WHITEPAPER

Data as a Force for Good

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Data as a Force for Good
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1. Executive summary

In this white paper, we give an overview of the current possibilities for using Big Data to help achieve the Sustainable Development Goals that the United Nations has set for 2030. We will focus mostly on the use of private Big Data coming from the telecommunications industry, though several of the aspects discussed are also applicable to the private sector in general. There are now about 8 billion mobile phones in the world and collectively, the activity of those mobile phones generates a substantial amount of data. Much research has shown that this Big Data can function as a proxy reflecting important changes happening to crowds of people during important events. The challenge is now to turn those promising research results into concrete systems that help improve the world and save lives on a continual basis. Issues to resolve include privacy and the structural involvement of the private sector, apart from the public sector.

2. Introduction

“On September 25th, 2015, the United Nations adopted a set of goals to end poverty, protect the planet, and ensure prosperity for all as part of a new sustainable development agenda. Each goal has specific targets to be achieved over the next 15 years. For the goals to be reached, everyone needs to do their part: governments, the private sector, civil society and people like you.” The 17 resulting Sustainable Development Goals of the United Nations have 169 targets to be achieved by 2030, and they are measured through 241 Key Performance Indicators (KPIs). Not all of the 241 indicators are equally easy to measure. The Inter-Agency and Expert Group on SDG Indicators has divided these indicators into three tiers (as of March 2016):

- Tier I is comprised of 98 indicators (41%) for which statistical methodologies are agreed and global data are regularly available;
- Tier II is comprised of 50 indicators (21%) with clear statistical methodologies, but little available data; and
- Tier III is comprised of 78 indicators (32%) where there are no agreed standards or methodology and there is no data available;
- 15 indicators (6%) are still unclassified.

It is the responsibility of the Offices of National Statistics to monitor all KPIs, and government Open Data is also set to play an important role. However, as we can see from the different tiers, there are still many KPIs without data or a measuring methodology. We believe that private Big Data from specific sectors can help measure those KPIs. In particular, data from mobile phone operators, satellite images, financial institutions and supermarkets could be particularly valuable. Figure 1 shows an overview of sectors whose private data has been used for research projects contributing to the SDGs.
Figure 2 shows some examples of how private Big Data can be used to estimate KPIs of the targets of the sustainable developments goals. For example, payment data from financial institutions can help to estimate a consumer price index or a poverty index. While there are official indicators to measure those indexes, they usually are difficult to execute in rural areas of developing countries. Additionally, it is desirable to minimize the cost of the KPI construction process itself (data harvesting, cleansing, and so on), as many countries struggle to allocate a budget for that. Search queries in Google have been used to estimate and/or follow the propagation of influenza outbreaks. Satellite images have been used to estimate GDP growth through measuring light emissions. Mobile phone data has been used to estimate the rate of illiteracy in developing countries (ratio between SMS and calls) and to predict socio-economic levels.

A quick analysis of all the Tier II and Tier III targets shows that initially there are about 10 clear KPIs where mobile phone data could be of help, as shown in Table 1. A more thorough analysis is needed to determine how private data can contribute to measuring of Tier II and Tier III KPIs, and to understand how it can improve some of the Tier I measurements in terms of frequency and geographical granularity.
3. Examples of Big Data for Social Good research pilots

In this section, we will briefly describe several pilot projects that show the relevance of Telco Big Data for helping to achieve the Sustainable Development Goals. Since they have been described extensively elsewhere, we will not enter in detail but rather provide links and references.

GOAL 1: NO POVERTY – Poverty Analysis in Senegal (Orange and the State University of New York at Buffalo USA).

By using mobile phone usage data and regional level mobility information, Orange and the State University of New York are creating poverty maps showcasing a wide range of perspectives which can be provide decision makers with better insights to eradicate poverty in the most efficient way possible in Senegal.

A similar approach was conducted in a policy research paper by the World Bank and Telefónica Research in this case, mobile phone data was used to create an estimated map of poverty in Guatemala. Interestingly, the authors demonstrate not only the potential of mobile data for estimating poverty but also to generate predictive models.

