

Cloud Computing and Big Data

Big Data Introduction

Oxford University
Software Engineering
Programme
July 2021



Contents

- Definitions
- Origins of Big Data
- Case Studies and Motivations



Big Data definition

- Data of a very large size, typically to the extent that its manipulation and management present significant logistical challenges
 - Oxford English Dictionary



Gartner

Big data is **high-volume**,
high-velocity and **high-variety**
information assets that demand
cost-effective, innovative forms of
information processing for enhanced
insight and decision making.



The three Vs

- Velocity
 - Need to be able to process data faster
 - Handle very large numbers of data elements/sec incoming
- Variety
 - Not just the same old columns
 - New formats, new sources, new details
- Volume
 - Massive volumes are becoming normal
 - Collecting the next level of data
 - E.g. Bank Trades, Website interactions, shopping experiences, etc



My Big Data definition

- Any data storage and analysis that:
 - Cannot be processed on a single machine in a timely manner
 - Over time needs more computation and resources than a fixed size system can provide



Origins of Big Data - 1997

Application-Controlled Demand Paging for Out-of-Core Visualization

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Abstract

In the area of scientific visualization, input data sets are often very large. In visualization of Computational Fluid Dynamics (CFD) in particular, input data sets today can surpass 100 Gbytes, and are expected to scale with the ability of supercomputers to generate them. Some visualization tools already partition large data sets into segments, and load appropriate segments as they are needed. However, this does not remove the problem for two reasons: 1) there are data sets for which even the individual segments are too large for the largest graphics workstations, 2) many practitioners do not have access to workstations with the memory capacity required to load even a segment, especially since the state-of-the-art visualization tools tend to be developed by researchers with much more powerful machines. When the size of the data that must be accessed is larger than the size of memory, some form of virtual memory is simply required. This may be by segmentation, paging, or by paged segments. In this paper we

1 Introduction

Visualization provides an interesting challenge for computer systems: data sets are generally quite large, taxing the capacities of main memory, local disk, and even remote disk. We call this the problem of *big data*. When data sets do not fit in main memory (*in core*), or when they do not fit even on local disk, the most common solution is to acquire more resources. This *write-a-check* algorithm has two drawbacks. First, if visualization algorithms and tools are worth developing, then they are worth deploying to more production-oriented scientists and engineers who may have on their desks machines with significantly less memory and disk. Some researchers have noted that their software tools were not used in practice for several years after development because the tools required more power and memory than were available on the average engineer's desk [15]. Second, there may not even be a machine that supports sufficiently large main memory or local disk for the data set one wishes to visualize. We find this in particular in the area of visualization of *Computational Fluid Dynamics (CFD)*



Map Reduce 2008

MapReduce: Simplified Data Processing on Large Clusters

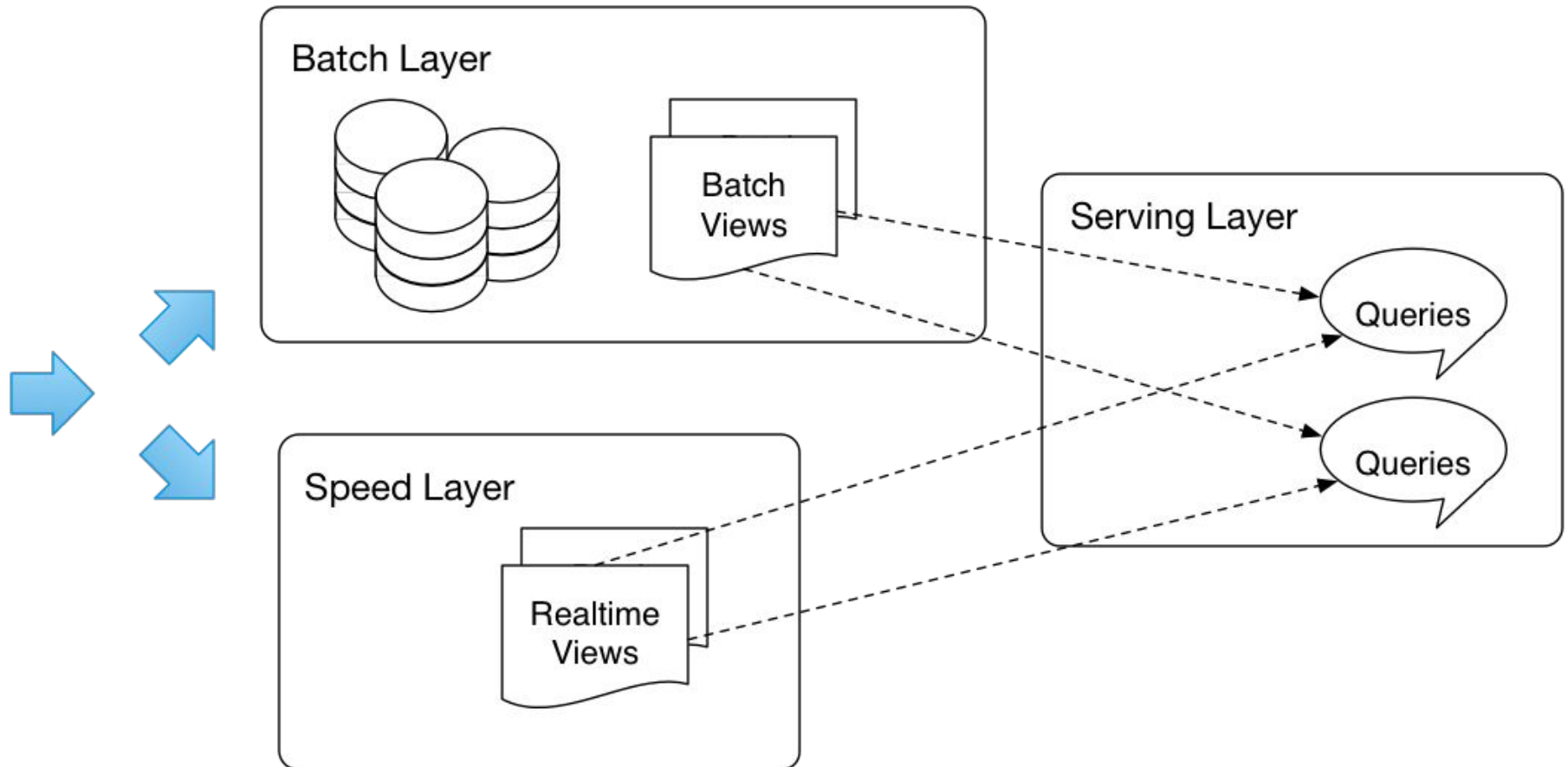
Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

