

# Large-Scale and Multi-Structured Databases

*The Big Data Era*

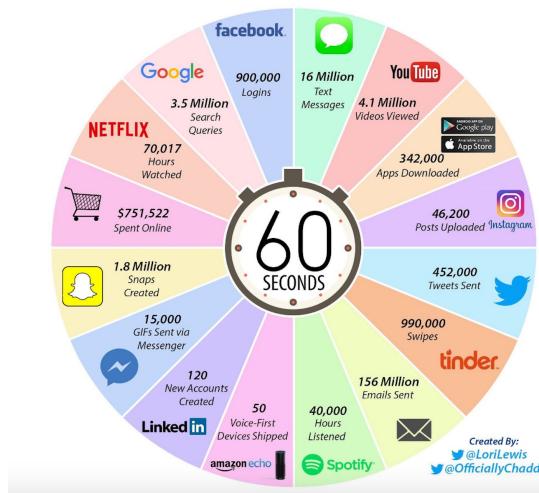
Prof Pietro Ducange

# Big Data: What, Who, Where, How

- ***Big Data*** is a fashion-trend ***buzz word***
- ***Everybody*** (and ***everywhere***) talk about Big Data
- Enterprises, Universities, Research Centers, Researchers, Software Developers, Consultants, etc., state that they work with Big Data
- ***The question is:*** what can we do with Big Data? How can we use Big Data?

# The Big Data Era (I)

**2017** This Is What Happens In An Internet Minute



**2019** This Is What Happens In An Internet Minute



**2021** This Is What Happens In An Internet Minute



# The Big Data Era (II)



**Social media and networks**  
(all of us are generating data)



**Scientific instruments**  
(collecting all sorts of data)

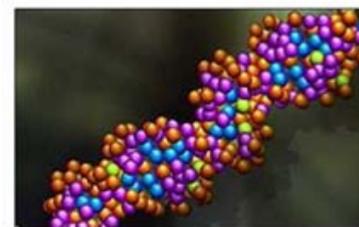
**Transactions**



**Mobile devices**  
(tracking all objects  
all the time)



**Sensor technology and networks**  
(measuring all kinds of data)

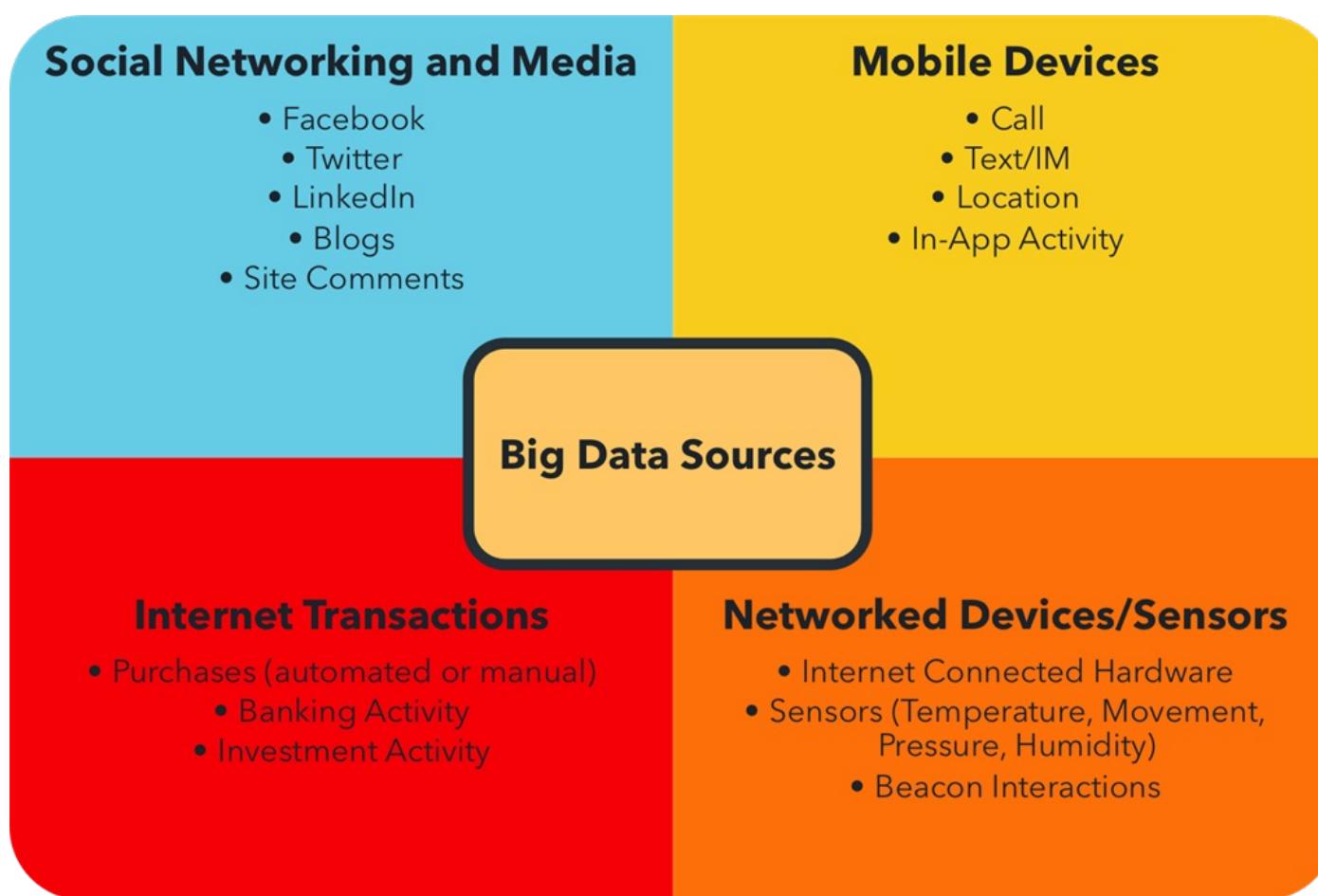


**Genomics**



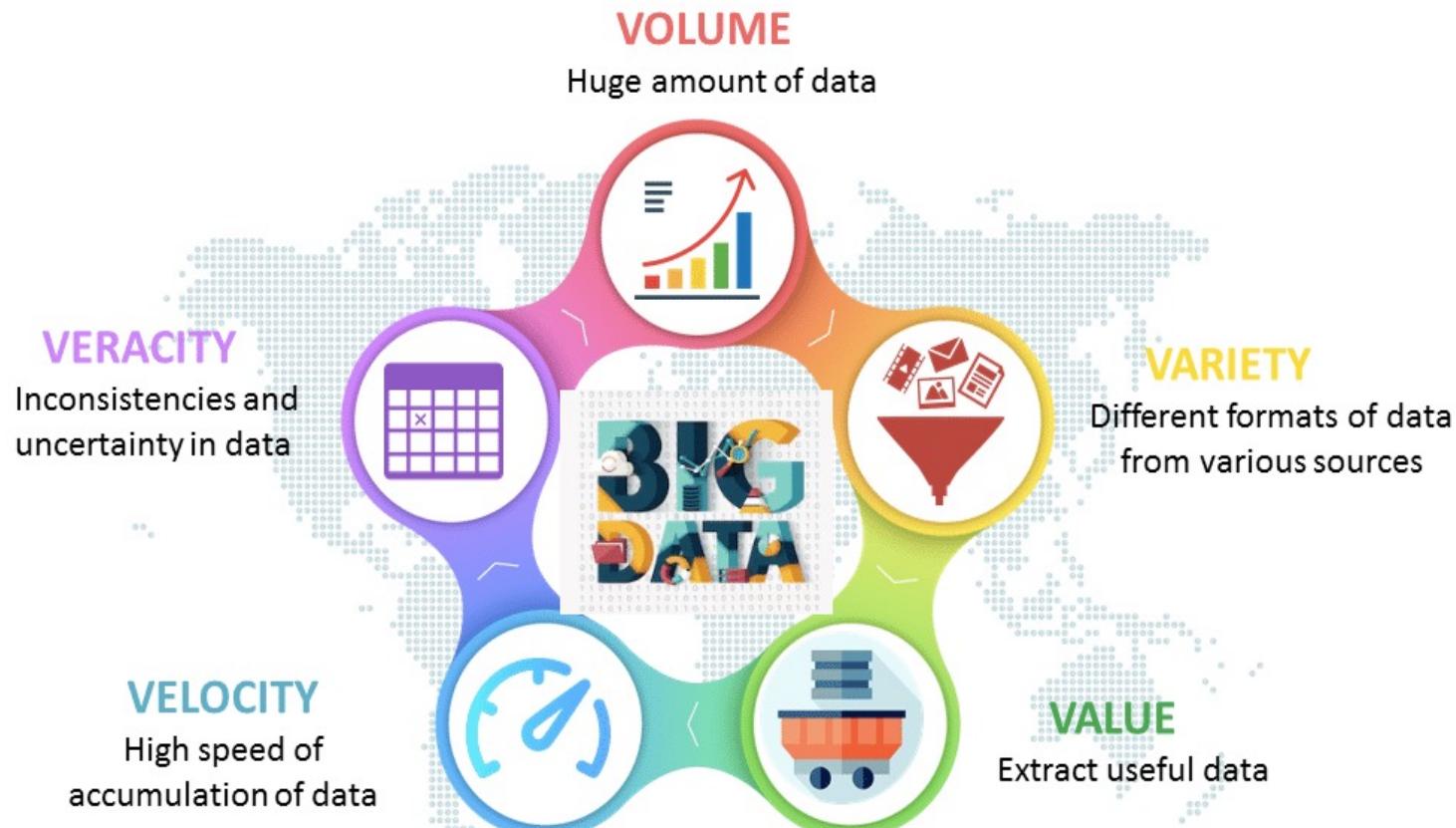
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# The Big Data Era (II)



