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BIG DATA AND SOCIAL SCIENCE

Data Science Methods and Tools for Research and Practice

SECOND EDITION

Edited by
Ian Foster, Rayid Ghani,
Ron S. Jarmin, Frauke Kreuter,
and Julia Lane

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Preface

The class on which this book is based was created in response to a very real challenge: how to introduce new ideas and methodologies about economic and social measurement into a workplace focused on producing high-quality statistics. Since the publication of the first edition, we have been fortunate to train more than 450 participants in the Applied Data Analytics classes, resulting in increased data analytics capacity, in terms of both human and technical resources. What we have learned in delivering these classes has greatly influenced the second edition. We also have added a new chapter on Bias and Fairness in Machine Learning as well as reorganized some of the chapters.

As with any book, there are many people to be thanked. The Coleridge Initiative team at New York University, the University of Maryland, and the University of Chicago have been critical in shaping the format and structure—we are particularly grateful to Clayton Hunter, Jody Derezinski Williams, Graham Henke, Jonathan Morgan, Drew Gordon, Avishek Kumar, Brian Kim, Christoph Kern, and all of the book chapter authors for their contributions to the second edition.

We also thank the critical reviewers solicited from CRC Press and everyone from whom we received revision suggestions online, in particular Stas Kolenikov, who carefully examined the first edition and suggested updates. We owe a great debt of gratitude to the copyeditor, Anna Stamm; the project manager, Arun Kumar; the editorial assistant, Vaishali Singh; the project editor, Iris Fahrer; and the publisher, Rob Calver, for their hard work and dedication.

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Ron S. Jarmin, PhD, is the deputy director at the U.S. Census Bureau. He earned a PhD in economics from the University of Oregon and has published in the areas of industrial organization, business dynamics, entrepreneurship, technology and firm performance, urban economics, Big Data, data access and statistical disclosure avoidance. He oversees the Census Bureau's large portfolio of data collection, research and dissemination activities for critical economic and social statistics including the 2020 Decennial Census of Population and Housing.

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Julia Lane, PhD, is a professor at the NYU Wagner Graduate School of Public Service. She is also an NYU Provostial Fellow for Innovation Analytics. She co-founded the Coleridge Initiative as well as UMETRICS and STAR METRICS programs at the National Science Foundation, established a data enclave at NORC/University of Chicago, and co-founded the Longitudinal Employer-Household Dynamics Program at the U.S. Census Bureau and the Linked Employer Employee Database at Statistics New Zealand. She is the author/editor of 10 books and the author of more than 70 articles in leading journals, including *Nature and Science*. She is an elected fellow of the American Association for the Advancement of Science and a fellow of the American Statistical Association.

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Chapter 1

Introduction

1.1 Why this book?

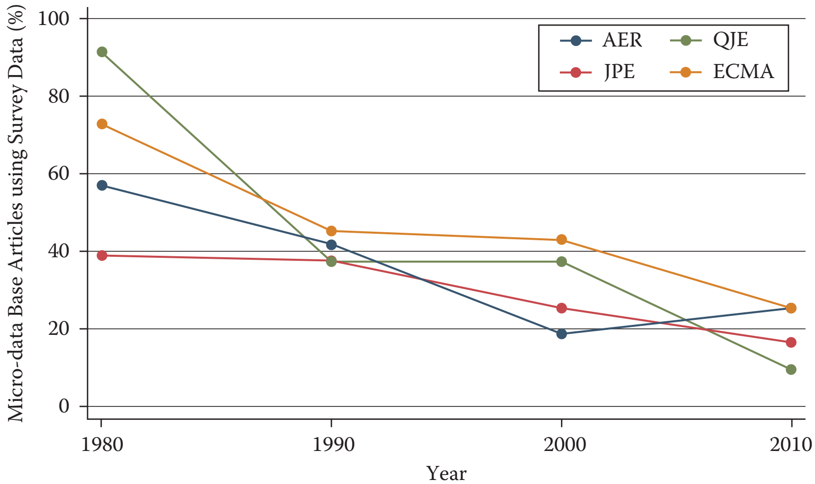
The world has changed for empirical social scientists. The new types of "big data" have generated an entire new research field—that of data science. That world is dominated by computer scientists who have generated new ways of creating and collecting data, developed new analytical techniques, and provided new ways of visualizing and presenting information. The results have been to change the nature of the work that social scientists do.

