Data Visualization in Sociology

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Abstract

Visualizing data is central to social scientific work. Despite a promising early beginning, sociology has lagged in the use of visual tools. We review the history and current state of visualization in sociology. Using examples throughout, we discuss recent developments in ways of seeing raw data and presenting the results of statistical modeling. We make a general distinction between those methods and tools designed to help explore data sets and those designed to help present results to others. We argue that recent advances should be seen as part of a broader shift toward easier sharing of code and data both between researchers and with wider publics, and we encourage practitioners and publishers to work toward a higher and more consistent standard for the graphical display of sociological insights.

INTRODUCTION

From the mind's eye to the Hubble telescope, visualization is a central feature of discovery, understanding, and communication in science. There are many different ways to see. Visual tools range from false-color photographs of telescopic images in astronomy to reconstructions of prehistoric creatures in paleontology. In the statistical sciences, images are often more abstract than models of fighting dinosaurs—depending as they must on conventions that link size, value, texture, color, orientation, or shape to quantities (Bertin 1967 [2010]). But statistical visualizations are nonetheless critical to promoting science. One need only think of the now iconic hockey-stick diagram of earth temperature for a clear case (Mann et al. 1999). Despite its ubiquity in most of the natural sciences, visualization often remains an afterthought in sociology.

In this article, we review the history and current state of data visualization in sociology. Our aim is to encourage sociologists to use these methods effectively across the research and publication process. We begin with a brief history, then present an overview of the theory of graphical presentation. The bulk of our review is organized around the uses of visualization in first the exploration and then the presentation of data, with exemplars of good practice. We also discuss workflow and software issues and the question of whether better visualization can make sociological research more accessible.

SOCIOLOGY LAGS

First, why are statistical visualizations so common in other fields and rare in sociology? Although model summaries offer exacting precision in expressing particular quantities—such as the slope of a line through data points—getting a sense of multiple patterns simultaneously is typically easier visually. The point is made forcefully by Anscombe's (1973) famous quartet, reproduced in **Figure 1*a***. Each data set contains 11 observations on two variables. The basic statistical properties of each data set are almost identical, up to and including their bivariate regression lines. But when visualized as a scatterplot, the differences are readily apparent (see also Chatterjee & Firat 2007). Lest we think such features are confined to carefully constructed examples, consider Jackman's (1980) intervention in a debate between Hewitt (1977) and Stack (1979) over a critical test of Lenski's (1966) theory of inequality and politics, reproduced in **Figure 1*b***. The argument is won at a glance, as the figure shows that the seemingly strong negative association between voter turnout and income inequality depends entirely on the inclusion of South Africa in the sample.

Given the power of statistical visualization, then, it is puzzling that quantitative sociology is so often practiced without visual referents. One need only compare a recent issue of the *American Sociological Review* or the *American Journal of Sociology* to *Science*, *Nature*, or the *Proceedings of the National Academy of Science* to see the radical difference in visual acuity. It is common for the premier journals in sociology to publish articles with many tables, but no figures. The opposite is true in the premier natural science journals. There, a key figure is often the heart of the article. In *Nature*, for example, the online table of contents includes a thumbnail of the central figure to serve as the link to the rest of the paper.

It has not always been so. Early in the history of the discipline, data visualizations were common and not appreciably out of step with the wider scientific community. Exemplars of bar charts (Hart 1896), line graphs (Marro 1899), parametric density plots and dot plots with standard errors (Chapin 1924), scatterplots (Sletto 1936), and social network diagrams (Lundberg & Steele 1938) are easy to find in early sociological journal articles. Du Bois's (1898 [1967]) *The Philadelphia Negro* is filled with innovative visualizations, including choropleth maps, table-and-histogram combinations, time series, and others. But somewhere along the line sociology became a field where sophisticated statistical models were almost invariably represented by dense tables of variables along rows and model numbers along columns. Though they may signal scientific rigor, such

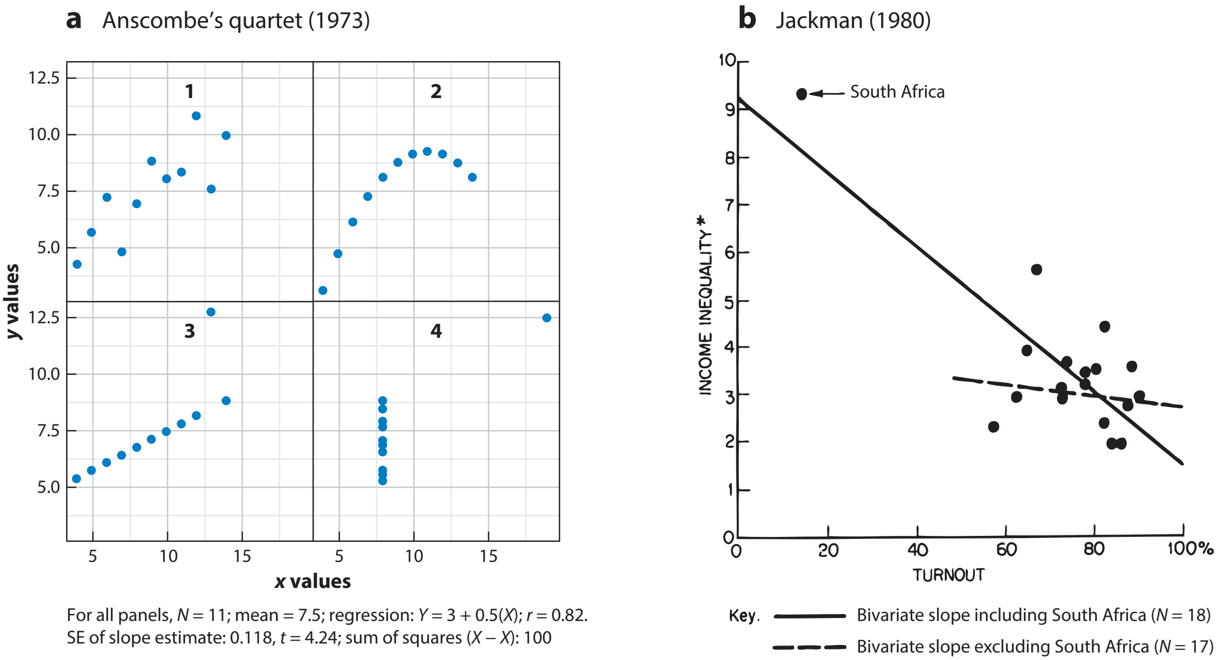


Figure 1

Visualizations reveal model summary failures: (*a*) Anscombe's quartet shows how statistically identical data sets can look very different; (*b*) visualization from Jackman (1980) decisively demonstrates the influence of outlying data points in an analysis.

tables can easily be substantively indecipherable to most readers and perhaps at times even to authors. The reasons for this are beyond the scope of this review, although several possibly complementary hypotheses suggest themselves. First, to the extent that graphical imagery was thought of as descriptive, statistical images may have been collateral damage in the war between causal-inferential modeling and descriptive reportage. Second, figures may have seemed unsophisticated. The very clarity of a (good) figure made the work seem too simple. Third, and more charitably, visualization in sociology might have been a victim of the field's relatively rapid embrace of quantitative methods. American sociology adopted sophisticated modeling techniques quite early compared with other social sciences. The range and variety of its research questions and data sources meant that the statistical tool kit in sociology in the late 1960s and into the 1970s was more varied than in economics or psychology at the time and much more developed than what was then current in political science. But this was also a period when the visualization tools of statistical software lagged well behind their strictly computational abilities. Conventions of data presentation may have standardized at a time when the possibilities for visualization were narrower. Finally, some of the resistance to figures may have come from the fact that the tables in early journal articles and monographs often contained actual data rather than summaries or model results. In a review of a history of graphical methods in statistics written in 1938, John Maynard Keynes remarked that he wished the author

> could have added a warning, supported by horrid examples, of the evils of the graphical method unsupported by tables of figures. Both for accurate understanding, and *particularly to facilitate the use of the same material by other people*, it is essential that graphs should not be

> published by themselves, but only when supported by the tables which lead up to them. It would be an exceedingly good rule to forbid in any scientific periodical the publication of graphs unsupported by tables. (Keynes 1938, p. 282, emphasis added)

To speak anachronistically, here Keynes is arguing that economists need the underlying data along with the visual summary for the sake of reproducibility. We are now at a point when the volume of data used in a typical quantitative article far exceeds what can be presented in a series of tables. But Keynes's point is worth bearing in mind. The utility of visualization methods—in particular their ability to effectively summarize large quantities of data or sophisticated modeling techniques—is partly dependent on related advances in our ability to easily share data and reproduce analyses. If data are accessible as needed, using figures instead of tables becomes much easier. Not coincidentally, this is another area where sociology has lagged behind other social sciences (Freese 2007).

Whatever their relative importance, the net result of these processes for sociology has been a training and publication standard that rarely includes graphical treatments of statistics. New students are typically not taught to think about graphics and statistics in a consistent, coherent way.

Our argument is not that sociologists should be producing more visualizations just because everyone else is doing it. Indeed, as we discuss below, there is considerable debate about what sort of visual work is most effective, when it can be superfluous, and how it can at times be misleading to researchers and audiences alike. Just like sober and authoritative tables, data visualizations have their own rhetoric of plausibility. Anscombe's quartet notwithstanding, summary statistics and modeling can be thought of as tools that deliberately simplify data to let us see past the cloud of data points. We do not think visualization will give us the right answer simply by looking. Rather, we should think about how visualization might be more effectively integrated into all stages of our work. Software now makes routinely generating figures easier than ever. Even if many disciplinary journals still lag in their editorial desire or ability to present good data visualizations, we argue that it is time for these methods to be fully integrated into sociology's research process.

