Systems for Machine Learning

Emmanuel Azuh CSE 550

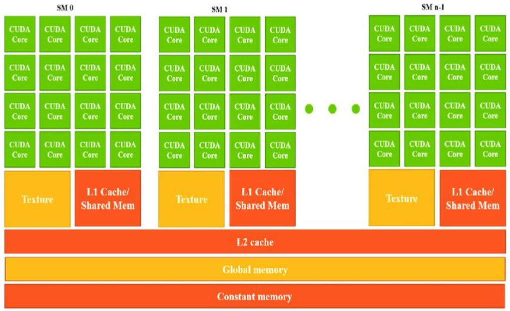
Outline

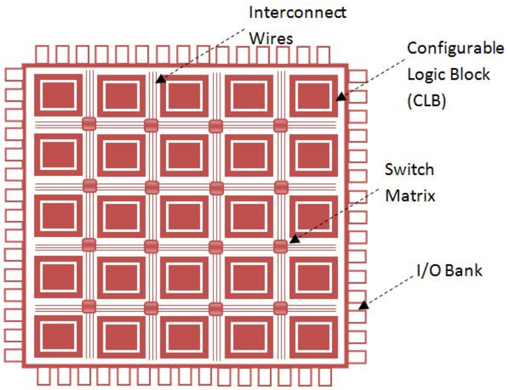
- Brief overview of ML and its applications (Broad categories of devices)
- Ecosystem of frameworks for machine learning
- Most famous system for ML on several devices (Tensorflow)
- Support on the two ends of the spectrum (High vs low resource)

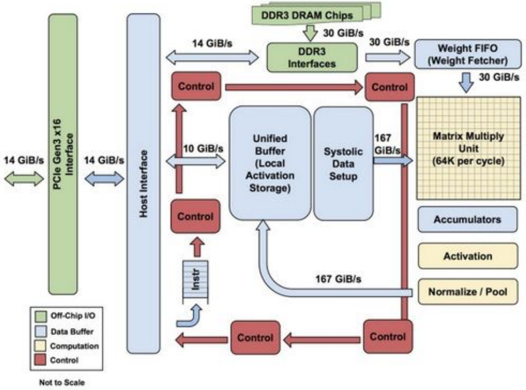
ML History

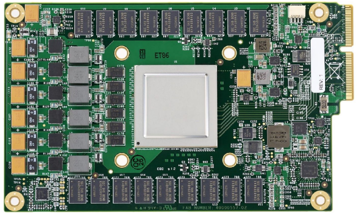
- Two AI winters (determined by funding - eg competition with Japan and pace of technology development to support running the models)
    - 1974 and 1980 slow processing speeds; funding cut from government (till Japan posed competition to become world leader in computer tech)
    - 1987 to 1993 expert systems were bulky and performed poorly so DARPA redirected funding
- Became popularized again when scanning technologies started using CNNs proposed by Yann LeCunn
    - Came back in early 1990s and by early 200s when CNNs processed 10-20% of checks in the US
- Nvidia in 2009 made advances in hardware (GPU) well suited for matrix/vector computations and increased training by about 100x
    - In 2011 for the first time, CNNs outperform humans at visual pattern recognition contest
- Now buzzword for funding (like SDN for networking). Other buzzwords?

Hardware









GPU

~3500 cores vs 16 of Intel Xeon or 32 of Xeon-Phi

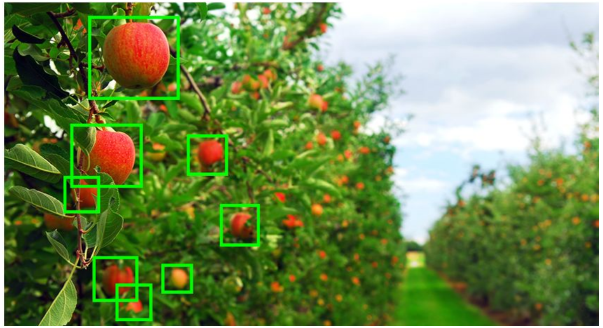
FPGA

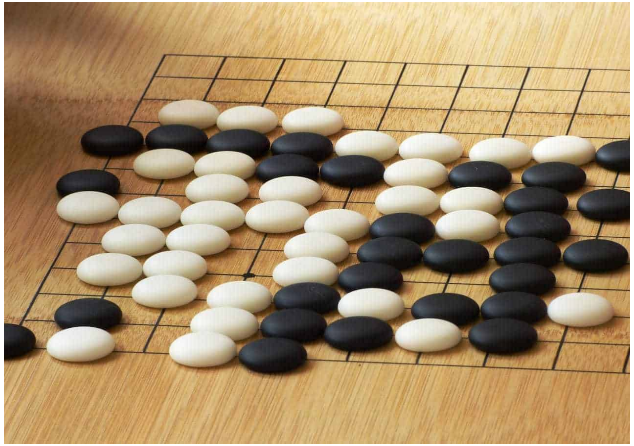
Highly reprogrammable

TPU

Highly optimized ASIC for inference [**upto 128000 operations** per cycle vs **tens of thousands** in GPU]

Use cases



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English
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English
Where is the train station?
Spanish
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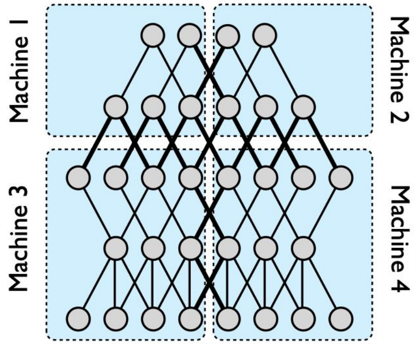
Tensorflow Overview



DistBelief (2011)

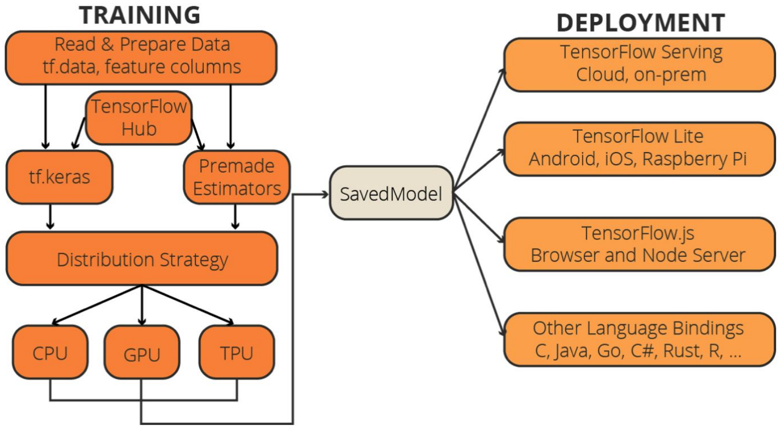


Figure X. Diagram of the TensorFlow Workflow (Figure by Author)

Tensorflow (2015)

