The Rise of Cloud Computing Systems

Jeff Dean
Google, Inc.

(Describing the work of thousands of people!)

Utility computing: Corbató & Vyssotsky, “Introduction and Overview of the Multics system”, AFIPS Conference, 1965.

Picture credit: http://www.multicians.org/


Google | google.com/datacenters

How Did We Get to Where We Are?

Prior to mid 1990s: Distributed systems emphasized:

- modest-scale systems in a single site (Grapevine, many others), as well as

- widely distributed, decentralized systems (DNS)

Adjacent fields

High Performance Computing:

Heavy focus on performance, but not on fault-tolerance

Transactional processing systems/database systems:

Strong emphasis on structured data, consistency

Limited focus on very large scale, especially at low cost

Caveats

Very broad set of areas:

Can’t possible cover all relevant work

Focus on few important areas, systems, and trends

Will describe context behind systems with which I am most familiar

What caused the need for such large systems?

Very **resource-intensive interactive services** like **search** were key drivers

Growth of web

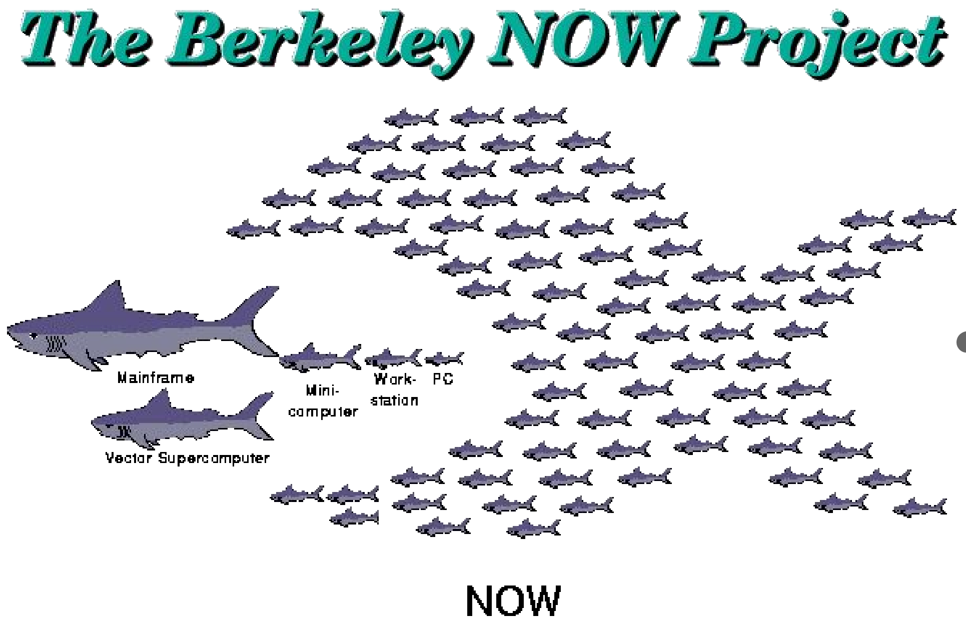
… from millions to hundreds of billions of pages

… and need to index it all,

… and search it millions and then billions of times per day

… with sub-second latencies

Inktomi



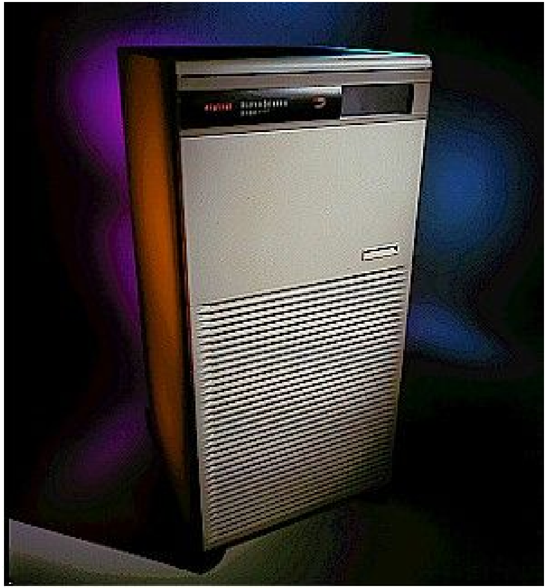
A Case for Networks of Workstations: NOW, Anderson, Culler, & Patterson. IEEE Micro, 1995

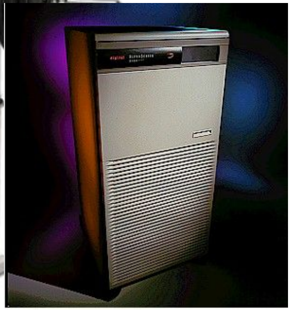
Cluster-Based Scalable Network Services, Fox, Gribble, Chawathe, Brewer, & Gauthier, SOSP 1997.

