09-12 Nov

CAEPIA'15

Albacete

Big Data

Tecnologías para el procesamiento y analítica de datos en big data

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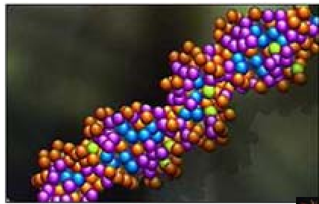
DECSAI

Universidad de Granada

Big Data

Nuestro mundo gira en torno a los datos

- Ciencia
  - Bases de datos de astronomía, genómica, datos medio-ambientales, datos de transporte, …



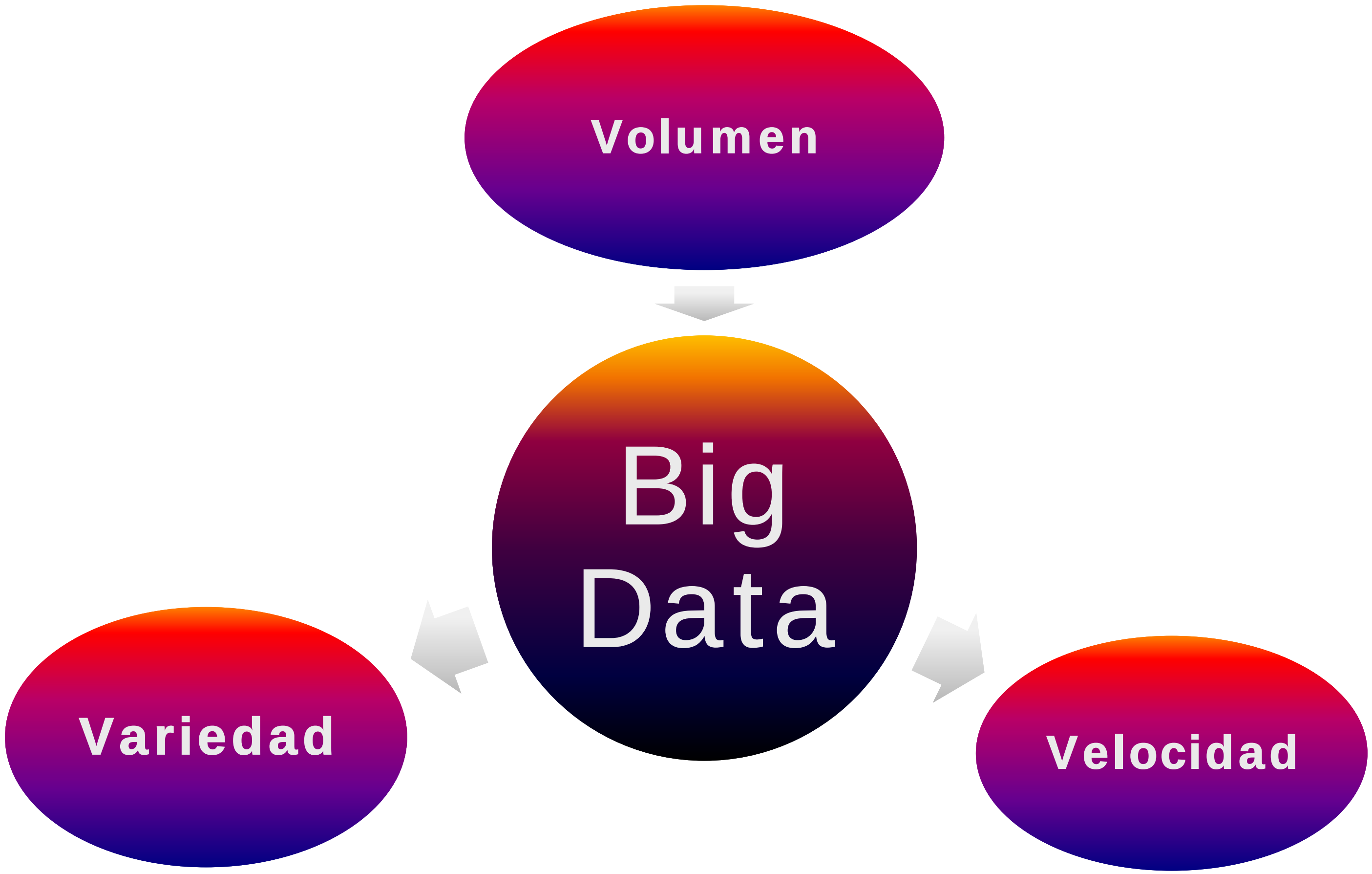
- Ciencias Sociales y Humanidades
  - Libros escaneados, documentos históricos, datos sociales, …
- Negocio y Comercio
  - Ventas de corporaciones, transacciones de mercados, censos, tráfico de aerolíneas, …

- Entretenimiento y Ocio
  - Imágenes en internet, películas, ficheros MP3, …

- Medicina
  - Datos de pacientes, datos de escaner, radiografías …
- Industria, Energía, …
  - Sensores, …

Big Data

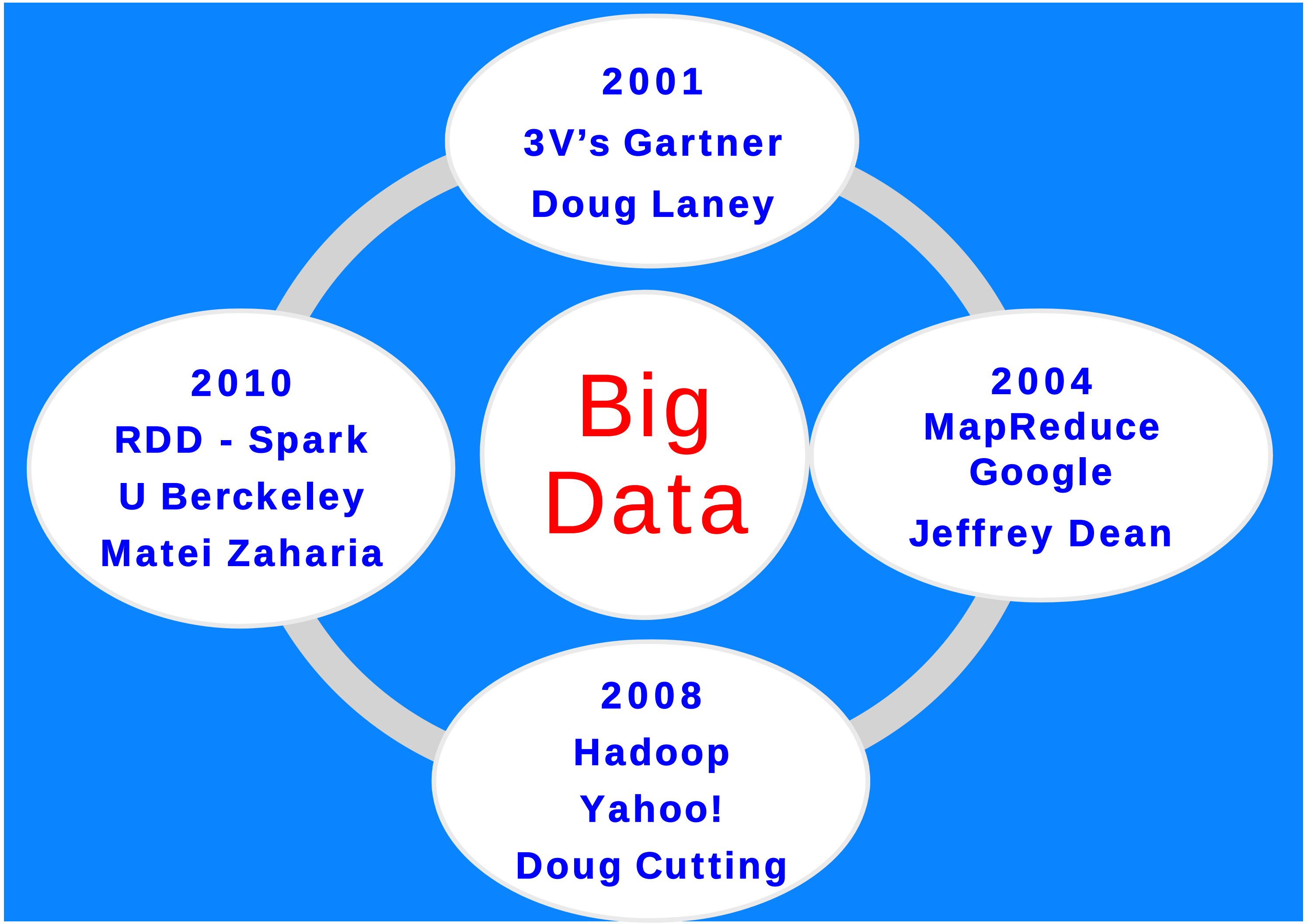
Big Data en 3 V's



Doug Laney, Gartner 2001

Big Data: Cronología

Una década: 2001-2010



2010-2015:

Big Data Analytics

Aplicaciones

Nuevas Tecnologías

Big Data: Google Flu

Aplicación de Google - 2009

Google Flu

Detect pandemic risk in real time

- 2009, nuevo virus gripe A: cepa H1N1
- Sanidad pública temía una pandemia similar a la de la gripe española de 1918
  - 500 millones de afectados
  - Decenas de millones de fallecidos
- No hay vacuna, hay que ralentizar la propagación
- Solución:
  - Los centros de control y prevención de enfermedades (CDC) recopilan datos de los médicos
  - ¡Se consigue un panorama de la pandemia con un desfase, retraso de 2 semanas!

Big Data: Google Flu

Google Flu

Detect pandemic risk in real time

“Google puede predecir la propagación de la gripe (...) analizando lo que la gente busca en internet”

+ de 3.000M de búsquedas a diario

J. Ginsberg, M.H. Mohebbi, R.S. Patel, L. Brammer, M.S. Smolinski, L. Brilliant.
Detecting influenza epidemics using search engine query data.
Nature 475 (2009) 1012-1014

Big Data: Google Flu

Google Flu

Detect pandemic risk in real time

"Google puede predecir la propagación de la gripe (...) analizando lo que la gente busca en internet"

- Google utilizó:
  - 50 M de términos de búsqueda más utilizados
  - Comparó esta lista con los datos de los CDC sobre propagación de gripe entre 2003 y 2008
    - Identificar a los afectados en base a sus búsquedas
    - Buscaron correlaciones entre frecuencia de búsquedas de información y propagación de la gripe en tiempo y espacio

Big Data: Google Flu

Google Flu

Detect pandemic risk in real time

- Encontraron una combinación de 45 términos de búsqueda que al usarse con un modelo matemático presentaba una correlación fuerte entre su predicción y las cifras oficiales de la enfermedad

Podían decir, como los CDC, a dónde se había propagado la gripe pero casi en tiempo real, no una o dos semanas después

Con un método basado en Big Data

- Se ha extendido a 29 países

Big Data: Google Flu

Google Flu

Detect pandemic risk in real time

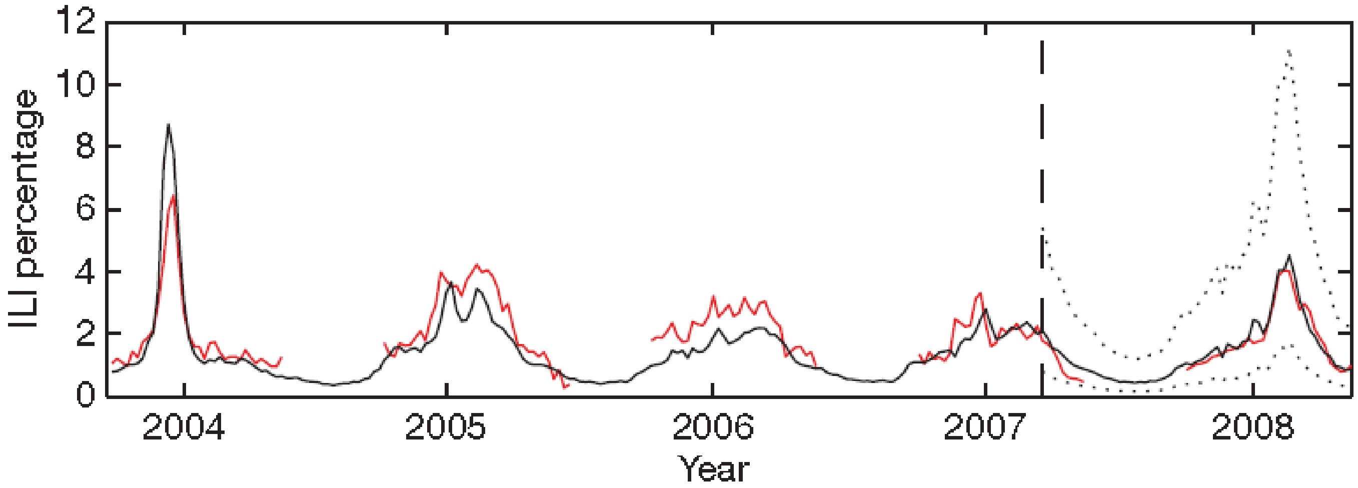


Figure 2 | A comparison of model estimates for the mid-Atlantic region (black) against CDC-reported ILI percentages (red), including points over which the model was fit and validated. A correlation of 0.85 was obtained over 128 points from this region to which the model was fit, whereas a correlation of 0.96 was obtained over 42 validation points. Dotted lines indicate 95% prediction intervals. The region comprises New York, New Jersey and Pennsylvania.

J. Ginsberg, M.H. Mohebbi, R.S. Patel, L. Brammer, M.S. Smolinski, L. Brilliant. Detecting influenza epidemics using search engine query data. Nature 475 (2009) 1012-1014

Big Data: Google Flu

Google Flu

Detect pandemic risk in real time

- En 2013 sobreestimó los niveles de gripe (x2 la estimación CDC)
  - La sobreestimación puede deberse a la amplia cobertura mediática de la gripe que puede modificar comportamientos de búsqueda
  - Los modelos se van actualizando anualmente

POLICYFORUM

BIG DATA

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer, Ryan Kennedy, Gary King, Alessandro Vespignani

Large errors in flu prediction were largely avoidable, which offers lessons for the use of big data.

www.sciencemag.org SCIENCE VOL 343 14 MARCH 2014

Big Data: Google Flu

Google Flu https://www.google.org/flutrends/about/

El modelo se ha actualizado hasta 2014.

El modelo se ha extendido al análisis del Dengue:

Google Dengue Trends data

- World
- Argentina
- Bolivia
- Brazil
- India
- Indonesia
- Mexico
- Philippines
- Singapore
- Thailand
- Venezuela

Google **Nota reciente:**

Thank you for stopping by.

Google Flu Trends and Google Dengue Trends are no longer publishing current estimates of Flu and Dengue fever based on search patterns. The historic estimates produced by Google Flu Trends and Google Dengue Trends are available below. It is still early days for nowcasting and similar tools for understanding the spread of diseases like flu and dengue – we're excited to see what comes next. Academic research groups interested in working with us should fill out this form.

Sincerely,

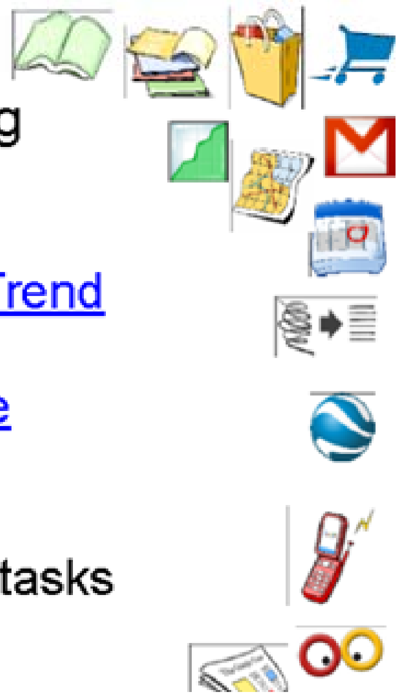
The Google Flu and Dengue Trends Team.

