Atlas of Forecasts & Mapping Science

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Data Visualization Lisboa

June 15, 2022
ATLAS OF FORECASTS & MAPPING SCIENCE

#31 MEETUP
28. APRIL
WILL BE WITH

KATY BÖRNER

Data Visualization Lisboa

Engineer, scholar, educator and author of Atlas of Forecasts: modeling and mapping desirable futures
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#vislis Data Visualization Lisboa
Places & Spaces: Mapping Science Exhibit

1st Decade (2005-2014)
Maps

2nd Decade (2015-2024)
Macroscopes

http://scimaps.org
Map of Scientific Collaborations from 2005-2009

VII.6 Stream of Scientific Collaborations Between World Cities - Olivier H. Beauchesne - 2012
A Topic Map of NIH Grants 2007

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

I.10 The Structure of Science - Kevin W. Boyack and Richard Klavans - 2005
Check out our **Zoom Maps** online!

Visit [scimaps.org](http://scimaps.org) and check out all our maps in stunning detail!
Iteration XI (2015)  
Macrosopes for Interacting with Science

Iteration XII (2016)  
Macrosopes for Making Sense of Science

Iteration XIII (2017)  
Macrosopes for Playing with Scale

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

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

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

http://idemo.cns.iu.edu/macroscope-kiosk
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
This is the Roanoke (Raleigh) megaregion.
VIRUS EXPLORER

<table>
<thead>
<tr>
<th>Envelope</th>
<th>Host(s)</th>
<th>Genome Type</th>
<th>Transmission</th>
<th>Vaccine</th>
</tr>
</thead>
</table>

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
RELATIVE SIZES

Rabies  Influenza  HIV  Coronavirus  Ebola

TMV  Adenovirus  T7 virus  Papillomavirus  Zika

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!
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

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

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

Atlas of Science
Visualizing What We Know
Katy Börner
2010

Atlas of Knowledge
Anyone Can Map
Katy Börner
2015

Atlas of Forecasts
Modeling and Mapping Desirable Futures
Katy Börner
2021

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.

<table>
<thead>
<tr>
<th>Level</th>
<th>Concern</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Society</td>
<td>GDP, Supply/Demand, Policy</td>
<td>Macroeconomic</td>
</tr>
<tr>
<td></td>
<td>Economic Cycles</td>
<td>System Dynamics</td>
</tr>
<tr>
<td></td>
<td>Intra-Firm Relations, Competition</td>
<td>Network Models</td>
</tr>
<tr>
<td>Organizations</td>
<td>Profit Maximization</td>
<td>Microeconomic</td>
</tr>
<tr>
<td></td>
<td>Competition</td>
<td>Game Theory</td>
</tr>
<tr>
<td></td>
<td>Investment</td>
<td>DCF, Options</td>
</tr>
<tr>
<td>Processes</td>
<td>Patient, Material Flow</td>
<td>Discrete-Event Models</td>
</tr>
<tr>
<td></td>
<td>Process Efficiency</td>
<td>Learning Models</td>
</tr>
<tr>
<td></td>
<td>Workflow</td>
<td>Network Models</td>
</tr>
<tr>
<td>People</td>
<td>Patient Behavior</td>
<td>Agent-Based Models</td>
</tr>
<tr>
<td></td>
<td>Risk Aversion</td>
<td>Utility Models</td>
</tr>
<tr>
<td></td>
<td>Discourse Progression</td>
<td>Markov, Bayes Models</td>
</tr>
</tbody>
</table>
### Modeling Goals

Models aim to capture key phenomena at the levels that are most relevant for the understanding, communication, and management of systems. This special description 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 activity) and complexity. Models that are static reference systems and no feedback cycles are introduced first, followed by phenomena that aim to predict evolving networks and activity patterns unfolding within, including feedback or causal loops.

