

# Applied Data Science Research for Social Good

Industrial session at UOK

2 October 2023

## At the end of the session you,

- Have a better understanding of applied Data Science Research and how it differs from traditional academic research & the private sector
- Are seriously considering AI 4 Social Good as an area you want to work in
- Know what LIRNEasia is and can explain the work we do to a friend
- Find our work as inspiring as we do and are seriously considering joining us
- Have enough information to decide LIRNEasia is a good fit for you and feel comfortable enough to reach out to us



## **Structure of the Session**

- Part 1 About LIRNEasia and our work
- Part 2 A Case study how we do applied research
- Part 3 Broader QnA



## **About LIRNEasia**



LIRNEasia is a non-profit, multi-disciplinary research organization that aims to bring about policy change and develop solutions through research to improve the lives of people in the Asia and Pacific using knowledge, information and technology. Our **experts come from diverse backgrounds such as economics, law, computer science, and social sciences, enabling us to approach problems in a multidisciplinary manner**.

Our research covers a wide range of topics including **ICT policy and regulation, infrastructure development, health, social safety nets, disability, and disaster risk reduction**. We work closely with governments, private sector organizations, and civil society groups to ensure our research has real-world impact and contributes to positive change in the region.

https://lirneasia.net/category/themes/



## LIRNEasia – Senior Staff



Rohan Samarajiva Chairman, Board of Directors



Tharaka Amarasinghe Project Manager & Statistician – Survey specialist



Helani Galpaya Chief Executive Officer



Gayani Hurulle Senior Research Manager - Economist



Nilusha Kapugama Chief Operating Officer



Isuru Samaratunga Research Manager – Qualitative specialist



Ayesha Zainudeen Senior Research Manager – Gender specialist

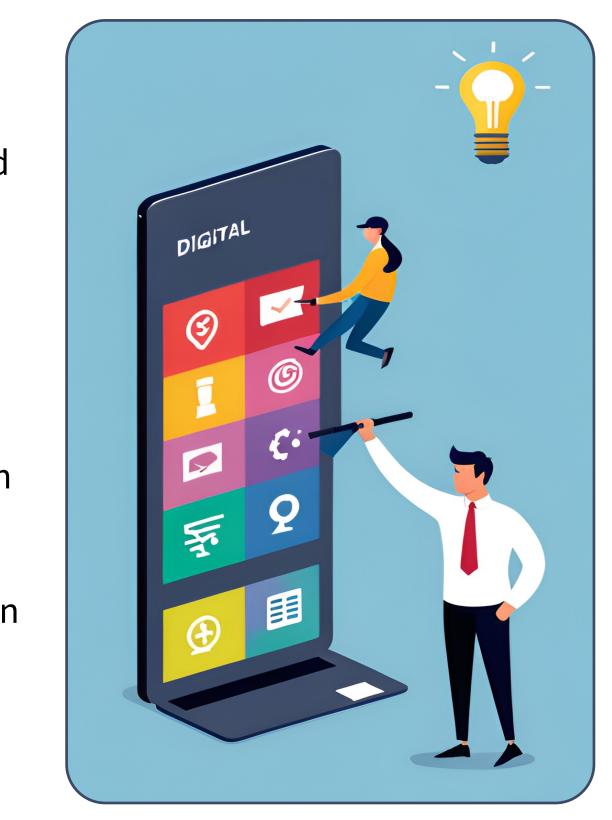


Chiranthi Rajapakshe Research Manager – Legal specialist

## A glimpse of "multi-disciplinary"

- **Social Safety Nets-** Using data and technology to understand poverty and improve the efficiency, reach, and effectiveness of social safety nets. We aim to inform/influence policy design and implementation, ensuring that the limited resources reach the most vulnerable groups. (*surveys, KIIs, FGDs, desk research, web scraping, ML, policy analysis*)
- **Misinformation experiments** Understanding which interventions will make people less susceptible to harmful effects of misinformation through randomized controlled trials (*Surveys, RCTs, desk research*)
- Data governance A comparative analysis of countries in the Asian Region with respect to their policies, regulations & strategies around data governance (Policy & legal analysis, KIIs)