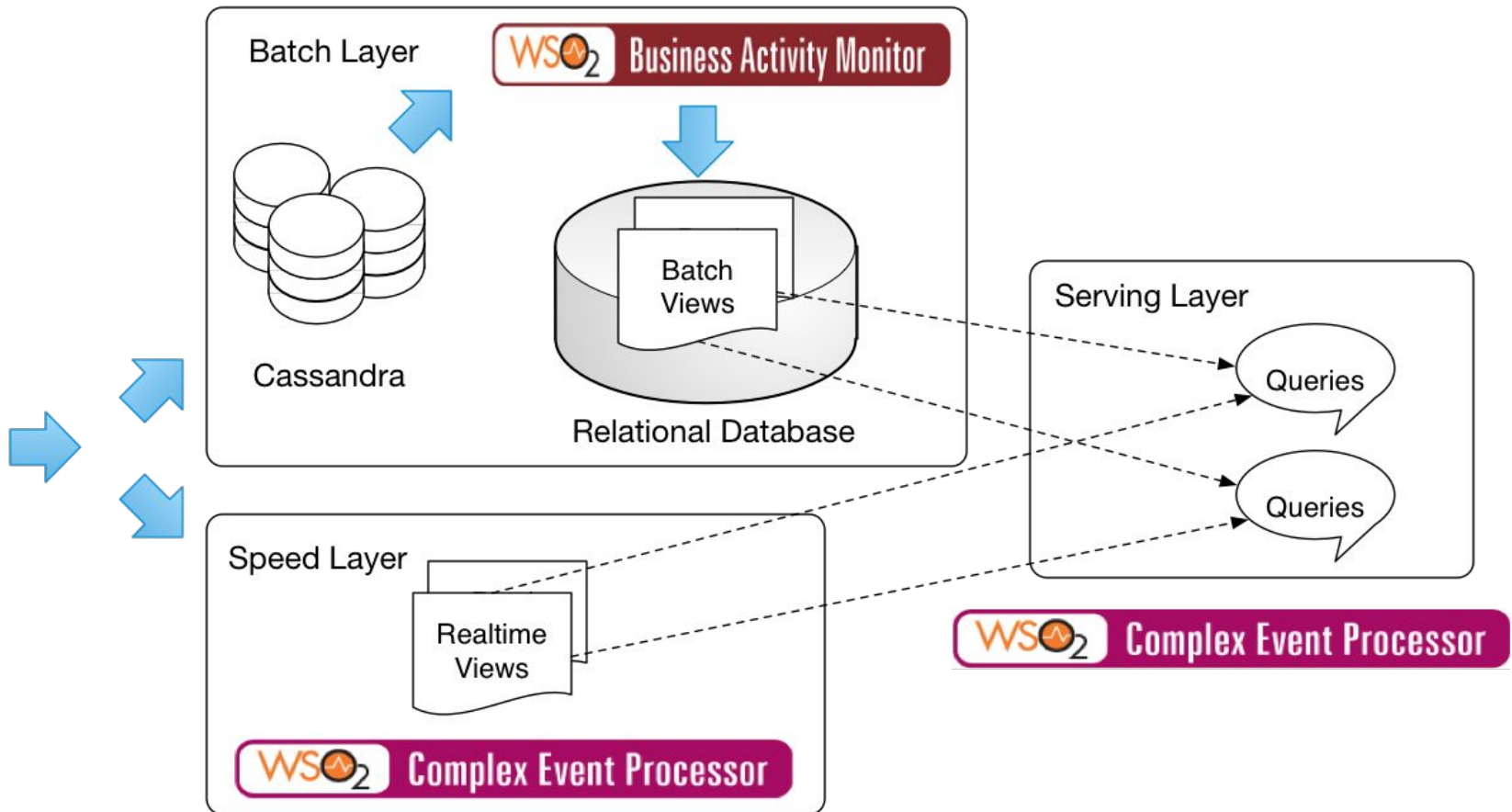
Google, Inc.



