

Modeling and Visualizing Complex Unifiable Systems

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*Forum on Complex Unifiable Systems: A Virtual Convocation
National Academy of Engineering*

April 28, 2020



Map of Scientific Collaborations from 2005-2009



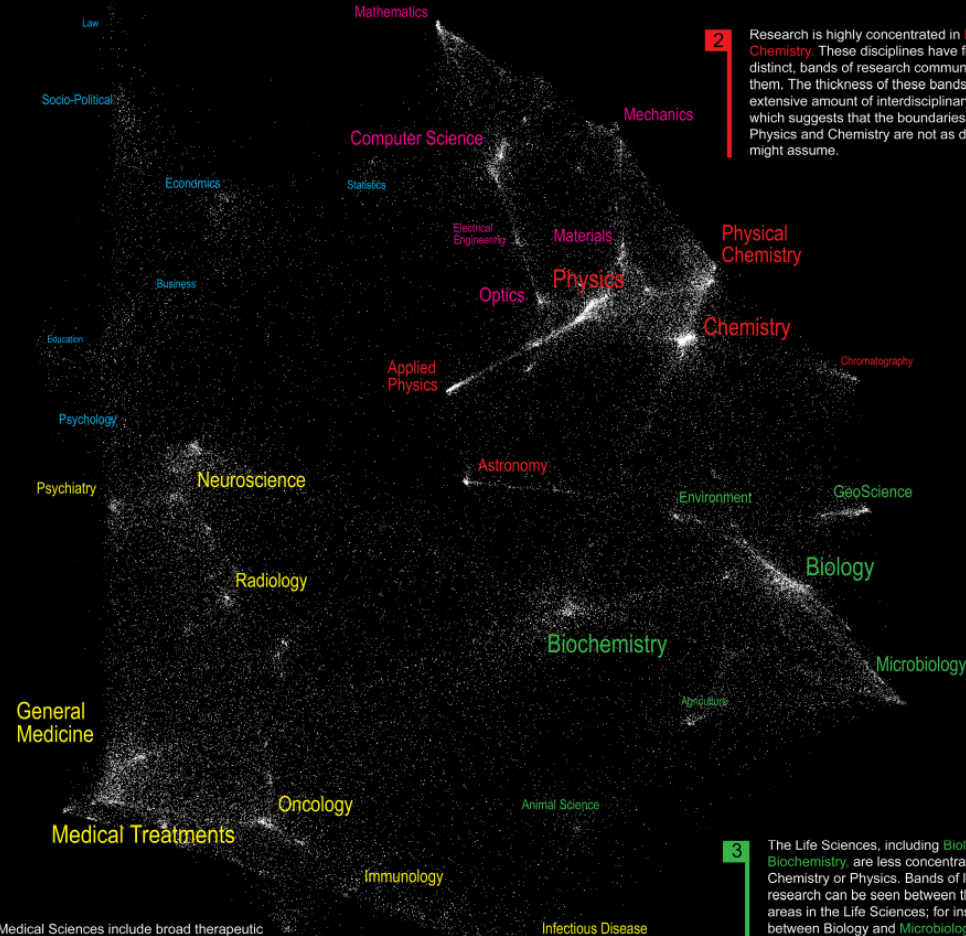
Computed Using Data from Elsevier's Scopus

The Structure of Science

5 The Social Sciences are the smallest and most diffuse of all the sciences. **Psychology** serves as the link between Medical Sciences (Psychiatry) and the Social Sciences. **Statistics** serves as the link with Computer Science and Mathematics.

1 **Mathematics** is our starting point, the purest of all sciences. It lies at the outer edge of the map. **Computer Science**, **Electrical Engineering**, and **Optics** are applied sciences that draw upon knowledge in Mathematics and Physics. These three disciplines provide a good example of a linear progression from one pure science (Mathematics) to another (Physics) through multiple disciplines. Although applied, these disciplines are highly concentrated with distinct bands of research communities that link them. Bands indicate interdisciplinary research.

2 Research is highly concentrated in **Physics** and **Chemistry**. These disciplines have few, but very distinct, bands of research communities that link them. The thickness of these bands indicates an extensive amount of interdisciplinary research, which suggests that the boundaries between Physics and Chemistry are not as distinct as one might assume.



4 The Medical Sciences include broad therapeutic studies and targeted areas of **Treatment** (e.g. central nervous system, cardiology, gastroenterology, etc.) Unlike Physics and Chemistry, the medical disciplines are more spread out, suggesting a more multi-disciplinary approach to research. The transition into Life Sciences (via Animal Science and Biochemistry) is gradual.

3 The Life Sciences, including **Biology** and **Biochemistry**, are less concentrated than **Chemistry** or **Physics**. Bands of linking research can be seen between the larger areas in the Life Sciences; for instance between **Biology** and **Microbiology**, and between **Biology** and **Environmental Science**. **Biochemistry** is very interesting in that it is a large discipline that has visible links to disciplines in many areas of the map, including **Biology**, **Chemistry**, **Neuroscience**, and **General Medicine**. It is perhaps the most interdisciplinary of the sciences.

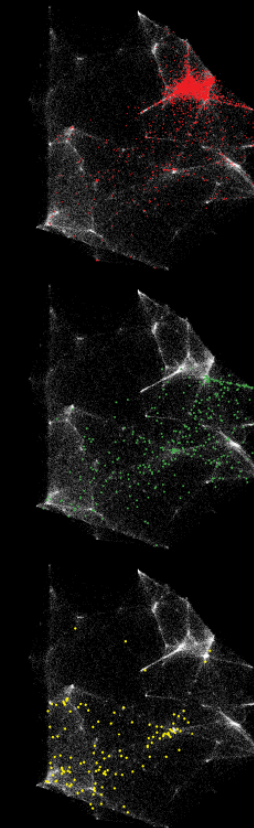
We are all familiar with traditional maps that show the relationships between countries, provinces, states, and cities. Similar relationships exist between the various disciplines and research topics in science. This allows us to map the structure of science.

One of the first maps of science was developed at the Institute for Scientific Information over 30 years ago. It identified 41 areas of science from the citation patterns in 17,000 scientific papers. That early map was intriguing, but it didn't cover enough of science to accurately define its structure.

Things are different today. We have enormous computing power and advanced visualization software that make mapping of the structure of science possible. This galaxy-like map of science (left) was generated at Sandia National Laboratories using an advanced graph layout routine (VxOrd) from the citation patterns in 800,000 scientific papers published in 2002. Each dot in the galaxy represents one of the 96,000 research communities active in science in 2002. A research community is a group of papers (9 on average) that are written on the same research topic in a given year. Over time, communities can be born, continue, split, merge, or die.

The map of science can be used as a tool for science strategy. This is the terrain in which organizations and institutions locate their scientific capabilities. Additional information about the scientific and economic impact of each research community allows policy makers to decide which areas to explore, exploit, abandon, or ignore.

We also envision the map as an educational tool. For children, the theoretical relationship between areas of science can be replaced with a concrete map showing how math, physics, chemistry, biology and social studies interact. For advanced students, areas of interest can be located and neighboring areas can be explored.



Nanotechnology

Most research communities in nanotechnology are concentrated in **Physics**, **Chemistry**, and **Materials Science**. However, many disciplines in the Life and Medical Sciences also have nanotechnology applications.

Proteomics

Research communities in proteomics are centered in **Biochemistry**. In addition, there is a heavy focus in the tools section of chemistry, such as **Chromatography**. The balance of the proteomics communities are widely dispersed among the Life and Medical Sciences.

Pharmacogenomics

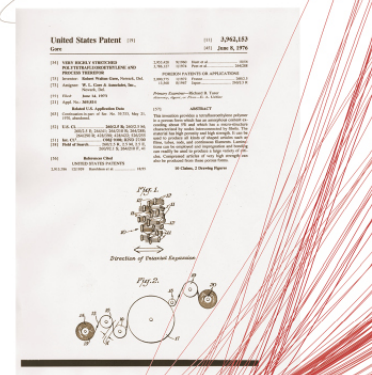
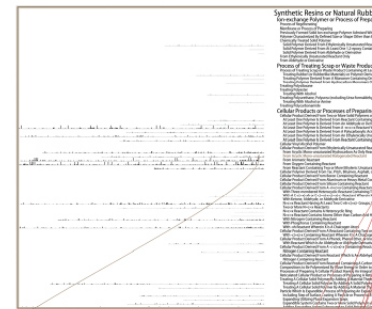
Pharmacogenomics is a relatively new field with most of its activity in **Medicine**. It also has many communities in **Biochemistry** and two communities in the Social Sciences.