Picture credit: http://now.cs.berkeley.edu/ and http://wikieducator.org/images/2/23/Inktomi.jpg

My Vantage Point

Joined DEC WRL in 1996 around





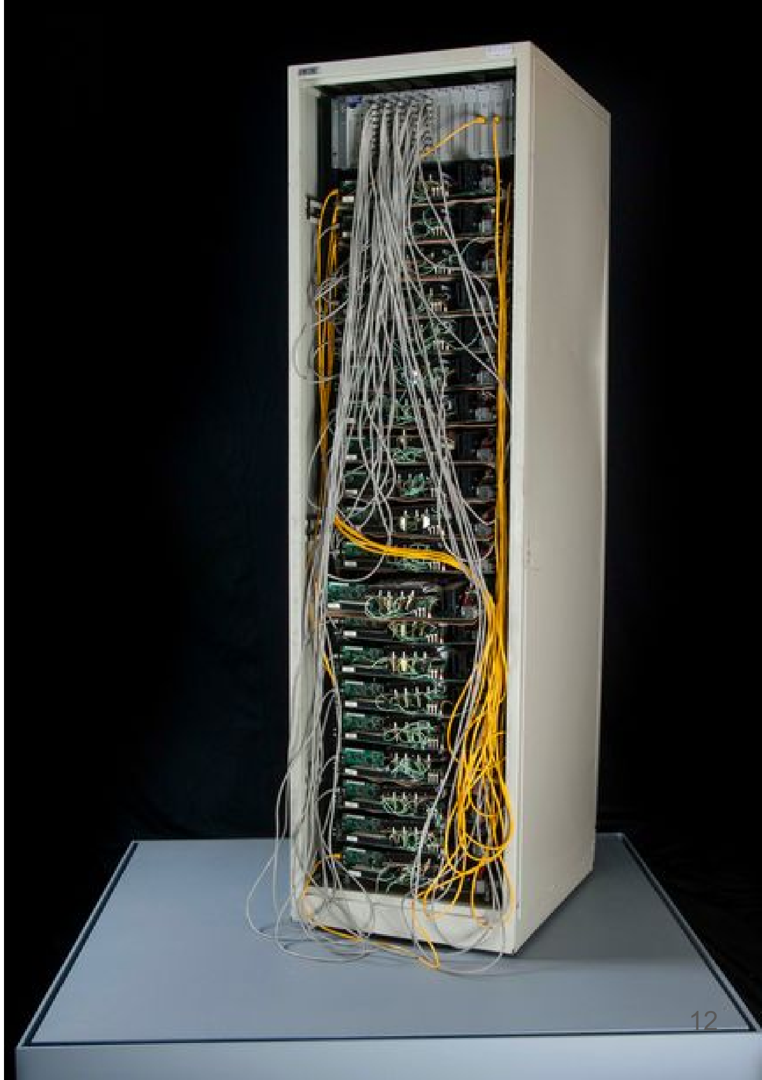
Picture credit: http://research.microsoft.com/en-us/um/people/gbell/digital/timeline/1995-2.htm

My vantage point, continued: Google, circa 1999

Early Google tenet:
Commodity PCs give **high perf/$**

Commodity components **even better!**

Aside: use of cork can land your computing platform in the Smithsonian



Picture credit: http://americanhistory.si.edu/exhibitions/preview-case-american-enterprise

At Modest Scale: Treat as Separate Machines

```
for m in a7 a8 a9 a10 a12 a13 a14 a16 a17 a18
a19 a20 a21 a22 a23 a24; do ssh -n $m "cd
/root/google; for j in "`seq $i $[$i+3]`'; do
j2=`printf %02d $j`; f=`echo '$files' | sed
s/bucket00/bucket$j2/g`; fgrun bin/buildindex
$f; done' & i=$[$i+4]; done
```

What happened to poor old `a11` and `a15`?

