CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY
SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

Atlas of Forecasts & Mapping Science

Katy Börner **@katycns**

Victor H. Yngve Distinguished Professor of
Intelligent Systems Engineering & Information Science
Director, Cyberinfrastructure for Network Science Center
Luddy School of Informatics, Computing, and Engineering
Indiana University, Bloomington, IN, USA

Data Visualization Lisboa

June 15, 2022

#vislis

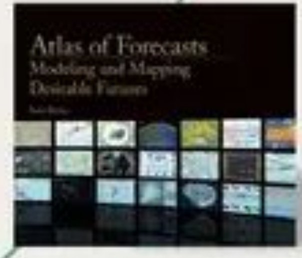
ATLAS OF FORECASTS & MAPPING SCIENCE

#31 MEETUP
28. APRIL
WILL BE **WITH**

Engineer, scholar, educator and author of *Atlas of Forecasts: modeling and mapping desirable futures*

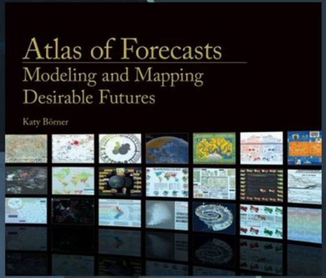
Data Visualization Lisboa

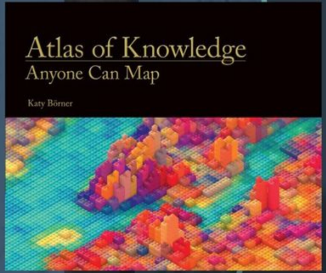
KATY BÖRNER

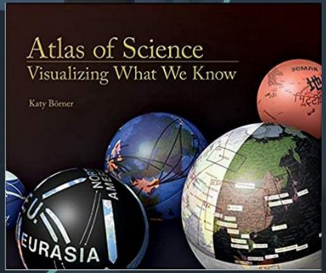


#vislis

ATLAS OF FORECASTS & MAPPING SCIENCE







#31 MEETUP
28. APRIL

WILL BE WITH
KATY BÖRNER

Data
Visualization
Lisboa

#vislis

28. APRIL

ATLAS OF FORECASTS & MAPPING SCIENCE

WITH

KATY BÖRNER

Engineer, scholar, educator and author of *Atlas of Forecasts: modeling and mapping desirable futures*

Data
Visualization
Lisboa

#vislis

15. JUNE

ATLAS OF FORECASTS & MAPPING SCIENCE

NEW DATE!

WITH

KATY BÖRNER

Engineer, scholar, educator and author of *Atlas of Forecasts: modeling and mapping desirable futures*

Data Visualization Lisboa

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.

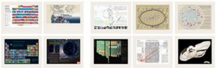
Places & Spaces: Mapping Science Exhibit

1st Decade (2005-2014)

Maps

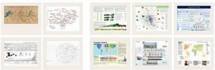
Iteration I (2005)
The Power of Maps

Iteration II (2006)
The Power of Reference Systems



Iteration III (2007)
The Power of Forecasts

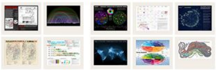
Iteration IV (2008)
Science Maps for Economic Decision Makers



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

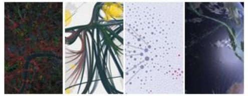
2nd Decade (2015-2024)

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.

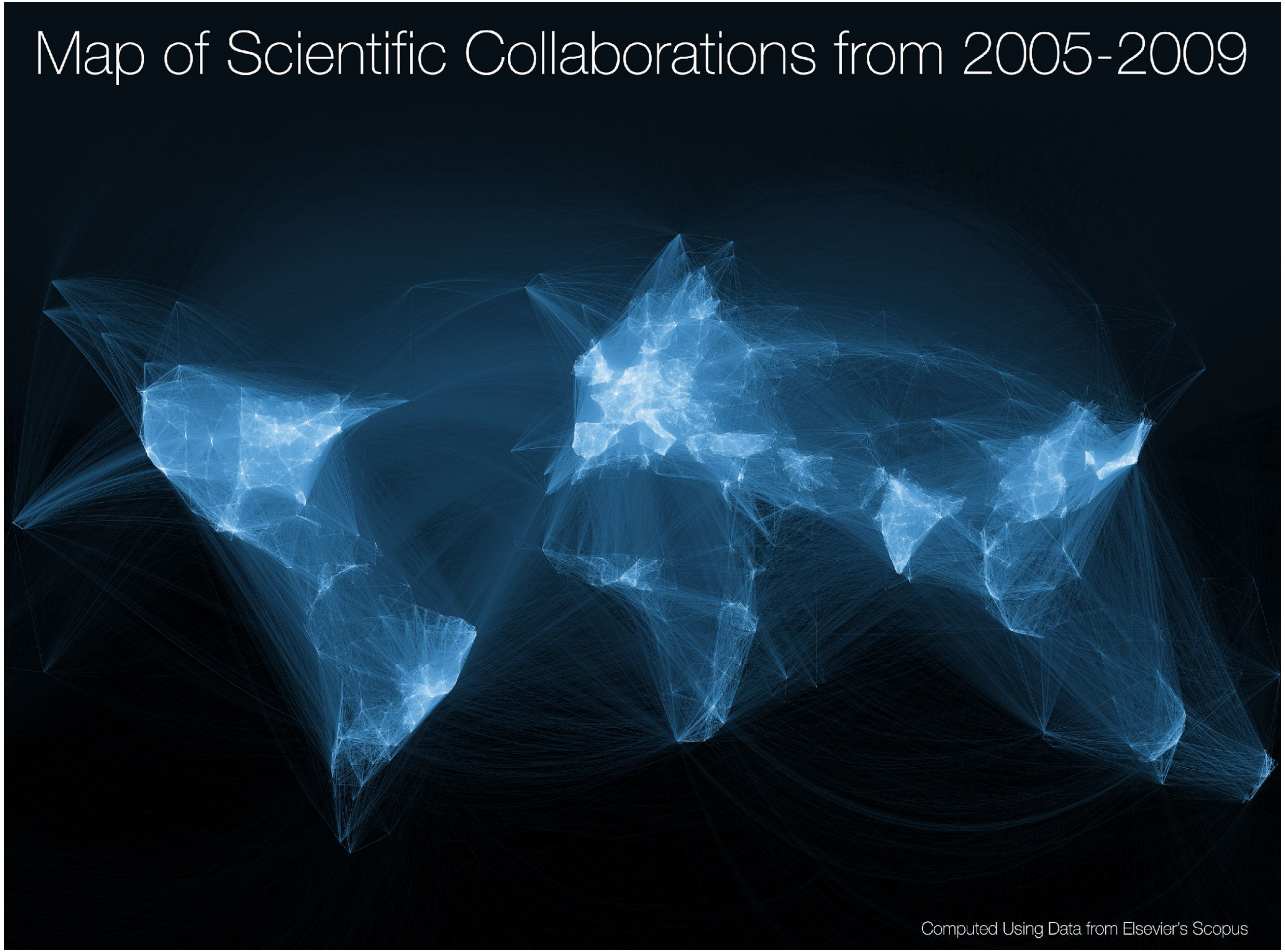
43
MACROSCOPE MAKERS
including one whose job title is "Truth and Beauty Operator."

20
MACROSCOPES
for touching all kinds of data.

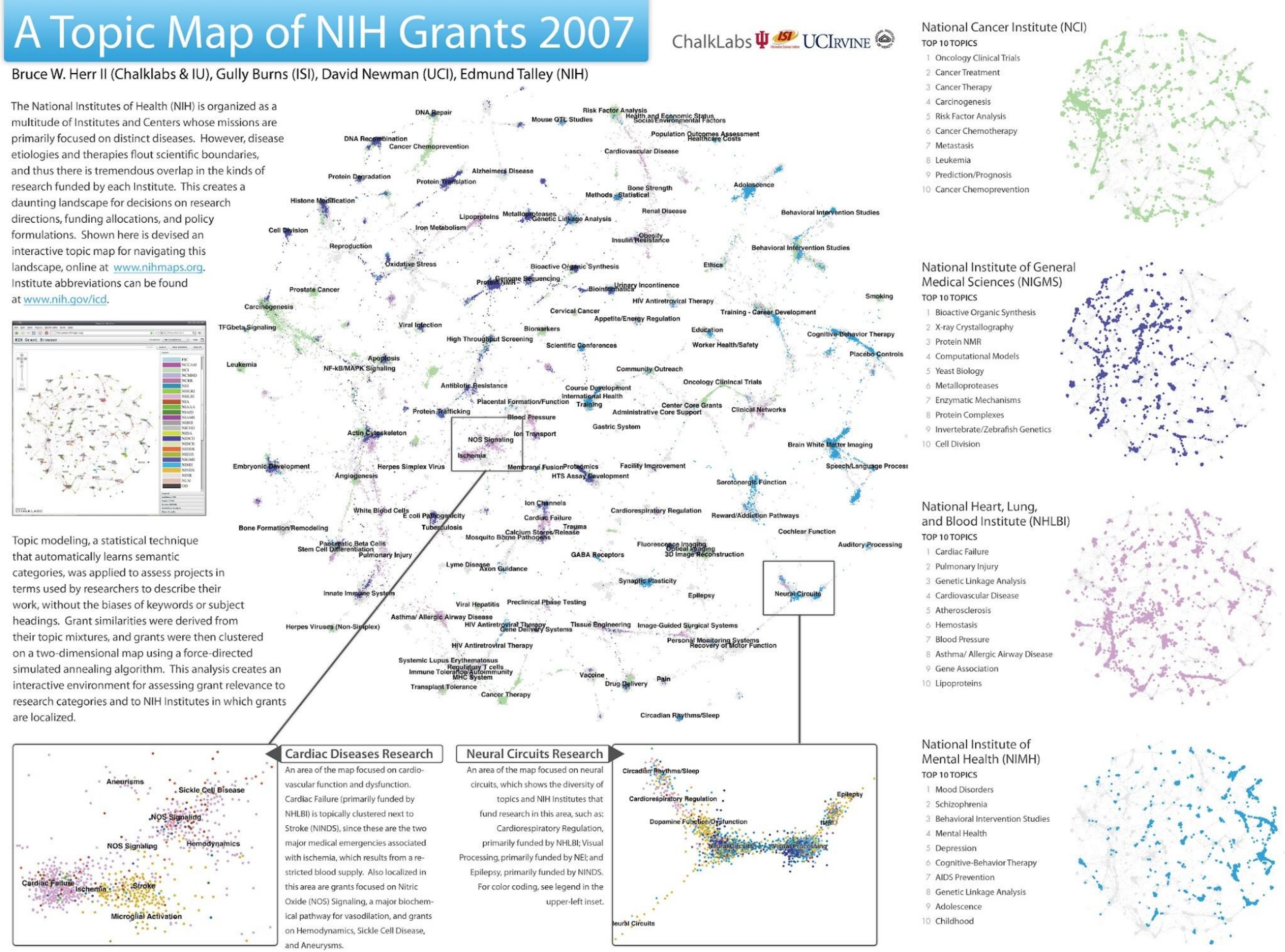
382
DISPLAY VENUES
from the Cannes Film Festival to the World Economic Forum.

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

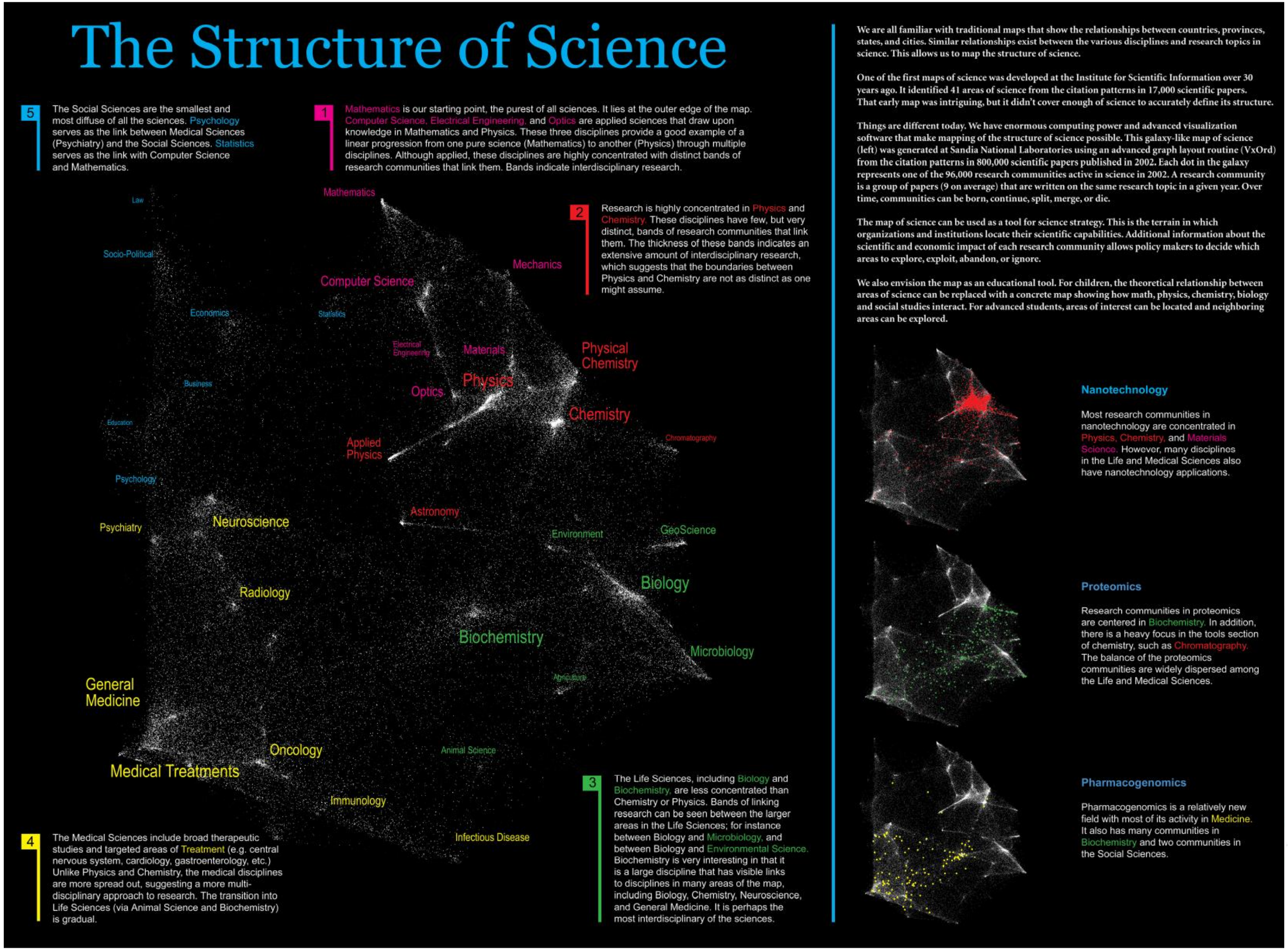
http://scimaps.org



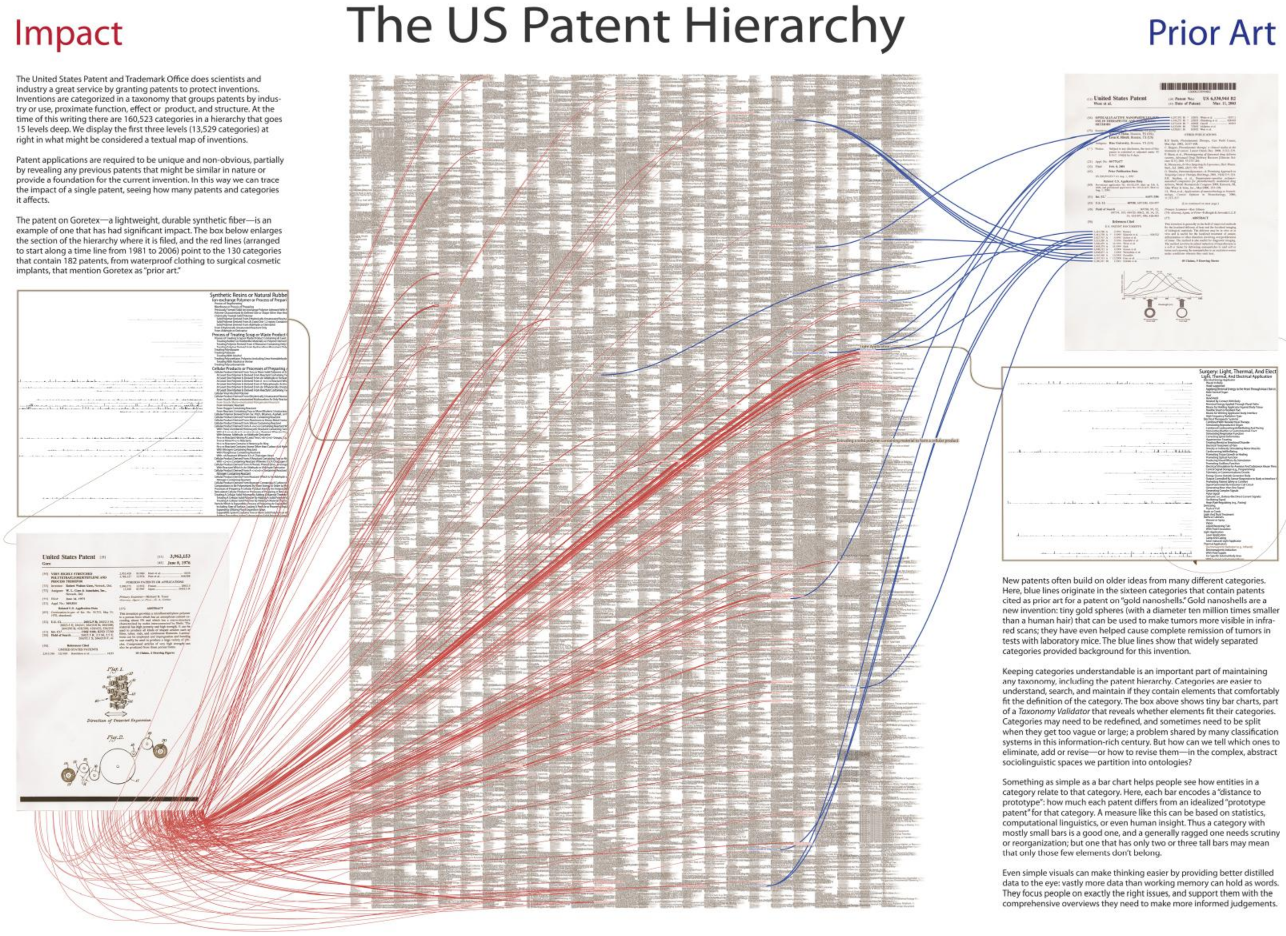
VII.6 Stream of Scientific Collaborations Between World Cities - Olivier H. Beauchesne - 2012



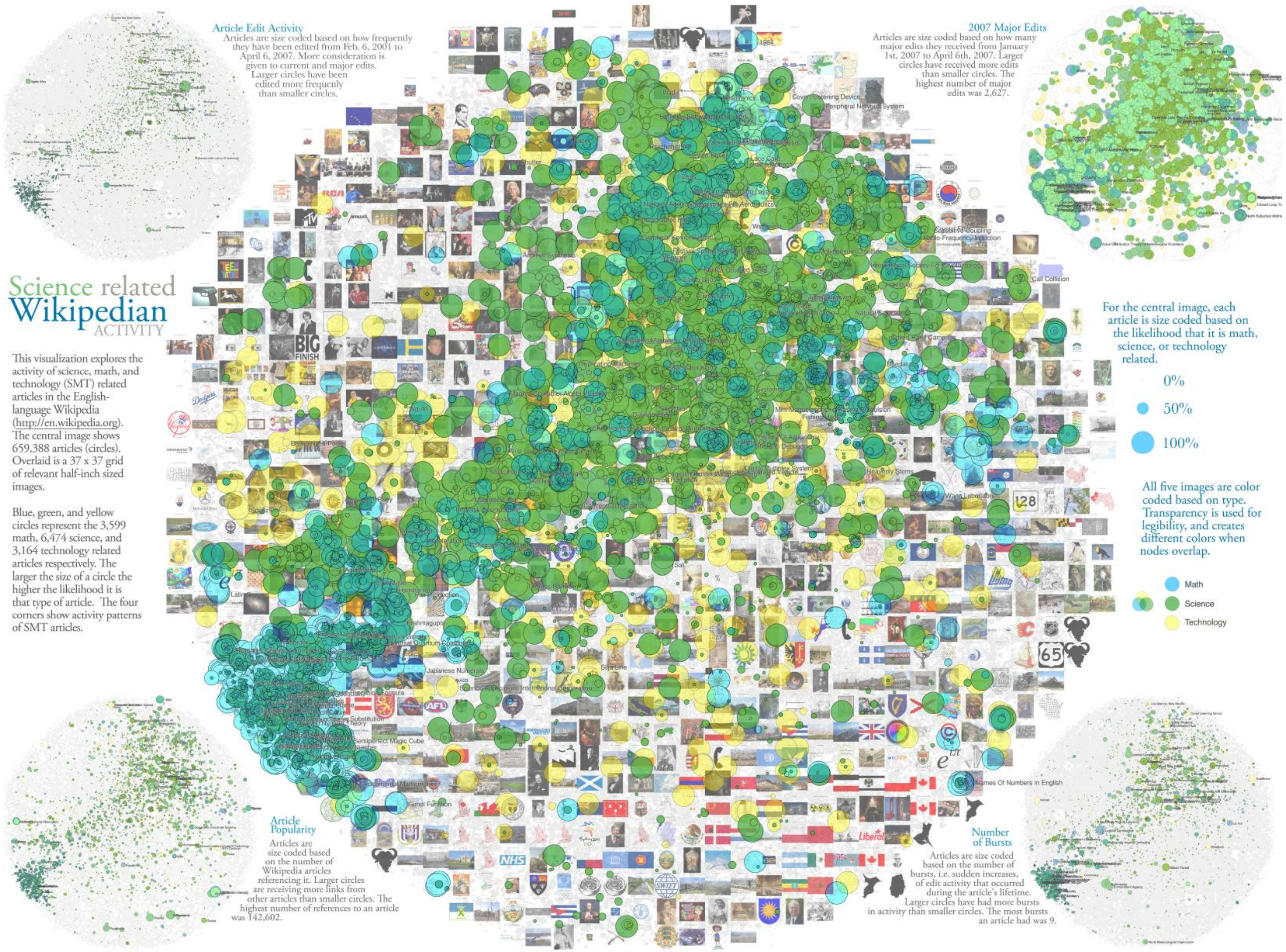
V.7 *A Topic Map of NIH Grants 2007* - Bruce W. Herr II, Gully A.P.C. Burns, David Newman, and Edmund Talley - 2009



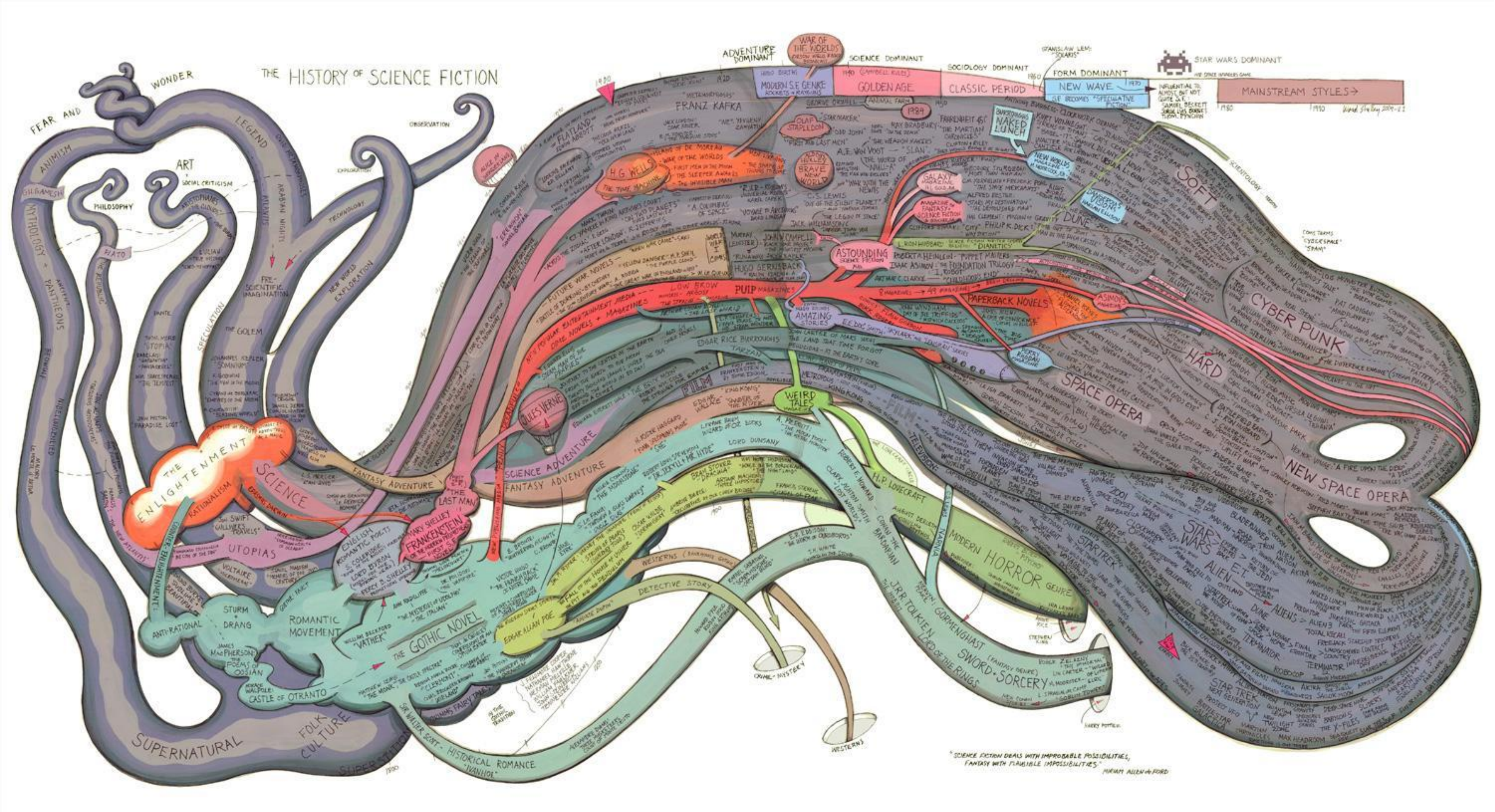
I.10 *The Structure of Science* - Kevin W. Boyack and Richard Klavans - 2005



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



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



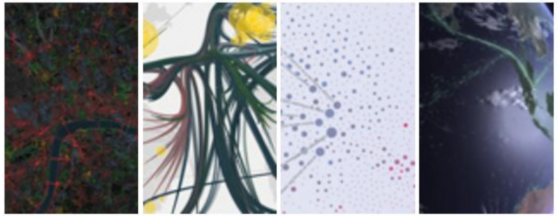
VII.10 *History of Science Fiction* - Ward Shelley - 2011

Check out our Zoom Maps online!