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.

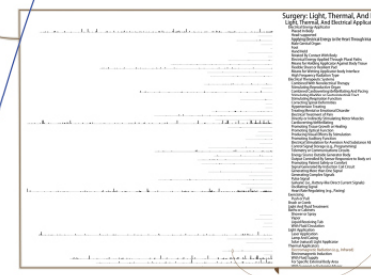
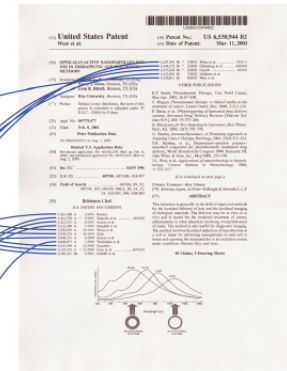
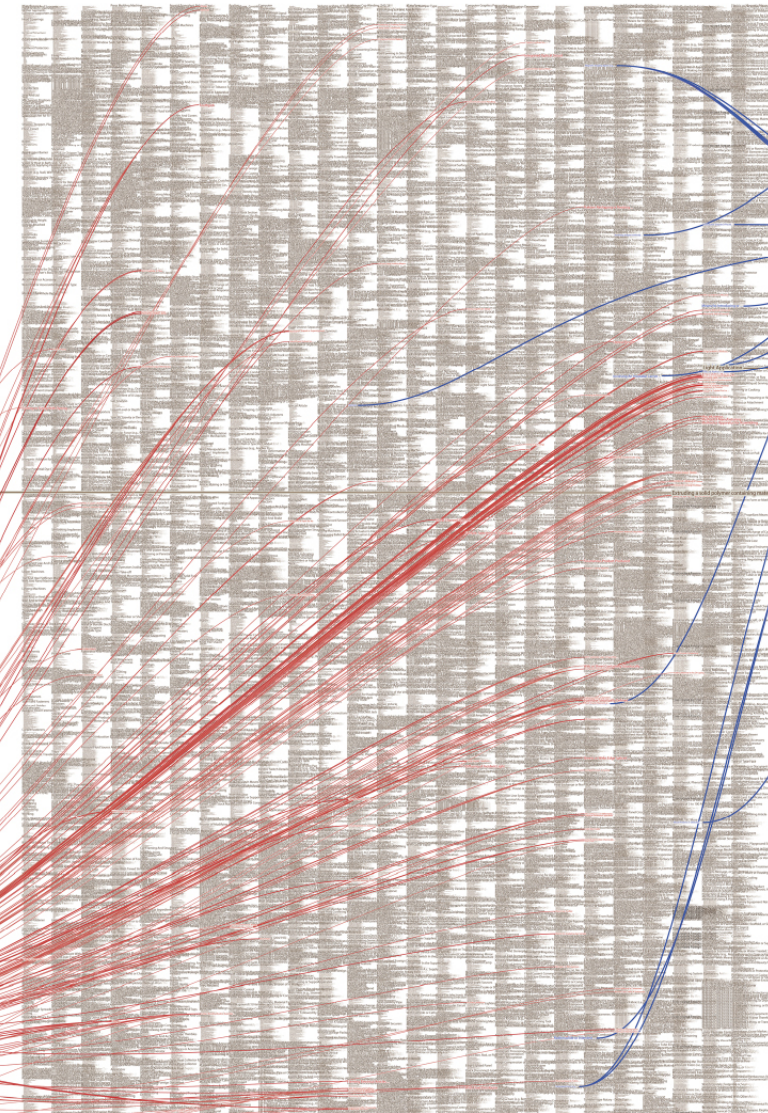
Patent applications are required to be unique and non-obvious, partially by revealing any previous patents that might be similar in nature or provide a foundation for the current invention. In this way we can trace the impact of a single patent, seeing how many patents and categories it affects.

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."



The US Patent Hierarchy

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 infrared 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?

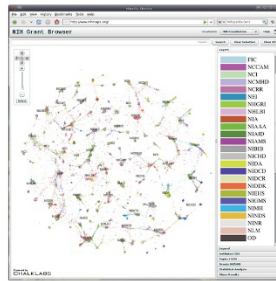
Something as simple as a bar chart helps people see how entities in a category relate to that category. Here, each bar encodes a "distance to prototype": how much each patent differs from an idealized "prototype patent" for that category. A measure like this can be based on statistics, computational 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.

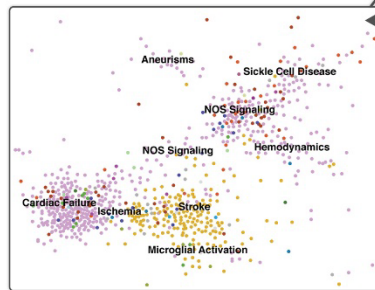
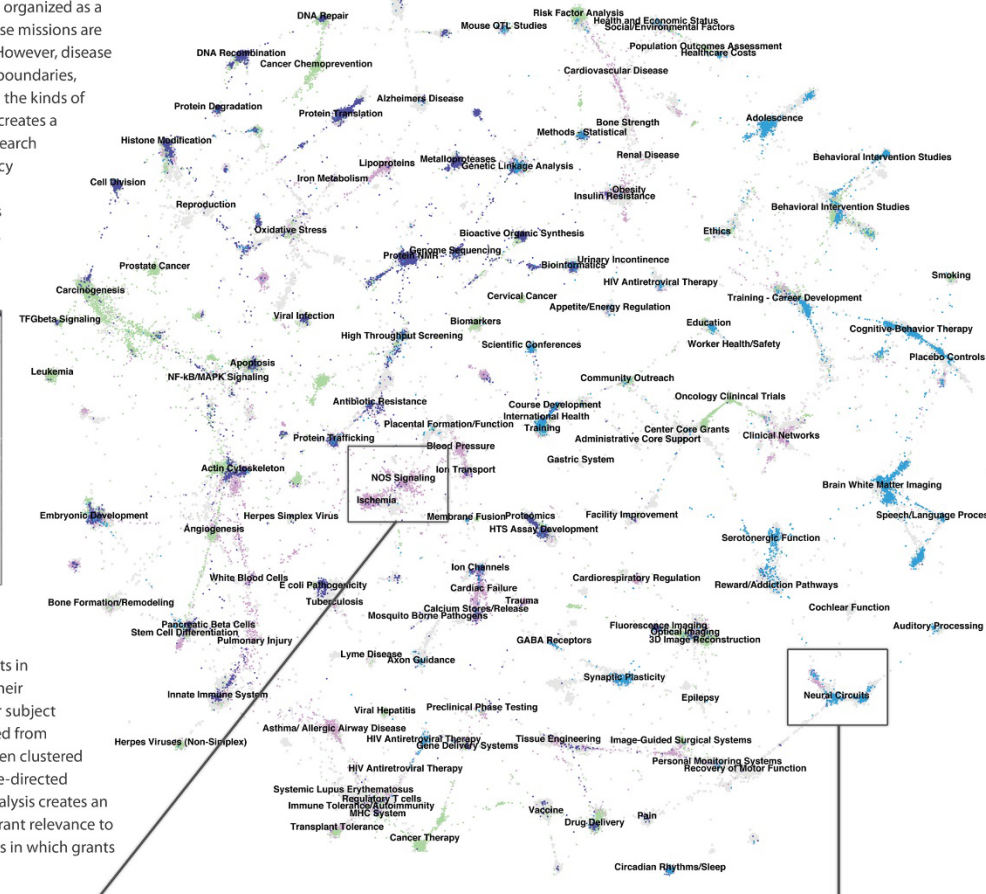
A Topic Map of NIH Grants 2007

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

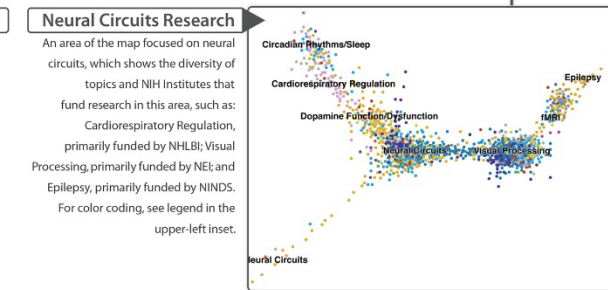
The National Institutes of Health (NIH) is organized as a multitude of Institutes and Centers whose missions are primarily focused on distinct diseases. However, disease etiologies and therapies flout scientific boundaries, and thus there is tremendous overlap in the kinds of research funded by each 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 cardiovascular function and dysfunction. Cardiac Failure (primarily funded by NHLBI) is typically clustered next to Stroke (NINDS), since these are the two major medical emergencies associated with ischemia, which results from a restricted blood supply. Also localized in this area are grants focused on Nitric Oxide (NOS) Signaling, a major biochemical pathway for vasodilation, and grants on Hemodynamics, Sickle Cell Disease, and Aneurysms.

