CS 795: Distributed Systems & Cloud Computing Fall 2018

Lec 0: Course introduction Yue Cheng

A brief intro

• Yue Cheng (<u>http://cs.gmu.edu/~yuecheng</u>)

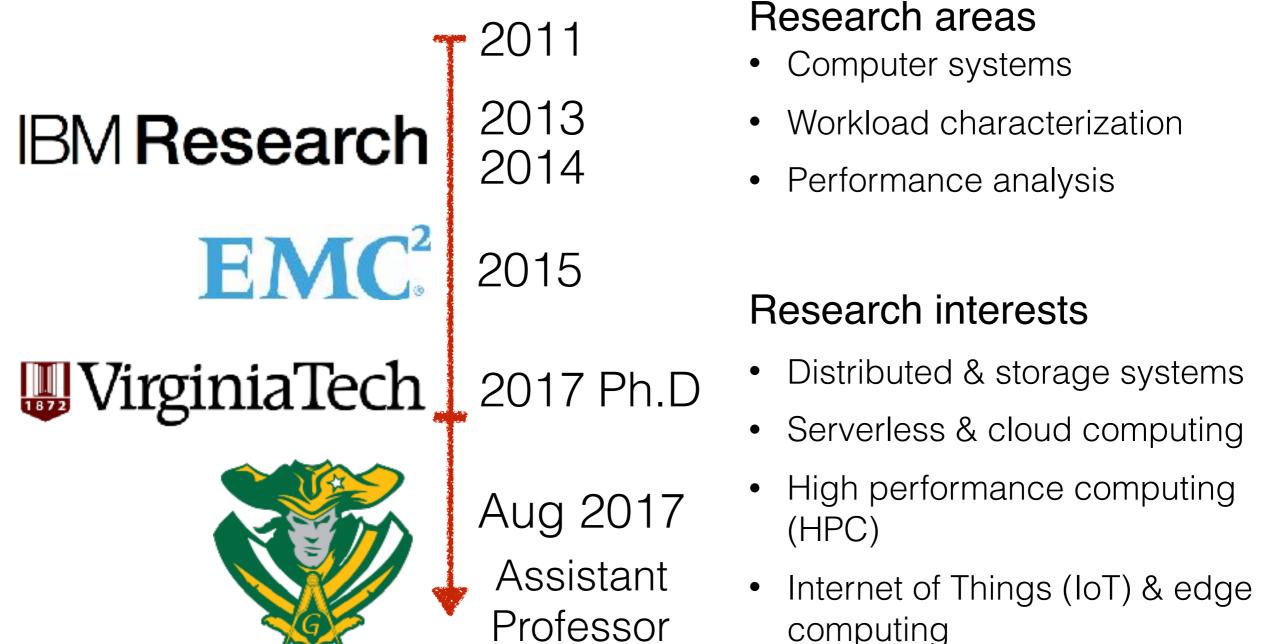




Aug 2017 Assistant Professor

A brief intro

Yue Cheng (<u>http://cs.gmu.edu/~yuecheng</u>)



Course info

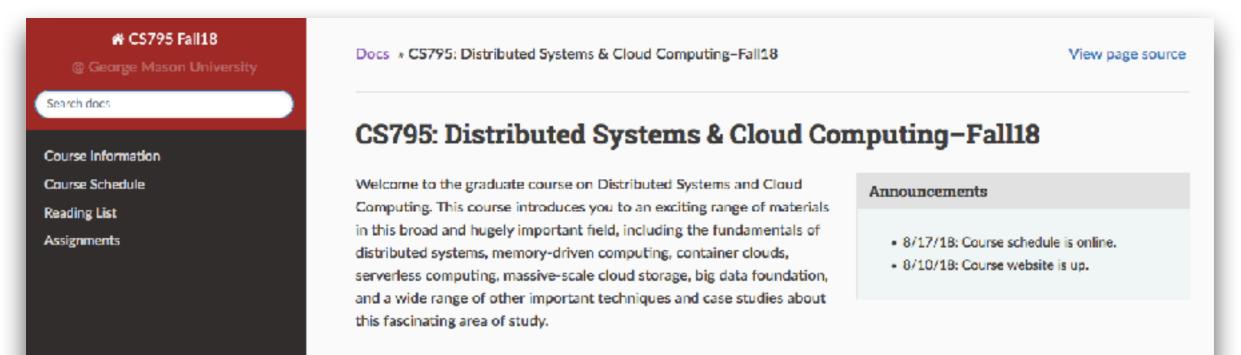
• Meeting time: Wed 4:30 — 7:10pm

• Location: Peterson Hall 1113

• Office hours: Thur 2 — 4pm or by appointment, Engineering 5324

Course info

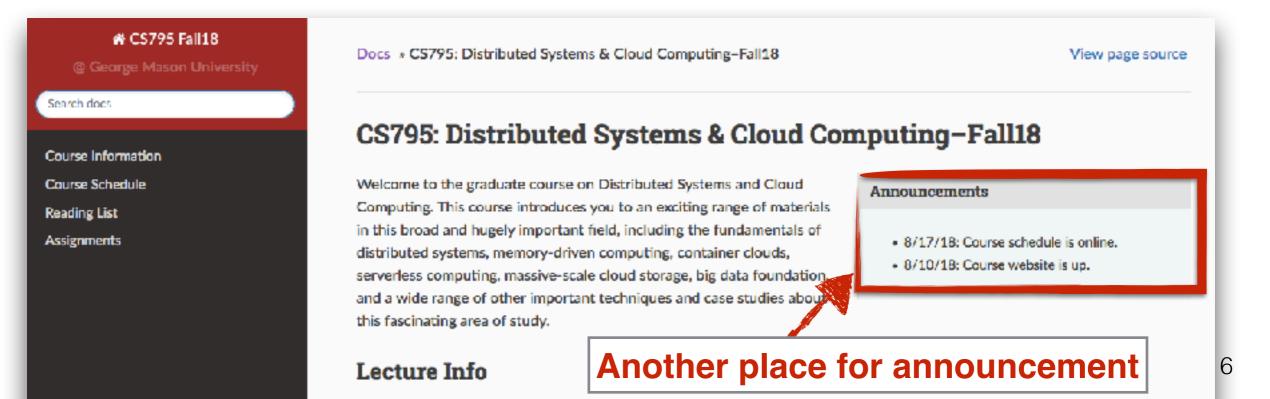
- Course website:
 - <u>https://cs.gmu.edu/~yuecheng/teaching/cs795_fall18/</u> index.html
 - Updated regularly throughout this semester
 - We will be using Piazza for communication and discussion



Lecture Info

Course info

- Course website:
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Prerequisites

- NO explicit prerequisite courses
- What I assume you already know:
 - Understanding of the undergrad-level operating systems concepts and principles
 - Programming skills in at least one of: Python, C/C++, Golang, Java
- Some familiarity with *NIX systems

Reading materials

- Primary reading is the assigned research papers
 - Look at the reading list on the class website
 - What would you like to present? What would you like to scribe? (later slides)

- NO textbook required
- One excellent source of OS-level knowledge & background (highly recommended)
 - Operating Systems: Three Easy Pieces, by Remzi H. Arpaci-Dusseau and Andrea C. Arpaci-Dusseau (v 0.92)
 - URL: <u>http://pages.cs.wisc.edu/~remzi/OSTEP/</u>

Course format

- Lectures + discussions
 - At the beginning of the semester: I give a few lectures covering fundamentals that you need to know
 - Starting from week 3 (tentatively): I give a short lecture (30+min) covering Why Today's Papers + 2 paper discussions (50-60min each) led by you

- Four student presentations
 - Two for assigned research papers (may +/-1 depending on class size and your motivation)
 - Two for research projects (1 proposal + 1 final)

Discussions

 Everyone reads the assigned papers (x2) before class

- Submit a brief evaluation form before each class
 - Proves that you've read the papers
 - Enable you to contribute to the discussion

- Each paper assigned to a scriber
 - Scriber writes reaction posts on Piazza after class

Paper evaluation form

- Submissions: Will send out a Google form for the two papers that you need to fill in (the Google form will close **10min** before the class)
- No late submissions will be accepted
- Instead, you will have three wildcards
 - Three dates on which you can skip evaluation forms without penalty
 - Need not be announced beforehand
- Contact instructor for exceptions in severe circumstances only

Paper evaluation form

- What problem does the paper attack? How does it relate to and improve upon previous work in its domain?
- What is the solution's main idea?
- Does the paper (or do you) identify any fundamental/hard tradeoffs?
- Write down **question/s** that you plan to bring up in the discussion

Your presentation

- Go through the reading list looking for papers from USENIX conferences
 - USENIX publishes all talks in form of **slides**, **audio**, and **video**
 - See how paper authors present
- Present research as if it were your own
 - Give background if necessary
- Evaluate research from your perspective
 - Add insights, criticism, etc.
 - In retrospect: Why did it succeed or fail?
- Be prepared to be interrupted
 - People ask questions in between

Scribe: Reaction post

- A 3-paragraph post for each paper on Piazza after each class
 - Due 11pm the day of the class
- Reaction post format
 - Summary (~3 lines)
 - What were the main doubts/questions raised in discussion?
 - Expanding (~3 lines)
 - What non-trivial technical aspects were missing in the presentation (but covered in paper)?
 - Brainstorming (~4 lines)
 - Any open interesting questions (e.g., unsolved challenges)? Extensions?
 - What possible applications could benefit from the paper?
 - Any flaws possibly (intentionally) hidden in the paper?

USENIX FAST'14 scribe report: https://www.usenix.org/system/files/login/articles/1406_fast14_reports.pdf

Conference Reports

In this issue:

59 FAST '14: 12th USENIX Conference on File

and Storage Technologies

Summarized by Matias Bjørlin, Jeremy C. W. Chan, Yue Cheng, Qian Ding, Qianzhou Du, Rik Farrow, Xing Lin, Sonam Mandal, Michelle Mazurek, Dutch Meyer, Tiratat Patana-anake, Kai Ren, and Kuei Sun

76 Linux FAST Summit '14

Summarized by Rik Farrow

FAST '14: 12th USENIX Conference on File and Storage Technologies

February 17-20, 2014, San Jose, CA

Opening Remarks

Summarized by Rik Farrow

Bianca Schroeder (University of Toronto) opened this year's USENIX Conference on File and Storage Technologies (FAST '14) by telling us that we represented a record number of attendees for FAST. Additionally, 133 papers were submitted, with 24 accepted. That's also near the record number of submissions, 137, which was set in 2012. The acceptance rate was 18%, with 12 academic, three industry, and nine collaborations in the author lists. The 28 PC members together completed 500 reviews, and most visited Toronto in December for the PC meeting. utilization. Existing garbage collectors, however, are expensive and scale poorly. They wait until a lot of free space is available (to amortize cleaning costs), which can require up to 5x overutilization of memory. When the garbage collector does run, it can consume up to three seconds, which is slower than just resetting the system and rebuilding the RAM store from the backup log on disk.

