The role of philanthropy in using data to address complex challenges: A global scan

Authors: Jordan Junge, Kendra Schreiner, Louise Pulford

Introduction

Foundations all over the world are grappling with their role in the emerging field of data and artificial intelligence. The field is fraught with potential controversy but also with possibility. Data has the potential to help us work at a larger scale than ever before, be more efficient, and solve problems more effectively.

Despite the potential, philanthropy isn't engaging in this field fast enough, and is well behind other sectors. Very few big foundations have the capacity or technical knowledge to either shape innovations or make sense of which ones to back, and when they do get involved they face complex challenges about transparency, ownership, and ethics.

Our purpose in writing this scan is to inspire foundations by showcasing how organisations and sectors around the world are already using data to create positive societal change. It highlights the different ways in which philanthropy is engaging in this field, and briefly outlines the key challenges of working with data before moving to the future opportunities for foundations.

The catalyst for this scan was a retreat hosted by SIX in 2017 on 'Aligning for Impact'. The retreat was one of the activities of the SIX Funders' Node – a programme which aims to shift the flow of funding to social innovation and systems change. Over the past two years, we have engaged more than 70 foundations from 17 different countries. Our aim is to catalyse a conversation on how foundations can use data to increase their impact with this scan, and accelerate peer learning.

This work is supported by, and carried out in partnership with, Nesta (UK), Lankelly Chase (UK), The McConnell Foundation (Canada) and the Robert Bosch Foundation (Germany).

This scan was completed through desk research, a call through our global network, and interviews with pioneering practitioners and foundations, alongside guidance from an informal advisory group.

A. How is data being used for social good and systematic change?

Our global scan revealed hundreds of examples, representing a wide range of sectors, methodologies, scales, regions, and contexts. In this section, we provide a snapshot into the different ways data can be used to solve complex problems. It features a range of organisations and initiatives. Most, but not all, of the examples below include a specific role for philanthropy.

a. Using predictive algorithms

Predictive algorithms can help improve human decision-making by quickly mining large amounts of data from similar cases and issues to provide recommendations based on predicted outcomes.

The Allegheny Family Screening Tool (AFST) uses predictive modelling to help improve child welfare call screening decisions. Designed by the Allegheny County Department of Human Services in the US, the AFST was the first globally to use a predictive algorithm to provide a second opinion in child welfare. The tool links administrative data from 29 data sources, including child protective services, mental health services, the justice department, and drug and alcohol services to provide a 'second-opinion' on every incoming call, in the hopes of better identifying the families and at-risk youth most in need of intervention. The system's accuracy is at over 90% now, helping flag cases that might have otherwise fallen through the cracks and prevent further abuse. The tool is owned by the county (as opposed to a private company), was developed in consultation with the community, and was evaluated by academics. The development and impact of the tool has attracted interest from others in the US.

In the UK, Medway Youth Trust has combined text-mining and integrating 30 partners' databases with predictive algorithms to determine young people's risk of becoming "Not Employed, in Education, or in Training". Manually looking through these various sources from different organisations and predicting risk based on the information was out of scope for case workers. The system has led to a 250% improvement in accuracy of identification compared to manual search techniques, and other local communities are now interested in deploying the software.

Predictive algorithms are also being used in environment and conservation. PAWS, a partnership between the Uganda Wildlife Authority and researchers at the University of Southern California, uses poaching data, GPS, and machine learning to predict routes for patrols based on where poaching is likely to occur, helping improve patrols' ability to catch poachers. GSMA's Big Data for Social Good has several projects. In one partnership with Telefonica Brazil, mobile network data is used to monitor air pollution in Sao Paulo and predict pollution problems up to two days before they occur, allowing the city to take precautions to protect public health.

b. Data warehouses and integrated datasets

Data warehousing collects vast amounts of data from different sources across a given sector or issue area and quickly analyses it together.

