CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY
SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

Models and Visualizations of Education, Scientific, and Job Market Developments

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Intelligent Systems Engineering & Information Science
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Indiana University Network Science Institute (IUNI)
Indiana University, Bloomington, IN, USA

U.S. Department of Energy Webinar Series on Portfolio Analytics – Tools for R&D Decision Making
https://science.osti.gov/Portfolio-Analytics

August 18, 2020

Overview

Modeling and Visualizing Education, Science and Technology

- https://www.pnas.org/modeling

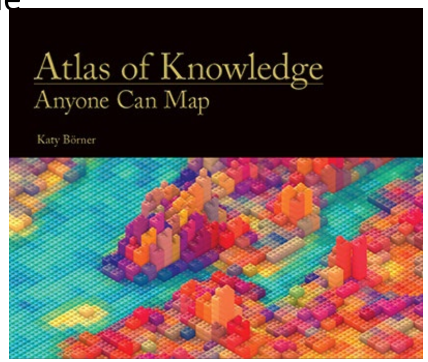
Skill Discrepancies

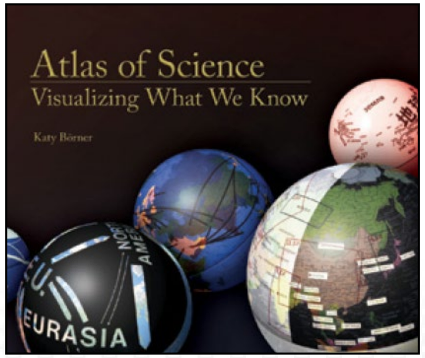
- Börner, Katy, Olga Scrivner, Michael Gallant, Shutian Ma, Xiaozhong Liu, Keith Chewning, Lingfei Wu, and James Evans. 2018. "Skill Discrepancies Between Research, Education, and Jobs Reveal the Critical Need to Supply Soft Skills for the Data Economy". *PNAS* 115 (50): 12630-12637. doi: 10.1073/pnas.1804247115.

Needed: Increase Data Visualization Literacy (https://visanalytics.cns.iu.edu)

- 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.

Places & Spaces: Mapping Science exhibit (http://scimaps.org)





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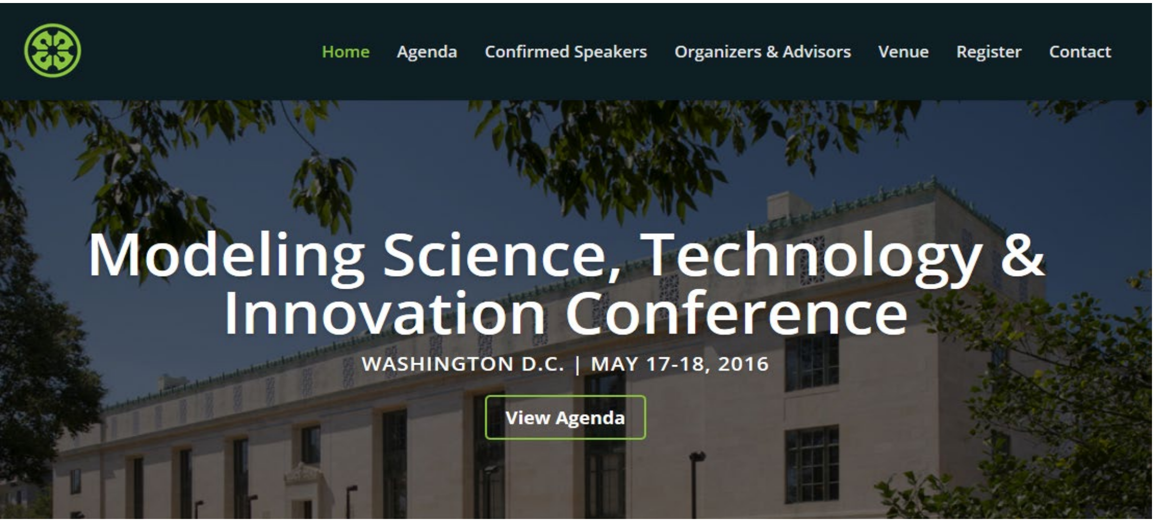
Modelling and Visualizing Education, Science and Technology,

Börner, Katy, William Rouse, Paul Trunfio, and H. Eugene Stanley. 2018. "Forecasting Innovations in Science, Technology, and Education". *PNAS* 115 (50): 12573-12581. doi: 10.1073/pnas.1818750115.

See also https://www.pnas.org/modeling



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

NSF | ETE FEDERAL IT | THOMSON REUTERS | INDIANA UNIVERSITY NETWORK SCIENCE INSTITUTE

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

Arthur M. Sackler COLLOQUIA OF THE NATIONAL ACADEMY OF SCIENCES | Clarivate | Microsoft

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

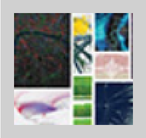
LabX

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

PNAS
Proceedings of the National Academy of Sciences of the United States of America

Keyword, Author, or DOI

Advanced Search

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

PNAS Proceedings of the National Academy of Sciences of the United States of America

Keyword, Author, or DOI

Advanced Search

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

- **Skill discrepancies between research, education, and jobs reveal the critical need to supply soft skills for the data economy**

  Katy Börner, Olga Scrivner, Mike Gallant, Shutian Ma, Xiaozhong Liu, Keith Chewning, Lingfei Wu, and James A. Evans

  PNAS December 11, 2018 115 (50) 12630-12637; first published December 10, 2018. https://doi.org/10.1073/pnas.1804247115

- **Changing demographics of scientific careers: The rise of the temporary workforce**

  Staša Milojević, Filippo Radicchi, and John P. Walsh

  PNAS December 11, 2018 115 (50) 12616-12623; first published December 10, 2018. https://doi.org/10.1073/pnas.1800478115

- **The chaperone effect in scientific publishing**

  Vedran Sekara, Pierre Deville, Sebastian E. Ahnert, Albert-László Barabási, Roberta Sinatra, and Sune Lehmann

  PNAS December 11, 2018 115 (50) 12603-12607; first published December 10, 2018. https://doi.org/10.1073/pnas.1800471115

- **Modeling research universities: Predicting probable futures of public vs. private and large vs. small research universities**

  William B. Rouse, John V. Lombardi, and Diane D. Craig

  PNAS December 11, 2018 115 (50) 12582-12589; first published December 10, 2018. https://doi.org/10.1073/pnas.1807174115

and more …

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

- Data and Crosswalks
- MaxMatch for NLP
- Causal Analyses
- Visualizations

Börner, Katy, Olga Scrivner, 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.

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Skill discrepancies between research, education, and jobs reveal the critical need to supply soft skills for the data economy

Katy Börner[a,b,1], Olga Scrivner[a], Mike Gallant[a], Shutian Ma[a,c], Xiaozhong Liu[a], Keith Chewning[d], Lingfei Wu[e,f,g,h], and James A. Evans[f,g,i,1]

[a]School of Informatics, Computing, and Engineering, Indiana University, Bloomington, IN 47408; [b]Educational Technology/Media Centre, Dresden University of Technology, 01062 Dresden, Germany; [c]Department of Information Management, Nanjing University of Science and Technology, 210094 Nanjing, China; [d]Burning Glass Technologies, Boston, MA 02110; [e]School of Journalism and Communication, Nanjing University, 210008 Nanjing, China; [f]Department of Sociology, University of Chicago, Chicago, IL 60637; [g]Knowledge Lab, University of Chicago, Chicago, IL 60637; [h]Tencent Research Institute, 100080 Beijing, China; and [i]Santa Fe Institute, Santa Fe, NM 87501

Edited by William B. Rouse, Stevens Institute of Technology, Hoboken, NJ, and accepted by Editorial Board Member Pablo G. Debenedetti September 12, 2018 (received for review March 14, 2018)

Rapid research progress in science and technology (S&T) and continuously shifting workforce needs exert pressure on each other and on the educational and training systems that link them. Higher education institutions aim to equip new generations of students with skills and expertise relevant to workforce participation for decades to come, but their offerings sometimes misalign with commercial needs and new techniques forged at the frontiers of research. Here, we analyze and visualize the dynamic skill (mis-)alignment between academic push, industry pull, and educational offerings, paying special attention to the rapidly emerging areas of data science and data engineering (DS/DE). The visualizations and computational models presented here can help key decision makers understand the evolving structure of skills so that they can craft educational programs that serve workforce needs. Our study uses millions of publications, course syllabi, and job advertisements published between 2010 and 2016. We show how courses mediate between research and jobs. We also discover responsiveness in the academic, educational, and industrial system in how skill demands from industry are as likely to drive skill attention in research as the converse. Finally, we reveal the increasing importance of uniquely human skills, such as communication, negotiation, and persuasion. These skills are currently underexamined in research and undersupplied through education for the labor market. In an increasingly data-driven economy, the demand for “soft” social skills, like teamwork and communication, increase with greater demand for “hard” technical skills and tools.

science of science | job market | data mining | visualization | market gap analysis

Education has been a critical vehicle of economic growth and social progress throughout the modern era. Higher education

doors. Some predictions say hundreds or even thousands of colleges and universities will close or merge in the coming years (4).

In addition, there seem to be major discrepancies and delays between leading scientific research, job market needs, and educational content. This has been particularly expressed with respect to science, technology, engineering, and mathematics jobs, where scientific and technological progress is rapid. Strategic decision making on what to teach, whom to hire, and what new research to fund benefits from a systematic analysis of the interplay between science and technology (S&T) developments, courses and degrees offered, and job market needs. Specifically, stakeholders in US higher education urgently need answers to the following questions. (*i*) Students: what jobs might exist in 5–10 years? What educational trajectories will best achieve my dream job? What core and specialized skills are required for what jobs and offered by what schools and programs? (*ii*) Teachers: what course updates are most needed? What balance of timely vs. timeless knowledge should I teach? How can I innovate in teaching and maintain job security or tenure? (*iii*) Universities: what programs should be created? What is my competition doing? How do I tailor programs to fit workforce needs? (*iv*) 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 (5)? (*v*) Employers: what skills are needed next year and in 5 and 10 years? Which institutions produce the right talent? What skills are listed in job advertisements by my competition? How do I hire and train

This paper results from the Arthur M. Sackler Colloquium of the National Academy of Sciences, “Modeling and Visualizing Science and Technology Developments,” held Decem-

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
- Social skills (project management, team leadership)
- Increasing team size

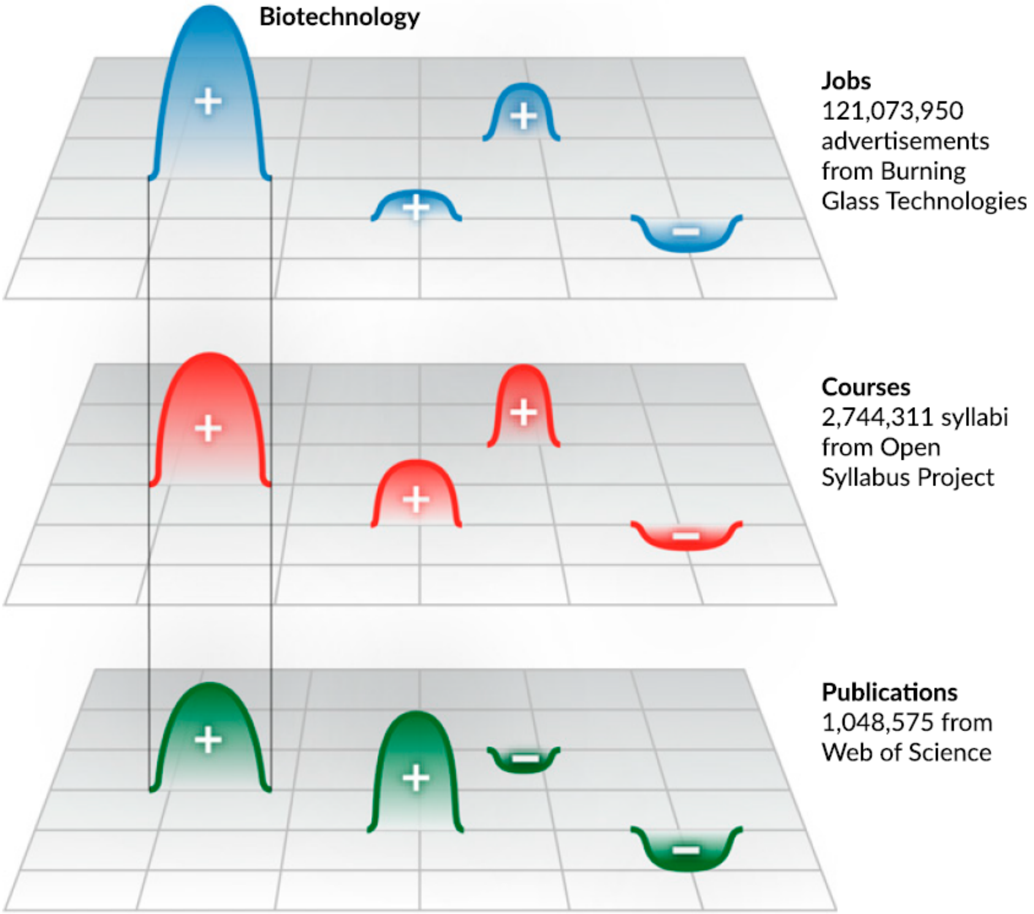

Fig. 1. The interplay of job market demands, educational course offerings, and progress in S&T as captured in publications. Color-coded mountains (+) and valleys (–) indicate different skill clusters. For example, skills related to Biotechnology might be mentioned frequently in job descriptions and taught 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.

