Transfer Learning from Deep Features for Remote Sensing and Poverty Mapping

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Why Poverty Mapping?

- #1 (of 17) UN Sustainable Development Goals
- Targeted non-profit efforts (GiveDirectly)
- Informed policy-making
- Understand poverty dynamics

Challenges with Poverty

- **Expensive** to conduct surveys ($400,000 to $1.5 million)
- **Poor** spatial and temporal **resolution** (Uganda dataset with 2,716 households)
- **Data scarcity**: lack of ground truth

Remote Sensing

- Remote sensing (e.g. satellite imagery) is cost-effective and global-scale.

- **Increasingly accurate** and **cheap** (DigitalGlobe, PlanetLabs, SkyBox).

Can we infer socioeconomic indicators (poverty, child mortality, etc.) from large-scale remotely sensed data?
Low-Cost, High-Resolution Remote Sensing

Infer poverty measures from satellite imagery

Example: vs.

Do this at scale, accurately, cost-effectively and with unprecedented spatial resolution:

Block poverty probabilities
District poverty probabilities
Uganda poverty rates (2005)
Addressing Data Scarcity

- Standard supervised approach cannot be directly applied:
  - Very little training data (few thousand data points)
  - Nontrivial for humans (hard to crowdsource labels)

- **Transfer learning**: store knowledge gained while solving one learning problem and use it to solve a different (but related) learning problem.
Night-time Lights: a Proxy for Economic Activities

- Idea: use nighttime light intensity as a proxy for economic development
- Typically the high-resolution remote sensing data of choice for economists
Transfer Learning Approach

Our approach: predict **nighttime light intensity** from **daytime images**

Data-rich proxy: global-scale labeled training data available

Goal: Automatically learn features useful for poverty task by first training a Deep Learning model for predicting nighttime light intensity
Our Model

- Key aspects:
  - Spatial context is important
  - Interested in an aggregate measure over the entire image

- Developed a **fully convolutional CNN** architecture:
  - Can handle arbitrary sized images (no cropping needed)
  - Average pooling layer in the last layer
  - 55 million parameters vs. 621 million parameters for a 400x400 image

- (Final accuracy: 73%)

Have we learned to identify useful features?
Learned Features: Roads

25 Maximally activating images

No supervision beyond nighttime lights - no labeled example of what a road looks like was provided!
Learned Features
Nightlights to Poverty Estimation

- Living Standards Measurement Survey (LSMS) data in Uganda (World Bank):
  - ~700 household clusters
  - Data on expenditures, above/below poverty line, noisy locations
- **Task**: predict if the majority of households in a cluster are above or below the poverty line from corresponding images

...
Nightlights to Poverty Estimation

- Compare against survey features which can feasibly be detected by satellite images (roof type, # of rooms, distance to population center)

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<thead>
<tr>
<th>Nonlinear mapping</th>
<th>Log. regression</th>
<th>“Poverty”</th>
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Features transferred from night-light task

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<th>Transf</th>
<th>Survey</th>
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<tr>
<td>AUC</td>
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<td>0.78</td>
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Nightlights to Poverty Estimation

- Compare against survey features which can feasibly be detected by satellite images (roof type, # of rooms, distance to population center)
- Dramatic improvement over the Night-Lights features currently used by economists

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Features transferred from night-light task
High Resolution Poverty Maps

Running model on about 400,000 images from Uganda:

Block poverty probabilities

District poverty probabilities

Uganda poverty rates (2005)

Most up-to-date map
Conclusion and Future Work

• Scalable and inexpensive approach to generate high resolution maps.
• Predicting real-valued consumption expenditure and asset index for more countries
• Spatial Graphical Models to encode spatial correlations
Thanks!