Temporal Poverty Prediction w/ Satellite Imagery

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Introduction

Description: Establish a complete pipeline for predicting the change in poverty level of a given region by utilizing publically accessible satellite images.

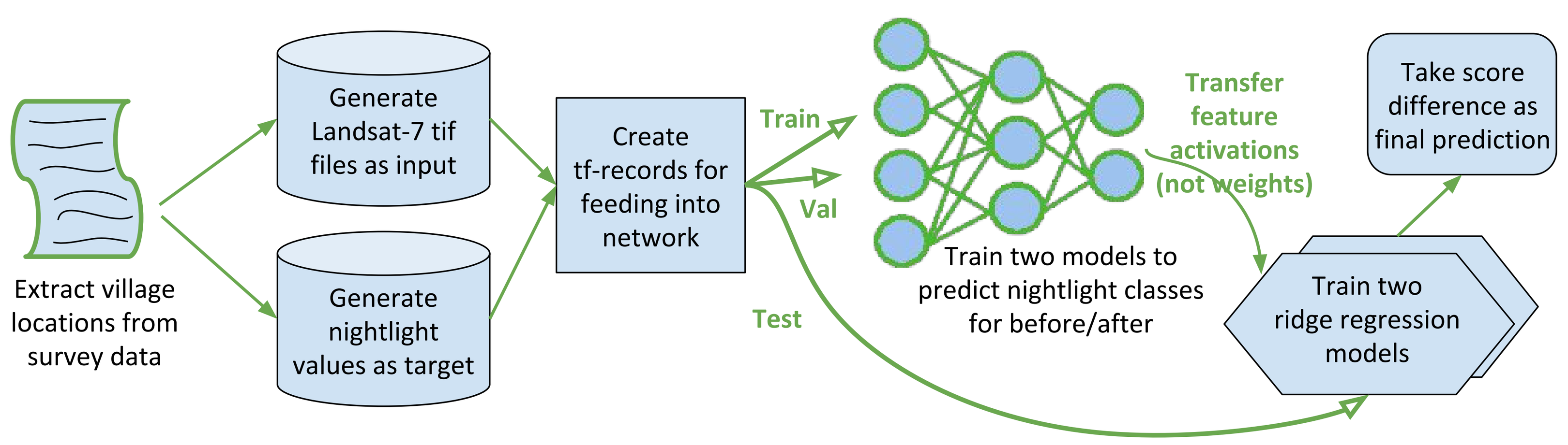
Motivation: Effective poverty alleviation goes beyond merely offering support, and necessarily requires monitoring the impact of such efforts to properly target aid and guide policy decisions. However, current methods are costly and time consuming, leading measurements to be extremely rare. By taking advantage of transfer learning, we can marginally circumvent the data sparsity issue by leveraging ConvNets to analyze widely available satellite imagery as a separate measurement tool beyond traditional on-the-ground, household surveys.

Methods

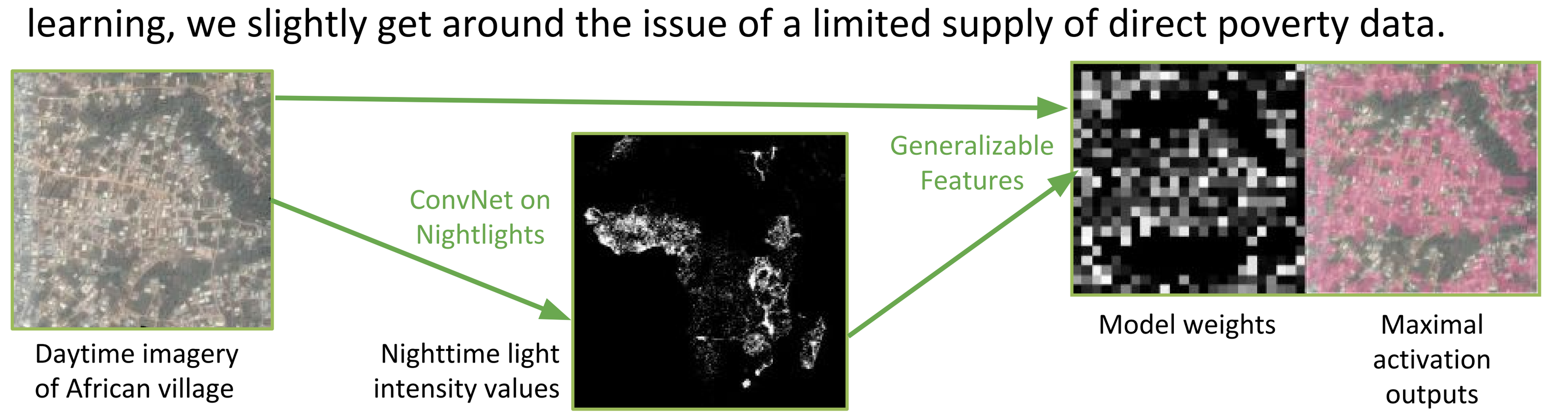
Experiments: Original project predicted poverty scores at a single point in time. Current project extends on this idea with seven different trial designs that attempt to predict a change in wealth score over time.

