Applications of Parallel Computers

Cloud Computing

https://sites.google.com/lbl.gov/cs267-spr2021

With slides from

Shivaram Venkataraman

Matei Zaharia

and from amplab UC BERKELEY

Cloud Computing, Big Data

Big data, Hardware, Software, Business

Data, Data, Data

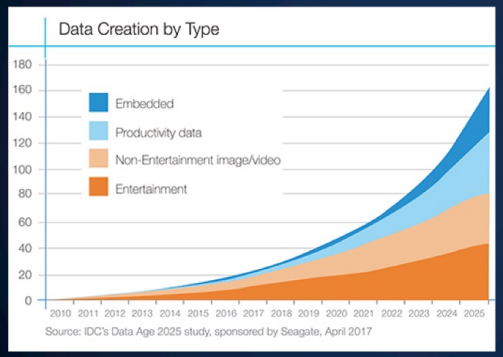
"…Storage space must be used efficiently to store indices and, optionally, the documents themselves. The indexing system must process hundreds of gigabytes of data efficiently…"

The Anatomy of a Large-Scale Hypertextual Web Search Engine

Sergey Brin and Lawrence Page

http://infolab.stanford.edu/~backrub/google.html

Data Growth

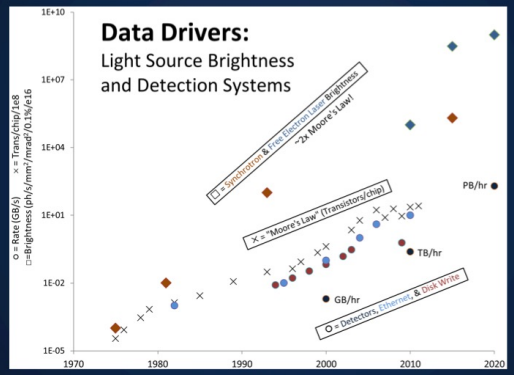


Facebook's daily logs:
500+ TB

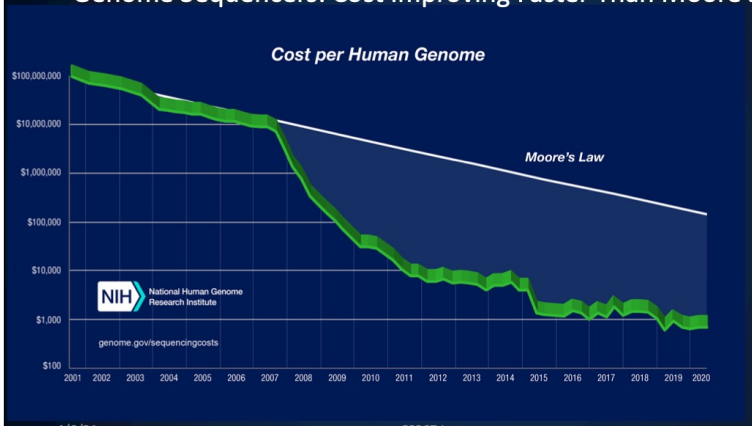
Sequence read archive:
35+ PB

Google web index:
100+ PB

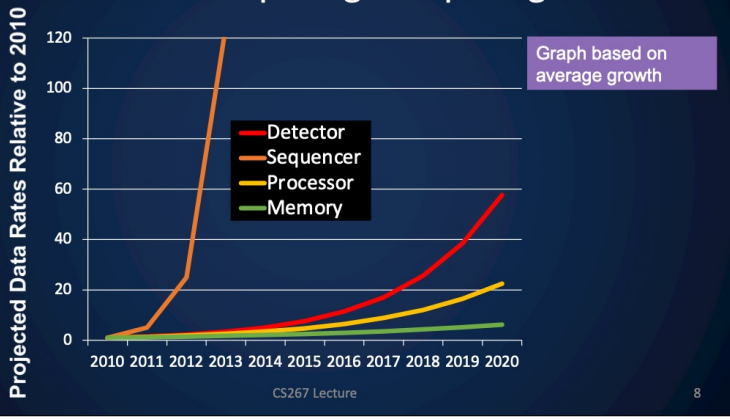
Data in Science: Light Sources data rates – Faster Than Moore's Law



Genome Sequencers: Cost Improving Faster Than Moore's Law



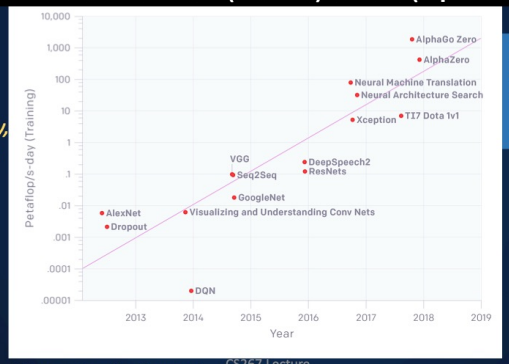
Data Growth is Outpacing Computing Growth



Growth in Computing for Machine Learning

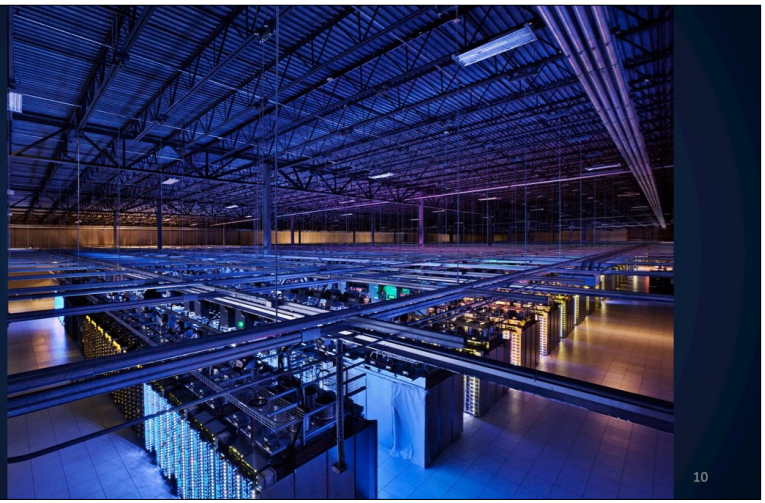
300,000x increase from 2011 (AlexNet) to 2018 (AlphaGoZero)