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

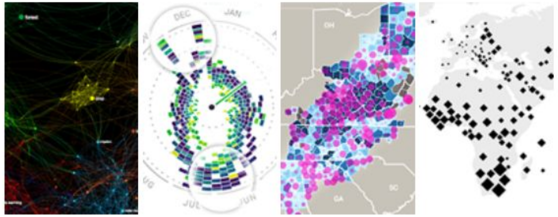
Iteration XI (2015)
Macroscopes for Interacting with Science

Iteration XII (2016)
Macroscopes for Making Sense of Science

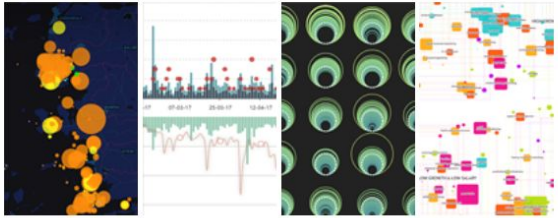


Iteration XIII (2017)
Macroscopes for Playing with Scale

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



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



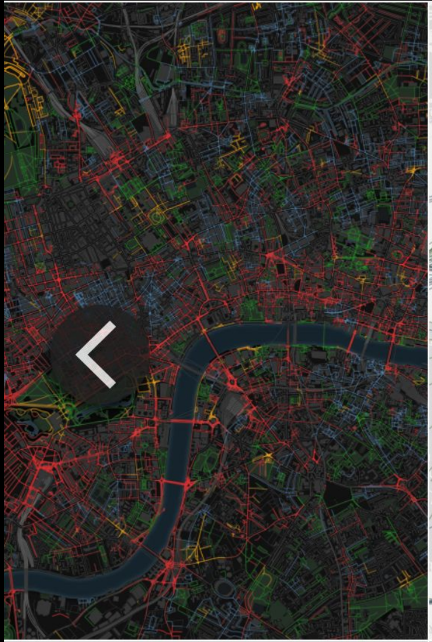
Iteration XVI (2020)
Macroscopes for Harnessing the Power of Data

http://idemo.cns.iu.edu/macroscope-kiosk

About *Places & Spaces*

PLACES & SPACES
MAPPING SCIENCE

About macroscopes

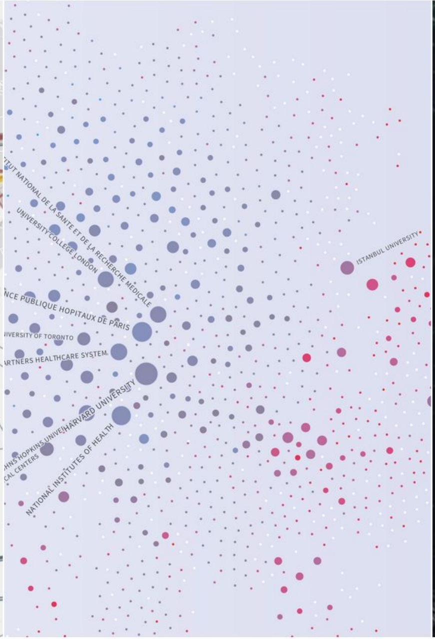


Smelly Maps

Charting urban smellscapes

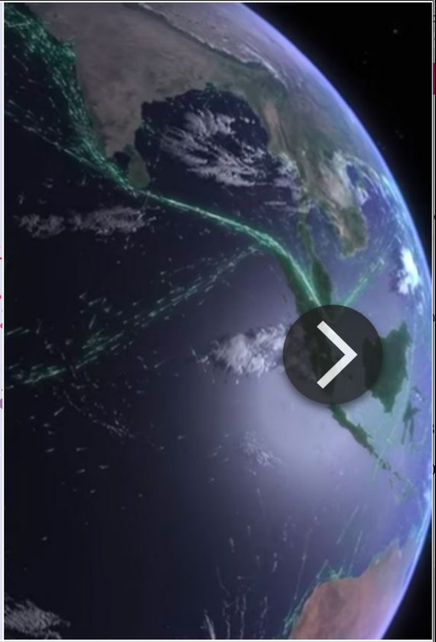
HathiTrust

Storehouse of knowledge



Excellence Networks

Publish or perish together



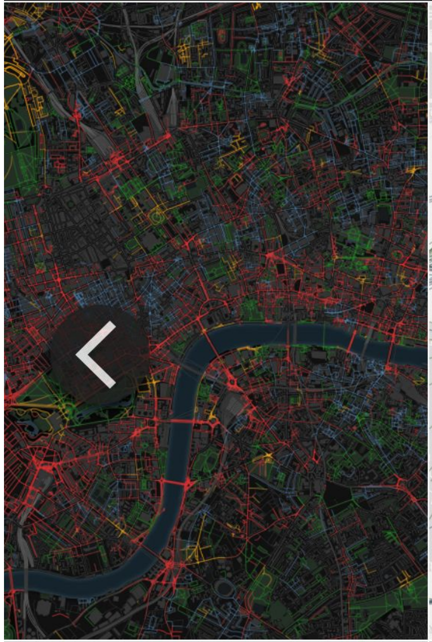
FleetMon Explorer

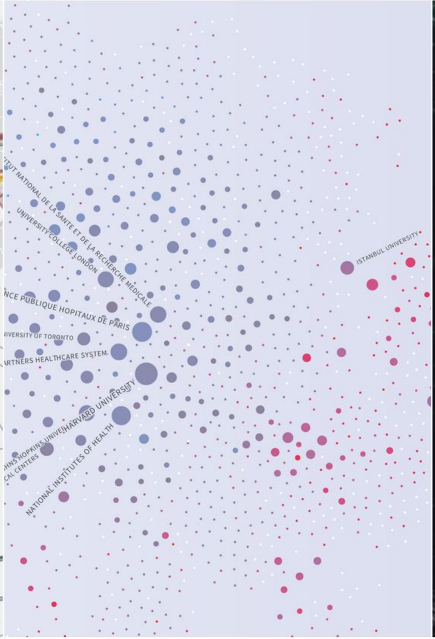
Tracking the seven seas

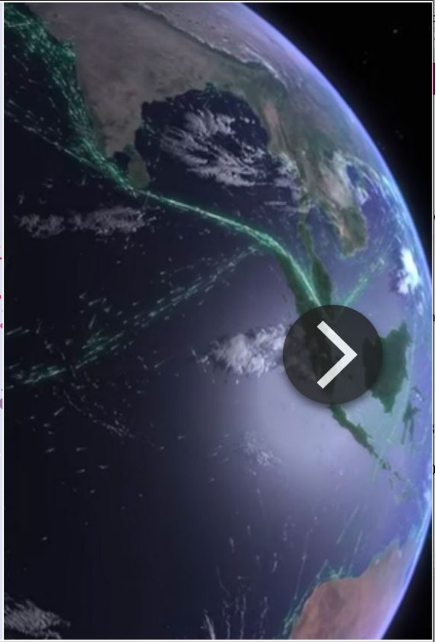
About *Places & Spaces*

PLACES & SPACES
MAPPING SCIENCE

About macroscopes







Smelly Maps
Charting urban smellscapes

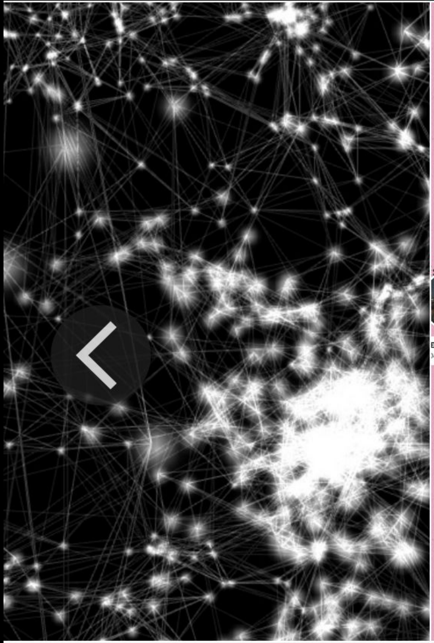
HathiTrust
Storehouse of knowledge

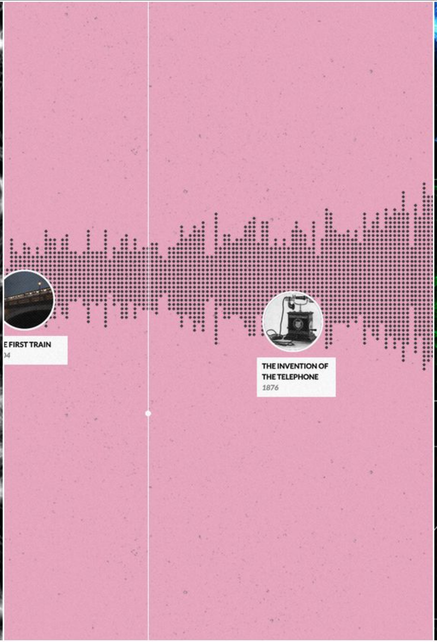
Excellence Networks
Publish or perish together

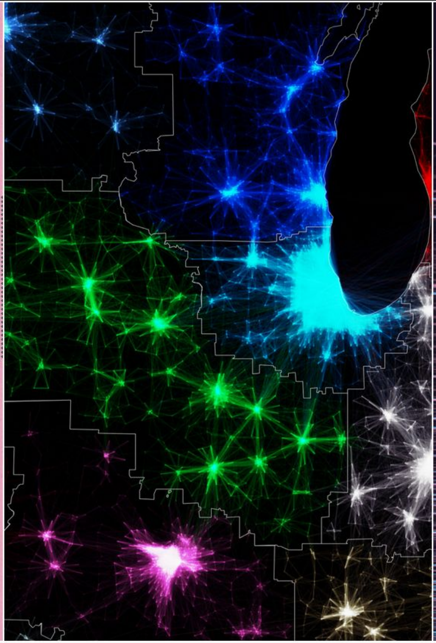
FleetMon Explorer
Tracking the seven seas

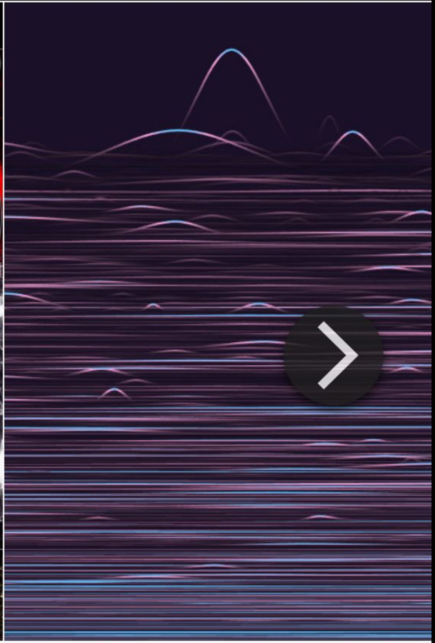
7 1

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







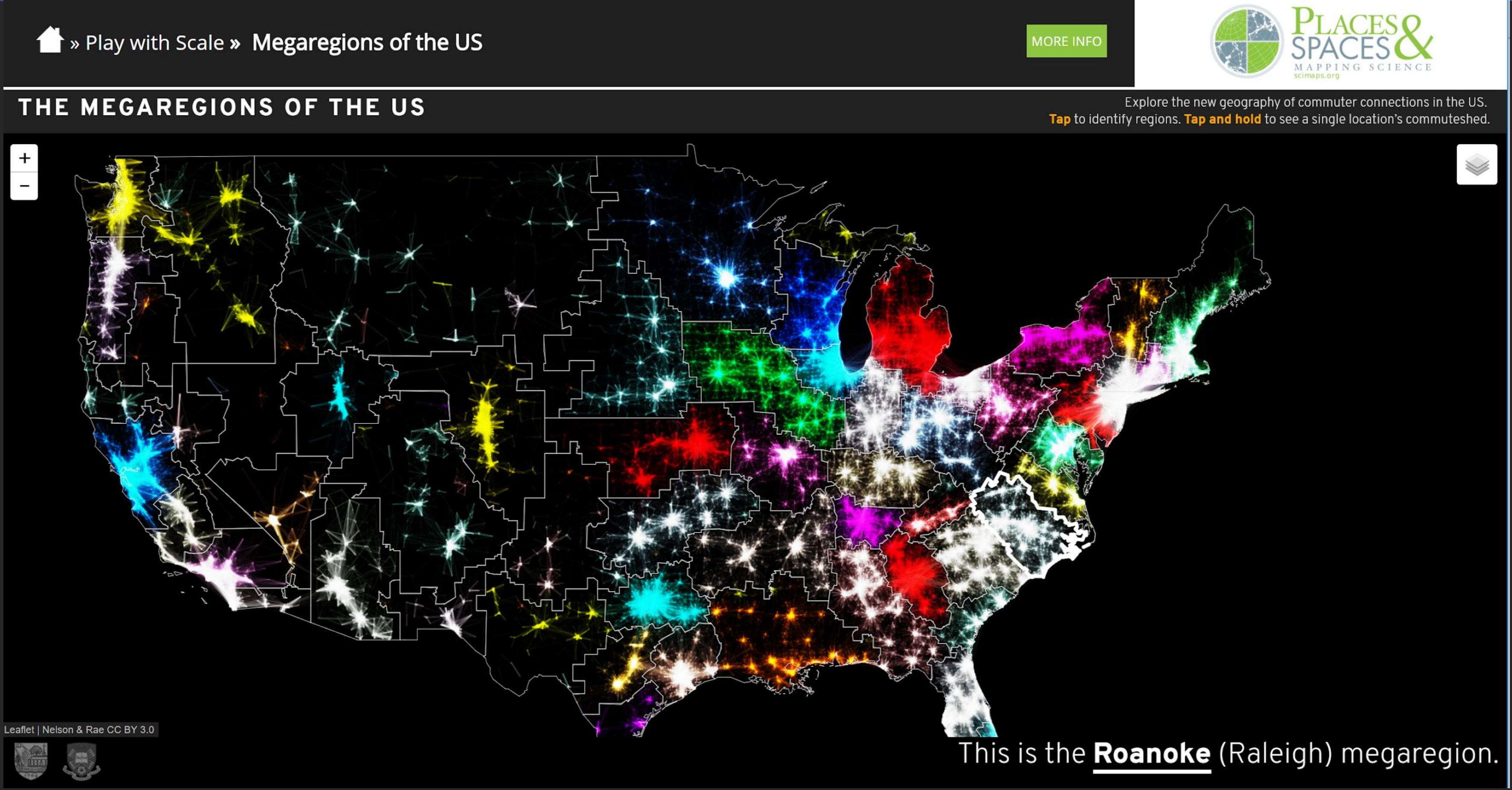


The Cosmic Web
And the network behind it

Histography
An interactive timeline

Megaregions of the US
Mapping commuter patterns

Science Paths
The random impact rule

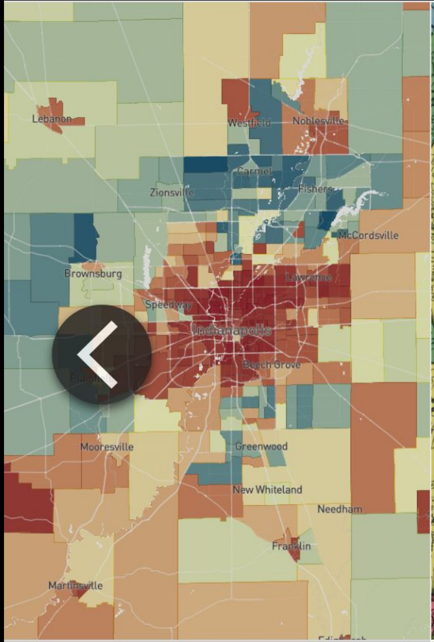


Megaregions of the US –Garrett Dash Nelson and Alasdair Rae – 2016

About *Places & Spaces*

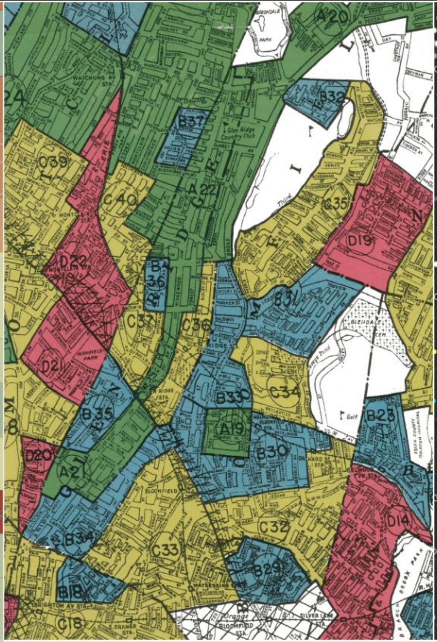
PLACES & SPACES
MAPPING SCIENCE

About macroscopes



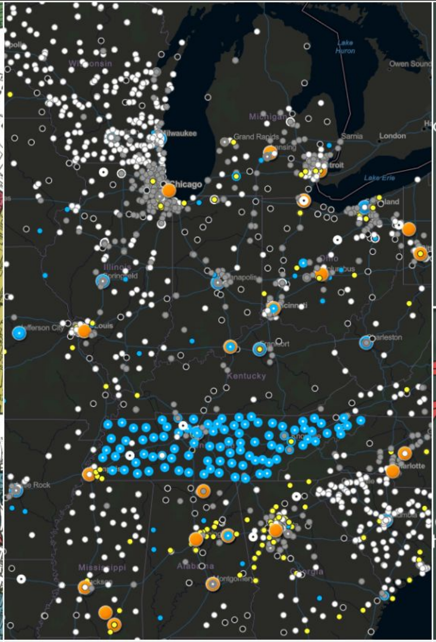
Opportunity Atlas

Different zip codes, different outcomes



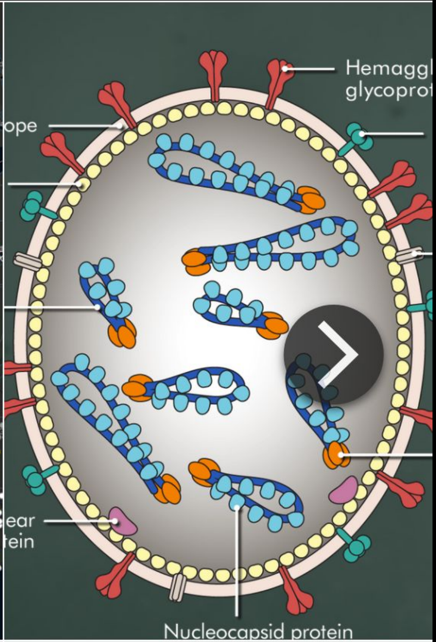
Mapping Inequality

Unequal by design



Atlas of Surveillance

One nation, under observation



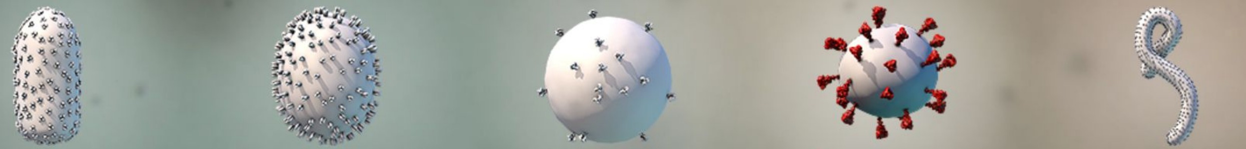
Virus Explorer

Bugs in the system

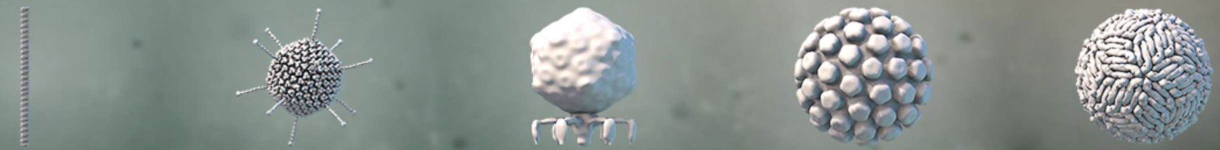
VIRUS EXPLORER

Envelope | Host(s) | Genome Type | Transmission | Vaccine

Select a category above to classify viruses according to shared characteristics.
Select any virus below to explore its structure and biology.



Rabies | Influenza A | HIV | Coronavirus | Ebola



TMV | Adenovirus | T7 | Papillomavirus | Zika

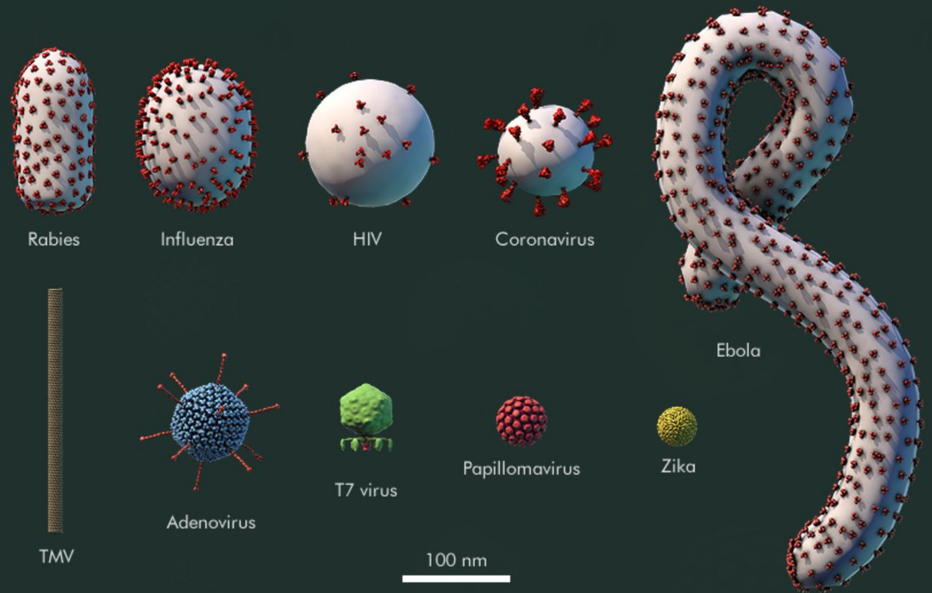
Show Relative Sizes

VIRUS EXPLORER

Envelope

accine

RELATIVE SIZES



The white line represents 100 nanometers (nm). For comparison, the width of a human hair is about 75,000 nm, so it would be 750 times as long!

Rabie
Ebola
TMV
Adenovirus
T7
Papillomavirus
Zika

Show Relative Sizes

Acknowledgements

Exhibit Curators

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

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

http://scimaps.org

Exhibit Advisory Board

Gary Berg-Cross
Cognitive psychologist (PhD, SUNY–Stony Brook). Potomac, MD, USA

Donna J. Cox, MFA, Ph.D.
Director of the Advanced Visualization Laboratory at the National Center for Supercomputing Applications, University of Illinois at Urbana-Champaign, IL, USA

Bonnie DeVarco
Media X Distinguished Visiting Scholar at Stanford University, Palo Alto, CA, USA

Peter A. Hook
Head of Digital and Scholarly Services and LawArXiv Administrator, Cornell Law Library. Ithaca, NY, USA

Francis Harvey
Professor of Visual Communication in Geography at the Liebnitz Institute for Regional Geography, Leipzig University, Germany

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

André Skupin
Associate Professor of Geography at San Diego State University, California

Moritz Stefaner
Freelance designer on the crossroads of data visualization, information aesthetics, and user interface design in Germany

Olga Subirós
Curator of Big Bang Data and Founder of Olga Subirós Studio in Barcelona, Spain

Stephen Uzzo
Vice President of Science and Technology for the New York Hall of Science

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

Call for Macroscopes: 19th Iteration

What to Submit

- Each entry needs to include:
- Title of macroscope
- Author(s) name, email address, affiliation, mailing address
- Link to online site that features the macroscope tool or to executable code
- Macroscope tool description (300 words max): user group and needs served, data used, data analysis performed, visualization techniques applied, and main insights gained
- References to relevant publications or online sites that should be cited, links to related projects or works
- Tell us about the impact your data visualization has had on public awareness, social policy, or political action.

Review Process

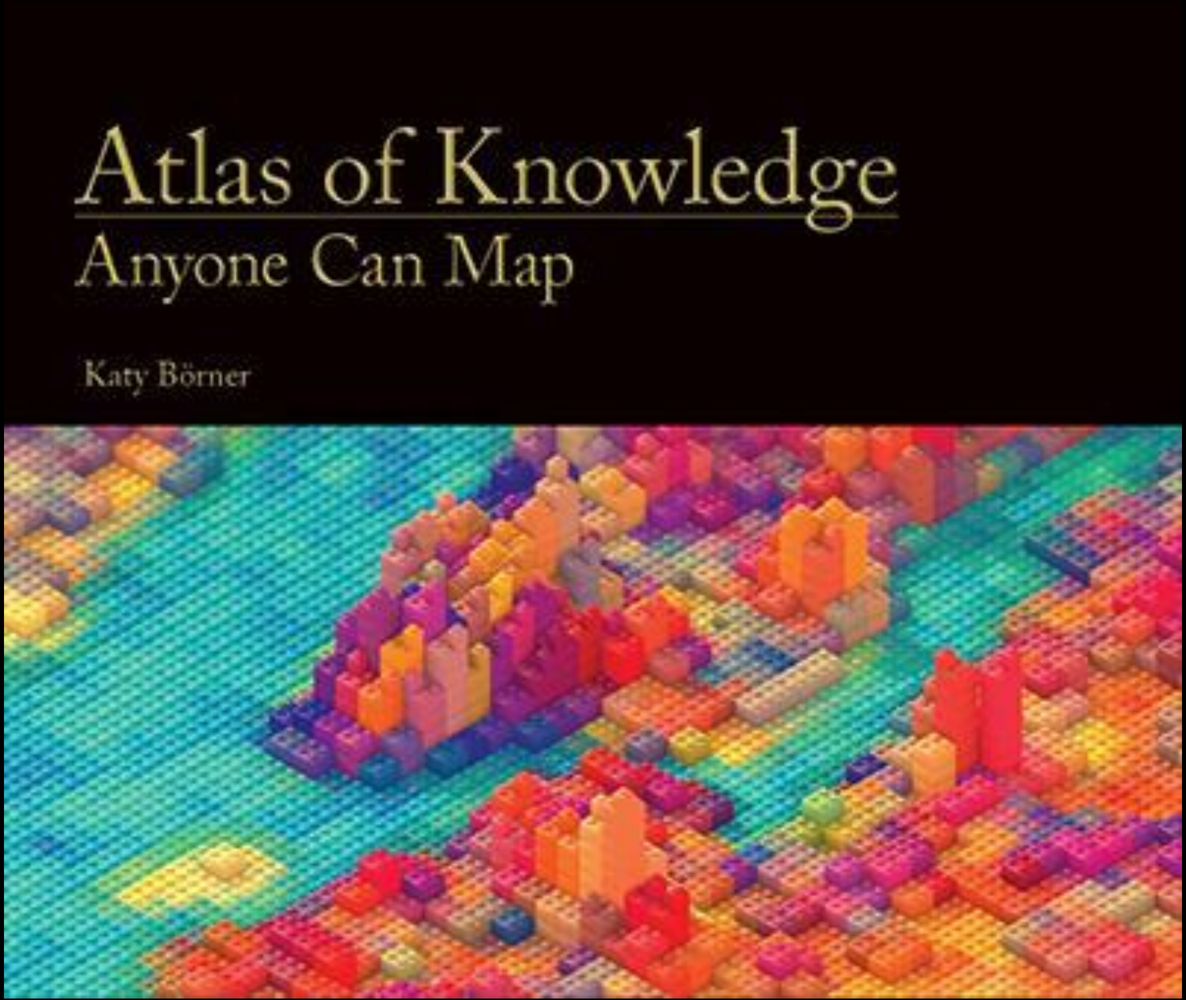
Submissions will be reviewed and evaluated by the exhibit advisory board (listed below) in terms of their:

- Scientific rigor
- Value as a tool for data exploration
- Ability to provide new, actionable insights
- Relevance for a general audience

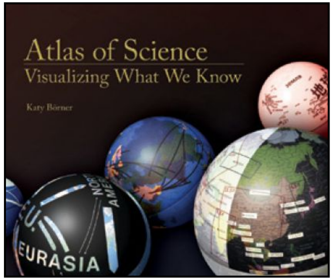
Important Dates

- Submissions due: Feb 15, 2023
- Notification to mapmakers: April 1, 2023
- Submit final entries: May 30, 2023
- Iteration ready for display: August 31, 2023

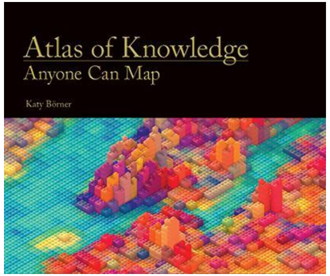
https://scimaps.org/call


Atlas of Knowledge
Anyone Can Map
Katy Börner

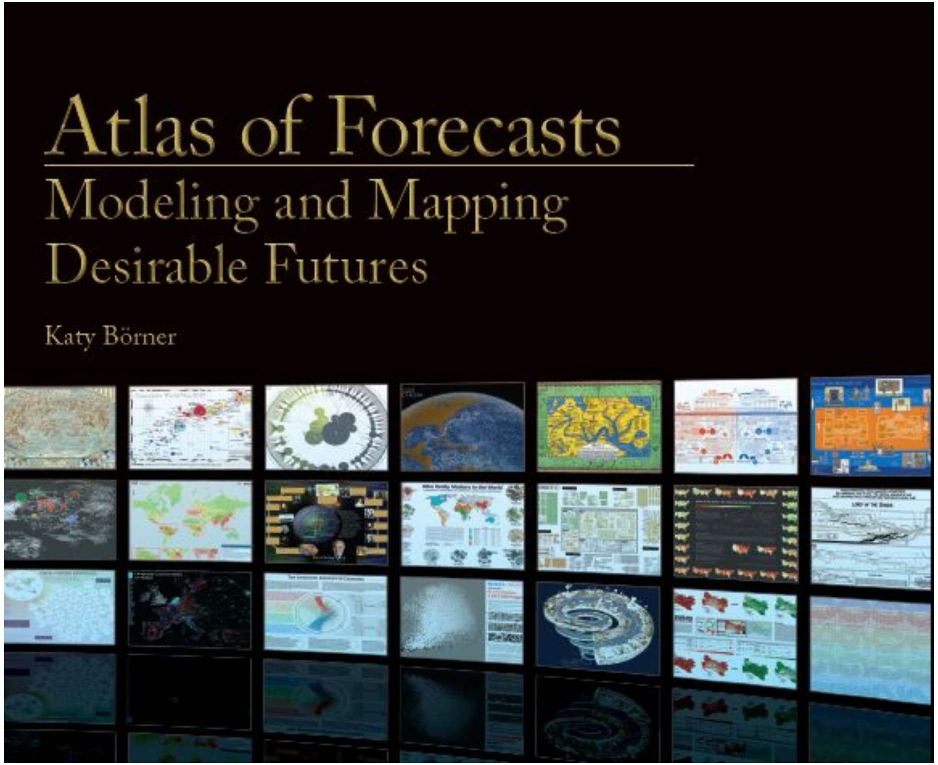
Atlas Trilogy



2010



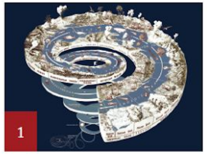
2015

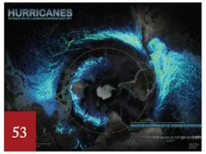


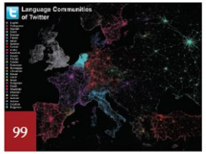
2021

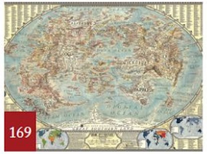
https://mitpress.mit.edu/books/atlas-forecasts

Contents









https://mitpress.mit.edu/books/atlas-forecasts

Acknowledgments

I am deeply grateful to all those who helped to make possible this *Atlas* and the exhibit maps it features. Financial support came from the National Science Foundation under Grants No. DRL-1223698, OCI-0940824, SBE-0738111, and CBET-0831636; the National Institutes of Health under Grants No. U01-GM098959, R21-DA024259, and U24-RR029822; the James S. McDonnell Foundation; the Bill & Melinda Gates Foundation; Indiana's 21st Century Fund; Thomson Reuters; Elsevier; the Cyberinfrastructure for Network Science Center, University Information Technology Services, and the former School of Library and Information Science—all three at Indiana University. Some of the data used to generate the science maps is from the Web of Science by Thomson Reuters and Scopus by Elsevier.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

A substantial part of the source review and initial writing was completed while I was a visiting professor at the Royal Netherlands Academy of Arts and Sciences (KNAW) in the spring of 2012. I would like to thank Paul Wouters of CWTS, Andrea Scharnhorst and Jeannette Haagsma of Meertens, and Peter Doorn, Linda Reijnhoudt, and Lucas Pasteuning of DANS for their support.

