Spatial Structure Evaluation of Unsupervised Deep Learning for Atmospheric Data

David John Gagne II, Sue Ellen Haupt, and Doug Nychka

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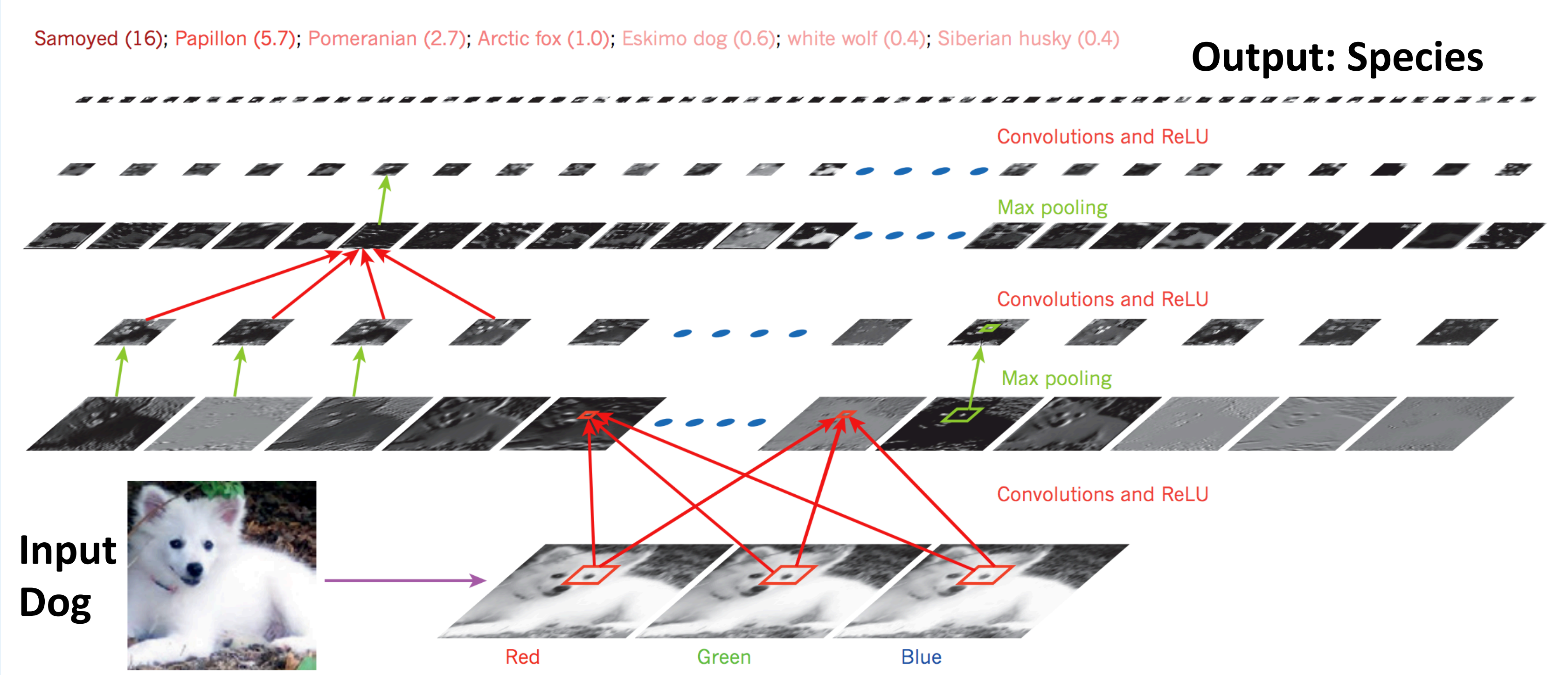
Motivation

- Random forests and other traditional machine learning models require statistical aggregation of spatial data
- Statistical aggregation does not encode spatial structure information
- Encoding spatial weather information may provide further gains in accuracy
- Two methods for encoding spatial information
  - Principal Component Analysis (AKA Empirical Orthogonal Functions)
  - Deep Neural Networks

Convolutional Neural Networks



Example of a convolutional neural network for classifying dog species from LeCun et al. 2015, doi:10.1038/nature14539

