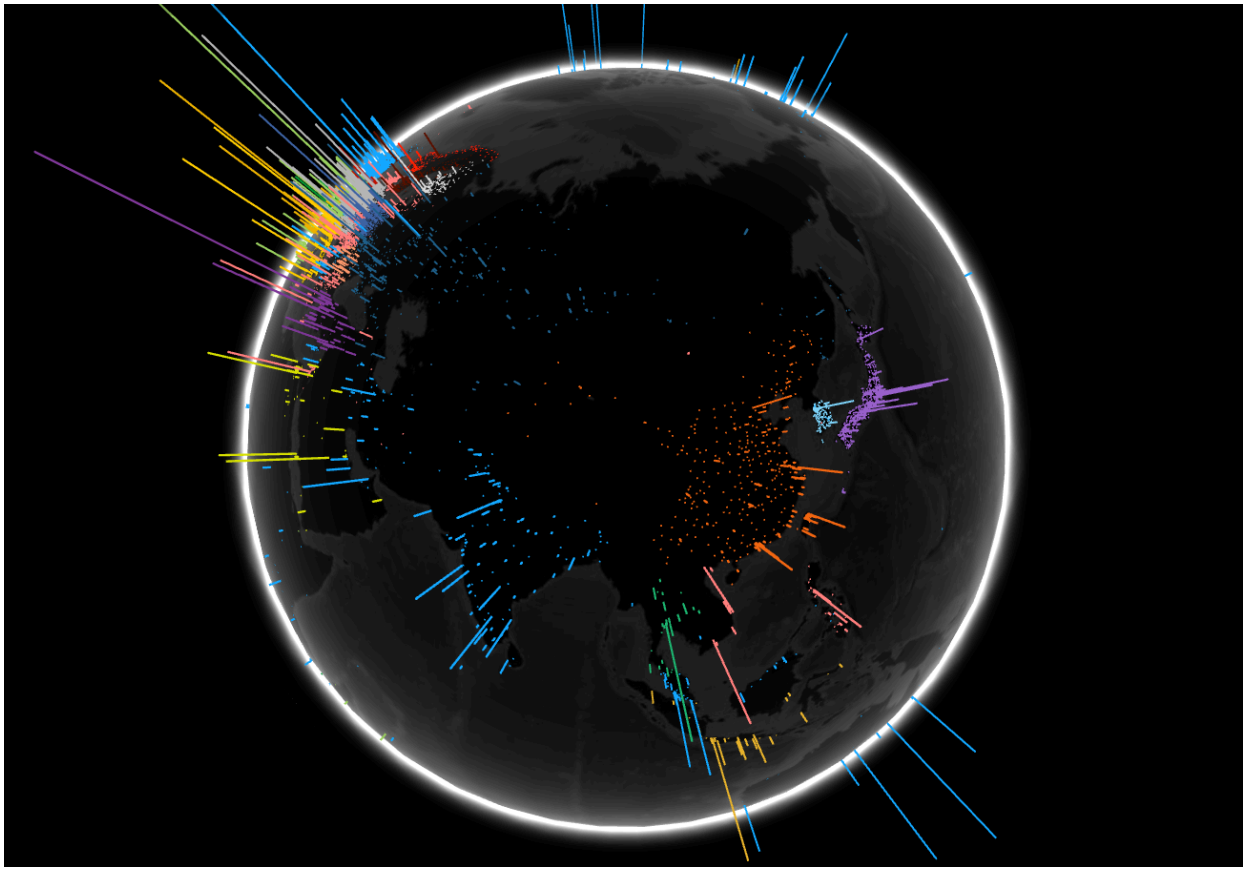


Big Data for Development: Challenges & Opportunities

May 2012

Acknowledgements

This paper was developed by UN Global Pulse, an initiative based in the Executive Office of the Secretary-General United Nations. Global Pulse is grateful to the Government of Australia, Government of Sweden, the Government of the United Kingdom, UNDP, UNICEF, WFP and the UN's Department of Public Information to their generous support to the initiative.

The paper was written by Emmanuel Letouzé, Senior Development Economist (2011), with research support from current and former Global Pulse colleagues who provided resources, feedback and helped shape the ideas that inform the contents of this paper. It was edited by Anoush Rima Tatevossian and Robert Kirkpatrick, with copyediting support from Cassandra Hendricks. The production and design of the report was supported by Charlotte Friedman.

We would like to thank Scott Gaul, Björn Gillsäter, and Samuel Mendelson, for their time in reviewing a number of draft versions of this paper, and providing detailed feedback.

Global Pulse has benefited from the experience and expertise of a wide range of colleagues both inside and outside of the UN system. Global Pulse acknowledges the extensive research conducted in this diverse and emerging field by partners such as the Billion Prices Project, JANA, Ushahidi, International Food Policy Research Institute (IFPRI), Google Flu Trends, the Global Viral Forecasting Initiative, Telefonica Research, the Institute for Quantitative Social Science at Harvard University, L'institut des Systèmes Complexes – Paris Île-de-France, SAS, Crimson Hexagon, and UNICEF.

The report is available online at **http://unglobalpulse.org/**

The analysis and recommendations of this paper do not necessarily reflect the views of the United Nations, or the Member States the United Nations. The views presented in this report are the sole responsibility of its authors.

To provide feedback, comments or for general inquiries, please contact:

Global Pulse
370 Lexington Ave, Suite 1707
New York, New York 10017
E-mail: info@unglobalpulse.org
Web: www.unglobalpulse.org

COVER ART: A visualization representing global Google search volume by language. Developed by the Google Data Arts Team. http://data-arts.appspot.com/globe-search

About Global Pulse:

Global Pulse is a United Nations initiative, launched by the Secretary-General in 2009, to leverage innovations in digital data, rapid data collection and analysis to help decision-makers gain a real-time understanding of how crises impact vulnerable populations. Global Pulse functions as an innovation lab, bringing together expertise from inside and outside the UN to harness today's new world of digital data and real-time analytics for global development. The initiative contributes to a future in which access to better information sooner makes it possible to keep international development on track, protect the world's most vulnerable populations, and strengthen resilience to global shocks.

To this end, Global Pulse is pursuing a three-fold strategy that consists of 1) researching innovative methods and techniques for analysing real-time digital data to detect early emerging vulnerabilities; 2) assembling free and open source technology toolkit for analyzing real-time data and sharing hypotheses; and 3) establishing an integrated, global network of Pulse Labs, anchored in Pulse Lab New York, to pilot the approach at country level.

For more information please visit www.unglobalpulse.org.

Abstract

Innovations in technology and greater affordability of digital devices have presided over today's Age of Big Data, an umbrella term for the explosion in the quantity and diversity of high frequency digital data. These data hold the potential—as yet largely untapped—to allow decision makers to track development progress, improve social protection, and understand where existing policies and programmes require adjustment.

Turning Big Data—call logs, mobile-banking transactions, online user-generated content such as blog posts and Tweets, online searches, satellite images, etc.—into actionable information requires using computational techniques to unveil trends and patterns within and between these extremely large socioeconomic datasets. New insights gleaned from such data mining should complement official statistics, survey data, and information generated by Early Warning Systems, adding depth and nuances on human behaviours and experiences—and doing so in real time, thereby narrowing both information and time gaps.

With the promise come questions about the analytical value and thus policy relevance of this data—including concerns over the relevance of the data in developing country contexts, its representativeness, its reliability—as well as the overarching privacy issues of utilising personal data. This paper does not offer a grand theory of technology-driven social change in the Big Data era. Rather it aims to delineate the main concerns and challenges raised by "Big Data for Development" as concretely and openly as possible, and to suggest ways to address at least a few aspects of each.

It is important to recognise that Big Data and real-time analytics are no modern panacea for age-old development challenges. That said, the diffusion of data science to the realm of international development nevertheless constitutes a genuine opportunity to bring powerful new tools to the fight against poverty, hunger and disease.

Table of Contents

"The hope is that as you take the economic pulse in real time, you will be able to respond to anomalies more quickly."
- Hal Varian, Google Chief Economist (Professor Emeritus, University of California, Berkeley)

Introduction

Since the turn of the century, innovations in technology and greater affordability of digital devices have presided over the *"Industrial Revolution of Data,"*[1] characterised by an explosion in the quantity and diversity of real-time[i] digital data resulting from the ever-increasing role of technology in our lives. As a result, we are *"entering an unprecedented period in history in terms of our ability to learn about human behaviour."*[2]

What was a hypothesis only a few years ago is today being confirmed by researchers and corporations, and has recently received significant coverage in the mainstream media[3]: analysis of this new wealth of digital data—the massive and ever-expanding archive of what we say and do using digital devices every day—may reveal remarkable insights into the collective behaviour of communities. No less significantly, just as this data is generated by people in real time, so it may now be analysed in real time by high performance computing networks, thus creating at least the potential for improved decision-making. It is time for the development community and policymakers around the world to recognise and seize this historical opportunity to address twenty-first century challenges, including the effects of global volatility, climate change, and demographic shifts, with twenty-first century tools.

What exactly is the potential applicability of "Big Data for Development?" At the most general level, properly analysed, these new data can provide snapshots of the well-being of populations at high frequency, high degrees of granularity, and from a wide range of angles, narrowing both time and knowledge gaps. Practically, analysing this data may help discover what Global Pulse has called "*digital smoke signals*"[4]—anomalous changes in how communities access services, that may serve as proxy indicators of changes in underlying well-being. Real-time awareness of the status of a population and real-time feedback on the effectiveness of policy actions should in turn lead to a more agile and adaptive approach to international development, and ultimately, to greater resilience and better outcomes.

Big data for development is about turning imperfect, complex, often unstructured data into actionable information.

Big Data for Development is about turning imperfect, complex, often unstructured data into actionable information. This implies leveraging advanced computational tools (such as machine learning), which have developed in other fields, to reveal trends and correlations within and across large data sets that would otherwise remain undiscovered. Above all, it requires human expertise and perspectives. Application of these approaches to development raises great expectations, as well as questions and concerns, chief of

[i] For the purposes of this paper, as discussed in Section 1.2, real time data is defined as *"data that (1) covers/is relevant to a relatively short and recent period of time—such as the average price of a commodity over a few days rather than a few weeks, and (2) is made available within a timeframe that allows action to be taken that may affect the conditions reflected in the data"*. The definition of "real time" is contextual: real time in the realm of fiber optics is not the same as in the realm of public policy.

which is the analytical value – and thus ultimately the policy relevance – of big data to address development challenges.

These must be discussed in a very open manner to ensure that there are no misunderstandings about what and how real-time data analytics can offer the field global development, and what it cannot.

This paper outlines the opportunities and challenges, which have guided the United Nations Global Pulse initiative since its inception in 2009. The paper builds on some of the most recent findings in the field of data science, and findings from our own collaborative research projects. It does not aim to cover the entire spectrum of challenges nor to offer definitive answers to those it addresses, but to serve as a reference for further reflection and discussion. The rest of this document is organised as follows: section one lays out the vision that underpins Big Data for Development; section two discusses the main challenges it raises; section three discusses its application. The concluding section examines options and priorities for the future.

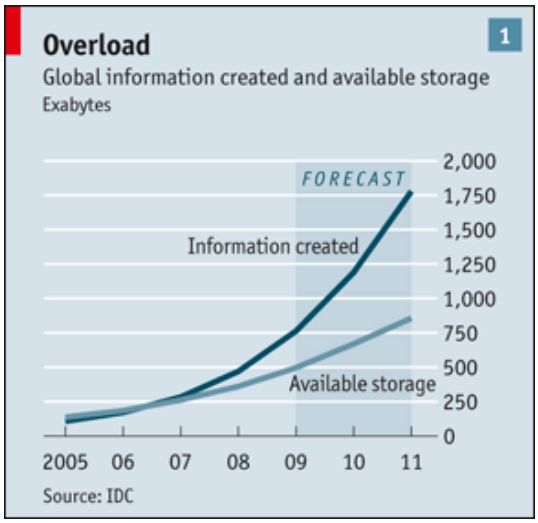
Section 1: Opportunity

1.1. Data Intent and Capacity

The Data Revolution

The world is experiencing a data revolution, or "*data deluge*" (Figure 1).[5] Whereas in previous generations, a relatively small volume of analog data was produced and made available through a limited number of channels, today a massive amount of data is regularly being generated and flowing from various sources, through different channels, every minute in today's Digital Age.[6] It is the speed and frequency with which data is emitted and transmitted on the one hand, and the rise in the number and variety of sources from which it emanates on the other hand, that jointly constitute the data deluge. The amount of available digital data at the global level grew from 150 exabytes in 2005 to 1200 exabytes in 2010.[7] It is projected to increase by 40% annually in the next few years, [8] which is about 40 times the much-debated growth of the world's population.[9] This rate of growth means that the stock of digital data is expected to increase 44 times between 2007 and 2020, doubling every 20 months.[ii]

Figure 1: The Early Years of the Data Revolution



Source: The Economist, based on IDC data

[ii] In September 2008, the "Jerusalem Declaration" stated: *"We are entering the era of a high rate of production of information of physical, biological, environmental, social and economic systems. The recording, accessing, data mining and dissemination of this information affect in a crucial way the progress of knowledge of mankind in the next years. Scientists should design, explore and validate protocols for the access and use of this information able to maximize the access and freedom of research and meanwhile protect and respect the private nature of part of it."(..) "several scientific disciplines once characterized by a low rate of data production have recently become disciplines with a huge rate of data production. Today a huge amount of data easily accessible in electronic form is produced by both research and, more generally, human activity."*

The revolution has various features and implications. The stock of available data gets younger and younger, i.e. the share of data that is "less than a minute old" (or a day, or a week, or any other time benchmark) rises by the minute.[iii] Further, a large and increasing percentage of this data is both produced and made available real-time (which is a related but different phenomenon).[iv] The nature of the information is also changing, notably with the rise of social media and the spread of services offered via mobile phones. The bulk of this information can be called "data exhaust," in other words, *"the digitally trackable or storable actions, choices, and preferences that people generate as they go about their daily lives."*[10] At any point in time and space, such data may be available for thousands of individuals, providing an opportunity to figuratively take the pulse of communities. The significance of these features is worth re-emphasising: this revolution is extremely recent (less than one decade old), extremely rapid (the growth is exponential), and immensely consequential for society, perhaps especially for developing countries.

