Machine Learning Systems

CSE 550: Systems for All
Autumn 2022

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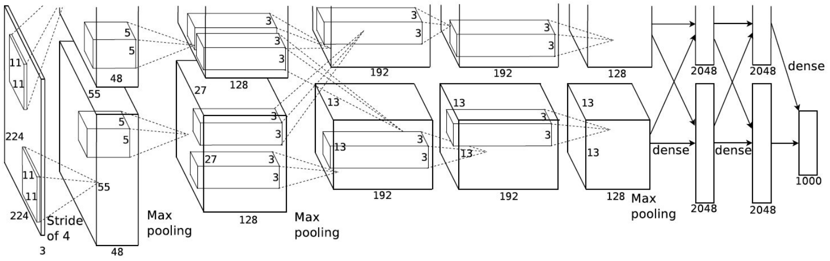
From Algorithm to Deployment

- ML Algorithms
  - Maths, Convergence, Proof, Models, Accuracy
- Programming
  - API
- Execution
- Hardware Design
  - Acceleration for specialized operators
  - Memory capacity, bandwidth
  - Memory hierarchy
  - Communication latency and bandwidth
  - Communication topology

API Abstraction

- Vallina C/Python/…
  - for-loops, array, scalar math ops
  - Tedious, Error-prone
- Vectorized representation
  - numpy, ndarray, dot. Linear algebra.
  - Multiple impls + Hide impl details
- Operators
  - MatMul, Softmax, Convolution
- Layers
  - Dense, Conv2D, Transformer
- Models
  - Layers
  - Control Flow




```
for y in range(1024):
  for x in range(1024):
    C[y][x] = 0
    for k in range(1024):
      C[y][x] += A[k][y] * B[k][x]
```

```
for yo in range(128):
  for xo in range(128):
    C[yo*8:yo*8+8][xo*8:xo*8+8] = 0
    for ko in range(128):
      for yi in range(8):
        for xi in range(8):
          for ki in range(8):
            C[yo*8+yi][xo*8+xi] +=
              A[ko*8+ki][yo*8+yi] * B[ko*8+ki][xo*8+xi]
```

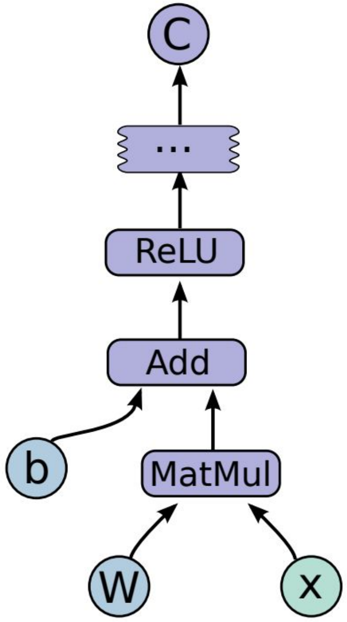
```
def softmax(x):
    x = x - np.max(x, axis=1, keepdims=True)
    x = np.exp(x)
    x = x / np.sum(x, axis=1, keepdims=True)
    return x
```

Machine Learning Frameworks / Compilers

- User-friendly APIs
  - Operators, Layers
  - Optimizers, Loss functions
  - Auto gradient, parameter update
  - Data loading
  - Multi-device, Multi-machine
- Intermediate Representation
  - Graph
  - High-level instruction sets (MLIR, LLVM)
  - Opportunities for auto optimization
    - (Imagine optimizing hand written C/Python)
- Support various accelerator hardware
  - Computation, Memory, Communication

TensorFlow: Graph

- Node: Op
  - Add, MatMul, Conv2D
  - Abstract device-, execution backend-, and language independent API
  - Implemented by Op Kernels written in C++, specialized on <Type, Device>
- Edge: Data dependency
  - Tensors (ref-counted, n-dimensional array buffers in device memory)
  - Control dependencies: A->B means A must finish before B can run
  - Resource handles to state (e.g. variables, input data pipelines)

