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Beyond Data Literacy:
Reinventing Community Engagement and Empowerment in the Age of Data

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September 2015

Working Paper for Discussion

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Foreword

About this document

This document is part of Data-Pop Alliance's White Papers Series developed in collaboration with our partners. This White Paper was developed in collaboration with the Internews Center for Innovation and Learning—who also provided funding—and researchers from the MIT Media Lab Center for Civic Media, as well as Data-Pop Alliance.

Data-Pop Alliance is a coalition on Big Data and development jointly created by the Harvard Humanitarian Initiative (HHI), the MIT Media Lab, and the Overseas Development Institute (ODI) to promote a people-centred Big Data revolution.

About the co-authors

This paper was written by the following co-authors:

- **Rahul Bhargava,** Research Scientist, MIT Media Lab Center for Civic Media
- **Erica Deahl,** Innovation Specialist, 18F, General Services Administration; formerly graduate student and research assistant, MIT Media Lab Center for Civic Media
- **Emmanuel Letouzé** (Lead and corresponding author), Director and co-Founder, Data-Pop Alliance; Visiting Scholar, MIT Media Lab. eletouze@datapopalliance.org
- **Amanda Noonan,** Director of Research Design & Learning Internews Center for Innovation & Learning
- **David Sangokoya,** Research Specialist, Data-Pop Alliance
- **Natalie Shoup,** Program Manager, Data-Pop Alliance

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Box 3 was written by Lauren Barrett, Communication Strategist, Data-Pop Alliance, who also provided comments. Appendix 3 was developed by Gabriel Pestre, Research Scientist, Data-Pop Alliance, and Carson Martinez, Research Intern, Data-Pop Alliance, who also edited the document.

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Glossary of key terms and concepts

Algorithms: In mathematics and computer science, an algorithm is a series of predefined instructions or rules – often written in a programming language intended for use by a computer – designed to define how to sequentially solve a recurrent problem through calculations and data processing. The use of algorithms for decision-making has grown in several sectors and services such as policing and banking.

Big Data: The ecosystem created by the concomitant emergence of 'the 3 Cs of Big Data':

- Digital *Crumbs*—pieces of data passively emitted and/or collected by digital devices which constitute very large data sets and streams and contain unique insights about their behaviors and beliefs;
- Big Data *Capacities*—what has also been referred to as Big Data Analytics, that is the set of tools and methods, hardware and software, know-how and skills, necessary to process and analyse these new kinds of data—including visualization techniques, statistical machine-learning and algorithms, etc.;
- Big Data *Communities*—which describe the various actors involved in the Big Data ecosystem, from the generators of data to their analysts and end-users—i.e. potentially the whole population.

Civic technology: A type of technology that enables citizen engagement or makes government more accessible, effective, and efficient for the economic and social good of society. This specific type of technology helps to connect people to resources, ideas, and other people needed to improve their societies or communities.

Data: An object, variable, or piece of information that has the perceived capacity to be collected, stored, and identifiable. It comes largely in two forms: structured and unstructured.

> *Structured data* are essentially answers to questions asked by the collector of data, are generally easy to organize and identify and have a strict hierarchy that is not easily manipulated (i.e. responses to a survey organized in a table format and information about people's years of education and income in a chart).
>
> *Unstructured data* are not readily amenable to automated analysis and often are used in ways that differ from the intended purpose when collected (such as photos, videos, tweets), and do not need to follow a hierarchical method of identification.

Data is also used as a policy concept and social phenomena (e.g. "data is changing the world"), or as a shortcut for data ecosystems, Big Data, etc.

Data ecosystems: Complex adaptive systems that include data infrastructure, tools, media, producers, consumers, curators, and sharers. They are complex organizations of dynamic social relationships through which data/information moves and transforms in flows.

Data exhaust: Data that are passively emitted from cell phones, sensors, social media and other platforms as digital translations of human actions and interactions.

Data inclusion: The universal ability of people to create, control, access and use data.

Data journalism: A new form of journalism stimulated by the open data movement, in which stories are presented or supplemented through graphics or visualizations of analyzed datasets. These static or interactive graphics include databases, maps, diagrams, grids, charts and many other forms of illustrations that have transformed the look of mainstream news media.

Data literacy: The desire and ability to engage constructively in society through and with data.

Data modeling: Using existing datasets to infer current conditions or predict future outcomes. The process involves resolving complex relationships among datasets in order to understand what data means and how the elements relate.

Data Revolution: A term that has become mainstream in the policy and development discourse since the High-Level Panel of Eminent Persons on the Post-2015 Development Agenda called for a *"Data Revolution"* to *"strengthen data and statistics for accountability and decision-making purposes"*. It refers to the applications and implications of data as a social phenomenon. The term *"Industrial Revolution of Data"* was coined by Computer Scientist Joseph Hellerstein in 2008.

Data science: A field of research and practice that focuses on solving real-world problems using large amounts of data by combining skills from often distinct areas of expertise: math, computer science (hacking and coding), statistics, social science, and even storytelling or art.

Digital divide: The differential access and ability to use information and communications technologies between individuals, communities and countries — and the resulting socioeconomic and political inequalities.

Literacy: As defined by UNESCO, "*the ability to identify, understand, interpret, create, communicate and compute, using printed and written materials associated with varying contexts. Literacy involves a continuum of learning in enabling individuals to achieve their goals, to develop their knowledge and potential, and to participate fully in their community and wider society.*"[4]

Literacy in the age of data: See Literacy in a post-2015 world.

Open data- Data that is easily accessible, machine-readable, accessible for free or at negligible cost, and with minimal limitations on its use, transformation, and distribution

Popular data: The practice of engaging, empowering and participatory approaches to data-driven presentation and decision-making (R. Bhargava).

Small data: Explicitly collected data – the data is collected in the open, with notice, and on purpose. Small Data can be analyzed by interested laymen. Small Data doesn't depend on technology-assisted analysis, but can engage it as appropriate." (R. Bhargava).

(Statistical) Machine learning- A subset of data science, falling at the intersection of traditional statistics and machine learning. Machine learning refers to the construction and study of computer algorithms — step-by-step procedures used for calculations and classification — that can 'learn' when exposed to new data. This enables better predictions and decisions to be made based on what was experienced in the past, as with filtering spam emails, for example. The addition of "statistical" reflects the emphasis on statistical analysis and methodology, which is the main approach to modern machine learning.

Executive Summary

The term 'data literacy' has gradually emerged as a mainstream term and potential buzzword of the 'Data Revolution' discussions, as experts, policymakers and advocates began considering what it would take to enable citizens to make better use of the vast amount of data available to them. Policymakers have advocated for more data science skills-training programs. Schools and non-profit organizations (such as Code for America, Girls Who Code, School of Data, etc.) have emerged to tackle the digital divide by providing coding programs and technical curricula for vulnerable populations, specifically for women and minorities. An increasing number of data journalists are using and writing about data. Open data and civic technology advocates have organized hackathons for civic hackers to use technical skills and foster new conversations on data for social good.

Despite its growing popularity as a much-needed "bottom-up" solution, data literacy is ill-defined or ambiguous at best. Are current conceptualizations of 'data literacy' adequate—or do they put too much emphasis on technical requirements and fail to challenge deeper structural and more politically controversial issues? What does it mean to be "data literate" in an age where data is everywhere—and how does it differ from being literate? Why and how should it be promoted? How might the promotion of 'data literacy' empower individuals and communities to keep governments accountable, solve local problems, and navigate their own data ecosystems? In a world of ubiquitous digital connectivity and rising inequity, should we in fact be concerned with and talking about *data inclusion* instead?

We first discuss 'data literacy' as an emerging concept within a much longer historical narrative of literacy promotion. History sheds light on how defining and promoting literacy—who was literate and who was not—has been often entrenched with the constructs and perpetuation of power structures within societies—at odds with the notion of literacy as a necessarily empowering and enlightenment force. There is a risk that the same processes may play out in the age of data, at a speed and scope commensurate with those of the spread of data as a social phenomenon.

We define data literacy as *"the desire and ability to constructively engage in society through and about data."* Five observations emerge from this definition:

1. "Desire and ability" highlights technology as a magnifier of human intent and capacity.
2. "Ability" underlines literacy as a continuum, moving away from the dichotomy of literate and illiterate.
3. "Data" is understood broadly as "individual facts, statistics, or items of information."
4. "Constructively engage in society" suggests an active purpose driving the desire and ability.
5. And "through or about data" offers the possibility for individuals to engage as data literate individuals without being able to conduct advanced analytics.

This definition—as well as the nature of data itself—encompasses elements and principles from each of these sub-kinds of literacy (such as media, statistical, scientific computational, information and digital literacies), moving away from medium-centred definitions of literacy towards a more encompassing one.

In utilizing a definition of data literacy that builds on the elements of current sub-categories of literacy and expands beyond particular media—and their technocrats—we describe four key pillars that form its foundation: data education, data visualizations, data modelling, and data participation.

Our exploration of data literacy pushes us to further consider what it would mean to be "literate in the age of data" and denote four core pillars in literacy promotion:

- Data literacy promotion must be agile and adaptive, focusing on helping to foster adaptive capacities and resilience rather than teaching platforms and technical languages that are bound to become outdated.
- Data literacy promotion must build on the key features and pillars from all core sub-categories of literacy, viewing literacy as a continuum.
- Data literacy promotion must involve empowering people to navigate their current ecosystems and societies in ways that are meaningful and effective for them.
- Data literacy promotion must involve providing multiple pathways for people with different data literacy needs and capacities to interact within a complex system.

At the center of the rationale and attention around data literacy promotion should be the goal of empowering citizens and communities as free agents. This can only be achieved by considering data literacy as a significant means and metric for social inclusion—where data literacy as defined and conceptualized above is promoted *for and via greater social inclusion*—or, more appropriately, *data inclusion.*

Here we highlight the following three critical challenges in designing data literacy programs:

- Making Big Data smaller, on scale where most or many more people are willing and able to engage than is the case today
- Understanding the importance of context and utilizing elements of human-centered design;
- Understanding and leveraging the power of words and language in communicating and visualizing data

As we revisit the larger context of the Data Revolution in the last section and concluding remarks in the light of data literacy and social inclusion, it becomes clear that if this Data Revolution is to bring about positive change, it has to be an evolution towards social inclusion in the age of data – towards data inclusion. If a 'business-as-usual' framing for the Data Revolution continues unabated, our efforts toward greater data literacy may reinforce existing power dynamics that promote social exclusion. This transitional period is the opportune time to create a path towards empowerment. Data literacy focused on building data inclusion offers a doorway to understanding, interpreting, and managing data-driven decisions and arguments for all people.

Supporting data literacy is not primarily about enabling individuals to master a particular skill or to become proficient in a certain technology platform. Rather it is about equipping individuals to understand the underlying principles and challenges of data. This understanding will in turn empower people to comprehend, interpret, and use the data they encounter—and even to produce and analyze their own data. This can only be achieved by considering data literacy as a means toward a necessary reinvention of community engagement and empowerment—towards what we term data inclusion.

Introduction

There is no shortage of discussions and initiatives about the promise and perils of leveraging data in various sizes and forms to meet the world's challenges as part of the "Data Revolution" called for by the United Nations and others.[1] But how exactly is data expected to change the world we live in? What is the 'theory of change'? In February 2010, about a century ago in data years, *The Economist* published a widely cited article titled "The Data Deluge: Businesses, Governments and Society Are Only Starting to Tap Its Vast Potential" (**Figure 1**). One of the first online comments read, *"Here's our 21st century jobs, America. Please understand and educate the next generation accordingly."*

Figure 1: "The Data Deluge" as depicted in 2010

Source: http://www.economist.com/node/15579717

Over the past couple of years, the concept of 'data literacy' has emerged as a key priority. Schools and nonprofit organizations have developed programs to teach children how to code at an early age. Advocates in the open data movement have long argued for expanding use of public data beyond experts and trained journalists. Millennial job seekers are taking courses on Coursera, edX, and other open online courses to develop data science skills and increase their competitiveness in the data era. The international development and civic technology communities have also emphasized the need for data literacy as a requirement of the data revolution. These organizations highlight both the potential economic and social impact of data literacy in the physical world and, to a lesser extent, its potential democratizing effect.

However, when it comes to the revolutionary potential of data—and the nature and features of the 'data revolution'—we often miss the big picture. For the most part, the 'data revolution' discourse is based on the notion that what the world misses (and therefore needs most) is more and better data, and more people who are able to collect, analyze, crunch data, to make better decisions. This line of argumentation, on which most calls for enhancing 'data literacy' rests, is not entirely wrong, but it leaves out many complex and controversial questions about why the world of 2015 is in such a bad shape.