VISUALIZATION IN PRINCIPLE

Book-length treatments of good statistical visualization practice abound. Their content ranges from the more theoretical—emphasizing, for instance, the nature and origins of visual conventions—to more pragmatic collections of current best practices meant to serve as an inspiration to practitioners. In between are efforts to codify practice and develop taste, and guides to working implementations. The most influential general treatments are probably Bertin's (1967 [2010]) *Semiology of Graphics*, Cleveland's *The Elements of Graphing Data* (1994) and *Visualizing Data* (1993), and Wilkinson's (1995 [2005]) *The Grammar of Graphics*. Overviews of contemporary practice can be had in Few (2009, 2012) and Yau (2012). There are also several books based specifically on visualization techniques within a particular software program, such as Friendly (2000) for SAS, Mitchell (2012) for Stata, Murrell (2011) for R, and Kleimean & Horton (2013) for comparisons of multiple programs. Sometimes the graphical capabilities of particular software applications are loosely related to the more theoretical work, taking from them a concern with aesthetic principles and possibly specific sorts of plots. In other cases, the linkage is closer. Sarkar (2008) describes a data visualization package for R that closely follows Cleveland's ideas (and some earlier associated software), and Wickham (2009, 2010) describes a software package for R that implements and extends principles worked out in Wilkinson's (1995 [2005]) *The Grammar of Graphics*.

The conceptual literature is deep and comprehensive, although its representatives do not always speak in one voice. This is to be expected in an area where theoretical development involves judgments of taste. The best-known critic and tastemaker by far in the field is Edward R. Tufte. It is fair to say that *The Visual Display of Quantitative Information* (Tufte 1983) is a classic in the field, and its three follow-up texts are also widely read (Tufte 1990, 1997, 2006). Described as "self-exemplifying" (Tufte 2006, p. 10), the bulk of the work is a series of negative and positive examples with more general principles (or rules of thumb) extracted from them rather than a direct guide to practice, akin more to a reference book on ingredients than to a cookbook for daily use in the kitchen. At the same time, Tufte's early work in political science shows that he applied his ideas well before codifying them in this way. His *Political Control of the Economy* (Tufte 1978) combines data tables, figures, and text in a manner that remains remarkably fresh almost 40 years later.

Across his work, Tufte preaches a consistent set of principles, though they vary in their degree of specificity. Thus,

> Graphical excellence is the well-designed presentation of interesting data—a matter of *substance*, of *statistics*, and of *design*. . . . [It] consists of complex ideas communicated with clarity, precision, and efficiency. . . . [It] is that which gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space. . . . [It] is nearly always multivariate. . . . And graphical excellence requires telling the truth about the data. (Tufte 1983, p. 51)

Tufte illustrates the point with Charles Joseph Minard's famous visualization of Napoleon's march on Moscow, reproduced in **Figure 2**. He remarks that this image "may well be the best statistical graphic ever drawn," and argues that it "tells a rich, coherent story with its multivariate data, far more enlightening than just a single number bouncing along over time. *Six* variables are plotted: the size of the army, its location on a two-dimensional surface, direction of the army's movement, and temperature on various dates during the retreat from Moscow" (Tufte 1983, p. 40). It is worth noting how different Minard's image is from most contemporary statistical graphics. Until recently, these

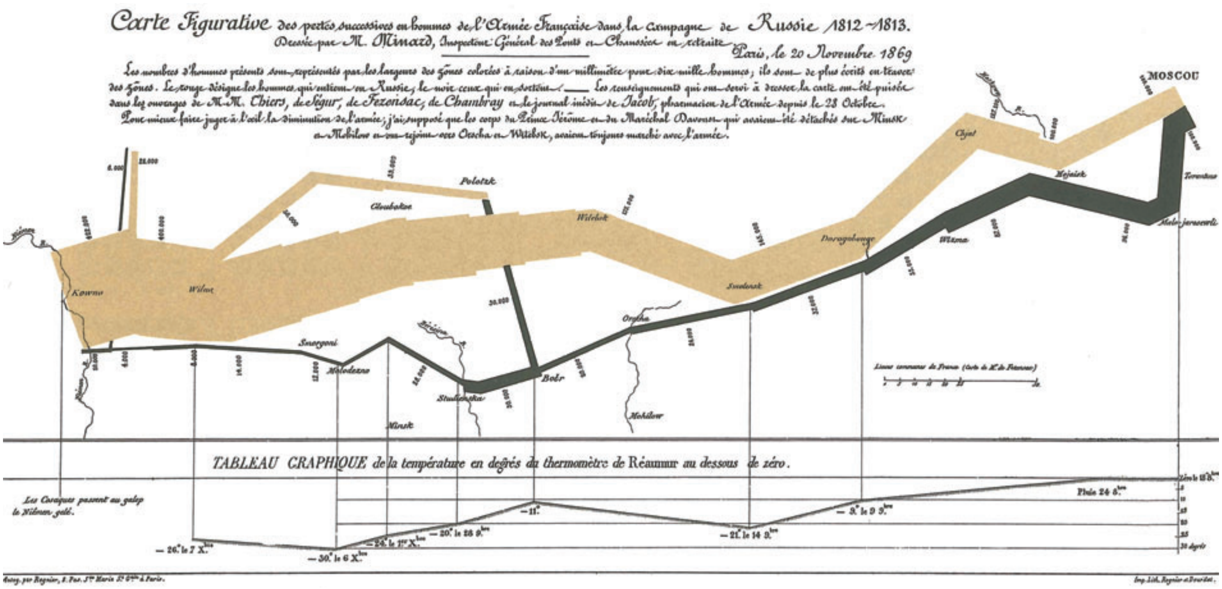


Figure 2

Minard's visualization of Napoleon's advance on and retreat from Moscow is a classic of visualization, but its design is in many ways atypical.

have tended to be generalizations of the scatterplot or barplot, either in the direction of seeing more data or seeing the output of models. The former looks for ways to increase the volume of data visible, the number of variables displayed within a panel, or the number of panels displayed within a plot. The latter looks for ways to see results of models—point estimates, confidence ranges, predicted probabilities, and so on. Tufte (1983, p. 177) acknowledges that a tour de force such as Minard's "can be described and admired, but there are no compositional principles on how to create that one wonderful graphic in a million." The best one can do for "more routine, workaday designs" is to suggest some guidelines such as "have a properly chosen format and design," "use words, numbers, and drawing together," "display an accessible complexity of detail," and "avoid content-free decoration, including chartjunk" (p. 177).

Among this set of general goals are some specific details that can be employed to good use across applications. This includes extensive use of layering and separation, for example, building on the insights of good cartography. Judicious use of stroke weight and color allows one to layer multiple meanings on a single visual plane. The ability to successfully pull off such effects depends on use of the smallest effective difference—lighter lines, smaller color variations, and simpler textures. It has long been a complaint of chart designers that accomplishing this often means working very much against the (highly detailed, drop-shadowed, rich, Corinthian leather) grain of the default settings in spreadsheet or other chart-making applications. Comparison and evaluation are often enhanced by the use of many small multiples—plots that repeatedly display some reference variable or relationship (e.g., gross domestic product versus health care costs over time) and iterate across some other variable of interest (e.g., country) in an ordered fashion (see also Bertin 1967 [2010], pp. 217–45). The use of such multiples highlights the notion of parallelism that allows a reader to carefully compare across instances of similar-but-crucially-different items. Combined, these features facilitate a simultaneous micro and macro reading where key points are clearly communicated at the surface, but deeper meaning is obtained through careful review and exploration.

A common complaint about Tufte's work is that there are so few direct instructions. Busy cooks want a cookbook, not a picture of a fantastic meal. The tendency for the codification of data visualization to vacillate between overly abstract maxims and overly specific examples is characteristic of any craft where a practical sense of how to proceed—a taste or feeling for the right choice—matters for successful execution. A long-standing and plausible response to the problem is to have the designer make many of the judicious choices in advance and then embed them for users in the default settings of graphics applications. Given that graphical software aimed at regular users has been around for several decades now, however, these efforts have proven less successful than initially hoped. In the foreword to the new edition of *Semiology of Graphics*, Howard Wainer (2010, p. xi) reflects on the hope he and others once felt that easy-to-use graphical tools and software would lead to better general practice by way of smarter defaults. But, he argues, this has not happened. In the end, high-quality graphical presentation requires crafting a deliberately designed message rather than accepting the pre-established setting. Recent theoretical work explicitly recognizes the limits of relying on defaults. Following Wilkinson in implementing ggplot's "grammar of graphics" for R, Wickham (2010, p. 3) notes that the analogy to grammar is useful because although "[a] good grammar will allow us to gain insight into the composition of complicated graphics, and reveal unexpected connections between seemingly different graphics[,] . . . there will still be many grammatically correct but nonsensical graphics. . . . [G]ood grammar is just the first step in creating a good sentence."

If software defaults cannot enforce the elements of good taste, the next best—or maybe better—thing is a means to easily expose the mechanics of good practice. One of the most positive developments in statistical software over the past 15 years has been its integration with a much broader set of tools built to facilitate the sharing of both data and code. The first wave of modern statistical graphics and information design could convey, in print, the general principles and the quality products. But the crucial piece in between—the design process and practical assembly—remained opaque. Subsequently, communities of users began to share not just output but code much more widely, whether under the auspices of a for-profit developer (as in the case of Stata) or actively backed by free or open-source licensed platforms (as with R) or expert user blogs (**http://sas-and-r.blogspot.com**, **http://flowingdata.com**, **http://www.r-statistics.com/tag/visualization**). Some of these have developed into comprehensive references aimed at the practicing researcher (Chang 2013). Most recently, pastebins and software development platforms backed by distributed version control systems—most notably Github—have made sharing code both technically much easier and normatively expected.