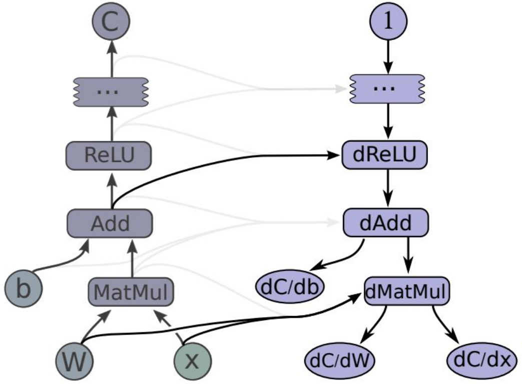


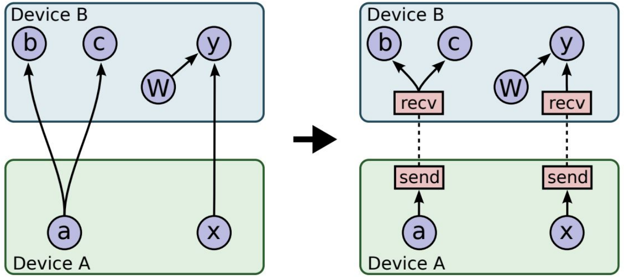
TensorFlow: Graph

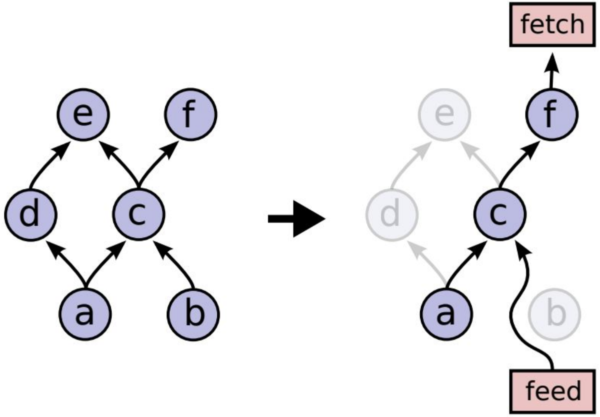
- Node: Op
- Edge: Data dependency

Graph Analysis & Transformation

- Auto gradient (chain rule)
- Dependency Analysis
- Split subgraph



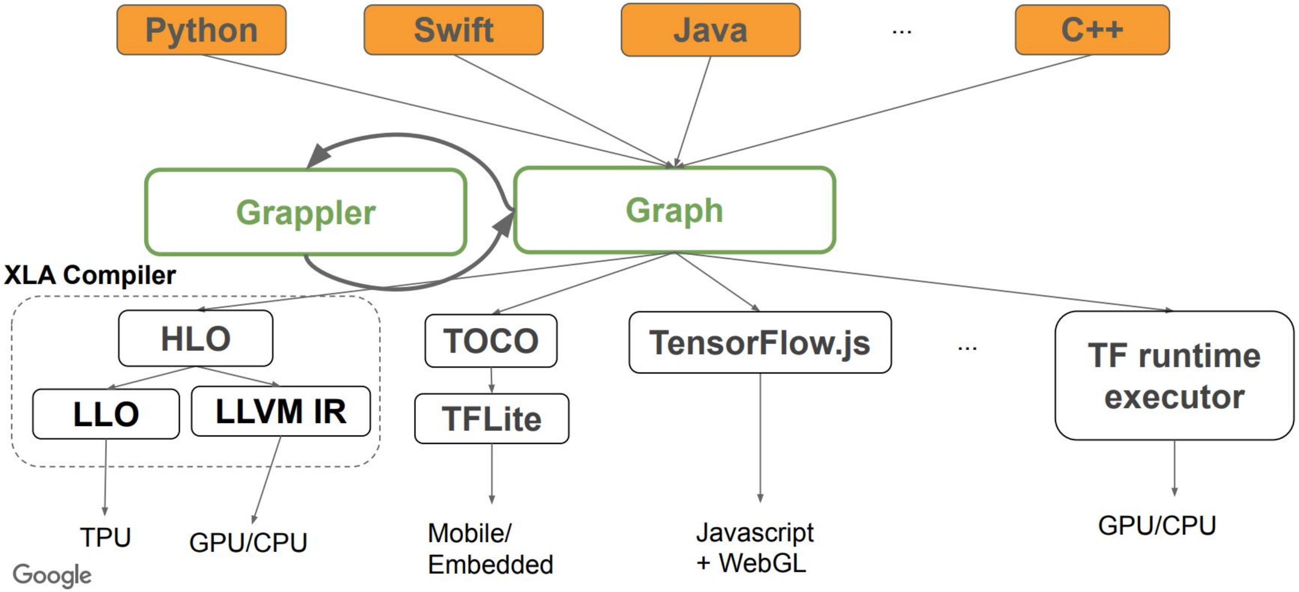




Grappler: TensorFlow Graph Optimizations

Graph: High-level IR

Not the only IR



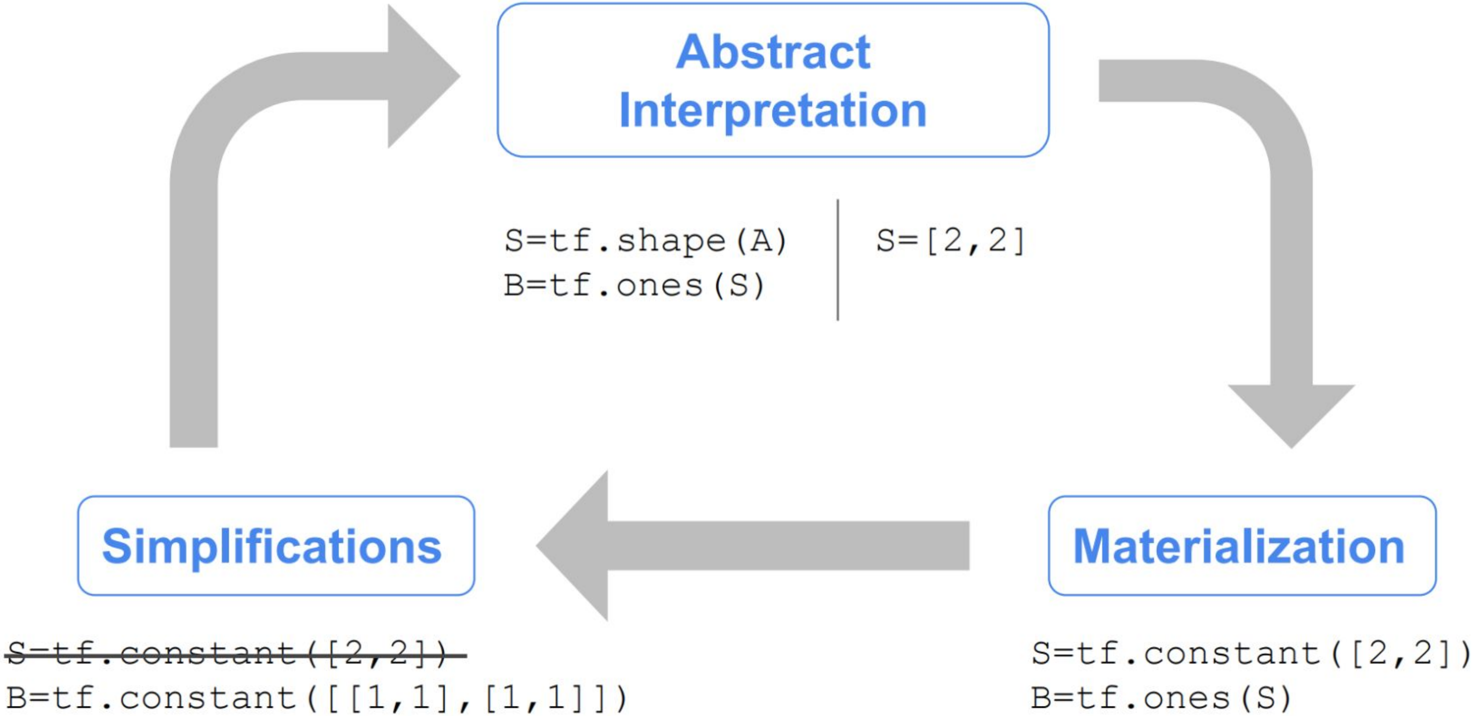
https://web.stanford.edu/class/cs245/slides/TFGraphOptimizationsStanford.pdf

Why transformations at the graph level?

- **Pros:**
  - Many optimizations can be easier to discover and express as high-level graph transformations
    - Example: **Matmul(Transpose(x), y) => Matmul(x,y, transpose_x=True)**
  - Graph is backend independent (TF runtime, XLA, TensorRT, TensorFlow.js, ...)
  - Interoperable with TensorFlow supported languages (protocol buffer format)
  - Optimizations can be applied at **runtime** or **offline** using our standalone tool
  - Lots of existing models (TF Hub, Google production models) available for learning
  - Pragmatic: Helps the most existing TensorFlow users get better "out-of-the-box" performance
- **Cons:**
  - Rewrites can be tricky to implement correctly, because of loosely defined graph semantics
    - In-place ops, side-effects, control flow, control dependencies
  - Protocol buffer dependence increases binary size
  - Currently requires extra graph format conversions in TF runtime

https://web.stanford.edu/class/cs245/slides/TFGraphOptimizationsStanford.pdf

Graph Simplifications



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Constant folding optimizer: `SimplifyGraph()`

