Estimating economic outcomes using conv. neural networks and satellite imagery

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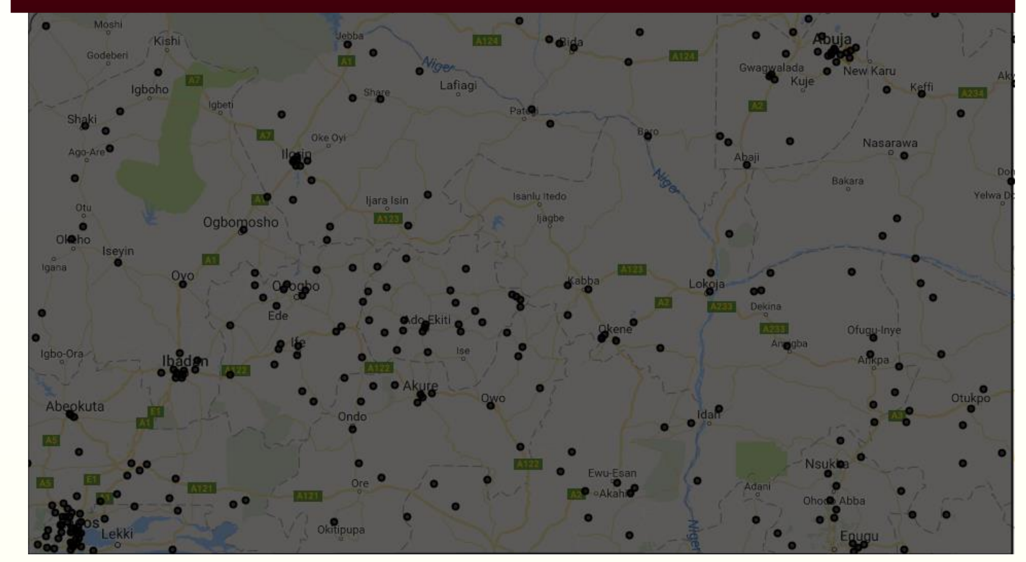
Background

•Developing economies can have few reliable measures of economic conditions

•QUESTION: can we use publicly available Landsat 7 satellite imagery to estimate ground-truth economic measures?

•SOLUTION: exploit transfer learning to train a convolutional neural network (CNN) to estimate wealth given publicly available satellite imagery

Data: DHS survey locations



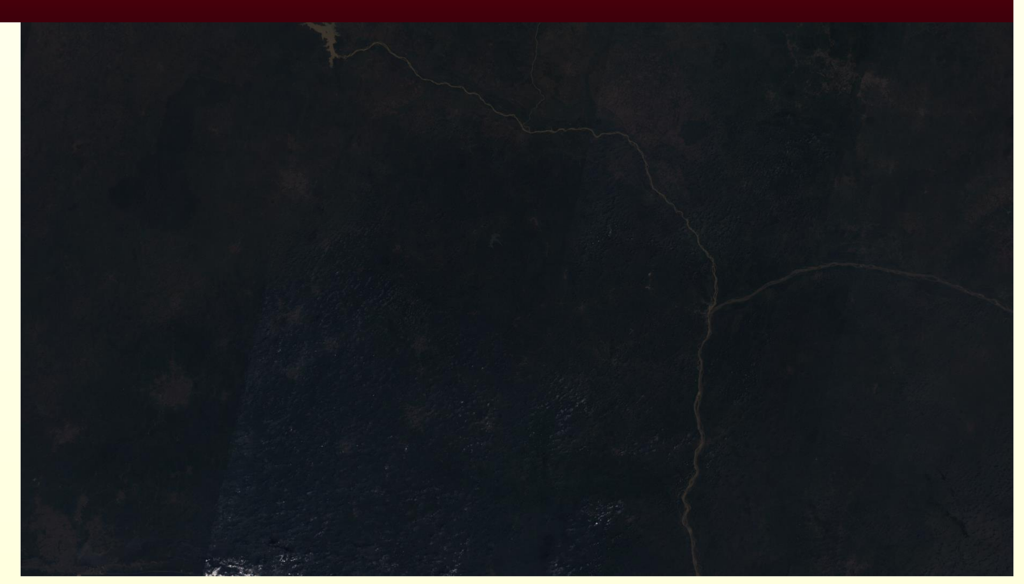
Cluster count	279
Mean asset index	54,925
Std asset index	72,651