As always, valuable lessons can be drawn from history. Claude Lévi-Strauss in his seminal book *Tristes tropiques*, argued that writing and the early decades of literacy promotion served the purposes of power elites. A recent partial evaluation of major data science programs by Stanford researchers also points to major shortcomings in the training of future data scientists.[2]

The rationale for promoting data literacy may seem straightforward. However, society as a whole has little clarity about what data literacy *is*, much less what they should expect from it. Vital questions require answers before we begin to promote data literacy as an answer to the world's pressing problems.

1. What is "data literacy"? What does it entail, and how is it distinguished from statistical literacy, mathematical literacy, digital literacy, numeracy, and similar concepts?
2. Why does data literacy matter? What societal goals is data literacy expected to serve? What is the theory of change that moves from improved data literacy to the achievement of those goals?
3. How adequate are current conceptualizations of data literacy? Does the current emphasis on technical requirements fail to address deeper structural issues? Are we moving toward a dystopian future in which we have to rely on world-class data scientists to fix all our problems for us? (Appendix 1)
4. How might we foster more inclusive approaches to data literacy? How can pervasive data literacy be a force for social inclusion – for data inclusion?

This paper argues for an expansion of the concept of data literacy. We argue that data literacy as a term is inadequate, reinforces existing inequities and should be replaced by the larger concept of inclusion. Fulfilling that vision will be much more demanding and disruptive than developing popular new software systems and delivering face-to-face trainings and MOOCS on statistical packages. Rather, it will involve understanding and defining data literacy in terms of how to effectively empower individuals to navigate their own data/information ecosystems to produce, engage with, communicate and use data. Additionally, as we promote data literacy, we must incorporate human-centered approaches by design, understanding the dynamic and appropriate context involved in curating, synthesizing and communicating data.

As we move forward with the Data Revolution, this is an opportune time to go beyond what we've described as 'data literacy' today and reconsider literacy in the age of data. Further, we must recognize data literacy as the means and metric towards a social inclusion revolution—the deeper goals that make the Data Revolution truly "revolutionary"—towards what we term data inclusion.

To make these points, this paper continues with a discussion of current mainstream approaches to the concept of data literacy. Section 2 advocates for a broader definition of data literacy, and proposes to conceptualize it as *literacy in the age of data*. Section 3 argues that data literacy ultimately ought to be the means and metric of greater social inclusion and *vice-versa*. Section 4 presents options and requirements to support this desirable evolution towards greater social inclusion in the age of data that we term *data inclusion*. Finally, we provide concluding thoughts on today's data generation and its contribution to the data revolution.

1 Genesis, contours and limits of 'data literacy'

1.1 Data literacy: an emerging concept of the 'Data Revolution'

In the new *"Industrial Revolution of Data*,"[3] more and more actors have become interested in tapping into data to solve complex problems. From open government data to sensor data to data exhaust from social media, cell-phones and other digital devices, the vast amount of data available should allow for policy-makers, experts, businesses and activists to ask more informed questions and thereby develop more effective policies and programs.

The term 'data literacy' has gradually emerged as a mainstream term and potential buzzword of the 'data revolution' discussions (Box 1), as experts, policymakers and advocates begin considering what it would take to enable citizens to make better use of the vast amount of data available to them. Arguments commonly put forth include the following:

1. **'Data literacy' increases the economic impact of Big, Small and Open Data.** As companies aim to capitalize on the potential business value generated from data, employees with data science skills have become highly valuable in today's economy. Businesses have begun investing in skill-based trainings to help their analysts "conduct data-driven experiments, to interpret data, and to create innovative data-based products and services."[4] For many managers and business owners, the more "data literate" their workforce, the bigger their profit margins;

2. **'Data literacy' enables local populations to understand and solve local problems.** Development actors and community advocates push data literacy as an opportunity to increase the efficiency and resilience of local actors and communities in solving local problems. Data literate local actors would need to be able to *"work…with very granular data, or data limited in geographic scope, as opposed to statistics that are often aggregated to a higher level."*[5] More critically, data literacy would empower local actors with the ability to not only work with existing data, but generate, own, use and monetize data;

3. **'Data literacy' empowers citizens to keep governments accountable and transparent.** Increased access to government data does not inherently create societal impact. Rather, citizens must be able to interpret, understand and effectively use the data in order to keep governments accountable and "spread the benefits of open government to marginalized communities."[6] Data literacy can help civil society groups catalogue rights violations, fuel data-driven journalism and spur citizen engagement in transparency and anti-corruption efforts. Additionally, advocates voice that increasing 'data literacy' can help bridge an ever-increasing digital divide.

Box 1: From the data revolution to data literacy in two UN-commissioned reports

In May 2013, as the UN began moving toward the post-2015 Sustainable Development Goals, a 'High-Level Panel of Eminent Persons on the Post-2015 Development Agenda' appointed by the UN Secretary-General published a report *"call[ing] for data revolution for sustainable development…to improve the quality of statistics and information available to people and governments."*[7] The report contained three mentions of "literacy", and those referred to "basic" literacy explicitly distinguished from "numeracy".

By contrast, a 2014 report by the UN Secretary-General's Independent Expert Advisory Group on a Data Revolution for Sustainable Development (IEAG) used the term *data literacy* four times and treated it as one of five pillars of its suggested action plan. The report called for an *"education program aimed at improving people's, infomediaries' and public servants' capacity and data literacy to break down barriers between people and data.*"[8]

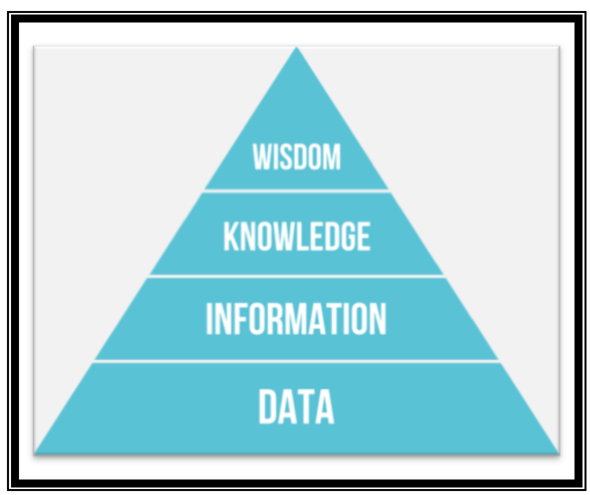
Despite this attention, descriptions of what exactly is meant by and expected from data literacy have been absent or unclear. For example, although the concept featured prominently in the IEAG report (**Box 1**), no definition was provided. In particular, it remained ambiguous whether and how the report distinguished the roles of *"capacity"* and *"data literacy"* in *"break(ing) down barriers between people and data"*—especially given that *"capacity"* was absent in an otherwise similar statement. It was also not clear whether and how the report distinguished *data literacy* and *statistical literacy,* and whether either separately or combined these concepts could be assimilated to *"numeracy"*. Last, it was not clear whether one or both should *"ensur(e) that all people have capacity to input into and evaluate the quality of data and use them for their own decisions, as well as to fully participate in initiatives to foster citizenship in the information age"*. Specifically, how much of the capacity "*to input into and evaluate the quality of data and use them for their own decisions"* versus *"to fully participate in initiatives to foster citizenship in the information age"* ought to be a result or expression of being data literate (versus statistically literate or a combination of both).

The point is not to criticize a report that contained many points and proposals that are currently shaping the global discussions about data, but to highlight how its ambiguities underline the inherent complexity of the issue at hand, beyond and beneath its surface. To date, the questions elaborated in the introduction do not have satisfactory answers.

1.2 Data literacy as competencies of an extractive and transformative industry?

As suggested above, the most commonly voiced argument in favor of 'data literacy' is that people must know how to understand and use data for it to have an impact. As alluded to, the Open Data community has long stressed that making government data 'open'—i.e. available on a website—is not enough; the 'theory of change' involves people having an incentive and the ability to access the site and data, the capability to download it, and the competencies and tools required to analyse it, etc. Similarly, when data in general and Big Data in particular were compared to *"the new oil of the digital economy"*[9] a few years ago, one implicit but obvious step was the 'refinement' or 'transformation' stage. And indeed, Big Data has been defined as *"a mindset (...) to turn mess into meaning"*[10]. The cover of The Economist's Data Deluge article conveys a similar argument about transforming a raw material into a source of growth.

Figure 2: The Classic DIKW Pyramid



These arguments reflect and fuel the main stages of the widely-used vision of a process of transformation from data to information, information to knowledge—all the way up to wisdom, summarized by the DIKW model (Figure 2).[11] The choice of a pyramid and its highly symbolic dimension may actually not be entirely coincidental.

'Data literacy' would refer to the set of skills and conditions for the first step up to occur. This approach and focus have been taken in most popular press articles on the subject. For example, a 2014 Forbes article defined data literacy as the *"ability or ease"* to *"collect, analyse and visualize 18,446,744,073,709,600,000 data points per person in less than one second."*[12]

Even when the bar is set lower than being able to process over 10^{18} data points per second, current conceptualizations of data literacy revolve closely around some version of *"the ability to use and analyse data"*. As we shall see, this definition and its underlying assumptions and expectations about data's potential to bring about change and inherent obstacles to this process is not flat-out wrong—but it focuses on *skills required to perform tasks*.

This conceptualization has implications that must be interrogated and challenged. For one, it says nothing about the ultimate objectives of the transformative process at play—at the top of the pyramid. It doesn't question either the level of data collection—taking the availability of data as a given—like oil sitting there to be extracted and processed. It leaves hardly any room for ethical and political considerations. And yet the analogy with the 'old oil' should serve as a warning: oil fuels economies and emergency vehicles as much as corruption, elite capture, and global warming.

To hammer in the point, it is tempting to bring up the Godwin's point[13] of Big Data: Edward Snowden's revelations about the nature and scope of the surveillance activities of the US National Security Agency. If 'data literacy' were just the ability to turn data into information, a society of junior NSA analysts (and their Amazon or Google counterparts) would be a highly data literate society. With quite a few caveats discussed below, in an era where concerns over data analytics-enabled government surveillance and corporate manipulations (as in the cases of the Facebook social experimentation[14] or the recent Volkswagen scandal[15]) are rising, one can feel intuitively that such a society may not be the most progressive and inclusive. This, *a minima*, suggests that current conceptualizations of what data literacy is, means and entails, are not fully adequate.

1.3 Reconsidering 'data literacy' through the lens of history

One way to probe the concept of 'data literacy' is to reflect on its metaphorical roots—i.e. 'standard' or 'traditional' or 'basic' literacy—to understand how both literacy and efforts to promote it have been defined and conceptualized. History sheds light on how defining and promoting literacy has been often entrenched with the constructs and perpetuation of power structures within societies—at odds with the notion of literacy as a necessarily empowering and enlightening force.

Box 2: Claude Lévi-Strauss on the function of writing and literacy programs in history

"Writing is a strange thing. It would seem as if its appearance could not have failed to wreak profound changes in the living conditions of our race, and that these transformations must have been above all intellectual in character. (…) Yet nothing of what we know of writing, or of its role in evolution, can be said to justify this conception. If my hypothesis is correct, the primary function of writing, as a means of communication, is to facilitate the enslavement of other human beings. …The use of writing for disinterested ends, and with a view to satisfactions of the mind in the fields either of science or the arts, is a secondary result of its invention and may even be no more than a way of reinforcing, justifying, or dissimulating its primary function. [T]he European-wide movement towards compulsory education in the nineteenth century went hand in hand with the extension of military service and the systematization of the proletariat. The struggle against illiteracy is indistinguishable from the increased control exerted over the individual citizen by the holders of power."

Claude Lévi-Strauss, *Tristes Tropiques,* 1955

For example, Claude Lévi-Strauss, in his famous book *Tristes tropiques,* studied the historical role of writing and the rationale for literacy programs during the Industrial Revolution in Europe. He reckoned that the notion that writing "*could not have failed to wreak profound changes in the living conditions of our race*" was a misconception. Rather, he argued, writing— this *"strange thing"*—was, for centuries, a means by which elites perpetuated and strengthened their control of the masses.[16] Further, Lévi-Strauss described literacy campaigns as means of making people able to serve the interests of the elites in power (Box 2 and Appendix 2).