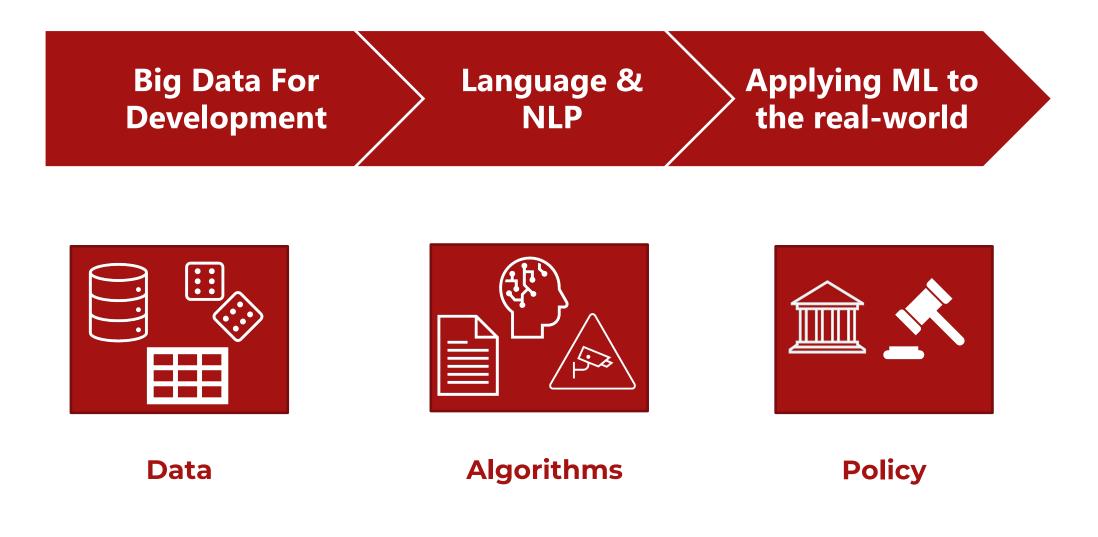
# The DAP Team

Data, Algorithms, and Policy

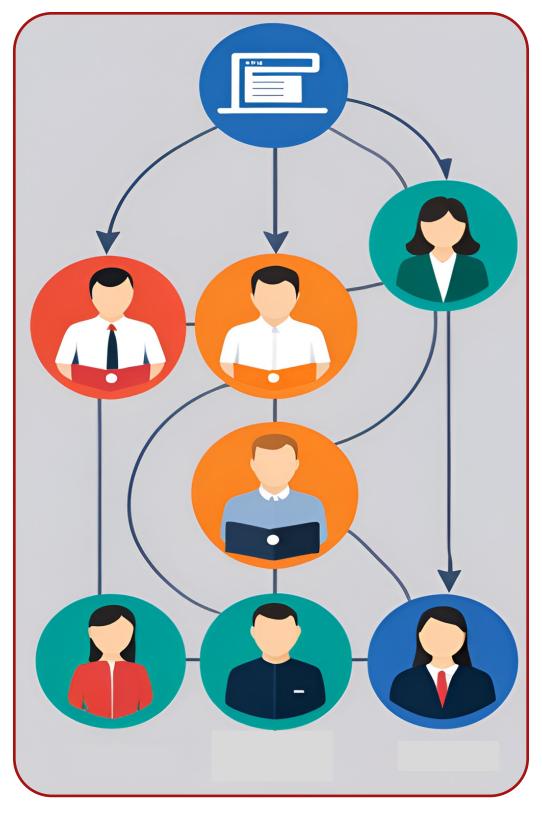


## **The DAP Team - Introduction**

# Apply data science and machine learning to inform policy & do social good







## Our team – DAP Team (the CORE team)



Merl Chandana Research Manager & Team Lead (Data, Algorithms, & Policy)