Relevance to the Developing World

The data revolution is not restricted to the industrialised world; it is also happening in developing countries—and increasingly so. The spread of mobile-phone technology to the hands of billions of individuals over the past decade might be the single most significant change that has affected developing countries since the decolonisation movement and the Green Revolution. Worldwide, there were over five billion mobile phones in use in 2010, and of those, over 80% in developing countries. That number continues to grow quickly, as analysts at the GSM Association/Wireless Intelligence predict six billion connections worldwide by the middle of 2012. The trend is especially impressive in Sub-Saharan Africa, where mobile phone technology has been used as a substitute for usually weak telecommunication and transport infrastructure as well as underdeveloped financial and banking systems.[v]

Across the developing world, mobile phones are routinely used not only for personal communications, but also to transfer money, to search for work, to buy and sell goods, or transfer data such as grades, test results, stock levels and prices of various commodities, medical information, etc. (For example, popular mobile services such as Cell Bazaar in Bangladesh allow customers to buy and sell products, SoukTel in the Middle East offers an SMS-based job-matching service, and the M-PESA mobile-banking service in Kenya allows individuals to make payments to banks, or to individuals.) In many instances, mobile services have outpaced the growth and availability of their traditional

[iii] As demographic theory shows, a population whose rate of growth has risen, as in the case of digital data, will eventually get younger for several years, and the process will continue if the rate of growth continues to increase; nonetheless a population of data will always be older than a population of humans subject to the same birth rate because the life expectancy of digital data is much higher than that of any human population.

[iv] Conceptually, not all newly produced data is real-time data as defined above and in section 1.2. For example, if all historical vital statistics records of the world were all of a sudden made available digitally, these newly produced digital data would obviously not be real-time data. In practice, it is the case that a large share of newly produced digital data tends to be high frequency.

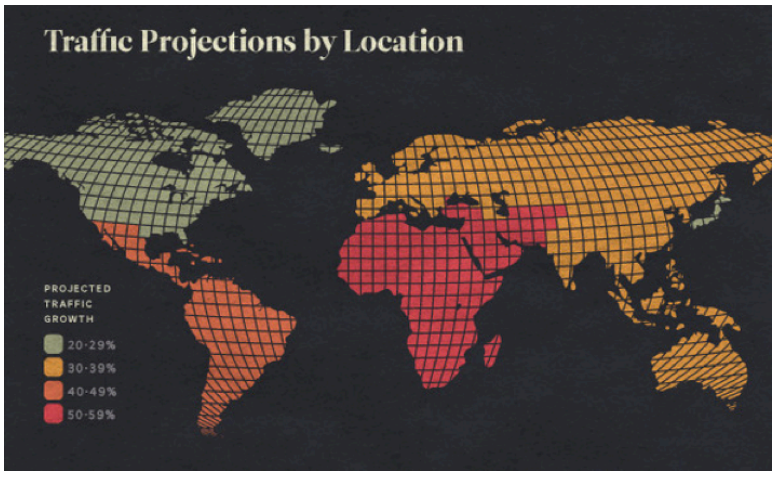
[v] For example, mobile phone penetration, measured by the number of mobile phones per 100 habitants, was 96% in Botswana, 63% in Ghana, 66% in Mauritania, 49% in Kenya, 47% in Nigeria, 44% in Angola, 40% in Tanzania, etc. <http://www.google.com/fusiontables/Home/> (Source: Google Fusion Tables)

counterparts. According to Gavin Krugel, director of mobile banking strategy at GSM Association, an industry group of 800+ wireless operators, *"one billion consumers in the world have a mobile phone but no access to a bank account"*. [11] Further, *"about 40 million people worldwide use mobile money, and the industry is growing. (...) Africa and Asia are the most active regions right now* [with] *18,000 new mobile banking users per day in Uganda, 15,000 in Tanzania and 11,000 in Kenya."*

Other real-time information streams are also growing in developing regions. While Internet traffic is expected to grow 25-30% between 2011 and 2015 in North America, Western Europe and Japan, the figure is expected to reach or surpass 50% in Latin America, the Middle East and Africa (Figure 2)[12]—and the bulk will come from mobile devices. There has also been a rise in local call-in radio shows, information hotlines and kiosks—such as Question Box or UNICEF's "Digital Drum"[vi]—that allow populations in remote areas to seek answers on issues ranging from agriculture, health, and education to business advice and entertainment, providing a window on the interests and concerns of information seekers whose location, age and gender are generally recorded.

The use of social media such as Facebook and Twitter is also growing rapidly; in Senegal, for example, Facebook receives about 100,000 new users per month.[13] Tracking trends in online news or social media can provide information on emerging concerns and patterns at the local level which can be highly relevant to global development. Furthermore, programme participation metrics collected by UN agencies and other development organisations providing services to vulnerable populations is another promising source of real-time data, particularly in cases where there is an Information and Communications Technology (ICT) component of service delivery and digital records are generated.

Figure 2: Global Internet usage by 2015



Source: The Atlantic, " Global Internet Traffic Expected to Quadruple by 2015."

[vi] Question Box is a pilot initiative that helps people find answers to everyday questions through hotlines, SMS, and kiosks (http://questionbox.org/). UNICEF's Digital Drum is a solar powered computer kiosk (http://is.gd/gVepRP)

Although the data revolution is unfolding around the world in different ways and with different speeds, the digital divide is closing faster than many had anticipated even a few years ago. Furthermore, in countries with weak institutional capacities, the data revolution may be especially relevant to supplement limited and often unreliable data. Increasingly, Big Data is recognised as creating *"new possibilities for international development."*[14] But data is a raw good that would be of little use without both *"intent and capacity"*[15] to make sense of it.

Intent in an Age of Growing Volatility

There is a general perception that our world has become more volatile, increasing the risk of severe hardship for vulnerable communities. Fluctuations in economic conditions—harvests, prices, employment, capital flows, etc.—are certainly not new, but it seems that our global economic system may have become more prone to large and swift swings in the past few years.

By the time hard evidence finds its way to the front pages of newspapers and the desks of decision makers, it is often too late or extremely expensive to respond.

The most commonly mentioned drivers are financial and climatologic shocks in a context of greater interconnection.[16] In the last five years alone, a series of crises have unfolded[17] with the food and fuel crisis of 2007 to 2008 followed by the 'Great Recession' that started in 2008. By the second half of 2011 the world economy entered yet another period of turmoil with a famine in the Horn of Africa and significant financial instability in Europe and the United States. Global volatility is unlikely to abate: according to the OECD, *"[d]isruptive shocks to the global economy are likely to become more frequent and cause greater economic and societal hardship. The economic spill-over effect of events like the financial crisis or a potential pandemic will grow due to the increasing interconnectivity of the global economy and speed with which people, goods and data travel"*.[18] For many households in developing countries, food price volatility—even more than price spikes—is the most severe challenge.[19]

For all this interconnectivity, local impacts may not be immediately visible and trackable, but may be both severe and long lasting. A rich literature on vulnerability[20] has highlighted the long-term impact of shocks on poor communities. Children who are forced to drop out of school may never go back or catch up; households forced to sell their productive assets or flee face a significant risk of falling back or deeper into poverty; undernourished infants and foetuses exposed to acute maternal malnutrition may never fully recover[21]—or worse die.[22] These processes often unfold beneath the radar of traditional monitoring systems. By the time hard evidence finds its way to the front pages of newspapers and the desks of decision makers, it is often too late or extremely expensive to respond. The main triggers will often be known—a drought, rising temperatures, floods, a global oil or financial shock, armed conflict—but even with sufficient macro-level contextual information it is hard to distinguish which groups are affected, where, when, and how badly.

Policymakers have become increasingly aware of the costs of this growing volatility; they know the simple fact that it is easier and less costly to prevent damages or to keep

them at a minimum than to reverse them. These arguments have been ringing in their ears in recent years as the words volatility, vulnerability, fragility and austerity have made headlines.

Various existing Early Warning Systems[vii] do help raise flags in the international community, but their coverage is limited (with a heavy focus on food security in rural areas) and they are expensive to scale. Some are also plagued with design and implementation problems.[viii] Survey data also provide important insights, but such data takes time to be collected, processed, verified, and eventually published. Surveys are too cumbersome and expensive to scale up to the point that they can function as an effective and proactive solution. These "traditional data" (which, for the purpose of this paper, refers to official statistics and survey data) will continue to generate relevant information, but the digital data revolution presents a tremendous opportunity to gain richer, deeper insights into human experience that can complement the development indicators that are already collected.

Meanwhile, examples of the private sector successfully embracing Big Data analytics[ix] and a growing volume of reports and discourse emphasising the promise of real-time data, and "data-driven decision-making" forwarded by leading institutes, institutions and media—from the World Economic Forum to the McKinsey Institute[23] to the New York Times—have begun to make their way into the public sector discourse.

Civil society organisations have also showed their eagerness to embrace more agile approaches to leveraging real-time digital data. This is evidenced by the growing role of 'crowdsourcing'[x] and other "participatory sensing"[24] efforts bringing together communities of practice and like-minded individuals through the use of mobile phones and other platforms including Internet, hand-held radio, and geospatial technologies etc.[xi] In many cases, these initiatives involve multiple partners from various fields in what constitutes a novel way of doing business.

[vii] A mapping conducted by Global Pulse found 39 such systems in operation in the UN system alone.

[viii] Reasons include their focus on climate-related shocks as a criterion for geographical coverage, lack of consistency of definitions, and lag in reporting. See in particular: WFP and UNICEF. *Food and Nutrition Security Monitoring and Analysis Systems: A Review of Five Countries (Madagascar, Malawi, Nepal, and Zambia)*. Rep. UN Global Pulse, Dec, 2011. <http://www.unglobalpulse.org/projects/rivaf-research-study-impact-global-economic-and-financial-crisis-vulnerable-people-five-cou>

[ix] For example MIT Professor Erik Brynjolfsson's research found significant differences in the data payoff—a 5 percent gap in productivity considered to be a decisive advantage—enjoyed by companies relying on "*data-driven decision-making processes*" on the one hand and those that continue to rely primarily on "*experience and intuition*" on the other hand. Source: Lohr, Steve. "When There's No Such Ting as Too Much Information." *The New York Times*. 23 Apr. 2011. <http://www.nytimes.com/2011/04/24/business/24unboxed.html?_r=1&src=tptw>

[x] The word "crowdsourcing" refers to the use of non-official actors ("the crowd") as (free) sources of information, knowledge and services, in reference and opposition to the commercial practice of outsourcing. "

[xi] Examples of such initiatives and approaches include Crisismappers, Ushahidi and participatory sensing. For additional information details, see "Crisis Mappers Net—The international Network of Crisis Mappers." <http://crisismappers.net>, http://haiti.ushahidi.com and Goldman et al., 2009

Slowly, governments the world over are realising the power of Big Data. Some choose conservative paths for managing the data deluge, involving crackdowns and strict controls (which will likely prove unsustainable), while others will devise institutional frameworks and support innovative initiatives, such as open data movements, that will help leverage its power for the common good.[xii]

Finally, many other applications in the social sciences have also strengthened the case for embracing Big Data for Development, as mentioned above and discussed in greater detail below.

It is the double recognition of the promise of the data revolution and the need for better, faster information in an age of growing global volatility that led the leaders of the G20 and the UN Secretary-General to call for the establishment of the Global Pulse initiative (in the wake of the on-going Global Economic Crisis), with the aim of developing of a new approach to "social impact monitoring" and behavioural analysis by building on new sources of data and new analytical tools.

…Big Data analytics refers to tools and methodologies that aim to transform massive quantities of raw data into "data about data" – for analytical purposes.

Beyond the *availability* of raw data alone, and beyond the *intent* to utilize it, there needs to be *capacity* to understand and use data effectively. In the words of Stanford Professor Andreas Weigend, "data is the new oil; like oil, it must be refined before it can be used."[25]

Big Data for Development: Getting Started

"Big Data" is a popular phrase used to describe a massive volume of both structured and unstructured data that is so large that it's difficult to process with traditional database and software techniques. The characteristics which broadly distinguish Big Data are sometimes called the "3 V's": more volume, more variety and higher rates of velocity. This data comes from everywhere: sensors used to gather climate information, posts to social media sites, digital pictures and videos posted online, transaction records of online purchases, and from cell phone GPS signals to name a few. This data is known as "Big Data" because, as the term suggests, it is huge in both scope and power.

To illustrate how Big Data might be applicable to a development context, imagine a hypothetical household living in the outskirts of a medium-size city a few hours from the capital in a developing country. The head of household is a mechanic who owns a small garage. His wife cultivates vegetables and raises a few sheep on their plot of land as well as sews and sells drapes in town. They have four children aged 6 to 18. Over the past couple of months, they have faced soaring commodity prices, particularly food and fuel. Let us consider their options.

[xii] Several governments, for example, have already taken significant steps to make government data open and available for analysis and use. Countries from regions across the globe – from Kenya to Norway, Brazil to South Korea, and international institutions like the World Bank – have begun adopting norms to standardize and publish datasets. See "Open Data Sites." < http://www.data.gov/opendatasites/> for a sample of existing sites and datasets.

The couple could certainly reduce their expenses on food by switching to cheaper alternatives, buying in bulk, or simply skipping meals. They could also get part of their food at a nearby World Food Programme distribution center. To reduce other expenses, the father could start working earlier in the morning in order to finish his day before nightfall to lower his electricity bill. The mother could work longer hours and go to town everyday to sell her drapes, rather than twice a week. They could also choose to top-off their mobile phone SIM cards in smaller increments instead of purchasing credit in larger sums and less-frequent intervals. The mother could withdraw from the savings accumulated through a mobile phone-based banking service which she uses.

If things get worse they might be forced to sell pieces of the garage equipment or a few sheep, or default on their microfinance loan repayment. They might opt to call relatives in Europe for financial support. They might opt to temporarily take their youngest child out of school to save on tuitions fees, school supplies and bus tickets. Over time, if the situation does not improve, their younger children may show signs of anaemia, prompting them to call a health hotline to seek advice, while their elder son might do online searches, or vent about his frustration on social media at the local cybercafé. Local aid workers and journalists may also report on increased hardships online.

Such a systemic—as opposed to idiosyncratic—shock will prompt dozens, hundreds or thousands of households and individuals to react in roughly similar ways.[26] Over time, these collective changes in behaviour may show up in different digital data sources. Take this series of hypothetical scenarios, for instance:

(1) The incumbent local mobile operator may see many subscribers shift from adding an average denomination of $10 on their SIM-cards on the first day of the month to a pattern of only topping off $1 every few days; The data may also show a concomitant significant drop in calls and an increase in the use of text messages;

(2) Mobile banking service providers may notice that subscribers are depleting their mobile money savings accounts; A few weeks into this trend, there may be an increase in defaults on mobile repayments of microloans in larger numbers than ever before;

(3) The following month, the carrier-supported mobile trading network might record three times as many attempts to sell livestock as is typical for the season.

(4) Health hotlines might see increased volumes of calls reporting symptoms consistent with the health impacts of malnutrition and unsafe water sources;

(5) Other sources may also pick up changes consistent with the scenario laid out above. For example, the number of Tweets mentioning the difficulty to "*afford food"* might begin to rise. Newspapers may be publishing stories about rising infant mortality;

(6) Satellite imaging may show a decrease in the movement of cars and trucks travelling in and out of the city's largest market;

(7) WFP might record that it serves twice as many meals a day than it did during the same period one year before. UNICEF also holds daily data that may indicate that school attendance has dropped.

The list goes on.

This example touches on some of the opportunities available for harnessing the power of real-time, digital data for development. But, let us delve a little deeper into what the relevant characteristics, sources, and categories of Big Data, which could be useful for global development in practice, might be.

