UVA HPC & BIG DATA COURSE

Introduction to Big Data

Adam Belloum

Content

- General Introduction
- Definitions
- Data Analytics
- Solutions for Big Data Analytics
- The Network (Internet)
- When to consider BigData solution
- Scientific e-infrastructure – some challenges to overcome

Jim Gray Vision in 2007

- " We have to do better at **producing tools** to support the **whole research cycle**—from **data capture and data curation to data analysis and data visualization.** Today, the **tools** for capturing data both at the mega-scale and at the milli-scale are just **dreadful**. After you have captured the data, you need to curate it before you can start doing any kind of data analysis, and **we lack good tools for both data curation and data analysis.**"

- "Then comes the **publication** of the results of your research, and the published literature is just the tip of the data iceberg. By this I mean that people collect a lot of data and then reduce this down to some number of column inches in Science or Nature—or 10 pages if it is a computer science person writing. **So what I mean by data iceberg is that there is a lot of data that is collected but not curated or published in any systematic way.**"

Based on the transcript of a talk given by Jim Gray
to the NRC-CSTB1 in Mountain View, CA, on January 11, 2007

Data keep on growing

- Google processes 20 PB a day (2008)
- Wayback Machine has 3 PB + 100 TB/month (3/2009)
- Facebook has 2.5 PB of user data + 15 TB/day (4/2009)
- eBay has 6.5 PB of user data + 50 TB/day (5/2009)
- CERN's Large Hydron Collider (LHC) generates 15 PB a year

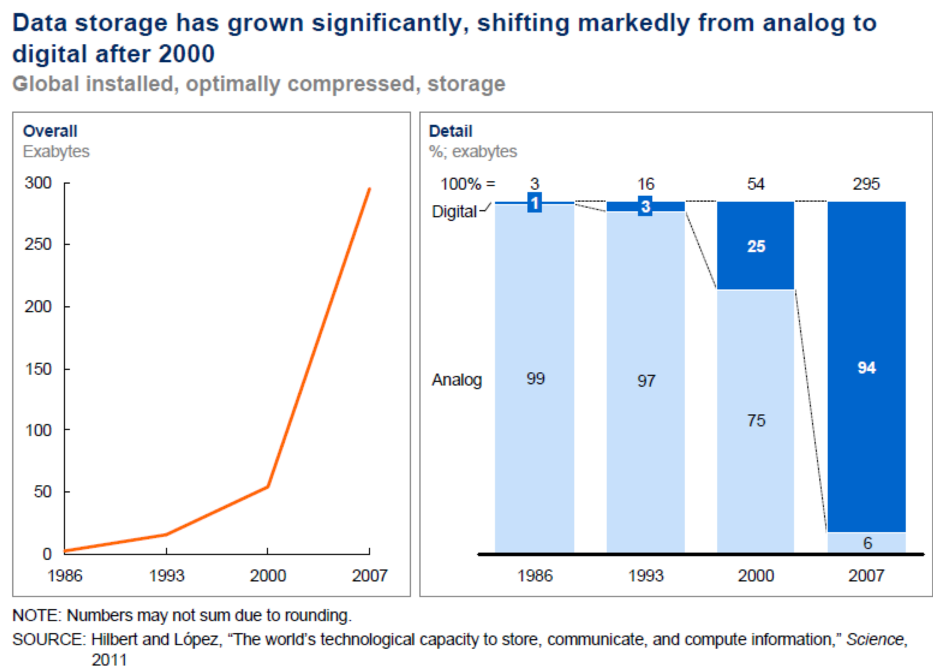
BigData.pptx - Computer Science www.cs.kent.edu/~jin/Cloud12Spring/**BigData.ppt**x

Data is Big If It is Measured in MW

- A good sweet spot for a data center is 15 MW
- Facebook's leased data centers are typically between 2.5 MW and 6.0 MW.
- Facebook's Pineville data center is 30 MW
- Google's computing infrastructure uses 260 MW

Big data was big news in 2012

- and probably in 2013 too.
- The Harvard Business Review talks about it as "*The Management Revolution*".
- The Wall Street Journal "*Meet the New Big Data*", "*Big Data is on the Rise, Bringing Big Questions*".



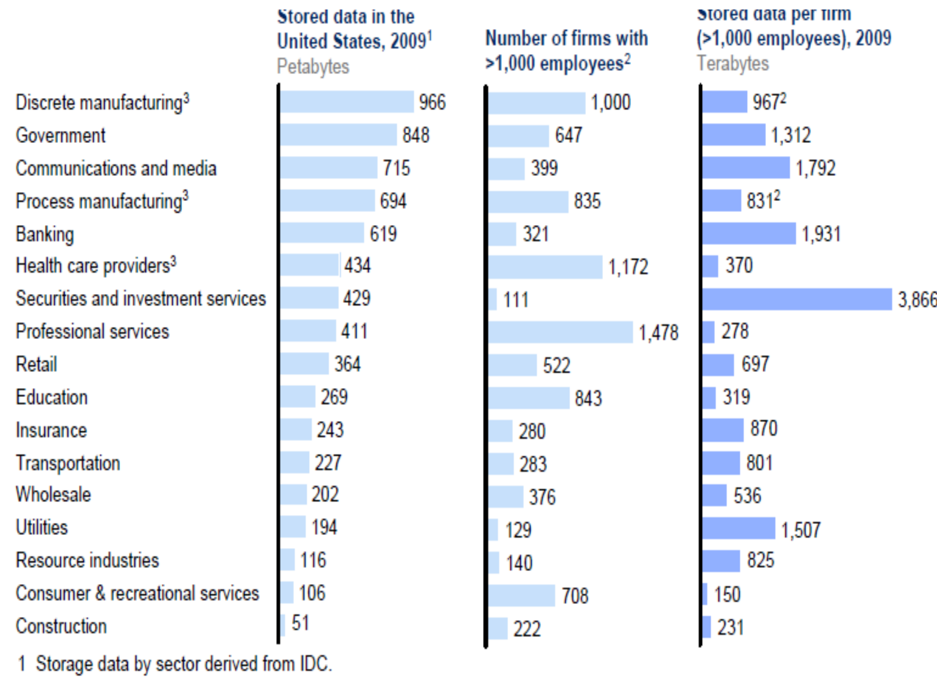
BigData is the new hype

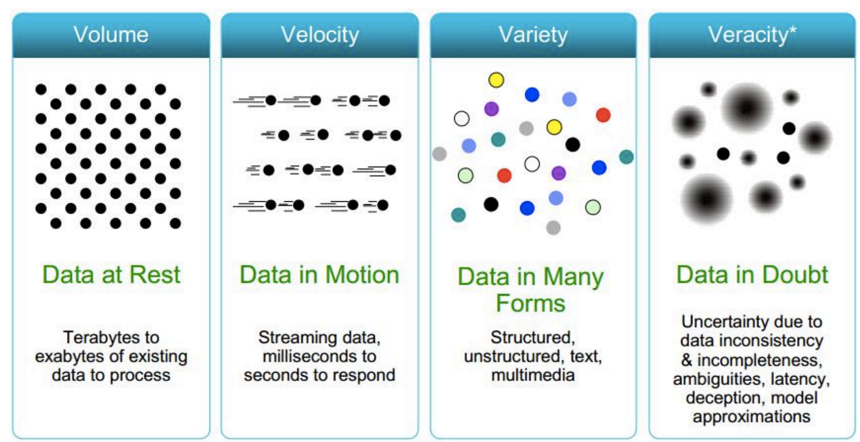
Figure 1. Hype Cycle for Emerging Technologies, 2015

Where Big Data Comes From?

