# IERG4300
# Web-Scale Information Analytics

## Overview: The Era of Big Data

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# Acknowledgements

- The slides used in this chapter are adapted from the following sources:
  - “Data-Intensive Information Processing Applications,” by Jimmy Lin, University of Maryland.



  - CS246 Mining Massive Data-sets, by Jure Leskovec, Stanford University.
  - Stat 260 Scalable Machine Learning of UC Berkeley, by Alex Smola, CMU.
  - 10-605 Machine Learning from Big Datasets, by William Cohen, CMU.
  - “Intro To Hadoop” in UCBerkeley i291 - Analyzing BigData with Twitter, by Bill Graham, Twitter.
- All copyrights belong to the original authors of the material.

# Course Administrivia

# What is this course about?

- Data-intensive Information Processing and Analytics
- “Web-Scale”, Big Data problems
- Focus on Algorithms that are scalable to “Web-scale” and their Applications in Practice !
- The Parallel and Distributed Platform for its Realization:
  - Mainly use MapReduce (and taste its limitations) ;
  - VERY BRIEF overview of other modern Big Data Distributed/Parallel Processing Frameworks and Programming models ;
    - In-depth Study of those modern, non-MapReduce approaches will only be covered in:

      IERG4330 Programming Big Data Systems,
      which requires this course (IERG4300) as pre-requisite

# Course Pre-requisites

- You MUST already have Strong Programming Skills
  - Comfortable with at least one high-level programming language, e.g. Java or C or C++ or Python, etc.
  - We will NOT teach you programming, instead we expect you to:
    - Be ready to use programming to solve new problems

    AND

    - Pick up Hadoop and other parallel programming + system debugging skills/ tools (quickly) along the way
- Focus on "thinking at scale" and algorithm design
- Solid knowledge of
  - Probability and statistics
- NO previous experience expected from you on:
  - MapReduce
  - Parallel and distributed programming

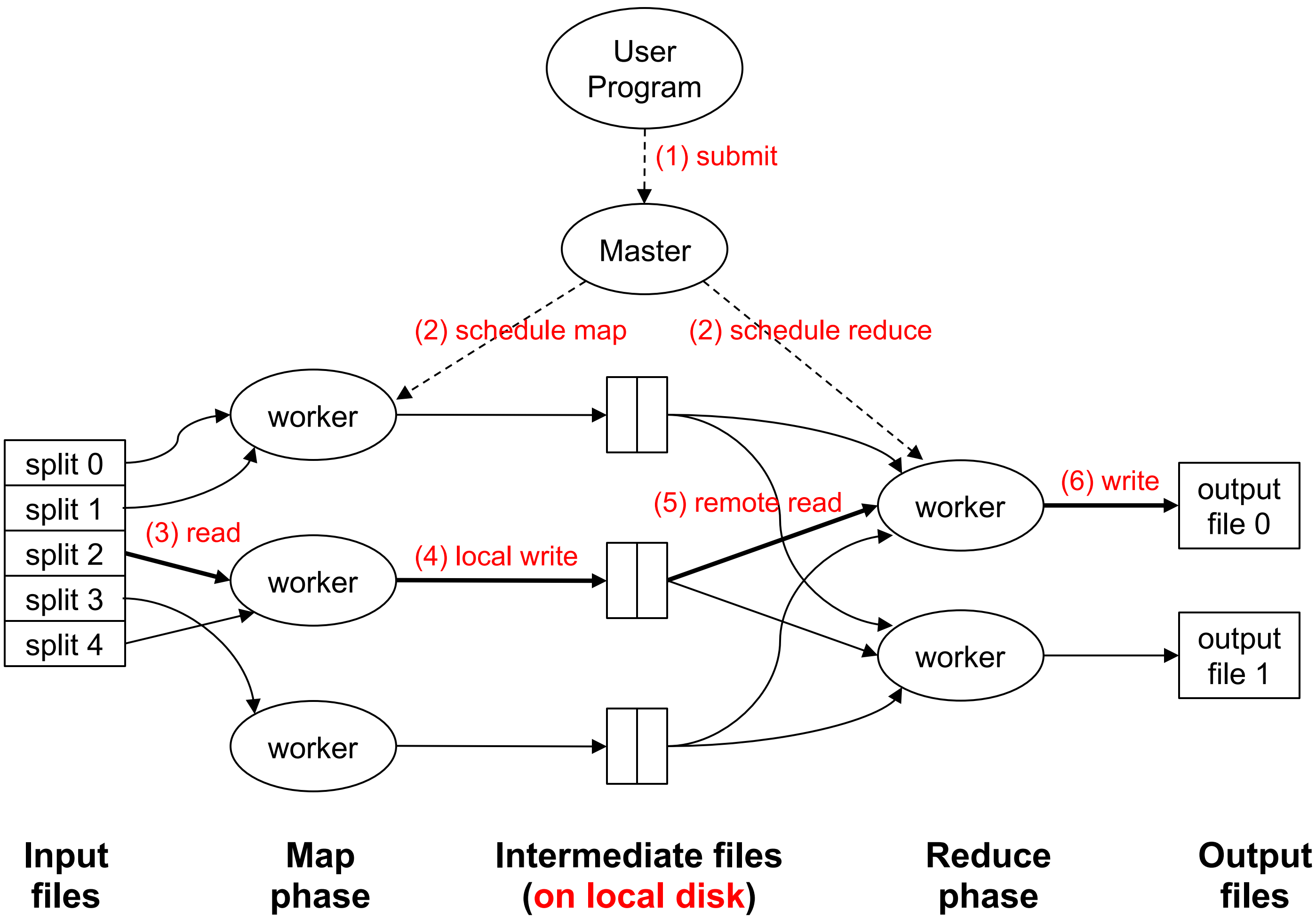
# What is MapReduce?

- The 1st widely-deployed (successful) Programming model for expressing distributed computations at a massive scale
- Execution framework (actual software system) for organizing and performing such computations
- Open-source implementation called Hadoop

# HW#0

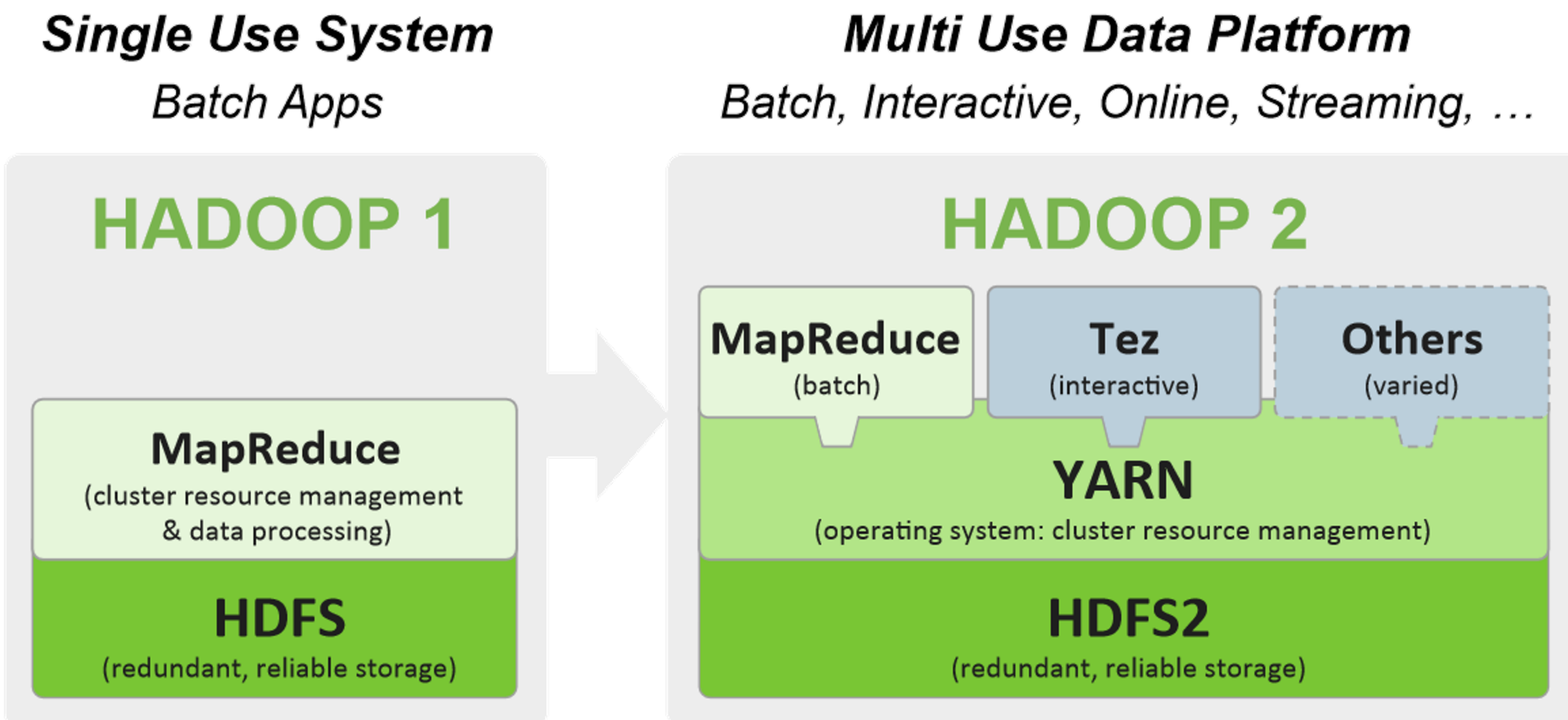
Set up your own
Hadoop 2.x Cluster +
run a sample MapReduce program
using
a Free Public Cloud Infrastructure

**Due in less than 2 weeks:**
**Due Date: Jan 21, 2023 11:59am**
**(noon-tme on CNY Eve !!)**




Adapted from (Dean and Ghemawat, OSDI 2004)

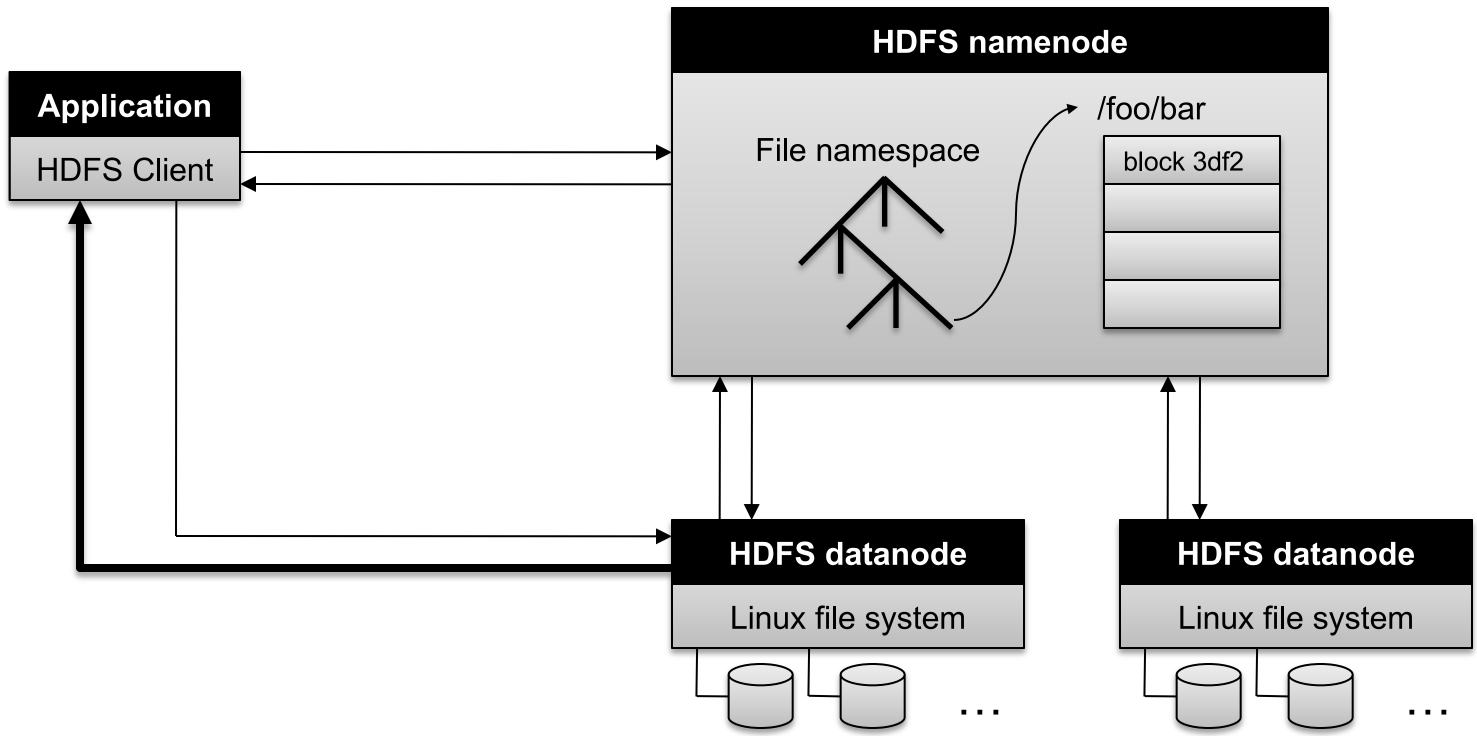
# YARN for Hadoop 2.0




- YARN (Yet Another Resource Negotiator)
  - Like an Operating System (OS) for a Data-center-scale Computing Cluster
  - Serve as the resource management platform for Cluster of Computers to support general Distributed/Parallel Applications/Frameworks beyond the MapReduce computational model.

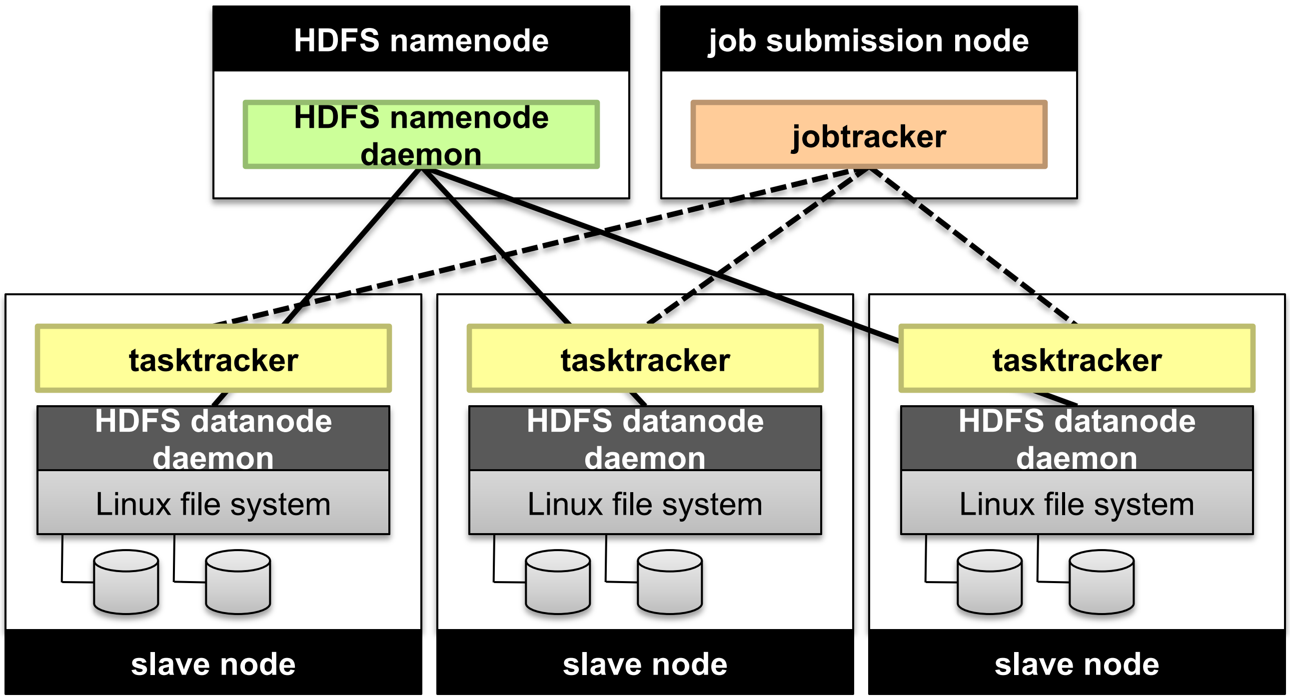
V. K. Vavilapalli, A. C. Murthy, "Apache Hadoop YARN: Yet Another Resource Negotiator", in ACM Symposium on Cloud Computing (SoCC) 2013.

# Hadoop Distributed File System (HDFS) Architecture

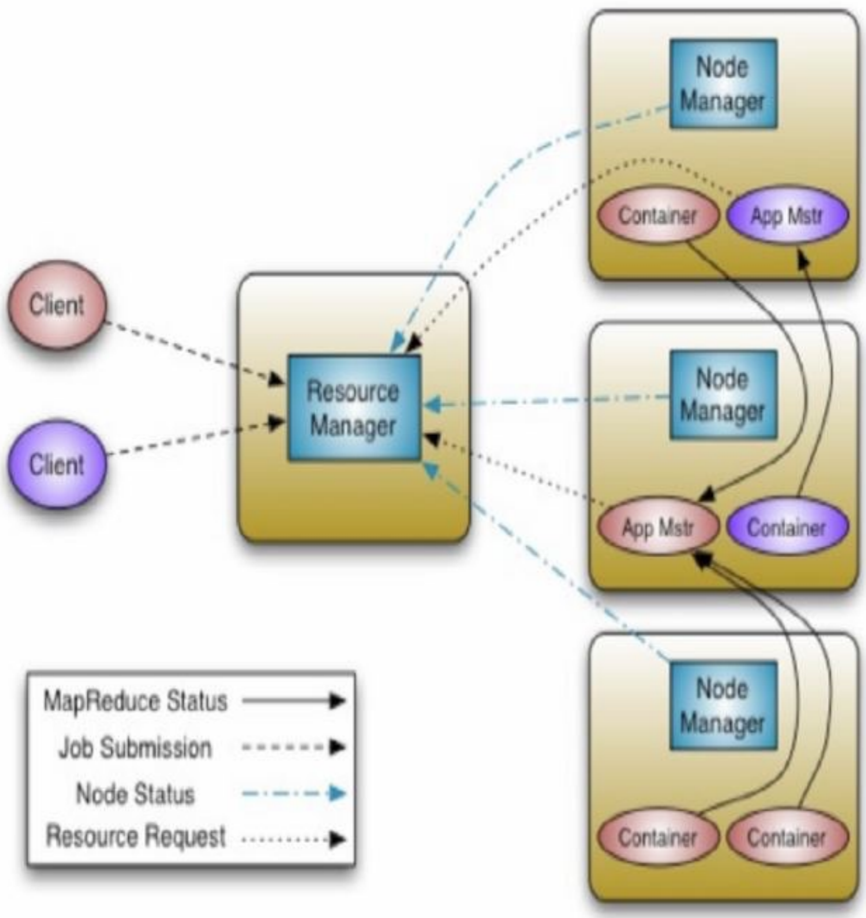



Adapted from (Ghemawat et al., SOSP 2003)

# Putting everything together under Hadoop 1.0



# Different Terminologies for Job and Task Tracking under Hadoop2.0 / YARN




- Scalability - Clusters of 6,000-10,000 machines
  - Each machine with 16 cores, 48G/96G RAM, 24TB/36TB disks
  - 100,000+ concurrent tasks
  - 10,000 concurrent jobs

- HDFS architecture and terminologies largely remain unchanged w.r.t. Hadoop 1.0 as shown in previous 2 slides

# Computing/ Cloud Resources

- Hadoop on your local machine
- Hadoop in a Virtual Machine on your local machine
- Sign-up for Freebie (limited-time) Trial accounts from Commercial Cloud Computing Services:
  - Amazon Web Service (AWS Educate), Google Compute Engine
    - Homework#0 requires each student to setup a Hadoop Cluster on one of the Public Cloud Services
- For subsequent homework sets, you may use your own cluster installed over the free public cloud service or use the IE DIC for different Parallel/ Distributed Programming tasks/ assignments.
  - The IE DIC (Data-Intensive Cluster):
    - Already Setup with Hadoop 2.0/ YARN, MapReduce, Hadoop Distributed File System (HDFS), etc

