Automated Detection of Weather Fronts Using a Deep Learning Neural Network

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Motivation

• The Goal – Understand how Precipitation Frequency estimates across North America (NA) will change as the climate changes.
• Extreme precipitation associated with weather fronts is the dominant contributor over most of North America.
• We need to understand how weather front behavior will change as the climate changes.
• Automated front detection will be required.
The Problem Space

• Weather front detection is still a manual process.
• Visual recognition problems are often good candidates for Neural Network solutions.
• A ”supervised learning” neural network approach requires truth data.
Training Data

- We used NASA Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) with data from 1980-2018 for our inputs. We used pressure difference from a moving 30-day mean, near-surface air temperature, specific humidity, and vector wind velocity.

- Used the Coded Surface Bulletin (CSB) digitized front polyline dataset with data from 2003-2018 for our labels to train against.
Training Data

• Used a 1x1° data grid centered over North America (10–70N x 171–31W).
• Converted the CSB polylines to gridded maps with lines drawn 3 grid cells wide.
• CSB data grid layers:
  – Cold fronts
  – Warm fronts
  – Stationary fronts
  – Occluded fronts
  – No front
Neural Networks

• Neural networks are composed of simplistic analogs of biological neurons organized in layers.

• Here is the basic structure of a machine learning neuron.

\[ O = f \left( b + \sum_i w_i I_i \right) \]

• A non-linear function of a linear superposition of a set of input values.
Neural Networks

\[ \sum_{i=1}^{n} \sum_{j=1}^{w} b_i + \sum_{i=1}^{n} w_i \sum_{j=1}^{w} + \sum_{i=1}^{n} w_n \sum_{j=1}^{w} \]
Neural Networks

- A neural network is formed by building layers where the outputs from one set of neurons are used as inputs to another set.
Neural Networks

• In the 1960s, mathematicians proved that any complex function of multiple inputs can be decomposed into a combination of linear superpositions and simple non-linear functions applied to the inputs.

• This is, in essence, a neural network with one interior (hidden) layer.

• The problem is finding the appropriate functions and weights!
In supervised machine learning, the weights are found through hyper-dimensional gradient descent.

- Produce outputs for a number of inputs with a network initialized with random weights and biases.
- Use the discrepancy between network outputs and “truth” outputs to update the weights and biases to minimize the difference.
- Repeat many times.
Neural Networks

• Finding a good network design for your problem is an art.
• Take care, because it is possible to memorize the right answer for each input rather than learn the underlying functional relationships (overfitting).
Network Design

2 pixel Zero Pad then 2D Convolution with 5x5 kernel and 80 filters with 50% 2D Dropout

5 data grids
80 feature maps
80 feature maps
80 feature maps
5 categories

2 pixel Zero pad then 2D Convolution with 5x5 kernel and 5 filters
Training

• Trained with data from 2008-2012.
• Randomly selected ¼ of the possible 17x17 grid cell input patches while also ensuring that there were twice as many “no front” patches as “front” patches.
• Limited training and testing to region around CONUS where the rate of front crossings was 40/year or better.
• Training took ~3 days on a NERSC GPU node.
Training Results

Network training loss
- Training
- Validation

Network training accuracy
- Training
- Validation
## Training Results

### CSB Labels 2003 - 2018

<table>
<thead>
<tr>
<th></th>
<th>Cold</th>
<th>Warm</th>
<th>Stationary</th>
<th>Occluded</th>
<th>None</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counts</td>
<td>8,551,914</td>
<td>4,631,517</td>
<td>12,797,269</td>
<td>3,893,614</td>
<td>182,795,286</td>
<td>212,669,600</td>
</tr>
<tr>
<td>Percent</td>
<td>4.02%</td>
<td>2.18%</td>
<td>6.02%</td>
<td>1.83%</td>
<td>85.95%</td>
<td></td>
</tr>
</tbody>
</table>

### MERRA-2 Predictions 2003 - 2018

<table>
<thead>
<tr>
<th></th>
<th>Cold</th>
<th>Warm</th>
<th>Stationary</th>
<th>Occluded</th>
<th>None</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counts</td>
<td>8,950,546</td>
<td>2,785,315</td>
<td>10,867,527</td>
<td>4,098,013</td>
<td>185,968,199</td>
<td>212,669,600</td>
</tr>
<tr>
<td>Percent</td>
<td>4.21%</td>
<td>1.31%</td>
<td>5.11%</td>
<td>1.93%</td>
<td>87.44%</td>
<td></td>
</tr>
</tbody>
</table>
# Training Results

