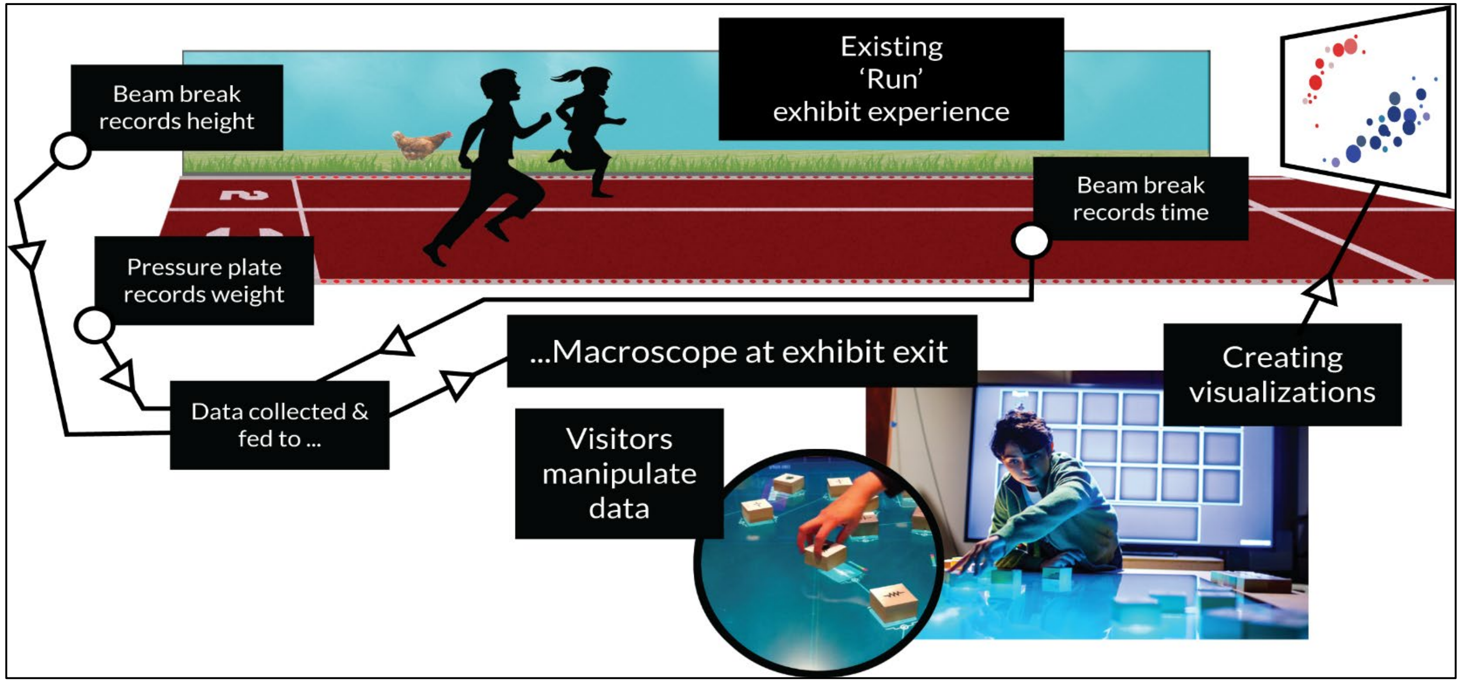
Scaling Up:

Teaching Data Visualization Literacy

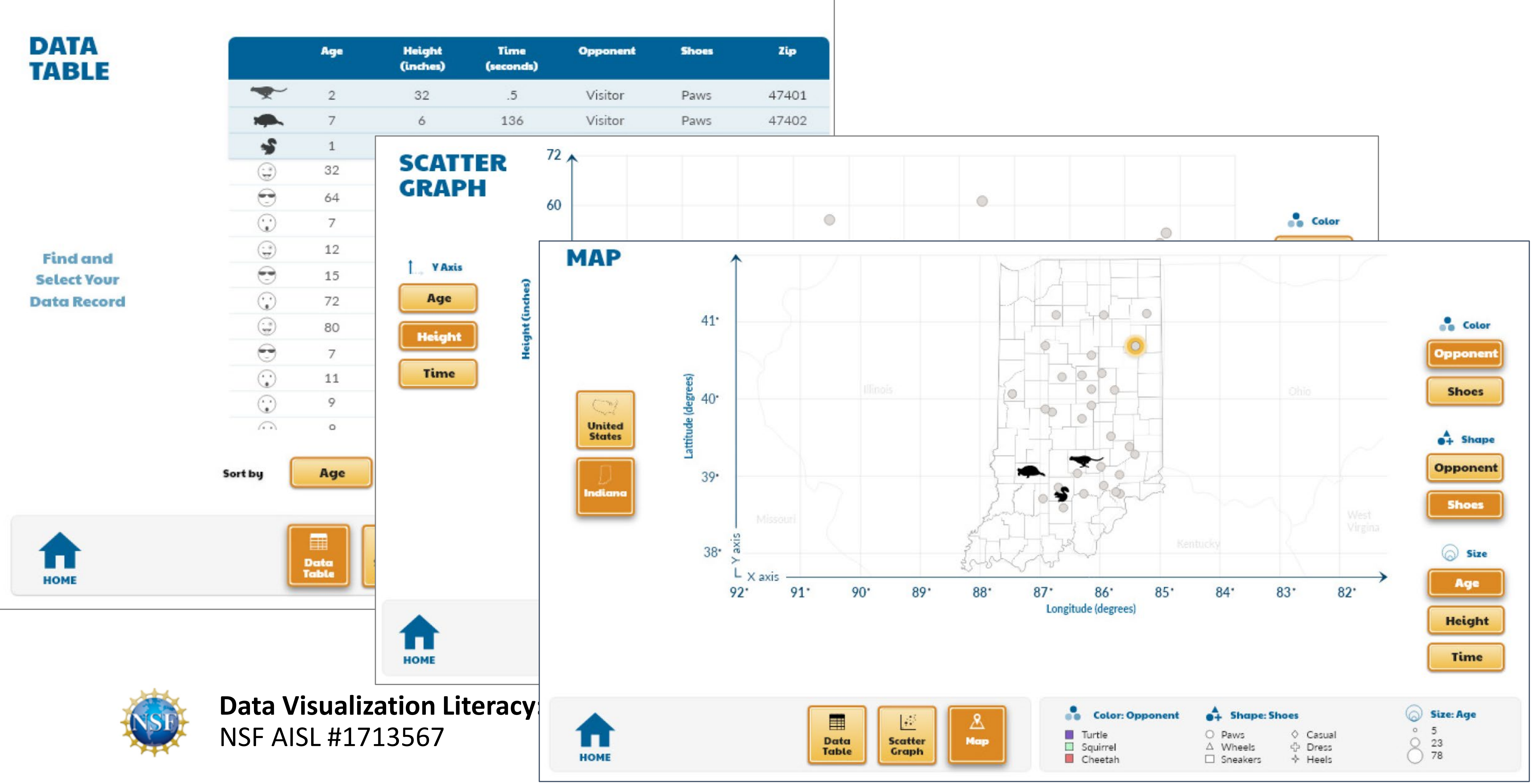
MAV in Science Museums

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

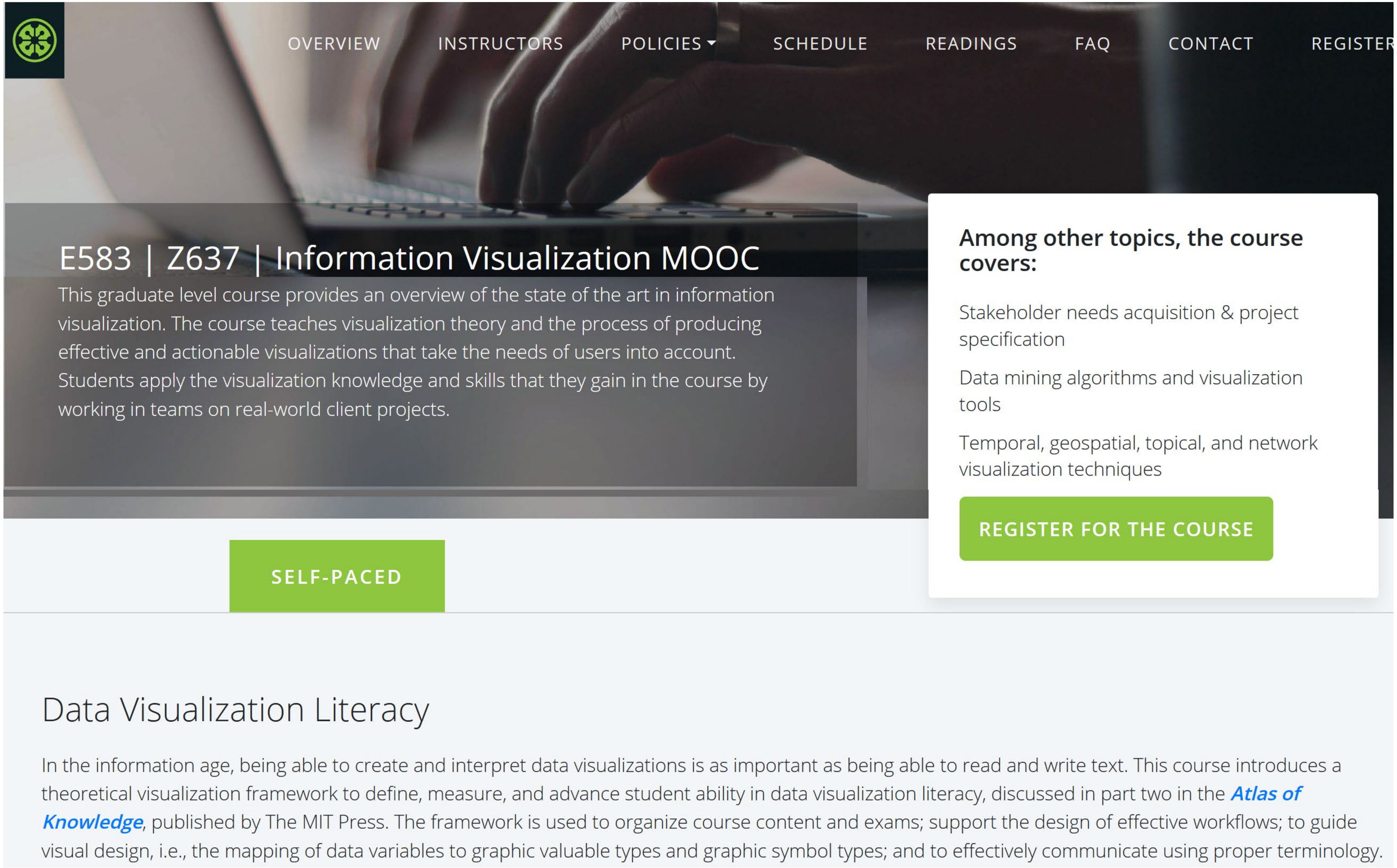
xMacroscopes in Science Museums



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



Data Visualization Literacy:
NSF AISL #1713567



https://ivmooc.cns.iu.edu

Course Listing: INFORMATION VISUALIZATION

Spring 2021, Bloomington

Information on this report reflects data as of the end of the day Sunday, December 06, 2020

Select another ENGR course | Select another department

```
                                                                  Seats  Avail  Wait

ENGR-E 583  INFORMATION VISUALIZATION (3 CR)