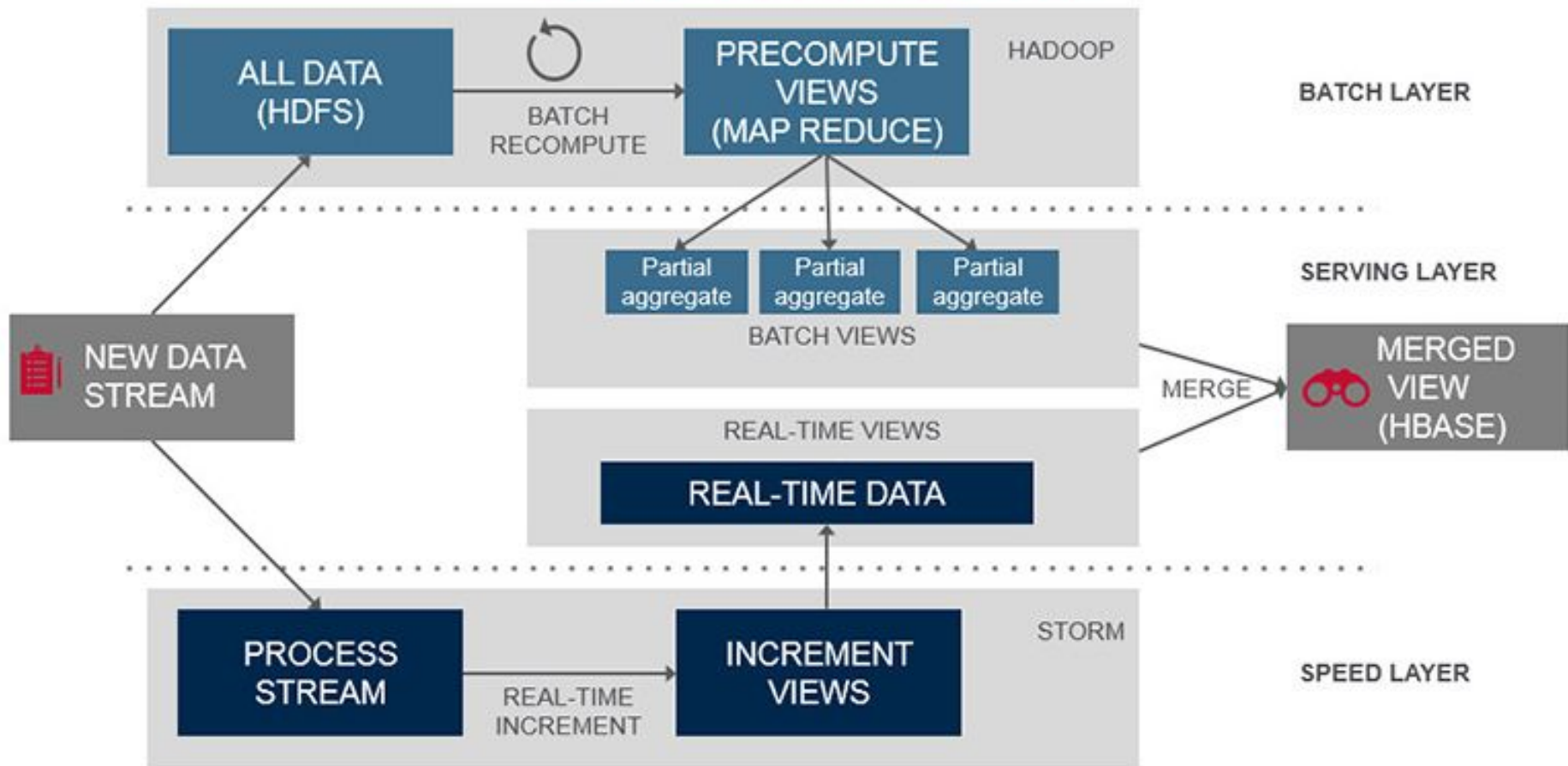
Lambda Architecture



Lambda Architecture instantiation (deprecated)



Lambda Architecture (MapR)



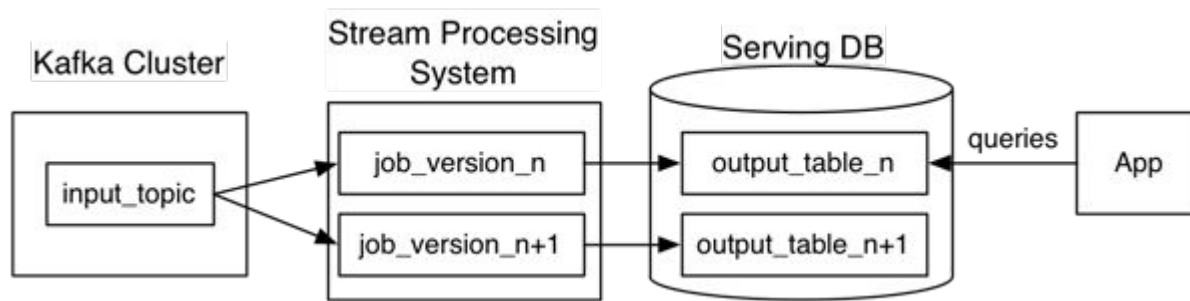
Master Data

- One widely used approach
- You ingest core data and never change it
 - You can create summaries, cleaned data, etc
 - But the original data is immutable
- Cheap disk space...
- Related to Event Sourcing



Kappa Architecture

- Everything is a stream!
- Event source database / log
- Jay Kreps
 - <https://www.oreilly.com/radar/questioning-the-lambda-architecture/>