Presente y futuro de big data analytics
Éxitos y limitaciones de una disciplina todavía muy joven

Big Data: Google Applications

MapReduce inside Google

Google

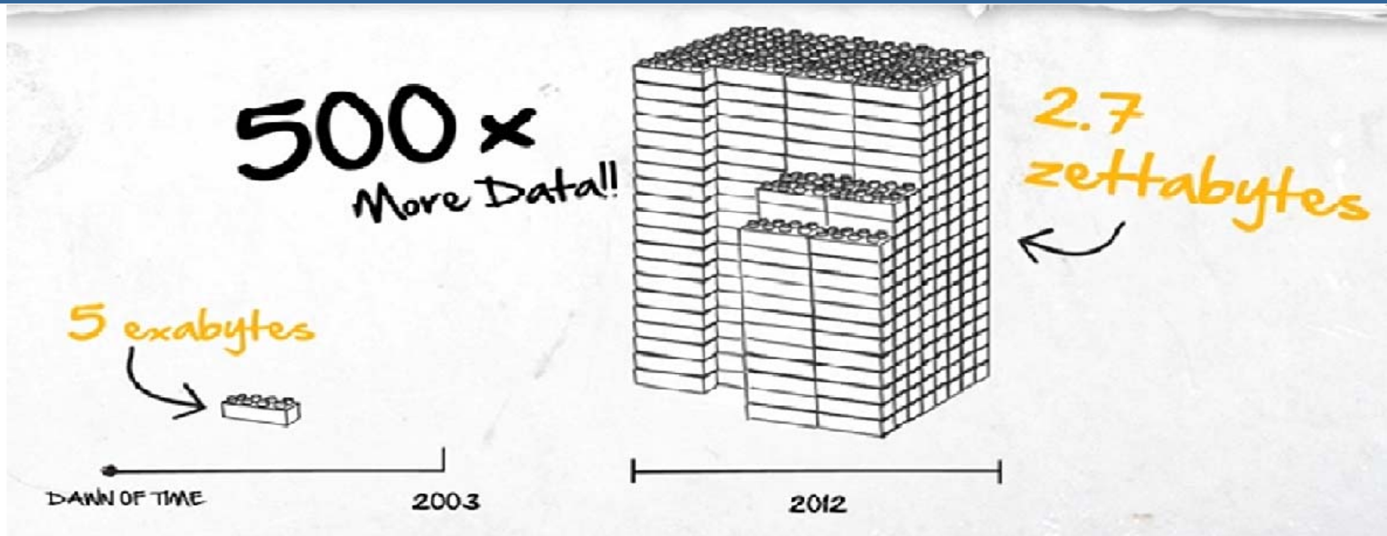


Googlers' hammer for 80% of our data crunching

- Large-scale web search indexing
- Clustering problems for Google News
- Produce reports for popular queries, e.g. Google Trend
- Processing of satellite imagery data
- Language model processing for statistical machine translation
- Large-scale machine learning problems
- Just a plain tool to reliably spawn large number of tasks
  - e.g. parallel data backup and restore

Enrique Alfonseca
Google Research Zurich

Big Data: La explosión de los datos



Índice

- Big Data. Big Data Science
- ¿Por qué Big Data? Google crea el Modelo de Programación MapReduce
- Tecnologías para Big Data: Ecosistema Hadoop (Hadoop, Spark, …)
- Big Data Analytics: Librerías para Analítica de Datos en Big Data. Casos de estudio
- Algunas aplicaciones: Salud, Social Media, Identificación
- Big Data en el grupo de investigación SCI^{2}S
- Comentarios Finales

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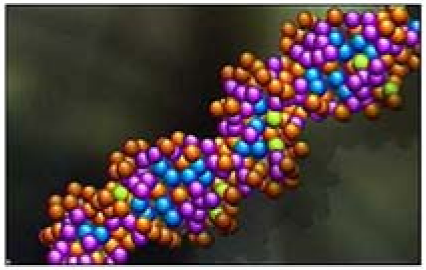
¿Qué es Big Data? **3 V's de Big Data**

Ej. Genómica



- 25,000 genes in human genome
- 3 billion bases
- 3 Gigabytes of genetic data

Ej. Astronomía

- Astronomical sky surveys
- 120 Gigabytes/week
- 6.5 Terabytes/year

Ej. Transacciones de tarjetas de crédito

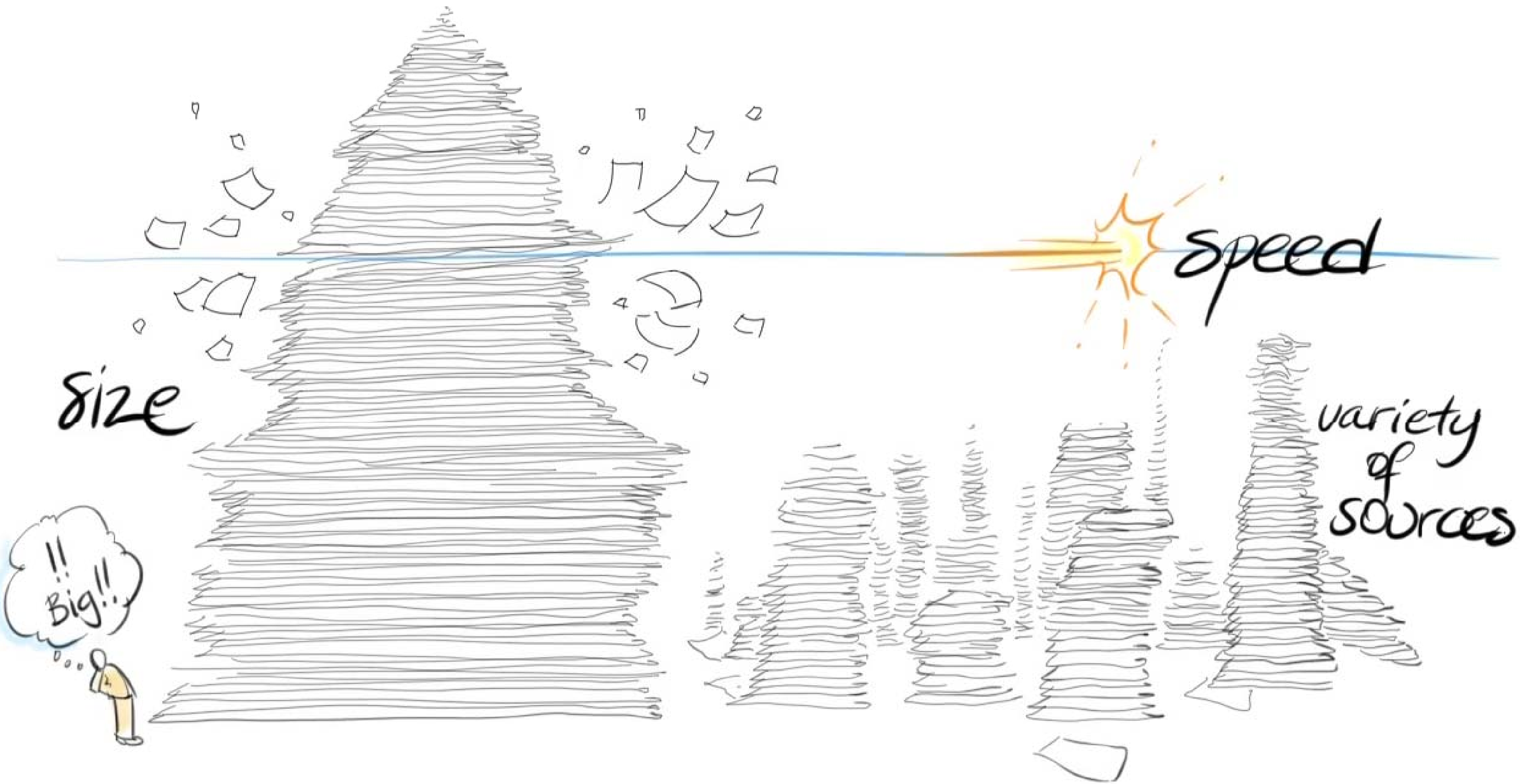
- 47.5 billion transactions in 2005 worldwide
- 115 Terabytes of data transmitted to VisaNet data processing center in 2004

¿Qué es Big Data? **3 V's de Big Data**

e PROMOTIONS

Ej. E-Promociones: **Basadas en la posición actual e historial de compra → envío de promociones en el momento de comercios cercanos a la posición**

¿Qué es Big Data? **3 V's de Big Data**



¿Qué es Big Data? **3 V's de Big Data**

Ej. Huella digital de pasajeros

Interior encarga un megacerebro capaz de localizar terroristas entre los pasajeros

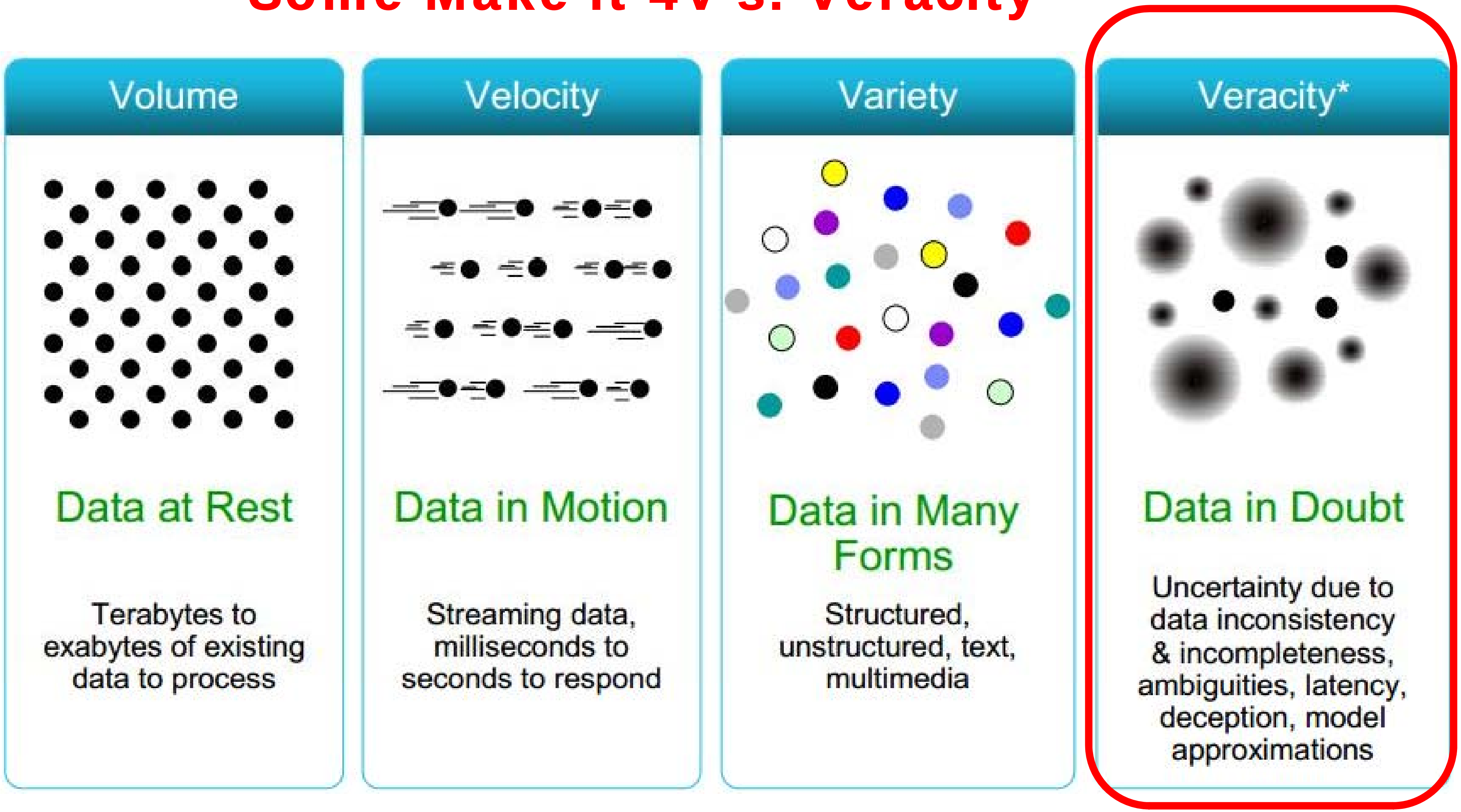
¿Un proyecto de ciencia ficción? El Ministerio del Interior cree que no. Que es posible tener un megacerebro electrónico capaz de localizar —a través de cálculos estadísticos y de cruzar ingentes cantidades de datos en milisengundos—...

> *"identificación automática del perfil demográfico y sociológico del pasajero"*

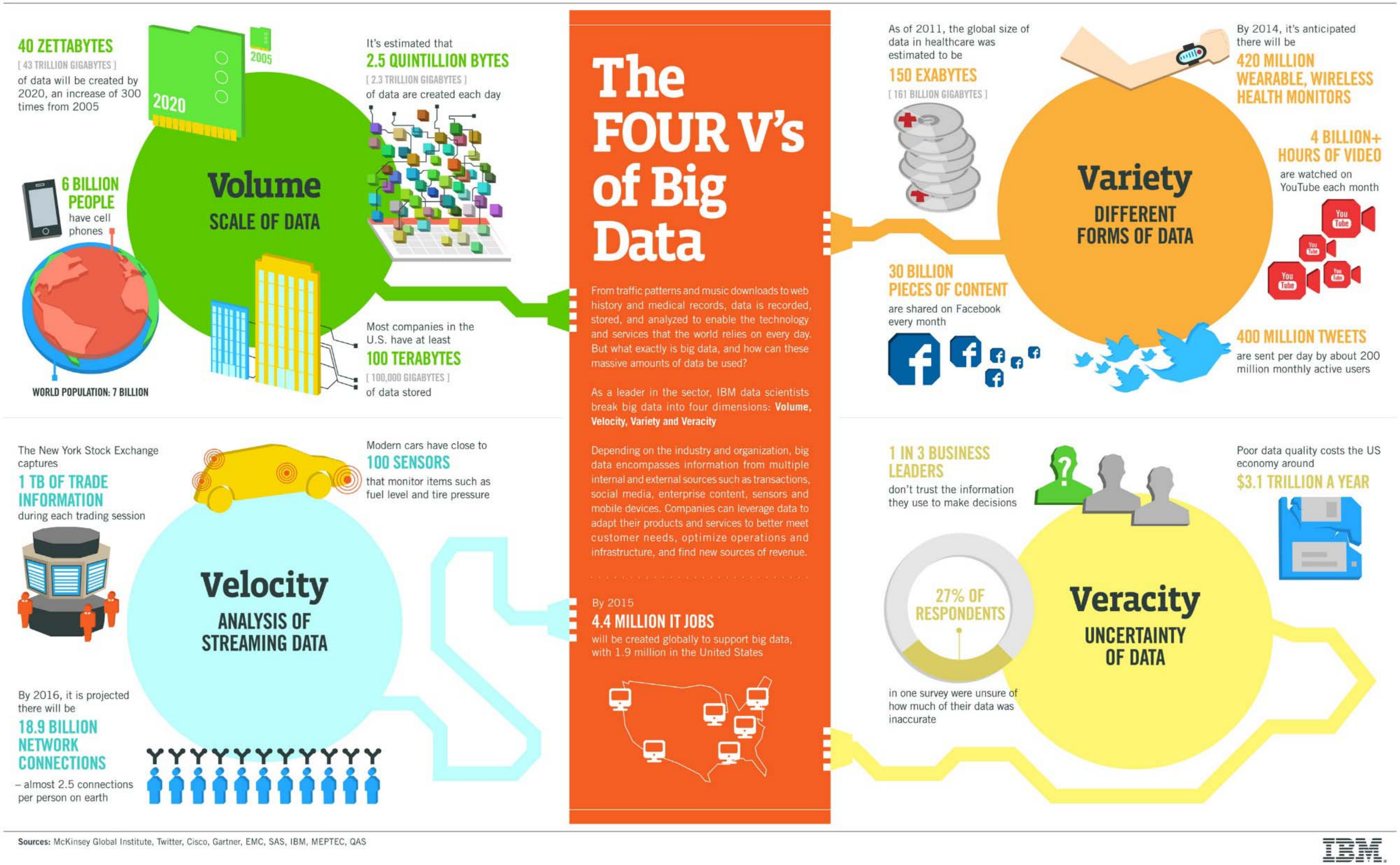
http://article.wn.com/view/2015/04/04/Interior_encarga_un_mega cerebro_capaz_de_localizar_terrorist_3/

¿Qué es Big Data? **3 V's de Big Data**

Some Make it 4V's: Veracity



¿Qué es Big Data?



¿Qué es Big Data?

