Using Machine Learning Techniques to Investigate Tornadogenesis

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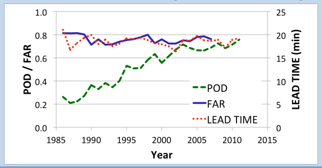
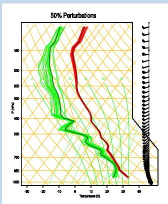
Motivation

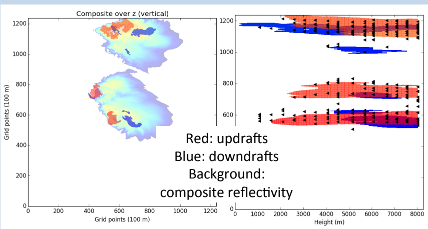
- Tornado warning lead times and POD have stalled in recent years
- Computational capabilities have increased, providing finer resolution simulations, but data cannot be analyzed using traditional techniques
- Machine learning & data mining can find patterns in large data sets
- **Goal: identify precursors of tornadoes in high-resolution simulations of supercells and tornadoes using machine learning/data mining**



Method



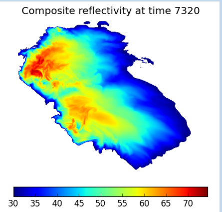
- Generate high-resolution simulations of supercell thunderstorms by varying initial environmental conditions from known tornadic environments (Cintineo and Stensrud 2013, Dahl 2014)
- Identify and extract high-level objects



- Apply machine learning/data mining to the high-level data
- Analyze and verify results

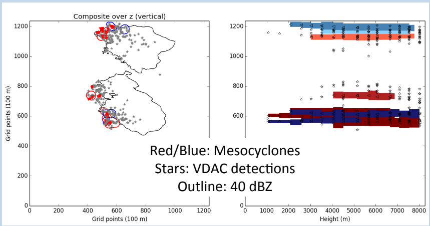
High-resolution simulations

- CM1 (Bryan and Fritsch 2002)
- 100 m horizontal resolution in center (125 km)
- Nested grid to 400 m at edges
- Stretched vertical grid (40 m to 500 m)
- 1536 x 1536 x 99 ≈ 234 million model grid points
- Data saved every grid point every 30 seconds of simulated time



Identifying High-level objects

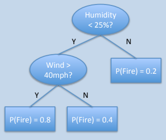
- Most objects extracted using thresholds
- Rotating objects use VDAC (Potvin, 2013)
- Mesocylone requires: 1 detection in 2-4 km and at least 4 total in 0-8 km, all greater than 750 m in diameter
- Tornado object requires: 1 VDAC detection at 100 m and at least one more detection between 500 m and 3km, all with radius less than 500 m



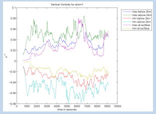
- Tornadic storm: low-level mesocyclone object (lowest height <= 2 km) co-located with a tornado object, both of which last at least 60 seconds
- Tornado-failure storm: low-level mesocylone object without a tornado object
- Training data taken from 30 minutes prior to start of tornado or low-level mesocyclone

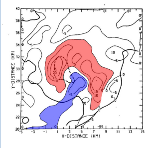
Name	Definition
Updraft	$w \geq 15 ms^{-1}$
Downdraft	$w \leq -6 ms^{-1}$
Radar reflectivity	$dBZ \geq 40$
Intense reflectivity	$dBZ \geq 60$
Cold pool	$\Theta' \leq -2°K$
Positive/negative vertical vorticity	$\zeta \geq 0.05 s^{-1}$
Convergence	$\nabla \geq 0.05 s^{-1}$
Positive/negative tilting	$T \geq 0.03 s^{-2}$
Positive/negative stretching	$S \geq 0.03 s^{-1}$
Positive/negative mesocyclone	VDAC (10 ms^{-1})
Positive/negative tornado	VDAC (10 ms^{-1})

Spatiotemporal Relational Random Forests



- SRRF is a Random Forest style algorithm composed of Spatiotemporal Relational Probability Trees (SRPT) (McGovern et al 2014 & to appear)
- SRPT: Decision tree type algorithm, probability estimation tree
- Each tree can make spatial, temporal, and spatiotemporal splits
  - Scalar Attribute: Is there an updraft with maximum speeds >= 25 m/s?
  - Temporal Exists: Is there a storm object that lasted at least 20 minutes?
  - Array Attribute: Did the updraft ever get larger than 20km^3?
  - Array Attribute Temporal Duration: Did the updraft maintain a volume of at least 20 km^3 for 5 minutes?
  - Array Partial Derivative: Did the strength of the updraft double within 5 minutes?
  - Scalar Field Attribute: Is the temperature in the near storm environment always greater than 80?
  - Shapes:
    - Can split on the shape of 2 and 3 dimensional objects
    - Can split on how 2 and 3D shapes change over time
    - Can split on the spatial relationships between 2 and 3D shapes
  - Time:
    - Can split on the temporal relationship between pairs of objects
    - Did a downdraft with a strength of at least -10 ms^{-1} appear before the updraft reached a strength of 20 ms^{-1}?



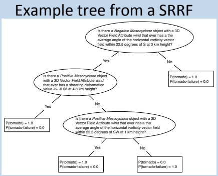


Adapted from Brandes (1984)

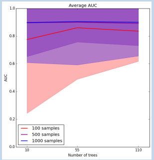
Preliminary Results

- Data: 34 tornadic storms, 21 tornado-failures
- Results averaged over 30 runs (different training/test sets)
- Measured performance using Area Under Receiver Operator Curve (AUC)

Example tree from a SRRF



Overall performance



Most frequently chosen question types and objects

Question type	Object	Percentage
Vector Field Vorticity	Positive Mesocyclone	24.2%
Vector Field Vorticity	Negative Mesocyclone	12.7%
Vector Field Deformation	Positive Mesocyclone	10.4%
Vector Field Divergence	Positive Mesocyclone	6.5%
Vector Field Deformation	Negative Mesocyclone	5.1%
Array Temporal Duration	Updraft	5.1%
Array Shapelet	Updraft	4.8%
Vector Field Vorticity	Updraft	3.4%

Current work

- Refining object definitions (tornadoes, gust fronts, etc)
- Generating additional simulations of both strong and weak storms
- Refining our post-processing and data mining pipeline to handle the volume of big data

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