*Image extracted from: <http://www.talismaniandigital.com/importance-of-big-data-analytics-in-digital-marketing/>*

# Big Data in a Snapshot



*Image extracted from: <https://www.edureka.co/blog/what-is-big-data/>*

# 10 Vs of Big Data



Image extracted from: <https://towardsdatascience.com/big-data-analysis-spark-and-hadoop-a11ba591c057>

# 42 Vs of Big Data (in 2017)

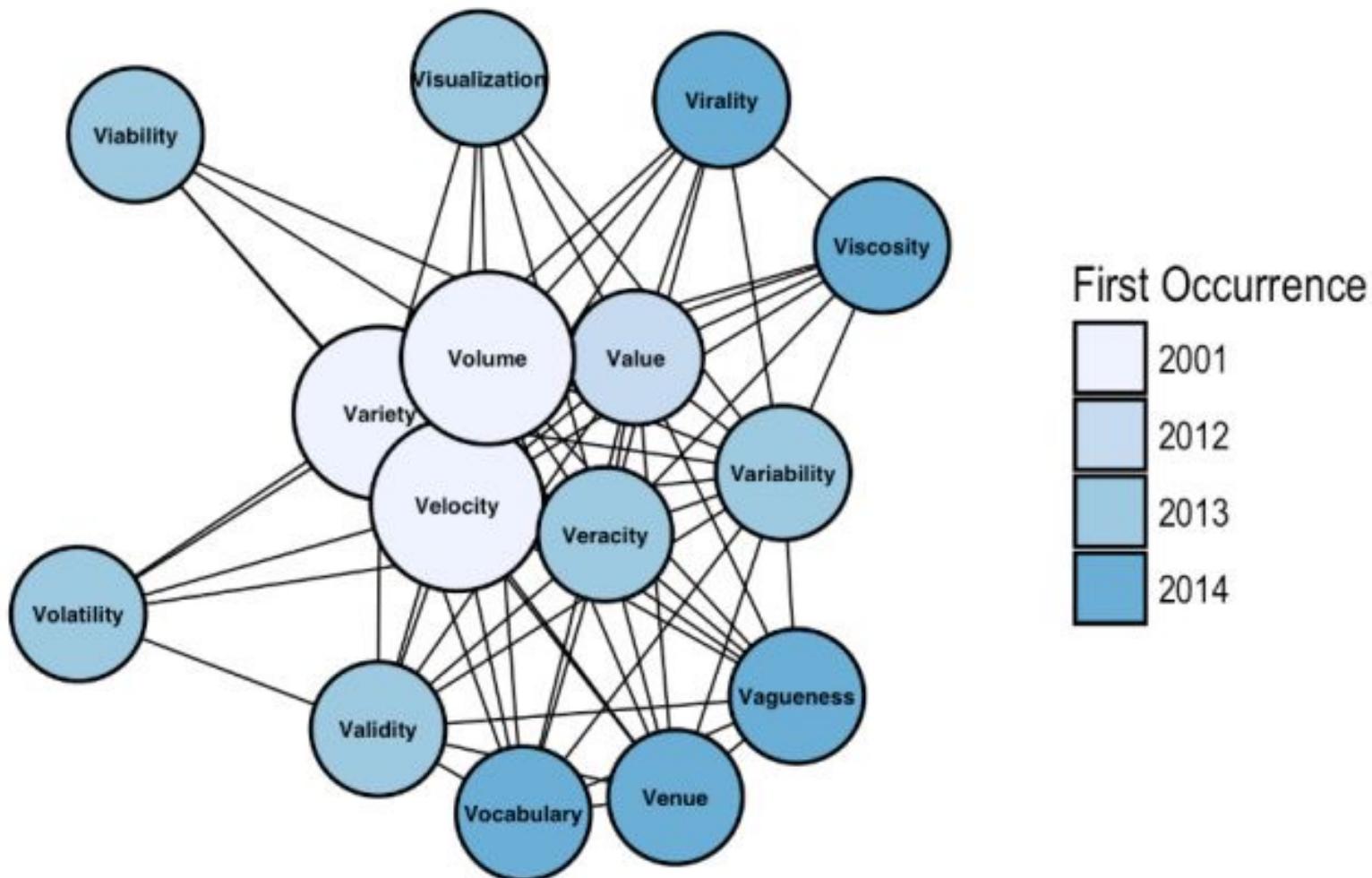
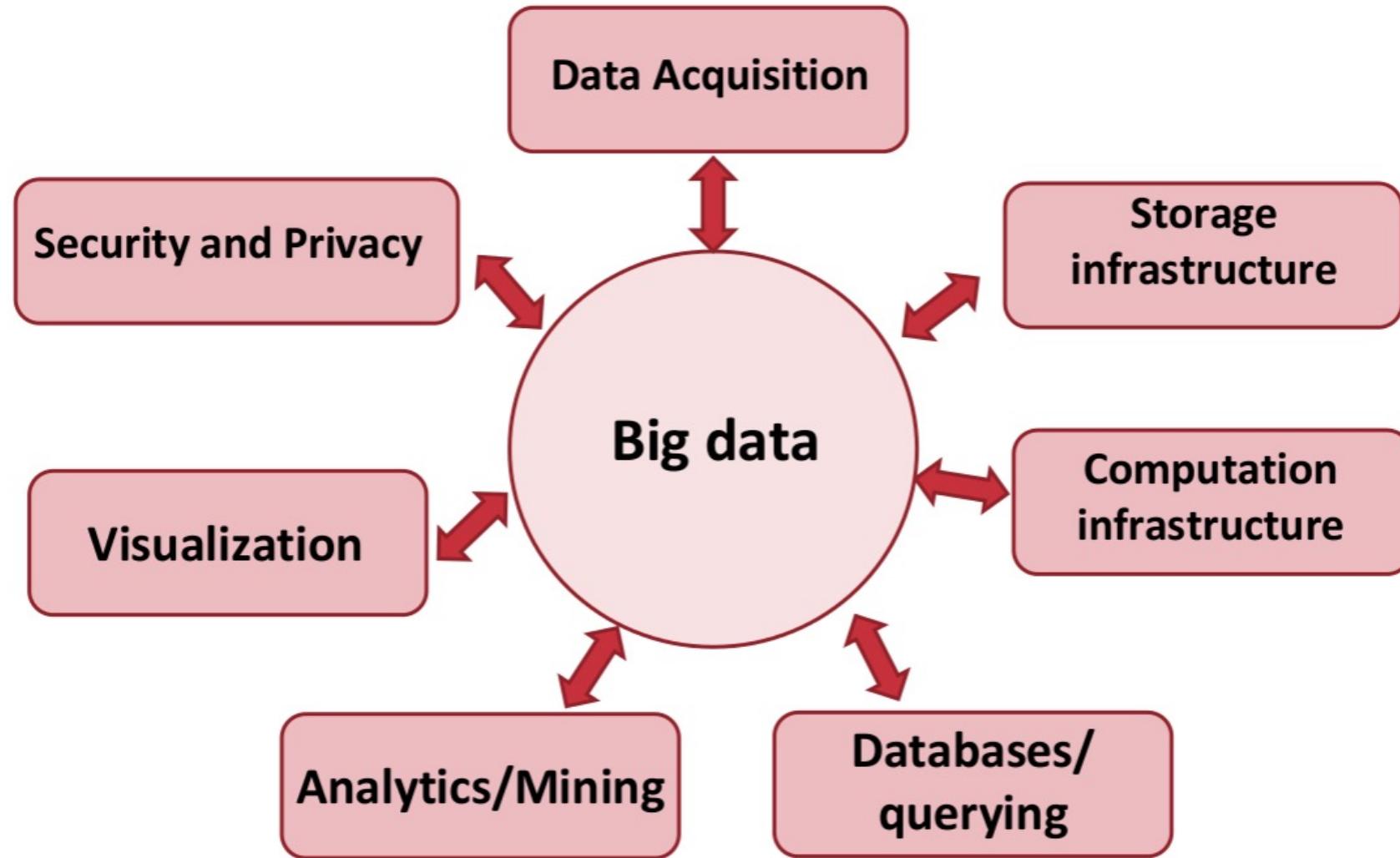


Image extracted from: <https://www.kdnuggets.com/2017/04/42-vs-big-data-data-science.html>

# Big data has many faces



Source: Yvan Saeys. A gentle Introduction to Big Data

# The Main Big Data Issue

Big data refers to any problem characteristic that represents a ***challenge*** to process it with ***traditional applications***

