

Digital sociology in the field of devices

*Adrian Mackenzie, Richard Mills, Stuart Sharples,
Matthew Fuller and Andrew Goffey*

6 Introduction

Digital sociology focuses on culture as it plays out in the vast, expanding, power-laden and complex media environments of the last few decades. In these media environments, feedback loops running between devices and social practices constantly re-define culture. Culture – that which is lived in places such as cities, cafes, airports, streets, shops, museums, parks, clinics, offices or living rooms – is rapidly rewoven by transient device-specific play of signals passing through news, entertainment, advertising and social networking platforms such as Twitter, Instagram, LiveJournal, YouTube, LinkedIn or Weibo. Digital sociology addresses the problem of how to make sense of the signals generated, captured, organised, shared, and constantly sorted in form of hyperlinks, messages, transactions, text, and images flowing across media platforms by people living with and through digital devices (Lupton 2012). Digital social researchers seek to learn about the coherence, modes of thought and value, practices, materials and forms of contemporary experience and social action as they are drawn into what recent observers have called ‘a massive, culturally saturated feedback loop’ (Schutt and O’Neil 2013: 5) interlacing what people do and what they experience. None of the devices, practices and subjects of this form of the social are coherent, well-understood or stable. Indeed, these feedback loops predicate constant processing, adjustment, realignment, transformation, variation and mutation in social worlds. Amidst this targeting of transformation, much hinges on interactions in what we might call, following Ruppert, Law and Savage (2013), the *field of devices*. The field of devices is a complex weave of technical elements, more or less connected to each other through relations of contact and contest, convergence and divergence, similarity, imitation and variation. It is inhabited by people who react to, who experience and are affected by durable and transient calls to order their actions with and through devices.

While digital sociology draws on well-established methods such as ethnography, rhetorical, discourse and visual analysis, in the analysis of device-specific transformations in culture new skills and digital tools, borrowed or copied from domains of statistics, software development, hacking, graphic design, audio, video and photographic recording and predictive modelling – that is, from the media-textual environments of contemporary culture themselves – must come into play, with lesser or greater relevance. Social research in such

1 settings, as Noortje Marres notes, ‘becomes noticeably a distributed accomplishment: online
2 platforms, users, devices and informational practices actively contribute to the performance
3 of digital social research’ (Marres 2012: 139). Given that the sociology of contemporary cul-
4 ture relies on the field of devices, the critical question is: how it will participate?

5 Digital sociology overlaps with, borrows from and seeks to make sense of much more
6 prestigious, well-financed and heavily equipped practices in marketing, in scientific research,
7 in government administration and commerce that target the expanded media environments
8 of contemporary culture by intensifying work on data (Cukier and Mayer-Schoenberger
9 2013). *Scale* and *pattern* are key concerns in many of these settings, and scale and pattern also
10 allure social researchers. As danah boyd and Kate Crawford suggest, ‘big Data tempts some
11 researchers to believe that they can see everything at a 30,000-foot view’ (boyd and Crawford
12 2012).¹ But the mode of ordering – ‘recurring patterns embodied within, witnessed by, gen-
13 erated in and reproduced as part of the ordering of human and non-human relations’ (Law
14 1994: 83) – of digital sociology diverge greatly from contenders and analogues such as ‘data
15 science’ (Schutt and O’Neil 2013) or ‘predictive analytics’ (Prediction Impact Inc. 2009)
16 or digital humanities. Aiming to pay close attention to the ways in which the data-driven
17 description of culture has become a key economic and social concern (Savage 2009; Thrift
18 2006), digital sociology might take shape less as a social science of digital culture than as the
19 study of how device-specific events pattern lives, experience, power and value on various
20 scales. This apparently limited ambition harbours some surprising expansive possibilities. It
21 might cultivate ‘a sociological sensibility not confined to the predominant lines of sight, the
22 focal points of public concern’ (Back and Puwar 2012: 12) but able to develop novel empirical
23 techniques of inquiry and evaluate the unprecedented volume of information we encounter.
24 Its device-specific emphasis might entail novel empirical practices and conceptions of the
25 empirical (Adkins and Lury 2009).

26 As we will see, particularly through the examples we draw from one moderately large
27 but critically relevant social networking platform, GitHub.com, the process of researching
28 device-specific events on the various scales and amidst the intricate patterns of practice in
29 contemporary media environments is not at all straightforward. Patterns and scales of action
30 and interaction it turns out, entwine with devices in both contemporary culture and in its
31 analysis. The case we draw on here – Github.com – is interesting precisely because what goes
32 on there – coding and software development amongst other things – is both typical of the
33 vast and somewhat incoherent work done on devices as part of contemporary culture, and at
34 the same time plays an important practical role in re-formatting that work so that it becomes
35 more publicly visible as a call to social order. Launched in late 2007, Github at the time of
36 writing (2014) claims to host around 13 million different code repositories made by around 6
37 million users who are mostly software developers (see <http://www.github.com/about>). While
38 these numbers, like all social media statistics, need to be disaggregated and analysed (for
39 instance, Github ‘users’ include automated software processes that hourly commit new code
40 to certain repositories; or many repositories are simply copies of other repositories, etc.), they
41 position Github as a mid-ranking social media platform in terms of size. But regardless of size,
42 Github certainly exemplifies the profuse work done on devices that texture increasingly large
43 parts of people’s lives. A panoply of practical implementations of algorithms (see Couldry this
44 volume), of graphic interfaces, of power-laden protocols, standards and infrastructures (such
45 as operating systems, databases, security systems) can be found there.

46 Code repositories might be seen as vectors that on varying scales comprise much of the
47 contemporary field of devices. These vectors display field-specific characteristics – code
48 repositories contain code written in programming languages, they are accompanied by

1 descriptions, they relate to a finite range of domains (science, business, publishing, gaming,
 2 graphic design, etc.) – and they also affect each other, as can be seen in the many imitations,
 3 variations, copies, re-implementations and versions found there. Moreover, Github increas-
 4 ingly serves as a model of social action that attracts many other practices not directly related
 5 to software: how-to guides, metadata on the Tate’s art collection, the White House’s open
 6 data policy, legal documents, recipes, books, and blogs are just some of the diversifying
 7 use-cases now found in repositories on Github. As a recent article in *The Atlantic* suggests,
 8 Github is increasingly of interest to non-programmers because the de-centralised, distrib-
 9 uted and trackable collaborative processes it offers for coding can be used for many kinds of
 10 work: designs, legal documents, maps, images, books, blogs or websites (Meyer 2013). In this
 11 respect, Github, we might say, is an ‘indexical icon’ (Lee and LiPuma 2002) of the scaling and
 12 patterning that characterise the contemporary metamorphoses of culture.

13 Scales, scaling and fields of devices

14 One problem for digital sociology is the question of where to stand in looking at such com-
 15 plex processes.² In some respects, platforms like Github could be seen as what Andrew Barry
 16 termed ‘technological zones of circulation.’ These are

17 spaces formed when technical devices, practices, artefacts and experimental materials are
 18 made more or less comparable or connectable. They therefore link together different sites
 19 of scientific and technical practice. Such zones take different forms. The points of access
 20 to the zones may be more or less clearly marked, with more or less well-defined and
 21 functioning gateways

(Barry 2001: 202–3).

