

Using Satellite Imagery and Machine Learning to Estimate Conflict in Syria and Poverty in Mexico

Jonathan Hersh (Chapman Argyros School of Business)

R Stats NYC

4/20/2018

Wild Speculations about the Future of Data Science

(from someone barely qualified)

with Two Applications

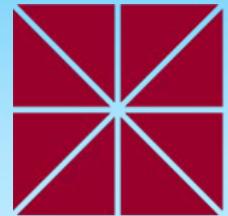
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Sole Qualifications: Tall and Jewish



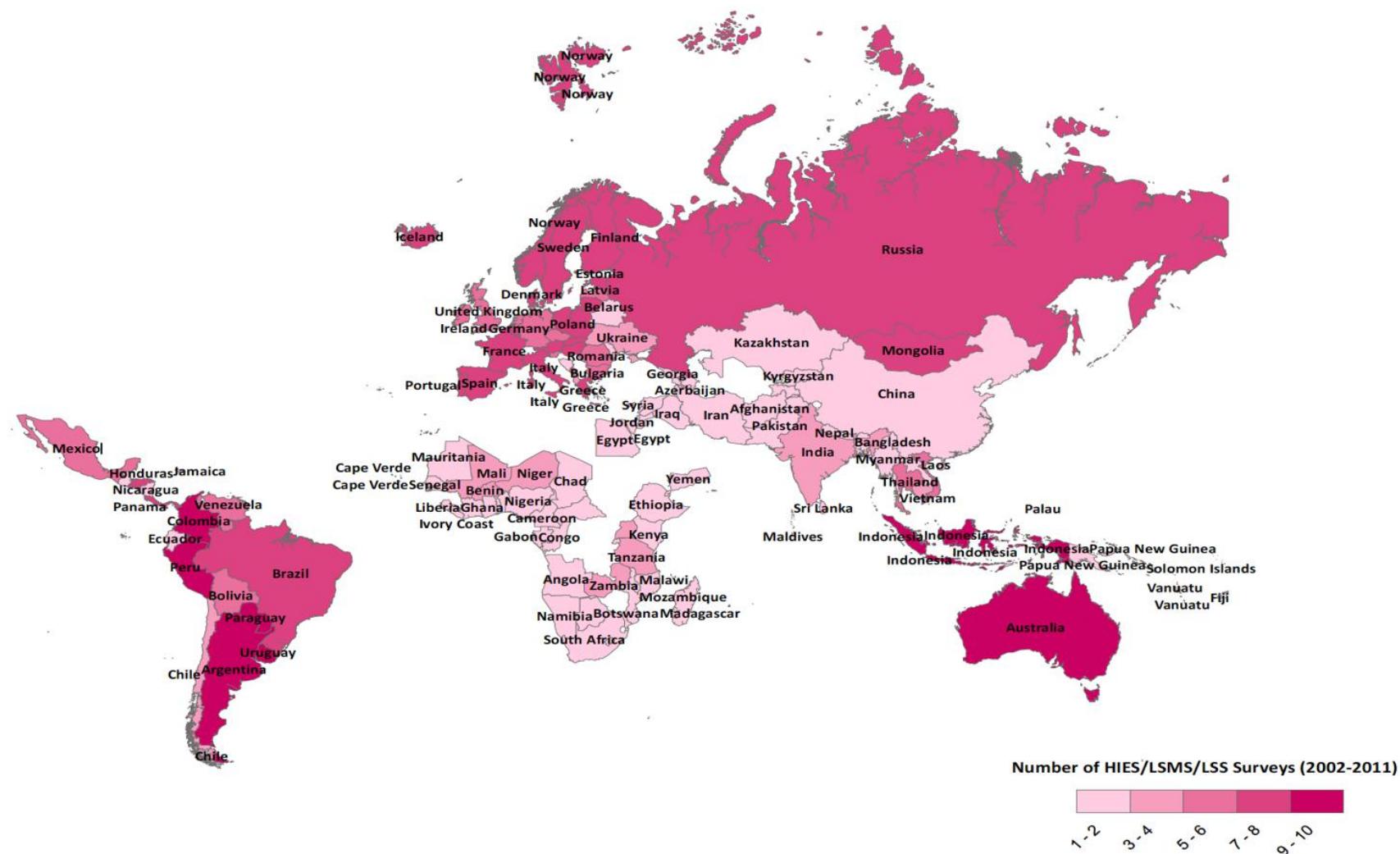


CHAPMAN UNIVERSITY



57 Countries Have Zero or One Poverty Estimate 2002-2011

Number of Poverty Data Points, 2002 - 2011



How Most Data is Collected





Lights at Night \approx GDP

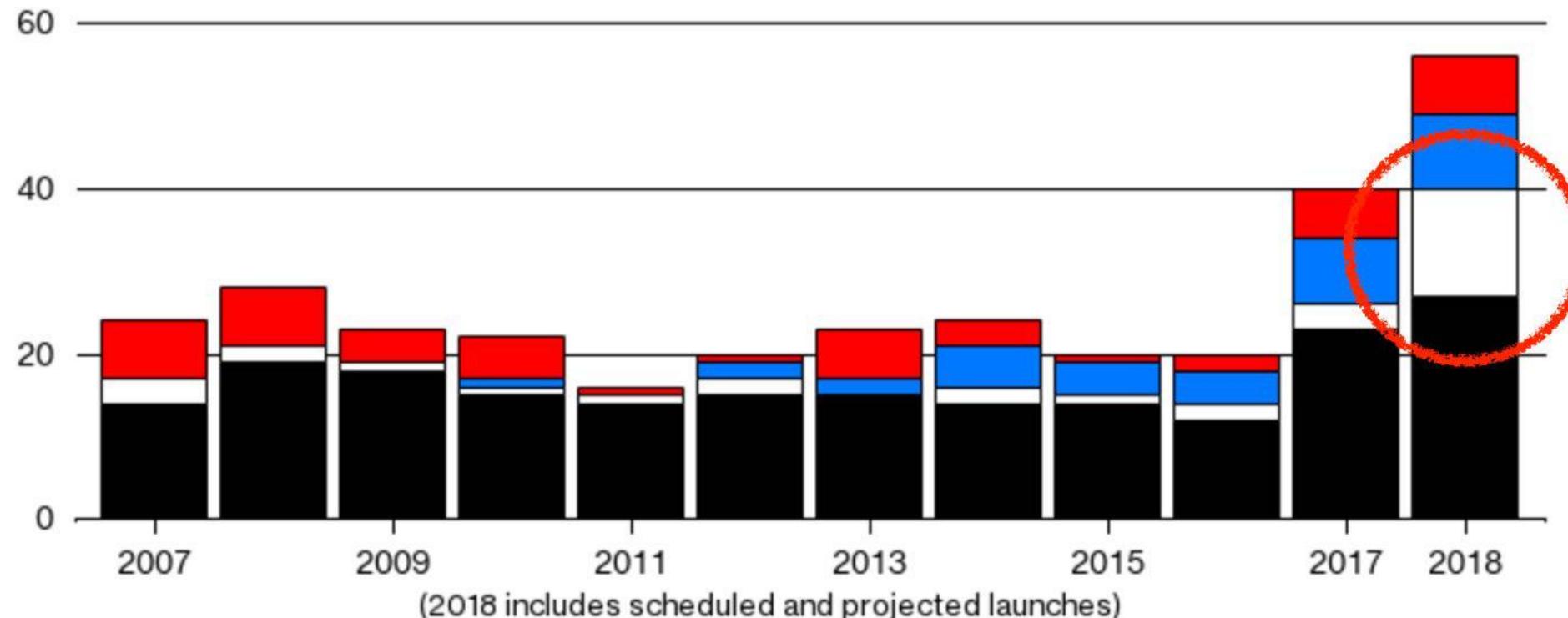
“Micro-Satellites” ~ Daily Revisit Rate