At Larger Scale: Becomes Untenable

Typical first year for a new Google cluster (circa 2006)

~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-min 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.

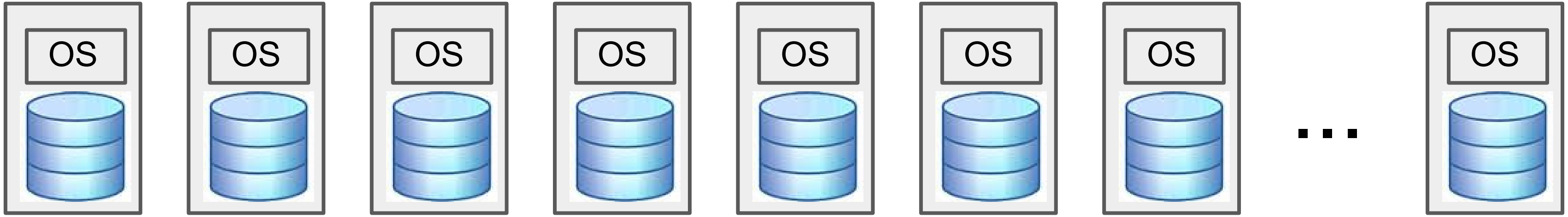
Long distance links: **wild dogs, sharks, dead horses, drunken hunters, etc.**

Reliability Must Come From Software

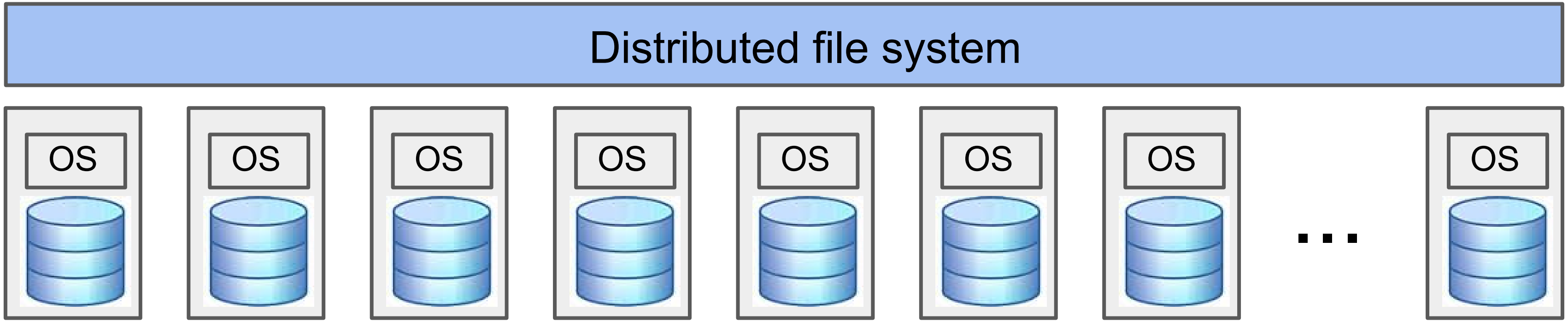
A Series of Steps,
All With Common Theme:

Provide Higher-Level View Than
"Large Collection of Individual Machines"

Self-manage and self-repair as much as possible



First Step:
Abstract Away Individual Disks



Long History of Distributed File Systems

Xerox Alto (1973), NFS (1984), many others:
    File servers, distributed clients

