BLUE WATERS

SUSTAINED PETASCALE COMPUTING

4/4/18

Machine Learning on Blue Waters Using TensorFlow with the Image Feature Detection Problem

Part Deux

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NCSA

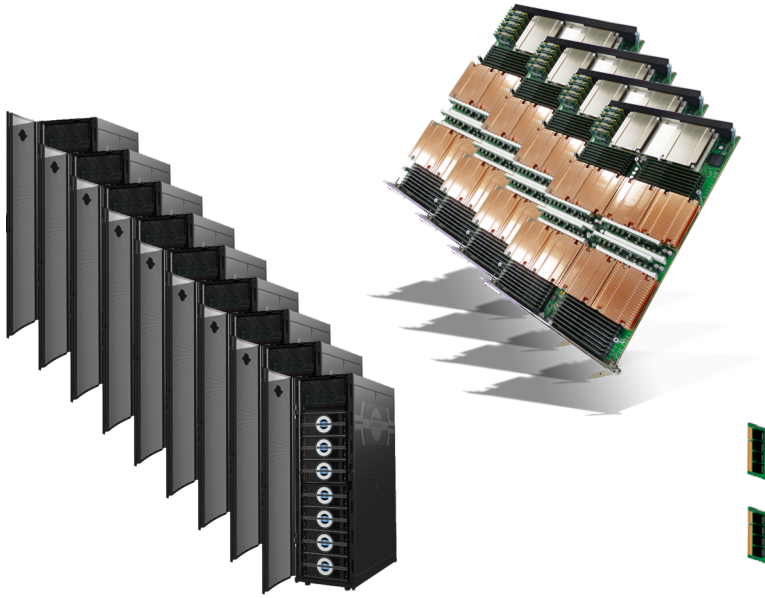
GREAT LAKES CONSORTIUM
FOR PETASCALE COMPUTATION

CRAY

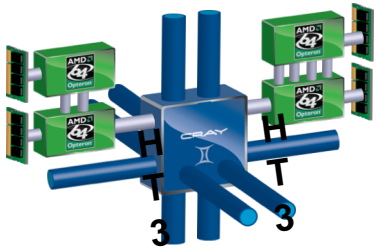
Todays Topics

- Continuation of,
  - https://bluewaters.ncsa.illinois.edu/webinars/data-analytics/ml-tensorflow
- Review Blue Waters
- NN Review
- TensorFlow Basics
- Distributed TensorFlow Overview
- Parallelization Scheme
- Code Tour and Demos

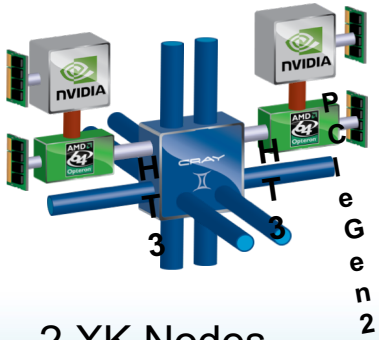
Blue Waters Overview



Sonexion: 26 usable PB



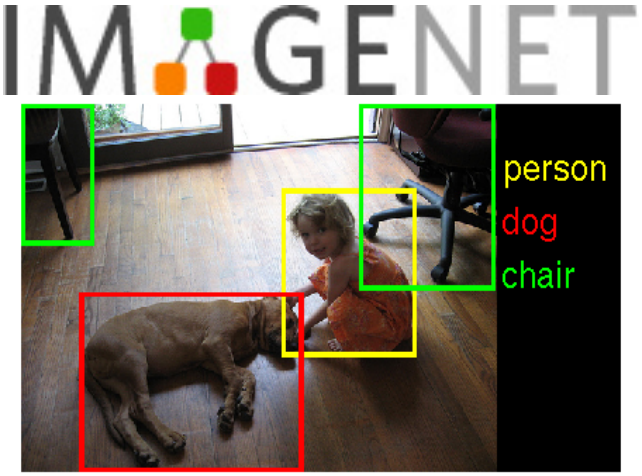
4 XE Nodes



2 XK Nodes

Nvidia K20
(circa 2012-13)

