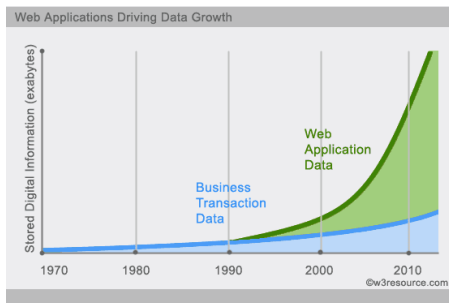


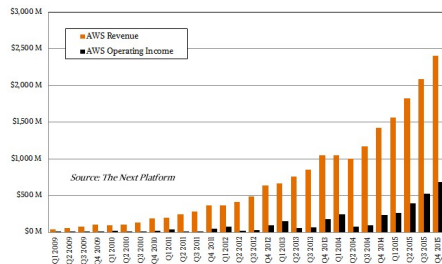
SMT Presentations: Computation

Motivation

Big data



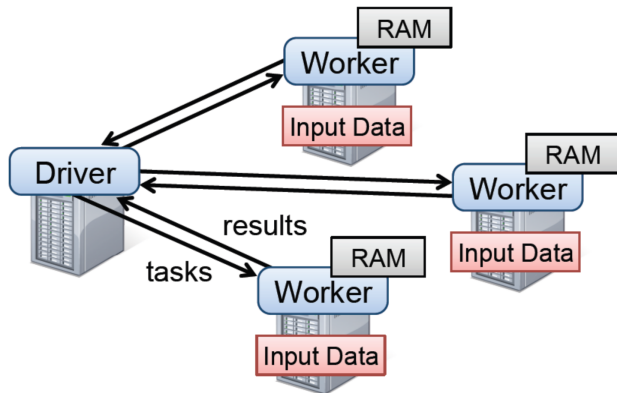
Cloud computing



Problem

Datasets no longer fit on a single machine!

Distributed Computing



New concerns:

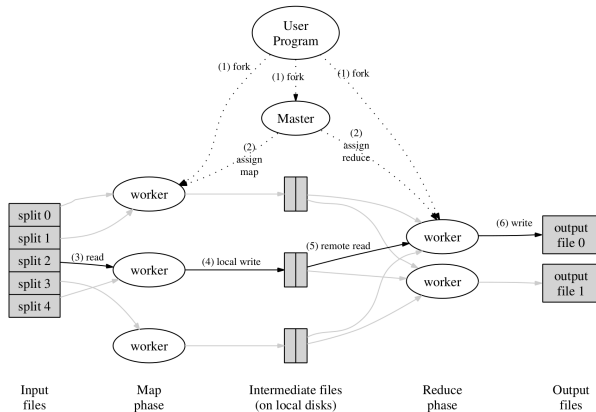
- 1 Consistency
- 2 Availability
- 3 Partition tolerance

CAP Theorem [GL02]

Choose two

MapReduce [DG08]

- Job-level dependency tracking
- Disk I/O every iteration



SparkNet

Training Deep Networks in Spark [MNSJ15]

Feynman Liang

CUED

May 17, 2016

Goals

- “Our goal is **not to outperform custom computational frameworks** but rather to propose a system that can be **easily implemented in popular batch frameworks** and that performs nearly as well. . .”
- “... integration with a fast and general engine for big data processing such as Spark **allows researchers and practitioners to draw from a rich ecosystem of tools to develop and deploy their models**”
- “In SparkNet, **training a deep network on the output of a SQL query, or a graph computation, or a streaming data source is straightforward**”

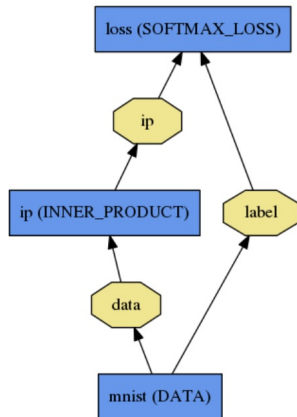
Caffe [JSD⁺14]

- Separation of concerns
 - Model specification
 - Solver
 - CPU ↔ GPU
- Model Zoo
- GPU parallelism

```

name: "LogReg"
layer {
  name: "mnist"
  type: "Data"
  top: "data"
  top: "label"
  data_param {
    source: "input_leveldb"
    batch_size: 64
  }
}
layer {
  name: "ip"
  type: "InnerProduct"
  bottom: "data"
  top: "ip"
  inner_product_param {
    num_output: 2
  }
}
layer {
  name: "loss"
  type: "SoftmaxWithLoss"
  bottom: "ip"
  bottom: "label"
  top: "loss"
}