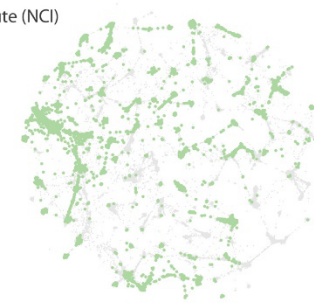


Neural Circuits Research
An area of the map focused on neural circuits, which shows the diversity of topics and NIH Institutes that fund research in this area, such as: Cardiorespiratory Regulation, primarily funded by NHLBI; Visual Processing, primarily funded by NEI; and Epilepsy, primarily funded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

National Cancer Institute (NCI)

TOP 10 TOPICS

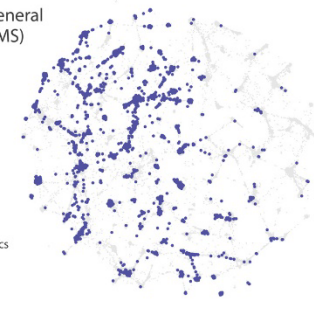
- 1 Oncology Clinical Trials
- 2 Cancer Treatment
- 3 Cancer Therapy
- 4 Carcinogenesis
- 5 Risk Factor Analysis
- 6 Cancer Chemotherapy
- 7 Metastasis
- 8 Leukemia
- 9 Prediction/Prognosis
- 10 Cancer Chemoprevention



National Institute of General Medical Sciences (NIGMS)

TOP 10 TOPICS

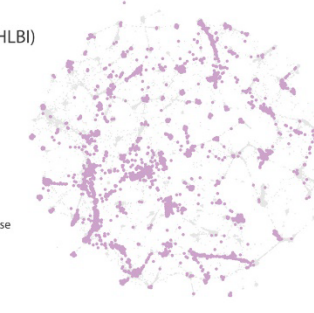
- 1 Bioactive Organic Synthesis
- 2 X-ray Crystallography
- 3 Protein NMR
- 4 Computational Models
- 5 Yeast Biology
- 6 Metalloproteases
- 7 Enzymatic Mechanisms
- 8 Protein Complexes
- 9 Invertebrate/Zebrafish Genetics
- 10 Cell Division



National Heart, Lung, and Blood Institute (NHLBI)

TOP 10 TOPICS

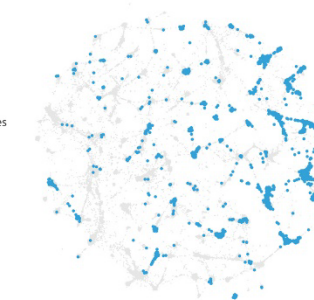
- 1 Cardiac Failure
- 2 Pulmonary Injury
- 3 Genetic Linkage Analysis
- 4 Cardiovascular Disease
- 5 Atherosclerosis
- 6 Hemostasis
- 7 Blood Pressure
- 8 Asthma/ Allergic Airway Disease
- 9 Gene Association
- 10 Lipoproteins



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



Science related Wikipedian ACTIVITY

This visualization explores the activity of science, math, and technology (SMT) related articles in the English-language Wikipedia (<http://en.wikipedia.org>). The central image shows 659,388 articles (circles). Overlaid is a 37 x 37 grid of relevant half-inch sized images.

Blue, green, and yellow circles represent the 3,599 math, 6,474 science, and 3,164 technology related articles respectively. The larger the size of a circle the higher the likelihood it is that type of article. The four corners show activity patterns of SMT articles.

Article Edit Activity
Articles are size coded based on how frequently they have been edited from Feb. 6, 2001 to April 6, 2007. More consideration is given to current and major edits. Larger circles have been edited more frequently than smaller circles.

2007 Major Edits
Articles are size coded based on how many major edits they received from January 1st, 2007 to April 6th, 2007. Larger circles have received more edits than smaller circles. The highest number of major edits was 2,627.

For the central image, each article is size coded based on the likelihood that it is math, science, or technology related.

- 0%
- 50%
- 100%

All five images are color coded based on type. Transparency is used for legibility, and creates different colors when nodes overlap.

- Math
- Science
- Technology

Article Popularity
Articles are size coded based on the number of Wikipedia articles referencing it. Larger circles are receiving more links from other articles than smaller circles. The highest number of references to an article was 142,602.

Number of Bursts
Articles are size coded based on the number of bursts, i.e. sudden increases, of edit activity that occurred during the article's lifetime. Larger circles have had more bursts in activity than smaller circles. The most bursts an article had was 9.

Check out our **Zoom Maps** online!

VII.10
History of Science Fiction, by Ward Shulley

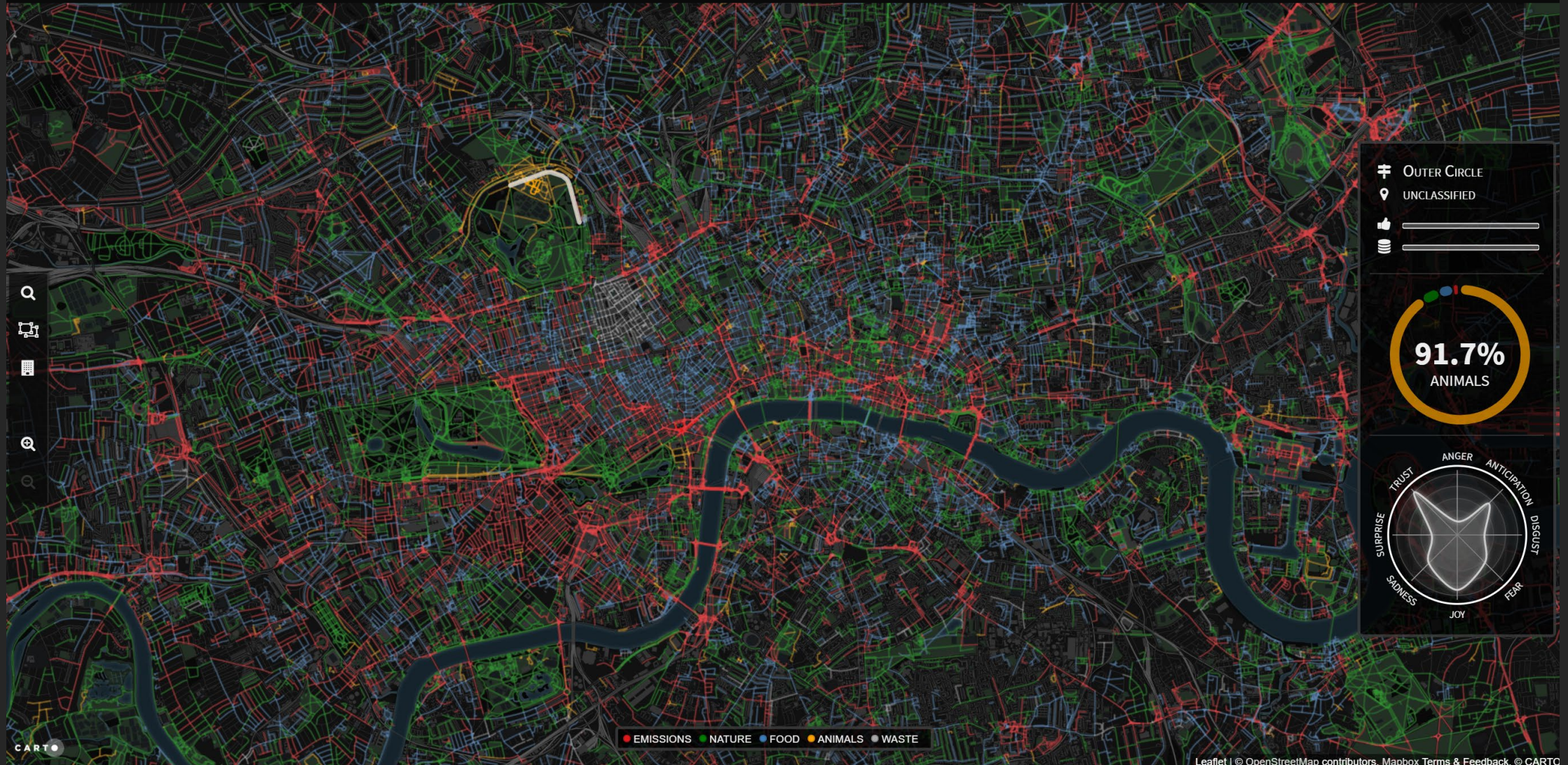
BROOKLYN, NY, 2011
Courtesy of Ward Shulley Studio

