

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

---

## ***Big Data and Social Science***



---

---

# *Contents*

---

<b>List of Tables</b>	<b>7</b>
<b>List of Figures</b>	<b>9</b>
<b>Preface</b>	<b>13</b>
<b>Preface</b>	<b>13</b>
<b>1 Introduction</b>	<b>15</b>
1.1 Why this book? . . . . .	15
1.2 Defining big data and its value . . . . .	17
1.3 Social science, inference, and big data . . . . .	18
1.4 Social science, data quality, and big data . . . . .	21
1.5 New tools for new data . . . . .	23
1.6 The book’s “use case” . . . . .	24
1.7 The structure of the book . . . . .	27
1.8 Resources . . . . .	32
<b>2 Working with Web Data and APIs</b>	<b>35</b>
2.1 Introduction . . . . .	35
2.2 Scraping information from the web . . . . .	37
2.3 Application Programming Interfaces (APIs) . . . . .	44
2.4 Using an API . . . . .	47
2.5 Another example: Using the ORCID API via a wrapper . . . . .	49
2.6 Integrating data from multiple sources . . . . .	51
2.7 Summary . . . . .	52
2.8 Acknowledgements and copyright . . . . .	52
<b>3 Record Linkage</b>	<b>53</b>
3.1 Motivation . . . . .	53
3.2 Introduction to record linkage . . . . .	55
3.3 Preprocessing data for record linkage . . . . .	59
3.4 Indexing and blocking . . . . .	61
3.5 Matching . . . . .	63
3.6 Classification . . . . .	70
3.7 Record linkage and data protection . . . . .	72
3.8 Summary . . . . .	73

3.9 Resources . . . . .	74
<b>4 Databases</b>	<b>75</b>
4.1 Introduction . . . . .	75
4.2 DBMS: When and why . . . . .	76
4.3 Relational DBMSs . . . . .	82
4.4 Linking DBMSs and other tools . . . . .	95
4.5 NoSQL databases . . . . .	98
4.6 Spatial databases . . . . .	104
4.7 Which database to use? . . . . .	106
4.8 Summary . . . . .	107
4.9 Resources . . . . .	107
<b>5 Scaling up through Parallel and Distributed Computing</b>	<b>109</b>
5.1 Introduction . . . . .	109
5.2 Examples . . . . .	110
5.3 MapReduce . . . . .	111
5.4 Apache Hadoop MapReduce . . . . .	113
5.5 Other MapReduce Implementations . . . . .	121
5.6 Apache Spark . . . . .	121
5.7 Summary . . . . .	125
5.8 Resources . . . . .	125
<b>6 Information Visualization</b>	<b>127</b>
6.1 Introduction . . . . .	127
6.2 Developing effective visualizations . . . . .	128
6.3 A data-by-tasks taxonomy . . . . .	133
6.4 Challenges . . . . .	142
6.5 Summary . . . . .	144
6.6 Resources . . . . .	145
<b>7 Machine Learning</b>	<b>147</b>
7.1 Introduction . . . . .	147
7.2 What is machine learning? . . . . .	148
7.3 Methods . . . . .	152
7.4 Individual-Level Explanations . . . . .	174
7.5 Evaluation . . . . .	174
7.6 Practical tips . . . . .	181
7.7 How can social scientists benefit from machine learning? . . . . .	183
7.8 Advanced topics . . . . .	184
7.9 Summary . . . . .	185
7.10 Resources . . . . .	186
<b>8 Text Analysis</b>	<b>187</b>
8.1 Understanding human generated text . . . . .	187
8.2 How is text data different than “structured” data? . . . . .	188

<i>0.0 Contents</i>	5
8.3 What can we do with text data? . . . . .	189
8.4 How to analyze text . . . . .	193
8.5 Word Embeddings and Deep Learning . . . . .	210
8.6 Text analysis tools . . . . .	211
8.7 Summary . . . . .	213
8.8 Resources . . . . .	214
<b>9 Networks: The Basics</b>	<b>217</b>
9.1 Introduction . . . . .	217
9.2 What are networks? . . . . .	218
9.3 Structure for this chapter . . . . .	220
9.4 Turning Data into a Network . . . . .	220
9.5 Network measures . . . . .	226
9.6 Case Study: Comparing collaboration networks . . . . .	236
9.7 Summary . . . . .	240
9.8 Resources . . . . .	240
<b>10 Data Quality and Inference Errors</b>	<b>243</b>
10.1 Introduction . . . . .	243
10.2 The total error paradigm . . . . .	244
10.3 Example: Google Flu Trends . . . . .	251
10.4 Errors in data analysis . . . . .	252
10.5 Detecting and Compensating for Data Errors . . . . .	264
10.6 Summary . . . . .	268
10.7 Resources . . . . .	269
<b>11 Bias and Fairness</b>	<b>271</b>
11.1 Introduction . . . . .	271
11.2 Sources of Bias . . . . .	272
11.3 Dealing with Bias . . . . .	276
11.4 Mitigating Bias . . . . .	286
11.5 Further Considerations . . . . .	289
11.6 Fairness in Decision Making: Case Studies . . . . .	294
11.7 Aequitas - A Toolkit for Auditing Bias and Fairness in Machine Learning Models . . . . .	299
<b>12 Privacy and Confidentiality</b>	<b>311</b>
12.1 Introduction . . . . .	311
12.2 Why is access important? . . . . .	315
12.3 Providing access . . . . .	317
12.4 Non-Tabular data . . . . .	319
12.5 The new challenges . . . . .	319
12.6 Legal and ethical framework . . . . .	321
12.7 Summary . . . . .	323
12.8 Resources . . . . .	324

<b>13 Workbooks</b>	<b>327</b>
13.1 Introduction . . . . .	327
13.2 Workbook Set 1 . . . . .	328
13.3 Workbook Set 2 . . . . .	330

---

---

## ***List of Tables***

---

2.1	Popular sources of data relevant to the analysis of research outputs . . . . .	45
4.1	When to use different data management and analysis technologies . . . . .	76
4.2	Types of databases: relational (first row) and various types of NoSQL (other rows) . . . . .	81
5.1	Home Mortgage Disclosure Act data size . . . . .	123
5.2	Home Mortgage Disclosure Act data size . . . . .	124
8.1	. . . . .	189
8.2	Wikipedia articles as potential labels generated by <i>n</i> -gram indexing of NSF awards . . . . .	202
9.2	Descriptive statistics for the main components of two university networks . . . . .	239
10.1	Positive predictive value (%) for rare subgroups, high specificity, and perfect sensitivity . . . . .	259
11.1	COMPAS Fairness Metrics . . . . .	295
11.2	<i>FDR</i> Values By Skin Tone and Predicted Gender (F = Female, M = Male, D = Dark Skin, L = Light Skin) . . . . .	296



---

---

## *List of Figures*

---

1.1	Use of pre-existing survey data in publications in leading journals, 1980–2010 (@Chetty2012) . . . . .	16
1.2	A visualization of the complex links between what and who is funded, and the results; tracing the direct link between funding and results is misleading and wrong . . . . .	26
1.3	The data science project workflow. Blue represents each step in the project, orange represents the tools used in that step, and green represents the methods for analysis. . . . .	28
1.4	The four chapters of Part I focus on *data capture* and *curation* . . . . .	29
1.5	The four chapters in Part II focus on data *modeling* and *analysis* . . . . .	31
1.6	The four chapters in Part III focus on *inference* and *ethics* . . . . .	32
2.1	Source HTML from the portion of an HHMI results page containing information on HHMI investigators; note that the web-scraping results in badly formatted html which is difficult to read. . . . .	39
3.1	The preprocessing pipeline . . . . .	58
3.2	Probabilistic (left) vs. machine learning (right) approaches to linking. Source: Köpcke et al. [@kopcke2010evaluation] . . . . .	69
4.1	A research project may use a NoSQL database to accumulate large amounts of data from many different sources, and then extract selected subsets to a relational or other database for more structured processing . . . . .	82
4.2	CSV files representing grants and investigators. Each line in the first table specifies a grant number, investigator name, total funding amount, and NSF program name; each line in the second gives an investigator name, institution name, and investigator email address . . . . .	83

4.3 Relational tables ‘Grants’ and ‘Investigators’ corresponding to the grants.csv and investigators.csv data in Figure 4.2, respectively. The only differences are the representation in a tabular form, the introduction of a unique numerical investigator identifier (‘ID’) in the ‘Investigators’ table, and the substitution of that identifier for the investigator name in the ‘Grants’ table . . . . .	84
4.4 Three types of *join* illustrated: the inner join, as used in Section 4.3.2, the left join, and left excluding join . . . . .	105
5.1 Top: The traditional parallel computing model where data are brought to the computing nodes. Bottom: Hadoop’s parallel computing model: bringing compute to the data [@HadoopParallelModel] . . . . .	114
5.2 Data transfer and communication of a MapReduce job in Hadoop. Data blocks are assigned to several maps, which emit key-value pairs that are shuffled and sorted in parallel. The reduce step emits one or more pairs, with results stored on the HDFS . . . . .	118
6.1 Anscombes quartet [@anscombe1973graphs] . . . . .	128
6.2 A data analysis browser of a selection of grants from the US Department of Agriculture was created by using the web-based tool Keshif . . . . .	130
6.3 Charting interface of Tableau . . . . .	130
6.4 A treemap visualization of agency and sub-agency spending breakdown . . . . .	131
6.5 Visual elements described by MacKinlay [@mackinlay1986automating] . . . . .	132
6.6 The US Cancer Atlas [@usca]. Interface based on [@maceachren2008design] . . . . .	136
6.7 Horizon graphs used to display time series . . . . .	137
6.8 EventFlow ( <a href="http://www.cs.umd.edu/hcil/eventflow">www.cs.umd.edu/hcil/eventflow</a> ) is used to visualize sequences of innovation activities by Illinois companies. Created with EventFlow; data sources include NIH, NSF, USPTO, SBIR. Image created by C. Scott Dempwolf, used with permission . .	137
6.9 SpaceTree ( <a href="http://www.cs.umd.edu/hcil/spacetree/">www.cs.umd.edu/hcil/spacetree/</a> ) . . . . .	139
6.10 The Finviz treemap helps users monitor the stock market ( <a href="http://www.finviz.com">www.finviz.com</a> ) . . . . .	139
6.11 NodeXL showing innovation networks of the Great Lakes manufacturing region. Created with NodeXL. Data source: USPTO. Image created by C. Scott Dempwolf, used with permission . .	140
6.12 An example from “Maps of Science: Forecasting Large Trends in Science,” 2007, The Regents of the University of California, all rights reserved [@borner2010atlas] . . . . .	141
6.13 Jigsaw used to explore a collection of car reviews . . . . .	142

7.1	Spectrum of machine learning methods from unsupervised to supervised learning . . . . .	151
7.2	Example of $k$ -means clustering with $k = 3$ . The upper left panel shows the distribution of the data and the three starting points $m_1, m_2, m_3$ placed at random. On the upper right we see what happens in the first iteration. The cluster means move to more central positions in their respective clusters. The lower left panel shows the second iteration. After six iterations the cluster means have converged to their final destinations and the result is shown in the lower right panel . . . . .	156
7.3	The same data set can produce drastically different clusters: (a) $k$ -means; (b) spectral clustering . . . . .	158
7.4	Example of $k$ -nearest neighbor with $k = 1, 3, 5$ neighbors. We want to predict the points A and B. The 1-nearest neighbor for both points is red ("Patent not granted"), the 3-nearest neighbor predicts point A (B) to be red (green) with probability $2/3$ , and the 5-nearest neighbor predicts again both points to be red with probabilities $4/5$ and $3/5$ , respectively. . . . .	162
7.5	Support vector machines . . . . .	163
7.6	An exemplary decision tree. The top figure is the standard representation for trees. The bottom figure offers an alternative view of the same tree. The feature space is partitioned into numerous rectangles, which is another way to view a tree, representing its nonlinear character more explicitly . . . . .	165
7.7	Validation methodologies: holdout set and cross-validation . .	176
7.8	Temporal validation . . . . .	176
7.9	A *confusion matrix* created from real-valued predictions . .	178
7.10	Precision-recall curve . . . . .	180
7.11	Precision or recall at different thresholds . . . . .	180
8.1	Topics are distributions over words. Here are three example topics learned by latent Dirichlet allocation from a model with 50 topics discovered from the *New York Times* [@sandhaus-08]. Topic 1 seems to be about technology, Topic 2 about business, and Topic 3 about the arts . . . . .	205
8.2	Allocations of documents to topics . . . . .	205
8.3	Each word is associated with a topic. Gibbs sampling inference iteratively resamples the topic assignments for each word to discover the most likely topic assignments that explain the document collection . . . . .	206
9.1	Undirected, binary, one-mode network data . . . . .	222
9.2	Directed, valued, one-mode network data . . . . .	223
9.3	Two-mode affiliation data . . . . .	224
9.4	Reachability and indirect ties . . . . .	227

9.5 Histogram of path lengths for university A employee network . . . . .	231
9.6 The main component of two university networks . . . . .	237
9.7 Degree distribution for two universities . . . . .	238
9.8 Distribution of path lengths for universities A and B . . . . .	240
10.1 A typical rectangular data file format . . . . .	246
10.2 An illustration of coincidental correlation between two variables: stork die-off linked to human birth decline [@sies1988new] . . . . .	253
10.3 Correlation as a function of sample size . . . . .	261
10.4 Correlation as a function of sample size . . . . .	262
10.5 Regression of *y* on *x* with and without variable error. On the left is the population regression with no error in the *x* variable. On the right, variable error was added to the *x*-values with a reliability ratio of 0.73. Note its attenuated slope, which is very near the theoretical value of 0.77 . . . . .	263
10.6 Comparison of tableplots for the Dutch Structural Business Statistics Survey for five variables before and after editing. Row bins with high missing and unknown numeric values are represented by lighter colored bars . . . . .	266
11.1 Example of Tays offensive output . . . . .	299
11.2 ML pipeline . . . . .	301
11.3 Data exploration screenshot from the Aequitas tutorial . . . . .	303
12.1 The privacy–utility tradeoff . . . . .	312

---

## **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. We are deeply grateful for the inspiration and support of Census Bureau Director John Thompson and Deputy Director Nancy Potok in designing and implementing the initial class content and structure.

As with any book, there are many people to be thanked. We are grateful to the over 450 participants in the Applied Data Analytics classes that have been delivered over the past three years. The Coleridge Initiative team at New York University, the University of Maryland and the University of Chicago were 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, and Brian Kim.

We are also grateful to the students of three “Big Data for Federal Statistics” classes in which we piloted the first edition of this book, and to the instructors and speakers beyond those who contributed as authors to this edited volume—Dan Black, Nick Collier, Alex Engler, Ophir Frieder, Lee Giles, Bob Goerge, Laure Haak, Madian Khabsa, Jonathan Ozik, Ben Schneiderman, and Abe Usher. The book would not exist without them.

We thank Trent Buskirk, Davon Clarke, Chase Coleman, Stephanie Eckman, Matt Gee, Laurel Haak, Jen Helsby, Madian Khabsa, Ulrich Kohler, Charlotte Oslund, Rod Little, Arnaud Sahuguet, Tim Savage, Severin Thaler, and Joe Walsh for their helpful comments on drafts of this material. In particular we thank Stas Kolenikov for a very detailed review of the first edition.

We also owe a great debt to the copyeditor, Richard Leigh; the project editor, Charlotte Byrnes; and the publisher, Rob Calver, for their hard work and dedication.



# 1

---

## *Introduction*

---

This section provides a brief overview of the goals and structure of the book.

---

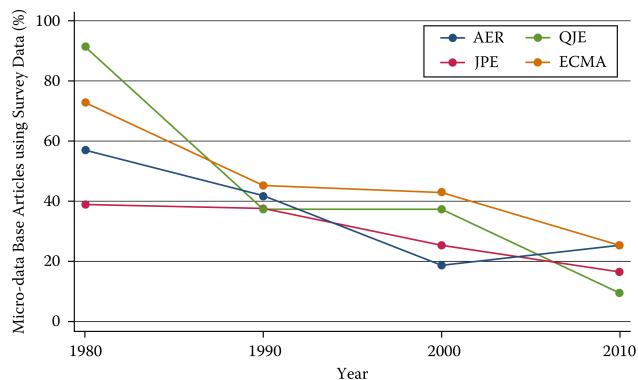
### **1.1 Why this book?**

The world has changed for empirical social scientists. The new types of data, methods, and tools have generated an entire new research field—that of data science. That world has traditionally been dominated by computer scientists who have generated new ways of creating and collecting data, developed (or rebranded) new analytical and statistical techniques, and provided new ways of visualizing and presenting information. These new sources of data and techniques have the potential to transform the way applied social science is done.

Research has certainly 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).

The way in which data are used has also changed for both government agencies and businesses. Chief data officers are becoming as common in federal and state governments as chief economists were decades ago, and in cities like New York and Chicago, mayoral offices of data analytics have the ability to provide rapid answers to important policy questions (Lee et al. 2012). But since federal, state, and local agencies often lack the capacity to do such analysis themselves (Alawadhi et al. 2012), they must make these data available either to consultants or to the research community. Businesses are also learning that making effective use of their data assets can have an impact on their bottom line (Brynjolfsson, Hitt, and Kim 2011).

And the jobs have changed. The new job title of “data scientist” is highlighted in job advertisements on CareerBuilder.com and Burning-glass.com—in the same category as statisticians, economists, and other quantitative social scientists if starting salaries are useful indicators.



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 (@Chetty2012)

The goal of this book is to provide social scientists with an understanding of the key elements of this new science, its value, and the opportunities for using it to improve their work. The goal is also to identify the many ways in which the analytical toolkits possessed by social scientists can inform data science research and result in new methods needed for social science research.

We take a pragmatic approach, drawing on our experience of working with data in a variety of real-world contexts. Most social scientists set out to solve a real-world social or economic problem: they frame the problem, identify the data, do 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 using big data techniques. While the example is specific and intended to show how abstract concepts apply in practice, the approach is completely generalizable to other important areas such as criminal justice, education, public health, sustainability, economic development, and workforce development. The web scraping, linkage, classification, and text analysis methods on display here are canonical in nature. The inference and privacy and confidentiality issues are no different than in any other study involving human subjects, and the communication of results through visualization is similarly generalizable.

## 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*<sup>1</sup>. Another approach is to define it as data with high volume, high velocity, and great variety. Our aim is not to create yet another definition. Instead , we choose the pragmatic 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).

While the term “big data” may be a buzzword, what’s real is the significant value of new types of data and new methods for social science. Personal data has been hailed as the “new oil” of the twenty-first century, and the benefits to policy, society, and public opinion research are undeniable (Greenwood et al. 2014). Policymakers have found that detailed data on human beings can be used to reduce crime, improve health delivery, and manage cities better (Keller, Koonin, and Shipp 2012). The scope is broad indeed: one of this book’s editors has used such data to not only help win political campaigns but also show its potential for social good and public policy. For public opinion research, social scientists can increase the scope of their data collection efforts while at the same time reducing costs and respondent burden, increasing timeliness, and increasing precision(Murphy et al. 2014). Society can gain as well—recent work shows data-driven businesses were 5% more productive and 6% more profitable than their competitors(Brynjolfsson, Hitt, and Kim 2011). In short, the vision is that social science researchers can potentially, by using new types of data and methods,increase the quality and impact of their work.

---

### Example: New data enable new analyses

Spotshotter data, which have fairly detailed information for each gunfire incident, such as the precise timestamp and the nearest address, as well as the type of shot, can be used to improve crime data (Carr and Doleac 2015); Twitter data can be used to improve understanding and predictions around job loss, job gain, and job postings (Antenucci et al. 2014); and eBay postings can be used to estimate demand elasticities (Einav and Levin 2013). 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.

---

<sup>1</sup>This topic is discussed in more detail in Chapter 5

But most interestingly, the new data can change the way we think about measuring and making inferences about behavior. For example, it enables the capture of information on the subject's entire environment—thus, for example, the effect of fast food caloric labeling in health interventions (Elbel, Gyamfi, and Kersh 2011); the productivity of a cashier if he is within eyesight of a highly productive cashier but not otherwise (Mas and Moretti 2009). So it offers the potential to understand the effects of complex environmental inputs on human behavior. In addition, more data enables us to study the tails of a distribution in a way that is not possible with small data. Much of interest in human behavior is driven by the tails of the distribution—health care costs by small numbers of ill people (Stanton and Rutherford 2006), economic activity and employment by a small number of firms (Evans 1987; Decker et al. to appear)—and is impossible to study with the small sample sizes available to researchers.

At the same time, we still face the same challenges and responsibilities as we did before in the survey and small data collection environment. Indeed, social scientists have a great deal to offer to a (data) world that is currently looking to computer scientists to provide answers. Two major areas to which social scientists can contribute, based on decades of experience and work with end users, are inference and attention to data quality.

---

### 1.3 Social science, inference, and big data

The goal of empirical social science is to make inferences about a population from available data. That requirement exists regardless of the data source—and is a guiding principle for this book. For probability-based survey data, methodology has been developed 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 adjustments are commonly used to mitigate errors in the survey process. Likewise for “broken” experimental data, techniques like propensity score adjustment and principal stratification are widely used to fix flaws in the data generating process (Imbens and Rubin 2015). Two books provide frameworks for *survey quality*<sup>2</sup> (Groves 2004; Biemer and Lyberg 2003).

Across the social sciences, including economics, public policy, sociology, management, (parts of) psychology and the like, we can identify three categories of analysis with three different inferential goals: description, causation, and prediction.

---

<sup>2</sup>This topic is discussed in more detail in Chapter 10.

## 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. Machine Learning on machine learning will cover methods that go beyond simple descriptive statistics, known as *unsupervised learning* Methods that include cluster analysis.

Descriptive statistics are usually created based on census data or sample surveys to generate some summary statistics like a mean, median, or a graphical distribution to describe the population of interest. In the case of a census, the work ends right there. With sample surveys the point estimates come with measures of uncertainties (standard errors). The estimation of standard errors has been worked out for most descriptive statistics and most common survey designs, even complex ones that include multiple layers of sampling and disproportional selection probabilities (Hansen, Hurwitz, and Madow 1993; Valliant, Dever, and Kreuter 2013).

---

### Example: Descriptive statistics

The US Bureau of Labor Statistics surveys about 60,000 households a month and from that survey is able to describe national employment and unemployment levels. For example, in November 2015, total nonfarm payroll employment increased by 211,000 in November, and the unemployment rate was unchanged at 5.0%. Job gains occurred in construction, professional and technical services, and health care. Mining and information lost jobs (Bureau of Labor Statistics 2015).

---

Proper inference, even for purely descriptive purposes, from a sample to the population rests usually on knowing that everyone from the target population had the chance to be included in the survey, and knowing 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. Getting the selection probabilities right is particularly important when reporting totals (Lohr 2009). Unfortunately in practice, samples that start out 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 (Meyer, Mok, and Sullivan 2015). Nevertheless, starting with a probability sample provides some degree of comfort that a sample will have limited coverage errors (nonzero probability of being in the sample), and there are methods for dealing with a variety of missing data problems (Little and Rubin 2014).

## Causation

In many cases, social scientists wish to test hypotheses, often originating in theory, about relationships between phenomena of interest. Ideally such tests stem from data that allow causal inference: typically randomized experiments or strong nonexperimental study designs. When examining the effect of  $X$  on  $Y$ , knowing how cases were selected into the sample or data set is much less important in the estimation of causal effects than for descriptive studies, for example, population means. What is important is that all elements of the inferential population have a chance of being selected for the treatment (Imbens and Rubin 2015). In the debate about probability and nonprobability surveys, this distinction is often overlooked. Medical researchers have operated with unknown study selection mechanisms for years: for example, randomized trials that enroll only selected samples.

---

### Example: New data and causal inference

One of the major risks with using big data without thinking about the data source is the misallocation of resources. Overreliance on, say, 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 led the *Literary Digest* to incorrectly call the 1936 election (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 inference about the role of death penalty policy in crime reduction (Donohue III and Wolfers 2006).

---

Of course, in practice it is difficult to ensure that results are generalizable, and there is always a concern that the treatment effect on the treated is different than the treatment effect in the full population of interest (Stuart 2010). Having unknown study selection probabilities makes it even more difficult to estimate population causal effects, but substantial progress is being made (DuGoff, Schuler, and Stuart 2014; Morgan and Winship 2014). As long as we are able to model the selection process, there is no reason not to do causal inference from so-called nonprobability data.

### Prediction

Forecasting or prediction tasks are a little less common among applied social science researchers as a whole, but are certainly an important element for users of official statistics—in particular, in the context of social and economic indicators—as generally for decision and policy makers in government and business. Here, similar to the causal inference setting, it is of utmost importance

that we do know the process that generated the data, and we can rule out any unknown or unobserved systematic selection mechanism.

---

### 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 Social science, data quality, and big data

Most data in the real world are noisy, inconsistent, and suffers from missing values, regardless of its source. Even if data collection is cheap, the costs of creating high-quality data from the source – *cleaning, curating, standardizing, and integrating*<sup>3</sup> – are substantial.

Data quality can be characterized in multiple ways (Christen 2012b):

---

<sup>3</sup>This topic is discussed in more detail in Chapter 3.

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

Social scientists have decades of experience in transforming messy, noisy, and unstructured data into a well-defined, clearly structured, and quality-tested data set. Preprocessing is a complex and time-consuming process because it is “hands-on”—it requires judgment and cannot be completely automated. It is difficult to overstate the value of preprocessing for any data analysis, but this is particularly true in new types of data that are becoming available. Data need to be parsed, standardized, deduplicated, and normalized.

**Parsing** is a fundamental step taken regardless of the data source, and refers to the decomposition of a complex variable into components. For example, a freeform address field like “1234 E 56th St” might be broken down into a street number “1234” and a street name “E 56th St.” The street name could be broken down further to extract the cardinal direction “E” and the designation “St.” Another example would be a combined full name field that takes the form of a comma-separated last name, first name, and middle initial as in “Miller, David A.” Splitting these identifiers into components permits the creation of more refined variables that can be used in the matching step.

In the simplest case, the distinct parts of a character field are delimited. In the name field example, it would be easy to create the separate fields “Miller” and “David A” by splitting the original field at the comma. In more complex cases, special code will have to be written to parse the field. Typical steps in a parsing procedure include:

1. Splitting fields into tokens (words) on the basis of delimiters,
2. Standardizing tokens by lookup tables and substitution by a standard form,
3. Categorizing tokens,
4. Identifying a pattern of anchors, tokens, and delimiters,
5. Calling subroutines according to the identified pattern, therein mapping of tokens to the predefined components.

**Standardization** refers to the process of simplifying data by replacing variant representations of the same underlying observation by a default value in order to improve the accuracy of field comparisons. For example, “First Street” and

“1st St” are two ways of writing the same street name, but a simple string comparison of these values will return a poor result. By standardizing fields—and using the same standardization rules across files!—the number of true matches that are wrongly classified as nonmatches (i.e., the number of false nonmatches) can be reduced.

Some common examples of standardization are:

- Standardization of different spellings of frequently occurring words: for example, replacing common abbreviations in street names (Ave, St, etc.) or titles (Ms, Dr, etc.) with a common form. These kinds of rules are highly country- and language-specific.
- General standardization, including converting character fields to all uppercase and removing punctuation and digits.

**Deduplication** consists of removing redundant records from a single list, that is, multiple records from the same list that refer to the same underlying entity. After deduplication, each record in the first list will have at most one true match in the second list and vice versa. This simplifies the record linkage process and is necessary if the goal of record linkage is to find the best set of one-to-one links (as opposed to a list of all possible links). One can deduplicate a list by applying record linkage techniques described in this chapter to link a file to itself.

**Normalization** is the process of ensuring that the fields that are being compared across files are as similar as possible in the sense that they could have been generated by the same process. At minimum, the same standardization rules should be applied to both files. For additional examples, consider a salary field in a survey. There are number different ways that salary could be recorded: it might be truncated as a privacy-preserving measure or rounded to the nearest thousand, and missing values could be imputed with the mean or with zero. During normalization we take note of exactly how fields are recorded.

---

## 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 not designed. Fortunately, the wider research and data analytics community has developed a wide variety of often more scalable and flexible tools—tools that we will introduce within this book.

Relational database management systems (DBMSs)<sup>4</sup> are used throughout business as well as the sciences to organize, process, and search large collections of structured data. NoSQL DBMSs are used for data that is extremely large and/or unstructured, such as collections of web pages, social media data (e.g., Twitter messages), sensor data, and clinical notes. Extensions to these systems and also specialized single-purpose DBMSs provide support for data types that are not easily handled in statistical packages such as geospatial data, networks, and graphs.

Open source programming languages such as Python (used extensively throughout this book) and R provide high-quality implementations of numerous data analysis and visualization methods, from regression to statistics, text analysis, network analysis, and much more. Finally, parallel computing platforms such as Hadoop and Spark can be used to harness parallel computer clusters for extremely large data sets and computationally intensive analyses.

These various components may not always work together as smoothly as do integrated packages such as SAS, SPSS, and Stata, but they allow researchers to take on problems of greater scale and complexity. Furthermore, they are developing at a tremendous rate as the result of work by thousands of people worldwide. For these reasons, the modern social scientist needs to be familiar with their capabilities.

---

## 1.6 The book’s “use case”

This book is about the uses of big data in social science. Our focus is on working through the use of data as a social scientist normally approaches research. That involves thinking through how to use such data to address a question from beginning to end, and thereby learning about the associated tools—rather than simply engaging in coding exercises and then thinking about how to apply them to a potpourri of social science examples.

There are many examples of the use of big data in social science Research. The chapters in the book draw heavily on a use case based on one of the first large-scale big data social science data infrastructures. This infrastructure, based on UMETRICS<sup>5</sup> data housed at the University of Michigan’s Institute for Research on Innovation and Science (IRIS)<sup>6</sup> and enhanced with data from the US Census Bureau, provides a new quantitative analysis and understanding

---

<sup>4</sup>This topic is discussed in more detail in Chapter 4.

<sup>5</sup>UMETRICS: Universities Measuring the Impact of Research on Innovation and Science (Lane et al. 2015)

<sup>6</sup>[iris.isr.umich.edu](http://iris.isr.umich.edu)

of science policy based on large-scale computational analysis of new types of data.

The infrastructure was developed in response to a call from the President's Science Advisor (Jack Marburger) for a *science of science policy* (Marburger 2005). He wanted a scientific response to the questions that he was asked about the impact of investments in science.

---

### Example: The Science of Science Policy

Marburger wrote (Marburger 2005): "How much should a nation spend on science? What kind of science? How much from private versus public sectors? Does demand for funding by potential science performers imply a shortage of funding or a surfeit of performers? These and related science policy questions tend to be asked and answered today in a highly visible advocacy context that makes assumptions that are deserving of closer scrutiny. A new 'science of science policy' is emerging, and it may offer more compelling guidance for policy decisions and for more credible advocacy. ...

"Relating R&D to innovation in any but a general way is a tall order, but not a hopeless one. We need econometric models that encompass enough variables in a sufficient number of countries to produce reasonable simulations of the effect of specific policy choices. This need won't be satisfied by a few grants or workshops, but demands the attention of a specialist scholarly community. As more economists and social scientists turn to these issues, the effectiveness of science policy will grow, and of science advocacy too."

---

Responding to this policy imperative is a tall order, because it involves using all the social science and computer science tools available to researchers. The new digital technologies can be used to capture the links between the inputs into research, the way in which those inputs are organized, and the subsequent outputs (Weinberg et al. 2014; Zolas et al. 2015). The social science questions that are addressable with this data infrastructure include the effect of research training on the placement and earnings of doctoral recipients, how university trained scientists and engineers affect the productivity of the firms they work for, and the return on investments in research. Figure 1.2 provides an abstract representation of the empirical approach that is needed: data about grants, the people who are funded on grants, and the subsequent scientific and economic activities.

First, data must be captured on what is funded, and since the data are in text format, computational linguistics tools must be applied (Text Analysis). Second, data must be captured on who is funded, and how they interact in teams, so network tools and analysis must be used (Networks: The Basics).

Third, information about the type of results must be gleaned from the web and other sources (Working with Web Data and APIs).

Finally, the disparate complex data sets need to be stored in databases (Databases), integrated (Record Linkage), analyzed (Machine Learning), and used to make inferences ([Errors and Inference]).



**FIGURE 1.2** A visualization of the complex links between what and who is funded, and the results; tracing the direct link between funding and results is misleading and wrong

The use case serves as the thread that ties many of the ideas together. Rather than asking the reader to learn how to code “hello world,” we build on data that have been put together to answer a real-world question, and provide explicit examples based on that data. We then provide examples that show how the approach generalizes.

For example, the text analysis chapter (Text Analysis) shows how to use natural language processing to describe *what* research is being done, using proposal and award text to identify the research topics in a portfolio (Talley et al. 2011; Evans and Foster 2011). But then it also shows how the approach can be used to address a problem that is not just limited to science policy—the conversion of massive amounts of knowledge that is stored in text to usable information.

Similarly, the network analysis chapter (Networks: The Basics) gives specific examples using the UMETRICS data and shows how such data can be used to create new units of analysis—the networks of researchers who do science, and the networks of vendors who supply research inputs. It also shows how networks can be used to study a wide variety of other social science questions.

In another example, we use APIs<sup>7</sup> provided by publishers to describe the results generated by research funding in terms of publications and other measures of scientific impact, but also provide code that can be repurposed for many similar APIs.

And, of course, since all these new types of data are provided in a variety of different formats, some of which are quite large (or voluminous), and with a variety of different timestamps (or velocity), we discuss how to store the data in different types of data formats.

**BOX \*\* Additional Examples\*\***

The methods covered in this book are broadly applicable across a variety of policy areas including health, education, criminal justice, sustainability, workforce development, social services, public safety, and urban infrastructure. These methods have been used to build systems to improve the understanding of critical questions such as: - ‘Which individuals graduating from four year colleges are at risk of being long-term unemployed and which education and training programs improve their earnings and employment outcomes?’

- ‘Which ex-offenders are likely to go back to prison and can proactive outreach to connect them with health and social services reduce their risk of recidivism and improve their outcomes?’, and
- ‘How do regulatory agencies move from reactive, complaint-based, health and safety inspections for workplaces and housing to a more proactive approach that focuses on prevention?’

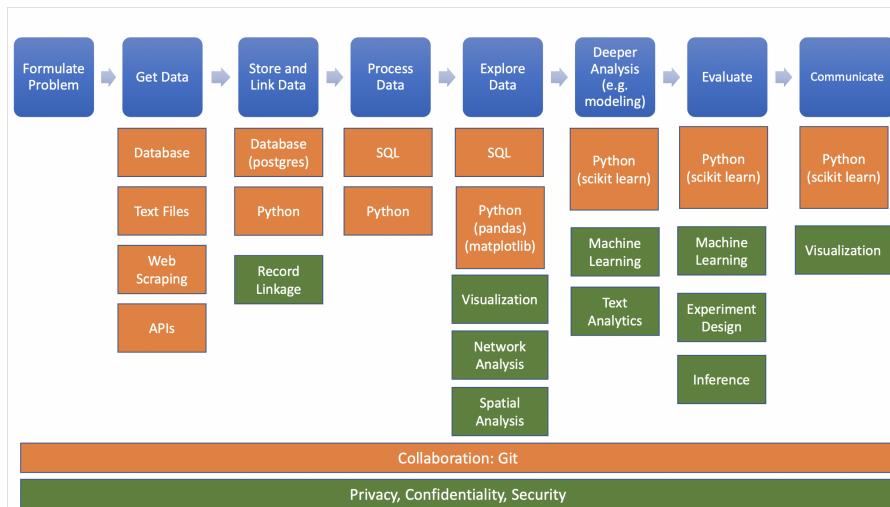
**BOX**

## 1.7 The structure of the book

We organize the book in three parts, based around the way social scientists approach doing research. The first set of chapters addresses the new ways to capture, curate, and store data. The second set of chapters describes what tools are available to process and analyze data. The last set deals with the appropriate handling of data on individuals and organizations as well as what inferences can be drawn from the data and the analysis that was done. Of course, we assume that before starting with the data and analysis, we have spent time on formulating the problem or question that is being addressed. We don’t cover that in this book but refer readers to resources such as “Data Science Project Scoping” (cite:) for more information.

---

<sup>7</sup> Application Programming Interfaces



**FIGURE 1.3** The data science project workflow. Blue represents each step in the project, orange represents the tools used in that step, and green represents the methods for analysis.

### 1.7.1 Part I: Capture and curation

The four chapters in Part I (see Figure 1.4) tell you how to collect, store, link, and manage data.

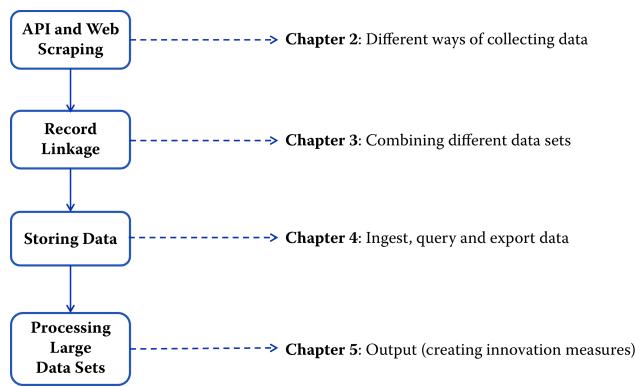
Working with Web Data and APIs describes how to extract information from data sources on the Web, including social media. The particular application will be to develop links to authors' articles on Twitter using PLOS articles and to pull information about authors and articles from web sources by using an API. You will learn how to retrieve link data from bookmarking services, citations from Crossref, links from Facebook, and information from news coverage. In keeping with the social science grounding that is a core feature of the book, the chapter discusses what data can be captured from online sources, what is potentially reliable, and how to manage data quality issues.

This data differs from survey data in that we must typically combine data from multiple sources to get a complete picture of the activities of interest. Although computer scientists may sometimes simply “mash” data sets together, social scientists are rightfully concerned about issues of missing links, duplicative links, and erroneous links. Record Linkage provides an overview of traditional rule-based and probabilistic approaches to data linkage, as well as machine learning approaches that are more adaptive and tunable.

Once data have been collected and linked, it is necessary to store and organize it. Social scientists are used to working with one analytical file, often in statistical

software tools such as SAS or Stata. Databases describes different approaches to storing data in ways that facilitate rapid, scalable, and reliable exploration and analysis.

Big data is sometimes defined as data that are too big to fit onto the analyst's computer. Programming with Big Data provides an overview of programming techniques that facilitate the scalable use of data (often using parallel computing). While the focus is on one of the most widely used big data programming paradigms and its most popular implementation, Apache Hadoop, the goal of the chapter is to provide a conceptual framework to the key challenges that the approach is designed to address.



**FIGURE 1.4** The four chapters of Part I focus on \*data capture\* and \*curation\*

### 1.7.2 Part II: Modeling and analysis

The four chapters in Part II (see Figure 1.5) introduce four of the most important tools that can be used by social scientists to do new and exciting research: information visualization, machine learning, text analysis, and social network analysis.

Information Visualization introduces information visualization methods and describes how you can use those methods to explore data and communicate results so that data can be turned into interpretable, actionable information. There are many ways of presenting statistical information that convey content in a rigorous manner. The goal of this chapter is to explore different approaches and examine the information content and analytical validity of the different approaches. It provides an overview of effective visualizations. Using visualization already in early analysis stages is key to a good understanding of data quality and potential pitfalls.

Machine Learning introduces machine learning methods. It shows the power

of machine learning in a variety of different contexts, particularly focusing on clustering, classification, and prediction. You will get an overview of basic approaches and how those approaches are applied. The chapter builds from a conceptual framework on how to formulate social science problems as machine learning problems, how to perform machine learning analysis, and how to evaluate the analysis. These concepts are then translated into code to ensure that the analysis can be put into practical use by social science researchers and practitioners.

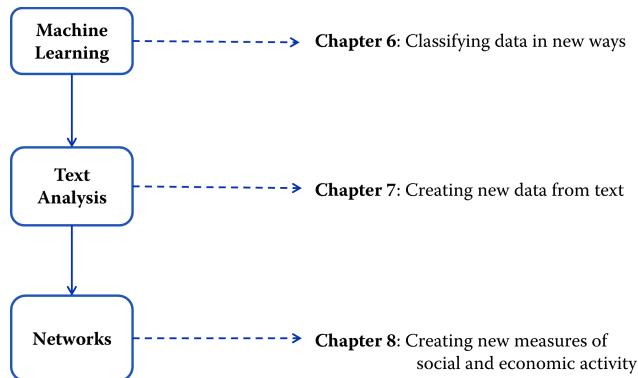
Text Analysis describes how social scientists can make use of text data through text analysis and natural language processing methods. Dealing with text and analysing text is not new to social scientists. What is different these days is that the vast amounts of data that are stored in documents can now be analyzed and searched and analyzed at scale, so that different types of information can be retrieved. Documents (and the underlying activities of the entities that generated the documents) can be categorized into topics or fields as well as summarized. In addition, machine translation can be used to compare documents in different languages.

Social scientists are typically interested in describing the activities of individuals and organizations (such as households and firms) in a variety of economic and social contexts. The frames within which data are collected have typically been generated from tax or other programmatic sources. The new types of data permit new units of analysis—particularly network analysis—largely enabled by advances in mathematical graph theory. Thus, Networks: The Basics describes how social scientists can use network theory to generate measurable representations of patterns of relationships connecting entities. As the author points out, the value of the new framework is not only in constructing different right-hand-side variables but also in studying an entirely new unit of analysis that lies somewhere between the largely atomistic actors that occupy the markets of neo-classical theory and the tightly managed hierarchies that are the traditional object of inquiry of sociologists and organizational theorists.

### 1.7.3 Part III: Inference and ethics

The three chapters in Part III (see Figure 1.6) cover three advanced topics relating to data inference and ethics—errors and inference, bias, and privacy and confidentiality—and introduce the workbooks that provide access to the practical exercises associated with the text.

[Errors and Inference] deals with inference and the errors associated with big data. Social scientists know only too well the cost associated with bad data—we highlighted the classic *Literary Digest* example in the introduction to this chapter, as well as the more recent Google Flu Trends. Although the consequences are well understood, the new types of data are so large and



**FIGURE 1.5** The four chapters in Part II focus on data \*modeling\* and \*analysis\*

complex that their properties often cannot be studied in traditional ways. In addition, the data generating function is such that the data are often selective, incomplete, and erroneous. Without proper data hygiene, errors can quickly compound. This chapter provides a systematic way to think about the error framework in a big data setting.

Bias and Fairness Interest in algorithmic fairness and bias has been growing recently, but it's easy to get lost in the large number of definitions and metrics. There are many different, often competing, ways to measure whether a given model and the resulting system is "fair". In this chapter, we provide an overview of these metrics along with some concrete examples to help navigate these concepts and understand the trade-offs involved in choosing to optimize one metric over others.

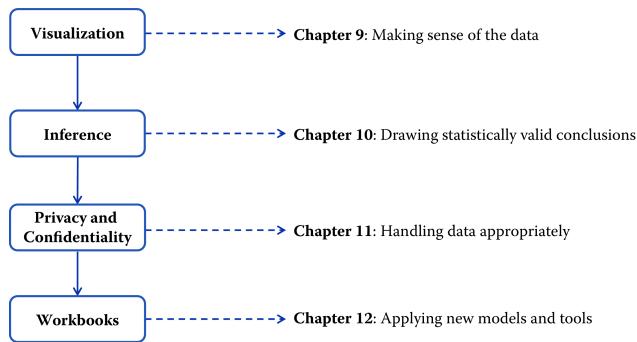
Privacy and Confidentiality addresses the issue that sits at the core of any study of human beings—privacy and confidentiality. In a new field, like the one covered in this book, it is critical that many researchers have access to the data so that work can be replicated and built on—that there be a scientific basis to data science. Yet the rules that social scientists have traditionally used for survey data, namely anonymity and informed consent, no longer apply when the data are collected in the wild. This concluding chapter identifies the issues that must be addressed for responsible and ethical research to take place.

Finally, Workbooks provides an overview of the practical work that accompanies each chapter—the workbooks that are designed, using *Jupyter notebooks*<sup>8</sup>, to enable students and interested practitioners to apply the new techniques and approaches in selected chapters. This last chapter gives a broad overview of the tools needed to work with these workbooks and some instructions on how to

---

<sup>8</sup>See [jupyter.org](http://jupyter.org).

use the workbooks if you decide to teach a class using this content. The chapter also informs broadly about the data and problems these workbooks tackle, and about the general structure of the workbooks. We are constantly expanding and updating the set of available workbooks, so check GitHub regularly if you want to see the latest version. We hope you have a lot of fun with them.



**FIGURE 1.6** The four chapters in Part III focus on \*inference\* and \*ethics\*

## 1.8 Resources

For more information on the **science of science policy**, see Husbands et al.'s book for a full discussion of many issues (Husband Fealing et al. 2011) and the online resources at the eponymous website (SOSP, n.d.).

This book is above all a *practical* introduction to the methods and tools that the social scientist can use to make sense of big data, and thus **programming** resources are also important. We make extensive use of the Python programming language and databases in both the book and its supporting workbooks. We recommend that any social scientist who aspires to work with large data sets become proficient in the use of these two systems and GitHub. All three, fortunately, are quite accessible and are supported by excellent online resources. Time spent mastering them will be repaid many times over in more productive research.

For **Python**<sup>9</sup>, Alex Bell's *Python for Economists* (available online (Bell 2012)) provides a wonderful 30-page introduction to the use of Python in the social sciences, complete with XKCD cartoons. Economists Tom Sargent and John Stachurski provide a very useful set of lectures and examples at <http://quant-econ.net/py/>

---

<sup>9</sup>Read this! <http://alexbell.net/pyseminar/pyseminar.html>

econ.net/. For more detail, we recommend Charles Severance's *Python for Informatics: Exploring Information* (Severance 2013), which not only covers basic Python but also provides material relevant to web data (the subject of Working with Web Data and APIs) and MySQL (the subject of Databases). This book is also freely available online and is supported by excellent online lectures and exercises.

For **SQL**, Chapter Databases provides introductory material and pointers to additional resources, so we will not say more here.

We also recommend that you master **GitHub**. A version control system is a tool for keeping track of changes that have been made to a document over time. GitHub is a hosting service for projects that use the Git version control system. As Strasser explains (Strasser 2014), Git/GitHub makes it straightforward for researchers to create digital lab notebooks that record the data files, programs, papers, and other resources associated with a project, with automatic tracking of the changes that are made to those resources over time. GitHub also makes it easy for collaborators to work together on a project, whether a program or a paper: changes made by each contributor are recorded and can easily be reconciled. For example, we used GitHub to create this book, with authors and editors checking in changes and comments at different times and from many time zones. We also use GitHub to provide access to the supporting workbooks. Ram (Ram 2013) provides a nice description of how Git/GitHub can be used to promote reproducibility and transparency in research.

One more resource that is outside the scope of this book but that you may well want to master is the **cloud** (Armbrust et al. 2010; Lifka et al. 2013). It used to be that when your data and computations became too large to analyze on your laptop, you were out of luck unless your employer (or a friend) had a larger computer. With the emergence of cloud storage and computing services from the likes of Amazon Web Services, Google, and Microsoft, powerful computers are available to anyone with a credit card. We and many others have had positive experiences using such systems for the analysis of urban (Catlett et al. 2014), environmental (Elliott et al. 2014), and genomic (Bhuvaneshwar et al. 2015) data analysis and modeling, for example.



# 2

---

## *Working with Web Data and APIs*

---

**Cameron Neylon**

In many social science problems we have to augment our primary data with external data sources. Often the external data are available on the web, either on web pages directly or accessible through Application Programming Interfaces (APIs). Gathering this data requires understanding how to scrape web pages or calling the APIs with parameters about the information we need. One common example of this is augmenting our primary data with data from the American Community Survey (ACS) or from Open Data Portals maintained by local, state, and federal agencies. These data sources can either be downloaded in bulk or used dynamically through APIs. Same is true for data from social media sources, such as Twitter, Instagram, and Facebook. In this chapter we will cover tools (specifically using Python) that can be used by social science researchers to programmatically gather this type of external data from web pages and APIs.

---

### **2.1 Introduction**

The Internet is an excellent resource for vast amounts of data on businesses, people, and their activity on social media. But how can we capture the information and make use of it as we might make use of more traditional data sources?

In social science, we often explore information on people, organizations, or locations. The web can be a rich source of additional information when doing this type of analysis, pointing to new sources of information, allowing a pivot from one perspective to another, or from one kind of query to another. Sometimes this data from the web is completely unstructured, existing in web pages spread across a site, and sometimes they are provided in a machine-

readable form. In order to deal with this variety, we need a sufficiently diverse toolkit to bring all of this information together.<sup>1</sup>

Using the example of data on researchers and research outputs, we will focus this chapter on obtaining information directly from web pages (*web scraping*) as well as explore the uses of APIs— web services that allow programmatic retrieval of data. Both in this chapter and the next, you will see how the crucial pieces of integration often lie in making connections between disparate data sets and how in turn making those connections requires careful quality control. The emphasis throughout this chapter is on the importance of focusing on the purpose for which the data will be used as a guide for data collection. While much of this is specific to data about research and researchers, the ideas are generalizable to wider issues of data and public policy. While we use Python as the programming language in this chapter, data collection through web scraping and APIs can be done in most modern programming languages as well as using software that's designed specifically for this purpose.

**BOX Examples** ——— In addition to the worked examples in this chapter here are a few other papers that show the wide variety of projects using data from web pages or APIs.<sup>2</sup>

Kim et al (<https://www.ncbi.nlm.nih.gov/pubmed/26920122>) use social media data about e-cigarettes from Twitter for public health research.

Goebel and Munzert (<https://journals.sagepub.com/doi/full/10.1177/0894439317703579>) used the online encyclopedia Wikipedia, to study how politicians enhance and change their appearance overtime. They trace changes to biographies coming from the parliament using data that cover the entire edit histories for biographies on all German members of parliament for the three last legislative periods. The authors have workshop material and code on GitHub how they performed the webscraping and API use for this project <https://github.com/simonmunzert/political-wikipedia-workshop>

King et al. (<https://gking.harvard.edu/files/censored.pdf>) investigate how censorship in China allows government criticism but silences collective expression using a system to locate, download, and analyze the content of millions of social media posts originating from nearly 1,400 different social media services all over China before the Chinese government is able to find, evaluate, and censor (i.e., remove from the Internet) the subset they deem objectionable.

## BOX

<sup>1</sup>The Privacy and Confidentiality chapter will discuss ethical issues when dealing with and using “publically” available data for research and policy purposes.

<sup>2</sup>If you have examples from your own research using the methods we describe in this chapter. Please submit a link to the paper (and/or code) here: todo: add website link

## 2.2 Scraping information from the web

With the range of information available on the web, our first task is to learn how to access it. The simplest approach is often to manually go to the web and look for data files or other information. For instance, on the NSF website (National Science Foundation, n.d.) it is possible to obtain data downloads of all grant information. Sometimes data are available through web pages or we only want a subset of this information. In this case web scraping is often a viable approach.

Web scraping involves writing code to download and process web pages programmatically. We need to look at the website, identify how to get the information we want from it, and then write code to do it. Many websites deliberately make this difficult to prevent easy access to their underlying data while some websites explicitly prohibit this type of activity in their terms of use. Another challenge when scraping data from websites is that the structure of the websites changes often, requiring researchers to keep updating their code. This is also important to note when using the code in this chapter. While the code accurately captures the data from the website at the time of this writing, it may not be valid in the future as the structure and content of the website changes.

### 2.2.1 Obtaining data from websites

Let us suppose we are interested in obtaining information on those investigators that are funded by the Howard Hughes Medical Institute (HHMI). HHMI has a website that includes a search function for funded researchers, including the ability to filter by field, state, and role. But there does not appear to be a downloadable data set of this information. However, we can automate the process with code to create a data set that you might compare with other data.

[https://www.hhmi.org/scientists/browse?sort\\_by=field\\_scientist\\_last\\_name&sort\\_order=ASC&items\\_per\\_page=24](https://www.hhmi.org/scientists/browse?sort_by=field_scientist_last_name&sort_order=ASC&items_per_page=24)

Getting information from this web page programmatically requires us to follow the following steps: 1. Constructing a URL that will give us the results we want 2. Getting the contents of the page using that URL 3. Processing the html response to extract the pieces of information we are looking for (such as names and specialties of the scientists)

\*\* Constructing the URL \*\* This process involves first understanding how to construct a URL that will do the search we want. This is most easily done by

playing with search functionality and investigating the URL structures that are returned.

With HHMI, if we do a general search and play with the structure of the URL, we can see some of the elements of the URL that we can think of as a query. As we want to see *all* investigators, we do not need to limit the search, and so with some fiddling we come up with a URL like the following. (We have broken the one-line URL into three lines for ease of presentation.)

```
http://www.hhmi.org/scientists/browse?kw=&sort_by=field_scientist_last_name&sort_order=ASC&items_per_page=24&page=0
```

We can click on different links on the page modify part of this URL to see how the search results change. For example, if we click on Sort by Institution, the URL changes to

```
https://www.hhmi.org/scientists/browse?sort_by=field_scientist_academic_institu&sort_order=ASC&items_per_page=24&page=0
```

If we click on next at the bottom, the url changes to https://www.hhmi.org/scientists/browse?sort\_by=field\_scientist\_academic\_institu&sort\_order=ASC&items\_per\_page=24&page=1

This allows us to see that the URL is constructed using a few parameters, such as sort\_by, sort\_order, items\_per\_page, and page that can be programmatically modified to give us the search results that we want.

### Getting the contents of the page from the URL

The `requests` module, available natively in Jupyter Python notebooks, is a useful set of tools for handling interactions with websites. It lets us construct the request that we just presented in terms of a base URL and query terms, as follows:

```
>> BASE_URL = "http://www.hhmi.org/scientists/browse"
>> query = {
    "kw" : "",
    "sort_by" : "field_scientist_last_name",
    "sort_order" : "ASC",
    "items_per_page" : 24,
    "page" : None
}
```

With our request constructed we can then make the call to the web page to get a response.

```
>> import requests
>> response = requests.get(BASE_URL, params=query)
```

The first thing to do when building a script that hits a web page is to make sure

that your call was successful. This can be checked by looking at the response code that the web server sent—and, obviously, by checking the actual HTML that was returned. A 200 code means success and that everything should be OK. Other codes may mean that the URL was constructed wrongly or that there was a server error.

```
>> response.status_code  
200
```

## Processing the html response

With the page successfully returned, we now need to process the text it contains into the data we want. This is not a trivial exercise. Web pages are typically written in a “markup” language called Hypertext Markup Language (HTML). This language tells the web browser how to display the content on that web page such as making a piece of text bold or in italics, creating numbered lists, or showing images. When we use Python to retrieve a webpage, running the code gives us the HTML text. We then have to process this text to extract the content that we care about. There are a range of tools in Python that can help with processing HTML data. One of the most popular is a module BeautifulSoup (Richardson, n.d.), which provides a number of useful functions for this kind of processing. The module documentation provides more details.

We need to check the details of the page source to find where the information we are looking for is kept (see, for example, 2.1). Here, all the details on HHMI investigators can be found in a `<div>` element with the class attribute `view-content`. This structure is not something that can be determined in advance. It requires knowledge of the structure of the page itself. Nested inside this `<div>` element are another series of divs, each of which corresponds to one investigator. These have the class attribute `view-rows`. Again, there is nothing obvious about finding these, it requires a close examination of the page HTML itself for any specific case you happen to be looking at.

**FIGURE 2.1** Source HTML from the portion of an HHMI results page containing information on HHMI investigators; note that the webscraping results in badly formatted html which is difficult to read.

We first process the page using the BeautifulSoup module (into the variable `soup`) and then find the `div` element that holds the information on investigators (`investigator_list`). As this element is unique on the page (I checked using my web browser), we can use the `find` method. We then process that `div` (using

`find_all`) to create an iterator object that contains each of the page segments detailing a single investigator (`investigators`).

```
>> from bs4 import BeautifulSoup
>> soup = BeautifulSoup(response.text, "html5lib")
>> investigator_list = soup.find('div', class_ = "view-content")
>> investigators = investigator_list.find_all("div", class_ =
    ↪ "views-row")
```

As we specified in our query parameters that we wanted 24 results per page, we should check whether our list of page sections has the right length.

```
>> len(investigators)
20
```

```
# Given a request response object, parse for HHMI investigators
def scrape(page_response):
    # Obtain response HTML and the correct <div> from the page
    soup = BeautifulSoup(response.text, "html5lib")
    inv_list = soup.find('div', class_ = "view-content")

    # Create a list of all the investigators on the page
    investigators = inv_list.find_all("div", class_ =
        ↪ "views-row")

    data = [] # Make the data object to store scraping results

    # Scrape needed elements from investigator list
    for investigator in investigators:
        inv = {} # Create a dictionary to store results

        # Name and role are in same HTML element; this code
        # separates them into two data elements
        name_role_tag = investigator.find("div",
            class_ =
                ↪ "views-field-field-scientist-classification")
        strings = name_role_tag.stripped_strings
        for string,a in zip(strings, ["name", "role"]):
            inv[a] = string

        # Extract other elements from text of specific divs or
        # from
        # class attributes of tags in the page (e.g., URLs)
        research_tag = investigator.find("div",
            class_ =
                ↪ "views-field-field-scientist-research-abs-nod")
```

```

inv["research"] = research_tag.text.lstrip()
inv["research_url"] = "http://hhmi.org"
    + research_tag.find("a").get("href")
institution_tag = investigator.find("div",
    class_ =
        → "views-field-field-scientist-academic-institu")
inv["institute"] = institution_tag.text.lstrip()
town_state_tag = investigator.find("div",
    class_ =
        → "views-field-field-scientist-institutionstate")
inv["town"], inv["state"] =
→ town_state_tag.text.split(",")
    inv["town"] = inv.get("town").lstrip()
    inv["state"] = inv.get("state").lstrip()

thumbnail_tag = investigator.find("div",
    class_ =
        → "views-field-field-scientist-image-thumbnail")
inv["thumbnail_url"] = thumbnail_tag.find("img")["src"]
inv["url"] = "http://hhmi.org"
    + thumbnail_tag.find("a").get("href")

# Add the new data to the list
data.append(inv)
return data

```

Listing 2.1. Python code to parse for HHMI investigators

Finally, we need to process each of these segments to obtain the data we are looking for. This is the actual “scraping” of the page to get the information we want. Again, this involves looking closely at the HTML itself, identifying where the information is held, what tags can be used to find it, and often doing some post-processing to clean it up (removing spaces, splitting different elements up, etc.).

Listing 2.1 provides a function to handle all of this. The function accepts the response object from the requests module as its input, processes the page text to soup, and then finds the `investigator_list` as above and processes it into an actual list of the investigators. For each investigator it then processes the HTML to find and clean up the information required, converting it to a dictionary and adding it to our growing list of data.

Let us check what the first two elements of our data set now look like. You can see two dictionaries, one relating to Laurence Abbott, who is a senior fellow at the HHMI Janelia Farm Campus, and one for Susan Ackerman, an HHMI investigator based at the Jackson Laboratory in Bar Harbor, Maine.

Note that we have also obtained URLs that give more details on the researcher and their research program (`research_url` and `url` keys in the dictionary) that could provide a useful input to textual analysis or topic modeling (see Text Analysis).

```
>> data = scrape(response)
>> data[0:2]
[{'institute': u'Janelia Research Campus ',
 'name': u'Laurence Abbott, PhD',
 'research': u'Computational and Mathematical Modeling of
 → Neurons and Neural... ',
 'research_url': u_
 → 'http://hhmi.org/research/computational-and-mathematical-modeling-neurons-and-neural
 → ,
 'role': u'Janelia Senior Fellow',
 'state': u'VA ',
 'thumbnail_url': u_
 → 'http://www.hhmi.org/sites/default/files/Our%20Scientists/Janelia/Abbott-112x112.jpg
 → ,
 'town': u'Ashburn',
 'url': u'http://hhmi.org/scientists/laurence-f-abbott'},
 {'institute': u'The Jackson Laboratory ',
 'name': u'Susan Ackerman, PhD',
 'research': u'Identification of the Molecular Mechanisms
 → Underlying... ',
 'research_url': u_
 → 'http://hhmi.org/research/identification-molecular-mechanisms-underlying-neurodegener
 → ,
 'role': u'Investigator',
 'state': u'ME ',
 'thumbnail_url':
 u_
 → 'http://www.hhmi.org/sites/default/files/Our%20Scientists/Investigators/Ackerman-112x112.jpg
 → ,
 'town': u'Bar Harbor',
 'url': u'http://hhmi.org/scientists/susan-l-ackerman'}]
```

\*\* Programmatically Iterating over the Search Results \*\*

Now we know we can process a page from a website to generate useful structured data. However, this was only the first page of results. We need to do this for each page of results if we want to capture all the HHMI investigators. We could just look at the number of pages that our search returned manually, but to make this more general we can actually scrape the page to find that piece of information and use that to calculate how many pages we need to iterate through.

The number of results is found in a `div` with the class “view-headers” as a piece of free text (“Showing 1–20 of 493 results”). We need to grab the text, split it up (we do so based on spaces), find the right number (the one that is before the word “results”) and convert that to an integer. Then we can divide by the number of items we requested per page (20 in our case) to find how many pages we need to work through. A quick mental calculation confirms that if page 0 had results 1–20, page 24 would give results 481–493.

```
>> # Check total number of investigators returned
>> view_header = soup.find("div", class_ = "view-header")
>> words = view_header.text.split(" ")
>> count_index = words.index("results.") - 1
>> count = int(words[count_index])

>> # Calculate number of pages, given count & items_per_page
>> num_pages = count/query.get("items_per_page")
>> num_pages
24
```

Then it is a matter of putting the function we constructed earlier into a loop to work through the correct number of pages. As we start to hit the website repeatedly, we need to consider whether we are being polite. Most websites have a file in the root directory called robots.txt that contains guidance on using programs to interact with the website. In the case of <http://hhmi.org> the file states first that we are allowed (or, more properly, not forbidden) to query <http://www.hhmi.org/scientists/> programmatically. Thus, you can pull down all of the more detailed biographical or research information, if you so desire. The file also states that there is a requested “Crawl-delay” of 10. This means that if you are making repeated queries (as we will be in getting the 24 pages), you should wait for 10 seconds between each query. This request is easily accommodated by adding a timed delay between each page request.

```
>> for page_num in range(num_pages):
>> # We already have page zero and we need to go to 24:
>> # range(24) is [0,1,...,23]
>>     query["items_per_page"] = page_num + 1
>>     page = requests.get(BASE_URL, params=query)
>> # We use extend to add list for each page to existing list
>>     data.extend(scrape(page))
>> print("Retrieved and scraped page number:",
->       query.get("items_per_page"))
>> time.sleep(10) # robots.txt at hhmi.org specifies a crawl
-> delay of 10 seconds
Retrieved and scraped page number: 1
Retrieved and scraped page number: 2
```

```
...  
Retrieved and scraped page number: 24
```

Finally we can check that we have the right number of results after our scraping. This should correspond to the 493 records that the website reports.

```
>> len(data)  
493
```

### 2.2.2 Limits of scraping

While scraping websites is often necessary, it can be a fragile and messy way of working. It is problematic for a number of reasons: for example, many websites are designed in ways that make scraping difficult or impossible, and other sites explicitly prohibit this kind of scripted analysis. (Both reasons apply in the case of the NSF and Grants.gov websites, which is why we use the HHMI website in our example.) The structure of websites also changes frequently, forcing you to continuously modify your code to keep up with the structure.

In many cases a better choice is to process a data download from an organization. For example, the NSF and Wellcome Trust both provide data sets for each year that include structured data on all their awarded grants. In practice, integrating data is a continual challenge of figuring out what is the easiest way to proceed, what is allowed, and what is practical and useful. The selection of data will often be driven by pragmatic rather than theoretical concerns.

Increasingly, organizations are providing APIs to enable scripted and programmatic access to the data they hold. These tools are much easier and generally more effective to work with. They are the focus of much of the rest of this chapter.

---

## 2.3 Application Programming Interfaces (APIs)

An API is simply a tool that allows a program to interface with a service. APIs can take many different forms and be of varying quality and usefulness. In this section we will focus on one common type of API and examples of important publicly available APIs relevant to research communications. We will also cover combining APIs and the benefits and challenges of bringing multiple data sources together.

### 2.3.1 Relevant APIs and resources

There is a wide range of other sources of information that can be used in combination with the APIs featured above to develop an overview of research outputs and of where and how they are being used. There are also other tools that can allow deeper analysis of the outputs themselves. Table 2.1 gives a partial list of key data sources and APIs that are relevant to the analysis of research outputs.

TABLE 2.1: Popular sources of data relevant to the analysis of research outputs

Source	Description	AP	Free
<b>Bibliographic Data</b>			
PubMed	An online index that combines bibliographic data from Medline and PubMed Central. PubMed Central and Europe PubMed Central also provide information.	Y	Y
Web of Science	The bibliographic database provided by Thomson Reuters. The ISI Citation Index is also available.	Y	N
Scopus	The bibliographic database provided by Elsevier. It also provides citation information.	Y	N
Crossref	Provides a range of bibliographic metadata and information obtained from members registering DOIs.	Y	Y
Google Scholar	Provides a search index for scholarly objects and aggregates citation information.	N	Y
Microsoft Academic Search	Provides a search index for scholarly objects and aggregates citation information. Not as complete as Google Scholar, but has an API.	Y	Y
<b>Social Media</b>			
Altmetric	A provider of aggregated data on social media and mainstream media attention of research outputs. Most comprehensive source of information across different social media and mainstream media conversations.	Y	N
Twitter	Provides an API that allows a user to search for recent tweets and obtain some information on specific accounts.	Y	Y
Facebook	The Facebook API gives information on the number of pages, likes, and posts associated with specific web pages	Y	Y
<b>Author Profiles</b>			
ORCID	Unique identifiers for research authors. Profiles include information on publication lists, grants, and affiliations.	Y	Y
LinkedIn	CV-based profiles, projects, and publications.	Y	*
<b>Funder Information</b>			

Source	Description	AP	Free
Gate-way to Research	A database of funding decisions and related outputs from Research Councils UK.	Y	Y
NIH Reporter	Online search for information on National Institutes of Health grants. Does not provide an API but a downloadable data set is available.	N	Y
NSF Award Search	Online search for information on NSF grants. Does not provide an API but downloadable data sets by year are available.	N	Y

\*The data are restricted: sometimes fee based, other times not.

### 2.3.2 RESTful APIs, returned data, and Python wrappers

The APIs we will focus on here are all examples of RESTful services. REST stands for Representational State Transfer (Wikipedia, n.d.; Fielding and Taylor 2002), but for our purposes it is most easily understood as a means of transferring data using web protocols. Other forms of API require additional tools or systems to work with, but RESTful APIs work directly over the web. This has the advantage that a human user can also with relative ease play with the API to understand how it works. Indeed, some websites work simply by formatting the results of API calls.

As an example let us look at the Crossref API. This provides a range of information associated with Digital Object Identifiers (DOIs) registered with Crossref. DOIs uniquely identify an object, and Crossref DOIs refer to research objects, primarily (but not entirely) research articles. If you use a web browser to navigate to <http://api.crossref.org/works/10.1093/nar/gni170>, you should receive back a webpage that looks something like the following. (We have laid it out nicely to make it more readable.)

```
{
  "status" : "ok",
  "message-type" : "work",
  "message-version" : "1.0.0",
  "message" :
    {
      "subtitle": [],
      "subject" : ["Genetics"],
      "issued" : { "date-parts" : [[2005,10,24]] },
      "score" : 1.0,
      "prefix" : "http://id.crossref.org/prefix/10.1093",
      "author" : [ "affiliation" : [],
                    "family" : "Whiteford",
                    "given" : "Stephen",
                    "order" : 1,
                    "type" : "person"
                  ],
      "title" : [
        {
          "content" : "A comparison of two methods for estimating the rate of evolution of protein-coding DNA sequences",
          "type" : "main"
        }
      ],
      "type" : "article-journal"
    }
}
```

```
        "given" : "N."}],
  "container-title" : ["Nucleic Acids Research"],
  "reference-count" : 0,
  "page" : "e171-e171",
  "deposited" : {"date-parts" : [[2013,8,8]],
                 "timestamp" : 1375920000000},
  "issue" : "19",
  "title" :
    ["An analysis of the feasibility of short read
     sequencing"],
  "type" : "journal-article",
  "DOI" : "10.1093/nar/gni170",
  "ISSN" : ["0305-1048","1362-4962"],
  "URL" : "http://dx.doi.org/10.1093/nar/gni170",
  "source" : "Crossref",
  "publisher" : "Oxford University Press (OUP)",
  "indexed" : {"date-parts" : [[2015,6,8]],
               "timestamp" : 1433777291246},
  "volume" : "33",
  "member" : "http://id.crossref.org/member/286"
}
}
```

This is a package of JavaScript Object Notation (JSON)<sup>3</sup> data returned in response to a query. The query is contained entirely in the URL, which can be broken up into pieces: the root URL (<http://api.crossref.org>) and a data “query,” in this case made up of a “field” (`works`) and an identifier (the DOI [10.1093/nar/gni170](http://10.1093/nar/gni170)). The Crossref API provides information about the article identified with this specific DOI.

## 2.4 Using an API

Similar to what we did with web scraping, using an API involves 1) constructing HTTP requests and 2) Processing the data that are returned. Here we use the Crossref API to illustrate how this is done. Crossref is the provider of DOIs used by many publishers to uniquely identify scholarly works. Crossref is not the only organization to provide DOIs. The scholarly communication space DataCite is another important provider. The documentation is available at the Crossref website (Ward, n.d.).

---

<sup>3</sup>JSON is an open standard way of storing and exchanging data.

Once again the `requests` Python library provides a series of convenience functions that make it easier to make HTTP calls and to process returned JSON. Our first step is to import the module and set a base URL variable.

```
>> import requests
>> BASE_URL = "http://api.crossref.org/"
```

A simple example is to obtain metadata for an article associated with a specific DOI. This is a straightforward call to the Crossref API, similar to what we saw earlier.

```
>> doi = "10.1093/nar/gni170"
>> query = "works/"
>> url = BASE_URL + query + doi
>> response = requests.get(url)
>> url
http://api.crossref.org/works/10.1093/nar/gni170
>> response.status_code
200
```

The `response` object that the `requests` library has created has a range of useful information, including the URL called and the response code from the web server (in this case 200, which means everything is OK). We need the JSON body from the response object (which is currently text from the perspective of our script) converted to a Python dictionary. The `requests` module provides a convenient function for performing this conversion, as the following code shows. (All strings in the output are in Unicode, hence the `u'` notation.)

```
>> response_dict = response.json()
>> response_dict
{ u'message' :
  { u'DOI' : u'10.1093/nar/gni170',
    u'ISSN' : [ u'0305-1048', u'1362-4962' ],
    u'URL' : u'http://dx.doi.org/10.1093/nar/gni170',
    u'author' : [ {u'affiliation' : [],
                  u'family' : u'Whiteford',
                  u'given' : u'N.'} ],
    u'container-title' : [ u'Nucleic Acids Research' ],
    u'deposited' : { u'date-parts' : [[2013, 8, 8]],
                    u'timestamp' : 1375920000000 },
    u'indexed' : { u'date-parts' : [[2015, 6, 8]],
                   u'timestamp' : 1433777291246 },
    u'issue' : u'19',
    u'issued' : { u'date-parts' : [[2005, 10, 24]] },
    u'member' : u'http://id.crossref.org/member/286',
```

```
u'page' : u'e171-e171',
u'prefix' : u'http://id.crossref.org/prefix/10.1093',
u'publisher' : u'Oxford University Press (OUP)',
u'reference-count' : 0,
u'score' : 1.0,
u'source' : u'Crossref',
u'subject' : [u'Genetics'],
u'subtitle' : [],
u'title' : [u'An analysis of the feasibility of short read
→ sequencing'],
u'type' : u'journal-article',
u'volume' : u'33'
},
u'message-type' : u'work',
u'message-version' : u'1.0.0',
u'status' : u'ok'
}
```

This data object can now be processed in whatever way the user wishes, using standard manipulation techniques.

The Crossref API can, of course, do much more than simply look up article metadata. It is also valuable as a search resource and for cross-referencing information by journal, funder, publisher, and other criteria. More details can be found at the Crossref website.

---

## 2.5 Another example: Using the ORCID API via a wrapper

ORCID, which stands for “Open Research and Contributor Identifier” (see [orcid.org](http://orcid.org); see also (Haak et al. 2012)), is a service that provides unique identifiers for researchers. Researchers can claim an ORCID profile and populate it with references to their research works, funding and affiliations. ORCID provides an API for interacting with this information. For many APIs there is a convenient Python wrapper that can be used. The ORCID–Python wrapper works with the ORCID v1.2 API to make various API calls straightforward. This wrapper only works with the public ORCID API and can therefore only access publicly available data.

Using the API and wrapper together provides a convenient means of getting this information. For instance, given an ORCID, it is straightforward to get

profile information. Here we get a list of publications associated with my ORCID and look at the the first item on the list.

```
>> import orcid
>> cn = orcid.get("0000-0002-0068-716X")
>> cn
<Author Cameron Neylon, ORCID 0000-0002-0068-716X>
>> cn.publications[0]
<Publication "Principles for Open Scholarly Infrastructures-v1">
```

The wrapper has created Python objects that make it easier to work with and manipulate the data. It is common to take the return from an API and create objects that behave as would be expected in Python. For instance, the `publications` object is a list populated with publications (which are also Python-like objects). Each publication in the list has its own attributes, which can then be examined individually. In this case the `external_ids` attribute is a list of further objects that include a DOI for the article and the ISSN of the journal the article was published in.

```
>> len(cn.publications)
70
>> cn.publications[12].external_ids
[<ExternalID DOI:10.1371/journal.pbio.1001677>, <ExternalID
→ ISSN:1545-7885>]
```

As a simple example of data processing, we can iterate over the list of publications to identify those for which a DOI has been provided. In this case we can see that of the 70 publications listed in this ORCID profile (at the time of testing), 66 have DOIs.

```
>> exids = []
>> for pub in cn.publications:
    if pub.external_ids:
        exids = exids + pub.external_ids
>> DOIs = [exid.id for exid in exids if exid.type == "DOI"]
>> len(DOIs)
66
```

Wrappers generally make operating with an API simpler and cleaner by abstracting away the details of making HTTP requests. Achieving the same by directly interacting with the ORCID API would require constructing the appropriate URLs and parsing the returned data into a usable form. Where a wrapper is available it is generally much easier to use. However, wrappers may not be actively developed and may lag the development of the API. Where possible, use a wrapper that is directly supported or recommended by the API provider.

## 2.6 Integrating data from multiple sources

We often must work across multiple data sources to gather the information needed to answer a research question. A common pattern is to search in one location to create a list of identifiers and then use those identifiers to query another API. In the ORCID example above, we created a list of DOIs from a single ORCID profile. We could use those DOIs to obtain further information from the Crossref API and other sources. This models a common path for analysis of research outputs: identifying a corpus and then seeking information on its performance.

One task we often want to do is to analyze relationships between people. As an exercise, we suggest writing code that is able to generate data about relationships between researchers working in similar areas. This could involve using data sources related to researchers, publications, citations and tweets about those publications, and researchers who are citing or tweeting about them. One way of generating this data for further analysis is to use APIs that give you different pieces of this information and connect them programmatically. We could take the following steps to do that:

Given a twitter handle, get the ORCID for that twitter handle From the ORCID, get a list of DOIs For each DOI Get citations, citing articles, tweets (and twitter handles) associated

The result is a list of related twitter handles that can be analyzed to look for communities and networks.

You can see how this would be done in a worked-out example here todo:  
INSERT LINK/REFERENCE to notebook code

The goal of this example is to use ORCID and Crossref to collect a set of identifiers and use a range of APIs to gather metadata and information the articles performance. The worked example is using the PLOS Lagotto API. Lagotto is the software that was built to support the Article Level Metrics program at PLOS, the open access publisher, and its API provides information on various metrics of PLOS articles. A range of other publishers and service providers, including Crossref, also provide an instance of this API, meaning the same tools can be used to collect information on articles from a range of sources.

---

## 2.7 Summary

This chapter focused on approaches to augment our data with external data sources on the Web. We provided steps and code to gather data web pages directly or through Application Programming Interfaces (APIs). While scraping websites is often necessary, it can be fragile because 1) many websites are designed in ways that make scraping difficult or impossible (or explicitly prohibit it), and 2) the structure of websites also changes frequently, forcing you to continuously modify your code to match their structure. Increasingly, organizations are providing APIs to enable scripted and programmatic access to the data they hold. There are many good introductions to web scraping using BeautifulSoup and other libraries as well as API usage in general. Given the pace at which APIs and Python libraries change, the best and most up to date source of information is likely to be a web search.

As we collect data through scraping and APIs, we then have to understand how to effectively integrate it with our primary data since we may not have access to unique and reliable identifiers. The next chapter Chapter Record Linkage) deal with issues of data cleaning, disambiguation, and linking different types of data sources to perform further analysis and research.

---

## 2.8 Acknowledgements and copyright

Section 2.3 is adapted in part from Neylon et al. (Neylon, Willmers, and King 2014), copyright International Development Research Center, Canada, used here under a Creative Commons Attribution v 4.0 License.

Section 2.9.4 is adapted in part from Neylon (Neylon 2014), copyright PLOS, used here under a Creative Commons Attribution v 4.0 License.

# 3

---

## *Record Linkage*

---

**Joshua Tokle and Stefan Bender**

As we mentioned in the last chapter, it is often necessary to combine data from multiple sources to get a complete picture of the activities of interest. In addition to just linking data to get additional information, we are also concerned about issues of missing links, duplicative links, and erroneous links. This chapter provides an overview of traditional rule-based and probabilistic approaches, as well as the modern approaches to record linkage using machine learning.

---

### 3.1 Motivation

New sources of data offer social scientists great opportunities to bring together many different types of data, from many different sources. Merging different data sets provides new ways of creating population frames that are generated from the digital traces of human activity rather than, say, tax records. These opportunities, however, create different kinds of challenges from those posed by survey data. Combining information from different sources about an individual, business, or geographic entity means that the social scientist must determine whether or not two entities in two different data sources are the same. This determination is not always easy.

We regularly run into situations where we need to combine data from different agencies about the same people to understand future employment or health outcomes for people on social service benefits or those who have recently been released from prison. In the UMETRICS data for example, if data are to be used to measure the impact of research grants, is David A. Miller from Stanford, CA, the same as David Andrew Miller from Fairhaven, NJ, in a list of inventors? Is IBM the same as Big Blue if the productivity and growth of R&D-intensive firms is to be studied? Or, more generally, is individual A the same person as the one who appears on a list that has been compiled? Does the product that a customer is searching for match the products that business B has for sale?

The consequences of poor record linkage decisions can be substantial. In the business arena, Christen reports that as much as 12% of business revenues are lost due to bad linkages (Christen 2012b). In the security arena, failure to match travelers to a “known terrorist” list may result in those individuals entering the country, while overzealous matching could lead to numbers of innocent citizens being detained. In finance, incorrectly detecting a legitimate purchase as a fraudulent one annoys the customer, but failing to identify a thief will lead to credit card losses. Less dramatically, in the scientific arena when studying patenting behavior, if it is decided that two inventors are the same person, when in fact they are not, then records will be incorrectly grouped together and one researcher’s productivity will be overstated. Conversely, if the records for one inventor are believed to correspond to multiple individuals, then that inventor’s productivity will be understated.

This chapter discusses current approaches to joining multiple data sets together—commonly called *record linkage*.<sup>1</sup>

We draw heavily here on work by Winkler, Scheuren, and Christen, in particular (Herzog, Scheuren, and Winkler 2007; Christen 2012a; Christen 2012b). To ground ideas, we use examples from a recent paper examining the effects of different algorithms on studies of patent productivity (Ventura, Nugent, and Fuchs 2015).

#### **BOX \*\* Examples \*\***

In addition to the worked examples in this chapter here are a few other papers that show the wide variety of projects using combining records from different sources.<sup>2</sup>

Glennon [?] used a unique matched firm-level dataset of H-1B visas and multinational firm activity show that restrictions on H-1B immigration caused increases in foreign affiliate employment. Restrictions also caused increases in foreign patenting, suggesting that there was also a change in the location of innovative activity.

Rodolfa et al [?] *todo*) use machine learning based record linkage to link data about the same individuals together from a criminal justice case management system to help the Los Angeles City Attorney’s office develop individually-tailored social service interventions in a fair and equitable manner. Because the system lacked a global unique person-level identifier, case-level defendant data was used to link cases belonging to the same person using first and last

<sup>1</sup>Other names associated with record linkage are entity disambiguation, entity resolution, co-reference resolution, matching, and data fusion, meaning that records which are linked or co-referent can be thought of as corresponding to the same underlying entity. The number of names is reflective of a vast literature in social science, statistics, computer science, and information sciences.

<sup>2</sup>If you have examples from your own research using the methods we describe in this chapter. Please submit a link to the paper (and/or code) here: *todo*: add website link

name, date of birth, address, driver's license number (where available), and California Information and Identification (CII) number (where available).

The National Center for Health Statistics (NCHS) links the data from the National Health Interview Survey (NHIS) to records from the Social Security Administration, the Centers for Medicare & Medicaid Services, and the National Death Index to investigate the relationship between health and sociodemographic information reported in the surveys and medical care costs, future use of medical services and mortality [?].

## BOX

---

### 3.2 Introduction to record linkage

There are many reasons to link data sets. Linking to existing data sources to solve a measurement need instead of implementing a new survey results in cost savings (and almost certainly time savings as well) and reduced burden on potential survey respondents. For some research questions (e.g., a survey of the reasons for death of a longitudinal cohort of individuals) a new survey may not be possible. In the case of administrative data or other automatically generated data, the sample size is much greater than would be possible from a survey.

Record linkage can be used to compensate for data quality issues. If a large number of observations for a particular field are missing, it may be possible to link to another data source to fill in the missing values. For example, survey respondents might not want to share a sensitive datum like income. If the researcher has access to an official administrative list with income data, then those values can be used to supplement the survey (Abowd, Stinson, and Benedetto 2006).

Record linkage is often used to create new longitudinal data sets by linking the same entities over time (Jarmin and Miranda 2002). More generally, linking separate data sources makes it possible to create a combined data set that is richer in coverage and measurement than any of the individual data sources (Abowd, Haltiwanger, and Lane 2004).

---

#### Example: The Administrative Data Research Network

The UK's Administrative Data Research Network<sup>3</sup> (ADRN) is a major invest-

---

<sup>3</sup>“Administrative data” typically refers to data generated by the administration of a government program, as distinct from deliberate survey collection.

ment by the United Kingdom to “improve our knowledge and understanding of the society we live in ... [and] provide a sound base for policymakers to decide how to tackle a range of complex social, economic and environmental issues” by linking administrative data from a variety of sources, such as health agencies, court records, and tax records in a confidential environment for approved researchers. The linkages are done by trusted third-party providers. (Economic and Social Research Council 2016)

---

Linking is straightforward if each entity has a corresponding unique identifier that appears in the data sets to be linked. For example, two lists of US employees may both contain Social Security numbers. When a unique identifier exists in the data or can be created, no special techniques are necessary to join the data sets.