The authors develop a new cleaning approach that avoids these problems. Because pointers in a file system are well-controlled, centrally stored, and have no circularities, it is possible to clean and copy incrementally (which would not work for a more general-purpose garbage-collection system). In the authors' approach, the cleaner continuously finds and cleans some segments with significant free space, reducing cleaning cost and improving utilization. Further, the authors distinguish between the main log, kept in expensive DRAM with high bandwidth (targeted at 90% utilization), and the backup log, stored on disk where capacity is cheap but bandwidth is lower (targeted at 50% utilization). They use a two-level approach in which one cleaner ("compaction") incrementally cleans one segment at a time in memory, while a second one ("combined cleaning") less frequently cleans across segments in both memory and disk. Both cleaners run in parallel to normal operations, with limited synchronization points to avoid interference with new writes.

Class participation

- Your participation is very important
- Usually as an indicator of how well you've got prepared
 - In-class discussions
 - After-class non-trivial response to reaction posts
- Don't be shy

 Lack of participation may lead to a loss of as much as a letter grade

Homework assignments

- 2 coding homework assignments
 - Pick your partner: a team of at most 2 students
 - #1: Build a consistent cloud object store atop weakly consistent S3: Due on Sep 14
 - #2: Optimize your object store service: Due on Oct 5
- You will learn how to leverage off-the-shelf open-source frameworks and public cloud services to build useful services
 - Assemble microservices together
 - Enable useful tool
- To get you warmed up for the final research projects

Homework assignments

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You will learn how to leve



Assemble microservices

https://aws.amazon.com/education/awseducate/

• To get you warmed up for the final research projects

Research-oriented term projects

- Investigate new ideas and solutions in a class research project
 - Define the problem
 - Execute the research
 - Write up and present your research

 Ideally, best projects will have the potential to become conference papers :)

Research projects: Steps

- I will distribute a list of projects (Week 5/6)
 - You can either choose one or come up with your own
- Pick your partner: a team of at most 2 students
- Milestones (tentative)
 - Project proposal presentation on Oct 17, proposal report due Oct 26
 - Project checkpoint report due Nov 16
 - Final presentation on Dec 5, final project report & src due Dec 14

Grading (tentative)

- Class participation necessary!
 - To get at least 5%
 - 5+ Non-trivial response to reaction posts counts (Piazza tracks post stats)
 - In-class discussions
- HW & Proj
 - START EARLY!!!

Homework assignments	10+10%	Two
Paper evaluations & scribe	10%	~14 evaluation forms + 2 scribe reports
Paper presentations	15%	Two
Class participation	5%	Get involved
Research projects	50%	Substantial!



Questions?

Warm-up & basics

What is Systems Research about?

- Manage resources
 - Memory, CPU, storage, network
 - Data (file systems, database systems, key-value stores)

- Provide abstractions to applications
 - Files
 - Processes, threads
 - Virtual machines (VMs), containers



 So we are using a whole bunch of Cloud-boosted services everyday...



Dropbox example

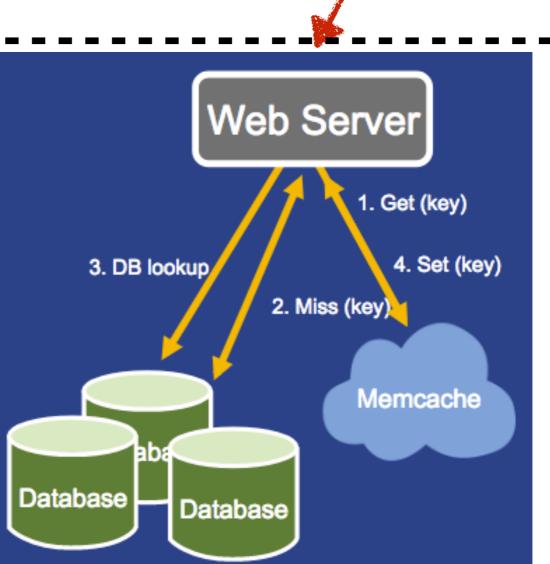
- As a startup, stored all data on AWS initially
- Became so popular so quickly
 - Latest number of users: 500 Million
 - Overall amount of data stored: 500 Petabytes
- Seriously considered to move data out of the public cloud
- Cloud lock-in
 - Egress costs



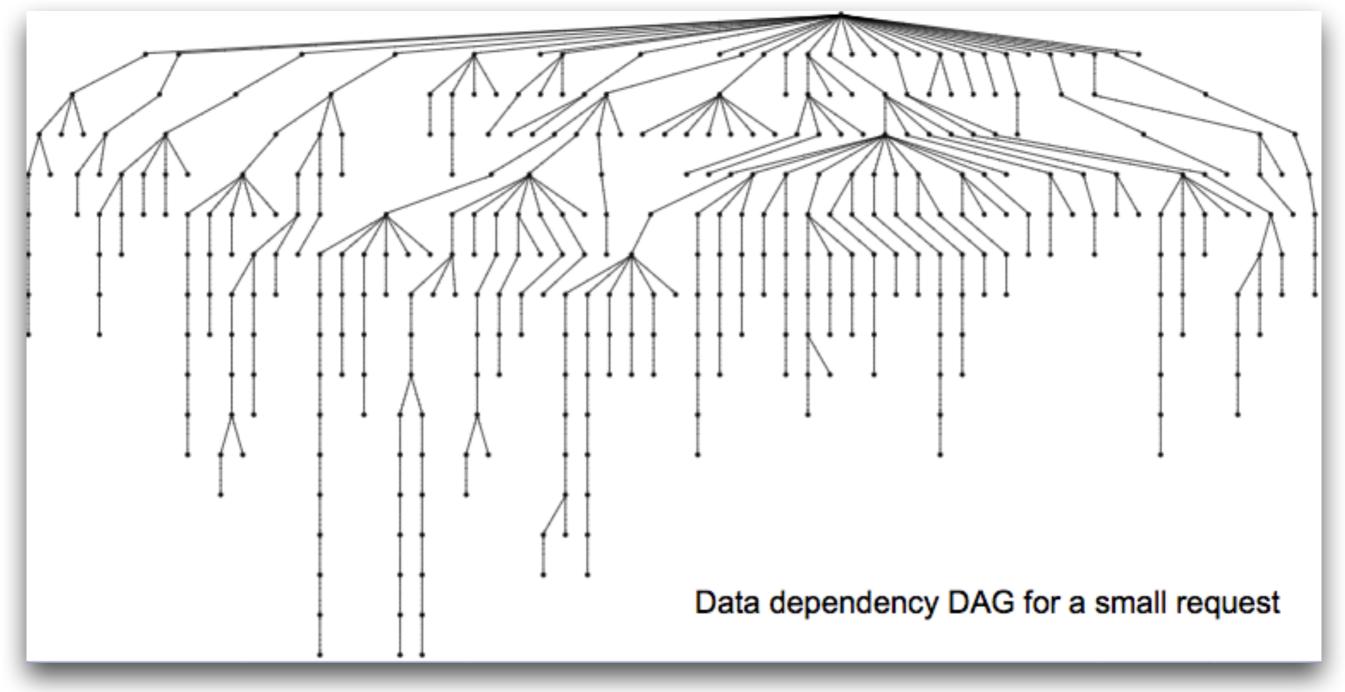
Now still part of its data services sitting atop AWS



