

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 [14].

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 To ensure a sustainable future society, we must use our new technologies to create a *nervous*
 56 *system* maintaining the stability of government, energy, and public health systems around the
 57 globe. Our digital feedback technologies are today capable of creating a level of dynamic respon-
 58 siveness our larger, more complicated modern society requires. We must reinvent the systems of
 59 societies within a control framework: sensing the situation, combining these observations with
 60 models of demand and dynamic reaction, and finally using the resulting predictions to tune the
 61 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 [24]. 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, 28, 42];
 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 [27].

72 The process of analyzing the patterns within these digital breadcrumbs is called reality
 73 mining [13, 32], 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 [33], or whether we are the sort of person who will pay back loans [34]. 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 [30]. 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 [17].

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” [23]. 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 [16], or create problems for the entire society in
 93 the long run, for example by limiting user choices and closing them into information bubbles [19].
 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 [32].

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 [26,33]. 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 [31]. 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 [6,18], 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 (aka 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 (See: <http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:31995L0046:EN:HTML>)

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,

153 the data belong to you, and you can access your data at any time. Data collectors thus
 154 play a role akin to a bank, managing the data on behalf of their customers.

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

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

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

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

169 In 2007, one author (Pentland) first proposed the New Deal on Data to the World Economic
 170 Forum [43]. Since then, this idea has run through various discussions and eventually helped
 171 shape the 2012 Consumer Data Bill of Rights in the United States, along with a matching
 172 declaration on Personal Data Rights in the EU. These new regulations hope to accomplish the
 173 combined trick of breaking data out of the current silos, thus enabling the public good, while
 174 at the same time giving individuals greater control over data about them. But, of course this is
 175 still a work in progress and the battle for individual control of personal data rages onward.

176 The World Economic Forum (WEF) has dubbed personal data as the “New Oil” or resource
 177 of the 21st century [43]. The discovery of oil and the subsequent development of the oil industry
 178 over the past 100 years has spurred not only the development of the automobile industry but also

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

186 If personal data, as the new oil, is to reach its global economic potential, there needs to be
 187 a productive collaboration between all the stakeholders in the establishment of a *personal data*
 188 *ecosystem*. As mentioned in [43], a number of fundamental questions about privacy, property,
 189 global governance, human rights — essentially around who should benefit from the products
 190 and services built upon personal data — are major uncertainties shaping the opportunity. The
 191 rapid rate of technological change and commercialization in using personal data is undermining
 192 end user confidence and trust.

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

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

206 economy.

207 Recently, we have shown how challenging, but also feasible, it is to open such institutional
 208 Big Data. In the Data For Development (D4D) Challenge <http://www.d4d.orange.com/home>,
 209 the telecom operator Orange opened access to a large dataset of call detail records (CDRs) from
 210 the Ivory Coast. Working with the data as part of a challenge, teams of researchers came up
 211 with life-changing insights for the country. For example, one team developed a model for how
 212 disease spread in the country and demonstrated that information campaigns based on one-to-one
 213 phone conversations among members of social groups can be an effective countermeasure [25].
 214 In releasing and analyzing this data, the privacy of the people who generated the data was
 215 protected not only by technical means, such as removal of Personally Identifiable Information
 216 (PIIs), but also by legal means, with the researchers signing an agreement they will not use the
 217 data for re-identification or other nefarious purposes. As we have seen in several cases, such as
 218 the Netflix Prize privacy disaster [29] and other similar privacy breaches [37], true anonymization
 219 is extremely hard. In the Unique in the Crowd [10], de Montjoye et al. showed that even though
 220 human beings are highly predictable [35], we are also very unique. Having access to one dataset
 221 may be enough to uniquely fingerprint someone based on just a few datapoints, and use this
 222 fingerprint to discover their true identity. The higher the resolution of the data, the easier it
 223 gets to identify a person from this type of data.

224 The report of the World Economic Forum [43] also suggest a way forward by recommending
 225 a number of areas where efforts could be directed:

- 226 • Alignment of key stakeholders: Citizens, the private sector and the public sector need to
 227 work in support of one another. Efforts such as NSTIC [38] — albeit still in its infancy —
 228 represent a promising direction for a global collaboration.
- 229 • Viewing “data as money”: There needs to be a new change in mindset where an individual’s
 230 personal data items are viewed and treated in the same way as their money. These personal
 231 data items would reside in an “account” (like a bank account) where it would be controlled,
 232 managed, exchanged and accounted for just like personal banking services operate today.

