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15th ANNUAL WORKSHOP 2019

ACCELERATING TENSORFLOW WITH RDMA FOR HIGH-PERFORMANCE DEEP LEARNING

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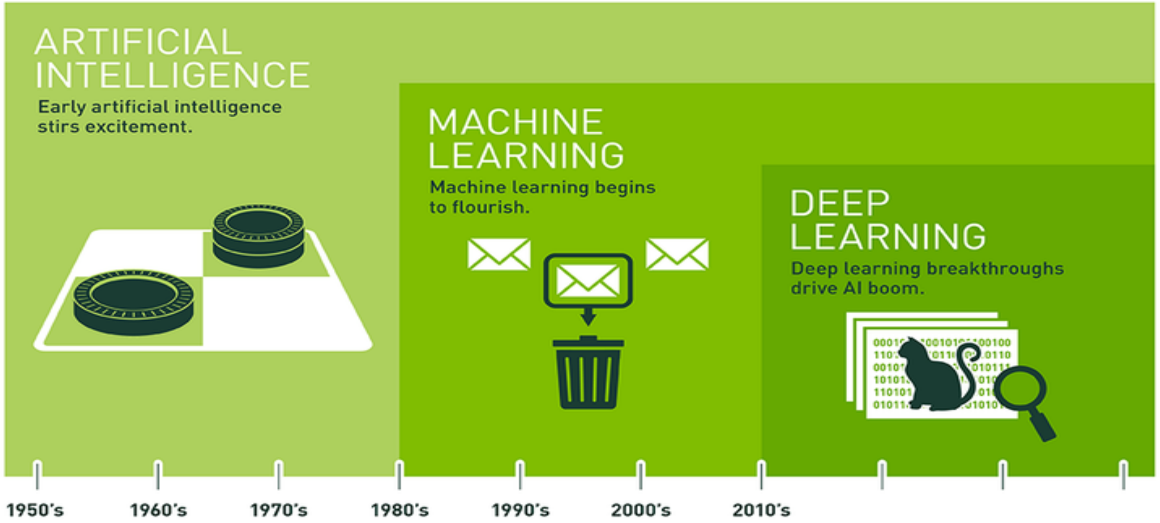
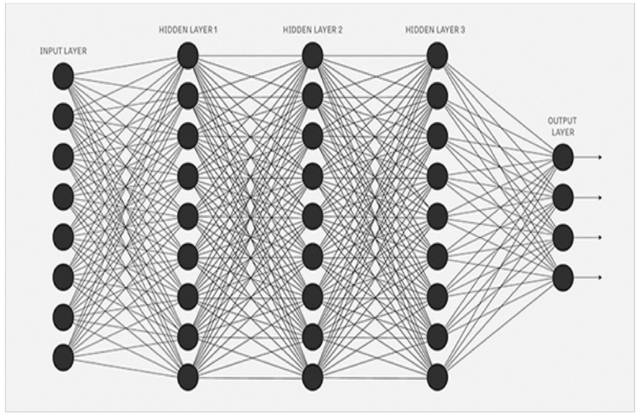
OVERVIEW OF HIGH-PERFORMANCE DEEP LEARNING

- **Deep Learning is a sub-set of Machine Learning**
  - But, it is perhaps the most radical and revolutionary subset
- **Deep Learning is going through a resurgence**
  - **Model**: Excellent accuracy for deep/convolutional neural networks
  - **Data**: Public availability of versatile datasets like MNIST, CIFAR, and ImageNet
  - **Capability**: Unprecedented computing and communication capabilities: Multi-/Many-Core, GPGPUs, Xeon Phi, InfiniBand, RoCE, etc.
- **Big Data has become one of the most important elements in business analytics**
  - Increasing demand for getting **Big Value** out of Big Data to drive the revenue continuously growing



http://www.zdnet.com/article/caffe2-deep-learning-wide-ambitions-flexibility-scalability-and-advocacy/

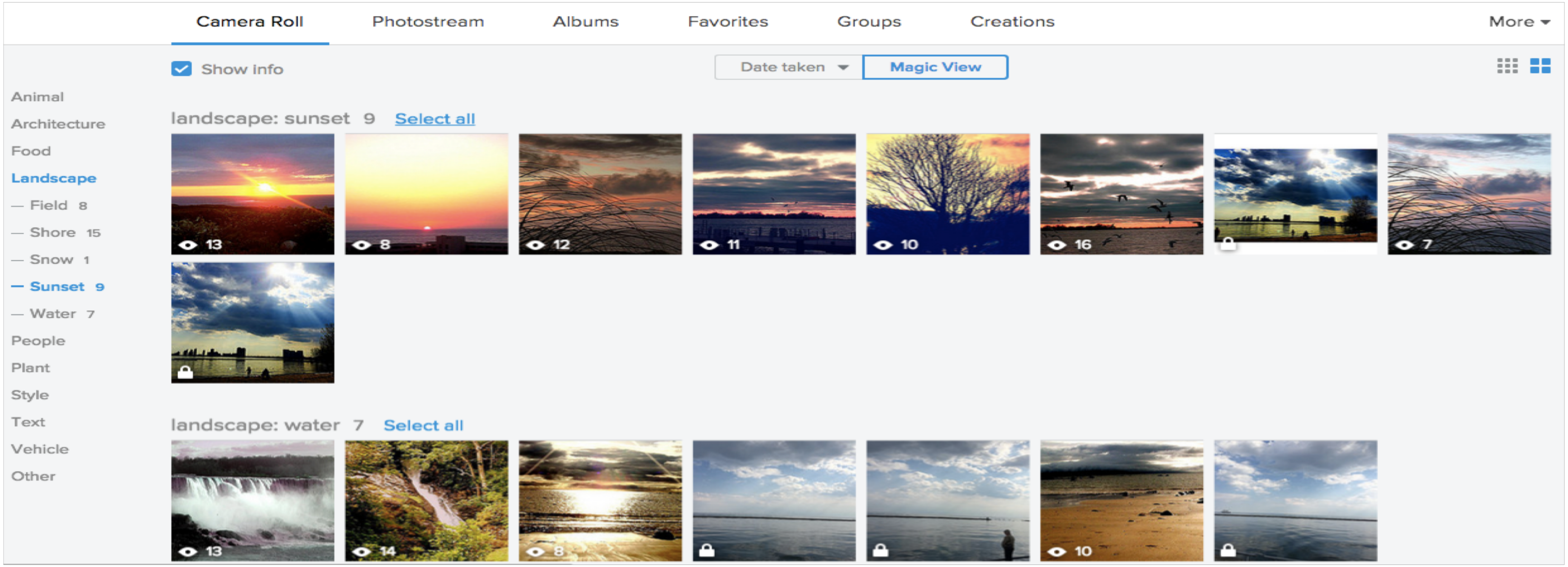
MNIST handwritten digits



Deep Neural Network

APPLICATION EXAMPLE: FLICKR'S MAGIC VIEW PHOTO FILTERING

- Image recognition to divide pictures into surprisingly accurate categories
- Magic of AI/DL: Generate accurate tags for billions of pictures



Courtesy: https://thenextweb.com/opinion/2015/05/22/flickrs-new-magic-view-photo-filtering-feature-works-so-well-it-convinced-me-to-ditch-iphoto/#.tnw_RaZEaD6g

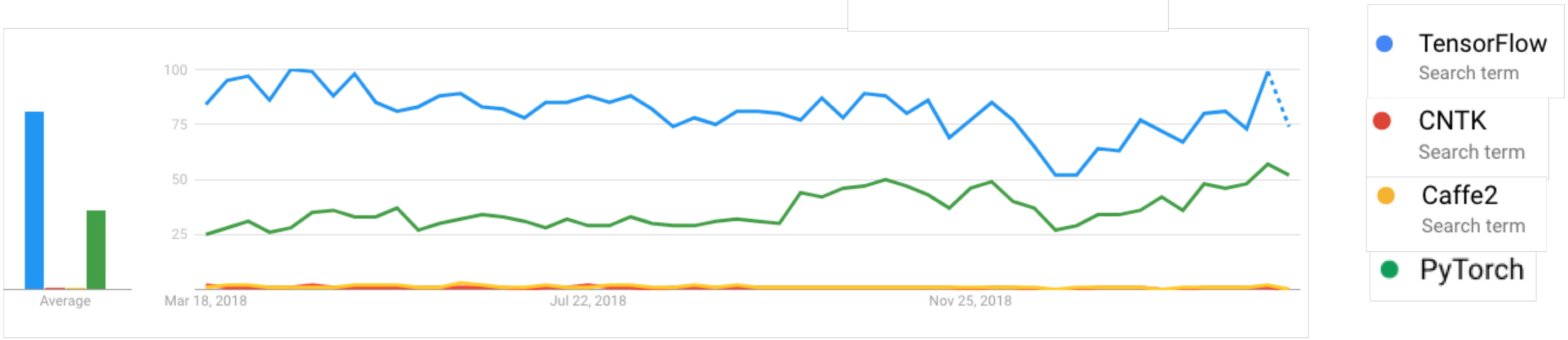
EXAMPLES OF DEEP LEARNING STACKS

- TensorFlow
- Caffe/Caffe2
- Torch
- SparkNet
- TensorFrame
- DeepLearning4J
- BigDL
- CNTK
- mmlspark
- Many others…