# This course is not for you…

- If you're not genuinely interested in the topic
- If you can't put in the time
- If you're not ready to do a lot of work
- If you're not open to thinking about computing in new ways
- If you can't cope with the uncertainty, unpredictability, etc. that comes with bleeding edge software

**Otherwise, this will be a richly rewarding course!**

Source: Wikipedia (Japanese rock garden)

# Zen

- We will be using open-source technologies
  - Bugs, undocumented features, inexplicable behavior
  - Data loss(!)
- Don’t get frustrated (take a deep breath)…
  - Those W$*#T@F! moments
- Be patient…
  - We will inevitably encounter “situations” along the way
- Be flexible…
  - We will have to be creative in workarounds
- Be constructive…
  - Tell me how I can make everyone’s experience better

# Web-Scale, Big Data

Source: Wikipedia (Everest)

# Why should we care about Big Data ?

- Ready-made large-data problems
  - Lots of user-generated content
  - Even more user behavior data
  - Examples: Facebook friend suggestions, Google ad placement
  - Business intelligence: gather everything in a data warehouse and run analytics to generate insight
- Utility computing
  - Provision Hadoop clusters on-demand in the cloud
  - Lower barrier to entry for tackling large-data problem
  - Commoditization and democratization of large-data capabilities

# How many users and objects?

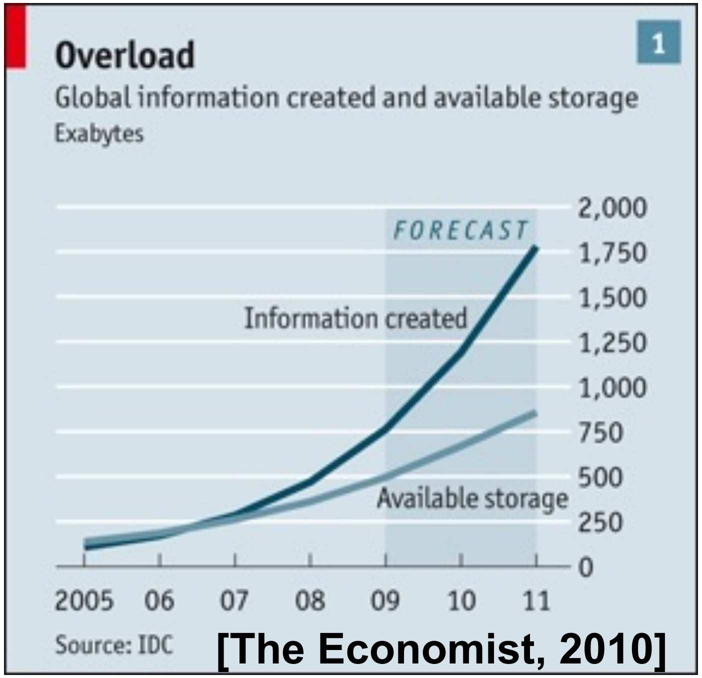
- Flickr has >6 billion photos
- Facebook has 1.15 billion active users
- Google is serving >1.2 billion queries/day on more than 27 billion items
- >2 billion videos/day watched on YouTube

# How much data?

- Modern applications use massive data:
  - Rendering 'Avatar' movie required >1 petabyte of storage
  - eBay has >6.5 petabytes of user data
  - CERN's LHC will produce about 15 petabytes of data per year
  - In 2008, Google processed 20 petabytes per day
  - German Climate computing center dimensioned for 60 petabytes of climate data
  - Someone estimated in 2013 that Google had

    10 exabytes on disk and ~ 5 exabytes on tape backup
  - NSA Utah Data Center is said to have 5 zettabyte (!)
- How much is a zettabyte?
  - 1,000,000,000,000,000,000,000 bytes
  - A stack of 1TB hard disks that is 25,400 km high

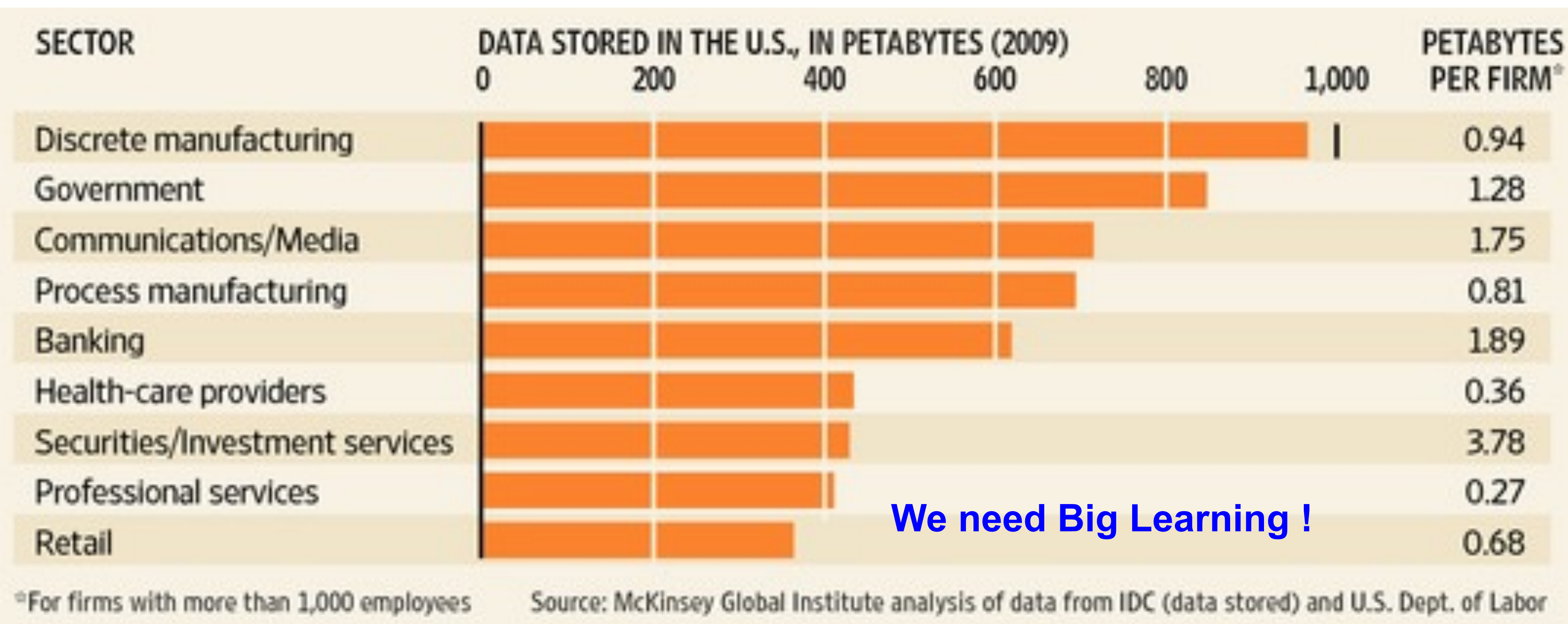
# How Big is Big ?




[The Economist, 2010]

We are producing more data than we are able to store!

http://en.wikipedia.org/wiki/Zettabyte




**We need Big Learning !**

# How much computation?

- No single computer can process that much data
  - Need many computers!
- How many computers do modern services need?
  - Facebook is thought to have more than 60,000 servers
  - Akamai has > 95,000 servers in 71 countries
  - Intel had ~100,000 servers in 97 data centers
  - Microsoft reportedly had at least 200,000 servers in 2008
  - Google was thought to have about 2.5 million servers by 2019; scattered across > 20 countries & > 35 locations ; was planning for 10 million (according to Jeff Dean 10 yrs ago)

# Data - User generated content

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
- Photos, Movies (Flickr, YouTube, Vimeo ...)
- Cookies / tracking info (see Ghostery)
- Installed apps (Android market etc.)
- Location (Latitude, Loopt, Foursquared)
- User generated content (Wikipedia & co)
- Ads (display, text, DoubleClick, Yahoo)
- Comments (Disqus, Facebook)
- Reviews (Yelp, Y!Local)
- Third party features (e.g. Experian)
- Social connections (LinkedIn, Facebook)
- Purchase decisions (Netflix, Amazon)
- Instant Messages (YIM, Skype, Gtalk)
- Search terms (Google, Bing)
- Timestamp (everything)
- News articles (BBC, NYTimes, Y!News)
- Blog posts (Tumblr, Wordpress)
- Microblogs (Twitter, Jaiku, Meme)
- Link sharing (Facebook, Delicious, Buzz)
- Network traffic

crawl it

**>1B images, 40h video/minute**

# Web-Scale Big Data

- **Webpages (content, graph)**
- **Clicks (ad, page, social)**
- **Users (OpenID, FB Connect)**
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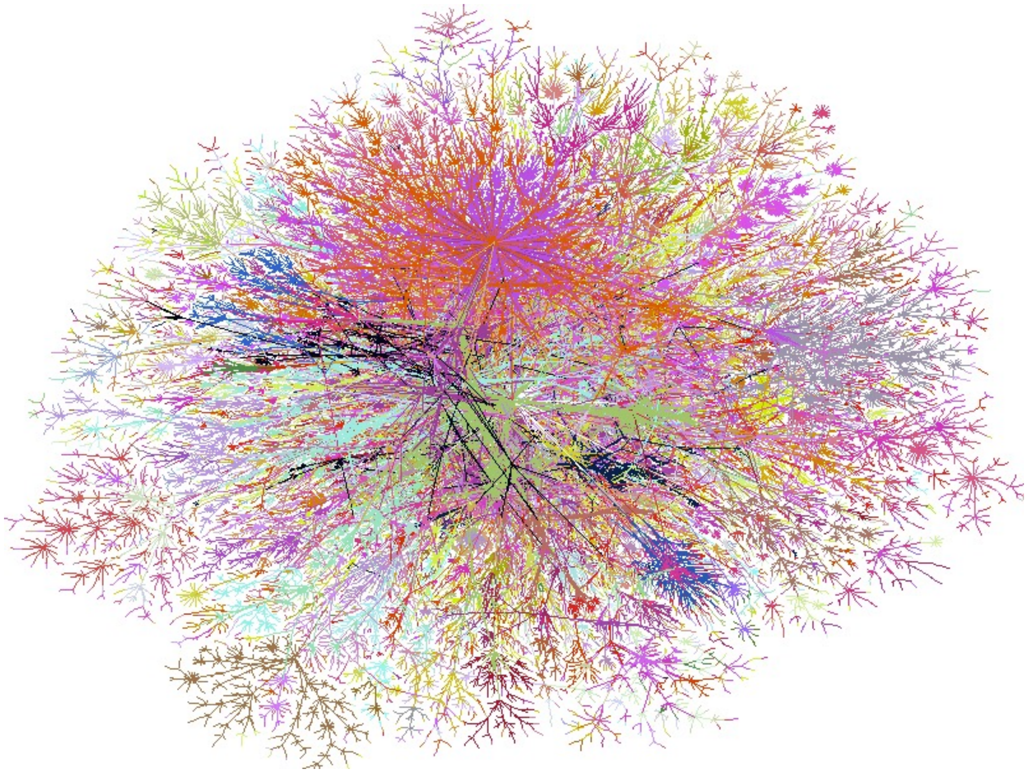

**>10B useful webpages**

# Crawling the Web for US$100k/month

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- **10 billion pages**
  (this is a small subset, maybe 10%)
  10k/page = 100TB
  ($10k for disks or EBS 1 month )
- **1000 machines**
  10ms/page = 1 day
  ($2.5k on EC2 for 0.085$/h)
- **10 Gbps link**
  ($10k/month via ISP or EC2)
  - Should only need 1 day to Tx the 100TB raw data over a 10Gbps link
  - BUT need to wait for web-server to respond (est. latency of 300ms/page) roundtrip
  - ?? Need 1000 servers to collect the 100TB data in parallel for 1 month ??
    ($75k on EC2 for 0.085$/h)

Rough estimate by Alex Smola

# Data - User Tracking

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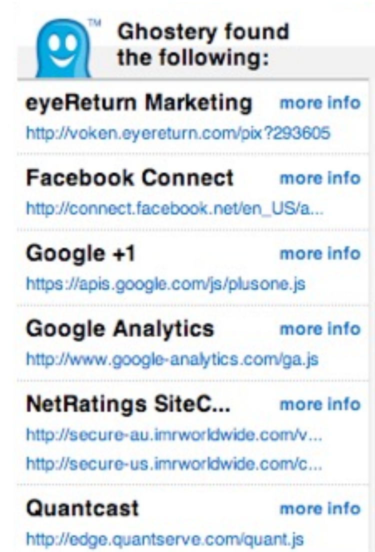


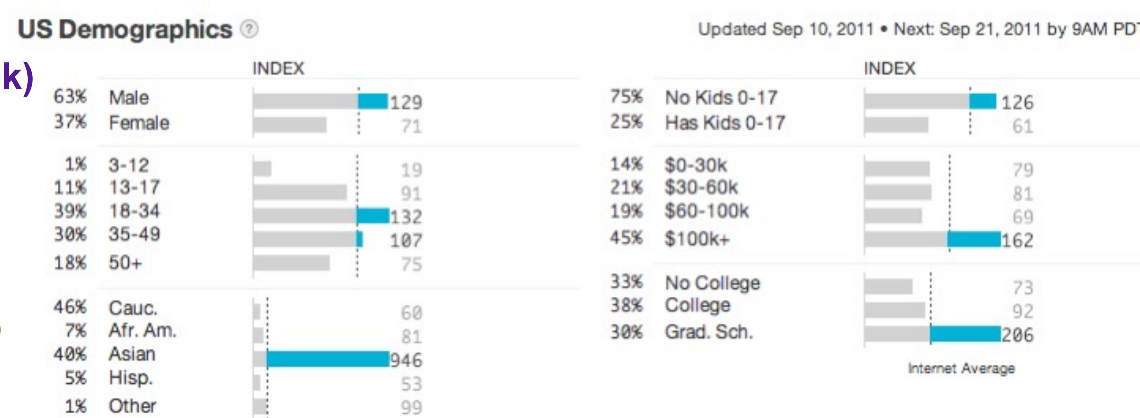


>1B 'identities'

# Data - User Tracking

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**Privacy Information**

**Privacy Policy:**

http://www.facebook.com/policy.php

**Data Collected:**

Anonymous (browser type, location, page views), Pseudonymous (IP address, "actions taken")

**Data Sharing:**

Data is shared with third parties.

**Data Retention:**

Data is deleted from backup storage after 90 days.

**Privacy Information**

**Privacy Policy:**

http://www.google.com/intl/en/priv...

**Data Collected:**

Anonymous (ad serving domains, browser type, demographics, language settings, page views, time/date), Pseudonymous (IP address)

**Data Sharing:**

Anonymous data is shared with third parties.

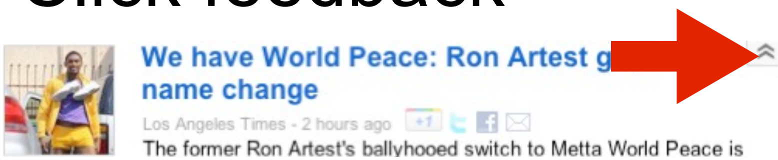
**Data Retention:**

Undisclosed

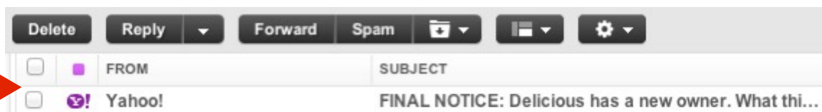
# (Implicitly) Labelled Data Vs. Un-Labelled Data

- Ads


- Click feedback



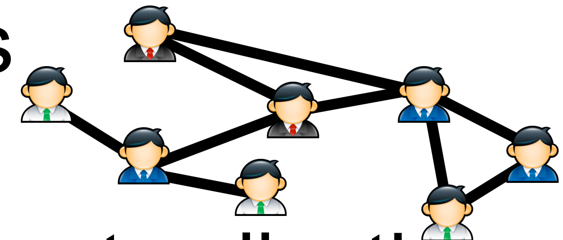

- Emails




- Tags

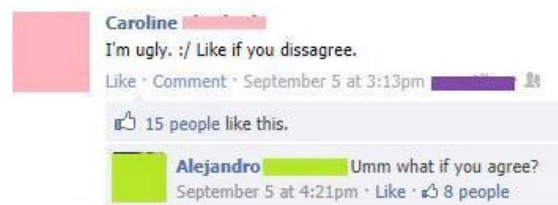

- Editorial (Manually Labelled) data is very expensive! Do not use!

