21st USENIX Symposium on Networked Systems Design and Implementation (NSDI'24)

Towards Domain-Specific Network Transport for Distributed DNN Training

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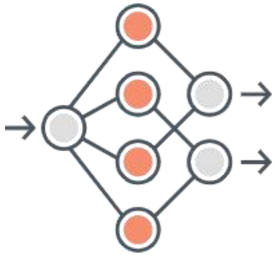
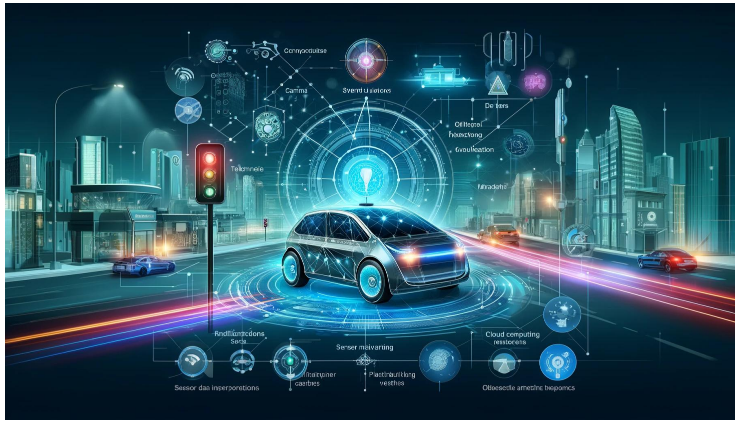
*Now with NVIDIA

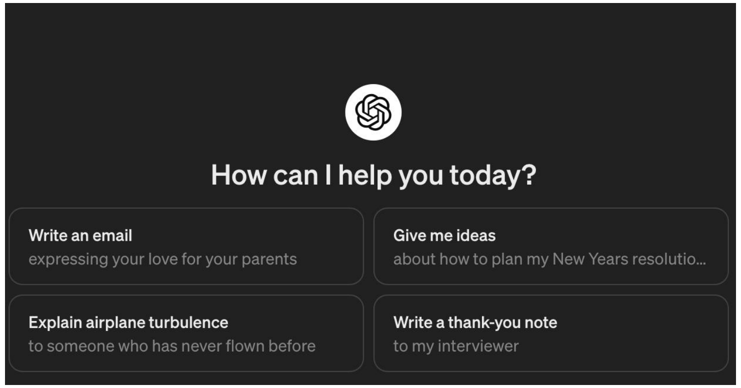
DNN empowers a wide range of applications

Face Recognition





Automatic Driving



ChatGPT

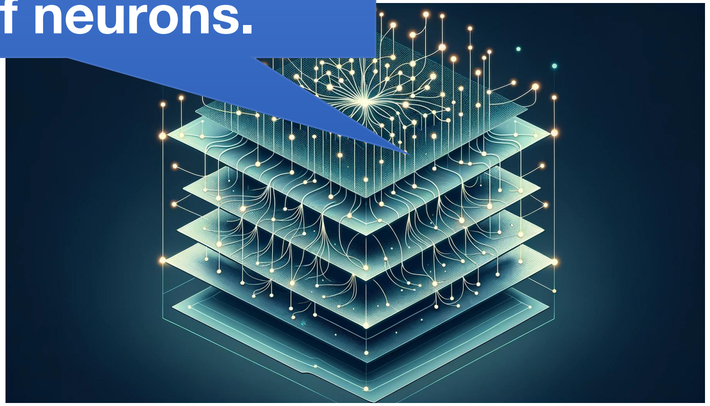
A bird scaring a scarecrow.

Paying for a quarter-sized pizza with a pizza-sized quarter.

DALL·E

Training DNN is time-consuming

DNN model can be very complicated, with tens to hundreds of layers and millions of neurons.



Complicated models

Dataset is huge, e.g., ImageNet contains more than 14 million images. Llama2 uses 2 trillion tokens of pretraining data.

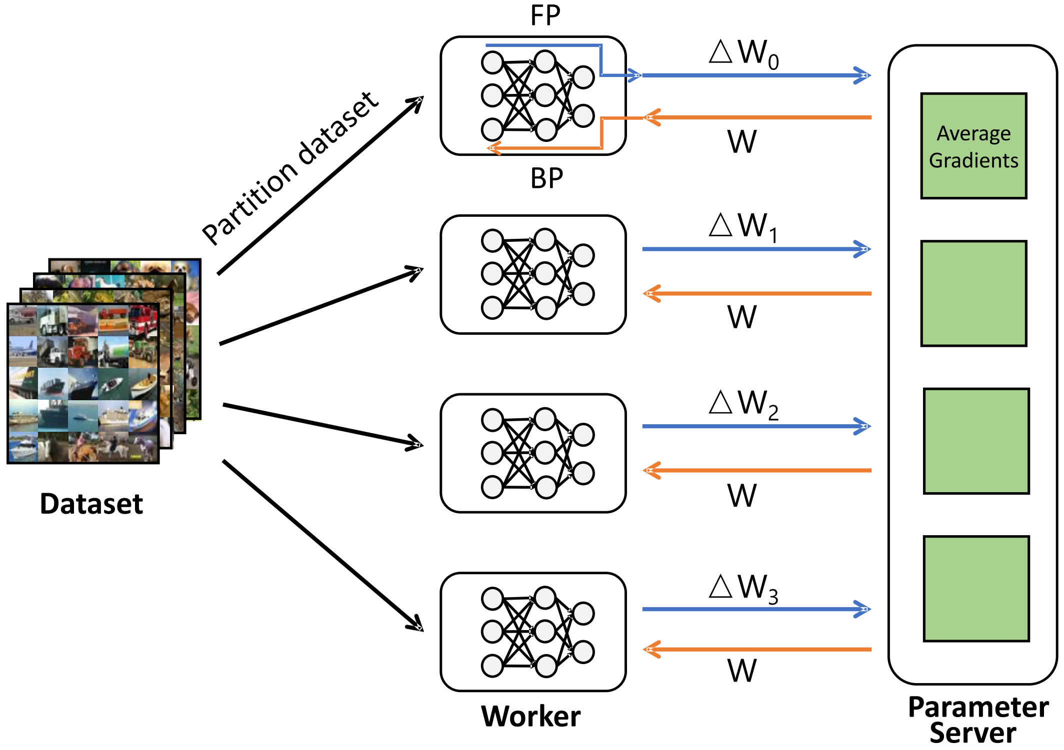
Huge amount of data

Model	$\text{BERT}_{\text{BASE}}$	Llama2-70B
Training time	4 days, 16 x TPU v3	1.7M GPU hours, A100

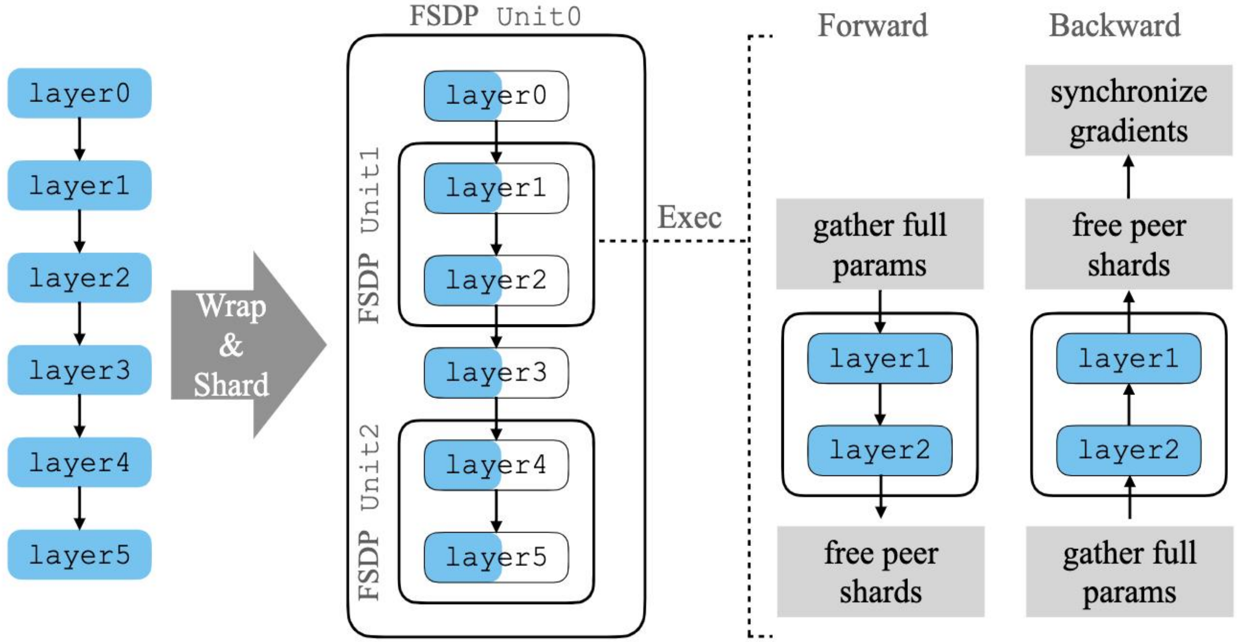
https://arxiv.org/pdf/1810.04805.pdf https://arxiv.org/pdf/2307.09288.pdf

Accelerating DNN training via data parallelism

- Example of data parallelism of synchronous SGD under the Parameter Server architecture



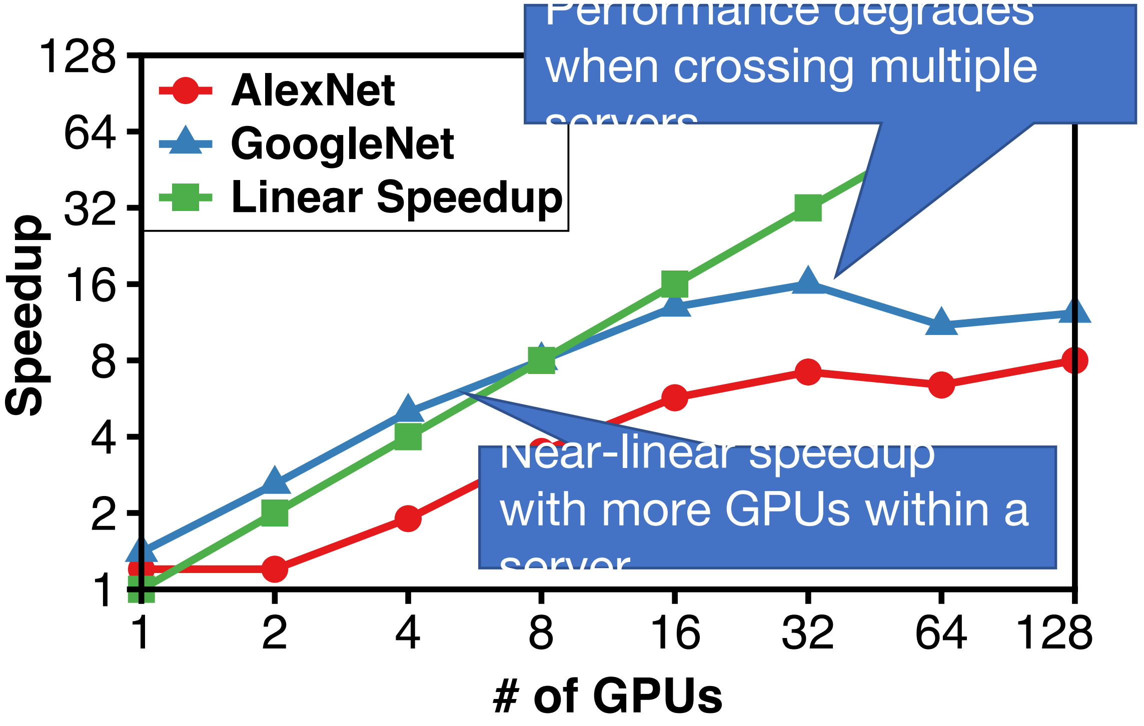
- Note that data parallelism is also widely used in LLM training, e.g., Zero and FSDP.



