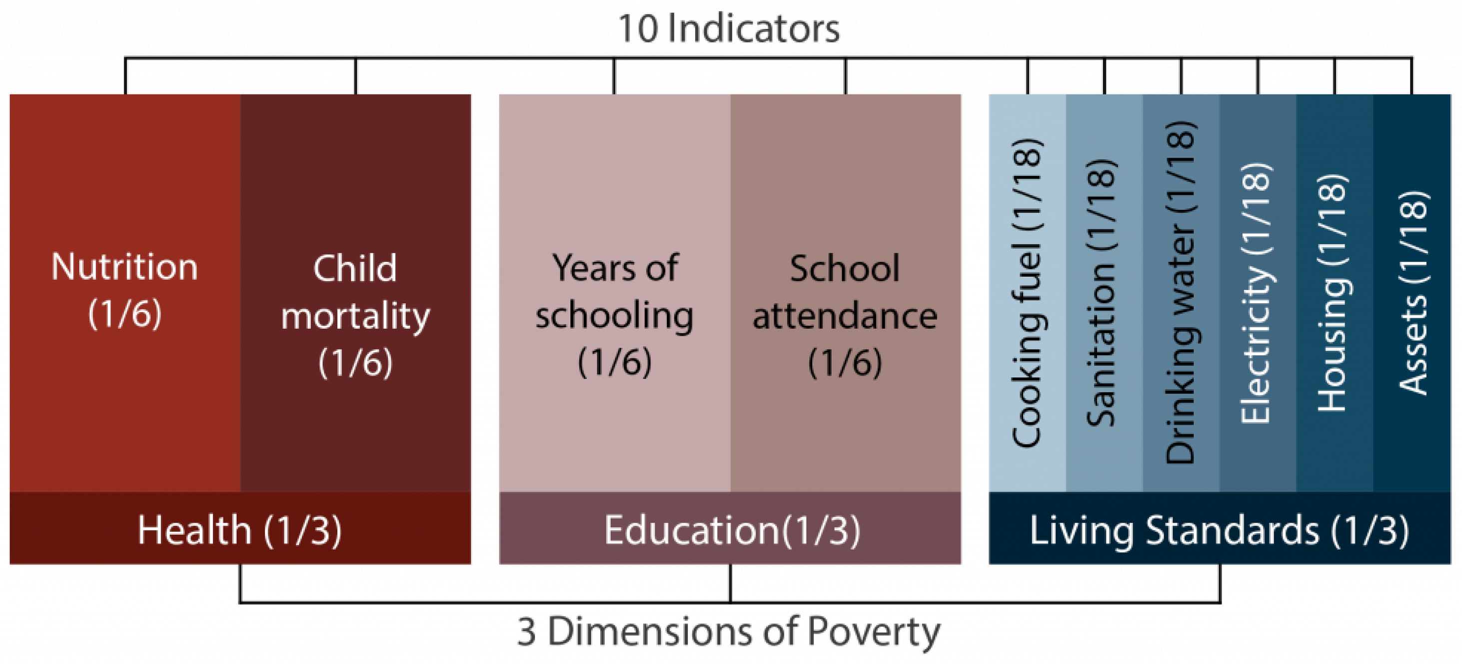
Multidimensional Poverty Prediction

Girela, Ignacio[1,2] & **Koplin, Eric**[3]

[1]CONICET, [2]Universidad Nacional de Córdoba, [3]Vanderbilt University Medical Center

Introduction

- The United Nations Development Program (UNDP) publishes the global Multidimensional Poverty Index (MPI), a weighted composite index based on indicators related to Sustainable Development Goals (SDGs) [3].
- The global MPI complements the World Bank's 2.15$-a-day international poverty measure to monitor progress in key dimensions of human-development.



Motivation

Carrying out multi-topic household surveys is the best way to monitor the socioeconomic welfare status of a society.

Fig 1: Right: Data collection in household surveys. Left: Household survey structure

However ...

- Clustered samples may fail to capture granular generality for guiding targeted interventions to reduce poverty indicators.
- Data collection requires high administrative costs.
- Developing countries often depend upon international NGOs or foreign aid.
- Qualified personnel are required for taking anthropometric measures.
- High levels of non-response can undermine the representativeness of a cluster sample.
- Conflicts or dangerous areas block proper data collection.

Objective

Assuming it is not possible to collect data of a multi-topic household survey in certain areas, we aim to **predict the multidimensional poverty levels of Primary Sample Units (PSU) using only the information of the closest clusters** $\longrightarrow$ *Inductive Learning task*

Data

Household surveys $\longrightarrow$ Structured data

We use the Nigeria 2018 Demographic Health Survey (DHS). Household survey data have strict privacy policies and permissions. Then, geographical information only includes the centroids of the clusters.

