OPENFABRICS ALLIANCE

2020 OFA Virtual Workshop

USING LIBFABRIC FOR SCALABLE DISTRIBUTED MACHINE LEARNING: USE CASES, LEARNINGS, AND BEST PRACTICES

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June, 2020

aws

AGENDA

- Introduction to distributed machine learning training
- Distributed machine learning training stack
- NCCL and its integration with libfabric
- Performance impact of running EFA for machine learning
- Deploying at scale – learnings and challenges

INTRODUCTION

DISTRIBUTED MACHINE LEARNING TRAINING

- **Supervised Machine learning (ML) training**
  - Train a model to determine optimal values for all the weights and bias from labelled examples
  - Apply learnt model to infer results for new real world data
  - Some applications: Image and Speech recognition, classification, prediction

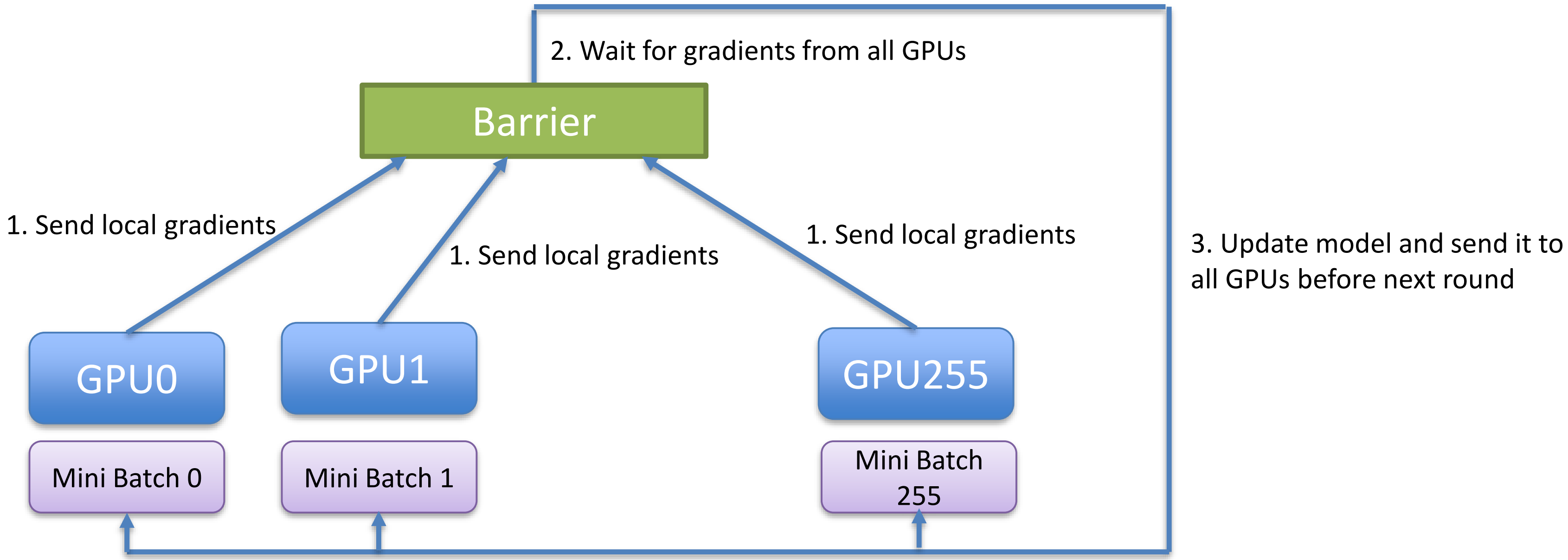
- **Size of ML models is growing way faster than Moore's law**
  - One of most popular ML algorithm (BERT) takes more than 9 days to train on biggest available single server

- **Meanwhile, ML researchers and commercial users are looking for results and experiments in hours, not days**

- **Solution: Run distributed ML training with Data Parallelism**
  - Same model, different training samples

SYNCHRONOUS STOCHASTIC GRADIENT DESCENT (SGD)

