HPC and AI convergence

Session IV

Alessandro Rigazzi, Cray Inc.

HPC and AI convergence

- **Why does AI need HPC?**
  - Problem size is getting larger and larger
    - Larger samples, e.g. high-resolution images
    - Larger datasets, e.g. full days of HD camera footage
    - Larger networks, e.g.
      - More layers: Resnet 152, Tiramisu
      - More computational demanding: Densenet
  - Need for speed
    - How fast can you train a network?
    - How often do you want to re-train?

DL challenges

- **Fast training**
  - Training of NNs usually happens in mini-batches
    - The larger the mini-batch, the faster the training
      - If learning rate is correctly set
    - Memory sets a hard upper bound on mini-batch size
      - Especially on GPUs
- **More accurate training**
  - NNs have lots of Hyper-Parameters
    - What is the best setting?
      - Learning rate, momentum, …
      - Number of layers or building blocks

Faster Training at Cray

The Benchmark: KITTI

- **KITTI is a project of Karlsruhe Institute of Technology and Toyota Technological Institute at Chicago**
  - Focusing on autonomous driving (tasks: stereo, optical flow, visual odometry, 3D object detection and 3D tracking)
  - Aims to develop novel challenging real-world computer vision benchmarks

2D Object Detection

- **This track focuses on 2D object detection and object orientation estimation**
- **Dataset**
  - 7481 training images (7000 for training and 481 for validation) – 5.9GB
    - These images are labeled with bounding boxes for objects
    - Relevant object classes are: Car, Pedestrian, Cyclist
    - Any other object can be labeled with DontCare
  - 7518 test images – 6GB
  - A total of 80,256 labeled objects
  - All images are color and saved as png

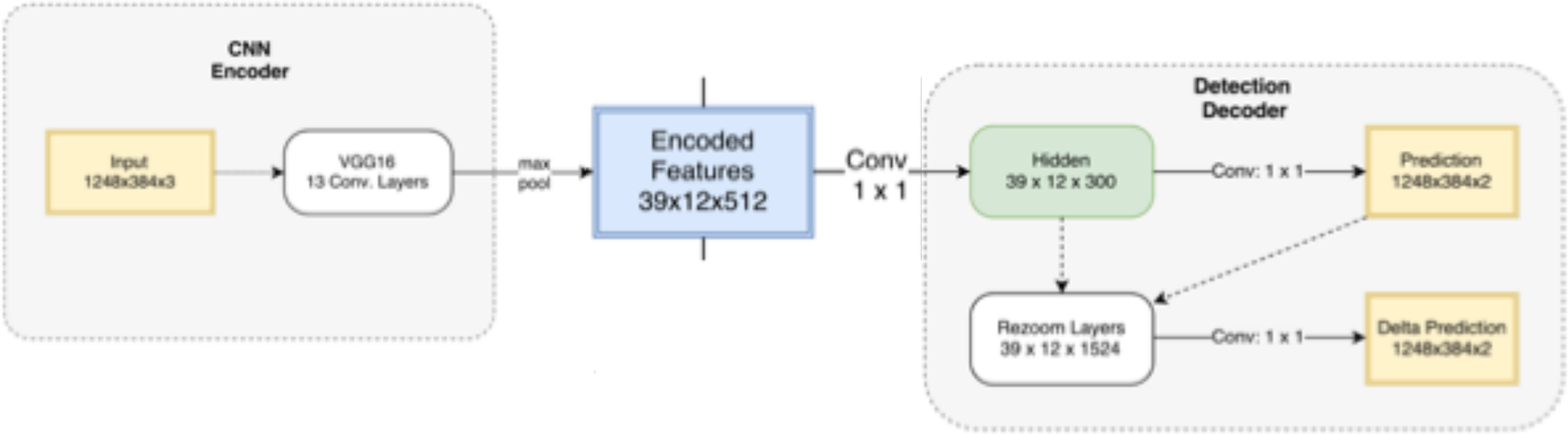
Object Detection Methods

- **Traditional deep learning approaches to object detection follow a two step process**
  - First, region proposals are generated
  - Then scored using a convolutional network
- **Some methods use CNNs for the proposal generation**
- **Recent methods use a single deep NN that is trainable end-to-end to directly perform detection**

