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Exploring Limits of ML Training on Google TPUs

Sameer Kumar, Dehao Chen
{sameerkm, dehao}@google.com

Hot Chips 2020 Tutorial on “Machine Learning Scaleout”
08/16/2020

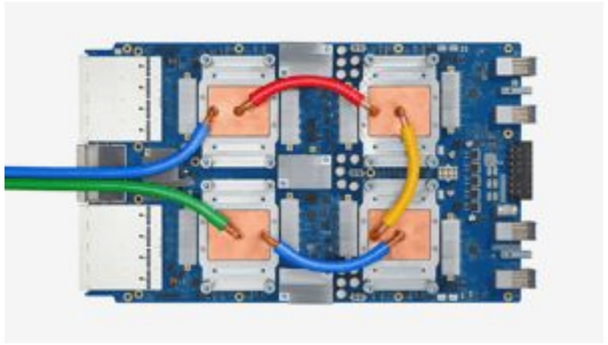
Overview

- Scalable Architecture
    - TPU-v3 **Multipods** with 4096 TPU-v3 chips
    - Fast and scalable collective implementation
- Scalability Techniques
    - Weight update sharding
    - Model parallelism
- Performance results and conclusion

Space-race for the biggest ML machine

- AI supercomputer at Azure with 10K GPUs
- NVIDIA DGX SuperPods with 2k GPUs
- Google TPU MultiPods with 4k chips

Tensor Processing Units (TPUv3)

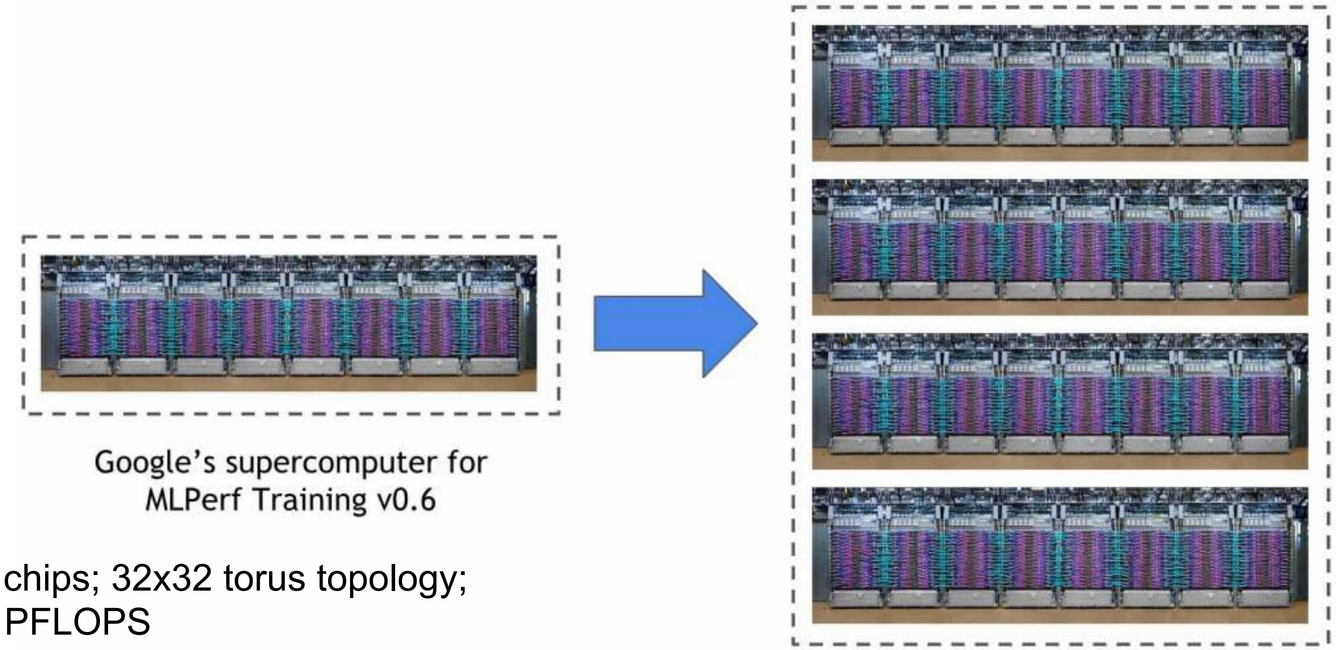


420 TFLOPS, 128 GB HBM

TPU Pod: 100+ PFLOPS, 32 TB HBM, 2-D Toroidal Mesh Network

Image Source: https://cloud.google.com/tpu/

The Google TPU multipods



Google's supercomputer for MLPerf Training v0.6

Google's supercomputer for MLPerf Training v0.7

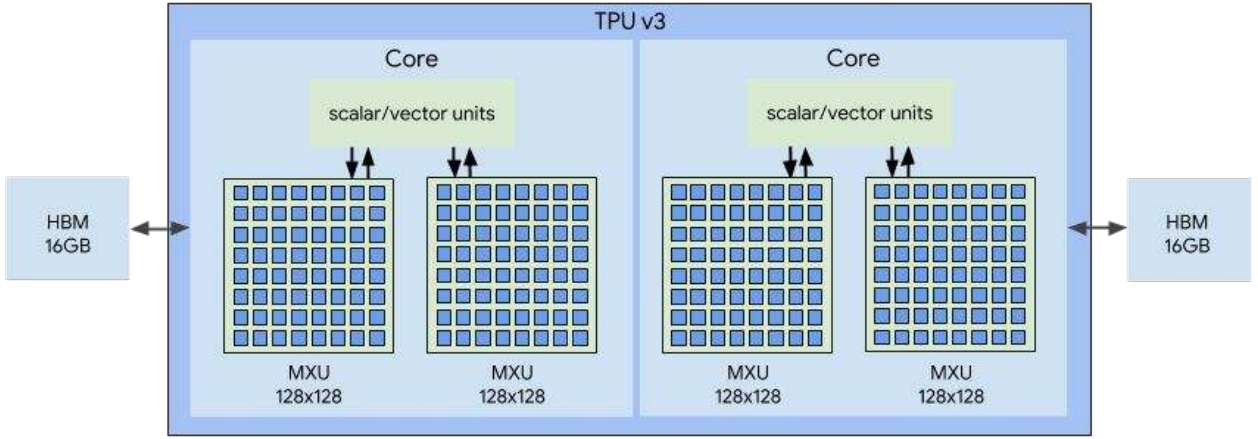
1024 chips; 32x32 torus topology; 100+ PFLOPS