- Big Data is not Specific application type, but rather a trend –or even a collection of Trends- napping multiple application types

- Data growing in multiple ways
  - More data (volume of data)
  - More Type of data (variety of data)
  - Faster Ingest of data (velocity of data)
  - More Accessibility of data (internet, instruments , …)
  - Data Growth and availability exceeds organization ability to make intelligent decision based on it

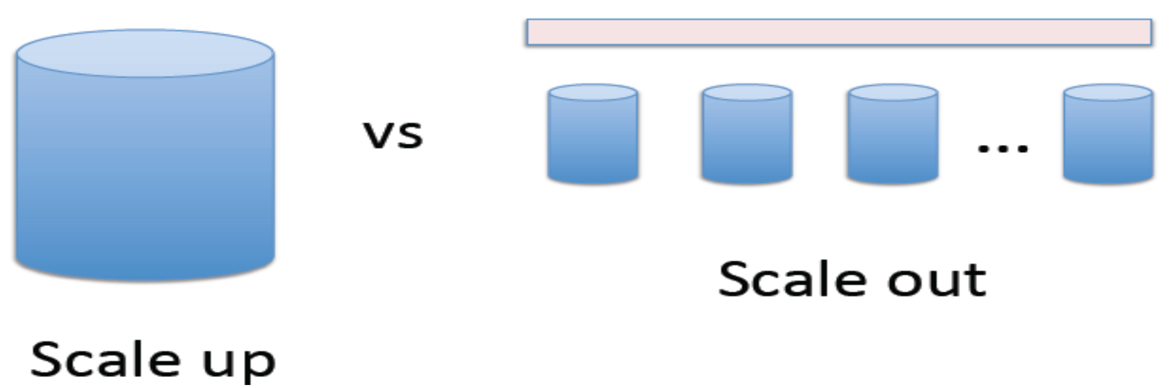




Addison Snell CEO**.** Intersect360, Research

How to deal with Big Data
Advice From Jim Gray

1. Analysing Big data requires scale-out solutions not scale-up solutions
2. **Move** the analysis to the data.
3. Work with scientists to find the most common "**20 queries**" and make them fast.
4. Go from "**working to working.**"



Source: Robert Grossman, Collin Bennec University of Chicago Open Data Group

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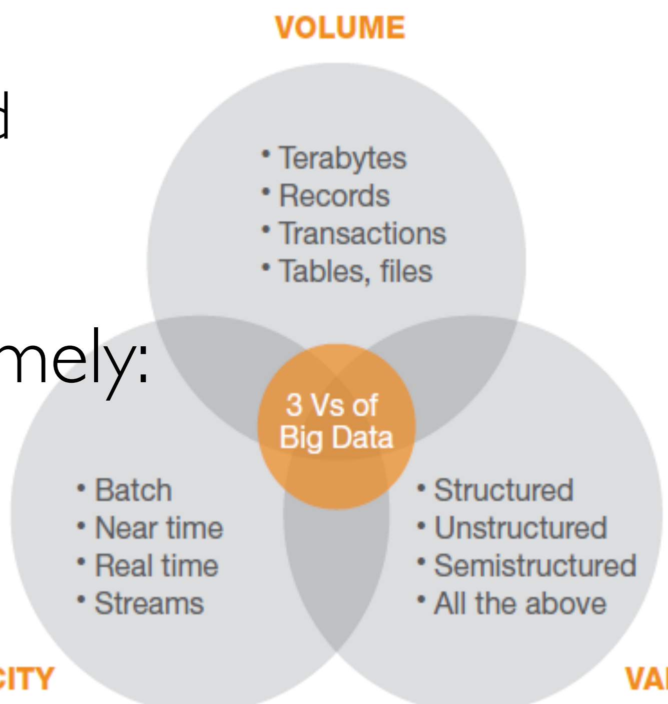
How do We Define Big Data

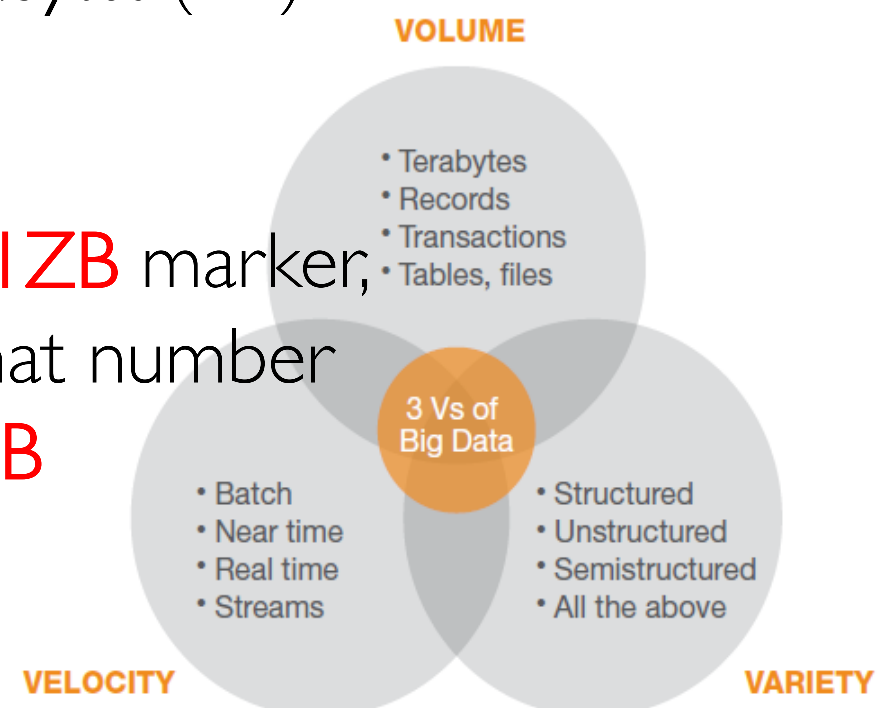
- Big in Big Data refers to:
  - Big size is the primary definition.
  - Big complexity rather than big volume. it can be small and not all large datasets are big data
  - size matters... but so does accessibility, interoperability and reusability.
- define Big Data using 3 Vs; namely:
  - volume, variety, velocity



volume, variety, and velocity

- Aggregation that used to be measured in petabytes (PB) is now referenced by a term: zettabytes (ZB).
  - A **zettabyte** is a **trillion gigabytes** (GB)
  - or a **billion terabytes**

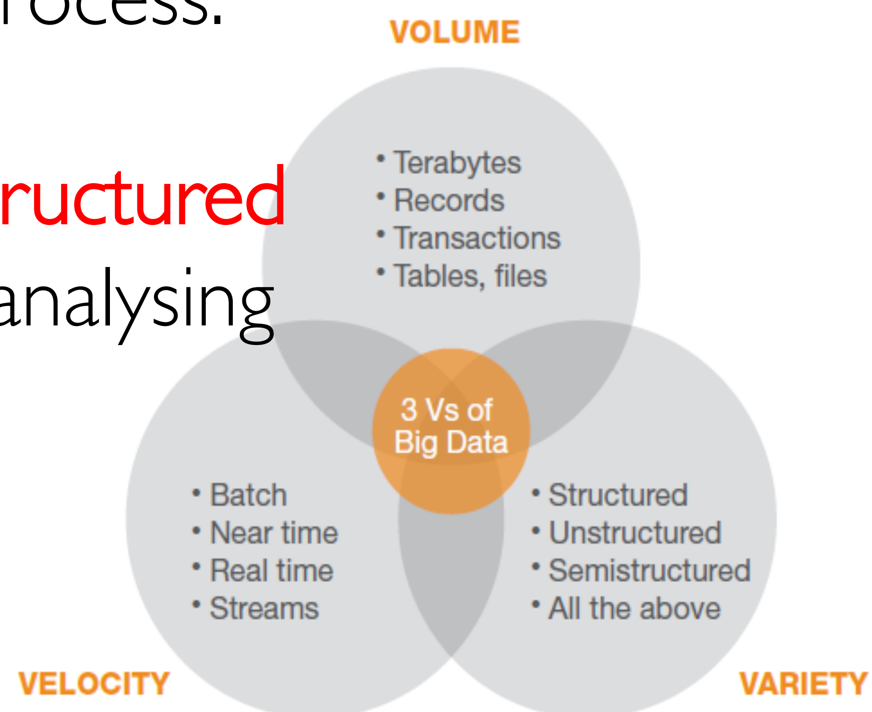
- in 2010, we crossed the 1ZB marker, and at the end of 2011 that number was estimated to be 1.8ZB



