



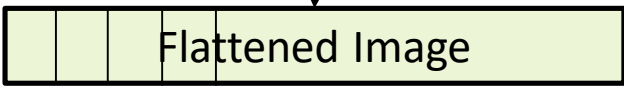
# **Bridging the Gap Between Deep Learning Algorithms and Systems**

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AUGUST 28<sup>TH</sup>, 2019

# A QUICK INTRODUCTION TO MACHINE LEARNING/DEEP LEARNING

Input (X)



$$f = W^T X$$

Task: Predict the correct class – Image classification



$f = W^T(W^T(W^T X))$  – complex function, still a linear function

$f = \sigma(W^T(\sigma(W^T(\sigma(W^T X)))))$  – non-linear complex function where  $\sigma$  is a non-linear function

Slide filter left to right; top to bottom



Predict the correct class  
Image classification

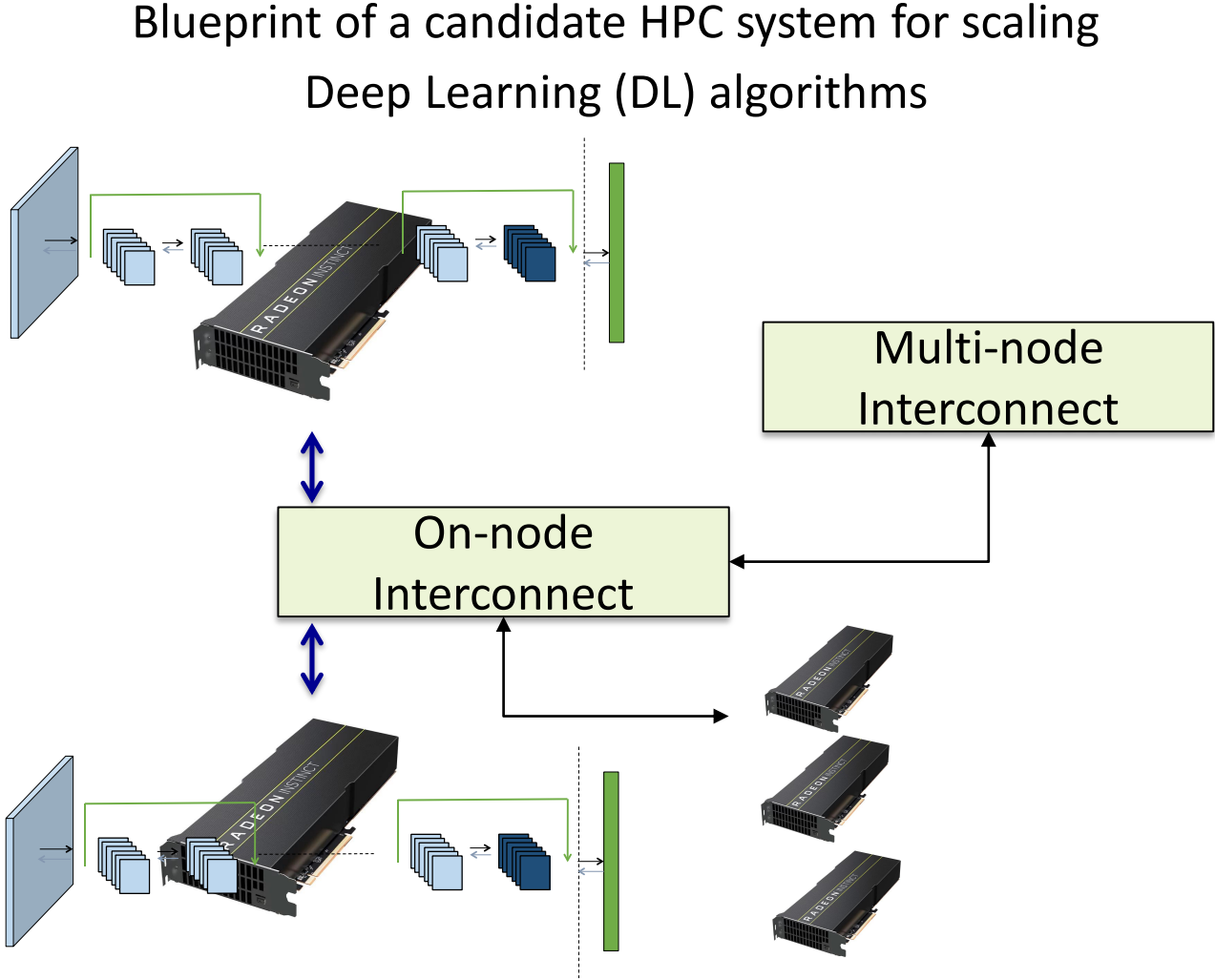
**Applicability to Science:** Problems can be represented using a combination of extracted features and/or images