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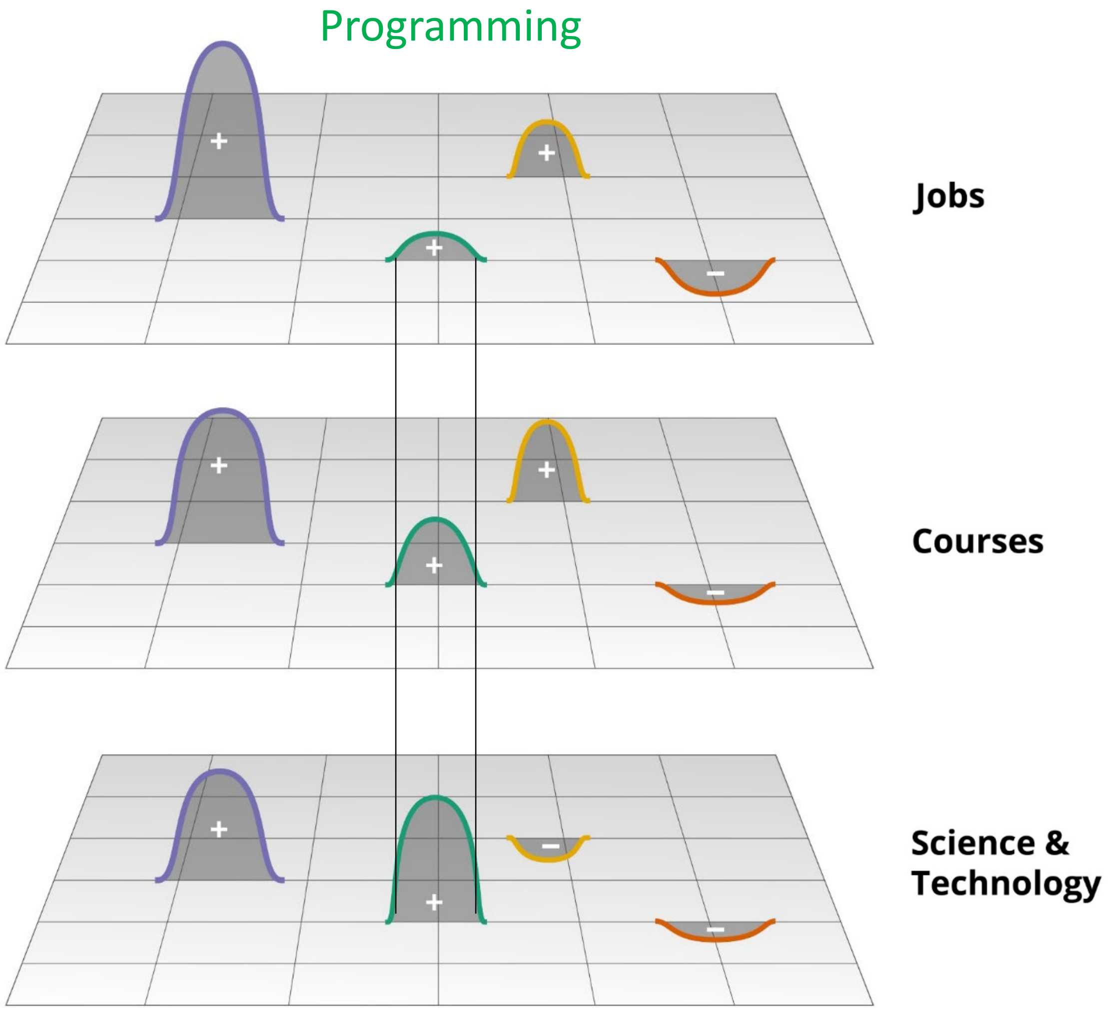
Programming
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Jobs
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Courses
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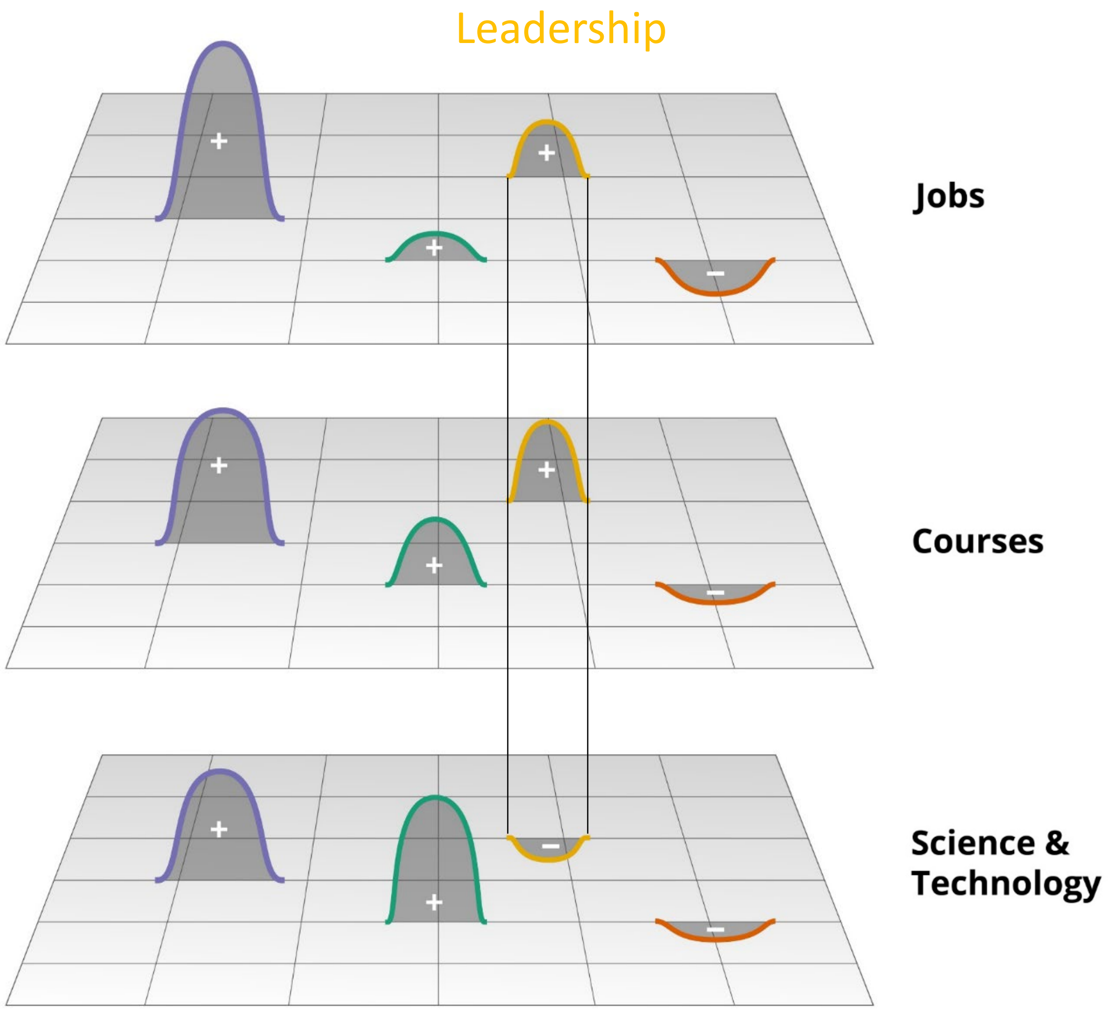
Science &
Technology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Science &
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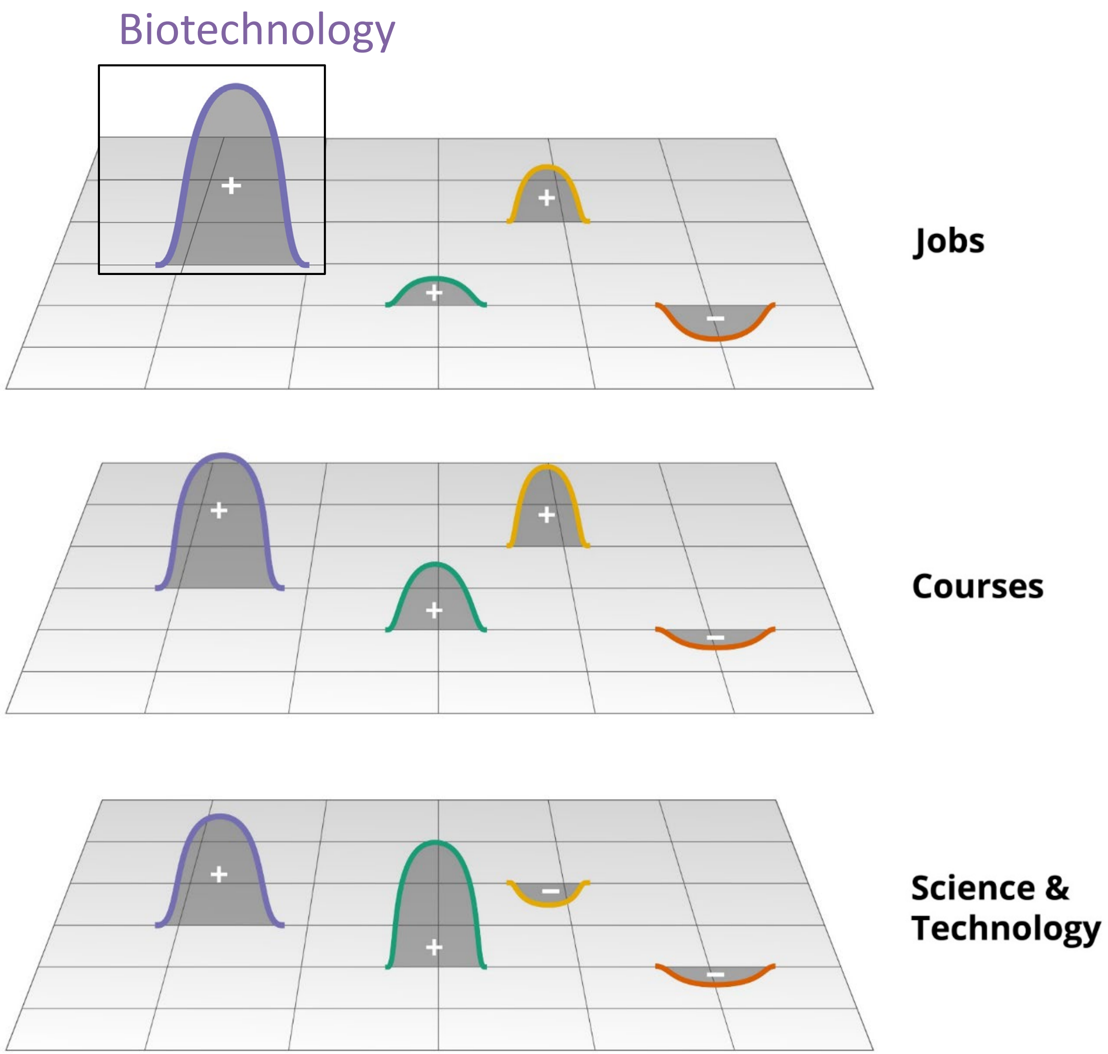

Biotechnology
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Science &
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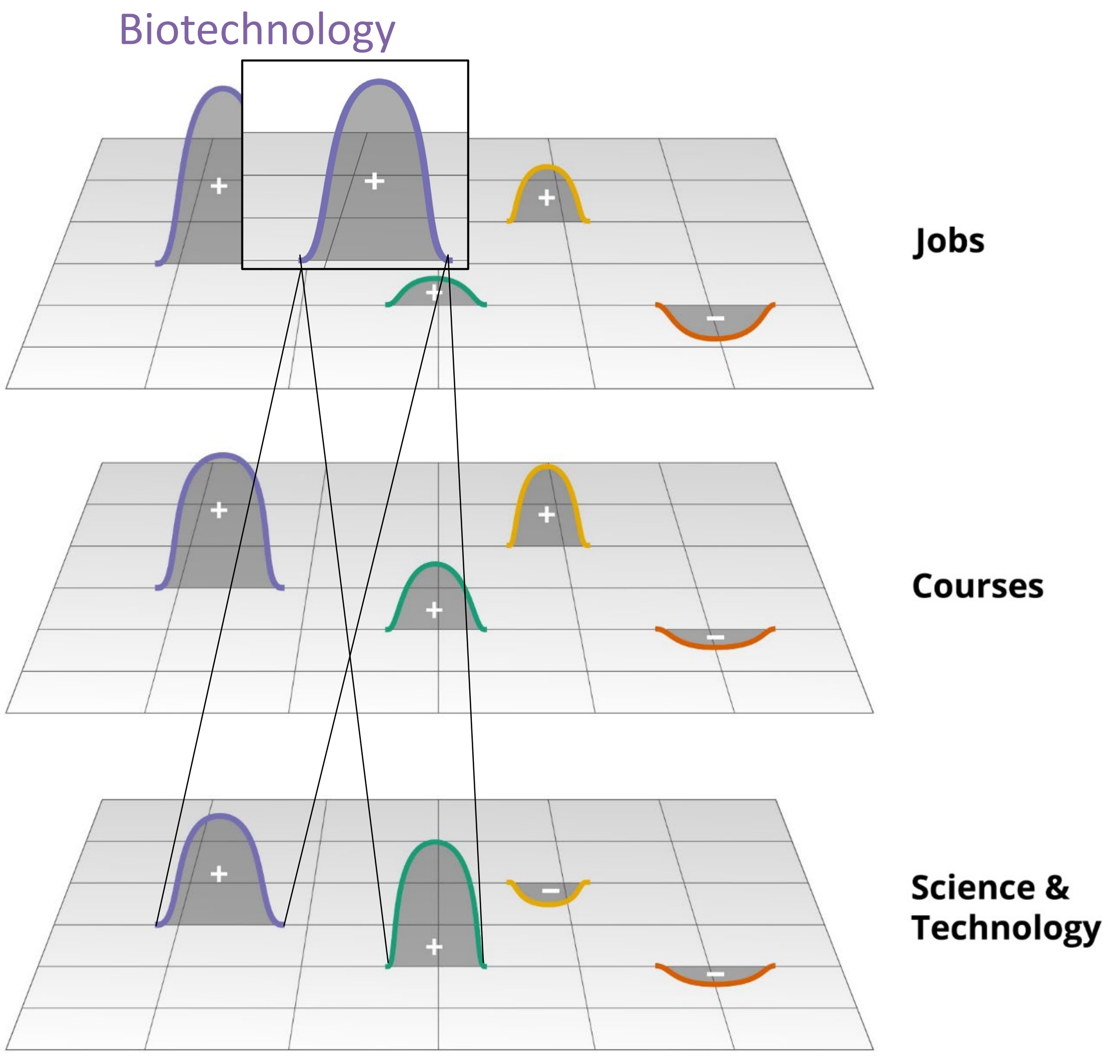
Biotechnology
Jobs
Courses
Science &
Technology

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 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. Auerswald PE (2017) The Code Economy: A Forty-thousand-year History; 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.

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

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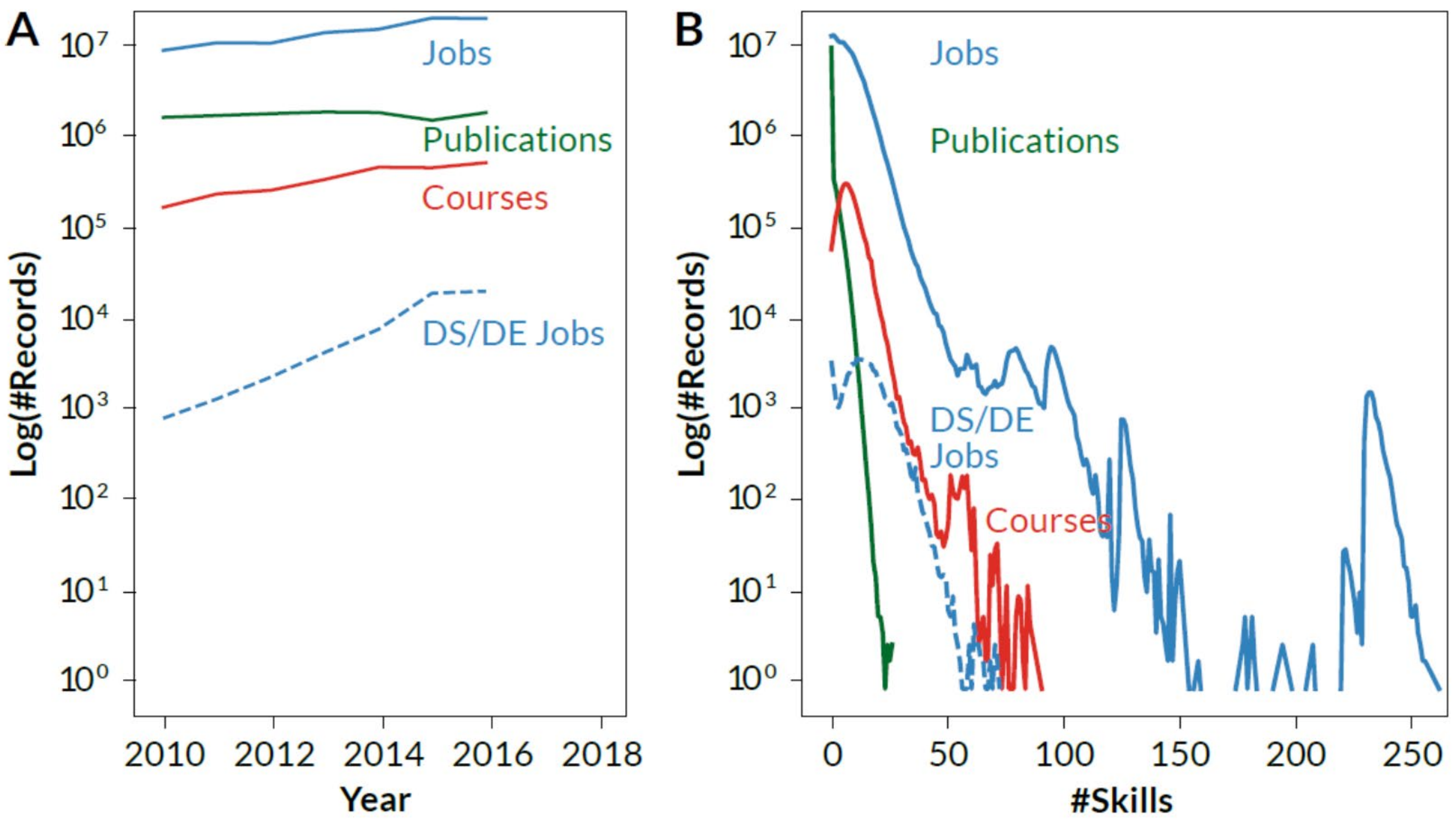
Datasets Used

Job advertisements by Burning Glass posted between Jan 2010-Dec 2016.

Web of Science publications published Jan 2010-Dec 2016.

Course descriptions from the Open Syllabus Project acquired in June 2018 for courses offered in 2010-2016.



Data Type	#Records	#Records with skills	#Records without skills
All Courses	3,062,277	2,744,311	54,733
All Jobs	132,011,926	121,073,950	10,937,976
DSDE Jobs	69,405	65,944	3,461
All Publications	15,691,162	1,048,575	14,642,587
DSDE Publications	1,048,575	807,756	240,819

Fig. 2. Basemap of 13,218 skills. In this map, each dot is a skill, triangles identify skill clusters, and squares represent skill families from the Burning Glass (BG) taxonomy. Labels are given for all skill family nodes and for the largest skill cluster (NA) to indicate placement of relevant subtrees. Additionally, hard and soft skills are overlaid using purple and orange nodes, respectively; node area size coding indicates base 10 log of skill frequency in DS/DE jobs. Skill area computation uses Voronoi tessellation.

