

Maps of Science, Technology, and Education

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Abstract and Keywords

For centuries, cartographic maps of earth and water have guided human exploration. They have marked the border between the known and the unknown, firing the imagination and fueling the desire for new knowledge and new experience. Today, science maps serve as visual interfaces to immense amounts of data, depicting people, objects, and their (social) relationships in ways that allow us to effectively discern apparent outliers, clusters, and trends. This chapter motivates and exemplifies the general process by which maps of science, technology, and education are created. It uses a theoretical visualization framework to review and compare different maps and the data mining and visualization workflows used to create them. It also showcases the value of (interactive) data visualizations to make data-driven decisions.

Keywords: data visualization, data mining, science maps, science studies, technology studies

(p. 598) FOR centuries, cartographic maps of earth and water have guided human exploration. They have marked the border between the known and the unknown, firing the imagination and fueling the desire for new knowledge and new experience. Today, science maps serve as visual interfaces to immense amounts of data, depicting people, objects, and their (social) relationships in ways that allow us to effectively discern apparent outliers, clusters, and trends. Exemplarily, the *Places & Spaces: Mapping Science* exhibit (<http://scimaps.org>) features more than 100 maps of science and technology (S&T) together with several interactive data visualizations, called macrosopes.

As an example, Figure 32.1 shows a world map with an overlay of the research collaboration network created by Olivier H. Beauchesne (2011a, 2011b). Elsevier's Scopus publication data was used to compute the number of times two authors in different cities appear on one paper together during the years 2005–2009. As can be seen, research collaborations are truly global. There is a high density of collaborations within Europe and, to a lesser extent, within North America. Africa and South America collaborate often with the countries that had formerly colonized them.



Figure 32.1 Scientific collaborations between world cities by Olivier H. Beauchesne. Full color figures available on Oxford Handbooks Online.

Background information on the history and utility of science maps together with many examples can be found in the *Atlas of Science* (Börner, 2010), *Atlas of Knowledge* (Börner, 2015), and science mapping review by Chen (2017). An overview of popular science mapping tools can be found in Cobo et al. (2011). Hands-on tutorials for diverse tools are available in the Information Visualization MOOC (<http://ivmooc.cns.iu.edu>).

In this chapter, we review the general process by which maps of S&T are created using the theoretical visualization framework introduced in Börner (2015). We showcase the power of maps to not only help locate us in physical space but also help us understand the social networks in which we operate, the extent and structure of our collective science and technology knowledge, and the learning pathways individuals and cohorts of students take. Sample maps of science, technology, and education will be used to illustrate the creation (p. 599) and usage of (interactive) data visualizations to make data-driven decisions. We conclude with a discussion and outlook.

Map Design

Making sense of data by designing appropriate visualizations is a complex process that involves human perception and cognition (Palmer, 1999; Ware, 2012), but also data mining, visualization algorithms, and user interfaces. Different conceptualizations of the overall process have been developed to understand and optimize this process and to improve human decision-making capabilities. Among others, process models focus on key sense-making leverage points (Pirulli & Card, 2005), the match between preconceptualizations and expectations of visualization designers and visualization readers (Hook & Börner, 2005), major data transformation and visual mappings (Chi, 2000), or visualization design and interpretation to support workflow optimization and tool design.

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When visualizing the structure and dynamics of science or technology, the data that needs to be represented is high dimensional and inherently complex. Many different types of visualizations can be used, and many different “mappings” of data attributes to visual attributes are possible. To ease the design of effective visualizations, different visualization frameworks (also called taxonomies or classifications) have been proposed in statistics, information visualization, and graphic design (Harris, 2000; Keim, 2001; Kosslyn, 1989; (p. 600) Mackinlay, 1986; Munzner, 2014; Shneiderman, 1996; Wilkinson, 2005). Börner (2015) provides predefined types for the process of data visualization including common “task types” and “insight need types” (see Table 32.1, left column).

In general, maps address one or more task types in Börner (2015) that answer different questions. There are four general task types and associated questions: (1) temporal, answering “when” questions; (2) spatial, “where”; (3) topical: “what”; and (4) trees and network layouts, “with whom.”