Tensorflow Usage Stats

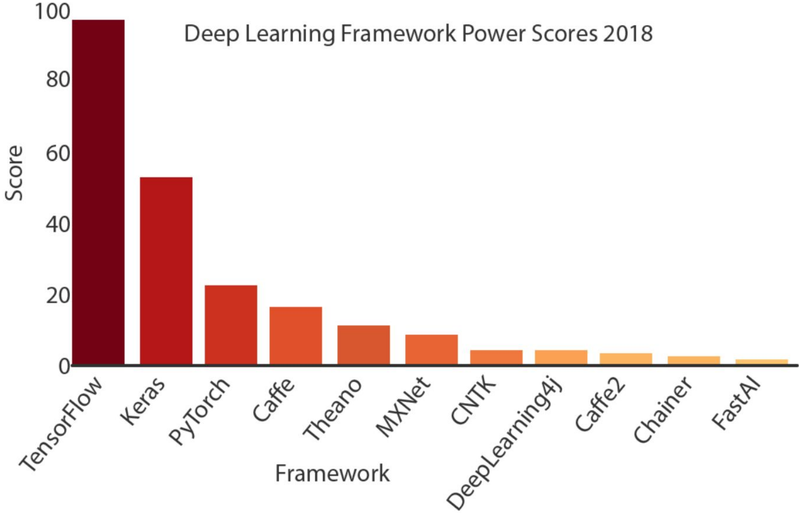
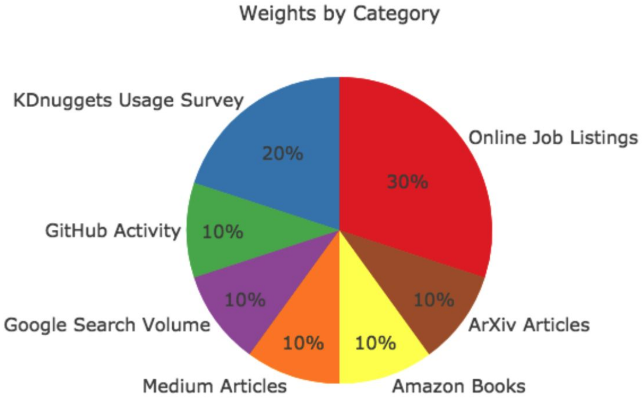
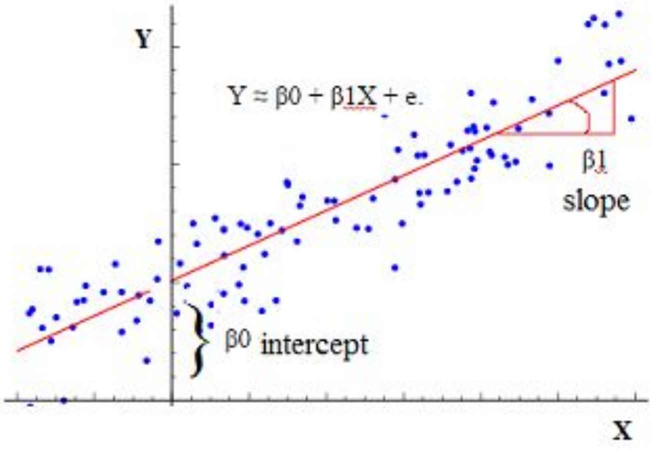


Figure X. Deep Learning Framework Power Scores 2018 by Jeff Hale (Figure by Author)



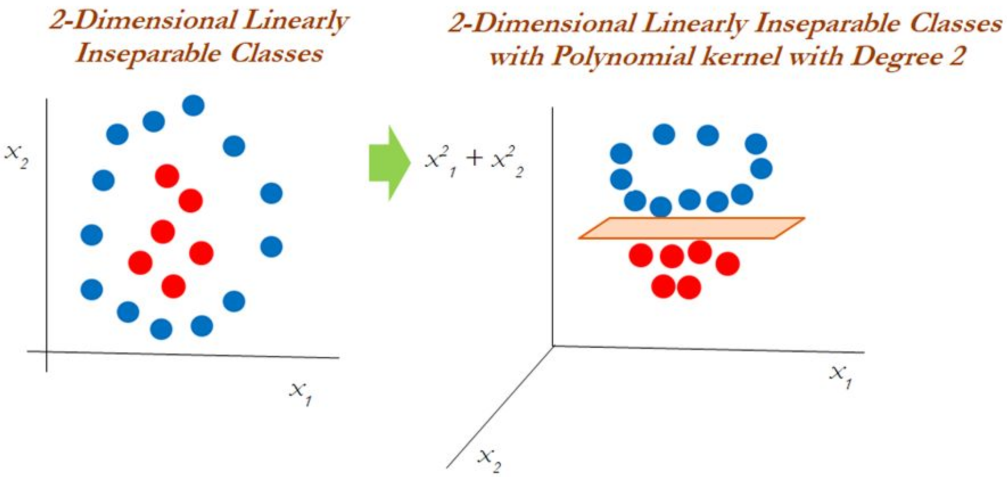
A toy problem formulation

Linear Regression



$Y = WX = [\boldsymbol{\beta}_0\ \boldsymbol{\beta}_1][1\ x]$^T

Kernel



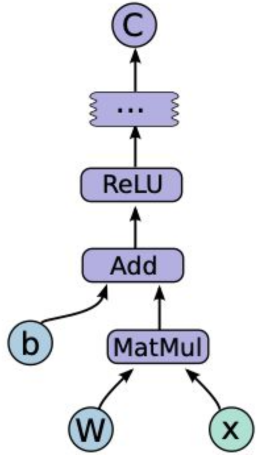
Tensorflow Implementation

```
import tensorflow as tf

b = tf.Variable(tf.zeros([100]))                   # 100-d vector, init to zeroes
W = tf.Variable(tf.random_uniform([784,100],-1,1)) # 784x100 matrix w/rnd vals
x = tf.placeholder(name="x")                       # Placeholder for input
relu = tf.nn.relu(tf.matmul(W, x) + b)             # Relu(Wx+b)
C = [...]                                          # Cost computed as a function
                                                   # of Relu

s = tf.Session()
for step in xrange(0, 10):
  input = ...construct 100-D input array ...       # Create 100-d vector for input
  result = s.run(C, feed_dict={x: input})          # Fetch cost, feeding x=input
  print step, result
```

Figure 1: Example TensorFlow code fragment



Tensors: **Multidimensional array** (types signed/unsigned int 8 - 64 bits, float, double, complex number

Create a custom Op

```cpp
#include "tensorflow/core/framework/op.h"
#include "tensorflow/core/framework/shape_inference.h"

using namespace tensorflow;

REGISTER_OP("ZeroOut")
    .Input("to_zero: int32")
    .Output("zeroed: int32")
    .SetShapeFn([](::tensorflow::shape_inference::InferenceContext* c) {
      c->set_output(0, c->input(0));
      return Status::OK();
    });
```

```cpp
#include "tensorflow/core/framework/op_kernel.h"

using namespace tensorflow;

class ZeroOutOp : public OpKernel {
 public:
  explicit ZeroOutOp(OpKernelConstruction* context) : OpKernel(context) {}

  void Compute(OpKernelContext* context) override {
    // Grab the input tensor
    const Tensor& input_tensor = context->input(0);
    auto input = input_tensor.flat<int32>();

    // Create an output tensor
    Tensor* output_tensor = NULL;
    OP_REQUIRES_OK(context, context->allocate_output(0, input_tensor.shape(),
                                                     &output_tensor));
    auto output_flat = output_tensor->flat<int32>();

    // Set all but the first element of the output tensor to 0.
    const int N = input.size();
    for (int i = 1; i < N; i++) {
      output_flat(i) = 0;
    }

    // Preserve the first input value if possible.
    if (N > 0) output_flat(0) = input(0);
  }
};
```

