

1 **Operational Framework: Institutional Controls - The New Deal** 2 **on Data**

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23 1 The New Realities of Living in a Big Data Society

24 To realize the promise and prospects of a Big Data society and avoid its security and confiden-
25 tiality perils, institutions are updating operational frameworks governing business, legal, and
26 technical dimensions of their internal organization and interactions with the outside world. In
27 this chapter we explore the emergence of the Big Data society, outline ways to support it in the
28 context of institutional controls within the framework of the New Deal on Data, and describe
29 future directions for research and development.

30 The control points traditionally relied upon as part of corporate governance, management
31 oversight, legal compliance, and enterprise architecture must evolve and expand to match oper-
32 ational frameworks for Big Data. An operational framework used for a Big Data driven organi-
33 zation requires a balanced set of institutional controls. These controls must support and reflect
34 greater user control over personal data, as well as large scale interoperability for data sharing be-
35 tween and among institutions. Core capabilities of these controls include responsive rule-based
36 systems governance and fine-grained authorizations for distributed rights management.

37 Sustaining a healthy, safe, and efficient society is a scientific and engineering challenge going
38 back to the 1800s when the Industrial Revolution spurred rapid urban growth, thereby creating
39 huge social and environmental problems. The remedy then was to build centralized networks
40 that delivered clean water and safe food, enabled commerce, removed waste, provided energy,
41 facilitated transportation, and offered access to centralized healthcare, police, and educational
42 services. Those networks formed the backbone of society as we know it today.

43 These century-old solutions are, however, becoming increasingly obsolete and inefficient. We
44 have cities jammed with traffic, world-wide outbreaks of disease that are seemingly unstoppable,
45 and political institutions that are deadlocked and unable to act. We face the challenges of global
46 warming, uncertain energy, water, and food supplies, and a rising population and urbanization
47 that will add 350 million people to the urban population by 2025 in China alone [15].

48 It does not have to be this way. We can have cities that are energy efficient, have secure food
49 and water supplies, are protected from pandemics, and enjoy much better governance. To reach
50 these goals, however, we need to radically rethink our approach. Rather than static fixed systems
51 separated by function — water, food, waste, transport, education, energy — we must consider
52 them as dynamic, data-driven networks. Instead of focusing only on access and distribution,
53 we need the networked and self-regulating systems, driven by the needs and preferences of the
54 citizens.

55 Sustainable future society depends on our new technologies being used to create a *nervous*
56 *system* maintaining the stability of government, energy, and public health systems around the
57 globe. The digital feedback technologies are today capable of creating a level of dynamic re-
58 sponsiveness that our larger, more complicated modern society requires. We must reinvent the
59 systems of societies within a control framework: sensing the situation, combining these observa-
60 tions with models of demand and dynamic reaction, and finally using the resulting predictions
61 to tune the system to match the demands.

62 The engine driving this nervous system is Big Data: the newly ubiquitous digital data, now
63 available about all aspects of human life. We can analyze patterns of human experience and
64 ideas exchange within the *digital breadcrumbs* that we all leave behind as we move through
65 the world: call records, credit card transactions, GPS location fixes, among others [25]. By
66 recording our choices, these data tell the story of our lives. And this may be very different from
67 what we decide to put on Facebook or Twitter; our postings there are what we choose to tell
68 people, edited according to the standards of the day and filtered to match the persona we are
69 building. Mining social networks can give some great insights about human nature [4, 29, 44];
70 who we really are, however, is even more accurately determined by where we spend our time
71 and which things we buy, rather than just what we say we do [28].

72 The process of analyzing the patterns within these digital breadcrumbs is called reality
73 mining [14, 33], and through it we can learn an enormous amount about who we are. The
74 Human Dynamics research group at MIT found that we can use them to tell if we are likely

75 to get diabetes [34], or whether we are the sort of person who will pay back loans [36]. By
 76 analyzing these patterns across many people, we are discovering that we can begin to explain
 77 many things — crashes, revolutions, bubbles — that previously appeared to be random acts of
 78 God [31]. For this reason, the magazine *Technology Review* named our development of reality
 79 mining as one of the ten technologies that will change the world [18].

80 2 The New Deal on Data

81 The digital breadcrumbs we leave behind provide clues about who we are, what we do and what
 82 we want. This makes personal data — data about individuals — immensely valuable, both for
 83 public good and for private companies. As European Consumer Commissioner, Meglena Kuneva
 84 said recently, “Personal data is the new oil of the Internet and the new currency of the digital
 85 world” [24]. This new ability to see the details of every interaction can be used for good or for
 86 ill. Therefore, maintaining protection of personal privacy and freedom is critical to our future
 87 success as a society. We need to enable even more data sharing for the public good; at the same
 88 time, we need to do a much better job in protecting the privacy of the individuals.

89 A successful data-driven society must be able to guarantee that our data will not be abused;
 90 perhaps especially that government will not abuse the power conferred by access to such fine-
 91 grain data. The abuses may be directly targeted at users, for example by offering them higher
 92 insurance rates based on their shopping history [17], or create problems for the entire society in
 93 the long run, for example by limiting user choices and closing them into information bubbles [20].
 94 To achieve the positive possibilities of the new society, we require the *New Deal on Data*, workable
 95 guarantees that the data needed for public good are readily available while at the same time
 96 protecting the citizenry [33].

97 The key insight that motivates the idea of the New Deal on Data is that our data are worth
 98 more when shared, because these aggregated data — averaged, combined across population, and
 99 often distilled to high-level features — inform improvements in systems such as public health,
 100 transportation, and government. For instance, we have demonstrated that data about the way

101 we behave and where we go can be used to minimize the spread of infectious disease [27,34]. Our
102 research has reported how we were able to use these digital breadcrumbs to track the spread of
103 influenza from person to person on an individual level. And if we can see it, we can stop it.

104 Similarly, if we are worried about global warming, these shared, aggregated data can show us
105 how patterns of mobility relate to productivity [32]. In turn, this provides us with the ability to
106 design cities that are more productive and, at the same time, more energy efficient. But in order
107 to obtain these results and make a greener world, we need to be able to see the people moving
108 around; this depends on many people willing to contribute their data, even if only anonymously
109 and in aggregate.

110 To enable sharing of personal data and experiences, we need secure technology and regulation
111 that allow individuals to safely and conveniently share personal information with each other,
112 with corporations, and with government. Consequently, the heart of the New Deal on Data
113 must be to provide both regulatory standards and financial incentives that entice owners to
114 share data, while at the same time serving the interests of both individuals and society at large.
115 We must promote greater idea flow among individuals, not just corporations or government
116 departments.

117 Unfortunately, today most personal data are siloed off in private companies and therefore
118 largely unavailable. Private organizations collect the vast majority of the personal data in the
119 form of mobility patterns, financial transactions, phone and Internet communications. These
120 data must not remain the exclusive domain of private companies, because then they are less
121 likely to contribute to the common good. Thus these private organizations must be the key
122 players in the New Deal on Data framework for privacy and data control. Likewise, these data
123 should not become the exclusive domain of the government, as this will not serve the public
124 interest of transparency; we should be suspicious of trusting the government with such power.
125 The entities who should be empowered to share and make decisions about their data, are the
126 people themselves: users, participants, citizens.