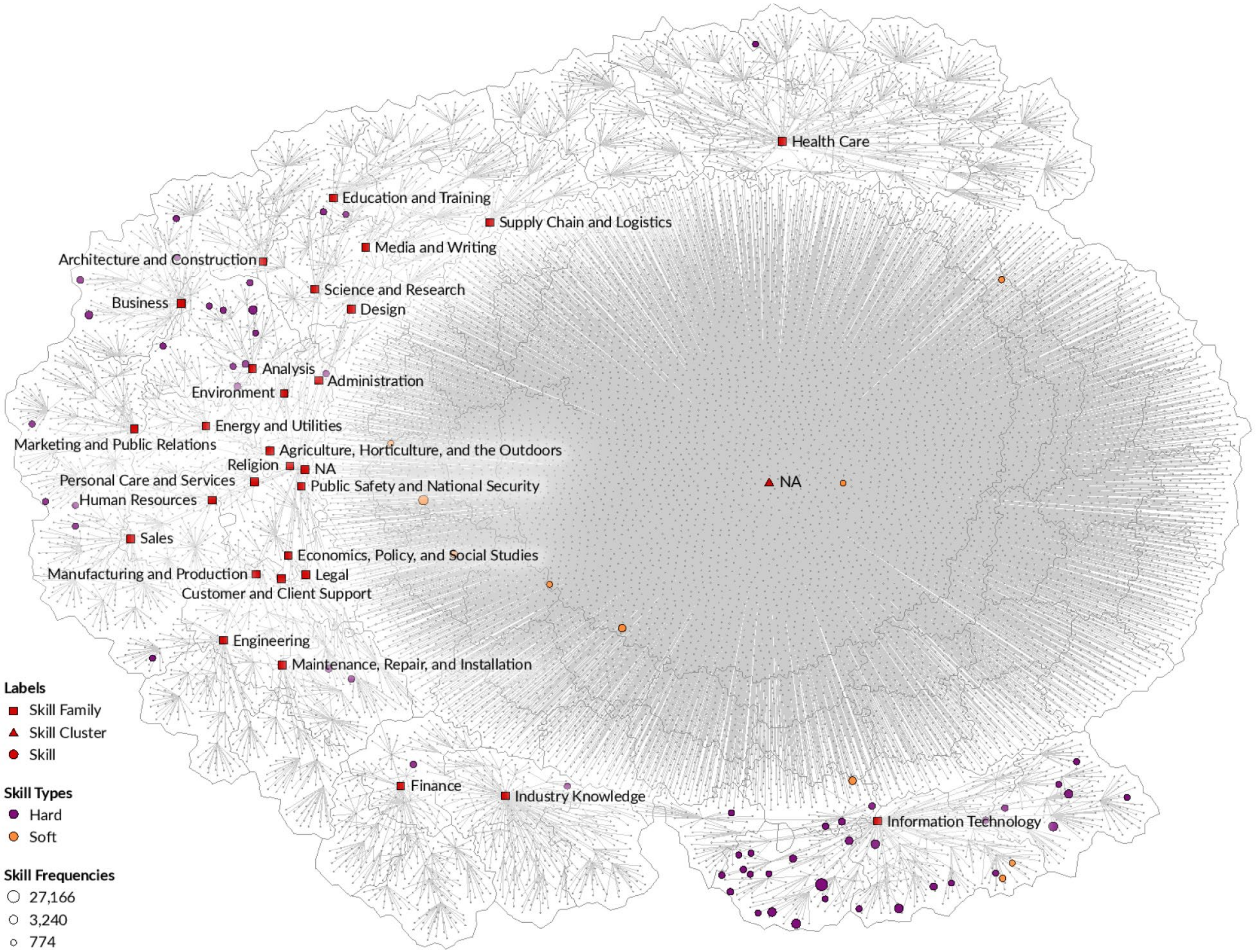
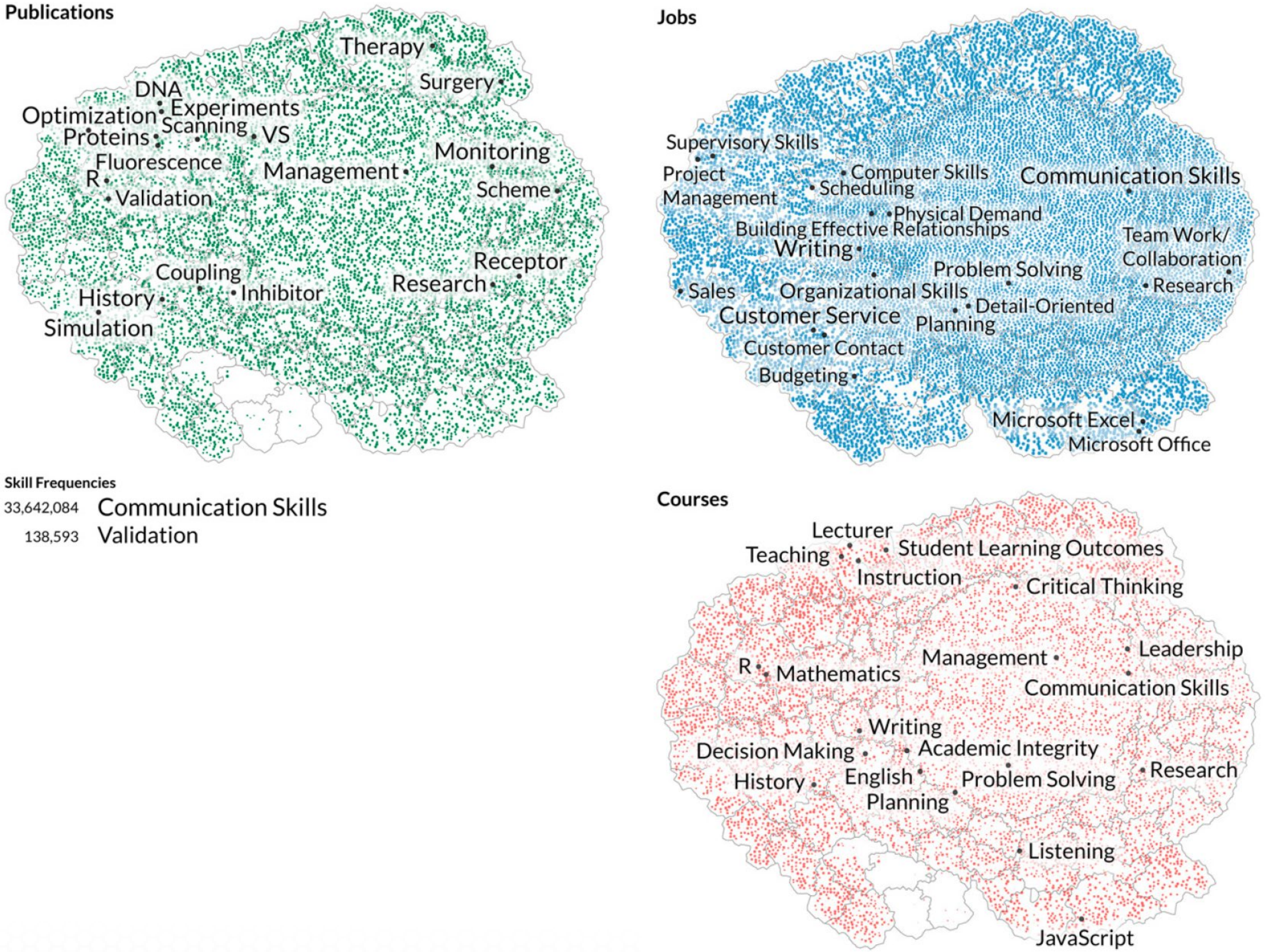


Fig. 3. Basemap of 13,218 skills with overlays of skill frequency in jobs, courses, and publications. This figure substantiates the conceptual drawing in Fig. 1 using millions of data records. Jobs skills are plotted in blue, courses are in red, and publications are in green. Node area size coding indicates base 10 log of skills frequency. The top 20 most frequent skills are labeled, and label sizes denote skill frequency.



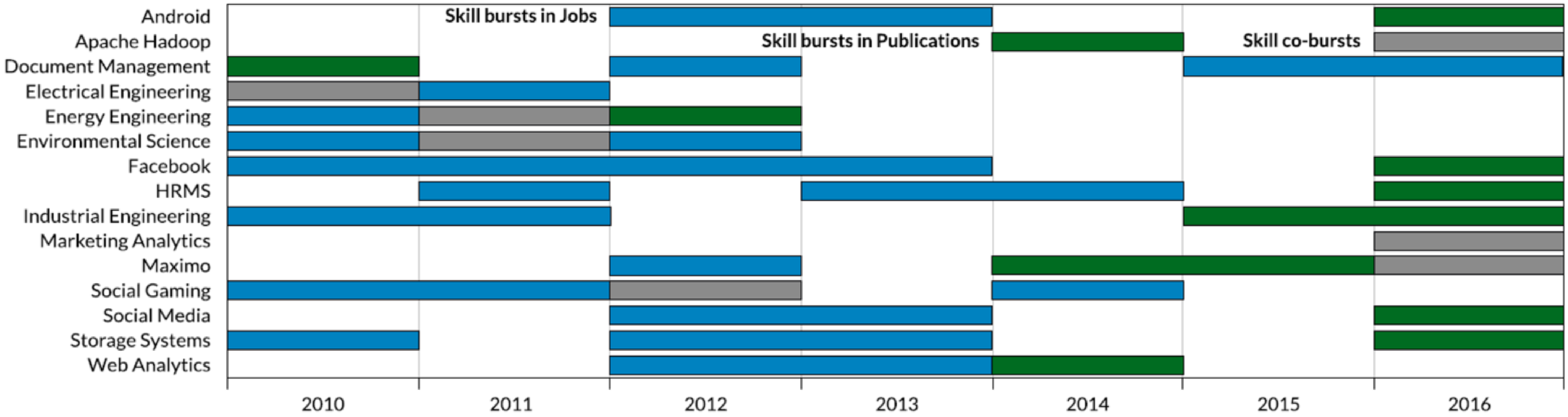


Fig. 4. Burst of activity in DS/DE skills in jobs and publications. Each burst is rendered as a horizontal bar with a start and an end date; skill term is shown on the left. Skills that burst in jobs are blue; skills bursting in publications are green. Seven skills burst in both datasets during the same years and are shown in gray. HRMS stands for human resources management system, and Maximo is an IBM system for managing physical assets.

Kullback-Leibler divergence

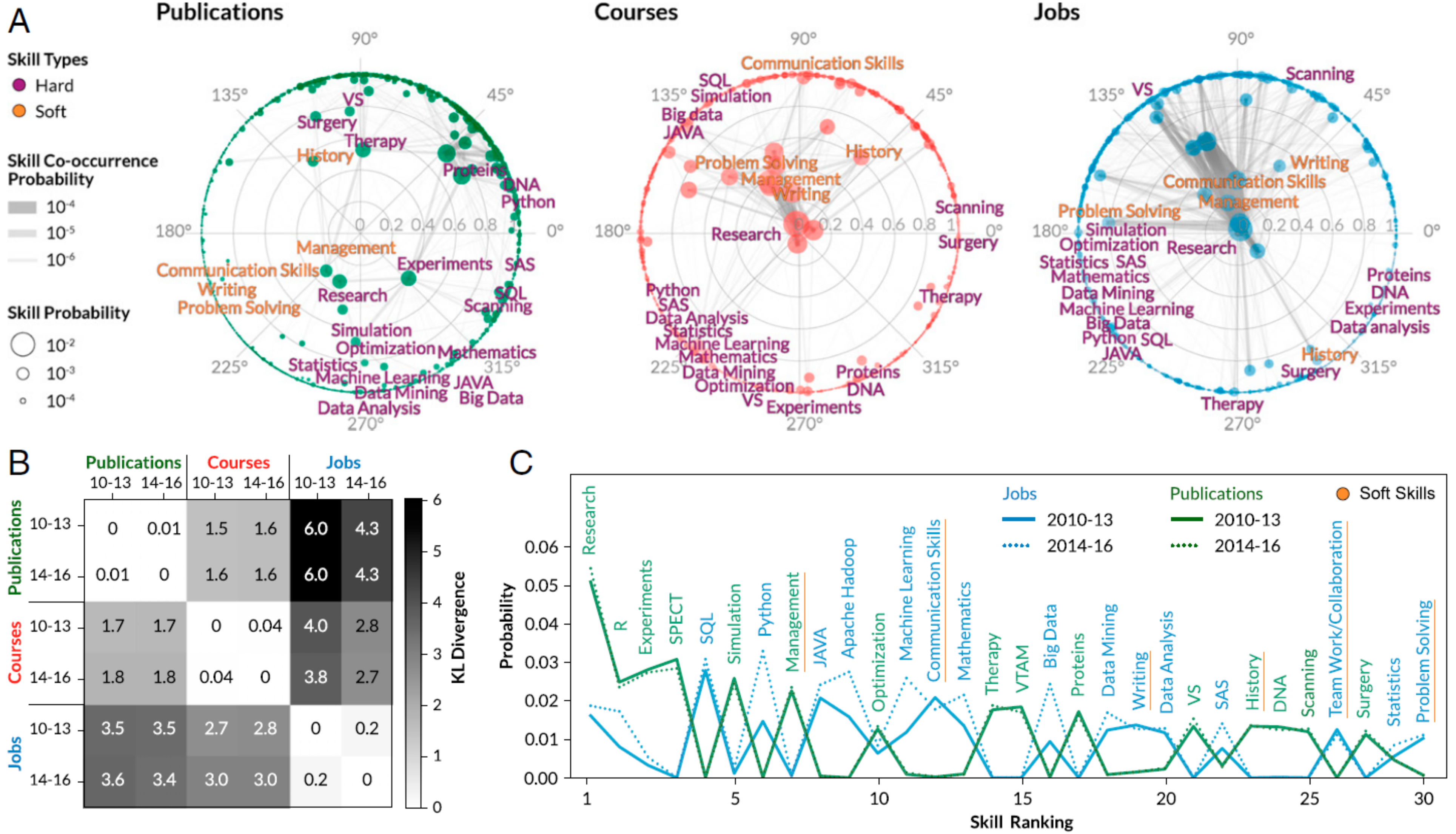


Fig. 5. Structural and dynamic differences between skill distributions in jobs, courses, and publications for 2010–2013 and 2014–2016. (*A*) Poincaré disks comparing the centrality of soft skills (orange) and hard skills (purple) across jobs, courses, and publications. (*B*) KL divergence matrix for jobs, courses, and publications in 2010–2013 and 2014–2016. (*C*) The most surprising skills in publications and jobs; *R* is a scripting language, VTAM refers to the IBM Virtual Telecommunication Access Method application, VS is the integrated development environment Visual Studio, and SAS is a data analytics software.