Kasun Amarasinghe Research Fellow & Consultant



Chanuka Algama Junior Researcher

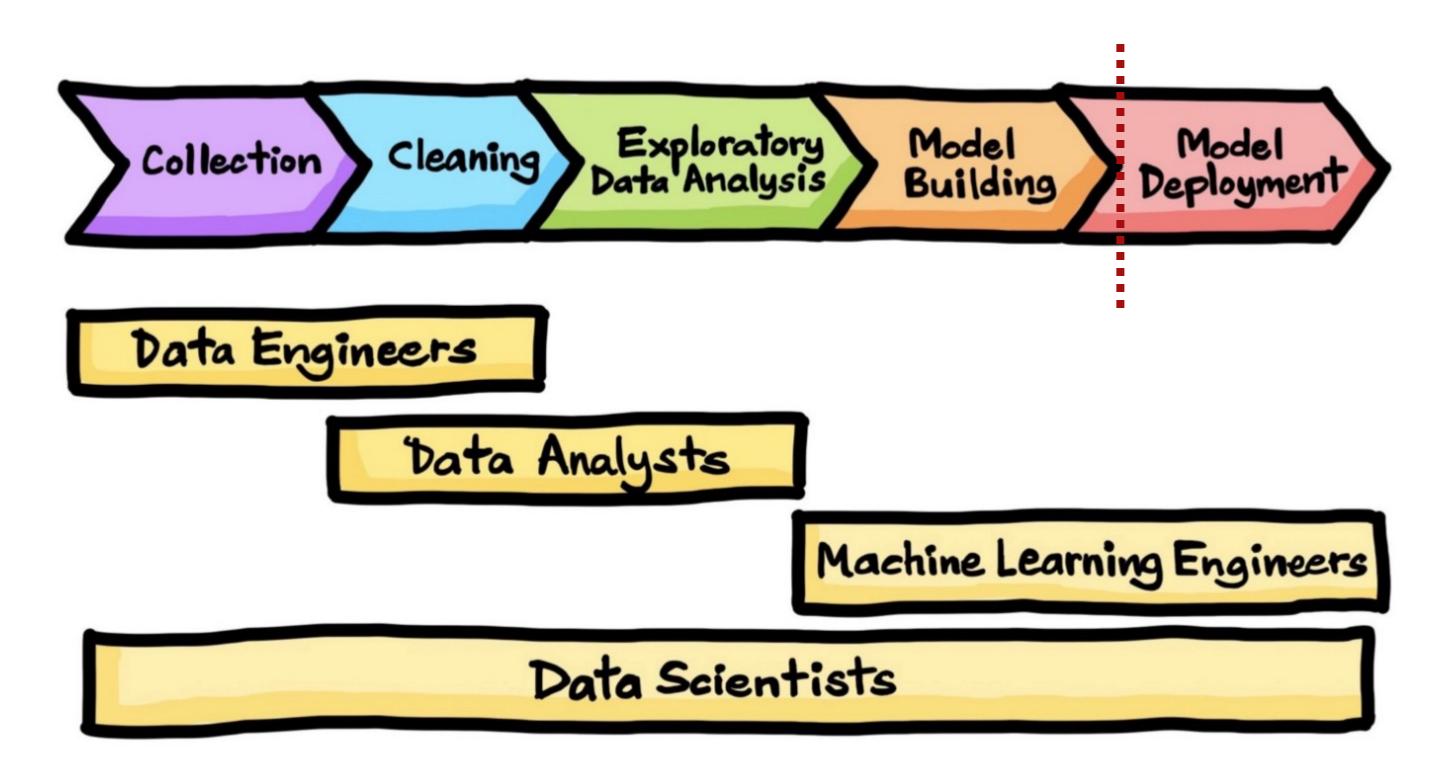
## The Process of Applied Data Science



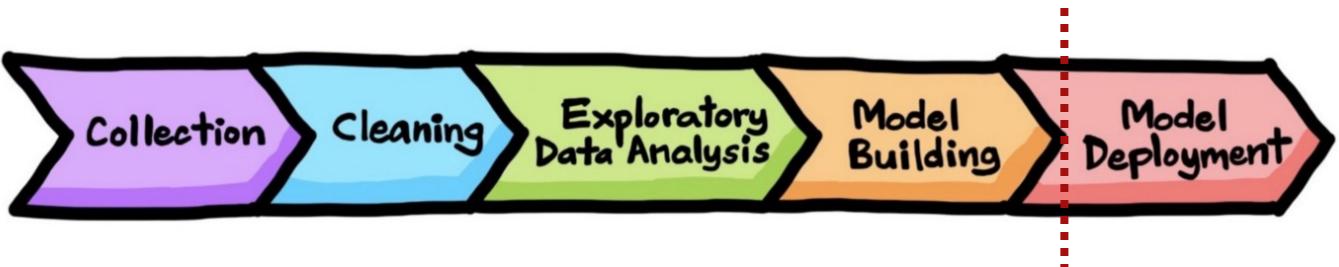
- **1.** Does this look right?
- 2. What is wrong with it?
- 3. What is missing?
- 4. How would you improve this?

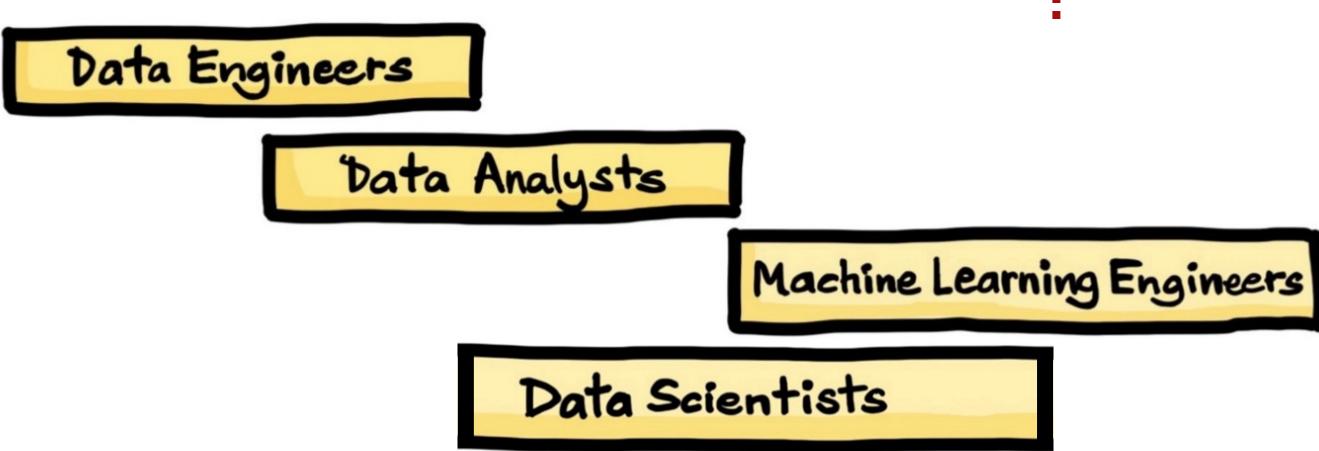


## **Roles Within the DAP Team - I**

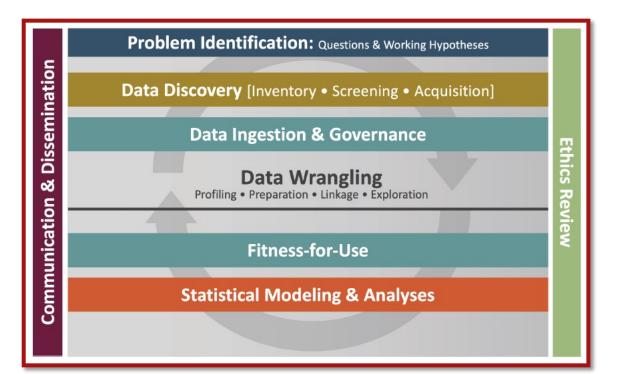


## **Roles within the DAP Team - II**





## **Data Science Project Ethics Checklist**



#### Problem Identification

Establish the ethical basis for undertaking the project as well as the project requirements of both the protection of research participant and the equitable allocation of all potential project benefits and risks. ✓ What are the expected benefits of the project to the "public good," and do they outweigh potential risks to certain

- populations?
- how will they be addressed?