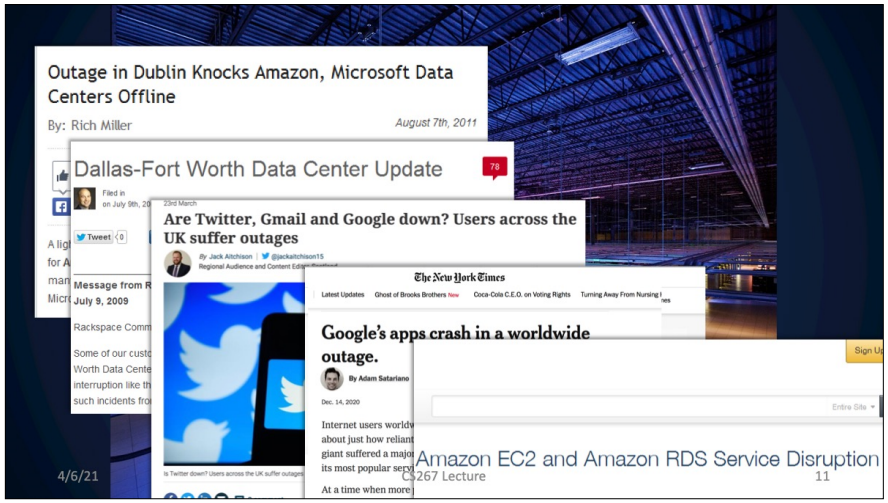
A petaflop/s-day = 10^{15} neural net operations per second for one day, ~= 10^{20} operations



From 2011-2017 the fastest Top500 machine grew < 10x

https://blog.openai.com/ai-and-compute/





Typical first year for a new cluster

Jeff Dean @ Google

- ~0.5 overheating (power down most machines in <5 mins, ~1-2 days to recover)
- ~1 PDU failure (~500-1000 machines suddenly disappear, ~6 hours to come back)
- ~1 rack-move (plenty of warning, ~500-1000 machines powered down, ~6 hours)
- ~1 network rewiring (rolling ~5% of machines down over 2-day span)
- ~20 rack failures (40-80 machines instantly disappear, 1-6 hours to get back)
- ~5 racks go wonky (40-80 machines see 50% packetloss)
- ~8 network maintenances (4 might cause ~30-minute random connectivity losses)
- ~12 router reloads (takes out DNS and external vips for a couple minutes)
- ~3 router failures (have to immediately pull traffic for an hour)
- ~dozens of minor 30-second blips for dns
- ~1000 individual machine failures
- ~thousands of hard drive failures, slow disks, bad memory, misconfigured machines, flaky machines, etc.

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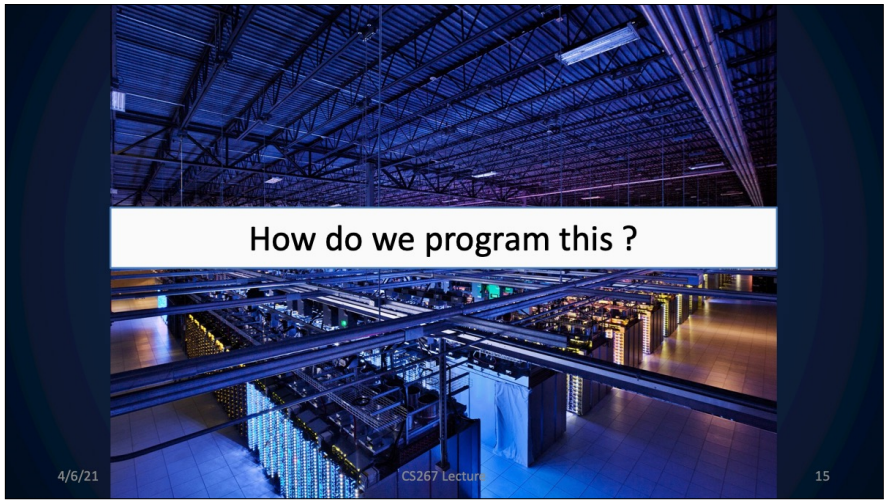
- Long distance links: wild dogs, sharks, dead horses, drunken hunters, etc.



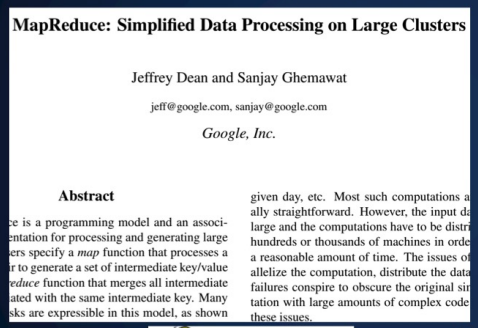
Data Programming Models

"Data" Parallel Models (loosely coupled)

- Restrict the programming interface
- Automatically handle failures, locality etc.

- "Here's an operation, run it on all of the data"
  - I don't care *where* it runs (you schedule that)
  - In fact, feel free to run it *retry* on different nodes

MapReduce



MapReduce: Simplified Data Processing on Large Clusters

Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

Google, Inc.

Abstract

ce is a programming model and an associ-
entation for processing and generating large
ers specify a *map* function that processes a
r to generate a set of intermediate key/value
educe function that merges all intermediate
ated with the same intermediate key. Many
sks are expressible in this model, as shown

given day, etc. Most such computations a
ally straightforward. However, the input da
large and the computations have to be distri
hundreds or thousands of machines in orde
a reasonable amount of time. The issues of
allelize the computation, distribute the data
failures conspire to obscure the original sir
tation with large amounts of complex code
these issues.