4096 chips; 128x32 mesh topology; 400+ PFFLOPS

TPUv3: System Architecture

Key Features

- 128x128 Systolic arrays provide the massive horsepower; bfloat16 numerics
- Scalar, vector units to perform data formatting and non-matmul operations
- HBM accessed via on-chip interconnect



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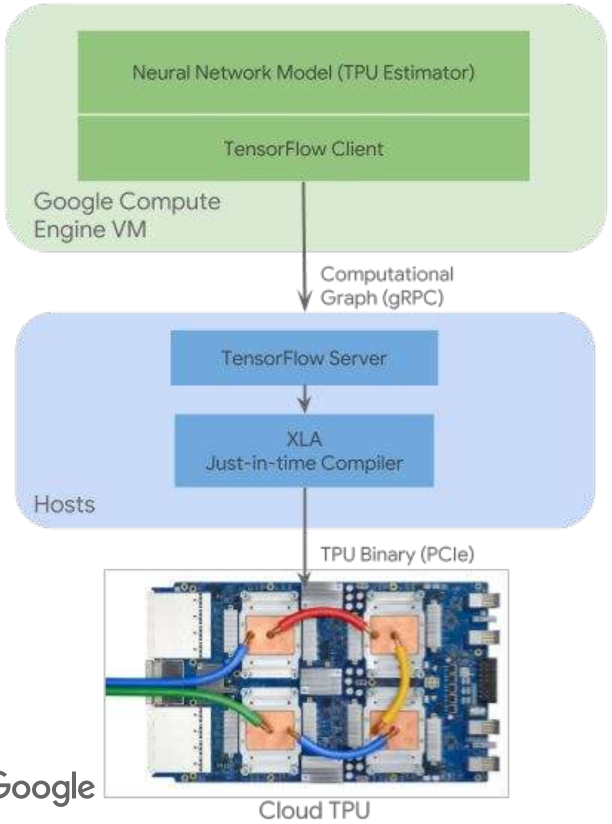
TPUv3: Software



Key Features

- Models → TensorFlow → XLA → TPU instructions
- Just-in-time compiled, launched synchronously on a “slice” of a TPU Pod
- Several communication primitives

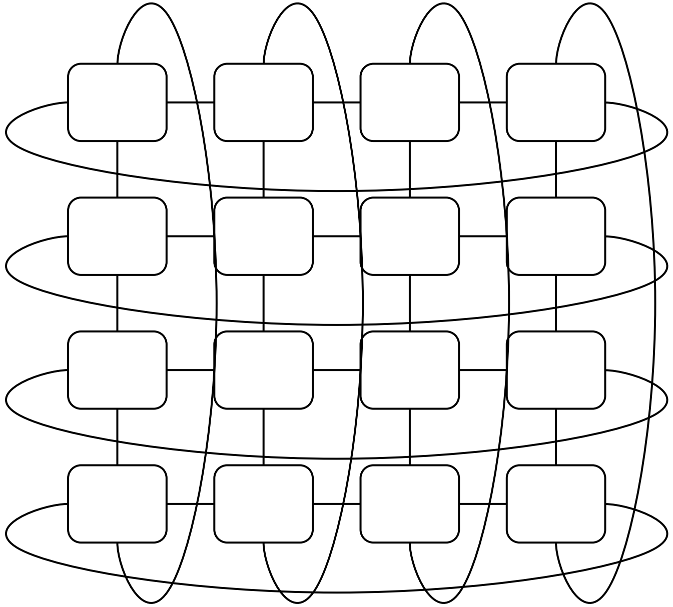
Multiple programming paradigms on TPUs

- TF
  - TF 1.x and TF 2.x enabled on TPUs
- JAX
  - Enable high performance machine learning research through composable transformations of Python and NumPy functions
- Pytorch

Challenges of large scale training

- Accelerate throughput of a large mini-batch SGD training
  - Execute linear algebra at high throughput on an accelerator (XLA Compiler)
  - Execute fast gradient summation
- Increase availability of this large machine : the fire fighter approach
- Scalable launch of ML Ops
- Scalable weight initialization
- Optimized host input pipelines