V --> Valor

Aproximaciones y tecnologías innovativas

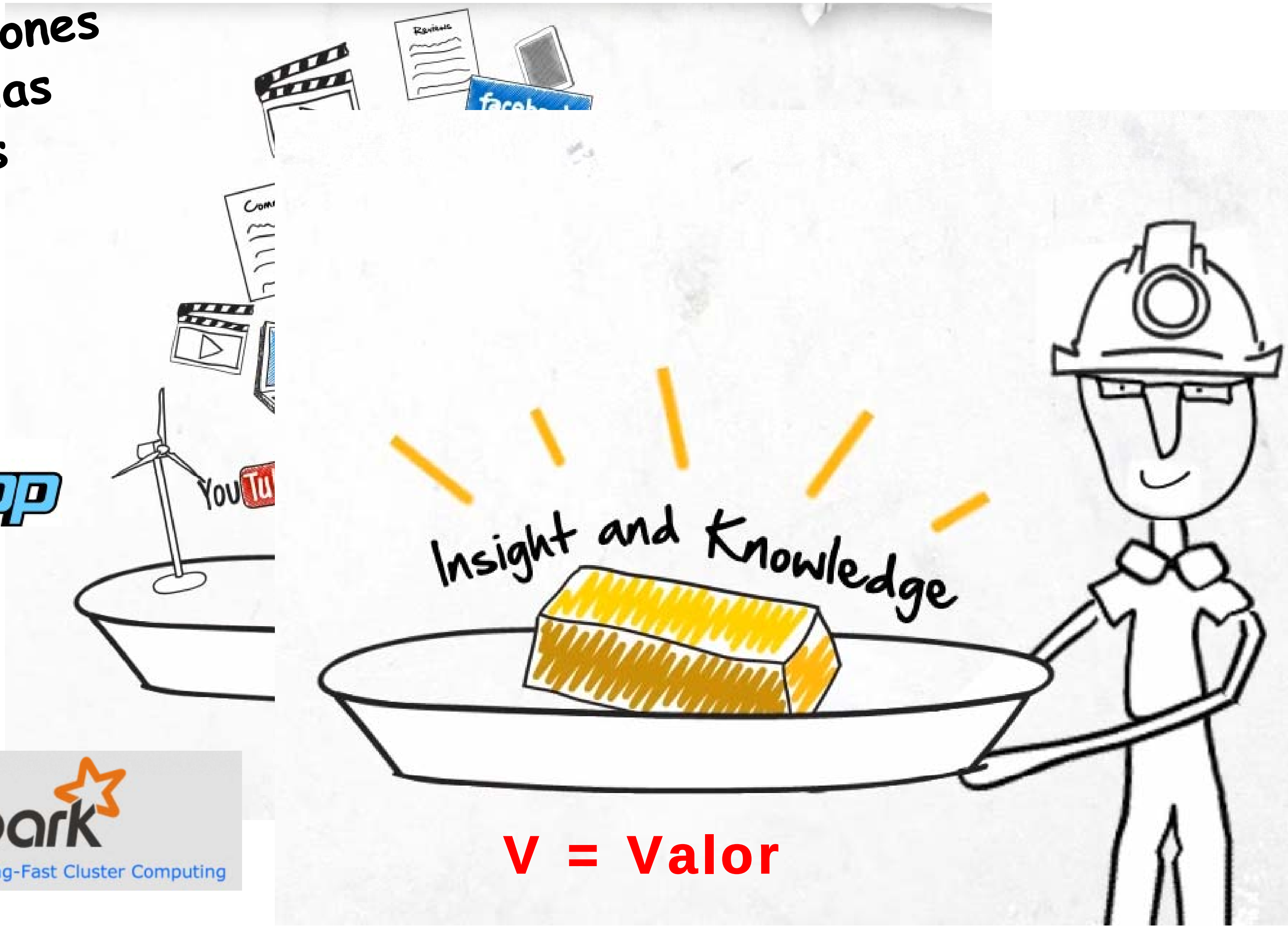
MapReduce

hadoop

mahout

APACHE GIRAPH

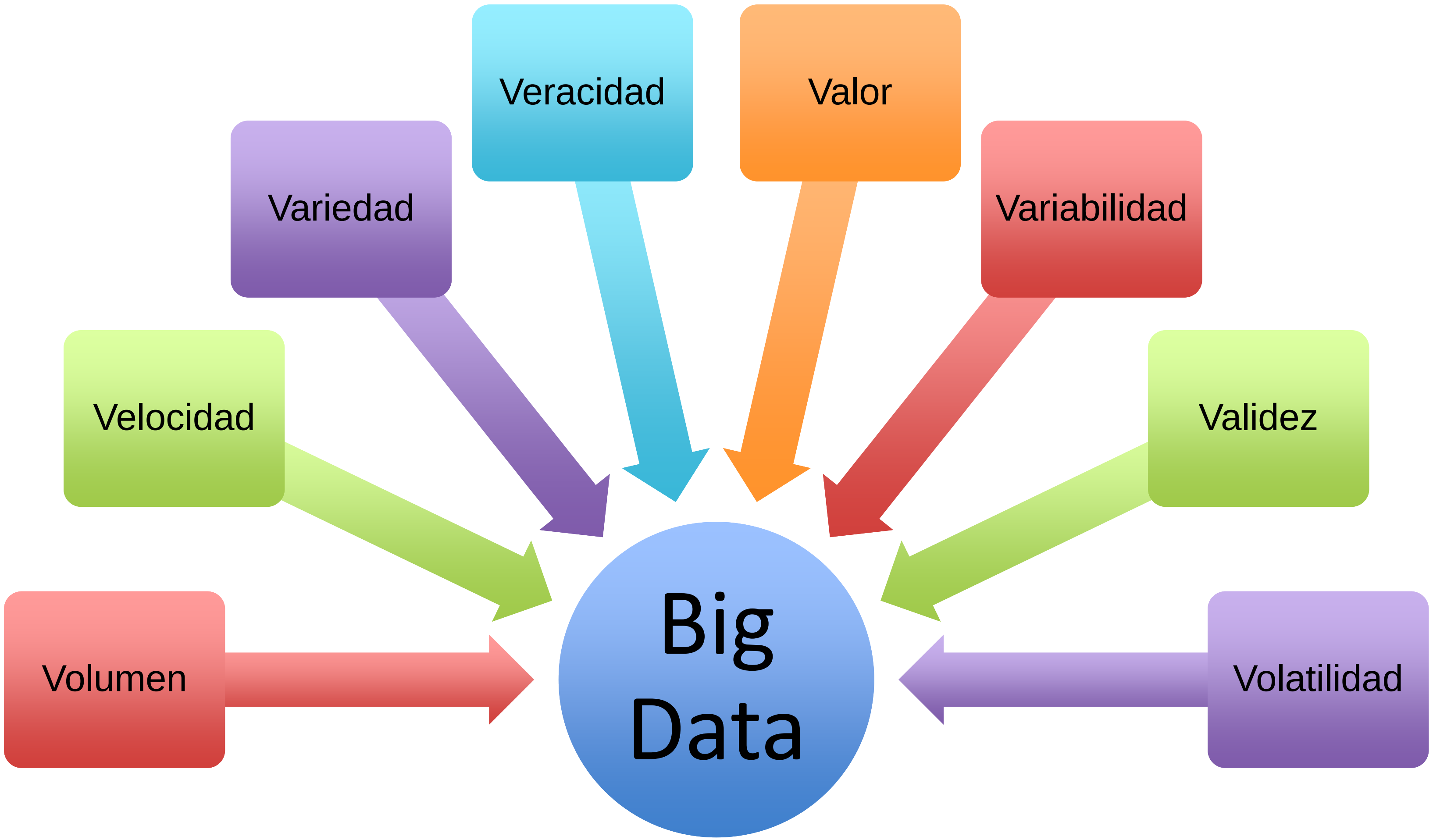
Spark Lightning-Fast Cluster Computing



V = Valor

¿Qué es Big Data?

Las 8 V's de Big Data

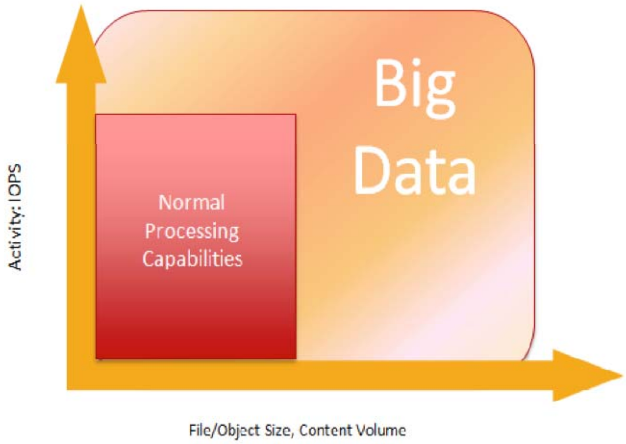


¿Qué es Big Data?

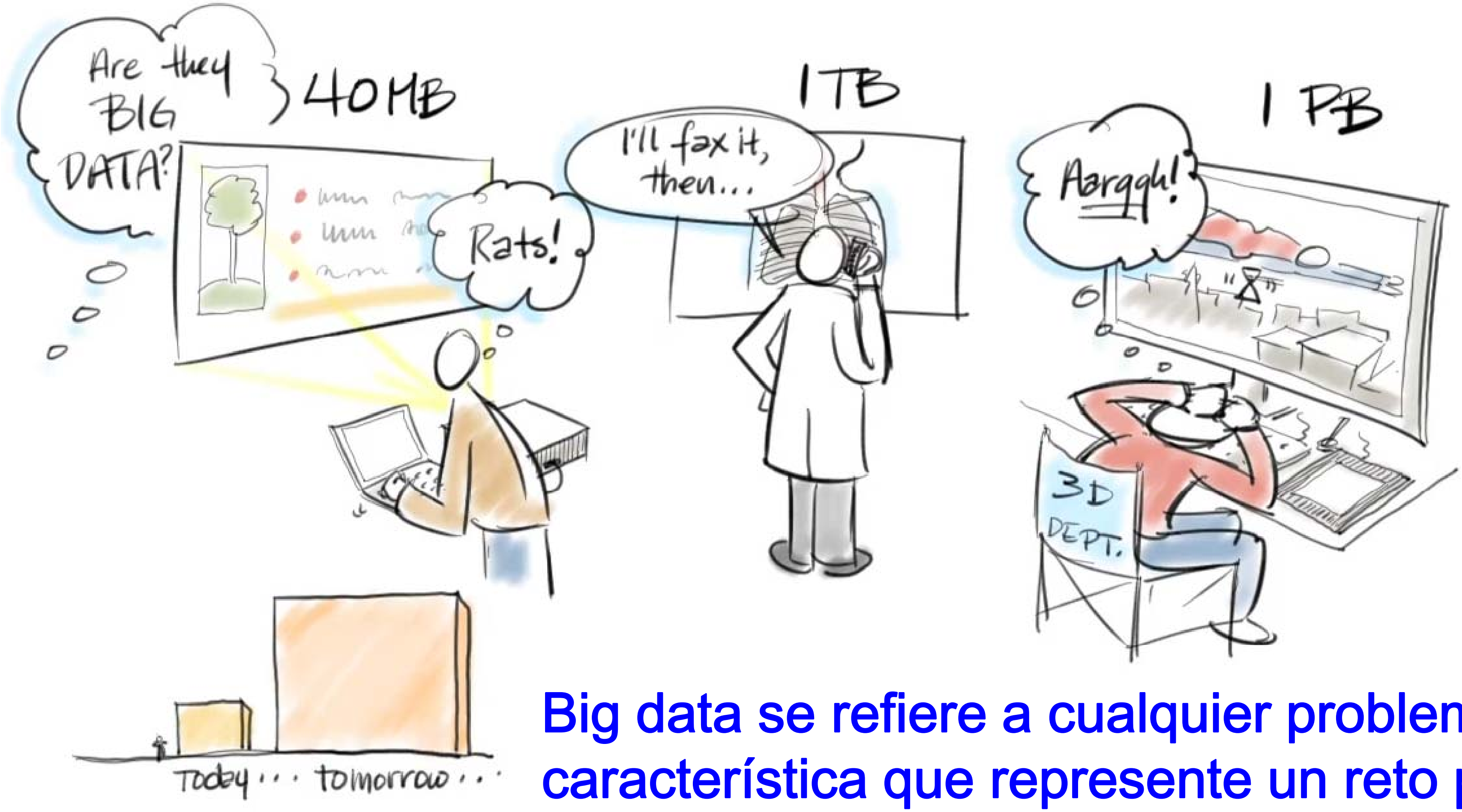
No hay una definición estándar 

Big data es una colección de datos grande, complejos, **muy difícil de procesar a través de herramientas de gestión y procesamiento de datos tradicionales**

"***Big Data***" son datos cuyo volumen, diversidad y complejidad **requieren nueva arquitectura, técnicas, algoritmos y análisis** para gestionar y extraer valor y conocimiento oculto en ellos …



¿Qué es Big Data?



Big data se refiere a cualquier problema o característica que represente un reto para ser procesado con aplicaciones tradicionales

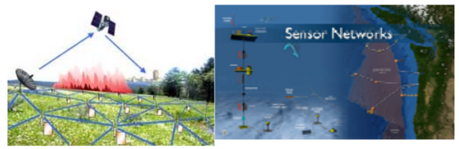
¿Qué es Big Data?

¿Quién genera Big Data?

Redes sociales y multimedia
(todos generamos datos)

Instrumentos científicos
(colección de toda clase de datos)

Dispositivos móviles
(seguimiento de objetos)



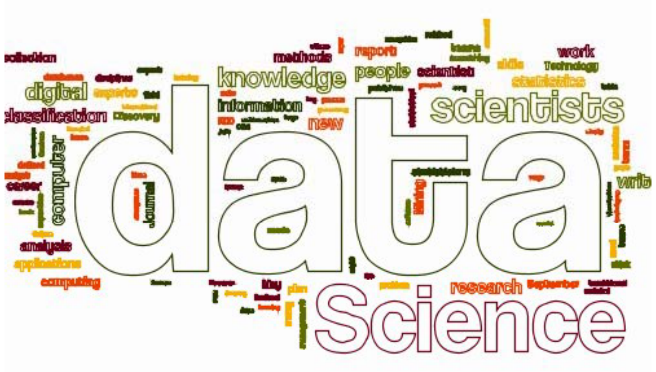
Redes de sensores
(se miden toda clase de datos)

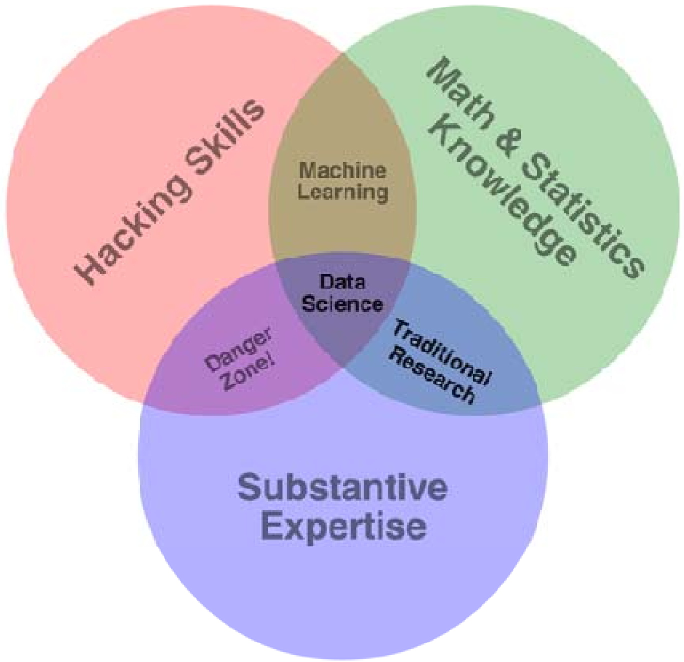
El progreso y la innovación ya no se ven obstaculizados por la capacidad de recopilar datos, sino por la capacidad de gestionar, analizar, sintetizar, visualizar, y descubrir el conocimiento de los datos recopilados de manera oportuna y en una forma escalable

(Big) Data Science

Data Science combines the traditional scientific method with the ability to explore, learn and gain deep insight for (Big) Data

It is not just about finding patterns in data … it is mainly about explaining those patterns





Data Science Process

Data Preprocessing

- Clean
- Sample
- Aggregate
- Imperfect data: missing, noise, …
- Reduce dim.
- …

> 70% time!

Data Processing

- Explore data
- Represent data
- Link data
- Learn from data
- Deliver insight
- …

Data Analytics

- Clustering
- Classification
- Regression
- Network analysis
- Visual analytics
- Association
- …

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¿Por qué Big Data?

- **Problema:** Escalabilidad de grandes cantidades de datos
- **Ejemplo:**
  - Exploración 100 TB en 1 nodo @ 50 MB/sec = 23 días
  - Exploración en un clúster de 1000 nodos = 33 minutos
- **Solución → Divide-Y-Vencerás**

Una sola máquina no puede gestionar grandes volúmenes de datos de manera eficiente

¿Por qué Big Data?

- **Problema:** Escalabilidad de grandes cantidades de datos
- **Ejemplo:**
  - Exploración 100 TB en 1 nodo @ 50 MB/sec = 23 días
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- **Solución → Divide-Y-Vencerás**

¿Cómo podemos procesar

1000 TB or 10000 TB?

¿Por qué Big Data?

- Escalabilidad de grandes cantidades de datos
  - Exploración 100 TB en 1 nodo @ 50 MB/sec = 23 días
  - Exploración en un clúster de 1000 nodos = 33 minutos

Solución → Divide-Y-Vencerás

¿Qué ocurre cuando el tamaño de los datos aumenta y los requerimientos de tiempo se mantiene?