Further, the literature on the effects of (and need for) literacy during the Industrial Revolution is rather ambiguous. By the mid-nineteenth century, the majority of European workers did not need to be literate, then measured by the ability *"to sign one's name,"* but there was a point below which the process of industrialization could not have happened, as *"it was useful to have a wide pool from which those who did need literacy—merchants, clerks, surveyors and engineers, for instance (end of the quote is missing?).*"[17] "As Lévi-Strauss points out too, this period corresponded with the heyday of European Nation-State building[18]—which in parts of Europe also implied the systematic and brutal cracking down on regional languages to impose that of the central authority.[19]

Spurred by international organizations such as UNESCO as well as governments and civil society organizations, efforts to promote universal mass literacy began in the 1950s. As literacy became part of the agenda for an emerging international community post-World War II, campaigns to eradicate "illiteracy" focused on promoting reading and writing as a basic set of skills for autonomy in and across countries. Yet, definitions of literacy differed across states and regions, and global campaigns against illiteracy became fragmented during the Cold War. Since then, the development of new technologies and globalization introduced new literacies, prompting literacy advocates to constantly reconsider the definition of the lowest bar for basic literacy.

The world has changed significantly since Lévi-Strauss wrote these lines. Various forms of literacy, including some related to the use of data, have undeniably made fundamental contributions to people's enlightenment and empowerment—from the civil rights movement to fights for gender equality and environmental protection. But whereas it is not completely clear whether these effects were 'secondary' or explicitly intended, it is evident that literacy programs have always been embedded in local ontologies.

Taking an objective look at the state of affairs today suggests that advanced data analytics techniques, despite their potential to spur human progress, have so far worked especially well for governments and corporations. It is unclear whether and how promoting 'data literacy' the way it is currently conceptualized—by providing skills without much in the way of questioning their ends and means—may reverse or repeat the history of literacy promotion. This invites us to reconsider current approaches to data literacy that are based on overly mechanistic views of the world and its problems.

2 Moving from 'data literacy' towards 'literacy in the age of data'

2.1 Attempt at (re)defining 'data literacy'

Two co-authors of this paper have previously[20] proposed to define data literacy as the ability to read, work with, analyse and argue with data:

- *Reading* data involves understanding what data is, and what aspects of the world it represents;
- *Working* with data involves creating, acquiring, cleaning, and managing it;
- *Analysing* data involves filtering, sorting, aggregating, comparing, and performing other such analytic operations on it;
- *Arguing* with data involves using data to support a larger narrative intended to communicate some message to a particular audience.

In this paper, we put forward a new definition of data literacy that goes one step further. We define data literacy as the **"*the desire and ability to constructively engage in society through or about data.*"**

At least five observations can be made about this definition.

1. *Desire and ability* echoes Kentaro Toyama's conceptualization of technology as a magnifier of human intent and capacity.[21] Awareness and opportunity to engage are front and center;
2. *Ability* allows for varying *levels* of data literacy, away from dichotomy between data literate and data illiterate individuals. Obviously different positions and different goals require different levels of data literacy. Certain basic thresholds might be established to define minimal data literacy, and these could change over time;
3. *Data* is understood in its broader sense; data has been defined as *"individual facts, statistics, or items of information, or "a body of facts"*, and in that sense a news article whether printed or online, a tweet, an Instagram photo, a video – all of these are data. In the realm of data analytics, the distinction overlaps in great part although not fully with the distinction between *unstructured* data (such as files) and *structured* data (typically databases) (Box 3). Though this notion may indeed seem very broad, as it suggests that potentially *everything,* from music[22] to a chair's molecular structure and thus aspect, are or could be data, a feature of the world's future may very well be ubiquitous data-ification;
4. *Constructively engage in society* suggests an active sense of *purpos*e—it suggests that literacy must be sought, deployed and measured in relation to specific goals that are deemed 'constructive'; of course these will be highly dependent on context but these rule out, for instance, any goal that infringes on Human Rights;[23]
5. *Through or about* offers the possibility for individuals to engage in society through *and/or about* data—i.e. one can be data literate without being able to conduct advanced analysis.

This definition also encompasses existing medium-based literacies. Evolutions in definitions of literacy have been on par with the emergence of 'sub-kinds' of literacies with their own specific definitions and requirements—statistical literacy, scientific literacy, media literacy, digital literacy and more. Breaking down 'literacy' into its constitutive pieces has practical value, but shaping various forms of literacy around emerging mediums increases the 'silo-ification' and technocracy around these mediums.

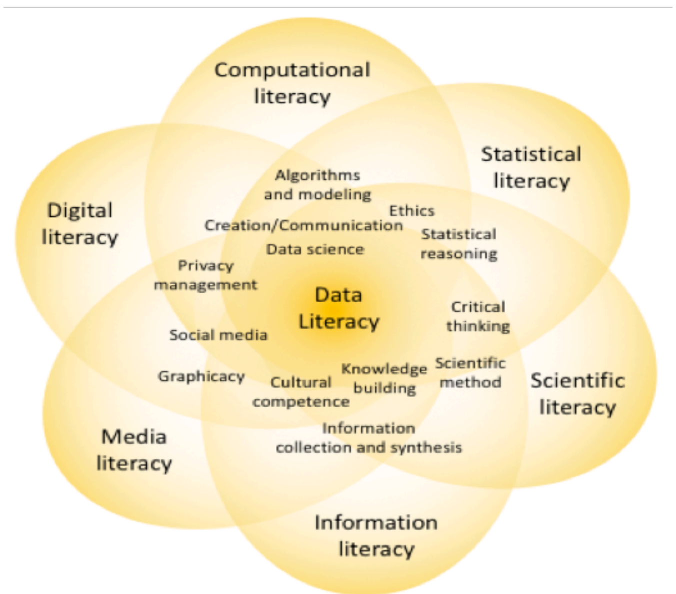
The attitudes and skills implied by our definition of data literacy can be pulled from the following sub-kinds of literacy:[24]

1. ***Information literacy*** is a pre-Internet era concept that emphasizes the importance of being able to locate and determine the credibility of information.
2. ***Scientific literacy*** focuses on the application of scientific concepts and experimentation methods needed for personal decision-making and civic participation.[25]
3. ***Media literacy*** in contrast deemphasizes the acquisition of technical skills and focuses instead on supporting media production and developing a critical understanding of issues such as modes of representation, language, production, and audience.[26]
4. ***Statistical literacy*** is about enabling individuals to critically assess and use statistics within their everyday lives.
5. ***Computational literacy*** encourages individuals to seek algorithmic approaches to problems, move between different levels of abstraction, and use modelling as a way to identify relationships.[27,28]

6. ***Digital literacy*** involves "the ability to find, evaluate, utilize, share, and create content using information technologies and the Internet."[29]

Data literacy interacts with and builds on all six of these approaches and requires a combination of the technical, critical, quantitative and conceptual skills on which they are based (Figure 3). This definition—as well as the nature of data itself—encompasses elements and principles from each of these sub-kinds of literacy, moving away from medium-centred definitions of literacy towards a more encompassing one.

Figure 3: How different modern types of literacies interact



Source: authors' elaboration based on secondary sources

Since data are used differently in various domains, researchers have proposed multiple, possible definitions of the competencies required to be data literate. These definitions differ in terms of the skills they emphasize, the level of technical proficiency they call for, and the methods and technologies they specify. Data literacy demands pedagogical approaches that are customized to the context of the learners, and every program will need to tailor its approach to focus on the competencies appropriate for its particular mission and audience.

One facet of this definition of data literacy that is valuable in a pedagogical and research context is that it emphasizes the importance of interdisciplinary thinking as a core component of data literacy. Discipline-specific approaches to data literacy focus on either quantitative or qualitative investigation, which can bias the resulting interpretations. Quantitative analysis makes it possible to uncover hidden patterns and gain insight into complex datasets, while qualitative analysis makes it possible to surface individual stories within those aggregations. Increasingly, institutions have recognized that these methods can be complementary; by learning both approaches, individuals can explore an issue from multiple perspectives and reach more balanced and comprehensive conclusions.

Similar to the history of other literacy efforts, data literacy will not be a quick fix, but a rather slow exercise in behaviour change. Spurring engagement and enhancing the universal perceived value of data literacy will require marketing the skills as essential to everyday functioning and long-term advancement and presenting data as accessible and applicable. It will be an evolution in intellectual dynamics.

As alluded to, the ethical and political implications of this new data age, such as human rights abuses, lie in our conceptualization of data literacy. To effectively *engage* participants in data ecosystems there will be a need to understand, design and communicate approaches that foster contextually relevant, human-centred, culturally resonant and effective engagement and use. The primary protection against encroachment of rights lies in data literate citizens with the *desire and ability* to comprehend and control the use of their data.

If we conceptualize—and indeed confine, as we will discuss below—data literacy within these parameters, what does it look like, entail, and require? How can it be further unpacked?

2.2 Foundational pillars of 'data literacy'

In employing a definition of data literacy that builds on the elements of current sub-categories of literacy and expands beyond particular media—and their technocrats—we describe four key pillars that form its foundation: data education, data visualizations, data modelling, and data participation.

The "data" in data literacy: data education

First, data literacy involves understanding what data is, or are, and does, or do—that is, basic data education. It entails, at minima, being able to define data; contrast and connect data with statistics[30]; distinguish structured and unstructured data, qualitative and quantitative data, etc. (Box 3). It also implies critically assessing what they contain, convey, represent, even at a fairly abstract level—pieces of information that result from the translation, the coding, of some human experience into a language; numbers, words, pixels—with full or limited awareness of the object (be it an individual, a community, a country) characterized in the data.

It follows that central to basic data education is acknowledging the imperfect and biased nature of data. The simplistic assumptions that data, especially when they get bigger, are a neutral and unbiased representation of reality has been criticized by Crawford and others who have brought attention to the ethical dilemmas inherent in these data practices. Datasets are still *"objects of human design"* and therefore vulnerable to error and biases.[31] This can happen at various stages of the process of data collection, analysis, and representation, unintentionally or through deliberate manipulation.

Specifically, structured data are created intentionally to answer a particular question, and their creators often bias the way the data are created to get the answers they want. This limits the usefulness of the data to their viewpoint. (In other words, structured data is answers, not raw data). Unstructured data on the other hand are primarily created with intentions other than what they are being used for (photos are created for fun and memory, tweets for connecting to friends, etc.). The interpretation for social purposes comes after the data creation, and it is then that biases—notably political—can creep in. Unstructured data, however, make it possible to revisit the data with different perspectives and purposes: they thus support debate and a broad range of knowledge creation.[32]

These are only a handful of the features of data that a data literate individual—someone *willing and able to constructively engage in society through and about data*—should grasp. These features, for the most part, are post-collection and pre-analysis. We can then examine three additional building blocks of data literacy: data visualization, data modelling, and data participation.

Box 3: What is Data?

There is no agreed-upon definition of data. In general, data is an object, variable, or information that has the perceived capacity to be collected, stored, and identified. According to Oxford Dictionaries, data is *"facts and statistics collected together for reference or analysis."*[33]

There are two main types of data: *structured* and *unstructured*. The former are created intentionally to answer a particular question; as a result they are easy to search for, organize, and identify and have a strict hierarchy. The hierarchy for a person's favorite food might be: food, fruit, apple, red delicious. Each variable is clearly defined and labeled in a way that fits the structure's taxonomy. Relational databases, popularized by IBM in the 1970s and 1980s, offered a significant improvement in the use of structured data in comparison to earlier hierarchical models.

Structured	Unstructured
• Hierarchal structure • Least flexible • ~10% of data and decreasing • Each unit corresponds with a specific row and column, i.e. hierarchy. Follows ACID model: Atomicity, Consistency, Isolation, Durability	• No set internal structure • Most flexible • ~90% of data and increasing • Each unit may have its own identifiable set of information and does not correspond to a particular hierarchy, such as film clips, pictures, and text documents

Unstructured data are everything else. It can be photos, word documents, and other variables that do not need to follow a hierarchical method of identification. For example, someone can input data, such as an 'apple', without having to sequence it under the category of 'fruits' or know that there is a subcategory of 'red delicious.'

Is unstructured data completely disorganized then? No. *Metadata* can be used to describe unstructured data. This can be *.jpeg* for example if it is used to describe a picture of an apple.

Over 90% of data is unstructured data, and it is growing exponentially in comparison to structured data because of the rapid creation of digital data, such as videos and tweets. As a World Bank report notes, "a 10-minute video of cats uploaded on YouTube may be quite heavy in terms of bytes but arguably contain less value than say Walt Whitman's *Leaves of Grass*." [34]

Qualitative	Quantitative	
Responses to a survey about people's activities during the weekend organized in a table format with columns and rows	Information about people's age (in years), years of education, income, and amount spent in a table format with columns and rows	**Structured**
Photos from weekend activities, which can be organized or unorganized by size, type of photo (*i.e. .jpeg*), and photo descriptions, etc.	Field notes about people's income, age or other quantitative data; or scans of the table described directly above	**Unstructured**

The Big Data revolution is a result of this rapidly growing unstructured data. Much of this unstructured data is qualitative, however, the large majority of tools used to derive insights from data are quantitative in nature, such as statistics.[35] As greater techniques and tools are needed to analyze and make use of this data – i.e. actionable insights – there is a greater need to create quantitative, structured metadata surrounding these unstructured big data sets in order to employ these analytical tools.