- Graphs

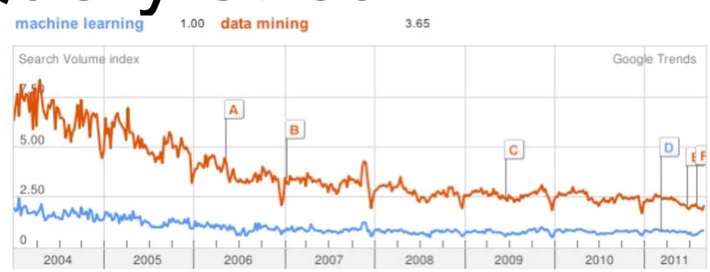


- Document collections

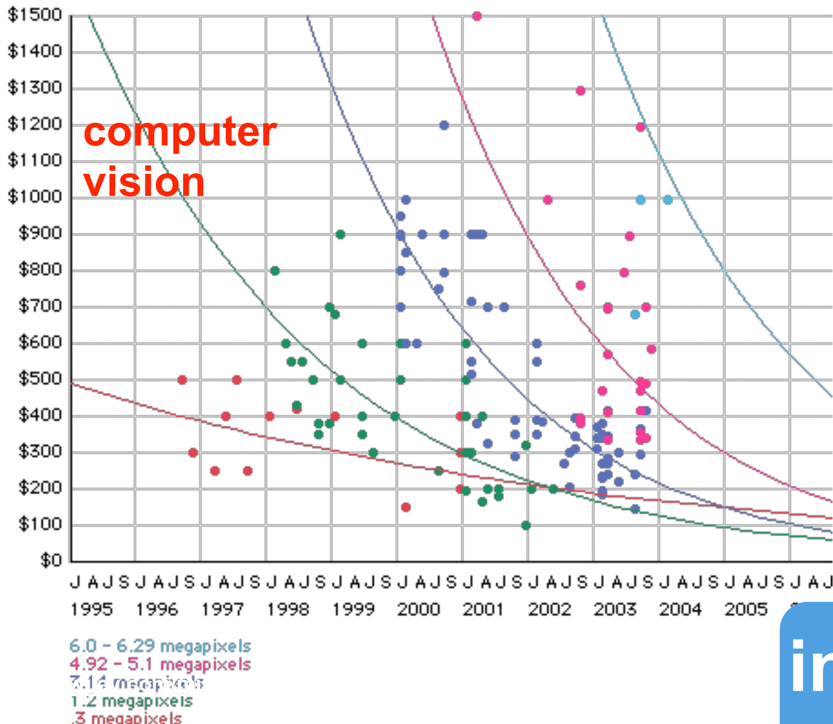

- Email/IM/Discussions



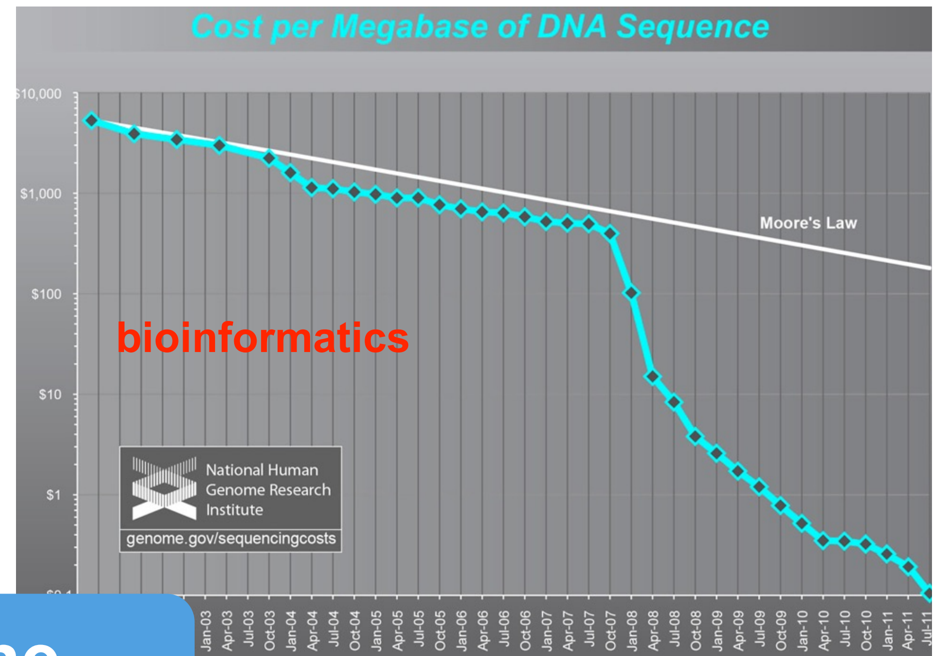

- Query stream



# Many more sources of Data




computer vision

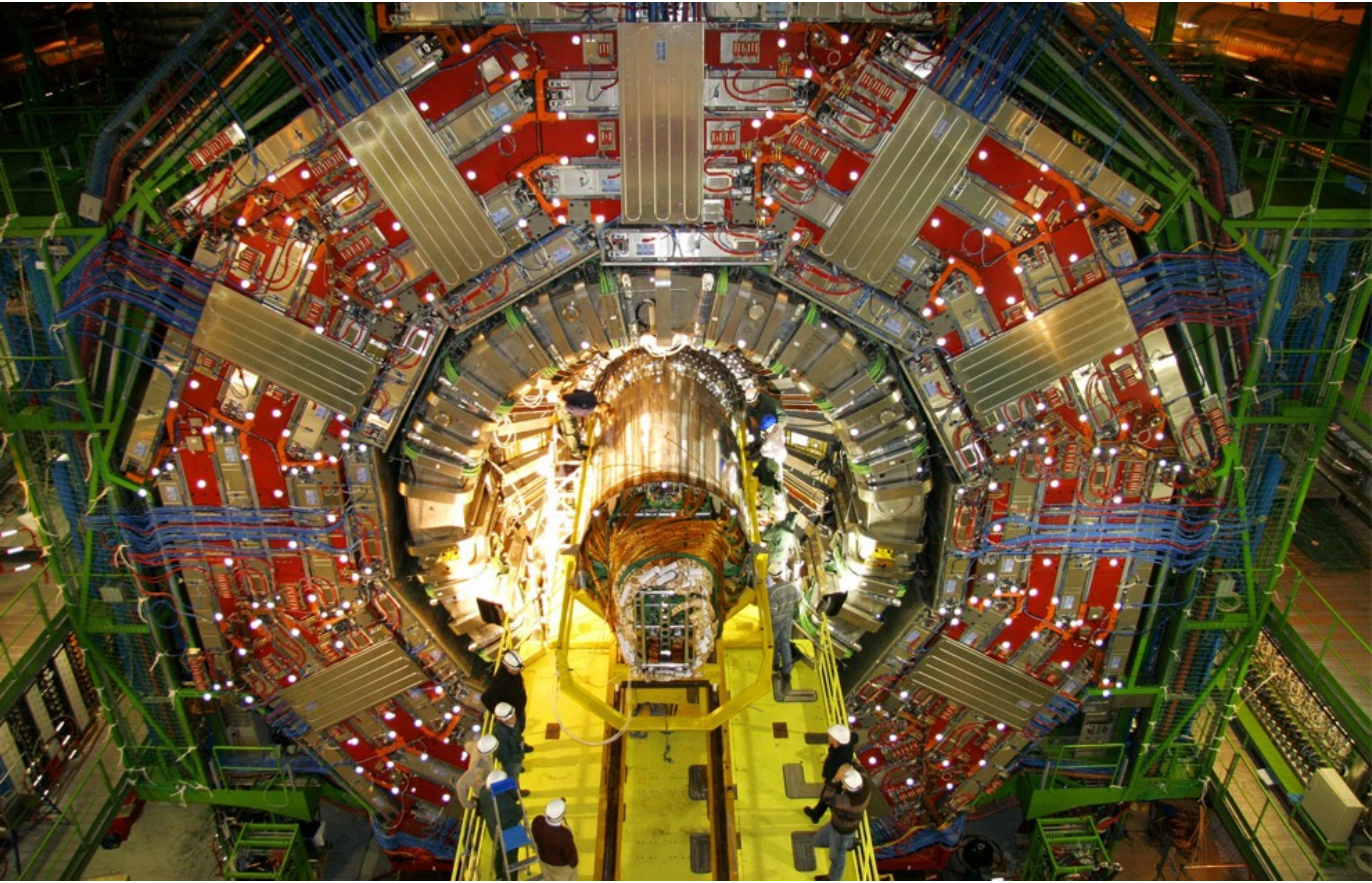



bioinformatics

in the Cloud

Personalized Sensors


Ubiquitous Control



**CERN Large Hadron Collider (LHC) will generate 15 PB/ yr (??)**

# What to do with More Data ?

- Answering factoid questions
  - Pattern matching on the Web
  - Works amazingly well

**Who shot Abraham Lincoln? --> ??? shot Abraham Lincoln**

- Learning relations
  - Start with seed instances
  - Search for patterns on the Web
  - Using patterns to find more instances

Wolfgang Amadeus Mozart (1756 - 1791)
Einstein was born in 1879

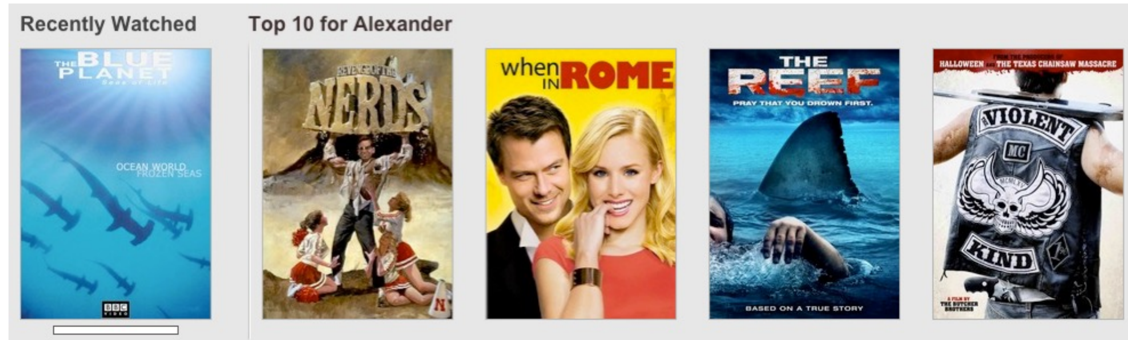
PERSON (DATE –
PERSON was born in DATE

Birthday-of(Mozart, 1756)
Birthday-of(Einstein, 1879)

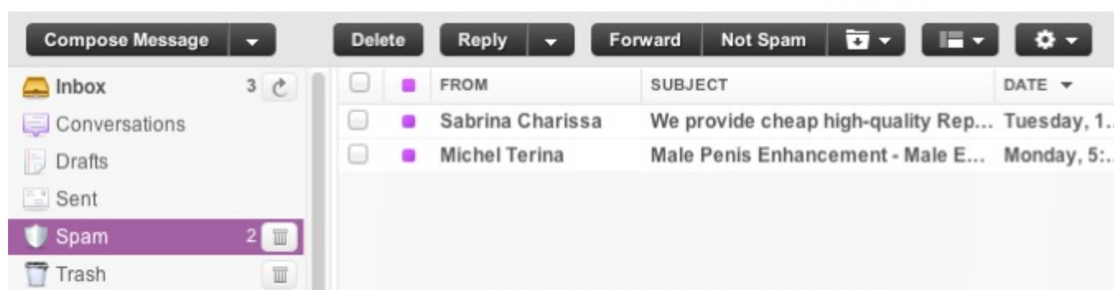
(Brill et al., TREC 2001; Lin, ACM TOIS 2007)
(Agichtein and Gravano, DL 2000; Ravichandran and Hovy, ACL 2002; … )

# What to do with More Data ? (cont'd) Personalization

- 100-1000M users
  - Spam filtering
  - Personalized targeting & collaborative filtering
  - News recommendation
  - Advertising







# What to do with More Data? (cont'd)

- User Behavior Analysis
- AB Test Analysis
- Ad Targetting
- Trending Topics
- User and Topic Modeling
- Recommendations (Collaborative Filtering)
- Predictions
- Novel Detection and More …



- Following Theory, Experiment and Simulation,

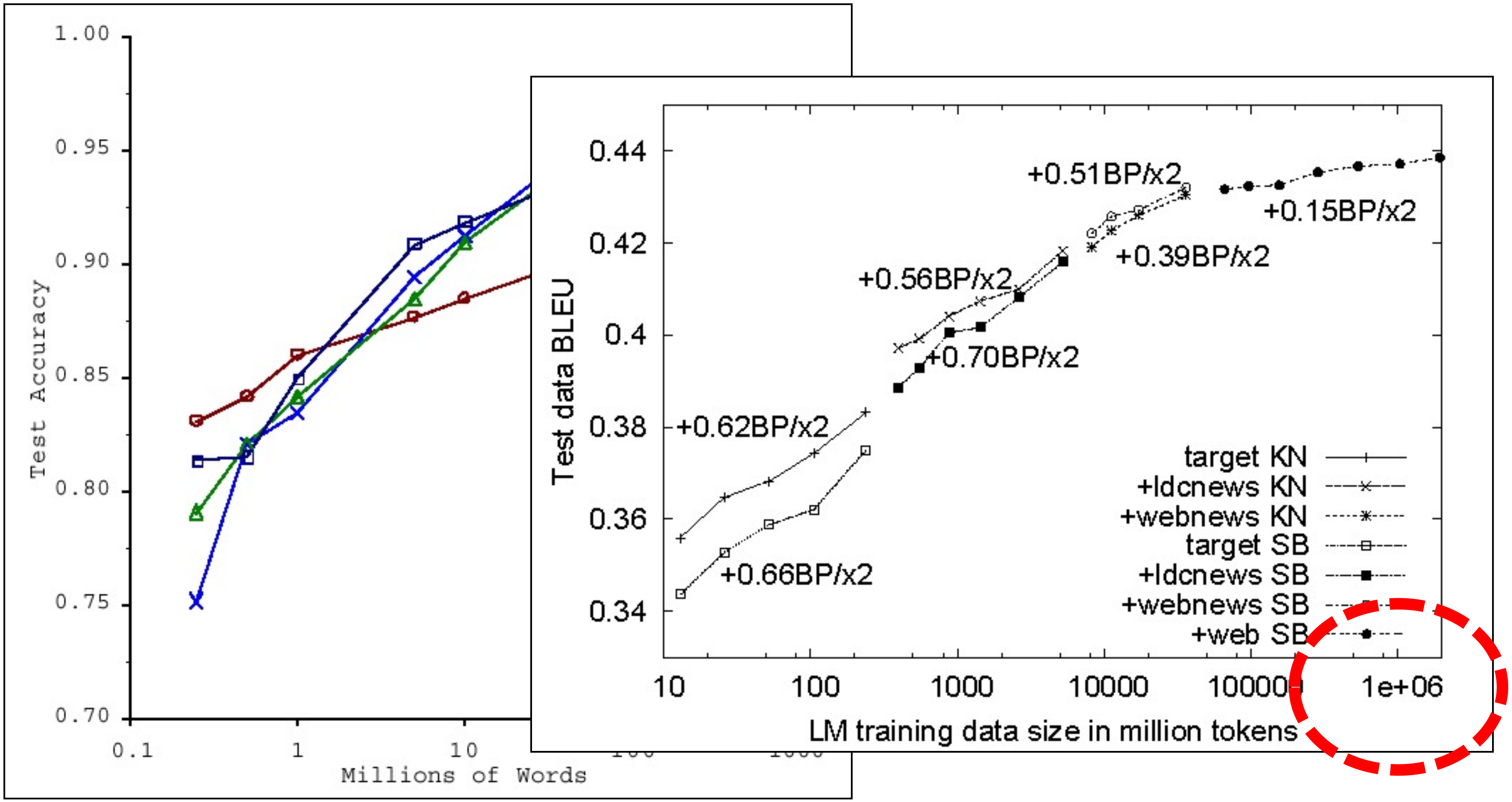
  Big Data has become the 4th-Paradigm of Science

  `s/knowledge/data/g`

Knowledge Discovery via **Scalable** Information Analytics, e.g.

Scalable Data Mining, Statistical Modeling, Machine Learning

# There’s no Data like more Data!




**How do we get here if we’re not Google?**

(Banko and Brill, ACL 2001)
(Brants et al., EMNLP 2007)

By 2001, we have learned that, for many tasks, there’s no real *substitute* for using lots of data

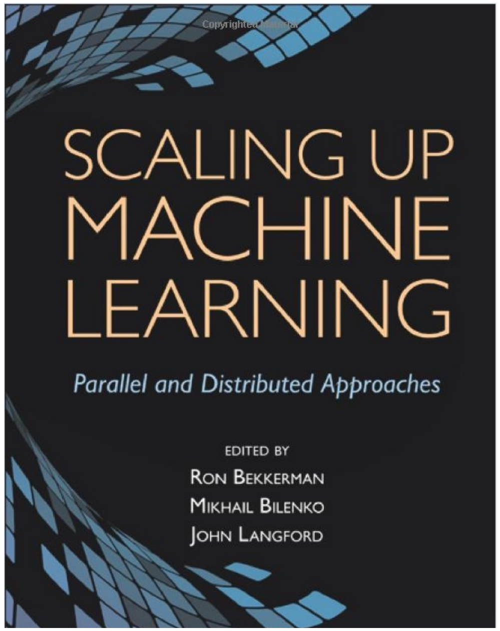
# …and in 2009

*Eugene Wigner's article "The Unreasonable Effectiveness of Mathematics in the Natural Sciences" examines why so much of physics can be neatly explained with simple mathematical formulas such as $f = ma$ or $e = mc^2$. Meanwhile, sciences that involve human beings rather than elementary particles have proven more resistant to elegant mathematics. Economists suffer from physics envy over their inability to neatly model human behavior. An informal, incomplete grammar of the English language runs over 1,700 pages.*

*Perhaps when it comes to natural language processing and related fields, we're doomed to complex theories that will never have the elegance of physics equations. But if that's so, we should stop acting as if our goal is to author extremely elegant theories, and instead embrace complexity and make use of the best ally we have: the unreasonable effectiveness of data.*

Norvig, Pereira, Halevy, "The Unreasonable Effectiveness of Data", 2009

# …and in 2012




Arthur Gretton, Michael Mahoney, Mehryar Mohri, Ameet Talwalkar

Gatsby Unit, UCL; Stanford; Google Research; UC Berkeley

**Workshop: Low-rank Methods for Large-scale Machine Learning**

7:30am - 6:30pm Saturday, December 11, 2010

Joseph Gonzalez, Sameer Singh, Graham Taylor, James Bergstra, Alice Zheng, Misha Bilenko, Yucheng Low, Yoshua Bengio, Michael Franklin, Carlos Guestrin, Andrew McCallum, Alexander Smola, Michael Jordan, Sugato Basu

Carnegie Mellon University; University of Massachusetts, Amherst; New York University; Harvard; Microsoft Research; Microsoft Research; Carnegie Mellon University; University of Montreal; UC Berkeley; Carnegie Mellon University; UMass Amherst; Yahoo! Research; University of California; Google Research

**Workshop: Big Learning: Algorithms, Systems, and Tools for Learning at Scale**

**Location:** Montebajo: Theater

SMLA Workshop 2010

*29 June - 01 July, 2010, Bradford, UK*

**International Workshop on**
**Scalable Machine Learning and Applications (SMLA-10)**
**In conjunction with CIT 2010**

# What is Data Mining?

- Discovery of **patterns and models that are:**
  - **Valid:** hold on new data with some certainty
  - **Useful:** should be possible to act on the item
  - **Unexpected:** non-obvious to the system
  - **Understandable:** humans should be able to interpret the pattern

# Data Mining Tasks

- **Descriptive Methods:** Find human-interpretable patterns that describe the data, e.g.
  - Clustering
  - Dimensionality Reduction
  - Association Rule Discovery
  - Sequential Pattern Discovery
- **Predictive Methods:** Use some variables to predict unknown or future values of other variables, e.g.
  - Classification
  - Regression
  - Novelty Detection

# Then, what is Machine Learning ?

- Arthur Samuel (1959). Machine Learning: Field of study that gives computers the ability to learn without being explicitly programmed.
- Tom Mitchell (1998) Well-posed Learning Problem: A computer program is said to *learn* from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.

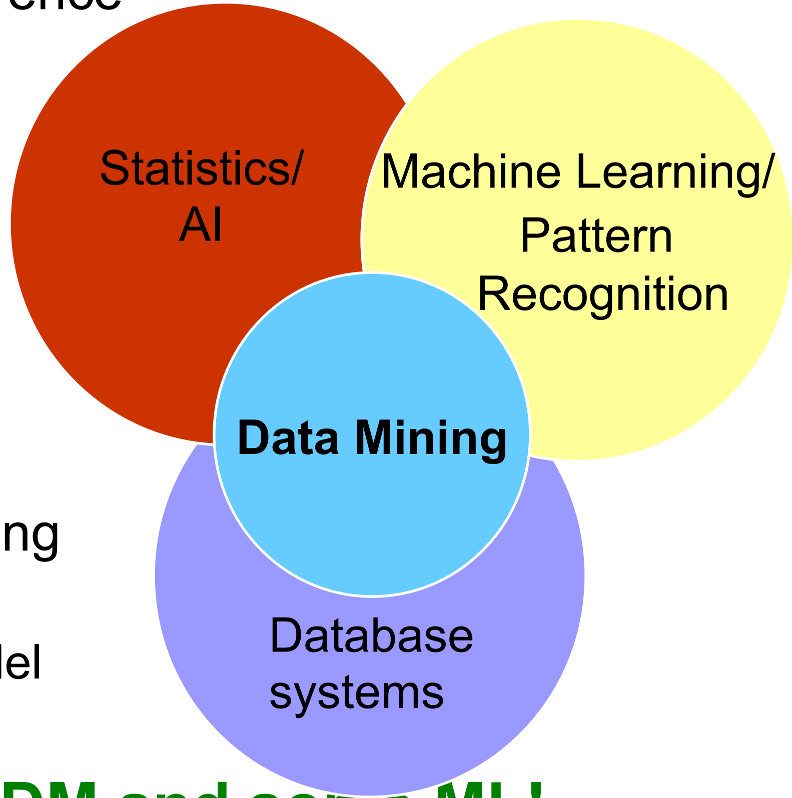
# Then, what is Machine Learning (cont'd) ?