23 Github is a kind of gateway to the linkages between devices. It offers analytic and empiri-
 24 cal descriptions and data streams as well as search functions that might help us engage with
 25 different scales and patterns of connection between technical configurations, platforms and
 26 practices. Wrangling these affordances in sociologically inventive ways entails much engage-
 27 ment with the practices and device specificities of the Github platform itself. As we craft
 28 ways of dealing with different scales, with wholes, with events and device-specific relations
 29 in Github, the allure of total or exhaustive description promised by the platform itself need
 30 to be reckoned with.

31 Given the heavily accumulative dynamics of the field of devices, there is a temptation for
 32 digital sociologists in their own empirical work to emulate the descriptive practices – the
 33 analytics – that accompany the scaling-up of digital media platforms. If digital sociology
 34 was simply a theoretically sophisticated version of media analytics or business intelligence,
 35 it would miss the transformations in culture attested by the availability of this data. The real
 36 analytical promise of large-scale data for digital sociology instead concerns the possibility
 37 of studying how re-scaling processes actually cut across pre-formatted notions of the indi-
 38 vidual or culture as a whole. The smooth conceptual poles of individual and whole culture
 39 constrain analytical purchase on open-ended, heterogeneous device-specific contestation of
 40 contemporary cultural spaces. They are attached to more static concepts of agency and struc-
 41 ture that have long been disputed (we are not re-visiting those debates here; see (Latour *et al.*
 42 2012) for a broader engagement with this problem, which arguably still thwarts ‘social phys-
 43 ics’). For instance, while ‘users’ or consumers remain the focus of much market research and
 44 advertising, their demographic attributes of race, age, ethnicity, income and educational level

1 are perhaps becoming less important as ‘postdemographic’ concerns of profiling in terms of
 2 groups, tastes, interests, device usage, etc., take hold (see Rogers 2013: 153–4). Furthermore,
 3 the feedback loops between social lives running through the field of devices mean that cul-
 4 tural processes change scale in many different ways. Like all fields, the field of digital devices
 5 is tensioned by many different vectoral relations (see Martin and Merriman, this volume for
 6 a relevant description of Pierre Bourdieu’s field theory). As Evelyn Ruppert, John Law and
 7 Mike Savage write, ‘fields of devices [are] relational spaces where some devices survive and
 8 dominate in particular locations while others are eclipsed, at least for the moment’ (Ruppert,
 9 Law and Savage 2013: 13).

10 We can glimpse some of these relational transients in Github as a platform. On the one
 11 hand, like many social media platforms, Github.com broadcasts data about what people are
 12 doing on the platform. At the time of writing (August 2014), around 220 million events
 13 are available on the so-called Github.com timeline since early 2012. The timeline is a com-
 14 prehensive time-stamped series of user-generated events.³ Many of these events are highly
 15 ephemeral. They have little afterlife. Someone creates a repository and puts something there,
 16 and then never returns. Millions of such events occur. On the other hand, the Github time-
 17 line data does not necessarily include events generated by Github itself as it develops the plat-
 18 form. Platform-level events – changes in architecture, modifications to interfaces, shifts in
 19 underlying design or management practice – are much harder to see from the data. Changes
 20 in the platform affect what people do. In the flow of events marked on the Github.com time-
 21 line, there are some surprising features. For instance, the 18 months of Github event data
 22 graphed in Figure 24.1 shows growth.

23 We might not be surprised to see a steadily increasing count of events on a social media
 24 platform. (Github is, after all, a social media platform for coding). While growth curves are
 25 common to many digital media platforms, here we see something anomalous. The number
 26 of events per week in April 2012 and especially September 2012 exceed the number of events
 27 per week at the end of 2013. Two peaks appear earlier than they should. These peaks reflect
 28 something about the way Github as a platform stored data rather than a dramatic change in
 29 what people were doing on Github. These kinds of features in the data suggest that even plat-
 30 forms in the field of devices themselves suffer from device-specific forces.

31 Even if we manage to filter these platform-generated effects or archival anomalies (stat-
 32 isticians and scientists often have to clean data before they analyse it), the plot in Figure 24.1

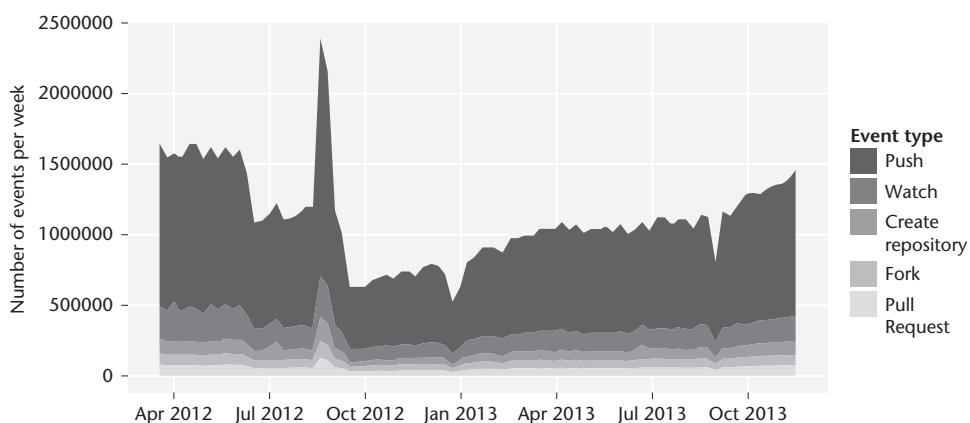


Figure 24.1 Events on the Github.com timeline

1 suggests other problems in analysing the field of devices. Events are not atomic social actions.
2 'Push' events, for instance, occur when software developers move code from a local repository
3 to a Github repository. While there are some atomic events on the Github's timeline (for
4 instance, a WatchEvent suggests that a person is interested in a particular code repository),
5 other events such as PullRequest or PushEvents may wrap around complicated sequences
6 and content 'payloads'. The payload complexity of events poses analytical problems. It steers
7 analytical work into the depths of highly localised practices and highlights the importance of
8 mapping local patches of action rather than general aggregates.

9 Yet the primary form of device-specific order in the vast textual fields of the Github
10 data is the formatted events. Github as a device formats data on the field of devices in ways
11 that encourage a focus on individuals and individual repositories. It affords little scope for
12 examination of transverse flows or cross-cutting vectors in the field. The all-important APIs,
13 the more or less real time data sources that GitHub exposes, effectively provide data about
14 individual repositories and individual users or individual organisations. This formatting of
15 data is typical of contemporary feedback loops: while device-specific data is readable by
16 many, its formatting affords certain interested uses. Indeed, Github.com itself presents and
17 encourages the production of various forms of visualisation and tabulation of what goes on
18 in code repositories (and as mentioned above, the fact that we can access an archived version
19 of the Github event timeline attests to this). GitHub ran a data competition in 2012 in which
20 data analysts sought to do something with the timeline data (Doll, 2012). But what is most
21 available from that data is the formatted events (as we saw in Figure 24.1) that more or less
22 reinforce Github's conception of itself as first of all a *hub* and secondly as a *social* media plat-
23 form. This means that we can easily, for instance, examine a most important or well-known
24 repository on Github such as the Linux kernel, a much-vaunted, commercially, culturally
25 and technically vital software device (<https://www.github.com/torvalds/linux>). Relatively
26 quickly, individual developer contributions can be analysed, and we could begin to charac-
27 terise the composition of the group of people who keep this important software object work-
28 ing and up-to-date. And indeed, this visualisation work is already supplied by Github.com
29 itself (as the screenshot in Figure 24.2 shows).