- 3. Web servers convert requests to:
 - DB queries
- Memcache queries

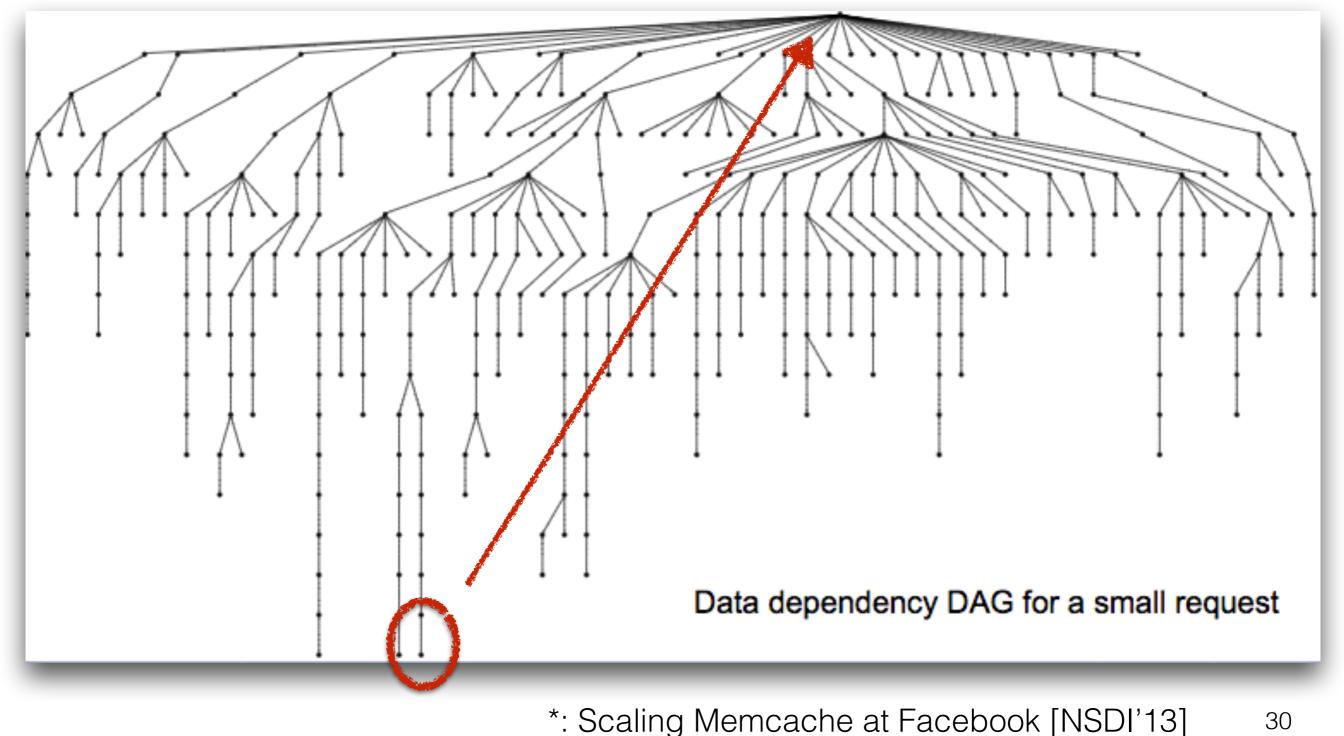


High fanout and multiple rounds of data fetching*



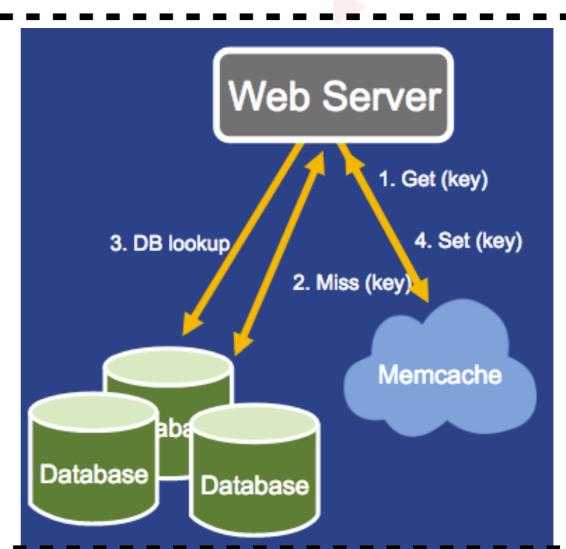
*: Scaling Memcache at Facebook [NSDI'13] 29

• High fanout and multiple rounds of data fetching*



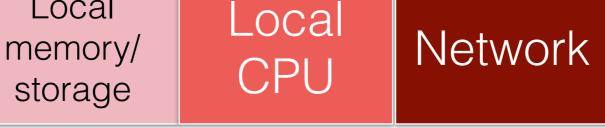
Our focus: To learn how backend magic manages resources

- 3. Web servers convert requests to:
 - DB queries
 - Memcache queries

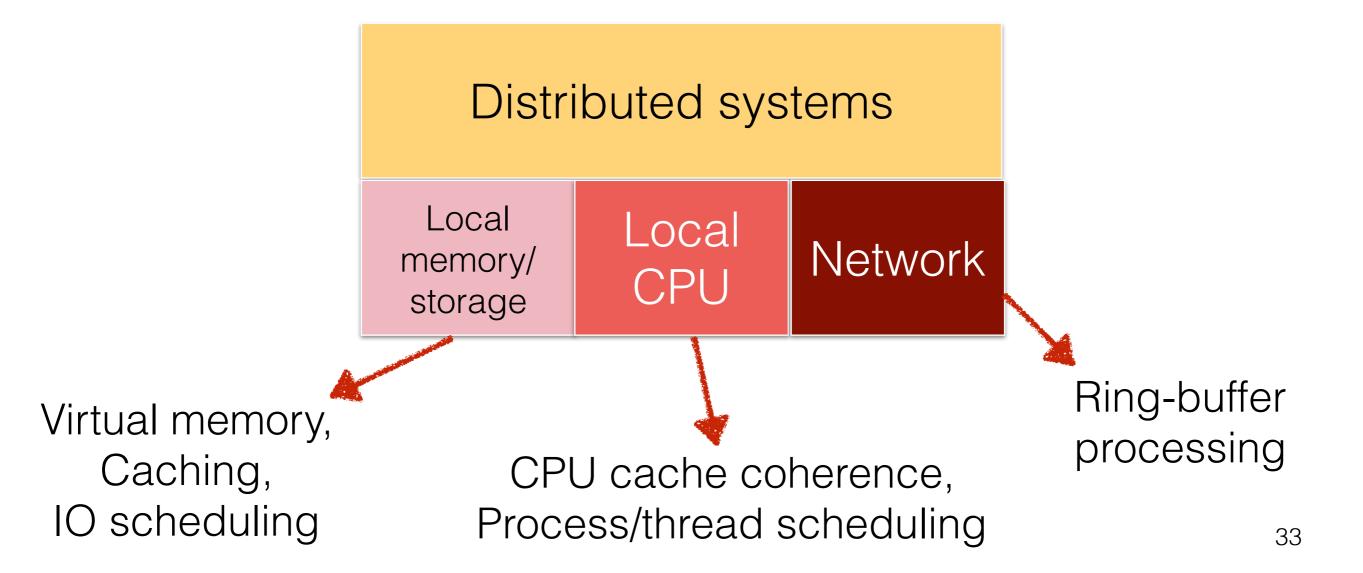


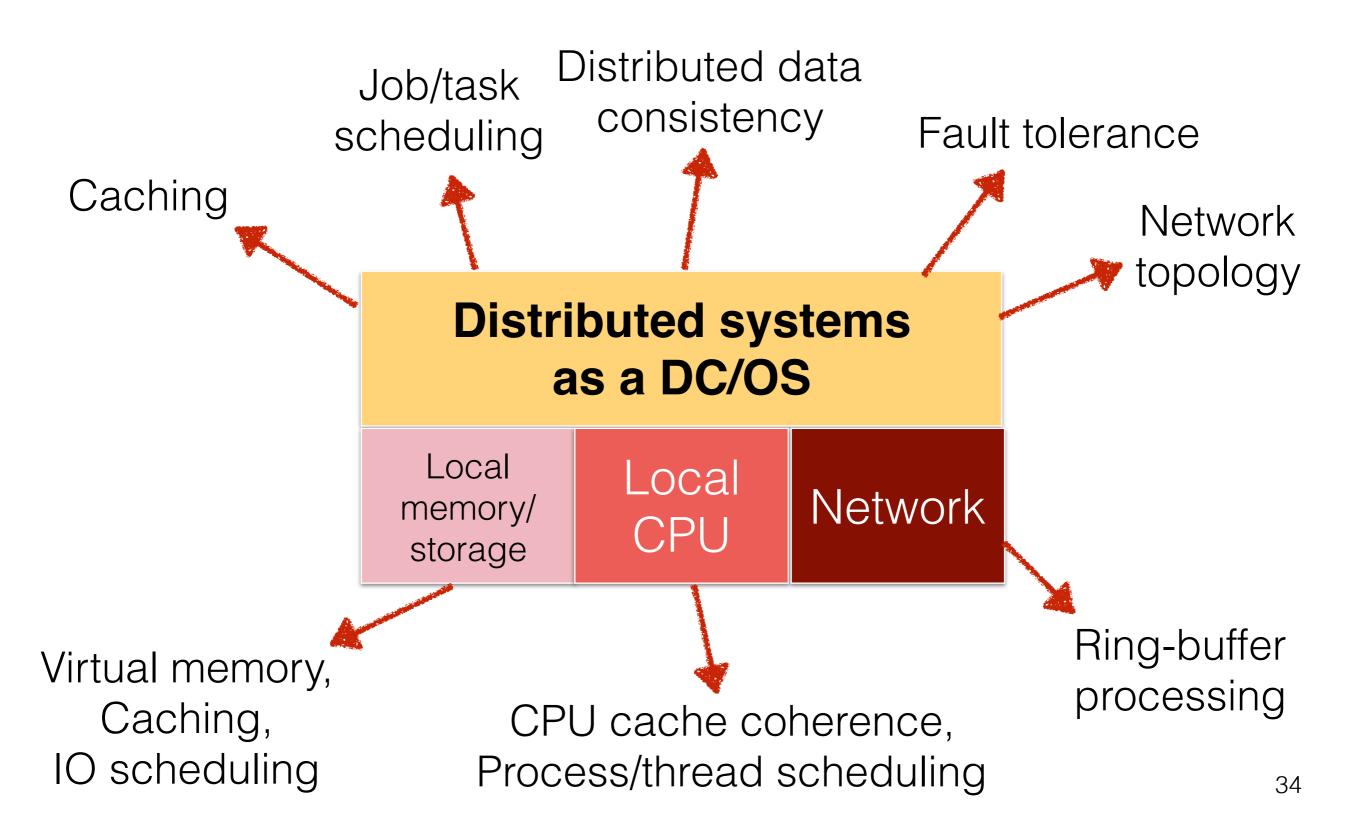
 Those applications/services are the Abstractions & Interfaces. So what is under the hood in the backend?

Applications
(Facebook, Dropbox, Netflix, ...)Distributed systems



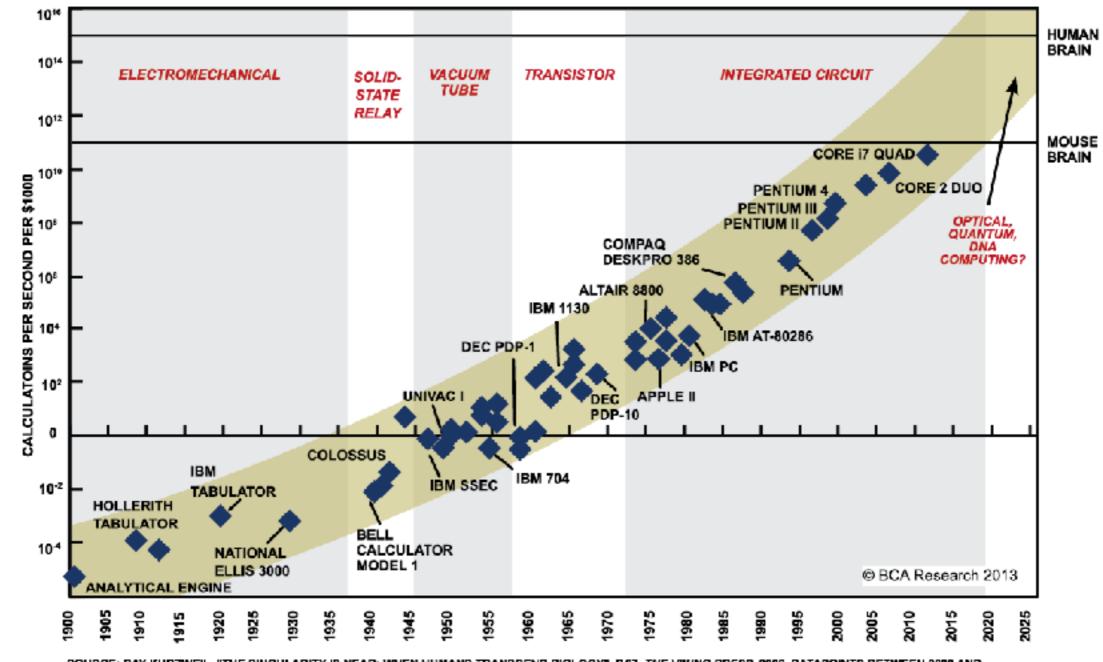
- At single-node level, OS manages all local resources
 - OS is essentially a mini distributed system manager