If there is no unique identifier available, then the task of identifying unique entities is challenging. One instead relies on fields that only partially identify the entity, like names, addresses, or dates of birth. The problem is further complicated by poor data quality and duplicate records, issues well attested in the record linkage literature (Christen 2012a) and sure to become more important in the context of big data. Data quality issues include input errors (typos, misspellings, truncation, extraneous letters, abbreviations, and missing values) as well as differences in the way variables are coded between the two data sets (age versus date of birth, for example). In addition to record linkage algorithms, we will discuss different data preprocessing steps that are necessary first steps for the best results in record linkage.

To find all possible links between two data sets it would be necessary to compare each record of the first data set with each record of the second data set. The computational complexity of this grows quadratically with the size of the data—an important consideration, especially with large amounts of data. To compensate for this complexity, the standard second step in record linkage, after preprocessing, is indexing or blocking, which uses some set of heuristics to create subsets of similar records and reduces the total number of comparisons.

The outcome of the matching step is a set of predicted links—record pairs that are likely to correspond to the same entity. After these are produced, the final stage of the record linkage process is to evaluate the result and estimate the resulting error rates. Unlike other areas of application for predictive algorithms, ground truth or gold standard data sets are rarely available. The only way to create a reliable truth data set sometimes is through an expensive human review process that may not be viable for a given application. Instead, error rates must be estimated.

An input data set may contribute to the linked data in a variety of ways, such as increasing coverage, expanding understanding of the measurement or mismeasurement of underlying latent variables, or adding new variables to

the combined data set. It is therefore important to develop a well-specified reason for linking the data sets, and to specify a loss function to proxy the cost of false negative matches versus false positive matches that can be used to guide match decisions. It is also important to understand the coverage of the different data sets being linked because differences in coverage may result in bias in the linked data. For example, consider the problem of linking Twitter data to a sample-based survey—elderly adults and very young children are unlikely to use Twitter and so the set of records in the linked data set will have a youth bias, even if the original sample was representative of the population. It is also essential to engage in critical thinking about what latent variables are being captured by the measures in the different data sets—an “occupational classification” in a survey data set may be very different from a “job title” in an administrative record or a “current position” in LinkedIn data.<sup>4</sup>

---

**Example: Employment and earnings outcomes of doctoral recipients**

A recent paper in *Science* matched UMETRICS data on doctoral recipients to Census data on earnings and employment outcomes. The authors note that some 20% of the doctoral recipients are not matched for several reasons: (i) the recipient does not have a job in the US, either for family reasons or because he/she goes back to his/her home country; (ii) he/she starts up a business rather than choosing employment; or (iii) it is not possible to uniquely match him/her to a Census Bureau record. They correctly note that there may be biases introduced in case (iii), because Asian names are more likely duplicated and harder to uniquely match (Zolas et al. 2015). Improving the linkage algorithm would increase the estimate of the effects of investments in research and the result would be more accurate.

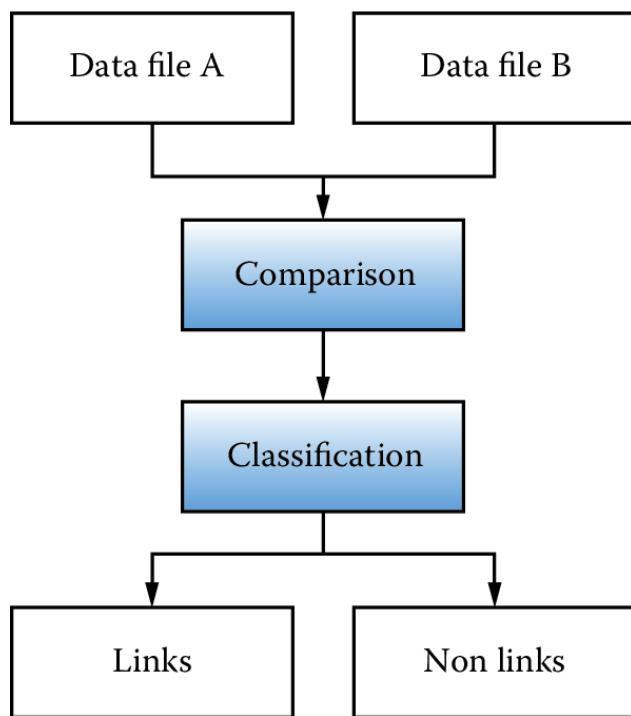
---

Comparing the kinds of heterogeneous records associated with big data is a new challenge for social scientists, who have traditionally used a technique first developed in the 1960s to apply computers to the problem of medical record linkage. There is a reason why this approach has survived: it has been highly successful in linking survey data to administrative data, and efficient implementations of this algorithm can be applied at the big data scale. However, the approach is most effective when the two files being linked have a number of fields in common. In the new landscape of big data, there is a greater need to link files that have few fields in common but whose noncommon fields provide additional predictive power to determine which records should be linked. In some cases, when sufficient training data can be produced, more modern machine learning techniques may be applied.

The canonical record linkage workflow process is shown in Figure 3.1 for two

---

<sup>4</sup>This topic is discussed in more detail in Chapter 10.



**FIGURE 3.1** The preprocessing pipeline

data files, A and B. The goal is to identify all pairs of records in the two data sets that correspond to the same underlying individual. One approach is to compare all data units from file A with all units in file B and classify all of the comparison outcomes to decide whether or not the records match. In a perfect statistical world the comparison would end with a clear determination of links and nonlinks.

Alas, a perfect world does not exist, and there is likely to be noise in the variables that are common to both data sets and that will be the main identifiers for the record linkage. Although the original files A and B are the starting point, the identifiers must be preprocessed before they can be compared. Determining identifiers for the linkage and deciding on the associated cleaning steps are extremely important, as they result in a necessary reduction of the possible search space.

In the next section we begin our overview of the record linkage process with a discussion of the main steps in data preprocessing. This is followed by a section on approaches to record linkage that includes rule-based, probabilistic, and machine learning algorithms. Next we cover classification and evaluation of links, and we conclude with a discussion of data privacy in record linkage.

---

### 3.3 Preprocessing data for record linkage

As noted in the introductory chapter, all data work involves preprocessing, and data that need to be linked is no exception. Preprocessing refers to a workflow that transforms messy and noisy data into a well-defined, clearly structured, and quality-tested data set. Elsewhere in this book, we discuss general strategies for data preprocessing.<sup>5</sup> In this section, we focus specifically on preprocessing steps relating to the choice of input fields for the record linkage algorithm. Preprocessing for any kind of a new data set is a complex and time-consuming process because it is “hands-on”: it requires judgment and cannot be effectively automated. It may be tempting to minimize this demanding work under the assumption that the record linkage algorithm will account for issues in the data, but it is difficult to overstate the value of preprocessing for record linkage quality. As Winkler notes: “In situations of reasonably high-quality data, preprocessing can yield a greater improvement in matching efficiency than string comparators and ‘optimized’ parameters. In some situations, 90% of the improvement in matching efficiency may be due to preprocessing” (Winkler 2009).

---

<sup>5</sup>This topic (quality of data, preprocessing issues) is discussed in more detail in Section 1.4.

The first step in record linkage is to develop link keys, which are the record fields that will be used to estimate if there is a link between two records. These can include common identifiers like first and last name. Survey and administrative data sets may include a number of clearly identifying variables like address, birth date, and sex. Other data sets, like transaction records or social media data, often will not include address or birth date but may still include other identifying fields like occupation, a list of interests, or connections on a social network. Consider this chapter's illustrative example of the US Patent and Trademark Office (USPTO) data (Ventura, Nugent, and Fuchs 2015):

USPTO maintains an online database of all patents issued in the United States. In addition to identifying information about the patent, the database contains each patent's list of inventors and assignees, the companies, organizations, individuals, or government agencies to which the patent is assigned. ... However, inventors and assignees in the USPTO database are not given unique identification numbers, making it difficult to track inventors and assignees across their patents or link their information to other data sources.

There are some basic precepts that are useful when considering identifying fields. The more different values a field can take, the less likely it is that two randomly chosen individuals in the population will agree on those values. Therefore, fields that exhibit a wider range of values are more powerful as link keys: names are much better link keys than sex or year of birth.

---

#### **Example: Link keys in practice**

“A Harvard professor has re-identified the names of more than 40 percent of a sample of anonymous participants in a high-profile DNA study, highlighting the dangers that ever greater amounts of personal data available in the Internet era could unravel personal secrets. ... Of the 1,130 volunteers Sweeney and her team reviewed, about 579 provided zip code, date of birth and gender, the three key pieces of information she needs to identify anonymous people combined with information from voter rolls or other public records. Of these, Sweeney succeeded in naming 241, or 42 percent of the total. The Personal Genome Project confirmed that 97 percent of the names matched those in its database if nicknames and first name variations were included” (Tanner 2013).

---

Complex link keys like addresses can be broken down into components so that the components can be compared independently of one another. This way, errors due to data quality can be further isolated. For example, assigning a single comparison value to the complex fields “1600 Pennsylvania” and “160 Pennsylvania Ave” is less informative than assigning separate comparison

values to the street number and street name portions of those fields. A record linkage algorithm that uses the decomposed field can make more nuanced distinctions by assigning different weights to errors in each component.

Sometimes a data set can include different variants of a field, like legal first name and nickname. In these cases match rates can be improved by including all variants of the field in the record comparison. For example, if only the first list includes both variants, and the second list has a single “first name” field that could be either a legal first name or a nickname, then match rates can be improved by comparing both variants and then keeping the better of the two comparison outcomes. It is important to remember, however, that some record linkage algorithms expect field comparisons to be somewhat independent. In our example, using the outcome from both comparisons as separate inputs into the probabilistic model we describe below may result in a higher rate of false negatives. If a record has the same value in the legal name and nickname fields, and if that value happens to agree with the first name field in the second file, then the agreement is being double-counted. By the same token, if a person in the first list has a nickname that differs significantly from their legal first name, then a comparison of that record to the corresponding record will unfairly penalize the outcome because at least one of those name comparisons will show a low level of agreement.

Preprocessing serves two purposes in record linkage. First, to correct for issues in data quality that we described above. Second, to account for the different ways that the input files were generated, which may result in the same underlying data being recorded on different scales or according to different conventions.

Once preprocessing is finished, it is possible to start linking the records in the different data sets. In the next section we describe a technique to improve the efficiency of the matching step.

---

### 3.4 Indexing and blocking

There is a practical challenge to consider when comparing the records in two files. If both files are roughly the same size, say 100 records in the first and 100 records in the second file, then there are 10,000 possible comparisons, because the number of pairs is the product of the number of records in each file. More generally, if the number of records in each file is approximately  $n$ , then the total number of possible record comparisons is approximately  $n^2$ . Assuming that there are no duplicate records in the input files, the proportion of record comparisons that correspond to a link is only  $1/n$ . If we naively proceed with

all  $n^2$  possible comparisons, the linkage algorithm will spend the bulk of its time comparing records that are not matches. Thus it is possible to speed up record linkage significantly by skipping comparisons between record pairs that are not likely to be linked.

Indexing refers to techniques that determine which of the possible comparisons will be made in a record linkage application. The most used technique for indexing is blocking. In this approach you construct a “blocking key” for each record by concatenating fields or parts of fields. Two records with identical blocking keys are said to be in the same block, and only records in the same block are compared. This technique is effective because performing an exact comparison of two blocking keys is a relatively quick operation compared to a full record comparison, which may involve multiple applications of a fuzzy string comparator.

---

### Example: Blocking in practice

Given two lists of individuals, one might construct the blocking key by concatenating the first letter of the last name and the postal code and then “blocking” on first character of last name and postal code. This reduces the total number of comparisons by only comparing those individuals in the two files who live in the same locality and whose last names begin with the same letter.

---

There are important considerations when choosing the blocking key. First, the choice of blocking key creates a potential bias in the linked data because true matches that do not share the same blocking key will not be found. In the example, the blocking strategy could fail to match records for individuals whose last name changed or who moved. Second, because blocking keys are compared exactly, there is an implicit assumption that the included fields will not have typos or other data entry errors. In practice, however, the blocking fields will exhibit typos. If those typos are not uniformly distributed over the population, then there is again the possibility of bias in the linked data set<sup>6</sup>. One simple strategy for dealing with imperfect blocking keys is to implement multiple rounds of blocking and matching. After the first set of matches is produced, a new blocking strategy is deployed to search for additional matches in the remaining record pairs.

Blocking based on exact field agreements is common in practice, but there are other approaches to indexing that attempt to be more error tolerant. For example, one may use clustering algorithms to identify sets of similar records. In this approach an index key, which is analogous to the blocking key above, is generated for both data sets and then the keys are combined into a single list. A distance function must be chosen and pairwise distances computed for all keys.

---

<sup>6</sup>This topic is discussed in more detail in Chapter 10.

The clustering algorithm is then applied to the combined list, and only record pairs that are assigned to the same cluster are compared. This is a theoretically appealing approach but it has the drawback that the similarity metric has to be computed for all pairs of records. Even so, computing the similarity measure for a pair of blocking keys is likely to be cheaper than computing the full record comparison, so there is still a gain in efficiency. Whang et al. (Whang et al. 2009) provide a nice review of indexing approaches.

In addition to reducing the computational burden of record linkage, indexing plays an important secondary role. Once implemented, the fraction of comparisons made that correspond to true links will be significantly higher. For some record linkage approaches that use an algorithm to find optimal parameters—like the probabilistic approach—having a larger ratio of matches to nonmatches will produce a better result.

---

### 3.5 Matching

The purpose of a record linkage algorithm is to examine pairs of records and make a prediction as to whether they correspond to the same underlying entity. (There are some sophisticated algorithms that examine sets of more than two records at a time (Steorts, Hall, and Fienberg 2014), but pairwise comparison remains the standard approach.) At the core of every record linkage algorithm is a function that compares two records and outputs a “score” that quantifies the similarity between those records. Mathematically, the match score is a function of the output from individual field comparisons: agreement in the first name field, agreement in the last name field, etc. Field comparisons may be binary—indicating agreement or disagreement—or they may output a range of values indicating different levels of agreement. There are a variety of methods in the statistical and computer science literature that can be used to generate a match score, including nearest-neighbor matching, regression-based matching, and propensity score matching. The probabilistic approach to record linkage defines the match score in terms of a likelihood ratio (Fellegi and Sunter 1969).

---

#### Example: Matching in practice

Long strings, such as assignee and inventor names, are susceptible to typographical errors and name variations. For example, none of Sony Corporation, Sony Corporatoin and Sony Corp. will match using simple exact matching. Similarly, David vs. Dave would not match (Ventura, Nugent, and Fuchs 2015).

Comparing fields whose values are continuous is straightforward: often one can simply take the absolute difference as the comparison value. Comparing character fields in a rigorous way is more complicated. For this purpose, different mathematical definitions of the distance between two character fields have been defined. Edit distance, for example, is defined as the minimum number of edit operations—chosen from a set of allowed operations—needed to convert one string to another. When the set of allowed edit operations is single-character insertions, deletions, and substitutions, the corresponding edit distance is also known as the Levenshtein distance. When transposition of adjacent characters is allowed in addition to those operations, the corresponding edit distance is called the Levenshtein–Damerau distance.

Edit distance is appealing because of its intuitive definition, but it is not the most efficient string distance to compute. Another standard string distance known as Jaro–Winkler distance was developed with record linkage applications in mind and is faster to compute. This is an important consideration because in a typical record linkage application most of the algorithm run time will be spent performing field comparisons. The definition of Jaro–Winkler distance is less intuitive than edit distance, but it works as expected: words with more characters in common will have a higher Jaro–Winkler value than those with fewer characters in common. The output value is normalized to fall between 0 and 1. Because of its history in record linkage applications, there are some standard variants of Jaro–Winkler distance that may be implemented in record linkage software. Some variants boost the weight given to agreement in the first few characters of the strings being compared. Others decrease the score penalty for letter substitutions that arise from common typos.

Once the field comparisons are computed, they must be combined to produce a final prediction of match status. In the following sections we describe three types of record linkage algorithms: rule-based, probabilistic, and machine learning.

### 3.5.1 Rule-based approaches

A natural starting place is for a data expert to create a set of ad hoc rules that determine which pairs of records should be linked. In the classical record linkage setting where the two files have a number of identifying fields in common, this is not the optimal approach. However, if there are few fields in common but each file contains auxiliary fields that may inform a linkage decision, then an ad hoc approach may be appropriate.

---

#### **Example: Linking in practice**

Consider the problem of linking two lists of individuals where both lists contain

first name, last name, and year of birth. Here is one possible linkage rule: link all pairs of records such that

- the Jaro–Winkler comparison of first names is greater than 0.9
- the Jaro–Winkler comparison of last names is greater than 0.9
- the first three digits of the year of birth are the same.

The result will depend on the rate of data errors in the year of birth field and typos in the name fields.

---

By *auxiliary field* we mean data fields that do not appear on both data sets, but which may nonetheless provide information about whether records should be linked. Consider a situation in which the first list includes an occupation field and the second list includes educational history. In that case one might create additional rules to eliminate matches where the education was deemed to be an unlikely fit for the occupation.

This method may be attractive if it produces a reasonable-looking set of links from intuitive rules, but there are several pitfalls. As the number of rules grows it becomes harder to understand the ways that the different rules interact to produce the final set of links. There is no notion of a threshold that can be increased or decreased depending on the tolerance for false positive and false negative errors. The rules themselves are not chosen to satisfy any kind of optimality, unlike the probabilistic and machine learning methods. Instead, they reflect the practitioner’s domain knowledge about the data sets.

### 3.5.2 Probabilistic record linkage

In this section we describe the probabilistic approach to record linkage, also known as the Fellegi–Sunter algorithm (Fellegi and Sunter 1969). This approach dominates in traditional record linkage applications and remains an effective and efficient way to solve the record linkage problem today.

In this section we give a somewhat formal definition of the statistical model underlying the algorithm. By understanding this model, one is better equipped to define link keys and record comparisons in an optimal way.

---

#### Example: Usefulness of probabilistic record linkage

In practice, it is typically the case that a researcher will want to combine two or more data sets containing records for the same individuals or units that possibly come from different sources. Unless the sources all contain the same unique identifiers, linkage will likely require matching on standardized

text strings. Even standardized data are likely to contain small differences that preclude exact matching as in the matching example above. The Census Bureau’s Longitudinal Business Database (LBD) links establishment records from administrative and survey sources. Exact numeric identifiers do most of the heavy lifting, but mergers, acquisitions, and other actions can break these linkages. Probabilistic record linkage on company names and/or addresses is used to fix these broken linkages that bias statistics on business dynamics (Jarmin and Miranda 2002).

---

Let  $A$  and  $B$  be two lists of individuals whom we wish to link. The product set  $A \times B$  contains all possible pairs of records where the first element of the pair comes from  $A$  and the second element of the pair comes from  $B$ . A fraction of these pairs will be matches, meaning that both records in the pair represent the same underlying individual, but the vast majority of them will be nonmatches. In other words,  $A \times B$  is the disjoint union of the set of matches  $M$  and the set of nonmatches  $U$ , a fact that we denote formally by  $A \times B = M \cup U$ .

Let  $\gamma$  be a vector-valued function on  $A \times B$  such that, for  $a \in A$  and  $b \in B$ ,  $\gamma(a, b)$  represents the outcome of a set of field comparisons between  $a$  and  $b$ . For example, if both  $A$  and  $B$  contain data on individuals’ first names, last names, and cities of residence, then  $\gamma$  could be a vector of three binary values representing agreement in first name, last name, and city. In that case  $\gamma(a, b) = (1, 1, 0)$  would mean that the records  $a$  and  $b$  agree on first name and last name, but disagree on city of residence.

For this model, the comparison outcomes in  $\gamma(a, b)$  are not required to be binary, but they do have to be categorical: each component of  $\gamma(a, b)$  should take only finitely many values. This means that a continuous comparison outcome—such as output from the string comparator—has to be converted to an ordinal value representing levels of agreement. For example, one might create a three-level comparison, using one level for exact agreement, one level for approximate agreement defined as a Jaro–Winkler score greater than 0.85, and one level for nonagreement corresponding to a Jaro–Winkler score less than 0.85.

If a variable being used in the comparison has a significant number of missing values, it can help to create a comparison outcome level to indicate missingness. Consider two data sets that both have middle initial fields, and suppose that in one of the data sets the middle initial is filled in only about half of the time. When comparing records, the case where both middle initials are filled in but are not the same should be treated differently from the case where one of the middle initials is blank, because the first case provides more evidence that the records do not correspond to the same person. We handle this in the model by defining a three-level comparison for the middle initial, with levels to indicate “equal,” “not equal,” and “missing.”

Probabilistic record linkage works by weighing the probability of seeing the result  $\gamma(a, b)$  if  $(a, b)$  belongs to the set of matches  $M$  against the probability of seeing the result if  $(a, b)$  belongs to the set of nonmatches  $U$ . Conditional on  $M$  or  $U$ , the distribution of the individual comparisons defined by  $\gamma$  are assumed to be mutually independent. The parameters that define the marginal distributions of  $\gamma|M$  are called *m-weights*, and similarly the marginal distributions of  $\gamma|U$  are called *u-weights*.

In order to apply the Fellegi–Sunter method, it is necessary to choose values for these parameters, *m*-weights and *u*-weights. With labeled data—a pair of lists for which the match status is known—it is straightforward to solve for optimal values. Training data are not usually available, however, and the typical approach is to use expectation maximization to find optimal values.

We have noted that primary motivation for record linkage is to create a linked data set for analysis that will have a richer than either of the input data sets alone. A natural application is to perform a linear regression using a combination of variables from both files as predictors. With all record linkage approaches it is a challenge to understand how errors from the linkage process will manifest in the regression. Probabilistic record linkage has an advantage over rule-based and machine learning approaches in that there are theoretical results concerning coefficient bias and errors (Scheuren and Winkler 1993; Lahiri and Larsen 2005). More recently, Chipperfield and Chambers have developed an approach based on the bootstrap to account for record linkage errors when making inferences for cross-tabulated

### 3.5.3 Machine learning approaches to record linkage

Computer scientists have contributed extensively in parallel literature focused on linking large data sets (Christen 2012b). Their focus is on identifying potential links using approaches that are fast, adaptive, and scalable, and approaches are developed based on work in network analysis and machine learning.

While simple blocking as described in Section Indexing and Blocking is standard in Fellegi–Sunter applications, machine learning based approaches are likely to use the more sophisticated clustering approach to indexing. Indexing may also use network information to include, for example, records for individuals that have a similar place in a social graph. When linking lists of researchers, one might specify that comparisons should be made between records that share the same address, have patents in the same patent class, or have overlapping sets of co-inventors. These approaches are known as semantic blocking, and the computational requirements are similar to standard blocking (Christen 2012b).

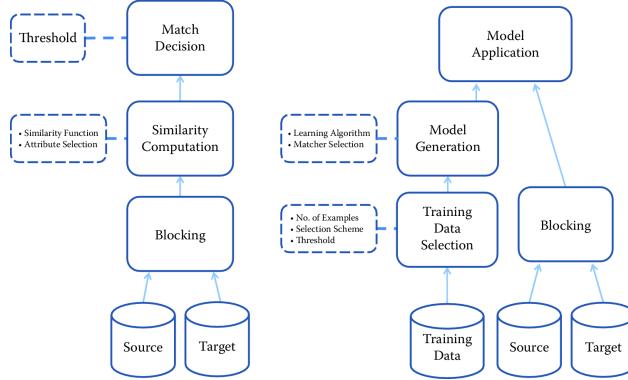
In recent years machine learning approaches<sup>7</sup> have been applied to record Linkage. As Wick et al. (Wick et al. 2013) note:

Entity resolution, the task of automatically determining which mentions refer to the same real-world entity, is a crucial aspect of knowledge base construction and management. However, performing entity resolution at large scales is challenging because (1) the inference algorithms must cope with unavoidable system scalability issues and (2) the search space grows exponentially in the number of mentions. Current conventional wisdom declares that performing coreference at these scales requires decomposing the problem by first solving the simpler task of entity-linking (matching a set of mentions to a known set of KB entities), and then performing entity discovery as a post-processing step (to identify new entities not present in the KB). However, we argue that this traditional approach is harmful to both entity-linking and overall coreference accuracy. Therefore, we embrace the challenge of jointly modeling entity-linking and entity discovery as a single entity resolution problem.

Figure 3.2 provides a useful comparison between classical record linkage and learning-based approaches. In machine learning there is a statistical model and an algorithm for “learning” the optimal set of parameters to use. The learning algorithm relies on a training data set. In record linkage, this would be a curated data set with true and false matches labeled as such. See (Ventura, Nugent, and Fuchs 2015) for an example and a discussion of how a training data set was created for the problem of disambiguating inventors in the USPTO database. Once optimal parameters are computed from the training data, the predictive model can be applied to unlabeled data to find new links. The quality of the training data set is critical; the model is only as good as the data it is trained on.

As shown in Figure 3.2, a major difference between probabilistic and machine learning approaches is the need for labeled training data to implement the latter approach. Usually training data are created through a painstaking process of clerical review. After an initial round of record linkage, a sample of record pairs that are not clearly matches or nonmatches is given to a research assistant who makes the final determination. In some cases it is possible to create training data by automated means. For example, when there is a subset of the complete data that contains strongly identifying fields. Suppose that both of the candidate lists contain name and date of birth fields and that in the first list the date of birth data are complete, but in the second list only about 10% of records contain date of birth. For reasonably sized lists, name and date of birth together will be a nearly unique identifier. It is then possible to perform probabilistic record linkage on the subset of records with date of birth and be confident that the error rates would be small. If the subset of

<sup>7</sup>This topic is discussed in more detail in Chapter 6.



**FIGURE 3.2** Probabilistic (left) vs. machine learning (right) approaches to linking. Source: Köpcke et al. [@kopcke2010evaluation]

records with date of birth is representative of the complete data set, then the output from the probabilistic record linkage can be used as “truth” data.

Given a quality training data set, machine learning approaches may have advantages over probabilistic record linkage. There are many published studies on the effectiveness of random forests and other machine learning algorithms for record linkage. Christen and Ahmed et al. provide some pointers (Christen 2012a; Elmagarmid, Ipeirotis, and Verykios 2007).

### 3.5.4 Disambiguating networks

The problem of disambiguating entities in a network is closely related to record linkage: in both cases the goal is to consolidate multiple records corresponding to the same entity. Rather than finding the same entity in two data sets, however, the goal in network disambiguation is to consolidate duplicate records in a network data set. By network we mean that the data set contains not only typical record fields like names and addresses but also information about how entities relate to one another: entities may be coauthors, coinventors, or simply friends in a social network.

The record linkage techniques that we have described in this chapter can be applied to disambiguate a network. To do so, one must convert the network to a form that can be used as input into a record linkage algorithm. For example, when disambiguating a social network one might define a field comparison whose output gives the fraction of friends in common between two records. Ventura et al. demonstrated the relative effectiveness of the probabilistic method and machine learning approaches to disambiguating a database of inventors in the USPTO database (Ventura, Nugent, and Fuchs 2015). Another

approach is to apply clustering algorithms from the computer science literature to identify groups of records that are likely to refer to the same entity. Huang et al. (Huang, Ertekin, and Giles 2006) have developed a successful method based on an efficient computation of distance between individuals in the network. These distances are then fed into the DBSCAN clustering algorithm to identify unique entities.

---

## 3.6 Classification

Once the match score for a pair of records has been computed using the probabilistic or random forest method, a decision has to be made whether the pair should be linked. This requires classifying the pair as either a “true” or a “false” match. In most cases, a third classification is required—sending for manual review and classification.

### 3.6.1 Thresholds

In the probabilistic and random forest approaches, both of which output a “match score” value, a classification is made by establishing a threshold  $T$  such that all records with a match score greater than  $T$  are declared to be links. Because of the way these algorithms are defined, the match scores are not meaningful by themselves and the threshold used for one linkage application may not be appropriate for another application. Instead, the classification threshold must be established by reviewing the model output.

Typically one creates an output file that includes pairs of records that were compared along with the match score. The file is sorted by match score and the reviewer begins to scan the file from the highest match scores to the lowest. For the highest match scores the record pairs will agree on all fields and there is usually no question about the records being linked. However, as the scores decrease the reviewer will see more record pairs whose match status is unclear (or that are clearly nonmatches) mixed in with the clear matches. There are a number of ways to proceed, depending on the resources available and the goal of the project.

Rather than set a single threshold, the reviewer may set two thresholds  $T_1 > T_2$ . Record pairs with a match score greater than  $T_1$  are marked as matches and removed from further consideration. The set of record pairs with a match score between  $T_1$  and  $T_2$  are believed to contain significant numbers of matches and nonmatches. These are sent to clerical review, meaning that research assistants will make a final determination of match status. The final set of links will

include clear matches with a score greater than  $T_1$  as well as the record pairs that pass clerical review. If the resources are available for this approach and the initial threshold  $T_1$  is set sufficiently high, then the resulting data set will contain a minimal number of false positive links. The collection of record pairs with match scores between  $T_1$  and  $T_2$  is sometimes referred to as the clerical review region.

The clerical review region generally contains many more pairs than the set of clear matches, and it can be expensive and time-consuming to review each pair. Therefore, a second approach is to establish tentative threshold  $T$  and send only a sample of record pairs with scores in a neighborhood of  $T$  to clerical review. This results in data on the relative numbers of true matches and true nonmatches at different score levels, as well as the characteristics of record pairs that appear at a given level. Based on the review and the relative tolerance for false positive errors and false negative errors, a final threshold  $T'$  is set such that pairs with a score greater than  $T'$  are considered to be matches.

After viewing the results of the clerical review, it may be determined that the parameters to the record linkage algorithm could be improved to create a clearer delineation between matches and nonmatches. For example, a research assistant may determine that many potential false positives appear near the tentative threshold because the current set of record linkage parameters is giving too much weight to agreement in first name. In this case the reviewer may decide to update the record linkage model to produce an improved set of match scores. The update may consist in an ad hoc adjustment of parameters, or the result of the clerical review may be used as training data and the parameter-fitting algorithm may be run again. An iterative approach like this is common when first linking two data sets because the clerical review process can improve one's understanding of the data sets involved.

Setting the threshold value higher will reduce the number of false positives (record pairs for which a link is incorrectly predicted) while increasing the number of false negatives (record pairs that should be linked but for which a link is not predicted). The proper tradeoff between false positive and false negative error rates will depend on the particular application and the associated loss function, but there are some general concerns to keep in mind. Both types of errors create bias, which can impact the generalizability of analyses conducted on the linked data set. Consider a simple regression on the linked data that includes fields from both data sets. If the threshold is too high, then the linked data will be biased toward records with no data entry errors or missing values, and whose fields did not change over time. This set of records may not be representative of the population as a whole. If a low threshold is used, then the set of linked records will contain more pairs that are not true links and the variables measured in those records are independent of each other. Including these records in a regression amounts to adding statistical noise to the data.

### 3.6.2 One-to-one links

In the probabilistic and machine learning approaches to record linkage that we have described, each record pair is compared and a link is predicted independently of all other record pairs. Because of the independence of comparisons, one record in the first file may be predicted to link to multiple records in the second file. Under the assumption that each input file has been deduplicated, at most one of these predictions can correspond to a true link. For many applications it is preferable to extract a set of “best” links with the property that each record in one file links to at most one record in the second file. A set of links with this property is said to be one-to-one.

One possible definition of “best” is a set of one-to-one links such that the sum of the match scores of all included links is maximal. This is an example of what is known as the *assignment problem* in combinatorial optimization. In the linear case above, where we care about the sum of match scores, the problem can be solved exactly using the Hungarian algorithm (Kuhn 2005)<sup>8</sup>.

## 3.7 Record linkage and data protection

In many social science applications data sets there is no need for data to include identifying fields like names and addresses. These fields may be left out intentionally out of concern for privacy<sup>9</sup>, or they may simply be irrelevant to the research question. For record linkage, however, names and addresses are among the best possible identifiers. We describe two approaches to the problem of balancing needs for both effective record linkage and privacy.

The first approach is to establish a trusted third party or safe center. The concept of trusted third parties (TTPs) is well known in cryptography. In the case of record linkage, a third party takes a place between the data owners and the data users, and it is this third party that actually performs the linkage work. Both the data owners and data users trust the third party in the sense that it assumes responsibility for data protection (data owners) and data competence (data users) at the same time. No party other than the TTP learns about the private data of the other parties. After record linkage only the linked records are revealed, with no identifiers attached. The TTP ensures that the released linked data set cannot be relinked to any of the source data sets. Possible third parties are safe centers, which are operated by lawyers, or official trusted institutions like the US Census Bureau. Some countries like the

<sup>8</sup>This topic is discussed in more detail in Chapter 6.

<sup>9</sup>See Chapter 11.

UK and Germany are establishing new institutions specifically to act as TTPs for record linkage work.

The second approach is known as privacy-preserving record linkage. The goal of this approach is to find the same individual in separate data files without revealing the identity of the individual (Clifton et al. 2006). In privacy-preserving record linkage, cryptographic procedures are used to encrypt or hash identifiers before they are shared for record linkage. Many of these procedures require exact matching of the identifiers, however, and do not tolerate any errors in the original identifiers. This leads to information loss because it is not possible to account for typos or other small variations in hashed fields. To account for this, Schnell has developed a method to calculate string similarity of encrypted fields using bloom filters (Schnell 2014; Schnell, Bachteler, and Reiher 2009).

In many countries these approaches are combined. For example, when the UK established the ADRN, the latter established the concept of trusted third parties. That third party is provided with data in which identifying fields have been hashed. This solves the challenge of trust between the different parties. Some authors argue that transparency of data use and informed consent will help to build trust. In the context of big data this is more challenging<sup>10</sup>.

---

## 3.8 Summary

Accurate record linkage is critical to creating high-quality data sets for analysis. However, outside of a few small centers for record linkage research, linking data sets historically relied on artisan approaches, particularly for parsing and cleaning data sets. As the creation and use of big data increases, so does the need for systematic record linkage. The history of record linkage is long by computer science standards, but new data challenges encourage the development of new approaches like machine learning methods, clustering algorithms, and privacy-preserving record linkage.

Record linkage stands on the boundary between statistics, information technology, and privacy. We are confident that there will continue to be exciting developments in this field in the years to come.

---

<sup>10</sup>This topic is discussed in more detail in Chapter 11.

---

### 3.9 Resources

Out of many excellent resources on the subject, we note the following:

- We strongly recommend Christen's book (Christen 2012b).
- There is a wealth of information available on the ADRN website (Economic and Social Research Council 2016).
- Winkler has a series of high-quality survey articles (Winkler 2014).
- The German Record Linkage Center is a resource for research, software, and ongoing conference activities (Schnell 2016).

# 4

---

## Databases

---

**Ian Foster and Pascal Heus**

Once the data have been collected and linked, it is necessary to store and organize them. Many social scientists are used to working with one analytical file, often in SAS, Stata, SPSS, or R. Most organizations store (or should store) their data in databases which makes it critical for social scientists to learn how to create, manage, and use databases for data storage and analysis. This chapter describes the concept of databases, different types of databases, and analysis languages (SQL) that allow storing and organizing of data for rapid and efficient data exploration and analysis.

---

### 4.1 Introduction

We turn now to the question of how to store, organize, and manage the data used in data-intensive social science. As the data with which you work grow in volume and diversity, effective data management becomes increasingly important to avoid scale and complexity from overwhelming your research processes. In particular, when you deal with data that get frequently updated, with changes made by different people, you will want to use database management systems (DBMSs) instead of maintaining data in text files or within siloed statistical packages such as SAS, SPSS, Stata, and R. Indeed, we go so far as to say: if you take away *just one thing* from this book, it should be this: *Use a database!*

As we explain in this chapter, DBMSs greatly simplify data management. They require a little bit of effort to set up, but are worth it. They permit large amounts of data to be organized in multiple ways that allow for efficient and rapid exploration via query languages; durable and reliable storage that maintain data consistency; scaling to large data sizes; and intuitive analysis, both within the DBMS itself and via connectors to other data analysis packages and tools. DBMSs have become a critical component of most real-world systems, from handling transactions in financial systems to delivering data to power websites, dashboards, and software that we use every day. If you are using a production-level enterprise system, chances are there is a database in the

back-end. They are multi-purpose and well suited for organizing social science data and for supporting data exploration and analysis.

DBMSs make many easy things trivial, and many hard things easy. They are easy to use but can appear daunting at first. A basic understanding of databases and of when and how to use DBMSs is an important element of the social data scientist's knowledge base. We therefore provide in this chapter an introduction to databases and how to use them. We describe different types of databases and their various features, and how they can be used in different contexts. We describe basic features like how to get started, setting up a database schema, ingesting data, querying and analyzing data within a database, and getting results out. We also discuss how to link from databases to other tools, such as Python, R, and (if you have to) Stata.

---

## 4.2 DBMS: When and why

Consider the following three data sets:

1. 10,000 records describing research grants, each specifying the principal investigator, institution, research area, proposal title, award date, and funding amount in a comma-separated-value (CSV) format.
2. 10 million records in a variety of formats from funding agencies, web APIs, and institutional sources describing people, grants, funding agencies, and patents.
3. 10 billion Twitter messages and associated metadata—around 10 terabytes ( $10^{13}$  bytes) in total, and increasing at a terabyte a month.

Which tools should you use to manage and analyze these data sets? The answer depends on the specifics of the data, the analyses that you want to perform, and the life cycle within which data and analyses are embedded. Table 4.1 summarizes relevant factors, which we now discuss.

TABLE 4.1: When to use different data management and analysis technologies

---

### When to use different data management and analysis technologies

---

#### Text files, spreadsheets, and scripting language

- Your data are small
- Your analysis is simple

---

**When to use different data management and analysis technologies**

---

- You do not expect to repeat analyses over time

**Statistical packages**

- Your data are modest in size
- Your analysis maps well to your chosen statistical package

**Relational database**

- Your data are structured
- Your data are large
- You will be analyzing changed versions of your data over time
- You want to share your data and analyses with others

**NoSQL database**

- Your data are unstructured
  - Your data are extremely large
- \* Your analysis will happen mostly outside the database in a programming language
- 

In the case of data set 1 (10,000 records describing research grants), it may be feasible to leave the data in their original file, use spreadsheets, pivot tables, or write programs in **scripting languages**<sup>1</sup> such as Python or R to analyze the data in those files. For example, someone familiar with such languages can quickly create a script to extract from data set 1 all grants awarded to one investigator, compute average grant size, and count grants made each year in different areas.

However, this approach also has disadvantages. Scripts do not provide inherent control over the file structure. This means that if you obtain new data in a different format, your scripts need to be updated. You cannot just run them over the newly acquired file. Scripts can also easily become unreasonably slow as data volumes grow. A Python or R script will not take long to search a list of 1,000 grants to find those that pertain to a particular institution. But what if you have information about 1 million grants, and for each grant you want to search a list of 100,000 investigators, and for each investigator, you want to search a list of 10 million papers to see whether that investigator is listed as an author of each paper? You now have  $1,000,000 \times 100,000 \times 10,000,000 = 10^{18}$  comparisons to perform. Your simple script may now run for hours or even days. You can speed up the search process by constructing indices, so that, for example, when given a grant, you can find the associated investigators in constant time rather than in time proportional to the number of investigators. However, the construction of such indices is itself a time-consuming and error-prone process.

---

<sup>1</sup>A scripting language is a programming language used to automate tasks that could otherwise be performed one by one by the user.

For these reasons, the use of scripting languages alone for data analysis is rarely to be recommended. This is not to say that all analysis computations can be performed in database systems. A programming language will also often be needed. But many data access and manipulation computations are best handled in a database.

Researchers in the social sciences frequently use statistical packages such as R, SAS, SPSS, and Stata for data analysis. Because these systems integrate some data management, statistical analysis, and graphics capabilities in a single package, a researcher can often carry out a data analysis project of modest size within the same environment. However, each of these systems has limitations that hinder its use for modern social science research, especially as data grow in size and complexity.

Take Stata, for example. Stata loads the entire data set into the computer's working memory, and thus you would have no problems loading data set 1. However, depending on your computer's memory, it could have problems dealing with data set 2 and most likely would not be able to handle data set 3. In addition, you would need to perform this data loading step each time you start working on the project, and your analyses would be limited to what Stata can do. SAS can deal with larger data sets, but is renowned for being hard to learn and use. Of course there are workarounds in statistical packages. For example, in Stata you can deal with larger file sizes by choosing to only load the variables or cases that you need for the analysis (Kohler and Kreuter 2012). Likewise, you can deal with more complex data by creating a system of files that each can be linked as needed for a particular analysis through a common identifier variable<sup>2</sup>.

Those solutions essentially mimic core functions of a DBMS, and you would be well advised to set up a database, especially if you find yourself in a situation where the data set is constantly updated through different users, if groups of users have different rights to use your data or should only have access to subsets of the data, and if the analysis takes place on a server that sends results to a client (browser). Some statistics packages also have difficulty working with more than one data source at a time—something that DBMSs are designed to do well.

Alas, databases are not perfectly suited for every need. For example, in social science research, the reproducibility of our analysis is critical and hence versioning of the data used for analysis is critical. Most databases don't do that out of the box. Typically, they do keep a log of all the operations (inserting, updating, updating data for example) which can facilitate versioning and rollbacks but we often need to configure the databases to allow versioning and support reproducibility.

---

<sup>2</sup>For example, the Panel Study of Income Dynamics [181] has a series of files that are related and can be combined through common identifier variables [182].

These considerations bring us to the topic of this chapter, namely **database management systems**. A DBMS<sup>3</sup> handles all of the issues listed above, and more. As we will see below when we look at concrete examples, a DBMS allows us to define a logical design that fits the structure of our data. The DBMS then creates a *data model* (more on this below) that allows these data to be stored, queried, and updated efficiently and reliably on disk, thus providing independence from underlying physical storage. It supports efficient access to data through *query languages* and (somewhat) automatic optimization of those queries to permit fast analysis. Importantly, it also supports concurrent access by multiple users, which is not an option for file-based data storage. It supports *transactions*, meaning that any update to a database is performed in its entirety or not at all, even in the face of computer failures or multiple concurrent updates. And it reduces the time spent both by analysts, by making it easy to express complex analytical queries concisely, and on data administration, by providing simple and uniform data administration interfaces.

A *database* is a structured collection of data about entities and their relationships. It models real-world objects—both entities (e.g., grants, investigators, universities) and relationships (e.g., “Steven Weinberg” works at “University of Texas at Austin”)—and captures structure in ways that allow these entities and relationships to be queried for analysis. A *database management system* is a software suite designed to safely store and efficiently manage databases, and to assist with the maintenance and discovery of the relationships that database represents. In general, a DBMS encompasses three key components: its *data model* (which defines how data are represented: see Box 4.1), its *query language* (which defines how the user interacts with the data), and support for *transactions and crash recovery* (to ensure reliable execution despite system failures).<sup>4</sup>

---

<sup>3</sup>DBMS is a system that interacts with users, other applications, and the database itself to capture and analyze data.

<sup>4</sup>Some key DBMS features are often lacking in standard statistical packages: a standard query language (with commands that allow analyses or data manipulation on a subgroup of cases defined during the analysis, for example “group by ...,” “order by ...”), keys (for speed improvement), and an explicit model of a relational data structure.

**Box 4.1: Data model** A *data model* specifies the data elements associated with the domain we are analyzing, the properties of those data elements, and how those data elements relate to one another. In developing a data model, we commonly first identify the entities that are to be modeled and then define their properties and relationships. For example, when working on the science of science policy (see Figure 4.1, the entities include people, products, institutions, and funding, each of which has various properties (e.g., for a person, their name, address, employer); relationships include “is employed by” and “is funded by.” This conceptual data model can then be translated into relational tables or some other database representation, as we describe next.

Hundreds of different open source, commercial, and cloud-hosted versions DBMSs are available and new ones pop up every day. However, you only need to understand a relatively small number of concepts and major database types to make sense of this diversity. Table 4.2 defines the major classes of DBMSs that we will consider in this chapter. We consider only a few of these in any detail.

Relational DBMSs are the most widely used systems, and will be the optimal solution for many social science data analysis purposes. We describe relational DBMSs in detail below, but in brief, they allow for the efficient storage, organization, and analysis of large quantities of *tabular* data<sup>5</sup>: data organized as tables, in which rows represent entities (e.g., research grants) and columns represent attributes of those entities (e.g., principal investigator, institution, funding level). The associated Structured Query Language (SQL) can then be used to perform a wide range of tasks, which are executed with high efficiency due to sophisticated indexing and query planning Techniques.

While relational DBMSs have dominated the database world for decades, other database technologies have become popular for various classes of applications in recent years. As we will see, these alternative NoSQL DBMSs have typically been motivated by a desire to scale the quantities of data and/or number of users that can be supported and/or to deal with unstructured data that are not easily represented in tabular form. For example, a key-value store can organize large numbers of records, each of which associates an arbitrary key with an arbitrary value. These stores, and in particular variants called *document stores* that permit text search on the stored values, are widely used to organize and process the billions of records that can be obtained from web crawlers. We review below some of these alternatives and the factors that may motivate their use.

<sup>5</sup>Sometimes, as discussed in Chapter 3, the links are one to one and sometimes one to many.

TABLE 4.2: Types of databases: relational (first row) and various types of NoSQL (other rows)

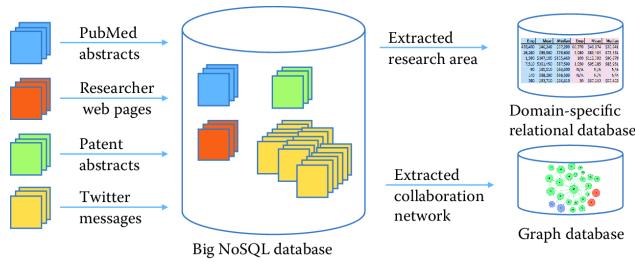
Type	Examples	Advantages	Disadvantages	Uses
Relational database	MySQL, PostgreSQL, Oracle, SQL Server, Teradata	Consistency (ACID)	Fixed schema; typically harder to scale	Transactional systems: order processing, retail, hospitals, etc.
Key-value store	Dynamo, Redis	Dynamic schema; easy scaling; high throughput	Not immediately consistent; no higher-level queries	Web applications
Column store	Cassandra, HBase	Same as key-value; distributed; better compression at column level	Not immediately consistent; using all columns is inefficient	Large-scale analysis
Document store	CouchDB, MongoDB	Index entire document (JSON)	Not immediately consistent; no higher-level queries	Web applications
Graph database	Neo4j, InfiniteGraph	Graph queries are fast	May not be efficient to do non-graph analysis	Recommendation systems, networks, routing

Relational and NoSQL databases (and indeed other solutions, such as statistical packages) can also be used together. Consider, for example, Figure 4.1, which depicts data flows commonly encountered in large research projects. Diverse data are being collected from different sources: JSON documents from web APIs, web pages from web scraping, tabular data from various administrative databases, Twitter data, and newspaper articles. There may be hundreds or even thousands of data sets in total, some of which may be extremely large. We initially have no idea of what **schema**<sup>6</sup> to use for the different data sets, and indeed it may not be feasible to define a unified set of schema, as the data may be diverse and new data sets may be getting acquired continuously.

<sup>6</sup>A schema defines the structure of a database in a formal language defined by the DBMS. See Section 4.3.3.

Furthermore, the way we organize the data may vary according to our intended purpose. Are we interested in geographic, temporal, or thematic relationships among different entities? Each type of analysis may require a different way of organizing.

For these reasons, a common storage solution may be to first load all data into a large NoSQL database. This approach makes all data available via a common (albeit limited) query interface. Researchers can then extract from this database the specific elements that are of interest for their work, loading those elements into a relational DBMS, another specialized DBMS (e.g., a graph database), or a package for more detailed analysis. As part of the process of loading data from the NoSQL database into a relational database, the researcher will necessarily define schemas, relationships between entities, and so forth. Analysis results can be stored in a relational database or back into the NoSQL store.



**FIGURE 4.1** A research project may use a NoSQL database to accumulate large amounts of data from many different sources, and then extract selected subsets to a relational or other database for more structured processing

### 4.3 Relational DBMSs

We now provide a more detailed description of relational DBMSs. Relational DBMSs implement the relational data model, in which data are represented as sets of records organized in tables. This model is particularly well suited for the structured data with which we frequently deal in the social sciences; we discuss in Section 4.5 alternative data models, such as those used in NoSQL databases.

We use the data shown in Figure 4.2 to introduce key concepts. These two CSV format files describe grants made by the US National Science Foundation (NSF). One file contains information about grants, the other information about investigators. How should you proceed to manipulate and analyze these data?

The file grants.csv
# Identifier,Person,Funding,Program 1316033,Steven Weinberg,666000,Elem. Particle Physics/Theory 1336199,Howard Weinberg,323194,ENVIRONMENTAL ENGINEERING 1500194,Irving Weinberg,200000,Accelerating Innovation Rsrch 12111853,Irving Weinberg,261437,GALACTIC ASTRONOMY PROGRAM
The file investigators.csv
# Name,Institution,Email Steven Weinberg,University of Texas at Austin,weinberg@utexas.edu Howard Weinberg,University of North Carolina Chapel Hill, Irving Weinberg,University of Maryland College Park,irving@umcp.edu

**FIGURE 4.2** CSV files representing grants and investigators. Each line in the first table specifies a grant number, investigator name, total funding amount, and NSF program name; each line in the second gives an investigator name, institution name, and investigator email address

The main concept underlying the relational data model is a *table* (also referred to as a *relation*): a set of rows (also referred to as tuples, records, or observations), each with the same columns (also referred to as fields, attributes or variables). A database consists of multiple tables. For example, we show in Figure 4.3 how the data contained in the two CSV files of Figure 4.2 may be as two tables. The **Grants** table contains one tuple for each row in grants.csv, with columns **GrantID**, **Person**, **Funding**, and **Program**. The table contains one tuple for each row in investigators.csv, with columns **ID**, **Name**, **Institution**, and **Email**. The CSV files and tables contain essentially the same information, albeit with important differences (the addition of an ID field in the **Investigators** table, the substitution of an ID column for the **Person** column in the **Grants** table) that we will explain below.

The use of the relational data model provides for physical independence: a given table can be stored in many different ways. SQL queries are sets of instructions to execute commands written in terms of the logical representation of tables (i.e., their schema definition). Consequently, even if the physical organization of the data changes (e.g., a different layout is used to store the data on disk, or a new index is created to speed up access for some queries), the queries need not change. Another advantage of the relational data model is that, since a table is a *set*, in a mathematical sense, simple and intuitive set operations (e.g., union, intersection) can be used to manipulate the data, as we discuss below. We can easily, for example, determine the intersection of two relations (e.g., grants that are awarded to a specific institution), as we describe in the following. The database further ensures that the data comply with the model (e.g., data types, key uniqueness, entity relationships), essentially providing core quality assurance.

Number	Person	Funding	Program
1316033	1	660,000	ELEM. PARTICLE PHYSICS/THEORY
1336199	2	323,194	ENVIRONMENTAL ENGINEERING
1500194	3	200,000	ACCELERATING INNOVATION RSRCH
1211853	3	261,437	GALACTIC ASTRONOMY PROGRAM

ID	Name	Institution	Email
1	Steven Weinberg	University of Texas at Austin	weinberg@utexas.edu
2	Howard Weinberg	University of North Carolina Chapel Hill	
3	Irving Weinberg	University of Maryland College Park	irving@ucmc.edu

**FIGURE 4.3** Relational tables ‘Grants’ and ‘Investigators’ corresponding to the grants.csv and investigators.csv data in Figure 4.2, respectively. The only differences are the representation in a tabular form, the introduction of a unique numerical investigator identifier (‘ID’) in the ‘Investigators’ table, and the substitution of that identifier for the investigator name in the ‘Grants’ table

#### 4.3.1 Structured Query Language (SQL)

We use query languages to manipulate data in a database (e.g., to add, update, or delete data elements) and to retrieve (raw and aggregated) data from a database (e.g., data elements that certain properties). Most Relational DBMSs support SQL, a simple, powerful query language with a strong formal foundation based on logic, a foundation that allows relational DBMSs to perform a wide variety of sophisticated optimizations. SQL is used for three main purposes:

- **Data definition:** e.g., creation of new tables,
- **Data manipulation:** queries and updates,
- **Control:** creation of assertions to protect data integrity.

We introduce each of these features in the following, although not in that order, and certainly not completely. Our goal here is to give enough information to provide the reader with insights into how relational databases work and what they do well; an in-depth SQL tutorial is beyond the scope of this book but we highly recommend checking the references at the end of this chapter.

#### 4.3.2 Manipulating and querying data

SQL and other query languages used in DBMSs support the concise, declarative specification of complex queries. Because we are eager to show you something immediately useful, we cover these features first, before talking about how to define data models.

---

**Example: Identifying grants of more than \$200,000** Here is an SQL query to identify all grants with total funding of at most \$200,000:

```
select * from Grants
where Funding <= 200,000;
```

Notice SQL’s declarative nature: this query can be read almost as the English language statement, “select all rows from the `Grants` table for which the `Funding` column has value less than or equal 200,000.” This query is evaluated as follows:

1. The input table specified by the `from` clause, `Grants`, is selected.
2. The condition in the `where` clause, `Funding <= 200,000`, is checked against all rows in the input table to identify those rows that match.
3. The `select` clause specifies which columns to keep from the matching rows, that is, which columns make the schema of the output table. (The “`*`” indicates that all columns should be kept.)

The answer, given the data in Figure 4.3, is the following single-row table. (The fact that an SQL query returns a table is important when it comes to creating more complex queries: the result of a query can be stored into the database as a new table, or passed to another query as input.)

Number	Person	Funding	Program
1500194	3	200,000	Accelerating Innovation Rsrch

DBMSs automatically optimize declarative queries such as the example that we just presented, translating them into a set of low-level data manipulations (an imperative *query plan*) that can be evaluated efficiently. This feature allows users to write queries without having to worry too much about performance issues—the database does the worrying for you. For example, a DBMS need not consider every row in the `Grants` table in order to identify those with funding less than \$200,000, a strategy that would be slow if the `Grants` table were large: it can instead use an index to retrieve the relevant records much more quickly. We discuss indices in more detail in Section 4.3.6.

The querying component of SQL supports a wide variety of manipulations on tables, whether referred to explicitly by a table name (as in the example just shown) or constructed by another query. We just saw how to use the `select` operator to both pick certain rows (what is termed *selection*) and certain columns (what is called *projection*) from a table.

---

#### Example: Finding grants awarded to an investigator

We want to find all grants awarded to the investigator with name “Irving Weinberg.” The information required to answer this question is distributed over two tables, `Grants` and `Investigators`, and so we *join* the two tables to combine tuples from both:

```
select Number, Name, Funding, Program
from Grants, Investigators
where Grants.Person = Investigators.ID
and Name = "Irving Weinberg";
```

This query combines tuples from the `Grants` and `Investigators` tables for which the `Person` and `ID` fields match. It is evaluated in a similar fashion to the query presented above, except for the `from` clause: when multiple tables are listed, as here, the conditions in the `where` clause are checked for all different combinations of tuples from the tables defined in the `from` clause (i.e., the cartesian product of these tables)—in this case, a total of  $3 \times 4 = 12$  combinations. We thus determine that Irving Weinberg has two grants. The query further selects the `Number`, `Name`, `Funding`, and `Program` fields from the result, giving the following:

Number	Person	Funding	Program
1500194	Irving Weinberg	200,000	Accelerating Innovation Rsrch
1211853	Irving Weinberg	261,437	GALACTIC ASTRONOMY PROGRAM

This ability to join two tables in a query is one example of how SQL permits concise specifications of complex computations. This joining of tables via a cartesian product operation is formally called a *cross join*. Other types of join are also supported. We describe one such, the *inner join*, in Section 4.6.

---

SQL aggregate functions allow for the computation of aggregate statistics over tables. For example, we can use the following query to determine the total number of grants and their total and average funding levels:

```
select count(*) as 'Number', sum(Funding) as 'Total',
       avg(Funding) as 'Average'
from Grants;
```

This yields the following:

Number	Total	Average
4	1444631	361158

The `group by` operator can be used in conjunction with the aggregate functions to group the result set by one or more columns. For example, we can use the following query to create a table with three columns: investigator name, the number of grants associated with the investigator, and the aggregate funding:

```
select Name, count(*) as 'Number',
       avg(Funding) as 'Average funding'
  from Grants, Investigators
 where Grants.Person = Investigators.ID
group by Name;
```

We obtain the following:

Name	Number	Average Funding
Steven Weinberg	1	666000
Howard Weinberg	1	323194
Irving Weinberg	2	230719

### 4.3.3 Schema design and definition

Todo: image of our database schema

When you're using a pre-existing database, you'll be given the database design that includes tables, rows, and columns. But, when you are starting with your own data and need to create a database, the first step is to come up with the design of the database.

We have seen that a relational database comprises a set of tables. The task of specifying the structure of the data to be stored in a database is called *logical design*. This task may be performed by a database administrator, in the case of a database to be shared by many people, or directly by users, if they are creating databases themselves. More specifically, the logical design process involves defining a *schema*. A schema comprises a set of tables (including, for each table, its columns and their types), their relationships, and integrity constraints.

The first step in the logical design process is to identify the entities that need to be modeled. In our example, we identified two important classes of entity: "grants" and "investigators." We thus define a table for each; each row in these two tables will correspond to a unique grant or investigator, respectively. (In a more complete and realistic design, we would likely also identify other entities, such as institutions and research products.) During this step, we will often find ourselves breaking information up into multiple tables, so as to avoid duplicating information.

For example, imagine that we were provided grant information in the form of one CSV file rather than two, with each line providing a grant number, investigator, funding, program, institution, and email. In this file, the name, institution, and email address for Irving Weinberg would then appear twice, as he has two grants, which can lead to errors when updating values and make it difficult to represent certain information. (For example, if we want to add an investigator who does not yet have a grant, we will need to create a tuple (row) with empty slots for all columns (variables) associated with grants.) Thus we would want to break up the single big table into the two tables that we defined here. This breaking up of information across different tables to avoid repetition of information is referred to as **normalization**.<sup>78</sup>

The second step in the design process is to define the columns that are to be associated with each entity. For each table, we define a set of columns. For example, given the data in Figure 4.2, those columns will likely include, for a grant, an award identifier, title, investigator, and award amount; for an investigator, a name, university, and email address. In general, we will want to ensure that each row in our table has a key: a set of columns that uniquely identifies that row. In our example tables, grants are uniquely identified by **Number** and investigators by **ID**.

The third step in the design process is to capture relationships between entities. In our example, we are concerned with just one relationship, namely that between grants and investigators: each grant has an investigator. We represent this relationship between tables by introducing a **Person** column in the **Grants** table, as shown in Figure 4.3. Note that we do not simply duplicate the investigator names in the two tables, as was the case in the two CSV files shown in Figure 4.2: these names might not be unique, and the duplication of data across tables can lead to later inconsistencies if a name is updated in one table but not the other.

The final step in the design process is to represent integrity constraints (or rules) that must hold for the data. In our example, we may want to specify that each grant must be awarded to an investigator; that each value of the grant identifier column must be unique (i.e., there cannot be two grants with the same number); and total funding can never be negative. Such restrictions can be achieved by specifying appropriate constraints at the time of schema creation, as we show in Listing 4.1, which contains the code used to create the two tables that make up our schema.

Listing 4.1 contains four SQL statements. The first two statements, lines 1

<sup>78</sup>Normalization involves organizing columns and tables of a relational database to minimize data redundancy.

<sup>8</sup>Normalization can be done in statistical packages as well. For example, as noted above, PSID splits its data into different files linked through ID variables. The difference here is that the DBMS makes creating, navigating, and querying the resulting data particularly easy.

and 2, simply set up our new database. The `create table` statement in lines 1 and 2 creates our first table. It specifies the table name (`Investigators`) and, for each of the four columns, the column name and its type.<sup>9</sup> Relational DBMSs offer a rich set of types to choose from when designing a table: for example, `int` or `integer` (synonyms); `real` or `float`(synonyms); `char(n)`, a fixed-length string of `n` characters; and `varchar(n)`, a variable-length string of up to `n` characters. Types are important for several reasons. First, they allow for more efficient encoding of data. For example, the `Funding` field in the `grants.csv` file of Figure 4.2 could be represented as a string in the `Grants` table, `char(15)`, say, to allow for large grants. By representing it as a floating point number instead (line 15 in Listing 4.1), we reduce the space requirement per grant to just four bytes. Second, types allow for integrity checks on data as they are added to the database: for example, that same type declaration for `Funding` ensures that only valid numbers will be entered into the database. Third, types allow for type-specific operations on data, such as arithmetic operations on numbers (e.g., `min`, `max`, `sum`).

Other SQL features allow for the specification of additional constraints on the values that can be placed in the corresponding column. For example, the `not null` constraints for `Name` and `Institution` (lines 6, 7) indicate that each investigator must have a name and an institution, respectively. (The lack of such a constraint on the `Email` column shows that an investigator need not have an email address.)

```
create database grantdata;
use grantdata;

create table Investigators ( --label{code:db:1}-
    ID int auto_increment, --label{code:db:9}-
    Name varchar(100) not null, --label{code:db:7}-
    Institution varchar(256) not null, --label{code:db:8}-
    Email varchar(100),
    primary key(ID)
); --label{code:db:2}-

create table Grants ( --label{code:db:10}-
    Number int not null, --label{code:db:6}-
    Person int not null,
    Funding float unsigned not null, --label{code:db:5}-
    Program varchar(100),
    primary key(Number)
); --label{code:db:11}
```

Listing 4.1. Code to create the `grantdata` database and its `Investigators` and `Grants` tables

---

<sup>9</sup>These storage types will be familiar to many of you from statistical software packages.

#### 4.3.4 Loading data

So far we have created a database and two empty tables. The next step is to fill in the tables with data. We can of course do that row by row manually but in most cases, we will be importing that data from another source, let's say a CSV file. Listing 4.2 shows the two statements that load the data of Figure 4.2 into our two tables. (Here and elsewhere in this chapter, we use the MySQL DBMS. The SQL syntax used by different DBMSs differs in various, mostly minor ways.) Each statement specifies the name of the file from which data is to be read and the table into which it is to be loaded. The `fields terminated by ","` statement tells SQL that values are separated by columns, and `ignore 1 lines` tells SQL to skip the header. The list of column names is used to specify how values from the file are to be assigned to columns in the table.

For the `Investigators` table, the three values in each row of the `investigators.csv` file are assigned to the `Name`, `Institution`, and `Email` columns of the corresponding database row. Importantly, the `auto_increment` declaration on the `ID` column (line 5 in Listing 4.1) causes values for this column to be assigned automatically by the DBMS, as rows are created, starting at 1. This feature allows us to assign a unique integer identifier to each investigator as its data are loaded.

```
load data local infile "investigators.csv"
    into table Investigators
    fields terminated by ","
    ignore 1 lines
    (Name, Institution, Email);

load data local infile "grants.csv" into table Grants --label{code:db:3}
    fields terminated by ","
    ignore 1 lines
    (Number, @var, Funding, Program)
set Person = (select ID from Investigators --label{code:db:4a}-
              where Investigators.Name=@var); --label{code:db:4}-
```

Listing 4.2. Code to load data into the `Investigators` and `Grants` tables

For the `Grants` table, the `load data` call (lines 7–12) is somewhat more complex. Rather than loading the investigator name (the second column of each line in our data file, represented here by the variable `@var`) directly into the database, we use an SQL query (the `select` statement in lines 11–12) to retrieve from the `Investigators` table the `ID` corresponding to that name. By thus replacing the investigator name with the unique investigator identifier, we avoid replicating the name across the two tables.

### 4.3.5 Transactions and crash recovery

A DBMS protects the data that it stores from computer crashes: if your computer stops running suddenly (e.g., your operating system crashes or you unplug the power), the contents of your database are not corrupted. It does so by supporting *transactions*. A transaction is an atomic sequence of database actions. In general, every SQL statement is executed as a transaction. You can also specify sets of statements to be combined into a single transaction, but we do not cover that capability here. The DBMS ensures that each transaction is executed completely even in the case of failure or error: if the transaction succeeds, the results of all operations are recorded permanently (“persisted”) in the database, and if it fails, all operations are “rolled back” and no changes are committed. For example, suppose we ran the following SQL statement to convert the funding amounts in the table from dollars to euros, by scaling each number by 0.9. The `update` statement specifies the table to be updated and the operation to be performed, which in this case is to update the `Funding` column of each row. The DBMS will ensure that either no rows are altered or all are altered.

```
update Grants set Grants.Funding = Grants.Funding*0.9;
```

Transactions are also key to supporting multi-user access. The *concurrency control* mechanisms in a DBMS allow multiple users to operate on a database concurrently, as if they were the only users of the system: transactions from multiple users can be interleaved to ensure fast response times, while the DBMS ensures that the database remains consistent. While entire books could be (and have been) written on concurrency in databases, the key point is that read operations can proceed concurrently, while update operations are typically serialized.

### 4.3.6 Database optimizations

A relational DBMS applies query planning and optimization methods with the goal of evaluating queries as efficiently as possible. For example, if a query asks for rows that fit two conditions, one cheap to evaluate and one expensive, a relational DBMS may filter first on the basis of the first condition, and then apply the second conditions only to the rows identified by that first filter. These sorts of optimization are what distinguish SQL from other programming languages, as they allow the user to write queries declaratively and rely on the DBMS to come up with an efficient execution strategy.

Nevertheless, the user can help the DBMS to improve performance. The single most powerful performance improvement tool is the index, an internal data structure that the DBMS maintains to speed up queries. While various types of indices can be created, with different characteristics, the basic idea is simple.

Consider the column in our table. Assume that there are  $N$  rows in the table. In the absence of an index, a query that refers to a column value (e.g., ) would require a linear scan of the table, taking on average  $N/2$  comparisons and in the worst case  $N$  comparisons. A binary tree index allows the desired value to be found with just  $\log_2 N$  comparisons.

### Example: Using indices to improve database performance

Consider the following query:

```
select ID, Name, sum(Funding) as TotalFunding
  from Grants, Investigators
    where Investigators.ID=Grants.Person
  group by ID;
```

This query joins our two tables to link investigators with the grants that they hold, groups grants by investigator (using `group by`), and finally sums the funding associated with the grants held by each investigator. The result is the following:

ID	Name	TotalFunding
1	Steven Weinberg	666000
2	Howard Weinberg	323194
3	Irving Weinberg	230719

In the absence of indices, the DBMS must compare each row in `Investigators` with each row in `Grants`, checking for each pair whether `Investigators.ID = Grants.Person` holds. As the two tables in our sample database have only three and four rows, respectively, the total number of comparisons is only  $3 \times 4 = 12$ . But if we had, say, 1 million investigators and 1 million grants, then the DBMS would have to perform 1 trillion comparisons, which would take a long time. (More importantly in many cases, it would have to perform a large number of disk I/O operations if the tables did not fit in memory.) An index on the `ID` column of the `Investigators` table reduces the number of operations dramatically, as the DBMS can then take each of the 1 million rows in the `Grants` table and, for each row, identify the matching row(s) in `Investigators` via an index lookup rather than a linear scan.

In our example table, the `ID` column has been specified to be a `primary key`, and thus an index is created for it automatically. If it were not, we could easily create the desired index as follows:

```
alter table Investigators add index(ID);
```

It can be difficult for the user to determine when an index is required. A good

rule of thumb is to create an index for any column that is queried often, that is, appears on the right-hand side of a `where` statement. However, the presence of indices makes updates more expensive, as every change to a column value requires that the index be rebuilt to reflect the change. Thus, if your data are highly dynamic, you should carefully select which indices to create. (For bulk load operations, a common practice is to drop indices prior to the data import, and re-create them once the load is completed.) Also, indices take disk space, so you need to consider the tradeoff between query efficiency and resources.

The `explain` command can be useful for determining when indices are required. For example, we show in the following some of the output produced when we apply `explain` to our query. (For this example, we have expanded the two tables to 1,000 rows each, as our original tables are too small for MySQL to consider the use of indices.) The output provides useful information such as the key(s) that could be used, if indices exist (`Person` in the `Grants` table, and the primary key, `ID`, for the `Investigators` table); the key(s) that are actually used (the primary key, `ID`, in the `Investigators` table); the column(s) that are compared to the index (`Investigators.ID` is compared with `Grants.Person`); and the number of rows that must be considered (each of the 1,000 rows in `Grants` is compared with one row in `Investigators`, for a total of 1,000 comparisons).

```
mysql> explain select ID, Name, sum(Funding) as TotalFunding
      from Grants, Investigators
     where Investigators.ID=Grants.Person group by ID;

+-----+-----+-----+-----+
| table | possible_keys | key   | ref    |
+-----+-----+-----+-----+
| Grants |          1 | NULL | NULL   | |
|       | 1000 |          1 | PRIMARY | Grants.Person |
| Investigators | PRIMARY | PRIMARY |          1 |
+-----+-----+-----+-----+
```

Contrast this output with the output obtained for equivalent tables in which `Person` is not a primary key. In this case, no keys are used and thus  $1,000 \times 1,000 = 1,000,000$  comparisons and the associated disk reads must be performed.

```
+-----+-----+-----+-----+
| table | possible_keys | key   | ref    | rows  |
+-----+-----+-----+-----+
```

Grants	Person	NULL	NULL	1000
Investigators	ID	NULL	NULL	1000

A second way in which the user can contribute to performance improvement is by using appropriate table definitions and data types. Most DBMSs store data on disk. Data must be read from disk into memory before it can be manipulated. Memory accesses are fast, but loading data into memory is expensive: accesses to main memory can be a million times faster than accesses to disk. Therefore, to ensure queries are efficient, it is important to minimize the number of disk accesses. A relational DBMS automatically optimizes queries: based on how the data are stored, it transforms a SQL query into a query plan that can be executed efficiently, and chooses an execution strategy that minimizes disk accesses. But users can contribute to making queries efficient. As discussed above, the choice of types made when defining schemas can make a big difference. As a rule of thumb, only use as much space as needed for your data: the smaller your records, the more records can be transferred to main memory using a single disk access. The design of relational tables is also important. If you put all columns in a single table (do not normalize), more data will come into memory than is required.

### 4.3.7 Caveats and challenges

It is important to keep the following caveats and challenges in mind when using SQL technology with social science data.

#### Data cleaning

Data created outside an SQL database, such as data in files, are not always subject to strict constraints: data types may not be correct or consistent (e.g., numeric data stored as text) and consistency or integrity may not be enforced (e.g., absence of primary keys, missing foreign keys). Indeed, as the reader probably knows well from experience, data are rarely perfect. As a result, the data may fail to comply with strict SQL schema requirements and fail to load, in which case either data must be cleaned before or during loading, or the SQL schema must be relaxed.

#### Missing values

Care must be taken when loading data in which some values may be missing or blank. SQL engines represent and refer to a missing or blank value as the built-in constant `null`. Counterintuitively, when loading data from text files (e.g., CSV), many SQL engines require that missing values be represented explicitly by the term `null`; if a data value is simply omitted, it may fail to

load or be incorrectly represented, for example as zero or the empty string ("") instead of `null`. Thus, for example, the second row in the `investigators.csv` file of Figure 4.2:

`Howard Weinberg,University of North Carolina Chapel Hill,`

may need to be rewritten as:

`Howard Weinberg,University of North Carolina Chapel Hill,null`

#### Metadata for categorical variables

SQL engines are metadata poor: they do not allow extra information to be stored about a variable (field) beyond its base name and type (`int`, `char`, etc., as introduced in Section 4.3.3). They cannot, for example, record directly the fact that the column `class` can only take one of three values, `animal`, `vegetable`, or `mineral`, or what these values mean. Common practice is thus to store information about possible values in another table (commonly referred to as a *dimension table*) that can be used as a lookup and constraint, as in the following:

Table `class_values`

Value	Description
<code>animal</code>	Is alive
<code>vegetable</code>	Grows
<code>mineral</code>	Isn't alive and doesn't grow

A related concept is that a column or list of columns may be declared `primary key` or `unique`. Either says that no two tuples of the table may agree in all the column(s) on the list. There can be only one `primary key` for a table, but several `unique` columns. No column of a `primary key` can ever be `null` in any tuple. But columns declared `unique` may have `nulls`, and there may be several tuples with `null`.

---

## 4.4 Linking DBMSs and other tools

Query languages such as SQL are not general-purpose programming languages; they support easy, efficient access to large data sets, are extremely efficient for specific types of analysis, but may not be the right choice for all analysis. When complex computations are required, one can embed query language statements into a programming language or statistical package. For example, we might want to calculate the interquartile range of funding for all grants.

While this calculation can be accomplished in SQL, the resulting SQL code will be complicated (depending on which flavor of SQL your database supports). Languages like Python make such statistical calculations straightforward, so it is natural to write a Python (or R, SAS, Stata, etc.) program that connects to the DBMS that contains our data, fetches the required data from the DBMS, and then calculates the interquartile range of those data. The program can then, if desired, store the result of this calculation back into the database.

Many relational DBMSs also have built-in analytical functions or often now support different programming languages, providing significant in-database statistical and analytical capabilities and alleviating the need for external processing.

```
from mysql.connector import MySQLConnection, Error
from python_mysql_dbconfig import read_db_config

def retrieve_and_analyze_data():
    try:
        # Open connection to the MySQL database
        dbconfig = read_db_config() --label{code:db:a}
        conn = MySQLConnection(**dbconfig)
        cursor = conn.cursor() --label{code:db:b} `\\label{code:db:c}`
        # Transmit the SQL query to the database
        cursor.execute('select Funding from Grants;')
        rows = [row for row in cur.fetchall()] --label{code:db:d}
        calculate_inter_quartile_range(rows) --label{code:db:e}
    except Error as e:
        print(e)
    finally:
        cursor.close()
        conn.close()

if __name__ == '__main__':
    retrieve_and_analyze_data()
```

Listing 4.3. Embedding SQL in Python

#### Example: Embedding database queries in Python

The Python script in Listing 4.3 shows how this embedding of database queries

in Python is done. This script establishes a connection to the database transmits the desired SQL query to the database (line 7–9), retrieves the query results into a Python array (line 11), and calls a Python procedure (not given) to perform the desired computation (line 14). A similar program could be used to load the results of a Python (or R, SAS, Stata, etc.) computation into a database.

---

---

### Example: Loading other structured data

We saw in Listing 4.2 how to load data from CSV files into SQL tables. Data in other formats, such as the commonly used JSON, can also be loaded into a relational DBMS. Consider, for example, the following JSON format data, a simplified version of data shown in Chapter Working with Web Data and APIs.

```
[  
  {  
    institute : Janelia Campus,  
    name : Laurence Abbott,  
    role : Senior Fellow,  
    state : VA,  
    town : Ashburn  
  },  
  {  
    institute : Jackson Lab,  
    name : Susan Ackerman,  
    role : Investigator,  
    state : ME,  
    town : Bar Harbor  
  }  
]
```

While some relational DBMSs (such as PostgresQL) provide built-in support for JSON objects, we assume here that we want to convert these data into normal SQL tables. Using one of the many utilities for converting JSON into CSV, we can construct the following CSV file, which we can load into an SQL table using the method shown earlier.

```
institute,name,role,state,town  
Janelia Campus,Laurence Abbott,Senior Fellow,VA,Ashburn  
Jackson Lab,Susan Ackerman,Investigator,ME,Bar Harbor
```

But into what table? The two records each combine information about a person with information about an institute. Following the schema design rules given

in Section 4.3.3, we should *normalize* the data by reorganizing them into two tables, one describing people and one describing institutes. Similar problems arise when JSON documents contain nested structures. For example, consider the following alternative JSON representation of the data above. Here, the need for normalization is yet more apparent.

```
[  
  {  
    name : Laurence Abbott,  
    role : Senior Fellow,  
    employer : { institute : Janelia Campus,  
                state : VA,  
                town : Ashburn}  
  },  
  {  
    name : Susan Ackerman,  
    role : Investigator,  
    employer: { institute : Jackson Lab,  
               state : ME,  
               town : Bar Harbor}  
  }  
]
```

Thus, the loading of JSON data into a relational database usually requires both work on schema design (Section 4.3.3) and data preparation.

## 4.5 NoSQL databases

While relational DBMSs have dominated the database world for several decades, other database technologies exist and indeed have become popular for various classes of applications in recent years. As we will see, these alternative technologies have typically been motivated by a desire to scale the quantities of data and/or number of users that can be supported, and/or to support specialized data types (e.g., unstructured data, graphs). Here we review some of these alternatives and the factors that may motivate their use.

### 4.5.1 Challenges of scale: The CAP theorem

For many years, the big relational database vendors (Oracle, IBM, Sybase, Microsoft) have been the mainstay of how data were stored. During the Internet boom, startups looking for low-cost alternatives to commercial relational DBMSs turned to MySQL and PostgreSQL. However, these systems proved inadequate for big websites as they could not cope well with large traffic spikes, for example when many customers all suddenly wanted to order the same item. That is, they did not *scale*.

An obvious solution to scaling databases is to partition and/or replicate data across multiple computers, for example by distributing different tables, or different rows from the same table, over multiple computers. However, partitioning and replication also introduce challenges, as we now explain. Let us first define some terms. In a system that comprises of multiple computers:

- **Consistency** indicates that all computers see the same data at the same time.
- **Availability** indicates that every request receives a response about whether it succeeded or failed.
- **Partition tolerance** indicates that the system continues to operate even if a network failure prevents computers from communicating.

An important result in distributed systems (the so-called “CAP theorem” (Brewer 2012)) observes that it is not possible to create a distributed system with all three properties. This situation creates a challenge with large transactional data sets. Partitioning is needed in order to achieve high performance, but as the number of computers grows, so too does the likelihood of network disruption among pair(s) of computers. As strict consistency cannot be achieved at the same time as availability and partition tolerance, the DBMS designer must choose between high consistency and high availability for a particular system.

The right combination of availability and consistency will depend on the needs of the service. For example, in an e-commerce setting, it makes sense to choose high availability for a checkout process, in order to ensure that requests to add items to a shopping cart (a revenue-producing process) can be honored. Errors can be hidden from the customer and sorted out later. However, for order submission—when a customer submits an order—it makes sense to favor consistency because several services (credit card processing, shipping and handling, reporting) need to access the data simultaneously. However, in almost all cases, availability is chosen over consistency.

### 4.5.2 NoSQL and key-value stores

Relational DBMSs were traditionally motivated by the need for transaction processing and analysis, which led them to put a premium on consistency and availability. This led the designers of these systems to provide a set of properties summarized by the acronym ACID (Gray 1981; Silberschatz, Korth, and Sudarshan 2010):

- **Atomic:** All work in a transaction completes (i.e., is committed to stable storage) or none of it completes.
- **Consistent:** A transaction transforms the database from one consistent state to another consistent state.
- **Isolated:** The results of any changes made during a transaction are not visible until the transaction has committed.
- **Durable:** The results of a committed transaction survive failures.

The need to support extremely large quantities of data and numbers of concurrent clients has led to the development of a range of alternative database technologies that relax consistency and thus these ACID properties in order to increase scalability and/or availability. These systems are commonly referred to as NoSQL (for “not SQL”—or, more recently, “not only SQL,” to communicate that they may support SQL-like query languages) because they usually do not require a fixed table schema nor support joins and other SQL features. Such systems are sometimes referred to as BASE (Fox et al. 1997): Basically Available (the system seems to work all the time), Soft state (it does not have to be consistent all the time), and Eventually consistent (it becomes consistent at some later time). The data systems used in essentially all large Internet companies (Google, Yahoo!, Facebook, Amazon, eBay) are BASE.

Dozens of different NoSQL DBMSs exist, with widely varying characteristics as summarized in Table 4.2. The simplest are *key-value stores* such as Redis, Amazon Dynamo, Apache Cassandra, and Project Voldemort. We can think of a key-value store as a relational database with a single table that has just two columns, key and value, and that supports just two operations: store (or update) a key-value pair, and retrieve the value for a given key.

---

**Example: Representing investigator data in a NoSQL database** We might represent the contents of the investigators.csv file of Figure 4.2 (in a NoSQL database) as follows.

Key	Value
Investigator	Steven Weinberg of Texas at Austin

Key	Value
Investigator_StevenWeinberg_Email	
Investigator_HowardWeinberg_Institution	of North Carolina Chapel Hill
Investigator_IrvingWeinberg_Institution	of Maryland College Park
Investigator_IrvingWeinberg_Email	

A client can then read and write the value associated with a given *key* by using operations such as the following:

- **Get(*key*)** returns the value associated with *key*.
- **Put(*key, value*)** associates the supplied *value* with *key*.
- **Delete(*key*)** removes the entry for *key* from the data store.

Key-value stores are thus particularly easy to use. Furthermore, because there is no schema, there are no constraints on what values can be associated with a key. This lack of constraints can be useful if we want to store arbitrary data. For example, it is trivial to add the following records to a key-value store; adding this information to a relational table would require schema modifications.

Key	Value
Investigator_StevenWeinberg_FavoriteColor	Blue
Investigator_StevenWeinberg_Awards	Nobel

Another advantage is that if a given key would have no value (e.g., Investigator\_HowardWeinberg\_Email), we need not create a record. Thus, a key-value store can achieve a more compact representation of sparse data, which would have many empty fields if expressed in relational form.

A third advantage of the key-value approach is that a key-value store is easily partitioned and thus can scale to extremely large sizes. A key-value DBMS can partition the space of keys (e.g., via a hash on the key) across different computers for scalability. It can also replicate key-value pairs across multiple computers for availability. Adding, updating, or querying a key-value pair requires simply sending an appropriate message to the computer(s) that hold that pair.

The key-value approach also has disadvantages. As we can see from the example, users must be careful in their choice of keys if they are to avoid name collisions. The lack of schema and constraints can also make it hard to detect erroneous keys and values. Key-value stores typically do not support join operations (e.g., “which investigators have the Nobel and live in Texas?”). Many key-value stores also relax consistency constraints and do not provide transactional semantics.

---

#### 4.5.3 Other NoSQL databases

The simple structure of key-value stores allows for extremely fast and scalable implementations. However, as we have seen, many interesting data cannot be easily modeled as key-value pairs. Such concerns have motivated the development of a variety of other NoSQL systems that offer, for example, richer data models: document-based (CouchDB and MongoDB), graph-based (Neo4J), and column-based (Cassandra, HBase) databases.

In document-based databases, the value associated with a key can be a structured document: for example, a JSON document, permitting the following representation of our `investigators.csv` file plus the additional information that we just introduced.