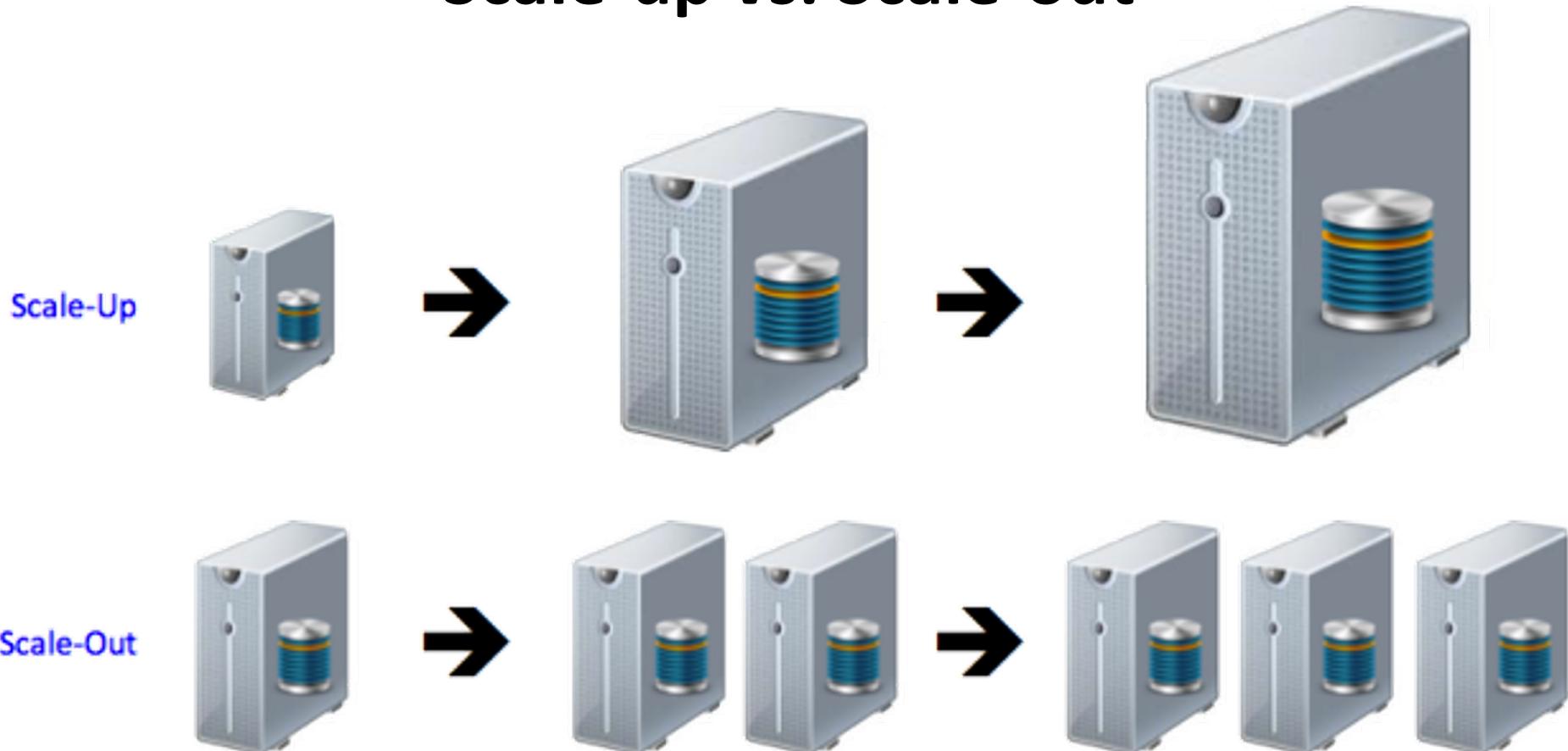
Big Data involves ***data*** whose volume, diversity and complexity requires ***new techniques, algorithms and analyses*** to fetch, to store and to elaborate them.

# The Main Big Data Computing Issue

- *Classical* data elaboration algorithms, such as the ones for analytics and data mining, cannot directly applied to Big Data
- **New** technologies are needed for both *storage* and *computational* tasks.
- *New paradigms* are needed for *designing*, *implementing* and *experimenting* algorithms for handling big data.

# How to deal with data intensive applications?

## Scale-up vs. Scale-out

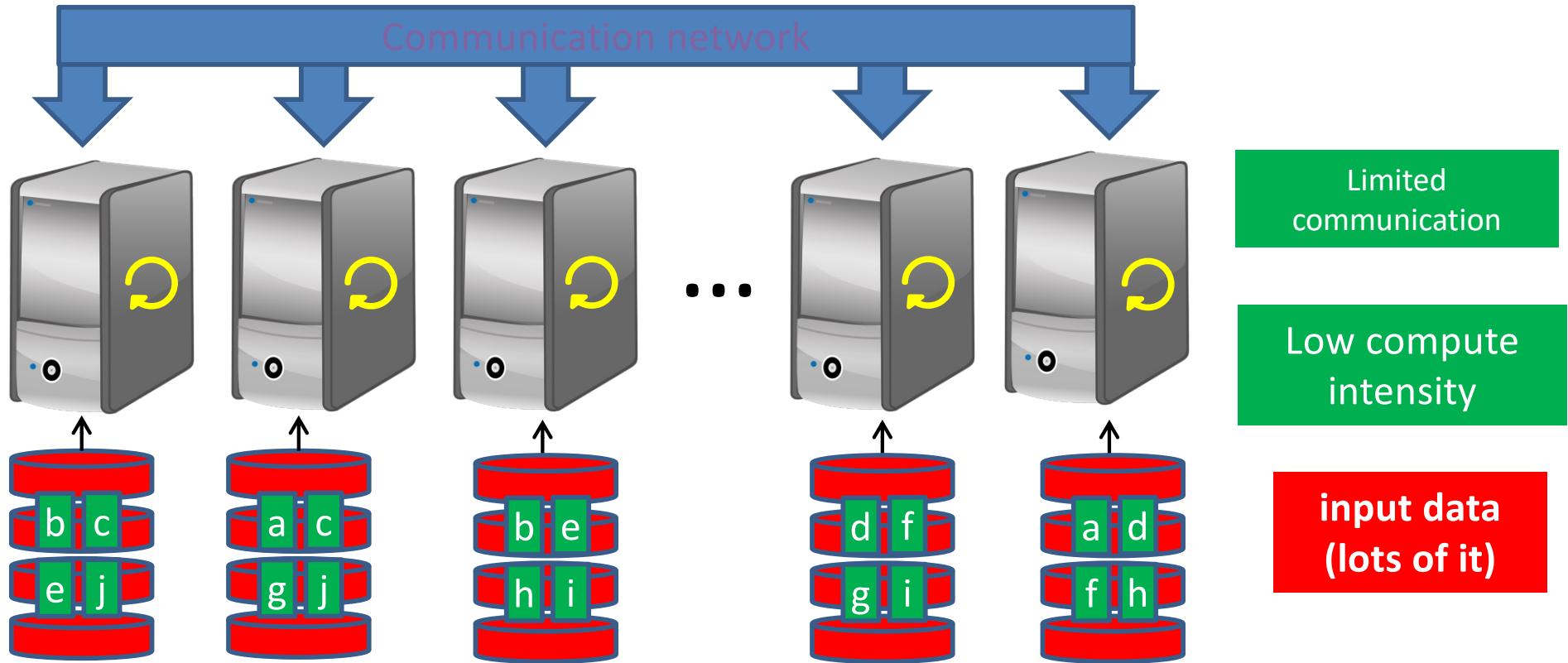


*Image extracted from: <https://hadoop4usa.wordpress.com/2012/04/13/scale-out-up/>*

# Distributed systems in Big Data

- **Objective:** To apply an operation to all data
  - One machine cannot process or store all data
    - Data is ***distributed*** in a cluster of computing nodes
    - It does ***not matter*** which machine executes the operation
    - It does not matter if it ***is run twice*** in different nodes (due to failures or straggler nodes)
    - We look for an ***abstraction of the complexity*** behind distributed systems
  - **DATA LOCALITY** *is crucial*
    - Avoid data transfers between machines as much as possible

Slide courtesy of F. Herrera, A. Fernandez, Isaac Triguero, Fuzzy Models for Data Science and Big Data, Tutorial @ FuzzIEEE 2017, Naples, Italy



**Solution:** store data on local disks of the nodes that perform computations on that data ("data locality")

*Slide courtesy of F. Herrera, A. Fernandez, Isaac Triguero, Fuzzy Models for Data Science and Big Data, Tutorial @ FuzzIEEE 2017, Naples, Italy*

# MapReduce (I)

New programming model: *MapReduce*

- “*Moving computation is cheaper than moving computation and data at the same time*”
- **Idea**
  - **Data** is **distributed** among nodes (distributed file system)
  - **Functions/operations** to process data are **distributed** to all the computing nodes
  - Each computing node works with the data stored in it
  - **Only the necessary data is moved across the network**

*Slide courtesy of F. Herrera, A. Fernandez, Isaac Triguero, Fuzzy Models for Data Science and Big Data, Tutorial @ FuzzIEEE 2017, Naples, Italy*

# MapReduce (II)

- Parallel Programming model
- Introduce by Google in 2004
- **Divide & conquer strategy**
  - **divide**: partition dataset into smaller, independent chunks to be processed in parallel (*map*)
  - **conquer**: combine, merge or otherwise aggregate the results from the previous step (*reduce*)

