OGNet: Towards a Global Oil and Gas Infrastructure Database using Deep Learning on Remotely Sensed Imagery

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O&G Methane Emissions

- Methane accounts for **>¼** of present day warming[1]
- Around **⅓** of anthropogenic methane emissions arise from fossil fuel sector[2]
- Focus on **oil and gas (O&G)** sector
- Multiple methane-measuring satellites in orbit or launching soon

MethaneSAT™

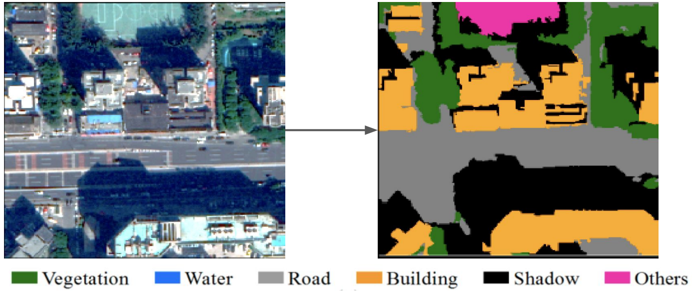
[1]Anthropogenic and natural radiative forcing. *IPCC 2013.*

[2]Global distribution of methane emissions, emission trends, and oh concentrations and trends inferred from an inversion of gosat satellite data for 2010–2015. *Atmospheric Chemistry & Physics 2019.*

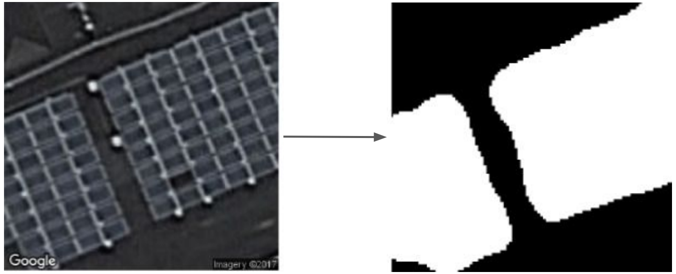
Oil and Gas Infrastructure Data

- To attribute methane emissions, need to know locations of O&G facilities
- Prior efforts to create O&G database
  - GOGI
  - GHGRP
  - HIFLD
  - EIA

Deep Learning on Remotely Sensed Imagery



Land use classification[4,5]



Energy infrastructure classification[6,7]

[4]Semantic segmentation-based building footprint extraction using very high-resolution satellite images and multi-source gis data. *Remote Sensing 2019.*

[5]Urban land use and land cover classification using novel deep learning models based on high spatial resolution satellite imagery. *Sensors 2018.*

[6]Deepsolar: A machine learning framework to efficiently construct a solar deployment database in the united states. *Joule 2018.*

[7]Deepwind: Weakly supervised localization of wind turbines in satellite imagery. *NeurIPS 2019.*

Can deep learning be used to map O&G infrastructure?

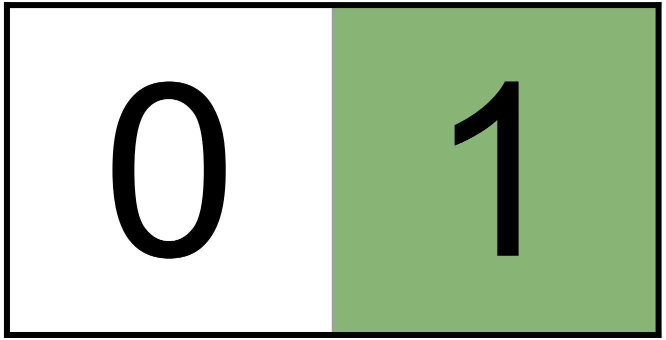
Methods

Task

Input

Aerial Image (NAIP)

Output



Binary Classification
(Contains Oil Refinery)

Dataset Instances

- Positive Examples
  - 149 locations of U.S. oil refineries from Enverus Drillinginfo
- Negative Examples
  - Random coordinates within the U.S.
  - “Difficult” examples via GeoVisual search tool[8]

	Train	Valid	Test
Positive	127	13	9
Negative	5,525	693	697

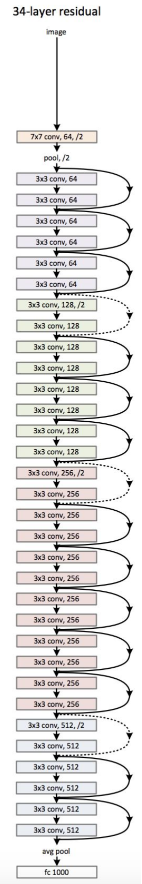
[8]Visual search over billions of aerial and satellite images. *Computer Vision and Image Understanding 2019.*