In the Province of Saskatchewan, Canada, the Hub model brings together service providers to collaborate, share information, and address complex local challenges. Traditional service delivery models were siloed and difficult to coordinate, while social issues are cross-sectoral and cross-jurisdictional in nature. The Hub is a regular meeting that brings together frontline service delivery staff, including social services and police, as well as local non-governmental organisations that provide social services. These meetings allow for identification of elevated risk situations and a joint response delivered by at least two service providers. This allows local service providers to collectively identify patterns in risk factors, which can be transmitted upwards in government. Data is anonymised and has restricted access. The Centre of Responsibility analyses and visualises data from Hubs across Saskatchewan to identify systemic issues that require a higher-level response. This level of data collection and synthesis is unprecedented in Canada, and enables fine-grained tracking of risk factors across the province and rapid identification of systemic issues.

Cincinnati's Heroin Overdose Tracker, part of the CincyInsights Data Hub in the US, compiles data from emergency services and various government departments to show a dashboard of heroin overdoses across the city. The dashboard is updated daily and is scrubbed of personal information and enables the city to deploy medical teams to areas where the highest incidents are likely to occur.

Statistics New Zealand's Integrated Data Infrastructure is a large research database containing anonymised microdata about people and households from a range of government agencies and NGOs, such as housing data, education, income and work, justice, health, and more. The data is accessible to researchers to answer research, policy, and evaluation questions to better inform policy-makers to help solve complex issues, such as crime and protecting vulnerable children. This has allowed the government and partner agencies to target limited resources to those areas where the greatest long-term benefit can be made. Oranga Tamariki (the Ministry for Children) uses the database to make evidence-based decisions and to improve the effectiveness of their services.

The Justice Data Lab, established by the Ministry of Justice in the UK and managed by New Philanthropy Capital, combines administrative data from criminal justice charities and public service organisations. It gives organisations working with offenders access to this central data, enabling them to assess the impact of their work. Previously, organisations relied on their own efforts to collect data from a range of sources, which tended to vary in quality and be piecemeal.

Overlaying different data sets can help to present a more holistic picture and context. VAMPIRE in Indonesia (Vulnerability Analysis Monitoring Platform for Impact of Regional Events) combines different databases to visually present an early warning system for climate impact. It has a baseline data layer of population data, socio-economic data, and World Food Programme food security surveys. The next layer visualises the climate including rainfall and vegetation health. This helps to depict the impact of climate on vulnerable populations and can help to identity priority areas.

c. Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) is a broad concept which covers a range of methods, including machine learning, computer vision and natural language processing. Machine learning (and deep learning) are the most prominent current stream of AI and involve algorithms being 'trained' to make better predictions – whether recognising a face or predicting who might be at most risk of a serious illness. This involves feeding large amounts of data to the algorithm and allowing it to adjust itself and improve. This has enormous potential for analysing complex systems and social challenges.

UNICEF developed Magic Box, an open source global platform to inform life-saving humanitarian responses. The platform takes data from public and private sector partners and uses machine learning techniques to generate insights on emerging epidemics and emergencies. It was used during the Zika crisis in 2015 and an Ebola outbreak in central Africa in 2017. The platform can analyse mobile connectivity to understand how communities are recovering after disasters and use satellite and mobile phone data to better understand indicators of poverty. It is currently piloting predictive modelling for diseases in Latin America.

Global Fishing Watch has created a global transparency platform and uses ships' transponders (Automatic Identification Systems), satellite data and machine learning to identify commercial fishing vessels to flag any illegal fishing. Their work has led to six new protected marine areas by helping to provide the evidence to governments that previously did not have the capacity to collect the data.