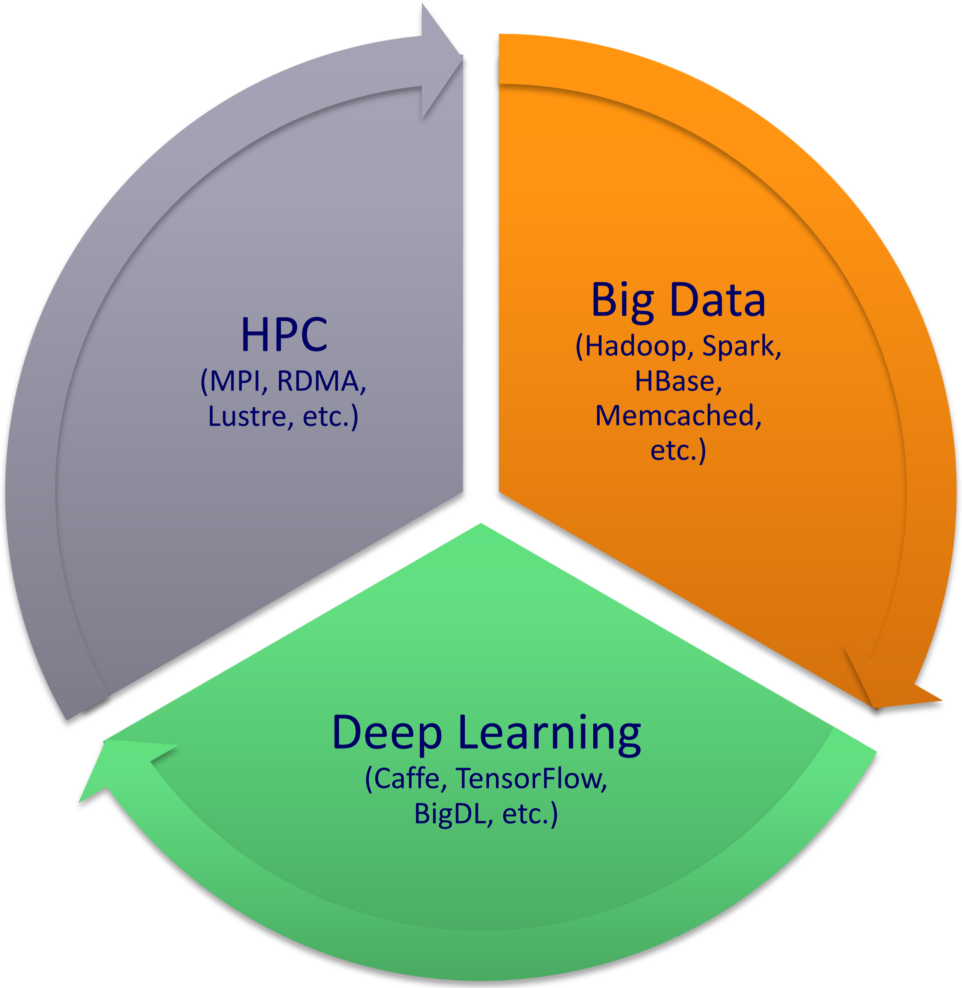
TRENDS OF DEEP LEARNING STACKS

- **Google TensorFlow**
- **Microsoft CNTK**
- **Facebook Caffe2 and PyTorch**

- **Google Search Trend (March, 2019)**



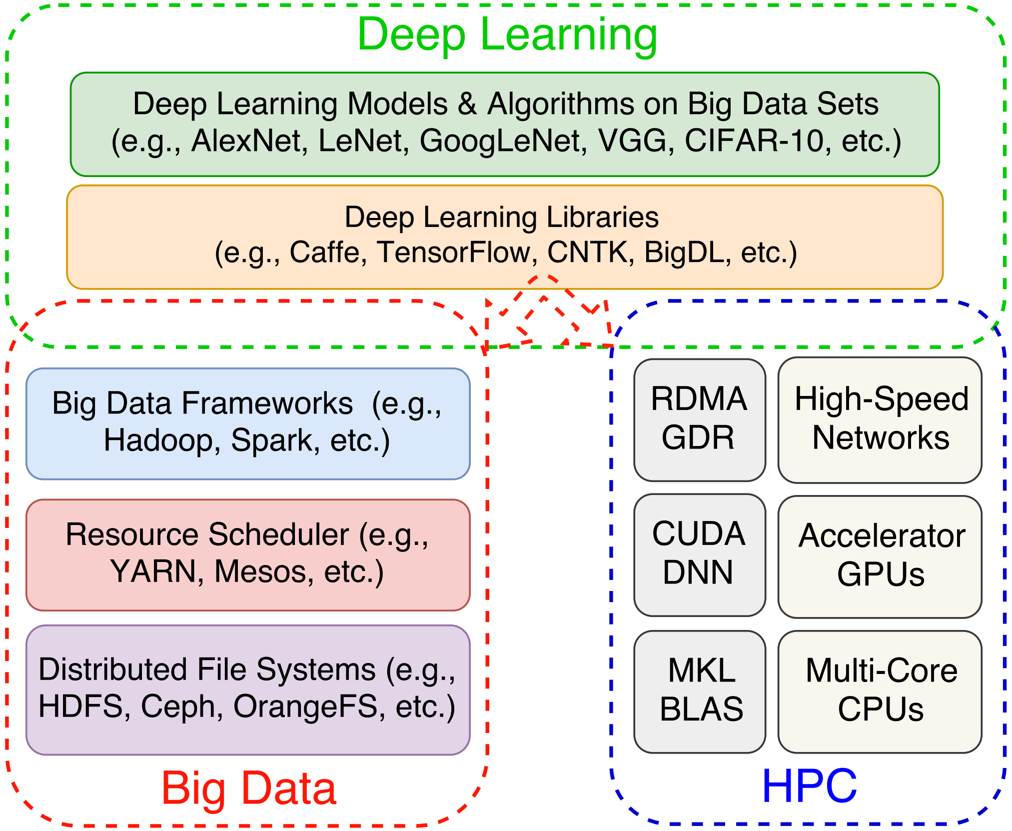
INCREASING USAGE OF HPC, BIG DATA AND DEEP LEARNING



Convergence of HPC, Big Data, and Deep Learning!!!

HIGHLY-OPTIMIZED UNDERLYING LIBRARIES WITH HPC TECHNOLOGIES

- **BLAS Libraries – the heart of math operations**
  - Atlas/OpenBLAS
  - NVIDIA cuBlas
  - Intel Math Kernel Library (MKL)
- **DNN Libraries – the heart of Convolutions!**
  - NVIDIA cuDNN (already reached its 7th iteration – cudnn-v7)
  - Intel MKL-DNN (MKL 2017) – recent but a very promising development
- **Communication Libraries – the heart of model parameter updating**
  - RDMA
  - GPUDirect RDMA



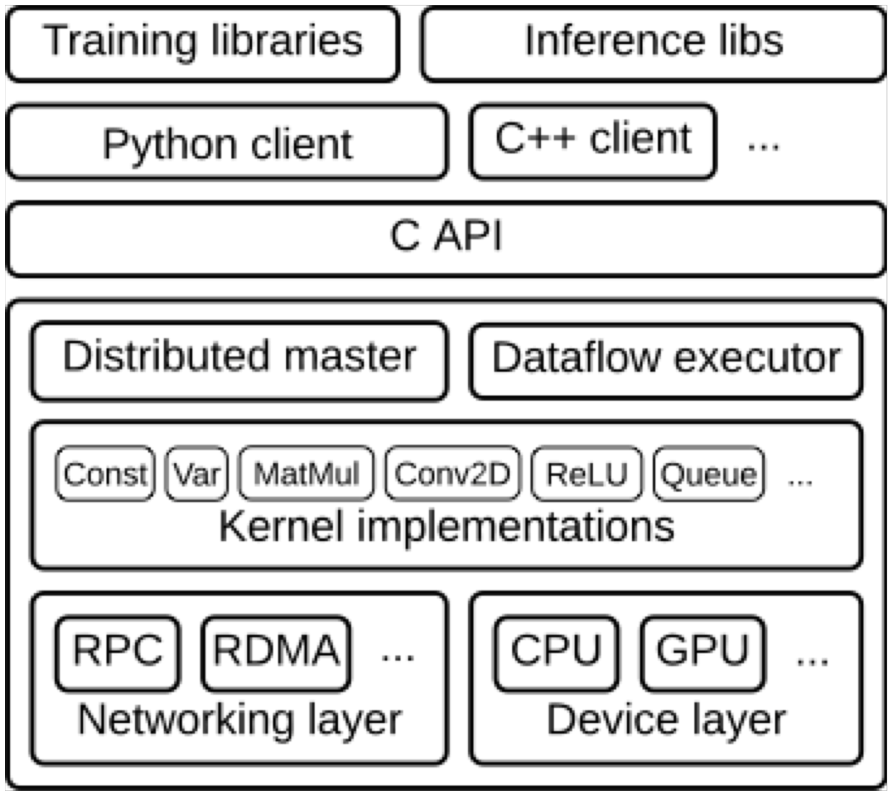
Xiaoyi Lu, Haiyang Shi, Rajarshi Biswas, M. Haseeb Javed, and Dhabaleswar K. (DK) Panda. DLoBD: A Comprehensive Study of Deep Learning over Big Data Stacks on HPC Clusters, in IEEE Transactions on Multi-Scale Computing Systems (TMSCS), 2018

OUTLINE

- Overview of TensorFlow and gRPC
- Accelerating gRPC and TensorFlow with RDMA
- Benchmarking gRPC and TensorFlow
- Performance Evaluation
- Conclusion

ARCHITECTURE OVERVIEW OF GOOGLE TENSORFLOW

- **Key Features:**
  - Widely used for Deep Learning
  - Open source software library for numerical computation using data flow graphs
  - Graph edges represent the multidimensional data arrays
  - Nodes in the graph represent mathematical operations
  - Flexible architecture allows to deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API
  - Used by Google, Airbnb, DropBox, Snapchat, Twitter
  - Communication and Computation intensive