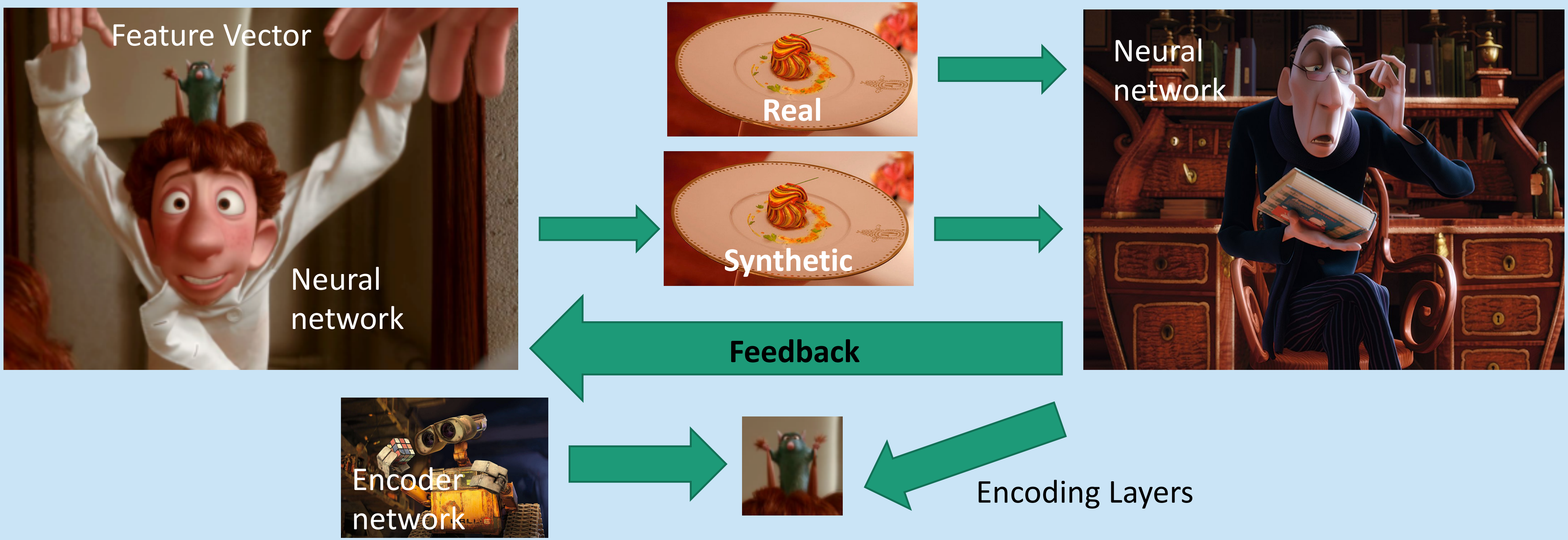
- Convolutional layers consist of convolutional feature maps
- Each feature map is applied over subsets of input to find matching features
- Convolutions in upper layers identify combinations of simpler features
- Final layer connects convolutional features with probability of event

Generative Adversarial Networks

Neural network training method to encode and sample from multivariate data distributions
Originally proposed by Goodfellow et al. (2014)

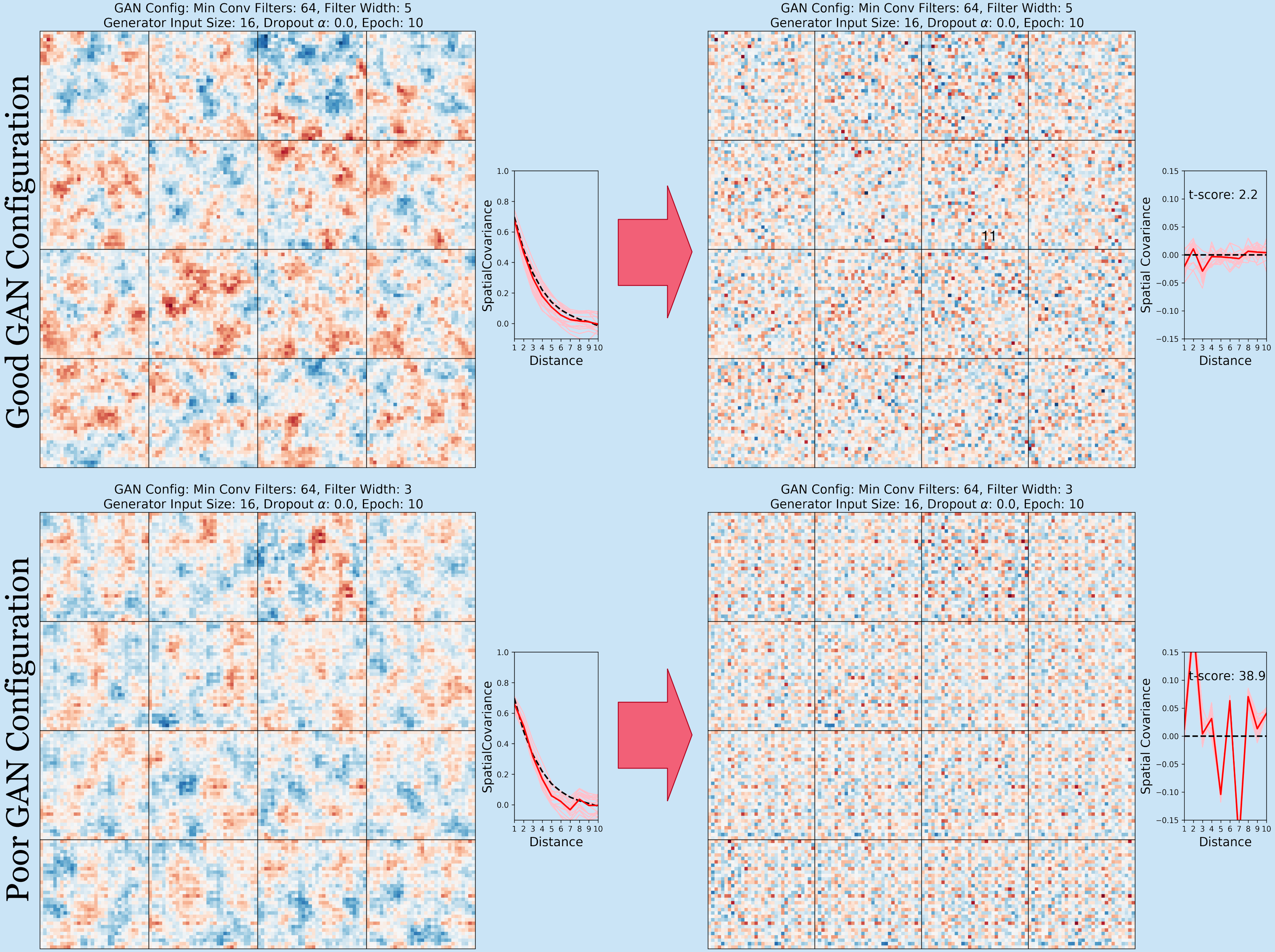
Generator: Creates synthetic samples drawn from training data based on low dimensional vector.