Part 2, "Envisioning Science," benefited deeply from my teaching of relevant courses at Indiana University over the last 14 years, including teaching Information Visualization MOOC (IVMOOC) to students from more than 100 countries in the spring of 2013.

The *Places & Spaces: Mapping Science* exhibit would not have been possible without the expertise and professional excellence of the more than 150 mapmakers and the 42 exhibit ambassadors around the globe. Exhibit advisers for the maps featured in this book include: Deborah MacPherson (Accuracy&Aesthetics), Kevin W. Boyack (SciTech Strategies, Inc.), Sara Irina Fabrikant (Geography Department, University of Zürich, Switzerland), Peter A. Hook (Law Librarian, Indiana University), André Skupin (Geography, San Diego State University), Bonnie DeVarco (BorderLink), and Dawn Wright (Geography and Oceanography, Oregon State University). External experts that reviewed iterations 4 through 7 included: John R. Hébert (Chief of the Geography and Map Division, Library of Congress), Thomas B. Hickey (OCLC), Michael Kurtz (Harvard-Smithsonian Center for Astrophysics), Denise A. Bedford (World Bank), William Ying (CIO ArtSTOR), Michael Krot (JSTOR), Carl Lagoze (Cornell University), Richard Furuta (Texas A&M University), Vincent Larivière (Université du Québec à Montréal, Canada), Adam Bly (CEO of SEED), Alex Wright (author of *Glut: Mastering Information Through The Ages*), and Mills Davis (Project10x.com).

Focused brainstorming workshops, organized with colleagues between 2008 and 2012, contributed greatly to the discussion of research and development (R&D) work that is contained in these pages. A total of 16 such workshops were held on a range of topics, including "How to Measure, Map, and Dramatize Science," "Mapping the History and Philosophy of Science," "Modeling Knowledge Dynamics," "Artists Envision Science & Technology," and "Plug-and-Play Macroscopes" (see group photos ||below).

It may seem unwise to devote a major part of one's research time to writing a series of books for readers who are unlikely to write papers or otherwise cite these books in academic circles. And yet it seems quite on target to enable those who finance science via tax dollars to benefit from the research results—forfeiting the maximization of citation counts via the production of research papers. Many others have taken this route, including the following luminaries who have inspired my own journey: Jacques-Yves Cousteau, the French explorer and researcher of the sea; David Attenborough, especially with his *Life on Earth* and *Living Planet* series; Paul Otlet, with his *Universal Atlas* or *Encyclopedia Universalis Mundaneum*; Stuart Brand, author of *The Whole World Catalog*; Richard Dawkins, famed for his "Growing Up in the Universe" lectures; Al Gore for his environmental efforts, as featured in the *Inconvenient Truth* documentary; and Hans Rosling, whose Gapminder effort gave rise to the motto, "Let my dataset change your mindset." It is my hope that this *Atlas* series joins in giving both inspiration and encouragement to future science communicators.

Copyediting of the *Atlas* was performed by Gordana Jelisijevic; *Atlas* layout and design by Tracey Theriault, with many of the images specifically created for this book by Perla Mateo-Lujan and Samuel T. Mills; reference checks and formatting by Todd N. Theriault; and copyright acquisition by Samantha Hale, Brianna Marshall, Joseph Shankweiler, and Michael P. Ginda. Other valued contributions are acknowledged in the **References & Credits (page 178)**.

This *Atlas* was influenced by research and developments in many areas of science; it also benefited from countless discussions and brainstorming sessions with esteemed colleagues. And yet the bittersweet decision making regarding content, format, structure, and design at every stage was mine alone to make.

I am indebted to family and friends for providing much inspiration, energy, and loving support. This book benefited deeply from nurturing and thought provoking family dinner discussions and empowering girls' nights out. My gratitude also rests with our cat, Jiji, who kept me company through the many long periods of writing.

October 1-2, 2009: NSF/JSMF Workshop on How to Measure, Map, and Dramatize Science, New York Hall of Science, NY

March 4-5, 2010: NSF/JSMF Workshop on Mapping of Science and Semantic Web, Indiana University, Bloomington, Indiana

October 9-10, 2010: Modelling Knowledge Dynamics, The Virtual Knowledge Studio, Amsterdam, The Netherlands

August 11-12, 2011: JSMF Workshop on Standards for Science Metrics, Classifications, and Mapping, Indiana University, Bloomington, Indiana

March 25-26, 2013: Exploiting Big Data Semantics for Translational Medicine, Indiana University, Bloomington, Indiana

May 5, 2014: Researchers and Staff at the Cyberinfrastructure for Network Science Center, Indiana University, Bloomington, Indiana

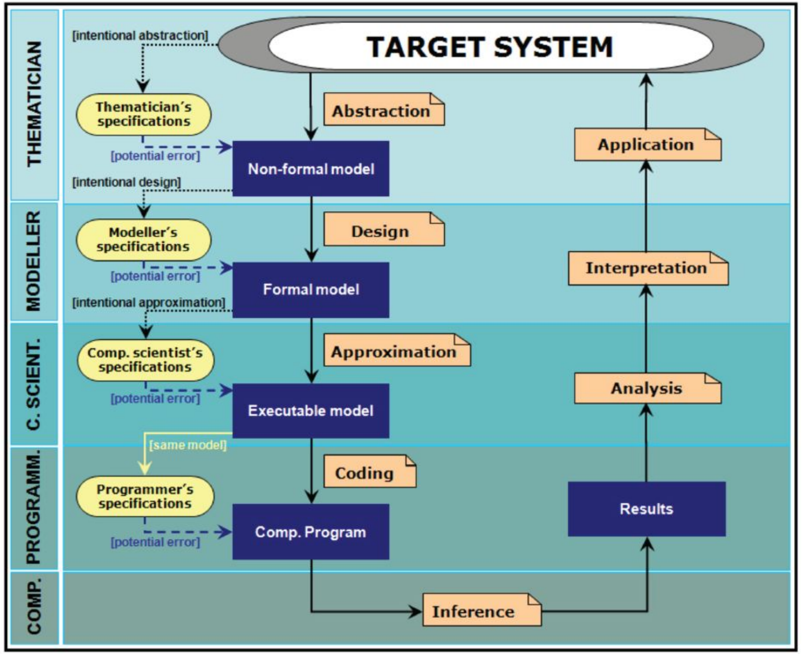
https://mitpress.mit.edu/books/atlas-forecasts

Atlas of Forecasts: Models of (Desirable) Futures

Model Classes

Many different modeling approaches exist. The table below by William B. Rouse shows exemplary levels of modeling, issues needing to be addressed, and models that have been successfully applied to support decision-making.

Level	Concern	Models
Society	GDP, Supply/Demand, Policy	Macroeconomic
	Economic Cycles	System Dynamics
	Intra-Firm Relations, Competition	Network Models
Organizations	Profit Maximization	Microeconomic
	Competition	Game Theory
	Investment	DCF, Options
Processes	Patient, Material Flow	Discrete-Event Models
	Process Efficiency	Learning Models
	Workflow	Network Models
People	Patient Behavior	Agent-Based Models
	Risk Aversion	Utility Models
	Disease Progression	Markov, Bayes Models



Modeling Goals

Models aim to capture key phenomena at the levels that are most relevant for the understanding, communication, and management of systems. This spread describes and exemplifies key phenomena that are commonly studied when aiming to understand complex systems. Phenomena are roughly organized by question type (temporal, geospatial, topical, and network) and complexity. Models that use static reference systems and no feedback cycles are introduced first, followed by phenomena that aim to capture evolving networks and activity patterns unfolding over them, including feedback or causal loops.

The greatest shortcoming of the human race is our inability to understand the exponential function.
Albert A. Bartlett

Phenomena of Interest

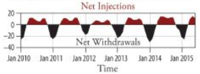
To the best of our knowledge, there exists no master list of key phenomena that could be used to characterize a target system and/or comprehensively define what system a model aims to capture. Yet any modeling effort should start with tabulations of the phenomena to be modeled, together with information on target system simplifications that may or may not be acceptable. Those tabulations can then be used to choose model class and parameter values (see **Model Class Overview, page 24**).

A model might have various aims: to answer particular types of questions (e.g., temporal/when or geospatial/where—see **Questions Overview, page 68**); to focus on a specific domain (e.g., education, science, and/or policy—see **Domains Overview, page 70**); and to capture diverse phenomena (such as those discussed in this spread) at one or more scales, from micro to macro (see **Scales Overview, page 72**).

Seasonality

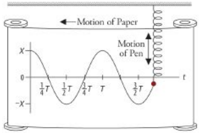
Many systems have an inherent seasonality. For instance, they might depend on changes in temperature, precipitation, or daylight over the year. As a specific example, natural-gas consumption patterns are predominantly driven by shifts in temperature. The largest net withdrawals occur in winter, when gas is used for heating, see figure below.

Natural Gas Storage Withdrawals and Injections, Jan. 2010–Jan. 2015 *(Billion Cubic Feet per Day)*



Oscillation

Any motion that repeats itself is called an oscillation. Examples are a swing, or a ball on a spring that oscillates using the energy minimum x_0 over time t. The figure below shows the latter example, with a pen attached to the red ball and paper moving from right to left as it records the movement of the ball.



Periodic functions can be used to describe a particular oscillation, with sine and cosine being the most common functions used. For example, the displacement oscillation of the red ball in the figure above can be described by $x(t)=X\cos(\Omega t+\Phi)$.

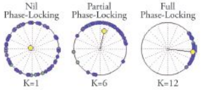
Alternatively, differential equations can be used to describe oscillations (e.g., predator-prey systems in which rabbit and fox populations oscillate with a particular phase offset—see the example under **Basic Model** in **Lotka-Volterra Predator-Prey Models, page 31**).

Synchronization

Some events coordinate over time so they happen simultaneously. For example, fireflies that periodically light up together, excitation patterns of neurons, people clapping in unison at an event, or the interdependent actions of traders in financial markets.

Yoshiki Kuramoto proposed a simple, elegant mathematical model in the 1970s that simulates synchronization as a set of coupled oscillators, represented by blue dots in the image below. Initially, the oscillators change values rhythmically—each at its own frequency. When the oscillators are connected, the oscillating nodes begin to influence each other's oscillation phases. When oscillators freeze into sync, they line up only in time, not space.

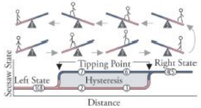
Kuramoto Oscillators



Tipping Point

A tipping point (also called a regime shift) refers to a critical point when gradual changes in external conditions (e.g., temperature or the availability of food) lead to a rapid change between the alternative stable states of a system. The changes can be irreversible (e.g., if wood burns to ashes or a species goes extinct).

Some changes might be reversible but without use of the original path, as the thresholds for those changes vary in different directions, which is known as hysteresis. An example is the idealized seesaw shown below, wherein two opposing states depend on the position of the figure walking past the midpoint (see nodes and images 3 and 7) and thus creating a distance between the two tipping points.

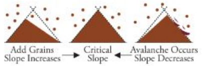


Phase Transition

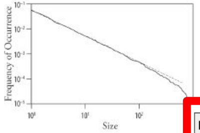
The transformation of a thermodynamic system from one phase or state of matter to another (e.g., from liquid to gas due to heat) is called phase transition. Phase transitions also refer to punctuated equilibria wherein periods of stability are interrupted by phases of rapid change. The rapid change is often due to positive feedback loops that drive the system far from equilibrium and result in exponential change. For example, the purposeful rewiring of a network can change a 1D string of nodes and links into a star-shaped network with completely different network diffusion dynamics (see the discussion in **Network Models, page 46**).

Self-Organized Criticality

Also known as chain reaction, self-organized criticality (SOC) refers to the fact that a system is able to sustain only a limited amount of stress. If stress exceeds a certain critical threshold, then the system relaxes locally to an unstressed state, and the stress is distributed to the neighborhood. Examples of SOCs are earthquakes and nuclear chain reactions. Another example is sand pile avalanches, which have been studied experimentally using physical sand piles (see the figure below) and analytically using cellular automata (page 40).

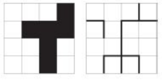


In 1987, Per Bak and colleagues showed that avalanches exhibit a power law distribution of $f(s)\sim s\text{–}1$ (see the log-log graph below of the frequency of occurrence $f(s)$ of an avalanche of size s versus avalanches rank-ordered by size, for a total of 200 avalanches).



Percolation

Percolation is studied by physicists and mathem[aticians] as a model for the flow of a substance (e.g., oil or water) through certain types of porous med[ia] (e.g., sand). In 1957, Simon Broadbent and John Hammersley introduced a percolation model usi[ng] the example of a porous stone immersed in a buc[ket] of water. They wanted to answer: What is the pro[b]ability that the center of the stone becomes wet? Site/node and bond/link percolation models exist [...] subsequent figure); the former focuses on removi[ng] nodes while the latter focuses on removing links.



Both approaches can be applied to understand the probability p that a path exists between two nodes/edges, or what fraction $1–p$ of failures is required for the network graph to become disconnected (see the model discussion in **Cellular Automata, page 40**).

Adaptation and Learning

In evolution, adaptation is the process that species use to become better suited to their environment. There are phenotype changes (e.g., different bird beaks exploit different food niches—see **Gause's Law, page 33**), and behavior changes (e.g., birds adapting to life in urban environments), which are also called learning. Phenotype and behavioral adaptation is often complementary, as can be seen in the illustration below of dung beetles evolving to have shorter horns (dashed arrow) that make it possible to sneak past fighting male competitors (solid arrow) in order to reach female mates (red symbol at bottom).

Fractals via Recursion

A fractal is a pattern that continuously repeats at different scales, such as can be seen in trees, rivers, [...] sively generated tree pattern, the algorithm takes an argument n and produces the five trees shown for n=1, 2, 3, 4, 8 respectively.

Fractals via Diffusion-Limited Aggregation

Diffusion is a widely studied phenomenon and the primary means of transport in many systems. Diffusion-limited aggregation (DLA) models can be applied to simulate system growth and behavior, such as that of the sample model result below. Exemplary systems are snowflakes, lightning, and cities. The fractal clusters grown by DLA models are also called Brownian trees, as particles undergo a random walk using Brownian motion until they get within a certain critical range, whereupon they are pulled into a cluster.

Reaction-Diffusion Dynamics

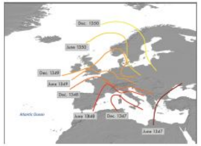
This phenomenon was initially studied in chemistry for systems in which the concentration of chemical substances changes due to local chemical reactions, with diffusion then causing those substances to be converted into each other and transported in space. The same dynamics [...]

[...]modeled using [...]mic Models, page [...] page 44; and [...]

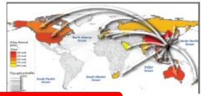
[...]onnected by [...]els, page 46). [...]rks, co-author [...]etworks of trade [...]s, and metabolic [...]an be changed by [...]odes and edges. [...]twork for the

Diffusion

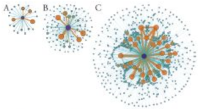
Diffusion (also called spreading) can unfold over discrete or continuous space, or via networks. It may involve the spread of tangible objects (e.g., goods, people, or even viruses) or intangible objects (e.g., media, news, or even bitcoin). In the 14th century, the devastating Black Death (also known as the Plague) spread throughout Europe via travel in waves—as fast as one person could travel per day, arriving first at the outskirts of populated areas (see map below).



Widespread availability and usage of the airline transportation system has led to vastly different diffusion patterns. Since the 20th century, many diseases have traveled via air traffic routes—from one major urban center to the next—quickly endangering millions (see the figure below, which shows virus path probability for SARS; see also *Impact of Air Travel on Global Spread of Infectious Diseases* in *Atlas of Science*, page 150).



Hungarian mathematician Paul Erdős is shown in the subsequent figure. The central purple node, denoting Erdős, has the highest number of links; orange nodes have more links than green ones. As time progresses from *A* to *C*, nodes and edges increase, as does the density of the network core.



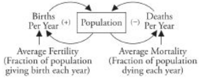
Braess's Paradox

Adding a road to a congested road traffic network can increase overall journey time. This paradox was discovered in 1968 by mathematician Dietrich Braess. Models now exist to explain why building new roads can increase traffic congestion, and conversely why closing major roads might improve traffic flow (see the **Faster Is Slower** example and model in **Game Theory, page 43**).

Positive and Negative Feedback Cycles

Many systems exhibit feedback loops—cyclic structures of cause and effect that feed system outputs back to system input, possibly via a series of secondary processes. There are positive/reinforcing and negative/balancing feedback cycles.

The book *Limits to Growth* (1972) discusses a number of feedback structures that aim to capture changes in population size. A causal loop diagram (see **Model Visualization, page 20**) of a population growth model is shown below: the central rectangle indicates population size; on the left is the positive/reinforcing cycle of births per year, parameterized by average fertility, which accounts for the observed exponential growth; on the right is the negative/balancing cycle of death per year, parameterized by average mortality.



Population growth rates for different stable and unstable scenarios are given on **page 7**, while diverse modeling approaches are discussed in **Dynamical Equations (page 32)** and **Agent-Based Models (page 48)**.

Phenomena	Model Classes		Target System Models	
Oscillation	Expert-Based Models	26	Predator-Prey Model (1925)	31
Synchronization	Descriptive Models: Indexes and Laws	28	Tinbergen's Gravity Model (1962)	33
Tipping Point	Predictive Models	30	Markov Chain Model (1913)	34
Phase Transition	Dynamical Equations (1687)	32	Kermack–McKendrick Epidemic Model (1927)	38
Self-Organized Criticality (SOC)	Probability Theory (1713)	34	Eden Growth Model (1961)	40
Percolation	Control Theory (1868)	36	Schelling's Segregation Model (1971)	41
Adaptation & Learning	Epidemic Models (1927)	38	Prisoner's Dilemma Model (1950s)	43
Fractals	Cellular Automata (1940s)	40	Braess's Paradox: Faster is Slower (1968)	43
Reaction Diffusion Dynamics	Game Theory (1950)	42	The Keller-Segel Model (1970)	45
Network Growth	Continuous Field Models (1952)	44	Erdös-Rényi Model (1959)	47
Network Gatekeepers	Network Models (1959)	46	Watts-Strogatz Model (1998)	47
Network Attack and Error	Agent Based Models (1980s)	48	Barabási–Albert Model (1999)	47
Diffusion/Spreading	Machine Learning Models (1990s)	50	Economics of Wealth Distribution Model (1996)	49

Modeling Framework

When developing a model of a real-world system, many critical decisions must be made regarding model components, their behavior, the environment, and system dynamics evolving over time. Any model design should start with a specification of stakeholders and their insight needs, followed by phenomena of interest, and finally the success criteria that define when a model is fit for purpose. Model validation and results communication must all be detailed. Diverse approaches have been proposed to provide templates and standards for systematic model development and documentation—in support of the replicability of results. This spread reviews prior work on modeling frameworks and then introduces and expands the data visualization framework presented in *Atlas of Knowledge*, **Part 2**, to cover the emergent phenomena discussed in the previous spread, as well as the expert-based, descriptive, and predictive models discussed throughout the *Atlas of Forecasts*.

We cannot stop the march of history, but we can influence its direction.
Yuval Noah Harari

Prior Work

There exist many frameworks that aim to guide novices and experts in the design, run, visualization, and validation of models. Most are domain-specific, focusing on a small number of model classes. Some aim to develop a typology of important concepts, while others try to codify the different process steps involved in modeling.

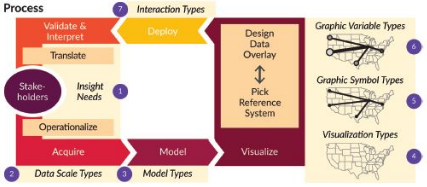
For example, the Open Collaboration for Policy Modelling (OCOPOMO) project has developed and demonstrated a policy development model/process that distinguishes six phases: (1) initial scenario definition, (2) evidence-based, stakeholder-generated scenario development, (3) development of conceptual models, (4) programming of policy models, (5) simulation and generation of model-based scenarios, and (6) evaluation. The model assumes a close collaboration between domain experts such as policy planners and strategic decision-makers, stakeholders, and modeling experts. In phase 5 of the process, modeling experts instantiate simulation models with particular variables, run the simulations, and visualize the model results using text and graphs. The visualizations help communicate system component dependencies and what system behavior is derivable from current scenario descriptions; as a result, domain experts, stakeholders, and modeling experts can provide feedback and help optimize model design.

The NIH Cancer Intervention and Surveillance Modeling Network (CISNET) aims to standardize the description of models in support of model comparison and reuse. They suggest using a set of seven documents: (1) Model Overview—an overview of the entire modeling effort, including the questions that the model was designed to answer; (2) Model Purpose—a description of the primary and secondary purposes and problems for which the model was designed; (3) Parameter Overview—an overview of the parameters that inform the model; (4) Assumption Overview—a preliminary overview for the model's assumptions, both explicit and implicit; (5) Component Overview—a summary of the model's major process components; (6) Output Overview—an introduction to the types of outputs generated by the model; and (7) Result Overview—a starting point or "reader's guide" to the various model results.

Uri Wilensky, developer of the agent-based programming language NetLogo, provides guidance and templates for the proper documentation of models: "What Is It?" encourages users to develop a general description of the phenomena being modeled; "How It Works" explains the model; "How to Use It" gives instructions on how to run the model and use the interface elements of the model; "Things to Notice" advises how to describe interesting phenomena that the model exhibits; "Things to Try" explains how a user can manipulate the model to produce new results; "Extending the Model" gives suggestions and challenges on how to change the model to examine new features and phenomena, similar to the future work section of a research paper; "NetLogo Features" discusses particularly interesting features of NetLogo that are used in the model; "Related Models" provides links to other related agent-based models; and "Credits and References" directs how to reference who created the model and where the user can go to find more information on the model. The templates have been widely used, resulting in a rich and diverse set of well-documented models that are widely used in research and teaching.

Volker Grimm and colleagues developed the Overview, Design concepts, and Details (ODD) protocol to standardize the description of individual- and agent-based models (IBMs and ABMs, respectively) in ecological modeling. ODD defines how to group information: "Overview" captures the purpose of the model; defines model entities, their states, and scales; and provides information on the model process and run. "Design concepts" aim to capture the phenomena that the model aims to reproduce. "Details" describe model initialization, input data, and submodels in a manner that supports reproducibility. In "Pattern-Oriented Modeling of Agent-Based Complex Systems," Grimm and colleagues argue to use phenomena such as growth or diffusion patterns to characterize a real-world system and its dynamics and to develop a model that might simulate those patterns.

The U.K. *Review of Quality Assurance of Government Analytical Models* details four model steps: (1) scope and specify, (2) build, (3) validate, and (4) deliver and use. Given the simplicity and broad U.K. government usage of those steps, we have attempted to align them with the data visualization literacy framework (DVL) in *Atlas of Knowledge* and the ModelDVL-FW presented here. The first step roughly corresponds to user needs acquisition, as discussed on **page 40** in *Atlas of Knowledge*; step 2 corresponds to model design and run (**page 18**); step 3 concerns model validation (**page 22**); and step 4 provides extensive detail on how to deliver and use models in practice (partly covered on **page 20**).



Typology

1 **Insight Needs**
Basic
- categorize/cluster
- order/rank/sort
- ...

Phenomena
- oscillation
- synchronization
- ...

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

3 **Models**
- descriptive
- predictive

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

5 **Graphic Symbols**
- geometric symbols
- linguistic symbols
- pictorial symbols

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

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

Methodology

The *Atlas of Forecasts* introduces a general modeling framework called ModelDVL-FW, which aims to extend and build on the work above. To our knowledge, this ambitious endeavor has not been attempted before, most likely since it would be difficult to implement for the following reasons: existing frameworks have been developed for a vast range of stakeholders—researchers, policymakers, and practitioners; there exists no unified language for core concepts, such as key phenomena; and existing models have been developed in different domains, amid different cultures, with various needs, affordances, and terminologies.

To overcome these challenges and to standardize language usage and methods across domains, we conducted a comprehensive review of more than 200 publications documenting work by mathematicians, statisticians, physicists, biologists, ecologists, and social scientists—in some cases even going back to seminal work from the 1600s. In addition, we conducted a series of workshops and conferences, bringing together world-leading experts to weigh in on general modeling frameworks and their usage in different domains (see **Acknowledgements, page x**).

The modeling framework presented here was shared with experts and societies working on unifying approaches to model design, execution, and validation (see **References & Credits, page 180**). The comments were incorporated to expand on the coverage, internal consistency, utility, and usability of the framework.

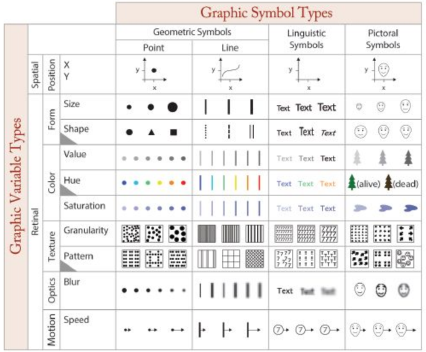
The resulting modeling framework aims to make it easy to specify, design, run, validate, and visualize the results of different types of models. It aims to empower decision-makers to simulate, understand, communicate, and manage education, science, technology, and policy (ESTP).

More than 300 model applications are presented throughout this *Atlas*—with a focus on those that were applied in practice and that made a positive difference. Additional examples can be found in special journal issues: "Science of Science: Conceptualizations and Models of Science" in *Journal of Informetrics* (2009), "Modeling Science: Studying the Structure and Dynamics of Science" in *Scientometrics* (2011), and "Simulating the Processes of Science, Technology, and Innovation" in *Scientometrics* (2016); in the Springer book *Models of Science Dynamics* (2012); and in "Modeling and Visualizing Science and Technology Developments" published in *Proceedings of the National Academies of Sciences of the United States of America* (2018).

This spread introduces the modeling framework; the remainder of **Part 2** details that framework and applies it to introduce expert-based, descriptive, and computational predictive modeling classes, which have been successfully used in ESTP research and practice.

Modeling Framework

Analogous to the data visualization literacy framework (DVL-FW) presented in *Atlas of Knowledge* (**pages 22–73**) and in the associated "Data Visualization Literacy: Definitions, Conceptual Frameworks, Exercises, and Assessments" paper, the modeling DVL framework (ModelDVL-FW) defines a typology of key terminology, together with the process of modeling and visualization design. As the name suggests, ModelDVL-FW extends the original DVL-FW to cover descriptive and predictive models that aim to capture and reproduce emergent phenomena introduced in the previous spread (**pages 14–15**).



Typology

The ModelDVL-FW uses visualizations to help design, optimize, and communicate the results of modeling efforts. It expands on the seven types defined by the DVL-FW typology (see numbers 1–7 in the figure on the opposite page) by adding *Phenomena to Insight Needs* under *Typology* (as suggested by Grimm and colleagues) and replacing *Analyses* (formerly shown) with *Models*, which are specifically descriptive and predictive subtypes.

Conceptually, phenomena types are a specialized insight need; in addition to seeing distributions, clusters, or sortings, stakeholders might be interested to identify oscillation or synchronization patterns, or to understand the inner workings of how networks grow and information diffuses.

Models now include descriptive subtypes to analyze data (using temporal, geospatial, topical, and network approaches to help answer when, where, what, and with whom types of questions) and predictive subtypes to simulate data (to help answer questions about why a target system might have a certain structure and/or dynamics).

Process

The original DVL-FW process model supports descriptive models (**page 28**) that analyze past and present data to identify patterns, outliers, and trends. In order to support the design, run, visualization, and validation of computational predictive models, stakeholders must be empowered to identify and detail phenomena in the target system. In the process shown on the opposite page, *Model* now appears instead of *Analyze* (formerly shown), thus matching *Models* under *Typology*, while *Validate* joins *Interpret* as one step.

In practice, most modeling exercises start with stakeholder-generated scenarios, or user stories, that characterize real-world evidence. The scenarios capture opinions, views, and expectations by one or more stakeholder groups. Scenarios may reflect alternative views of a real-world target system; they may even contradict each other, providing excellent prompts for rich and meaningful discussions. Scenario development is benefited by the presentation of real-world data and results from prior data analyses and scenario design efforts. Data visualizations can help capture model ideas (see **Model Visualization, page 20**).