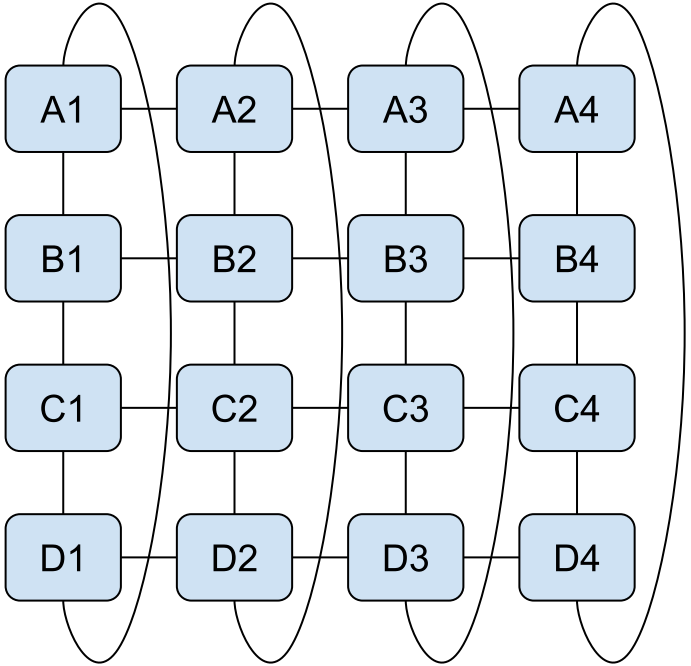
N-D Mesh/Torus Network Overview



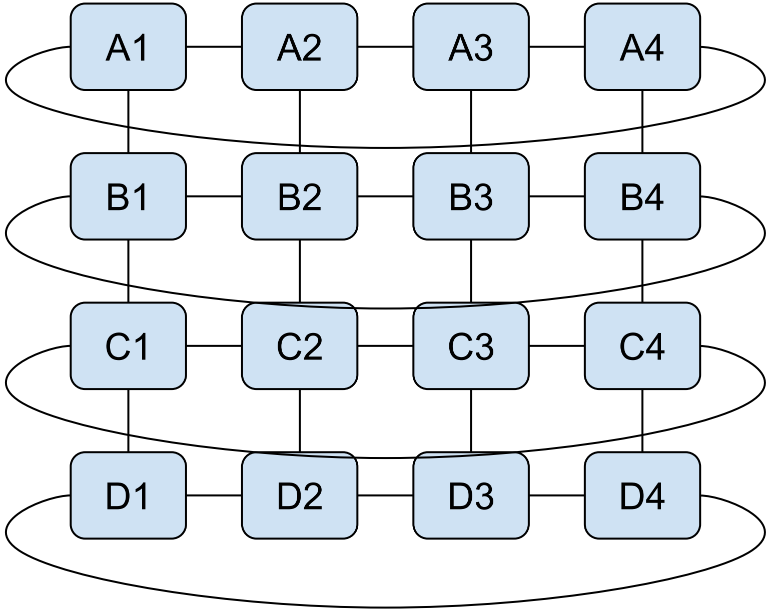
- Nodes connected 2*n neighbors via bidirectional network links
- Optimized for near neighbor communication
- All-to-all traffic can be bisection limited

Allreduce on a 2-D Torus

Phase 0: Execute sums along columns



Phase 1: Execute sums along rows. Payload in phase 1 is scaled down by the size of the columns



We enable global summation in float32 and bfloat16 precision

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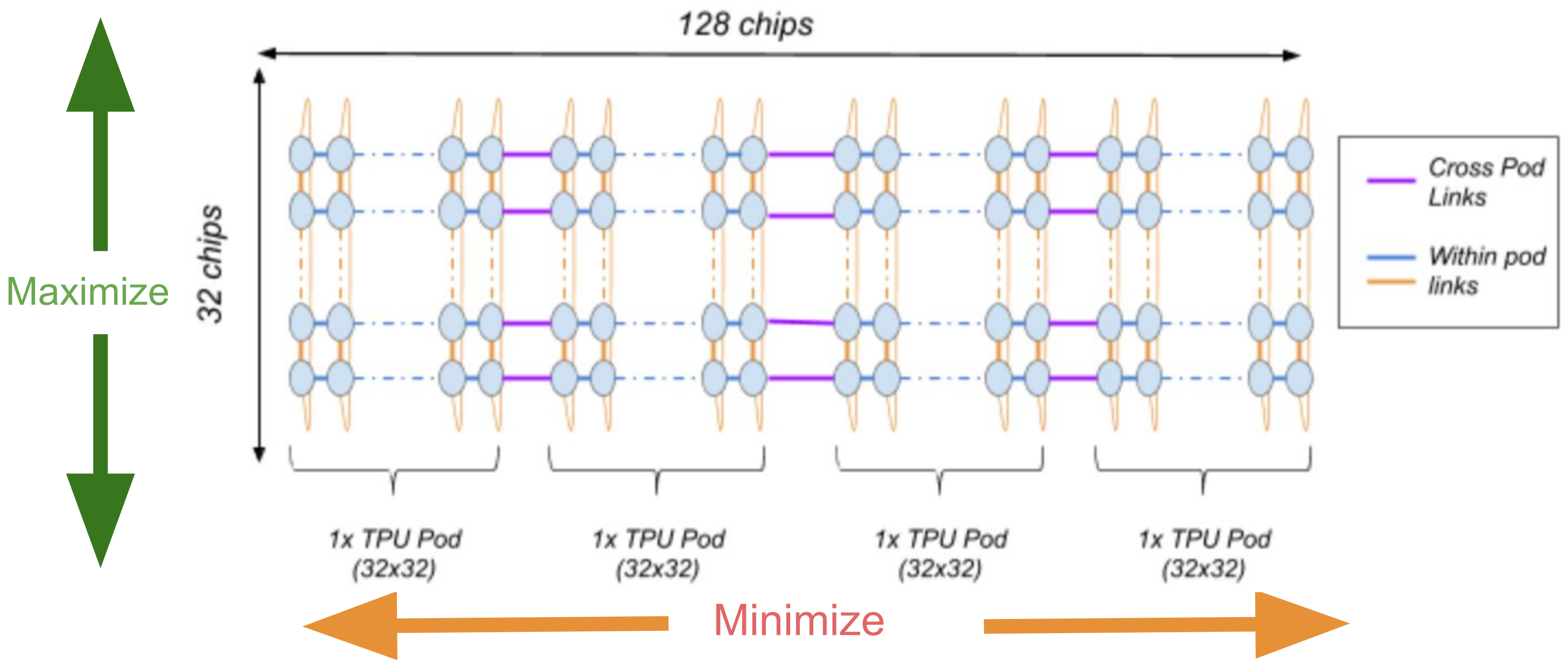
Communication Scaling on Multipods