127 Through the years, the great goal of human societies was to find the efficient ways of gov-

ernance. The Big Data transformation can contribute to this ultimate goal of providing the society with tools to analyze and understand what needs to be done, and to reach the consensus on how to do it. This goes beyond simple creation of more communication platforms; the assumption that more interactions between users will result in better decisions being made, may be very misleading. Although in the recent years we have seen some great examples of using social networks for better organization in society, for example during political protests [6,19], we are not even close to the point where we can start reaching consensus about the big problems: epidemics, climate change, pollution. We can improve the discussions by making them data driven, involving both experts and wisdom of the crowds – users themselves interested in improving the society. The problems we are dealing with as a now global society are more difficult than ever. We are responsible for many of them, and being able to tackle them on a global scale is necessary for our survival as a people.

3 Personal Data: Emergence of a New Asset Class

It has long been recognized that the first step to promoting liquidity in land and commodity markets is to guarantee ownership rights so that people can safely buy and sell. Similarly, the first step toward creating more new ideas and greater flow ideas (idea liquidity) is to define ownership rights. The only politically viable course is to give individual citizens key rights over data that are about them and in fact, these types of rights have undergirded the European Union’s Privacy Directive since 1995 [13].

We need to recognize personal data as a valuable asset of the individual that is given to companies and government in return for services.

The simplest approach to defining what it means to own your own data is to draw an analogy with the English common law on ownership rights of possession, use, and disposal:

- You have the right to possess data about you. Regardless of what entity collects the data, the data belong to you, and you can access your data at any time. Data collectors thus

153 play a role akin to a bank, managing the data on behalf of their customers.

154 • You have the right to full control over the use of your data. The terms of use must be opt-
 155 in and clearly explained in plain language. If you are not happy with the way a company
 156 uses your data, you can remove the data, just as you would close your account with a bank
 157 that is not providing satisfactory service.

158 • You have the right to dispose of or distribute your data. You have the option to have data
 159 about you destroyed or redeployed elsewhere.

160 Individual rights to personal data must be balanced with the need of corporations and govern-
 161 ments to use certain data-account activity, billing information, and so on-to run their day-to-day
 162 operations. This New Deal on Data therefore gives individuals the right to possess, control, and
 163 dispose of copies of these required operational data, along with copies of the incidental data
 164 collected about you such as location and similar context.

165 Note that these ownership rights are not exactly the same as literal ownership under modern
 166 law, but the practical effect is that disputes are resolved in a different, simpler manner than
 167 would be the case for land ownership disputes, for example.

168 In 2007, one author (Pentland) first proposed the New Deal on Data to the World Economic
 169 Forum [45]. Since then, this idea has run through various discussions and eventually helped
 170 shape the 2012 Consumer Data Bill of Rights in the United States, along with a matching
 171 declaration on Personal Data Rights in the EU. These new regulations hope to accomplish the
 172 combined trick of breaking data out of the current silos, thus enabling the public good, while
 173 at the same time giving individuals greater control over data about them. But, of course this is
 174 still a work in progress and the battle for individual control of personal data rages onward.

175 The World Economic Forum (WEF) has dubbed personal data as the “New Oil” or resource
 176 of the 21st century [45]. The discovery of oil and the subsequent development of the oil industry
 177 over the past 100 years has spurred not only the development of the automobile industry but also
 178 the creation of the global transportation infrastructure, including the massive freeway networks

179 that we see today in the developed nations. The “personal data sector” of the economy today is
 180 still in its infancy, its state akin to the oil industry at the late 1890s prior to the development of
 181 the Model-T Ford automobile. The productive collaboration between the Government (building
 182 the state owned freeways), the private sector (mining and refining oil, building automobiles),
 183 and the citizen (the user-base of these services) allowed the developed nations to expand their
 184 economies by creating new markets adjacent to the automobile and oil industries.

185 If personal data, as the new oil, is to reach its global economic potential, there needs to be
 186 a productive collaboration between all the stakeholders in the establishment of a *personal data*
 187 *ecosystem*. As mentioned in [45], a number of fundamental questions about privacy, property,
 188 global governance, human rights — essentially around who should benefit from the products
 189 and services built upon personal data — are major uncertainties shaping the opportunity. The
 190 rapid rate of technological change and commercialization in using personal data is undermining
 191 end user confidence and trust.

192 The current personal data ecosystem is fragmented and inefficient. Too much leverage is
 193 currently being accorded to service providers that enroll and register end-users. These siloed
 194 repositories of personal data exemplify the fragmentation of the ecosystem. These repositories
 195 contain data of varying qualities. Some are attributes of persons that are unverified, while
 196 other represent higher quality data that have been cross-correlated with other data points of the
 197 end-user.

198 For many participants, the risks and liabilities exceed the economic returns. Besides not
 199 having the infrastructure and tools to manage personal data, many end-users simply do not see
 200 the benefit of fully participating in the ecosystem. The current focus of many Internet-based
 201 service providers is to capture as much personal data from the end-user and to sell this data
 202 into the advertising industry. Personal privacy concerns are thus inadequately addressed at
 203 best, or simply overlooked in the majority of cases. The current technologies and laws fall short
 204 of providing the legal and technical infrastructure needed to support a well-functioning digital
 205 economy.

206 Recently, we have shown how challenging, but also feasible, it is to open such institu-
 207 tional Big Data. In the Data For Development (D4D) Challenge <http://www.d4d.orange.com>,
 208 the telecommunication operator Orange opened access to a large dataset of call detail records
 209 (CDRs) from the Ivory Coast. Working with the data as part of a challenge, teams of researchers
 210 came up with life-changing insights for the country. For example, one team developed a model
 211 for how disease spread in the country and demonstrated that information campaigns based on
 212 one-to-one phone conversations among members of social groups can be an effective counter-
 213 measure [26]. In releasing and analyzing this data, the privacy of the people who generated
 214 the data was protected not only by technical means, such as removal of Personally Identifiable
 215 Information (PIIs), but also by legal means, with the researchers signing an agreement they will
 216 not use the data for re-identification or other nefarious purposes. As we have seen in several
 217 cases, such as the Netflix Prize privacy disaster [30] and other similar privacy breaches [39],
 218 true anonymization is extremely hard. In the Unique in the Crowd [10], de Montjoye et al.
 219 showed that even though human beings are highly predictable [37], we are also very unique.
 220 Having access to one dataset may be enough to uniquely fingerprint someone based on just a
 221 few datapoints, and use this fingerprint to discover their true identity.

222 The report of the World Economic Forum [45] also suggest a way forward by recommending
 223 a number of areas where efforts could be directed:

- 224 • Alignment of key stakeholders: Citizens, the private sector and the public sector need to
 225 work in support of one another. Efforts such as NSTIC [40] — albeit still in its infancy —
 226 represent a promising direction for a global collaboration.
- 227 • Viewing “data as money”: There needs to be a new change in mindset where an individual’s
 228 personal data items are viewed and treated in the same way as their money. These personal
 229 data items would reside in an “account” (like a bank account) where it would be controlled,
 230 managed, exchanged and accounted for just like personal banking services operate today.
- 231 • End-user centricity: All entities in the ecosystem need to recognize that end-users are

232 vital and independent stakeholders in the co-creation and value exchange of services and
233 experiences. Efforts such as the *User Managed Access* (UMA) initiative [2] point in the
234 right direction by designing systems that are user-centric and managed by the user.