Google 2004

Build search index
Compute
PageRank

Hadoop: Open-source
at Yahoo, Facebook

MapReduce Programming Model

Data type: Each record is (key, value)

Map function:

$(K_{in}, V_{in}) \rightarrow list(K_{inter}, V_{inter})$

Reduce function:

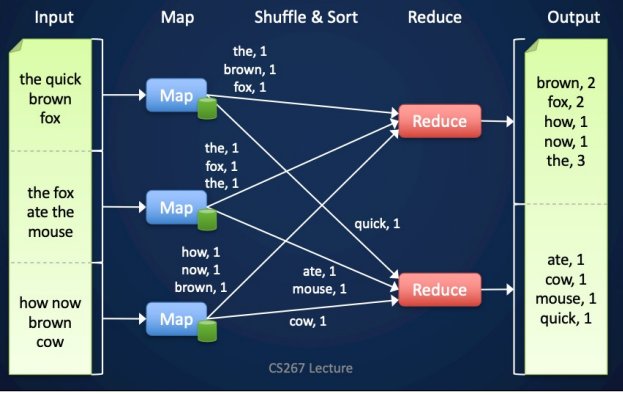
$(K_{inter}, list(V_{inter})) \rightarrow list(K_{out}, V_{out})$

Example: Word Count

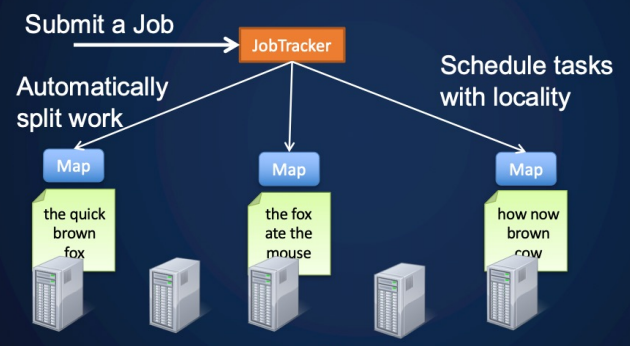
```
def mapper(line):
    for word in line.split():
        output(word, 1)

def reducer(key, values):
    output(key, sum(values))
```


Word Count Execution



Word Count Execution



Fault Recovery

If a task crashes:

- Retry on another node
- If the same task repeatedly fails, end the job

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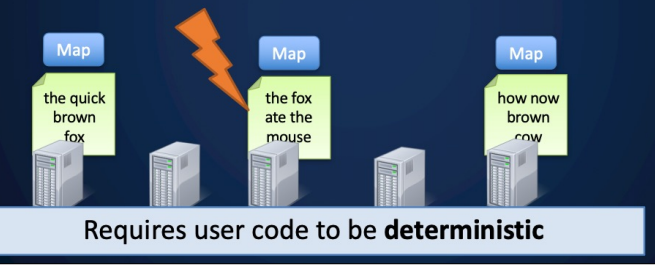


Fault Recovery

If a node crashes:

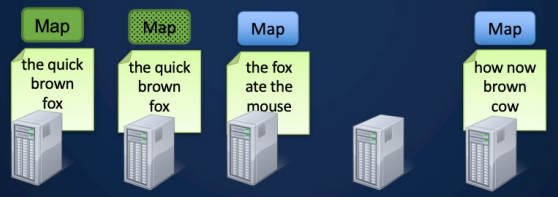
- Relaunch its current tasks on other nodes

What about task inputs ? File system replication

Fault Recovery

If a task is going slowly (straggler):

- Launch second copy of task on another node
- Take the output of whichever finishes first



When an Abstraction is Useful…

People want to compose it!

Most real applications require multiple MR steps

- Google indexing pipeline: 21 steps
- Analytics queries (e.g. sessions, top K): 2-5 steps
- Iterative algorithms (e.g. PageRank): 10's of steps

Programmability

Multi-step jobs create spaghetti code

- 21 MR steps → 21 mapper and reducer classes

Lots of boilerplate wrapper code per step

API doesn't provide type safety

Performance

MR only provides one pass of computation

- Must write out data to file system in-between

Expensive for apps that need to *reuse* data

- Multi-step algorithms (e.g. PageRank)
- Interactive data mining

Spark

Programmability: clean, functional API

- Parallel transformations on collections
- 5-10x less code than MR
- Available in Scala, Java, Python and R

Performance

- In-memory computing primitives
- Optimization across operators

Spark Programmability

```
#include "mapreduce/mapreduce.h"

int main(int argc, char** argv) {
  ParseCommandLineFlags(argc, argv);
  MapReduceSpecification spec;
  for (int i = 1; i < argc; i++) {
    MapReduceInput* in= spec.add_input();
    in->set_format("text");
    in->set_filepattern(argv[i]);
    in->set_mapper_class("SplitWords");
  }

  // Specify the output files
  MapReduceOutput* out = spec.output();
  out->set_filebase("/gfs/test/freq");
  out->set_num_tasks(100);
  out->set_format("text");
  out->set_reducer_class("Sum");

  // Do partial sums within map
  out->set_combiner_class("Sum");

  // Tuning parameters
  spec.set_machines(2000);
  spec.set_map_megabytes(100);
  spec.set_reduce_megabytes(100);

  // Now run it
  MapReduceResult result;
  if (!MapReduce(spec, &result)) abort();
  return 0;
}
```

```
// User's map function
class SplitWords: public Mapper {
  public:
  virtual void Map(const MapInput& input)
  {
    const string& text = input.value();
    const int n = text.size();
    for (int i = 0; i < n; ) {
      // Skip past leading whitespace
      while (i < n && isspace(text[i]))
        i++;
      // Find word end
      int start = i;
      while (i < n && !isspace(text[i]))
        i++;
      if (start < i)
        Emit(text.substr(
            start,i-start),"1");
    }
  }
};

REGISTER_MAPPER(SplitWords);
```

```
// User's reduce function
class Sum: public Reducer {
  public:
  virtual void Reduce(ReduceInput* input)
  {
    // Iterate over all entries with the
    // same key and add the values
    int64 value = 0;
    while (!input->done()) {
      value += StringToInt(
                  input->value());
      input->NextValue();
    }
    // Emit sum for input->key()
    Emit(IntToString(value));
  }
};

REGISTER_REDUCER(Sum);
```

Google MapReduce WordCount

Spark Programmability

Spark WordCount:

```
val file = spark.textFile(hdfs://...)
val counts = file.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _)

counts.save("out.txt")
```


Spark Performance

Iterative algorithms:

Spark Concepts

Resilient distributed datasets (RDDs)
- Immutable, partitioned collections of objects
- May be cached in memory for fast reuse

Operations on RDDs
- *Transformations* (build RDDs)
- *Actions* (compute results)

Restricted shared variables
- Broadcast, accumulators

Example: Log Mining

Find error messages present in log files interactively (Example: HTTP server logs)

