Predict Household Assets with Satellite Imagery and Machine Learning

Measuring the economic well-being accurately has important implications for policy on reducing poverty and food insecurities in developing countries. However, policy makers often lack the information required to identify the right populations to allocate the scarce resources to (Barrett and Headey 2014). Most of African countries have conducted less than two nationally representative census in the first decade of the 21 centuries (World Bank 2015), mostly because it is costly to do so. The data gap hinders the efforts on effectively targeting the population in need and calls for the use of data and method that are cost-effective and accurate.

Several studies in the literature have used novel data to fill this data gap. Night lights data (Chen and Nordhaus 2011; Henderson et al. 2012.) serves as a good proxy for economic activity but the variation over time is little in areas that are either extreme poor or relatively better off. Mobile phone data (Blumenstock et al.,2015; Steele et al.,2017) is more frequent and less expensive compared to census surveys. But in the short term, it is not feasible to roll out cellphone surveys in the entire sub-Saharan Africa. Very high-resolution satellite imagery is becoming cheaper but is constrained by lack of structure (Engstrom, 2018; Donaldson and Storeygard, 2016). Convolutional Neural Network (CNN) models (Jean et al., 2016; Babenko et al. 2017) based on satellite imageries can explains up to an average 46% of the variation at village level in terms of wealth and asset measures.

In this paper, we combine CNN models with satellite imagery to predict household level assets. In particular, we are interested in the errors of predication and how it is correlated with geospatial location, urban/rural status. The outcome of this study, the predicated asset and roof types, can be used to predict food security status when combined with weather, market access variables.

Data:

We will use satellite imagery to help our prediction. Specifically, we will be using RGB daytime images and greyscale nightlight images. The RGB images are pulled using the Google Static Maps API and the nightlight data is available through The National Oceanic and Atmospheric Administration (NOAA). The RGB images are 640 pixels by 640 pixels in size, with each pixel have a resolution of about 2.63 meters by 2.63 meters, while the nightlight image is 43201 pixels by 16801 pixels and covers the entire Earth from -180 to 180 degrees longitude and -65 to 75 degrees latitude which puts each pixel at about 240 meters by 240 meters resolution.

The reference data we are using is Malawi’s Integrated Household Surveys. Malawi has run its Integrated Household Survey (IHS) in 2010-2011, 2013-2014, and most recently in 2016-2017. Households surveyed are designed to be a nationally representative sample and are diverse in terms of spatial location and month of interview time. From the surveys we can obtain variables of interest: household wealth and assets, food security measures, and geospatial data. We are interested in predicating the average roof types and asset index in this study. However, in order to keep the confidentiality of each respondent, the IHS does not give the exact coordinates of the respondents. Instead, they first break the dataset into clusters (about the size of a village) and assign every household in the cluster the average coordinates of everyone in the cluster, then assign a randomized offset from this center point. In urban areas, this offset is between 0-2km and in rural areas this offset is between 0-5km (with 1% of rural clusters receiving another 0-10km offset). The implication of this spatial distortion suggests that the lowest spatial aggregation level of analysis would be at the clusters with a 2-5 km buffer.

Method:

We will use a convolutional neural network on the RGB images to predict the average amount of assets and the consumption budget at the cluster level. This network will be trained through supervised learning with the reference being Malawi’s IHS data. To avoid possible measurement error, similar to Jean et al (2016), we will train the convolutional neural network on ImageNet and then on the nightlight data as a proxy using a transfer learning approach. The Nightlight data has been shown to be a good proxy for economic activity, so by using it through transfer learning it should help negate some of the problems associated with the lack of data in Malawi’s IHS. The final step is to use the trained model directly onto the wealth and asset measures in the IHS survey from the RGB images. After the model has been trained, its prediction will then be combined with soil modules, crop modules, and market access modules to build the food security prediction.