Ward Shulley is an artist identified with the Williamsburg scene in Brooklyn, New York. He is a writer, a painter, and a musician. This map plots the science fiction literary genre from its nascent beginnings in the 18th century, through the Romantic period, to the modern era. Emerging out of the data, here the narrative structure perceives and organizes the data. The map's structure is like a tree, tracing roots to pre-historical sources and whose body, the branches, are like the roots of the modern era. The map is a complex network of colored lines and text, representing the evolution of science fiction literature. It includes various sub-genres like 'SCIENCE ADVENTURE', 'FANTASY ADVENTURE', 'SPACE OPERA', 'CYBER PUNK', and 'NEW SPACE OPERA'. It also lists numerous authors and works, such as Jules Verne, Mary Shelley, Frankenstein, and the first SF novel. The map is presented in a zoomed-in view within a digital interface, showing navigation controls like a compass and zoom in/out buttons.

PLACES & SPACES
MAPPING & DESIGN

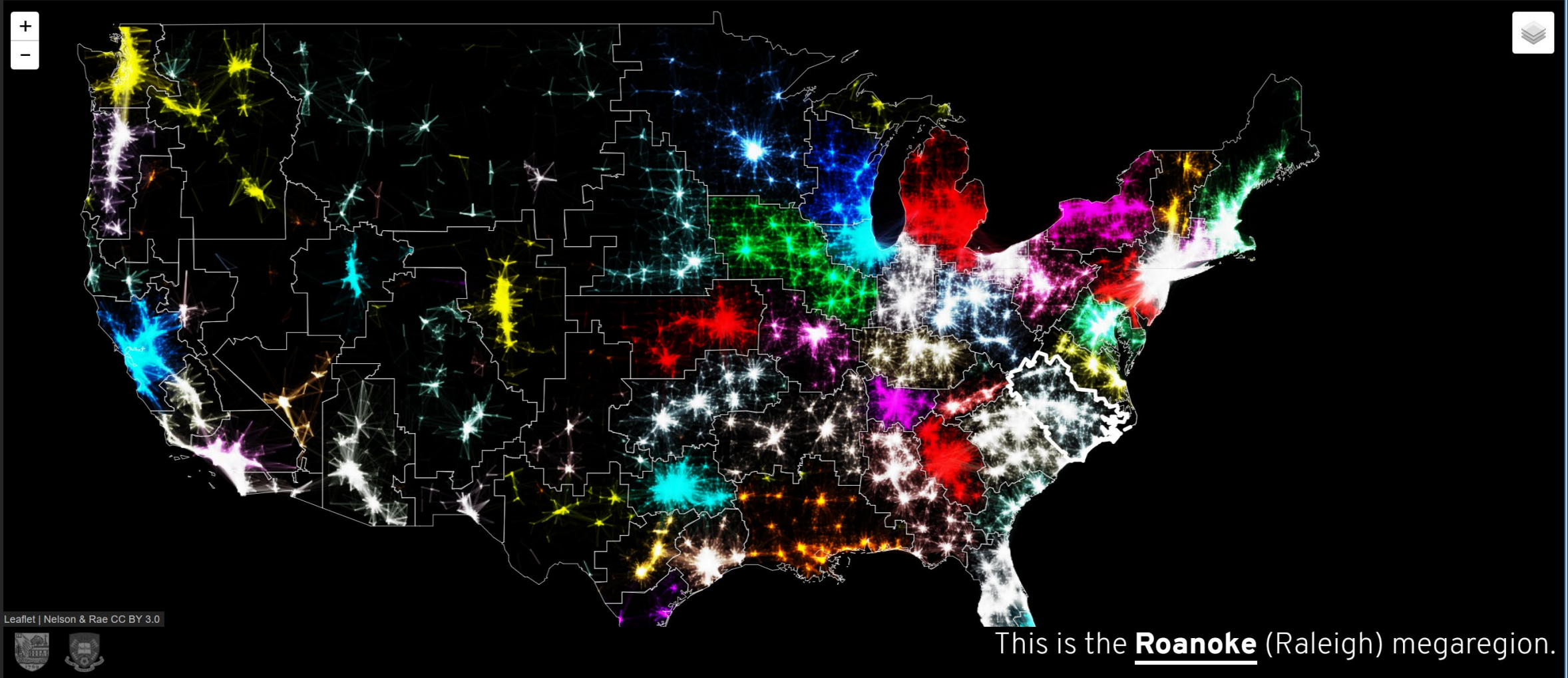
Visit scimaps.org and check out all our maps in stunning detail!

SMELLY MAPS



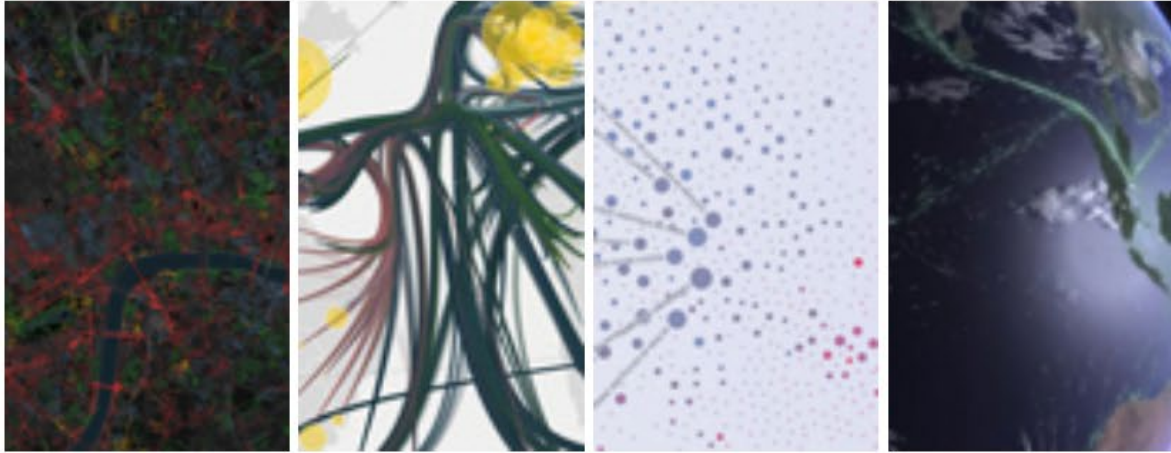
THE MEGAREGIONS OF THE US

Explore the new geography of commuter connections in the US.
Tap to identify regions. Tap and hold to see a single location's commuted.