Google's DeepMind has partnered with the UK's National Health Service to use AI to improve and seed up how diseases, like acute kidney failure, are diagnosed and treated. Their app, Streams, integrates different types of data and test results in one place and alerts nurses to serious issues.[1]

Artificial Intelligence in Medical Epidemiology (AIME) in the US uses AI for public health, helping to forewarn governments of disease outbreaks. They analysed public health data, weather reports, scanned social media for rumour reports and more to predict a dengue outbreak three months early in two countries with 86% accuracy.

d. Real-Time Monitoring

Real-time monitoring harnesses data from a range of sources and presents it immediately, in real-time. This allows decisions to be made with the most up-to-date information, rather than based on months or years old data.

Mobile data is often provided by private organisations as a form of philanthropy. LIRNEasia in Sri Lanka uses mobile phone big data for development in South Asia. They have used this data to track infectious diseases, traffic patterns, and inform urban planning. GovLab, UNICEF, Universidad del Desarrollo/Telefónica R&D Center, ISI Foundation, and DigitalGlobe are using mobile phone data and high-definition satellite imagery to map the journeys of the city's female residents and understand their ease and safety of moving around the city of Santiago, Chile.

Satellite data: Global Forest Watch uses satellite data combined with cloud computing and crowdsourcing to analyse huge datasets to allow for near real-time information about how and where forests are changing around the world. Still in its pilot phase, the Zeitz Foundation is launching Big Data, Small Screens in Kenya to send agricultural and environmental information from satellite data directly to farmers to improve productivity by sending real-time climate information and sharing new farming methods.

[1] It should be noted that this partnership resulted in criticism from the UK's Information Commission in 2017 for failure to inform patients how their data was being used. More on this in the challenges section of the scan.

Social Media can be used to track societal trends in real-time, from disasters, diseases to community recovery and development. UN Global Pulse Lab in Jakarta followed social media to understand food prices and food insecurity.

Internet of Things is the interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data. This is being used in smart city projects across the world. In the traditional Korean village of Bukchon in Seoul, South Korea, the city collaborated with citizens and startups to use IoT technology in the village and improve services and preserve cultural heritage. Chicago's Array of Things uses sensors placed on objects and vehicles to provide real-time information to enhance urban planning, improve emergency service provision, update travel routes, and more. In Kentucky, AIR Louisville distributed smart inhalers to asthmatic residents and placed sensors around the city to monitor air quality in real-time and generate heat maps of asthma attacks to allow more effective responses to air quality problems. The NHS (UK) is using smart technology to help make it safer for dementia patients to stay in their own homes, allowing clinicians to check in on the patients remotely.

B. How is philanthropy engaging in this work?

Whilst the examples in the above section come from the private, public, non-profit and philanthropic fields, the following section highlights specifically how philanthropy is (and could be) engaging in this work.

1. **Funding Social Data Projects through traditional grants -** One of the main ways foundations are supporting social good data projects is through traditional grant making, which enables charities to innovate, experiment, and scale pilot projects. There are many examples here. The Howard G. Buffett Foundation and Conagra Brands Foundation support Map the Meal Gap, which analyses local level food insecurity in the US. Microsoft Philanthropy and Splunk4Good helped scale the Global Emancipation Network into a global network. Google.org recently announced it would invest $1 billion and one million volunteer hours to non-profits tackling complex challenges. The Robert Wood Johnson Foundation (USA) supports many initiatives that are using data for public health, in specific projects like AIR Louiseville (as mentioned above) or those organisations that are working to make health data useful and accessible for more audiences.

2. **Funding enabling environments -** Beyond simply funding individual projects using a data-based approach, foundations are also funding social data infrastructures to create enabling environments. For example, Omidyar Network funded the Open Data Institute (UK) to advocate for open data across the world, which was the largest investment they made in a non-profit. The Ontario Trillium Foundation, one of the largest granting foundations in Canada, is supporting Transform the Sector in Canada, which aims to build a data-driven social sector by engaging with and amongst funders, non-profit organisations and the government. So far they have produced a series of reports on data capacity, administrative data, data ethics and open data. The Nuffield Foundation in the UK recently announced £20 million to support data for good. As part of this fund, they are working in partnership with the Alan Turing Institute, the British

Academy, and the Royal Statistical Society to establish an independent Convention on Data Ethics. The Convention will bring together stakeholders from a range of sectors to explore solutions for fairer and safer data use arising from technological innovation, regulation, or changes in public behaviour.

