

Quantitative Methods for Human Rights:

From Statistics to “Big Data”

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“There are three kinds of lies: Lies, damned lies, and statistics” -Benjamin Deisraeli, former British Prime Minister.

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The following paper is the unedited version of a chapter that will eventually be published in a collection.¹

Quantitative methods in human rights refer to methods that seek to harness the power of numbers and relatively large amounts of data to highlight certain types of human rights violations. Such methods are obviously not exclusive of other approaches (and in fact “some combination of quantitative and qualitative methodologies provides advantages over either alone”)² but may in some circumstances provide insights into human rights violations that few other tools can approximate.

The use of quantitative methods to analyze human rights violations is an interesting example of a contribution from the social sciences—and from the boom in high-tech networked communications, more recently—to the practice of human rights. Many of the tools relied on were not developed specifically with human rights work in mind, and long remained on the margin of its practice. This may be because of the traditional individualism of rights, one which did not particularly require in-depth comparative or cross-societal analysis. It may also be because of the domination in the international human rights legal field of interpretative and normative debates, as opposed to the relatively murkier factual work of actually documenting rights violations. And it may be because of the domination of a broad “qualitative” approach to documenting rights violations (e.g.: victim interviews), one that may have shunned from the relatively vulgar

¹ *Research Methodologies in Legal Human Rights Scholarship*, (Martin Scheinin ed., forthcoming).
² Molly K. Land, “*Democratizing Human Rights Fact-Finding*”, in *The Transformation of Human Rights Fact-Finding*, 406 (Philip Alston and Sarah Knuckey eds., 2015).

act of “quantifying” the unquantifiable. In fact, social scientists themselves did not seem particularly interested in putting some of their tools to work to study the human rights “object,” perhaps because human rights seemed to raise problematic normative issues that would form a poor basis for quantitative analysis.

Nonetheless, one may speculate that a range of factors have made looking at rights issues with a quantitative lens increasingly more appealing. First, the human rights movement is in fact not concerned only with individual violations but with a range of trends, domestic but also global, that are hard to grasp except through some sort of quantitative analysis. Second, the growing importance of issues of discrimination between groups has necessitated the development of specific tools that can detect and understand societal sources of rights violations which also are hard to grasp without underlying trends and patterns. Third, the growing recognition of economic and social rights makes the development of various quantitative indicators an almost inevitable development. Fourth, the recurrence of massive human rights violations in the form notably of war-time atrocities and their prosecution before international criminal tribunals has made at least accounting for numbers of victims an urgent exercise. Fifth, “numbers” exercise a certain fascination and can provide powerful signposts to trigger international action and policy changes.³ As goes the aphorism: What’s gets measured gets done.

Finally, in the past decade, rapid (and still emergent) developments have added further appeal to the use of a quantitative lens. Increased “datafication” of communications and many other human activities has made the use of computational methods (a form of quantitative practices) virtually inevitable.⁴ And data itself is becoming more readily available, tipping its market balance from supply-based to demand-based (this also drives expectations that adequate levels of policy or norm development will encompass quantitative dimensions).

These various factors all appear and overlap throughout the below paper. Quantitative methods is an admittedly immense and varied field. This chapter therefore seeks to present a basic and overarching inventory of different quantitative approaches to human rights work. It does not focus exclusively on judicial or even strictly juridical methodologies, but instead examines a range of quantitative practices engaged in under the human rights banner. In doing so, the chapter expands the notion of human rights methods to include a range of tools that can be used, with normative goals, by human rights actors, including lawyers, policy experts, and activists.

The chapter has two parts, which reflect chronological changes in the field. Part one explores the use of traditional statistical methods for human rights, which until the last decade, constituted the backbone of quantitative methods in human. It is not meant as a technical introduction to statistics but rather as a broad overview of the uses that statistics have been put to in the human rights field. The second part, reflecting changes spurred by the digital revolution and beginning in the 2000s, focuses on the emergence

³ Brian Root, “Numbers Are Only Human: Lessons for Human Rights Practitioners from the Numeracy Movement”, in *The Transformation of Human Rights Fact-Finding*, 356 (Philip Alston & Sarah Knuckey eds., 2015).

⁴ Datafication refers to the here aspects of our lives are transformed into computerised data, which is increasingly common as a result of the digital revolution.

of huge amounts of data generated amongst other things by the Internet. Although that data is also subject to statistical analysis, it comes with its own set of analytical practices and potential implications for the work of detecting, highlighting, and possibly disrupting and preventing human rights violations. Although both sections are distinct, they are intrinsically linked by a shared quantitative ethos. In this way, readers will benefit from a “big picture” assessment of quantitative methods and its evolutionary arc over recent decades.

The chapter is aimed at academics, human rights lawyers, development practitioners, and human rights activists. The incentives to explore the uses, both current and potential, of quantitative methods are sharper than ever: quantitative methods are arguably the fastest changing and growing area of human rights work, by way of the digital revolution. Big data is effectively shaping a “new normal” in myriad professions, and there is no reason to think that the field of human rights is exempt. In this context the field’s traditional reluctance towards numbers should be surmounted to harness the power of statistical methods to greater human rights understanding, promotion and enforcement.

I. The Use of Statistics in International Human Rights Law

Statistics consists of summarizing and analyzing a set of numerical facts. For past decades, this was based on processing datasets collected directly from samples in the field, and from print and analogue sources such as newspapers and government archives. Such conventional statistical work constituted the backbone of human rights quantitative methods throughout these years. There is a significant social scientific interest in drawing on large numbers to establish macro-correlations, for example between certain types of regimes and certain types of human rights violations.⁵ This sort of work sheds light on the broader facilitative conditions of human rights compliance but this section will only survey instances of statistics being used for legal purposes. Below are three examples of how human rights professionals have leveraged statistical work of this type.

Identifying Group and Indirect Discrimination

Statistics have a clear role in international human rights in establishing certain patterns, mostly of discrimination. Unlike many other internationally protected rights, discrimination involves the sometimes subtle unjustified differentiated treatment of certain persons in relation to others. If the discrimination is blatant in a law or practice, then statistical evidence may have at best a supplementary role to show that the law does indeed have the consequences it was intended to have. If the discrimination, as is most likely to be the case, is not evident on its face (and perhaps not even intentional), then statistics may prove the only means of proving that discrimination is actually

⁵ The relevant literature is too vast to reference here. See, for instance, H. S. Park, *Correlates of human rights: Global tendencies*, 9 HUM. RIGHTS Q. 405–413 (1987); S. C. Poe & C. N. Tate, *Repression of human rights to personal integrity in the 1980s: A global analysis*, 88 AM. POLIT. SCI. REV. 853–872 (1994); Christian Davenport & David A. Armstrong, *Democracy and the violation of human rights: A statistical analysis from 1976 to 1996*, 48 AM. J. POLIT. SCI. 538–554 (2004); David L. Cingranelli & David L. Richards, *The Cingranelli and Richards (CIRI) human rights data project*, 32 HUM. RIGHTS Q. 401–424 (2010).

happening. Statistics are not the only means to prove discrimination,⁶ but they often provide particularly incontrovertible evidence to that effect.

As a result, statistics have long helped shed light on patterns of indirect or systemic discrimination. Bodies such as CEDAW and the CRC have repeatedly asked states to provide statistical information disaggregated so as to evidence the situation of women and children respectively.⁷ Statistics have helped to uncover, for example, the particularly high incidence of violence against women in Canada in the context of the examination of that country's report to the Human Rights Committee.⁸ The examination of a country's human rights record frequently leads to calls for the development of more fine-grained statistics to put in evidence practices of discrimination.⁹ More generally, the High Commissioner for Human Rights compiles statistics to evaluate trends and practices internationally that may then inform norm development, for example relating to the age of marriage.¹⁰ More ambitiously, the OHCHR now advocates a "Human-Rights Based Approach to Data" and has formulated a set of objectives and strategies to guide global efforts by governments and civil society for poverty reduction and addressing discrimination.¹¹

Indirect discrimination is notoriously difficult to establish, something which the European Court of Human Rights (ECtHR) has often noted, to the point of relaxing evidentiary rules.¹² Determining discrimination requires attention to the way in which a law is applied in practice to the detriment of certain groups, a task to which statistical method is uniquely suited. In the EU context, Council Directives 97/80/EC and 2000/43/EC encourage persons who suspect they have been discriminated against to adduce statistical evidence before domestic authorities. The European Court of Justice has accepted such evidence. The ECtHR has considered that "when it comes to assessing the impact of a measure or practice on an individual or group statistics which appear on critical examination to be reliable and significant will be sufficient to constitute the prima facie evidence the applicant is required to produce."¹³ This is crucial because it shifts the burden of proof to the respondent state, effectively compelling it to prove that a measure is not discriminatory, in a context where the lack of discriminatory intent is not conclusive.