Key	Value
Investigator	StevenWeinberg
	institution
	:
	University
	of Texas
	at Austin,
	email :
	wein-
	berg@utexas.edu,
	favcolor :
	Blue,
	award :
	Nobel }

Key	Value
Investigator_HowardWeinberg	institution : University of North Carolina Chapel Hill }
Investigator_IrvingWeinberg	institution : University of Maryland College Park, email : irv- ing@ucmc.edu }

Associated query languages may permit queries within the document, such as regular expression searches, and retrieval of selected fields, providing a form of a relational DBMS's selection and projection capabilities (Section 4.3.2). For example, MongoDB allows us to ask for documents in a collection called `that` that have “University of Texas at Austin” as their institution and the Nobel as an award.

```
db.investigators.find( { institution: 'University of Texas at
Austin', award: 'Nobel' } )
```

A column-oriented DBMS stores data tables by columns rather than by rows, as is common practice in relational DBMSs. This approach has advantages in settings where aggregates must frequently be computed over many similar data items: for example, in clinical data analysis. Google Cloud BigTable and Amazon RedShift are two cloud-hosted column-oriented NoSQL databases. HBase and Cassandra are two open source systems with similar characteristics. (Confusingly, the term *column oriented* is also often used to refer to SQL database engines that store data in columns instead of rows: for example, Google BigQuery, HP Vertica, Terradata, and the open source MonetDB.)

Such systems are not to be confused with column-based NoSQL databases.)

Graph databases store information about graph structures in terms of nodes, edges that connect nodes, and attributes of nodes and edges. Proponents argue that they permit particularly straightforward navigation of such graphs,

as when answering queries such as “find all the friends of the friends of my friends”—a task that would require multiple joins in a relational database.

---

## 4.6 Spatial databases

Social science research commonly involves spatial data. Socioeconomic data may be associated with census tracts, data about the distribution of research funding and associated jobs with cities and states, and crime reports with specific geographic locations. Furthermore, the quantity and diversity of such spatially resolved data are growing rapidly, as are the scale and sophistication of the systems that provide access to these data. For example, just one urban data store, Plenario, contains many hundreds of data sets about the city of Chicago (Catlett et al. 2014).

Researchers who work with spatial data need methods for representing those data and then for performing various queries against them. Does crime correlate with weather? Does federal spending on research spur innovation within the locales where research occurs? These and many other questions require the ability to quickly determine such things as which points exist within which regions, the areas of regions, and the distance between two points. Spatial databases address these and many other related requirements.

---

### Example: Spatial extensions to relational databases

Spatial extensions have been developed for many relational databases: for example, Oracle Spatial, DB2 Spatial, and SQL Server Spatial. We use the PostGIS extensions to the PostgreSQL relational database here. These extensions implement support for spatial data types such as `point`, `line`, and `polygon`, and operations such as `st_within` (returns `true` if one object is contained within another), `st_dwithin` (returns `true` if two objects are within a specified distance of each other), and `st_distance` (returns the distance between two objects). Thus, for example, given two tables with rows for schools and hospitals in Illinois (`illinois_schools` and `illinois_hospitals`, respectively; in each case, the column `the_geom` is a polygon for the object in question) and a third table with a single row representing the city of Chicago (`chicago_citylimits`), we can easily find the names of all schools within the Chicago city limits:

```
select illinois_schools.name  
from illinois_schools, chicago_citylimits
```

```
where st_within(illinois_schools.the_geom,
    chicago_citylimits.the_geom);
```

We join the two tables and , with the constraint constraining the selected rows to those representing schools within the city limits. Here we use the inner join introduced in Section 4.3.2. This query could also be written as:

```
select illinois_schools.name
  from illinois_schools left join chicago_citylimits
    on st_within(illinois_schools.the_geom,
        chicago_citylimits.the_geom);
```

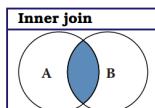
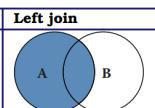
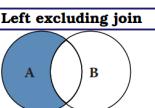
We can also determine the names of all schools that do *not* have a hospital within 3,000 meters:

```
select s.name as 'School Name'
  from illinois_schools as s
    left join illinois_hospitals as h
      on st_dwithin(s.the_geom, h.the_geom, 3000)
    where h.gid is null;
```

Here, we use an alternative form of the join operator, the *left join*—or, more precisely, the *left excluding join*. The expression

```
table1 left join table2 on constraint
```

returns all rows from the left table (`table1`) with the matching rows in the right table (`table2`), with the result being `null` in the right side when there is no match. This selection is illustrated in the middle column of Figure 4.4. The addition of the `where h.gid is null` then selects only those rows in the left table with no right-hand match, as illustrated in the right-hand column of Figure 4.4. Note also the use of the `as` operator to rename the columns `illinois_schools` and `illinois_hospitals`. In this case, we rename them simply to make our query more compact.

Inner join	Left join	Left excluding join
		
<code>select columns from Table_A A inner join Table_B B on A.Key = B.Key</code>	<code>select columns from Table_A A left join Table_B B on A.Key = B.Key</code>	<code>select columns from Table_A A left join Table_B B on A.Key = B.Key where B.Key is null</code>

**FIGURE 4.4** Three types of \*join\* illustrated: the inner join, as used in Section 4.3.2, the left join, and left excluding join

## 4.7 Which database to use?

The question of which DBMS to use for a social science project depends on many factors. We introduced some relevant rules in Table 4.1. We expand on those considerations here.

### 4.7.1 Relational DBMSs

If your data are structured into rows and columns, then a relational DBMS is almost certainly the right technology to use. Many open source, commercial, and cloud-hosted relational DBMSs exist. Among the open source DBMSs, MySQL and PostgreSQL (often simply called Postgres) are particularly widely used. MySQL is the most popular. It is particularly easy to install and use, but does not support all features of the SQL standard. PostgreSQL is fully standard compliant and supports useful features such as full text search and the PostGIS extensions mentioned in the previous section. [bold]We recommend you start with Postgres[bold].

Popular commercial relational DBMSs include Microsoft SQL Server, Oracle, IBM DB2, Teradata, and Sybase. These systems are heavily used in commercial settings. There are free community editions, and some large science projects use enterprise features via licensing: for example, the Sloan Digital Sky Survey uses Microsoft SQL Server (Szalay et al. 2002) and the CERN high-energy physics lab uses Oracle (Girone 2008).

We also see increasing use being made of cloud-hosted relational DBMSs such as Amazon Relational Database Service (RDS; this supports MySQL, PostgreSQL, and various commercial DBMSs), Microsoft Azure, and Google Cloud SQL. These systems obviate the need to install local software, administer a DBMS, or acquire hardware to run and scale your database. Particularly if your database is bigger than can fit on your workstation, a cloud-hosted solution can be a good choice, both for scalability but also for ease of configuration and management.

### 4.7.2 NoSQL DBMSs

Some social science problems have the scale that might motivate the use of a NoSQL DBMS. Furthermore, while defining and enforcing a schema can involve some effort, the benefits of so doing are considerable. Thus, the use of a relational DBMS is usually to be recommended.

Nevertheless, as noted in Section 4.2, there are occasions when a NoSQL

DBMS can be a highly effective, such as when working with large quantities of unstructured data. For example, researchers analyzing large collections of Twitter messages frequently store the messages in a NoSQL document-oriented database such as MongoDB. NoSQL databases are also often used to organize large numbers of records from many different sources, as illustrated in Figure 4.1.

---

## 4.8 Summary

A key message of this book is that you should, whenever possible, use a database. Database management systems are one of the great achievements of information technology, permitting large amounts of data to be stored and organized so as to allow rapid and reliable exploration and analysis. They have become a central component of a great variety of applications, from handling transactions in financial systems to serving data published in websites. They are particularly well suited for organizing social science data and for supporting analytics for data exploration.

DBMSs provide an environment that greatly simplifies data management and manipulation. They make many easy things trivial, and many hard things easy. They automate many other error-prone, manual tasks associated with query optimization. While they can be daunting to those unfamiliar with their concepts and workings, they are in fact easy to use. A basic understanding of databases and of when and how to use DBMSs is an important element of the social data scientist's knowledge base.

---

## 4.9 Resources

The enormous popularity of DBMSs means that there are many good books to be found. Classic textbooks such as those by Silberschatz et al. (Silberschatz, Korth, and Sudarshan 2010) and Ramakrishnan and Gehrke (Ramakrishnan and Gehrke 2002) provide a great deal of technical detail. The DB Engines website collects information on DBMSs (Solid IT, n.d.). There are also many also useful online tutorials, and of course StackExchange and other online forums often have answers to your technical questions.

Turning to specific technologies, the *SQL Cookbook* (Molinaro 2005) provides a wonderful introduction to SQL. We also recommend the SQL Cheatsheet (Art

Branch Inc., n.d.) and a useful visual depiction of different SQL join operators (Moffatt 1999). Two good books on the PostGIS geospatial extensions to the PostgreSQL database are the *PostGIS Cookbook* (Corti et al. 2014) and *PostGIS in Action* (Obe and Hsu 2015). The online documentation is also excellent (PostGIS Project Steering Committee, n.d.). The monograph *NoSQL Databases* (Strauch 2009) provides much useful technical detail.

We did not consider in this chapter the native extensible Markup Language (XML) and Resource Description Framework (RDF) triple stores, as these are not typically used for data management. However, they do play a fundamental role in metadata and knowledge management. See, for example, Sesame (Broekstra, Kampman, and Van Harmelen 2002; Sesame, n.d.)

If you are interested in the state of database and data management research, the recent Beckman Report (Abadi et al. 2014) provides a useful perspective.

# 5

---

## *Scaling up through Parallel and Distributed Computing*

---

**Huy Vo and Claudio Silva**

This chapter provides an overview of techniques that allow us to analyze large amounts of data using distributed computing (multiple computers concurrently). While the focus is on a widely used framework called MapReduce and popular implementations such as Apache Hadoop and Spark, the goal of the chapter is to provide a conceptual and practical framework to deal with large amounts of data that may not fit in memory or take too long to analyze on a single computer. It is important to note that these frameworks do not result in analysis that is better - they are useful because they allow us to process large amounts of data faster and/or without getting access to a single massive computer with lots of memory (RAM) and processing power (CPU).

---

### **5.1 Introduction**

As the amount of data available for social science research increases, we have to determine how to perform our analysis quickly and efficiently. One way to deal with large amounts of data that may not fit in memory or take too long to analyze on a single computer is to subsample the data or to simplify the analysis. Another approach is to use all the data by making use of multiple computers concurrently to do the analysis. The use of parallel computing to deal with large amounts of data has been a common approach in physical sciences. Data analysts have routinely been working on data sets much larger than a single machine can handle for several decades, especially at the DOE National Laboratories (Sethian et al. 1991; Crossno, Cline, and Jortner 1993) where high-performance computing has been a major technology trend. This is also demonstrated by the history of research in distributed computing and data management going back to the 1980s (Wikipedia, n.d.).

There are many ways to do distributed and parallel computing, ranging from completely flexible (but more complex to use) approaches such as Message

Passing Interface (MPI) (Gropp, Lusk, and Skjellum 2014) to more restrictive (but much easier to use) approaches such as MapReduce. MPI allows you to do anything with as much efficiency as your MPI skills allow you to code while MapReduce allows a more restrictive set of analysis to be done (possibly less efficiently) but is much easier to learn and implement.

This chapter focuses on one such framework, called MapReduce, to do large-scale data analysis distributed across multiple computers. We describe the MapReduce framework, work through an example of using it, and highlight one implementation of the framework called Hadoop in detail.

**BOX**

---

## 5.2 Examples

Aghbari, Bahutair, and Kamel (2019) introduce GeoSim, an algorithm used for clustering users in any social network site into communities based on the semantic meaning of the nodes interests as well as their relationships with each other. The parallelised version of GeoSim utilizes the MapReduce model to run on multiple machines simultaneously and get faster results.

Kolb et al developed a tool DeDoop that uses Hadoop to do efficient record linkage (remember chapter Record Linkage?) and scale to large data sets. Tasks such as record linkage where we can easily break down the larger task into smaller chunks (such as comparing two records to see if they belong to the same entity) that can be done in parallel are ideally suited for MapReduce frameworks.

<https://www.facebook.com/notes/facebook-engineering/under-the-hood-scheduling-mapreduce-jobs-more-efficiently-with-corona/10151142560538920/> describes the data infrastructure at Facebook with MapReduce at the core of Facebook’s data analytics engine. Over half a petabyte of new data arrives in the warehouse every 24 hours, and ad-hoc queries, data pipelines, and custom MapReduce jobs process this raw data around the clock to generate more meaningful features and aggregations.

**BOX**

### 5.3 MapReduce

The MapReduce framework was proposed by Jeffrey Dean and Sanjay Ghemawat at Google in 2004 (Dean and Ghemawat 2004). Its origins date back to conceptually similar approaches first described in the early 1980s. Using the MapReduce framework requires turning the analysis problem we have into operations that the framework supports - these are map and reduce. The “map” operation takes the input and splits up the task into multiple (parallel) components, and the “reduce” operation consolidates the results of the parallel “mapped” tasks and produces the final output. In order to use the MapReduce framework, we need to break up our tasks in to map and reduce operations and implement these two operations.

---

#### Example: Counting NSF awards

To gain a better understanding of these MapReduce operations, let’s take a trivial task that may need to be done on billions of records, causing scalability challenges. Imagine that we have a list of NSF principal investigators, along with their email information and award IDs as below. Our task is to count the number of awards for each institution. For example, given the four records below, we will discover that the Berkeley Geochronology Center has two awards, while New York University and the University of Utah each have one.

```
AwardId,FirstName,LastName,EmailAddress  
0958723,Roland,Mundil,rmundil@bge.org  
0958915,Randall,Irmis,irmis@umnh.utah.edu  
1301647,Zaher,Hani,zh8@nyu.edu  
1316375,David,Shuster,dshuster@bge.org
```

We observe that institutions can be distinguished by their email address domain name. Thus, we adopt of a strategy of first grouping all award IDs by domain names, and then counting the number of distinct award within each group. In order to do this, we first set the function to scan input lines and extract institution information and award IDs. Then, in the function, we simply count unique IDs on the data, since everything is already grouped by institution. Python pseudo-code is provided in Listing 5.1.

```
# Input : a list of text lines  
# Output : a list of domain name and award ids  
def MAP(lines):  
    for line in lines:  
        fields      = line.strip('\n').split(',')  
        awardId    = fields[0]
```

```

domainName = fields[3].split('@')[-1].split('.')[0]
yield (domainName, awardId)

# Input : a list of domain name and award ids
# Output : a list of domain name and award count
def REDUCE(pairs):
    for (domainName, awardIds) in pairs:
        count = len(set(awardIds))
        yield (domainName, count)

```

Listing 5.1. Python pseudo-code for the `map` and `reduce` functions to count the number of awards per institution

In the map phase, the input will be transformed into tuples of institutions and award ids:

```

"0958723,Roland,Mundil,rmundil@bgc.org" → ("bgc.org", 0958723)
"0958915,Randall,Irmis,irmis@umnh.utah.edu" → ("utah.edu",
0958915) "1301647,Zaher,Hani,zh8@nyu.edu" → ("nyu.edu", 1301647)
"1316375,David,Shuster,dshuster@bgc.org" → ("bgc.org", 1316375)

```

Then the tuples will be grouped by institutions and be counted by the function.

```

("bgc.org", [0958723,1316375]) → ("bgc.org", 2) ("utah.edu",
\[0958915\]) → ("utah.edu", 1) ("nyu.edu", \[1301647\]) →
("nyu.edu", 1)

```

As we have seen so far, the MapReduce programming model is quite simple and straightforward, yet it supports a simple parallelization model. In fact, it has been said to be *too* simple and criticized as “a major step backwards” (DeWitt and Stonebraker 2008) for large-scale, data-intensive applications. It is hard to argue that MapReduce is offering something truly innovative when MPI has been offering similar scatter and reduce operations since 1995, and Python has had high-order functions (`map`, `reduce`, `filter`, and `lambda`) since its 2.2 release in 1994. However, the biggest strength of MapReduce is its simplicity. Its simple programming model has brought many non-expert users to analyzing large amounts of data. Its simple architecture has also inspired many developers to develop advanced capabilities, such as support for distributed computing, data partitioning, and streaming processing. (footnote: A downside of this diversity of interest is that available features and capabilities can vary considerably, depending on the specific implementation of MapReduce that is being used.)

As mentioned above, MapReduce is a programming model. In order to implement an analysis in MapReduce, we need to select an implementation of MapReduce. Two most commonly used implementations of the MapReduce model are Hadoop and Spark, that we describe in more detail below.

## 5.4 Apache Hadoop MapReduce

Apache Hadoop (or Hadoop)<sup>1</sup> was originally designed to run in environments with thousands of machines. Supporting such a large computing environment puts several constraints on the system; for instance, with so many machines, the system had to assume computing nodes would fail. Hadoop is an enhanced MapReduce implementation with the support for fault tolerance, distributed storage, and data parallelism through two added key design features: (1) a distributed file system called the Hadoop Distributed File System (HDFS); and (2) a data distribution strategy that allows computation to be moved to the data during execution.

### 5.4.1 The Hadoop Distributed File System

The Hadoop Distributed File System (Apache Software Foundation, n.d.) (Apache Hadoop, n.d.) is a distributed file system that stores data across all the nodes (machines) of a Hadoop cluster. HDFS splits large data files into smaller blocks (chunks of data) which are managed by different nodes in a cluster. Each block is also replicated across several nodes as an attempt to ensure that a full copy of the data is still available even in the case of computing node failures. The block size as well as the number of replications per block are fully customized by users when they create files on HDFS. By default, the block size is set to 64 MB with a replication factor of 3, meaning that the system may encounter at least two concurrent node failures without losing any data. HDFS also actively monitors failures and re-replicates blocks on failed nodes to make sure that the number of replications for each block always stays at the user-defined settings. Thus, if a node fails, and only two copies of some data exist, the system will quickly copy those data to a working node, thus raising the number of copies to three again. This dynamic replication the primary mechanism for fault tolerance in Hadoop.

Note that data blocks are replicated and distributed across several machines. This could create a problem for users, because if they had to manage the data manually, they might, for example, have to access more than one machine to fetch a large data file. Fortunately, Hadoop provides infrastructure for managing this complexity seamlessly, including command line programs as well as an API that users can employ to interact with HDFS as if it were a local file system. For example, one can run simple linux commands such as ls and mkdir to list and create a directory on HDFS, or even use to inspect file

---

<sup>1</sup>The term *Hadoop* refers to the creator's son's toy elephant.

contents the same way as one would do in a Linux file system. The following code shows some examples of interacting with HDFS.

```
# Creating a folder
hadoop dfs -mkdir /hadoopiseeasy

# Upload a CSV file from our local machine to HDFS
hadoop dfs -put importantdata.csv /hadoopiseeasy

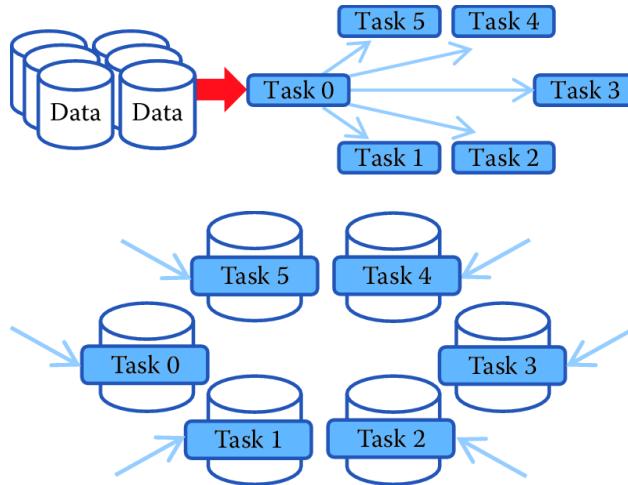
# Listing all files under hadoopiseeasy folder
hadoop dfs -ls /hadoopiseeasy

# Download a file to our local machine
hadoop dfs -get /hadoopiseeasy/importantdata.csv
```

#### 5.4.2 Hadoop Setup: Bringing compute to the data

There are two parts of the computing environment when using Hadoop: a *compute cluster* with substantial computing power (e.g., thousands of computing cores) 2. a *storage cluster* with lots of disk space, capable of storing and serving data quickly to the compute cluster.

These two clusters have quite different hardware specifications: the first is optimized for CPU performance and the second for storage. The two systems are typically configured as separate physical hardware.



**FIGURE 5.1** Top: The traditional parallel computing model where data are brought to the computing nodes. Bottom: Hadoop's parallel computing model: bringing compute to the data [©HadoopParallelModel]

Running compute jobs on such hardware often goes like this. When a user requests to run an intensive task on a particular data set, the system will first reserve a set of computing nodes. Then the data are partitioned and copied from the storage server into these computing nodes before the task is executed. This process is illustrated in Figure 5.1 (top). This computing model will be referred to as *bringing data to computation*. In this model, if a data set is being analyzed in multiple iterations, it is very likely that the data will be copied multiple times from the storage cluster to the compute nodes without reusability. This is because the compute node scheduler normally does not have or keep knowledge of where data have previously been held. The need to copy data multiple times tends to make such a computation model inefficient, and I/O becomes the bottleneck when all tasks constantly pull data from the storage cluster (the green arrow). This in turn leads to poor scalability; adding more nodes to the computing cluster would not increase its performance.

To solve this problem, Hadoop implements a *bring compute to the data* strategy that combines both computing and storage at each node of the cluster. In this setup, each node offers both computing power and storage capacity. As shown in Figure 5.1 (bottom), when users submit a task to be run on a data set, the scheduler will first look for nodes that contain the data, and if the nodes are available, it will schedule the task to run directly on those nodes. If a node is busy with another task, data will still be copied to available nodes, but the scheduler will maintain records of the copy for subsequent use of the data. In addition, data copying can be minimized by increasing the data duplication in the cluster, which also increases the potential for parallelism, since the scheduler has more choices to allocate computing without copying. Since both the compute and data storage are closely coupled for this model, it is best suited for data-intensive applications.

Given that Hadoop was designed for batch data processing at scale, this model fits the system nicely, especially with the support of HDFS. However, in an environment where tasks are more compute intensive, a traditional high-performance computing environment is probably best since it tends to spend more resources on CPU cores. It should be clear now that the Hadoop model has hardware implications, and computer architects have optimized systems for data-intensive computing.

### 5.4.3 Hardware provisioning

Hadoop requires a distributed cluster of machines to operate efficiently. (It can be set up to run entirely on a single computer, but this should only be done for technology demonstration purposes.) This is mostly because the MapReduce performance heavily depends on the total I/O throughput (i.e., disk read and write) of the entire system. Having a distributed cluster, where each machine

has its own set of hard drives, is one of the most efficient ways to maximize this throughput.

A typical Hadoop cluster consists of two types of machine: masters and workers. Master machines are those exclusively reserved for running services that are critical to the framework operations. Some examples are the NameNode and the JobTracker services, which are tasked to manage how data and tasks are distributed among the machines, respectively. The worker machines are reserved for data storage and for running actual computation tasks (i.e., map and reduce). It is normal to have worker machines that can be included or removed from an operational cluster on demand. This ability to vary the number of worker nodes makes the overall system more tolerant of failure. However, master machines are usually required to be running uninterrupted.

Provisioning and configuring the hardware for Hadoop, like any other parallel computing, are some of the most important and complex tasks in setting up a cluster, and they often require a lot of experience and careful consideration. Major big data vendors provide guidelines and tools to facilitate the process (Apache Software Foundation, n.d.; Cloudera, n.d.; Baldeschwieler 2011). most decisions will be based on the types of analysis to be run on the cluster, for which only you, as the user, can provide the best input.

#### 5.4.4 Programming in Hadoop

Now that we are equipped with the knowledge that Hadoop is a MapReduce implementation that runs on HDFS and a bring-compute-to-the-data model, we can go over the design of a Hadoop MapReduce job. A MapReduce job is still composed of three phases: map, shuffle, and reduce. However, Hadoop divides the map and reduce phases into smaller tasks.

Each map phase in Hadoop is divided into five tasks: **input format**, **record reader**, **mapper**, **combiner**, and **partitioner**. An input format task is in charge of talking to the input data presumably sitting on HDFS, and splitting it into partitions (e.g., by breaking lines at line breaks). Then a record reader task is responsible for translating the split data into the key–value pair records so that they can be processed by the mapper. By default, Hadoop parses files into key–value pairs of line numbers and line contents. However, both input formats and record readers are fully customizable and can be programmed to read custom data including binary files. It is important to note that input formats and record readers only provide data partitioning; they do not move data around computing nodes.

After the records are generated, mappers are spawned—typically on nodes containing the blocks—to run through these records and output zero or more new key–value pairs. A mapper in Hadoop is equivalent to the `map` function of the MapReduce model that we discussed earlier. The selection of the key

to be output from the mapper will heavily depend on the data processing pipeline and could greatly affect the performance of the framework. Mappers are executed concurrently in Hadoop as long as resources permit.

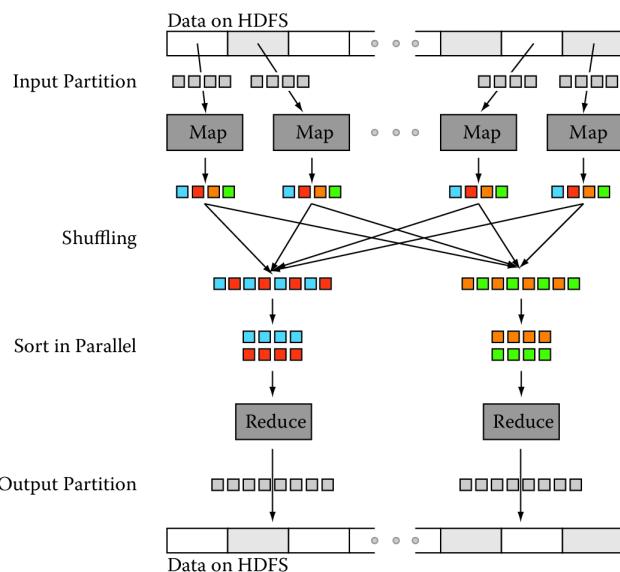
A combiner task in Hadoop is similar to a function in the MapReduce framework, but it only works locally at each node: it takes output from mappers executed on the same node and produces aggregated values. Combiners are optional but can be used to greatly reduce the amount of data exchange in the shuffle phase; thus, users are encouraged to implement this whenever possible. A common practice is when a `reduce` function is both commutative and associative, and has the same input and output format, one can just use the `reduce` function as the combiner. Nevertheless, combiners are not guaranteed to be executed by Hadoop, so this should only be treated as a hint. Its execution must not affect the correctness of the program.

A partitioner task is the last process taking place in the map phase on each mapper node, where it hashes the key of each key–value pair output from the mappers or the combiners into bins. By default, the partitioner uses object hash codes and modulus operations to direct a designated reducer to pull data from a map node. Though it is possible to customize the partitioner, it is only advisable to do so when one fully understands the intermediate data distribution as well as the specifications of the cluster. In general, it is better to leave this job to Hadoop.

Each reduce phase in Hadoop is divided into three tasks: **reducer**, **output format**, and **record writer**. The **reducer** task is equivalent to the `reduce` function of the MapReduce model. It basically groups the data produced by the mappers by keys and runs a `reduce` function on each list of grouping values. It outputs zero or more key–value pairs for the output format task, which then translates them into a writable format for the record writer task to serialize on HDFS. By default, Hadoop will separate the key and value with a tab and write separate records on separate lines. However, this behavior is fully customizable. Similarly, the map phase reducers are also executed concurrently in Hadoop.

#### 5.4.5 Programming language support

Hadoop is written entirely in Java, thus it is best supporting applications written in Java. However, Hadoop also provides a *streaming API* that allows arbitrary code to be run inside the Hadoop MapReduce framework through the use of UNIX pipes. This means that we can supply a mapper program written in Python or C++ to Hadoop as long as that program reads from the standard input and writes to the standard output. The same mechanism also applies for the combiner and reducer. For example, we can develop from the



**FIGURE 5.2** Data transfer and communication of a MapReduce job in Hadoop. Data blocks are assigned to several maps, which emit key–value pairs that are shuffled and sorted in parallel. The reduce step emits one or more pairs, with results stored on the HDFS

Python pseudo-code in Listing 5.1 to a complete Hadoop streaming mapper (Listing 5.2) and reducer (Listing 5.3).

```
#!/usr/bin/env python
import sys

def parseInput():
    for line in sys.stdin:
        yield line

if __name__=='__main__':
    for line in parseInput():
        fields      = line.strip('\n').split(',')
        awardId    = fields[0]
        domainName = fields[3].split('@')[-1].split('.')[-2:]
        print('%s\t%s' % (domainName,awardId))
```

Listing 5.2. A Hadoop streaming mapper in Python

```
#!/usr/bin/env python
import sys

def parseInput():
    for line in sys.stdin:
        yield line

if __name__=='__main__':
    for line in parseInput():
        (domainName, awardIds) = line.split('\t')
        count = len(set(awardIds))
        print('%s\t%s' % (domainName, count))
```

Listing 5.3. A Hadoop streaming reducer in Python

It should be noted that in Hadoop streaming, intermediate key-value pairs (the data flowing between mappers and reducers) must be in tab-delimited format, thus we replace the original `yield` command with a `print` formatted with tabs. Though the input format and record reader are still customizable in Hadoop streaming, they must be supplied as Java classes. This is one of the biggest limitations of Hadoop for Python developers. They not only have to split their code into separate mapper and reducer programs, but also need to learn Java if they want to work with nontextual data.

### 5.4.6 Benefits and Limitations of Hadoop

- **Fault Tolerance:** By default, HDFS uses checksums to enforce data integrity on its file system use data replication for recovery of potential data losses. Taking advantage of this, Hadoop also maintains fault tolerance of MapReduce jobs by storing data at every step of a MapReduce job to HDFS, including intermediate data from the combiner. Then the system checks whether a task fails by either looking at its heartbeats (data activities) or whether it has been taking too long. If a task is deemed to have failed, Hadoop will kill it and run it again on a different node. The time limit for the heartbeats and task running duration may also be customized for each job. Though the mechanism is simple, it works well on thousands of machines. It is indeed highly robust because of the simplicity of the model.
- **Performance:** Hadoop has proven to be a scalable implementation that can run on thousands of cores. However, it is also known for having a relatively high job setup overheads and suboptimal running time. An empty task in Hadoop (i.e., with no mapper or reducer) can take roughly 30 seconds to complete even on a modern cluster. This overhead makes it unsuitable for real-time data or interactive jobs. The problem comes mostly from the fact that Hadoop monitoring processes only lives within a job, thus it needs to start and stop these processes each time a job is submitted, which in turns results in this major overhead. Moreover, the brute force approach of maintaining fault tolerance by storing everything on HDFS is expensive, especially for large data sets.
- **Hadoop streaming support for non-Java applications:** As mentioned previously, non-Java applications may only be integrated with Hadoop through the Hadoop streaming API. However, this API is far from optimal. First, input formats and record readers can only be written in Java, making it impossible to write advanced MapReduce jobs entirely in a different language. Second, Hadoop streaming only communicates with Hadoop through Unix pipes, and there is no support for data passing within the application using native data structure (e.g., it is necessary to convert Python tuples into strings in the mappers and convert them back into tuples again in reducers).
- **Real-time applications:** With the current setup, Hadoop only supports batch data processing jobs. This is by design, so it is not exactly a limitation of Hadoop. However, given that more and more applications are dealing with real-time massive data sets, the community using MapReduce for real-time processing is constantly growing. Not having support for streaming or real-time data is clearly a disadvantage of Hadoop over other implementations.
- **Limited data transformation operations:** This is more of a limitation of MapReduce than Hadoop per se. MapReduce only supports two operations, map and reduce, and while these operations are sufficient to describe a variety of data processing pipelines, there are classes of applications that

MapReduce is not suitable for. Beyond that, developers often find themselves rewriting simple data operations such as data set joins, finding a min or max, and so on. Sometime, these tasks require more than one map-and-reduce operation, resulting in multiple MapReduce jobs. This is both cumbersome and inefficient. There are tools to automate this process for Hadoop; however, they are only a layer above, and it is not easy to integrate with existing customized Hadoop applications.

---

## 5.5 Other MapReduce Implementations

In addition to Apache Hadoop, other notable MapReduce implementations include MongoDB, GreenplumDB, Disco, Riak, and Spark. MongoDB, Riak, and Greenplum DB are all database systems<sup>2</sup> and thus their MapReduce implementations focus more on the interoperability of MapReduce and the core components such as MongoDB's aggregation framework, and leave it up to users to customize the MapReduce functionalities for broader tasks. Some of these systems, such as Riak, only parallelize the map phase, and run the reduce phase on the local machine that request the tasks. The main advantage of the three implementations is the ease with which they connect to specific data stores. However, their support for general data processing pipelines is not as extensive as that of Hadoop.

Disco, similar to Hadoop, is designed to support MapReduce in a distributed computing environment, but it written in Erlang with a Python interface. Thus, for Python developers, Disco might be a better fit. However, it has significantly fewer supporting applications, such as access control and workflow integration, as well as a smaller developing community. This is why the top three big data platforms, Cloudera, Hortonworks, and MapR, still build primarily on Hadoop.

---

## 5.6 Apache Spark

Apache Spark is another implementation that aims to support beyond MapReduce. The framework is centered around the concept of resilient distributed data sets and data transformations that can operate on these objects. An innovation in Spark is that the fault tolerance of resilient distributed data sets can be maintained without flushing data onto disks, thus significantly

---

<sup>2</sup>See Chapter 4.

improving the system performance (with a claim of being 100 times faster than Hadoop). Instead, the fault-recovery process is done by replaying a log of data transformations on check-point data. Though this process could take longer than reading data straight from HDFS, it does not occur often and is a fair tradeoff between processing performance and recovery performance.

Beyond map and reduce, Spark also supports various other transformations (Hadoop, n.d.), including filter, data join, and aggregation. Streaming computation can also be done in Spark by asking Spark to reserve resources on a cluster to constantly stream data to/from the cluster. However, this streaming method might be resource intensive (still consuming resources when there is no data coming). Additionally, Spark plays well with the Hadoop ecosystem, particularly with the distributed file system (HDFS) and resource manager (YARN), making it possible to be built on top of current Hadoop applications.

Another advantage of Spark is that it supports Python natively; thus, developers can run Spark in a fraction of the time required for Hadoop. Listing 5.4 provides the full code for the previous example written entirely in Spark. It should be noted that Spark's concept of the `reduceByKey` operator is not the same as Hadoop's, as it is designed to aggregate all elements of a data set into a single element. The closest simulation of Hadoop's MapReduce pattern is a combination of `mapPartitions`, `groupByKey` and `mapPartitions`, as shown in the next example.

```
import sys
from pyspark import SparkContext
def mapper(lines):
    for line in lines:
        fields      = line.strip('\n').split(',')
        awardId    = fields[0]
        domainName = fields[3].split('@')[-1].split('.')[-2:]
        yield (domainName, awardId)

def reducer(pairs):
    for (domainName, awardIds) in pairs:
        count = len(set(awardIds))
        yield (domainName, count)

if __name__=='__main__':
    hdfsInputPath = sys.argv[1]
    hdfsOutputFile = sys.argv[2]
    sc = SparkContext(appName="Counting Awards")
    output = sc.textFile(hdfsInputPath) \
        .mapPartitions(mapper) \
        .groupByKey() \
        .mapPartitions(reducer)
```

```
output.saveAsTextFile(hdfsInputPath)
```

Listing 5.4. Python code for a Spark program that counts the number of awards per institution using MapReduce

### **Example: Analyzing home mortgage disclosure application data**

We use a financial services analysis problem to illustrate the use of Apache Spark.

Mortgage origination data provided by the Consumer Protection Financial Bureau provide insightful details of the financial health of the real estate market. The data (Consumer Financial Protection Bureau, n.d.), which are a product of the Home Mortgage Disclosure Act (HMDA), highlight key attributes that function as strong indicators of health and lending patterns.

Lending institutions, as defined by section 1813 in Title 12 of the HMDA, decide on whether to originate or deny mortgage applications based on credit risk. In order to determine this credit risk, lenders must evaluate certain features relative to the applicant, the underlying property, and the location. We want to determine whether census tract clusters could be created based on mortgage application data and whether lending institutions' perception of risk is held constant across the entire USA.

For the first step of this process, we study the debt-income ratio for loans originating in different census tracts. This could be achieved simply by computing the debt-income ratio for each loan application and aggregating them for each year by census tract number. A challenge, however, is that the data set provided by HMDA is quite extensive. In total, HMDA data contain approximately 130 million loan applications between 2007 and 2013. As each record contains 47 attributes, varying in types from continuous variables such as loan amounts and applicant income to categorical variables such as applicant gender, race, loan type, and owner occupancy, the entire data set results in about 86 GB of information. Parsing the data alone could take up to hours on a single machine if using a naïve approach that scans through the data sequentially. Tables 5.1 and 5.2 highlight the breakdown in size per year and data fields of interest.

TABLE 5.1: Home Mortgage Disclosure Act data size

Year	Records	File Size (Gigabytes)
2007	26,605,696	18
2008	17,391,571	12
2009	19,493,492	13
2010	16,348,558	11
2011	14,873,416	9.4

Year	Records	File Size (Gigabytes)
2012	18,691,552	12
2013	17,016,160	11
<b>Total</b>	<b>130,420,445</b>	<b>86.4</b>

TABLE 5.2: Home Mortgage Disclosure Act data size

Index	Attribute	Type
0	Year	Integer
1	State	String
2	County	String
3	Census Tract	String
4	Loan Amount	Float
5	Applicant Income	Float
6	Loan Originated	Boolean
...	...	...

Observing the transactional nature of the data, where the aggregation process could be distributed and merged across multiple partitions of the data, we could complete this task in much less time by using Spark. Using a cluster consisting of 1,200 cores, the Spark program in Listing 5.5 took under a minute to complete. The substantial performance gain comes not so much from the large number of processors available, but mostly from the large I/O bandwidth available on the cluster thanks to the 200 distributed hard disks and fast network interconnects.

```

import ast
import sys
from pyspark import SparkContext

def mapper(lines):
    for line in lines:
        fields = ast.literal_eval('(%s)' % line)
        (year, state, county, tract) = fields[:4]
        (amount, income, originated) = fields[4:]

        key = (year, state, county, tract)
        value = (amount, income)

        # Only count originated loans
        if originated:
            yield (key, value)

```

```
def sumDebtIncome(debtIncome1, debtIncome2):
    return (debtIncome1[0] + debtIncome2[0], debtIncome1[1] + debtIncome2[1])

if __name__=='__main__':
    hdfsInputPath = sys.argv[1]
    hdfsOutputFile = sys.argv[2]
    sc = SparkContext(appName="Counting Awards")
    sumValues = sc.textFile(hdfsInputPath) \
        .mapPartitions(mapper) \
        .reduceByKey(sumDebtIncome)

    # Actually compute the aggregated debt income
    output = sumValues.mapValues(lambda debtIncome: debtIncome[0]/debtIncome[1])

    output.saveAsTextFile(hdfsInputPath)
```

Listing 5.5. Python code for a Spark program to aggregate the debt-income ratio for loans originated in different census tracts

---

## 5.7 Summary

Analyzing large amounts of data means that it is necessary to both store very large collections of data and perform aggregate computations on those data. This chapter describes an important data storage approach (the Hadoop Distributed File System) and a way of processing large-scale data sets (the MapReduce model, as implemented in both Hadoop and Spark). This model enables not only large-scale data analysis but also provides easy to use implementations for more flexibility for social scientists to work with large amounts of data. This increases the analytic throughput as well as the time to insight, speeding up the decision-making process and thus increasing impact.

---

---

## 5.8 Resources

There are a wealth of online resources describing both Hadoop and Spark. See, for example, the tutorials on the Apache Hadoop (Apache Software

Foundation, n.d.) and Spark (Apache Software Foundation, n.d.) websites. Albanese describes how to use Hadoop for social science (Albanese, n.d.), and Lin and Dyer discuss the use of MapReduce for text analysis (Lin and Dyer 2010).

# 6

---

## *Information Visualization*

---

**M. Adil Yalcin and Catherine Plaisant**

This chapter will show you how to use visualization to explore data in the early phases of a project as well as to communicate results so that data can be turned into interpretable, actionable information. There are many ways of presenting statistical information that convey content in a rigorous manner. The goal of this chapter is to present an introductory overview of effective visualization techniques for a range of data types and tasks, and to explore the foundations and challenges of information visualization at different stages of a project.

---

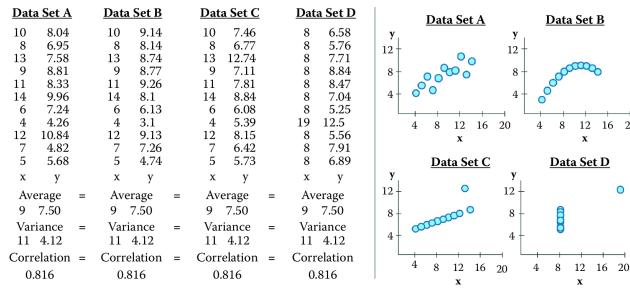
### **6.1 Introduction**

One of the most famous discoveries in science—that disease was transmitted through germs, rather than through pollution— resulted from insights derived from a visualization of the location of London cholera deaths near a water pump (Snow 1855). Information visualization in the twenty-first century can be used to generate similar insights: detecting financial fraud, understanding the spread of a contagious illness, spotting terrorist activity, or evaluating the economic health of a country. But the challenge is greater: many ( $10^2$ – $10^7$ ) items may be manipulated and visualized, often extracted or aggregated from yet larger data sets, or generated by algorithms for analytics.

Visualization tools can organize data in a meaningful way that lowers the cognitive and analytical effort required to make sense of the data and make data-driven decisions. Users can scan, recognize, understand, and recall visually structured representations more rapidly than they can process nonstructured representations. The science of visualization draws on multiple fields such as perceptual psychology, statistics, and graphic design to present information, and on advances in rapid processing and dynamic to design user interfaces that permit powerful interactive visual

Figure 6.1, “Anscombe’s quartet” (Anscombe 1973), provides a classic example

of the value of visualization compared to basic descriptive statistical analysis. The left-hand panel includes raw data of four small number-pair data sets (A, B, C, D), which have the same average, median, and standard deviation and have correlation across number pairs. The right-hand panel shows these data sets visualized with each point plotted on perpendicular axes (scatterplots), revealing dramatic differences between the data sets, trends, and outliers visually.



**FIGURE 6.1** Anscombes quartet [@anscombe1973graphs]

In broad terms, visualizations are used either to present results or for analysis and open-ended exploration. This chapter provides an overview of how modern information visualization, or visual data mining, can be used to in the context of big data.

## 6.2 Developing effective visualizations

The effectiveness of a visualization depends on both analysis needs and design goals. Sometimes, questions about the data are known in advance; in other cases, the goal may be to explore new data sets, generate insights, and answer questions that are unknown before starting the analysis. The design, development, and evaluation of a visualization is guided by understanding the background and goals of the target audience (see Box 9.1<sup>1</sup>).

<sup>1</sup>See Chapters 2, 3, 4, and 5 for an overview of collecting, merging, storing, and processing data sets.

**Box 9.1:** The development of an effective visualization is an iterative process that generally includes the following steps:

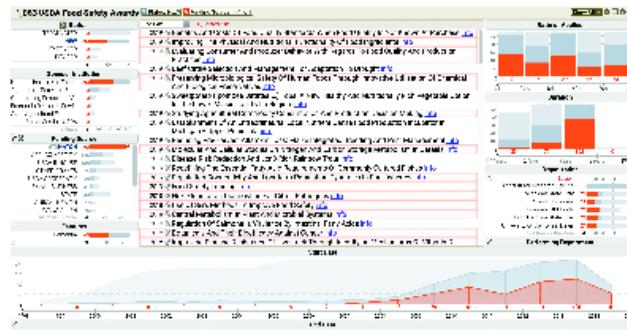
- Specify user needs, tasks, accessibility requirements and criteria for success.
- Prepare data (clean, transform).
- Design visual representations.
- Design interaction.
- Plan sharing of insights, provenance.
- Prototype/evaluate, including usability testing.
- Deploy (monitor usage, provide user support, manage revision process).

If the goal is to present results, there is a wide spectrum of users and a wide range of options. If the audience is broad, then *infographics* can be developed by graphic designers, as described in classic texts (see (Few 2009; Tufte 2001; Tufte 2006) or the examples compiled by Harrison et al. (Harrison, Reinecke, and Chang 2015; Keshif, n.d.)). If, on the other hand, the audience comprises domain experts interested in monitoring the overview status of dynamic processes on a continuous basis, *dashboards* can be used. Examples include the monitoring of sales, or the number of tweets about people, or symptoms of the flu and how they compare to a baseline (Few 2013). Dashboards can increase situational awareness so that problems can be noticed and solved early and better decisions can be made with up-to-date information.

Another goal of visualization is to enable *interactive exploratory analysis* for casual users as well as professional analysts. One casual example is BabyNameVoyager (Harrison, Reinecke, and Chang, n.d.), which lets users type in a name and see a graph of its popularity over the past century<sup>2</sup>.

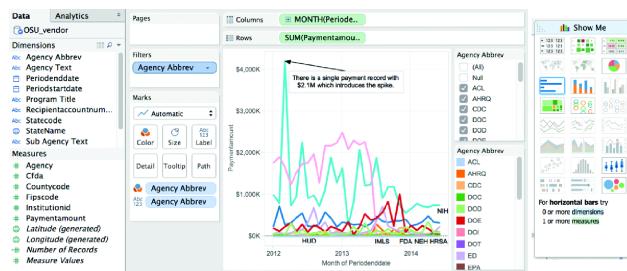
Data analysis tools can enable analysis of structured and generic data sets. Figure 6.2 shows an exploratory browser of a selection of awards (grants) from the US Department of Agriculture, created using the web-based data exploration tool Keshif (<http://www.keshif.me>). The awards (records) are listed in the middle panel by latest start date first. Attributes of the awards, such as funding source, are shown on side panels, revealing the range of their values. The awards with status *new* are focused per the filtering selection, and are visualized using darker gray colors. Lighter gray colors provide visual cues to the distribution of all awards. The orange selection highlights distributions of awards with formula funding, known as *Hatch funding*. The analyst can

<sup>2</sup>As the baby name is typed letter by letter, BabyNameVoyager visualizes the popularity of all the names starting with the letters entered so far, and it animates smoothly with each new letter input. For example, typing “Jo” shows all the names starting with “Jo”. This view reveals that Joyce and Joan were popular girl names in the 1930s, and the use of “John” has declined since the 1960s.



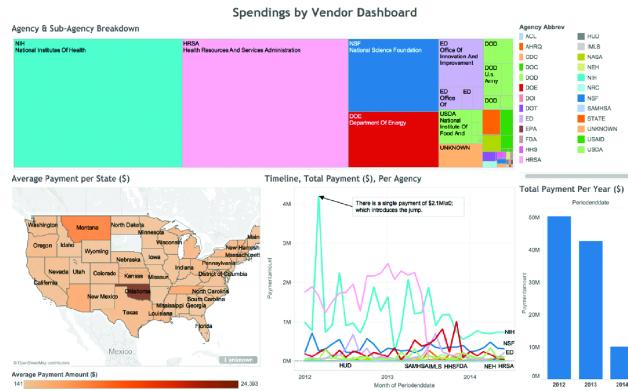
**FIGURE 6.2** A data analysis browser of a selection of grants from the US Department of Agriculture was created by using the web-based tool Keshif

explore trends in new or old awards, funding resources, and other attributes in this rich award portfolio.



**FIGURE 6.3** Charting interface of Tableau

Commercial tools such as Spotfire and Tableau, among many other tools (see Section Resources), allow users to create visualizations by offering chart types and visual design environments to analyze their data, and to combine them in potent dashboards rapidly shared with colleagues. For example, Figure 6.3 shows the charting interface of Tableau on a transaction data set. The left-hand panel shows the list of attributes associated with vendor transactions for a given university. The visualization (center) is constructed by placing the month of spending in chart columns, and the sum of payment amount on the chart row, with data encoded using line mark type. Agencies are broken down by color mapping. The agency list, to the right, allows filtering the chart view, which can be used to simplify the chart view. A peak in the line chart is annotated with an explanation of the spike. On the rightmost side, the Show Me panel suggests the applicable chart types potentially appropriate for the selected attributes. This chart can be combined with other charts focusing on other aspects in interactive dashboards. Figure 6.4 shows a treemap (Johnson and Shneiderman 1991) for agency and sub-agency spending breakdown, combined

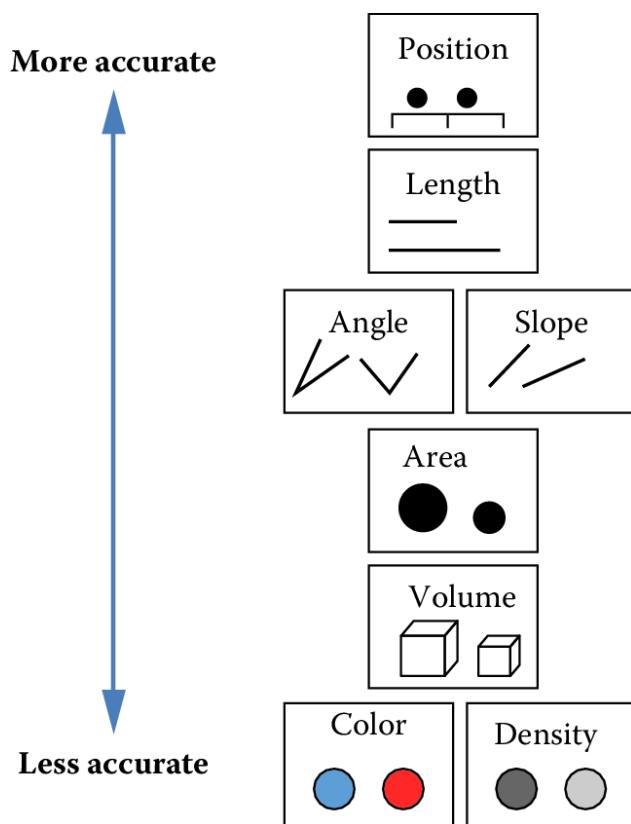


**FIGURE 6.4** A treemap visualization of agency and sub-agency spending breakdown

with a map showing average spending per state. Oklahoma state stands out with few but large expenditures. Mousing-over Oklahoma reveals details of these expenditures. An additional histogram provides an overview of spending change across three years.

Creating effective visualizations requires careful consideration of many components. Data values may be encoded using one or more visual elements, like position, length, color, angle, area, and texture (Figure 6.5; see also (Cleveland and McGill 1984; Tufte 2001)). Each of these can be organized in a multitude of ways, discussed in more detail by Munzner (Munzner 2014). In addition to visual data encoding, units for axes, labels, and legends need to be provided as well as explanations of the mappings when the design is unconventional. (The website “A World of Terror” provides some compelling examples (PERISCOPIC, n.d.).) Annotations or comments can be used to guide viewer attention and to describe related insights. Providing attribution and data source, where applicable, is an ethical practice that also enables validating data, and promotes reuse to explore new perspectives.

The following is a short list of guidelines: provide immediate feedback upon interaction with the visualization; generate tightly coupled views (i.e., so that selection in one view updates the others); and use a high “data to ink ratio” (Tufte 2001). Use color carefully and ensure that the visualization is truthful (e.g., watch for perceptual biases or distortion). Avoid use of three-dimensional representations or embellishments, since comparing 3D volumes is perceptually challenging and occlusion is a problem. Labels and legends should be meaningful, novel layouts should be carefully explained, and online visualizations should adapt to different screen sizes. For extended and in-depth discussions, see various textbooks (Few 2009; Kirk 2012; Ward, Grinstein, and Keim 2010; Munzner 2014; Tufte 2001; Tufte 2006).



**FIGURE 6.5** Visual elements described by MacKinlay [@mackinlay1986automating]

We provide a summary of the basic tasks that users typically perform during visual analysis of data in the next section.

---

### 6.3 A data-by-tasks taxonomy

We give an overview of visualization approaches for six common data types: multivariate, spatial, temporal, hierarchical, network, and text (Shneiderman and Plaisant 2015). For each data type listed in this section, we discuss its distinctive properties, the common analytical questions, and examples. Real-life data sets often include multiple data types coming from multiple sources. Even a single data source can include a variety of data types. For example, a single data table of countries (as rows) can have a list of attributes with varying types: the growth rate in the last 10 years (one observation per year, time series data), their current population (single numerical data), the amount of trade with other countries (networked/linked data), and the top 10 exported products (if grouped by industry, hierarchical data). Furthermore, we provide an overview of common tasks for visual data analysis in Box 9.2, which can be applied across different data types based on goals and types of visualizations.

**Box 9.2: A task categorization for visual data analysis**

## Select/Query

- Filter to focus on a subset of the data
- Retrieve details of item
- Brush linked selections across multiple charts
- Compare across multiple selections

## Navigate

- Scroll along a dimension (1D)
- Pan along two dimensions (2D)
- Zoom along the third dimension (3D)

## Derive

- Aggregate item groups and generate characteristics
- Cluster item groups by algorithmic techniques
- Rank items to define ordering

## Organize

- Select chart type and data encodings to organize data
- Layout multiple components or panels in the interface

## Understand

- Observe distributions
- Compare items and distributions
- Relate items and patterns

## Communicate

- Annotate findings
- Share results
- Trace action histories

Interactive visualization design is also closely coupled with the targeted devices. Conventionally, visualizations have been designed for mouse and keyboard interaction on desktop computers. However, a wider range of device forms, such as mobile devices with small displays and touch interaction, is becoming common. Creating visualizations for new forms requires special care, though basic design principles such as “less is more” still apply.

### 6.3.1 Multivariate data

In common tabular data, each record (row) has a list of attributes (columns), whose value is mostly categorical or numerical. The analysis of multivariate data with basic categorical and interval types aims to understand patterns within and across data. Given a larger number of attributes, one of the challenges in data exploration and analytics is to select the attributes and relations to

focus on. Expertise in the data domain can be helpful for targeting relevant attributes.

Multivariate data can be presented in multiple forms of charts depending on the data and relations being explored. One-dimensional (1D) charts present data on a single axis only. An example is a *box-plot*, which shows quartile ranges for numerical data. So-called 1.5D charts list the range of possible values on one axis, and describe a measurement of data on the other. *Bar charts* are a ubiquitous example, in order to show, for example, a numeric grade per student, or grade average for aggregated student groups by gender. Records can also be grouped over numerical ranges, and bars can show the number of items in each grouping, which generates a *histogram* chart. Two-dimensional charts plot data along two attributes, such as *scatterplots*. Matrix (grid) charts can also be used to show relations between two attributes. *Heatmaps* visualize each matrix cell using color to represent its value. *Correlation matrices* show the relation between attribute pairs.

To show relations of more than two attributes (3D+), one option is to use additional visual encodings in a single chart, for example, by adding point size/shape as a data variable in scatterplots. Another option is to use alternative visual designs that can encode multiple relations within a single chart. For example, a *parallel coordinate plot* (Inselberg 2009) has multiple parallel axes, each one representing an attribute; each record is shown as connected lines passing through the record's values on each attribute. Charts can also show part-of-whole relations using appropriate mappings based on subdividing the chart space, such as stacked charts or pie charts.

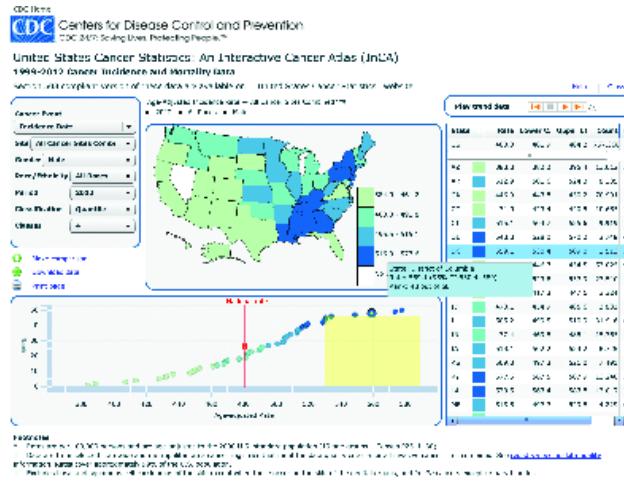
Finally, another approach to analyzing multidimensional data is to use clustering algorithms to identify similar items. Clusters are typically represented as a tree structure (see Section Hierarchical data). For example, *k*-means clustering starts by users specifying how many clusters to create; the algorithm then places every item into the most appropriate cluster. Surprising relationships and interesting outliers may be identified by these techniques on mechanical analysis algorithms. However, such results may require more effort to interpret.

### 6.3.2 Spatial data

Spatial data convey a physical context, commonly in a 2D space, such as geographical maps or floor plans. Several of the most examples of information visualization include maps, from the 1861 representation of Napoleon's ill-fated Russian campaign by Minard (popularized by Tufte (Tufte 2001) and Kraak (Kraak 2014)) to the interactive HomeFinder application that introduced the concept of dynamic queries (Ahlberg, Williamson, and Shneiderman 1992). The tasks include finding adjacent items, regions containing certain items or

with specific characteristics, and paths between items—and performing the basic tasks listed in Box 9.1.

The primary form of visualizing spatial data is *maps*. In *choropleth maps*, color encoding is used to add represent one data attribute. *Cartograms* aim to encode the attribute value with the size of regions by distorting the underlying physical space. *Tile grid maps* reduce each spatial area to a uniform size and shape (e.g., a square) so that the color-coded data are easier to observe and compare, and they arrange the tiles to approximate the neighbor relations between physical locations (DeBelius 2015; Stanford Visualization Group, n.d.). Grid maps also make selection of smaller areas (such as small cities or states) easier. *Contour (isopleth) maps* connect areas with similar measurements and color each one separately. *Network maps* aim to show network connectivity between locations, such as flights to/from many regions of the world. Spatial data can be also presented with a nonspatial emphasis (e.g., as a hierarchy of continents, countries, and cities).



**FIGURE 6.6** The US Cancer Atlas [@usca]. Interface based on [@maceachren2008design]

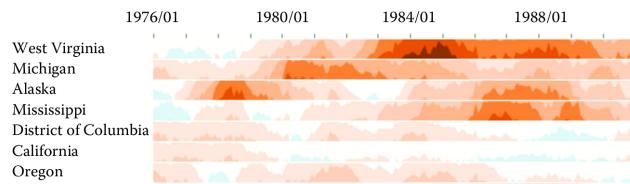
Maps are commonly combined with other visualizations. For example, in Figure 6.6, the US Cancer Atlas combines a map showing patterns across states on one attribute, with a sortable table providing additional statistical information and a scatterplot that allows users to explore correlations between attributes.

### 6.3.3 Temporal data

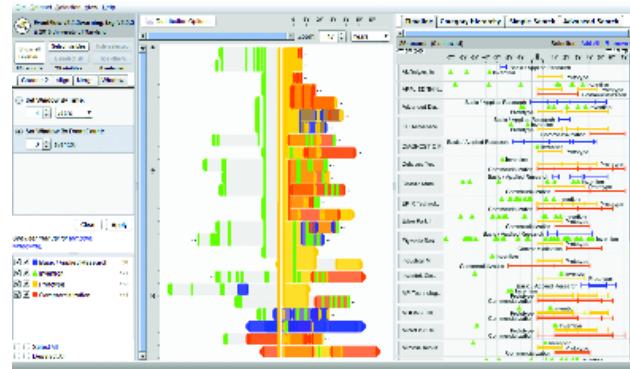
Time is the unique dimension in our physical world that steadily flows forward. While we cannot control time, we frequently record it as a point or interval.

Time has multiple levels of representation (year, month, day, hour, minute, and so on) with irregularities (leap year, different days per month, etc.). As we measure time based on cyclic events in nature (day/night), our representations are also commonly cyclic. For example, January follows December (first month follows last). This cyclic nature can be captured by circular visual encodings, such as the conventional clock with hour, minute, and second hands.

Time series data (Figures 6.7 and 6.8) describe values measured at regular intervals, such as stock market or weather data. The focus of analysis is to understand temporal trends and anomalies, querying for specific patterns, or prediction. To show multiple time-series trends across different data categories in a very compact chart area, each trend can be shown with small height using a multi-layered color approach, creating horizon graphs. While perceptually effective after learning to read its encoding, this chart design may not be appropriate for audiences who may lack such training or familiarity.



**FIGURE 6.7** Horizon graphs used to display time series



**FIGURE 6.8** EventFlow ([www.cs.umd.edu/hcil/eventflow](http://www.cs.umd.edu/hcil/eventflow)) is used to visualize sequences of innovation activities by Illinois companies. Created with EventFlow; data sources include NIH, NSF, USPTO, SBIR. Image created by C. Scott Dempwolf, used with permission

Another form of temporal analysis is understanding sequences of events. The study of human activity often includes analyzing event sequences. For example, students' records include events such as attending orientation, getting a

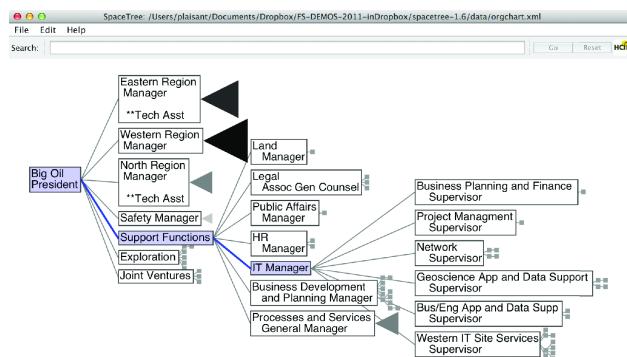
grade in a class, going on internship, and graduation. In the analysis of event sequences, finding the most common patterns, spotting rare ones, searching for specific sequences, or understanding what leads to particular types of events is important (e.g., what events lead to a student dropping out, precede a medical error, or a company filing bankruptcy). Figure 6.8 shows EventFlow used to visualize sequences of innovation activities by Illinois companies. Activity types include research, invention, prototyping, and commercialization. The timeline (right panel) shows the sequence of activities for each company. The overview panel (center) summarizes all the records aligned by the first prototyping activity of the company. In most of the sequences shown here, the company's first prototype is preceded by two or more patents with a lag of about a year.

### 6.3.4 Hierarchical data

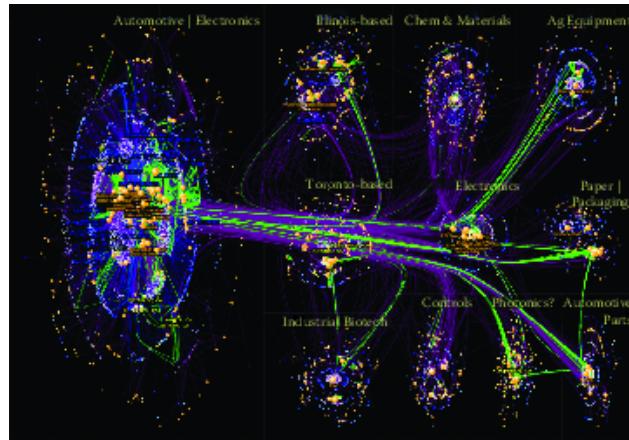
Data are often organized in a hierarchical fashion. Each item appears in one grouping (e.g., like a file in a folder), and groups can be grouped to form larger groups (e.g., a folder within a folder), up to the root (e.g., a hard disk). Items, and the relations between items and their grouping, can have their own attributes. For example, the National Science Foundation is organized into directorates and divisions, each with a budget and a number of grant recipients.

Analysis may focus on the structure of the relations, by questions such as “how deep is the tree?”, “how many items does this branch have?”, or “what are the characteristics of one branch compared to another?” In such cases, the most appropriate representation is usually a node-link diagram (Plaisant, Grosjean, and Bederson 2002; Card and Nation 2002). In Figure 6.9, Spacetree is used to browse a company organizational chart. Since not all the nodes of the tree fit on the screen, we see an iconic representation of the branches that cannot be displayed, indicating the size of each branch. As the tree branches are opened or closed, the layout is updated with smooth multiple-step animations to help users remain oriented.

When the structure is less important but the attribute values of the leaf nodes are of primary interest, treemaps, a space-filling approach, are preferable as they can show arbitrary-sized trees in a fixed rectangular space and map one attribute to the size of each rectangle and another to color. For example, Figure 6.10 shows the Finviz treemap that helps users monitor the stock market. Each stock is shown as a rectangle. The size of the rectangle represents market capitalization, and color indicates whether the stock is going up or down. Treemaps are effective for situation awareness: we can see that today is a fairly bad day as most stocks are red (i.e., down). Stocks are organized in a hierarchy of industries, allowing users to see that “healthcare technology” is not doing as poorly as most other industries. Users can also zoom on healthcare to focus on that industry.

**FIGURE 6.9** SpaceTree ([www.cs.umd.edu/hcil/spacetree/](http://www.cs.umd.edu/hcil/spacetree/))**FIGURE 6.10** The Finviz treemap helps users monitor the stock market ([www.finviz.com](http://www.finviz.com))

### 6.3.5 Network data



**FIGURE 6.11** NodeXL showing innovation networks of the Great Lakes manufacturing region. Created with NodeXL. Data source: USPTO. Image created by C. Scott Dempwolf, used with permission

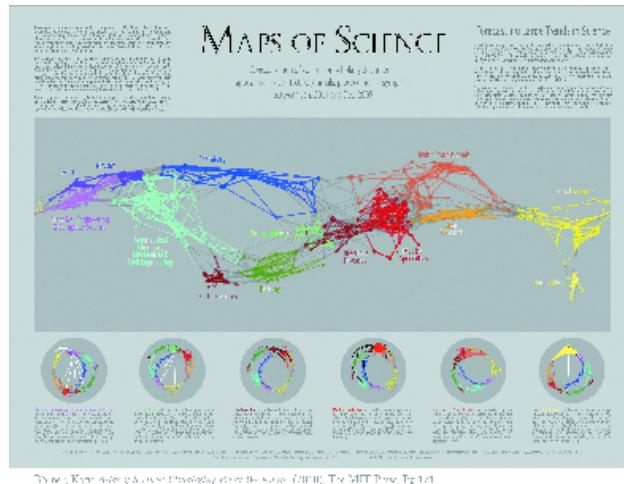
Network data encode relationships between items<sup>3</sup>: for example, social connection patterns (friendships, follows and reposts, etc.), travel patterns (such as trips between metro stations), and communication patterns (such as emails). The network overviews attempt to reveal the structure of the network, show clusters of related items (e.g., groups of tightly connected people), and allow the path between items to be traced. Analysis can also focus on attributes of the items and the links in between, such as age of people in communication or the average duration of communications.

Node-link diagrams are the most common representation of network structures and overviews (Figures 6.11 and 6.12, and may use linear (arc), circular, or force-directed layouts for positioning the nodes (items). Matrices or grid layouts are also a valuable way to represent networks (Henry and Fekete 2006). Hybrid solutions have been proposed, with powerful ordering algorithms to reveal clusters (Hansen, Shneiderman, and Smith 2010). A major challenge in network data exploration is in dealing with larger networks where nodes and edges inevitably overlap by virtue of the underlying network structure, and where aggregation and filtering may be needed before effective overviews can be presented to users.

Figure 6.11 shows the networks of inventors (white) and companies (orange) and their patenting connections (purple lines) in the network visualization NodeXL. Each company and inventor is also connected to a location node (blue

---

<sup>3</sup>See Chapter 8.



**FIGURE 6.12** An example from "Maps of Science: Forecasting Large Trends in Science," 2007, The Regents of the University of California, all rights reserved [[@borner2010atlas](#)]

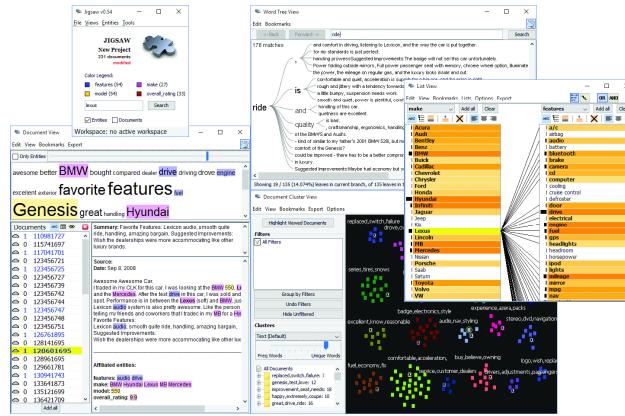
= USA; yellow = Canada). Green lines are weak ties based on patenting in the same class and subclass, and they represent potential economic development leads. The largest of the technology clusters are shown using the *group-in-a-box* layout option, which makes the clusters more visible. Note the increasing level of structure moving from the cluster in the lower right to the main cluster in the upper left. NodeXL is designed for interactive network exploration; many controls (not shown in the figure) allow users to zoom on areas of interest or change options. Figure 6.12 shows an example of network visualization on science as a topic used for data presentation in a book and a traveling exhibit. Designed for print media, it includes a clear title and annotations and shows a series of topic clusters at the bottom with a summary of the insights gathered by analysts.

### 6.3.6 Text data

Text is usually preprocessed (for word/paragraph counts, sentiment analysis, categorization, etc.) to generate metadata about text segments, which are then visualized<sup>4</sup>. Simple visualizations like tag clouds display statistics about word usage in a text collection, or can be used to compare two collections or text segments. While visually appealing, they can easily be misinterpreted and are often replaced by word indexes sorted by some count of interest. Specialized

<sup>4</sup>See Chapter 7 for text analysis approaches.

visual text analysis tools combine multiple visualizations of data extracted from the text collections, such as matrices to see relations, network diagrams, or parallel coordinates to see entity relationships (e.g., between what, who, where, and when). Timelines can be mapped to the linear dimension of text. Figure 6.13 shows an example using Jigsaw (Stasko, Görg, and Liu 2008) for the exploration of car reviews. Entities have been extracted automatically (in this case make, model, features, etc.), and a cluster analysis has been performed, visualized in the bottom right. A separate view (rightmost) allows analysts to review links between entities. Another view allows traversing word sequences as a tree. Reading original documents is critical, so all the visualization elements are linked to the corresponding text.



**FIGURE 6.13** Jigsaw used to explore a collection of car reviews

## 6.4 Challenges

While information visualization is a powerful tool, there are many obstacles to its effective use. We note here four areas of particular concern: scalability, evaluation, visual impairment, and visual literacy.

### 6.4.1 Scalability

Most visualizations handle relatively small data sets (between a thousand and a hundred thousand, sometimes up to millions, depending on the technique) but scaling visualizations from millions to billions of records does require careful coordination of analytic algorithms to filter data or perform rapid aggregation,

effective visual summary designs, and rapid refreshing of displays (Shneiderman 2008). The visual information seeking mantra, “Overview first, zoom and filter, then details on demand,” remains useful with data at scale. To accommodate a billion records, aggregate markers (which may represent thousands of records) and density plots are useful (Dunne and Shneiderman 2013). In some cases the large volume of data can be aggregated meaningfully into a small number of pixels. One example is Google Maps and its visualization of road conditions. A quick glance at the map allows drivers to use a highly aggregated summary of the speed of a large number of vehicles and only a few red pixels are enough to decide when to get on the road.

While millions of graphic elements may be represented on large screens (Fekete and Plaisant 2002), perception issues need to be taken into consideration (Yost, Haciahmetoglu, and North 2007). Extraction and filtering may be necessary before even attempting to visualize individual records (Wongsuphasawat and Lin 2014). Preserving interactive rates in querying big data sources is a challenge, with a variety of methods proposed, such as approximations (Fisher et al. 2012) and compact caching of aggregated query results (Lins, Kłosowski, and Scheidegger 2013). Progressive loading and processing will help users review the results as they appear and steer the lengthy data processing (Glueck, Khan, and Wigdor 2014; Fekete 2015). Systems are starting to emerge, and strategies to cope with volume and variety of patterns are being described (Shneiderman and Plaisant 2015).

#### 6.4.2 Evaluation

Human-centric evaluation of visualization techniques can generate qualitative and quantitative assessments of their potential quality, with early studies focusing on the effectiveness of basic visual variables (MacKinlay 1986). To this day, user studies remain the workhorse of evaluation. In laboratory settings, experiments can demonstrate faster task completion, reduced error rates, or increased user satisfaction. These studies are helpful for comparing visual and interaction designs. For example, studies are reporting on the effects of latency on interaction and understanding (Liu and Heer 2014), and often reveal that different visualizations perform better for different tasks (Saket et al. 2014; Plaisant, Grosjean, and Bederson 2002). Evaluations may also aim to measure and study the amount and value of the insights revealed by the use of exploratory visualization tools (Saraiya, North, and Duca 2005). Diagnostic usability evaluation remains a cornerstone of user-centered design. Usability studies can be conducted at various stages of the development process to verify that users are able to complete benchmark tasks with adequate speed and accuracy. Comparisons with the technology previously used by target users may also be possible to verify improvements. Metrics need to address the learnability and utility of the system, in addition to performance and user

satisfaction (Lam et al. 2012). Usage data logging, user interviews, and surveys can also help identification of potential improvements in visualization and interaction design.

#### **6.4.3 Visual impairment**

Color impairment is a common condition that needs to be taken into consideration (Olson and Brewer 1997). For example, red and green are appealing for their intuitive mapping to positive or negative outcomes (also depending on cultural associations); however, users with red-green color blindness, one of the most common forms, would not be able to differentiate such scales clearly. To assess and assist visual design under different color deficiencies, color simulation tools can be used (see additional resources). The impact of color impairment can be mitigated by careful selection of limited color schemes, using double encoding when appropriate (i.e., using symbols that vary by both shape and color), and allowing users to change or customize color palettes. To accommodate users with low vision, adjustable size and zoom settings can be useful. Users with severe visual impairments may require alternative accessibility-first interface and interaction designs.

#### **6.4.4 Visual literacy**

While the number of people using visualization continues to grow, not everyone is able to accurately interpret graphs and charts. When designing a visualization for a population of users who are expected to make sense of the data without training, it is important to adequately estimate the level of visual literacy of those users. Even simple scatterplots can be overwhelming for some users. Recent work has proposed new methods for assessing visual literacy (Boy et al. 2014), but user testing with representative users in the early stages of design and development will remain necessary to verify that adequate designs are being used. Training is likely to be needed to help analysts get started when using more visual analytics tools. Recorded video demonstrations and online support for question answering are helpful to bring users from novice to expert levels.

---

### **6.5 Summary**

The use of information visualization is spreading widely, with a growing number of commercial products and additions to statistical packages now available.

Careful user testing should be conducted to verify that visual data presentations go beyond the desire for eye-candy in visualization, and to implement designs that have demonstrated benefits for realistic tasks. Visualization is becoming increasingly used by the general public and attention should be given to the goal of universal usability so the widest range of users can access and benefit from new approaches to data presentation and interactive analysis.

---

## 6.6 Resources

We have referred to various textbooks throughout this chapter. Tufte's books remain the classics, as inspiring to read as they are instructive (Tufte 2001; Tufte 2006). We also recommend Few's books on information visualization (Few 2009) and information dashboard design (Few 2013). See also the book's website for further readings.

Given the wide variety of goals, tasks, and use cases of visualization, many different data visualization tools have been developed that address different needs and appeal to different skill levels. In this chapter we can only point to a few examples to get started. To generate a wide range of visualizations and dashboards, and to quickly share them online, Tableau and Tableau Public provide a flexible visualization design platform. If a custom design is required and programmers are available, d3 is the de facto low-level library of choice for many web-based visualizations, with its native integration to web standards and flexible ways to convert and manipulate data into visual objects as a JavaScript library. There exist other JavaScript web libraries that offer chart templates (such as Highcharts), or web services that can be used to create a range of charts from given (small) data sets, such as Raw or DataWrapper. To clean, transform, merge, and restructure data sources so that they can be visualized appropriately, tools like Trifacta and Alteryx can be used to create pipelines for data wrangling. For statistical analysis and batch-processing data, programming environments such as R or libraries for languages such as Python (for example, the Python Plotly library) can be used.

An extended list of tools and books is available at <http://www.keshif.me/demo/VisTools>.



# 7

---

## *Machine Learning*

---

**Rayid Ghani and Malte Schierholz**

This chapter introduces you to the use of machine learning in tackling social science and public policy problems. We cover the end-to-end machine learning process and focus on clustering and classification methods. After reading this chapter, you should have an overview of the components of a machine learning pipeline and methods, and know how to use those in solving social science problems. We have written this chapter to give an intuitive explanation for the methods and to provide a framework and practical tips on how to use them in practice.

---

### 7.1 Introduction

You have probably heard of “machine learning” but are not sure exactly what it is, how it differs from traditional statistics, and what you, as social scientists, can do with it. In this chapter, we will demystify machine learning, draw connections to what you already know from statistics and data analysis, and go deeper into some of the novel concepts and methods that have been developed in this field. Although the field originates from computer science, it has been influenced quite heavily by math and statistics in the past 15-20 years. As you will see, many of the concepts you will learn are not entirely new, but are simply called something else. For example, you already are familiar with logistic regression (a classification method that falls under the supervised learning framework in machine learning) and cluster analysis (a form of unsupervised learning). You will also learn about new methods

that are more exclusively used in machine learning, such as random Forests, support vector machines, and neural networks. We will keep formalisms to a minimum and focus on getting the intuition across, as well as providing practical tips. Our hope is this chapter will make you comfortable and familiar with machine learning vocabulary, concepts, and processes, and allow you to

further explore and use these methods and tools in your own research and practice.

---

## 7.2 What is machine learning?

When humans improve their skills with experience, they are said to learn. Is it also possible to program computers to do the same? Arthur Samuel, who coined the term *machine learning* in 1959 (Samuel 1959), was a pioneer in this area, programming a computer to play checkers. The computer played against itself and human opponents, improving its performance with every game. Eventually, after sufficient *training* (and experience), the computer became a better player than the human programmer. Today, machine learning has grown significantly beyond learning to play checkers. Machine learning systems have learned to drive (and park) autonomous cars, are embedded inside robots, can recommend books, products, and movies we are (sometimes) interested in, identify drugs, proteins, and genes that should be investigated further to cure diseases, detect cancer and other pathologies in x-rays and other types of medical imaging, help us understand how the human brain learns language, help identify which voters are persuadable in elections, detect which students are likely to need extra support to graduate high school on time, and help solve many more problems. Over the past 20 years, machine learning has become an interdisciplinary field spanning computer science, artificial intelligence, databases, and statistics. At its core, machine learning seeks to design computer systems that improve over time with more experience. In one of the earlier books on machine learning, Tom Mitchell gives a more operational definition, stating that: “A computer program is said to learn from experience  $E$  with respect to some class of tasks  $T$  and performance measure  $P$ , if its performance at tasks in  $T$ , as measured by  $P$ , improves with experience  $E$ ” (Mitchell 1997). We like this definition because it is task-focused and allows us to think of machine learning as a tool used inside a larger system to improve outcomes that we care about.

**Box 7.1: Commercial machine learning examples**

- **Speech recognition:** Speech recognition software uses machine learning algorithms that are built on large amounts of initial training data. Machine learning allows these systems to be tuned and adapt to individual variations in speaking as well as across different domains.
- **Autonomous cars:** The ongoing development of self-driving cars applies techniques from machine learning. An onboard computer continuously analyzes the incoming video and sensor streams in order to monitor the surroundings. Incoming data are matched with annotated images to recognize objects like pedestrians, traffic lights, and potholes. In order to assess the different objects, huge training data sets are required where similar objects already have been identified. This allows the autonomous car to decide on which actions to take next.
- **Fraud detection:** Many public and private organizations face the problem of fraud and abuse. Machine learning systems are widely used to take historical cases of fraud and flag fraudulent transactions as they take place. These systems have the benefit of being adaptive, and improving with more data over time.
- **Personalized ads:** Many online stores have personalized recommendations promoting possible products of interest. Based on individual shopping history and what other similar users bought in the past, the website predicts products a user may like and tailors recommendations. Netflix and Amazon are two examples of companies whose recommendation software predicts how a customer would rate a certain movie or product and then suggests items with the highest predicted ratings. Of course there are some caveats here, since they then adjust the recommendations to maximize profits.
- **Face recognition:** Surveillance systems, social networking platforms, and imaging software all use face detection and face recognition to first detect faces in images (or video) and then tag them with individuals for various tasks. These systems are trained by giving examples of faces to a machine learning system which then learns to detect new faces, and tag known individuals. The bias and fairness chapter will highlight some concerns with these types of systems.

**Box 7.2: Social Science machine learning examples** Potash et al (reference) worked with the Chicago Department of Public Health and used random forests (a machine learning classification method) to predict which children are at risk of lead poisoning. This early warning system was then used to prioritize lead hazard inspections to detect and remediate lead hazards before they had an adverse effect on the child.

Carton et al (reference) used a collection of machine learning methods to identify police officers at risk of adverse behavior, such as unjustified use of force or unjustified shootings or sustained complaints, to prioritize preventive interventions such as training and counseling.

Athey and Wager (<https://obsstudies.org/277-2/>) use a modification of random forests to estimate heterogeneous treatment effects using a data set from The National Study of Learning Mindsets to evaluate the impact of interventions to improve student achievement.

Voigt et al (<http://web.stanford.edu/~eberhard/downloads/2017-LanguageFromPoliceBodyCameraFootage.pdf>) uses machine learning methods to analyze footage from body-worn cameras and understand the respectfulness of police officer language toward white and black community members during routine traffic stops.

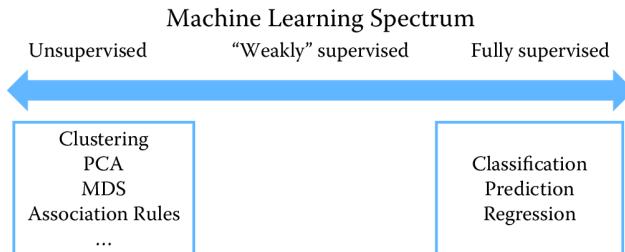
• ““

Machine learning grew from the need for systems that were adaptive, scalable, and cost-effective to build and maintain. A lot of tasks now being done using machine learning used to be done by rule-based systems, where experts would spend considerable time and effort developing and maintaining the rules. The problem with those systems was that they were rigid, not adaptive, hard to scale, and expensive to maintain. Machine learning systems started becoming popular because they could improve the system along all of these dimensions<sup>1</sup>. Box 7.1 mentions several examples where machine learning is being used in commercial applications today. Social scientists are uniquely placed today to take advantage of the same advances in machine learning by having better methods to solve several key problems they are tackling. Box 7.2 describes a few social science and policy problems that are being tackled using machine learning today.

This chapter is not an exhaustive introduction to machine learning. There are many books that have done an excellent job of that [@Flach; @HastieTibshirani; @mitchell1997machine]. Instead, we present a short and accessible introduction to machine learning for social scientists, give an overview of the overall machine learning process, provide an intuitive introduction to machine learning methods, give some practical tips that will be helpful in using these methods, and leave a lot of the statistical theory to machine learning textbooks. As you read more about machine learning in the research literature or the media, you will encounter names of other fields that are related (and practically the same for most social science audiences), such as statistical learning, data mining, and pattern recognition.