Iteration XII (2016)

Macrosopes for Making Sense of Science



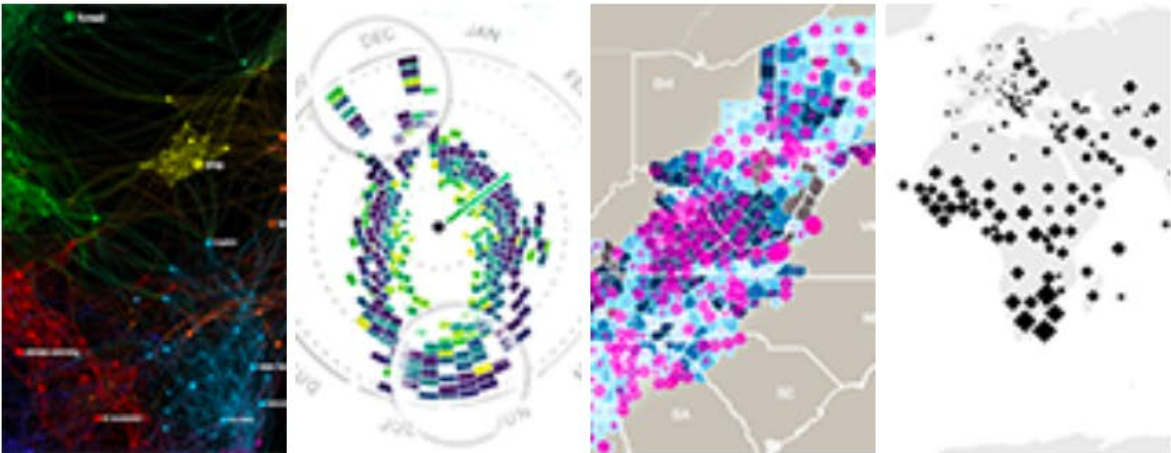
Iteration XIII (2017)

Macrosopes for Playing with Scale



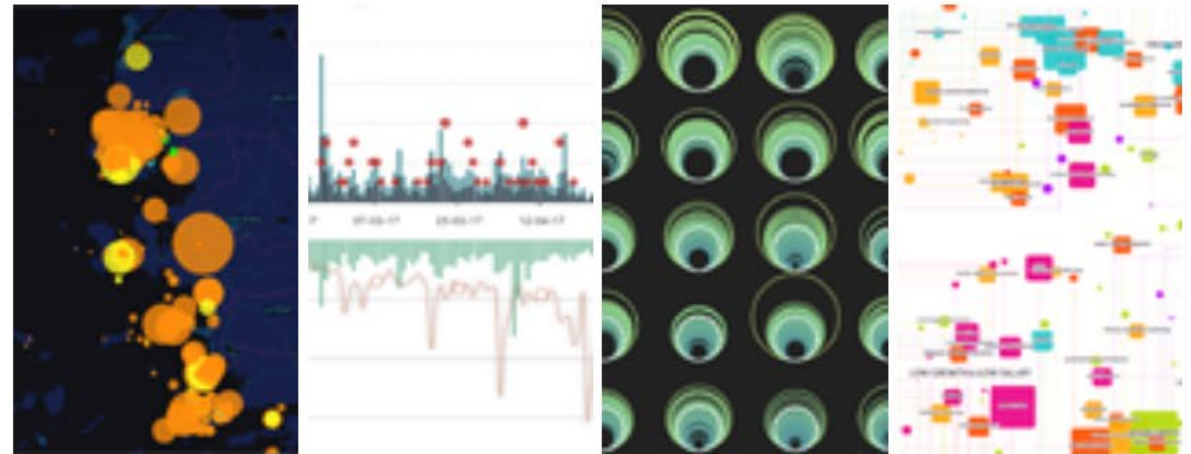
Iteration XIV (2018)

Macrosopes for Ensuring our Well-being



Iteration XV (2019)

Macrosopes for Tracking the Flow of Resources





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.



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 at <http://modsti.cns.iu.edu/report>





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



Arthur M. Sackler Colloquium on Modeling and Visualizing Science and Technology Developments

✔ **Twin-Win Model: A human-centered approach to research success**

Ben Shneiderman

PNAS December 11, 2018 115 (50) 12590-12594; first published December 10, 2018. <https://doi.org/10.1073/pnas.1802918115>

✔ **Forecasting innovations in science, technology, and education**

FROM THE COVER

Katy Börner, William B. Rouse, Paul Trunfio, and H. Eugene Stanley

PNAS December 11, 2018 115 (50) 12573-12581; first published December 10, 2018. <https://doi.org/10.1073/pnas.1818750115>

✔ **How science and technology developments impact employment and education**

Wendy Martinez

PNAS December 11, 2018 115 (50) 12624-12629; first published December 10, 2018. <https://doi.org/10.1073/pnas.1803216115>

✔ **Scientific prize network predicts who pushes the boundaries of science**

Yifang Ma and Brian Uzzi

PNAS December 11, 2018 115 (50) 12608-12615; first published December 10, 2018. <https://doi.org/10.1073/pnas.1800485115>

✔ **The role of industry-specific, occupation-specific, and location-specific knowledge in the growth and survival of new firms**

C. Jara-Figueroa, Bogang Jun, Edward L. Glaeser, and Cesar A. Hidalgo

PNAS December 11, 2018 115 (50) 12646-12653; first published December 10, 2018. <https://doi.org/10.1073/pnas.1800475115>

<https://www.pnas.org/modeling>

Skill Discrepancies Between Research, Education, and Jobs Reveal the Critical Need to Supply Soft Skills for the Data Economy

Study the **(mis)match** and **temporal dynamics** of S&T progress, education and workforce development options, and job requirements.

Challenges:

- Rapid change of STEM knowledge
- Increase in tools, AI, robotics
- Social skills (project management, team leadership) become ever more important
- Increasing team size

Börner, Katy, Olga Scriver, Mike Gallant, Shutian Ma, Xiaozhong Liu, Keith Chewning, Lingfei Wue, and James A. Evans. 2018. "Skill Discrepancies Between Research, Education, and Jobs Reveal the Critical Need to Supply Soft Skills for the Data Economy." *PNAS* 115(50): 12630-12637.

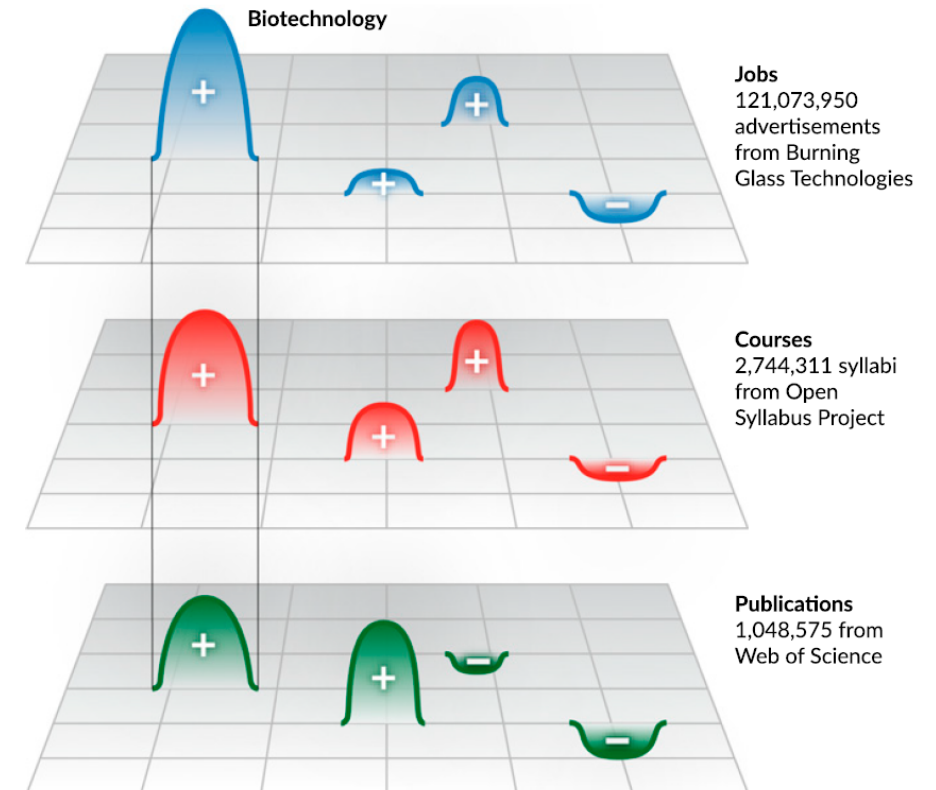


Fig. 1. The interplay of job market demands, educational course offerings, and progress in S&T as captured in publications. Color-coded mountains (+) and valleys (-) indicate different skill clusters. For example, skills related to Biotechnology might be mentioned frequently in job descriptions and taught in many courses, but they may not be as prevalent in academic publications. In other words, there are papers that mention these skills, but labor demand and commercial activity might be outstripping publication activity in this area. The numbers of jobs, courses, and publications that have skills associated and are used in this study are given on the right.