# MapReduce: Basic Working (I)

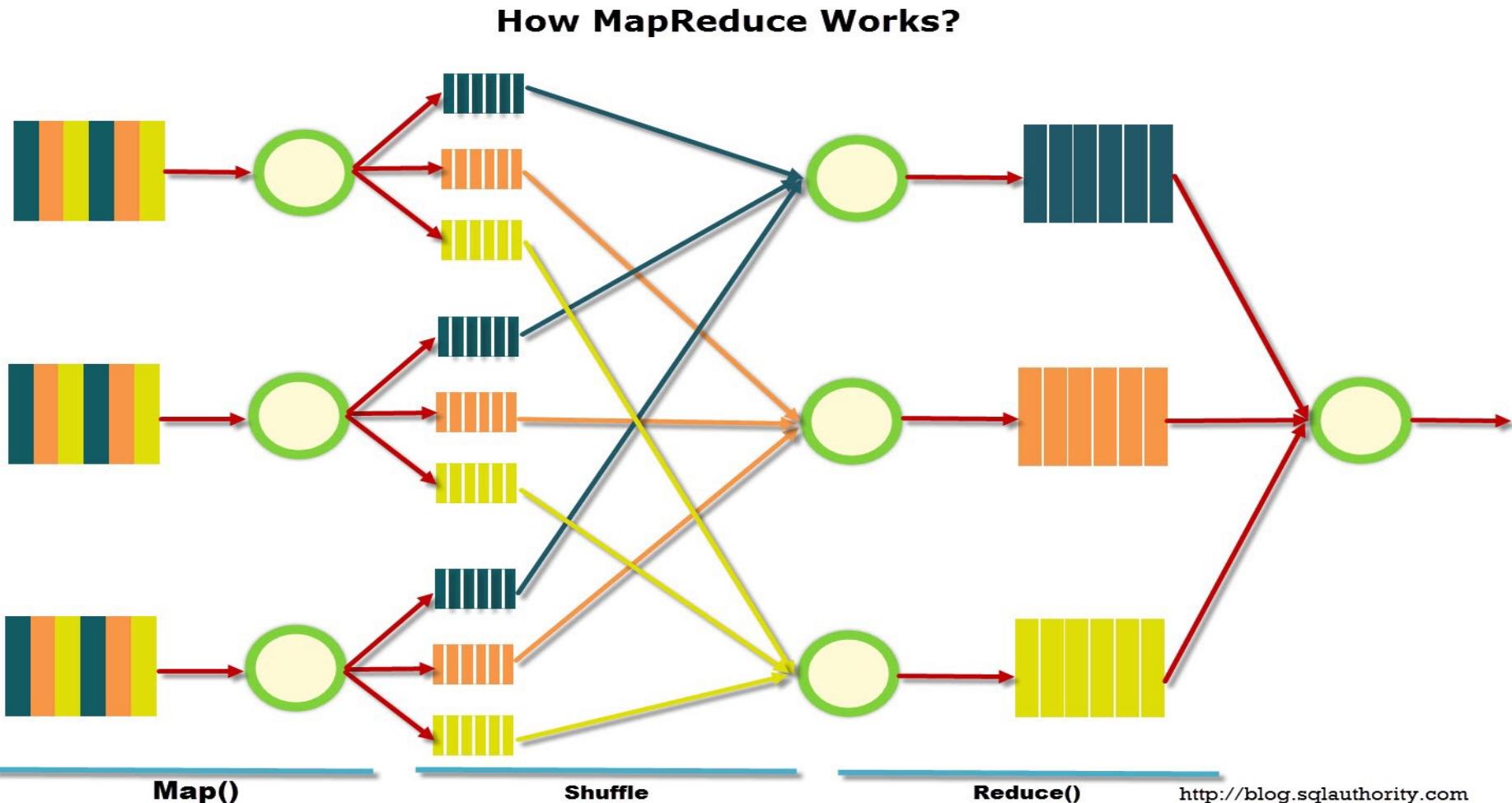


Image extracted from: Elkano, Mikel, et al. "CHI-BD: A fuzzy rule-based classification system for Big Data classification problems." Fuzzy Sets and Systems (2017).

# MapReduce: Basic Working (II)

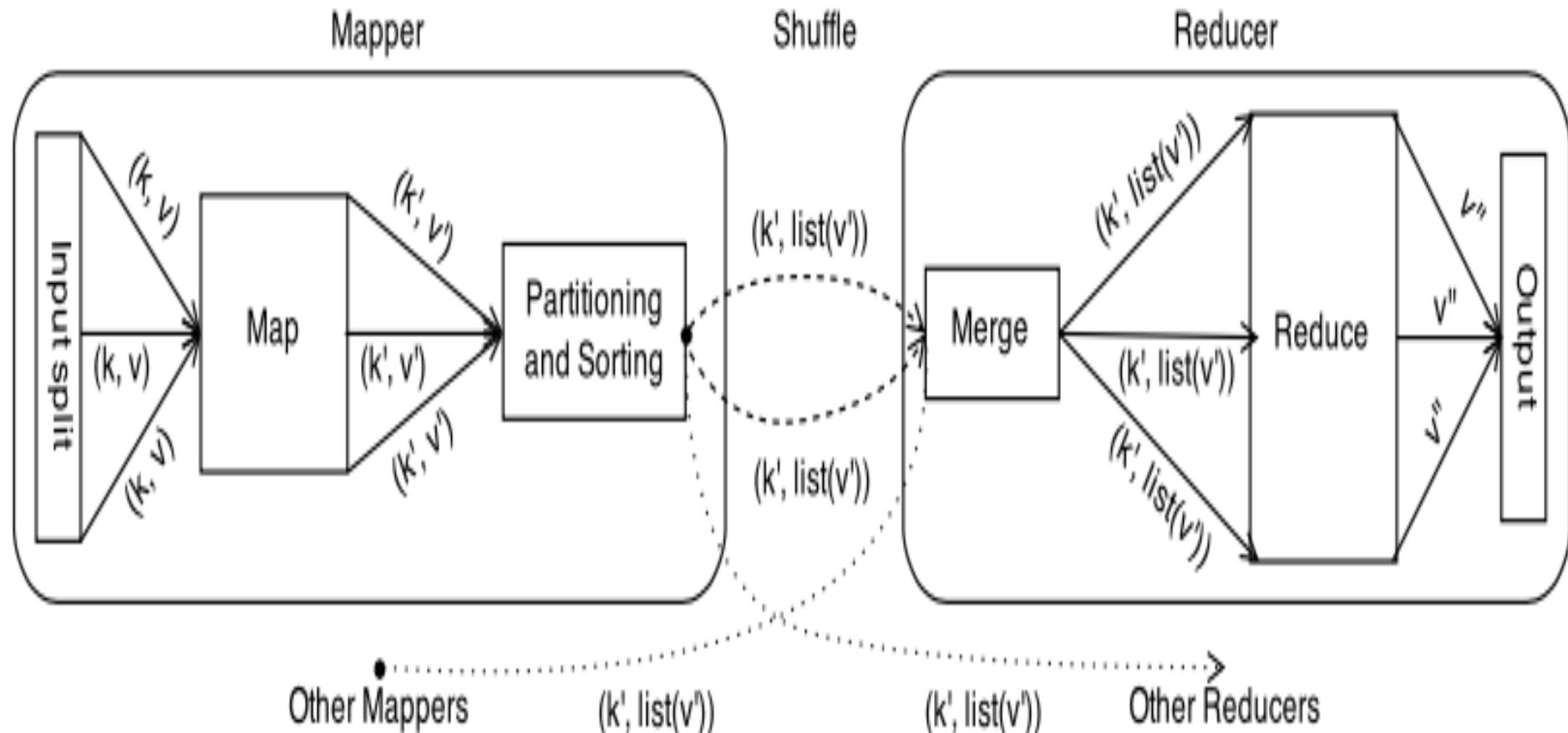
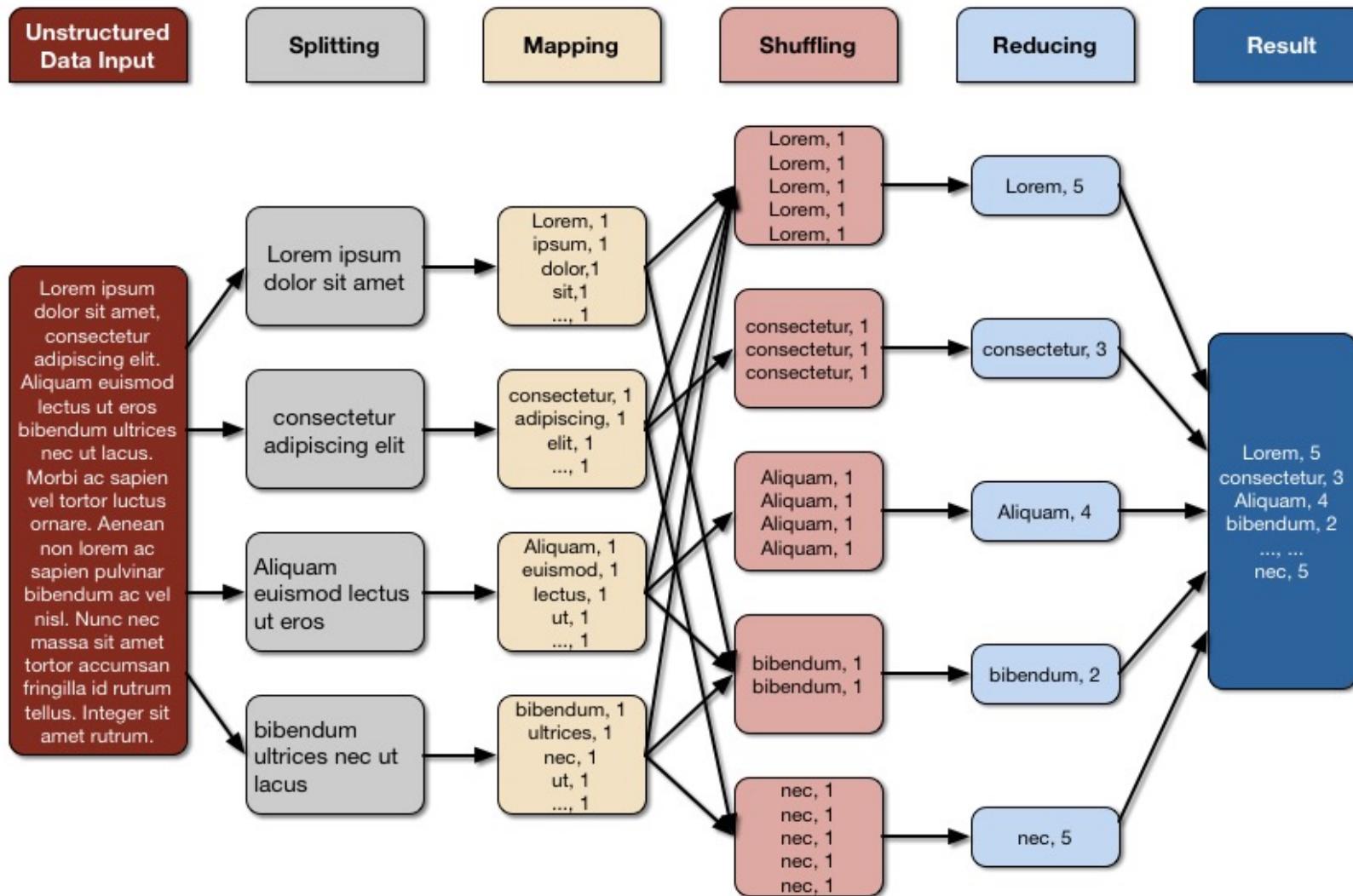