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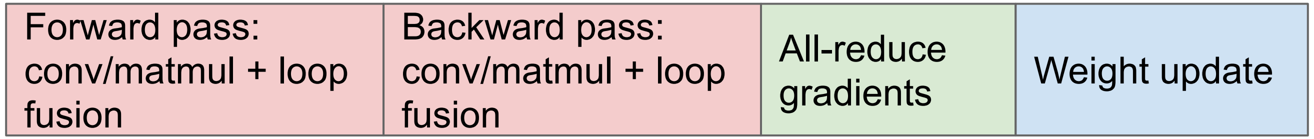
Scalability Techniques

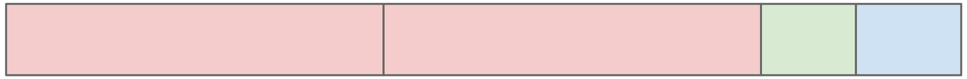
How do we scale training to this large system

- Compiler (XLA) automatically optimizes for scalability
  - Automatic fusion to overlap different computations
  - Automatic layout optimization to minimize data formatting
  - Automatic memory locality optimization to get most out of SRAM
  - Automatic cross replica optimization to maximize parallelism
- Simple API with compiler optimization to partition the model
  - Flexible annotation on a small part of the model
  - Automatic propagation to fully partition the model
  - Model compiled by SPMD to achieve good compile time and run time performance

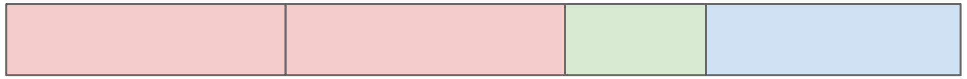
Inside a training step


Forward pass: conv/matmul + loop fusion
Backward pass: conv/matmul + loop fusion
All-reduce gradients
Weight update

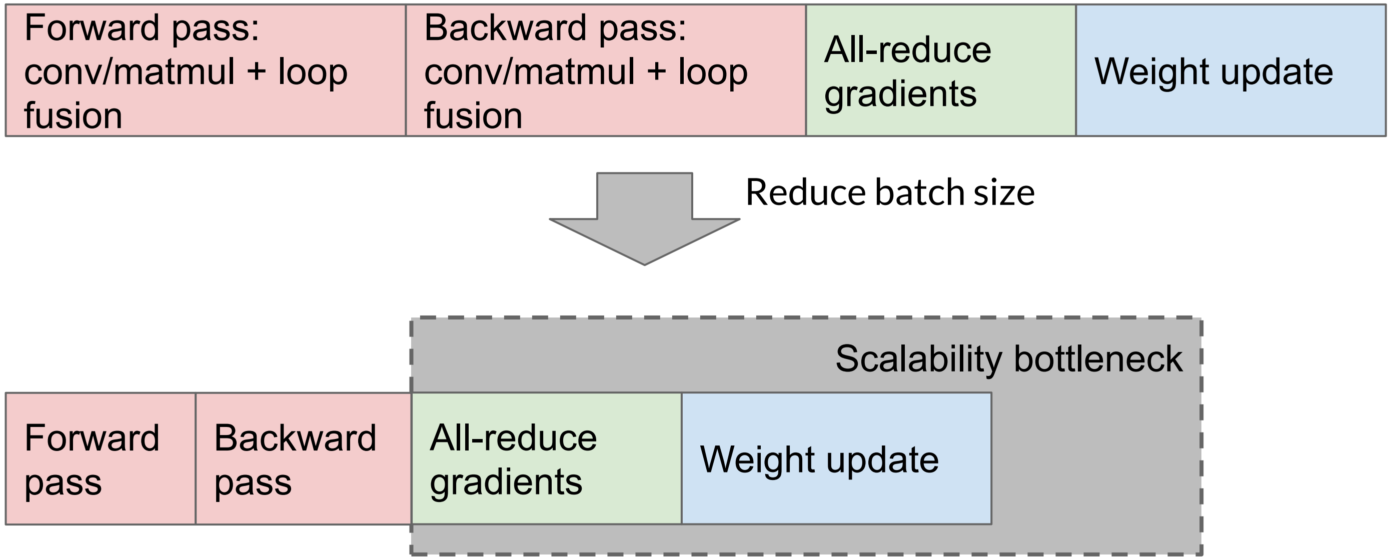
Typical image models: small weights, large input