A classic example of indirect discrimination being proved statistically is the *D.H. and others v. Czech Republic* Case. Czech citizens of Roma origin alleged that they were

⁶ ECtHR, *Opuz v. Turkey* (no. 33401/02), 9 June 2009 (in which the Court accepted the notion that women were more likely to face domestic violence in Turkey based on an Amnesty International report and in the absence of reliable data).

⁷ CEDAW, acronym for the Convention on the Elimination of all Forms of Discrimination Against Women; CRC, acronym for the Convention on the Rights of the Child

⁸ Indian and Northern Affairs Canada, *Aboriginal Women: A Demographic, Social and Economic Profile*, (Summer 1996).

⁹ Amnesty International, Canada Follow Up to the Concluding Observations of the United Nations Committee on the Elimination of Discrimination Against Women (2009), p. 5.

¹⁰ UN Statistics Division, "Legal Age for Marriage", (2012), online: <<http://data.un.org/DocumentData.aspx?id=336>>.

¹¹ Office of the United Nations High Commissioner for Human Rights "A Human Rights-Based Approach to Data: Guidance Note to Data Collection and Disaggregation to Leave No One Behind in the 2030 Development Agenda", (OHCHR 2015).

¹² *Nachova and others v. Bulgari*, ECtHR, Judgment of 6 July 2005.

¹³ ECtHR, *DH v. Czech Republic*, ECtHR, Judgment of 13 November 2007 (No. 57325/00), para 188.

placed in special schools for children with learning difficulties, which resulted in segregation and racial discrimination. Although the law on its face did not mention the Roma and merely introduced a test of abilities, it was argued that it resulted in the existence of two autonomous educational systems, an “ordinary” one for the majority of the population and a “special” one for the Roma.¹⁴ After losing before the Constitutional Court and a Chamber of the ECtHR, the case was referred to the Grand Chamber. The evidence disclosed that 56% of all pupils placed in special schools were Roma, and that conversely the Roma represented only 2.26% of the total of number of pupils in ordinary schools. Even though the Grand Chamber found that these statistics might not be entirely reliable because of the lack of official information on the ethnic origin of pupils, the Court considered that “these figures reveal a dominant trend that has been confirmed both by the respondent State and the independent supervisory bodies which have looked into the question.”¹⁵

Statistics used to prove discrimination may be existing official statistics. These will often carry an evident weight in terms of reversing the burden of proof.¹⁶ Interestingly such official statistics often exist, proving a relatively damning piece of evidence against the state produced by its own administration. For example in the D.H. case the Czech authorities could hardly claim lack of knowledge of existing patterns of discrimination against Roma children given that their own report under Article 25 para. 1 of the Framework Convention for the Protection of National Minorities indicated that between 80 and 90% of the pupils in special schools were Roma. An advantage of official statistics is they are often not based on samples but on a census of the entire population. Nonetheless, statistics can also be produced by human rights activists or litigants through normal means of data collection, including devising representative random samples.

Establishing Responsibility

In addition to broad purposes of highlighting discrimination, statistics have also been used for more forensic purposes, in the context of establishing individual criminal responsibility before domestic or international courts for various atrocity crimes. International criminal trials often raise complex issues of determination of the number of victims, their identity and whether they were intentionally targeted as such. The findings of the Human Rights Data Analysis Group (HRDAG), a group that has been key in popularizing a statistical approach in the human rights field, confirmed earlier qualitative accounts in Chad of prisoner conditions and high mortality within the Security Directorate (DDS) prisons. An analysis of thousands of documents found in a cache at the abandoned headquarters of the DDS,¹⁷ including Situation Journals and death certificates, revealed that the mortality rate within the DDS prisons varied from 30 per 1,000 to 87 per 1,000 prisoners. This rate was substantially higher than the overall death rate of Chad in the 1970s and 1990s, which was less than 25 per 1,000.

¹⁴ ECtHR, *DH v. Czech Republic*, ECtHR, Judgment of 13 November 2007 (No. 57325/00).

¹⁵ ECtHR, *DH v. Czech Republic*, ECtHR, Judgment of 13 November 2007 (No. 57325/00), para 191.

¹⁶ *Hoogendijk v. the Netherlands* (dec.) (no. 58641/00), 6 January 2005.

¹⁷ Romesh Silva, Jeff Klinger, and Scott Weikart, “State Coordinated Violence in Chad under Hissène Habré, A Statistical Analysis of Reported Prison Mortality in Chad’s DDS Prisons and Command Responsibility of Hissène Habré, 1982-1990”, (BENETECH, 2010).

The report found that detainees within the DDS prisons were at least 16 times more likely to die than the general public. The HRDAG report was given to a Belgian judge to inform his preparation of an indictment against Habré.¹⁸

In addition to assessing the gross number of victims of particular episodes, statistical methods may help in highlighting the nature of the events that led to such victimization and in particular establish their criminal character. In the context of the trial of former Yugoslav president Slobodan Milošević at the International Criminal Tribunal for the Former Yugoslavia (ICTY) in The Hague, for example, one of the questions was whether people fleeing Kosovo had done so because of the NATO strikes or because of campaign of ethnic cleansing by Milošević's. The HRDAG submitted a report that was entered as a trial exhibit. Because Kosovo Albania border guards had actually kept a record of refugees that went through, it was possible—by creating a complex model—to correlate refugee flows and exogenous events. The report concluded that the mass exodus of refugees from Kosovo was not correlated to NATO bombings but instead seemed to reveal a centrally organized campaign by the Serb government. This in turn would prove crucial in establishing the responsibility of the authorities.

Another great challenge of international criminal justice is establishing the responsibility of commanders, particularly head of states. The HRDAG has used statistics to establish a pattern of responsibility of Hissène Habré in Chad. Hissène Habré claimed that he was not aware of crimes committed by his security services (the Documentation and Security Directorate, DDS). The quantitative analysis completed by HRDAG assessed the retrieved DDS documents against the doctrine's main criteria (existence of a superior-subordinate relationship, superior's knowledge of the subordinates' crimes, and superior's failure to act). It found that Habré had received 1,265 direct communications from the DDS about the status of 898 detainees, such that he must have known about their conditions and situation. The analysis of the document flow "included more than 2,700 administrative records that together illustrate a clear communication and command link between Habré and his state security force."¹⁹

Transitional Justice

Statistics may also be used in a broader way to establish governmental and societal responsibilities in transitional contexts, beyond individual guilt. They may, to begin with, help document patterns of victimization. For example, the Truth and Reconciliation Commission of Canada made use of statistical analysis to determine whether the death rate in residential schools had been higher than the ordinary death rate in Canada. The Commission established that "The death rates for Aboriginal children in the residential schools were far higher than those experienced by members of the general Canadian population."²⁰ In fact until the 1940s, the rate was 4.9 times higher, due in particular to a chronic tuberculosis crisis which in turn evidenced the

¹⁸ Miguel Cruz, Kristen Cibelli and Jana Dudukovic, "Preliminary Statistical Analysis of AVRCP & DDS Documents - A report to Human Rights Watch about Chad under the government of Hissène Habré", (BENETECH, November 4, 2003).

¹⁹ HRDAG (summary of Chad investigation conducted in Chad), online: <<https://hrdag.org/chad/>>.