GOAL 3: GOOD HEALTH AND WELL BEING – Mobility Data Analysis in Mexico during the H1N1 Flu Outbreak (Movistar).

Scientific experts in the Telefónica Research and Development team used analytics on Telefónica data to understand the efficiency of government measures during the H1N1 flu outbreak of 2009. Human movement directly accelerates the spread of diseases, so researchers analysed mobility patterns before and after the government advised citizens to stay at home, uncovering that only 30% of people stayed at home, whilst 70% barely showed any changes in their day to day behaviour. In the future, this data-driven approach to handling health pandemics will inevitably save lives and help governments to optimize their response.
GOAL 7: AFFORDABLE AND CLEAN ENERGY – Using Mobile Data for Electrification Planning in Senegal (University of Manchester, Ecole supérieure polytechnique de Dakar UCAD and the Santa Fe Institute).

Mobile phone data has proved to be an accurate proxy of the energy needs of populations in Senegal, allowing telecommunications operators to help utilities providers build bottom-up demand models. This is especially important where there is scarce information on the constantly evolving energy needs of people and companies in developing countries. In the future, mobile data will be crucial in helping governments and utilities providers decide where to invest in renewable energies – ultimately making them more affordable for citizens.

GOAL 11: SUSTAINABLE CITIES AND COMMUNITIES – Crime Prediction in the city of London in the UK (O2 Telefónica and the University of Trento)

Academic and mobile data experts used anonymized and aggregated mobile data and police data to predict crime hotspots in London. These hotspots were identified with an accuracy of 70%, 6% higher than when police data was used on its own. The analysis showed that some components of mobile phone data are more important than others. For example, the data about the phone’s home location showed a strong correlation with crime patterns. In the future, these insights could be invaluable to law enforcement authorities in making our cities safer.

GOAL 13: CLIMATE ACTION – Using Mobile Data to measure CO2 emissions in Nuremberg, Germany (O2 Telefónica, Teralytics and the South Pole Group)

Local governments are facing immense challenges with accelerating rates of CO2 emissions causing serious air pollution problems in cities. The first and most important step to combat this is to collect accurate data to identify where the major air pollution hotspots are, even ahead of investing in solutions such as improved public transport or new infrastructure. In Nuremberg, local government decision makers are working with O2, Teralytics and the South Pole Group to understand mobility patterns using mobile data, extracting insights on traffic which allow them to make predictions on pollution in a more cost-efficient way than surveys or sensors.
4. Towards supporting managing humanitarian disasters – a case study in Colombia in collaboration with UNICEF

In this section, we analyse three natural disasters, and explore how each of them is reflected in our mobile phone data, and what that can mean for improving the way humanitarian agencies and governments manage natural disasters.

The disasters happened in Colombia in 2015, and include (see Figure 3):

- An Earthquake that took place on March 10 near Los Santos, with 41,000 people affected, causing 9 injuries and destroying 275 houses.
- A landslide in Salgar on May 18, killing 62 people.
- A flood in San Miguel on July 22, impacting more than 1,600 families.

While these disasters were on a much smaller scale than the 2004 tsunami in the Indian Ocean or the 2010 earthquake in Haiti, they still affected many people who deserve adequate support as soon as possible.

In order to support humanitarian agencies, it is important to know how they operate in the event of emergencies. There are three phases, as can be seen in Figure 4.