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Table 32.1 Visualization Framework Designed to Ease the Selection and Design of Data Visualizations

Insight Need Types	Data Scale Types	Visualization Types	Graphic Symbol Types	Graphic Variable Types	Interaction Types
<ul style="list-style-type: none"> • categorize/cluster • order/rank/sort • distributions (also outliers, gaps) • comparisons • trends (process and time) • geospatial • compositions (also of text) • corrections/relationships 	<ul style="list-style-type: none"> • normal • ordinal • interval • ratio 	<ul style="list-style-type: none"> • table • chart • graph • map • network layout 	<ul style="list-style-type: none"> • geometric symbols point line area surface volume • linguistic symbols text numerals punctuation marks • pictorial symbols images icons statistical graphs 	<ul style="list-style-type: none"> • spatial position • retinal form color optics motion 	<ul style="list-style-type: none"> • overview • zoom • search and locate • filter • details on demand • history • extract • link and brush • projection • distortion

Adapted from Börner (2015).

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Given well-defined general task types and specific insight need types, the final visualization will also depend on the type of data (see “data scale types,” Table 32.1, column 2), the available “visualization types” (Table 32.1, column 3), “graphic symbol types” (Table 32.1, column 4), and “graphic variable types” (Table 32.1, column 5; each type is further detailed in Börner, 2015; e.g., “retinal: form” includes size, shape, rotation, curvature, angle, and closure) that can be used, and the level of interaction required by the final visualization (Table 32.1, column 6). Each type is well defined and exemplified; see Table 32.2 on visualization types.

Table 32.2 Visualization Types and Examples

Name	Description	Examples
Tables	Ordered arrangements of rows and columns in a grid. Grid cells may contain geometric, linguistic, or pictorial symbols.	Figures 32.6–32.9, 32.12
Charts	Depict quantitative and qualitative data without using a well-defined reference system.	Examples are pie charts in which the sequence of “pie slices” and the overall size of a “pie” are arbitrary, or word clouds.
Graphs	Plot quantitative and/or qualitative data variables to a well-defined reference system, such as coordinates on a horizontal or vertical axis.	Bar graphs in Figures 32.6–32.10, 32.12
Maps	Display data records visually according to their physical (spatial) relationships and show how data are distributed spatially.	Figures 32.1, 32.9
Network layouts	Use nodes to represent sets of data records, and link connecting nodes to represent relationships between those records.	Treemap in Figures 32.4, 32.5 Tree layout in Figures 32.11, 32.12 Network layouts in Figures 32.3, 32.6–32.8, 32.10

Any visualization can theoretically be analyzed and interpreted as a path along the columns of Table 32.1. For example, given a scientific question, the question type and detailed insight need are identified, and then data of different scale(s) are acquired, a visualization type is selected, and relevant geometric symbol types are chosen and visually modified (e.g., color-coded) using different graphic variable types. Last but not least, different interaction types might be implemented to facilitate the interactive exploration of the visualization (see examples discussed in later sections).

(p. 601) Map Utility

Maps of science can be used to explore, understand, and communicate social and scholarly networks and their interdependence, as well as the expertise profiles of institutes or nations; to chart career trajectories; and to identify emerging research frontiers; among others. They can show homogeneity versus heterogeneity, cause and effect, and relative speed of progress. They allow us to track the emergence, evolution, and disappearance of topics and help to identify the most promising areas of research.

Maps can be created for (interactive) exploration or the communication of insights. Maps might be created at the individual (micro) level or the global (macro) level to support different levels of decision making (see Figure 32.2). They may address one or more task types and associated questions such as (1) temporal, answering “when” questions; (2) spatial, “where”; (3) topical: “what”; and (4) trees and network layouts, “with whom.”

Maps are used by policymakers, industry, scholars, or children to make more informed personal or professional decisions.