Hace unos años: Había que aumentar los recursos de hardware (número de nodos). Esto tiene limitaciones de espacio, costes, …

Google 2004: Paradigma **MapReduce**

MapReduce

- Escalabilidad de grandes cantidades de datos
  - Exploración 100 TB en 1 nodo @ 50 MB/sec = 23 días
  - Exploración en un clúster de 1000 nodos = 33 minutos

Solución → Divide-Y-Vencerás

MapReduce

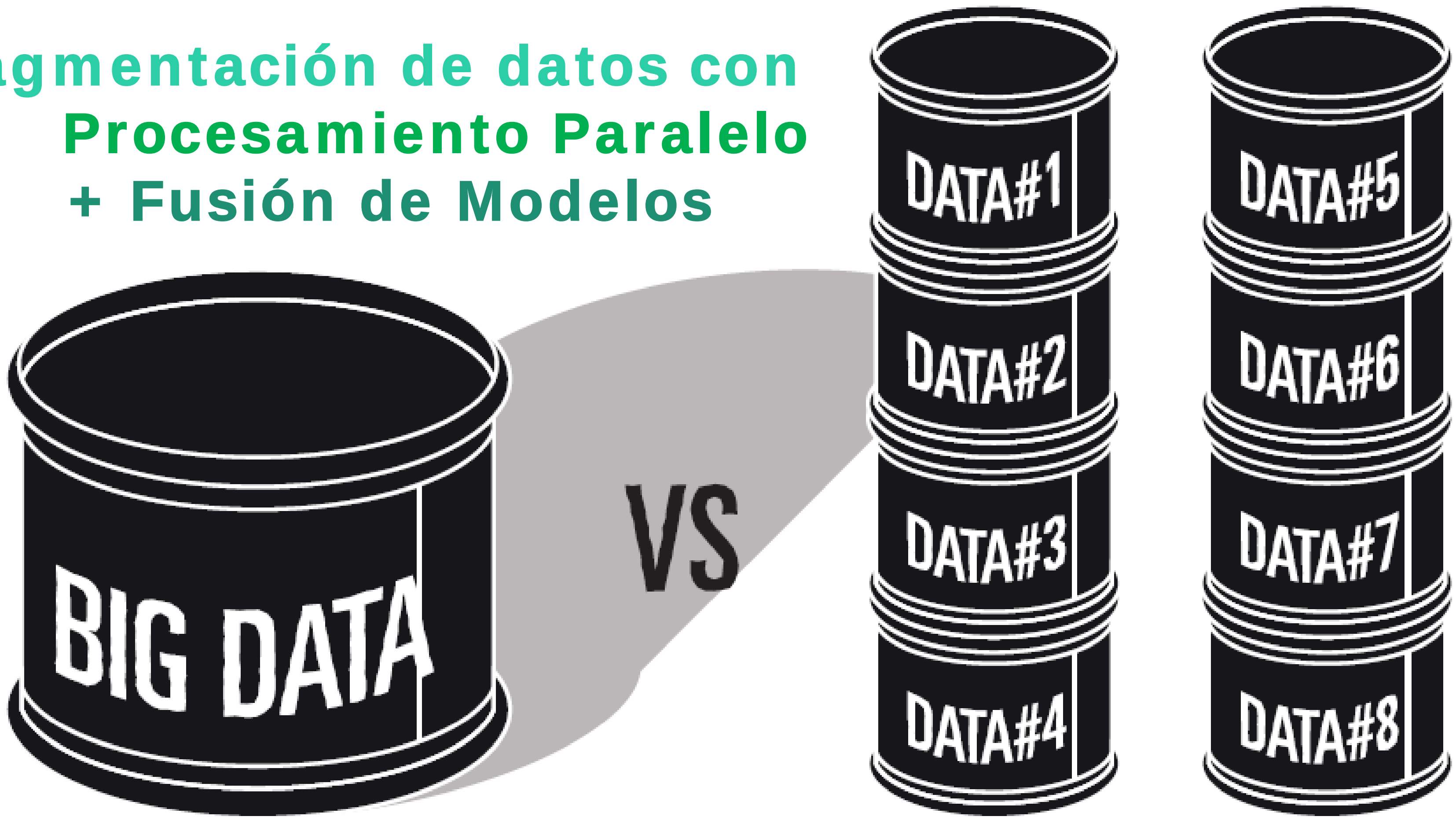
- Modelo de programación de datos paralela
- Concepto simple, elegante, extensible para múltiples aplicaciones

- **Creado por Google (2004)**
  - Procesa 20 PB de datos por día (2004)
- **Popularizado por el proyecto de codigo abierto Hadoop**
  - Usado por Yahoo!, Facebook, Amazon, …

MapReduce

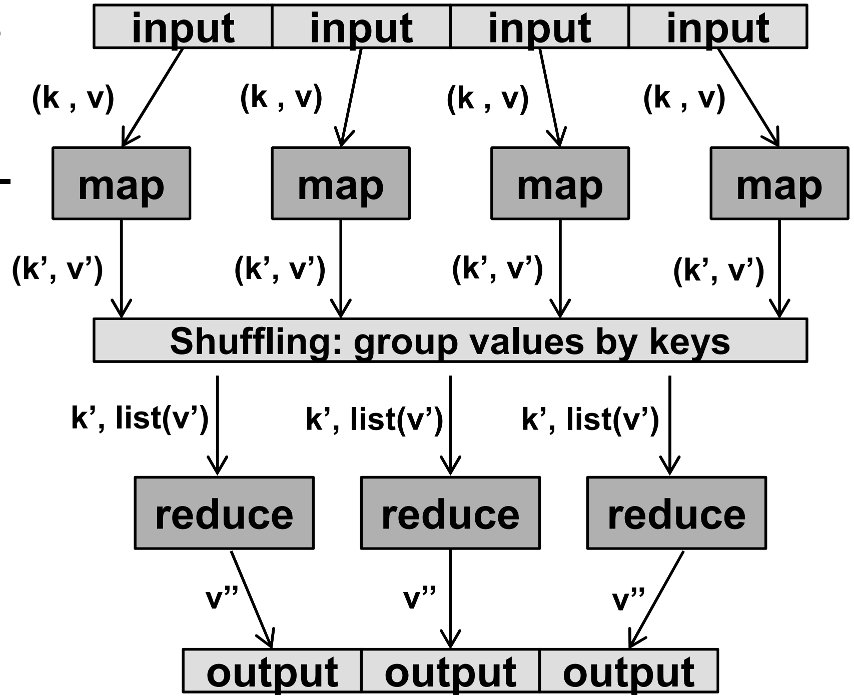
MapReduce es la aproximación más popular para Big Data

Fragmentación de datos con
Procesamiento Paralelo
+ Fusión de Modelos



MapReduce

- MapReduce es el entorno más popular para Big Data
- Basado en la estructura Valor-llave.
- Dos operaciones:
  1. **Función Map : Procesa bloques de información**
  2. **Función Reduce function: Fusiona los resultados previous de acuerdo a su llave.**
- + Una etapa intermedia de agrupamiento por llave **(Shuffling)**



map (k, v) → list (k', v')
reduce (k', list(v')) → v''

J. Dean, S. Ghemawat, MapReduce: Simplified data processing on large clusters, Communications of the ACM 51 (1) (2008) 107-113.

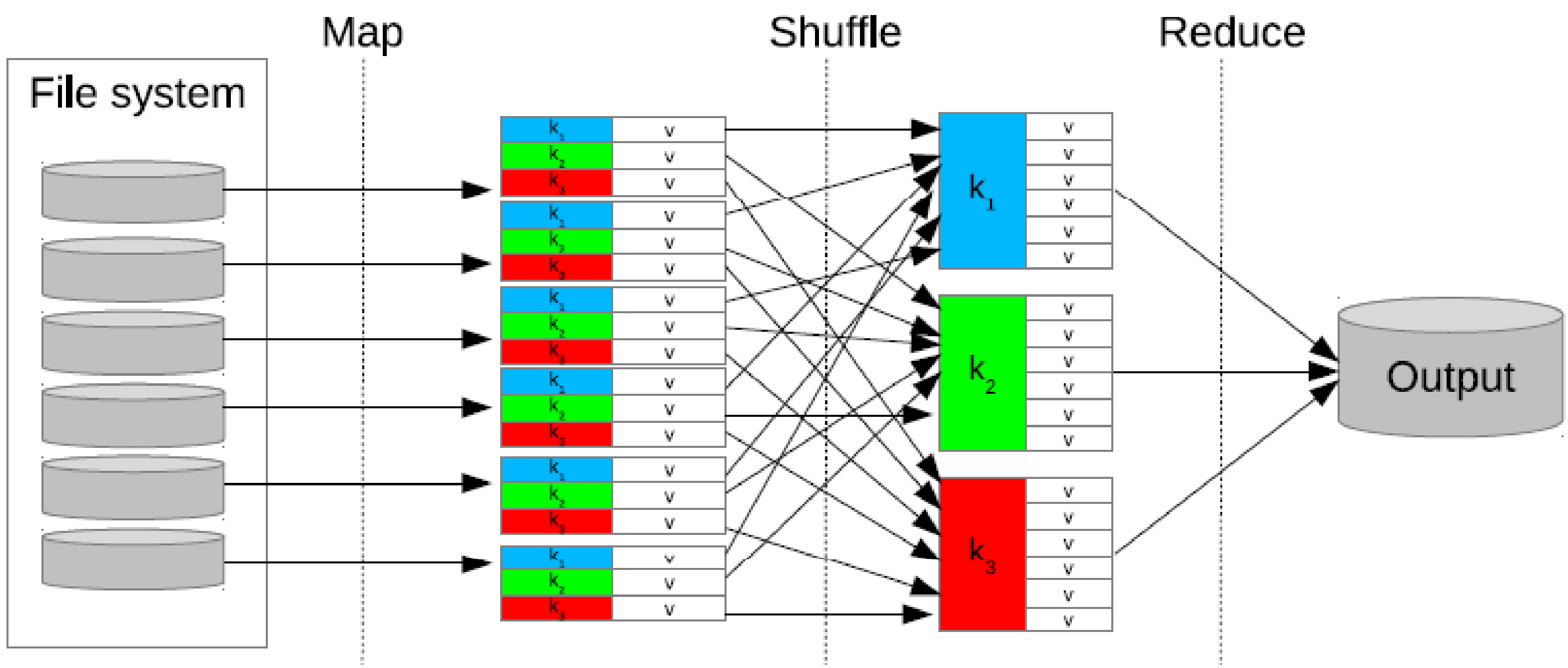
MapReduce

Características

- **Paralelización automática:**
  - Dependiendo del tamaño de ENTRADA DE DATOS➔ se crean mutiples tareas MAP
  - Dependiendo del número de intermedio <clave, valor> particiones ➔ se pueden crear varias tareas REDUCE
- **Escalabilidad:**
  - Funciona sobre cualquier cluster de nodos/procesadores
  - Puede trabajar desde 2 a 10,000 máquinas
- **Transparencia programación**
  - Manejo de los fallos de la máquina
  - Gestión de comunicación entre máquina

MapReduce

Flujo de datos en MapReduce, transparente para el programador



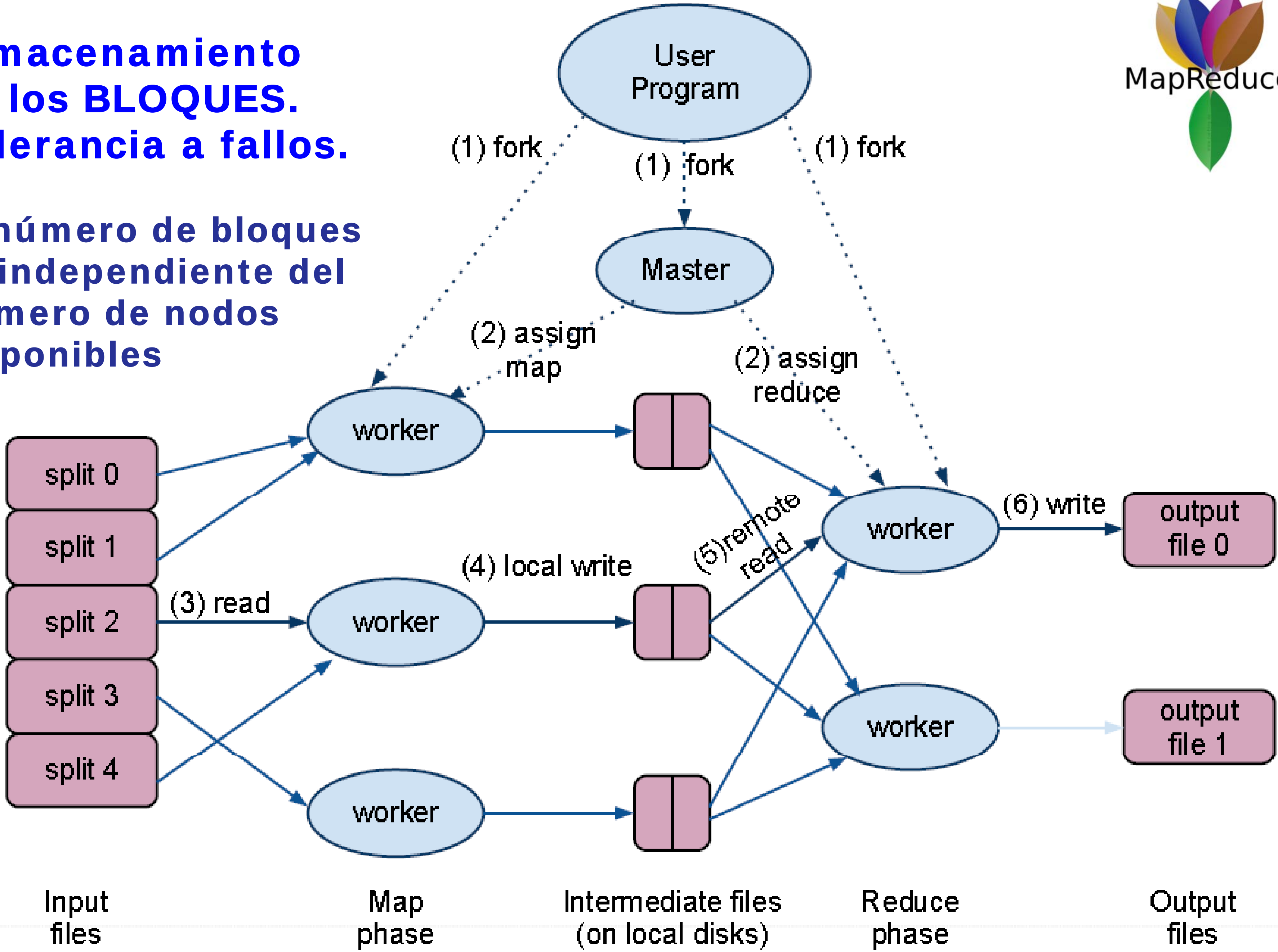
Ficheros de entrada Particionamiento en bloques

Ficheros Intermedios

Ficheros salida

Almacenamiento de los BLOQUES. Tolerancia a fallos.

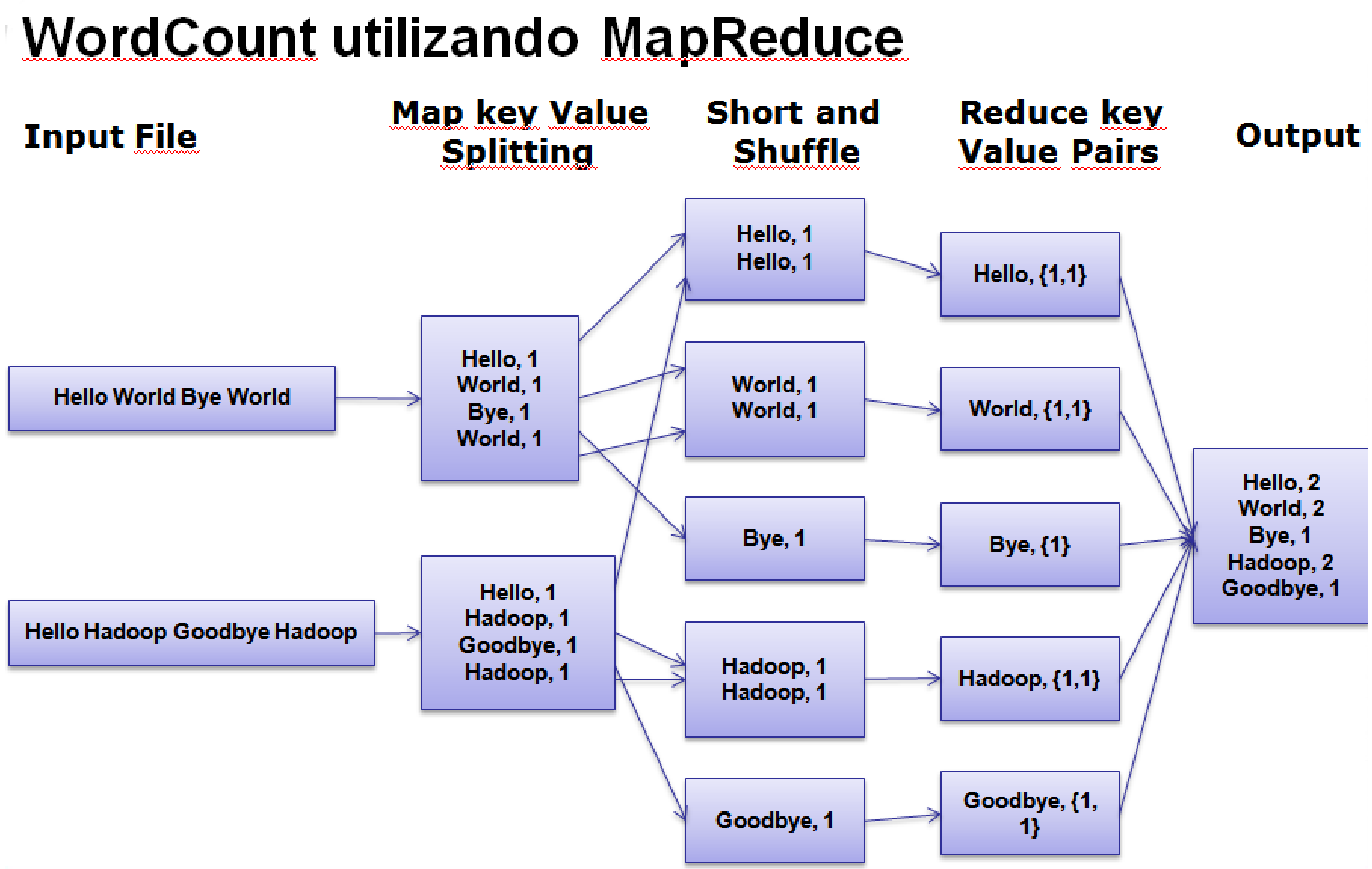
El número de bloques es independiente del número de nodos disponibles



Almacenamiento con copias, normalmente r=3

MapReduce

Una imagen completa del proceso MapReduce



MapReduce

MapReduce: WordCound pseudo-code!