ImageNet

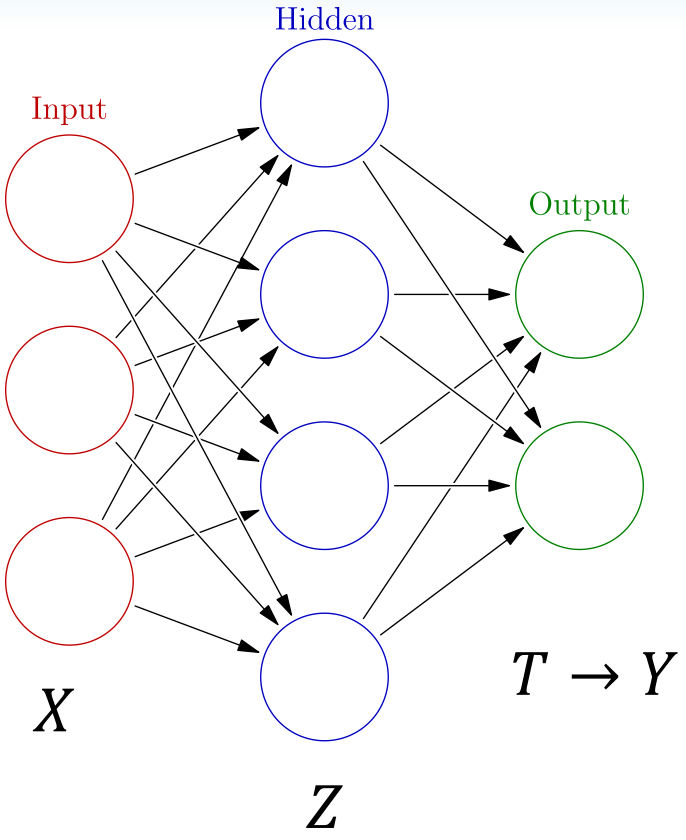


- www.image-net.org
- Large High Quality Dataset
  - 14,197,122 Images
  - 21841 synsets
- Runs the Large Scale Visual Recognition Challenge (ILSVRC)
- Annotated
  - Bounding Boxes
  - synset
    - WordNet (http://wordnet.princeton.edu)

Neural Networks

- Parameterized function
  - $Z_M = \sigma(\alpha_{0m} + \alpha_m X)$
  - $T_K = \beta_{0k} + \beta_k Z$
  - $f_K(X) = g_k(T)$

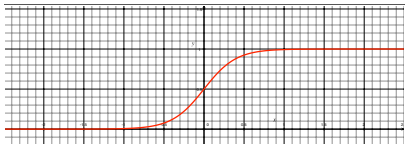
- $\beta_{0i}, \beta_i, \alpha_{0m}, \alpha_m$
  - Weights to be optimized



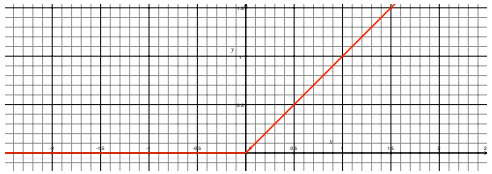
Neural Networks

- Activation functions

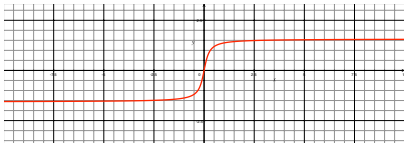
Logistic

$\sigma(x) =$ 

ReLU (Rectified Linear Unit)