Critic: Determines which samples are real or synthetic. Adaptive loss function.



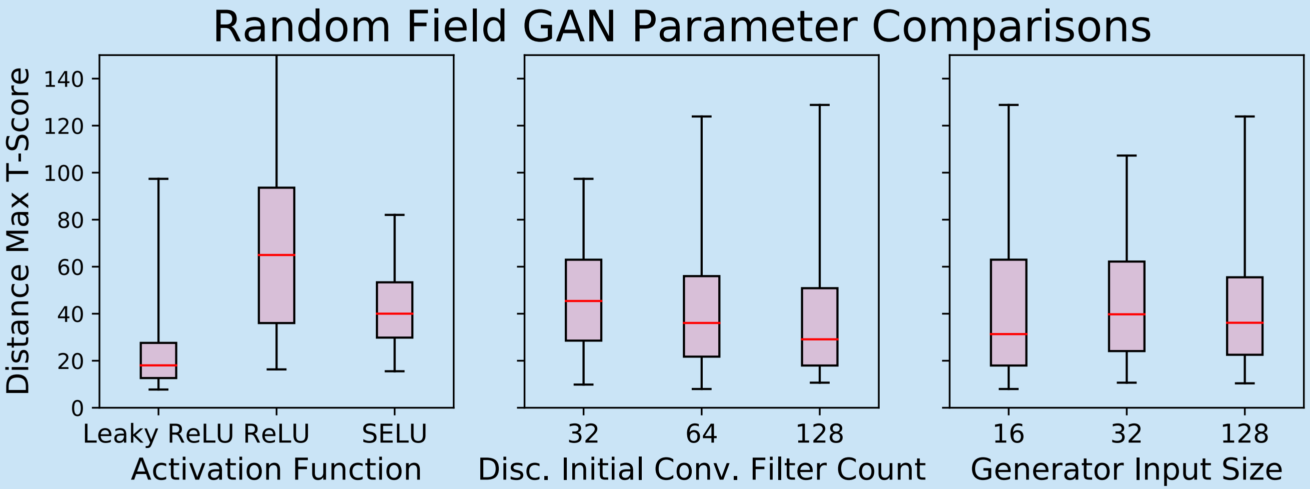
https://upload.wikimedia.org/wikipedia/en/e/e1/Ratatouille-remy-control-linguini.png
http://www.imdb.com/character/ch0009859/mediaviewer/rm988253440