- Iterative algorithm to calculate optimal training parameters
- Results of each round is incorporated into the model for the next round.
- Applies to only set of inputs called as mini-batch



DISTRIBUTED ML TRAINING IN REAL LIFE

- **Ideal goal: Scale linearly with number of GPU servers**
- **Catch: You need to balance Time-to-Converge while scaling the Teraflops**
- **Classic trade-off:**

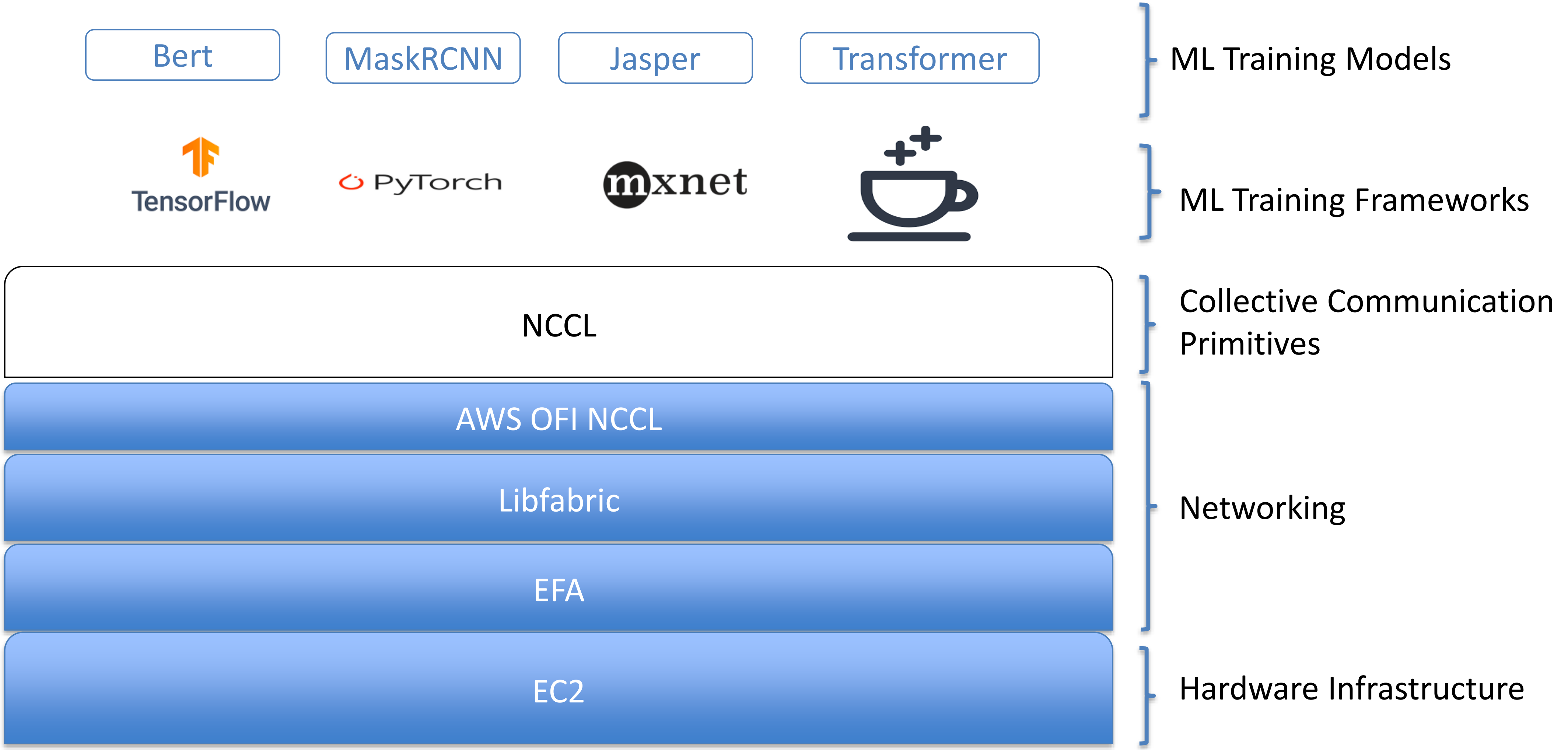
Compute per epoch	Pros	Cons
Large	Reduce communication overhead per compute	Slower convergence time
Short	Faster convergence time	Higher communication overhead per compute