Image extracted from: Elkano, Mikel, et al. "CHI-BD: A fuzzy rule-based classification system for Big Data classification problems." Fuzzy Sets and Systems (2017).

# MapReduce: WordCount Example



# Google Software Architecture for Big Data

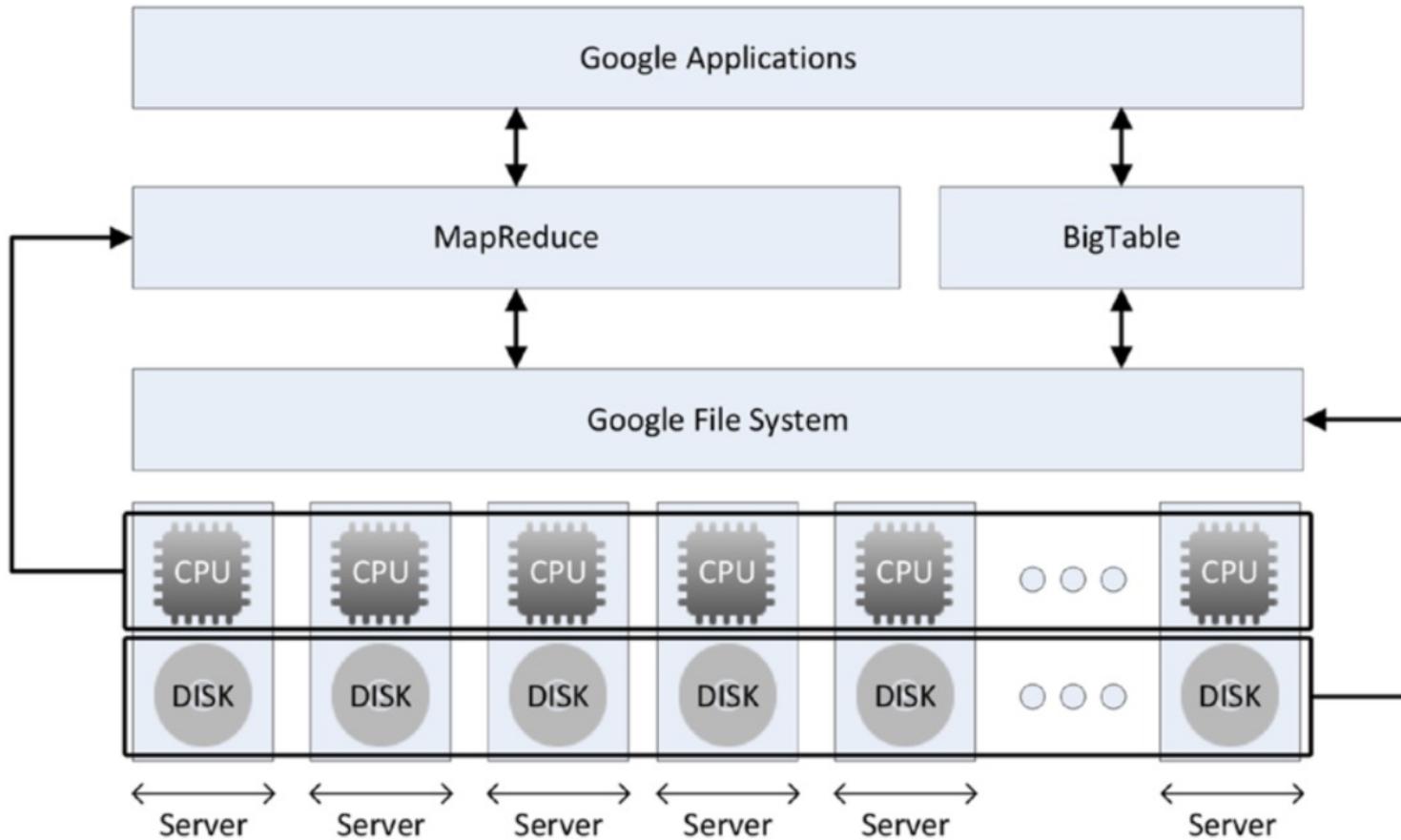


Image extracted from: “Guy Harrison, *Next Generation Databases*, Apress, 2015”

# Hadoop

- Hadoop is:
  - An **open-source** (the first) framework written in Java
  - Distributed storage of very large data sets (Big Data)
  - Distributed processing of very large data sets
- This framework consists of a **number of modules**
  - ***Hadoop Common***: the common utilities that support the other Hadoop modules.
  - ***Hadoop Distributed File System (HDFS)***
  - ***Hadoop YARN*** – A framework for job scheduling and cluster resource management
  - ***Hadoop MapReduce*** – programming model



<http://hadoop.apache.org/>

# Distributed File System: HDFS

## HDFS – Hadoop Distributed File System

- Distributed File System written in Java
- Scales to clusters with **thousands of computing nodes**
  - Each node stores part of the data in the system
- **Fault tolerant** due to data replication
- Designed for big files and low-cost hardware
  - GBs, TBs, PBs
- **Efficient for read and append operations** (random updates are rare)

# Hadoop Limits

- Hadoop is optimized for ***one-pass batch*** processing of on-disk data
- It suffers for ***interactive data exploration*** and more complex multi-pass analytics algorithms
- Due to a ***poor inter-communication*** capability and inadequacy for ***in-memory computation***, Hadoop ***is not suitable*** for those applications that require ***iterative and/or online computation***

# SPARK

- **Apache Spark** is an open-source which has emerged as the next generation big data processing tool due to its enhanced **flexibility** and **efficiency**.
- Spark allows employing **different distributed programming models**, such as **MapReduce** and **Pregel**, and has proved to perform **faster** than Hadoop , especially in case of **iterative and online applications**.
- Unlike the disk-based MapReduce paradigm supported by Hadoop, Spark employs the concept of **in-memory cluster computing**, where datasets are cached in memory to reduce their access latency.