Exciting times in <u>Distributed Systems</u> <u>& Cloud Computing Research</u>

Moore's law ending —> many challenges

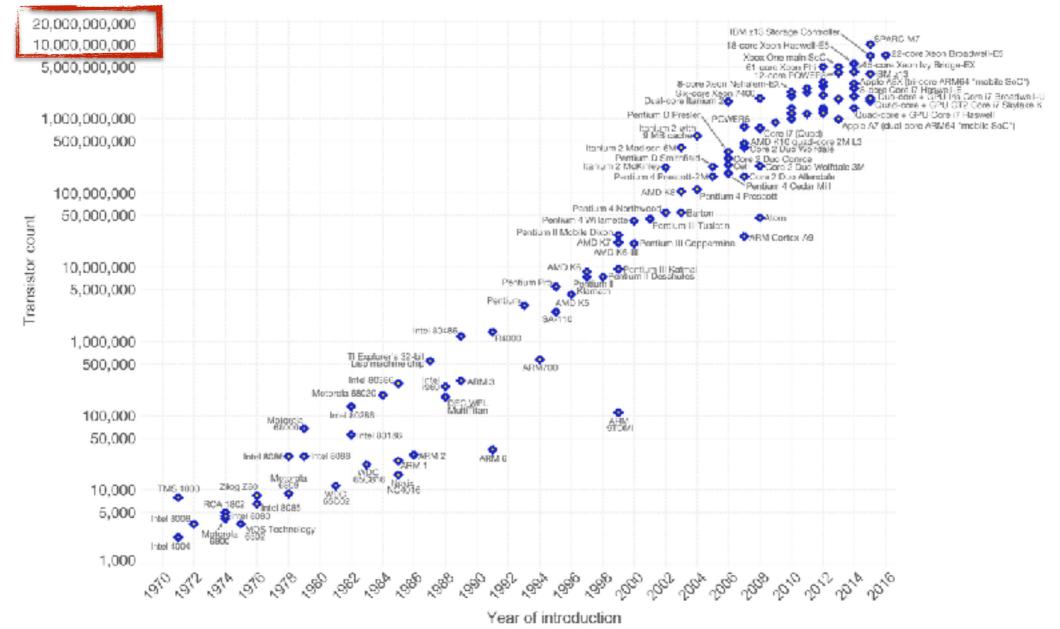


SOURCE: RAY KURZWEIL, "THE SINGULARITY IS NEAR: WHEN HUMANS TRANSCEND BIOLOGY", P.67, THE VIKING PRESS, 2006. DATAPOINTS BETWEEN 2000 AND 2012 REPRESENT BCA ESTIMATES.

Exciting times in <u>Distributed Systems</u> <u>& Cloud Computing Research</u>

• Moore's law ending —> many challenges

Moore's Law – The number of transistors on integrated circuit chips (1971-2016) Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important as other aspects of technological progress – such as processing speed or the price of electronic products – are strongly linked to Moore's law.



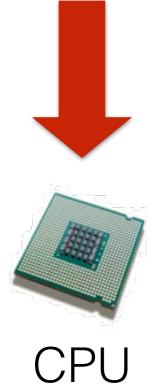
Data source: Wikipedia (https://en.wikipedia.org/wiki/Transistor_count) The data visualization is available at OurWorldinData.org. There you find more visualizations and research on this topic.

Exciting times in <u>Distributed Systems</u> <u>& Cloud Computing Research</u>

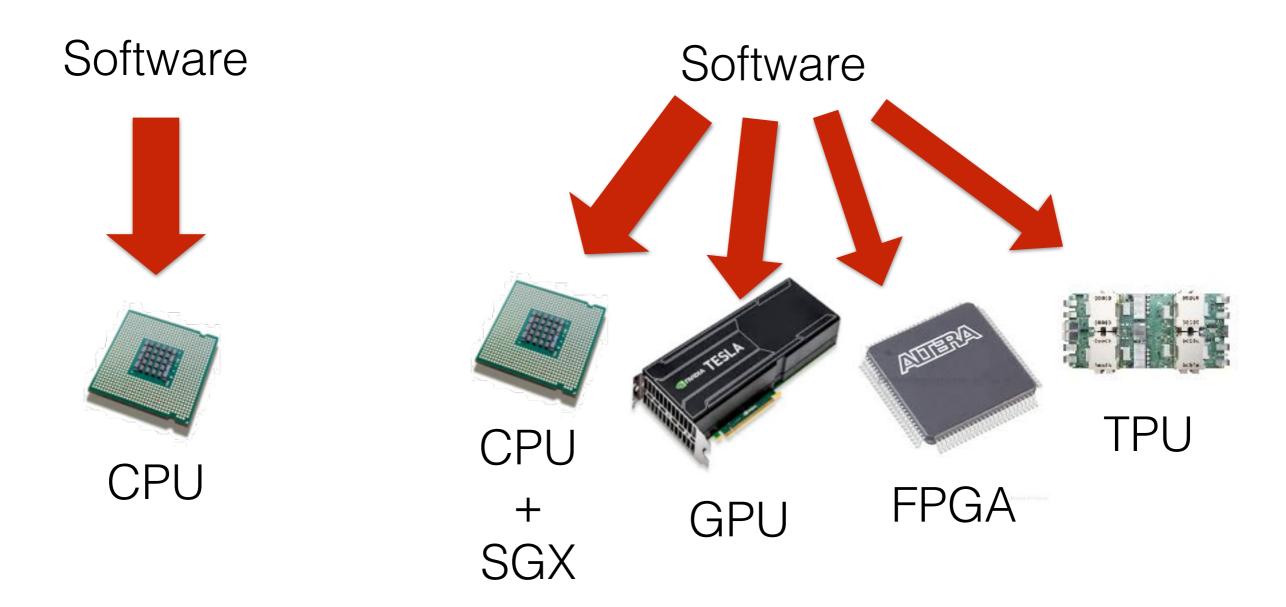
- Many-core machines
 - Amazon's X1 instances: 128 scores and 2TB DRAM
- Large-scale distributed systems maturing, but many challenges remain
- Specialized hardware
 - [GP]GPUs, FPGAs, etc.
- New memory technologies: Non-Volatile Memories (NVMs)
 - 3D XPoint

Increased complexity — Computation

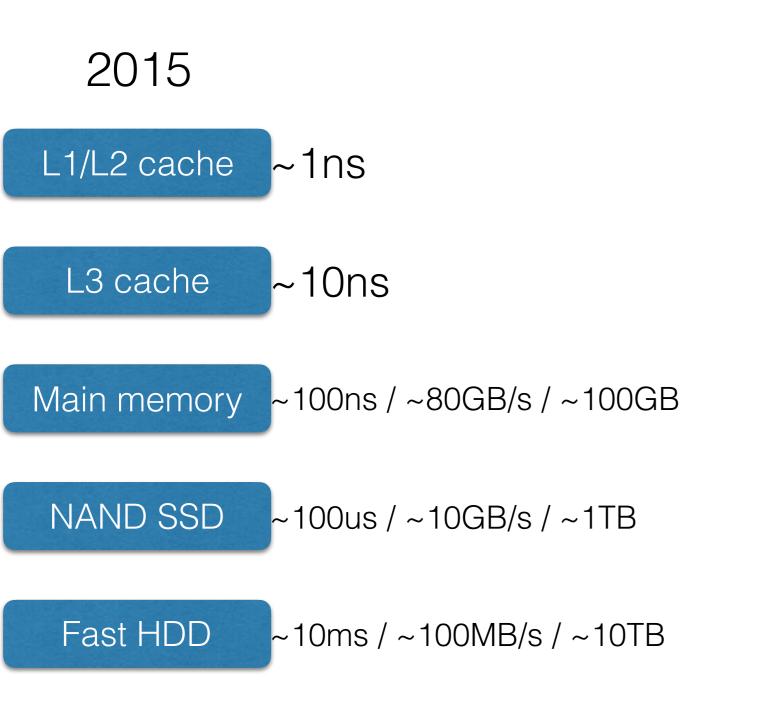




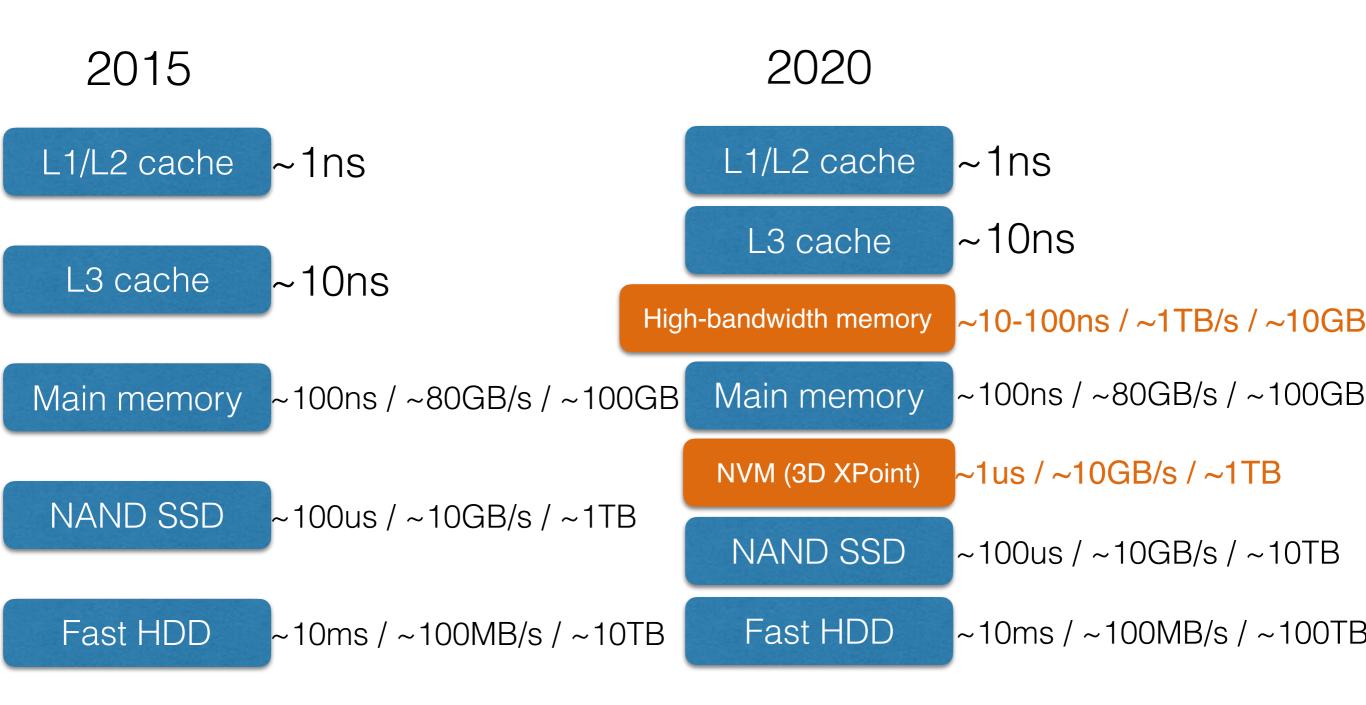
Increased complexity — Computation



Increased complexity — Memory



Increased complexity — Memory



Increased complexity — More and more choices — **Decision Paralysis!**

Basic tier: A0, A1, A2, A3, A4 Optimized Compute : D1, D2, D3, D4, D11, D12, D13 D1v2, D2v2, D3v2, D11v2,... Latest CPUs: G1, G2, G3, ... Network Optimized: A8, A9 Compute Intensive: A10, A11,...