- **Frameworks used for training**
  - Caffe, Pytorch, scikit-learn, MatLab, TensorFlow
- **All of them train on a single node (some multi-GPU)**

FastBox – The Network Architecture

- FastBox
  - Based on a encoder-decoder architecture



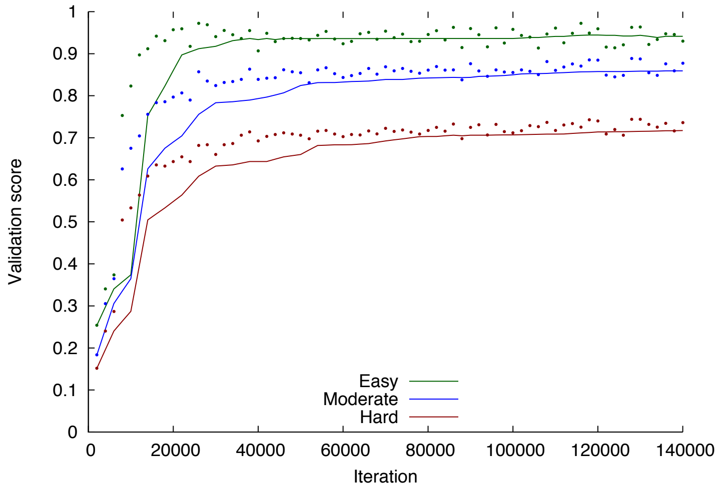
- KittiBox
  - A collection of scripts to train the FastBox model on the KITTI Object Detection dataset

KittiBox Implementation

- **Uses TensorVision**
  - A library to build, train and evaluate neural networks in TensorFlow
  - A json file is used to specify
    - The dataset
    - The architecture
    - The training schedule (optimizer, learning rate, loss, etc)
- **Runs on a single GPU**
- **Trains the model for 140,000 iterations where each iteration processes a mini batch of 5 images**

KittiBox Training on P100

- **Full run on 1 P100 node on an XC50 Cray system**
- **Run time is 27h30min**
  - Validation time is **3h**
    - Includes evaluation every 2000 iterations
  - Training time is **24h30min**
    - On average 0.63 sec (per Batch); 7.93 imgs/sec
- **Evaluation results (end of training)**
  - easy : 0.93
  - medium : 0.87
  - hard : 0.73
  - Speed (msec per image) : 37.89



Source: Diana Moise, Cray Performance team

Computational Scaling of the Training

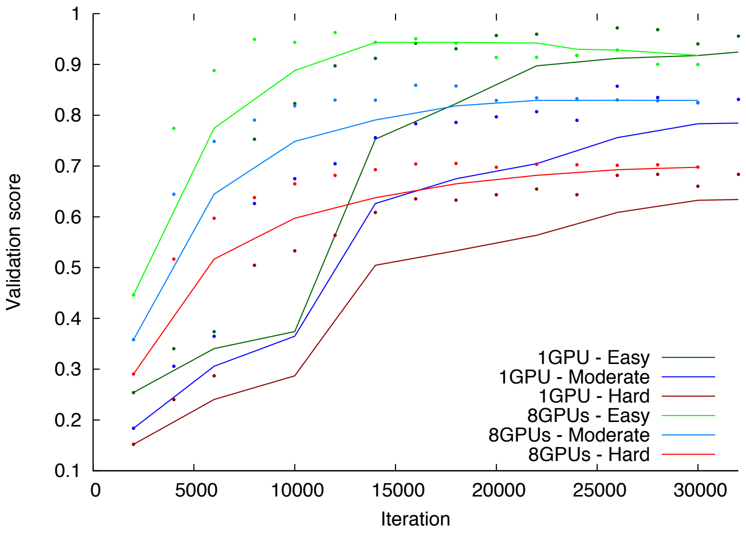
- **Cray's ML plugin allows to easily scale the training to multiple nodes**
- **Original scripts were slightly modified to use the plugin**
- **Data parallelism is already supported**
  - Implemented via a shuffling of the file names in the input queue