- End-user centricity: All entities in the ecosystem need to recognize that end-users are vital and independent stakeholders in the co-creation and value exchange of services and experiences. Efforts such as the *User managed Access* (UMA) initiative [2] point in the right direction by designing systems that are user-centric and managed by the user.

Opening data from the silos by publishing static datasets — collected at some point and unchanging — is important, but it is only the first step. We can do even more substantial things when the data is available in real time and can become part of a society’s nervous system. Epidemics can be monitored and prevented in real time [33], underperforming students can be helped, and people with health risks can be treated before they get sick [9]. The same data can potentially be used for stalking, burglarizing one’s home, and as justification to charge people more for an insurance policy.

4 Enforcing the New Deal on Data

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

One current best practice is a system of data sharing called trust networks. Trust networks are a combination of networked computers and legal rules defining and governing expectations regarding data. With respect to data belonging to individuals, these networks of technical and legal rules keeps track of user permissions for each piece of personal data, and a legal contract that specifies both what you can and cannot do with the data and what happens if there is a

violation of the permissions. For example, in such a system all personal data can have attached labels specifying what the data can and cannot be used for. These labels are exactly matched by the network's system rules and terms in legal contracts between all the participants, stating penalties for not obeying the permission labels. These rules can, and often do, reference or require audits of relevant systems and data use, demonstrating how traditional internal controls can be leveraged as part of the transition to more novel trust models.

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

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

Having system rules applicable to the networks, applications, and data as well as all the services providers other intermediaries, and the users themselves is the mechanism for establishing and operating a trust network. System rules are sometimes called operating regulations in the credit card context, or known as trust frameworks in the identity federations context, or trading partner agreements in a supply value chain context. There are many general examples of multi-party shared architectural and contractual rules that share the generic characteristic of creating binding obligations and enforceable expectations on all participants in scalable networks. Another common characteristic of the system rules design pattern is that the participants in the network can be widely distributed across very heterogeneous business ownership boundaries, legal governance structures, and technical security domains. Yet, the parties need not agree

285 to conform to all or most aspects of their basic roles, relationships, and activities in order to
286 connect to systems of a trust network. Cross-domain trusted systems must, by their nature,
287 focus mandatory and enforceable rules narrowly upon the critical items that must be commonly
288 agreed in order for that network to achieve its purpose.

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

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

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

309 The Human Dynamics Lab has applied the system rules approach to development of in-
310 tegrated business, technical architecture, and rules large scale institutional use of personal
311 data stores, available as an example under MIT’s creative commons license by MIT, at <https://github.com/HumanDynamics/openPDS>

312 `//github.com/HumanDynamics/SystemRules.`

313 The capacity to apply the appropriate methods of enforcement for a trust network depend
 314 upon a clear understanding and agreement among parties about the purpose of the trusted
 315 system and the respective roles or expectations of those connecting as participants. Therefore,
 316 an anchor is needed to a clear context of a Big Data operational framework and institutional
 317 controls appropriate for access and confidentiality or privacy. The following section posits the
 318 trust model and signature traits of such a context, through the lens of the New Deal on Data.

319 **5 Transitioning End-User Assent Practices**

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

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

338 promote the privacy of the users, effectively pushing them to press *I Agree* in every presented
339 window.

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

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

361 6 Business, Legal, and Technical Dimensions of Big Data Sys- 362 tems

363 When it comes to data intended to be accessible over networks — whether big, personal, or
364 otherwise — the traditional container of an institution makes less and less sense. Institutional
365 controls apply, by definition by or to some type of institutional entity such as a business, gov-
366 ernmental, or religious organization. A combined view of the business, legal, and technical facts
367 and circumstances surrounding Big Data is necessary to know what access, confidentiality, and
368 other expectations exist. The relevant contextual aspects of Big Data of one institution is often
369 profoundly different from that of another. As more and more organizations use and rely upon
370 Big Data, a single formula for institutional controls will not work for increasingly heterogeneous
371 business, legal and technical environments in play.

