A Deep Learning Approach for Precipitation Nowcasting with RNNs using Analytics Zoo on BigDL

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Agenda

- **Introduction**
  - Urika-XC
  - Analytics Zoo on BigDL
  - Precipitation Nowcasting
- **Models**
  - Convolutional Long Short-Term Memory Network
  - Sequence to sequence model
- **Results**
- **Q&A**

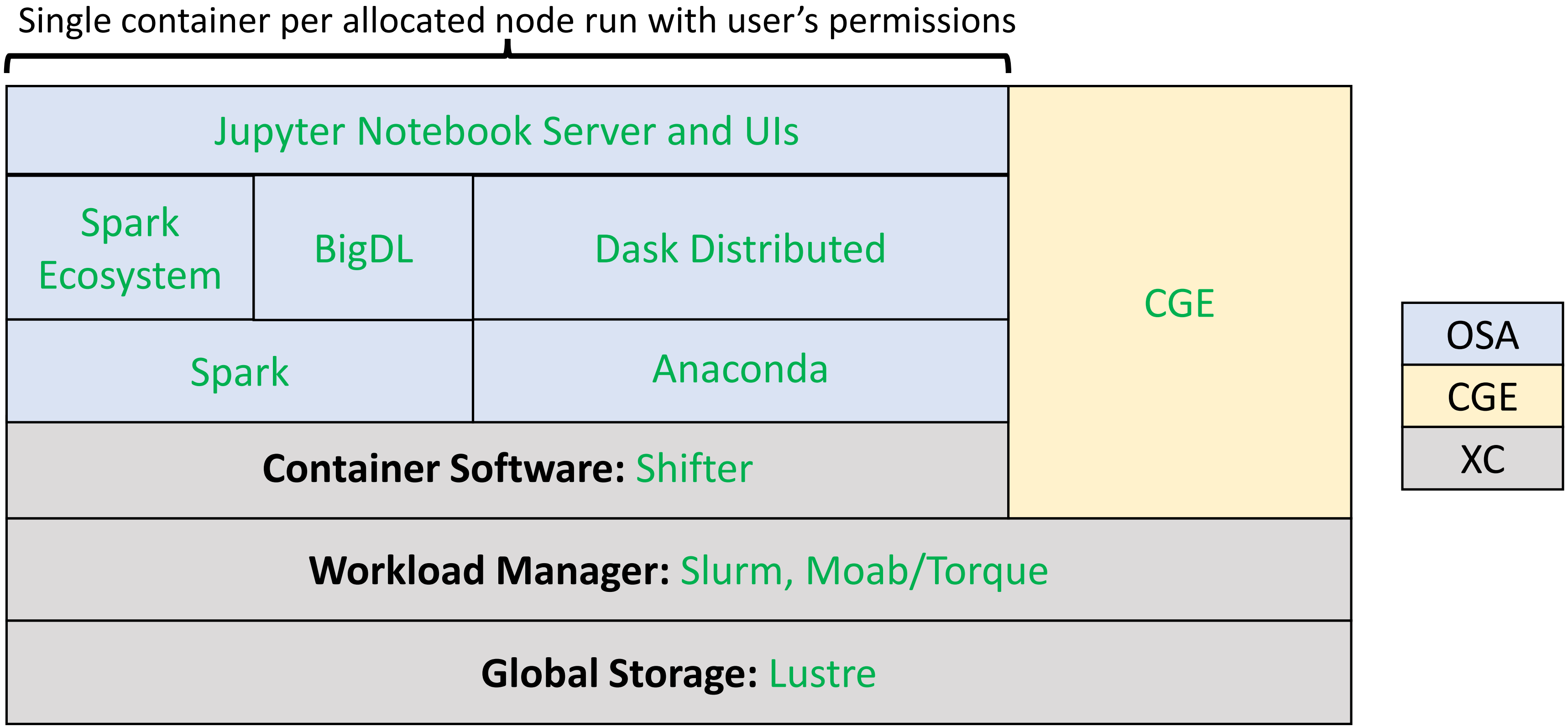
Introduction - Urika-XC

- Enabled through containerization – Shifter
- Brings Analytics software to the Cray XC
  - Apache Spark
  - Anaconda Python
  - Intel BigDL
  - Cray Graph Engine (CGE)
  - Dask Distributed
- Productivity Tools
  - Jupyter Notebooks, Tensorboard