Capacity building is an important part of the enabling environment. As we outline in the challenges section below, data experts are extremely expensive. And even when organisations do have the finance, finding data specialists who are interested in social challenges, and entrepreneurial enough to find new ways to work in this unknown territory is very hard. For third sector organisations, funding a data focused position is almost impossible. Even UNICEF, a large global organisation, was unable to establish a data programme until Bloomberg funded a Researcher-in-Residence program.

3. **As a convener -** Foundations can contribute to developing data partnerships. They often have large networks of different kinds of actors. Foundations can help coordinate and align these actors, encouraging and inspire new partnerships. A leading example of this is the role the McConnell Foundation play in the further development of the Saskatchewan Hub model, highlighted in the section above. The McConnell Foundation works closely with Saskatchewan officials and other partners on creating an environment in the province ripe for the deployment of social innovation tools, including social finance, labs, prototypes and the use of data for evidence-based decision-making to expand outcome oriented programs such as the Hub model.

4. **Funders supporting new datasets -** A small number of funders have created new datasets, either unilaterally or in partnerships. These datasets can help to provide evidence to influence funding decisions, programme design and policy. The Fay Fuller Foundation provided significant funding to the South Australia Health and Medical Research Institute (SAHMRI) to compile a comprehensive dataset on health outcomes and social determinants for Aboriginal people in 18 geographical areas across the state. It is likely to be the first time that many Aboriginal people will have a large range of data specifically on their communities and it is hoped it will drive more control for local actors. Bloomberg Philanthropies works with low and middle income governments through Data for Health to strengthen public health data in order to prioritise health challenges, develop policy and track impact in a particular country. To date, 20 countries have partnered with Data for Health reaching more than one billion people. The Universal Cancer Databank, funded by the Minderoo Foundation in Australia, aims to create a global databank on rare and deadly cancers and offers patients the right to donate their own personal data for research. The Databank is 100% philanthropically funded and is being established in conversation with health department heads around the world and researchers. In a new project, Nesta is working with the Robert Wood Johnson Foundation to find the best health innovations globally using web scrapping techniques. This will help to find new innovations and organisations that RWJF could support and will result in an open-source, interactive online database, search, and mapping tool that is capable of illuminating new swaths of the global health innovation landscape for policymakers, researchers, innovators, and funders.

5. **Giving data as a form of philanthropy -** This new form of philanthropy is represented in many of the above examples, with organisations giving data sets or pro bono expertise in analysis. Facebook has donated multiple data sets, including population density and satellite data, as well as data processing technology, to the Red Cross's Missing Maps (global) to map over 20 million vulnerable people who are not represented on maps. Facebook also collaborated with the World Bank and donated satellite data to the Center for International Earth Science Information Network in the US to improve rural settlement data and improve their mobile connectivity. The Mastercard Center for Inclusive Growth analysed consumer spending in the Middle East and North Africa and was able to map political violence. They gave the data to researchers and academics to spot patterns. Team Rubicon, a team of marine volunteers, used Palantir's software as a 'real-time mission planning platform to provide relief efforts after tornadoes, hurricanes, floods, and other natural disasters.'

6. **Open data platforms to show who is funding what -** WASHfunders.org, a project of the Foundation Center in the US, maps projects related to water or basic sanitation to help identify gaps and opportunities, track progress and explore success case studies. Fundtracker in Canada was developed as a tool for fundraisers within non-profits. It takes open and public data to create a comprehensive view of the foundation landscape in Canada, mapping who is funding what, where, and how much. Much of the data was obtained from federal tax returns. The team at Ajah who developed Fundtracker have been key players in the open data landscape and are liaising with the government to require more reporting from foundations.

