

Università degli Studi di Milano - Bicocca

Dipartimento di Informatica Sistemistica e Comunicazione

Infosphere BigInsights

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La tradizionale filiera BI





La filiera delle IBM Big Data & Analytics





Biginsights basato su Hadoop perchè?



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- CPU istruzioni al secondo miglioramenti significativi
 1990 44 Mips at 40 Mhz
 2000 3.562 Mips at 1.2 Ghz
 2010 147.600 Mips at 3.3 Ghz
- RAM Memory miglioramenti significativi
 - 1990 640 K2000 64 Mb2010 8-32 GB
- Disk capacity miglioramenti significativi
 - 199020 MB200010 GB20101 TB

Disk latency (velocità di leggere e scrivere su disco) - miglioramenti poco significativi

Negli ultimi 7-10 anni non ci sono state enormi migliorie correntemente la velocita è di circa 70 – 80 MB / sec

Quanto tempo ci vuole per scandire 1 TB?



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□1 TB (at 80 MB / sec)

1 disk	3.4 hours
10 disks	20 min
100 disks	2 min
1000 disks	12 sec

Per ovviare alla Disc Latency la risposta è la ..elaborazione parallela

Hadoop : un nuovo modo per memorizzare ed elaborare i dati

Scritto in Java
 Progettato per lavorare su hardware non specializzato
 Gira in ambiente Linux
 Scalabile, Flessibile, Robusto



What is Hadoop?



- Apache Hadoop = free, open source framework for data-intensive applications
 - Inspired by Google technologies (MapReduce, GFS)
 - Yahoo has been the largest contributor to the project (Doug Cutting),
 - Well-suited to batch-oriented, read-intensive applications
 - Originally built to address scalability problems of Nutch, an open source Web search technology
- Enables applications to work with thousands of nodes and petabytes of data in a highly parallel, cost effective manner
 - CPU + disks of commodity box = Hadoop "node"
 - Boxes can be combined into clusters
 - New nodes can be added as needed without changing
 - Data formats
 - How data is loaded
 - How jobs are written



Two Key Aspects of Hadoop



MapReduce framework

- MapReduce is a software framework introduced by Google to support distributed computing on large data sets of clusters of computers.
- How Hadoop understands and assigns work to the nodes (machines)

Hadoop Distributed File System = HDFS

- -Where Hadoop stores data
- A file system that spans all the nodes in a Hadoop cluster
- It links together the file systems on many local nodes to make them into one big file system

Hadoop ed il paradigma Map Reduce

- I dati sono memorizzati su un sistema distribuito di server
- Le funzioni elaborative vengono inviate dove ci sono I dati
- Ogni server elabora I dati di propria competenza e condivide i risultati
- Il sistema può scalare raggiungendo migliaia di nodi e PB di dati





- 1. Map Phase
 - (spezza il job in piccole parti)
- 2. Shuffle
 - (riordina I risultati parziali per le elaborazione finale)
- 3. Reduce Phase (rielabora il tutto per ottenere un singolo risultato)

Scale-out vs scale-up

□ Just reading 100 terabytes is slow

-Standard computer (100 MBPS) ~11 days

- -Across 10Gbit link (high end storage) 1 day
- -1000 standard computers 15 minutes!

Seek times for random disk access is a problem

-1 TB data set with 10¹⁰ 100-byte records Updates to 1% would require 1 month Reading and rewriting the whole data set would take 1 day*

One node is not enough!

□ Need to scale out not up!



Scale up



Scaling out



- **Bad news: nodes fail, especially if you have many**
 - Mean time between failures for 1 node = 3 years, 1000 nodes = 1 day
 - Super-fancy hardware still fails and commodity machines give better performance per dollar
- Bad news II: distributed programming is hard
 - Communication, synchronization, and deadlocks
 - Recovering from machine failure
 - Debugging
 - Optimization

Bad news III: repeat for every problem

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In 2003/4 Google publishes seminal whitepapers on a new programming paradigm

to handle data at Internet Scale.

Original assumptions:

- scale-out architecture
- build a super computer on commodity hardware (commodity != low-end not tied to expensive, proprietary offerings from a single vendor)
- hides system-level details from the developers (the datacenter is the computer)
- move processing to the data (because cluster have limited bandwith)
- process data sequentially (seeks are expensive)
- expect failure
- shared-nothing architecture (processing tasks have no dependency on one other)

Google: 3 significant papers



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The Google File System Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung Lake George, NY, October, 2003.

MapReduce: Simplified Data Processing on Large Clusters

<u>Jeffrey Dean</u> and <u>Sanjay Ghemawat</u> San Francisco, CA, December, 2004.