Pseudo-code:

```
map(key, value):
// key: document ID; value: text of document
   FOR (each word w in value)
         emit(w, 1);

reduce(key, value-list):
// key: a word; value-list: a list of integers
         result = 0;
         FOR (each count v on value-list)
                  result += v;
         emit(key, result);
```

MapReduce

Resumiendo:

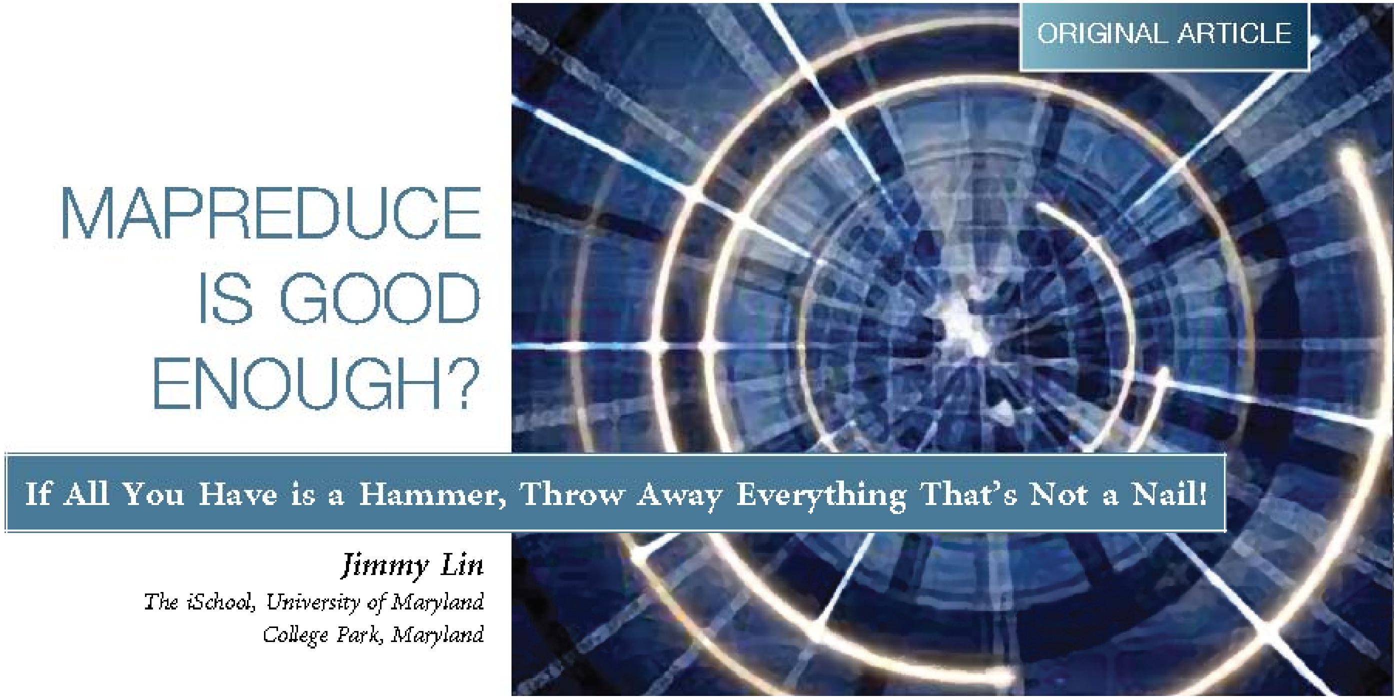
- **Ventaja frente a los modelos distribuidos clásicos:** El modelo de programación paralela de datos de MapReduce oculta la complejidad de la distribución y tolerancia a fallos.
- **Claves de su filosofía**: Es
  - ***escalable:*** *se olvidan los problemas de hardware*
  - ***más barato:*** *se ahorran costes en hardware, programación y administración (Commodity computing).*
- **MapReduce no es adecuado para todos los problemas, pero cuando funciona, puede ahorrar mucho tiempo**

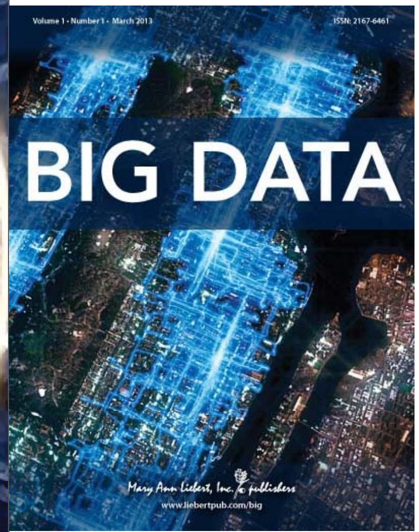
Bibliografía: A. Fernandez, S. Río, V. López, A. Bawakid, M.J. del Jesus, J.M. Benítez, F. Herrera, **Big Data with Cloud Computing: An Insight on the Computing Environment, MapReduce and Programming Frameworks.** *WIREs Data Mining and Knowledge Discovery 4:5 (2014) 380-409*

MapReduce

Limitaciones

"If all you have is a hammer, then everything looks like a nail."





Los siguientes tipos de algoritmos son ejemplos en los que MapReduce no funciona bien:

Iterative Graph Algorithms
Gradient Descent
Expectation Maximization

Limitaciones de MapReduce

Algoritmos de grafos iterativos. **Existen muchas limitaciones para estos algoritmos.**

Ejemplo: Cada iteración de PageRank se corresponde a un trabajo de MapReduce.

Se han propuesto una serie de extensiones de MapReduce o modelos de programación alternativa para acelerar el cálculo iterativo:

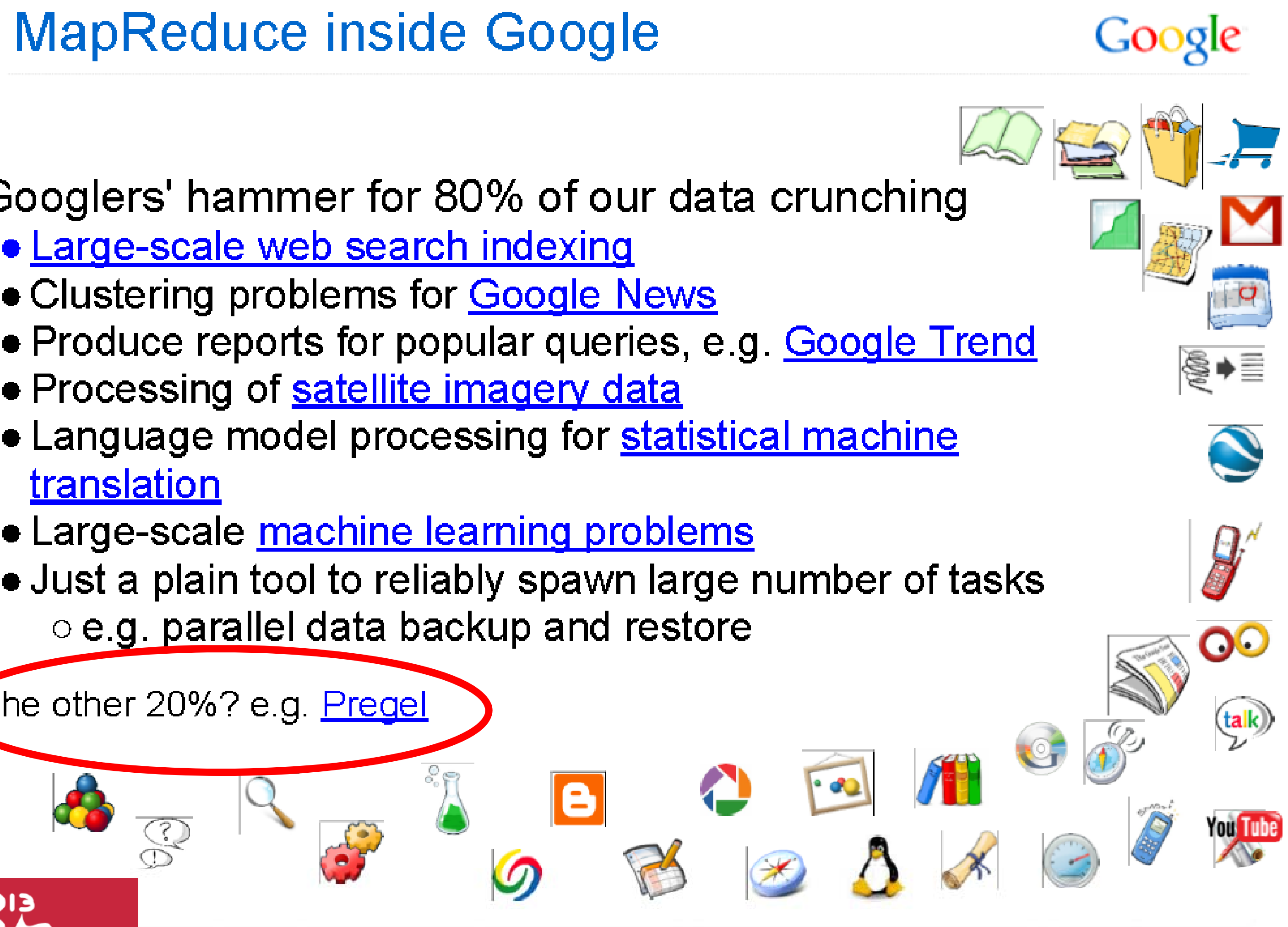
Pregel (Google)

Pregel: A System for Large-Scale Graph Processing

Implementación: http://www.michaelnielsen.org/ddi/pregel/

Malewicz, G., Austern, M., Bik, A., Dehnert, J., Horn, I., Leiser, N., and Czajkowski, G. Pregel: A system for large escale graph processing. ACM SIGMOD 2010.

Limitaciones de MapReduce



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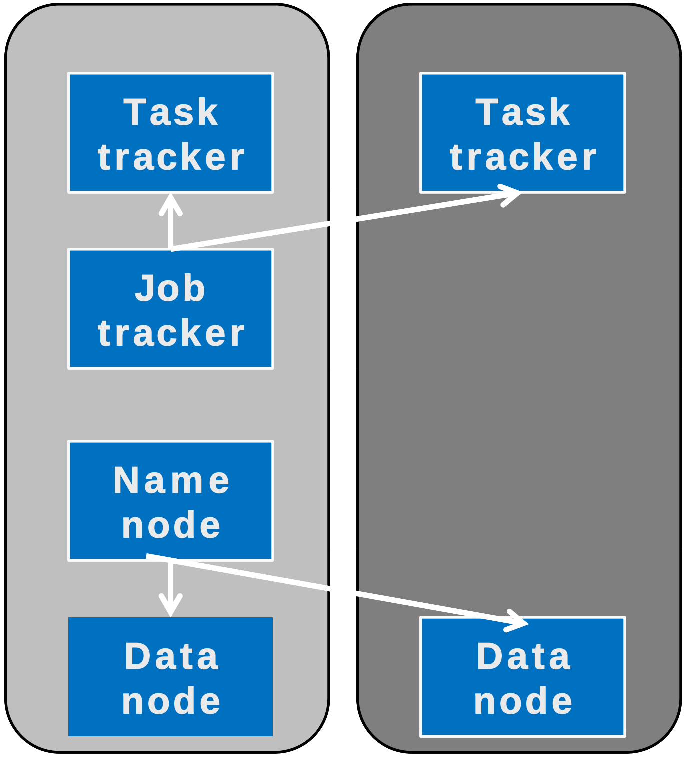
Hadoop

Hadoop es una implementación de código abierto del paradigma computacional MapReduce

http://hadoop.apache.org/

Hadoop

Hadoop Distributed File System (HDFS) es un sistema de archivos distribuido, escalable y portátil escrito en **Java** para el framework Hadoop



Map Reduce Layer

HDFS Layer

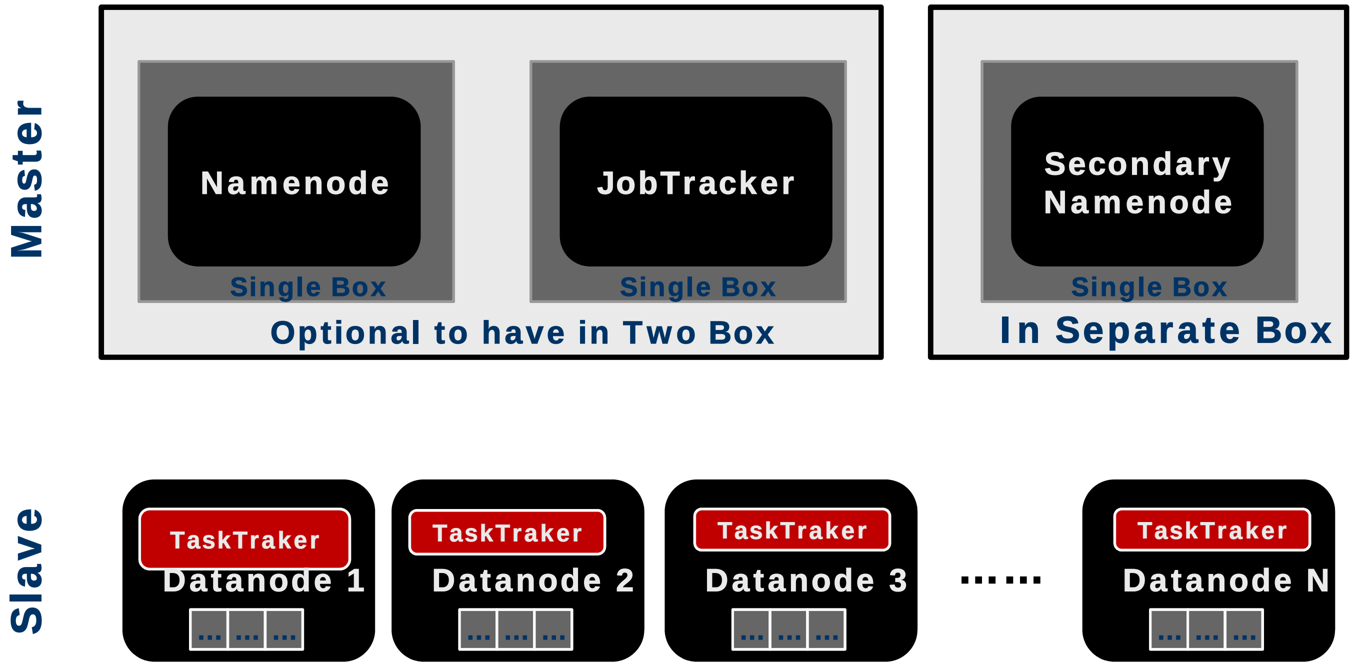
Creado por Doug Cutting (chairman of board of directors of the Apache Software Foundation, 2010)

http://hadoop.apache.org/

Hadoop

Hadoop: A master/slave architecture

- **Master**: NameNode, JobTracker
- **Slave**: {DataNode, TaskTraker}, …, {DataNode, TaskTraker}



Hadoop

http://sortbenchmark.org/

Primer hito de Hadoop: July 2008 - Hadoop Wins Terabyte Sort Benchmark

Uno de los grupos de Yahoo Hadoop ordenó 1 terabyte de datos en 209 segundos, superando el récord anterior de 297 segundos en la competición anual de ordenación de un terabyte (Daytona). Esta es la primera vez que un programa en Java de código abierto ganó la competición.

2008, 3.48 minutes

Hadoop

910 nodes x (4 dual-core processors, 4 disks, 8 GB memory)

Owen OMalley, Yahoo

2007, 4.95 min

TokuSampleSort

tx2500 disk cluster

400 nodes x (2 processors, 6-disk RAID, 8 GB memory)

Bradley C. Kuszmaul , MIT

	Daytona
Gray	2013, 1.42 TB/min **Hadoop** 102.5 TB in 4,328 seconds 2100 nodes x (2 2.3Ghz hexcore Xeon E5-2630, 64 GB memory, 12x3TB disks) Thomas Graves Yahoo! Inc.

http://developer.yahoo.com/blogs/hadoop/hadoop-sorts-petabyte-16-25-hours-terabyte-62-422.html

Ecosistema Hadoop

El proyecto Apache Hadoop incluye los módulos:

Hadoop Common: Las utilidades comunes que apoyan los otros módulos de Hadoop.
Hadoop Distributes File System (HDFS): El sistema de ficheros que proporciona el acceso
Hadoop YARN: Marco para el manejo de recursos de programación y grupo de trabajo.
Hadoop MapReduce: Un sistema de basado en YARN o para el procesamiento en paralelo de grandes conjuntos de datos.

http://hadoop.apache.org/

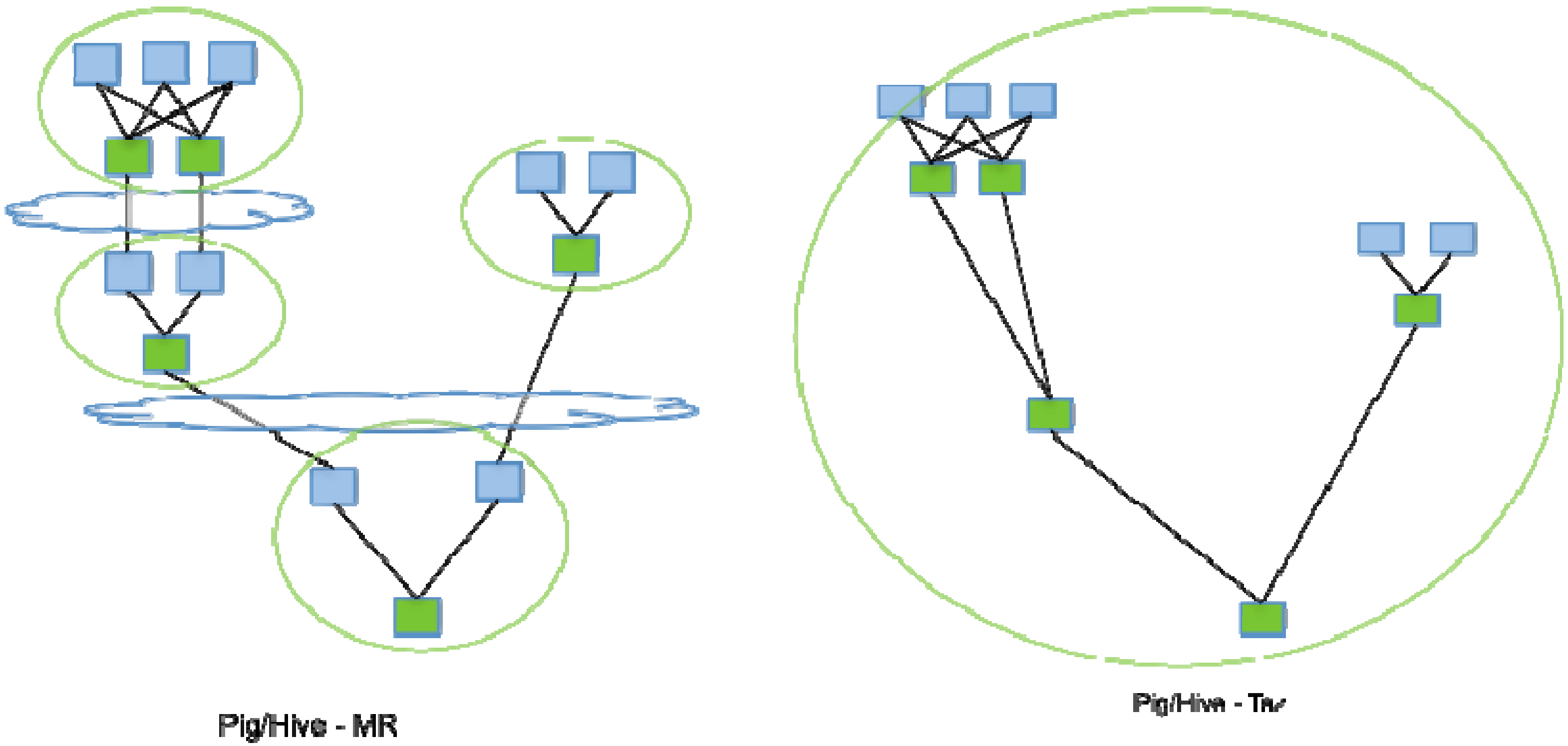
Ecosistema Apache Hadoop incluye más de 150 proyectos:

Avro: Un sistema de serialización de datos.
Cassandra: Una base de datos escalable multi-master sin puntos individuales y fallo
Chukwa: Un sistema de recogida de datos para la gestión de grandes sistemas distribuidos.
Hbase: Una base de datos distribuida, escalable que soporta estructurado de almacenamiento de datos para tablas de gran tamaño.
Hive: Un almacén de datos que proporciona el Resumen de datos para tablas de gran tamaño.
Pig: Lenguaje para la ejecución de alto nivel de flujo de datos para computación paralela.
Tez: Sustituye al modelo "MapShuffleReduce" por un flujo de ejecución con grafos acíclico dirigido (DAG)
Giraph: Procesamiento iterativo de grafos
Mahout: Aprendizaje automático escalable (biblioteca de minería de datos)

Recientemente: Apache Spark

Limitaciones de MapReduce

Procesos con flujos acíclicos de procesamiento de datos



http://tez.apache.org/

Limitaciones de MapReduce: Nuevas herramientas

GIRAPH (APACHE Project)
(http://giraph.apache.org/)
Procesamiento iterativo de grafos

Twister (Indiana University)
http://www.iterativemapreduce.org/
Clusters propios

GPS - A Graph Processing System, (Stanford)
http://infolab.stanford.edu/gps/
para Amazon's EC2

PrIter (University of Massachusetts Amherst, Northeastern University-China)
http://code.google.com/p/priter/
Cluster propios y Amazon EC2 cloud

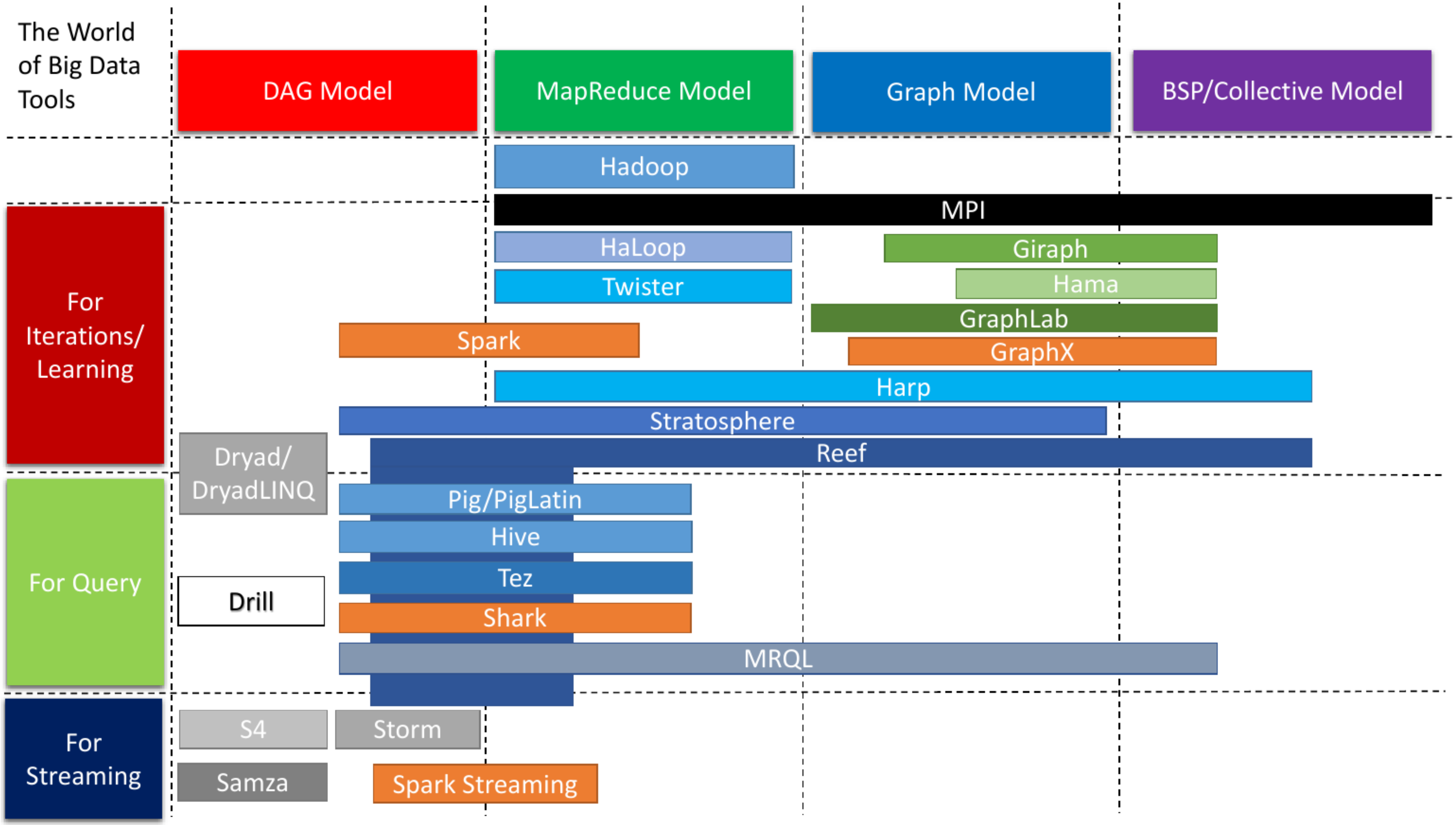
Distributed GraphLab (Carnegie Mellon Univ.)
https://github.com/graphlab-code/graphlab
Amazon's EC2

HaLoop (University of Washington)
http://clue.cs.washington.edu/node/14
http://code.google.com/p/haloop/
Amazon's EC2

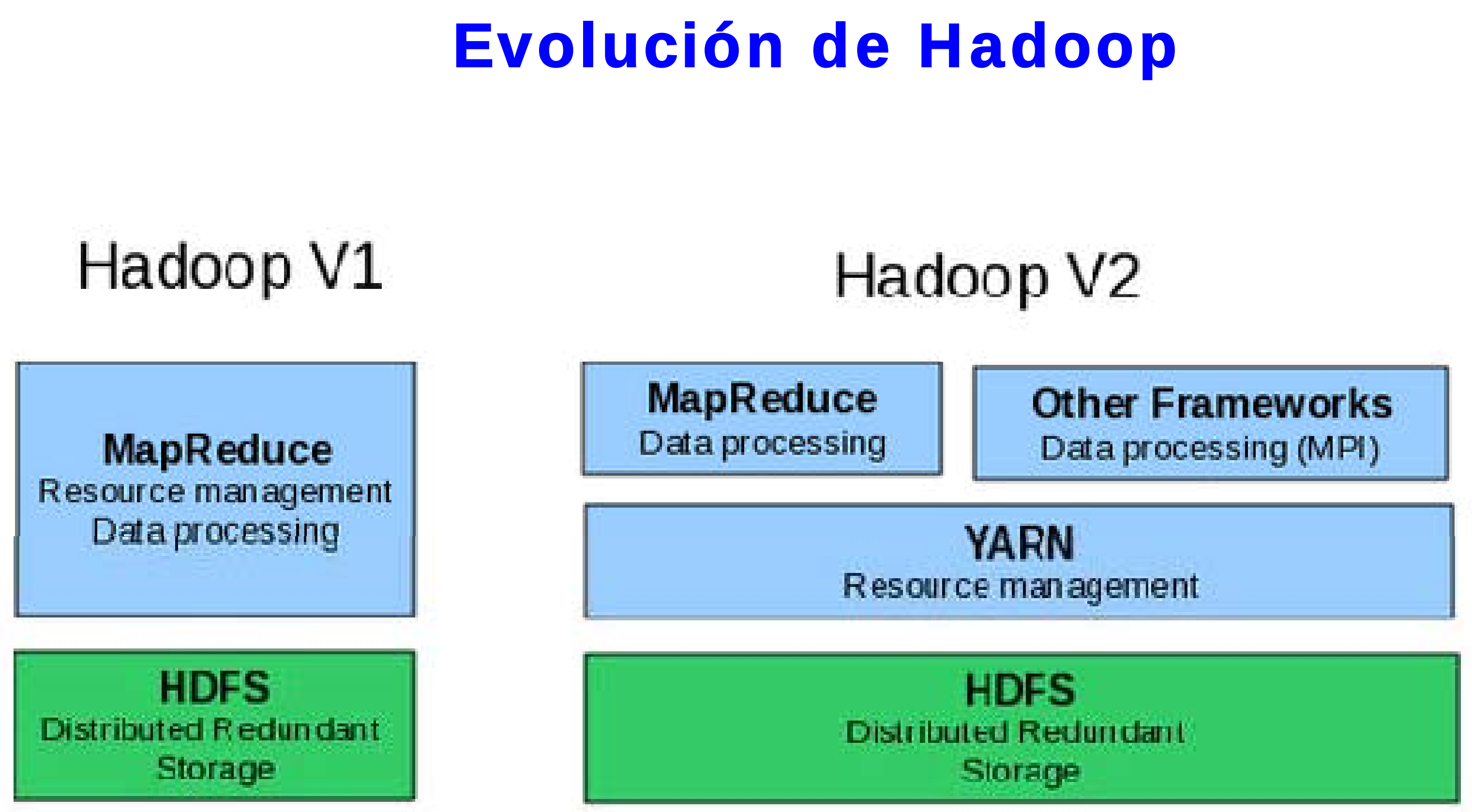
Spark (UC Berkeley)
(Apache Foundation)
http://spark.incubator.apache.org/research.html

GPU based platforms
Mars
Grex
GPMR

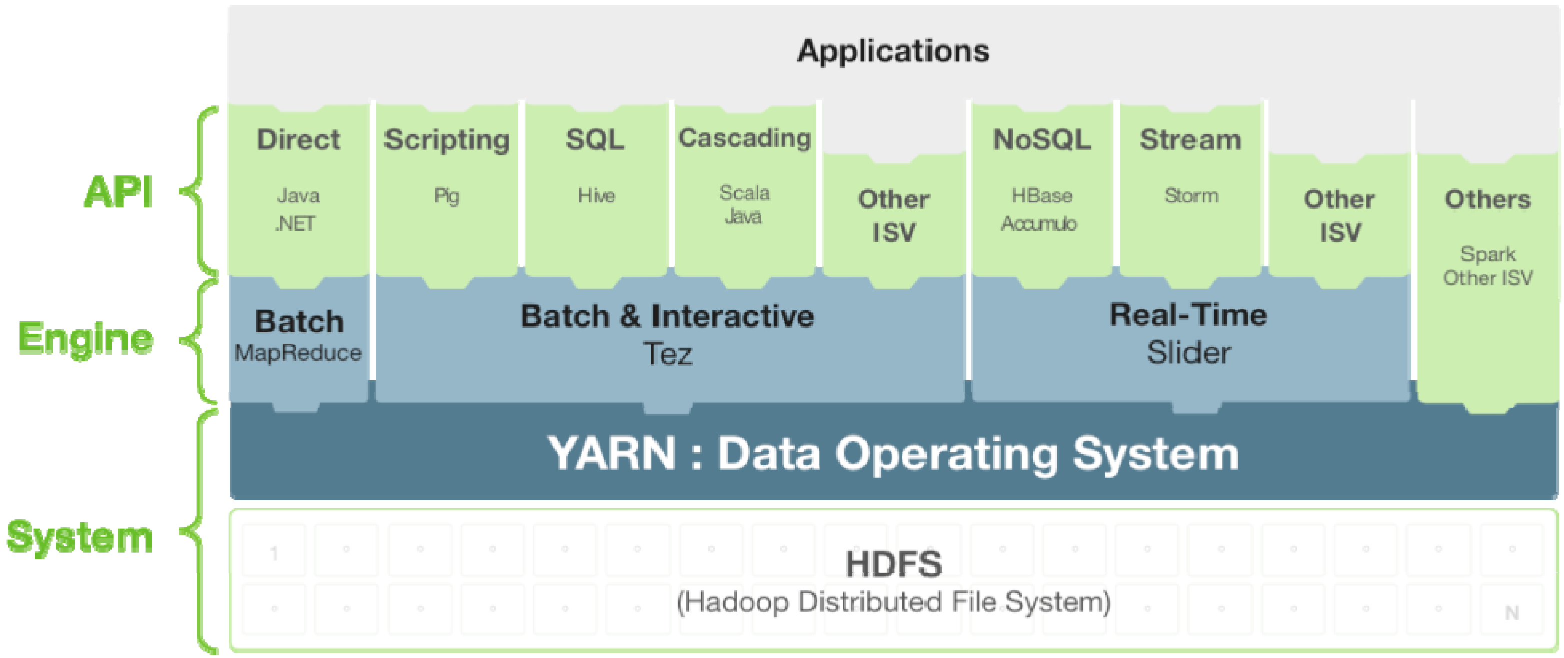
Limitaciones de MapReduce: Nuevas herramientas



Evolución de Hadoop

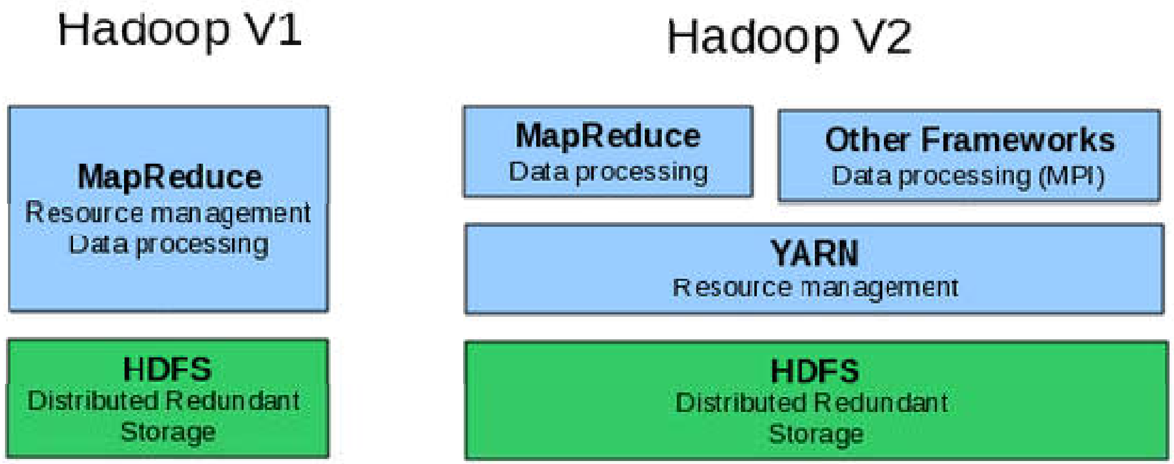


Apache Hadoop YARN



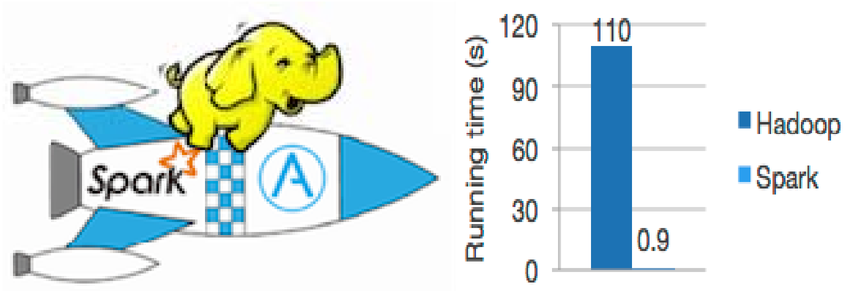
Apache Hadoop YARN es el sistema operativo de datos de Hadoop 2, responsable de la gestión del acceso a los recursos críticos de Hadoop. YARN permite al usuario interactuar con todos los datos de múltiples maneras al mismo tiempo, haciendo de Hadoop una verdadera plataforma de datos multi-uso y lo que le permite tomar su lugar en una arquitectura de datos moderna.