7. **Integrating data into operations -** Data and AI are being used in internal operations of foundations (and charities) to improve efficiency and effectiveness and reduce costs. This blog by Geoff Mulgan of Nesta highlights different things foundations can do. These include smarter sifting of initial grant applications to save time and reduce human biases; enabling smarter grant applications, such as through speech to text technology; enabling smarter scans of needs and issue areas to better understand what is being done and where value can be added, and even to provide philanthropic advice. Some of these remain simply possibilities, while others are being piloted. For example, Philanthropy.ai, formerly Astrient Foundation in the US, provides micro-scholarships to students and through their AI-based application system, which uses a stream of data from the applicant and other sources to create a picture of the applicant's need, and removes the need for a panel of judges and their possible bias. Donaco aims to facilitate the relationship between donors and charities using AI to place pop-up boxes next to relevant news articles that allow readers to instantly give money to that cause. Donaco emerged from a hackathon at Imperial College London and won Microsoft's Imagine Cup. While still in its trial phase, results have been promising, with 20% of readers engaging.

B. Challenges in working with data

It is clear that there are lots of ways data is already being used to solve large complex social problems more effectively, but the challenges of working in this new way are significant, deep, and cultural. Below we highlight four main challenges and offer some examples of how they are starting to be tackled.

1. **Privacy and Ethics -** Privacy, especially in light of recent scandals like Cambridge Analytica's, is at the forefront of everyone's minds. Whilst in many of the cases above, the data is anonymised and aggregated, questions remain as to whether the anonymisation processes are, and will be, good enough. It may still be possible to re-identify customers or users despite anonymisation, and it is not clear how secure the data is. There are also legal uncertainties, as data protection laws, like General Data Protection Regulation in the EU, differ from place to place and companies are not always certain what is permissible.

   The NHS was censured over the breach of patients' privacy in their partnership with Google's DeepMind. It was found that they 'had concentrated on building tools for clinicians rather than thinking about how the project should be shaped by the needs of patients and the public' when patient information was shared without consultation.

   Transparency and openness can mitigate these risks and help make data more democratic. Statistics New Zealand has maintained transparency as a core value. They undertook a study on the public attitudes towards data integration, invited public feedback and complaints, and published everything on their website, including records on all the ways data is being used in research.

2. **Algorithms can't always replace humans -** Although AI provides opportunities to improve public and social services, there is potential for it to amplify biases that may be built-in by human programmers, that could have serious negative consequences, especially for poorer communities and minorities. Algorithms are not a straightforward replacement for human decision-makers, and must be designed with care. In some fields they have directly replaced people (from credit scoring to shopping recommendations), in others they tend to be used in conjunction with human decision making.

   Openness and co-creation can help avoid anxieties about potential harm or unintended consequences of using data for social good. Allegheny's Family Screening Tool is an example of a human centred approach (they start with people, as opposed to starting with looking at data). They conducted extensive consultations with the community, which both created buy-in and reassurance and helped develop the predictive algorithm, which now has over 90 percent accuracy.

3. **Lack of specialist capacity -** Using data for good requires a combination of data skills and much broader skills and experience. There are very few data scientists working within social organisations, or foundations, who have the skills to capture, analyse and use data. Where these experts exist, they tend to be on temporary and expensive contracts. They also tend not to have a deep understanding of the complexity of social challenges. Since there is no blueprint of how to use data to tackle complex social problems, we need people who are entrepreneurial, innovative, and socially minded, as well as technically proficient.

As David Kroodsma of Global Fishing Watch said, 'our biggest bottleneck is the lack of data analysts and engineers to understand this data and it's only going to get worse with the more data we produce'.