#### Types of analysis

A lot of the data analysis tasks that social scientists do can be broken down into four types Description: The goal is to describe patterns or groupings in historical data. You’re already familiar with descriptive statistics and exploratory data analysis methods, and we will cover more advanced versions of those later in this chapter under Unsupervised Learning. Detection: The goal here is not to necessarily understand



**FIGURE 7.1** Spectrum of machine learning methods from unsupervised to supervised learning

### 7.2.3 Features

Before we get to models and methods, we need to turn our raw data into “features”. In social science, they are not called features but instead are known as variables or Predictors (or covariates if you’re doing regression). Good features are what makes machine learning systems effective. Feature generation (or engineering, as it is often called) is where a large chunk of the time is spent in the machine learning process. This is also the phase where previous research and learnings from the domain being tackled can be incorporated into the machine learning process. As social science researchers or practitioners, you have spent a lot of time constructing features, using transformations, dummy variables, and interaction terms. All of that is still required and critical in the machine learning framework. One difference you will need to get comfortable with is that instead of carefully selecting a few predictors, machine learning systems tend to encourage the creation of *lots* of features and then empirically use holdout data to perform regularization and model selection. It is common to have models that are trained on thousands of features. Of course, it is important to keep in mind that increasing the number of features requires you to have enough data so that you’re not overfitting. Commonly used approaches to create features include:

- **Transformations**, such as log, square, and square root.
- **Dummy (binary) variables**: This is often done by taking categorical variables (such as city) and creating a binary variable for each value (one variable for each city in the data). These are also called indicator variables.
- **Discretization**: Several methods require features to be discrete instead of continuous. Several approaches exist to convert continuous variables into discrete ones, the most common of which is equal-width binning.
- **Aggregation**: Aggregate features often constitute the majority of features for a given problem. These aggregations use different aggregation functions (count, min, max, average, standard deviation, etc.), often over varying

windows of time and space. For example, given urban data, we would want to calculate the number (and min, max, mean, variance) of crimes within an  $m$ -mile radius of an address in the past  $t$  months for varying values of  $m$  and  $t$ , and then to use all of them as features in a classification problem. Spatiotemporal aggregation features are going to be extremely important as you build machine learning models.

In general, it is a good idea to have the complexity in features and use a simple model, rather than using more complex models with simple features. Keeping the model simple makes it faster to train and easier to understand and explain.

[ideally give a reference with list of features]

---

### 7.3 Methods

We will start by describing unsupervised learning methods and then go on to supervised learning methods. We focus here on the intuition behind the methods and the algorithm, as well as some practical tips, rather than on the statistical theory that underlies the methods. We encourage readers to refer to machine learning books listed in Section Resources. Box 7.2 gives brief definitions of several terms we will use in this section.

**Box 7.2: Machine learning vocabulary**

- **Learning:** In machine learning, you will notice the term *learning* that will be used in the context of “learning” a model. This is what you probably know as *fitting* or *estimating* a function, or *training* or *building* a model. These terms are all synonyms and are used interchangeably in the machine learning literature.
- **Examples:** These are data points, rows, or instances.
- **Features:** These are independent variables, attributes, predictor variables, and explanatory variables.
- **Labels:** These include the response variable, dependent variable, target Variable, or outcomes.
- **Underfitting:** This happens when a model is too simple and does not capture the structure of the data well enough.
- **Overfitting:** This happens when a model is possibly too complex and models the noise in the data, which can result in poor generalization performance. Using in-sample measures to do model selection can result in that.
- **Regularization:** This is a general method to avoid overfitting by applying additional constraints to the model that is learned. For example, in building logistic regression models, a common approach is to make sure the model weights are, on average, small in magnitude. Two common regularizations are  $L_1$  regularization (used by the lasso), which has a penalty term that encourages the sum of the absolute values of the parameters to be small; and  $L_2$  regularization, which encourages the sum of the squares of the parameters to be Small.

### 7.3.1 Unsupervised learning methods

As mentioned earlier, unsupervised learning methods are used when we do not have a target variable to estimate or predict but want to understand clusters, groups, or patterns in the data. These methods are often used for data exploration, as in the following examples:

1. When faced with a large corpus of text data—for example, email records, congressional bills, speeches, or open-ended free-text survey responses—unsupervised learning methods are often used to understand and get a handle on the patterns in our data.
2. Given a data set about students and their behavior over time (academic performance, grades, test scores, attendance, etc.), one might want to understand typical behaviors as well as trajectories of these

behaviors over time. Unsupervised learning methods (clustering) can be applied to these data to get student “segments” with similar behavior.

3. Given a data set about publications or patents in different fields, we can use unsupervised learning methods (association rules) to figure out which disciplines have the most collaboration and which fields have researchers who tend to publish across different fields.
4. Given a set of people who are at high risk of recidivism, clustering can be used to understand different groups of people within the high risk set, to determine intervention programs that may need to be created.

### Clustering

Clustering is the most common unsupervised learning technique and is used to group data points together that are similar to each other. The goal of clustering methods is to produce with high intra-cluster (within) similarity and low inter-cluster (between) similarity.

Clustering algorithms typically require a distance (or similarity) metric<sup>5</sup> to generate clusters. They take a data set and a distance metric (and sometimes additional parameters), and they generate clusters based on that distance metric. The most common distance metric used is Euclidean distance, but other commonly used metrics are Manhattan, Minkowski, Chebyshev, cosine, Hamming, Pearson, and Mahalanobis. Often, domain-specific similarity metrics can be designed for use in specific problems. For example, when performing the record linkage tasks discussed in Chapter Record Linkage, you can design a similarity metric that compares two first names and assigns them a high similarity (low distance) if they both map to the same canonical name, so that, for example, Sammy and Sam map to Samuel.

Most clustering algorithms also require the user to specify the number of clusters (or some other parameter that indirectly determines the number of clusters) in advance as a parameter. This is often difficult to do a priori and typically makes clustering an iterative and interactive task. Another aspect of clustering that makes it interactive is often the difficulty in automatically evaluating the quality of the clusters. While various analytical clustering metrics have been developed, the best clustering is task-dependent and thus must be evaluated by the user. There may be different clusterings that can be generated with the same data. You can imagine clustering similar news stories based on the topic content, based on the writing style or based on

---

<sup>5</sup>Distance metrics are mathematical formulas to calculate the distance between two objects. For example, *Manhattan distance* is the distance a car would drive from one place to another place in a grid-based street system, whereas *Euclidean distance* (in two-dimensional space) is the “straight-line” distance between two points.

sentiment. The right set of clusters depends on the user and the task they have. Clustering is therefore typically used for exploring the data, generating clusters, exploring the clusters, and then rerunning the clustering method with different parameters or modifying the clusters (by splitting or merging the previous set of clusters). Interpreting a cluster can be nontrivial: you can look at the centroid of a cluster, look at frequency distributions of different features (and compare them to the prior distribution of each feature), or you can build a decision tree (a supervised learning method we will cover later in this chapter) where the target variable is the cluster ID that can describe the cluster using the features in your data. A good example of a tool that allows interactive clustering from text data is Ontogen (Fortuna, Grobelnik, and Mladenic 2007).

### ***k*-means clustering**

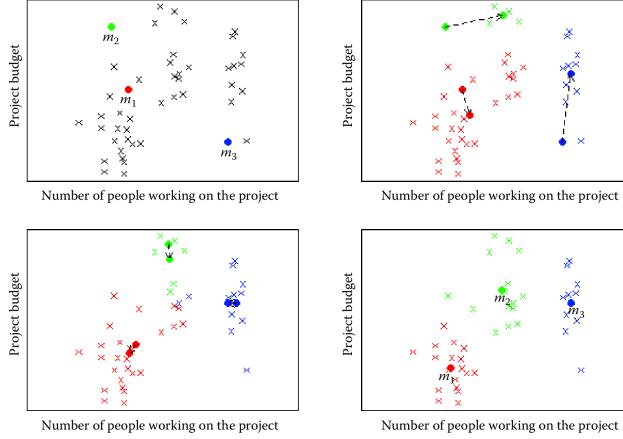
The most commonly used clustering algorithm is called *k*-means, where *k* defines the number of clusters. The algorithm works as follows:

1. Select *k* (the number of clusters you want to generate).
2. Initialize by selecting *k* points as centroids of the *k* clusters. This is typically done by selecting *k* points uniformly at random.
3. Assign each point a cluster according to the nearest centroid.
4. Recalculate cluster centroids based on the assignment in (3) as the mean of all data points belonging to that cluster.
5. Repeat (3) and (4) until convergence.

The algorithm stops when the assignments do not change from one iteration to the next (Figure 7.2). The final set of clusters, however, depend on the starting points. If they are initialized differently, it is possible that different clusters are obtained. One common practical trick is to run *k*-means several times, each with different (random) starting points. The *k*-means algorithm is fast, simple, and easy to use, and is often a good first clustering algorithm to try and see if it fits your needs. When the data are of the form where the mean of the data points cannot be computed, a related method called *K*-medoids can be used (Park and Jun 2009).

### **Expectation-maximization (EM) clustering**

You may be familiar with the EM algorithm in the context of imputing missing data. EM is a general approach to maximum likelihood in the presence of incomplete data. However, it is also used as a clustering method where the missing data are the clusters a data point belongs to. Unlike *k*-means, where each data point gets assigned to only one cluster, EM does a soft assignment where each data point gets a probabilistic assignment to various clusters. The EM algorithm iterates until the estimates converge to some (locally) optimal solution.



**FIGURE 7.2** Example of  $k$ -means clustering with  $k = 3$ . The upper left panel shows the distribution of the data and the three starting points  $m_1$ ,  $m_2$ ,  $m_3$  placed at random. On the upper right we see what happens in the first iteration. The cluster means move to more central positions in their respective clusters. The lower left panel shows the second iteration. After six iterations the cluster means have converged to their final destinations and the result is shown in the lower right panel

The EM algorithm is fairly good at dealing with outliers as well as high-dimensional data, compared to  $k$ -means. It also has a few limitations. First, it does not work well with a large number of clusters or when a cluster contains few examples. Also, when the value of  $k$  is larger than the number of actual clusters in the data, EM may not give reasonable results.

### Mean shift clustering

Mean shift clustering works by finding dense regions in the data by defining a window around each data point and computing the mean of the data points in the window. Then it shifts the center of the window to the mean and repeats the algorithm till it converges. After each iteration, we can consider that the window shifts to a denser region of the data set. The algorithm proceeds as follows:

1. Fix a window around each data point (based on the bandwidth parameter that defines the size of the window).
2. Compute the mean of data within the window.
3. Shift the window to the mean and repeat till convergence.

Mean shift needs a bandwidth parameter  $h$  to be tuned, which influences the convergence rate and the number of clusters. A large  $h$  might result in merging

distinct clusters. A small  $h$  might result in too many clusters. Mean shift might not work well in higher dimensions since the number of local maxima is pretty high and it might converge to a local optimum quickly.

One of the most important differences between mean shift and  $k$ -means is that  $k$ -means makes two broad assumptions: the number of clusters is already known and the clusters are shaped spherically (or elliptically). Mean shift does not assume anything about the number of clusters (but the value of  $h$  indirectly determines that). Also, it can handle arbitrarily shaped clusters.

The  $k$ -means algorithm is also sensitive to initializations, whereas mean shift is fairly robust to initializations. Typically, mean shift is run for each point, or sometimes points are selected uniformly randomly. Similarly,  $k$ -means is sensitive to outliers, while mean shift is less sensitive. On the other hand, the benefits of mean shift come at a cost—speed. The  $k$ -means procedure is fast, whereas classic mean shift is computationally slow but can be easily parallelized.

### Hierarchical clustering

The clustering methods that we have seen so far, often termed *partitioning* methods, produce a flat set of clusters with no hierarchy. Sometimes, we want to generate a hierarchy of clusters, and methods that can do that are of two types:

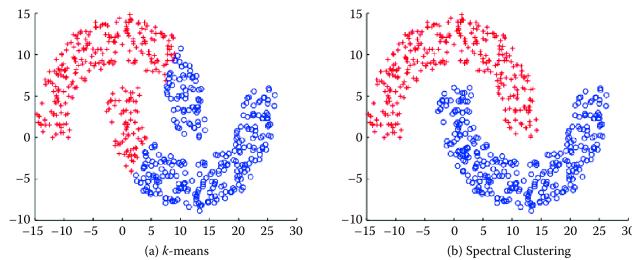
1. **Agglomerative (bottom-up)**: Start with each point as its own cluster and iteratively merge the closest clusters. The iterations stop either when the clusters are too far apart to be merged (based on a predefined distance criterion) or when there is a sufficient number of clusters (based on a predefined threshold).
2. **Divisive (top-down)**: Start with one cluster and create splits recursively.

Typically, agglomerative clustering is used more often than divisive clustering. One reason is that it is significantly faster, although both of them are typically slower than direct partition methods such as  $k$ -means and EM. Another disadvantage of these methods is that they are *greedy*, that is, a data point that is incorrectly assigned to the “wrong” cluster in an earlier split or merge cannot be reassigned again later on.

### Spectral clustering

Figure 7.3 shows the clusters that  $k$ -means would generate on the data set in the figure. It is obvious that the clusters produced are not the clusters you would want, and that is one drawback of methods such as  $k$ -means. Two points that are far away from each other will be put in different clusters even if there are other data points that create a “path” between them. Spectral

clustering fixes that problem by clustering data that are connected but not necessarily (what is called) compact or clustered within convex boundaries. Spectral clustering methods work by representing data as a graph (or network), where data points are nodes in the graph and the edges (connections between nodes) represent the similarity between the two data points.



**FIGURE 7.3** The same data set can produce drastically different clusters: (a)  $k$ -means; (b) spectral clustering

The algorithm works as follows:

1. Compute a similarity matrix from the data. This involves determining a pairwise distance function (using one of the distance functions we described earlier).
2. With this matrix, we can now perform graph partitioning, where connected graph components are interpreted as clusters. The graph must be partitioned such that edges connecting different clusters have low weights and edges within the same cluster have high values.
3. We can now partition these data represented by the similarity matrix in a variety of ways. One common way is to use the normalized cuts method. Another way is to compute a graph Laplacian from the similarity matrix.
4. Compute the eigenvectors and eigenvalues of the Laplacian.
5. The  $k$  eigenvectors are used as proxy data for the original data set, and they are fed into  $k$ -means clustering to produce cluster assignments for each original data point.

Spectral clustering is in general much better than  $k$ -means in clustering performance but much slower to run in practice. For large-scale problems,  $k$ -means is a preferred clustering algorithm to run because of efficiency and speed.

### Principal components analysis

Principal components analysis is another unsupervised method used for finding

patterns and structure in data. In contrast to clustering methods, the output is not a set of clusters but a set of *principal components* that are linear combinations of the original variables. PCA is typically used when you have a large number of variables and you want a reduced number that you can analyze. This approach is often called *dimensionality reduction*. It generates linearly uncorrelated dimensions that can be used to understand the underlying structure of the data. In mathematical terms, given a set of data on  $n$  dimensions, PCA aims to find a linear subspace of dimension  $d$  lower than  $n$  such that the data points lie mainly on this linear subspace.

PCA is related to several other methods you may already know about. Multidimensional scaling, factor analysis, and independent component analysis differ from PCA in the assumptions they make, but they are often used for similar purposes of dimensionality reduction and discovering the underlying structure in a data set.

### Association rules

Association rules are a different type of analysis method and originate from the data mining and database community, primarily focused on finding frequent co-occurring associations among a collection of items. This method is sometimes referred to as “market basket analysis,” since that was the original application area of association rules. The goal is to find associations of items that occur together more often than you would randomly expect. The classic example (probably a myth) is “men who go to the store to buy diapers will also tend to buy beer at the same time.” This type of analysis would be performed by applying association rules to a set of supermarket purchase data. For social scientists, this method can be used on data that contains social services that individuals have received in the past to determine what types of services “co-occur” in people and proactively offer those services to people in need.

Association rules take the form  $X_1, X_2, X_3 \Rightarrow Y$  with support  $S$  and confidence  $C$ , implying that when a transaction contains items  $\{X_1, X_2, X_3\}$   $C\%$  of the time, they also contain item  $Y$  and there are at least  $S\%$  of transactions where the antecedent is true. This is useful in cases where we want to find patterns that are both *frequent* and *statistically significant*, by specifying thresholds for support  $S$  and confidence  $C$ .

Support and confidence are useful metrics to generate rules but are often not enough. Another important metric used to generate rules (or reduce the number of spurious patterns generated) is *lift*. Lift is simply estimated by the ratio of the joint probability of two items,  $x$  and  $y$ , to the product of their individual probabilities:  $P(x, y)/[P(x)P(y)]$ . If the two items are statistically independent, then  $P(x, y) = P(x)P(y)$ , corresponding to a lift of 1. Note that anti-correlation yields lift values less than 1, which is also an interesting pattern, corresponding to mutually exclusive items that rarely occur together.

Association rule algorithms work as follows: Given a set of transactions (rows) and items for that transaction:

1. Find all combinations of items in a set of transactions that occur with a specified minimum frequency. These combinations are called *frequent itemsets*.
2. Generate association rules that express co-occurrence of items within frequent itemsets.

For our purposes, association rule methods are an efficient way to take a *basket* of features (e.g., areas of publication of a researcher, different organizations an individual has worked at in their career, all the cities or neighborhoods someone may have lived in) and find co-occurrence patterns. This may sound trivial, but as data sets and number of features get larger, it becomes computationally expensive and association rule mining algorithms provide a fast and efficient way of doing it.

### 7.3.2 Supervised learning

We now turn to the problem of supervised learning, which typically involves methods for classification, prediction, and regression. We will mostly focus on classification methods in this chapter since many of the regression methods in machine learning are fairly similar to methods with which you are already familiar. Remember that classification means predicting a discrete (or categorical) variable. Most of the classification methods that we will cover can also be used for Regression (predicting continuous outcomes).

In general, supervised learning methods take as input pairs of data points  $(X, Y)$  where  $X$  are the predictor variables (features) and  $Y$  is the target variable (label). The supervised learning method then uses these pairs as *training data* and *learns* a model  $F$ , where  $F(X) \sim Y$ . This model  $F$  is then used to predict  $Y$ 's for new data points  $X$ . As mentioned earlier, the goal is not to build a model that best fits known data but a model that is useful for future predictions and minimizes future generalization error. This is the key goal that differentiates many of the methods that you know from the methods that we will describe next. In order to minimize future error, we want to build models that are not just *overfitting* on past data.

Another goal, often prioritized in the social sciences, that machine learning methods do not optimize for is getting a structural form of the model. Machine learning models for classification can take different structural forms (ranging from linear models, to sets of rules, to more Complex non-linear forms), and it may not always be possible to write them down in a compact form as an equation. This does not, however, make them incomprehensible or uninterpretable.

Another focus of machine learning models for supervised learning is prediction, and not necessarily causal inference<sup>6</sup>. Some of these models can be used to help with causal inference, but they are typically optimized for prediction tasks. We believe that there are many social science and policy problems where better prediction methods can be extremely beneficial. Cite Kleingberg et al (<https://www.cs.cornell.edu/home/kleinber/aer15-prediction.pdf>)

In this chapter, we mostly deal with binary classification problems: that is, problems in which the data points are to be classified into one of two categories. Several of the methods that we will cover can also be used for multiclass classification (classifying a data point into one of  $n$  categories) or for multi-label classification (classifying a data point into  $m$  of  $n$  categories where  $m \geq 1$ ). There are also approaches to take multiclass problems and turn them into a set of binary problems that we will mention briefly at the end of the chapter.

Before we describe supervised learning methods, we want to recap a few principles as well as terms that we have used and will be using in the rest of the chapter.

### Training a model

Once we have finished data exploration, filled in missing values, created predictor variables (features), and decided what our target variable (label) is, we now have pairs of  $X, Y$  to start training (or building) the model.

### Using the model to score new data

We are building this model so we can predict  $Y$  for a new set of  $X$ s—using the model means, getting new data, generating the same features to get the vector  $X$ , and then applying the model to produce  $Y$ .

One common technique for supervised learning is logistic regression, a method you will already be familiar with. We will give an overview of some of the other methods used in machine learning. It is important to remember that as you use increasingly powerful classification methods, you need more data to *train* the models.

### *k*-nearest neighbor

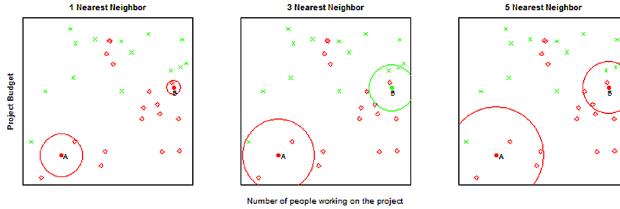
The method *k*-nearest neighbor (*k*-NN) is one of the simpler classification methods in machine learning. It belongs to a family of models sometimes known as *memory-based models* or *instance-based models*. An example is classified by finding its *k* nearest neighbors and taking majority vote (or some other aggregation function). We need two key things: a value for *k* and a distance metric with which to find the *k* nearest neighbors. Typically, different values of *k* are used to empirically find the best one. Small values of *k* lead to predictions having high variance but can capture the local structure of the data. Larger

---

<sup>6</sup>The topic of causal inference is addressed in more detail in Chapter 10.

values of  $k$  build more global models that are lower in variance but may not capture local structure in the data as well.

Figure 7.4 provides an example for  $k = 1, 3, 5$  nearest neighbors. The number of neighbors ( $k$ ) is a parameter, and the prediction depends heavily on how it is determined. In this example, point B is classified differently if  $k = 3$ .



**FIGURE 7.4** Example of  $k$ -nearest neighbor with  $k = 1, 3, 5$  neighbors. We want to predict the points A and B. The 1-nearest neighbor for both points is red ("Patent not granted"), the 3-nearest neighbor predicts point A (B) to be red (green) with probability  $2/3$ , and the 5-nearest neighbor predicts again both points to be red with probabilities  $4/5$  and  $3/5$ , respectively.

Training for  $k$ -NN just means storing the data, making this method useful in applications where data are coming in extremely quickly and a model needs to be updated frequently. All the work, however, gets pushed to scoring time, since all the distance calculations happen when a new data point needs to be classified. There are several optimized methods designed to make  $k$ -NN more efficient that are worth looking into if that is a situation that is applicable to your problem.

In addition to selecting  $k$  and an appropriate distance metric, we also have to be careful about the scaling of the features. When distances between two data points are large for one feature and small for a different feature, the method will rely almost exclusively on the first feature to find the closest points. The smaller distances on the second feature are nearly irrelevant to calculate the overall distance. A similar problem occurs when continuous and categorical predictors are used together. To resolve the scaling issues, various options for rescaling exist. For example, a common approach is to center all features at mean 0 and scale them to variance 1.

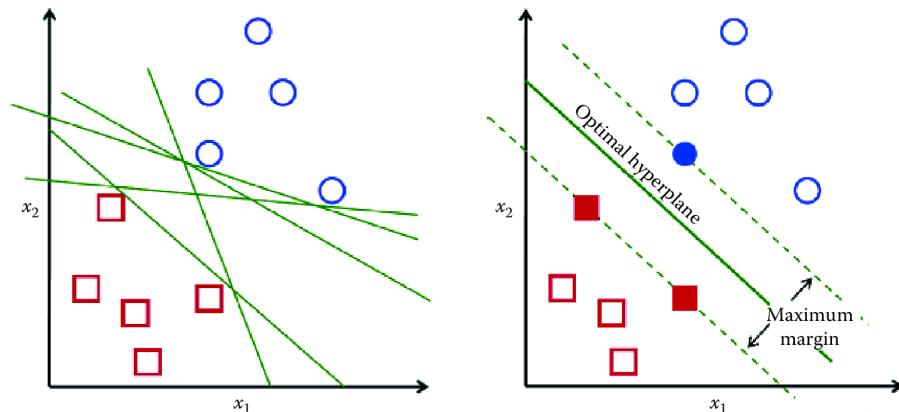
There are several variations of  $k$ -NN. One of these is weighted nearest neighbors, where different features are weighted differently or different examples are weighted based on the distance from the example being classified. The method  $k$ -NN also has issues when the data are sparse and has high dimensionality, which means that every point is far away from virtually every other point, and hence pairwise distances tend to be uninformative. This can also happen when a lot of features are irrelevant and drown out the relevant features' signal in the distance calculations.

Notice that the nearest-neighbor method can easily be applied to regression problems with a real-valued target variable. In fact, the method is completely oblivious to the type of target variable and can potentially be used to predict text documents, images, and videos, based on the aggregation function after the nearest neighbors are found.

### Support vector machines

Support vector machines are one of the most popular and best-performing classification methods in machine learning today. The mathematics behind SVMs has a lot of prerequisites that are beyond the scope of this book, but we will give you an intuition of how SVMs work, what they are good for, and how to use them.

We are all familiar with linear models that separate two classes by fitting a line in two dimensions (or a hyperplane in higher dimensions) in the middle (see Figure 7.5). An important decision that linear models have to make is which linear separator we should prefer when there are several we can build.



**FIGURE 7.5** Support vector machines

You can see in Figure 7.5 that multiple lines offer a solution to the problem. Is any of them better than the others? We can intuitively define a criterion to estimate the worth of the lines: A line is bad if it passes too close to the points because it will be noise sensitive and it will not generalize correctly. Therefore, our goal should be to find the line passing as far as possible from all points.

The SVM algorithm is based on finding the hyperplane that maximizes the *margin* of the training data. The training examples that are closest to the hyperplane are called *support vectors* since they are *supporting* the margin (as the margin is only a function of the support vectors).

An important concept to learn when working with SVMs is *kernels*. SVMs are a specific instance of a class of methods called *kernel methods*. So far, we

have only talked about SVMs as linear models. Linear works well in high-dimensional data but sometimes you need nonlinear models, often in cases of low-dimensional data or in image or video data. Unfortunately, traditional ways of generating nonlinear models get computationally expensive since you have to explicitly generate all the features such as squares, cubes, and all the interactions. Kernels are a way to keep the efficiency of the linear machinery but still build models that can capture nonlinearity in the data without creating all the nonlinear features.

You can essentially think of kernels as similarity functions and use them to create a linear separation of the data by (implicitly) mapping the data to a higher-dimensional space. Essentially, we take an  $n$ -dimensional input vector  $X$ , map it into a high-dimensional (infinite-dimensional) feature space, and construct an optimal separating hyperplane in this space. We refer you to relevant papers for more detail on SVMs and nonlinear kernels (Shawe-Taylor and Cristianini 2004; Scholkopf and Smola 2001). SVMs are also related to logistic regression, but use a different loss/penalty function (Hastie, Tibshirani, and Friedman 2001).

When using SVMs, there are several parameters you have to optimize, ranging from the *regularization* parameter  $C$ , which determines the tradeoff between minimizing the training error and minimizing model complexity, to more kernel-specific parameters. It is often a good idea to do a grid search to find the optimal parameters. Another tip when using SVMs is to normalize the features; one common approach to doing that is to normalize each data point to be a vector of unit length.

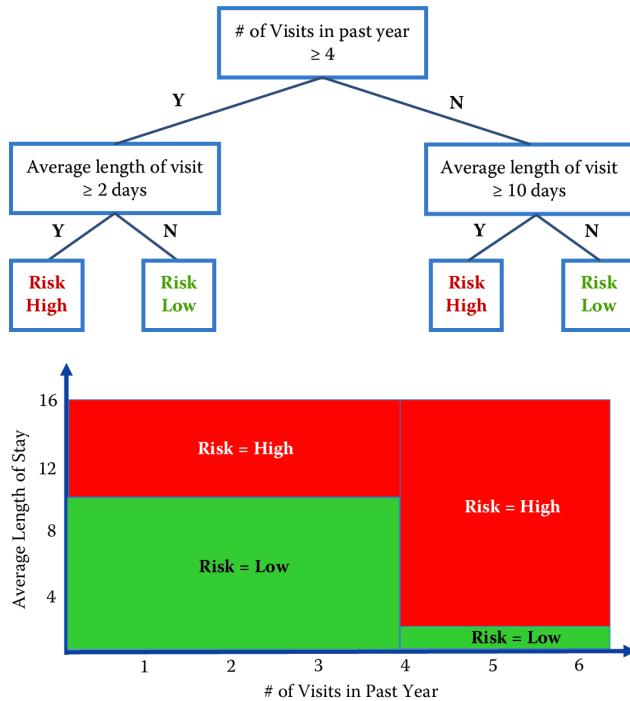
Linear SVMs are effective in high-dimensional spaces, especially when the space is sparse such as text classification where the number of data points (perhaps tens of thousands) is often much less than the number of features (a hundred thousand to a million or more). SVMs are also fairly robust when the number of irrelevant features is large (unlike the  $k$ -NN approaches that we mentioned earlier) as well as when the class distribution is skewed, that is, when the class of interest is significantly less than 50% of the data.

One disadvantage of SVMs is that they do not directly provide probability estimates. They assign a score based on the distance from the margin. The farther a point is from the margin, the higher the magnitude of the score. This score is good for ranking examples, but getting accurate probability estimates takes more work and requires more labeled data to be used to perform probability calibrations.

In addition to classification, there are also variations of SVMs that can be used for regression (Smola and Schölkopf 2004) and ranking (Chapelle and Keerthi 2010).

### Decision trees

Decision trees are yet another set of methods that are helpful for prediction. Typical decision trees learn a set of rules from training data represented as a tree. An exemplary decision tree is shown in Figure 7.6. Each level of a tree *splits* the tree to create a branch using a feature and a value (or range of values). In the example tree, the first split is made on the feature *number of visits in the past year* and the value 4. The second level of the tree now has two splits: one using *average length of visit* with value 2 days and the other using the value 10 days.



**FIGURE 7.6** An exemplary decision tree. The top figure is the standard representation for trees. The bottom figure offers an alternative view of the same tree. The feature space is partitioned into numerous rectangles, which is another way to view a tree, representing its nonlinear character more explicitly

Various algorithms exist to build decision trees. C4.5, CHAID, and CART (Classification and Regression Trees) are the most common. Each needs to determine the next best feature to split on. The goal is to find feature splits that can best reduce class impurity in the data, that is, a split that will ideally put all (or as many as possible) positive class examples on one side and all (or as many as possible) negative examples on the other side. One common measure of impurity that comes from information theory is *entropy*, and it is calculated

as

$$H(X) = - \sum_x p(x) \log p(x).$$

Entropy is maximum (1) when both classes have equal numbers of examples in a node. It is minimum (0) when all examples are from the same class. At each node in the tree, we can evaluate all the possible features and select the one that most reduces the entropy given the tree so far. This expected change in entropy is known as *information gain* and is one of the most common criteria used to create decision trees. Other measures that are used instead of information gain are Gini and chi-squared.

If we keep constructing the tree in this manner, selecting the next best feature to split on, the tree ends up fairly deep and tends to overfit the data. To prevent overfitting, we can either have a stopping criterion or *prune* the tree after it is fully grown. Common stopping criteria include minimum number of data points to have before doing another feature split, maximum depth, and maximum purity. Typical pruning approaches use holdout data (or cross-validation, which will be discussed later in this chapter) to cut off parts of the tree.

Once the tree is built, a new data point is classified by running it through the tree and, once it reaches a terminal node, using some aggregation function to give a prediction (classification or regression). Typical approaches include performing maximum likelihood (if the leaf node contains 10 examples, 8 positive and 2 negative, any data point that gets into that node will get an 80% probability of being positive). Trees used for regression often build the tree as described above but then fit a linear regression model at each leaf node.

Decision trees have several advantages. The interpretation of a tree is straightforward as long as the tree is not too large. Trees can be turned into a set of rules that experts in a particular domain can possibly dig deeper into, validate, and modify. Trees also do not require too much feature engineering. There is no need to create interaction terms since trees can implicitly do that by splitting on two features, one after another.

Unfortunately, along with these benefits come a set of disadvantages. Decision trees, in general, do not perform well, compared to SVMs, random forests, or logistic regression. They are also unstable: small changes in data can result in very different trees. The lack of stability comes from the fact that small changes in the training data may lead to different splitting points. As a consequence, the whole tree may take a different structure. The suboptimal predictive performance can be seen from the fact that trees partition the predictor space into a few rectangular regions, each one predicting only a single value (see the bottom part of Figure 7.6. Todo: trees as simple baselines

### Ensemble methods

Combinations of models are generally known as model ensembles. They are among the most powerful techniques in machine learning, often outperforming other methods, although at the cost of increased algorithmic and model complexity.

The intuition behind building ensembles of models is to build several models, each somewhat different. This diversity can come from various sources such as: training models on subsets of the data; training models on subsets of the features; or a combination of these two.

Ensemble methods in machine learning have two things in common. First, they construct multiple, diverse predictive models from adapted versions of the training data (most often reweighted or resampled). Second, they combine the predictions of these models in some way, often by simple averaging or voting (possibly weighted).

### Bagging

Bagging stands for “bootstrap aggregation”<sup>7</sup>: we first create bootstrap samples from the original data and then aggregate the predictions using models trained on each bootstrap sample. Given a data set of size  $N$ , the method works as follows:

1. Create  $k$  bootstrap samples (with replacement), each of size  $N$ , resulting in  $k$  data sets. Only about 63% of the original training examples will be represented in any given bootstrapped set.
2. Train a model on each of the  $k$  data sets, resulting in  $k$  models.
3. For a new data point  $X$ , predict the output using each of the  $k$  models.
4. Aggregate the  $k$  predictions (typically using average or voting) to get the prediction for  $X$ .

A nice feature of this method is that any underlying model can be used, but decision trees are often the most commonly used base model. One reason for this is that decision trees are typically high variance and unstable, that is, they can change drastically given small changes in data, and bagging is effective at reducing the variance of the overall model. Another advantage of bagging is that each model can be trained in parallel, making it efficient to scale to large data sets.

### Boosting

Boosting is another popular ensemble technique, and it often results in improving the base classifier being used. In fact, if your only goal is improving

---

<sup>7</sup>Bootstrap is a general statistical procedure that draws random samples of the original data with replacement.

accuracy, you will most likely find that boosting will achieve that. The basic idea is to keep training classifiers iteratively, each iteration focusing on examples that the previous one got wrong. At the end, you have a set of classifiers, each trained on smaller and smaller subsets of the training data. Given a new data point, all the classifiers predict the target, and a weighted average of those predictions is used to get the final prediction, where the weight is proportional to the accuracy of each classifier. The algorithm works as follows:

1. Assign equal weights to every example.
2. For each iteration:
  1. Train classifier on the weighted examples.
  2. Predict on the training data.
  3. Calculate error of the classifier on the training data.
  4. Calculate the new weighting on the examples based on the errors of the classifier.
  5. Reweight examples.
3. Generate a weighted classifier based on the accuracy of each classifier.

One constraint on the classifier used within boosting is that it should be able to handle weighted examples (either directly or by replicating the examples that need to be overweighted). The most common classifiers used in boosting are decision stumps (single-level decision trees), but deeper trees can also work well.

Boosting is a common way to *boost* the performance of a classification method but comes with additional complexity, both in the training time and in interpreting the predictions. A disadvantage of boosting is that it is difficult to parallelize since the next iteration of boosting relies on the results of the previous iteration.

A nice property of boosting is its ability to identify outliers: examples that are either mislabeled in the training data, or are inherently ambiguous and hard to categorize. Because boosting focuses its weight on the examples that are more difficult to classify, the examples with the highest weight often turn out to be outliers. On the other hand, if the number of outliers is large (lots of noise in the data), these examples can hurt the performance of boosting by focusing too much on them.

### Random forests

Given a data set of size  $N$  and containing  $M$  features, the random forest training algorithm works as follows:

1. Create  $n$  bootstrap samples from the original data of size  $N$ . Remember, this is similar to the first step in bagging. Typically  $n$  ranges from 100 to a few thousand but is best determined empirically.
2. For each bootstrap sample, train a decision tree using  $m$  features (where  $m$  is typically much smaller than  $M$ ) at each node of the tree. The  $m$  features are selected uniformly at random from the  $M$  features in the data set, and the decision tree will select the best split among the  $m$  features. The value of  $m$  is held constant during the forest growing.
3. A new test example/data point is classified by all the trees, and the final classification is done by majority vote (or another appropriate aggregation method).

Random forests are probably the most accurate classifiers being used today in machine learning. They can be easily parallelized, making them efficient to run on large data sets, and can handle a large number of features, even with a lot of missing values. Random forests can get complex, with hundreds or thousands of trees that are fairly deep, so it is difficult to interpret the learned model. At the same time, they provide a nice way to estimate feature importance, giving a sense of what features were important in building the classifier.

Another nice aspect of random forests is the ability to compute a proximity matrix that gives the similarity between every pair of data points. This is calculated by computing the number of times two examples land in the same terminal node. The more that happens, the closer the two examples are. We can use this proximity matrix for clustering, locating outliers, or explaining the predictions for a specific example.

### Stacking

Stacking is a technique that deals with the task of learning a meta-level classifier to combine the predictions of multiple base-level classifiers. This meta-algorithm is trained to combine the model predictions to form a final set of predictions. This can be used for both regression and classification. The algorithm works as follows:

1. Split the data set into  $n$  equal-sized sets:  $set_1, set_2, \dots, set_n$ .
2. Train base models on all possible combinations of  $n - 1$  sets and, for each model, use it to predict on  $set_i$  what was left out of the training set. This would give us a set of predictions on every data point in the original data set.
3. Now train a second-stage stacker model on the predicted classes

or the predicted probability distribution over the classes from the first-stage (base) model(s).

By using the first-stage predictions as features, a stacker model gets more information on the problem space than if it were trained in isolation. The technique is similar to cross-validation, an evaluation methodology that we will cover later in this chapter.

### Neural networks and deep learning

Neural networks are a set of multi-layer classifiers where the outputs of one layer feed into the inputs of the next layer. The layers between the input and output layers are called *hidden layers*, and the more hidden layers a neural network has, the more complex functions it can learn. Neural networks were popular in the 1980s and early 1990s, but then fell out of fashion because they were slow and expensive to train, even with only one or two hidden layers. Since 2006, a set of techniques has been developed that enable learning in deeper neural networks. These techniques, with access to massive computational resources and large amounts of data, have enabled much deeper (and larger) networks to be Trained and it turns out that these perform far better on many problems than shallow neural networks (with just a single hidden layer). The reason for the better performance is the ability of deep nets to build up a complex hierarchy of concepts, learning multiple levels of representation and abstraction that help to make sense of data such as images, sound, and text.

There are a few different types of neural networks that are popular today:

Convolutional Neural Networks (CNNs): These are often used in detecting objects in images and in doing image search, but their applicability goes beyond just image analysis and they can be used to find patterns in other types of data as well. CNNs treat input data (such as images) in a spatial manner (in two or three dimensions for example), and are able to capture spatial dependencies in the data. Recurrent Neural Networks (RNNs): are suitable for modeling sequential data that has temporal dependencies. They are trained to generate the next steps in a sequence, such as the next letters in a word, or the next words in a sentence, voice recording, or video. They are typically used in translation, speech generation, and time series prediction tasks (references). A popular variation of RNNs is LSTM (Long Short Term Memory) that are used because of their ability and effectiveness in modeling long-range dependencies. Generative Adversarial Network (GANs): have been shown to be quite adept at generating new, realistic images based on other training images. GANs train two models in parallel. One network (called generator) is trained to generate data (based on historical examples of previously occurring data such as images or text or video). The other network (discriminator) tries to classify these generated images as real or synthetic. During training a GAN, the goal is to generate data that is realistic enough that the discriminator network is fooled

to the point that it cannot distinguish the difference between the real and the synthetic input data.

Currently, deep neural networks are popular for a certain class of problems and a lot of research is being done on them. It is, however, important to keep in mind that they may often require a lot more data than are available in many problems. In many problems, such as natural language processing, image , and video analysis, there are techniques to start from a pre-trained neural network model, that reduces the need for additional training data. Training deep neural networks also requires a lot of computational power, but that is less likely to be an issue for most people today with increased access to computing resources. Typical cases where deep learning has been shown to be effective involve lots of images, video, and text data. We are in the early stages of development of this class of methods, and although there seems to be a lot of potential, we need a much better understanding of why they are effective and the problems for which they are well suited.

### 7.3.3 Binary vs Multiclass classification problems

In the discussion above, we framed classification problems as binary classification problems with a 0 or 1 output. There are many problems where we have multiple classes, such as classifying companies into their industry codes or predicting whether a student will drop out, transfer, or graduate. Several solutions have been designed to deal with the multiclass classification problem:

- **Direct multiclass:** Use methods that can directly perform multiclass classification. Examples of such methods are  $K$ -nearest neighbor, decision trees, and random forests. There are extensions of support vector machines that exist for multiclass classification as well (Crammer and Singer 2002), but they can often be slow to train.
- **Convert to one versus all (OVA):** This is a common approach to solve multiclass classification problems using binary classifiers. Any problem with  $n$  classes can be turned into  $n$  binary classification problems, where each classifier is trained to distinguish between one versus all the other classes. A new example can be classified by combining the predictions from all the  $n$  classifiers and selecting the class with the highest score. This is a simple and efficient approach, and one that is commonly used, but it suffers from each classification problem possibly having an imbalanced class distribution (due to the negative class being a collection of multiple classes). Another limitation of this approach is that it requires the scores of each classifier to be calibrated so that they are comparable across all of them.
- **Convert to pairwise:** In this approach, we can create binary classifiers to distinguish between each pair of classes, resulting in  $(^n_2)$  binary classifiers. This results in a large number of classifiers, but each classifier usually has a

balanced classification problem. A new example is classified by taking the predictions of all the binary classifiers and using majority voting.

### 7.3.4 Skewed or imbalanced classification problems

A lot of problems you will deal with will not have uniform (balanced) distributions for both classes. This is often the case with problems in fraud detection, network security, and medical diagnosis where the class of interest is not very common. The same is true in many social science and public policy problems around behavior prediction, such as predicting which students will not graduate on time, which children may be at risk of getting lead poisoning, or which homes are likely to be abandoned in a given city. You will notice that applying standard machine learning methods may result in all the predictions being for the most frequent category in such situations, making it problematic to detect the infrequent classes. There has been a lot of work in machine learning research on dealing with such problems (Chawla 2005; Kuhn and Johnson 2013) that we will not cover in detail here. Common approaches to deal with class imbalance include oversampling from the minority class and undersampling from the majority class. It is important to keep in mind that the sampling approaches do not need to result in a 1 : 1 ratio. Many supervised learning methods described in this chapter (such as Random Forests and SVMs) can work well even with a 10 : 1 imbalance. Also, it is critical to make sure that you only resample the training set; keep the distribution of the test set the same as that of the original data since you will not know the class labels of new data in practice and will not be able to resample.

#### Model interpretability

As social scientists (or good machine learning practitioners), we do not only care about building machine learning models but also want to understand what the models “learned”, and how to use them to make inferences and decisions. Understanding, or interpreting machine learning models is a key requirement for most social science and policy problems. There are various reasons for this including:

##### *Debugging and improving models*

Creating trust in the models and hence increasing adoption  
Improving the decisions being made using the models  
Selecting appropriate interventions  
Legal Requirements

##### *Global versus Individual Interpretability*

When thinking about model interpretability, there are two levels of interpretability: Global: At the overall model level Individual: Explaining an individual classification/prediction that's made by a model.

Both of these are important for different reasons. We need global interpretability to help understand the overall model but we also need explanations for individual classifications when these models are helping a person make decisions about individual cases. A social worker identifying the risk of a client going back to the homeless shelter and determining appropriate interventions to reduce that risk, or a counselor in an employment agency determining how likely an individual is to be long-term unemployed and connecting them with appropriate training programs or job opportunities need individual-level explanations of predictions/recommendations that the machine learning model is generating.

### Global Interpretability

Each method/model needs to be interpreted in a way that is appropriate for that method. For example, for a decision tree, we may want to print the tree and use that to understand what types of classifications are being made. This can of course get cumbersome and difficult if the tree is extremely large. For logistic regression models, we look at the coefficients and odds-ratios, but it may be difficult to mentally account for different variables controlling for each other. In general, the models discussed above have different ways of exposing “feature importances”: how important it found different features that it was provided, and we often use that as a proxy for global model interpretability.

Another way of interpreting the model is not by digging deeper into what the model but by how the model scores individual data points. We can take the set of entities that are scored by the model, and generate cross-tabs that highlight how the top x% of the scored/predicted entities are different from the rest of the entities. This approach allows us to get a high level idea of what the model is doing on the entities of interest to us and makes interpretability a little more intuitive and generalizable across different model types.

A different approach that some have taken in this area has been to build well-performing models that are sparse, hence inherently more interpretable, and don’t require sophisticated approaches to interpret. Examples of such work include (cite: rudin, Caruana..). These models may not perform well in every task so it’s important for us to explore the range of models in terms of performance and complexity, and decide what level and type of interpretability we need and how to balance that with the accuracy<sup>8</sup> of those models.

---

<sup>8</sup>We are using accuracy as a proxy for different confusion-matrix based performance metrics such as precision, recall, etc.

## 7.4 Individual-Level Explanations

There has been a lot of recent work on methods for generating individual-level explanations for predictions made by machine learning models. These fall into two areas: Model specific methods: These are used to generate explanations for predictions made by a specific class of methods, such as neural networks or random forests. Model agnostic methods: These can be used to generate explanations for individual predictions made by any type of model. Examples of this include LIME (cite: lime), MAPLE (cite), SHAP scores (cite)

It's important to keep in mind though that these "explanations" are typically not causal, and are often restricted to be a ranked list of "features". One way to think about them is that the features were most important in assigning this data point the score it was given by a particular model. This is currently an active area of machine learning research and will hopefully mature into a set of methods and tools that are useful for social scientists that are using machine learning to solve problems that require a better and deeper understanding of the models their predictions.

---

## 7.5 Evaluation

The previous section introduced us to a variety of methods, all with certain pros and cons, and no single method guaranteed to outperform others for a given problem. This section focuses on evaluation methods, with three primary goals:

1. Model selection: How do we select a method to use in the future?  
What parameters should we select for that method?
2. Performance estimation: How do we estimate how well our model will perform once it is deployed and applied to new data?
3. A deeper understanding of what types of models work well and don't  
model can point to the effectiveness and applicability of existing  
methods and provide a better understanding of the structure of the  
data and the problem we are tackling.

This section will cover evaluation methodologies as well as metrics that are commonly used. We will start by describing common evaluation methodologies

that use existing data and then move on to field trials. The methodologies we describe below apply both to regression and classification problems.

### 7.5.1 Methodology

#### In-sample evaluation

As social scientists, you already evaluate methods on how well they perform in-sample (on the set that the model was trained on). As we mentioned earlier in the chapter, the goal of machine learning methods is to generalize to new data, and validating models in-sample does not allow us to do that. We focus here on evaluation methodologies that allow us to optimize (as best as we can) for generalization performance. The methods are illustrated in Figure 7.7.

#### Out-of-sample and holdout set

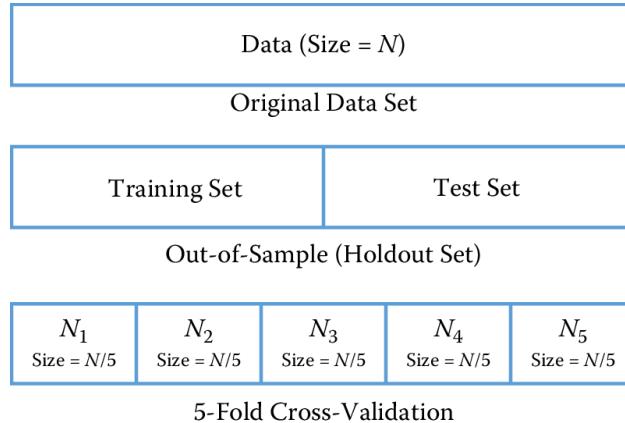
The simplest way to focus on generalization is to *pretend* to generalize to new (unseen) data. One way to do that is to take the original data and randomly split them into two sets: a *training set* and a *test set* (sometimes also called the *holdout* or *validation set*). We can decide how much to keep in each set (typically the splits range from 50–50 to 80–20, depending on the size of the data set). We then train our models on the training set and classify the data in the test set, allowing us to get an estimate of the relative performance of the methods.

One drawback of this approach is that we may be extremely lucky or unlucky with our random split. One way to get around the problem that is to repeatedly create multiple training and test sets. We can then train on  $TR_1$  and test on  $TE_1$ , train on  $TR_2$  and test on  $TE_2$ , and so on. The performance measures on each test set can then give us an estimate of the performance of different methods and how much they vary across different random sets.

#### Cross-validation

Cross-validation is a more sophisticated holdout training and testing procedure that takes away some of the shortcomings of the holdout set approach. Cross-validation begins by splitting a labeled data set into  $k$  partitions (called folds). Typically,  $k$  is set to 5 or 10. Cross-validation then proceeds by iterating  $k$  times. In each iteration, one of the  $k$  folds is held out as the test set, while the other  $k - 1$  folds are combined and used to train the model. A nice property of cross-validation is that every example is used in one test set for testing the model. Each iteration of cross-validation gives us a performance estimate that can then be aggregated (typically averaged) to generate the overall estimate.

An extreme case of cross-validation is called leave-one-out cross-validation, where given a data set of size  $N$ , we create  $N$  folds. That means iterating over each data point, holding it out as the test set, and training on the rest of

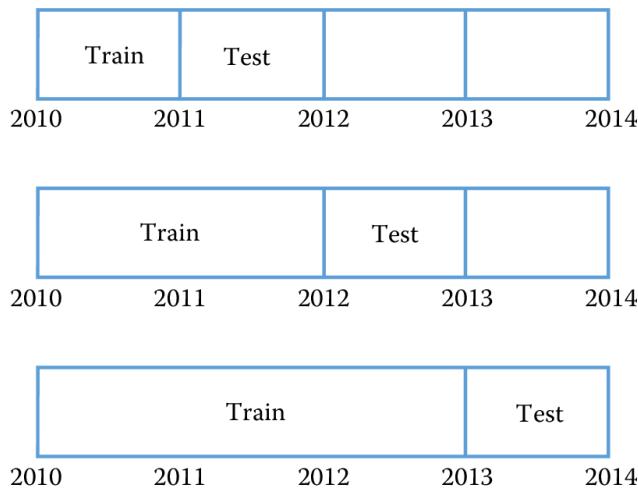


**FIGURE 7.7** Validation methodologies: holdout set and cross-validation

the  $N - 1$  examples. This illustrates the benefit of cross-validation by giving us good generalization estimates (by training on as much of the data set as possible) and making sure the model is tested on each data point.

#### Temporal validation

The cross-validation and holdout set approaches described above assume that the data have no time dependencies and that the distribution is stationary over time. This assumption is almost always violated in practice and affects performance estimates for a model.



**FIGURE 7.8** Temporal validation

In most practical problems, we want to use a validation strategy that emulates the way in which our models will be used and provides an accurate performance estimate. We will call this *temporal validation*. For a given point in time  $t_i$ , we train our models only on information available to us before  $t_i$  to avoid training on data from the “future.” We then predict and evaluate on data from  $t_i$  to  $t_i + d$  and iterate, expanding the training window while keeping the test window size constant at  $d$ . Figure 7.8 shows this validation process with  $t_i = 2010$  and  $d = 1$  year. The test set window  $d$  depends on a few factors related to how the model will be deployed to best emulate reality:

1. How far out in the future do predictions need to be made? For example, if the set of students who need to be targeted for interventions has to be finalized at the beginning of the school year for the entire year, then  $d = 1$  year.
2. How often will the model be updated? If the model is being updated daily, then we can move the window by a day at a time to reflect the deployment scenario.
3. How often will the system get new data? If we are getting new data frequently, we can make predictions more frequently.

Temporal validation is similar to how time series models are evaluated (also known as backtesting) and should be the validation approach used for most practical problems.

### 7.5.2 Metrics

The previous subsection focused on validation methodologies assuming we have an evaluation metric in mind. This section will go over commonly used evaluation metrics. You are probably familiar with using  $R^2$ , analysis of the residuals, and mean squared error (MSE) to evaluate the quality of regression models. For regression problems, the MSE calculates the average squared differences between predictions  $\hat{y}_i$  and true values  $y_i$ . When prediction models have smaller MSE, they are better. However, the MSE itself is hard to interpret because it measures quadratic differences. Instead, the root mean squared error (RMSE) is more intuitive as it is a measure of mean differences on the original scale of the response variable. Yet another alternative is the mean absolute error (MAE), which measures average absolute distances between predictions and true values.

We will now describe some additional evaluation metrics commonly used in machine learning for classification. Before we dive into metrics, it is important to highlight that machine learning models for classification typically do not predict 0/1 values directly. SVMs, random forests, and logistic regression all

produce a score (which is sometimes a probability) that is then turned into 0 or 1 based on a user-specific threshold. You might find that certain tools (such as scikit-learn\footnote{you should never use the predict function in sci-kit-learn since it assumes a 0.5 threshold}) use a default value for that threshold (often 0.5), but it is important to know that it is an arbitrary threshold and you should select the threshold based on the data, the model, and the problem you are solving. We will cover that a little later in this section.

Once we have turned the real-valued predictions into 0/1 classification, we can now create a *confusion matrix* from these predictions, shown in Figure 7.9. Each data point belongs to either the positive class or the negative class, and for each data point the prediction of the classifier is either correct or incorrect. This is what the four cells of the confusion matrix represent. We can use the confusion matrix to describe several commonly used evaluation metrics.

		Predicted Class		
		1	0	total
True Class	1	True Positives	False Negatives	$P'$
	0	False Positives	True Negatives	
total		$P$	$N$	$N'$

**FIGURE 7.9** A \*confusion matrix\* created from real-valued predictions

Accuracy is the ratio of correct predictions (both positive and negative) to all predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{TP + TN}{P + N} = \frac{TP + TN}{P' + N'},$$

where  $TP$  denotes true positives,  $TN$  true negatives,  $FP$  false positives,  $FN$  false negatives, and other symbols denote row or column totals. Accuracy is the most commonly described evaluation metric for classification but is surprisingly the least useful in practical situations (at least by itself). One problem with accuracy is that it does not give us an idea of *lift* compared to baseline. For example, if we have a classification problem with 95% of the data as positive and 5% as negative, a classifier with 85% is performing worse than a dumb classifier that predicts positive all the time (and will have 95% accuracy).

Two additional metrics that are often used are precision and recall, which are defined as follows:

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{TP}{P},$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{TP}{P'}$$

(see also Box 7.3). Precision measures the accuracy of the classifier when it predicts an example to be positive. It is the ratio of correctly predicted positive examples ( $TP$ ) to all examples predicted as positive ( $TP + FP$ ). This measure is also called *positive predictive value* in other fields. Recall measures the ability of the classifier to find positive examples. It is the ratio of all the correctly predicted positive examples ( $TP$ ) to all the positive examples in the data ( $TP + FN$ ). This is also called *sensitivity* in other fields.

You might have encountered another metric called *specificity* in other fields. This measure is the true negative rate: the proportion of negatives that are correctly identified.

Another metric that is used is the  $F_1$  score, which is the harmonic mean of precision and recall:

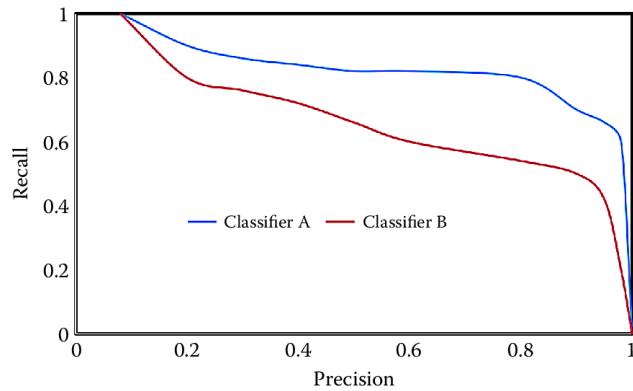
$$F_1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

(see also equation 7.1). This is often used when you want to balance both precision and recall.

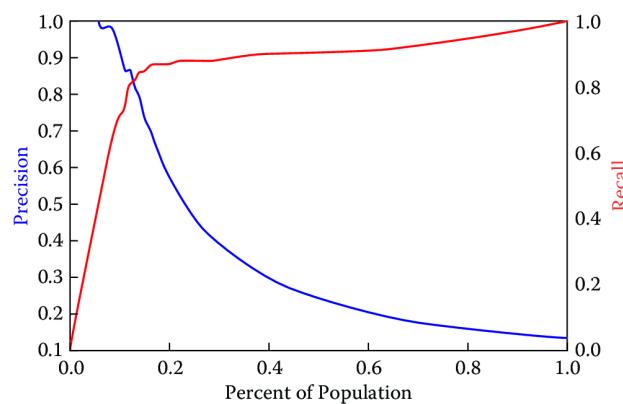
There is often a tradeoff between precision and recall. By selecting different classification thresholds, we can vary and tune the precision and recall of a given classifier. A highly conservative classifier that only predicts a 1 when it is absolutely sure (say, a threshold of 0.9999) will most often be correct when it predicts a 1 (high precision) but will miss most 1s (low recall). At the other extreme, a classifier that says 1 to every data point (a threshold of 0.0001) will have perfect recall but low precision. Figure 7.10 show a precision–recall curve that is often used to represent the performance of a given classifier.

If we care about optimizing for the entire precision recall space, a useful metric is the *area under the curve* (AUC-PR), which is the area under the precision–recall curve. AUC-PR must not be confused with AUC-ROC, which is the area under the related receiver operating characteristic (ROC) curve. The ROC curve is created by plotting recall versus  $(1 - \text{specificity})$ . Both AUCs can be helpful metrics to compare the performance of different methods and the maximum value the AUC can take is 1. If, however, we care about a specific part on the precision–recall curve, we have to look at finer-grained metrics.

Let us consider an example from public health. Most public health agencies conduct inspections of various sorts to detect health hazard violations (lead hazards, for example). The number of possible places (homes or businesses) to inspect far exceeds the inspection resources typically available. Let us assume



**FIGURE 7.10** Precision-recall curve



**FIGURE 7.11** Precision or recall at different thresholds

further that they can only inspect 5% of all possible places; they would clearly want to prioritize the inspection of places that are most likely to contain the hazard. In this case, the model will score and rank all the possible inspection places in order of hazard risk. We would then want to know what percentage of the top 5% (the ones that will get inspected) are likely to be hazards, which translates to the precision in the top 5% of the most confidence predictions—precision at 5%, as it is commonly called (see Figure 7.11). *Precision at top k percent* is a common class of metrics widely used in information retrieval and search engine literature, where you want to make sure that the results retrieved at the top of the search results are accurate. More generally, this metric is often used in problems in which the class distribution is skewed and only a small percentage of the examples will be examined manually (inspections, investigations for fraud, etc.). The literature provides many case studies of such applications (Kumar, Ghani, and Mei 2010; Lakkaraju et al. 2015; Potash et al. 2015).

One last metric we want to mention is a class of cost-sensitive metrics where different costs (or benefits) can be associated with the different cells in the confusion matrix. So far, we have implicitly assumed that every correct prediction and every error, whether for the positive class or the negative class, has equal costs and benefits. In many practical problems, that is not the case. For example, we may want to predict whether a patient in a hospital emergency room is likely to go into cardiac arrest in the next six hours. The cost of a false positive in this case is the cost of the intervention (which may be a few extra minutes of a physician's time) while the cost of a false negative could be death. This type of analysis allows us to calculate the expected value of the predictions of a classifier and select the model that optimizes this cost-sensitive metric.

---

## 7.6 Practical tips

Here we highlight some practical tips that will be helpful when working with machine learning methods.

### 7.6.1 Avoiding Leakage

One of the most common mistakes that gets made in machine learning is called leakage - accidentally giving information data to your model that is not available at prediction time which allows the model to perform better in the training phase than it actually will in the future. Leakage often results in sub-optimal models being selected for use in the future and artificially inflated

performance metrics. Leakage can happen in obvious ways, such as including the target variable (or some transformation of it) as an input variable (or feature), or temporally, where the model, at training time, might use data that will only become available in the future.

It is critical to consider different sources of leakage when building machine learning models.

Scaling/Standardizing: If the data being used is temporal, the scaling or standardization of variables should only happen on the training data and not on *all* of the data. Since the range of a variable on the entire data may be different than the range of that variable in the training set, using the entire range is effectively the same as using information from the “future”.

Imputation: The same is true for imputation methods that use statistics from the data. If we’re using mean imputation, the mean needs to be calculated from the training set and not from the entire data set that we have access to.

There are more subtle forms of leakage getting introduced in your models such as ... When training a machine learning model, our methodology should only use data that is available at the time the model is being trained.

As a general rule, if you encounter a machine learning model that is performing really well, it’s probably because you’ve made an error that is resulting in leakage. One way to dig deeper is to look at the feature importances of your model to see if the most important feature(s) may be the source of that leakage.

### 7.6.2 Machine learning pipeline

When working on machine learning projects, it is a good idea to structure your code as a modular pipeline so you can easily try different approaches and methods without major restructuring. The Python workbooks supporting this book will give you an example of a machine learning pipeline. A good pipeline will contain modules for importing data, doing exploration, feature generation, classification, and evaluation. You can then instantiate a specific workflow by combining these modules.

An important component of the machine learning pipeline is comparing different methods. With all the methods out there and all the hyperparameters they come with, how do we know which model to use and which hyperparameters to select? And what happens when we add new features to the model or when the data have “temporal drift” and change over time? One simple approach is to have a nested set of loops that loop over all the methods you have access to, then enumerate all the hyperparameters for that method, create a cross-product, and loop over all of them, comparing them across different evaluation metrics and selecting the best one to use going forward. You can even add different feature subsets and time slices to this loop, as the example in the

supporting workbooks will show. Triage (<http://github.com/dssg/triage>) is a good example of a machine learning pipeline that is designed to solve many public policy problems.

---

## 7.7 How can social scientists benefit from machine learning?

In this chapter, we have introduced you to some new methods (both unsupervised and supervised), validation methodologies, and evaluation metrics. All of these can benefit social scientists as they tackle problems in research and practice. In this section, we will give a few concrete examples where what you have learned so far can be used to improve some social science tasks:

- **Use of better prediction methods and methodology:** Traditional statistics and social sciences have not focused much on methods for prediction. Machine learning researchers have spent the past 30 years developing and adapting methods focusing on that task. We believe that there is a lot of value for social science researchers and practitioners in learning more about those methods, applying them, and even augmenting them (Kleinberg et al. 2015). Two common tasks that can be improved using better prediction methods are generating counterfactuals (essentially a prediction problem) and matching. In addition, holdout sets and cross-validation can be used as a model selection methodology with any existing regression and classification methods, resulting in improved model selection and error estimates.
- **Model misspecification:** Linear and logistic regressions are common techniques for data analysis in the social sciences. One fundamental assumption within both is that they are additive over parameters. Machine learning provides tools when this assumption is too limiting. Hainmueller and Hazlett (Hainmueller and Hazlett 2014), for example, reanalyze data that were originally analyzed with logistic regression and come to substantially different conclusions. They argue that their analysis, which is more flexible and based on supervised learning methodology, provides three additional insights when compared to the original model. First, predictive performance is similar or better, although they do not need an extensive search to find the final model specification as it was done in the original analysis. Second, their model allows them to calculate average marginal effects that are mostly similar to the original analysis. However, for one covariate they find a substantially different result, which is due to model misspecification in the original model. Finally, the reanalysis also discovers interactions that were missed in the original publication.

- **Better text analysis:** Text is everywhere, but unfortunately humans are slow and expensive in analyzing text data. Thus, computers are needed to analyze large collections of text. Machine learning methods can help make this process more efficient. Feldman and Sanger (Feldman and Sanger 2006) provide an overview of different automatic methods for text analysis. Grimmer and Stewart (Grimmer and Stewart 2013) give examples that are more specific for social scientists, and Chapter Text analysis provides more details on this topic.
- **Adaptive surveys:** Some survey questions have a large number of possible answer categories. For example, international job classifications describe more than 500 occupational categories, and it is prohibitive to ask all categories during the survey. Instead, respondents answer an open-ended question about their job and machine learning algorithms can use the verbatim answers to suggest small sets of plausible answer options. The respondents can then select which option is the best description for their occupation, thus saving the costs for coding after the interview.
- **Estimating heterogeneous treatment effects:** A standard approach to causal inference is the assignment of different treatments (e.g., medicines) to the units of interest (e.g., patients). Researchers then usually calculate the average treatment effect—the average difference in outcomes for both groups. It is also of interest if treatment effects differ for various subgroups (e.g., is a medicine more effective for younger people?). Traditional subgroup analysis has been criticized and challenged by various machine learning techniques (Green and Kern 2012; Imai, Ratkovic, and others 2013).
- **Variable selection:** Although there are many methods for variable selection, regularized methods such as the lasso are highly effective and efficient when faced with large amounts of data. Varian (Varian 2014) goes into more detail and gives other methods from machine learning that can be useful for variable selection. We can also find interactions between pairs of variables (to feed into other models) using random forests, by looking at variables that co-occur in the same tree, and by calculating the strength of the interaction as a function of how many trees they co-occur in, how high they occur in the trees, and how far apart they are in a given tree.

---

## 7.8 Advanced topics

This has been a short but intense introduction to machine learning, and we have left out several important topics that are useful and interesting for you to know about and that are being actively researched in the machine learning

community. We mention them here so you know what they are, but will not describe them in detail. These include:

- Semi-supervised learning, where a combination of labeled and unlabeled data are used for training, given a set of assumptions. Such methods are useful when labeling data is costly and where unlabeled (not manually labeled/tagged data) can help improve the machine learning models . See the MIT Press edited volume <https://www.molgen.mpg.de/3659531/MITPress--SemiSupervised-Learning.pdf> for explanations and examples.
- Active learning, a set of machine learning algorithms that query the user or some other information source to get labels for data points that are most beneficial for the machine learning models. This is in contrast to the standard machine learning process where we often select data points to label/tag randomly. Active Learning approaches to selecting data points to label have been shown to reduce the effort needed to train machine learning models.
- Reinforcement learning: The “supervised” machine learning methods we’ve covered in this chapter are “one-shot” and take data points and labels as inputs. Reinforcement Learning is a different machine learning paradigm where the machine learning program takes a series of actions/decisions, and gets delayed feedback (reward or penalty) when performing a task. The goal of reinforcement learning is to determine the next best action to take in order to maximize long term performance. This has been applied to scenarios such as playing games (checkers, chess, backgammon, etc.) and in robotics (cite:)

---

## 7.9 Summary

Machine learning is an active research field, and in this chapter we have given you an overview of how the work developed in this field can be used by social scientists. We covered the overall machine learning process, methods, evaluation approaches and metrics, and some practical tips, as well as how all of this can benefit social scientists. The material described in this chapter is a snapshot of a fast-changing field, and as we are seeing increasing collaborations between machine learning researchers and social scientists, the hope and expectation is that the next few years will bring advances that will allow us to tackle social and policy problems much more effectively using new types of data and improved methods.

## 7.10 Resources

Literature for further reading that also explains most topics from this chapter in greater depth:

- Hastie et al.'s *The Elements of Statistical Learning* (Hastie, Tibshirani, and Friedman 2001) is a classic and is available online for free.
- James et al.'s *An Introduction to Statistical Learning* (James et al. 2013), from the same authors, includes less mathematics and is more approachable. It is also available online.
- Mitchell's *Machine Learning* (Mitchell 1997) is a classic introduction to some of the methods and gives a good motivation underlying them.
- Provost and Fawcett's *Data Science for Business* (Provost and Fawcett 2013) is a good practical handbook for using machine learning to solve real-world problems.
- Wu et al.'s "Top 10 Algorithms in Data Mining" (Wu et al. 2008).

Software:

- Python (with libraries like `scikit-learn`, `pandas`, and more).
- R has many relevant packages (Hothorn, n.d.).
- Cloud-based: AzureML, Amazon ML, Google
- Free: KNIME, Rapidminer, Weka (mostly for research use).
- Commercial: IBM Modeler, SAS Enterprise Miner, Matlab.

Many excellent courses are available online (Z., n.d.), including Hastie and Tibshirani's *Statistical Learning* (Hastie and Tibshirani, n.d.).

Major conferences in this area include the International Conference on Machine Learning (ICML, n.d.), the Annual Conference on Neural Information Processing Systems (NeurIPS) (???), and the ACM International Conference on Knowledge Discovery and Data Mining (KDD) (KDD, n.d.).

# 8

---

## *Text Analysis*

---

**Evgeny Klochikhin and Jordan Boyd-Graber**

This chapter provides an overview of how social scientists can make use of text data using computational data analysis methods. We cover the types of analysis that can be done with text data (search, topic detection, classification, etc.), give an overview of how to do these analysis, social science tasks that they're useful for, and how to evaluate the results produced. We also provide pointers to some tools that are commonly used for doing text analysis.

---

### **8.1 Understanding human generated text**

As social scientists, we often deal with text data that comes from a variety of sources: open ended survey responses, phone call transcriptions, social media data, notes from electronic health records, news articles, and research publications. A challenge we face when dealing with these types of data is how to efficiently analyze it just like we analyze traditional tabular data. For example, when analyzing survey responses or electronic health records data, both of which contain narrative text (from the respondents and medical practitioners respectively), the text data often gets ignored or selectively read by the analysts (manually) and used anecdotally. Text analysis techniques described in this chapter allow you to use all of the data available (structured and unstructured), and incorporate large amounts of text data in your analysis.

---

#### **Text analysis vocabulary**

- Corpus
- Token
- Term
- Frequency
- TFIDF
- Part of speech tags
- Parsing

- n-grams
  - embeddings
- 

## 8.2 How is text data different than “structured” data?

We’re comfortable analyzing structured data that is organized as rows and columns. Text data, often also known as unstructured data,(footnote: this is often the term used but is a fallacy. There is a lot of structure in text - the structure of chapters, paragraphs, sentences, and syntax within a sentence allows you reader, to understand what we’re writing here. Unstructured often refers to not having defined rows and columns in our data.) is harder to analyze using traditional data analysis tools because it doesn’t come as a set of rows and columns, but instead consists of characters, words, sentences, and paragraphs. In traditional, “structured”, data, a human has already decided what constitutes a row (a person for example), what constitutes a column (their age, gender, address, for example), and the relationship between them. We covered that in the Database chapter where we created a data model for a given domain. When dealing with text data, we have to create that structure ourselves.

While creating that structure, we have to deal with human language being complex and nuanced, which makes automatically analyzing it difficult. We often make simplifying assumptions: we assume our input is perfect text; we ignore humor (Halevy, Norvig, and Pereira 2009) and deception (Niculae et al. 2015; Ott et al. 2011); and we assume “standard” English (Kong et al. 2014)<sup>1</sup>. Text data also often reflects human observations that are exceptions to regular processes—the ubiquitous “other” or the “anything else you want to tell us” field in questionnaires. Recognizing this complexity, the goal of text analysis is to efficiently extract important information from large amounts of text, and use it for/in our analysis just like we use tabular data.

---

<sup>1</sup>See Chapter 6 for a discussion of speech recognition, which can turn spoken language into text

---

### 8.3 What can we do with text data?

There are a lot of types of analysis that we can do with text data. Table 8.1 gives a summary of these types of analysis.

TODO: finish table

TABLE 8.1:

Type of Analysis	Description	Examples
Search	Finding relevant content based on some information need, often specified as a set of key words/phrases but can be more structured.	For example, we used these techniques in systematic literature reviews to facilitate the discovery and retrieval of relevant publications related to early grade reading in Latin America and the Caribbean.
Topic Detection / Clustering	Used to explore and understand what types of words, phrases, and topics exist in text data	<b>Need good example</b> survey text analysis
Classification	Used to classify text content into one or more predefined categories	<b>Need good example</b> research papers classification

Type of Analysis	Description	Examples
Sentiment analysis	Detection of sentiment or opinions at different levels of granularity - document, para-graph/sen-tence or entity (person, organization, etc.) level.	Examples using machine learning to analyze the flow and topic segmentation of political debates and behaviors (Nguyen, Boyd-Graber, and Resnik 2012; Nguyen et al. 2015) and to assign automated tags to documents (Tuarob, Pouchard, and Giles 2013).
Word Clustering/ <del>Synonyms</del>	Finding words that are similar to each other. Depending on the problem need, similarity can be defined as strictly synonyms or aliases (such as IBM and Deep Blue)	<b>Need good example</b>

Type of Analysis	Description	Examples
Named Entity Extraction	Recognition, tagging and extraction of named entities (typically of type Person, Location, Organization) from text data. Typically limited to proper nouns.	
General Extraction	Recognition, tagging, and extraction of specific classes of words/phrases that may be entities, events, relationships between entities etc.	<b>Need good example</b>
Visualization	Visualization of text data and/or visual mashups combining text with other forms of data (such as maps or networks)	<b>Need good example</b>

Type of Analysis	Description	Examples
Summarization	Summarization of a document (or a set of documents), either as a set of important keywords, or important sentences extracted from the text, or new sentences generated to produce a summary.	<b>Need good example</b> For example, Wang et al. (Wang et al. 2009) use topic modeling to produce category-sensitive text summaries and annotations on large-scale document collections.
Translation	Automatic translation of text from one language to another	Look at reaction to a political event in newspapers of different countries in different languages

For this chapter, we will focus on two types of use cases that social scientists deal with concerning text data:

1. We have some text “corpus”, for example open-ended survey responses or news articles or research publications, and our goal is to understand the content - patterns, themes, trends - of that data. This often involves methods from unsupervised machine learning (that we covered in the previous chapter). The analysis can then be combined with tabular data that might accompany the text. For example, the survey responses may also have structured information that the respondent filled out, or the news article or research publication has meta-data that can be augmented with information generated from the text analysis.
2. The second use case is less focused on “discovery” and “understanding new content” and instead focuses on efficiently classifying content into a pre-defined set of categories. The text data is similar to the

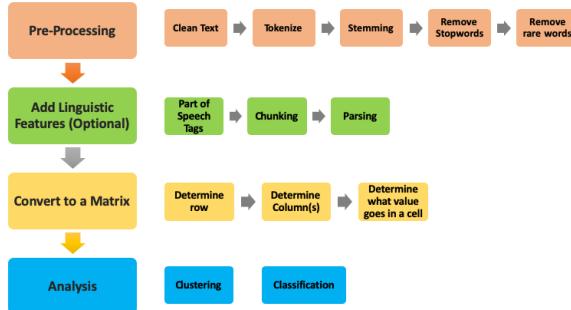
previous use case but the task is different, and can often be a followup task to the previous use case. We might have news articles about politics that we need to automatically classify into issue areas that are being discussed such as healthcare, education, foreign policy, etc. Another example is analyzing research publications that we need to classify into topics or research areas. This falls into supervised learning in the machine learning framework that we covered in the previous chapter.

---

## 8.4 How to analyze text

Text analysis, specially related to the clustering and classification use cases, requires us to build an analysis pipeline that processes data through a series of steps:

- **Initial Processing:** We take raw text data (word documents, html content scraped from webpages, etc.) and run it through some initial processing where the goal is to clean the text (dealing with content that is redundant or dirty, such as cleaning up html if processing data from web pages), turning sentences or documents into words or phrases, or removing words that we don't consider useful for a specific analysis.
- **Adding Linguistic Features:** This step is only needed when the problem requires deeper linguistic analysis. For example, when trying to understand the structure of a sentence, we can use a part of speech tagger to tag words with their corresponding part of speech (noun phrase for example) and use a statistical parser to generate what's called a parse tree that shows relationships between different components of a sentence.
- **Converting the enriched text to a matrix:** Once we've cleaned up the text and split them into sentences, phrases, words, and their corresponding linguistic attributes, the goal of this step is to make decisions that turn our "document" into a matrix. The matrix is then used to run different analysis algorithms, such as clustering or classification methods covered in the previous chapter. The key decisions in this step we have to make are 1) defining what a row is, 2) defining what a column is, and 3) what do we put as the value for a cell in a given row and column.
- **Analysis:** Once we have a matrix, then we can apply the methods we covered in the Machine Learning chapter (such as clustering and classification) as well as any other data analysis methods available to us. Later in this chapter, we'll go deeper into applying these methods to text data as well as describe new methods that are specifically designed for text analysis.



#### 8.4.1 Initial Processing

The first important step in working with text data is cleaning and processing<sup>2</sup>. Textual data are often messy and unstructured, which makes many researchers and practitioners overlook their value. Depending on the source, cleaning and processing these data can require varying amounts of effort but typically involve a set of established techniques.

##### Tokenization

The first step in processing text is deciding what terms and phrases are meaningful. Tokenization separates sentences and terms from each other. The Natural Language Toolkit (NLTK) (Bird, Klein, and Loper 2009) provides simple reference implementations of standard natural language processing algorithms such as tokenization—for example, sentences are separated from each other using punctuation such as period, question mark, or exclamation mark. However, this does not cover all cases such as quotes, abbreviations, or informal communication on social media. While separating sentences in a single language is hard enough, some documents “code-switch,” combining multiple languages in a single document. These complexities are best addressed through data-driven machine learning frameworks (Kiss and Strunk 2006).

##### Stop words

Once the tokens are clearly separated, it is possible to perform further text processing at a more granular, token level. Stop words are a category of words that have limited semantic meaning (and hence utility) regardless of the document content. Such words can be prepositions, articles, common nouns, etc. For example, the word “the” accounts for about 7% of all words in the Brown Corpus, and “to” and “of” are more than 3% each (Malmkjær 2002). We may choose to remove stopwords if we think that they won’t be useful in our analysis. For example, words such as “the”, “is”, “or” may not be useful

<sup>2</sup>Cleaning and processing are discussed extensively in Chapter 3.

if the task is to classify news articles into the topic of the article. On the other hand, they may provide information if the task is to classify a document into the genre it belongs to or in identifying the author of the document.

*Hapax legomena* are rarely occurring words that might have only one instance in the entire corpus. These words—names, misspellings, or rare technical terms—are also unlikely to bear significant contextual meaning. Similar to stop words, these tokens are often disregarded in further modeling either by the design of the method or by manual removal from the corpus before the actual analysis.

### N-grams

However, individual words are sometimes not the correct unit of analysis. For example, blindly removing stop words can obscure important phrases such as “systems of innovation,” “cease and desist,” or “commander in chief.” Identifying these *N*-grams requires looking for statistical patterns to discover phrases that often appear together in fixed patterns (Dunning 1993). These combinations of phrases are often called *collocations*, as their overall meaning is more than the sum of their parts.

### Stemming and lemmatization

Text normalization is another important aspect of preprocessing textual data. Given the complexity of natural language, words can take multiple forms dependent on the syntactic structure with limited change of their original meaning. For example, the word “system” morphologically has a plural “systems” or an adjective “systematic.” All these words are semantically similar and—for many tasks—should be treated the same. For example, if a document has the word “system” occurring three times, “systems” once, and “systematic” twice, one can assume that the word “system” with similar meaning and morphological structure can cover all instances and that variance should be reduced to “system” with six instances.

The process for text normalization is often implemented using established lemmatization and stemming algorithms. A *lemma* is the original dictionary form of a word. For example, “go,” “went,” and “goes” will all have the lemma “go.” The stem is a central part of a given word bearing its primary semantic meaning and uniting a group of similar lexical units. For example, the words “order” and “ordering” will have the same stem “ord.” Morphy (a lemmatizer provided by the electronic dictionary WordNet), Lancaster Stemmer, and Snowball Stemmer are common tools used to derive lemmas and stems for tokens, and all have implementations in the NLTK (Bird, Klein, and Loper 2009).

### 8.4.2 Linguistic Analysis

So far, we've treated words as tokens without regard to the meaning of the word or the way it is used, or even what language the word comes from. There are several techniques in text analysis that are language specific that go deeper into the syntax of the document, paragraph, and sentence structure to extract linguistic characteristics of the document.

#### Part-of-speech tagging

When the examples  $x$  are individual words and the labels  $y$  represent the grammatical function of a word (e.g., whether a word is a noun, verb, or adjective), the task is called part-of-speech tagging. This level of analysis can be useful for discovering simple patterns in text: distinguishing between when "hit" is used as a noun (a Hollywood hit) and when "hit" is used as a verb (the car hit the guard rail).

Unlike document classification, the examples  $x$  are not independent: knowing whether the previous word was an adjective makes it far more likely that the next word will be a noun than a verb. Thus, the classification algorithms need to incorporate structure into the decisions. Two common algorithms for this problem are hidden Markov models (Rabiner 1989) and conditional random fields (Lafferty, McCallum, and Pereira 2001).

#### Parsing

All text-processing steps are critical to successful analysis. Some of them bear more importance than others, depending on the specific application, research questions, and properties of the corpus. Having all these tools ready is imperative to producing a clean input for subsequent modeling and analysis. Some simple rules should be followed to prevent typical errors. For example, stop words should not be removed before performing  $n$ -gram indexing, and a stemmer should not be used where data are complex and require accounting for all possible forms and meanings of words. Reviewing interim results at every stage of the process can be helpful.

### 8.4.3 Turning text data into a matrix: How much is a word worth?

The processing stages described above provide us with the columns in our matrix. Now we have to decide what value we assign that word/phrase/column. In text analysis, we typically refer to them as tokens (where a token can be a word or a phrase). One simple approach would be to give each column a binary 0 or 1 value - if this token occurs in a document, we assign that cell a value of 1 and 0 otherwise. Another approach would be to assign it the value of how many times this token occurs in that document (often known as frequency

of that term or token). This is essentially a way to define the importance or value of this token in this document. Not all words are worth the same; in an article about economics, “free market” is more important than “social good.” Appropriately weighting<sup>3</sup> and calibrating words is important for both human and machine consumers of text data: humans do not want to see “the” as the most frequent word of every document in summaries, and classification algorithms benefit from knowing which features are actually important to making a decision.

Weighting words requires balancing how often a word appears in a local context (such as a document) with how much it appears overall in the document collection. Term frequency-inverse document frequency (TFIDF) (Salton 1968) is a weighting scheme to explicitly balance these factors and prioritize the most meaningful words. The TFIDF model takes into account both the term frequency of a given token and its document frequency (Box 7.1) so that if a highly frequent word also appears in almost all documents, its meaning for the specific context of the corpus is negligible. Stop words are a good example when highly frequent words also bear limited meaning since they appear in virtually all documents of a given corpus.

**Box 7.1: TFIDF**

For every token  $t$  and every document  $d$  in the corpus  $D$ , TFIDF is calculated as

$$tfidf(t, d, D) = tf(t, d) \times idf(t, D),$$

where term frequency is either a simple count,

$$tf(t, d) = f(t, d),$$

or a more balanced quantity,

$$tf(t, d) = 0.5 + \frac{0.5 \times f(t, d)}{\max\{f(t, d) : t \in d\}},$$

and inverse document frequency is

$$idf(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}.$$

---

<sup>3</sup>Term weighting is an example of feature engineering discussed in Chapter 6.

### 8.4.4 Analysis

Now that we have a matrix with documents as rows, words/phrases as columns and let's say the TFIDF score as the value of that word in that document, we are now ready to run different machine learning methods on this data. We will not recap all of the methods and evaluation methodologies already covered in Chapter 6 here but they can all be used with text data.

We'll focus on three types of analysis: finding similar documents, clustering, and classification. For each type of analysis, we'll focus on what it allows us to do, what types of tasks social scientists will find it useful for, and how to evaluate the results of the analysis.