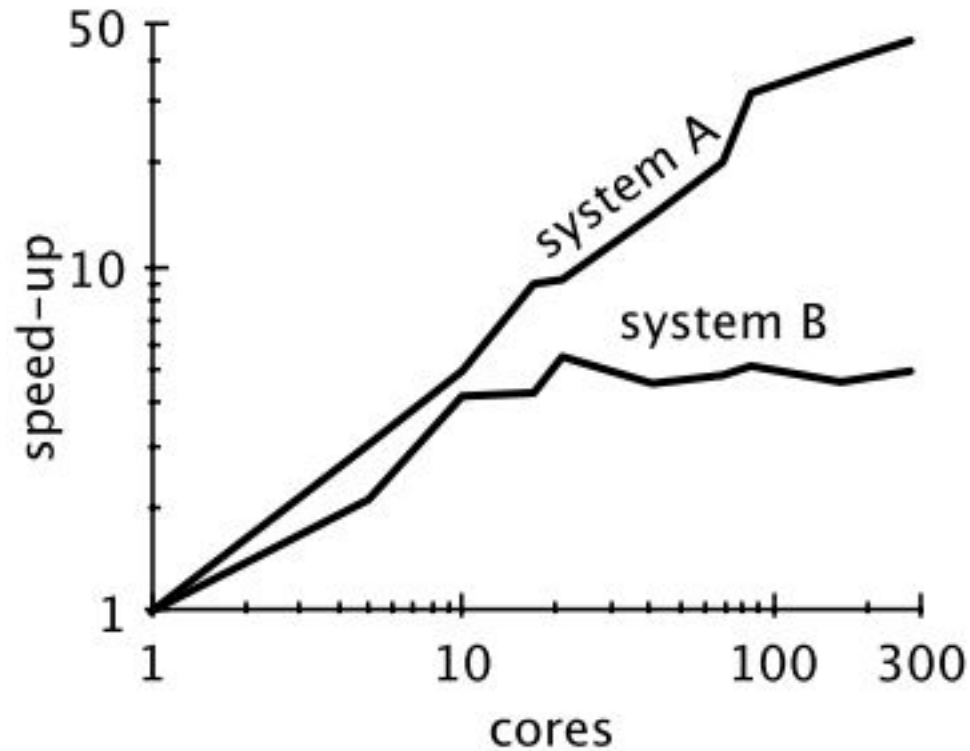


Big Data technologies

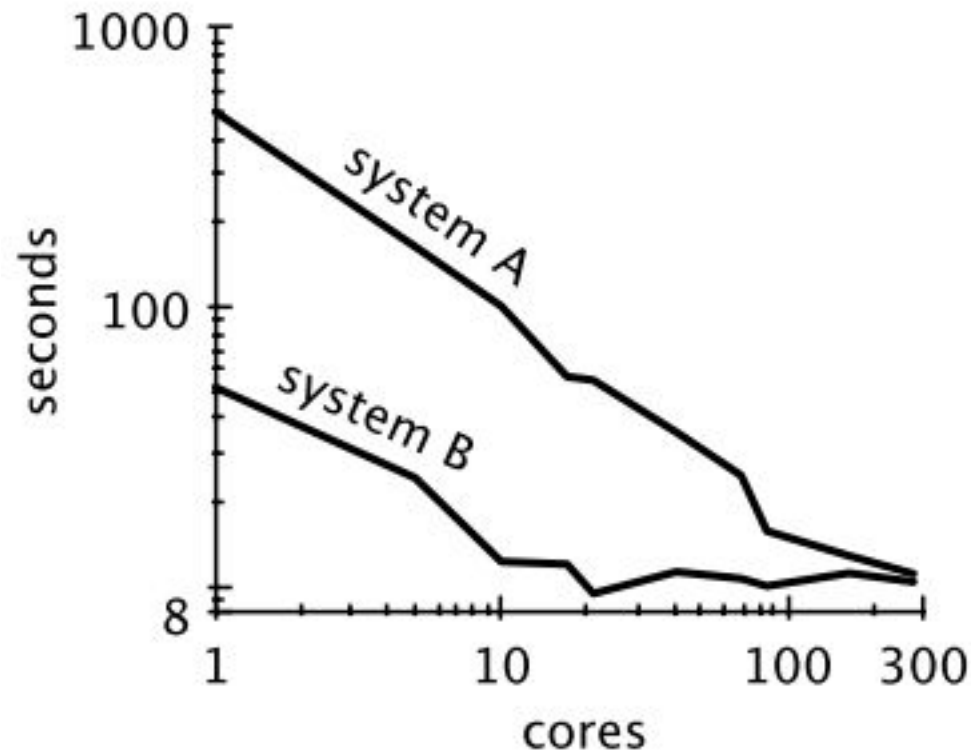
- Map Reduce
 - Hadoop, Spark, etc
- In-Memory Directed Acyclic Graphs
 - Spark, Tez
- Realtime Stream processing
 - Kafka, Spark Streaming, Storm, Siddhi
- NoSQL
 - Cassandra, Mongo, CouchDB, etc
- Statistical Analysis
 - R, SparkR, MapR
- Machine Learning
 - Mahout, MLlib, TensorFlow



Warning

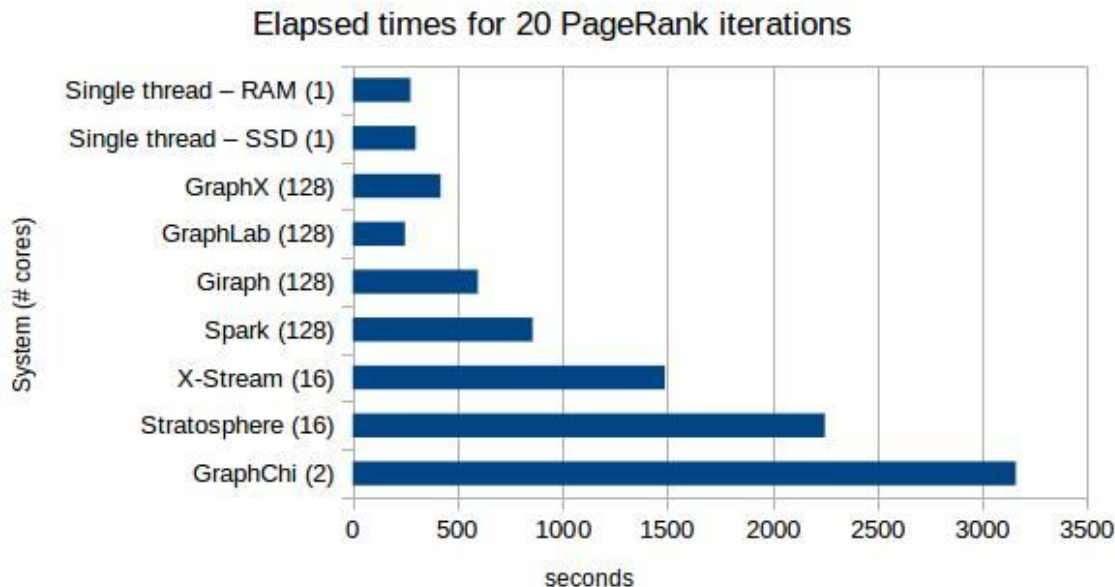


Same systems, new diagram



Scalability at what COST

- COST = Configuration that Outperforms a Single Thread
 - <http://www.frankmcsherry.org/assets/COST.pdf>
 - <http://www.frankmcsherry.org/graph/scalability/cost/2015/01/15/COST.html>





WHY PYTHON?



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Python for Big Data

- Python is a great language for Data Science
 - NumPy, Pandas, many graphic packages
- Python is a great language for Spark
 - Lambdas, concise statements, DataFrames
- Ipython/Jupyter is a great notebook



Other options

- C/C++ are fast to run, but generally slow to develop
- Scala is an even better language for Spark
 - But not so strong in wider data science
- Java is too wordy for Data Science!
- R is a great model for both Data Science and Spark, if you are a statistician
- Do not even consider Perl ;-)



Notebooks

- Web-based systems that combine documentation, code and graphics into one place
- Two front runners for Big Data
 - Jupyter (formerly IPython)
 - Based on Python but supporting other languages
 - Apache Zeppelin
 - More language neutral but newer and more buggy (this may be changing of course)



This is a markdown cell used for documentation

The above cell was written as: "### This is a markdown cell", followed by Shift+Enter

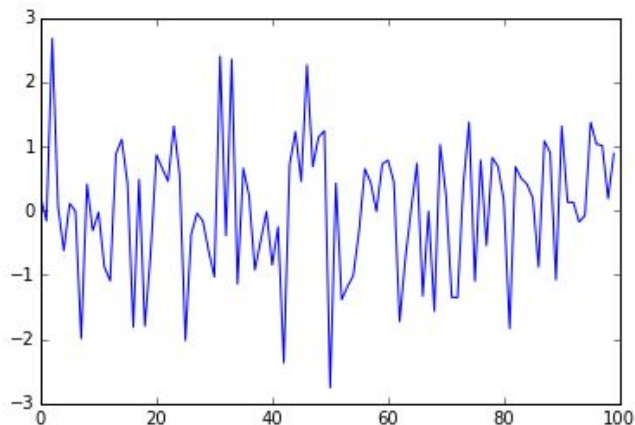
```
In [12]: import math  
print "This is a code cell... and Pi is = ", math.pi
```

This is a code cell... and Pi is = 3.14159265359

```
In [13]: # to enable inline graphs, etc.  
%pylab inline  
  
plot(randn(100))
```

Populating the interactive namespace from numpy and matplotlib

Out[13]: [<matplotlib.lines.Line2D at 0x7fe2a2496cd0>]



Numpy

- Numerical and scientific analysis library in Python
- (sudo) pip install numpy
- Foundation of most data analysis in Python
- Based on arrays of data



Base ecosystem

scipy

pandas

matplotlib

numpy

Pandas

- A rich relational data model built on top of Python's numpy
 - Emerged from the finance industry
 - Like R's data.frame (but maybe better?)