FSDP workflowhttps://arxiv.org/pdf/2304.11277.pdf

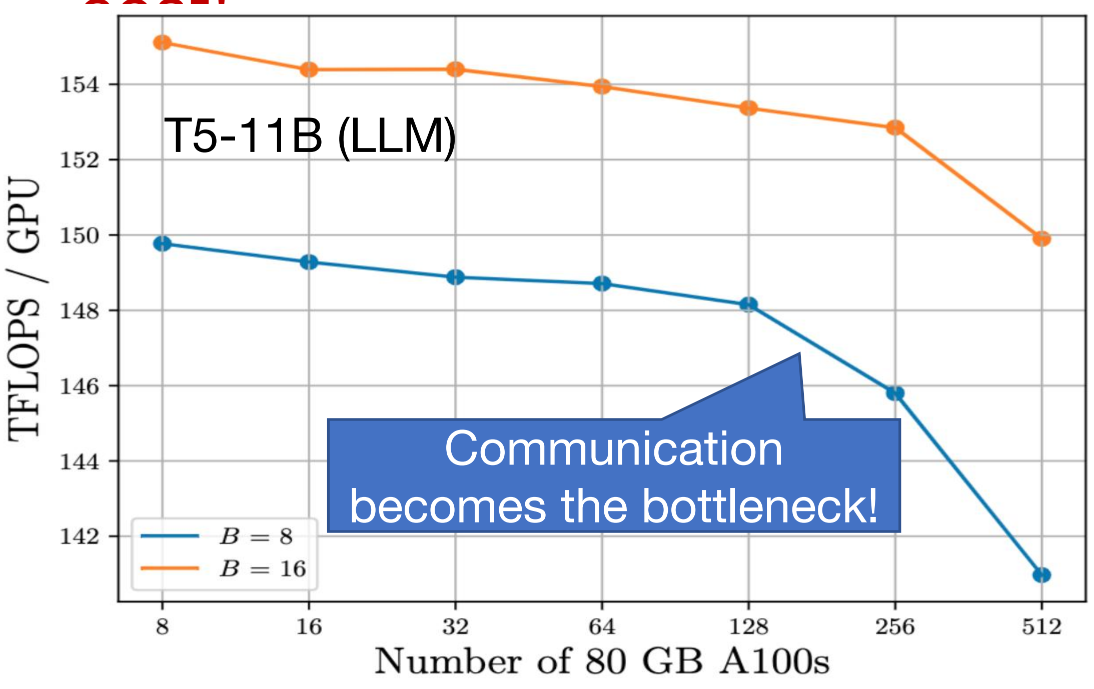
The speedup of data parallelism: a close look

- Speedup with more GPUs: not always linear!



https://arxiv.org/pdf/1609.06870.pdf

- Root cause for failing to achieve linear speedup: communication cost!



PyTorch FSDP: https://arxiv.org/pdf/2304.11277.pdf

Application layer solution: reducing traffic volume

➢ Gradient Sparsification

- Reduce communication bandwidth by only sending important gradients
- Use gradient magnitude as a simple heuristics for importance
- Only gradients larger than a threshold are transmitted (e.g., top 0.1%)

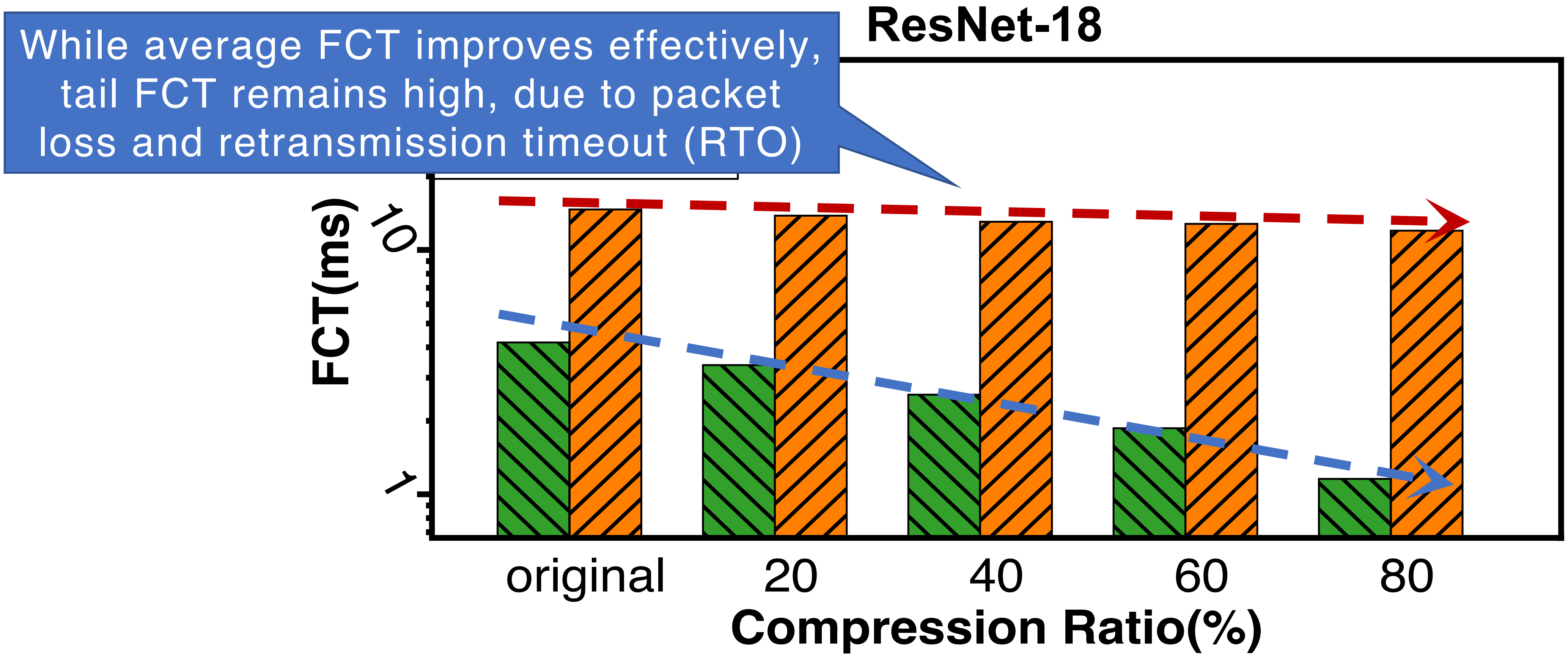
Reducing the **number** of gradients transmitted

➢ Gradient Quantization

- Obtain the min and max gradient values of each layer
- Represent the gradients with low-precision float (e.g., 32 bits -> 8 bits)
- The results are composed by an array containing the quantized value, and the min and max value

Reducing the **precision** of gradients transmitted

Reducing traffic volume doesn't eliminate the problem



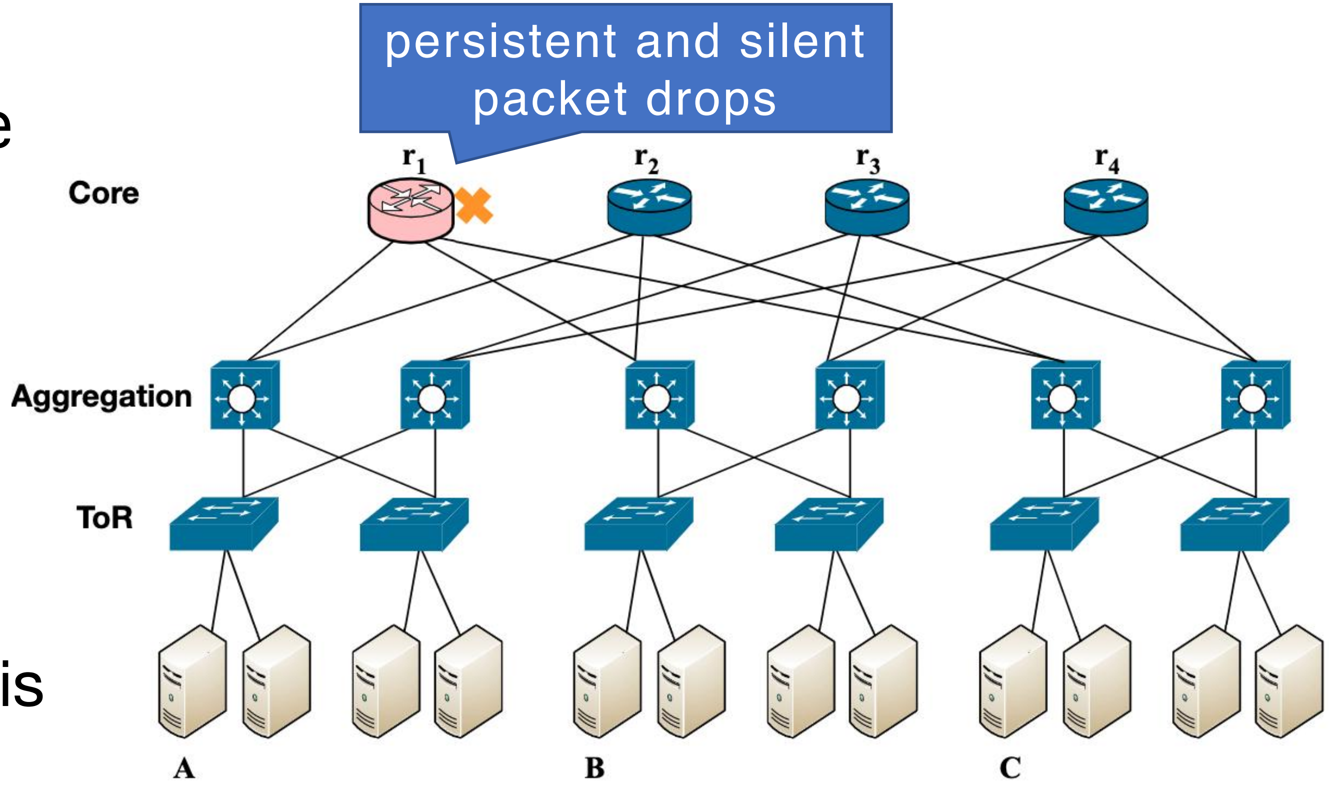
- ➢ Lesson learned: tail latency is often caused by the communication pattern, not only the traffic volume. **This calls for network transport solutions!**

Gray failure: potential pitfalls of large-scale training

- Fault-tolerance and reliability are crucial for distributed training

- Gray failure refers to subtle and often undetectable issues in data center

- A common example of gray failure is the persistent and silent packet drops experienced by a network device or link.