- Support for most HPC workload managers
  - Slurm, Moab Torque, PBS Pro
- Example (Slurm): salloc –N 34 ./start_analytics
  - Starts an interactive shell on a XC compute node and will bring up Spark and Dask Distributed clusters
  - Experience for users will be similar to running jobs from a login node on the Urika-GX analytics platform

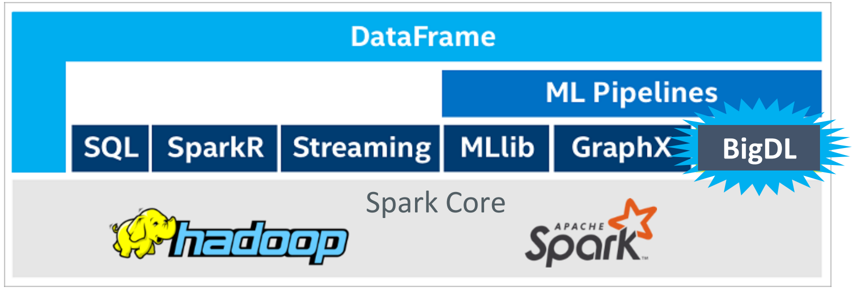
https://www.cray.com/products/analytics/urika-xc

Architecture



Introduction - Intel BigDL

HIGH PERFORMANCE DEEP LEARNING FOR APACHE SPARK* ON CPU INFRASTRUCTURE



BigDL is an **open-source** distributed deep learning library for Apache Spark* that can run directly on top of existing Spark or Apache Hadoop* clusters

Ideal for DL Models TRAINING and INFERENCE

Designed and Optimized for Intel® Xeon®

No need to deploy costly accelerators, duplicate data, or suffer through scaling headaches!

Feature Parity & Model Exchange with TensorFlow*, Caffe*, Keras, Torch*

Lower TCO and improved ease of use with existing infrastructure

Deep Learning on Big Data Platform, Enabling **Efficient Scale-Out**

Powered by Intel® MKL and multi-threaded programming

Introduction - Intel Analytics Zoo

Build and Productionize Deep Learning Apps for Big Data at Scale

Reference Use Cases	• Anomaly detection • Sentiment analysis • Fraud detection • Chatbot, sequence prediction, etc.
Built-In Deep Learning Models	• Image classification • Object detection • Text classification • Recommendations • Sequence-to-sequence, GAN, etc.
Feature Engineering	Feature transformations for • Image, text, 3D imaging, time series, speech, etc.
High-Level Pipeline APIs	• Native deep learning support in Spark DataFrames and ML Pipelines • Autograd, Keras and transfer learning APIs for model definition • Support for model serving/inference pipelines
Backbends	Spark, BigDL etc.

https://github.com/intel-analytics/analytics-zoo/ https://analytics-zoo.github.io/

Introduction – Intel Analytics Zoo

Build end-to-end deep learning applications for big data

- E2E analytics + AI **pipelines** (natively in Spark DataFrames and ML Pipelines) using ***nnframes***
- Flexible **model definition** using ***autograd, Keras-style & transfer learning APIS***
- **Data preprocessing** using built-in ***feature engineering operations***
- Out-of-the box **solutions** for a variety of problem types using ***built-in deep learning models and reference use cases***
- Large-scale distributed **TensorFlow model** inference using ***TFNet***