#### Data Discovery, Inventory, Screening, & Acquisition

Consider potential biases that may be introduced through the choice of datasets and variables. Do the data include disproportionate coverage of the different communities of study?

- Do data have adequate geographic coverage?
- Have checks and balances been established to identify and address implicit biases in the data?

#### Data Ingestion and Governance

Put in place data platforms and processes to ensure data transfer, storage, and database development adheres to data governance agreements and best practices for data quality assurance.  $\checkmark$  Have team members reviewed standard operating procedures (SOPs) and data management plans? Do additional procedures need to be defined for this project?

#### Fitness-for-Use Assessment

Critically assess the overall utility of the results in achieving the predicted benefits of the study, to be transparent about potential limitations of the study, and to ensure that unintended biases haven't been introduced as a result of data choice and model refinement.

- $\checkmark$  What are the limitations of the results? Are the results useful given the purpose of the study?
- Do the statistical results support the potential benefits of the study previously stated?
- Do the statistical results support the mitigation of the potential risks of the study previously stated?
- through the choice of datasets and variables?

✓ Are there implicit assumptions and biases in the framing of the project regarding the studied communities and

What type of Institutional Review Board approval process is needed? Has the team reviewed the protocol?

Have any data been deemed unusable that require revisiting the question of potential biases being introduced

## **Microsoft's Principles of Responsible Al**

## Defining what's important

Microsoft's six principles to guide AI development and use.



#### Fairness

Ai systems should treat all people fairly



#### Inclusiveness

Ai systems should empower everyone and engage people.

#### **Reliability and Safety**

Ai systems should perform reliably and safely

Ai systems should be secure and respect privacy



Transperancy

Ai systems should be understandable

People should be accountible for AI systems







#### **Privacy and Security**



#### Accountability

## **Google's AI Principles**

## AI SHOULD:

- 1. Be socially benificial
- 2. Avoid creating or reinforcing unfair bias
- 3. Be built and tested for safety
- 4. Be accountable to people
- 5. Incorporate privacy design principles
- 6. Uphold high standards of scientific excellence
- 7. Be made available for uses that accord with these

principles

- primary purpose and use
- Nature and uniqueness
- Scale
- Nature of google involvement

## **APPLICATIONS WE WILL NOT PURSUE:**

- 1. Likely to cause overall harm
- 2. Principle purpose to direct injury
- 3. Surveiliance violating internationally accepted norms
- 4. Purpose contravenes international law and human

rights

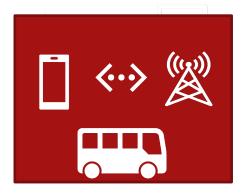




# Our Work

Past & Present

## A few snapshots from the past





## <u>Understanding Human Mobility</u>

Determining the need for roads and bridges. Evaluating their effects upon completion Understanding the spread of infectious diseases Studying patterns of internal migration

## Policy analysis at the intersection of data, AI and ethics

Comparative study of policies, regulations, and applications of AI in Singapore and India Developing a discussion paper on the elements of a potential AI policy for Sri Lanka



### **Online job portal data for labor market analysis**

Scoping study on job portals of 12 countries in the region Analyzing online job advertisements to understand the demand for skills



## **Ongoing project 1: Building machine learning** datasets on electricity consumption

**Problem/Context:** The project aims to address the need for a comprehensive dataset for machine learning research related to household electricity consumption. Understanding the factors that drive electricity consumption is essential for optimizing energy usage, promoting energy efficiency, and making informed policy decisions.

#### **Data Sources:**

- Electricity Consumption Data: The primary data source is the electricity • consumption data obtained from electricity providers.
- Longitudinal Survey Data: This survey will consist of three rounds of data • collection, capturing various demographic and behavioral factors that influence electricity consumption.