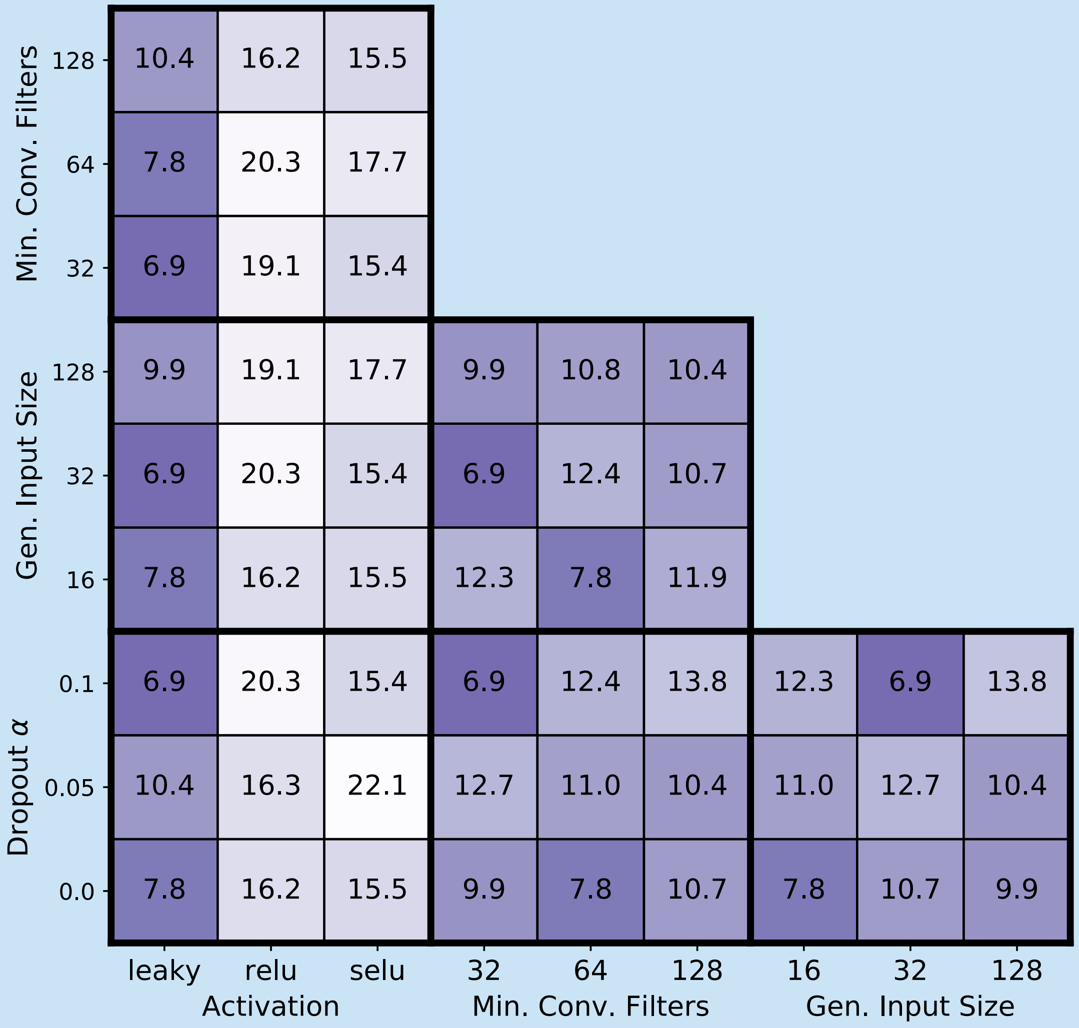
Gaussian Spatial Random Fields



- Gaussian random spatial fields are white noise multiplied by a specified covariance structure
- GANs are trained to generate random fields
- Evaluated by reversing the process and comparing GAN noise with white noise spatial covariance

Results: Gaussian Random Fields





- Lower t-scores indicate a more realistic random field
- Activation function has the biggest impact on spatial realism
- Increasing the number of filters can improve representation but also makes fitting the network harder

NCAR Ensemble Storm Patches

Run Dates: 3 May – 3 June 2016

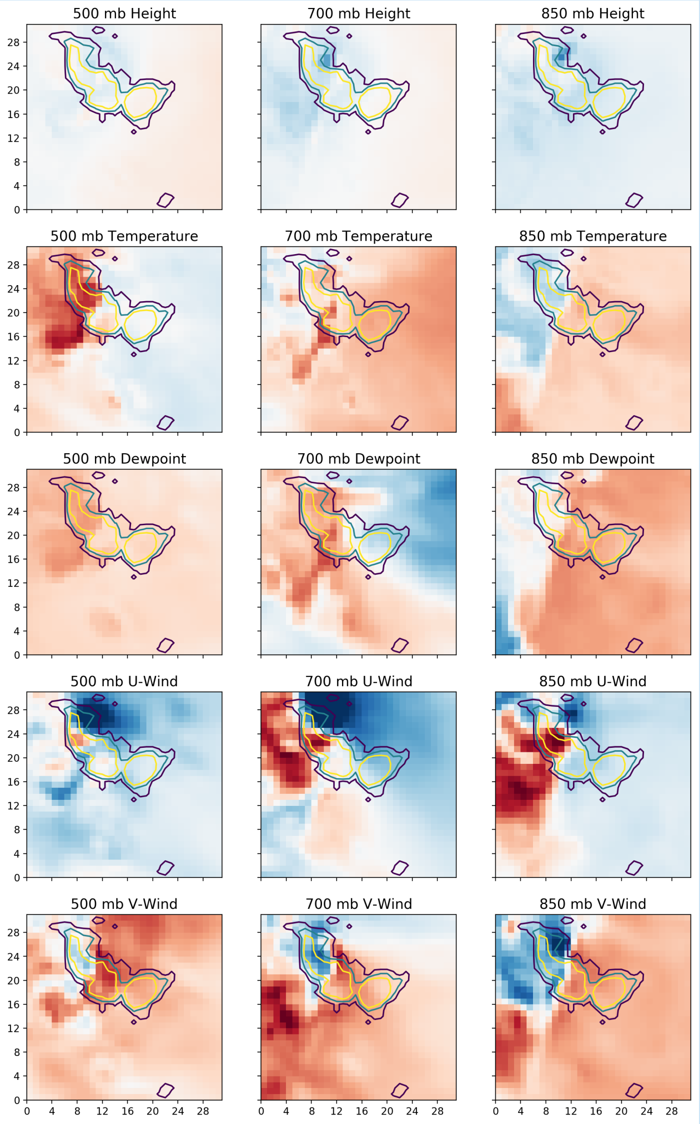
22 training days (81652 storms)

10 testing days (32577 storms)