Data: Landsat 7 satellite

•3 bands (Red-Green-Blue)

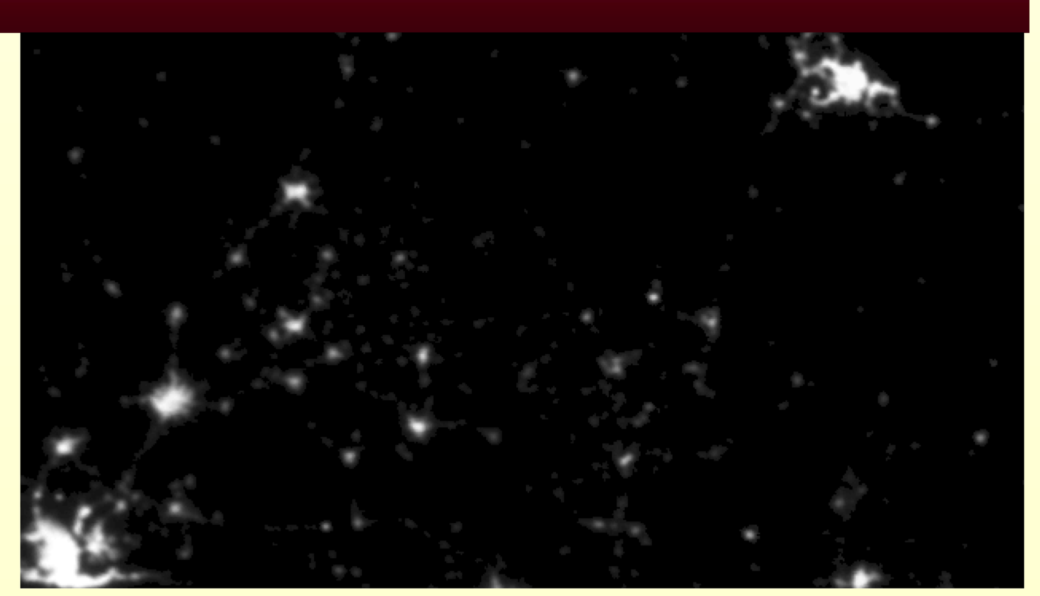
•30 meter resolution

•Region around mega-city of Lagos, Nigeria



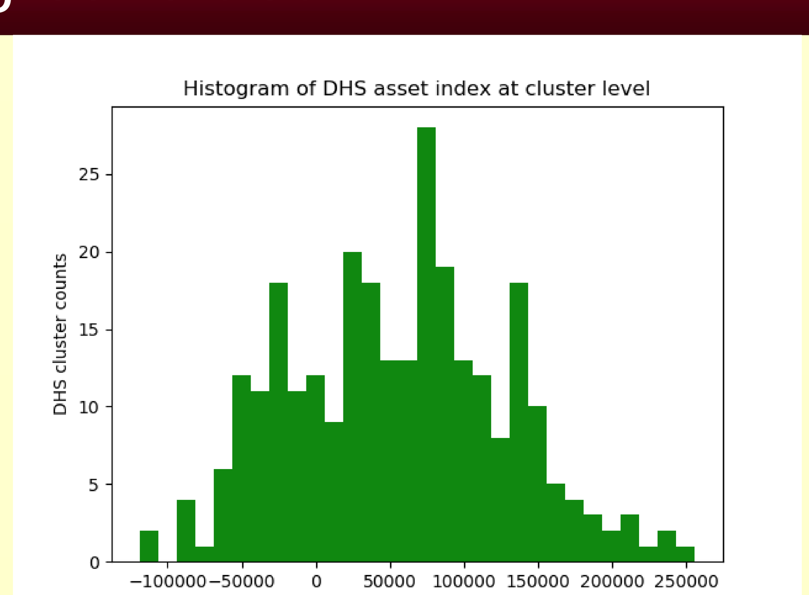
Data: Night-time luminosity

- 1 band (1-63 light intensity)
- 1 km resolution
- Night-time luminosity is correlated with economic activity