$\sigma(x) =$ 

Arctan

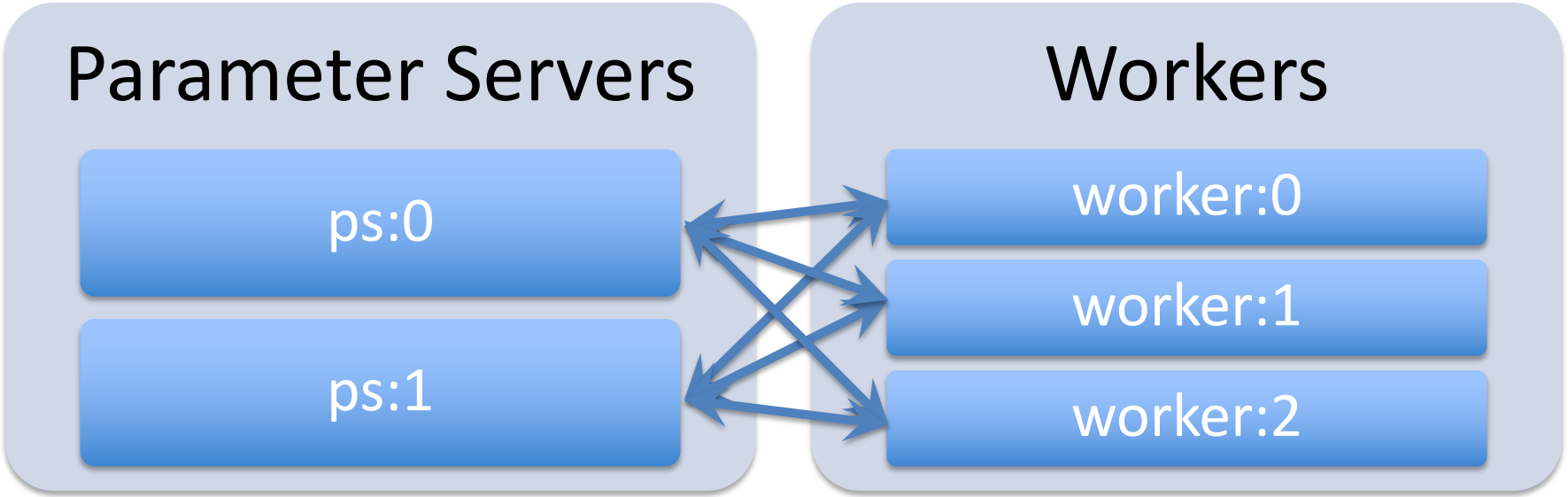
$\sigma(x) =$ 

- Softmax
  - $g_k(x_1, x_2, \ldots, x_N) = \frac{e^{x_k}}{\sum e^{x_i}}$

TensorFlow Basics

- Python API
  - C++ under the hood
- Mediator Design Pattern
  - Uses python context manager (`with`)
- Workflow
  - Construct operations
  - Assign to name scope and or device
  - Enter Session context
    - run()
- www.tensorflow.org/programmers_guide/low_level_intro

Distributed TensorFlow: Parameter Sever/Worker



- Parameter Server contains and coordinates parameters
- Workers ask for and return computed results
- Resilient to Worker/PS failure

Parallelization Schemes: What we are trying to Parallelize

Input Data

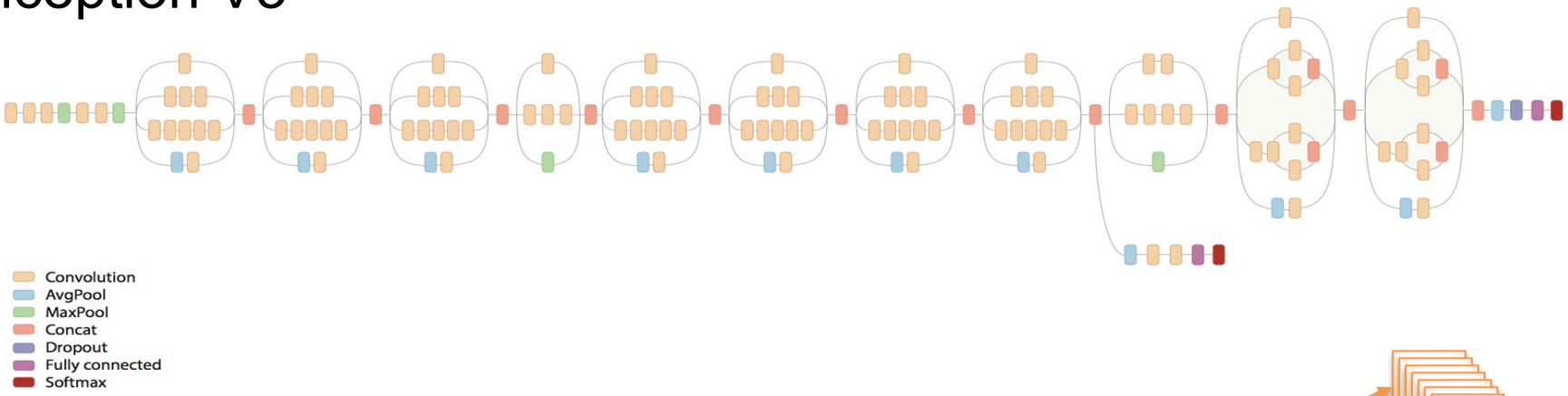
- List of Images
- Annotation (1,000 classes)