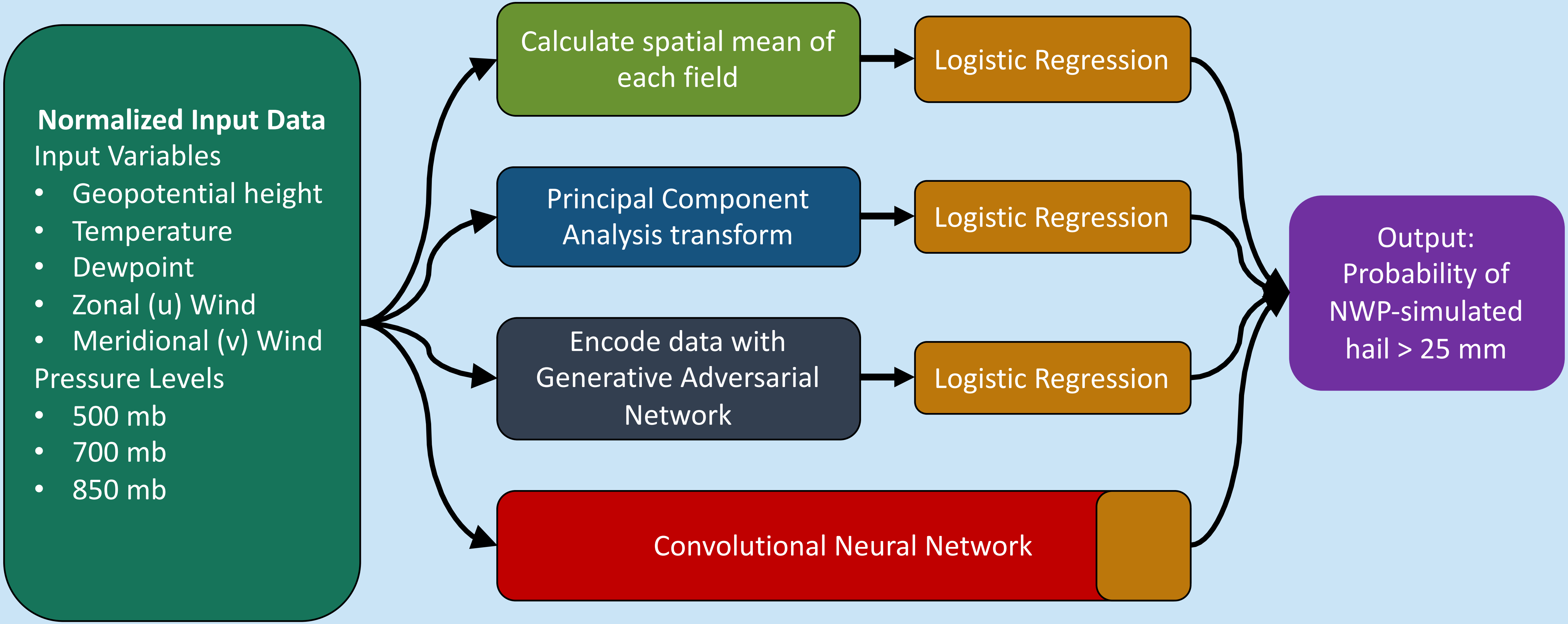
Storm Extraction: Identified updrafts with vertical velocity > 10 m/s

Storm Patch: 32x32 box centered on updraft track

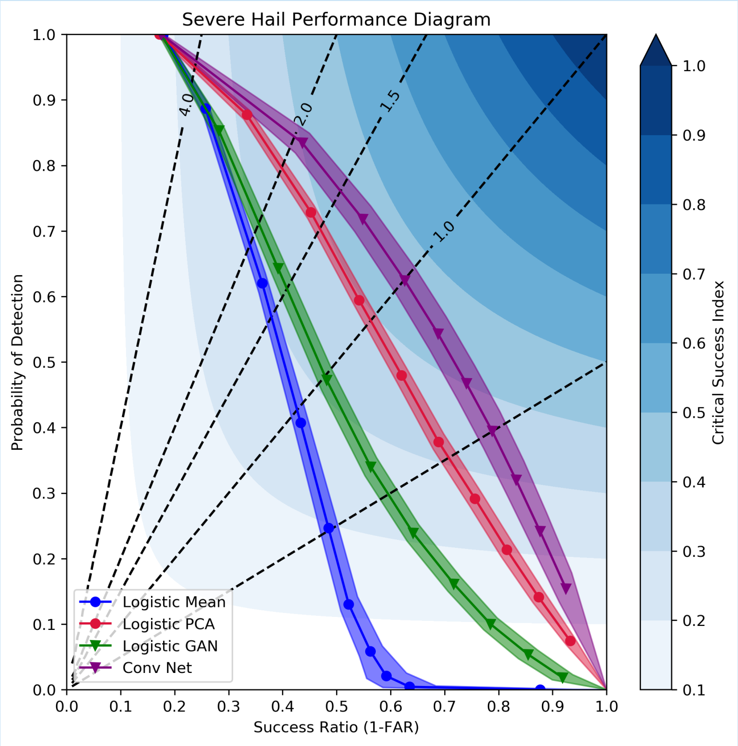
Target: If the model max hail size over the following hour exceeded 25 mm