Data visualizations

Data visualizations, the typical vehicle through which data are conveyed to the public, are not necessarily accurate, accessible or appropriate within their contexts. A data visualization calls attention to a specific pattern or story within a dataset, illustrating one of many possible interpretations; a visualization cannot communicate the full complexity of a dataset. This raises the issue of the questions we ask of data – questions that inevitably will involve a degree of bias at least to some extent.

Creating and understanding data visualizations requires *graphicacy*. Graphicacy is *"the ability to understand and present information in the form of sketches, photographs, diagrams, maps, plans, charts, graphs and other non-textual, two-dimensional formats"*.[36] It is a complementary skill that is necessary for the effective communication of data-derived information. Beyond graphicacy, it is also necessary to understand how different ways of communication may or may not be cultural appropriate in terms of symbols, visuals and media. At present our understanding of such effective and culturally appropriate communication is sparse. The challenge and opportunity will be to work with communities and individuals to surface their contextual understanding of data and the ways to understand, find, capture, use and communicate these, as illustrated in Box 4.

Furthermore, the bias in visualizations is often deliberate.[37,38] A highly data literate person or public will understand not only how to interpret data visualizations, but also how to assess the reliability and objectivity of the sources.

Box 3: Understanding data; case study in graphicacy

To test the accessibility and utility of data visualizations created for the Kenyan media, Internews led a pilot investigation. In Kenya and elsewhere, the publication of data visualizations in print news media is a recent phenomenon, linked to the popularization of data journalism.

The study tested four different textual and graphical representations of data. There was no significant difference in participants' comprehension of text-based analysis versus graphic. Among the graphic representations, simple bar charts were most easily interpreted.

Pinker's theory of graph comprehension contends that viewers must be able to recognize specific types of graphs to be able to translate their visual information into quantitative information. "If this type is unknown to the viewer, s/he will almost always struggle with interpretation at first glance. According to Pinker, there are three routes to comprehension: "being told," induction, and deduction.

Improvement in the ability to read graphs may be best enhanced by explicit instruction. Furthermore, aesthetic preference and even the ability to read a graph may be culturally determined. Picture stories with which the audience can identify appear to facilitate recall. This finding aligns with the "active audience" theory in media reception studies.

Data modelling

Data modelling—using existing datasets to infer current conditions or predict future outcomes—has become a prominent practice among corporations and municipalities because it has proven to be so profitable. Overreliance on data modelling often fails to fully account for human error, oversimplifies complex factors, makes it difficult to verify the quality of the original data, and points toward solutions that overlook human needs.

A well-known example of data modelling's potential for failure due to human bias and flawed methods is the series of devastating fires in the Bronx in the 1970s that resulted from the RAND Corporation's recommendation to close numerous fire stations in one of New York City's poorest neighbourhoods.[39] Another common issue that is as old as statistical analysis is spurious correlations and confusing correlation with causation; one new challenge is the fact that, with more data, spurious correlations and meaningless patterns are easier to find—this has been referred to as *"apophenia*[40]*"*—which some policymakers, salespersons and various advocates have been known to use and abuse to advance their own agendas or embellish their accomplishments.[41]

These examples illustrate the perils of an overreliance on data and data analytics when data modelling is used without taking into consideration existing local knowledge and the agility of human behaviours. Further, using abstruse methods of data analysis that seem authoritative makes policies harder for opponents to verify and critique. These issues all have a profound impact on individuals, most of whom do not know what predictive data modelling is, let alone have the knowledge to evaluate and point out its shortcomings.

The public needs to be more data literate to interrogate and potentially challenge these very decisions and processes. This highlights the critical need for usable tools and trusted intermediaries that are able to open the 'black boxes' and unpack these processes and expose their potential biases in comprehensible and engaging ways.

Participation

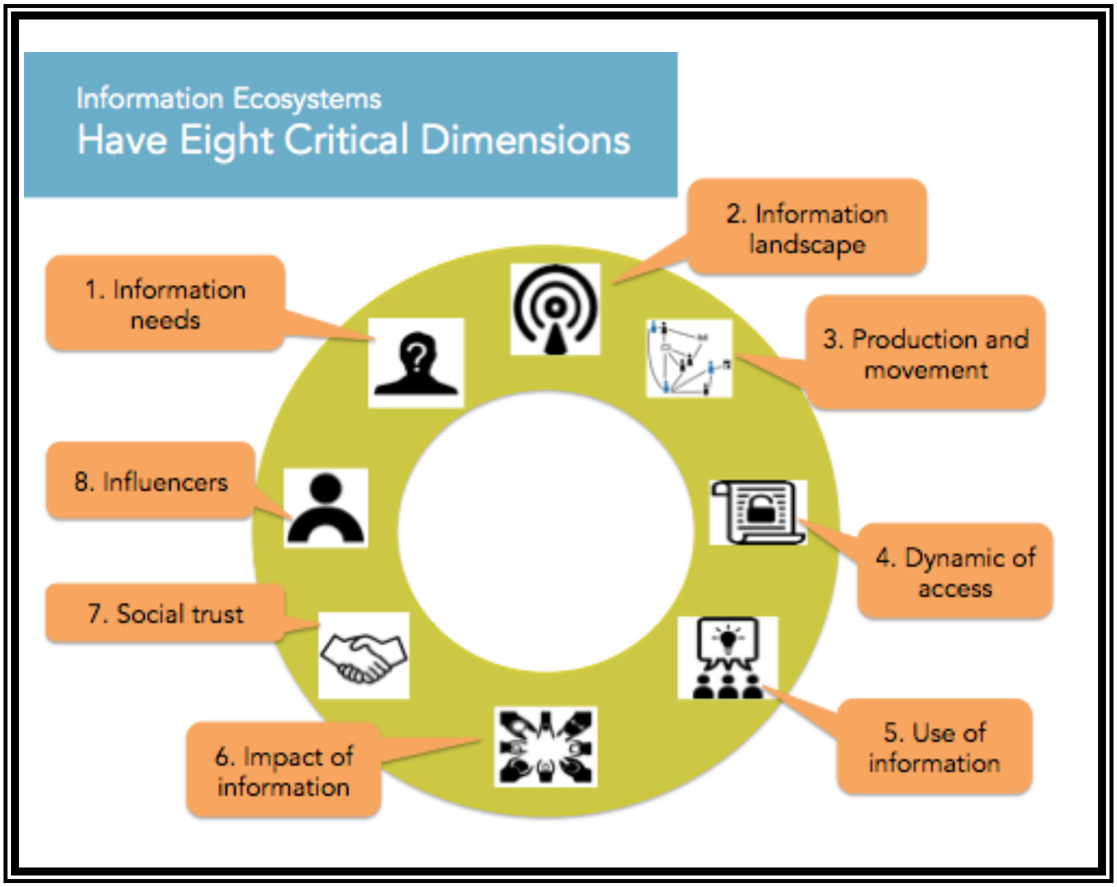
Most people are excluded from engaging with data for a host of technological, technical, cognitive and practical barriers. As a result, they are unable to influence the types of applications that are built, and to direct those efforts toward outcomes that may benefit their communities. Even applications that are intended to engage diverse communities in contributing data run the risk of overlooking underserved communities who may lack access to the technology necessary to participate.[42,43]

The open data movement attempts to address this issue by making data free and readily available, thereby increasing the transparency of public institutions and encouraging public participation. As it stands, most of the individuals taking advantage of open data resources are civic technologists with existing expertise who come with their own biases and perspectives. Most people are still excluded from engaging with data since they require access to education, infrastructure, and technology.

Data literacy as a concept involves the interaction of multiple ecosystems containing both literate and illiterate actors. The ability to use data and to create actionable knowledge requires understanding of local information ecosystems: how data is transformed into information, then knowledge, as it flows through different points and channels in a dynamic, non-linear, networked system. The function or role of any node or point within an information ecosystem changes depending on the context. A farmer can be a consumer of information received through a mobile phone alert, a producer of information as they transcribe the information on a bag of rice, and a mover and influencer of information as they share it with the rest of their community and at the market.

An information ecosystem is not a static entity; it is by nature constantly evolving and changing. Nor is it a discrete form; it can be defined at many levels, from global to national to community to interest-based groupings within communities. It is a complex, adaptive system that includes information infrastructure, tools, media, producers, consumers, curators, and sharers. Data and data-derived information and communications are increasingly critical elements of information ecosystems. Research by the Internews Center for Innovation & Learning has described eight critical dimensions common to any data/information ecosystem (Figure 4).

Figure 4: Eight Critical Dimensions of Information Ecosystems



Key features here not only include logistical aspects such as demand, structures, applications and flow of information but also place a heavy focus on context; ease of accessing, finding, using, sharing, and exchanging different types of information; barriers to interaction and participation; and relevance of information. Extremely significant to these ecosystems as well, and a resulting feature of their complexity, is social trust – the influence of trust networks on the flow and use of information – which involves the data itself, the consumer and the influencers of the system.

Understanding how data/information ecosystems function and evolve is critical to fostering and expanding data literacy and therefore data engagement. This approach does not simply empower voices "from the ground up" – it accounts for needs, challenges, and opportunities for all nodes within a system to be appreciated and valued, be they governments, community leaders, telecoms, epidemiologists, technologists, patients, farmers, or others. Trust, transparency and better control of the flow of data and information are all supported as feedback loops that continually feed the flow of data, information and impact. For the ever-expanding communities of "Data Revolutionaries" there is an urgent and magnificent opportunity to ensure the innovative uses of data are in the service of supporting more inclusive, appropriate and transparent solutions. We need to ensure the inclusion and empowerment of all members of the data ecosystem—producers, consumers, movers and users—to expand everyone's opportunities to make meaningful and relevant decisions.

2.3 Conceptualizing 'data literacy' as 'literacy in the age of data'

Despite our attempt to clarify and broaden the definition of *data literacy*, it may not stand the test of time. Artificial intelligence, virtual reality, and other new technologies threaten to completely disrupt our current conceptualizations of data and how to use it. Data literacy, defined and conceptualized as "*the desire and ability to engage constructively in society through or about data,"* may not be enough to empower global citizens to use various kinds data to improve their lives and strengthen their communities.

As new discoveries and media change, data literacy must be able to adapt as well, focusing on fostering adaptive capacities and resilience rather than teaching platforms and technical languages that are bound to become out-dated. An even broader concept is needed to ensure citizens may identify, navigate and participate in the rapidly changing data ecosystem. Promoting data literacy needs to move beyond the constraints of a sub-type of literacy and expand to promoting *literacy in the age of data*.

Promoting literacy in the age of data must be adaptive. Despite our increasing capacities to collect and capture data, we are still navigating the possibilities of data. Discovering the impact of a current dataset could take years: the emergence of new technologies and datasets may challenge our acceptance of current datasets and increase the risks involved in using them.

Promoting literacy in the age of data should not solely be based in new technologies or mediums, but involve empowering people to navigate their current ecosystems and societies in ways that are meaningful and effective for them. In the age of data, new data and technologies will continue to challenge and shape our individual and collective capacities to learn, communicate and make decisions. Data literacy promotion must move beyond solely focusing on platform-based skill development (e.g. writing, coding, etc.).

As it turns out, this is exactly in line with the evolution in the thinking about 'standard' literacy. In setting its goal for universal literacy under the motto of "Literacy as Freedom" in the mid-2000s—before the emergence of data and Big Data as core policy concepts—UNESCO noted:

> *"At first glance, 'literacy' would seem to be a term that everyone understands. But at the same time, literacy as a concept has proved to be both complex and dynamic, continuing to be interpreted and defined in a multiplicity of ways."*

It then proposed an expansive definition of literacy:

> *"[T]he conception of literacy has moved beyond its simple notion as the set of technical skills of reading, writing and calculating—the so-called 'three Rs'—to a plural notion encompassing the manifold meanings and dimensions of these undeniably vital competencies. Such a view, attending recent economic, political and social transformations, including globalization, and the advancement of information and communication technologies (ICTs), recognizes that there are many practices of literacy embedded in different cultural processes, personal circumstances and collective structures"* (UNESCO 2004, 6).[44]

Today, UNESCO defines literacy in a broad encompassing definition as follows:

> Literacy refers to the "*ability to identify, understand, interpret, create, communicate and compute, using printed and written materials associated with varying contexts. Literacy involves a continuum of learning in enabling individuals to achieve their goals, to develop their knowledge and potential, and to participate fully in their community and wider society*".[4]

Although this definition did not make any reference to data, it is consistent with and includes core aspects of data literacy—although less emphasis is placed on 'desire'.