30 It would even be possible through careful reconstruction to graph the changes in the
31 network of relations that comprise the Linux kernel development teams, and perhaps to see
32 how patterns of work on Linux kernel have changed over time as its economic and technical
33 significance has extended through the popularity of the Android phones that rely on Linux
34 and through the many corporate and industry users/producers invested in Linux. Issues,
35 conversations, team and organisational changes could all be mapped. We could look further
36 at the thousands of 'forks' and 'mirrors' (copies) of Linux to be found on Github, and charac-
37 terise in fine-grained ways how processes of imitation generate flows of readers/writers, how
38 meanings and practices are stabilised through repetition, and how invention might occur at
39 intersections or overlaps between fields.

40 This leaves digital sociology in an interesting position. On the one hand, the Github
41 data allows us to locate an important device – Linux – in the field of devices. The way
42 certain devices attract work, imitations, and variations can be seen from the event data.
43 And the incorporation of Linux into other devices – for instance, the Android platform –
44 can also be gauged. These ongoing alignments and associations are important features of
45 the field of devices. Yet other great patterns of practice on other scales do not immediately
46 surface in the Github data. For instance, we know that particular code constructs are
47 imitated or reinvented in thousands of different projects. We know too that same kinds of
48 software device are re-implemented or imitated across different languages, or for different



Figure 24.2 Top contributors to Linux on Github

1 platforms, often with only small variations. These common patterns striate the field of
 2 devices, but barely appear in the Github-formatted data. Those cross-cutting patterns span
 3 devices and weave them together in surprising conjunctions: the same code constructs
 4 might be found in projects focusing on an ecommerce platform, ecological models of rain-
 5 forest species diversity, Mozilla Foundation's Firefox browser, the Linux kernel, a library
 6 to manipulate financial data, or a modified version of the Android operating system for
 7 smart phones. In short, despite the domain-spanning dynamics of the field of devices, the
 8 way in which code migrates across social fields cannot be readily analysed. In exploring
 9 the field of devices, digital sociology finds highly diverse domains of social action and
 10 transaction, linked by the common practices, formats and materials (code patterns, reposi-
 11 tory mechanisms).⁴

12 Although it might seem a purely technical or practical issue, the problem of traversing such
 13 data flows lies at the heart of digital sociology as well as many parts of contemporary culture.
 14 One response to the problem of traversing data flows is to make devices that capture, reduce
 15 or visualise data.

16 The scaling up of the information infrastructures needed to deal with diverse data flows,
 17 for instance, is a salient concern of the software projects on Github.com. Many Github reposi-
 18 tories explicitly address problems of scale and data. For instance, over 1500 repositories relate
 19 to 'MapReduce,' a parallel-processing algorithm first developed at Google to improve web
 20 search engine response times (<https://github.com/search?q=map+reduce>); 3700 repositories
 21 engage with Hadoop, a widely used Java-language implementation of the MapReduce algo-
 22 rithm (<https://github.com/search?q=hadoop>). This scaling attests to auratic effects propagat-
 23 ing in the field of devices as patterns of imitation. That is, the infrastructures that increasingly
 24 bring people into various forms of relationality are difficult to concretely manage. One can
 25 gaze on somewhat sublime images of earth-spanning information flows or visualisations of

1 networks of hundreds of millions of Facebook users, but it is the work on devices such as
 2 Hadoop that shows us how people concretely grapple with the auratic promise of data flows.
 3 A second response, common in the field of devices, is to make judgements about what
 4 is happening to data. Why does Google make available via its 'BigQuery' service a massive
 5 public archive of all the data produced by Github since early 2012? While social researchers
 6 might find it enormously useful to have an aggregated, hourly-updated timeline of all Github
 7 actions, it is very unlikely that some group at Google marketing or engineering concerned
 8 with data architectures for cloud computing has social researchers particularly in mind. Much
 9 more likely, they seek to attract the attention of the millions of software developers who
 10 use Github.com for coding work. Trying to see themselves and others in this high volume
 11 datastream, software developers and programmers familiarise themselves with Google's
 12 BigQuery architecture, and perhaps use it more thereafter. On the one hand, work on the
 13 Github timeline data demonstrates the power of Google Inc.'s cloud computing services. On
 14 the other hand, it promotes those services to software developers by inviting them to explore
 15 an important aspect of their own work – coding – as a data flow, and to produce second
 16 order judgements on it, including many largely aesthetic judgements of taste (see Martin and
 17 Merriman, this volume). But the developers' interest in doing this presupposes that they have
 18 an interest or investment in making judgements about code, or finding patterns in coding
 19 work. For social researchers too working on Github.com, the Google BigQuery datasets
 20 enable a widely differing scale of exploration of practice in the field of devices, and constantly
 21 increase the risk of being drawn away from the singularity and variability of practices to pro-
 22 duce large scale tabulations of results.

23 **Against the flow: Anti-patterns in digital sociology**

24 A final response to data flows – and this is one that we have pursued – asks: what work needs
 25 to be done against the data flows and against its inevitably device-specific formatting of
 26 data in order to apprehend forces tensioning the field of devices? One possibility here is to
 27 examine how people act in the field of devices to make sense of patterns in data. An interest
 28 in patterns lies at the heart of digital data flows. The problem of finding patterns in data is a
 29 chronic concern in science, business and government data practices. And certainly patterns
 30 and the seeing of patterns are the central pre-occupation in many contemporary sciences,
 31 in financial markets, in biomedicine and in business analytics (see for instance, the fields of
 32 'pattern recognition' and 'machine learning', Hastie, Tibshirani and Friedman 2009). But a
 33 prior and crucial question here is how to think about the value of pattern, or pattern find-
 34 ing as aesthetics of the social. As we have seen, in sociological thought more generally, pat-
 35 tern is a long-standing concern. John Law speaks of 'recurring patterns of the social' Nick
 36 Couldry of 'patterns of flow', and Andrew Abbott suggests that 'if most things that could
 37 happen don't happen, then we are far better off trying first to find local patterns in data and
 38 only then looking for regularities among those patterns' (Abbott, 2001: 241). As Mike Savage
 39 suggests, we need to understand 'how pattern is derived and produced in social inscription
 40 devices' (Savage 2009: 171), whether these devices are objects of analysis or part of our own
 41 methods. A broader philosophical re-conceptualisation of patterns runs through some social
 42 and cultural theory (for instance, in recent work influenced by A.N. Whitehead, who writes
 43 'beyond all questions of quantity, there lie questions of pattern' (Whitehead 1958: 195).