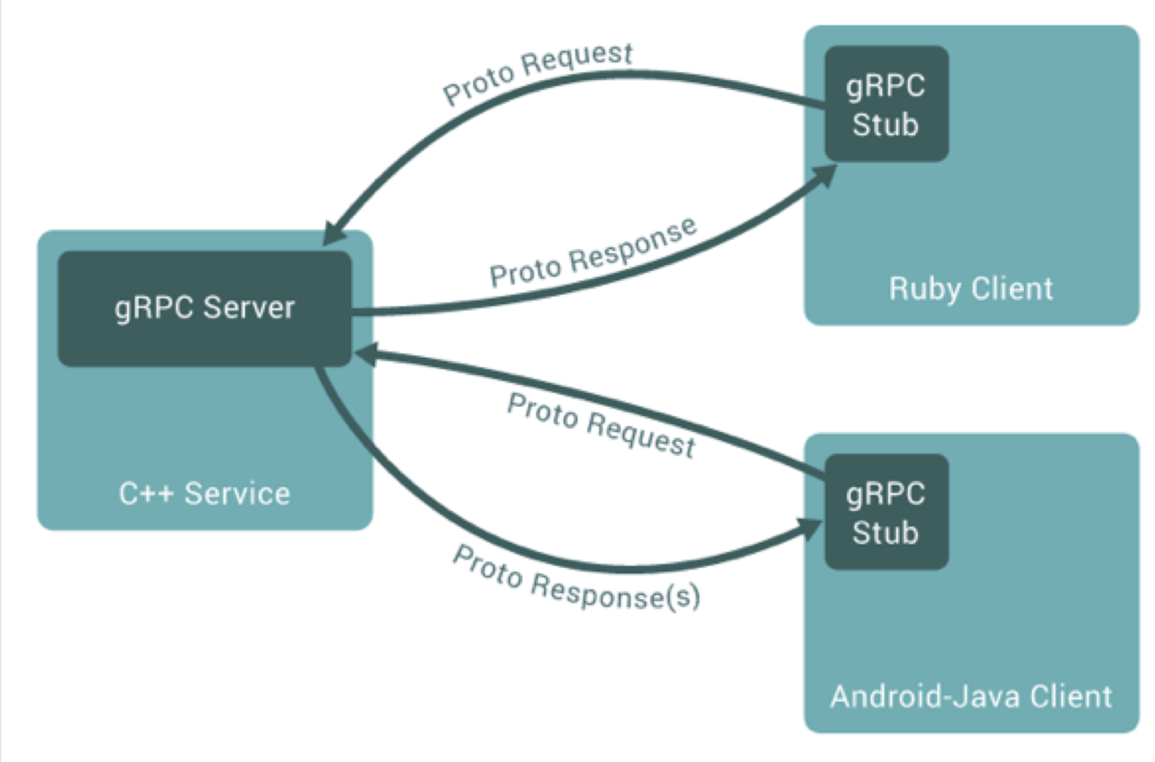


Architecture of TensorFlow

Source: https://www.tensorflow.org/

ARCHITECTURE OVERVIEW OF GRPC

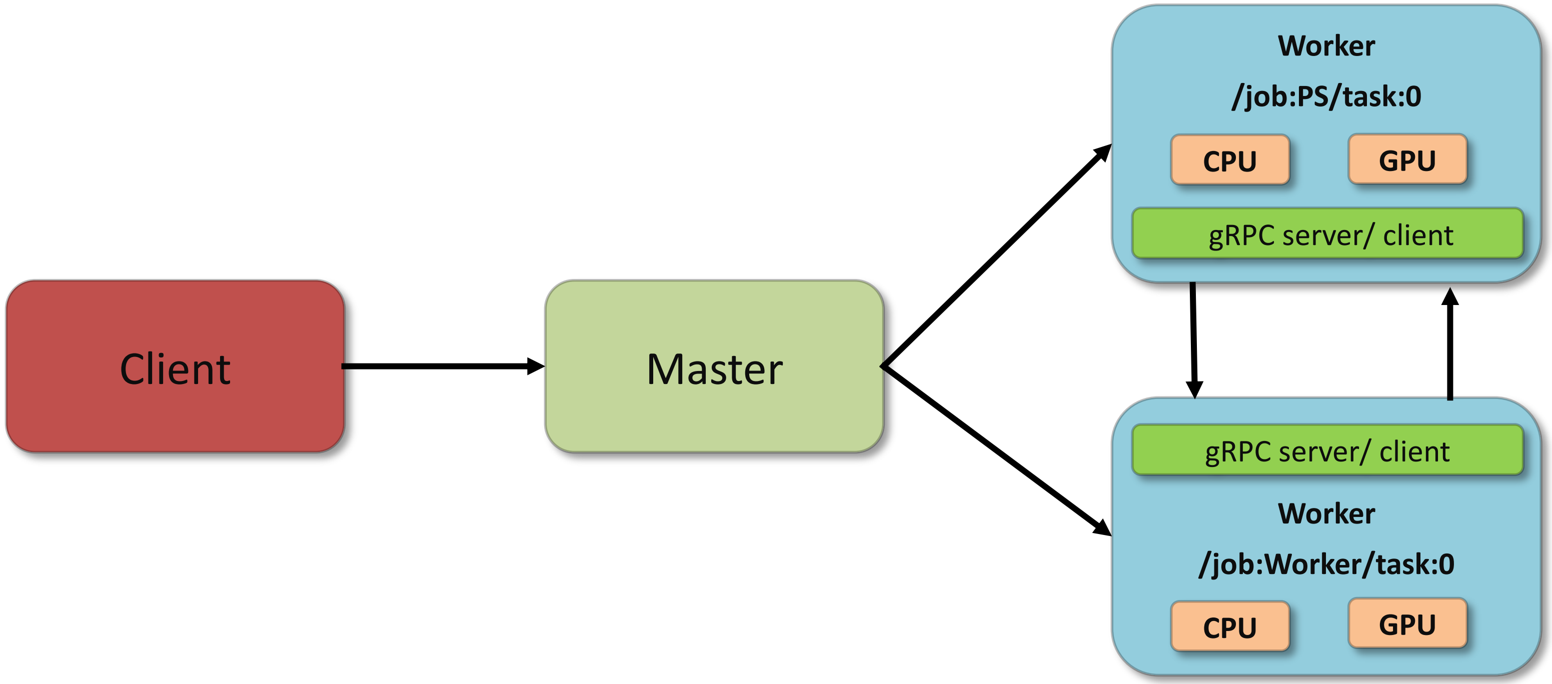
- Key Features:
  - Simple service definition
  - Works across languages and platforms
    - C++, Java, Python, Android Java etc
    - Linux, Mac, Windows
  - Start quickly and scale
  - Bi-directional streaming and integrated authentication
  - Used by Google (several of Google's cloud products and Google externally facing APIs, TensorFlow), NetFlix, Docker, Cisco, Juniper Networks etc.
  - Uses sockets for communication!



Large-scale distributed systems composed of micro services

Source: http://www.grpc.io/

DISTRIBUTED DEEP LEARNING WITH TENSORFLOW AND GRPC



Worker services communicate among each other using gRPC, or gRPC+X!

THE HIGH-PERFORMANCE BIG DATA (HIBD) PROJECT

- RDMA for Apache Spark
- RDMA for Apache Hadoop 3.x (RDMA-Hadoop-3.x)
- RDMA for Apache Hadoop 2.x (RDMA-Hadoop-2.x)
  - Plugins for Apache, Hortonworks (HDP) and Cloudera (CDH) Hadoop distributions
- RDMA for Apache Kafka
- RDMA for Apache HBase
- RDMA for Memcached (RDMA-Memcached)
- RDMA for Apache Hadoop 1.x (RDMA-Hadoop)
- OSU HiBD-Benchmarks (OHB)
  - HDFS, Memcached, HBase, and Spark Micro-benchmarks
- http://hibd.cse.ohio-state.edu
- Users Base: 300 organizations from 35 countries
- More than 29,350 downloads from the project site

Available for InfiniBand and RoCE

Also run on Ethernet

Available for x86 and OpenPOWER

Support for Singularity and Docker

HiBD High-Performance Big Data

Network Based Computing Laboratory

The Ohio State University

MOTIVATION

- **Can similar designs be done for gRPC and TensorFlow to achieve significant performance benefits by taking advantage of native RDMA support?**

- **How do we benchmark gRPC and TensorFlow for both deep learning and system researchers?**

- **What kind of performance benefits we can get through native RDMA-based designs in gRPC and TensorFlow?**

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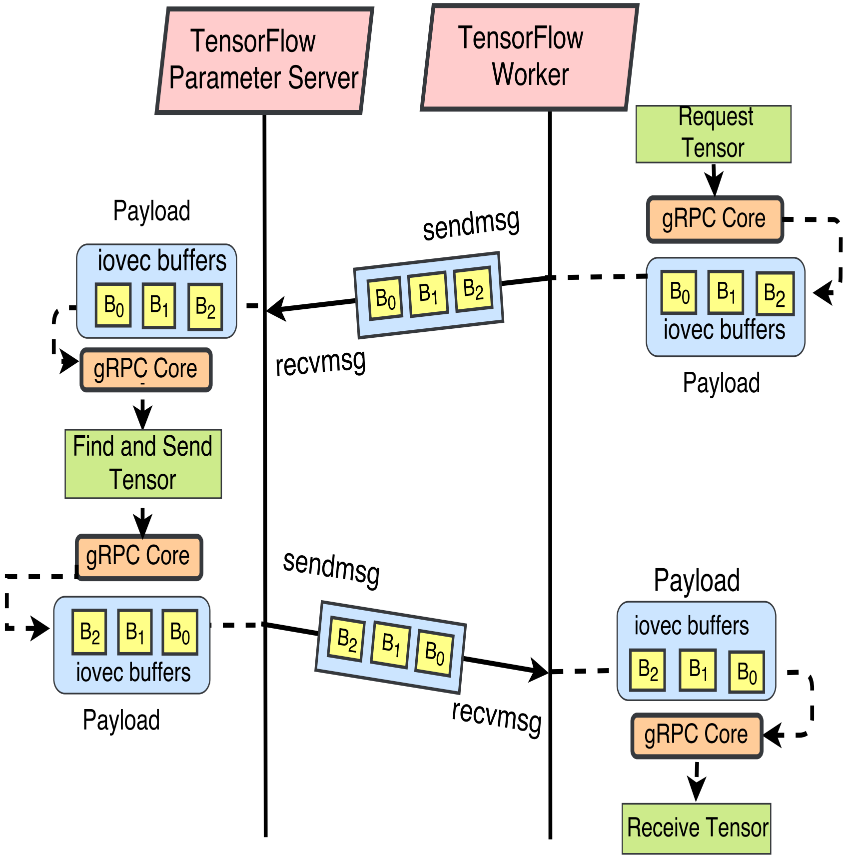
TENSOR COMMUNICATION OVER GRPC CHANNEL

- **Rendezvous protocol**
  - TensorFlow worker (tensor receiving process) actively requests for tensors to the parameter server (tensor sending process)
- **Worker issues Tensor RPC request that to Parameter Server (PS)**
- **PS finds the requested tensor, and responds to the worker**
- **gRPC core uses recvmsg and sendmsg primitives for receiving and sending payloads**
- **Tensor Transmission uses iovec structures**



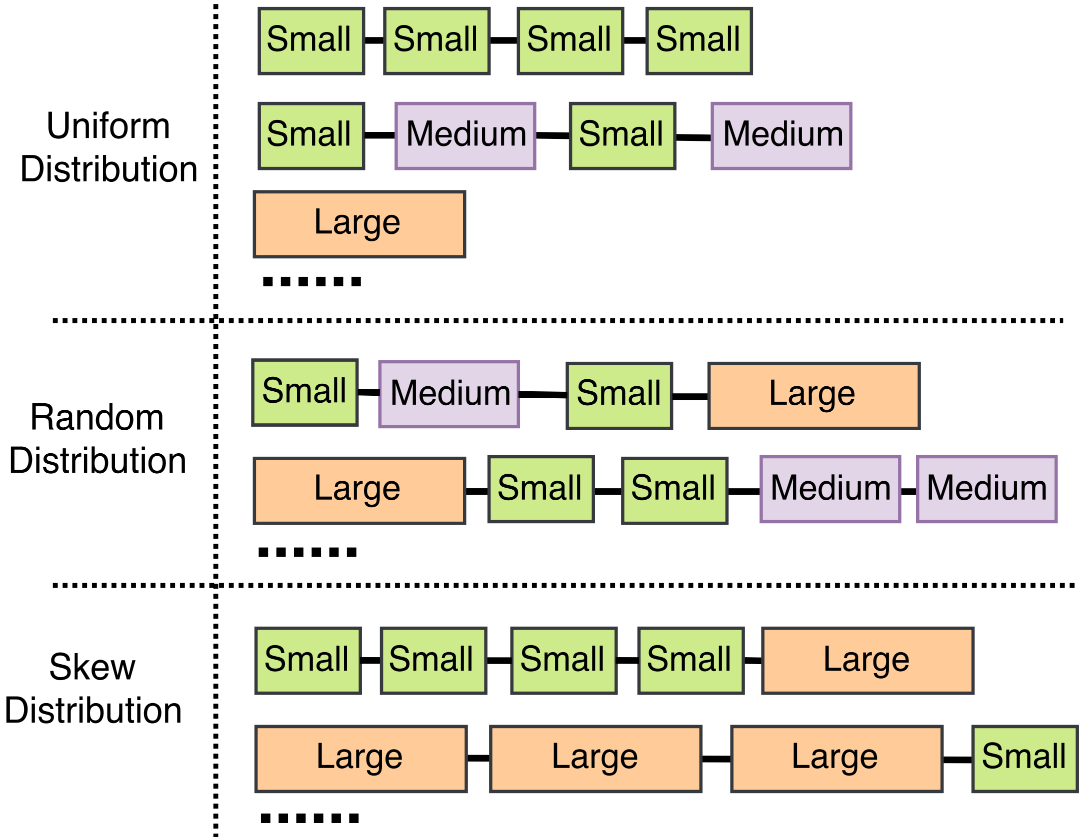
R. Biswas, X. Lu, and D. K. Panda, Designing a Micro-Benchmark Suite to Evaluate gRPC for TensorFlow: Early Experiences, BPOE, 2018.

