

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 (Arek)

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 New Deal on Data, and describe future
29 directions of 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 must support and reflect greater
34 user control over personal data, and large scale interoperability for data sharing between and
35 among institutions. Core capabilities of these controls include responsive rule-based systems
36 governance and fine-grained authorizations for distributed rights management.

37 Sustaining a healthy, safe, and efficient society is a scientific and engineering challenge go-
38 ing back to the 1800s, when the Industrial Revolution spurred rapid urban growth, 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 the 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 protected from pandemics, energy
 49 efficient, have secure food and water supplies, and have much better government. To reach these
 50 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 re-
 58 sponsiveness that our larger, more complicated modern society requires. We must reinvent the
 59 systems of the societies within a control framework: sensing the situation, combining these obser-
 60 vations 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 the
 65 world: call records, credit card transactions, GPS location fixes, among others. By recording
 66 our choices, these data tell the story of our lives. And this may be very different from what
 67 we decide to put on Facebook or Twitter; our postings there are what we choose to tell people,
 68 edited according to the standards of the day and filtered to match the persona we are building.
 69 Mining social networks can give some great insights about human nature [4, 27, 41]; who we
 70 really are is however even more accurately determined by where we spend our time and which
 71 things we buy, rather than just what we say we do [26].

72 The process of analyzing the patterns within these digital breadcrumbs is called reality
 73 mining [13, 31], and through it we can learn an enormous amount about who we are. The
 74 Human Dynamics research group at MIT have found that we can use them to tell if we are

likely to get diabetes [32], or whether we are the sort of person who will pay back loans [33]. By analyzing these patterns across many people, we are discovering that we can begin to explain many things — crashes, revolutions, bubbles — that previously appeared to be random acts of God [29]. For this reason the magazine *Technology Review* named our development of reality mining as one of the ten technologies that will change the world [16].

2 The New Deal on Data (Arek)

The digital breadcrumbs we leave behind provide clues about who we are, what we do and want. This makes these personal data — data about individuals — immensely valuable, both for public good and for private companies. As European Consumer Commissioner, Meglena Kuneva said recently, “Personal data is the new oil of the Internet and the new currency of the digital world” [22]. This new ability to see the details of every interaction can be however used for good or for ill. Therefore, maintaining protection of personal privacy and freedom is critical to our future success as a society. We need to enable even more data sharing for the public good; at the same time, we need to do a much better job in protecting the privacy of the individuals.

A successful data-driven society must be able to guarantee that our data will not be abused; perhaps especially that government will not abuse the power conferred by access to such fine-grain data. The abuses may be directly targeted at users, for example by offering them higher insurance rates based on their shopping history, or create problems for the entire society in longer run, for example by limiting user choices and closing them into information bubbles [18]. To achieve the positive possibilities of the new society, we require the *New Deal on Data*, workable guarantees that the data needed for public good are readily available while at the same time protecting the citizenry [31].

The key insight that motivates the idea of the New Deal on Data is that our data are worth more when shared, because these aggregated data — averaged, combined across population, and often distilled to high-level features — inform improvements in systems such as public health, 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 [25,32]. 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 [30]. 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. These private organizations must be thus 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 Ultimately, the entities who should be empowered to share and make decisions about their data,
126 are people themselves: users, participants, citizens.

127 The ultimate goal is to provide the society with tools to analyze and understand what needs

128 to be done, and to reach the consensus on how to do it. This goes beyond just creating more
 129 communication platforms; the assumption that more interactions between users will result in
 130 better decisions being made, may be very misleading. Although in the recent years we have
 131 seen some great examples of using social networks for better organization in society, for example
 132 during political protests [6, 17], we are not even close to the point where we can start reaching
 133 consensus about the big problems: epidemics, climate change, pollution. The discussions must
 134 be data driven, involving both experts and wisdom of the crowds – users themselves interested
 135 in improving the society. The problems we are dealing with as a now global society are not
 136 easy. We are responsible for many of them, and being able to tackle them on a global scale is
 137 necessary for our, mankind, survival.