Stakeholders and Insight Needs

- **Students:** What jobs will exist in 1-4 years? What program/learning trajectory is best to get/keep my dream job?
- **Teachers:** What course updates are needed? What balance of timely and timeless knowledge (to get a job vs. learn how to learn) should I teach? How to innovate in teaching and maintain job security or tenure?
- **Universities:** What programs should be created? What is my competition doing? How do I tailor programs to fit local needs?
- **Science Funders:** How can S&T investments improve short- and long-term prosperity? Where will advances in knowledge also yield advances in skills and technology?
- **Employers:** What skills are needed next year and in 5 and 10 years? Which institutions produce the right talent? What skills does my competition list in job advertisements?
- **Economic Developers:** What critical skills are needed to improve business retention, expansion, and recruitment in a region?

What is the ROI of my time, money, compassion?

Urgency

- **35% of UK jobs, and 30% in London**, are at high risk from automation over the coming 20 years. <https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/uk-futures/london-futures-agiletown.pdf>
- The aerospace industry and NASA have a disproportionately large percentage of workers aged 50 and older compared to the national average, and up to **half of the current workforce** will be eligible for retirement within the coming five years. Astronautics AIAA (2012) Recruiting, retaining, and developing a world-class aerospace workforce. https://www.aiaa.org/uploadedFiles/Issues_and_Advocacy/Education_and_Workforce/Aerospace%20Workforce-%20030112.pdf
- The rise of artificial intelligence will lead to the displacement of **millions of blue-collar as well as white-collar jobs** in the coming decade. Beyer D (2016) The future of machine intelligence: Perspectives from leading practitioners ; Brynjolfsson E, McAfee A (2014) The second machine age: Work, progress, and prosperity in a time of brilliant technologies; Ford M (2015) Rise of the Robots: Technology and the Threat of a Jobless Future.
- COVID-19 economic freeze **could cost 47 million jobs** and send the **unemployment rate past 32%**, according to St. Louis Fed projections.

NSF RAISE: C-Accel Pilot: 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), automation, COVID-19, and other developments.

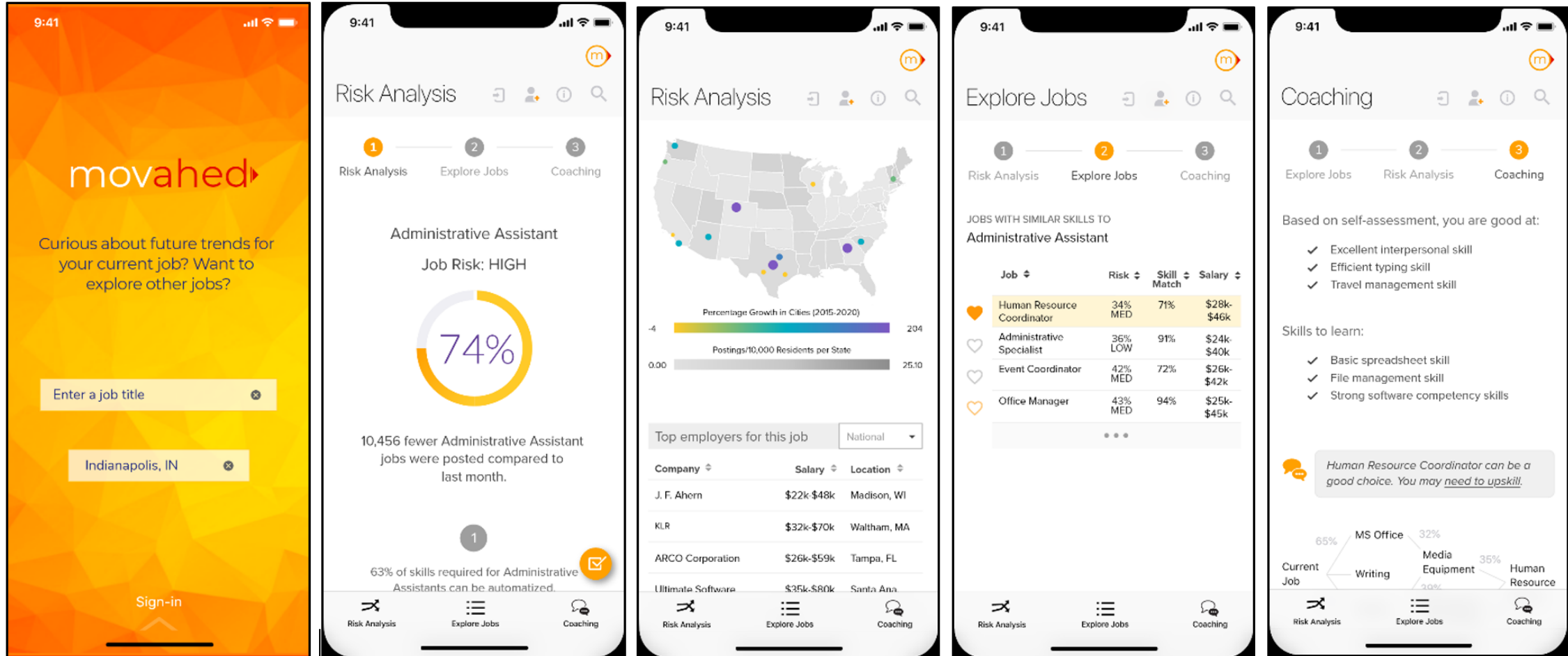
The project will demonstrate how labor market and course syllabi data, learning analytics, and insights on transferability of learned skills can be combined and visualized in novel ways to support a learner's decision-making about, sustained engagement in, and application to their job of professional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



<https://www.nsf.gov/od/oia/convergence-accelerator/>



Develop and deploy **socio-technical systems** that encourage US workers to explore the **evolving landscape of new jobs** and re/up-skilling opportunities—to not only recover from current risks/crisis but to leap forward into more resilient and more desirable futures.

Data Visualization Literacy

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

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.

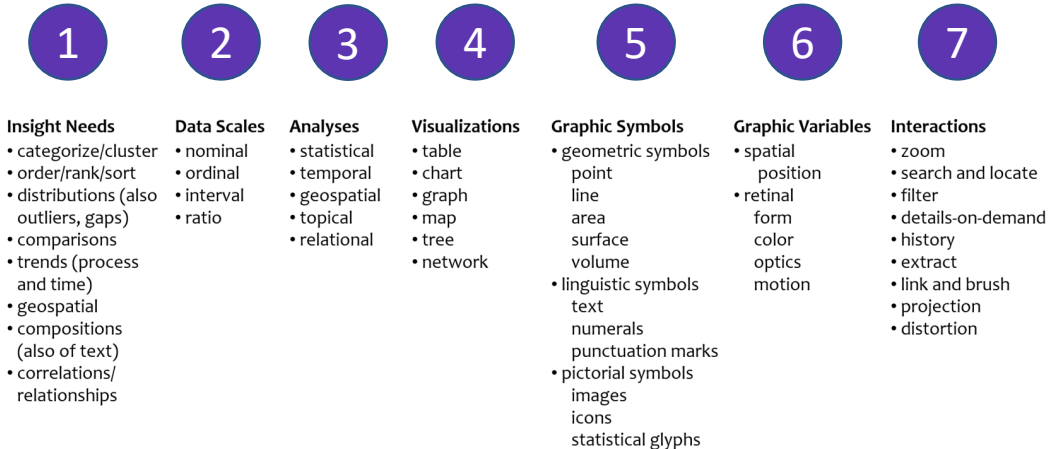
Börner, Katy, Andreas Bueckle, and Michael Ginda. 2019. Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. *PNAS*, 116 (6) 1857-1864.