volume, variety, and velocity

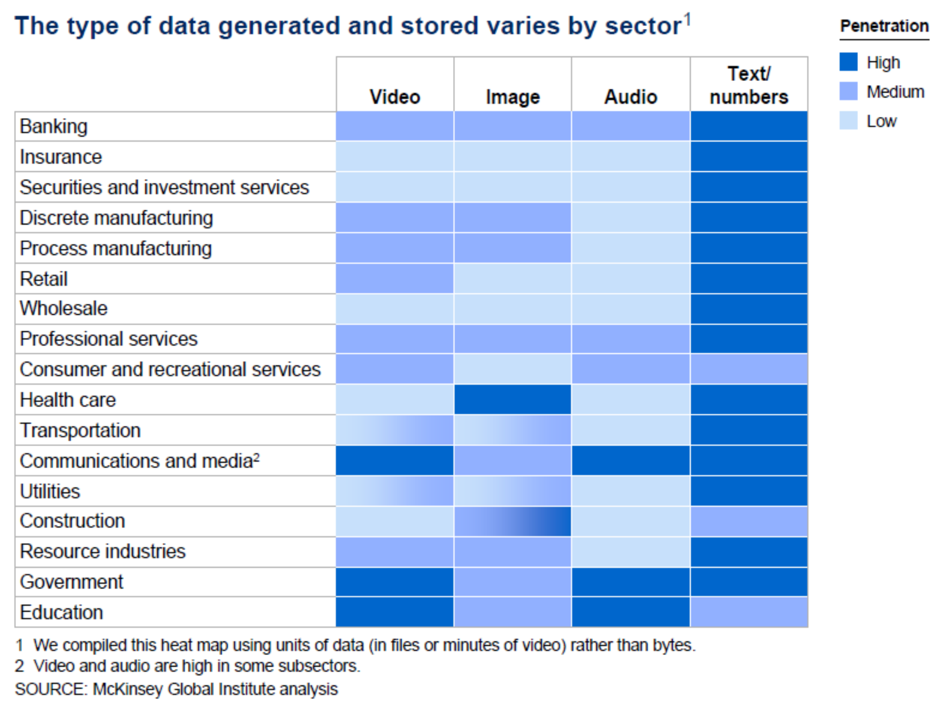
- The variety characteristic of Big Data is really about trying to **capture all** of the data that pertains to our decision-making process.

- Making sense out of unstructured data, such as opinion, or analysing images.



volume, variety, and velocity (Type of Data)

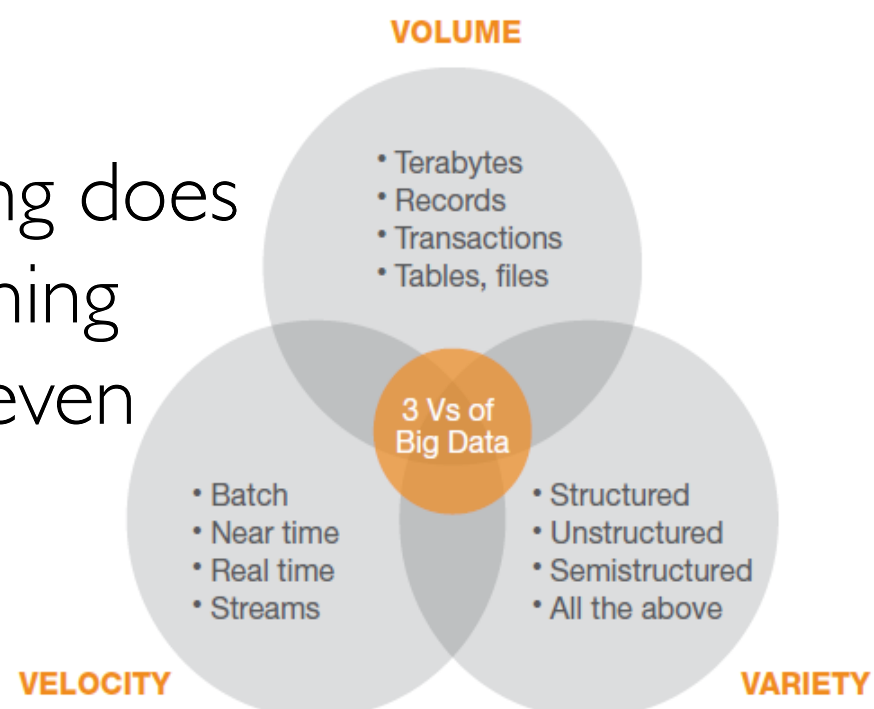
- Relational Data (Tables/Transaction/Legacy Data)
- Text Data (Web)
- Semi-structured Data (XML)
- Graph Data
  - Social Network, Semantic Web (RDF), …
- Streaming Data
  - You can only scan the data once



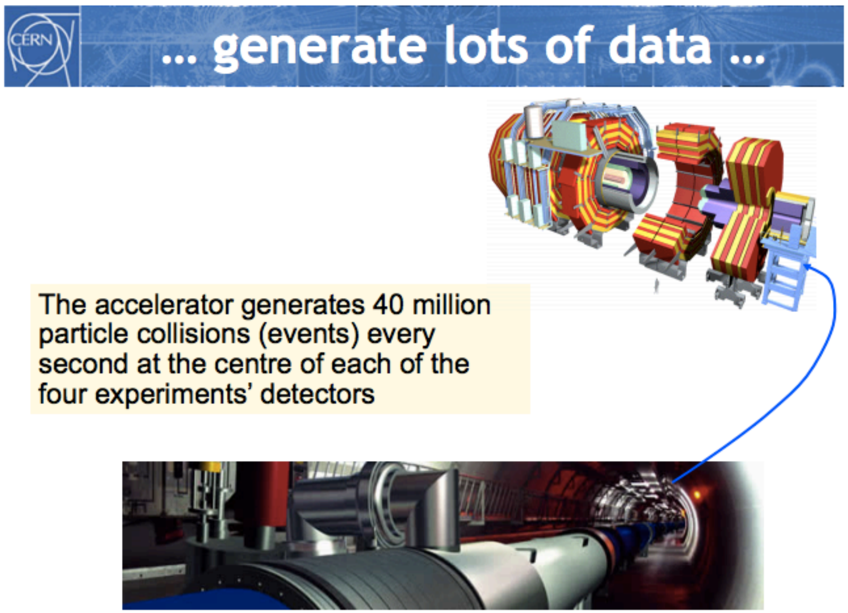
volume, variety, and velocity

- velocity is the rate at which data arrives at the enterprise and is processed or well understood

- In other terms "How long does it take you to do something about it or know it has even arrived?"



volume, variety, and velocity



Today, it is possible using real-time analytics to optimize Like buttons across both website and on Facebook.

FaceBook use anonymised data to show the number of times people:

- saw Like buttons,
- clicked Like buttons,
- saw Like stories on Facebook,
- and clicked Like stories to visit a given website.

volume, variety, velocity, and veracity

- Veracity refers to the quality or trustworthiness of the data.

- A common complication is that the data is saturated with both **useful signals** and lots of noise (data that can't be trusted)

LHC ATLAS detector generates about 1 Petabyte raw data per second, during the collision time (about 1 ms)

Big Data platform must include the six key imperatives

	Big Data Platform Imperatives	Technology Capability
1	Discover, explore, and navigate Big Data sources	Federated Discovery, Search, and Navigation
2	Extreme performance–run analytics closer to data	Massively Parallel Processing Analytic appliances
3	Manage and analyze unstructured data	Hadoop File System/MapReduce Text Analytics
4	Analyze data in motion	Stream Computing
5	Rich library of analytical functions and tools	In-Database Analytics Libraries Big Data Visualization
6	Integrate and govern all data sources	Integration, Data Quality, Security, Lifecycle Management, MDM, etc

The Big Data platform manifesto: imperatives and underlying technologies

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Data Analytics

Analytics Characteristics are not new

- Value: produced when the analytics output is put into action
- Veracity: measure of accuracy and timeliness
- Quality:
  - well-formed data
  - Missing values
  - cleanliness
- Latency: time between measurement and availability
- Data types have differing pre-analytics needs

The Real Time Boom..