#### Phenomena of Interest

<table>
<thead>
<tr>
<th>Oscillation</th>
<th>Any processes that repeat itself in a cycle, such as a pendulum swinging back and forth or a biological cycle like the circadian rhythm.</th>
<th>Target System Models</th>
<th>[\text{Target System Models}]</th>
<th>[\text{Target System Models}]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synchronization</td>
<td>The alignment of periodic oscillations, such as the synchronized flashing of fireflies or the coordinated beating of heart cells.</td>
<td>[\text{Synchronization}]</td>
<td>[\text{Synchronization}]</td>
<td></td>
</tr>
<tr>
<td>Feedback</td>
<td>Processes in which the output of a system feeds back to affect the system itself, such as homeostatic mechanisms.</td>
<td>[\text{Model Classes}]</td>
<td>[\text{Model Classes}]</td>
<td></td>
</tr>
<tr>
<td>Phase Transition</td>
<td>The transformation of a thermodynamic system from one state of matter to another (e.g., from solid to gas to liquid) through a phase transition point.</td>
<td>[\text{Synchronization}]</td>
<td>[\text{Synchronization}]</td>
<td></td>
</tr>
</tbody>
</table>

#### Phenomena

- Oscillation
- Synchronization
- Feedback
- Phase Transition

#### Model Classes

- Descriptive Models
- Inductive Models
- Predictive Models
- Prescriptive Models
- Experiential Models
- Predictive Models
- Prescriptive Models
- Experiential Models

#### Habitat

- Forests
- Cells
- Ants
- Bees
- Machine Learning

#### Conclusion

The phenomenon of interest is the state of a system at a particular time. Phenomena are often used to explain why a system behaves in a certain way. They are also used to predict how a system will behave in the future. Phenomena are often associated with specific models, which are used to describe and analyze the behavior of a system.
Modeling Framework

When developing a model of a real-world system, many critical decisions must be made regarding model components, their behavior, and the system dynamics over time. Any model design must start with a specification of stakeholders and their interest needs, followed by an analysis of the system, and then the success criteria that define when a model is fit for purpose. Model validation and verification (V&V) details must be detailed. Diverse approaches have been proposed to provide templates and standards for systematic model development and documentation—be it the role of the exploratory system. This special review paper on modeling frameworks and then examines and updates the data validation framework for modeling frameworks. Part 2 introduces the emerging challenges discussed in the previous issue, as well as the expert-based, descriptive, and predictive models discussed throughout the Atlas of Permaculture.

We cannot step away from history, but we can move forward. Damon Southall

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Graphic Symbol Type

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Modeling Framework
Model Visualization

Model assumptions, designs, and results should together be communicated in a format that is appropriate for a wide range of model stakeholders and experts. Visualizations can help explain the model, and to collaboratively and creatively share and evaluate the model architecture, design, and results. Visualizations can help bridge the communication gap between experts of different domains, and can communicate them to experts of different audiences. Visualizations can be static, dynamic, or interactive.

Types of Visualizations

The design of effective visualizations requires identifying many needs and potential solutions. Several important design criteria for visualizations include:

- **Relevance**: The visualization must be relevant to the problem being solved.
- **Clarity**: The visualization must be clear and easy to understand.
- **Accuracy**: The visualization must accurately represent the data.
- **Interactivity**: The visualization must allow users to interact with the data.
- **Usability**: The visualization must be user-friendly.
- **Aesthetic appeal**: The visualization must be visually appealing.

In addition, the visualization must be designed to meet the needs of the audience.

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Model Validation

Model validation aims to capture the behavior of real-world systems in a simplified yet mature manner that can be validated across scales. At the meso 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 models, oscillations, or data patterns must reflect the phenomena observed in the real world. Models must be evaluated on the accuracy and generality of their predictions. Evaluation needs should be used to verify the accuracy, specificity, or generality of the model, or to make model results easier to understand and see by decision-makers.

The more a quantitative social indicator is used for social decision-making, the more subject it will be to corruption. Potential impacts of the up to will be to exaggerate and cover the social processes it is intended to monitor.