Promoting literacy in the age of data should build on the key features and pillars from all core sub-categories of literacy – literacy as a continuum. Historically, a main feature of literacy has been the evolutionary nature and instrumental dimension of its definition and measurement: we noted earlier how it was once defined and measured by the ability to sign one's name as opposed to tracing a cross. Over time, the standards by which literacy has been assessed have risen alongside literacy rates; at all times, literacy has been fundamentally redefined according to its purpose. The definition, promotion and evaluation of literacy have been and remain context and purpose-specific—not a-contextual, abstract and absolute. Even more so, literacy is only relevant within shared ontologies. This makes literacy both an instrument of power, and the condition for challenging it.

Further on this point, promoting literacy in the age of data must go beyond the binary conceptualization of being literate or illiterate. There are perilous dangers in thinking that a given individual or group are data literate, and thereby assuming the completeness of their potential ability to engage with and use data. The subtleties and grades of literacy are numerous and continue to evolve; as this evolution unfolds, so too must the fidelities of its systems, tools and supports.

Promoting literacy in the age of data must involve providing multiple pathways for people with different data literacy needs and capacities to interact within a complex system. In understanding literacy as a "continuum of learning," efforts to promote literacy in the age of data must provide multiple entry-points for people to understand and consider data literacy in conjunction with their own goals for knowledge development and participation in their community and societies. In this sense, there are many levels of literacy as a way for people with different capacities and needs to interact in the complex ecosystems that exist.

3 Promoting data literacy for and via social inclusion

At the center of the rationale for data literacy promotion must sit the goal of empowering citizens and communities as free agents. This can only be achieved by considering data literacy as a significant means and metric for social inclusion—where data literacy as defined and conceptualized above is promoted *for and via greater social inclusion*; which we term *data inclusion*.

3.1 Making Big Data small(er)

Data may reinforce existing power structures and processes. This risk is most evident in the case of Big Data; the sources and features of Big Data's potentially 'disempowering' effect have by now been well identified, notably by Boyd and Crawford who as early as 2010 noted the existence of *"significant questions of truth, control and power in Big Data studies: researchers have the tools and the access, while social media users as a whole do not."*[45] In a recent paper, Bhargava and D'Ignazio summarized that *"Big Data has an empowerment problem"*[46], adding *"one might argue that having Big Data be in service of the subjects needs is sufficient to argue it is beneficial, but empowerment is not handed from those in power to those without, it bubbles from the bottom up."*

Some will argue that enhancing '(Big) Data literacy' would precisely help veer the cursor towards greater empowerment, depending on what is involved in and expected from data literacy. Mastering Python is neither a sufficient nor a necessary condition to pass the data literacy test if, for instance, the data used has been collected without the subjects' informed consent (Box 5), extracted without a solid understanding of the risks and implications involved, or used to discriminate against people.

This argument implies that the conceptualization and promotion of data literacy should not be disconnected from ethical considerations. Indeed it can be argued that data literacy is essentially an *ethical imperative*.

Box 5: Do you know where your data are?

In 2014, the Federal Trade Commission's report on data brokers—companies that collect and sell personal consumer information—revealed that most consumers are unaware of how their personal data is being collected and used.[47]Although the work of data brokers can benefit consumers and the economy by, for example, enabling fraud protection, most consumers simply do not know how extensively their personally identifiable information (PII), property information, and social media use are being sold for profit.

For example, CoreLogic's database includes over 147 million records containing property-specific data for over 99% of all U.S. residential properties. RapLeaf's data aggregator contains at least one data point, including PII, for over 80% of all U.S. consumer email addresses.[ii]

As the FTC report and many well-publicized data leaks brought attention to the risks to consumer privacy, marketers and data brokers responded to pressure to make terms-of-service agreements more accessible and detailed. However, many Americans still do not know how much of their data is being shared nor the extent to which they can opt out of these practices. A study by the Annenberg School for Communication at the University of Pennsylvania concluded that marketers often frame data sharing as a tradeoff for the delivery of services or discounts. However, most consumers do not have the data literacy to make informed decisions to give up their data.[48]

Experts have suggested remedies based on the E.U.'s data protection directive and similar initiatives. For example, Alex Pentland of the MIT Media Lab and Data-Pop Alliance calls for a "new deal on data" to give users ownership of their data and control over its use.[49]

A dichotomy of Big Data versus Small Data is often delineated especially in relation to empowerment. While both concepts are significant to discussions of empowerment and engagement, the demarcation is not without limitations. As a particular type of data, 'Big Data' is actually a bit of a misnomer since the data in question are in fact many little data points related to people's behaviors and beliefs to make up very large data streams and sets.

As a field of research and practice, Big Data typically refers to the algorithmic analysis of large, passively collected, sets and streams to discover patterns and relationships, often not obvious at the onset of the analysis. The results provide insights into systems that otherwise wouldn't have been revealed but for the massive collection and automated, computer-enabled, analysis of data. Small Data, in contrast, centers on active data collection by engaged, willful participants, with analysis using manual or computer-assisted techniques. Both practices may use qualitative and quantitative datasets and both can entail structured or unstructured data.

However, a distinctive characteristic of Big Data is that it always involves structured quantitative data *at some point* in the analytics process. For example, in applying machine-learning, no matter the character or configuration of the source data, it is necessary to quantify the data in order to perform the necessary operations to give a result.

In sum, typical Small and Big Data approaches currently differ along four major aspects:

Big Data Versus Small Data		
Aspect	**Big Data**	**Small Data**
Level of awareness by the subjects of the data	Null or limited	Aware and engaged
Nature of data used	Quantitative and qualitative	Qualitative and quantitative
Technique used for analysis	Algorithmic, computer-enabled with room for human inputs (for classification purposes in supervised-machine learning)	Manual and computer-assisted
'Traditional' uses and requirements	• Developing and using algorithmic analysis techniques; • Understanding what data people generate in their daily lives; • Making decisions about the ethical use of data; • Creating detailed visualizations to understand what the data may represent or indicate.	• Collecting data to answer questions; • Finding stories in data that exists; • Picking effective techniques for telling data-driven stories.

This dichotomy between Big Data and Small Data should not persist indefinitely. Small Data will increasingly use and rely on 'Big Data' techniques and tools as they become more widely available, easy to use and eventually adopted (e.g. Google Maps). Big Data, on the other hand, needs to learn from 'Small Data' when it comes to enhancing people's awareness and engagement. An additional requirement of all this Big Data, Open Data and data of any kind is simply the raising of awareness. For users of both approaches, it is important to stress here the importance of understanding and incorporating context (Box 6).

Box 6: The importance of context in data literacy

Data, design and implementation cycle has yet to begin to fully embrace the benefits of understanding and incorporating context. This is a vital part of data literacy that is too often limited or even entirely absent in the way data scientists approach data. To make data truly relevant, actionable and therefore impactful, analysis should take into account the context and the direct experience and insights of those about whom or for whom data-driven solutions are provided.

To achieve this potential, the data need to be analyzed with contextual knowledge, the ground truth, as part of the data scientists' mindset as they consider what the data may be revealing in terms of experiences and potential solutions. Context in data literacy should encompass input from civil society, from industry, from individuals, from local and national governments—from all of the stakeholders that comprise the data/ info ecosystem.

In the future, as almost every aspect of human life will potentially be subject to data-ification and data literacy increases (expanding to literacy in the age of data), the boundaries between Small and Big Data should blur, and the result will become 'All Data'. 'All Data' would then refer to all the applications and implications of data for societies, and data literacy will be the means and measure of people's desire and ability to actively craft that future.

Designers of data literacy initiatives face a challenging path ahead, fraught with concerns over appropriateness of activities and ever-changing technology. The Big Data – Small Data divide is not an easy gap to negotiate. Some will be inclined to focus on Big Data from an activist/awareness raising point of view, while others will focus on Small Data because it is more tractable and accessible.

Today, a major imperative and challenge is to make Big Data 'smaller', on a scale where most or many more people are willing and able to be engaged than is the case today. A taxonomy of potential functions of Big Data has already been put forth that both stresses the need for and provides an entry point for making Big Data smaller (?).[50] These four functions of Big Data are:

1. *Descriptive*; i.e. to use of data to produce maps, visualizations, etc.;
2. *Predictive*; i.e. to make inferences about current conditions and forecasts about future events;
3. *Prescriptive*—also referred to as *diagnostic*—to draw causal inferences with Big Data; and lastly and critically,
4. *Discursive*—also referred to as *engagement*—which *"concerns spurring and shaping dialogue within and between communities and with key stakeholders,"* recognizing that *"the longer-term potential of Big Data lies in its capacity to raise citizens' awareness and empower them to take action."*[51]

In other words, Big Data—and, by extension, all data and data approaches—can and must be leveraged to empower citizens. This requires increasing their levels of data literacy understood as their desire and ability to argue through and about data.

Consequently, one of the requirements and features of a more data literate society is a society where citizens demand to have a voice in how and by whom data is used, what it is used for, and use data to fulfill their goals in an ethical and equitable manner. And so, a data literate society is a more inclusive society.

3.2 Understanding and designing for data literacy and inclusion using human-centered approaches

As previously stated, for the much-touted promise of inclusion and empowerment through data to be realized, individuals and groups in all parts of the data ecosystem have to be data literate; and this fostering of data literacy is highly contextual (see Box 5).

At the heart of such an approach is the need to empower all members of a data ecosystem – producers, consumers, movers and users – to expand all participants' opportunities to make meaningful and relevant data-informed decisions and actions. There is no 'one size fits all' approach. All the participants have different attributes, different needs and challenges, and these may be distinct depending on the roles of the participants at a given time. While some of the challenges are clearly evident, many are far more opaque.

Elements of human-centered design

At the root of understanding data literacy and designing for inclusion is an urgent need to rethink approaches for the design, creation and support of data driven systems, that are more human-centered and based on inclusion, empathy and responsiveness. Contextual, human-centered approaches are arguably a critical and currently too often absent element in the design and development of data-related activities.

These methods can identify the complex and nuanced needs, challenges and aspirations of individuals and groups within a data ecosystem. Central to human-centered approaches are discovery and learning related to experience. Empathy is a truly powerful and necessary tool to understand the experiences of others. With mindful attention to the explicit, implicit and indeed unconscious needs of different individuals and groups, appropriate activities, tools, supports and communications for data and data-informed actions can be designed and supported.

A human-centered approach to data literacy would foster:

- *Greater inclusiveness:* Human-centered design serves to surface complex and nuanced needs, challenges and aspirations of all individuals and their communities in relation to understanding, creating, using and communicating data.
- *Enhanced community participation:* Understanding how to convey data-derived insights using appropriate, accessible and trusted language, visuals and media etc. will enable audiences to actively participate in the data ecosystem.
- *Prioritization of critical needs*: By embracing local context with empathy and mindfulness, the most pertinent questions to ask of data emerge. Explicit, implicit and previously unknown benefits and harms can be identified. This serves to strengthen networks of trust, manage risks, enable effective policies and more fully value the uniqueness of all individuals.
- *Increased resilience*: Human-centered methods help all stakeholders listen, learn and adapt to change and uncertainty. Fluid, open and agnostic, such approaches provide the means to continually learn and revisit core assumptions that can cloud judgment, increase risks and drive poor utility and impact.

4 Fostering social inclusion as data inclusion

4.1 Understanding and leveraging the power of words and language(s)

The words we use to describe an object, concept, idea or field are critical to their understanding. In data literacy programs, this can take many routes. At the most basic level, using "information" instead of "data" can be significant. The processes employed similarly need more familiar names. Instead of *data analysis*, a more enticing term might be *story-finding*. Instead of *visualization*, a more appealing term might be *storytelling*. Both of these terms employ the frame of "story" to make the critical connection between data and action.

Story-finding is a scaffolding for data analysis. People can be intimidated by the idea of 'analyzing data,' which is not the sole but certainly a key component of being data literate. The story-finding framing can assuage that intimidation. Story-finding also connects data analysis with the critical question of "why?" Asking "why" creates a natural link between the exercise of analyzing data and the changes one hopes to bring about, creating a natural connection with the ethical considerations discussed above by placing the ends above the means.

Storytelling allows for more creativity in the approach to data presentation. The term 'data visualization' brings about imagery of fancy graphics or analytics that may create unnecessary semantic and cognitive barriers. The far more approachable concept of 'storytelling' acknowledges there are many ways to present data, not just in complex visualizations that may appeal to audiences who have capacity in different domains—such as performance, painting, photography, or drawing. Art has historically been one of the best tools for engagement and can be a key point of entry to engage people with data.

This story-finding and storytelling framing also stresses a fundamental point that echoes the aforementioned need to recognize the non-neutral nature of data. Data-driven arguments are very often used to support *opinions*—i.e. statements that are, in Bachelard's terms, *"inherently wrong."*[52] Being aware of the propensity of data-driven arguments to pass for objective facts and seeking to critically engage with and interrogate their validity is a major feature and benefit of data literacy.