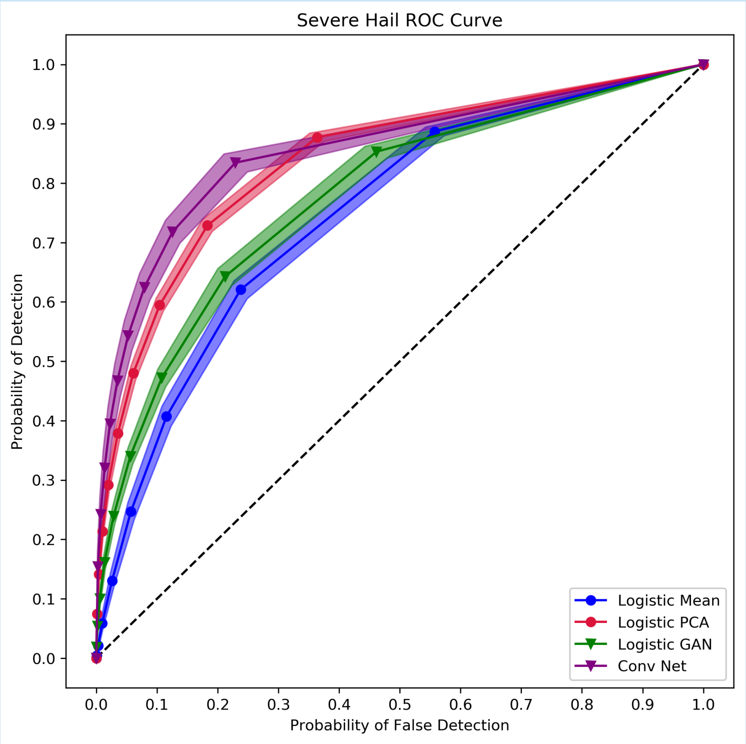


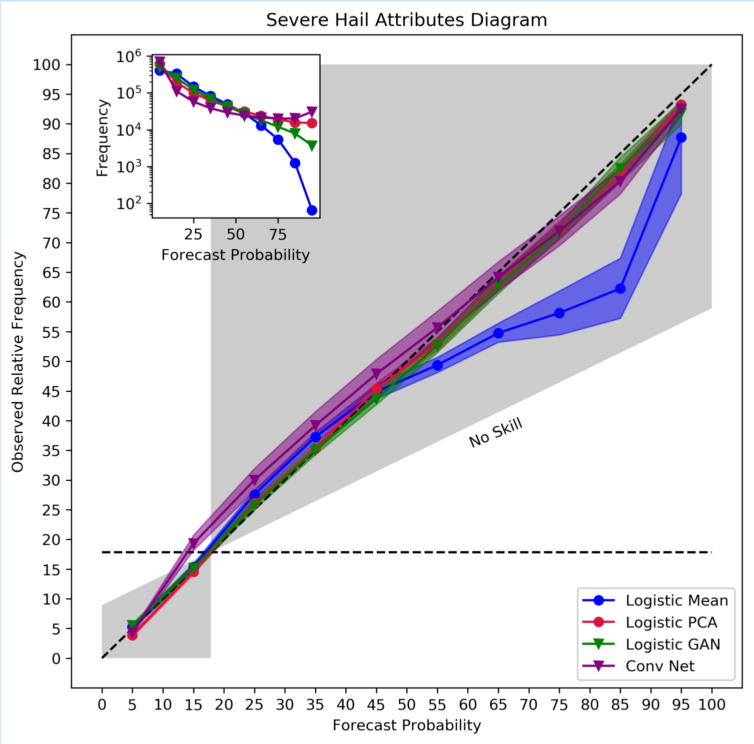
Machine Learning Procedure



Severe Hail Verification







Model	AUC	BSS	BS Reliability	BS Resolution
Logistic Mean	0.748	0.107	0.00339	0.0192
Logistic GAN	0.777	0.172	0.00272	0.0276
Logistic PCA	0.837	0.285	**0.00185**	0.0425
Convolutional Neural Net	**0.854**	**0.350**	0.00333	**0.0540**

Feature Rankings

Spatial Means

Variable	Coefficient
500 mb Height	-2.50
850 mb Height	1.36
850 mb Dewpoint	1.07
850 mb Temperature	0.89
850 mb U-Wind	-0.58
850 mb V-Wind	-0.44
700 mb Temperature	0.34
700 mb Dewpoint	0.25
700 mb U-Wind	0.20
500 mb V-Wind	-0.14

Convolutional Neural Net

Variable	Score
500 mb Height	134.6
850 mb Temperature	73.9
850 mb Height	66.8
850 mb Dewpoint	60.9
700 mb Height	33.2
850 mb U-Wind	29.4
700 mb U-Wind	28.8
850 mb V-Wind	26.6
500 mb Temperature	21.3
700 mb Dewpoint	21.14

Generating an Exemplar Hailstorm

1. Start with all 0s storm patch

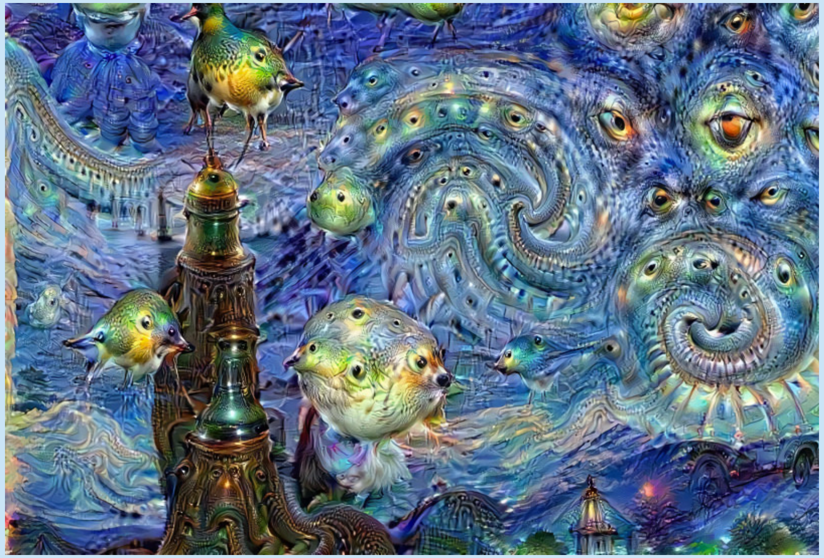
Storm Patch → Conv Net with fixed weights → Desired Label