Facebook Real Time
Social Analytics

SaaS Real Time
User Tracking

Google Real Time
Web Analytics

Twitter paid tweet analytics

New Real Time
Analytics Startups..

mixpanel

totango

Google Real Time Search

Example of Analytics
(from Analytics @ Twitter)

- Counting
  - How many request/day?
  - What's the average latency?
  - How many signups, sms, tweets?

Real time (msec/sec)

- Correlating
  - Desktop vs Mobile user ?
  - What devices fail at the same time?
  - What features get user hooked?

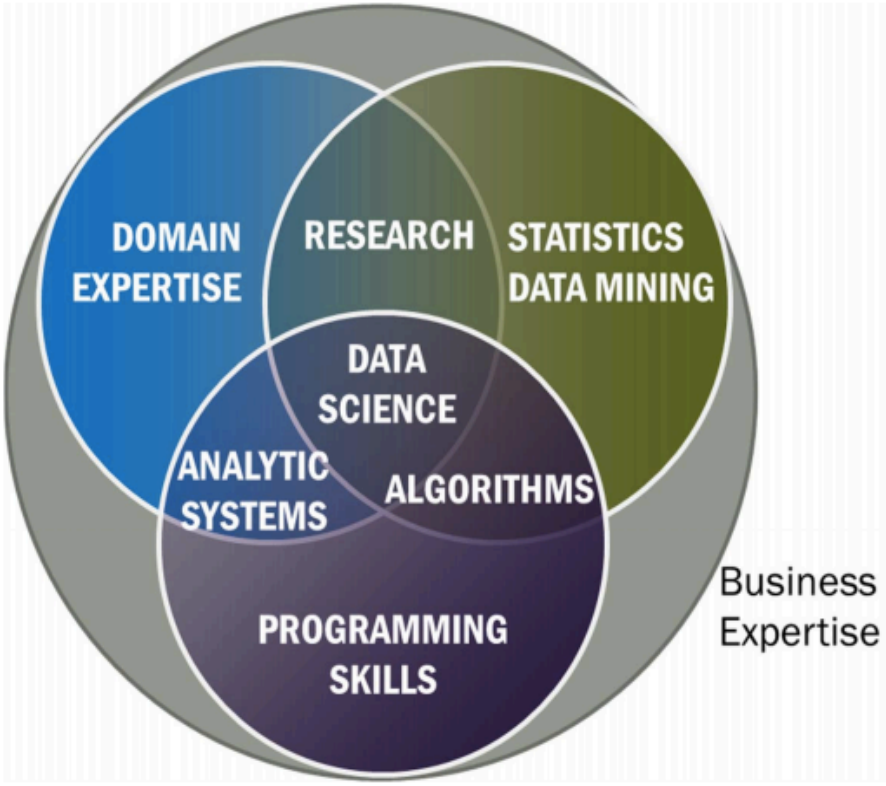
Near real time(Min/Hours)

- Researching
  - What features get re-tweeted
  - Duplicate detection
  - Sentiment analysis

Batch (Days..)

Skills required for Big Data Analytics (A.K.A Data Science)

- Store and process
  - Large scale databases
  - Software Engineering
  - System/network Engineering
- Analyse and model
  - Reasoning
  - Knowledge Representation
  - Multimedia Retrieval
  - Modelling and Simulation
  - Machine Learning
  - Information Retrieval
- Understand and design
  - Decision theory
  - Visual analytics
  - Perception Cognition



Nancy Grady, PhD, SAIC Co-Chair Definitions and Taxonomy Subgroup NIST Big Data Working Group

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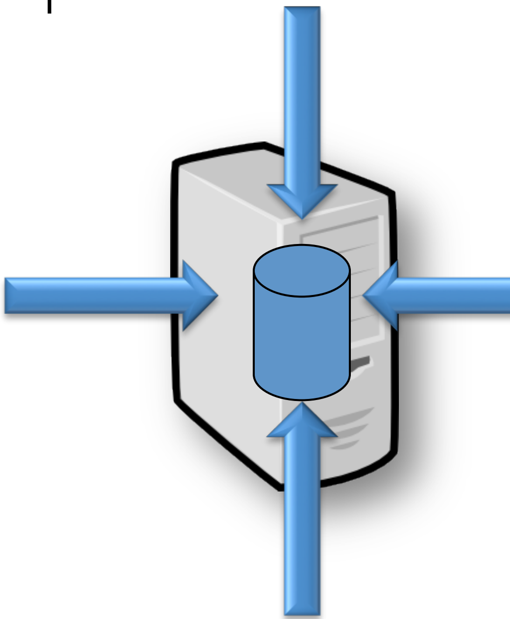
Traditional analytics applications

- Scale-up Database
  - Use traditional SQL database
  - Use stored procedure for event driven reports
  - Use flash-based disks to reduce disk I/O
  - Use read only replica to scale-out read queries
- Limitations
  - Doesn't scale on write
  - Extremely expensive (HW + SW)



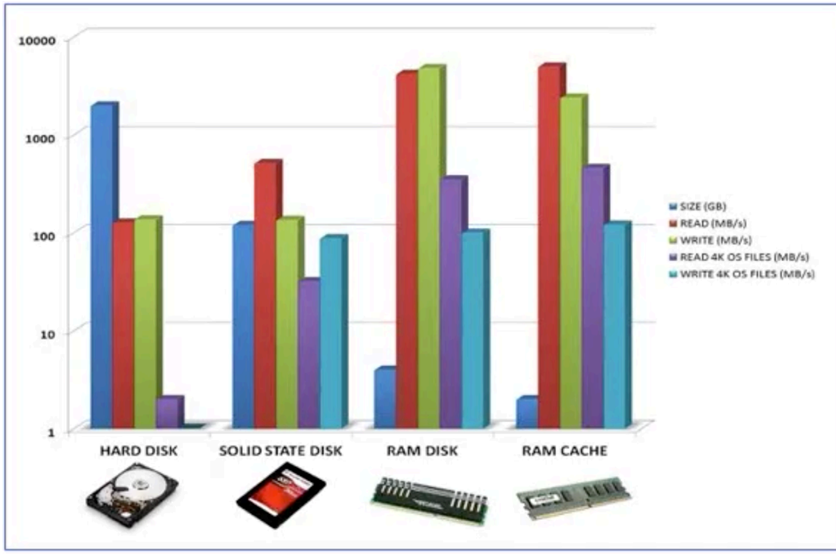
CEP – Complex Event Processing

- Process the data as it comes
- Maintain a window of the data in-memory

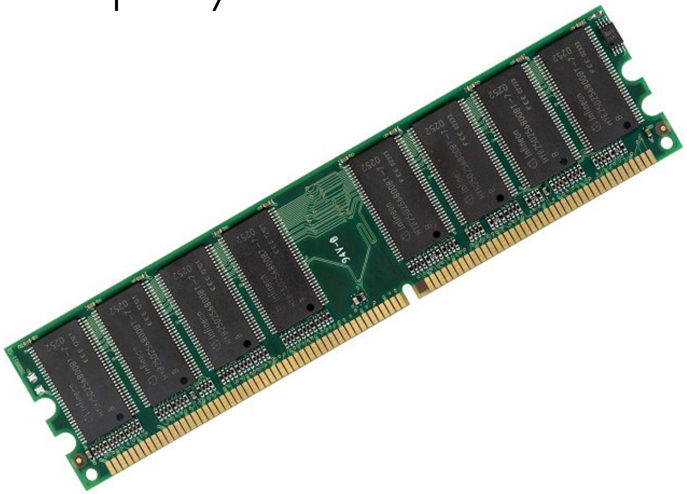
- Pros:
  - Extremely low-latency
  - Relatively low-cost

- Cons
  - Hard to scale (Mostly limited to scale-up)
  - Not agile - Queries must be pre-generated
  - Fairly complex