Big Data ***for* the purposes of *development*** relates to, but differs from, both 'traditional development data' (e.g. survey data, official statistics), and what the private sector and mainstream media call 'Big Data' in a number of ways.

For example, microfinance data (e.g. number and characteristics of clients, loan amounts and types, repayment defaults) falls somewhere between 'traditional development data' and 'Big Data.' It is similar to 'traditional development data' because the nature of the information is important for development experts. Given the expansion of mobile and online platforms for giving and receiving microloans means that today a large amount of microfinance data is available digitally and can be analysed in real time, thus qualifying it to be considered Big Data for Development.

At the other end of the spectrum, we might include Twitter data, mobile phone data, online queries, etc. These types of data can firmly be called 'Big Data', as popularly defined (massive amounts of digital data passively generated at high frequency). And, while these streams of information may not have traditionally been used in the field of development, but they could prove to be very useful indicators of human well-being. Therefore, we would consider them to be *relevant* Big Data sources for development.

Big Data for Development sources generally share some or all of these features:

(1) **Digitally generated** – i.e. the data are created digitally (as opposed to being digitised manually), and can be stored using a series of ones and zeros, and thus can be manipulated by computers.

(2) **Passively produced** – a by product of our daily lives or interaction with digital services

(3) **Automatically collected** – i.e. there is a system in place that extracts and stores the relevant data as it is generated

(4) **Geographically or temporally trackable** – e.g. mobile phone location data or call duration time.

(5) **Continuously analysed** – i.e. information is relevant to human well-being and development and can be analysed in real-time

It is important to distinguish that for the purposes of global development, "real-time" does not always mean occurring immediately. Rather, "real-time" can be understood as information which is produced and made available in a relatively short and *relevant period of time*, and information which is made available within a timeframe that allows action to be taken in response i.e. creating a feedback loop.[xiii] Importantly, it is the

[xiii] "A **feedback loop** involves four distinct stages. First comes the data: A behaviour must be measured, captured and stored. This is the evidence stage. Second, the information must be relayed to the individual, not in the raw-data form in which it was captured but in a context that makes it emotionally resonant. This

intrinsic time dimensionality of the data, *and* that of the feedback loop that jointly define its characteristic as real-time. (One could also add that the real-time nature of the data is ultimately contingent on the analysis being conducted in real-time, and by extension, where action is required, used in real-time.)

With respect to spatial granularity, finer is not necessarily better. Village or community level data may in some cases be preferable to household or individual level data because it can provide richer insights and better protect privacy. As per the time dimensionality, any immediacy benchmark is difficult to set precisely, and will become out-dated, as higher frequency data are made available in greater volumes and with a higher degree of immediacy in the next few years. It must also be noted that real-time is an attribute that doesn't last long: sooner or later, it becomes contextual, i.e. non-actionable data. These include data made available on the spot about average rainfalls or prices, or phone calls made over a relatively long period of time in the past (even a few months), as well as the vast majority of official statistics—such as GDP, or employment data.

Without getting too caught up in semantics at length, it is important to recognise that Big Data for Development is an evolving and expanding universe best conceptualised in terms of continuum and relativeness.

For purposes of discussion, Global Pulse has developed a loose taxonomy of types of new, digital data sources that are relevant to global development:

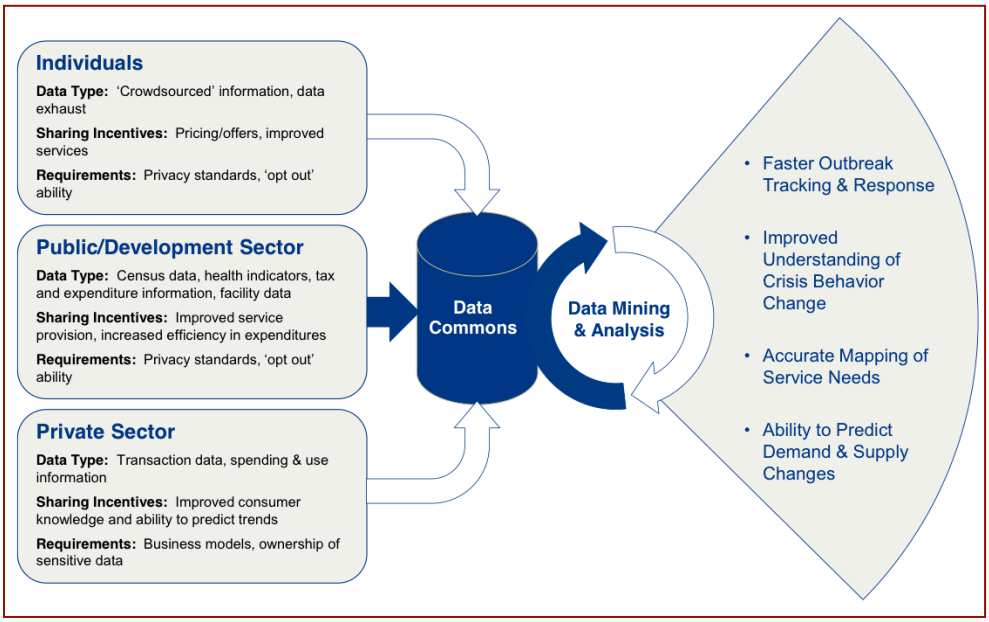
(1) **Data Exhaust** – passively collected transactional data from people's use of digital services like mobile phones, purchases, web searches, etc., and/or operational metrics and other real-time data collected by UN agencies, NGOs and other aid organisations to monitor their projects and programmes (e.g. stock levels, school attendance); these digital services create networked sensors of human behaviour;
(2) **Online Information** – web content such as news media and social media interactions (e.g. blogs, Twitter), news articles obituaries, e-commerce, job postings; this approach considers web usage and content as a sensor of human intent, sentiments, perceptions, and want.
(3) **Physical Sensors** – satellite or infrared imagery of changing landscapes, traffic patterns, light emissions, urban development and topographic changes, etc; this approach focuses on remote sensing of changes in human activity
(4) **Citizen Reporting or Crowd-sourced Data** – Information actively produced or submitted by citizens through mobile phone-based surveys, hotlines, user-generated maps, etc; While not passively produced, this is a key information source for verification and feedback

---

is the relevance stage. But even compelling information is useless if we don't know what to make of it, so we need a third stage: consequence. The information must illuminate one or more paths ahead. And finally, the fourth stage: action. There must be a clear moment when the individual can recalibrate a behaviour, make a choice and act. Then that action is measured, and the feedback loop can run once more, every action stimulating new behaviours that inch us closer to our goals." Goetz, Thomas. "Harnessing the Power of Feedback Loops." *Wired.com.* Conde Nast Digital, 19 June 2011. <http://www.wired.com/magazine/2011/06/ff_feedbackloop/all/1>.

Yet another perspective breaks down the types of data that might be relevant to international development by how it is produced or made available: by individuals, by the public/development sector, or by the private sector (Figure 3).

Figure 3: "Understanding the Dynamics of the Data Ecosystem"



The new data ecosystem, as illustrated by the World Economic Forum, which we are in today includes various data types, incentives, and requirements of actors. Source: WEF White Paper, "Big Data, Big Impact: New Possibilities for International Development" http://www3.weforum.org/docs/WEF_TC_MFS_BigDataBigImpact_Briefing_2012.pdf

Capacity: Big Data Analytics

The expansion of technical *capacity* to make sense of Big Data in various sectors and academia abounds. Initially developed in such fields as computational biology, biomedical engineering, medicine, and electronics, Big Data analytics refers to tools and methodologies that aim to transform massive quantities of raw data into "data about the data"—for analytical purposes. They typically rely on powerful algorithms that are able to detect patterns, trends, and correlations over various time horizons in the data, but also on advanced visualization techniques as "*sense-making tools.*"[27] Once trained (which involves having training data), algorithms can help make predictions that can be used to detect anomalies in the form of large deviations from the expected trends or relations in the data.

Discovering patterns and trends in the data from the observation and juxtaposition of different kinds of information requires defining a common framework for information processing. At minimum, there needs to be a simple lexicon that will help tag each datum. This lexicon would specify the following:

(1) *What*: i.e. the type of information contained in the data,

(2) *Who*: the observer or reporter,
(3) *How*: the channel through which the data was acquired,
(4) *How much*: whether the data is quantitative or qualitative,
(5) *Where and when*: the spatio-temporal *granularity* of the data—i.e. the level of geographic disaggregation (province, village, or household) and the interval at which data is collected.

Then, the data that will eventually lend itself to analysis needs to be adequately prepared. This step may include:

(1) *Filtering*—i.e. keeping instances and observations of relevance and getting rid of irrelevant pieces of information
(2) *Summarising*—i.e. extracting keyword or set of keywords from a text
(3) *Categorising, and/or turning the raw data into an appropriate set of indicators*—i.e. assigning a qualitative attribute to each observation when relevant—such as 'negative' vs. 'positive' comments, for instance. Yet another option is simply to calculate indicators from quantitative data such as growth rates of price indices (i.e. inflation).

Once the data is ready to be analysed, data analytics per se imply letting powerful algorithms and computational tools dive into the data. A characteristic of these algorithms is their ability to adapt their parameters in response to new streams of data by creating algorithms of their own to take care of parts of the data. This is necessary because these advanced models—non-linear models with many heterogeneous interacting elements—require more data to calibrate them with a data-driven approach.[28]

This intensive mining of socioeconomic data, known as "reality mining,"[29] can shed light on processes and interactions in the data that would not have appeared otherwise. Reality mining can be done in three main ways:[42]

(1) *"Continuous data analysis over streaming data,"* using tools to scrape the Web to monitor and analyse high-frequency online data streams, including uncertain, inexact data. Examples include systematically gathering online product prices in real-time for analysis.
(2) *"Online digestion of semi-structured data and unstructured ones"* such as news items, product reviews etc., to shed light on hot topics, perceptions, needs and wants.
(3) "*Real-time correlation of streaming data (fast stream) with slowly accessible historical data repositories*." This terminology refers to "mechanisms for correlating and integrating real-time (fast streams) with historical records…in order to deliver a contextualised and personalised information space [that adds] considerable value to the data, by providing (historical) context to new data."[30]

Big Data for Development could use all three techniques to various degrees depending on the availability of data and the specific needs.

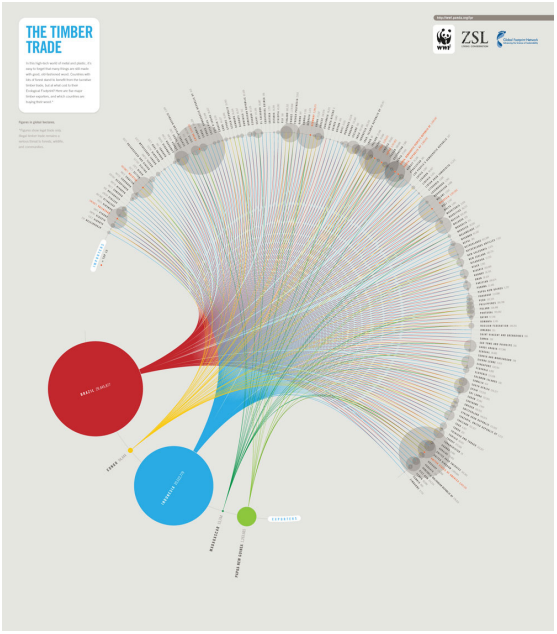
Further, an important feature of Big Data analytics is the role of visualisation, which can provide new perspectives on findings that would otherwise be difficult to grasp. For example, "word clouds" (Figure 4), which are a set of words that have appeared in a certain body of text – such as blogs, news articles or speeches, for example – are a simple

and common example of the use of visualisation, or "information design," to unearth trends and convey information contained in a dataset, but there exist many alternatives to word clouds (Figure 5).[xiv]

Figure 4: A word cloud of this paper

Source: The full text of this paper; world cloud created using www.Wordle.net

Figure 5: Data Visualization of the Global Legal Timber Trade



Graphic designer Paul Butt created a data visualization that shows the top five timber exporting countries of the world, and maps out the countries to which the timber is sold, and at what cost.

Source: http://awesome.good.is/transparency/web/1102/timber-trade/flat.html

[xiv] Global Pulse has been working with the global community, Vizualizing.org to explore different styles and methods for data visualization and information design. See "Data Channels, UN Global Pulse." <http://www.visualizing.org/data/channels/un-global-pulse.>

1.2 Social Science and Policy Applications

A Growing Body of Evidence

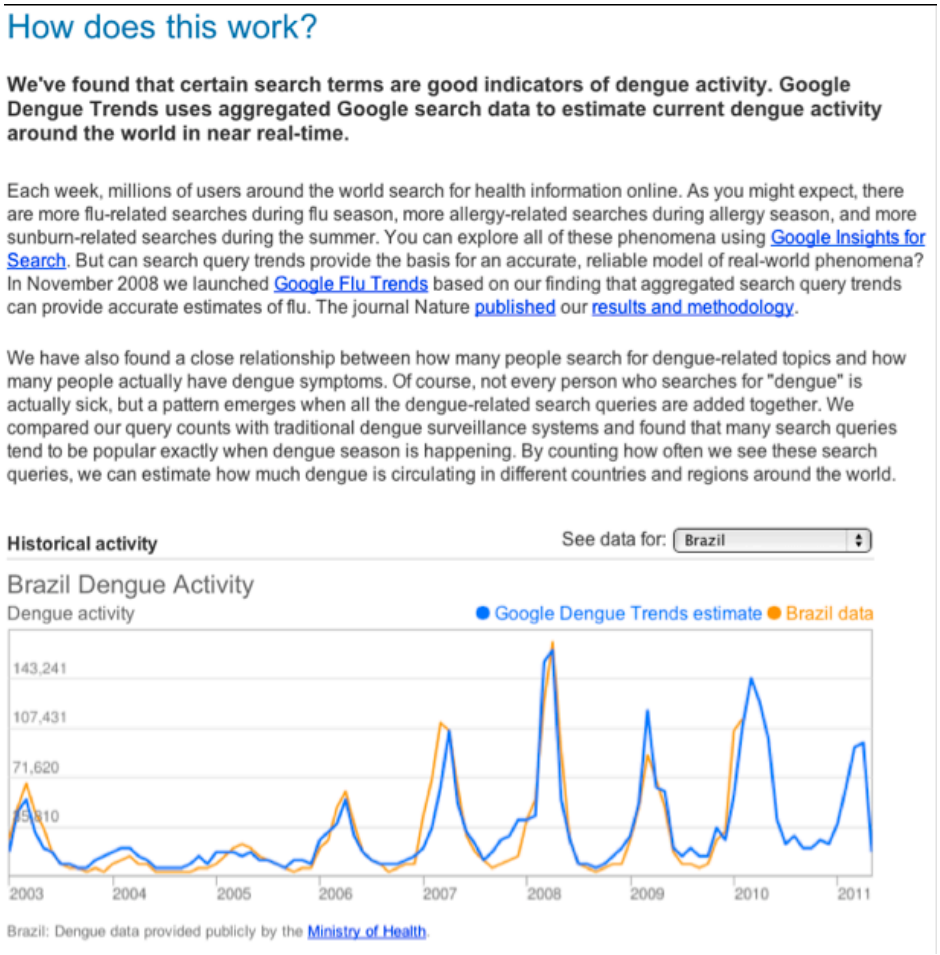
There is already evidence of the power of data analytics beyond the fields of hard sciences and business. In the field of social science and public policy it is the predictive power of the data that has attracted the most attention, as academic teams across the world are discovering the insights on human behaviour that can be gleaned from these data.