"A simple and powerful interface that enables automatic parallelization and distribution of largescale computations, combined with an implementation of this interface that achieves high performance on large clusters of commodity PCs"

Bigtable: A Distributed Storage System for Structured Data

Fay Chang, Jeffrey Dean, Sanjay Ghemawat, Wilson C. Hsieh, Deborah A. Wallach, Mike Burrows, Tushar Chandra, Andrew Fikes, and Robert E. Gruber Seattle, WA, November, 2006.

A brief history of Hadoop





So what exactly is Hadoop?



A framework for running applications (aka jobs) on large clusters built on **commodity hardware** capable of processing **petabytes of data**



it implements a computational paradigm named
 Map/Reduce, where the application is divided into self
 contained units of work, each of which may be
 executed or re-executed on any node in the cluster

tit provides a distributed file system (HDFS) that stores data on the compute nodes, providing very high aggregate bandwidth across the cluster.

node failures are automatically handled by the framework.



The largest known production environments:

- By 2011: Facebook, which consisted of 4,000 nodes (including 8- and 16-core CPUs) and supported 21PB of storage
- By (October) 2013: Yahoo!, spanning more than 35,000 nodes

Facebook Datawarehousing Hadoop cluster (2011 data):

- 12 TB of compressed data added per day
- 800 TB of compressed data scanned per day
- 25,000 map-reduce jobs per day
- 65 millions files in HDFS
- 30,000 simultaneous clients to the HDFS NameNode

Nowadays Facebook Datawarehouse is 300 PB and add about 600 TB of compressed data per day

Hadoop is not for all types of work

Not good for

- Not to process transactions (random access)
- Not good when work cannot be parallelized
- Not good for low latency data access
- Not good for processing lots of small files
- Not good for intensive calculations with little data



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Good for

 Data intensive, bulk-processing oriented, typically "embarrassingly parallel"
 Examples
 Index building at Google and Yahoo!
 Article clustering
 Statistical machine translation
 Spam detection

c3Ad optimization

- SNatural Language Processing
- ∽Image analysis

COSOCR

C3IBM's Watson

Hadoop and the Apache ecosystem





Hadoop term is also used for a family of related projects that fall under the umbrella of infrastructure for distributed computing and large-scale data processing



HADOOP







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Node n



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Hadoop cluster





- Hadoop file system that runs on top of existing file system
- Designed to handle very large files with streaming data access patterns
- Uses <u>blocks</u> to store a file or parts of a file
- Can create, delete, copy, but NOT update



HDFS: organization



- Files are divided into chunks (blocks)
- Chunks are replicated at different compute nodes (usually 3+)
- Nodes holding copies of one chunk are located on different racks
- Chunk size and the degree of replication can be decided by the user
- A special node (the NameNode) stores, for each file, the positions of its chuncks



NameNode



- Entire metadata is kept in RAM
 - Ensure enough RAM in NameNode
 - If run out of RAM, NameNode will crash
- NameNode mainly consists of:
 - fsimage: Contains the metadata <u>on disk</u> (not exact copy of what is in RAM, but a checkpoint copy)
 - edit logs: Records all write operations, synchronizes with metadata in RAM after each write
- In case of 'power failure' on NameNode
 - Can recover using fsimage + edit logs
- Need to format NameNode to use it:
 - \circ hadoop namenode -format





- Many per Hadoop cluster
- Manages blocks with data and serves them to clients
- Periodically reports to NameNode the list of blocks it stores
- Use inexpensive commodity hardware for this node



- 1) Some number of Map tasks each are given one or more chunks of data.
- 2) These Map tasks turn the chunk into a sequence of key-value pairs. The way key-value pairs are produced is determined by the code written by the user for the Map function.
- 3) The key-value pairs from each Map task are collected by a master controller and sorted and grouped by key (Shuffle and sort).
- 4) The keys are divided among all the Reduce tasks, so all key-value pairs with the same key wind up at the same Reduce task.
- 5) The Reduce tasks work on one key at a time, and combine all the values associated with that key in some way. The way values are combined is determined by the code written by the user for the Reduce function. 6) Output key-value pairs from each reducer are written persistently back onto the distributed file system 7) The output ends up in r files, where r is the number of reducers. The r files often serve as input to yet another MapReduce job

Example: word count

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Problem: counting the number of occurrences for each word in a collection of

documents.

Input: a repository of documents, each document is an element

Map: reads a document and emits a sequence of key-value pairs where keys are words

of the documents and values are equal to 1:

(w1, 1), (w2, 1), . . . , (wn, 1)

Grouping: groups by key and generates pairs of the form

(w1, [1, 1, ..., 1]), ..., (wn, [1, 1, ..., 1])

Reduce: adds up all the values and emits:

(w1, k),..., (wn, l)

Output: (w,m) pairs, where w is a word that appears at least once among all the input

documents and m is the total number of occurrences of w among all those documents.





output

A,1 B,2 C,1 D,1





<k1, v1>

A,1 B,2 C,1 D,1





A,1 B,2 C,1 D,1







C,1

D,1

Simple data flow example







BIGINSIGHTS

IBM InfoSphere BigInsights offre una serie completa di funzionalità di analytics avanzate che consentono alle aziende di analizzare volumi elevati di dati strutturati e non strutturati nel loro formato nativo.