      *****        ARR            ARR    WB WEB    Borner K              30     18     0
         Above class open to graduates only
         Discussion (DIS)
      10331        ARR            ARR    WB WEB    Borner K              30     10     0
         Above class meets with with ENGR-E 483
         Above class meets 100% Online through Asynchronous
         instruction.  For more information visit
         https://covid.iu.edu/learning-modes/index.html
ENGR-E 583  INFORMATION VISUALIZATION (3 CR)
      10379 RSTR   ARR            ARR    WB WEB    Borner K              50     29     0
         This is a 100% online class taught by IU Bloomington. No
         on-campus class meetings are required. A distance education
         fee may apply; check the SCU website for more information at
         https://studentcentral.indiana.edu
         Above class for students not in residence on the Bloomington
         Campus
         Above class meets 100% Online through Asynchronous
         instruction.  For more information visit
         https://covid.iu.edu/learning-modes/index.html
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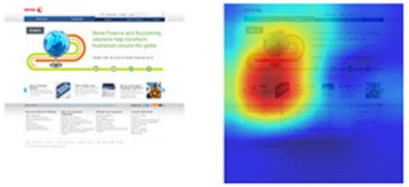
OVERVIEW INSTRUCTORS POLICIES SCHEDULE READINGS FAQ CONTACT REGISTER

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 studying how website design has changed over time, and how these changes reflect changes

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BioSim is a participatory simulation where young students (grades K-3) enact the roles of ants and biological systems through the assistance of electronically-enhanced e-puppets. It is