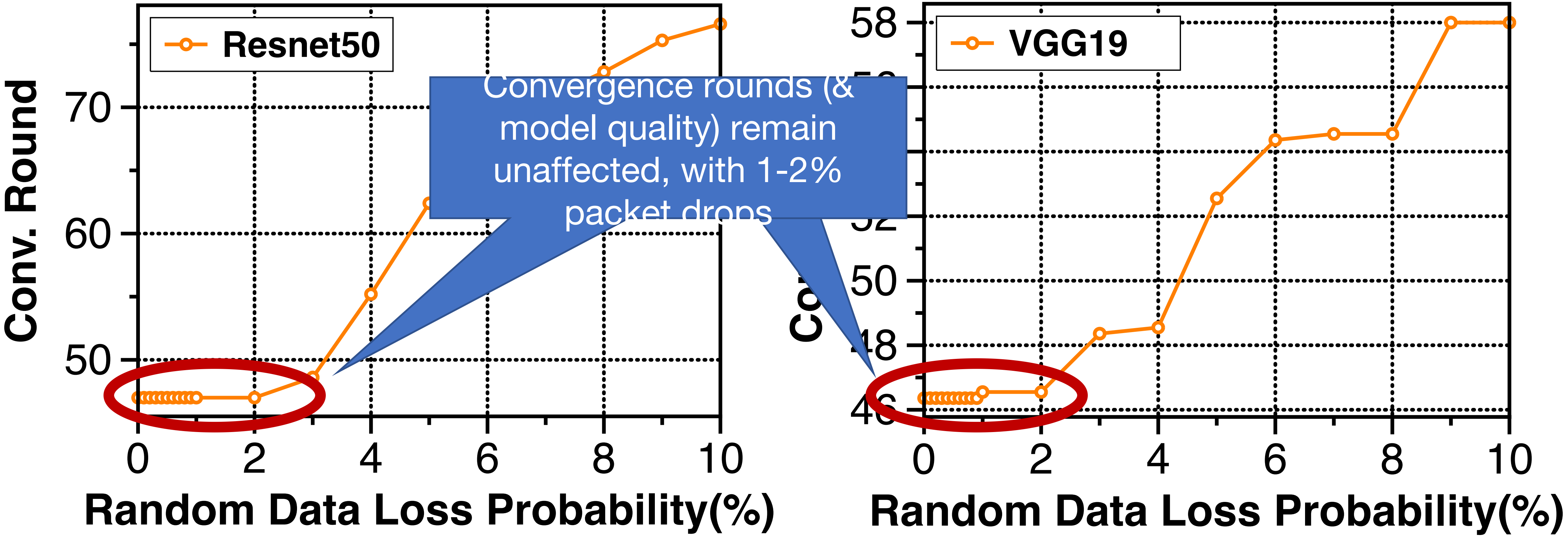


Gray Failure: The Achilles' Heel of Cloud-Scale Systems

➢ Transport for AI-centric Networking (AICN) must be resilient to such gray failure.

Observation 1: bounded-loss tolerance

➢ The DNN training process is bounded-loss tolerant: certain packet drops don't affect model convergence much!



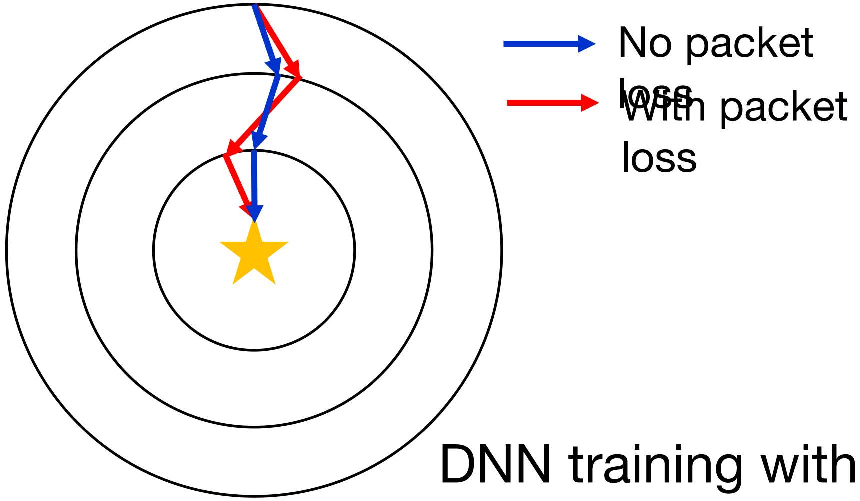
Dataset Used: Caltech101

Insight behind observation 1

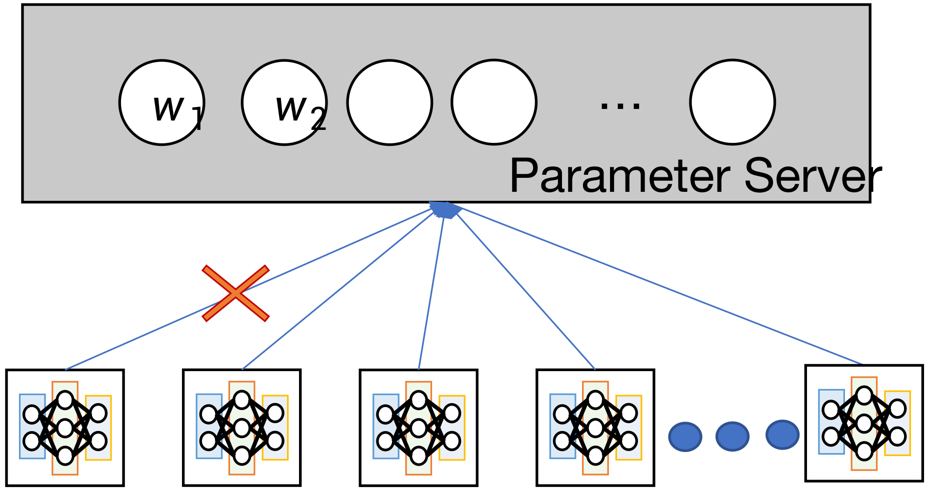
- **The learning direction doesn't deviate much:** With bounded packet losses, the direction of the gradient vector (or tensor) will not deviate much from the original, steepest direction.

- **The learning step size doesn't change much:** With bounded packet losses, the step length of the gradient vector remains similar.

- **The SGD algorithm is robust to loss (self-healing):** SGD recalculates the learning objective function towards the optimal at each step, noise caused by loss in earlier iterations won't be carried to latter iterations, but instead can be fixed later!



DNN training with SGD



$$E_D[1/99\,(g_2 + g_3 \ldots + g_{100})] = E_D[1/100(g_1 + g_2 + g_3 \ldots + g_{100})]$$

Inspiration from observation 1

➢ Reliability requirement for AI-centric Networking (AICN)

- TCP (or RDMA-RC):
  Good model quality with 100% reliability, but suffer from high communication overhead (long tail latency)

- MLT:
  Cutting long tail latency with bounded-loss tolerance, while maintaining good model quality; Resilient to gray failure in the network

- UDP (or RDMA-UD):
  Low communication overhead, but no packet delivery guarantee at all, leading to very bad model quality