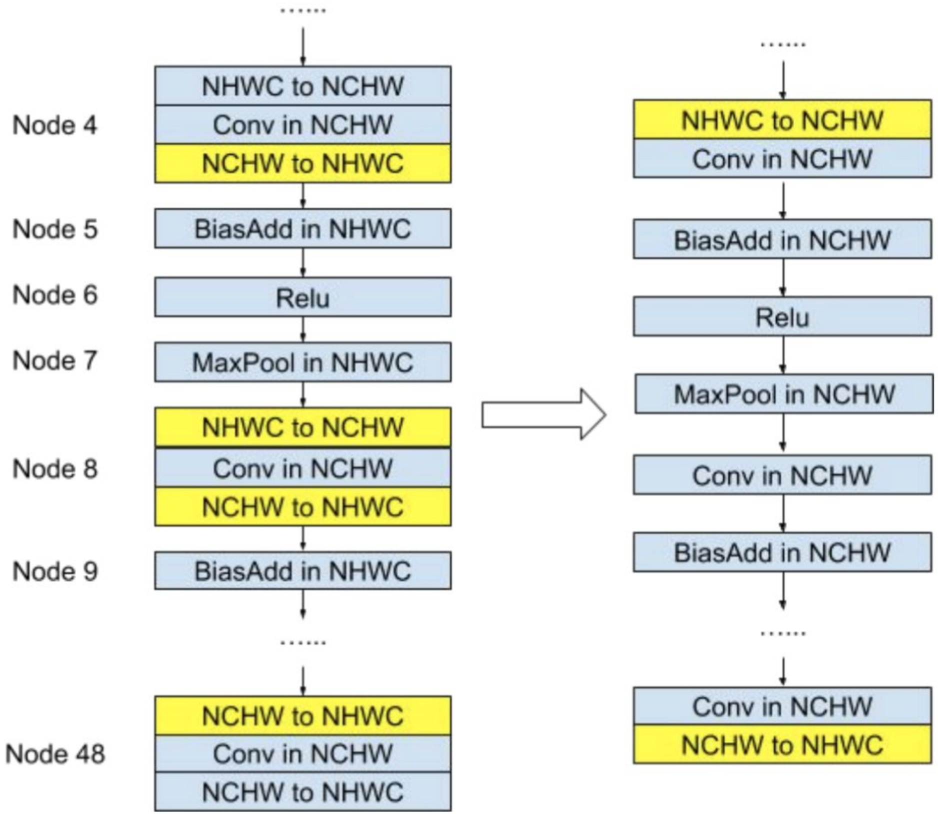
- Removes trivial ops, e.g. identity Reshape, Transpose of 1-d tensors, Slice(x) = x, etc.
- Rewrites that enable further constant folding, e.g.
  - Constant propagation through Enter
  - Switch(pred=x, value=x) => propagate False through port0, True through port1
  - Partial constant propagation through IdentityN
- Arithmetic rewrites that rely on known shapes or inputs, e.g.
  - Constant push-down:
    - Add(c1, Add(x, c2)) => Add(x, c1 + c2)
    - ConvND(c1 * x, c2) => ConvND(x, c1 * c2)
  - Partial constfold:
    - AddN(c1, x, c2, y) => AddN(c1 + c2, x, y),
    - Concat([x, c1, c2, y]) = Concat([x, Concat([c1, c2]), y)
  - Operations with neutral & absorbing elements:
    - x * Ones(s) => Identity(x), if shape(x) == output_shape
    - x * Ones(s) => BroadcastTo(x, Shape(s)), if shape(s) == output_shape
    - Same for x + Zeros(s) , x / Ones(s), x * Zeros(s) etc.
    - Zeros(s) - y => Neg(y), if shape(y) == output_shape
    - Ones(s) / y => Recip(y) if shape(y) == output_shape

https://web.stanford.edu/class/cs245/slides/TFGraphOptimizationsStanford.pdf

Arithmetic optimizer:

- Arithmetic simplifications
    - Flattening: a+b+c+d => AddN(a, b, c, d)
    - Hoisting: AddN(x * a, b * x, x * c) => x * AddN(a+b+c)
    - Simplification to reduce number of nodes:
        - Numeric: x+x+x => 3*x
        - Logic: !(x > y) => x <= y
- Broadcast minimization
    - Example: (matrix1 + scalar1) + (matrix2 + scalar2) => (matrix1 + matrix2) + (scalar1 + scalar2)
- Better use of intrinsics
    - Matmul(Transpose(x), y) => Matmul(x, y, transpose_x=True)
- Remove redundant ops or op pairs
    - Transpose(Transpose(x, perm), inverse_perm)
    - BitCast(BitCast(x, dtype1), dtype2) => BitCast(x, dtype2)
    - Pairs of elementwise involutions f(f(x)) => x (Neg, Conj, Reciprocal, LogicalNot)
    - Repeated Idempotent ops f(f(x)) => f(x) (DeepCopy, Identity, CheckNumerics...)
- Hoist chains of unary ops at Concat/Split/SplitV
    - Concat([Exp(Cos(x)), Exp(Cos(y)), Exp(Cos(z))]) => Exp(Cos(Concat([x, y, z])))
    - [Exp(Cos(y)) for y in Split(x)] => Split(Exp(Cos(x), num_splits)

Layout optimizer



Google

https://web.stanford.edu/class/cs245/slides/TFGraphOptimizationsStanford.pdf

Remapper optimizer: Op fusion

- Replaces commonly occurring subgraphs with optimized fused “monolithic” kernels
  - Examples of patterns fused:
    - Conv2D + BiasAdd + <Activation>
    - Conv2D + FusedBatchNorm + <Activation>
    - Conv2D + Squeeze + BiasAdd
    - MatMul + BiasAdd + <Activation>
- Fusing ops together provides several performance advantages:
  - Completely eliminates Op scheduling overhead (big win for cheap ops)
  - Increases opportunities for ILP, vectorization etc.
  - Improves temporal and spatial locality of data access
    - E.g. MatMul is computed block-wise and bias and activation function can be applied while data is still “hot” in cache.
- A separate mechanism allows the TensorFlow compiler to cluster subgraphs and generate fused kernel code on-the-fly

https://web.stanford.edu/class/cs245/slides/TFGraphOptimizationsStanford.pdf

TensorFlow 2.0: Eager Execution

Graph Execution

- Build graph
- tf.Session: owns all states
- sess.run(): run the graph

Eager Execution:

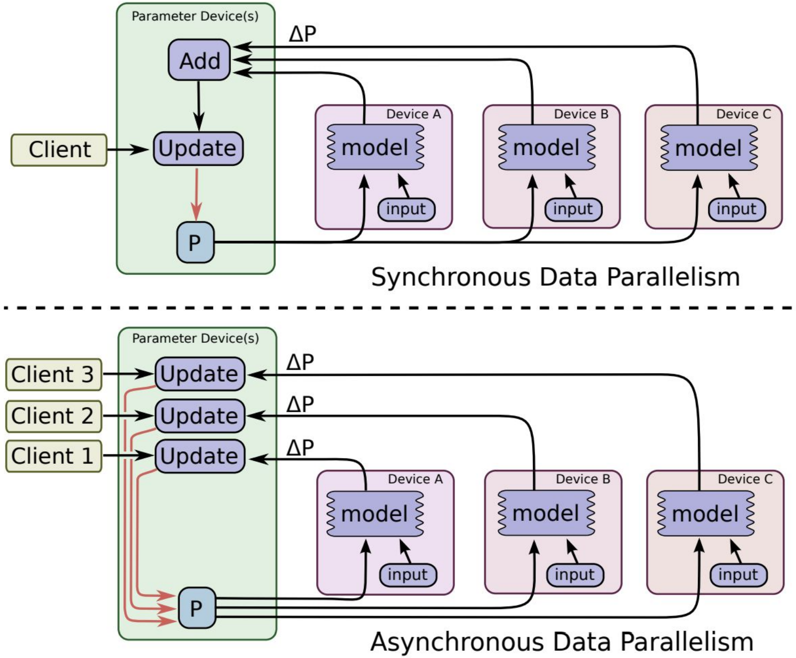
- Numpy-like
- PyTorch gain popularity because of eager execution
- print(x)
- Support for dynamic models using easy-to-use Python control flow

TensorFlow 2.0: Eager Execution

- Upside:
  - Fast debugging with immediate run-time errors and integration with Python tools
  - Support for dynamic models using easy-to-use Python control flow
- Downside:
  - Slow
    - Interpreting Python code
    - Fixed, unoptimized code path
    - Issue kernels one by one
    - No op fusion
    - No graph optimizations
- User friendly + Performance
  - tf.function() / torch.jit.script()
    - Trace Python code once for given input specs (function signature, e.g., dtype, shape)
    - Eager code -> Graph

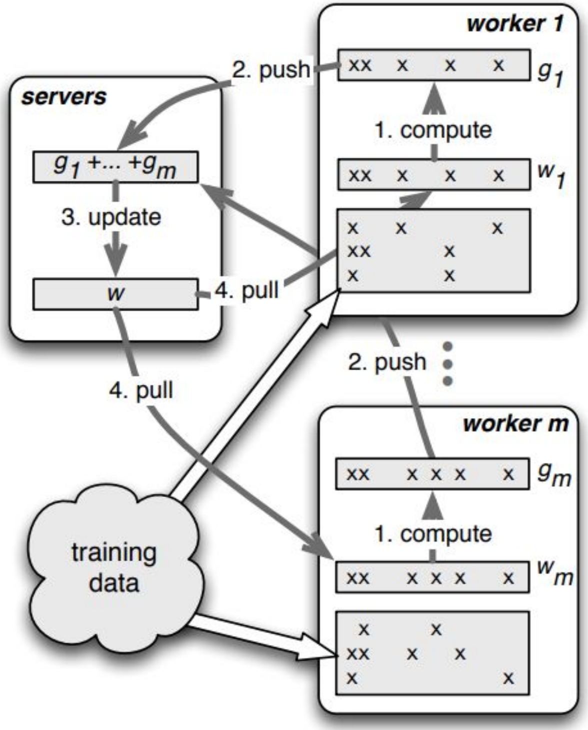
TensorFlow: Data Parallel Training

- One 1000-element mini-batch == Ten 100-element mini-batches
- Easiest way to use multiple GPUs
  - Replicate the model across GPUs
  - Shard data across GPUs
  - Compute gradient on each GPU
  - Aggregate gradients
    - Sync: wait for slowest
    - Async: different semantics
      - Gradient of old parameters
      - Convergence?



Data Parallelism: Parameter Server

- API:
  - ps.push(key, gradient)
  - ps.pull(key)
- Roles:
  - Server: Key-value store; Merge gradient
  - Worker: Calculate gradient
- Consistency Model
  - Sequential (Sync)
  - Eventual (Async)
  - Bounded Delay (tuneable)
- Server bottleneck:
  - High bandwidth demand
  - Synchronized burst
  - How to fix it? (Multi-server!)