As with the move toward replication data sets, everyday sharing of code allows novices to look behind the curtain much more easily than before. And perhaps unlike the earlier emphasis on accepting sensible defaults, it encourages new users to tinker with various methods and learn by doing. In many cases, software now allows users to control very detailed layout elements in their program scripts, which (with a little extra language work) allows one to override defaults with principled graphical choices. This ongoing integration of guidebooks, how-to websites, code repositories, and fully reproducible examples is a major step forward for improving visualization practice. As one particularly well-developed example among many, UCLA's Institute for Digital Research and Education has a large library of worked graphical examples implemented across several statistics packages (**http://www.ats.ucla.edu/stat/dae**). Finally, because most statistical packages can now produce graphics as editable vector graphics files, one can use any graphical editor to fine-tune elements (such as line thickness, greater subtlety in color selection, etc.) for production.

These developments do not make questions of judgment and good practice go away. Statistical visualization needs to be thought of as part and parcel of analysis and presentation. We should be crafting visualizations thoughtfully in the same way we craft arguments or build models. Resources of this sort cannot by themselves guarantee that code snippets will not simply be mechanically copied or inappropriately applied by users looking for a shortcut to a good outcome. But, to paraphrase Keynes from a different context, they do seem to promise if not civilized visualization, at least the possibility of civilized visualization.

VISUALIZATION IN PRACTICE

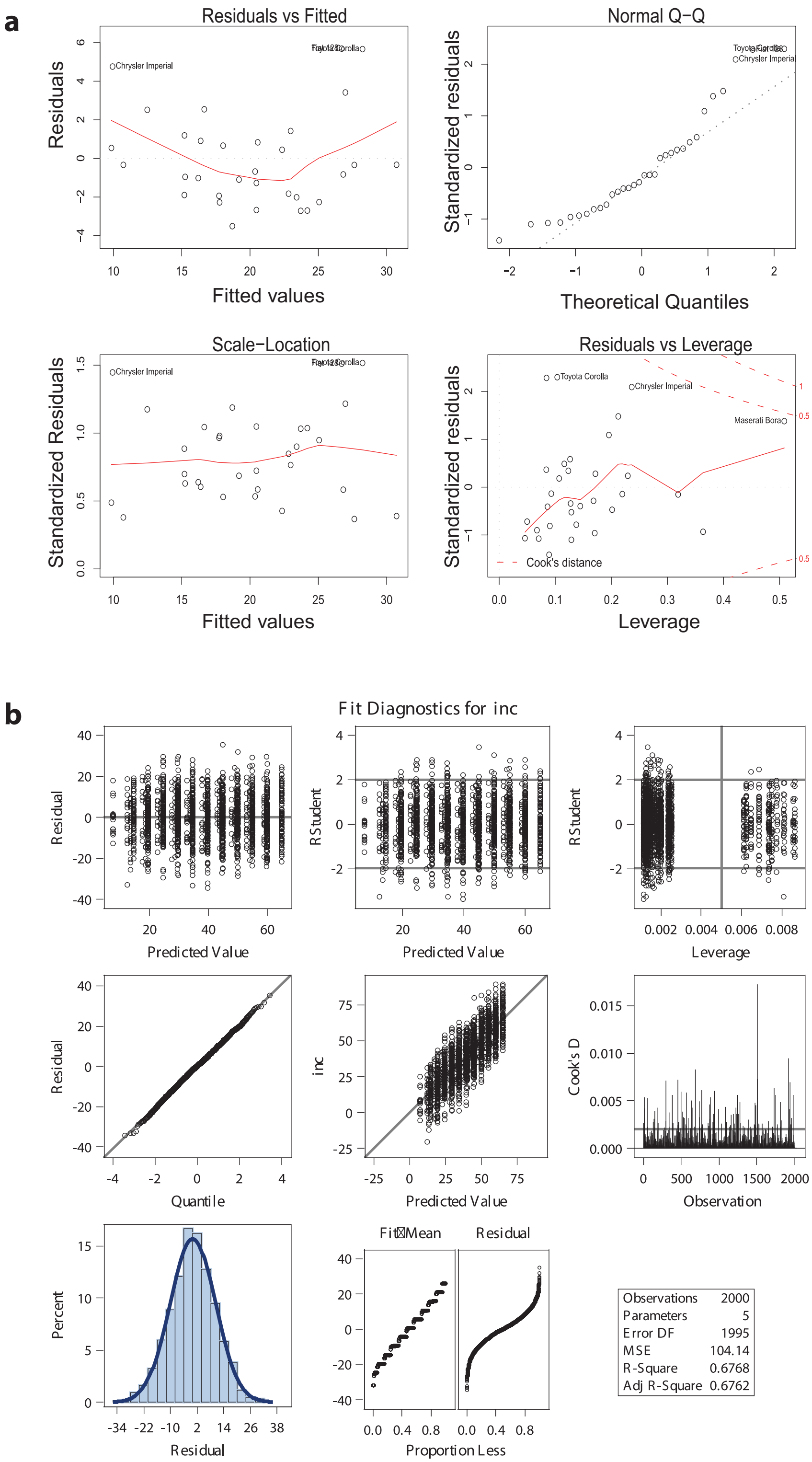
We have argued that there are several promising ways that general principles of visualization can become more tangible in everyday use. We now turn to the question of current practice in a little more detail. Here we follow the common distinction between visualization for exploration versus presentation of a final finding. The former is meant for internal consumption, as the researcher examines the data to figure out what is going on; the latter is designed to convince a wider audience. Naturally, these processes overlap to some degree. The general principles covered in the previous section—regarding clarity, honesty, showing the data, and so on—apply equally to both the backstage and frontstage of visualization work. But what is needed in each case does differ. Some recent developments on each side are worth highlighting.

Exploring the Data

Graphical methods are now well integrated into the process of checking assumptions and robustness in most statistical packages and are often generated by default. **Figure 3** shows a typical example of some diagnostic plots of an ordinary least squares regression. They were produced on demand and by default, with no

Figure 3

Default diagnostic plots for a linear model: (*a*) R, (*b*) SAS. Though automatically produced, both panels present information clearly and with judicious use of labeling and color.



further tweaking or polishing. Note that although we voiced some skepticism above about the ability of defaults to shape practice, these plots are models of clarity. They could be called into service for presentation purposes in a pinch. Their real utility, however, is the ease with which they can be produced and viewed as part of one's everyday workflow as a social scientist: With tools like these, comments on outliers such as Jackman's (1980) should never again be necessary.

Diagnostic plots of this kind are—in principle—what you look at after a model has been chosen. They are confirmatory rather than strictly exploratory. Advocacy of exploratory data analysis (EDA), of looking carefully and creatively before modeling, is most closely associated with John Tukey (1972, 1977). Historically, EDA has been closely tied to the rise of graphical capabilities in statistical computing, particularly tools that allow rapid interactive visualization. A mild sense of unease with EDA is a feature of the statistical literature. The approach is explicitly inductive and concerned with exploring data in a relatively freewheeling fashion as an aid to discovery, which at times can seem uncomfortably opportunistic or unstructured. To working social scientists these are often virtues, but statistics is also the discipline where the avoidance of spurious associations is a major focus of technical work.

As data sets have continued to increase in both size and dimensionality, and as computing power and graphical methods have tried to keep up, there has been a rapprochement between the strictly exploratory and strictly confirmatory approaches. Working social scientists routinely explore their data as part of the process of cleaning and checking it. It would be naive to think researchers were not on the lookout—literally—for interesting patterns in complex data sets. Recent developments in EDA have focused on extending established methods of easily looking at a lot of data at once, and on developing new ways for visually checking the validity of apparent relationships. The idea is to make the exploratory a little more confirmatory.

A first useful tool for this sort of exploration is a generalized scatterplot matrix. In a standard pairs plot, the goal is to see all the bivariate relationships in the data at once, presented in a grid so that quick comparisons can easily be made. An unfortunate limitation, particularly for the social sciences, is that these plots do a poor job with categorical variables. Ideally we would like to see the panels of the matrix display the data in a form appropriate to the underlying variable. A generalized pairs plot (Emerson et al. 2013) accomplishes this, using barcode plots, boxplots, mosaic plots, and other methods. **Figure 4** shows an example. The specific software implementation adds additional functionality, including the ability to display different plots—such as barcode and mosaic plots—in the upper and lower triangles of the plot matrix, histograms along the main diagonal, and the option of adding smoothed or linear regression lines to panels.

Generalized pairs plots can be extended even further, depending on the software, by allowing further partitioning within panels. For instance, we can show separate histograms of a continuous variable broken out by the values of a categorical variable. Multipanel plots are intrinsically rich in information. When combined with several within-panel types of representation and a large number of variables, they can become quite complex. But, again, the main utility of this approach is less in the presentation of finished work—although it can certainly be useful for that—and more in the way it enables the working researcher to quickly investigate aspects of her own data. The goal is not to pithily summarize a single point one already knows, but to open things up for further exploration. Harrell (2001) remains an exemplary book-length demonstration of the virtues of integrating graphical methods with the process of data exploration (including exploring patterns of missingness in the data) right across the process of model building, diagnostics, and presentation.