Il software unisce la tecnologia Apache Hadoop open source con le innovazioni IBM, quali analytics dei testi avanzata, IBM BigSheets e Big SQL per la consultazione dei dati e una serie di funzioni amministrative, di sicurezza e prestazioni. Il risultato è una soluzione economica e facile da utilizzare per l'analytics di big data complessi

InfoSphere BigInsights is 100% standard, open source Hadoop

Avoid proprietary lock-in. BigInsights is based on Open Data Platform and includes the rich tools that Hadoop users expect. Where IBM does provide valueadded features, they are carefully implemented so that customers have a choice whether to use IBM enhancements or standard Hadoop functionality.



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VESTAS ha ottimizzato una analisi predittiva su 2.5 Peta



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Vestas optimizes capital investments based on 2.5 Petabytes of information

- Model the weather to optimize placement of turbines, maximizing power generation and longevity
- Reduce time required to identify placement of turbine from weeks to hours
- Reduces IT footprint and costs, and decreases energy consumption by 40 % – while increasing computational power
- Incorporate 2.5 PB of structured and semistructured information flows. Data volume expected to grow to 6 PB

Vestas

Open Data Platform Initiative

Why is IBM involved?

Strong history of leadership in open source & standards Supports our commitment to open source currency in all future releases

Accelerates our innovation within Hadoop & surrounding applications

Open Data Platform (ODP) vs. Apache Software Foundation (ASF)

ODP supports the ASF mission

ASF provides a governance model around individual projects without looking at ecosystem

ODP aims to provide a vendor-led consistent packaging model for core Apache components as an ecosystem

UDEC Man Deduce Charles Hive Hocetalan	
	Pig
YARN Ambari HBase Flume Sqoop	\$olr/Lucene
ODP	





Big SQL – Lightning fast, ANSI compliant, native Hadoop formats

While some Hadoop vendors are building their own SQL-on-Hadoop implementations from scratch, Big SQL is ANSI compliant, lightning fast and runs on native Hadoop file formats. Brought to you by the inventors of SQL, Big SQL provides federated access so customers can query IBM and third party data sources with the same feature rich SQL.





SQL Access for Hadoop: Why?

Data warehouse modernization is a leading Hadoop use case



- Limited availability of skills in MapReduce, Pig, etc.
- SQL opens the data to a much wider audience
 Familiar, widely known syntax
 Common catalog for identifying data and structure



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IBM InfoSphere BigInsights – Big SQL

- IBM's SQL for Hadoop
- Makes Hadoop data accessible to a wider audience
- Familiar, widely known syntax
- Leverage native Hadoop data sources Complements the Data Warehouse
- Exploratory analytics
- Sandbox, Data Lake
- Included in BigInsights
- Use familiar SQL tools
- Cognos, SPSS, Tableau, MicroStrategy







A word about . . . query federation

- Data rarely lives in isolation
- Big SQL transparently queries heterogeneous systems Join Hadoop to RDBMSs
 - Query optimizer understands capabilities of external system
 - Luery optimizer understands capabilities of exte
 - Including available statistics
 - As much work as possible is pushed to each system to process





Created by IBM

The Big Data Decision Support Benchmark (Hadoop-DS) is inspired by, and is highly compliant with TPC-DS

□ Fully complies with the TPC-DS schema requirement

□ Uses all 99 queries

□ Meets the multi-user requirement

□ Has been audited by a TPC-DS auditor but as a non-TPC benchmark

+Select deviations from TPC-DS due to Hadoop limitations:

No data maintenance operations, referential integrity enforcement, or ACID property validation as these are not feasible with HDFS

□ Additional statistics used

□ Metric adjustments

□ No price/performance measures included

□ Not an official TPC benchmark result

IBM Big SQL – Runs 100% of the TPC-DS queries



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Competitive environments require significant effort

Query Querv

Query Query

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Query 1 Query 1

Query 1

Query 1 Query 1 Query 2 Query 2 Query 2 Query 2

Query:

Query 2 Query 2 Query 2

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Query 3

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Query 25	Query 58	Query 91
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Query 31	Query 64	Query 97
Query 32	Query 65	Query 98
Query 33	Querv 66	Query 99

Key points

- With competing solutions, many queries needed to be re-written, some significantly
- Owing to various restrictions, some queries could not be re-written or failed at run-time
- Re-writing queries in a benchmark scenario where results are known is one thing – doing this against real databases in production is another





BigSheets – Spreadsheet-like data access for business users

Shockingly, there are those who prefer not to code in Java or write Pig scripts to get data from Hadoop. BigSheets provides an easy-to-use spreadsheet interface allowing business users to extract, manipulate and visualize data from a variety of Hadoop and non-Hadoop data sources.