Further adding to this non-neutrality, another obvious and yet largely ignored obstacle to broad data literacy is the fact that the majority of online content is in English.[53] In today's and probably even more so tomorrow's world, not being able to read or understand English may be an impediment to data literacy. To give a French-speaking person an important message, a good starting point would probably be to use French. This may seem obvious; however, where communicating important data is concerned there is little research into what might be the optimal 'languages' for a given message and a given community.

Beyond the boundaries presented by the language that data and information are communicated in, barriers to entry for data literacy persist, stemming from the various and rapidly evolving languages that data are captured, manipulated, and analyzed in (Appendix 4). Once inside this community of programmers and data scientists, tools and knowledge are often easily accessible and highly participatory—with the free and open-source programming language R and its community being a good case in point.[54] However, currently this community is isolated from and often esoteric to outsiders. There is a need and potential to produce accessible, usable tools to enable users of data to verify the information that is produced from the process of data aggregation and analysis. Research is needed to develop such tools that reverse-engineer the data path and present this information clearly and intelligibly to users. And perhaps more importantly, there is a need to train trusted 'data translators and connectors'—once called *infomediaries* — to connect this community to the rest of the world.

In attempting to teach data literacy, educators are faced with a formidable challenge: the vast gap between the smaller, more orderly datasets and problems that learners typically work on in the classroom, and the large, unstructured problems that individuals face in the real world. Some organizations are attempting to bridge this gap through progressive data education that transitions from entry-level, pre-defined problems to more complex and uncertain ones, although these interventions are rare (Box 7).

Journalists and other communicators have access to an ever-burgeoning range of tools and techniques to manipulate and present data. However, there seems to be relatively little understanding of which of these approaches may be the most appropriate for a given audience or type of information.

Internews, Kenya's data journalism training experience, took place in the context of a virtual absence of data literacy skills among trainees (Box 8). *"Some journalists were hardly numerate; they didn't know how to express simple ratios and had a phobia of Excel",* says Dorothy Otieno, Internews in Kenya's lead data journalism trainer.[55] Otieno describes how in 2011, when Internews conducted its first data journalism training, journalists had no notion that they could demand data from policy makers or researchers. The launch of the Kenyan Open Data Initiative (KODI) in 2012 was a digital leapfrog into data accessibility in a country where journalists hardly dared ask for data – either because access would be denied or the data would simply be cumbersome to access. Two years later, Internews has gained valuable insights about the steps involved in teaching data literacy to content creators, which in turn translates to a more data literate media audience, able to engage with data and empowered through use of data.

Box 7: Progressive Data Education Initiatives

Working with elementary schools, the Oceans of Data Institute, a science education research group within the Education Development Center (EDC), has developed a model to define the cognitive stages that learners need to progress through in order to move from pre-defined problems to ill-defined ones, and from discrete cases to abstract patterns.[56] The ODI's four stages of learning progression towards "data scientist" are:

1. Unstructured observation through human senses;
2. Student-collected small data sets;
3. Professionally collected large datasets and well-structured problems;
4. Professionally collected large datasets and ill-structured problems.

Learners develop increasing proficiency as they progress through these stages and must make significant leaps in learning to transition from one stage to the next. The ODI has also developed a series of curricula that aim to support students in making these progressions. The EDC Earth Science curriculum, for example, asks students to compare temperature and precipitation data from the NOAA's National Climate Data Center to similar data from their local area, helping them to transition from analyzing small local data to larger professionally-collected datasets. Another curriculum, Ocean Tracks,[57] deepens students' understanding of professionally collected data by enabling them to explore the migration patterns of large marine species and analyze the relationship between migration patterns and factors of the ocean environment.

City Digits, an interactive mapping platform and series of high school math curricula developed by researchers and designers from the MIT Civic Data Design Lab, Brooklyn College, and the Center for Urban Pedagogy, helps students to bridge the gap between ODI's stages two and four.[58] Students use data to analyze a local social justice issue from two perspectives: first they collect their own datasets by conducting interviews in their neighborhood, and then they explore citywide datasets that illuminate larger-scale patterns. These activities help students compare the small-scale, highly personal and large-scale, statistical implications of an issue, and to understand the relationship of individual data points to the larger system of which they are part. The first iteration of the curriculum focuses on the issue of state lotteries and their impact on low-income communities, and the second applies the methodology to the topic of pawnshops and "fringe banking."

The Internews experience suggests some simple tips for addressing data literacy and empowering data narrative creators and audiences:

- Allow time for discovery and recognize that this is a new field for many;
- Harness the distinct skills of data researchers, coders, developers, designers and journalists and team these together in collaborative projects;
- Acknowledge that data-derived journalism is time consuming, but that the effort pays off in the form of unique insights and rewarding opportunities for audience engagement and crowd projects;
- Apply rigor and discipline, critical thinking and alertness to unreliable data.

By applying these principles, data journalism teams in Kenya have produced stories with impact, which have transformed the look of mainstream media in Kenya. It is now typical for data-derived feature stories or investigations to claim double spread space in the newspaper and for television features with data visualizations to be broadcast in prime time.

Box 8: Case Study - Training Data Journalists in Kenya

In early 2014, five Kenyan media professionals, including two print journalists, a TV journalist, a developer and a graphic designer, graduated as Internews data journalism fellows. They had completed a 16-week data journalism training and production that raised awareness about the misspending, corruption and inequality that plague Kenya's public healthcare system. Fellows learned how to access, scrape, analyze and visualize data using digital tools. They also gained an appreciation of interconnections in data – with the ultimate aim of unearthing stories buried in data through investigative journalism.[59]

Such examples point to the power of data-driven investigations to foster a culture of accountability. Greater investment in these activities is needed to nurture data translators, able to harness rich data sets in order to reach conclusions that matter to citizens and are communicated in an understandable manner, in order to spur further audience engagement with the data.

4.2 Politicizing the (Data) Revolution: towards data inclusion

The 2014 IEAG report emphasizes that *"revolutions begin with people, not with reports, and the data revolution is no different."*[60] As we revisit the larger context of the Data Revolution in the light of data literacy and social inclusion, it becomes clear that if this Data Revolution is to bring about positive change, it has to be an evolution towards greater social inclusion that goes beyond the current discourse.

A key problem in the current discourse is the disconnect between the goals of the revolution (specifically in social inclusion and empowerment) and the ramifications of its current framing. The current 'data revolution' narrative suggests that most of the ills of the world are due to a lack of data and data skills in the hands of 'decision-makers,' often consciously or unconsciously equated with 'policy-makers.' It is indeed common to read and hear that what 'we' need is "better data, more timely data, more accurate data, more disaggregated data." As it is framed, this "better data" will provide greater information on the desks and briefing notes of policymakers and their advisers, and, secondarily, better skills in the hands and brains of average citizens.

This framing focuses attention on a subset of relatively uncontroversial issues, while shying away from addressing the more complex and controversial barriers. These lie in politics and power. Since words—that are data, projecting meaning and assumptions—matter, we should use them with care. What is at play or should be at stake is not a data revolution, a 'revolution of the data," but a revolution via data, a social revolution, or a social evolution led by empowered citizens with, via, and in the age of data. This is data inclusion.

If a 'business-as-usual' framing for the Data Revolution continues unabated, the future data-driven society will fail to realize the aims of the Data Revolution and will reinforce existing power dynamics that promote social exclusion. This transitional period is the opportune time to create a path towards empowerment. Data literacy focused on building social inclusion offers a doorway to understanding, interpreting, and managing data-driven decisions and arguments for all people. The alternative future we must strive for is one where people are incentivized and empowered to control their own data and its use. This is data inclusion.

What does politics look like in an age of data inclusion?

Recent political campaigns in the US have been heralded as data-driven successes—using insights from algorithmic mining to target messages that appeal to particular potential donors or voters. These methodologies are similar to those of the advertising industry, casting citizens as consumers who are opting to purchase a particular candidate. While some might argue this is an apt metaphor, it suggests just one definition of citizenship. The classical notion of the informed citizen involves choice in governmental representation based on information they receive from various sources. There are, of course, alternative definitions of citizenship that provide more opportunities to engage than simply donating to a campaign or voting for a candidate.

A better alternative for politics in the age of data is the idea of citizens as monitors of government policy and activity. This presents a future politics centered on the idea of accountability through data empowerment. Citizens could monitor and collect data about governmental roles, responsibilities, and services. These crowd-sourced data could be used to advocate for changes, expose corruption and more. Nascent versions of these types of tools are springing up across the globe, but only scratch the surface of what is possible when combined with affordable sensors, mobile phones, and strong community partnerships.

What does education look like in an age of data inclusion?

Current data literacy programs in formal education settings are few and far between. Schools tend to play catch up with grand societal-level changes, and the data revolution is no exception to this rule. Most existing programs and curricula focus on numeracy and more math-related concepts (to be in line with local or federal curriculum guidelines). In fact most data literacy work in formal schooling is targeted at teachers, helping them understand and use data about their students performance. These foci ignore the strong potentials to use data literacy activities to connect schooling to community, action, and citizenship.

A better alternative for education in the age of data is data literacy programs in formal education that focus on empowering students to collect, work with, analyze, and use data to create change in their communities. These programs should focus on existing problems in communities, empower students to collect and analyze data about the problems, and then to try and effect change.

What does law look like in an age of data inclusion?

In the areas of law and law enforcement, the business-as-usual framing could play out in terrifying ways over the next decade. Surveillance cameras already cover huge areas of our main cities. In the United States, police cars are passively collecting license plates as they drive around without strong rules of data retention and access control. These programs are more recently beginning to focus on threat modeling and predictive analytics. Certainly there is a place for data analysis in law and policing, but data divorced from context and ethics very quickly dissolves into a morass of poor short-term decision making. Forays into predictive analytics, when combined with insufficient legal frameworks, will not play out well in the real world.

A better alternative for law in the age of data is strong privacy protection to act as the anchor of this alternative future. A shift in attitude must be made towards respecting data ownership and removing passive detection as the norm. This will certainly require major legislative changes to accomplish, but it is not out of reach.

These visions of data-empowered futures for education, politics, and law are just pieces of the larger puzzle we must put together – a puzzle with data literacy at its heart. Technical and social infrastructure must be built to support these changes. Remembering that most data is simple information about our interactions in the world, we are forced to recognize that more data will be created each minute. This rate is increasing as more and more of daily interactions become governed by digital technologies, which lend themselves to easy data gathering. Most technologies currently being developed lend themselves to these types of large-scale data gathering exercises, but to return to an earlier theme, we need to ensure that the small-data efforts are similarly supported.

Our data-empowered future is creative, not consumptive. People will create the datasets they need to solve problems they are concerned about. People will create powerful stories that pull the data together in relevant ways. People will create effective presentations of those stories to bring about change.

Concluding Remarks: The data revolution, data inclusion and data generations

Data literacy is a *"strange thing"* that should not be promoted without specifying what is meant and expected from it. We put forth two main counter proposals with strong historical and political undertones. One is to talk about—or at least think in terms of— *'literacy in the age of data'* as a much more useful concept, simply defined as *"the desire and ability to constructively engage in society through and about data."* The second is to promote it via and for social inclusion.

To date, the appeal and success of 'data literacy' in the public discourse and psyche reflect and fuel a relatively narrow conceptualization of the 'Data Revolution,' itself rooted in a simplistic diagnostic of the world's problems and what data can do about them. For too many champions of data literacy, the main solutions focus on technical capacity gaps that need to be filled and fixed, so that more people can become better at analyzing data. As we noted, this is of course, partly accurate: to varying degrees, the vast majority of the world's population—including those crafting and implementing public policies or other public service functions—are ill-equipped to deal with the 'data deluge' that is only in its early years. There are massive and pressing needs to strengthen technical capacities for the positive transformative power of data to be unleashed in sectors and regions where lack of relevant and timely information has been a real impediment to social progress. Priority constituencies will include national statistical officers, elected officials, journalists, down to communities and individuals. Building those key skills requires significant investment over many years if they are to remain relevant in the age of data.

However, the current data literacy narrative overlooks many more complex and controversial questions. History has repeatedly shown how technology could entrench rather than challenge power structures that perpetuate detrimental outcomes—for instance inequity, poverty, corruption, and environmental degradation. This is obviously because technology is often invented and used first and primarily, when not exclusively, by those in power. The promotion and diffusion of technology to the masses is not necessarily at odds with this model, as Lévi-Strauss argued about literacy promotion. This is old news, but history has a tendency to repeat itself as its lessons are forgotten. There is a real risk that the same processes may play out in the age of data, at a speed and scope commensurable with those of the spread of data as a social phenomenon.