## Confusion Matrix

### 2008-2015

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cold</td>
<td>Warm</td>
<td>Stationary</td>
<td>Occluded</td>
<td>None</td>
</tr>
<tr>
<td>Cold</td>
<td>4,118,370</td>
<td>166,264</td>
<td>754,909</td>
<td>231,514</td>
<td>3,280,857</td>
</tr>
<tr>
<td>Warm</td>
<td>214,405</td>
<td>1,104,025</td>
<td>743,101</td>
<td>300,147</td>
<td>2,269,839</td>
</tr>
<tr>
<td>Actual Stationary</td>
<td>990,596</td>
<td>244,167</td>
<td>4,464,480</td>
<td>127,063</td>
<td>6,970,963</td>
</tr>
<tr>
<td>Occluded</td>
<td>194,304</td>
<td>128,904</td>
<td>201,375</td>
<td>1,643,822</td>
<td>1,725,209</td>
</tr>
<tr>
<td>None</td>
<td>3,432,871</td>
<td>1,141,955</td>
<td>4,703,662</td>
<td>1,795,467</td>
<td>171,721,331</td>
</tr>
</tbody>
</table>
### Front/No-Front Confusion Matrix 2003-2018

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Front</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>15,627,446</td>
<td>14,246,868</td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>11,073,955</td>
<td>171,721,331</td>
<td></td>
</tr>
</tbody>
</table>
Training Results

Receiver Operating Characteristic (All Front Types)

Precision-Recall (All Front Types)
Training Results

Front Identification Comparison

Human Surface Analysis

Deep Learning Analysis

2009-01-01 00:00:00

- Cold
- Warm
- Occluded
- Stationary
Training Results

• The performance of the network may be better than the metrics suggest.
• It may be more conservative about drawing weak fronts.
• Slight geographic offsets count as misses.
• Differences in type of front count as misses.
Front Climatologies

• Goal of the front detection work was to develop front climatologies.
• Decided to measure the rate at which fronts of each type crossed each 1°x1° grid cell.
• Also measured the rate at which fronts of any type crossed each cell.
• Calculated climatologies for CSB and for MERRA-2 network outputs.
Front Climatologies

- For MERRA-2, extracted polylines from the front probability data grids produced by the network.
- Produced hard-edged 3-cell-wide data grids on 3-hourly time steps.
- Stacked the data grids to produce a “front event” time series for each front type for each grid cell.
Front Climatologies

• Filtered each time series by removing the front events that were within 24 hours after each initial event to prevent overcounting.
• Produced front-crossing rates by month and season from the counts.
• Averaged the rates by month and season over years to produce monthly and seasonal front crossing rate climatologies.
MERRA-2 vs CSB Climatology

- Produced climatologies as described for MERRA-2 network outputs.
- Produced climatologies the same way for the CSB dataset.
- Used the 2003-2018 overlapping time frame for each.
- Also averaged the results over a CONUS-centered region spanning 20N – 50N, 125W – 65W.
MERRA-2 vs CSB Climatology

CSB

Dec-Jan-Feb

Mar-Apr-May

Jun-Jul-Aug

Sep-Oct-Nov

MERRA-2
MERRA-2 vs CSB Climatology

Dec-Jan-Feb

- $R = 0.938$
- mean = 0.000
- $\sigma = 0.333$
- $b = -0.577$
- $m = 1.166$

Mar-Apr-May

- $R = 0.915$
- mean = 0.000
- $\sigma = 0.290$
- $b = -0.323$
- $m = 1.060$

Jun-Jul-Aug

- $R = 0.939$
- mean = $-0.000$
- $\sigma = 0.316$
- $b = -0.285$
- $m = 1.042$

Sep-Oct-Nov

- $R = 0.907$
- mean = 0.000
- $\sigma = 0.297$
- $b = -0.485$
- $m = 1.116$
MERRA-2 vs CSB Climatology

Front Crossing Rate Climatologies
Mean over CONUS ROI

Events/Week

DjF    MAM    JJA    SON

CSB
MERRA-2
Conclusions

• The network appears to perform well.
• Hard to determine if further training is warranted.
• Need to try different network architectures.
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