Precipitation Nowcasting: Leveraging Deep Convolutional Recurrent Neural Networks

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Agenda

- Precipitation Nowcasting
- Motivation
- Data Pipeline
- Deep Learning Architecture
- Experiments
- Results
- Summary
- Q&A

Precipitation Nowcasting

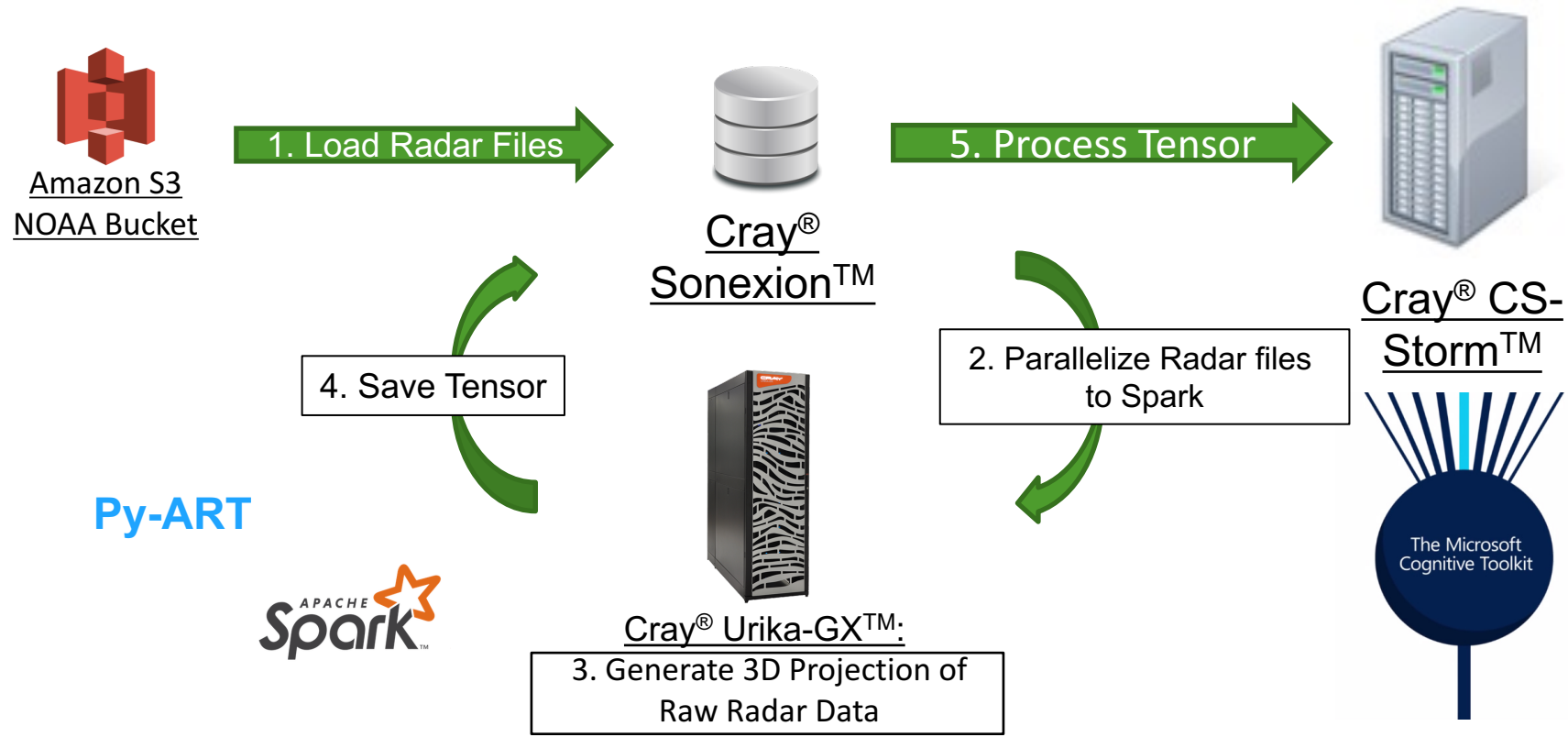
- **Problem: Predict precipitation locations and rates at a regional level over a short timeframe**
  - Neighborhood level predictions
  - T+0 – T+6 hours
- **Standard Approach: Numerical Weather Prediction**
  - Physics based simulations
  - High computational cost limits performance and accessibility
- **Cutting edge approach: Deep Learning**
  - Predict rainfall by learning from historical data
  - Heavy computation occurs ahead of time
  - Pre-Trained models can be deployed as soon as data is available