In Memory Data Grid



- Distributed in-memory database
  - Scale out (Horizontal scaling)
- Pros
  - Scale on write/read
  - Fits to event driven (CEP style) , ad-hoc query model
- Cons
  - Cost of memory vs disk
  - Memory capacity is limited

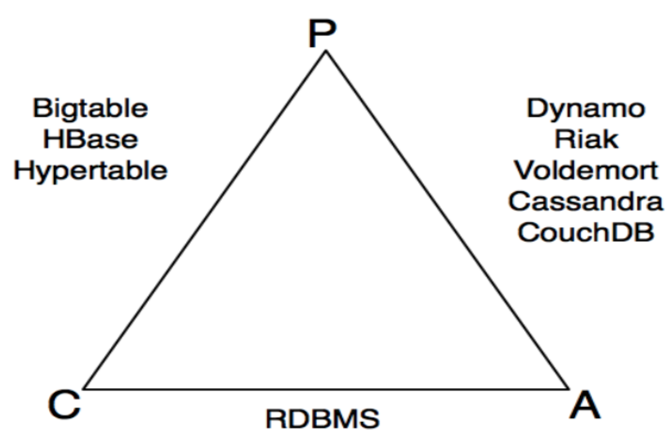


In Memory Data Grid products

- Hazelcast
  hazelcast.org
- JBOSS Infinispan
  www.infinispan.org
- IBM eXtreme Scale:
  ibm.com/software/products/en/websphere-extreme-scale
- Gigaspace XAP Elastic caching edition:
  www.gigaspaces.com/xap-in-memory-caching-scaling/datagrid
- Oracle Coherence
  www.oracle.com/technetwork/middleware/coherence
- Terracotta entreprise suite
  www.terracotta.org/products/enterprise-suite
- Pivotal Gemfire
  pivotal.io/big-data/pivotal-gemfire

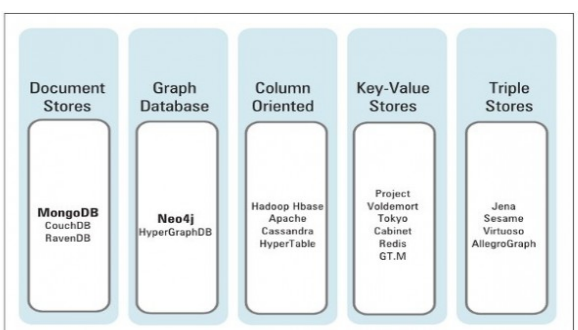
NoSQL

- Use distributed database
  - Hbase, Cassandra, MongoDB
- Pros
  - Scale on write/read
  - Elastic
- Cons
  - Read latency
  - Consistency tradeoffs are hard
  - Maturity – fairly young technology



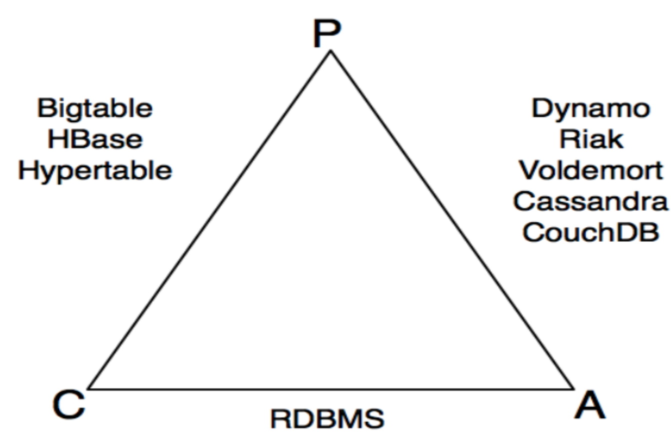
NoSQL

Year	System/ Paper	Scale to 1000s	Primary Index	Secondary Indexes	Transactions	Joins/ Analytics	Integrity Constraints	Views	Language/ Algebra	Data model	my label
1971	RDBMS	O	✔	✔	✔	✔	✔	✔	✔	tables	sql-like
2003	memcached	✔	✔	O	O	O	O	O	O	key-val	nosql
2004	MapReduce	✔	O	O	O	✔	O	O	O	key-val	batch
2005	CouchDB	✔	✔	✔	record	MR	O	✔	O	document	nosql
2006	BigTable (Hbase)	✔	✔	✔	record	compat. w/MR	/	O	O	ext. record	nosql
2007	MongoDB	✔	✔	✔	EC, record	O	O	O	O	document	nosql
2007	Dynamo	✔	✔	O	O	O	O	O	O	ext. record	nosql
2008	Pig	✔	O	O	O	✔	/	O	✔	tables	sql-like
2008	HIVE	✔	O	O	O	✔	✔	O	✔	tables	sql-like
2008	Cassandra	✔	✔	✔	EC, record	O	✔	✔	O	key-val	nosql
2009	Voldemort	✔	✔	O	EC, record	O	O	O	O	key-val	nosql
2009	Riak	✔	✔	✔	EC, record	MR	O			key-val	nosql
2010	Dremel	✔	O	O	O	/	✔	O	✔	tables	sql-like
2011	Megastore	✔	✔	✔	entity groups	O	/	O	/	tables	nosql
2011	Tenzing	✔	O	O	O	O	✔	✔	✔	tables	sql-like
2011	Spark/Shark	✔	O	O	O	✔	✔	O	✔	tables	sql-like
2012	Spanner	✔	✔	✔	✔	?	✔	✔	✔	tables	sql-like
2012	Accumulo	✔	✔	✔	record	compat. w/MR	/	O	O	ext. record	nosql
2013	Impala	✔	O	O	O	✔	✔	O	✔	tables	sql-like



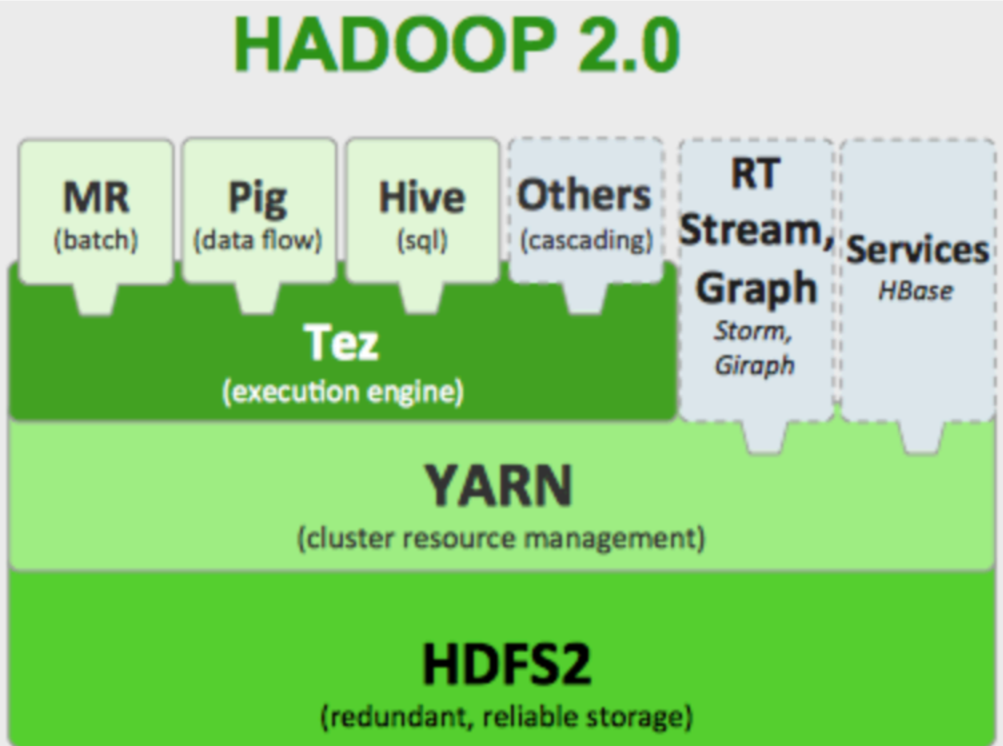
Scale was the primary motivation!