- Given "a few" examples (labelled data for training), make a machine learn how to:
  - **Predict** on NEW Samples or
  - **Discover** Patterns in Data
- Major Learning Paradigms:
  - **Supervised Learning**
    - Regression (to predict a continuous output, like curve fitting)
    - Classification (to predict a class or category)
    - Ranking (to predict rank ordering)
  - **Unsupervised Learning**
    - Clustering
    - Density Estimation
    - Dimensionality Reduction
  - **There is also Semi-supervised Learning**
    - Large amount of unlabelled data + small amount of labelled ones

# Different Cultures of: Data Mining, Statistics, Machine Learning

- **Data mining overlaps with:**
  - **Databases:** Large-scale data, simple queries
  - **Machine learning:** Traditionally with Small data, Complex models
  - **Statistics:** Traditionally focus on using as little data as possible to construct Predictive Models for inference

- **Different cultures:**
  - To a DB person, data mining is an extreme form of **analytic processing** – queries that examine large amounts of data
    - Result is the query answer
  - To a statistics/ML person, data-mining is the **inference of models**
    - Result is the parameters of the model




- **In this class we will do mainly DM and some ML!**

# Emphasis of this course

- **We will stress on**
  - **Scalability** (Web-Scale)
  - **Algorithms** and **Architecture (mainly MapReduce)**
  - Automation for handling
    **Massive Datasets !**

# What will we learn?

- **We will learn to mine/ learn from different types of data:**
  - Data is of Large Volume (Terabyte-sized files)
  - Data is High Dimensional
  - Data is Infinite/never-ending
- **We will learn to use different models of computation:**
  - Single machine in-memory
  - MapReduce ...
  - Stream-based algorithms

# What will we learn?

- **We will learn to solve real-world problems:**
  - Association rules
  - Finding Similar Items/ Near-duplicate detection
  - Clustering
  - Dimension Reduction
  - Recommender systems
  - Dealing with Data Streams
- **We will learn various "tools":**
  - Linear algebra (SVD, Rec. Sys., Communities)
  - Optimization (Stochastic Gradient Descent)
  - Hashing (Min-Hash, LSH, Bloom filters)

  And Other neat Algorithmic Techniques and Tricks…

# How Topics in this Course fit Together ?

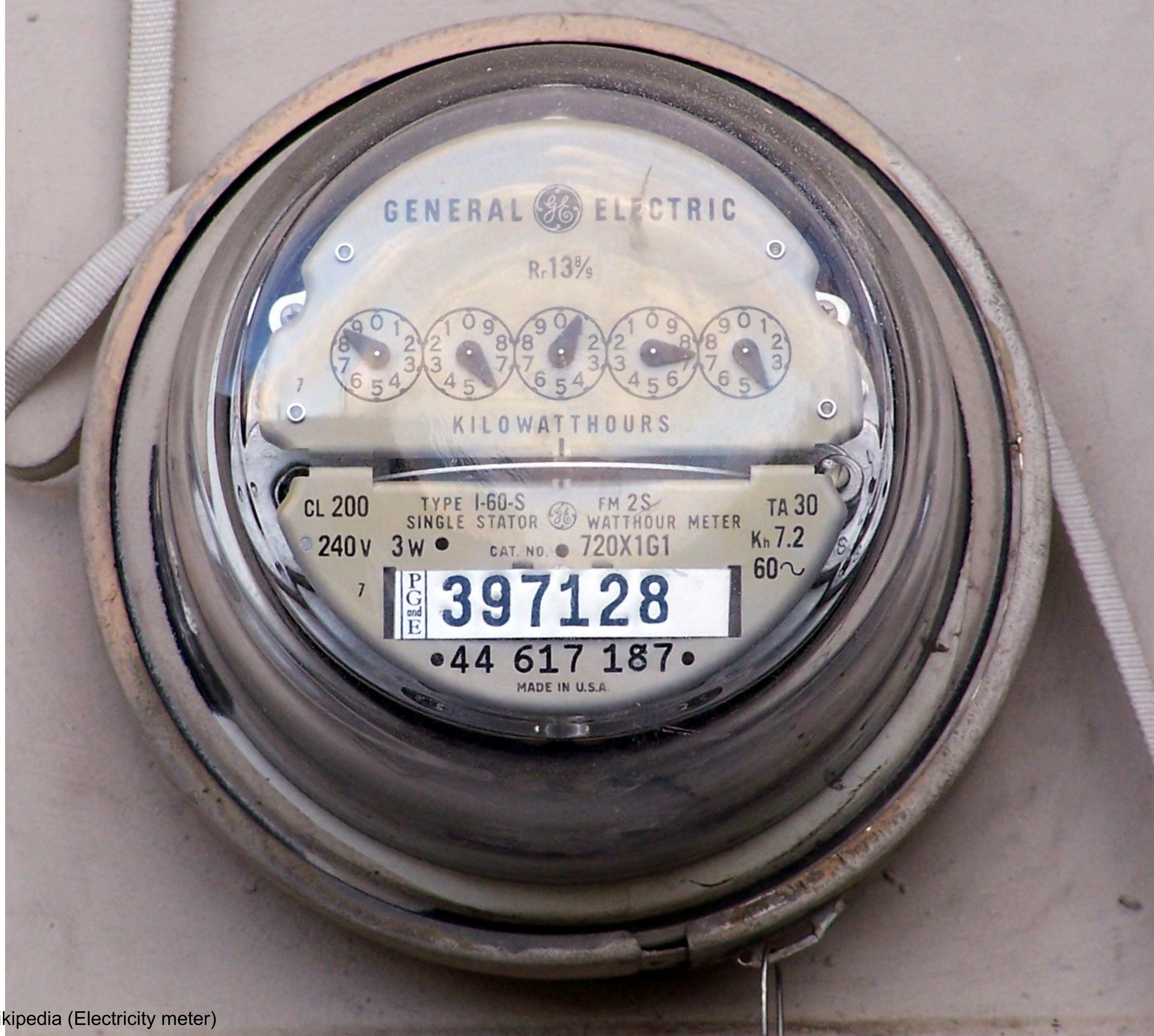
| High dim. Data | Infinite Data | Machine Learning | Apps |
|---|---|---|---|
| Locality sensitive hashing | Queries on Data Stream | Regression | Recommender systems |
| Clustering | Heavy Hitters Detection | kNN | Association Rules |
| Dimensionality reduction | | Decision Trees (time-permitting) | Duplicate document detection |


# How do you want that data?


What is cloud computing?

# The best thing since sliced bread?

- Before clouds…
  - Grids
  - Vector supercomputers
  - …
- Cloud computing means many different things:
  - Large-data processing
  - Rebranding of web 2.0
  - Utility computing
  - Everything as a service



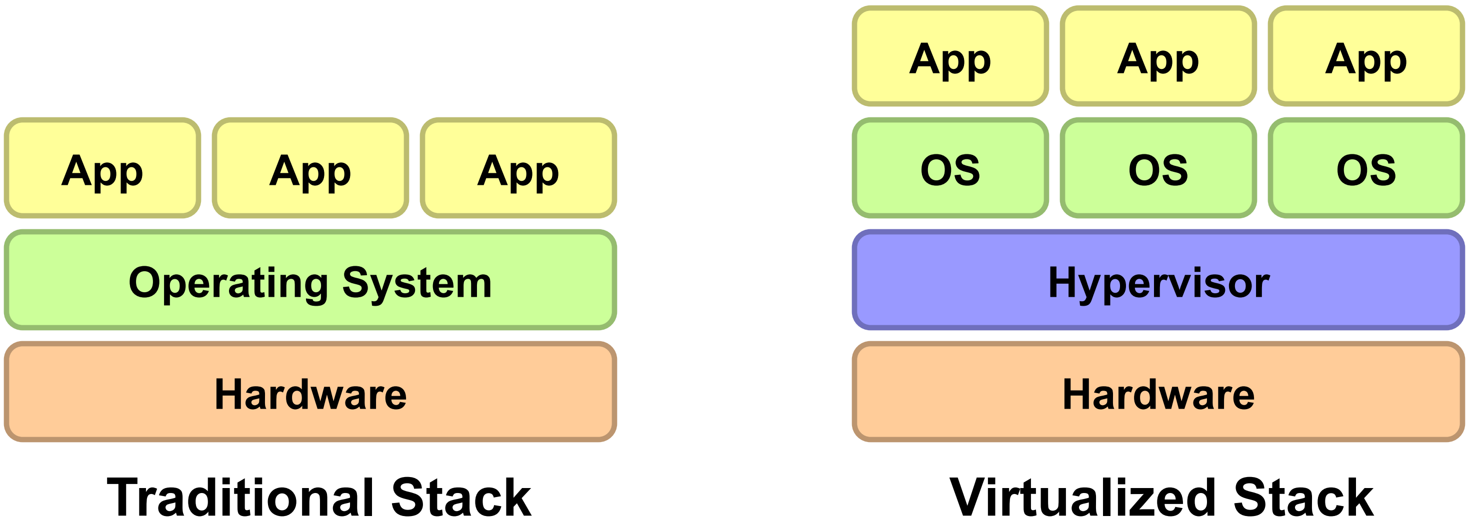

Source: Wikipedia (Electricity meter)

# Utility Computing

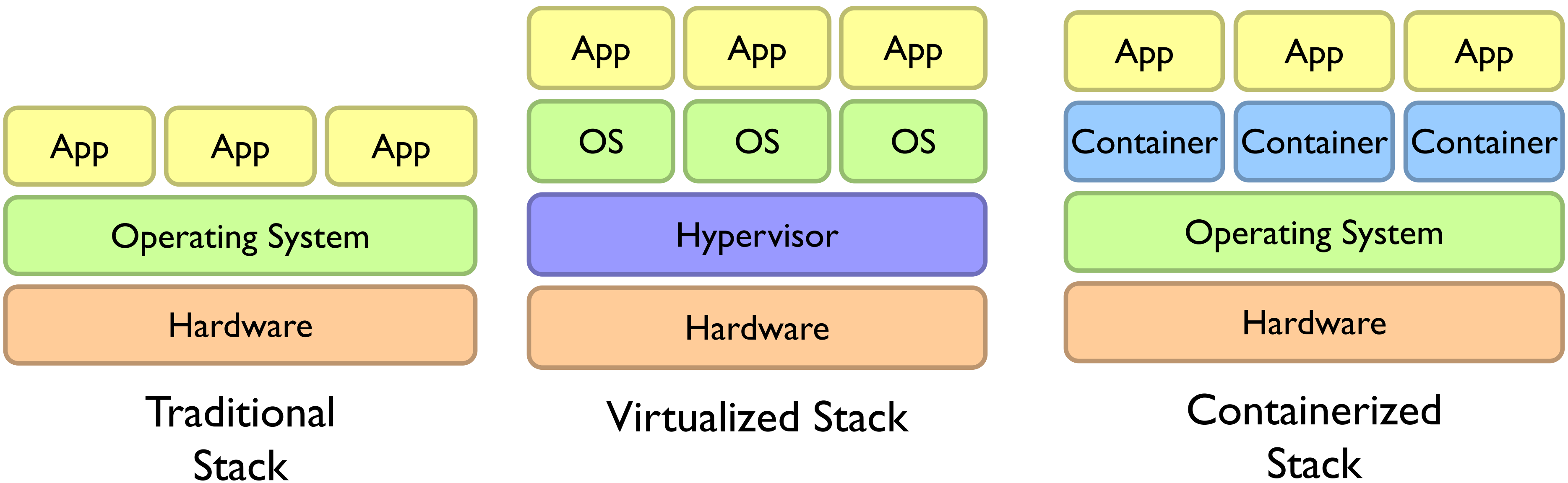
- What?
  - Computing resources as a metered service ("pay as you go")
  - Ability to dynamically provision virtual machines
- Why?
  - Cost: capital vs. operating expenses
  - Scalability: "infinite" capacity
  - Elasticity: scale up or down on demand
- Does it make sense?
  - Benefits to cloud users
  - Business case for cloud providers

**I think there is a world market for about five computers.**
**– Thomas J Watson of IBM, 1943**

# Enabling Technology: Virtualization



# Evolution of the Virtualization Stack



# Everything as a Service

- Utility computing = Infrastructure as a Service (IaaS)
  - Why buy machines when you can rent cycles?
  - Examples: Amazon's EC2, Rackspace, Google Compute Engine
- Platform as a Service (PaaS)
  - Give me nice API and take care of the maintenance, upgrades, …
  - Example: Google App Engine
- Software as a Service (SaaS)
  - Just run it for me!
  - Example: Gmail, Salesforce

Which type(s) of services do a typical Public Cloud Service Provider, e.g. Google Cloud, Microsoft Azure, Amazon Web Service (AWS) offer today ?

Answer: YES !

# Offerings of a Leading Cloud Computing Service Provider: Amazon Web Services (AWS)

# Overview of AWS Services

Databases

**Relational Database Service (RDS)**
**SimpleDB**
**DynamoDB**
ElastiCache

Network/ Distribution

CloudFront
Route 53

Computation

**Elastic Compute Cloud (EC2)**
**Elastic MapReduce**
**Elastic Beanstalk**

Data Storage

**Simple Storage Service (S3)**
**Elastic Block Store (EBS)**

**Auto Scaling**
**Elastic Load Balance**
Simple Notification Service (SNS)
Simple Workflow Service (SWF)

*Coordination services*

# What is Amazon Web Services (AWS) ?

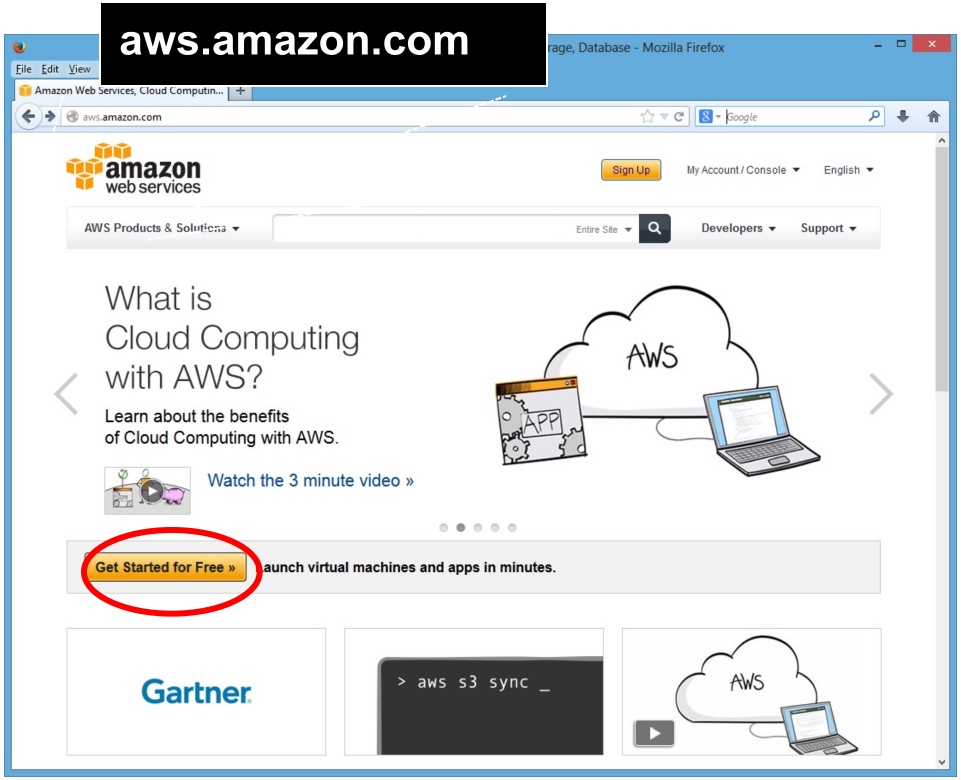
- AWS provides a collection of services for building cloud applications
- Services for:
  - **Storage**: S3, EBS
  - **Computation**: Elastic Cloud Computing (EC2), scaling/load balancer, Elastic Map/Reduce, Elastic Beanstalk
  - **Databases**: RDS, DynamoDB, ElastiCache
  - **Coordination**: Simple Notification Service, Simple Workflow Framework
  - Content delivery network
  - Amazon CloudFront
  - Amazon Mechanical Turk (MTurk)
    A 'marketplace for work’
  - …
- All services are paid depending on use

***http://phx.corporate-ir.net/phoenix.zhtml?c=176060&p=irol-corporateTimeline***

# Using AWS Services

- AWS Management Console
  - Easy to use, great for manual configurations
  - Use **username** / **password** provided
- Command line tools
  - For writing scripts
    - e.g., create a set of machines to analyze data every day
  - Use **access key ID** and **secret access key,** or **certificates for EC2**
- AWS API
  - Integrating cloud services into your applications
    - e.g., storing data on the cloud, running computation in the background
  - Use **access key ID** and **secret access key, or certificates for EC2**
- SSH into EC2 instances is performed using a different keypair

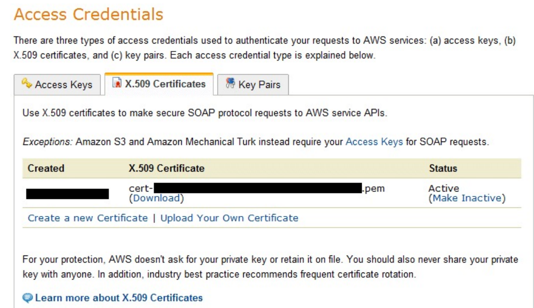
# Setting up an AWS account




- Sign up for an account on aws.amazon.com
  - **You need to choose an username and a password**
  - These are for the management interface only
  - **Your programs will use other credentials (RSA keypairs, access keys, ...) to interact with AWS**

# AWS credentials

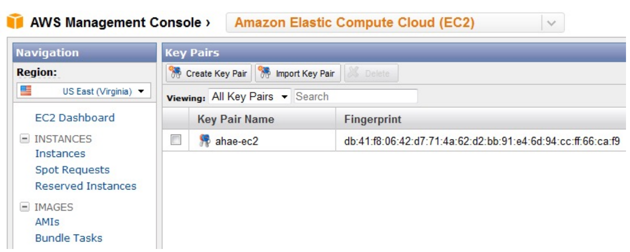
**Command-line tools**
**SOAP APIs**

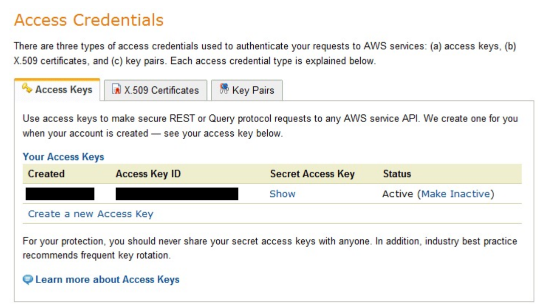




**AWS web site and management console**

**Sign-in credentials**

**X.509 certificates**




**Connecting to an instance (e.g., via ssh)**

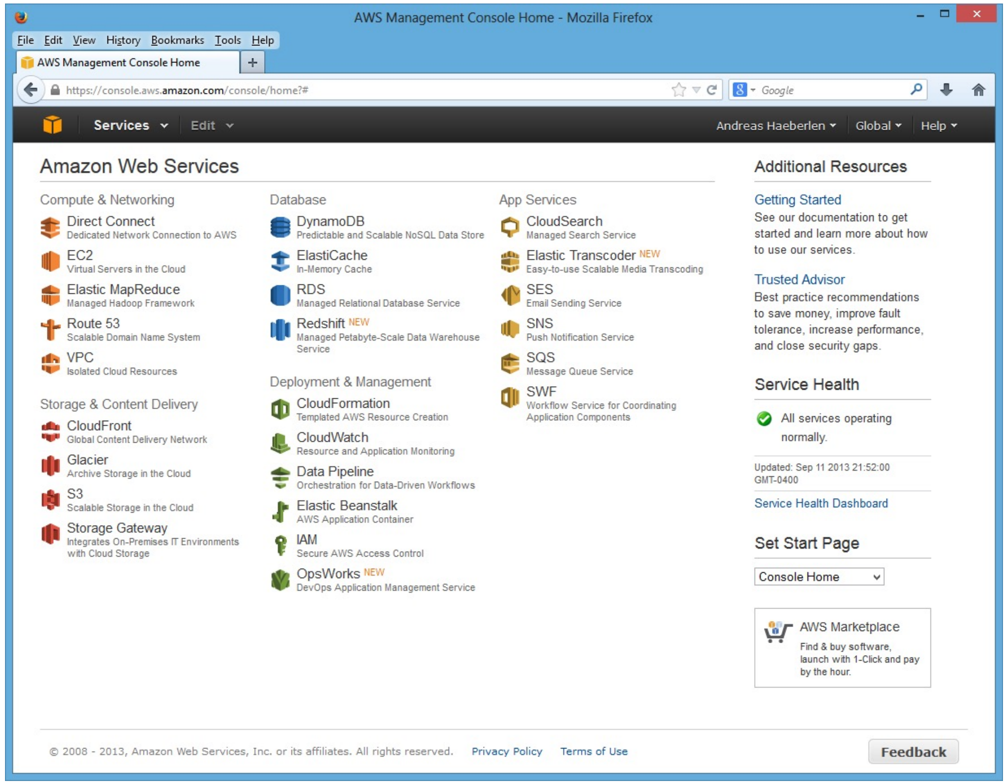
**EC2 key pairs**

**Access keys**

**REST APIs**

- Why so many different types of credentials?

