# Classifying Rainfall Regions in Weather Radar Mosaics

ALEX HABERLIE

LOUISIANA STATE UNIVERSITY

AHABERLIE1@LSU.EDU

PROJECT COLLABORATORS: WALKER ASHLEY (NIU), VICTOR GENSINI (NIU), RUSS SCHUMACHER (CSU)

# Useful Information

https://github.com/ahaberlie/unidata-workshop-2018

Haberlie and Ashley (2018)

McGovern et al. (2017) – Great overview of current machine learning trends in Meteorology

Storm Identification and Feature Extraction

- WDSS-II (Lakshmanan et al. 2007)
- TITAN (Han et al. 2009)
- THoR (Houston 2015)
- Hagelslag (Gagne 2018)

Machine Learning and Forecasting:

- MCS initiation (Ahijevych et al. 2016)
- Damaging Straight-Line Wind Prediction (Lagerquist et al. 2017)
- Heavy rain forecasting (Herman and Schumacher 2018)



### Mesoscale Convective Systems

#### Source: NOAA Storm Prediction Center



Source: Arturo Fernandez/Rockford Register Star via AP.

Source: Walker Ashley





Source: NOAA Storm Prediction Center



#### Parker and Johnson (2000)

Gallus et al. (2008)

### Are These MCSs?







### What about these?







# Problem Description

How do you generate a climatology of mesoscale convective systems (MCSs) with a huge dataset of composite radar mosaics?

- NOWrad (~2 km)
- Over 95% of 15 minute periods from 1996-2017
- ~10<sup>6</sup> images
- Many well-known issues, but the analyses can be useful (Fabry et al. 2017)

#### Parker and Johnson (2000) objective definition:

- Convective cells organized on a horizontal scale of at least 100 km
- Must last for at least 3 hours

#### **Computing Resources:**

• Ryzen 1700 (8 C, 16 T), nVidia GTX 1070, 32 gb RAM

# Why Machine Learning?

"Reducing time to science"

~5.5 million "MCS Snapshots"

Automate classification of MCSs and four common false positives after segmentation

- Tropical Systems
- Synoptic Systems
- Unorganized clusters
- Ground Clutter / Noise / Etc.

		120-		
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
0615_00001.png	0615_00002.png	0615_00003.png	0630_00000.png	0630_00001.png
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
0645_00002.png	0645_00003.png	0645_00004.png	0700_00000.png	0700_00001.prg
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
0730_00001.png	0730_00002.png	0730_00003.png	0745_00000.png	0745_00001.png
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
0815_00001.png	0830_00000.png	0830_00001.png	0830_00002.png	0830_00003.png
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
0915_00001.png	0930_00000.png	0930_00001.png	0945_00000.png	0945_00001.prg
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
1045_00000.png	1045_00001.png	1045_00002.png	1100_00000.png	1100_00001.png
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
1130_00003.png	1130_00004.png	1145_0000.png	1145_00001.png	1200_00000.png
BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_	BREF_150625_
1245_00000.png	1300_00000.png	1315_00000.png	1330_00000.png	1345_00000.prg

081

### Related Work

Baldwin et al. 2005
Linear, cellular, stratiform
Gagne et al. 2009
Pulse, multicellular, MCSs
Lack and Fox 2012
Supercell, QLCS, rotating storms, pulse, etc.
Hobson et al. 2012

#### Supercell, pulse, multicellular, linear

#### **Visual Depiction**



User Label: Supercell

#### Features

Area: 9,000 sq. km Mean Intensity: 35 dBZ Eccentricity: 0.3

Area: 70,000 sq. km Mean Intensity: 31 dBZ Eccentricity: 0.8



# Sample Training Workflow

1) Ask yourself a few questions:

- What are the classes you want to identify?
- What are distinguishing features of each class?
- What data do you need to gather samples?
- What algorithm should I use?
- 2) Identify class examples
- 3) Extract features
  - Area, Shape, Intensity, etc.
- 4) Generate training and testing data
- 5) Train machine learning model
  - Always test model performance on data **<u>not</u>** used to generate model





### Notebook Examples

**Training Process** 

**Extraction Process** 



### Machine Learning vs. Manual

Manual MCS slice positions (2003-2013)

#### Automated Approach (2015)

0.95 threshold 40-hr isopleth





0.5 threshold 40-hr fill

No threshold 40-hr isopleth

### Quasi-linear convective systems

Quasi-linear convective systems (QLCSs) can produce severe weather (Trapp et al. 2005)

Convection-permitting models have trouble with QLCSs (Lawson and Gallus 2016)

Implications for people, weather forecasting, and high resolution climate simulations





### Visual differences



First Try

Select 3000 random highprobability MCS "snapshots"

Label as QLCS or Non-QLCS based only on their visual features

- Subjective
- Looking for common visual traits

Use features to train tree-based ensemble

°~70% accuracy



# Second Try

Employ a convolutional neural network (Krizhevsky et al. 2012)