For example, a team of physicists from Northeastern University conducted a study in which they were able to predict, with over 93% accuracy, where a person is physically located at any given time based on analysis of cell-phone information generated from their past movements.[31] Another two-year research effort provided evidence of the power of mobile phones as sensors and predictors of human behaviour, prompting the academic Dr. Alex Pentland of the Massachusetts Institute of Technology, who led the initiative, to conclude: "phones can know."[32] Mobile phones give researchers the ability to "quantify human movement on a scale that wasn't possible before," including to "detect changes from standard commuting patterns" based on their radius of gyration after losing a job. [33]

It has also been found that a country's GDP could be estimated in real time by measuring light emissions at night through remote sensing.[34]

Another well-known example is Google Flu Trends, a tool launched in 2008 based on the prevalence of Google queries for flu-like symptoms. A research paper[35] found that *"because the relative frequency of certain queries is highly correlated with the percentage of physician visits in which a patient presents with influenza-like symptoms,"* it was possible to *"accurately estimate the current level of weekly influenza activity in each region of the United States, with a reporting lag of about one day."* The conclusion was that it is *"possible to use search queries to detect influenza epidemics in areas with a large population of web search users."* When applied to public health, online data has been used as part of syndromic surveillance efforts also known as infodemiology.[36] According to the US Center for Disease Control and Prevention (CDC), mining vast quantities of health-related online data can help detect disease outbreaks *"before confirmed diagnoses or laboratory confirmation."*[37] Google Dengue Trends works in the exact same way, and has shown similar promise (Figure 6).

Figure 6: Screen Shot of Google Dengue Trend Website

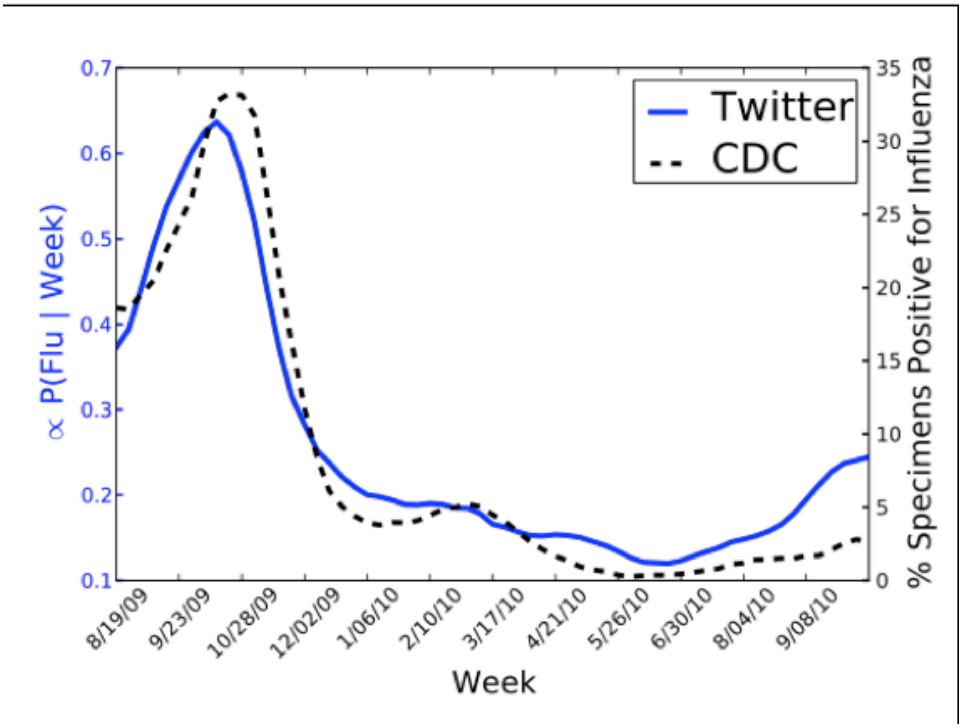


Source: http://www.google.org/denguetrends/about/how.html

Twitter may serve a similar purpose. Computer scientists at John Hopkins University analysed over 1.6 million health-related tweets (out of over 2 billion) posted in the US between May 2009 and October 2010 using a sophisticated proprietary algorithm and found a 0.958 correlation between the flu rate they modelled based on their data and the official flu rate (Figure 7).[38]

The prevalence and spread of other types of health conditions and ailments in a community can also be analysed via Twitter data, including obesity and cancer.[39] Information about Twitter users' location that they provide publicly can be used to study the geographic spread of a disease or virus, as evidenced by a study of the H1N1 epidemic in the US.[40]

Figure 7: Twitter-based vs. Official Influenza Rate in the U.S.



Source: « You Are What You Tweet: Analyzing Twitter for Public Health. M. J. Paul and M. Dredze, 2011. http://www.cs.jhu.edu/%7Empaul/files/2011.icwsm.twitter_health.pdf

Note: "Influenza rate from August 2009 to October 2010 as measured by CDC FluView (measured as percentage of specimen's that tested positive for influenza) and ATAM+'s "flu" ailment (the normalised probability of the "flu" ailment given the week): correlation coefficient of 0.958." (p. 4)

Another application for which Twitter is especially suited is to provide richer information on health-related behaviours, perceptions, concerns, and beliefs. Important sociological insights were gleaned from the John Hopkins study. These included detailed information about the use and misuse of medication (such as self-prescribed antibiotics to treat the flu, which are by nature irrelevant, and other over-the-counter misuse) and exercise routines among various socioeconomic groups—relevant for both research and policy. Still in the realm of social media, a study showed that Facebook updates, photos and posts could help identify drinking problems among college students, a major public health concern.[41] An important difference between Twitter and Facebook is, of course, the fact that the latter is a closed network, whereas the vast majority of tweets are public, thus theoretically (but not necessarily) accessible for analysis.

Other data streams can also be brought in or layered against social media data, notably to provide geographical information: the Healthmap project, for example, compiles disparate data from online news, eyewitness reports and expert-curated discussions, as well as validated official reports, to *"achieve a unified and comprehensive view of the current global state of infectious diseases"* that can be visualised on a map.[42] In the words of one of its creators, *"[i]t's really taking the local-weather forecast idea and*

making it applicable to disease."[43] This may help communities prepare for outbreaks as they do for storms.

Another example of the use of new data for policy purposes was Ushahidi's[xv] use of crowdsourcing following the earthquake that devastated Haiti, where a centralised text messaging system was set up to allow cell-phone users to report on people trapped under damaged buildings. Analysis of the data found that the concentration of aggregated text messages was highly correlated with areas where the damaged buildings were concentrated.[xvi] According to Ushahidi's Patrick Meier these results were evidence of the system's ability to *"predict, with surprisingly high accuracy and statistical significance, the location and extent of structural damage post-earthquake."*

This section has aimed to illustrate how leveraging Big Data for Development can reduce human inputs and time-lags in production, collection, and transmission of information, and allow for more onus to be placed on analysis and interpretation, and making informed and effective evidence-based decisions from the data.

With all this available data, a growing body of evidence, and all the existing technological and analytical capacity to use it, the question must be asked: why hasn't Big Data for Development taken hold as a common practice ?

The answer is because it is not easy. Section 2 turns to the challenges with using Big Data for Development.

[xv] Ushahidi is a nonprofit tech company that was developed to map reports of violence in Kenya following the 2007 post-election fallout. Ushahidi specializes in developing "*free and open source software for information collection, visualization and interactive mapping."* <http://ushahidi.com>

[xvi] Conducted by the European Commission's Joint Research Center against data on damaged buildings collected by the World Bank and the UN from satellite images through spatial statistical techniques.

Section II: Challenges

Applying Big Data analytics to the fuel of development faces several challenges. Some relate to the data—including its acquisition and sharing, and the overarching concern over privacy. Others pertain to its analysis. This section discusses the most salient of the challenges (recognising that there are others).

2.1 Data

Privacy

Privacy is the most sensitive issue, with conceptual, legal, and technological implications. In its narrow sense, privacy is defined by the International Telecommunications Union as the *"right of individuals to control or influence what information related to them may be disclosed."* Privacy can also be understood in a broader sense as encompassing that of companies wishing to protect their competitiveness and consumers and states eager to preserve their sovereignty and citizens. In both these interpretations, privacy is an overarching concern that has a wide range of implications for anyone wishing to explore the use of Big Data for development—vis-à-vis data acquisition, storage, retention, use and presentation.

Because privacy is a pillar of democracy, we must remain alert to the possibility that it might be compromised by the rise of new technologies, and put in place all necessary safeguards.

Privacy is a fundamental human right that has both intrinsic and instrumental values. Two authors, Helbing and Balietti[44], stress the necessity to ensure an appropriate level of privacy for individuals, companies and societies at large. In their words, *"a modern society needs [privacy] in order to flourish."*[45] Without privacy, safety, diversity, pluralism, innovation, our basic freedoms are at risk. Importantly, these risks concern even individuals who have "*nothing to hide.*"[46] There is no need to expand at length on the importance and sensitivity of information for corporations and states.

Focusing on individual privacy, it is likely that, in many cases, the primary producers—i.e. the users of services and devices generating data—are unaware that they are doing so, and/or what it can be used for. For example, people routinely consent to the collection and use of web-generated data by simply ticking a box without fully realising how their data might be used or misused.[47] It is also unclear whether bloggers and Twitter users, for instance, actually consent to their data being analysed.[48] In addition, recent research showing that it was possible to 'de-anonymise' previously anonymised datasets raises concerns.[49]

The wealth of individual-level information that Google, Facebook, and a few mobile phone and credit card companies would jointly hold if they ever were to pool their information is in itself concerning. Because privacy is a pillar of democracy, we must remain alert to the possibility that it might be compromised by the rise of new

technologies, and put in place all necessary safeguards.

Access and Sharing

Although much of the publicly available online data (data from the "open web") has potential value for development, there is a great deal more valuable data that is closely held by corporations and is not accessible for the purposes described in this paper. One challenge is the reluctance of private companies and other institutions to share data about their clients and users, as well as about their own operations. Obstacles may include legal or reputational considerations, a need to protect their competitiveness, a culture of secrecy, and, more broadly, the absence of the right incentive and information structures. There are also institutional and technical challenges—when data is stored in places and ways that make it difficult to be accessed, transferred, etc. (For example, MIT professor Nathan Eagle often anecdotally describes how he spent weeks in the basements of mobile-phone companies in Africa searching through hundreds of boxes filled with magnetic back-up tapes to gather data. An Indonesian mobile carrier estimated that it would take up to half a day of work to extract one day's worth of backup data currently stored on magnetic tapes.[50]) Even within the UN system it can prove difficult to get agencies to share their programme data, for a combination of some or all of reasons listed above.

Engaging with appropriate partners in the public and private sectors to access non-public data entails putting in place non-trivial legal arrangements in order to secure (1) reliable access to data streams and (2) get access to back up data for retrospective analysis and data training purposes. There are other technical challenges of inter-comparability of data and inter-operability of systems, but these might be relatively less problematic to deal with than getting formal access or agreement on licensing issues around data.

For Big Data for Development to gain traction, these are serious, make-or-break challenges. Any initiative in the field ought to fully recognise the salience of the privacy issues and the importance of handling data in ways that ensure that privacy is not compromised. These concerns must nurture and shape on-going debates around data privacy in the digital age in a constructive manner in order to devise strong principles and strict rules—backed by adequate tools and systems—to ensure "*privacy-preserving analysis*."[51]

At the same time, the promise will not be fulfilled if institutions—primarily private corporations—refuse to share data altogether. In light of these necessities, Global Pulse, for instance, is putting forth the concept of *"data philanthropy,"*[52] whereby *"corporations* [would] *take the initiative to anonymize (strip out all personal information) their data sets and provide this data to social innovators to mine the data for insights, patterns and trends in realtime or near realtime."*[53] Whether the concept of data philanthropy takes hold or not, it certainly points to the challenges and avenues for consideration in the future (Figure 8), and we can expect to see further refinements and alternative models proposed for how to deal with privacy, and data share.

Figure 8: Future challenges for social science data

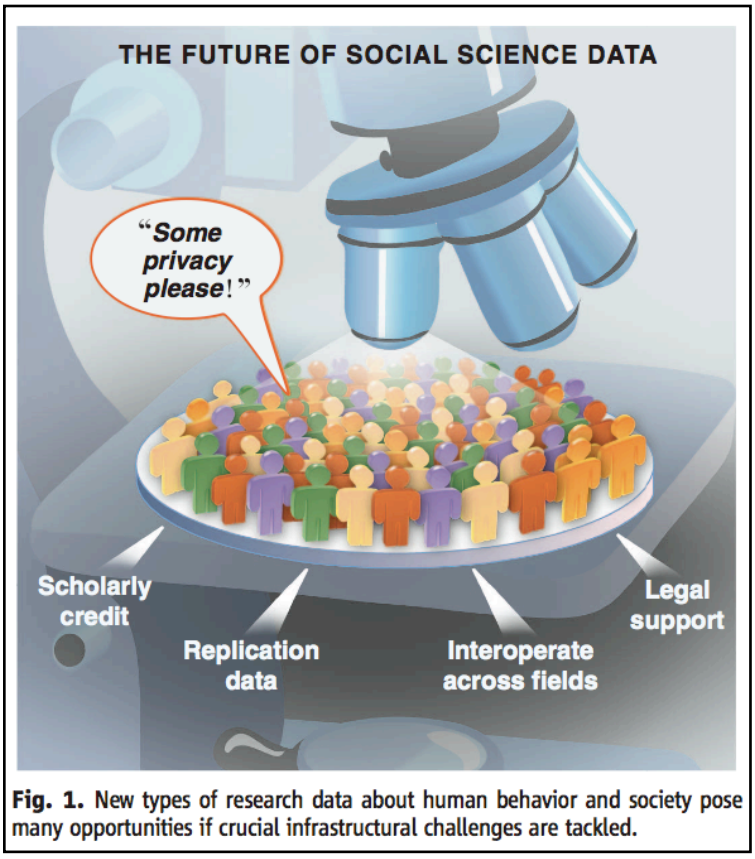


Fig. 1. New types of research data about human behavior and society pose many opportunities if crucial infrastructural challenges are tackled.