#### Use Case: Finding Similar Documents

One task social scientists may be interested in is finding similar documents to a document they're analyzing. This is a routine task for lawyers where they are looking at a case file and want to find all prior cases similar to this case or during literature review where we may have a paper and we're interested in finding similar papers. The key challenge here is to define what makes two documents similar and what similarity metrics we should use. Typical metrics involved in this process include cosine similarity and Kullback–Leibler divergence (Kullback and Leibler 1951).

Cosine similarity is a popular measure in text analysis. Given two documents  $d_a$  and  $d_b$  presented as term vectors  $\vec{t}_a$  and  $\vec{t}_b$ , the cosine similarity is

$$SIM_C(\vec{t}_a, \vec{t}_b) = \frac{\vec{t}_a \cdot \vec{t}_b}{|\vec{t}_a| * |\vec{t}_b|}.$$

---

#### Example: Measuring cosine similarity between documents

NSF awards are not labeled by scientific field—they are labeled by program. This administrative classification is not always useful to assess the effects of certain funding mechanisms on disciplines and scientific communities. One approach is to understand how awards are similar to each other even if they were funded by different programs. Cosine similarity allows us to do just that.

#### Example code

The Python `numpy` module is a powerful library of tools for efficient linear algebra computation. Among other things, it can be used to compute the cosine similarity of two documents represented by numeric vectors, as described above. The `gensim` module that is often used as a Python-based topic modeling implementation can be used to produce vector space representations of textual data. Notebook XXX provides an example of measuring cosine similarity using these modules.

Kullback–Leibler (KL) divergence is a measure that allows us to compare probability distributions in general and is often used to compare two documents represented as vectors. Given two term vectors  $\vec{t}_a$  and  $\vec{t}_b$ , the KL divergence from vector  $\vec{t}_a$  to  $\vec{t}_b$  is

$$D_{KL}(\vec{t}_a || \vec{t}_b) = \sum_{t=1}^m w_{t,a} \times \log \left( \frac{w_{t,a}}{w_{t,b}} \right),$$

where  $w_{t,a}$  and  $w_{t,b}$  are term weights in two vectors, respectively.

An averaged KL divergence metric is then defined as

$$D_{AvgKL}(\vec{t}_a || \vec{t}_b) = \sum_{t=1}^m (\pi_1 \times D(w_{t,a} || w_t) + \pi_2 \times D(w_{t,b} || w_t)),$$

where  $\pi_1 = \frac{w_{t,a}}{w_{t,a} + w_{t,b}}$ ,  $\pi_2 = \frac{w_{t,b}}{w_{t,a} + w_{t,b}}$ , and  $w_t = \pi_1 \times w_{t,a} + \pi_2 \times w_{t,b}$  (Huang 2008).

A Python-based `scikit-learn` library provides an implementation of these measures as well as other machine learning models and approaches.

### **Augmenting Similarity Calculations with External Knowledge repositories**

Similarity calculations can be significantly enriched by the use of external resources that provide relationships between words, documents, or concepts present in specific domains. Established corpora, such as the Brown Corpus and Lancaster–Oslo–Bergen Corpus, are one type of such preprocessed repositories.

Wikipedia and WordNet are examples of another type of lexical and semantic resources that are dynamic in nature and that can provide a valuable basis for consistent and salient information retrieval and clustering. These repositories have the innate hierarchy, or ontology, of words (and concepts) that are explicitly linked to each other either by inter-document links (Wikipedia) or by the inherent structure of the repository (WordNet). In Wikipedia, concepts thus can be considered as titles of individual Wikipedia pages and the contents of these pages can be considered as their extended semantic representation.

Information retrieval techniques build on these advantages of WordNet and Wikipedia. For example, Meij et al. (Meij et al. 2009) mapped search queries to the DBpedia ontology (derived from Wikipedia topics and their relationships), and found that this mapping enriches the search queries with additional context and concept relationships. One way of using these ontologies is to retrieve a predefined list of Wikipedia pages that would match a specific taxonomy. For example, scientific disciplines are an established way of tagging documents—some are in physics, others in chemistry, engineering, or computer science. If a user retrieves four Wikipedia pages on “Physics,” “Chemistry,” “Engineering,” and “Computer Science,” they can be further mapped to a given set of scientific

documents to label and classify them, such as a corpus of award abstracts from the US National Science Foundation.

*Personalized PageRank* is a similarity system that can help with the task. This system uses WordNet to assess semantic relationships and relevance between a search query (document  $d$ ) and possible results (the most similar Wikipedia article or articles). This system has been applied to text categorization (Navigli et al. 2011) by comparing documents to *semantic model vectors* of Wikipedia pages constructed using WordNet. These vectors account for the term frequency and their relative importance given their place in the WordNet hierarchy, so that the overall  $wiki$  vector is defined as:

$$SMV_{wiki}(s) = \sum_{w \in Synonyms(s)} \frac{tf_{wiki}(w)}{|Synsets(w)|}$$

,

where  $w$  is a token within  $wiki$ ,  $s$  is a WordNet synset that is associated with every token  $w$  in WordNet hierarchy,  $Synonyms(s)$  is the set of words (i.e., synonyms) in the synset  $s$ ,  $tf_{wiki}(w)$  is the term frequency of the word  $w$  in the Wikipedia article  $wiki$ , and  $Synsets(w)$  is the set of synsets for the word  $w$ .

The overall probability of a candidate document  $d$  (e.g., an NSF award abstract or a PhD dissertation abstract) matching the target query, or in our case a Wikipedia article  $wiki$ , is

$$wiki_{BEST} = \sum_{w_t \in doc} \max_{s \in Synsets(w_t)} SMV_{wiki}(s),$$

where  $Synsets(w_t)$  is the set of synsets for the word  $w_t$  in the target document document (e.g., NSF award abstract) and  $SMV_{wiki}(s)$  is the semantic model vector of a Wikipedia page, as defined above.

**Evaluating “Find Similar” Methods:** When developing methods to find similar documents, we want to make sure that we find all relevant documents that are similar to the document under consideration, and we want to make sure we don’t find any non-relevant documents. Chapter Machine Learning already touched on the importance of precision and recall for evaluating the results of machine learning models (Box 7.3 provides a reminder of the formulae). The same metrics can be used to evaluate the two goals we have in finding relevant and similar documents.

**Box 7.3: Precision and recall** Precision computes the type I errors—*false positives*—and is formally defined as

$$\text{Precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}.$$

Recall accounts for type II errors—*false negatives*—and is defined as

$$\text{Recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}.$$

We assume that a user has three sets of documents  $D_a = \{d_{a1}, d_{a2}, \dots, d_n\}$ ,  $D_b = \{d_{b1}, d_{b2}, \dots, d_k\}$ , and  $D_c = \{d_{c1}, d_{c2}, \dots, d_i\}$ . All three sets are clearly tagged with a disciplinary label:  $D_a$  are computer science documents,  $D_b$  are physics, and  $D_c$  are chemistry.

The user also has a different set of documents—Wikipedia pages on “Computer Science,” “Chemistry,” and “Physics.” Knowing that all documents in  $D_a$ ,  $D_b$ , and  $D_c$  have clear disciplinary assignments, let us map the given Wikipedia pages to all documents within those three sets. For example, the Wikipedia-based query on “Computer Science” should return all computer science documents and none in physics or chemistry. So, if the query based on the “Computer Science” Wikipedia page returns only 50% of all computer science documents, then 50% of the relevant documents are lost: the recall is 0.5.

On the other hand, if the same “Computer Science” query returns 50% of all computer science documents but also 20% of the physics documents and 50% of the chemistry documents, then all of the physics and chemistry documents returned are false positives. Assuming that all document sets are of equal size, so that  $|D_a| = 10$ ,  $|D_b| = 10$  and  $|D_c| = 10$ , then the precision is  $\frac{5}{12} = 0.42$ .

#### F score\*

The *F score* combines precision and recall. In formal terms, the *F score* is a weighted average of the precision and recall:

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}.$$

In terms of type I and type II errors:

$$F_\beta = \frac{(1 + \beta^2) \cdot \text{true positive}}{(1 + \beta^2) \cdot \text{true positive} + \beta^2 \cdot \text{false negative} + \text{false positive}},$$

where  $\beta$  is the balance between precision and recall. Thus,  $F_2$  puts more emphasis on the recall measure and  $F_{0.5}$  puts more emphasis on precision.

### Examples

Some examples from our recent work can demonstrate how Wikipedia-based labeling and labeled LDA (Ramage et al. 2009; Nguyen et al. 2014) cope with the task of document classification and labeling in the scientific domain. See Table 8.2.

TABLE 8.2: Wikipedia articles as potential labels generated by  $n$ -gram indexing of NSF awards

Abstract excerpt	Pro- Quest subject	Wikipedia- La- based cate- gory	bele label- LDAng
<b>Reconfigurable computing platform for smallscale resource-constrained robot.</b> Specific applications often require robots of small size for reasons such as costs, access, and stealth. Smallscale robots impose constraints on resources such as power or space for modules...	Engineering, Electronics and Electrical; Engineering, Robotics	Robotics, Robot, controlled- pro- grammable gate array	Robotics, Robot, controlled- pro- grammable gate array
<b>Genetic mechanisms of thalamic nuclei specification and the influence of thalamocortical axons in regulating neocortical area formation.</b> Sensory information from the periphery is essential for all animal species to learn, adapt, and survive in their environment. The thalamus, a critical structure in the diencephalon, receives sensory information...	Biology, Neurobiology	HSDSonic neurobiology edge- hog, In- duced stem cell, Ner- vous system	Sonic neurobiology edge- hog, In- duced stem cell, Ner- vous system
<b>Poetry 'n acts: The cultural politics of twentieth century American poets' theater.</b> This study focuses on the disciplinary blind spot that obscures the productive overlap between poetry and dramatic theater and prevents us from seeing the cultural work that this combination can perform...	Literature, American; Theater	Audi- ture, ture of the 1960s, Novel, Modernism	Cultural- ture, ture of the 1960s, Novel, Modernism

### Use Case: Clustering

Another task social scientists often perform is finding themes, topics, and

patterns in a text data set, such as open-ended survey responses, news articles, or publications. Given open ended responses from a survey on how people feel about a certain issue, we may be interested in finding out the common themes that occur in these responses. Clustering methods are designed to do exactly that. With text data, clustering is often used to explore what topics and concepts are present in a new corpus (collection of documents). It is important to note that if we already have a pre-specified set of categories and documents that are tagged with those categories, and the goal is to tag new documents, then we would use classification methods instead of clustering methods. As we covered in the previous chapter, clustering is a form of unsupervised learning where the goal is exploration and understanding of the data.

As we covered earlier, unsupervised analysis of large text corpora without extensive investment of time provides additional opportunities for social scientists and policymakers to gain insights into policy and research questions through text analysis. The clustering methods described in the Machine Learning chapter, such as k-means clustering, can be used for text data as well once the text has been converted to a matrix as described earlier. We will describe Topic Modeling, that provides us with another clustering approach specifically designed for text data.

#### 8.4.5 Topic modeling

Topic modeling is an approach that describes *topics* that constitute the high-level themes of a text corpus. Topic modeling is often described as an *information discovery* process: describing what “concepts” are present in a corpus. We refer to them as “concepts” or “topics” (in quotes) because they typically will be represented as a probability distribution over the words (that the topic modeling method groups together) which may or may not be semantically coherent as a “topic” to social scientists.

As topic modeling is a broad subfield of natural language processing and machine learning, we will restrict our focus to a single methods called Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003). LDA is a fully Bayesian extension of probabilistic latent semantic indexing (Hofmann 1999), itself a probabilistic extension of latent semantic analysis (Landauer and Dumais 1997). Blei and Lafferty (Blei and Lafferty 2009) provide a more detailed discussion of the history of topic models.

LDA, like all topic models, assumes that there are topics that form the building blocks of a corpus. Topics are distributions over words and are often shown as a ranked list of words, with the highest probability words at the top of the list (8.1). However, we do not know what the topics are a priori; the goal is to discover what they are (more on this shortly).

## Topic 1

Computer,  
technology,  
system,  
service, site,  
phone, internet,  
machine

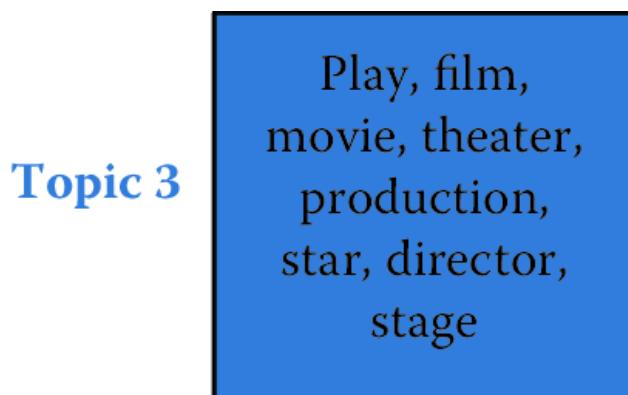
## Topic 2

Sell, sale,  
store, product,  
business,  
advertising,  
market,  
consumer

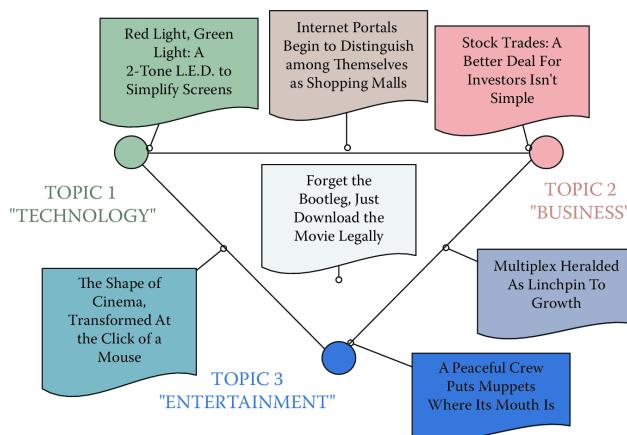
In addition to assuming that there exist some number of topics that explain a corpus, LDA also assumes that each document in a corpus can be explained by a small number of topics. For example, taking the example topics from Figure 8.1, a document titled “Red Light, Green Light: A Two-Tone LED to Simplify Screens” would be about Topic 1, which appears to be about technology. However, a document like “Forget the Bootleg, Just Download the Movie Legally” would require all three of the topics. The set of topics that are used by a document is called the document’s *allocation* (Figure 8.2). This terminology explains the name *latent Dirichlet allocation*: each document has an allocation over latent topics governed by a Dirichlet distribution.

### 8.4.5.1 Inferring “topics” from raw text

Algorithmically, the problem can be viewed as a black box. Given a corpus and an integer  $K$  as input, provide the topics that best describe the document collection: a process called *posterior inference*. The most common algorithm



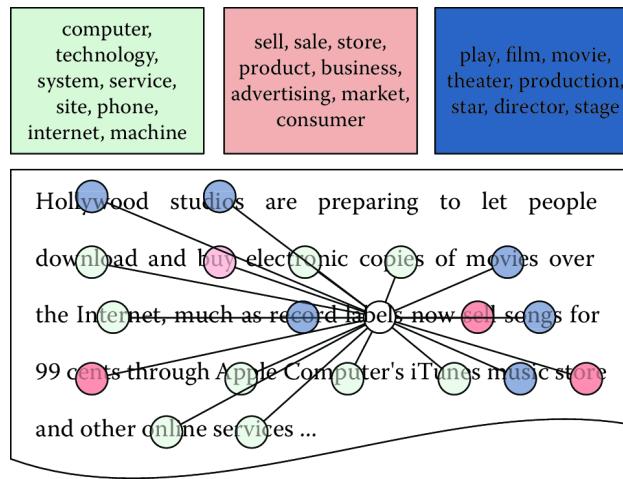
**FIGURE 8.1** Topics are distributions over words. Here are three example topics learned by latent Dirichlet allocation from a model with 50 topics discovered from the \*New York Times\* [@sandhaus-08]. Topic 1 seems to be about technology, Topic 2 about business, and Topic 3 about the arts



**FIGURE 8.2** Allocations of documents to topics

for solving this problem is a technique called *Gibbs sampling* (Geman and Geman 1990).

Gibbs sampling works at the word level to discover the topics that best describe a document collection. Each word is associated with a single topic, explaining why that word appeared in a document. For example, consider the sentence “Hollywood studios are preparing to let people download and buy electronic copies of movies over the Internet.” Each word in this sentence is associated with a topic: “Hollywood” might be associated with an arts topic; “buy” with a business topic; and “Internet” with a technology topic (Figure 8.3).



**FIGURE 8.3** Each word is associated with a topic. Gibbs sampling inference iteratively resamples the topic assignments for each word to discover the most likely topic assignments that explain the document collection

This is where we should eventually get. However, we do not know this to start. So we can initially assign words to topics randomly. This will result in poor topics, but we can make those topics better. We improve these topics by taking each word, pretending that we do not know the topic, and selecting a new topic for the word.

A topic model wants to do two things: it does not want to use many topics in a document, and it does not want to use many words in a topic. So the algorithm will keep track of how many times a document  $d$  has used a topic  $k$ ,  $N_{d,k}$ , and how many times a topic  $k$  has used a word  $w$ ,  $V_{k,w}$ . For notational convenience, it will also be useful to keep track of marginal counts of how many words are in a document,

$$N_{d,\cdot} \equiv \sum_k N_{d,k},$$

and how many words are associated with a topic,

$$V_{k,\cdot} \equiv \sum_w V_{k,w}.$$

The algorithm removes the counts for a word from  $N_{d,k}$  and  $V_{k,w}$  and then changes the topic of a word (hopefully to a better topic than the one it had before). Through many thousands of iterations of this process, the algorithm can find topics that are coherent, useful, and characterize the data well.

The two goals of topic modeling—balancing document allocations to topics and topics’ distribution over words—come together in an equation that multiplies them together. A good topic will be both common in a document and explain a word’s appearance well.

### Example: Gibbs sampling for topic models

The topic assignment  $z_{d,n}$  of word  $n$  in document  $d$  is proportional to

$$p(z_{d,n} = k) \propto \left( \frac{N_{d,k} + \alpha}{N_{d,\cdot} + K\alpha} \right) \left( \frac{V_{k,w_{d,n}} + \beta}{V_{k,\cdot} + V\beta} \right),$$

where  $\alpha$  and  $\beta$  are smoothing factors that prevent a topic from having zero probability if a topic does not use a word or a document does not use a topic (Wallach, Mimno, and McCallum 2009). Recall that we do not include the token that we are sampling in the counts for  $N$  or  $V$ .

For the sake of concreteness, assume that we have three documents with the following topic assignments:

- Document 1:  $^A\text{dog}_3 ^B\text{cat}_2 ^C\text{cat}_3 ^D\text{pig}_1$
- Document 2:  $^E\text{hamburger}_2 ^F\text{dog}_3 ^G\text{hamburger}_1$
- Document 3:  $^H\text{iron}_1 ^I\text{iron}_3 ^J\text{pig}_2 ^K\text{iron}_2$

If we want to sample token B (the first instance of “cat” in document 1), we compute the conditional probability for each of the three topics ( $z = 1, 2, 3$ ):

$$p(z_B = 1) = \frac{1 + 1.000}{3 + 3.000} \times \frac{0 + 1.000}{3 + 5.000} = 0.333 \times 0.125 = 0.042,$$

$$p(z_B = 2) = \frac{0 + 1.000}{3 + 3.000} \times \frac{0 + 1.000}{3 + 5.000} = 0.167 \times 0.125 = 0.021, \text{ and}$$

$$p(z_B = 3) = \frac{2 + 1.000}{3 + 3.000} \times \frac{1 + 1.000}{4 + 5.000} = 0.500 \times 0.222 = 0.111.$$

To reiterate, we do not include token B in these counts: in computing these

conditional probabilities, we consider topic 2 as never appearing in the document and “cat” as never appearing in topic 2. However, “cat” does appear in topic 3 (token C), so it has a higher probability than the other topics. After renormalizing, our conditional probabilities are (0.24, 0.12, 0.64). We then sample the new assignment of token B to be topic 3 two times out of three. Griffiths and Steyvers (Griffiths and Steyvers 2004) provide more details on the derivation of this equation.

#### 8.4.5.2 Applications of topic models

Topic modeling is most often used for topic exploration, allowing users to understand the contents of large text corpora. Thus, topic models have been used, for example, to understand what the National Institutes of Health funds (Talley et al. 2011); to compare and contrast what was discussed in the North and South in the Civil War (Nelson 2010); and to understand how individuals code in large programming projects (Maskeri, Sarkar, and Heafield 2008).

Topic models can also be used as features to more elaborate algorithms such as machine translation (Hu et al. 2014), detecting objects in images (Wang, Blei, and Fei-Fei 2009), or identifying political polarization (Paul and Girju 2010). Boyd-Graber, Hu, and Mimno (2017) summarizes applications of topic models in the humanities, information retrieval, and social sciences.

Blei and McAuliffe (2007) apply topic models to classification and regression tasks such as sentiment analysis. As discussed in the previous chapter, such methods require a feature-based representation of the data. An advantage of using topic models is that the distribution over topics itself can serve as a feature.

For example, to predict whether a legislator will vote on a bill, Gerrish and Blei (2012) learn a topic model that encodes each bill (proposed piece of legislation) as a vector. To predict how a legislator will vote on a bill, the model takes a dot product between the bill’s distribution over topics and a legislators ideology vector. The higher score, the more compatible they are and the more likely the legislator is to vote on the bill. Conversely, the lower the score, the less likely it is the legislator will vote on the bill.

This formulation should remind you of logistic regression; however, the features are learned automatically rather than the feature engineering approach described in the last chapter.

#### Use Case: Document classification

The section above focused on the task of finding topics and themes in a new text data set. In many cases, we already know a set of topics—this could be the set of topics or research fields as described by the Social Science Research Network or the set of sections (local news, international, sports,

finance, etc.) in a news publication. The task we often face is to automatically categorize new documents into an existing set of categories. In text analysis, this is called text classification or categorization and uses supervised learning techniques from machine learning described in the earlier chapter.

Text classification typically requires two things: A set of categories we want documents to be categorized into (each document can belong to one or more categories) Set of documents annotated/tagged with one or more categories from Step 1.

For example, if we want to classify twitter or facebook posts as being about health or finance, a classification method would take a small number of posts, manually tagged as belonging to either health or finance, and train a classification model. This model can then be used to automatically classify new posts as belonging to either health or finance.

All of the classification (supervised learning) methods we covered in the Machine Learning chapter can be used here once the text data has been processed and converted to a matrix. Neural Networks [reference], Random Forests [ref], and Support Vector Machines [ref] are some of the commonly used methods applied to text data.

---

### Example: Using text to categorize scientific fields

The National Center for Science and Engineering Statistics, the US statistical agency charged with collecting statistics on science and engineering, uses a rule-based system to manually create categories of science; these are then used to categorize research as “physics” or “economics” (Mortensen, Bloch, and others 2005; Economic Co-operation and Development 2004). In a rule-based system there is no ready response to the question “how much do we spend on climate change, food safety, or biofuels?” because existing rules have not created such categories. Text analysis techniques can be used to provide such detail without manual collation. For example, data about research awards from public sources and about people funded on research grants from UMETRICS can be linked with data about their subsequent publications and related student dissertations from ProQuest. Both award and dissertation data are text documents that can be used to characterize what research has been done, provide information about which projects are similar within or across institutions, and potentially identify new fields of study (Talley et al. 2011).

### Applications

#### Spam Detection

One simple but ubiquitous example of document classification is spam detection: an email is either an unwanted advertisement (spam) or it is not. Document classification techniques such as naïve Bayes (Lewis 1998) touch essentially

every email sent worldwide, making email usable even though most emails are spam.

### Sentiment analysis

Instead of being what a document is about, a label  $y$  could also reveal the speaker. A recent subfield of natural language processing is to use machine learning to reveal the internal state of speakers based on what they say about a subject (Pang and Lee 2008). For example, given an example of sentence  $x$ , can we determine whether the speaker is a Liberal or a Conservative? Is the speaker happy or sad?

Simple approaches use dictionaries and word counting methods (Pennebaker and Francis 1999), but more nuanced approaches make use of *domain-specific* information to make better predictions. One uses different approaches to praise a toaster than to praise an air conditioner (Blitzer, Dredze, and Pereira 2007); liberals and conservatives each frame health care differently from how they frame energy policy (Nguyen, Boyd-Graber, and Resnik 2013).

### Evaluating Text Classification Methods

The metrics used to evaluate text classification methods are the same as those used in supervised learning, as described in the Machine Learning chapter. The most commonly used metrics include accuracy, precision, recall, AUC, and F1 score. [include example in notebook]

---

## 8.5 Word Embeddings and Deep Learning

In discussing topic models, we learned a vector that summarized the content of each document. This is useful for applications where you can use a single, short vector to summarize a document for a downstream machine learning application. However, modern research doesn't stop there, it learns vector representations of everything from documents down to sentences and words.

First, let's consider this from a high-level perspective. The goal of representation learning (Bengio, Courville, and Vincent 2013) is to take an input and transform it into a vector that computers can understand. Similar inputs should be close together in vector space. E.g., "dog" and "poodle" should have similar vectors, while "dog" and "chainsaw" do not.

A well-known technique for word representation is word2vec (Mikolov et al. 2013). Using an objective function similar to logistic regression, it predicts, given a word, whether another word will appear in the same context. For example, the dot product for "dog" and "pet", "dog" and "leash", and "dog" and "wag"

will be high but those for “dog” and “rectitude”, “dog” and “examine”, and “dog” and “cloudy” will be lower. Training a model to do this for all of the words in English will produce vector representations for “dog” and “poodle” that are quite close together.

This model has been well adopted throughout natural language processing (Ward 2017). Downloading word2vec vectors for words and using them as features in your machine learning pipeline (e.g., for document classification by averaging the words in the document) will likely improve supervised classification task.

But word representations are not the end of the story. A word only makes sense in the context of the sentence in which it appears: e.g., “I deposited my check at the bank” vs. “The airplane went into a bank of clouds”. A single word per vector does not capture these subtle effects. More recent models named after Muppets (long, uninteresting story) tries to capture broader relationships between words within sentences to create *contextualized representations*.

ELMO (Peters et al. 2018) and BERT (Devlin et al. 2019) both use deep learning to take word vectors (a la word2vec) to create representations that make sense given a word’s context. These are also useful features to use in supervised machine learning contexts if higher accuracy is your goal.

However, these techniques are not always the best tools for social scientists. They are not always interpretable—it is often hard to tell why you got the answer you did (Ribeiro, Singh, and Guestrin 2016), and slightly changing the input the models can dramatically change the results (Feng et al. 2018). Given that our goal is often understanding our data, it is probably better to start first with the simpler (and faster methods) mentioned here to understand your data first.

---

## 8.6 Text analysis tools

We are fortunate to have access to a set of powerful open source text analysis tools. We describe three here.

### The Natural Language Toolkit

The NLTK is a commonly used natural language toolkit that provides a large number of relevant solutions for text analysis. It is Python-based and can be easily integrated into data processing and analytical scripts by a simple `import nltk` (or similar for any one of its submodules).

The NLTK includes a set of tokenizers, stemmers, lemmatizers and other

natural language processing tools typically applied in text analysis and machine learning. For example, a user can extract tokens from a document *doc* by running the command `tokens = nltk.word_tokenize(doc)`.

Useful text corpora are also present in the NLTK distribution. For example, the stop words list can be retrieved by running the command `stops=nltk.corpus.stopwords.words(language)`. These stop words are available for several languages within NLTK, including English, French, and Spanish.

Similarly, the Brown Corpus or WordNet can be called by running `from nltk.corpus import wordnet/brown`. After the corpora are loaded, their various properties can be explored and used in text analysis; for example, `dogsyn = wordnet.synsets('dog')` will return a list of WordNet synsets related to the word “dog.”

Term frequency distribution and *n*-gram indexing are other techniques implemented in NLTK. For example, a user can compute frequency distribution of individual terms within a document *doc* by running a command in Python: `fdist=nltk.FreqDist(text)`. This command returns a dictionary of all tokens with associated frequency within *doc*.

*N*-gram indexing is implemented as a chain-linked collocations algorithm that takes into account the probability of any given two, three, or more words appearing together in the entire corpus. In general, *n*-grams can be discovered as easily as running `bigrams = nltk.bigrams(text)`. However, a more sophisticated approach is needed to discover statistically significant word collocations, as we show in Listing 7.4.

Bird et al. (Bird, Klein, and Loper 2009) provide a detailed description of NLTK tools and techniques. See also the official NLTK website (NLTK Project, n.d.).

```
def bigram_finder(texts):
    # NLTK bigrams from a corpus of documents separated by new
    → line
    tokens_list = nltk.word_tokenize(re.sub("\n", " ", texts))
    bgm     = nltk.collocations.BigramAssocMeasures()
    finder  = nltk.collocations.BigramCollocationFinder.from_words_
    → (tokens_list)
    scored = finder.score_ngrams( bgm.likelihood_ratio  )

    # Group bigrams by first word in bigram.
    prefix_keys = collections.defaultdict(list)
    for key, scores in scored:
        prefix_keys[key[0]].append((key[1], scores))

    # Sort keyed bigrams by strongest association.
```

```
for key in prefix_keys:  
    prefix_keys[key].sort(key = lambda x: -x[1])
```

Listing 7.4. Python code to find bigrams using NLTK

### Stanford CoreNLP

While NLTK's emphasis is on simple reference implementations, Stanford's CoreNLP (Stanford, n.d.; Manning et al. 2014) is focused on fast implementations of cutting-edge algorithms, particularly for syntactic analysis (e.g., determining the subject of a sentence).

### MALLET

For probabilistic models of text, MALLET, the MAchine Learning for LanguagE Toolkit (McCallum 2002), often strikes the right balance between usefulness and usability. It is written to be fast and efficient but with enough documentation and easy enough interfaces to be used by novices. It offers fast, popular implementations of conditional random fields (for part-of- speech tagging), text classification, and topic modeling.

### Spacy.io

While NLTK is optimized for teaching NLP concepts to students, Spacy.io [<http://spacy.io>] is optimize for practical application. It is super-fast, contains many models for well-trodden tasks (classification, finding entities in sentences, etc.). It also has pre-trained models (including word and sentence representations) that can help practitioners quickly build competitive models.

### Pytorch

For the truly adventurous who want to build their own deep learning models for text, PyTorch [<http://pytorch.org>] offers the flexibility go from word vectors to complete deep representations of sentences.

---

## 8.7 Summary

Many of the new sources of data that are of interest to social scientists is text: tweets, Facebook posts, corporate emails, and the news of the day. However, the meaning of these documents is buried beneath the ambiguities and noisiness of the informal, inconsistent ways by which humans communicate with each other and traditional data analysis methods do not work with text data directly. Despite attempts to formalize the meaning of text data through asking users to tag people, apply metadata, or to create structured representations, these

attempts to manually curate meaning are often incomplete, inconsistent, or both.

These aspects make text data difficult to work with, but also a rewarding object of study. Unlocking the meaning of a piece of text helps bring machines closer to human-level intelligence—as language is one of the most quintessentially human activities—and helps overloaded information professionals do their jobs more effectively: understand large corpora, find the right documents, or automate repetitive tasks. And as an added bonus, the better computers become at understanding natural language, the easier it is for information professionals to communicate their needs: one day using computers to grapple with big data may be as natural as sitting down for a conversation over coffee with a knowledgeable, trusted friend.

---

## 8.8 Resources

Text analysis is one of the more complex tasks in big data analysis. Because it is unstructured, text (and natural language overall) requires significant processing and cleaning before we can engage in interesting analysis and learning. In this chapter we have referenced several resources that can be helpful in mastering text mining techniques:

- The Natural Language Toolkit is one of the most popular Python-based tools for natural language processing. It has a variety of methods and examples that are easily accessible online (NLTK Project, n.d.). The book by Bird et al. (Bird, Klein, and Loper 2009), available online, contains multiple examples and tips on how to use NLTK.
- A paper by Anna Huang (Huang 2008) provides a brief overview of the key similarity measures for text document clustering discussed in this chapter, including their strengths and weaknesses in different contexts.
- Materials at the MALLET website (McCallum 2002) can be specialized for the unprepared reader but are helpful when looking for specific solutions with topic modeling and machine classification using this toolkit.
- David Blei, one of the authors of the latent Dirichlet allocation algorithm (topic modeling), maintains a helpful web page with introductory resources for those interested in topic modeling (Blei, n.d.).
- We provide an example of how to run topic modeling using MALLET on textual data from the National Science Foundation and Norwegian Research Council award abstracts (Boyd-Graber, n.d.).

- Text corpora: A set of multiple similar documents is called a *corpus*. For example, the Brown University Standard Corpus of Present-Day American English, or just the Brown Corpus (Francis and Kucera 1979), is a collection of processed documents from works published in the United States in 1961. The Brown Corpus was a historical milestone: it was a machine-readable collection of a million words across 15 balanced genres with each word tagged with its part of speech (e.g., noun, verb, preposition). The British National Corpus (University of Oxford 2006) repeated the same process for British English at a larger scale. The Penn Treebank (Marcus, Santorini, and Marcinkiewicz 1993) provides additional information: in addition to part-of-speech annotation, it provides *syntactic* annotation. For example, what is the object of the sentence “The man bought the hat”? These standard corpora serve as training data to train the classifiers and machine learning techniques to automatically analyze text (Halevy, Norvig, and Pereira 2009).



# 9

---

## *Networks: The Basics*

---

**Jason Owen-Smith**

Social scientists are typically interested in describing the activities of individuals and organizations (such as households and firms) in a variety of economic and social contexts. The frame within which data has been collected will typically have been generated from tax or other programmatic sources. The new types of data permit new units of analysis—particularly network analysis—largely enabled by advances in mathematical graph theory. This chapter provides an overview of how social scientists can use network theory to generate measurable representations of patterns of relationships connecting entities. The value of the new framework is not only in constructing different right-hand-side variables but also in studying an entirely new unit of analysis that lies somewhere between the largely atomistic actors that occupy the markets of neo-classical theory and the tightly managed hierarchies that are the traditional object of inquiry of sociologists and organizational theorists.

---

### **9.1 Introduction**

Social Scientists have studied networks for a long time. A lot of the theory behind network analysis in fact comes from the social sciences where we studied relationships between people, groups, and organizations [citation Moreno, J.L., Jennings, H.H.: Who Shall Survive?: A New Approach to the Problem of Human Interrelations. Nervous and Mental Disease Publishing Co., Washington, D.C. (1934)]. What's different today is the scale of the data available to us to perform this analysis. Instead of studying a group of 25 participants in a karate club (Zachary, W. W. (1977). “An Information Flow Model for Conflict and Fission in Small Groups”. *Journal of Anthropological Research*. 33 (4): 452–473.), we now have data about hundreds of millions of people communicating with each other through social media channels, or hundreds of thousands of employees in a large multinational organizations collaborating on projects. This increased scale requires us to explore new methods of answering the same questions

that we used to be interested in, as well as opens up avenues to answer new questions that could not be answered before.

---

**todo: finish examples in this box*****Box with examples or references to these examples***

Survey paper: (maybe at end in further reading) <http://keg.cs.tsinghua.edu.cn/jietang/publications/WWW17-Tang-Comp-Social-Science-Survey.pdf>

<http://www.sn.ethz.ch> Zurich Networks Labs

Example 1: <https://cs.stanford.edu/people/jure/pubs/recurrence-www16.pdf>

Example 2: <https://abjer.github.io/project/social-fabric/> or <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4000208/> (same study)

Example 3: diffusion of information

Facebook graph example: <http://snap.stanford.edu/class/cs224w-readings/backstrom12fb.pdf>

---

This chapter provides a basic introduction to the analysis of large networks for social science research and practice. We describe how to use data from existing social networks as well as how to turn “non-network” data into a network to perform further analysis. We then describe different measures that can be calculated to understand the properties of the network being analyzed, show different network visualization techniques, and discuss social science questions that these network measures and visualizations can help us answer.

We use the comparison of the collaboration networks of two research-intensive universities to show how to perform network analysis but the same approach generalizes to other types of problems. The collaboration networks and a grant co-employment network for a large public university examined in this chapter are derived from data produced by the multi-university Committee on Institutional Cooperation (CIC)’s UMETRICS project (Lane et al. 2015). The snippets of code that are provided are from the `igraph` package for network analysis as implemented in Python.

---

## 9.2 What are networks?

Networks are measurable representations of relationships connecting entities. What this means is that there are two fundamental questions to ask of any

network representation: First, what are the nodes? Second, what are the relationships (ties or edges) connecting the nodes? Once we have the representation, we can then analyze the underlying data and relationships through the measures and methods described in this chapter. This is of great interest because a great deal of research in social sciences demonstrates that networks are essential to understanding behaviors and outcomes at both the individual and the organizational level.

Networks offer not just another convenient set of right-hand-side variables, but an entirely new unit of analysis that lies somewhere between the largely atomistic actors that occupy the markets of neo-classical theory and the tightly managed hierarchies that are the traditional object of inquiry of sociologists and organizational theorists. As Walter W. Powell (Powell 2003) puts it in a description of buyer supplier networks of small Italian firms: “when the entangling of obligation and reputation reaches a point where the actions of the parties are interdependent, but there is no common ownership or legal framework ... such a transaction is neither a market exchange nor a hierarchical governance structure, but a separate, different mode of exchange.”

Existing as they do between the uncoordinated actions of independent individuals and coordinated work of organizations, networks offer a unique level of analysis for the study of scientific and creative teams (Wuchty, Jones, and Uzzi 2007), collaborations (Kabo et al. 2015), and clusters of entrepreneurial firms (Owen-Smith and Powell 2004).

The following sections will introduce you to this approach to studying innovation and discovery, focusing on examples drawn from high-technology industries and particularly from the scientific collaborations among grant-employed researchers at UMETRICS universities. We make particular use of a network that connects individual researchers to grants that paid their salaries in 2012 for a large public university. The grants network for university A includes information on 9,206 individuals who were employed on 3,389 research grants from federal science agencies in a single year. The web of partnerships that emerges from university scientists’ decentralized efforts to build effective collaborations and teams generates a distinctive social infrastructure for cutting-edge Science.

While this chapter focuses on social networks, the techniques described here have been used to examine the structure of networks such as the World Wide Web, the national railway route map of the USA, the food web of an ecosystem, or the neuronal network of a particular species of animal.

### 9.3 Structure for this chapter

The chapter first introduces the most common structures for large network data, briefly introduce three key social “mechanisms of action” by which social networks are thought to have their effects, and then present a series of basic measures that can be used to quantify characteristics of entire networks and the relative position individual people or organizations hold in the differentiated social structure created by networks.

Taken together, these measures offer an excellent starting point for examining how global network structures create opportunities and challenges for the people in them, for comparing and explaining the productivity of collaborations and teams, and for making sense of the differences between organizations, industries, and markets that hinge on the pattern of relationships connecting their participants.

Understanding the productivity and effects of university research thus requires an effort to measure and characterize the networks on which it depends. As suggested, those networks influence outcomes in three ways: first, they distinguish among individuals; second, they differentiate among teams; and third, they help to distinguish among research-performing universities. Most research-intensive institutions have departments and programs that cover similar arrays of topics and areas of study. What distinguishes them from one another is not the topics they cover but the ways in which their distinctive collaboration networks lead them to have quite different scientific capabilities.

---

### 9.4 Turning Data into a Network

Networks are comprised of *nodes*, which represent things that can be connected to one another, and of ties that represent the relationships connecting nodes. When ties are undirected (representing a relationship between the nodes that is not directional) they are called *edges*. When they are directed (as when I lend money to you and you do or do not reciprocate) they are called *arcs*. Nodes, edges and arcs can, in principle, be anything: patents and citations, web pages and hypertext links, scientists and collaborations, teenagers and intimate relationships, nations and international trade agreements. The very flexibility of network approaches means that the first step toward doing a network analysis is to first turn our data into a graph by clearly defining what counts as a node and what counts as a tie. In traditional social network analysis studies, there is a natural representation of the data as a network. People are often nodes, and

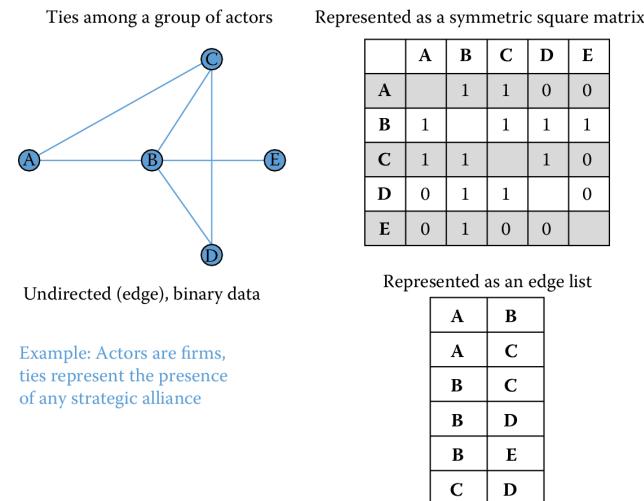
some type of communication between them form the “ties”. While this seems like an easy move, it often requires deep thought. For instance, an interest in innovation and discovery could take several forms. We could be interested in how universities differ in their capacity to respond to new requests for proposals (a macro question that would require the comparison of full networks across campuses). We could wonder what sorts of training arrangements lead to the best outcomes for graduate students (a more micro- level question that requires us to identify individual positions in larger networks). Or we could ask what team structure is likely to lead to more or less radical discoveries (a decidedly meso-level question that requires we identify substructures and measure their features).

Each of these is a network question that relies on the ways in which people are connected to one another. The first challenge of measurement is to identify the nodes (what is being connected) and the ties (the relationships that matter) in order to construct the relevant networks. The next is to collect and structure the data in a fashion that is sufficient for analysis. Finally, measurement and visualization decisions must be made.

#### 9.4.1 Types of Networks

Network ties can be directed (flowing from one node to another) or undirected. In either case they can be binary (indicating the presence or absence of a tie) or valued (allowing for relationships of different types or strengths). Network data can be represented in matrices or as lists of edges and arcs. All these types of relationships can connect one type of node (what is commonly called *one-mode* network data) or multiple types of nodes (what is called *two-mode* or *affiliation* data). Varied data structures correspond to different classes of network data. The simplest form of network data represents instances where the same kinds of nodes are connected by undirected ties (edges) that are binary. An example of this type of data is a network where nodes are firms and ties indicate the presence of a strategic alliance connecting them (Powell et al. 2005). This network would be represented as a square symmetric matrix or a list of edges connecting nodes. Figure 9.1 summarizes this simple data structure, highlighting the idea that network data of this form can be represented either as a matrix or as an edge list. If this data was representing acquisitions, we could turn it into a directed graph where the edge would be directed from the acquiring firm to the acquired firm.

A much more complicated network would be one that is both directed and valued. One example might be a network of nations connected by flows of international trade. Goods and services flow from one nation to another and the value of those goods and services (or their volume) represents ties of different strengths. When networks connecting one class of nodes (in this case nations)



**FIGURE 9.1** Undirected, binary, one-mode network data

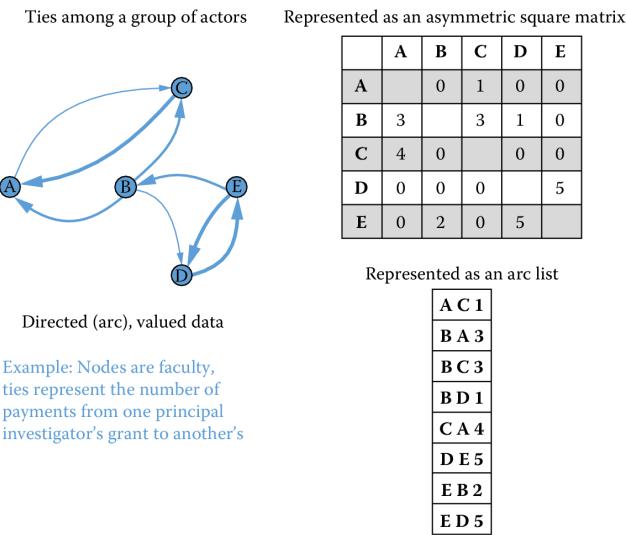
are directed and valued, they can be represented as asymmetric valued matrices or lists of arcs with associated values. (See Figure 9.1.)

While many studies of small- to medium-sized social networks rely on one-mode data. Large-scale social network data of this type are relatively rare, but one-mode data of this sort are fairly common in relationships among other types of nodes such as web pages or citations connecting patents or publications. Nevertheless, much “big” social network analysis is conducted using two-mode data. The UMETRICS employee data set is a two-mode network that connects people (research employees) to the grants that pay their wages. These two types of nodes can be represented as a rectangular matrix that is either valued or binary. It is relatively rare to analyze untransformed two-mode network data. Instead, most analyses take advantage of the fact that such networks are *dual* (White, Boorman, and Breiger 1976). In other words, a two-mode network connecting grants and people can be conceptualized (and analyzed) as two one-mode networks, or *projections*<sup>1</sup>.

#### 9.4.2 Inducing one-mode networks from two-mode data

The most important trick in large-scale social network analysis is that of inducing one-mode, or unipartite, networks (e.g., employee × employee relationships) from two-mode, or bipartite, data. But the ubiquity and potential value of two-mode data can come at a cost. Not all affiliations are equally likely to

<sup>1</sup>Key insight: A two-mode network can be conceptualized and analyzed as two one-mode networks, or projections.

**FIGURE 9.2** Directed, valued, one-mode network data

represent real, meaningful relationships. While it seems plausible to assume that two individuals paid by the same grant have interactions that reasonably pertain to the work funded by the grant, this need not be the case.

For example, consider the two-mode grant  $\times$  person network for university A. I used SQL to create a representation of this network that is readable by a freeware network visualization program called Pajek (Batagelj and Mrvar 1998). In this format, a network is represented as two lists: a *vertex list* that lists the nodes in the graph and an *edge list* that lists the connections between those nodes. In our grant  $\times$  person network, we have two types of nodes, people and grants, and one kind of edge, used to represent wage payments from grants to individuals.

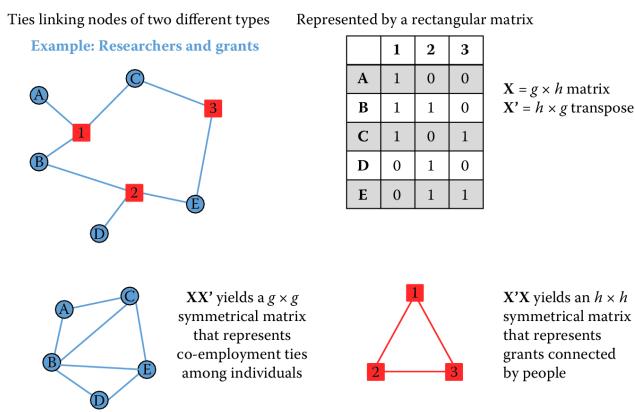
I present a brief snippet of the resulting network file in what follows, showing first the initial 10 elements of the vertex list and then the initial 10 elements of the edge list, presented in two columns for compactness. (The complete file comprises information on 9,206 employees and 3,389 grants, for a total of 12,595 vertices and 15,255 edges. The employees come first in the vertex list, and so the 10 rows shown below all represent employees.) Each vertex is represented by a vertex number-label pair and each edge by a pair of vertices plus an optional value. Thus, the first entry in the edge list (1 10419) specifies that the vertex with identifier 1 (which happens to be the first element of the vertex list, which has value "00100679") is connected to the vertex with identifier 10419 by an edge with value 1, indicating that employee "00100679" is paid by the grant described by vertex 10419.

\*Grant-Person-Network

	*Vertices	12595	9206		*Edges
1		"00100679"	1		10419
2		"00107462"	2		10422
3		"00109569"	3		9855
4		"00145355"	3		9873
5		"00153190"	4		9891
6		"00163131"	7		10432
7		"00170348"	7		12226
8		"00172339"	8		10419
9		"00176582"	9		11574
10		"00203529"	10		11196

The network excerpted above is two-mode because it represents relationships between two different classes of nodes, grants, and people. In order to use data of this form to address questions about patterns of collaboration on UMETRICS campuses, we must first transform it to represent collaborative relationships.

A person-by-person projection of the original two-mode network assumes that ties exist between people when they are paid by the same grant. By the same token, a grant-by-grant projection of the original two-mode network assumes that ties exist between grants when they pay the same people. Transforming two-mode data into one-mode projections is a fairly simple matter. If  $\mathbf{X}$  is a rectangular matrix,  $p \times g$ , then a one-mode projection,  $p \times p$ , can be obtained by multiplying  $\mathbf{X}$  by its transpose  $\mathbf{X}'$ . Figure 9.3 summarizes this transformation.



**FIGURE 9.3** Two-mode affiliation data

In the following snippet of code, I use the `igraph` package in Python to read in

a Pajek file and then transform the original two-mode network into two separate projections. Because my focus in this discussion is on relationships among people, I then move on to work exclusively with the employee-by-employee projection. However, every technique that I describe below can also be used with the grant-by-grant projection, which provides a different view of how federally funded research is put together by collaborative relationships on campus.

```
from igraph import *

# Read the graph
g = Graph.Read_Pajek("public_a_2m.net")

# Look at result
summary(g)

# IGRAPH U-WT 12595 15252 --
# + attr: color (v), id (v), shape (v), type (v), x (v), y (v),
#   z (v), weight (e)
# ...
# ...

# Transform to get 1M projection
pr_g_proj1, pr_g_proj2= g.bipartite_projection()

# Look at results
summary(pr_g_proj1)

# IGRAPH U-WT 9206 65040 --
# + attr: color (v), id (v), shape (v), type (v), x (v), y (v),
#   z (v), weight (e)

summary(pr_g_proj2)
# IGRAPH U-WT 3389 12510 --
# + attr: color (v), id (v), shape (v), type (v), x (v), y (v),
#   z (v), weight (e)

# pr_g_proj1 is the employeeXemployee projection, n=9,206 nodes
# Rename to emp for use in future calculations

emp=pr_g_proj1
```

We now can work with the graph `emp`, which represents the collaborative network of federally funded research on this campus. Care must be taken

when inducing one-mode network projections from two-mode network data because not all affiliations provide equally compelling evidence of actual social relationships. While assuming that people who are paid by the same research grants are collaborating on the same project seems plausible, it might be less realistic to assume that all students who take the same university classes have meaningful relationships. For the remainder of this chapter, the examples I discuss are based on UMETRICS employee data rendered as a one-mode person-by-person projection of the original two-mode person-by-grants data. In constructing these networks I assume that a tie exists between two university research employees when they are paid any wages from the same grant during the same year. Other time frames or thresholds might be used to define ties if appropriate for particular analyses<sup>2</sup>.

---

## 9.5 Network measures

The power of networks lies in their unique flexibility and ability to address many phenomena at multiple levels of analysis. But harnessing that power requires calculating measures that take into account the overall structure of relationships represented in a given network. The key insight of structural analysis is that outcomes for any individual or group are a function of the complete pattern of connections among them. In other words, the explanatory power of networks is driven as much by the pathways that *indirectly* connect nodes as by the particular relationships that *directly* link members of a given dyad. Indirect ties create reachability in a network<sup>3</sup>.

### 9.5.1 Reachability

Two nodes are said to be reachable when they are connected by an unbroken chain of relationships through other nodes. For instance, two people who have never met may nonetheless be able to reach each other through a common acquaintance who is positioned to broker an introduction (Obstfeld 2005) or the transfer of information and resources (Burt 2004). It is the reachability that networks create that makes them so important for understanding the work of science and innovation.

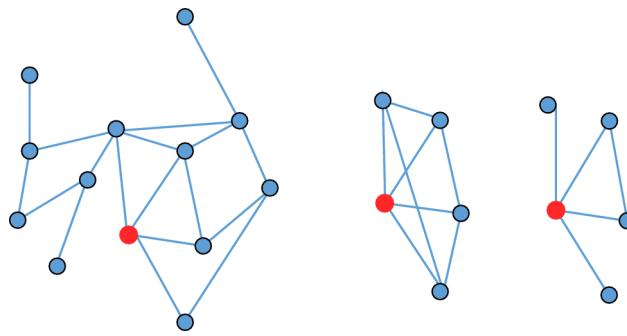
Consider Figure 9.4, which presents three schematic networks. In each, one

---

<sup>2</sup>Key insight: Care must be taken when inducing one-mode network projections from two-mode network data because not all affiliations provide equally compelling evidence of actual social relationships.

<sup>3</sup>Key insight: Structural analysis of outcomes for any individual or group are a function of the complete pattern of connections among them.

focal node, ego, is colored orange. Each ego has four alters, but the fact that each has connections to four other nodes masks important differences in their structural positions. Those differences have to do with the number of other nodes they can reach through the network and the extent to which the other nodes in the network are connected to each other. The orange node (ego) in each network has four partners, but their positions are far from equivalent. Centrality measures on full network data can tease out the differences. The networks also vary in their gross characteristics. Those differences, too, are measurable<sup>4</sup>.



**FIGURE 9.4** Reachability and indirect ties

Networks in which more of the possible connections among nodes are realized are denser and more cohesive than networks in which fewer potential connections are realized. Consider the two smaller networks in Figure 9.4, each of which is comprised of five nodes. Just five ties connect those nodes in the network on the far right of the figure. One smaller subset of that network, the triangle connecting ego and two alters at the center of the image, represents a more cohesively connected subset of the networks. In contrast, eight of the nine ties that are possible connect the five nodes in the middle figure; no subset of those nodes is clearly more interconnected than any other. While these kinds of differences may seem trivial, they have implications for the orange nodes, and for the functioning of the networks as a whole. Structural differences between the positions of nodes, the presence and characteristics of cohesive “communities” within larger networks (Girvan and Newman 2002), and many important properties of entire structures can be quantified using different classes of network measures. Newman (Newman 2010) provides the most recent and most comprehensive look at measures and algorithms for network research.

The most essential thing to be able to understand about larger scale networks

---

<sup>4</sup>Key insight: Much of the power of networks (and their systemic features) is due to indirect ties that create reachability. Two nodes can reach each other if they are connected by an unbroken chain of relationships. These are often called indirect ties.

is the pattern of indirect connections among nodes. What is most important about the structure of networks is not necessarily the ties that link particular pairs of nodes to one another. Instead, it is the chains of indirect connections that make networks function as a system and thus make them worthwhile as new levels of analysis for understanding social and other dynamics.

### 9.5.2 Whole-network measures

The basic terms needed to characterize whole networks are fairly simple. It is useful to know the size (in terms of nodes and ties) of each network you study. This is true both for the purposes of being able to generally gauge the size and connectivity of an entire network and because many of the measures that one might calculate using such networks should be standardized for analytic use. While the list of possible network measures is long, a few commonly used indices offer useful insights into the structure and implications of entire network structures.

#### Components and reachability

As we have seen, a key feature of networks is reachability. The reachability of participants in a network is determined by their membership in what network theorists call *components*, subsets of larger networks where every member of a group is indirectly connected to every other. If you imagine a standard node and line drawing of a network, a component is a portion of the network where you can trace paths between every pair of nodes without ever having to lift your pen.

Most large networks have a single dominant component that typically includes anywhere from 50% to 90% of its participants as well as many smaller components and isolated nodes that are disconnected from the larger portion of the network. Because the path length centrality measures described below can only be computed on connected subsets of networks, it is typical to analyze the largest component of any given network. Thus any description of a network or any effort to compare networks should report the number of components and the percentage of nodes reachable through the largest component. In the code snippet below, I identify the weakly connected components of the employee network, `emp`.

```
# Add component membership
emp.vs[["membership"]] = emp.clusters(mode="weak").membership

# Add component size
emp.vs[["csize"]] = [emp.clusters(mode="weak").sizes()[i] for i
                     in emp.clusters(mode="weak").membership]

# Identify the main component
```

```

# Get indices of max clusters
maxSize = max(emp.clusters(mode="weak").sizes())
emp.vs["largestcomp"] = [1 if maxSize == x else 0 for x in
→ emp.vs["csize"]]

# Add component membership

emp.vs["membership"] = emp.clusters(mode="weak").membership

```

The main component of a network is commonly analyzed and visualized because the graph-theoretic distance among unconnected nodes is infinite, which renders calculation of many common network measures impossible without strong assumptions about just how far apart unconnected nodes actually are. While some researchers replace infinite path lengths with a value that is one plus the longest path, called the network's diameter, observed in a given structure, it is also common to simply analyze the largest connected component of the network.

### Path length

One of the most robust and reliable descriptive statistics about an entire network is the average path length,  $l_G$ , among nodes. Networks with shorter average path lengths have structures that may make it easier for information or resources to flow among members in the network. Longer path lengths, by comparison, are associated with greater difficulty in the diffusion and transmission of information or resources. Let  $g$  be the number of nodes or vertices in a network. Then

$$l_G = \frac{1}{g(g-1)} \sum_{i \neq j} d(n_i, n_j).$$

As with other measures based on reachability, it is most common to report the average path length for the largest connected component of the network because the graph-theoretic distance between two unconnected nodes is infinite. In an electronic network such as the World Wide Web, a shorter path length means that any two pages can be reached through fewer hyperlink clicks.

The snippet of code below identifies the distribution of shortest path lengths among all pairs of nodes in a network and the average path length. I also include a line of code that calculates the network distance among all nodes and returns a matrix of those distances. That matrix (saved as `empdist`) can be used to calculate additional measures or to visualize the graph-theoretic proximities among nodes.

```

# Calculate distances and construct distance table

dfreq=emp.path_length_hist(directed=False)

```

```

print(dfreq)

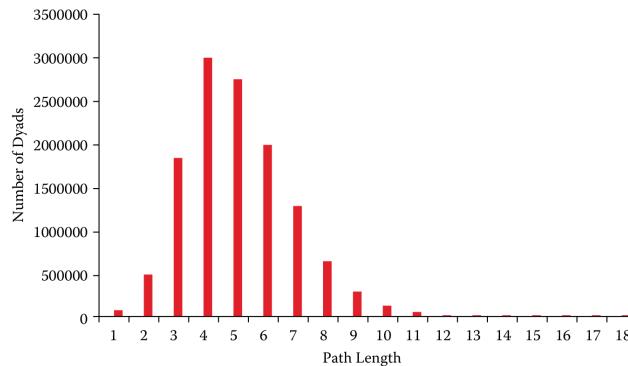
# N = 12506433, mean +- sd: 5.0302 +- 1.7830
# Each * represents 51657 items
# [ 1,  2): * (65040)
# [ 2,  3): **** (487402)
# [ 3,  4): ***** (1831349)
# [ 4,  5):
#   **** (2996157)
# [ 5,  6): ***** (2733204)
# [ 6,  7): ***** (1984295)
# [ 7,  8): ***** (1267465)
# [ 8,  9): ***** (649638)
# [ 9, 10): **** (286475)
# [10, 11): ** (125695)
# [11, 12): * (52702)
# [12, 13): (18821)
# [13, 14): (5944)
# [14, 15): (1682)
# [15, 16): (403)
# [16, 17): (128)
# [17, 18): (28)
# [18, 19): (5)
print(dfreq.unconnected)
# 29864182

print(emp.average_path_length(directed=False))
#[1] 5.030207

empdist= emp.shortest_paths()

```

These measures provide a few key insights into the employee network we have been considering. First, the average pair of nodes that are connected by indirect paths are slightly more than five steps from one another. Second, however, many node pairs in this network (`$unconnected = 29,864,182`) are unconnected and thus unreachable to each other. Figure 9.5 presents a histogram of the distribution of path lengths in the network. It represents the numeric values returned by the `distance.table` command in the code snippet above. In this case the diameter of the network is 18 and five pairs of nodes are reachable at this distance, but the largest group of dyads is reachable ( $N = 2,996,157$  dyads) at distance 4. In short, nearly 3 million pairs of nodes are collaborators of collaborators of collaborators of collaborators.



**FIGURE 9.5** Histogram of path lengths for university A employee network

### Degree distribution

Another powerful way to describe and compare networks is to look at the distribution of centralities across nodes. While any of the centrality measures described above could be summarized in terms of their distribution, it is most common to plot the degree distribution of large networks. Degree distributions commonly have extremely long tails. The implication of this pattern is that most nodes have a small number of ties (typically one or two) and that a small percentage of nodes account for the lion's share of a network's connectivity and reachability. Degree distributions are typically so skewed that it is common practice to plot degree against the percentage of nodes with that degree score on a log–log scale.

High-degree nodes are often particularly important actors. In the UMETRICS networks that are employee  $\times$  employee projections of employee  $\times$  grant networks, for instance, the nodes with the highest degree seem likely to include high-profile faculty—the investigators on larger institutional grants such as National Institutes of Health-funded Clinical and Translational Science Awards and National Science Foundation-funded Science and Technology Centers, and perhaps staff whose particular skills are in demand (and paid for) by multiple research teams. For instance, the head technician in a core microscopy facility or a laboratory manager who serves multiple groups might appear highly central in the degree distribution of a UMETRICS network.

Most importantly, the degree distribution is commonly taken to provide insight into the dynamics by which a network was created. Highly skewed degree distributions often represent scale-free networks (Powell et al. 2005; Barabási and Albert 1999; Newman 2005), which grow in part through a process called *preferential attachment*, where new nodes entering the network are more likely to attach to already prominent participants. In the kinds of scientific collaboration networks that UMETRICS represents, a scale-free degree distribution

might come about as faculty new to an institution attempt to enroll more established colleagues on grants as coinvestigators. In the comparison exercise outlined below, I plot degree distributions for the main components of two different university networks.

### Clustering coefficient

The third commonly used whole-network measure captures the extent to which a network is cohesive, with many nodes interconnected. In networks that are more cohesively clustered, there are fewer opportunities for individuals to play the kinds of brokering roles that we will discuss below in the context of betweenness centrality. Less cohesive networks, with lower levels of clustering, are potentially more conducive to brokerage and the kinds of innovation that accompany it.

However, the challenge of innovation and discovery is both the moment of invention, the “aha!” of a good new idea, and the often complicated, uncertain, and collaborative work that is required to turn an initial insight into a scientific finding. While less clustered, open networks are more likely to create opportunities for brokers to develop fresh ideas, more cohesive and clustered networks support the kinds of repeated interactions, trust, and integration that are necessary to do uncertain and difficult collaborative work.

While it is possible to generate a global measure of cohesiveness in networks, which is generically the number of closed triangles (groups of three nodes all connected to one another) as a proportion of the number of possible triads, it is more common to take a local measure of connectivity and average it across all nodes in a network. This local connectivity measure more closely approximates the notion of cohesion around nodes that is at the heart of studies of networks as means to coordinate difficult, risky work. The code snippet below calculates both the global clustering coefficient and a vector of node-specific clustering coefficients whose average represents the local measure for the employee  $\times$  employee network projection of the university A UMETRICS data.

```
# Calculate clustering coefficients
emp.transitivity_undirected()
# 0.7241

local_clust=emp.transitivity_local_undirected(mode="zero")
# (isolates="zero" sets clustering to zero rather than
# → undefined)

import pandas as pd
print(pd.Series(local_clust).describe())
# count    9206.000000
# mean      0.625161
# std       0.429687
```

```
# min      0.000000
# 25%     0.000000
# 50%     0.857143
# 75%     1.000000
# max     1.000000
#-----#
```

Together, these summary statistics—number of nodes, average path length, distribution of path lengths, degree distribution, and the clustering coefficient—offer a robust set of measures to examine and compare whole networks. It is also possible to distinguish among the positions nodes hold in a particular network. Some of the most powerful centrality measures also rely on the idea of indirect ties<sup>5</sup>.

### Centrality measures

This class of measures is the most common way to distinguish between the positions individual nodes hold in networks. There are many different measures of centrality that capture different aspects of network positions, but they fall into three general types. The most basic and intuitive measure of centrality, *degree centrality*, simply counts the number of ties that a node has. In a binary undirected network, this measure resolves into the number of unique alters each node is connected to. In mathematical terms it is the row or column sum of the adjacency matrix that characterizes a network. Degree centrality,  $C_D(n_i)$ , represents a clear measure of the prominence or visibility of a node. Let

$$C_D(n_i) = \sum_j x_{ij}.$$

The degree of a node is limited by the size of the network in which it is embedded. In a network of  $g$  nodes the maximum degree of any node is  $g - 1$ . The two orange nodes in the small networks presented in Figure 9.4 have the maximum degree possible (4). In contrast, the orange node in the larger, 13-node network in that figure has the same number of alters but the possible number of partners is three times as large (12). For this reason it is problematic to compare raw degree centrality measures across networks of different sizes. Thus, it is common to normalize degree by the maximum value defined by  $g - 1$ :

$$C'_D(n_i) = \frac{\sum_j x_{ij}}{g - 1}.$$

While the normalized degree centrality of the two orange nodes of the smaller networks in Figure 9.4 is 1.0, the normalized value for the node in the large network of 13 nodes is 0.33. Despite the fact that the highlighted nodes in the

---

<sup>5</sup>Key insight: Some of the most powerful centrality measures also rely on the idea of indirect ties.

two smaller networks have the same degree centrality, the pattern of indirect ties connecting their alters means they occupy meaningfully different positions. There are a number of degree-based centrality measures that take more of the structural information from a complete network into account by using a variety of methods to account not just for the number of partners a particular ego might have but also for the prominence of those partners. Two well-known examples are eigenvector centrality and page rank (see (Newman 2010 Ch. 7.2 and 8.4)).

Consider two additional measures that capture aspects of centrality that have more to do with the indirect ties that increase reachability. Both make explicit use of the idea that reachability is the source of many of the important social and economic benefits of salutary network positions, but they do so with different substantive emphases. Both of these approaches rely on the idea of a network geodesic, the longest shortest path<sup>6</sup> connecting any pair of actors. Because these measures rely on reachability, they are only useful when applied to components. When nodes have no ties (degree 0) they are called *isolates*. The geodesic distances are infinite and thus path-based centrality measures cannot be calculated. This is a shortcoming of these measures, which can only be used on connected subsets of graphs where each node has at least one tie to another and all are indirectly connected.

Closeness centrality,  $C_C$ , is based on the idea that networks position some individuals closer to or farther away from other participants. The primary idea is that shorter network paths between actors increase the likelihood of communication and with it the ability to coordinate complicated activities. Let  $d(n_i, n_j)$  represent the number of network steps in the geodesic path connecting two nodes  $i$  and  $j$ . As  $d$  increases, the network distance between a pair of nodes grows. Thus a standard measure of closeness is the inverse of the sum of distances between any given node and all the others that are reachable in a network:

$$C_C(n_i) = \frac{1}{\sum_{j=1}^g d(n_i, n_j)}.$$

The maximum of closeness centrality occurs when a node is directly connected to every possible partner in the network. As with degree centrality, closeness depends on the number of nodes in a network. Thus, it is necessary to standardize the measure to allow comparisons across multiple networks:

$$C'_C(n_i) = \frac{g - 1}{\sum_{j=1}^g d(n_i, n_j)}.$$

Like closeness centrality, betweenness centrality,  $C_B$ , relies on the concept

---

<sup>6</sup>A *shortest path* is a path that does not repeat any nodes or ties. Most pairs have several of those. The *geodesic* is the longest shortest path. So, if two people are directly connected (path length 1) and connected through shared ties to another person (path length 2), then their geodesic distance is two.

of geodesic paths to capture nuanced differences the positions of nodes in a connected network. Where closeness assumes that communication and the flow of information increase with proximity, betweenness captures the idea of brokerage that was made famous by Burt (Burt 1993). Here too the idea is that flows of information and resources pass between nodes that are not directly connected through indirect paths. The key to the idea of brokerage is that such paths pass through nodes that can interdict, or otherwise profit from their position “in between” unconnected alters. This idea has been particularly important in network studies of innovation (Owen-Smith and Powell 2003; Burt 2004), where flows of information through strategic alliances among firms or social networks connecting individuals loom large in explanations of why some organizations or individuals are better able to develop creative ideas than others.

To calculate betweenness as originally specified, two strong assumptions are required (Freeman 1979). First, one must assume that when people (or organizations) search for new information through their networks, they are capable of identifying the shortest path to what they seek. When multiple paths of equal length exist, we assume that each path is equally likely to be used. Newman (Newman 2005) describes an alternative betweenness measure based on random paths through a network, rather than shortest paths, that relaxes these assumptions. For now, let  $g_{jk}$  equal the number of geodesic paths linking any two actors. Then  $1/g_{jk}$  is the probability that any given path will be followed on a particular node’s search for information or resources in a network. In order to calculate the betweenness score of a particular actor,  $i$ , it is then necessary to determine how many of the geodesic paths connecting  $j$  to  $k$  include  $i$ . That quantity is  $g_{jk}(n_i)$ . With these (unrealistic) assumptions in place, we calculate  $C_B(n_i)$  as

$$C_B(n_i) = \sum_{j < k} g_{jk}^{(n_i)} / g_{jk}.$$

Here, too, the maximum value depends on the size of the network.  $C_B(n_i) = 1$  if  $i$  sits on every geodesic path in the network. While this is only likely to occur in small, star-shaped networks, it is still common to standardize the measure. Instead of conceptualizing network size in terms of the number of nodes, however, this measure requires that we consider the number of possible pairs of actors (excluding ego) in a structure. When there are  $g$  nodes, that quantity is  $(g - 1)(g - 2)/2$  and the standardized betweenness measure is

$$C'_B(n_i) = \frac{C_B(n_i)}{(g - 1)(g - 2)/2}.$$

Centrality measures of various sorts are the most commonly used means to examine network effects at the level of individual participants in a network. In the context of UMETRICS, such indices might be applied to examine the

differential scientific or career success of graduate students as a function of their positions in the larger networks of their universities. In such an analysis, care must be taken to use the standardized measures as university collaboration networks can vary dramatically in size and structure. Describing and accounting for such variations and the possibility of analyses conducted at the level of entire networks or subsets of networks, such as teams and labs, requires a different set of measures. The code snippet presented below calculates each of these measures for the university A employee network we have been examining.

```
# Calculate centrality measures
emp.vs["degree"]=emp.degree()
emp.vs["close"]=emp.closeness(vertices=emp.vs)
emp.vs["btc"]=emp.betweenness(vertices=emp.vs, directed=False)
```

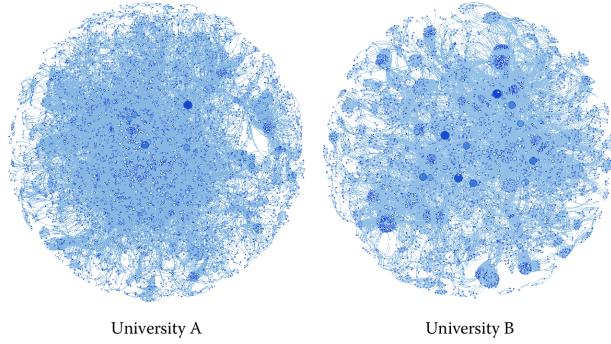
## 9.6 Case Study: Comparing collaboration networks

Consider Figure 9.6, which presents visualizations of the main component of two university networks. Both of these representations are drawn from a single year (2012) of UMETRICS data. Nodes represent people, and ties reflect the fact that those individuals were paid with the same federal grant in the same year. The images are scaled so that the physical location of any node is a function of its position in the overall pattern of relationships in the network. The size and color of nodes represent their betweenness centrality. Larger, darker nodes are better positioned to play the role of brokers in the network. A complete review of the many approaches to network visualization and their dangers in the absence of descriptive statistics such as those presented above is beyond the scope of this chapter, but consider the guidelines presented in Chapter Information Visualization on information visualization as well as useful discussions by Powell et al. (Powell et al. 2005) and Healy and Moody (Healy and Moody 2014).

Consider the two images. University A is a major public institution with a significant medical school. University B, likewise, is a public institution but lacks a medical school. It is primarily known for strong engineering. The two networks manifest some interesting and suggestive differences. Note first that the network on the left (university A) appears much more tightly connected. There is a dense center and there are fewer very large nodes whose positions bridge less well-connected clusters. Likewise, the network on the right (university B) seems at a glance to be characterized by a number of densely interconnected groups that are pulled together by ties through high-degree brokers. One part of this may have to do with the size and structure of university A's medical school,

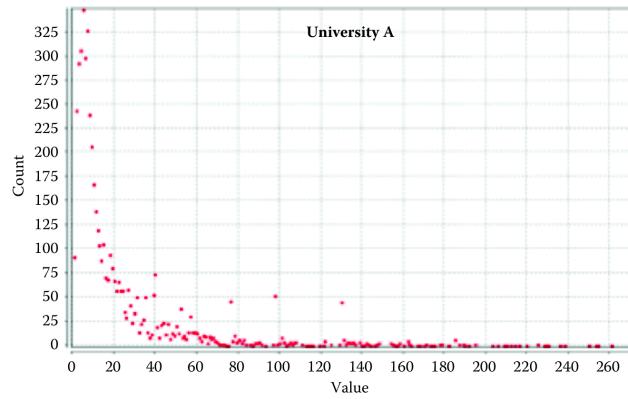
whose significant NIH funding dominates the network. In contrast, university B's engineering-dominated research portfolio seems to be arranged around clusters of researchers working on similar topic areas and lacks the dominant central core apparent in university B's image.

The implications of these kinds of university-level differences are just starting to be realized, and the UMETRICS data offer great possibilities for exactly this kind of study. These networks, in essence, represent the local social capacity to respond to new problems and to develop scientific findings. Two otherwise similar institutions might have quite different capabilities based on the structure and composition of their collaboration networks.

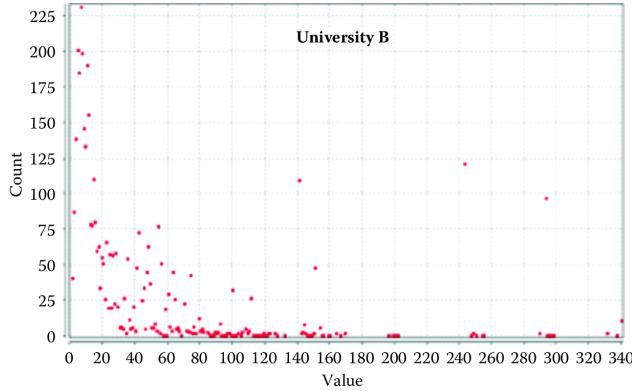


**FIGURE 9.6** The main component of two university networks

The intuitions suggested by Figure 9.6 can also be checked against some of the measures we have described. Figure 9.7, for instance, presents degree distributions for each of the two networks. Figure 9.8 presents the histogram of path lengths for each network.



It is evident from Figure 9.7 that they are quite different in character. University A's network follows a more classic skewed distribution of the sort that is often



**FIGURE 9.7** Degree distribution for two universities

associated with the kinds of power-law degree distributions common to scale-free networks. In contrast, university B's distribution has some interesting features. First, the left-hand side of the distribution is more dispersed than it is for university A, suggesting that there are many nodes with moderate degree. These nodes may also have high betweenness centrality if their ties allow them to span different subgroups within the networks. Of course this might also reflect the fact that each cluster also has members that are more locally prominent. Finally, consider the few instances on the right-hand end of the distribution where there are relatively large numbers of people with surprisingly high degree. I suspect these are the result of large training grants or center grants that employ many people. A quirk of relying on one-mode projections of two-mode data is that every person associated with a particular grant is connected to every other. More work needs to be done to bear out these hypotheses, but for now it suffices to say that the degree distribution of the networks bears out the intuition we drew from the images that they are significantly different.

The path length histogram presented in Figure 9.8 suggests a similar pattern. While the average distance among any pair of connected nodes in both networks is fairly similar (see Table 9.2, university B has a larger number of unconnected nodes and university A has a greater concentration of more closely connected dyads. The preponderance of shorter paths in this network could also be a result of a few larger grants that connect many pairs of nodes at unit distance and thus shorten overall path lengths.

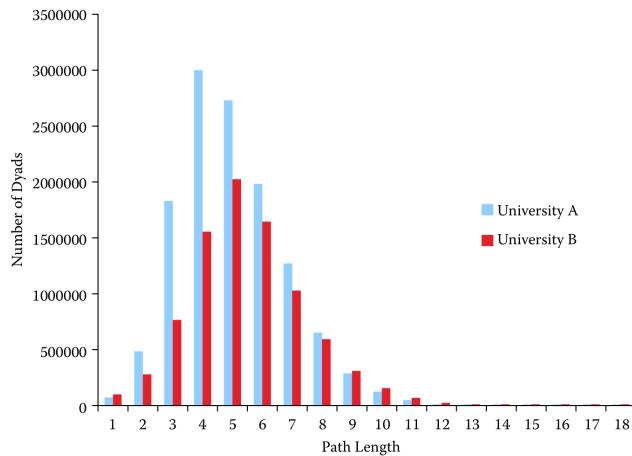
	<b>University A</b>	<b>University B</b>
--	---------------------	---------------------

TABLE 9.2: Descriptive statistics for the main components of two university networks

	<b>University A</b>	<b>University B</b>
Nodes	4,999	4,144
Edges (total)	57,756	91,970
% nodes in main component	68.67%	67.34%
Diameter	18	18
Average degree	11.554	44.387
Clustering coefficient	0.855	0.913
Density	0.005	0.011
Average path length	5.034	5.463

But how do the descriptive statistics shake out? Table 9.2 presents the basic descriptive statistics we have discussed for each network. University A’s network includes 855 more nodes than university B’s, a difference of about 20%. In contrast, there are far fewer edges connecting university A’s research employees than connecting university B’s, a difference that appears particularly starkly in the much higher density of university B’s network. Part of the story can be found in the average degree of nodes in each network. As the degree distributions presented in Figure 9.6 suggested, the average researcher at university B is much more highly connected to others than is the case at university A. The difference is stark and quite likely has to do with the presence of larger grants that employ many individuals.

Both schools have a low average path length (around 5), suggesting that no member of the network is more than five acquaintances away from any other. Likewise, the diameter of both networks is 18, which means that on each campus the most distant pair of nodes is separated by just 18 steps. University A’s slightly lower path length may be accounted for by the centralizing effect of its large medical school grant infrastructure. Finally, consider the clustering coefficient. This measure approaches 1 as it becomes more likely that two partners to a third node will themselves be connected. The likelihood that collaborators of collaborators will collaborate is high on both campuses, but substantially higher at university B.



**FIGURE 9.8** Distribution of path lengths for universities A and B

## 9.7 Summary

This chapter has provided a brief overview of the basics of networks and how to do large-scale network analysis. While network measures can produce new and exciting ways to characterize social dynamics, they are also important levels of analysis in their own right. Concepts such as reachability, cohesion, brokerage, and reciprocity are important, for a variety of reasons—they can be used to describe networks in terms of their composition and community structure. This chapter provides a classic example of how well social science meets data science. Social science is needed to identify the nodes (what is being connected) and the ties (the relationships that matter) in order to construct the relevant networks. Computer science is necessary to collect and structure the data in a fashion that is sufficient for analysis. The combination of data science and social science is key to making the right measurement and visualization decisions.

## 9.8 Resources

For more information about network analysis *in general*, the International Network for Social Network Analysis (<http://www.insna.org/>) is a large, interdisciplinary association dedicated to network analysis. It publishes a

traditional academic journal, *Social Networks*, an online journal, *Journal of Social Structure*, and a short-format journal, *Connections*, all dedicated to social network analysis. Its several listservs offer vibrant international forums for discussion of network issues and questions. Finally, its annual meetings include numerous opportunities for intensive workshops and training for both beginning and advanced analysts.

A new journal, *Network Science* (<http://journals.cambridge.org/action/displayJournal?jid=NWS>), published by Cambridge University Press and edited by a team of interdisciplinary network scholars, is a good venue to follow for cutting-edge articles on computational network methods and for substantive findings from a wide range of social, natural, and information science applications.

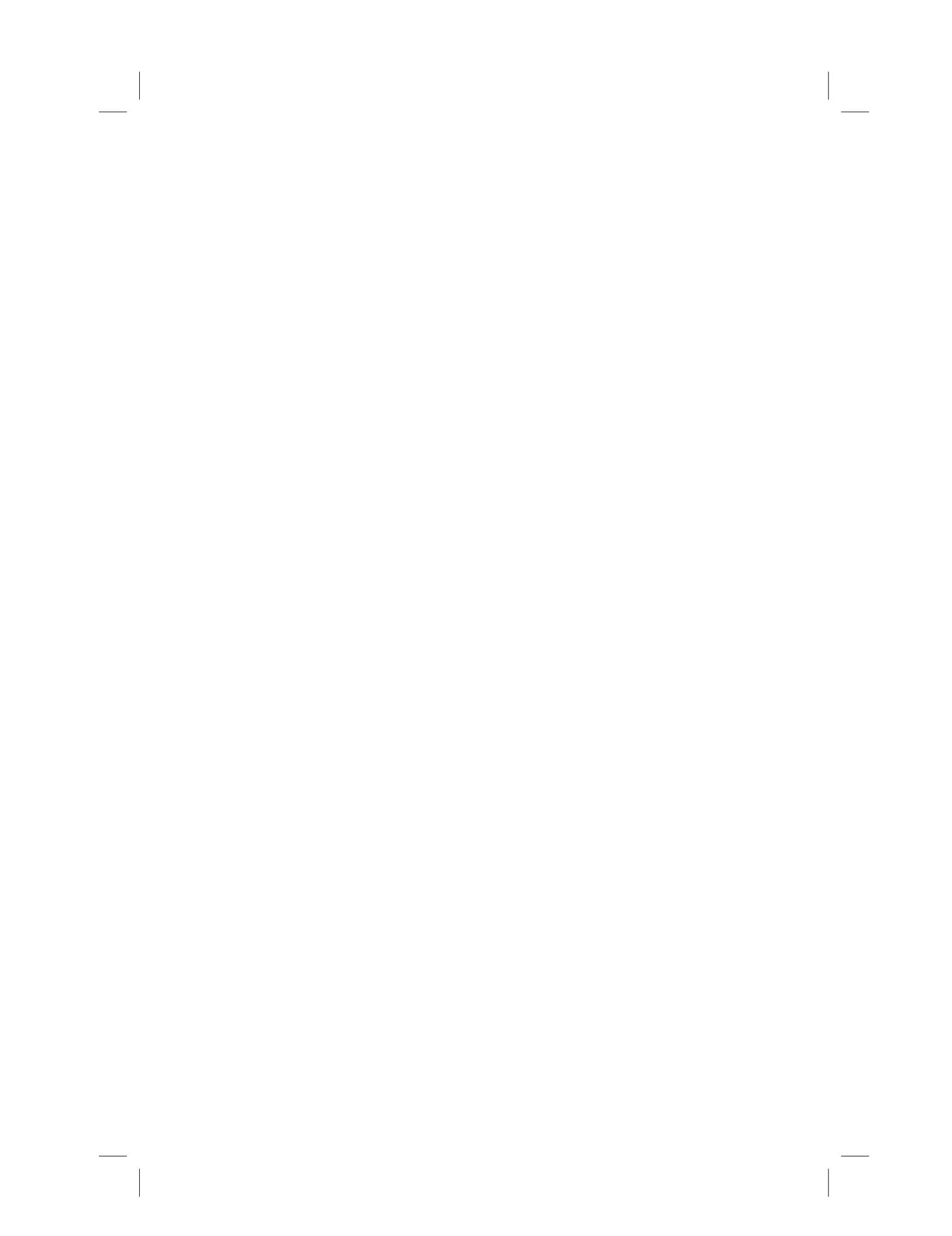
There are some good software packages available. *Pajek* (<http://mrvar.fdv.uni-lj.si/pajek/>) is a freeware package for network analysis and visualization. It is routinely updated and has a vibrant user group. Pajek is exceptionally flexible for large networks and has a number of utilities that allow import of its relatively simple file types into other programs and packages for network analysis. *Gephi* (<https://gephi.org/>) is another freeware package that supports large-scale network visualization. Though I find it less flexible than Pajek, it offers strong support for compelling visualizations.