The *Model* process step covers the design, implementation, and run of a descriptive or predictive model. *Atlas of Knowledge* (**pages 44–71**) covered the design of temporal, geospatial, topical, and network analyses and visualizations. The subsequent spread (**pages 18–19**) discusses the design and run of computational predictive models, and presents 10 different classes of predictive models (further discussed on **pages 30–51**).

As noted above in **Prior Work**, model validation is critical for any modeling effort (see also the iterative model refinement figure in **Which Model, page 4**). During validation, empirical real-world data is compared to analyses and visualizations of modeling results. Comparable visualizations of empirical and simulated data make it possible for domain experts, modeling experts, and model implementation experts (computer scientists and programmers) to comment on results and suggest model improvements, which in turn may lead to a better match of simulated and empirical data (see **Model Validation, page 22**). Typically, iterative model refinement is required to arrive at more accurate, easier-to-understand models that capture important patterns, trends, and phenomena in real-world systems.

Data visualization is central to both the DVL-FW and the ModelDVL-FW. Given the interdisciplinary nature of most data analysis and modeling efforts, it is of utmost importance to communicate model structure, dynamics, and results effectively across disciplinary as well as institutional boundaries—within academia, industry, and government policymaking. The DVL-FW generally provides a principled way to map data variables to graphic symbols and their graphic variables. Visualization design starts with the selection of a visualization type (e.g., a graph or map). Types of graphic symbols and graphic variables are then selected (see types 4–6 in the figure on the opposite page, and types 5 and 6 in the table at left). Graphic symbols include geometric symbols (e.g., point, line, area, surface, and volume) and also linguistic and pictorial symbols. Graphic variables can be grouped into spatial and retinal variables, with the latter further subdivided into form, color, texture, optics, and motion. Some graphic variables are qualitative (e.g., shape, color hue, and pattern) and are used to represent qualitative data (e.g., education, training, and job type). Others are quantitative (e.g., size, color value or saturation, or speed) and are commonly used to represent quantitative data (e.g., weight, temperature, and diffusion patterns). *Atlas of Knowledge* details visualization types (**page 30**), graphic symbol types (**page 32**), and graphic variable types (**page 34**), with discussion of which graphic variables are preattentively processed (i.e., recognized quickly and independently of cultural influences) and which graphic variables most accurately convey comparisons of data variables.

The subsequent pages introduce model design and usage, and also model visualization and validation, as guided by the typology and process defined in the ModelDVL-FW.

Model Visualization

Model assumptions, designs, and results should together be communicated in a format that is appropriate for a wide range of modeling stakeholders and experts. Visualizations can help domain, modeling, and programming experts to collaborate closely in the conceptualization and design of models. With those visualizations of model setup and run, the impact of different parameter values on model results—including emergent phenomena—can be visually explored. Further visualizations may help stakeholders compare and interpret model results, and then communicate them to experts or general audiences. Visualizations can be static, dynamic, or interactive.

The height of sophistication is simplicity.
Clare Boothe Luce

Visualization Types

The design of effective data visualizations requires identifying insight needs and phenomena; selecting the appropriate data, analysis, model class, and visualization types; and performing an accurate mapping of data variables to graphic symbols, as well as variables to interactivity design, if beneficial (see the visualization and modeling frameworks presented in *Atlas of Knowledge*, **Part 2**, and expanded here in **Modeling Framework, page 16**).

As discussed in **Model Design and Run (page 18)**, modeling often involves a team of experts, including decision-makers with deep domain knowledge, as well as modeling experts, algorithm developers, and interface designers. It is of utmost importance that all team members have the same understanding of model goals, structure, and dynamics.

Visualizations can play a major role in communicating model assumptions, model design, simulation results, or model comparison results. They make it possible to keep track of a potentially large set of model components and state variables, in order to get an understanding of dynamic behavior, and to compare multiple model runs or model types. Simple, easy-to-read visualizations are best.

This spread presents general visualization types and examples that have been successfully used to support model conceptualization, design, and run; visualizations that communicate model results are featured on **pages 32–97**.

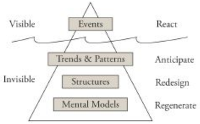
Model Conceptualization

The ODD Protocol, introduced on **page 16**, argues that model conceptualization must define all the relevant model entities, state variables, and scales. Different types of visualizations can be used to support that task.

Iceberg Model

The iceberg model provides a systematic approach for detailing what is observable about real-world systems. As the figure below shows, the model contains four parts: *Events*, *Trends & Patterns*, *Structures*, and *Mental Models*. Like an iceberg tip above the water, *Events* are visible; like the underwater base of that iceberg, the other three parts are invisible and thus harder to capture.

Events indicate what has happened or what was observed. *Trends & Patterns* refer to what is changing; they intend to capture changes in state variables as well as model structures and dynamics that occur over time. *System Structures* refer to the elements that support, create, and influence the temporal and spatial patterns which lead to system dynamics; with a focus on physical entities, organizational structures, existing policies, or rituals and their interrelations, they aim to answer "What causes the patterns we are observing in the empirical data?" Finally, *Mental Models* seek to capture the attitudes, beliefs, morals, expectations, and values that drive behavior in a target system.



The iceberg model allows for events, patterns, and structures to be identified, and for changes in mental models (e.g., power/incentive structures) to be productively discussed.

Connected Circles

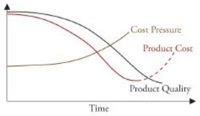
This method helps identify and interlink the major components of a target system using either paper or digital means. The paper example above shows how major components, written on small pieces of paper, may be placed around the outside of a large circle according to their similarity. System components can then be interlinked via lines to uncover structural and dynamic relationships. Particularly important parts can be highlighted or underlined. Lines of different colors can be used to represent different types of component relationships.

Model Design Visualizations

The structure and dynamics of models can be characterized using conceptual models (causal loop diagrams), mathematical formulas, computer models (e.g., pseudocode or computer languages), or physical models (see examples in **Which Model, page 4**). Scripting languages such as NetLogo, Repast, or Stellar help facilitate model design, run, and verification by nonprogrammers, because their code syntax more closely resembles natural language than other programming languages. Here, we introduce different visualizations that support model design.

Behavior-Over-Time Graphs

Typically called BOTGs, these are line graphs that communicate patterns of change over time, such as the seasonality of a variable or the delays between two variables; see the example in **Limits to Growth Model (page 7)** and the graph below.



The x-axis of a BOTG represents units of time; there are well-defined start and end points, and a resolution (seconds, minutes, hours, days, years, etc.) that is relevant for capturing system dynamics. The y-axis represents one or more variables of interest; it is labeled with that variable's name, has a well-defined scale that can be numeric (e.g., income or funds spent per year on a scale of $0 to $1 million) or descriptive (e.g., low vs. high), and includes a legend so that different variables can be easily distinguished.

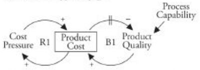
BOTGs might be used to understand if all domain and/or modeling experts plot variable change over time in the same way: Did they all use the same general curve or shape (linear, exponential, S-shape)? How do the slopes compare (with steeper lines indicating faster growth or decay, and flat lines indicating no change)? Do they start or end at around the same time, and are there major differences in y values at those points?

If multiple variables are graphed, are they interdependent, or are there causal relationships between them (e.g., educational investment eventually leads to higher income)? The interrelated behavior of variables over time can be visualized using causal loop diagrams (CLDs), as described below. System lags (e.g., the average time it takes from the completion of an educational degree to a salary increase) can then be visualized and discussed. Feedback cycles (e.g., more funding leads to more publications and citations, increasing the chances to win future funding) can be captured and visualized using state-transition graphs (see the opposite page).

BOTGs can also help identify the type of data that is most valuable for model design and evaluation. Given a collective understanding of why certain data is critical for modeling a target system, resources might become available to acquire such data for the most critical variables, rather than using only data that is readily available.

Causal Loop Diagrams

In serial systems, each variable continually impacts the next. In other systems, there exist feedback cycles, which may involve numerous variables—causal loop diagrams (CLDs) can be used to represent those systems. Variables might have positive (+) or negative (–) impacts on each other: positive feedback occurs when an increase in variable *A* increases variable *B*; negative feedback, in contrast, is an increase in variable *A* decreasing variable *B*. There are also balancing feedback loops wherein positive and negative impacts result in a balanced dynamic. In addition, there can be external variables, or constraints, that impact overall system behavior. For instance, in the process capability model below, cost pressure positively impacts product cost, which negatively impacts product quality (the two vertical parallel lines denoting a delay), which positively impacts product cost. The dynamic behavior of this model can be plotted over time using a BOTG, as shown on the opposite page.



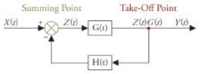
Another example of a CLD is given in **Limits to Growth Model (page 7)**.

Block Diagrams

Block diagrams are widely used in engineering to describe systems at a general level (e.g., to identify principal parts or functions and their interrelationships). Graphic symbols include rectangles that present mathematical or logical operations, with arrows showing the relationships between blocks. Each block has a single input, output and transfer function; the output is the product of the input and transfer functions.

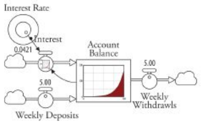
A take-off point passes a signal to two or more blocks or summing points. Each summing point has two or more inputs and a single output; it produces the algebraic sum of the positive or negative inputs.

Shown below is a block diagram with two blocks labeled $G(t)$ and $H(t)$, one take-off point (in red), and one summing point (in gold). The transfer function $G(t)$ reads $Z(t)$ and outputs $Z(t)G(t)$. In this closed-loop control system, the output is fed back to the input to control the desired output (see the discussion in **Control Theory, page 36**).



Stock-and-Flow Diagrams

While CLDs enable a system to be qualitatively understood, stock-and-flow diagrams can be used to perform a detailed quantitative analysis. A stock denotes any entity that accumulates or depletes over time; a flow is the rate of change in that stock. Stock-and-flow diagrams are usually built and simulated using computer software. The figure below uses the STELLA visual programming language to model bank account dynamics: The interest and the weekly deposits increase the account balance, and the weekly withdrawals decrease that balance. The interest rate, as well as the deposits and withdrawals, might change over time. In addition, the account balance is graphed over time within the central block.

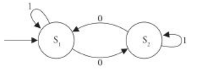


Another example using STELLA is given for predator-prey models on **page 31**.

State-Transition Graphs

Also known as a state diagram, a state-transition graph (STG) can be used to visualize the dynamics of systems with discrete and finite states. The graph is designed by first enumerating all the possible states and state transitions of the system. Next, states are represented by nodes in a network, and state transitions by directed edges. Edges are labeled by the input of the next state. The initial or start state of the system is commonly represented by an arrow with no origin pointing to the state. The final or accepting state is indicated by a double circle. Not all systems have start and end states.

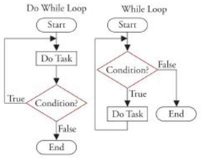
The example below shows a system with two states and an acceptor for strings over {0,1}. S_1 is the start state, as indicated by the furthest left arrow. If S_1 is 0, the system transitions to S_2. The system remains in state S_2 until a 0 string returns the system to S_1. There is no end state.



An STG for a three-type market system is discussed on **page 34**.

Flowcharts

A flowchart is a graph that uses graphic symbols to define different logic steps in a process (e.g., the loops shown in the subsequent two figures). Symbols include a rounded rectangle to indicate the start or end of a (sub)process; a rectangle denoting an operation that changes data; a diamond for any conditional operation that determines which of two paths a program will take; a parallelogram to represent data input and output (not used in figure shown); and arrows to indicate the order of operation.



Flowcharts differ from STGs in that they transition between nodes automatically upon completion of activities, while STGs require explicit external events to transition from one node to the next.

Model Run Visualizations

Model results can be presented via tables, graphs, and geospatial or topical maps—including 2D and 3D maps, which are used in computational drug design (see the lower right figure on **page 171**) or to show developments such as the spreading of diseases (see **Diffusion Phenomena, page 15**), the evolution of artificial life (**page 41**), and neural network activations (***StarCraft II*: A New Challenge for Reinforcement Learning, page 51**). Model results can also be communicated using trees, such as to trace the evolution of organizational hierarchies or genealogies; or by networks, like those used to track international air travel.

Visualizations might be static or dynamic/animated; they can also be interactive—allowing viewers, for instance, to speed up or slow down time, or to zoom in and out of areas of interest (see interactivity types in **Modeling Framework, page 16**).

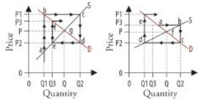
Simulation tools (e.g., NetLogo, Repast) support changes in model parameters during model runs, which makes it possible to explore system behavior and on-the-fly dynamics.

Exemplarily, we discuss cobweb and state space graphs here.

Cobweb Graphs

Cobweb graphs can be used to plot the evolution of a state variable. For example, the subsequent figure plots product price over quantity in convergent and divergent modes (at left and right, respectively).

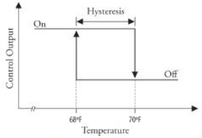
The supply function (diagonal black "S" line) is denoted as $S_t = S(t-1)$; the demand function (diagonal red "D" line) is denoted as $D_t = D(P)$. Market equilibrium is reached when supply equals demand: $S_t = D_t$. The convergent mode (left graph) starts with (a) low prices and low supply, which causes (b) prices to rise; as (c) supply is increased, (d) prices fall; as more is sold, there is (e) lower supply and therefore (f) higher prices; when prices and supply finally stabilize, (g) equilibrium is reached.



State Space Graphs

A system's abstract state space, or phase space, can be used to depict that system's state over time; a sequence of states can then be animated to reveal system dynamics. A state space is commonly represented using a graph in Euclidean space, with the state variables indicated on the axes.

The state space of a temperature control unit is shown below. The horizontal axis plots temperature; the vertical axis plots control output. There are two states: *On* when the temperature falls below a certain value; *Off* when the temperature is too high. *Hysteresis* occurs when the temperature is between 68 and 70 degrees Fahrenheit; thus, the state change threshold for *Off* is lower than it is for *On*.



In the ball on a spring (oscillation) example on **page 14**, the state space can be characterized by the position and the momentum of the ball. In the Lotka-Volterra differential equations discussed on **page 31**, the state space plots the state of the system as a vector within the space that is defined by the number of predators and preys.

State space can be either discrete or continuous in terms of time and space (see **page 13**).

Model Validation

Models should aim to capture the behavior of real-world systems in a simple yet useful manner that can be validated across scales. At the micro level, the type and behavior of individual components (e.g., agents for agent-based models or nodes for network models) need to match up with their real-world counterparts. At the macro level, the aggregate, emergent properties of the model (e.g., oscillation or adaptation) must reflect the phenomena observed in the real world. Models must be evaluated based on the accuracy and generality of their predictions. Evaluation results should be used to increase the accuracy, specificity, or generality of the model, or to make model results easier to understand and use by decision-makers.

The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor.

Donald T. Campbell

Quality Assurance Framework

Quality assurance (QA) refers to processes that help ensure (1) a model's inputs and outputs meet existing requirements; (2) model errors are understood and can be managed; and (3) the model is robust and fit for purpose. *The Review of Quality Assurance of Government Analytical Models* report, commissioned by the U.K. Department for Transport, identified major types of QA methods and graphed them in terms of business risks versus model complexity (see the figure below right). QA techniques used by industry, government, academic, and other leading entities range from relatively simple version control (in the lower left corner) to full external model audit (in the top right corner); in between are developer testing, periodic review, internal or external peer review, and other techniques, which vary according to model complexity and business risk.

Model Simplicity

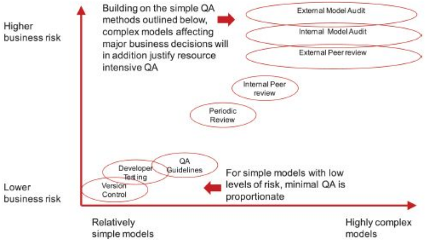
Occam's razor principle states that "Entities should not be multiplied beyond necessity." As applied to modeling, that means if there are two models with equal predictive power, the simpler one should be chosen. That is, if any components, variables, parameters, rules, or assumptions can be eliminated from the model without losing the model's explanatory power, they should be omitted.

Model Robustness

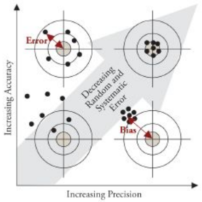
The robustness of a model is determined by measuring change in model predictions given minor variations in input data and/or parameter settings. Ideally, variations and uncertainty in data, and their impact on model results, can be quantified and communicated to model designers and users. Similarly, it is important to analyze, visualize, and communicate how sensitive a model is to particular parameters; toward that end, parameter sweeps might be run to identify which model results are most sensitive, and to which input and parameter changes.

Model Precision and Accuracy

Accuracy refers to the closeness of a measured value to a standard or known (true) value. Precision refers to the closeness of two or more measurements to each other. Typically, the more that measurements are made, the better the precision and the smaller the error.



The image below illustrates combinations of low and high precision and accuracy using a bullseye graph. While there are no bullseye hits in the lower left corner of low precision and accuracy, there are many hits in the top right corner of high precision and accuracy.



The large gray arrow indicates decreasing random and systematic error across the diagonal. Random error (at the top left corner) decreases with more-accurate data and better-parametrized models. Systematic error, or bias (at the lower right corner), makes all values wrong by a certain amount, which can be due to many factors (e.g., wrong model assumptions, imperfect data processing, or suboptimal model parameters) leading to invalid results. Model validation aims to identify and reduce both types of errors to arrive at higher model precision and accuracy.

QA at Different Model Stages

As discussed in **Model Design and Run** (**page 18**), there are various model stages, with appropriate types of validation for each. Here, we discuss QA for all four model stages: conceptualization, design, build, and test and deliver. Detailed guidance for the latter three, as identified in the *Review of Quality Assurance of Government Analytical Models*, is listed in the text box on the opposite page.

Conceptualization

The most efficient and robust methods should be used to support target system selection, delineation, abstraction, and documentation of the nonformal model—and that nonformal model should be documented such that domain experts, modeling experts, and computer-scientist programmers can understand, question, and advance the model. Consequently, model visualizations (**page 20**) are often used to facilitate and validate the ideation, abstraction, and translation process.

Design

When designing the formal model, modeling experts should keep future model stages in mind so that implementation, deployment, and testing can be effectively performed. Internal or external domain experts should conduct QA reviews—of model structure, logic, and assumptions—as well as assessments of the quality, accuracy, completeness, and suitability of input and output data.

Build

The formal model is then implemented by computer-scientist programmers. Any differences from the original design should be documented and communicated to model designers and domain experts. The completed model implementation should be verified, and test results should be shared to ensure the model is fit for purpose.

Test and Deliver

Computer-scientist programmers will test-run the model and fully document results. In collaboration with modeling experts, they will develop any needed training materials, and finally test both (documentation and training) with domain experts to ensure model assumptions and limitations are understood.

All Model Stages

During the model development process, all model documentation must match model complexity and risks. For instance, simple models with low business risks will require far less documentation than complex models with high business risks; the latter might require extensive formal documentation and training materials, regular training sessions, and continuous review to ensure proper usage.

Model Validation

Model validation is the process of determining whether an implemented model is a reasonable representation of some phenomenon in the real world; that it reproduces system behavior with sufficient fidelity to satisfy stakeholder needs; and that model results are precise and accurate. It aims to ensure the model has been correctly implemented and is sufficiently general to capture new system states (i.e., not overfitted or too closely adjusted to a specific set of real-world data or observations at the cost of generalizability).

Model Verification

Model verification aims to make sure a model does what it is intended to do. Target system abstraction, formal model design, and model code (see **page 18**) all need to be verified. The former two verifications benefit from expert reviews. Model code verification uses techniques typically used to develop, debug, or maintain large computer programs. Examples are proper code version control; regular code reviews; logging code runs (e.g., recording and analyzing the number of components/agents that are generated and terminated during a model run, their local behavior, and any emergent behavior); and keeping records of user interactions (e.g., input data or parameter changes, and accessing analysis results or visualizations) in support of model and user interface optimization.

Model Replication

Replication occurs when a model result initially published by one expert team is reproduced by another, independent expert team. To make that possible, model design and run should be documented at a level of detail that supports redesign, reimplementation, and rerun by other teams. Development and adoption of model documentation standards (see the discussion on **page 19**) make writing and reading model descriptions easier, with direct benefits to those using the standards.

Model Comparison

Modeling efforts conducted by different teams often yield disparate results that are difficult or impossible to reconcile. Common reasons are insufficient documentation, proprietary data that cannot be shared across teams, or differences in exactly how a model is implemented and run. Comparative modeling explores commonalities and differences between two or more models in a systematic way. It is commonly done as a joint collaboration across teams; data and code-use agreements might need to be put in place to ensure all teams have access to the same resources. The teams agree on the target system and the insight needs to be addressed—including emergent phenomena to be modeled. The teams might then pick the same or different model classes and associated parameter settings. An agreed-upon common set of intermediate and final model results is considered; the results are compared to each other and to empirical data (e.g., changes in model output values over time).

Comparative modeling greatly enhances the credibility of modeling results, as it helps identify model errors and biases; communicates advantages and disadvantages of different model classes for capturing well-defined target system behavior; and results in more detailed model documentation that increases reproducibility. Sometimes, model results differ substantially, making it necessary to question model assumptions and inspiring future research.

Model Limitations

Every model is a simplification of a real-world target system that captures key system structure and behavior; a perfect facsimile would be of limited value for understanding the world. A literature review by Mohamed Saleh and colleagues in "A Survey on Futures Studies Methods" identified a list of typical model limitations, including: "(1) You cannot know the future, but a range of possible futures can be known. (2) The likelihood of a future event or condition can be changed by policy, and policy consequences can be forecasted. (3) Gradations of foreknowledge and probabilities can be made; we can be more certain about the sunrise than about the rise of the stock market. (4) Humans will have more influence on the future than they did in the past. (5) No single method should be trusted by itself; cross-referencing methods improves foresight. (6) Anticipation and planning must be dynamic and able to respond to new information and insights." Model designers and users are strongly encouraged to document all known model limitations and all validation results to ensure their models and model results are used intelligently and optimally.

Model Design QA

Developer testing—use of a range of developer tools including parallel build and analytical review or sense check.

Internal peer review—obtaining a critical evaluation from a third party independent of the development of the model, but from within the same organisation.

External peer review—formal or informal engagement of a third party to conduct critical evaluation, from outside the organisation in which the model is being developed.

Use of version control—use of unique identifier for different versions of a model.

Internal model audit—formal audit of a model within the organisation, perhaps involving use of internal audit functions.

Quality assurance guidelines and checklists—model development refers to department's guidance or other documented QA processes (e.g., third-party publications).

External model audit—formal engagement of external professionals to conduct a critical evaluation of the model, perhaps involving audit professionals.

Governance—at least one of planning, design and/or sign-off of model for use is referred to a more senior person. There is a clear line of accountability for the model.

Transparency—model is placed in the wider domain for scrutiny, and/or results are published.

Periodic review—model is reviewed at intervals to ensure it remains fit for the intended purpose, if used on an ongoing basis.

Model Build QA

Version control—systems in place to manage the development of the model and ensure any changes are captured.

Unit testing—individual testing of components of a model to ensure they are correctly coded and give the right result.

Logic testing—the logic flow within the model follows that defined at the model design stage, (at the level of individual units, multiple units or the complete code).

Internal code review—independent review of model coding may be worthwhile to ensure it meets the specification and is as free from errors as possible. This should be conducted by someone who is not part of the development team.

Internal test review—independent review of the verification testing results to ensure results are consistent with the model design specification. This should be conducted by someone who is not part of the development team.

External code review—peer-review of model logic, assumptions and coding to ensure the model meets the specification and is as free from errors as possible. This will generally be conducted by someone external to the organisation.

Test review—independent review of the verification testing results to ensure results are consistent with the model design specification. This will generally be conducted by someone external to the organisation; and

Parallel builds—for complex, high-risk models there may be value in developing parallel builds to ensure cross-checking of results.

Model Test and Deliver QA

Checking against data—checking model outputs against available data, for example recreating historical datasets.

Reviewing assumptions—checking that assumptions remain valid e.g. circumstances haven't changed since the assumptions were originally set.

Limit testing—sample testing of the range of validity of all input variables—this may not be possible for complex models, but parameter ranges of key variables should be tested. Input values outside the accepted ranges should also be included to test any exception and error handling within the model.

Cross checking—checking model output with similar independent models where available.

Internal independent testing—independent testing of the full system may be advisable at this stage.

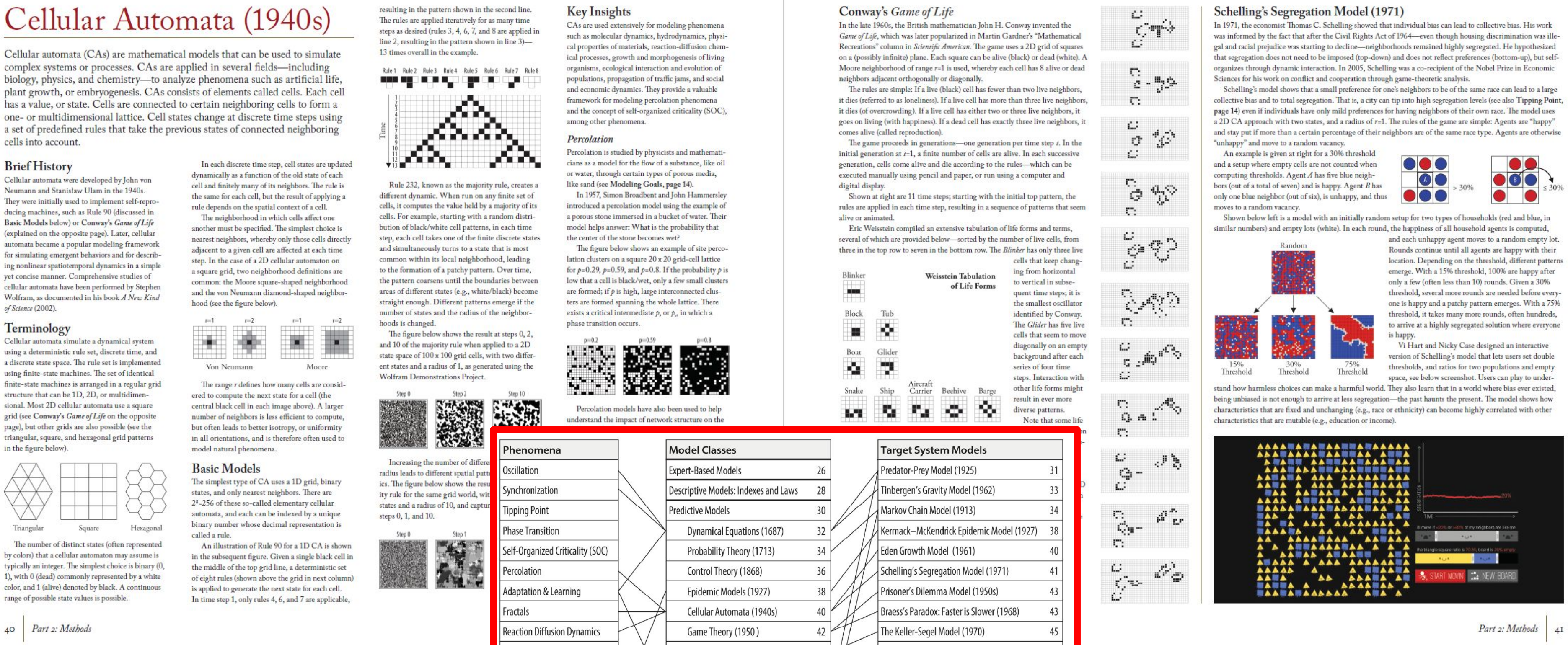
Reviewing outputs—checking that outputs are sufficient for the purpose of the decisions being taken, including assessment of limitations, alternative scenarios, etc.

Transparency—publication of the model itself, or the test schedule and results, may provide additional external review if appropriate.

External independent testing—external peer-review of the full system.

Internal audit—a formal audit conducted within the organisation. This would need to be supported by full model specification and test documentation.

External audit—a comprehensive formal model audit supported by full model specification and test documentation, although a results-oriented audit might be a better alternative if model is regularly updated and usage and "lower level" checks such as internal peer review are already in place.



Cellular Automata (1940s)

Cellular automata (CAs) are mathematical models that can be used to simulate complex systems or processes. CAs are applied in several fields—including biology, physics, and chemistry—to analyze phenomena such as artificial life, plant growth, or embryogenesis. CAs consists of elements called cells. Each cell has a value, or state. Cells are connected to certain neighboring cells to form a one- or multidimensional lattice. Cell states change at discrete time steps using a set of predefined rules that take the previous states of connected neighboring cells into account.

Brief History

Cellular automata were developed by John von Neumann and Stanislaw Ulam in the 1940s. They were initially used to implement self-reproducing machines, such as Rule 90 (discussed in **Basic Models** below) or **Conway's *Game of Life*** (explained on the opposite page). Later, cellular automata became a popular modeling framework for simulating emergent behaviors and for describing nonlinear spatiotemporal dynamics in a simple yet concise manner. Comprehensive studies of cellular automata have been performed by Stephen Wolfram, as documented in his book *A New Kind of Science* (2002).

Terminology

Cellular automata simulate a dynamical system using a deterministic rule set, discrete time, and a discrete state space. The rule set is implemented using finite-state machines. The set of identical finite-state machines is arranged in a regular grid structure that can be 1D, 2D, or multidimensional. Most 2D cellular automata use a square grid (see **Conway's *Game of Life*** on the opposite page), but other grids are also possible (see the triangular, square, and hexagonal grid patterns in the figure below).