➔ Idea: A faster and lower latency interconnect allows scaling to large number of nodes while keeping short epoch

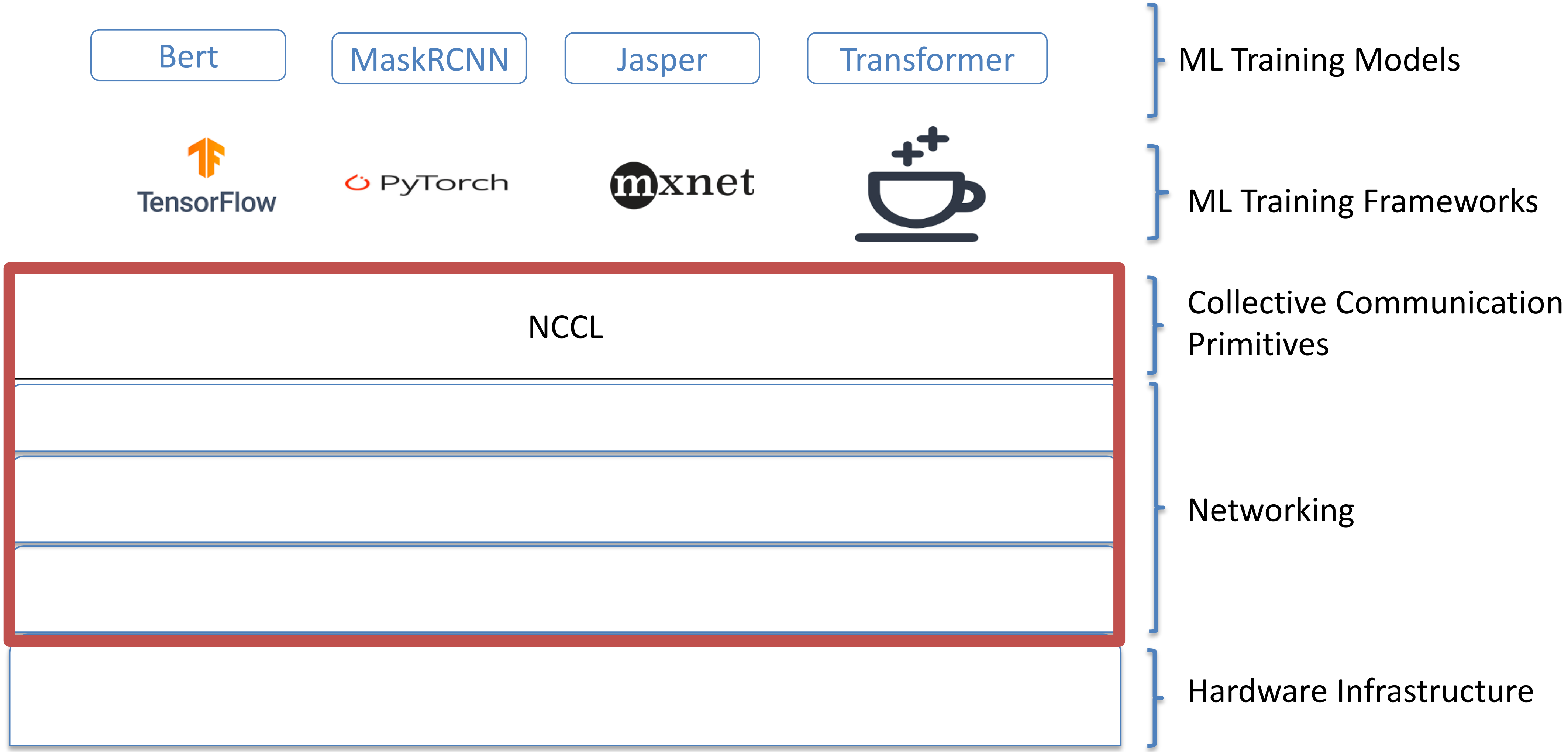
- Or allows model to converge faster for same number of nodes by offering lower communication per compute