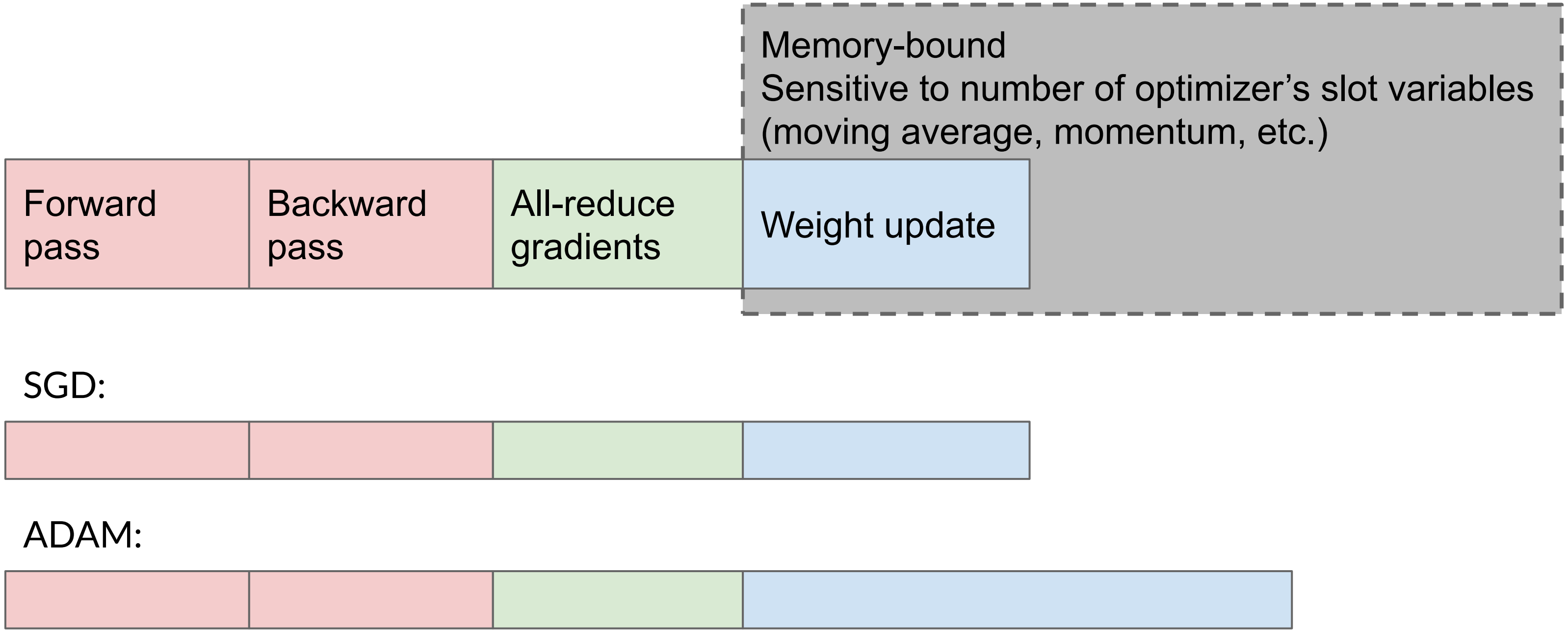
Typical sequence models: large weights, small input



Batch only affects forward/backward passes

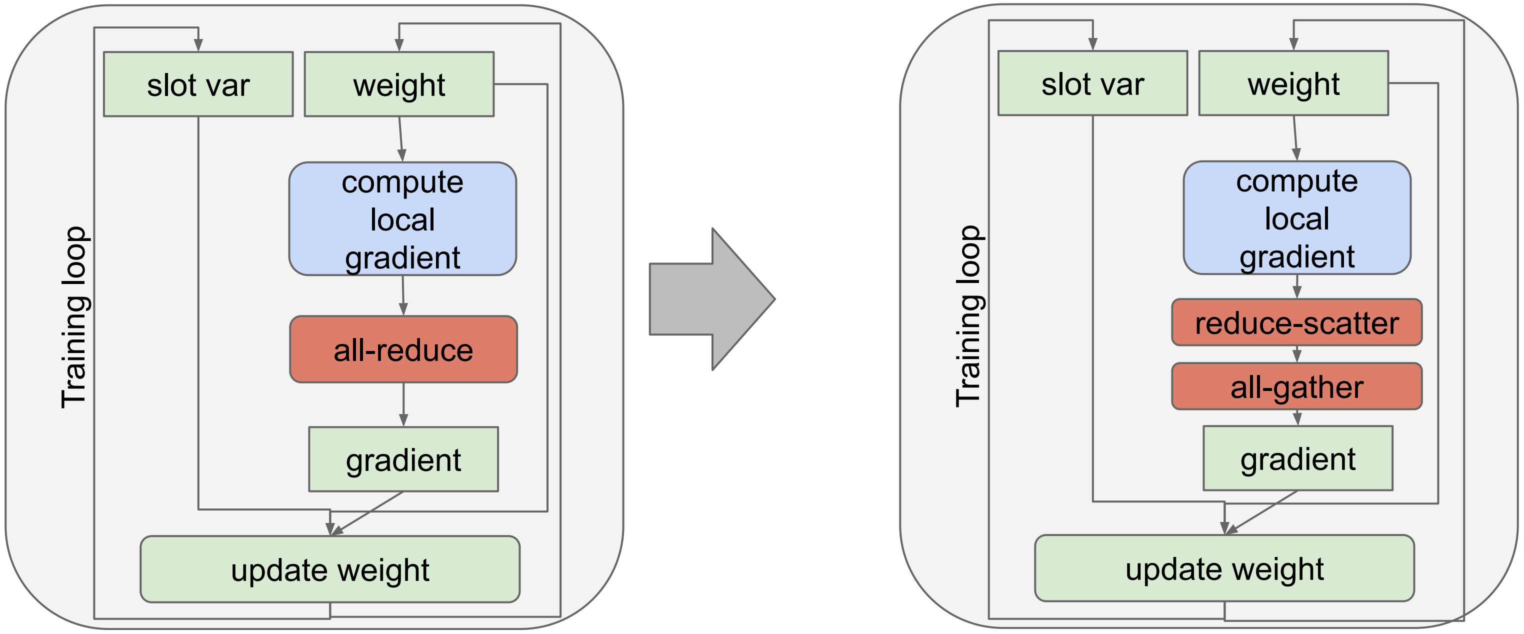


Weight-update time sensitive to optimizers


Memory-bound
Sensitive to number of optimizer’s slot variables (moving average, momentum, etc.)
Forward pass
Backward pass
All-reduce gradients
Weight update
SGD:
ADAM:

Weight-update sharding

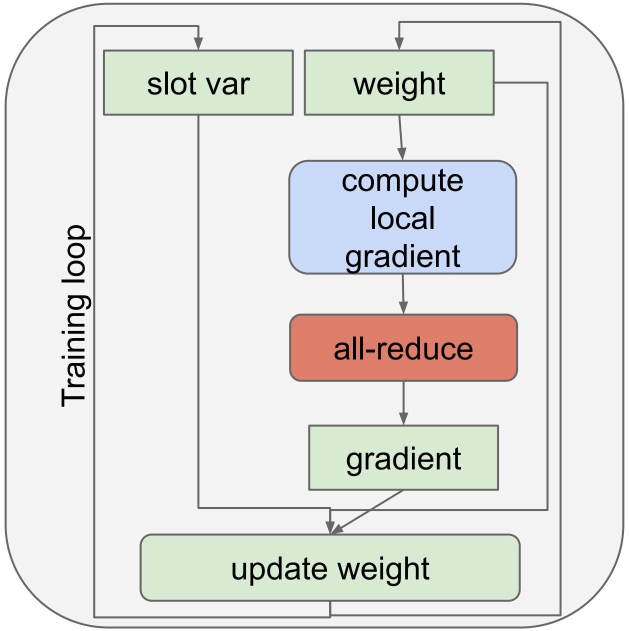
Replicated weight update

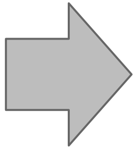


[Yuanzhong Xu et al: Automatic Cross-Replica Sharding of Weight Update in Data-Parallel Training]

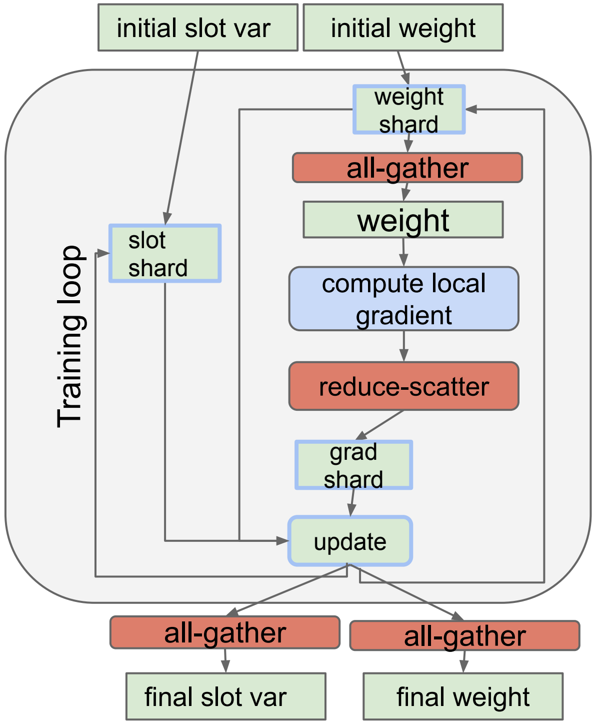
Weight-update sharding

Replicated weight update





Sharded weight update



[Yuanzhong Xu et al: Automatic Cross-Replica Sharding of Weight Update in Data-Parallel Training]

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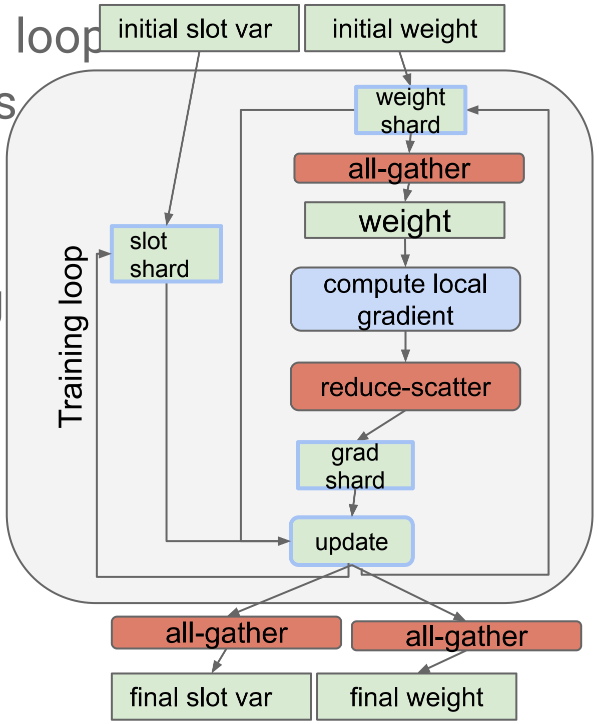
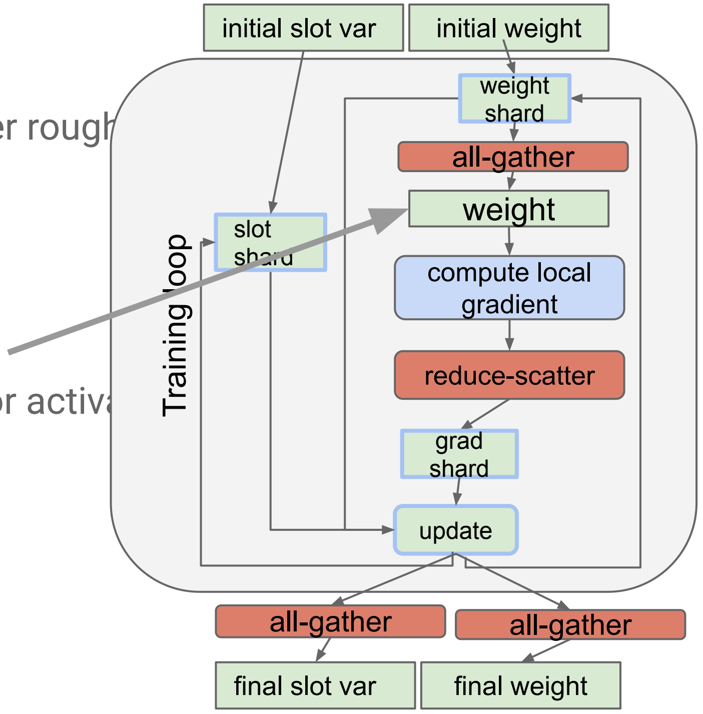
Weight-update sharding