There are a few promising approaches to tackle this challenge. One example is the Seoul Big Data Academy, a partnership between Seoul Metropolitan Government and Seoul National University in South Korea. It provides a free education programme for Seoul residents which goes beyond simply teaching citizens about big data by giving them opportunities to directly practise and utilise big data skills with urban issues. Uptake.org in the US runs a six-month Data Fellows programme designed to connect data professionals with non-profits, foundations, and social enterprises to share skills and network. Uptake.org also granted $1 million to Carnegie Mellon University's School of Computer Science to establish the Machine Learning for Social Good fund, which provides free machine learning and data science to non-profit and governmental organisations.

4. **Infrastructure that enables better data sharing -** Most data is held within private organisations. Sharing this data amongst organisations and sectors in a consistent and secure way and in real-time is a challenge. Manuel Garcia Herranz, Chief Scientist at UNICEF, highlighted that creating the infrastructure for Magic Box was a serious challenge - 'data was first just shared by email, which isn't sustainable. Getting datasets that were readable and useable was also a challenge.'

5. **Data is expensive** - Despite that the number of private organisations wanting to give data as philanthropy is growing, there are still costs involved in developing these partnerships and extracting, cleaning, sharing, and processing the data. There is a commercial challenge as data has a large market value and most methods surrounding data have been designed for profit.

   With AI researchers in the private sector now making upwards of $1million per year, a lack of the right capacity is a major challenge. Even if data is produced in-house or is donated, the costs of processing can be quite high. Medway Youth Trust contracted IBM to build their predictive algorithm platform for £100,000. Pro or even low bono work will not build the much-needed in-house capacity. With these costs being insurmountable for small organisations and governments, there is a risk of big data usage being concentrated in only a few hands.

   There is a cultural challenge that cuts across all these technicalities – most people still don't see the value of using data to create social good, and in particular, there is an apprehension towards the dominance of the private sector in relation to data. There are signs of private companies working more collaboratively: John Snow Labs, a private data analytics company based in the US, independently became excited about the idea of data philanthropy and sought out third sector partners who they could assist.

   All of these challenges and risks should be carefully managed. Stefaan Verhulst of GovLab warned that 'progressives have become obsessed with risks (which is good), but it is now easier to complain than to recognise potential value that data can bring.'

D. Cross-sector partnerships and data

This work is complex. Data for good projects require technical expertise, funding, research, people who understand and work with local communities, and often policy makers and governments at local, regional, and national levels. So how do people coming from very different backgrounds and cultures work together effectively?

Nearly all the above examples were collective efforts between multiple partners, often from different sectors. Based on these examples, and our interviews, we have identified three features that make data for good cross-sector partnerships work.

1. **Trust building between partners -** We all know that building trust is central to any partnership, but it is particularly crucial in data collaboratives, where concerns around privacy and ethics are high (and justified), and where there are few clear blueprints and procedures because of the newness of this work.

   One of the main reasons that Saskatchewan's Hub Model for Community Safety has been so successful in reducing crime is its trust-based model of working. The Hub is a regular conversation that brings together frontline practitioners, the community, and the police to identify risk patterns, mitigate risk and integrate responses. All partners meet twice weekly to build a trusted relationship that helps them more effectively deliver services. They all know such a collaborative approach takes time, and all partners have invested in that.

   The case of the City of Boston and Uber in 2016 demonstrates the danger of not building trust between partners. The City and Uber made an agreement to share data in hopes of improving transportation and urban planning, but Uber did not live up to its hype when it highly limited the data it would share, rendering it useless for the intended purposes.

2. **A dedicated facilitator and broker -** Working together does not just happen. Bridging sectors and expertise requires careful facilitation and project management; this is especially true in data collaboratives, where data scientists and experts in a social challenge may have little shared understanding. David Kroodsma of Global Fishing Watch said 'working with the scientists and analysts and connecting them to the researchers requires a lot of handholding. It requires time, trust, and the ability to communicate between different disciplines and expertise. Working with data for social good will never require one person at this stage - it will always be the analyst/engineer on the data side and the researcher/project on the other.'