Data: economic ground truth

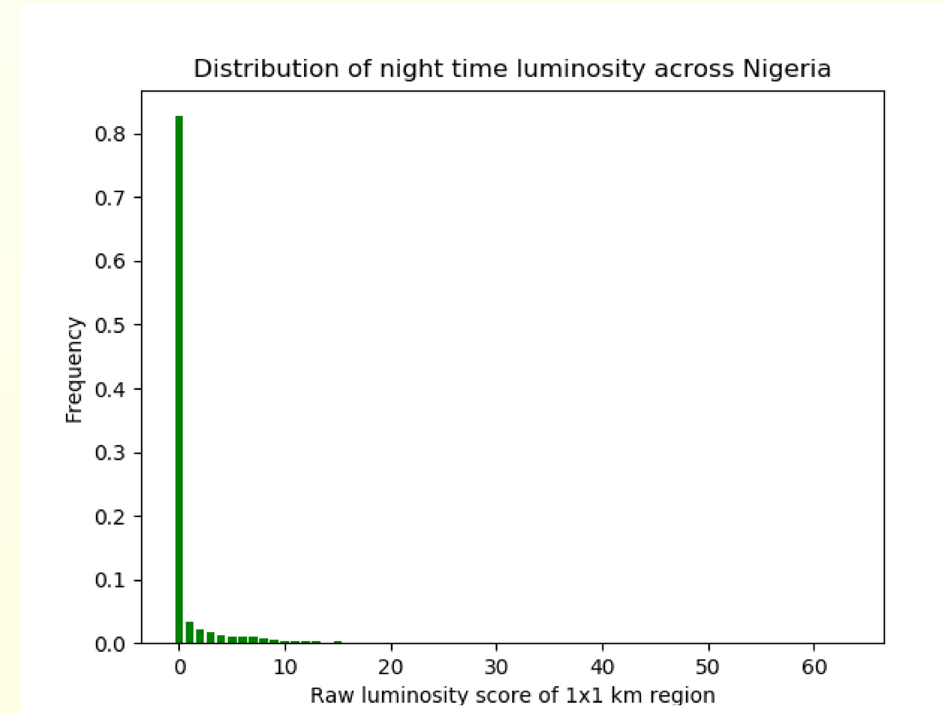
- Asset index from DHS survey Nigeria
- Households aggregated to cluster level analysis