- Weight and slot vars are sharded before training loop
- All-gather right before forward/backward passes
- Reduce-scatter on gradients
- Weight-update on shards
- An automatic optimization with no model chang



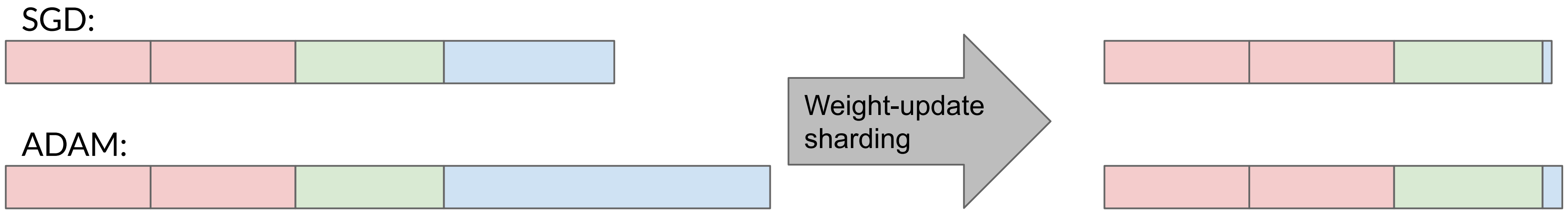
Weight-update sharding

- Performance
    - Weight-update takes much less time
    - In each step: 1 reduce-scatter Inside + 1 all-gather rough
    - Automatically convert weight to BF16
        - Faster all-gather
        - Faster convolutions
- Memory saving
    - Slot vars are sharded, memory could be reused for activa



Weight-update sharding

- Step time will be less sensitive to optimizers: weight-update is already fast



Use Model Parallelism for Small Batch per Core

Graph Partitioning: place subgraphs of operators across different cores (e.g. Inception)

Spatial Partitioning: partition individual operator (e.g. conv) across different cores (e.g., ResNet-like)

GPipe: place layers on different cores and pipeline the execution (e.g., RNN)

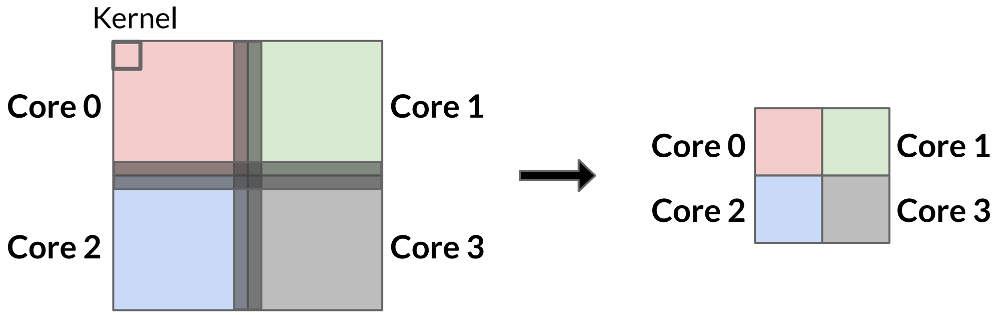
GShard: partition individual operator across different cores using data-parallelism (e.g., Xformer)

