Interpretable Deep Learning Representations of Hail Growth Processes

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Motivation

• Most current hail forecast methods are built on storm environment variables (e.g., CAPE, shear)

• However, storm morphology and the spatial distribution of wind, temperature, and moisture also influence the size of hail produced by a storm

• Deep learning models have the ability to encode spatial features

• Questions
  • Can deep learning create representations of spatial weather data that increase skill of hail predictions?
  • What storm features do deep learning models encode, and are they physically relevant for hail prediction?
What Is Deep Learning?

**Artificial Intelligence**
Methods for computer systems to perform human tasks

**Expert Systems**
Operate autonomously with human specified rules. (e.g. fuzzy logic)

**Machine Learning**
Mathematical models with specified structure learn to perform tasks from data

**Deep Learning**
Neural networks with multiple specialized layers for encoding structural information
Neural Network Basics

Artificial Neural Network Structure

Training Procedure
1. Send batch of training examples through network
2. Calculate prediction error
3. Calculate error gradients back through layers and update weights
4. Repeat over all training examples until errors are satisfactory

Definitions
Batch: subset of training examples used to update weights
Epoch: One pass through all examples in training set

Images from http://cs231n.github.io/convolutional-networks/
Convolutional Neural Network

Deep neural network that encodes spatial information with iteratively optimized convolutional filters

Source:
Test Problem: Hail Prediction with Perfect Model

**NWP Model:** NCAR MMM Convection-Allowing Ensemble (10 3-km WRF-ARW members)

**Run Dates:** 3 May – 3 June 2016
- 22 training days (~82000 storms)
- 10 testing days (~32000 storms)

**Storm Extraction:** Identified updrafts with vertical velocity > 10 m/s

**Storm Patch:** 32x32 box centered on updraft track

**Target:** Microphysics max surface hail size in next hour > 25 mm?
Machine Learning Procedure

Normalized Input Data
Input Variables
• Geopotential height
• Temperature
• Dewpoint
• Zonal (u) Wind
• Meridional (v) Wind
Pressure Levels
• 500 mb
• 700 mb
• 850 mb

Randomly split data into train and test days 30 times

Calculate spatial mean of each field
Principal Component Analysis transform
Encode data with Generative Adversarial Network

Logistic Regression
Logistic Regression
Logistic Regression
Logistic Regression

Convolutional Neural Network

Output:
Probability of NWP-simulated hail > 25 mm

Validate different combinations of model parameters and pick best ones
Severe Hail Verification

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th>Brier Skill Score</th>
<th>BSS Reliability</th>
<th>BSS Resolution</th>
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<tbody>
<tr>
<td>Logistic Mean</td>
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</tbody>
</table>
Feature Visualization by Optimization

1. Start with all 0s storm patch
2. Send input forward through net to get error
3. Pass error back through net to get change in input
4. Update input by subtracting error derivative

Repeat steps 2-4 until prediction matches desired output
Optimized Conv Net Hailstorm

Red: Temperature
Green: Dewpoint
Filled Contours: Geopotential Height

Confluent warm, moist air
Strong lapse rates
Directional wind shear
Optimized Conv Net Hailstorm

Red: Temperature
Green: Dewpoint
Filled Contours: Geopotential Height

Feeder-Seeder Mechanism (Heymsfield 1980)
Hailstorm Neuron Activations

Top Convolution Filter Gradients: Network 3
Spatio-temporal Distribution of Storm Types

Activated Storm Spatial Distributions

Activated Storm Diurnal Distribution

- Filter 0 (Bow Echo)
- Filter 2 (Supercell)
Variable Importance Scores

Conv Net AUC

Conv Net BSS

Logistic Mean AUC

Logistic Mean BSS
Summary

• Convolutional neural networks produce more skilled hail predictions than other methods thanks to optimized spatial feature encoding
• Convolutional neural networks encode storm structures associated with large hail
• Internal neurons represent different storm morphologies
• Monthly Weather Review paper in preparation
• Try out deep learning for mesocyclone prediction: github.com/djgagne/swirlnet

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How do I get started?

• Software
  • Anaconda Python Distribution
  • Tensorflow and Keras (available in Python and R)
  • PyTorch

• Books
  • Deep Learning by Ian Goodfellow et al.
  • Deep Learning with Python by Francois Chollet

• Tutorials
  • Swirlnet: https://github.com/djgagne/swirlnet
    • Predict mesocyclones with deep learning
  • Stanford CS231n: http://cs231n.github.io/
    • Great notes and visuals explaining convolutional neural networks