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

383 Defining as a ‘system’ the thing to which institutional controls apply provides an achievable
384 and measurable basis for balancing privacy, access and other interests in Big Data. Within a
385 given institution, there may in fact be many different discernable organizations and correspond-
386 ing 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 [40]:

“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

412 controls: governmental controls; proprietary controls; enforcement tools; and infor-
413 mational devices.”

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

415 “Institutional controls are administrative and legal controls that help minimize the
416 potential for human exposure to contamination and/or protect the integrity of the
417 physical remedy. They can include recorded restrictive covenants, but land use
418 laws and regulations, deed restrictions, department consent orders, and conservation
419 easements are all institutional controls.”

420 In domains of information technology, this approach is most commonly reflected as “enter-
421 prise controls” related to security. See, for example, the Juniper Networks enterprise security
422 report [22] stating: “Enterprise mobility technologies, especially those designed to retrofit en-
423 terprise controls on top of consumer mobile devices, are rapidly evolving. This was a message
424 we heard loud and clear in the study.” This study and analysis also reveals much about the
425 internal controls needed to accommodate mobile device use by employees. In both capacities as
426 employee, consumer, and other roles, the use of mobile devices triggers myriad legal, policy, and
427 other implications for institutional controls.

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

438 Consider again the analogy of institutional controls in the context of environmental law, and
439 how these types of measures can be applied in the Big Data, privacy, and access context to
440 digital environments. Given the relatively mature and stable state of environmental regulation,
441 there is much to be learned by examining this context of institutional controls. Environmental
442 regulatory compliance with waste management cleanup requirements could include institutional
443 controls restricting land use on adjacent property. In these situations, it is possible that the
444 remediation strategy requires significant use of land outside the property boundaries of the
445 cleanup site. In these cases, the regulators and the land owner responsible for the regulated
446 property must find ways to ensure a common approach among multiple owners and across
447 multiple property environments. Clauses on the relevant deeds, an enforceable consent order,
448 or targeted regulations and zoning rules are examples of more severe institutional controls that
449 can be employed to ensure consistent and effective actions are taken across ownership and real
450 property boundaries.

451 See, for example, Florida Department of Environmental Protection (FDEP), Division of
452 Waste Management [15] which states that “...RMO III does contemplate contamination beyond
453 the Property boundaries, which would require agreement by the adjacent owners to put an RC
454 on their properties as well.”

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

464 The EPA provides considerable information on the nature and use of institutional controls,

465 including situations when the situational scope extends to adjacent properties owned by third
466 parties. See, generally, *EPA Hazardous Waste Corrective Action Guidance on Institutional Con-*
467 *trols* [40]. Also see: *Institutional Controls Bibliography: Institutional Control, Remedy Selection,*
468 *and Post-Construction Completion Guidance and Policy, December 2005* [39].

469 When institutional controls would apply to “separately owned neighboring properties” a
470 number of issues arise that are very relevant to the problems associated with managing personal
471 and big data across legal, business and other systemic boundaries. Requiring the party respon-
472 sible for site cleanup to use “best efforts” to attain agreement by third parties to institute the
473 relevant institutional controls is perhaps the most direct and least prescriptive approach. When
474 direct negotiated agreement is not successful, then use of third party neutrals to resolve disagree-
475 ments regarding institutional controls can be required. If necessary, environmental regulation
476 can force an acquisition of neighboring land by compelling the party responsible to purchase the
477 other property or by purchase of the property directly by the EPA [41].

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

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

491 The use of system rules and integrated participation agreements by developers and end-

492 users is a way to ensure intended operational frameworks conform to applicable institutional
 493 controls. The example of Living Informed Consent described in this chapter, demonstrates how
 494 institutional controls comprised of legal and definite workflow measures, in concert with technical
 495 methods, can result in a higher level of performance, while appropriately balancing legitimate
 496 interests of various parties regarding use and access to personal data.