3. **Shared goals and long-term commitment -** Many cross-sector data partnerships currently are ad-hoc, one-off collaborations or donations of data or data science. This often means that some partners lose out, and that the value of the project is limited by a timeline. Magic Box has made this a priority in their work with academia, public and private sectors, by developing long-term agreements with Amadeus and Telefonica so all partners achieve success that is relevant to their own organisation. Richard Benjamins, who leads Telefónica's Big Data for Social Good initiative, commented: 'we now need to shift from pilots and 'one-offs' to real operative systems

which provide a continuous data feed. Data needs to come from both the public and private sector and therefore partnerships like this one are key.'

What's the role for philanthropy in moving this field forward?

Philanthropy has not been a big player in the data field to date, but that does not mean that it cannot be in the future. If data for social good is to reach its potential, it needs support.

Philanthropy can help. And as we set out in the scan above, it can do more than just give grants. Philanthropy can fund the enabling environment and build capacity, they can act as a convener bringing together other partners, they can create or give data, and fund open data platforms, and they can integrate data into their operations. Philanthropy has privilege to fund where others do not. Philanthropy can take the long-view where others cannot. Philanthropy can take risks, which is what most data projects are at this stage.

Some fear that foundations, and those they fund, may be attracted to the newness and flashiness of these methods, and misunderstand (or lose sight of) the problem they are trying to solve (and potential solution). Data is not the answer; it is a tool and we have highlighted some of the different ways that it can be used.

As funders begin to take an interest in this work, there are some key questions they should consider about their role:

- Foundations should be aware of the whole data value chain - how is the data being collected? Stored? Sustained? Shared? How can foundations make investments across the data life cycle to ensure that it's more sustainable?
- What is the role of philanthropy in protecting the public interest?
- How can foundations use their influence and leverage to engage more actors, including the private sector, to donate more data and expertise?
- How can philanthropy help to de-risk these partnerships and this work? Could they help with feasibility studies to determine scalability?
- What is the best way to develop capacity throughout the sector?
- How can we gather the data on data? What is the evidence base to support that this work is making an impact?

If you are interested in learning more about this work, or if you have feedback, additions and comments on this piece, please get in touch with Jordan.Junge@socialinnovationexchange.org

Useful resources

Five Principles for Applying Data Science for Social Good - How to go from well-intentioned efforts to lasting impact with your data projects by Jake Porway. Published in October 2015.

The 6 Challenges of Big Data for Social Good - Outlines the challenges businesses who want to contribute to data for social good should consider. By V. Richard Benjamins of Telefonica. Published in October 2016.

Robotic Alms: Is Artificial Intelligence the Future of Philanthropy Advice? - Explores several ways AI could transform philanthropic advice, including reducing cost, identifying giving methods, identifying the most pressing needs, identifying donor aims, identifying the most effective interventions or organisations and maximising donor satisfaction. Published in May 2017.

A New Type of Philanthropy: Donating Data - Robert Kirkpatrick of UN Global Pulse, one of the pioneers of the concept of “Data Philanthropy”, defines the concept, the need for partnership with the private sector, and the value of data as a public good. Published in May 2013.

Big Data for Development: Challenges and Opportunities - This white paper by UN Global Pulse discusses at length the potential applications and growing evidence of big data for international development as well as the main challenges. Published in May 2012.

An Introduction to Data Collaboratives: Creating Public Value by Exchanging Data - GovLab outlines what data collaboratives are and the different ways in which they create public value and provides a data responsibility framework.

Ten articles to read on the future of inclusion in AI: Why AI matters in social innovation - A curated list of articles that explore how everyday voices can be included in the AI debate, how AI can be designed for the common good, and how to ensure accessibility to non-technical sectors. Published March 2018.

10 principles for public sector use of algorithmic decision making - Eddie Copeland of Nesta suggests 10 principles that might go into a Code of Standards for Government and Public Sector Use of AI in Algorithmic Decision Making. Published in February 2018.