Forward pass to infer probability →

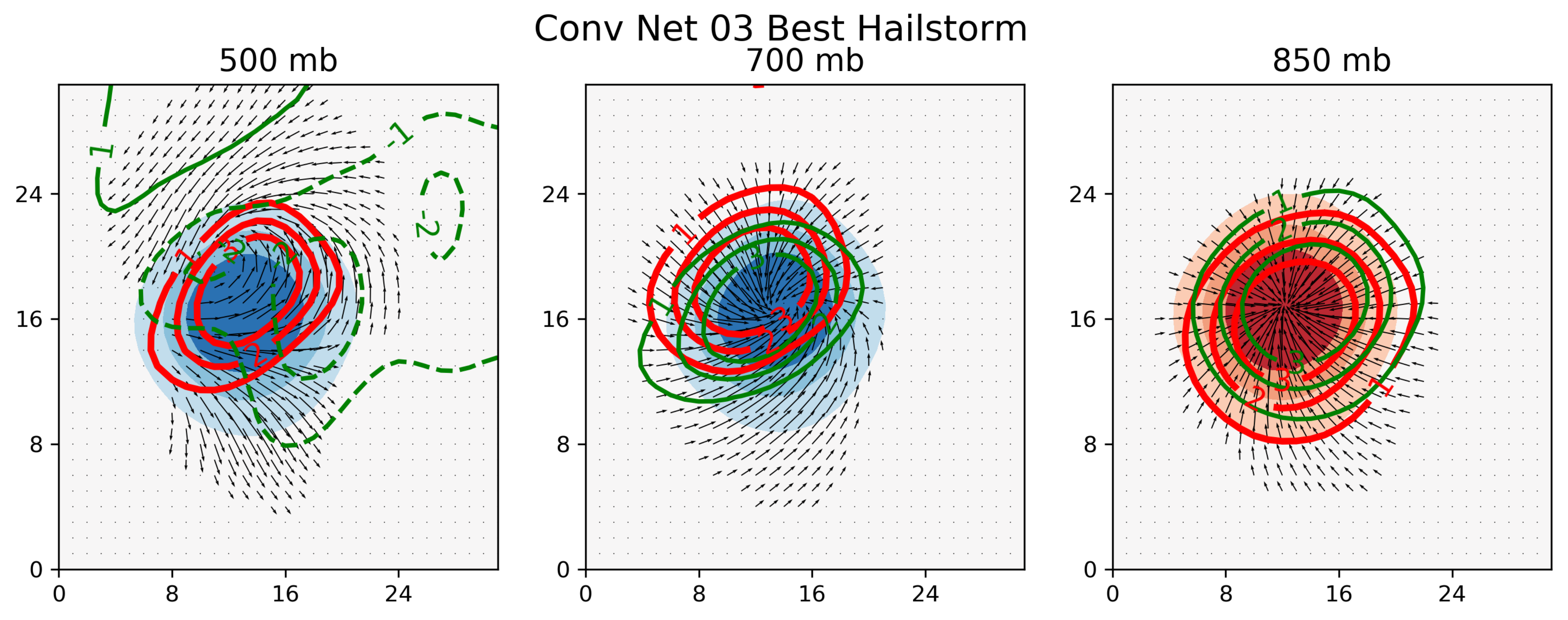
2. Perform gradient descent on input patch until convergence