Imagery Satellites Launched in 2018

Worldwide commercial orbital launches by type

- Communications satellite
- Imaging satellite
- Cargo, astronaut delivery
- Other commercial satellites, technology demonstrations



Data: FAA Office of Commercial Space Transportation; graphic by Bloomberg Businessweek.

Previous Research (Engstrom, Hersh, Newhouse, 2017) Using Intermediate Features to Estimate Poverty in Sri Lanka

Satellite Image



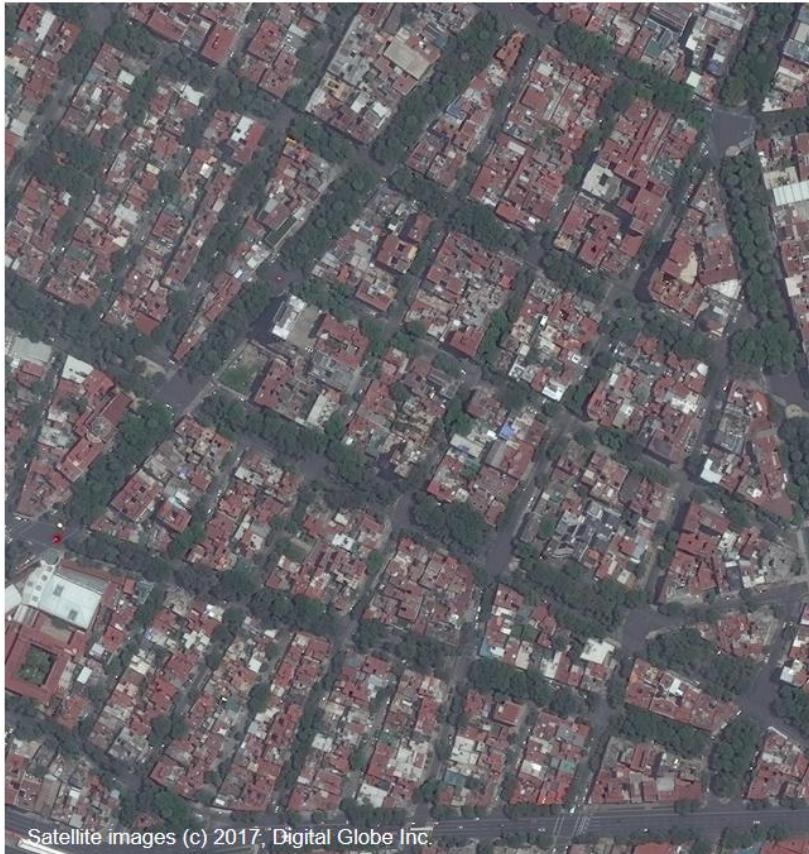
Buildings



Estimate Poverty Directly from Daytime Satellite Images?

Well-off Area (Mexico City)

Severe Poverty	Moderate Poverty	Not Poor
16.6%	18.6%	64.8%



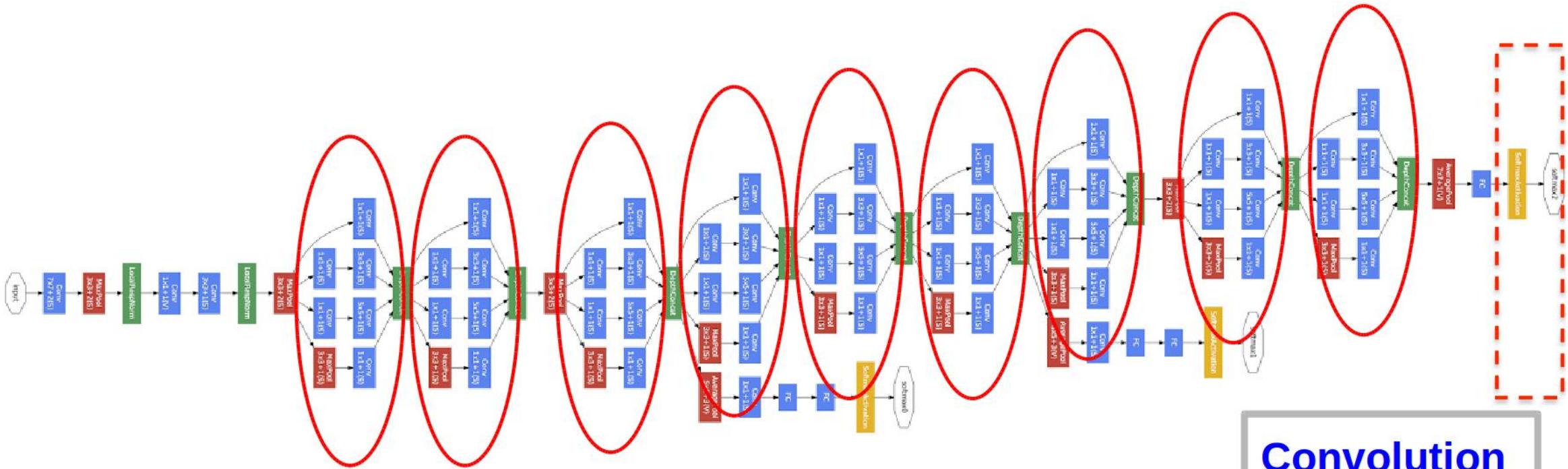
Satellite images (c) 2017, Digital Globe Inc.

Poor Area (Santiago)

Severe Poverty	Moderate Poverty	Not Poor
37.0%	38.9%	24.1%



CNN Architecture: GoogLeNet with Transfer Learning



Convolution
Pooling
Softmax
Concat/Normalize

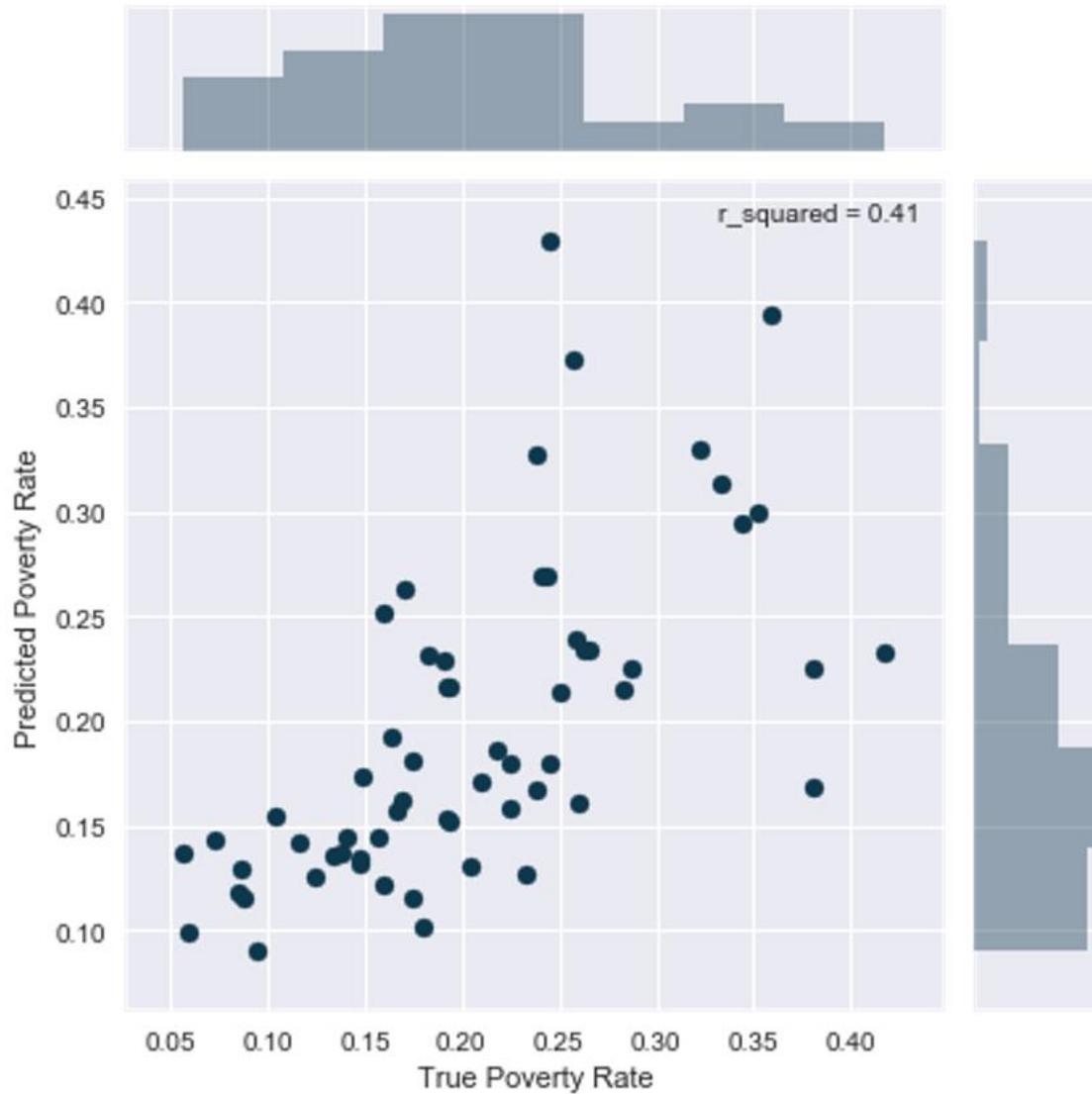
- Use pre-trained weights at values trained on ImageNet

Mexico CNN: Training Details

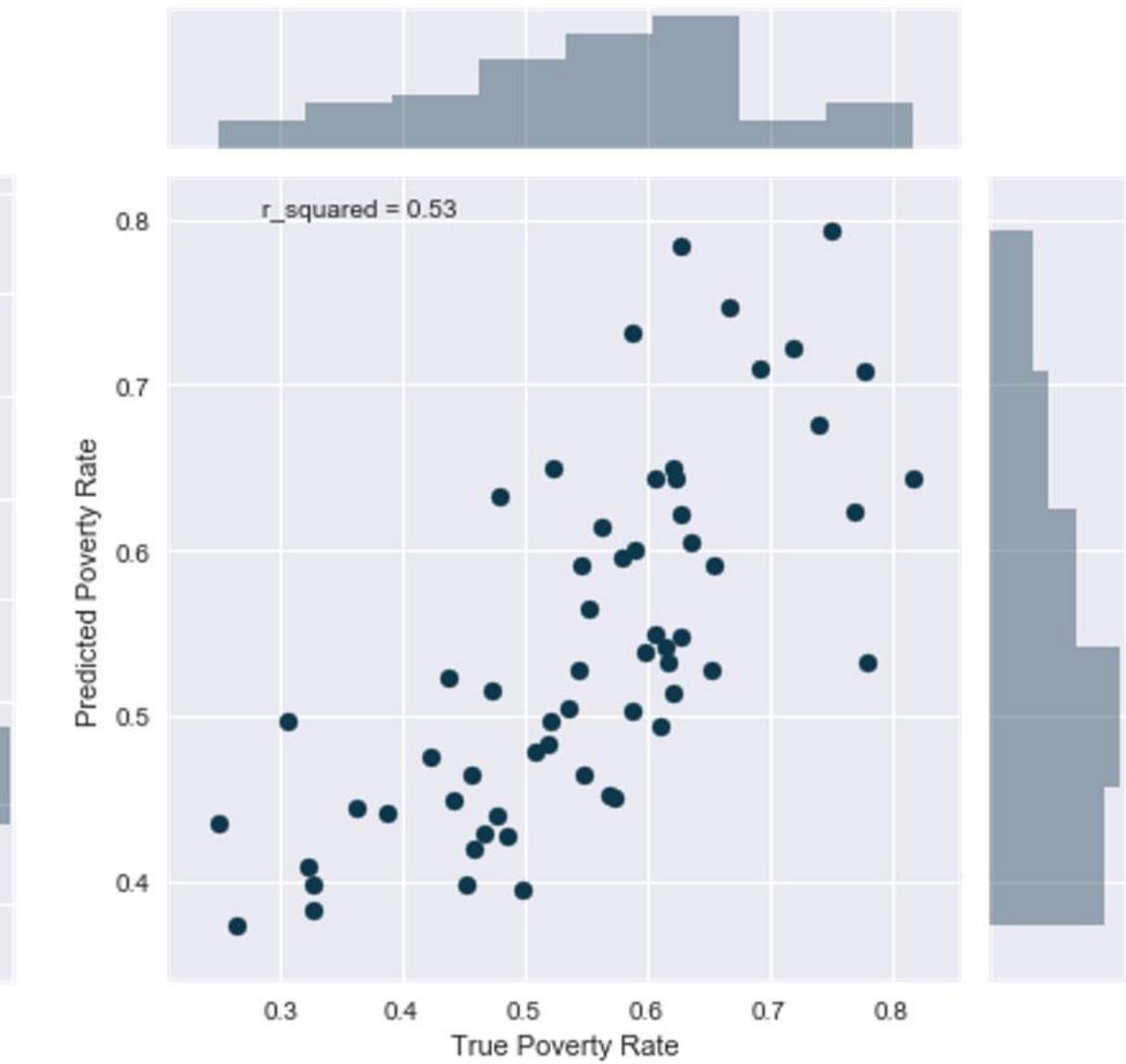
- **Poverty Levels**
 - Use two poverty levels: **severe and moderate poverty**
 - Calculate fraction in each municipality falling in this category
- **Training Details**
 - Withhold 10% of municipalities (90 out of 896 in MCS-ENIGH) to validate results
 - Divided remaining 806 into training and test samples
 - Train CNN → optimize using test sample → predict into validation sample

Urban Municipalities: Predicted vs True

Severe Poverty

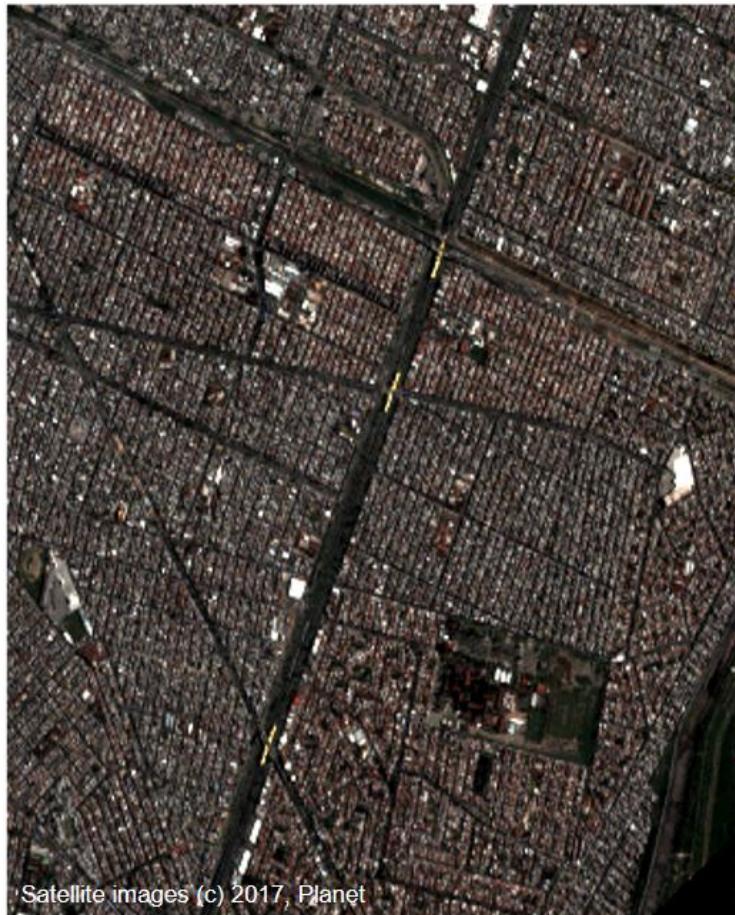


Moderate Poverty



Intermediate Land Use Classification

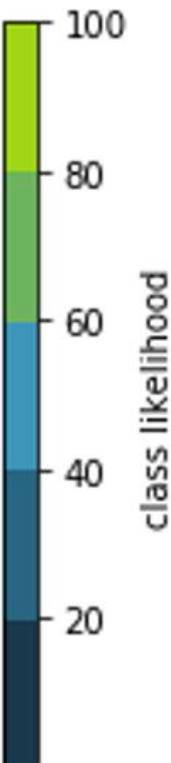
Satellite Image



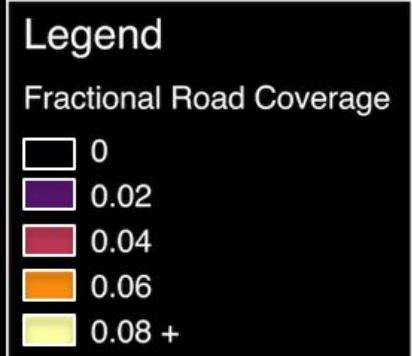
Road Probability



Building Probability



Satellite images (c) 2017, Planet



Every Road in Mexico

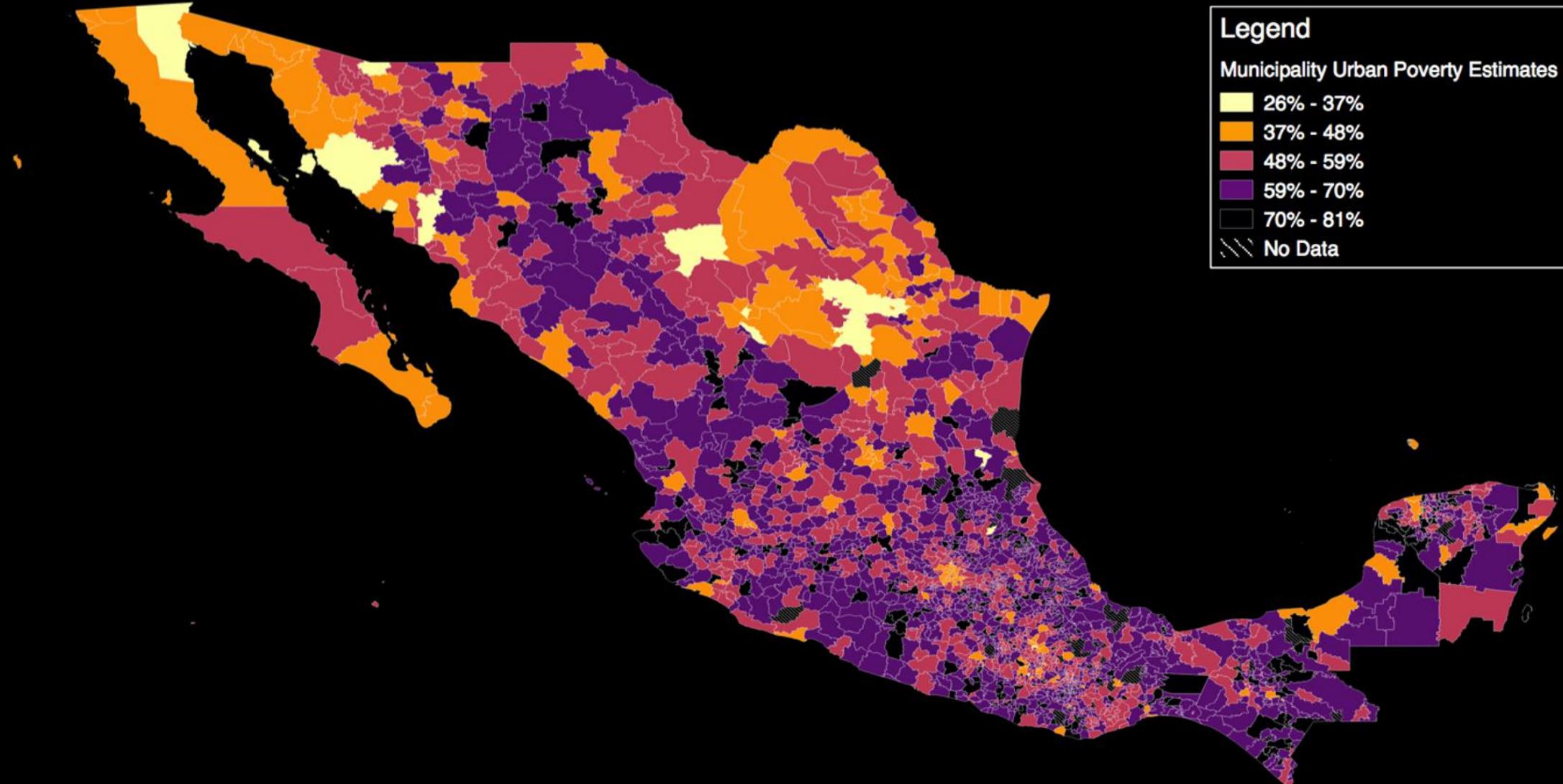


Monterrey

Guadalajara

Mexico City

Predicted Poverty Rates: Urban Municipalities



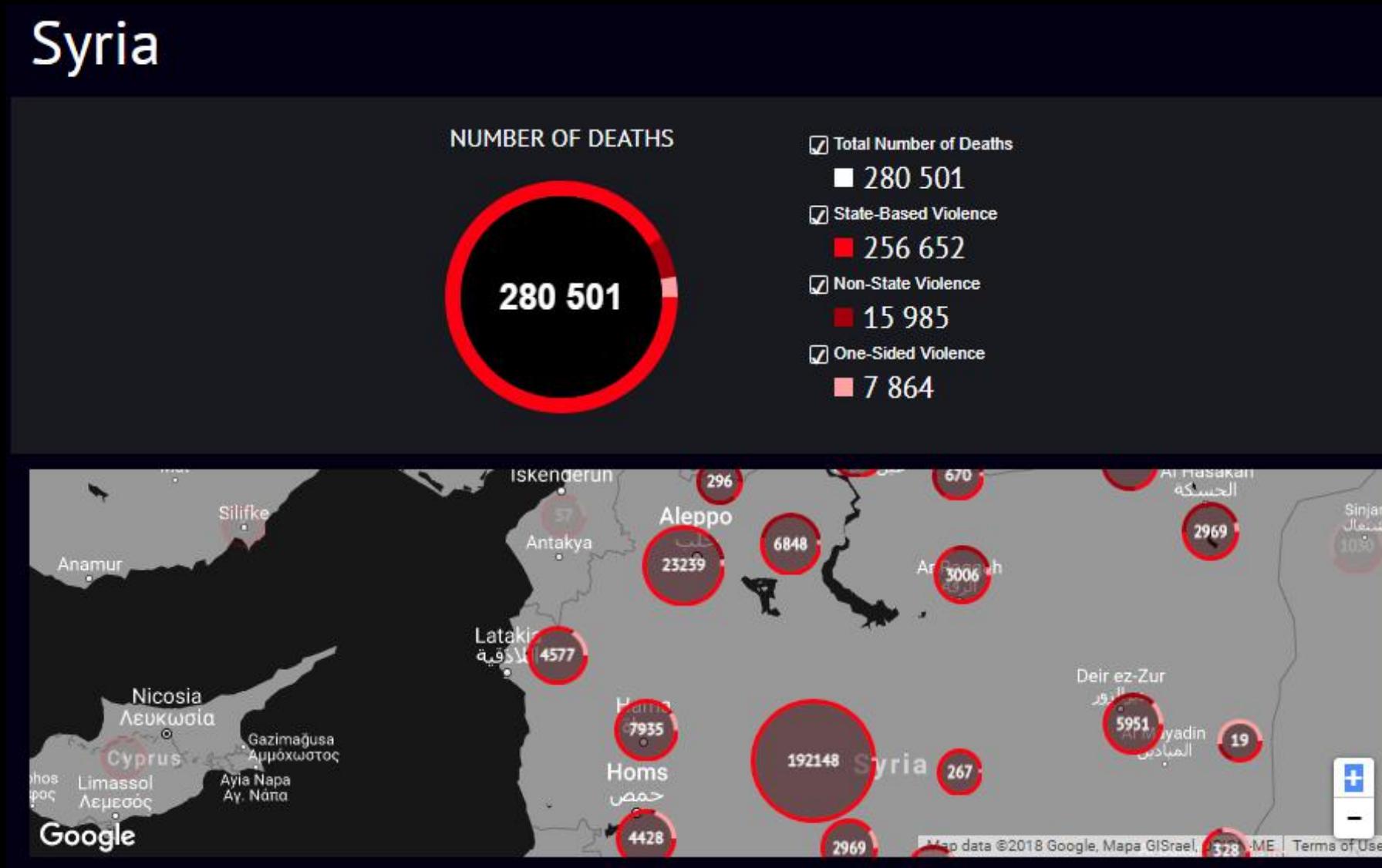
Lesson 1:

Using Off-the-Shelf Data is for
Suckers

Use Machine Learning to
Generate Data No One Else Has

Information on ongoing violence biased, outdated, and imprecise

Syria



Detecting Conflict from Satellite Imagery

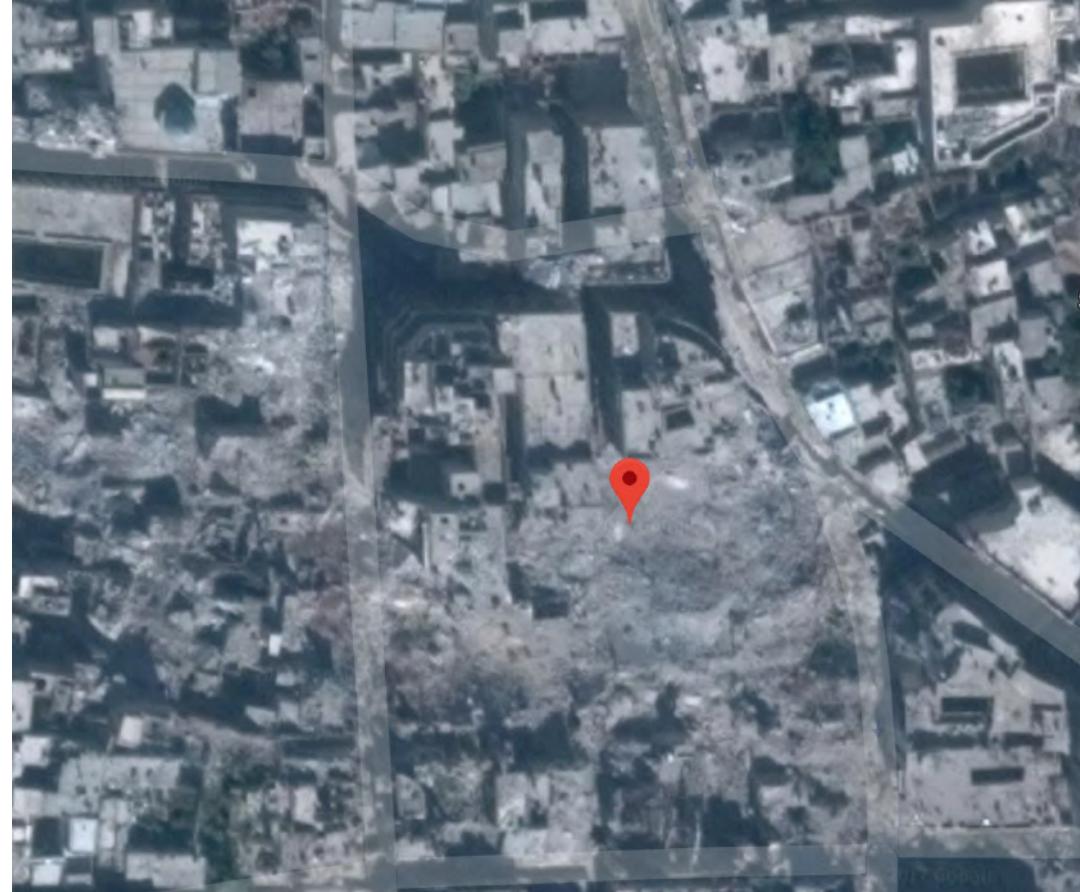


The Dream: Real Time Detection



Training sites in Syria

- Located **380 locations** in Syria with visually identified building damage
 - Eventually increase to 1,000+
- With data augmentation ~ 5,000 training images
- **Train two classifiers: one for Planet and one for Google Maps API**



Labeling process



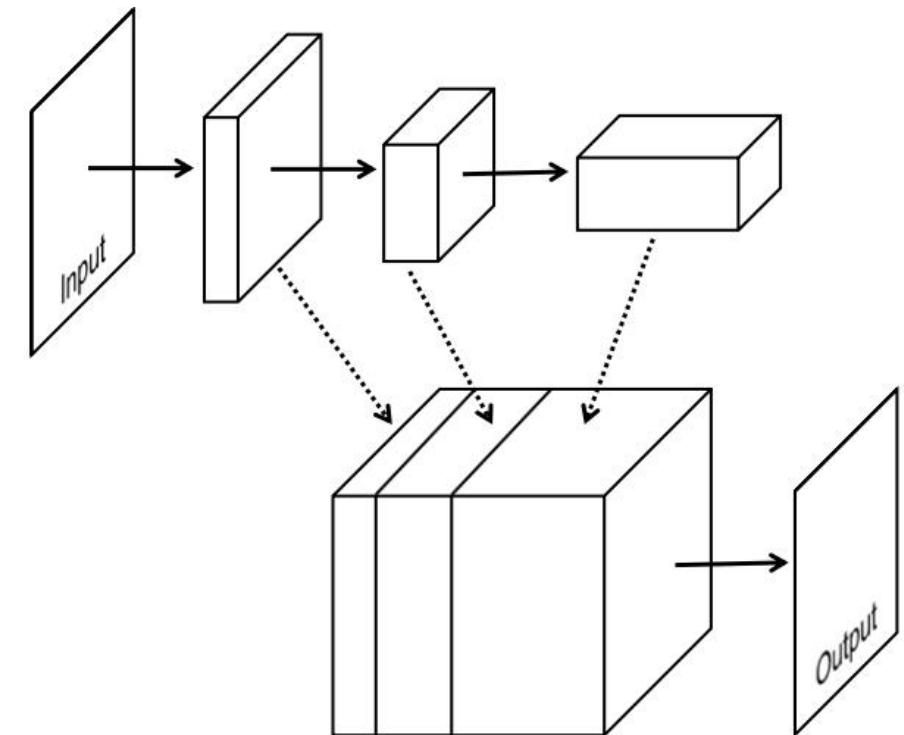
Satellite Image (Google Maps)



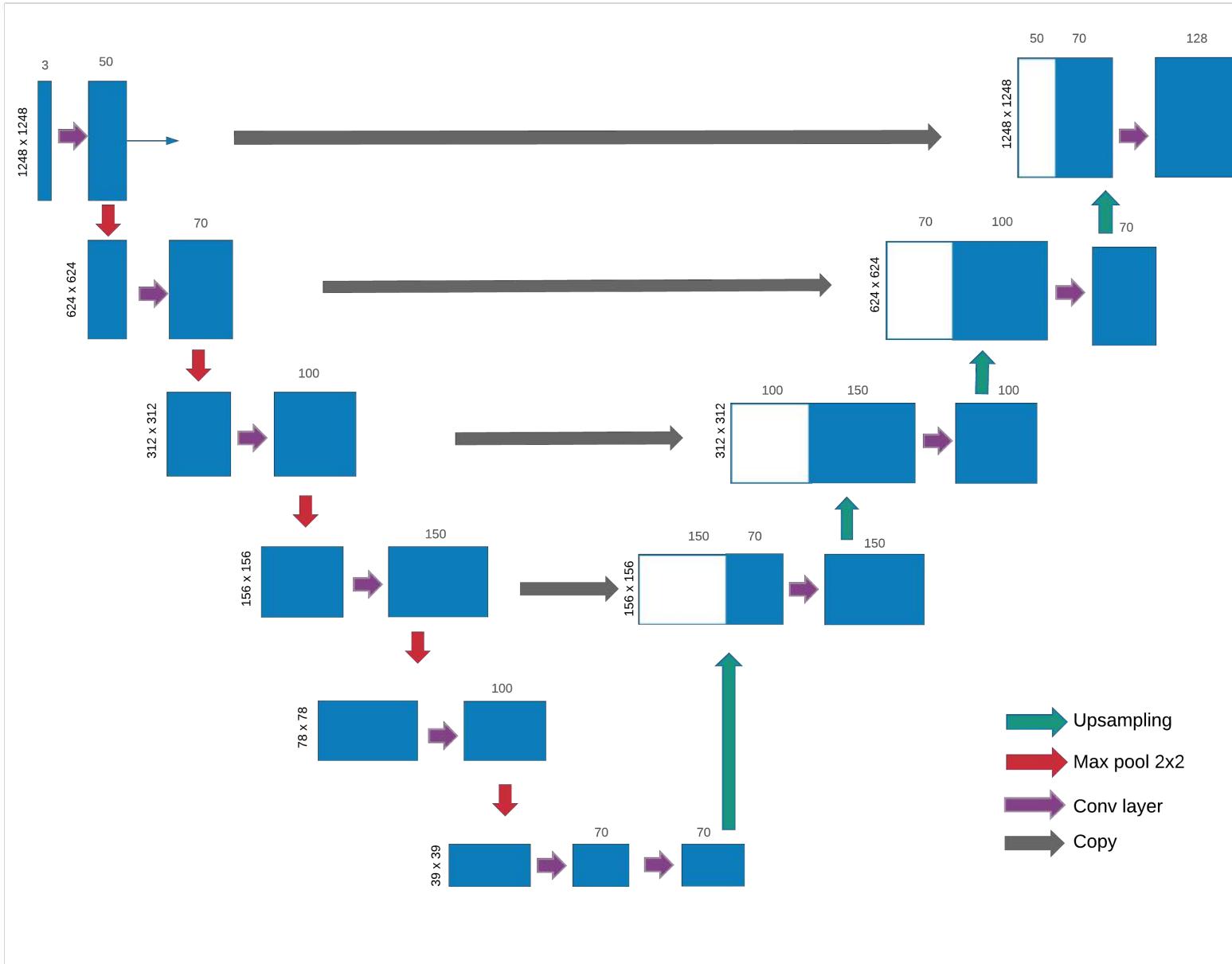
Labeled Image

CNN Architecture

- Starting point Yuan (2016)
- **7 CNNs** (with pooling in-between) with **20% dropout** between layers
- Output from 1st, 2nd, and 7th layer up-sampled and combined (“stacked”) into feature map
- **Pixel-wise prediction** at final layer



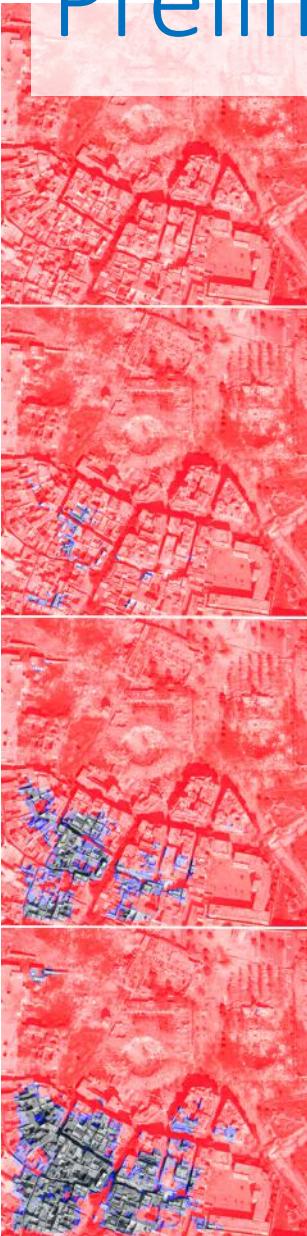
CNN Architecture: U-Net Variation



Training notes

- Implemented in Theano
- Microsoft Azure Server w/ 2 K80 GPUs
 - ~4 days
- Adam optimization
- Adjusted loss function for class imbalance
- Received \$20,000 La Caixa grant on socioeconomic well-being
- Only show results for Google Maps imagery & trained on a subset of images

Preliminary learning

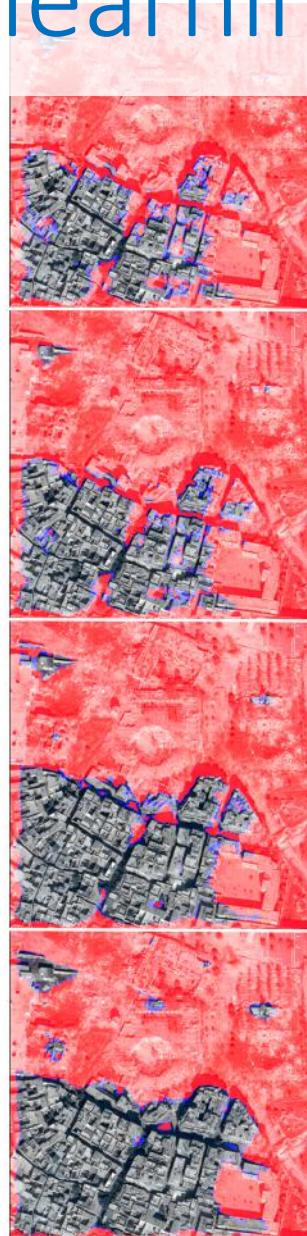


Epoch 1

Epoch 9

Epoch 14

Epoch 29



Epoch 37

Epoch 40

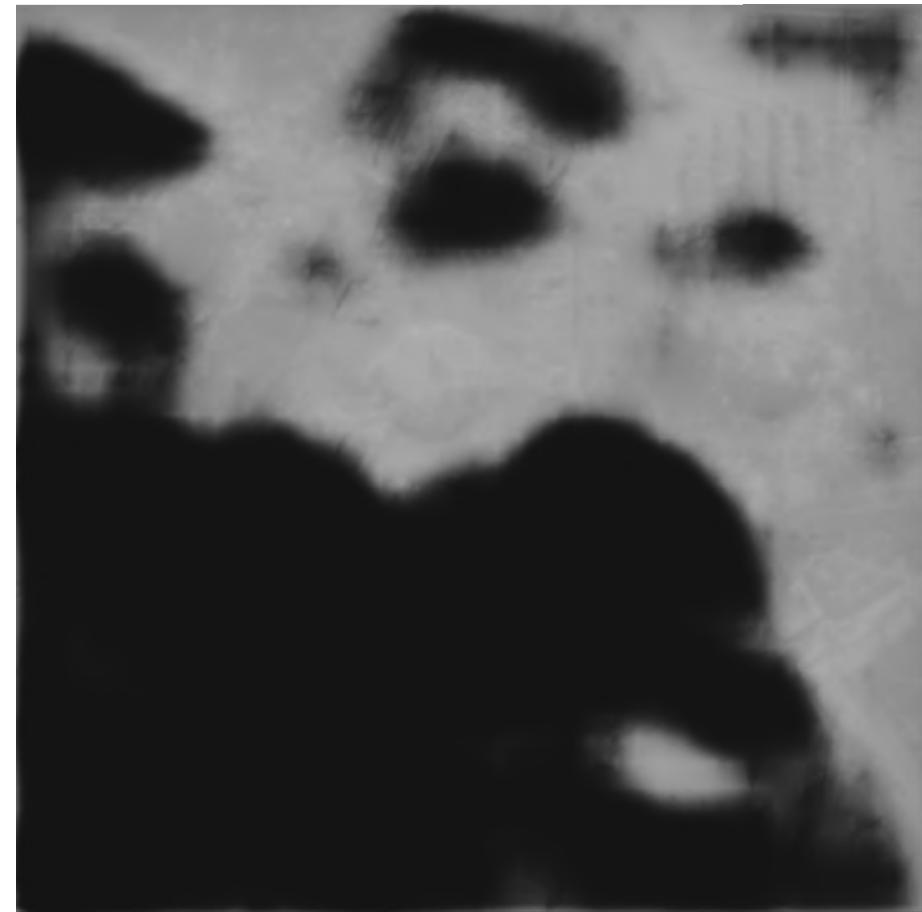
Epoch 48

Epoch 53

Final output: 800 Epochs



Labeled Destroyed Area

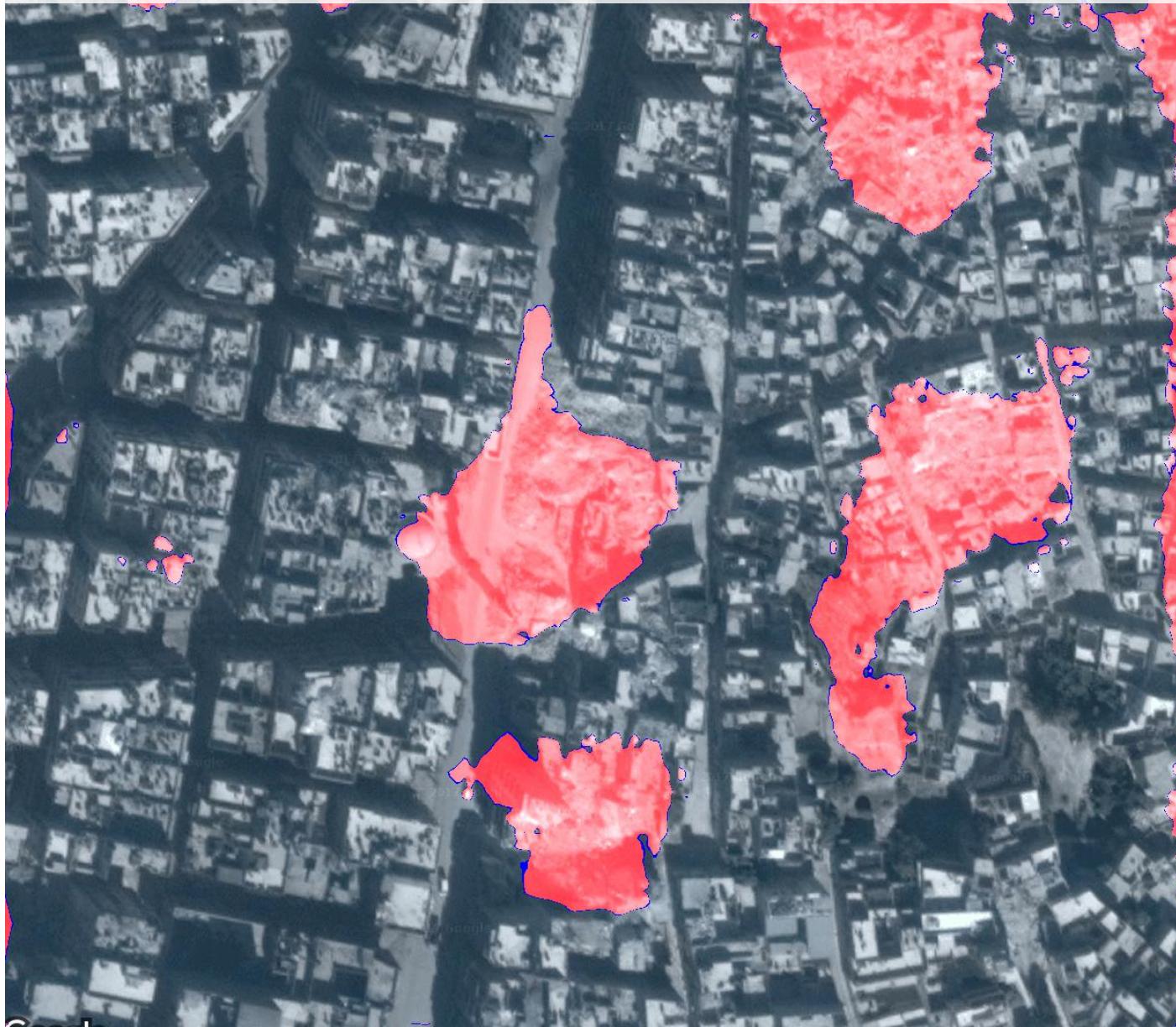


Predicted Destroyed Area

Example: Out of Sample



Example: Out of Sample



Accuracy Summary

<u>True positive rate (TPR)</u> , <u>Recall</u> , <u>Sensitivity</u> ,	<u>False positive rate (FPR)</u> , <u>Fall-out</u> ,
0.9847595837	0.139072130447
<u>False negative rate (FNR)</u> ,	<u>True negative rate (TNR)</u> , <u>Specificity (SPC)</u>
0.0152404162998	0.860927869553

Next steps

- Planet imagery (daily revisit)
- A history of violence in Syria during the civil war (2011-2017)
- Predict refugee flows
- Analyze reporting biases (compare to Carter Center)
- Domain transfer to learn generalizable features (e.g. Yemen?)

Lesson 2:

Data flows in real time

Static models > Dynamic models

Comments/suggestions appreciated!

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(Please talk to me if you know about Hierarchical/Group Lasso)

(Or want to give me research \$)