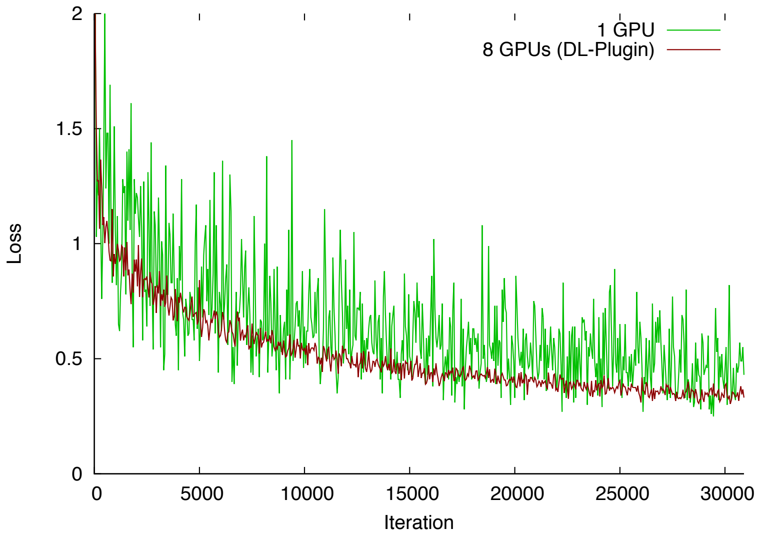
- **Several SGD schemas available with the plugin**
  - Preliminary tests use Synchronous SGD
    - This will speed up the learning process, without affecting the accuracy

- **When using multiple GPUs, training time can be reduced (by reducing the number of steps)**
  - Good scaling would reduce the training time by the same factor as the number of GPUs

Training on 1GPU vs 8GPUs (DL-plugin)

- **When using multiple GPUs, the validation precision increases earlier on, leading to faster convergence**
  - The noise in the loss curve is also greatly reduced





Scaling Results

#GPUs	#steps	training time (h)	validation accuracy (raw values)			performance (img/s)
Mini batch size = 5						
			easy	medium	hard	
1	140000	24.5	0.930	0.877	0.736	7.93
8	17500	3.2	0.958	0.894	0.753	60.8
16	8750	1.62	0.960	0.892	0.744	122.24
Mini batch size = 16						
1	43750	23.55	0.959	0.890	0.745	8.28
8	5470	3.02	0.936	0.866	0.735	64.64
16	2735	1.52	0.967	0.867	0.738	129.28

Scaling Results (cont.)

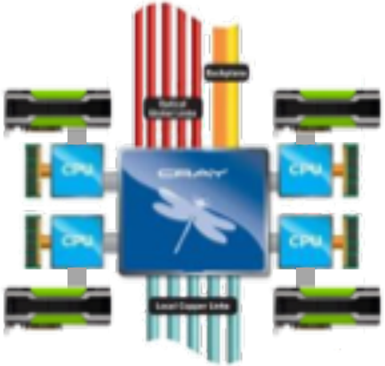
- **A larger mini-batch size enables**
  - Better GPU utilization, thus better performance and shorter training time, while reaching similar accuracy
- **With the DL-plugin, almost perfect scaling is achieved**
  - Small fraction of time spent on communication
  - Training time substantially reduced from 24.5 hours to 1.5 hours when using 16 GPUs
- **Better scaling and easier to use than Horovod**

Deep Learning on Piz Daint at CSCS – Cray XC50

CSCS
Centro Svizzero di Calcolo Scientifico
Swiss National Supercomputing Centre

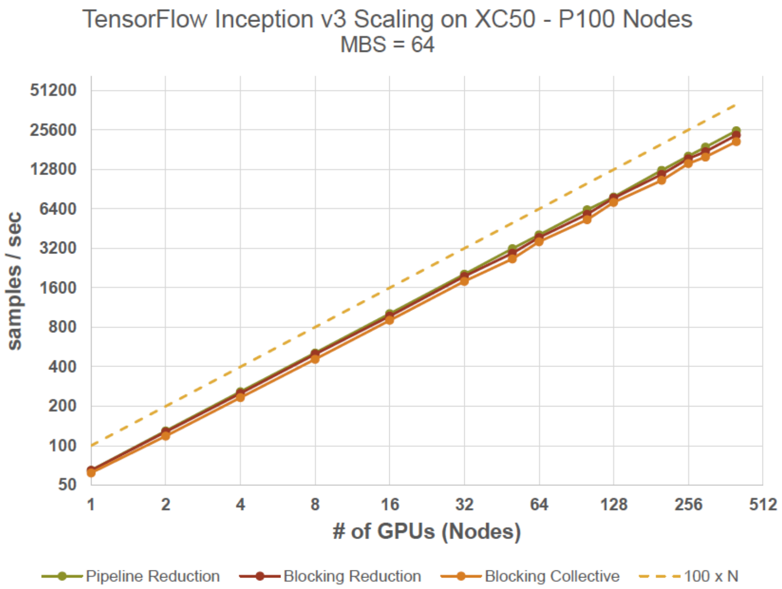
- 4500 NVIDIA P100 GPUs
- #8 on the November 2016 Top500 List
- #2 on the November 2016 Green500 List