²⁰ *Final Report of the Truth and Reconciliation Commission of Canada, Volume One, The Truth and Reconciliation Commission of Canada* (2015) 92.

health crisis that affected the aboriginal population more generally. The legacy of such social misery could be measured in contemporary terms by data provided by Statistics Canada itself, which found in one study that “14,225 or 3.6% of all First Nations children aged fourteen and under were in foster care, compared with 15,345 or 0.3% of non-Aboriginal children”,²¹ a situation that led the Committee on the Rights of the Child to raise concerns on the occasion of the submission of the Canadian report.

Statistics may also help disaggregate victims by categories, and in the process highlight the peculiar dynamics of atrocities. For example, the HRDAG helped the Liberian Truth and Reconciliation Commission with quantitative methodology. The report contained information about 86,647 victims and 163,615 total violations including 124,225 violations suffered by individual victims; 39,376 suffered by groups; and 14 by institutions. It found that older men were at a greater risk of being killed, a counter-intuitive result. It speculated that the reason was that younger men were more at risk of being recruited as combatants, and therefore spared for that purpose. Finally, statistical work may help apportion responsibility between groups, a perennial issue in reckoning with the past. For example, the data suggested that the National Patriotic Front of Liberia (NPFL) was “responsible for more than three times the number of reported violations as the next closest perpetrator group, the Liberians United for Reconciliation and Democracy (LURD),” amounting to “approximately 40 percent of the violations reported to the TRC.”²² The TRC data gathering process also explored statistics on expectations regarding future expectations, rather than only focusing on the past. The report evidenced a striking willingness by between 50 and 70 percent of respondents to meet with the perpetrator who caused their suffering. A practice of “Forgive and forget” also seemed to be favoured by the majority.

II. A Big Data Revolution?

For decades, quantitative methods for human rights boiled down to leveraging statistics on primary datasets manually gathered in the field or from print or analogue datasets.²³ Whilst this kind of use of quantitative methods has achieved significant results in the practice of international human rights, it is in practice limited by the difficulty of accessing the data, the protracted nature of that process and the challenges inherent to social scientific methods. Moreover, the statistical methods suggested above all have a retrospective and forensic nature: they evidently seek to establish human rights violations *after* the facts and it is in their nature that they cannot be developed in real time.²⁴

It is here that the “big data revolution,” as it has become known, could have a radical effect or at least significantly contribute to shaking up traditional statistical work. The

²¹ *Final Report of the Truth and Reconciliation Commission of Canada, Volume One, The Truth and Reconciliation Commission of Canada* (2015) 186.

²² HRDAG (summary of Liberia investigation), online: <<https://hrdag.org/liberia/>>.

²³ Concept defined: Statistics involves summarizing and analyzing a set of numerical facts. Statistics are usually used on aggregates of data too large to be intelligible by ordinary observation.

²⁴ The exception to this is statistics on discrimination, that can be used to disrupt ongoing human rights violations—but still there, the collection, processing and application of statistics can typically take months if not years.

buzzword “big data” generally refers to the exponential growth of available data in the last two decades as a product of the digital revolution.²⁵ Conceptually, big data is associated with soaring levels of connectivity via new and networked Information Communications Technologies such as mobile phone and cyberspace. Today, for example, there are more cellphones than humans on earth and connectivity has soared from 350 million people in 2000 to nearly 3.5 billion as of Nov 2015. Big data also refers to the digital revolution’s massive *recording* of human activity—as every digital phone call, mouse click, upload and download, in theory can (and often is) recorded. Furthermore, this data is inherently quantifiable, its building blocks made of small discrete units called “bytes”. In fact, increasingly all human activities are datafied in a way that they can be processed by computers for analysis (for example, the way Twitter has datafied stray thoughts).²⁶ The Internet, it is said, never forgets.

The consequence of the above combination of connectivity, datafication, and logging is a veritable data deluge: For example, there are 200 hours of video uploaded per minute and there is more data produced in the last two years than in the previous 3000 years of human activity.²⁷ Not only is this continuous log of human activity without precedence in terms of its massive quantity; it is also radically more open than previous large-scale registries such as official government data or CCTV camera footage that remained centralized and closed-off. It also applies to situations of intense human rights concerns such as warzones. For example, the Syrian civil war has been dubbed “the first YouTube war” and has in fact generated more hours of online war footage than actual hours of combat on the ground.²⁸ At their core, big data and its concomitant digital revolution herald at least three major trends for quantitative practices and human rights: more data, more automatization of analytical work, and more crowd-sourcing. In this section we present a number of innovative practices that highlight the interplay of these trends. These often go beyond conventional methods that might be used in court to include a range of tools that can be used, with normative goals, by human rights actors, including lawyers, policy experts, and activists

Detecting and tracking societal trends

The so called transition from small to big data presents alluring new opportunities to detect and explore patterns and trends useful to human rights work (as opposed to finding individual incidents of interest). The prized example of big data for analysis of social trends is arguably the use of Google’s search data. It uses records from people’s online searches on Google’s search engine. Google dominates the Internet search engine

²⁵ How to define the buzzword big data is hotly contested. Various strict quantitative definitions exist (for example: A dataset with over a billion data nodes). Various qualitative definitions exist (such as the dataset’s approximation to capturing the entire data population we intend to measure, or the inability for typical database software tools to process data because it is too large, unstructured, and complex. This chapter emphasizes the importance of the digital. This is similar to the UN OHCHR’s definition: “Extremely large data sets associated with new information technology and which can be analysed computationally to reveal possible patterns, trends and correlations” (OHCHR 2015).

²⁶ “Rise of Big Data”, *Foreign Affairs* (2013), online: <<https://www.foreignaffairs.com/articles/2013-04-03/rise-big-data>>.

²⁷ Stephen Spratt and Justin Baker, “Big Data and International Development: Impacts, Scenarios and Policy Options” (Institute of Development Studies, December 2015) 4.

²⁸ The Carter Centre’s Syrian Mapping Project documented this trend and has measured at times in the civil war’s duration an average of over 600 videos uploaded per day from the war (Authors’ interview, July 2014).

market in most countries. This means that Google users generate a staggering 40,000 queries per second (over a trillion per year).²⁹ The allure in using data like Google to find and analyze social trends is its omnipresence: An unfiltered panopticon for all facets of life from searches for jobs or the day's weather, to queries on extraordinary issues such as violent mass killings in Paris or Peshawar. What is more, Google tracks not only search words, but other data including user's location via IP addresses, and these data are combined and analyzed through automated computational methods to derive, for example, statistical averages made quickly, openly, and freely available to the public on platforms like Google Trends.³⁰

Google attracted considerable attention and generated appetite for its data with its apparent ability in 2008 to predict the spread of flu in the USA two weeks in advance of the conventional data and statistics generated by the US Centre for Disease Control and Prevention (the latter, basing itself on random sampling of "real world data"), based on an analysis of search queries associated with flu symptoms. Google data has since been used to tackle myriad issues including human rights. For example, 2014 and 2015 studies analyzed the geographic distribution of racism in America towards African Americans.³¹ Mostly using free Google Trends data, the lead researcher Seth Stephens-Davidowitz reviewed the search volume in the USA for the discriminatory term "nigger". Google's search data from the United States is disaggregated geographically (by county and state), which allowed Stephens-Davidowitz to correlate the highest volume of such searches with regions traditionally associated with racism towards African Americans (such as Appalachia and the USA's Deep South).

As is the case for conventional statistical work covered in this chapter's Part 1, correlation does not = causation. For example, it is not clear why the term "nigger" is used more intensely in those regions—however, such statistical results point to potential problem spots in a way that traditional methods like interviewing people on the street might not.³² In combination with more conventional data collection it might put in evidence certain strong geographic and temporal connections. And of course, such widely available statistics open the door to myriad research possibilities—for example, the findings were used to explore the existence of a correlation between these attitudes and higher rates of African American mortality.³³

More recently and with the aim of exploring "real time" events, similar Google data was used to investigate racism and potential race-base violence against Muslims in the hours and days following the December 2 2015 San Bernardino shooting in California. The researchers searched for, and found, a correlation in the USA between anti-Muslim

²⁹ Internet Live Stats, *Google Search Statistics* (2016), online: <<http://www.internetlivestats.com/google-search-statistics/>>.