Algorithm

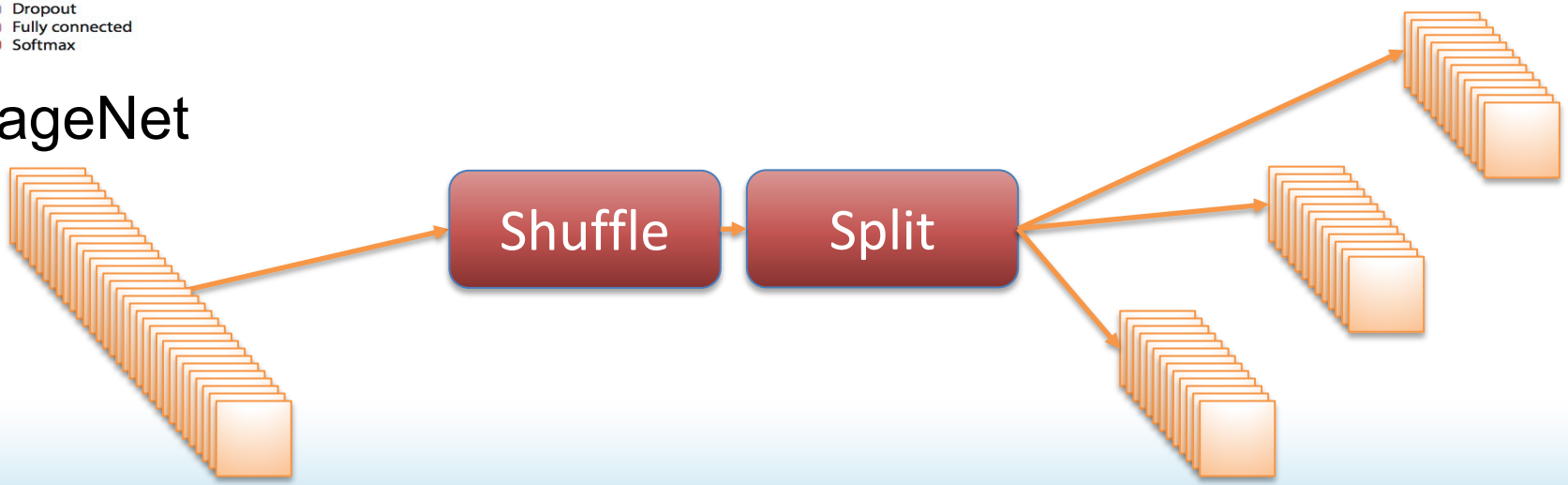
- Inference
- Loss
- Optimize

Algorithm, Data

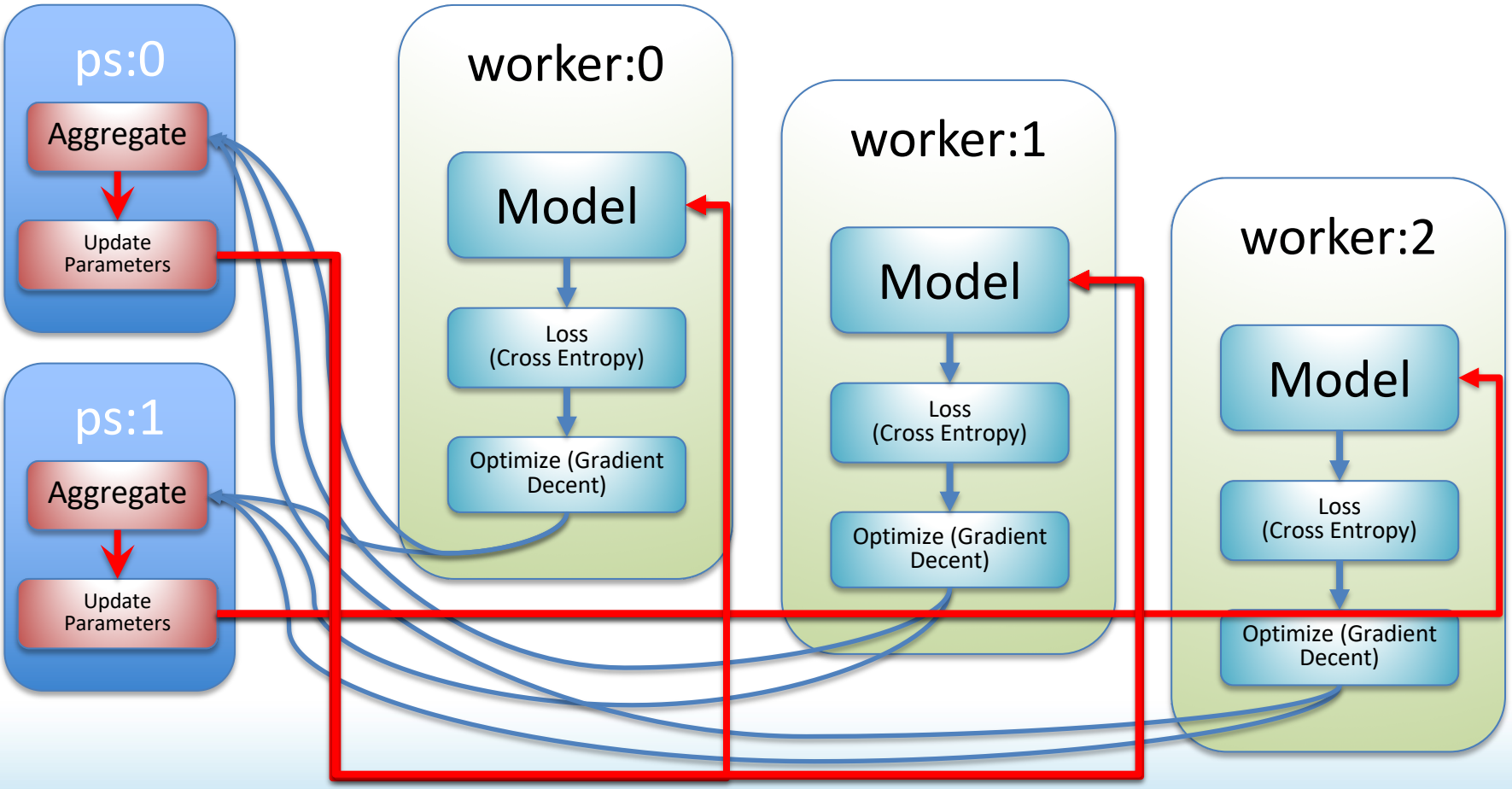
Inception V3



ImageNet



Distributed TensorFlow: Parameter Sever/Worker



Defining the Distributed Tensor Flow Cluster

- Blue Waters Job Details
  - qsub –l nodes=8:ppn=16:xk inception_imagenet_distributed_train.pbs
    - Makes 8*16 (128) processing elements available.
  - aprun -n 8 -N 1 -- python ${RUN_CMD_WITH_ARGS}
  - 1 processing element per XK node
    - Job will hang if multiple workers are competing for same GPU
- Each Blue Waters node has a host name
  - nidxxxxx
  - Construct list
    - ps: nid00001:2222
    - worker: nid00002:2222, nid00003:2222, nid00004:2222

Defining the Distributed Tensor Flow Cluster