Matplotlib

- A simple graphing library for Python
- Works well with Pandas and Numpy
- Integrated into Jupyter
- There are many alternatives
 - E.g. Bokeh



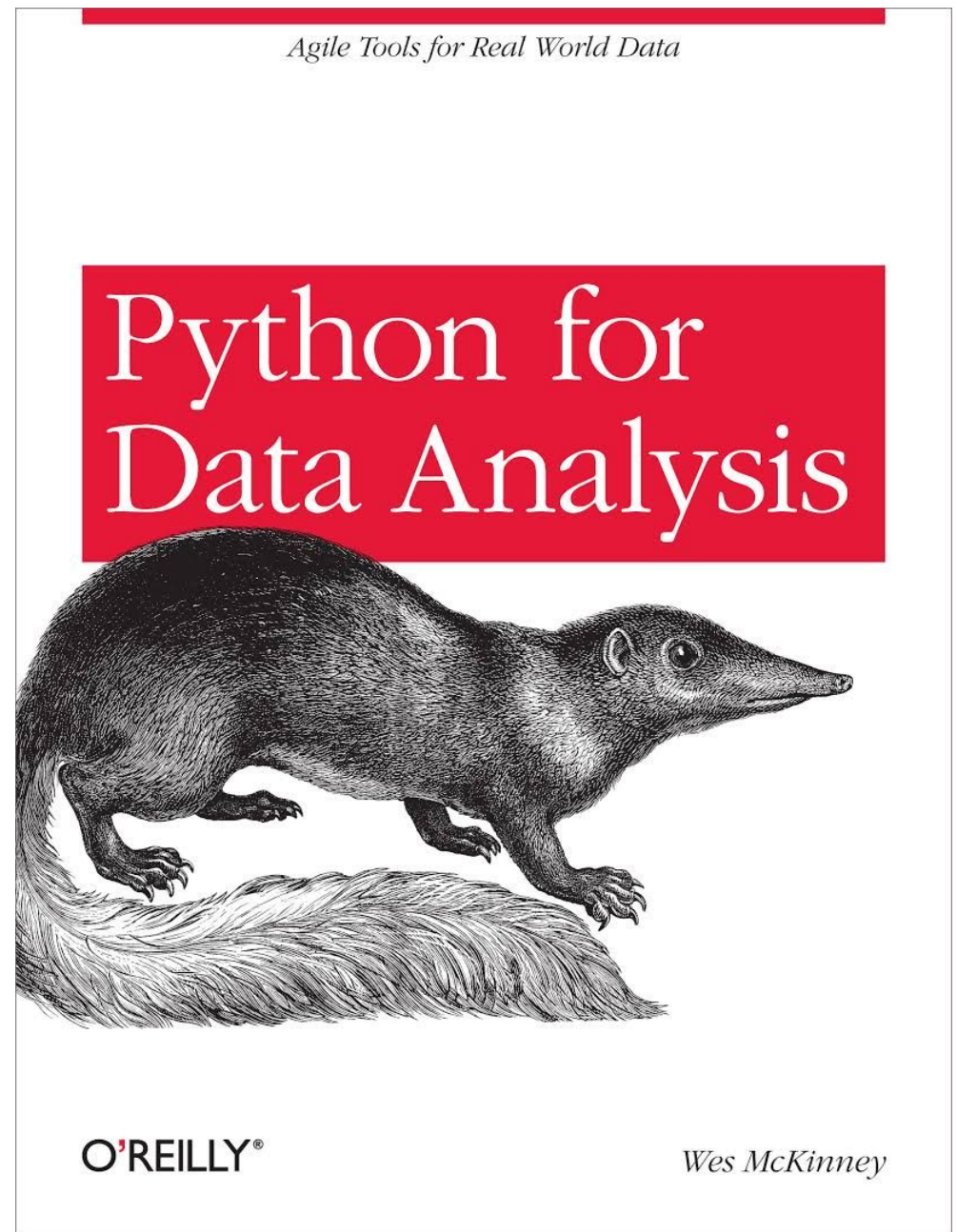
This course

- Python
- pandas
- matplotlib
- pyspark
 - Apache Spark with Python
- Jupyter
- Some other libraries etc as we go



Recommended Reading!

(take a look at
my copy)