HIGH PERFORMANCE TENSOR COMMUNICATION CHANNEL

- **gRPC + Verbs**
  - Dedicated verbs channel for tensor communication
  - gRPC channel for administrative task communication
- **gRPC + MPI**
  - Dedicated MPI channel for tensor communication
  - gRPC channel for administrative task communication
- **Uber Horovod**
  - Uber’s approach of MPI based distributed TensorFlow
- **Baidu Tensorflow-Allreduce**
  - Baidu’s approach of MPI based distributed TensorFlow

TENSORFLOW WORKLOAD VIA GRPC

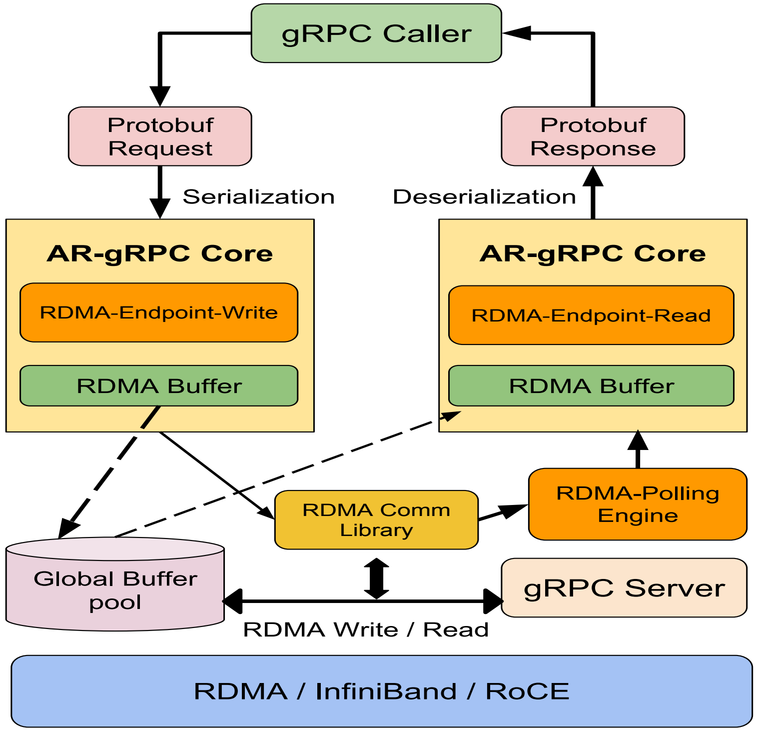
- **Small, Medium and Large indicate buffers of few Bytes, KBytes and MBytes of length**
- **gRPC payload may contain a uniform distribution of such Small buffers**
- **A lot of Large buffers and a few Small buffers may create a skew distribution of such buffers in one gRPC payload**

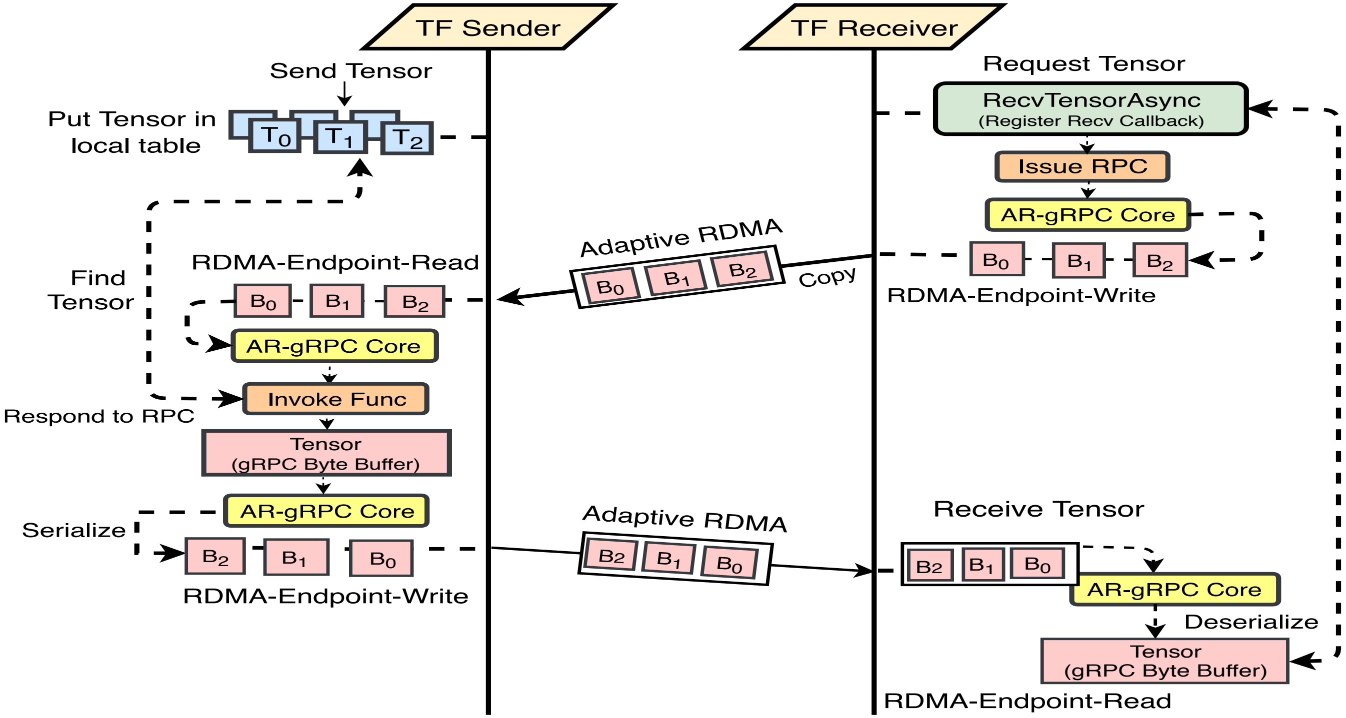


iovec Buffer Distribution Observed for TensorFlow training over gRPC

R. Biswas, X. Lu, and D. K. Panda, Designing a Micro-Benchmark Suite to Evaluate gRPC for TensorFlow: Early Experiences, BPOE, 2018.

OSU AR-GRPC AND AR-GRPC ENHANCED TENSORFLOW





- **Adaptive RDMA gRPC**
- **Features**
  - Hybrid Communication engine
    - Adaptive protocol selection between eager and rendezvous
  - Message pipelining and coalescing
    - Adaptive chunking and accumulation
    - Intelligent threshold detection
  - Zero copy transmission
    - Zero copy send/recv

R. Biswas, X. Lu, and D. K. Panda, Accelerating TensorFlow with Adaptive RDMA-based gRPC, In Proceedings of the 25th IEEE International Conference on High Performance Computing, Data, and Analytics (HiPC), 2018.

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- **Benchmarking gRPC and TensorFlow**
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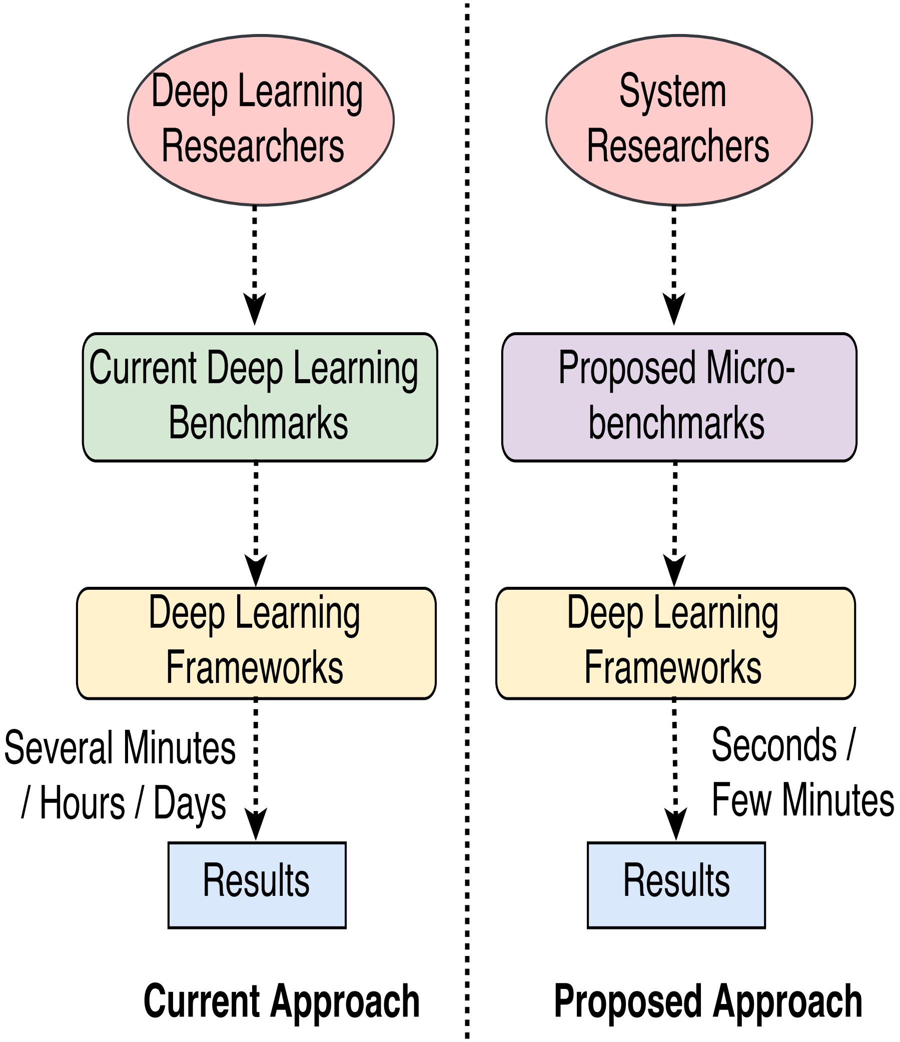
AVAILABLE BENCHMARKS, MODELS, AND DATASETS

	MNIST	CIFAR-10	ImageNet
Category	Digit Classification	Object Classification	Object Classification
Resolution	28 × 28 B&W	32 × 32 Color	256 × 256 Color
Classes	10	10	1000
Training Images	60 K	50 K	1.2 M
Testing Images	10 K	10 K	100 K

Model	Layers (Conv. / Full-connected)	Dataset	Framework
LeNet	2 / 2	MNIST	TensorFlow, CaffeOnSpark, TensorFlowOnSpark
SoftMax Regression	NA / NA	MNIST	TensorFlow, TensorFlowOnSpark
CIFAR-10 Quick	3 / 1	CIFAR-10	CaffeOnSpark, TensorFlowOnSpark, MMLSpark
VGG-16	13 / 3	CIFAR-10	TensorFlow, BigDL
AlexNet	5 / 3	ImageNet	TensorFlow, CaffeOnSpark
GoogLeNet	22 / 0	ImageNet	TensorFlow, CaffeOnSpark
Resnet-50	53/1	Synthetic	TensorFlow