235 Opening data from the silos by publishing static datasets — collected at some point and
236 unchanging — is important, but it is only the first step. We can do even more substantial things
237 when the data is available in real time and can become part of a society’s nervous system.
238 Epidemics can be monitored and prevented in real time [34], underperforming students can be
239 helped, and people with health risks can be treated before they get sick [9].

240 4 Enforcing the New Deal on Data

241 How can we enforce this New Deal? The threat of legal action alone is important, but insufficient,
242 because if you cannot see abuses then you cannot prosecute them. Moreover, who wants more
243 lawsuits anyway? Enforcement can be addressed in significant ways without prosecution of public
244 statute or regulation at all. In many fields, companies and governments rely upon multi-party
245 frameworks of agreed upon rules governing common business, legal, and technical practices to
246 create effective self-organization and enforcement. These approaches hold promise as a method
247 for using institutional controls to form a reliable operational framework balancing the needs for
248 Big Data, privacy, and access.

249 One current best practice is a system of data sharing called trust networks. Trust networks
250 are a combination of networked computers and legal rules defining and governing expectations
251 regarding data. With respect to data belonging to individuals, these networks of technical and
252 legal rules keeps track of user permissions for each piece of personal data, and a legal contract
253 that specifies both what you can and cannot do with the data and what happens if there is a
254 violation of the permissions. For example, in such a system all personal data can have attached
255 labels specifying what the data can and cannot be used for. These labels are exactly matched
256 by the network’s system rules and terms in legal contracts between all the participants, stating

257 penalties for not obeying the permission labels. These rules can, and often do, reference or
258 require audits of relevant systems and data use, demonstrating how traditional internal controls
259 can be leveraged as part of the transition to more novel trust models.

260 Complete tracking and regulation of every aspect of a trust network is not the goal or
261 even desirable in order to achieve effective enforcement. Rather, the rules for a trust network
262 align enforcement with the highest priority issues and those upon which trust of participants is
263 premised. The relevant issues for a given trust network arise from that systems underlying trust
264 models and the contextual scenarios within which the networked data and the relationships of
265 parties occur.

266 When a trust network involves use of personal data, then the user permissions and corre-
267 sponding limits on use are fundamental to the trust model. In this context, the permissions,
268 including the provenance of the data, should require appropriate levels of audit. A well designed
269 trust network, elegantly integrating computer and legal rules, allows automatic auditing of data
270 use and allows individuals to change their permissions and withdraw data.

271 Having system rules applicable to the networks, applications, and data as well as all the ser-
272 vices providers, other intermediaries, and the users themselves is the mechanism for establishing
273 and operating a trust network. System rules are sometimes called operating regulations in the
274 credit card context or known as trust frameworks in the identity federations context or trading
275 partner agreements in a supply value chain context. There are many general examples of multi-
276 party shared architectural and contractual rules that share the generic characteristic of creating
277 binding obligations and enforceable expectations on all participants in scalable networks. An-
278 other common characteristic of the system rules design pattern is that the participants in the
279 network can be widely distributed across very heterogeneous business ownership boundaries,
280 legal governance structures, and technical security domains. Yet, the parties need not agree
281 to conform to all or most aspects of their basic roles, relationships, and activities in order to
282 connect to systems of a trust network. Cross-domain trusted systems must, by their nature,
283 focus mandatory and enforceable rules narrowly upon the critical items that must be commonly

284 agreed in order for that network to achieve its purpose.

285 For example, institutions participating in credit card and automated clearing house debit
286 transactional networks are subject to profoundly different sets of regulations, business practices,
287 economic conditions, and social expectations. The network rules focus upon the topmost agreed
288 items affecting interoperability, reciprocity, risk, and revenue allocation. The knowledge that
289 fundamental rules are subject to enforcement actions is one of the foundations of trust as well
290 as a motivation to prevent or address violations before they trigger penalties. A clear example
291 of this approach can be found with the Visa Operating Rules, covering a vast global real-time
292 network of parties that agree to rules governing their roles in the system as merchants, banks,
293 transaction processors, individual or business card holders, and other key system roles.

294 A system like this has made the interbank money transfer system among the safest systems
295 in the world and the daily backbone for exchanges of trillions of dollars, but until recently such
296 systems were only for the ‘big guys’. To give individuals a similarly safe method of managing
297 personal data, the Human Dynamics research group at MIT, in partnership with the Insti-
298 tute for Data Driven Design, co-founded by John Clippinger and one author (Pentland), have
299 helped build open Personal Data Store (openPDS) [11]. See <http://openPDS.media.mit.edu>
300 for project information and <https://github.com/HumanDynamics/openPDS> for the open source
301 code.

302 The openPDS is a consumer version of a personal cloud trust network that we are now
303 testing with a variety of industry and government partners. Soon, sharing your personal data
304 could become as safe and secure as transferring money between banks.

305 The Human Dynamics Lab has applied the system rules approach to development of in-
306 tegrated business, technical architecture, and rules large scale institutional use of personal
307 data stores, available as an example under MIT’s creative commons license by MIT, at [https:](https://github.com/HumanDynamics/SystemRules)
308 [//github.com/HumanDynamics/SystemRules](https://github.com/HumanDynamics/SystemRules).

309 The capacity to apply the appropriate methods of enforcement for a trust network depend
310 upon a clear understanding and agreement among parties about the purpose of the trusted

311 system and the respective roles or expectations of those connecting as participants. Therefore,
 312 an anchor is needed to a clear context of a Big Data operational framework and institutional
 313 controls appropriate for access and confidentiality or privacy. The following section posits the
 314 trust model and signature traits of such a context, through the lens of the New Deal on Data.

315 5 Transitioning End-User Assent Practices

316 The way users grant authorizations to their data is not a trivial matter. The flow of personal
 317 information, such as location data, purchases and health records can be very complex. Every
 318 tweet, geo-tagged picture, phone call, or purchase with credit card, provide the user's location
 319 not only to the primary service, but also to all the applications and services that have been
 320 authorized to access and reuse these data. The authorizations may come from the end-user
 321 or be granted by the collecting service, based on an umbrella terms of service, allowing the
 322 re-use of the data. Implementation of such flows was a crucial part of the Web 2.0 revolution,
 323 realized with RESTful APIs, mashups, and authorization-based access. The way the personal
 324 data travel between the services has however become arguably too complex for a user to handle
 325 and manage.

326 Increasing the amount of data controlled by the user and granularity of this control is mean-
 327 ingless if it cannot be exercised in an informed way. For many years, the End User License
 328 Agreements (EULAs), long incomprehensible texts have been accepted blindly by the user,
 329 trusting they have not agreed to anything that could harm them. The process of granting the
 330 authorizations cannot be too complex, as it would prevent the user from understanding her deci-
 331 sions. At the same time, it cannot be too simplistic, as it may not sufficiently convey the weight
 332 of the privacy-related decisions. It is a challenge in itself, to build the end-user assent systems
 333 that allow the user to understand and adjust their privacy settings. Complex EULAs do not
 334 promote the privacy of the users, effectively pushing them to press *I Agree* in every presented
 335 window.

336 This gap between the interface — single click — and the effect, can render the data owner-

337 ship meaningless; the click may wrench people and their data into systems and rules that are
 338 antithetical to fair information practices, such as is prevalent with today's end-user licenses in
 339 cloud services or applications. Managing the potentially long term and opposite dynamics fueled
 340 by old deal systems operating simultaneously with the new deal systems is an important design
 341 and migration challenge during the transition to a Big Data economy. During this transition
 342 and after the New Deal on Data is no longer new, personal data must continue to flow in order
 343 to be useful. Protecting the data of people outside of the user-controlled domain is very hard
 344 without a combination of cost effective and useful business practices, legal rules, and technical
 345 solutions.