Name	*Description*
Baseline	Direct correlation between nightlight difference and wealth score difference.
Single Year/Model	Before: **2011 Tanzania**, After: **2013 Tanzania** (and Uganda 2012/2014, Nigeria 2011/2013)
Aggregate by Time	Before: **2010/2012 Uganda**, After: **2012/2014 Uganda** (and Tanzania 2009/2011 vs. 2011/2013)
Aggregate by Location	Before: **2011 Tanzania/Nigeria/Malawi**, After: **2013 Tanzania/Nigeria/Malawi**
Combine All	All years and locations that have before/after pairs of data fed into two respective ResNet models
Stacked Inputs	Feed a stacked image into a *single* model that directly tries to predict the difference in poverty score rather than just the poverty score for one year. Goes from two 224x224x8 images into a single 224x224x16 image
New Data Source	Go beyond LSMS data to different data sources that correlate better with nightlights data

Process: End-to-end pipeline includes 7 steps for predicting a difference in wealth score.



Key Breakthrough: By training on abundant nightlights data and then employing transfer learning, we slightly get around the issue of a limited supply of direct poverty data.



Data

LSMS Panel Surveys
Household survey responses used as ground truth in determining poverty levels. Questions are asked such as "Do you own a refrigerator?" or "Do you own a cell phone?"
Alternates: REDS panels for India, IFLS report for Indonesia

USGS Landsat-7 Program
Composite satellite photos combining higher resolution pan-sharpened images with lower resolution multi-spectral images containing rgb, infrared and thermal bands. Provides continuous coverage from 1999 to 2016, long span is critical for observing wealth trends changing over time.
Alternates: Landsat-8, Planet Labs

DMSP Nightlights
Measurement of nightlight intensity across the globe used as a proxy for measuring poverty in transfer learning. Cloud coverage was removed to produce best results. Alternates provided to show potential to generalize once newer survey data is released that can be matched to higher-res satellite imagery.
Alternate: VIIRS Nightlights also from NOAA