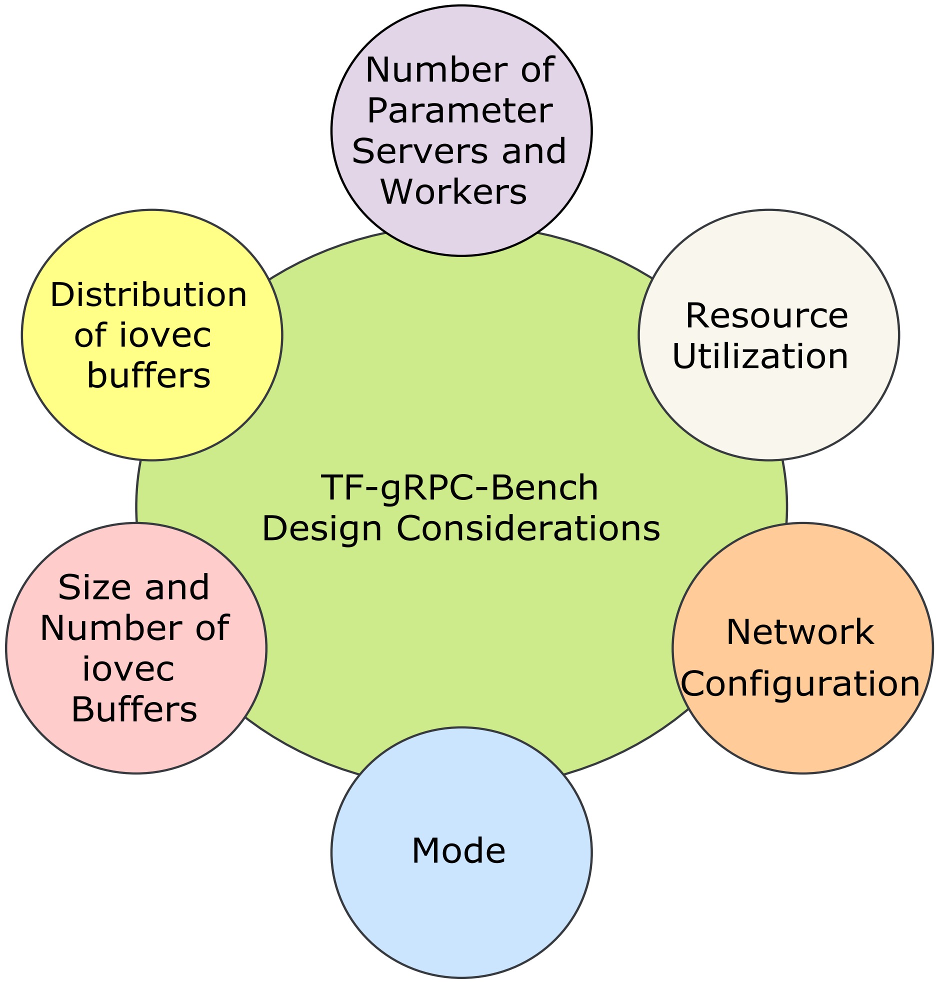
ARE CURRENT BENCHMARKS SUFFICIENT?

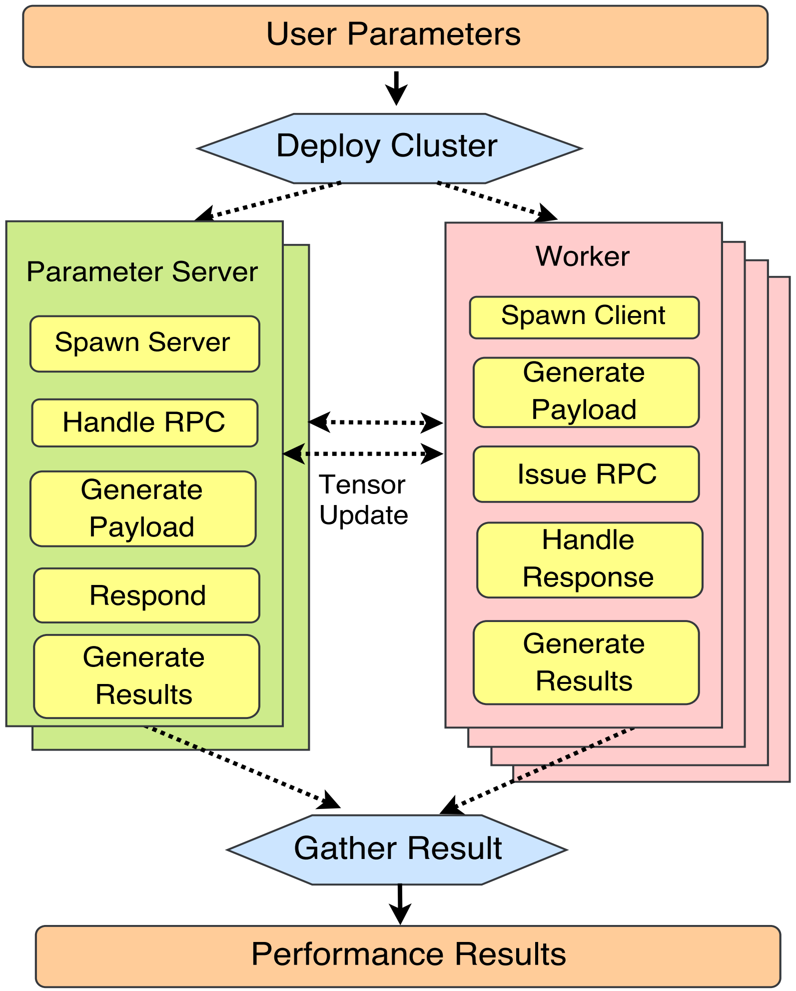
- **Current DL models and benchmarks are deep learning research oriented**
  - Example: Facebook caffe2 takes 1 hour to train ImageNet data[1]
- **However, many system researchers are focused on improving the communication engine of deep learning frameworks**
  - A fast benchmark that models deep learning characteristics is highly desirable



1. Goyal, Priya, et al. "Accurate, large minibatch SGD: training imagenet in 1 hour." arXiv preprint arXiv:1706.02677 (2017).

TENSORFLOW DL MICRO-BENCHMARKS FOR GRPC





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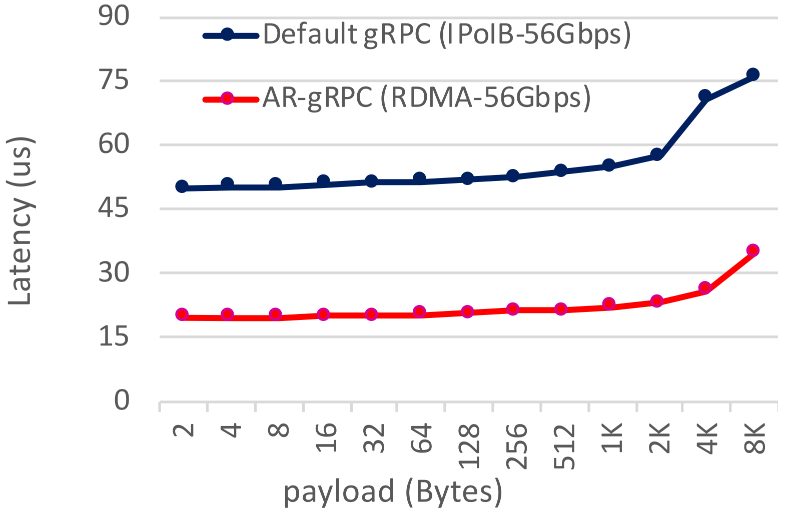
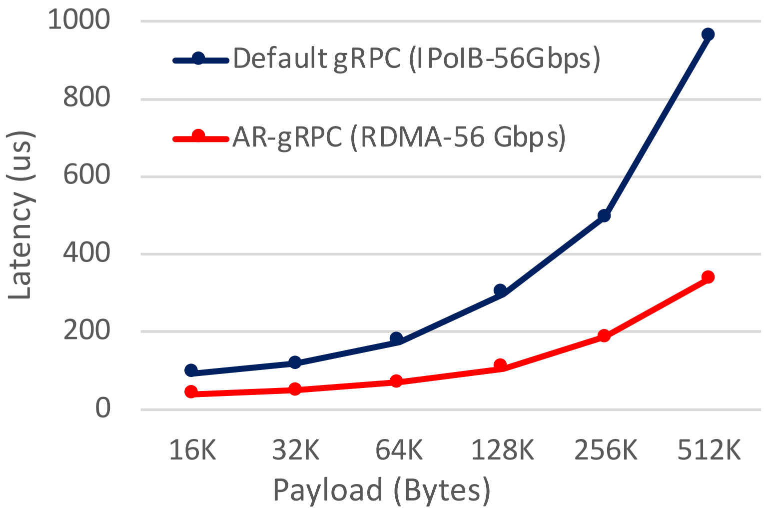
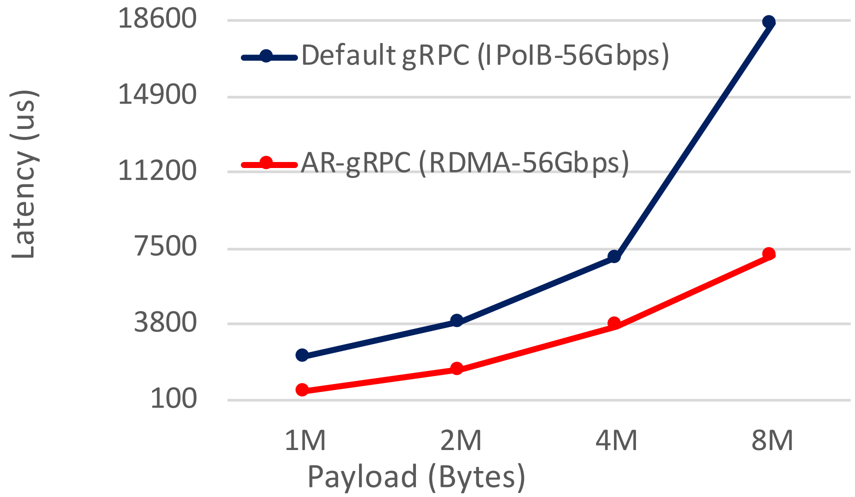
PERFORMANCE BENEFITS FOR AR-GRPC WITH MICRO-BENCHMARK