Bill Howe, UW

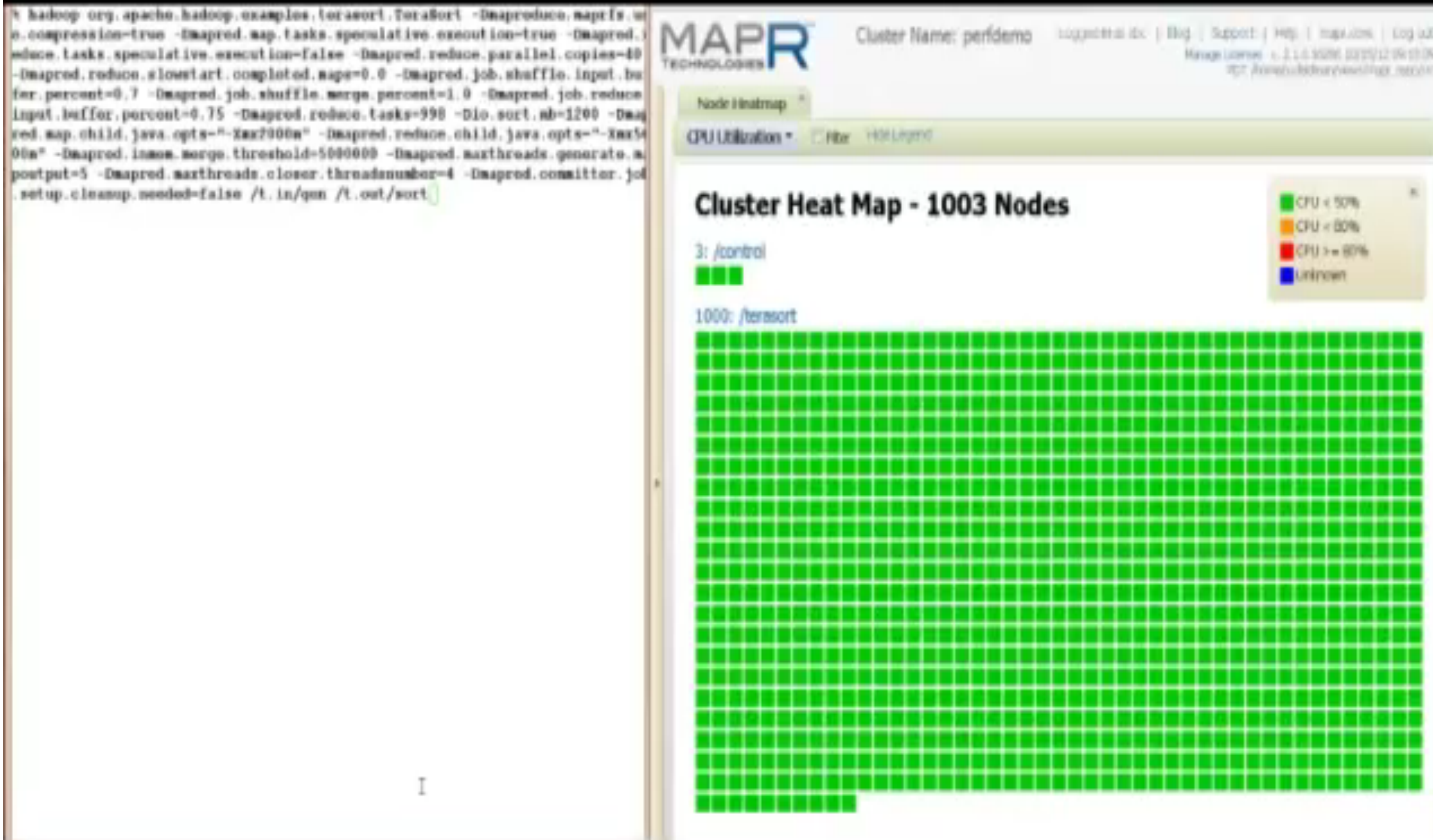


Hadoop MapReudce

- Distributed batch processing
- Pros
  - Designed to process massive amount of data
  - Mature
  - Low cost
- Cons
  - Not real-time



Sorting 1 TB of DATA



MapReduce vs. Databases

- A. Pavlo, et al. "A comparison of approaches to large-scale data analysis," in *SIGMOD '09: Proceedings of the 35th SIGMOD international conference on Management of data*, New York, NY, USA, 2009, pp. 165-178
- Conclusions: … at the scale of the experiments we conducted, both parallel database systems displayed a significant performance advantage over Hadoop MR in executing a variety of data intensive analysis benchmarks.

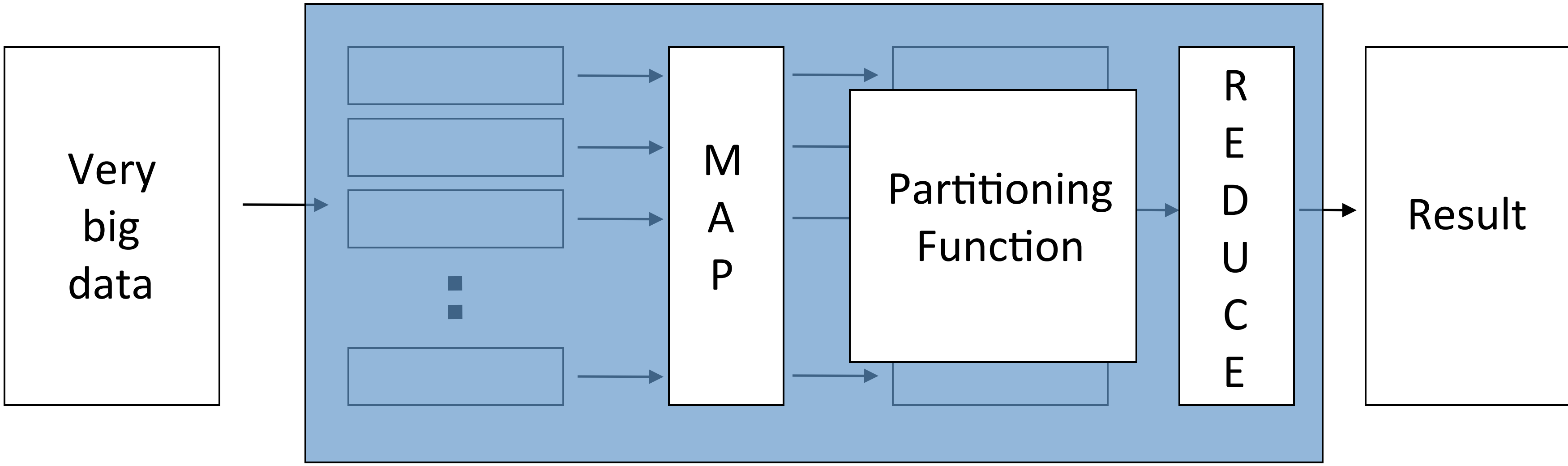
Hadoop Map/Reduce – Reality check..

"With the paths that go through Hadoop [at Yahoo!], the latency is about fifteen minutes. … [I]t will never be true real-time.." (**Yahoo** CTO Raymie Stata)

Hadoop/Hive..Not realtime. Many dependencies. Lots of points of failure. Complicated system. Not dependable enough to hit realtime goals (Alex Himel, Engineering Manager at **Facebook**.)