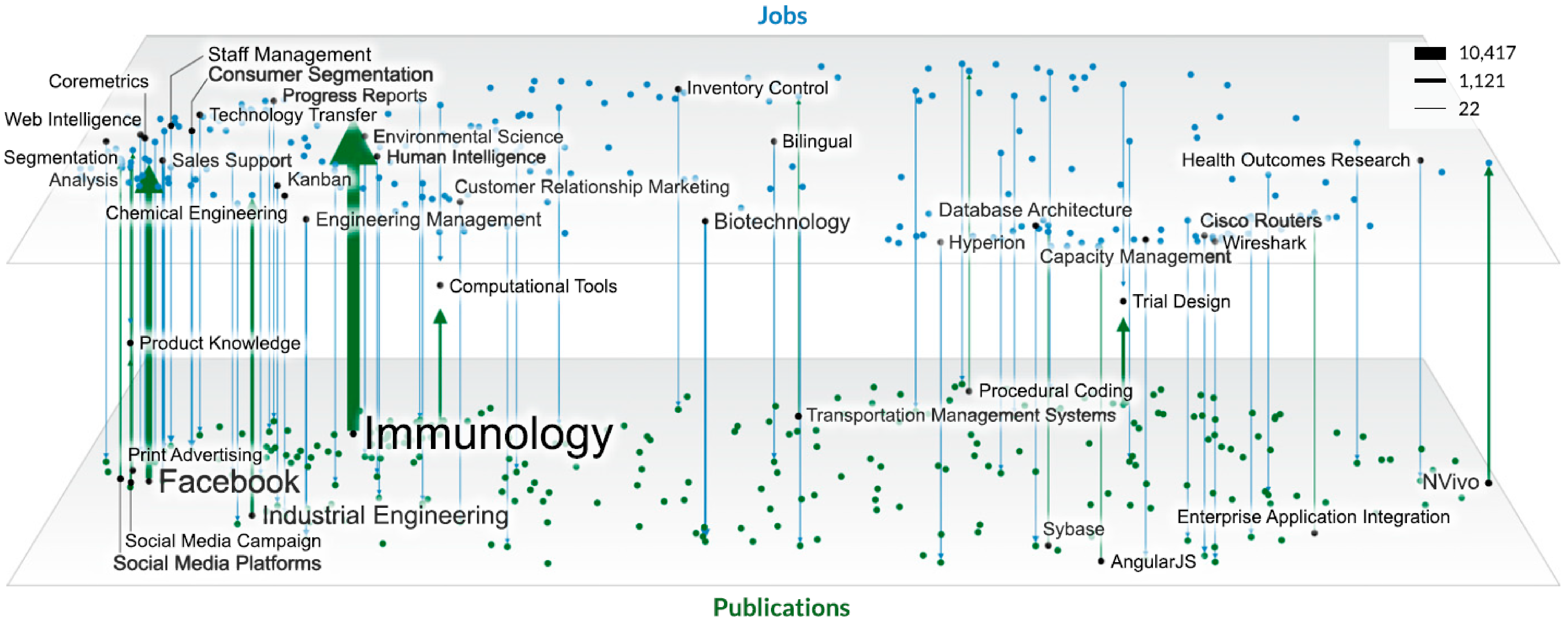


Fig. 6. Strength of influence mapping. Top 200 most frequent skills in jobs (blue) and in publications (green) plotted on the skills basemap from Fig. 2. Arrows represent skills with significant Granger causality (P value < 0.05). Line thickness and label size indicate skill frequency. The direction and thickness of each arrow indicate the F-value strength and direction.

Fig. 7. Multivariate Hawkes Process influence network of DS/DE skills within job advertisements 2010–2016. Each of the 45 nodes represents a top-frequency skill (29 soft and 16 hard skills) with a strong influence edge from/to other skill(s) in job advertisements between 2010 and 2016. Node and label size correspond to the number of times that the skill appeared in a job advertisement. Thickness of the 75 directed edges indicates influence strength.

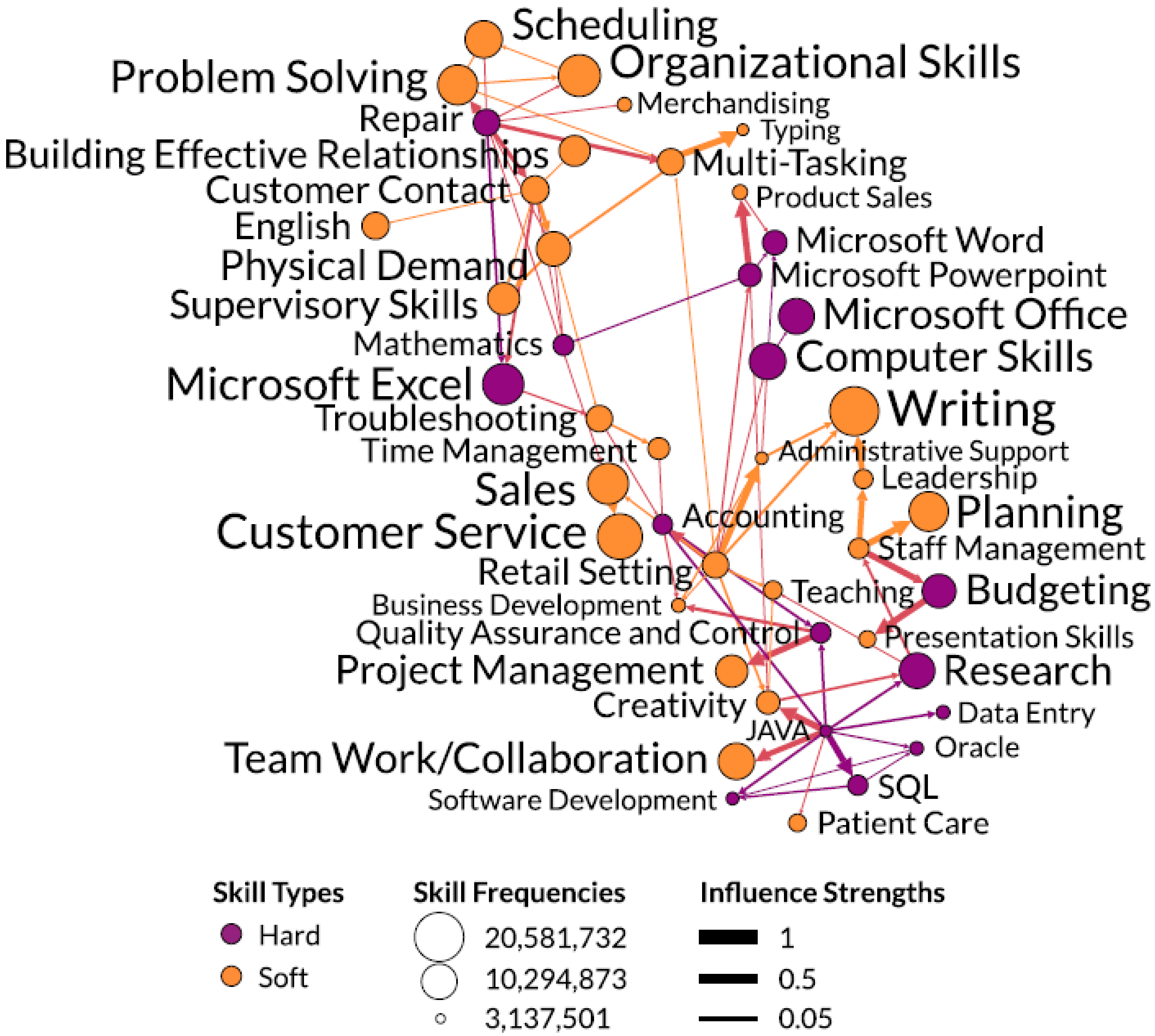


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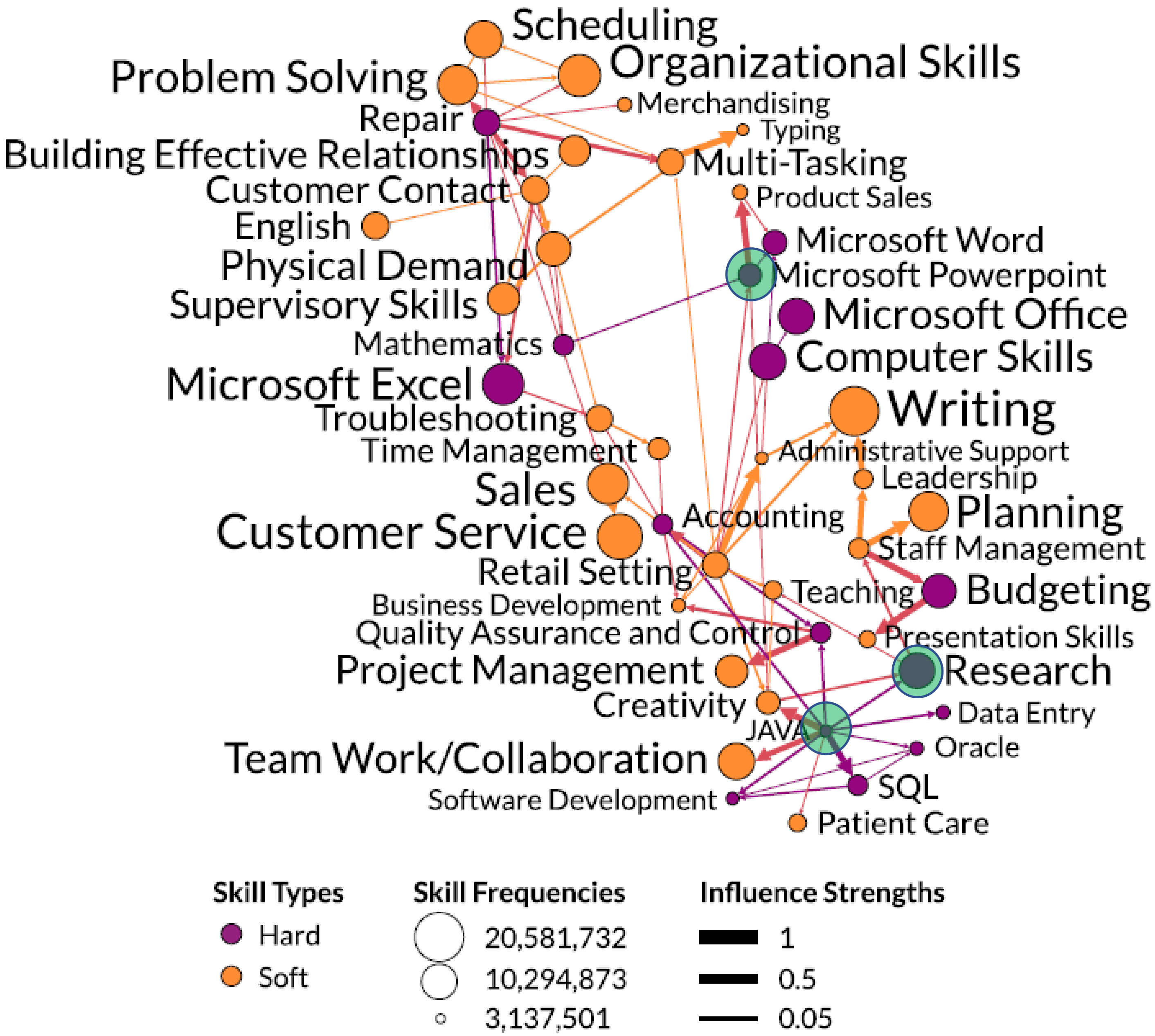
Fig. 7. Hawkes influence network of DS/DE skills within job advertisements 2010–2016. Each of the 45 nodes represents a top-frequency skill (29 soft and 16 hard skills) with a strong influence edge from/to other skill(s) in job advertisements between 2010 and 2016. Node and label size correspond to the number of times that the skill appeared in a job advertisement. Thickness of the 75 directed edges indicates influence strength.



Results

- Novel cross-walk for mapping publications, course offerings, and job via skills.
- Timing and strength of burst of activity for skills (e.g., Oracle, Customer Service) in publications, course offerings, and job advertisements.
- Uniquely human skills such as communication, negotiation, and complex service provision are currently underexamined in research and undersupplied through education for the labor market in an increasingly automated and AI economy.
- The same pattern manifests in the domain of DS/DE where teamwork and communication skills increase in value with greater demand for data analytics skills and tools.
- Skill demands from industry are as likely to drive skill attention in research as the converse.

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INDIANA UNIVERSITY
SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

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.

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

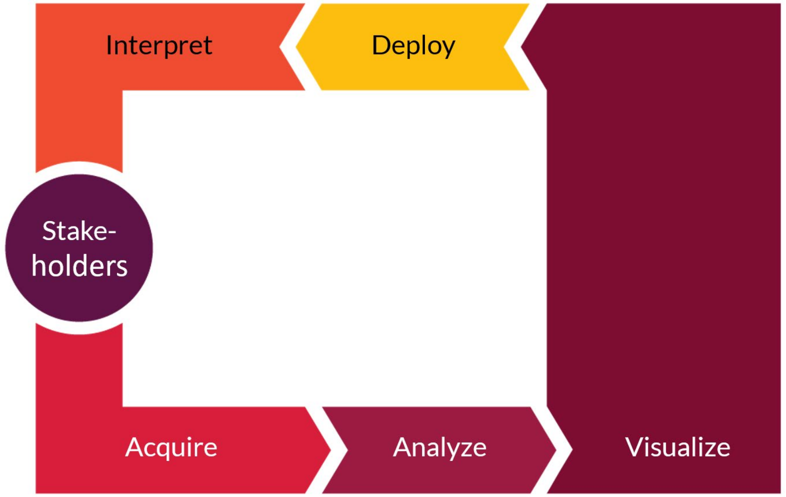
5 Graphic Symbols
- geometric symbols
  - point
  - line
  - area
  - surface
  - volume
- linguistic symbols
  - text
  - numerals
  - punctuation marks
- pictorial symbols
  - images
  - icons
  - statistical glyphs

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

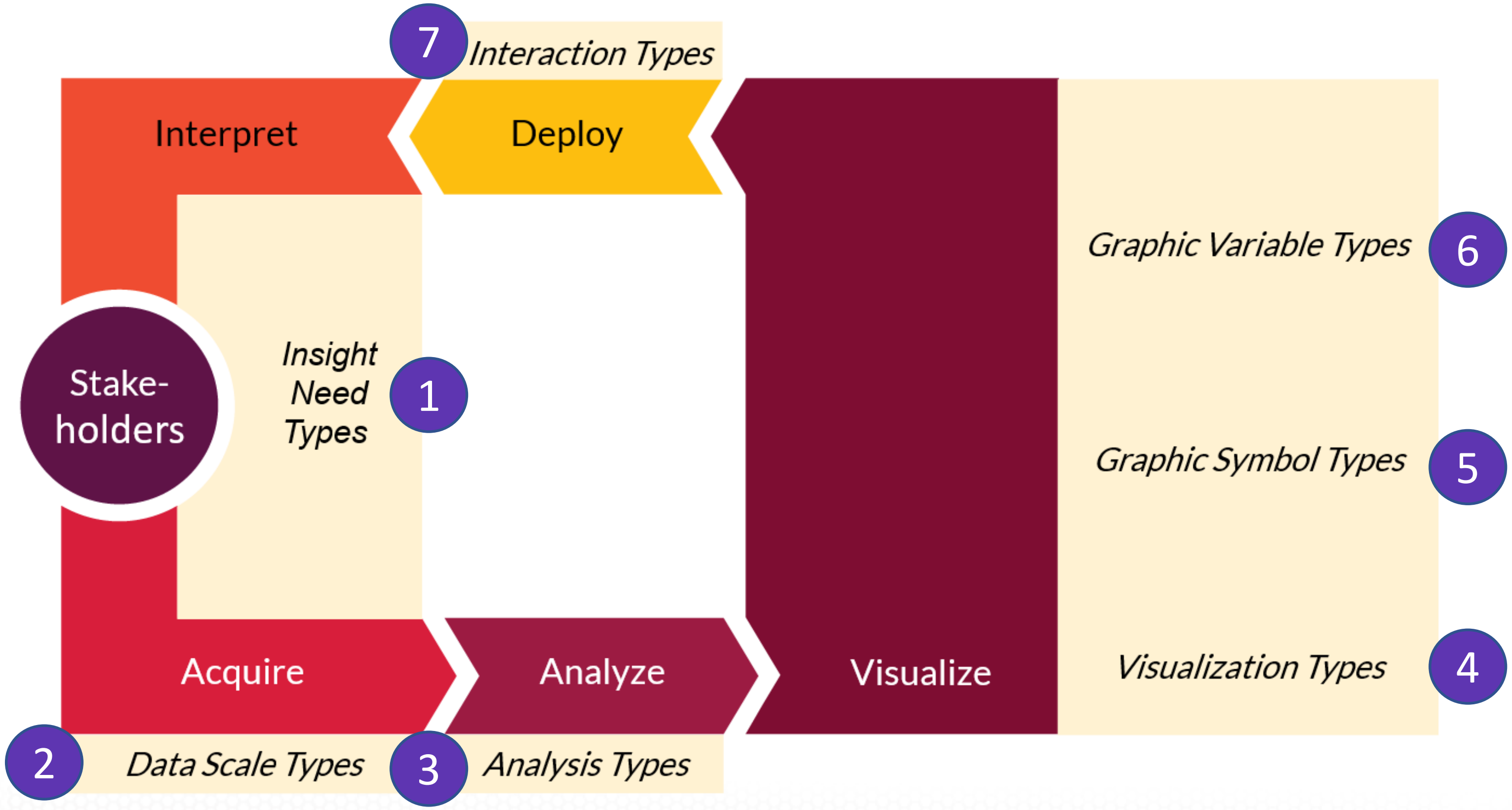
Defines 5 steps required to render data into insights.