³⁰ Google Trends, online : <<https://www.google.com/trends/>>. Of course, this raises questions of authenticity and representativeness of data, which will be addressed later in the chapter.

³¹ Seth Stephens-Davidowitz, "□ The cost of racial animus on a black candidate: Evidence using Google search data" (2014) 118 *Journal of Public Economics* 26-40.

³² David Auerbach, "Big Anecdota" *Slate* (May 6 2015), online: <http://www.slate.com/articles/technology/bitwise/2015/05/google_searches_and_racism_why_big_data_studies_dont_explain_society_as.html>

³³ David Chae et al., "Association between an Internet-Based Measure of Area Racism and Black Mortality" (April 2014) 10:4 *PLoS ONE*, online: <<http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0122963>>.

searches and anti-Muslim hate crimes in the 2004-2013 period. They could break these findings down further, to the state and even to the county level, to find pockets of potential race-based violent sentiments in real time. The authors of the study suggest that the data could eventually allow observers to not only detect concentrations of racism, but also to respond pre-emptively to potential race-based, for example as the researcher noted: “The data (...) could tell police chiefs when sending a cop to do an extra drive through a Muslim neighbourhood, or making sure that the town mosque was safe overnight, would be a good idea.”³⁴

One obvious challenge in the swirl of big data is sifting through the “noise” of unrelated data. To address this, researchers resort to innovative Boolean searches to filter through big data’s mountains of text-based content.³⁵ For example, Stephens-Davidowitz screened out variant spellings commonly used in rap lyrics, such as *nigga*, though false positives may remain in the data. Other researchers have decided to monitor highly niche content – which is less likely to survey broad social trends, and more likely to zero-in on extreme fringe segments of society. A study of public online content by the Canada-based SecDev Group on extremist White Supremacists found it useful to mine the phrase “the 14 words”, a verse from the bible associated with White supremacist groups.³⁶ The use of these highly targeted phrases in Boolean queries mean that, although less frequent, they are also less likely to be drowned out in numerous “false positive” searches and they may correlate more often with actual events and attitudes of concern to human rights professionals.

Mapping Social Data

Big data can be combined with commercial or even freely available online relational mapping tools to understand the social backdrop to human rights phenomena.³⁷ An example of this Very Large Scale Conversation Mapping (LSCM) of social media activity, which can detect, map and monitor social relations among groups, conversations, particular messages, and individuals (for example, tens of thousands of messages and online accounts). For instance, organizations ranging from Government to NGOs have been gathering, organizing, and analyzing the totality of certain conversations on public Facebook pages or on Twitter around human rights violations in Syria. Twitter and public Facebook data can be readily “scrapped” online and is available from third party vendors and even from free applications.³⁸ This data is then analyzed by location, content, and actors to identify relevant content. It can then be processed in relational software to identify social networks and their relations. The result is “very large scale

³⁴ Evan Soltas and Seth Stephens-Davidowitz, “The Rise of Hate Speech” *New York Times* (Dec. 12 2015), online: <http://www.nytimes.com/2015/12/13/opinion/sunday/the-rise-of-hate-search.html?smprod=nytcore-iphone&smid=nytcore-iphone-share&_r=0>.

³⁵ Even if formalized in the 19th century, Boolean logic remains pivotal in much of today’s big data processing due to its recognition by myriad “electronic searching tools as a way of defining a search string”, Elmer Rasmuson Library, “Boolean Searching”, online: <<http://library.uaf.edu/lis101-boolean>>.

³⁶ The 14 words are “we must secure the existence of our people and a future for white children”. See: “Detecting Toxic Content using Open Source Social Media: A Content Centric Approach” (The SecDev Group, 2014), online:

<https://preventviolentextremism.info/sites/default/files/Detecting%20Toxic%20Content%20using%20Open%20Source%20Social%20Media-%20A%20Content%20Centric%20Approach.pdf>

³⁷ An example of widely used and free software of this sort is “Gephi”, online: <<https://gephi.org/users/>>.

³⁸ For example, one leading vendor of such data is “GNIP”, online: <<https://gnip.com/sources/>>.

conversation mapping” that can, for example, capture an impression of the totality of the conversation in Syria on Twitter over a given period of time linked to a serious human rights issue, such as a military campaign. This type of analysis can help identify and highlight key communicators (the dots), key messages (the lines, that connect the dots together), and the communities of interest (in different colours). The image below for example contains over 100,000 messages generated from nearly 30,000 users, and its analysis reveals the presence of several major groups including Assad regime members and supporters, armed anti-Assad rebels, non-violent NGOs, Kurdish resistance movements, and International media.³⁹

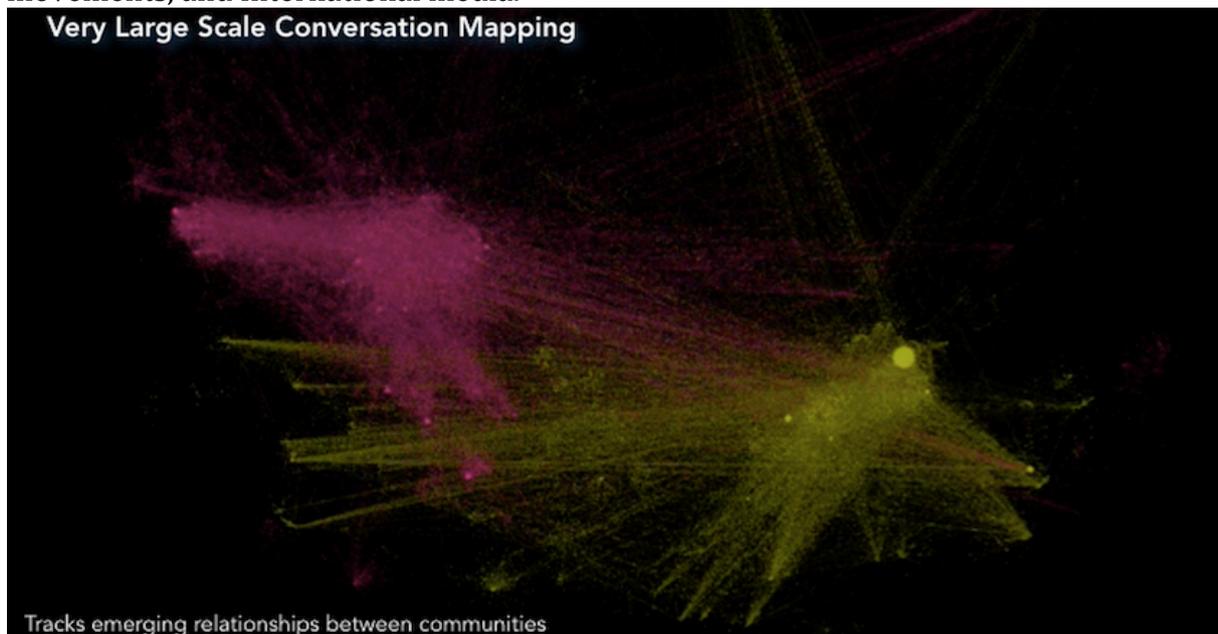


Image: Syrian Militants (FSA) and Kurdish network of Twitter users emerging from a localized Jan 2013 armed clash between both sides in Ras al-Ain (Northeast Syria). Research conducted by the SecDev Group.

Such data creates over time an index of who are the key communicators - what defines a particular community. Researchers can query: Where and with whom does violent or extremist content resonate online? How do online alliances evolve over the course of a battle or war? Which groups are actively engaged in disinformation online through the use of “botnets”?⁴⁰ Where does false content on human rights incidents emerge from and which online communities do its creators associate with? In addition, some experts argue that unlike traditional inventories of background data on actors and narratives that organizations have created for decades and are usually formulated on the basis of subject matter experts, very large scale conversation mapping allows the data to speak for itself. The concentration of actors and of messages in such analysis is formed not on the basis of an a priori hypotheses subject to the biases of a researcher, but rather by the raw levels of interaction that exist in the data and as inferred through relational software’s statistical analysis.⁴¹

³⁹ SecDev Group Research, 2013.