← Backpropagate error to update input image

Similar process to DeepDream



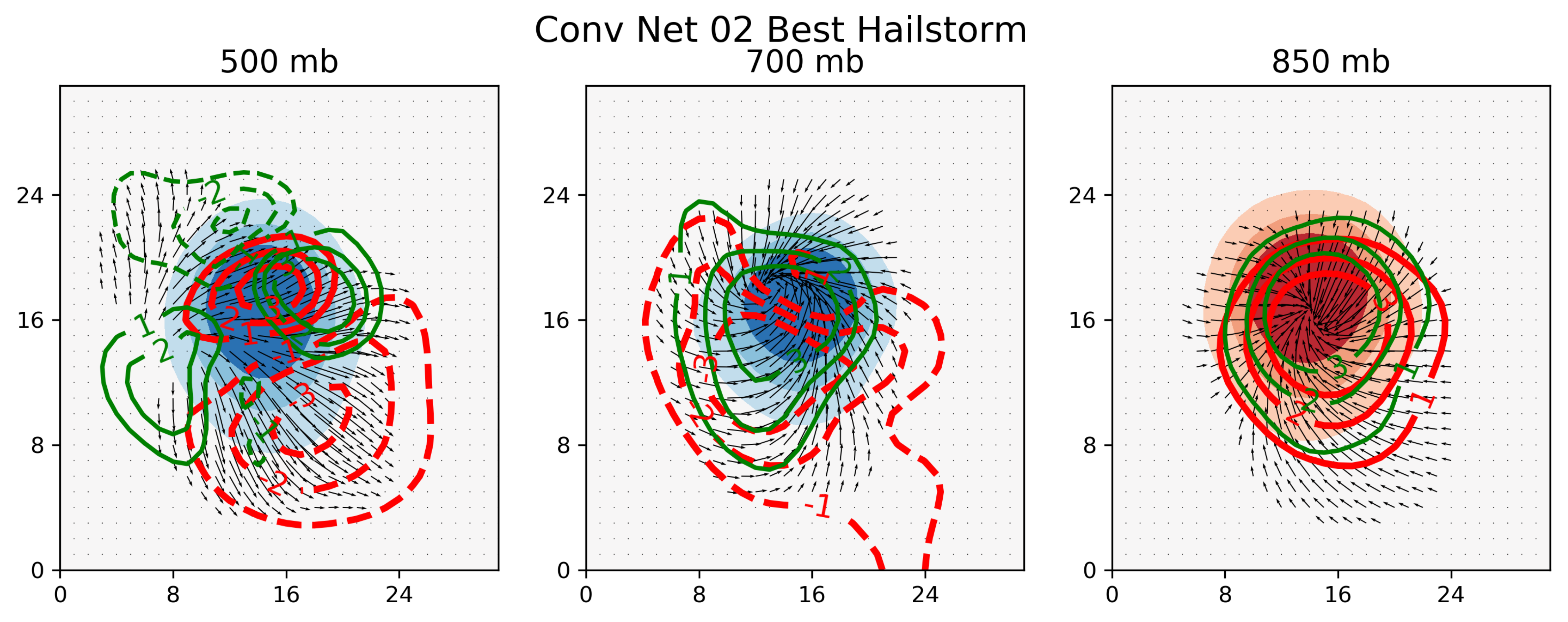
Exemplar Conv Net Hailstorm



Red: Temperature
Green: Dewpoint

Filled Contours: Geopotential Height

Exemplar Conv Net Hailstorm



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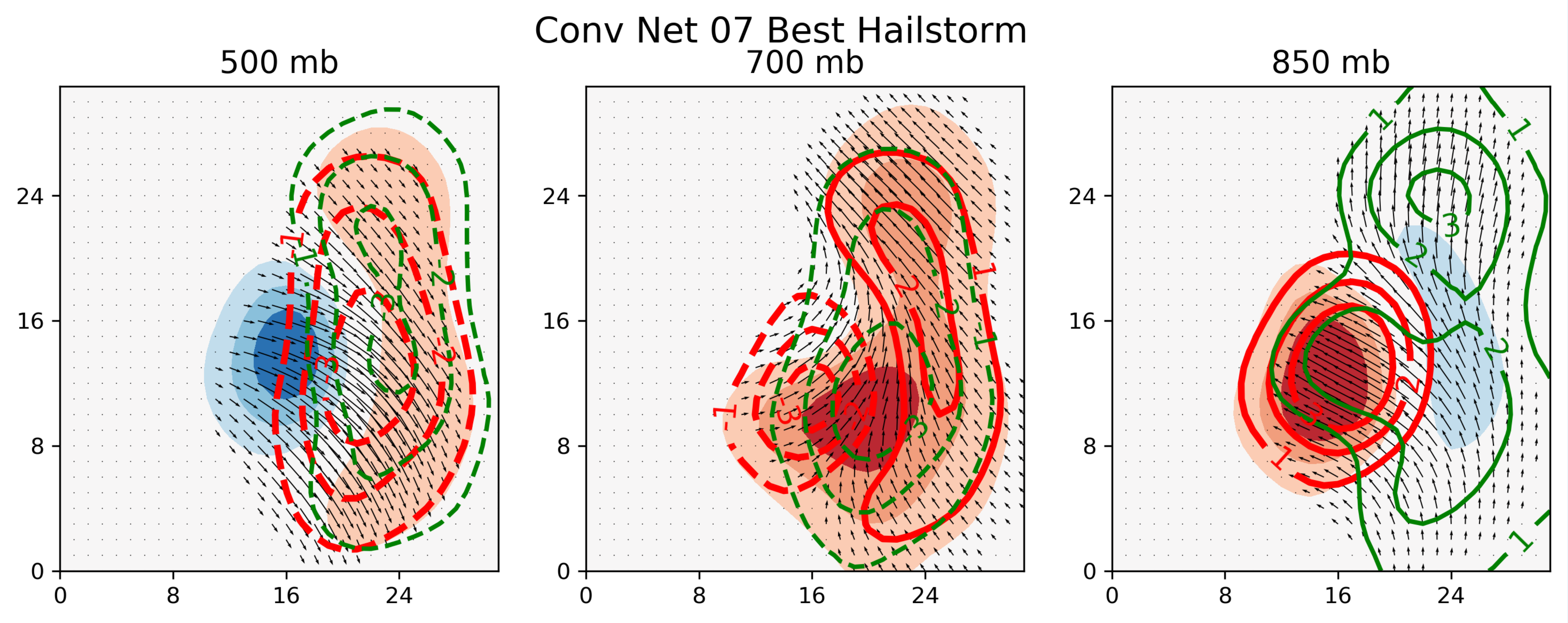
Exemplar Conv Net Hailstorm



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Summary

- Convolutional neural networks and generative adversarial networks can encode spatial information into a form amenable for classification
- The choice of activation function and number of convolutional filters has the largest impact on realistic GAN generation of random fields
- Convolutional neural networks perform the best at encoding spatial storm data for hail prediction
- Physical information about the exemplar neural network representation of a storm can be extracted through backpropagation on the input image

Contact Information
Email: dgagne@ucar.edu
Twitter: @DJGagneDos
Github: djgagne