- **Early warning or alerts.** In this phase, once a disaster is detected, they start to collect information to prepare for the next phase. Ideally this happens as soon as possible in real-time, but at most in a matter of hours.
- **Critical response.** In this phase, help and support is directed to the people who are most affected. Where exactly did the disaster happen, and where are the affected people located immediately after the disaster? Have they moved to specific (safe) locations? This should happen in a matter of hours or days.
- **Recovery monitoring.** In this phase, agencies need to know that things are getting back to usual, and people start to recover their normal lives again (if possible). Depending on the size of the disaster, this is usually a matter of days or weeks, but in larger disasters it might be months or years.
As much previous research\(^2,3,6\) has already shown, there is a clear correlation between the occurrence of natural disasters or other events (terrorist attacks, large sports events, etc.) and unusual mobile phone activity. It is this correlation that is leveraged to detect the occurrence of disasters. The basic task is to find deviations from normal cell phone activity reflected in mobile antennas. But not all disasters are reflected in the same way in activity of mobile antennas (some disasters show a decrease in activity rather than an increase\(^2\)), and the same disaster might be reflected in different ways in mobile antenna activity. As an example of the latter, in Figure 5, we see three different ways of how an earthquake can be reflected in mobile phone data. In 1) we see changes in antenna activity (calls, SMS) when an earthquake happens. This earthquake happened in Mexico in 2012. Antennas located in the more impacted zones, show higher activity. In 2) we see how international call activity is increasing at the day of the earthquake in Italy in 2016. Each coloured line represents calls to Italy from a different country. For all countries, we see a large peak in calls on the day of the earthquake. In 3) we see changes in mobility patterns just after the earthquake in Los Santos, Colombia in 2015. Mobility patterns are calculated using an Origin-Destination matrix to generate dwells and journeys.

Activity in mobile phone antennas – which we use as a proxy for human activity – is usually used to understand:

- When, how much and how long people communicate between each other
• When and where people move to (journeys) and stay (dwell). Here, it is important to note that mobility is represented from a partition of the territory in cells, which are intimately related to the antenna's locations. Cell-based location is not as precise as GPS but still shows a great value for mobility analysis.

• How people or locations are connected to form communities

We will illustrate the first two points with the aforementioned disasters we studied in Colombia.

4.1 Earthquake

Figure 6 shows 2G call activity for the days before and immediately after the earthquake. The reduced call activity in the nights and the large peak at the day of the earthquake are readily identifiable.

![Figure 6: Hourly calls by day for the earthquake. One can easily spot the night/day pattern and the large peak during the earthquake.](image)

4.1.Flood

For the flood in San Miguel, we don’t see an increase in call activity, but rather an increase in non-terminated calls (Figure 7). This might suggest network congestion: many people trying to make a call at the same but not being able to reach the destination.

![Figure 7: Increase in non-terminated calls around the days of the flood, suggesting network congestion.](image)
Apart from seeing the flood reflected in antenna activity, it is also reflected in a change in mobility patterns extracted from the antennas in the zone. In Figure 8 we can see that the number of people that usually move towards San Jose (where the earthquake took place) is significantly reduced.

§ FIGURE 8: REDUCED MOBILITY AROUND THE DAYS OF THE FLOODING.

### 4.2. Landslide

During the days of the landslide, we see an increased call activity in antennas in the zone, as can be seen in Figure 9.

§ FIGURE 9: INCREASE CALL ACTIVITY DURING THE DAYS OF THE LANDSLIDE.

### Trends, seasonality and residual

Due to its temporal nature, call traffic and mobility data can be modelled using time series analysis. In order to be reasonably sure that the peaks we have seen in the figures above really correspond to deviations and not to the inner trend or seasonality, we need to filter them out. Figure 10 shows again the call activity around the days of the earthquake, where we clearly see the week/weekend pattern (less calls in the weekends) and the peak of the earthquake.
After filtering out eventual trends and seasonality, we obtain what is called the “residual”, which is shown in Figure 11. The “normal” pattern is now approaching a “flat” line, but the large peak remains. This means that the peak cannot be explained by trends of seasonality but really reflects an anomaly. In commercial applications of Big Data, usually the trends and seasonality are most important (as they are the base for predicting future values), and the residual is often considered noise. But in event detection, it is the residual that can trigger relevant alerts that something is deviating from the normal situation.