Device Placement

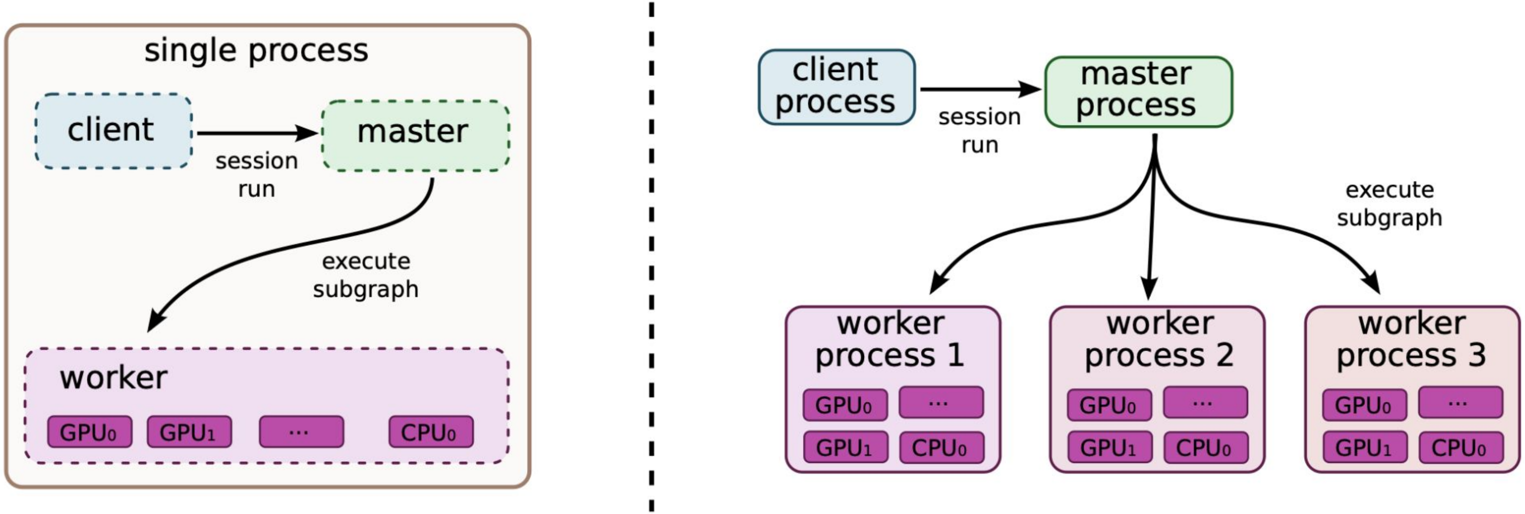
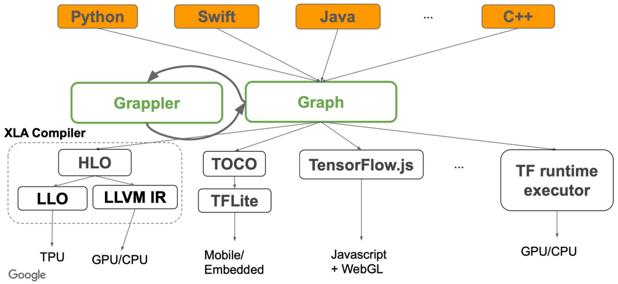


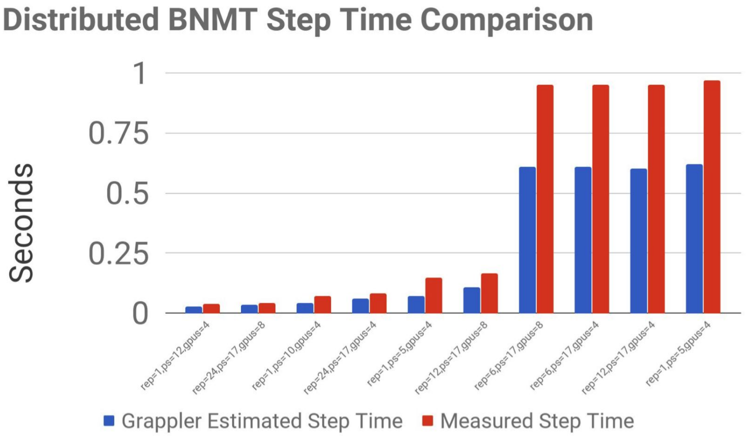
Figure 3: Single machine and distributed system structure

Device naming: “/job:localhost/device:cpu:0”,"/job:worker/task:17/device:gpu:3"

Device Placement (Grappler)



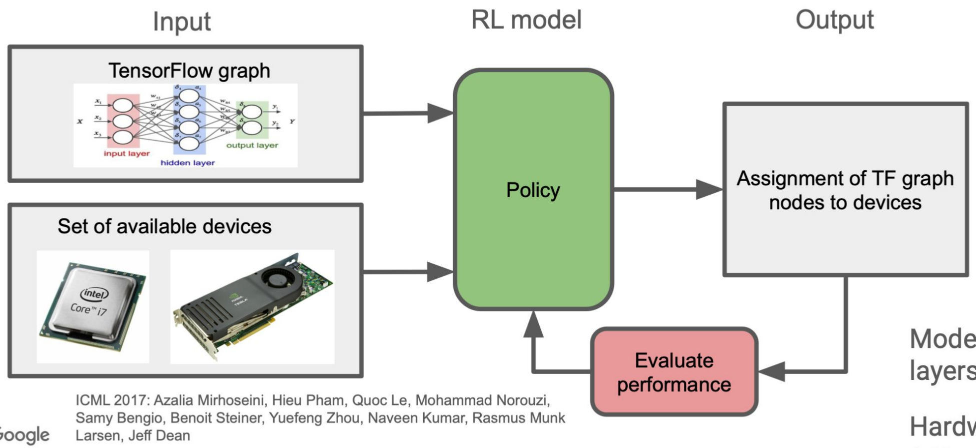
- Measurement
  - Outliers filtering: warmup + robust statistics
  - Captures all the side effects: memory fragmentation, cache pollution, …
  - Fairly slow and requires access to input data
- Simulation
  - Per op cost based on roofline estimates
  - Propagation based on plausible schedule
  - Fast but optimistic and requires robust shape inference




```
A+2*B+2*C+Identity(A) => 2*A+2*B+2*C => 2*AddN(A,B,C)
```

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

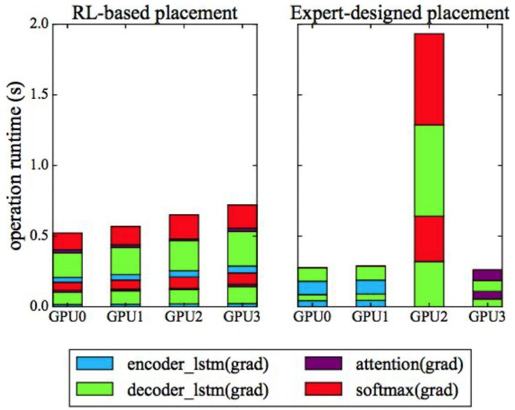
Device Placement (Reinforcement Learning)