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Marvelous Visualization Opportunity:

HuBMAP: Mapping 30+ 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

Vision

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

https://commonfund.nih.gov/HuBMAP

Goals

1. Accelerate the development of the next generation of 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

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

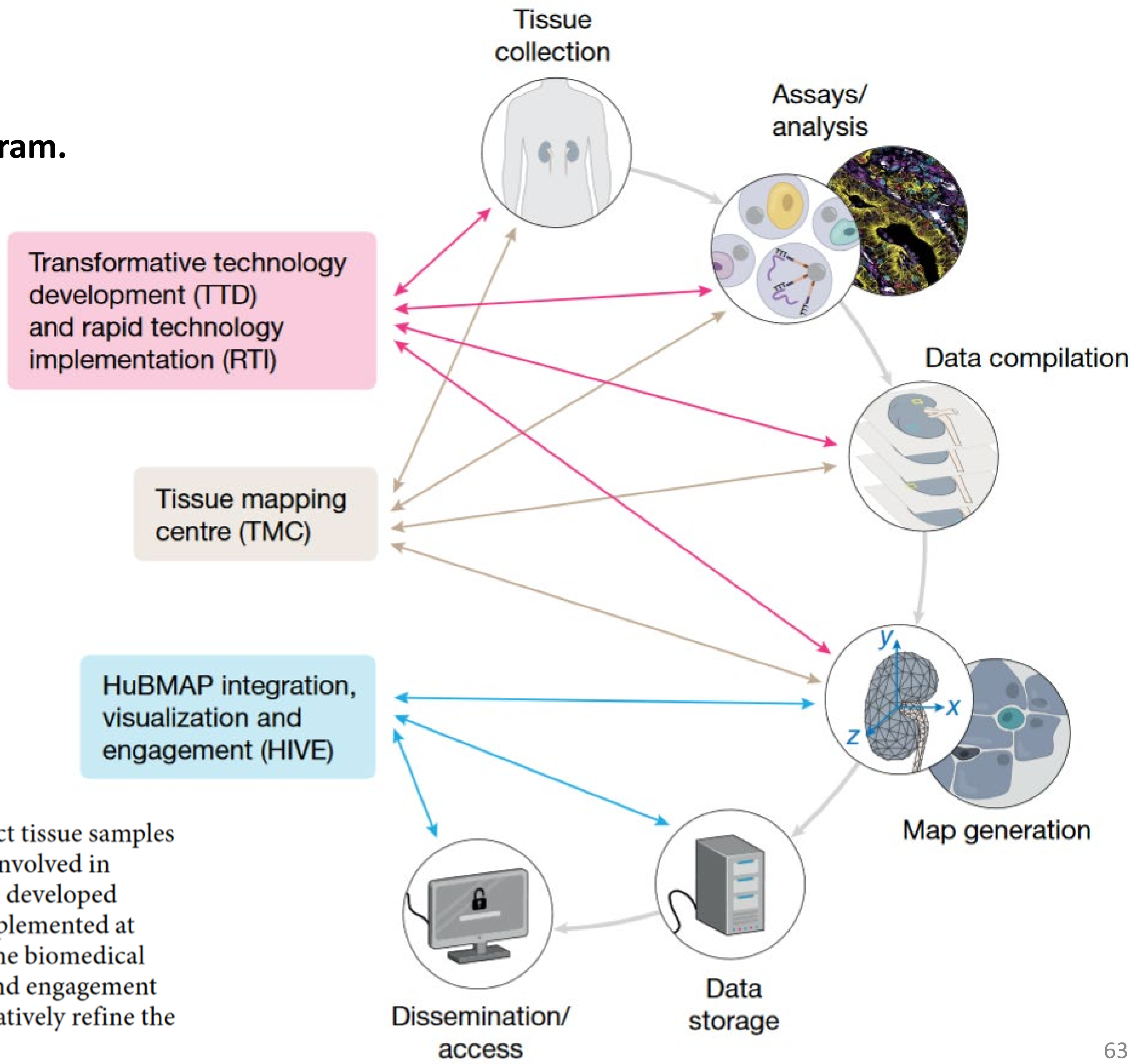


Fig. 1 | The HubMAP consortium. The TMCs will collect tissue samples and generate spatially resolved, single-cell data. Groups involved in TTD and RTI initiatives will develop emerging and more developed technologies, respectively; in later years, these will be implemented at scale. Data from all groups 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.