**Data requirements:** Complex representations (such as images) require large amount of labeled data

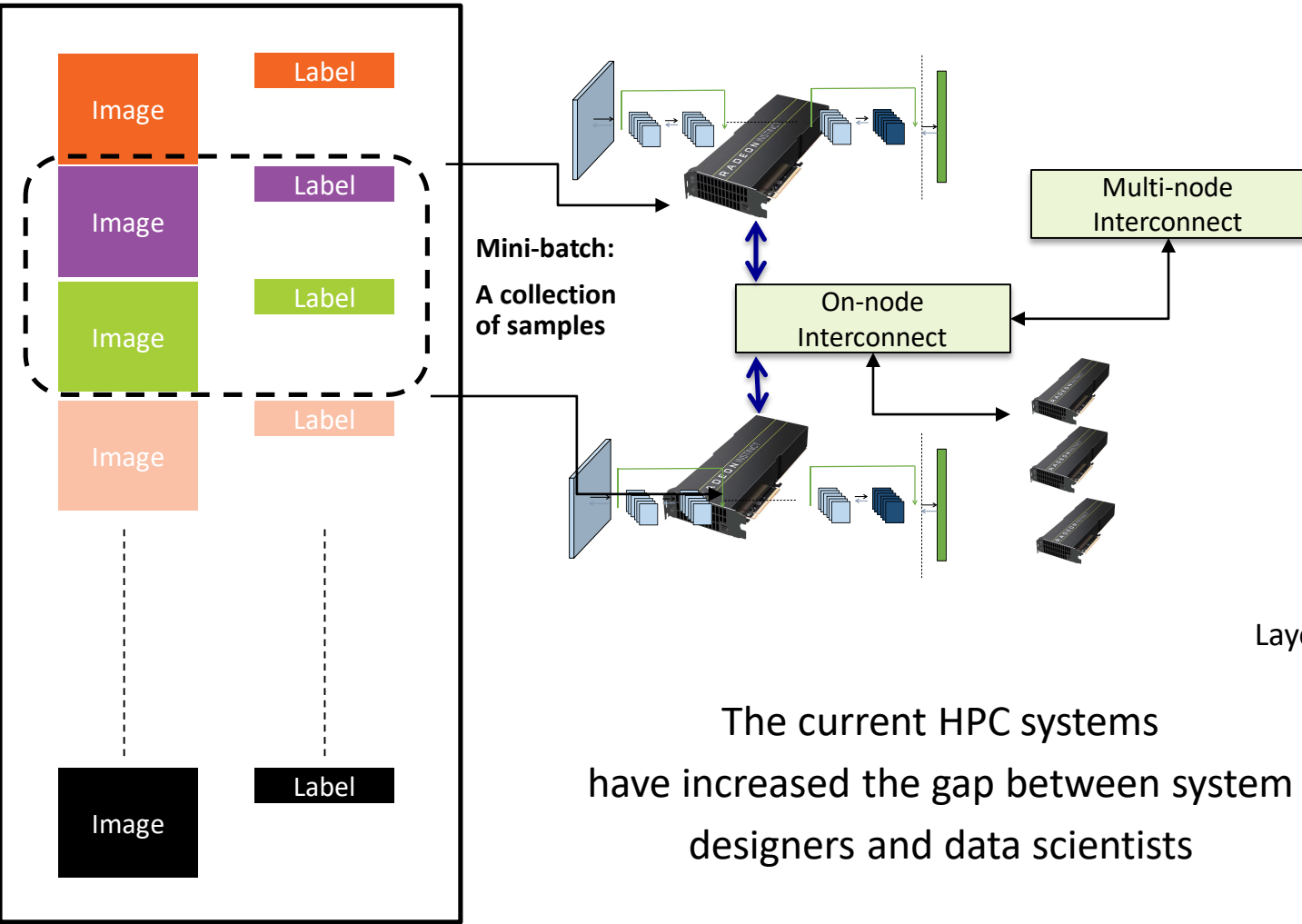
**Compute requirements:** Models with complex representations have large compute requirements requiring HPC systems