Model: NMT with 4 layers

Hardware: 4 K40 GPUS, 1 Haswell CPU

Performance improved by **2.4x**



Google

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

Multi Device Execution

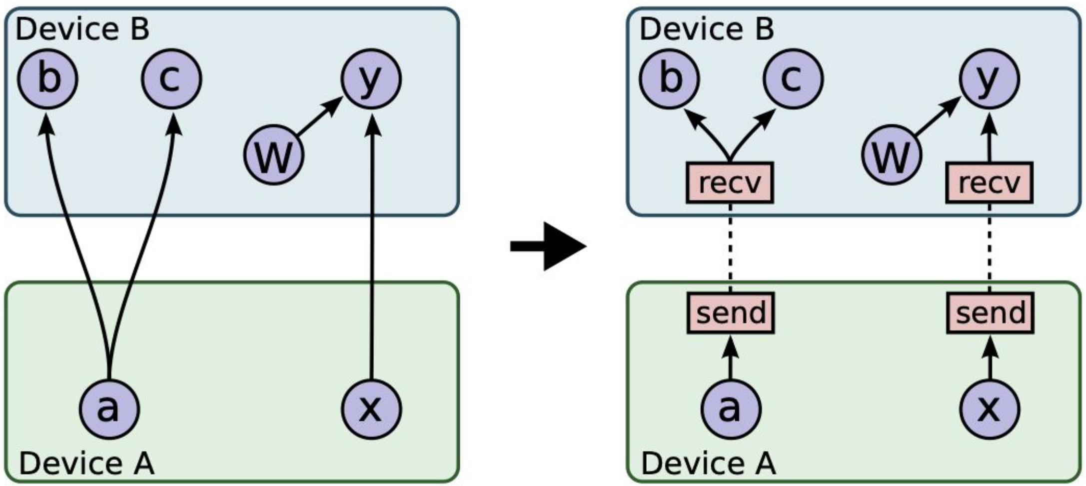


Figure 4: Before & after insertion of Send/Receive nodes

Auto Grad

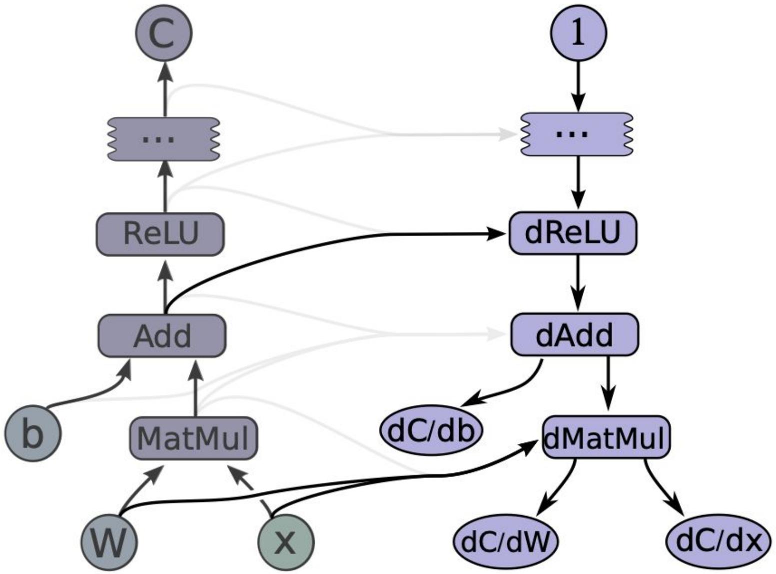


Figure 5: Gradients computed for graph in Figure 2

Partial Execution & Parallel Loop

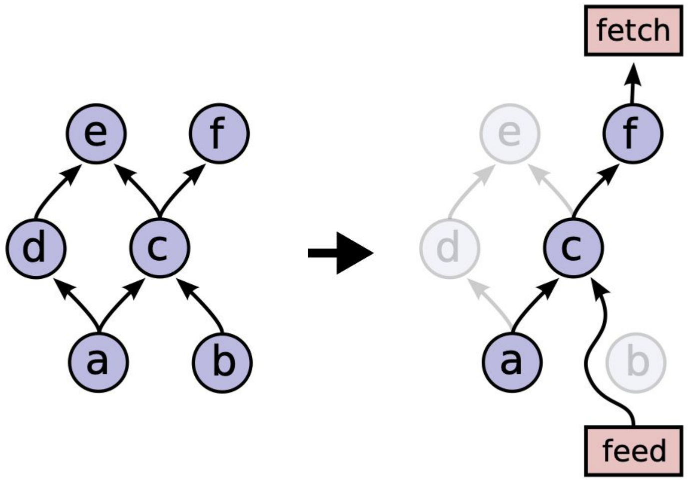
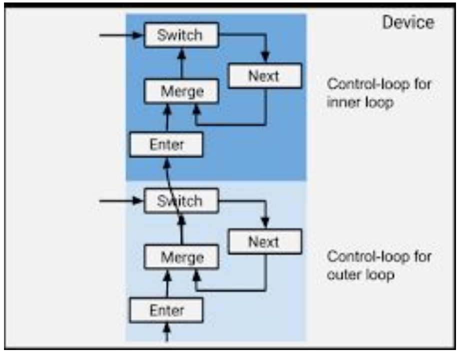


Figure 6: Before and after graph transformation for partial execution

session.run(“c:0”, [“f:0”])



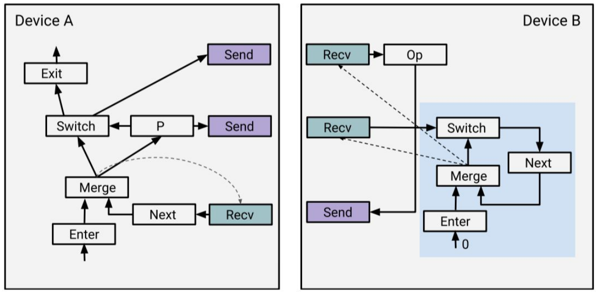
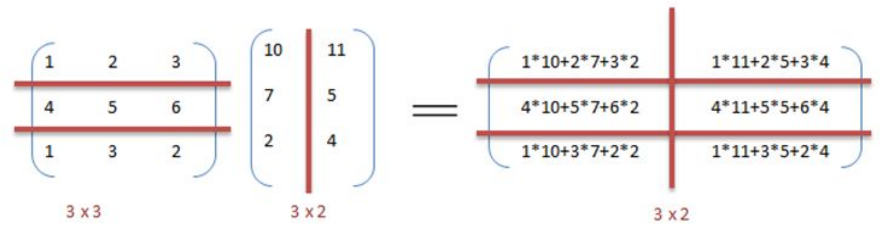


Figure 6: Distributed execution of a while-loop.

Data Parallelism

$$\begin{array}{ccc} A & B & C \\ \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} & \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ b_{31} & b_{32} \end{pmatrix} = & \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \\ c_{31} & c_{32} \end{pmatrix} \end{array}$$

```
//Matrix Multiplication
for(i=0; i<row_length_A; i++)
{
        for (k=0; k<column_length_B; k++)
        {
                sum = 0;
                for (j=0; j<column_length_A; j++)
                {
                        sum += A[i][j]*B[j][k];
                }
                C[i][k]=sum;
        }
}
```