Settling for a medium-based, technical conceptualization of 'data literacy' may realize rather than mitigate this risk—a world where the latest data advances 'work' first and foremost to serve surveillance and commercial ends, with 'data literacy' serving the function of a nice sugarcoat. In a world where fewer than half of governments represented at the United Nations—all of which supported the SDGs—are not near being democratic and rule over half of the global population, educating and creating a data literate global citizenry would mean putting a lot of politicians and members of supporting elites out of power.

Conceptualizing and promoting 'data literacy' as 'literacy in the age of data' is consistent with the expansion and deepening of the concept of literacy over time to continuously and increasingly consider its requirements and metrics in light of its intended purposes—agency, empowerment, enlightenment, inclusion. Today and tomorrow, being literate ought to be defined and measured by how individuals are "*enabled to achieve their goals, to develop their knowledge and potential, and to participate fully in their community and wider society."*

We go one step further. We argue that this requires putting social inclusion front and center of policy and community discussions and initiatives. A data literate society—a literate society in the age of data—is a more inclusive society. Data as a concept and object is a powerful means to affect social inclusion positively or negatively; and reciprocally, the future of data as a concept and object will be determined in great part by how inclusive versus exclusionary or fragmented our societies are. Spurring literacy in the age of data must advance inclusive economic and social impact; and vice versa. We call the end of this process data inclusion.

Should kids learn how to code in school? Of course. And outside of school? They will. Any parent and anyone who interacts with a young child realize from their own recent experience how quickly and fundamentally technology and the world are changing in tandem, and what that may mean for their future. A term like the "Snapchat generation" reflects how new technologies and the increasing volumes of data associated with new devices now define the experiences, interactions and education and the future of children and teenagers. This generation is actually the first of the many 'data generations' to come.

By the time the children of this 'data generation' turn 15, by 2030, a lot of them may be able to write sophisticated code in Python and R to run analysis on various kinds of data sets and streams—including some or many *about them*, that they may collect and use themselves. The quantified-self movement of today will probably grow in size and significance, and tomorrow quantified communities will emerge. People may have gained full or partial access to the rights to data about them; data may be born with a built-in finite life expectancy; legal and technological systems radically changing informed consent will be in place. The very definition of individual and group privacy will continue to be challenged and adapted. These processes will not be solely relevant and confined to the micro-worlds of the US East and West Coasts, highly developed pockets of Europe, Asia, Oceania, and a few other cities of the Global South.

It is impossible to predict which power systems and structures will then govern societies in which their own children will live—except that they will probably look very different from what past and current generations have known. Will representative governments still be the norm? Maybe not. One thing is sure—data will be pervasive and infuse almost all aspects of human life, from the societal to the individual levels. The ethical and political responsibility of those in positions of power today is to empower people to shape this future themselves.

Appendices

Appendix 1: "Data science without conscience…."

Emmanuel Letouzé, 2014

Appendix 2: Claude Lévi-Strauss on writing and illiteracy programs in the original

"C'est une étrange chose que l'écriture. Il semblerait que son apparition n'eût pu manquer de déterminer des changements profonds dans les conditions d'existence de l'humanité; et que ces transformations dussent être surtout de nature intellectuelle. La possession de l'écriture multiplie prodigieusement l'aptitude des hommes à préserver les connaissances. On la concevrait volontiers comme une mémoire artificielle, dont le développement devrait s'accompagner d'une meilleure conscience du passé, donc d'une plus grande capacité à organiser le présent et l'avenir. Après avoir éliminé tous les critères proposés pour distinguer la barbarie de la civilisation, on aimerait au moins retenir celui-là : peuples avec ou sans écriture, les uns capables de cumuler les acquisitions anciennes et progressant de plus en plus vite vers le but qu'ils se sont assigné, tandis que les autres, impuissants à retenir le passé au delà de cette frange que la mémoire individuelle suffit à fixer, resteraient prisonniers d'une histoire fluctuante à laquelle manqueraient toujours une origine et la conscience durable du projet.

Pourtant, rien de ce que nous savons de l'écriture et de son rôle dans l'évolution ne justifie une telle conception. Une des phases les plus créatrices de l'histoire de l'humanité se place pendant l'avènement du néolithique, responsable de l'agriculture, de la domestication des animaux et d'autres arts. Pour y parvenir, il a fallu que, pendant des millénaires, de petites collectivités humaines observent, expérimentent et transmettent le fruit de leurs réflexions. Cette immense entreprise s'est déroulée avec une rigueur et une continuité attestées par le succès, alors que l'écriture était encore inconnue. Si celle-ci est apparue entre le 4e et le 3e millénaire avant notre ère, on doit voir en elle un résultat déjà lointain (et sans doute indirect) de la révolution néolithique, mais nullement sa condition. À quelle grande innovation est-elle liée ? Sur le plan de la technique, on ne peut guère citer que l'architecture. Mais celle des Égyptiens ou des Sumériens n'était pas supérieure aux ouvrages de certains Américains qui ignoraient l'écriture au moment de la découverte. Inversement, depuis l'invention de l'écriture jusqu'à la naissance de la science moderne, le monde occidental a vécu quelque cinq mille années pendant lesquelles ses connaissances ont fluctué plus qu'elles ne se sont accrues. On a souvent remarqué qu'entre le genre de vie d'un citoyen grec ou romain et celui d'un bourgeois européen du XVIIIe siècle il n'y avait pas grande différence. Au néolithique, l'humanité a accompli des pas de géant sans le secours de l'écriture ; avec elle, les civilisations historiques de l'Occident ont longtemps stagné. Sans doute concevrait-on mal l'épanouissement scientifique du XIXe et du XXe siècle sans écriture. Mais cette condition nécessaire n'est certainement pas suffisante pour l'expliquer.

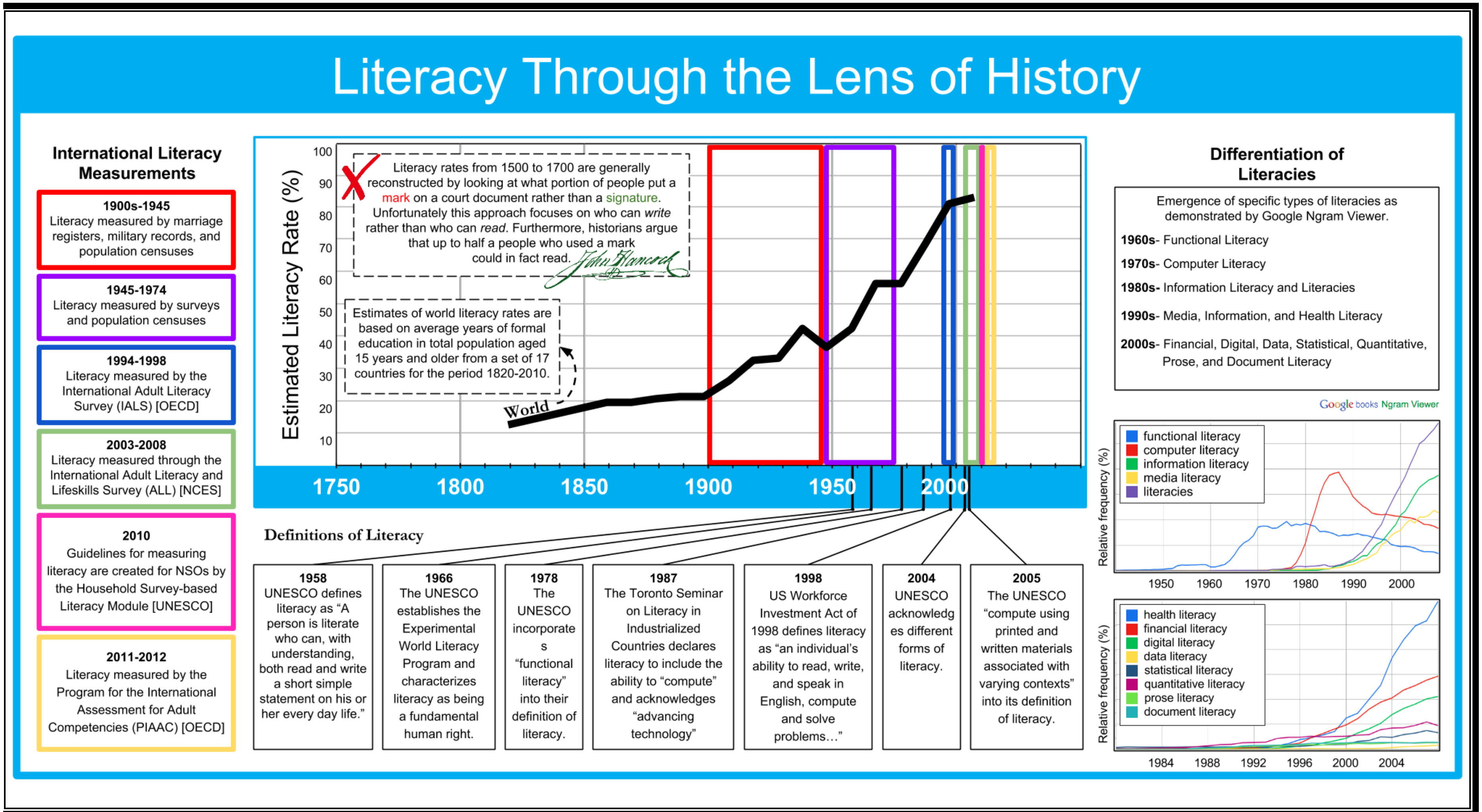
Si l'on veut mettre en corrélation l'apparition de l'écriture avec certains traits caractéristiques de la civilisation, il faut chercher dans une autre direction. Le seul phénomène qui l'ait fidèlement accompagnée est la formation des cités et des empires, c'est-à-dire l'intégration dans un système politique d'un nombre considérable d'individus et leur hiérarchisation en castes et en classes. Telle est, en tout cas, l'évolution typique à laquelle on assiste, depuis l'Égypte jusqu'à la Chine, au moment où l'écriture fait son début : elle paraît favoriser l'exploitation des hommes avant leur illumination. Cette exploitation, qui permettait de rassembler des milliers de travailleurs pour les astreindre à des tâches exténuantes, rend mieux compte de la naissance de l'architecture que la relation directe envisagée tout à l'heure. Si mon hypothèse est exacte, il faut admettre que la fonction primaire de la communication écrite est de faciliter l'asservissement. L'emploi de l'écriture à des fins désintéressées, en vue de tirer des satisfactions intellectuelles et esthétiques, est un résultat secondaire, si même il ne se réduit pas le plus souvent à un moyen pour renforcer, justifier ou dissimuler l'autre. […]

Si l'écriture n'a pas suffi à consolider les connaissances, elle était peut-être indispensable pour affermir les dominations. Regardons plus près de nous : l'action systématique des États européens en faveur de l'instruction obligatoire, qui se développe au cours du XIXe siècle, va de pair avec l'extension du service militaire et la prolétarisation. La lutte contre l'analphabétisme se confond ainsi avec le renforcement du contrôle des citoyens par le Pouvoir. Car il faut que tous sachent lire pour que ce dernier puisse dire : nul n'est censé ignorer la loi.