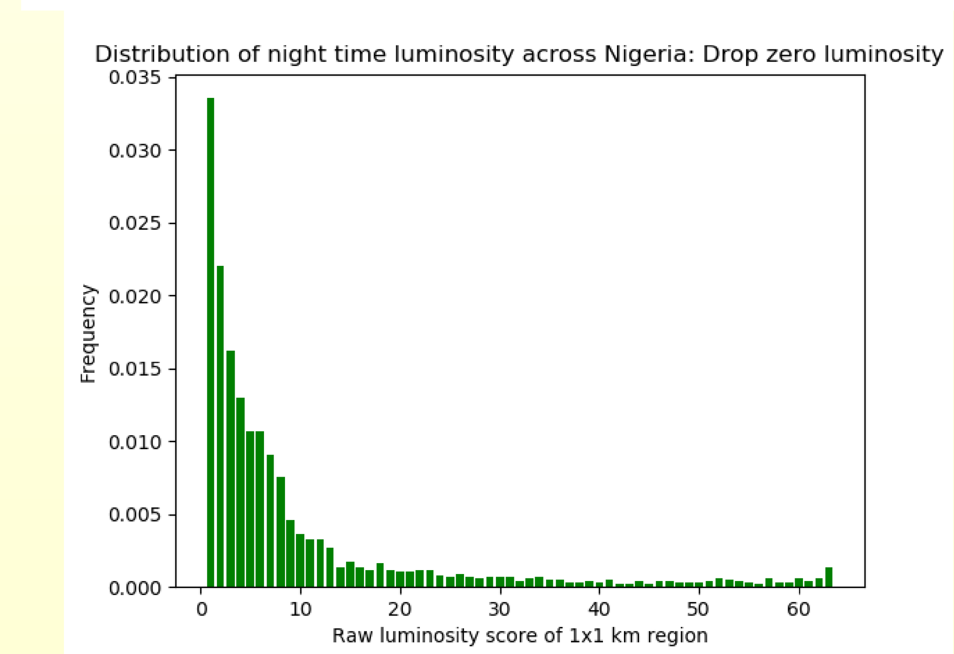


Training #1: Landsat to Luminosity

- Insufficient DHS cluster data to directly train CNN (279 clusters)
- Train CNN to predict night-time luminosity given a daytime Landsat image (>30,000 image pairs)

But luminosity is unbalanced



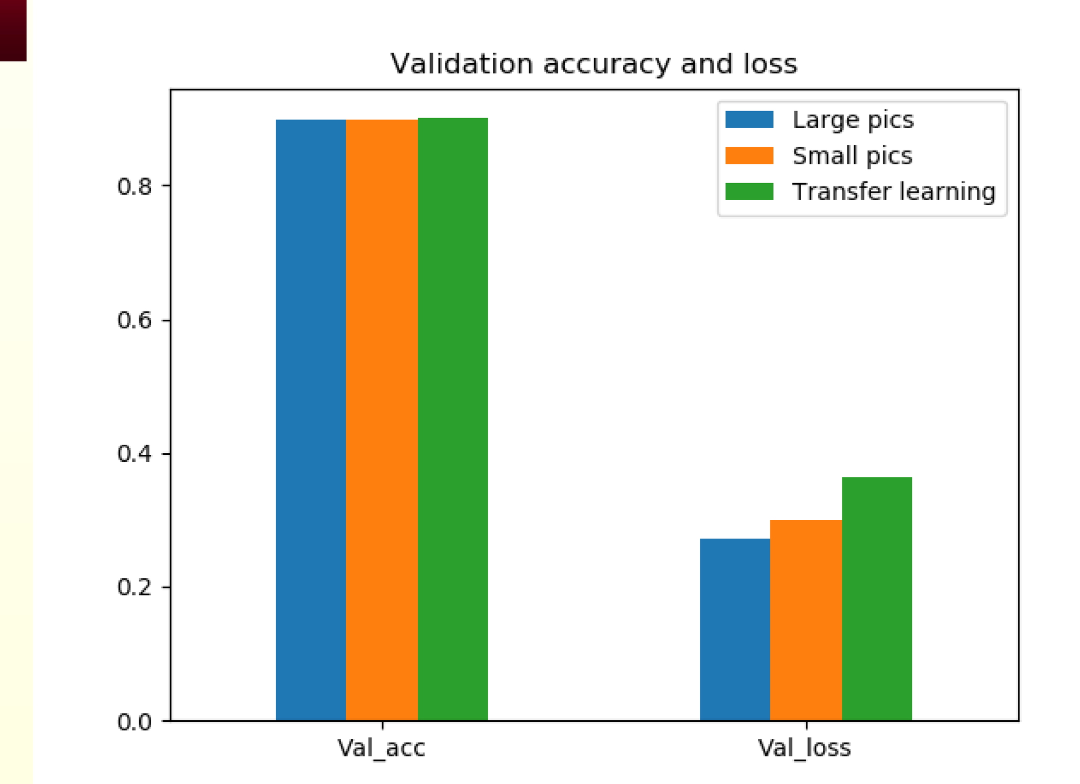


And 30m resolution does not allow for traditional object detection

- Resulting 34x34 pixel images are much smaller than most computer vision tasks
- Can meaningful features be extracted from coarse imagery?
- Does transfer learning from ImageNet-trained models still apply?