Data Parallelism in matrix multiplication

```
//Matrix multiplication in parallel
#pragma omp parallel for schedule(dynamic,1) collapse(2)
for(i=0; i<row_length_A; i++){
        for (k=0; k<column_length_B; k++){
                sum = 0;
                for (j=0; j<column_length_A; j++){
                        sum += A[i][j]*B[j][k];
                }
                C[i][k]=sum;
        }
}
```

https://en.wikipedia.org/wiki/Data_parallelism

Tensorflow Data Parallelism

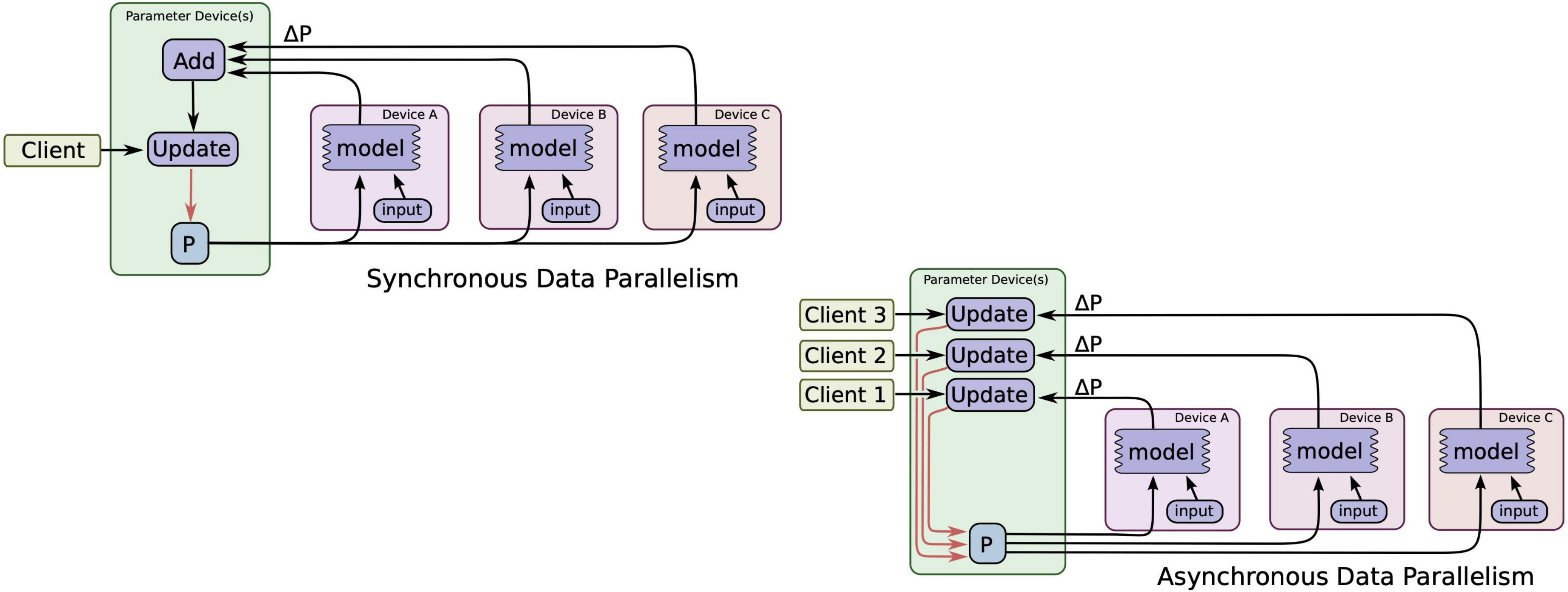


Figure 7: Synchronous and asynchronous data parallel training

Model Parallel Training & Concurrent Steps

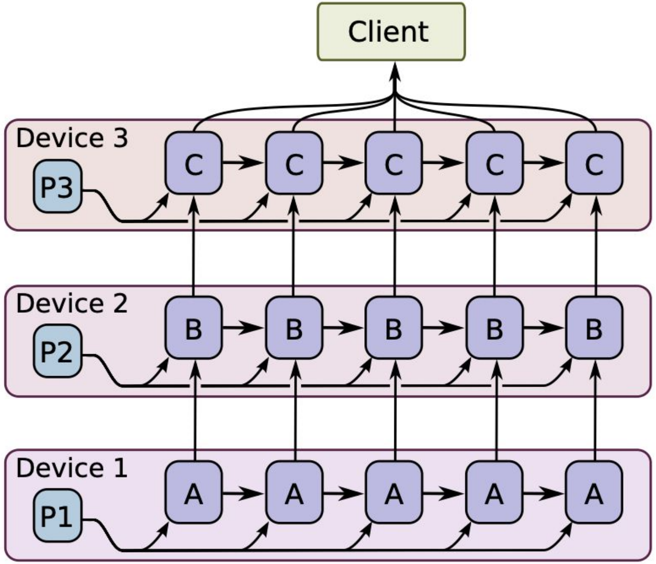


Figure 8: Model parallel training

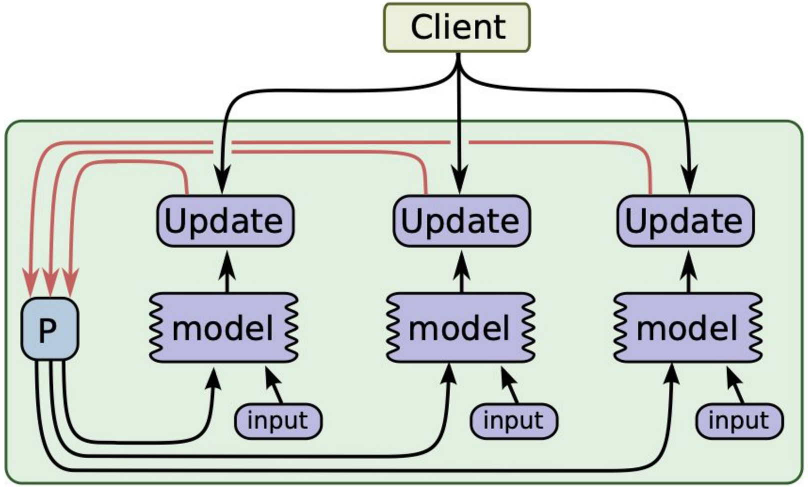


Figure 9: Concurrent steps

Tensorboard Visualization

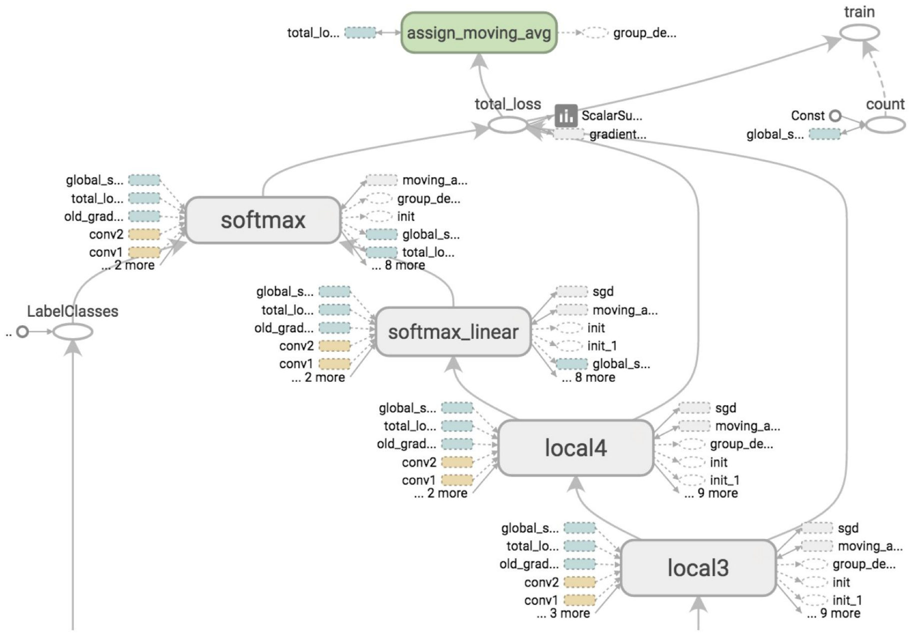


Figure 10: TensorBoard graph visualization of a convolutional neural network model