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
messages.cache()
```

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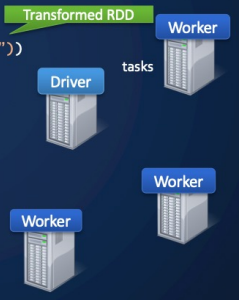

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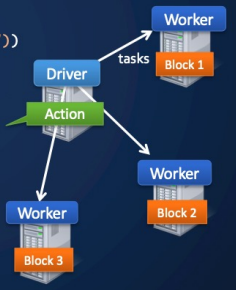
messages.filter(_.contains("foo")).count
```



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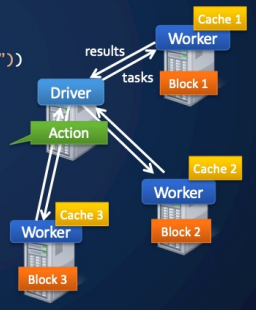

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```

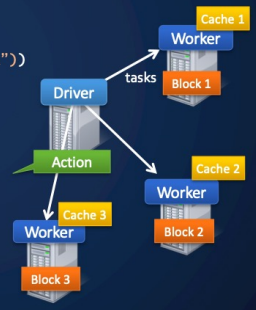

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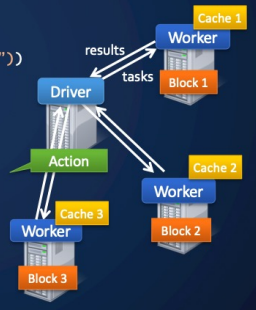

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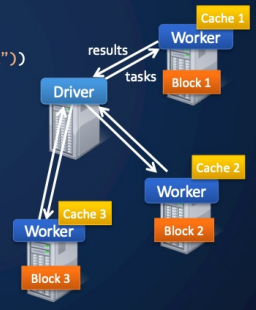

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

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(Example: HTTP server logs)

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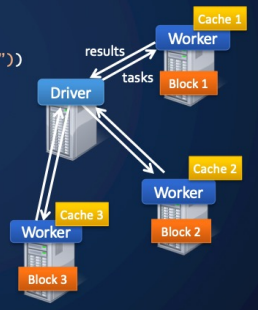


Result: search 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

Fault Recovery

RDDs track *lineage* information that can be used to efficiently reconstruct lost partitions

Ex:

```
messages = textFile(...).filter(_.startsWith("ERROR"))
                        .map(_.split('\t')(2))
```

Pi in Java SPARK

```
List<Integer> l =
   new ArrayList<>(NUM_SAMPLES);
for (int i = 0; i < NUM_SAMPLES; i++) {
  l.add(i);
}
long count = sc.parallelize(l).filter(i -> {
          double x = Math.random();
          double y = Math.random();
          return x*x + y*y < 1; }).count();
System.out.println("Pi is roughly " +
                   4.0 * count / NUM_SAMPLES);
```


Other RDD Operations

Transformations (define a new RDD)	map filter sample groupByKey reduceByKey cogroup	flatMap union join cross mapValues ...
Actions (output a result)	collect reduce take fold	count saveAsTextFile saveAsHadoopFile ...

Java

```
JavaRDD<String> lines = sc.textFile(...);
lines.filter(new Function<String, Boolean>() {
  Boolean call(String s) {
    return s.contains("error");
  }
}).count();
```

Python

```
lines = sc.textFile(...)
lines.filter(lambda x: "error" in x).count()
```

R

```
lines ← textFile(sc, ...)
filter(lines, function(x) grepl("error", x))
```

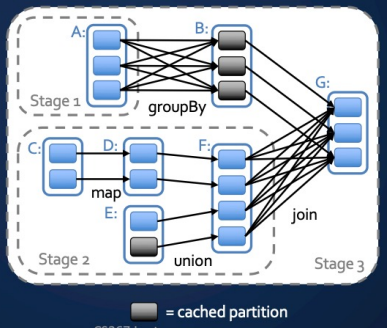

Job Scheduler

Captures RDD dependency graph

Pipelines functions into "stages"

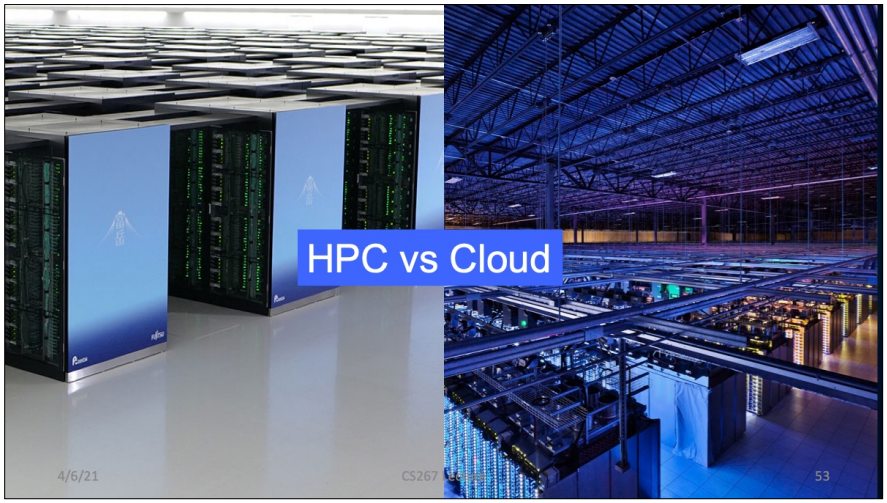
Cache-aware for data reuse & locality

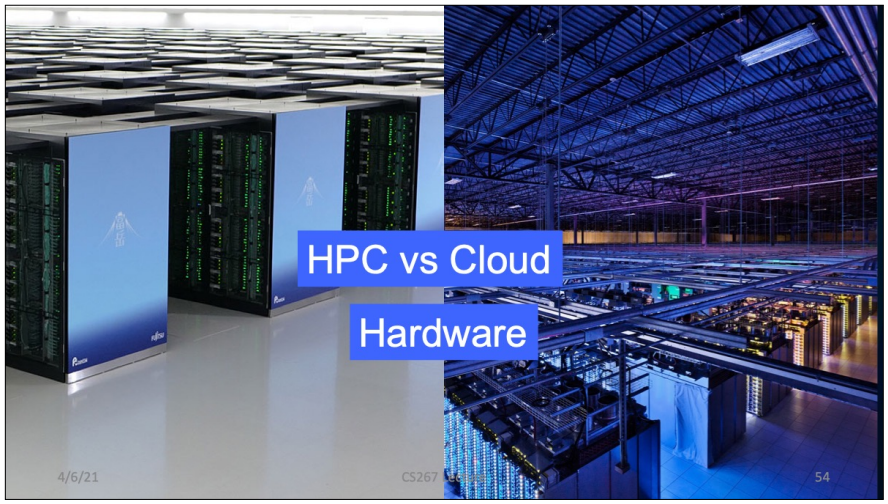
Partitioning-aware to avoid shuffles



Higher-Level Abstractions

- SparkStreaming: API for streaming data
- GraphX: Graph processing model
- MLLib: Machine learning library
- SparkSQL: SQL queries, DataFrames
- TensorFlowOnSpark: Deep learning
- …