**FIGURE 10: HOURLY CALLS BY DAY FOR THE EARTHQUAKE. ONE CAN EASILY SPOT THE WEEK/WEEKEND PATTERN AND THE LARGE PEAK DURING THE EARTHQUAKE.**

2G versus 3G

Another relevant aspect to consider for detection of natural disasters is the type of mobile technology used. Figure 12 shows 2G activity around the earthquake and Figure 13 shows 3G activity. We can observe that the peak (the earthquake) is much more pronounced in 2G than in 3G. This is probably due to the facts that the earthquake took place in a rural area where there is less 3G coverage, and because smartphone penetration is less in poorer rural areas. What it shows is that 2G is still an important technology when speaking about humanitarian disasters in developing countries.

**FIGURE 11: RESIDUALS OF CALL ACTIVITY AROUND THE EARTHQUAKE AFTER FILETRING POSSIBLE TRENDS AND SEASONALITY**
Towards a tool for humanitarian disaster management

We can combine all the insights discussed earlier in an interactive tool that allows humanitarian workers to detect disasters, to investigate their impact and to monitor recovery. Figure 14 and Figure 15 illustrate such a tool. The tool also integrates other data sources relevant for the analysis, like weather conditions and country census. The first tab (at the top) is an alarm panel where, over time, alerts show when the system detects important deviations from normal mobile antenna activity. Ideally, alerts are generated in real-time.
There is, however, an important challenge in this detection/alarm phase. Even accessing real-time data and using sophisticated analytics, is difficult to determine solely using telco data which "data anomalies" actually correspond to disasters and not to other kind of events (sport massive events, strikes...) with a similar impact in mobile traffic or mobility alteration. That is, many false positives might appear. Robustness in the detection can only be achieved by integrating several data-sources, all with a similar time-response. Thus, cooperation and data integration amongst public and private bodies is critical in order to create reliable disaster monitoring systems.

The following tabs correspond to the different disasters. Figure 15 shows the tab for the earthquake. In the top left we see the large peak (already the residual). The different colours of the bars correspond to mobile antennas closer and farther away from the disaster’s epicentre. In the right part, we can see in what areas around the epicentre deviations are larger; the colours represent the size of the deviations in terms of the standard deviation. This is very important for the “response” phase where first help needs to be focused on the most affected areas. At the bottom left, we can see the hourly distribution of call activities, with a large peak at 16h00, the exact time the earthquake took place.
Figure 16 shows the prototype tool for the flood. We selected here, in the top left pane, the days of the flood and the days immediately after. The top right pane indicates that the activity is slowly recovering its normal situation. And after 4 days, it is completely back to normal. This is important for humanitarian agencies for knowing when things get back to normal, although, of course, mobile phone activity is not the only indicator of recovery. In the bottom left pane, we also plotted data about rainfall in the area, and it can be seen that a week before the floods extremely heavy rainfall occurred.

![Tool to study the flood](image)

**FIGURE 16: TOOL TO STUDY THE FLOOD.**

5. From research pilots to operational systems – challenges and solution directions

In this collaboration between UNICEF and Telefónica, we have confirmed what many other research works have also demonstrated: that there is indeed a strong correlation between important events such as disasters and mobile phone activity registered by mobile antennas. In addition, we also have shown how Big Data analysis can help humanitarian agencies to optimize the way they perform disaster management through supporting early warnings, critical response and recovery monitoring. However, as with many other similar projects, so far this has been a retrospective analysis.

Imagine a system that gets real-time data feeds from different private companies and public bodies, as well as from Open Data. This would allow humanitarian agencies set up a “control centre” to react much more timely and with greater precision to humanitarian disasters. Therefore, the main goal is now to move from retrospective analyses to operational systems that work with near real-time data. In general, this is currently the most relevant challenge for scaling up Big Data for Social Good so that it has more real impact on the ground, and can actually save and improve the lives of people.

The main reason for this challenge is that it is hard to get the required data feeds in real-time. Most relevant real-time data feeds have to come from private enterprises, and that is where the challenge lies. Public Administrations, either directly or through Open Data, also need to supply data feeds, but they usually face “only” a technical, budget and...
skills challenge. The main challenges private enterprises face are based on considerations of privacy and data protection, and on commercial and strategical considerations.