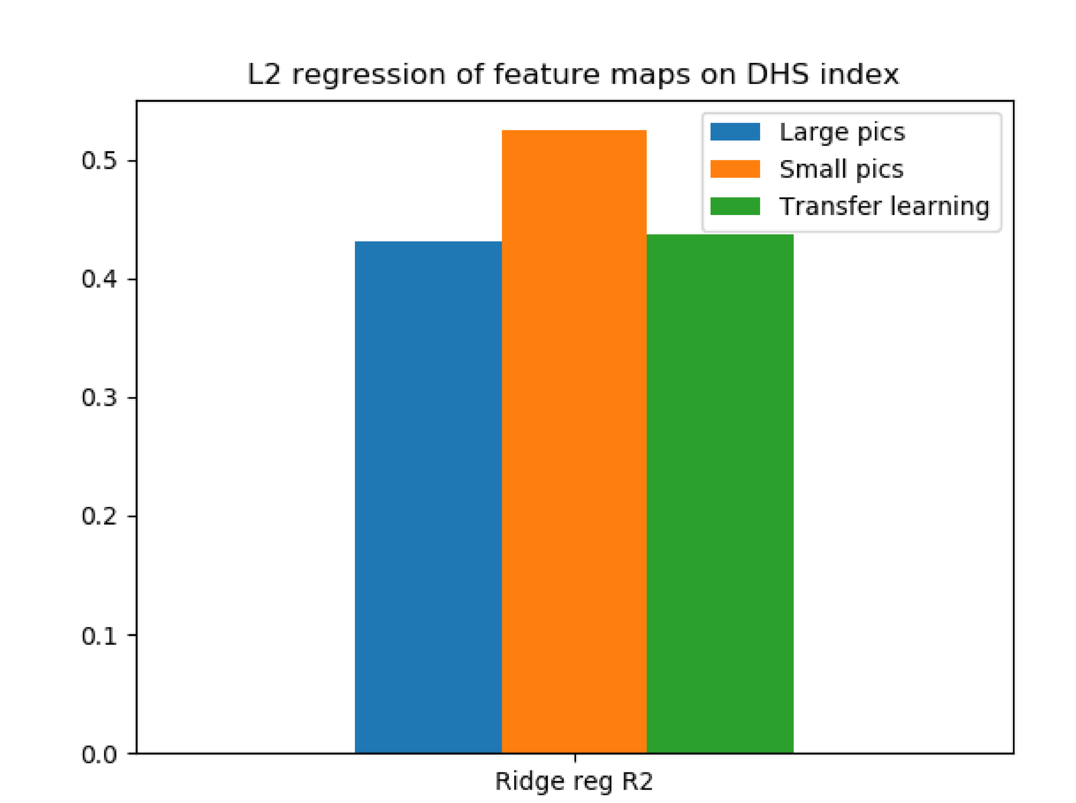
Results of CNN training

Model	Param count	Weight init
Large pic	2,602,179	Rand
Small pic	11,275,779	Rand
Transfer	877,571	VGG16



Training #2: Using the trained CNN as a feature extractor

- Features derived from Landsat images that are predictive of night-time luminosity which is correlated with economic activity



Conclusion

Features learned by convolutional neural networks when identifying night-time luminosity from day-time Landsat images do explain cross-sectional variations in economic outcomes, as measured by an asset index

Limitations

- Model is highly unbalanced – need to implement asymmetric loss function or stratified sample from map
- More fine-tuning of CNN structure
- Transfer learning options in Keras are extremely limited and often incompatible
- Computational restraints from using free trial Google Compute

Future developments

- All satellite data exists as time-series as well
- Can apply video classification techniques to identify patterns in time-series developments of economic conditions

Acknowledgements

Relies heavily on Jean (2016) “Combining satellite imagery and machine learning to predict poverty”