Motivation

- **Increase the quality and availability of very short term (0-1 hour) precipitation forecasts**
  - Will it rain on my walk home from work if it I leave right now?
  - Which bike-route should I take to avoid the rain?
- **Improve tracking quality of severe precipitation events**
  - Where do we issue severe weather warning?
  - Is a flash flood imminent? Do we need to evacuate?

- **Gain insights into the full deep learning workflow**
- **Accelerate the integration of deep learning in operational meteorology**

Data Pipeline

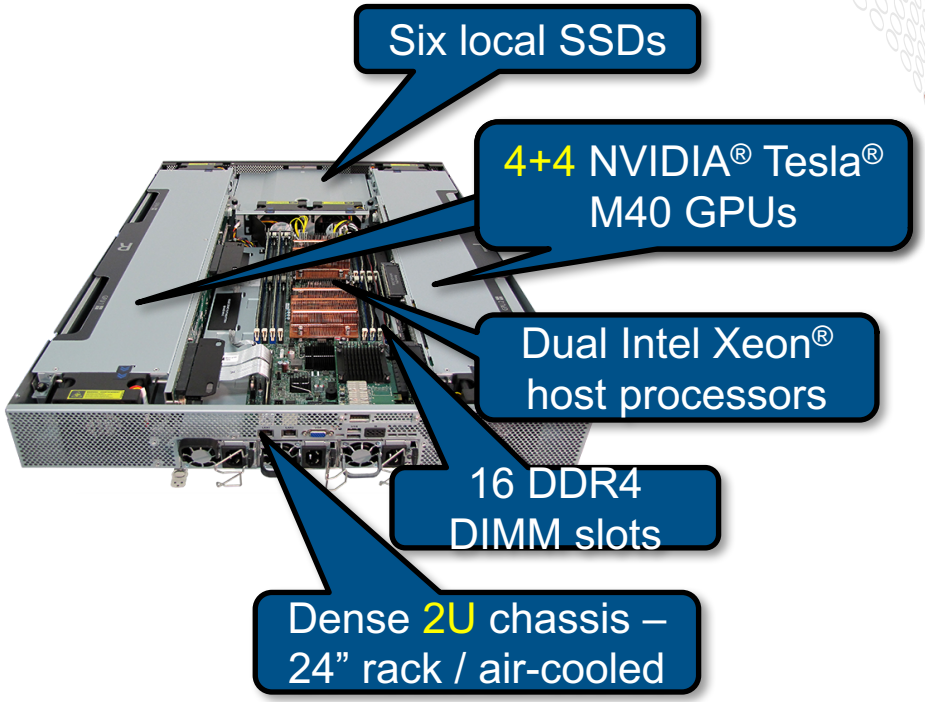


Data Preprocessing – Urika GX

- **Allowed us to easily leverage multiple analytics software frameworks and libraries**
  - Apache Spark
  - pyData
  - Jupyter Notebooks
- **Data processing was easily distributed among dozens of nodes and hundreds of cores.**
- **Full year of radar data processed and stored for training in just over 3 hours**