DISTRIBUTED ML STACK

DISTRIBUTED ML TRAINING ARCHITECTURE IN AWS



DISTRIBUTED ML TRAINING ARCHITECTURE IN AWS



USING LIBFABRIC WITH NCCL

- **Why NCCL?**
  - Multi-GPU and Multi-node collective communication primitives
  - Provides routines such as all-gather, all-reduce, broadcast, reduce, reduce-scatter
  - Performance optimized for NVIDIA GPUs

- **NCCL collective communication flow**
  - Determines system topology for efficient communication
  - Builds collective operations topology like ring, double binary tree
  - Schedules CUDA kernels on GPU which reduces and moves the data

- **AWS OFI NCCL**
  - Open source plug in which enables to use libfabric as a network provider while running NCCL based applications
  - Enables to use Elastic Fabric Adapter (EFA) on AWS EC2 cloud

ELASTIC FABRIC ADAPTER

- Libfabric provider optimized for high performance and machine learning workloads
- Low latency for inter node communication in cloud
- Scales to thousands of CPUs / GPUs
- Bypasses operating system
- Uses underlying Scalable Reliable Datagram Protocol
- To learn more: https://aws.amazon.com/hpc/efa/

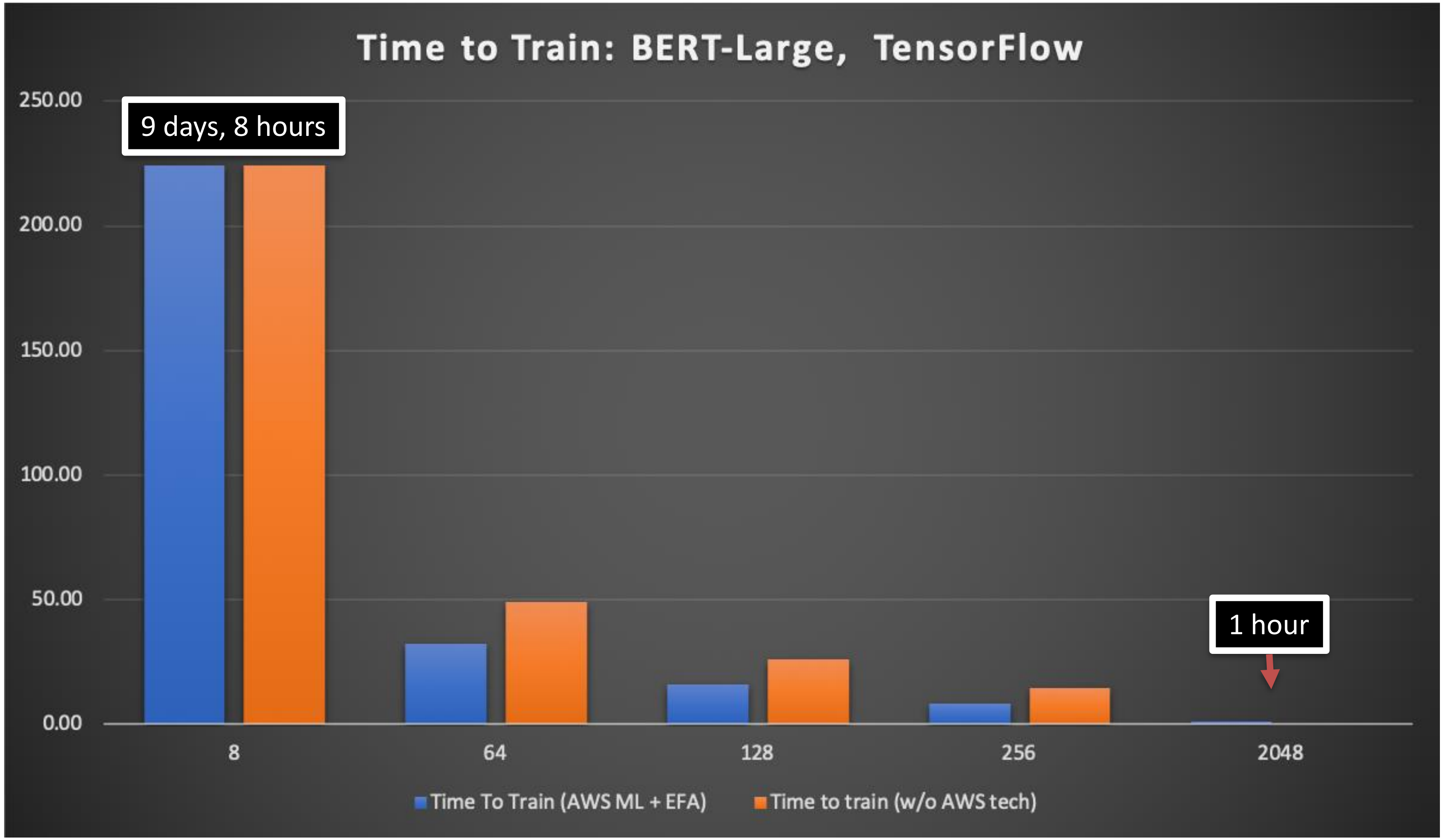
PERFORMANCE RESULTS

PERFORMANCE BENCHMARKS

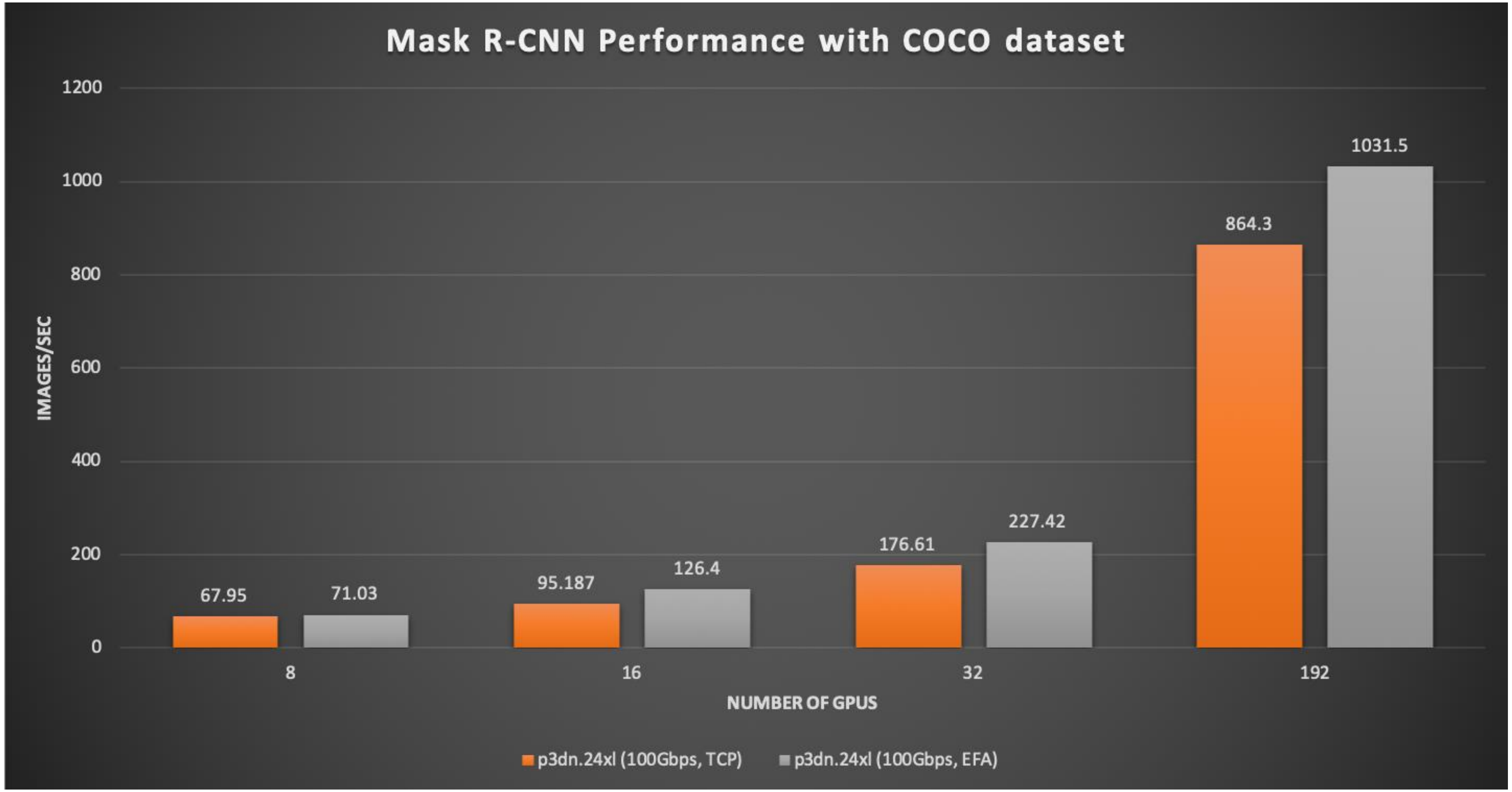
- **BERT training**
  - Dataset by NVIDIA - concatenation of Wikipedia as well as Book Corpus
  - Gradient accumulation to simulate larger batch size
  - Smaller sequence length and higher batch size to speed up the training
  - **Throughput Scaling efficiency: 87% - Scale training time from 9 days to <1 hour**
  - **EFA improves training time by 2X for a cluster of 256 GPUs vs TCP**