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

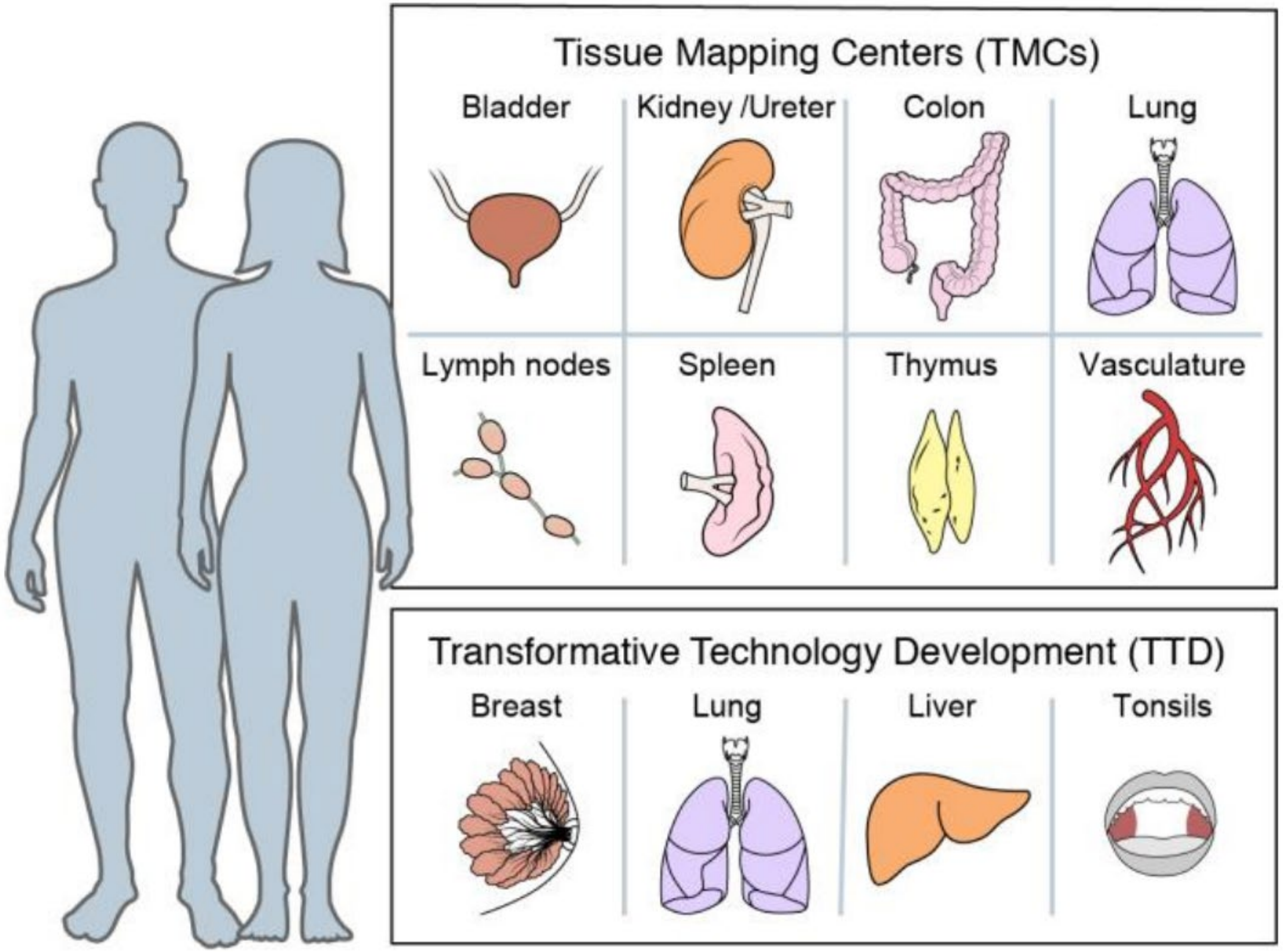


Fig. 2 | Key tissues and organs initially analysed by the consortium. Using innovative, production-grade ('shovel ready') technologies, HuBMAP TMCs will generate data for single-cell, three-dimensional maps of various human tissues. In parallel, TTD projects (and later RTI projects) will refine assays 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.