# The AWS management console

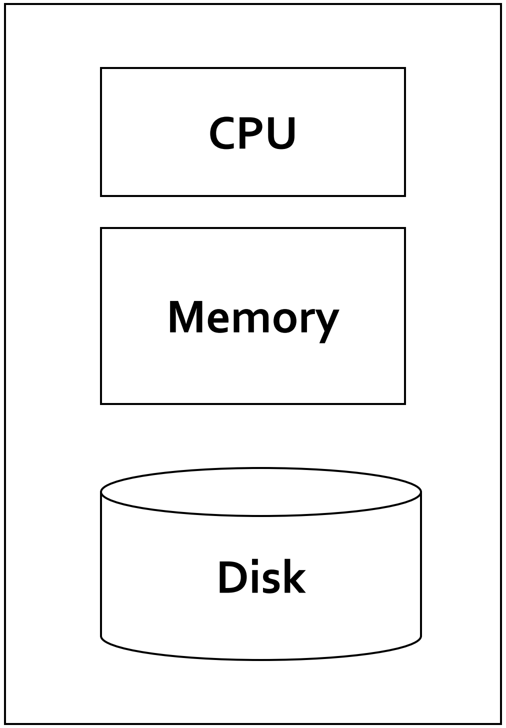



- Used to control many AWS services:
  - For example, start/stop EC2 instances, create S3 buckets...

# How do we scale up processing for Big Data ?

**Or: How to run Algorithms on MANY REAL and FAULTY boxes ?**

# Single Node Architecture




**“Classical”**
**Machine Learning, Statistics, Data Mining**

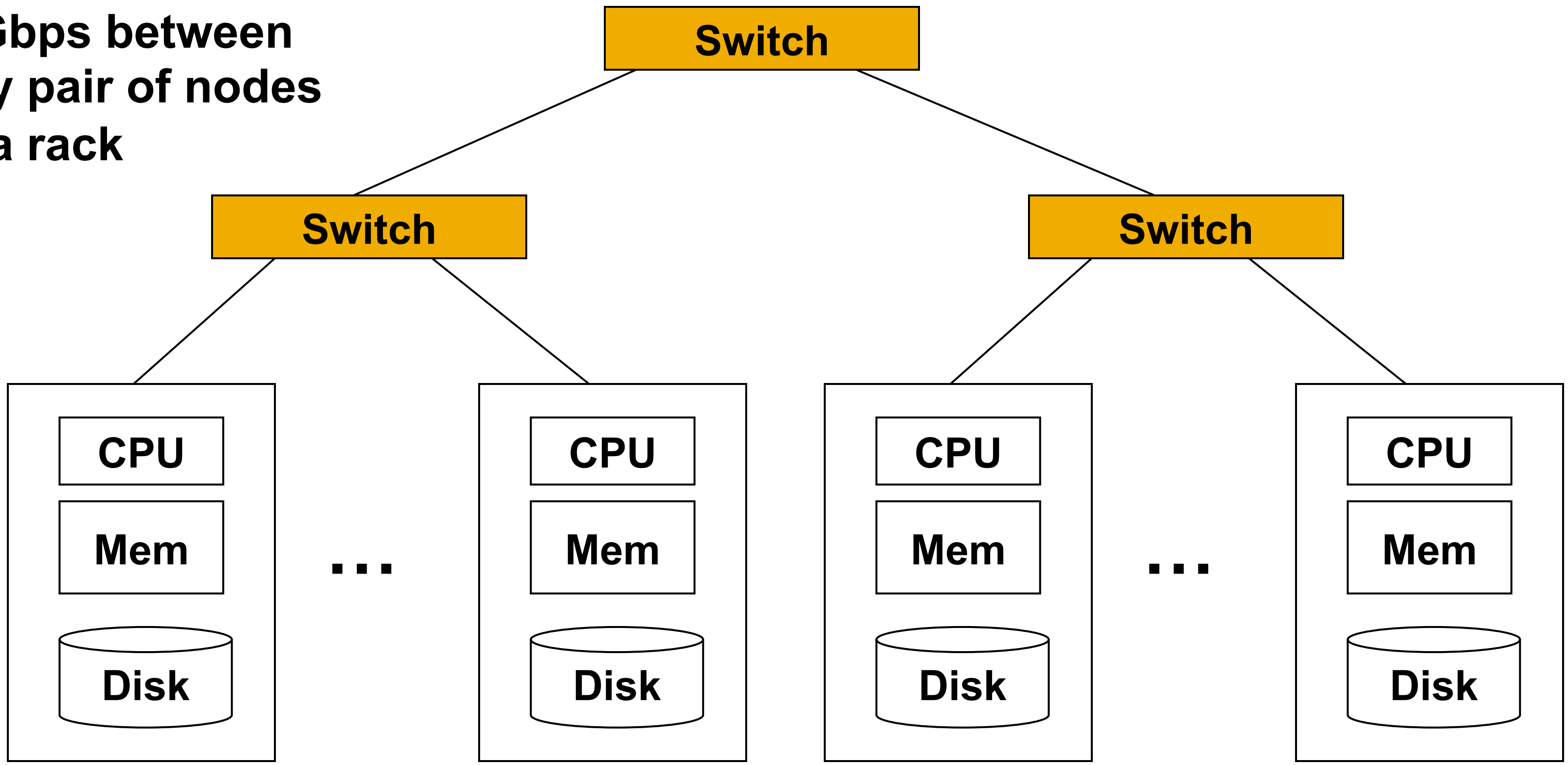
# Motivation: Google Example

- 20+ billion web pages x 20KB = 400+ TB
- 1 computer reads 80-160 MB/sec from disk (circa 2015)
  - ~4 months to read the web
- ~300 hard drives to store the web
- Takes even more to **do** something useful with the data!
- **Today, a standard architecture for such problems is emerging:**
  - Cluster of commodity Linux nodes
  - Commodity network (Ethernet) to connect them

# Cluster Architecture

**2-10 Gbps backbone between racks**

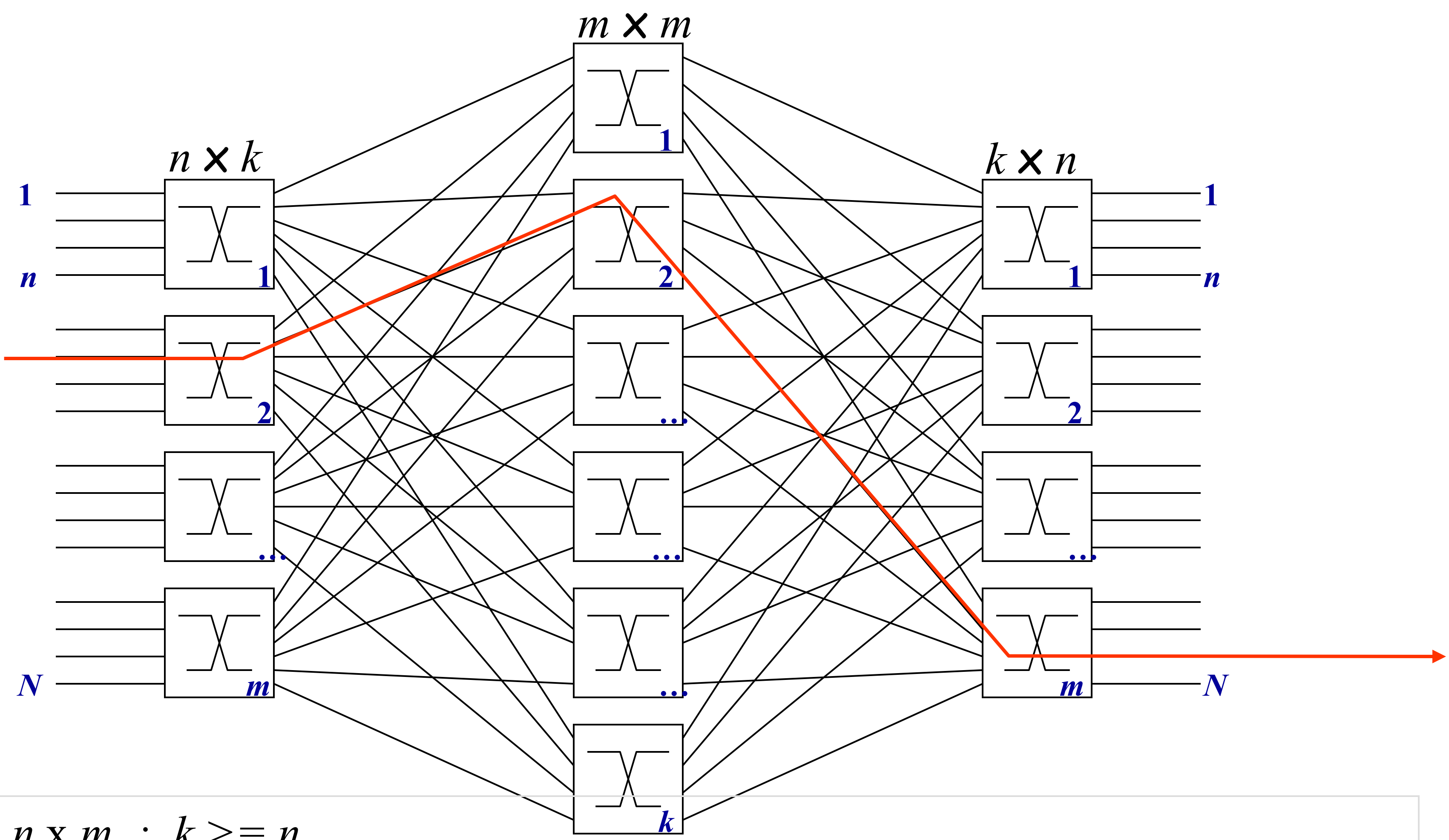
**1 Gbps between any pair of nodes in a rack**




**Each rack contains 16-64 nodes**

In 2011, it was guestimated that Google had 1M machines, http://bit.ly/Shh0RO
In July 2013, Steve Ballmer, then CEO of Microsoft said his company had
> 1 Million Servers, which was fewer than Google but a little more than Amazon

# Interconnection via a 3-stage Clos Network (instead of a Tree)



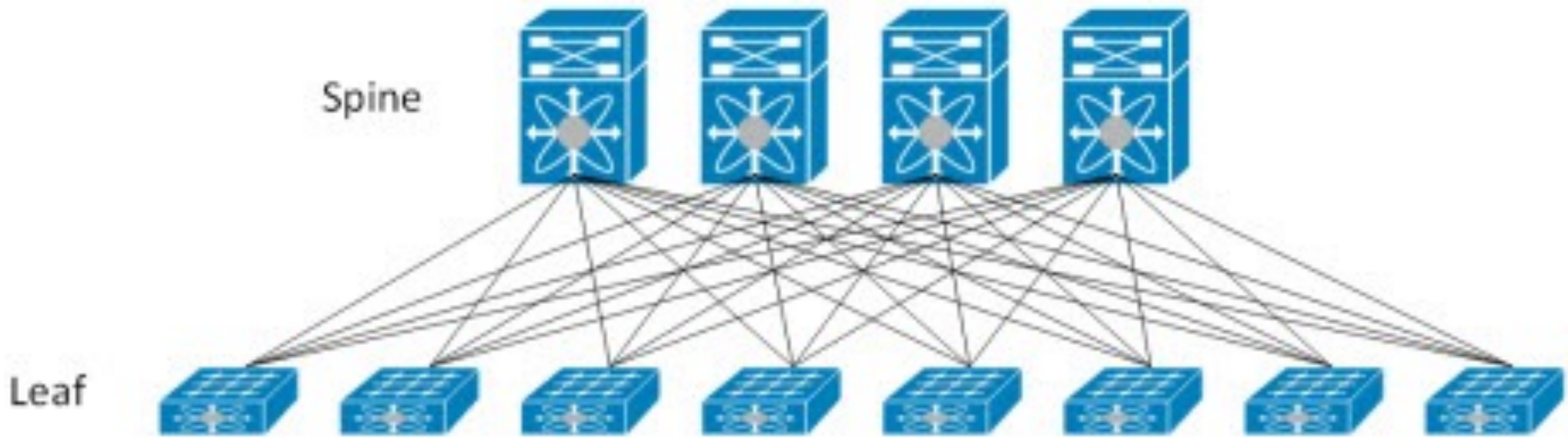

$N = n \times m$ ; $k >= n$

*e.g. k = 16, n = 16, m = 4,*

**Course on this subject:**

**IERG5020 Telecommunication Switching and Network Systems**

# Clos Networks' Reappearance in Datacenter Networks (aka the Spine and Leaf Topology, or Folded Clos, or Fat-Trees)

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# of Uplinks (of each ToR) = # of Spine switches
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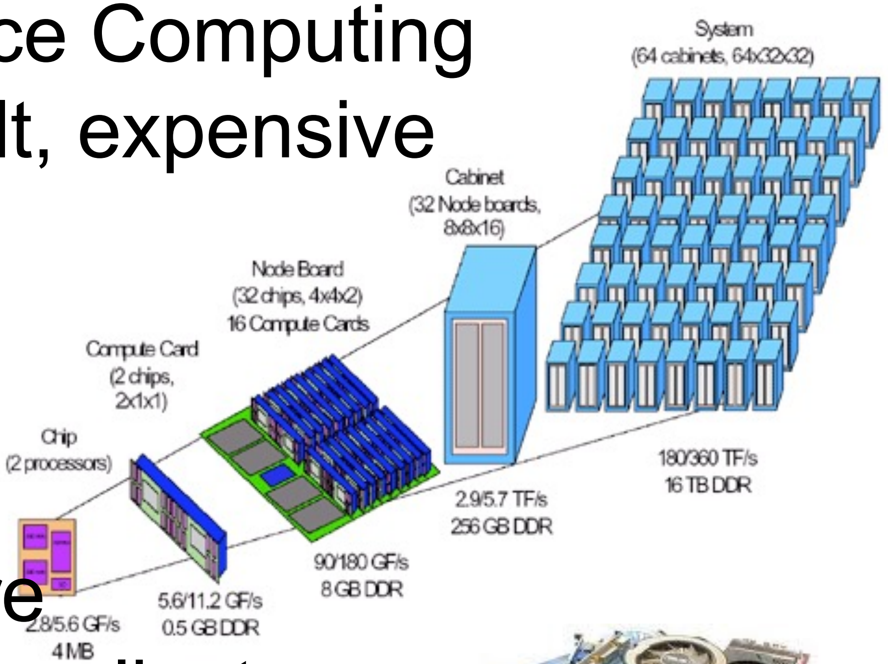
Multiple ECMP exists for every pair of Leaf switches
Support Incrementally "Scale-out" by adding more Leaf and Spine switches



"Jupiter Rising: A Decade of Clos Topologies and Central Control in Google's Datacenter Networks," ACM Sigcomm 2015.

# Using Commodity Hardware

- 80-90's: High Performance Computing
  Very reliable, custom built, expensive




- Now: Consumer hardware
  Cheap, efficient, easy to replicate,
  BUT not very reliable,

- MUST deal with it!

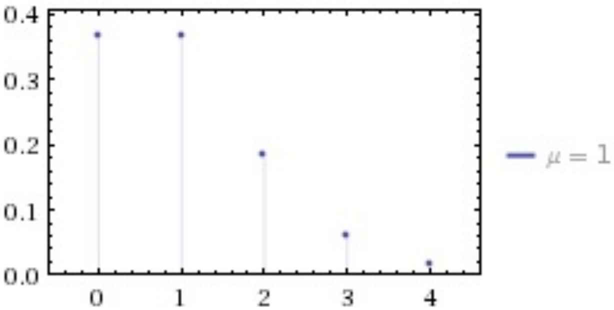
# Why commodity machines?

| | HP INTEGRITY SUPERDOME-ITANIUM2 | HP PROLIANT ML350 G5 |
|---|---|---|
| Processor | 64 sockets, 128 cores (dual-threaded), 1.6 GHz Itanium2, 12 MB last-level cache | 1 socket, quad-core, 2.66 GHz X5355 CPU, 8 MB last-level cache |
| Memory | 2,048 GB | 24 GB |
| Disk storage | 320,974 GB, 7,056 drives | 3,961 GB, 105 drives |
| TPC-C price/performance | $2.93/tpmC | $0.73/tpmC |
| price/performance (server HW only) | $1.28/transactions per minute | $0.10/transactions per minute |
| Price/performance (server HW only) (no discounts) | $2.39/transactions per minute | $0.12/transactions per minute |

Source: Barroso and Urs Hölzle (2009); performance figures from late 2007

# Fault Tolerance

- Performance goal
  - 1 failure per year
  - for a 1000-machine Cluster
- Poisson approximation




$$\Pr(n) = \frac{1}{n!} e^{-\mu} \mu^n$$

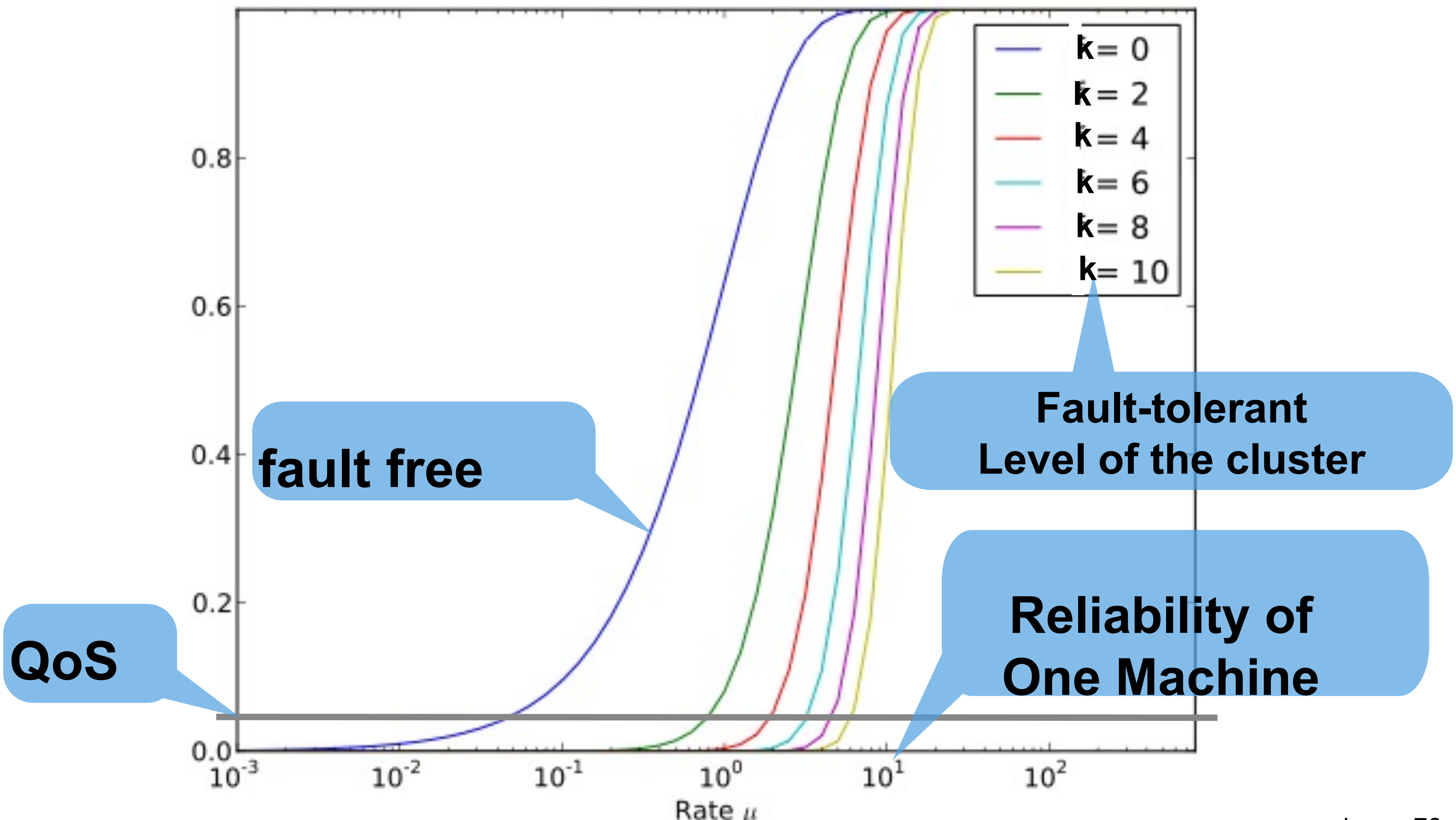
  - Assume failure rate $\mu$ per machine
  - Poisson rates of independent random variables are additive, so we can combine

=> With Fault Intolerant Engineering
We need a rate of 1 failure per 1000 years per machine

- Fault tolerance
  Assume we can tolerate k faults among m machines in t time units

$$\Pr(f > k) = 1 - \sum_{n=0}^{k} \frac{1}{n!} e^{-\lambda t} (\lambda t)^n$$

# Fault tolerance



# Performance Characteristics of Hardware in a Datacenter-scale Computer

# The Joys of Real Hardware

Typical first year for a new cluster:

~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.