Donald C. Feldman
Cellular Automata (1940s)

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

**Key Insights**

CAs are used extensively for modeling phenomena with cellular dynamics, including reaction-diffusion systems, physical properties of materials, reaction-diffusion chains in processes, growth and development of biological objects, sociological and economic phenomena, and natural and social systems. CA rules can be simple, like a rule that blocks or deleting the block, and more complex, like a rule that blocks or deleting the block. A rule's behavior can be predictable or chaotic. The behavior of CAs can be studied using computer simulations and mathematical analysis. CAs are used in various fields, including physics, biology, and computer science.

**术语**

**Cellular Automata** refers to a discrete system using a deterministic rule or rules, and a discrete space. The system is represented using finite-state machines. The set of all finite-state machines is arranged in a regular grid or in a regular sequence (e.g., a von Neumann neighborhood). A cellular automaton is a set of cells that evolve over time according to a local rule. The state of each cell is updated based on the states of its neighbors. The state of a cell can be updated synchronously or asynchronously.

**Basic Models**

The simplest type of CA is a one-dimensional cellular automaton. The state of a cell can be updated synchronously or asynchronously. The state of a cell can be updated based on its own state and the states of its neighbors. The state of a cell can be updated based on the states of its neighbors and the states of the cells in the next row. The state of a cell can be updated based on the states of the cells in the previous row.

**目标系统模型**

The target system models include predator-prey models, predator-prey models with age structure, predator-prey models with age structure and immune response, and predator-prey models with age structure and immune response. The target system models include predator-prey models, predator-prey models with age structure, predator-prey models with age structure and immune response, and predator-prey models with age structure and immune response.
Model Questions Overview

Given the constraints discussed in the previous two 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, five EISTP domains (education, science, technology, and policy), and three scales (indicators, metrics, and exemplars) that are then given for all 12 fields-wide combinations. This Atlas expands on Atlas of Knowledge—which introduced temporal, geographic, topical, and network models to answer when, where, what, and why with 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 of the evolution of a system help us understand the future states of that system?

Temporal Models—"When"

Historical Progression

Network Models—"With Whom"

Geospatial Models—"Where"

Individuals with the same interests are more likely to interest students and teachers who either see within common interests, more likely to be connected. In fact, these relationships are not limited to those within a single community, interest-related interest, or in this case, between two individuals. The result is likely to be more connected, with each other's interests than within a single community, interest-related interest. The result is likely to be more connected, with each other's interests than within a single community, interest-related interest. The result is likely to be more connected, with each other's interests than within a single community, interest-related interest. The result is likely to be more connected, with each other's interests than within a single community, interest-related interest. The result is likely to be more connected, with each other's interests than within a single community, interest-related interest.
**Sciences**

Science refers to the systematic study of the structure and behavior of the world through observation and experimentation. At its heart, science is a method for investigating and understanding the natural world. It is characterized by the pursuit of knowledge through research and inquiry, leading to the formulation of theories and laws that describe natural phenomena.

**Education**

Education refers to the process of acquiring knowledge, skills, and values through formal classroom instruction or informal learning in various settings. Education is often facilitated by teachers, parents, or other trained individuals, and it includes the acquisition of skills such as reading, writing, and critical thinking.

**Technology**

Technology refers to the application of scientific knowledge for practical purposes, such as creating new products, improving existing ones, or solving problems. It encompasses a wide range of fields, from computer science and engineering to medicine and agriculture.

**Policy**

Policy refers to the process of determining policies in education, health, or other domains. It involves making decisions and implementing strategies to achieve specific goals. Policies can be developed at various levels, from local to national, and they often involve collaboration between different stakeholders.
Scales Overview

The model discussed in the alt text trilogy offers the micro (individual), meso (team/interinstitutional/regional), and macro (population/global scales). Frequently, multiple scales need to be considered to arrive at workable solutions that have the intended scale effect. For example, in social, cognitive, and behavioral factors at the micro scale impact effects on the macro scale, which impact global scale policies. This relationship between the three scales is known as the "nested" or "chessboard" effect.

In the alt text trilogy, the micro scale refers to the scale of our individual—activity, society, ethics, and interconnected space with specific environments. Network modeling (page 48) applies concepts and theories from network science to understand the complex interactions within a biological system, including the emergent properties that arise from the interplay of microscale factors with other factors. Multi-scale modeling (page 48) allows us to model macroscopic phenomena, including the aggregation of microscale behaviors into larger-scale patterns. Interactions between the micro and macro scales, therefore, are critical in understanding how complex systems behave and respond to changes.