Triangular Square Hexagonal

The number of distinct states (often represented by colors) that a cellular automaton may assume is typically an integer. The simplest choice is binary (0, 1), with 0 (dead) commonly represented by a white color, and 1 (alive) denoted by black. A continuous range of possible state values is possible.

In each discrete time step, cell states are updated dynamically as a function of the old state of each cell and finitely many of its neighbors. The rule is the same for each cell, but the result of applying a rule depends on the spatial context of a cell.

The neighborhood in which cells affect one another must be specified. The simplest choice is nearest neighbors, whereby only those cells directly adjacent to a given cell are affected at each time step. In the case of a 2D cellular automaton on a square grid, two neighborhood definitions are common: the Moore square-shaped neighborhood and the von Neumann diamond-shaped neighborhood (see the figure below).

r=1 r=2 r=1 r=2
Von Neumann Moore

The range r defines how many cells are considered to compute the next state for a cell (the central black cell in each image above). A larger number of neighbors is less efficient to compute, but often leads to better isotropy, or uniformity in all orientations, and is therefore often used to model natural phenomena.

Basic Models

The simplest type of CA uses a 1D grid, binary states, and only nearest neighbors. There are 2^8=256 of these so-called elementary cellular automata, and each can be indexed by a unique binary number whose decimal representation is called a rule.

An illustration of Rule 90 for a 1D CA is shown in the subsequent figure. Given a single black cell in the middle of the top grid line, a deterministic set of eight rules (shown above the grid in next column) is applied to generate the next state for each cell. In time step 1, only rules 4, 6, and 7 are applicable, resulting in the pattern shown in the second line. The rules are applied iteratively for as many time steps as desired (rules 3, 4, 6, 7, and 8 are applied in line 2, resulting in the pattern shown in line 3)—13 times overall in the example.

Rule 1 Rule 2 Rule 3 Rule 4 Rule 5 Rule 6 Rule 7 Rule 8
Time

Rule 232, known as the majority rule, creates a different dynamic. When run on any finite set of cells, it computes the value held by a majority of its cells. For example, starting with a random distribution of black/white cell patterns, in each time step, each cell takes one of the finite discrete states and simultaneously turns to a state that is most common within its local neighborhood, leading to the formation of a patchy pattern. Over time, the pattern coarsens until the boundaries between areas of different states (e.g., white/black) become straight enough. Different patterns emerge if the number of states and the radius of the neighborhoods is changed.

The figure below shows the result at steps 0, 2, and 10 of the majority rule when applied to a 2D state space of 100 x 100 grid cells, with two different states and a radius of 1, as generated using the Wolfram Demonstrations Project.

Step 0 Step 2 Step 10

Increasing the number of differe[nt] ... radius leads to different spatial patt[erns] ... ics. The figure below shows the resu[lt] ... ity rule for the same grid world, wit[h] ... states and a radius of 10, and captur[ed at] steps 0, 1, and 10.

Step 0 Step 1

Key Insights

CAs are used extensively for modeling phenomena such as molecular dynamics, hydrodynamics, physical properties of materials, reaction-diffusion chemical processes, growth and morphogenesis of living organisms, ecological interaction and evolution of populations, propagation of traffic jams, and social and economic dynamics. They provide a valuable framework for modeling percolation phenomena and the concept of self-organized criticality (SOC), among other phenomena.

Percolation

Percolation is studied by physicists and mathematicians as a model for the flow of a substance, like oil or water, through certain types of porous media, like sand (see **Modeling Goals, page 14**).

In 1957, Simon Broadbent and John Hammersley introduced a percolation model using the example of a porous stone immersed in a bucket of water. Their model helps answer: What is the probability that the center of the stone becomes wet?

The figure below shows an example of site percolation clusters on a square 20 x 20 grid-cell lattice for p=0.29, p=0.59, and p=0.8. If the probability p is low that a cell is black/wet, only a few small clusters are formed; if p is high, large interconnected clusters are formed spanning the whole lattice. There exists a critical intermediate p, or p_c, in which a phase transition occurs.

p=0.2 p=0.59 p=0.8

Percolation models have also been used to help understand the impact of network structure on the

Conway's *Game of Life*

In the late 1960s, the British mathematician John H. Conway invented the *Game of Life*, which was later popularized in Martin Gardner's "Mathematical Recreations" column in *Scientific American*. The game uses a 2D grid of squares on a (possibly infinite) plane. Each square can be alive (black) or dead (white). A Moore neighborhood of range r=1 is used, whereby each cell has 8 alive or dead neighbors adjacent orthogonally or diagonally.

The rules are simple: If a live (black) cell has fewer than two live neighbors, it dies (referred to as loneliness). If a live cell has more than three live neighbors, it dies (of overcrowding). If a live cell has either two or three live neighbors, it goes on living (with happiness). If a dead cell has exactly three live neighbors, it comes alive (called reproduction).

The game proceeds in generations—one generation per time step t. In the initial generation at t=1, a finite number of cells are alive. In each successive generation, cells come alive and die according to the rules—which can be executed manually using pencil and paper, or run using a computer and digital display.

Shown at right are 11 time steps; starting with the initial top pattern, the rules are applied in each time step, resulting in a sequence of patterns that seem alive or animated.

Eric Weisstein compiled an extensive tabulation of life forms and terms, several of which are provided below—sorted by the number of live cells, from three in the top row to seven in the bottom row. The *Blinker* has only three live cells that keep changing from horizontal to vertical in subsequent time steps; it is the smallest oscillator identified by Conway. The *Glider* has five live cells that seem to move diagonally on an empty background after each series of four time steps. Interaction with other life forms might result in ever more diverse patterns.

Note that some life

Weisstein Tabulation of Life Forms

Blinker Block Tub Boat Glider Snake Ship Aircraft Carrier Beehive Barge

Schelling's Segregation Model (1971)

In 1971, the economist Thomas C. Schelling showed that individual bias can lead to collective bias. His work was informed by the fact that after the Civil Rights Act of 1964—even though housing discrimination was illegal and racial prejudice was starting to decline—neighborhoods remained highly segregated. He hypothesized that segregation does not need to be imposed (top-down) and does not reflect preferences (bottom-up), but self-organizes through dynamic interaction. In 2005, Schelling was a co-recipient of the Nobel Prize in Economic Sciences for his work on conflict and cooperation through game-theoretic analysis.

Schelling's model shows that a small preference for one's neighbors to be of the same race can lead to a large collective bias and to total segregation. That is, a city can tip into high segregation levels (see also **Tipping Point, page 14**) even if individuals have only mild preferences for having neighbors of their own race. The model uses a 2D CA approach with two states, and a radius of r=1. The rules of the game are simple: Agents are "happy" and stay put if more than a certain percentage of their neighbors are of the same race type. Agents are otherwise "unhappy" and move to a random vacancy.

An example is given at right for a 30% threshold and a setup where empty cells are not counted when computing thresholds. Agent A has five blue neighbors (out of a total of seven) and is happy. Agent B has only one blue neighbor (out of six), is unhappy, and thus moves to a random vacancy.

> 30% ≤ 30%

Shown below left is a model with an initially random setup for two types of households (red and blue, in similar numbers) and empty lots (white). In each round, the happiness of all household agents is computed, and each unhappy agent moves to a random empty lot. Rounds continue until all agents are happy with their location. Depending on the threshold, different patterns emerge. With a 15% threshold, 100% are happy after only a few (often less than 10) rounds. Given a 30% threshold, several more rounds are needed before everyone is happy and a patchy pattern emerges. With a 75% threshold, it takes many more rounds, often hundreds, to arrive at a highly segregated solution where everyone is happy.

Random
15% Threshold 30% Threshold 75% Threshold

Vi Hart and Nicky Case designed an interactive version of Schelling's model that lets users set double thresholds, and ratios for two populations and empty space, see below screenshot. Users can play to understand how harmless choices can make a harmful world. They also learn that in a world where bias ever existed, being unbiased is not enough to arrive at less segregation—the past haunts the present. The model shows how characteristics that are fixed and unchanging (e.g., race or ethnicity) can become highly correlated with other characteristics that are mutable (e.g., education or income).

Phenomena	Model Classes		Target System Models	
Oscillation	Expert-Based Models	26	Predator-Prey Model (1925)	31
Synchronization	Descriptive Models: Indexes and Laws	28	Tinbergen's Gravity Model (1962)	33
Tipping Point	Predictive Models	30	Markov Chain Model (1913)	34
Phase Transition	Dynamical Equations (1687)	32	Kermack–McKendrick Epidemic Model (1927)	38
Self-Organized Criticality (SOC)	Probability Theory (1713)	34	Eden Growth Model (1961)	40
Percolation	Control Theory (1868)	36	Schelling's Segregation Model (1971)	41
Adaptation & Learning	Epidemic Models (1927)	38	Prisoner's Dilemma Model (1950s)	43
Fractals	Cellular Automata (1940s)	40	Braess's Paradox: Faster is Slower (1968)	43
Reaction Diffusion Dynamics	Game Theory (1950)	42	The Keller-Segel Model (1970)	45
Network Growth	Continuous Field Models (1952)	44	Erdös-Rényi Model (1959)	47
Network Gatekeepers	Network Models (1959)	46	Watts-Strogatz Model (1998)	47
Network Attack and Error	Agent Based Models (1980s)	48	Barabási–Albert Model (1999)	47
Diffusion/Spreading	Machine Learning Models (1990s)	50	Economics of Wealth Distribution Model (1996)	49

Model Questions Overview

Given the constraints discussed in the previous six spreads, how can rich data and validated models be used to provide actionable insights for different decision-makers? The remainder of **Part 3** presents an overview of key questions, four ESTP domains (education, science, technology, and policy), and three scales (micro, meso, macro); examples are then given for all 12 domain-scale combinations. This *Atlas* expands on *Atlas of Knowledge*—which introduced temporal, geospatial, topical, and network methods to answer when, where, what, and with whom types of questions, respectively—by helping readers answer questions regarding why or how. For instance, why is past system performance an indicator for future performance, or how does knowledge about the evolution of a system help us understand the future states of that system?

Temporal Models—"When"

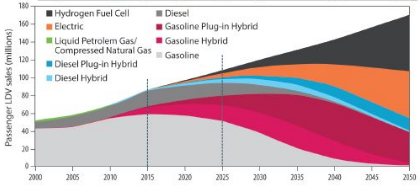
Atlas of Science and *Atlas of Knowledge* both focused on descriptive models. Several studies and visualizations featured there are able to predict future developments; the remainder of **Part 3** features many more models and visualizations that aim to forecast the future.

For example, regression models can be used to project current trends into the future (see **Machine Learning Models, page 50**; and *Atlas of Knowledge*, **Statistical Studies, page 44**).

Alan L. Porter and team employed a combination of expert opinion modeling (see **Expert-Based Models, page 26**) and technology mining to forecast passenger vehicle sales from 2000 through 2050. The graph below shows predicted composite world sales for different vehicle types, with a table that lists numbers for electric vehicles (EVs) and plug-in hybrid EVs (PHEVs). In 2009, that 41-year prediction of a fast-evolving market used data by the International Energy Agency (IEA), with a modeling approach that considered different market segments and technology solutions. As of 2019, EVs had a 2.8% car market share, according to McKinsey's proprietary Electric Vehicle Index (EVI). In 30 years' time, it will be interesting to compare the 2050 predictions with the figures of actual sales.

Temporal studies of Twitter data and other real-time data were discussed in *Atlas of Knowledge* (**page 173**); insights gained from cyclic changes and general trends can be used to communicate and optimize system evolution or information diffusion over time.

	2012	2015	2020	2025	2030	2040	2050
PHEV	0.05	0.7	4.7	12.0	24.6	54.8	49.1
EV	0.03	0.5	2.5	4.4	9.3	25.1	52.2



Geospatial Models—"Where"

Geospatial position and context are significant. Some countries are landlocked, with no direct access to marine travel routes. Others are islands, making them difficult or even impossible to reach during the winter season (see **ORBIS, page 154**). Countries that are centrally located are more likely to be natural hubs of activity. The same logic impacts individuals, corporations, and regions in terms of how isolated or connected they are.

Many models aim to represent the environment in which different agents operate (see **Modeling Overview, page 12**). Some models present multiple and possibly nested spatial environments (e.g., counties, states, countries, continents, the world).

Part 2 discussed models that can represent discrete space, such as grids or lattices, (see **Cellular Automata, page 40**; and **Network Models, page 46**). It also covered models that capture continuous space and can be used to predict human migration or the diffusion of information (see **Continuous-Field Models, page 44**); Spatially explicit models are also used in traffic optimization (see **Braess's Paradox: Faster Is Slower, page 43**).

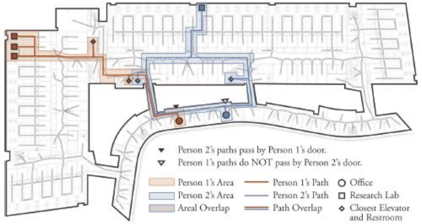
Work by Jason Owen-Smith and colleagues goes one step further in that they not only study the impact of existing space on system dynamics, but also use computational predictive models to design a built environment that optimizes desirable system behavior. Specifically, the team aims to predict the collaboration patterns that are likely to emerge from different building layouts. The work is predicated on the general understanding that distance increases coordination costs, and co-location increases productivity; passive contacts increase as individuals share more required paths through their space, increasing information diffusion and collaboration, and thus influencing the dynamics and outcomes of collaboration (see also **Alan Curve, page 28**).

Their model aims to capture (1) the physical or functional distance among occupants of a built environment; (2) the mechanisms of action, such as serendipity, prospecting, mobilization, and awareness; and (3) science examples, as shared equipment and facilities may facilitate interdisciplinary communication, co-location of interdisciplinary lab members, and the location of principal investigators' offices relative to labs.

The model also captures the state spaces of collaboration in terms of (a) scientific concepts shared, (b) social links, (c) institutional units and disciplines, (d) organizational communication and hierarchies, (e) physical proximity, and (f) virtual access via computer-mediated communication.

The model was validated using empirical data from 172 faculty and research staff members in three buildings on the University of Michigan campus. Study results show the dramatic impact of co-location on the increased likelihood of forming new collaborations and obtaining joint funding. For example, researchers who occupy the same building are 33% more likely to form new collaborations than researchers who occupy different buildings; and researchers who occupy the same floor are 57% more likely to form new collaborations than those who occupy different buildings.

Interestingly, the linear distance between offices was less important than the overlap in daily walking paths; see the figure below of a floor plan and the overlap of two persons' pathways from their offices to research lab spaces.



Topical Models—"What"

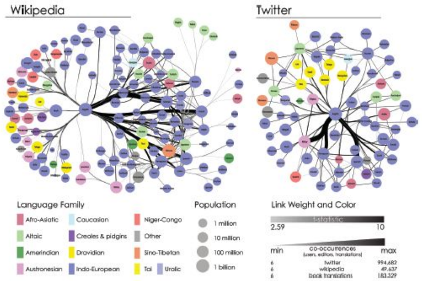
Individuals with the same interests are more likely to interact. Students and teachers who take or teach the same classes are more likely to talk. Researchers in the same discipline are more likely to collaborate. In general, the academic or professional world is organized into clusters of people, courses, jobs, industry sectors, and policy areas, according to topical similarity.

Different ESTP topic areas have different dynamics. For example, scholarly domains that publish results via e-prints are much faster in communicating results than those that mostly utilize books; interdisciplinary scholarly publications have a broader impact than those within one domain (see **Interdisciplinary Collaborations Lead to Higher Scientific Impact, page 93**). Similarly, different industry sectors are differently impacted by stock-market developments and also by technology innovation, such as AI (see **Macro: Technology, page 94**).

Global pandemics like COVID-19 have particular implications for different demographics, industry sectors, and associated unemployment rates (see **Meso: Policy, page 88**). Many types of literacy are taught, all variously impacting workers' skills portfolios (see **Micro: Education, page 74**).

Models should aim to take the topical traits of literacy types, scientific domains, and industry sectors into account in order to better capture real-world system behavior. Topical information might be modeled as agent/node metadata and/or behavior; it can also be represented by topical maps, such as the map of science shown in **Interdisciplinary Collaborations Lead to Higher Scientific Impact, page 93**.

As described on **page 54**, Shahar Ronen and colleagues studied three global language networks (GLNs) using book translations, multiple language editions of Wikipedia, and Twitter to understand the influence of various language writing systems on the visibility and possible impact of its speakers. Network layouts of the Wikipedia and Twitter GLNs are given below. The nodes represent different languages and are each labeled with the appropriate language name, color-coded per language family, and size-coded per the number of people that speak that language. The links denote which languages are co-spoken, with link weight indicating the number of co-occurrences. In both networks, English is a global hub, with a handful of intermediate hub languages, including Spanish, German, French, Russian, Portuguese, and Chinese. Languages that are found in the center of the network contribute to the visibility of its speakers and the global popularity of the cultural content they produce. For example, scholarly papers written in English are more likely to be read, cited, and recommended than papers written in languages that appear in the outer periphery of the networks.

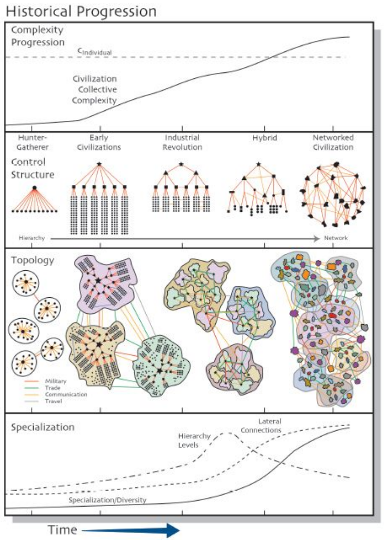


Network Models—"With Whom"

Network topology and node positions and attributes (e.g., the number of node neighbors) have a major impact on diffusion patterns as well as on network growth (see **Network Models, page 46**).

Many network studies have been run and visualizations designed to further the understanding of social, collaboration, citation, and trade networks. Results reveal the strong impact of such factors as mentorship and co-authorship networks on scientific success (see **The Impact of Network Ties in Scientific Careers, page 77**; and **Best Author Combinations for Innovation, page 85**).

Networks change over time. The figure below by Yaneer Bar-Yam shows the rising complexity in network topologies, sizes, and interconnectivity patterns, from early-human hunter-gatherer communities to the global networked civilization. As time progresses, specialization and diversity increase, yet network efficiency is maintained via decreasing hierarchy levels and more lateral links.



Domains Overview

Descriptive and predictive models can be applied to improve the understanding and management of complex systems in many different domains. This spread explores the four ESTP domains. Exemplary models in this spread and on **pages 74–97** were selected based on utility and impact as well as their capacity to highlight the traits of the 12 different domain-scale combinations. For each of the four domains, we discuss major stakeholder groups, key insight needs, and unique challenges and opportunities. Although certain needs and challenges are domain-dependent, all domains are affected by rapid S&T progress, such as in robotics and AI; and many questions require a cross-domain, multiscale approach to modeling.

Ⓔ Education

Education refers to the process of acquiring knowledge, skills, and values via formal classroom instruction or informal learning in relevant settings. Education is often facilitated by teachers, parents, or other trusted guides, and might be supported by technology, such as computer hardware and software used to deliver interactive exercises.

Educational attainment impacts all areas of life—from income to health and longevity. Scaling up education to become globally accessible is critical for ensuring a just society. Given today's rapid S&T advances, innovation in education—along with the development of and training in tools and human-computer interfaces that augment human cognitive and physical abilities—must be embraced to ensure it amplifies the capabilities of all individuals.

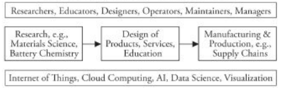
There are many different types of stakeholders who care deeply about education. Among them are students (and their parents), who must identify which degree(s) and courses to select; teachers, who need to keep educational materials up to date and select the appropriate instructional methods and technologies; researchers interested in understanding and documenting how people learn, so that both teaching and learning can be optimized and personalized; and also educational technology developers, who aim to support effective course design and delivery that scales to billions of people worldwide.

Major global education challenges were discussed in **Population: Health and Education** (**page 56**), and opportunities will be presented in the **Micro** to **Macro** spreads on **Education** (**pages 74, 82**, and **90**). In general, there is a disconnect between the S&T progress made thus far, the knowledge and skills currently being taught, and the skills now required by industry. In fact, many cutting-edge technology jobs cannot be filled due to the lack of qualified applicants.

Large-scale data about scientific progress (e.g., publications), technological advances (e.g., patents, news, and other documents), course offerings, and job advertisements can be used to identify existing gaps and enable educational offerings, both timely and perennial, that can satisfy the industry needs of today and tomorrow.

A key challenge now is the preparation of students and workers for advanced human-AI collaboration; see **Modeling Opportunities** (**page 170**) for the **Living with Robots, Human-Machine Symbiosis,** and **Human Augmentation** discussions. The graph below by William B. Rouse shows the numerous stakeholders (top), work processes (middle), and technologies (bottom) that are directly impacted by the transformative progress of AI.

Advanced Human-Artificial Intelligence Co-Work

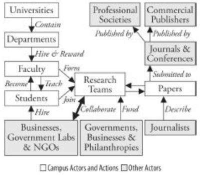


Ⓢ Science

Science is defined as the systematic scholarly study of the structure and behavior of the world through observation and experiment. As humankind continues to impact nearly all aspects of the natural world, it becomes ever more vital to study the effects of social and technical systems on the world as we know it. Frequently, there is a complex interplay of infrastructure (including robots and AI) and human behavior, making it necessary to study sociotechnical systems (e.g., in factories or cities).

Many scholars have attempted to develop conceptual models of science, featuring basic actors/components and fundamental categories of symbolic capital. *Atlas of Science* discussed Pierre Bourdieu's symbolic capital categories (of social, economic, and cultural capital) as well as Bruno Latour and Steve Woolgar's Cycle of Credibility, which illustrates the cyclic conversion of different types of capital (e.g., scholarly recognition might be converted into successful grant applications; funding is then converted into hiring excellent students and also gaining access to equipment, data, and software that make it possible to develop arguments and theories, which can be written up in papers that further increase scholarly recognition—see **page 59** in *Atlas of Science*).

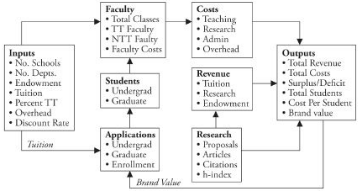
Ben Shneiderman published a conceptual model of the research ecosystem, shown at top right, which promotes team-based research motivated by real-world problems. The model aims to deliver breakthrough theories in published papers, alongside validated solutions that are ready for widespread dissemination—the so-called twin-win successes. At the center are research teams, comprised of faculty and students, who are hired and rewarded by departments within universities.



Research papers first published in journals and for conferences are subsequently published by professional societies or commercial publishers, gaining scholarly recognition and influence. Journalists describe the results reported in papers to communicate scientific advances to larger audiences. Importantly, research teams collaborate with business, government laboratories, and nongovernmental organizations (NGOs), as indicated by the thick double-headed arrow near the bottom; those institutions might hire students, increasing the diffusion of knowledge and expertise into practice. Finally, research teams are accordingly funded by governments, businesses, and philanthropies.

William B. Rouse developed *Economics of Research Universities*, the conceptual model shown below, which aims to interlink inputs and outputs via costs and faculty—tenured (TT) and nontenured (NTT)—in order to clarify (1) the impact of brand value on the quality of student applications and enrollments, and (2) the importance of research outputs in generating that brand value, which can be converted into tuition and other revenue (see model details in **Meso: Education, page 82**).

Economics of Research Universities



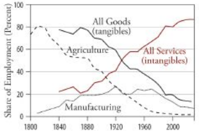
Ⓣ Technology

Technology can be defined as the application of scientific knowledge for practical purposes (e.g., in industry or business for innovation). Technology opportunities arise by the pressure of scientific discovery (push) and the demands of societal needs (pull). Technology delivery requires access to resources (e.g., capital, skills, materials, and software) but also the effective management of relationships with customers, government bodies, competitors, and other stakeholders.

Models are widely used in industry to optimize supply chains, product development and optimization, and delivery services, or to provide personalized experiences. The goal is to speed up the conversion of capital (material and intellectual) into success (e.g., market share, name recognition, and a highly skilled and well-paid workforce). The higher the "conversion rate," the faster the growth. Most startups try to grow fast. Established corporations typically focus on sustaining or slowly expanding their market position and dominance.

While task specialization and divide-and-conquer strategies were widely used in the industrial age, a systems science approach to problem-solving and interdisciplinary teamwork is needed to succeed in the innovation age, when much of capital is intangible (e.g., expertise and skills, patents, intellectual property, and reputation) rather than tangible (e.g., buildings, machines, and trucks).

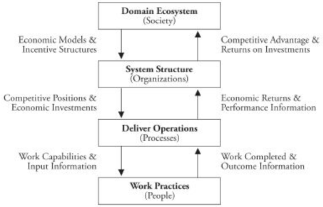
The expertise, skills, and attitudes of employees are more important than ever for developing innovative products. The graph above right shows the steady decline in the share of employment in agriculture (dashed line) relative to manufacturing (dotted line) and other sectors that produce tangible



goods (solid black line)—while workforce needs for intangible services (red line) steadily increase. Ongoing progress in robotics may lead to further decline in the share of employment for manufacturing; in contrast, the share of work for physical and cognitive nonroutine work that cannot be easily automatized will likely increase (see the top image on **page 89**).

Rapid S&T progress makes the survival of companies less certain. A key measure of a company's survival is its tenure in a stock market index, such as the S&P 500 (for the 500 largest U.S. companies). In 1937, the average number of years that a company was listed in the S&P 500 was 75 years; in 2011, it was 15 years; and in 2025, it will be 5 years as predicted by KPMG.

Survival requires continuously evolving multilevel system integration and management within a complex ecosystem (see the figure below). For the production and delivery of any product or service, the relevant work practices, delivery operations, system structures, and domain ecosystem in which a company operates must be understood, managed, and continuously optimized—often across various, independent, and geographically dispersed organizational units.



Ⓟ Policy

Policymaking—or the process of formulating policies in education, health, politics, or other domains—might variously involve the need to optimize resource distribution, improve safety, ensure competitive advantage, reduce inequality, or increase societal benefits.

While industry has embraced the power of computational predictive models, policymakers have been slower to adopt data-driven decision-making. Typically, policy advice is provided by senior researchers in universities, industry, and government; yet rarely do experts employ the high-quality, high-coverage data sets and advanced data-mining and modeling tools that are now available.

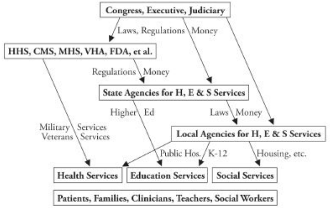
The conceptual model at top right describes the two overlapping cycles of the strategic planning process: In the internal, long-range planning cycle on the right, setting goals leads to the implementing, monitoring, and forecasting processes that are needed to achieve those goals. In the external perspective cycle on the left, results gained from internal monitoring are used in external scanning, with valuable input thus offered toward evaluating ranking and forecasting. Plus, an external scanning and evaluation exercise can be used to inform internal planning.

Models are also valuable in overcoming the regulatory challenges that arise when aiming to develop more resilient and future-proof systems in water supply, transportation, or health care. Models enable policymakers to deal with asymmetric incentives (e.g., if a system change results in some failure, blame is appointed; yet lack of accountability might prevent any system change, even if potentially beneficial); to deal with encrusted regulation (i.e., when excessive rules lead to systems that are too difficult to understand and manage); and to agree on ethical values (e.g., whether to pursue genetic modification to stop the transmission of unwanted genes from mother to child).

Strategic Planning Process

Models and model visualizations can help different decision-makers agree on the structure and dynamics of a target system to be managed and optimized, as well as on the roles that different stakeholders might play in that process.

The conceptual model below by William B. Rouse and colleagues shows the fragmented system of U.S. health, education, and social systems. Close collaboration between all the listed entities—CMS (Centers for Medicare and Medicaid Services), E (Education Services), FDA (Food and Drug Administration), H (Health Services), HHS (Department of Health and Human Services), MHS (Military Health System), S (Social Services), and VHA (Veterans Health Administration)—is required to overcome fragmentation in order to develop and implement holistic solutions to universally improve services. Those health, education, and social services would be funded by state and/or federal money, with the appropriate separation of powers at the local, state, and federal levels.



Scales Overview

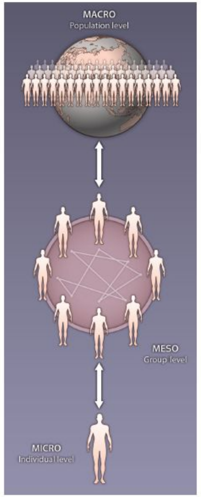
The models discussed in the *Atlas* trilogy span the micro (individual), meso (team/institutional/regional), and macro (population/global) scales. Frequently, multiple scales need to be considered to arrive at workable solutions that have the intended effect. For example, social, cognitive, and behavioral factors at the micro scale impact organizational factors at the meso scale, which impact global science and entire nations at the macro scale. The reverse is also true: global or national policies either restrict or enable activities at the meso or micro levels; institutional rules and regulations impact individual behavior. This spread details and exemplifies the three main scales used in the *Atlas* trilogy, while arguing for a holistic systems science approach to modeling.

Systems Science

Complex systems are ubiquitous—present around us in nature and society, and within our cognition and anatomy—and comprised of many components that often span multiple scales. Systems science aims to study these multilevel systems. Here, we focus on the models of the ESTP domains. The relevance of different stakeholders varies according to scale. Some stakeholders might be relevant for more than one scale, but will likely have very different concerns at each scale.