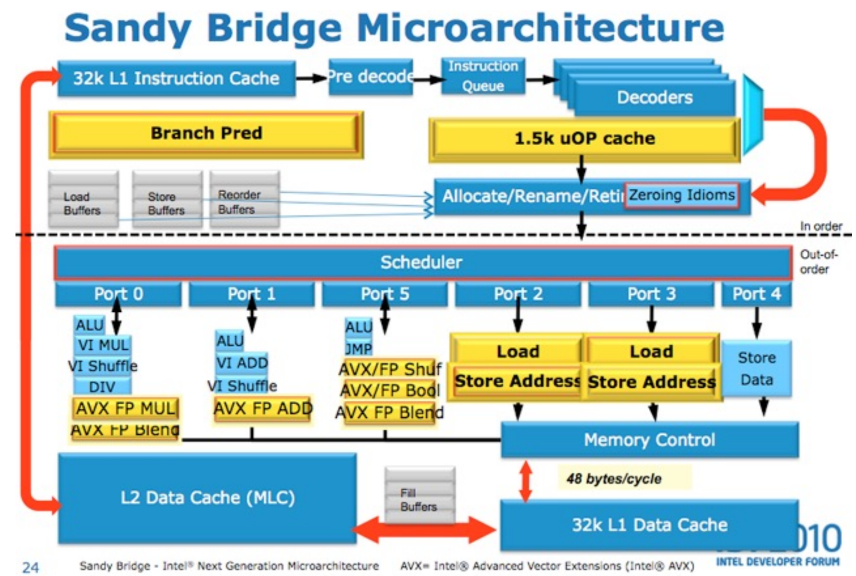
**Slide from talk of Jeff Dean:**
**http://research.google.com/people/jeff**/stanford-295-**talk**.pdf

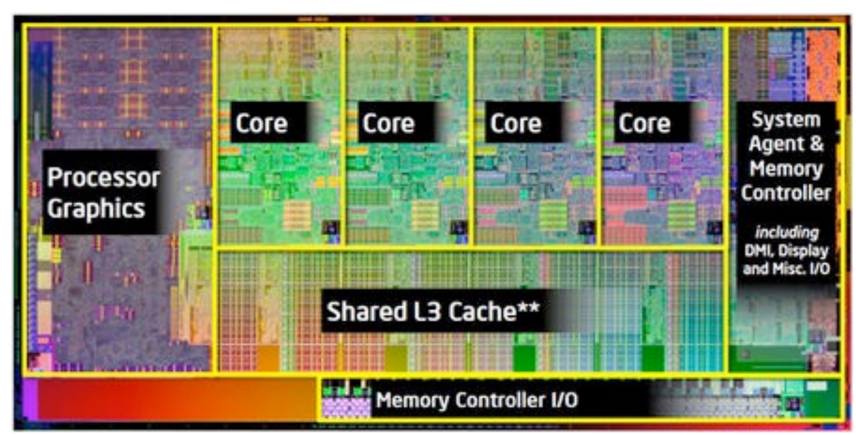
# “Facts” about Jeff Dean

- Compilers don’t warn Jeff Dean.  Jeff Dean warns compilers.
- Jeff Dean builds his code before committing it, but only to check for compiler and linker bugs.
- Jeff Dean writes directly in binary. He then writes the source code as a documentation for other developers.
- Jeff Dean once shifted a bit so hard, it ended up on another computer.
- When Jeff Dean has an ergonomic evaluation, it is for the protection of his keyboard.
- gcc -O4 emails your code to Jeff Dean for a rewrite.
- When he heard that Jeff Dean's autobiography would be exclusive to the platform, Richard Stallman bought a Kindle.
- Jeff Dean puts his pants on one leg at a time, but if he had more legs, you’d realize the algorithm is actually only O(log n)

# CPU

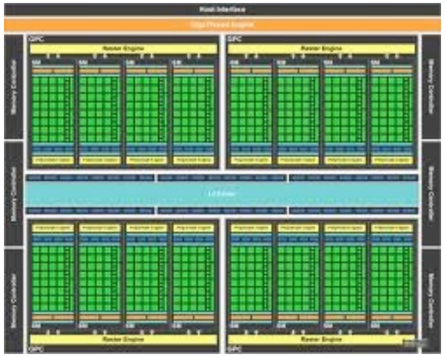
- Multiple cores (e.g. Intel Xeon E7 series has 4-24 cores per CPU @2016)
- Multiple sockets (1-4) per board
- 2-4 GHz clock
- 10-100W power
- Several cache levels (hierarchical, 8-16MB total)
- Vector processing units (SSE4, AVX) http://software.intel.com/en-us/avx
- Perform several operations at once
- Use this for fast linear algebra (4-8 multiply adds in one operation)
- Memory interface 20-40GB/s
- Internal bandwidth >100GB/s
- 100+ GFlops for matrix matrix multiply
- Integrated low end GPU



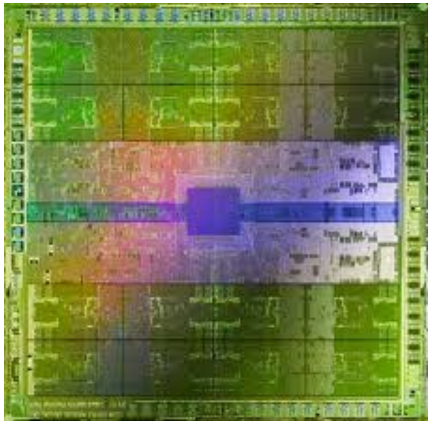



# GPU

- Nvidia GeForce10 has 400 to 4000 cores / drawing many 100’s of Watt

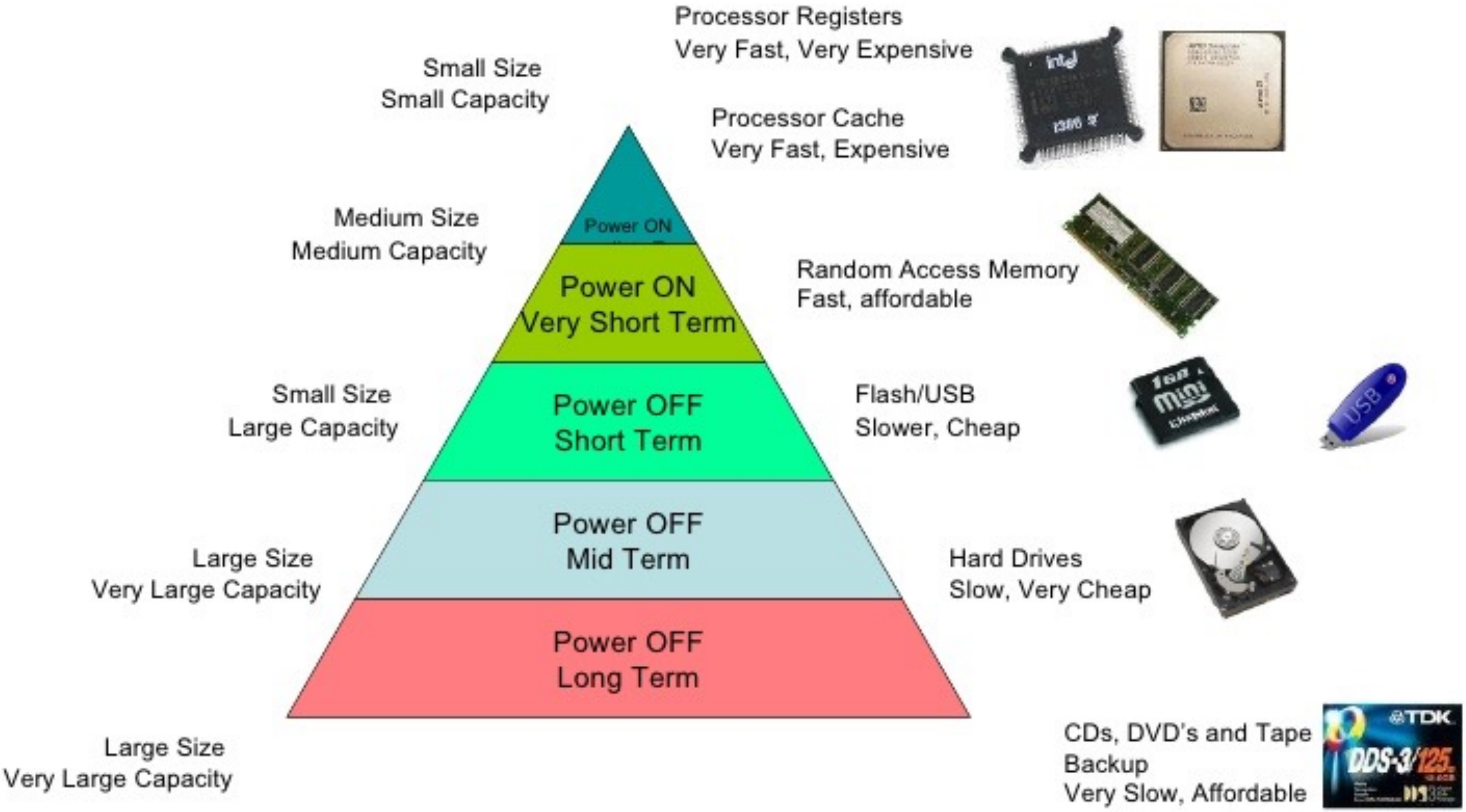


- Cores have hierarchical structure tricky to synchronize threads (interrupts, semaphores, etc.)



- 1 to 10’s GB internal GPU memory
  - Nvidia Tesla: 6GB ; A100: 80GB
- A few upto > 100 TFlops
  - Depending on data Precision format
- Max. Internal Memory Bandwidth ~ 2000GB/s
- 192GB/s PCIe 4.0 bus bottleneck?

# Computer Memory Hierarchy



# DRAM

- 2-4 channels (32 bit wide)
- 1GHz speed
- High latency ( ~10ns for DDR4)
- High burst data rate (>10 GB/s)
- Avoid random access in code if possible.
- Memory align variables
- Know your platform (FBDIMM vs. DDR)
  (code may run faster on old MacBookPro than a Xeon)

# Storage

- Harddisks (SATA3 – 6 Gbps) circa 2020 -
  - 4-16 TB of storage (50GB/ $)
  - 150 MB/s bandwidth (sequential)
  - 5 ms seek (200 IOPS)
  - cheap

- SSD (SATA3 – 6Gbps) circa 2020 -
  - 128GB - 4TB storage (3-8GB / $)
  - 500 MB/s bandwidth (sequential read/write)
  - 100,000 IOPS / < 1 ms seek (queueing)
  - Reads a little faster than writes
    - e.g. 550 vs. 520 MB/s for Samsung 850Pro
  - reliable (but limited lifetime - NAND)

- NVMe (M.2 port) /PCIe SSD circa 2020 -
  - 128GB - 8TB storage
  - (Intel 3D XPoint: 0.7GB/ $ ; NAND-based ~ 5 GB/ $)
  - 1500 – 3500 MB/s (sequential read/write)
  - 150,000 – 500,000 IOPS


# Numbers (Jeff Dean says) Everyone Should Know

| | | | | | | |
|---|---|---|---|---|---|---|
| L1 cache reference | 0.5 | ns | | | | |
| Branch mispredict | 5 | ns | | | | |
| L2 cache reference | 7 | ns | | | | 14x L1 cache |
| Mutex lock/unlock | 25 | ns | | | | |
| Main memory reference | 100 | ns | | | | 14x L2 cache, 200xL1 cache |
| Compress 1K bytes with Zippy | 3,000 | ns | 3 us | | | |
| Send 1K bytes over 1 Gbps network | 10,000 | ns | 10 us | | | |
| Read 4K randomly from SSD* | 150,000 | ns | 150 us | | | ~1GB/sec SSD |
| Read 1 MB sequentially from memory | 250,000 | ns | 250 us | | | |
| Round trip within same datacenter | 500,000 | ns | 500 us | | | |
| Read 1 MB sequentially from SSD* | 1,000,000 | ns | 1,000 us | 1 ms | | ~1GB/sec SSD, 4X memory |
| Disk seek | 10,000,000 | ns | 10,000 us | 10 ms | | 20x datacenter roundtrip |
| Read 1 MB sequentially from disk | 20,000,000 | ns | 20,000 us | 20 ms | | 80x memory, 20X SSD |
| Send packet CA->Netherlands->CA | 150,000,000 | ns | 150,000 us | 150 ms | | |

Notes
-----
1 ns = 10^-9 seconds
1 us = 10^-6 seconds = 1,000 ns
1 ms = 10^-3 seconds = 1,000 us = 1,000,000 ns

------
Originally by Peter Norvig: http://norvig.com/21-days.html#answers

# A typical disk

# What do we count?

- Compilers don’t warn Jeff Dean.  Jeff Dean warns compilers.
- ….
- Memory access/instructions are *qualitatively different* from disk access
- Seeks are *qualitatively different* from sequential reads on disk
- Cache, disk fetches, etc work best when you stream through data *sequentially*
- **Best case for data processing: stream through the data *once* in *sequential order,* as it’s found on disk.**

# Seeks vs. Scans

- Consider a 1 TB database with 100 byte records
  - We want to update 1 percent of the records
- Scenario 1: random access
  - Each update takes ~30 ms (seek, read, write)
  - $10^8$ updates = ~35 days
- Scenario 2: rewrite all records
  - Assume 100 MB/s throughput
  - Time = 5.6 hours(!)
- Lesson: avoid random seeks!

Source: Ted Dunning, on Hadoop mailing list

# Other lessons (circa 2007)

## Encoding Your Data

- CPUs are fast, memory/bandwidth are precious, ergo…
  - Variable-length encodings
  - Compression
  - Compact in-memory representations
- Compression very important aspect of many systems
  - inverted index posting list formats
  - storage systems for persistent data

but not important

•This “conventional” wisdom may become out-dated already !

# More recent Observations on Spark Performance Analysis

[K. Ousterhout et al, NSDI 2015]

up to 10x

spark.apache.org

**I/O related**

**19%**

6x or more

amplab.cs.berkeley.edu/benchmark/

(on-disk data)

serialized + compressed **on-disk** data

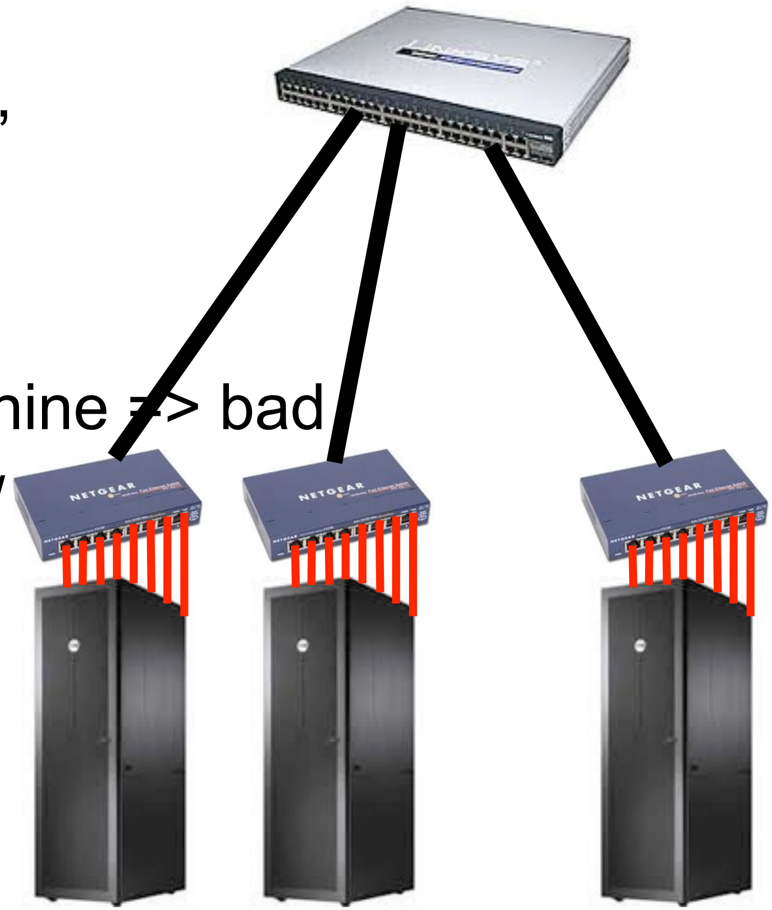
serialized + compressed **in-memory** data

**deserialized** in-memory data

Faster

# Switches & Colos

- In theory perfect point to point bandwidth (e.g. 1Gb Ethernet)
- Big switches are expensive
  crossbar bandwidth linear in #ports,
  BUT price superlinear
- Real switches have finite buffers
  - many connections to a single machine => bad
  - buffer overflow / dropped packets / collision avoidance
- Hierarchical structure
  - more bandwidth within rack
  - lower latency within rack
  - lots of latency between Colos
- Hadoop gives you machines where the data is (not necessarily on same rack!)