Data Visualization Literacy Framework (DVL-FW)

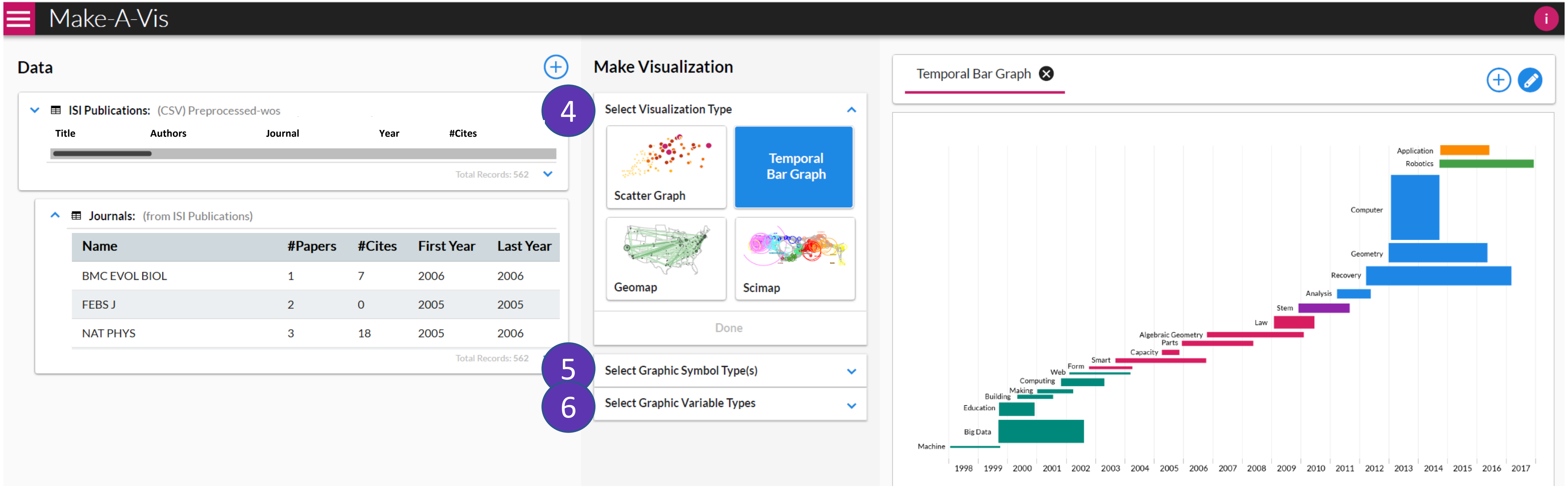
Consists of two parts that are interlinked:

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.



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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

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. 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

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

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- ratio

Analyses
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- topical
- relational

Visualizations
- table
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  - punctuation marks
- pictorial symbols
  - images
  - icons
  - statistical glyphs

6

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. 34-35.

Graphic Variable Types

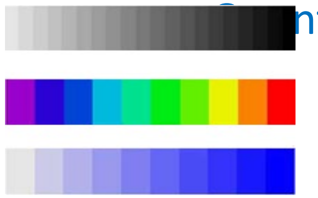
Position: x, y; possibly z

Form:

- Size
- Shape
- Rotation (Orientation)

Color:

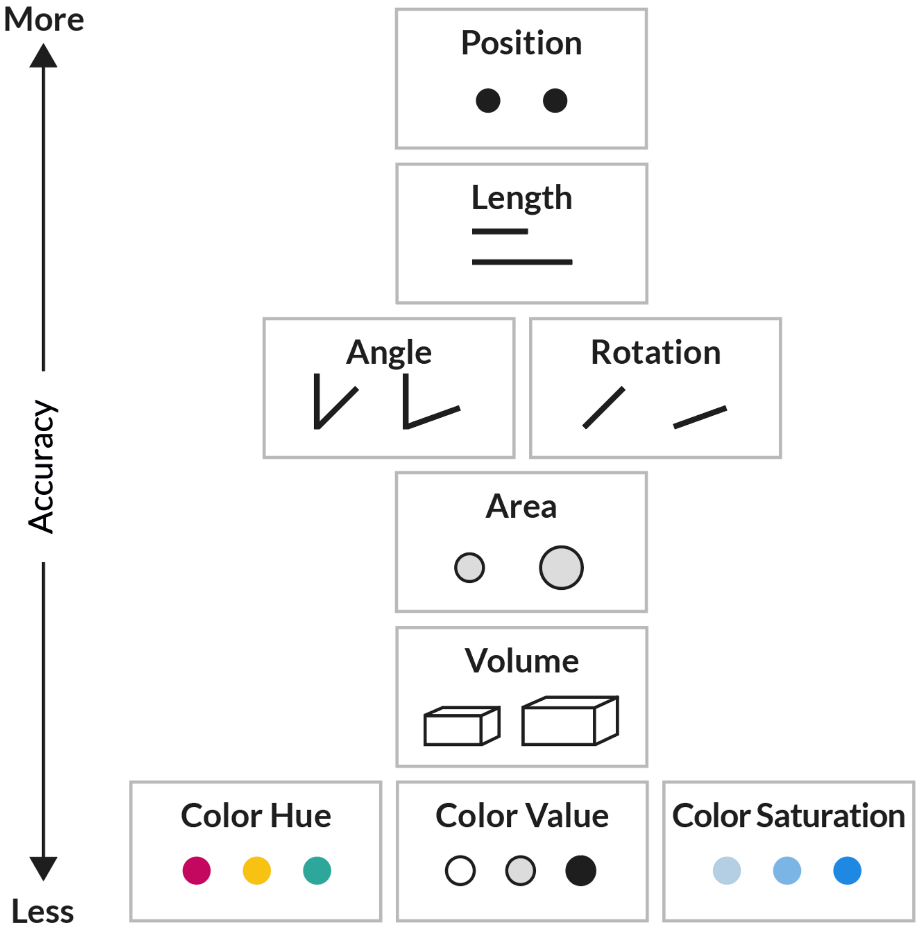
- Value (Lightness)
- Hue (Tint)
- Saturation (Intensity)



Optics: Blur, Transparency, Shading, Stereoscopic Depth

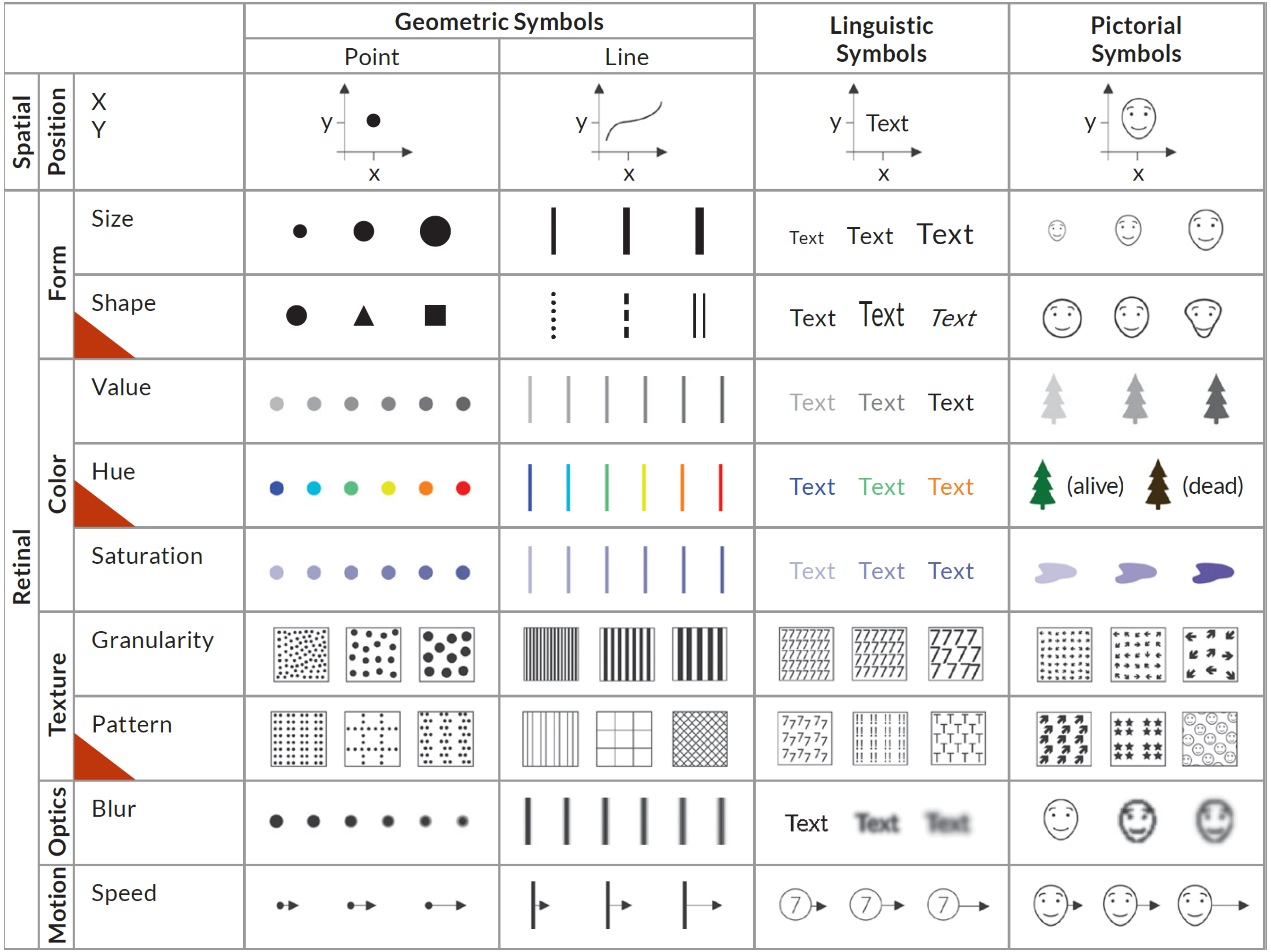
Texture: Spacing, Granularity, Pattern, Orientation, Gradient

Motion: Speed, Velocity, Rhythm



Graphic Symbol Types

Graphic Variable Types



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

Qualitative

Also called:

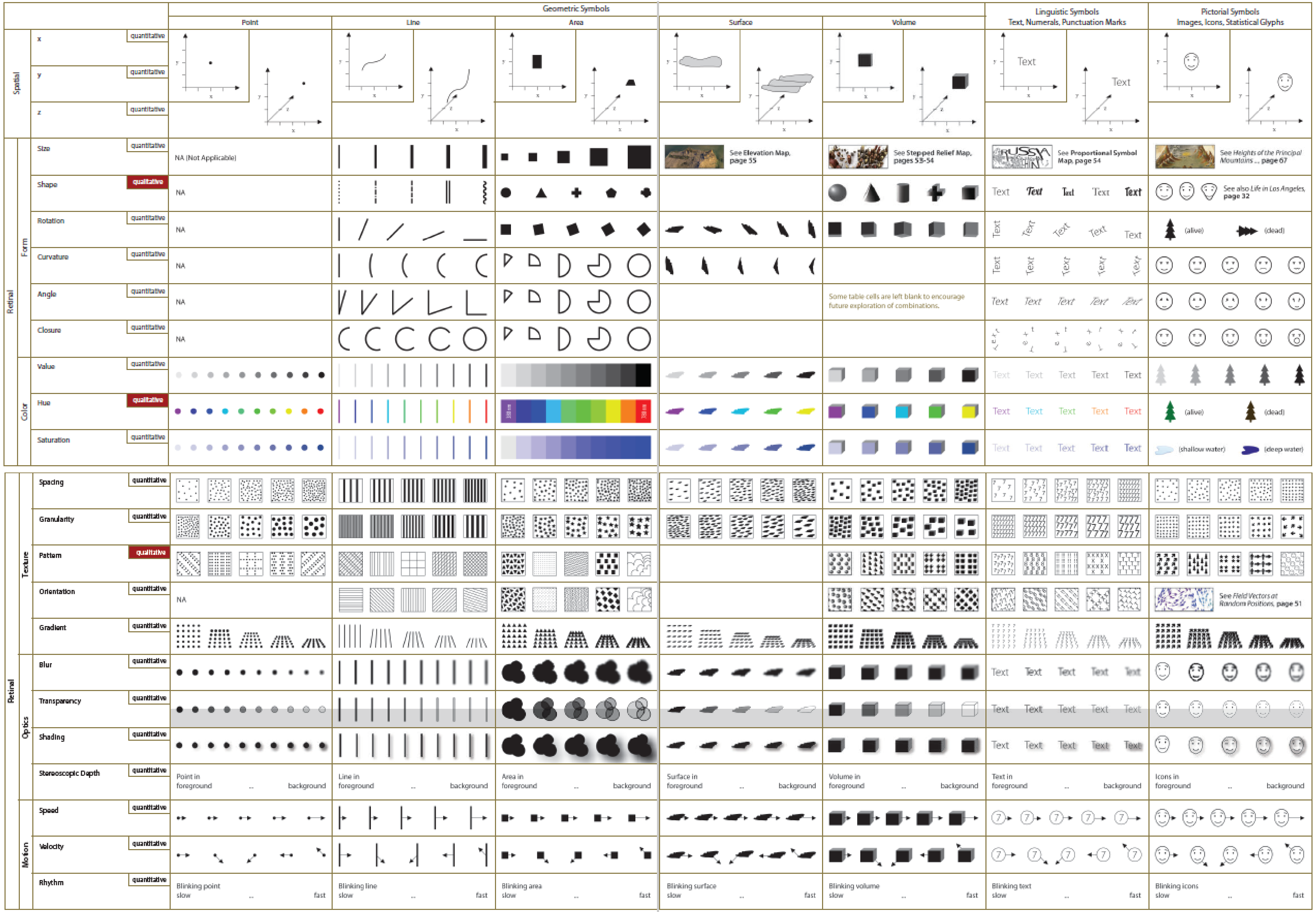
Categorical Attributes
Identity Channels

Quantitative

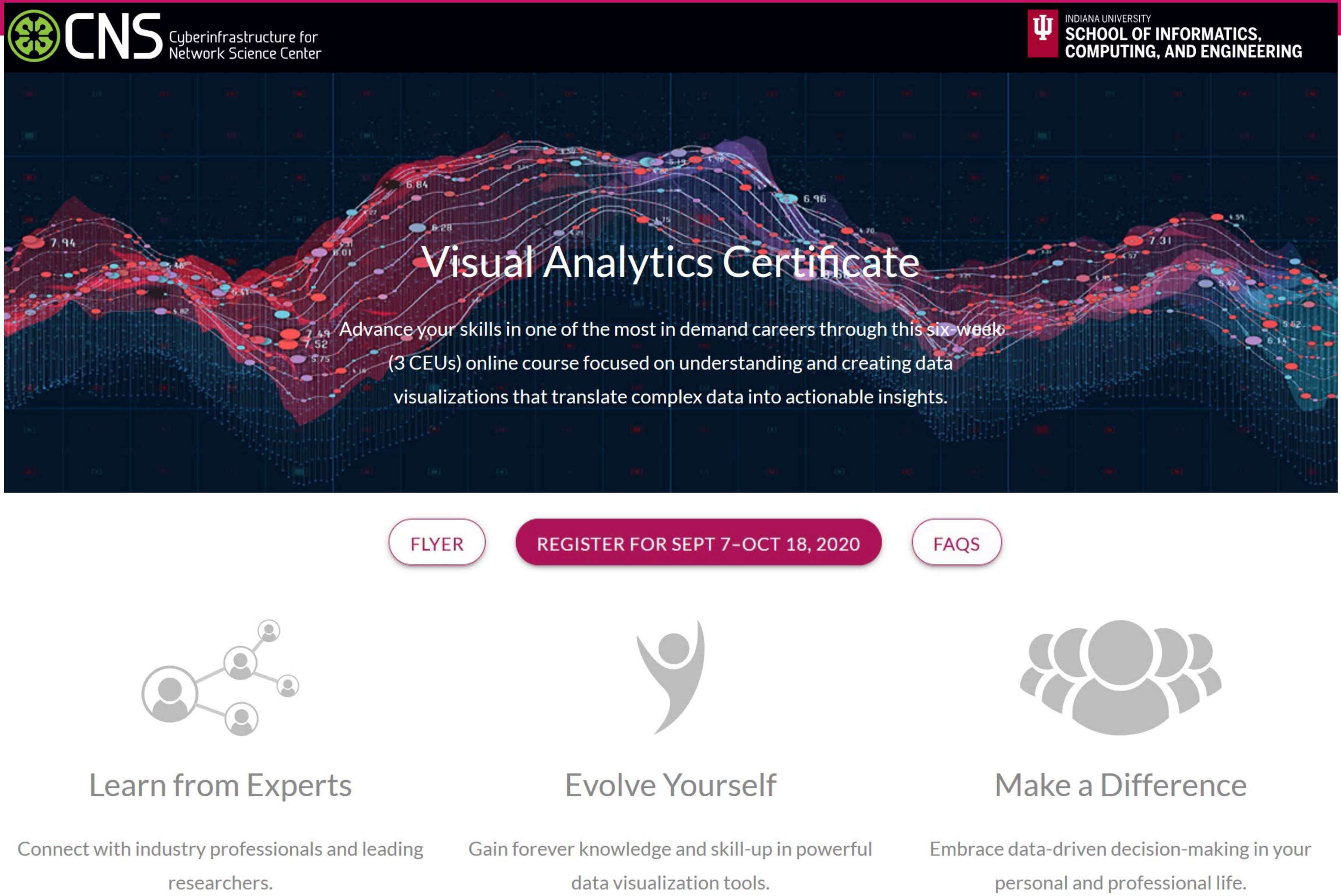
Also called:

Ordered Attributes
Magnitude Channels

Graphic Variable Types Versus Graphic Symbol Types



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



https://visanalytics.cns.iu.edu

Next course starts Sept 7, 2020

CNS Cyberinfrastructure for Network Science Center

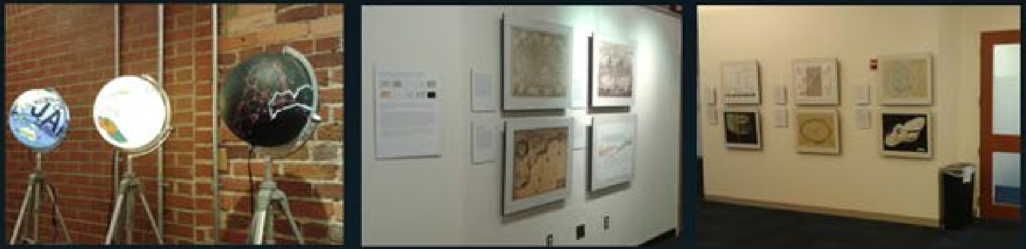
Indiana University School of Informatics, Computing, and Engineering

Places & Spaces: Mapping Science Exhibit

http://scimaps.org

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

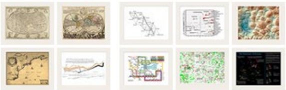
The David J. Sencer CDC Museum, Atlanta, GA.
January 25 - June 17, 2016.