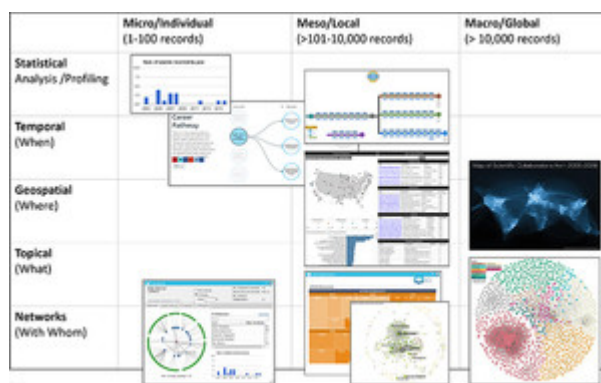


Figure 32.2 Type of analysis versus level of analysis. Full color figures available on Oxford Handbooks Online.

User and needs analysis studies are used to identify the best task type(s) and level (micro, meso, macro) of analysis and visualization design (see Figure 32.2). Studies at the micro-level might be possible by hand. Most tools support micro-to-meso-level studies. Macro-level studies might require highly scalable algorithms and advanced supercomputing infrastructures. The best approaches and tools depend on the type of analysis; for example, major geospatial tools are developed in cartography, while topical analysis tools are developed by linguists.

Ultimately, user studies and/or validation studies should be conducted to ensure that the maps can be used by the intended stakeholder group and results are correct and easy to understand. Subsequently, we introduce maps that are designed for different stakeholder groups, address different insight needs, and view science, technology, and education data at different levels of analysis.

Exemplary Maps of Science, Technology, and Education

For many, science is rather abstract and nebulous. Maps of science give scholarly activity a physical space, also called a basemap; data overlays can be used to indicate the ever-changing structure and dynamics of social networks, diffusion pathways, scholarly and societal impact, or bursts and trends. Maps of science might be created using publication, funding, or social media data; maps of technology typically show patent, trademark, or stock market data; and maps of education use student learning activity data collected from student information systems of learning management systems.

Four interactive maps of science and technology are discussed. The *Springer Nature SciGraph* shows the multimodal network of journal articles, books and chapters, organizations, institutions, funders, research grants, patents, clinical trials, substances, conference series, events, citations but also reference networks, altmetrics results, and links to research datasets. The *NSF Graph Tool DIA2* visualizes National Science Foundation (NSF) funding data so that collaboration networks and funding portfolios can be better understood. The *NIH CTSA Expertise Explorer* helps biomedical researchers understand what expertise and resources different research National Institutes of Health (NIH) centers (p. 603) offer. The *NIH Twitter Data Explorer* shows the retweeting networks of NIH-relevant tweets. We also discuss two online visualization services that are intended to provide guidance for not only learners and teachers/curriculum designers but also employers and counselors interested in keeping up with the increasing speed of science and technology progress.

Springer Nature SciGraph

The Springer Nature SciGraph comprises 1.5 to 2 billion triples.¹ Each triple has the format “subject→predicate→object” and may connect any subject or concept via a predicate (verb) to any other object to show the type of relationship existing between the subject and the object. An example would be “Smith→coauthored→Paper” or “Paper→acknowledges funding by→Award.” SciGraph links metadata extracted from journals and articles, books and chapters, organizations, institutions, funders, research grants, patents, clinical trials, substances, conference series, events, citations but also reference networks and altmetrics results. Other linked open data from trusted, high-quality sources such as Springer Nature are added continuously.

SciGraph visualizations reveal how the rich semantic descriptions are related, overcoming former boundaries by relating comprehensive information about the research landscape. See Figure 32.3 for a rendering of the linked open data cloud by Evangelos Kalamakis.

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The overall goal is to increase discoverability of high-quality data as larger parts of the SciGraph data will be made freely available in various formats (CSV, JSON, XML) under a CC BY-NC 4.0 license.²