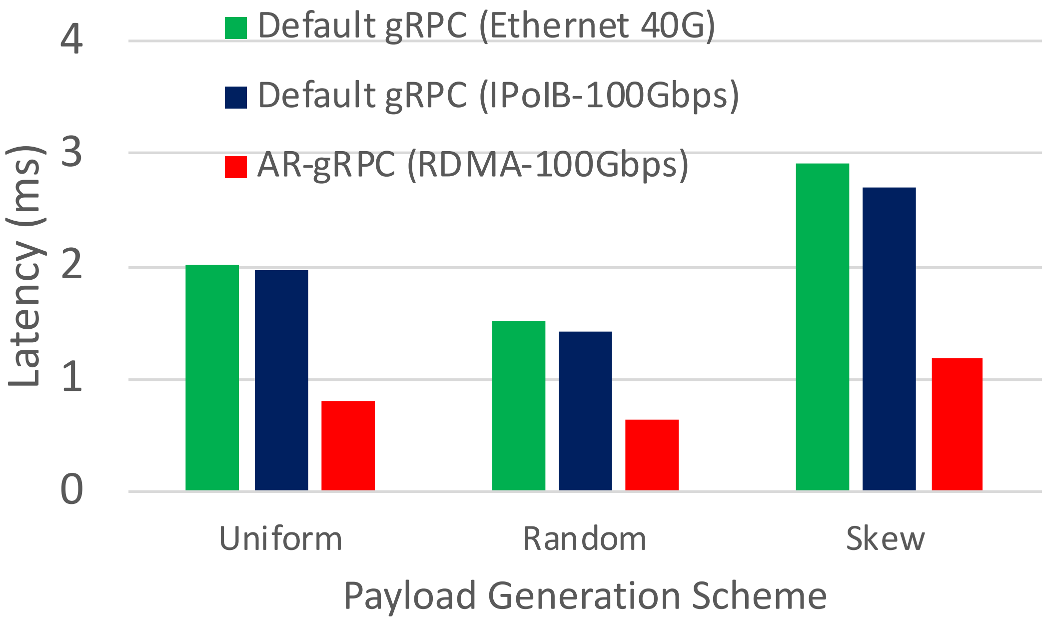




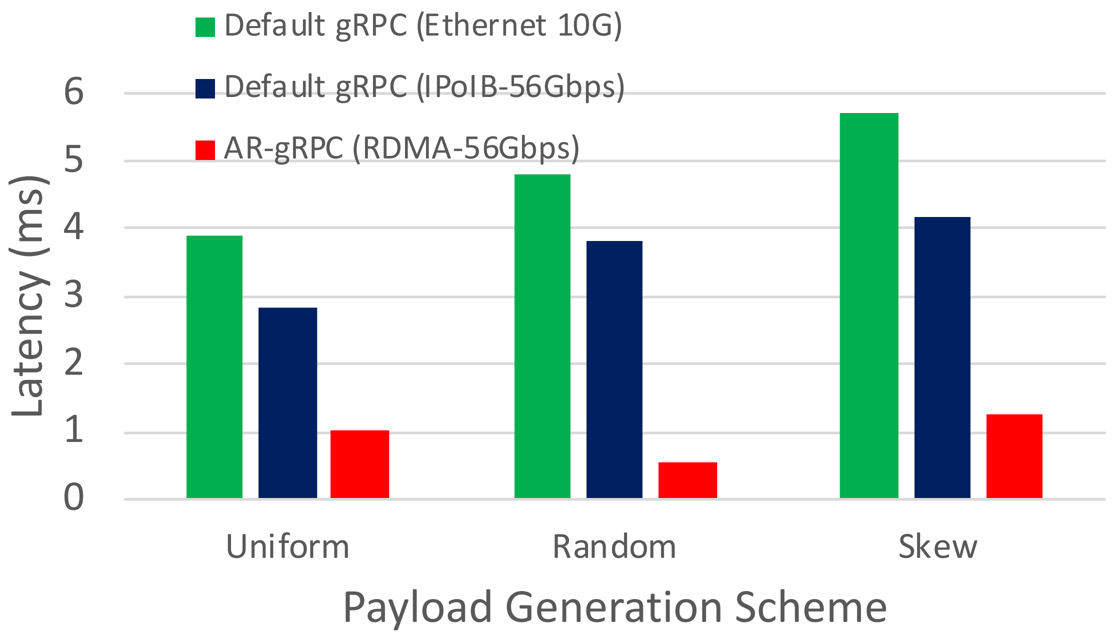
- AR-gRPC (OSU design) Latency on SDSC-Comet-FDR
  - Up to 2.7x performance speedup over Default gRPC (IPoIB) for Latency for small messages.
  - Up to 2.8x performance speedup over Default gRPC (IPoIB) for Latency for medium messages.
  - Up to 2.5x performance speedup over Default gRPC (IPoIB) for Latency for large messages.

R. Biswas, X. Lu, and D. K. Panda, Accelerating TensorFlow with Adaptive RDMA-based gRPC, In Proceedings of the 25th IEEE International Conference on High Performance Computing, Data, and Analytics (HiPC), 2018.

TF-GRPC-P2P-LATENCY



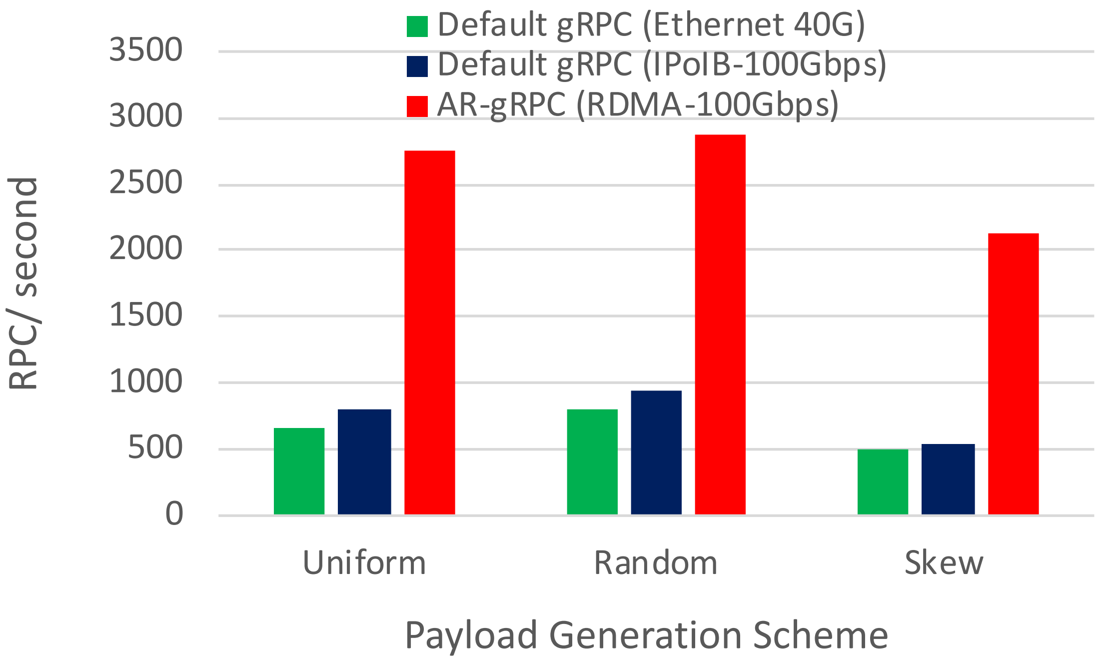
OSU-RI2-IB-EDR



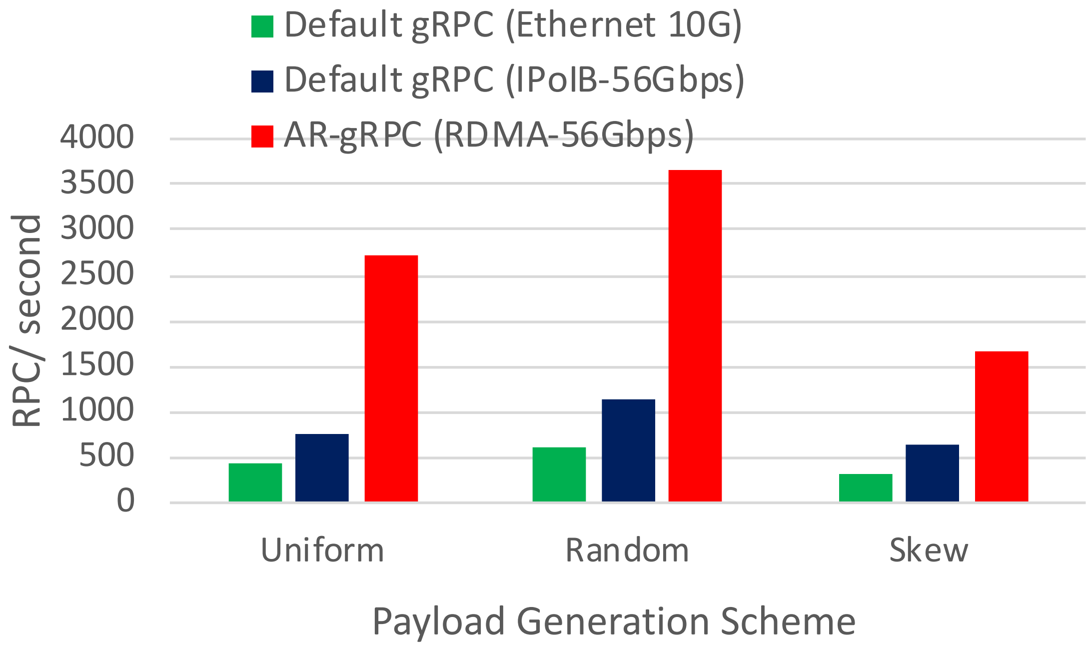
SDSC-Comet-IB-FDR

- OSU-RI2-IB-EDR: AR-gRPC (RDMA) reduces latency by 59% and 56% compared to Default gRPC over 40G Ethernet and IPoIB
- SDSC-Comet-IB-FDR: AR-gRPC (RDMA) reduces 78% latency compared to 10G (Default gRPC) Ethernet and 69% compared to IPoIB (Default gRPC)