*Stanford Network Analysis Platform (SNAP)* (<[snap.stanford.edu](http://snap.stanford.edu)>) is a general purpose library for network analysis and graph mining. It scales to very large networks, efficiently manipulates large graphs, calculates structural properties, generates regular and random graphs.

*Network Workbench* (<http://nwb.cns.iu.edu/>) is a freeware package that supports extensive analysis and visualization of networks. This package also includes numerous shared data sets from many different fields that can be used to test and hone your network analytic skills.

*iGraph* (<http://igraph.org/redirect.html>) is my preferred package for network analysis. Implementations are available in R, in Python, and in C libraries. The examples in this chapter were coded in iGraph for Python.

*Nexus* ([http://nexus.igraph.org/api/dataset\\_info?format=html&limit=10&offset=20&operator=or&order=date](http://nexus.igraph.org/api/dataset_info?format=html&limit=10&offset=20&operator=or&order=date)) is a growing repository for network data sets that includes some classic data dating back to the origins of social science network research as well as more recent data from some of the best-known publications and authors in network science.



# 10

---

## *Data Quality and Inference Errors*

---

**Paul P. Biemer**

This chapter deals with inference and the errors associated with big data. Social scientists know only too well the cost associated with bad data—we highlighted both the classic *Literary Digest* example and the more recent Google Flu Trends problems in Chapter Introduction. Although the consequences are well understood, the new types of data are so large and complex that their properties often cannot be studied in traditional ways. In addition, the data generating function is such that the data are often selective, incomplete, and erroneous. Without proper data hygiene, the errors can quickly compound. This chapter provides, for the first time, a systematic way to think about the error framework in a big data setting.

---

### 10.1 Introduction

The Machine Learning chapter and the Bias and Fairness chapter discuss how analysis errors can lead to bad inferences and suboptimal decision making. In fact the whole workflow we depicted in chapter 1 – and the decisions made along the way – can contribute to errors. In this chapter, we will focus on frameworks that help to detect errors in our data, highlight in general how errors can lead to incorrect inferences, and discuss some strategies to mitigate the inference risk from errors.

The massive amounts of high-dimensional and unstructured data that have recently become available to social scientists, such as data from social media platforms and micro-data from administrative data sources, bring both new opportunities and new challenges. Many of the problems with these types of data are well known (see, for example, the AAPOR report by Japec et al. (Japec et al. 2015)): this data often has selection bias, is incomplete, and erroneous. As it is processed and analyzed, new errors can be introduced in downstream operations.

These new sources of data are typically aggregated from disparate sources at

various points in time and integrated to form data sets for further analysis. The processing pipeline involve linking records together, transforming them to form new attributes (or variables), documenting the actions taken (although sometimes inadequately), and interpreting the newly created features of the data. These activities may introduce new errors into the data set: errors that may be either *variable* (i.e., errors that create random noise resulting in poor reliability) or *systematic* (i.e., errors that tend to be directional, thus exacerbating biases). Using these new sources of data in statistically valid ways is increasingly challenging in this environment; however, it is important for social scientists to be aware of the error risks and the potential effects of these errors on inferences and decision-making. The massiveness, high dimensionality, and accelerating pace of data, combined with the risks of variable and systematic data errors, requires new, robust approaches to data analysis.

The core issue that is often the cause of these errors is that such data may not be generated from instruments and methods designed to produce valid and reliable data for scientific analysis and discovery. Rather, this is data that are being repurposed for uses not originally intended. It has been referred to as “found” data or “data exhaust” because it is generated for purposes that often do not align with those of the data analyst. In addition to inadvertent errors, there are also errors from mischief in the data generation process; for example, automated systems have been written to generate bogus content in the social media that is indistinguishable from legitimate or authentic data. Social scientists using this data must be keenly aware of these limitations and should take the necessary steps to understand and hopefully mitigate the effects of hidden errors on their results.

---

## 10.2 The total error paradigm

We now provide a framework for describing, mitigating, and interpreting the errors in essentially any data set, be it structured or unstructured, massive or small, static or dynamic. This framework has been referred to as the total error framework or paradigm. We begin by reviewing the traditional paradigm, acknowledging its limitations for truly large and diverse data sets, and we suggest how this framework can be extended to encompass the new error structures described above.

### 10.2.1 The traditional model

Dealing with the risks that errors introduce in big data analysis can be facilitated through a better understanding of the sources and nature of those errors. Such knowledge is gained through in-depth understanding of the data generating mechanism, the data processing/transformation infrastructure, and the approaches used to create a specific data set or the estimates derived from it. For survey data, this knowledge is embodied in the well-known *total survey error* (TSE) framework that identifies all the major sources of error contributing to data validity and estimator accuracy (Groves 2004; Biemer and Lyberg 2003; Biemer 2010). The TSE framework attempts to describe the nature of the error sources and what they may suggest about how the errors could affect inference. The framework parses the total error into bias and variance components that, in turn, may be further subdivided into subcomponents that map the specific types of errors to unique components of the total mean squared error. It should be noted that, while our discussion on issues regarding inference has quantitative analyses in mind, some of the issues discussed here are also of interest to more qualitative uses of big data.

For surveys, the TSE framework provides useful insights regarding how data generating, reformatting, and file preparation processes affect estimation and inference, and suggest methods for either reducing the errors at their source or adjusting for their effects in the final products to produce inferences of higher quality. (Add classic TSE citations)

The traditional TSE framework is quite general in that it can be applied to essentially any data set that conform to the format in Figure 10.1. However, in most practical situations it is quite limited because it makes no attempt to describe how the processes that the data may have contributed to what could be construed as data errors. In some cases, these processes constitute a “black box,” and the best approach is to attempt to evaluate the quality of the end product. For survey data, the TSE framework provides a fairly complete description of the error-generating processes for survey data and survey frames (Biemer 2010). In addition, there has been some effort to describe these processes for population registers and administrative data (Wallgren and Wallgren 2007). But at this writing, little effort has been devoted to enumerating the error sources and the error generating processes for big data.

#### 10.2.1.1 Types of Errors

Many administrative data sets have a simple tabular structure, as do survey sampling frames, population registers, and accounting Spreadsheets. Figure 10.1 is a representation of tabular data as an array consisting of rows (records) and columns (variables), with their size denoted by  $N$  and  $p$ , respectively. The rows typically represent units or elements of our target population, the

columns represent characteristics, variables (or features) of the row elements, and the cells correspond to values of the column features for elements on the rows.

Record #	V <sub>1</sub>	V <sub>2</sub>	...	V <sub>P</sub>
1				
2				
...				
N				

**FIGURE 10.1** A typical rectangular data file format

The total error for this data set may be expressed by the following heuristic formula:

$$\text{Total error} = \text{Row error} + \text{Column error} + \text{Cell error}.$$

### Row error

For the situations considered in this chapter, the row errors may be of three types:

- **Omissions:** Some rows are missing, which implies that elements in the target population are not represented on the file.
- **Duplications:** Some population elements occupy more than one row.
- **Erroneous inclusions:** Some rows contain elements or entities that are not part of the target population.

Omissions:

For survey sample data sets, omissions include members of the target population that are either inadvertently or deliberately absent from the frame, as well as nonsampled frame members. For other types of data, the selectivity of the capture mechanism is a common cause of omissions. For example, a data set consisting of people who did a Google search in the past week can be used to make inferences about that specific population but if our goal was to make inferences about the larger population of internet users, this data set will exclude people who did not use Google Search. This selection bias can lead to inference errors if the people who did not use Google Search were different from those who did.

Such exclusions can therefore be viewed as a source of selectivity bias if inference is to be made about an even larger set of people, such as the general population. For one, persons who do not have access to the Internet are excluded from the data set. These exclusions may be biasing in that persons with Internet

access may have quite different demographic characteristics from persons who do not have Internet access (Dutwin and Buskirk 2017). The selectivity of big data capture is similar to frame noncoverage in survey sampling and can bias inferences when researchers fail to consider it and compensate for it in their analyses.

---

### Example: Google searches

As an example, in the United States, the word “Jewish” is included in 3.2 times more Google searches than “Mormon” (Stephens-Davidowitz and Varian 2015). This does not mean that the Jewish population is 3.2 times larger than the Mormon population. Other possible explanations could that Jewish people use the Internet in higher proportions, have more questions that require using the word “Jewish”, or there could be more searches for “Jewish food” food than “Mormon food.” Thus Google search data are more useful for relative comparisons than for estimating absolute levels.

---

A well-known formula in the survey literature provides a useful expression for the so-called *coverage bias* in the mean of some variable,  $V$ . Denote the mean by  $\bar{V}$ , and let  $\bar{V}_T$  denote the (possibly hypothetical because it may not be observable) mean of the target population of  $N_T$  elements, including the  $N_T - N$  elements that are missing from the observed data set. Then the bias due to this *noncoverage* is  $B_{NC} = \bar{V} - \bar{V}_T = (1 - N/N_T)(\bar{V}_C - \bar{V}_{NC})$ , where  $\bar{V}_C$  is the mean of the *covered* elements (i.e., the elements in the observed data set) and  $\bar{V}_{NC}$  is the mean of the  $N_T - N$  *noncovered* elements. Thus we see that, to the extent that the difference between the covered and noncovered elements is large or the fraction of missing elements ( $1 - N/N_T$ ) is large, the bias in the descriptive statistic will also be large. As in survey research, often we can only speculate about the sizes of these two components of bias. Nevertheless, speculation is useful for understanding and interpreting the results of data analysis and cautioning ourselves regarding the risks of false inference.

Duplication:

We can also expect that big data sets, such as a data set containing Google searches during the previous week, could have the same person represented many times. People who conducted many searches during the data capture period would be disproportionately represented relative to those who conducted fewer searches. If the rows of the data set correspond to tweets in a Twitter feed, duplication can arise when the same tweet is retweeted or when some persons are quite active in tweeting while others lurk and tweet much less frequently. Whether such duplications should be regarded as “errors” depends upon the goals of the analysis.

For example, if inference is to be made to a population of persons, persons

who tweet multiple times on a topic would be overrepresented. If inference is to be made to the population of tweets, including retweets, then such duplication does not bias inference. This is also common in domains such as healthcare or human services where certain people have more interactions with the systems (medical appointments, consumption of social services, etc.) and can be over-represented when doing analysis at an individual interaction level.

When it is a problem, it still may not be possible to identify duplications in the data. Failing to account for them could generate duplication biases in the analysis. If these unwanted duplications can be identified, they can either be removed from the data file (i.e., deduplication). Alternatively, if a certain number of rows, say  $d$ , correspond to the same population unit, those row values can be weighted by  $1/d$  to correct the estimates for the duplications.

#### Erroneous inclusions:

Erroneous inclusions can also create biases. For example, Google searches or tweets may not be generated by a person but rather by a computer either maliciously or as part of an information-gathering or publicity-generating routine. Likewise, some rows may not satisfy the criteria for inclusion in an analysis—for example, an analysis by age or gender includes some row elements not satisfying the criteria. If the criteria can be applied accurately, the rows violating the criteria can be excluded prior to analysis. However, with big data, some out-of-scope elements may still be included as a result of missing or erroneous information, and these inclusions will bias inference.

#### Column error

The most common type of column error in survey data analysis is caused by inaccurate or erroneous labeling of the column data—an example of metadata error. In the TSE framework, this is referred to as a *specification* error. For example, a business register may include a column labeled “number of employees,” defined as the number of persons in the company who received a payroll check in the month preceding. Instead the column contains the number of persons on the payroll whether or not they received a check in the prior month, thus including, for example, persons on leave without pay.

When analyzing a more diverse set of data sources, such errors could happen because of the complexities involved in producing a data set. For example, data generated an individual tweet may undergo a number of transformations before it is included in the analysis data set. This transformative process can be quite complex, involving parsing phrases, identifying words, and classifying them as to subject matter and then perhaps further classifying them as either positive or negative expressions about some phenomenon like the economy or a political figure. There is considerable risk of the resulting variables being either inaccurately defined or misinterpreted by the data analyst.

**Example: Specification error with Twitter data**

As an example, consider a Twitter data set where the rows correspond to tweets and one of the columns supposedly contains an indicator of whether the tweet contained one of the following key words: marijuana, pot, cannabis, weed, hemp, ganja, or THC. Instead, the indicator actually corresponds to whether the tweet contained a shorter list of words; say, either marijuana or pot. The mislabeled column is an example of specification error which could be a biasing factor in an analysis. For example, estimates of marijuana use based upon the indicator could be underestimates.

---

**Cell errors**

Finally, cell errors can be of three types: content error, specification error, or missing data.

**Content Error:** A content error occurs when the value in a cell satisfies the column definition but still deviates from the true value, whether or not the true value is known. For example, the value satisfies the definition of “number of employees” but is outdated because it does not agree with the current number of employees. Errors in sensitive data such as drug use, prior arrests, and sexual misconduct may be deliberate. Thus, content errors may be the result of the measurement process, a transcription error, a data processing error (e.g., keying, coding, editing), an imputation error, or some other cause.

**Specification Error:** Specification error is just as described for column error but applied to a cell. For example, the column is correctly defined and labeled; however, a few companies provided values that, although otherwise highly accurate, were nevertheless inconsistent with the required definition.

**Missing data:** Missing data, as the name implies, are just empty cells. As described in Kreuter and Peng (Kreuter and Peng 2014), data sets derived from big data are notoriously affected by all three types of cell error, particularly missing or incomplete data, perhaps because that is the most obvious deficiency.

Missing data can take two forms: missing information in a cell of a data matrix (referred to as *item missingness*) or missing rows (referred to as *unit missingness*), with the former being readily observable whereas the latter can be completely hidden from the analyst. Much is known from the survey research literature about how both types of missingness affect data analysis (see, for example, Little and Rubin (Little and Rubin 2014; Rubin 1976)). Rubin (Rubin 1976) introduced the term *missing completely at random (MCAR)* to describe data where the data that are available (say, the rows of a data set) can be considered as a simple random sample of the inferential population (i.e., the population to which inferences from the data analysis will be made). Since the data set represents the population, MCAR data provide results that are generalizable to this population.

A second possibility also exists for the reasons why data are missing. For example, students who have high absenteeism may be missing because they were ill on the day of the test. They may otherwise be average performers on the test so, in this case, it has little to do with how they would score. Thus, the values are missing for reasons related to another variable, health, that may be available in the data set and completely observed. Students with poor health tend to be missing test scores, regardless of those student's performance on the test. Rubin (Rubin 1976) uses the term *missing at random (MAR)* to describe data that are missing for reasons related to completely observed variables in the data set. It is possible to compensate for this type of missingness in statistical inferences by modeling the missing data mechanism.

However, most often, missing data may be related to factors that are not represented in the data set and, thus, the missing data mechanism cannot be adequately modeled. For example, there may be a tendency for test scores to be missing from school administrative data files for students who are poor academic performers. Rubin calls this form of missingness *nonignorable*. With nonignorable missing data, the reasons for the missing observations depend on the values that are missing. When we suspect a nonignorable missing data mechanism, we need to use procedures much more complex than will be described here. Little and Rubin (Little and Rubin 2014) and Schafer (Schafer 1997) discuss methods that can be used for nonignorable missing data. Ruling out a nonignorable response mechanism can simplify the analysis considerably.

In practice, it is quite difficult to obtain empirical evidence about whether or not the data are MCAR or MAR. Understanding the data generation process is invaluable for specifying models that appropriately represent the missing data mechanism and that will then be successful in compensating for missing data in an analysis. (Schafer and Graham (Schafer and Graham 2002) provide a more thorough discussion of this issue.)

One strategy for ensuring that the missing data mechanism can be successfully modeled is to have available on the data set many variables that may be causally related to missing data. For example, features such as personal income are subject to high item missingness, and often the missingness is related to income. However, less sensitive, surrogate variables such as years of education or type of employment may be less subject to missingness. The statistical relationship between income and other income-related variables increases the chance that information lost in missing variables is supplemented by other completely observed variables. Model-based methods use the multivariate relationship between variables to handle the missing data. Thus, the more informative the data set, the more measures we have on important constructs, the more successfully we can compensate for missing data using model-based Approaches.

In the next section, we consider the impact of errors on some forms of analysis that are common in the big data literature. We will limit the focus on the effects

of content errors on data analysis. However, there are numerous resources available for studying and mitigating the effects of missing data on analysis such as books by Little and Rubin (Little and Rubin 2014), Schafer (Schafer 1997), and Allison (Allison 2001).

### 10.3 Example: Google Flu Trends

A well-known example of the risks of bad inference is provided by the Google Flu Trends series that uses Google searches on flu symptoms, remedies, and other related key words to provide near-real-time estimates of flu activity in the USA and 24 other countries<sup>1</sup>. Compared to CDC data, the Google Flu Trends provided remarkably accurate indicators of flu incidence in the USA between 2009 and 2011. However, for the 2012–2013 flu seasons, the Google Flu Trends estimates were almost double the CDC’s (Butler 2013). Lazer et al. (Lazer et al. 2014) cite two causes of this error: big data hubris and algorithm dynamics.

Hubris occurs when the big data researcher believes that the volume of the data compensates for any of its deficiencies, thus obviating the need for traditional, scientific analytic approaches. As Lazer et al. (Lazer et al. 2014) note, big data hubris fails to recognize that “quantity of data does not mean that one can ignore foundational issues of measurement and construct validity and reliability.”

Algorithm dynamics refers to properties of algorithms that allow them to adapt and “learn” as the processes generating the data change over time. Although explanations vary, the fact remains that Google Flu Trends was too high and by considerable margins for 100 out of 108 weeks starting in July 2012. Lazer et al. (Lazer et al. 2014) also blame “blue team dynamics,” which arises when the data generating engine is modified in such a way that the formerly highly predictive search terms eventually failed to work. For example, when a Google user searched on “fever” or “cough,” Google’s other programs started recommending searches for flu symptoms and treatments—the very search terms the algorithm used to predict flu. Thus, flu-related searches artificially spiked as a result of these changes to the algorithm and the impact these changes had on user behavior. In survey research, this is similar to the measurement biases induced by interviewers who suggest to respondents who are coughing that they might have flu, then ask the same respondents if they think they might have flu.

Algorithm dynamic issues are not limited to Google. Platforms such as Twitter

<sup>1</sup>See the discussion in Section 1.3.

and Facebook are also frequently modified to improve the user experience. A key lesson provided by Google Flu Trends is that successful analyses using big data today may fail to produce good results tomorrow. All these platforms change their methodologies more or less frequently, with ambiguous results for any kind of long-term study unless highly nuanced methods are routinely used. Recommendation engines often exacerbate effects in a certain direction, but these effects are hard to tease out. Furthermore, other sources of error may affect Google Flu Trends to an unknown extent. For example, selectivity may be an important issue because the demographics of people with Internet access are quite different from the demographic characteristics related to flu incidence (Thompson, Comanor, and Shay 2006). Thus, the “at risk” population for influenza and the implied population based on Google searches do not correspond. This illustrates just one type of representativeness issue that often plagues big data analysis. In general it is an issue that algorithms are not (publicly) measured for accuracy, since they are often proprietary. Google Flu Trends is special in that it publicly failed. From what we have seen, most models fail privately and often without anyone at all noticing. —————

---

## 10.4 Errors in data analysis

The total error framework described above focuses on different types of errors in the data that can lead to incorrect inference. In addition to direct inference errors because of errors in the data, our analysis can also be incorrect because of these data errors. This section goes deeper into these common types of analysis errors when analyzing a diverse set of data sources. We begin by exploring errors that can happen under the assumption of accurate data and then go on to consider errors in three common types of analysis when data is not accurate: classification, correlation, and regression.

### Analysis errors despite accurate data

Data deficiencies represent only one set of challenges for the big data analyst. Even if data is correct, other challenges can arise solely as a result of the massive size, rapid generation, and vast dimensionality of the data (Meng 2018). Fan et al. (Fan, Han, and Liu 2014) identify three issues—noise accumulation, spurious correlations, and incidental endogeneity—which will be discussed in this section. These issues should concern social scientists even if the data could be regarded as infallible. Content errors, missing data, and other data deficiencies will only exacerbate these problems.

#### Noise accumulation\*\*

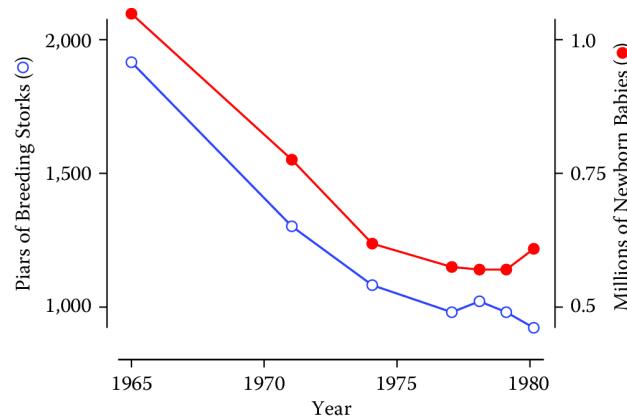
To illustrate noise accumulation, Fan et al. (Fan, Han, and Liu 2014) consider

the following scenario. Suppose an analyst is interested in classifying individuals into two categories,  $C_1$  and  $C_2$ , based upon the values of 1,000 variables in a big data set. Suppose further that, unknown to the researcher, the mean value for persons in  $C_1$  is 0 on all 1,000 variables while persons in  $C_2$  have a mean of 3 on the first 10 variables and 0 on all other variables. Since we are assuming the data are error-free, a classification rule based upon the first  $m \leq 10$  variables performs quite well, with little classification error. However, as more and more variables are included in the rule, classification error increases because the uninformative variables (i.e., the 990 variables having no discriminating power) eventually overwhelm the informative signals (i.e., the first 10 variables). In the Fan et al. (Fan, Han, and Liu 2014) example, when  $m > 200$ , the accumulated noise exceeds the signal embedded in the first 10 variables and the classification rule becomes equivalent to a coin-flip classification rule.

---

#### Spurious correlations\*\*

High dimensionality can also introduce coincidental (or *spurious*) correlations in that many unrelated variables may be highly correlated simply by chance, resulting in false discoveries and erroneous inferences. The phenomenon depicted in Figure 10.2, is an illustration of this. Many more examples can be found on a website and in a book devoted to the topic (Vigen, n.d.; Vigen 2015). Fan et al. (Fan, Han, and Liu 2014) explain this phenomenon using simulated populations and relatively small sample sizes. They illustrate how, with 800 independent (i.e., uncorrelated) variables, the analyst has a 50% chance of observing an absolute correlation that exceeds 0.4. Their results suggest that there are considerable risks of false inference associated with a purely empirical approach to predictive analytics using high-dimensional data.



**FIGURE 10.2** An illustration of coincidental correlation between two variables: stork die-off linked to human birth decline [@sies1988new]

### Incidental Endogeneity\*\*

Finally, turning to incidental endogeneity, a key assumption in regression analysis is that the model covariates are uncorrelated with the residual error; endogeneity refers to a violation of this assumption. For high-dimensional models, this can occur purely by chance—a phenomenon Fan and Liao (Fan and Liao 2014) call *incidental endogeneity*. Incidental endogeneity leads to the modeling of spurious variation in the outcome variables resulting in errors in the model selection process and biases in the model predictions. The risks of incidental endogeneity increase as the number of variables in the model selection process grows large. Thus it is a particularly important concern for big data analytics.

Fan et al. (Fan, Han, and Liu 2014) as well as a number of other authors (Stock and Watson 2002; Fan, Samworth, and Wu 2009) (see, for example, Hall and Miller (Hall and Miller 2009); Fan and Liao, (Fan and Liao 2012)) suggest robust statistical methods aimed at mitigating the risks of noise accumulation, spurious correlations, and incidental endogeneity. However, as previously noted, these issues and others are further compounded when data errors are present in a data set. Biemer and Trewin (Biemer and Trewin 1997) show that data errors will bias the results of traditional data analysis and inflate the variance of estimates in ways that are difficult to evaluate or mitigate in the analysis process.

#### 10.4.1 Analysis errors resulting from inaccurate data

The previous sections examined some of the issues social scientists face as either  $N$  or  $p$  in Figure 10.1 becomes extremely large. When row, column, and cell errors are added into the mix, these problems can be further exacerbated. For example, noise accumulation can be expected to accelerate when random noise (i.e., content errors) afflicts the data. Spurious correlations that give rise to both incidental endogeneity and coincidental correlations can render correlation analysis meaningless if the error levels in big data are not mitigated. In this section, we consider some of the issues that arise in classification, correlation, and regression analysis as a result of content errors that may be either variable or systematic.

There are various important findings in this section. First, for rare classes, even small levels of error can impart considerable biases in classification analysis. Second, variable errors will attenuate correlations and regression slope coefficients; however, these effects can be mitigated by forming meaningful aggregates of the data and substituting these aggregates for the individual units in these analyses. Third, unlike random noise, systematic errors can bias correlation and regression analysis in unpredictable ways, and these biases cannot be effectively mitigated by aggregating the data. Finally, multilevel

modeling can – under certain circumstances – be an important mitigation strategy for dealing with systematic errors emanating from multiple data sources. These issues will be examined in some detail in the remainder of this section.

We will start by focusing on two types of errors: variable (uncorrelated) errors and correlated errors. We'll first describe these errors for continuous data and then extend it to categorical variables in the next section

#### 10.4.1.1 Variable (uncorrelated) and correlated error in continuous variables

Error models are essential for understanding the effects of error on data sets and the estimates that may be derived from them. They allow us to concisely and precisely communicate the nature of the errors that are being considered, the general conditions that give rise to them, how they affect the data, how they may affect the analysis of these data, and how their effects can be evaluated and mitigated. In the remainder of this chapter, we focus primarily on content errors and consider two types of error, variable errors and correlated errors, the latter a subcategory of systematic errors.

Variable errors are sometimes referred to as *random noise* or *uncorrelated* errors. For example, administrative databases often contain errors from a myriad of random causes, including mistakes in keying or other forms of data capture, errors on the part of the persons providing the data due to confusion about the information requested, difficulties in recalling information, the vagaries of the terms used to request the inputs, and other system deficiencies.

Correlated errors, on the other hand, carry a systematic effect that results in a nonzero covariance between the errors of two distinct units. For example, quite often, an analysis data set may combine multiple data sets from different sources and each source may impart errors that follow a somewhat different distribution. As we shall see, these differences in error distributions can induce correlated errors in the merged data set. It is also possible that correlated errors are induced from a single source as a result of different operators (e.g., computer programmers, data collection personnel, data editors, coders, data capture mechanisms) handling the data. Differences in the way these operators perform their tasks have the potential to alter the error distributions so that data elements handled by the same operator have errors that are correlated (Biemer and Lyberg 2003).

These concepts may be best expressed by a simple error model. Let  $y_{rc}$  denote the cell value for variable  $c$  on the  $r$ th unit in the data set, and let  $\varepsilon_{rc}$  denote the error associated with this value. Suppose it can be assumed that there is a true value underlying  $y_{rc}$ , which is denoted by  $\mu_{rc}$ . Then we can write

$$y_{rc} = \mu_{rc} + \varepsilon_{rc}.$$

At this point,  $\varepsilon_{rc}$  is not stochastic in nature because a statistical process for generating the data has not yet been assumed. Therefore, it is not clear what *correlated error* really means. To remedy this problem, we can consider the hypothetical situation where the processes generating the data set can be repeated under the same general conditions (i.e., at the same point in time with the same external and internal factors operating). Each time the processes are repeated, a different set of errors may be realized. Thus, it is assumed that although the true values,  $\mu_{rc}$ , are fixed, the errors,  $\varepsilon_{rc}$ , can vary across the hypothetical, infinite repetitions of the data set generating process. Let  $E(\cdot)$  denote the expected value over all these hypothetical repetitions, and define the variance,  $\text{Var}(\cdot)$ , and covariance,  $\text{Cov}(\cdot)$ , analogously.

For the present, error correlations between variables are not considered, and thus the subscript,  $c$ , is dropped to simplify the notation. For the uncorrelated data model, we assume that  $E(y_r|r) = \mu_r$ ,  $\text{Var}(y_r|r) = \sigma_\varepsilon^2$ , and  $\text{Cov}(y_r, y_s|r, s) = 0$ , for  $r \neq s$ . For the correlated data model, the latter assumption is relaxed. To add a bit more structure to the model, suppose the data set is the product of combining data from multiple sources (or operators) denoted by  $j = 1, 2, \dots, J$ , and let  $b_j$  denote the systematic effect of the  $j$ th source. Here we also assume that, with each hypothetical repetition of the data set generating process, these systematic effects can vary stochastically. (It is also possible to assume the systematic effects are fixed. See, for example, Biemer and Stokes (Biemer and Stokes 1991) for more details on this model.) Thus, we assume that  $E(b_j) = 0$ ,  $\text{Var}(b_j) = \sigma_b^2$ , and  $\text{Cov}(b_j, b_k) = 0$  for  $j \neq k$ .

Finally, for the  $r$ th unit within the  $j$ th source, let  $\varepsilon_{rj} = b_j + e_{rj}$ . Then it follows that

$$\text{Cov}(\varepsilon_{rj}, \varepsilon_{sk}) = \begin{cases} \sigma_b^2 + \sigma_\varepsilon^2 & \text{for } r = s, j = k, \\ \sigma_\varepsilon^2 & \text{for } r = s, j \neq k, \\ 0 & \text{for } r \neq s, j \neq k. \end{cases}$$

The case where  $\sigma_b^2 = 0$  corresponds to the uncorrelated error model (i.e.,  $b_j = 0$ ) and thus  $\varepsilon_{rj}$  is purely random noise.

---

### Example: Speed sensor

Suppose that, due to calibration error, the  $j$ th speed sensor in a traffic pattern study underestimates the speed of vehicle traffic on a highway by an average of 4 miles per hour. Thus, the model for this sensor is that the speed for the  $r$ th vehicle recorded by this sensor ( $y_{rj}$ ) is the vehicle's true speed ( $\mu_{rj}$ ) minus 4 mph ( $b_j$ ) plus a random departure from -4 for the  $r$ th vehicle ( $\varepsilon_{rj}$ ). Note that to the extent that  $b_j$  varies across sensors  $j = 1, \dots, J$  in the study,  $\sigma_b^2$  will be large. Further, to the extent that ambient noise in the readings for  $j$ th sensor causes variation around the values  $\mu_{rc} + b_j$ , then  $\sigma_\varepsilon^2$  will be large. Both sources of variation will reduce the reliability of the measurements. However,

as shown in Section [Correlation analysis], the systematic error component is particularly problematic for many types of analysis.

#### 10.4.1.2 Extending Variable and Correlated Error to Categorical Data

For variables that are categorical, the model of the previous section is not appropriate because the assumptions it makes about the error structure do not hold. For example, consider the case of a binary (0/1) variable. Since both  $y_r$  and  $\mu_r$  should be either 1 or 0, the error in equation (10.1) must assume the values of -1, 0, or 1. A more appropriate model is the misclassification model described by Biemer (Biemer 2011), which we summarize here.

Let  $\phi_r$  denote the probability of a false positive error (i.e.,  $\phi_r = \Pr(y_r = 1 | \mu_r = 0)$ ), and let  $\theta_r$  denote the probability of a false negative error (i.e.,  $\theta_r = \Pr(y_r = 0 | \mu_r = 1)$ ). Thus, the probability that the value for row  $r$  is correct is  $1 - \theta_r$  if the true value is 1, and  $1 - \phi_r$  if the true value is 0.

As an example, suppose an analyst wishes to compute the proportion,  $P = \sum_r y_r / N$ , of the units in the file that are classified as 1, and let  $\pi = \sum_r \mu_r / N$  denote the true proportion. Then under the assumption of uncorrelated error, Biemer (Biemer 2011) shows that

$$P = \pi(1 - \theta) + (1 - \pi)\phi,$$

where  $\theta = \sum_r \theta_r / N$  and  $\phi = \sum_r \phi_r / N$ .

In the classification error literature, the sensitivity of a classifier is defined as  $1 - \theta$ , that is, the probability that a true positive is correctly classified. Correspondingly,  $1 - \phi$  is referred to as the specificity of the classifier, that is, the probability that a true negative is correctly classified. Two other quantities that will be useful in our study of misclassification error are the positive predictive value (PPV) and negative predictive value (NPV) given by

$$\text{PPV} = \Pr(\mu_r = 1 | y_r = 1), \quad \text{NPV} = \Pr(\mu_r = 0 | y_r = 0).$$

The PPV (NPV) is the probability that a positive (negative) classification is correct.

#### 10.4.1.3 Errors when analyzing rare population groups

{#sec:10-4.2.3}

One of the attractions of newer sources of data such as social media is the ability to study rare population groups that seldom show up in large enough numbers in designed studies such as surveys and clinical trials. While this is

true in theory, in practice content errors can affect the inferences that can be drawn from this data. We illustrate this using the following contrived and somewhat amusing example. The results in this section are particularly relevant to the approaches considered in Chapter Machine Learning.

---

### Example: Thinking about probabilities

Suppose, using big data and other resources, we construct a terrorist detector and boast that the detector is 99.9% accurate. In other words, both the probability of a false negative (i.e., classifying a terrorist as a nonterrorist,  $\theta$ ) and the probability of a false positive (i.e., classifying a nonterrorist as a terrorist,  $\phi$ ) are 0.001. Assume that about 1 person in a million in the population is a terrorist, that is,  $\pi = 0.000001$  (hopefully, somewhat of an overestimate). Your friend, Terry, steps into the machine and, to Terry's chagrin (and your surprise) the detector declares that he is a terrorist! What are the odds that the machine is right? The surprising answer is only about 1 in 1000. That is, 999 times out of 1,000 times the machine classifies a person as a terrorist, the machine will be wrong!

---

How could such an accurate machine be wrong so often in the terrorism example? Let us do the math.

The relevant probability is the PPV of the machine: given that the machine classifies an individual (Terry) as a terrorist, what is the probability the individual is truly a terrorist? Using the notation in Section [Models for categorical data] and Bayes' rule, we can derive the PPV as

$$\begin{aligned} \Pr(\mu_r = 1 | y_r = 1) &= \frac{\Pr(y_r = 1 | \mu_r = 1) \Pr(\mu_r = 1)}{\Pr(y_r = 1)} \\ &= \frac{(1 - \theta)\pi}{\pi(1 - \theta) + (1 - \pi)\phi} \\ &= \frac{0.999 \times 0.000001}{0.000001 \times 0.999 + 0.99999 \times 0.001} \\ &\approx 0.001. \end{aligned}$$

This example calls into question whether security surveillance using emails, phone calls, etc. can ever be successful in finding rare threats such as terrorism since to achieve a reasonably high PPV (say, 90%) would require a sensitivity and specificity of at least  $1 - 10^{-7}$ , or less than 1 chance in 10 million of an error.

To generalize this approach, note that any population can be regarded as a *mixture* of subpopulations. Mathematically, this can be written as

$$f(y|\mathbf{x}; \mathfrak{D}) = \pi_1 f(y|\mathbf{x}; \mathfrak{D}_1) + \pi_2 f(y|\mathbf{x}; \mathfrak{D}_2) + \dots + \pi_K f(y|\mathbf{x}; \mathfrak{D}_K),$$

where  $f(y|\mathbf{x}; \boldsymbol{\theta})$  denotes the population distribution of  $y$  given the vector of explanatory variables  $\mathbf{x}$  and the parameter vector  $\boldsymbol{\theta} = (\theta_1, \theta_2, \dots, \theta_K)$ ,  $\pi_k$  is the proportion of the population in the  $k$ th subgroup, and  $f(y|\mathbf{x}; \theta_k)$  is the distribution of  $y$  in the  $k$ th subgroup. A rare subgroup is one where  $\pi_k$  is quite small (say, less than 0.01).

Table 10.1 shows the PPV for a range of rare subgroup sizes when the sensitivity is perfect (i.e., no misclassification of true positives) and specificity is not perfect but still high. This table reveals the fallacy of identifying rare population subgroups using fallible classifiers unless the accuracy of the classifier is appropriately matched to the rarity of the subgroup. As an example, for a 0.1% subgroup, the specificity should be at least 99.99%, even with perfect sensitivity, to attain a 90% PPV.

TABLE 10.1: Positive predictive value (%) for rare subgroups, high specificity, and perfect sensitivity

$\pi_k$	Specificity		
	99%	99.9%	99.99%
0.1	91.70	99.10	99.90
0.01	50.30	91.00	99.00
0.001	9.10	50.00	90.90
0.0001	1.00	9.10	50.00

#### 10.4.1.4 Errors in Correlation analysis

In Section [Errors resulting from volume, velocity, and variety, assuming perfect veracity], we considered the problem of incidental correlation that occurs when an analyst correlates pairs of variables selected from big data stores containing thousands of variables. In this section, we discuss how errors in the data can exacerbate this problem or even lead to failure to recognize strong associations among the variables. We confine the discussion to the continuous variable model of Section [Variable and correlated error] and begin with theoretical results that help explain what happens in correlation analysis when the data are subject to variable and systematic errors.

For any two variables in the data set,  $c$  and  $d$ , define the covariance between  $y_{rc}$  and  $y_{rd}$  as

$$\sigma_{y|cd} = \frac{\sum_r E(y_{rc} - \bar{y}_c)(y_{rd} - \bar{y}_d)}{N},$$

where the expectation is with respect to the error distributions and the sum extends over all rows in the data set. Let

$$\sigma_{\mu|cd} = \frac{\sum_r (\mu_{rc} - \bar{\mu}_c)(\mu_{rd} - \bar{\mu}_d)}{N}$$

denote the *population covariance*. (The population is defined as the set of all units corresponding to the rows of the data set.) For any variable  $c$ , define the variance components

$$\sigma_{y|c}^2 = \frac{\sum_r (y_{rc} - \bar{y}_c)^2}{N}, \quad \sigma_{\mu|c}^2 = \frac{\sum_r (\mu_{rc} - \bar{\mu}_c)^2}{N},$$

and let

$$R_c = \frac{\sigma_{\mu|c}^2}{\sigma_{\mu|c}^2 + \sigma_{b|c}^2 + \sigma_{\varepsilon|c}^2}, \quad \rho_c = \frac{\sigma_{b|c}^2}{\sigma_{\mu|c}^2 + \sigma_{b|c}^2 + \sigma_{\varepsilon|c}^2},$$

with analogous definitions for  $d$ . The ratio  $R_c$  is known as the *reliability ratio*, and  $\rho_c$  will be referred to as the *intra-source correlation*. Note that the reliability ratio is the proportion of total variance that is due to the variation of true values in the data set. If there were no errors, either variable or systematic, then this ratio would be 1. To the extent that errors exist in the data,  $R_c$  will be less than 1.

Likewise,  $\rho_c$  is also a ratio of variance components that reflects the proportion of total variance that is due to systematic errors with biases that vary by data source. A value of  $\rho_c$  that exceeds 0 indicates the presence of systematic error variation in the data. As we shall see, even small values of  $\rho_c$  can cause big problems in correlation analysis.

Using the results in Biemer and Trewin (Biemer and Trewin 1997), it can be shown that the correlation between  $y_{rc}$  and  $y_{rd}$ , defined as  $\rho_{y|cd} = \sigma_{y|cd}/\sigma_{y|c}\sigma_{y|d}$ , can be expressed as

$$\rho_{y|cd} = \sqrt{R_c R_d} \rho_{\mu|cd} + \sqrt{\rho_c \rho_d}.$$

Note that if there are no errors (i.e., when  $\sigma_{b|c}^2 = \sigma_{\varepsilon|c}^2 = 0$ ), then  $R_c = 1$ ,  $\rho_c = 0$ , and the correlation between  $y_c$  and  $y_d$  is just the population correlation.

Let us consider the implications of these results first without systematic errors (i.e., only variable errors) and then with the effects of systematic errors.

### Variable errors only

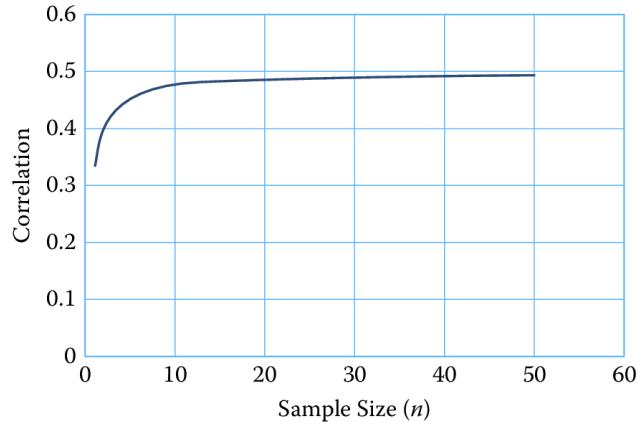
If the only errors are due to random noise, then the additive term on the right in equation (10.2) is 0 and  $\rho_{y|cd} = \sqrt{R_c R_d} \rho_{\mu|cd}$ , which says that the correlation is attenuated by the product of the root reliability ratios. For example, suppose  $R_c = R_d = 0.8$ , which is considered excellent reliability. Then the observed correlation in the data will be about 80% of the true correlation; that is, correlation is attenuated by random noise. Thus,  $\sqrt{R_c R_d}$  will be referred to as the *attenuation factor* for the correlation between two variables.

Quite often in the analysis of big data, the correlations being explored are for aggregate measures, as in Figure 10.2. Therefore, suppose that, rather than being a single element,  $y_{rc}$  and  $y_{rd}$  are the means of  $n_{rc}$  and  $n_{rd}$  independent

elements, respectively. For example,  $y_{rc}$  and  $y_{rd}$  may be the average rate of inflation and the average price of oil, respectively, for the  $r$ th year, for  $r = 1, \dots, N$  years. Aggregated data are less affected by variable errors because, as we sum up the values in a data set, the positive and negative values of the random noise components combine and cancel each other under our assumption that  $E(\varepsilon_{rc}) = 0$ . In addition, the variance of the mean of the errors is of order  $O(n_{rc}^{-1})$ .

To simplify the result for the purposes of our discussion, suppose  $n_{rc} = n_c$ , that is, each aggregate is based upon the same sample size. It can be shown that equation (10.2) still applies if we replace  $R_c$  by its aggregated data counterpart denoted by  $R_c^A = \sigma_{\mu|c}^2 / (\sigma_{\mu|c}^2 + \sigma_{\varepsilon|c}^2/n_c)$ . Note that  $R_c^A$  converges to 1 as  $n_c$  increases, which means that  $\rho_{y|cd}$  will converge to  $\rho_{\mu|cd}$ . Figure 10.3 illustrates the speed at which this convergence occurs.

In this figure, we assume  $n_c = n_d = n$  and vary  $n$  from 0 to 60. We set the reliability ratios for both variables to 0.5 (which is considered to be a “fair” reliability) and assume a population correlation of  $\rho_{\mu|cd} = 0.5$ . For  $n$  in the range [2, 10], the attenuation is pronounced. However, above 10 the correlation is quite close to the population value. Attenuation is negligible when  $n > 30$ . These results suggest that variable error can be mitigated by aggregating like elements that can be assumed to have independent errors.



**FIGURE 10.3** Correlation as a function of sample size

#### Both variable and systematic errors

If both systematic and variable errors contaminate the data, the additive term on the right in equation (10.2) is positive. For aggregate data, the reliability ratio takes the form

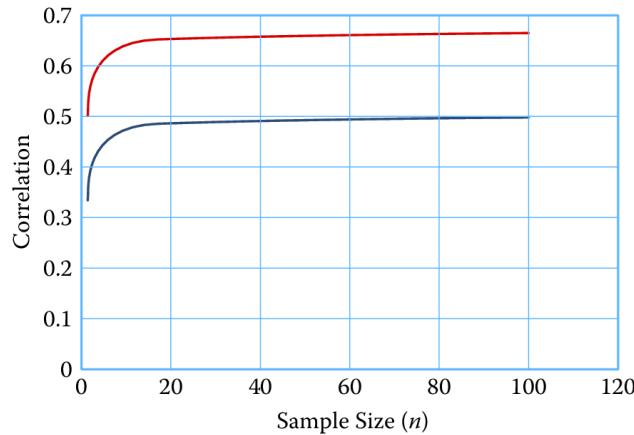
$$R_c^A = \frac{\sigma_{\mu|c}^2}{\sigma_{\mu|c}^2 + \sigma_{b|c}^2 + n_c^{-1}\sigma_{\varepsilon|c}^2},$$

which converges not to 1 as in the case of variable error only, but to  $\sigma_{\mu|c}^2/(\sigma_{\mu|c}^2 + \sigma_{b|c}^2)$ , which will be less than 1. Thus, some attenuation is possible regardless of the number of elements in the aggregate. In addition, the intra-source correlation takes the form

$$\rho_c^A = \frac{\sigma_{b|c}^2}{\sigma_{\mu|c}^2 + \sigma_{b|c}^2 + n_c^{-1}\sigma_{\varepsilon|c}^2},$$

which converges to  $\rho_c^A = \sigma_{b|c}^2/(\sigma_{\mu|c}^2 + \sigma_{b|c}^2)$ , which converges to  $1 - R_c^A$ . Thus, the systematic effects may still operate for correlation analysis without regard to the number of elements comprising the aggregates.

For example, consider the illustration in Figure 10.3 with  $n_c = n_d = n$ , reliability ratios (excluding systematic effects) set at 0.5 and population correlation at  $\rho_{\mu|cd} = 0.5$ . In this scenario, let  $\rho_c = \rho_d = 0.25$ . Figure 10.4 shows the correlation as a function of the sample size with systematic errors compared to the correlation without systematic errors. Correlation with systematic errors is both inflated and attenuated. However, at the assumed level of intra-source variation, the inflation factor overwhelms the attenuation factors and the result is a much inflated value of the correlation across all aggregate sizes.



**FIGURE 10.4** Correlation as a function of sample size

To summarize these findings, correlation analysis is attenuated by variable errors, which can lead to null findings when conducting a correlation analysis and the failure to identify associations that exist in the data. Combined with systematic errors that may arise when data are extracted and combined from multiple sources, correlation analysis can be unpredictable because both attenuation and inflation of correlations can occur. Aggregating data mitigates the effects of variable error but may have little effect on systematic errors.

### 10.4.1.5 Errors in Regression analysis

The effects of variable errors on regression coefficients are well known (Cochran 1968; Fuller 1991; Biemer and Trewin 1997). The effects of systematic errors on regression have been less studied. We review some results for both types of errors in this section.

Consider the simple situation where we are interested in computing the population slope and intercept coefficients given by

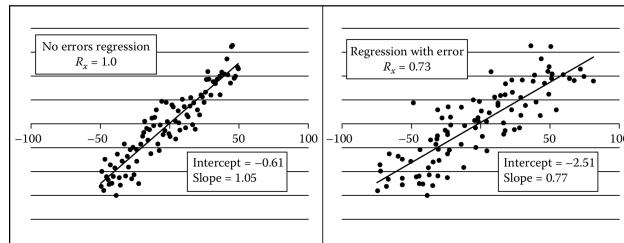
$$b = \frac{\sum_r (y_r - \bar{y})(x_r - \bar{x})}{\sum_r (x_r - \bar{x})^2} \quad \text{and} \quad b_0 = \bar{y} - b\bar{x},$$

where, as before, the sum extends over all rows in the data set. When  $x$  is subject to variable errors, it can be shown that the observed regression coefficient will be attenuated from its error-free counterpart. Let  $R_x$  denote the reliability ratio for  $x$ . Then

$$b = R_x B,$$

where  $B = \sum_r (y_r - \bar{y})(\mu_{r|x} - \bar{\mu}_x) / \sum_r (\mu_{r|x} - \bar{\mu}_x)^2$  is the population slope coefficient, with  $x_r = \mu_{r|x} + \varepsilon_{r|x}$ , where  $\varepsilon_{r|x}$  is the variable error with mean 0 and variance  $\sigma_{\varepsilon|x}^2$ . It can also be shown that  $\text{Bias}(b_0) \approx B(1 - R_x)\bar{\mu}_x$ .

As an illustration of these effects, consider the regressions displayed in Figure 10.5, which are based upon contrived data. The regression on the left is the population (true) regression with a slope of 1.05 and an intercept of -0.61. The regression on the left uses the same  $y$ - and  $x$ -values. The only difference is that normal error was added to the  $x$ -values, resulting in a reliability ratio of 0.73. As the theory predicted, the slope was attenuated toward 0 in direct proportion to the reliability,  $R_x$ . As random error is added to the  $x$ -values, reliability is reduced and the fitted slope will approach 0.



**FIGURE 10.5** Regression of \*y\* on \*x\* with and without variable error. On the left is the population regression with no error in the \*x\*-variable. On the right, variable error was added to the \*x\*-values with a reliability ratio of 0.73. Note its attenuated slope, which is very near the theoretical value of 0.77

When the dependent variable,  $y$ , only is subject to variable error, the regression

deteriorates, but the expected values of the slope and intercept coefficients are still equal to true to their population values. To see this, suppose  $y_r = \mu_{y|r} + \varepsilon_{r|y}$ , where  $\mu_{r|y}$  denotes the error-free value of  $y_r$  and  $\varepsilon_{r|y}$  is the associated variable error with variance  $\sigma_{\varepsilon|y}^2$ . The regression of  $y$  on  $x$  can now be rewritten as

$$\mu_{y|r} = b_0 + bx_r + e_r - \varepsilon_{r|y},$$

where  $e_r$  is the usual regression residual error with mean 0 and variance  $\sigma_e^2$ , which is assumed to be uncorrelated with  $\varepsilon_{r|y}$ . Letting  $e' = e_r - \varepsilon_{r|y}$ , it follows that the regression in equation (10.3) is equivalent to the previously considered regression of  $y$  on  $x$  where  $y$  is not subject to error, but now the residual variance is increased by the additive term, that is,  $\sigma_e'^2 = \sigma_{\varepsilon|y}^2 + \sigma_e^2$ .

Chai (Chai 1971) considers the case of systematic errors in the regression variables that may induce correlations both within and between variables in the regression. He shows that, in the presence of systematic errors in the independent variable, the bias in the slope coefficient may either attenuate the slope or increase its magnitude in ways that cannot be predicted without extensive knowledge of the error properties. Thus, like the results from correlation analysis, systematic errors greatly increase the complexity of the bias effects and their effects on inference can be quite severe.

One approach for dealing with systematic error at the source level in regression analysis is to model it using, for example, random effects (Hox 2010). In brief, a random effects model specifies  $y_{ijk} = \beta_{0i}^* + \beta x_{ijk} + \varepsilon'_{ijk}$ , where  $\varepsilon'_{ijk} = b_i + \varepsilon_{ijk}$  and  $\text{Var}(\varepsilon'_{ijk}) = \sigma_b^2 + \sigma_{\varepsilon|j}^2$ . The next section considers other mitigation strategies that attempt to eliminate the error rather than model it.

## 10.5 Detecting and Compensating for Data Errors

For survey data and other *designed* data collections, error mitigation<sup>2</sup> begins at the data generation stage by incorporating design strategies that generate high-quality data that are at least adequate for the purposes of the data users. For example, missing data can be mitigated by repeated follow-up of nonrespondents, questionnaires can be perfected through pretesting and experimentation, interviewers can be trained in the effective methods for obtaining highly accurate responses, and computer-assisted interviewing instruments can be programmed to correct errors in the data as they are generated. For data where the data generation process is often outside the purview of the data collectors, as noted in Section Introduction, there is limited opportunity to

---

<sup>2</sup>Data errors further complicate analysis and exacerbate the analytical problems. There are essentially three solutions: prevention, remediation, and the choice of analysis methodology.

address deficiencies in the data generation process. Instead, error mitigation must necessarily begin at the data processing stage. We illustrate this error mitigation process using two types of techniques - data editing and cleaning.

Data editing is a set of methodologies for identifying and correcting (or transforming) anomalies in the data. It often involves verifying that various relationships among related variables of the data set are plausible and, if they are not, attempting to make them so. Editing is typically a rule-based approach where rules can apply to a particular variable, a combination of variables, or an aggregate value that is the sum over all the rows or a subset of the rows in a data set. Recently, data mining and machine learning techniques have been applied to data editing with excellent results (see Chandola et al. (Chandola, Banerjee, and Kumar 2009) for a review). Tree-based methods such as classification and regression trees and random forests are particularly useful for creating editing rules for anomaly identification and resolution (Petrakos et al. 2004). However, some human review may be necessary to resolve the most complex situations.

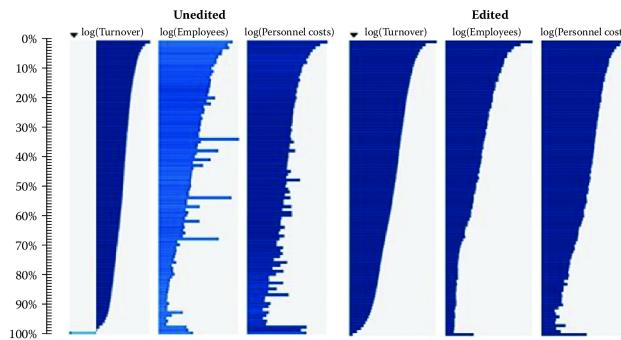
For larger amounts of data, the identification of data anomalies could result in possibly billions of edit failures. Even if only a tiny proportion of these required some form of manual review for resolution, the task could still require the inspection of tens or hundreds of thousands of query edits, which would be infeasible for most applications. Thus, micro-editing must necessarily be a completely automated process unless it can be confined to a relatively small subset of the data. As an example, a representative (random) subset of the data set could be edited using manual editing for purposes of evaluating the error levels for the larger data set, or possibly to be used as a training data set, benchmark, or reference distribution for further processing, including recursive learning.

To complement fully automated micro-editing, data editing involving large amounts of data usually involves *top-down* or *macro-editing* approaches. For such approaches, analysts and systems inspect aggregated data for conformance to some benchmark values or data distributions that are known from either training data or prior experience. When unexpected or suspicious aggregates are identified, the analyst can “drill down” into the data to discover and, if possible, remove the discrepancy by either altering the value at the source (usually a micro-data element) or delete the edit-failed value.

There are a variety of methods that may be effective in macro-editing. Some of these are based upon data mining (Natarajan, Li, and Koronios 2010), machine learning (Clarke 2014), cluster analysis (Duan et al. 2009; He, Xu, and Deng 2003), and various data visualization tools such as treemaps (Johnson and Shneiderman 1991; Shneiderman 1992; Tennekes and Jonge 2011) and tableplots (Tennekes, Jonge, and Daas 2013; Puts, Daas, and Waal 2015; Tennekes, Jonge, and Daas 2012). We further explore tableplots below.

TablePlots Like other visualization techniques examined in Chapter Information Visualization, the tableplot has the ability to summarize a large multivariate data set in a single plot (Malik, Unwin, and Gribov 2010). In editing data, it can be used to detect outliers and unusual data patterns. Software for implementing this technique has been written in R and is available from the Comprehensive R Archive Network (<https://cran.r-project.org/>). Figure 10.6 shows an example. The key idea is that micro-aggregates of two related variables should have similar data patterns. Inconsistent data patterns may signal errors in one of the aggregates that can be investigated and corrected in the editing process to improve data quality. The tableplot uses bar charts created for the micro-aggregates to identify these inconsistent data patterns.

Each column in the tableplot represents some variable in the data table, and each row is a “bin” containing a subset of the data. A statistic such as the mean or total is computed for the values in a bin and is displayed as a bar (for continuous variables) or as a stacked bar for categorical variables.



**FIGURE 10.6** Comparison of tableplots for the Dutch Structural Business Statistics Survey for five variables before and after editing. Row bins with high missing and unknown numeric values are represented by lighter colored bars

The sequence of steps typically involved in producing a tableplot is as follows:

1. Sort the records in the data set by the key variable.
2. Divide the sorted data set into  $B$  bins containing the same number of rows.
3. For continuous variables, compute the statistic to be compared across variables for each row bin, say  $T_b$ , for  $b = 1, \dots, B$ , for each continuous variable,  $V$ , ignoring missing values. The level of missingness for  $V$  may be represented by the color or brightness of the bar. For categorical variables with  $K$  categories, compute the proportion in the  $k$ th category, denoted by  $P_{bk}$ . Missing values are assigned to a new  $(K + 1)$ th category (“missing”).

4. For continuous variables, plot the  $B$  values  $T_b$  as a bar chart. For categorical variables, plot the  $B$  proportions  $P_{bk}$  as stacked bar chart.

Typically,  $T_b$  is the mean, but other statistics such as the median or range could be plotted if they aid in the outlier identification process. For highly skewed distributions, Tennekes and de Jonge (Tennekes and Jonge 2011) suggest transforming  $T_b$  by the log function to better capture the range of values in the data set. In that case, negative values can be plotted as  $\log(-T_b)$  to the left of the origin and zero values can be plotted on the origin line. For categorical variables, each bar in the stack should be displayed using contrasting colors so that the divisions between categories are apparent.

Tableplots appear to be well suited for studying the distributions of variable values, the correlation between variables, and the occurrence and selectivity of missing values. Because they can help visualize massive, multivariate data sets, they seem particularly well suited for big data. Currently, the R implementation of tableplot is limited to 2 billion records.

The tableplot in Figure 10.6 is taken from Tennekes and de Jonge (Tennekes and Jonge 2011) for the annual Dutch Structural Business Statistics survey, a survey of approximately 58,000 business units annually. Topics covered in the questionnaire include turnover, number of employed persons, total purchases, and financial results. Figure 10.6 was created by sorting on the first column, viz.,  $\log(\text{turnover})$ , and dividing the 57,621 observed units into 100 bins, so that each row bin contains approximately 576 records. To aid the comparisons between unedited and edited data, the two tableplots are displayed side by side, with the unedited graph on the left and the edited graph on the right. All variables were transformed by the log function.

The unedited tableplot reveals that all four of the variables in the comparison with  $\log(\text{turnover})$  show some distortion by large values for some row bins. In particular,  $\log(\text{employees})$  has some fairly large nonconforming bins with considerable discrepancies. In addition, that variable suffers from a large number of missing values, as indicated by the brightness of the bar color. All in all, there are obvious data quality issues in the unprocessed data set for all four of these variables that should be dealt with in the subsequent processing steps.

The edited tableplot reveals the effect of the data checking and editing strategy used in the editing process. Notice the much darker color for the number of employees for the graph on the left compared to same graph on the right. In addition, the lack of data in the lowest part of the turnover column has been somewhat improved. The distributions for the graph on the right appear smoother and are less jagged.

---

## 10.6 Summary

As social scientists, we are deeply concerned with making sure that the inferences we make from our analysis are valid. Since many of the newer data sources we are using are not collected or generated from instruments and methods designed to produce valid and reliable data for scientific analysis and discovery, they can lead to inference errors. This chapter described different types of errors that we encounter to make us aware of these limitations and take the necessary steps to understand and hopefully mitigate the effects of hidden errors on our results.

In addition to describing the types of errors, this chapter also gives an example of a solution to clean up the data before analysis. Another option that was not discussed is the possibility of using analytical techniques that attempt to model errors and compensate for them in the analysis. Such techniques include the use of latent class analysis for classification error (Biemer 2011), multilevel modeling of systematic errors from multiple sources (Hox 2010), and Bayesian statistics for partitioning massive data sets across multiple machines and then combining the results (Ibrahim and Chen 2000; Scott et al. 2013).

While this chapter has focused on the accuracy of the data and the validity of the inference, other data quality dimensions such as timeliness, comparability, coherence, and relevance that we have not considered in this chapter are also important. For example, timeliness often competes with accuracy because achieving acceptable levels of the latter often requires greater expenditures of resources and time. In fact, some applications of data analysis prefer results that are less accurate for the sake of timeliness. Biemer and Lyberg (Biemer and Lyberg 2003) discuss these and other issues in some detail.

It is important to understand that we will rarely, if ever, get perfect data for our analysis. Every data source will have some limitation - some will be inaccurate, some will become stale, and some will have sample bias. The key is to 1) be aware of the limitations of each data source, 2) incorporate that awareness into the analysis that is being done with it, and 3) understand what type of inference errors it can lead to in order to appropriately communicate the results and make sound decisions.

## 10.7 Resources

The American Association of Public Opinion Research has a number of resources on its website (AAPOR, n.d.). See, in particular, its report on big data (Japec et al. 2015).

The *Journal of Official Statistics* (JOS, n.d.) is a standard resource with many relevant articles. There is also an annual international conference on the total survey error framework, supported by major survey organizations (TSE15, n.d.).



# 11

---

## *Bias and Fairness*

---

**Kit T. Rodolfa, Pedro Saleiro, and Rayid Ghani**

Interest in algorithmic fairness and bias has been growing recently, but it's easy to get lost in the large number of definitions and metrics. There are many different, often competing, ways to measure whether a given model is "fair". In this chapter, we provide an overview of these metrics along with some concrete examples to help navigate these concepts and understand the trade-offs involved in choosing to optimize to one metric over others, focusing on the metrics relevant to binary classification methods used frequently in risk-based models for policy settings.

---

### 11.1 Introduction

In Chapter Machine Learning, you learned about several of the concepts, tools, and approaches used in the field of machine learning and how they can be used in the social sciences. In chapter Machine Learning, we focused on evaluation metrics such as precision (positive predictive value), recall (sensitivity), area-under-curve (AUC), and accuracy, that are often used to measure the performance of machine learning methods. In most (if not every) public policy problems, a key goal for the analytical systems being developed is to help achieve equitable outcomes.

When machine learning models are being used in these systems, they cannot be separated from the social and ethical context in which they are applied, and those developing and deploying these models must take care to do so in a manner that accounts for both accuracy and fairness. In this chapter, we will discuss sources of potential bias in your modeling pipeline, as well as some of the ways that bias introduced by a model can be measured, with a particular focus on classification problems. Unfortunately, just as there is no single machine learning algorithm that is best suited to every application, no one fairness metric will fit every situation. However, we hope this chapter will provide you with a grounding in the available ways of measuring algorithmic

fairness that will help you navigate the trade-offs involved putting these into practice in your own applications.

---

## 11.2 Sources of Bias

Bias may be introduced into a machine learning project at any step along the way and it is important to carefully think through each potential source and how it may affect your results. In many cases, some sources may be difficult to measure precisely (or even at all), but this doesn't mean these potential biases can be readily ignored when developing interventions or performing analyses.

### 11.2.1 Sample Bias

You're likely familiar with sampling issues as a potential source of bias in the contexts of causal inference and external validity in the social science literature. A biased sample can be just as problematic for machine learning as it can be for inference, and predictions made on individuals or groups not represented in the training set are likely to be unreliable. As such, any application of machine learning should start with a careful understanding of data generating process for the training and test sets. What is the relevant population for the project and how might some individuals be incorrectly excluded or included from the data available for modeling or analysis?

If there is a mismatch between the available training data and the population to whom the model will be applied, you may want to consider whether it is possible to collect more representative data. A model to evaluate the risk of health violations at restaurants may be of limited applicability if the only training data available is based on inspections that resulted from reported complaints. In such a case, an initial trial of randomized inspections might provide a more representative dataset. However, this may not always be possible. For instance, in the case of bail determinations, labeled data will only be available for individuals who are released under the existing system.

How does the available training data relate to the population that the model will be applied to? If there is a mismatch here, is it possible to collect more appropriate data? Example of bail determination – only have subsequent outcome data for individuals who were released in the past

Even if the training data matches the population, are their underlying systemic biases involved in defining that population in general? For instance, over-policing of black neighborhoods

For data with a time component or models that will be deployed to aid future decisions, are there relevant policy changes in the past that may make data from certain periods of time less relevant? Pending policy changes going forward that may affect the modeling population?

Measurement here might be difficult, but helpful to think through each of these questions in detail. Often, other sources of data (even in aggregate form) can provide some insight on how representative your data may be, including census data, surveys, and academic studies in the relevant area.

### 11.2.2 Label Bias

Regardless of whether your dataset reflects a representative sample of the relevant population for your intervention or analysis, there may also be bias inherent in the labels (that is, the measured outcomes) associated with individuals in that data.

One mechanism by which bias may be introduced is in how the label itself is defined. For instance, a study of recidivism might use a new arrest as an outcome variable when it really cares about committing a new crime. However, if some groups are policed more heavily than others, using arrests to define the outcome variable may introduce bias into the system's decisions. Similarly, a label that relies on the number of days an individual has been incarcerated would reflect known biases in sentence lengths between black and white defendants.

A related mechanism is measurement error. Even when the outcome of interest is well-defined and can be measured directly, bias may be introduced through differential measurement accuracy across groups. For instance, data collected through survey research might suffer from language barriers or cultural differences in social desirability that introduce measurement errors across groups.

### 11.2.3 Machine Learning Pipeline Bias

Biases can be introduced by the handling and transformation of data throughout the machine learning pipeline as well, requiring careful consideration as you ingest data, create features, and model outcomes of interest. Below are a few examples at each stage of the process, but these are far from exhaustive and intended to help motivate thinking about how bias might be introduced in your own projects.

\*\*Ingesting Data:\*\* The process of loading, cleaning, and reconciling data from a variety of data sources (often referred to as ETL) can introduce a number of errors that might have differential downstream impacts on different populations:

- Are your processes for matching individuals across data sources equally accurate across different populations? For instance, married vs maiden names may bias match rates against women, while inconsistencies in handling of multi-part last names may make matching less reliable for hispanic individuals.
- Nickname dictionaries used in record reconciliation might be derived from different populations than your population of interest.
- A data loading process that drops records with “special characters” might inadvertently exclude names with accents or tildes.

**Feature Engineering:** Biases are easy to introduce during the process of constructing features, both in the handling of features that relate directly to protected classes as well as information that correlates with these populations (such as geolocation). A few examples include:

- Dictionaries to infer age or gender from name might be derived from a population that is not relevant to your problem.
- Handling of missing values and combining “other” categories can become problematic, especially for multi-racial individuals or people with non-binary gender.
- Thought should be given to how race and ethnicity indicators are collected – are these self-reported, recorded by a third party, or inferred from other data? The data collection process may inform the accuracy of the data and how errors differ across populations.
- Features that rely on geocoding to incorporate information based on distances or geographic aggregates may miss homeless individuals or provide less predictive power for more mobile populations.

**Modeling:** The model itself may introduce bias into decisions made from its scores by performing worse on some groups relative to others (many examples have been highlighted in popular press recently, such as racial biases in facial recognition algorithms and gender biases in targeting algorithms for job advertisement on social media). Because of the complex correlation structure of the data, it generally isn’t sufficient to simply leave out the protected attributes and assume this will result in fair outcomes. Rather model performance across groups needs to be measured directly in order to understand and address any biases. However, there are many (often incompatible) ways to define fairness and Section metrics will take a closer look at these options in much more detail.

Much of the remainder of this chapter focuses on how we might define and measure fairness at the level of the machine learning pipeline itself. In Section metrics, we will introduce several of the metrics used to measure algorithmic

fairness and in Section applications we discuss how these can be used in the process of evaluating and selecting machine learning models.

#### 11.2.4 Application Bias

A final potential source of bias worth considering is how the model or analysis might be put into use in practice. One way this might happen is through heterogeneity in the effectiveness of an intervention across groups. For instance, imagine a machine learning model to identify individuals most at risk for developing diabetes in the next 3 years for a particular preventive treatment. If the treatment is much more effective for individuals with a certain genetic background relative to others, the overall outcome of the effort might be to exacerbate disparities in diabetes rates even if the model itself is modeling risk in an unbiased way.

Likewise, it is important to be aware of the risk of discriminatory applications of a machine learning model. Perhaps a model developed to screen out unqualified job candidates is only “trusted” by a hiring manager for female candidates but often ignored or overridden for men. In a perverse way, applying an unbiased model in such a context might serve to increase inequities by giving bad actors more information with which to (wrongly) justify their discriminatory practices.

While there may be relatively little you can do to detect or mitigate these types of bias at the modeling stage, performing a trial to compare current practice with a deployed model can be instructive where doing so is feasible. Keep in mind, of course, that the potential for machine learning systems to be applied in biased ways shouldn’t be construed as an argument against developing these systems at all any more than it would be reasonable to suggest that current practices are likely to be free of bias. Rather, it is an argument for thinking carefully about both the status quo and how it may change in the presence of such a system, putting in place legal and technical safeguards to help ensure that these methods are applied in socially responsible ways.

#### 11.2.5 Considering Bias When Deploying Your Model

Ultimately, what we care about is some global idea of how putting a model into practice will affect some overall concept of social welfare and fairness influenced by all of these possible sources of bias. While this is generally impossible to measure in a quantitative way, it can provide a valuable framework for qualitatively evaluating the potential impact of your model. For most of the remainder of this chapter, we consider a set of more quantitative metrics that can be applied to the predictions of a machine learning pipeline specifically, but it is important to keep in mind that these metrics only apply to the sample

and labels you have and ignoring other sources of bias that may be at play in the underlying data generating process could result in unfair outcomes even when applying a model that appears to be “fair” by your chosen metric.

---

### 11.3 Dealing with Bias

#### 11.3.1 Define Bias

Section bias examples provided some examples for how bias might be introduced in the process of using machine learning to work with a dataset. While far from exhaustive as a source of potential bias in an overall application, these biases can be more readily measured and addressed through choices made during data preparation, modeling, and model selection. This section focuses on detecting and understanding biases introduced at this stage of the process.

One key challenge, however, is that there is no universally-accepted definition of what it means for a model to be fair. Take the example of a model being used to make bail determinations. Different people might consider it “fair” if:

- It makes mistakes about denying bail to an equal number of white and black individuals
- The chances that a given black or white person will be wrongly denied bail is equal, regardless of race
- Among the jailed population, the probability of having been wrongly denied bail is independent of race
- For people who should be released, the chances that a given black or white person will be denied bail is equal

In different contexts, reasonable arguments can be made for each of these potential definitions, but unfortunately, not all of them can hold at the same time. The remainder of this section explores these competing options and how to approach them in more detail.

#### 11.3.2 Definitions

Most of the metrics used to assess model fairness relate either to the types of errors a model might make or how predictive the model is across different groups. For binary classification models (which we focus on here), these are generally derived from values in the *confusion matrix* (see Figure 6.9 and Section 6.6.2 for more details):

- **True Positives (TP)** are individuals for whom both the model prediction and actual outcome are positive labels.
- **False Positives (FP)** are individuals for whom both the model predicts a positive label, but the actual outcome is a negative label.
- **True Negatives (TN)** are individuals for whom both the model prediction and actual outcome are negative labels.
- **False Negatives (FN)** are individuals for whom both the model predicts a negative label, but the actual outcome is a positive label.

Based on these four categories, we can calculate several ratios that are instructive for thinking about the equity of a model's predictions in different situations (Sections punitive example and assistive example provide some detailed examples here):

- **False Positive Rate (FPR)** is the fraction of individuals with negative actual labels who the model misclassifies with a positive predicted label:  $FPR = FP/(FP + TN)$
- **False Negative Rate (FNR)** is the fraction of individuals with positive actual labels who the model misclassifies with a negative predicted label:  $FNR = FN/(FN + TP)$
- **False Discovery Rate (FDR)** is the fraction of individuals who the model predicts to have a positive label but for whom the actual label is negative:  $FDR = FP/(FP + TN)$
- **False Omission Rate (FOR)** is the fraction of individuals who the model predicts to have a negative label but for whom the actual label is positive:  $FOR = FN/(FN + TN)$
- **Precision** is the fraction of individuals who the model predicts to have a positive label about whom this prediction is correct: precision =  $TP/(FP + TP)$
- **Recall** is the fraction of individuals with positive actual labels who the model has correctly classified as such: recall =  $TP/(FN + TP)$

For the first two metrics ( $FPR$  and  $FNR$ ), notice that the denominator is based on actual outcomes (rather than model predictions), while in the next two ( $FDR$  and  $FOR$ ) the denominator is based on model predictions (whether an individual falls above or below the threshold used to turn model scores into 0/1 predicted classes). The final two metrics relate to correct predictions rather than errors, but are directly related to error measurements (that is,  $\text{recall} = 1 - FNR$  and  $\text{precision} = 1 - FDR$ ) and may sometimes have better properties for calculating model bias.

Notice that the metrics defined here require the use of a threshold to turn modeled scores into 0/1 predicted classes and are therefore most useful when

either a threshold is well-defined for the problem (e.g., when available resources mean a program can only serve a given number of individuals) or where calculating these metrics at different threshold levels might be used (along with model performance metrics) to choose a threshold for application. In some cases, it may also be of interest to think about equity across the full distribution of the modeled score. Common practices in these situations are to look at how model performance metrics such as the area under the receiver-operator curve (*AUC – ROC*) or model calibration compare across subgroups (such as by race, gender, age). Or, in cases where the underlying causal relationships are well-known, counterfactual methods may also be used to assess a model’s bias (these methods may also be useful when you suspect label bias to be an issue in your data). We don’t explore these topics deeply here, but refer you out to the relevant references if you would like to learn more \*\*\*\*.

### 11.3.3 Choosing Bias Metrics

Any of the metrics defined above can be used to calculate disparities across groups in your data and (unless you have a perfect model) many of them cannot be balanced across subgroups at the same time. As a result, one of the most important — and frequently most challenging — aspects of measuring bias in your machine learning pipeline is simply understanding how “fairness” should be defined for your particular case.

In general, this requires consideration of the project’s goals and a detailed discussion between the data scientists, decision makers, and those who will be affected by the application of the model. Each perspective may have a different concept of fairness and a different understanding of harm involved in making different types of errors, both at individual and societal levels. Importantly, data scientists have a critical role in this conversation, both as the experts in understanding how different concepts of fairness might translate into metrics and measurement and as individuals with experience deploying similar models. While there is no universally correct definition of fairness, nor one that can be learned from the data, this doesn’t excuse the data scientists from responsibility for taking part in the conversation around fairness and equity in their models and helping decision makers understand the options and trade-offs involved.

Practically speaking, coming to an agreement on how fairness should be measured in a purely abstract manner is likely to be difficult. Often it can be instructive instead to explore different options and metrics based on preliminary results, providing tangible context for potential trade-offs between overall performance and different definitions of equity and helping guide stakeholders through the process of deciding what to optimize. The remainder of this section looks at some of the metrics that may be of particular interest in different types of applications:

- If your intervention is punitive in nature (e.g., determining whom to deny bail), individuals may be harmed by intervening on them in error so you may care more about metrics that focus on false positives. Section punitive example provides an example to guide you through what some of these metrics mean in this case.
- If your intervention is assistive in nature (e.g., determining who should receive a food subsidy), individuals may be harmed by failing to intervene on them when they have need, so you may care more about metrics that focus on false positives. Section assistive example provides an example to guide you through metrics that may be applicable in this case.
- If your resources are significantly constrained such that you can only intervene on a small fraction of the population at need, some of the metrics described here may be of limited use and Section constrained assistive describes this case in more detail.

#### 11.3.4 Punitive Example

When the application of a risk model is punitive in nature, individuals may be harmed by being incorrectly included in the “high risk” population that receives an intervention. In an extreme case, we can think of this as incorrectly detaining an innocent person in jail. Hence, with punitive interventions, we focus on bias and fairness metrics based on false positives.

We might naturally think about the number of people wrongly jailed from each group as reasonable place to start for assessing whether our model is biased. Here, we are concerned with statements like “twice as many people from Group A were wrongly convicted as from Group B.”

In probabilistic terms, we could express this as:

$$P(\text{wrongly jailed, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FP_i}{FP_j} = 1 \quad \forall i, j$$

Where  $FP_i$  is the number of false positives in group  $i$ .

However, it is unclear whether differences in the number of false positives across groups reflect unfairness in the model. For instance, if there are twice as many people in Group A as there are in Group B, some might deem the situation described above as fair from the standpoint that the composition of the false positives reflects the composition of the groups. This brings us to our second metric:

By accounting for differently sized groups, we ask the question, “just by virtue of the fact that an individual is a member of a given group, what are the chances they’ll be wrongly convicted?”

That is, in terms of probability,

$$P(\text{wrongly jailed} \mid \text{group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FP_i}{FP_j} = \frac{n_i}{n_j} \quad \forall i, j$$

Where  $FP_i$  is the number of false positives and  $n_i$  the total number of individuals in group  $i$ .

While this metric might feel like it meets a reasonable criteria of avoiding treating groups differently in terms of classification errors, there are other sources of disparities we might care about as well. For instance, suppose there are 10,000 individuals in Group A and 30,000 in Group B. Suppose further that 100 individuals from each group are jail, with 10 Group A people wrongly convicted and 30 Group B people wrongly convicted. We’ve balanced the number of false positives by group size (0.1% for both groups) so there are no disparities as far as this metric is concerned, but note that 10% of the jailed Group A individuals are innocent compared to 30% of the jailed Group B individuals. The next metric is concerned with unfairness in this way:

The False Discovery Rate (*FDR*) focuses specifically on the people who are affected by the intervention — in the example above, among the 200 people in jail, what are the group-level disparities in rates of wrong convictions. The jail example is particularly instructive here as we could imagine the social cost of disparities manifesting directly through inmates observing how frequently different groups are wrongly convicted.

In probabilistic terms,

$$P(\text{wrongly jailed} \mid \text{jailed, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FP_i}{FP_j} = \frac{k_i}{k_j} \quad \forall i, j$$

Where  $FP_i$  is the number of false positives and  $k_i$  the total number of *jailed* individuals in group  $i$ .

The False Positive Rate (*FPR*) focuses on a different subset, specifically, the individuals who should **not** be subject to the intervention. Here, this would ask, “for an *innocent* person, what are the chances they will be wrongly convicted by virtue of the fact that they’re a member of a given group?”

In probabilistic terms,

$$P(\text{wrongly jailed} \mid \text{innocent, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FP_i}{FP_j} = \frac{n_i \times (1 - p_i)}{n_j \times (1 - p_j)} \quad \forall i, j$$

Where  $FP_i$  is the number of false positives,  $n_i$  the total number of individuals, and  $p_i$  is the prevalence (here, rate of being truly guilty) in group  $i$ .

The difference between the choosing to focus on the  $FPR$  and group size-adjusted false positives is somewhat nuanced and warrants highlighting:

- Having no disparities in group size-adjusted false positives implies that, if I were to choose a random person from a given group (regardless of group-level crime rates or their individual guilt or innocence), I would have the same chance of picking out a wrongly convicted person across groups.
- Having no disparities in  $FPR$  implies that, if I were to choose a random *innocent* person from a given group, I would have the same chance of picking out a wrongly convicted person across groups.

By way of example, imagine you have a society with two groups (A and B) and a criminal process with equal  $FDR$  and group-size adjusted false positives with:

- Group A has 1000 total individuals, of whom 100 have been jailed with 10 wrongfully convicted. Suppose the other 900 are all guilty.
- Group B has 3000 total individuals, of whom 300 have been jailed with 30 wrongfully convicted. Suppose the other 2700 are all innocent.

In this case,

$$\frac{FP_A}{n_A} = \frac{10}{1000} = 1.0\%$$

$$FDR_A = \frac{10}{100} = 10.0\%$$

$$FPR_A = \frac{10}{10} = 100.0\%$$

while,

$$\frac{FP_B}{n_B} = \frac{30}{3000} = 1.0\%$$

$$FDR_B = \frac{30}{300} = 10.0\%$$

$$FPR_B = \frac{30}{2730} = 1.1\%$$

That is,

- A randomly chosen individual has the same chance (1.0%) of being wrongly convicted regardless of which group they belong to
- In both groups, a randomly chosen person who is convicted has the same chance (10.0%) of actually being innocent
- HOWEVER, an innocent person in Group A is certain to be wrongly convicted, nearly 100 times the rate of an innocent person in Group B

While this is an exaggerated case for illustrative purposes, there is a more general principle at play here, namely: when prevalences differ across groups, disparities cannot be eliminated from both the *FPR* and group-size adjusted false positives at the same time (in the absence of perfect prediction). This can be seen pretty readily from definitions of these metrics:

$$\begin{aligned} \frac{FP_i}{FP_j} &= \frac{n_i}{n_j} = \frac{n_i \times (1 - p_i)}{n_j \times (1 - p_j)} \\ \implies p_i &= p_j \end{aligned}$$

(note that this can also be satisfied with perfect prediction, where  $FP_i = FP_j = 0 \quad \forall i, j$ )

While there is no universal rule for choosing a bias metric (or set of metrics) to prioritize, it is important to keep in mind that there are both theoretical and practical limits on the degree to which these metrics can be jointly optimized.

Balancing these trade-offs will generally require some degree of subjective judgment on the part of policy makers. For instance, if there is uncertainty in the quality of the labels (e.g., how well can we truly measure the size of the innocent population?), it may make more sense in practical terms to focus on the group-size adjusted false positives than *FPR*.

### 11.3.5 Assistive Example

By contrast to the punitive case, when the application of a risk model is assistive in nature, individuals may be harmed by being incorrectly excluded from the “high risk” population that receives an intervention. Here, we use identifying families to receive a food assistance benefit as a motivating example. Where the punitive case focused on errors of inclusion through false positives, most of the metrics of interest in the assistive case focus on analogues that measure errors of omission through false negatives.

#### 11.3.5.1 Count of False Negatives

A natural starting point for understanding whether a program is being applied fairly is to count how many people it is missing from each group, focusing on

statements like “twice as many families with need for food assistance from Group A were missed by the benefit as from Group B.”

In probabilistic terms, we could express this as:

$$P(\text{missed by benefit, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FN_i}{FN_j} = 1 \quad \forall i, j$$

Where  $FN_i$  is the number of false negatives in group  $i$ .

Differences in the number of false negatives by group, however, may be relatively limited in measuring equity when the groups are very different in size. If there are twice as many families in Group A as in Group B in the example above, the larger number of false negatives might not be seen as inequitable, which motivates our next metric:

#### 11.3.5.2 Group Size-Adjusted False Negatives

To account for differently sized groups, one way of phrasing the question of fairness is to ask, “just by virtue of the fact that an individual is a member of a given group, what are the chances they will be missed by the food subsidy?”

That is, in terms of probability,

$$P(\text{missed by benefit} \mid \text{group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FN_i}{FN_j} = \frac{n_i}{n_j} \quad \forall i, j$$

Where  $FN_i$  is the number of false negatives and  $n_i$  the total number of families in group  $i$ .

While avoiding disparities on this metric focuses on the reasonable goal of treating different groups similarly in terms of classification errors, we may also want to directly consider two subsets within each group: (1) the set of families not receiving the subsidy, and (2) the set of families who would benefit from receiving the subsidy. We take a closer look at each of these cases below.