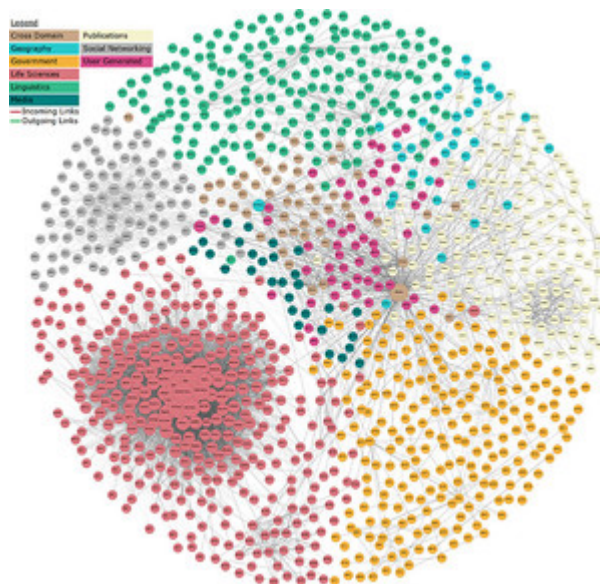


Figure 32.3 Major structure of the #LinkedData cloud by Evangelos Kalampokis. Full color figures available on Oxford Handbooks Online. Interactive version is available at <http://lod-cloud.net/versions/2017-01-26/cloudImage2017.svg>.

NSF Graph Tool DIA2

DIA2 (short for *Deep Insights Anytime, Anywhere*) was designed as a central resource for researchers, educators, and learners who are transforming undergraduate education in science, technology, engineering, and mathematics (STEM) (Madhavan et al., 2014). Using data on 246,902 NSF funding awards made between 1995 and 2016, it renders diverse visualizations in support of six well-defined user needs: (1) understanding the NSF organizational structure and the number of awards distributed across directorates (see Figure 32.4)—clicking on a specific directorate brings up a treemap with all programs, and clicking on a specific program results in a listing of awards and their (co-)principal investigators, institutions, program officers, and geolocations; (2) searching using the thesaurus concept to find out to what program to use to submit a proposal (see Figure 32.5); (3) exploring the network of funded investigators via the People Explorer to understand existing scholarly networks and identify collaborators and competitors (see query result for “Borner” in Figure 32.6); (4) exploring the network of institutions to identify potential collaborators at a specific institution (see query result for “Indiana University” in Figure 32.7); (5) examining NSF programs in DIA2 (Madhavan et al., 2014); (p. 604) and

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(6) searching for funded projects on specific topics (see query result for “visualization” in Figure 32.8).

Each user-requested visualization is added to his or her personal dashboard. Dashboards can be easily optimized by adding/modifying/deleting new visualizations or changing the placement of visualizations. DIA2 is easy to use and addresses important user needs. It was designed for a user group characterized by high domain expertise yet not necessarily high data visualization literacy. By adhering to user experience standards, providing an easy-to-use and self-instructive interface, and selecting easy-to-read visualizations that can be progressively refined, DIA2 minimizes visual complexity and enjoys wide usage. In 2016 alone, there were 1,000,000 hits and 145,000 unique queries.

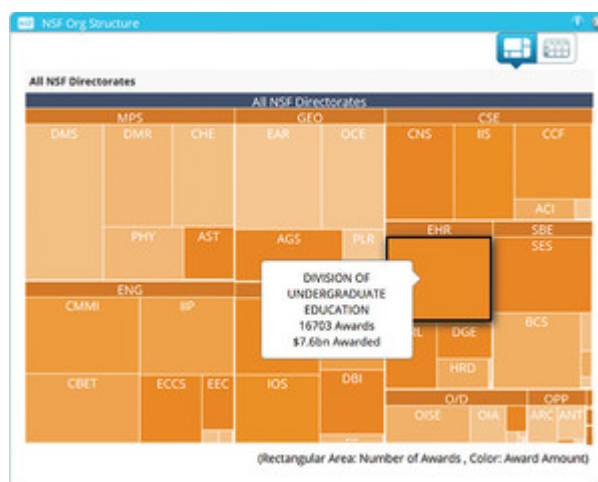


Figure 32.4 DIA2 NSF Org Structure view.

