Temporal Poverty Prediction In Developing Countries

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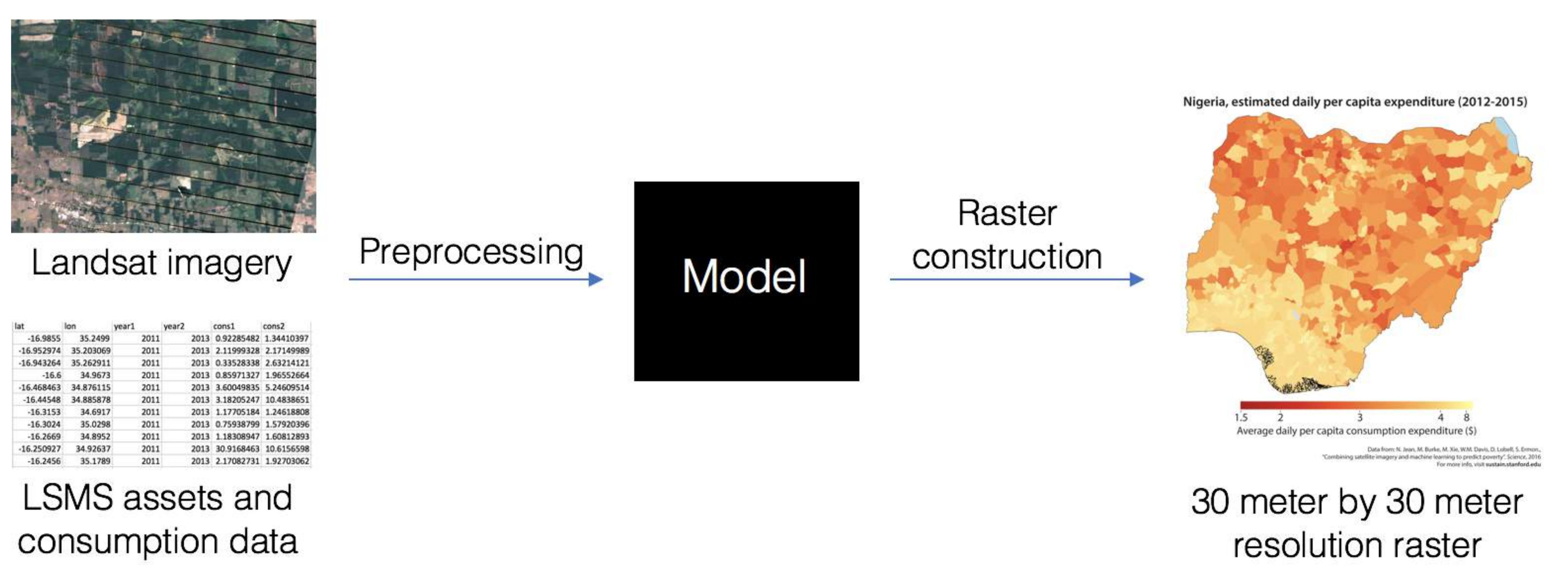
Introduction