Introduction - 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

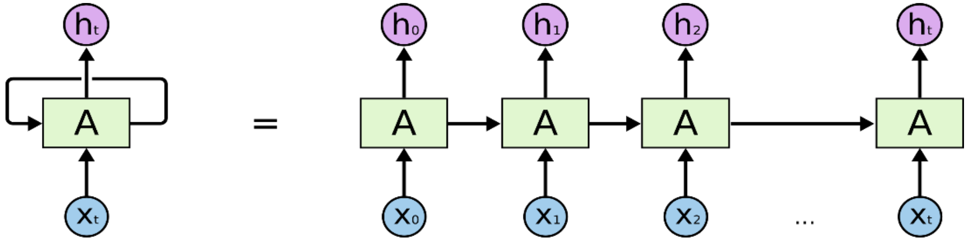
Precipitation Nowcasting - Motivation

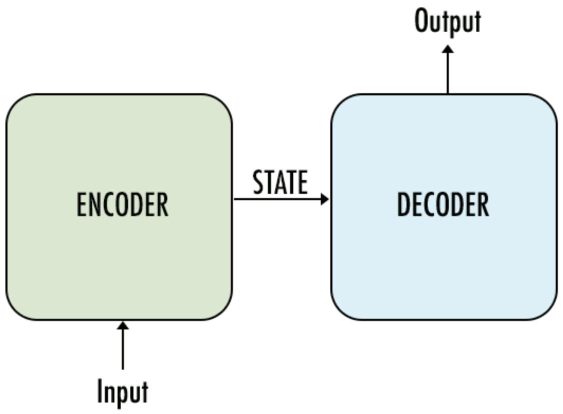
- Increase the quality and availability of very short term (0-1 hour) precipitation forecasts
  - Will it rain on my walk home from work if it I leave right now?
  - Which bike-route should I take to avoid the rain?
- Improve tracking quality of severe precipitation events
  - Where do we issue severe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

Precipitation Nowcasting Model

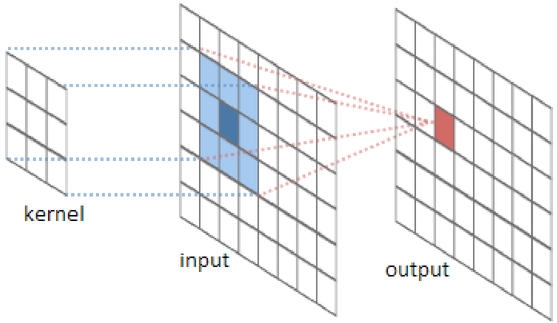
- Convolutional Recurrent Neural Network
  - Convolutional Neural Network – Spatial Patterns
  - Recurrent Neural Network – Temporal Patterns
  - ConvLSTM – Convolutional Long Short-Term Memory Network
- Sequence to Sequence
  - Encoder Decoder
  - Use recent history to predict future changes