# TRENDS IN LABELED DATA AND MODEL LEARNING (TRAINING) TIME

Name	Number of Images	Model Learning (Training Time)/Device
ImageNet	1.1M	~1 day
Tencent-ML	18M	Few Weeks
JFT-Google	300M	Not reported
Facebook	3.5B	Not reported

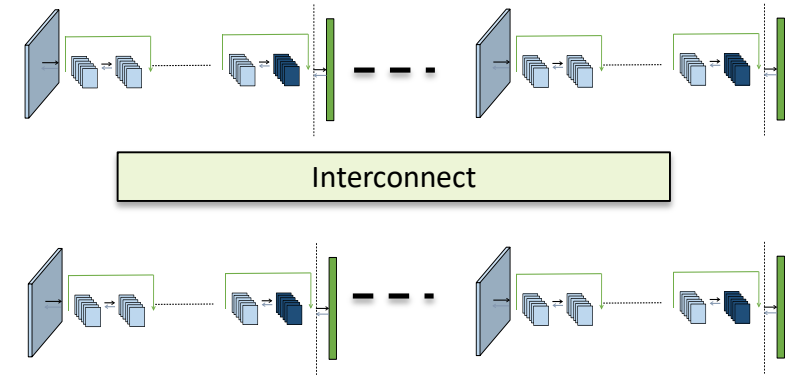


# TRAINING DEEP LEARNING ALGORITHMS ON HPC SYSTEMS

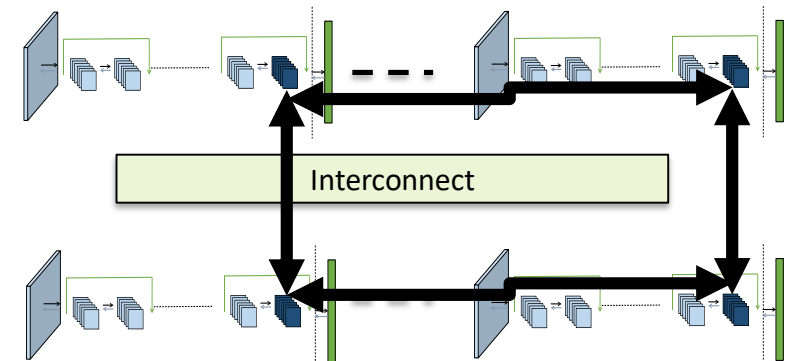


The current HPC systems have increased the gap between system designers and data scientists