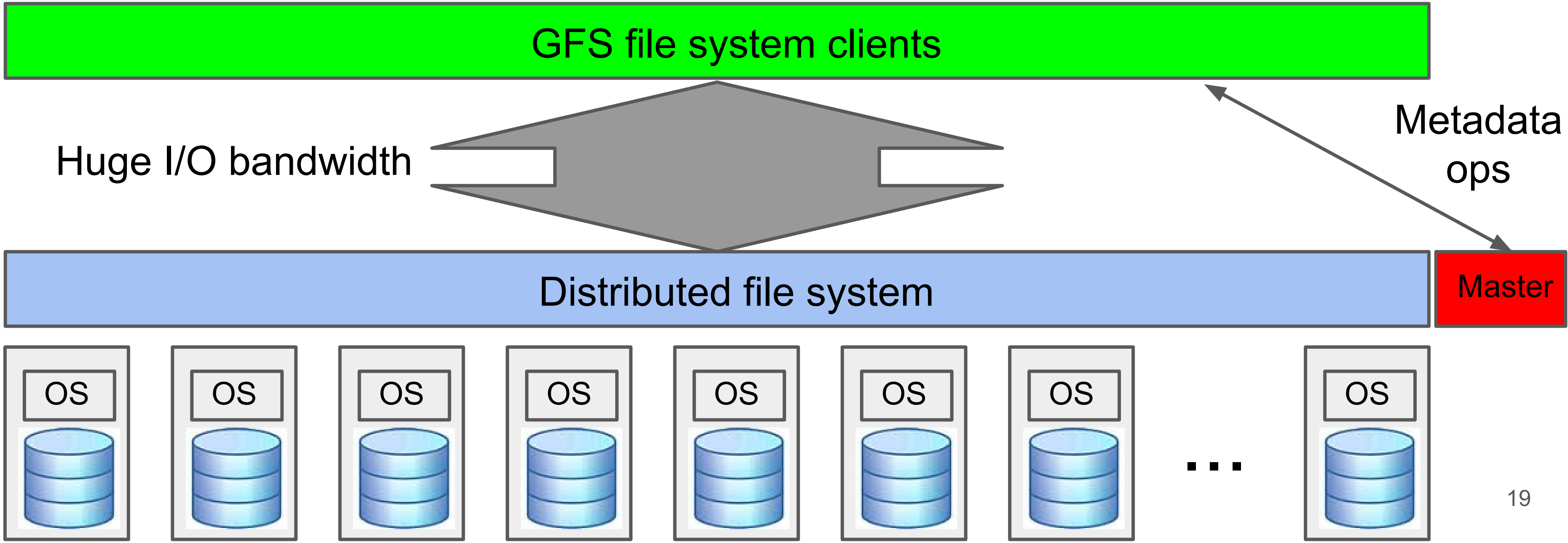
AFS (Howard et al. ‘88):
    1000s of clients, whole file caching, weakly consistent

xFS (Anderson et al. ‘95):
    completely decentralized

Petal (Lee & Thekkath, ‘95), Frangipani (Thekkath et al., ‘96):
    distributed virtual disks, plus file system on top of Petal

Google File System (Ghemawat, Gobioff, & Leung, SOSP'03)

- Centralized master manages metadata
- 1000s of clients read/write directly to/from 1000s of disk serving processes
- Files chunks of 64 MB, each replicated on 3 different servers
- High fault tolerance + automatic recovery, high availability



Disks in datacenter basically self-managing

Successful design pattern:

Centralized master for metadata/control, with thousands of workers and thousands of clients

Once you can store data, then you want to be able to process it efficiently

Large datasets implies need for highly parallel computation

One important building block:
Scheduling jobs with 100s or 1000s of tasks

Multiple Approaches

- Virtual machines
- “Containers”: akin to a VM, but at the process level, not whole OS

Virtual Machines

- Early work done by MIT and IBM in 1960s
    - Give separate users their own executing copy of OS
- Reinvigorated by Bugnion, Rosenblum *et al.* in late 1990s
    - simplify effective utilization of multiprocessor machines
    - allows consolidation of servers

Raw VMs: key abstraction now offered by cloud service providers

Cluster Scheduling Systems

- **Goal: Place containers or VMs on physical machines**
    - handle resource requirements, constraints
    - run multiple tasks per machine for efficiency
    - handle machine failures

Similar problem to earlier HPC scheduling and distributed workstation cluster scheduling systems

e.g. Condor [Litzkow, Livny & Mutkow, ‘88]

Many Such Systems

- Proprietary:
  - **Borg** [Google: Verma *et al.*, published 2015, in use since 2004]
    (unpublished predecessor by Liang, Dean, Sercinoglu, *et al.* in use since 2002)
  - **Autopilot** [Microsoft: Isaard *et al.*, 2007]
  - **Tupperware** [Facebook, Narayanan slide deck, 2014]
  - **Fuxi** [Alibaba: Zhang *et al.*, 2014]

- Open source:
  - **Hadoop Yarn**
  - **Apache Mesos** [Hindman *et al.*, 2011]
  - **Apache Aurora** [2014]
  - **Kubernetes** [2014]

