Introduction

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(Tehran Polytechnic)

Course Information

Course Objective

- Introduction to main concepts and principles of cloud computing and data intensive computing.

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- Introduction to main concepts and principles of cloud computing and data intensive computing.

- How to read, review and present a scientific paper.

Topics of Study

- Topics we will cover include:
  - Cloud platforms
  - Cloud storage, NoSQL and NewSQL databases
  - Cloud resource management
  - Batch processing frameworks
  - Stream processing frameworks
  - Graph processing frameworks

Course Material

- Mainly based on research papers.
- You will find all the material on the course web page:
  http://www.sics.se/∼amir/cloud14.htm

Course Examination

- Mid term exam: 20%
- Final exam: 20%
- Reading assignments: 27%
- Final presentation: 23%
- Final project: 10%
- Lab assignments: 0% :)

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- Nine reading assignments.

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- Students will work in groups of two.

Presentation

- Each group give a 30 minutes talk on a scientific paper.
- The list of papers will be available in the course web page.
- You are also free to choose any other paper, but it should be confirmed.

Lab Assignments and the Project

- Implement simple applications on different frameworks through the course.
- The solution of each lab assignment will be uploaded on the course page, one week after their start dates.
- The final project on top of Spark.

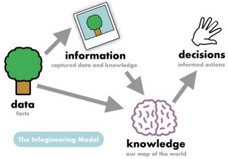
Discussion Forum

- Use the course discussion forum if you have any questions: http://www.sics.se/∼amir/cloud14.htm

Course Overview

Data is not information, information is not knowledge, knowledge is not understanding, understanding is not wisdom.

- Clifford Stoll



Big Data

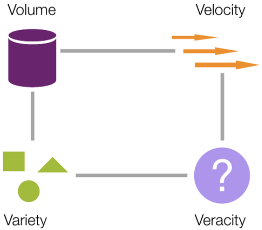
small data

big data

- Big Data refers to datasets and flows large enough that has outpaced our capability to store, process, analyze, and understand.

The Four Dimensions of Big Data

- Volume: data size
- Velocity: data generation rate
- Variety: data heterogeneity
- This 4th V is for Vacillation: Veracity/Variability/Value



Where Does Big Data Come From?

Big Data Market Driving Factors

The number of web pages indexed by Google, which were around one million in 1998, have exceeded one trillion in 2008, and its expansion is accelerated by appearance of the social networks.∗

[∗Wei Fan et al., Mining big data: current status, and forecast to the future, 2013]

Big Data Market Driving Factors

The amount of mobile data traffic is expected to grow to 10.8 Exabyte per month by 2016.*

[*Dan Vesset et al., Worldwide Big Data Technology and Services 2012-2015 Forecast, 2013]

Big Data Market Driving Factors

More than 65 billion devices were connected to the Internet by 2010, and this number will go up to 230 billion by 2020.∗

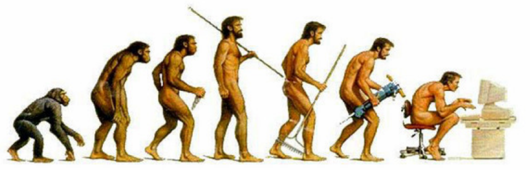
[∗John Mahoney et al., The Internet of Things Is Coming, 2013]

Open source communities

Big Data Market Driving Factors

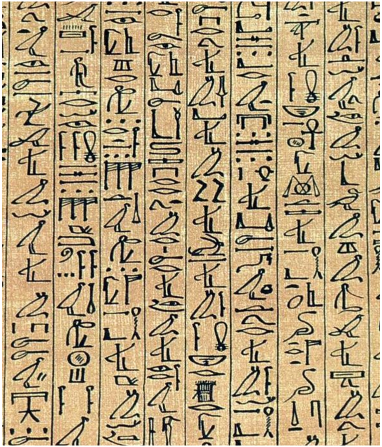
Many companies are moving towards using Cloud services to access Big Data analytical tools.