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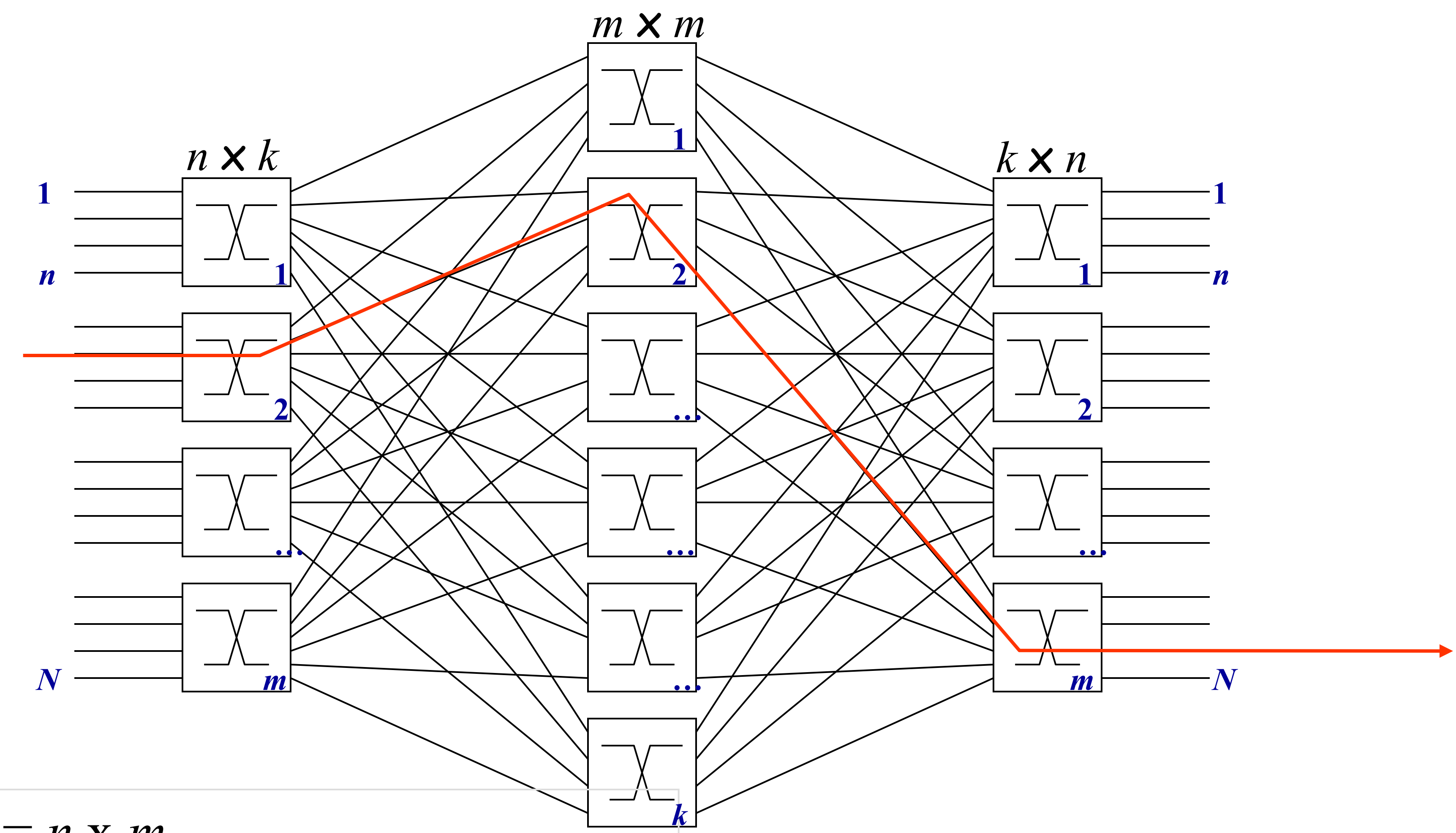
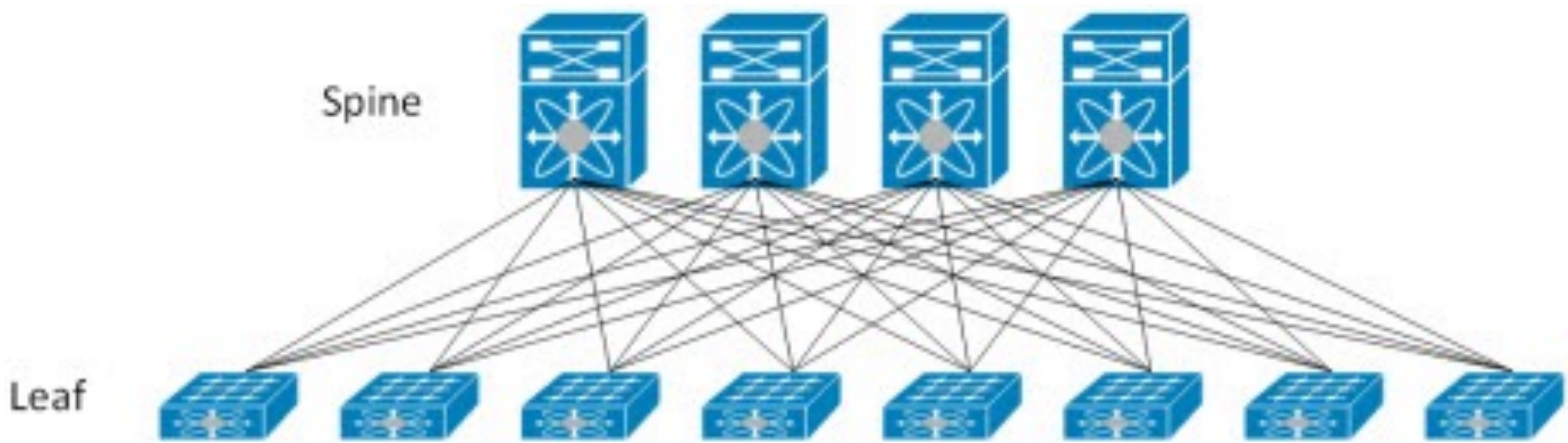



$N = n \text{ x } m$

$k >= n$

$k = 16,\ n = 16,\ m = 4,$

# Clos Networks' Reappearance in Datacenter Networks (aka the Spine and Leaf Topology, or Folded Clos, or Fat-Trees)

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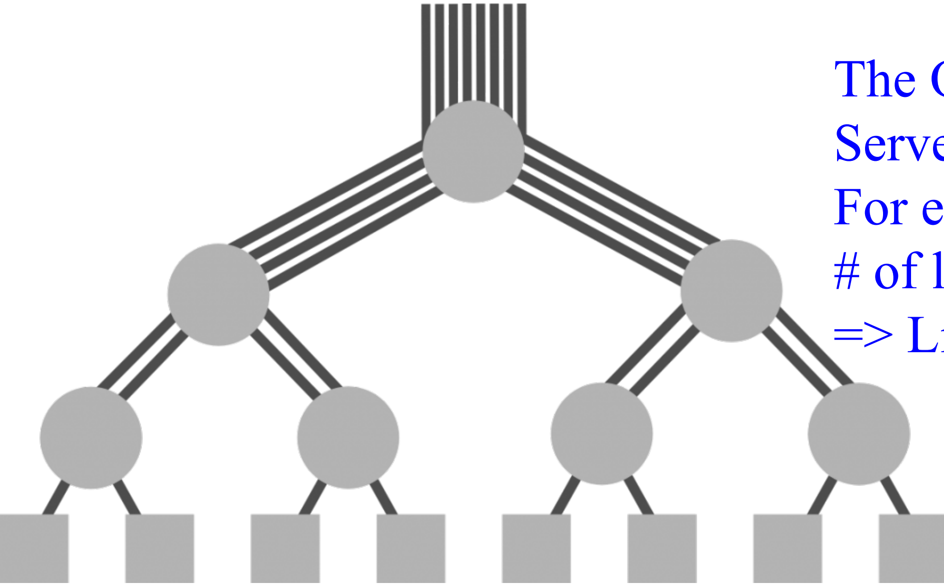
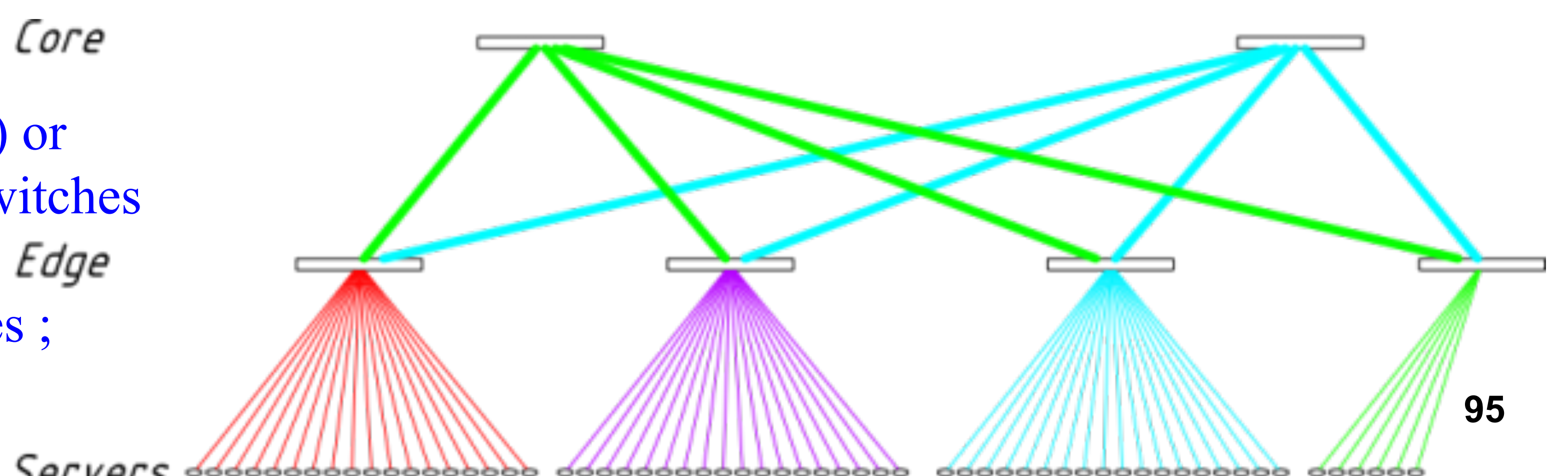


The Original Fat-Tree Topology [Leiserson 85]:
Servers (Processors) are the leafs ;
For every non-leaf node (Switch) in the tree,
# of links to its Parent = # of links to its Children
=> Links at "Fatter" towards the top of the tree

Source: http://clusterdesign.org/fat-trees/

Example:
All Leaf (Edge) or
Spine (Core) switches
are identical
36-port switches ;



# Communication Cost ?

- Nodes need to talk to each other!
  - SMP (Symmetric Multi-Processor machine): latencies ~100 ns
  - LAN: latencies ~100 μs
- Scaling "up" vs. Scaling "out"
  - Smaller cluster of SMP machines vs. larger cluster of commodity machines
  - E.g., 8 128-core machines vs. 128 8-core machines
  - Note: no single SMP machine is big enough
- Let's model communication overhead…

Source: analysis on this and subsequent slides from Barroso and Urs Hölzle, "The Datacenter as a Computer," 2009.

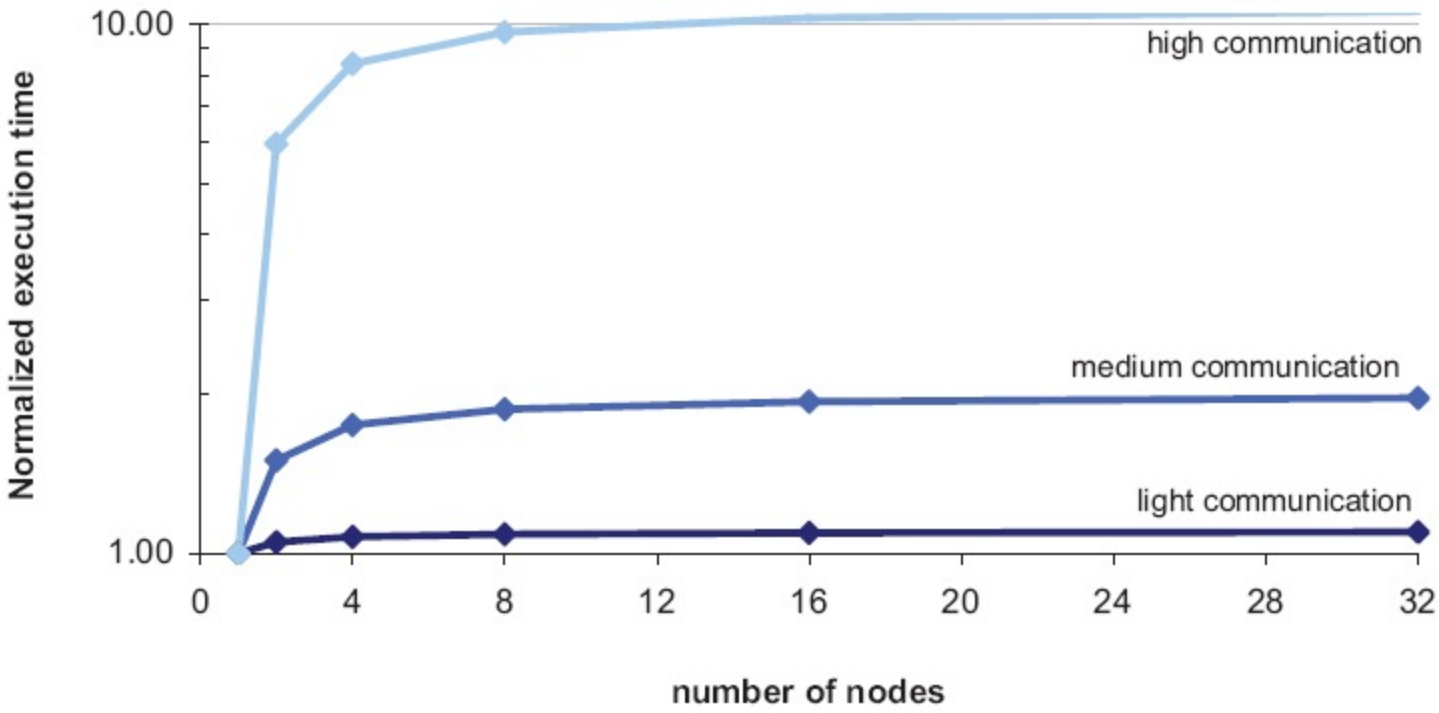
# Modeling Communication Costs

- Simple execution cost model:
  - Fraction of local access inversely proportional to size of cluster
  - *n* nodes (each node is a shared-memory SMP domain)
  - Total no. of cores in the cluster (sum up all nodes) remains the same
  - Total cost = cost of computation + cost to access global data

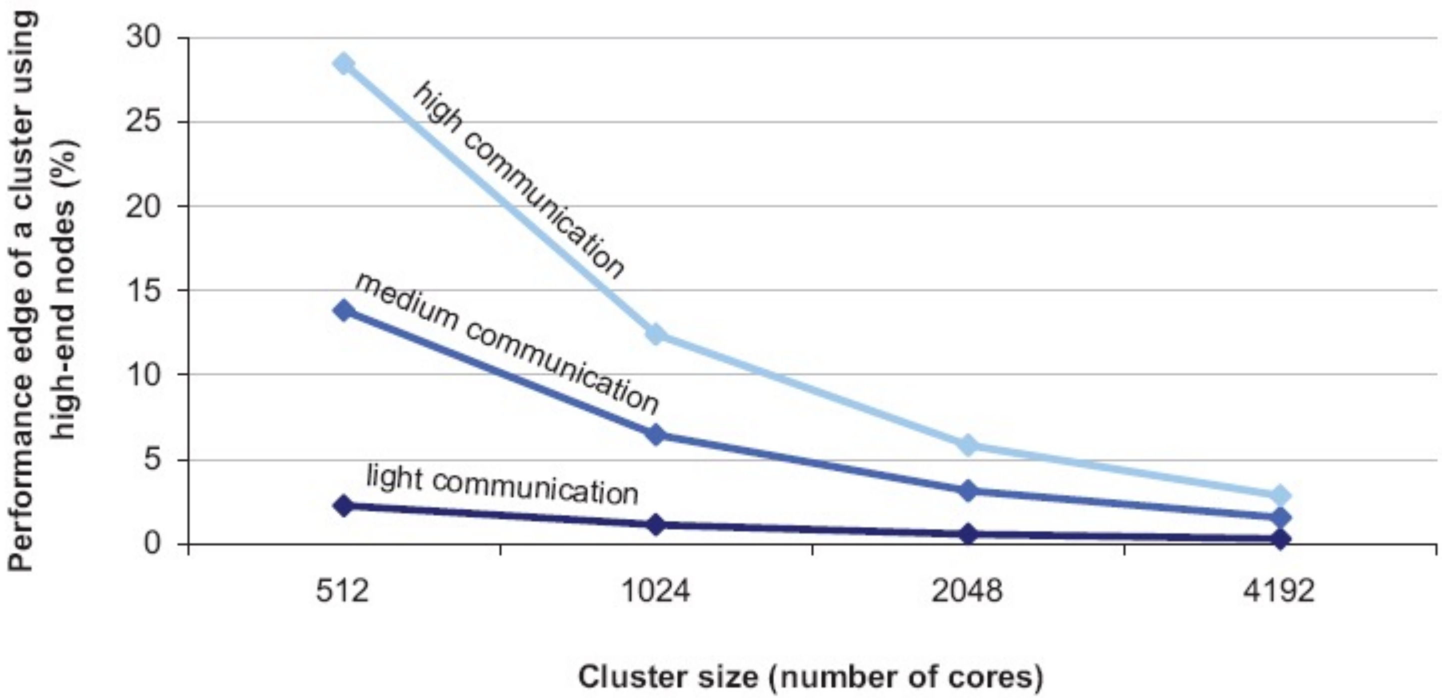
$$= 1 \text{ ms} + f \times [100 \text{ ns} / n + 100\ \mu\text{s} \times (1 - 1/n)]$$

    - Light communication: $f = 1$
    - Medium communication: $f = 10$
    - Heavy communication: $f = 100$
- What are the costs in parallelization?

# Cost of Parallelization



# Advantages of scaling "out"




**So why not?**

# Data Intensive Computing

- Data collection too large to transmit economically over Internet --- Petabyte data collections
- Computation produces small data output containing a high density of information
- Implemented in “Clouds”
- Easy to write programs, fast turn around.
- MapReduce, Google File System, BigTable
  - Map(k1, v1) -> list (k2, v2)
  - Reduce(k2,list(v2)) -> list(v3)
- Apache Hadoop (YARN), PIG, Hive, HDFS, Hbase, Spark, Flink, Storm/Heron

# The datacenter *is* the computer

# “Big Ideas”

- Scale “out”, not “up”
  - Limits of SMP and large shared-memory machines
- Move processing to the data
  - Cluster have limited bandwidth
- Process data sequentially, avoid random access
  - Seeks are expensive, disk throughput is reasonable
- Seamless scalability
  - From the mythical man-month to the tradable machine-hour

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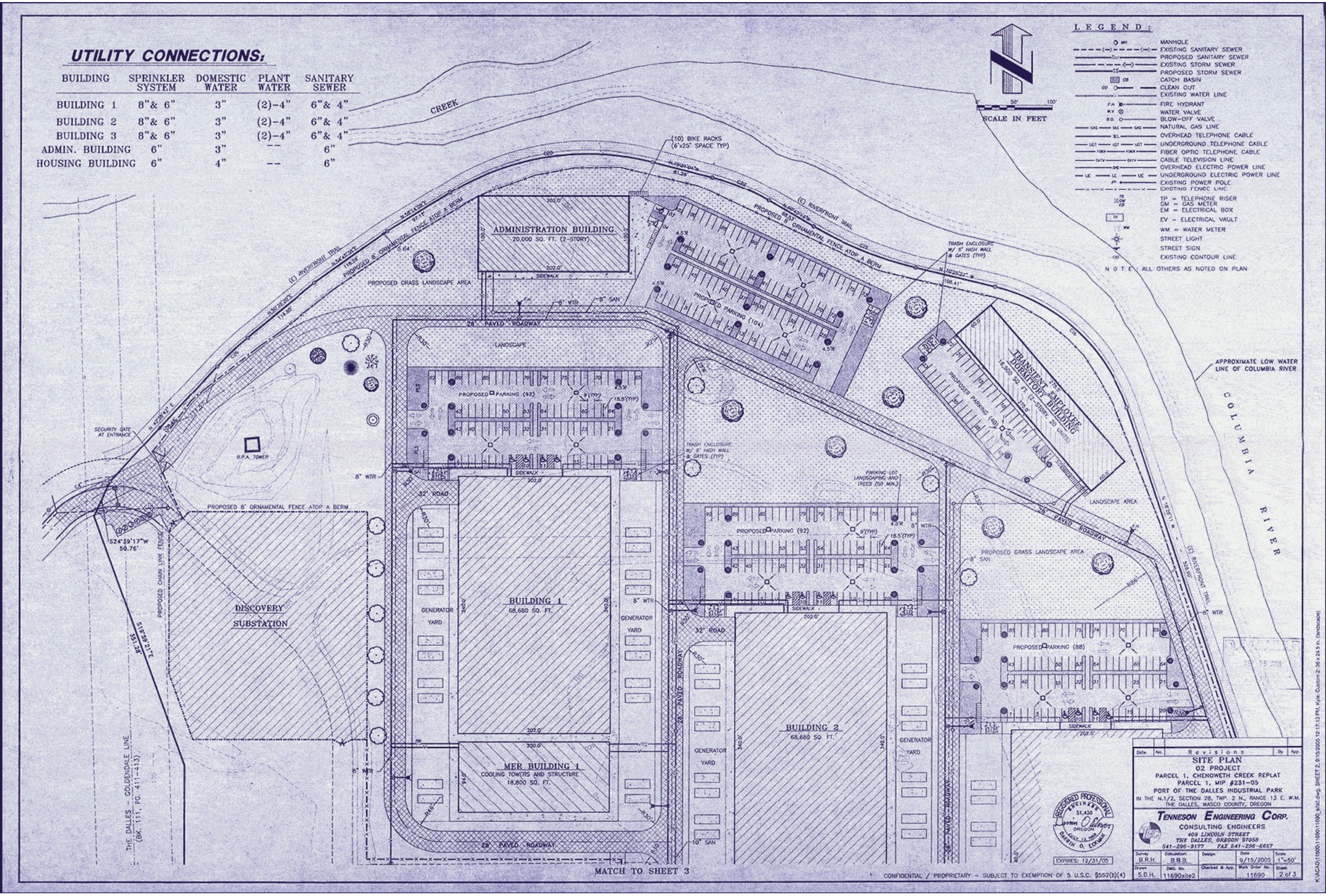
Source: Wikipedia (The Dalles, Oregon)