346 We envision Living Informed Consent, where the user is entitled to know what data is being
 347 collected about her by which entities, empowered to understand the implications of data sharing,
 348 and finally put in charge of the sharing authorizations. We suggest the readers ask themselves a
 349 question: *Which services know which city I am in today?*. Google? Apple? Twitter? Amazon?
 350 Facebook? Flickr? This small application we have authorized a few years ago to access our
 351 Facebook check-ins and forgot since then? This is an example of a fundamental question related
 352 to user privacy and assent, and yet finding the answer to it may be surprisingly difficult in today's
 353 ecosystem. We can hope that most of the services treat the data responsibly and according to
 354 user authorizations. In the complex network of data flows however, it is relatively easy for the
 355 data to leak to careless or malicious services [7]. We need to build the solutions to help the user
 356 to make well informed decisions about data sharing.

357 6 Business, Legal, and Technical Dimensions of Big Data Sys- 358 tems

359 When it comes to data intended to be accessible over networks — whether big, personal, or
 360 otherwise — the traditional container of an institution makes less and less sense. Institutional
 361 controls apply, by definition by or to some type of institutional entity such as a business, gov-

ernmental, or religious organization. A combined view of the business, legal, and technical facts and circumstances surrounding Big Data is necessary to know what access, confidentiality, and other expectations exist. The relevant contextual aspects of Big Data of one institution is often profoundly different from that of another. As more and more organizations use and rely upon Big Data, a single formula for institutional controls will not work for increasingly heterogeneous business, legal, and technical environments in play.

Looking at an institution as a business, legal, and technical ‘system’ is one effective approach for dealing with the inherent complexity of managing heterogeneous and distributed networks of actors and interactions. The business models, interface-point operational practices and relevant assumptions must be consistent and frequently carefully agreed upon at an executive level by and with institutions as part of the value exchange involving data and access to high value, mission critical or sensitive systems and services. The applicable legal frameworks, common assumptions regarding likely allocation of liability and resolution of disputes in the event of losses, and expected types of contracting practices need to reflect and support the business goals and purposes for the system and data. When technical standards are selected, configured and applied to systems they too must support and reflect the business and legal dimensions and be supported and reflected by those dimensions.

Defining as a ‘system’ the thing to which institutional controls apply provides an achievable and measurable basis for balancing privacy, access and other interests in Big Data. Within a given institution, there may in fact be many different discernable organizations and corresponding systems. Meanwhile the system of one institution frequently exists across many different external institutions. The application of Big Data institutional controls can be applied across the board to a unit of a given institution or targeted by agreement to certain types of data or particular transactions spanning many institutions. Once a systems view is adopted, there is a tractable starting point to narrow or broaden the scope of view, to focus on material dimensions of a system and therefore enable more effective use and control of Big Data.

Many organizations are structured with clear leadership on business, legal, and technical

issues functionally assigned to top level executive roles. Business issues are typically allocated to roles such as CEO, COO, or CFO, while leadership on legal issues is commonly assigned to roles like general counsel and regulatory compliance and technical leads are often the roles of CIO, CTO, or CSO. Having top level leadership for each of the business, legal, and technical aspects of a trust network is a critical success factor.

7 Big Data and Personal Data Institutional Controls

The phrase “institutional controls” refers to safeguards and protections by use of legal, policy, governance, and other non-strictly technical, engineering, or mechanical measures. The phrase institutional controls in a Big Data context can perhaps best be understood by examining how the concept has been applied to other domains. The most prevalent use of institutional controls has been in the field of environmental regulatory frameworks.

A good example of how this concept supports and reflects the goals and objectives of environmental regulation can be found in the policy documents of the Environmental Protection Agency (EPA). This following definition is instructive, and is part of the Institutional Control Glossary of Terms [42]:

Institutional Controls - Non-engineering measures intended to affect human activities in such a way as to prevent or reduce exposure to hazardous substances. They are almost always used in conjunction with, or as a supplement to, other measures such as waste treatment or containment. There are four categories of institutional controls: governmental controls; proprietary controls; enforcement tools; and informational devices.

Going deeper, the article by DeMeo and Doar [12] defines institutional controls thusly:

Institutional controls are administrative and legal controls that help minimize the potential for human exposure to contamination and/or protect the integrity of the physical remedy. They can include recorded restrictive covenants, but land use laws

414 *and regulations, deed restrictions, department consent orders, and conservation ease-*
 415 *ments are all institutional controls.*

416 In domains of information technology, this approach is most commonly reflected as “enter-
 417 prise controls” related to security. See, for example, the Juniper Networks enterprise security
 418 report [23] stating: “Enterprise mobility technologies, especially those designed to retrofit en-
 419 terprise controls on top of consumer mobile devices, are rapidly evolving. This was a message
 420 we heard loud and clear in the study.” This study and analysis also reveals much about the
 421 internal controls needed to accommodate mobile device use by employees. In both capacities as
 422 employee, consumer, and other roles, the use of mobile devices triggers myriad legal, policy, and
 423 other implications for institutional controls.

424 In the legal domain, this concept frequently emerges under the moniker “regulatory compli-
 425 ance” or “legal compliance” anchored in legal and regulatory frameworks such as Health Insur-
 426 ance Portability and Accountability Act (HIPAA) and Sarbanes-Oxley (SOX). These statutory
 427 legal frameworks require covered organizations to establish integrated sets of governance, legal,
 428 transactional, security, and other internal controls to avoid violating the rules. The institutional
 429 controls are accomplished in tight integration with engineering and other measures in order
 430 to ensure compliance and to control legal and security risk. The use of institutional controls
 431 of this type are fundamental methods for achieving and maintaining the transition to a dig-
 432 ital, networked, and Big Data footing for any private company, government agency, or other
 433 organization.

434 Consider again the analogy of institutional controls in the context of environmental law, and
 435 how these types of measures can be applied in the Big Data, privacy, and access context to
 436 digital environments. Given the relatively mature and stable state of environmental regulation,
 437 there is much to be learned by examining this context of institutional controls. Environmental
 438 regulatory compliance with waste management cleanup requirements could include institutional
 439 controls restricting land use on adjacent property. In these situations, it is possible that the
 440 remediation strategy requires significant use of land outside the property boundaries of the

441 cleanup site. In these cases, the regulators and the land owner responsible for the regulated
 442 property must find ways to ensure a common approach among multiple owners and across
 443 multiple property environments. Clauses on the relevant deeds, an enforceable consent order,
 444 or targeted regulations and zoning rules are examples of more severe institutional controls that
 445 can be employed to ensure consistent and effective actions are taken across ownership and real
 446 property boundaries.

447 See, for example, Florida Department of Environmental Protection (FDEP), Division of
 448 Waste Management [16] which states that “...RMO III does contemplate contamination beyond
 449 the Property boundaries, which would require agreement by the adjacent owners to put an RC
 450 on their properties as well.”