Inspiration / model configuration came from astronomy (Dieleman et al. 2015)

Much harder to generate training / testing data for CNNs





### Training data approach



# Training / testing data creation

All images must be the same size

Find largest contiguous region of 50+ dBZ

Center a box on the intensityweighted centroid

Extract intensity information within box







## Data Augmentation

#### Addressing overfitting

Only ~3000 samples

#### Keras ImageDataGenerator

 Randomly apply slight modifications to images during training

#### Physically Reasonable?

- Scale is important
- Orientation might be important





#### QLCS Sample



#### Non-QLCS Sample





### Notebook Examples

**QLCS** Detection

### Application



#### QLCS Occurrence June – August (2001-2013)



Percent of MCS events that were QLCSs June – August (2001-2013)

### References

HABERLIE, ALEX M., and WALKER S. ASHLEY. "A Method for Identifying Midlatitude Mesoscale Convective Systems in Radar Mosaics. Part I: Segmentation and Classification." Journal of Applied Meteorology and Climatology 2018 (2018).

McGovern, Amy, Kimberly L. Elmore, David John Gagne, Sue Ellen Haupt, Christopher D. Karstens, Ryan Lagerquist, Travis Smith, and John K. Williams. "Using Artificial Intelligence to Improve Real-Time Decision-Making for High-Impact Weather." Bulletin of the American Meteorological Society 98, no. 10 (2017): 2073-2090.

Lakshmanan, Valliappa, Travis Smith, Gregory Stumpf, and Kurt Hondl. "The warning decision support system-integrated information." Weather and Forecasting 22, no. 3 (2007): 596-612.

Han, Lei, Shengxue Fu, Lifeng Zhao, Yongguang Zheng, Hongqing Wang, and Yinjing Lin. "3D convective storm identification, tracking, and forecasting—An enhanced TITAN algorithm." Journal of Atmospheric and Oceanic Technology 26, no. 4 (2009): 719-732.

Houston, Adam L., Noah A. Lock, Jamie Lahowetz, Brian L. Barjenbruch, George Limpert, and Cody Oppermann. "Thunderstorm observation by radar (ThOR): An algorithm to develop a climatology of thunderstorms." Journal of Atmospheric and Oceanic Technology 32, no. 5 (2015): 961-981

Gagne II, David John. "hageIslag Documentation." (2018).

Ahijevych, David, James O. Pinto, John K. Williams, and Matthias Steiner. "Probabilistic forecasts of mesoscale convective system initiation using the random forest data mining technique." Weather and Forecasting 31, no. 2 (2016): 581-599.

Herman, Gregory R., and Russ S. Schumacher. "Money Doesn't Grow on Trees, but Forecasts Do: Forecasting Extreme Precipitation with Random Forests." Monthly Weather Review 146, no. 5 (2018): 1571-1600.

Lagerquist, Ryan, Amy McGovern, and Travis Smith. "Machine Learning for Real-Time Prediction of Damaging Straight-Line Convective Wind." Weather and Forecasting 32, no. 6 (2017): 2175-2193.

Baldwin, Michael E., John S. Kain, and S. Lakshmivarahan. "Development of an automated classification procedure for rainfall systems." Monthly weather review 133, no. 4 (2005): 844-862.

Gagne, David John, Amy McGovern, and Jerry Brotzge. "Classification of convective areas using decision trees." Journal of Atmospheric and Oceanic Technology 26, no. 7 (2009): 1341-1353.

Lack, Steven A., and Neil I. Fox. "Development of an automated approach for identifying convective storm type using reflectivity-derived and near-storm environment data." Atmospheric research 116 (2012): 67-81.

Hobson, Angelyn G. Kolodziej, Valliappa Lakshmanan, Travis M. Smith, and Michael Richman. "An automated technique to categorize storm type from radar and near-storm environment data." Atmospheric research 111 (2012): 104-113.

Lawson, John, and William A. Gallus Jr. "On contrasting ensemble simulations of two Great Plains bow echoes." Weather and Forecasting 31, no. 3 (2016): 787-810.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." In Advances in neural information processing systems, pp. 1097-1105. 2012.

Dieleman, Sander, Kyle W. Willett, and Joni Dambre. "Rotation-invariant convolutional neural networks for galaxy morphology prediction." Monthly notices of the royal astronomical society 450, no. 2 (2015): 1441-1459.

Gallus Jr, William A., Nathan A. Snook, and Elise V. Johnson. "Spring and summer severe weather reports over the Midwest as a function of convective mode: A preliminary study." Weather and Forecasting 23, no. 1 (2008): 101-113.

Parker, Matthew D., and Richard H. Johnson. "Organizational modes of midlatitude mesoscale convective systems." Monthly weather review 128, no. 10 (2000): 3413-3436.

### Thank You