138 3 Personal Data: Emergence of a New Asset Class (Thomas)

139 It has long been recognized that the first step to promoting liquidity in land and commodity
 140 markets is to guarantee ownership rights so that people can safely buy and sell. Similarly, the
 141 first step toward creating greater idea and idea flow (‘idea liquidity’) is to define ownership rights.
 142 The only politically viable course is to give individual citizens rights over data that are about
 143 them and in fact, in the European Union these rights flow directly from the constitution **AS:**
 144 **Citation? There is no ‘EU constitution’ per se.** . We need to recognize personal data
 145 as a valuable asset of the individual that is given to companies and government in return for
 146 services.

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

- 149 • You have the right to possess data about you. Regardless of what entity collects the data,
 150 the data belong to you, and you can access your data at any time. Data collectors thus
 151 play a role akin to a bank, managing the data on behalf of their customers.
- 152 • You have the right to full control over the use of your data. The terms of use must be opt-

153 in and clearly explained in plain language. If you are not happy with the way a company
 154 uses your data, you can remove the data, just as you would close your account with a bank
 155 that is not providing satisfactory service.

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

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

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

166 In 2007, one author (Pentland) first proposed the New Deal on Data to the World Economic
 167 Forum [42]. Since then, this idea has run through various discussions and eventually helped
 168 shape the 2012 Consumer Data Bill of Rights in the United States, along with a matching
 169 declaration on Personal Data Rights in the EU. These new regulations hope to accomplish the
 170 combined trick of breaking data out of the current silos, thus enabling public goods, while at
 171 the same time giving individuals greater control over data about them. But, of course this is
 172 still a work in progress and the battle for individual control of personal data rages onward.

173 The World Economic Forum (WEF) has dubbed personal data as the “New Oil” or resource
 174 of the 21st century [42]. The discovery of oil and the subsequent development of the oil industry
 175 over the past 100 years has spurred not only the development of the automobile industry but also
 176 the creation of the global transportation infrastructure, including the massive freeway networks
 177 that we see today in the developed nations. The “personal data sector” of the economy today is
 178 still in its infancy, its state akin to the oil industry at the late 1890s prior to the development of
 179 the Model-T Ford automobile. The productive collaboration between the Government (building

180 the state owned freeways), the private sector (mining and refining oil, building automobiles) and
 181 the citizen (the user-base of these services) allowed the develop nations to expand its economies
 182 by creating new markets adjacent to the automobile and oil industries.

183 If personal data, as the new oil, is to reach its global economic potential, there needs to be
 184 a productive collaboration between all the stakeholders in the establishment of a *personal data*
 185 *ecosystem*. As mentioned in [42], a number of fundamental questions about privacy, property,
 186 global governance, human rights — essentially around who should benefit from the products
 187 and services built upon personal data — are major uncertainties shaping the opportunity. The
 188 rapid rate of technological change and commercialization in using personal data is undermining
 189 end user confidence and trust.

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

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

204 Recently, we have shown how challenging, but also feasible, it is to open such institutional
 205 Big Data. In the Data For Development (D4D) Challenge <http://www.d4d.orange.com/home>,
 206 the telecom operator Orange opened access to a large dataset of call detail records (CDRs) from

the Ivory Coast. Working with the data as part of a challenge, teams of researchers came up with life-changing insights for the country. For example, one team developed a model for how disease spread in the country and demonstrated that information campaigns based on one-to-one phone conversations among members of social groups can be an effective countermeasure [24]. In releasing and analysing this data, the privacy of the people who generated the data was protected not only by the technical means, such as removal of the Personally Identifiable Information (PIIs), but also by legal means, with the researchers signing an agreement they will not use the data for re-identification or other nefarious purposes. As we have seen in several cases, such as the Netflix Prize privacy disaster [28] and other similar privacy breaches [36], true anonymization is extremely hard. In the Unique in the Crowd [10], de Montjoye et al. showed that even though human beings are highly predictable [34], we are also very unique. Having access to one dataset, it may be easy to uniquely fingerprint someone based on just few datapoints, and use this fingerprint to discover their true identity. The higher the resolution of the data, the easier it gets to identify a person from this type of data.