Source*:* "Ensuring the Data-Rich Future of the Social Sciences". Gary King, Science Magazine, Vol. 331, 11 February 2011.
http://gking.harvard.edu/files/datarich.pdf

2.2 Analysis

Working with new data sources brings about a number of analytical challenges. The relevance and severity of those challenges will vary depending on the type of analysis being conducted, and on the type of decisions that the data might eventually inform. The question "*what is the data really telling us*?" is at the core of any social science research and evidence-based policymaking, but there is a general perception that "new" digital data sources poses specific, more acute challenges. It is thus essential that these concerns be spelled out in a fully transparent manner. The challenges are intertwined and difficult to consider in isolation, but for the sake of clarity, they can be split into three distinct categories: (1) getting the picture right, i.e. summarising the data (2) interpreting, or making sense of the data through inferences, and (3) defining and detecting anomalies.[54]

Getting the Picture Right

One is reminded of Plato's allegory of the cave: the data, as the shadows of objects passing in front of the fire, is all the analyst sees.[55] But how accurate a reflection is the data? Sometimes the data might simply be false, fabricated.

For example, unverified citizen reporters or bloggers could be publishing false information.[xvii] Individuals speaking under their actual identity—citizen reporters, bloggers, even journalists—may also fabricate or falsify facts. External actors or factors might interfere in ways that could make data paint a misleading picture of reality. For example, "*if SMS streams are used to try to measure public violence [...] the perpetrators will be actively trying to suppress reporting, and so the SMS streams will not just measure where the cell phones are, they'll measure where the cell phones that perpetrators can't suppress are. We'll have many more "false negative"*[xviii] *zones where there seems to be no violence, but there's simply no SMS traffic. And we'll have dense, highly duplicated reports of visible events where there are many observers and little attempt to suppress texting."*[56] In all of these cases there is a willingness to alter the perception of reality that the observer will get out of the data. This challenge is probably most salient with unstructured user-generated text-based data (such as blogs, news, social media messages, etc.) because of its relatively more spontaneous nature and looser verification steps.

In addition, a significant share of the new, digital data sources which make up Big Data are derived from people's own perceptions—information extracted from calls to health hotlines and online searches for symptoms of diseases, for example. Perceptions differ from feelings in that they are supposed to convey objective facts—such as health symptoms. But perceptions can be inaccurate and thus misleading.

A good example is Google Flu Trends, whose ability to "*detect influenza epidemics in areas with a large population of web search users"* was previously discussed. A team of medical experts compared data from Google Flu Trends from 2003 to 2008 with data from two distinct surveillance networks[xix] and found that while Google Flu Trends did a very good job at predicting nonspecific respiratory illnesses (bad colds and other

[xvii] For example, Tom MacMaster, a Scotland-based heterosexual male caused quite the controversy during the 2011 Arab Spring when he regularly posted blogposts on the web in the persona of a lesbian woman in Syria. The blog, "A Gay Girl in Damascus," managed to gather a growing following as MacMaster published regularly between February and June, until it was revealed that the blog was a hoax. The incident raised or intensified concerns about unverified user-generated information. While Tom MacMaster claimed he used the hypothetical persona to try to illuminate the events in the Middle East for a western audience, any reader would have been ultimately relying on fabricated information. Addley, Esther. "Syrian lesbian blogger is revealed conclusively to be a married man." *The Guardian.* 12 Jun. 2011 <http://www.guardian.co.uk/world/2011/jun/13/syrian-lesbian-blogger-tom-macmaster>

[xviii] False negatives refer to cases where some event of interest fails to be noticed.

[xix] The CDC's influenza-like-illness surveillance network reporting the proportion of people who visit a physician with flu-like symptoms (fever, fatigue and cough) and the CDC's virologic surveillance system reporting on the proportion of people who visit a physician and actually have lab-confirmed influenza Liu, Bing "Sentiment Analysis and Subjectivity." *Handbook of Natural Language Processing* 2 (2010): 1-38. Department of Computer Science at the University of Illinois at Chicago. <http://www.cs.uic.edu/~liub/FBS/NLP-handbook-sentiment-analysis.pdf>

infections like SARS) that **seem like the flu**, it did not predict **actual flu** very well. The mismatch was due to the presence of infections causing symptoms that resemble those of influenza, and the fact that influenza is not always associated with influenza-like symptoms. According to one of the researchers, *"[t]his year, up to 40% of people with pandemic flu did not have 'influenza-like illness' because they did not have a fever (...) Influenza-like illness is neither sensitive nor specific for influenza virus activity—it's a good proxy, it's a very useful public-health surveillance system, but it is not as accurate as actual nationwide specimens positive for influenza virus.*" This mismatch may have important policy implications. Doctors using Google Flu Trends may overstock on flu vaccines or be inclined to conclude that the flu-like symptoms of their patients are attributable to influenza, even when they are not. Similar caveats apply to the analysis of Tweets or calls to health hotlines.

Another challenge relates to sentiment analysis (or opinion mining). The term refers to "*the computational study of opinions, sentiments and emotions expressed in text*"[57] that aims at "*translating the vagaries of human emotion into hard data.*"[58] Scraping blogs and other social media content has become a common undertaking of corporations and academic researchers. Sentiment analysis aims at finding out and quantifying whether, how many, and how strongly people are happy vs. unhappy, pessimistic vs. optimistic, what they like or dislike, support or reject, fear or look forward to something—and any "shades of grey" in between.

Difficulties in conducting sentiment analysis can be organised in various ways.[59] One perspective distinguishes challenges related to "*conceptualisation*" (i.e. defining categories, clusters), *"measurement"* (i.e. assigning categories and clusters to unstructured data, or vice-versa) and *"verification"* (i.e. assess how well steps 1 and 2 fare in extracting relevant information). Another focuses on the main challenges of selecting *"target documents," "identifying the overall sentiment expressed"* in the target documents, and lastly *"present[ing] these sentiments [...] in some reasonable summary fashion."*[xx]

Overall, the fundamental challenge is getting to the true intent of a statement, in terms of polarity, intensity, etc. Many obstacles may impede this, from the use of slang, local dialect, sarcasm, hyperboles, and irony, to the absence of any key words. These are, in a sense, technical or measurement challenges that become easier to handle as the degree of sophistication of sentiment analysis algorithms improves. But the conceptualisation and classification phase of any analysis which is to be conducted is non-trivial. This implies deciding, for instance, whether what matters is frequency or presence of key word(s). Thus, the human analyst's input is critical. Classification is "*one of the most central and generic of all our conceptual exercises. [...] Without classification, there could be no advanced conceptualization, reasoning, language, data analysis, or, for that matter, social science research*."[60]

[xx] Options considered include "(a) aggregation of "votes" that may be registered on different scales (e.g., one reviewer uses a star system, but another uses letter grades), (b) selective highlighting of some opinions (c) representation of points of disagreement and points of consensus (d) identification of communities of opinion holders (e) accounting for different levels of authority among opinion holders." (Source: Pang and Lee, 2008.)

Text mining goes beyond sentiment analysis to the extraction of key words or events. It may involve scraping websites for facts such as deaths, job announcements or losses, foreclosures, weddings, and financial difficulties, etc. The difficulty here, again, is extracting the true significance of the statements in which these facts are reported. For example, if our hypothetical couple's son reports having lost "*a*" job (possibly out of two or more), it is different from having lost one's *only* job (just like losing a part-time job is different from losing a full-time job). Text mining may also involve looking for trending topics in online news and other publications. This type of analyses—text categorisation—is technically relatively easier to conduct, but aggregating topics within larger clusters also requires inputs from the analyst.

A somewhat different problem is the fact that a significant share of new, digital data sources are based on *expressed intentions* as revealed through blogposts, online searches, or mobile-phone based information systems for checking market prices, etc., which may be a poor indicator of actual intentions and ultimate decisions. An individual searching for information about or discussing "moving to the UK" may have no intention of moving to the UK at all, or may not follow through on his/her intentions even if he or she initially did.

These examples are meant to illustrate just some of the difficulties in summarising facts from user-generated text; the line between reported feelings and facts may not be as easy to distinguish as it may seem—because "*facts all come with points of view.*"[61] With an understanding of the kinds of issues related to the 'accuracy' of the variety of new digital data sources that make up "Big Data," let us now turn to the challenge of interpretation.

Interpreting Data

In contrast to user-generated text, as described in the section above, some digital data sources—transactional records, such as the number of microfinance loan defaults, number of text messages sent, or number of mobile-phone based food vouchers activated—are as close as it gets to indisputable, hard data. But whether or not the data under consideration is thought to be accurate, interpreting it is never straightforward.

A frequently voiced concern is the sampling selection bias, i.e. the fact that the people who use mobile or other digital services (and thus generate the real-time digital data being considered for analysis) are not a representative sample of the larger population considered. Cell-phones, computers, food vouchers, or microfinance products, are neither used at random nor used by the entire population. Depending on the type of data, one can expect younger or older, wealthier or poorer, more males than females, and educated or uneducated individuals, to account for a disproportionate share of producers.[xxi]

For instance, *"[c]hances are that older adults are not searching in Google in the same proportion as a younger, more Internet-bound, generation."*[62]It is the combination of the self-selection of individuals with specific attributes and the fact that these attributes affect

[xxi] Note that the fact that some respondents in a representative sample may yield more data points than others does not jeopardize the representativeness of the sample—once will simply infer that the same behavior will appear in the larger population within which the sample was drawn.

their behaviours in other ways that causes the bias.[xxii] There are other practical reasons why the sample may be non-representative. For example, it could be that only data for one mobile phone companies is available for analysis. The resulting sample will most likely be non-representative of either the population of mobile-phone holders or of the population of the area. More traditional datasets are generally less subject to such a bias.[xxiii]

The problem with findings based on non-representative samples is that they lack external validity.[xxiv] They cannot be generalised beyond the sample. Suppose that, in the village where our hypothetical household lives, the number of cases of cholera reported through a mobile-phone hotline doubles in a week following a rise in temperature. Because the sample is not representative—since individuals using cell-phones tend to have specific characteristics—one cannot infer that there are twice as many cases of cholera in the entire community,[xxv] nor that in general a rise in temperature leads to more cases of cholera. But while findings based on non-representative datasets need to be treated with caution, they are not valueless—as discussed in section three.

Further, with massive quantities of data there is a risk of focusing exclusively on finding patterns or correlations and subsequently rushing to judgements without a solid understanding of the deeper dynamics at play. Such a wealth of data *"tempts some researchers to believe that they can see everything at a 30,000-foot view. It is the kind of data that encourages the practice of apophenia: seeing patterns where none actually exist, simply because massive quantities of data can offer connections that radiate in all directions."*[63] It also "*intensifies the search for interesting correlations*"[64], which might be (mis)interpreted as causal relationships.

The latter tendency is problematic with any type of data, but new data sources—

[xxii] Importantly, the sampling bias issue is only about the sample—i.e. the individuals who are observed—not about the type or number of 'data' they generate. Some individuals may generate many more observations (such as phone calls, or visits to clinics) than others but as long as the difference is not due to any other measurement problems—and the sample is representative—the data is unbiased.

[xxiii] This can be avoided in one of three ways: one is obviously to ensure complete coverage of the unit of analysis, another is to observe or survey individuals truly at random on a sufficiently–large scale. For instance, random samples can be constructed using a computer that 'picks up' some individual specific numbers at random and a (less rigorous way) third way is to purposefully 'build' a representative sample ex-ante or ex-post. The latter technique is used by pollsters who 'redress' the results obtained from a sample thought to be non-representative by using 'weights'

[xxiv] The term 'validity' refers to the degree to which a conclusion or inference accurately describes a real-world process. It is standard to contrast internal versus external validity. The former refers to "the approximate truth about inferences regarding cause-effect or causal relationships." In other words, the extent to which a study demonstrates the existence of a causal relationship. The latter refers to the degree to which an internally valid conclusion can be generalised to a different setting. A causal relationship is different from a causal effect, which is the quantifiable difference between two potential outcomes if some initial condition changed. For the purposes of this paper, internal validity is understood to encompass the extent to which the existence of some recurrent pattern in the data—a stylised fact, a correlation—can be established. (Sources: King, Gary and Powell, Eleanor. "How Not to Lie Without Statistics." Harvard University. National Science Foundation (2008) <http://gking.harvard.edu/files/mist.pdf>) and "Internal Validity." Research Methods Knowledge Base. <http://www.socialresearchmethods.net/kb/intval.php>)

[xxv] Some may treat this as an internal validity problem but it is only because they wrongfully confound the sample and the larger unit of analysis it is drawn from.

particularly social media, crowd-sourced information, or other user-created content—may pose specific challenges. Considering the claims of Ushahidi in Haiti after the earthquake. A prominent ICT4D blogger, Jim Fruchterman[65] discussed the problems with drawing the types of conclusions that Ushahidi's staff had drawn on the basis of crowd-reported information. As he explains:

> *[t]he correlation found in Haiti is an example of a "confounding factor." A correlation was found between building damage and SMS streams, but only because both were correlated with the simple existence of buildings. Thus the correlation between the SMS feed and the building damage is an artifact or spurious correlation…once you control for the presence of any buildings (damaged or undamaged), the text message stream seems to have a weak* ***negative*** *correlation with the presence of damaged buildings. That is, the presence of text messages suggests there are fewer (not more) damaged buildings in a particular area.*[xxvi]

According to Fruchterman and his colleagues, the Ushahidi system's apparent ability to *"predict (…) the location and extent of structural damage post-earthquake"* simply reflected this spurious correlation, which was so strong that it more than offset the actual *negative* correlation between the number of SMS text messages and the damages.[xxvii] Why was that correlation negative? *"It may be that people move away from damaged buildings (perhaps to places where humanitarian assistance is being given) before texting."* This would explain, all other things being equal, the *underreporting* of damages in places worst hit.

Importantly, this example actually illustrates two very different analytical issues. One is the presence of a confounding factor.[xxviii] But higher mortality or departure from the zone of interest is a problem of *attrition*, a form of selection bias (not related to the initial sample) that undermines internal validity (not external as in the case of a sampling bias).