Google 1997

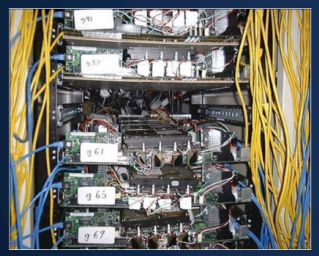
NERSC 1996

Cray T3E 900: 460 Gflop/s

850 GB of disk

106 TB Data archive

Google 2001



Commodity CPUs

Lots of disks

Low bandwidth network

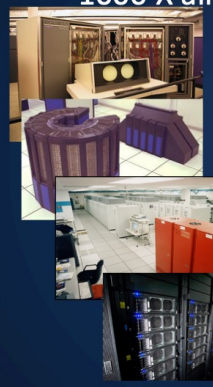
Cheap !

NERSC 2001: Seaborg

2001 5 Tflop/s 3.3 TB upgraded in 2002 to 10 Tflop/s, 6.6 TB

Supercomputers Designed for Big Compute

1000 X almost every decade



CDC 6600 in 1964, Megaflops

Cray 2 in 1985 Gigaflops

ASCI Red (Intel)in 1998 Teraflops

IBM Roadrunner in 2008 Petaflops

Original Clouds Designed for Big Data

Capacity:

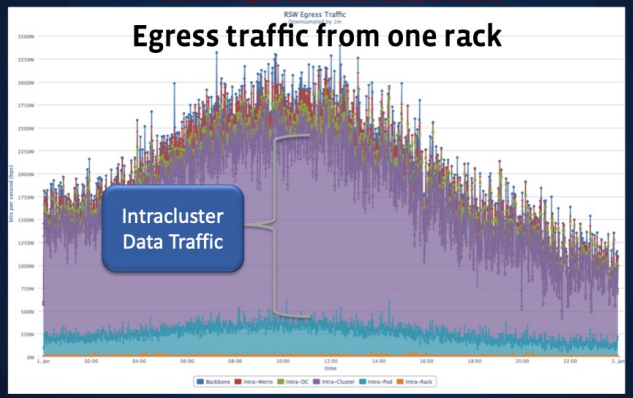
~10000 machines

Bandwidth:
12-24 disks per node

Latency:
256GB RAM cache

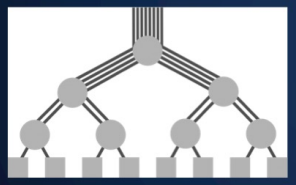
Majority of Facebook Traffic is Intra-Cluster

(Heather Farrington, Facebook Inc., Presented at OFC'013)



Datacenter Networking

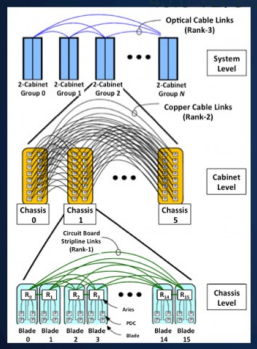
Initially tree topology
Over subscribed links

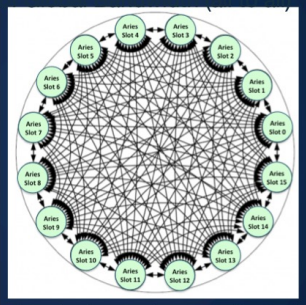


Fat tree, Bcube, VL2 etc.

Lots of research to get
full bisection bandwidth

Cori's Cray Aries Interconnect





Intra-chassis network connects 16 network interfaces (Aries ASICs) to every other. This is done through the backplane and requires no cables.

But How's the Situation Today?

In the literature of the last 10 years, there have been several efforts to measure the performance of scientific applications in the cloud:

The Magellan report concluded that high latency network, virtualization overhead, performance variability and lack of batch scheduling are the main bottleneck

Netto et al. surveyed the contemporary literature and concluded that the lack of low-latency network is the main challenge for the cloud

He et al. concluded that the high latency network is the main bottleneck and that virtualization has no significant overhead

Gupta et al. also concluded that the high latency network, virtualization overhead and performance variability are the main bottleneck

? ?

A key take away is that the lack of a low-latency network has prevented the cloud from achieving competitive performance on a broad scale and this has not changed in 8 years between 2010 and 2018

Experimental Setting

To carry out our study we used four machines: Compare performance at modest scale

	Platform	Age	Core/P	Fr (GHz)	Processor	Memory (GiB)	Network (Gbps)	L1	L2	L3
HPC	Cori Haswell	4	32	2.3	Xeon E5-2698V3	120	82	64 KB	256 KB	40 MB
HPC	Cori KNL	4	68	1.4	Xeon Phi 7250	90	82	64 KB	1 MB	-
Cloud	AWS r5dn.16xlarge (R5)	1	32	2.5	Xeon Platinum 8259CL	512	75	64 KB	1 MB	36MB
Cloud	AWS c5.18xlarge (C5)	1	36	3.0	Xeon Platinum 8124M[1]	144	25	64 KB	1 MB	25MB

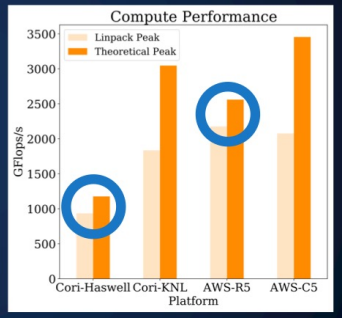
- AWS ParallelCluster to set up the cluster
- AWS instances run as dedicated instances
- AWS instances placed in the same placement group
- Cori has the Cray Aries "Dragonfly" topology for its interconnect
- C5 instances use Amazon in-house Elastic Fabric Adapter (EFA) as network interface
- High-end instances, i.e. expensive instances