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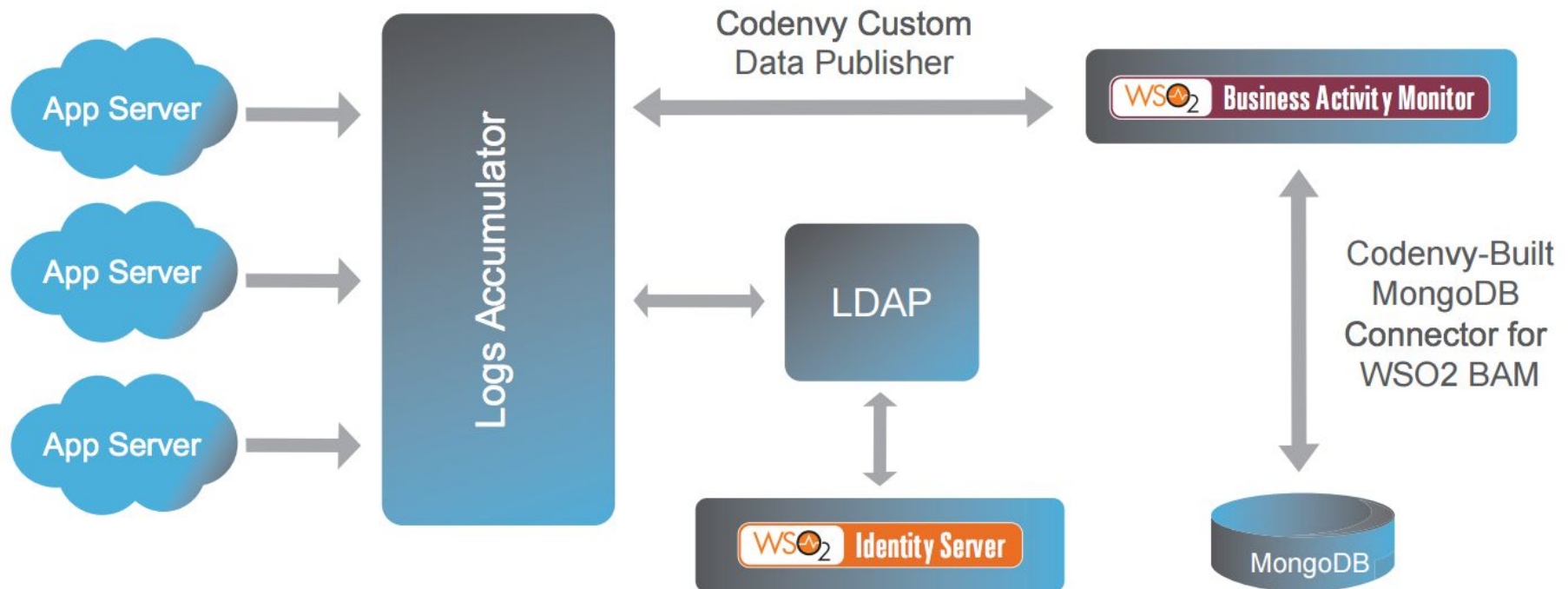
CASE STUDIES