There are many other cases where correlations should not be misinterpreted as causations. Google Correlate, for example, is a tool that helps identify best-fit correlations between two sets of terms in online searches patterns. Playing with the tool revealed a 0.9 (90%) fit between the terms "weight gain" and "apartments for rent" in US

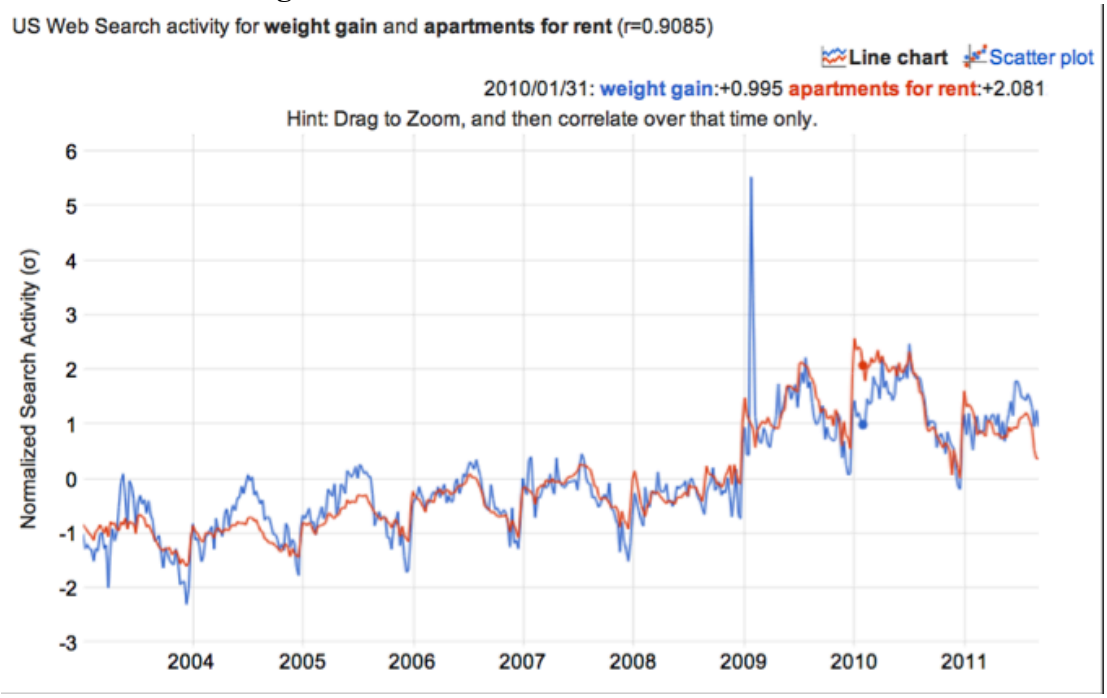
[xxvi] Jim Fruchterman provided two additional examples of spurious correlations are their implications for policy: "*Children's reading skill is strongly correlated with their shoe size -- because older kids have bigger feet and tend to read better. You wouldn't measure all the shoes in a classroom to evaluate the kids' reading ability. Locations with high rates of drowning deaths are correlated with locations with high rates of ice cream sales because people tend to eat ice cream and swim when they're at leisure in hot places with water, like swimming pools and seasides. If we care about preventing drowning deaths, we don't set up a system to monitor ice cream vendors."*

[xxvii] In other words, when the number of buildings was not controlled for, its effect was then picked up by (added to) the effect the number of texts from or about these buildings, turning the 'true' negative correlation into an overall strong, statistically significant positive correlation.

[xxviii] Clearly, this is not a sampling bias problem, because the dependent variable (the number of buildings that actually collapsed) is observed for *all* observations in the data, not just for a sample. At the same time, the realization that internal validity—i.e. the ability to infer the existence of a causal relation—is compromised does prevent generalization—i.e. negates the possibility of external validity: internal validity is a necessary but insufficient condition of external validity.

searches since 2004 (Figure 9). It is unclear how one could cause the other.

Figure 9: Correlation Does Not Mean Causation



Source: Google Correlate

The problems highlighted here can have serious policy implications since "*[m]isunderstanding relationships in data (…) can lead to choosing less effective, more expensive data instead of choosing obvious, more accurate starting points."* In the Ushahidi case, Fruchterman argued, *"if decision makers simply had a map [of pre-earthquake buildings] they could have made better decisions more quickly, more accurately, and with less complication."*[xxix]

Another temptation when faced with the availability of massive amounts of disparate data is to throw in a large number of controls in regression analysis to find 'true' relationships in the data. Doing so can strengthen the analysis' internal validity by 'netting out' of the effects of other endogenous factors on the dependent variable, but it brings about several potential challenges. First, it downplays the fact that combining data from multiple sources may also mean "*magnifying*"[66] their flaws. If the results are contingent on factors specific to the unit of analysis, they also become hard to generalise to other settings with vastly different mean values of the included controls: external validity is then weakened. There is another econometric downside to throwing in a large number of controls indiscriminately. If many of them are correlated, the resulting multicollinearity will lead to non-unique parameter fits and more or less arbitrary parameter choices, meaning that the results may be misleading. This suggests that theory and context matter even (or,

[xxix] Note that the 'causal link' in question does not imply that text messages 'cause' actual damage, but that more texts *mean* more damage because of the features of the system.

especially) with large amounts of data.

Transposing insights gleaned from static analysis across time and space is also a challenge. Imagine that the prevalence of the phrase "runny nose" in Google searches doubles over a week. Most data is subject to a confirmation or 'mimicking' bias creating a 'self-fulfilling prophecy' similar to the case of inflation: if the rise is widely covered in the media, it is possible that more people will search for these terms. Various other events may affect people's incentive to search for "runny nose": if a cholera epidemic broke out, flu symptoms would become less of a concern. Conversely if the epidemic was brought under control, people may suddenly become more concerned about runny noses.[xxx] In other words, "*Google's data are likely to be sensitive to factors that modify human behaviour but which are not related to true disease rate*" as noted by Elena Naumova, Director of Tufts University Initiative for the Forecasting and Modeling of Infectious Diseases[67] The same observation applies to other data streams—hotlines, purchases, Twitter, other user-generated content, etc. In addition, individuals being 'surveyed' in new data streams are usually different between two points in time—imagine how the population of a large university town changes in the summer—such that changes in behaviours may simply reflect this.

The challenge here lies partly in the fact that (as discussed in the previous section) a significant share of the new data sources in question reflects perceptions, intentions, and desires. Understanding the mechanisms by which people express perceptions, intentions and desires—as well as how they differ between region or linguistic culture, and change over time—is hard. Other difficulties clearly find their root in the samples. Both internal and external validities can be threatened, depending on the exact set up and question. It can be difficult to establish a form of causality for a given area between two points in time, or for two different areas at a given point in time. Even once this is established, such that internal validity is ensured, the difficulty is to transpose the insight(s) to either a different point in time, or a different area, which relates to external validity.

Above and beyond simply determining *accuracy*, these are just some of the key challenges associated with trying to draw valid *inferences and conclusions* from certain types of digital data sources. It should be clear that while some of these challenges are specific to dealing with new digital data sources, most are pervasive in social science and policymaking relying on *any* data.

As discussed in section three, the best remedy is to rely on analysts who are fully aware of these limitations and keep the claims and decisions made on the basis of the data within acceptable boundaries—which are wide enough.

Defining and Detecting Anomalies in Human Ecosystems

An overarching challenge when attempting to measure or detect anomalies in human ecosystems is the characterization of (ab)normality. The nature and detection of what may constitute socioeconomic 'anomalies' differ—indeed may be less clear-

[xxx] This observation echoes that made in Solzhenitsyn's "One Day in the Life of Denis Denisovich," where his hero realizes that whenever his situation improves along some dimension, he notices a problem that had until then been hidden, concealed, by the graver concern.

cut—from those in the realm of disease outbreak detection or malfunction monitoring in other types of dynamic systems (such as car engines). Even within a well-specified human ecosystem—a village or a household—it is difficult to determine precisely *ex ante* a set of 'outputs' to be expected from a given set of inputs: adaptive and agile systems such as human groups will produce 'anomalies' provided the model forecasting expected behaviours or outputs is excessively stringent.

Human organs function in a similar way: a well-functioning heart beats irregularly; a heart that beats with a steady regularity is a heart that is most likely about to fail precisely because it signals the cardiac system's inability to adapt. These elements suggest the need to develop methodologies to characterise and detect socioeconomic anomalies in context.

Several examples point to the challenges of sensitivity versus specificity of monitoring systems. *Sensitivity* refers to the ability of a monitoring system to detect *all* cases it is set up to detect while *specificity* refers to its ability to detect *only* relevant cases. Failures to achieve the latter yields "Type I decision error", also known as "false positive"; failures to achieve the former "Type II error"[xxxi], or "false negative." Both errors are undesirable when attempting to detect malfunctions or anomalies, however defined, for different reasons. False positives undermine the credibility of the system while false negatives cast doubt on its relevance.

But whether false negatives are more or less problematic than false positives depends on what is being monitored, and why it is being monitored.

Recognizing these challenges, the final section discusses the specific application of Big Data for the field of global development.

[xxxi] Conducting repeated tests on a dynamic system with a very low probability of making a type I error *"in any single trip"* (or any single day) has a substantial probability of leading to such an error at least once after *n* trips (or tries). In contrast, a system that would have an unrealistically high probability of making a type II error (missing an actual problem) in any given trip has a very low probability of missing a problem after *n* trips for any N sufficiently large. Under all realistic scenarios, a malfunction will eventually be detected, such that in most cases "*it would seem prudent to balance the probability of making type I and II errors in favor of reducing the chances of Type I errors*" (Source: Box, George, Spencer Graves, Soren Bisgaard, John Van Gilder, Ken Marko, John James, Mark Poublon and Frank Fodale. "Detecting Malfunctions in Dynamic Systems." Center for Quality and Productivity Improvement (1999): 1-10. University of Wisconsin, Mar. 1999 (p. 4).)

Section III: Application

Big Data is not perfect—no data is—but it holds a tremendous wealth of information. Further, as this paper argues, the relevance of Big Data for global development hinges primarily on the type of analysis it is subjected to and the use that is made of the resulting information.

3.1 What New Data Streams Bring to the Table

Know Your Data

A fundamental misconception of both its strongest advocates and fiercest sceptics is that Big Data is expected to be—or contain—the answer to all human problems. Advocates may hastily and blindly jump into the data without further consideration, fuelling the criticisms of the sceptics already prone to discard Big Data on the sole basis of its imperfection. "New," "Big," "official" or "traditional": data is data. It has its flaws and its value. New, digital data sources considered relevant for the purposes of this paper—i.e. Big Data for Development—are certainly not perfect data, but their value is tremendous if they are both properly understood and analysed.

There are certainly flaws in new data streams—in particular about their reliability, accuracy and representativeness—but these are not crippling provided they are understood. Certainly, some online user-created content will indeed be fakes or hoaxes. But these have plagued public debates—think of the Timisoara scandal[68] some 20 years ago—way before the advent of the Internet and social media. Importantly, the power of technology and social media cuts both ways: *"what's new about the world of social media is the speed with which information can be disseminated, questioned, and, where necessary, debunked."*[69] Some media organizations, such as the BBC, stand by the utility of citizen reporting of current events: *"there are many brave people out there, and some of them are prolific bloggers and Tweeters. We should not ignore the real ones because we were fooled by a fake one."*[70] And have thus devised internal strategies to confirm the veracity of the information they receive and chose to report, offering an example of what can be done to mitigate the challenge of false information. At the same time, not all user-generated content should be taken at face value. The fundamental, and still open-ended, question is: how much user-generated content is fake, or misrepresentative, and how much does it alter the overall picture?

There is also much to be said about data that convey perceptions either explicitly (in blogs for example) or implicitly (through online searches or calls to health hotlines, for example). Some of these perceptions may be wrong or unwarranted, as previously discussed. This does not make them necessarily misleading. In response to its critics, Google reasserted that Flu Trends was not designed to monitor confirmed flu infections: *"If you have a daughter who is ill, you wouldn't be able to tell the difference between flu and influenza-like illness when you're searching online,"* explained Google Flu Trends' lead engineer. "*And it's just as important to monitor clusters of symptoms as it is to monitor specific infections. There are many cases where it makes more sense to look at the clinical [data] in combination with the virologic [data] in order to get a full picture*

of what's going on." Thus Google Flu Trends might provide some unique advantages precisely because it is perception-based, and broad—provided the information it contains is not misinterpreted. Only those who wrongfully assume that the data is an accurate picture of reality can be deceived. Furthermore, there are instances where wrong perceptions are precisely what is desirable to monitor because they might determine collective behaviours in ways that can have catastrophic effects. For example, if HIV positive males in a community spread the word that having sex with a virgin will cure them, it is essential to pick up these signals as early as possible and act to counter the misinformation. Similarly, picking up reports coming from a community that aliens are invading from space is valuable to anticipate and manage the potential reaction by a panicked population. The point is that perceptions can also shape reality. Detecting and understanding perceptions quickly can help change outcomes.

…the promise of Big Data for Development is, and will be, best fulfilled when its limitations, biases and ultimately features, are adequately understood and taken into account when interpreting the data.

Signals emanating from non-representative samples can also be informative. The sampling selection bias can clearly be a challenge, especially in regions or communities where technological penetration is low. But this does not mean that the data has no value. For one, data from "non-representative" samples (such as mobile phone users) provide representative information *about the sample itself*—and do so in close to real time and on a potentially large and growing scale, such that the challenge will become less and less salient as technology spreads across and within developing countries.

There have even been instances where the sample selection bias can be useful: for example, researchers from MIT's Billion Prices Project found that the few retailers in Latin America use websites to advertise—definitely a non-representative sample—raise their online prices two to three weeks before price increases hit the physical market, because they know that their wealthier customer base (online shoppoers) can absorb the shock.[71] In all cases, being aware of the potential bias and understanding its likely implication when considering the data should help avoid most of the associated pitfalls including unwarranted generalisations.

The promise of Big Data for Development is, and will be, best fulfilled when its limitations, biases, and ultimately features, are adequately understood and taken into account when interpreting the data. As some of the examples discussed in this paper demonstrate, any challenge with utilizing Big Data source of information cannot be assessed divorced from the intended use of the information. These new, digital data sources may not be the best suited to conduct airtight scientific analysis, but they have a huge potential for a whole range of other applications that can greatly affect development outcomes.

Applications of Big Data for Development

A much-debated avenue is finding correlations and stylised facts in large datasets. Section two laid out some of the challenges and risks associated with rushing to find and interpret correlations. Yet, if done correctly, finding correlations is *"enough to do*

interesting things".[72] Observing that X and Y are consistently correlated in a given setting is useful information to predict what Y may look like if X is known, and vice-versa. In other words X and Y can be used as proxy indicators, even if no causality is claimed. As noted by Google Chief Economist Hal Varian, *"even if all you have got is a contemporaneous correlation, you've got a 6-week lead on the reported values. The hope is that as you take the economic pulse in real time, you will be able to respond to anomalies more quickly".*[73]

The temptation to find any correlations in big datasets must certainly be kept in check to avoid misinterpretations and abuses, but there are many cases where correlations are relevant. In some cases, new data sources may mirror official statistics, offering cheaper and faster proxies. For example, as noted above, MIT researchers have been estimating inflation by collecting and analysing the daily price of goods *sold or advertised on the web* with impressive accuracy.[74] The key value-add of this method is that online prices can be obtained daily whilst consumer price indices in most countries are only published on a monthly basis. Thus, this approach may help detect inflation spikes sooner than traditional methods, or offer new insights into the transmission of price fluctuations to various goods and areas.

Beyond correlations, analysing large quantities of data can help unveil stylised facts—i.e. broadly recurring behaviours and patterns. Stylised facts should not be considered as laws that would always hold true, but they give a sense of the likelihood that some deviation from the trend may occur. As such, they form the basis of anomaly detection. When it comes to defining and detecting anomalies, important and promising work is being done.