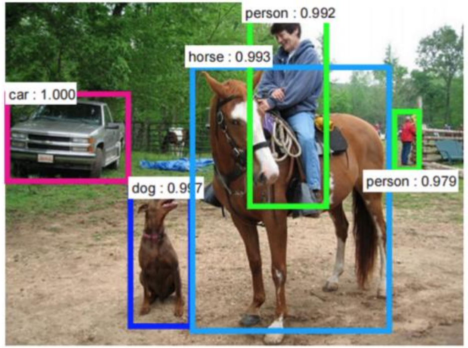


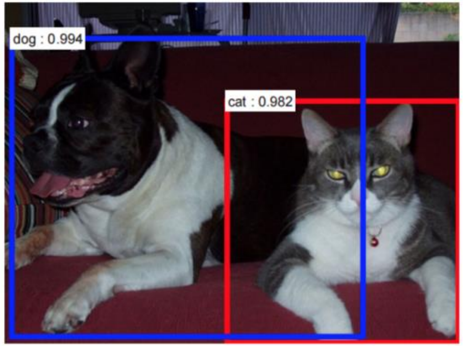


Convolutional Neural Networks

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

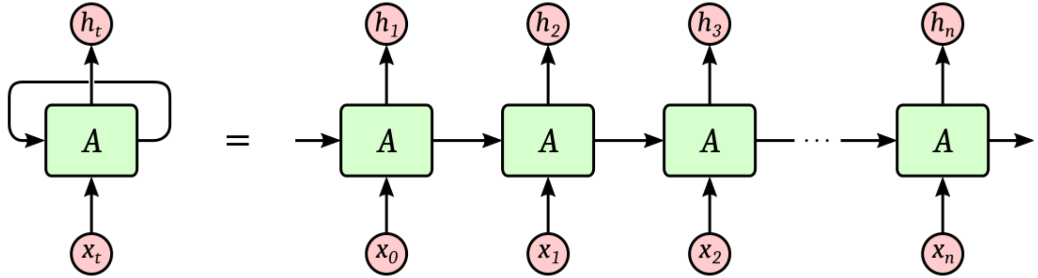






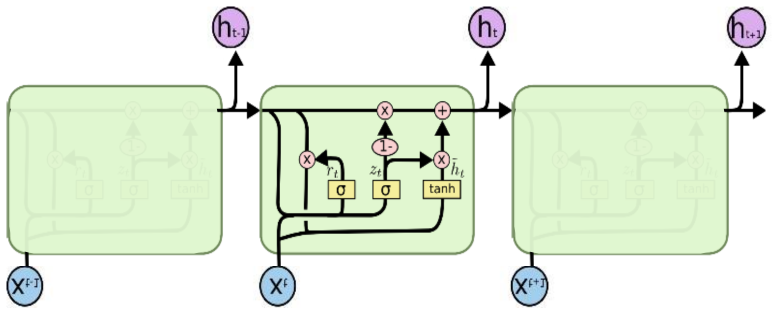
Recurrent Neural Network

- Has a "memory" which captures information about what has been calculated so far
- Designed to extract temporal relationships
  - Language Modeling
  - Speech Recognition
  - Machine Translation
- Examples: Simple-RNN, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM)



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.



LSTM Gate and Output Functions

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

Convolutional Long Short-Term Memory Network

- Convolutional LSTM
  - Variant of the standard LSTM
  - Embedded convolutional operations
  - State vectors replaced with N-D tensors

LSTM Gate and Output Functions

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

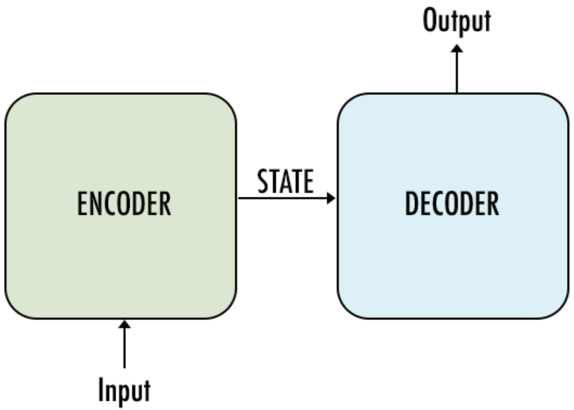
ConvLSTM Gate and Output Functions

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

Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting
https://arxiv.org/abs/1506.04214

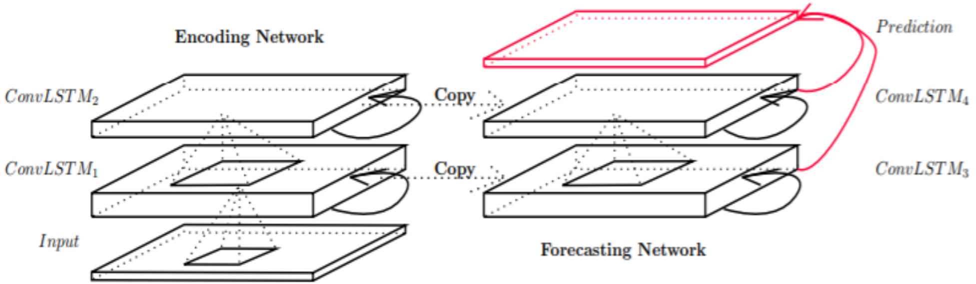
Sequence To Sequence

- **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 (Green) digests the input sequence and compress into a hidden state
  - Decoder (Blue) takes previous images as input and produces predictions of the next image.



Precipitation Nowcasting model

- encoding network and forecasting network
- formed by stacking several ConvLSTM layers



Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting
https://arxiv.org/abs/1506.04214

