Pixel Level Smoke Detection Model with Deep Neural Network

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Introduction

- Biomass burning smoke has numerous detrimental environmental and ecological impacts
  - Respiratory and cardiovascular illnesses
  - Radiation budget
  - Nutrient availability
- Impacts realized both near source and potentially thousands of kilometers downwind depending on
  - Fire duration
  - Amount and type of biomass burned
  - Meteorological and fuel conditions
  - Vertical distribution in the atmosphere

Spatial distribution of MODIS fire occurrence and NOAA HMS smoke for summer 2006-2015. From Kaufus et al. 2017 Figure 2.
Introduction

- Current methods present challenges for continuous smoke detection and monitoring
  - In-situ monitoring
    - Temporal, spatial, and tracer limitations
  - Remote sensing
    - Polar orbiting, once-daily overpass
    - Manual or computational intensive multispectral analysis
    - Large data volumes
    - Multiple class multispectral classification
Objectives

• Deploy a smoke detection model using machine learning on satellite remote sensing observations
  • Leverage observations from the new generation of geostationary satellite
    • High spatial and temporal resolutions over large domains
  • Alternative to multispectral analysis
  • Eliminate time consuming, subjective manual analysis
Truth Dataset

• Geostationary Operational Environmental Satellite 16 shortwave reflectance data
  • Bands 1-6 (0.47, 0.64, 0.86, 1.37, 1.6 and 2.2 μm)
  • Access L1B radiance data from AWS
  • Convert to reflectance
  • Spatially resample to 1km
• National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) smoke analysis
  • Satellite based operational daily analysis of smoke extent over the US and surrounding areas
  • Manual quality controlled by subject matter expert to correctly match smoke extent in GOES 16 image

GOES 16 band 1 radiance with nearest in time HMS shapefiles (magenta and purple)
Truth Dataset

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GOES 16 band 1 radiance with nearest in time HMS shapefiles (magenta and purple) with subject matter quality controlled shapefile (blue).
• Analyze 122 scenes containing smoke
  • 962,691 smoke pixels
    • Over low and high background reflectances (land and ocean)
    • Low and high optical thicknesses
    • Full range of sun angles
  • Contain relevant classes to discriminate smoke from including
    • Snow and ice
    • Clouds
    • Dust
  • 60% - 20% - 20% distribution of smoke pixels between training, validation and testing datasets
• Apply a pixel based Convolutional Neural Network (CNN)
  • Input \((N*2)*(N*2)\) neighborhood of reflectance values surrounding a center pixel (sample)
  • 3 convolutional layers
  • Each convolutional layer followed by max-pooling layer
  • Convolutional outputs are flattened into vectors
Model Architecture

- Apply a pixel based Convolutional Neural Network (CNN)
  - Input \((N*2)^2\) neighborhood of reflectance values surrounding a center pixel (sample)
  - 3 convolutional layers
    - Each convolutional layer followed by max-pooling layer
    - Convolutional outputs are flattened into vectors
Model Architecture
Model Architecture

Input Channel

Filter

190 + 210 + 200 =

Convolved Feature

14

1024

40 25 10 5 1
Model Architecture

- Apply a pixel based Convolutional Neural Network (CNN)
  - Input (N*2)*(N*2) neighborhood of reflectance values surrounding a center pixel (sample)
  - 3 convolutional layers
  - Each followed by max-pooling layer
  - Convolutional outputs are flattened into vectors
Model Architecture

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Model Architecture

• Apply a pixel based Convolutional Neural Network (CNN)
  • 4 fully connected layers with activation function calculation $g(Wx + b)$
    • $x$ is the flattened input vector
    • $W$ is the weight matrix
    • $b$ is the bias vector
  • Dropout for each fully connected layer
Model Architecture

- Apply a pixel based Convolutional Neural Network (CNN)
  - 4 fully connected layers with activation function calculation $g(Wx + b)$
    - $x$ is the flattened input vector
    - $W$ is the weight matrix
    - $b$ is the bias vector
  - Dropout randomly for each fully connected layer
Model Architecture