Meso Scale

In the meso scale, the model scales to the level of a group or community, including organization structures, social and institutional dynamics, and landscape differences. Model examples (page 48) include earthquake modeling to predict seismic risk and for disaster planning. In the meso scale, models can be used to study the effects of large-scale events on local communities, such as the impacts of climate change on agricultural productivity or the effects of urbanization on wildlife habitats.

Macro Scale

In the macro scale, the model scales to the global scale of phenomena or systems. Model examples (page 48) include modeling climate change, population dynamics, and global economic systems. These models can help us understand the interactions between different regions and how changes in one part of the world can affect other parts. For example, models can be used to predict the spread of diseases across borders or to assess the impact of climate change on global food security.

Challenge and Opportunities

The globalized education, science, and governance landscape, a result of the challenges that humankind is experiencing (e.g., climate change, environmental degradation, and emerging global challenges), requires an international and multidisciplinary collaborative approach. Addressing such challenges requires a concerted effort across disciplines and stakeholders. In this context, the implications of macro-scale models in providing insights into the complex interactions between the micro, meso, and macro scales become increasingly important.
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 warning student engagement and performance. More advanced models are under development to support personalized education. Given the success of massive 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

Instrumentation 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 humains can learn and work together.

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

What are the best learning formats for science knowledge and skills? Where is one most successful vs. active learning? How can active learning in teaching be encouraged?

The study of science, technology, engineering, and mathematics (STEM) education, including the much-


Visual Analytics of MOOCs

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

With introductions of MOOCs in 2008 and software of massive online courses, it becomes possible to scope, analyze, and assess teaching and learning trends under diverse learning and instructional options. Data from MOOCs has been used to explore learner engagements, performance, and trends in online courses.

The visualization below shows learning trajectories by LSI learning styles taking the MIT-HPC course "Architecture of Computer Systems" delivered in fall 2016. More than 15 million students are involved in teaching various online assignments, submitting work, etc., over a period and evaluated in this figure. Graph B shows the six-week course structure in pre- and post-assessment. Graph A shows transition's timeline of different learning metrics, with understandings (red), self-confidence (blue), and learning strategies compared for the pre and post-semester for online courses. Graph C presents learning analytics using data plots and visualizations in relation to learning style (top line) and gender (bottom line). Green circle indicates male students transitioning, while blue circle indicates female students transitioning, while teaching and learning strategies match with the patterns of learning metrics.
**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-technology cooperation is beneficial to facilitate technological innovation as well as innovation transfer (see Shimp/Clark’s twin-waves success discussed on page 79).

**Examples**

Data models and visualizations can be employed to analyze and communicate the impact of science funding on the science of IT sectors. Models can be applied to compute how innovative different U.S. regions or counties are. Business dynamics models achieve our conscious ambition from the customer to end to another part of the supply chain can lead to innovating inefficiencies, including excessive inventory investments, 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 80% 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.

**Regional and Global Innovation Index**

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

Many development practitioners and other regional leaders need to answer such questions in order to target additional resources to innovation, achieve higher capacity for innovation, and achieve knowledge exchange, technology diffusion, and other similar outcomes.

Dense innovation indices can help develop the innovative capacity and regional leaders make data-driven decisions to drive their daily work. The Global Innovation Index (GII) is published annually by Cornell University, INSEAD, the World Intellectual Property Organization, and other partner organizations. Because of the world’s current economic and climate pressures for action, Russia is in innovation.

The Innovation Index 3.0 Plugin helps companies against innovating performance in the area of science, research, and development. The areas tested, in general terms, are on the corporate front and depend on the nature of the region.