With many variables and large amounts of data, a square matrix of plots can become unwieldy even to the trained eye. Seeing more

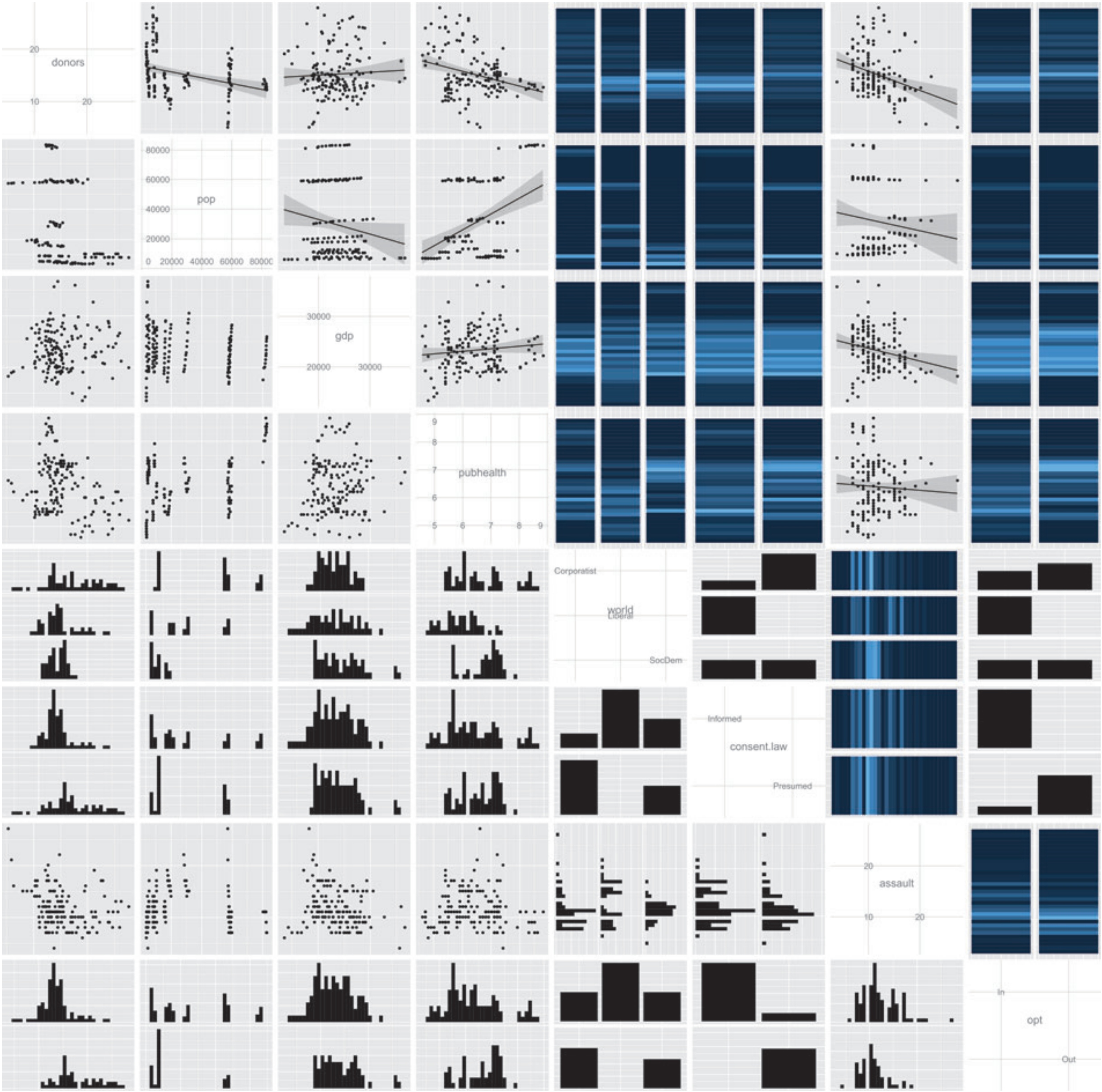


Figure 4

A generalized pairs plot handles categorical data easily, and in different ways.

data more quickly, and in particular exploring high-dimensional data in a controlled way, has been a focus of recent visualization research. Early work—going back to Tukey, and others—allowed for the exploration of data in three dimensions, for instance by way of rotating a cloud of points on a screen. This sort of approach "demoed well," as spinning around a cloud of colored points looks quite impressive to the casual observer. But interpreting these displays is another matter. Thus, methods for interactively exploring

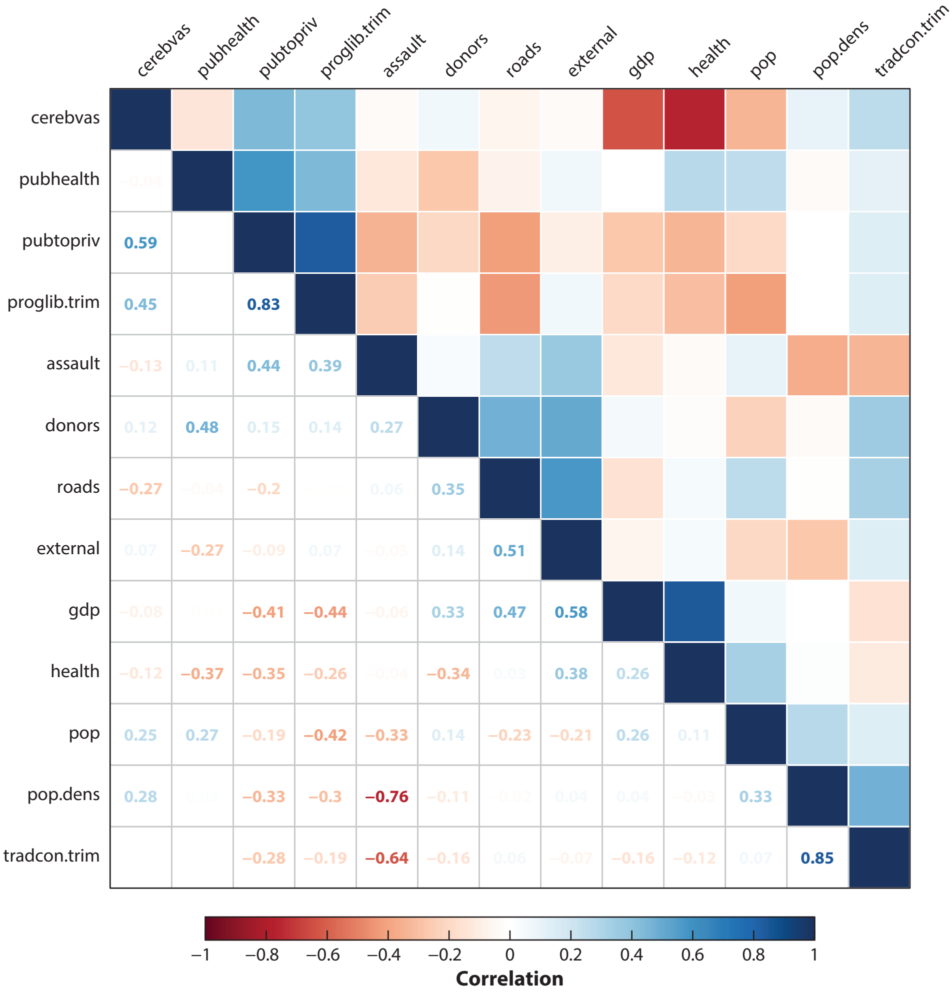


Figure 5

A correlation matrix represented as a tiled heat map (*upper triangle*) with color-keyed correlation coefficients (*lower triangle*).

data sets advanced on two fronts. The first moved toward further development of multiple panels, notably with innovative ways of visually conditioning on additional variables or highlighting interactively selected cases across panels. Co-plots, shingles, and contour or surface plots are all examples of this kind of development (Cleveland 1993, pp. 186–271; Sarkar 2008, pp. 67–115). Increasingly, these methods take advantage of color for presenting data, as with heatmaps or tiled representations of a correlation matrix (see **Figure 5**). Tools for permuting correlation matrices, either in the order produced by factor-analytic techniques or other direct optimization, allow one to identify higher-order patterns in such figures (Breiger & Melamed 2014).