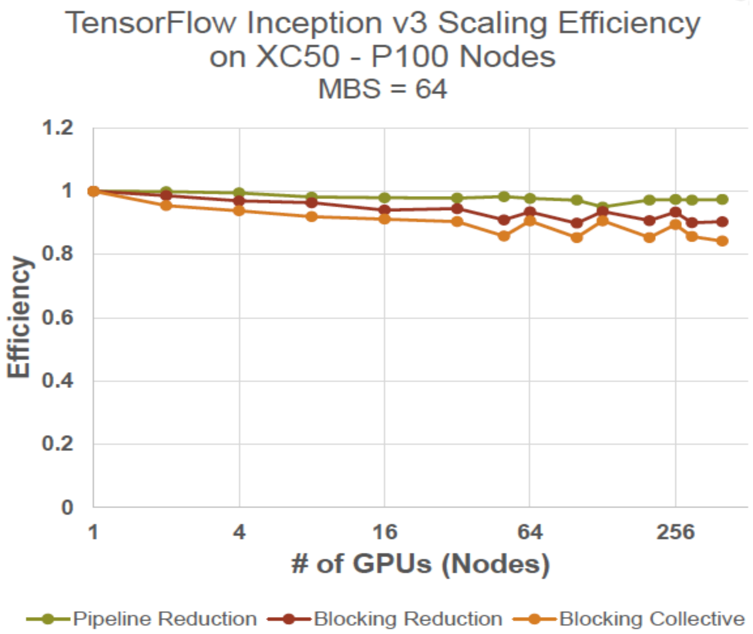
1CPU:1GPU node architecture



Differentiating Results: TensorFlow

HPC Thinking: Message-size, MPI-collective, Global all-reduce modifications





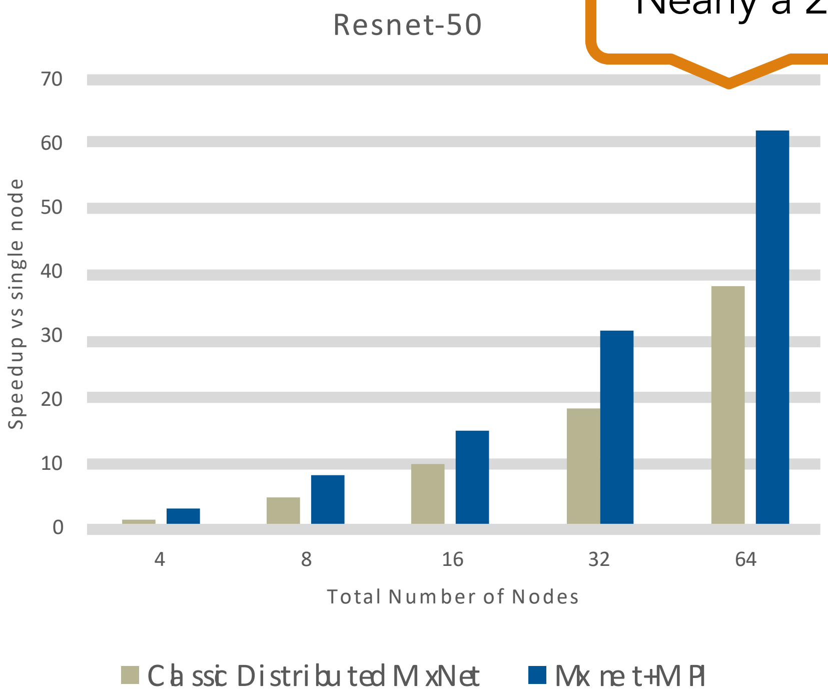
90%+ scalability efficiency that can reduce training time from days to hours