The Innovation Index 3.0 contains an innovative analysis routine that incorporates consensus science on measuring innovation, including how account innovation knowledge, innovation diffusion, and driving direct investment, as well as social capital. It has been designed to help regional leaders work at assessing economic future-proof strategies. Innovation Index 3.0 visualization can be shared with all stakeholders to identify a region’s capacities, shortages, and potentials, and guide complex decisions making in support of collective action in a common plan.

Has developed countries in Europe, America, Asia, and other countries in the world, developed a richer and more diverse new economy, and which one is the largest in terms of science and technology?

The government should support the region of the country, which region is the largest in terms of science and technology, and which one is the largest in terms of science and technology.

**Knowledge Creation and Technology Diffusion by County**

How do changes in innovation impact business processes?

Jeff Pfeffer was a leader of systematic dynamics, which seeks to model the dynamics of innovation processes in complex social systems. In 1984, his Industrial Dynamics, he introduced the use of system dynamics to analyze industrial business cycles and the business effects. Business dynamics is a part of the industrial effect, which describes the cumulative large demand value that we see today along the supply chain from raw materials, manufacturing, and final products. "Productivity, a critical tool of competitive advantage, is more and more visible across the supply chain, which is driving the development of new products and processes, and possibly supply shortcuts (also called a productivity effect—see Control Charts, page 90).

For example, the dynamic analysis of system dynamics is critical in the supply chain. The figure above shows changes in order (also called an increase in total sales, which decreases an 18% change in overall sales in the firm), a 4% increase in factory productivity output. Also graphed (also called the impact on several countries, including the United States, and the world, which graph is published) a technological model would be used to analyze the target system, which model was used for one of the early systems, and the model results were used in the supply chain.

A detailed look in 1972, Fortune ranked all states using the ADM (ADMA) Model. A customer simulation language—which has been highly developed in analyzing and synthesizing successful innovation management in industries—evidently the Louis or Crown world model method, one of the first computer models with multiple feedback loops.

In Wave Dynamics (1977) and numerous papers, Fortune sought to model the world economy, population, and stopping the record that computer simulation models are the answer to simple questions—by exploring the structure and dynamics of real-world systems, identifying the root causes of problems, and determining the real effects of complex dynamic systems.

In Second Edition: System Modeling and Planning for a Complex World (2009), John D. Sterman, a model of Economics (econometric system dynamics models, together with tools for system dynamics modeling, and tools as consistency and self-learning—making it easier for many more to model effectively.)
Part 4: Science Maps in Action

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, 350 maps by 255 mapmakers have been displayed at 350 venues, in more than 28 countries, on 6 continents. Each unique venue adds its own voice. Ultimately, the exhibit is like the open-source engine in the story of data science—with experts around the globe contributing singular visualizations that ask new questions while offering solutions to meet local contexts and needs.

The Aveiro for Renato stars the 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 35 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.

The exhibition toured the International Conference for High Performance Computing, Networking, Storage, and Analysis, New Orleans, LA.

The exhibition toured to the Pitt Innovation Theatre, James P. Hines, Jr. Library, North Carolina, Jan. 2020, Raleigh, NC.

The exhibition toured to the University of Miami, Coral Gables, FL.

The exhibition toured to the University of Maryland, College Park, MD.

The exhibition toured to the University of Miami, Coral Gables, FL.

The exhibition toured to the University of Minnesota, St. Paul, MN.

The exhibition toured to the University of Minnesota, St. Paul, MN.
Reducing Human Bias

Humans tend to be subjective, often acting according to biased opinions rather than objective judgments. Cognitive biases are systematic deviations from normative rationality, as evidenced in fields like psychology and economic decision-making. While many such biases have been confirmed in independently reproducible research, scientists are always aware that their conclusions are subject to making objective, well-informed decisions, we need to understand and proactively mitigate existing biases. This article discusses the philosophical, behavioral, and ethical dimensions of human biases, including the role of gender, race, and personality, and how they can impact our ability to make fair and just decisions. The article concludes 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 first step in improving our understanding of the world around us.