Microsoft Azure

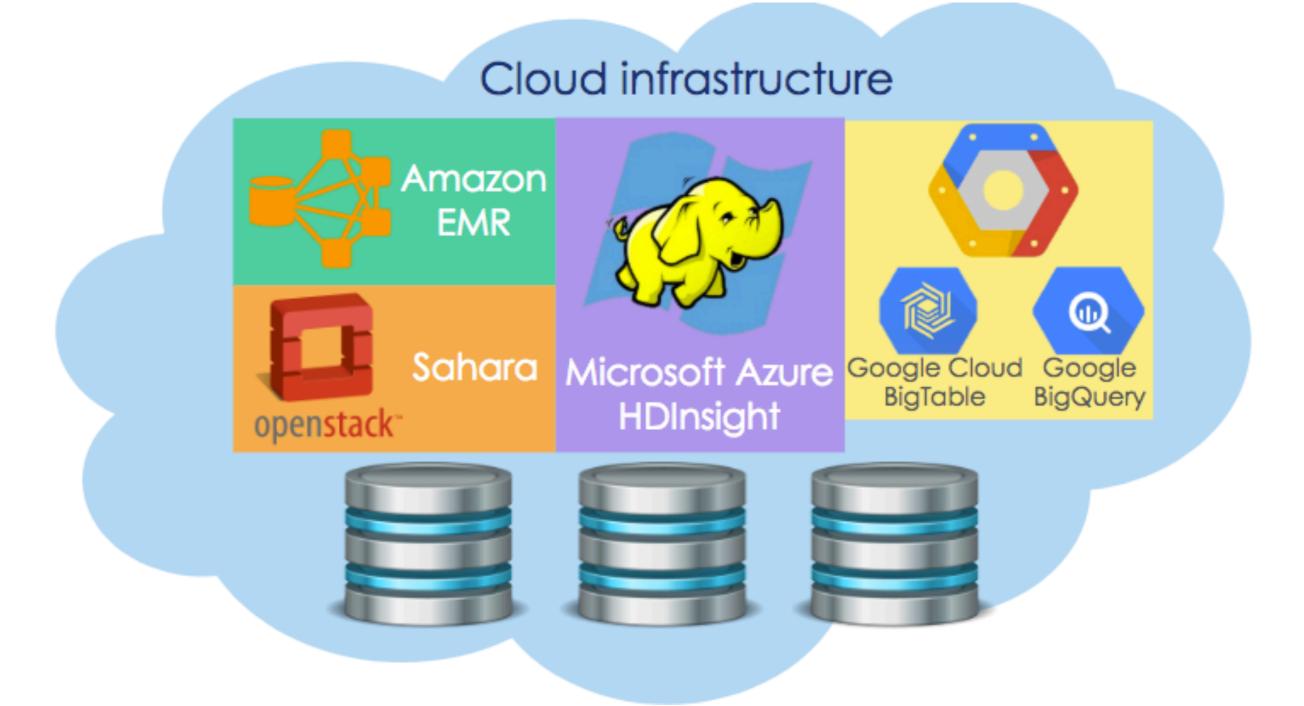
n1-standard-1, ns1-standard-2, ns1-standard-4, ns1-standard-8, ns1-standard-16, ns1highmem-2, ns1-highmem-4, ns1-highmem-8, n1-highcpu-2, n1-highcpu-4, n1highcpu-8, n1-highcpu-16, n1highcpu-32, f1-micro, g1-small...

Google Cloud Engine

t2.nano, t2.micro, t2.small m4.large, m4.xlarge, m4.2xlarge, m4.4xlarge, m3.medium, c4.large, c4.xlarge, c4.2xlarge, c3.large, c3.xlarge, c3.4xlarge, r3.large, r3.xlarge, r3.4xlarge, i2.2xlarge, i2.4xlarge, d2.xlarge d2.2xlarge, d2.4xlarge,...

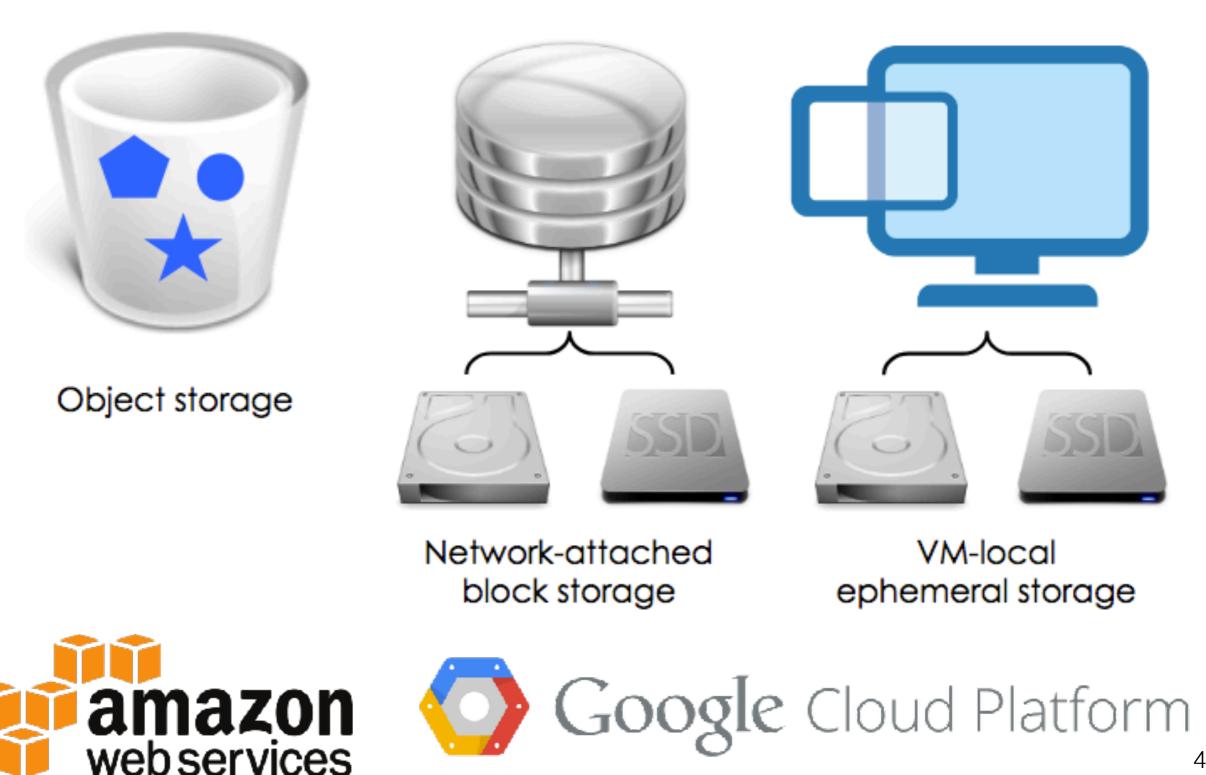
AWS EC2

Case study: Choices of cloud storage for big data analytics



*: CAST: Tiering Storage for Data Analytics in the Cloud [HPDC'15]

Vast variety of cloud storage services



Storage type	Capacity (GB/volume)	Throughput (MB/sec)	IOPS (4KB)	Cost (\$/month)
ephSSD	375	733	100000	0.218×375
persSSD	100	48	3000	0.17×100
	250	118	7500	0.17×250
	500	234	15000	0.17×500
persHDD	100	20	150	0.04×100
	250	45	375	0.04×250
	500	97	750	0.04×500
objStore	N/A	265	550	0.026/GB

ephSSD: VM-local ephemeral SSD, persSSD: Network-attached persistent SSD, persHDD: Network-attached persistent HDD, objStore: Google cloud object storage

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Ephemeral SSDs offer best perf but without data persistence!

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Perf of the network-attached EBS (block storage) depends on size of the volume!

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Object store provides the cheapest service but offers comparable sequential IO throughput!

To make things worse: Heterogeneity in data analytics workloads

Application	I/O-intensive			CPU-intensive
	Мар	Shuffle	Reduce	
Sort	×	 Image: A second s	×	×
Join	×	 Image: A second s	 Image: A second s	×
Grep	 Image: A second s	×	×	×
KMeans	×	×	×	 Image: A second s

Decision paralysis...