44 However it is conceptualised, the fact remains that concrete work on patterns largely takes
 45 a quite limited number of forms. This limitation in forms suggests that the device-specific
 46 formatting of data is hard to resist, and that the social aesthetics generated by the field of

1 devices is a symptom of this. People craft many data visualisations. But the principal vis-
 2 ible forms of pattern are rather limited. They include plots that show lines, curves, peaks
 3 and clusters of points, networks, trees, and maps. Drawing on the spectrum of plots, graphs
 4 and diagrams developed in the last few centuries (see <http://www.datavis.ca/milestones/>
 5 for a catalogue; Edward Tufte's work (Tufte 2001) is a standard reference for quantitative
 6 digital data), contemporary visual displays of pattern abound in 'predictive analytics and the
 7 move back to visualization in social statistics, the new cartography and associated Web 2.0
 8 innovations, [and] visual montages designed to represent amalgams of "variables"' (Burrows
 9 2012: 585). These patterns can take the form of plots (bar graphs, scatter plots, lines and
 10 curves drawn through clouds of data points, network diagrams), maps on many different
 11 scales (especially maps that superimpose different geo-located datasets), information visu-
 12 alisations (typically combining data graphics, text and typographic design elements), as well
 13 as tables and textual-graphic forms (word clouds), with varying degrees of animation and
 14 with many different forms of scale. Practices of data visualisation are routinised through
 15 the proliferation of certain visual forms (the network diagram, heat maps, bubble plots and
 16 choropleth maps are widely found) in different places. They have field-specific attributes.
 17 Although network visualisations, tag clouds, stream graphs and the like have abounded in
 18 data visualisation on the web, especially with the growth of graphics libraries and packages
 19 such as Hadley Wickham's *ggplot2* (Wickham 2009), Mike Bostock's *d3.js*, or widely-used
 20 scientific plotting packages such as *matplotlib* (software projects all currently hosted on Github),
 21 we have little sense yet of the visual culture of these devices and their visual forms. While
 22 devices of various kinds may have been involved in producing them (for instance, many
 23 smoothing algorithms used to draw lines through points effectively fit a series of local linear
 24 models – splines – in building a smooth curve), the models themselves are not interpreted
 25 as such but act in the world more like things than thoughts. If pattern matching and pattern
 26 recognition are becoming mundane parts of contemporary culture in many different ways,
 27 it is partly because these forms of judgement or perception are endemic in the field of
 28 devices. (For instance, in the face recognition logic now built into many digital cameras,
 29 or the much-discussed recommendation systems typical of online commerce). They are in
 30 any case widely distributed through various social fields where visual devices associated
 31 with displays, gauges, metrics, dashboards, graphs, and visualisations form part and parcel of
 32 social life, whether in the graphic displays that users of supply chain and inventory manage-
 33 ment systems or financial traders gaze at (Knorr Cetina and Bruegger 2004), or in the many
 34 news-related visualisations produced by data journalists for news sites such as *The Guardian*
 35 datablog (n.d.) or the *New York Times* (2012).

36 Some commentators suggest that the production and use of such visualizations is a key
 37 concern for contemporary sociology: 'the discipline . . . will have to take visualization meth-
 38 odologies far more seriously than we have hitherto' writes Roger Burrows (Burrows 2012:
 39 585) because of the ways that they are being used and could be used to understand 'particular
 40 patterns of association that exist between persons, objects, symbols, technologies and so on'
 41 (585). The renewed emphasis on visualization in digital sociology differs somewhat from
 42 adjacent efforts such as computational social science (Giles 2012; Housley *et al.* 2013) where
 43 visualisation is usually close evaluation of statistical or predictive models. Sociological work
 44 on the transformations of data visualisation is still rather scarce. Scientific visualisation offers
 45 some leads here (Latour *et al.* 1990; Myers 2008) alongside work on visualisation in finance
 46 (Pryke 2010), but the visual culture of data as it moves out of scientific publication has
 47 received little attention. There is much scope for investigation of the seeing in data visualisa-
 48 tion as forms of visual culture in which, as Gillian Rose writes, 'different ways of seeing are

bound up into different, more-or-less conscious, more-or-less elaborate, more-or-less consistent practices' (Rose 2012: 549). This is a challenge to methodological practices precisely because the visual forms attest to a shift away from some traditional sociological concerns with abstractions, models and structures as deep explanations of social processes, and a lighter, perhaps more responsive descriptive attunement to patterns, groupings and flows.⁵ What do they make visible? Both in the visual culture of data, and in its own visualisation of digital data, digital sociology faces the problem of describing how patterns are produced at the intersection of various concretisations and abstractions as reactions to certain aspects of experience. Digital sociology, we suggest, might take data graphics and the many judgements and discussions of data graphics seriously as a form of judgement endemic to the field of devices.

Patterns arise in very different ways. Many data visualisations seek to render perceptible something that occurs on spatio-temporal scales that are difficult to directly see, but they often struggle to distinguish something amidst the generic schematic formatting of the data. For instance, Figure 24.3 seeks to convey something of the patterns associated with different scales of activity in Github repositories by counting events that appear in the Github timeline over an interval of two years (2012–2013). The general pattern shown here is the somewhat ubiquitous 'power law' distribution of events, a distribution that often shows up in social media data. At the left hand end, the high point refers to the millions of Github repositories consisting of one or two events. At the low end on the right, where the curve approaches the x-axis, a small number of repositories receive many thousands of events. The power law distribution of events in social media often vexes data analysis and data visualisation. Many social media datasets yield heavy-tailed distributions when graphed. This common scaling of

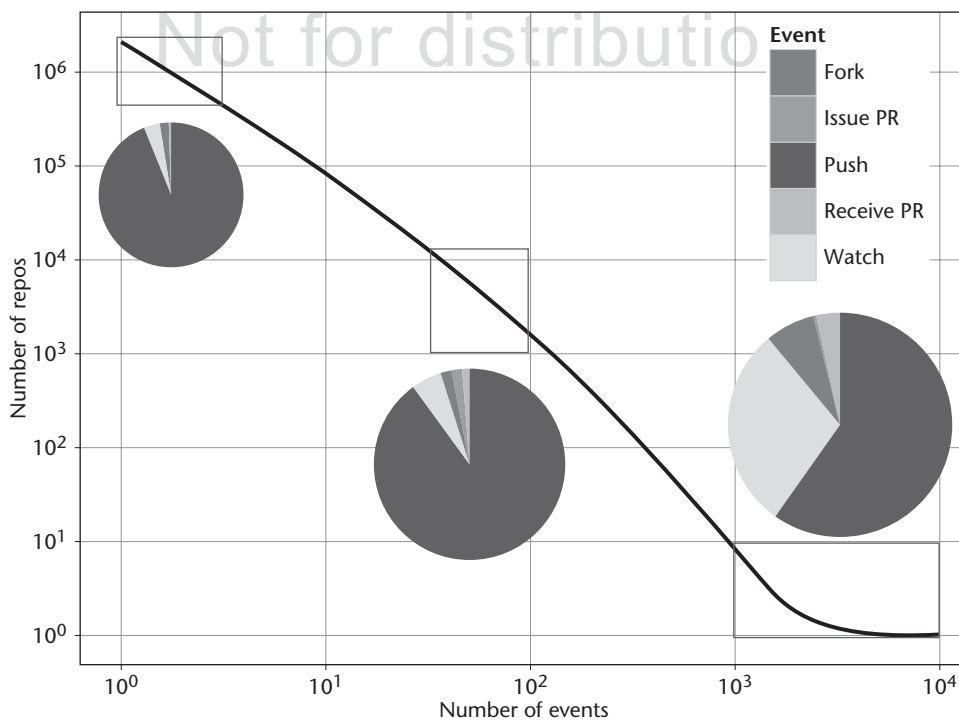


Figure 24.3 Patterns of repository events on Github

1 events across the ‘many-some-rare’ scales (Conte *et al.* 2012: 334) requires site-specific work.
 2 The visualisation of repository event counts begins to do this by showing something of the
 3 different composition of the repositories on the different scales. The many small repository
 4 ries mainly consist of the a few Push events. Mid-scale repositories show the presence of
 5 more social events such as Watch and Fork. The rarer very large repositories attract many
 6 more social events – Fork, Watch and PullRequest. But if this patterning across many-
 7 some-rare is so common as a reaction to something in the contemporary field of devices
 8 (‘In recent years, due to ubiquitous computerization, networking and obsessive data col-
 9 lection, reports of heavy-tailed distributions have almost become a routine’ (Muchnik *et al.*
 10 2013: 1), what does it say about the global organization of the field of devices?