One example is the education system: At the individual level, there are concerns about learning performance and engagement, literacy tests and grades, and future-proof, labor-market-valued skills and career trajectories (see **Micro: Education, page 74**). At the organizational level, there is interest in high enrollment rates and rankings, low dropout and suicide rates, organizational learning curves, and also general optimization of how people learn (see **Micro: Technology, page 78**; and **Meso: Education, page 82**). At the global level, there is the need to align educational offerings with S&T trends and job market demands, and to stay globally competitive (see **Macro: Education, page 90**).

Given the extensive diversity in data and stakeholder concerns, the relevance of models largely depends on insight needs and scale (see **Model Classes Overview, page 24**). For example, models that take individual behavior into account, such as **network models (page 46)** and **agent-based modeling (page 48)**, are more common at the individual or micro scale. Models that aim to optimize collaboration and competition, as well as profit and reputation maximization by organizations, might employ **control theory (page 36)** and **game theory (page 42)**. Models at the global societal scale often use **expert-based models (page 26)** and **dynamical equations (page 32)** to capture general trends.



Micro Scale

In the *Atlas* trilogy, the micro scale refers to the scale of one individual—their concerns, abilities, and impact on a well-specified environment. **Network models (page 46)** or **agent-based models (page 48)**, using one node to represent each person, might be employed to understand the context in which one individual is operating, and the emergent behavior that arises when multiple individuals interact with each other. Models might group individuals into clusters according to either types of attributes (e.g., age or gender) or a given network structure (e.g., links denoting social, family, or business relationships). For example, the graph below shows U.S. bachelor's degrees grouped by category; for each category, the midrange salary is graphed within the total salary range. Individuals can use the graph to make more-informed career decisions.

In professional and private life, we frequently seek to understand what influence an individual has on their peers, family, community, or society. It is just as important, conversely, to understand how the behavior of an individual is impacted by their peers, family, community, or society—as discussed on **page 56**, with specific regard to the impact of family and social networks on an individual's behavior, including (over)eating, smoking, and even happiness.

Challenges and Opportunities

One person's life span of 80 years equals about 29,200 days, or 700,800 hours. Much of that time may be spent on satisfying basic needs, such as eating and sleeping. Even so, a significant amount of time could be spent on efforts that ultimately advance both individual and collective well-being.

In reality, most human concerns are focused on short time spans and immediate relationships—those within a locally based spatial, topical, and networked environment (e.g., close friends, family, and colleagues). It is rare for individuals to have a global perspective that extends to several future generations (e.g., beyond their children's lifetime) and considers planetary challenges, or other concerns within a broader geospatial and more highly networked context.

Regardless, humankind's ability to cause massive and possibly irreversible change on Earth is steadily increasing.

Model Examples

Microscale ESTP models are discussed on **pages 74–81**.

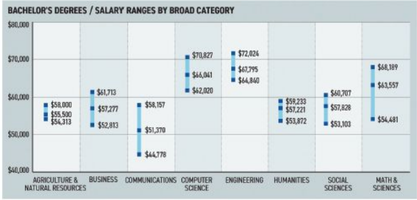
Micro: Education (page 74) considers the impact of individual decisions on career trajectories, and skill sets that are valued in the workforce.

Micro: Science (page 76) discusses inequality in faculty production and hiring; productivity and innovation; and the growth of scholarly networks and their impact on scientific careers.

Micro: Technology (page 78) examines the learning needed to optimize the manufacturing process for one product.

Micro: Policy (page 80) explores the impact of increased life expectancy on worker demographics and associated policy challenges.

Different life stages, through retirement and beyond, pose different opportunities and challenges in terms of making favorable individual decisions (e.g., optimizing time spent on learning vs. working; evaluating income and spending patterns; making efforts to understand the concerns of others; and contributing to society).



Meso Scale

In the *Atlas* trilogy, the meso scale refers to the level at which organizations, institutions, and regions make decisions. For example, in education, it might be beneficial to study and model learning cohorts and thereby optimize teaching and learning modules for different learning styles. In science, it is important to assemble productive scholarly teams, often combining expertise from different disciplines and involving representatives from academia, industry, and government. Industry collaborations within and across different sectors are generally advantageous (e.g., to optimize supply chains or improve customer service). Government agencies routinely benefit from data and expertise exchange, as well as from the coordinated implementation of new policies, within and across regional boundaries.

Challenges and Opportunities

Coordinating modeling efforts within and across teams, organizations, and regions can be a herculean feat. Data is often held by multiple owners, and privacy-preserving data sharing might be needed to run meta-analyses using all data or to validate models against all data.

Similarly, algorithms and other code that are needed to implement a complete model might be owned by different institutions, such that license and intellectual property issues must be resolved before a computational model can be constructed and run.

Different stakeholders typically have correspondingly different needs, expectations, cultures, responsibilities, and capabilities. Agreeing on mutually beneficial goals, finding a shared language, and agreeing on the best process for developing, implementing, validating, using, and communicating a model can be time-consuming. However, collective buy-in makes it possible to benefit from the wisdom, resources, and (social) networks of many experts; it can lead to transformational solutions that exploit existing synergies for widespread benefit.

Model Examples

Mesoscale ESTP models are discussed on **pages 82–89**.

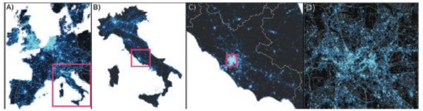
In the education domain (**pages 82–83**), models are applied to understand how people learn and how to scale up education in an equitable manner.

In the science domain (**pages 84–85**), models are applied to identify cultural disconnects or gaps in scholarly communication, and to determine the most innovative author combinations or the factors that decide which researchers have a long and successful career in science.

In the technology domain (**pages 86–87**), models help identify and communicate the impact of government funding on economic success. They can be used to compute how innovative different regions and cities are, and also to understand the impact of changes in product sales volume on business process dynamics.

The policy domain (**pages 88–89**) greatly benefits from the holistic understanding of a region or city within the global and local context in which it operates—see the sequence below of zooms from a map of Europe (panel *A*), into Italy (panel *B*), the Lazio region (panel *C*), and finally Rome, Italy's capital (panel *D*). Examples presented in **Meso: Policy** discuss the impact of policy decisions on gross domestic product and unemployment rates, as well as public attitudes, knowledge, and interest with regard to education, science, technology, and societal issues.

Just as there are different stakeholders and concerns at different geospatial levels, there also exist different stakeholders and concerns at different levels of aggregation within education areas, scientific disciplines, and industry sectors. Ultimately, decision-makers should aim to understand and involve all stakeholders that are affected when revising an old or implementing a new model.



Macro Scale

In the *Atlas* trilogy, the macro scale refers to global considerations at planetary scale. Models might study interactions between the Earth system and the anthroposphere, which comprises human-made systems such as cities, connected by street and airline transportation systems, power grids, and the Internet (see **Anthropocene Animation, page 65**). Long-term global monitoring and modeling efforts require the development of new data recording, aggregation, mining, and visualization infrastructures (see **International Science Observatory** in *Atlas of Science*, **page 176**) to properly manage the complexity of the Earth system that supports our existence.

Challenges and Opportunities

The globalization of education, science, business, and government, as well as the challenges that humankind is increasingly facing (e.g., extreme poverty, environmental degradation, and global warming), require international and interdisciplinary collaboration. Agreeing on priorities, timelines, and the allocation of resources across nations and institutional boundaries is a major challenge.

Measuring and optimizing ESTP progress is nontrivial due to the systemic heterogeneity of different educational systems and needs, scientific cultures and values, technological opportunities and demands in different industry sectors, and the context and history of different policy systems. However, clear metrics and success criteria are beneficial when aiming to model and optimize co-evolving systems at the global scale.

Model Examples

Macroscale ESTP models are discussed on **pages 90–97**.

Increasing networked complexity (e.g., the aggregation of people and corporations in large cities) leads to ever-faster communication and innovation, yet also more-complex interdependencies based on global risks (see **WEF Risk Trends Network, page 97**). Faster transport, mainly via densely connected cities and efficient airline networks, leads to faster spreading of not only information but also, potentially, diseases (see **Epidemic Models, page 38**).

Increased human life expectancy will impact the workforce (see **Changes in Working-Age Population, page 81**) and possibly also humankind's global innovation potential (see **Age Dynamics in Scientific Creativity and Achievement, page 77; Regional and Global Innovation Indexes, page 87**; and **AI Vibrancy in R&D, Economy, and Inclusion, page 94**).

Several indexes exist to model and monitor global progress. The Global Competitiveness Index (GCI 4.0), developed by the World Economic Forum, identifies 12 main drivers of productivity, called pillars, that are expected to grow in significance over time. The table below shows regional performance by pillar, and the four main categories (at top) used to classify those 12 indicators, with darker shades indicating better performance. Europe and North America perform well in many of the pillars. East Asia and the Pacific lead in terms of *Financial system*. All regions score above 60% on *Macroeconomic stability* and above 50% on *Business dynamism*.

Table 1: Regional performance, by pillar
Average score (0–100)

	Enabling environment				Human capital		Markets				Innovation ecosystem	
Region	Institutions	Infrastructure	ICT adoption	Macroeconomic stability	Health	Skills	Product market	Labour market	Financial system	Market size	Business dynamism	Innovation capability
East Asia and the Pacific	61.6	74.3	67.3	88.9	84.3	66.9	62.2	65.9	72.8	67.2	65.7	52.9
Eurasia	53.0	66.3	57.1	71.7	73.4	65.6	57.1	61.6	50.8	49.8	60.1	34.8
Europe and North America	64.5	78.7	66.0	91.8	90.7	74.2	62.0	66.2	69.5	59.6	68.3	58.1
Latin America and the Caribbean	47.8	61.1	46.4	74.0	82.7	57.5	53.9	55.3	59.5	52.5	52.4	33.8
Middle East and North Africa	54.3	69.0	54.1	79.6	80.0	61.4	54.7	52.3	61.8	60.3	56.7	39.9
South Asia	50.1	59.6	33.0	74.1	68.4	49.7	47.3	51.7	59.0	66.9	56.5	36.4
Sub-Saharan Africa	47.5	46.3	29.6	66.9	48.0	43.4	50.4	53.8	50.4	36.8	51.1	28.4

Source: World Economic Forum analysis.
Note: See the At a Glance section on page xi for regional classification. Darker shades indicate better performance.

⊙ Ⓔ Meso: Education

In the education domain, computational predictive models are widely applied. For example, logistic regression models are used to predict and reduce student dropout or waning student engagement and performance. More advanced models are under development to support personalized education. Given the success of massively open online courses (MOOCs)—and the massive usage of online education during the COVID-19 pandemic—it becomes more important to study how people learn online.

Examples

Computational models of research universities can simulate the impact of different funding and enrollment strategies—up to 20 years into the future. MOOCs make it possible to scale up education to millions of students, by generating rich data that supports the development of learning analytics models, which increase our understanding of how people learn and also offer personalized learning support.

Key Insights

Innovation in education is required to ensure the survival of institutions, as well as to scale up education so that billions can be educated for a future wherein robots, AI, and humans can learn and work together.

Probable Futures of Public vs. Private and Large vs. Small Research Universities

Hundreds of colleges and universities are in a financial crisis, according to the Hechinger Report. MOOCs make it possible to teach thousands of students in one class, considerably reducing the costs (and income) per student. Which institutions will survive?

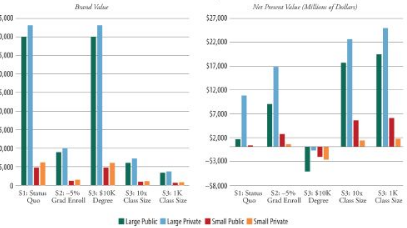
William B. Rouse and colleagues developed a computational model to simulate different potential futures of the American academic research enterprise. They started with a conceptual economic model of a research university (see the figure at lower right of **page 70**). Next, they collected empirical data to characterize the resources available to the 160 best-resourced research universities, a small subset of the 2,285 U.S. four-year, nonprofit, higher education institutions. Then, they developed and ran a computational model for four types of universities: (i) large public, (ii) large private, (iii) small public, and (iv) small private. The large institutions (i and ii) topped the list of 160 in terms of resources, leaving the small ones (iii and iv) near the bottom. The model makes it possible to simulate three strategic scenarios: (*S1*) status quo, or business as usual, (*S2*) steady decline in foreign graduate student enrollments, and (*S3*) downward tuition pressures from high-quality, online professional master's programs. Scenario *S3* has three different instances, with an external force that is the same for all three, but a different system response for each: Instance *S3: $10K* refers to some universities being able to offer entire degrees for as little at $10,000, which is possible only by cannibalizing the income generated by other professional master's degree programs; since revenue then decreases substantially while the number of students to be taught stays the same, this instance is the worst-case scenario for all university types. Instances *S3: 10x* and *S3: 1K* refer to a tenfold increase in students, and 1,000 students per class, respectively; both instances lead to a substantially smaller number of faculty needed to teach (as does *S2*), which in turn reduces publishing productivity and brand value.

All three scenarios were run for the four types of universities, and the predictions for year 20 of the model run are shown in the two graphs below. The left graph shows brand value computed using data on publications, citations, and h-index, but not funding. Units are arbitrary, but useful for relative comparisons. The right graph shows the net present value (NPV), a financial metric that equals the current value of projected future cash flows, discounted by the interest rate due to cash flows being delayed. Typically, institutions will aim for a zero NPV, so they break even.

Additional model projections make it clear that the percentage of tenure-track (TT) faculty has an enormous impact. Non-TT faculty members are assumed to teach twice as many classes as TT faculty members at a lower salary—substantially reducing costs. The predictions show that in some situations, it is beneficial for a university to substantially reduce research activities in order to avoid the costs that these activities require.

In general, model results showcase the need to rethink and fundamentally change the economic business model of universities, particularly for those institutions without large resources.

20-Year Outlook by Scenario

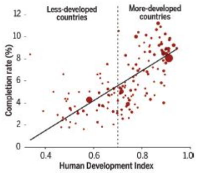


Active Learning Increases Student Performance in Science, Engineering, and Mathematics

What are the best learning formats for any given knowledge or skills? When is it best to use passive vs. active learning? How can active listening and learning be encouraged?

The quality of science, technology, engineering, and mathematics (STEM) education, including the methods used, impacts learning outcomes. According to *The State of U.S. Science and Engineering 2020*, the National Science Board biennial report of science and engineering indicators, the United States placed ninth in both mathematics and science, when examining average scores in an international comparisons of 19 advanced economies participating in the Trends in International Mathematics and Science Study (TIMSS) study.

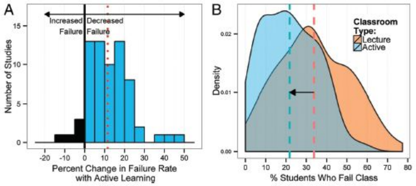
Work by René F. Kizilcec and team shows completion rates for 1.8 million learners taking 55 MOOCs as a function of the United Nations Human Development Index. The results are graphed at right; each dot represents a country, size-coded by the number of learners. MOOC completion rates are higher for learners from more developed countries.



A number of metastudies have been conducted to analyze which learning methods achieve the best educational outcomes. Scott Freeman and his team performed a metastudy analyzing the results of 225 studies that reported data on performance scores and failure rates for STEM courses for traditional lecturing that dominates U.S. STEM instruction vs. active learning. They found that active learning results in increased performance, which raises average grades by half a letter, as shown in the two-part figure below. Graph *A* plots the number of students over the percent change in the failure rate for active learning. As the percentage of active learning increases, the failure rates decrease (in blue). The mean change at 12% is plotted as a dashed vertical line (in red). Graph *B* shows the density of students who fail class for active learning (in blue) relative to lecturing (in orange), with mean failure rates at 21.8% and 33.8%, respectively. As can be seen, active learning substantially decreases failure rates. The team also shows that failure rates under traditional lecturing increase by 55% relative to active learning. Their work argues for abandoning traditional lecturing in favor of active learning.

Matthew T. Hora critiques the study and results by pointing out that no apt definition of "lecturing" exists, and commonly practiced lecturing might range from a teacher exclusively presenting while students consume that content, to a teacher providing guidance and explanations while students actively work through materials.

Despite the critique, it seems highly desirable that teachers add active learning techniques to their pedagogical toolkit; choose the best (or explore alternative) pedagogic strategies for each learning module; and aim to understand and support (or expand) the various study habits of students. Kylie Peppler and team explain how the results of learning analytics and learning sciences can be used by course designers and instructors to better align course assignments, learning objectives, and assessment measures with learner needs and interests.

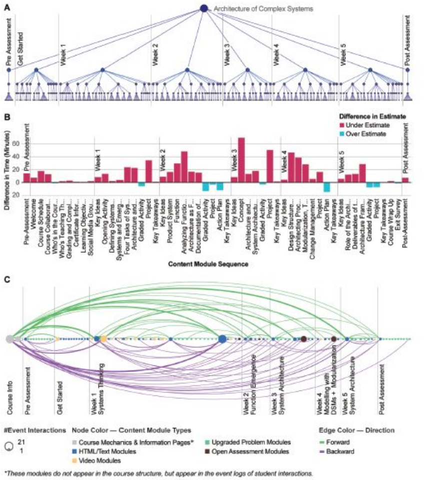


Visual Analytics of MOOCs

How do people learn? How can they learn most effectively online? What learning styles do different student cohorts exhibit? How can course design be optimized to serve the needs of individual learners?

With the advent of MOOCs in 2008 and millions of students taking courses online, it becomes possible to capture, analyze, and use teaching and learning data to understand human learning and to optimize teaching. Data from MOOCs has been used to examine learners' engagement, performance, and trajectories in online courses.

The visualization below shows learning trajectories by 1,608 Boeing engineers taking the MIT xPRO course "Architecture of Complex Systems" delivered in fall 2016. More than 30 million separate events (students accessing videos or assignments, submitting work, etc.) were captured and analyzed to create this figure. Graph *A* plots the five-week course structure with pre- and post-assessment. Graph *B* shows instructors' time estimates for different learning modules, with underestimates (in red) and overestimates (in blue)—and some discrepancies when compared to the time students actually spent per module on average. Graph *C* presents learning modules via circles placed in sequence from left to right; modules are color-coded by module type (see legend). Green arcs indicate students' forward transitions, from one learning module to the next; purple arcs denote backward transitions, to revisit earlier learning modules—typically when preparing for exams.



Meso: Technology

Increasing international competition and shareholder demands for short-term returns lead to ever-shorter product cycles. Higher costs for research and development (R&D) make continuous innovation mandatory for survival. Industry-university cooperation is beneficial to facilitate technological innovation as well as innovation transfer (see Shneiderman's twin-win success discussed on **page 70**).

Examples

Data models and visualizations can be employed to analyze and communicate the impact of science funding on the success of IT sectors. Models can be applied to compute how innovative different U.S. regions or counties are. Business dynamics models advise how erroneous information from the customer end to other parts of the supply chain can lead to devastating inefficiencies, including excessive inventory investment, ineffective transportation, missed production schedules, poor product quality and customer service, and lost revenues.

Key Insights

Edwin Mansfield explored eight industries during 1975–1994, concluding that over 10% of the new products and processes introduced could not have been developed without (substantial delays in the loss of) academic research. Thus, research funded by government, academic, and charitable research institutions is crucial for private-sector technology development and innovation.

IT Sectors with Large Economic Impact

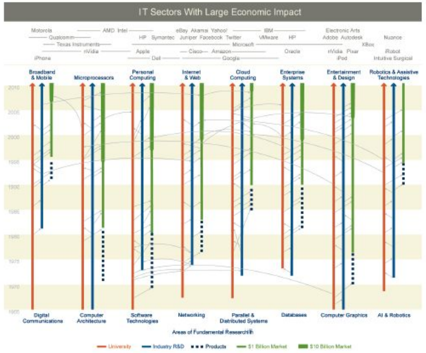
How do federal funding and scientific progress together impact industry R&D? Which research specifically led to the development of key products, and how large a market was created via those various lines of research?

The 2016 "tire tracks" graph below—updated since its 2012 creation—was published in the *Continuing Innovation in Information Technology* workshop report by the Computer Science and Telecommunications Board (CSTB), a unit within the National Academies of Sciences, Engineering, and Medicine. The visualization shows the IT sectors that benefited from federal funding for fundamental research; that funding helped create not only those IT sectors but also firms and products with ultimately large and far-reaching economic impact.

In the graph, time runs vertically upward, from 1965 to 2010. Eight R&D tracks are featured. Each track shows how federally funded university research (in red) is joined by industrial R&D (in blue), which results in the introduction of new product categories, some of which become billion-dollar industries (black dots merging into solid green lines). Arrows interlinking the tracks indicate documented, multidirectional flows of technology within or across areas—showcasing the cross-fertilization of ideas, technologies, and people between academic research, industry research, and product development. Above the tracks, in gray type, are the corporate brands that have a major market share in the eight IT sectors.

The visualization was originally developed by the National Research Council to illustrate how federally funded university research, together with industry R&D, precede the emergence of large IT industries by decades (see also the discussion of a 20-year timeline in chemical science, from conception to commercialization, in *Atlas of Knowledge*, **Chemical R&D Powers the U.S. Innovation Engine, page 112**). The graph shows "old" areas like *Microprocessors*, which exceeded $1 billion in annual revenue in the early 1980s and then exceeded $10 billion around 1995. It also features new areas like *Robotics*, which has reached $1 billion but not yet $10 billion in annual revenue.

While necessarily incomplete, symbolic, and backward-looking in nature, the graph inspires reflection and action. It has been used in National Academies workshop reports and other documents that aim to demonstrate the impact of and make a case for federal investments in foundational research.



Regional and Global Innovation Indexes

How innovative is the region in which you live, and how does it compare to other regions? Is it well connected to both the local and global economic landscape?

Many development practitioners and other regional leaders need to answer such questions in order to properly address economic challenges, strengthen capacity for innovation, and exploit new knowledge creation, technology diffusion, and other similar opportunities.

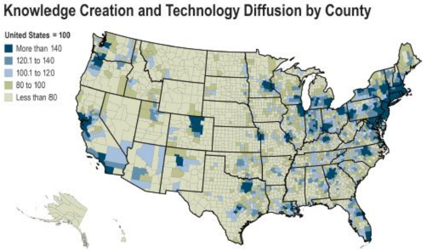
Diverse innovation indexes exist to help development practitioners and regional leaders make data-driven decisions in their daily work. The Global Innovation Index (GII) is published annually by Cornell University, INSEAD, the World Intellectual Property Organization, and other partner organizations. It ranks the world's countries and economies by their capacity for, and success in, innovation.

The Innovation Index by StatsAmerica compares a region's innovation performance to that of another state or region, or to overall U.S. performance. The service is provided by the Indiana Business Research Center at Indiana University's Kelley School of Business. The annual index is calculated from four component indexes that are differently weighted: human capital (30% weight), economic dynamics (30%), productivity and employment (30%), and economic well-being (10%). The data used to compile the Innovation Index comes from government statistical agencies as well as from private, proprietary sources, including Moody's Analytics, Decision Data Resources, EMSI, and VentureDeal.

The Innovation Index 2.0 is an interactive online resource that incorporates new research on measuring innovation, by taking into account regional knowledge spillovers, technology diffusion, and foreign direct investment, as well as social capital. It was designed to help regional leaders arrive at a strong consensus on future-proof strategies. Innovation Index 2.0 visualizations can be shared with all stakeholders to identify a region's capabilities, shortfalls and potentials, and to guide complex decision-making in support of collective action toward a common plan.

MapTool makes it possible to explore, spatially, any innovation metric—including prime working-age population or business incubator spillover effects. The map below shows knowledge creation and technology diffusion at the county level. The U.S. average is set at 100; counties with a lower-than-average index (in beige) are most prevalent, while those with a higher index (all blue) contain areas of exceptionally high knowledge creation and technology diffusion (in dark blue).

Decision-makers can examine their own region in the context of others, select one region as a standard against which all others may then be compared, or zoom into detailed data. Any content can be downloaded (as a spreadsheet or PDF) at the county, metro area, or Economic Development District (EDD) level for further analysis and examination.



Business Dynamics: Response to Sudden 10% Retail Sales Increase

How do changes in sales impact business process dynamics?

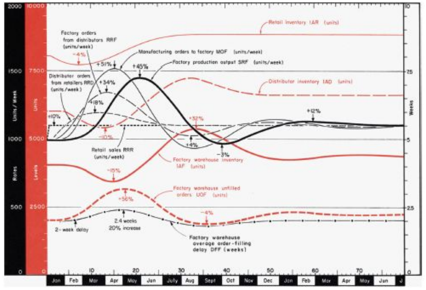
Jay W. Forrester was a founder of system dynamics, which aims to model the interactions between objects in complex dynamic systems. In his 1961 book *Industrial Dynamics*, he introduced the use of system dynamics to analyze industrial business cycles and the Forrester effect, better-known today as the bullwhip effect, which describes the increasingly large demand distortions that tend to occur along the supply chain—from customers to retailers, distributors, manufacturers, and finally to suppliers. For instance, a predicted or actual 15-unit (minor) increase in retail sales might lead to a 20-unit increase in warehouse stocks, an even larger unit increase in safety or backup stock within the distribution center, and onward. As the "whip" moves away from the customer, the effect amplifies, causing not only excess inventory but also quality control issues and other inefficiencies. Similarly, as forecasting predictions move further away from the customer, or further upstream along the supply chain, the less accurate they become. Poor communication and lack of visibility, along with process constraints such as capacity, batch sizes, and time lags, all further increase demand distortion, oscillation in inventory levels, and possibly supply shortages (also called a production flywheel effect—see **Control Theory, page 36**).

Exemplarily, the dynamic behavior of an inventory system is captured in the graph below. The figure shows unit-per-week changes in orders (in black)—including a 10% increase in retail sales, which motivates an 18% change in distributor orders, causing a 34% increase in factory orders, resulting in a 45% increase in factory production output. Also graphed (in red, from top to bottom) are the inventory units for retailers, distributors, and the factory warehouse. In 1961, when this graph was published, a mathematical model was used to describe the target system, that model was run on some of the early computers, and the model results were used to plot system behaviors.

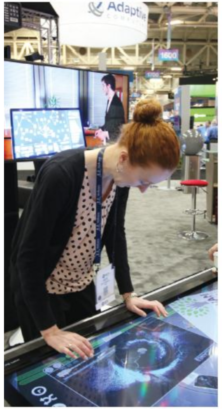
A decade later, in 1972, Forrester and his students used the DYNAMO (DYNAmic MOdeling) simulation language—which they had originally developed for analyzing problems such as inventory management in industrial dynamics—to develop *The Limits to Growth* world model (**page 7**), one of the first computer models with multiple feedback loops.

In *World Dynamics* (1971) and numerous papers, Forrester sought to model the world economy, population, and ecology. He argued that computerized system models are far superior to simple debate—for capturing the structure and dynamics of real-world systems, identifying the root causes of problems, and also determining the likely effects of proposed systemic changes.

In *System Dynamics: System Thinking and Modeling for a Complex World* (2000), John D. Sterman, a student of Forrester, (re)introduced system dynamics models, together with tools for systems thinking, modeling, and testing as exemplified by real-world examples—making it easier for many to use models effectively.



Part 4: Science Maps in Action



Places & Spaces maps on a touch table at the International Conference for High Performance Computing, Networking, Storage, and Analysis, New Orleans, LA

Places & Spaces: Mapping Science

Introduction to the Exhibit

Created by experts in science, humanities, and the arts, the works collected in the *Places & Spaces: Mapping Science* exhibit convey the excitement of scientific progress and discovery. Maps of science chart the more abstract spaces of data and knowledge, helping us forecast new fields of inquiry and enabling us to tell stories that we can all understand and act upon. An interdisciplinary and international advisory board chose each of these exhibited works as an outstanding example of how visualization can bring patterns in data into focus.

As of 2020, 100 maps by 215 mapmakers have been displayed at 396 venues, in more than 28 countries, on 6 continents. Each unique venue adds its own value. Ultimately, the exhibit is like the eponymous stone in the story of stone soup—with experts around the globe contributing singular visualizations that ask new questions while offering solutions to meet local contexts and needs.

The *Atlas of Forecasts* features maps designed for kids—the next generation of experts and leaders; maps showing trends and dynamics in the past, present, and future; and maps that foreshadow the future of science mapping. The 30 maps featured here communicate complex data; help bridge gaps between experts in academia, industry, and government; and help align forces toward the identification and implementation of desirable futures.

Geoffrey West, distinguished professor and past president, Santa Fe Institute, introduces Börner's Betazone talk at the World Economic Forum, Davos, Switzerland

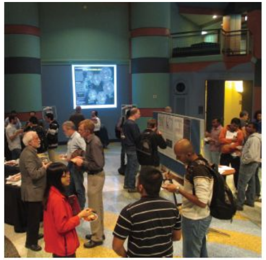
Places & Spaces digital display in the iPearl Immersion Theater, James B. Hunt Jr. Library, North Carolina State University, Raleigh, NC

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

Illuminated Diagram display at the Smithsonian Folklife Festival, Washington, D.C.