"MapReduce and other batch-processing systems cannot process small updates individually as they rely on creating large batches for efficiency," (**Google** senior director of engineering Eisar Lipkovitz)

Map Reduce

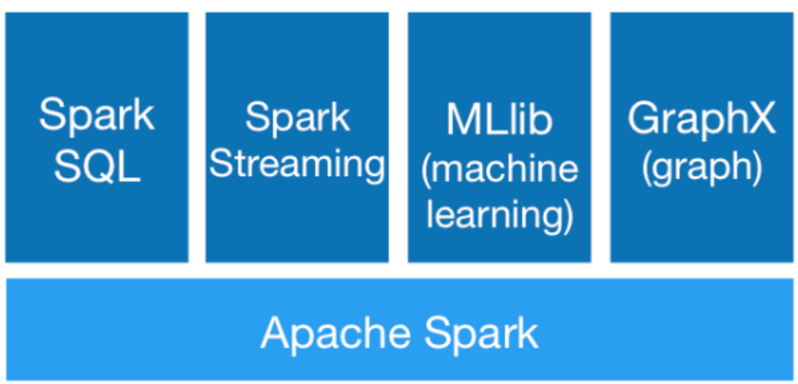


- Map:
  - Accepts
    - *input* key/value pair
  - Emits
    - *intermediate* key/value pair
- Reduce :
  - Accepts
    - *intermediate* key/value* pair
  - Emits
    - *output* key/value pair

Apache Spark

Lightning-fast cluster computing

- Generality
  - Combine SQL, streaming, complex analytics.
- Runs Everywhere
  - Spark runs on Hadoop, Mesos, standalone, or in the cloud. It can access diverse data sources (HDFS, Cassandra, HBase, and S3)
- Ease of Use
  - Write applications quickly in Java, Scala, Python, R.



Developer(s)	Apache Software Foundation, UC Berkeley AMPLab, Databricks
Initial release	May 30, 2014; 18 months ago
Stable release	v1.5.2 / November 9, 2015; 51 days ago
Development status	Active
Written in	Scala, Java, Python, R
Operating system	Linux, Mac OS, Windows
Type	data analytics, machine learning algorithms
License	Apache License 2.0
Website	spark.apache.org

Apache Storm

By Nathan Marz

- Storm is a distributed real-time computation system that solves typical
  - downsides of queues & workers systems.
  - Built with Big Data in mind (the "Hadoop of realtime").
- Storm Trident (high level abstraction over Storm core)
  - Micro-batching (~ streaming)

Distributed and fault-tolerant realtime computation

Developer(s)	Backtype, Twitter
Stable release	0.9.5 / 4 June 2015
Preview release	0.10.0-beta / 15 June 2015
Development status	Active
Written in	Clojure & Java
Operating system	Cross-platform
Type	Distributed stream processing
License	Apache License 2.0
Website	storm.apache.org

Apache Kafka

A high-throughput distributed messaging system

- Apache Kafka is publish-subscribe messaging rethought as a distributed commit log.
- Kafka maintains feeds of messages in categories called *topics*.
  - Processes can publish messages to a Kafka (topic *producers*).
  - processes can subscribe to topics and process the feed of published messages *consumers*.
- Kafka is run as a cluster comprised of one or more servers each of which is called a *broker*.

Developer(s)	Apache Software Foundation
Stable release	0.9 / November 2015; 1 month ago
Development status	Active
Written in	Scala
Operating system	Cross-platform
Type	Message broker
License	Apache License 2.0
Website	kafka.apache.org

Performance

http://www.slideshare.net/JamesSirota/cisco-opensoc

https://twitter.com/nathanmarz/status/207989068519317505

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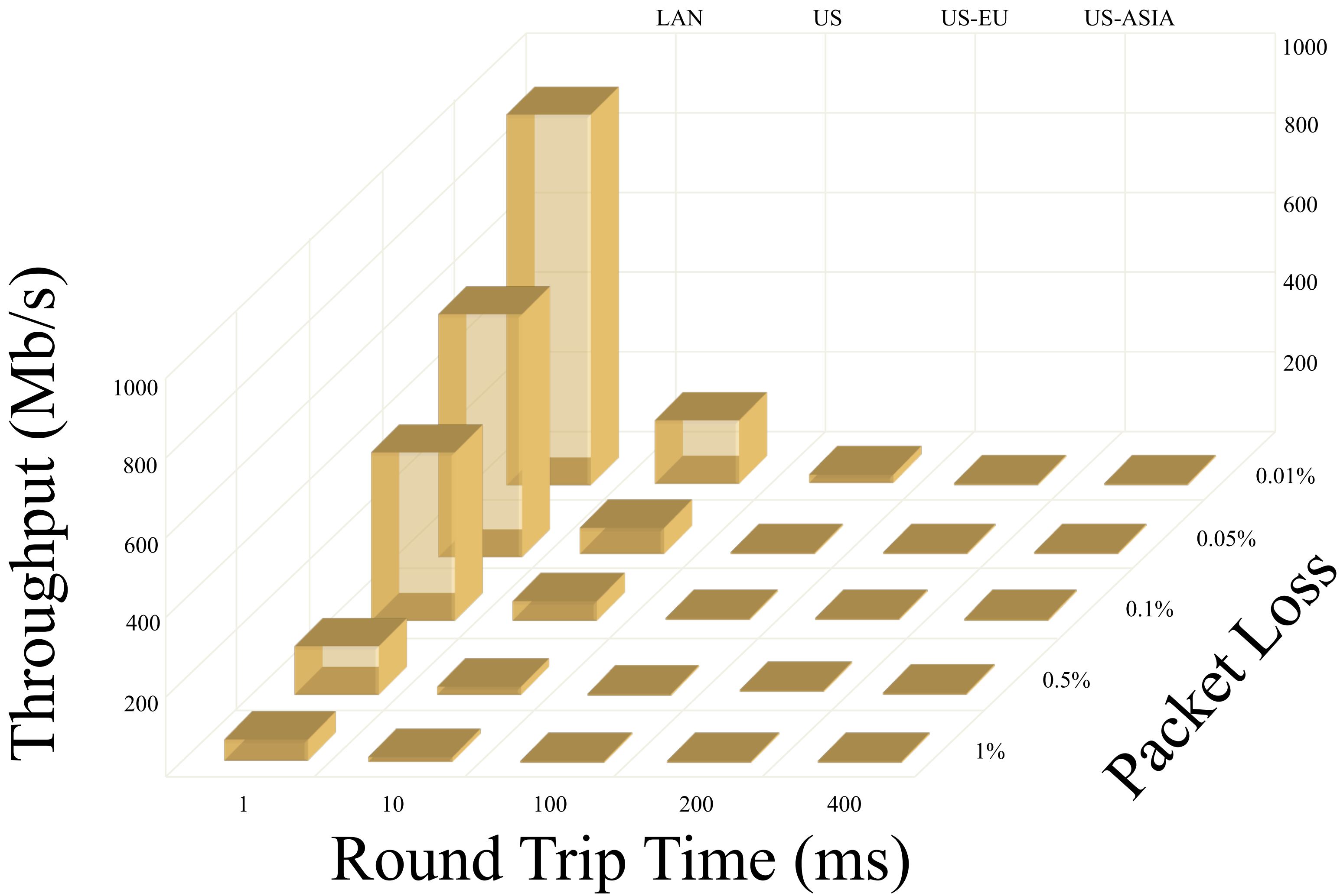
The problem

- TCP Was never designed to move large datasets over wide area high Performance Networks.

- For loading a webpage, TCP is great.
- For sustained data transfer, it is far from ideal.
  - Most of the time even though the connection itself is good (let say 45Mbps), transfers are much slower.
  - There are two reason for a slow transfer over fast connections:
    - Latency
    - and packet loss bring TCP-based file transfer to a crawl.

TCP Throughput vs RTT and Packet Loss



Source: Yunhong Gu, 2007, experiments over wide area 1G.