For example, researchers at the International Food Policy Research Institute (IFPRI) have developed a methodology to detect "*excessive food price volatility, (…) i.e. a period of time in which a large number of extreme positive returns"* usually defined as a value of return that is exceeded with low probability: 5% or 1%)[75] in order to *"determine appropriate country- level food security responses, such as the release of physical food stocks."* Similar methods can be applied to the detection of anomalies in how community members use their cell-phones, sell their livestock, etc.

Access to large-scale sources of real time data can help save lives. The United States Geological Survey (USGS) has developed a system that monitors Twitter for significant spikes in the volume of messages about earthquakes.[76] Location information is then extracted and passed on to USGS's team of seismologists to verify that an earthquake occurred, locate its epicentre and quantify its magnitude. As it turns out, 90% of the reports that trigger an alert have turned out to be valid. Similarly, a recent retrospective analysis of the 2010 cholera outbreak in Haiti conducted by researchers at Harvard and MIT demonstrated that mining Twitter and online news reports could have provided health officials a highly accurate indication of the actual spread of the disease with two weeks lead time.[77]

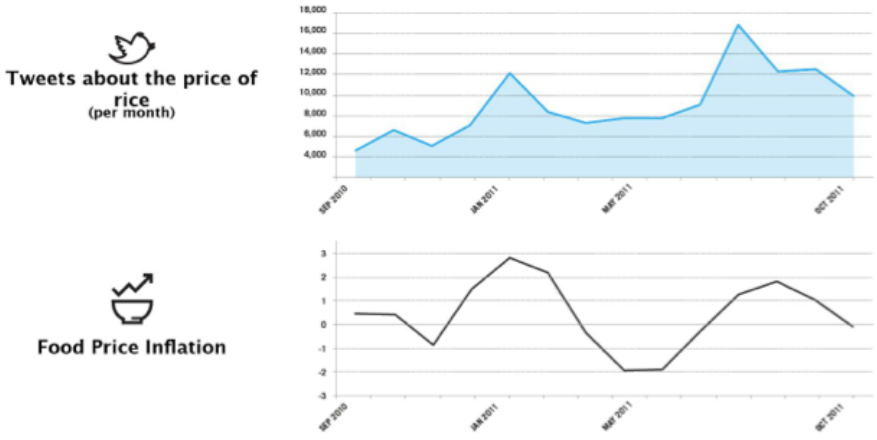
Further, as various examples have shown, it is not just the size and speed but also the nature, the *richness* of the information that many new data streams contain that has great value. In many cases Big Data for Development is not meant to replace or act as a proxy for official statistics, but to complement them by adding depth and nuance, as in the aforementioned John Hopkins study showed. Indeed, even in the field of

syndromic surveillance, experts agree that new data streams—Tweets in that case—are *"not accurate enough to replace traditional methods"* of sentinel surveillance.[78] But the same experts add: "*[t]here is a lot of potential to learn so much about people that they don't share with their doctors."* The more qualitative social media information helps paint a picture that quickly reacts to changing conditions. In turn, all of this information can be factored in to affect these very same conditions in a much more agile way.

It is clear from these examples that it is the combination of the size, speed, and nature of the data that is highly valuable to affect certain outcomes.

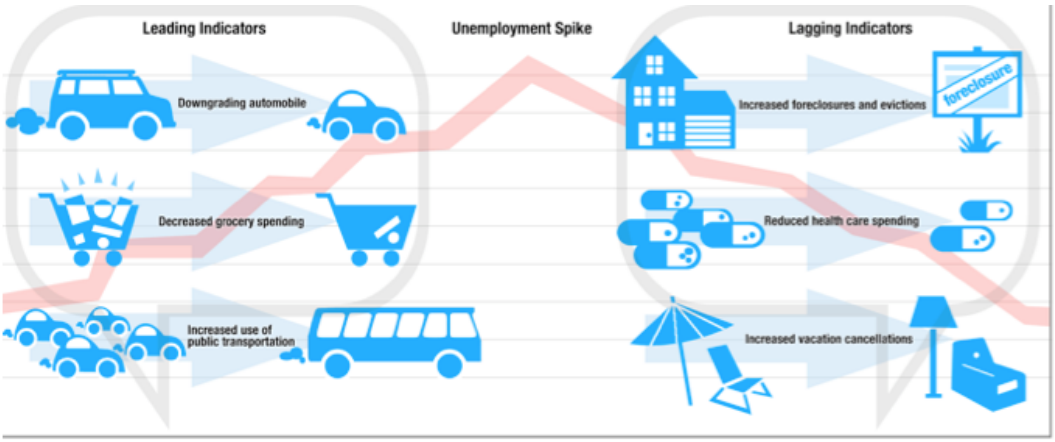
A recent joint research project between Global Pulse and social media analysis firm Crimson Hexagon analysed over 14 million Tweets related to food, fuel, and housing in the US and Indonesia, to better understand people's concerns.[79] The research analysed trends in these topics in conjunction with themes such as "afford," showing how the volume and topics of the conversations changed over time reflecting populations' concerns. Interestingly, changes in the number of Tweets mentioning the price of rice and actual food price inflation (official statistics) in Indonesia proved to be closely correlated (Figure 9). Another collaborative research project between Global Pulse and the SAS Institute analysing unemployment through the lens of social media in the US and Ireland revealed that the increases in the volume of employment-related conversations on public blogs, online forums and news in Ireland which were characterised by the sentiment "confusion" show up three months before official increases in unemployment, while in the US conversations about the loss of housing increased two months after unemployment spikes (Figure 10).[80] Similar research could be conducted in developing countries with high Internet penetration, such as Indonesia or Brazil for instance.

Figure 9: Tweets about the price of rice vs. actual price of rice in Indonesia



Source: http://www.unglobalpulse.org/projects/twitter-and-perceptions-crisis-related-stress

Figure 10: Infographic depicting some of the leading and lagging indicators of unemployment spikes, as discovered through a joint SAS-Global Pulse research project examining unemployment through the lens of social media



Source: "Can a Country's Online Mood Predict Unemployment Spikes?" *SAS.* http://www.sas.com/news/preleases/un-sma.html and http://www.unglobalpulse.org/projects/can-social-media-mining-add-depth-unemployment-statistics

Properly analysed, Big Data offers the opportunity for an improved understanding of human behaviour that can support the field of global development in three main ways:

1) **Early warning:** early detection of anomalies in how populations use digital devices and services can enable faster response in times of crisis;
2) **Real-time awareness:** Big Data can paint a fine-grained and current representation of reality which can inform the design and targeting of programs and policies;
3) **Real-time feedback:** the ability to monitor a population in real time makes it possible to understand where policies and programs are failing and make the necessary adjustments.

These applications are highly promising. But, as has been emphasised over and over, there is nothing automatic, lest simple, about turning Big Data sources into actionable information in development contexts.

3.2. Making Big Data Work for Development

Contextualisation is Key

The examples and arguments presented so far have all underscored the importance of contextualisation—understood in two complementary ways.

1) Data context. Indicators should not be interpreted in isolation. If one is concerned with anomaly detection, it is not so much the occurrence of one seemingly unusual fact or trend that should be concerning, but that of two, three or more;

2) Cultural context. Knowing what is "normal" in a country or regional context is prerequisite for recognising anomalies. Cultural practices vary widely the world over and these differences certainly extend to the digital world. There is a deeply ethnographic dimension in using Big Data. Different populations use services in different ways, and have different norms about how they communicate publicly about their lives.

Becoming Sophisticated Users of Information

The critical role of analysts is key at all stages, from the choice of taxonomies to the interpretation of results when and as appropriate. First and foremost, it requires relying on a variety of sources of information and assessing them with a critical eye. It implies avoiding the pitfalls exposed in the previous pages. Jim Fruchterman, in a blog series debunking the excessive hype around crowd-sourcing, acknowledged that while there are risks and limitations of crowd-sourced data for decision making, there is value in that data – provided that it is employed by, what he termed, "sophisticated users of information."[81]

…Real-time information does not replace the quantitative statistical evidence, which governments traditionally use for decision-making, but if understood correctly, it can inform where further targeted investigation is necessary, or even inform immediate response if necessary, and thus change outcomes like nothing else can.

In a February 2012 presentation on the topic of "Real-Time Awareness,"[82] Craig Fugate, Administrator of the United States' Federal Emergency Management Agency (FEMA), illustrated what it actually means for a government agency to become a "sophisticated user of information." In 2011, during a series of devastating tornadoes in the American mid-west, FEMA began monitoring Twitter and noticed an unusual number of different geographical locations being mentioned for tornado damage. Mr. Fugate proposed dispatching relief supplies to the long list of locations immediately and received pushback from his team who were concerned that they did not yet have an accurate estimate of the level of damage. His challenge was to get the staff to understand that the priority should be one of *changing outcomes*, and thus even if half of the supplies dispatched were never used and sent back later, there would be no chance of reaching communities in need if they were in fact suffering tornado damage already, without getting trucks out immediately. He explained, "*if you're waiting to react to the aftermath of an event until you have a formal assessment, you're going to lose 12-to-24 hours…Perhaps we shouldn't be waiting for that. Perhaps we should make the assumption that if something bad happens, it's bad. Speed in response is the most perishable commodity you have…We looked at social media as the public telling us enough information to suggest this was worse than we thought and to make decisions to spend [taxpayer] money to get moving without waiting for formal request, without waiting for assessments, without waiting to know how bad because we needed to change that outcome.*" [83] Fugate also emphasised that using social media as an information source isn't a precise science and the response isn't going to be precise either. "*Disasters are like horseshoes, hand grenades and thermal nuclear devices, you just need to be close—preferably more than less*," he said.[84]

His point was that real-time information does not replace the quantitative statistical evidence which governments traditionally use for decision making, but if understood correctly, it can inform where further targeted investigation is necessary (in less time-critical situations) or even inform immediate response if necessary (in disaster situations, such as tornadoes) and thus change outcomes like nothing else can.

Abiding by these guiding principles should allow Big Data for Development to meet its ultimate objective: to help policymakers and development practitioners gain richer and timelier insights on the experiences of vulnerable communities and implement better-informed and more agile interventions.

Concluding Remarks on the Future of Big Data for Development

Big Data is a sea change that, like nanotechnology and quantum computing, will shape the twenty-first century. According to some experts, "*[by] employing massive data-mining, science can be pushed towards a new methodological paradigm which will transcend the boundaries between theory and experiment."* Another perspective frames this new ability to unveil stylised facts from large datasets as "*the fourth paradigm of science*".[85]

This paper does not claim that Big Data will simply replace the approaches, tools and systems that underpin development work. What it does say, however, is that Big Data constitutes an historic opportunity to advance our common ability to support and protect human communities by understanding the information they increasingly produce in digital forms.

The question is neither "if," nor "when," but "how."

If we ask how much development work will be transformed in 5 to 10 years as Big Data expands into the field, the answer is not straightforward. Big Data will affect development work somewhere between significantly and radically, but the exact nature and magnitude of the change to come is difficult to project. First, because the new types of data that people will produce in ten years is unknown. Second, because the same uncertainty holds for computing capacities, given that Moore's Law[xxxii] with certainly not hold in an era of quantum computing. Third, because a great deal will depend on the future strategic decisions taken by a myriad of actors—chief of which are policymakers. Many open questions remain—including the potential misuse of Big Data, because information is power.

If, however, we ask how Big Data for Development can fulfil its immense potential to enhance the greater good, then the answer is clearer. What is needed is both *intent* and *capacity* to be sustained and strengthened, on the basis of a full recognition of the opportunities and challenges. Specifically, its success hinges on two main factors. One is the level of institutional and financial support from public sector actors, and the willingness of private corporations and academic teams to collaborate with them, including by sharing data and technology and analytical tools. Two is the development and implementation of new norms and ontologies for the responsible use and sharing of Big Data for Development, backed by a new institutional architecture and new types of partnerships.

Our hope is that this paper contributes to generating exchanges, debates and interest among a wide range of readers to advance Big Data for Development in the twenty-first century.

[xxxii] Moore's Law (an observation made by Intel co-founder Gordon Moore in 1965) predicts that computer chips shrink by half in size, and processors double in complexity, every two years. It is often referred to as a rule of thumb for understanding exponential improvement; although some argue that the world will soon see a period where progress in technology outpaces Moore's prediction of two-year cycles.

Endnotes

[1] Referenced by Nathan Eagle in video interview for UN Global Pulse, July 2011. Though, the term seems to have been originally coined by Joe Hellerstein, a computer scientist at the University of California, Berkeley <http://www.economist.com/node/15557443>

[2] Onella, Jukka- Pekka. "Social Networks and Collective Human Behavior." *UN Global Pulse*. 10 Nov. 2011. <http://www.unglobalpulse.org/node/14539>

[3] Lohr, Steve. "The Age of Big Data." *New York Times*. 11 Feb, 2012. <http://www.nytimes.com/2012/02/12/sunday-review/big-datas-impact-in-the-world.html?_r=2&pagewanted=all>

[4] Kirkpatrick, Robert. "Digital Smoke Signals." *UN Global Pulse*. 21 Apr. 2011. <http://www.unglobalpulse.org/blog/digital-smoke-signals>

[5] "The Data Deluge." *The Economist*. 25 Feb 2010. <http://www.economist.com/node/15579717> and Ammirati, Sean. "Infographic: Data Deluge – 8 Zettabytes of Data by 2015." *Read Write Enterprise*. <http://www.readwriteweb.com/enterprise/2011/11/infographic-data-deluge---8-ze.php>

[6] King, Gary. "Ensuring the Data-Rich Future of Social Science." *Science Mag* 331 (2011) 719-721. 11 Feb, 2011 Web. <http://gking.harvard.edu/sites/scholar.iq.harvard.edu/files/gking/files/datarich_0.pdf>

[7] Helbing, Dirk , and Stefano Balietti. "From Social Data Mining to Forecasting Socio-Economic Crises." *Arxiv* (2011) 1-66. 26 Jul 2011 http://arxiv.org/pdf/1012.0178v5.pdf.

[8] Manyika, James, Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh and Angela H. Byers. "Big data: The next frontier for innovation, competition, and productivity." *McKinsey Global Institute* (2011): 1-137. May 2011. <http://www.mckinsey.com/mgi/publications/big_data/pdfs/MGI_big_data_full_report.pdf>

[9] " World Population Prospects, the 2010 Revision." *United Nations Development Programme*. <http://esa.un.org/unpd/wpp/unpp/panel_population.htm>

[10] "Data Exhaust." <http://www.wordspy.com/words/dataexhaust.asp>

[11] Cornu, Celine. "Mobil Banking' Moving Through Developing Countries." *Jakarta Globe.* 21 Feb, 2010. <http://www.thejakartaglobe.com/business/mobile-banking-moving-through-developing-countries/359920>

[12] "Global Internet Usage by 2015 [Infographic]." *Alltop.* <http://holykaw.alltop.com/global-internet-usage-by-2015-infographic?tu3=1>

[13] Rao, Dr. Madanmohan. "Mobile Africa Report: Regional Hubs of Excellence and Innovation." *Mobile Monday* (2011): 1-68. Mar. 2011. <http://www.mobilemonday.net/reports/MobileAfrica_2011.pdf>

[14] "Big Data, Big Impact: New Possibilities for International Development." *World Economic Forum* (2012): 1-9. Vital Wave Consulting. Jan. 2012 <http://www.weforum.org/reports/big-data-big-impact-new-possibilities-international-development>.