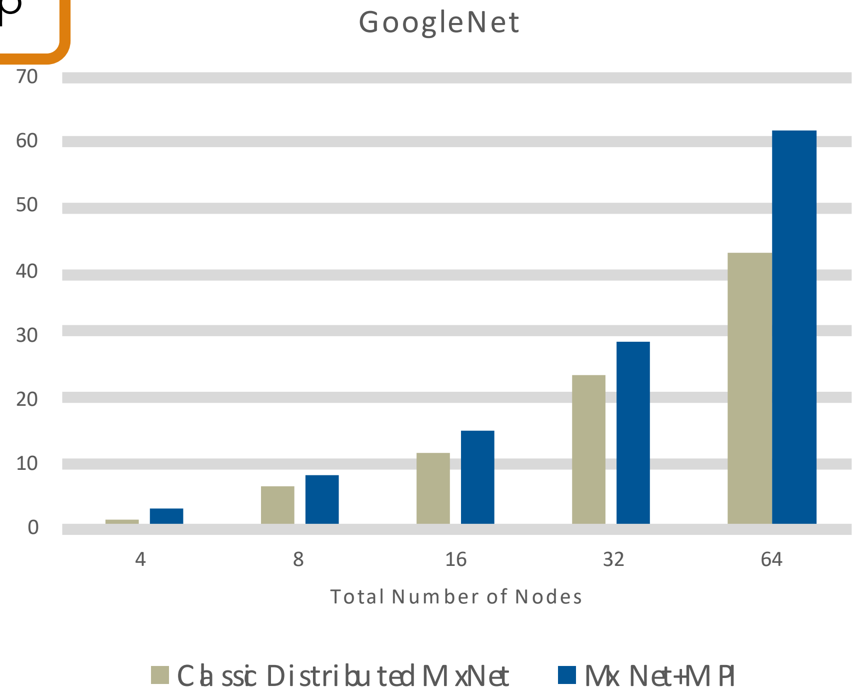
Source: Peter Mendygral and Jef Dawson, Cray PE and Performance

Differentiating Results: MXNet

Distributed vs. Cray MPI approach

Nearly a 2x speedup





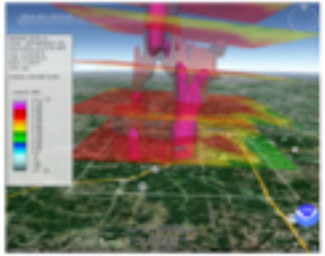
What is missing? End-to-end workflows!

- **A DL/AI problem is not only about training or inference**
- **Many other challenges**
  - Data preparation and ingestion
  - Handling of AI output
  - Interpretability and reliability of prediction
- **For example**
  - **Precipitation Nowcasting Leveraging Deep Learning and HPC Systems to Optimize the Data Pipeline**
    - **[Alex Heye (Cray), AMS 98th Annual Meeting, 2018]**

Dataset Processing

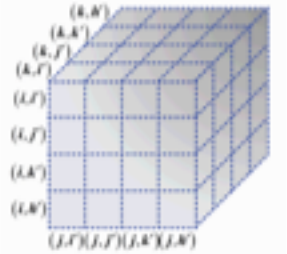
Data Collection

- Historical Radar Data (NETCDF)
- Geographical Region
- Days with over 0.1 inches of precipitation, info from NOAA – NCDC
- Radar scans every 5-10 minutes throughout the day



Transformation

- Raw radial data structure converted to evenly spaced Cartesian grid (Tensors with float 32)
- Resolution scaling and clipping
- Configure dimensionality
- Sequencing
- 2 channels – Reflectivity, Velocity
- Uses Py-ART package