Apache Spark



https://spark.apache.org/

Enfoque InMemory
HDFS Hadoop + SPARK



Fast and expressive cluster computing system compatible with Apache Hadoop

Apache Spark (Birth 2009-2010)

Spark
Lightning-Fast Cluster Computing

Fast and Expressive Cluster Computing Engine Compatible with Apache Hadoop

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

2-5× less code

Efficient

- General execution graphs
- In-memory storage

Usable

- Rich APIs in Java, Scala, Python
- Interactive shell

http://spark.apache.org/talks/pydata-july-2013.pdf

Apache Spark

Spark Programming Model

KEY Concept: RDD (Resilient Distributed Datasets)

Write programs in terms of operations on distributed data sets

- Collection of objects spread across a cluster, stored in RAM or on Disk
- Built through parallel transformations on distributed datasets
- An RDD is a fault-tolerant collection of elements that can be operated on in parallel.
- There are two ways to create RDDs:

  Parallelizing an existing collection in your driver program

  Referencing a dataset in an external storage system, such as a shared filesystem, HDFS, Hbase.
- *Can be cached for future reuse*
- Built through parallel transformations on distributed datasets
- RDD operations: transformations and actions

  Transformations (e.g. map, filter, groupBy)...

  (Lazy operations to build RDSs from other RDSs)

  Actions (eg. Count, collect, save ...)

  (Return a result or write it a storage)

Zaharia-2012- Zaharia M, Chowdhury M, Das T, Dave A, Ma J, McCauley M, Franklin MJ, Shenker S, Stoica I. Resilient distributed datasets: a fault-tolerant abstraction for in-memory cluster computing. In: *9th USENIX Conference on Networked Systems Design and Implementation, San Jose, CA, 2012,* 1–14.

Apache Spark

Spark Operations

Transformations (define a new RDD)	map filter sample groupByKey reduceByKey sortByKey	flatMap union join cogroup cross mapValues
Actions (return a result to driver program)	collect reduce count save lookupKey	

Zaharia-2012- Zaharia M, Chowdhury M, Das T, Dave A, Ma J, McCauley M, Franklin MJ, Shenker S, Stoica I. Resilient distributed datasets: a fault-tolerant abstraction for in-memory cluster computing. In: *9th USENIX Conference on Networked Systems Design and Implementation, San Jose, CA, 2012,* 1–14.

Apache Spark

	Hadoop World Record	Spark 100 TB *
Data Size	102.5 TB	100 TB
Elapsed Time	72 mins	23 mins
# Nodes # Cores	2100 50400	206 6592
# Reducers	10,000	29,000
Rate	1.42 TB/min	4.27 TB/min
Rate/node	0.67 GB/min	20.7 GB/min
Sort Benchmark Daytona Rules	Yes	Yes
Environment	dedicated data center	EC2 (i2.8xlarge)

October 10, 2014

Using Spark on 206 EC2 nodes, we completed the benchmark in 23 minutes. This means that Spark sorted the same data 3X faster using 10X fewer machines. All the sorting took place on disk (HDFS), without using Spark's in-memory cache.

http://databricks.com/blog/2014/10/10/spark-petabyte-sort.html

Apache Spark

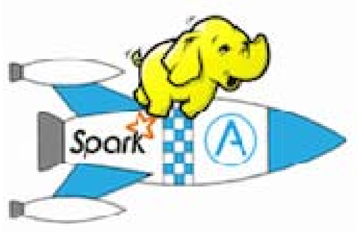
November 5, 2014

	Daytona
Gray	2013, 1.42 TB/min **Hadoop** 102.5 TB in 4,328 seconds 2100 nodes x (2 2.3Ghz hexcore Xeon E5-2630, 64 GB memory, 12x3TB disks) Thomas Graves Yahoo! Inc.

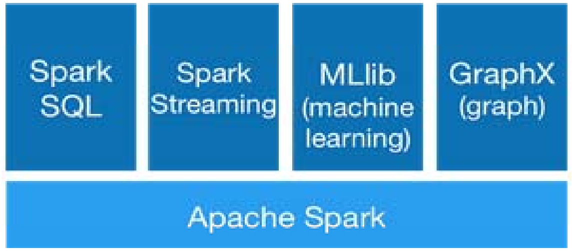
	Daytona
Gray	2-way tie: 2014, 4.35 TB/min **TritonSort** 100 TB in 1,378 seconds 186 Amazon EC2 i2.8xlarge nodes x (32 vCores - 2.50Ghz Intel Xeon E5-2670 v2, 244GB memory, 8x800 GB SSD) Michael Conley, Amin Vahdat, George Porter University of California, San Diego 2014, 4.27 TB/min **Apache Spark** 100 TB in 1,406 seconds 207 Amazon EC2 i2.8xlarge nodes x (32 vCores - 2.5Ghz Intel Xeon E5-2670 v2, 244GB memory, 8x800 GB SSD) Reynold Xin, Parviz Deyhim, Xiangrui Meng, Ali Ghodsi, Matei Zaharia Databricks

http://sortbenchmark.org/

Apache Spark

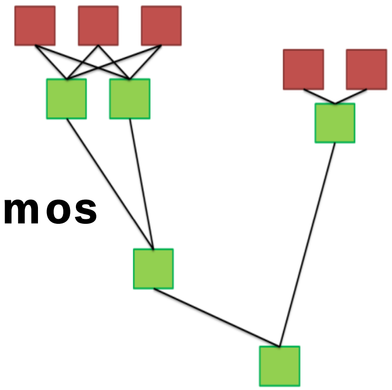


[Ecosistema Apache Spark]()



• Big Data "in-memory". Spark permite realizar trabajos paralelizados totalmente en memoria, lo cual reduce mucho los tiempos de procesamiento. Sobre todo si se trata de unos procesos iterativos. En el caso de que algunos datos no quepan en la memoria, Spark seguirá trabajando y usará el disco duro para volcar aquellos datos que no se necesitan en este momento (Hadoop **"commodity hardware")**.

KEY Concept: RDD (Resilient Distributed Datasets)
Write programs in terms of operations on distributed data sets



• Esquema de computación más flexible que MapReduce.
Permite la flujos acíclicos de procesamiento de datos, algoritmos iterativos

• Spark ofrece una API para Java, Python y Scala

• Spark / Wiki Homepage
Powered By Spark
Creado por Andy Konwinski, modificado por última vez por Reynold Xin el sep 08, 2015

Databricks, Groupon, eBay inc., Amazon, Hitachi, Nokia, Yahoo!, ...

https://cwiki.apache.org/confluence/display/SPARK/Powered+By+Spark

Hadoop

¿Cómo accedo a una plataforma Hadoop?

Plataformas Cloud con instalación de Hadoop

Amazon Elastic Compute Cloud (Amazon EC2)

http://aws.amazon.com/es/ec2/

Windows Azure

http://www.windowsazure.com/

Instalación en un cluster

Ejemplo ATLAS, infraestructura del grupo SCI²S

Cluster ATLAS: 4 super servers from Super Micro Computer Inc. (4 nodes per server)
The features of each node are:

- Microprocessors: 2 x Intel Xeon E5-2620 (6 cores/12 threads, 2 GHz, 15 MB Cache)
- RAM 64 GB DDR3 ECC 1600MHz, Registered
- 1 HDD SATA 1TB, 3Gb/s; (system)
- 1 HDD SATA 2TB, 3Gb/s; (distributed file system)

Distribución que ofrece Cloudera para Hadoo

http://www.cloudera.com/content/cloudera/en/why-cloudera/hadoop-and-big-data.html

Tecnologías para Big Data: Ecosistema Hadoop (Hadoop, Spark, …) (Una instantánea)

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.

There are two main issues related to Big Data:

1. **Database/storage frameworks: to write, read, and manage data.**
2. **Computational models: to process and analyze data.**

Recently, there are the following Big Data frameworks:

1. **Storage frameworks: Google File System (GFS), Hadoop Distributed File Systems (HDFS).**
2. **Computational models: MapReduce (Apache Hadoop), Resilient Distributed Datasets (RDD by Apache Spark).**

Índice

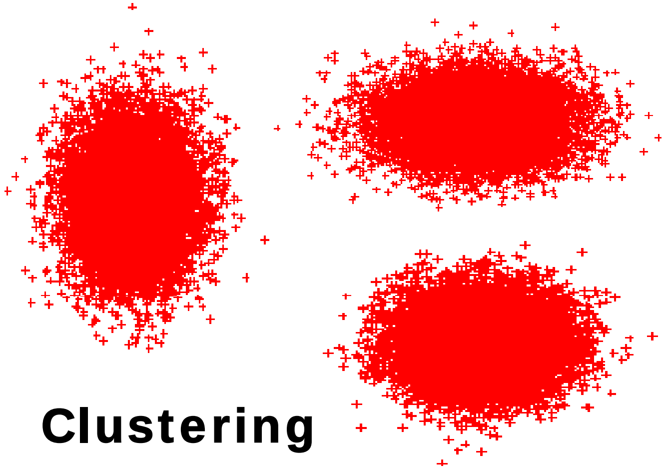
- **Big Data. Big Data Science**
- **¿Por qué Big Data? Google crea el Modelo de Programación MapReduce**
- **Tecnologías para Big Data: Ecosistema Hadoop (Hadoop, Spark, …)**
- **Big Data Analytics: Librerías para Analítica de Datos en Big Data. Casos de estudio**
- Algunas aplicaciones: Salud, Social Media, Identificación
- Big Data en el grupo de investigación SCI²S
- Comentarios Finales

Big Data Analytics

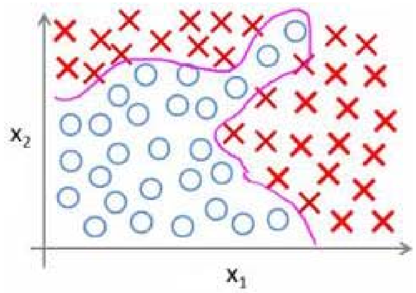
- **Big Data Analytics: Escenario**
- **Big Data Analytics: Tools**
  (Mahout, MLLib, H2O, Deep Learning)
- **Caso de estudio: Random Forest**
- **Aprendizaje no supervisado: Caso de estudio K-Means**
- **Big Data Analytics: 3 Comentarios finales.**
  - Without Analytics, Big data is just noise
  - Big data preprocessing: Es necesario
  - Los expertos en Ciencia de Datos son necesarios en el uso de herramientas de Analytics y Big Data.

Big Data Analytics

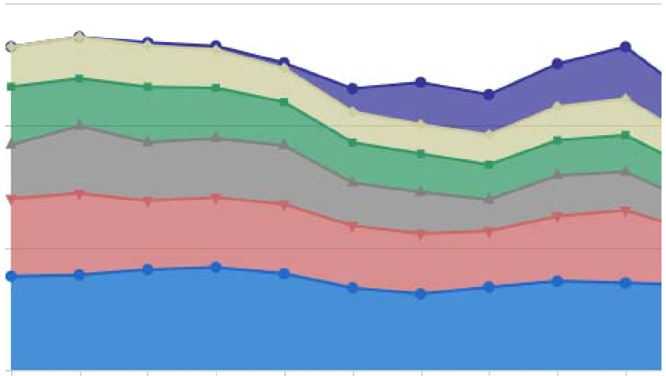
Potentiales escenarios:



Clustering

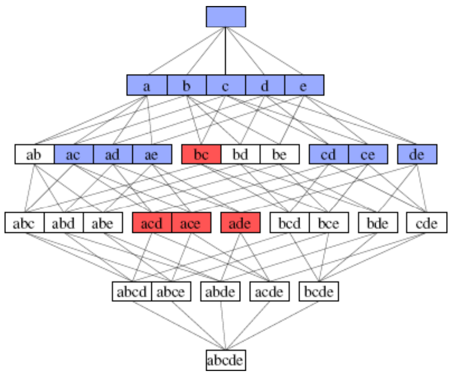


Classification



Real Time Analytics / Big Data Streams

Association



Recommendation Systems

Social Media Mining

Social Big Data

Big Data Analytics: **Tools**

Generation	1st Generation	2nd Generation	3nd Generation
Examples	SAS, R, Weka, SPSS, KEEL	Mahout, Pentaho, Cascading	Spark, Haloop, GraphLab, Pregel, Giraph, ML over Storm
Scalability	Vertical	Horizontal (over Hadoop)	Horizontal (Beyond Hadoop)
Algorithms Available	Huge collection of algorithms	Small subset: sequential logistic regression, linear SVMs, Stochastic Gradient Decendent, k-means clustsering, Random forest, etc.	Much wider: CGD, ALS, collaborative filtering, kernel SVM, matrix factorization, Gibbs sampling, etc.
Algorithms Not Available	Practically nothing	Vast no.: Kernel SVMs, Multivariate Logistic Regression, Conjugate Gradient Descendent, ALS, etc.	Multivariate logistic regression in general form, k-means clustering, etc. – Work in progress to expand the set of available algorithms
Fault-Tolerance	Single point of failure	Most tools are FT, as they are built on top of Hadoop	FT: HaLoop, Spark Not FT: Pregel, GraphLab, Giraph

Big Data Analytics: **Tools**

Mahout

Classification	Single Machine	MapReduce
Logistic Regression - trained via SGD	x	
Naive Bayes / Complementary Naive Bayes		x
Random Forest		x
Hidden Markov Models	x	
Multilayer Perceptron	x	

MLlib

Lightning-Fast Cluster Computing

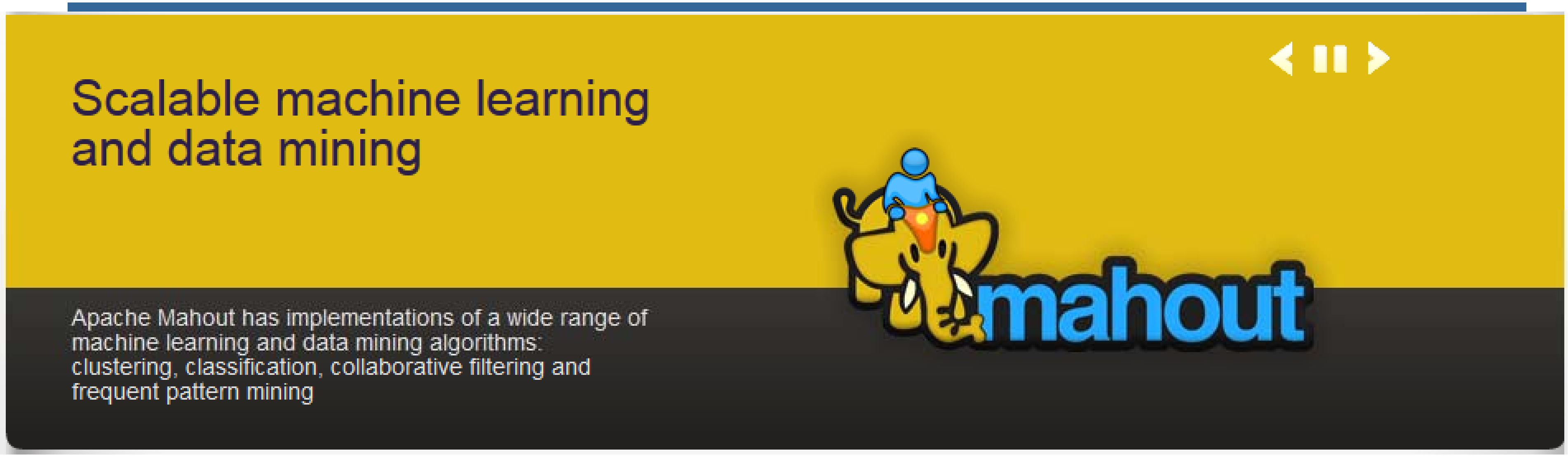
MLlib types, algorithms and utilities

This lists functionality included in `spark.mllib`, the main MLlib API.

- Data types
- Basic statistics
  - summary statistics
  - correlations
  - stratified sampling
  - hypothesis testing
  - random data generation
- Classification and regression
  - linear models (SVMs, logistic regression, linear regression)
  - naive Bayes
  - decision trees
  - ensembles of trees (Random Forests and Gradient-Boosted Trees)
  - isotonic regression
- Collaborative filtering
  - alternating least squares (ALS)
- Clustering
  - k-means
  - Gaussian mixture
  - power iteration clustering (PIC)
  - latent Dirichlet allocation (LDA)
  - streaming k-means
- Dimensionality reduction
  - singular value decomposition (SVD)
  - principal component analysis (PCA)
- Feature extraction and transformation
- Frequent pattern mining
  - FP-growth
- Optimization (developer)
  - stochastic gradient descent
  - limited-memory BFGS (L-BFGS)
- PMML model export

https://spark.apache.org/mllib/

Mahout



Biblioteca de código abierto

Currently Mahout supports mainly three use cases: Recommendation mining takes users' behavior and from that tries to find items users might like. Clustering takes e.g. text documents and groups them into groups of topically related documents. Classification learns from existing categorized documents what documents of a specific category look like and is able to assign unlabelled documents to the (hopefully) correct category.

http://mahout.apache.org/

Latest release version 0.9 has

- User and Item based recommenders
- Matrix factorization based recommenders
- K-Means, Fuzzy K-Means clustering
- Latent Dirichlet Allocation
- Singular Value Decomposition
- Logistic regression classifier
- (Complementary) Naive Bayes classifier
- Random forest classifier
- High performance java collections
- A vibrant community

Mahout

Historia

25 July 2013 - Apache Mahout 0.8 released

Visit our release notes page for details.

16 June 2012 - Apache Mahout 0.7 released

Visit our release notes page for details.

6 Feb 2012 - Apache Mahout 0.6 released

Visit our release notes page for details.

9 Oct 2011 - Mahout in Action released

The book Mahout in Action is available in print. Sean Owen, Robin Anil, Ted Dunning and Ellen Friedman thank the community (especially those who were reviewers) for input during the process and hope it is enjoyable.