Better

Model quality

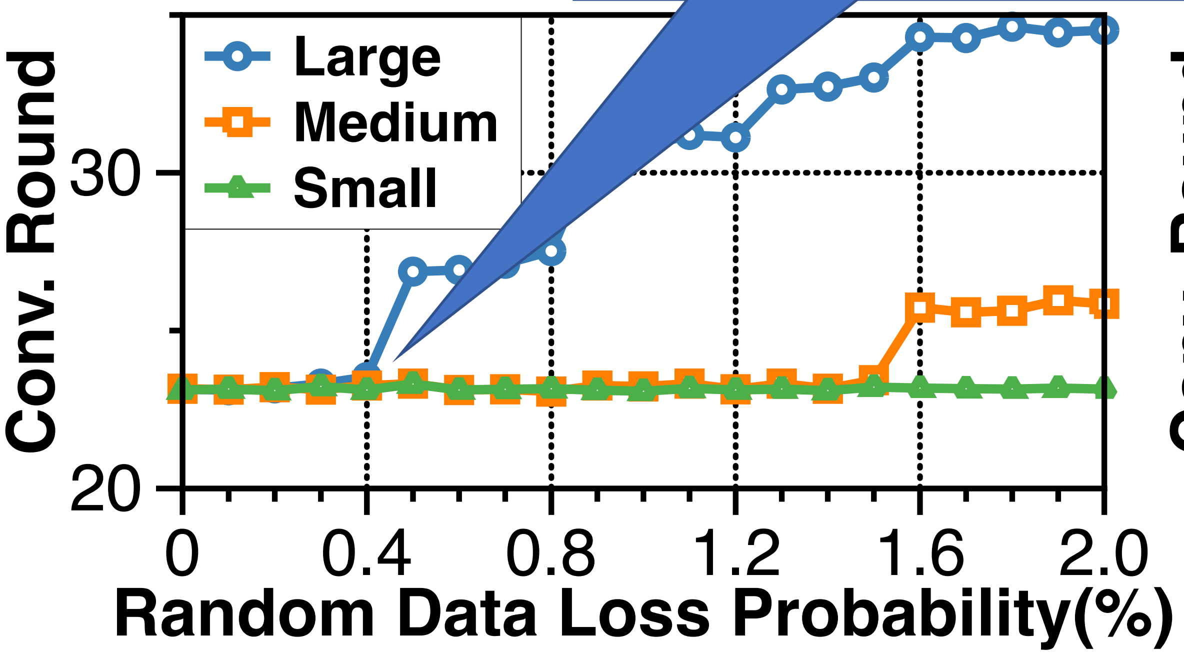
Communication efficiency

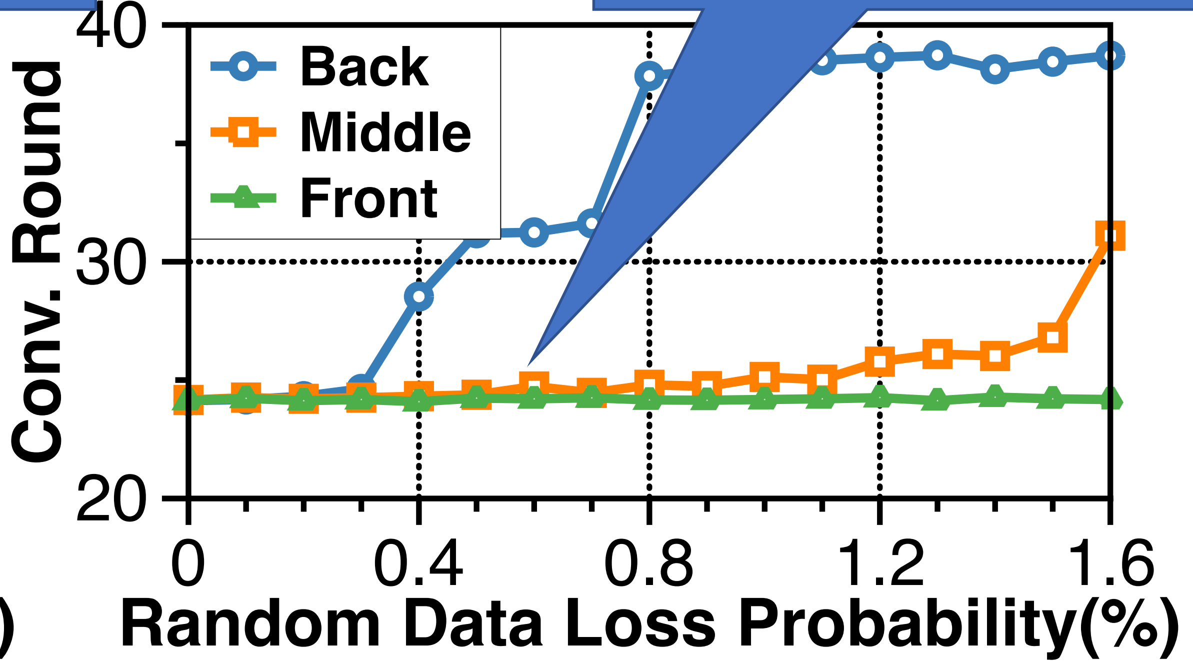
Observation 2: Different gradients have different impacts

➢ **Losing different gradients may generate different impacts on model converge**

Magnitude-wise: larger gradients are more sensitive to loss

Layer-wise: back-layer gradients are more sensitive to loss



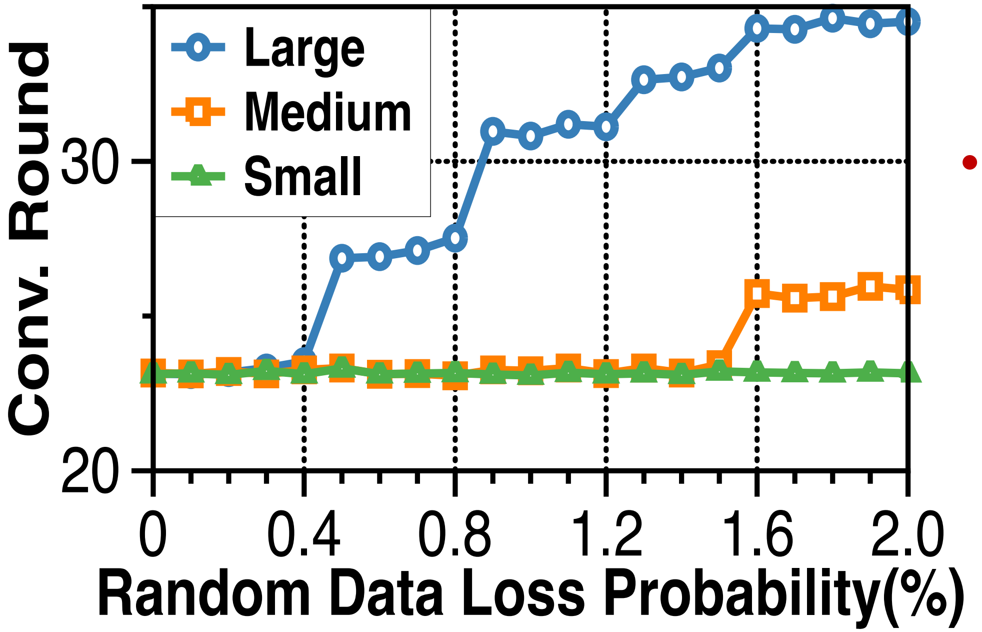


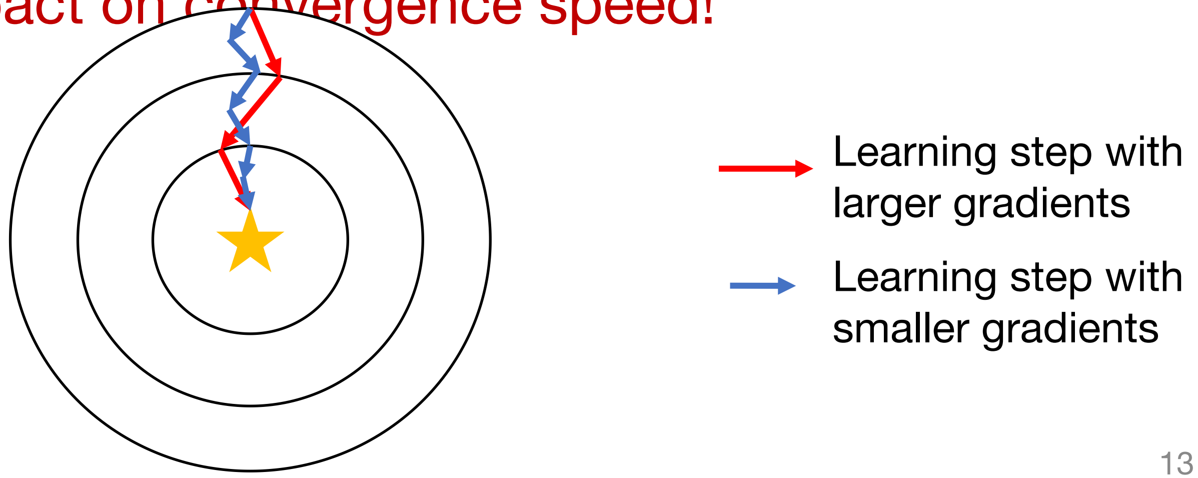
ResNet50 on Cifar100

Insight behind magnitude-wise impact

➢ **Magnitude-wise impact:** larger gradients are less loss-tolerant than small gradients

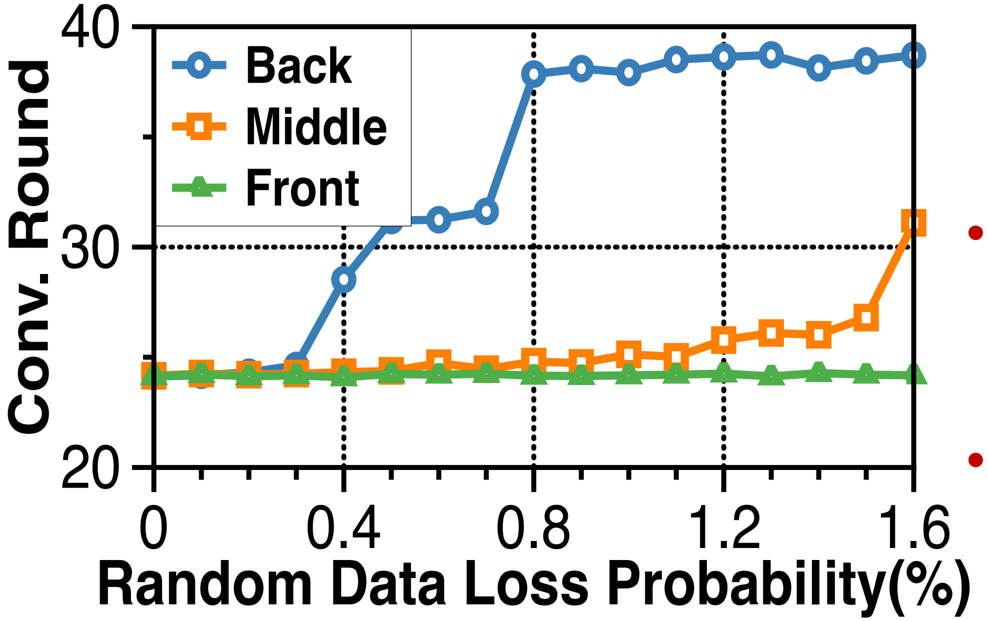
- Larger gradient contains stronger correlation between the extracted feature and the objective task than smaller gradient does, more impact on model accuracy!
- Larger gradient indicates bigger learning step size, smaller gradient indicates smaller step size, more impact on convergence speed!

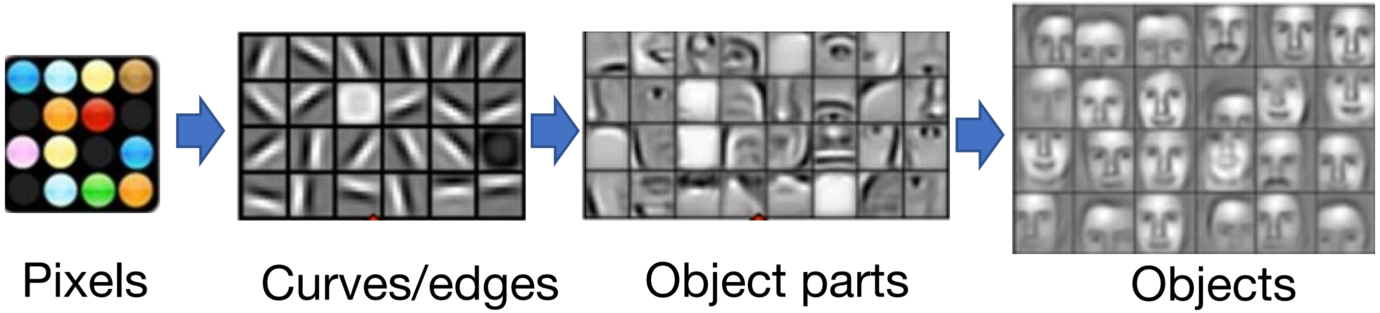




Insight behind layer-wise impact

➢ **Layer-wise impact:** front-layer gradients are more loss-tolerant than back-layer gradients





- Front layers extract simple, class-independent features and can be trained from almost all samples, e.g., from pre-training dataset, thus easier to learn!
- Back layers extract class-specific features (e.g., earrings) and can be trained only from specific samples with certain classes (e.g., women), thus much harder to learn!