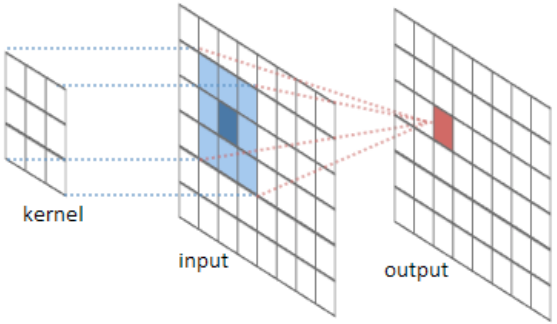
Model Training – CS-Storm

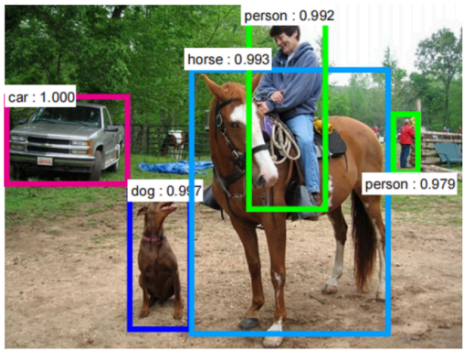
- Training a Neural Network is computationally demanding
- NVIDIA® CUDA® and CuDNN® libraries help accelerate the training time
- Cray CS-Storm cluster provides a GPU dense environment with 8 NVIDIA® Tesla® GPUs per node
- Training is performed in a data parallel setting
  - Copy of model weights stored on each GPU
  - Mini-batch split and distributed amongst them
- Deep Learning with Docker
  - Microsoft Cognitive Toolkit on a Docker image
  - Highly Portable and scalable

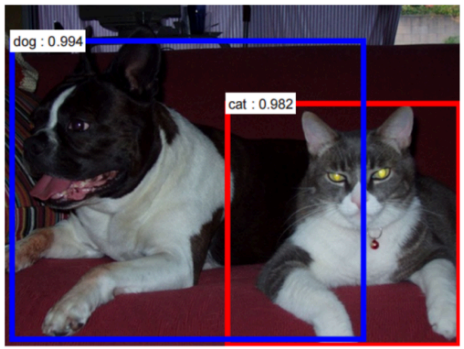


Convolutional Neural Networks

- Rely on a convolutional operation
- Strong ability to extract spatial relationships
  - Computer Vision
  - Board Games
- Examples: LeNet, AlexNet, ResNet

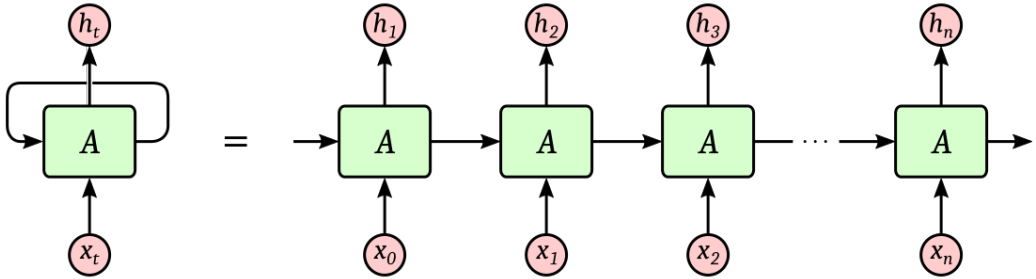






Recurrent Neural Networks

- Includes a recurrent connection and a mechanism of retaining state
- Designed to extract temporal relationships
  - Language Modeling
  - Speech Recognition
  - Machine Translation
- Examples: Simple-RNN, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM)



Convolutional Long Short-Term Memory Network

- **Long Short-Term Memory (LSTM)**
  - RNN with a defined cell-state representing an encoded version of the sequential history.
  - Cell-State is updated through “gating functions” that control information retention, loss and acquisition.
  - LSTMs have a remarkable ability to retain and apply long-term dependencies of a sequence.
- **Convolutional LSTM**
  - Variant of the standard LSTM
  - Embedded convolutional operations
  - State vectors replaced with N-D tensors

LSTM Gate and Output Functions

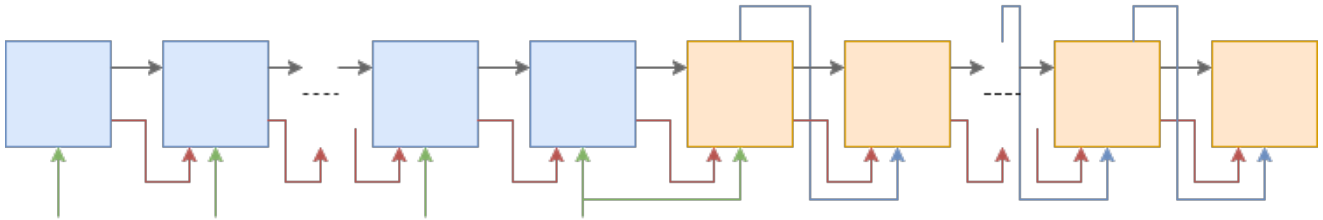
$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci} \circ c_{t-1} + b_i) \\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf} \circ c_{t-1} + b_f) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co} \circ c_t + b_o) \\
h_t &= o_t \circ \tanh(c_t)
\end{aligned}
$$