451 The concept of an “institutional control boundary” is especially clarifying and powerful when
 452 applied to the networked and digital boundaries of an institution. In the context of Florida’s
 453 environmental regulation frameworks, the phrase is applied to describe the various types of
 454 combinations risk management levels related to target cleanup standards and extend beyond
 455 the area of a physical property boundary. Also see a recent University of Florida report on
 456 Development of Cleanup Target Levels (CTLs) [8] stating “Risk Management Options Level
 457 III, like Level II, allows concentrations above the default groundwater CTLs to remain on site.
 458 However, in some rare situations, the institutional control boundary at which default CTLs must
 459 be met can extend beyond the site property boundary.”

460 The EPA provides considerable information on the nature and use of institutional controls,
 461 including situations when the situational scope extends to adjacent properties owned by third
 462 parties. See, generally, *EPA Hazardous Waste Corrective Action Guidance on Institutional Con-*
 463 *trols* [42]. Also see: *Institutional Controls Bibliography: Institutional Control, Remedy Selection,*
 464 *and Post-Construction Completion Guidance and Policy, December 2005* [41].

465 When institutional controls would apply to “separately owned neighboring properties” a
 466 number of issues arise that are very relevant to the problems associated with managing personal
 467 and big data across legal, business and other systemic boundaries. Requiring the party respon-

sible for site cleanup to use “best efforts” to attain agreement by third parties to institute the relevant institutional controls is perhaps the most direct and least prescriptive approach. When direct negotiated agreement is not successful, then use of third party neutrals to resolve disagreements regarding institutional controls can be required. If necessary, environmental regulation can force an acquisition of neighboring land by compelling the party responsible to purchase the other property or by purchase of the property directly by the EPA [43].

In the context of Big Data, privacy, and access, institutional controls are seldom, if ever, the result of government regulatory frameworks such as are seen in the environmental waste management oversight by the EPA. Rather, institutions applying measures constituting institutional controls in the Big Data and related information technology and enterprise architecture contexts will typically employ governance safeguards, business practices, legal contracts, technical security, reporting, and audit programs and various risk management measures.

Inevitably, institutional controls for Big Data will have to operate effectively across institutional boundaries, just as environmental waste management internal controls must sometimes be applied across real property boundaries and may subject multiple different owners to enforcement actions corresponding to the applicable controls. Short of government regulation, the use of system rules as a general model are one widely understood, accepted, and efficient method for defining, agreeing, and enforcing institutional and other controls across business, legal, and technical domains of ownership, governance, and operation.

The use of system rules and integrated participation agreements by developers and end-users is a way to ensure intended operational frameworks conform to applicable institutional controls. The example of Living Informed Consent described in this chapter, demonstrates how institutional controls comprised of legal and definite workflow measures, in concert with technical methods, can result in a higher level of performance, while appropriately balancing legitimate interests of various parties regarding use and access to personal data.

Following the World Economic Forum recommendations of treating personal data stores in the manner of bank accounts [45], there are a number of infrastructure improvements that need to

495 be realized, if the personal data ecosystem is to flourish and deliver new economic opportunities.
 496 We believe the following infrastructure improvements are necessary for the coming personal data
 497 ecosystem:

- 498 • *New global data provenance network:* In order for personal data to be treated like bank
 499 accounts, the origin information regarding data items coming into the data store must be
 500 maintained [22]. In other words, the provenance of all data items must be accounted for
 501 by the IT infrastructure upon which the personal data store operates. The heterogeneous
 502 provenance databases must then be interconnected in order to provide a resilient and
 503 scalable platform for audit and accounting systems to track and reconcile the movement
 504 of personal data from the respective data stores.
- 505 • *Trust network for computational law:* In order for trust to be established between parties
 506 who wish to exchange personal data, we foresee that some degree of “computational law”
 507 technologies may have to be integrated into the design of personal data systems. Such
 508 technologies should not only verify terms of contracts (e.g. terms of data use) against user-
 509 defined policies but also have mechanisms built-in to ensure non-repudiation of entities who
 510 have accepted these digital contracts. Efforts such as [1,2] are beginning to bring better
 511 evidentiary proof and enforceability of contracts into the technical protocol flows.
- 512 • *Development of institutional controls for digital institutions:* Currently there are a number
 513 of proposals for the creation of virtual currencies (e.g. BitCoin [5], Ven [38]) in which the
 514 systems have the potential to evolve into self-governing “digital institutions” [21]. Such
 515 systems and institutions that operate on them will necessitate the development of a new
 516 paradigm to understand the aspects of institutional control within their context.

517 8 Scenarios of Use in Context

518 Development of frameworks for Big Data that effectively balance economic, legal, security, and
 519 other interests requires an understanding of the relevant context and applicable scenarios within

520 which the Big Data exists. Although Big Data straddles multiple business, legal, and technical
521 boundaries it will nonetheless have one or more institutions that are capable of, or in some
522 situations required to, manage and control it. The public good referred to in the title of this
523 book can be articulated through the use of system, service and software modeling, requirements
524 setting, development, testing, and certification processes. Discrete use cases of actors and actions
525 is one approach to model business, legal and technical requirements in a way that can objectively
526 be agreed in advance and traceably be tested against implemented systems and components.
527 However, user cases are typically atomic or very low level of granularity and operate deep within
528 layers of assumed context. Higher level contexts and corresponding scenarios of multiple use
529 cases can describe fundamental expectations about matters like interests in property, rights to
530 liberty and honoring the social compact.

531 Institutional controls and other system requirements or safeguards are important methods
532 to ensure context-appropriate outcomes consistent with clearly applicable system scenarios that
533 set the contours and underpinnings for a greater public good. The New Deal on Data can
534 be achieved in part by sets of institutional controls involving governance, business, legal, and
535 technical aspects of Big Data and interoperating systems. The following scenarios demonstrate
536 signature features of the New Deal on Data in various contexts and serve as an anchor to evaluate
537 what institutional controls are well aligned.

538 The basic common law inspired ownership tenants of the New Deal on Data are general
539 principles that guide and inform basic relationships and expectations. However, the dynamic
540 bundle of recombinant rights and responsibilities constituting “ownership” interests in personal
541 data and expectations pertaining to Big Data vary significantly from context to context and
542 even from one scenario to another within a given general context. The applicable scenario
543 within which the data exists can provide a method and mechanisms of sorts to establish the
544 basic ownership, control, and other expectations of the key parties. For example, it may not
545 be sufficient to describe the exchange of money and financial information because the nature of
546 the transaction and their respective data and systems are not identified enough to predict the

rights and obligations or other outcomes reasonably expected by individuals and organizations that engage in the activity of a financial exchange. The sale of used cars via an app, the conduct of a counseling session via Google Hangout, and the earning of a Master's degree via an online university all represent scenarios wherein the use case of a financial exchange takes place. However, each of these scenarios occurs in contexts that are easily identifiable, involving the sale of goods and deeper access to financial information if the car is financed or involving the practice of therapy by a licensed professional involving confidential mental health data or involving elearning services and protected educational records and possibly deeper financial information if the program is funded by scholarship or loans. Identifying the people (a consumer and a used car dealer) the transaction (purchase of a used car) the data (sales and title data, finance information, etc.) and the systems (the third party app and its relevant services or functions, state DMV services, credit card and bank services, etc.) provide enough context to establish generally what existing consumer rights under the relevant state lemon laws, the Uniform Commercial Code and other applicable rules will govern when duties arise or are terminated, what must be promised, what can be repudiated, by whom data must be kept secure and other requirements or constraints on the use of personal data and Big Data. These and other factors vary when a transaction that is otherwise identical seeming operates within different scenarios, and even scenarios will differ depending upon which contexts apply.