Honglak Lee, NIPS'10

Inspiration from observation 2

Not all gradients are equal in terms of the impacts on model convergence and training pipelining

When queue builds up

Prioritize front-layer gradients over back-layer gradients, to speed up training pipelining

Priority Queueing
(both at end-host and in network)

When buffer overflows

Selectively drop front-layer gradients over back-layer gradients, smaller gradients over larger gradients, to maintain model convergence/quality

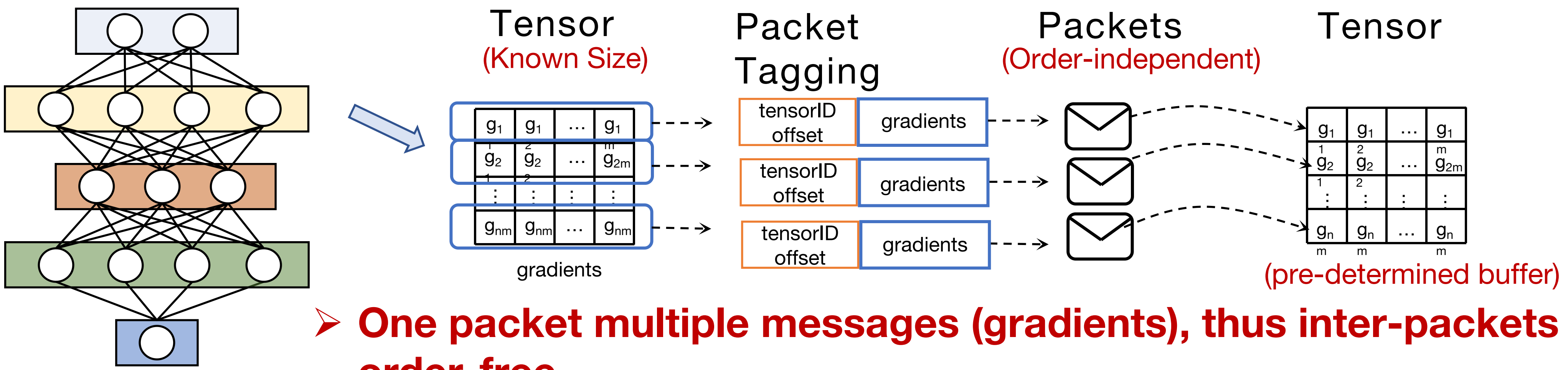
Selective Dropping

Observation 3: Inter-packet order-independence

Traditional Network Apps

- **One message multiple packets, thus packet ordering matters**

DNN Training



- **One packet multiple messages (gradients), thus inter-packets are order-free**
- **The traffic in DNN training is periodic and predictable**

Inspiration from observation 3

Tradeoff for traditional network applications

Per-flow ECMP:
coarse-grained, large flow hash-collision, low efficiency

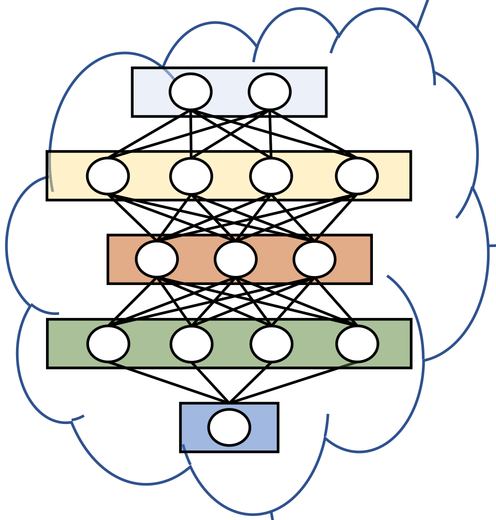
Per-packet load balancing:
fine-grained, but suffer from reordering problems

Flowlet-based load balancing:
make a tradeoff in-between

For DNN training, we can break the tradeoff: per-packet load balancing *without worrying about out-of-order issues!*

MLT - Machine Learning Transport for AI-centric networking

➢ Inspired by the previous observations, MLT performs the following domain-specific communication optimization:



Bounded-loss tolerance → Cutting tail latency with bounded-loss tolerance

➢ To address the problem that cannot be solved with application layer solutions

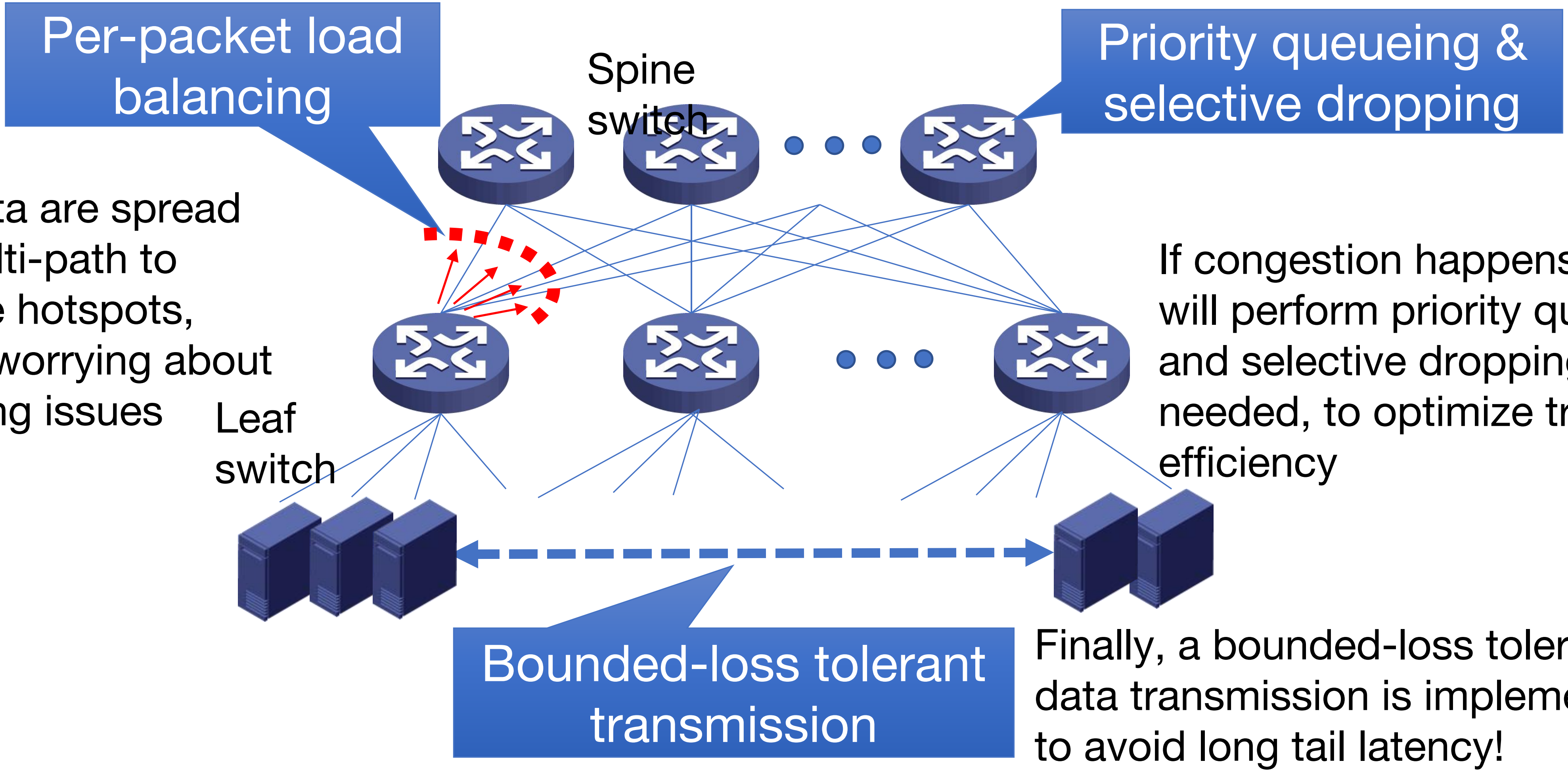
Not all gradients are equal, in terms of impacts on model convergence/ quality and training pipelining → Optimizing training efficiency with gradient-aware queueing and dropping

➢ To improve model convergence and speed up training pipelining

Inter-packet order-independence → Enabling per-packet load balancing based on packet-level order-independence

➢ To maximize network utilization and minimize hotspots

MLT design overview



First, data are spread onto multi-path to minimize hotspots, without worrying about reordering issues

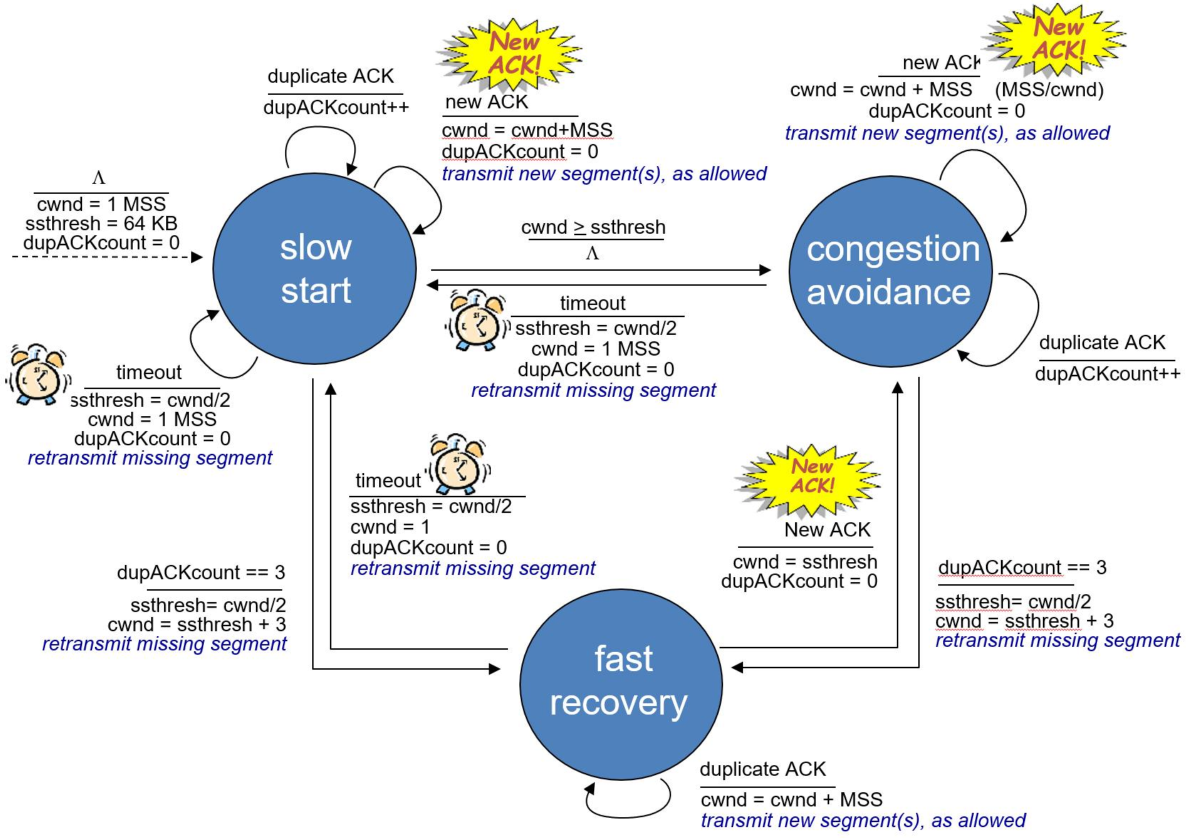
If congestion happens, switch will perform priority queueing and selective dropping, if needed, to optimize training efficiency

Finally, a bounded-loss tolerant data transmission is implemented to avoid long tail latency!