A second direction has been the development of parallel coordinate plots, which show multiple variables side by side in a way that allows for the visualization of both specific outliers and clusters of association across many variables at once (Moustafa & Wegman 2006, Inselberg 2009). **Figure 6** gives a simple

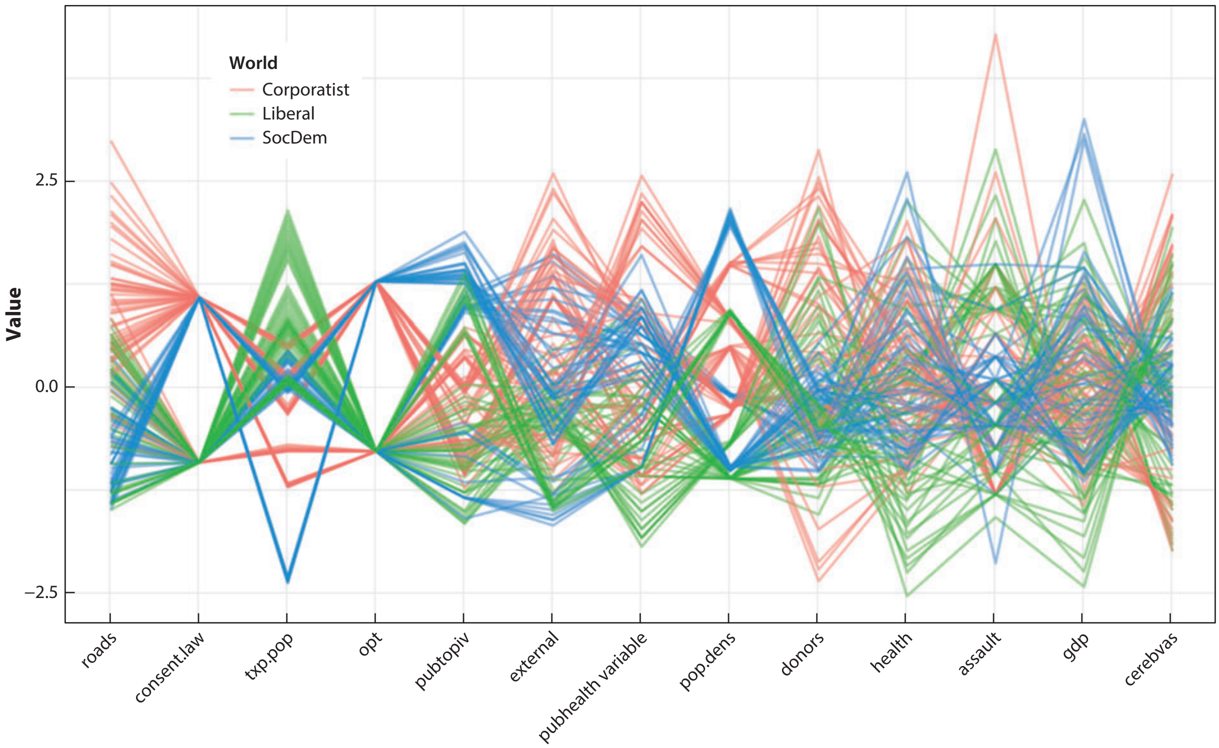


Figure 6

A parallel coordinates plot highlighting a possibly relevant grouping variable.

example, although the approach is best suited to much larger numbers of variables and observations than shown here. This sort of plot also benefits from being used interactively, as the ordering of the variables (and the highlighting of possible grouping variables) can change the interpretability of the graph quickly. The GGobi system, for example, is designed to provide interactive, semiautomated facilities for "touring" large, high-dimensional data in real time using parallel plots and a variety of other methods (Cook & Swaine 2007).

This broad EDA tradition has recently begun to reconnect with the model-checking or diagnostic approach, with convergence happening from both directions. The longstanding concern here is that a striking visualization might not correspond to any robust underlying phenomenon. Early advocates of data visualization typically presented a "parade of horribles" (e.g., Wainer 1984) showing how bad visual presentation can distort or misrepresent the data. But even properly presented visualizations can be vulnerable to spurious pattern attribution on the part of researchers and observers. From the EDA side, Wickham et al. (2010) and Buja et al. (2009) provide some principled ways for assessing, in a broadly graphical manner, whether or not the patterns one is seeing are likely to be spurious. For example, a permutation lineup presents observed data in a small-multiple context surrounded by null plots of generated data. "Which plot shows the real data?" Buja et al. (2009, p. 4372) ask. If observers cannot reliably pick it out, then we should doubt both the utility of the plot and the soundness of any inferences (or arguments) based on it. From the modeling side, Gelman (2004, pp. 773–74) argues that a Bayesian approach provides a principled framework for assessing "the implicit model checking involved in virtually any data display."

Although we have argued that sociologists have been relatively slow to adopt data visualization, several of the issues we have discussed have independently appeared within the sociological literature. Sociologists routinely deal with data where almost all the variables of interest are categorical, for example. And, as noted above, the routine and effective display of categorical data (especially cross-classified categorical data) has not been a trivial problem to solve. Furthermore, sociology has a long tradition of using methods that reduce high-dimensional data in some way—especially via factor analysis, principal components, correspondence analysis, or other related methods. In *Distinction*, for example, Bourdieu (1984, pp. 128–29, 262, 266, 343) presents his analysis of the space of French social class and taste in a way that is both highly visual but also—for some critics—decidedly difficult to interpret. This family of methods lends itself to suggestive visualization in what might be called a configurational mode. This is somewhat inimical to the Anglo-American tradition of seeking causal relations in statistical models. Breiger (2000) provides a useful discussion of some of the issues here, emphasizing points of convergence.

Dimensional reduction of this sort typically characterizes the problem of interest in terms of space or distance, which naturally encourages the mapping of social systems. Sociologists have been among the earliest users of these visualization tools, particularly with network analysis. The earliest interactive network tools were literally peg boards and rubber bands (Freeman 2004) or pins-and-strings.[1] Interactive exploration of social network data has obviously been made much easier with the advent of efficient computer programs. Released in 1996, PAJEK was one of the earliest completely interactive visualization tools that was also optimized for large networks. Earlier software typically separated the visualization and analysis steps. There has since been rapid growth in the development of interactive network exploration tools, including on the web (**http://www.theyrule.net**, **http://dirtyenergymoney.com**). The challenge for such work is excess reduction in the inherent complexity of the data, which has led methodologists to propose fit statistics for network layouts (Moody et al. 2005, Brandes et al. 2012).

The rapid availability of fully dynamic network data has created opportunities and challenges for visualization. Network movies, for example, allow one to capture the relational dynamics as they unfold in space and time (Moody et al. 2005, Bender-deMoll et al. 2008, Morris et al. 2009). The clear advantage of a network movie is that one can reserve the two dimensions of the visual plane for mapping the topography of the social system and watch the shape of the system change as the animation runs. This is particularly useful for exploration, as it makes visible dynamic features that are otherwise difficult to capture in summary statistics. But there are also costs. People tend to have poor visual memories, so comparing nonadjacent moments in time is challenging, and the analyst must make strong assumptions about how to aggregate the network events over time. Similar visualization challenges are becoming common in dynamic statistical displays, such as the GapMinder data set, which allows one to explore associations over time (**http://www.gapminder.org**).

Presenting the Results

These considerations lead naturally to the question of presenting data. Most of the principles discussed above regarding the construction of figures for exploring data also apply to presenting it, if only because the audiences are often the same—that is, experts in a particular field. But effective statistical graphics have a rhetorical aspect, too (Kostelnick 2008). In general, the goal is to look for ways of presenting the data that are both effective with respect to one's argument and honest with respect to the data.

Though conceptually simple and among the earliest examples of statistical visualizations,

[1] See **http://www.soc.duke.edu/~jmoody77/VizARS/sna_peg.jpg**.

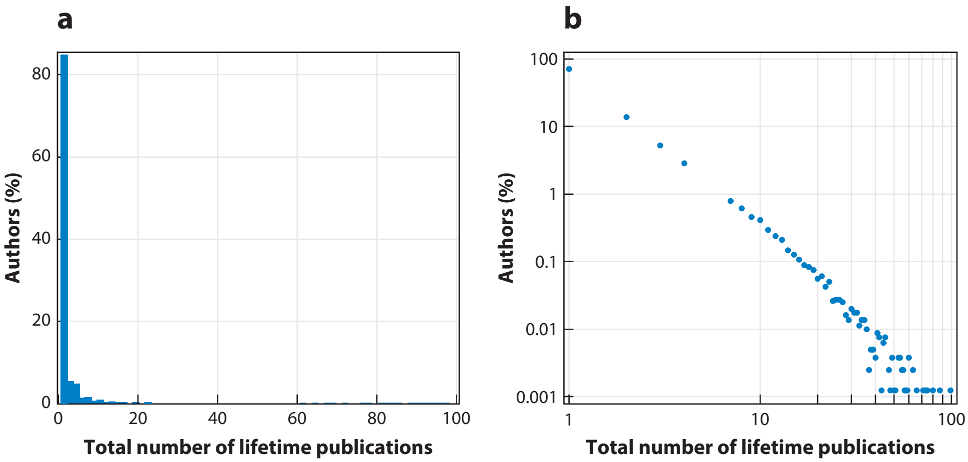


Figure 7

The distribution of authors' lifetime number of publications in three very selective sociology journals is highly skewed. In comparison to a standard histogram (*a*), a log-log histogram (*b*) is much better at revealing details in the "long tail" of the distribution.

variable distributions remain of keen substantive interest. Many of the distributions typically studied in sociology are extremely skewed and difficult to display as simple histograms. Consider, for example, some data on the number of times authors publish in a select set of journals (here the *American Sociological Review*, *American Journal of Sociology*, and *Social Forces*) over the course of their career. **Figure 7*a*** presents a standard histogram, whereas **Figure 7*b*** follows the convention now common in the physical sciences of presenting the distribution on a log-log scale.

When comparing distributions across categorical variables, comparative boxplots allow one to examine multiple moments of a distribution across multiple categories or over time (with some loss of resolution). The presentation of joint distributions of multiple categorical variables has similarly been improved with area-accurate Venn diagrams (see for example, **http://www.eulerdiagrams.org/eulerAPE**). An important contribution to this literature is the work of Handcock & Morris (1999) on relative distribution methods. By comparing the ratio of two distributions at each point along the x-axis, one is quickly able to identify differences in both shape and central tendency. **Figure 8** reproduces the relative distribution in permanent wage growth for two cohorts of the National Longitudinal Survey. If the wage distributions were identical, the density would be a simple horizontal line at 1.0; instead we see much greater inequality (heavier tails at both ends) in the recent cohort.

A related problem involves effectively displaying trends over time, particularly when attempting to demonstrate strong variability across units. The convention of reserving the x-axis for time and the y-axis for magnitude becomes tricky if many series are given equal weight. An effective solution involves carefully choosing colors, line weights, and labels to highlight a particular strand among many (see **Figure 10** below). Moody et al. (2011) are able to demonstrate the wild variability in adolescent popularity sequences by generating a scatterplot of trajectory summaries with exemplar labels.[2] Because each position in the

[2]See **http://www.soc.duke.edu/~jmoody77/VizARS/Figure5.jpg** for trendspace; **http://www.soc.duke.edu/~jmoody77/VizARS/Figure%206.pdf** for application of this space to model prediction outcomes.

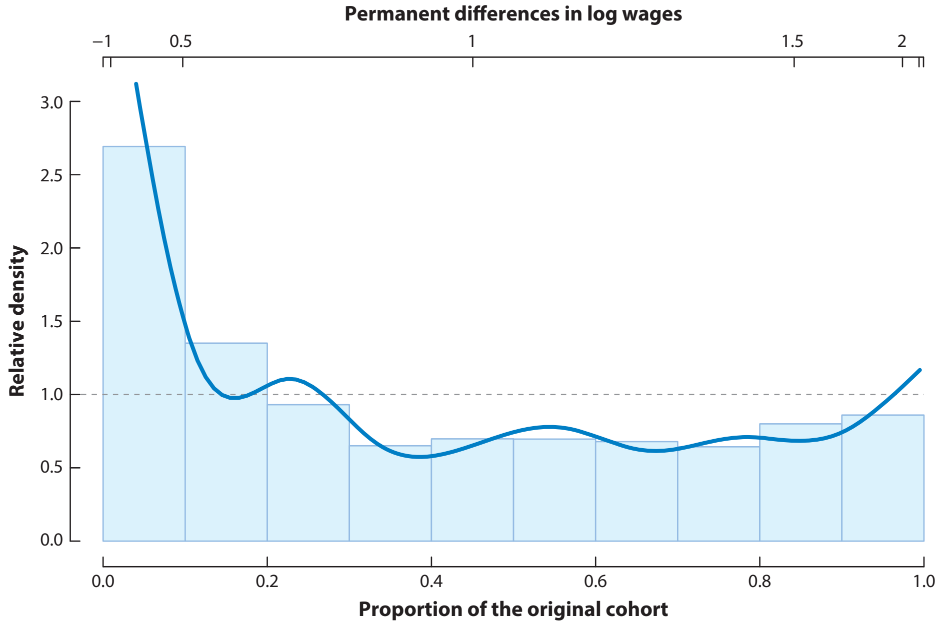


Figure 8

The relative probability density function distribution of permanent wage growth in the original and recent National Longitudinal Survey cohorts. A decile bar chart is superimposed on the density estimate. The upper axis is labeled in permanent differences in log wages (adapted from Handcock & Morris 1999).

field captures a unique trend, the distributional coverage of the space suggests there is no typical sequence.

Moving beyond simple variable comparison displays, the bulk of statistical work in sociology involves complex multivariate models. Even with good statistical training, tables of coefficients are hard to decipher quickly and tend to foreground statistical significance over substantive magnitudes. Straightforwardly interpreting the effects of independent variables is rarely intuitive, especially for models with complex link functions, categorical components, or interaction terms. Although odds ratios are margin free and thus nominally interpretable, knowing whether an effect is substantively large is often difficult without comparative context and may be impossible to discern directly from the table without intimate knowledge of the underlying distribution of control variables. The simplest solution to this problem is to use the model to predict outcome variables at different levels or combinations of the independent variables of interest. **Figure 9*a*** shows a powerful example from Mirowsky & Ross (2007). They use a new style of vector graphs for latent growth models by age (see Mirowsky & Kim 2007) to display predicted values from interaction terms. This enables them to take results from a complex structural equation model of people's perceived sense of control and simultaneously illustrate both within-cohort and between-cohort changes at varying levels of education in a way that would be otherwise very difficult to represent.

The figure allows one to identify changes within cohorts (change within vector) and over time (sequence of arrows by group). Here we see that high school dropouts have a lower sense of control overall but a dramatic drop in sense of control during youth that levels out as they age. College-educated respondents, in contrast, have a generally high sense of control that is continuously optimistic through adulthood, turning negative only after about age 60. Recent advances in the use of statistical graphics

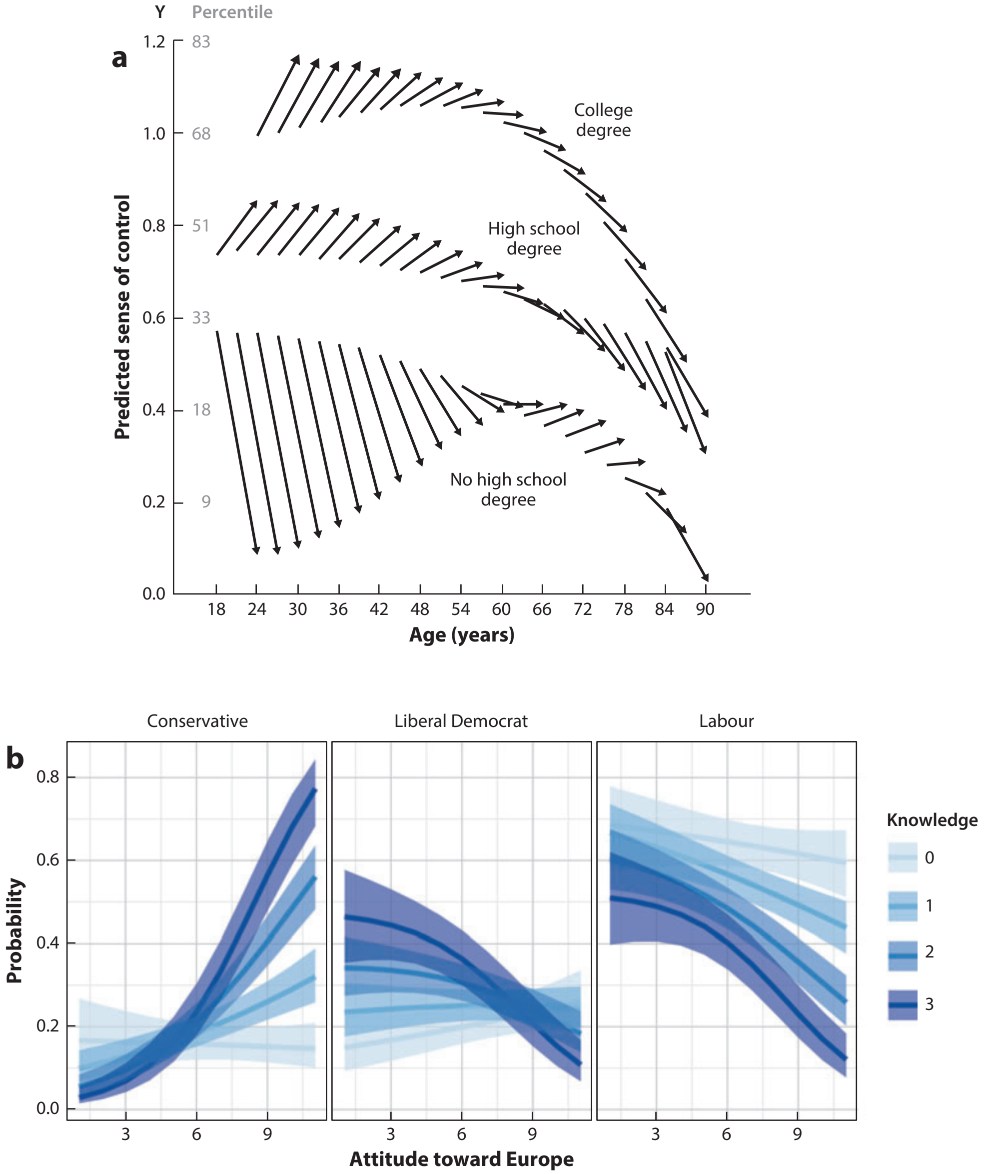


Figure 9

(*a*) Vector diagram for latent trajectory model of perceived control by age, cohort, and education (adapted from Mirowsky & Ross 2007, with permission from the University of Chicago Press). (*b*) Predicted probabilities and standard errors plotted from a multinomial model (adapted from Fox & Hong 2009).

for model interpretation include estimates of the uncertainty of the model predictions. Most software now provides easy access to model predictions from the data, and this allows one to provide results under varying scenarios (see, for example, Alkema et al. 2011). In this case, the hard work is done before the plot is made. **Figure 9*b*** shows a series of predicted probabilities from a multinomial model at different levels of various predictors and outcomes, with appropriate standard errors shown. Here no conceptual advances are needed on the