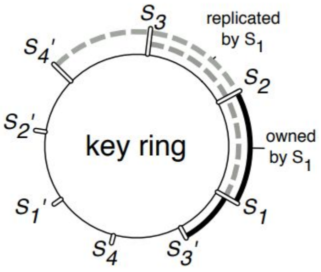
(a) Sequential (b) Eventual (c) 1 Bounded delay

https://www.cs.cmu.edu/~muli/file/parameter_server_osdi14.pdf

Data Parallelism: Parameter Server

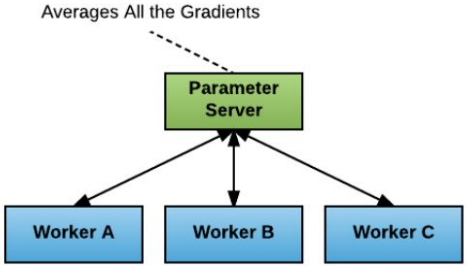
- Multiple servers
    - Shard across Key space.
- How to deal with skewed key space (e.g., string as keys)?
- How to deal with server load imbalance?
- This reminds you of a paper…

Data Parallelism: Parameter Server

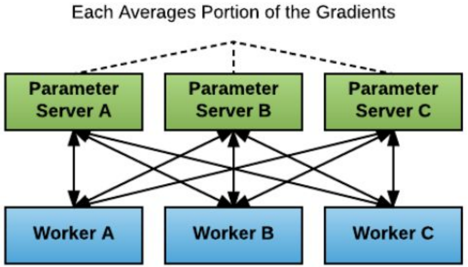


- Multiple servers
  - Shard across Key space.
  - Each server is responsible for a range of keys.
  - Chord?!
    - Load balancing of keys: hashing
    - Load balancing of servers: virtual nodes

Uber Horovod: Challenges with PS



- Worker:PS ratio
  - Single PS: bottleneck
  - One PS per worker: all-to-all, may saturate network switch
- Integration with existing TensorFlow program
  - Service discovery for PS and worker
  - Modify code to shard parameters explicitly



https://arxiv.org/pdf/1802.05799.pdf

Data Parallelism: Collective Communication

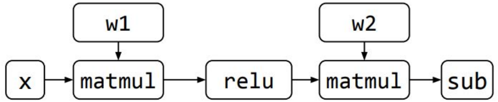
https://images.nvidia.com/events/sc15/pdfs/NCCL-Woolley.pdf

Page 4-7,11-12,18-47

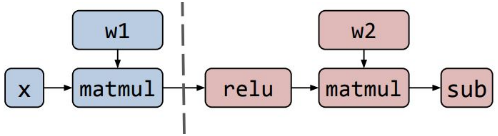
- Advantage:
    - The number of devices does not affect the latency
    - Bandwidth optimal
    - Interconnect topology aware
    - Minimal modification to code (allreduce)

Machine Learning Parallelism

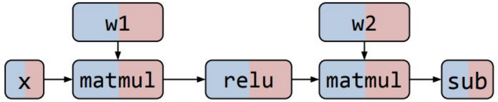
- Data Parallelism
  - Small model; Large dataset;
  - Replicate model; Shard dataset; Sync update
  - Collective communication



- Model Parallelism
  - Large model: a model might require multiple devices
  - Pipeline parallelism
    - Partition a model into several stages
    - Less communication; More idle time



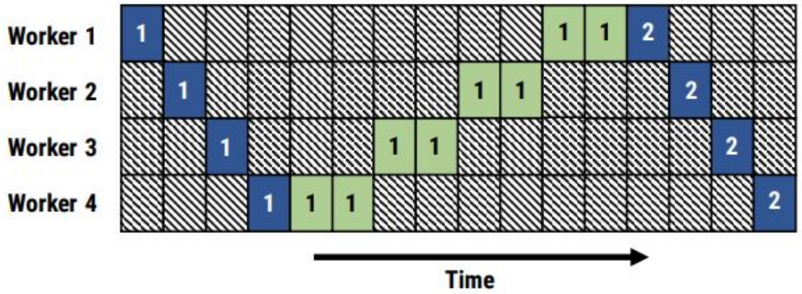
  - Operator parallelism
    - Partition an operator along some dimensions
    - More communication; Less idle time