Bounded-loss tolerant data transmission

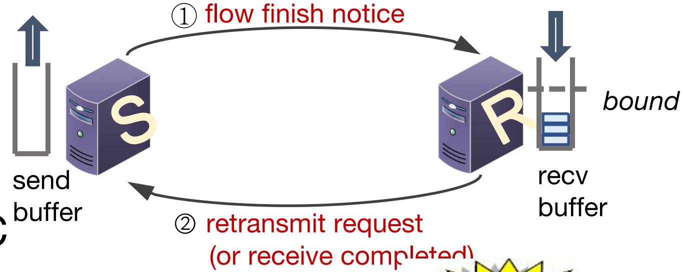
TCP Congestion Control

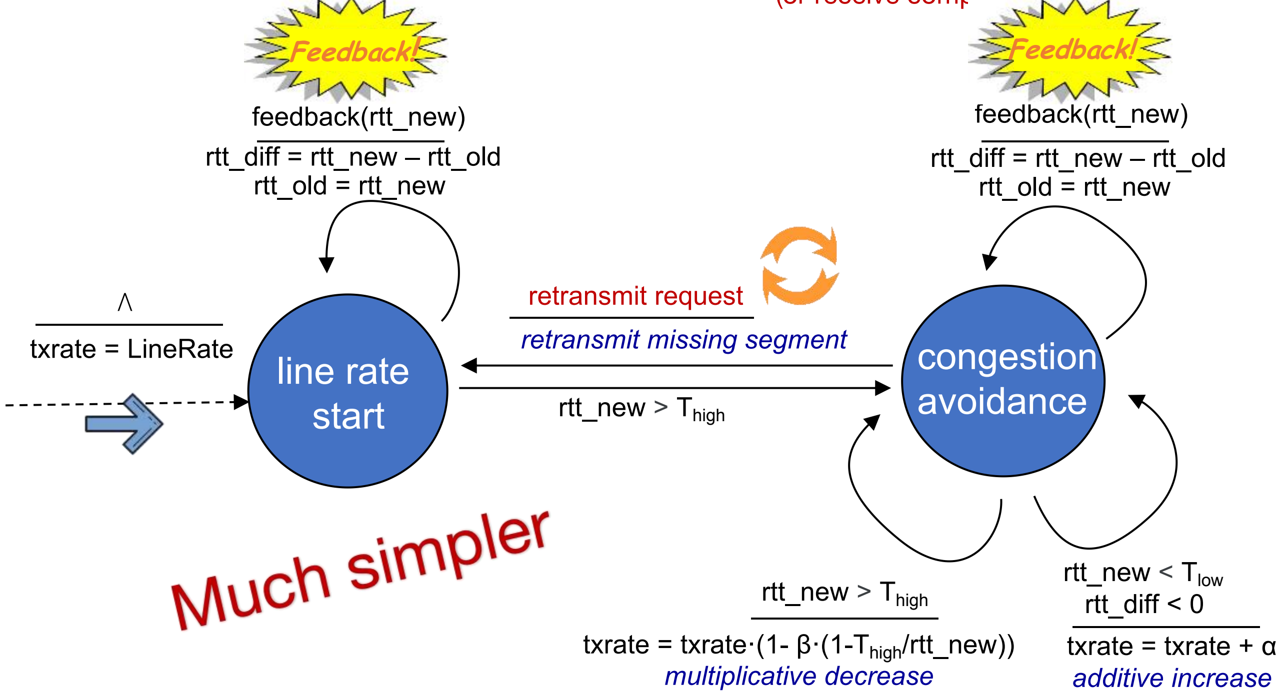
- Slow start (exponential)
- Timeout
- 3 dupACK and fast recovery