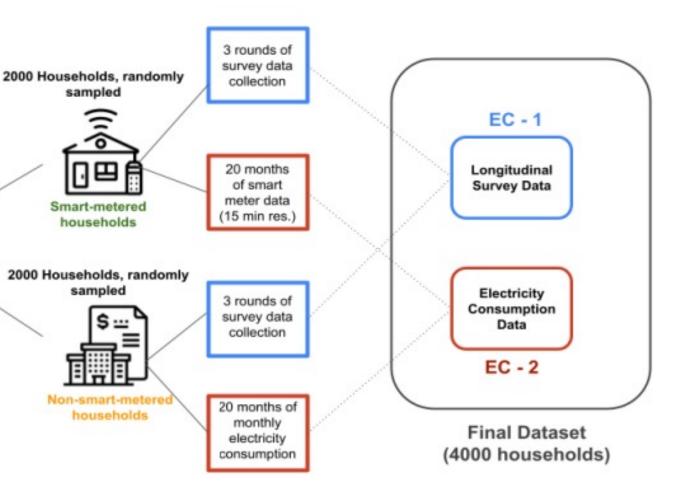
#### **Methods:**

Sampling, Data collection, Data integration, Data processing and cleaning, Hosting the data for public access, Machine learning analysis(Predictive modeling, clustering and feature engineering to uncover patterns and insights related to electricity consumption).

**Expected Outputs:** A comprehensive two-part dataset







## Ongoing project 2: Urban boundary mapping: Towards a Better Understanding of Sri Lankan Cities Using Satellite Imagery

**Problem/Context:** The research project addresses the critical need for accurate and up-to-date information on urbanization in Sri Lanka. Urbanization is a complex process with significant implications for urban planning, infrastructure development, and resource allocation.

#### **Data Sources:**

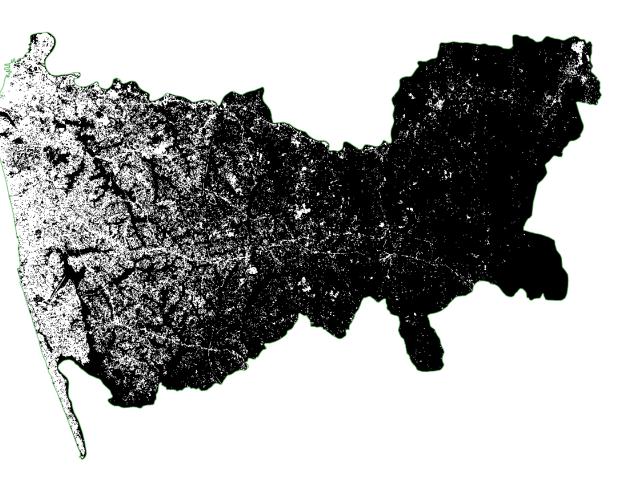
- Satellite Imagery: The primary data source is high-resolution satellite imagery of Sri Lanka. This imagery captures spatial and spectral information about the landscape, including urban and non-urban areas.
- Remote Sensing Data: The study involves processing and analyzing large volumes of remote sensing data, which may include various spectral bands, resolution levels, and temporal information.

### **Methods:**

Data collection, Image processing, Machine learning (to differentiate urban areas from nonurban areas within satellite imagery), Spectral analysis, Spatial analysis, validation

**Expected Outputs:** Urbanization maps, urbanization trends, Machine learning models, policy recommendations





10-meter built-up area map of the Colombo district for the year 2020. White denotes built-up; black denotes non-built-up

# Ongoing project 3: Understanding spatial disparity of poverty: Leveraging Mobile Call Records and Remote Sensing Data

**Problem/Context:** How public and private data sources commonly available for low- and middle-income countries can provide novel insight into the spatial distribution of poverty.