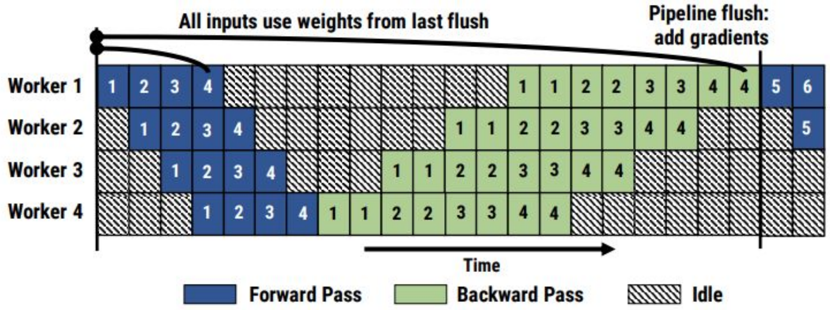


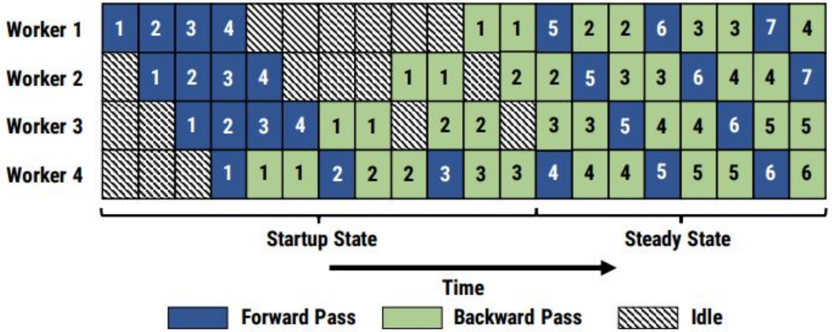
  - Point-to-point communication

Pipeline Parallelism

- No pipeline: bubbles
- GPipe
  - Split a mini-batch as many “micro-batch”
  - Memory: linear to micro-batches
- PipeDream
  - Async update (1F1B)
  - Lose accuracy

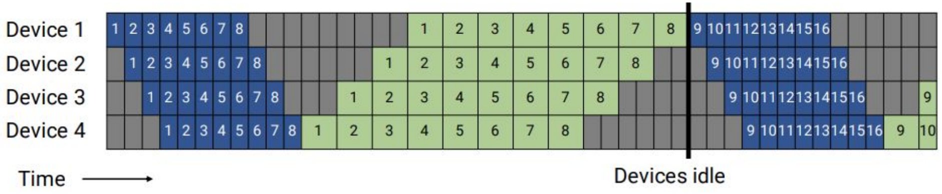


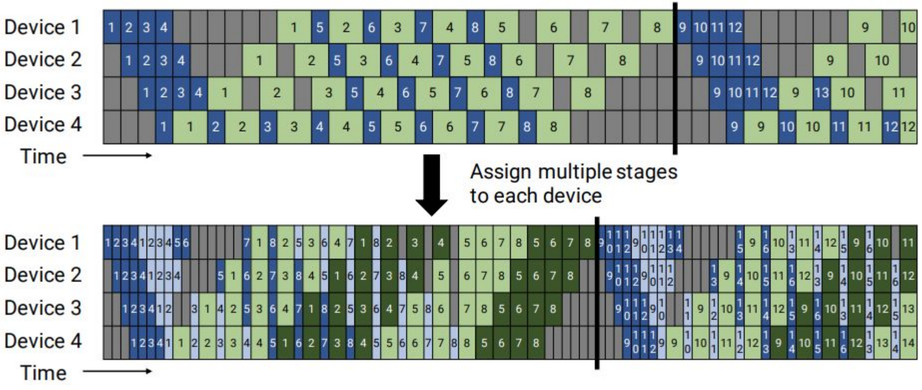




Pipeline Parallelism

- No pipeline: bubbles
- GPipe
  - Split a mini-batch as many “micro-batch”
  - Memory: linear to micro-batches
- PipeDream
  - Async update (1F1B)
  - Lose accuracy
- PipeDream-Flush
  - Sync; Alternate Forward & Backward
  - Save memory: linear to pipeline stages
- Megatron-2 Virtual Pipeline
  - Place multiple stages on the same device
  - More communication; Less bubble





Operator Parallelism

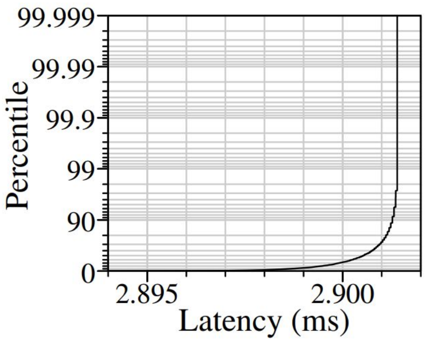
- Alpa
  - https://www.usenix.org/sites/default/files/conference/protected-files/osdi22_slides_zheng-lianmin.pdf
  - Data + Pipeline + Operator parallelism
  - Two tier network topology

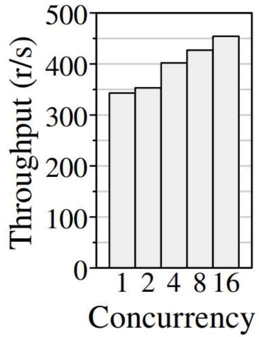
Model Serving (Inference)

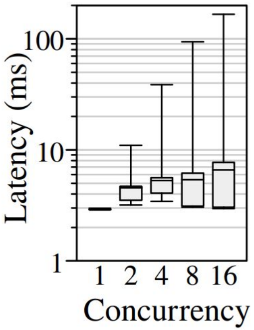
- Latency constraint for real-time tasks
  - e.g., end-to-end latency < 10ms
- Multi-tenancy
  - e.g., multiple models on one GPU cluster
- Request rate fluctuation
  - Piecewise stationary + burst
- Hardware utilization
  - batching under latency constraint
- GPU cluster management
  - load balancing
  - horizontal scaling