(a) Standard Neural Net

(b) After applying dropout.
The model outputs the probability, ranging from 0 to 1, that a pixel is smoke determined by a sigmoid function:

\[ p(x) = \frac{1}{1 + e^{-x}} \]

\( p > 0.5 \) threshold applied to define smoke
Neighborhood Selection

- Best neighborhood size (N) determined by iterating model development and testing for increasing N
  - All other parameters including data, learning rate and model hyper-parameters are held constant
- Best model selected when validation loss did not improve for 20 epochs
Development Testing

<table>
<thead>
<tr>
<th>N</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Accuracy</th>
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<tr>
<td>1</td>
<td>0.654</td>
<td>0.328</td>
<td>0.437</td>
<td>0.897</td>
</tr>
<tr>
<td>3</td>
<td>0.650</td>
<td>0.384</td>
<td>0.483</td>
<td>0.900</td>
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<tr>
<td>5</td>
<td>0.724</td>
<td>0.449</td>
<td>0.554</td>
<td>0.912</td>
</tr>
<tr>
<td>7</td>
<td>0.835</td>
<td>0.419</td>
<td>0.558</td>
<td>0.919</td>
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<tr>
<td>9</td>
<td>0.639</td>
<td>0.498</td>
<td>0.560</td>
<td>0.905</td>
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</table>

The F1 Scores, or the harmonic mean of Precision and Recall, for N=5,7,9 is comparable

- Trade-off between quality and quantity of smoke predictions
- Best model has low false positive detection rate which drives high precision
  - Prefer conservative identification over incorrect classification
- Accuracy artifact of large number of True Negatives

\[
\text{Precision} = \frac{TP}{TP + FP} \\
\text{Recall} = \frac{TP}{TP + FN} \\
\text{Accuracy} = \frac{TP + TN}{TP + TN + TP + FN} \\
F1 \text{ Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}
\]
Results

- Model updated to account for variation in solar zenith angle
  - The training and testing datasets for the updated model differ from that used for the initial development
  - Results are comparable between the initial and updated models
- Better predictive capability of smoke over water
  - Compared to land, the relative decrease in true negatives over water drives a slight decrease in accuracy

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<td>Dev.</td>
<td>0.835</td>
<td>0.419</td>
<td>0.558</td>
<td>0.919</td>
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<tr>
<td>All</td>
<td>0.736</td>
<td>0.453</td>
<td>0.561</td>
<td>0.923</td>
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<tr>
<td>Land</td>
<td>0.631</td>
<td>0.383</td>
<td>0.476</td>
<td>0.928</td>
</tr>
<tr>
<td>Water</td>
<td>0.923</td>
<td>0.585</td>
<td>0.717</td>
<td>0.900</td>
</tr>
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</table>
• Smoke identified over both land and ocean
  • Model identifies well defined plumes for scenes with absence of complex features
  • Probabilities resemble visually observed optical thickness
• Predictions closer resemblance to quality controlled shapefiles

GOES 16 pseudo-RGB with contoured model predictions (shading), HMS shapefiles (magenta and purple), and subject matter quality controlled shapefile (blue).
• Distinguishable from chlorophyll commonly found in coastal settings
• Discriminate smoke from fair weather cumulus cloud
• Spectral information for other classes not provided to the model

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<thead>
<tr>
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<th>Accuracy</th>
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<tbody>
<tr>
<td>All</td>
<td>0.744</td>
<td>0.604</td>
<td>0.666</td>
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<tr>
<td>Land</td>
<td>0.847</td>
<td>0.244</td>
<td>0.379</td>
<td>0.976</td>
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<tr>
<td>Water</td>
<td>0.742</td>
<td>0.623</td>
<td>0.677</td>
<td>0.943</td>
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GOES 16 pseudo-RGB (left) with shaded contoured model predictions (right).
• Successfully discriminates land surface snow/ice from smoke
  • Over snow capped mountains for this case
• Detection challenges for optically thin smoke over arid regions