11 On the one hand, many data visualisations, whether in the form of networks, scatter plots
 12 or line graphs today present the power-law or scale-free pattern of digital media. It is often
 13 said that patterns are supplanting causes as modes of explanation in many places, and the
 14 growth of data visualisations might be understood in these terms. These descriptive visuali-
 15 sations might prompt some causal interpretation in their viewers but they are not premised
 16 on any such abstraction. Might they be seen perhaps more generally as an integral part of
 17 the cultural saturated feedback loop running through the field of devices? As technological
 18 concretisation binds practices, habits, emotions, and interactions through digital devices and
 19 infrastructures and devices, the derivation of patterns increasingly depends on abstractive
 20 devices that classify, cluster, calculate and predict events precisely in order to shape them.
 21 Predictive analytics, as demonstrated in Google Research’s work on how users’ searches fore-
 22 shadow airline ticket bookings or car sales (Varian and Choi, 2009), derives patterns from
 23 data using a much more technical armature of machine learning techniques. This modelling
 24 is an increasingly dense force affecting the feedback loop between people and digital infra-
 25 structures (Pariser 2011). Algorithmic classificatory techniques such as k-means clustering,
 26 nearest neighbour classification, linear regression, logistic regression, principal component
 27 analysis, neural networks, decision trees, random forests, and support vector machines are
 28 rapidly becoming an integral part of every level and niche of digital assemblages, rang-
 29 ing from playful mundane devices such as ‘kittydar’, a neural network to detect cat photos
 30 (<https://github.com/harthur/kittydar>) through to thousands of projects implementing ‘face
 31 detectors’ or ‘motion detectors’ for smart phones, web browsers, and for different operating
 32 systems. Even a single technique like the popular random forest classifier (Breiman 2001) can
 33 be found hundreds of thousands of times in Github.com repositories, and tens of thousands
 34 of times in popular programming languages such as R (R Development Core Team n.d.).
 35 Again, the proliferation of these classificatory or pattern finding techniques is perhaps much
 36 less visible, and the ways in which they imprint or weave through flows of meaning and things
 37 is harder to analyse. They are somewhat withdrawn elements in the feedback loops of cultural
 38 space. These predictive models and classifiers sometimes operationally shape the experience
 39 and action (as in Netflix or Amazon recommendation systems, or in the classifiers that detect
 40 and classify body gestures in the Microsoft Kinect game controller), and sometimes they
 41 are analytic tools used by people working on platforms trying to make sense of emerging or
 42 divergent patterns in practice. As always, the feedback loops between knowing and acting
 43 are hard to disentangle precisely because they are becoming more tightly coupled. If decision
 44 trees were an analytic technique developed by statisticians in the late 1970s trying to make
 45 sense of air pollution measurements in Los Angeles (Breiman *et al.* 1984), in the Kinect game
 46 controller they become predictive devices that intensify the immediacy of computer game
 47 play. Online learning – the constant updating of predictive models in response to the flow
 48 of current events – is increasingly common in social network media and online transactions.

1 In the field of devices, patterns are generated, acted upon, altered and re-imprinted.
 2 Pattern recognition is no longer a practice conducted at leisure by expert interpreters or elite
 3 analysts. Patterns are operational components of device-specific zones of culture. The trans-
 4 formation of abstract analytic devices of many different kinds (linear regression models, clus-
 5 tering algorithms, Bayesian models, etc.) into things that either circulate much more widely
 6 in the world in gadgets and devices or into meta-things such as search engines that modulate
 7 flows on a large scale is a central component of the flow of texts, meanings, audiences, view-
 8 ers, visitors, spectators, readers and players in many settings. These abstractions exercise an
 9 auratic effect akin to the data infrastructures we were discussing above. Journalists, social
 10 researchers and commentators on digital technology tend to attribute great potency to algo-
 11 rithms in general. The proliferation of algorithms is hard to deny, but digital sociology might
 12 play an important role in describing what happens as these algorithms shift shape and move
 13 into different settings ranging from pay day loans to computer game play, from web search
 14 engines or ecommerce recommendations to face recognition in digital cameras. The aura of
 15 algorithms as epistemic prime movers akin to steam power or electricity covers over their
 16 diverse provenance (they do not come just from computer science but also from statistics, psy-
 17 chology, cognitive science, ecology, archaeology or geology) and their diversity in practice.
 18 Perhaps more significantly the patterns that these algorithms produce or derive from data are
 19 neither obviously legible in descriptive devices, nor is their relation to existing structures,
 20 groupings, or classifications direct.

21 For digital sociology, recognising the effects of this pattern-making is a significant chal-
 22 lenge. The imprinting of flows of meaning, media and practices is sometimes legible (for
 23 instance, in the 'induced viralities' seen in various social media platforms that identify trends
 24 using pattern recognition techniques and then shape flow of messages or network connections
 25 accordingly), but not always. Another difficulty is much more challenging. While descrip-
 26 tive devices can relatively easily slip into the analytical toolkit of social researchers – the
 27 spread of tag-clouds or Wordle graphics would be a typical instance of this – the appropri-
 28 ation and re-purposing of machine learning, pattern recognition or data mining approaches is
 29 more problematic. Many of these devices rely on formidable mathematical apparatus, ranging
 30 across linear algebra, probability theory, function analysis and numerical optimisation. The
 31 diverse provenance of the techniques means that, although they operate abstractly (that is,
 32 with little regard for the concrete specificities of a given situation), they handle notions of
 33 group, classification, difference and similarity heterogeneously. Nearly all of them bring to
 34 bear powerful scaling processes that reduce the high dimensions and volume of data to legible
 35 forms of variation and pattern.

36 Conclusion

37 While Bourdieu's comments on devices are not abundant, he wrote about traffic lights:

38 The social world is full of calls to order which function as such only for individuals who
 39 are predisposed to notice them, and which, as a red light causes braking, trigger deep-
 40 rooted bodily dispositions without passing through consciousness and calculation
 41 *(Bourdieu 2000: 176).*

42 Contemporary culture is deeply textured by device-specific calls to order. Reactions to these
 43 signals, for those who notice them, are often deep-rooted and bodily enacted. The reposi-
 44 tories of Github.com, which we have only lightly explored here, illustrate something of the

1 variety of signals flashing in contemporary social worlds. It points to forms of reactions that
 2 go well beyond braking or accelerating, yet remain for all that somewhat non-conscious or
 3 largely affective. The experience of spiralling in and out of device-specific feedback loops
 4 generates many forms of reaction and reactivity.

5 In the field of devices, relations between devices connect, disconnect, attract, configure,
 6 imitate, intensify and re-distribute signals for ordered social action. The case of Github shows
 7 too that attempts to configure social patterns of action have animated the growth of large-
 8 scale digital infrastructures and social media. The algorithmic elements of search engines
 9 such as Google Web Search's *PageRank* algorithm or Facebook's *Social Graph* are two better
 10 known instances of the ways in which the detection of social patterns and flows of meanings,
 11 texts and readers has been pivotal in the growth of digital culture. Devices devoted to pat-
 12 tern recognition or data visualisations themselves flash signals amidst a field of devices.
 13 In analysing the vectoral components of the field of devices or tracing the reactions to that
 14 field, digital sociology is not doing anything radically different to people who inhabit this
 15 field. Savage suggests that:

16 a core concern [for social research] might be to scrutinise how pattern is derived and
 17 produced in social inscription devices, as a means of considering the robustness of such
 18 derivations, what may be left out or made invisible from them, and so forth. We need to
 19 develop an account which seeks to criticize notions of the descriptive insofar as this
 20 involves the simple generation of categories and groups, and instead focus on the fluid
 21 and intensive generation of potential

(Savage 2009: 171).