Model

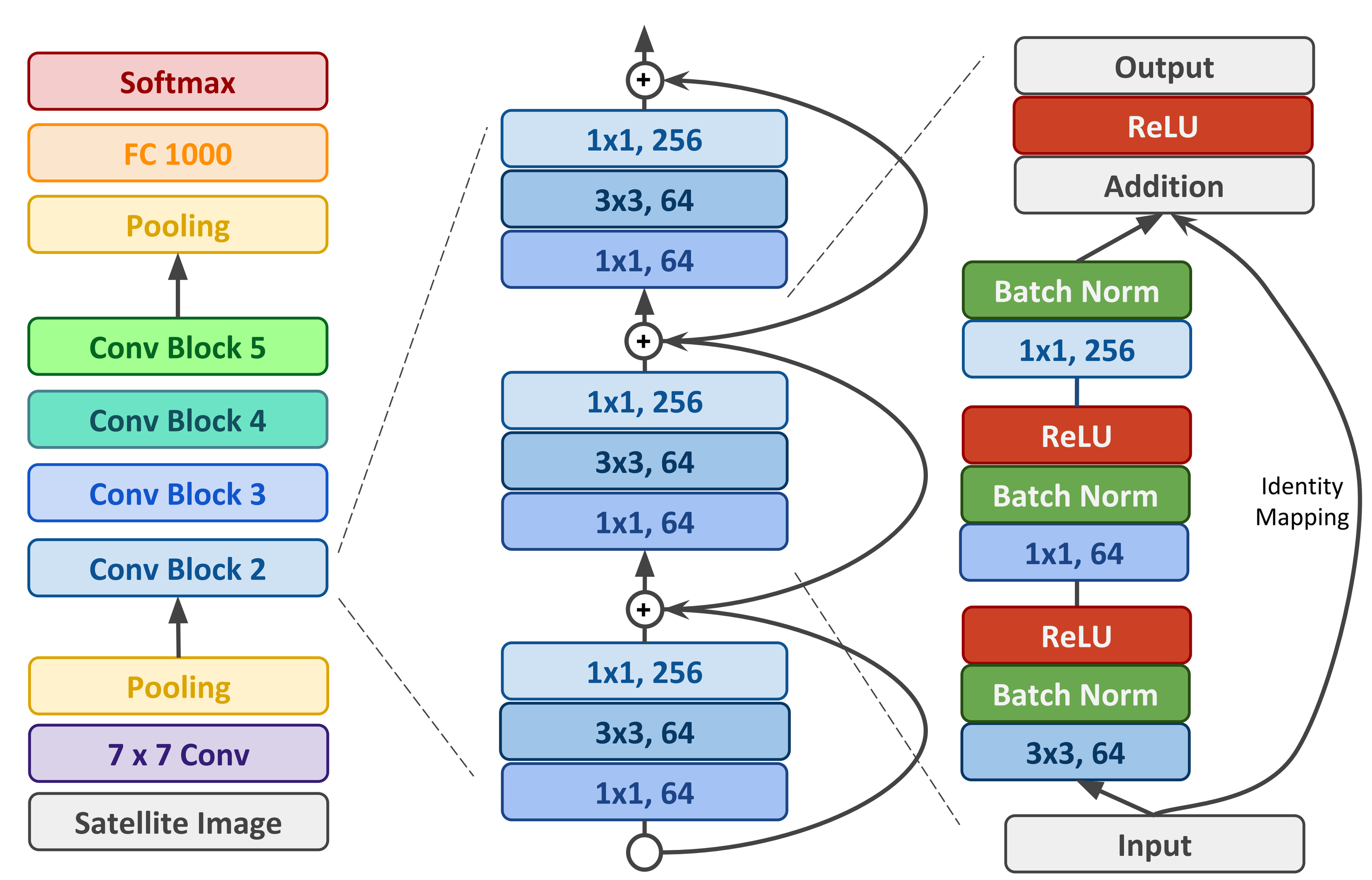
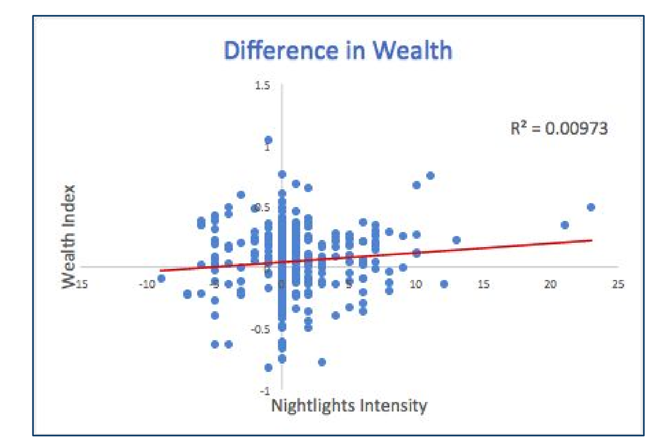