⁴⁰ “What is a Botnet?”, Microsoft Security Intelligence Report, online: <<https://www.microsoft.com/security/sir/story/default.aspx#!botnetsection>>.

⁴¹ Ragheb Abdo, “Assessment of a Foreign Fighter’s Twitter Trajectory” (The SecDev Group, 2014) 3 online:

<https://preventviolentextremism.info/sites/default/files/Assessment%20of%20a%20Foreign%20Fighter%E2%80%99s%20Twitter%20Trajectory-%20Before%20and%20After%20Travel_1.pdf>. Still, this kind of research raises several questions on authenticity and representativeness, as well as regarding the

This mapping of social background and chatter provides a new set of eyes and ears around macro phenomena such as conflicts. Importantly, this analysis of social media content can also be used to identify specific human rights or humanitarian violations (for example, video footage of the killing of unarmed prisoners of war or the use of banned cluster munitions) or human rights related content (for example, the flow of illegal weapons). This data can then be mined to generate evidence, as explored next. Together, these methods are especially useful in cases where authorities have few actual eyes and ears on the ground such as Syria's civil war.

Producing Evidence

While the above can provide valuable information to human rights professionals, it does not document actual human rights violations. Searching “kill Muslims” on Google or the general ebbs and flows of the online strategic communications of ISIS or the Syrian Assad regime generally are not unto themselves patterns of human right violations. However, as practitioners as well as academics like Jay Aronson and Daniel Neil and Feng Chen have noted, this big data can also be drilled for patterns or individual cases of “Human Rights Events” (HREs) or human rights-related evidence.⁴² Critically—and differently from statistical analysis—for the discovery of such the “needle in the haystack” evidence, it is not decisive whether the HREs are representative of larger phenomenon; what matters most is that the evidence is accurate.

One example is the role of analysing social media content similar to that in very large scale conversation mapping, but to detect particular data points that can be used for evidence. For example, one issue in the Syrian conflict is tracing the origin of various weapons that feed violence and human rights violations. As one professional weapons tracker put it, however, “the path to Syria can be quite circuitous,” he says. “Unless you have a fairly robust paper trail, which we don't have, identifying the government or trafficking networks that provided the weapons really isn't possible.”⁴³ In this context, for example, the Carter Center and Carnegie Mellon University used an image recognition script to sweep through the vast quantity of videos of the Syrian conflict to detect the presence of TOW ATGMs (an anti-tank missile).⁴⁴ This data could then be automatically set aside for further analysis such as mapping. Because TOW ATGMs are not in the Syrian Army's stocks, anyone using one must have obtained it abroad. This gives researchers a hint to document that such groups are getting weapons from foreign countries, and researchers can begin mapping a pattern of where they are. Similarly, the analysis of social media channels has proved key to identifying the source of MANPADS smuggled into Syria providing considerable visual evidence that was particularly useful in a context where few journalists and official observers were able to operate on the

“bias” generated by the algebra that undergirds analytical software such as Gephi—issues explored in the conclusion and section on challenges, below.

⁴² Feng Chen et al, “Non-parametric Scan Statistics for Event Detection and Forecasting in Heterogeneous Social Media Graphs”, Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (2014), 1166.

⁴³ Matt Schroeder in “Syrian rebels have stockpile of anti-aircraft weapons” (Small Arms Survey, Aug 19 2014), online: <http://www.swissinfo.ch/directdemocracy/small-arms-survey-report_syrian-rebels-have-stockpile-of-anti-aircraft-weapons/40562956>.

⁴⁴ Authors' interview with Carter Center's Syrian Mapping Project (2016).

ground.⁴⁵

While the above examples focus on weapons, this sort of evidence-discovery in big data applies to myriad other forms of HREs: War crimes, sexual assault, crimes against humanity, for example, can also be documented online. The innovation in the above is that sifting through the big data deluge of digital data allows the discovery of HREs that are otherwise not readily found offline.

The point is that big data, even if simply too vast for a single researcher or small team, to explore manually, can be filtered through automated methods such as word and image filtering, or, as discussed below, via crowd-sourcing (another big data related method). Importantly, once individual HREs are identified, they can be verified and eventually used in courts.⁴⁶

III. From Small to Big Data: Potential and Challenges

Whilst it is tempting to find the transition from small to big data appealing, this is a development that must be analyzed critically and with care to understand its true potential and some of its limitations. There is no doubt that the rise of Big Data is rich with challenges as well as potential.

Open empowerment

Big data for human rights can transform how data is collected. As Molly K. Land puts it, new technologies and their concurrent decentralized tendencies “enable the collection of much more information than is possible with traditional techniques” which “rely heavily on interviewing victims, witnesses, and perpetrators as a primary source of generating information about human rights issues.”⁴⁷ Together, this issue is both one that can affect how evidence is created, as well as how it is managed—and often both occur at once: For example, a data platform may crowd-source its content, as well as utilize the public’s crowd sourced labour to analyze data.

One of the most significant changes brought about by big data, according to Molly K. Land is that the very nature of human rights fact-finding may well come to change. This is because new technologies:

... provide opportunities for ordinary individuals to investigate the human rights issues that affect them. Those who were formerly the ‘subjects’ of human rights investigations now have the potential to be agents in their own right. This new kind of fact-finding, which I call ‘participatory fact-finding’ may not be as effective

⁴⁵ “Syrian rebels have stockpile of anti-aircraft weapons” (Small Arms Survey, Aug 19 2014), online: <http://www.swissinfo.ch/directdemocracy/small-arms-survey-report_syrian-rebels-have-stockpile-of-anti-aircraft-weapons/40562956>.

⁴⁶ Initiatives are on the rise to facilitate the admissibility in courts of such evidence drawn from social media’s big data. One nascent example is the eyeWitness project, that is developing an app that records and bundles metadata in social media such as coordinates, time of day, author and camera data, nearby cell towers, and nearby Wi-Fi signals. See, eyeWitness Project, online: <www.eyewitnessproject.org/>.

in ‘naming and shaming’ states and companies that violate human rights, because the absence of the imprimatur of an established organization may render the information collected vulnerable to critique. At the same time ... Participatory fact-finding has the potential to be fact-finding as empowerment – the collection of information and documentation of facts as means for empowering those affected by abuses to advocate for their change.⁴⁸

Jay Aronson goes on to characterize these changes as a challenge, in that they diminish the formal human rights field, leading to an “increasing fragmentation of the fact-finding community, where the boundary of the professional and amateur community is being blurred.”⁴⁹ Indeed, these changes are often happening outside the bounds of formal human rights institutions. As some have argued, the increasing scale and scope of quantification is accelerating faster than institutions’ ability to adapt existing rules and norms. However, perhaps this trend is best viewed as an expansion of the human rights community’s work, rather than a fragmentation. It is hard not to see how such changes in and of themselves reconnect with a radical, grass-roots, and decentralized human rights ethos.⁵⁰ At any rate, seeking to work with crowd-sourcing to leverage “the crowd” may be more fruitful than seeking to manage the professional silo within the sea change.

Looking ahead, one bright opportunity may be highlighted by the Humanitarian Sector (disaster and emergency response). This consists of professionalizing crowd-sourced initiatives. For example, with UN-backing a Standby Task Force (SBTF) and the Digital Humanitarian Network (DHN) were formed from digital volunteers across the globe that can respond on short notice to assist in emergencies. Nicknamed “digital jedis”, the SBTF for example numbers over 1800 individuals in over 100 countries.⁵¹ In the recent 2015 Nepal Earthquake, within a week, more that 1200 of these digital jedis sifted through 35,000 images and 7,000 tweets to identify building and neighbourhoods of Kathmandu most at risk of prolonged crisis. They even leveraged a fleet of Unmanned Aerial Drones (UAVs). This resulted within a week in over 300 relevant pictures of disaster damage displayed on maps available to professionals on the ground.⁵² The result of the above is “the leading interface between established humanitarian networks...[the]dinosaurs” and “these very tech-savvy distributed, very agile volunteer groups”, states one of the networks’ founders, Patrick Meir.⁵³ The same could be done with human rights work, were the power of the crowd could be leveraged with expert guidance (and awareness and guidance on important ethical questions and inter-institutional expertise), and mainstreamed into operational work such as investigations.