23 Patterns in cultural life today derive from social inscription devices assembled in wide-
 24 ranging feedback loops. Feedback runs between recording what people do, visualising or
 25 graphing what they do, finding/generating patterns in the recording, and shaping what
 26 they encounter next. If digital sociology attempts to describe what is happening in contem-
 27 porary textual and media environments, it needs to map the paths of these feedback loops
 28 running across publics, infrastructures, techniques, textual and media forms, and diverse,
 29 expanding practices. At the same time, patterns themselves are increasingly heavily anal-
 30 ysed and modelled inside the culturally saturated feedback loop between people and social
 31 inscription devices. Digital social research is not alone in its interest in these processes.
 32 Reputational, attentional and sentiment economies (Arvidsson 2011) directly act on that
 33 patterning.

34 Identifying events that animate this patterning and scaling is a key concern for digital soci-
 35 ology. The 'massive, culturally-saturated feedback loop' arises from device -saturated social
 36 action. As the case of Github shows, the process of making, configuring, arranging and align-
 37 ing devices is itself a highly dynamic field of linkages, associations, and imitations, where
 38 social action is often concerned with problems of pattern and of scale. The 'simple generation
 39 of categories and groups' that Savage refers to can certainly be found there, replicating and
 40 propagating at scale.

41 We have suggested that social researchers in the field of devices react, like other partici-
 42 pants, to calls to order in their own practice. Digital sociology and certainly social research
 43 more generally is not immune from the auratic imperatives to methodologically emulate and
 44 align themselves with the infrastructures and practices of the field of devices (such as 'big
 45 data'). It grapples with the reflexive-recursive problem of its own implication in methods,
 46 techniques and infrastructures for deriving pattern. Digital social researchers find ourselves

lost in the labyrinth of technical possibilities opening up around platforms, tools, visual forms and data flows. The experience of being somewhat caught up in the entanglements of pattern and scale might for digital sociology be a necessary step towards sensing the fluid generative potentials in the field of devices. These entanglements between scale and pattern, and especially between the different ways in which pattern might be found could offer a way for sociology to deviate from the scaled-up homogeneity and uniformity of predictive analytics with their highly constrained commitment to increasing advertising revenue or sales.

8 Notes

1 We largely leave aside any further discussion, analysis or critique of these developments. They are extensive and multi-faceted, and can be seen at work in the digital humanities (Galloway 2014), in cultural analytics (Manovich 2011), in social physics and computational social science (Pentland 2014). The constant updating of events, the relatively frequent advent of new flows of data, the teeming and burgeoning ways of inhabiting the reefs of digital infrastructures, many of which are developed and publicly available, confront digital sociology with challenges and alluring possibilities. Unlike the major social media platforms or even the legion of startup companies in London, New York, San Francisco, Shanghai, Berlin or Amsterdam who offer ways of packaging, summarising, monitoring or shaping flows of data in networks, digital sociologists do not have hundreds of developers to wrangle data, dozens of computers and disk-drives arrayed in racks to expedite the process of searching or exploring the data. Given the billions of events welling-up in diverse APIs, what can digital sociology do? Should it sample and filter according to the criteria of adequacy and representativeness? The expansive forms of textual environment we have just been describing are writ large at the moment under the broad banner of 'big data'. The proliferating discussions of 'big data' need to be analysed in their own right in terms of how they intensify desires to connect information flows, previously disparate infrastructures and systems (energy, telecommunications, entertainment, transport, retail and manufacturing), and how they actually reorganise work, domestic lives, forms of sociality and value in the name of flows of data. 'Big data' is certainly part of the feedback loop or accumulation strategy in which social practices recorded as data become the basis of new textualities that seek to enrol further readers or writers, to align reading, viewing and buying, writing and working, as well as other forms of value. The physical, life and environmental sciences offer both a lead and something distracting here. The term 'data' carries with it an aura of scientificity, objectivity or neutrality that digital sociology is still wrestling with. 'Big data' is an expansive grouping and its membership continues to grow: house prices, clicks on hyperlinks, vehicle detection loops on roads, mobile phone call details, satellite photos of crops, electronic payment, stellar images from orbiting telescopes, transactional data such as credit card authorisation or supermarket checkout scanners – these are just examples in a list that keeps growing. The listing of data sources is an interminable feature of most talk about big data (and digital sociology shares this habit). Scientific data, however, has a particular resonance and perhaps anchors some forms of referentiality in data talk. The standard reference to allude to transformations in scientific data is *The Fourth Paradigm: Data-Intensive Scientific Discovery* (Hey, Tansley and Tolle 2009), a book published by Microsoft Research Press (a publisher that probably lies quite close to the source of much business data practice). This book furnishes vignettes of a range of scientific enterprises ranging across physical, earth, environmental and life sciences in which flows of data have transformed knowledge-making practices. The data intensive sciences authorise data practices in specific ways. The auratic power of scientific instruments such as DNA sequences or infrared satellite photos differ, as Mike Savage observes, from the 'mundane descriptions,... ordinary transactions, websites, Tesco loyalty cards, CCTV cameras in your local shopping centre, etc., that are the stuff of the new social' (Savage, 2009: 171). It may be that this auratic/mundane difference, important though it is in differentiating certain practices, also usefully links different domains of the social. Auratic scientific instrument data, with its referential links to the diversity of life, the fate of the planet or the conundrums of missing matter in the universe, rivets data to things. The scientific examples allow data more generally in all its administrative, transactional or media-derived forms to carry universalising epistemic value. It suggests that the birth of stars in remote galaxies can be analysed in similar terms to the birth of stars in the media environments of Xfactor or reality TV shows. In this respect, the popularity of the term 'data science' suggests that the referential power of science matters to business, commerce, industry and government as they seek to commodify, extract or regulate contemporary cultural spaces.