Tension: Multiplexing resources & performance isolation

- Sharing machines across completely different jobs and tenants necessary for effective utilization
  - But leads to unpredictable performance blips
- Isolating while still sharing
  - Memory “ballooning” [Waldspurger, OSDI 2002]
  - Linux containers
  - ...
- Controlling tail latency very important [Dean & Barroso, 2013]
  - Especially in large fan-out systems

Higher-Level Computation Frameworks

Give programmer a high-level abstraction for computation

Map computation automatically
onto a large cluster of machines

MapReduce

[Dean & Ghemawat, OSDI 2004]

- simple Map and Reduce abstraction
- **hides messy details** of locality, scheduling, fault tolerance, dealing with slow machines, etc. in its implementation
- **makes it very easy** to do very wide variety of large-scale computations

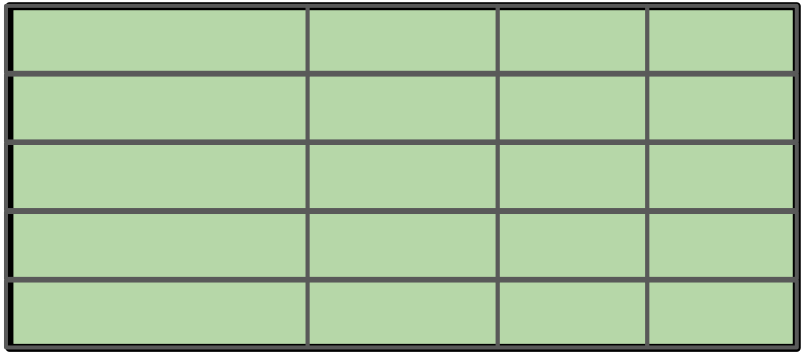
Hadoop - open source version of MapReduce

Succession of Higher-Level Computation Systems

- Dryad [Isard *et al.*, 2007] - general dataflow graphs
- Sawzall [Pike *et al.* 2005], PIG [Olston *et al.* 2008], DryadLinq [Yu *et al.* 2008], Flume [Chambers *et al.* 2010]
  - higher-level languages/systems using MapReduce/Hadoop/Dryad as underlying execution engine
- Pregel [Malewicz *et al.*, 2010] - graph computations
- Spark [Zaharia *et al.*, 2010] - in-memory working sets
- ...

Many Applications Need To Update Structured State With Low-Latency and Large Scale

keys



TBs to 100s of PBs of data

10^6, 10^8, or more reqs/sec

Desires:

- Spread across many machines, **grow and shrink** automatically
- **Handle machine failures** quickly and transparently
- Often prefer **low latency and high performance** over consistency

Distributed Semi-Structured Storage Systems

- BigTable [Google: Chang *et al.* OSDI 2006]
  - higher-level storage system built on top of distributed file system (GFS)
  - data model: rows, columns, timestamps
  - no cross-row consistency guarantees
  - state managed in small pieces (tablets)
  - recovery fast (10s or 100s of machines each recover state of one tablet)
- Dynamo [Amazon: DeCandia *et al.*, 2007]
  - versioning + app-assisted conflict resolution
- Spanner [Google: Corbett *et al.*, 2012]
  - wide-area distribution, supports both strong and weak consistency

Successful design pattern:

Give each machine hundreds or thousands of units of work or state

Helps with:
dynamic capacity sizing
load balancing
faster failure recovery

The Public Cloud

Making these systems available to developers everywhere

Cloud Service Providers

- Make computing resources available on demand
  - through a growing set of simple APIs
  - leverages economies of scale of large datacenters
  - … for anyone with a credit card
  - … at a large scale, if desired