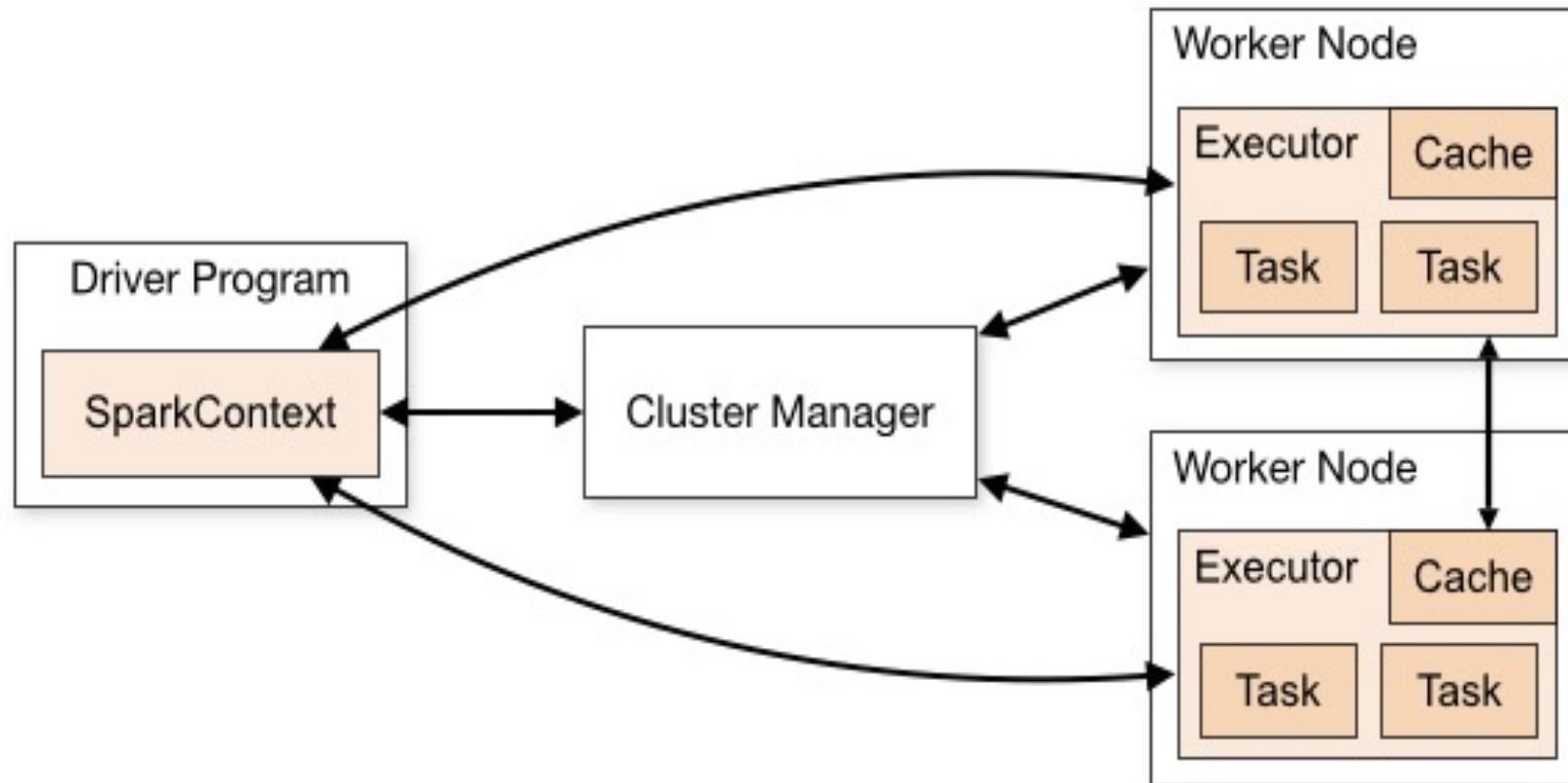
# Driver and Executors

At high level, a Spark application runs as a set of ***independent processes*** on the top of the dataset distributed across the machines of the cluster and consists of one driver program and several executors

The ***driver program***, hosted in the master machine, ***runs*** the user's ***main function*** and ***distributes*** operations on the cluster by sending several units of work, called tasks, to the executors.

***Each executor***, hosted in a ***slave machine***, runs tasks in ***parallel*** and keeps data in memory or disk storage across them.

# Driver and Executors



*Image extracted from: <https://spark.apache.org/docs/latest/cluster-overview.html>*

# SPARK RDD

- The main abstraction provided by Spark is the ***resilient distributed dataset*** (RDD)
- RDD is a ***fault-tolerant*** collection of elements partitioned across the machines of the cluster that can be processed in parallel
- These collections are ***resilient***, because they ***can be rebuilt*** if a portion of the dataset is lost
- The applications developed using the Spark framework are ***totally independent*** of the ***file system*** or the ***database management*** system used for storing data
- Indeed, there exist ***connectors*** for reading data, creating the RDD and writing back results on files or on databases
- In the last years, ***Data Frames*** and ***Datasets*** have been recently released as an abstraction on top of the RDD.

# Spark Ecosystem

Open Source  
Ecosystem

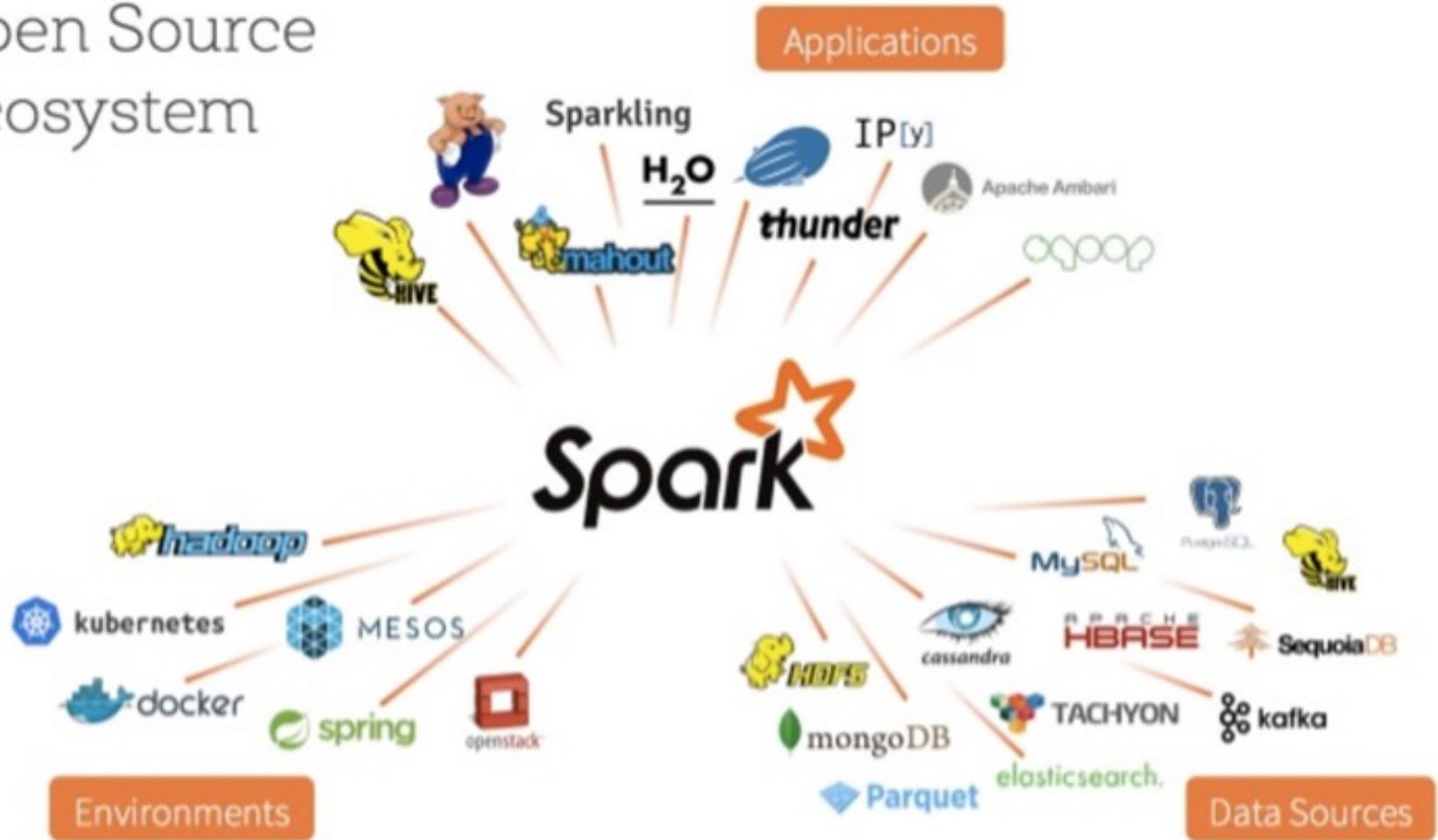
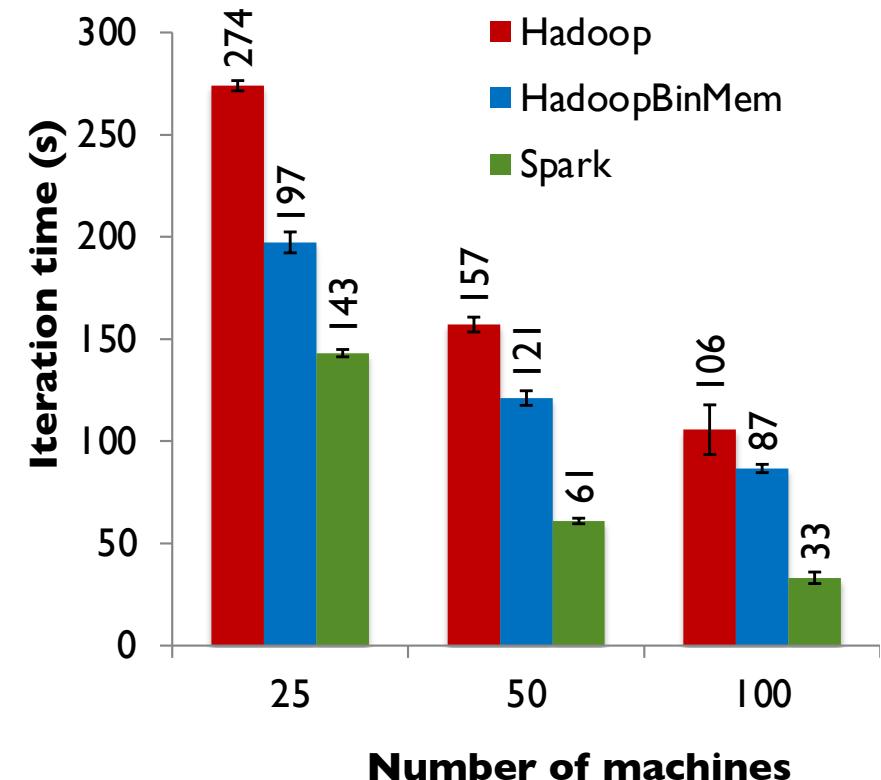


Image extracted from: <https://www.zdnet.com/article/the-future-of-the-future-spark-big-data-insights-streaming-and-deep-learning-in-the-cloud/>

# Hadoop vs SPARK

Up to **10x** faster on disk,  
**100x** in memory

**2-5x less code**



More details can be found in: Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation. USENIX Association, 2012.