⁴⁸ Molly K. Land, “Democratizing Human Rights Fact-Finding”, in *The Transformation of Human Rights Fact-Finding*, 400 (Philip Alston and Sarah Knuckey eds., 2015).

⁴⁹ Jay Aronson, “Mobile Phones, Social Media, and Big Data in Human Rights Fact-Finding”, in *The Transformation of Human Rights Fact-Finding*, 442 (Philip Alston and Sarah Knuckey eds., 2015).

⁵⁰ It is here too that it may be positive to expand the notion of human rights methods beyond the sort of conventional methods that might be used in court to include a range of tools that can be used, with normative goals, by human rights actors, including lawyers, policy experts, and activists.

⁵¹ Stand by Task Force, online : <<http://standbytaskforce.com/>>.

⁵² “A Force for Good: How Digital Jedis are Responding to the Nepal Earthquake” (iRevolutions, April 2015), online: <<https://irevolutions.org/2015/04/27/digital-jedis-nepal-earthquake/>>.

⁵³ “Crisis Mapping and the Digital Revolution in Humanitarian Data with Patrick Meier” (The Robert Strauss Centre for International Security and Law, November 2015), online: <<https://www.youtube.com/watch?v=7JgJ7xAq4m0>>.

Accuracy, interpretation, and representativeness

Data abundance, of course, is not necessarily synonymous with more acuity and in fact some big data may create colossal problems of verification. It is sometimes claimed that big data is in a sense more “honest” in that it is produced in massively decentralized fashion and with a strong expectation of privacy. Stephens-Davidowitz (a former Google employee himself) who authored the study on racism based on Google search, for example, has argued that such data acts like ““a confessional box” that can gauge public sentiment on controversial views that polls and surveys cannot always capture— “Sometimes people type just random thoughts they have into Google...These searches tend to feel like confessionals. They're admitting things that they might not want to admit in polite company or might not tell to a survey.”⁵⁴

Nonetheless even if big data is more “honest” (and further accessible) it may mislead and confuse as much, or more, than traditional sources of data. Recent field research in Pakistan for example reveals that it is common for Facebook users to create and manage several accounts, all serving distinct social purposes and personas—and that ample behaviour that would be considered unrestrained in other social contexts, is dramatically altered there by local mores.⁵⁵ Without understanding these complex nuances in terms of users’ underlying intent and identity, it is would be hard for an outsider to infer observations on the basis of a dataset made of such user activity.

Further, big data can be plainly wrong. The Boston Marathon explosion in 2013 led to a massive spike in social media activity and was a “case study” in how data generated by ordinary bystanders to crises can be the most rapid source of information. However, of the 8 million tweets that went out around the bombing, astoundingly only 20% were accurate, as revealed by an extensive ex post facto analysis.⁵⁶ The reality is that people lie, overstate, are confused, misrepresent, and parrot information and this remains unchanged and potentially increased online. The “crowd” is not always right, and often far less in situations of crisis. Compounding concerns on accuracy, in the case of the Boston Bombing, the crowd-sourced detective work on popular wiki platforms like Reddit led to a “witch hunt” where persons were unfairly singled out and accused of wrongdoing.⁵⁷

Finally, behaviour online is often shaped by proprietary algorithms created by software platform and that are not accessible to public scrutiny. These algorithms determine, for example, what people look for online and what messages they see. For instance, Google search patterns are based on “suggested” preferences, as is the content and friends Facebook users engage with. Search results can change depending on cookies, country of

⁵⁴ “What Google can tell us about people’s secret thoughts” (PRI, Jan 3 2016), online:

<<http://www.pri.org/stories/2016-01-03/what-google-can-tell-us-about-people-s-secret-thoughts>>.

⁵⁵ Emrys Shoemaker, “Digital purdah, or how Facebook maintains traditional practices of gender segregation” (LSE, July 2015), online:

<<http://blogs.lse.ac.uk/parenting4digitalfuture/2015/07/29/around-the-world-3/>>.

⁵⁶ Colin Schultz, “In the Wake of the Boston Marathon Bombing, Twitter Was Full of Lies”

(Smithsonian.com, Oct 2013), online: <<http://www.smithsonianmag.com/smart-news/in-the-wake-of-the-boston-marathon-bombing-twitter-was-full-of-lies-5294419/?no-ist>>.

⁵⁷ Hueypriest (official Reddit moderator), “Reflections on the Recent Boston Crisis” (Blog.Reddit, April 2012), online: <<http://www.redditblog.com/2013/04/reflections-on-recent-boston-crisis.html>>.

origin, behaviour patterns, and even laptop model.⁵⁸ Further complicating matters, the algorithms and their parameters are unique from platform to platform, and can change within the same platform depending on a user's country.⁵⁹ What's more, these "traffic rules" on online content's flow can and are regularly tweaked and changed by the corporations that run the platforms.⁶⁰ These nuances are rarely explicit and, without transparency, are hard or impossible for researchers to account for.

Another concern with accuracy is the risk of error among those handling the data. Data is not in and of itself usable or does not speak independently of the analysis that is made of it. Traditionally, data at the very least needs to be coded according to relevant functional, geographic, temporal criteria, based on what one is looking for. The experience of the HRDAG in Sierra Leone shows some of the difficulties encountered. For example, how does one:

"avoid counting certain violations twice under different labels, to keep track of multiple perpetrators of single violations, or to understand how one can simultaneously be a victim, perpetrator and witness. For example, what distinguishes "rape" from "sexual abuse"? The two categories must be defined clearly so that people doing the coding apply the definitions in a standard way. The definition must be so clear that if the same narrative statement is assigned to the entire coding staff, they will classify it in precisely the same way."⁶¹

Problems may be compounded by the multiplicity of those involved in the coding process to ensure consistency (hence the importance of a tool such as inter-rater reliability (IRR)). These methodological problems are likely to continue to haunt Big Data-based human rights research and practitioners will arguably be hobbled by the same limitations that have long made statistical work challenging. While data processing tools like algorithms, scripts, and robots can sift through massive datasets for "automated" fact finding, their parameters need to be guided by qualitative field experience to be effective (often referred to as "fusion" teams and methodologies, combining technical expertise in big data with qualitative subject matter expertise). For example, if seeking cases of torture or murder in the context of Mexico's narco war on the basis of big data scrapped from online activity, specialized knowledge of vocabulary or of the online environment is needed to guide whatever automated tool will be used.⁶² It is insufficient to guide such tools with stock vocabulary like "torture" and "execution" or to look up content on standard social media platforms like Twitter and YouTube. In cases like these, niche online platforms like *Blog del Narco* will be central to uncovering

⁵⁸ For definitions of online terms such as cookies, see TechTerms.com, a dictionary maintained by computer scientist Per Christensson, online: <<http://techterms.com/definition/cookie>>.

⁵⁹ For example: "Google stores and reports final searches submitted, after auto-completion is done, as opposed to the text actually typed by the user" and "Twitter dismantles retweet chains by connecting every retweet back to the original source (rather than the post that triggered that retweet)". Derek Ruths and Jürgen Pfeffer (28 Nov 2014), "Social Media for Large Studies of Behaviour" 346:6213 Science 1063-1064.

⁶⁰ *Id.*

⁶¹ HRDAG (summary of Liberia investigation), online: <<https://hrdag.org/liberia/>>.

⁶² Antoine Nouvet and James Farwell, "Strategic communications and cyberspace in Mexico's drug war", in *Open Empowerment: From Digital Protest to Cyber War* (Robert Muggah and Rafal Rohozinski eds., 2016).