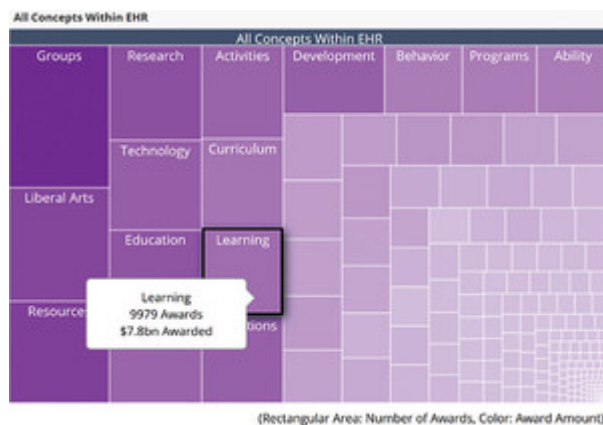


Figure 32.5 DIA2 Thesaurus Concepts view.

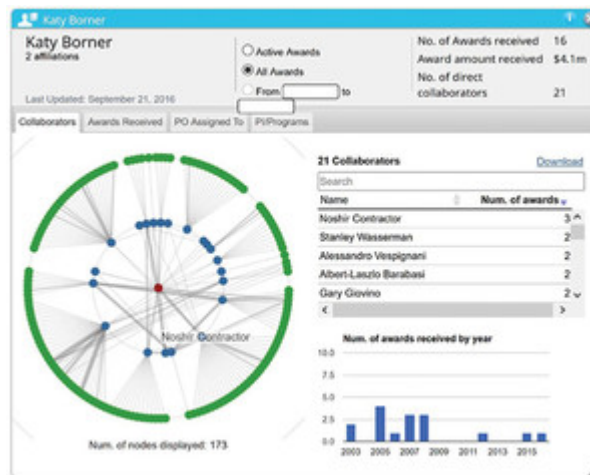


Figure 32.6 DIA2 People Explorer view with query result for “Borner.” Full color figures available on Oxford Handbooks Online.



Figure 32.7 DIA2 Institution Explorer view with query result for “Indiana University.” Full color figures available on Oxford Handbooks Online.

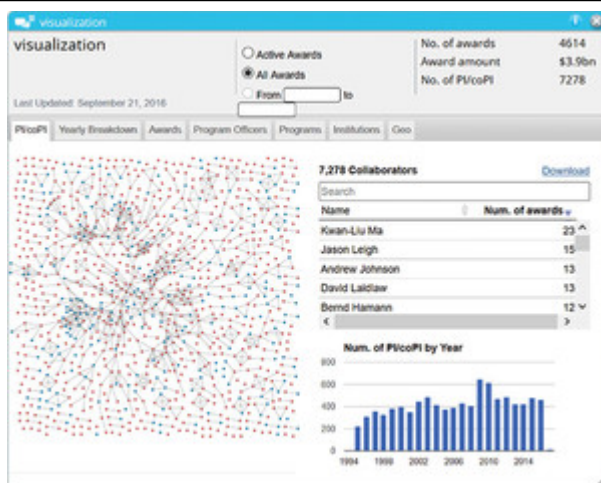


Figure 32.8 DIA2 Topic Explorer view with query result for “visualization.” Full color figures available on Oxford Handbooks Online.

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NIH CTSA Expertise Explorer

The CTSA Explorer supports the interactive exploration of expertise available via the NIH/National Center for Advancing Translational Sciences (NCATS)-funded Clinical and Translational Science Awards (CTSAs) using data provided by NIH RePORTER (NIH Reporter, n.d.).³ Users can search for a keyword (e.g., disease, drug, or gene names) and explore and compare the number and topical coverage of clinical trials (CTs), publications, and funding awards, and the expertise held by the different geospatially distributed CTSA centers. The visualization is interactive, allowing users to select one CTSA and explore all its CTs, publications, awards, and expertise profiles. Links in the respective listings lead to full-text documents with information on CTs, publications, and award details. Figure 32.9 shows a screenshot of the interface filtered for “malaria.”

In addition to helping non-CTSA-funded researchers benefit from the NCATS-funded centers, the visualization also makes it possible to gain a global overview of potential overlap with other privately funded biomedical research efforts to identify opportunities for collaboration or leveraging resources.