The report of the World Economic Forum [42] also suggest a way forward by recommending a number of areas where efforts could be directed:

- Alignment of key stakeholders: Citizens, the private sector and the public sector need to work in support of one another. Efforts such as NSTIC [37] — albeit still in its infancy — represents a promising direction for a global collaboration.
- Viewing “data as money”: There needs to be a new change in mindset where an individual’s personal data items are viewed and treated in the same way as their money. These personal data items would reside in an “account” (like a bank account) where it would be controlled, 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

233 right direction by designing systems that are user-centric and managed by the user.

234 Opening data from the silos by publishing static datasets — collected at some point and
 235 unchanging — is important, but it is only the first step. We can do even more substantial things
 236 when the data is available in real time and can become part of a society’s nervous system.
 237 Epidemics can be monitored and prevented in real time [32], underperforming students can be
 238 helped, and people with health risks can be treated before they get sick [9]. The same data can
 239 potentially be used for stalking, burglarizing one’s home, and as justification to charge people
 240 more for an insurance policy.

241 4 Enforcing the New Deal on Data (Dazza)

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

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

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

261 Complete tracking and regulation of every aspect of a trust network is not the goal or
262 even desirable in order to achieve effective enforcement. Rather, the rules for a trust network
263 align enforcement with the highest priority issues and those upon which trust of participants is
264 premised. The relevant issues arise from the dynamics of data flows, underlying trust models,
265 and contextual scenarios within which the networked data and the relationships of parties in
266 the trust network **AS: This sentence is hard to understand. Missing verb?** . When
267 a trust network involves use of personal data, then the user permissions and corresponding
268 limits on use are fundamental to the trust model. In this context, the permissions, including
269 the provenance of the data, should require appropriate levels of audit. A well designed trust
270 network, elegantly integrating computer and legal rules, allows automatic auditing of data use
271 and allows individuals to change their permissions and withdraw data.

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

285 in order for that network to achieve it's purpose.

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

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

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

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

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

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

316 5 Transitioning End-User Assent Practices (Arek)

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

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

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

6 Business, Legal, and Technical Dimensions of Big Data Systems (Dazza)

When it comes to data intended to be accessible over networks — whether big, personal, or otherwise — the traditional container of an institution makes less and less sense. Institutional controls apply, by definition by or to some type of institutional entity such as a business, governmental, or religious organization. A combined view of the business, legal, and technical facts

363 and circumstances surrounding big data is necessary to know what access, confidentiality, and
364 other expectations exist. The relevant contextual aspects of Big Data of one institutional is often
365 profoundly different from that of another. As more and more organizations use and rely upon
366 big data, a single formula for institutional controls will not work for increasingly heterogeneous
367 business, legal and technical environments in play.

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

379 Once a systems view is adopted, there is a tractable starting point to narrow or broaden
380 the scope of view to see the smaller and larger systems and to make better and more effective
381 use and control of big data. Within a given institution, there may in fact be many different
382 discernable institutions and corresponding systems and any given system of one institution will
383 frequently in fact exist across many different discernable institutions. However, defining as a
384 ‘system’ the thing to which institutional controls apply provides an achievable and measurable
385 basis for balancing privacy, access and other interests in big data. **AS: The paragraph above**
386 **is hard to understand I think.**

387 Many organizations are structured with clear leadership on business, legal, and technical
388 issues functionally assigned to top level executive roles. Business issues are typically allocated
389 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 (Thomas)

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 [39]:

“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 and regulations, deed restrictions, department consent orders, and conservation easements are all institutional controls.”

415 In domains of information technology, this approach is most commonly reflected as “enter-
416 prise controls” related to security. See, for example, the report [21] stating: “Enterprise mobility
417 technologies, especially those designed to retrofit enterprise controls on top of consumer mobile
418 devices, are rapidly evolving. This was a message we heard loud and clear in the study.” This
419 study and analysis also reveals much about the internal controls needed to accommodate mobile
420 device use by employees. In both capacities as employee, consumer, and other roles, the use of
421 mobile devices triggers myriad legal, policy, and other implications for institutional controls.