Distributed Training: Use Case in Uber

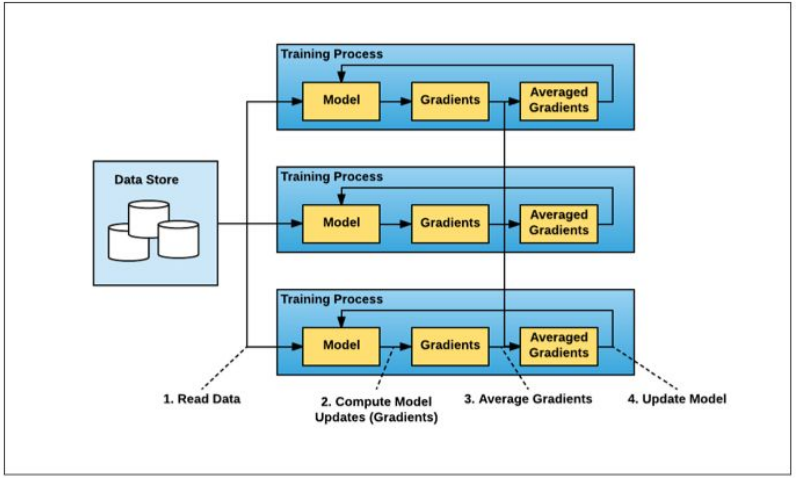
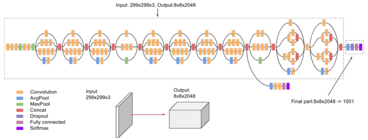
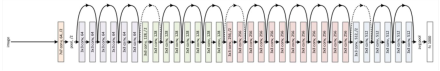
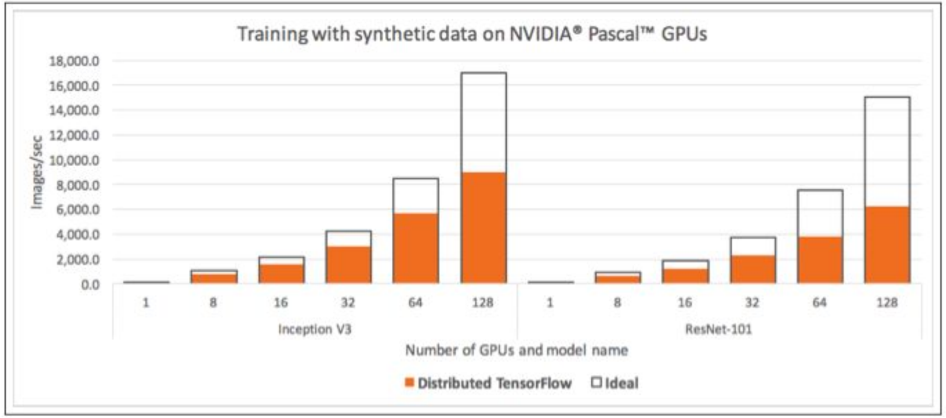


Figure 2: The "data parallel" approach to distributed training involves splitting up the data and training on multiple nodes in parallel. In synchronous cases, the gradients for different batches of data are calculated separately on each node but averaged across nodes to apply consistent updates to the model copy in each node.





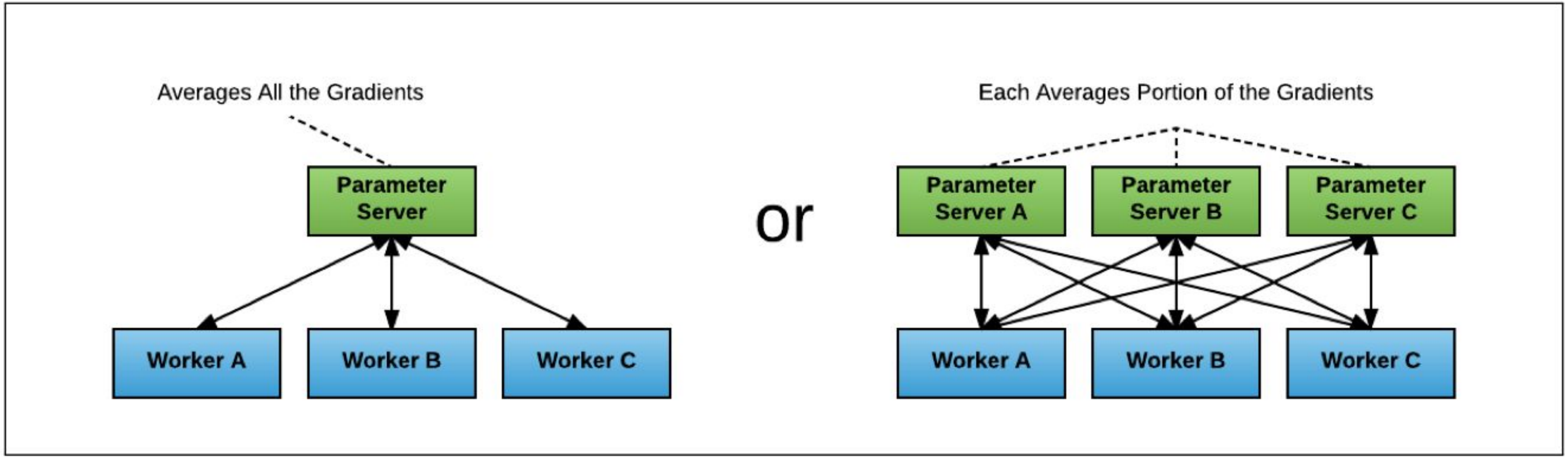


24 M Parameters
48 layers

29.4 M Parameters
101 layers

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

Bottleneck?