ConvLSTM Gate and Output Functions

$$
\begin{aligned}
i_t &= \sigma(W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1} + W_{ci} \circ \mathcal{C}_{t-1} + b_i) \\
f_t &= \sigma(W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1} + W_{cf} \circ \mathcal{C}_{t-1} + b_f) \\
\mathcal{C}_t &= f_t \circ \mathcal{C}_{t-1} + i_t \circ \tanh(W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1} + b_c) \\
o_t &= \sigma(W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1} + W_{co} \circ \mathcal{C}_t + b_o) \\
\mathcal{H}_t &= o_t \circ \tanh(\mathcal{C}_t)
\end{aligned}
$$

Sequence To Sequence

- **Nowcasting is a sequence to sequence problem**
  - Input: Sequence of radar images leading up to the current time
  - Output: Sequence of predicted radar images arbitrarily far in the future
- **Solution: Encoder-Decoder Networks**
  - Encoder (Blue) digests the input sequence and produces a single tensor representation
  - This tensor is used to initialize the decoder
  - Decoder (Orange) takes previous images as input and produces predictions of the next image.



Data

- **Source: NOAA NEXRAD Level-II Reflectivity Data from station KATX, outside of Seattle, Wa.**
  - 2015 calendar year
  - All sequences from full days with over 0.1 inches of precipitation
- **Radial Reflectivity data projected onto a 3-dimensional Cartesian grid with help from pyart**
  - Grid shape: 5 x 100 x 100
  - Area covered: 12km x 200km x 200km
  - Spatial resolution of roughly 2km

Metrics

- Hit: Correct prediction of precipitation at a location
- Miss: Failure to predict precipitation at that location
- False-Alarm: Prediction of Precipitation when none was detected
- True-Negative: No Precipitation was observed nor predicted - ignored

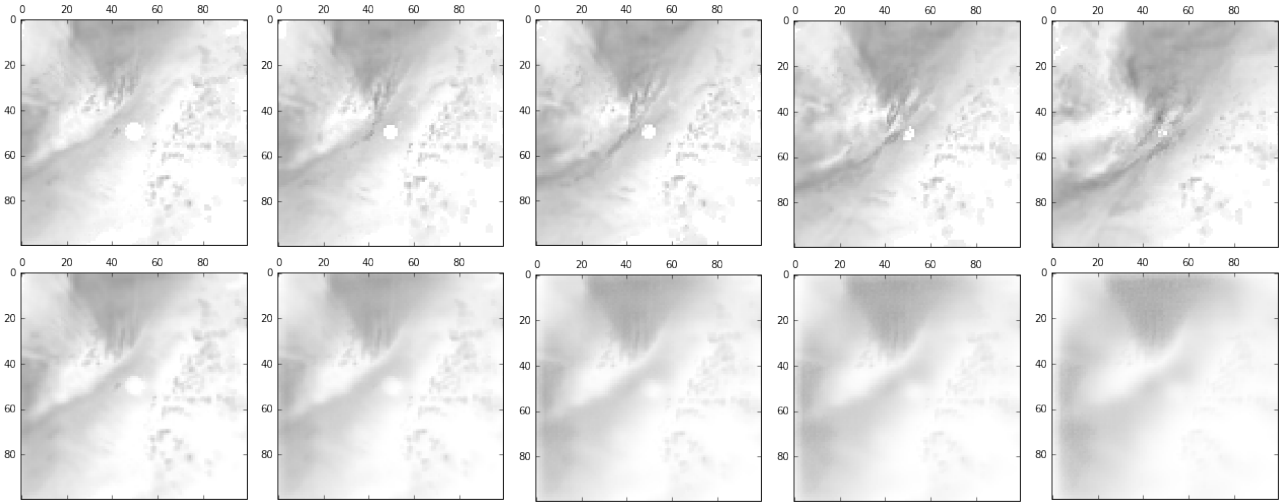
	Observed Precipitation	No Observed Precipitation
Predicted Precipitation	Hit	False Alarm
No Predicted Precipitation	Miss	True Negative