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

432 Consider again the analogy of institutional controls in the context of environmental law, and
433 how these types of measures can be applied in the Big Data, privacy, and access context to digital
434 environments. Given the relatively mature and stable state of environmental regulation, there is
435 much to be learned by examining this context of institutional controls. Environmental regulatory
436 compliance with waste management cleanup requirements could include institutional controls
437 restricting land use on adjacent property. In these situations, it is possible that the remediation
438 strategy requires significant use of land outside the property boundaries of the cleanup site.
439 In these cases, the regulators and the land owner responsible for the regulated property must
440 find ways to ensure a common approach among multiple owners and across multiple property
441 environments. Use of measures such as a clauses on the relevant deeds, an enforceable consent

order, or regulations and zoning rules are examples of more severe institutional controls that can be employed to ensure consistent and effective actions are taken across ownership and real property boundaries.

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

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

The EPA provides considerable information on the nature and use of institutional controls, including situations when the situational scope extends to adjacent properties owned by third parties. See, generally, *EPA Hazardous Waste Corrective Action Guidance on Institutional Controls* [39]. Also see: *Institutional Controls Bibliography: Institutional Control, Remedy Selection, and Post-Construction Completion Guidance and Policy, December 2005* [38].

When institutional controls would apply to “separately owned neighboring properties” a number of issues arise. Engagement with affected third parties, requiring the party responsible for site cleanup to use “best efforts” to attain agreement by third parties to institute the relevant institutional controls, use of third party neutrals to resolve disagreements regarding the application with institutional controls, or forcing an acquisition of the neighboring land by forcing the party responsible to purchase the property or by purchase of the property directly by the

469 EPA [40].

470 In the context of Big Data, privacy, and access, institutional controls are seldom, if ever,
 471 the result of government regulatory frameworks such as are seen in the environmental waste
 472 management oversight by the EPA. Rather, institutions applying measures constituting institu-
 473 tional controls in the big data and related information technology and enterprise architecture
 474 contexts will typically employ governance safeguards, business practices, legal contracts, techni-
 475 cal security, reporting, and audit programs and a various risk management measures. Inevitably,
 476 institutional controls for Big Data will have to operate effectively across institutional boundaries,
 477 just as environmental waste management internal controls must sometimes be applied across real
 478 property boundaries and may subject multiple different owners to enforcement actions corre-
 479 sponding to the applicable controls. Short of government regulation, the use of system rules as a
 480 general model are one widely understood, accepted, and efficient method for defining, agreeing,
 481 and enforcing institutional and other controls across business, legal, and technical domains of
 482 ownership, governance, and operation.

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

489 Following the World Economic Forum recommendations of treating personal data stores in
 490 the manner of bank accounts [42], there are a number of infrastructure improvements that need to
 491 be realized, if the personal data ecosystem is to flourish and deliver new economic opportunities.
 492 We believe the following infrastructure improvements are necessary for the coming personal data
 493 ecosystem: **AS: We should remove the bullets, turn them into continuous text.**

- 494 • *New global data provenance network:* In order for personal data to be treated like bank
 495 accounts, the origin information regarding data items coming into the data store must be

maintained [20]. In other words, the provenance of all data items must be accounted for by the IT infrastructure upon which the personal data store operates. The heterogeneous provenance databases must then be interconnected in order to provide a resilient and scalable platform for audit and accounting systems to track and reconcile the movement of personal data from the respective data stores.

- *Trust network for computational law*: In order for trust to be established between parties who wish to exchange personal data, we foresee that some degree of “computational law” technologies may have to be integrated into the design of personal data systems. Such technologies should not only verify terms of contracts (e.g. terms of data use) against user-defined policies but also have mechanisms built-in to ensure non-repudiation of entities who have accepted these digital contracts. Efforts such as [1, 2] are beginning to bring non-repudiation and enforceability of contracts into the technical protocol flows.
- *Development of institutional controls for digital institutions*: Currently there are a number of proposal for the creation of virtual currencies (e.g. BitCoin [5], Ven [35]) in which the systems have the potential to evolve into self-governing “digital institutions” [19]. Such systems and institutions that operate on them will necessitate the development of a new paradigm to understand the aspects of institutional control within their context.