Highly heterogeneous cloud storage services Highly heterogeneous analytics workloads

How do I get the MOST BANG-for-thebuck? \$\$

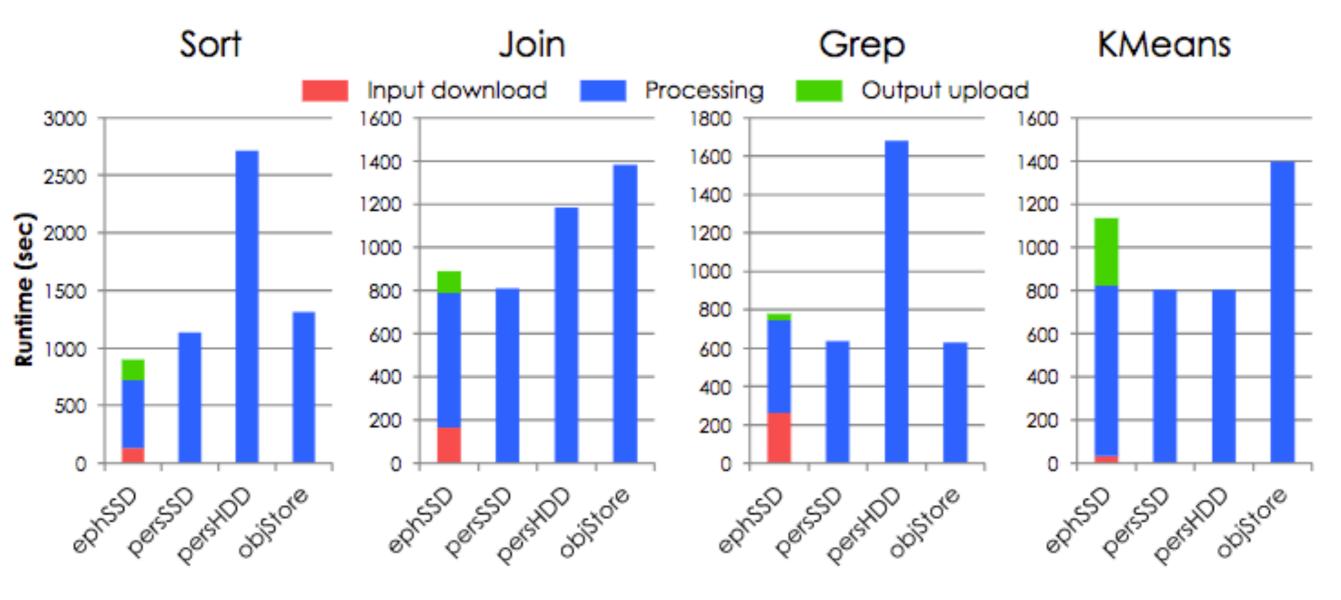
Cloud tenant

What to do?

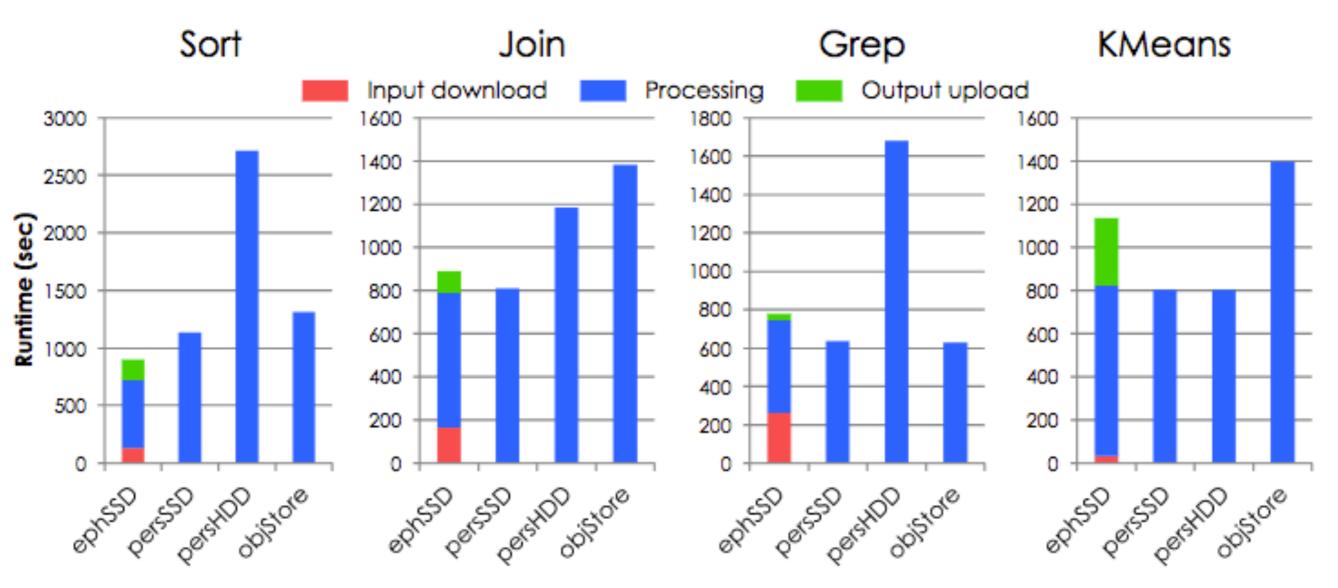
 Not much is known about how current data analytics workloads perform on various cloud storage services

• So, measure...