Source: NY Times (6/14/2006)

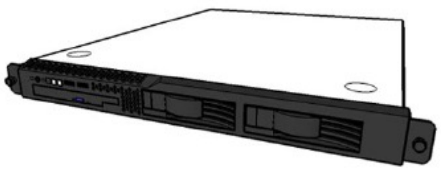
Source: www.robinmajumdar.com

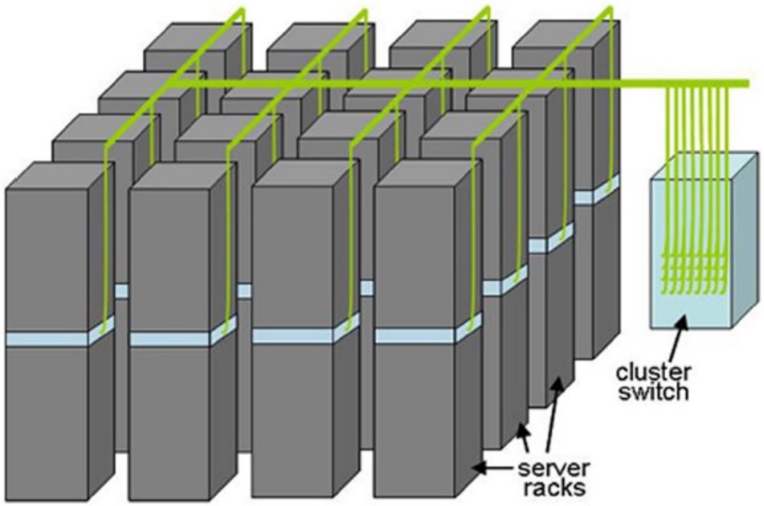



Source: Harper's (Feb, 2008)

Source: Bonneville Power Administration

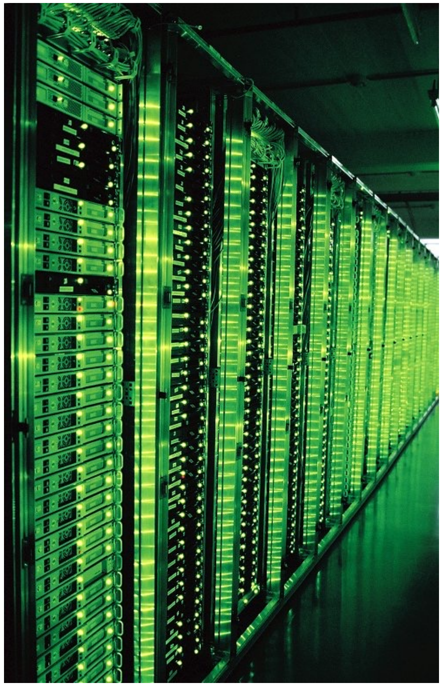
# Building Blocks





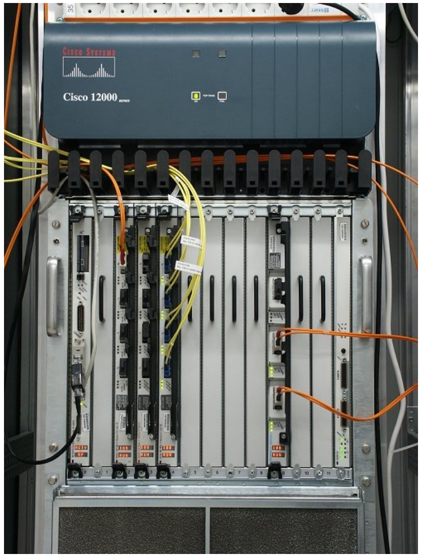

Source: Barroso and Urs Hölzle (2009)

# What's in a data center?



- Hundreds or thousands of racks

# What's in a data center?



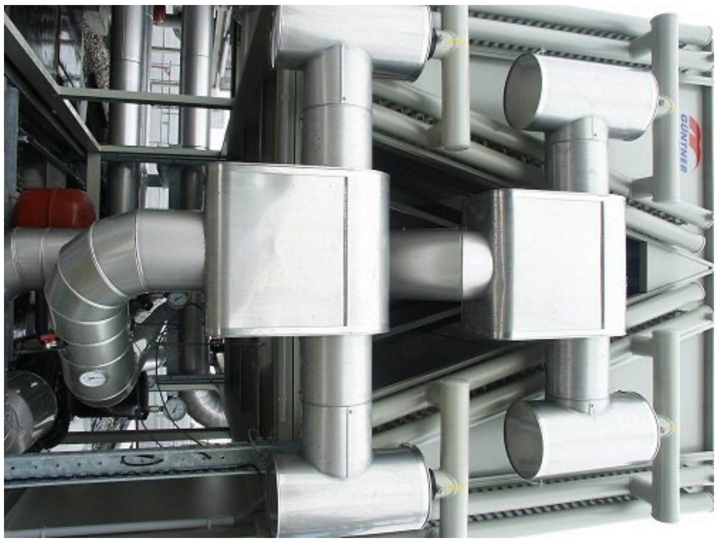

- Massive networking

# What's in a data center?



- Emergency power supplies

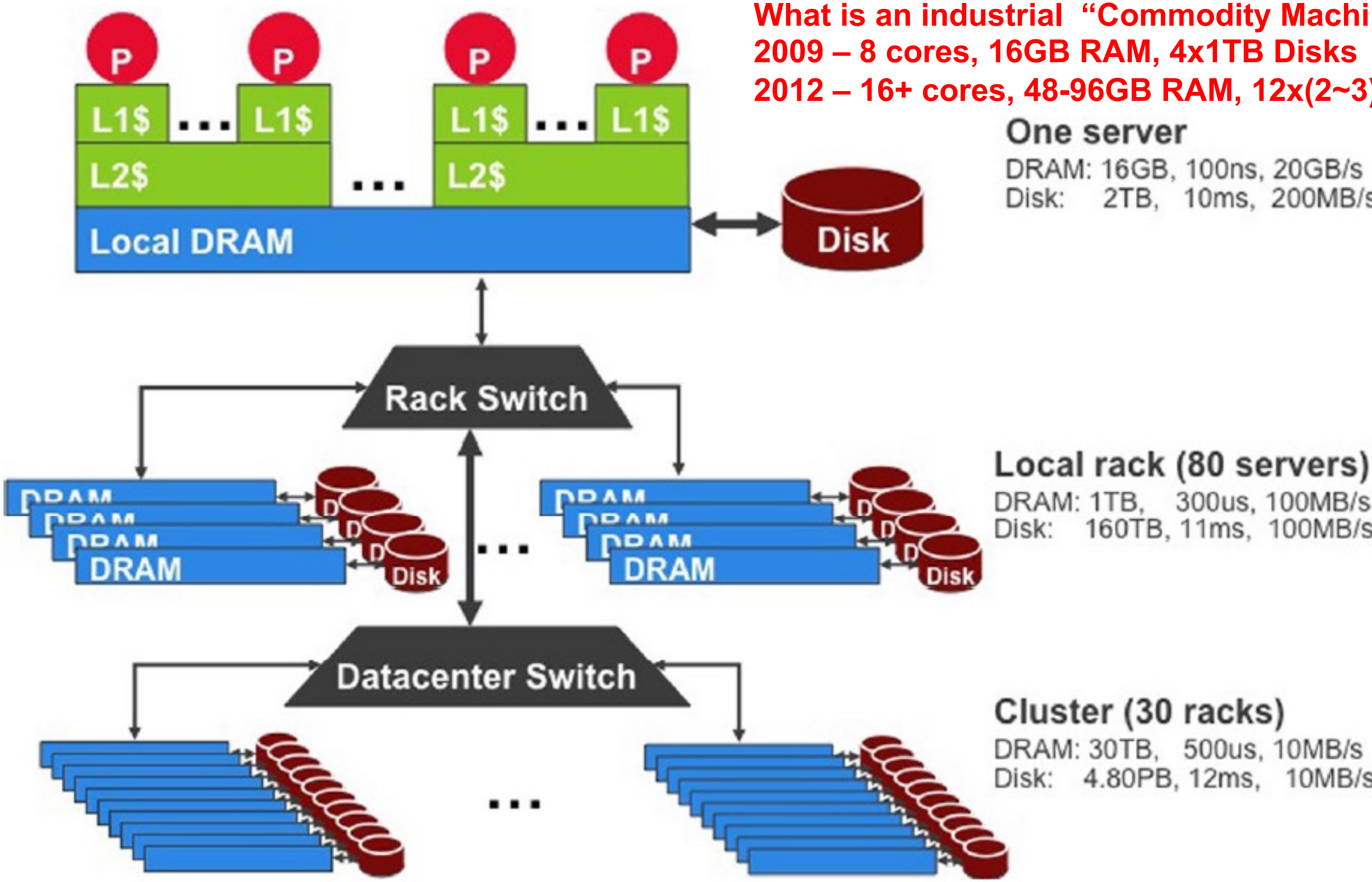
# What's in a data center?



- Massive cooling

# Storage Hierarchy

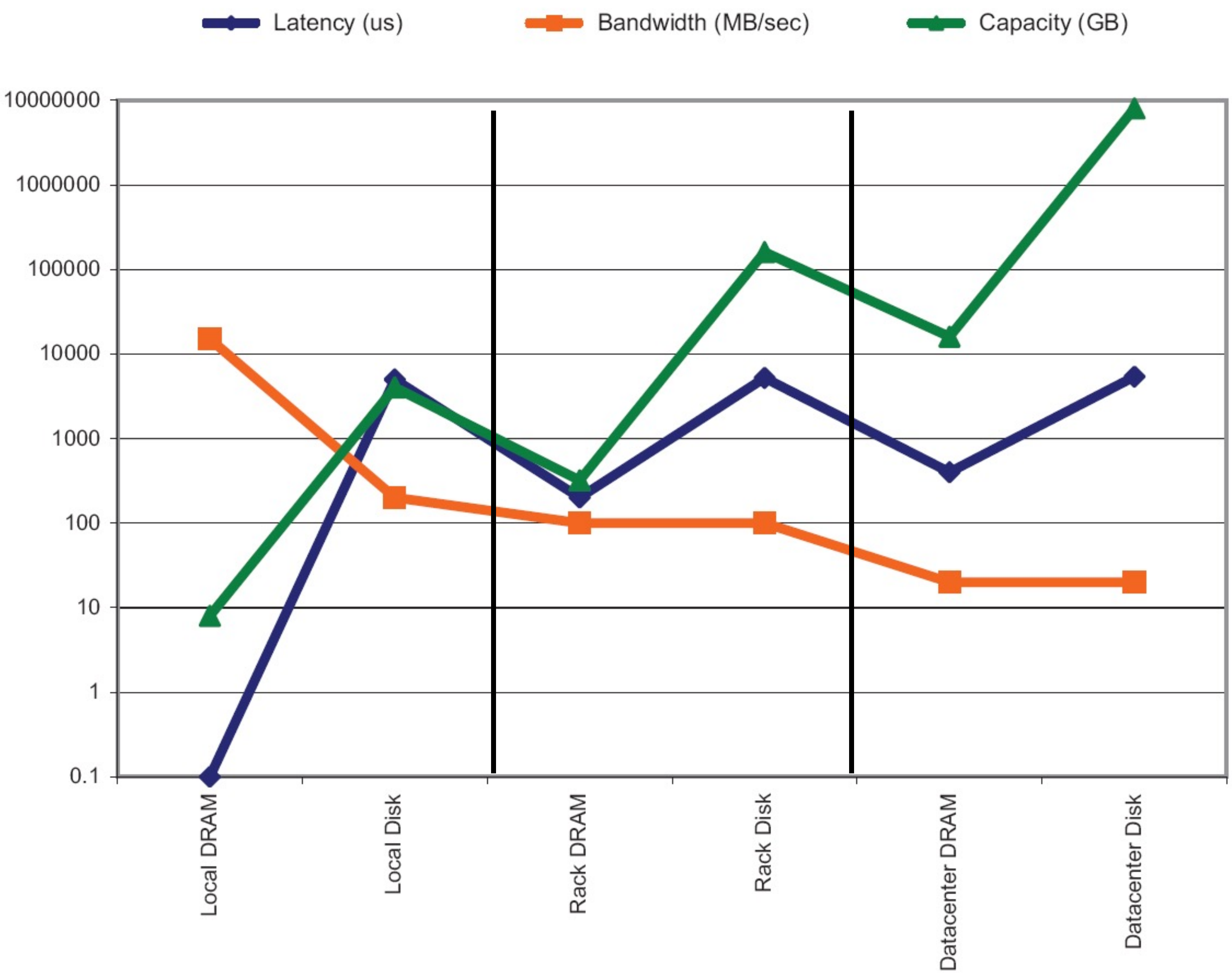
**What is an industrial "Commodity Machine" ?**
**2009 – 8 cores, 16GB RAM, 4x1TB Disks**
**2012 – 16+ cores, 48-96GB RAM, 12x(2~3)TB Disks**




**The sense of scale…**

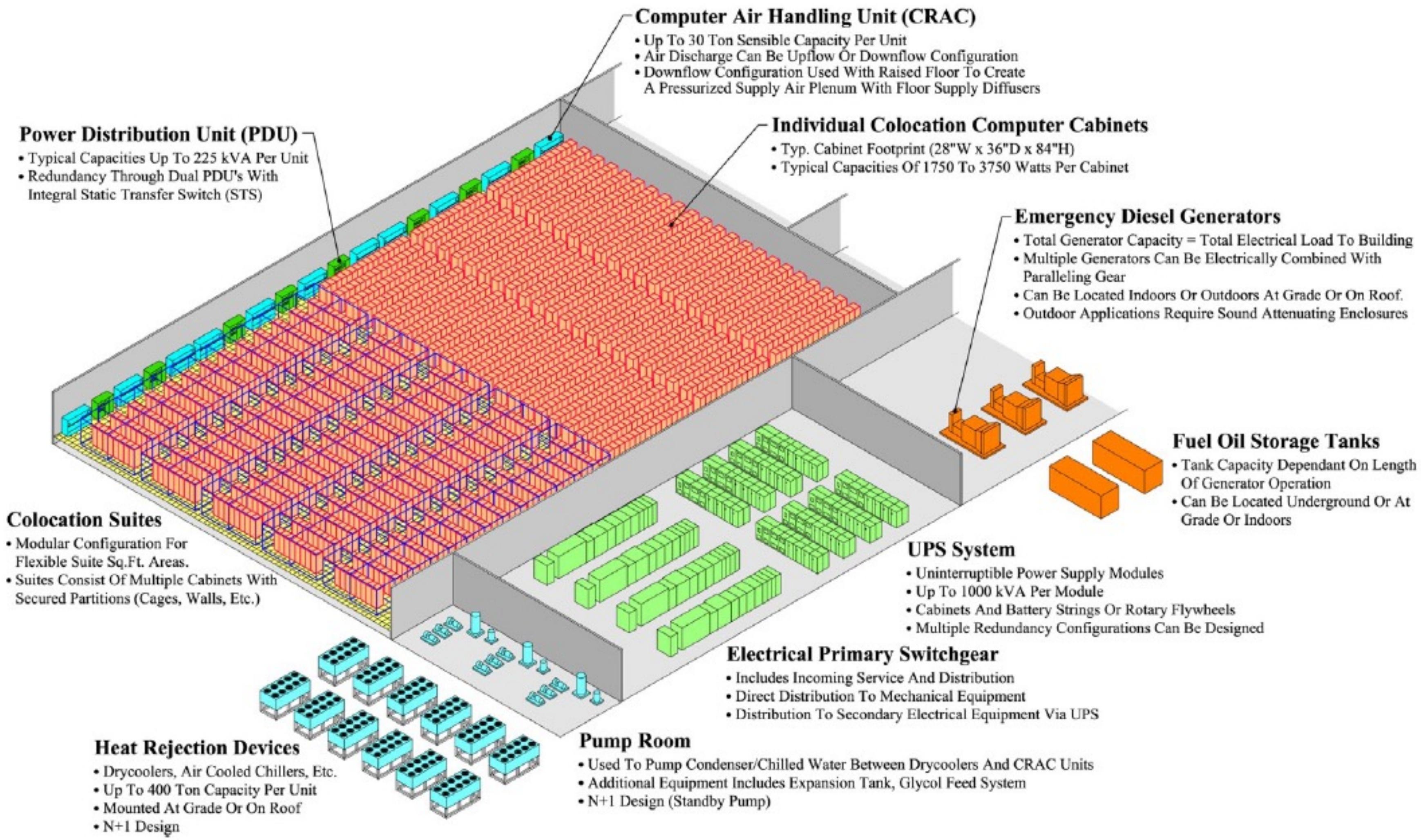
Source: Barroso and Urs Hölzle (2009)

# Storage Hierarchy




Source: Barroso and Urs Hölzle (2009)

# Anatomy of a Datacenter




Source: Barroso and Urs Hölzle (2009)

# Energy matters!

| Company | Servers | Electricity | Cost |
|---|---|---|---|
| eBay | 16K | ~$0.6*10^5$ MWh | ~$3.7M/yr |
| Akamai | 40K | ~$1.7*10^5$ MWh | ~$10M/yr |
| Rackspace | 50K | ~$2*10^5$ MWh | ~$12M/yr |
| Microsoft | >200K | >$6*10^5$ MWh | >$36M/yr |
| Google | >500K | >$6.3*10^5$ MWh | >$38M/yr |
| USA (2006) | **10.9M** | **$610*10^5$ MWh** | **$4.5B/yr** |

- Data centers consume a lot of energy
  - Makes sense to build them near sources of cheap electricity
  - Example: Price per KWh is 3.6ct in Idaho (near hydroelectric power), 10ct in California (long distance transmission), 18ct in Hawaii (must ship fuel)
  - Most of this is converted into heat → Cooling is a big issue!

# Scaling up

- What if even a data center is not big enough?
  - Build additional data centers
  - Where? How many?

# Global distribution



- Data centers are often globally distributed
  - Example above: Google data center locations (inferred)
- Why?
  - Need to be close to users (physics!)
  - Cheaper resources
  - Protection against failures

# Trend: Modular data center


- Need more capacity? Just deploy another container!

# Justifying the “Big Ideas”

- Scale “out”, not “up”
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# Recap

- Web-Scale Data – their sources and uses
- What is Web-Scale Information Analytics:
  - Data Mining, Statistical Modeling, Machine Learning, and…
- What is this Course about ?
- Computing Infrastructure for Web-scale Data Processing
- How to scale up hardware for Web-scale Data processing ?