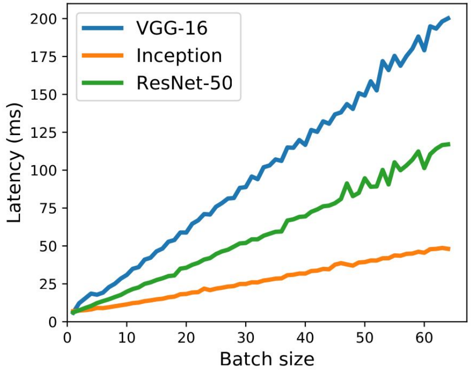
Inference Characteristics on GPUs

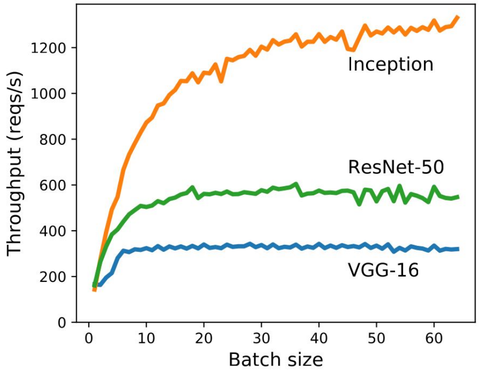
- Very predictable execution latency
- Concurrent execution increases throughout but significantly sacrifices predictability
- Execution latency is linear to batch size
  - latency(bs) := k * bs + c
  - throughput(bs) := bs/latency(bs) ∝ -1/bs











https://www.usenix.org/system/files/osdi20-gujarati.pdf

Model Serving Systems

- Roles:
  - Client
  - Frontend servers
    - Accept client requests
    - Preprocessing (e.g., image decoding)
    - Forward request to backend
    - Postprocessing (e.g., index to label)
    - Send response back to client
  - Backend servers
    - Run models with GPU
  - Scheduler
    - Backend allocation
    - Model mapping
    - Execution plan

Model Serving System: Scheduling

- Schedule:
  - Which GPU to run this batch?
  - Which requests are included in this batch?
  - When to start running this batch?
- Distributed scheduling (Nexus [SOSP’19])
  - Request lifetime: Client -> Frontend -> Backend -> Frontend -> Client
  - Frontend, Backend -> Scheduler: stats
  - Scheduler -> Frontend: List of backends for round robin
  - Scheduler -> Backend: Duty cycle (list of model + batch size)
  - Backend: pick requests for the next batch; run DNN on GPU back-to-back
  - Scheduler, Frontend, Backend all make parts of scheduling decisions

Model Serving System: Scheduling

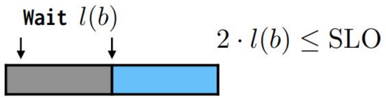
- Schedule:
  - Which GPU to run this batch?
  - Which requests are included in this batch?
  - When to start running this batch?
- Distributed scheduling (Nexus [SOSP'19])
  - Scheduler, Frontend, Backend all make parts of scheduling decisions
- Centralized scheduling (Clockwork [OSDI'20])
  - Client -> Frontend -> **Scheduler** -> Backend -> **Scheduler** -> Client
  - Scheduler can have precision control over backend execution
  - Frontend, Backend are simple, non-decision-making.
  - Scheduler on every request's data path
    - Bottleneck! (Network bandwidth & CPU)

Model Serving System: Scheduling

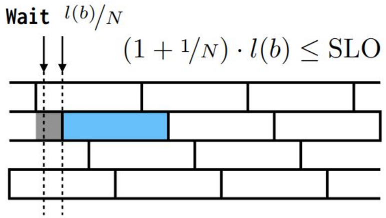
- Schedule:
  - Which GPU to run this batch?
  - Which requests are included in this batch?
  - When to start running this batch?
- Distributed scheduling (Nexus [SOSP’19])
  - Scheduler, Frontend, Backend all make parts of scheduling decisions
- Centralized scheduling (Clockwork [OSDI’20])
  - Scheduler can have precision control over backend execution
  - Bottleneck! (Network bandwidth & CPU)
- Centralized scheduling (Symphony [under review])
  - Scheduler only exchange metadata
  - Multi-core scalable scheduling algorithm
  - Better scheduling quality (bigger batch size, higher goodput under latency constraint)

Model Serving System: Scheduling

- Notation:
  - b: batch size
  - l(b): latency of batch size b
  - N: the number of GPUs
- Variables: b, N
- Batching equations
  - Total throughput > Request rate
    - N * b/l(b) > RPS
  - Queuing delay + Execution < latency SLO
    - Non-coordinated: (1 + 1) * l(b) < SLO
    - Coordinated: (1/N + 1) * l(b) < SLO



(a) Backends run independently



(b) Staggered execution