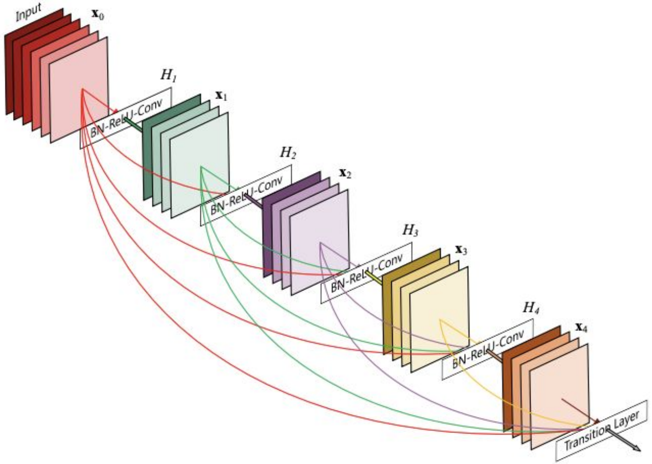
Aerial Imagery

- National Agriculture Imagery Program (NAIP)
  - Publicly available
  - Visible bands (RGB)
  - 2.5m resolution
  - 500 x 500 pixels
- Mosaics of most recent captures

Model Development

- Experimented with ResNet and DenseNet architectures
- Pre-trained on ImageNet
- Data augmentation
  - Vertical/horizontal flips
  - Affine transformation
  - Color jitter





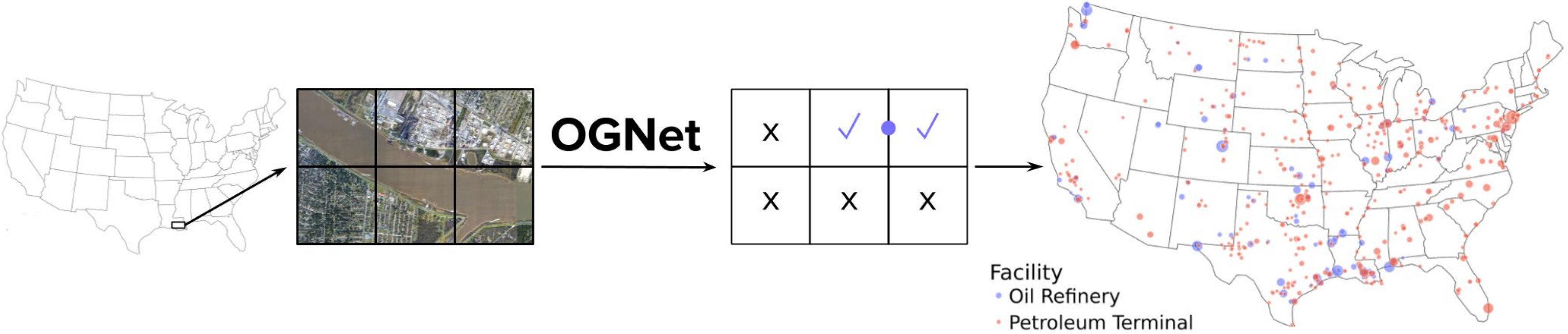
Deep Residual Learning for Image Recognition. *CVPR 2016*.
Densely Connected Convolutional Networks. *CVPR 2017*.

OGNet Test Set Performance

- Best Model: **OGNet** - **O**il & **G**as **Net**work
- 121-layer DenseNet
- Threshold selected for highest precision (0.81) subject to 1.0 recall on the validation set

Accuracy	Precision	Recall	F1-Score
0.996	0.75	1.0	0.857

OGNet Deployment



- Partition continental U.S. into 500 x 500 pixel tiles at 2.5m resolution
  - 5,082,722 total tiles
- Positive-predicted tiles merged with positive-predicted adjacent tiles
  - Coordinate calculated as the mean of tile centroids from merged group

Human Review

- Manually reviewed OGNet detections with expert-designed procedure:
  - Removed false positives
  - Classified as oil refineries or petroleum terminals
  - Identified number of storage tanks per facility

OGNet Deployment Results

	Oil Refinery	Petroleum Terminal
Total Detections	114	336
Coverage of Benchmark Datasets	73.5% (108/147)	23.9% (292/1222)
New Detections	6	142
Example Image		

Limitations and Future Work

High resolution imagery like NAIP not publicly available worldwide

Human review was necessary

0/1

Framing as classification may not work for other infrastructure

Thank you!