```



SparkNet's Net API

Java Native Access (JNA) wrapper around Caffe

```
class Net {  
    def Net(netParams: NetParams): Net  
    def setTrainingData(data: Iterator[(NDArray,Int)])  
    def setValidationData(data: Iterator[(NDArray,Int)])  
    def train(numSteps: Int)  
    def test(numSteps: Int): Float  
    def setWeights(weights: WeightCollection)  
    def getWeights(): WeightCollection  
}
```


Example CNN NetParams

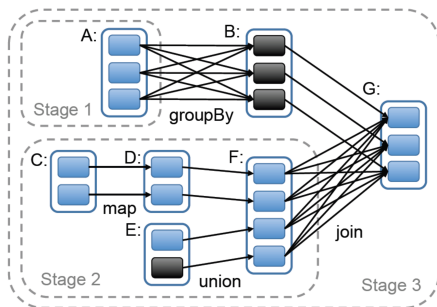
Compiled to protobuf Caffe network specification

```
val netParams = NetParams(
  RDDLayer("data", shape=List(batchsize, 1, 28, 28)),
  RDDLayer("label", shape=List(batchsize, 1)),
  ConvLayer("conv1", List("data"), kernel=(5,5), numFilters=20),
  PoolLayer("pool1", List("conv1"), pool=Max, kernel=(2,2), stride=(2,2)),
  ConvLayer("conv2", List("pool1"), kernel=(5,5), numFilters=50),
  PoolLayer("pool2", List("conv2"), pool=Max, kernel=(2,2), stride=(2,2)),
  LinearLayer("ip1", List("pool2"), numOutputs=500),
  ActivationLayer("relu1", List("ip1"), activation=ReLU),
  LinearLayer("ip2", List("relu1"), numOutputs=10),
  SoftmaxWithLoss("loss", List("ip2", "label"))
)
```

Spark [ZCD⁺12]

Resilient Distributed Datasets (RDDs)

- 1 *Lineage graph* describing lazy dataset
- 2 Aggressive in-memory caching (project Tungsten)
- 3 Partition-level dependency tracking

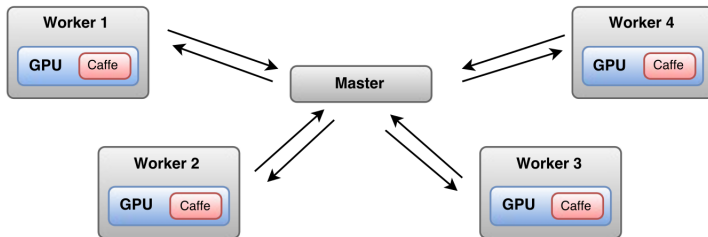


Parallelizing SGD

- ➊ Master broadcasts model parameters to workers
- ➋ Each worker runs SGD on its subset for $\tau = 50$ iterations
- ➌ Worker model parameters collected and averaged on master

```
var trainData = loadData(...)
var trainData = preprocess(trainData).cache()
var nets = trainData.foreachPartition(data => {
  var net = Net(netParams)
  net.setTrainingData(data)
  net
})
var weights = initialWeights(...)
for (i <- 1 to 1000) {
  var broadcastWeights = broadcast(weights)
  nets.map(net => net.setWeights(broadcastWeights.value))
  weights = nets.map(net => {
    net.train(50)
    net.getWeights()
  }).mean() // an average of WeightCollection objects
}
```

SparkNet Architecture



Problems in distributed optimization

Inter-machine communication bottleneck

Worker machines must frequently read and write the global shared parameters.

Question: How does SparkNet's $\tau = 50$ affect communication?
Convergence rate?

Problems in distributed optimization

Inter-machine communication bottleneck

Worker machines must frequently read and write the global shared parameters.

Question: How does SparkNet's $\tau = 50$ affect communication?
Convergence rate?

- Communication once every τ instead of every single SGD iteration
- Workers obtain parameter estimates more biased to own partition

Problems in distributed optimization

The straggler problem

Many algorithms require synchronization barriers, which are rate-limited by the slowest machines.

Question: Why might some machines be slower than others?

Problems in distributed optimization

The straggler problem

Many algorithms require synchronization barriers, which are rate-limited by the slowest machines.