- False Alarm Rate: Fraction of false alarms to predicted precipitation
  - FAR = false-alarms / (hits + false-alarms)
- Probability of Detection: Fraction of hits to observed precipitation
  - POD = hits / (hits + misses)
- Critical Success Index: Fraction of hits to measured and observed precipitation
  - CSI = hits / (hits + misses + false-alarms)

Example Predictions

Observed Reflectivity

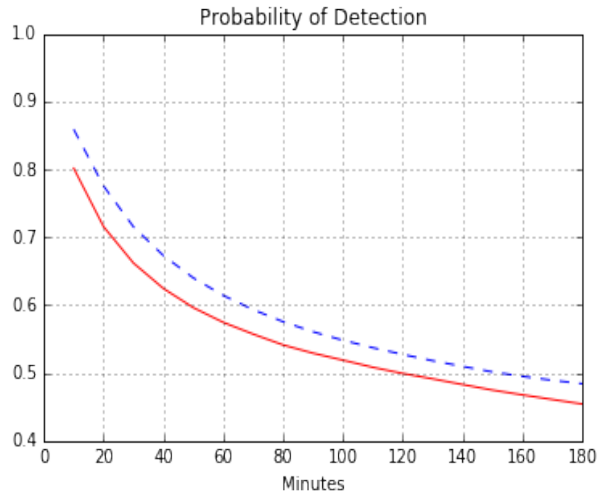
Predicted Reflectivity

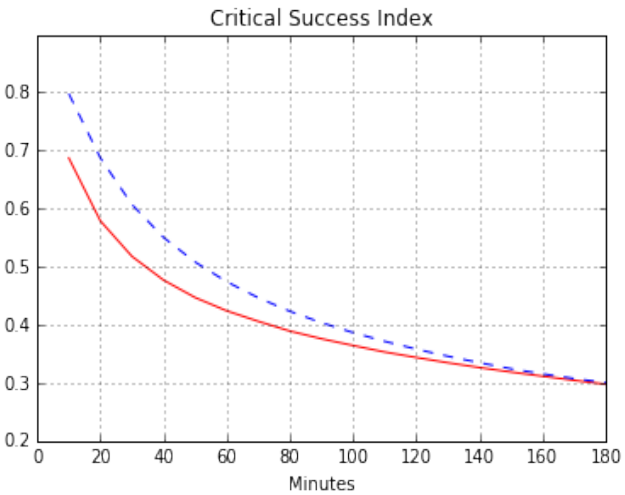


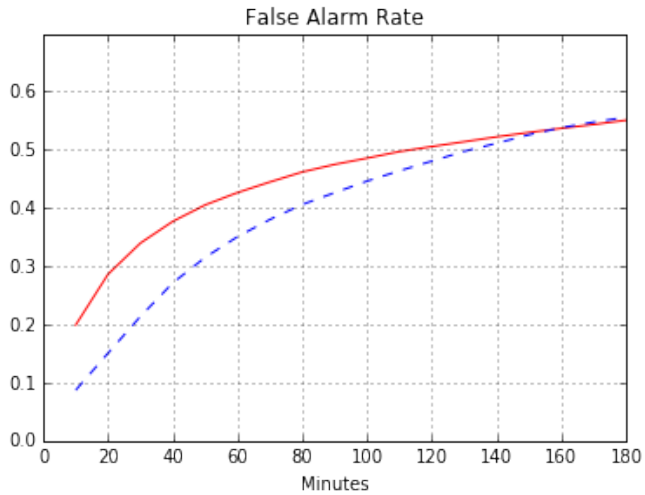
Time Since Last Obs. (Min)

10 30 50 70 90

Results over time







Summary

- **Build a Precipitation Nowcasting deep learning model**
  - Gain insights into the full deep learning workflow
  - Improve the quality and speed of precipitation nowcasting
- **Big-Data task**
  - Exploring possible data-sources
  - Building a trainable dataset from raw radar data
- **Neural Network Model**
  - Convolutional Long Short-Term Memory Neural Network
  - Encoder Decoder
- **Results**
  - Beating persistence
  - More to come…

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Q&A
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