497 Following the World Economic Forum recommendations of treating personal data stores in
 498 the manner of bank accounts [43], there are a number of infrastructure improvements that need to
 499 be realized, if the personal data ecosystem is to flourish and deliver new economic opportunities.
 500 We believe the following infrastructure improvements are necessary for the coming personal data
 501 ecosystem:

- 502 • *New global data provenance network:* In order for personal data to be treated like bank
 503 accounts, the origin information regarding data items coming into the data store must be
 504 maintained [21]. In other words, the provenance of all data items must be accounted for
 505 by the IT infrastructure upon which the personal data store operates. The heterogeneous
 506 provenance databases must then be interconnected in order to provide a resilient and
 507 scalable platform for audit and accounting systems to track and reconcile the movement
 508 of personal data from the respective data stores.
- 509 • *Trust network for computational law:* In order for trust to be established between parties
 510 who wish to exchange personal data, we foresee that some degree of “computational law”
 511 technologies may have to be integrated into the design of personal data systems. Such
 512 technologies should not only verify terms of contracts (e.g. terms of data use) against user-
 513 defined policies but also have mechanisms built-in to ensure non-repudiation of entities who
 514 have accepted these digital contracts. Efforts such as [1,2] are beginning to bring better
 515 evidentiary proof and enforceability of contracts into the technical protocol flows.
- 516 • *Development of institutional controls for digital institutions:* Currently there are a number
 517 of proposals for the creation of virtual currencies (e.g. BitCoin [5], Ven [36]) in which the

518 systems have the potential to evolve into self-governing “digital institutions” [20]. Such
 519 systems and institutions that operate on them will necessitate the development of a new
 520 paradigm to understand the aspects of institutional control within their context.

521 8 Scenarios of Use in Context

522 Development of frameworks for Big Data that effectively balance economic, legal, security and
 523 other interests requires an understanding of the relevant context and applicable scenarios within
 524 which the Big Data exists. Although Big Data straddles multiple business, legal and technical
 525 boundaries it will nonetheless have one or more institutions that are capable of, or in some
 526 situations required to, manage and control it. The public good referred to in the title of this
 527 book can be articulated through the use of system, service and software modeling, requirements
 528 setting, development, testing and certification processes. Discrete use cases of actors and actions
 529 is one approach to model business, legal and technical requirements in a way that can objectively
 530 be agreed in advance and traceably be tested against implemented systems and components.
 531 However, user cases are typically atomic or very low level of granularity and operate deep within
 532 layers of assumed context. Higher level contexts and corresponding scenarios of multiple use
 533 cases can describe fundamental expectations about matters like interests in property, rights to
 534 liberty and honoring the social compact. Institutional controls and other system requirements
 535 or safeguards are important methods to ensure context-appropriate outcomes consistent with
 536 clearly applicable system scenarios defining and describing the greater public good referred to
 537 in the title of this book.

538 In particular, the New Deal on Data can be achieved in part by sets of institutional controls
 539 involving governance, business, legal, and technical aspects of Big Data and interoperating
 540 systems. The following scenarios demonstrate signature features of the New Deal on Data in
 541 various contexts and serve as an anchor to evaluate what institutional controls are well aligned.

542 Which scenarios are relevant and what lower level use cases apply are knowable in detail
 543 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 (eg who are the parties involved and what are their respective roles and relationships)?
2. What are the relevant interactions (eg: what transactions or other actions are conducted by or with the people involved)?
3. What are the relevant data and data sets (eg: what types of data are created, stored, computed, transmitted, modified or deleted)?
4. What are the relevant systems (eg: what services or other software is used by the people, for the transactions or with the data)?

Retail marketing is a common context within which personal data is important. Personal data is critical to many different scenarios in the context of retail marketing. Consider the scenario whereby a merchant conducts an online promotion for an app or service by using a purchased direct marketing database of consumers who have expressed interest in similar products. Data such as the names, email addresses, phone numbers and other personal information can be used to lower costs and increase revenue by better targeting promotional messages and increasing sales. However, there are risks to the merchant and consumer alike, including the potential of a data breach and resulting identity theft and fraud. There is also risk that some consumers will feel annoyed or violated when their personal information is used in this manner without their prior knowledge or consent. The information available from such third party marketing lists and databases may be out of date and lead to the waste of marketing dollars and the failure to inform potentially interested consumers of a product they might have purchased if the solicitation had gone to their current email or appropriate network. Imagine that the same consumers had individual personal data stores and were able to "intent-cast" their interest in

571 the product. This can be done without revealing all the other personal data of that person. The
572 The openPDS system could be configured to provide permission based answers to questions such
573 as whether the consumer is over the age of 18 or lives in a city, suburb or rural area. Sectors
574 such as real estate could be transformed by such intent-casting by qualified buyers.

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

597 The scenario below describes the deeper fact-based situations and circumstances in the con-

text 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.