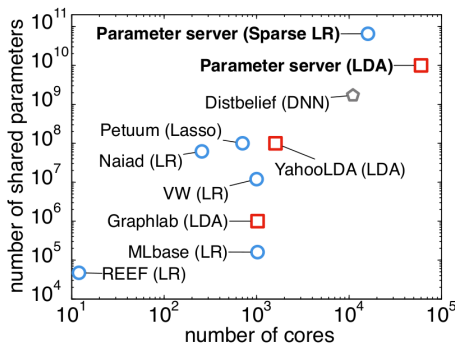
Question: Why might some machines be slower than others?

- Imbalanced workload partitioning
- Network congestion
- Other processes in multi-tenant environments

Addressing the straggler problem: asynchronous SGD

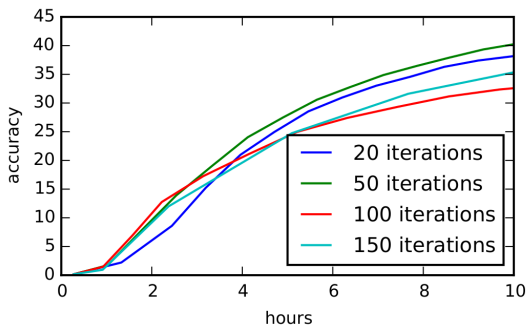
Not addressed by SparkNet, but an active research area:

- HogWild! – Correctness guarantees [RRWN11]
- Parameter server – Distributed implementation [HCC⁺13], flexible consistency models in V3 [LZY⁺13]



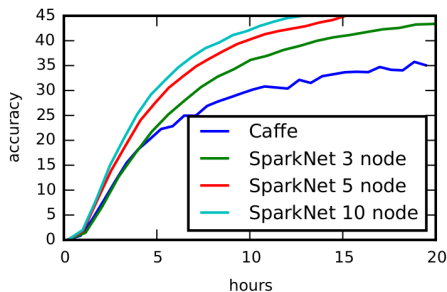
Tuning τ

- All experiments on EC2 g2.8xlarge nodes
- AlexNet [KSH12]
- $K = 5$ workers

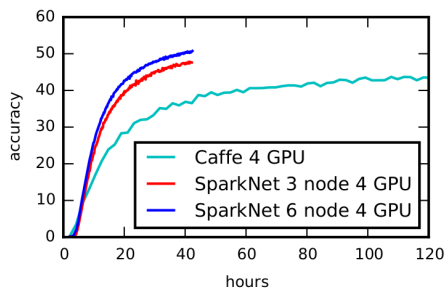


Training curves

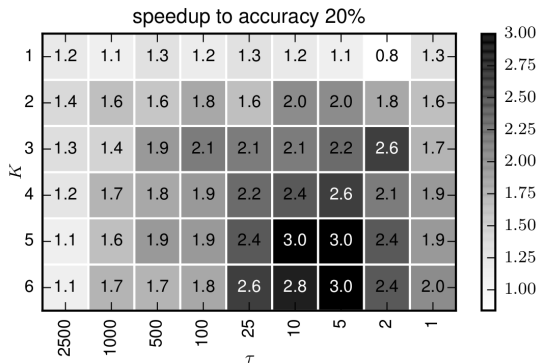
- AlexNet [KSH12]
- 8 layer CNN, ILSVRC2010
- $\tau = 50$



- GoogLeNet [SLJ⁺15]
- 22 layer CNN, ILSVRC2014
- $\tau = 50$



Speedups relative to single-GPU Caffe



- Why is $K = 1$ largely unaffected by τ ?
- Why does performance deteriorate with increasing K ? Increasing τ ?

Related work

- Distbelief [DCM⁺12]
 - Both data-parallel and **model-parallel** DNNs
 - Asynchronous (downpour SGD) and batch (sandblaster L-BFGS)
 - Google Borg CPU cluster
- FireCaffe [IAMK15]
 - Caffe parameter server
 - Cray GPU cluster
 - **SoA** $47\times$ **speedup** training GoogLeNet on 128 GPUs
- Yahoo/CaffeOnSpark [CNF16]
 - Infiniband/ethernet for GPU parameter exchange
 - **Spark and EC2 integration**

Conclusion

- Contributions

- Data-parallel integration between a popular deep CNN tool (*Caffe*) and a general-purpose cluster computing (*Spark*) framework
- Empirical studies on τ and K




- Criticisms

- Does not solve straggler problem: synchronization barrier at each parameter collection step
- No comparison against related work
- Experiments are too small (10 nodes max)

- Future work

- Mathematical analysis of τ 's effects on learning convergence
- Lock-free parameter updates (will require extending Spark)

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