TF-GRPC-PS-THROUGHPUT



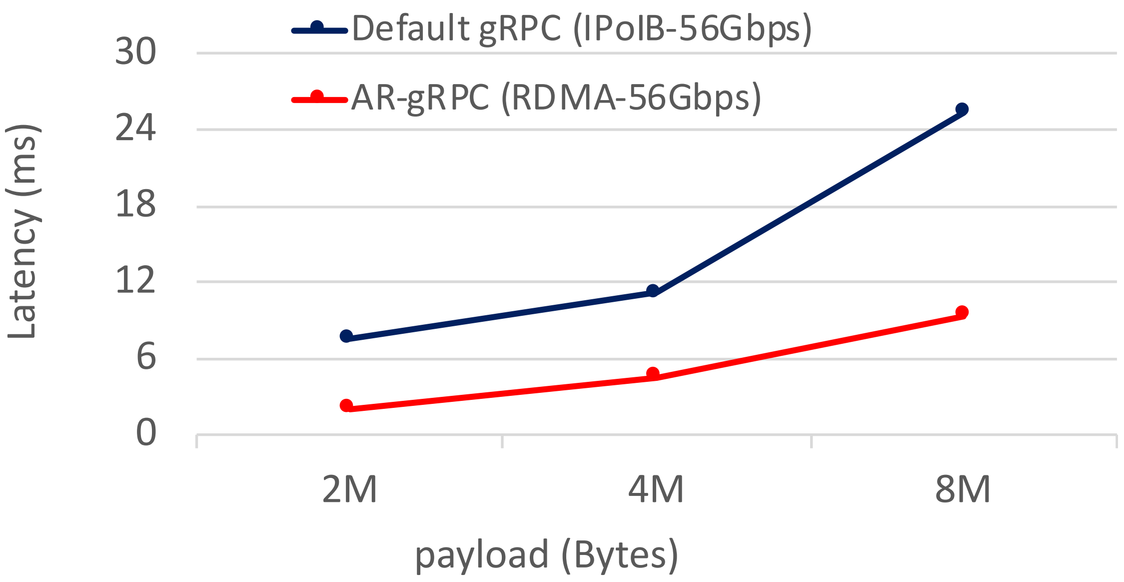
OSU-RI2-IB-EDR

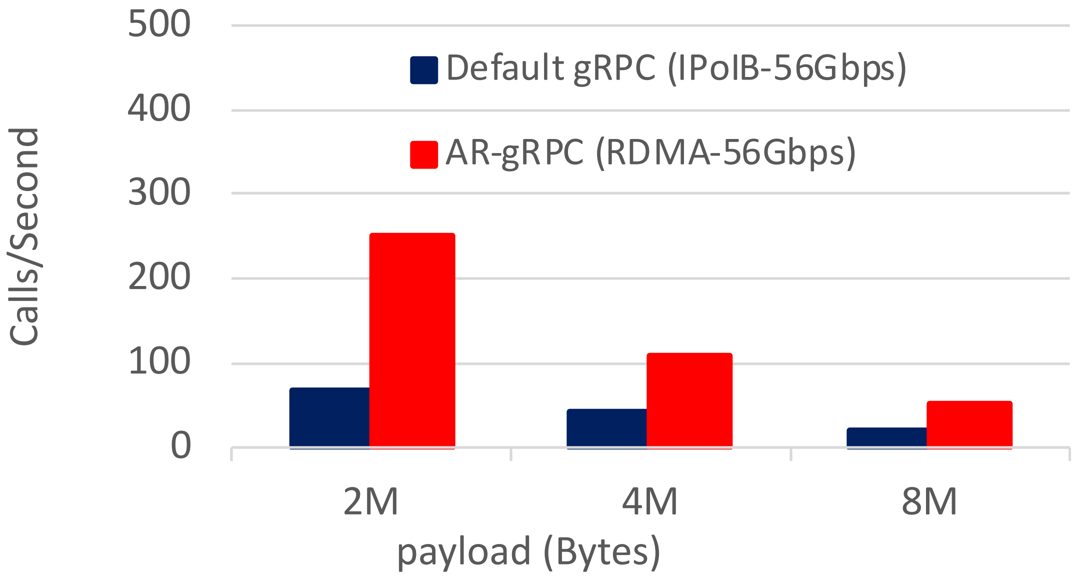


SDSC-Comet-IB-FDR

- OSU-RI2-IB-EDR: AR-gRPC (RDMA) gRPC achieves a 3.4x speedup compared to Default gRPC over IPoIB for uniform scheme
- SDSC-Comet-IB-FDR: AR-gRPC (RDMA) achieves 3.6x bandwidth compared to Default gRPC over IPoIB for uniform scheme

PERFORMANCE BENEFITS FOR AR-GRPC WITH TENSORFLOW MIMIC TEST

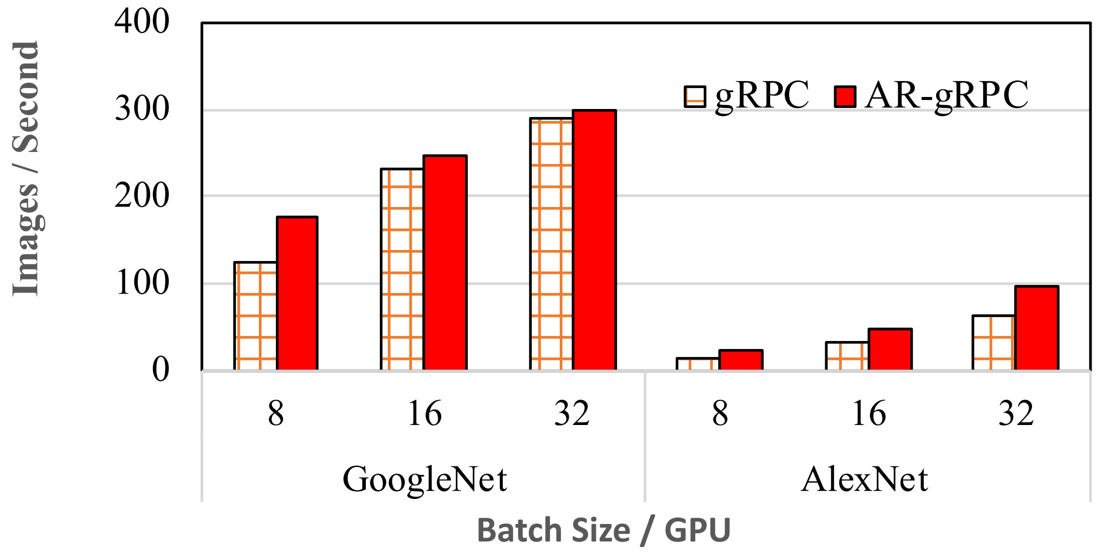




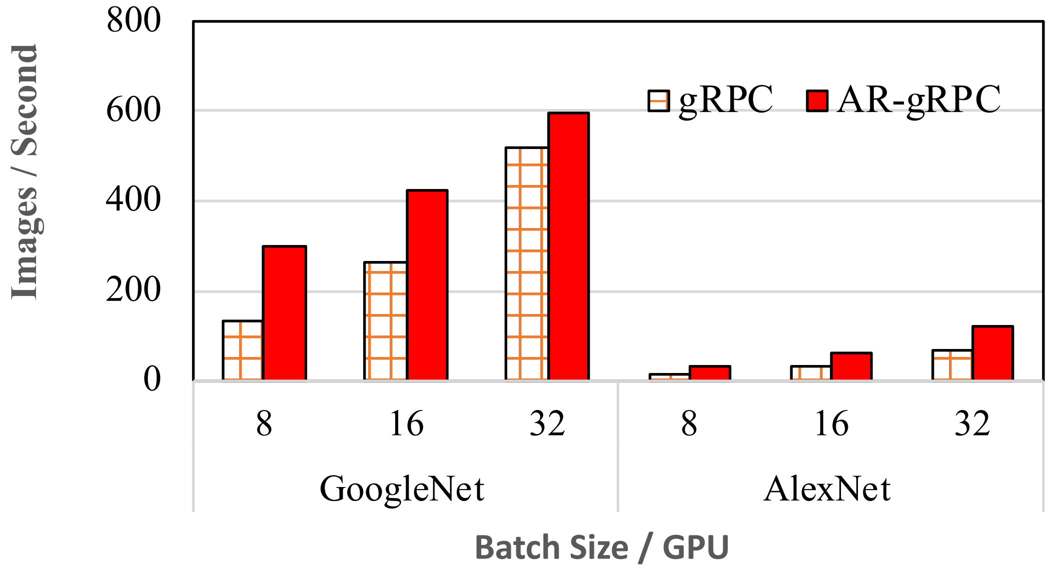
Fully-Connected Architecture (Mimic TensorFlow communication)

- AR-gRPC (OSU design) TensorFlow Mimic test on SDSC-Comet-FDR
  - Up to 60% reduction in average latency over Default gRPC (IPoIB)
  - Up to 2.68x performance speedup over Default gRPC (IPoIB)

EVALUATION OF TENSORFLOW: GOOGLENET & ALEXNET



8 Nodes

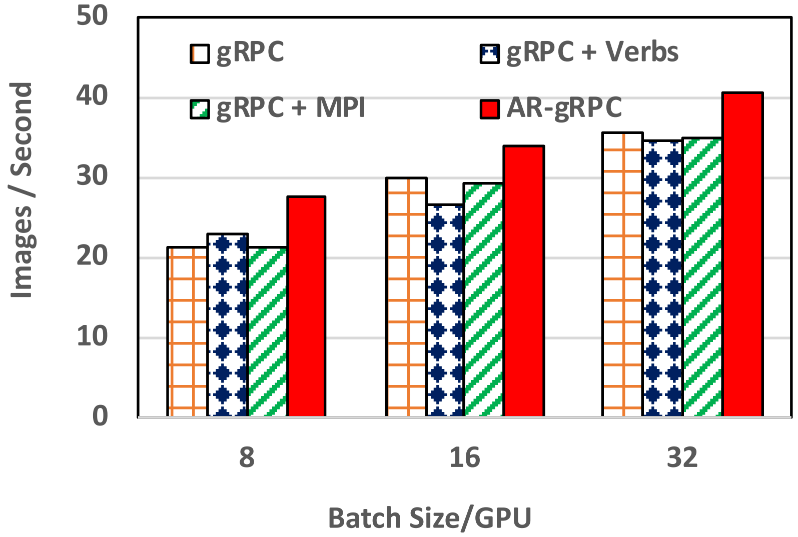


12 Nodes

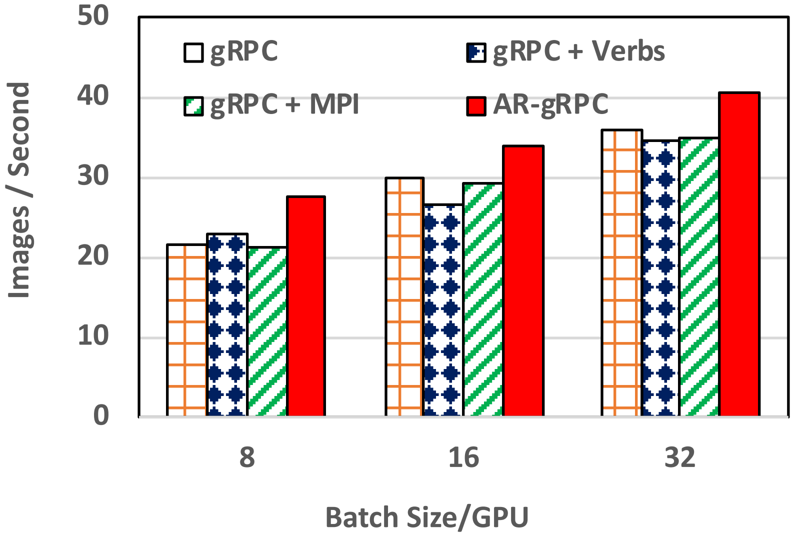
GoogleNet & AlexNet Evaluation on OSU-RI2-IB-EDR (Higher Better); *TotalBatchSize* = (*BatchSize/GPU*)×*NUMofGPUs*

- GoogleNet has only 5 Million parameters, whereas AlexNet has about 60 Million parameters
- AR-gRPC scales better as we go from 4 nodes to 8 nodes
- For large batch size (32/GPU, total 224) the GoogleNet improvement is about 15% (597 vs 517)
  - GoogleNet results in less network intensive gradient updates
- However, AR-gRPC shows 89% (124 vs 65) performance improvement for Alexnet compared to default gRPC