No communication during Feedforward(error calculation) step



Layer-wise All-to-all reduction during Back-propagation (model learning) step



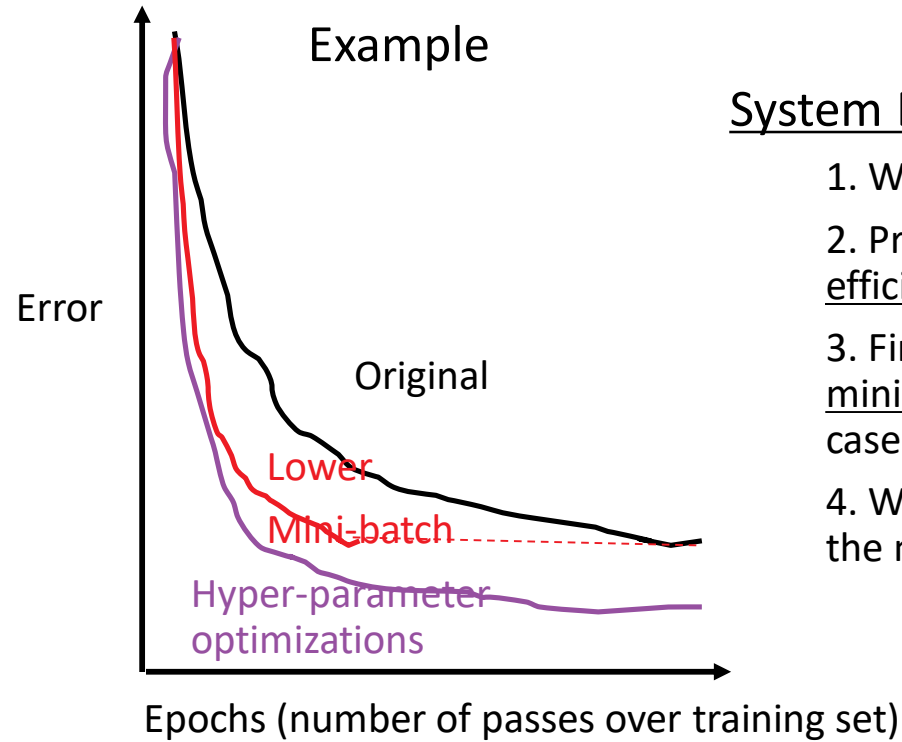
Popular Ring algorithm in DL algorithms



# THE MIS-MATCH BETWEEN SYSTEM DESIGNERS AND DATA SCIENTISTS

## Data Scientist

1. Wants small mini-batch size
2. Primary objective is faster convergence
3. Defines an application model for system architect to optimize with generalizability to other problems
4. Work on algorithmic (hyper-parameter) optimizations to improve accuracy

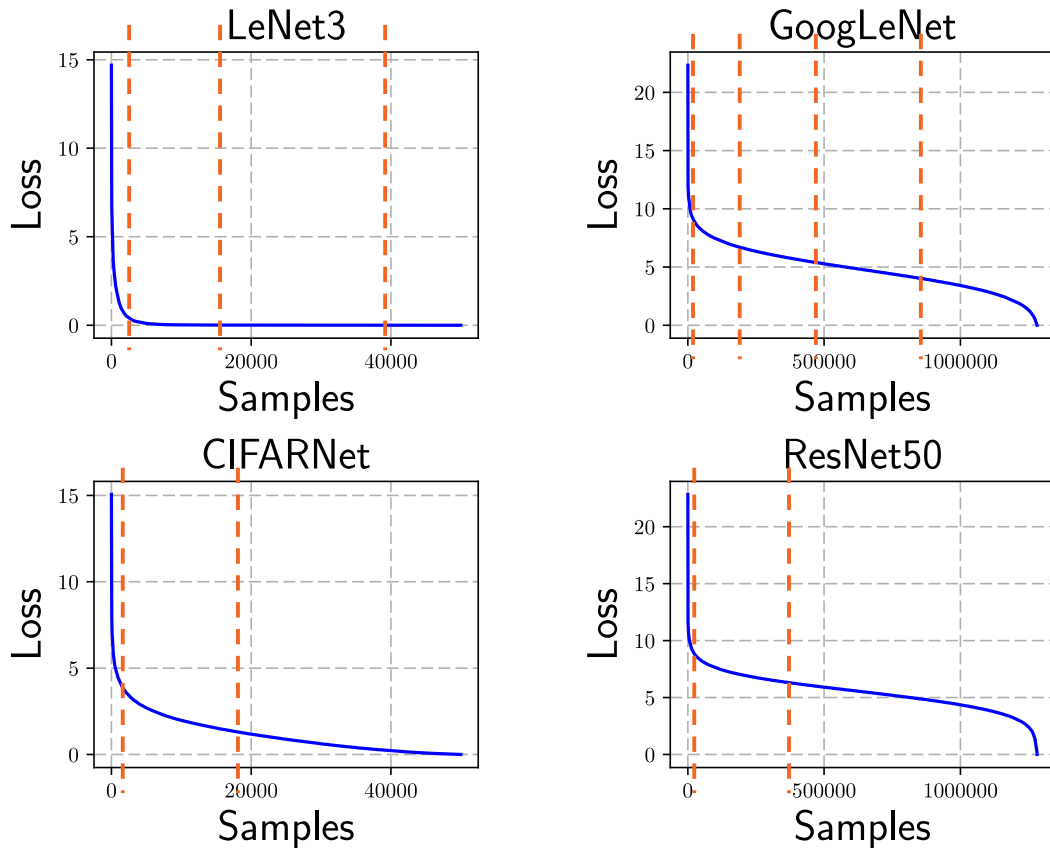


## System Designer

1. Wants large mini-batch size
2. Primary objective is higher compute efficiency given convergence constraints
3. Find the inter-play between maximum mini-batch size and accuracy for the use-cases; generalizability is not the focus
4. Work on holistic system design to enable the maximum mini-batch size