- 1 2 The anthropologist Anna Tsing writes: ‘scale is the spatial dimensionality necessary for a particular kind
2 of view, whether up close or from a distance, microscopic or planetary. I argue that scale is not just a
3 neutral frame for viewing the world; scale must be brought into being: proposed, practiced and evaded,
4 as well as taken for granted’ (Tsing, 2005: 58). *Scale* refers to the relative dimensions of enlargement
5 or reduction in a map, picture or model, as well as the marks or degrees used to measure intervals (as
6 in the scale on the axes of a scatter plot), but it implicitly positions observers as well. *Scale*, however,
7 is a verb as well as a noun. In digital culture, re-scaling or re-dimensioning is common. The *scaling-up*
8 of databases, of transactions, of geographies (e.g. Amazon’s data-centres divide the globe into eight
9 regions), and capacities in many settings testifies to one aspect of this re-scaling.
- 10 3 While the textual environment for online code repositories such as Github includes the many forms
11 of text and graphic visible on Github webpages, it also includes the flows of data that these platforms
12 generate for use by others. As millions of people interact even with mid-level platforms such as Github,
13 their actions generate large volumes of data that can be streamed as time-stamped events. So, like many
14 other social media platforms, Github publishes all of these individual time-stamped events to anyone
15 who wants to use them. (While some users may pay to have their repositories and working practices
16 remain invisible, very many do not.) The events are available more or less as they happen (through
17 the Github API – application programmer interface) or in bulk through various archives ([https://](https://www.githubarchive.org/)
18 www.githubarchive.org/; a mirror of the data is also published by Google as a demonstration of their
19 ‘BigQuery’ cloud computing service). The data derived from what people do on social media is mixed
20 in form. It includes when things were done (date-time), various free textual forms (descriptions, tags,
21 titles, etc.), structured text (links or URLs of associated webpages; names of associated organisations
22 and groups; names of user), categorical attributes (on Github these are limited: the event type and the
23 programming languages used), and often a mathematically encoded summary of the result of actions
24 that change the contents of the repository (in the case of Github, the *hash digest* of any new content or
25 change to existing contents of the repository). Github events are categorised according to 18 different
26 event types (PushEvent, CommitEvent, AddUserEvent, DeleteEvent). These event types are organic to
27 Github.com, but as variables in any data analysis they are defined by the platform designers rather than
28 by any questions that social researchers might bring to bear on what people do on Github. ‘Source-
29 defined variables’ are a central concomitant of data analysis practice in digital sociology. We might say
30 that in the new social fields, data has an ‘organic’ aura: it is generated and collected by virtue of the
31 existence of the infrastructures and platforms that are part and parcel of the social field rather than from
32 instruments or measuring devices introduced by market or social researchers. But even this relationship
33 is becoming increasingly complicated by virtue of the intricate and shifting relations between ‘organic
34 data’ and ‘paid for data’ (Google Inc. 2009). Even if this data is ‘observational’ rather than experimental,
35 the fact that it is generated intrinsically as part of a social field has powerful referential attractions, and
36 attracts much work.
- 37 4 In much social research, problems of scale largely related to scarcity. Where data was abundant, scale
38 problems were handled by setting limits on data through sampling strategies, research methods and
39 research designs that allowed social researchers to be more or less confident that their research covers
40 the social field of interest (for instance, making sure that differences in age, gender, ethnicity, sexuality,
41 nationality, education-level, or income are represented in the data; many of the chapters in a typical
42 introductory statistics textbook for social science address these problems of scarcity and representative-
43 ness). Selecting and sampling strategies seem to work differently in digital sociology as it encounters
44 expanding textual environments where data scarcity is rarely an issue. The much discussed problem
45 is how to cope with the vast amount of material. What is worse, textual environments such as social
46 media are explicitly expansive.
- 47 5 This contrast has been extensively debated in sociology. (See Andrew Abbot’s discussion of patterns versus
48 causes; the ‘empirical crisis in sociology’ literature; as well as the explicit focus on digital devices in recent
49 sociology (Abbott 2001; Ruppert 2013; Savage and Burrows 2007) and we will not rehearse these debates
50 in great detail here. They have been debated fairly widely elsewhere (see Burrows 2012 for an overview).

51 References

- 52 Abbott, A. (2001) *Time Matters: On Theory and Method*, Chicago: University of Chicago Press.
53 Adkins, L. and C. Lury (2009) ‘Introduction: What Is the Empirical?’ *European Journal of Social Theory*, 12(1):
54 5–20.

- 1 Arvidsson, A. (2011) 'General Sentiment: How Value and Affect Converge in the Information Economy',
- 2 *The Sociological Review*, 59: 39–59.
- 3 Back, L. and N. Puwar (2012) *Live Methods*, Oxford: Wiley-Blackwell.
- 4 Barry, A. (2001) *Political Machines: Governing a Technological Society*, London: Athlone.
- 5 Bourdieu, P. (2000) *Pascalian Meditations*, Stanford: Stanford University Press.
- 6 Boyd, d. and K. Crawford (2012) 'Critical Questions for Big Data', *Information, Communication and Society*,
- 7 15(5): 662–79.
- 8 Breiman, L. (2001) 'Random Forests', *Machine Learning*, 45(1): 5–32.
- 9 Breiman, L., J. Friedman, R. Olshen and C.J. Stone (1984) *CART: Classification and Regression Trees*,
- 10 Belmont, CA: Wadsworth, 156.
- 11 Burrows, R. (2012) 'Digitalization, Visualization and the "Descriptive Turn"', in Heywood, I., Sandywell, B.
- 12 (eds), *The Handbook of Visual Culture*, London: Berg, 572–88.
- 13 Conte R., N. Gilbert, G. Bonelli, C. Cioffi-Revilla, G. Deffuant, J. Kertesz, V. Loreto, S. Moat, J.P. Nadal,
- 14 A. Sanchez, A. Nowak, A. Flache, M. San Miguel, and D. Helbing (2012) 'Manifesto of Computational
- 15 Social Science', *European Physical Journal-Special Topics*, 214(1): 325–46.
- 16 Couldry, N. (2000) *Inside Culture: Reimagining the Method of Cultural Studies*, London: SAGE.
- 17 Cukier, K.N. and V. Mayer-Schoenberger (2013) 'The Rise of Big Data. How It's Changing the Way We
- 18 Think About the World', *Foreign Affairs*, Available online at [http://www.foreignaffairs.com/articles/139104/](http://www.foreignaffairs.com/articles/139104/kenneth-neil-cukier-and-viktor-mayer-schoenberger/the-rise-of-big-data)
- 19 [kenneth-neil-cukier-and-viktor-mayer-schoenberger/the-rise-of-big-data](http://www.foreignaffairs.com/articles/139104/kenneth-neil-cukier-and-viktor-mayer-schoenberger/the-rise-of-big-data) (accessed 10 February 2014).
- 20 Doll, B. (2012) *Data at Github*, GitHub, Available online at <https://github.com/blog/1112-data-at-github>
- 21 (accessed 3 March 2014).
- 22 Galloway, A.R. (2014) 'The Cybernetic Hypothesis', *differences*, 25(1): 107–131.
- 23 Giles, J. (2012) 'Computational Social Science: Making the Links', *Nature*, 488(7412): 448–50.
- 24 Hastie, T., R. Tibshirani and J.H. Friedman (2009) *The Elements of Statistical Learning: Data Mining,*
- 25 *Inference, and Prediction*, New York: Springer.
- 26 Hey, T., S. Tansley, and K. Tolle (2009) 'The Fourth Paradigm: Data-Intensive Scientific Discovery',
- 27 *Microsoft Research*.
- 28 Housley, W., M. Williams, M. Williams, and A. Edwards (2013) 'Computational Social Science: Research
- 29 Strategies, Design and Methods Introduction' *International Journal of Social Research Methodology*, 16(3):
- 30 173–5.
- 31 Knorr Cetina, K.K. and U. Bruegger (2004) 'Traders' Engagement with Markets: A Postsocial
- 32 Relationship', in Ash A. and Thrift N., *The Blackwell Cultural Economy Reader*, Oxford: Blackwell.
- 33 Latour, B., M. Lynch, and S. Woolgar (1990) 'Drawing Things Together', in M. Lynch and S. Woolgar
- 34 (eds), *Representation in Scientific Practice*, Cambridge, MA: MIT Press.
- 35 Latour, B., P. Jensen, T. Venturini, S. Grauwin, and D. Boullier (2012) 'The Whole is Always Smaller
- 36 than its Parts. How Digital Navigation May Modify Social Theory', *British Journal of Sociology*, 63(4):
- 37 590–615.
- 38 Law, J. (1994) *Organizing Modernity*, Oxford: Blackwell.
- 39 Lee, B. and E. LiPuma (2002) 'Cultures of Circulation: The Imaginations of Modernity', *Public Culture*,
- 40 14(1): 191–213.
- 41 Lupton, D. (2012) *Digital Sociology: An Introduction*, Sydney: University of Sydney, Available online at
- 42 <http://prijipati.library.usyd.edu.au/handle/2123/8621> (accessed 14 November 2013).
- 43 Manovich, L. (2011) 'Trending: The Promises and the Challenges of Big Social Data', *Debates in the Digital*
- 44 *Humanities*, Available online at [http://manovich.net/index.php/projects/trending-the-promises-and-](http://manovich.net/index.php/projects/trending-the-promises-and-the-challenges-of-big-social-data)
- 45 [the-challenges-of-big-social-data](http://manovich.net/index.php/projects/trending-the-promises-and-the-challenges-of-big-social-data) (accessed 15 April 2013).
- 46 Marres, N. (2012) 'The Redistribution of Methods: On Intervention in Digital Social Research, Broadly
- 47 Conceived', *The Sociological Review*, 60(1): 139–65.
- 48 Meyer, R. (2013) 'Github, Object of Nerd Love, Makes Play for Non-Programmers', *The Atlantic*, Available
- 49 online at [http://www.theatlantic.com/technology/archive/2013/08/github-object-of-nerd-love-](http://www.theatlantic.com/technology/archive/2013/08/github-object-of-nerd-love-makes-play-for-non-programmers/278971/)
- 50 [makes-play-for-non-programmers/278971/](http://www.theatlantic.com/technology/archive/2013/08/github-object-of-nerd-love-makes-play-for-non-programmers/278971/) (accessed 13 February 2014).
- 51 Muchnik, L., S. Pei, L.C. Parra, S.D.S. Reis, J.S. Andrade Jr., S. Havlin, and H.A. Makse (2013) 'Origins
- 52 of Power-Law Degree Distribution in the Heterogeneity of Human Activity in Social Networks',
- 53 *Scientific Reports*, 3, Available online at [http://www.nature.com.ezproxy.lancs.ac.uk/srep/2013/130507/](http://www.nature.com.ezproxy.lancs.ac.uk/srep/2013/130507/srep01783/full/srep01783.html)
- 54 [srep01783/full/srep01783.html](http://www.nature.com.ezproxy.lancs.ac.uk/srep/2013/130507/srep01783/full/srep01783.html) (accessed 1 March 2014).
- 55 Myers, N. (2008) 'Molecular Embodiments and the Body-Work of Modeling in Protein Crystallography',
- 56 *Social Studies of Science*, 38(2): 163–99.
- 57 Pariser, E. (2011) *The Filter Bubble: What the Internet is Hiding from You*, London: Penguin.