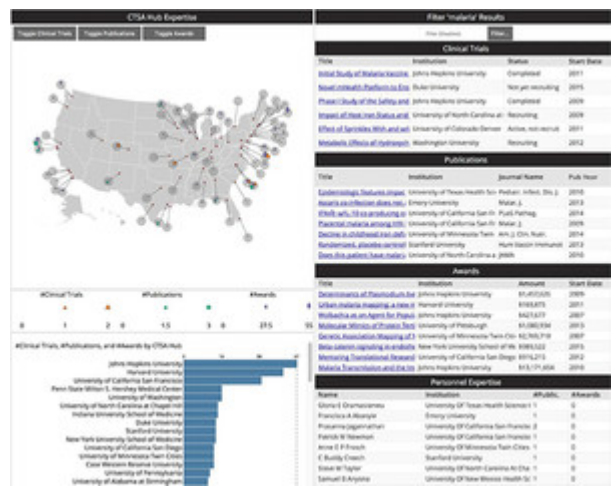


Figure 32.9 Geospatial map of CTSA Hub expertise showing symbols for clinical trials (triangles) publications (squares), and funding awards (diamonds) with size coded by the number of trials/publications/awards. Below the map is a sorted listing of CTSA hubs by total number of trials/publications/awards. Shown on right are listings of major trials/publications/awards with active hyperlinks that lead to full-text publications, funding awards, etc., for closer study. Full color figures available on Oxford Handbooks Online. Interactive version for “malaria” is available at <http://demo.cns.iu.edu/client/iai/expertise.html?set=malaria>.

(p. 608) **NIH Twitter Activity Explorer**

This interactive visualization shows Twitter data related to usernames and hashtags identified to relate to NIH efforts or goals (e.g., health). The purpose of this visualization is to understand how the NIH and health-related information diffuses and to identify “super spreaders” that can be used to speed up the dissemination of NIH/health-relevant information to the experts and the public.

Twitter data was collected using Twitter’s public API for hashtags and usernames identified in advance. Shown in Figure 32.10 is data for 57 Twitter accounts associated with the NIH’s CTSA and CTSA Hubs collected since May 18, 2015.

The data was processed to produce networks of Twitter retweeting activity by identified accounts and hashtags and visualized using the Sci2 and Gephi tools (Mathieu, Heymann, & Jacomy, 2009; Sci2 Tool, 2009) (see Figure 32.10, top left). In the network, each node represents a Twitter user account and each directed link denotes retweets. Nodes are size coded by the (p. 609) number of mentions and colored by user type. Links are directed from accounts that retweeted a post to the account that was retweeted; they are sized and colored proportionally to the number of times one user retweeted another. Clicking on any node (or vertical bar) brings up user account details such as major sources and

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followers for a given account (see Figure 32.10, top right). A list of all usernames is given on the right, sorted by number of tweets.

The networks can help to identify communities of Twitter users that are interested in the various projects associated with the NIH and the users that have the most influence and ability to spread information in and outside various information networks, and determine the reach of various NIH social media campaigns.



Figure 32.10 Directed retweet networks of Twitter data for accounts associated with NIH and NCATS grant programs (left) together with ego-centric details (top right) and sorted listing of most active users (lower right). Full color figures available on Oxford Handbooks Online. Interactive version is available at <http://demo.cns.iu.edu/client/iai/twitter.html>.

The visualization can help the NIH form and encourage specific social media strategies to help CTSA social media accounts to engage with other Twitter users. The network supports examination of accounts that are hubs of information broadcast to the social network and accounts that act as authorities within the network; the relationships between CTSA hub accounts and other users; and the various social media and translational strategies used by CTSA hubs on Twitter.

Learning LeX Subway Maps

Nesbitt used a subway metaphor to communicate his PhD plans to his adviser (Nesbitt, 2003, 2004). In the hand-drawn map, interconnecting ideas running through the PhD thesis are represented by different colors. Related ideas correspond to category stations along that track. Overlapping ideas are shown as connected stations. The familiarity of metro maps makes it possible to understand the many different “trains of thought” and their complex interdependencies.