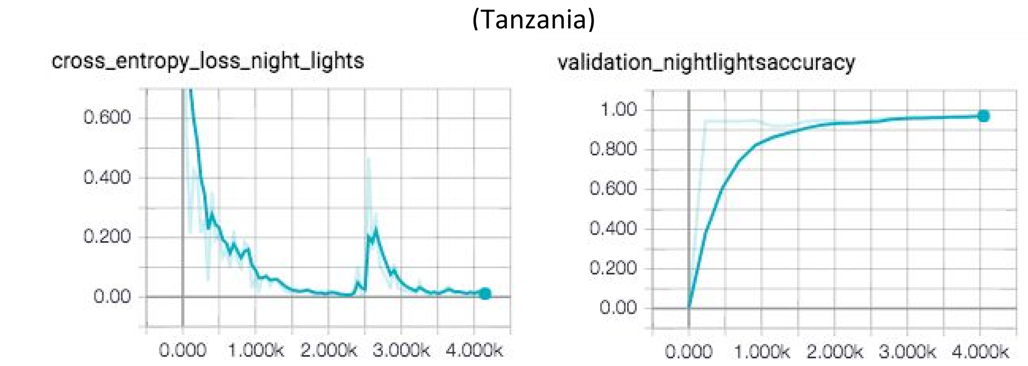
Figure 1: 50-layer ResNet architecture expanded to show detail on the skip connections in each convolution block that allow for smoother gradient flow, and then further expanded to show individual components within each bottleneck layer.

Results

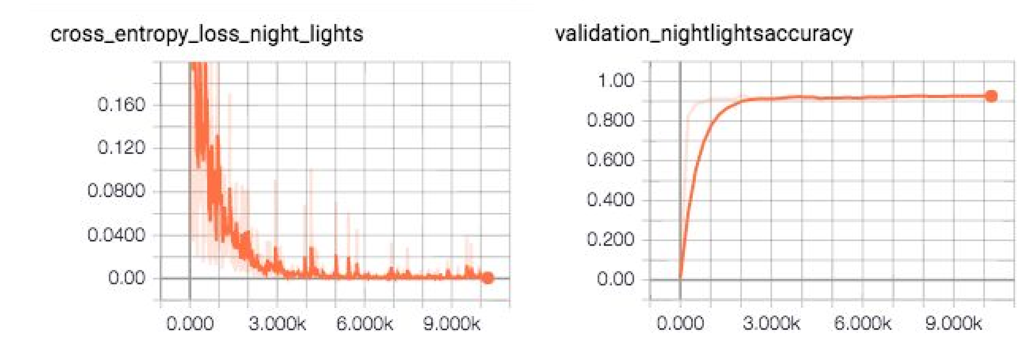
Baseline



Single Year/Model
(Tanzania)



Aggregate by Time
(Uganda)



Final Predictions

Single Year/Model:
Tanzania: 0.032, Nigeria: 0.015 , Uganda: 0.041

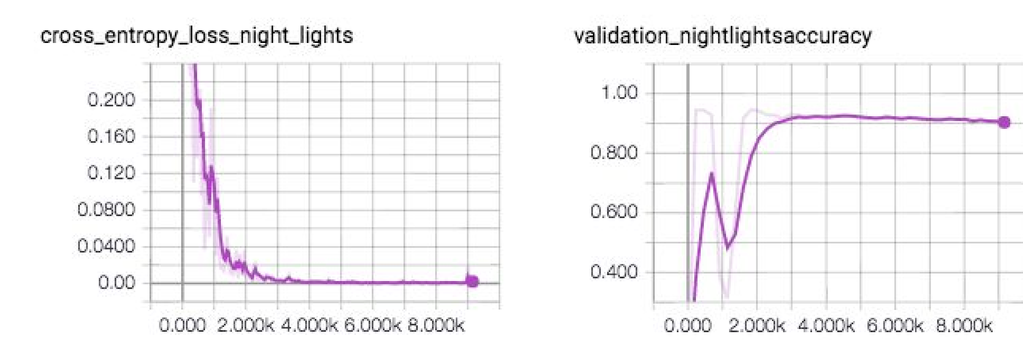
Aggregate by Time:
Tanzania: 0.218, **Uganda: 0.236**