- 1 Pentland, A. (2014) *Social Physics: How Good Ideas Spread—The Lessons from a New Science*, New York: The
- 2 Penguin Press.
- 3 Pryke, M. (2010) 'Money's Eyes: The Visual Preparation of Financial Markets', *Economy and Society*, 39(4):
- 4 427–59.
- 5 Rogers, R. (2013) *Digital Methods*, Cambridge, Massachusetts, London: The MIT Press.
- 6 Rose, G. (2012) 'The Question of Method: Practice, Reflexivity and Critique in Visual Culture Studies', in
- 7 I. Heywood and B. Sandywell (eds) *The Handbook of Visual Culture*, London: Berg.
- 8 Ruppert, E. (2013) 'Rethinking Empirical Social Sciences', *Dialogues in Human Geography*, 3(3): 268–73.
- 9 Ruppert, E., J. Law and M. Savage (2013) 'Reassembling Social Science Methods: The Challenge of
- 10 Digital Devices' *Theory, Culture and Society*, 30(4): 22–46.
- 11 Savage, M. (2009) 'Contemporary Sociology and the Challenge of Descriptive Assemblage', *European Journal*
- 12 *of Social Theory*, 12(1): 155–74.
- 13 Savage, M. and R. Burrows (2007) 'The Coming Crisis of Empirical Sociology', *Sociology*, 41(5): 885–99.
- 14 Schutt, R. and O'Neil, C. (2013) *Doing Data Science*, Sebastopol, CA: O'Reilly & Associates Inc.
- 15 Thrift, N. (2006) 'Re-Inventing Invention: New Tendencies in Capitalist Commodification', *Economy and*
- 16 *Society*, 35(2): 279–306.
- 17 Tsing, A.L. (2005) *Friction?: An Ethnography of Global Connection*, Princeton, NJ: Princeton University Press.
- 18 Tufte, E. (2001) *The Visual Display of Quantitative Informations*, second ed., Cheshire, CT.: Graphics Press.
- 19 Varian, H. and H. Choi (2009) 'Official Google Research Blog: Predicting the Present with Google Trends',
- 20 Available online at [http://googleresearch.blogspot.com/2009/04/predicting-present-with-google-trends.](http://googleresearch.blogspot.com/2009/04/predicting-present-with-google-trends.html)
- 21 [html](http://googleresearch.blogspot.com/2009/04/predicting-present-with-google-trends.html) (accessed 23 May 2011).
- 22 Whitehead, A.N. (1958) *Modes of Thought; Six Lectures Delivered in Wellesley College, Massachusetts, and Two*
- 23 *Lectures in the University of Chicago*, New York: Capricorn Books.
- 24 Wickham, H. (2009) *ggplot2: Elegant Graphics for Data Analysis*, New York: Springer. Available online at
- 25 <http://ggplot2.org/>.

26 Online Sources

- 27 Google Inc. (2009) Back to Basics: Direct, Referral or Organic – Definitions Straight from the Source –
- 28 Analytics Blog. *Google Analytics Blog*, Available online at [http://analytics.blogspot.co.uk/2009/08/](http://analytics.blogspot.co.uk/2009/08/back-to-basics-direct-referral-or.html)
- 29 [back-to-basics-direct-referral-or.html](http://analytics.blogspot.co.uk/2009/08/back-to-basics-direct-referral-or.html) (accessed 7 February 2014).
- 30 *The Guardian* (n.d.) Data Journalism and Data Visualization from the Datablog. Available online at
- 31 <http://www.theguardian.com/news/datablog> (accessed 30 January 2014).
- 32 New York Times (2012) *2012: The Year in Graphics*. Available online at [http://www.nytimes.com/](http://www.nytimes.com/interactive/2012/12/30/multimedia/2012-the-year-in-graphics.html)
- 33 [interactive/2012/12/30/multimedia/2012-the-year-in-graphics.html](http://www.nytimes.com/interactive/2012/12/30/multimedia/2012-the-year-in-graphics.html) (accessed 30 January 2014).
- 34 Prediction Impact Inc. (2009) Predictive Analytics World Conference: Agenda. Available online at
- 35 <http://www.predictiveanalyticsworld.com/sanfrancisco/2009/agenda.php#usergroup> (accessed 24
- 36 May 2011).
- 37 R Development Core Team (n.d.) The R Project for Statistical Computing. Available online at [http://](http://www.r-project.org/)
- 38 www.r-project.org/ (accessed 11 June 2010).