Microsoft’s Subway Maps LeX⁴ uses subway maps to provide visual overviews and easy-to-use interfaces to online course released within the official Microsoft Learning eXperi-

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ences (LeX) program that was designed to help individuals and organizations maximize the use of Microsoft products. An exemplary map for cloud productivity is shown in Figure 32.11. Each stop is one online course that consists of four modules with a total duration of 8 to 16 hours. Courses with a green filling are released; those with white filling are unscheduled. The map is read from left to right: indicated by the track at the center of the map, the *Fundamental IT Pro Skills* course should be taken first, followed by *Office 365 Administrator* courses. There are three specializations as seen by the three-pronged “fork” in this track: *Communication Professional*, *Messaging Administrator*, and *Share-Point Administrator*. In addition, courses on general Collaboration Skills (the lower track) are offered. The map is interactive—clicking on a released course brings up the course description, information on what students will learn, and a link to the course on edX.

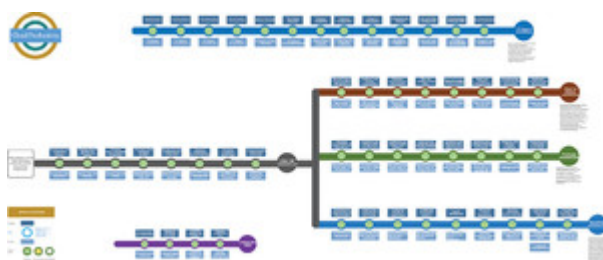


Figure 32.11 Subway map for courses on *Cloud Productivity*.

CyberSeek Career Maps

In 2016, there were 128,000 openings for information security analysts in the United States but only 88,000 workers currently employed in those positions; that is, 40,000 jobs remained unfilled according to CyberSeek,⁵ putting digital privacy and infrastructure at risk. In addition, there were 220,000 additional openings requesting cybersecurity-related skills, but employers were struggling to find workers who possess these skills.

CyberSeek joined with Burning Glass to create career pathways for those interested in becoming cybersecurity workers and protect important and private information, from bank accounts to sensitive military communications. The maps show detailed pathways from entry- to advanced-level jobs (see Figure 32.12, top). Clicking on a node, for example, *Cyber Crime Analyst/Investigator*, brings up details on average salary, required education, top skills, certifications, and more (see Figure 32.12, bottom).



Figure 32.12 CyberSeek career pathways map. Interactive version is available at <http://cyberseek.org/pathway.html>.

The maps are intended to serve the needs of three stakeholder groups: (1) employers, by answering questions such as “How large is the cybersecurity workforce in my and/or neighboring regions?” or “How much does it cost on average to hire cybersecurity workers in my region?”; (2) educators and career counselors interested in answering questions such as “Should I offer a cybersecurity training program and what skills/certificates should be taught?” or “What entry-level jobs should students target?”; and (3) students interested in knowing the demand for cybersecurity jobs in their region or salary levels given certain skills and educational credentials.

Discussion and Outlook

In an age of information overload, the ability to make sense of vast amounts of data and to render insightful visualizations is as important as the ability to read and write.

(p. 611) (p. 612) Scalable, Multilevel Maps

Going forward, there is a need to scale up visualizations so they do the following:

- Cover multiple record types (see previous discussion of the *Springer Nature Sci-Graph* and visualization of linked open data in Figure 32.3)
- Add new data in real time—that is, data is added dynamically as papers are published or funding awards are made
- Show overlapping areas of research (see work on using sparse Markov chains to efficiently reveal overlapping and hierarchically nested community structure in citation flow networks: Bae et al., 2017)

- Support mining and exploration of diagrams, visualizations, and photographs featured in scholarly records (see recent work on Viziometrics: Lee, West, & Howe, 2017)
- Support exploration or communication at multiple levels of aggregation (micro, meso, macro) (see recent work on multilevel graphs: Lazega & Snijders, 2016; Schreiber et al., 2014)
- (p. 613) • Build on and expand standardization efforts such as the University of California, San Diego (UCSD) map of science (Börner et al., 2012) to provide a scientifically validated “basemap” reference system that is widely used instead of hundreds of maps with limited validation and utility
- Are easy to read and use by not only experts but also general audiences

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