History of Data



4000 B.C

- Manual recording
- From tablets to papyrus, to parchment, and then to paper

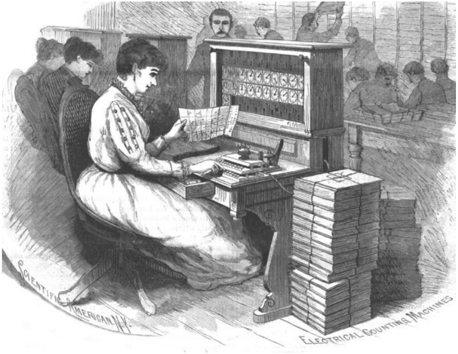


1450

- Gutenberg's printing press

1800's - 1940's

- Punched cards (no fault-tolerance)
- Binary data
- 1890: US census
- 1911: IBM appeared



IBM

1940's - 1950's

- Magnetic tapes

1950's - 1960's

- Large-scale mainframe computers
- Batch transaction processing
- File-oriented record processing model (e.g., COBOL)

1960's - 1970's

- Hierarchical DBMS (one-to-many)
- Network DBMS (many-to-many)
- VM OS by IBM $\rightarrow$ multiple VMs on a single physical node.

1970's - 1980's

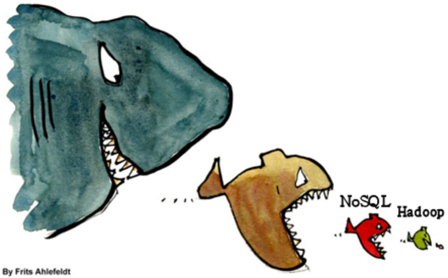
- Relational DBMS (tables) and SQL
- ACID
- Client-server computing
- Parallel processing

1990's - 2000's

- Virtualized Private Network connections (VPN)
- The Internet...

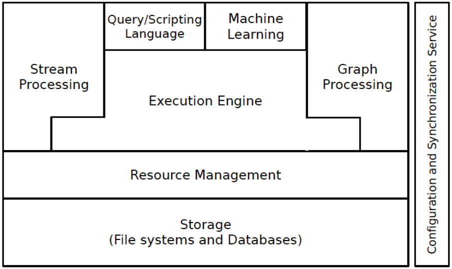
2000's - Now

- Cloud computing
- NoSQL: BASE instead of ACID
- Big Data

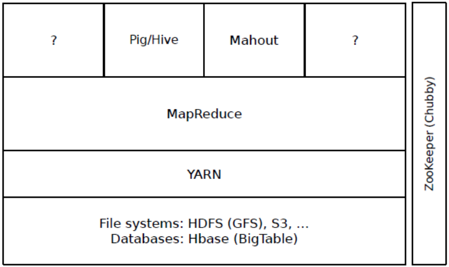


Cloud and Big Data

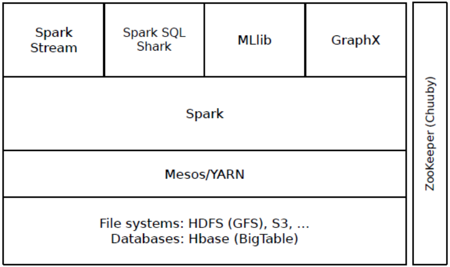
Big Data Analytics Stack



Hadoop Big Data Analytics Stack

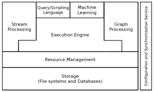


Spark Big Data Analytics Stack



Big Data - File systems

- Traditional file-systems are not well-designed for large-scale data processing systems.



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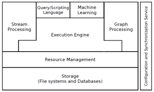

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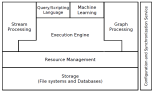

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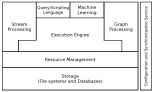
- HDFS/GFS, Amazon S3, ...



Big Data - Database

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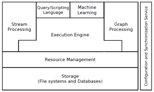

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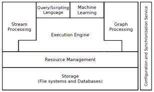

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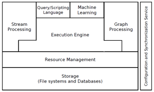

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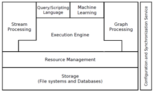
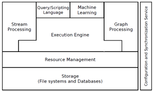
- Hbase/BigTable, Dynamo, Scalaris, Cassandra, MongoDB, Voldemort, Riak, Neo4J, ...