Machine Learning models and system architecture/software needs to be co-designed to help bridge the gap between data scientists and system designer

# POTENTIAL SOLUTION: ADAPTIVE MINI-BATCHING

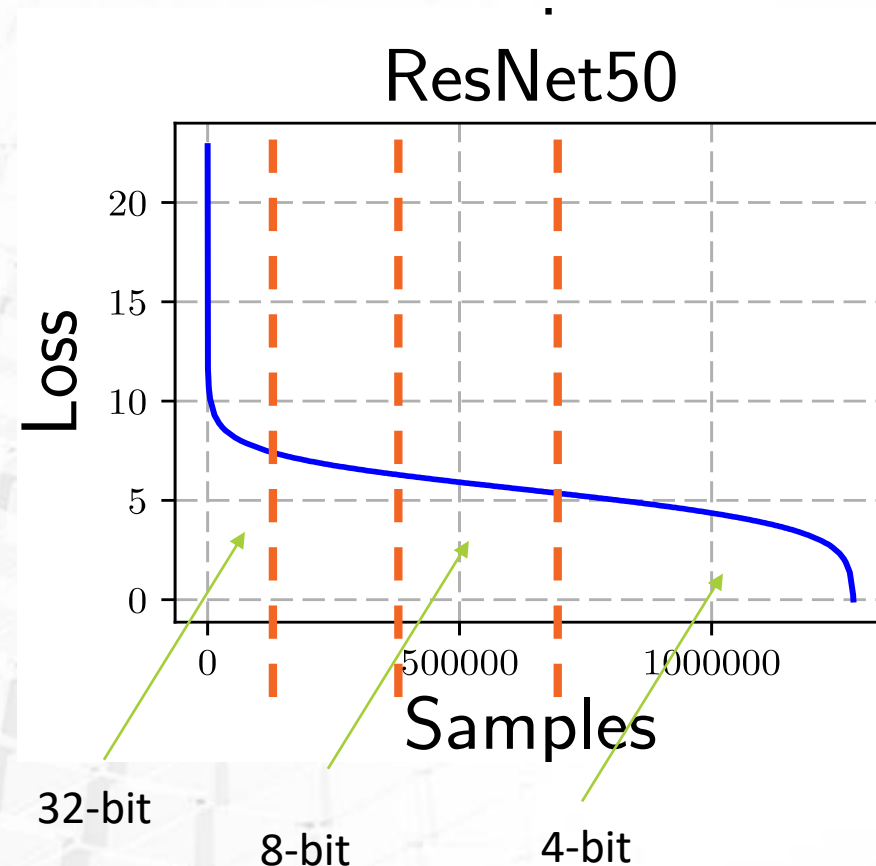


Three datasets, four networks

- ▲ The error magnitude is computed by adding the error from samples in the training dataset
- ▲ However, only a handful of samples contribute to the error
  - For example consider ResNet50 (after one epoch) on the adjacent figure
- ▲ Few samples have very high error, most samples have low error
  - The error curve becomes flatter with epochs
  - Low error samples contribute less to model learning
- ▲ A combination of large and small mini-batches may be created by epoch-wise analysis of the error/loss. An example is shown on the left
- ▲ Communication overhead is also reduced with adaptive mini-batching