1 Custom model for Amazon AWS

A Hardware and System View

Processor: LINPACK benchmark

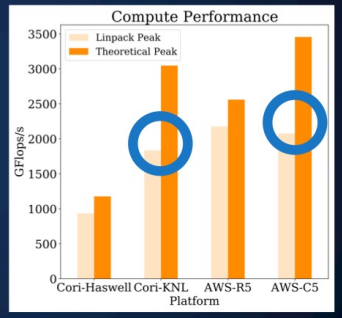
- Cori Haswell and R5 peak performance much closer to their theoretical peak than the other two machines



A Hardware and System View

Processor: LINPACK benchmark

- Cori Haswell and R5 peak performance much closer to their theoretical peak than the other two machines
- Closing the gap between theoretical peak and LINPACK peak on Cori KNL is notoriously difficult
- C5's profiling revealed relatively low core utilization which could explain the gap



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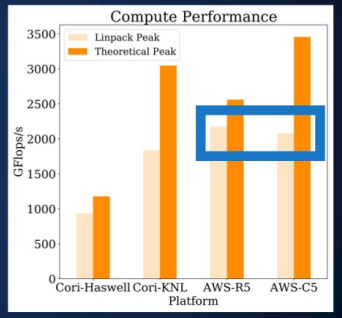
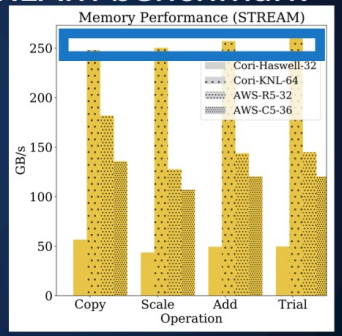
Take away: Cloud's faster procurement cycles —thus the newer hardware —may explain the greater processing power



A Hardware and System View

Memory Bandwidth: STREAM benchmark

- Cori KNL has the higher memory bandwidth thanks to the on-chip multi-channel DRAM chip of 16GB



A Hardware and System View

Memory Bandwidth: STREAM benchmark

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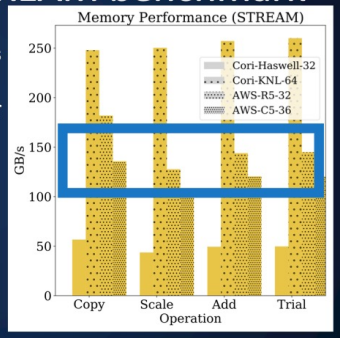
- If no on-chip memory, cloud instances show higher memory bandwidth than Cori Haswell



A Hardware and System View

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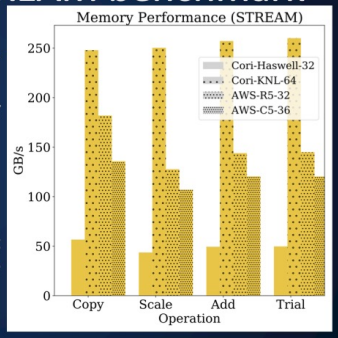
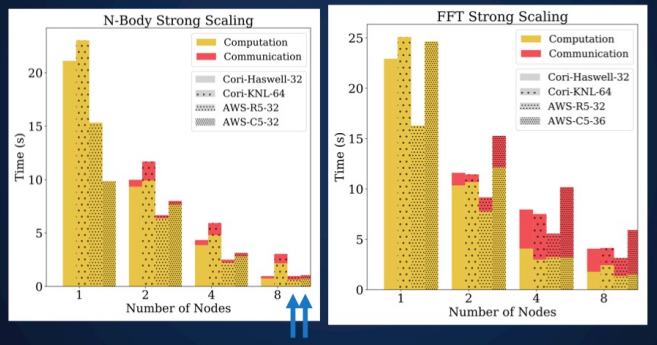
- If no on-chip memory, cloud instances show higher memory bandwidth than Cori Haswell

Take away: A faster hardware turnaround could benefit both compute-intensive workload and data-intensive ones



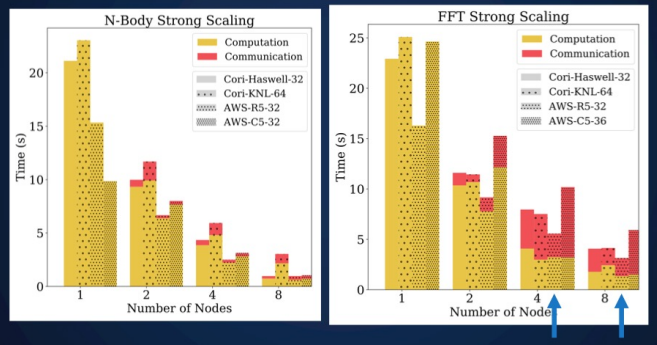
A User Application View

Parallel Performance



A User Application View

Parallel Performance



From Mid 2006

Rent virtual computers in the "Cloud"

On-demand machines, spot pricing

Demand and Spot Pricing

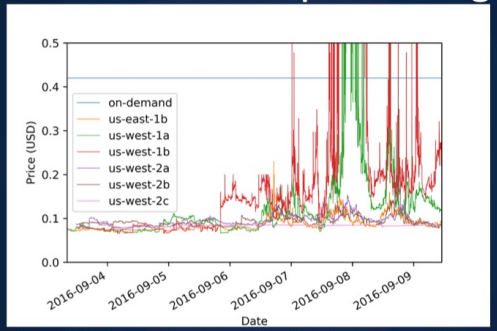


Image from: Baughman, Matthew & Haas, Christian & Wolski, Rich & Foster, Ian & Chard, Kyle. (2018). Predicting Amazon Spot Prices with LSTM Networks. 1-7. 10.1145/3217880.3217881.