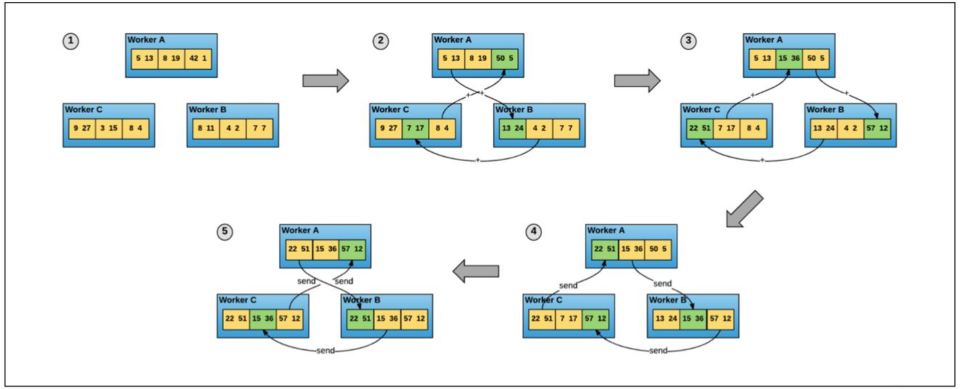


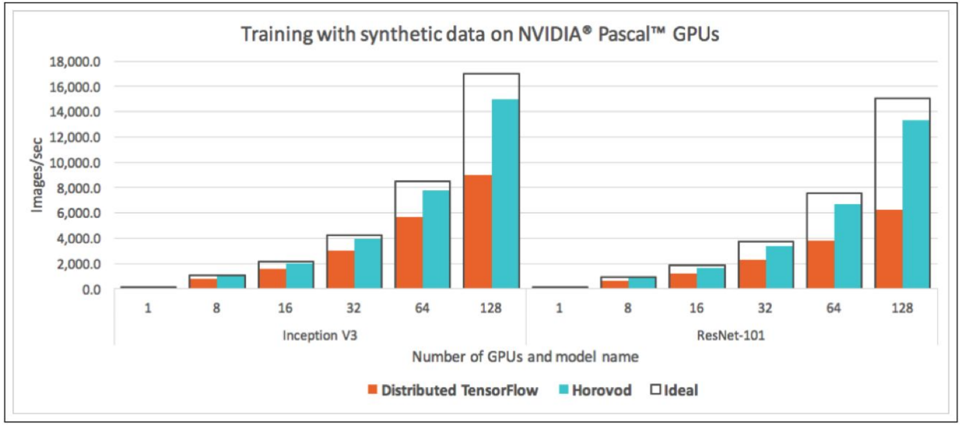
https://arxiv.org/pdf/1802.05799.pdf

All Scatter + All Reduce

https://andrew.gibiansky.com/blog/machine-learning/baidu-allreduce/

Uber’s Horovod





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

Device Specific Kernel Accelerator: Eyeriss

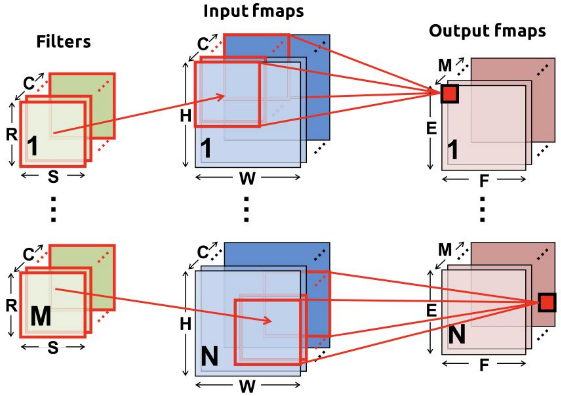
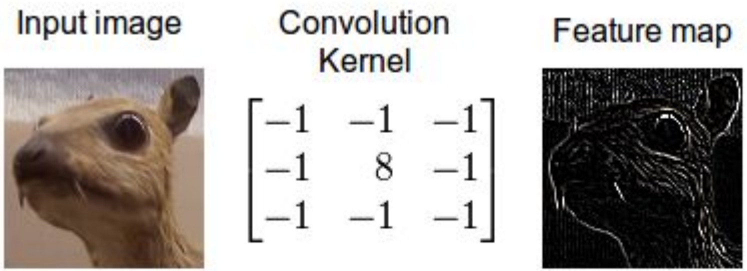
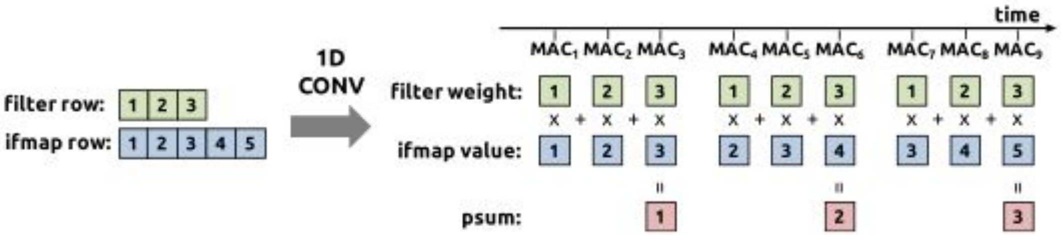


Fig. 1. Computation of a CNN layer.



Accelerator: Eyeriss



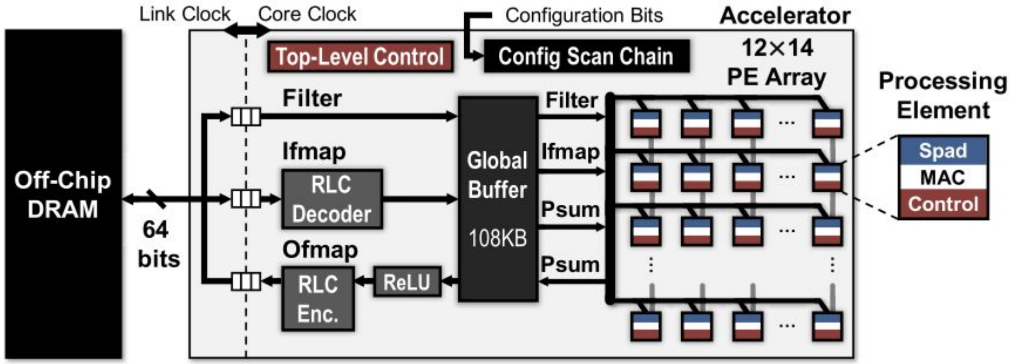


Fig. 2. Eyeriss system architecture.

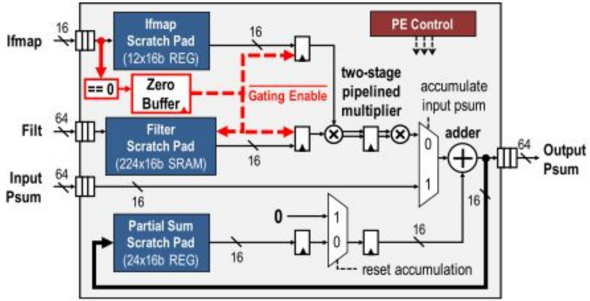
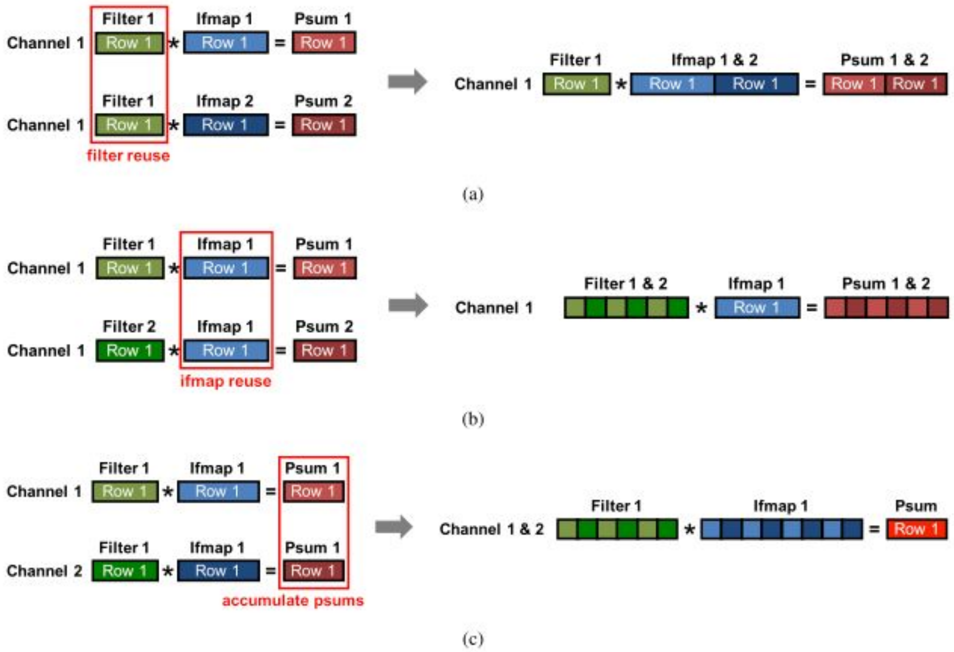
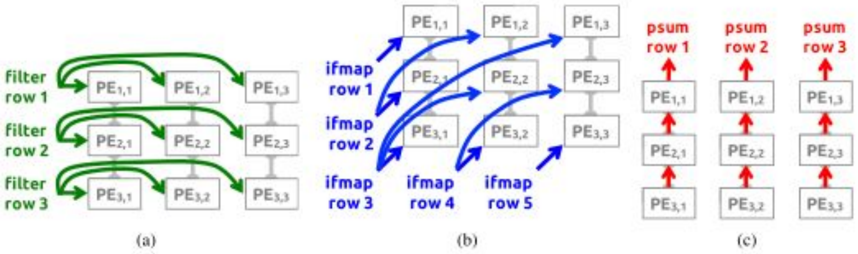