- **Maskrcnn Training for Object Detection**
  - Used COCO dataset
  - Configured model hyperparameters for different system scale.
  - **EFA outperformed TCP at all scales, processing >1000 images/second with 192 GPUs**

TRAINING TIME IMPROVEMENT WITH BERT



PERFORMANCE IMPROVEMENT WITH MASKRCNN



DEPLOYING AT SCALE

LEARNING FROM DEMANDING CUSTOMER WORKLOADS

- **Working with customers running different ML models for training**
  - Spanning from 8 GPUs to 1200 GPUs
  - Using different ML frameworks like PyTorch, MxNet and Tensorflow
- **P3DN servers**
  - Complex instances built for running ML training at scale
  - More than 5kW per each server, 1TB of DRAM, 10 chips with 200Watt+ each and 100s of billions of transistors in one chip
  - Careful design for reliability
- **Successful multi day trainings with consistent performance, reliability, and no hick-ups**
  - Robust testing and qualification of all software stack: Drivers / Kernel / NCCL / LibFabric / ML Framework
  - Non distributive firmware updates
  - Robust power and network delivery
  - Developed auto-recovery mechanisms to recover from transient failures like GPU memory errors

BEST PRACTICES FOR SCALE

- **Know your software stack**
  - *Challenge:* Many components involved and small bugs magnify at scale
  - Fast moving code which addresses these bugs
  - Use latest NVIDIA toolkit, OS distribution etc.

- **Choose appropriate hardware / services**
  - *Challenge:* Highly demanding and resource intensive applications.
  - Make sure you're sizing appropriately to avoid bottlenecks
  - Amazon FSx for lustre, EC2 Hardware, VPC and 100G EFA

- **Design for robustness**
  - *Challenge:* Complicated components and applications which are sensitive to failure
  - Add capability to snapshot and restart from saved checkpoint. Eg: ParallelCluster with Slurm
  - AWS monitors hardware components for failure and recovers automatically. Adding similar monitoring and resiliency for VMs is also helpful.

SUMMARY

- **Lower latency interconnect allows distributed ML models to converge faster**
- **EFA and libfabric enables fast, low latency communication**
- **Order of magnitude improvements in scalability compared to a TCP networking stack**
- **Running demanding ML applications at scale requires:**
  - Careful hardware sizing
  - Failure tolerance
  - Keeping up to date with latest versions

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THANK YOU

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