Class Twenty-Four: Neural Networks

ER290: Data, Energy and Justice
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RESEARCH ARTICLES

ECONOMICS

Combining satellite imagery and machine learning to predict poverty

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Reliable data on economic livelihoods remain scarce in the developing world, hampering efforts to study these outcomes and to design policies that improve them. Here we demonstrate an accurate, inexpensive, and scalable method for estimating consumption expenditure and asset wealth from high-resolution satellite imagery. Using survey and satellite data from five African countries—Nigeria, Tanzania, Uganda, Malawi, and Rwanda—we show how a convolutional neural network can be trained to identify image features that can explain up to 75% of the variation in local-level economic outcomes. Our method, which requires only publicly available data, could transform efforts to track and target poverty in developing countries. It also demonstrates how powerful machine learning techniques can be applied in a setting with limited training data, suggesting broad potential application across many scientific domains.

The challenge

- International aid agencies want information on where to spend effort
- Knowing where the poorest people are can inform these decisions
- But surveying a country's population is expensive, and most survey results are not in the public domain.
  - About 25% of African countries did not run any surveys between 2000-2010 from which poverty measures could be computed.
- Question: can one train a model that uses remote sensing data to predict poverty?

Night lights

- Some folks have used night satellite imagery to estimate spatial distributions of wealth
  - Basic idea: satellites can see lighting activity at night
  - People with more money use more night lighting.
- These methods are not accurate at extreme poverty income levels ($< \$1.90$ per person per day)
- There is little data on extreme poverty (see previous slide) so there isn't a large data set to train models with.

Jean *et al's* idea

1. Use *daytime* satellite imagery, not night time
   - Landcover type and structures, for example, ought to help to predict poverty.
2. Deal with the data paucity problem via "transfer learning"
   - The idea here is pretty simple: train a neural net on a well known set of images (ImageNet – labelled data from 1,000 categories, e.g. "boneshaker", "crutch", "miniature schnauzer")



   - the model learns to identify low- level image features such as edges and corners that are common to many vision tasks

A bit more on Jean *et al's* transfer learning

3. ImageNet-trained model then "fine tuned" to use daytime satellite imagery inputs to predict the nighttime light intensities outputs.
   - In doing this Jean *et al* are falling back on the idea of using night lights (or a prediction of night lights) to measure income and wealth
   - It's desirable to use night lights because it's a globally available data set and is a better proxy for economic activity than the daytime images would be.
4. Then use mean cluster-level values from *survey* data (where available) along with the corresponding image features extracted from daytime imagery by the NN are used to train ridge regression models that can estimate cluster-level expenditures or assets.
   - Clusters are geographic areas approximately the size of a village.
   - Survey data approximate hhld expenditures as well as wealth

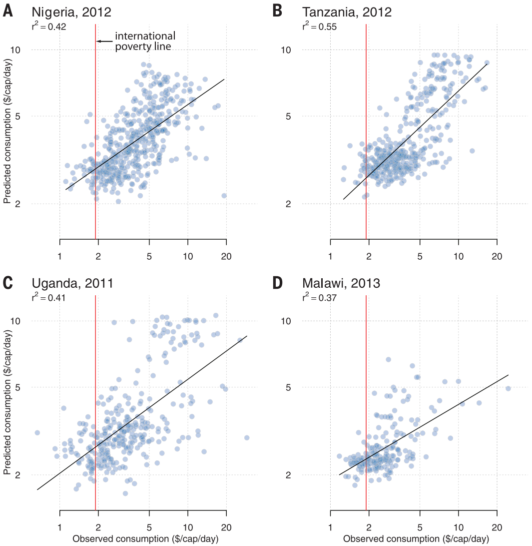
Basic summary of process

- Old: night lights $\rightarrow$ predict wealth and income
- New: daytime imagery $\rightarrow$ predict night lights $\rightarrow$ predict wealth and income.

Wait – I thought night lights were a lousy proxy for economic activity at low income levels?