8 Scenarios of Use in Context (Dazza)

Supporting the effective development of institutional controls for big data requires an understanding of how to define and work with the applicable context surrounding the scenarios within which the Big Data exists. In particular, the New Deal on Data will require a set of Institutional Controls involving governance, business, legal, and technical aspects that are knowable only with reference to the relevant context of a factually based scenario of use. The following scenarios demonstrate signature features of the New Deal on Data in various contexts and serve as an anchor to evaluate what Institutional Controls are well aligned.

521 8.1 Example Scenario: Research Systems

522 **AS: This entire section requires significant write-through.**

523 Computational Social Science (CSS) studies are based on data collected often with an ex-
524 tremely high resolution and scale [23]. Using computational power combined with mathematical
525 models, such data can be used to provide insights into human nature. Much of the data collected,
526 for example mobility traces are sensitive and private; most individuals would feel uncomfortable
527 sharing them publicly. The need for solutions to ensure the privacy of the individuals has grown
528 alongside the data collection efforts.

529 The data collection in the CSS context is based on the informed consent of the partici-
530 pants. Countries have different bodies regulating such studies, for example Institutional Research
531 Boards (IRBs) in the US. Although certain minimal requirements for implementing informed
532 consent exist **AS: reference** , they are often not very well suited for the large-scale studies,
533 where the amount and sensitivity of the data calls for sophisticated privacy controls. As the
534 scale of the studies grows, in terms of the number of participants, collected bits per user, and
535 duration, the EULA-style informed consent is no longer sufficient and makes it hard to claim
536 that participants in fact expressed informed consent.

537 One author (Stopczynski) deployed this year a 1,000 phones study at Technical University
538 of Denmark, freshmen students received mobile phones in order to study their networks and
539 social behavior in the important change moment of their lives, when joining the university.
540 The study, called SensibleDTU (<https://www.sensible.dtu.dk/?lang=en>), uses not only data
541 collected from the mobile phones (location, Bluetooth-based proximity, call and sms logs etc.)
542 but also data collected from social networks, questionnaires filled out by participants, behavior
543 in economic games and so on. As the data is collected in the context of the university, there is
544 potentially a big issue of students feeling obliged to participate in the study, feeling that their
545 grades may depend on it, or that the data may influence their grades. In this context, we see
546 the implementation of Living Informed Consent not only as a technical mean to put participants
547 in control of the data we collect, but also to convey the message about the opt-in nature of the

548 study, the boundaries of the data usage, and parties accessing the data.

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

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

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

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

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

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

596 8.2 Scenarios of Use Today, Tomorrow and the Day After

597 **AS: This paragraph is impossible to follow for someone without deep background**
 598 **knowledge of what is the message. Too many random made up scenarios, entities,**
 599 **all mashed together.**

600 By inquiring into and noting the four facets of relevant context described above, it is pos-

sible to describe the basic material contours of any scenario within which Big Data exists such that the operational framework and adequate approaches to access, use, confidentiality, and other key interests can be sustainably balanced. In a commercial scenario the relevant people might be a consumer, merchants, banks, products manufacturers, third party app developers, and individual members of that consumers bowling team. The relevant transactions might be a purchase of goods by the consumer from the merchant and the corresponding app that was embedded in the goods and the downstream transaction of involving the consumer now transacting with the merchant bowling alley and interacting with a bowling team, with whom activity and sports performance data are shared and aggregated and further mashed up. The rest of the context can be described for any given scenario and this all could be expressed specifically rather than by role simply by running a report from the system to indicate it was in fact John Doe, of openpds.org/owner/571 purchasing a smart bowling ball from Bowl-a-Tronic of bowlapp-good.com/store/221 and so on for each party that played a role in the relevant scenario. The same techniques, used for scenarios in other economic sectors and social endeavors shed light on the fundamental nature and implications of Big Data and options for the use of operational frameworks acting across domains to balance privacy and access, among other interests.