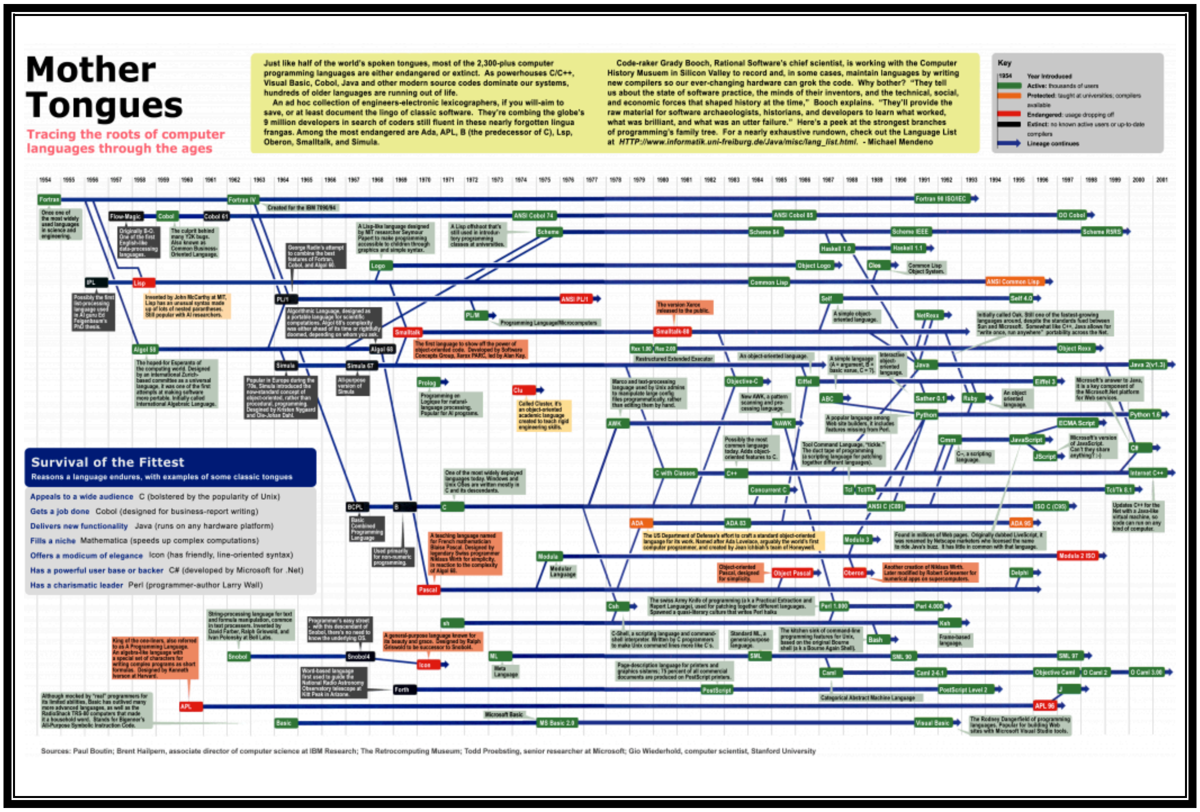
Du plan national, l'entreprise est passée sur le plan international, grâce à cette complicité qui s'est nouée, entre de jeunes États - confrontés à des problèmes qui furent les nôtres il y a un ou deux siècles - et une société internationale de nantis, inquiète de la menace que représentent pour sa stabilité les réactions de peuples mal entraînés par la parole écrite à penser en formules modifiables à volonté, et à donner prise aux efforts d'édification. En accédant au savoir entassé dans les bibliothèques, ces peuples se rendent vulnérables aux mensonges que les documents imprimés propagent en proportion encore plus grande."

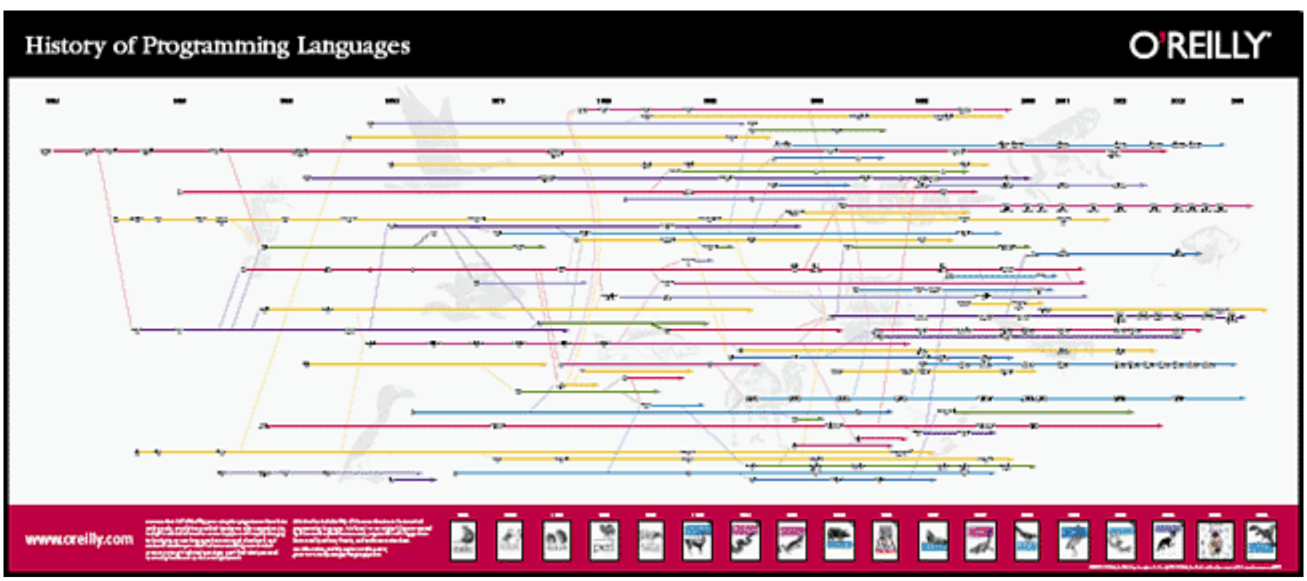
Claude Lévi-Strauss, *Tristes tropiques*, 1955.

Appendix 3: Literacy throughout history



Appendix 4: The evolution of programming languages





Endnotes

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1 http://www.post2015hlp.org/the-report/
[2] One Size Does Not Fit All: The Shortcomings of the Mainstream Data Scientist Working for Social Good. A. Albright and Levine, 2015, forthcoming.
[3] Hellerstein, Joseph. 2015. 'The Commoditization Of Massive Data Analysis - O'reilly Radar'. Radar.Oreilly.Com. Accessed September 3 2015. http://radar.oreilly.com/2008/11/the-commoditization-of-massive.html .
[4] https://hbr.org/2012/09/data-is-useless-without-the-skills
[5]http://data.worldbank.org/sites/default/files/issue-paper-financing-the-data-revolution-data-literacy-and-use.pdf
[6] http://idatosabiertos.org/wp-content/uploads/2014/04/OD4DProposaversionfinal11.pdf
[7] "A New Global Partnership: Eradicate Poverty and Transform Economies Through Sustainable Development", May 2013 http://www.un.org/sg/management/pdf/HLP_P2015_Report.pdf
[8] "A World that Counts" Nov 2014, http://www.undatarevolution.org/report/
[9] http://www.wired.com/insights/2014/07/data-new-oil-digital-economy/
[10] Technology Services Industry Association, 2015. 'The New Data Refineries: Transforming Big Data Into Decisions'. Blog.Tsia.Com. Accessed September 3 2015. http://blog.tsia.com/blog/the-new-data-refineries-transforming-big-data-into-decisions.
[11] Rowley, J. 2007. 'The Wisdom Hierarchy: Representations Of The DIKW Hierarchy'. Journal Of Information Science 33 (2): 163-180. SAGE Publications. doi:10.1177/0165551506070706.
[12] Maycotte, H.O. "Data Literacy – What It Is and Why None of Us Have It", Oct 2014, Forbes, http://www.forbes.com/sites/homaycotte/2014/10/28/data-literacy-what-it-is-and-why-none-of-us-have-it/
[13] https://en.wikipedia.org/wiki/Godwin%27s_law
[14] Kramer, Adam, Guillory and Hancock, "Experimental evidence of massive-scale emotional contagion through social networks" http://www.pnas.org/content/111/24/8788.full.pdf
[15] " Volkswagen boss quits over diesel emissions scandal", Reuters, Sept 2015, http://www.reuters.com/article/2015/09/24/us-usa-volkswagen-idUSKCN0RL0II20150924
[16] Leví Strauss, Claude, *Triste tropiques*, 1955
[17] More, Charles. Understanding the industrial revolution. Routledge, 2002.
[18] http://www.nationalismproject.org/what/hobsbawm.htm
[19] In some primary schools in Brittany at the end of the 19th century, it was forbidden to "spit on the ground and speak Breton". (« Il est interdit de parler breton et de cracher par terre »)
[20] Deahl, 2014 and Bhargava, 2015
[21] Fallows, James. 2011. 'Technology Is Not The Answer'. The Atlantic. http://www.theatlantic.com/technology/archive/2011/03/technology-is-not-the-answer/73065/.
[22] Pitchfork. 2015. 'James Murphy Shares Remixes Made With Tennis Data Album'. Accessed September 3 2015. http://pitchfork.com/news/57887-james-murphy-shares-remixes-made-with-tennis-data-album/.
[23] http://www.un.org/en/documents/udhr/
[24] We take concise definitions here to broadly outline the major aspects of each of these terms largely characterized by their literatures, acknowledging the rich and complex histories of each of these terms.
[25] http://www.nap.edu/openbook.php?record_id=4962
[26] Livingstone, Sonia, Elizabeth Van Couvering, and N. Thumin. "Converging traditions of research on media and information literacies." Handbook of research on new literacies (2008): 103-132.
[27] Steen, Lynn Arthur. "Numeracy: The new literacy for a data-drenched society." Educational Leadership 57 (1999): 8-13.

[28] Barr, Valerie, and Chris Stephenson. "Bringing computational thinking to K-12: what is Involved and what is the role of the computer science education community?." ACM Inroads 2, no. 1 (2011): 48-54.
29 https://digitalliteracy.cornell.edu
[30] *Statistic is "i.e. the science that deals with the collection, classification, analysis, and interpretation of numerical facts or data, and that, by use of mathematical theories of probability, imposes order and regularity on aggregates of more or less disparate elements*" and the result of this practice http://dictionary.reference.com/browse/statistics
[31] Crawford, Kate. "Think Again: Big Data." Foreign Policy 9 (2013). http://www.foreignpolicy.com/articles/2013/05/09/think_again_big_data.
[32] We are grateful to Alex Pentland for these comments.
[33] Oxford Dictionaries. Oxford Dictionaries Language Matters' definition of "data". Accessed September 2015. http://www.oxforddictionaries.com/us/definition/american_english/data
[34] Hilbert, Martin. "How Big is Big Data?" Input to the World Bank 2016 World Development Report. June 2015: 2.
[35] The American Statistical Association uses M. Davidian and T.A. Louis' definition of "statistics" as "the science of learning from data, and of measuring, controlling, and communicating uncertainty; and it thereby provides the navigation essential for controlling the course of scientific and societal advances." Science. 2012 Apr 6;336(6077):12. doi: 10.1126/science.1218685.
[36] Aldrich, F. and Sheppard, L. 'Graphicacy': the fourth 'R'?, Primary Science Review, 64 (2000): 8-11.
[37] Manovich, Lev. "What is visualisation?." Visual Studies 26, no. 1 (2011): 36-49.
[38] Deahl 2014
[39] https://en.wikipedia.org/wiki/Planned_shrinkage
[40] For a fuller discussion see boyd and Crawford, 2010-2011 Letouzé, 2012
[41] For a fuller discussion see boyd and Crawford, 2010-2011 Letouzé, 2012
[42] Crawford 2013
[43] Deahl 2014
[44] UNESCO Education Sector. "The plurality of literacy and its implications for policies and programs: Position paper." Paris: United National Educational, Scientific and Cultural Organization (2004): 13.
[45] boyd, danah and Kate Crawford. (2012). "Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon."Information, Communication, & Society 15:5, p. 662-679. http://www.danah.org/papers/2012/BigData-ICS-Draft.pdf
[46] Approaches to Building Big Data Literacy, forthcoming
[47] "Data Brokers: A Call for Transparency and Accountability." Federal Trade Commission, 2014. https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf
[48] "The Network Society: From knowledge to policy." Center for Transatlantic Relations, 2005. http://www.umass.edu/digitalcenter/research/pdfs/JF_NetworkSociety.pdf
[49] "The Global Education Technology Report 2008-2009: Mobility in a Networked World." World Economic Forum, 2009. http://hd.media.mit.edu/wef_globalit.pdf
[50] Big Data for Climate Change Resilience Report, Data-Pop Alliance, September 2015.
[51] "Big data for Resilience" World Humanitarian Summit https://www.worldhumanitariansummit.org/file/504310/.../549514
[52] https://books.google.com/books?id=8eTeAAAAQBAJ&pg=PA5&lpg=PA5&dq=bachelard+opinions+wrong&source=bl&ots=j-W1PyE4vj&sig=WvifaTprDoJQAbvHaKLkcdrfxDg&hl=en&sa=X&ved=0CCYQ6AEwAmoVChMI2rvB4eiYyAIVgho-Ch3EIQBt#v=onepage&q=bachelard%20opinions%20wrong&f=false
[53] Note: this paper will be translated in French and Spanish
[54] https://www.r-project.org
[55] Interview with Dorothy Otieno on 24 September 2014
For more information and examples of data journalism, see "Data Dredger," a Kenyan site on data journalism: http://internewskenya.org/dataportal/

[56] Internews in Kenya website. https://edc.org/newsroom/media_coverage/big_data_classroom
[57] Internews in Kenya website. https://edc.org/newsroom/media_coverage/big_data_classroom
[58] City Digits website. http://www.citydigits.org/
[59] "Kenya Data Journalism Fellows Shed Light on Complex Health Issues," Internews website. http://www.internews.org/our-stories/news/kenyan-data-journalism-fellows-shed-light-complex-health-issues
[60] "A World that Counts" Nov 2014, http://www.undatarevolution.org/report/