The solutions

- Use parallel TCP streams
  - GridFTP
- Use specialized network protocols
  - UDT, FAST, etc.
- Use RAID to stripe data across disks to improve throughput when reading
- These techniques are well understood in HEP, astronomy, but not yet in biology

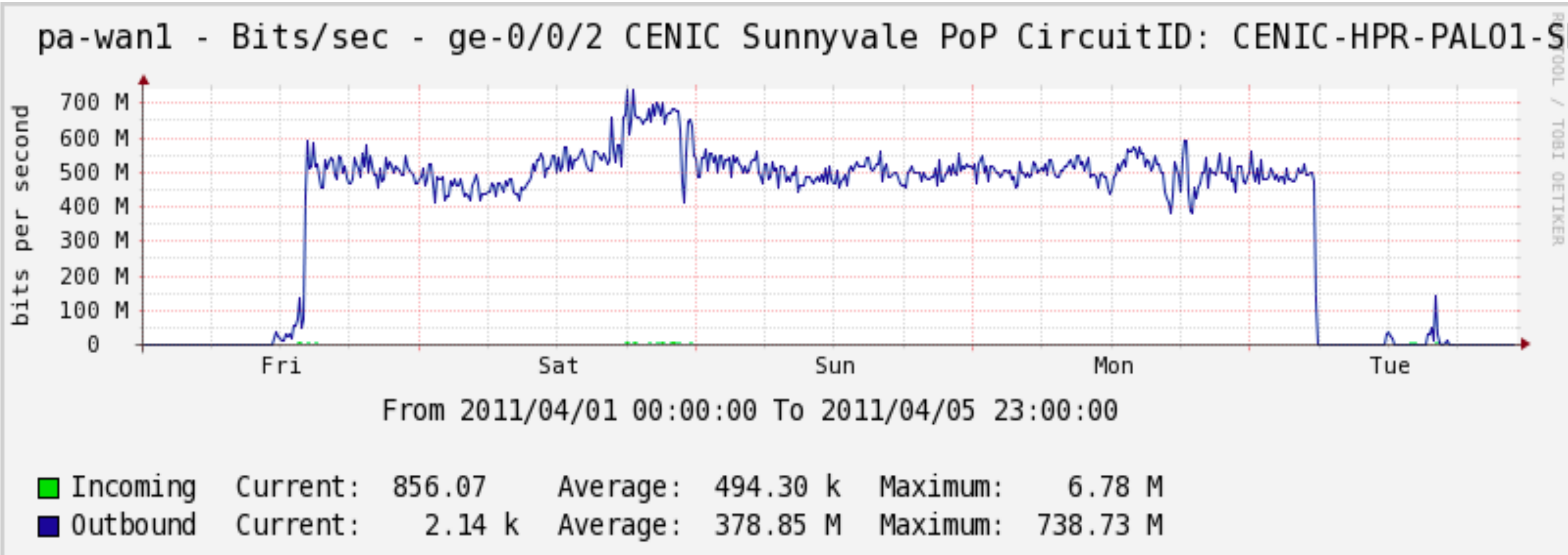
Moving 113GB of Bio-mirror Data

-

Site	RTT	TCP	UDT	TCP/UDT	Km
NCSA	10	139	139	1	200
Purdue	17	125	125	1	500
ORNL	25	361	120	3	1,200
TACC	37	616	120	55	2,000
SDSC	65	750	475	1.6	3,300
CSTNET	274	**3722**	304	12	12,000

- GridFTP TCP and UDT transfer times for 113 GB from gridip.bio---mirror.net/biomirror/ blast/ (Indiana USA).
  - All TCP and UDT times in minutes.
  - Source: http://gridip.bio-mirror.net/biomirror/

Case study: CGI 60 genomes



- Trace by Complete Genomics showing performance of moving 60 complete human genomes from Mountain View to Chicago using the open source Sector/UDT.
- Approximately 18 TB at about 0.5 Mbs on 1G link.

How FedEx Has More Bandwidth Than the Internet—and When That'll Change

- If you're looking to transfer hundreds of gigabytes of data, it's still—weirdly—faster to ship hard drives via FedEx than it is to transfer the files over the internet.
- "Cisco estimates that total internet traffic currently averages **167 terabits per second**. FedEx has a fleet of 654 aircraft with a lift capacity of 26.5 million pounds daily. A solid-state laptop drive weighs about 78 grams and can hold up to a terabyte. That means FedEx is capable of transferring 150 exabytes of data per day, or **14 petabits per second**—**almost a hundred times the current throughput of the internet**.

http://gizmodo.com/5981713/how-fedex-has-more-bandwidth-than-the-internetand-when-thatll-change

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When to Consider a Big Data Solution
User point of view

- You're limited by your current platform or environment because you can't process the amount of data that you want to process

- You want to involve new sources of data in the analytics, but you can't, because it doesn't fit into schema-defined rows and columns without sacrificing fidelity or the richness of the data

When to Consider a Big Data Solution

- You need to ingest data as quickly as possible and need to work with a schema-on-demand
  - You‘re forced into a schema-on-write approach (the schema must be created before data is loaded),
  - but you need to ingest data quickly, or perhaps in a discovery process, and want the cost benefits of a schema-on-read approach (data is simply copied to the file store, and no special transformation is needed) until you know that you've got something that's ready for analysis?

When to Consider a Big Data Solution

- You want to analyse not just raw structured data, but also semi-structured and unstructured data from a wide variety of sources

- you're not satisfied with the effectiveness of your algorithms or models
  - when all, or most, of the data needs to be analysed
  - or when a sampling of the data isn't going to work

When to Consider a Big Data Solution

- you aren't completely sure where the investigation will take you, and you want elasticity of compute, storage, and the types of analytics that will be pursued—all of these became useful as we added more sources and new methods

If your answers to any of these questions are "yes," you need to consider a Big Data solution.

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Scientific e-infrastructure – some challenges to overcome

- Collection
  - How can we make sure that data are collected together with the **information** necessary **to re- use them**?
- Trust
  - How can we make informed judgements about whether certain data are **authentic** and can be **trusted**?
  - How can we judge which repositories we can trust? How can appropriate access and use of resources be granted or controlled

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Scientific e-infrastructure – some challenges to overcome

- Usability
  - How can we move to a situation where non-specialists can overcome the barriers and be able to start sensible work on unfamiliar data

- Interoperability
  - How can we implement interoperability within disciplines and move to an overarching multi-disciplinary way of understanding and using data?
  - How can we find unfamiliar but relevant data resources beyond simple keyword searches, but involving a deeper probing into the data
  - How can automated tools find the information needed to tackle data

Scientific e-infrastructure – some challenges to overcome

- Diversity
  - How do we overcome the problems of diversity – heterogeneity of data, but also of backgrounds and data-sharing cultures in the scientific community?
  - How do we deal with the diversity of data repositories and access rules – within or between disciplines, and within or across national borders?
- Security
  - How can we guarantee data integrity?
  - How can we avoid data poisoning by individuals or groups intending to bias them in their interest?

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Scientific e-infrastructure – a wish list

- **Open deposit**, allowing user-community centres to store data easily
- **Bit-stream preservation**, ensuring that data authenticity will be guaranteed for a specified number of years
- **Format and content migration**, executing CPU-intensive transformations on large data sets at the command of the communities

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Scientific e-infrastructure – a wish list

- Persistent identification, allowing data centres to register a huge amount of markers to track the origins and characteristics of the information
- Metadata support to allow effective management, use and understanding
- Maintaining proper access rights as the basis of all trust
- A variety of access and curation services that will vary between scientific disciplines and over time

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Scientific e-infrastructure – a wish list

- Execution services that allow a large group of researchers to operate on the stored date
- High reliability, so researchers can count on its availability
- Regular quality assessment to ensure adherence to all agreements
- Distributed and collaborative authentication, authorisation and accounting
- A high degree of interoperability at format and semantic level

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Google BigQuery

- Google BigQuery is a web service that lets you do interactive analysis of massive datasets—up to billions of rows. Scalable and easy to use, BigQuery lets developers and businesses tap into powerful data analytics on demand
  - http://www.youtube.com/watch?v=P78T_ZDwQyk

IBM BigInsights

- BigInsights = analytical platform for persistent "big data"
  - Based on open sources & IBM technologies

- Distinguishing characteristics
  - Built-in Analytics

Big Data: Frequently Asked Questions for IBM InfoSphere BigInsights
http://www.youtube.com/watch?v=I4hsZa2jwAs

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- Science as an open enterprise: open data for open science http://royalsociety.org/uploadedFiles/Royal_Society_Content/policy/projects/sape/2012-06-20-SAOE.pdf
- Realtime Analytics for Big Data: A Facebook Case Study http://www.youtube.com/watch?v=viPRny0nq3o