#### **Data Sources:**

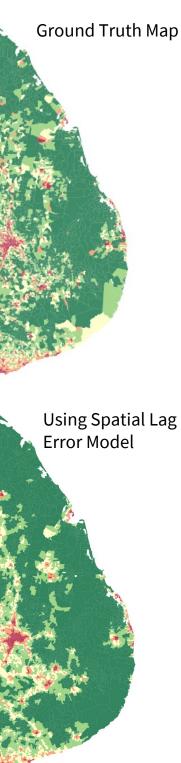
- Call detail records: Phone usage patterns, location/ mobility of the user, social network, handset type
- Remote Sensing Data: Provide features such as Accessibility, Population, Climate, Nighttime lights, Elevation, Vegetation, Distance to roads and waterways, Urban/rural, Protected area, landcover, and demographic features.

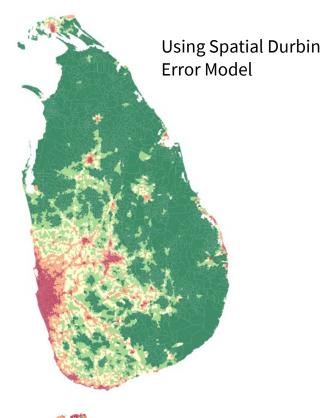
### **Methods:**

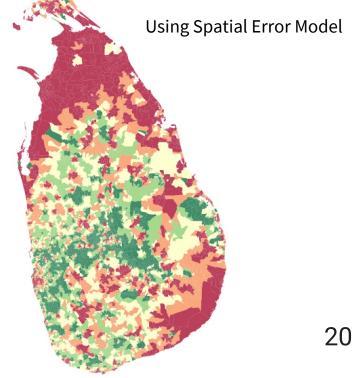
Data collection, Data integration, Machine learning (using Spatial error models, spatial lag error models, spatial durbin error models), Spectral analysis, Spatial analysis, validation

**Expected Outputs:** Poverty maps, insights into poverty disparities, Machine learning models, policy recommendations









## **Ongoing project 4: Global Index on Responsible Al**

In this context, the term "responsible Al" is used here to refer to the development, use, and governance of AI in ways that fully uphold human rights and democratic values throughout the AI lifecycle and value chain (development, deployment, and maintenance).

# How do we measure progress on the implementation of responsible AI principles and practice?

The Global Index on Responsible AI is a new tool being developed to support the implementation of responsible AI principles by countries around the world. The Global Index will equip governments, civil society, and stakeholders with the critical evidence needed to support the efforts of countries to meet their human rights obligations and uphold principles for responsible use of AI.

The Global Index is a project of Research ICT Africa and the Data for Development Network (D4D.net). The project is being carried out with the aid of a grant from the International Development Research Centre (IDRC) and is funded by the Government of Canada.



## A week-in-life at LIRNEasia

And the required skills











## Journal Clubs & Colloquiums





## Research Admin





## A few of our past folks



Nisansa De Silva Senior Lecturer - University of Moratuwa PhD, University of Oregon, NLP





Danaja Maldeniya Research Fellow - LIRNEasia PhD, University of Michigan Computational Social Science



Lasantha Fernando Research Fellow - LIRNEasia PhD, University of Waterloo (reading), Distributed Systems



Yudhanjaya Wijeratne Research Fellow - LIRNEasia Award winning author (Nebulanominated and Gratiaen-winning), Self-taught



#### For more information www.lirneasia.net

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## **CDR Dataset Description**

Table 1: Sample observations from a CDR dataset.

Call Direction	Subscriber ID	Other ID	Tower ID	Timestamp	Duration
Incoming	A	В	A024	2012/11/10 06:35:37	20 seconds
Outgoing	В	A	A375	2012/11/10 06:35:37	20 seconds
Outgoing	С	D	A129	2013/05/29 20:07:55	35 seconds
Incoming	E	F	A754	2013/03/22 00:03:22	153 seconds

#### Notes

- The **subscriber ID** and **other ID** are pseudonymized to protect the subscriber's privacy.
- If both parties of a call belong to the same operator, there will be two **reciprocal** records to represent the call. Eg: rows 1 and 2 in the table above.
- A subscriber will preferentially connect to the **nearest** tower.
- The latitude and longitude corresponding to each **tower ID** is known.
- The **timestamp** is accurate to a second.
- The **duration** is accurate to a second.



s privacy. **cal** records to represent the call. Eg: