Teaching Machines to Measure Economic Activities from Satellite Images: Challenges and Solutions

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Our Main Question

How can we teach machines to quantify economic activities from satellite images?

population, consumption, production, income, ...

This Paper

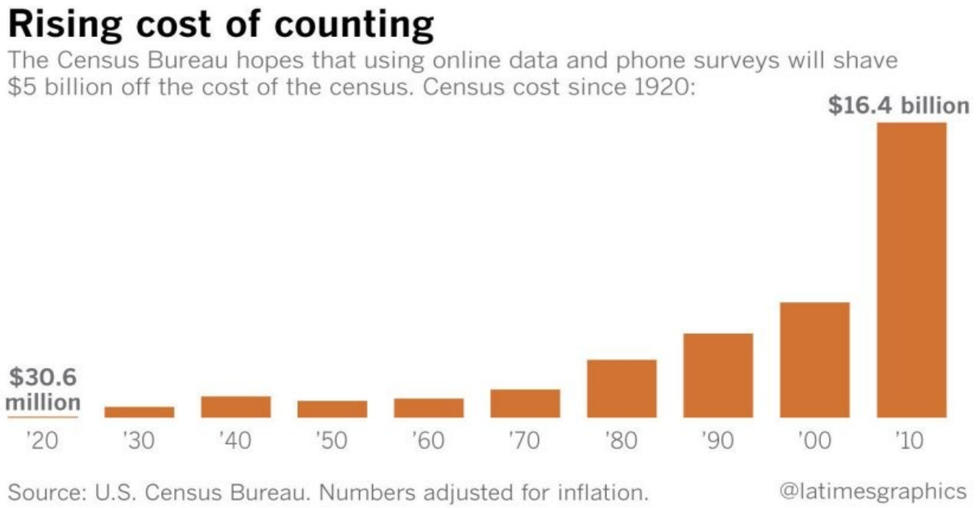
- **Advantages & challenges of using satellite imagery**
- **Some of our solutions**
  - when there's no economic data to begin with
  - mismatch in data representation of "economic data-image data"
- **Our future research agenda**
  - Model improvement
  - Validation of the measures
  - economic applications

Satellite Images in the Economic Literature

- **Nightlight imagery**
  - as a proxy for economic output: Chen and Nordhaus (2011), Henderson et al. (2012), Pinkovskiy and Sala-i-Martin (2016)
  - energy consumption: Xie and Weng (2016)
  - urban growth in developing countries: Dingel et al. (2019), Michalopoulos and Papaioannou (2013), Storeygard (2016)
- **High-resolution daytime satellite imagery**
  - land cover classification: Jayachandran et al. (2017) - measure deforestation in Uganda, Baragwannath et al. (2019) - detecting urban markets in India
  - Jean et al. (2016) predict poverty across African countries

Advantages of Satellite Images & Geospatial Data

- **Advantages in using daytime satellite imagery & geospatial data for economic measurements**
  - wide geographic coverage
  - high spatial resolution (hyperlocality)
  - consistency
  - high-frequency
  - automatability
  - time-/cost- efficiency



Applying Deep Learning to Satellite Images

- **Our goal**

Population: 30,000,
Income: $1.8B,
Inequality (Gini): 0.3

- **Data we need to train the machine**
    - a set of satellite images
    - a corresponding economic data set (ground-truth) - a set of numbers that we eventually want to predict for each image
    - labels for each image: it'll guide machines to what to look for in images when they learn 'image-number' matches

Challenges in Applying Deep Learning to Satellite Images

1) **Defining economic labels**
    - Urban vs. rural
    - Production labels
    - Land cover categories
2) **Data labeling to construct ground-truth**
    - Construction of a big, labeled data set of high quality

Challenges in Applying Deep Learning to Satellite Images

3) **Lack of available ground-truth economic data**
   - Developing countries with poor infrastructure of traditional surveys
   - North Korea
4) **Mismatch in data representation**
   - Machines need to match district-level economic data with grid-level image data

Challenges in Applying Deep Learning to Satellite Images

5) **Overfitting problem**
6) **Generalizability problem**
7) **Black box problem - lack of interpretability**

Challenges that We've Tackled

1) Defining economic labels
2) Data labeling to construct ground-truth
3) **Lack of available ground-truth economic data**
4) **Mismatch in data representation: district-level vs. grid-level**
5) Overfitting problem
6) Generalizability problem
7) Black box problem - lack of interpretability

Challenges that We’ve Tackled

1) Defining economic labels
2) Data labeling to construct ground-truth
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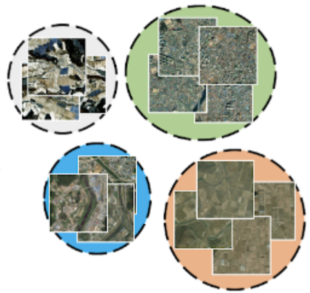
When There's No Ground-Truth

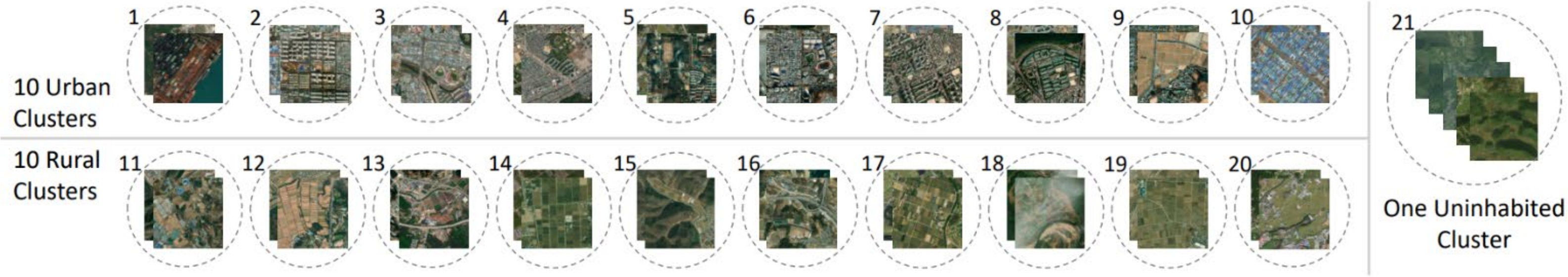
- **Our task here: How can we measure economic development without ground truth?**
- *"Learning to Score Economic Development from Satellite Imagery"* KDD 2020
- **Idea**
    - learn to "rank" relative scores for given satellite images
    - *Human-in-the-loop* solution: light-weight annotating of relative scores

Model - 1st stage: Clustering

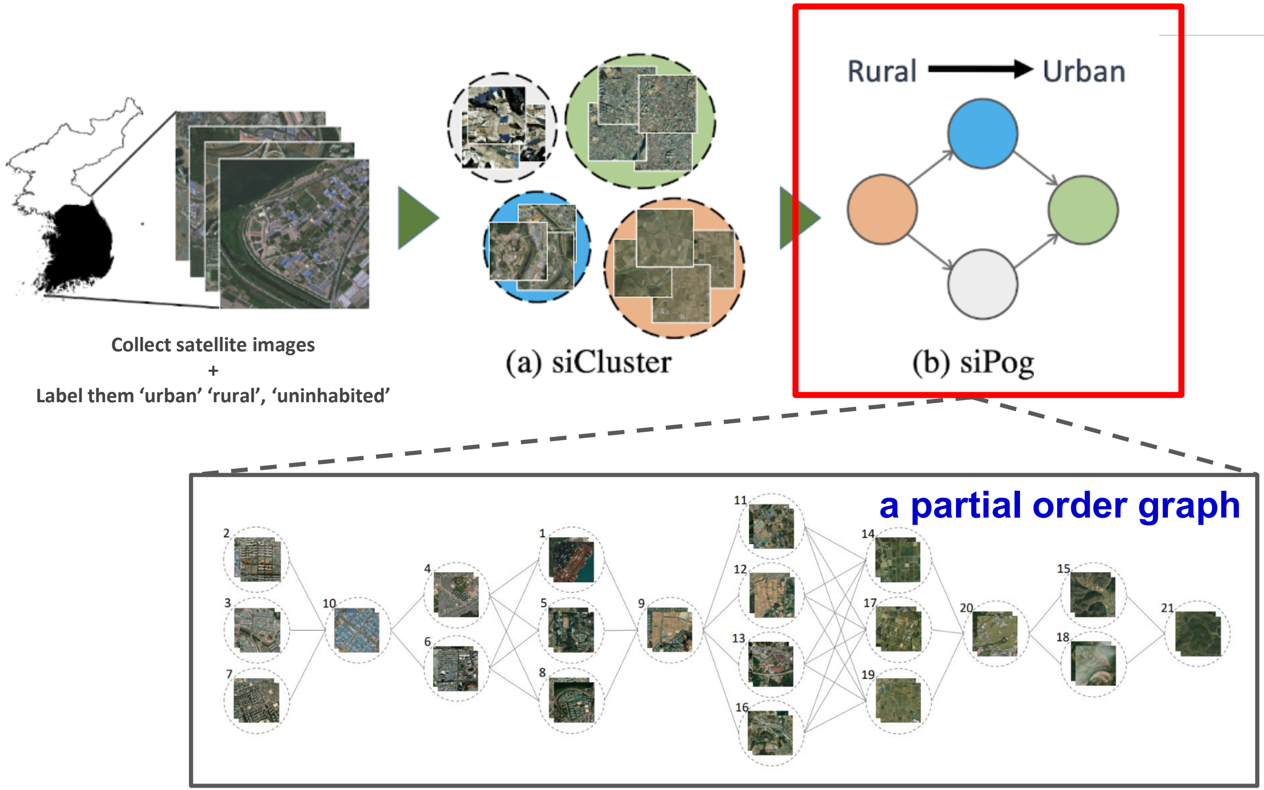
Collect satellite images
+
Label them ‘urban’ ‘rural’, ‘uninhabited’



(a) siCluster



Model - 2nd stage: Partial Order Graph (POG)



Cluster order

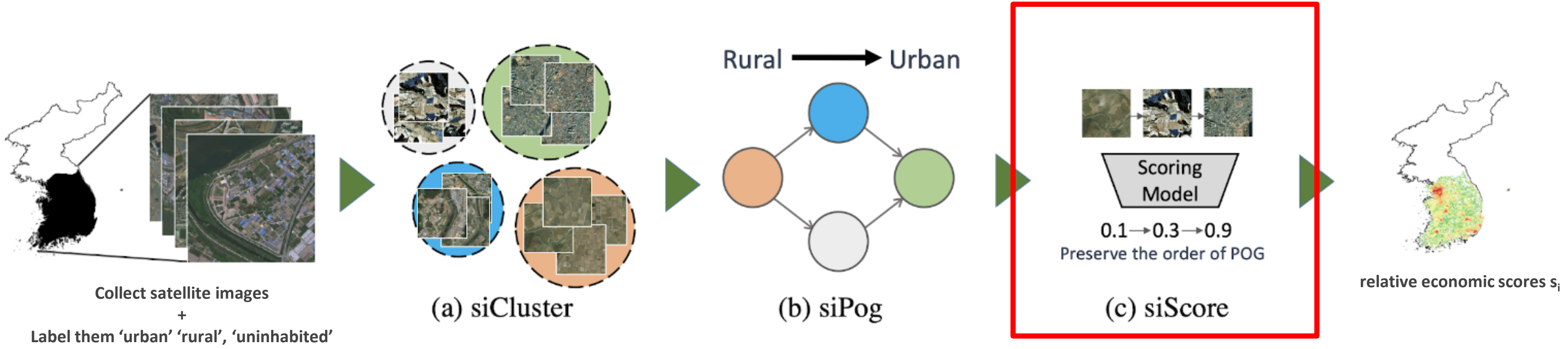
Human guided

- (Local) experts

Data guided

- Existing economic stats
- Nightlight data

Model - 3rd stage: Scoring



Maximize the spearman's rank correlation with the differentiable sorter $rank(s_i)$.

$$\max_{f} \left(1 - \frac{6||rank(\mathbf{s}_i) - \mathbf{r}_j||_2^2}{m(m^2-1)}\right)$$

Experiment

Satellite Image Data
Daytime satellite images from DigitalGlobe
(zoom level = 15, 4.8m resolution)

South Korea
96,131 images

Vietnam
226,305 images

Malawi
64,303 images

Partial Order Graph

by human experts based on the criteria “which cluster is more urbanized”

by population density from census

by nightlight intensity

Result

Our model outperforms other baselines and all components contribute to performance gain.

	Method	Gross Floor Area		Population	
		Spearman	Pearson	Spearman	Pearson
A	Human-guided (Avg)	0.825	0.787	0.764	0.766
	Human-guided (Max)	**0.851**	0.800	**0.795**	0.778
	Census-guided	0.826	0.799	0.792	0.788
	Nightlight-guided	0.846	0.801	0.794	0.789
B	Nightlight-only	0.664	0.655	0.728	0.731
	Pairwise (Human)	0.651	0.610	0.300	0.302
C	K-means	0.434	0.587	0.451	0.557
	DeepCluster	0.618	0.559	0.532	0.551
D	Triplet (POG)	0.807	0.754	0.768	0.726
	Pairwise (POG)	0.825	0.759	0.767	0.739
	w/o Score model	0.737	0.675	0.678	0.673

A : Our model, B : Baselines, C : siCluster ablation, D : siScore ablation

Limitations

- **Model sensitivity**
    - image resolution
    - construction of POG
    - other model parameters
- **Generalizability over more countries and over time**
- **Linearity**
    - cannot sum up the scores for an arbitrary size area

Our Future Research Agenda - Technical

- **Model Improvement**
  - improve the model precision
  - solve the linearity issue
- **Model validation**
  - for cross-region and time-series analysis
  - for different economic measures
  - over different image resolutions
- **How can make it interpretable?**

Our Future Research Agenda - Applications

- **Alternative measure for regional inequality**
- **Applications on developing countries**
  - focus on developing economies in Africa and Southeast asia
- **Studies on North Korean economies**
  - regime changes, sanctions, market institutions, …

THE END OF MAIN SLIDES

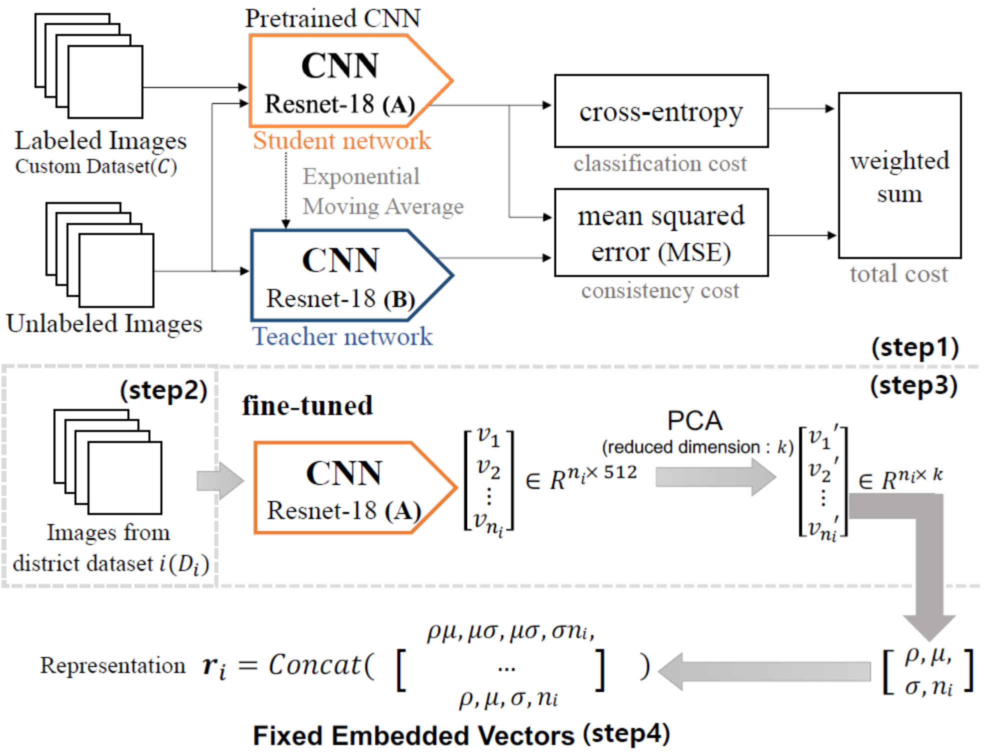
Extra Slides for the Other Model

“Lightweight and Robust Representation of Economic Scales from Satellite Imagery,” AAAI 2019

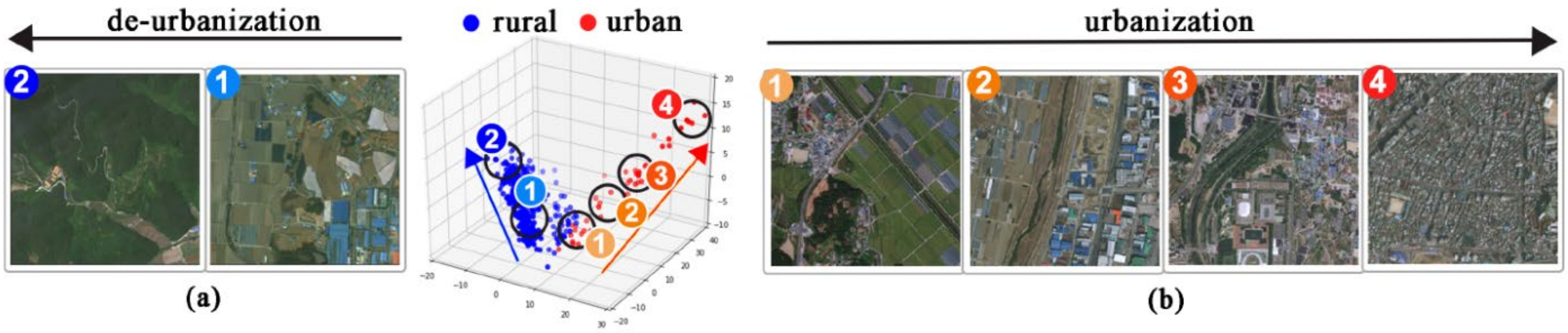
Mismatch in Representation

- **Challenge: adjusting units of economic data & geospatial data**
  - grid-level or administrative units?
  - Information loss when a grid-level data is aggregated into administrative units
- **Our task here: constructing a representation per administrative unit of area from grid-level satellite images, minimizing loss of information**
- **Idea: learn spatial features and extract key fixed-length features from any number of satellite images**

Model Structure



Graphical Representation of an Embedded



Prediction Performance

Model	MSE	R-Squared
Nightlight	0.4254±0.0664	0.6133±0.0635
Auto-Encoder	1.6242±0.3445	0.6347±0.0823
No-Proxy	0.2800±0.1118	0.7359±0.1117
JMOP	0.4448±0.0998	0.8985±0.0253
SOTA	-	**0.9231**
READ w/o μ	0.2612±0.0632	0.9429±0.0155
READ w/o ρ	0.2165±0.0596	0.9527±0.0140
READ w/o n	0.1921±0.0471	0.9579±0.0119
READ w/o σ	0.1902±0.0592	0.9586±0.0130
READ	**0.1761±0.0383**	**0.9617±0.0090**

Note: The performance tests were made for prediction of population density.