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Big Data

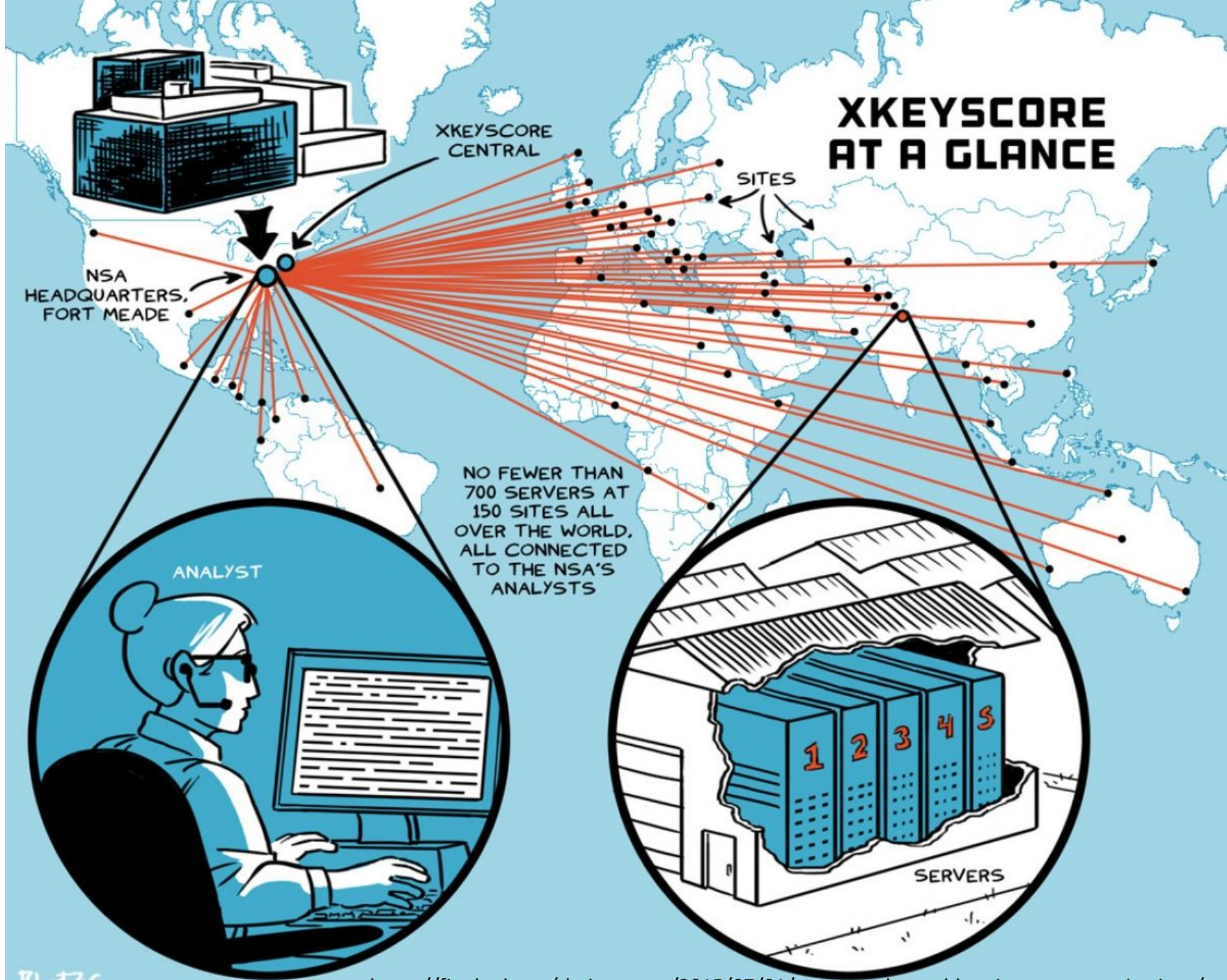
Cloud management analytics



Realtime Big Data

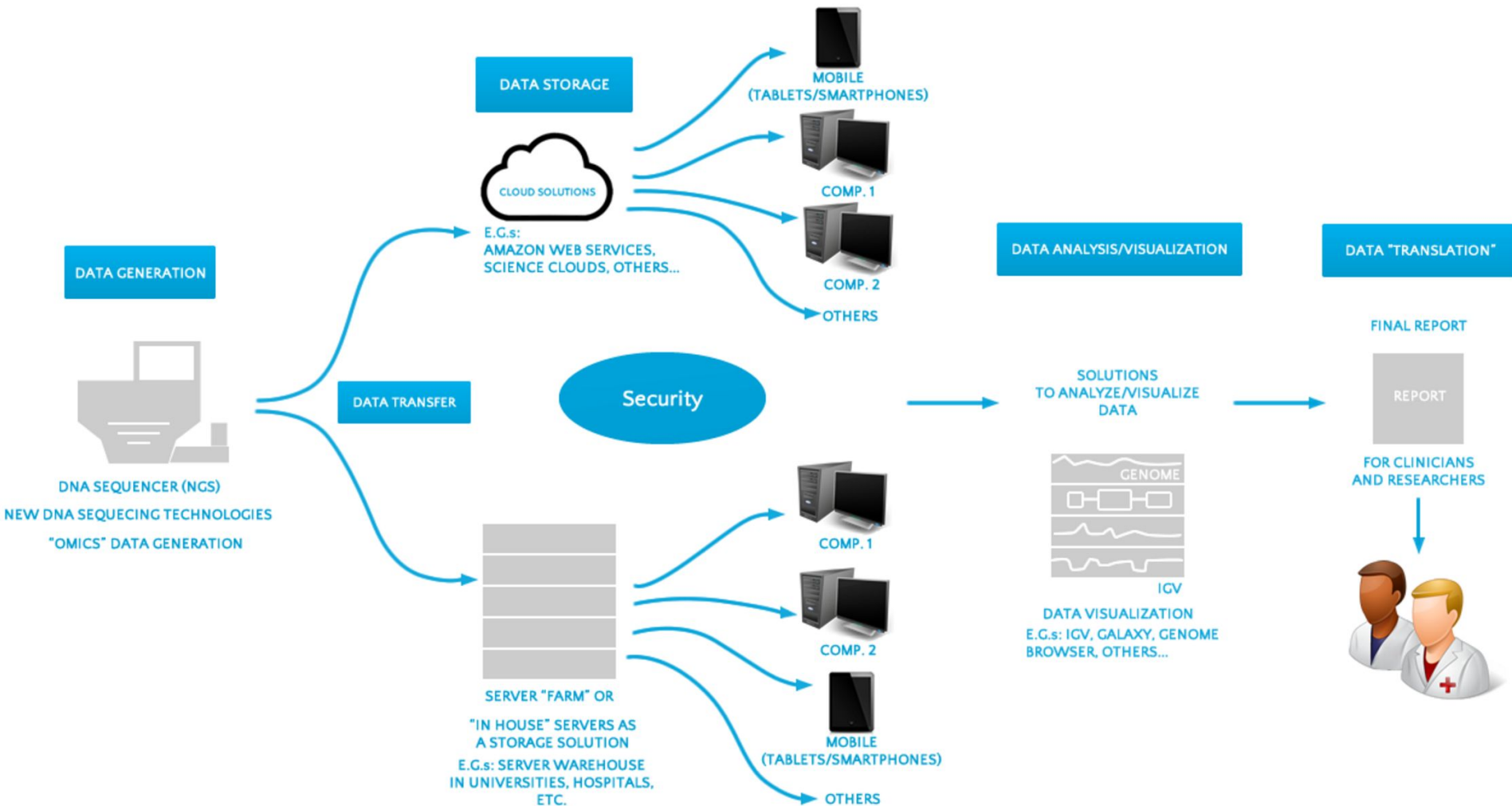
- New York-based Bank
- 25 servers in a cluster analysing trading and system data from operational systems
- Siddhi-based engine processing data in realtime
- Handling 10,000s of events/second





Big Data in Genomics

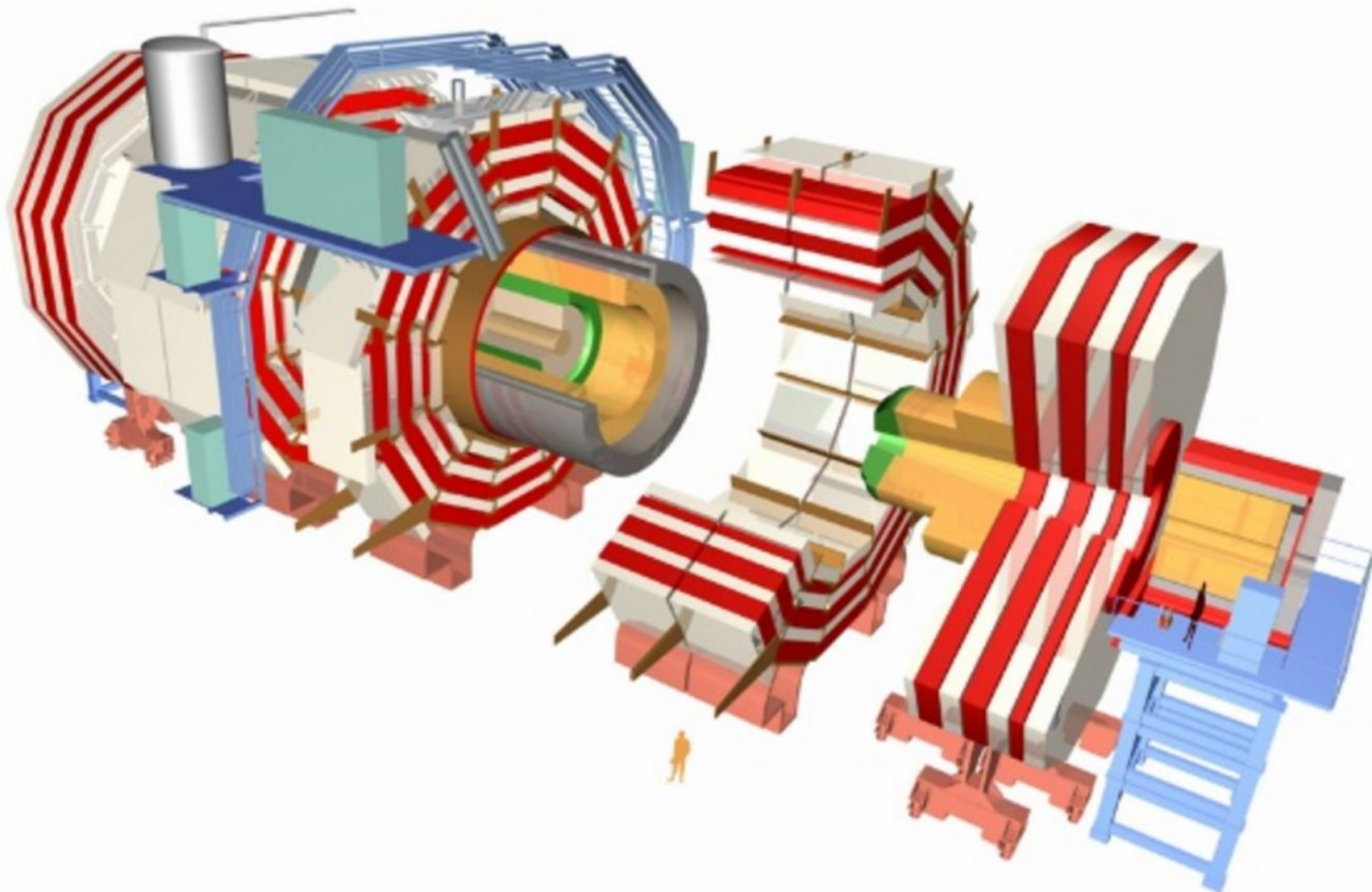
<http://www.laboratory-journal.com/science/information-technology-it/big-data-genomics-challenges-and-solutions>