# Open source solutions for Big Data

## FRAMEWORK



## QUERY / DATA FLOW



## DATA ACCESS



## COORDINATION



## STREAMING



## STAT TOOLS



## AI / MACHINE LEARNING / DEEP LEARNING



## SEARCH



## LOGGING & MONITORING



## VISUALIZATION



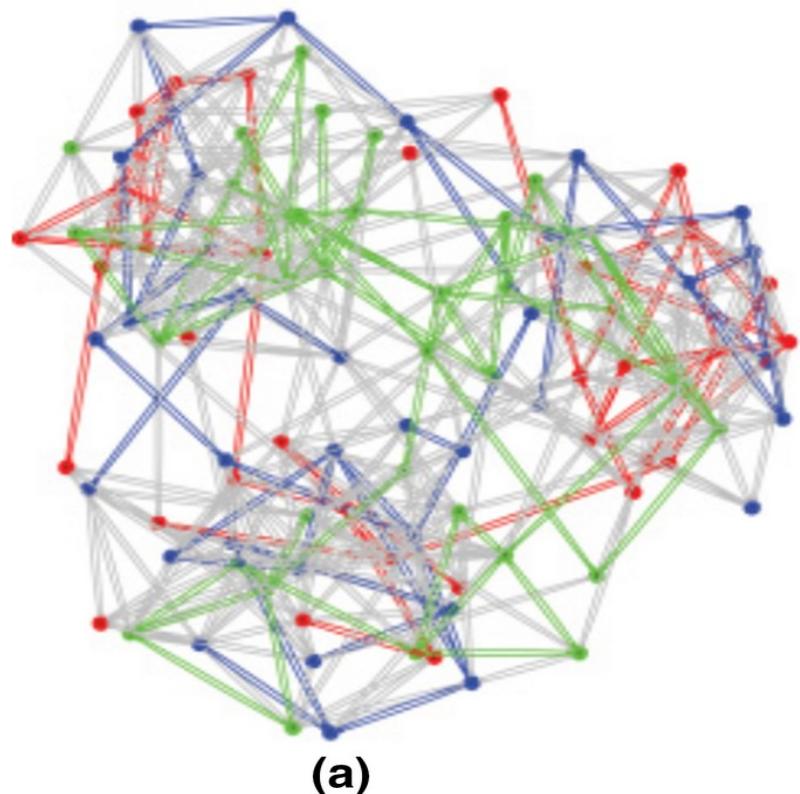
## COLLABORATION



## SECURITY

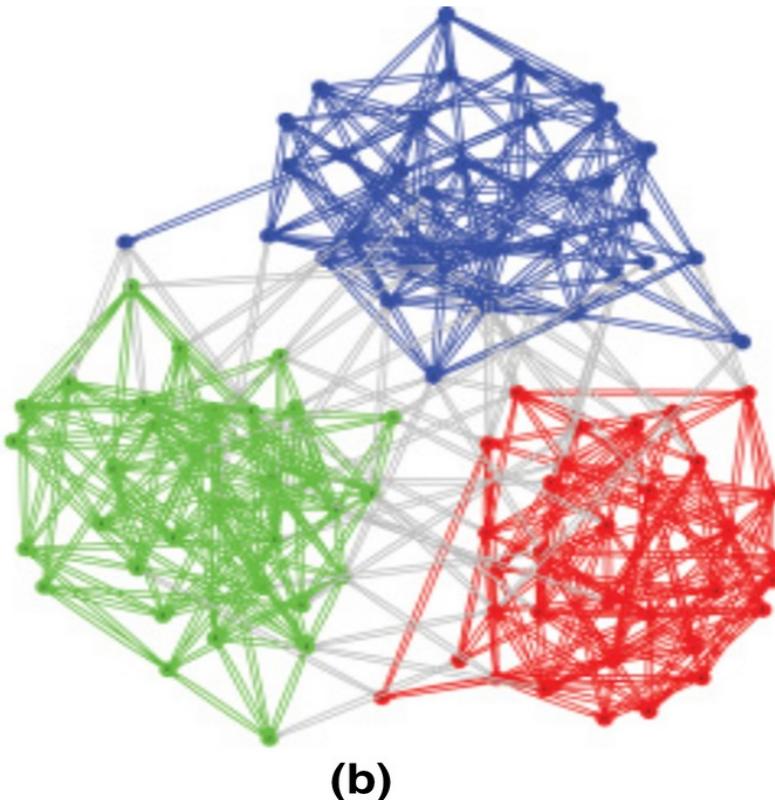


# A distributed algorithm for large-scale graph partitioning



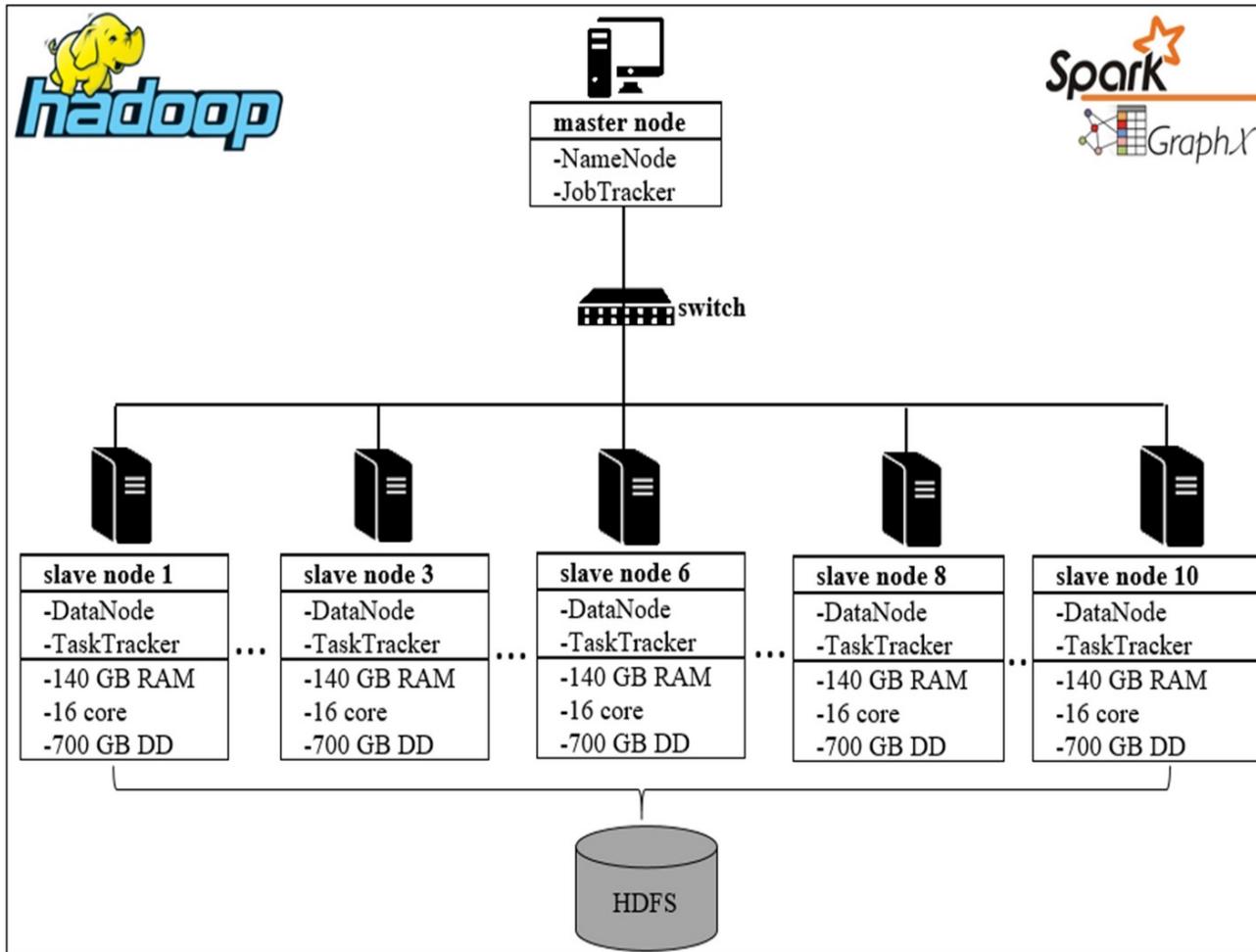
Shoddy Partitioning

<https://journalofbigdata.springeropen.com/articles/10.1186/s40537-020-00357-y>



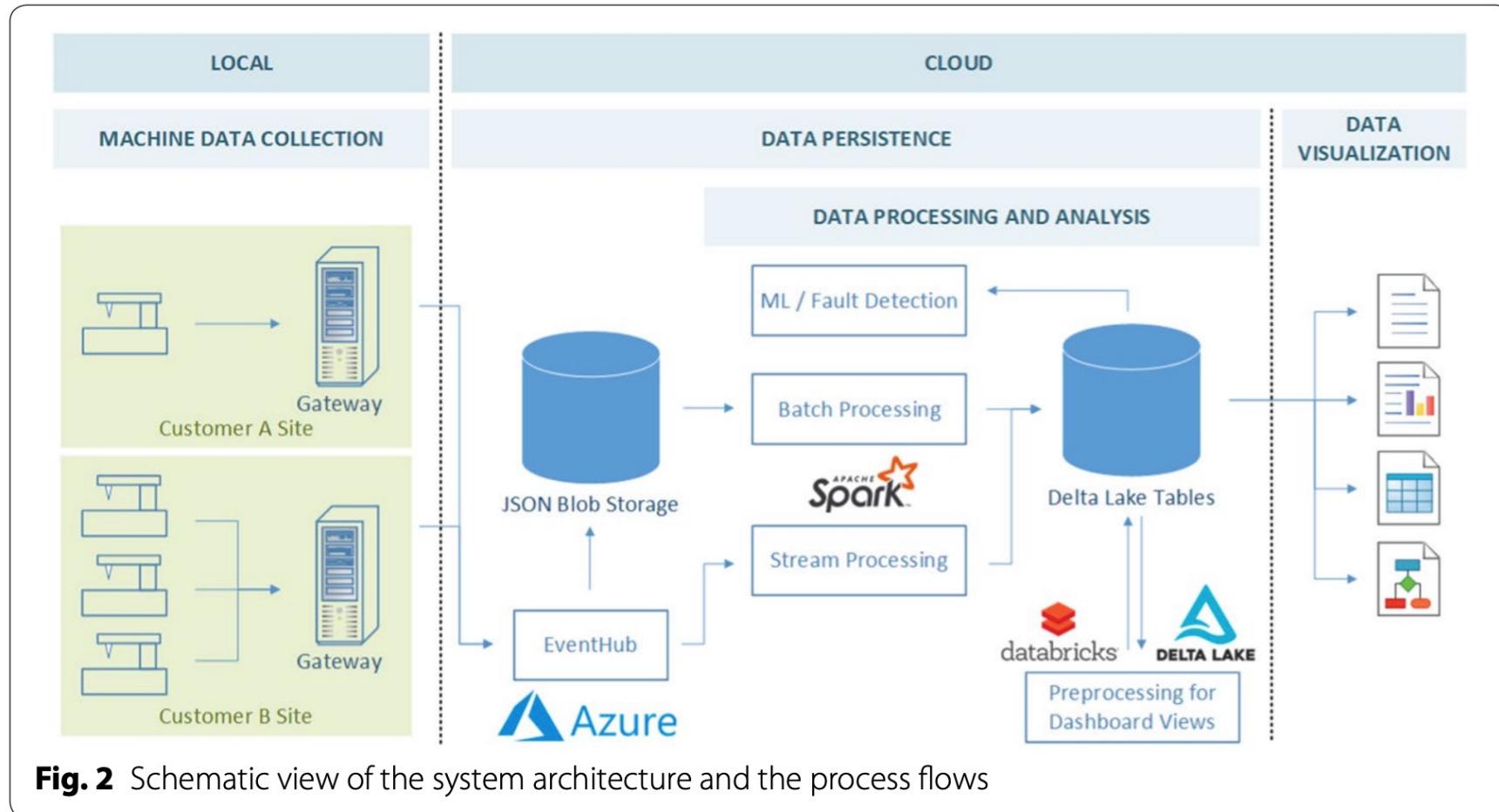
Optimal Partitioning

# A distributed algorithm for large-scale graph partitioning



| Designation | Type       | Vr      | Ed       |
|-------------|------------|---------|----------|
| Biosnap     | Undirected | 1018524 | 24735503 |
| Twitter     | Directed   | 81306   | 1768149  |