Which scenarios are relevant and what lower level use cases apply are knowable in detail only with reference to the relevant context of a factually based situation. Relevant scenario of use are comprised of people conducting transactions through systems in which personal data and Big Data exists or flows. It is possible to test whether frameworks for engagement successfully address Big Data, privacy and the public good by testing outcomes of relevant scenarios. Scenarios are capable of adequately defining these high level goals and objectives when they identify each of the following four elements:

1. Who are the people in the scenario (e.g. who are the parties involved and what are their respective roles and relationships)?

- 574 2. What are the relevant interactions (e.g. what transactions or other actions are conducted
575 by or with the people involved)?
- 576 3. What are the relevant data and data sets (e.g. what types of data are created, stored,
577 computed, transmitted, modified or deleted)?
- 578 4. What are the relevant systems (e.g. what services or other software is used by the people,
579 for the transactions or with the data)?

580 Retail marketing is a common context within which personal data is important. Personal
581 data is critical to many different scenarios in the context of retail marketing. Consider the
582 scenario whereby a merchant conducts an online promotion for an app or service by using a
583 purchased direct marketing database of consumers who have expressed interest in similar prod-
584 ucts. Data such as the names, email addresses, phone numbers, and other personal information
585 can be used to lower costs and increase revenue by better targeting promotional messages and
586 increasing sales. However, there are risks to the merchant and consumer alike, including the
587 potential of a data breach and resulting identity theft and fraud. There is also risk that some
588 consumers will feel annoyed or violated when their personal information is used in this man-
589 ner without their prior knowledge or consent. The information available from such third party
590 marketing lists and databases may be out of date and lead to the waste of marketing dollars and
591 the failure to inform potentially interested consumers of a product they might have purchased if
592 the solicitation had gone to their current email or appropriate network. Imagine that the same
593 consumers had individual personal data stores and were able to “intent-cast” their interest in
594 the product. This can be done without revealing all the other personal data of that person. The
595 openPDS system could be configured to provide permission based answers to questions such as
596 whether the consumer is over the age of 18 or lives in a city, suburb or rural area. Sectors such
597 as real estate could be transformed by such intent-casting by qualified buyers.

598 Another common context involving personal data is governmental transactions with the
599 public. Government filings, registrations, permits, and other such public sector transactions with

the individuals or organizations create a large volume and variety of personal data flow. Consider the scenario whereby a person runs a small business and must comply with tax, employee related, licensing, and other rules by filing forms with multiple government agencies at the federal, state, and local levels. Individuals names, addresses, occupations, dates of birth, social security numbers, and many other types of personal information are common elements of such filings. Similarly to the retail marketing scenario above, the parties to government filing transactions also risk unauthorized access to the personal data by interception during transmission or by breach of data storage systems. In addition, the costs associated with requiring the same data by many different agencies and updating or correcting data are born by both the filer and the regulator. What if the people who own or operate such businesses had access to the services and functions of a personal data store for themselves individually and also for the corporate entity they operated? Routine changes in status, such as a change of address or name, could be accomplished in a secure manner once via their own data service and leveraged again and again by the many faces of government requiring that data. When the authoritative source of such information can be deemed to be housed within or logically connected to a person's data store, then the laborious task of address verification and tedious forms and other processes required by each government entity could be avoided. The saving of direct and indirect costs, the regaining of time spent by each agency and business and avoidance of delays and uncertainty are of significant value to all parties (See: <http://kansasbusinesscenter.com> and see the data files at <https://github.com/kansasbusinesscenter>)

The scenario below describes deeper fact-based situations and circumstances in the context of social science research and studies involving personal data and Big Data. Note how the roles of people, their interactions, the use of data and the design of the corresponding systems reflect and support the New Deal on Data in ways that deliberately provide immediate and increasing value to the stakeholders than is typical or expected typically.

625 8.1 Example Scenario: Research System for Computational Social Science

626 Computational Social Science (CSS) studies are based on data collected often with an extremely
 627 high resolution and scale [25]. Using computational power combined with mathematical models,
 628 such data can be used to provide insights into human nature. Much of the data collected, for
 629 example mobility traces are sensitive and private; most individuals would feel uncomfortable
 630 sharing them publicly. The need for solutions to ensure the privacy of the individuals has grown
 631 alongside the data collection efforts.

632 The data collection in the CSS context is based on the informed consent of the partici-
 633 pants. Countries have different bodies regulating such studies, for example Institutional Research
 634 Boards (IRBs) in the US. Although certain minimal requirements for implementing informed
 635 consent in these contexts exist [35], they are often not very well suited for the large-scale studies,
 636 where the amount and sensitivity of the data calls for sophisticated privacy controls. As the
 637 scale of the studies grows, in terms of the number of participants, collected bits per user, and
 638 duration, the EULA-style informed consent is no longer sufficient and makes it hard to claim
 639 that participants in fact expressed informed consent.

640 One author (Stopczynski) deployed this year a 1,000 phones study at Technical University
 641 of Denmark, freshmen students received mobile phones in order to study their networks and
 642 social behavior in the important change moment of their lives, when joining the university.
 643 The study, called SensibleDTU (<https://www.sensible.dtu.dk/?lang=en>), uses not only data
 644 collected from the mobile phones (location, Bluetooth-based proximity, call and sms logs etc.)
 645 but also data collected from social networks, questionnaires filled out by participants, behavior
 646 in economic games and so on. As the data is collected in the context of the university, there is
 647 potentially a big issue of students feeling obliged to participate in the study, feeling that their
 648 grades may depend on it, or that the data may influence their grades. In this context, we see the
 649 implementation of Living Informed Consent not only as a technical mean to put participants in
 650 control of the data we collect, but also to clearly and comprehensibly convey broader New Deal
 651 on Data principles such as the opt-in nature of the study, the boundaries of the data usage, and

652 parties accessing the data.

653 It is not feasible to explain the terms and answer all the questions to all 1,000 students
654 personally. The controls must be self-explanatory as much as possible, and guide the user from
655 the first opening of the link to the study to the grant of the authorizations. At the same time,
656 every click made by the user should be an expression of an informed decision, so the user journey
657 must be a balance of guidance and understanding. For this reason we have created a set of web
658 applications, allowing the users to enroll into the study, express informed consent, and interact
659 with their data.

660 As the study will last for several years, hopefully allowing us to see the life of a student from
661 the very first friendships made until the graduation party, the consent must remain alive. It is
662 again a matter of balance: we do not want the participants to feel under constant surveillance
663 (as they are not, the data is used mostly in aggregated form), at the same time to remember that
664 in fact, the data is being collected and used. We are still trying to understand how to achieve
665 this equilibrium: how often should we remind the users about the collection effort? Should they
666 re-authorize applications from time to time? We see a great hope in the applications we create
667 for the users to provide certain services, simple such as life-logging where they can see how
668 active they are, what are their top places etc. and more advanced, such as artistic visualizations
669 of their social networks. Making the user aware of the data by transforming them into value,
670 can greatly benefit the privacy, making users constantly aware what is being collected, but also
671 what kind of value they can get out of it.