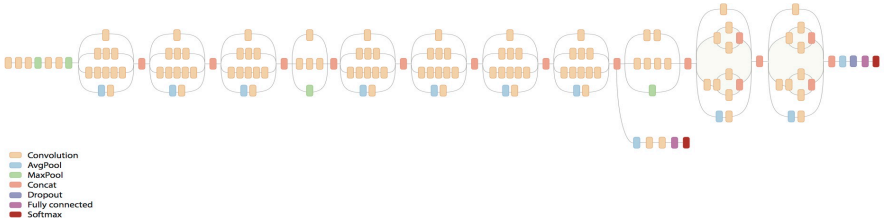
- Get unique hostnames of job
  - socket.gethostname()
  - mpi4py allgather(my_hostname)
- Decide which hosts will be parameter servers and which will be works
  - tf_ps_hosts_ports = ['nid25428:2222']
  - tf_worker_hosts_ports = ['nid25429:2222','nid25430:2222']
- tf.train.ClusterSpec()
- tf.train.Server()

Defining the Distributed Tensor Flow Cluster

Demo
(Code Tour)

Defining the Distributed Tensor Flow Cluster

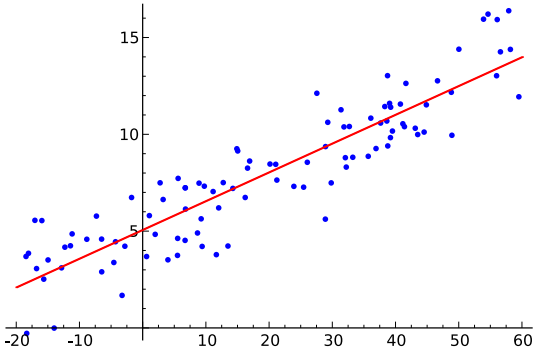
- tf.device() and tf.train.replica_device_setter()
  - replica_device_setter()
    - All the magic happens
  - Default round robin PS scheme



Defining the Distributed Tensor Flow Cluster

Demo
(Code Tour)

TensorFlow Basics



Demo
Simple Regression

Blue Waters TensorFlow Process

Demo
(Code Tour)