| Usroad      | Directed   | 126146  | 161950   |
| Email       | Undirected | 36692   | 183831   |
| Astro       | Undirected | 18772   | 198110   |
| ageRRN      | Directed   | 860000  | 2360000  |
| cptTRM      | Directed   | 1070000 | 6000000  |
| elsaRR      | Directed   | 1508000 | 9000000  |
| osmMA       | Directed   | 4526700 | 12670000 |

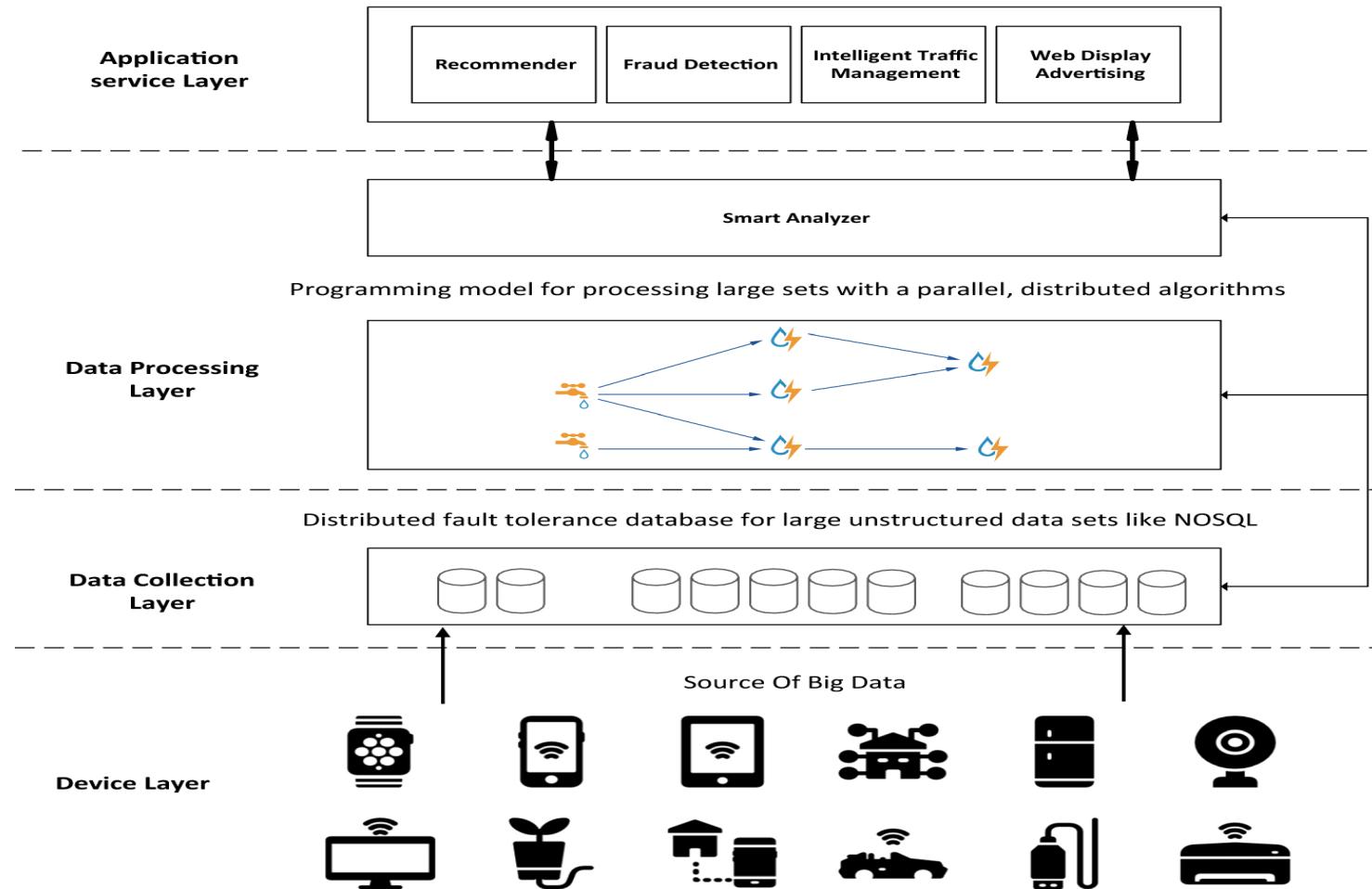
# Big Data architecture for intelligent maintenance



**Fig. 2** Schematic view of the system architecture and the process flows

<https://link.springer.com/article/10.1186/s40537-020-00340-7>

# Evaluation of distributed stream processing frameworks for IoT applications in Smart Cities



<https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0215-2>

# Suggested Readings

Chapter 2 of the book “*Guy Harrison, Next Generation Databases, Apress, 2015*”

<https://hadoop.apache.org/>

<https://spark.apache.org/>