Sampling

- Time-series
- Inputs and Labels
- Random sampling

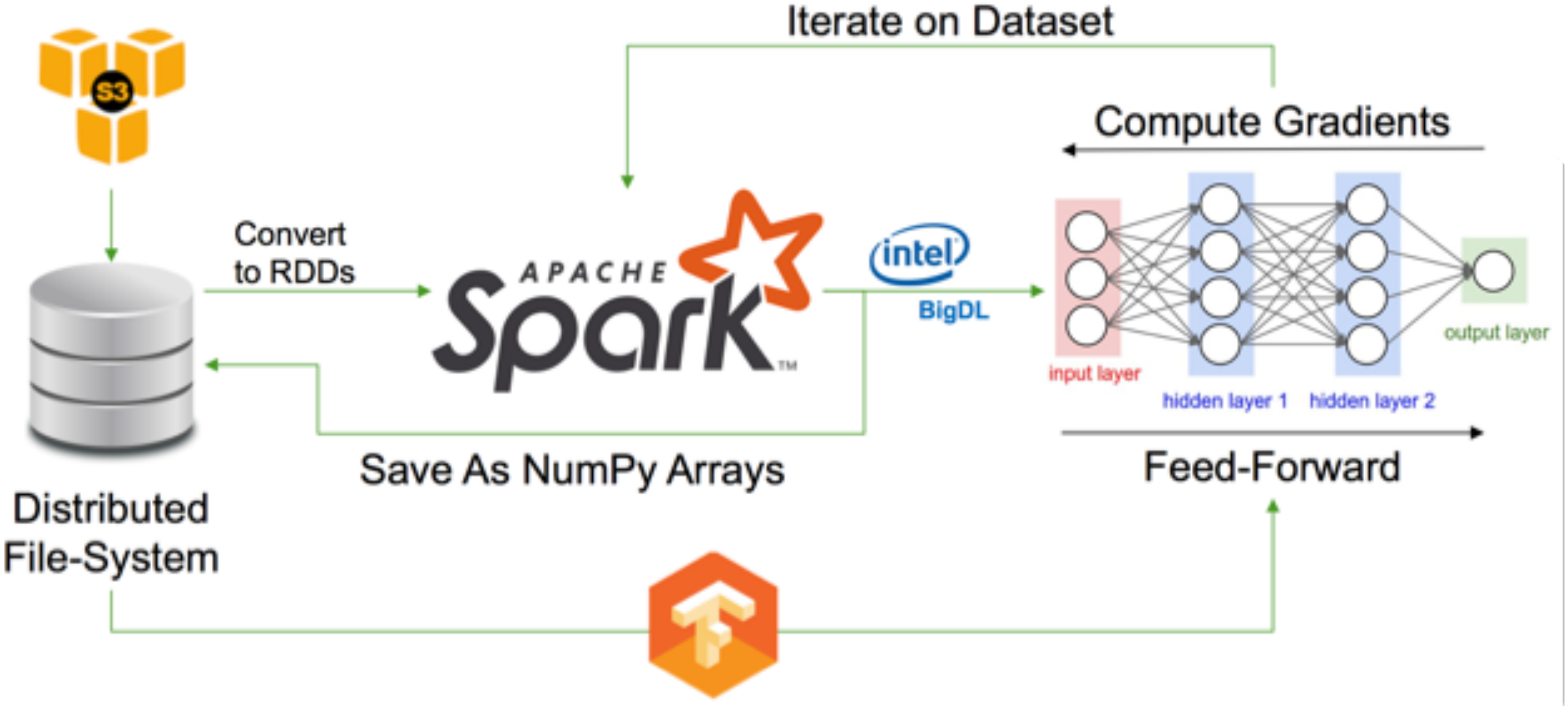
intel

BigDL

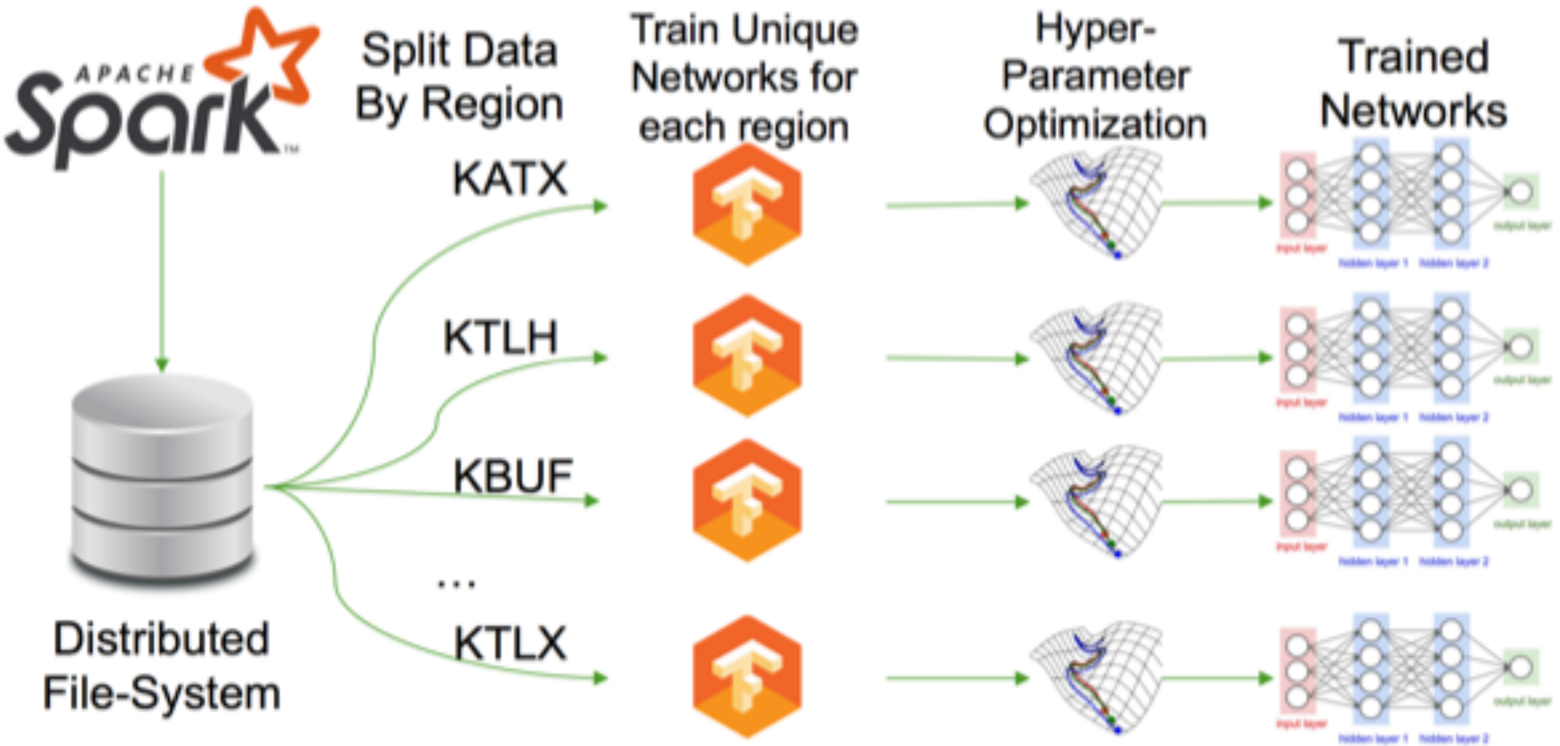
Framework

- Apache Spark on Urika-XC/GX
- Implemented in Jupyter notebooks and Python

Data Processing Pipeline



Distributed Training



Idealized Timeline

- **Station: KATX**
- **Dataset size:**
  - 118,342 Sequences
  - 101GB
- **Parameters**
- **Systems:**
  - Data processing: Cray Urika-GX – 1024 cores
  - Training: Cray CS-Storm – 8 Nvidia P100 GPUs

Process	Wall-Time	Proportion
Download	13 hours	32%
Spark	4 hours	10%
Training	24 hours	58%
Inference	10 seconds	0%

Scaling

- Tensorflow via Cray MPI Com. Plugin
- Nvidia Tesla P100 GPUs
- Batchsize of 4 samples per device
- Throughput in Samples/Second

Device Count	Throughput	Scaling Efficiency
1	25.8	1.0
2	51.6	1.0
4	102.7	.995
8	205.4	.995
16	410.5	.994

$$\frac{\text{Training } 58\%}{(16*0.994)} + \text{Rest } 42\% = \cancel{100\%}\ \ 45.65\%$$

>2x speedup

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Q & A

Overall Session