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

To ErE Is Human

Though humans are the most intelligent and versatile species, no human is ever completely rational. Even in our most advanced societies, human errors and irrationalities are unavoidable. Despite our technological prowess, we are still subject to our cognitive limitations, such as our tendency to ignore complex information, our inability to process large amounts of data quickly, and our tendency to make decisions based on heuristics rather than deep analysis. As a result, we are often caught off guard by sudden events, such as economic crashes, natural disasters, or political upheavals. These events can cause emotional distress and lead to irrational behavior, such as panic buying or selling, or refusing to take necessary precautions. Yet, by understanding the root causes of our cognitive biases, we can work to mitigate their effects and make better decisions.

Gender Bias

The gender bias in perception has been a topic of concern for many years, with authors such as brainstorm, which argue that men and women have different ways of thinking and processing information. Research suggests that men are more likely to be analytical and logical, while women are more likely to be emotional and empathetic. However, the evidence is mixed, with some studies showing no significant gender differences in cognitive abilities.

Data Bias

Data is critical to our understanding of the world around us. However, the quality and quantity of data we collect can affect the accuracy of our conclusions. For example, if we sample data from a specific group of people, we may miss important insights from other groups. Additionally, if we use biased data, our conclusions may be flawed. For instance, if we only sample from one age group, we may miss important trends or insights from other age groups.

Species Bias

Species bias refers to the tendency to overestimate or underestimate the intelligence, capabilities, or potential of other species. This bias can manifest in various ways, such as attributing human-like qualities to animals or低估ing the abilities of other species. One example of species bias is the belief that dogs are more intelligent than other species, even though studies have shown that chimpanzees have similar cognitive abilities.

Exposing Biases

People tend to misuse their own biases and information to shape their own views. Despite the wealth of information available, biases can still lead to inaccurate conclusions. For example, people may be biased in their interpretation of data, such as preferring information that confirms their existing beliefs or ignoring information that contradicts them.

Part 5: Envisioning Desirable Futures

Modeling Opportunities

Reducing Human Bias

Managing Risks

Building Capacity

Achievable Policies

52

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Achievable Policies

52

53
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
Visualizing big science projects, with Filipi N. Silva and Staša Milojević, is out in @NatRevPhys, see rduc.be /cyEG5. Explore interactive vis at bigscience.github.io then use code to map your very own projects. @IUNetSci @IUluddy @cnscenter @ieeveis @issi_pres

Visualizing big science projects

Katy Börner, Filipe Nascimento Silva and Staša Milojević

Abstract | The number, size and complexity of big science projects are growing— as are the issues of privacy, complexity and value of the data sets and software services they produce. In this context, big data gives a new way to analyze, understand, manage and communicate the inner workings of big data projects that involve thousands of experts. Big data projects can be visualized 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 described as ‘unmaking’ in which big science projects are not just larger and more expensive than other projects, but also bring specific organizational and management structures. Different knowledge production processes are being transformed, new roles and a division of labour and adjustment in formal and informal scholarly communication. One way to communicate some aspects of big science on which this perspective focuses is to use 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—or to early sixteenth-century natural history expeditions. 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, Germanwissenschaft) by classic philosopher and Prussian Academy of Sciences member Theodor Mommsen. 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 and the world’s first large-scale neutron project. The term ‘big science’, however, was introduced in the 1960s by Alvin M. Weinberg and Derek J. De Solla Price 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. 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. 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. Although most of the early focus regarding big science was on space, as early as 1955, Weinberg proposed that biomedical science and biomedical technology were ready to enter the ‘big science’ era. This entry was made only in the 1990s with the Human Genome Project (HGP), the first big science project in biology. The expansion of the big science model 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. This new collaboration created opportunities for new scientific and technological knowledge and, as a result, new scientific and technological opportunities. However, the power of instruments, such as scanning tunnelling microscopy, can be realized only when they engage a community of researchers in what has been called an ‘inventorship community’ eventually leading to the formation of new scientific fields, such as nanotechnology. Furthermore, the relationship between science and technology is complex and interdependent, with science also contributing to technology development.

Early scientists, such as Galileo Galilei and Isaac Newton, engaged in instrument building as well as theoretical and experimental work. 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://24hourssciencemap.info

Dec 11, noon - Dec 12, noon ET, 2021
Data Visualization Literacy


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.