Social scientists have been enthusiastic in responding to the new opportunity. Python and R are becoming as, and hopefully more, well-known as SAS and Stata—indeed, the 2018 Nobel Laureate in Economics, Paul Romer, is a Python convert (Kopf, 2018). Research also has changed. Researchers draw on data that are "found" rather than "made" by federal agencies; those publishing in leading academic journals are much less likely today to draw on preprocessed survey data (Figure 1.1). Social science workflows can become more automated, replicable, and reproducible (Yarkoni et al., 2019).

Policy also has changed. The Foundations of Evidence-based Policy Act, which was signed into law in 2019, requires agencies to utilize evidence and data in making policy decisions (Hart, 2019). The Act, together with the Federal Data Strategy (Office of Management and Budget, 2019), establishes both Chief Data Officers to oversee the collection, use of, and access to many new types of data and a learning agenda to build the data science capacity of agency staff.

In addition, the jobs have changed. The new job title of "data scientist" is highlighted in job advertisements on CareerBuilder.com and Burningglass—supplanting the demand for statisticians, economists, and other quantitative social scientists if starting salaries are useful indicators. At the federal level, the Office of Personnel Management has created a new data scientist job title.

The goal of this book is to provide social scientists with an understanding of the key elements of this new science, the value of the



Note: "Pre-existing survey" data sets refer to micro surveys such as the CPS or SIPP and do not include surveys designed by researchers for their study. Sample excludes studies whose primary data source is from developing countries.

Figure 1.1. Use of pre-existing survey data in publications in leading journals, 1980–2010 (Chetty, 2012)

tools, and the opportunities for doing better work. The goal is also to identify the many ways in which the analytical toolkits possessed by social scientists can enhance the generalizability and usefulness of the work done by computer scientists.

We take a pragmatic approach, drawn on our experience of working with data to tackle a wide variety of policy problems. Most social scientists set out to solve a real world social or economic problem: they frame the problem, identify the data, conduct the analysis, and then draw inferences. At all points, of course, the social scientist needs to consider the ethical ramifications of their work, particularly respecting privacy and confidentiality. The book follows the same structure. We chose a particular problem—the link between research investments and innovation—because that is a major social science policy issue, and one in which social scientists have been addressing the use of big data techniques.

1.2 Defining big data and its value

There are almost as many definitions of big data as there are new types of data. One approach is to define big data as anything too big to fit onto your computer. Another approach is to define it as data with high volume, high velocity, and great variety. We choose the description adopted by the American Association of Public Opinion Research: "The term 'Big Data' is an imprecise description of a rich and complicated set of characteristics, practices, techniques, ethical issues, and outcomes all associated with data" (Japec et al., 2015).

▶ This topic will be discussed in more detail in Chapter 5.

The value of the new types of data for social science is quite substantial. Personal data have been hailed as the "new oil" of the 21st century (Greenwood et al., 2014). Policymakers have found that detailed data on human beings can be used to reduce crime (Lynch, 2018), improve health delivery (Pan et al., 2017), and better manage cities (Glaeser, 2019). Society can gain as well—much cited work shows data-driven businesses are 5% more productive and 6% more profitable than their competitors (Brynjolfsson et al., 2011). Henry Brady provides a succinct overview when he says, "Burgeoning data and innovative methods facilitate answering previously hard-to-tackle questions about society by offering new ways to form concepts from data, to do descriptive inference, to make causal inferences, and to generate predictions. They also pose challenges as social scientists must grasp the meaning of concepts and predictions generated by convoluted algorithms, weigh the relative value of prediction versus causal inference, and cope with ethical challenges as their methods, such as algorithms for mobilizing voters or determining bail, are adopted by policy makers" (Brady, 2019).