Places & Spaces: Mapping Science Exhibit

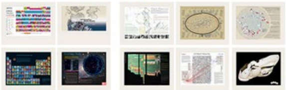
1st Decade (2005-2014)

Maps

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)

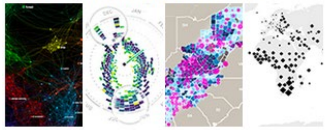
Macroscopes

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."

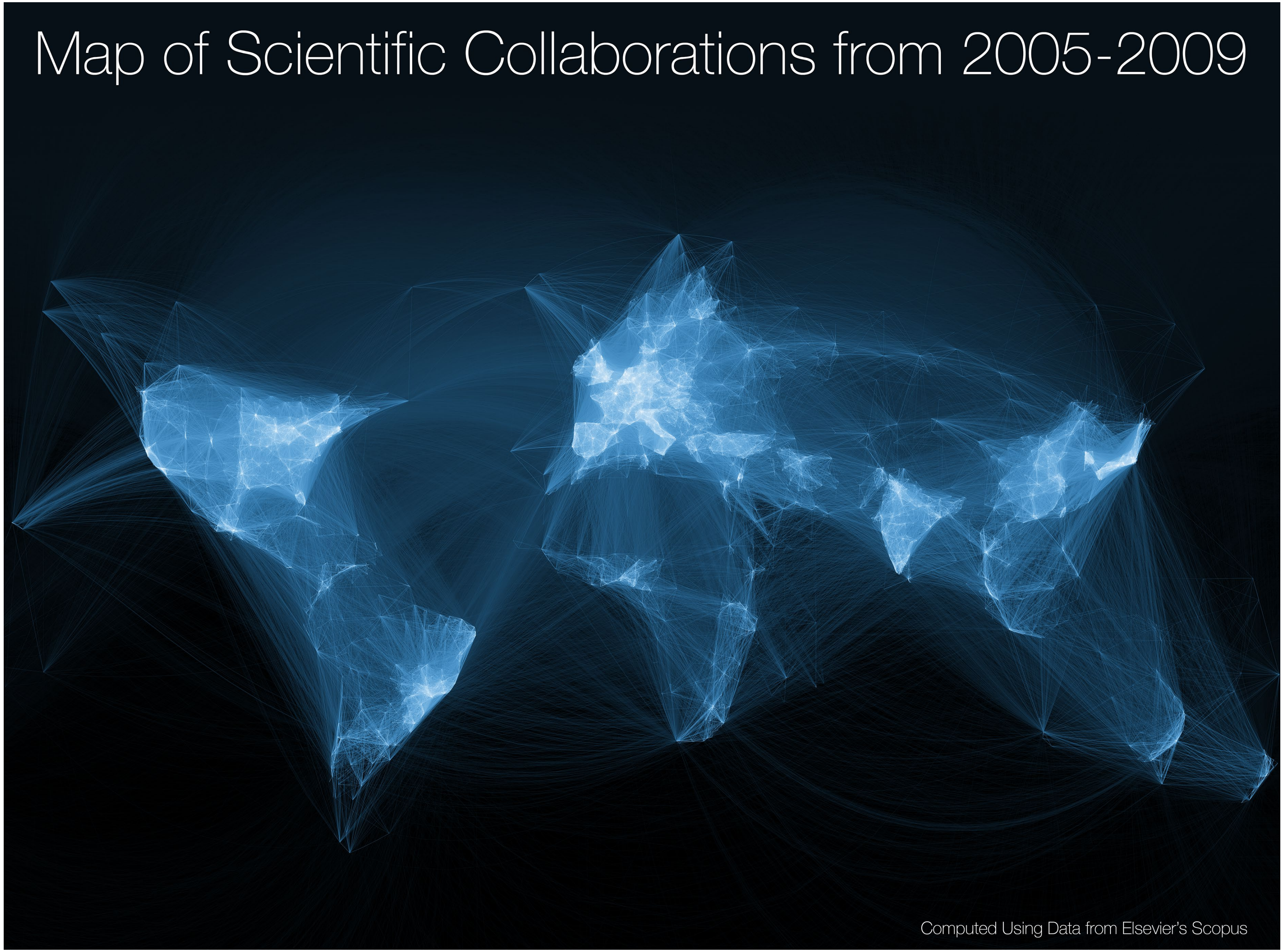
20
MACROSCOPES
for touching all kinds of data.

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

CNS Cyberinfrastructure for Network Science Center



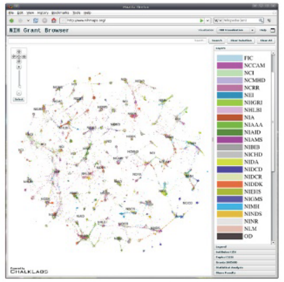
VII.6 Stream of Scientific Collaborations Between World Cities - Olivier H. Beauchesne - 2012

A Topic Map of NIH Grants 2007

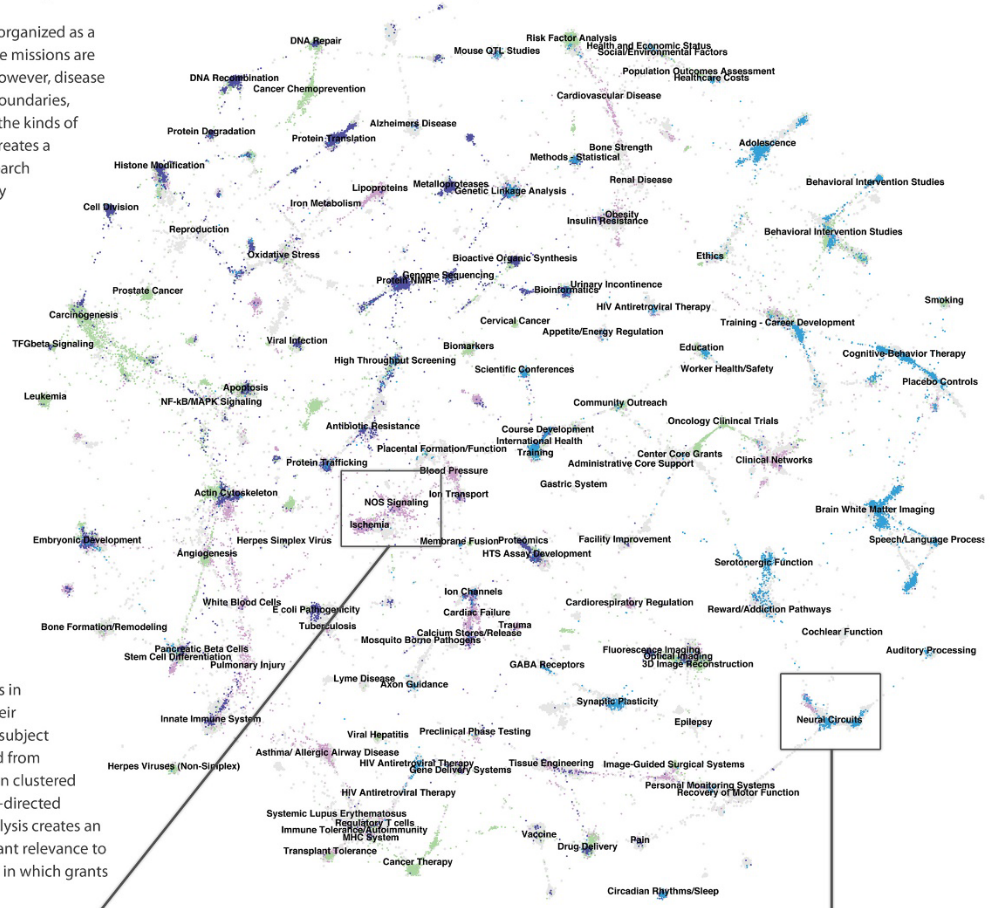
ChalkLabs UCIrvine

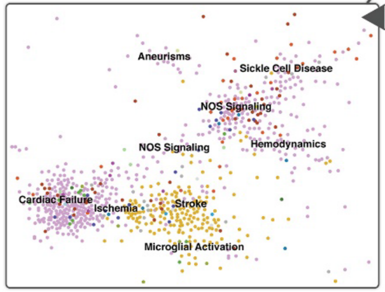
Bruce W. Herr II (Chalklabs & IU), Gully Burns (ISI), David Newman (UCI), Edmund Talley (NIH)

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.



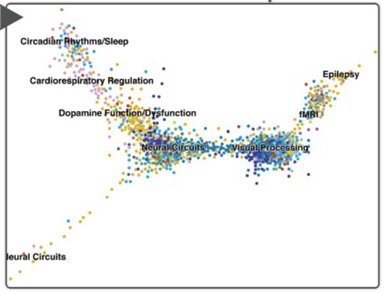


Cardiac Diseases Research

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 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

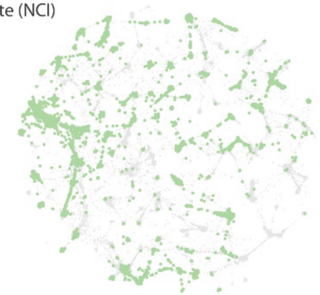
An area of the map focused on neural circuits, which shows the diversity of topics and NIH Institutes that fund research in this area, such as: Cardiorespiratory Regulation, primarily funded by NHLBI; Visual Processing, primarily funded by NEI; and Epilepsy, primarily funded by NINDS. For color coding,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



National Cancer Institute (NCI)

TOP 10 TOPICS

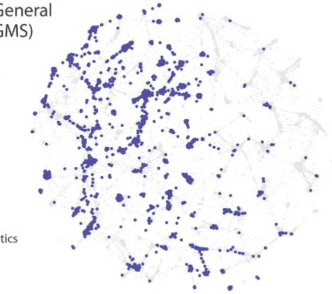
1. Oncology Clinical Trials
2. Cancer Treatment
3. Cancer Therapy
4. Carcinogenesis
5. Risk Factor Analysis
6. Cancer Chemotherapy
7. Metastasis
8. Leukemia
9. Prediction/Prognosis
10. Cancer Chemoprevention



National Institute of General Medical Sciences (NIGMS)

TOP 10 TOPICS

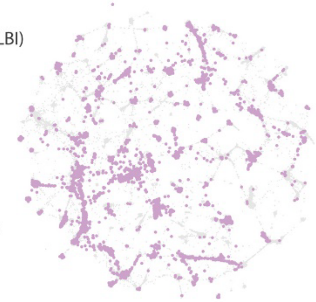
1. Bioactive Organic Synthesis
2. X-ray Crystallography
3. Protein NMR
4. Computational Models
5. Yeast Biology
6. Metalloproteases
7. Enzymatic Mechanisms
8. Protein Complexes
9. Invertebrate/Zebrafish Genetics
10. Cell Division



National Heart, Lung, and Blood Institute (NHLBI)

TOP 10 TOPICS

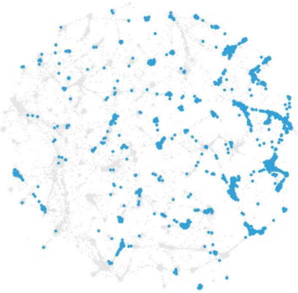
1. Cardiac Failure
2. Pulmonary Injury
3. Genetic Linkage Analysis
4. Cardiovascular Disease
5. Atherosclerosis
6. Hemostasis
7. Blood Pressure
8. Asthma/ Allergic Airway Disease
9. Gene Association
10. Lipoproteins



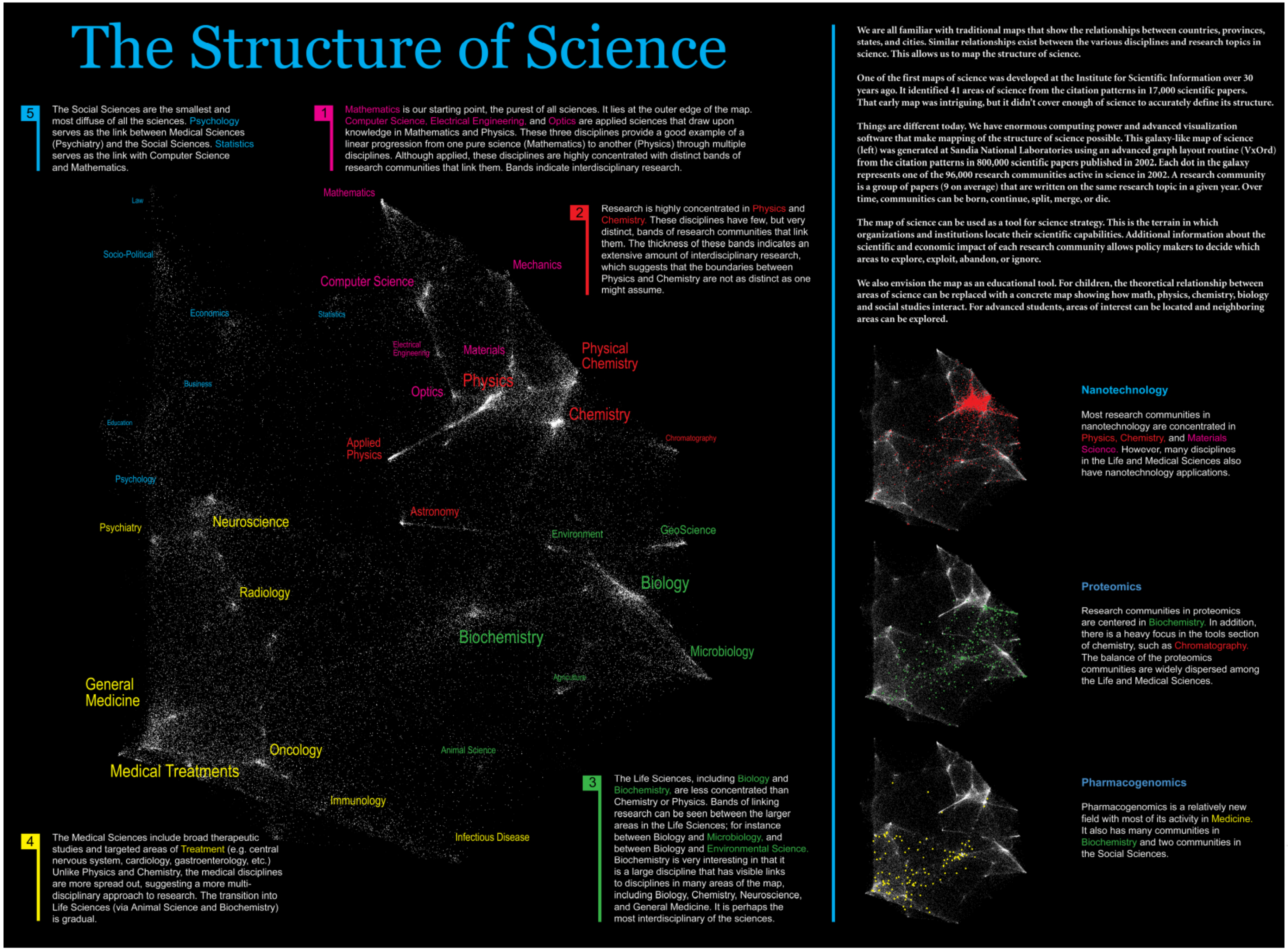
National Institute of Mental Health (NIMH)