8.1 Example Scenario: Research System for Computational Social Science

Computational Social Science (CSS) studies are based on data collected often with an extremely high resolution and scale [24]. Using computational power combined with mathematical models, such data can be used to provide insights into human nature. Much of the data collected, for example mobility traces are sensitive and private; most individuals would feel uncomfortable sharing them publicly. The need for solutions to ensure the privacy of the individuals has grown alongside the data collection efforts.

The data collection in the CSS context is based on the informed consent of the participants. Countries have different bodies regulating such studies, for example Institutional Research Boards (IRBs) in the US. Although certain minimal requirements for implementing informed consent in these contexts exist (See: http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6632), they are often not very well suited for the large-scale studies, where the amount and sensitivity of the data calls for sophisticated privacy controls. As the scale of the studies grows, in terms of the number of participants, collected bits per user, and duration, the EULA-style informed consent is no longer sufficient and makes it hard to claim that participants in fact expressed informed consent.

One author (Stopczynski) deployed this year a 1,000 phones study at Technical University of Denmark, freshmen students received mobile phones in order to study their networks and social behavior in the important change moment of their lives, when joining the university. The study, called SensibleDTU (<https://www.sensible.dtu.dk/?lang=en>), uses not only data collected from the mobile phones (location, Bluetooth-based proximity, call and sms logs etc.) but also data collected from social networks, questionnaires filled out by participants, behavior

624 in economic games and so on. As the data is collected in the context of the university, there is
625 potentially a big issue of students feeling obliged to participate in the study, feeling that their
626 grades may depend on it, or that the data may influence their grades. In this context, we see the
627 implementation of Living Informed Consent not only as a technical mean to put participants in
628 control of the data we collect, but also to clearly and comprehensibly convey broader New Deal
629 on Data principles such as the opt-in nature of the study, the boundaries of the data usage, and
630 parties accessing the data.

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

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

650 When a study of such scale is deployed, the particular experiments and sub-studies may

not be exactly defined from the very beginning. The initial deployment is a creation of a testbed, where shorter or longer experiments can take place; for example part of the population may participate in the experiment of quantifying the impact of feedback application on their activity levels. Being able to create such experiments in an efficient way is a huge value for the researchers. To do that in the most frictionless way, we give the users the choice to opt-in to those additional experiments, providing some financial or other benefits. This is only possible if there is a notion of identity of the participants, stronger and more useful than a piece of paper with a signature. This identity allows us to reach out to people, offer them additional experiments, and let them agree or disagree to them.

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

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

678 8.2 Scenarios of Use Today, Tomorrow and the Day After

679 The New Deal on Data is designed to provide good value to all stakeholders creating, using or
680 benefiting from personal data, but the entire vision need not be adopted before value starts to
681 flow. The social science research study scenario (below) demonstrates how researchers and study
682 participants alike derive value from New Deal on Data principles today. As more researchers
683 and students use the types of systems described above, the value is predicted to increase based
684 upon a network effect. The same dynamic is expected in other contexts as well.

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

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

700 Developing relevant context and scenarios defines a clear anchor for measuring whether a
701 given use of Big Data and personal data is consistent with measurable criteria. Such criteria
702 can be used to establish compliance with the rules of a Trust Network and for certification by
703 government for the right to safe harbor or other protections. Criteria applicable to business,
704 legal and technical aspects of a system or set of systems can be assessed, evaluated and trace-

ably proven. Such criteria can provide a basic lowest common denominator requirements and constraints for work flow, transaction flow, data flow and service flow within the relevant contexts and scenarios of use. The New Deal on Data provides a clear basis routed in common law and broad understandings of the social compact. Therefore, with the New Deal on Data the appropriate bundle of rights and expectations intended to cover privacy and other personal data interests in Big Data can be explicitly enumerated, debated and eventually agreed in ways that fit relevant contexts.

9 Future Research

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

The reason is that with such rich data, you can easily uncover misleading or unactionable correlations. For instance, let us imagine we discover that people who are unusually active are more likely to get the flu. This is a real example: when we examined the minute-by-minute behavior of a small university community - a real-time flow of gigabytes per day for an entire year - we noticed that an unusual level of running around often predicted onset of the flu [26]. But if we can only analyze the data using traditional statistical methods, we have the problem of discerning why this is true. Is it because the flu virus makes us more active in order to spread itself more quickly? While it is more likely that interacting with many more people than usual makes you more likely to catch the flu, you can't be sure that this is the true cause based on the real-time stream of data alone.