Maclaren Formula 1



- Collects 1Gb/race
- Analysing in real-time to tune and manage the car



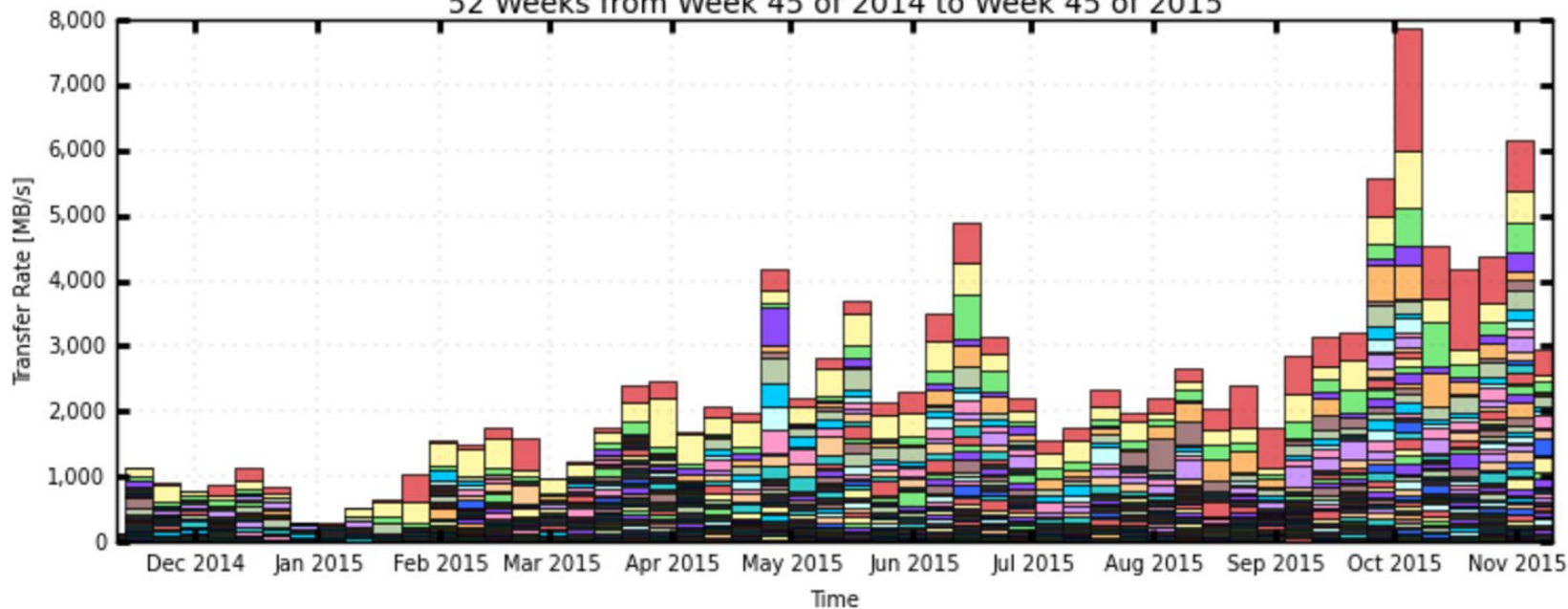
Large Hadron Collider

Compact Muon Solenoid Experiment

Source: <http://cmsweb.cern.ch/phedex>

CMS PhEDEx - Transfer Rate

52 Weeks from Week 45 of 2014 to Week 45 of 2015



- | | | | | |
|-------------------|--------------------|---------------------|----------------------|-------------------|
| T1_US_FNAL_Disk | T0_CH_CERN_Export | T2_CH_CERN | T2_US_Nebraska | T1_US_FNAL_Buffer |
| T2_US_MIT | T1_IT_CNAF_Disk | T1_UK_RAL_Disk | T1_ES_PIC_Disk | T1_DE_KIT_Disk |
| T1_DE_KIT_Buffer | T1_FR_CCIN2P3_Disk | T2_US_Vanderbilt | T1_RU_JINR_Disk | T2_US_Wisconsin |
| T2_EE_Estonia | T2_US_Florida | T2_US_UCSD | T1_FR_CCIN2P3_Buffer | T2_US_Purdue |
| T2_DE_DESY | T2_CH_CSCS | T2_UK_London_IC | T2_IT_Legnaro | T2_IN_TIFR |
| T2_UK_SGrid_RALPP | T2_IT_Rome | T2_BE_IHHE | T1_ES_PIC_Buffer | T2_US_Caltech |
| T3_US_FNALLPC | T2_IT_Pisa | T2_FR_GRIF_IRFU | T2_FR_GRIF_LL | T1_IT_CNAF_Buffer |
| T1_UK_RAL_Buffer | T2_DE_RWTH | T2_PL_Warsaw | T2_BR_UERJ | T2_BR_SPRACE |
| T2_IT_Bari | T2_KR_KNU | T2_UK_London_Brunel | T2_ES_CIEMAT | T2_FR_IPHC |
| T2_FR_CCIN2P3 | T2_HU_Budapest | T2_FI_HIP | T2_BE_UCL | ... plus 47 more |

Maximum: 7,867 MB/s, Minimum: 125.02 MB/s, Average: 2,340 MB/s, Current: 2,939 MB/s

Questions?



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