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

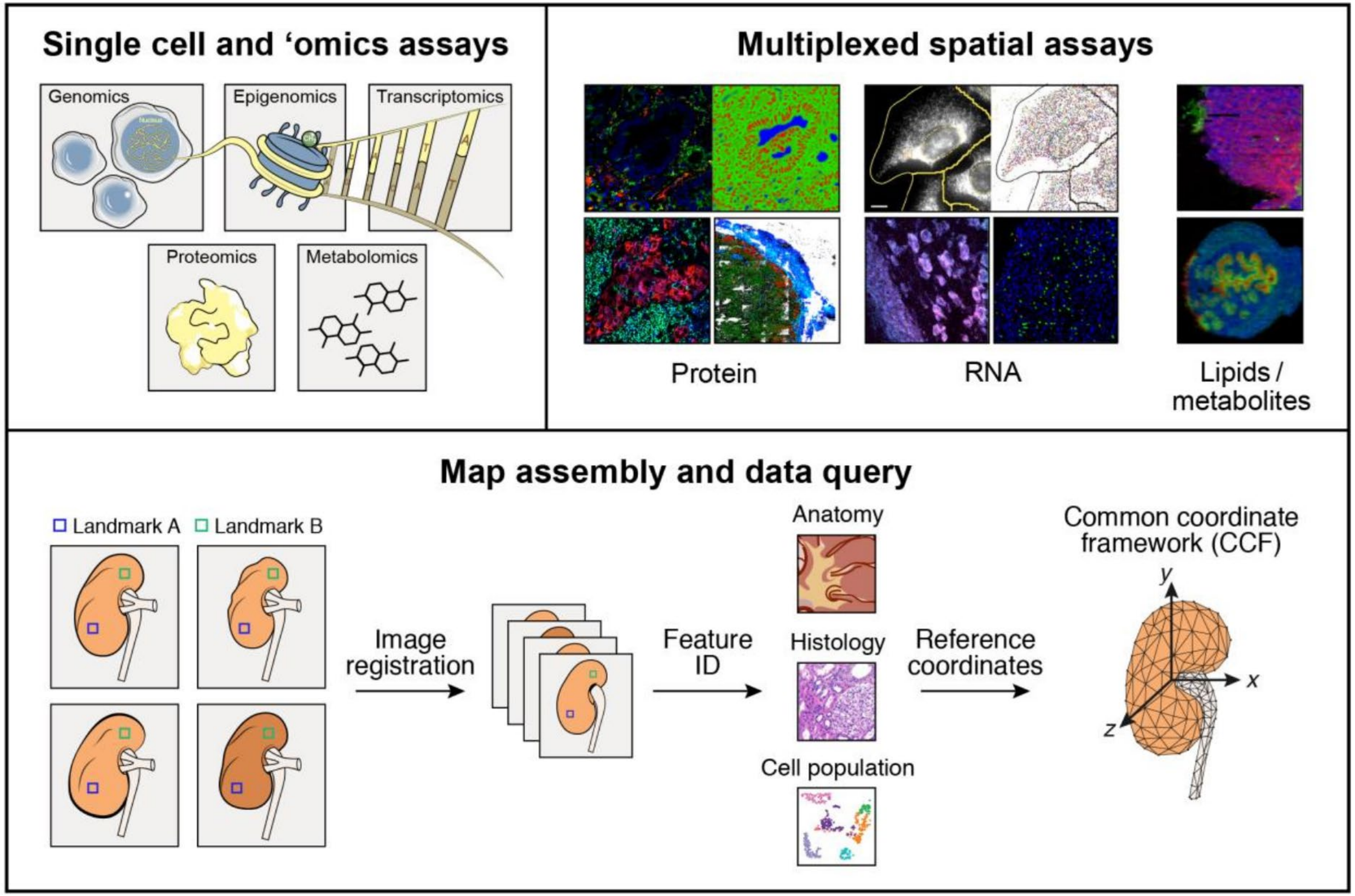
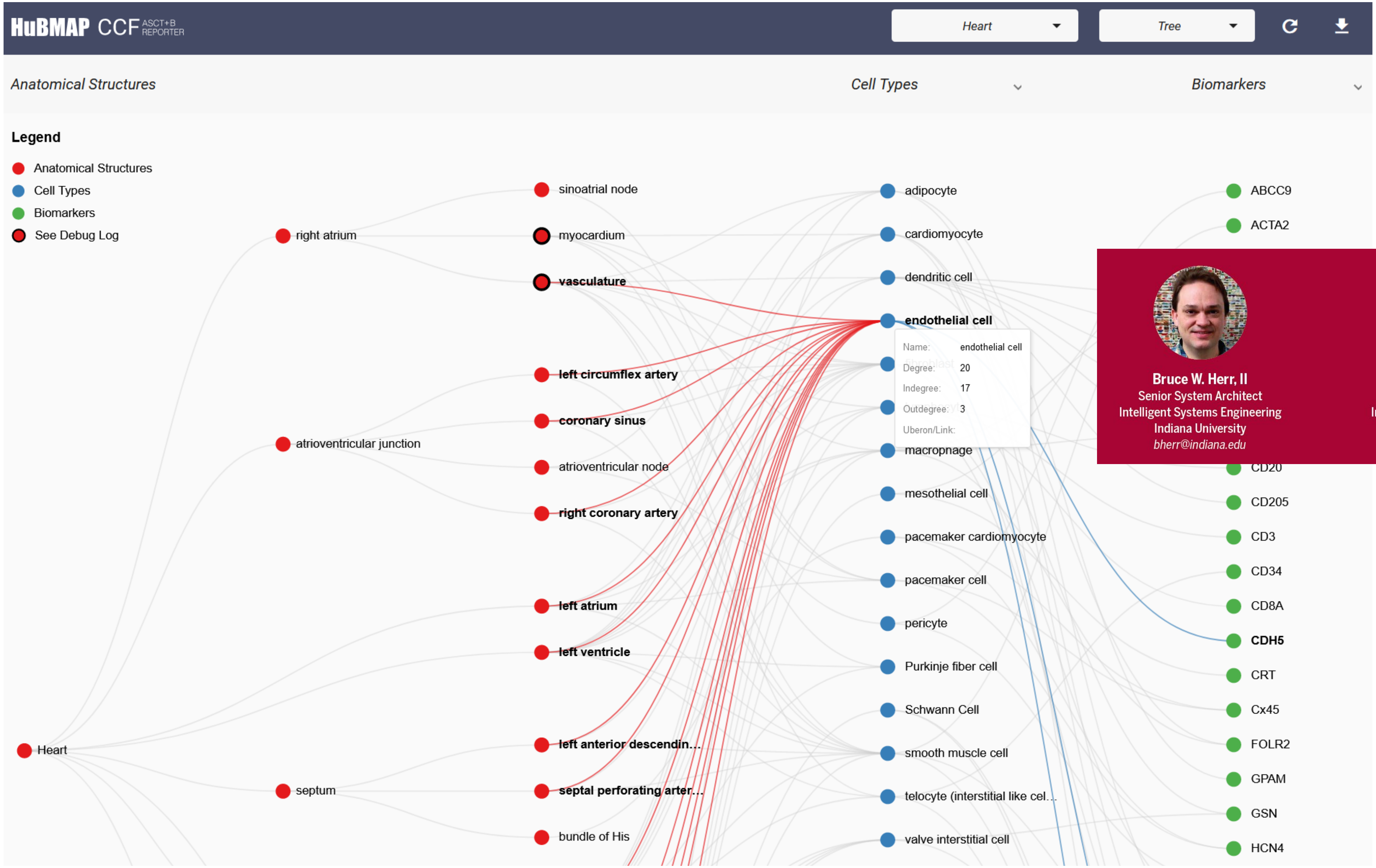


Fig. 3 | Map generation and assembly across cellular and spatial scales. HuBMAP aims to produce an atlas in which users can refer to a histological slide from a specific part of an organ and, in any given cell, understand its contents on multiple ’omic levels—genomic, epigenomic, transcriptomic, proteomic, and/or metabolomic. To achieve these ends, centres will apply a combination of imaging, ’omics 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.