#### 11.3.5.3 False Omission Rate

The False Omission Rate (*FOR*) focuses specifically on people on whom the program doesn’t intervene – in our example, the set of families not receiving

the food subsidy. Such families will either be true negatives (that is, those not in need of the assistance) or false negatives (that is, those who did need assistance but were missed by the program), and the *FOR* asks what fraction of this set fall into the latter category.

In probabilistic terms,

$$P(\text{missed by program} \mid \text{no subsidy, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FN_i}{FN_j} = \frac{n_i - k_i}{n_j - k_j} \quad \forall i, j$$

Where  $FN_i$  is the number of false negatives,  $k_i$  the number of families receiving the subsidy, and  $n_i$  is the total number of families in group  $i$ .

In practice, the *FOR* can be a useful metric in many situations, particularly because need can often be more easily measured among individuals not receiving a benefit than among those who do (for instance, when the benefit affects the outcome on which need is measured). However, when resources are constrained such that a program can only reach a relatively small fraction of the population, its utility is more limited. See constrained assistive for more details on this case.

#### 11.3.5.4 False Negative Rate

The False Negative Rate (*FNR*) focuses instead on the set of people with need for the intervention. In our example, this asks the question, “for a family that needs food assistance, what are the chances they will be missed by the subsidy by virtue of the fact they’re a member of a given group?”

In probabilistic terms,

$$P(\text{missed by subsidy} \mid \text{need assistance, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{FN_i}{FN_j} = \frac{n_i \times p_i}{n_j \times p_j} \quad \forall i, j$$

Where  $FN_i$  is the number of false negatives,  $n_i$  the total number of individuals, and  $p_i$  is the prevalence (here, rate of need for food assistance) in group  $i$ .

As with the punitive case, there is some nuance in the difference between choosing to focus on group-size adjusted false negatives and the *FNR* that are worth pointing out:

- Having no disparities in group size-adjusted false negatives implies that, if I were to choose a random family from a given group (regardless of group-level nutritional outcomes or their individual need), I would have the same chance of picking out a family missed by the program person across groups.
- Having no disparities in *FNR* implies that, if I were to choose a random family *with need for assistance* from a given group, I would have the same chance of picking out one missed by the subsidy across groups.
- Unfortunately, disparities in both of these metrics cannot be eliminated at the same time, except where the level of need is identical across groups or in the generally unrealist case of perfect prediction.

### 11.3.6 Special Case: Resource-Constrained Programs

In many real-world applications, programs may only have sufficient resources to serve a small fraction of individuals who might benefit. In these cases, some of the metrics described here may prove less useful. For instance, where the number of individuals served is much smaller than the number of individuals with need, the false omission rate will converge on the overall prevalence, and it will prove impossible to balance *FOR* across groups.

In such cases, group-level recall may provide a useful metric for thinking about equity, asking the question, “given that the program cannot serve everyone with need, is it at least serving different populations in a manner that reflects their level of need?”

In probabilistic terms,

$$P(\text{received subsidy} \mid \text{need assistance, group } i) = C \quad \forall i$$

Where  $C$  is a constant value. Or, alternatively,

$$\frac{TP_i}{TP_j} = \frac{n_i \times p_i}{n_j \times p_j} \quad \forall i, j$$

Where  $TP_i$  is the number of true positives,  $n_i$  the total number of individuals, and  $p_i$  is the prevalence (here, rate of need for food assistance) in group  $i$ .

Note that, unlike the metrics described above, using recall as an equity metric doesn’t explicitly focus on the mistakes being made by the program, but rather on how it is addressing need within each group. Nevertheless, balancing recall is equivalent to balancing the false negative rate across groups (note that  $\text{recall} = 1 - \text{FNR}$ ), but may be a more well-behaved metric for resource-constrained programs in practical terms. When the number of individuals served is small relative to need, *FNR* will approach 1 and ratios between group-level *FNR* values will not be particularly instructive, while ratios between group-level recall values will be meaningful.

As an aside, a focus on recall can also provide a lever that a program can use to consider options for achieving programmatic or social goals. For instance, if underlying differences in prevalence across groups is believed to be a result of social or historical inequities, a program may want to go further than balancing recall across groups, focusing even more heavily on historically under-served groups. One rule of thumb we have used in these cases is to balance recall relative to prevalence (however, there's no theoretically "right" choice here and it's generally best to consider a range of options):

$$\frac{recall_i}{recall_j} = \frac{p_i}{p_j} \quad \forall i, j$$

The idea here is that (assuming the program is equally effective across groups), balancing recall will seek to improve outcomes at an equal rate across groups without impacting underlying disparities while a heavier focus on previously under-served groups might seek to both improve outcomes across groups while attempting to close these gaps as well.

## 11.4 Mitigating Bias

The metrics described in this chapter can be put to use in a variety of ways: auditing existing models and processes for equitable results, in the process of choosing a model to deploy, or in making choices about how a chosen model is put into use. This section provides some details about how you might approach each of these tasks.

### 11.4.1 Auditing Model Results

Because the metrics described here rely only on the predicted and actual labels, no specific knowledge of the process by which the predicted labels are determined is needed to make use of them to assess bias and fairness in the results. Given this sort of labeled outcome data for any existing or proposed process, these tools can be applied to help understand whether that process is yielding equitable results (for the various possible definitions of "equitable" described above).

Note that the existing process need not be a machine learning model: these equity metrics can be calculated for any set of decisions and outcomes, regardless of whether the decisions are derived from a model, judge, case worker, heuristic rule, or other process. And, in fact, it will generally be useful to make

measures of equity in any existing processes which a model might augment or replace to help understand whether application of the model might improve, degrade, or leave unchanged the fairness of the existing system.

### 11.4.2 Model Selection

As described in Chapter 6, many different types of models (each in turn with many tuneable hyperparameters) can be brought to bear on a given machine learning problem, making the task of selecting a specific model to put into use an important step in the process of model development. Chapter 6 described how this might be done by considering a model's performance on various evaluation metrics, as well as how consistent that performance is across time or random splits of the data. This framework for model selection can naturally be extended to incorporate equity metrics, however doing so introduces a layer of complexity in determining how to evaluate trade-offs between overall performance and predictive equity.

Just as there is no one-size-fits-all metric for measuring equity that works in all contexts, you might choose to incorporate fairness in the model selection process in a variety of different ways. Here are a couple of options we have considered (though certainly not an exhaustive list):

- If many models perform similarly on overall evaluation metrics of interest (say, above some reasonable threshold), how do they vary in terms of equitability?
- How much “cost” in terms of performance do you have to pay to reach various levels of fairness? Think of this as creating a menu of options to explicitly show the trade-offs involved. For instance, imagine your best-performing model has a precision of 0.75 but FDR ratio of 1.3, but you can reach an FDR ratio of 1.2 by selecting a model with precision of 0.73, or a ratio of 1.1 at a precision of 0.70, or FDR parity at a precision of 0.64.
- You may want to consider several of the equity metrics described above and might look at the model that performs best on each metric of interest (perhaps above some overall performance threshold) and consider choosing between these options.
- If you are concerned about fairness across several subgroups (e.g., multiple categories of race/ethnicity, different age groups, etc), you might consider exploring the models that perform best for each subgroup in addition to those that perform similarly across groups
- Another option might be to develop a single model selection parameter that penalizes performance by how far a model is from equity and explore how model choice changes based on how heavily you weight the equity parameter. Note, however, that when you are comparing equity across more than two groups, you will need to find a means of aggregating these to a single value

(e.g., you might look at the average disparity, largest disparity, or use some weighting scheme to reflect different costs of disparities favoring different groups)

In most cases, this process will yield a number of options for a final model to deploy: some with better overall performance, some with better overall equity measures, and some with better performance for specific subgroups. Unlike model selection based on performance metrics alone, the final choice between these will generally involve a judgment call that reflects the project's dual goals of balancing accuracy and equity. As such, the final choice of model from this narrowed menu of options is best treated as a discussion between the data scientists and stakeholders in the same manner as choosing how to define fairness in the first place.

#### 11.4.3 Other Options for Mitigating Bias

Beyond incorporating measurements of equity into your model selection process, they can also inform how you put the model you choose into action. In general, disparities will vary as you vary the threshold used for turning continuous scores into 0/1 predicted classes. While many applications will dictate the total number of individuals who can be selected for intervention, it may still be useful to consider lower thresholds. For instance, in one project we saw large *FDR* disparities across age and race in our models when selecting the top 150 individuals for an intervention (a number dictated by programmatic capacity), but these disparities were mitigated by considering the top 1000 with relatively little cost in precision. This result suggested a strategy for deployment: use the model to select the 1000 highest risk individuals and randomly select 150 individuals from this set to stay within the program's capacity while balancing equity and performance.

Another approach that can work well in some situations is to consider using different thresholds across groups to achieve more equitable results. This is perhaps most robust where the metric of interest is monotonically increasing or decreasing with the number of individuals chosen for intervention (such as recall). This can be formulated in two ways:

- For programs that have a target scale but may have some flexibility in budgeting, you can look at what extent the overall size of the program would need to increase to achieve equitable results (or other fairness goals such as those described in constrained assistive). In this case, interventions don't need to be denied to any individuals in the interest of fairness, but the program would incur some additional cost in order to achieve a more equitable result.
- If the program's scale is a hard constraint, you may still be able to use subgroup-specific thresholds to achieve more equitable results by selecting

fewer of some groups and more of others relative to the single threshold. In this case, the program would not need additional costs of expansion, but some individuals who might have received the intervention based just on their score would need to be substituted for individuals with somewhat lower scores of under-represented subgroups.

As you're thinking about equity in the application of your machine learning models, it's also particularly important to keep in mind that measuring fairness in a model's predictions is only a proxy for what you fundamentally care about: fairness in outcomes in the presence of the model. As a model is put into practice, you may find that the program itself is more effective for some groups than others, motivating either additional changes in your model selection process or customizing interventions to the specific needs of different populations (or individuals). Incorporating fairness into decisions about who is chosen to receive an intervention is an important first step, but shouldn't be mistaken for a comprehensive solution to disparities in a program's application and outcomes.

Some work is also being done investigating means for incorporating bias and fairness more directly in the process of model development itself. For instance, in many cases different numbers of examples across groups or unmeasured variables may contribute to a model having higher error rates on some populations than others and additional data collection (either more examples or new features) may help mitigate these biases where doing so is feasible \*\*\*\*. Other work is being done to explore the results of incorporating equity metrics directly into the loss functions used to train some classes of machine learning models, making balancing accuracy and equity an aspect of model training itself \*\*\*\*. While we don't explore these more advanced topics in depth here, we refer you to the cited articles for more detail.

---

## 11.5 Further Considerations

### 11.5.1 Compared to What?

While building machine learning models that are completely free of bias is an admirable goal, it may not always be an achievable one. Nevertheless, even an imperfect model may provide an improvement over current practices depending on the degree of bias involved in existing processes. It's important to be cognizant of the existing context and make measurements of equity for current practices as well as new algorithms that might replace or augment them. The status quo shouldn't be assumed to be free of bias because it is familiar any more than algorithms should be assumed capable of achieving

perfection simply because they are complex. In practice, a more nuanced view is likely to yield better results: new models should be rigorously compared with current results and implemented when they are found to yield improvements but continually refined to improve on their outcomes over time as well.

### 11.5.2 Costs to Both Errors

In the examples in Section metrics, we focused on programs that could be considered purely assistive or purely punitive to illustrate some of the relevant metrics for such programs. While this classification may work for some real-world applications, in many others there will be costs associated with both errors of inclusion and errors of exclusion that need to be considered together in deciding both on how to think about fairness and how to put those definitions into practice through model selection and deployment. For the bail example, there are of course real costs to society both of jailing innocent people and releasing someone who does, in fact, commit a subsequent crime. In many programs where individuals may be harmed by being left out, errors of inclusion may mean wasted resources or even political backlash about excessive budgets.

In theory, you might imagine being able to assign some cost to each type of error — as well as to disparities in these errors across groups — and make a single, unified cost-benefit calculation of the net result of putting a given model into application in a given way. In practice, of course, making an even reasonable quantitative estimate of the individual and social costs of these different types of errors is likely infeasible in most cases. Instead, a more practical approach generally involves exploring a number of different options through different choices of models and parameters and using these options to motivate a conversation about the program’s goals, philosophy, and constraints.

### 11.5.3 What is the Relevant Population?

Related to the sample bias discussed in bias sources, understanding the relevant population for your machine learning problem is important both to the modeling itself and to your measures of equity. Calculation of metrics like the group-size adjusted false positive rate or false negative rate will vary depending on who is included in the denominator.

For instance, imagine modeling who should be selected to receive a given benefit using data from previous applicants and looking at racial equity based on these metrics. What population is actually relevant to thinking about equity in this case? It might be the pool of applicants available in your data, but it just as well might be the set of people who might apply if they had knowledge of the program (regardless of whether or not they actually do), or perhaps even the population at large (for instance, as measured by the census). Each of

those choices could potentially lead to different conclusions about the fairness of the program’s decisions (either in the presence or absence of a machine learning model), highlighting the importance of understanding the relevant population and who might potentially be left out of your data as an element of how fairness is defined in your context. Keep in mind that determining (or at least making a reasonable estimate of) the correct population may at times require collecting additional data.

#### 11.5.4 Continuous Outcomes

For the sake of simplicity, we focused here on binary classification problems to help illustrate the sorts of considerations you might encounter when thinking about fairness in the application of machine learning techniques. However, these considerations do of course extend to other types of problems, such as regression models of continuous outcomes.

In these cases, bias metrics can be formulated around aggregate functions of the errors a model makes on different types of individuals (such as the mean squared error and mean absolute error metrics you are likely familiar with from regression) or tests for similarity of the distributions of these errors across subgroups. Working with continuous outcomes adds an additional layer of complexity in terms of defining fairness to account for the magnitude of the errors being made (e.g., how do you choose between a model that makes very large errors on a small number of individuals vs one that makes relatively small errors on a large number of individuals?).

If you would like to learn more about understanding bias and fairness in machine learning problems with continuous outcomes, we suggest consulting \*\*\*\* for a useful overview.

#### 11.5.5 Considerations for Ongoing Measurement

The role of a data scientist is far from over when their machine learning model gets put into production. Making use of these models requires ongoing curation, both to guard against degradation in terms of performance or fairness as well as to constantly improve outcomes. The vast majority of models you put into production will make mistakes, and a responsible data scientist will seek to look closely at these mistakes and understand — on both individual and population levels — how to learn from them to improve the model. Ensuring errors are balanced across groups is a good starting point, but seeking to reduce these errors over time is an important aspect of fairness as well.

One challenge you may face in making these ongoing improvements to your model is with measuring outcomes in the presence of a program that seeks

to change them. In particular, the measurement of true positives and false positives in the absence of knowledge of a counterfactual (that is, what would have happened in the absence of intervention) may be difficult or impossible. For instance, among families who have improved nutritional outcomes after receiving a food subsidy, you may not be able to ascertain which families' outcomes were actually helped by the program versus which would have improved on their own, obfuscating any measure of recall you might use to judge performance or equity. Likewise, for individuals denied bail, you cannot know if they actually would have fled or committed a crime had they been released, making metrics like false discovery rate impossible to calculate.

During a model's pilot phase, initially making predictions without taking action or using the model in parallel with existing processes can help mitigate some of these measurement problems over the short term. Likewise, when resources are limited such that only a fraction of individuals can receive an intervention, using some degree of randomness in the decision-making process can help establish the necessary counterfactual. However, in many contexts, this may not be practical or ethical, and you will need to consider other means for ongoing monitoring of the model's performance. Even in these contexts, however, it is important to continually review the performance of the models and seek to both improve its performance in terms of both equity and efficiency. In practice, this may include some combination of considering proxies for the counterfactual, quasi-experimental inference methods, and expert/stakeholder review of the model's results (both in aggregate and of selected individual cases).

### 11.5.6 Equity in Practice

Much of the discussion here has been about fairness in the machine learning pipeline, focused on the ways in which a model may be correct or incorrect in its predictions and how these might vary across groups. As a responsible practitioner of data science, these issues are no doubt important to understand and seek to get correct in your models, but fundamentally they can only serve as a proxy for a bigger concept of fairness – ultimately, we care about equity in terms of differences in outcomes across groups. Ensuring fairness in decisions (whether made by machines, humans, or some combination) is an element of achieving this goal, but neither is it the only element nor, in many cases, is it likely to be the largest one. In the face of other potential sources of bias — sample, label, application, historical, and societal — even fair decisions at the machine learning level may not lead to equitable results in society and the decision-making process may need to compensate for these other inequities. Some of these other sources of bias may be more challenging to quantify or incorporate into models directly, but data scientists have a shared responsibility

to understand the broader context in which their models will be applied and seek equitable outcomes in these applications.

### 11.5.7 Other Names You Might See

The metrics described here have been given a variety of names in the literature. While we have tried to use language focused on the underlying statistics in this chapter, here are some other names you might see for several of these metrics in the literature:

- Equalizing **false discovery rates** (*FDR*) is sometimes referred to as **predictive parity** or the “**outcome test**”. Note that this is mathematically equivalent to having equal **precision** (also called **positive predictive value**) across groups.
- Equalizing **false omission rates** (*FOR*) is mathematically equivalent to equalizing the **negative predictive value** (*NPV*).
- When both *FOR* and *FDR* are equal across groups at the same time, this is sometimes referred to as **sufficiency** or **conditional use accuracy equality**.
- Equalizing the **false negative rate** (*FNR*), which is equivalent to equalizing **recall** (also called the **true positive rate** or **sensitivity**), is also sometimes called **equal opportunity**.
- Equalizing the **false positive rates** (*FPR*), which is equivalent to equalizing the **true negative rate** (also known as **specificity**), is sometimes called **predictive equality**.
- When both *FNR* and *FPR* are equal across groups (that is, when both **equal opportunity** and **predictive equality** are satisfied), various authors have referred to this as **error rate balance**, **separation**, **equalized odds**, **conditional procedure accuracy equality**, or **disparate mistreatment**.
- When members of every group have an equal probability of being assigned to the positive predictive class, this condition is referred to as **group fairness**, **statistical parity**, **equal acceptance rate**, **demographic parity**, or **benchmarking**. When this is true up to the contributions of only a set of “legitimate” attributes allowed to affect the prediction, this is called **conditional statistical parity** or **conditional demographic parity**.
- One definition, termed **treatment equality**, suggests considering disparities in the ratio of false negatives to false positives across groups.
- Metrics that look at the entirety of the score distribution across groups include **AUC parity** and **calibration** (also called **test fairness**, **matching conditional frequencies**, or under certain conditions, **well-calibration**).

Similarly, **balance for the positive class** and **balance for the negative class** look at average scores across groups among individuals with positive or negative labels, respectively.

- Additional work is being done looking at the fairness through the lens of similarity between individuals (...) and causal reasoning (...).

As a field, we have yet to settle on a single widely-accepted terminology for thinking about bias and fairness, but rather than get lost in competing naming conventions, we would encourage you to focus on what disparities in the different underlying metrics actually mean for how models you build might actually affect different populations in your particular context.

---

## 11.6 Fairness in Decision Making: Case Studies

The active conversation about algorithmic bias and fairness in both the academic and popular press has contributed to a more well-rounded evaluation of many of the models and technologies that are already in everyday use. This section highlights several recent cases, discussing them through the context of the metrics described above as well as providing some resources for you to read further about each one.

### 11.6.1 Recidivism Predictions with COMPAS

Over the course of the last two decades, models of recidivism risk have been put into use in many jurisdictions around the country. These models show a wide variation in methods (from heuristic rule-based scores to machine learning models) and have been developed by a variety of academic researchers, government employees, and private companies, many built with little or no evaluation of potential biases (Desmarais and Singh). Different jurisdictions put these models to use in a variety of ways, including identifying individuals for diversion & treatment programs, making bail determinations, and even in the course of sentencing decisions.

In May 2016, journalists at ProPublica undertook an exploration of accuracy and racial bias in these algorithms, focusing on one the commercial solutions called Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), built by a company called Northpointe. Their analysis focused on some of the errors made by the model, finding dramatic disparities between black and white defendants: among black defendants who would did not end

up with another arrest in the subsequent two years, 45% were labeled by the system as high risk, almost twice the rate for whites (23%). Likewise, among individuals who did recidivate within two years, 48% of white defendants were labeled low risk, compared with 28% of black defendants.

Here, ProPublica was focusing on *FPR* and *FNR* metrics for their definition of fairness: e.g., if you're a person who, in fact, will not recidivate, do your chances of being mislabeled as high risk by the model differ depending on your race? In their response, Northpointe argued that this was the wrong fairness metric in this context — instead, they claimed, *FDR* should be the focus: If the model labels you as high risk, do the chances that it was wrong in doing so depend on your race? By this definition, COMPAS is fair: 37% of black defendants labeled as high risk did not recidivate, compared to 41% of white defendants. Table 11.1 summarizes these metrics for both racial groups.

TABLE 11.1: COMPAS Fairness Metrics

Metric	Caucasian	African American
False Positive Rate ( <i>FPR</i> )	23%	45%
False Negative Rate ( <i>FNR</i> )	48%	28%
False Discovery Rate ( <i>FDR</i> )	41%	37%

In a follow-up article in December 2016, the ProPublica authors remarked on the surprising result that a model could be “simultaneously fair and unfair.” The public debate around COMPAS also inspired a number of academic researchers to look closer at these definitions of fairness, showing that in the presence of different base rates, it would be impossible for a model to satisfy both definitions of fairness at the same time. The case of COMPAS demonstrates the potentially dramatic impact of decisions about how equity is defined and measured in real applications with considerable implications for individual’s lives. It’s incumbent upon the researchers developing such a model, the policymakers deciding to put it into practice, and the users making decisions based upon its scores to understand and explore the options for measuring fairness as well as the trade-offs involved in making that choice.

### 11.6.2 Facial Recognition

A growing number of applications for facial recognition software are being found, from tagging friends in photos on social media to recognizing suspects by police departments, and off-the-shelf software is available from several large technology firms, including Microsoft, IBM, and Amazon. However, growth in the use of technologies has seen a number of embarrassing stumbles related to how well they work across race along the way: In 2015, Google released

an automated image annotation app that mistakenly tagged several African American users as gorillas; and a number of early applications deployed on digital cameras would erroneously tell Asian users to open their eyes or fail to detect users with darker skin tones entirely.

Despite the broad uses of these technologies, even in policing, relatively little work had been done to quantify their racial bias prior to 2018 when a researcher at MIT’s Media Lab undertook a study to assess racial bias in the ability to correctly detect gender of three commercial facial recognition applications (developed by Microsoft, Face++, and IBM). She developed a benchmark dataset reasonably well-balanced across race and gender by collecting 1,270 photos of members of parliament in several African and European nations, scoring each photo for skin tone using the Fitzpatrick Skin Type classification system commonly used in dermatology.

The results of this analysis showed stark differences across gender and skin tone, focusing on false discovery rates for predictions of each gender. Overall, *FDR* was very low for individuals predicted to be male in the dataset, ranging from 0.7% to 5.6% between systems, while it was much higher among individuals predicted to be female (ranging from 10.7% to 21.3%). Notice that the models here are making a binary classification of gender, so individuals with a score on one side of a threshold are predicted as male and on the other side are predicted as female. The overall gender disparities seen here, then, indicate that at least relative to this dataset, all three thresholds were chosen in such a way that the models are more certain when making a prediction that an individual is male than making a prediction that they are female. In theory, these thresholds could be readily tuned to produce a better balance in errors, but Buolamwini notes that all three APIs provide only predicted classes rather than the underlying scores, precluding users from choosing a different balance of error rates by predicted gender.

The disparities were even more stark when considering skin tone and gender jointly. In general model performance was much worse for individuals with darker skin tones than those with lighter skin. Most dramatically, the *FDR* for individuals with darker skin who were predicted to be female ranged from 20.8% to 34.7%. At the other extreme, the largest *FDR* for lighter-skinned individuals predicted to be male was under 1%. Table 11.2 shows these results in more detail.

TABLE 11.2: *FDR* Values By Skin Tone and Predicted Gender (F = Female, M = Male, D = Dark Skin, L = Light Skin)

<b>System</b>	<b>All F</b>	<b>All M</b>	<b>DF</b>	<b>DM</b>	<b>LF</b>	<b>LM</b>
Microsoft	10.7%	2.6%	20.8%	6.0%	1.7%	0.0%
Face++	21.3%	0.7%	34.5%	0.7%	6.0%	0.8%
IBM	20.3%	5.6%	34.7%	12.0%	7.1%	0.3%

One factor contributing to these disparities is likely sample bias. While the training data used for these particularly commercial models is not available, many of the widely available public data sets for developing similar facial recognition algorithms have been heavily skewed, with as many as 80% of training images being of white individuals and 75% being of men. Improving the representativeness of these data sets may be helpful, but wouldn't eliminate the need for ongoing studies of disparate performance of facial recognition across populations that might arise from other characteristics of the underlying models as well.

These technologies also provide a case study for when policy makers might decide against putting a given model to use for certain applications entirely. In 2019, the city of San Francisco, CA, announced that it would become the first city in the country to ban the use of facial recognition technologies entirely from city services, including its police department. There, city officials reached the conclusion that any potential benefits of these technologies were outweighed by the combination of potential biases and overall privacy concerns, with the city's Board of Supervisors voting 8-1 to ban the technology. While the debate around appropriate uses for facial recognition is likely to continue for some time across jurisdictions, San Francisco's decision highlights the role of legal and policy constraints around how models are used in addition to ensuring that the models are fair when and where they are applied.

### 11.6.3 Facebook Advertisement Targeting

Social media has created new opportunities for advertisers to quickly and easily target their advertisements to particular subsets of the population. Additionally, regardless of this user-specified targeting, these advertising platforms will make automated decisions about who is shown a given advertisement, generally optimizing to some metric of cost efficiency. Recently, however, these tools have begun to come under scrutiny surrounding the possibility that they might violate US Civil Rights laws that make it illegal for individuals to be excluded from job or housing opportunities on the basis of protected characteristics such as age, race, or sex.

Public awareness that Facebook's tools allowed advertisers to target content based on these protected characteristics began to form in 2016 with news reports highlighting the feature. While the company initially responded that their policies forbid advertisers from targeting ads in discriminatory ways, there were legitimate use cases for these technologies as well, suggesting that the responsibility fell to the people placing the ads. By 2018, however, it was clear that the platform was allowing some advertisers to do just that and the American Civil Liberties Union filed a complaint of gender discrimination with the US Equal Employment Opportunity Commission. The complaint pointed to 10 employers that had posted job ads targeted exclusively to men, including

positions such as truck drivers, tire salesmen, mechanics, and security engineers. Similar concerns were cited by the US Department of Housing and Urban Development in 2019 when it filed charges against the social media company alleging it had served ads that violate the Fair Housing Act. Responding to the growing criticism, Facebook began to limit the attributes advertisers could use to target their content.

However, these limitations might not be sufficient in light of the platform's machine learning algorithms that are determining who is shown a given ad regardless of the specific targeting parameters. Research performed by Ali, et al. (2019), confirmed that the content of an advertisement could have a dramatic impact on who it was served to despite broad targeting parameters. Users who were shown a job posting for a position as a lumberjack were more than 90% men and more than 70% white, while those seeing a posting for a janitorial position were over 75% women and 65% black. Similarly wide variety was seen for housing advertisements, ranging from an audience nearly 65% black in some conditions to 85% white in others. A separate study of placement of STEM career ads with broad targeting found similar gender biases in actual impressions, with content shown to more men than women.

Unlike the other case studies described above, the concept of fairness for housing and job advertisements is provided by existing legislation, focusing not on errors of inclusion or exclusion, but rather on representativeness itself. As such, the metric of interest here is disparity in the probability of being assigned to the predicted positive class (e.g., being shown the ad) across groups, unrelated to potentially differential propensities of each group to respond. To address these disparities, Facebook (as well as other ad servers) may need to modify their targeting algorithms to directly ensure job and housing ads are shown to members of protected groups at similar rates. This, in turn, would require a reliable mechanism for determining whether a given ad is subject to these requirements, which poses technical challenges in its own right. As of this writing, understanding how best to combat discrimination in ad targeting is an ongoing area of research as well as an active public conversation.

#### 11.6.4 Tay: Microsoft's AI Twitter Bot

In March, 2016, Microsoft released a Twitter chatbot named Tay with the intention of showcasing their AI technology for understanding conversational language. The bot was targeted at younger Twitter users, hoping to carry on fun, colloquial conversations with them while learning to improve its conversational skills through these interactions. Resulting at least in part from an attack coordinated on 4Chan, within 24 hours, Tay's tweets had taken a decidedly dark turn, generating tweets with racist, misogynistic, and anti-Semitic messages (Figure 11.1. In the face of this hateful, offensive content, Microsoft had shut Tay down by the end of its first day. Issuing a public apology, the company

## 11.7 Aequitas - A Toolkit for Auditing Bias and Fairness in Machine Learning Models 299

indicated that although they had “stress-tested” the bot in several contexts, they had failed to anticipate the type of abuse of it encountered in the wild.



**FIGURE 11.1** Example of Tay's offensive output

Although the stakes are arguably relatively low for a chatbot built for entertainment, the story of Tay is a cautionary one for more consequential applications of these technologies. In practice, this experience can be seen through the lens of sample and application biases: not only was the corpus of data on which Microsoft initially trained Tay vastly different from the data on which it ultimately operated, but the way in which people ultimately used the system was out of step with its anticipated use. While these issues may be particularly dramatic for models like Tay that learn on the fly, they can certainly have an adverse effect on more static models as well. Tay's nearly immediate transformation from a fun, playful chatbot to one spewing cruelty and hate showcases not only the need for data scientists to anticipate how their models and technologies might be abused as well as the critical need for continual monitoring for both performance metrics and biases in any deployed application.

---

## 11.7 Aequitas - A Toolkit for Auditing Bias and Fairness in Machine Learning Models

To help data scientists and policymakers make informed decisions about bias and fairness in their applications, we developed Aequitas, an open source<sup>1</sup> bias

<sup>1</sup><https://github.com/dssg/aequitas>

and fairness audit toolkit that was released in May 2018.<sup>2</sup> It is an intuitive and easy to use addition to the machine learning workflow, enabling users to seamlessly audit models for several bias and fairness metrics in relation to multiple population sub-groups. Aequitas can be used directly as a Python library, via command line interface or a web application, making it accessible and friendly to a wide range of users (from data scientists to policymakers).

Because the concept of fairness is highly dependent on the particular context and application, Aequitas provides comprehensive information on how its results should be used in a public policy context, taking the resulting interventions and its implications into consideration. It is intended to be used not just by data scientists but also policymakers, through both seamless integration in the machine learning workflow as well as a web app tailored for non-technical users auditing these models' outputs.

In Aequitas, bias assessments can be made prior to model selection, evaluating the disparities of the various models developed based on whatever training data was used to tune it for its task. The audits can be performed prior to a model being operationalized, based on operational data of how biased the model proved to be in holdout data. Or they can involve a bit of both, auditing bias in an A/B testing environment in which limited trials of revised algorithms are evaluated whatever biases were observed in those same systems in prior production deployments.

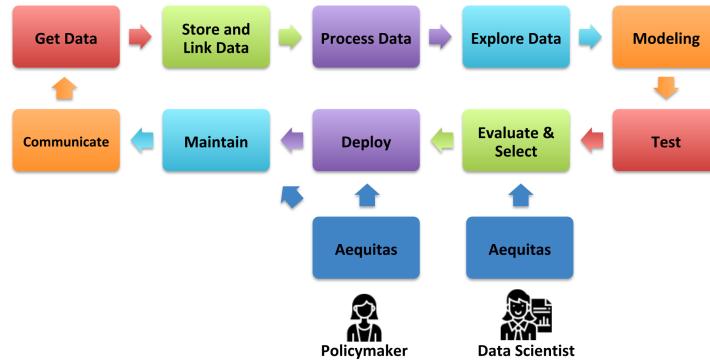
Aequitas was designed to be used by two types of users:

1. Data Scientists and AI Researchers who are building systems for use in risk assessment tools. They will use Aequitas to compare bias measures and check for disparities in different models they are building during the process of model building and selection.
2. Policymakers who, before “accepting” an AI system to use in a policy decision, will run Aequitas to understand what biases exist in the system and what (if anything) they need to do in order to mitigate those biases. This process must be repeated periodically to assess the fairness degradation through time of a model in production.

![Aequitas in the larger context of the machine learning pipeline. Audits must be carried out internally by data scientists before evaluation and model selection. Policymakers (or clients) must audit externally before accepting a model in production as well as perform periodic audits to detect any fairness degradation over time.]

Figure 11.2 puts Aequitas in the context of the machine learning workflow and shows which type of user and when the audits must be made. The main goal of Aequitas is to standardize the process of understanding model biases. By

<sup>2</sup><https://twitter.com/datascifellows/status/994204100542783488>



**FIGURE 11.2** ML pipeline

providing a toolkit for auditing by both data scientists and decision makers, it makes it possible for these different actors to take bias and fairness into consideration at all stages of decision-making in the modeling process: model selection, whether or not to deploy a model, when to retrain, the need to collect more and better data, and so on.

### 11.7.1 Getting Started with Aequitas

Aequitas is a python package that can be used in several ways: as an imported module in your code or jupyter notebooks, as a command-line utility, or served as a web interface. To help orient you to its interface and explore some of the concepts covered in this chapter in more detail, we have developed a tutorial notebook around the COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) case study described in Section COMPAS case that you can find in the book's supplemental materials. Each of the tutorial's sections is described briefly below.

### 11.7.2 Requirements

To work with the Aequitas tutorial, you will need a jupyter notebook server running a python 3.6 (or higher) kernel with the `pandas` and `seaborn` packages installed. In addition, you will need to install the `aequitas` module:

```
pip install aequitas
```

Alternatively, you can install from source with:

```
git clone https://github.com/dssg/aequitas.git
cd aequitas
```

```
python setup.py install
```

### 11.7.3 Data Preparation

Included with the tutorial notebook is a sample dataset, `compas_for_aequitas.csv`, representing two years of COMPAS recidivism predictions and subsequent arrest outcomes from Broward County, Florida. The data provided here represent the same data used in the ProPublica analysis described above, cleaned somewhat and structured for use with Aequitas.

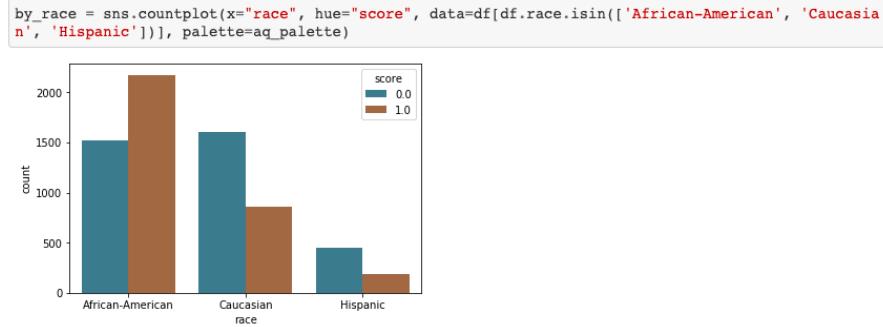
The example dataset has been preprocessed into the format required in order to use Aequitas. To do so, your input data should be provided at the individual entity level, and contain the following columns:

- A `score` column, which may be either a binary (0 or 1) or continuous (between 0.0 and 1.0) value representing the output of a predictive model (for a continuous case, you will need to provide a classification threshold for the analysis). For the example data included here, the COMPAS scores have been mapped to a binary score based on ProPublica's interpretation of Northpointe's practitioner guide, with 0 representing a `low` COMPAS score and 1 representing a `medium` or `high` score.
- A `label_value` column, provided as a binary (0 or 1) value, representing the actual outcome for each entity. Again following ProPublica, the example dataset defines a recidivism outcome (`label_value = 1`) as a new arrest within two years.
- One or more attribute columns for which you would like to evaluate predictive fairness and disparities. Here, you can consider any attributes of interest for your particular application. For instance, the example dataset includes the columns `race`, `sex`, and `age_cat` that will be used for our tutorial.

As you follow along in the tutorial notebook, we start with a little bit of descriptive data exploration just to get a feel for the data. Figure 11.3 shows the large difference in the distribution of COMPAS scores across race. The notebook guides you through several additional initial analyses and you should feel free to further explore the data as well.

Applying Aequitas programmatically is a three step process represented by three python classes that will be described in the following sections:

- `Group()`: Define groups
- `Bias()`: Calculate disparities
- `Fairness()`: Assert fairness

**FIGURE 11.3** Data exploration screenshot from the Aequitas tutorial

#### 11.7.4 Working with Bias Metrics

In the second section of the notebook, you will learn how to use Aequitas to understand the distribution of your data and outcomes, as well as measure, visualize, and interpret bias metrics of interest. To perform these analyses, you'll make use of the `Group()` and `Plot()` classes, which can be imported with:

```
from aequitas.group import Group
from aequitas.plotting import Plot
```

Aequitas's `Group()` class enables researchers to evaluate biases across all subgroups in their dataset by assembling a confusion matrix of each subgroup, calculating commonly used metrics such as false positive rate and false omission rate, as well as counts by group and group prevalence among the sample population.

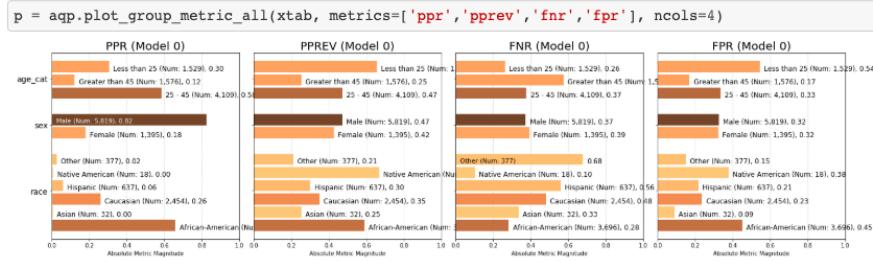
Following the notebook, after constructing a `Group` object, you can use the `Group.get_crosstabs()` method to calculate a confusion matrix for each subgroup in your data. This method expects as input a `pandas.DataFrame` object formatted with the columns described above, and will infer the names and distinct values of your attribute columns defining the subgroups in your data. Calling `get_crosstabs` with your input data will return a `pandas.DataFrame` at the subgroup level with confusion matrix counts and ratios. The tutorial notebook walks through some exploration of this dataframe and interpreting biases across groups.

Absolute group bias metrics metrics from the crosstabs dataframe created by the `Group.get_crosstabs()` method can be visualized with two methods in the Aequitas `Plot()` class. After instantiating a `Plot` object, you can plot the results of a single metric by passing the crosstabs dataframe and metric name to `Plot.plot_group_metric()`, as well as optionally specifying a threshold below which to exclude small groups which may be particularly noisy. The

tutorial notebook walks through an example of visualizing the false negative rates of groups using:

```
aqp = Plot()
fnr = aqp.plot_group_metric(xtab, 'fnr', min_group_size=0.05)
```

Additionally, you can visualize several metrics at the same time in small multiples using the `Plot.plot_group_metric_all()` method. Figure @ref(fig:tutorial\_plot\_crosstabs) shows an example of this method from notebook. In it, you can see that the largest `race` group, **African American**, is predicted positive more often than any other race group (predicted positive rate *PPR* of 0.66), and are more likely to be incorrectly classified as 'high' risk (false positive rate *FPR* of 0.45) than incorrectly classified as 'low' or 'medium' risk (false negative rate *FNR* of 0.28).



Data exploration screenshot from the Aequitas tutorial workbook, showing the predicted positive rate *PPR*, predicted prevalence *PPrev*, false negative rate *FNR*, and false positive rate *FPR* across subgroups in the COMPAS data.

To graph specific metrics of interest, you can pass a list to `plot_group_metric_all()` using the `metrics` keyword. Alternatively, you can pass '`all`' to visualize all calculated metrics or omit the keyword to plot the default metrics:

- Predicted Prevalence ('pprev')
- Predicted Positive Rate ('ppr')
- False Discovery Rate ('fdr')
- False Omission Rate ('for')
- False Positive Rate ('fpr')
- False Negative Rate ('fnr')

You can explore these options in more detail in the tutorial notebook.

### 11.7.5 Measuring Disparities

We use the Aequitas `Bias()` class to calculate disparities between groups based on the crosstabs returned by the `Group.get_crosstabs()` method described above. Disparities are calculated as a ratio of a metric for a group of interest compared to a base group. For example, the False Negative Rate Disparity for black defendants vis-a-vis whites is:

$$\text{Disparity}_{FNR} = \frac{FNR_{black}}{FNR_{white}}$$

Aequitas provides a couple of options for determining the reference group for each attribute's disparity calculations: using `Bias.get_disparity_predefined_groups()` allows you to specify the reference groups directly, while `Bias.get_disparity_major_group()` will choose the largest group as the reference and `Bias.get_disparity_min_metric()` will use the group with the smallest value of the metric being calculated. Note in this last case that different reference groups may be used for different metrics.

In the tutorial notebook, you can walk through a couple examples of disparity calculations and how your choice of reference groups affects the results. Each of the `get_disparity_` methods will return a `pandas.DataFrame` containing the results of disparity calculations as well as (optionally) tests of statistical significance. For instance, the call below will calculate disparities relative to the specified groups and determine statistical significance at a level of  $\alpha = 0.05$  (`mask_significance` means values of `True` or `False` will be returned rather than the p-value itself).

```
b = Bias()
bdf = b.get_disparity_predefined_groups(
    xtab,
    original_df=df,
    ref_groups_dict={
        'race':'Caucasian', 'sex':'Male', 'age_cat':'25 - 45'
    },
    alpha=0.05,
    check_significance=True,
    mask_significance=True
)
```

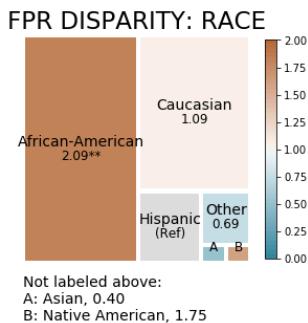
Notice that because disparities are calculated as ratios, the reference group will always have a disparity of 1.0. They can be interpreted as how much more prone the model is to making a certain type of mistake for one group relative to the reference group. For instance, calculating the `fpr_disparity` values by race with the COMPAS data indicates that black people are falsely identified

as being high or medium risks 1.9 times the rate for white people, while the `fdr_disparity` values are much closer to 1.

The Aequitas `Plot()` class provides methods to visualize the results of your disparity calculations, with a similar interface to the methods described for plotting the absolute metrics described above. `Plot.plot_disparity()` allows for plotting a single specified disparity metric for a single attribute while `Plot.plot_disparity_all()` allows you to plot multiple disparities and attributes in small multiples at once.

Figure @ref(fig:tutorial\_plot\_disparity) shows an example of using the `plot_disparity()` method from the tutorial notebook. Each disparity is plotted as a treemap, with the size of the rectangle representing the size of the group and color indicating the level of disparity (with values over 1.0 in orange and those under 1.0 in blue). Notice in the figure that the reference group is colored gray and labeled (Ref). Statistically significant disparities (at the level specified with `significance_alpha`) will be labeled with two asterisks (\*\*), as seen for the African-American group in Figure @ref(fig:tutorial\_plot\_disparity).

```
aqp.plot_disparity(hbdf, group_metric='fpr_disparity', attribute_name='race', significance_alpha=0.05)
```



Data exploration screenshot from the Aequitas tutorial workbook, showing racial disparities on the false positive rate *FPR*. Note that the reference group, Hispanic, is indicated in gray and a statistically significant disparity for African-Americans is labeled with two asterisks (\*\*).

The tutorial notebook walks through several additional examples of using `plot_disparity()` and `plot_disparity_all()`. When visualizing more than one disparity using `plot_disparity_all()`, you can specify a list of disparity metrics, 'all' disparity metrics, or use the Aequitas default disparity metrics by not supplying an argument:

- Predicted Positive Group Rate Disparity (`pprev_disparity`)
- Predicted Positive Rate Disparity (`ppr_disparity`)

- False Discovery Rate Disparity (`fdr_disparity`)
- False Omission Rate Disparity (`for_disparity`)
- False Positive Rate Disparity (`fpr_disparity`)
- False Negative Rate Disparity (`fnr_disparity`)

### 11.7.6 Assessing Model Fairness

Finally, the Aequitas `Fairness()` class provides three functions that provide a high level summary of fairness. This class builds on the dataframe returned from one of the three `Bias.get_disparity_` methods. By specifying a threshold within which you would consider disparities to meet a reasonable level of fairness, this class allows you to evaluate at the group, attribute, and overall levels. For example, evaluating group-level FPR fairness with the default thresholds evaluates:

$$0.8 < \text{Disparity}_{FPR} = \frac{FPR_{group}}{FPR_{base\_group}} < 1.25$$

Calling `Fairness.get_group_value_fairness()` with your bias dataframe as an argument will return a `pandas.DataFrame` with boolean results indicating where your fairness criteria is met for each of the disparity metrics, as well as:

- **Type I Parity:** Fairness in both FDR Parity and FPR Parity
- **Type II Parity:** Fairness in both FOR Parity and FNR Parity
- **Equalized Odds:** Fairness in both FPR Parity and TPR Parity
- **Unsupervised Fairness:** Fairness in both Statistical Parity and Impact Parity
- **Supervised Fairness:** Fairness in both Type I and Type II Parity
- **Overall Fairness:** Fairness across all parities for all attributes

You can also assess whether each of these metrics meets your fairness threshold for all groups across each attribute at the same time using `Fairness.get_group_attribute_fairness()`. That is, this method will return a boolean at the level of each attribute (e.g., `race`, `sex`, or `age`) if the criteria is met for every subgroup defined by that attribute. For a further roll-up across all attributes as well, you can use `Fairness.get_overall_fairness()` to see a high-level assessment of unsupervised fairness, supervised fairness, and overall fairness. Below is a quick example of the usage for each of these methods, which you can explore further in the tutorial notebook:

```

f = Fairness()

# group-level fairness:
fdf = f.get_group_value_fairness(bdf)    # input is the result of a Bias.get_disparity_

# attribute-level fairness:
gaf = f.get_group_attribute_fairness(fdf)    # input is group-level fairness result fro

# overall fairness:
gof = f.get_overall_fairness(fdf)           # input is group-level fairness result fro

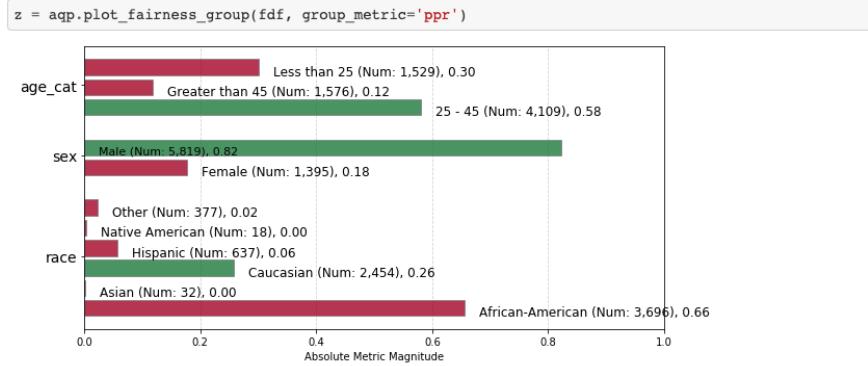
```

In the tutorial notebook, you can calculate these metrics using the COMPAS data. There, the African-American false omission and false discovery are within the bounds of fairness (when assessed using Aequitas's default thresholds), which should be expected because COMPAS is calibrated. On the other hand, African-Americans are roughly twice as likely to have false positives and 40 percent less likely to false negatives. In real terms, 44.8% of African-Americans who did not recidivate were marked high or medium risk (with potential for associated penalties), compared with 23.4% of Caucasian non-reoffenders. This result doesn't meet the fairness threshold and thus returns `False` in the resulting dataframe. These findings mark an inherent trade-off between FPR Fairness, FNR Fairness and calibration, which is present in any decision system where base rates are not equal as discussed in Section COMPAS case. Aequitas helps bring this trade-off to the forefront with clear metrics and asks system designers to make a reasoned decision based on their use case.

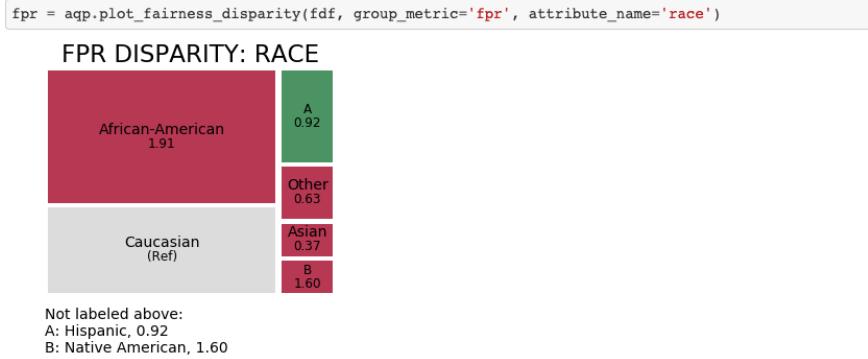
The Aequitas `Plot()` class provides four methods to allow you to visualize the results of these various fairness calculations:

- Using `Plot.plot_fairness_group()`, you can plot a graph of a single fairness metric across different groups showing the absolute metric values. Example usage is shown in Figure @ref(fig:tutorial\_plot\_fairness1).
- `Plot.plot_fairness_group_all()` allows you to plot small multiples of several fairness metrics' absolute values at the group level
- With `Plot.plot_fairness_disparity()`, you can plot a treemap of the fairness results (similar to the disparity plot in Figure @ref(fig:tutorial\_plot\_disparity)) showing the values of disparities relative to a base group and fairness results. Figure @ref(fig:tutorial\_plot\_fairness2) shows example usage of this method.
- `Plot.plot_fairness_disparity_all()` allows you to plot small multiples of several disparity treemaps across different groups and metrics.

## 11.7 Aequitas - A Toolkit for Auditing Bias and Fairness in Machine Learning Models 309



Data exploration screenshot from the Aequitas tutorial workbook, showing the fairness results for predicted positive rate *PPR* across subgroups in the COMPAS data. Absolute values of *PPR* are plotted for each group with bars colored by the results of applying fairness criteria to these disparities with groups meeting the criteria shown in green and those not meeting the criteria shown in red.



Data exploration screenshot from the Aequitas tutorial workbook, showing a treemap representing *FPR* disparities across racial groups in the COMPAS data. The size of each square represents the size of the group, with labels indicating the disparity values, and color indicating whether these values meet specified fairness thresholds (green for those meeting the criteria, red for those not meeting the criteria, and reference groups shown in gray).

The graphs generated by these methods will generally show similar information to the plots of absolute metric values and disparities described above, however the application of fairness criteria is overlayed on these plots to indicate whether a group meets the specified fairness criteria for a given metric (those meeting the threshold are shown in green and those failing to meet it are shown in red). The tutorial notebook will walk you through several examples of using each of

these methods, and you should feel free to explore their usage further, including how fairness results change with the application of different thresholds.

# 12

---

## *Privacy and Confidentiality*

---

**Stefan Bender, Ron Jarmin, Frauke Kreuter, and Julia Lane**

This chapter addresses the issue that sits at the core of any study of human beings—privacy and confidentiality. In a new field, like the one covered in this book, it is critical that many researchers have access to the data so that work can be replicated and built upon—that there be a scientific basis to data science. Yet the rules that social scientists have traditionally used for survey data, namely anonymity and informed consent, no longer apply when data are collected in the wild. This concluding chapter identifies the issues that must be addressed for responsible and ethical research to take place.

---

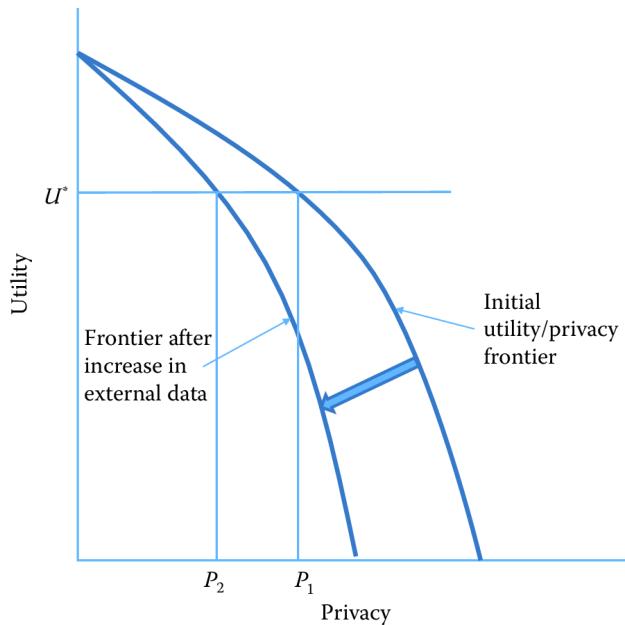
### 12.1 Introduction

Most applications in the social sciences involve data on units such as individuals, households, and different types of business, educational, and government organizations. Indeed, the example running throughout this book involves data on individuals (such as faculty and students) and organizations (such as universities and firms). In circumstances such as these, researchers must ensure that such data are used responsibly and ethically—that the subjects under study suffer no harm from their data being accessed, analyzed, and reported. A clear distinction must be made between analysis done for the public good and that done for private gain. In practical terms, this requires that the interests of individual privacy and data confidentiality be balanced against the social benefits of research access and use.

**Privacy** “encompasses not only the famous ‘right to be left alone,’ or keeping one’s personal matters and relationships secret, but also the ability to share information selectively but not publicly” (Advisors on Science and Technology 2014). A useful way of thinking about privacy is the notion of preserving the appropriate flow of information (Nissenbaum 2009). There is no specific data type or piece of information that is too sensitive to be shared in all circumstances. In some context providing detailed information about one’s health is very appropriate, for example if it helps finding the right treatment

for a disease. It is generally important to understand the context and the contextual integrity of the data flow when deciding which data to collect and how to analyze and share them.

**Confidentiality** is “preserving authorized restrictions on information access and disclosure, including means for protecting personal privacy and proprietary information” (McCallister, Grance, and Scarfone 2010). Doing so is not easy—the challenge to the research community is how to balance the *risk* of providing access with the associated utility (Duncan, Elliot, and Salazar-González 2011). To give a simple example, if means and percentages are presented for a *large* number of people, it will be difficult to infer an individual’s value from such output, even if one knew that a certain individual or unit contributed to the formation of that mean or percentage. However, if those means and percentages are presented for subgroups or in multivariate tables with small cell sizes, the risk for disclosure increases (Doyle et al. 2001). As a result, the quality of data analysis is typically degraded with the production of public use data (Duncan, Elliot, and Salazar-González 2011).



**FIGURE 12.1** The privacy–utility tradeoff

In general, the greater the access to data and their original values, the greater the risk of reidentification for individual units. We depict this tradeoff graphically in Figure 12.1. The concave curves in this hypothetical example depict the technological relationship between data utility and privacy for an organization such as a business firm or a statistical agency. At one extreme, all information

is available to anybody about all units, and therefore high analytic utility is associated with the data that are not at all protected. At the other extreme, nobody has access to any data and no utility is achieved. Initially, assume the organization is on the outer frontier. Increased external data resources (those not used by the organization) increase the risk of reidentification. This is represented by an inward shift of the utility/privacy frontier in Figure 12.1. Before the increase in external data, the organization could achieve a level of data utility  $U^*$  and privacy  $P_1$ . The increase in externally available data now means that in order to maintain utility at  $U^*$ , privacy is reduced to  $P_2$ . This simple example represents the challenge to all organizations that release statistical or analytical products obtained from underlying identifiable data. As more data from external sources becomes available, it becomes more difficult to maintain privacy.

Previously, national statistical agencies had the capacity and the mandate to make dissemination decisions: they assessed the risk, they understood the data user community and the associated utility from data releases. And they had the wherewithal to address the legal, technical, and statistical issues associated with protecting confidentiality (Trewin et al. 2007).

But in a world of massive amounts of data, many once-settled issues have new complications, and wholly new issues arise that need to be addressed, albeit under the same rubrics. The new types of data have much greater potential utility, often because it is possible to study small cells or the tails of a distribution in ways not possible with small data. In fact, in many social science applications, the tails of the distribution are often the most interesting and hardest-to-reach parts of the population being studied; consider health care costs for a small number of ill people (Stanton and Rutherford 2006), or economic activity such as rapid employment growth by a small number of firms (Decker et al. to appear).

---

## BOX

### **Example: The importance of activity in the tails**

Spending on health care services in the United States is highly concentrated among a small proportion of people with extremely high use. For the overall civilian population living in the community, the latest data indicate that more than 20% of all personal health care spending in 2009 (\$275 billion) was on behalf of just 1% of the population (Schoenman 2012).

---

## BOX

---

It is important to understand where the risk of privacy breaches comes from. Let us assume for a moment that we conducted a traditional small-scale survey

with 1,000 respondents. The survey contains information on political attitudes, spending and saving in a given year, and income, as well as background variables on income and education. If name and address are saved together with this data, and someone gets access to the data, obviously it is easy to identify individuals and gain access to information that is otherwise not public. If the personal identifiable information (name and address) are removed from this data file, the risk is much reduced. If someone has access to the survey data and sees all the individual values, it might be difficult to assess with certainty who among the 320 million inhabitants in the USA is associated with an individual data record. However, the risk is higher if one knows some of this information (say, income) for a person, and knows that this person is in the survey. With these two pieces of information, it is likely possible to uniquely identify the person in the survey data.

Larger amounts of data increase the risk precisely for this reason. Much data is available for reidentification purposes (Ohm 2010). Most obviously, the risk of reidentification is much greater because the new types of data have much richer detail and a much larger public community has access to ways to reidentify individuals. There are many famous examples of reidentification occurring even when obvious personal information, such as name and social security number, has been removed and the data provider thought that the data were consequently deidentified. In the 1990s, Massachusetts Group Insurance released “deidentified” data on the hospital visits of state employees; researcher Latanya Sweeney quickly reidentified the hospital records of the then Governor William Weld using nothing more than state voter records about residence and date of birth (Sweeney 2001). In 2006, the release of supposedly de-identified web search data by AOL resulted in two *New York Times* reports being able to reidentify a customer simply from her browsing habits (Barbaro, Zeller, and Hansell 2006). And in 2012, statisticians at the department store, Target, used a young teenager’s shopping patterns to determine that she was pregnant before her father did (Hill 2012).

But there are also less obvious problems. What is the legal framework when the ownership of data is unclear? In the past, when data were more likely to be collected and used within the same entity—for example, within an agency that collects administrative data or within a university that collects data for research purposes—organization-specific procedures were (usually) in place and sufficient to regulate the usage of these data. Today, legal ownership is less clear.

Who has the legal authority to make decisions about permission, access, and dissemination and under what circumstances? The answer is often not clear. The challenge today is that data sources are often combined, collected for one purpose, and used for another. Data providers often have a poor understanding of whether or how their data will be used.

**Example: Knowledge is power**

In a discussion of legal approaches to privacy in the context of big data, Strandburg (Strandburg 2014) says: “‘Big data’ has great potential to benefit society. At the same time, its availability creates significant potential for mistaken, misguided or malevolent uses of personal information. The conundrum for the law is to provide space for big data to fulfill its potential for societal benefit, while protecting citizens adequately from related individual and social harms. Current privacy law evolved to address different concerns and must be adapted to confront big data’s challenges.”

---

It is critical to address privacy and confidentiality issues if the full public value of big data is to be realized. This chapter highlights why the challenges need to be met (i.e., why access to data is crucial), review the pre-big data past, point out challenges with this approach in the context of big data, briefly describe the current state of play from a legal, technical, and statistical perspective, and point to open questions that need to be addressed in the future.

---

## 12.2 Why is access important?

This book gives detailed examples of the potential of data to provide insights into a variety of social science questions—particularly the relationship between investments in R&D and innovation. But that potential is only realized if researchers have access to the data (Lane 2007): not only to perform primary analyses but also to validate the data generation process (in particular, data linkage), replicate analyses, and build a knowledge infrastructure around complex data sets.

### Validating the data generating process

Research designs requiring a combination of data sources and/or analysis of the tails of populations challenge the traditional paradigm of conducting statistical analysis on deidentified or aggregated data. In order to combine data sets, someone in the chain that transforms raw data into research outputs needs access to link keys contained in the data sets to be combined. High-quality link keys uniquely identify the subjects under study and typically are derived from items such as individual names, birth dates, social security numbers, and business names, addresses, and tax ID numbers. From a privacy and confidentiality perspective, link keys are among the most sensitive information in many data sets of interest to social scientists. This is why many organizations

replace link keys containing personal identifiable information (PII)<sup>1</sup> with privacy-protecting identifiers (Schnell, Bachteler, and Reiher 2009). Regardless, at some point in the process those must be generated out of the original information, thus access to the latter is important.

### Replication

John Ioannidis has claimed that most published research findings are false (Ioannidis 2005); for example, the unsuccessful replication of genome-wide association studies, at less than 1%, is staggering (Bastian 2013). Inadequate understanding of coverage, incentive, and quality issues, together with the lack of a comparison group, can result in biased analysis—famously in the case of using administrative records on crime to make inference about the role of death penalty policy in crime reduction (Donohue III and Wolfers 2006; Levitt and Miles 2006). Similarly, overreliance on, say, 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), just as bad survey methodology led the *Literary Digest* to incorrectly call the 1936 election (Squire 1988). The first step to replication is data access; such access can enable other researchers to ascertain whether the assumptions of a particular statistical model are met, what relevant information is included or excluded, and whether valid inferences can be drawn from the data (Kreuter and Peng 2014).

### Building knowledge infrastructure

Creating a community of practice around a data infrastructure can result in tremendous new insights, as the Sloan Digital Sky Survey and the Polymath project have shown (Nielsen 2012). In the social science arena, the Census Bureau has developed a productive ecosystem that is predicated on access to approved external experts to build, conduct research using, and improve key data assets such as the Longitudinal Business Database (Jarmin and Miranda 2002) and Longitudinal Employer Household Dynamics (Abowd, Haltiwanger, and Lane 2004), which have yielded a host of new data products and critical policy-relevant insights on business dynamics (Haltiwanger, Jarmin, and Miranda 2013) and labor market volatility (Brown, Haltiwanger, and Lane 2008), respectively. Without providing robust, but secure, access to confidential data, researchers at the Census Bureau would have been unable to undertake the innovations that made these new products and insights possible.

<sup>1</sup>PII is “any information about an individual maintained by an agency, including (1) any information that can be used to distinguish or trace an individual’s identity, such as name, social security number, date and place of birth, mother’s maiden name, or biometric records; and (2) any other information that is linked or linkable to an individual, such as medical, educational, financial, and employment information” [254].

### 12.3 Providing access

The approaches to providing access have evolved over time. Statistical agencies often employ a range of approaches depending on the needs of heterogeneous data users (Doyle et al. 2001; Foster, Jarmin, and Riggs 2009). Dissemination of data to the public usually occurs in three steps: an evaluation of disclosure risks, followed by the application of an anonymization technique, and finally an evaluation of disclosure risks and analytical quality of the candidate data release(s). The two main approaches have been *statistical disclosure* control techniques to produce anonymized public use data sets, and controlled access through a *research data center*.

#### Statistical disclosure control techniques

Statistical agencies have made data available in a number of ways: through tabular data, public use files, licensing agreements and, more recently, through synthetic data (Reiter 2012). Hundepool et al. (Hundepool et al. 2010) define statistical disclosure control as follows:

concepts and methods that ensure the confidentiality of micro and aggregated data that are to be published. It is methodology used to design statistical outputs in a way that someone with access to that output cannot relate a known individual (or other responding unit) to an element in the output.

Traditionally, confidentiality protection has been accomplished by releasing only *aggregated tabular data*. This practice works well in settings where the primary purpose is enumeration, such as census taking. However, tabular data are poorly suited to describing the underlying distributions and covariance across variables that are often the focus of applied social science research (Duncan, Elliot, and Salazar-González 2011).

To provide researchers access to data that permitted analysis of the underlying variance–covariance structure of the data, some agencies have constructed public use micro-data samples. To protect confidentiality in such *public use files*, a number of statistical disclosure control procedures are typically applied. These include stripping all identifying (e.g., PII) fields from the data, topcoding highly skewed variables (e.g., income), and swapping records (Doyle et al. 2001; Zayatz 2007). However, the mosaic effect—where disparate pieces of information can be combined to reidentify individuals—dramatically increases the risk of releasing public use files (Czajka et al. 2014). In addition, there is more and more evidence that the statistical disclosure procedure applied to produce them decreases their utility across many applications (Burkhauser, Feng, and Larrimore 2010).

Some agencies provide access to confidential micro-data through *licensing* arrangements. A contract specifies the conditions of use and what safeguards must be in place. In some cases, the agency has the authority to conduct random inspections. However, this approach has led to a number of operational challenges, including version control, identifying and managing risky researcher behavior, and management costs (Doyle et al. 2001).

Another approach to providing access to confidential data that has been proposed by a group of theoretical computer scientists Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith (Dwork and Roth 2014). Here statistics or other reported outputs are injected with noise, and are called “differentially private” if the inclusion or exclusion of the most at-risk person in the population does not change the probability of any output by more than a given factor. The parameter driving this factor (usually referred to as epsilon) quantifies how sensitive the aggregate output is to any one person’s data. If it is low, the output is highly “private” in the sense that it will be very difficult to reconstruct anything based on it. If it is high, reconstruction is easy. For a discussion of the applications to Census data see (Ruggles et al. 2019; Abowd 2018).

Another approach that has had some resurgence is the use of *synthetic data* where certain properties of the original data are preserved but the original data are replaced by “synthetic data” so that no individual or business entity can be found in the released data (Drechsler 2011). One of the earlier examples of such work was the IBM Quest system (cite : <http://www.vldb.org/conf/1994/P487.PDF>) that generated synthetic transaction data. Two more recent examples of synthetic data sets are the SIPP Synthetic-Beta (Abowd, Stinson, and Benedetto 2006) of linked Survey of Income and Program Participation (SIPP) and Social Security Administration earnings data, and the Synthetic Longitudinal Business Database (SynLBD) (Kinney et al. 2011). Jarmin et al. (Jarmin, Louis, and Miranda 2014) discuss how synthetic data sets lack utility in many research settings but are useful for generating flexible data sets underlying data tools and apps such as the Census Bureau’s OnTheMap.

It is important to keep in mind that the utility of synthetic data sets as a general purpose “anonymization” tool is fairly limited. Synthetic data generation typically requires explicitly defining which properties of the original data need to be preserved (such as univariate or bivariate distributions of certain variables), and as such can be of limited use in most social science research.

### Research data centers

The second approach is establishing research data centers. Here, qualified researchers gain access to micro-level data after they are sworn in to protect the confidentiality of the data they access. Strong input and output controls are in place to ensure that published findings comply with the privacy and confidentiality regulations (Hayden 2012). Some RDCs allow access through

remote execution, where no direct access to the data is allowed, but it is not necessary to travel; others allow remote direct access

---

## 12.4 Non-Tabular data

In addition to tabular data, a lot of new sources of data consist of text, audio, image, and video content. The above approaches primarily deal with maintaining the privacy and confidentiality of entities in tabular data but it is equally important to do the same in non-tabular data. Medical records, sensitive crime records, notes and comments in administrative records, camera footage (from police body-cams or security cameras for example) are all examples of data that is being used for analysis and requires robust techniques to maintain the privacy and confidentiality of individuals. Although the techniques there are not as mature, there is some work in these areas:

Text Anonymization. Typical approaches here range from simply removing Personally identifiable information (PII) through regular expressions and dictionaries ([cite:<https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/1472-6947-8-32>](https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/1472-6947-8-32)) to machine learning based approaches that balance the confidentiality of the entities in the data and the utility of the text ([cite:<https://www.aaai.org/ocs/index.php/IAAI/IAAI-11/paper/viewPaper/3528>](https://www.aaai.org/ocs/index.php/IAAI/IAAI-11/paper/viewPaper/3528)) Image and Video Anonymization: The most common use of anonymization techniques in image and video data is to redact, blur, or remove faces of individuals in order to protect their identity. This can be extended to other attributes of the person, such as clothing or the rest of the body but the primary focus so far has been on detecting, and then blurring or modifying the faces of individuals in the data. <https://www.spiedigitallibrary.org/journals/journal-of-electronic-imaging/volume-26/issue-05/051406/Video-redaction-a-survey-and-comparison-of-enabling-technologies/10.1117/1.JEI.26.5.051406.full?SSO=1> provide a survey of video redaction methods. Cite: <https://arxiv.org/abs/1909.04538> recently presented a method to automatically anonymize faces in images while retaining the original data distribution.

---

## 12.5 The new challenges

While there are well-established policies and protocols surrounding access to and use of survey and administrative data, a major new challenge is the lack

of clear guidelines governing the collection of data about human activity in a world in which all public, and some private, actions generate data that can be harvested (Advisors on Science and Technology 2014; Ohm 2010; Strandburg 2014). The twin pillars on which so much of social science have rested—*informed consent* and *anonymization*—are virtually useless in a big data setting where multiple data sets can be and are linked together using individual identifiers by a variety of players beyond social scientists with formal training and whose work is overseen by institutional review boards. This rapid expansion in data and their use is very much driven by the increased utility of the linked information to businesses, policymakers, and ultimately the taxpayer. In addition, there are no obvious data stewards and custodians who can be entrusted with preserving the privacy and confidentiality with regard to both the source data collected from sensors, social media, and many other sources, and the related analyses (Lane and Stodden 2013).

It is clear that informed consent as historically construed is no longer feasible. As Nissenbaum (Nissenbaum 2011) points out, notification is either comprehensive or comprehensible, but not both. While ideally human subjects are offered true freedom of choice based on a sound and sufficient understanding of what the choice entails, in reality the flow of data is so complex and the interest in the data usage so diverse that simplicity and clarity in the consent statement unavoidably result in losses of fidelity, as anyone who has accepted a Google Maps agreement is likely to understand (Hayden 2015). In addition, informed consent requires a greater understanding of the breadth of type of privacy breaches, the nature of harm as diffused over time, and an improved valuation of privacy in the big data context. Consumers may value their own privacy in variously flawed ways. They may, for example, have incomplete information, or an overabundance of information rendering processing impossible, or use heuristics that establish and routinize deviations from rational decision-making (Acquisti 2014).

It is also nearly impossible to truly anonymize data. Big data are often structured in such a way that essentially everyone in the file is unique, either because so many variables exist or because they are so frequent or geographically detailed, that they make it easy to reidentify individual patterns (Narayanan and Shmatikov 2008). It is also no longer possible to rely on sampling or measurement error in external files as a buffer for data protection, since most data are not in the hands of statistical agencies.

There are no data stewards controlling access to individual data. Data are often so interconnected (think social media network data) that one person's action can disclose information about another person without that person even knowing that their data are being accessed. The group of students posting pictures about a beer party is an obvious example, but, in a research context, if the principal investigator grants access to the proposal, information could be divulged about colleagues and students. In other words, volunteered information

of a minority of individuals can unlock the same information about many—a type of “tyranny of the minority” (Barocas and Nissenbaum 2014b).

There are particular issues raised by the new potential to link information based on a variety of attributes that do not include PII. Barocas and Nissenbaum write as follows (Barocas and Nissenbaum 2014a):

Rather than attempt to deanonymize medical records, for instance, an attacker (or commercial actor) might instead infer a rule that relates a string of more easily observable or accessible indicators to a specific medical condition, rendering large populations vulnerable to such inferences even in the absence of PII. Ironically, this is often the very thing about big data that generate the most excitement: the capacity to detect subtle correlations and draw actionable inferences. But it is this same feature that renders the traditional protections afforded by anonymity (again, more accurately, pseudonymity) much less effective.

In light of these challenges, Barocas and Nissenbaum continue

the value of anonymity inheres not in namelessness, and not even in the extension of the previous value of namelessness to all uniquely identifying information, but instead to something we called “reachability,” the possibility of knocking on your door, hauling you out of bed, calling your phone number, threatening you with sanction, holding you accountable—with or without access to identifying information.

It is clear that the concepts used in the larger discussion of privacy and big data require updating. How we understand and assess harms from privacy violations needs updating. And we must rethink established approaches to managing privacy in the big data context. The next section discusses the framework for doing so.

---

## 12.6 Legal and ethical framework

The Fourth Amendment to the US Constitution, which constrains the government’s power to “search” the citizenry’s “persons, houses, papers, and effects” is usually cited as the legal framework for privacy and confidentiality issues. In the US a “sectoral” approach to privacy regulation, for example, the Family Education Rights and Privacy Act and the Health Insurance Portability and Accountability Act, is also used in situations where different economic areas have separate privacy laws (Ohm 2014). In addition, current legal restrictions and guidance on data collection in the industrial setting include the Fair Information Practice Principles dating from 1973 and underlying the Fair

Credit Reporting Act from 1970 and the Privacy Act from 1974 (Strandburg 2014). Federal agencies often have statutory oversight, such as Title 13 of the US Code for the Census Bureau, the Confidential Information Protection and Statistical Efficiency Act for federal statistical agencies, and Title 26 of the US Code for the Internal Revenue Service.

Yet the generation of big data often takes place in the open, or through commercial transactions with a business, and hence is not covered by these frameworks. There are major questions as to what is reasonably private and what constitutes unwarranted intrusion (Strandburg 2014). There is a lack of clarity on who owns the new types of data—whether it is the person who is the subject of the information, the person or organization who collects these data (the data custodian), the person who compiles, analyzes, or otherwise adds value to the information, the person who purchases an interest in the data, or society at large. The lack of clarity is exacerbated because some laws treat data as property and some treat it as information (Cecil and Eden 2003).

The ethics of the use of big data are also not clear, because analysis may result in being discriminated against unfairly, being limited in one's life choices, being trapped inside stereotypes, being unable to delineate personal boundaries, or being wrongly judged, embarrassed, or harassed. There is an entire research agenda to be pursued that examines the ways that big data may threaten interests and values, distinguishes the origins and nature of threats to individual and social integrity, and identifies different solutions (Boyd and Crawford 2012). The approach should be to describe what norms and expectations are likely to be violated if a person agrees to provide data, rather than to describe what will be done during the research.

What is clear is that most data are housed no longer in statistical agencies, with well-defined rules of conduct, but in businesses or administrative agencies. In addition, since digital data can be alive forever, ownership could be claimed by yet-to-be-born relatives whose personal privacy could be threatened by release of information about blood relations.

The new European Data Protection Regulation (GDPR), which is in effect since May, 2018, was designed to address some of the challenges. In addition to ensuring lawful data collection practices, GDPR pushes for purpose limitation and data minimisation. This principle requires organisations to clearly state for what purpose personal data is collected, to collect the data only for the time needed to complete the purpose, and to collect only those personal data that is needed to achieve the specified processing purposes. In the U.S. the California Consumer Privacy Act (CCPA) is in effect since January 2020, and here too companies have now have time limits to process customer data.

However, GDPR and other regulations of this type, still rely on traditional regulatory tools for managing privacy, which is notice, and consent. Both have failed to provide a viable market mechanism allowing a form of self-

regulation governing industry data collection. Going forward, a more nuanced assessment of tradeoffs in the big data context, moving away from individualized assessments of the costs of privacy violations, is needed (Strandburg 2014).

Ohm advocates for a new conceptualization of legal policy regarding privacy in the big data context that uses five guiding principles for reform: first, that rules take into account the varying levels of inherent risk to individuals across different data sets; second, that traditional definitions of PII need to be rethought; third, that regulation has a role in creating and policing walls between data sets; fourth, that those analyzing big data must be reminded, with a frequency in proportion to the sensitivity of the data, that they are dealing with people; and finally, that the ethics of big data research must be an open topic for continual reassessment (Ohm 2014).

---

## 12.7 Summary

The excitement about how big data can change the social science research paradigm should be tempered by a recognition that existing ways of protecting confidentiality are no longer viable (Karr and Reiter 2014). There is a great deal of research that can be used to inform the development of such a structure, but it has been siloed into disconnected research areas, such as statistics, cybersecurity, and cryptography, as well as a variety of different practical applications, including the successful development of remote access secure data enclaves. We must piece together the knowledge from these various fields to develop ways in which vast new sets of data on human beings can be collected, integrated, and analyzed while protecting them (Lane et al. 2014).

It is possible that the confidentiality risks of disseminating data may be so high that traditional access models will no longer hold; that the data access model of the future will be to take the analysis to the data rather than the data to the analyst or the analyst to the data. One potential approach is to create an integrated system including (a) unrestricted access to highly redacted data, most likely some version of synthetic data, followed by (b) means for approved researchers to access the confidential data via remote access solutions, combined with (c) verification servers that allows users to assess the quality of their inferences with the redacted data so as to be more efficient with their use (if necessary) of the remote data access. Such verification servers might be a web-accessible system based on a confidential database with an associated public micro-data release, which helps to analyze the confidential database (Karr and Reiter 2014). Such approaches are starting to be developed, both in the USA and in Europe (Elias 2014; Jones and Elias 2006).

There is also some evidence that people do not require complete protection, and will gladly share even private information provided that certain social norms are met (Wilbanks 2014; Pentland et al. 2014). There is a research agenda around identifying those norms as well; characterizing the interests and wishes of actors (the information senders and recipients or providers and users); the nature of the attributes (especially types of information about the providers, including how these might be transformed or linked); and identifying transmission principles (the constraints underlying the information flows).

However, it is likely that it is no longer possible for a lone social scientist to address these challenges. One-off access agreements to individuals are conducive to neither the production of high-quality science nor the high-quality protection of data (Schermann et al. 2014). The curation, protection, and dissemination of data on human subjects cannot be an artisan activity but should be seen as a major research infrastructure investment, like investments in the physical and life sciences (Bird 2011; Abazajian et al. 2009; Human Microbiome Jumpstart Reference Strains Consortium et al. 2010). In practice, this means that linkages become professionalized and replicable, research is fostered within research data centers that protect privacy in a systematic manner, knowledge is shared about the process of privacy protections disseminated in a professional fashion, and there is ongoing documentation about the value of evidence-based research. It is thus that the risk–utility tradeoff depicted in Figure 12.1 can be shifted in a manner that serves the public good.

---

## 12.8 Resources

The American Statistical Association’s Privacy and Confidentiality website provides a useful source of information (American Statistical Association, n.d.).

An overview of federal activities is provided by the Confidentiality and Data Access Committee of the Federal Committee on Statistics and Methodology (Confidentiality and Data Access Committee, n.d.).

The World Bank and International Household Survey Network provide a good overview of data dissemination “best practices” (International Household Survey Network, n.d.).

There is a *Journal of Privacy and Confidentiality* based at Carnegie Mellon University (JPC, n.d.), and also a journal called *Transactions in Data Privacy* (TDP, n.d.).

The United Nations Economic Commission on Europe hosts workshops and

conferences and produces occasional reports (United Nations Economic Commission for Europe, n.d.).

Collection of lectures from the semester on privacy at the Simons Institute for the Theory of Computing <https://simons.berkeley.edu/programs/privacy2019> (available on youtube <https://www.youtube.com/user/SimonsInstitute/>)

% FK notes from 1/3/2020 % Brian – let's change your personal repository to coleridge for the binder (or anywhere else) % make use of the side notes for the printed version (we will have them back like the old layout was) % 4 levels down in the structuring is too much. Check with the editor how they want to do this. I would recommend just going with non-numbered sections at that point.



# 13

---

## Workbooks

---

**Brian Kim, Christoph Kern, Jonathan Scott Morgan, Christina Jones, and Ahmad Emad**

This final chapter provides an overview of the Python workbooks that accompany this book. The workbooks combine text explanation and code you can run, implemented in *Jupyter notebooks* (<https://jupyter.org/>), to explain techniques and approaches selected from each chapter and to provide thorough implementation details, enabling students and interested practitioners to quickly get up to speed on and start using the technologies covered in the book. We hope you have a lot of fun with them.

---

### 13.1 Introduction

We provide accompanying Jupyter workbooks for most chapters in this book. The workbooks are structured in two sets. *Workbook Set 1* includes workbooks that can be run online, which allows you to quickly interact with the code examples. *Workbook Set 2* provides additional workbooks that can be run locally or on a Server (that needs to be configured first). The workbooks of these sets explain and exemplify techniques and approaches from the book chapters by using different substantive examples and data sources.

In summary, the workbooks provide a thorough overview of the work needed to implement the selected technologies. They combine explanation, basic exercises, and substantial additional Python code to provide a conceptual understanding of each technology, give insight into how key parts of the process are implemented through exercises, and then lay out an end-to-end pattern for implementing each in your own work. The workbooks are implemented using Jupyter notebooks, interactive documents that mix formatted text and Python code samples that can be edited and run in real time in a Jupyter notebook server, allowing you to run and explore the code for each technology as you read about it.

## 13.2 Workbook Set 1

The workbooks of set 1 are designed to be run online using Binder (<https://mybinder.org/>) and don't need additional software installed locally. Individual workbooks can be opened by following the corresponding Binder link. The full set of workbooks is available in the *Big-Data-Social-Science GitHub repository* (<https://github.com/Coleridge-Initiative/bdss-notebooks>). Additional workbooks may be added over time and made available in this repository.

To launch Binder and work on the notebooks, you can use the following link: (<https://mybinder.org/v2/gh/Coleridge-Initiative/bdss-notebooks/master>). At this point, online workbooks are available for selected topics that are covered in the book. Below is a list of the online workbooks, along with a short summary of the content that each covers. Links to each of the individual workbooks are also provided in each section.

### 13.2.1 Databases

The Databases notebook builds the foundation of using SQL to query data. Much of the later notebooks will involve using these tools. This workbook also introduces you to the main data source that is used in the online workbooks, the North Carolina Department of Corrections Data (<https://webapps.doc.state.nc.us/opi/downloads.do?method=view>). In this notebook, you will

- Build basic queries using SQL,
- Understand and perform various joins.

### 13.2.2 Dataset Exploration

Link to workbook:

The *Dataset Exploration* further explores the North Carolina Department of Correction data, demonstrating how to work with missing values and date variables and join tables by using SQL in Python. Though some of the SQL from the Databases notebook is revisited here, the focus is on practicing Python code and using Python for data analysis. The workbook also explains how to pull data from a database into a dataframe in Python and continues by exploring the imported data using the `numpy` and `pandas` packages. In this workbook, you will learn how to:

- Connect to and query a database through Python,

- Explore aggregate statistics in Python.

### 13.2.3 APIs

The APIs notebook introduces you to the use of Internet-based web service APIs for retrieving data from online data stores. This notebook walks through the process of retrieving data about patents from the PatentsView API from the United States Patent and Trademark Office. The data consist of information about patents, inventors, companies, and geographic locations since 1976. In this workbook, you will learn how to:

- Construct a URL query,
- Get a response from the URL,
- Retrieve the data in JSON form.

### 13.2.4 Text Analysis

In the Text Analysis notebook, you will use the data that you pulled from the PatentsView API in the API notebook to find topics from patent abstracts. This will involve going through every step of the process, from extracting the data to cleaning and preparing to using topic modeling algorithms. In this workbook, you will learn how to:

- Clean and prepare text data,
- Apply Latent Dirichlet Allocation for topic modeling,
- Improve and iterate models to focus in on identified topics.