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

731 9.1 Research on Design and Deployment of Big Data Systems

732 In order to achieve low risk, high value outcomes efficiently, design and deployment of the coming
 733 global wave of Big Data systems should apply relevant research, such as that identified in this
 734 chapter and the book generally. To understand and address the unique problems and prospects
 735 associated with big personal data, the relevant context must be identified and corresponding
 736 rules-driven capabilities must be designed into the underlying systems.

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

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

750 Some capabilities will likely be essential to all Big Data systems, such as highly scalable
 751 active storage, standard methods for integration with other Big Data systems, and a processing
 752 architecture enabling high speed statistical analytics. But there are and will continue to emerge
 753 multiple types of Big Data systems. Some functions or controls will likely be important —
 754 or even feasible — only for certain types of future systems. For instance, it is reasonable to
 755 expect some systems will specialize in enormous volumes of entirely non-personal data from
 756 many real-time sources (e.g. for soil science, materials engineering, astronomy) while other Big
 757 Data systems will hinge upon mass quantities of highly sensitive personal information (e.g. for

758 clinical medicine, education and lifelong learning, social entertainment).

759 While some capabilities, such as ingesting and processing astronomical data-sets, will be
760 unique to only a subset of Big Data systems, it is reasonable to anticipate that data will be
761 increasingly cross-tabulated, merged, and otherwise shared with other systems and data. It can
762 be nearly impossible to conclusively predict for the entire life of a system what data will be
763 received by, created in, or transmitted from that system at the design phase. This prediction is
764 all the harder to make when the systems are intended for Big Data.

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

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

784 9.2 Research on Big Data for Design of Institutions

785 Using massive, live data to design institutions and policies is outside of our normal way of
786 managing things. We live in an era that builds on centuries of science and engineering, and
787 the standard choices for improving systems, governments, organizations, and so on are fairly
788 well understood. Therefore our scientific experiments normally need only consider a few clear
789 alternatives, ‘plausible hypotheses’.

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

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

806 An example of such a Living Lab is the ‘open data city’ just launched by one author (Pent-
807 land) with the city of Trento in Italy, along with Telecom Italia, Telefonica, the research uni-
808 versity Fondazione Bruno Kessler, the Institute for Data Driven Design, and local companies.
809 Importantly, this Living Lab has the approval and informed consent of all its participants. Not
810 only do these participants consent to sharing of their data, they know that they are part of a

811 gigantic experiment whose goal is to invent a better way of living. This can be a model followed
812 by many types of systems within and beyond the social science research contexts. More detail
813 on this Living Lab can be found at <http://www.mobileterritoriallab.eu/>.

814 The goal of this Living Lab is to develop new ways of sharing data to promote greater civic
815 engagement and exploration. One specific goal is to build upon and test trust-network software
816 such as our openPDS system. Tools such as openPDS make it safe for individuals to share
817 personal data (e.g., health data, facts about your children) by controlling where your data go
818 and what is done with them.

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

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

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

836 The Trento Living Lab will let us investigate how to deal with the sensitivities of collecting
837 and using deeply personal data in real-world situations. In particular, the Lab will be used as a

838 pilot for the New Deal on Data and for new ways to give users control of the use of their personal
 839 data. For example, we will explore different techniques and methodologies to protect the users
 840 privacy while at the same time being able to use these personal data to generate a useful data
 841 commons. We will also explore different user interfaces for privacy settings, for configuring the
 842 data collected, for the data disclosed to applications and for those shared with other users, all
 843 in the context of a trust framework.

844 10 Conclusions

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

858 The New Deal on Data is still new. Here we described our efforts in understanding the
 859 technical means of how it can be implemented, the legal framework around it, business rami-
 860 fications, and the direct value that can be derived from researchers, companies, governments,
 861 and users having more access to the data. It is clear that companies must play the major role
 862 in the implementation of the New Deal, incentivized by business opportunities and pressured
 863 by the legislation and demand of the users. Only with such orchestration will it be possible to

change the current feudal system of data ownership and finally put the immense quantities and capabilities of collected personal data to good use.

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