Predicting poverty from satellite imagery

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Why poverty?

1. **No Poverty**
2. **Zero Hunger**
3. **Good Health and Well-being**
4. **Quality Education**
5. **Gender Equality**

- **#1 UN Sustainable Development Goal**
  - Global poverty line: $1.90/person/day
- Understanding poverty can lead to:
  - Informed policy-making
  - Targeted NGO and aid efforts
Data scarcity

Consumption/Income Survey Availability, 2000-2010

Wealth Survey Availability, 2000-2010
Lack of quality data is a huge challenge

• **Expensive** to conduct surveys:
  – $400,000 to $1.5 million

• **Data scarcity**:
  – <0.01% of total households covered by surveys

• **Poor** spatial and temporal **resolution**
Satellite imagery is low-cost and globally available

Simultaneously becoming **cheaper** and **higher resolution** (DigitalGlobe, Planet Labs, Skybox, etc.)
What if... we could infer socioeconomic indicators from large-scale, remotely-sensed data?
Standard supervised learning won’t work

- Very little training data (few thousand data points)
- Nontrivial for humans (hard to crowdsource labels)
Transfer learning overcomes data scarcity

**Transfer learning:** Use knowledge gained from one task to solve a different (but related) task.
Transfer learning bridges the data gap

A. Satellite images

B. Proxy outputs

C. Poverty measures

Deep learning model

Plenty of data!

Less data needed

Not enough data!

Would this work?
Nighttime lights as proxy for economic development
Why not use nightlights directly?

A. Satellite images
B. Nighttime light intensities
C. Poverty measures
Not so fast...

Almost no variation below the poverty line
Lights aren’t useful for helping the poorest
Step 1: Predict nighttime light intensities

A. Satellite images
B. Nighttime light intensities
C. Poverty measures

Deep learning model
Training data on the proxy task is plentiful

Labeled input/output training pairs

( )

Low nightlight intensity

\( \ldots \) 

High nightlight intensity

( )

Millions of training images sampled from these locations
Images summarized as low-dimensional feature vectors

**Inputs:** daytime satellite images

**Convolutional Neural Network (CNN)**

**Outputs:** Nighttime light intensities

Nonlinear mapping

Linear regression

Convolutional Neural Network (CNN)

Inputs: daytime satellite images

Outputs: Nighttime light intensities

f_1, f_2, ..., f_{4096}

Night-Light

{Low, Medium, High}
Feature learning

\[
\min_{\theta, \theta'} \sum_{i=1}^{m} l(y_i, \hat{y}_i) = \min_{\theta, \theta'} \sum_{i=1}^{m} l(y_i, \theta^T f(x_i, \theta'))
\]

Over 50 million parameters to fit

Run gradient descent for a few days
Transfer Learning

**Inputs**: daytime satellite images

**Feature Learning**

Inputs:
- daytime satellite images

Outputs:
- Nighttime light intensities
  - {Low, Medium, High}

**Target task**

- Poverty

**Have we learned to identify useful features?**
Model learns relevant features automatically

Satellite image

Filter activation map

Overlaid image
Target task: Binary poverty classification

- Living Standards Measurement Study (LSMS) data in Uganda (World Bank)
  - Collected data on household features
    - Roof type, number of rooms, distance to major road, etc.
  - Report household consumption expenditures

- **Task**: Predict if the majority of households in a cluster are above or below the poverty line
How does our model compare?

Survey-based model is the gold standard for accuracy but...
- Relies on expensively collected data
- Is difficult to scale, not comprehensive in coverage

![Accuracy Bar Chart]

Accuracy

Survey

0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

0.75
Advantages of transfer learning approach:

- Relies on inexpensive, publicly available data
- Globally scalable, doesn’t require unifying disparate datasets
Our model maps poverty at high resolution

Case study: Uganda

- Most recent poverty map over a decade old
- Lack of ground truth highlights need for more data
We can differentiate different levels of poverty

2 continuous measures of wealth:

- Consumption expenditures
- Household assets

We outperform recent methods based on mobile call record data

Blumenstock et al. (2015) Predicting Poverty and Wealth from Mobile Phone Metadata, *Science*
Transfer Learning

**Inputs:** daytime satellite images

**Feature Learning**

- \( f_1 \)
- \( f_2 \)
- ... 
- \( f_{4096} \)

**Outputs:** Nighttime light intensities

\{Low, Medium, High\}

**Target task**

Expenditures

Nonlinear mapping

**Expenditures Assets**

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Models travels well across borders

Models trained in one country perform well in other countries

Can make predictions in countries where no data exists at all
What do we still need?

- Develop models that account for spatial and temporal dependencies of poverty and health
Take full advantage of incredible richness of images
We have introduced an **accurate**, **inexpensive**, and **scalable** approach to predicting poverty and wealth.
Satellite Images Can Pinpoint Poverty Where Surveys Can’t

Economic View
By SENDHIL MULLAINATHAN APRIL 1, 2015