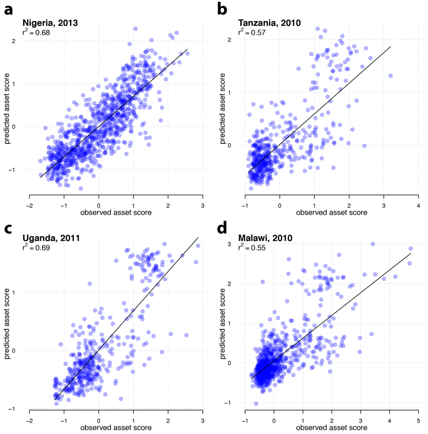
- Jean *et al* address (or try to address) this head on.
- Their claim is that because they're using a linear model (ridge regression) to map day time imagery to night lights, the model is going to be driven by light-economic relationships at higher income levels.
  - If they're lucky, the lower income relationship between *estimated* night lights and economic activity will be decent.

Result - consumption (income) prediction



Result - wealth (asset) prediction

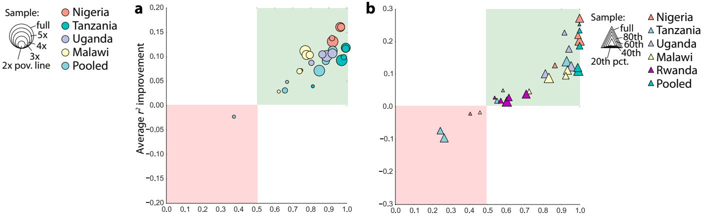
Figure S3: **Predicted cluster-level asset index from transfer learning approach (y-axis) compared to DHS-measured asset index (x-axis) for 5 countries.** Predictions and reported r^2 values in each panel are from 5-fold cross validation. Both axes shown in log-scale. Black line is the best fit line.



Some tests

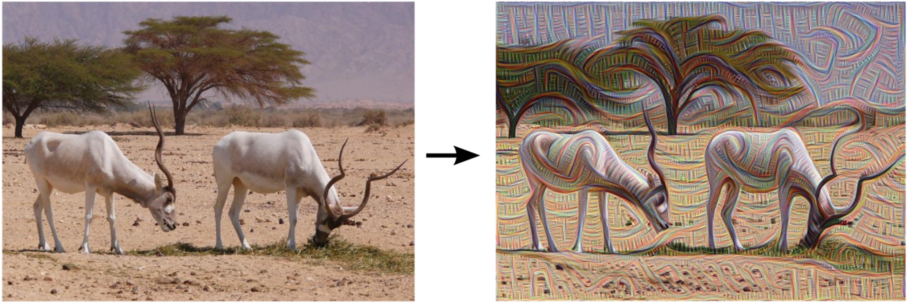
Their approach:

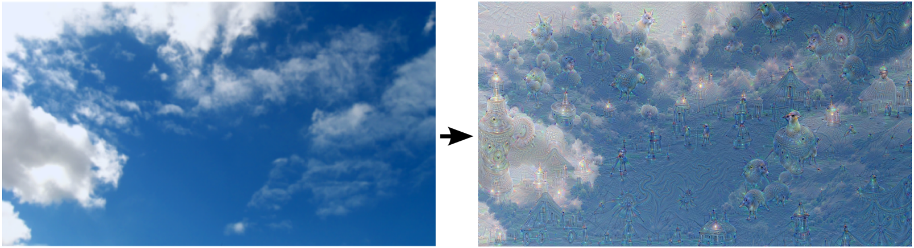
- model is on average substantially more predictive of variation in consumption and assets than nightlights alone



- performs as well as or better than an intuitive approach of using data from past surveys to predict outcomes in more recent surveys
- far outperforms common general-purpose image features such as color histograms

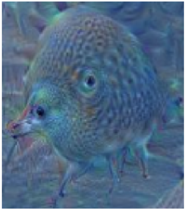
A side note on using models trained on one data set to interpret another





"Admiral Dog!"

"The Pig-Snail"



"The Camel-Bird"

"The Dog-Fish"