Application performance

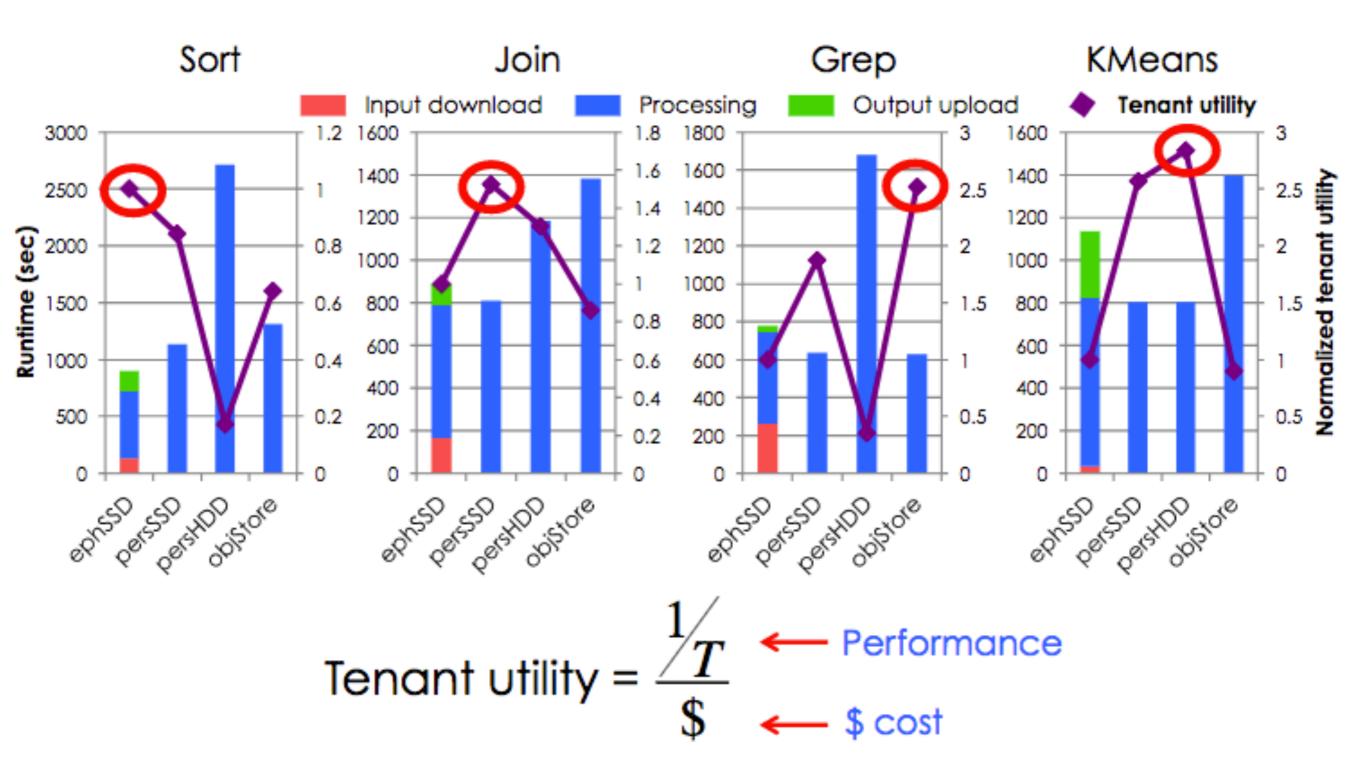


Application performance

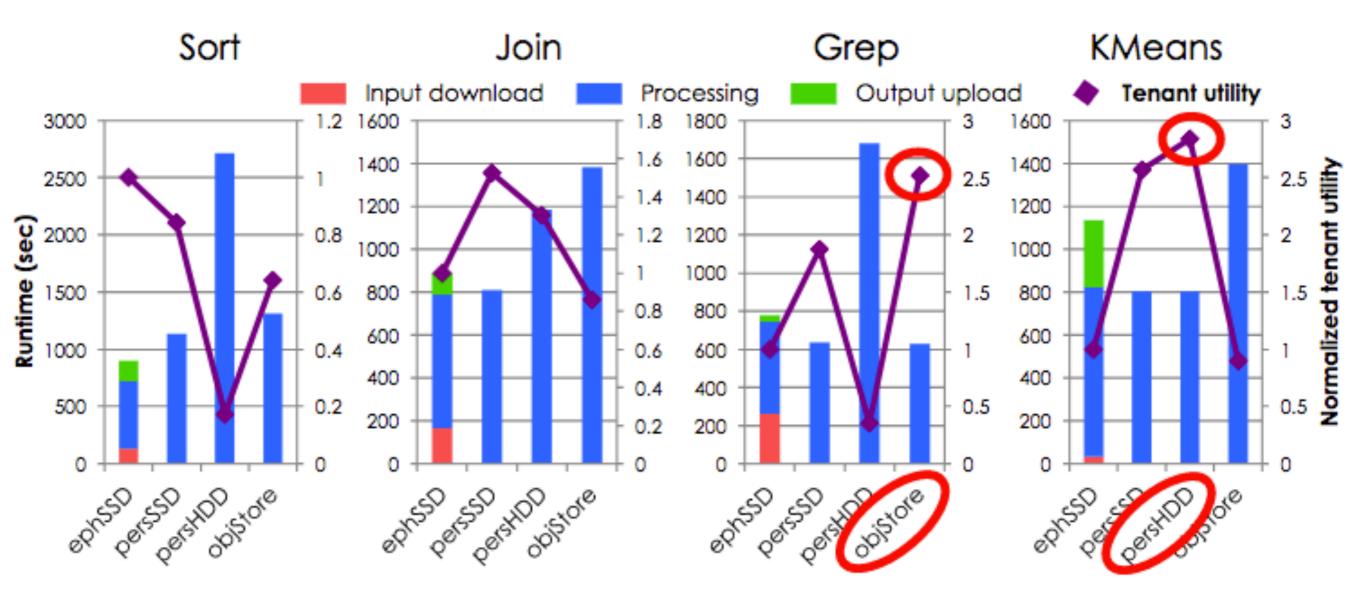


No storage service is the best in terms of performance

Application performance/\$cost

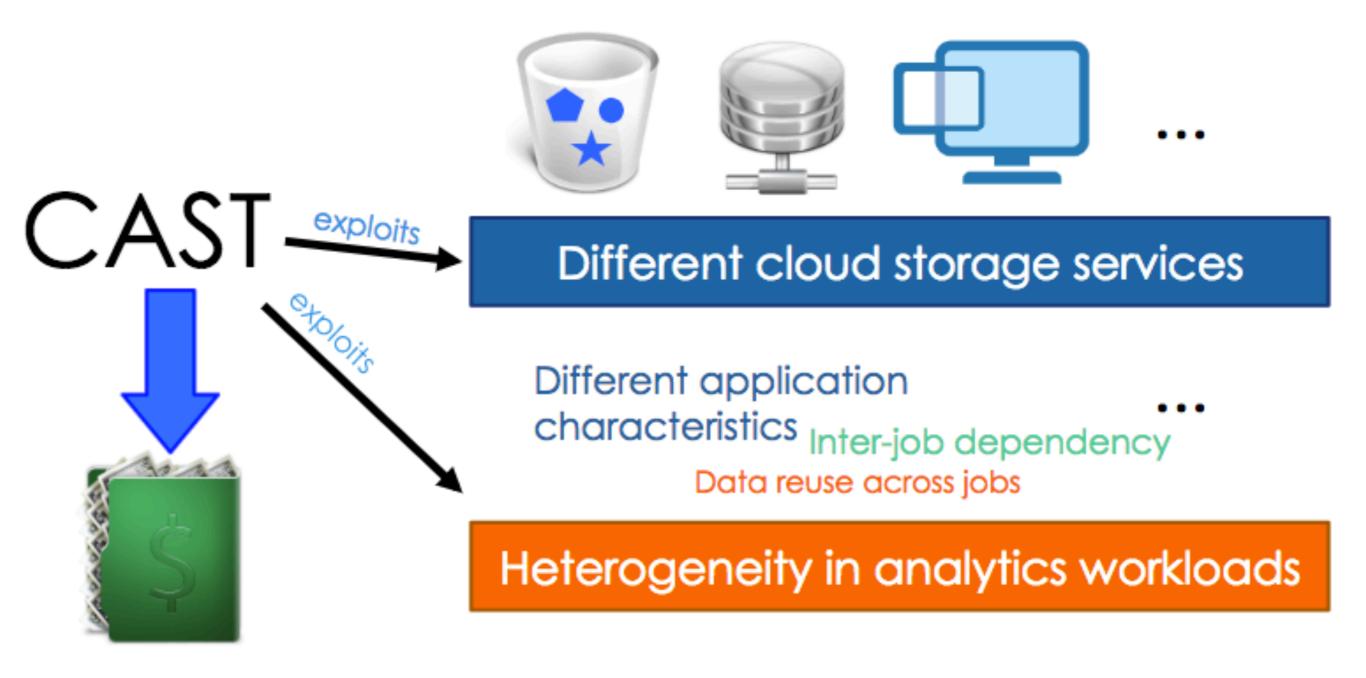


Application performance/\$cost

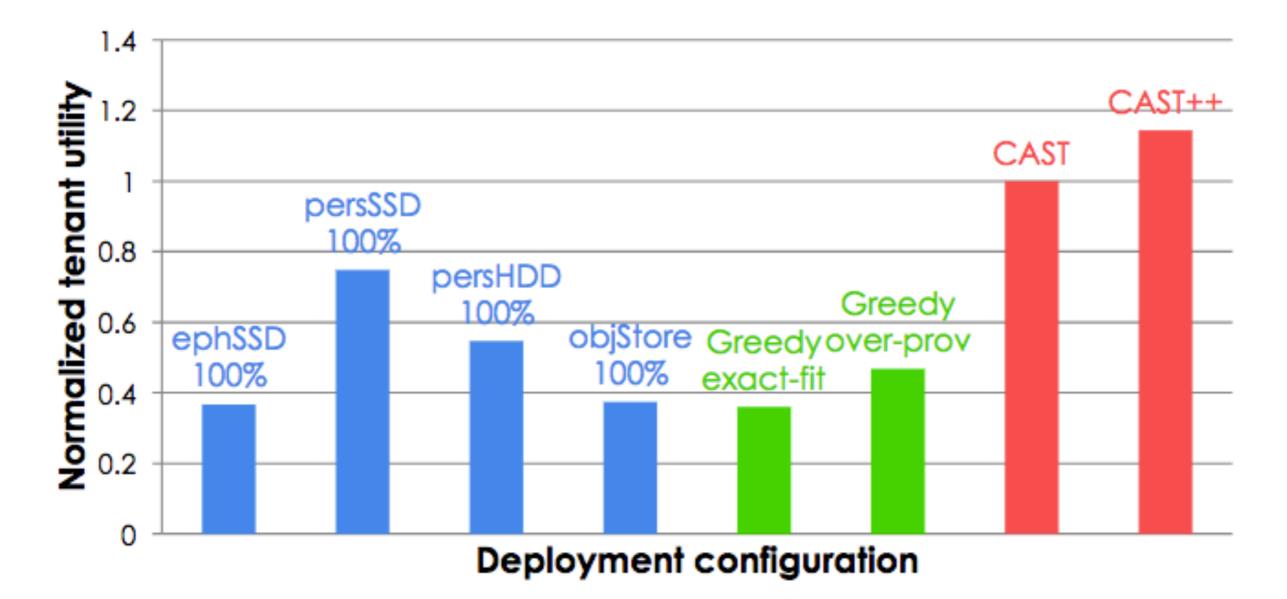


Slower storage, in some case, may provide higher utility and comparable performance

So we built CAST: A <u>C</u>loud <u>A</u>nalytics <u>S</u>torage <u>T</u>iering framework



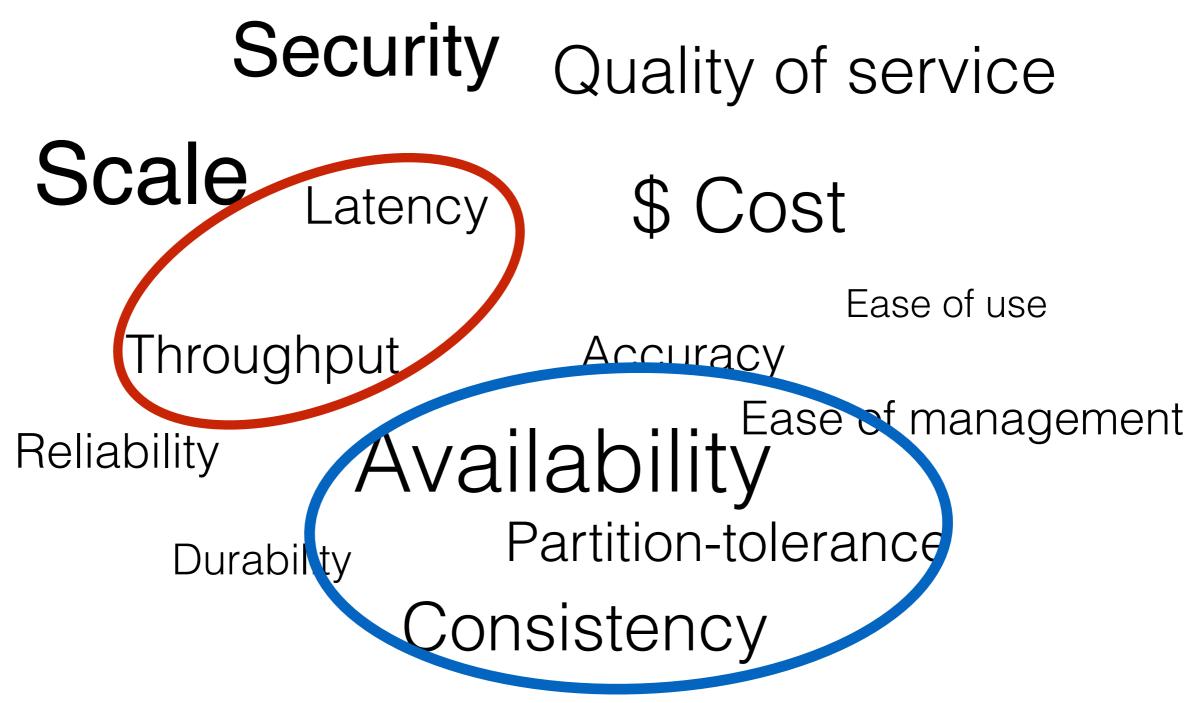
Some results



100-job Hadoop workload, simulating behaviors of Facebook's 3000-machine Hadoop clusters

Increased complexity — More and more requirements Security Quality of service Scale Latency \$ Cost Ease of use Throughput Accuracy Ease of management Availability Reliability Partition-tolerance Durability Consistency

What are hard/fundamental tradeoffs?



- Top-tier systems research conferences
 - USENIX OSDI, ACM SOSP (bi-annually)
 - ACM EuroSys
 - USENIX NSDI, ACM SIGCOMM
 - USENIX ATC, USENIX FAST