The *Visionary Approaches Timeline* from the *Atlas of Science* on display at the Mundaneum, Mons, Belgium

"New Trends in eHumanities Research" workshop at the Royal Netherlands Academy of Arts and Sciences, Amsterdam, Netherlands



Ken Kennedy Institute for Information Technology, Rice University, Houston, TX

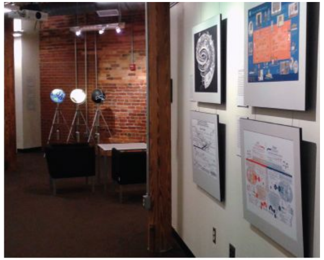


Exhibit maps and Ingo Günther's WorldProcessor globes on display at Duke University, Durham, NC

Katy Börner debuts the exhibit at the University of Miami, Coral Gables, FL

100 science maps on display at the University of Miami, Coral Gables, FL

Maps on display at the European Commission, Directorate-General for Research and Innovation, Brussels, Belgium

Jax and the Big Data Beanstalk theater piece introduces visitors to data visualizations and science maps at the Science Museum of Minnesota, St. Paul, MN

Katy Börner presents "Maps & Macroscopes" at TEDxBloomington, Bloomington, IN

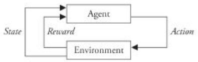
Reducing Human Bias

Humans tend to be subjective, often acting according to biased opinions rather than objective facts. Cognitive biases are systematic deviations from normative rationality in judgment, as studied in fields like psychology and behavioral economics. While many such biases have been confirmed in independently reproducible research, controversies abound as to their possible origins and causes. In order to make objective, well-informed decisions, we need to understand and proactively neutralize existing biases. This spread explains some of the known biases, beliefs, and behaviors, with suggestions for how to counteract them. Ultimately, biases and beliefs have a major impact on life satisfaction. Understanding our own biases is an important step toward experiencing a fulfilling present and future.

All models are wrong, but some are useful.
George Box

To Err Is Human

Though human brains are powerful and efficient, human error inevitably occurs at every level of society. Some errors are systematic and systemic. Many are self-reinforcing via positive or negative feedback cycles (see the figure below and **Modeling Goals, page 14**). Frequently, specific individual or institutional actions (e.g., funding of highly funded scholars) influence the structures and/or dynamics of the environment (e.g., more funding created for already highly funded scholars), leading in turn to rewards for potentially erroneous actions (e.g., favoring older vs. younger scholars; thus, older scholars are able to further their impact, while younger scholars are not afforded resources to perform high-end research, which falsely confirms funding of older scholars as the best strategy for maximizing the number of citations per dollar spent).



Extensive literature exists on why human judgment fails, particularly when long-term or global decisions are at stake. In addition, considerable research aims to uncover why people violate norms of action through social misbehaviors (e.g., conforming with false majority judgments or failing to help those in need) and norms of reasoning through cognitive errors (e.g., polarized black-and-white thinking or overgeneralization). The goal is enhanced understanding of the bases for good behavior and accurate judgment, coherent explanations of occasional lapses, and theoretically grounded suggestions for improvement. In-depth discussion on this subject, with significant examples and theoretical models, can be found in *Networks, Crowds, and Markets: Reasoning about a Highly Connected World* (2010) by David Easley and Jon Kleinberg.

Data Bias

Any system modeling effort starts with data, which is gathered by surveying human experts, retrieved from databases or the Internet, and collected via IoT sensors or other sources. Using the most appropriate and highest-quality data is crucial for arriving at actionable insights. Unfortunately, imperfect data is frequently used with confidence.

Convenience sampling is often employed, drawing on a part of the population that is close at hand—such as colleagues, friends, or neighbors with experiences and opinions similar to those of the data collector—so that findings are thus more likely to reflect the views of the data collector than of the general population. This kind of nonprobability sampling can be useful for pilot testing, but is often not a good choice for designing, parametrizing, or validating a model for a target system.

Other common data sampling mistakes include: selective attention, whereby a person's limited capacity allows for only certain stimuli to be noticed while others are tuned out, when several occur simultaneously; base-rate neglect, when a person focuses heavily on new information without properly taking into account original or base assumptions; confirmation bias, whereby new evidence is interpreted according to existing beliefs or theories; Simpson's paradox, in which separate sets of data show one particular trend that is reversed when those sets are combined; and out-group devaluation of an in-group based on out-group criteria (i.e., when individuals outside of an in-group devalue aspects in which they fare poorly relative to that in-group, but overvalue aspects in which they fare well relative to their out-group). Sampling errors carry over to subsequent data use, model or visualization design, and interpretations—and are nearly impossible to detect and correct unless the proper documentation of data sources is secured and data preprocessing is performed.

Gender Bias

The well-known bias of gender stereotyping has proven pervasive and difficult to overcome. Sheryl Sandberg, author of *Lean In: Women, Work, and the Will to Lead* (2013), confirms that women are called bossy when exhibiting the same behaviors for which men are considered assertive. Sandberg, with psychologist Adam Grant, also points out how the workplace expects a man to be ambitious, but a woman to be helpful; ergo, if a man does not help, he is "busy," but if a woman does not help, she is "selfish." Similarly, the words used to describe male and female college faculty differ greatly. In analyzing the language of about 14 million reviews on RateMyProfessors.com, Ben Schmidt found that, while male professors are typically regarded as brilliant, awesome, and knowledgeable, female professors are characterized as bossy, annoying, disorganized, and even beautiful or ugly. Furthermore, students generally give professors much higher ratings when they believe them to be male, regardless of their actual gender.

Gender bias regularly factors into performance reviews and selection committees—women are far more likely than men to receive critical feedback, and women leaders in particular are frequently described as abrasive, aggressive, and emotional.

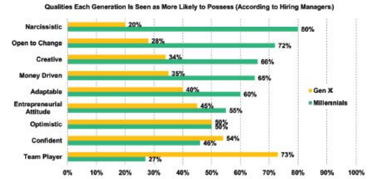
Bias is also present in the grading of students' assignments. Many teachers seem to have the

endogenous belief that girls are not as good as boys in math and science; even when girls perform similarly to boys, their work may be graded more critically. Since that unconscious bias in turn has a profound and systematic effect on whether female students pursue degrees and professions in those fields, such endogenous belief leads to self-fulfilling prophecies.

Gender bias is also present in blinded grant proposal reviews, as the fact that women tend to use "weaker" language (e.g., "we hope to" instead of "we will"; results "might be" rather than "will be") leads to their proposals being dismissed for sounding less confident than those authored by males.

Nevertheless, in the past few decades, blind hiring practices have led to progress—namely in symphony orchestras. Though now widespread, the practice of using screens in auditions to conceal candidates from the jury was gradually implemented. As a result, the percent of female musicians in the five highest-ranked U.S. orchestras increased from 6% in 1970 to 21% in 1993; one study found that blind auditions accounted for up to 46% more female musicians by 1996. However, blind recruitment is not viable in most industries; instead, many institutions require members of job search committees to attend professional training sessions on existing biases and how to remedy them.

Systematic, proactive efforts toward ensuring more equitable outcomes have resulted in an increasing fraction of U.S. bachelor's degrees being awarded to women in the science, technology, engineering, and mathematics (STEM) fields (see top graph on opposite page)—yet much work still needs to be done to increase the number of graduate and PhD degrees awarded, and the number of tenure-track and leadership positions held by women.



Generational Bias

There are presumed to be major differences across generations in terms of education, work ethics, tech-savviness, and cost-effectiveness. The bottom figure on left graphs the average view of 200 hiring managers on whether Generation X-ers (born 1965–1980) or millennials (born 1981–1996) are more likely to have certain qualities relevant to performance and the workplace. Generational differences and associated biases can easily lead to miscommunication and misunderstandings in personal and professional life. Disparities across multiple generations (e.g., between teenagers and their grandparents) can be even more challenging. However, understanding differences is the first step toward counteracting and overcoming them.

Own-Species Bias

Also called speciesism, this prejudice holds one's own species as superior—essentially, humans favoring humans (their own species) over animals (other species), even if their needs are equivalent.

In a world where humans and AI-empowered robots and other machines live, learn, and work together, it becomes important to understand our relationships to this new man-made species.
perceive them to be our creations and allies,
objects entirely artificial and separate from u
we strive to include or exclude them? Will w
about their "well-being" and act accordingly
what will we do when their needs conflict w
own (e.g., if only one can earn income or get
for a job that both could hold)?

More research is needed into people's emo
and ethical response to smart environments,
wearables, and the like. Smart environments
that use augmented reality (AR) data visuali
tions to provide pertinent details (such as lo
weather, costs, or history for house hunters–
the DataWorld image above by Niklas Elmq

and his team) can make data access more efficient, comprehensive, and entertaining, while improving data-driven decision-making by professionals, policymakers, and citizens. The aim of creating robots that look ever more humanlike (see the information-desk android on **page 179**) is to fully resolve the experience of "uncanny valley" (when a robot's imperfect human resemblance evokes unsettling feelings). Extensive interaction with simulated game characters, consistent use of life-tracking wearables, and reliance on smartphones can all offer a profound sense of connectivity; they seem to readily become part of our identity, such that being without them can leave us with a deep sense of anxiety or loss.

Self-Perpetuating Bias

As discussed earlier in "To Err Is Human," deep-seated beliefs in how the world works can inform expectations that lead to self-fulfilling prophecies: If one is inclined to grasp a particular situation in a negative way, one might truly have a negative experience; if that same scenario is seen in a positive light, it may well have a positive outcome. The experience one has then further reinforces one's existing beliefs in how the world works.

That premise is central, for example, to Jayson L. Lusk and Anne Rozan's research on the deep endogenous belief that many U.S. consumers have about the safety of genetically modified (GM) food, which in turn has implications on their consumption of it. Using survey data, the experimenters developed an econometric model in which beliefs about labeling policy, the safety of GM food, and the willingness to consume GM food are endogenously determined. They then assessed and compared the attitudes of life scientists (who

logical choice by consumers and by firms, and the localized nature of crime and political movements.

In a 1960s study on the drawing power of different-size crowds, psychologists Stanley Milgram, Leonard Bickman, and Lawrence Berkowitz had a group of up to 15 people stand on a street corner, with a select number staring up at the sky; they then counted how many passersby stopped and also looked up at the sky. When only one person in a group was staring upward, very few passersby stopped; with five people staring upward, more passersby stopped but few looked up; with all 15 people staring upward, nearly half of all passersby stopped and also looked up at the sky. The experimenters concluded that social pressures, or social conformity, grows stronger as group size increases. Extensive general advice exists on how to neutralize the negatives of peer pressure, such as by making friends with those who resist peer pressure, asking for help when necessary, and either getting out of the problem situation or providing your own positive pressure.

However, humans are social animals, and our habits are reinforced by those we surround ourselves with. Nicholas A. Christakis and James H. Fowler showed that behaviors such as smoking, obesity, and cooperation, or even feelings of happiness, can spread via social networks. For example, a married person's chances of smoking were decreased by 67% when their spouse quit smoking; and people surrounded by cooperative colleagues are likely to be more cooperative. Study results have implications for the composition of teams, clinical and public health interventions, and personal relationship formations.

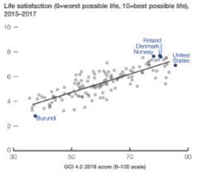
Herd behavior also leads to the "paradox of unanimity"—as described by Derek Abbott for Lachlan J. Gunn et al.—whereby certainty is not definitively reliable. The researchers found, for instance, that in a police lineup, the probability of an individual's guilt increases with the first three unanimous witness identifications, but then decreases with subsequent unanimous identifications. In other words, it is highly unlikely in such
es for many people to all agree. In
his, the researchers cite how ancient
rescribed that a suspect on trial should
if found unanimously guilty. Though
this counterintuitive, the legislators of
d observed that unanimous agreement
ed the presence of systemic error in the
ess. Without necessarily understanding
ture of the error, they derived what for
working solution.

tisfaction

nitive bias has been shown to have a
on an individual's overall life satisfaction as it impacts motivation, engagement, performance, and happiness.

The figure below, from *The Global Competitiveness Report 2018* by the World Economic Forum (WEF), shows life satisfaction for 135 countries, as measured on Cantril's Ladder of Life Scale—whereby participants, using the numbers 0 (for worst possible life) to 10 (best possible life), answered the question, "How satisfied are you with your life as a whole these days?" Finland, Denmark, Norway, and the United States appear to have the highest Global Competitiveness Index (GCI) 4.0 scores, while the Republic of Burundi, landlocked in the African Great Lakes region, seems to score lowest. As the WEF states, the fact that life satisfaction accounts for over two-thirds of differences per the GCI 4.0 scores is remarkable given how vastly distinct the 135 nations are otherwise, in terms of culture, history, and politics.

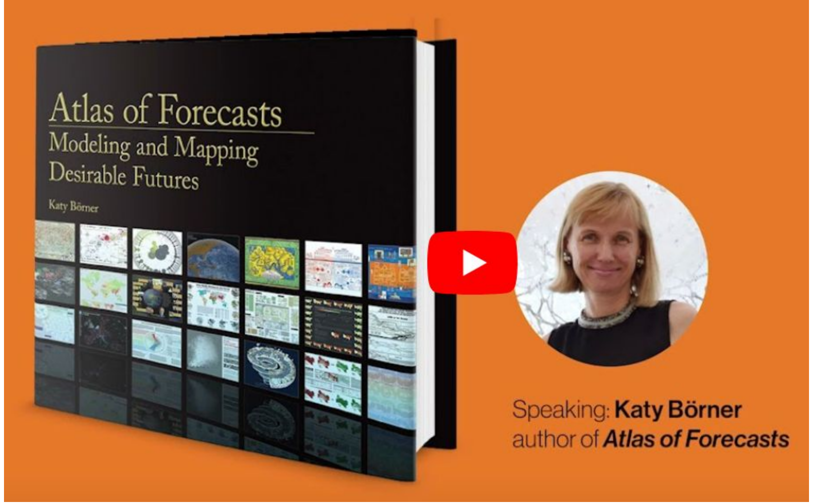
How can positive cognitive bias be introduced to educational, scholarly, industrial, or government environments to arrive at even higher GCI values?



Exposing Biases

People tend to be unaware of their own biases and believe they make decisions objectively. Project Implicit aims to educate individuals about hidden biases and to generate data for research. Investigations using their data have found, for example, that "states higher in racial bias spend less on disabled Medicaid enrollees" and that "Blacks' death rate due to circulatory diseases is positively related to Whites' explicit racial bias." The organization provides users with easy access to exercises designed to expose implicit social cognition (thoughts and feelings outside of conscious awareness and control). It also allows anyone to test their own biases by taking part in surveys related to race, gender, ethnicity, obesity, age, religion, disability, and sexual orientation. When biases are known, they can be counteracted.

Part 5: Envisioning Desirable Futures



https://www.youtube.com/watch?v=ScWYg1FuwZE

Award

2022 PROSE Award Winner, Engineering & Technology

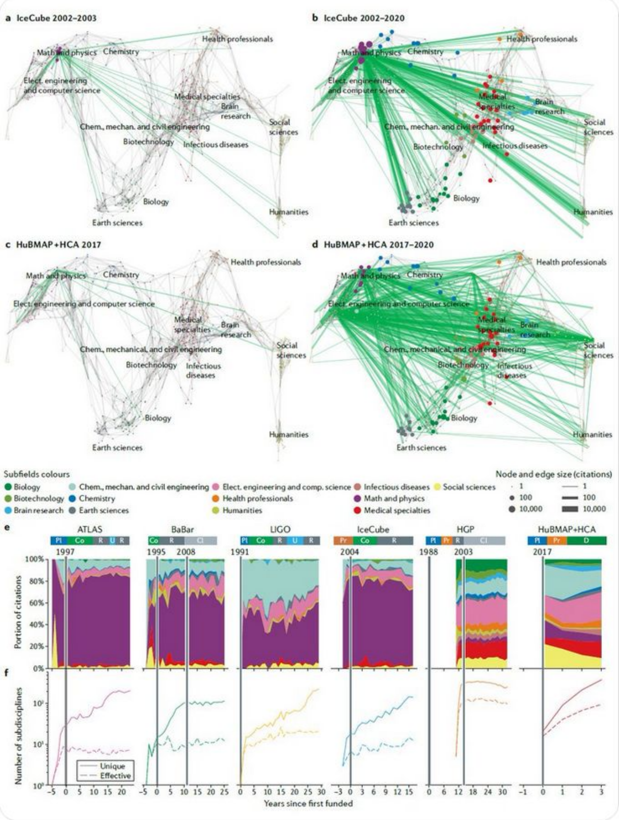
Endorsement

"The future is not waiting to reveal itself. It's all around us, in the shifting and changing consequences of every one of the quintillion interactions going on every second, everywhere. We make the future, unknowing of the consequences. If we were able to model and predict the result of all those interactions, we could reshape them and generate a future we want. This magnificent *Atlas* is a first step toward being able to do that."

James Burke, author of Connections

Katy Borner
@katycns

Visualizing big science projects, with Filipi N. Silva and Staša Milojević, is out in @NatRevPhys, see rdcu.be/cyEG5. Explore interactive vis at bigscience.github.io then use code to map your very own projects. @IUNetSci @IULuddy @cnscenter @ieeevis @issi_pres



Check for updates

Visualizing big science projects

Katy Börner, Filipi Nascimento Silva and Staša Milojević

Abstract | The number, size and complexity of 'big science' projects are growing — as are the size, complexity and value of the data sets and software services they produce. In this context, big data gives a new way to analyse, understand, manage and communicate the inner workings of collaborations that often involve thousands of experts, thousands of scholarly publications, hundreds of new instruments and petabytes of data. We compare the evolving geospatial and topical impact of big science projects in physics, astronomy and biomedical sciences. A total of 13,893 publications and 1,139 grants by 21,945 authors cited more than 333,722 times are analysed and visualized to help characterize the distinct phases of big science projects, document increasing internationalization and densification of collaboration networks, and reveal the increase in interdisciplinary impact over time. All data sets and visual analytics workflows are freely available on GitHub in support of future big science studies.

'Big science' today is international, interdisciplinary and inter-institutional. Big science projects are anchored around expensive, large and complex instruments, they can run for several decades and they involve thousands of experts. Big science projects make breakthroughs not only in basic research but also in innovation that impacts economy and solves challenging societal needs. As more science fields move towards the big science model of knowledge creation, the lessons learned from previous successful endeavours become essential. This is because big science projects are not just larger and more expensive than other projects but they require specific organizational and management structures. Different knowledge production processes also bring new research roles, changes in the division of labour and adjustment in formal and informal scholarly communication. One way to communicate these aspects of big science, on which this Perspective focuses, is to use various visualizations. Visualizations in this Perspective — and interactive online ones — show that big science projects go through phases with different input needs, expected outputs and impacts. As big science projects mature, their collaborations densify and internationalize; at the same time, scholarly impact increases in terms of citation counts and interdisciplinary reach.

Big science as a phenomenon can be traced all the way back to fifteenth-century cartography and astronomy[1–3] or to eighteenth-century natural history expeditions[2,4]. Nineteenth-century extensive archival projects (the Corpus Inscriptionum Latinarum and the Carte du Ciel) had many characteristics of present-day big science in terms of funding (state backing by Prussia and France), workforce and timescale (requiring more than a lifetime of effort), and were associated with the initial coinage of the term 'big science' (or, originally, Gorswissenschaft) by classical philologist and Prussian Academy of Sciences member Theodor Mommsen[5]. The better known and more immediate precursors of what became known as big science are the establishment of the University of California cyclotron by Ernest Lawrence in the 1930s for energy research[6] and the World War II Manhattan Project[7]. The term 'big science', however, was introduced in the 1960s by Alvin M. Weinberg[8,9] and Derek J. De Solla Price[1] to describe post-World War II developments in physics that built large and very expensive instruments (reactors and accelerators), accompanied by the growth in scientific team sizes working on nuclear-related research[7]. Making advances in nuclear and, later, particle physics became part of the competition among superpowers, with the expectation that breakthroughs would lead to both scientific and technological superiority[10,11]. In addition, big science has been propelled into the general public's awareness by the founding of the National Aeronautics and Space Administration (NASA) and its active and publicly visible space programme[2]. Although most of the early focus regarding big science was on physics, as early as 1965, Weinberg[12] proposed that biomedical science and biomedical technology were ready to enter the 'big biology' era. This entry was made only in the 1990s with the Human Genome Project (HGP), the first big science project in biology[13]. The expansion of the big science mode of knowledge production to other areas of science, such as big biology, brought with it new organizational and collaborative forms, such as 'networked' science enabled by information and communication technologies[14] and some debates as to whether such coordinated efforts can be called big science[15,16].

Big science accentuated the central role instruments play in the development of science as "engines of discovery"[17]. Historically, instruments such as the telescope, the microscope and the air pump opened new vistas and led to scientific revolution, fundamentally changing the nature of scholarship[18–21]. The quest for increased sensitivity and accuracy of instruments led to their constant evolution, making these ever more expensive tools[19,22] obsolete fairly quickly[19]. This process has been described[23] as 'tinkering', in which 'lineages of technology' are adapted and combined, leading to networks, or 'genealogies' of technologies. However, the power of instruments, such as a scanning tunnelling microscope, can be realized only when they engage a community of researchers in what has been called 'an instrumental community,' eventually leading to the formation of new scientific fields, such as nanotechnology[24]. Furthermore, the relationship between science and technology is complex and interdependent, with science also contributing to technology development[25–27].

Early scientists, such as Galileo Galilei and Isaac Newton, engaged in instrument building as well as theoretical and experimental work[28,29]. While not without precedent, instrument building

The Future of Learning & Work Workshop

Open Digital Future. Perspectives on data at the intersection of education and job markets.
Toward a new role of visual and learning analytics.

https://cns-iu.github.io/workshops/2022-03-14-futurium

Indiana University Bloomington will host the

International Society of Scientometrics & Informetrics Conference *(ISSI)*

July 2-5, 2023

https://cns-iu.github.io/workshops/2023-07-02_issi/

24 Hour Science Map Event

https://24hoursciencemap.info

Dec 11, noon - Dec 12, noon ET, 2021

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.

Börner, Katy (2015) *Atlas of Knowledge: Anyone Can Map*. The MIT Press.

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

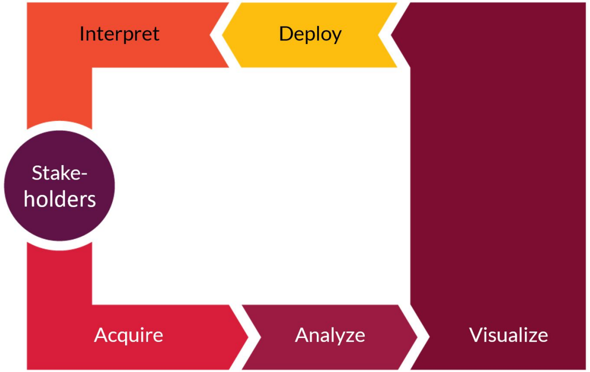
5 **Graphic Symbols**
- geometric symbols
  - point
  - line
  - area
  - surface
  - volume
- linguistic symbols
  - text
  - numerals
  - punctuation marks
- pictorial symbols
  - images
  - icons
  - statistical glyphs

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

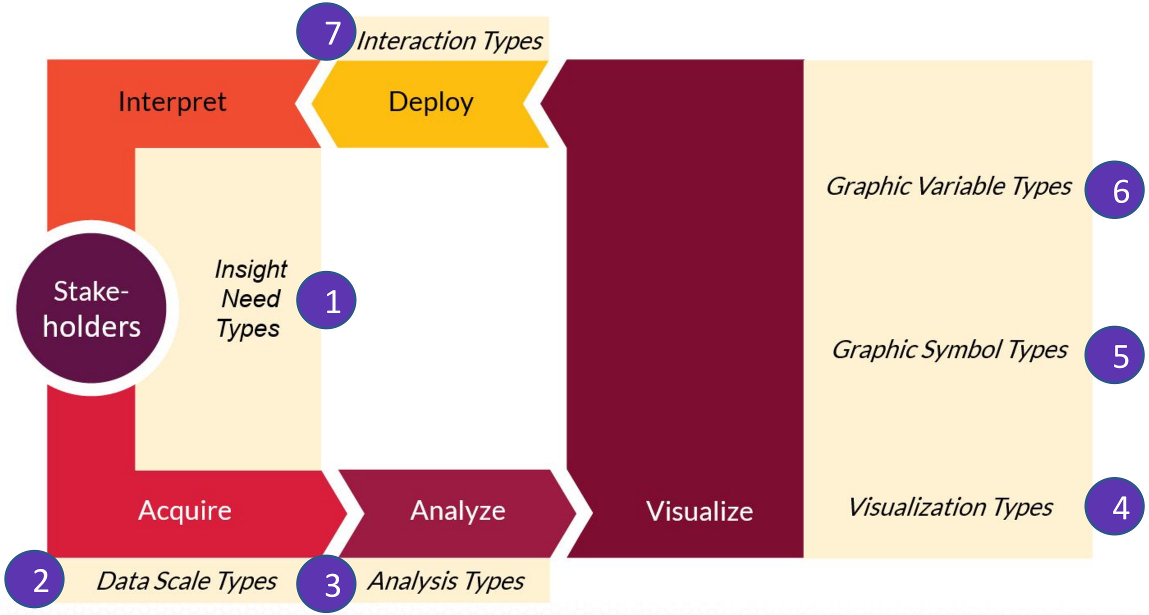
Defines 5 steps required to render data into insights.