AS: Bold claims here, not sure if we have sufficient support for them in the chapter.

This book represents a high value opportunity to take stock of the current state and dominant trends related to Big Data and help to illuminate important choices at a moment of early adoption, dynamic innovation, and wide open possibilities. By contemplating the relevant contexts of today's scenarios of use in, say, the fields of education, entertainment, government, manufacturing, transportation, and many other core anchors of human activity, we have traction to postulate how today's prevailing trends are likely to result and what changes - perhaps quite small but of profound long term impact - could lead to materially different better outcomes. Consider that if the essence of the New Deal on Data was accepted today, or soon, the nature, tenor, capabilities, and experience of living by future generations could be unrecognizably

628 better. Simply extrapolate from the current anomalous practices regarding personal data and
 629 individual identity and push forward the timeline by 5, 10, 20 years and beyond. The current
 630 trajectory ends up with dystopian scenarios that effectively reverse hard fought, but easily lost
 631 constitutional deal of the United States and social compact of common law societies.

632 By contrast, by adopting the New Deal on Data now it is possible to set conditions that
 633 promote prosperity and invention even before the New Deal on Data frameworks are formally
 634 launched. This is because the uncertainty and confusion about the basic premises and expecta-
 635 tions around personal data and identity will be resolved and so investment and risk taking on
 636 a firm foundation can be unleashed. The value of Big Data can be accessed at less direct cost
 637 and lower risk when uncertainties about privacy liability are addressed and significant the new
 638 value is created by enabling wide scale permission based access to personal data and compu-
 639 tations about such data. Adopting use of personal data services in phases, such one economic
 640 sector, transaction type or data type at a time enables access to the lower costs and new value
 641 in a reasonable manner that allows for time to prepare for and stage each phase of adoption.
 642 By staging and phasing the New Deal on Data typical objections to change based on grounds
 643 of cost, disruption or over regulation can be addressed. Policy incentives can further address
 644 these objections, such as allowing safe harbor protections for conduct of organizations operating
 645 under the rules of a trust network. Policy makers can resolve other difficulties by combina-
 646 tions of strategic transition management methods like allowing safe harbor compliance delays,
 647 or approving alternative adoption paths and granting other non-substantive waivers to ease any
 648 burdens of migrating to new business methods. The key point is change management can be
 649 designed to achieve enough value at every phase for every key stakeholder group such that self
 650 interests and the broader interests are all aligned with the public good.

651 **9 Future Research (Brian)**

652 Our traditional methods of testing and improving government, organizations, and so on are of
 653 limited use in building a data-driven society. Even the scientific method that we normally use

do not work as well as we might expect, because 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 [25]. 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 this type 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.

9.1 Research on Design and Deployment of Big Data Systems

AS: I do not understand this paragraph? What is top current research? Where is it applied? In order to achieve low risk, high value outcomes efficiently, design and deployment of the coming global wave of Big Data systems should apply top current research. To understand and address the unique problems and prospects associated with big personal data, the relevant context must be identified and corresponding rules-driven capabilities must be designed into the underlying systems.

People or systems can determine the right rules to apply to data when the right information is reliably attached to or logically associated with that data in a standard manner **AS: I think I**

680 **understand this previous sentences but I' m not sure. What is 'a standard manner'**
 681 **here? What is the right information? It seems it is described in the next sentences,**
 682 **maybe remove this one then? .** Any system that can make, use, receive, or share Big Data
 683 must be capable of associating provenance and purpose for all data in a common and actionable
 684 manner. Requiring a lot of narrative documentation and background about the nuances and
 685 circumstances surrounding every data set is both impractical and counterproductive. By con-
 686 trast, a small amount of metadata listing or reliably linking the parties, transactions, systems
 687 and provenance of the data would suffice. This relevant context together with the data forms
 688 the basis for accountable analysis on big personal data.

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

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

702 **AS: I feel Big Data term is abused in this section...**

703 While some capabilities, such as ingesting and processing astronomical data-sets, will be
 704 unique to only a subset of Big Data systems, it is reasonable to anticipate that data will be
 705 increasingly cross-tabulated, merged, and otherwise shared with other systems and data. It can
 706 be nearly impossible to conclusively predict for the entire life of a system what data will be

received by, created in, or transmitted from that system at the design phase. This prediction is all the harder to make when the systems are intended for Big Data.