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<tbody>
<tr>
<td>All</td>
<td>0.848</td>
<td>0.318</td>
<td>0.462</td>
<td>0.977</td>
</tr>
<tr>
<td>Land</td>
<td>0.848</td>
<td>0.319</td>
<td>0.463</td>
<td>0.977</td>
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<tr>
<td>Water</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.984</td>
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</tbody>
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GOES 16 pseudo-RGB (left) with shaded contoured model predictions (right).
• Large and small plumes
• Identification over both land and ocean
• Coastal stratus clouds

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<tbody>
<tr>
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<td>0.970</td>
<td>0.919</td>
<td>0.944</td>
<td>0.961</td>
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<tr>
<td>Land</td>
<td>0.904</td>
<td>0.754</td>
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<tr>
<td>Water</td>
<td>0.986</td>
<td>0.965</td>
<td>0.975</td>
<td>0.980</td>
</tr>
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Smoke not detected at very low sun angles
  * Compounded by low optical thickness over relatively high reflective surface
  * Probability of being smoke is low for few pixels that are identified

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<tbody>
<tr>
<td>All</td>
<td>0.995</td>
<td>0.093</td>
<td>0.171</td>
<td>0.823</td>
</tr>
<tr>
<td>Land</td>
<td>0.995</td>
<td>0.093</td>
<td>0.171</td>
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<td>0.923</td>
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<td>0.717</td>
<td>1.000</td>
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GOES 16 pseudo-RGB (left) with shaded contoured model predictions (right).
• Overprediction of plume extent
  • Artifact of large (N=7) neighborhood size
  • Non-zero floor to number of false positives

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<tbody>
<tr>
<td>All</td>
<td>0.830</td>
<td>0.738</td>
<td>0.781</td>
<td>0.981</td>
</tr>
<tr>
<td>Land</td>
<td>0.830</td>
<td>0.738</td>
<td>0.781</td>
<td>0.981</td>
</tr>
<tr>
<td>Water</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.993</td>
</tr>
</tbody>
</table>

GOES 16 pseudo-RGB (left) with shaded contoured model predictions (right).
• Other atmospheric aerosols not classified as smoke
• Large dust storm case
  • Represents a major source of aerosols in the atmosphere
  • Expected over regions where smoke is also common

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<tr>
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<td>N/A</td>
<td>N/A</td>
<td>0.996</td>
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<tr>
<td>Land</td>
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GOES 16 pseudo-RGB (left) with shaded contoured model predictions (right).
Operational Capabilities

- Currently testing new deployment in operational environment
  - Anticipate operational October 2019
- Fully deployed in the cloud using Amazon S3 and Cloud Computing Services
- End-to-end prediction and visualization pipeline
  - Model prediction available ~15 min after data availability
    - Preprocessing ~10 min
    - Prediction and Postprocessing ~5min
  - Full disk GOES observation available ~10 min intervals
Operational Capabilities - Postprocessing

• Spatial grouping of predicted pixels to define plumes
  • Convert predicted pixels to bitmap image
  • Blurring to smoothen edges
  • Contour blurred image to group smoke pixels into plumes
  • Plumes visualized and geojson representation of plume extents available for download in the Phenomena Portal (http://phenomena.surge.sh)
Summary

• Developed end-to-end machine learning smoke detection pipeline for next-generation of geostationary satellites
  • Well curated smoke extent dataset
  • Scalable smoke detection deep learning model, requiring only smoke information, and capable of detecting smoke with:
    • Varying optical thicknesses
    • Over low and high reflectance background surfaces
    • Discriminates from features with spectral similarities
  • Fully automated operational deployment of model in development
    • Plume visualization and extent data accessible in online platform
Future work

• Expand the training data to account for identified weaknesses
  • Low sun angles
  • Thin smoke over arid regions
  • Thin clouds
• Refinement of the machine learning model
  • Confirmation of N=7 as best performing model
    • Explore trade-off between neighborhood size and prediction capabilities
  • Stepwise band selection considering all 16 GOES bands
  • Robust model validation
    • Band exclusion to identify contribution to feature learning
• Performance assessment for operational improvements
Thank you!

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