Cloud Service Providers

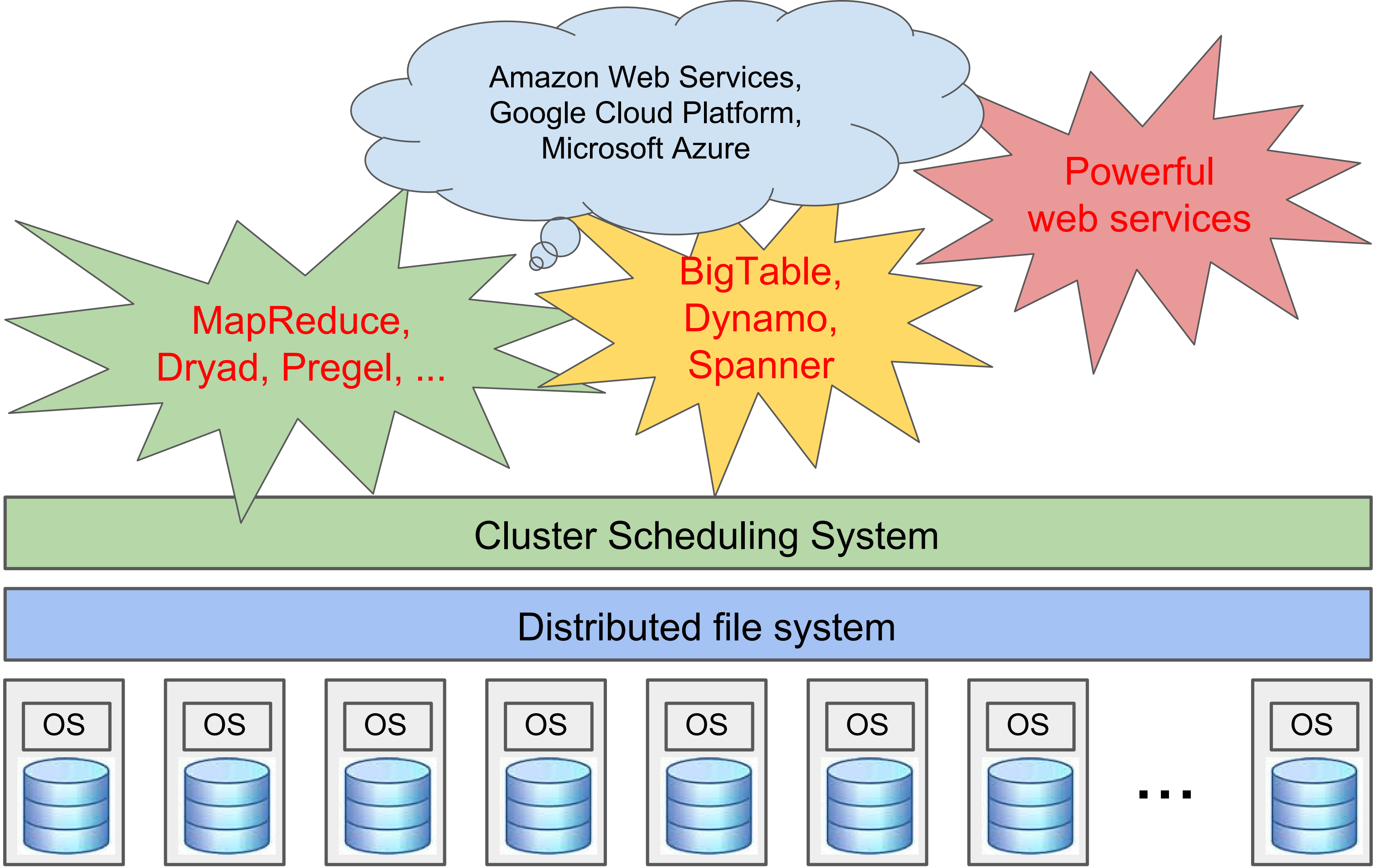
Amazon: Queue API in 2004, EC2 launched in 2006
Google: AppEngine in 2005, other services starting in 2008
Microsoft: Azure launched in 2008.

Millions of customers using these services

Shift towards these services is accelerating

Comprehensiveness of APIs increasing over time

So where are we?


Amazon Web Services,
Google Cloud Platform,
Microsoft Azure
Powerful
web services
MapReduce,
Dryad, Pregel, ...
BigTable,
Dynamo,
Spanner
Cluster Scheduling System
Distributed file system
OS
OS
OS
OS
OS
OS
OS
...
OS

What's next?

- Abstractions for interactive services with 100s of subsystems
  - less configuration, much more automated operation, self-tuning, …
- Systems to handle greater heterogeneity
  - e.g. automatically split computation between mobile device and datacenters

Thanks for listening!

Thanks to
Ken Birman, Eric Brewer, Peter Denning,
Sanjay Ghemawat, and Andrew Herbert for
comments on this presentation