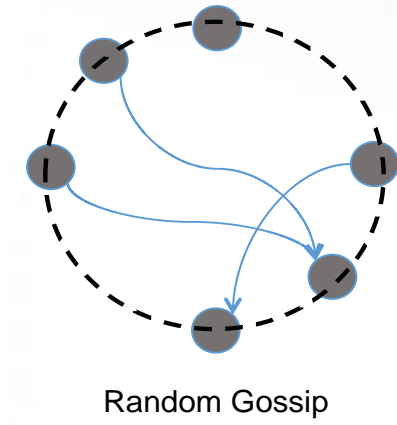
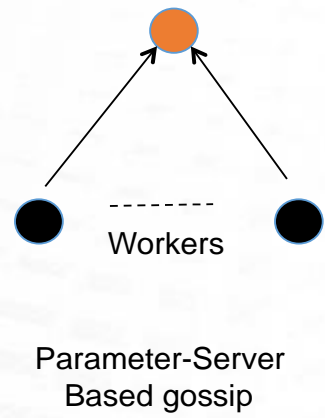
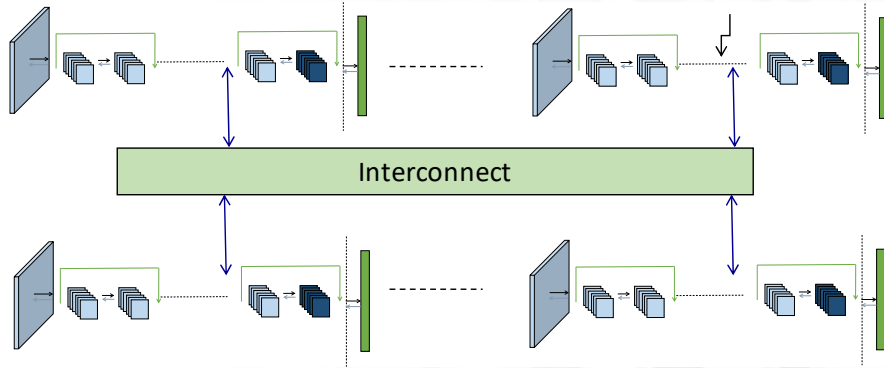
# ACCELERATION USING ADAPTIVE PRECISION

- ▲ Split the samples in multiple buckets of different precision
- ▲ The buckets may be defined by sorting the samples using non-increasing error
  - Flatter loss implies lower number of bits may be enough to encode the weight updates in that bucket
  - Loss becomes flatter with increasing epochs
- ▲ Reset the precision if validation loss increases
  - Reduce the precision adaptively after the reset
  - Self-corrects the problems due to aggressive reduction in precision



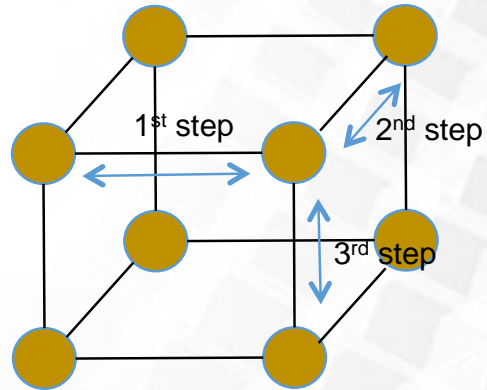
# REDUCING COMMUNICATION CARDINALITY

Communication complexity of the ring algorithm is linear, but the achievable bandwidth is lower with decreasing chunk sizes



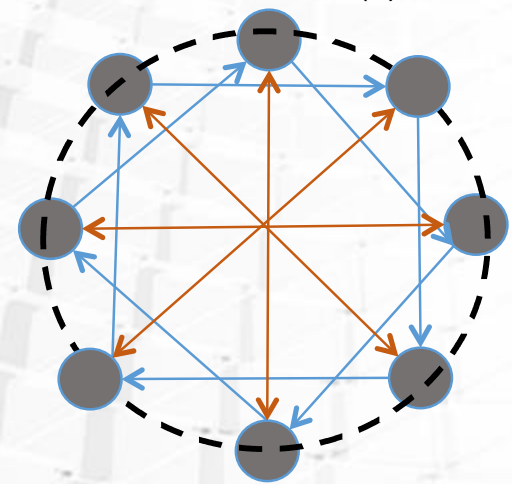
(a)

(b)



(a)

Hypercube-based Gossip



(b)

Dissemination-based Gossip



# CONCLUSIONS

- ▲ Deep Learning (DL) algorithms are becoming popular as they leverage complex representations (such as raw input with images) in addition to extracted features
- ▲ HPC systems play an important role in reducing the time-to-solution for DL algorithms
- ▲ There is a widening gap in primary metrics of concern between a data scientist and a system designer
- ▲ We proposed approaches to bridge the gap by using adaptive mini-batching
  - For high error samples, use small mini-batches
  - For low error samples, use large mini-batches under the memory and compute constraints of the system
  - Proposed adaptive precision (high precision for high error samples) that matches well with the compute capabilities of today's systems
  - Proposed solution for addressing the limitations of all-to-all reduction by using reduced communication cardinality
- ▲ We hope to work with the scientific community to enhance these solutions and present results through publications and open source software

THANKS FOR LISTENING!!

QUESTIONS?



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