672 When a study of such scale is deployed, the particular experiments and sub-studies may
673 not be exactly defined from the very beginning. The initial deployment is a creation of a
674 testbed, where shorter or longer experiments can take place; for example part of the population
675 may participate in the experiment of quantifying the impact of feedback application on their
676 activity levels. Being able to create such experiments in an efficient way is a huge value for the
677 researchers. To do that in the most frictionless way, we give the users the choice to opt-in to
678 those additional experiments, providing some financial or other benefits. This is only possible

679 if there is a notion of identity of the participants, stronger and more useful than a piece of
680 paper with a signature. This identity allows us to reach out to people, offer them additional
681 experiments, and let them agree or disagree to them.

682 This touches upon the re-usability of data, as the new experiments may require additional
683 data to be collected, but also have access to all the existing data, based on user authorization.
684 We can imagine going even further, where entirely different studies can reuse participants data
685 from a previous study based on their authorization. When the data are owned by the users, they
686 are free to authorize access to them to any party that requests it. We can see a New Deal on Data
687 pattern here: rather than services (studies) talking to each other about the user data, they talk
688 directly to the users, seeking their authorization. This can address a very important problem
689 in the research context, the data re-use in a privacy-aware manner. Rather than publishing
690 a static dataset, where the users have lost control over their data, live and fresh data can be
691 continuously accessed by any study that the user agrees to be a part of.

692 Many studies will be willing to offer money or other value for the access to the data. Other
693 will provide the user the opportunity to have new data collected. This way, the data collection
694 becomes an opportunity for the user to enrich their personal dataset, and to benefit from it
695 in the future. Join our study and we will provide you with a smartphone and collect your
696 movement patterns for a year; we will do science and you will gain new data that can get you
697 better value or deals in different services. You may now be eligible for a different study. Or your
698 music recommendation may get better, because your music service can make a use of this extra
699 data. Your data.

700 8.2 Scenarios of Use Today, Tomorrow and the Day After

701 The New Deal on Data is designed to provide good value to all stakeholders creating, using or
702 benefiting from personal data, but the entire vision need not be adopted before value starts to
703 flow. The social science research study scenario (below) demonstrates how researchers and study
704 participants alike derive value from New Deal on Data principles today. As more researchers

705 and students use the types of systems described above, the value is predicted to increase based
706 upon a network effect. The same dynamic is expected in other contexts as well.

707 Adopting New Deal on Data principles on a large scale can be accomplished iteratively, such
708 one economic sector, transaction type or data type at a time. A reasonable success metric for
709 adoption of large scale visions such as the New Deal on Data is whether change management
710 has been designed to achieve enough value at every phase for every key stakeholder group to
711 make the change worth the effort. Value to all parties participating in the New Deal on Data
712 increases as direct or indirect use and re-use of personal data is available in greater volumes and
713 varieties. Such volume and variety of personal data increases as more parties and transaction
714 types and data sets and systems adopt and interoperate within the New Deal on Data.

715 By staging and phasing adoption of the New Deal on Data typical objections to change based
716 on grounds of cost, disruption or over regulation can be addressed. Policy incentives can further
717 address these objections, such as allowing safe harbor protections for conduct of organizations
718 operating under the rules of a trust network. Policy makers can resolve other difficulties by
719 combinations of strategic transition management methods like allowing safe harbor compliance
720 delays, or approving alternative adoption paths and granting other non-substantive waivers to
721 ease any burdens of migrating to new business methods.

722 Developing relevant context and scenarios defines a clear anchor for measuring whether a
723 given use of Big Data and personal data is consistent with measurable criteria. Such criteria
724 can be used to establish compliance with the rules of a Trust Network and for certification by
725 government for the right to safe harbor or other protections. Criteria applicable to business,
726 legal and technical aspects of a system or set of systems can be assessed, evaluated and trace-
727 ably proven. Such criteria can provide a basic lowest common denominator requirements and
728 constraints for work flow, transaction flow, data flow and service flow within the relevant con-
729 texts and scenarios of use. The New Deal on Data provides a clear basis routed in common law
730 and broad understandings of the social compact. Therefore, with the New Deal on Data the
731 appropriate bundle of rights and expectations intended to cover privacy and other personal data

732 interests in Big Data can be explicitly enumerated, debated and eventually agreed in ways that
733 fit relevant contexts.

734 9 Future Research

735 Our traditional methods of testing and improving government, organizations, and so on are
736 of limited use in building a data-driven society. With Big Data, there are so many potential
737 connections that our standard statistical tools generate less than useful results.

738 The reason is that with such rich data, you can easily uncover misleading or unactionable
739 correlations. For instance, let us imagine we discover that people who are unusually active are
740 more likely to get the flu. This is a real example: when we examined the minute-by-minute
741 behavior of a small university community - a real-time flow of gigabytes per day for an entire
742 year - we noticed that an unusual level of running around often predicted onset of the flu [27].
743 But if we can only analyze the data using traditional statistical methods, we have the problem
744 of discerning why this is true. Is it because the flu virus makes us more active in order to spread
745 itself more quickly? While it is more likely that interacting with many more people than usual
746 makes you more likely to catch the flu, you can't be sure that this is the true cause based on
747 the real-time stream of data alone.

748 Normal analysis methods do not suffice to answer these types questions, because we do not
749 know all the possible alternatives, and so we cannot form a limited, testable number of clear
750 hypotheses. Instead, we need to devise new ways to test the causality of connections in the real
751 world. We can no longer rely on laboratory experiments; we need to do the experiments in the
752 real world, typically on massive, real-time streams of data.

753 9.1 Research on Design and Deployment of Big Data Systems

754 In order to achieve low risk, high value outcomes efficiently, design and deployment of the coming
755 global wave of Big Data systems should apply relevant research, such as that identified in this
756 chapter and the book generally. To understand and address the unique problems and prospects

757 associated with big personal data, the relevant context must be identified and corresponding
758 rules-driven capabilities must be designed into the underlying systems.

759 Any system that can make, use, receive, or share Big Data must be capable of associat-
760 ing provenance and purpose for all data in a common and actionable manner. Requiring a
761 unstructured volumes of narrative documentation and background about the nuances and cir-
762 cumstances surrounding every data set is both impractical and counterproductive. By contrast,
763 a small amount of metadata listing or reliably linking the parties, transactions, systems and
764 provenance of the data would suffice. This relevant context together with the data forms the
765 basis for accountable analysis on big personal data. People or systems can determine the appro-
766 priate rules to apply to data when the relevant information is reliably attached to or logically
767 associated with that data in a standard manner

768 It is important for science and research to develop further solutions and options ensuring
769 contextually appropriate rules can be applied by Big Data systems. For rules to be effectively
770 applied, systems must not only be able to establish which rules apply but also support the right
771 functional capabilities and have appropriate information structure, format, and meta-data.

772 Some capabilities will likely be essential to all Big Data systems, such as highly scalable
773 active storage, standard methods for integration with other Big Data systems, and a processing
774 architecture enabling high speed statistical analytics. But there are and will continue to emerge
775 multiple types of Big Data systems. Some functions or controls will likely be important —
776 or even feasible — only for certain types of future systems. For instance, it is reasonable to
777 expect some systems will specialize in enormous volumes of entirely non-personal data from
778 many real-time sources (e.g. for soil science, materials engineering, astronomy) while other Big
779 Data systems will hinge upon mass quantities of highly sensitive personal information (e.g. for
780 clinical medicine, education and lifelong learning, social entertainment).