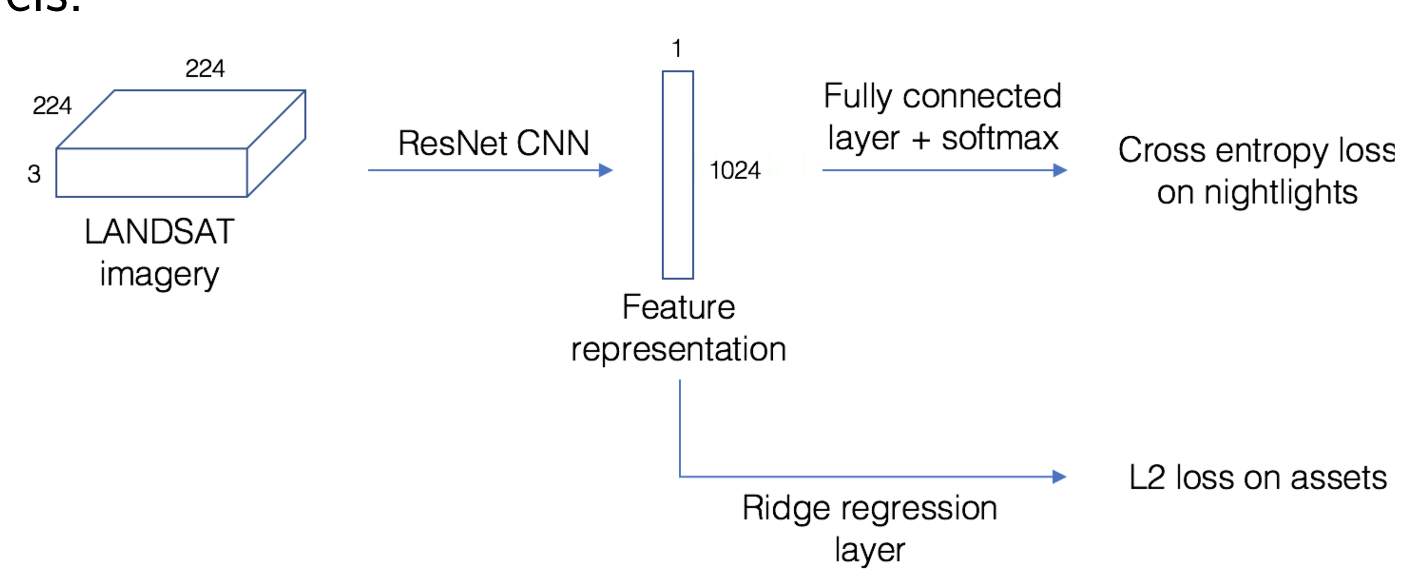
Measuring poverty levels is an integral part of alleviating poverty because it allows policy makers to analyze resource allocation strategies and the effectiveness of previous efforts. However, in developing countries in Africa, poverty data is particularly scarce. The goal of this project is to use hyperspectral satellite imagery to predict poverty levels in specific years and over time.

Pipeline



Models

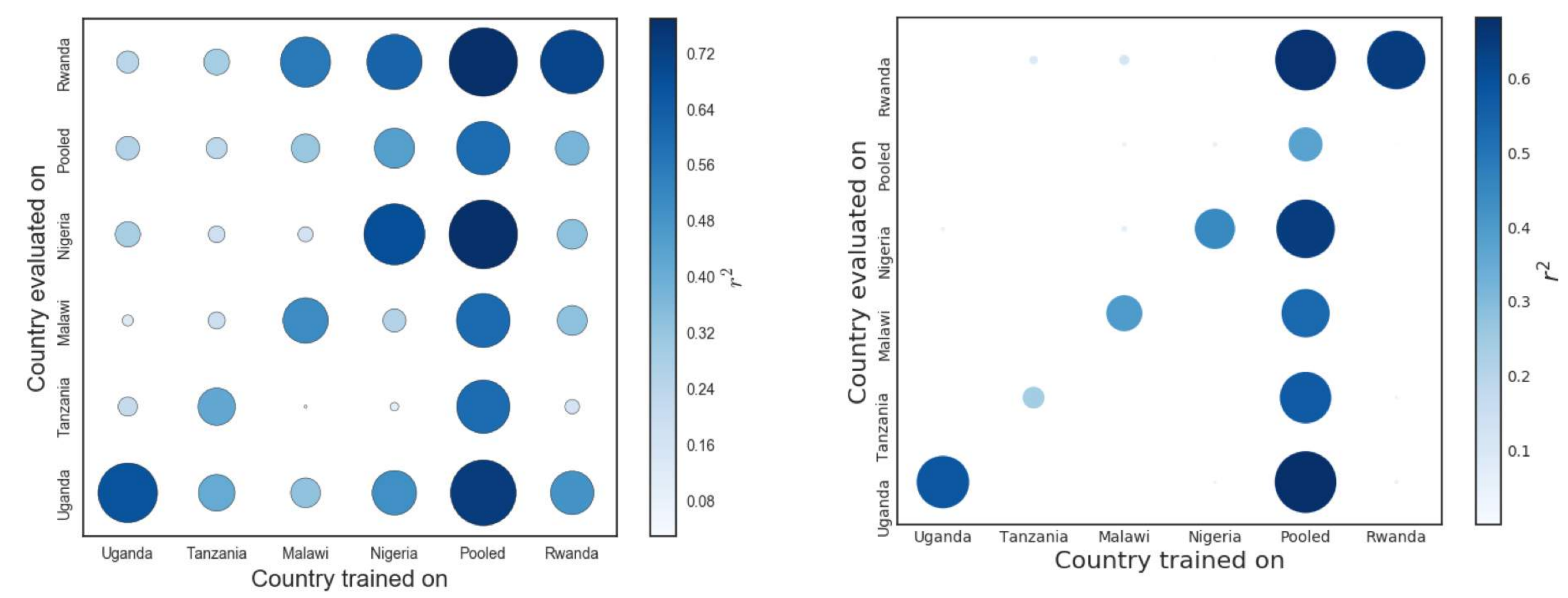
The scarcity of poverty data also means that there is a scarcity of data for our model to train on. Since most deep learning models require a large amount of data, we use a transfer learning approach and train a CNN on publicly available nightlights data, since nightlights are known to be correlated with poverty levels.