HRE-related content, as will distinct local and constantly evolving slang.⁶³ Finally, a “spiral” methodology is applied where the highly tailored search parameters must be constantly reviewed in a continuous iterative process.

Further hobbling researchers and as Patrick Ball has noted, human rights data is precisely the kind of data that persons try to hide and that is less likely to be online. Big data analysis methods from other contexts such as industry and business will not work—a company can analyze perfectly the movement of its goods along a supply chain; such precision is usually unimaginable if tracking, for example, how many people were tortured and killed by a state’s security apparatus.⁶⁴ The risks of miscounting and miscoding are various, as has been outlined with empirical examples by researchers ranging from Iraq and Syria, to Colombia and the USA.⁶⁵

At a more conceptual level, quantities do not tell us much about gravity, or why certain violations were committed, or how we are to assess them normatively even though in theory there is no end to what amount information can be coded. Even “the most readily measurable” violence, homicide (as remarks the UNODC in its annual survey of global homicide rates), has vast limitations when examined for human rights-related purposes.⁶⁶ As the global mass atrocity prevention specialist Birger Heldt has noted, when conducting analysis for example of a mass atrocity, it is important not just to quantify that persons were killed, but that they were intentionally targeted and part of a specific group, rather than unintentionally shot in cross fire.⁶⁷ When recording the amount of people killed by gunfire, researchers need to document not just persons killed, but intent. How do researchers programme an algorithm for that purpose? Other human rights like the right to privacy or freedom of expression, may be much harder to assess quantitatively unless one can identify some limited proxy (e.g.: cases of unauthorized surveillance executed by the police, or where a student was asked to remove her hijab).⁶⁸

Finally, alongside accuracy is the often overlapping and inseparable challenge of representativeness. The difference is that even if all the above considerations on accuracy and interpretation were adequately dealt with for veracity, the analysis may still miss-lead given the underlying data is not representative of what users imagine or purport it to be. The classic way of correcting for accuracy is by obtaining large data samples that minimize individual distortions. The work of statisticians is hence traditionally characterized by the search for representative samples. For example, in

⁶³ *Blog del Narco* is one of the myriad unofficial, but widely used, wiki platforms documenting violence and rights abuses associated with Mexico’s narco war. *Id.*

⁶⁴ Patrick Ball, “Digital Echoes: Understanding Patterns of Mass Violence with Data and Statistics” (Data and Society Institute presentation, March 2016), online : <<https://www.youtube.com/watch?v=KNnvZVKWas8>>.

⁶⁵ *Id.*

⁶⁶ “Global Study on Homicide” (UNODC, 2013) 9, online : <https://www.unodc.org/documents/data-and-analysis/statistics/GSH2013/2014_GLOBAL_HOMICIDE_BOOK_web.pdf>.

⁶⁷ Authors’ interview with Birger Heldt (February 2016).

⁶⁸ In some cases, this is increasingly possible: For example, organizations like the University of Toronto’s Citizen Lab seek to apply empirical methods to “watch the watchers” and measure, for example: the flow of internet traffic into countries to detect and investigate patterns of censorship; computer attacks on websites such as DDOS attacks numbering in the order of 100,000s; or to track patterns of surveillance of internet servers. “Fireside Chat: Ron Deibert, Edward Snowden & Amie Stephanovich” (RightsCon Conference presentation, 2016), online: <<https://www.youtube.com/watch?v=yGDqXokPGiE>>.

Guatemala, discovery of massive paper archives of the National Police Archives could not be examined manually, as they numbered 80 million text records. Instead, statistical sampling of the documents was applied to find a representative sample of their content.⁶⁹

Is the use of Big Data instead of stats better? Is more better? The size of these data sets, some like Victor Mayer-Schonberger and Kenneth Cukier argue, means they result in a representative snapshot of human activity.⁷⁰ Some pundits even contend that datasets will eventually be complete; such datasets will capture “all the things in the universe” we intend to measure, what in statistical terminology means $N=All$. Indeed, some have argued that big data might eventually lead to the end of statistics. Why select a sample, when the entire data population is available? Why test a hypothesis on what’s going on, when the data can speak for itself, live, on what is happening? The idea is that flaws in representativeness get drained out in the sheer size of the samples. In practice, for the most utopian among big data enthusiasts, big data would provide a pseudo “census-like” snapshot available live and anytime, thus doing away with much of the painstaking work that historically made up statistics such as those in Guatemala.⁷¹

Long-time experts on the use of statistics, like Megan Price and Patrick Ball contend that the reality is far more complex. Big Data is not the “full population”. One can casually observe that the reach of mobile phones, Facebook, or Google is omnipresent—but in the literal sense, they are not. Social media’s big data is an apt example: a lot of the population of interest is not online and important biases can be built into the data as a result. To suggest that because many are online, the sample from big data is representative of the broader population, creates various problems.

In short when it comes to representativeness, more data does not mask a data bias.⁷² Indeed, Patrick Ball contends that the argument that big data leads to more accurate findings is a debate that was as already argued and settled 80 year ago by the leading mathematicians of the time—*it does not*. What matters now, like then, is improved sample quality and the “probability model used to link the sample to the world”.⁷³

Ultimately, quantitative analysis is only as good as the data it relies on. Whilst the massive availability of spontaneously generated data as a result of cyberspace may seem like a boon for the development of human rights research, it creates methodological complications of its own. There is no avoiding that depending on the relative breadth and depth that any analysis of human rights violations seeks to achieve, trade-offs will exist between quantitative and other research methods.⁷⁴

⁶⁹ Daniel Guzmán (2011), “Speaking Stats to Justice: Expert Testimony in a Guatemalan Human Rights Trials Based on Statistical Sampling”, 24:3 CHANCE 23-29.

⁷⁰ Victor Mayer-Schonberger and Kenneth Cukier, *Big Data: The Revolution That Will Transform How We Live, Work and Think* (2013).

⁷² Patrick Ball notes that social media data used in research is often “collected nonrandomly” and constitutes a sort of “convenience samples”. Patrick Ball, “The Bigness of Big Data”, in *The Transformation of Human Rights Fact-Finding*, 428 (Philip Alston and Sarah Knuckey eds., 2015).

⁷³ 438, *Id.*

⁷⁴ M. Satterthwaite & Justice C. Simeone, “A Conceptual roadmap for social science methods in human rights fact-finding”, in *The Transformation of Human Rights Fact-Finding*, 344 (Philip Alston & Sarah Knuckey eds., 2015).

From Detection to Prevention?

Another implication of the rise of big data in human rights work is the increasing possibility to disrupt and prevent human rights violations, rather than only react ex-post facto. In addition to changing where and how human rights data is collected, big data could also affect the entire sequencing behind human rights data processing. The big data revolution means a faster data collection, analysis, and dissemination cycle that can alter the relationship between incidents and actions. While most use of data discussed so far both in part one and part two has been forensic and retrospective in nature, the increased speed enabled by cyberspace means data could be used to detect and even possibly, predict and prevent future human rights violations. Data can be mined for patterns, and patterns analyzed for triggers, with statistical methods used to derive some predictive knowledge.

Possibilities abound and may be unavoidable. For example, it bears mention that outside the bounds of formal human rights work, civil society and other will use rapidly accessible data from social media or other means to shed light on HREs. Corporations such as Google are already applying their search pattern data to redirect potentially violent “Islamic State” search behaviour towards results focused on extremism prevention material. In real-time, Google search data in becomes not only a source for HRE-related data, but also the medium in which interventions are implemented to prevent future HREs.⁷⁵ The implications of new actors, whether corporate or grassroots, being able in the future to take the front-stage in reacting to human rights issues merits reflection.