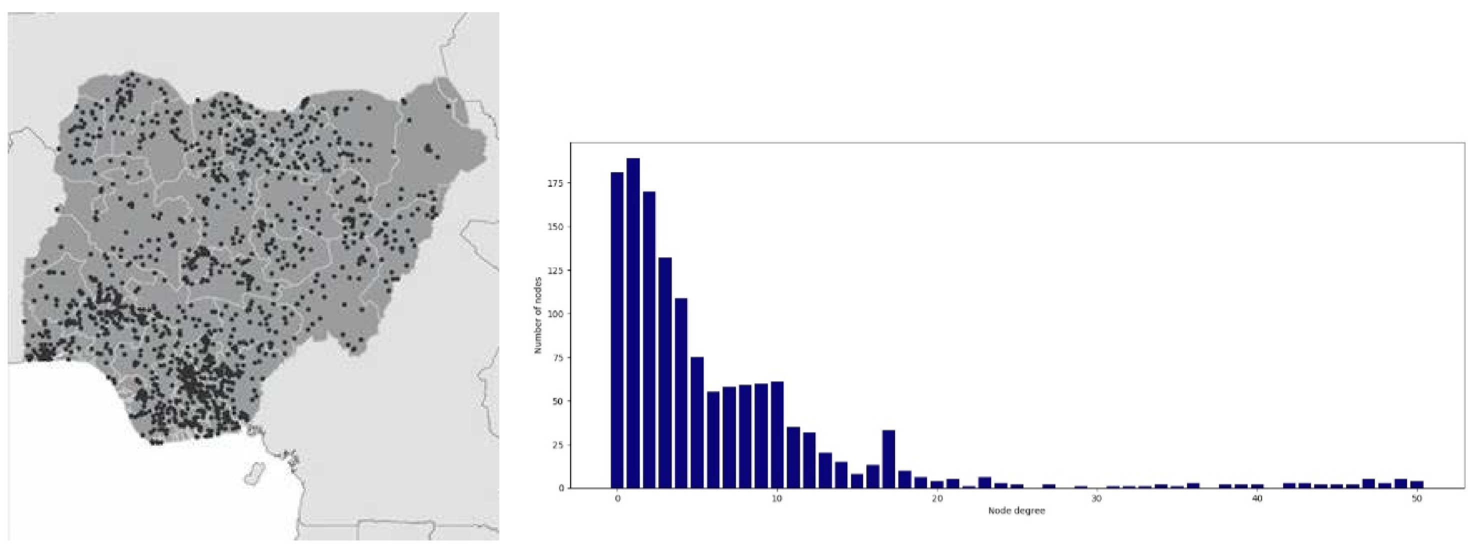


Fig 2: Right: Clusters distribution Nigeria DHS. Left: Nodes degree distribution

Methodology & Experiments

Given that we need to learn the importance of each cluster's neighbor information, we apply a **Graph Attention Network** (GAT) for regression [4, 1].

Procedure:

1. Compute the adjacency matrix based on PSU centroids.
2. Select sociodemographic features
   (a) Without including MPI indicators (assuming no MPI measurement)
   (b) Including MPI indicators
3. Split graph data: train/validation/test sets.
4. Build GAT architecture

```
print(model)

GAT(
  (gat1): GATv2Conv(53, 32, heads=16)
  (norm1): LayerNorm((512,), eps=1e-05, elementwise_affine=True)
  (gat2): GATv2Conv(512, 1, heads=1)
  (norm2): LayerNorm((256,), eps=1e-05, elementwise_affine=True)
  (gat3): GATv2Conv(256, 16, heads=1)
)
```

5. Train the model and predict the MPI level in test clusters.

Results

\# Nodes: 1389
\# Edges: 8956
\# Features: (a) 33 and (b) 43

	GAT		Rigde RBF-Kernel	Bounds
	(a)	(b)		
MSE	0.0186	**0.00641**	0.0163	0.00102
r^2	**0.473**	**0.819**	0.4139	0.963

Table 1: Comparison of results

Conclusions

Predicting multidimensional poverty levels in areas where data is not available is a critical challenge in the context of poverty reduction strategies.

Widely used spatial statistical learning methods rely on measurement features of target clusters (features in test sets). **In cases where features are unavailable due to administrative costs associated with survey data collection, Graph Attention Networks demonstrate significant potential in predicting cluster-level multidimensional poverty.**

Such exercise allows to **recover granularity for policy interventions** related to in-kind interventions (improve access to services, such as electricity, sewage system, etc.).

Discussion & Analysis

Limitations:

- GIS data derived from household surveys is seldom openly accessible. Thinking on alternatives?

Further research:

- A more detailed exploration of results: in which 'kind of' clusters the model perform poorly? (e.g., isolated rural areas? rural areas far from water sources?).
- Explore how partially observed (easy-to-access) data of target nodes can be included in the model (e.g., satellite imagery). This approach can improve practical uses of existing applications with no policy-responsive poverty indicators [2].

References

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ignacio.girela@unc.edu.ar