Example: New potential for social science

The billion prices project is a great example of how researchers can use new web-scraping techniques to obtain online prices from hundreds of websites and thousands of webpages to build datasets customized to fit specific measurement and research needs in ways that were unimaginable 20 years ago (Cavallo and Rigobon, 2016); other great examples include the way in which researchers use text analysis of political speeches to study political polarization (Peterson and Spirling, 2018) or of Airbnb postings to obtain new insights into racial discrimination (Edelman et al., 2017).

Of course, these new sources come with their own caveats and biases that need to be considered when drawing inferences. We will cover this later in the book in more detail.

But most interestingly, the new data can change the way we think about behavior. For example, in a study of environmental effects on health, researchers combine information on public school cafeteria deliveries with children's school health records to show that simply putting water jets in cafeterias reduced milk consumption and also reduced childhood obesity (Schwartz et al., 2016). Another study which sheds new light into the role of peers on productivity finds that the productivity of a cashier increases if they are within eyesight of a highly productive cashier but not otherwise (Mas and Moretti, 2009). Studies such as these show ways in which clever use of data can lead to greater understanding of the effects of complex environmental inputs on human behavior.

New types of data also can enable us to study and examine small groups—the tails of a distribution—in a way that is not possible with small data. Much of the interest in human behavior is driven by those tails, such as health care costs by small numbers of ill people (Stanton and Rutherford, 2006) or economic activity and employment by a small number of firms (Evans, 1987; Jovanovic, 1982).

Our excitement about the value of new types of data must be accompanied by a recognition of the lessons learned by statisticians and social scientists from their past experience with surveys and small scale data collection. The next sections provide a brief overview.

1.3 The importance of inference

It is critically important to be able to use data to generalize from the data source to the population. That requirement exists, regardless of the data source. Statisticians and social scientists have developed methodologies for survey data to overcome problems in the data-generating process. A guiding principle for survey methodologists is the total survey error framework, and statistical methods for weighting, calibration, and other forms of adjustment are commonly used to mitigate errors in the survey process. Likewise for "broken" experimental data, techniques such as propensity score adjustment and principal stratification are widely used to fix flaws in the data-generating process.

If we take a look across the social sciences, including economics, public policy, sociology, management, (parts of) psychology, and the like, their scientific activities can be grouped into three categories with three different inferential goals: Description, Causation, and Prediction.

1.3.1 Description

The job of many social scientists is to provide descriptive statements about the population of interest. These could be univariate, bivariate, or even multivariate statements.

Usually, descriptive statistics are created based on census data or sample surveys to create some summary statistics such as a mean, a median, or a graphical distribution to describe the population of interest. In the case of a census, the work ends there. With sample surveys, the point estimates come with measures of uncertainties (standard errors). The estimation of standard errors has been established for most descriptive statistics and common survey designs, even complex ones that include multiple layers of sampling and disproportional selection probabilities (Hansen et al., 1993; Valliant et al., 2018).

Example: Descriptive statistics

The Census Bureau's American Community Survey (ACS) "helps local officials, community leaders, and businesses understand the changes taking place in their communities. It is the premier source for detailed population and housing information about our nation" (https://www.census.gov/programs-surveys/acs). The summary statistics are used by planners to allocate resources—but it's important to pay attention to the standard errors, particularly for small samples. For example, in one county (Autauga) in Alabama, with a total population of about 55,000, the ACS estimates that 139 children under age 5 live in poverty—plus or minus 178! So the plausible range is somewhere between 0 and 317 (Spielman and Singleton, 2015).

Proper inference from a sample survey to the population usually depends on (1) knowing that everyone from the target population has had the chance to be included in the survey and (2) calculating the selection probability for each element in the population. The latter does not necessarily need to be known prior to sampling, but eventually a probability is assigned for each case. Obtaining correct selection probabilities is particularly important when reporting totals (Lohr, 2009). Unfortunately in practice, samples that begin as probability samples can suffer from a high rate of nonresponse. Because the survey designer cannot completely control which units respond, the set of units that ultimately respond cannot be considered to be a probability sample. Nevertheless, starting with a probability sample provides some degree of assurance that a sample will have limited coverage errors (nonzero probability of being in the sample).

1.3.2 Causation

Identifying causal relationships is another common goal for social science researchers (Varian, 2014). Ideally, such explanations stem from data that allow causal inference: typically randomized experiments or strong non-experimental study designs. When examining the effect of X on Y, knowing how cases have been selected into the sample or dataset is much less important for estimating causal effects than they are for descriptive studies, e.g., population means. What is important is that all elements of the inferential population have a chance to be selected for the treatment (Imbens and Rubin, 2015). In the debate about probability and non-probability surveys, this distinction often is overlooked. Medical researchers have operated with unknown study selection mechanisms for years, e.g, randomized trials that enroll very select samples.

Example: New data and causal inference

If the data-generating process is not understood, resources can be badly misallocated. Overreliance on, for example, Twitter data, in targeting resources after hurricanes can lead to the misallocation of resources towards young internet-savvy people with cell phones and away from elderly or impoverished neighborhoods (Shelton et al., 2014). Of course, all data collection approaches have had similar risks. Bad survey methodology is what led the *Literary Digest* to incorrectly call the 1936 election for Landon, not Roosevelt (Squire, 1988). Inadequate understanding of coverage, incentive, and quality issues, together with the lack of a comparison group, has hampered the use of administrative records—famously in the case of using administrative records on crime to make inferences about the role of death penalty policy in crime reduction (Donohue and Wolfers, 2006).

In practice, regardless of how much data are available, researchers must consider at least two things: (1) how well the results generalize to other populations (Athey and Imbens, 2017) and (2) whether the treatment effect on the treated population is different than the treatment effect on the full population of interest (Stuart, 2010). New methods to address generalizability are under development (DuGoff et al., 2014). While unknown study selection probabilities usually make it difficult to estimate population causal effects, as long as we are able to model the selection process there is no reason not to do causal inference from so-called non-probability data.

1.3.3 Prediction

Forecasting or prediction tasks. The potential for massive amounts of data to improve prediction is undeniable. However, just like the causal inference setting, it is of the utmost importance that we know the process that has generated the data, so that biases due to unknown or unobserved systematic selection can be minimized. Predictive policing is a good example of the challenges. The criminal justice system generates massive amounts of data that can be used to better allocate police resources—but if the data do not represent the population at large, the predictions could be biased and, more importantly, the interventions assigned using those predictions could harm society.

Example: Learning from the flu

"Five years ago [in 2009], a team of researchers from Google announced a remarkable achievement in one of the world's top scientific journals, *Nature*. Without needing the results of a single medical check-up, they were nevertheless able to track the spread of influenza across the US. What's more, they could do it more quickly than the Centers for Disease Control and Prevention (CDC). Google's tracking had only a day's delay, compared with the week or more it took for the CDC to assemble a picture based on reports from doctors' surgeries. Google was faster because it was tracking the outbreak by finding a correlation between what people searched for online and whether they had flu symptoms." . . .

"Four years after the original *Nature* paper was published, *Nature News* had sad tidings to convey: the latest flu outbreak had claimed an unexpected victim: Google Flu Trends. After reliably providing a swift and accurate account of flu outbreaks for several winters, the theory-free, data-rich model had lost its nose for where flu was going. Google's model pointed to a severe outbreak but when the slow-and-steady data from the CDC arrived, they showed that Google's estimates of the spread of flu-like illnesses were overstated by almost a factor of two.

The problem was that Google did not know—could not begin to know—what linked the search terms with the spread of flu. Google's engineers weren't trying to figure out what caused what. They were merely finding statistical patterns in the data. They cared about correlation rather than causation" (Harford, 2014).

1.4 The importance of understanding how data are generated

The costs of realizing the benefits of the new types of data are nontrivial. Even if data collection is cheap, the costs of cleaning, curating, standardizing, integrating, and using the new types of data are substantial. In essence, just as with data from surveys, data still need to be processed—cleaned, normalized, and variables coded—but this needs to be done at scale. But even after all of these tasks are completed, social scientists have a key role in describing the quality of the data. This role is important, because most data in the real world are noisy, inconsistent, and exhibit missing values. Data quality can be characterized in multiple ways (see Christen, 2012a; National Academies of Sciences, Engineering, and Medicine and others [2018]), such as:

► This topic will be discussed in more detail in Section 1.5.

- Accuracy: How accurate are the attribute values in the data?
- Completeness: Are the data complete?
- Consistency: How consistent are the values in and between different database(s)?
- Timeliness: How timely are the data?
- Accessibility: Are all variables available for analysis?

In the social science world, the assessment of data quality has been integral to the production of the resultant statistics. That has not necessarily been easy when assessing new types of data. A good example of the importance of understanding how data are generated arose in one of our classes a few years ago, when class participants were asked to develop employment measures for ex-offenders in the period after they were released from prison (Kreuter et al., 2019).

For people working with surveys, the definition was already preconstructed: in the Current Population Survey (CPS), respondents were asked about their work activity in the week covering the 12th of the month. Individuals were counted as employed if they had at least one hour of paid work in that week (with some exceptions for family and farm work). But the class participants were working with administrative records from the Illinois Department of Employment Security and the Illinois Department of Corrections (Kreuter et al., 2019). Those records provided a report of all jobs in every quarter that each individual held in the state; when matched to data about formerly incarcerated individuals, it could provide rich information about their employment patterns. A group of class participants produced Figure 1.2—the white boxes represent quarters in which an individual does not have a job and the blue boxes represent quarters in which an individual does have a job.

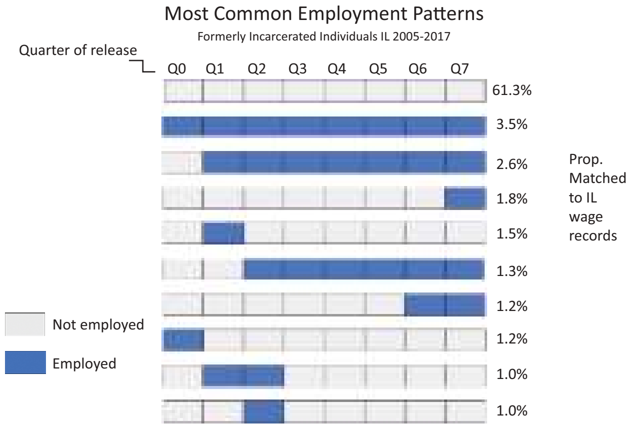


Figure 1.2. Most common employment patterns, formerly incarcerated individuals in Illinois, 2005–2017

A quick look at the results is very interesting. First, the participants present an entirely new dynamic way of looking at employment—not just the relatively static CPS measure. Second, the results are a bit shocking. More than 61% of Illinois exoffenders do not have a job in any of the eight quarters after their release. Only 3.5% have a job in all of the quarters. This is where social scientists and government analysts can contribute—because they know how the data are generated. The matches between the two agencies have been conducted on (deidentified) Social Security numbers (SSNs). It is likely that there are several gaps in those matches. First, agency staff know that the quality of SSNs in prisons is quite low, so that may be one reason for the low match rate. Second, the matches are only to Illinois jobs, and many formerly incarcerated individuals could be working across state lines (if allowed). Third, the individuals may be attending community college, or accepting social assistance, or reincarcerated. More data can be used to examine these different possibilities—but we believe this illustrates the value that social scientists and subject matter experts provide to measuring the quality issues we highlight at the beginning of this section.

1.5 New tools for new data

The new data sources that we have discussed frequently require working at scales for which the social scientist's familiar tools are