781 While some capabilities, such as ingesting and processing astronomical data-sets, will be
782 unique to only a subset of Big Data systems, it is reasonable to anticipate that data will be
783 increasingly cross-tabulated, merged, and otherwise shared with other systems and data. It can

784 be nearly impossible to conclusively predict for the entire life of a system what data will be
 785 received by, created in, or transmitted from that system at the design phase. This prediction is
 786 all the harder to make when the systems are intended for Big Data.

787 The four contextual facets of people, interactions, data and systems provide a sound under-
 788 pinning for the design of new Big Data and Web 2.0 systems. The existing systems design and
 789 development processes of establishing business cases, use cases, agile stories, functional require-
 790 ments, etc. do not reliably identify the factors most relevant to use of Big Data, especially in a
 791 Web 2.0 massively distributed environment. The four facets can also be used to analyze appro-
 792 priate, required or prohibited uses for existing Big Data systems. However, it can be difficult
 793 to extract the relevant information from or apply any effective control on systems used for Big
 794 Data but designed to achieve limited purposes in hierarchical closed environments.

795 Big Data, by its nature, represents a new set of business, legal, and technical capabilities and
 796 requirements. Most of the world's systems today are not capable of ingesting, storing, using, or
 797 dynamically flowing Big Data with other systems. Considering that a) Big Data is of high value
 798 immediately and higher value in the short and long terms, and b) the young but competitive
 799 marketplace of Big Data system components, platforms, applications, and other solutions is a
 800 hotbed of innovation it can be predicted that a transition to Big Data systems will continue.
 801 The key observation is that virtually all Big Data systems have yet to be designed, implemented,
 802 customized, or deployed. Institutions that are the current early adopters of today's Big Data
 803 system will soon replace those systems and the rest of the world will adopt Big Data systems in
 804 phases over time. Based upon this observation, it follows that design improvements made now
 805 or soon will have much greater impact than can be had after mass-scale adoption has occurred.

806 **9.2 Research on Big Data for Design of Institutions**

807 Using massive, live data to design institutions and policies is outside of our normal way of
 808 managing things. We live in an era that builds on centuries of science and engineering, and
 809 the standard choices for improving systems, governments, organizations, and so on are fairly

810 well understood. Therefore our scientific experiments normally need only consider a few clear
811 alternatives, ‘plausible hypotheses’.

812 With the coming of Big Data, we are going to be operating very much out of our old,
813 familiar ballpark. These data are often indirect and noisy, and so interpretation of the data
814 requires greater care than usual. Even more importantly, a great deal of the data is about
815 human behavior, and the questions are ones that seek to connect physical conditions to social
816 outcomes. Until we have a solid, well-proven, and quantitative theory of social physics, we will
817 not be able to formulate and test hypotheses in the way we can when we design bridges or
818 develop new drugs.

819 Therefore, we must move beyond the closed, laboratory-based question-and-answering pro-
820 cess that we currently use, and begin to manage our society in a new way. We must begin to test
821 connections in the real world far earlier and more frequently than we have ever had to do before,
822 using the methods the Human Dynamics research group have developed with our collaborators
823 for the Friends and Family [3] or the SensibleDTU (<https://www.sensible.dtu.dk>) study. We
824 need to construct Living Laboratories — communities willing to try a new way of doing things
825 or, to put it bluntly, to be guinea pigs — in order to test and prove our ideas. This is new
826 territory and so it is important for us to constantly try out new ideas in the real world in order
827 to see what works and what does not.

828 An example of such a Living Lab is the ‘open data city’ just launched by one author (Pent-
829 land) with the city of Trento in Italy, along with Telecom Italia, Telefonica, the research uni-
830 versity Fondazione Bruno Kessler, the Institute for Data Driven Design, and local companies.
831 Importantly, this Living Lab has the approval and informed consent of all its participants. Not
832 only do these participants consent to sharing of their data, they know that they are part of a
833 gigantic experiment whose goal is to invent a better way of living. This can be a model followed
834 by many types of systems within and beyond the social science research contexts. More detail
835 on this Living Lab can be found at <http://www.mobileterritoriallab.eu/>.

836 The goal of this Living Lab is to develop new ways of sharing data to promote greater civic

837 engagement and exploration. One specific goal is to build upon and test trust-network software
838 such as our openPDS system. Tools such as openPDS make it safe for individuals to share
839 personal data (e.g., health data, facts about your children) by controlling where your data go
840 and what is done with them.

841 The specific research questions we are exploring depend upon a set of “personal data ser-
842 vices” designed to enable users to collect, store, manage, disclose, share, and use data about
843 themselves. These data can be used for the personal self-empowerment of each member, or
844 (when aggregated) for the improvement of the community through data commons that enable
845 social network incentives. The ability to share data safely should enable better idea flow among
846 individuals, companies, and government, and we want to see if these tools can in fact increase
847 productivity and creative output at the scale of an entire city.

848 An example of an application enabled by the openPDS trust framework is sharing of best
849 practices among families with young children. How do other families spend their money? How
850 much do they get out and socialize? Which preschools or doctors do people stay with for the
851 longest time? Once the individual gives permission, our openPDS system allows such personal
852 data to be collected, anonymized, and shared with other young families safely and automatically.

853 The openPDS system lets the community of young families learn from each other without
854 the work of entering data by hand or the risk of sharing through current social media. While
855 the Trento experiment is still in its early days, the initial reaction from participating families is
856 that these sorts of data sharing capabilities are valuable, and they feel safe sharing their data
857 using the openPDS system.

858 The Trento Living Lab will let us investigate how to deal with the sensitivities of collecting
859 and using deeply personal data in real-world situations. In particular, the Lab will be used as a
860 pilot for the New Deal on Data and for new ways to give users control of the use of their personal
861 data. For example, we will explore different techniques and methodologies to protect the users
862 privacy while at the same time being able to use these personal data to generate a useful data
863 commons. We will also explore different user interfaces for privacy settings, for configuring the

864 data collected, for the data disclosed to applications and for those shared with other users, all
865 in the context of a trust framework.

866 10 Conclusions

867 Our societies today face unprecedented challenges. Solving these problems will require access
868 to personal data, so we can understand how the society works, how we move around, what
869 makes us productive, and how everything from ideas to diseases spread. The insights must be
870 actionable, available in real-time, and engaging the population, creating the nervous system of
871 the society. In this chapter we have reviewed how Big Data collected in institutional context
872 can be used for the public good. In many cases, the data needed for creating better society is
873 already collected and exists closed in silos of companies and governments. Using well designed
874 and implemented sets of institutional controls, covering business, legal, and technical dimensions,
875 we described how the silos can be opened. The framework for doing this — the New Deal on
876 Data — postulates that the primary driver of the change must be by recognizing ownership of
877 personal data rests with the people about whom that data is about. This ownership, the right
878 to use, transfer, and remove the data ensures that the data is available for public good, while
879 at the same time protecting the privacy of the citizens.

880 The New Deal on Data is still new. Here we described our efforts in understanding the
881 technical means of how it can be implemented, the legal framework around it, business rami-
882 fications, and the direct value that can be derived from researchers, companies, governments,
883 and users having more access to the data. It is clear that companies must play the major role
884 in the implementation of the New Deal, incentivized by business opportunities and pressured
885 by the legislation and demand of the users. Only with such orchestration will it be possible to
886 change the current feudal system of data ownership and finally put the immense quantities and
887 capabilities of collected personal data to good use.

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