Distributed energy resource and infrastructure assessment using overhead imagery

Duke University Energy Data Analytics Lab

Kyle Bradbury, Jordan Malof, Bohao Huang, Artem Streltsov, and Leslie Collins
Global, automated assessment of energy infrastructure…

…to develop pathways to sustainably meet energy needs.
1. Supply
2. Transmission & Distribution
3. Demand
4. Access
1 Distributed energy supply
Goal: estimate solar array locations, power capacity, and energy generation

Public estimates of distributed solar are generally limited to state or national scales (U.S. EIA)
Estimating Energy from Distributed Solar Using Satellite Imagery

Process:
1. Input Satellite Imagery
2. Solar Array Detection
3. Power Capacity Estimation
4. Generated Energy Estimation
5. Regional insolation data
6. High-resolution estimates of solar energy

Example:
- 4,750 Watts
- 6.94 MWh

Malof et al. 2017
Solar PV Data

Dataset created by summer 2015 Data+ team and published in Scientific Data

19,000+ manually annotated solar arrays from 4 CA cities

Can be used to train deep learning techniques


Available for download at: https://doi.org/10.6084/m9.figshare.c.3255643.v2
Convolutional Neural Networks

Input Image

Convolution → ReLU → rectified linear units → Pooling → Convolution → ReLU → rectified linear units → Pooling → Convolution → ReLU → rectified linear units → Pooling → Convolution → ReLU → rectified linear units → Pooling → FC

→ Flower
→ Cup
→ Car
→ Tree

Every feature map output is the result of applying a filter to the image. The new feature map is the next input.

Activations of the network at a particular layer

Image from the Mathworks
Sample Results
Using convolutional neural networks (CNN)

Original Image  VGG CNN  SegNet CNN

Capacity & Energy Estimation

Solar array area $\rightarrow$ capacity (kW)

Solar array capacity $\rightarrow$ energy generation (kWh)

---

So et al., 2017
Results

Pixel-wise results:

Object-wise results:

<table>
<thead>
<tr>
<th>City</th>
<th>Precision</th>
<th>Recall</th>
<th>F₁ score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fresno</td>
<td>0.77</td>
<td>0.78</td>
<td>0.77</td>
</tr>
<tr>
<td>Modesto</td>
<td>0.73</td>
<td>0.75</td>
<td>0.74</td>
</tr>
<tr>
<td>Stockton</td>
<td>0.73</td>
<td>0.70</td>
<td>0.71</td>
</tr>
<tr>
<td>Overall</td>
<td>0.76</td>
<td>0.77</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Malof et al., 2019
Installed solar PV capacity estimates
Automated estimates of residential solar PV capacity for CT municipalities

Correlation coefficient of 0.89

(Covers over 14,000 km²)

Reported
Hsu et al., CT Solar Scorecard

Predicted
Malof et al., 2019
2 Transmission & Distribution

Bohao Huang, Artem Streltsov, Kyle Bradbury, Jordan Malof, Submitted 2019

Sample images from Google Maps for demonstration purposes
Over 800 million people lack electricity access

Electricity infrastructure data enables the planning of optimized pathways for electrification for rural communities.
Transmission Data

Annotated transmission, distribution, substation, and power plant imagery data

Data are available at: http://bit.ly/2jy7WvL
Challenge #1

Data resolution and availability

0.15 meter, Airborne (proprietary)

0.3 meter, Satellite WorldView-3 & 4 (proprietary)

0.5 meter, Satellite WorldView-1 & 2 (proprietary)

1 meter, Airborne NAIP (free, extent: USA)

3 meter, Satellite Planet CubeSats (proprietary)

10 meter, Satellite Sentinel (free, extent: global)
Challenge #2
Geographic diversity

Hartford, CT
Tucson, AZ
Colwich, KS
Clyde, NC
References