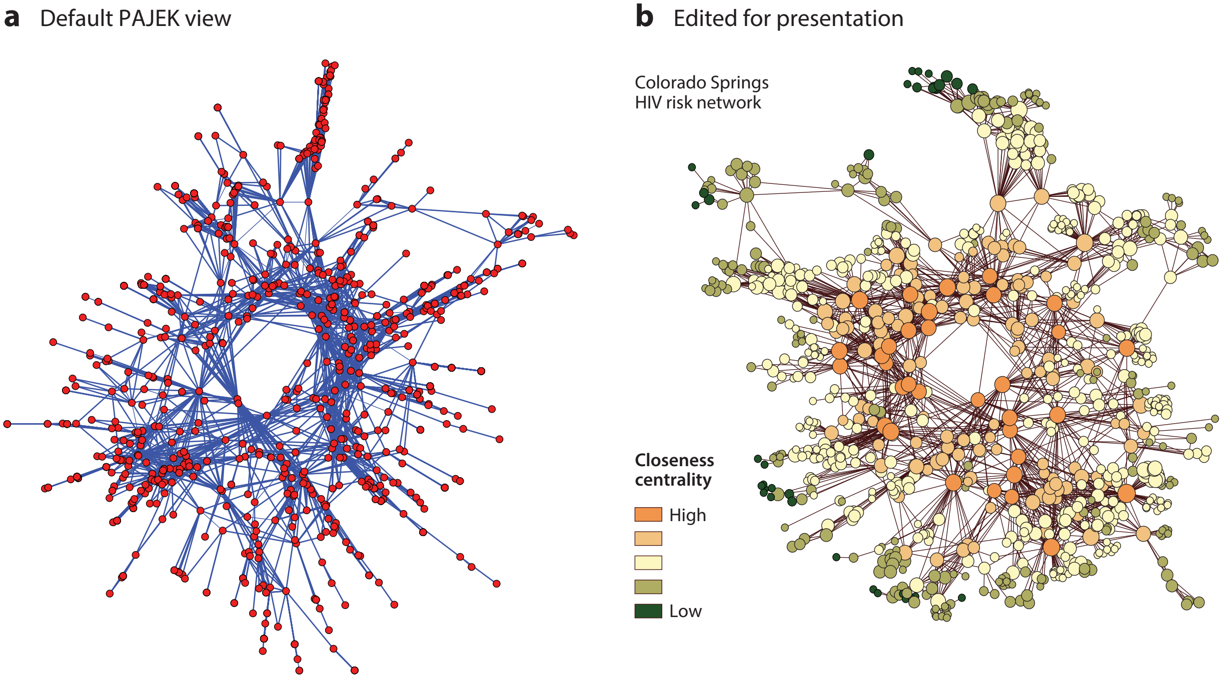


Figure 10

Network exemplar of moving between software default and presentation results. Subtle adjustments to line widths and color palettes and the addition of a centrality scale greatly aid interpretability in (*b*).

graphical side, just the ability to get information out of the model in a readily interpretable form (Fox 2003, Fox & Hong 2009).

The distance between exploratory and presentation graphics is most pronounced as the density of information necessary to display increases. Network images are particularly interesting in this case. A little effort with layering and coloring makes a real difference. Consider also **Figure 10**, which shows a before and after of the same data. The basic layout is retained (with the addition of a little jittering to alleviate algorithmically induced stacking), but the result is much more interpretable.

Recent work on constructing visually interpretable social networks has focused on careful data reduction, either by suppressing nodes entirely in favor of contour-style diagrams (Moody 2004, Moody & Light 2006) or by deleting or bundling edges to highlight structure (Crnovrsanin et al. 2014). Other work has focused explicitly on quantifying the layout model using stress or multidimensional scaling–related techniques (Frank & Yasumoto 1998, Brandes & Pich 2006, Brandes et al. 2012; see Lima 2011 for exemplars).

Our focus so far has been on presenting results to professional peers. But in recent years the clear presentation of data to broader publics has become increasingly important. It has never been easier to circulate full-color graphics of original data analysis to large groups of people. Social sharing of data through the Internet generally, but especially through services such as Facebook and Twitter, has accelerated the rise of infographics or info-visualization. To many working statisticians, infographics are the descendants of Tufte's Ducks—those "self-promoting graphics" where "the overall design purveys Graphical Style rather than quantitative information" (Tufte 1983, p. 116). The contemporary infographic in its pure form is a supercharged megaduck incorporating not only the bells and whistles derided by

Tufte but far more besides, such as a spurious quasi-narrative structure, pictographic sequencing, or excessive dynamic elements. Gelman & Unwin (2013) discuss Infovis-style work from a statistical point of view. They argue that most infographics do not meet the standards normally demanded of statistical visualizations, but they concede that sometimes the goals of the latter are not those of the former.

It seems clear, though, that information visualization tools will become ever more widespread. In keeping with our general argument that good visualization is a component of broader good practice around data analysis, a key issue is the openness of standards and tools for data analysis on the web. Social scientists have typically worked within dedicated statistical applications to produce static graphics in a format geared primarily for print publication. But there has been tremendous development over the past decade, and even just within the past five years, in tools designed to present data interactively on the web. The development of powerful libraries written in JavaScript has allowed developers to present statistical graphics in a way that is quite open with respect to both code and data. Mike Bostock's D3 library, for instance, is increasingly used by statisticians and media analysts alike and provides a powerful set of dynamic visual methods (Murray 2013). It is always difficult to know ex ante which particular software tool kits have staying power in the long run—functionally similar platforms and libraries have come and gone before—which is why static formats such as Postscript and portable document format, or PDF, are so long-lived. But even so, the leading edge of development in this area seems to be moving to further integrate specific statistical tools such as R with data formats (notably JavaScript Object Notation, or JSON) that can be presented effectively and interactively in the browser. For some kinds of data, notably the generation of dynamic choropleth maps and cartograms, the standard of presentation in some media outlets is now very high. It can be difficult to interpret complex and colorful maps with data chunked into units that vary radically by size (e.g., US counties). Nevertheless, a map such as the one shown in **Figure 11**, which appeared in the *New York Times* (Bloch & Gebeloff 2009), makes for a very engaging way to explore patterns both spatially and over time. Presenting data of this sort in an effective, interactive package is difficult for small teams of researchers to accomplish. But it is not impossible. Katz's (2013) dialect survey maps are a compelling recent example of what is now within reach. Developers seem interested in building the production of web-enabled content into the software sociologists are used to using, and thus these tools are likely to continue to become more powerful and easier to use.

For sociologists thinking about the public impact of their work, it is worth bearing in mind that, the sins of Infovis notwithstanding, a well-crafted statistical graphic is the fastest way to propagate one's findings. Moreover, it is easy to forget how revelatory the general public can find even a relatively ordinary descriptive image if it is properly constructed. The panels in **Figure 12** show two examples. **Figure 12*a*** shows the rate of deaths due to assault in 24 OECD countries between 1960 and 2011. The point of the image is to emphasize the exceptionally high death rate in the United States compared with other countries (as well as the large changes in the US number that are visible over the timeframe), and so the US series is colored separately from the rest, with every other country getting their own smoothed line and data points, but not individual colors. The unique trajectory of the United States is immediately apparent. The use of color probably helped the image circulate more widely in social media and traditional outlets than it otherwise might have. Color is not strictly necessary, however, as the superb image in **Figure 12*b*** makes clear. Taken from Kenworthy (2014), **Figure 12*b*** shows trends in life expectancy plotted against a measure of health expenditures for 20 countries. The United States is singled out with a bolder line than the others. Individual data points are not plotted. There are only seven numbers labeled on the graph (including the one in "19 other rich countries"), yet a strong argument based

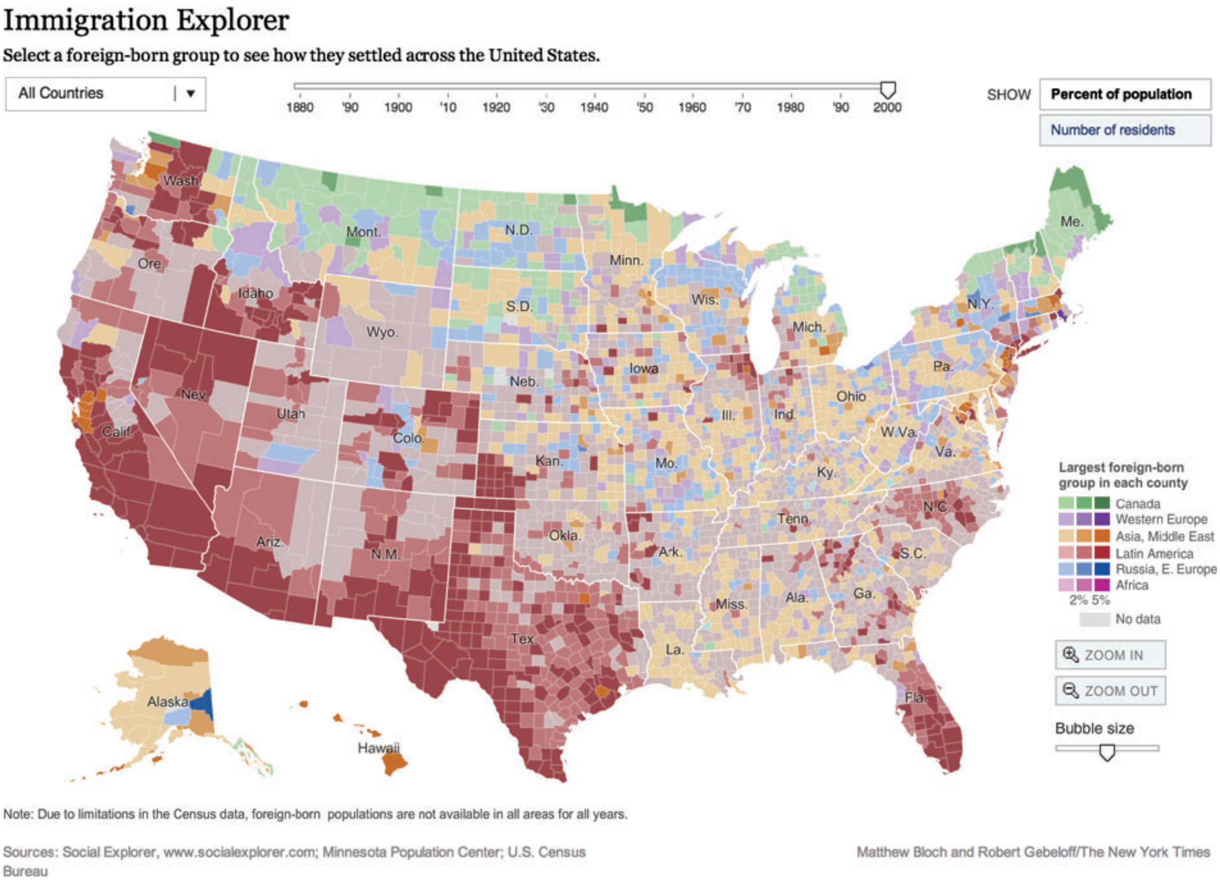


Figure 11

A *New York Times* interactive choropleth map allows users to explore historical and geographical patterns of migration to the United States (Bloch & Gebeloff 2009, adapted with permission from the *New York Times*; the interactive map is available at **http://www.nytimes.com/interactive/2009/03/10/us/20090310-immigration-explorer.html**).

on rich data is beautifully made about what has happened to the returns to health spending in the OECD generally, and in the United States in particular. In the original presentation, Kenworthy characterizes the data and measures with a compact note in the caption, specifying the methods and measures. There is nothing about this figure that is conceptually or technically new. And yet a clearly conceived and cleanly executed image like this is still relatively uncommon in the sociological literature.