Ref: TPU Model Parallelism

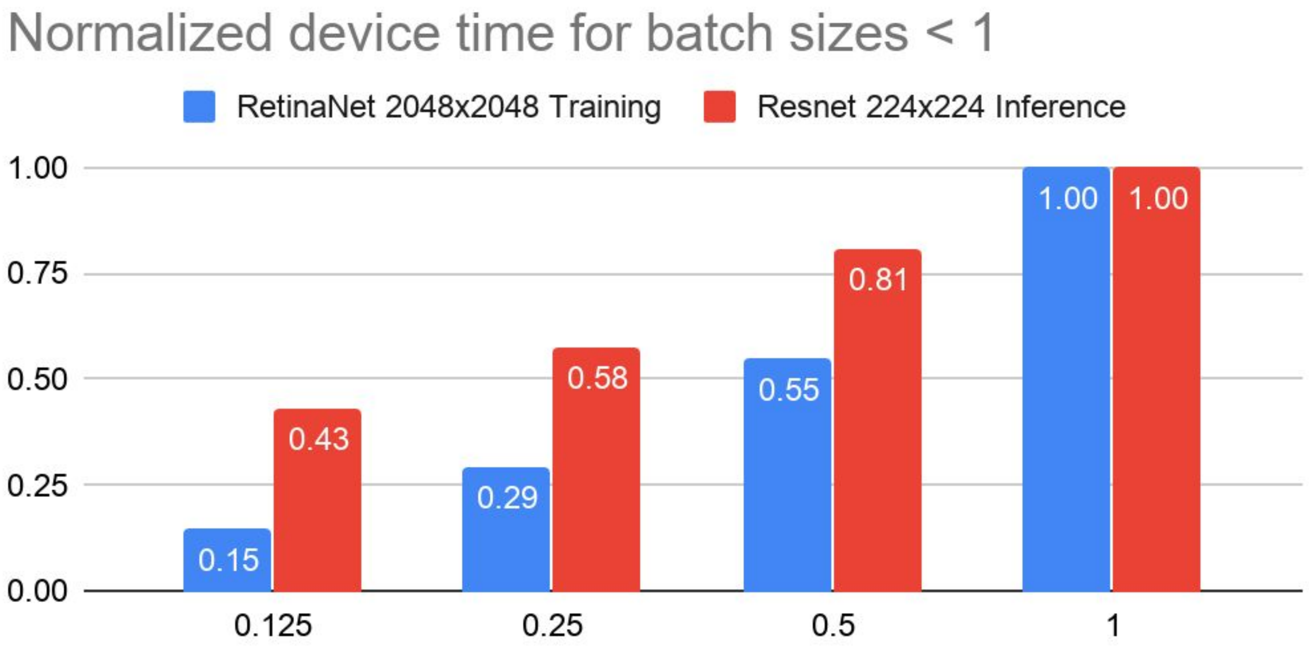
Spatial Partitioning for Image Models

- Halo exchange is required for overlapping windows
- Weights are replicated; only activations are partitioned

```
tpu_config=tpu_config.TPUConfig(
    iterations_per_loop=100,
    num_shards=2,
    num_cores_per_replica=4,
    input_partition_dims=[[1, 2, 2, 1], None]]
)
```



An example of 4-way convolution partitioning


Normalized device time for batch sizes < 1
RetinaNet 2048x2048 Training
Resnet 224x224 Inference
1.00
0.75
0.50
0.25
0.00
0.15
0.43
0.29
0.58
0.55
0.81
1.00
1.00
0.125
0.25
0.5
1

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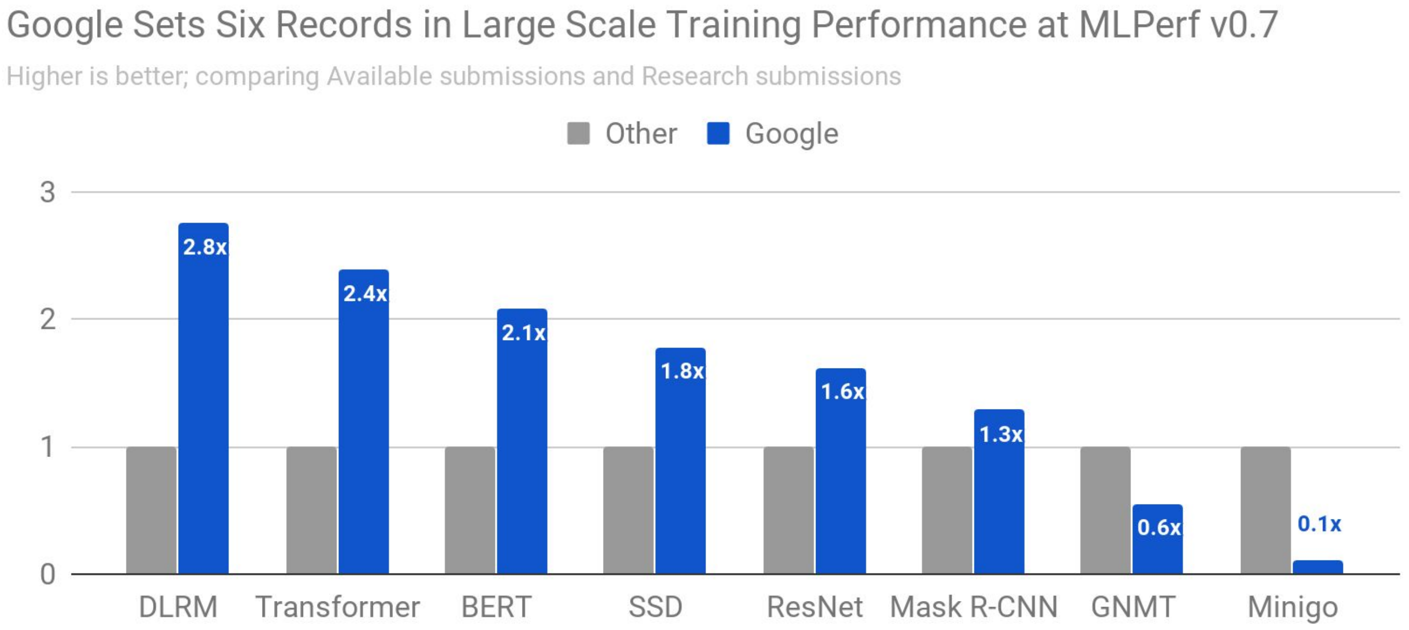
MLPerf 0.7 results



Takeaways

- Scaling workloads to large systems is hard
- Fast and flexible interconnect is essential
- Software innovations can remove bottlenecks in scaling
- Model parallelism helps to further scale up

TPUs are available on Google Cloud