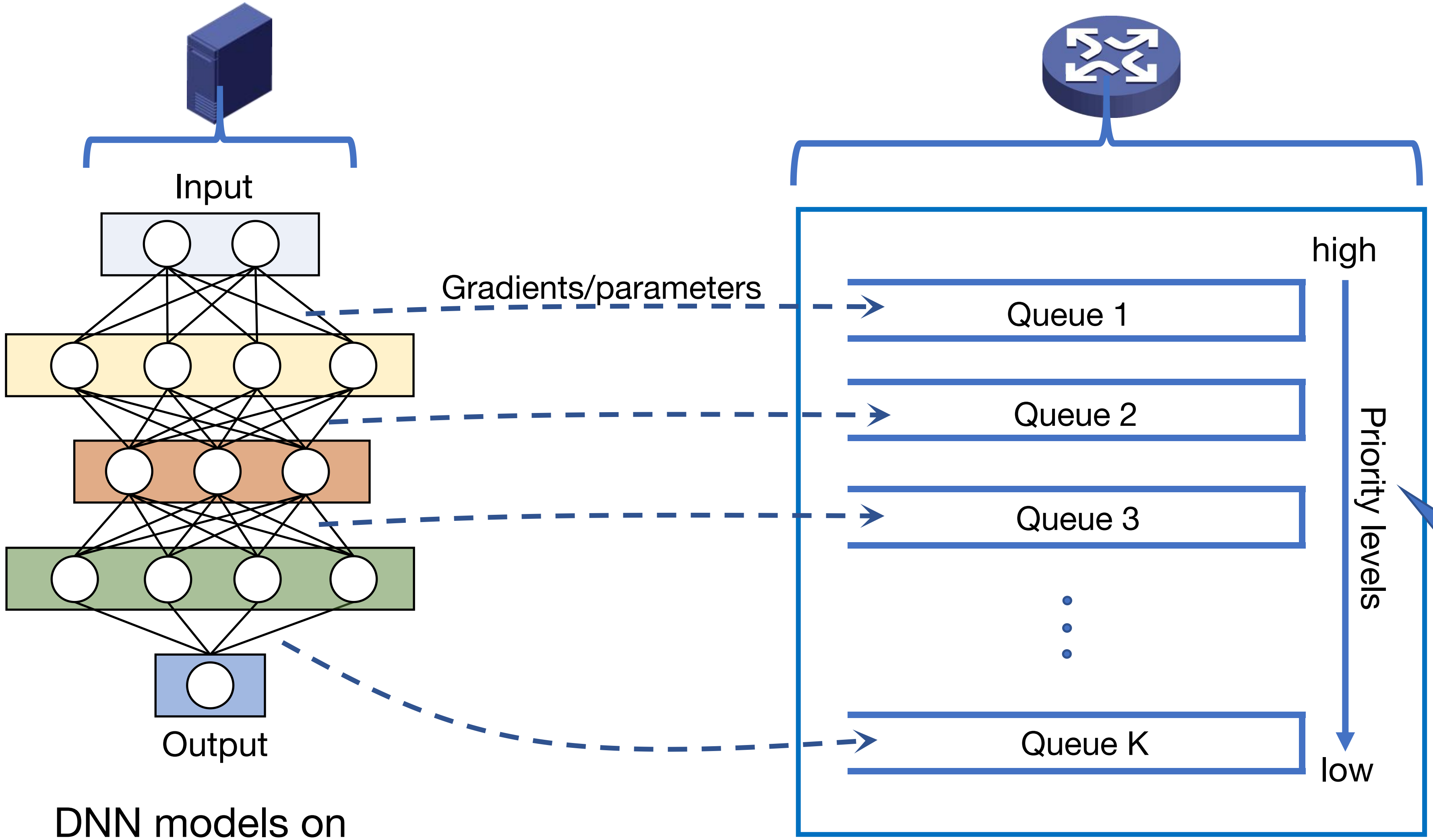
MLT Rate Control

- Line rate start
- No timeout
- No need fast recovery
- Timely-like RTT-base CC





Gradient-aware **priority queueing** & selective dropping



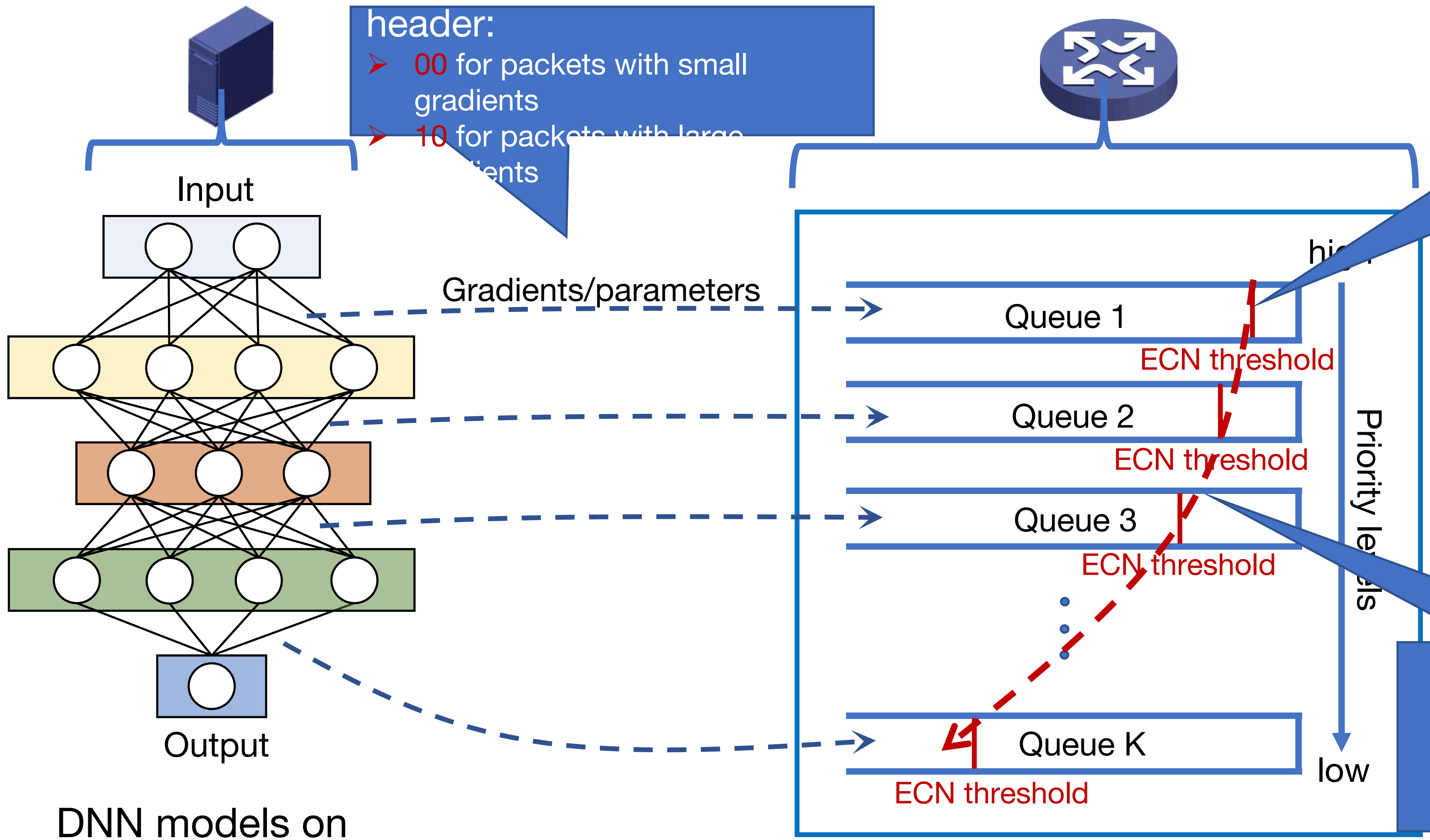
DNN models on worker/server

Queueing/dropping at switch

Priority queueing to speed up training pipelining: front layers first

Gradient-aware priority queueing & selective dropping

header:
- 00 for packets with small gradients
- 10 for packets with large



DNN models on worker/server

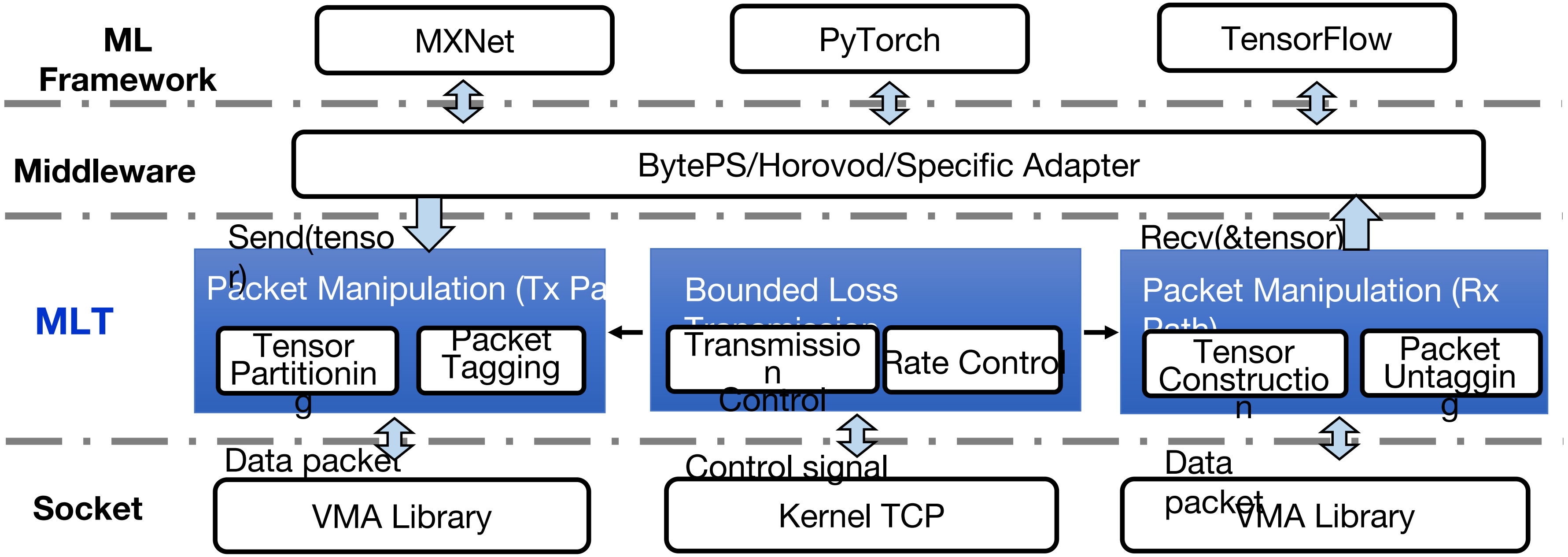
Queueing/dropping at

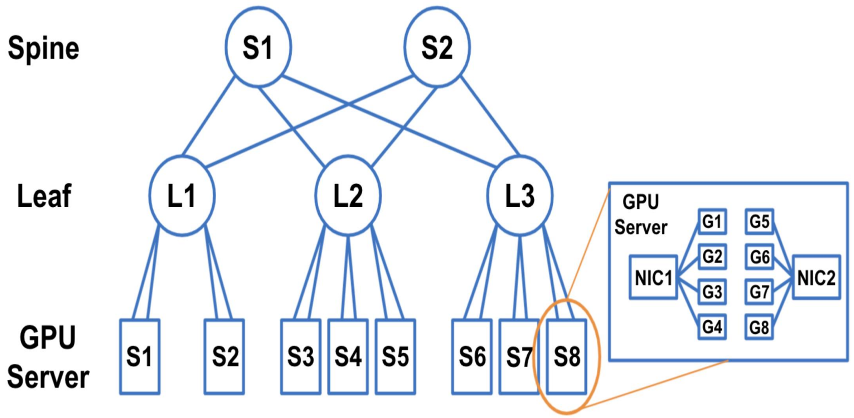
Re-interpret ECN/RED for selective dropping*: selectively drop packets with smaller gradients

*Hu S., Chen K. et al, Aeolus: A Building Block for Proactive Transport in Datacenters, SIGCOMM 2020

thresholds to try to drop front-layer gradients first, while keeping back-layer

Implementation and testbed setting



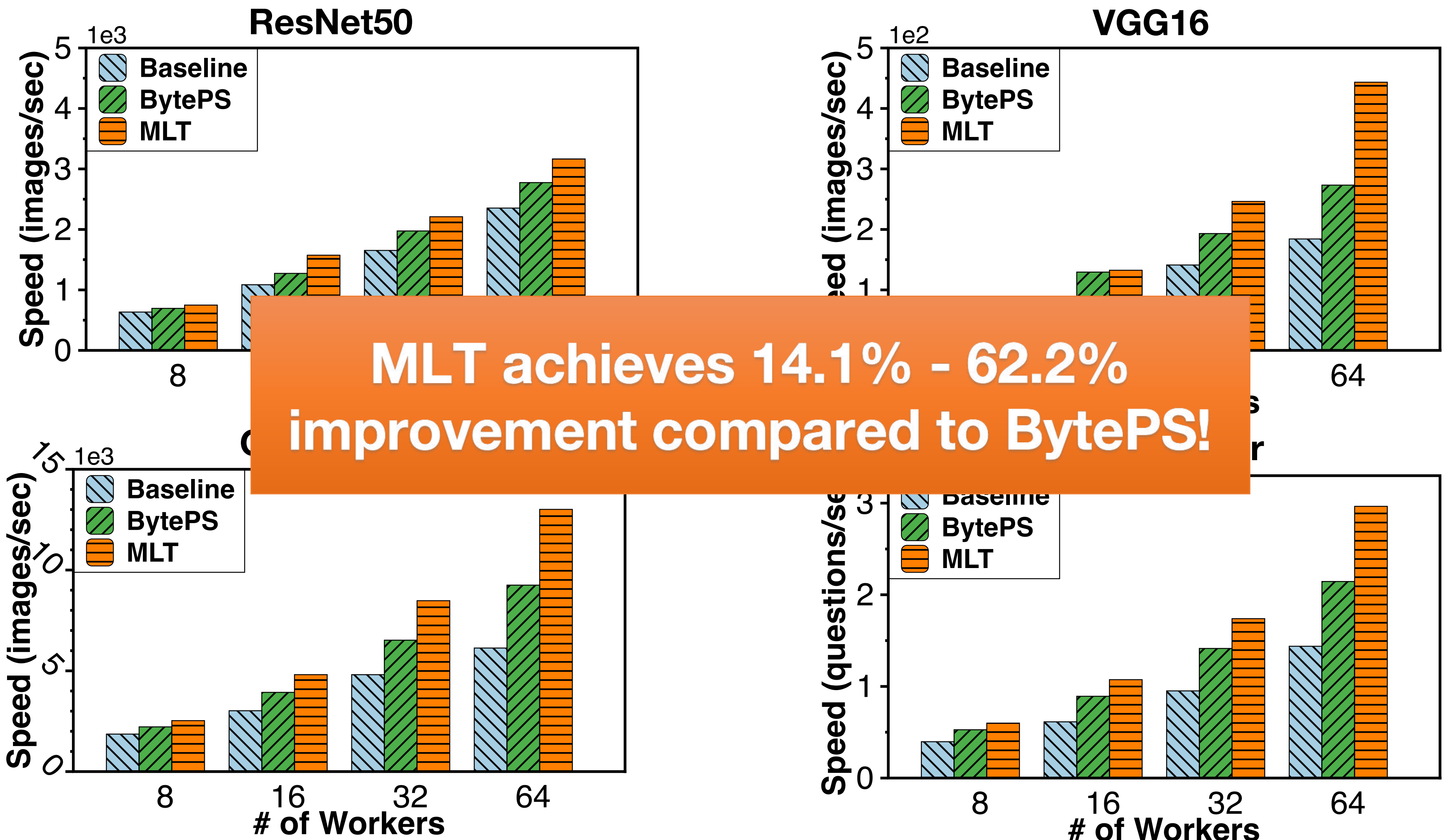


Experiment Setting:

- Testbed: 8x GPU servers each with 8x 3090 GPUs, 4 Mellanox SN2100 switches.
- Topology: 2x3 Spine-Leaf*, 100Gbps
- Models: ResNet50, VGG16, GoogleNet, Transformer, T5
- Comparison Target: vanilla ML frameworks, BytePS

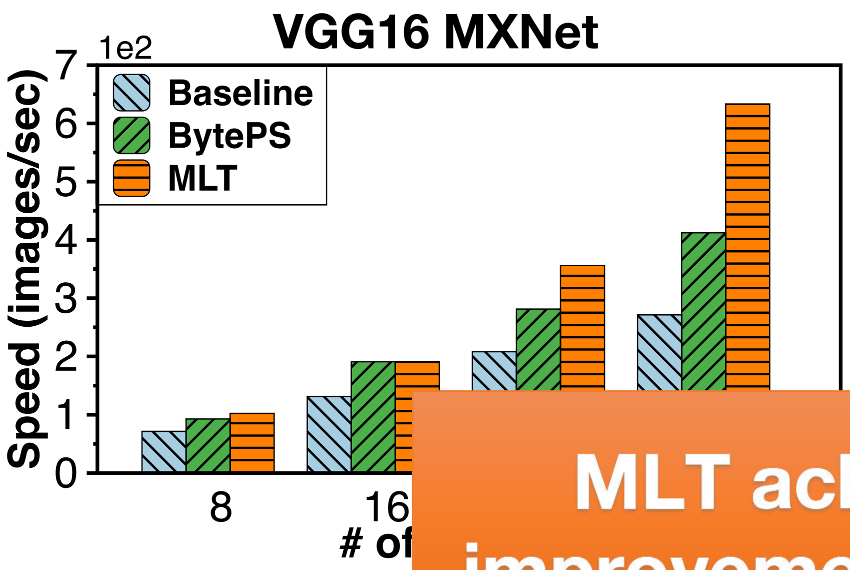
*Each leaf switch has two 100Gbps links connecting to the spine switch, thus logically we have two spine switches.