6. The privacy and data protection challenge

In order for humanitarian agencies to combine different types of data to optimize disaster management, they need to receive the data in their platform, either on premise or in the cloud. This implies that private data needs to leave the company premises, and this is exactly what companies worry about. It is not just about one concern, but about a set of interrelated concerns, each of which needs to be addressed in some way before companies feel comfortable and have the required “peace of mind”.

• Before data leaves the company, for Social Good purposes, the data is anonymized and aggregated, such that re-identification is impossible. Data protection laws do not apply to non-personal data, and therefore sharing is possible. However, from a pure technical point of view, 100% anonymization is debatable, even though in practice it is impossible to re-identify individuals. Still, this discussion does not generate the needed “peace of mind” for most enterprises.

• The new General Data Protection Rule (GDPR) comes into force in May 2018. For European countries, this means some important changes in the data protection and privacy laws. One change is related to consent – companies are required to ask for explicit, informed consent before they can use personal data. Another change is related to what is considered anonymized data. In the GDPR there is a distinction between personal data, pseudonomized and anonymized data. Some of the data that is considered anonymous pre-GDPR will be considered personal data under GDPR. This increases the first concern, as the perceived risk for potentially breaching the GDPR is increasing.

• Security is always an important issue for enterprises. When data is stored within the company premises, all in-house security procedures can be applied as required. However, when data leaves the company premises, they lose control over the data, even if it is anonymized and aggregated.

• The last concern is a reputational one. A company that works in the area of Big Data for Social Good, and contributes to the greater good, in principle gains a better reputation. However, if something happens to the company data once the data has left its premises, then there might actually be a reputational risk.

Those are the primary concerns that make companies hesitate when contributing their data for Social Good, and the more so if this happens in a philanthropic way (pro bono). With the current approach, it is likely only the most experienced companies will be ready to participate in the creation of operational systems for supporting humanitarian agencies. Less prepared companies will probably stick with research pilots. UNICEF’s Magic Box is currently the most advanced initiative working towards an operational real-time system to support humanitarian disaster management. It partners with Amadeus, IBM, Google and Telefónica.

One possible way to address those concerns is that companies ask their customers for explicit consent before their data (anonymized and aggregated) is shared for humanitarian purposes. Once explicit and informed consent is given, companies act on behalf of individual customers and are less exposed to privacy issues. This is what Telefónica is pioneering with AURA.

Another possible solution is that the data does not leave the company premises, but rather the (auditable and open) algorithms are executed within the company premises and only the aggregated insights leave the company. This scenario is the focus of the OPAL project. OPAL (for Open Algorithms) will consist of an open source platform and algorithms that can be run on the servers of partner companies behind their firewalls to extract key development indicators for society, in a privacy preserving, commercially sensitive, stable, scalable and sustainable manner.
Hopefully, this cutting-edge approach to Big Data will allow for more private and public sector partnerships to thrive, providing better and deeper insights to policy makers around the world. The recently started GSMA taskforce on Big Data for Social Good will use the same OPAL-like approach.

7. The commercial and strategic challenge

Another important challenge is commercial and strategic. The current ecosystem of Big Data for Social Good is incipient, and apart from some exceptions, most initiatives are carried out on a philanthropic pro bono basis: companies do not receive any economic compensation to cover the costs incurred, let alone be able to generate a commercial margin. In other words, companies donate their data for the greater good. Since most current initiatives are pilot or research projects, they require relatively little effort and investment from companies. However, this is not a sustainable model when we move from “one-off” pilots to operational systems with continuous data feeds. For the future, we are convinced the ecosystem will understand that operational systems, even for social good, have a cost. Moreover, governments and humanitarian agencies are currently spending budget on monitoring and achieving the SDGs, and like in the commercial world, with transformational changes, budget will be re-allocated from old processes to digital ones. We particularly like the view expressed in a paper from Volans commissioned by the Business and Sustainable Development Commission: “Breakthrough Business Models: Exponentially More Social, Lean, Integrated and Circular.” Finally, think about how “green” and “sustainable/fair supply chains” started: some companies were leading in showing the world that it was important to respect the environment, and to care about the situation of offshore workers. Now “green” and “fair supply chains” are business musts. We foresee that the same will happen with Big Data for Social Good.