The four contextual facets of people, interactions, technology, and data provide a sound underpinning for the design of new Big Data and Web 2.0 systems. The existing systems design and development processes of establishing business cases, use cases, agile stories, functional requirements, etc. do not reliably identify the factors most relevant to use of Big Data, especially in a Web 2.0 massively distributed environment. The four facets can also be used to analyze appropriate, required or prohibited uses for existing Big Data systems. However, it can be difficult to extract the relevant information from or apply any effective control on systems used for Big Data but designed to achieve limited purposes in hierarchical closed environments.

Big Data, by its nature, represents a new set of business, legal, and technical capabilities and requirements. Most of the worlds systems today are not capable of ingesting, storing, using, or dynamically flowing big data with other systems. Considering that a) Big Data is of high value immediately and higher value in the short and long terms, and b) the young but competitive marketplace of Big Data system components, platforms, applications, and other solutions is a hotbed of innovation it can be predicted that a transition to Big Data systems will continue. The key observation is that virtually all Big Data systems have yet to be designed, implemented, customized, or deployed. Institutions that are the current early adopters of todays Big Data system will soon replace those systems and the rest of the world will adopt big data systems in phases over time. Based upon this observation, **AS: ??????????????**

9.2 Research on Big Data for Design of Institutions

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

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

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

749 An example of such a Living Lab is the ‘open data city just launched by one author (Pentland)
 750 with the city of Trento in Italy, along with Telecom Italia, Telefonica, the research university
 751 Fondazione Bruno Kessler, the Institute for Data Driven Design, and local companies. Import-
 752 tantly, this Living Lab has the approval and informed consent of all its participants they know
 753 that they are part of a gigantic experiment whose goal is to invent a better way of living. More
 754 detail on this Living Lab can be found at <http://www.mobileterritoriallab.eu/>.

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

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

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

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

777 The Trento Living Lab will let us investigate how to deal with the sensitivities of collecting
778 and using deeply personal data in real-world situations. In particular, the Lab will be used as a
779 pilot for the New Deal on Data and for new ways to give users control of the use of their personal
780 data. For example, we will explore different techniques and methodologies to protect the users
781 privacy while at the same time being able to use these personal data to generate a useful data
782 commons. We will also explore different user interfaces for privacy settings, for configuring the
783 data collected, for the data disclosed to applications and for those shared with other users, all
784 in the context of a trust framework.

785 10 Conclusions

786 Our societies today face unprecedented challenges. Solving those problems will require access
 787 to the personal data, so we can understand how the society works, how we move around, what
 788 makes us productive, how the ideas and diseases spread. The insights must be actionable,
 789 available in real-time, and engaging the population, creating the nervous system of the society.
 790 In this chapter we have reviewed how Big Data collected in institutional context can be used for
 791 the public good. In many cases, the data needed for creating better society is already collected
 792 and exists closed in silos of companies and governments. Using well designed and implemented
 793 set of institutional controls, covering business, legal, and technical dimensions, we described how
 794 the silos can be opened. The framework for doing this — the New Deal on Data — postulates
 795 that the primary driver of the change must be the ownership of the personal data, given to
 796 people about whom the data is. This ownership, the right to use, transfer, and remove the data
 797 ensures that the data is available for public good, while at the same time protecting the privacy
 798 of the citizens.

799 The New Deal on Data is still new. Here we described our efforts in understanding the
 800 technical means of how it can be implemented, the legal framework around it, business ramifi-
 801 cations, and the direct value that can be derived from researchers, companies, governments, and
 802 users having more access to the data. It is clear that companies must play the major role in the
 803 implementation of the New Deal, incentivized by business opportunities and pressured by the
 804 legislation and demand of the users. Only with such orchestration it will be possible to change
 805 the current feudal system of the data ownership and finally put the immense quantities of the
 806 collected personal data to good use.

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