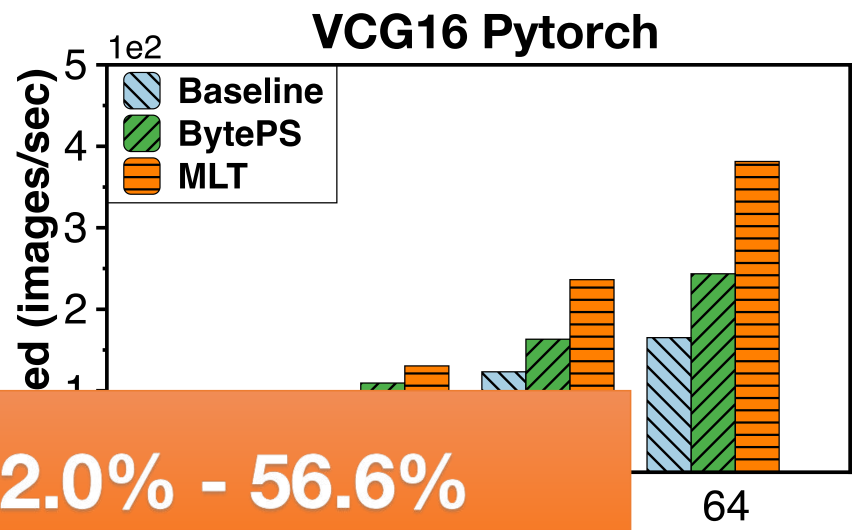
Speedup under different DNN models (Tensorflow, PS)



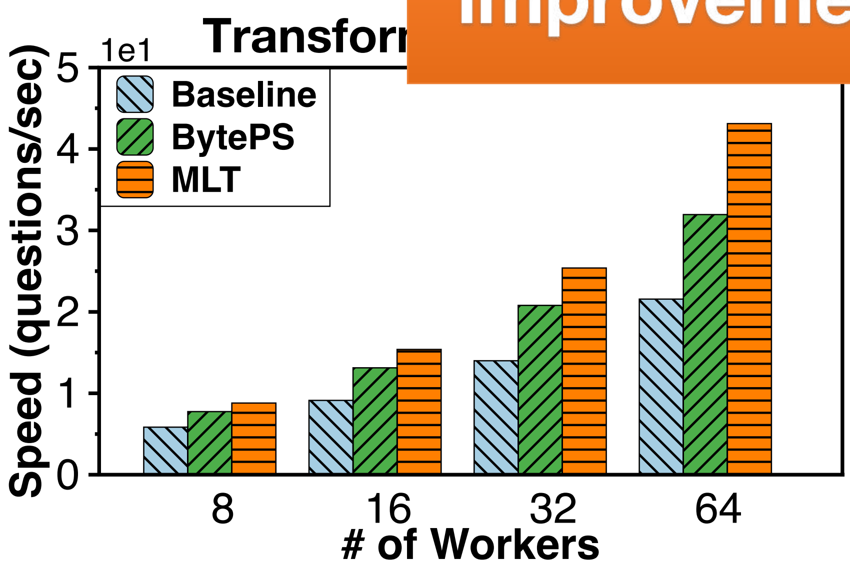
MLT achieves 14.1% - 62.2% improvement compared to BytePS!

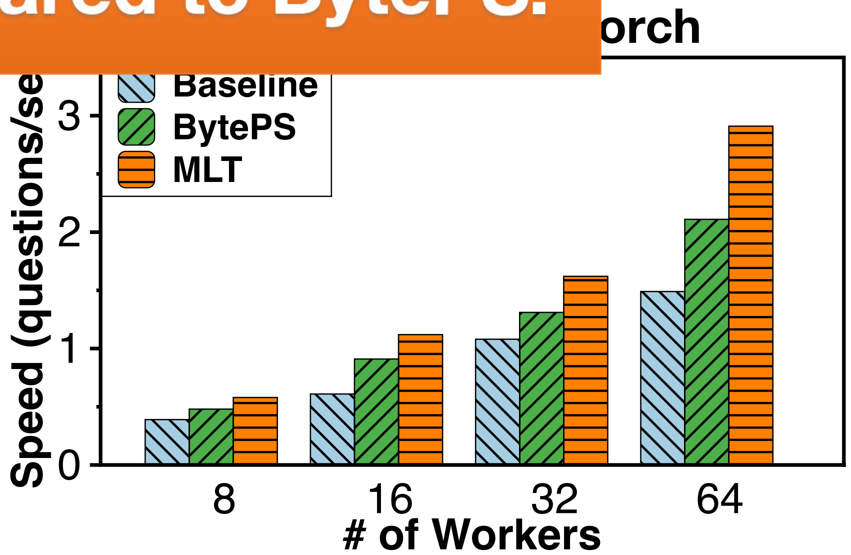
Speedup under different ML frameworks



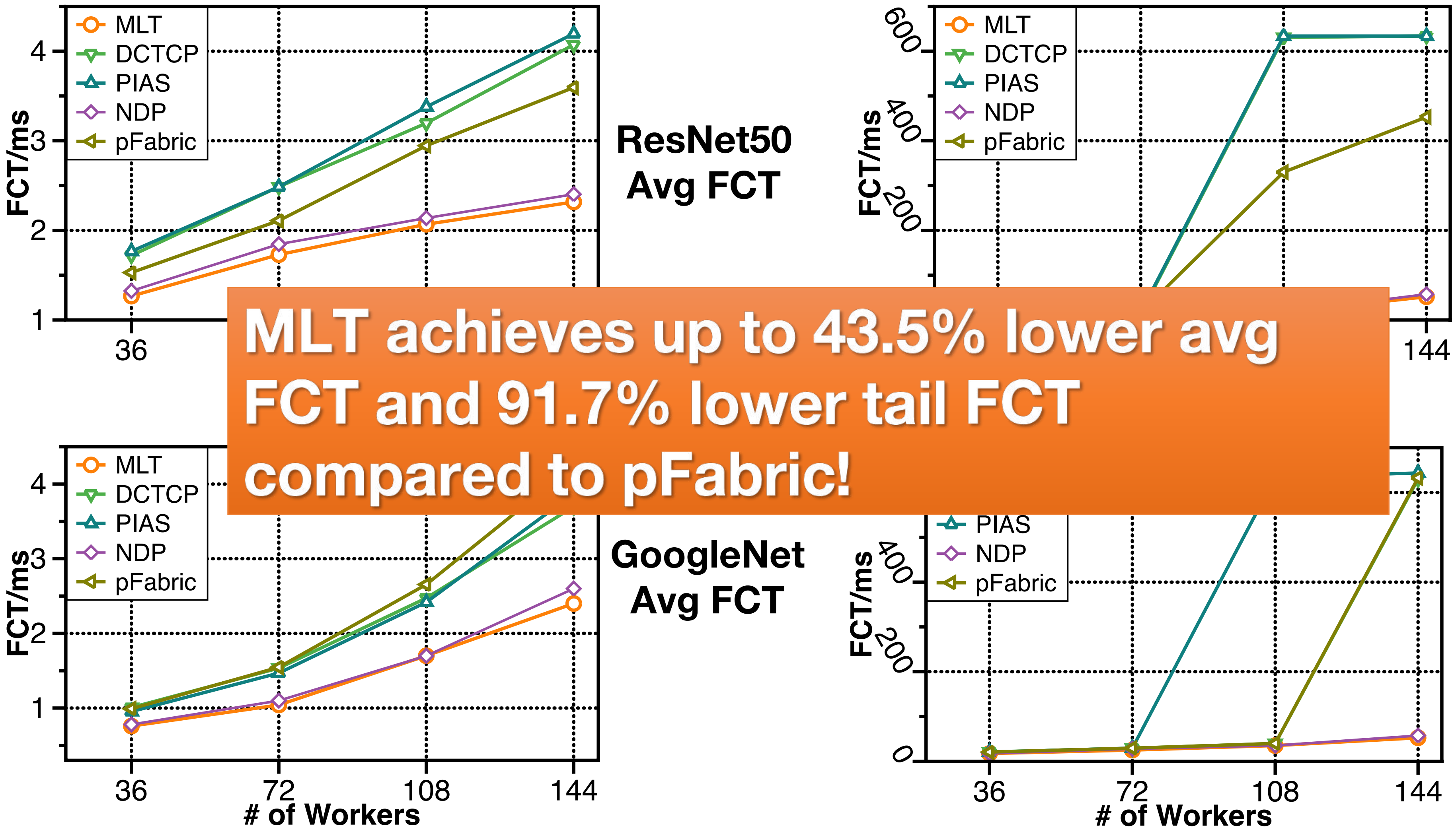


MLT achieves 12.0% - 56.6% improvement compared to BytePS!





Network performance in larger-scale simulations



ResNet50 Avg FCT

ResNet50 Tail FCT

GoogleNet Avg FCT

GoogleNet Tail FCT

MLT achieves up to 43.5% lower avg FCT and 91.7% lower tail FCT compared to pFabric!

Setting: topology 144 node leaf-spine, bandwidth 100Gbps, #servers/#workers 1/3

Conclusion

- MLT (Machine Learning Transport for AI-centric networking) exploits domain-specific properties of deep learning to optimize communication for distributed DNN training!
- MLT made three key observations:
  - Bounded-loss tolerance
  - Different gradients generate different impacts
  - Inter-packet order-independence
- MLT conceived three main ideas:
  - Cutting tail latency via bounded-loss tolerant data transmission
  - Improving training efficiency through gradient-aware priority queueing and selective dropping
  - Maximizing network utilization by enabling per-packet load balancing due on inter-packet order-independence

Thank you!