Big Data - Resource Management

- Different frameworks require different computing resources.



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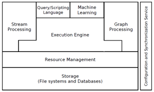

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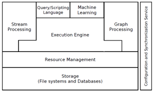

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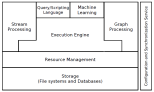
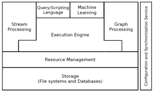
- Mesos, YARN, Quincy, ...



Big Data - Execution Engine

- Scalable and fault tolerance parallel data processing on clusters of unreliable machines.



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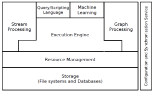

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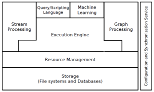
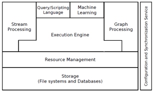


Big Data - Query/Scripting Language

- Low-level programming of execution engines, e.g., MapReduce, is not easy for end users.



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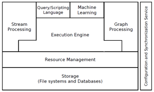

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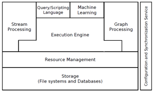

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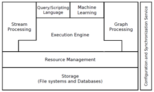
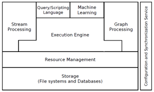
- Pig, Hive, Shark, Meteor, DryadLINQ, SCOPE, ...



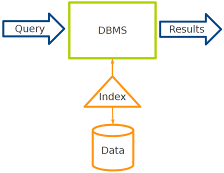
Big Data - Stream Processing

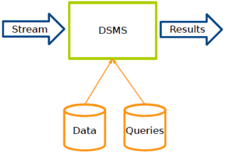
- Providing users with fresh and low latency results.

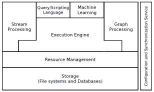


Big Data - Stream Processing

- Providing users with fresh and low latency results.
- Database Management Systems (DBMS) vs. Data Stream Management Systems (DSMS)







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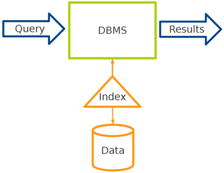
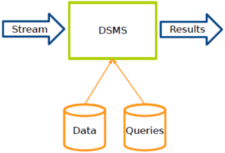
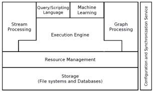




- Storm, S4, SEEP, D-Stream, Naiad, ...



Big Data - Graph Processing

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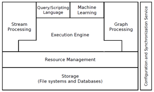

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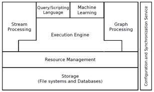

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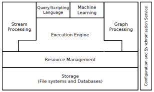

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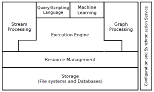
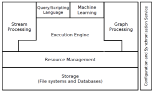
- Pregel, Giraph, GraphX, GraphLab, PowerGraph, GraphChi, ...



Big Data - Machine Learning

- Implementing and consuming machine learning techniques at scale are difficult tasks for developers and end users.



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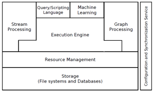

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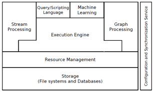
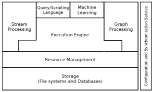
- Mahout, MLBase, SystemML, Ricardo, Presto, ...



Big Data - Configuration and Synchronization Service

- A means to synchronize distributed applications accesses to shared resources.



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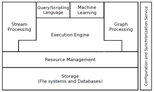

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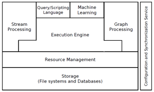
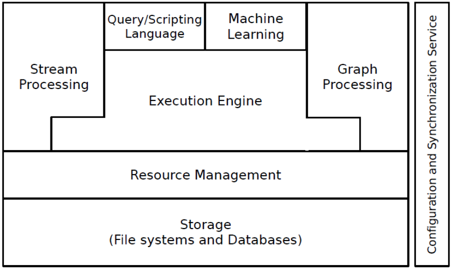
- Zookeeper, Chubby, ...



Summary

Summary


Query/Scripting Language
Machine Learning
Stream Processing
Execution Engine
Graph Processing
Resource Management
Storage
(File systems and Databases)
Configuration and Synchronization Service

Questions?