Visualizations of categorical data remain more difficult to convey effectively, partly because the general public is not always familiar with conventional ways to present it. Mosaic plots, for instance, can be effective representations of contingency tables, but people are not taught to read them in the same way they can read bar charts or scatterplots. The effective visualization of network data presents similar issues. The dual problems of dimensionality and scale require creative ways to layer and aggregate information in a manner that highlights the key features of interest. In an attempt to characterize trends in political polarization in the US Senate, Moody & Mucha (2013) relied on a combination of multiple aggregation strategies and visual “identity arcs” linking individuals over time that effectively pushed “party loyalists” to the background while

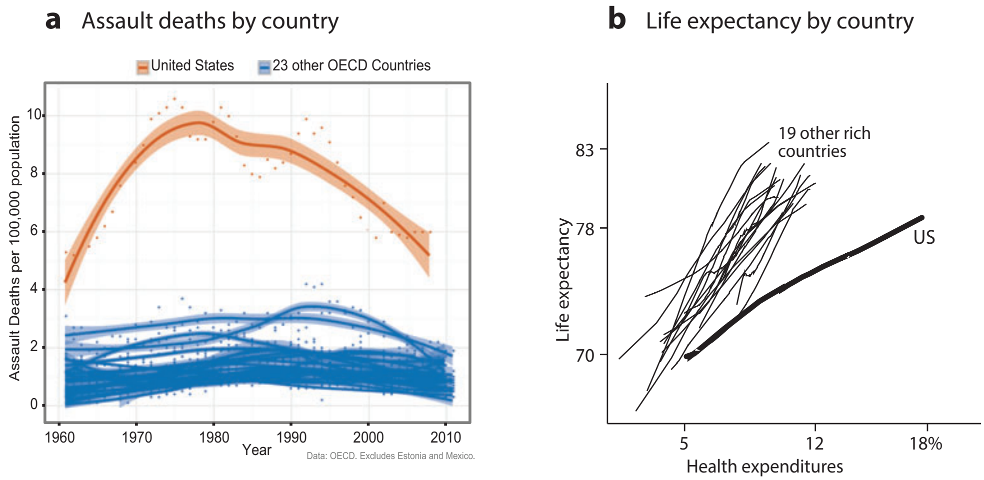


Figure 12

(*a*) Assault deaths in the United States and 23 other OECD countries (Healy 2012). (*b*) Health expenditure (as a percentage of GDP) and life expectancy in the United States and 19 other rich countries (see Kenworthy 2014; image courtesy of L. Kenworthy).

highlighting those (increasingly rare) senators who reach across the aisle (**Figure 13**).

CONCLUSION

We have argued that quantitative visualization is a core feature of social-scientific practice from start to finish. All aspects of the research process from the initial exploration of data to the effective presentation of a polished argument can benefit from good graphical habits. Good graphics are not, of course, the only thing—see Godfrey (2013) for a discussion of the situation of blind and visually impaired users of current statistical software. But the dominant trend is toward a world where the visualization of data and results is a routine part of what it means to do social science.

Getting general audiences comfortable with different kinds of data visualization is a long-term project, and not one that any particular researcher or journal editor has any meaningful control over. But given that the interpretability of statistical graphics rests on both their internal coherence as objects and the shared representational conventions they embody, a first step is to insist on good standards in the peer review process. A glance at recent issues of, say, the *American Sociological Review* shows that the standards for publishable graphical material vary wildly between and even within articles—far more than the standards for data analysis, prose, and argument. Variation is to be expected, but the absence of consistency in elements as simple as axis labeling, gridlines, or legends is striking. Just as training in elementary visualization methods should be a standard component of graduate education, our flagship journals should encourage their authors to think about the most effective ways to encourage visual clarity. This should not take the form of overly strict style guides but instead aim for an ideal of consistent, considered good judgment in the presentation of data and results in the service of sociological argument.

Effective data visualization is part of a broader shift in the social sciences where data are more easily available, code and coding tools are more widely accessible, and high-quality graphical work is easy to produce and share. We hope for professional audiences who expect to see effective graphics as a routine aspect of presented work, and we look forward to wider publics who are able to comfortably read and interpret good graphical work. Sociologists should take advantage of the remarkable

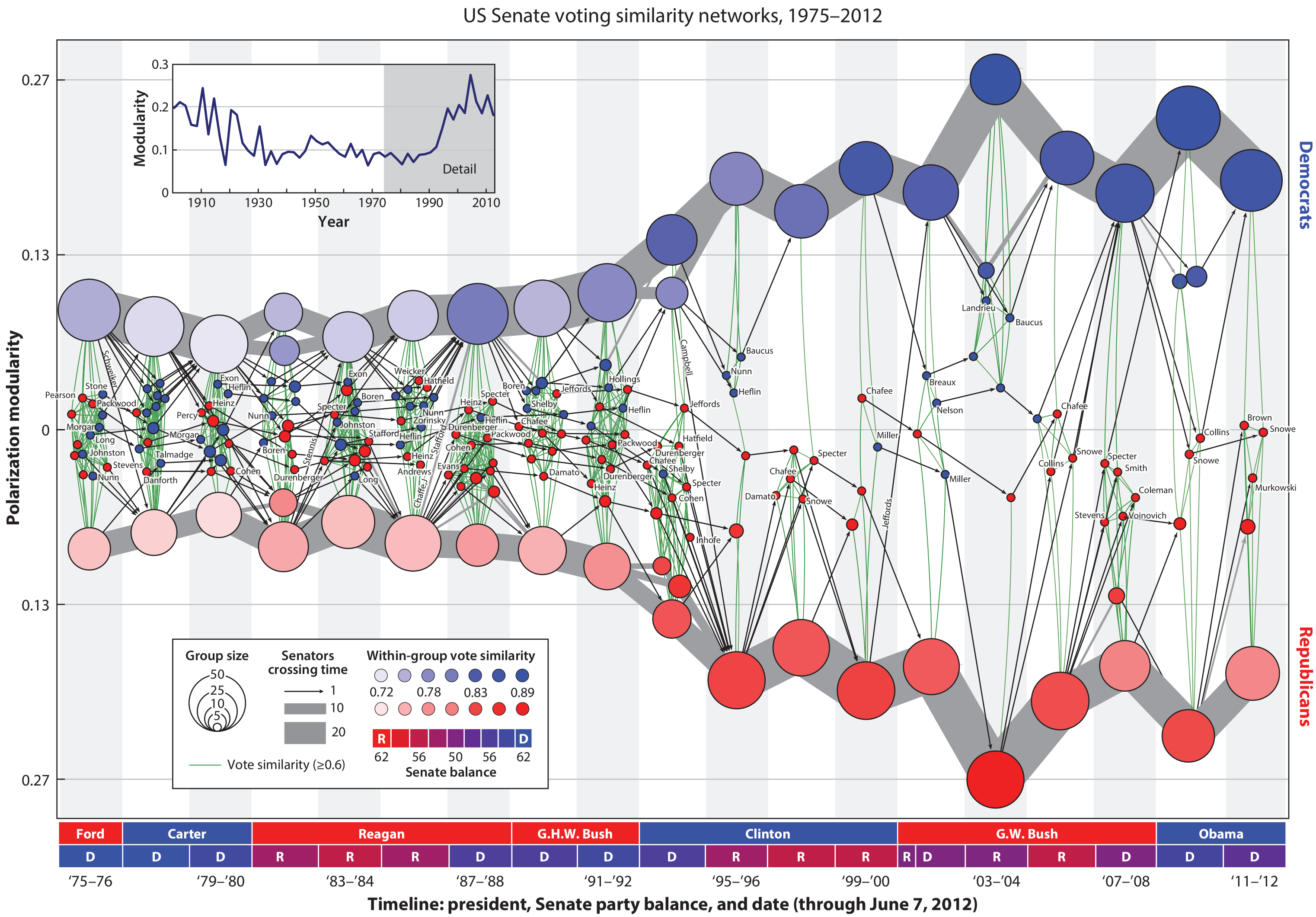


Figure 13

Aggregation and a known dimension (a polarization scale) simplify a complex network layout. (Adapted from Moody & Mucha 2013 with permission from Cambridge University Press.)

progress in methods, tools, and means to share—from statistics to computational social science to web development—the better to see the social world, and help others see it, too.

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