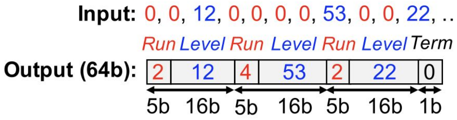
Fig. 12. PE architecture. The datapaths in red show the data gating logic to skip the processing of zero ifmap data.

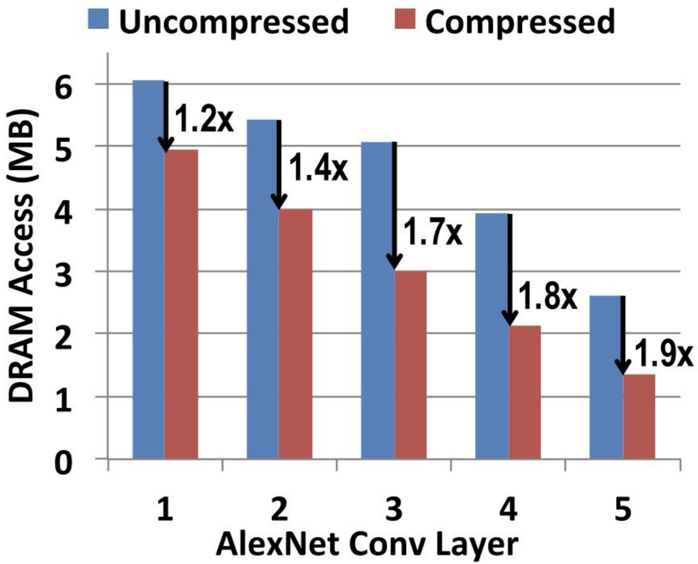
Accelerator: Eyeriss





Eyeriss: Run Length Coding





Tensorflow: Federated Learning on mobile

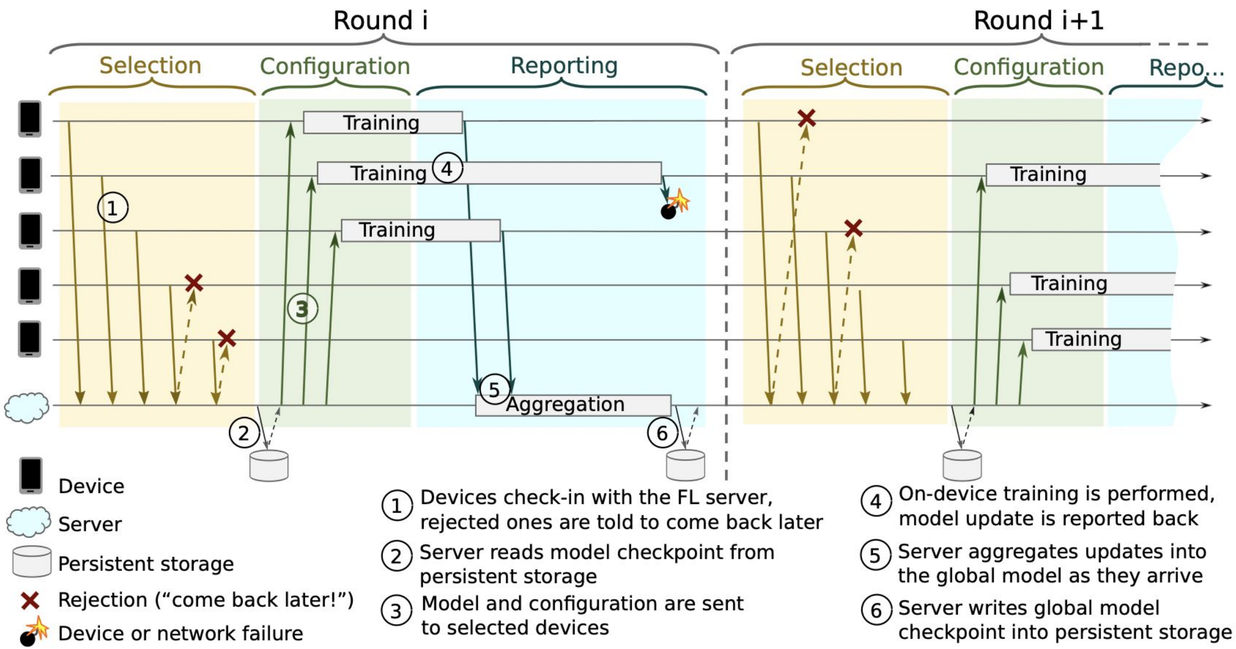


Figure 1: Federated Learning Protocol

Bonawitz, Keith, et al. "Towards federated learning at scale: System design." *arXiv preprint arXiv:1902.01046* (2019).

Tensorflow: Federated Learning on mobile

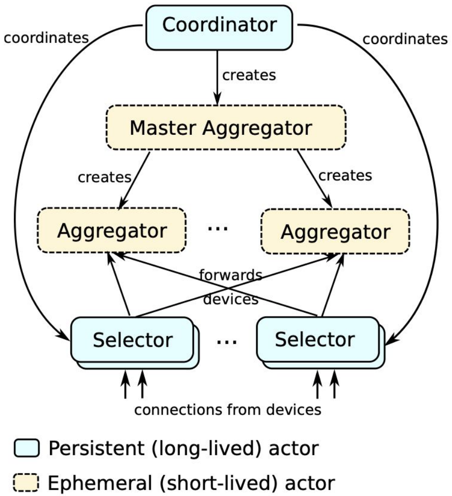


Figure 3: Actors in the FL Server Architecture

3 DEVICE

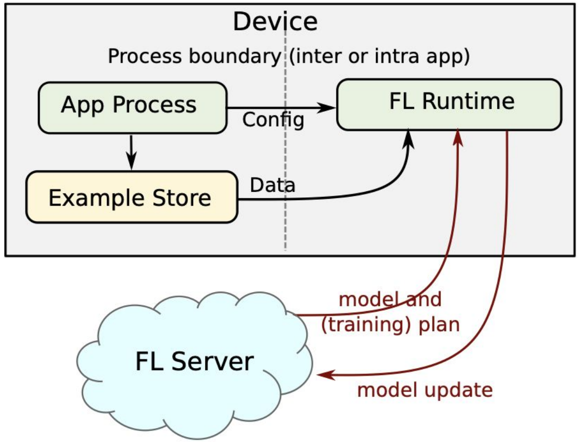


Figure 2: Device Architecture