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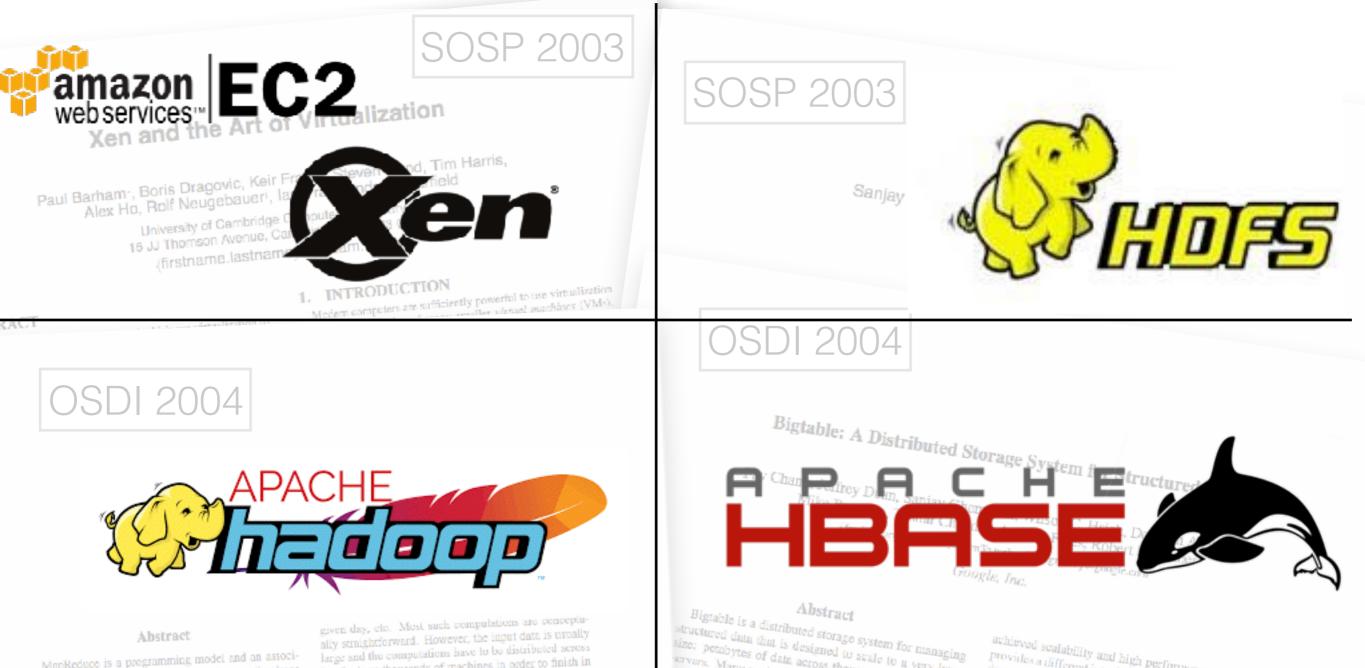


provides a different

MapReduce is a programming model and an associ-

ally straightforward. However, the input data is usually large and the computations have to be distributed scross ends of machines in order to finish in

- Top-tier systems research conferences
 - USENIX OSDI, ACM SOSP (bi-annually)



- Top-tier systems research conferences
 - USENIX OSDI, ACM SOSP (bi-annually)



TensorFlow: A System for Large-Scale Machine Learning

Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, Manjunath Kudlur, Josh Levenberg, Rajat Monga, Sherry Moore, Derek G. Murray, Benoit Steiner, Paul Tucker, Vijay Vasudevan, Pete Warden, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng, *Google Brain*

https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi

This paper is included in the Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI '16). Google File System

Storage System for Structured Data

amawat, Wilson C. Hsich, Deborah A. Wallach dra, Andrew Fikes, Robert E. Gruber ^{m3h,ushar,Fikes,gmber})©google.com

achieved scalability and high performant

Top-tier systems research conferences

USENIX OSDI, ACM SOSP (bi-annually)

[PDF] TensorFlow: A System for Large-Scale Machine Learning - Usenix https://www.usenix.org/system/files/conference/osdi16/osdi16-abadi.pdf by M Abadi - Cited by 5662 - Related articles and Implementation (OSDI '16). November 2-4, 2016 • Savannah, GA, USA. ISBN 978-1-931971-33-1. Open access to the Proceedings of the. 12th USENIX ...

[PDF] MapReduce: Simplified Data Processing on ... - Research - Google https://research.google.com/archive/mapreduce-osdi04.pdf by J Dean - 2004 - Cited by 25231 - Related articles Abstract. MapReduce is a programming model and an associ- ... sand MapReduce jobs are executed on Google's clusters ... To appear in OSDI 2004. 1 ...

[PDF] The Google File System - Research

https://research.google.com/archive/gfs-sosp2003.pdf ABSTRACT. We have designed and implemented the Ge system for large distributed data-intensive applications.

by S Ghemawat - 2003 - Cited by 7915 - Related articles Xen and the art of virtualization - ACM Digital Library - Association for ... https://dl.acm.org/citation.cfm?id=945462 by P Barham - 2003 - Cited by 8433 - Related articles SOSP '03 Proceedings or the nineteenth ACM symposium on Operating systems 2003. http://www.ensim.com/products/materials/datasheet_vps_051003.pdf.

Abstract · Authors · References · Cited By

- Top-tier systems research conferences
 - USENIX OSDI, ACM SOSP (bi-annually)
 - ACM EuroSys
 - USENIX NSDI,

NSDI 2012

Resilient Distributed Datasets: A Fault-Tolerant Abstraction In-Memory Cluster Computing

Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justir Murphy McCauley, Michael J. Franklin, Scott Shenker, Ion Stoica University of California, Berkeley

Abstract

We present Resilient Distributed Datasets (RDDs), a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a fault-tolerant manner. RDDs are motivated by two types of applications that current computing frameworks handls inefficiently: iterative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude. To achieve fault tolerance efficiently, RDDs provide a restricted form of shared memory, based on coarsegrained transformations rather than fine-grained updates to shared state. However, we show that RDDs are expressive enough to capture a wide class of computations, including recent specialized programming models for iterative jobs, such as Pregel, and new applications that these tion, which can dominate application of

Recognizing this problem, research, specialized frameworks for some apquire data reuse. For example, Pregel [iterative graph computations that keeps in memory, while HaLoop [7] offers a duce interface. However, these framew specific computation patterns (e.g., le MapReduce steps), and perform data for these patterns. They do not provis more general reuse, e.g., to let a user lo into memory and run ad-hoc queries a

In this paper, we propose a new abs silient distributed datasets (RDDs) the data reuse in a broad range of applic fault-tolerant, parallel data structures plicitly persist intermediate results in

EuroSys 2015

Large-scale cluster management at Google with Borg

Abhishek Verma[†] Luis Pedrosa[‡] Madhukar Korupolu David Oppenheimer Eric Tune John Wilkes

Google Inc.

Abstract

Google's Borg system is a cluster manager that runs hundreds of thousands of jobs, from many thousands of different applications, across a number of clusters each with up to tens of thousands of machines.

It achieves high utilization by combining admission control, efficient task-packing, over-commitment, and machine sharing with process-level performance isolation. It supports high-availability applications with runtime features that minimize fault-recovery time, and scheduling policies that reduce the probability of correlated failures. Borg simplifies life for its users by offering a declarative job specification language, name service integration, real-time job monitoring, and tools to analyze and simulate system behavior.

We present a summary of the Borg system architecture and features, important design decisions, a quantitative analysis of some of its policy decisions, and a qualitative examination of lessons learned from a decade of operational experience with it.

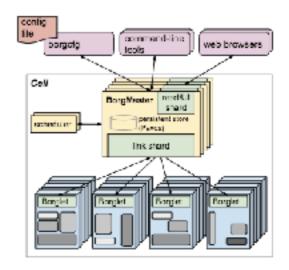


Figure 1: The high-level architecture of Borg. Only a tiny fraction of the thousands of worker nodes are shown.

cluding with a set of qualitative observations we have made from uncertaine Bors in production for more than a decade

- Top-tier systems research conferences
 - USENIX OSDI, ACM SOSP (bi-annually)
 - ACM EuroSys
 - USENIX NSDI,

NSDI 2012

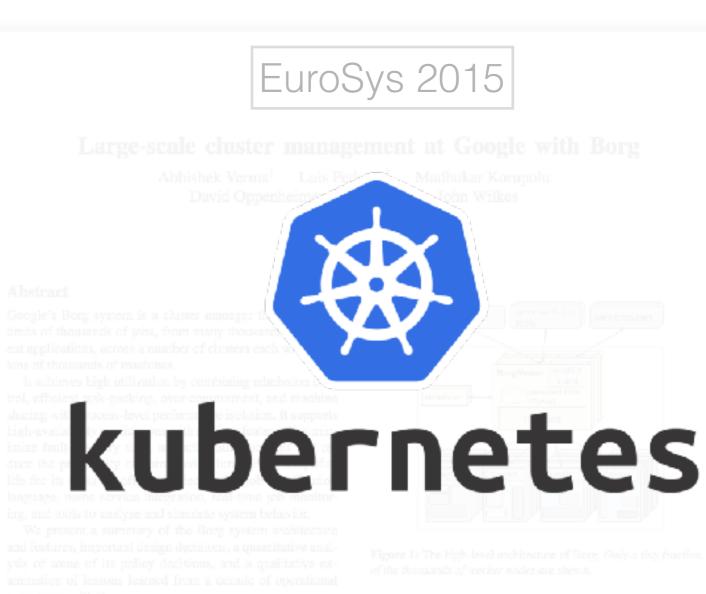
Resilient Distributed Datasets: A Fault-Terrent Abstracti In-Memory Cluster Company

or application that current computing frameworks handle inefficient citerative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude. To achieve fault tolerance efficiently, RDDs provide a restricted form of shared memory, based on coarsegrained transformations rather than fine-grained updates to shared state. However, we show that RDDs are expressive enough to capture a wide class of computations, including recent specialized programming models for iterative jobs, such as Presel, and new applications that these

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in minimum, while constant one that keep in minimum, while constant Q(M) offers a duce interface. However, these frames specific computation patterns (e.g., 1 MapReduce steps), and perform that for these patterns. They do not provimore general reuse, e.g., to let a user lo into memory and run ad-hoc queries a

In this paper, we propose a new ab silient distributed datasets (RDDs) th data reuse in a broad range of applifault-tolerant, parallel data structures olicitly persist intermediate results it



cluding with a set of qualitative observations we have made from operating Boys in production for more than a decade

- Distributed systems foundation
 - Distributed consensus algorithms: 2PC, 3PC, Paxos, Raft
 - Data consistency: Strong consistency, Eventual consistency, causal consistency

- Cloud storage
 - Amazon Dynamo, Hybrid-cloud storage, Azure cloud storage, Google Spanner, LinkedIn Ambry object store, *BespoKV* [Sneak peek: our must recent paper:)]

- Container-based virtualization
 - Container virtualization, container registry, IBM's Docker registry workload characterization

- Serverless computing
 - Serverless architecture, current state, innovative applications

- Distributed machine learning
 - Ray, Tensorflow, Parameter server

- Big data systems
 - Google MapReduce, Google File System (GFS), Google Bigtable, Hadoop YARN, Apache Spark

- Cluster and datacenter resource management
 - Google Borg, Apache Mesos, Omega, Sparrow, Quasar, etc.

- Memory-driven computing
 - Distributed memory caching, RAMCloud, Facebook's Memcache
 - Memcached's load balancing, Tachyon's erasure coding based load balancing

Announcement

- Homework assignment #0 (0%):
 - A one-pager self-intro (get to know each other better :)
 - Piazza sign-up
 - Paper presentation sign-up (FCFS: will send out a Doodle link)
 - AWS Educate sign-up
- Next class
 - Distributed consensus algorithms
 - Data consistency
 - Take a look at all papers on website for next class
 - Release of homework assignment #1