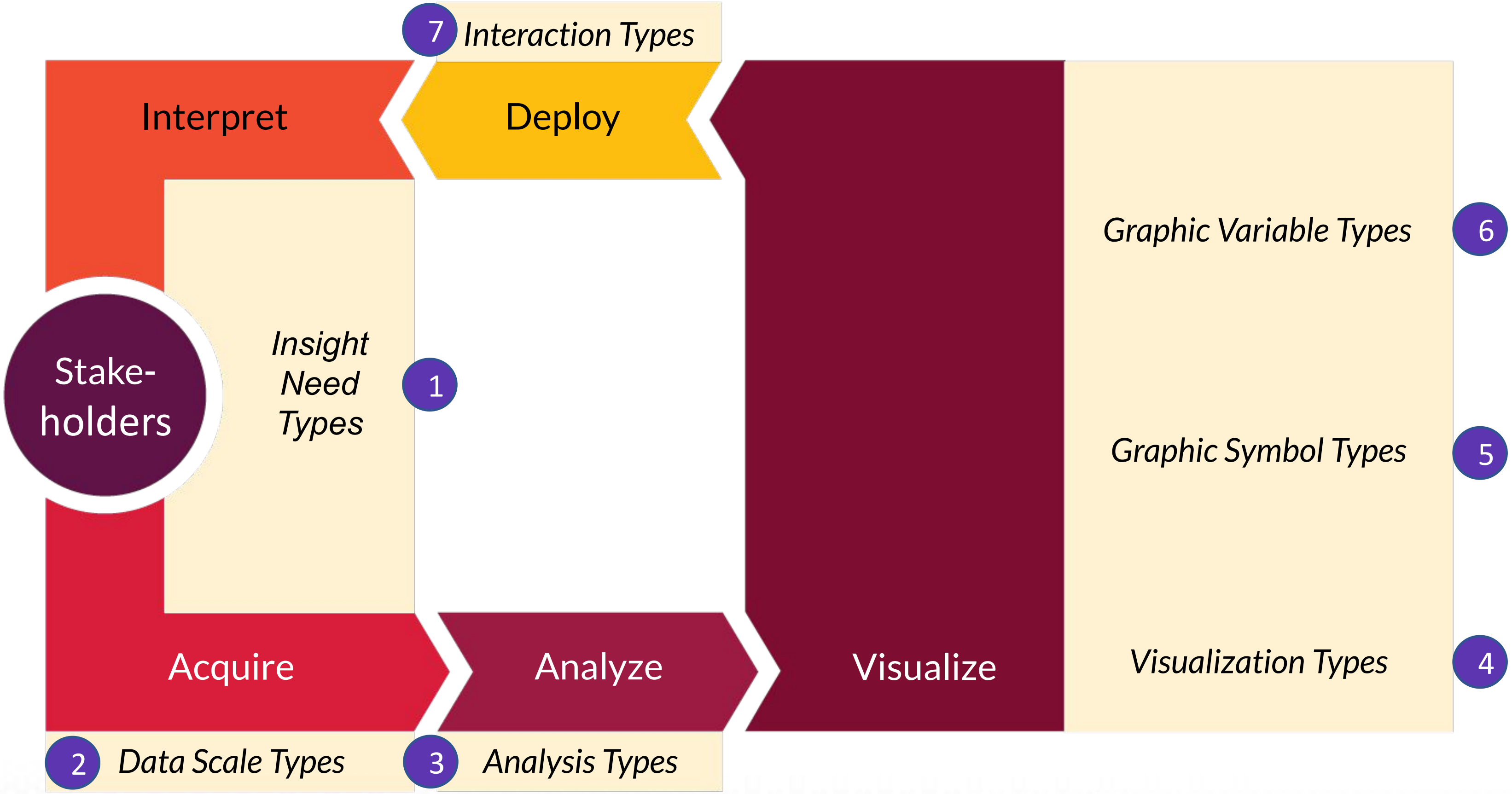


Data Visualization Literacy Framework (DVL-FW)

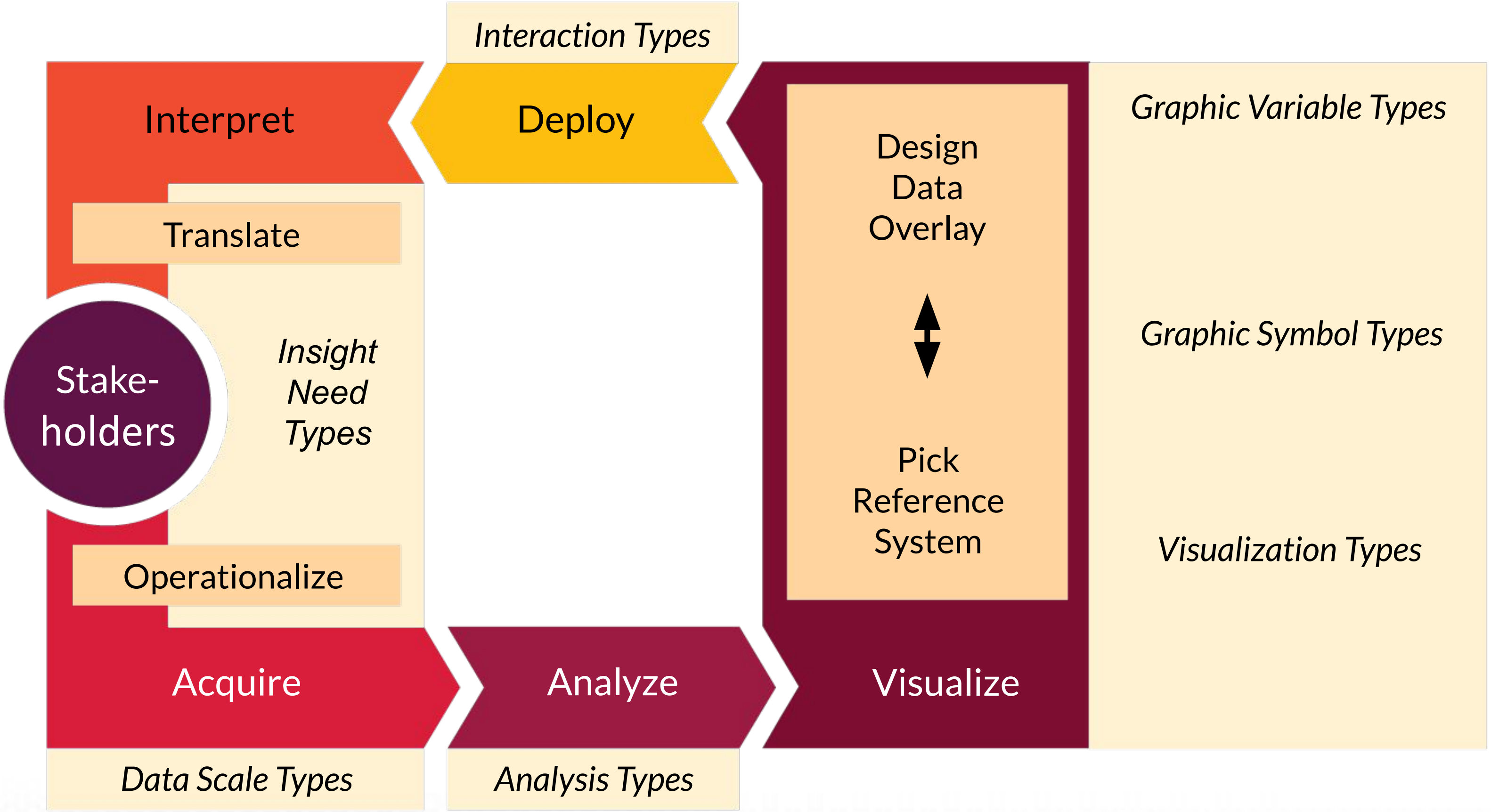
Consists of two parts that are interlinked:

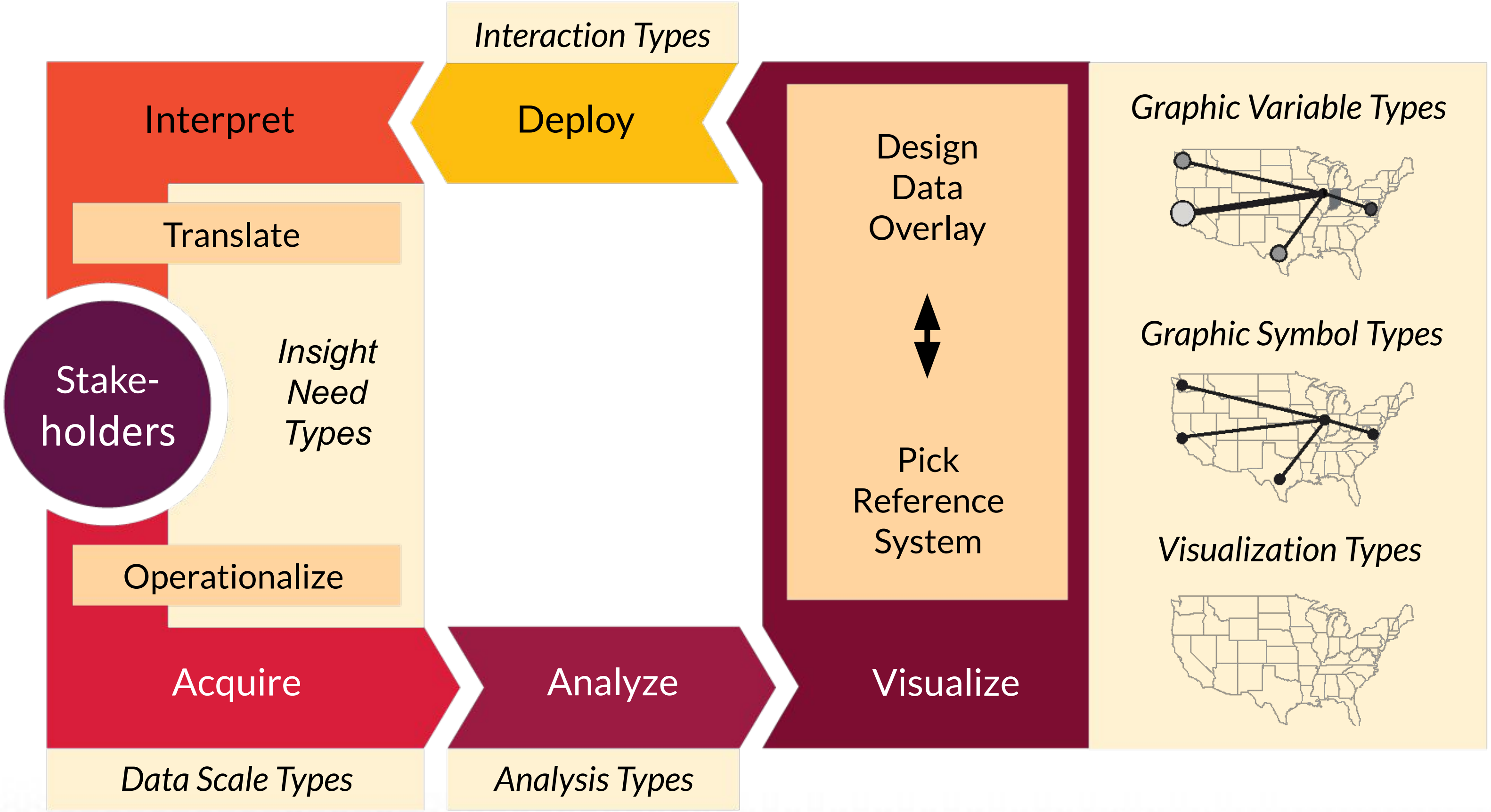
DVL Typology +
DVL Workflow
Process





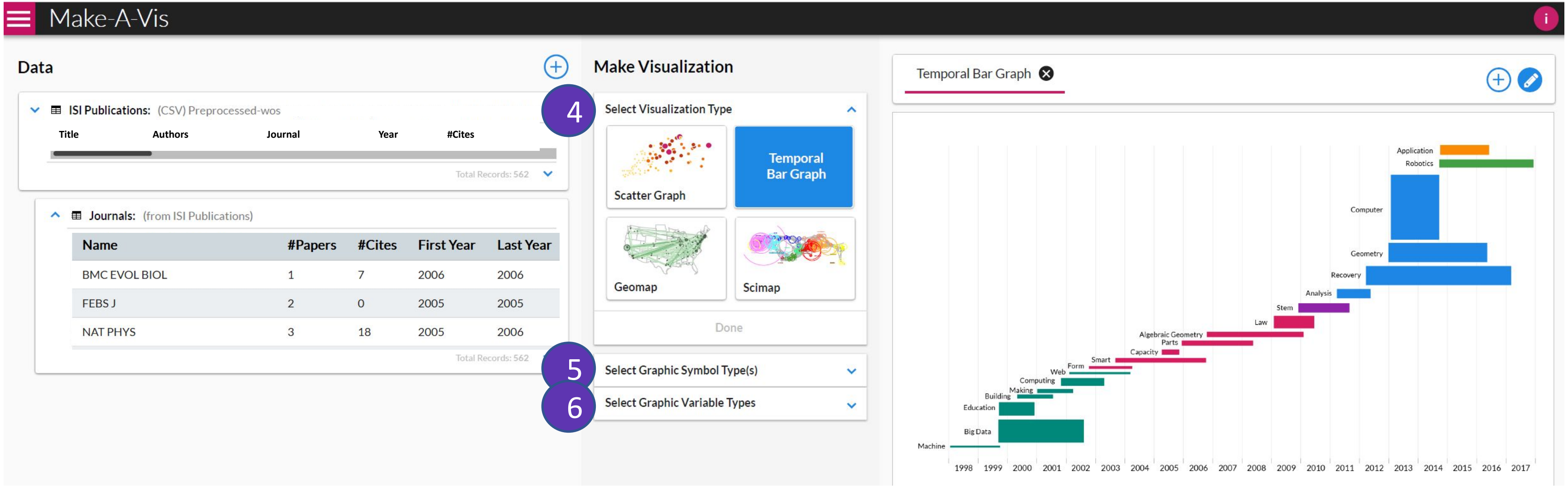
CNS Cyberinfrastructure for Network Science Center


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


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

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

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
• comparisons	• ratio	• topical	• map	area	form	• details-on-demand
• trends (process and time)		• relational	• tree	surface	color	• history
• geospatial			• network	volume	optics	• extract
• compositions (also of text)				• linguistic symbols	motion	• link and brush
• correlations/ relationships				text		• projection
				numerals		• distortion
				punctuation marks		
				• pictorial symbols		
				images		
				icons		
				statistical glyphs		

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

4

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

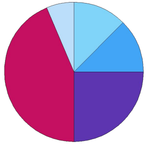
Graphic Variables
- spatial
  - position
- retinal
  - form
  - color
  - optics
  - motion

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

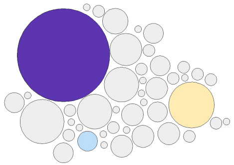
Börner, Katy. 2015. *Atlas of Knowledge: Anyone Can Map*. Cambridge, MA: The MIT Press. 30-31.

Visualization Types

Chart

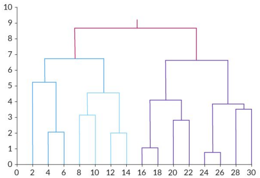


Pie Chart



Bubble Chart

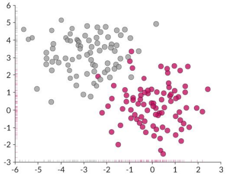
Tree



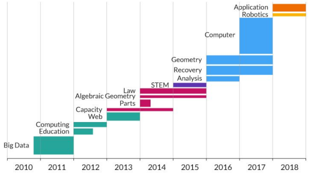
Dendrogram

Tree Map

Graph

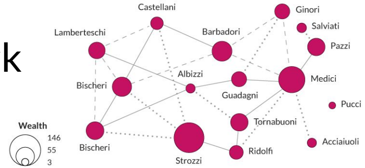


Scatter Graph

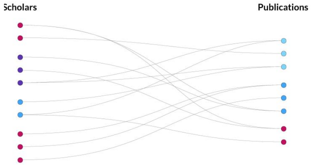


Temporal Bar Graph

Network

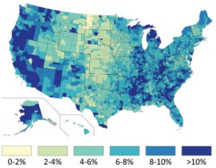


Force-Directed Network Layout

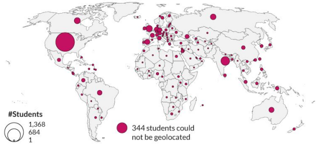


Bimodal Network Layout

Map



Choropleth Map



Proportional Symbol Map

Visualize: Reference Systems

4

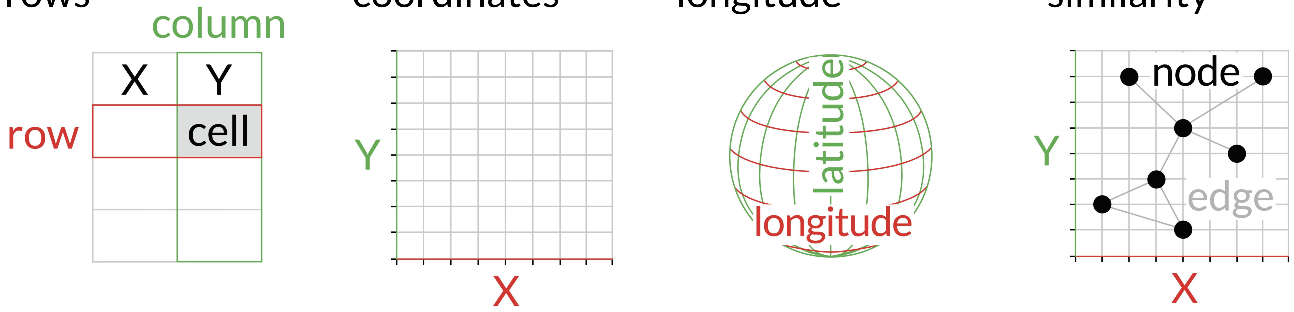
Visualization Types
- table
- chart
- graph
- map
- network layout

Table
columns by rows

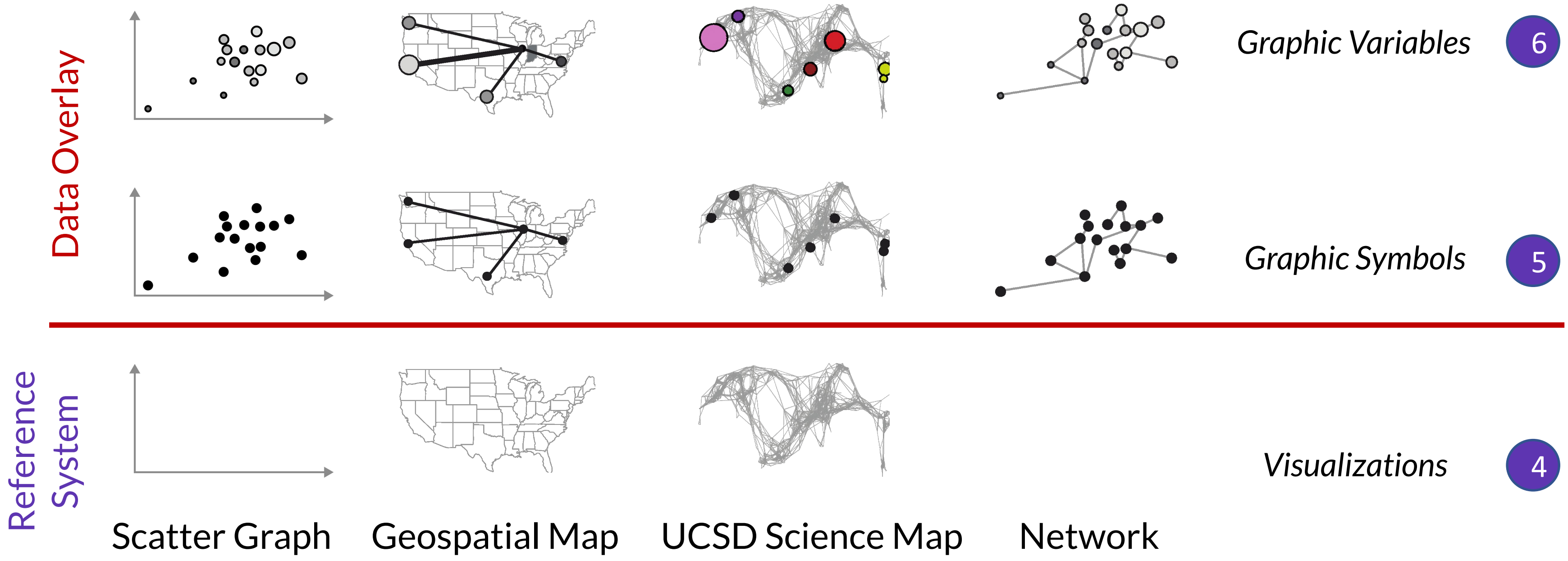
Graph
x-y coordinates

Map
latitude/ longitude

Network
local similarity



Visualize: Reference Systems, Graphic Symbols and Variables



Typology of the Data Visualization Literacy Framework

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

5

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

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

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

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

Typology of the Data Visualization Literacy Framework

6

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. 34-35.

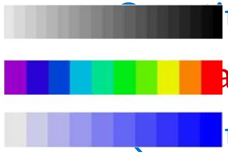
Graphic Variable Types

Position: x, y; possibly z — Quantitativ

Form:

- Size — Quantitativ
- Shape — Qualitative
- Rotation (Orientation) — Quar

Color:

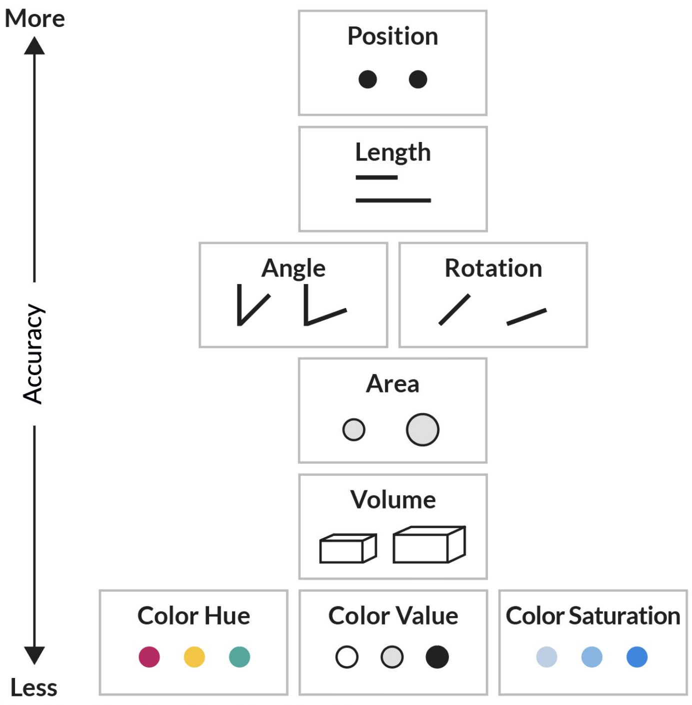


- Value (Lightness) — tativ
- Hue (Tint) — ative
- Saturation (Intensity) — tativ

Optics: Blur, Transparency, Shading, Stereoscopic Depth

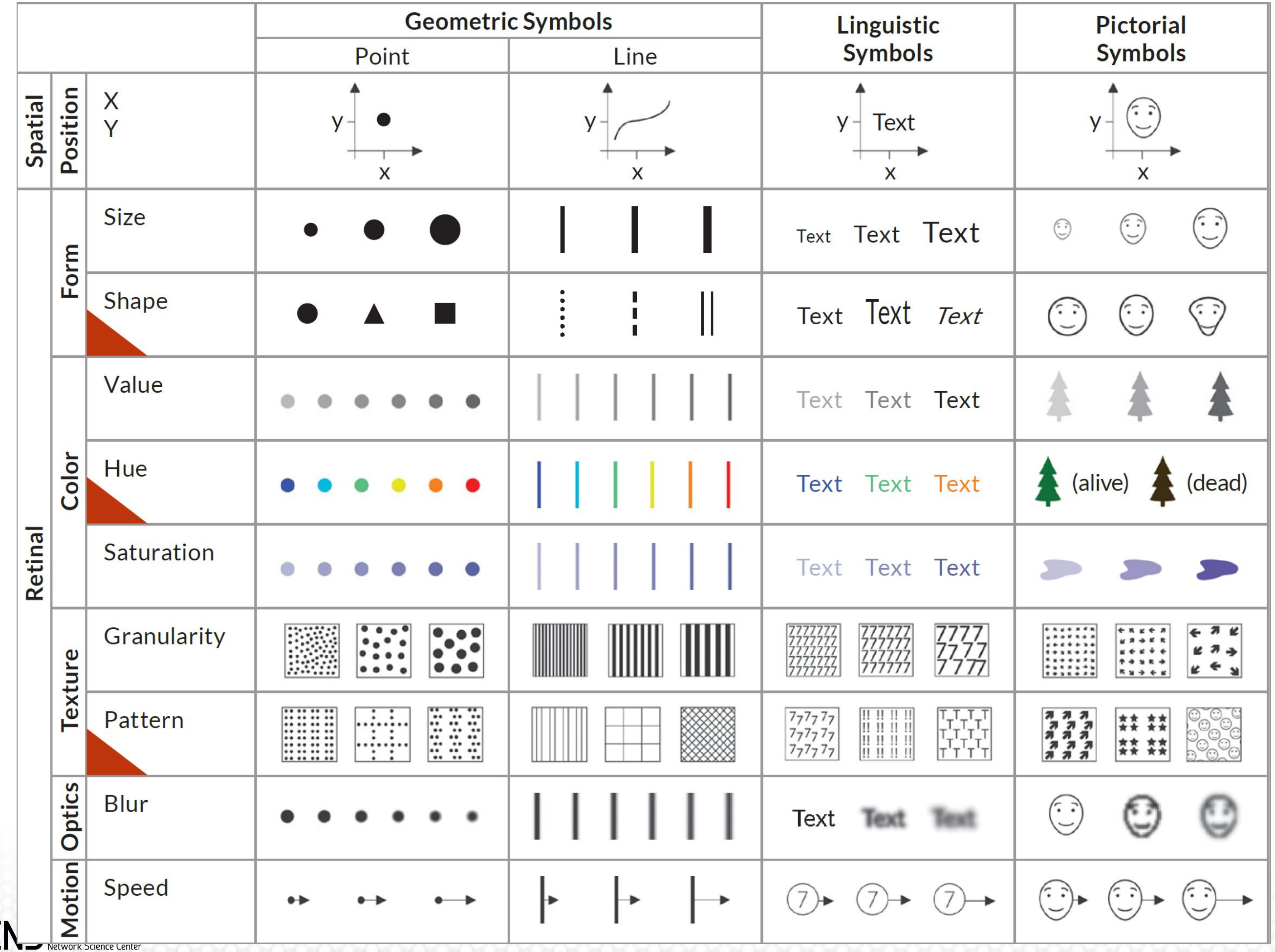
Texture: Spacing, Granularity, Pattern, Orientation, Gradient

Motion: Speed, Velocity, Rhythm



Graphic Symbol Types

Graphic Variable Types



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

Qualitative

Also called:

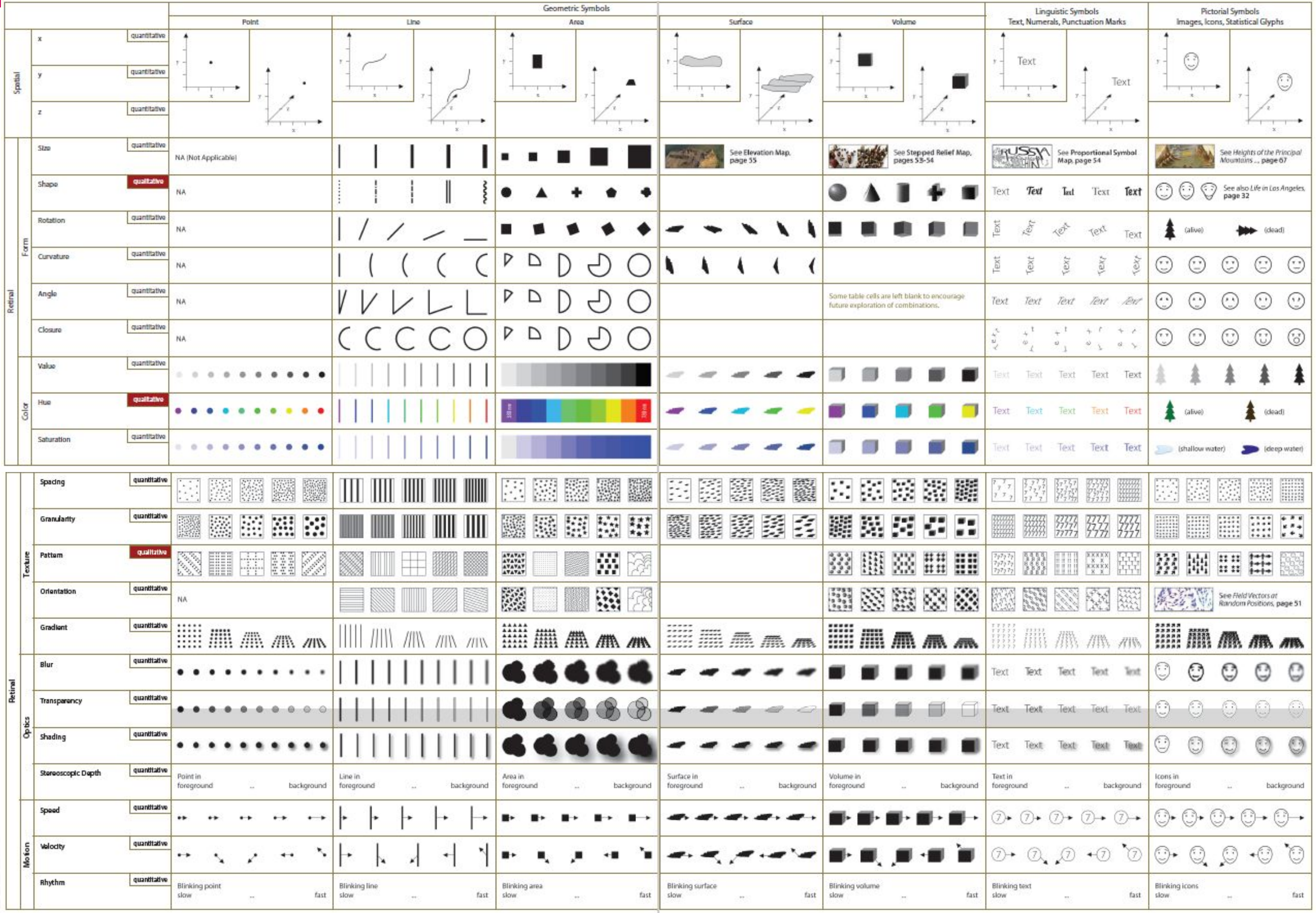
Categorical Attributes
Identity Channels

Quantitative

Also called:

Ordered Attributes
Magnitude Channels

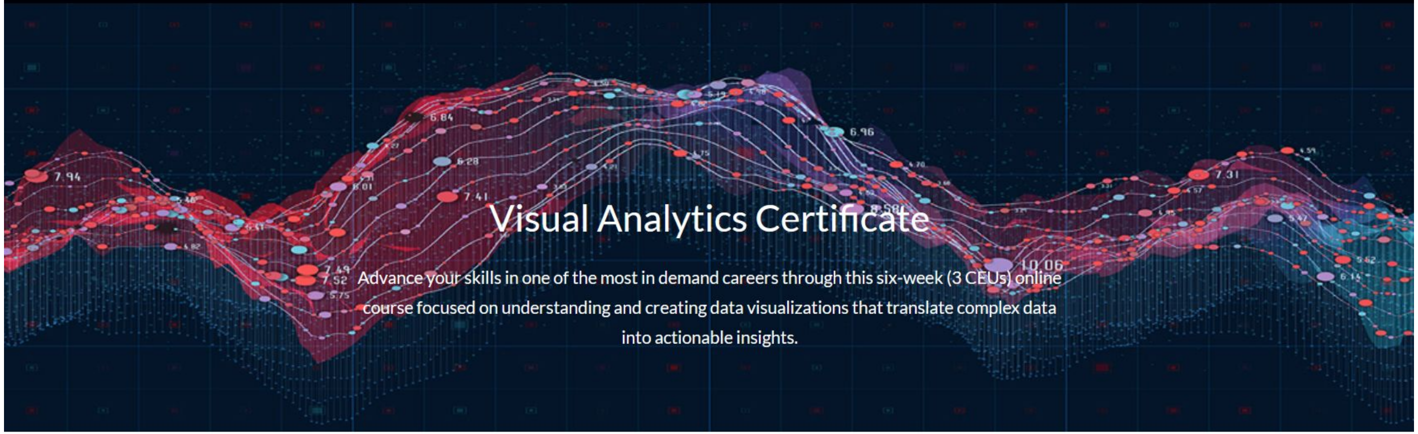
Graphic Variable Types Versus Graphic Symbol Types



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

CNS Cyberinfrastructure for Network Science Center

INDIANA UNIVERSITY LUDDY SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING



FLYER | REGISTER FOR JAN 10-FEB 20, 2022 | FAQS

Learn from Experts

Connect with industry professionals and leading researchers.

Evolve Yourself

Gain forever knowledge and skill-up in powerful data visualization tools.

Make a Difference

Embrace data-driven decision-making in your personal and professional life.

https://visanalytics.cns.iu.edu

US Employers which have sent students include
The Boeing Company, Eli Lilly, DOE, CDC, NSWC Crane.

Upcoming Events