### 13.2.5 Machine Learning – Creating Labels

The *Machine Learning Creating Labels* workbook exemplifies how to create an outcome variable (label) for a machine learning task by using SQL in Python. It uses the North Carolina Department of Corrections Data to build an outcome that measures recidivism, i.e. whether a former inmate returns to jail in a given period of time. It also shows how to define a Python function to automate programming tasks. In this workbook, you will learn how to:

- Define and compute a prediction target in the machine learning framework,
- Use SQL with data that has a temporal structure (multiple records per observation).

### 13.2.6 Machine Learning – Creating Features

The *Machine Learning Creating Features* workbook prepares predictors (features) for the machine learning task that has been introduced in the *Machine Learning Creating Labels* workbook. It is shown how to use SQL in Python for generating features that are expected to predict recidivism, such as the number of times someone has been admitted to prison prior to a given date. In this workbook, you will learn how to:

- Generate features with SQL for a given prediction problem,
- Automate SQL tasks by defining Python functions.

### 13.2.7 Machine Learning – Model Training and Evaluation

The *Machine Learning Model Training and Evaluation* workbook uses the label and features that were created in the previous workbooks to construct a training and test set for model building and evaluation. It exemplifies how to train machine learning models using `scikit-learn` in Python and how to evaluate prediction performance for classification tasks. In addition, it is shown how to construct and compare multiple machine learning models in a for-loop in Python. In this workbook, you will learn how to:

- Pre-process data to provide valid inputs for machine learning models
- Properly divide data with a temporal structure into training and test sets,
- Train and evaluate machine learning models for classification using Python.

---

## 13.3 Workbook Set 2

The workbooks of set 2 and related files are stored in the *Big-Data-Workbooks GitHub repository* (<https://github.com/BigDataSocialScience/Big-Data-Workbooks>), and so are freely available to be downloaded by anyone at any time and run on any appropriately configured computer. These workbooks are a live set of documents that could potentially change over time, so see the repository for the most recent set of information.

The *Big-Data-Workbooks GitHub repository* provides two different types of workbooks, each needing a different Python setup to run. The first type of workbooks is intended to be downloaded and run locally by individual users. The second type is designed to be hosted, assigned, worked on, and graded on a single server, using `jupyterhub` (<https://github.com/jupyter/jupyterhub>)

to host and run the notebooks and `nbgrader` (<https://github.com/jupyter/nbgrader>) to assign, collect, and grade.

The text, images, and Python code in the workbooks are the same between the two versions, as are the files and programs needed to complete each.

The differences in the workbooks themselves relate to the code cells within each notebook where users implement and test exercises. In the workbooks intended to be used locally, exercises are implemented in simple interactive code cells. In the `nbgrader` versions, these cells have additional metadata and contain the solutions for the exercises, making them a convenient answer key even if you are working on them locally.

### 13.3.1 Running workbooks locally

To run workbooks locally, you will need to install Python on your system, then install `ipython`, which includes a local Jupyter server you can use to run the workbooks. You will also need to install additional Python packages needed by the workbooks, and a few additional programs.

The easiest way to get this all working is to install the free Anaconda Python distribution provided by Continuum Analytics (<https://www.continuum.io/downloads>). Anaconda includes a Jupyter server and precompiled versions of many packages used in the workbooks. It includes multiple tools for installing and updating both Python and installed packages. It is separate from any OS-level version of Python, and is easy to completely uninstall.

Anaconda also works on Windows as it does on Mac and Linux. Windows is a much different operating system from Apple's OS X and Unix/Linux, and Python has historically been much trickier to install, configure, and use on Windows. Packages are harder to compile and install, the environment can be more difficult to set up, etc. Anaconda makes Python easier to work with on any OS, and on Windows, in a single run of the Anaconda installer, it integrates Python and common Python utilities like `pip` into Windows well enough that it approximates the ease and experience of using Python within OS X or Unix/Linux (no small feat).

You can also create your Python environment manually, installing Python, package managers, and Python packages separately. Packages like `numpy` and `pandas` can be difficult to get working, however, particularly on Windows, and Anaconda simplifies this setup considerably regardless of your OS.

### 13.3.2 Central workbook server

Setting up a server to host workbooks managed by `nbgrader` is more involved. Some of the workbooks consume multiple gigabytes of memory per user and substantial processing power. A hosted implementation where all users work on a single server requires substantial hardware, relatively complex configuration, and ongoing server maintenance. Detailed instructions are included in the Big-Data-Workbooks GitHub repository. It is not rocket science, but it is complicated, and you will likely need an IT professional to help you set up, maintain, and troubleshoot. Since all student work will be centralized in this one location, you will also want a robust, multi-destination backup plan.

For more information on installing and running the workbooks that accompany this book, see the Big-Data-Workbooks GitHub repository.

### 13.3.3 Workbook details

Most chapters have an associated workbook, each in its own directory in the Big-Data-Workbooks GitHub repository. Below is a list of the workbooks, along with a short summary of the topics that each covers.

### 13.3.4 Social Media and APIs

The Social Media and APIs workbook introduces you to the use of Internet-based web service APIs for retrieving data from online data stores. Examples include retrieving information on articles from Crossref (provider of Digital Object Identifiers used as unique IDs for publications) and using the PLOS Search and ALM APIs to retrieve information on how articles are shared and referenced in social media, focusing on Twitter. In this workbook, you will learn how to:

- Set up user API keys,
- Connect to Internet-based data stores using APIs,
- Collect DOIs and Article-Level Metrics data from web APIs,
- Conduct basic analysis of publication data.

### 13.3.5 Database basics

In the Database workbook you will learn the practical benefits that stem from using a database management system. You will implement basic SQL commands to query grants, patents, and vendor data, and thus learn how to

interact with data stored in a relational database. You will also be introduced to using Python to execute and interact with the results of SQL queries, so you can write programs that interact with data stored in a database. In this workbook, you will learn how to:

- Connect to a database through Python,
- Query the database by using SQL in Python,
- Begin to understand to the SQL query language,
- Close database connections.

### 13.3.6 Data Linkage

In the Data Linkage workbook you will use Python to clean input data, including using regular expressions, then learn and implement the basic concepts behind the probabilistic record linkage: using different types of string comparators to compare multiple pieces of information between two records to produce a score that indicates how likely it is that the records are data about the same underlying entity. In this workbook, you will learn how to:

- Parse a name string into first, middle, and last names using Python's `split` method and regular expressions,
- Use and evaluate the results of common computational string comparison algorithms including Levenshtein distance, Levenshtein–Damerau distance, and Jaro–Winkler distance,
- Understand the Fellegi–Sunter probabilistic record linkage method, with step-by-step implementation guide.

### 13.3.7 Machine Learning

In the Machine Learning workbook you will train a machine learning model to predict missing information, working through the process of cleaning and prepping data for training and testing a model, then training and testing a model to impute values for a missing categorical variable, predicting the academic department of a given grant's primary investigator based on other traits of the grant. In this workbook, you will learn how to:

- Read, clean, filter, and store data with Python's `pandas` data analysis package,
- Recognize the types of data cleaning and refining needed to make data more compatible with machine learning models,
- Clean and refine data,

- Manage memory when working with large data sets,
- Employ strategies for dividing data to properly train and test a machine learning model,
- Use the `scikit-learn` Python package to train, fit, and evaluate machine learning models.

### 13.3.8 Text Analysis

In the Text Analysis workbook, you will derive a list of topics from text documents using MALLET, a Java-based tool that analyzes clusters of words across a set of documents to derive common topics within the documents, defined by sets of key words that are consistently used together. In this workbook, you will learn how to:

- Clean and prepare data for automated text analysis,
- Set up data for use in MALLET,
- Derive a set of topics from a collection of text documents,
- Create a model that detects these topics in documents, and use this model to categorize documents.

### 13.3.9 Networks

In the Networks workbook you will create network data where the nodes are researchers who have been awarded grants, and ties are created between each researcher on a given grant. You will use Python to read the grant data and translate them into network data, then use the `networkx` Python library to calculate node- and graph-level network statistics and `igraph` to create and refine network visualizations. You will also be introduced to graph databases, an alternative way of storing and querying network data. In this workbook, you will learn how to:

- Develop strategies for detecting potential network data in relational data sets,
- Use Python to derive network data from a relational database,
- Store and query network data using a graph database like `neo4j`,
- Load network data into `networkx`, then use it to calculate node- and graph-level network statistics,
- Use `networkx` to export graph data into commonly shared formats (`graphml`, edge lists, different tabular formats, etc.),

- Load network data into the `igraph` Python package and then create graph visualizations.

### 13.3.10 Visualization

The Visualization workbook introduces you to Tableau, a data analysis and visualization software package that is easy to learn and use. Tableau allows you to connect to and integrate multiple data sources into complex visualizations without writing code. It allows you to dynamically shift between views of data to build anything from single visualizations to an interactive dashboard that contains multiple views of your data. In this workbook, you will learn how to:

- Connect Tableau to a relational database,
- Interact with Tableau's interface,
- Select, combine, and filter the tables and columns included in visualizations,
- Create bar charts, timeline graphs, and heat maps,
- Group and aggregate data,
- Create a dashboard that combines multiple views of your data.

---

## 13.4 Resources

We noted in Section Introduction: Resources the importance of Python, MySQL, and Git/GitHub for the social scientist who intends to work with large data. See that section for pointers to useful online resources, and also this book's website, at <https://github.com/BigDataSocialScience>, where we have collected many useful web links, including the following.

For more on getting started with Anaconda, see Continuum's Anaconda documentation (Analytics, n.d.), Anaconda FAQ (Analytics, n.d.), and Anaconda quick start guide (Analytics, n.d.).

For more information on IPython and the Jupyter notebook server, see the IPython site (IPython development team, n.d.), IPython documentation (IPython development team, n.d.), Jupyter Project site (Jupyter, n.d.), and Jupyter Project documentation (Jupyter, n.d.).

For more information on using `jupyterhub` and `nbgrader` to host, distribute, and grade workbooks using a central server, see the `jupyterhub` GitHub repository (Jupyter, n.d.), `jupyterhub` documentation (Jupyter, n.d.), `nbgrader`

GitHub repository (Jupyter, n.d.), `nbgrader` and documentation (Jupyter, n.d.).

AAPOR. n.d. "American Association for Public Opinion Research Website." <http://www.aapor.org>. Accessed February 1, 2016.

Abadi, Daniel, Rakesh Agrawal, Anastasia Ailamaki, Magdalena Balazinska, Philip A Bernstein, Michael J Carey, Surajit Chaudhuri, et al. 2014. "The Beckman Report on Database Research." *ACM SIGMOD Record* 43 (3). ACM: 61–70.

Abazajian, Kevork N., Jennifer K. Adelman-McCarthy, Marcel A. Agüeros, Sahar S. Allam, Carlos Allende Prieto, Deokkeun An, Kurt S. J. Anderson, et al. 2009. "The Seventh Data Release of the Sloan Digital Sky Survey." *Astrophysical Journal Supplement Series* 182 (2). IOP Publishing: 543.

Abowd, J. M. 2018. "The US Census Bureau Adopts Differential Privacy." Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 2867–2867). ACM.

Abowd, John M., John Haltiwanger, and Julia Lane. 2004. "Integrated Longitudinal Employer-Employee Data for the United States." *American Economic Review* 94 (2). JSTOR: 224–29.

Abowd, John M., Martha Stinson, and Gary Benedetto. 2006. "Final Report to the Social Security Administration on the SIPP/SSA/IRS Public Use File Project." Suitland, MD: Census Bureau, Longitudinal Employer-Household Dynamics Program.

Acquisti, Alessandro. 2014. "The Economics and Behavioral Economics of Privacy." In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, 98–112. Cambridge University Press.

Advisors on Science, President's Council of, and Technology. 2014. "Big Data and Privacy: A Technological Perspective." Washington, DC: Executive Office of the President.

Ahlberg, Christopher, Christopher Williamson, and Ben Shneiderman. 1992. "Dynamic Queries for Information Exploration: An Implementation and Evaluation." In *Proceedings of the Sigchi Conference on Human Factors in Computing Systems*, 619–26. ACM.

Alawadhi, Suha, Armando Aldama-Nalda, Hafedh Chourabi, J. Ramon Gil-Garcia, Sofia Leung, Sehl Mellouli, Taewoo Nam, Theresa A. Pardo, Hans J. Scholl, and Shawn Walker. 2012. "Building Understanding of Smart City Initiatives." In *Electronic Government*, 40–53. Springer.

Albanese, Ed. n.d. "Scaling Social Science with Hadoop." <http://blog.cloudera>.

com/blog/2010/04/scaling-social-science-with-hadoop/. Accessed February 1, 2016.

Allison, Paul D. 2001. *Missing Data*. Sage Publications.

American Statistical Association. n.d. “ASA Privacy and Confidentiality Subcommittee.” <http://community.amstat.org/cpc/home>.

Analytics, Continuum. n.d. “Anaconda.” <http://docs.continuum.io/anaconda>. Accessed February 1, 2016.

———. n.d. “Anaconda FAQ.” <http://docs.continuum.io/anaconda/faq>. Accessed February 1, 2016.

———. n.d. “Anaconda Quick Start Guide.” <https://www.continuum.io/sites/default/files/Anaconda-Quickstart.pdf>. Accessed February 1, 2016.

Anscombe, Francis J. 1973. “Graphs in Statistical Analysis.” *American Statistician* 27 (1). Taylor & Francis Group: 17–21.

Antenucci, Dolan, Michael Cafarella, Margaret Levenstein, Christopher Ré, and Matthew D. Shapiro. 2014. “Using Social Media to Measure Labor Market Flows.” National Bureau of Economic Research.

Apache Hadoop. n.d. “HDFS Architecture.” <http://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html>. Accessed April 16, 2016.

Apache Software Foundation. n.d. “Apache Ambari.” <http://ambari.apache.org>. Accessed February 1, 2016.

———. n.d. “Apache Hadoop.” <https://hadoop.apache.org/docs/stable/>.

———. n.d. “Apache Hadoop Documentation Site.” <https://hadoop.apache.org/docs/current/>. Accessed February 1, 2016.

———. n.d. “Apache Spark Documentation Site.” <https://spark.apache.org/docs/current/>. Accessed February 1, 2016.

Armbrust, Michael, Armando Fox, Rean Griffith, Anthony D. Joseph, Randy Katz, Andy Konwinski, Gunho Lee, et al. 2010. “A View of Cloud Computing.” *Communications of the ACM* 53 (4). ACM: 50–58.

Art Branch Inc. n.d. “SQL Cheatsheet.” <http://www.sql-tutorial.net/SQL-Cheat-Sheet.pdf>. Accessed December 1, 2015.

Baldeschwieler, Eric. 2011. “Best Practices for Selecting Apache Hadoop Hardware.” *Hortonworks*, <http://hortonworks.com/blog/best-practices-for-selecting-apache-hadoop-hardware/>.

Barabási, Albert-László, and Réka Albert. 1999. “Emergence of Scaling in Ran-

- dom Networks.” *Science* 286 (5439). American Association for the Advancement of Science: 509–12.
- Barbaro, Michael, Tom Zeller, and Saul Hansell. 2006. “A Face Is Exposed for AOL Searcher No. 4417749.” *New York Times*, August.
- Baracas, Solon, and Helen Nissenbaum. 2014a. “Big Data’s End Run Around Procedural Privacy Protections.” *Communications of the ACM* 57 (11). ACM: 31–33.
- . 2014b. “The Limits of Anonymity and Consent in the Big Data Age.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum. Cambridge University Press.
- Bastian, Hilda. 2013. “Bad Research Rising: The 7th Olympiad of Research on Biomedical Publication.” *Scientific American*, <http://blogs.scientificamerican.com/absolutely-maybe/bad-research-rising-the-7th-olympiad-of-research-on-biomedical-publication/>.
- Batagelj, Vladimir, and Andrej Mrvar. 1998. “Pajek—Program for Large Network Analysis.” *Connections* 21 (2): 47–57.
- Bell, Alex. 2012. “Python for Economists.” <http://cs.brown.edu/~ambell/pyseminar/pyseminar.html>.
- Bengio, Y., A. Courville, and P. Vincent. 2013. “Representation Learning: A Review and New Perspectives.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 35 (8): 1798–1828. doi:10.1109/TPAMI.2013.50.
- Bhuvaneshwar, Krithika, Dinanath Sulakhe, Robinder Gauba, Alex Rodriguez, Ravi Madduri, Utpal Dave, Lukasz Lacinski, Ian Foster, Yuriy Gusev, and Subha Madhavan. 2015. “A Case Study for Cloud Based High Throughput Analysis of NGS Data Using the Globus Genomics System.” *Computational and Structural Biotechnology Journal* 13. Elsevier: 64–74.
- Biemer, Paul P. 2010. “Total Survey Error: Design, Implementation, and Evaluation.” *Public Opinion Quarterly* 74 (5). AAPOR: 817–48.
- . 2011. *Latent Class Analysis of Survey Error*. John Wiley & Sons.
- Biemer, Paul P., and Lars E. Lyberg. 2003. *Introduction to Survey Quality*. John Wiley & Sons.
- Biemer, Paul P., and S. L. Stokes. 1991. “Approaches to Modeling Measurement Error.” In *Measurement Errors in Surveys*, edited by Paul P. Biemer, R. Groves, L. Lyberg, N. Mathiowetz, and S. Sudman, 54–68. John Wiley.
- Biemer, Paul P., and Dennis Trewin. 1997. “A Review of Measurement Error Effects on the Analysis of Survey Data.” In *Survey Measurement and Process*

- Quality*, edited by L. Lyberg, P. Biemer, M. Collins, E. De Leeuw, C. Dippo, N. Schwarz, and D. Trewin, 601–32. John Wiley & Sons.
- Bird, Ian. 2011. “Computing for the Large Hadron Collider.” *Annual Review of Nuclear and Particle Science* 61. Annual Reviews: 99–118.
- Bird, Steven, Ewan Klein, and Edward Loper. 2009. *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*. O’Reilly Media.
- Blei, David M. n.d. “Topic Modeling.” <http://www.cs.columbia.edu/~blei/topicmodeling.html>. Accessed February 1, 2016.
- Blei, David M., and John Lafferty. 2009. “Topic Models.” In *Text Mining: Theory and Applications*, edited by Ashok Srivastava and Mehran Sahami. Taylor & Francis.
- Blei, David M., and Jon D. McAuliffe. 2007. “Supervised Topic Models.” In *Advances in Neural Information Processing Systems*.
- Blei, David M., Andrew Ng, and Michael Jordan. 2003. “Latent Dirichlet Allocation.” *Journal of Machine Learning Research* 3: 993–1022.
- Blitzer, John, Mark Dredze, and Fernando Pereira. 2007. “Biographies, Bollywood, Boom-Boxes and Blenders: Domain Adaptation for Sentiment Classification.” In *Proceedings of the Association for Computational Linguistics*.
- Boy, Jeremy, Ronald Rensink, Enrico Bertini, Jean-Daniel Fekete, and others. 2014. “A Principled Way of Assessing Visualization Literacy.” *IEEE Transactions on Visualization and Computer Graphics* 20 (12). IEEE: 1963–72.
- Boyd, Danah, and Kate Crawford. 2012. “Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon.” *Information, Communication & Society* 15 (5). Taylor & Francis: 662–79.
- Boyd-Graber, Jordan. n.d. [http://www.umiacs.umd.edu/~jbg/lda\\_demo](http://www.umiacs.umd.edu/~jbg/lda_demo). Accessed February 1, 2016.
- Boyd-Graber, Jordan, Yuening Hu, and David Mimno. 2017. *Applications of Topic Models*. Edited by Doug Oard. Vol. 11. Foundations and Trends in Information Retrieval 2–3. NOW Publishers. <http://www.nowpublishers.com/article/Details/INR-030>.
- Brewer, Eric. 2012. “CAP Twelve Years Later: How the ‘Rules’ Have Changed.” *Computer* 45 (2). IEEE: 23–29.
- Broekstra, Jeen, Arjohn Kampman, and Frank Van Harmelen. 2002. “Sesame:

- A Generic Architecture for Storing and Querying RDF and RDF Schema.” In *The Semantic Web—ISWC 2002*, 54–68. Springer.
- Brown, Clair, John Haltiwanger, and Julia Lane. 2008. *Economic Turbulence: Is a Volatile Economy Good for America?* University of Chicago Press.
- Brynjolfsson, Erik, Lorin M. Hitt, and Heekyung Hellen Kim. 2011. “Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance?” Available at SSRN 1819486.
- Bureau of Labor Statistics. 2015. “The Employment Situation—November 2015.” [http://www.bls.gov/news.release/archives/empstat\\_12042015.pdf](http://www.bls.gov/news.release/archives/empstat_12042015.pdf).
- Burkhauser, Richard V., Shuaizhang Feng, and Jeff Larrimore. 2010. “Improving Imputations of Top Incomes in the Public-Use Current Population Survey by Using Both Cell-Means and Variances.” *Economics Letters* 108 (1). Elsevier: 69–72.
- Burt, Ronald S. 1993. “The Social Structure of Competition.” *Explorations in Economic Sociology* 65. New York: Russel Sage Foundation: 103.
- . 2004. “Structural Holes and Good Ideas.” *American Journal of Sociology* 110 (2). JSTOR: 349–99.
- Butler, Declan. 2013. “When Google Got Flu Wrong.” *Nature* 494 (7436): 155.
- Card, Stuart K., and David Nation. 2002. “Degree-of-Interest Trees: A Component of an Attention-Reactive User Interface.” In *Proceedings of the Working Conference on Advanced Visual Interfaces*, 231–45. ACM.
- Carr, Jillian B., and Jennifer L. Doleac. 2015. “The Geography, Incidence, and Underreporting of Gun Violence: New Evidence Using ShotSpotter Data.” Technical report, [http://jenniferdoleac.com/wp-content/uploads/2015/03/Carr\\_Doleac\\_gunfire\\_underreporting.pdf](http://jenniferdoleac.com/wp-content/uploads/2015/03/Carr_Doleac_gunfire_underreporting.pdf).
- Catlett, Charlie, Tanu Malik, Brett Goldstein, Jonathan Giuffrida, Yetong Shao, Alessandro Panella, Derek Eder, et al. 2014. “Plenario: An Open Data Discovery and Exploration Platform for Urban Science.” *Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, 27–42.
- Cecil, Joe, and Donna Eden. 2003. “The Legal Foundations of Confidentiality.” In *Key Issues in Confidentiality Research: Results of an Nsf Workshop*. National Science Foundation.
- Chai, John J. 1971. “Correlated Measurement Errors and the Least Squares Estimator of the Regression Coefficient.” *Journal of the American Statistical Association* 66 (335). Taylor & Francis Group: 478–83.
- Chandola, Varun, Arindam Banerjee, and Vipin Kumar. 2009. “Anomaly Detection: A Survey.” *ACM Computing Surveys* 41 (3). ACM: 15.
- Chapelle, O., and S. S. Keerthi. 2010. “Efficient Algorithms for Ranking

with SVMs.” *Information Retrieval* 13 (3). Hingham, MA: Kluwer Academic Publishers: 201–15. doi:10.1007/s10791-009-9109-9.

Chawla, Nitesh V. 2005. “Data Mining for Imbalanced Datasets: An Overview.” In *The Data Mining and Knowledge Discovery Handbook*, edited by Oded Maimon and Lior Rokach, 853–67. Springer. <http://dblp.uni-trier.de/db/books/collections/datamining2005.html#Chawla05>.

Christen, Peter. 2012a. “A Survey of Indexing Techniques for Scalable Record Linkage and Deduplication.” *IEEE Transactions on Knowledge and Data Engineering* 24 (9). IEEE: 1537–55.

———. 2012b. *Data Matching: Concepts and Techniques for Record Linkage, Entity Resolution, and Duplicate Detection*. Springer Science & Business Media.

Clarke, Claire. 2014. “Editing Big Data with Machine Learning Methods.” Paper presented at the Australian Bureau of Statistics Symposium, Canberra.

Cleveland, William S., and Robert McGill. 1984. “Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods.” *Journal of the American Statistical Association* 79 (387). Taylor & Francis: 531–54.

Clifton, C., M. Kantarciooglu, A. Doan, G. Schadow, J. Vaidya, A.K. Elmagarmid, and D. Suciu. 2006. “Privacy-Preserving Data Integration and Sharing.” In *9th ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery*, edited by G. Das, B. Liu, and P. S. Yu, 19–26. ACM.

Cloudera. n.d. “Cloudera Manager.” <https://www.cloudera.com/content/www/en-us/products/cloudera-manager.html>. Accessed April 16, 2016.

Cochran, William G. 1968. “Errors of Measurement in Statistics.” *Technometrics* 10 (4). Taylor & Francis Group: 637–66.

Confidentiality and Data Access Committee. n.d. “Federal Committee on Statistics and Methodology.” <http://fcsm.sites.usa.gov/committees/cdac/>. Accessed April 16, 2016.

Consumer Financial Protection Bureau. n.d. “Home Mortgage Disclosure Act Data.” <http://www.consumerfinance.gov/hmda/learn-more>. Accessed April 16, 2016.

Corti, Paolo, Thomas J. Kraft, Stephen Vincent Mather, and Bborie Park. 2014. *PostGIS Cookbook*. Packt Publishing.

Crammer, Koby, and Yoram Singer. 2002. “On the Algorithmic Implementation of Multiclass Kernel-Based Vector Machines.” *Journal of Machine Learning Research* 2. JMLR.org: 265–92. <http://dl.acm.org/citation.cfm?id=944790.944813>.

Crossno, Patricia J., Douglas D. Cline, and Jeffrey N Jortner. 1993. “A Hetero-

geneous Graphics Procedure for Visualization of Massively Parallel Solutions.” *ASME FED 156*. ASME: 65–65.

Czajka, John, Craig Schneider, Amang Sukasih, and Kevin Collins. 2014. “Minimizing Disclosure Risk in HHS Open Data Initiatives.” US Department of Health & Human Services.

Dean, Jeffrey, and Sanjay Ghemawat. 2004. “MapReduce: Simplified Data Processing on Large Clusters.” In *Proceedings of the 6th Conference on Symposium on Operating Systems Design & Implementation—Volume 6*. OSDI’04. USENIX Association. <http://dl.acm.org/citation.cfm?id=1251254.1251264>.

DeBelius, Danny. 2015. “Let’s Tesselate: Hexagons for Tile Grid Maps.” *NPR Visuals Team Blog*, <http://blog.apps.npr.org/2015/05/11/hex-tile-maps.html>.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. to appear. “Where Has All the Skewness Gone? The Decline in High-Growth (Young) Firms in the US.” *European Economic Review*.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. “BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding.” In *Conference of the North American Chapter of the Association for Computational Linguistics*.

DeWitt, David J., and Michael Stonebraker. 2008. “MapReduce: A Major Step Backwards.” [http://www.dcs.bbk.ac.uk/~dell/teaching/cc/paper/dbc08/dewitt\\_mr\\_db.pdf](http://www.dcs.bbk.ac.uk/~dell/teaching/cc/paper/dbc08/dewitt_mr_db.pdf).

Donohue III, John J., and Justin Wolfers. 2006. “Uses and Abuses of Empirical Evidence in the Death Penalty Debate.” National Bureau of Economic Research.

Doyle, Pat, Julia I. Lane, Jules J. M. Theeuwes, and Laura V. Zayatz. 2001. *Confidentiality, Disclosure, and Data Access: Theory and Practical Applications for Statistical Agencies*. Elsevier Science.

Drechsler, Jörg. 2011. *Synthetic Datasets for Statistical Disclosure Control: Theory and Implementation*. Springer.

Duan, Lian, Lida Xu, Ying Liu, and Jun Lee. 2009. “Cluster-Based Outlier Detection.” *Annals of Operations Research* 168 (1). Springer: 151–68.

DuGoff, Eva H., Megan Schuler, and Elizabeth A. Stuart. 2014. “Generalizing Observational Study Results: Applying Propensity Score Methods to Complex Surveys.” *Health Services Research* 49 (1). Wiley Online Library: 284–303.

Duncan, G., M. Elliot, and J. J. Salazar-González. 2011. *Statistical Confidentiality: Principles and Practice*. Springer.

Dunne, Cody, and Ben Shneiderman. 2013. “Motif Simplification: Improving Network Visualization Readability with Fan, Connector, and Clique Glyphs.”

In *Proceedings of the Sigchi Conference on Human Factors in Computing Systems*, 3247–56. ACM.

Dunning, Ted. 1993. “Accurate Methods for the Statistics of Surprise and Coincidence.” *Computational Linguistics* 19 (1). Cambridge, MA: MIT Press: 61–74. <http://dl.acm.org/citation.cfm?id=972450.972454>.

Dutwin, David, and Trent D. Buskirk. 2017. “Reply.” *Public Opinion Quarterly* 81 (S1): 246–49.

Dwork, C., and A. Roth. 2014. “The Algorithmic Foundations of Differential Privacy.” *Foundations and Trends in Theoretical Computer Science* 9 (3–4): 211–407.

Economic and Social Research Council. 2016. “Administrative Data Research Network.”

Economic Co-operation, Organisation of, and Development. 2004. “A Summary of the Frascati Manual.” *Main Definitions and Conventions for the Measurement of Research and Experimental Development* 84.

Einav, Liran, and Jonathan D. Levin. 2013. “The Data Revolution and Economic Analysis.” National Bureau of Economic Research.

Elbel, B., J. Gyamfi, and R. Kersh. 2011. “Child and Adolescent Fast-Food Choice and the Influence of Calorie Labeling: A Natural Experiment.” *International Journal of Obesity* 35 (4). Macmillan Publishers Limited: 493–500. <http://dx.doi.org/10.1038/ijo.2011.4>.

Elias, Peter. 2014. “A European Perspective on Research and Big Data Access.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, 98–112. Cambridge University Press.

Elliott, Joshua, David Kelly, James Chryssanthacopoulos, Michael Glotter, Kanika Jhunjhnuwala, Neil Best, Michael Wilde, and Ian Foster. 2014. “The Parallel System for Integrating Impact Models and Sectors (pSIMS).” *Environmental Modelling & Software* 62. Elsevier: 509–16.

Elmagarmid, Ahmed K., Panagiotis G. Ipeirotis, and Vassilios S. Verykios. 2007.

- “Duplicate Record Detection: A Survey.” *IEEE Transactions on Knowledge and Data Engineering* 19 (1). IEEE: 1–16.
- Evans, David S. 1987. “Tests of Alternative Theories of Firm Growth.” *Journal of Political Economy* 95. JSTOR: 657–74.
- Evans, J. A., and J. G. Foster. 2011. “Metaknowledge.” *Science* 331 (6018): 721–25.
- Fan, Jianqing, and Yuan Liao. 2012. “Endogeneity in Ultrahigh Dimension.” Princeton University.
- . 2014. “Endogeneity in High Dimensions.” *Annals of Statistics* 42 (3). NIH Public Access: 872.
- Fan, Jianqing, Fang Han, and Han Liu. 2014. “Challenges of Big Data Analysis.” *National Science Review* 1 (2). Oxford University Press: 293–314.
- Fan, Jianqing, Richard Samworth, and Yichao Wu. 2009. “Ultrahigh Dimensional Feature Selection: Beyond the Linear Model.” *Journal of Machine Learning Research* 10. JMLR.org: 2013–38.
- Fekete, Jean-Daniel. 2015. “ProgressiVis: A Toolkit for Steerable Progressive Analytics and Visualization.” Paper presented at 1st Workshop on Data Systems for Interactive Analysis, Chicago, IL, October 26.
- Fekete, Jean-Daniel, and Catherine Plaisant. 2002. “Interactive Information Visualization of a Million Items.” In *IEEE Symposium on Information Visualization*, 117–24. IEEE.
- Feldman, Ronen, and James Sanger. 2006. *Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*. Cambridge University Press.
- Fellegi, Ivan P., and Alan B. Sunter. 1969. “A Theory for Record Linkage.” *Journal of the American Statistical Association* 64 (328). Taylor & Francis Group: 1183–1210.
- Feng, Shi, Eric Wallace, Alvin Grissom II, Pedro Rodriguez, Mohit Iyyer, and Jordan Boyd-Graber. 2018. “Pathologies of Neural Models Make Interpretation Difficult.” In *Empirical Methods in Natural Language Processing*. Brussels, Belgium. docs/2018\_emnlp\_rs.pdf.
- Few, Stephen. 2009. *Now You See It: Simple Visualization Techniques for Quantitative Analysis*. Analytics Press.
- . 2013. *Information Dashboard Design: Displaying Data for at-a-Glance Monitoring*. Analytics Press.
- Fielding, Roy T., and Richard N. Taylor. 2002. “Principled Design of the

Modern Web Architecture.” *ACM Transactions on Internet Technology* 2 (2). ACM: 115–50.

Fisher, Danyel, Igor Popov, Steven Drucker, and m. c. schraefel. 2012. “Trust Me, I’m Partially Right: Incremental Visualization Lets Analysts Explore Large Datasets Faster.” In *Proceedings of the Sigchi Conference on Human Factors in Computing Systems*, 1673–82. ACM.

Fortuna, Blaz, Marko Grobelnik, and Dunja Mladenic. 2007. “OntoGen: Semi-Automatic Ontology Editor.” In *Proceedings of the 2007 Conference on Human Interface: Part II*, 309–18. Beijing, China: Springer. <http://dl.acm.org/citation.cfm?id=1766591.1766627>.

Foster, Lucia, Ron S. Jarmin, and T. Lynn Rigs. 2009. “Resolving the Tension Between Access and Confidentiality: Past Experience and Future Plans at the US Census Bureau.” 09-33. US Census Bureau Center for Economic Studies.

Fox, Armando, Steven D. Gribble, Yatin Chawathe, Eric A. Brewer, and Paul Gauthier. 1997. “Cluster-Based Scalable Network Services.” *ACM SIGOPS Operating Systems Review* 31 (5). ACM.

Francis, W. N., and H. Kucera. 1979. “Brown Corpus Manual.” Department of Linguistics, Brown University, Providence, Rhode Island, US. <http://icame.uib.no/brown/bcm.html>.

Freeman, Linton C. 1979. “Centrality in Social Networks Conceptual Clarification.” *Social Networks* 1 (3). Elsevier: 215–39.

Fuller, Wayne A. 1991. “Regression Estimation in the Presence of Measurement Error.” In *Measurement Errors in Surveys*, edited by Paul P. Biemer, Robert M. Groves, Lars E. Lyberg, Nancy A. Mathiowetz, and Seymour Sudman, 617–35. John Wiley & Sons.

Geman, S., and D. Geman. 1990. “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images.” In *Readings in Uncertain Reasoning*, edited by Glenn Shafer and Judea Pearl, 452–72. Morgan Kaufmann.

Gerrish, Sean M., and David M. Blei. 2012. “The Issue-Adjusted Ideal Point Model.” *arXiv*.

Girone, Maria. 2008. “CERN Database Services for the LHC Computing Grid.” In *Journal of Physics: Conference Series*, 119:052017. 5. IOP Publishing.

Girvan, Michelle, and Mark E. J. Newman. 2002. “Community Structure in Social and Biological Networks.” *Proceedings of the National Academy of Sciences* 99 (12). National Acad Sciences: 7821–6.

Glueck, Michael, Azam Khan, and Daniel J. Wigdor. 2014. “Dive in! Enabling Progressive Loading for Real-Time Navigation of Data Visualizations.” In

*Proceedings of the Sigchi Conference on Human Factors in Computing Systems*, 561–70. ACM.

Gray, Jim. 1981. “The Transaction Concept: Virtues and Limitations.” In *Proceedings of the Seventh International Conference on Very Large Data Bases*, 7:144–54.

Green, Donald P., and Holger L. Kern. 2012. “Modeling Heterogeneous Treatment Effects in Survey Experiments with Bayesian Additive Regression Trees.” *Public Opinion Quarterly* 76. AAPOR: 491–511.

Greenwood, Daniel, Arkadiusz Stopczynski, Brian Sweatt, Thomas Hardjono, and Alex Pentland. 2014. “The New Deal on Data: A Framework for Institutional Controls.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, 192. Cambridge University Press.

Griffiths, Thomas L., and Mark Steyvers. 2004. “Finding Scientific Topics.” *Proceedings of the National Academy of Sciences* 101 (Suppl. 1): 5228–35.

Grimmer, Justin, and Brandon M. Stewart. 2013. “Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts.” *Political Analysis* 21 (3). SPM-PMSAPSA: 267–97.

Gropp, William, Ewing Lusk, and Anthony Skjellum. 2014. *Using MPI: Portable Parallel Programming with the Message-Passing Interface*. MIT Press.

Groves, Robert M. 2004. *Survey Errors and Survey Costs*. John Wiley & Sons.

Haak, Laurel L., Martin Fenner, Laura Paglione, Ed Pentz, and Howard Ratner. 2012. “ORCID: A System to Uniquely Identify Researchers.” *Learned Publishing* 25 (4). Association of Learned; Professional Society Publishers: 259–64.

Hadoop, Apache. n.d. “HDFS Architecture.” <http://spark.apache.org/docs/latest/programming-guide.html#transformations>.

Hainmueller, Jens, and Chad Hazlett. 2014. “Kernel Regularized Least Squares: Reducing Misspecification Bias with a Flexible and Interpretable Machine Learning Approach.” *Political Analysis* 22 (2). SPM-PMSAPSA: 143–68.

Halevy, Alon, Peter Norvig, and Fernando Pereira. 2009. “The Unreasonable Effectiveness of Data.” *IEEE Intelligent Systems* 24 (2). Piscataway, NJ: IEEE Educational Activities Department: 8–12.

Hall, P., and H. Miller. 2009. “Using Generalized Correlation to Effect Variable Selection in Very High Dimensional Problems.” *Journal of Computational and Graphical Statistics* 18: 533–50.

Haltiwanger, John, Ron S. Jarmin, and Javier Miranda. 2013. “Who Creates

- Jobs? Small Versus Large Versus Young.” *Review of Economics and Statistics* 95 (2). MIT Press: 347–61.
- Hansen, Derek, Ben Shneiderman, and Marc A. Smith. 2010. *Analyzing Social Media Networks with NodeXL: Insights from a Connected World*. Morgan Kaufmann.
- Hansen, Morris H., William N. Hurwitz, and William G. Madow. 1993. *Sample Survey Methods and Theory*. John Wiley & Sons.
- Harford, Tim. 2014. “Big Data: A Big Mistake?” *Significance* 11 (5). Wiley Online Library: 14–19.
- Harrison, Lane, Katharina Reinecke, and Remco Chang. 2015. “Infographic Aesthetics: Designing for the First Impression.” In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1187–90. ACM.
- . n.d. “Baby Name Voyager.” <http://www.babynamewizard.com/voyager/>. Accessed February 1, 2016.
- Hastie, Trevor, and Rob Tibshirani. n.d. “Statistical Learning Course.” <https://lagunita.stanford.edu/courses/HumanitiesandScience/StatLearning/Winter2015/about>. Accessed February 1, 2016.
- Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. 2001. *The Elements of Statistical Learning*. Springer.
- Hayden, Erica Check. 2015. “Researchers Wrestle with a Privacy Problem.” *Nature* 525 (7570): 440.
- Hayden, Erika Check. 2012. “A Broken Contract.” *Nature* 486 (7403). Macmillan Publishers Ltd., London, England: 312–14.
- He, Zengyou, Xiaofei Xu, and Shengchun Deng. 2003. “Discovering Cluster-Based Local Outliers.” *Pattern Recognition Letters* 24 (9). Elsevier: 1641–50.
- Healy, Kieran, and James Moody. 2014. “Data Visualization in Sociology.” *Annual Review of Sociology* 40. Annual Reviews: 105–28.
- Henry, Nathalie, and Jean-Daniel Fekete. 2006. “MatrixExplorer: A Dual-Representation System to Explore Social Networks.” *IEEE Transactions on Visualization and Computer Graphics* 12 (5). IEEE: 677–84.
- Herzog, Thomas N., Fritz J. Scheuren, and William E. Winkler. 2007. *Data Quality and Record Linkage Techniques*. Springer.
- Hill, Kashmir. 2012. “How Target Figured Out a Teen Girl Was Pregnant Before Her Father Did.” *Forbes*, <http://www.forbes.com/sites/kashmirhill/>

- 2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/#7280148734c6.
- Hofmann, Thomas. 1999. “Probabilistic Latent Semantic Analysis.” In *Proceedings of Uncertainty in Artificial Intelligence*.
- Hothorn, Torsten. n.d. “CRAN Task View: Machine Learning & Statistical Learning.” <https://cran.r-project.org/web/views/MachineLearning.html>. Accessed February 1, 2016.
- Hox, Joop. 2010. *Multilevel Analysis: Techniques and Applications*. Routledge.
- Hu, Yuening, Ke Zhai, Vlad Eidelman, and Jordan Boyd-Graber. 2014. “Polylingual Tree-Based Topic Models for Translation Domain Adaptation.” In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*. Baltimore, MD.
- Huang, Anna. 2008. “Similarity Measures for Text Document Clustering.” Paper presented at New Zealand Computer Science Research Student Conference, Christchurch, New Zealand, April 14–18.
- Huang, Jian, Seyda Ertekin, and C. Lee Giles. 2006. “Efficient Name Disambiguation for Large-Scale Databases.” In *Knowledge Discovery in Databases: PKDD 2006*, 536–44. Springer.
- Human Microbiome Jumpstart Reference Strains Consortium, K. E. Nelson, G. M. Weinstock, and others. 2010. “A Catalog of Reference Genomes from the Human Microbiome.” *Science* 328 (5981). American Association for the Advancement of Science: 994–99.
- Hundepool, Anco, Josep Domingo-Ferrer, Luisa Franconi, Sarah Giessing, Rainer Lenz, Jane Longhurst, E. Schulte Nordholt, Giovanni Seri, and P. Wolf. 2010. “Handbook on Statistical Disclosure Control.” Network of Excellence in the European Statistical System in the Field of Statistical Disclosure Control.
- Husband Fealing, Kaye, Julia Ingrid Lane, Jack Marburger, and Stephanie Shipp. 2011. *Science of Science Policy: The Handbook*. Stanford University Press.
- Ibrahim, Joseph G., and Ming-Hui Chen. 2000. “Power Prior Distributions for Regression Models.” *Statistical Science* 15 (1). JSTOR: 46–60.
- ICML. n.d. “International Conference on Machine Learning.” <http://icml.cc/>. Accessed February 1, 2016.
- Imai, Kosuke, Marc Ratkovic, and others. 2013. “Estimating Treatment Ef-

- fect Heterogeneity in Randomized Program Evaluation.” *Annals of Applied Statistics* 7 (1). Institute of Mathematical Statistics: 443–70.
- Imbens, Guido W., and Donald B. Rubin. 2015. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. Cambridge University Press.
- Inselberg, Alfred. 2009. *Parallel Coordinates*. Springer.
- International Household Survey Network. n.d. “Data Dissemination.” <http://www.ihsn.org/home/projects/dissemination>. Accessed April 16, 2016.
- Ioannidis, J. P. A. 2005. “Why Most Published Research Findings Are False.” *PLoS Medicine* 2 (8): e124.
- IPython development team. n.d. “IPython Documentation.” <http://ipython.readthedocs.org/>. Accessed February 1, 2016.
- . n.d. “IPython Website.” <http://ipython.org/>. Accessed February 1, 2016.
- James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An Introduction to Statistical Learning*. Springer.
- Japec, Lilli, Frauke Kreuter, Marcus Berg, Paul Biemer, Paul Decker, Cliff Lampe, Julia Lane, Cathy O’Neil, and Abe Usher. 2015. “Big Data in Survey Research: AAPOR Task Force Report.” *Public Opinion Quarterly* 79 (4). AAPOR: 839–80.
- Jarmin, Ron S., and Javier Miranda. 2002. “The Longitudinal Business Database.” Available at SSRN 2128793.
- Jarmin, Ron S., Thomas A. Louis, and Javier Miranda. 2014. “Expanding the Role of Synthetic Data at the US Census Bureau.” *Statistical Journal of the IAOS* 30 (2): 117–21.
- Johnson, Brian, and Ben Shneiderman. 1991. “Tree-Maps: A Space-Filling

- Approach to the Visualization of Hierarchical Information Structures.” In *Proceedings of the Ieee Conference on Visualization*, 284–91. IEEE.
- Jones, Paul, and Peter Elias. 2006. “Administrative Data as a Research Resource: A Selected Audit.” ESRC National Centre for Research Methods.
- JOS. n.d. “Journal of Official Statistics Website.” Journal of Statistics Sweden; <http://www.jos.nu>. Accessed February 1, 2016.
- JPC. n.d. “Journal of Privacy and Confidentiality.” <http://repository.cmu.edu/jpc/>. Accessed April 16, 2016.
- Jupyter. n.d. “Jupyter Project Documentation.” <http://jupyter.readthedocs.org/>. Accessed February 1, 2016.
- . n.d. “Jupyter Project Website.” <http://jupyter.org/>. Accessed February 1, 2016.
- . n.d. “Jupyterhub GitHub Repository.” <https://github.com/jupyter/jupyterhub/>. Accessed February 1, 2016.
- . n.d. “Jupyterhyb Documentation.” <http://jupyterhub.readthedocs.org/>. Accessed February 1, 2016.
- . n.d. “Nbgrader Documentation.” <http://nbgrader.readthedocs.org/>. Accessed February 1, 2016.
- . n.d. “Nbgrader GitHub Repository.” <https://github.com/jupyter/nbgrader/>. Accessed February 1, 2016.
- Kabo, Felichism, Yongha Hwang, Margaret Levenstein, and Jason Owen-Smith. 2015. “Shared Paths to the Lab: A Sociospatial Network Analysis of Collaboration.” *Environment and Behavior* 47 (1). SAGE Publications: 57–84.
- Karr, Alan, and Jerome P. Reiter. 2014. “Analytical Frameworks for Data Release: A Statistical View.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum. Cambridge University Press.
- KDD. n.d. “ACM International Conference on Knowledge Discovery and Data Mining (KDD).” <http://www.kdd.org>. Accessed February 1, 2016.
- Keller, Sallie Ann, Steven E. Koonin, and Stephanie Shipp. 2012. “Big Data and City Living: What Can It Do for Us?” *Significance* 9 (4). Blackwell: 4–7.
- Keshif. n.d. “Infographics Aesthetics Dataset Browser.” [http://keshif.me/demo/infographics\\_aesthetics](http://keshif.me/demo/infographics_aesthetics). Accessed February 1, 2016.
- Kinney, Satkartar K., Jerome P. Reiter, Arnold P. Reznek, Javier Miranda, Ron S. Jarmin, and John M. Abowd. 2011. “Towards Unrestricted Public

- Use Business Microdata: The Synthetic Longitudinal Business Database.” *International Statistical Review* 79 (3). Wiley Online Library: 362–84.
- Kirk, Andy. 2012. *Data Visualization: A Successful Design Process*. Packt Publishing.
- Kiss, Tibor, and Jan Strunk. 2006. “Unsupervised Multilingual Sentence Boundary Detection.” *Computational Linguistics* 32 (4). Cambridge, MA: MIT Press: 485–525.
- Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer. 2015. “Prediction Policy Problems.” *American Economic Review* 105 (5): 491–95. <http://EconPapers.repec.org/RePEc:aea:aecrev:v:105:y:2015:i:5:p:491-95>.
- Kohler, Ulrich, and Frauke Kreuter. 2012. *Data Analysis Using Stata, 3rd Edition*. Stata Press.
- Kong, Lingpeng, Nathan Schneider, Swabha Swamydipta, Archna Bhatia, Chris Dyer, and Noah A. Smith. 2014. “A Dependency Parser for Tweets.” In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (Emnlp)*, 1001–12. Association for Computational Linguistics. <http://www.aclweb.org/anthology/D14-1108>.
- Kraak, Menno-Jan. 2014. *Mapping Time: Illustrated by Minard’s Map of Napoleon’s Russian Campaign of 1812*. ESRI Press.
- Kreuter, Frauke, and Roger D. Peng. 2014. “Extracting Information from Big Data: Issues of Measurement, Inference, and Linkage.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, 257–75. Cambridge University Press.
- Kuhn, H. W. 2005. “The Hungarian Method for the Assignment Problem.” *Naval Research Logistics* 52 (1). Wiley Online Library: 7–21.
- Kuhn, Max, and Kjell Johnson. 2013. *Applied Predictive Modeling*. Springer Science & Business Media.
- Kullback, Solomon, and Richard A. Leibler. 1951. “On Information and Sufficiency.” *Annals of Mathematical Statistics* 22 (1). JSTOR: 79–86.
- Kumar, Mohit, Rayid Ghani, and Zhu-Song Mei. 2010. “Data Mining to Predict and Prevent Errors in Health Insurance Claims Processing.” In *Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 65–74. KDD ’10. ACM. doi:10.1145/1835804.1835816.
- Lafferty, John D., Andrew McCallum, and Fernando C. N. Pereira. 2001. “Conditional Random Fields: Probabilistic Models for Segmenting and Labeling

- Sequence Data." In *Proceedings of the Eighteenth International Conference on Machine Learning*, 282–89. Morgan Kaufmann.
- Lahiri, Partha, and Michael D Larsen. 2005. "Regression Analysis with Linked Data." *Journal of the American Statistical Association* 100 (469). Taylor & Francis: 222–30.
- Lakkaraju, Himabindu, Everaldo Aguiar, Carl Shan, David Miller, Nasir Bhanupuri, Rayid Ghani, and Kecia L. Addison. 2015. "A Machine Learning Framework to Identify Students at Risk of Adverse Academic Outcomes." In *Proceedings of the 21th Acm Sigkdd International Conference on Knowledge Discovery and Data Mining*, 1909–18. KDD '15. ACM. doi:10.1145/2783258.2788620.
- Lam, Heidi, Enrico Bertini, Petra Isenberg, Catherine Plaisant, and Sheelagh Carpendale. 2012. "Empirical Studies in Information Visualization: Seven Scenarios." *IEEE Transactions on Visualization and Computer Graphics* 18 (9). IEEE: 1520–36.
- Landauer, T., and S. Dumais. 1997. "Solutions to Plato's Problem: The Latent Semantic Analysis Theory of Acquisition, Induction and Representation of Knowledge." *Psychological Review* 104 (2): 211–40.
- Lane, Julia. 2007. "Optimizing Access to Micro Data." *Journal of Official Statistics* 23: 299–317.
- Lane, Julia I., Jason Owen-Smith, Rebecca F. Rosen, and Bruce A. Weinberg. 2015. "New Linked Data on Research Investments: Scientific Workforce, Productivity, and Public Value." *Research Policy* 44. Elsevier: 1659–71.
- Lane, Julia, and Victoria Stodden. 2013. "What? Me Worry? What to Do About Privacy, Big Data, and Statistical Research." *AMSTAT News* 438. American Statistical Association: 14.
- Lane, Julia, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, eds. 2014. *Privacy, Big Data, and the Public Good: Frameworks for Engagement*. Cambridge: Cambridge University Press.
- Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. "The Parable of Google Flu: Traps in Big Data Analysis." *Science* 343 (14 March).
- Lee, Yang, WooYoung Chung, Stuart Madnick, Richard Wang, and Hongyun Zhang. 2012. "On the Rise of the Chief Data Officers in a World of Big Data." In *Pre-Icis 2012 Sim Academic Workshop, Orlando, Florida*.
- Levitt, Steven D., and Thomas J. Miles. 2006. "Economic Contributions to the Understanding of Crime." *Annual Review of Law Social Science* 2. Annual Reviews: 147–64.
- Lewis, David D. 1998. "Naive (Bayes) at Forty: The Independence Assumption

- in Information Retrieval.” In *Proceedings of European Conference of Machine Learning*, 4–15.
- Lifka, D., I. Foster, S. Mehringer, M. Parashar, P. Redfern, C. Stewart, and S. Tuecke. 2013. “XSEDE Cloud Survey Report.” Technical report, National Science Foundation, USA, <http://hdl.handle.net/2142/45766>.
- Lin, Jimmy, and Chris Dyer. 2010. *Data-Intensive Text Processing with MapReduce*. Morgan & Claypool Publishers.
- Lins, Lauro, James T Klosowski, and Carlos Scheidegger. 2013. “Nanocubes for Real-Time Exploration of Spatiotemporal Datasets.” *IEEE Transactions on Visualization and Computer Graphics* 19 (12). IEEE: 2456–65.
- Little, Roderick J. A., and Donald B Rubin. 2014. *Statistical Analysis with Missing Data*. John Wiley & Sons.
- Liu, Zhicheng, and Jeffrey Heer. 2014. “The Effects of Interactive Latency on Exploratory Visual Analysis.” *IEEE Transactions on Visualization and Computer Graphics* 20 (12). IEEE: 2122–31.
- Lohr, Sharon. 2009. *Sampling: Design and Analysis*. Cengage Learning.
- MacKinlay, Jock. 1986. “Automating the Design of Graphical Presentations of Relational Information.” *ACM Transactions on Graphics* 5 (2). ACM: 110–41.
- Malik, Waqas Ahmed, Antony Unwin, and Alexander Gribov. 2010. “An Interactive Graphical System for Visualizing Data Quality—Tableplot Graphics.” In *Classification as a Tool for Research*, 331–39. Springer.
- Malmkjær, K. 2002. *The Linguistics Encyclopedia*. Routledge. <https://books.google.ca/books?id=uCrXOLvD7fMC>.
- Manning, Christopher D., Mihai Surdeanu, John Bauer, Jenny Finkel, Steven J. Bethard, and David McClosky. 2014. “The Stanford CoreNLP Natural Language Processing Toolkit.” In *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, 55–60.
- Marburger, John H. 2005. “Wanted: Better Benchmarks.” *Science* 308 (5725). American Association for the Advancement of Science: 1087.
- Marcus, Mitchell P., Beatrice Santorini, and Mary A. Marcinkiewicz. 1993. “Building a Large Annotated Corpus of English: The Penn Treebank.” *Computational Linguistics* 19 (2): 313–30.
- Mas, Alexandre, and Enrico Moretti. 2009. “Peers at Work.” *American Economic Review* 99 (1): 112–45. <http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.1.112>.
- Maskeri, Girish, Santonu Sarkar, and Kenneth Heafield. 2008. “Mining Business Topics in Source Code Using Latent Dirichlet Allocation.” In *Pro-*

- ceedings of the 1st India Software Engineering Conference, 113–20. ACM. doi:<http://doi.acm.org/10.1145/1342211.1342234>.
- McCallister, Erika, Timothy Grance, and Karen A Scarfone. 2010. *SP 800-122. Guide to Protecting the Confidentiality of Personally Identifiable Information (Pii)*. National Institute of Standards; Technology.
- McCallum, Andrew Kachites. 2002. “MALLET: A Machine Learning for Language Toolkit.” <http://mallet.cs.umass.edu>.
- Meij, Edgar, Marc Bron, Laura Hollink, Bouke Huurnink, and Maarten Rijke. 2009. “Learning Semantic Query Suggestions.” In *Proceedings of the 8th International Semantic Web Conference*, 424–40. ISWC ’09. Chantilly, VA: Springer. doi:10.1007/978-3-642-04930-9\_27.
- Meng, Xiao-Li. 2018. “Statistical Paradises and Paradoxes in Big Data (I): Law of Large Populations, Big Data Paradox, and the 2016 Us Presidential Election.” *The Annals of Applied Statistics* 12 (2): 685–726.
- Meyer, Bruce D., Wallace K. C. Mok, and James X. Sullivan. 2015. “Household Surveys in Crisis.” *Journal of Economic Perspectives* 29 (4): 199–226.
- Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. “Distributed Representations of Words and Phrases and Their Compositionality.” In *Advances in Neural Information Processing Systems*, 3111–9. Morgan Kaufmann.
- Mitchell, Tom M. 1997. *Machine Learning*. McGraw-Hill.
- Moffatt, C. L. 1999. “Visual Representation of SQL Joins.” <http://www.codeproject.com/Articles/33052/Visual-Representation-of-SQL-Joins>.
- Molinaro, Anthony. 2005. *SQL Cookbook: Query Solutions and Techniques for Database Developers*. O’Reilly Media.
- Morgan, Stephen L., and Christopher Winship. 2014. *Counterfactuals and Causal Inference*. Cambridge University Press.
- Mortensen, Peter Stendahl, Carter Walter Bloch, and others. 2005. *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*. Organisation for Economic Co-operation; Development.
- Munzner, Tamara. 2014. *Visualization Analysis and Design*. CRC Press.
- Murphy, Joe, Michael W Link, Jennifer Hunter Childs, Casey Langer Tesfaye, Elizabeth Dean, Michael Stern, Josh Pasek, Jon Cohen, Mario Callegaro, and Paul Harwood. 2014. “Social Media in Public Opinion Research: Report of the AAPOR Task Force on Emerging Technologies in Public Opinion Research.” *Public Opinion Quarterly* 78 (4): 788–94.
- Narayanan, Arvind, and Vitaly Shmatikov. 2008. “Robust de-Anonymization of

- Large Sparse Datasets.” In *IEEE Symposium on Security and Privacy*, 111–25. IEEE.
- Natarajan, Kalaivany, Jiuyong Li, and Andy Koronios. 2010. *Data Mining Techniques for Data Cleaning*. Springer.
- National Science Foundation. n.d. “Download Awards by Year.” <http://nsf.gov/awardsearch/download.jsp>. Accessed February 1, 2016.
- Navigli, Roberto, Stefano Faralli, Aitor Soroa, Oier de Lacalle, and Eneko Agirre. 2011. “Two Birds with One Stone: Learning Semantic Models for Text Categorization and Word Sense Disambiguation.” In *Proceedings of the 20th ACM International Conference on Information and Knowledge Management*. ACM.
- Nelson, Robert K. 2010. “Mining the Dispatch.” <http://dsl.richmond.edu/dispatch/>.
- Newman, Mark. 2005. “A Measure of Betweenness Centrality Based on Random Walks.” *Social Networks* 27 (1). Elsevier: 39–54.
- . 2010. *Networks: An Introduction*. Oxford University Press.
- Neylon, Cameron. 2014. “Altmetrics: What Are They Good for?” <http://blogs.plos.org/opens/2014/10/03/altmetrics-what-are-they-good-for/>.
- Neylon, Cameron, Michelle Willmers, and Thomas King. 2014. “Impact Beyond Citation: An Introduction to Altmetrics.” <http://hdl.handle.net/11427/2314>.
- Nguyen, Viet-An, Jordan Boyd-Graber, and Philip Resnik. 2012. “SITS: A Hierarchical Nonparametric Model Using Speaker Identity for Topic Segmentation in Multiparty Conversations.” In *Proceedings of the Association for Computational Linguistics*. Jeju, South Korea.
- . 2013. “Lexical and Hierarchical Topic Regression.” In *Advances in Neural Information Processing Systems*. Lake Tahoe, Nevada.
- Nguyen, Viet-An, Jordan Boyd-Graber, Philip Resnik, and Jonathan Chang. 2014. “Learning a Concept Hierarchy from Multi-Labeled Documents.” In *Proceedings of the Annual Conference on Neural Information Processing Systems*. Morgan Kaufmann.
- Nguyen, Viet-An, Jordan Boyd-Graber, Philip Resnik, and Kristina Miler. 2015. “Tea Party in the House: A Hierarchical Ideal Point Topic Model and Its Application to Republican Legislators in the 112th Congress.” In *Association for Computational Linguistics*. Beijing, China.
- Niculae, Vlad, Srijan Kumar, Jordan Boyd-Graber, and Cristian Danescu-Niculescu-Mizil. 2015. “Linguistic Harbingers of Betrayal: A Case Study on an

- Online Strategy Game.” In *Association for Computational Linguistics*. Beijing, China. docs/2015\_acl\_diplomacy.pdf.
- Nielsen, Michael. 2012. *Reinventing Discovery: The New Era of Networked Science*. Princeton University Press.
- Nissenbaum, H. 2009. *Privacy in Context: Technology, Policy, and the Integrity of Social Life*. Stanford University Press.
- Nissenbaum, Helen. 2011. “A Contextual Approach to Privacy Online.” *Daedalus* 140 (4). MIT Press: 32–48.
- NLTK Project. n.d. “NLTK: The Natural Language Toolkit.” <http://www.nltk.org>. Accessed February 1, 2016.
- Obe, Regina O., and Leo S. Hsu. 2015. *PostGIS in Action, 2nd Edition*. Manning Publications.
- Obstfeld, David. 2005. “Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation.” *Administrative Science Quarterly* 50 (1). SAGE Publications: 100–130.
- Ohm, Paul. 2010. “Broken Promises of Privacy: Responding to the Surprising Failure of Anonymization.” *UCLA Law Review* 57: 1701.
- . 2014. “The Legal and Regulatory Framework: What Do the Rules Say About Data Analysis?” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Helen Nissenbaum, and Stefan Bender. Cambridge University Press.
- Olson, Judy M., and Cynthia A. Brewer. 1997. “An Evaluation of Color Selections to Accommodate Map Users with Color-Vision Impairments.” *Annals of the Association of American Geographers* 87 (1). Taylor & Francis: 103–34.
- Ott, Myle, Yejin Choi, Claire Cardie, and Jeffrey T. Hancock. 2011. “Finding Deceptive Opinion Spam by Any Stretch of the Imagination.” In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies—Volume 1*, 309–19. HLT ’11. Stroudsburg, PA: Association for Computational Linguistics. <http://dl.acm.org/citation.cfm?id=2002472.2002512>.
- Owen-Smith, Jason, and Walter W. Powell. 2003. “The Expanding Role of University Patenting in the Life Sciences: Assessing the Importance of Experience and Connectivity.” *Research Policy* 32 (9). Elsevier: 1695–1711.
- . 2004. “Knowledge Networks as Channels and Conduits: The Effects of

- Spillovers in the Boston Biotechnology Community.” *Organization Science* 15 (1). INFORMS: 5–21.
- Pang, Bo, and Lillian Lee. 2008. *Opinion Mining and Sentiment Analysis*. Paperback; Now Publishers.
- Park, Hae-Sang, and Chi-Hyuck Jun. 2009. “A Simple and Fast Algorithm for K-Medoids Clustering.” *Expert Systems with Applications* 36 (2). Elsevier: 3336–41.
- Paul, Michael, and Roxana Girju. 2010. “A Two-Dimensional Topic-Aspect Model for Discovering Multi-Faceted Topics.” In *Association for the Advancement of Artificial Intelligence*.
- Pennebaker, James W., and Martha E. Francis. 1999. *Linguistic Inquiry and Word Count*. Loose Leaf; Lawrence Erlbaum.
- Pentland, Alex, Daniel Greenwood, Brian Sweatt, Arek Stopczynski, and Yves-Alexandre de Montjoye. 2014. “Institutional Controls: The New Deal on Data.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, 98–112. Cambridge University Press.
- PERISCOPIC. n.d. “A World of Terror.” <http://terror.periscopic.com/>. Accessed February 1, 2016.
- Peters, Matthew, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. “Deep Contextualized Word Representations.” In *Conference of the North American Chapter of the Association for Computational Linguistics*.
- Petrakos, George, Claudio Conversano, Gregory Farmakis, Francesco Mola, Roberta Siciliano, and Photis Stavropoulos. 2004. “New Ways of Specifying Data Edits.” *Journal of the Royal Statistical Society, Series A* 167 (2). Wiley Online Library: 249–74.
- Plaisant, Catherine, Jesse Grosjean, and Benjamin B. Bederson. 2002. “Space-Tree: Supporting Exploration in Large Node Link Tree, Design Evolution and Empirical Evaluation.” In *IEEE Symposium on Information Visualization*, 57–64. IEEE.
- PostGIS Project Steering Committee. n.d. “PostGIS Documentation.” <http://postgis.net/documentation/>. Accessed December 1, 2015.
- Potash, Eric, Joe Brew, Alexander Loewi, Subhabrata Majumdar, Andrew Reece, Joe Walsh, Eric Rozier, Emile Jorgenson, Raed Mansour, and Rayid Ghani. 2015. “Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning.” In *Proceedings of the 21th Acm Sigkdd International Con-*

- ference on Knowledge Discovery and Data Mining, 2039–47. KDD '15. ACM. doi:10.1145/2783258.2788629.
- Powell, W. 2003. “Neither Market nor Hierarchy.” *Sociology of Organizations: Classic, Contemporary, and Critical Readings* 315: 104–17.
- Powell, Walter W., Douglas R. White, Kenneth W. Koput, and Jason Owen-Smith. 2005. “Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences.” *American Journal of Sociology* 110 (4). JSTOR: 1132–1205.
- Provost, Foster, and Tom Fawcett. 2013. *Data Science for Business: What You Need to Know About Data Mining and Data-Analytic Thinking*. O’Reilly Media.
- Puts, Marco, Piet Daas, and Ton de Waal. 2015. “Finding Errors in Big Data.” *Significance* 12 (3). Wiley Online Library: 26–29.
- Rabiner, Lawrence R. 1989. “A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition.” *Proceedings of the IEEE* 77 (2): 257–86. doi:10.1109/5.18626.
- Ram, Karthik. 2013. “Git Can Facilitate Greater Reproducibility and Increased Transparency in Science.” *Source Code for Biology and Medicine* 8 (1): 7.
- Ramage, Daniel, David Hall, Ramesh Nallapati, and Christopher Manning. 2009. “Labeled LDA: A Supervised Topic Model for Credit Attribution in Multi-Labeled Corpora.” In *Proceedings of Empirical Methods in Natural Language Processing*.
- Ramakrishnan, Raghu, and Johannes Gehrke. 2002. *Database Management Systems, 3rd Edition*. McGraw-Hill.
- Reiter, Jerome P. 2012. “Statistical Approaches to Protecting Confidentiality for Microdata and Their Effects on the Quality of Statistical Inferences.” *Public Opinion Quarterly* 76 (1). AAPOR: 163–81.
- Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. 2016. “‘Why Should I Trust You?’: Explaining the Predictions of Any Classifier.” In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, ca, Usa, August 13-17, 2016*, 1135–44.
- Richardson, Leonard. n.d. “Beautiful Soup.” <http://www.crummy.com/software/BeautifulSoup/>. Accessed February 1, 2016.
- Rubin, Donald B. 1976. “Inference and Missing Data.” *Biometrika* 63: 581–92.
- Ruggles, S., C. Fitch, Magnuson D., and J. Schroeder. 2019. “Differential Privacy and Census Data: Implications for Social and Economic Research.” AEA Papers; Proceedings (Vol. 109, pp. 403–08).
- Saket, Bahador, Paolo Simonetto, Stephen Kobourov, and Katy Börner. 2014.

- “Node, Node-Link, and Node-Link-Group Diagrams: An Evaluation.” *IEEE Transactions on Visualization and Computer Graphics* 20 (12). IEEE: 2231–40.
- Salton, Gerard. 1968. *Automatic Information Organization and Retrieval*. McGraw-Hill.
- Samuel, Arthur L. 1959. “Some Studies in Machine Learning Using the Game of Checkers.” *IBM Journal of Research and Development* 3 (3). IBM: 210–29.
- Saraiya, Purvi, Chris North, and Karen Duca. 2005. “An Insight-Based Methodology for Evaluating Bioinformatics Visualizations.” *IEEE Transactions on Visualization and Computer Graphics* 11 (4). IEEE: 443–56.
- Schafer, Joseph L., and John W. Graham. 2002. “Missing Data: Our View of the State of the Art.” *Psychological Methods* 7 (2). American Psychological Association: 147.
- Schafer, Joseph L. 1997. *Analysis of Incomplete Multivariate Data*. CRC Press.
- Schermann, Michael, Holmer Hemsen, Christoph Buchmüller, Till Bitter, Helmut Krcmar, Volker Markl, and Thomas Hoeren. 2014. “Big Data.” *Business & Information Systems Engineering* 6 (5). Springer: 261–66.
- Scheuren, Fritz, and William E. Winkler. 1993. “Regression Analysis of Data Files That Are Computer Matched.” *Survey Methodology* 19 (1): 39–58.
- Schnell, Rainer. 2014. “An Efficient Privacy-Preserving Record Linkage Technique for Administrative Data and Censuses.” *Statistical Journal of the IAOS* 30: 263–70.
- . 2016. “German Record Linkage Center.”
- Schnell, Rainer, Tobias Bachteler, and Jörg Reiher. 2009. “Privacy-Preserving Record Linkage Using Bloom Filters.” *BMC Medical Informatics and Decision Making* 9 (1). BioMed Central Ltd: 41.
- Schoenman, Julie A. 2012. “The Concentration of Health Care Spending.” NI-HCM Foundation Data Brief. National Institute for Health Care Management.
- Scholkopf, Bernhard, and Alexander J. Smola. 2001. *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*. MIT Press.
- Scott, Steven L., Alexander W. Blocker, Fernando V. Bonassi, H. Chipman, E. George, and R. McCulloch. 2013. “Bayes and Big Data: The consensus Monte Carlo Algorithm.” In *EFaB Bayes 250 Conference*. Vol. 16.
- Sesame. n.d. “Sesame RDF Triple Store.” <http://rdf4j.org>. Accessed February 1, 2016.
- Sethian, James A., Jean-Philippe Brunet, Adam Greenberg, and Jill P. Mesirov. 1991. “Computing Turbulent Flow in Complex Geometries on a Massively

- Parallel Processor.” In *Proceedings of the 1991 Acm/Ieee Conference on Supercomputing*, 230–41. ACM. doi:10.1145/125826.125954.
- Severance, Charles. 2013. “Python for Informatics: Exploring Information.” <http://www.pythonlearn.com/book.php>; CreateSpace.
- Shawe-Taylor, John, and Nello Cristianini. 2004. *Kernel Methods for Pattern Analysis*. Cambridge University Press.
- Shelton, Taylor, Ate Poorthuis, Mark Graham, and Matthew Zook. 2014. “Mapping the Data Shadows of Hurricane Sandy: Uncovering the Sociospatial Dimensions of ‘Big Data.’” *Geoforum* 52. Elsevier: 167–79.
- Shneiderman, Ben. 1992. “Tree Visualization with Tree-Maps: 2-D Space-Filling Approach.” *ACM Transactions on Graphics* 11 (1). ACM: 92–99.
- . 2008. “Extreme Visualization: Squeezing a Billion Records into a Million Pixels.” In *Proceedings of the 2008 Acm Sigmod International Conference on Management of Data*, 3–12. ACM.
- Shneiderman, Ben, and Catherine Plaisant. 2015. “Sharpening Analytic Focus to Cope with Big Data Volume and Variety.” *Computer Graphics and Applications, IEEE* 35 (3). IEEE: 10–14.
- Silberschatz, Abraham, Henry F. Korth, and S. Sudarshan. 2010. *Database System Concepts, 6th Edition*. McGraw-Hill.
- Smola, Alex J., and Bernhard Schölkopf. 2004. “A Tutorial on Support Vector Regression.” *Statistics and Computing* 14 (3). Hingham, MA: Kluwer Academic Publishers: 199–222. doi:10.1023/B:STCO.0000035301.49549.88.
- Snow, John. 1855. *On the Mode of Communication of Cholera*. John Churchill.
- Solid IT. n.d. “DB Engines.” <http://db-engines.com/en/>. Accessed February 1, 2016.
- SOSP. n.d. “Science of Science Policy.” <http://www.scienceofsciencepolicy.net/>. Accessed February 1, 2016.
- Squire, Peverill. 1988. “Why the 1936 Literary Digest Poll Failed.” *Public Opinion Quarterly* 52 (1). AAPOR: 125–33.
- Stanford. n.d. “Stanford CoreNLP—a Suite of Core NLP Tools.” <http://nlp.stanford.edu/software/corenlp.shtml>. Accessed February 1, 2016.
- Stanford Visualization Group. n.d. “Dorling Cartograms in ProtoVis.” <http://mbostock.github.io/protovis/ex/cartogram.html>. Accessed January 10, 2015.
- Stanton, Mark W, and MK Rutherford. 2006. *The High Concentration of Us Health Care Expenditures*. Agency for Healthcare Research; Quality.
- Stasko, John, Carsten Görg, and Zhicheng Liu. 2008. “Jigsaw: Supporting Inves-

- tigative Analysis Through Interactive Visualization.” *Information Visualization* 7 (2). SAGE Publications: 118–32.
- Steorts, Rebecca C, Rob Hall, and Stephen E Fienberg. 2014. “SMERED: A Bayesian Approach to Graphical Record Linkage and de-Duplication.” Preprint, arXiv 1403.0211.
- Stephens-Davidowitz, S., and H. Varian. 2015. “A Hands-on Guide to Google Data.” <http://people.ischool.berkeley.edu/~hal/Papers/2015/primer.pdf>. Accessed October 12.
- Stock, James H., and Mark W. Watson. 2002. “Forecasting Using Principal Components from a Large Number of Predictors.” *Journal of the American Statistical Association* 97 (460). Taylor & Francis: 1167–79.
- Strandburg, Katherine J. 2014. “Monitoring, Datafication and Consent: Legal Approaches to Privacy in the Big Data Context.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum. Cambridge University Press.
- Strasser, Carly. 2014. “Git/GitHub: A Primer for Researchers.” <http://datapub.cdlib.org/2014/05/05/github-a-primer-for-researchers/>.
- Strauch, Christof. 2009. “NoSQL Databases.” <http://www.christof-strauch.de/nosqldb.pdf>.
- Stuart, Elizabeth A. 2010. “Matching Methods for Causal Inference: A Review and a Look Forward.” *Statistical Science* 25 (1). NIH Public Access: 1.
- Sweeney, Latanya. 2001. “Computational Disclosure Control: A Primer on Data Privacy Protection.” MIT.
- Szalay, Alexander S., Jim Gray, Ani R. Thakar, Peter Z. Kunszt, Tanu Malik, Jordan Raddick, Christopher Stoughton, and Jan vandenBerg. 2002. “The SDSS Skyserver: Public Access to the Sloan Digital Sky Server Data.” In *Proceedings of the 2002 ACM SIGMOD International Conference on Management of Data*, 570–81. ACM.
- Talley, Edmund M., David Newman, David Mimno, Bruce W. Herr II, Hanna M. Wallach, Gully A. P. C. Burns, A. G. Miriam Leenders, and Andrew McCallum. 2011. “Database of NIH Grants Using Machine-Learned Categories and Graphical Clustering.” *Nature Methods* 8 (6). Nature Publishing Group: 443–44.
- Tanner, Adam. 2013. “Harvard Professor Re-Identifies Anonymous Volunteers in DNA Study.” *Forbes*, <http://www.forbes.com/sites/adamtanner/>

2013/04/25/harvard-professor-re-identifies-anonymous-volunteers-in-dna-study/#6cc7f6b43e39.

TDP. n.d. "Transactions on Data Privacy." <http://www.tdp.cat/>. Accessed April 16, 2016.

Tennekes, M., E. de Jonge, and P. Daas. 2012. "Innovative Visual Tools for Data Editing." Presented at the United Nations Economic Commission for Europe Work Session on Statistical Data. Available online at [http://www.pietdaas.nl/beta/pubs/pubs/30\\_Netherlands.pdf](http://www.pietdaas.nl/beta/pubs/pubs/30_Netherlands.pdf).

Tennekes, Martijn, and Edwin de Jonge. 2011. "Top-down Data Analysis with Treemaps." In *Proceedings of the International Conference on Imaging Theory and Applications and International Conference on Information Visualization Theory and Applications*, 236–41. SciTePress.

Tennekes, Martijn, Edwin de Jonge, and Piet J. H. Daas. 2013. "Visualizing and Inspecting Large Datasets with Tableplots." *Journal of Data Science* 11 (1). ??????? 43–58.

Thompson, William W., Lorraine Comanor, and David K. Shay. 2006. "Epidemiology of Seasonal Influenza: Use of Surveillance Data and Statistical Models to Estimate the Burden of Disease." *Journal of Infectious Diseases* 194 (Supplement 2). Oxford University Press: S82–S91.

Trewin, D., A. Andersen, T. Beridze, L. Biggeri, I. Fellegi, and T. Toczynski. 2007. "Managing Statistical Confidentiality and Microdata Access: Principles and Guidelines of Good Practice." Geneva: Conference of European Statisticians, United Nations Economic Commision for Europe.

TSE15. n.d. "2015 International Total Survey Error Conference Website." <https://www.tse15.org>. Accessed February 1, 2016.

Tuarob, Suppawong, Line C. Pouchard, and C. Lee Giles. 2013. "Automatic Tag Recommendation for Metadata Annotation Using Probabilistic Topic Modeling." In *Proceedings of the 13th Acm/Ieee-Cs Joint Conference on Digital Libraries*, 239–48. JCDL '13. ACM. doi:10.1145/2467696.2467706.

Tufte, Edward. 2001. *The Visual Display of Quantitative Information, 2nd Edition*. Cheshire, CT: Graphics Press.

———. 2006. *Beautiful Evidence, 2nd Edition*. Cheshire, CT: Graphics Press.

United Nations Economic Commission for Europe. n.d. "Statistical confi-

- dentiality and disclosure protection.” <http://www.unece.org/stats/mos/meth/confidentiality.html>. Accessed April 16, 2016.
- University of Oxford. 2006. “British National Corpus.” <http://www.natcorp.ox.ac.uk/>.
- Valliant, Richard, Jill A Dever, and Frauke Kreuter. 2013. *Practical Tools for Designing and Weighting Survey Samples*. Springer.
- Varian, Hal R. 2014. “Big Data: New Tricks for Econometrics.” *Journal of Economic Perspectives* 28 (2): 3–28. doi:10.1257/jep.28.2.3.
- Ventura, Samuel L., Rebecca Nugent, and Erica R. H. Fuchs. 2015. “Seeing the Non-Stars:(Some) Sources of Bias in Past Disambiguation Approaches and a New Public Tool Leveraging Labeled Records.” *Research Policy*. Elsevier.
- Vigen, Tyler. 2015. *Spurious Correlations*. Hachette Books.
- . n.d. “Spurious Correlations.” <http://www.tylervigen.com/spurious-correlations>. Accessed February 1, 2016.
- Wallach, Hanna, David Mimno, and Andrew McCallum. 2009. “Rethinking LDA: Why Priors Matter.” In *Advances in Neural Information Processing Systems*.
- Wallgren, Anders, and Britt Wallgren. 2007. *Register-Based Statistics: Administrative Data for Statistical Purposes*. John Wiley & Sons.
- Wang, Chong, David Blei, and Li Fei-Fei. 2009. “Simultaneous Image Classification and Annotation.” In *Computer Vision and Pattern Recognition*.
- Wang, Yi, Hongjie Bai, Matt Stanton, Wen-Yen Chen, and Edward Y. Chang. 2009. “PLDA: Parallel Latent Dirichlet Allocation for Large-Scale Applications.” In *International Conference on Algorithmic Aspects in Information and Management*.
- Ward, Karl J. n.d. “Crossref REST API.” <http://api.crossref.org>. Accessed February 1, 2016.
- Ward, Kenneth Church. 2017. “Word2Vec.” *Natural Language Engineering* 23 (1). Cambridge University Press: 155–62. doi:10.1017/S1351324916000334.
- Ward, Matthew O., Georges Grinstein, and Daniel Keim. 2010. *Interactive Data Visualization: Foundations, Techniques, and Applications*. CRC Press.
- Weinberg, Bruce A., Jason Owen-Smith, Rebecca F Rosen, Lou Schwarz, Barbara McFadden Allen, Roy E. Weiss, and Julia Lane. 2014. “Science Funding and Short-Term Economic Activity.” *Science* 344 (6179). NIH Public Access: 41.
- Whang, Steven Euijong, David Menestrina, Georgia Koutrika, Martin Theobald, and Hector Garcia-Molina. 2009. “Entity Resolution with Iterative Blocking.” In

*Proceedings of the 2009 ACM SIGMOD International Conference on Management of Data*, 219–32. ACM.

White, Harrison C., Scott A. Boorman, and Ronald L. Breiger. 1976. “Social Structure from Multiple Networks. I. Block Models of Roles and Positions.” *American Journal of Sociology*. JSTOR, 730–80.

Wick, Michael, Sameer Singh, Harshal Pandya, and Andrew McCallum. 2013. “A Joint Model for Discovering and Linking Entities.” In *Proceedings of the 2013 Workshop on Automated Knowledge Base Construction*, 67–72. ACM.

Wikipedia. n.d. “List of Computer Science Conferences.” [http://en.wikipedia.org/wiki/List\\_of\\_computer\\_science\\_conferences](http://en.wikipedia.org/wiki/List_of_computer_science_conferences). Accessed April 16, 2016.

Wikipedia. n.d. “Representational State Transfer.” [https://en.wikipedia.org/wiki/Representational\\_state\\_transfer](https://en.wikipedia.org/wiki/Representational_state_transfer). Accessed January 10, 2016.

Wilbanks, John. 2014. “Portable Approaches to Informed Consent and Open Data.” In *Privacy, Big Data, and the Public Good: Frameworks for Engagement*, edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, 98–112. Cambridge University Press.

Winkler, William E. 2009. “Record Linkage.” In *Handbook of Statistics 29a, Sample Surveys: Design, Methods and Applications*, edited by D. Pfeffermann and C. R. Rao, 351–80. Elsevier.

———. 2014. “Matching and Record Linkage.” *Wiley Interdisciplinary Reviews: Computational Statistics* 6 (5). John Wiley & Sons, Inc.: 313–25. doi:10.1002/wics.1317.

Wongsuphasawat, Krist, and Jimmy Lin. 2014. “Using Visualizations to Monitor Changes and Harvest Insights from a Global-Scale Logging Infrastructure at Twitter.” In *Proceedings of the IEEE Conference on Visual Analytics Science and Technology*, 113–22. IEEE.

Wu, Xindong, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey J. McLachlan, et al. 2008. “Top 10 Algorithms in Data Mining.” *Knowledge and Information Systems* 14 (1). Springer: 1–37.

Wuchty, Stefan, Benjamin F Jones, and Brian Uzzi. 2007. “The Increasing Dominance of Teams in Production of Knowledge.” *Science* 316 (5827). American Association for the Advancement of Science: 1036–9.

Yost, Beth, Yonca Hacihametoglu, and Chris North. 2007. “Beyond Visual Acuity: The Perceptual Scalability of Information Visualizations for Large

Displays." In *Proceedings of the Sigchi Conference on Human Factors in Computing Systems*, 101–10. ACM.

Z., Zygmunt. n.d. "Machine Learning Courses Online." <http://fastml.com/machine-learning-courses-online>, January 7, 2013.

Zayatz, Laura. 2007. "Disclosure Avoidance Practices and Research at the US Census Bureau: An Update." *Journal of Official Statistics* 23 (2). Statistics Sweden (SCB): 253.

Zolas, Nikolas, Nathan Goldschlag, Ron Jarmin, Paula Stephan, Jason Owen-Smith, Rebecca F Rosen, Barbara McFadden Allen, Bruce A Weinberg, and Julia Lane. 2015. "Wrapping It up in a Person: Examining Employment and Earnings Outcomes for Ph.D. Recipients." *Science* 350 (6266). American Association for the Advancement of Science: 1367–71.