Data Visualization Literacy Framework (DVL-FW)

Consists of two parts:

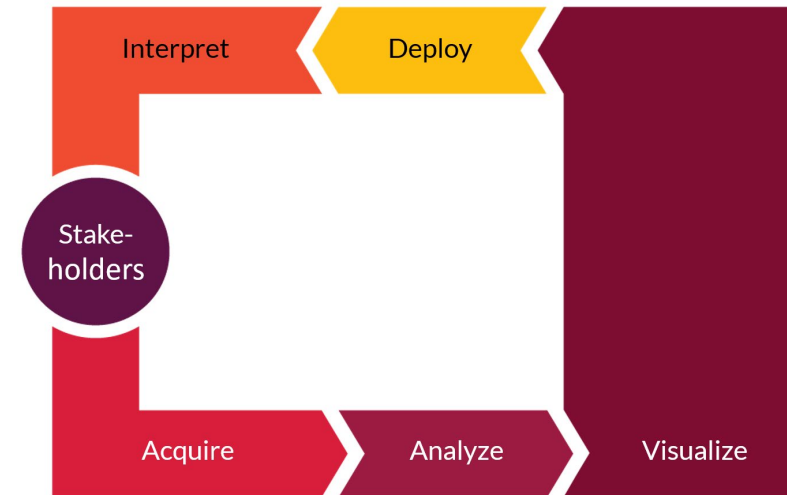
DVL Typology

Defines 7 types with 4-17 members each.

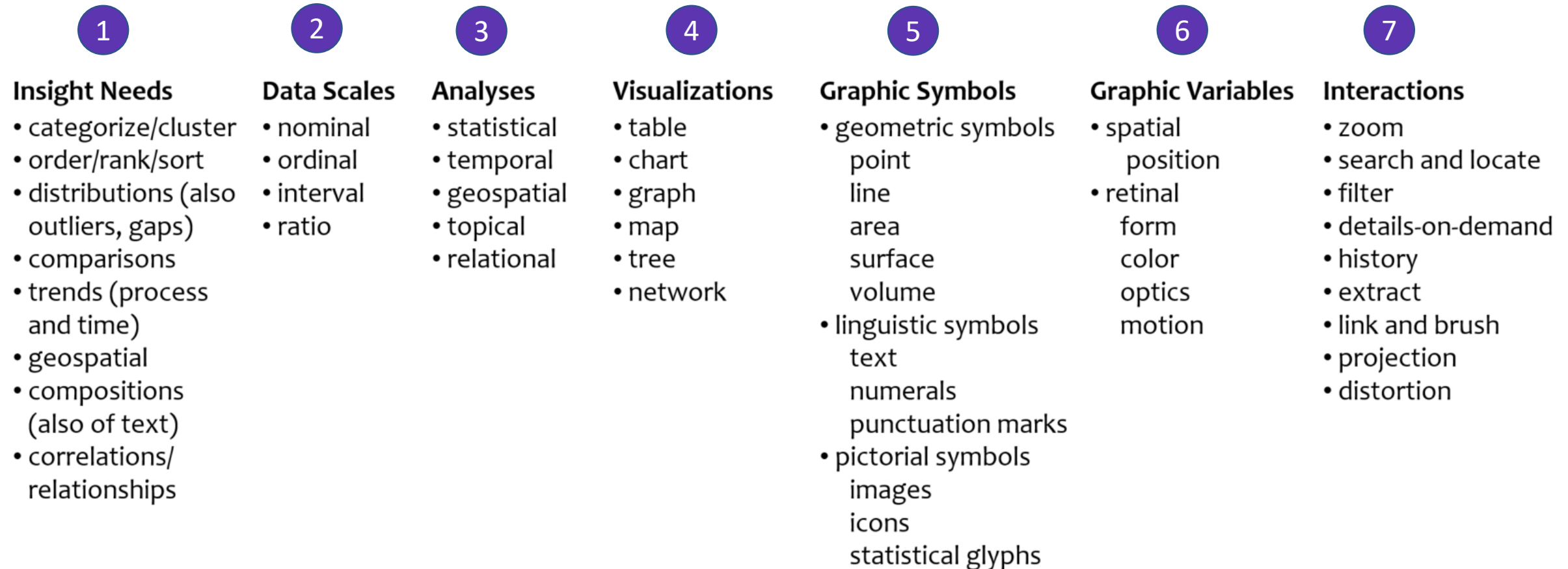


DVL Workflow Process

Defines 5 steps required to render data into insights.



Typology of the Data Visualization Literacy Framework

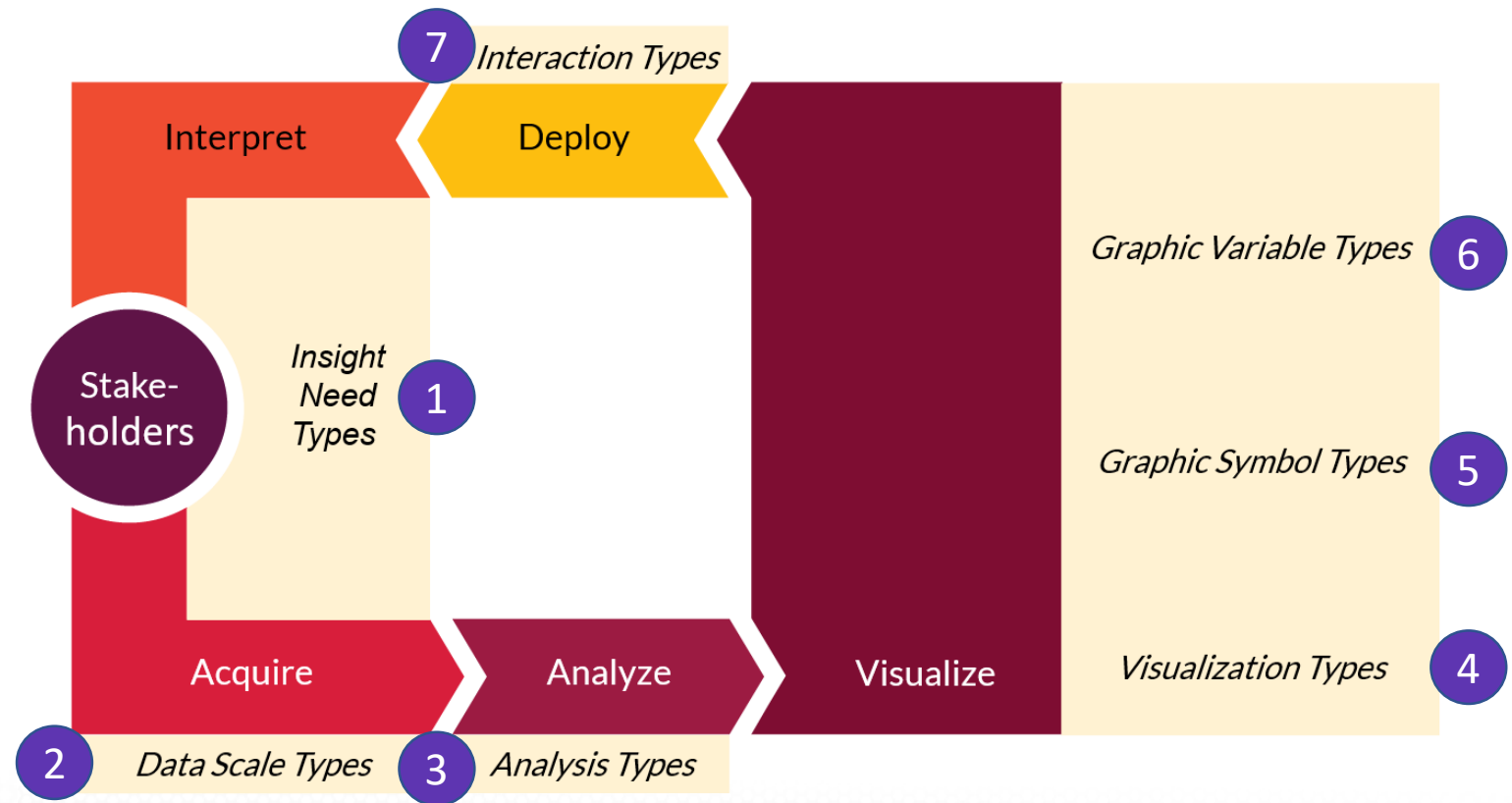


Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 25.

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.