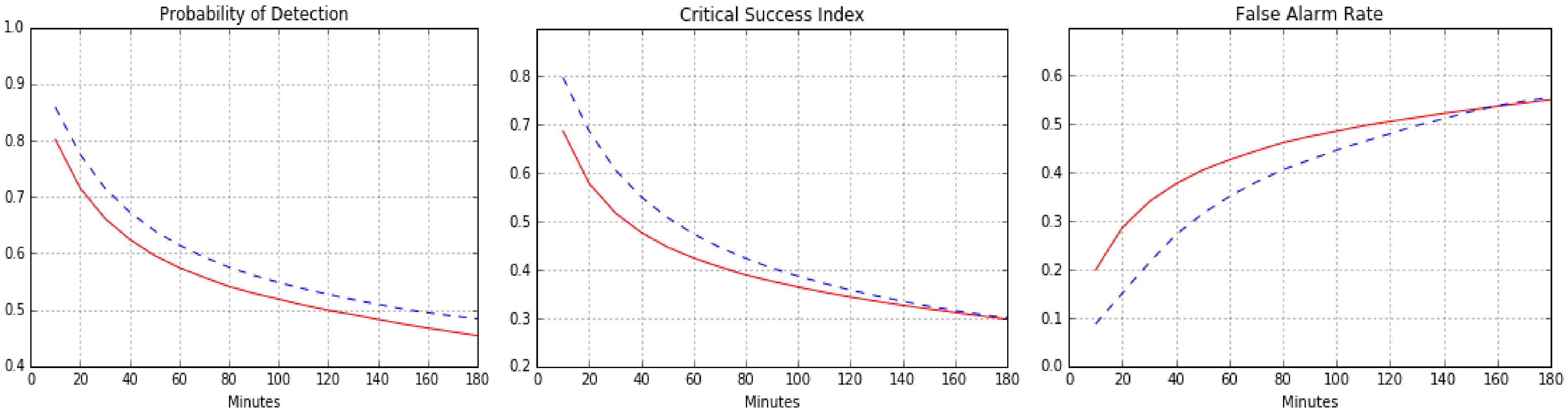
Metrics

- **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)

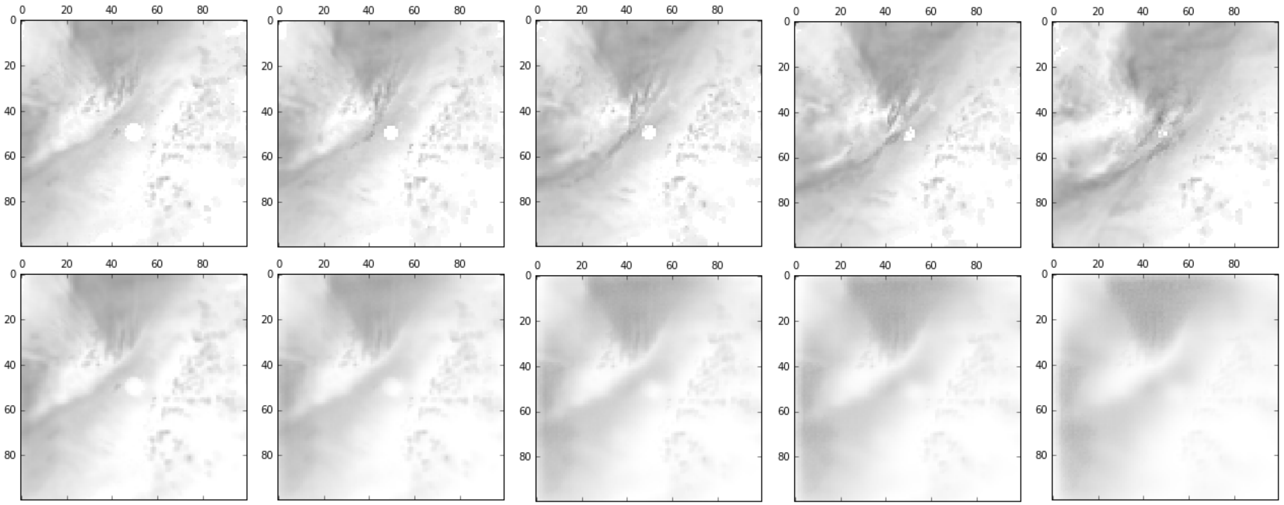
Results over time



Example Predictions

Observed Reflectivity

Predicted Reflectivity



Time Since Last Obs. (Min)

10 30 50 70 90

Further Reading ☺

https://github.com/intel-analytics/analytics-zoo

https://analytics-zoo.github.io/master/index.html

https://github.com/intel-analytics/BigDL/

https://bigdl-project.github.io/master/index.html

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