Spreadsheet style analysis tool for business users

	IBM InfoSphere BigInsights	Quick Start Edition	Welco	ome biadmin Log out About Help <u>IBM</u> ,	
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1	19 GB	{"Title":"CIO","Id":"14968020","ExtKey":"d5fef4	2 English	English	
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Spreadsheet style analysis tool for business users



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Big Text – Simplify text analytics and natural language processing

Building applications able to extract meaning from text is hard. Rather than build your own solution, stand on the shoulders of the inventors of Watson, the reigning Jeopardy champ. Build your own advanced analytic applications, parse jargon-laden text in multiple languages, and do what your competitors cannot.





BigInsights and Text Analytics



- Distills structured info from unstructured text
 - Sentiment analysis
 - Consumer behavior

• • •

- Illegal or suspicious activities
- Parses text and detects meaning with annotators
- Understands the context in which the text is analyzed
- Features pre-built extractors for names, addresses, phone numbers, etc.

Unstructured text (document, email, etc)

Football World Cup 2010, one team distinguished themselves well, losing to the eventual champions 1-0 in the Final. Early in the second half, Netherlands' striker, Arjen Robben, had a breakaway, but the keeper for Spain, Iker Casillas made the save. Winger Andres Iniesta scored for Spain for the win.

Classification and Insight

World Cup 2010 Highlights

	Name	Position	Country	
	Arjen Robben	Striker	Netherlands	
	Iker Casillas	Keeper	Spain	
_	Andres Iniesta	Winger	Spain	-



Big R – Deep R language integration on Hadoop

It seems that everyone has a solution for R on Hadoop. What's unique about Big R is that it implements standard R-language functions for parallel processing, supports routines available from the Comprehensive R Archive Network (CRAN), it uses standard R developer tools, and supports advanced machine analytic functions in R.





Big R Data Structures: Proxy to entire dataset





Appears and acts like all of the data is on your



In-Hadoop Analytics – Deploy the analytics to the data

The whole point of Hadoop is to move the compute to the data, but IBM takes this to the next level with native analytic functions accessible from R, SQL and other languages. Provide seamless access to advanced in Hadoop statistical and machine learning functions avoiding the cost and complexity of software development and additional tooling.







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Link utili



Try it for free!

Non-production, no-limit version of IBM InfoSphere BigInsights

http://IBM.co/QuickStart





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New! InfoSphere BigInsights Quick Start Edition





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A few essential links



IBM Analytics



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IBM Big Data http://www-01.ibm.com/software/data/bigdata/

IBM Watson

http://www.ibm.com/smarterplanet/us/en/ibmwatson/

For more info

Other relevant links



IBM Big Data Youtube Channel

https://www.youtube.com/user/

IBM Big Data case

http://www.ibm.com/bigdata/us/en/big-data-andanalytics/casestudies.html#filter2=customerinsight

Due buoni libri ...free...sui Big Data



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https://www.ibm.com/developerworks/community/blogs/Susan Visser/entry/the power of now real time analytics and ibmi nfosphere_streams?lang=en

Big Data Beyond the Hype

A Guide to Conversations for Today's Data Center

- Expand what you know about Big Batz, putting you on track to go beyond the type
- Stay or Tapor' di the charges, including he chard, Prancy-ansathandytica, in contragrandytica, varieturain, (including Big SOL), NASOL, integration, governance, and more
- See how IBM Watern and so association indek cuch so IBM El particion dissonrial dimensions to the Big Extension
- Learn about the Big Bata Zones. More that brings a new approach to managing data, tester to deploy, Leater to insights , and with leasinsk
- Scin confidence in your Big Data process and ical nicholit the importance of governance in a Big Data work;



Paul Zikopoulos Dirk deRoos Chris Bienko Bick Buglio Marc Andrews

https://www.ibm.com/developerworks/commu nity/blogs/SusanVisser/entry/big data beyond the hype a guide to conversations for today s data center?lang=en



Uno degli ultimi COURSES...su SPARK

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hest Released!	>	Audience: Time to complete: Available in: Data scientists, engineers, or anyone who is interested in 03:00 English
PART COPPERPORT		rearning about span.
Big Data	> ,	Apache Spark is an open source processing engine built around speed, ease of use, and analytics. If you have large amounts of
Big Data	>	Apache Spark is an open source processing engine built around speed, ease of use, and analytics. If you have large amounts of requires low latency processing that a typical Map Reduce program cannot provide. Spark is the alternative. Spark performs at sy to 100 times taskes than Map Berlives for iterative alcontities or interactive data mining. Spark provides in memory cluster composi-



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Mi fermo qui GRAZIE a tutti voi