Amazon EC2 (2014)

Machine	Memory (GB)	Compute Units (ECU)	Local Storage (GB)	Cost / hour
t1.micro	0.615	1	0	$0.02
m1.xlarge	15	8	1680	$0.48
cc2.8xlarge	60.5	88 (Xeon 2670)	3360	$2.40

1 ECU = CPU capacity of a 1.0-1.2 GHz 2007 Opteron or 2007 Xeon processor

Amazon EC2 (2018)

Machine	Memory (GB)	Compute Units (ECU)	Local Storage (GB)	Cost / hour
t2.nano	0.5	1	0	$0.006
r3.8xlarge	244	104 (32 Ivy Bridge)	640 (SSD)	~~$2.66~~ $2.37
x1.32xlarge	2 TB	4 * Xeon E7	3.8 TB (SSD)	$13.338
p2.16xlarge	732 GB	16 Nvidia K80 GPUs	0	$14.40

Hopper vs. Datacenter

	Hopper	Datacenter[2]
Nodes	6384	1000s to 10000s
CPUs (per node)	2x12 cores	~2x6 cores
Memory (per node)	32-64GB	~48-128GB
Storage (overall)	~4 PB	120-480 PB
Interconnect	~ 66.4 Gbps	~10Gbps

[2]http://blog.cloudera.com/blog/2013/08/how-to-select-the-right-hardware-for-your-new-hadoop-cluster/

~~Hopper~~ Cori Phase 1 vs. Datacenter

	~~Hopper~~ Cori Phase 1	Datacenter[2]
Nodes	~~6384~~ 2399	1000s to 10000s
CPUs (per node)	~~2x12~~ 2x16 cores 1.2 Tf/s	~2x6 cores
Memory (per node)	~~32-64GB~~ 128 GB	~48-128GB
Storage (overall)	~~~4 PB~~ ~30PB	120-480 PB
Interconnect	~ 66.4 Gbps	~10Gbps

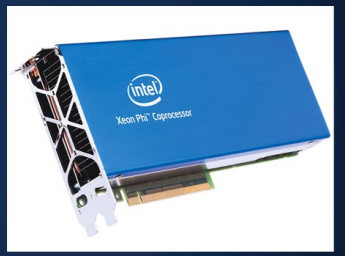
[2]http://blog.cloudera.com/blog/2013/08/how-to-select-the-right-hardware-for-your-new-hadoop-cluster/

Cori: Intel Xeon Phi

Many Core
Integrated Architecture

60 cores per node
(68 in Cori)

Vector Processing



~~Hopper~~ Cori Phase 2 vs. Datacenter

	~~Hopper~~ Cori KNL	Datacenter[2]
Nodes	~~6384 2388~~ 9688	1000s to 10000s
CPUs (per node)	~~2x12~~ 1x68 cores ~~1.2 Tf/s.~~ 3 Tf/s	~2x6 cores
Memory (per node)	~~32 64128~~ 96 GB	~48-128GB
Storage (overall)	~~~4 PB~~ ~30PB +1.8 PB SSD	120-480 PB
Interconnect	~ 66.4 Gbps	~10Gbps

[2]http://blog.cloudera.com/blog/2013/08/how-to-select-the-right-hardware-for-your-new-hadoop-cluster/

Summit (#1 machine) System Overview

System Performance

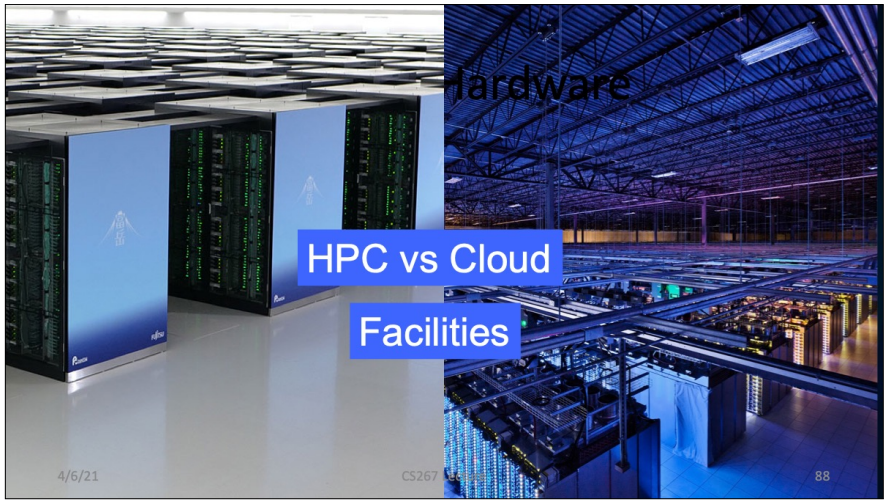
- Peak performance of 200 petaflops for modeling & simulation
- Peak of 3.3 ExaOps for data analytics and artificial intelligence

Each node has

- 2 IBM POWER9 processors
- 6 NVIDIA Tesla V100 GPUs
- 608 GB of fast memory
- 1.6 TB of NVMe memory

The system includes

- 4608 nodes
- Dual-rail Mellanox EDR InfiniBand network
- 250 PB IBM Spectrum Scale file system transferring data at 2.5 TB/s



Datacenter Design

Goals

Economies of scale

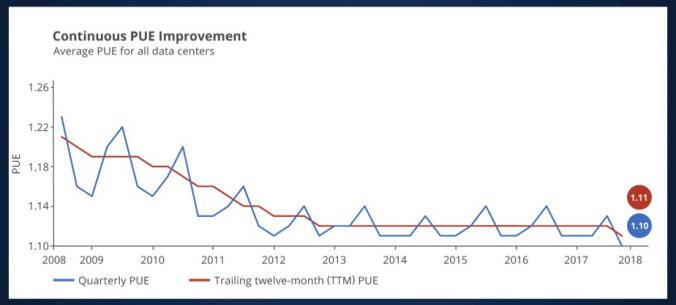
Power usage effectiveness (PUE)

Cost-efficiency

Custom machine design

Energy Efficiency in Data Centers (at LBNL)