Aggregate by Location:
2011 vs 2013: 0.135

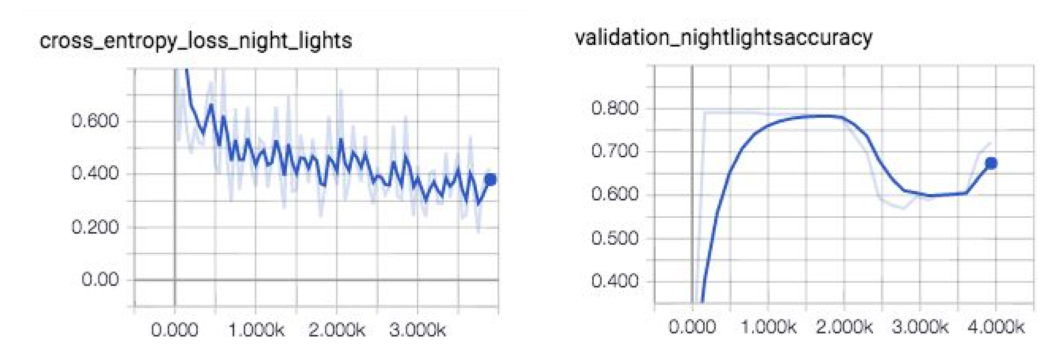
Combine All:
Every country: 0.089

R^2 values of difference in wealth scores per village

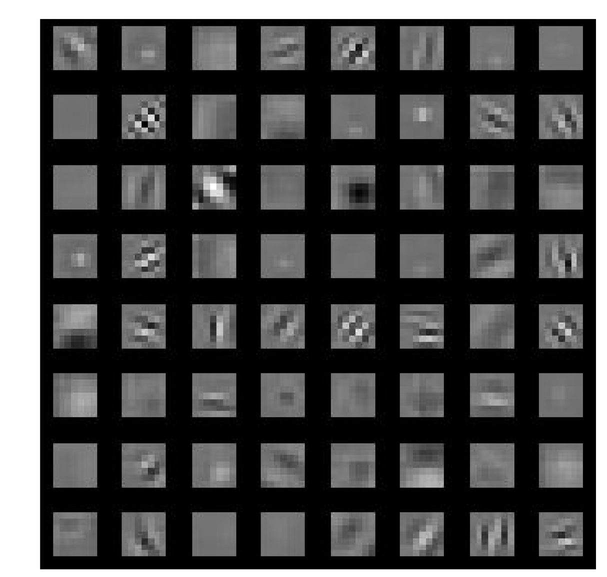
Aggregate by Location



Combine All



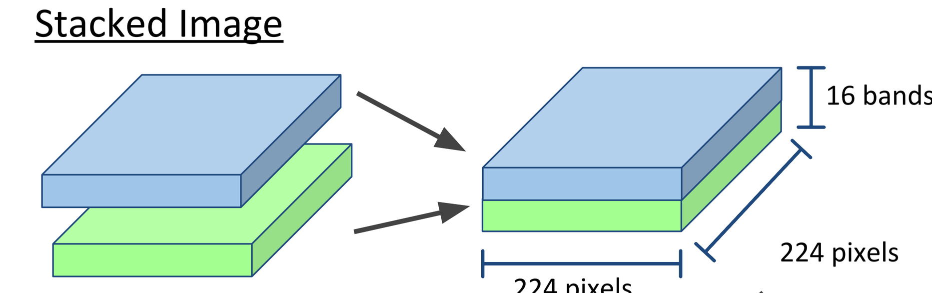
First Layer Weights



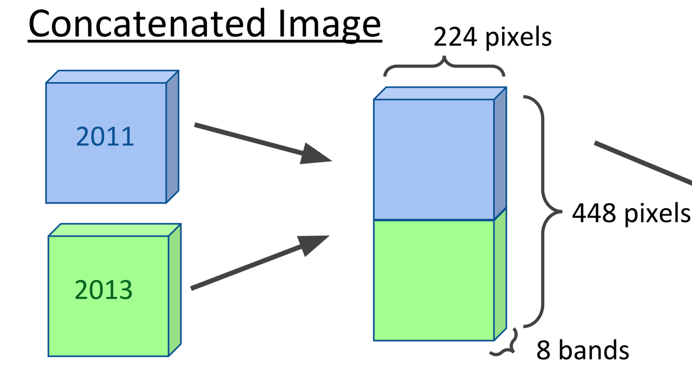
Model has learned to identify edges and shapes later used to capture geographical features

Future Work

Stacked Image



Concatenated Image



Use joined images to directly predict the difference in nightlights rather than predicting one year at a time.

New Survey Data

Use Aggregation by Time Method in Indonesia, using the IFLS household panels to predict nightlights, which shows higher correlation.