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



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

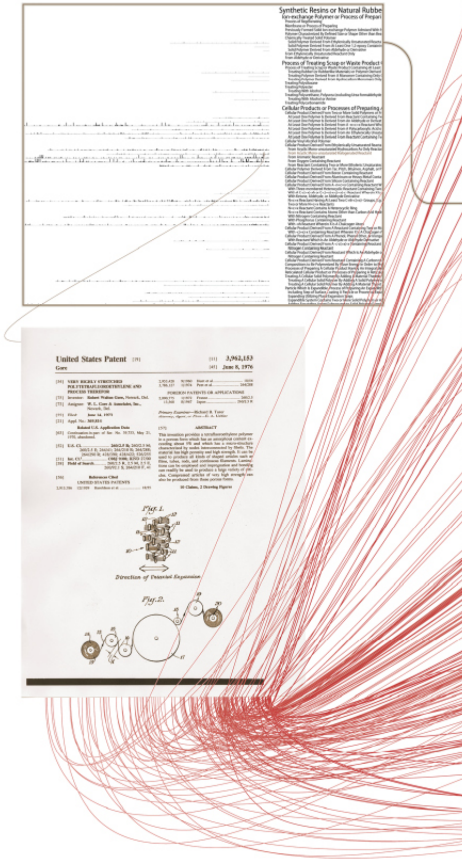
The US Patent Hierarchy

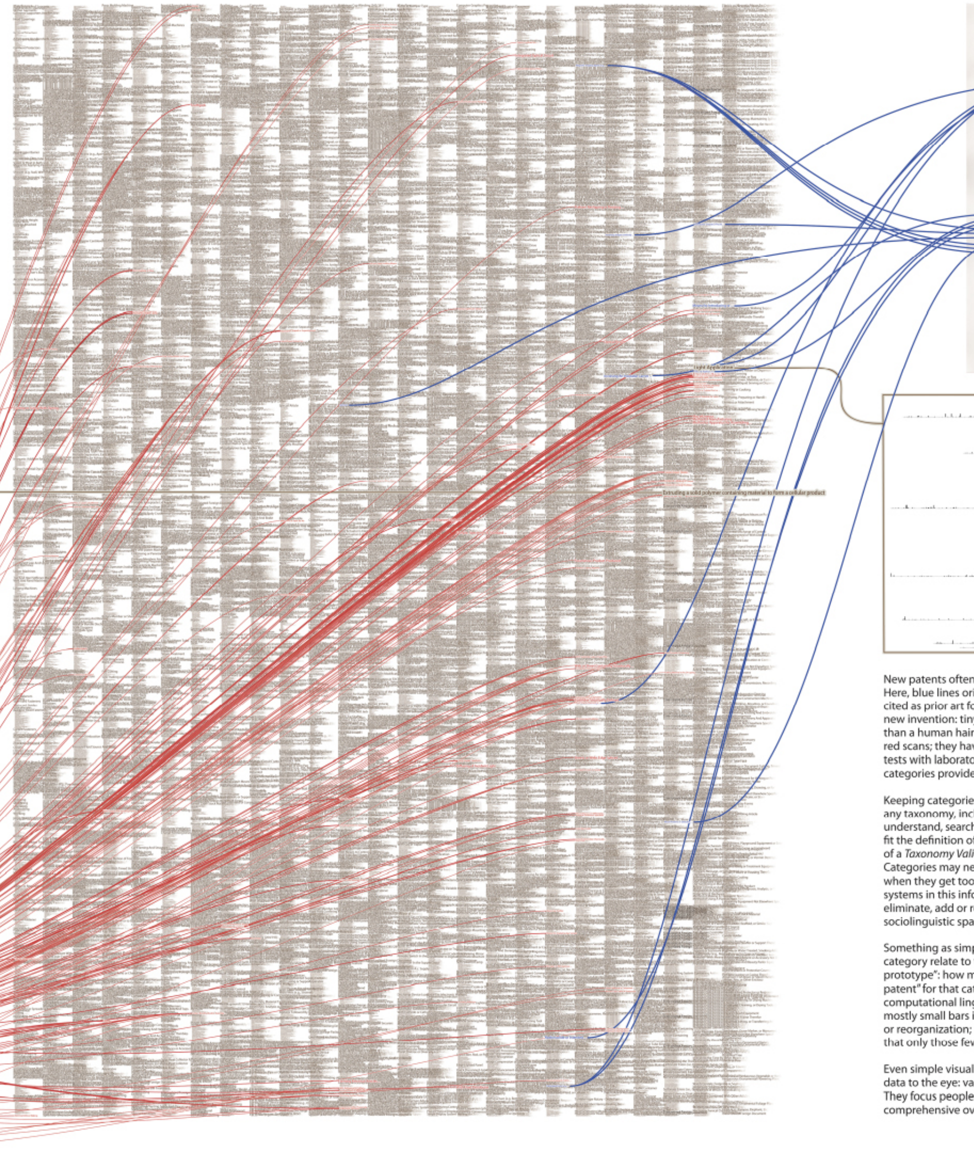
Impact

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.

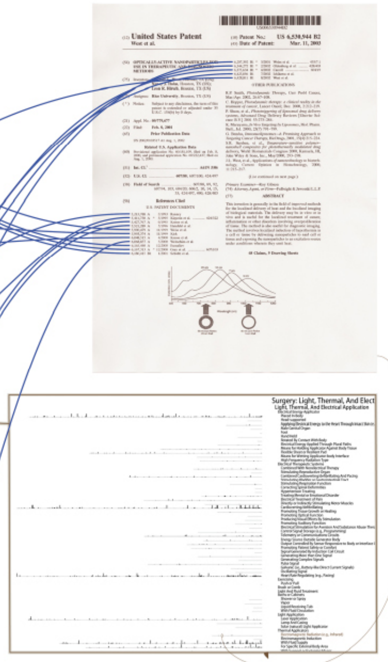
Patent applications are required to be unique and non-obvious, partially by revealing any previous patents that might be similar in nature or provide a foundation for the current invention. In this way we can trace the impact of a single patent, seeing how many patents and categories it affects.

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



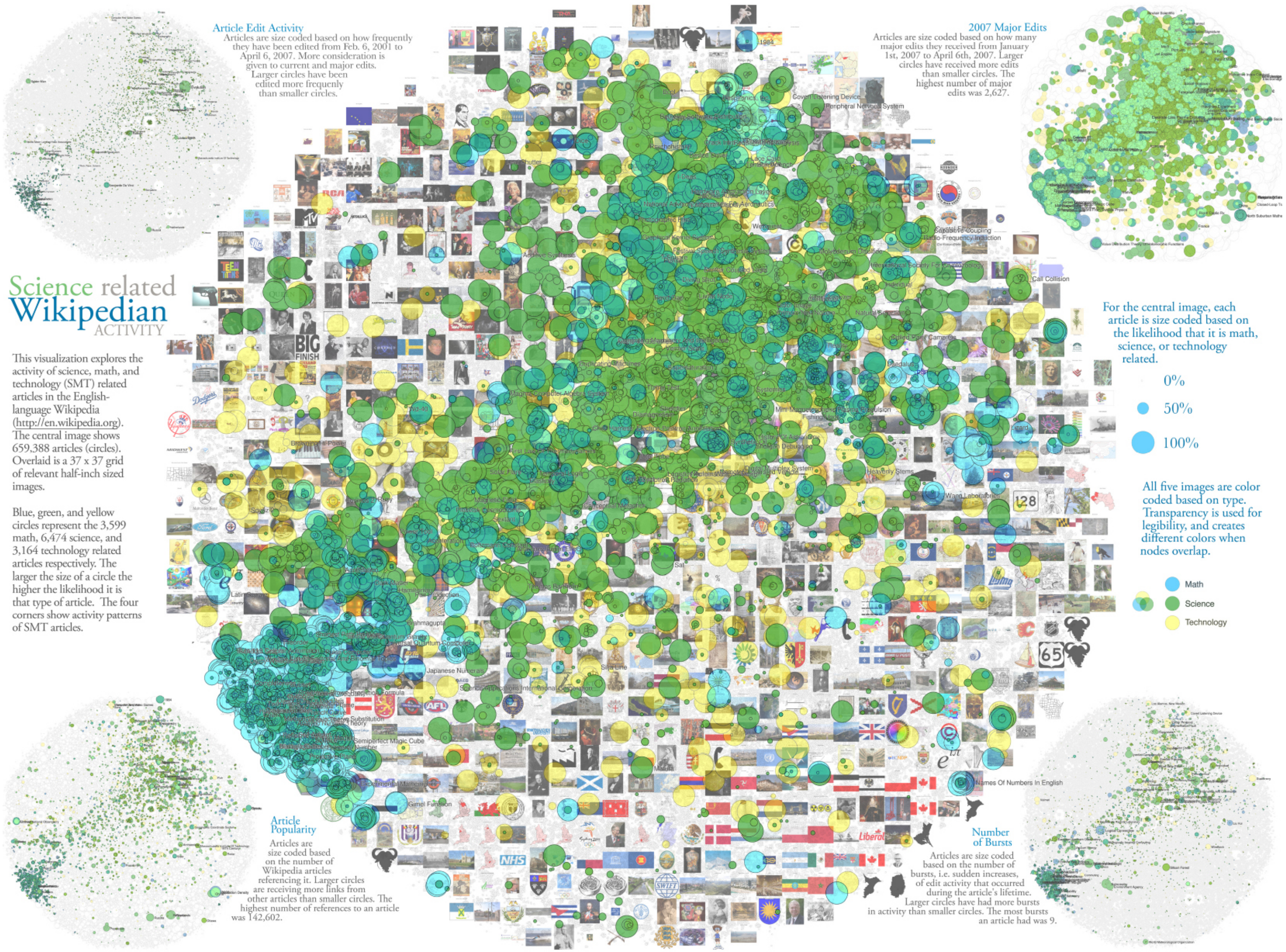
New patents often build on older ideas from many different categories. Here, blue lines originate in the sixteen categories that contain patents cited as prior art for a patent on "gold nanoshells." Gold nanoshells are a new invention: tiny gold spheres (with a diameter ten million times smaller than a human hair) that can be used to make tumors more visible in 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?

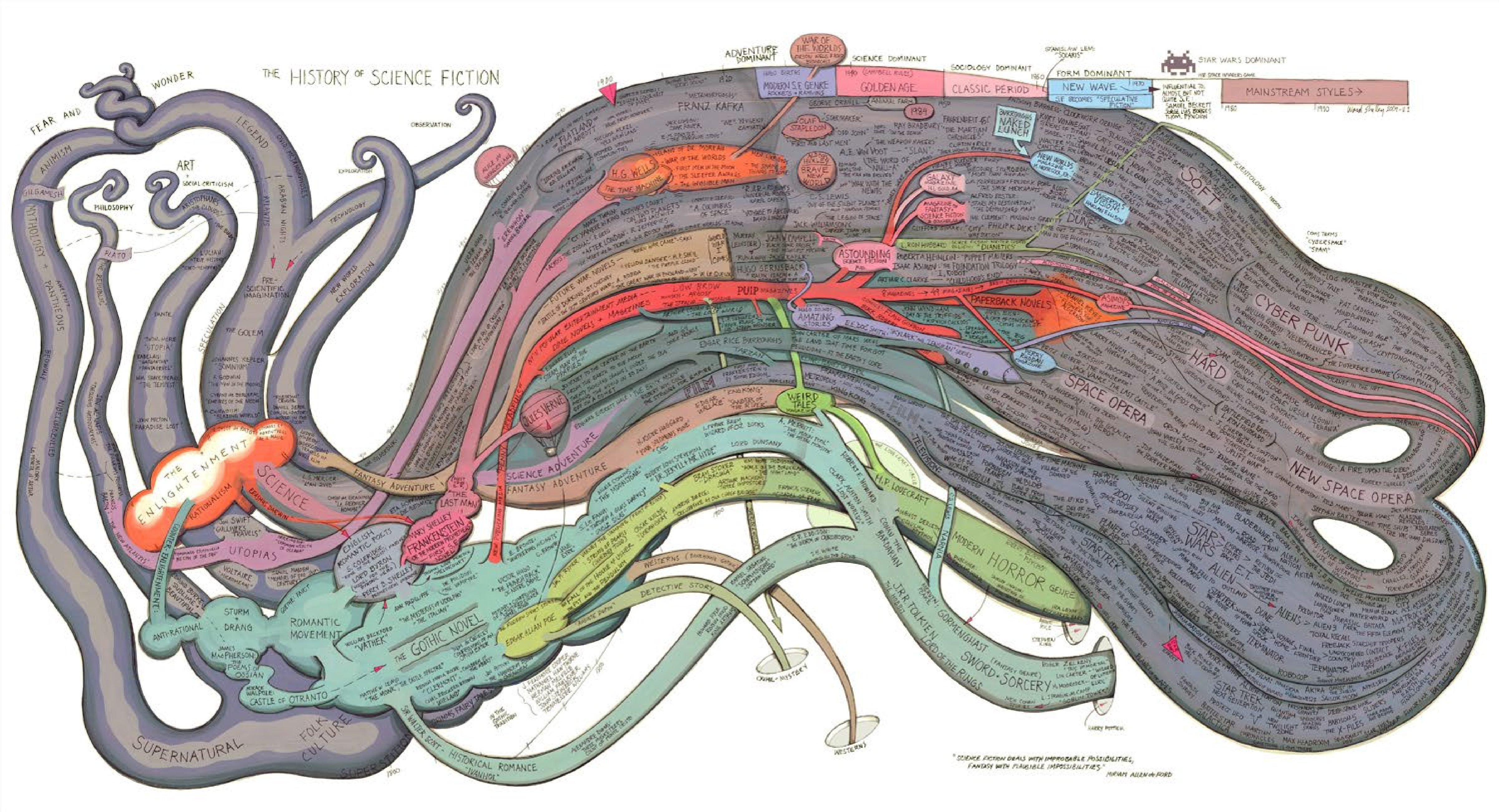
Something as simple as a bar chart helps people see how entities in a category relate to that category. Here, each bar encodes a "distance to prototype": how much each patent differs from an idealized "prototype patent" for that category. A measure like this can be based on statistics, computational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