So, we believe that in the very short term, apart from some exceptions, Big Data for Social Good will mostly be a philanthropic activity. And in this sense, there are some additional challenges.

- Does this use of data for social good cannibalize some of my external Big Data revenue? What if it jeopardizes an existing business opportunity in order to carry out a Big Data for Social Good project? It is not uncommon that the same company is having parallel conversations with governmental organizations about using Big Data for social and commercial purposes. We foresee that this will co-exist from some time to come, and the best solution is to coordinate well.
- Another challenge is a strategic one. Many companies have just learned that their data is a strategic asset rather than an exhaust; a side effect of their operation. So then, why would they give away for free projects based on that strategic asset?

However, we believe that, rather than cannibalizing business opportunities, it can work as a “teaser”, where the “free” activity serves as a proof of concept to win over customers for a larger project. In particular, we see four possibilities where such pro-bono projects can generate more business.

- Many international organizations are spending a significant part of their budgets on monitoring and achieving the Sustainable Development Goals, including The World Bank, United Nations, UN Global Pulse, UNICEF and the Inter-American Development Bank. While it may not be appropriate to charge commercial rates, it may be possible to have an “at-cost” model.
- Several philanthropists are donating large amounts of funds for social purposes such as the Bill & Melinda Gates Foundation for gender equality, or Facebook’s founder, Mark Zuckerberg, who committed to donate €3bn to fight diseases.
- Many projects with a social purpose are high priority for local and national governments. For example, generating a poverty index, anticipating pandemic spreads or reducing CO2 emissions in large cities. Governments are spending considerable amounts of their budgets on such projects and there is no reason why initiatives with a social purpose couldn’t also have a charge.
• Sometimes a freemium model works: pilots (or proofs of concepts) are done free of charge, but putting the project into production requires investment. Or, insights with limited granularity (frequency and geography) are free of charge, but more detailed insights have a price tag.

The key point for Big Data for Social Good becoming mainstream is the creation of successful Public-Private Partnerships (PPPs) between private enterprises holding Big Data, governments, humanitarian agencies and national statistics offices. Successful public-private partnerships (PPPs) in the area of Big Data for Social Good are no different than successful partnerships in other areas. There must be a win for all involved. We don’t believe in forming large PPPs in areas like Big Data for Social Good because many members would want to join, and most effort would be spent on how to collaborate rather than on actually collaborating. In our experience, successful PPPs in BD4SG think big, but start small. Moreover, they need to be balanced concerning top-down versus bottom-up support. If started from top management only, it likely will remain in nice words. However, if there is no top management support, it will not endure and scale.

8. The need for standardised (cross-country and cross-operator) insights

The final challenge for Big Data for Social Good to scale is to have standard ways of generating insights, otherwise results cannot be compared between countries and/or the enterprises involved. For example, if one operator calculates a poverty index based on cell phone usage data, while another operator uses top-up information, then the results might not be comparable. Or, when we want to understand and predict the spreading of ZIKA over multiple countries, crossing borders, probably mobility data is needed from different operators. It is therefore important that those mobility matrices are constructed in the same way. So, international standards are needed in the areas of data sources used and algorithms to calculate insights. This is exactly the approach followed in the OPAL project and in the GSMA taskforce on BD4SG.

This is also the reason that the last Sustainable Development Goal (nr. 17) is so important: to foster partnerships for achieving the goals. Only by bringing together all relevant stakeholders in an agile and collaborative way, Big Data for Social Good will become a real force for good.

9. Acknowledgements

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About LUCA

LUCA’s mission is to bring Telefónica’s know-how in transforming into a data-driven organisation to other private and public sector organisations in a wide range of sectors including Retail, Tourism, Outdoor Media, Financial Services and Transport, just to name a few. Our diverse product portfolio, which brings together expertise in Data Engineering, Data Science, Infrastructure, Cybersecurity and Business Insights, enables companies to continue their Big Data journey with a wide range of solutions to propel them to double-digit growth.

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