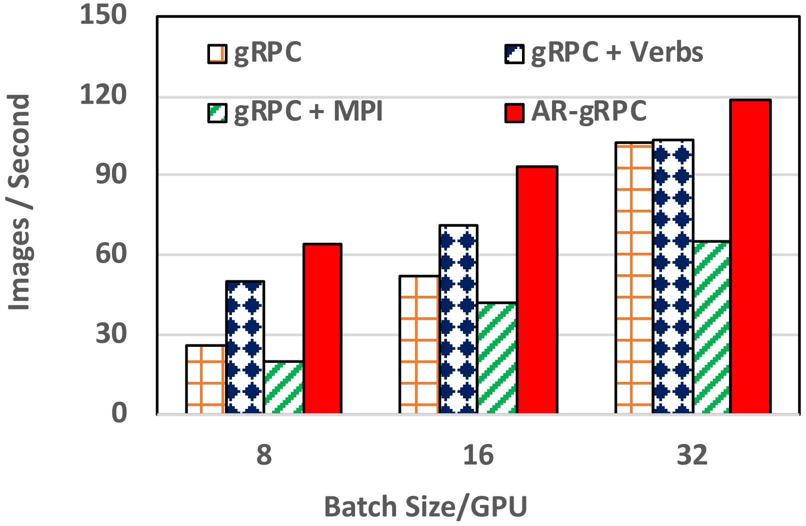
EVALUATION OF TENSORFLOW: INCEPTION-V4



4 Nodes



8 Nodes

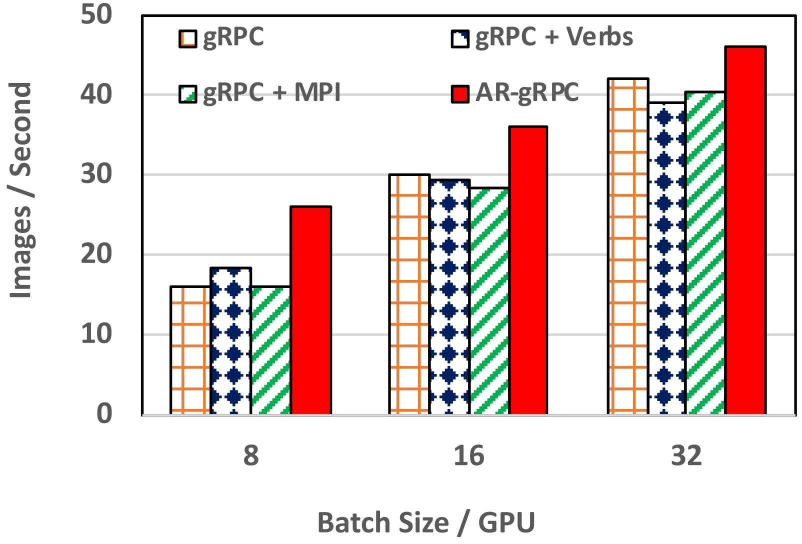


12 Nodes

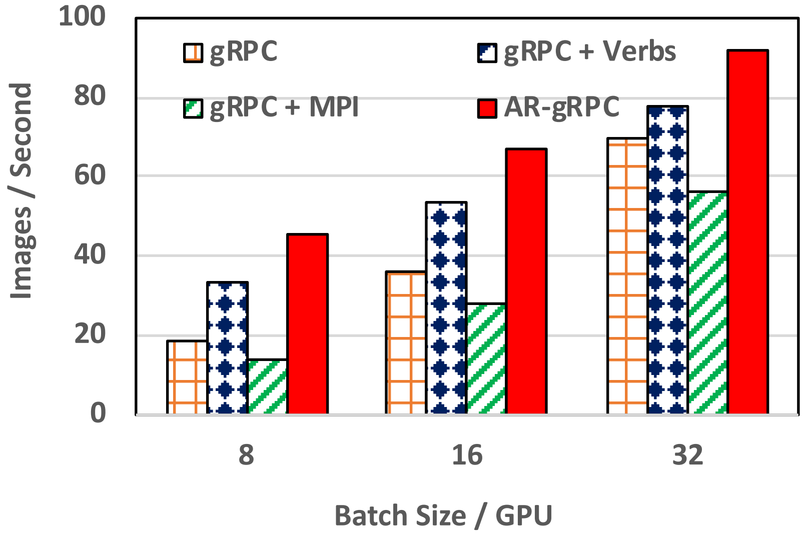
Inception4 Evaluation on Cluster A (Higher Better); *TotalBatchSize* = (*BatchSize*/*GPU*)×*NUMofGPUs*

- AR-gRPC improves TensorFlow performance by a maximum of 29%, 80%, and 144% compared to default gRPC on 4, 8, and 12 nodes, respectively
  - For example: Improvement of 80% (93 vs 51 images) for batch size 16/GPU (total 176) on 12 nodes
- AR-gRPC process a maximum of 27%, 12%, and 31% more images than Verbs channel
- AR-gRPC outperforms MPI channel by a maximum of 29%, 151%, and 228% for 4, 8, and 12 nodes

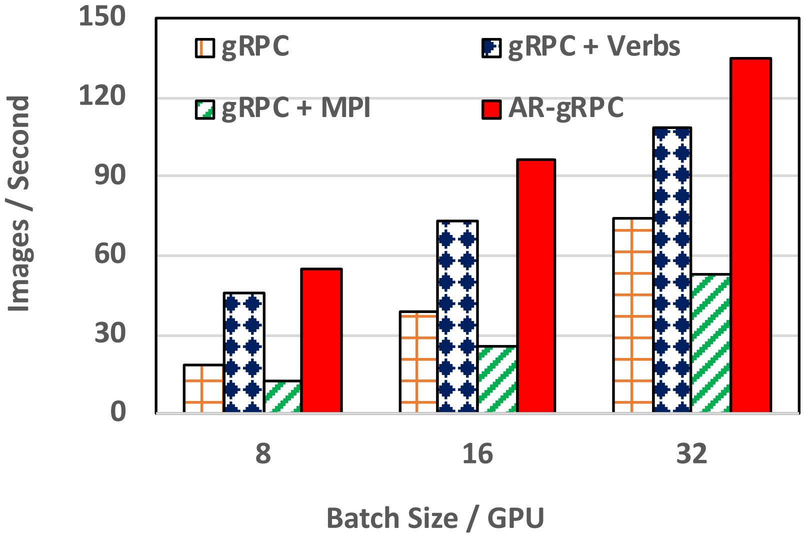
EVALUATION OF TENSORFLOW: RESNET152



4 Nodes



8 Nodes

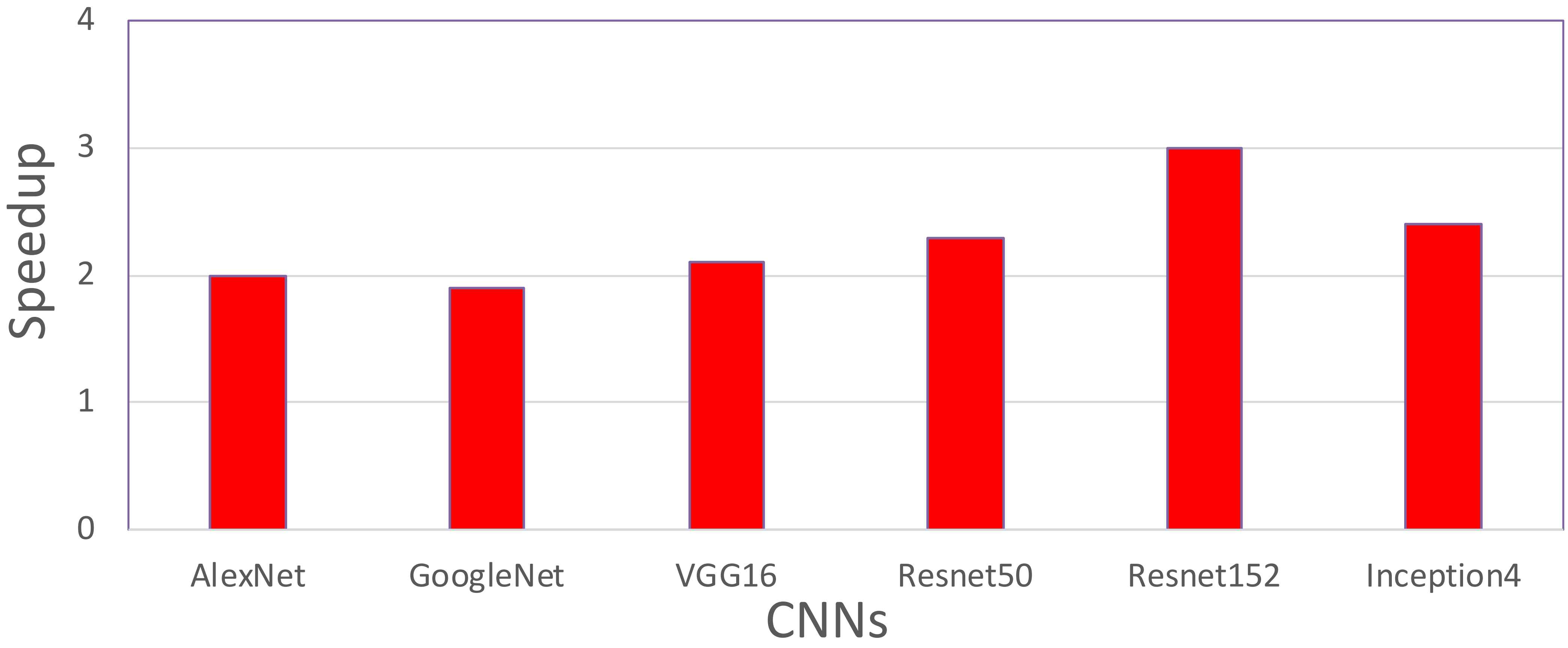


12 Nodes

Resnet152 Evaluation on Cluster A (Higher Better); *TotalBatchSize = (BatchSize/GPU)×NUMofGPUs*

- AR-gRPC accelerates TensorFlow by 62% (batch size 8/GPU) more compared to default gRPC on 4 nodes
- AR-gRPC improves Resnet152 performance by 32% (batch size 32/GPU) to 147% on 8 nodes
- AR-gRPC incurs a maximum speedup of 3x (55 vs 18 images) compared to default gRPC 12 nodes
    - Even for higher batch size of 32/GPU (total 352) AR-gRPC improves TensorFlow performance by 82% 12 nodes
- AR-gRPC processes a maximum of 40%, 35%, and 30% more images, on 4, 8, and 12 nodes, respectively, than Verbs
- AR-gRPC achieves a maximum speedup of 1.61x, 3.3x and 4.5x compared to MPI channel on 4, 8, and 12 nodes, respectively

AR-GRPC SPEEDUP COMPARED TO DEFAULT GRPC



OSU RDMA-TENSORFLOW DISTRIBUTION

- **High-Performance Design of TensorFlow over RDMA-enabled Interconnects**
  - High performance RDMA-enhanced design with native InfiniBand support at the verbs-level for gRPC and TensorFlow
  - RDMA-based data communication
  - Adaptive communication protocols
  - Dynamic message chunking and accumulation
  - Support for RDMA device selection
  - Easily configurable for different protocols (native InfiniBand and IPoIB)
- **Current release: 0.9.1**
  - Based on Google TensorFlow 1.3.0
  - Tested with
    - Mellanox InfiniBand adapters (e.g., EDR)
    - NVIDIA GPGPU K80
    - Tested with CUDA 8.0 and CUDNN 5.0
  - http://hidl.cse.ohio-state.edu

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CONCLUSION

- **Present architecture overview of TensorFlow and gRPC**
- **Discuss challenges in accelerating and benchmarking TensorFlow and gRPC**
- **RDMA can benefit DL workloads as showed by our AR-gRPC and the corresponding enhanced TensorFlow**
  - Unified high-performance communication runtime throughout the TensorFlow stack
    - Up to 4.1x speedup compared to the default gRPC
    - Up to 3x performance improvement on TensorFlow when using AR-gRPC compared to default gRPC channel
    - Significant improvement over Verbs and MPI channel
    - Consistently good performance for different CNNs
- **Plan to explore TensorFlow runtime to find more bottlenecks**
- **Our work is publicly available: http://hidl.cse.ohio-state.edu/**

OPENFABRICS ALLIANCE

15th ANNUAL WORKSHOP 2019

THANK YOU

Xiaoyi Lu, Dhabaleswar K. (DK) Panda

The Ohio State University

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