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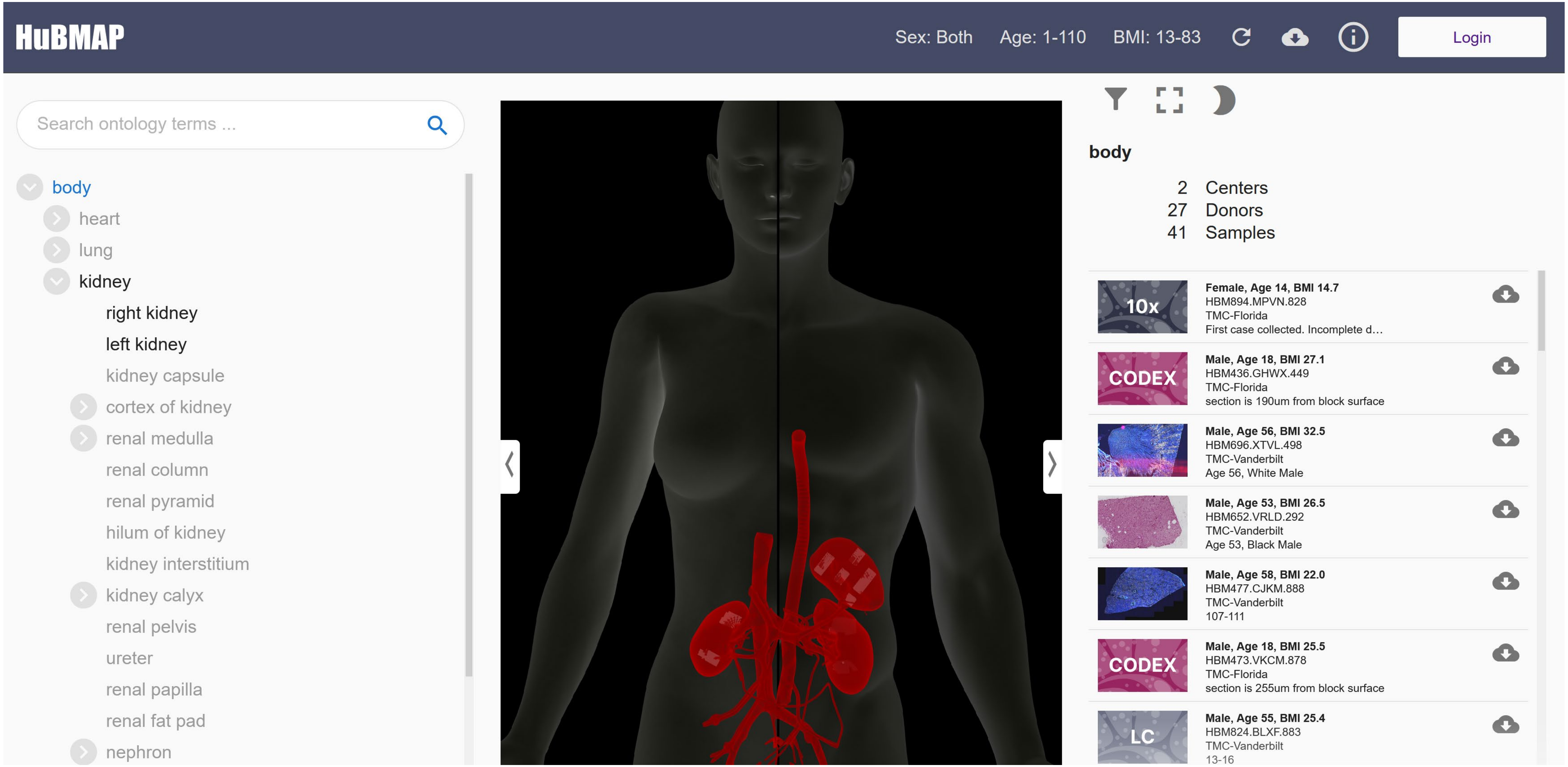
https://hubmapconsortium.github.io/ccf-asct-reporter



https://portal.hubmapconsortium.org/ccf-eui

Acknowledgements

HuBMAP Consortium (https://hubmapconsortium.org)

Thanks go to all the **patients** that agreed to volunteer healthy tissue and open use of their data.

NIH National Institutes of Health

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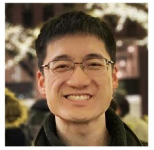

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Understanding complex networked systems is key to solving some of the most vexing problems confronting humankind, from discovering how dynamic brain connections give rise to thoughts and behaviors, to detecting and preventing the spread of misinformation or unhealthy behaviors across a population. Graduate training, however, typically occurs in one of two dimensions: experimental and observational methods in a specific area such as biology and sociology, or in general methodologies such as machine learning and data science.

CNS NRT

https://cns-nrt.indiana.edu

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