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

[Diagram showing the workflow process with stages: Acquire, Analyze, Visualize, Interpret, Deploy, Stakeholders]
Data Visualization Literacy Framework (DVL-FW)

Consists of two parts that are interlinked:

DVL Typology +
DVL Workflow
Process

1. Stakeholders
2. Data Scale Types
3. Analysis Types
4. Visualization Types
5. Graphic Symbol Types
6. Graphic Variable Types
7. Interaction 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

### Typology of the Data Visualization Literacy Framework

<table>
<thead>
<tr>
<th><strong>Insight Needs</strong></th>
<th><strong>Data Scales</strong></th>
<th><strong>Analyses</strong></th>
<th><strong>Visualizations</strong></th>
<th><strong>Graphic Symbols</strong></th>
<th><strong>Graphic Variables</strong></th>
<th><strong>Interactions</strong></th>
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<tbody>
<tr>
<td>• categorize/clustering</td>
<td>• nominal</td>
<td>• statistical</td>
<td>• table</td>
<td>• geometric symbols</td>
<td>• spatial</td>
<td>• zoom</td>
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<td>• order/rank/sort</td>
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<td>• chart</td>
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<td>• distributions (also outliers, gaps)</td>
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<td>• comparisons</td>
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<td>• topical</td>
<td>• map</td>
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<td>• details-on-demand</td>
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**CNS Center for Network Science**

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Typology of the Data Visualization Literacy Framework

Insight Needs
- categorize/clustering
- order/rank/sorting
- 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

Visualization Types

Chart
- Pie Chart
- Bubble Chart

Graph
- Scatter Graph
- Temporal Bar Graph

Map
- Choropleth Map
- Proportional Symbol Map

Tree
- Dendrogram
- Tree Map

Network
- Force-Directed Network Layout
- Bimodal Network Layout
Visualize: Reference Systems

**Visualization Types**
- table
- chart
- graph
- map
- network layout
Visualize: Reference Systems, Graphic Symbols and Variables

Data Overlay

Reference System

Scatter Graph  Geospatial Map  UCSD Science Map  Network

Graphic Symbols

Graphic Variables

Visualizations
## Typology of the Data Visualization Literacy Framework

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  - icons
  - statistical glyphs

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  - form
  - color
  - optics
  - motion

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

Graphic Variable Types

Position: \( x, y; \) possibly \( z \)

Form:

- Size \( \text{Quantitative} \)
- Shape \( \text{Qualitative} \)
- Rotation (Orientation) \( \text{Quantitative} \)

Color:

- Value (Lightness) \( \text{Quantitative} \)
- Hue (Tint) \( \text{Qualitative} \)
- Saturation (Intensity) \( \text{Quantitative} \)

Optics: Blur, Transparency, Shading, Stereoscopic Depth

Texture: Spacing, Granularity, Pattern, Orientation, Gradient

Motion: Speed, Velocity, Rhythm
<table>
<thead>
<tr>
<th>Graphic Symbol Types</th>
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<tbody>
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<td><strong>Graphic Variable Types</strong></td>
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<td><strong>Qualitative</strong></td>
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<tr>
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<td>Categorical Attributes</td>
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</tbody>
</table>

### Qualitative

**Form**
- Also called: Categorical Attributes
- Identity Channels

**Shape**
- Also called: Categorical Attributes
- Identity Channels

**Value**
- Also called: Categorical Attributes
- Identity Channels

**Color**
- Also called: Categorical Attributes
- Identity Channels

**Saturation**
- Also called: Categorical Attributes
- Identity Channels

**Texture**
- Also called: Categorical Attributes
- Identity Channels

**Pattern**
- Also called: Categorical Attributes
- Identity Channels

### Quantitative

**Size**
- Also called: Ordered Attributes
- Magnitude Channels

**Orientation**
- Also called: Ordered Attributes
- Magnitude Channels

**Blur**
- Also called: Ordered Attributes
- Magnitude Channels

**Speed**
- Also called: Ordered Attributes
- Magnitude Channels

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