Hyperparameters for the CNN were chosen using a grid search.

Single Year Model Optimizations

The hyperspectral satellite imagery collected from Landsat 7 contains both RGB bands and non-RGB bands. We first test which bands are more useful for predicting asset levels.



(a) RGB bands (b) Non-RGB bands

Figure: Average cross-validated (n = 5) test R^2 values for predicting asset levels

Next, we optimize the number of layers used in the model. Both ResNet models tested are pretrained on ImageNet data.

	Assets	Consumption
18-layer ResNet	0.47	0.31
50-layer ResNet	0.35	0.26
Nightlights (baseline)	0.38	0.19

Table: Average cross-validated (n = 5) test R^2 values

Temporal Model Results

We design a temporal model to predict the change in assets and consumption over two years given their respective satellite imagery.

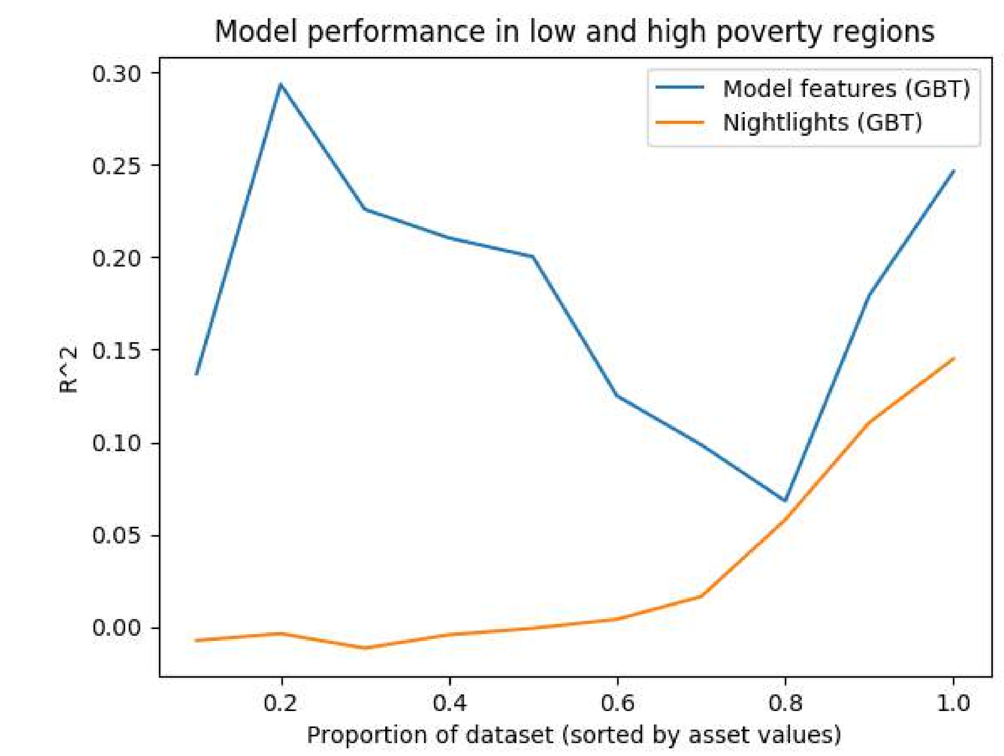
Figure: Model input

	Δ Assets	Δ Consumption
Model (linear)	0.19	0.12
Model (GBT)	0.25	0.16
Δ Nightlights	0.07	0.04

Table: Average cross-validated (n = 5) test R^2 values

Temporal Model Results (cont.)

To determine where our model makes errors, we then plotted the R^2 values for different poverty level percentiles.



Difficulties with Temporal Models

- Images contain little information about changes in poverty over time

(a) 2005 (b) 2011 (c) Difference

Figure: Landsat Images of Kampala, capital of Uganda, over time

- Δ nightlights is not correlated with changes in poverty

Future Work

- Incorporate better proxies whose change over time is more correlated with change in assets and consumption
- Use semi-supervised learning to incorporate prior knowledge that poverty is spatially correlated