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



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

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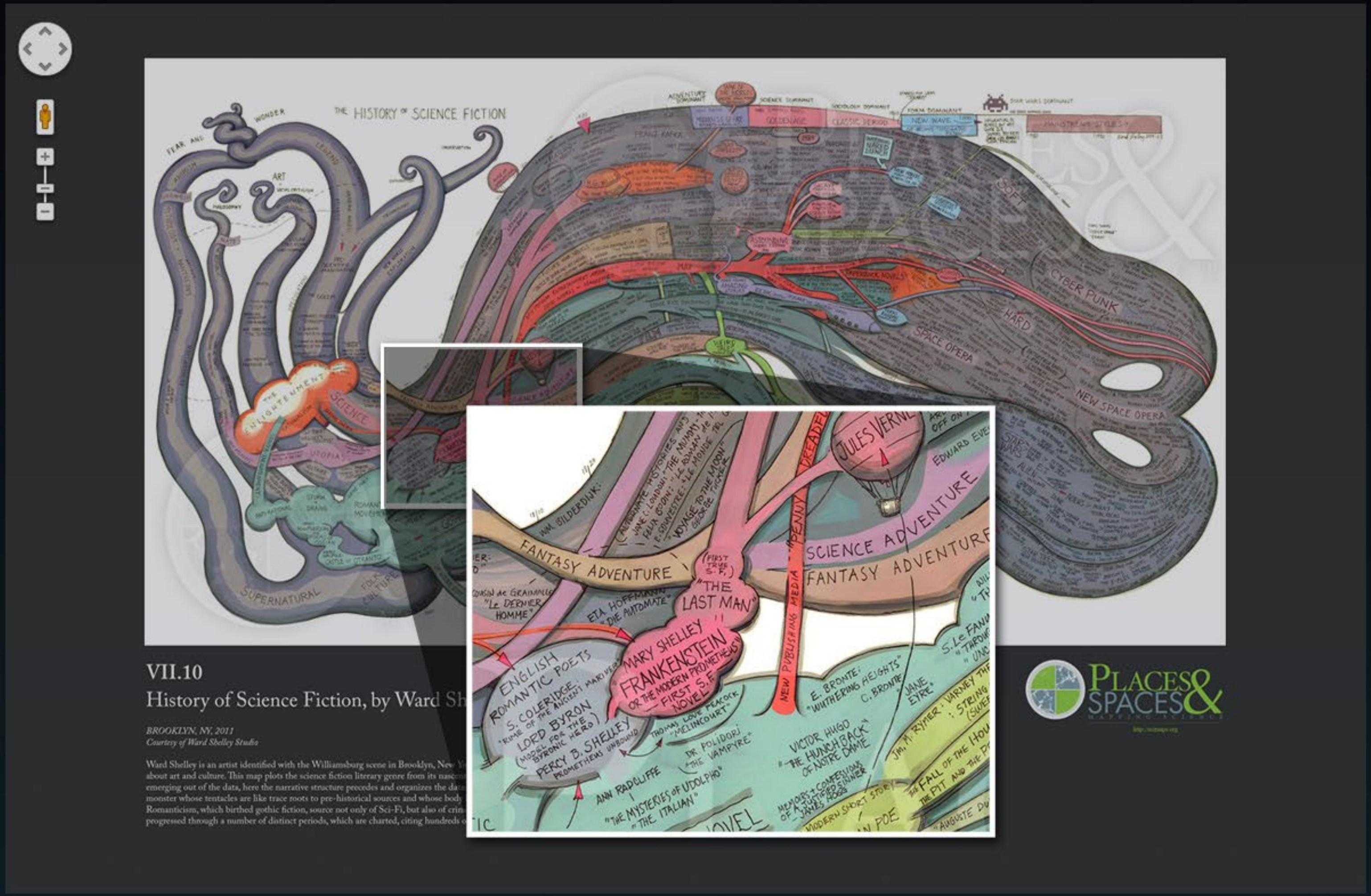

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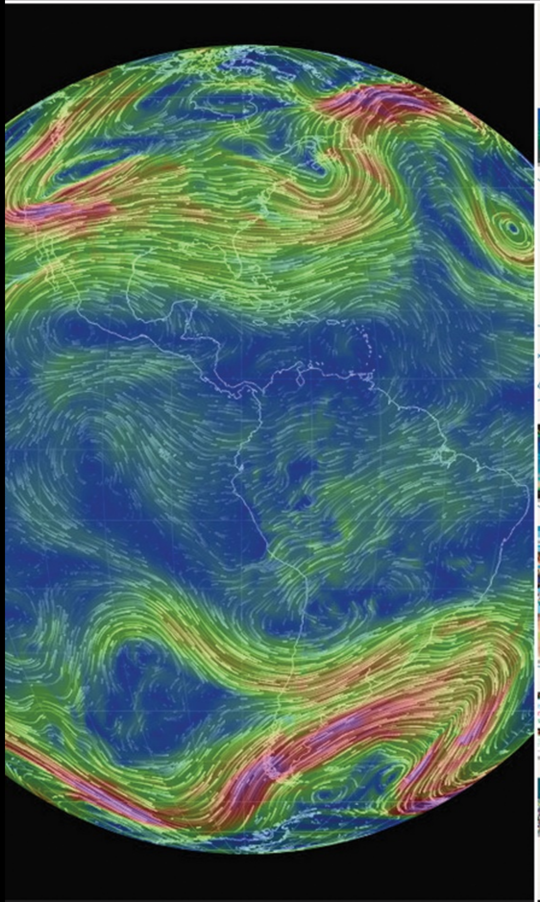
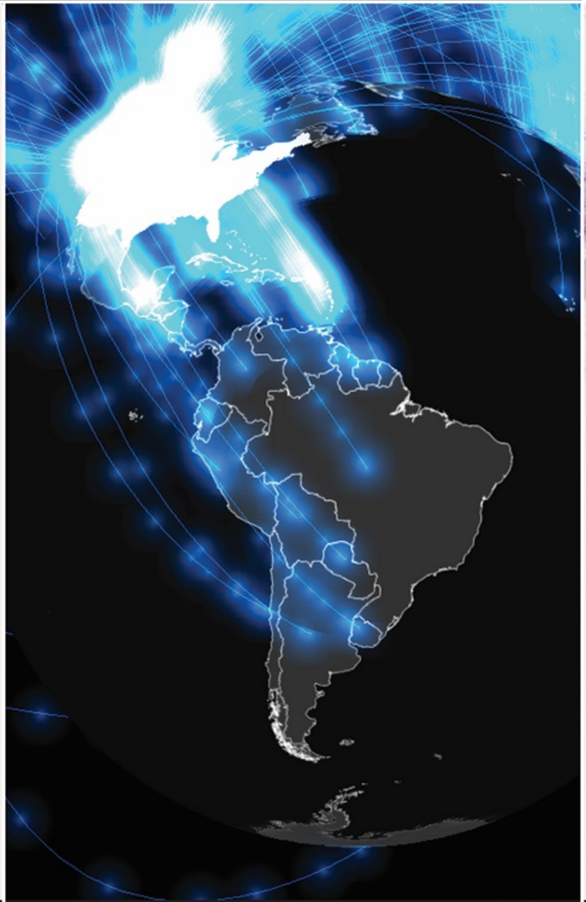


Earth

Weather on a worldwide scale

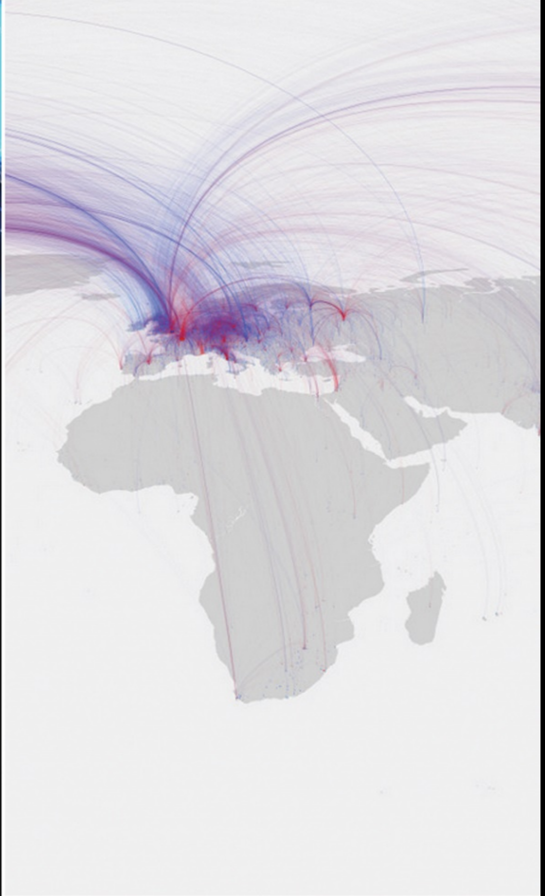
AcademyScope

Exploring the scientific landscape



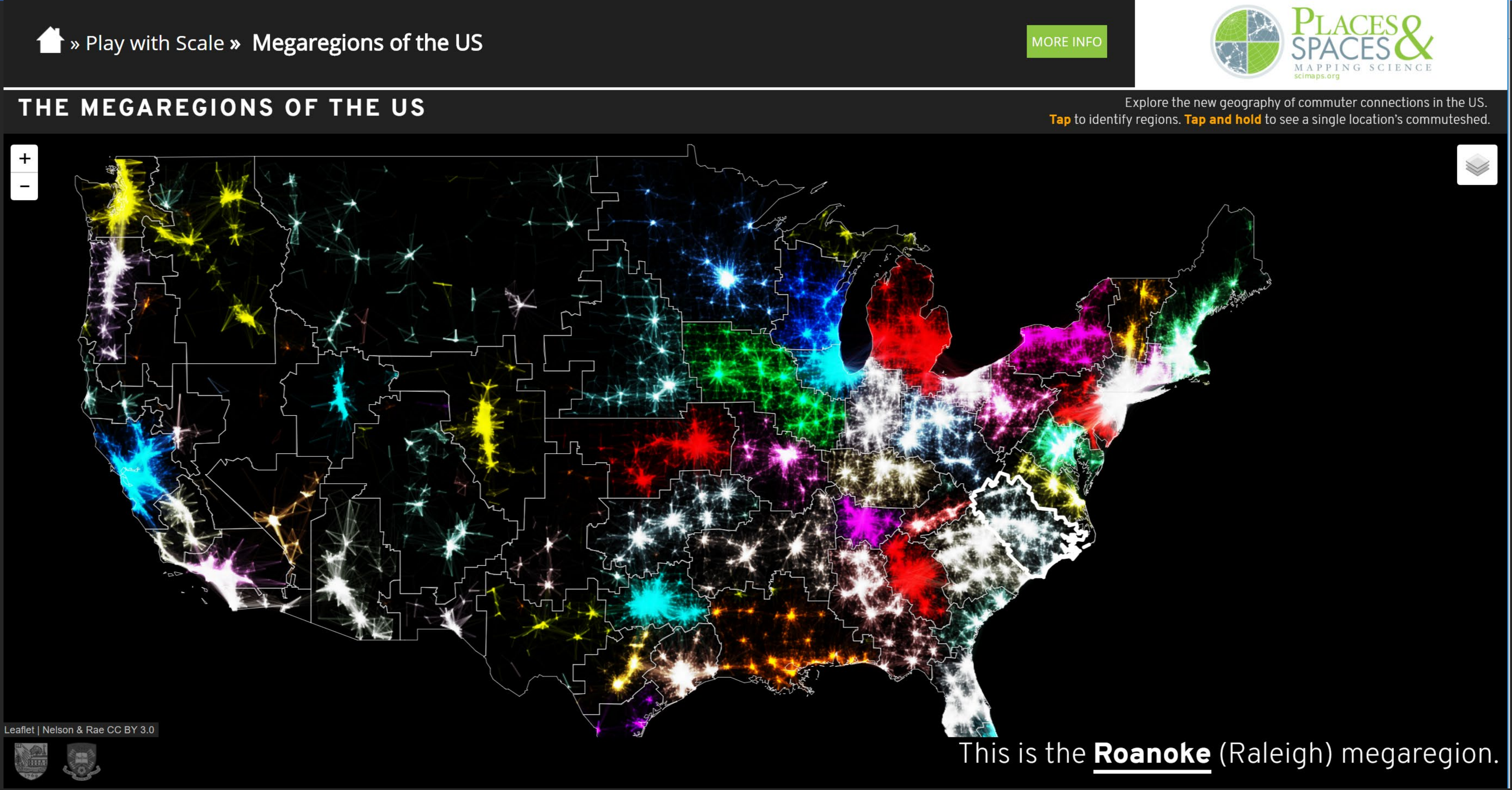
Mapping Global Society

Local news from a global perspective



Charting Culture

2,600 years of human history in 5 minutes

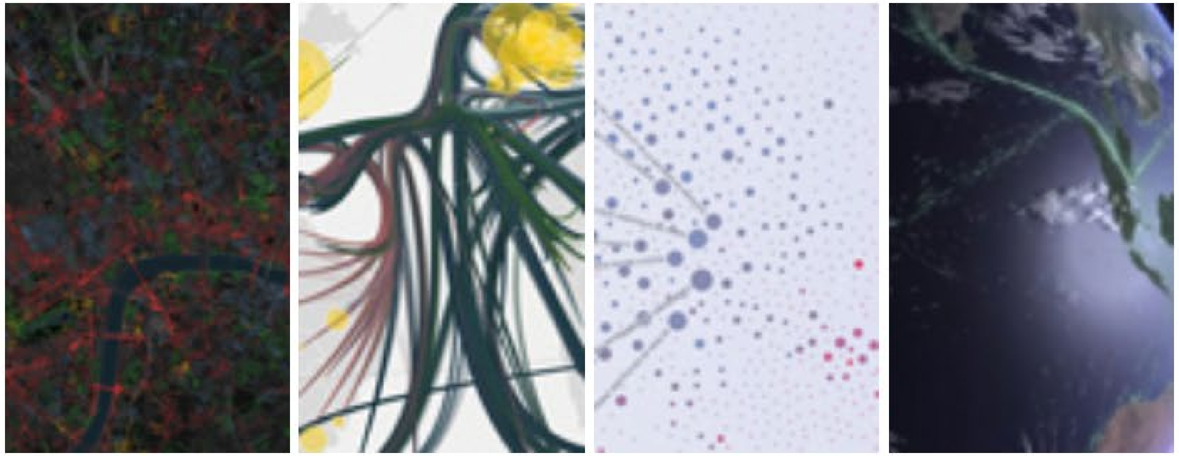


Megaregions of the US –Garrett Dash Nelson and Alasdair Rae – 2016

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

Iteration XII (2016)

Macroscopes for Making Sense of Science

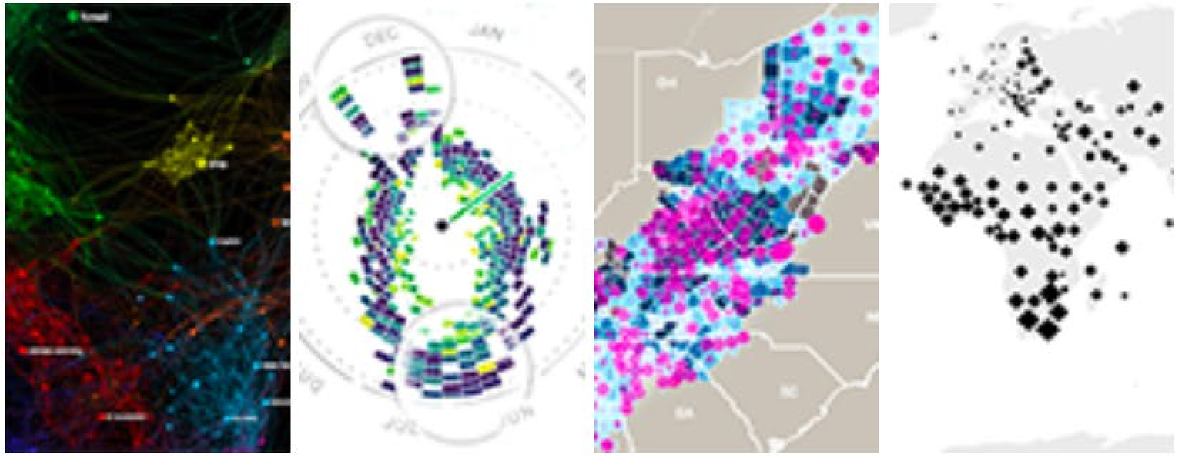


Iteration XIII (2017)

Macroscopes for Playing with Scale

Iteration XIV (2018)

Macroscopes for Ensuring our Well-being



Iteration XV (2019)

Macroscopes for Tracking the Flow of Resources

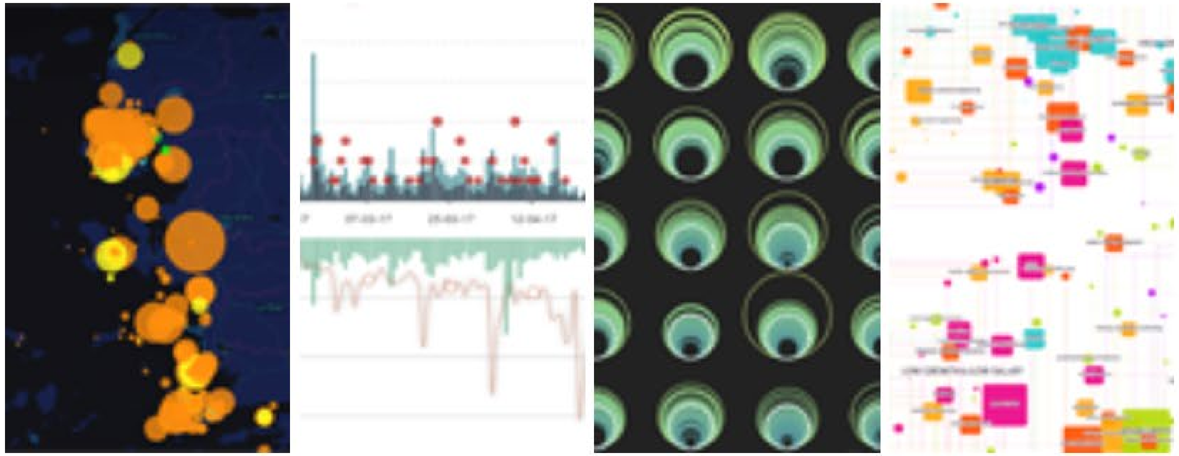


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Exhibit Curators

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