☰ Make-A-Vis i

Data

ISI Publications: (CSV) Preprocessed-wos

Title	Authors	Journal	Year	#Cites
Total Records: 562				

Journals: (from ISI Publications)

Name	#Papers	#Cites	First Year	Last Year
BMC EVOL BIOL	1	7	2006	2006
FEBS J	2	0	2005	2005
NAT PHYS	3	18	2005	2006

Total Records: 562

Make Visualization

Select Visualization Type

Scatter Graph

Temporal Bar Graph

Geomap

Scimap

Done

Select Graphic Symbol Type(s) ▼

Select Graphic Variable Types ▼

Temporal Bar Graph ✕

+

✎

4

5

6

Graphic Variable Types

Position: x, y; possibly z

Form:

- Size
- Shape
- Rotation (Orientation)

Color:

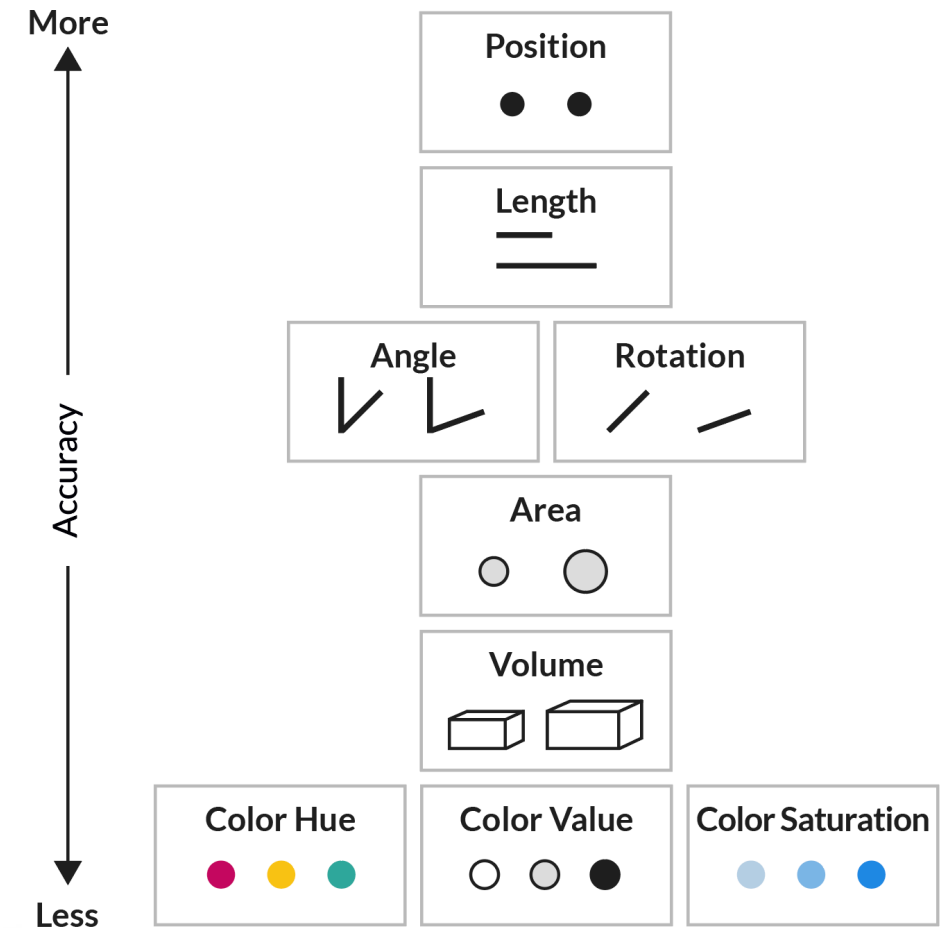
- Value (Lightness)
- Hue (Tint)
- Saturation (Intensity)



Optics: Blur, Transparency, Shading, Stereoscopic Depth

Texture: Spacing, Granularity, Pattern, Orientation, Gradient

Motion: Speed, Velocity, Rhythm



Graphic Symbol Types

			Geometric Symbols		Linguistic Symbols	Pictorial Symbols
			Point	Line		
Spatial	Position	X Y				
		Retinal	Form	Size		
Shape					Text Text Text	
Color	Value				Text Text Text	
	Hue				Text Text Text	
	Saturation				Text Text Text	
Texture	Granularity					
	Pattern					
Motion Optics	Blur				Text Text Text	
	Speed					

Graphic Variable Types

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

Qualitative

Also called:
Categorical Attributes
Identity Channels

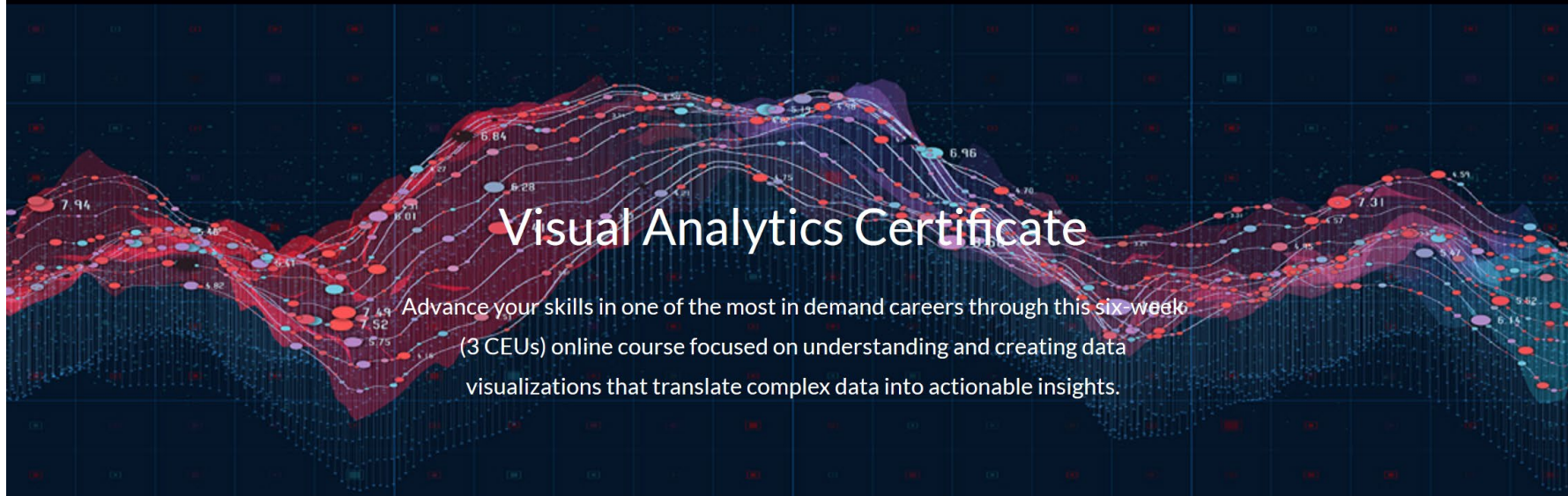
Quantitative

Also called:
Ordered Attributes
Magnitude Channels

Graphic Variable Types Versus Graphic Symbol Types

			Geometric Symbols					Linguistic Symbols Text, Numerals, Punctuation Marks					Pictorial Symbols Images, Icons, Statistical Glyphs					
			Point	Line	Area	Surface	Volume											
Spatial	x	quantitative																
	y	quantitative																
	z	quantitative																
Retinal	Form	Size	quantitative	NA (Not Applicable)														
		Shape	qualitative	NA														
		Rotation	quantitative	NA														
		Curvature	quantitative	NA														
	Angle	quantitative	NA															
	Closure	quantitative	NA															
	Value	quantitative																
	Color	Hue	qualitative															
Saturation	quantitative																	
Retinal	Texture	Spacing	quantitative															
		Granularity	quantitative															
		Pattern	qualitative															
		Orientation	quantitative	NA														
		Gradient	quantitative															
	Optics	Blur	quantitative															
		Transparency	quantitative															
		Shading	quantitative															
	Motion	Stereoscopic Depth	quantitative	Point in foreground .. background	Line in foreground .. background	Area in foreground .. background	Surface in foreground .. background	Volume in foreground .. background	Text in foreground .. background					Icons in foreground .. background				
		Speed	quantitative															
Velocity		quantitative																
Rhythm	quantitative	Blinking point slow .. fast	Blinking line slow .. fast	Blinking area slow .. fast	Blinking surface slow .. fast	Blinking volume slow .. fast	Blinking text slow .. fast					Blinking icons slow .. fast						

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



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References

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