Energy Efficiency



Data center average about 1.7, NERSC also under 1.1

https://www.google.com/about/datacenters/efficiency/internal/

Supercomputing Center Evolution

NERSC Center in Berkeley

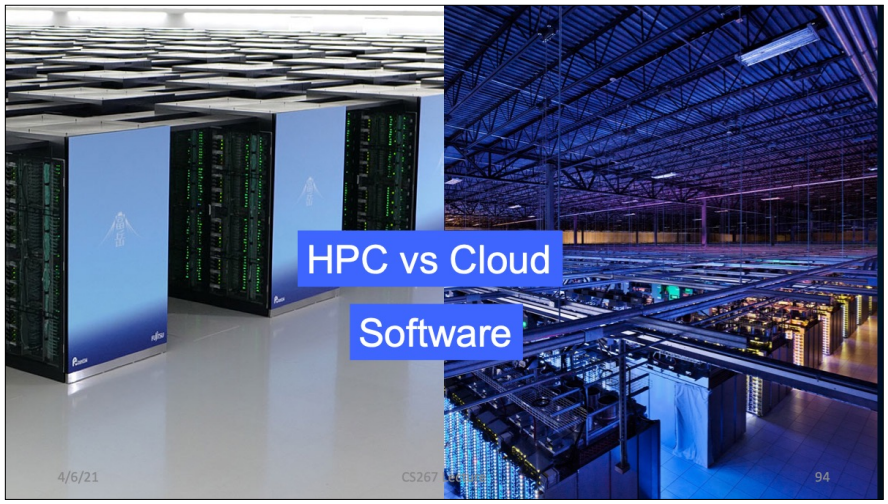
- 27K sf of compute center space
- ~250 people in building
- 12.5 MW today
- Upgrading to 25MW

Datacenter Evolution

Google data centers in The Dalles, Oregon

- 200K SF + 164K sf in (3 buildings total)
- $1.2 B investment in site
- 175 people employed on site
- 70 Megawatts (when it was 200K SF)

Google in the Netherlands: 30MW Solar Farm



Software

MPI

hadoop

Open MPI

MPICH

MVAPICH

Spark

Scientific Computing on Spark

Computation

- Efficient native operations using JNI
- Use BLAS / OpenMP per-node

Communication

- Limited programming model
- Shuffle could add latency, bandwidth

HPC: Programming Models

Message Passing Models (MPI)

- Fine-grained messages + computation

- Hard to deal with disk locality, failures, stragglers
- 1 server fails every 3 years →
- 10K nodes see 10 faults/day

- Exascale research: Fault Tolerant MPI (FTMPI)
- Checkpointing-based techniques

Data Programming Models

"Data" Parallel Models (loosely coupled)

- Restrict the programming interface
- Automatically handle failures, locality etc.

- "Here's an operation, run it on all of the data"
  - I don't care *where* it runs (you schedule that)
  - In fact, feel free to run it *retry* on different nodes

MPI

- High performance focus

MapReduce

- Convenience focus

MPI

- High performance focus
- SPMD parallelism model

MapReduce

- Convenience focus
- High level data-parallel

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- Automate locality based on data in files

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- Communication implicit in "reduce" collective

MPI

- High performance focus
- SPMD parallelism model
- Manually control layout and locality
- Collective and point-to-point communication
- No automatic support for faults or load imbalance

MapReduce

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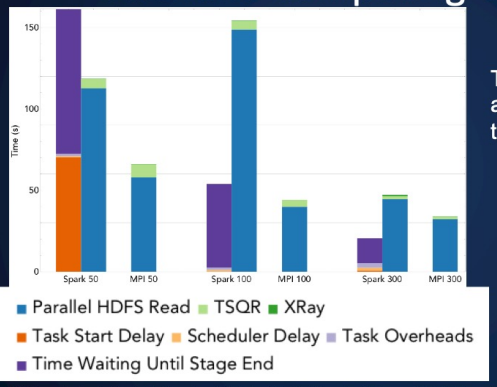
- Automate locality based on data in files
- Communication implicit in "reduce" collective
- Automated fault tolerance and load balance

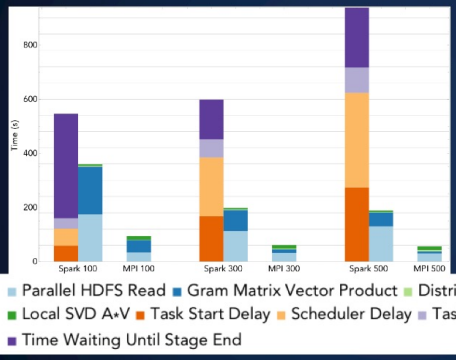
Scientific Computing on SPARK



Time for rank 10 approximation using NMF on the 1.6TB Daya Bay matrix

Gittens, A., Devarakonda, A., Racah, E., Ringenburg, M., Gerhardt, L., Kottalam, J., ... & Sharma, P. (2016, December). Matrix factorizations at scale: A comparison of scientific data analytics in Spark and C+ MPI using three case studies. In *Big Data (Big Data)*.

Scientific Computing on SPARK



Running time for PCA on the 2.2TB Ocean matrix on Cori

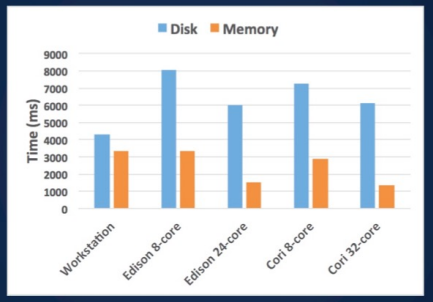
Gittens, A., Devarakonda, A., Racah, E., Ringenburg, M., Gerhardt, L., Kottalam, J., ... & Sharma, P. (2016, December). Matrix factorizations at scale: A comparison of scientific data analytics in Spark and C+ MPI using three case studies. In *Big Data (Big Data)*.

Scientific Computing on Spark

Large Scale Machine Learning (AMPLab, Aspire)
- KeystoneML: Framework for ML
- Improved Algorithms

Spark on HPC systems (NERSC, Cray, AMPLab)
- Real world applications
- Profiling, hardware customizations

Supercomputer Node 2x Slower Than Workstation



Spark SQL Big Data Benchmark

I/O is the problem:

Supercomputer matches workstation when data is cached

Chaimov, N., Malony, A., Canon, S., Iancu, C., Ibrahim, K. Z., & Srinivasan, J. (2016, May). Scaling spark on HPC systems. *ACM International Symposium on High-Performance Parallel and Distributed Computing*

Summary of Traditional Differences
(both are changing)

Cloud	HPC
Focus on storage and data	Focus on computing (flop/s)
Cheap(est) commodity component	High end components (some specialization)
Commodity networks	High performance networks
Pay as you go	Purchased for mission; pay in non-fungible "hours"
< 50% utilization	> 90% utilization
On-demand access	Large jobs wait in queues
Multiple jobs per node	Dedicated nodes
On-node disks (air cooled)	Separate storage (compute liquid cooled)

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Policy and business model