As exciting as this prospect sounds, three caveats bear mention: First, it appears that more evidence, available more quickly, does not of course necessarily mean more action. For example, even though it has been frequently posited that lighting on streets can reduce instances of street crime,⁷⁶ it is not clear at all if this principle applies to the “internet spotlight” cast on human rights violations like Syria’s civil war.⁷⁷ Secondly, the robustness of the data on which projections and trend analysis would be needed for effective pre-emptive work— an issue discussed further below under the interlinked issues of accuracy and representativeness – would be key, in a context where trends and patterns cannot easily be equated with hard facts, and the risk of manipulations lurks. Thirdly, creating the type of indicators that could capture the desired trends is challenging. As Aronson points out “to detect abnormality one must have some picture of normal baseline conditions”.⁷⁸ Compounding the difficulties of collecting such a

⁷⁵ Menchie Mendoza, “Google To Counter Radicalization By Serving Anti-ISIS Ads As Results To Extremist Search Queries” (Tech Times, Feb 2016), online: <http://www.techtimes.com/articles/131042/20160206/google-to-counter-radicalization-by-serving-anti-isis-ads-as-results-to-extremist-search-queries.htm>.

⁷⁶ For example: “24/7 electricity boosts jobs and reduces crime” (World Bank, Aug 2015), online: <http://www.worldbank.org/en/news/feature/2015/08/27/lese-crime-more-jobs-thanks-to-electricity>.

⁷⁷ Indeed, the notion that Syria’s is “the first YouTube war” (generating unprecedented hours of near-realtime coverage online) has clearly not resulted in a restrained or short conflict.

⁷⁸ Jay Aronson, “Mobile Phones, Social Media, and Big Data in Human Rights Fact-Finding”, in *The Transformation of Human Rights Fact-Finding*, 447 (Philip Alston and Sarah Knuckey eds., 2015).

baseline are the risks of arbitrarily codifying data, given the perennial reality that local and global understanding of what constitutes human rights can differentiate vastly.⁷⁹ Warning units already exist within various institutions for mass atrocity crimes, including the UN's office for Genocide Prevention (OSAPG). However, the OSAPG with its roughly 150 early-warning indicators of atrocity crimes has opted entirely for qualitative metrics because it has not found readily possible means to convert these to quantitative measures.⁸⁰

Conclusion: Implications for Human Rights Work

Quantitative methods have a relatively recent pedigree among human rights methodologies but seem increasingly useful in the complex world of domestic, transnational and global rights violations. The use of quantitative methods in human rights is clearly on the rise and there is reason to welcome this. Such methods often add a layer of breadth and understanding to what may otherwise be unduly anecdotal. They also modify evidentiary practices including burdens of proof, the nature of fact-finding, and even the very relationship of human rights enforcement with time and place. In this context, big data represents both continuity and radical change for quantitative practices engaged under the human rights banner. How radical the change it portends remains a matter of significant speculation at this stage.

It may be that quantitative methods are particularly suited to certain tasks. It is trite to say, for example, that quantitative methods measure what is quantifiable. They thus seem naturally suited to assessing the numbers of casualties in an armed conflict and as a result shed light on its dynamics; or a hidden situation of indirect discrimination on which statistics shed a crude light; or in detecting emerging patterns of human rights violations through analysis of big data. But, precisely, not everything in human rights is quantifiable, or at least not in a way that would avoid the impoverishment of the discourse of human rights. Quantitative methods may be uniquely suited to evaluating human rights that can be understood in terms of having been relatively straightforwardly violated or not, for example persons being unlawfully killed in the context of a campaign of violence. One potentially pernicious consequence of an excessive focus on the quantifiable would be a focus on those relatively few violations that lend themselves more easily to quantitative methodology: such a process might even reinforce prejudices about certain rights being non-enforceable, aspirational or non-justiciable.

Indeed there may be something a bit discomfiting about the narrow positivism of quantitative methods, something unappealing about number crunching for its own sake if that is what is involved. Quantitative data, especially in view of its power, needs to be read and understood carefully so as not to be made to say more than it can actually say, and cannot be a substitute for qualitative methods. It requires one to interrogate the methodology both as regards data collection and analysis. Even as apparently simple a

⁷⁹ This paradox of human rights measures is explored in depth in: *The Human Rights Paradox: Universality and Its Discontent* (Scott Straus and Steve J. Stern eds., 2014).

⁸⁰ "Framework of Analysis for Atrocity Crimes" (OSAPG, 2014), online: <http://www.un.org/en/preventgenocide/adviser/pdf/framework%20of%20analysis%20for%20atrocity%20crimes_en.pdf>.

question as what constitutes a human rights “violation” may in fact lead to multilayered definitions, that will then have to be broken down for coding purposes, leaving ample opportunity for interpretation, error, overlap, etc. Bias is a constant feature of quantitative, and not just of qualitative investigation and may be particularly at work given the clandestine nature of many human rights violations (so that quantitative analysis may contribute to make even more visible what is already most visible and vice versa).

This all goes to show that for all the potential and uses of big data listed in this chapter, we are still very much *in an age of proofs of concept*. As Letouzé, Meier, and Vinck note, systems such as these are often “best characterized by [their potential rather than by [their] track record”.⁸¹ The UN has also insisted that, in the context of development, the promise of big data “will be best fulfilled when its limitations, biases, and ultimately features are adequately understood and taken into account when interpreting the data”.⁸² Indeed, human rights practitioners must recognize the double-edged nature of these changes: As notes Aronson: “the major caveats...are that merely gathering and analyzing this information does not guarantee its utility (indeed such endeavours may lead to false or misleading conclusions), and that human rights abusers and repressive states often have access to the same (or better) tools and techniques than human rights advocates and investigators do. Thus ... social media and big data analysis will likely be a proverbial double-edged sword that both enhances and detracts from our ability to protect and promote human rights”.⁸³ Naturally, these strengths may also pose risks, as governments take increasing control of the web.

Still, if international human rights law is not to become an exclusively and narrowly adjudicative enterprise focused on individual violations and is to be seen as part of global processes of governance geared towards maximizing rights through carefully calibrated data on where and when harms occur, then quantitative methods indisputably have a place. Take an apparently eminently “qualitative” issue such as the ability to wear the hijab in a Turkish university in the *Leyla Şahin v. Turkey* case, one criss-crossed by competing discourses of freedom of thought, religion, secularism, terrorism, gender equality, etc... One might think that such issues are only the realm of careful principled reasoning from the law, with attention at best to individual facts. Yet there could have been a place for quantitative analysis even there. The Turkish government claimed that there was a connection between the hijab and proselytizing in ways that made non-practicing students feel threatened, and perhaps even a link with terrorism. This is a claim that the ECtHR was basically ready to accept at face value, but it is one that could have been dissected from a statistical perspective to see if it rested on anything else than political prejudice and expediency. What is the proportion of students who wear the hijab, what percentage of them is inclined to proselytize or even be politically active, how many to radicalize, and what proportion of students is likely to actually feel intimidated? In discussing these issues as issues of broad policy not needing

⁸¹ Emmanuel Letouzé, “Big data for development: challenges & opportunities” 36 (UN Global Pulse, 2012), online: < <http://www.unglobalpulse.org/sites/default/files/BigDataforDevelopment-UNGlobalPulseJune2012.pdf>>.

⁸² 36 *Id.*

⁸³ Jay Aronson, “Mobile Phones, Social Media, and Big Data in Human Rights Fact-Finding”, in *The Transformation of Human Rights Fact-Finding*, 444 (Philip Alston and Sarah Knuckey eds., 2015).

to be informed by quantitative data, the ECtHR was arguably led to defer excessively to Turkey's margin of appreciation and reify a number of implausible generalities.

At any rate, the changes heralded specially by the digital revolution and big data may simply make engagement of quantitative methods unavoidable. The increasing scale and scope of quantification is accelerating faster than institutions' ability to adapt existing rules and norms. Concerns about accuracy and representativeness are unlikely to curb the appetite to apply statistical tools to big data sources for human rights. The challenges of sample validity and representativeness are hardly unique to digital data that constitutes most big data. Ultimately, perhaps the best thing that can be said of quantitative methods in international human rights is that, as one course description put it, they "provide certain kinds of answers to certain kinds of questions."⁸⁴

⁸⁴ Personal website of legal scholar Todd Landman, online:<www.todd-landman.com/quantitative-methods-for-human-rights-research>.