[15] Toyama, Kentaro. "Can Technology End Poverty?" *Boston Review.* Dec 2010. <http://bostonreview.net/BR35.6/toyama.php>

[16] OECD, Future Global Shocks, Improving Risk Governance, 2011

[17] *Global Monitoring Report 2009: A Development Emergency*. Rep. Washington DC: International Bank for Reconstruction and Development/ The World Bank, 2009. <http://siteresources.worldbank.org/INTGLOMONREP2009/Resources/5924349-1239742507025/GMR09_book.pdf>

[18] "Economy: Global Shocks to Become More Frequent, Says OECD." *Organisation for Economic Co-operation and Development.* 27 June. 2011. <http://www.oecd.org/document/15/0,3746,en_21571361_44315115_48252559_1_1_1_1,00.html>

[19] FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI and the UN HLTF.

"Price Volatility in Food and Agricultural Markets: Policy Responses." 2 June, 2011. <http://www.foodsecurityportal.org/sites/default/files/g20_interagency_report_food_price_volatility.pdf>

[20] For a recent review, see: Fuentes, Nieva Ricardo, and Papa A. Seck. *Risks, Shocks and Human Development: On the Brink.* Basingstoke, England: Palgrave Macmillan, 2010.

[21] Almond, Douglas, Lena Edlund, Hongbin Li and Junsen Zhang. "*Long-term Effects of the 1959-1961 China Famine: Mainland China and Hong Kong"* Working Paper no. 13384. National Bureau of Economic Research, Sept. 2007. <http://www.nber.org/papers/w13384.pdf>

[22] Friedman, Jed, and Norbert Schady. *How Many More Infants Are Likely to Die in Africa as a Result of the Global Financial Crisis?* Rep. The World Bank. <http://siteresources.worldbank.org/INTAFRICA/Resources/AfricaIMR_FriedmanSchady_060209.pdf>

[23] Big data: The next frontier for innovation, competition, and productivity. McKinsey Global Institute, June 2011. http://www.mckinsey.com/mgi/publications/big_data/pdfs/MGI_big_data_full_report.pdf

[24] Burke, J., D. Estrin, M. Hansen, A. Parker, N. Ramanthan, S. Reddy and M.B. Srivastava. *Participatory Sensing.* Rep. Escholarship, University of California, 2006. <http://escholarship.org/uc/item/19h777qd>.

[25] Opening remarks to UN Global Pulse briefing presentation to the UN General Assembly <http://youtu.be/lbmsDH8RJA4> (Nov. 8, 2011)

[26] "Kenya-Somalia: The Nitty-Gritty of Flight." *Irin News Africa.* 23 Aug. 2011. <http://www.irinnews.org/report.aspx?reportid=93564>.

[27] Bollier, David. *The Promise and Peril of Big Data.* The Aspen Institute, 2010. <http://www.aspeninstitute.org/publications/promise-peril-big-data>

[28] Helbing, Dirk and Stefano Balietti. "From Social Data Mining to Forecasting Socio-Economic Crisis."

[29] Eagle, Nathan and Alex (Sandy) Pentland. "Reality Mining: Sensing Complex Social Systems", *Personal and Ubiquitous Computing*, 10.4 (2006): 255-268. <http://reality.media.mit.edu/pdfs/realitymining.pdf>

[30] Helbing and Balietti, "From Social Data Mining to Forecasting Socio-Economic Crisis."

[31] Hotz, Robert Lee. "The Really Smart Phone." *The Wall Street Journal.* 22 Apr. 2011. <http://online.wsj.com/article/SB10001424052748704547604576263261679848814.html>

[32] Alex Pentland cited in "When There's No Such Thing As Too Much Information". *The New York Times*. 23 Apr. 2011 <http://www.nytimes.com/2011/04/24/business/24unboxed.html?_r=1&src=tptw>.

[33] Nathan Eagle also cited in "When There's No Such Thing As Too Much Information". *The New York Times*. 23 Apr. 2011. <http://www.nytimes.com/2011/04/24/business/24unboxed.html?_r=1&src=tptw>.

[34] Helbing and Balietti. "From Social Data Mining to Forecasting Socio-Economic Crisis."

[35] Ginsberg, Jeremy, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant. "Detecting Influenza Epidemics Using Search Engine Query Data." *Nature* 457.7232 (2008): 1012-1014. <http://static.googleusercontent.com/external_content/untrusted_dlcp/research.google.com/en/us/archive/papers/detecting-influenza-epidemics.pdf >.

[36] Eysenbach G. *Infodemiology: tracking flu-related searches on the Web for syndromic surveillance.* AMIA (2006) <http://yi.com/home/EysenbachGunther/publications/2006/eysenbach2006c-infodemiology-amia-proc.pdf>

[37] Syndromic Surveillance (SS)." *Centers for Disease Control and Prevention.* 06 Mar. 2012. <http://www.cdc.gov/ehrmeaningfuluse/Syndromic.html>.

[38] Paul, M.J. and M. Dredze. *You Are What You Tweet: Analyzing Twitter for Public Health*. Rep. Center for Language and Speech Processing at Johns Hopkins University, 2011. <http://www.cs.jhu.edu/%7Empaul/files/2011.icwsm.twitter_health.pdf>

[39] Eke, P.I.. "Using Social Media for Research and Public Health Surveillance." (Abstract). *Journal of Dental Research* 90.9 (2011). <http://jdr.sagepub.com/content/early/2011/07/15/0022034511415273>

[40] Signorini, Alessio, Alberto M. Segre, and Phillip M. Polgren. "The Use of Twitter to Track Levels of Disease Activity and Public Concern in the U.S. during the Influenza A H1N1 Pandemic." *PLos One* 6.5 (2011). Pub Med. 4 May 2011. <http://www.ncbi.nlm.nih.gov/pubmed/21573238>

[41] Moreno, Megan A., Dimitiri A. Christakis, Katie G. Egan, Libby N Brockman and Tara Becker. "Associations Between Displayed Alcohol Reference on Facebook and Problem Drinking Amoung College Students." *Archives of Pediatrics and Adolescent Medicine* (2011). <http://archpedi.ama-assn.org/cgi/content/abstract/archpediatrics.2011.180v1?maxtoshow=&hits=10&RESULTFORMAT=&fulltext=facebook&searchid=1&FIRSTINDEX=0&resourcetype=HWCIT>.

[42] Health Map <http://healthmap.org/en/>

[43] Walsh, Bryan. ":Outbreak.com: Using the Web to Track Deadly Diseases in Real Time." *Time Science.* 16 Aug. 2011. <http://www.time.com/time/health/article/0,8599,2088868,00.html>.

[44] Helbing and Balietti. "From Social Data Mining to Forecasting Socio-Economic Crisis." *The European Physical Journal-Special Topics.* (Volume 195, Number 1, 3-68, pg. 24) 26 July 2011. <http://arxiv.org/abs/1012.0178>

[45] Ibid.

[46] Ibid.

[47] Efrati, Amir. "'Like' Button Follows Web Users." *The Wall Street Journal.* 18 May 2011. <http://online.wsj.com/article/SB10001424052748704281504576329441432995616.html>

[48] Boyd, Dana and Crawford, Kate. "Six Provocations for Big Data*." Working Paper - Oxford Internet Institute*. 21 Sept. 2011 <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1926431>

[49] A. Narayan and V. Shmatikov (2008)

[50] Both examples gleaned from conversations and consultations with Global Pulse staff.

[51] Both examples gleaned from conversations and consultations with Global Pulse staff.

[52] Krikpatrick, Robert. "Data Philanthropy: Public and Private Sector Data Sharing for Global Resilience." *UN Global Pulse.* 16 Sept. 2011. <http://www.unglobalpulse.org/blog/data-philanthropy-public-private-sector-data-sharing-global-resilience>

[53] "Data Philanthropy: A New Frontier?" *Rally the Cause.* 2 Mar. 2011. <http://rallythecause.com/2011/03/02/data-philanthropy-a-new-frontier/>

[54] King, Gary N. and Eleanor Powell. *How Not to Lie Without Statistics.* Working Paper. Harvard University, 22 Aug. 2008. <http://gking.harvard.edu/gking/files/nolie.pdf>

[55] For a short but useful introduction, see http://faculty.washington.edu/smcohen/320/cave.htm

[56] Fruchterman, Jim. "Issues with Crowdsourced Data Part 2." *Beneblog: Technology Meets Society.* 28 Mar. 2011. < http://benetech.blogspot.com/2011/03/issues-with-crowdsourced-data-part-2.html>

[57] Liu, Bing "Sentiment Analysis and Subjectivity." *Handbook of Natural Language Processing* 2 (2010): 1-38. Department of Computer Science at the University of Illinois at Chicago. <http://www.cs.uic.edu/~liub/FBS/NLP-handbook-sentiment-analysis.pdf>

[58] Wright, Alex. "Mining For Feelings, not Facts." *The New York Times*. 24 Aug. 2009. <http://www.nytimes.com/2009/08/24/technology/internet/24emotion.html?pagewanted=2>

[59] Pang, Bo and Lillian Lee. "Opinion Mining and Sentiment Analysis." *Foundations and Trends in Information Retrieval* 2.1-2 (2008): 1-135. NOW. <http://www.cs.cornell.edu/home/llee/omsa/omsa.pdf> and Hopkins, Daniel and Gary King. "Extracting Systematic Social Science Meaning from Text." Harvard University. Institute for Qualitative Social Science, 15 Sept. 2007.

[60] Cited in King and Powell (2008)

[61] David Byrne, quoted in <http://www.nytimes.com/2009/08/24/technology/internet/24emotion.html>

[62] "Google Flu Trends Do Not Match CDC Data." *Popular Mechanics.* 17 Mar. 2010. <http://www.popularmechanics.com/science/health/med-tech/google-flu-trends-cdc-data>

[63] Boyd, Dana and Crawford, Kate. "Six Provocations for Big Data." *Working Paper - Oxford Internet Institute*. 21 Sept. 2011 <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1926431>

[64] Boyd, Dana and Crawford, Kate.

[65] Jim Fruchterman. "Issues with Crowdsourced Data Part 2." *Beneblog: Technology Meets Society.* 28 Mar. 2011. <http://benetech.blogspot.com/2011/03/issues-with-crowdsourced-data-part-2.html>. Ball, Patrick, Jeff Klingner, and Kristian Lum. "Crowdsourcing Data is Not a Substitute for Real Statistics." *Beneblog.* 17 Mar. 2011. <http://benetech.blogspot.com/2011/03/crowdsourced-data-is-not-substitute-for.html>

[66] Bollier, David. *The Promise and Peril of Big Data*, pg. 13

[67] Wenner, Melinda. "Google Flu Trends Do Not Match CDC Data." *Popular Mechanics.* 17 May 2010. <http://www.popularmechanics.com/science/health/med-tech/google-flu-trends-cdc-data>

[68] "Twenty Years Later, Timisoara Affairs Exposes Media Credulity." *France 24.* 22 Dec. 2009. <http://www.france24.com/en/20091220-twenty-years-later-timisoara-affair-exposes-media-credulity>

[69] Lustig, Robin. "Why were we fooled by the fake Syria blog?" *BBC News.* 13 Jun. 2011. <http://www.bbc.co.uk/blogs/worldtonight/2011/06/why_were_we_fooled_by_the_fake.html>

[70] Murray, Alex. "BBC Processes for Verifying Social Media Content." BBC News. 18 May 2011. http://www.bbc.co.uk/journalism/blog/2011/05/bbcsms-bbc-procedures-for-veri.shtml

[71] Referenced by Dr. Alberto Cavallo (PriceStats) in research consultations with UN Global Pulse, 2011.

[72] Lise Getoor cited in David Bollier's *The Promise and Peril of Big Data*, pg. 16 <http://www.foodsecurityportal.org/policy-analysis-tools/excessive-food-price-variability-early-warning-system>

[73] Bollier, David. *The Promise and Peril of Big Data.*

[74] Cavallo, Alberto. "BPP and PriceStats." *The Billion Prices Project and MIT.* 6 May 2011. <http://bpp.mit.edu/bpp-and-pricestats/>

[75] "Excessive Food Price Variability Early Warning System." *Food Security Portal.*

[76] "Shaking and Tweeting: The USGS Twitter Earthquake Detection Program." *USGS.* 14 December 2009. <http://gallery.usgs.gov/audios/326#.T7um0r9J_sU>

[77] Chunara, R., Andrews, J., and Brownstein, J. "Social and News Media Enable Estimation of Epidemiological Patterns Early in the 2010 Haitian Cholera Outbreak." *American Journal of Tropical Medicine and Hygiene*. 2012 86:39-45. <http://www.ajtmh.org/content/86/1/39.abstract>

[78] " You Are What You Tweet: Analyzing Twitter for Public Health." <http://www.cs.jhu.edu/~mpaul/files/2011.icwsm.twitter_health.pdf>

[79] "Twitter and Perceptions of Crisis-Related Stress." *UN Global Pulse.* <http://www.unglobalpulse.org/projects/twitter-and-perceptions-crisis-related-stress>

[80] "Unemployment Through the Lens of Social Media." *UN Global Pulse.* <http://www.unglobalpulse.org/projects/can-social-media-mining-add-depth-unemployment-statistics>

[81] Fruchterman, Jim. "More on Using Crowdsourced Data to Find Big Picture Patterns (Take 3)." *Beneblog: Technology Meets Society.* 7 Apr. 2011. <http://benetech.blogspot.com/2011/04/more-on-using-crowdsourced-data-to-find.html>

[82] http://tech.state.gov/profiles/blogs/tech-state-real-time-awareness-agenda

[83] Video of Craig Fugate's keynote address at US State Department Tech@State Event, 3 February, 2012: <http://www.livestream.com/techstate/video?clipId=pla_a1cef922-7b17-400b-b67c-a21cb877b1f9&utm_source=lslibrary&utm_medium=ui-thumb>

[84] Stelter, Leischen. "FEMA's Fugate says Social Media is Valuable, but 'No Tweet Stops the Bleeding.'" *In Pulic Safety.* 16 Feb. 2012. <http://inpublicsafety.com/2012/02/femas-fugate-says-social-media-is-valuable-but-no-tweet-stops-the-bleeding/>

[85] Gray, Jim (ed. Gray, J., Tansley, S. and Tolle, K.). "eScience: A transformed scientific method." *The Fourth Paradigm: Data-Intensive Scientific Discovery*. Microsoft Research. Redmond, Washington, 2009. < http://research.microsoft.com/en-us/collaboration/fourthparadigm/contents.aspx>.