Find it at your favorite bookstore, or order print and eBook copies from Manning -- use discount code "mahout37" for 37% off.

Mahout

Historia

1 February 2014 - Apache Mahout 0.9 released

Apache Mahout has reached version 0.9. All developers are encouraged to begin using version 0.9. Highlights include:

- New and improved Mahout website based on Apache CMS - MAHOUT-1245
- Early implementation of a Multi Layer Perceptron (MLP) classifier - MAHOUT-1265
- Scala DSL Bindings for Mahout Math Linear Algebra. See this blogpost and MAHOUT-1297
- Recommenders as Search. See [https://github.com/pferrel/solr-recommender] and MAHOUT-1288
- Support for easy functional Matrix views and derivatives - MAHOUT-1300
- JSON output format for ClusterDumper - MAHOUT-1343
- Enabled randomised testing for all Mahout modules using Carrot RandomizedRunner - MAHOUT-1345
- Online Algorithm for computing accurate Quantiles using 1-dimensional Clustering - See this pdf and MAHOUT-1361
- Upgrade to Lucene 4.6.1 - MAHOUT-1364

Changes in 0.9 are detailed in the release notes.

The following algorithms that were marked deprecated in 0.8 have been removed in 0.9:

- Switched LDA implementation from Gibbs Sampling to Collapsed Variational Bayes
- Meanshift - removed due to lack of actual usage and support
- MinHash - removed due to lack of actual usage and support
- Winnow - removed due to lack of actual usage and support
- Perceptron - removed due to lack of actual usage and support
- Slope One - removed due to lack of actual usage
- Distributed Pseudo recommender - removed due to lack of actual usage
- TreeClusteringRecommender - removed due to lack of actual usage

Mahout

Historia

Mahout News

25 April 2014 - Goodbye MapReduce

The Mahout community decided to move its codebase onto modern data processing systems that offer a richer programming model and more efficient execution than Hadoop MapReduce. **Mahout will therefore reject new MapReduce algorithm implementations from now on**. We will however keep our widely used MapReduce algorithms in the codebase and maintain them.

We are building our future implementations on top of a DSL for linear algebraic operations which has been developed over the last months. Programs written in this DSL are automatically optimized and executed in parallel on Apache Spark.

Furthermore, there is an experimental contribution undergoing which aims to integrate the h20 platform into Mahout.

Mahout

Algoritmos

All Single Machine and MapReduce features are available in the latest 0.9 release

Collaborative Filtering	Single Machine	MapReduce
User-Based Collaborative Filtering	x	
Item-Based Collaborative Filtering	x	x
Matrix Factorization with ALS	x	x
Matrix Factorization with ALS on Implicit Feedback	x	x
Weighted Matrix Factorization, SVD++	x	

Classification		
Logistic Regression - trained via SGD	x	
Naive Bayes / Complementary Naive Bayes		x
Random Forest		x
Hidden Markov Models	x	
Multilayer Perceptron	x	

Clustering		
Canopy Clustering	*deprecated*	*deprecated*
k-Means Clustering	x	x
Fuzzy k-Means	x	x
Streaming k-Means	x	x
Spectral Clustering		x

Dimensionality Reduction * note: most scala-based dimensionality reduction algorithms are available through the Mahout Math-Scala Core Library for all engines *

Singular Value Decomposition	x	x	x	x
Lanczos Algorithm	*deprecated*	*deprecated*		
Stochastic SVD	x	x	x	x
PCA (via Stochastic SVD)	x	x	x	x
QR Decomposition	x	x	x	x

Es una buena librería para introducirse en el uso de MapReduce sobre Hadoop

Spark Libraries

https://spark.apache.org/releases/spark-release-1-5-1.html

Lightning-fast cluster computing

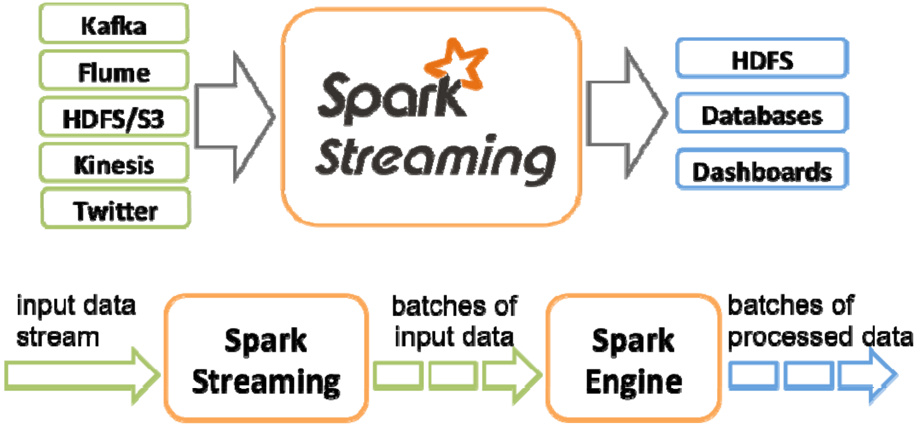
Download | Libraries ▾ | Documentation ▾ | Examples | Community ▾ | FAQ

- APIs: RDD, DataFrame and SQL
- Backend Execution: DataFrame and SQL
- Integrations: Data Sources, Hive, Hadoop, Mesos and Cluster Management
- R Language
- Machine Learning and Advanced Analytics
- Spark Streaming
- Deprecations, Removals, Configs, and Behavior Changes
  - Spark Core
  - Spark SQL & DataFrames
  - Spark Streaming
  - MLlib
- Known Issues
  - SQL/DataFrame
  - Streaming
- Credits

MLlib

Spark MLlib

https://spark.apache.org/docs/latest/mllib-guide.html



GraphX

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- Optimization (developer)
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- PMML model export

MLlib

Spark Lightning-Fast Cluster Computing

https://spark.apache.org/mllib/

MLlib

Spark MLlib

http://spark.apache.org/mllib/

MLlib is Apache Spark's scalable machine learning library.

Ease of Use

Usable in Java, Scala and Python.

MLlib fits into Spark's APIs and interoperates with NumPy in Python (starting in Spark 0.9). You can use any Hadoop data source (e.g. HDFS, HBase, or local files), making it easy to plug into Hadoop workflows.

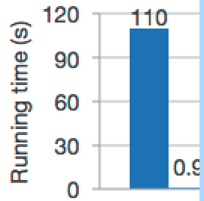
```
points = spark.textF
               .map(p
model = KMeans.trair
```

Calling MLlib

Performance

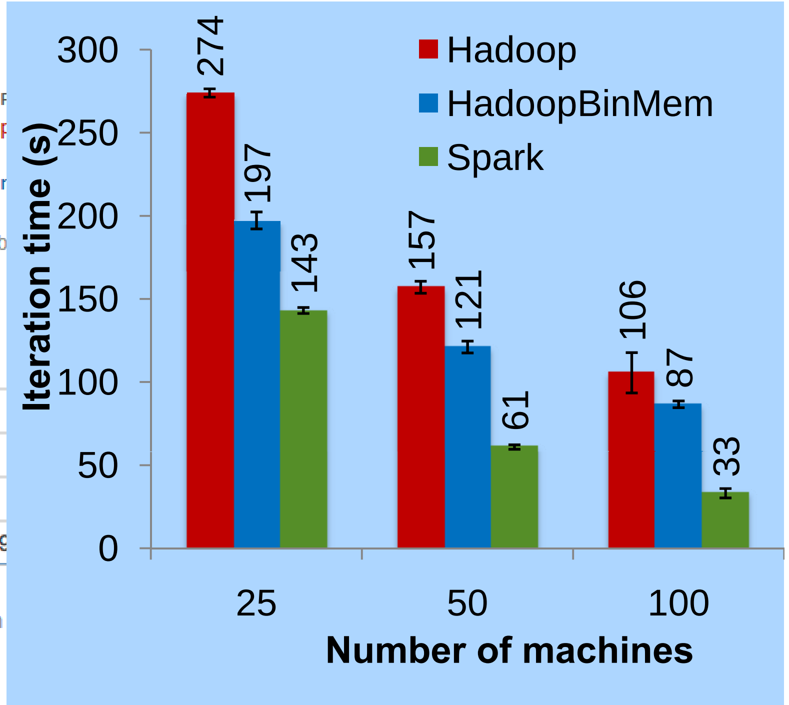
High-quality algorithms, 100x faster than MapReduce.

Spark excels at iterative computation, enabling MLlib to run fast. At the same time, we care about algorithmic performance: MLlib contains high-quality algorithms that leverage iteration, and can yield better results than the one-pass approximations sometimes used on MapReduce.



Logistic regression in

K-Means



[Zaharia et. al, NSDI'12]

Easy to Deploy

Runs on existing Hadoop clusters and data.

If you have a Hadoop 2 cluster, you can run Spark and MLlib without any pre-installation. Otherwise, Spark is easy to run standalone or on EC2 or Mesos. You can read from HDFS, HBase, or any Hadoop data source.

hadoop

MLlib

Spark MLlib

https://spark.apache.org/docs/latest/mllib-guide.html

Machine Learning Library (MLlib) Guide

MLlib is Spark's scalable machine learning library consisting of common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, as well as underlying optimization primitives, as outlined below:

- Data types
- Basic statistics
  - summary statistics
  - correlations
  - stratified sampling
  - hypothesis testing
  - random data generation
- Classification and regression
  - linear models (SVMs, logistic regression, linear regression)
  - naive Bayes
  - decision trees
  - ensembles of trees (Random Forests and Gradient-Boosted Trees)
  - isotonic regression
- Collaborative filtering
  - alternating least squares (ALS)
- Clustering
  - k-means
  - Gaussian mixture
  - power iteration clustering (PIC)
  - latent Dirichlet allocation (LDA)
  - streaming k-means
- Dimensionality reduction
  - singular value decomposition (SVD)
  - principal component analysis (PCA)
- Feature extraction and transformation
- Frequent pattern mining
  - FP-growth
- Optimization (developer)
  - stochastic gradient descent
  - limited-memory BFGS (L-BFGS)

MLlib is under active development. The APIs marked `Experimental`/`DeveloperApi` may change in future releases, and the migration guide below

http://spark-packages.org/

Spark Packages

A community index of packages for Apache Spark.

Librería H_2O

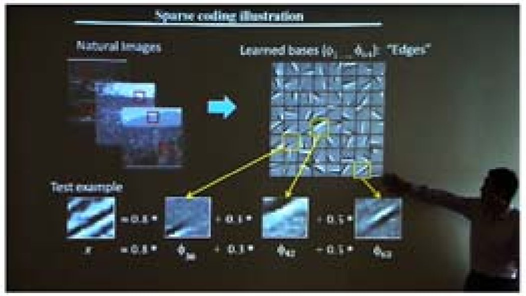
http://0xdata.com/

Data Science in H_2O

- Cox Proportional Hazards Model
- Deep Learning
- Generalized Linear Model
- Gradient Boosted Regression and Classification
- K-Means
- Naive Bayes
- Principal Components Analysis
- Random Forest
- Summary
- Data Science and Machine Learning
- Stochastic Gradient Descent
- References

Soporte para R, Hadoop y Spark

Funcionamiento: Crea una máquina virtual con Java en la que optimiza el paralelismo de los algoritmos



Deep learning
make sense of images, audio

- Librería que contiene algoritmos de Deep Learning
  - Récord del mundo en el problema MNIST sin preprocesamiento

http://0xdata.com/blog/2015/02/deep-learning-performance/

Librería H_20

H_2O APIs

Overview and walkthroughs for the different APIs to H_2O.

- R On H_2O
- Tableau on H_2O

http://docs.h2o.ai/Ruser/top.html

http://cran.r-project.org/src/contrib/h2o_2.8.4.4.tar.gz

Sparkling Water Integration

Information, tutorials, and meetup slide decks for Sparkling Water.

- Sparkling Water

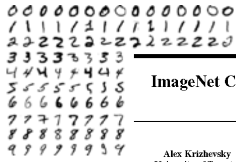
Deployment and Big Data Management

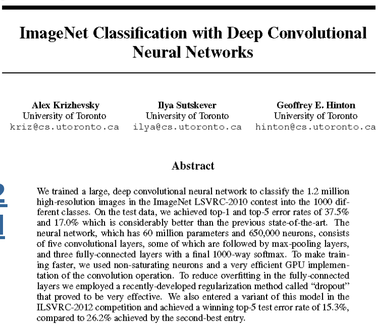
- H_2O on EC2
- H_2O on Hadoop
- H2O on a Multi-Node Cluster

Deep Learning

http://0xdata.com/blog/2015/02/deep-learning-performance/

- Librería que contiene algoritmos de Deep Learning
  - Récord del mundo en el problema MNIST sin preprocesamiento





ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
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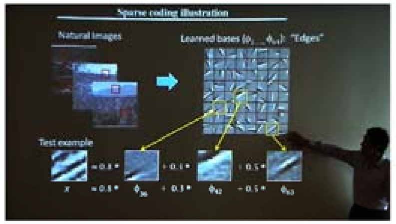
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.



Deep learning
make sense of images, audio

Google DeepMind

INTELIGENCIA ARTIFICIAL »

Este programa juega mejor a los 'marcianitos' que un humano

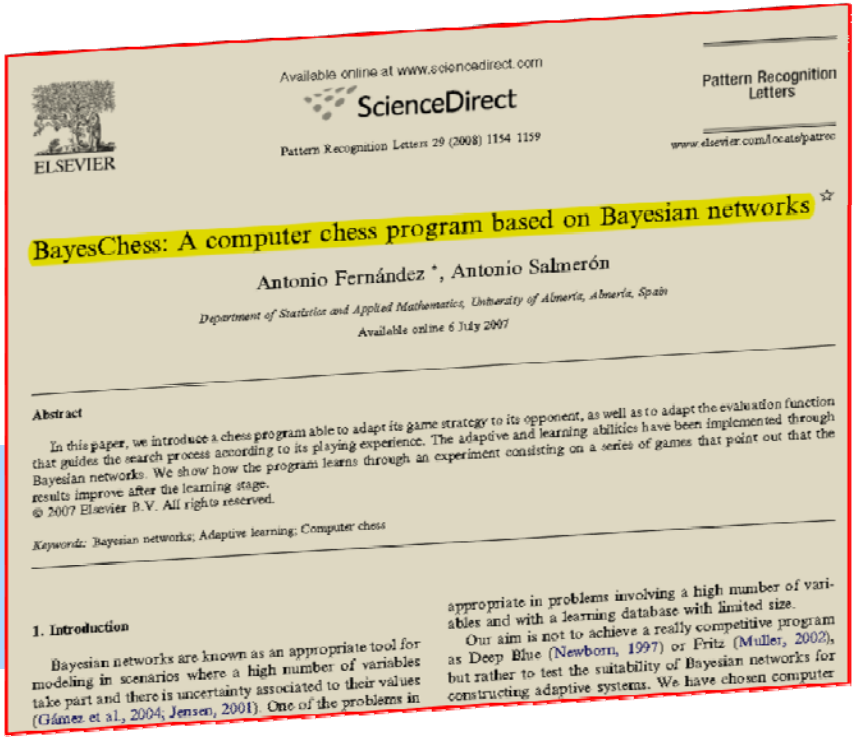
• Expertos en inteligencia artificial de Google crean un algoritmo que aprende por sí solo a jugar con decenas de videojuegos de los años 80 como 'Space Invaders' o el 'Comecocos'

http://elpais.com/elpais/2015/02/25/ciencia/1424860455_667336.html

Deep Mind: Start up-2011, Demis Hassabis Shane Legg y Mustafa Suleyman
Juegos Arcade (Breakout)

Emerging Technology From the arXiv
September 14, 2015

Deep Learning Machine Teaches Itself Chess in 72 Hours, Plays at International Master Level



Available online at www.sciencedirect.com
ScienceDirect
Pattern Recognition Letters 29 (2008) 1154–1159
ELSEVIER
Pattern Recognition Letters
www.elsevier.com/locate/patrec

BayesChess: A computer chess program based on Bayesian networks ☆

Antonio Fernández *, Antonio Salmerón
Department of Statistics and Applied Mathematics, University of Almería, Almería, Spain

Available online 6 July 2007

Abstract

In this paper, we introduce a chess program able to adapt its game strategy to its opponent, as well as to adapt the evaluation function that guides the search process according to its playing experience. The adaptive and learning abilities have been implemented through Bayesian networks. We show how the program learns through an experiment consisting on a series of games that point out that the results improve after the learning stage.

Keywords: Bayesian networks; Adaptive learning; Computer chess

1. Introduction

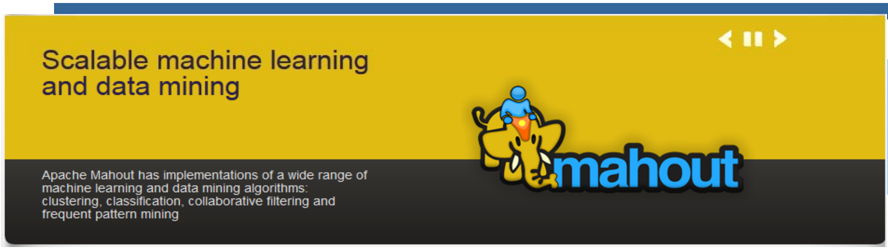
Bayesian networks are known as an appropriate tool for modeling in scenarios where a high number of variables take part and there is uncertainty associated to their values (Gámez et al., 2004; Jensen, 2001). One of the problems in appropriate in problems involving a high number of variables and with a learning database with limited size.

Our aim is not to achieve a really competitive program as Deep Blue (Newborn, 1997) or Fritz (Muller, 2002), but rather to test the suitability of Bayesian networks for constructing adaptive systems. We have chosen computer

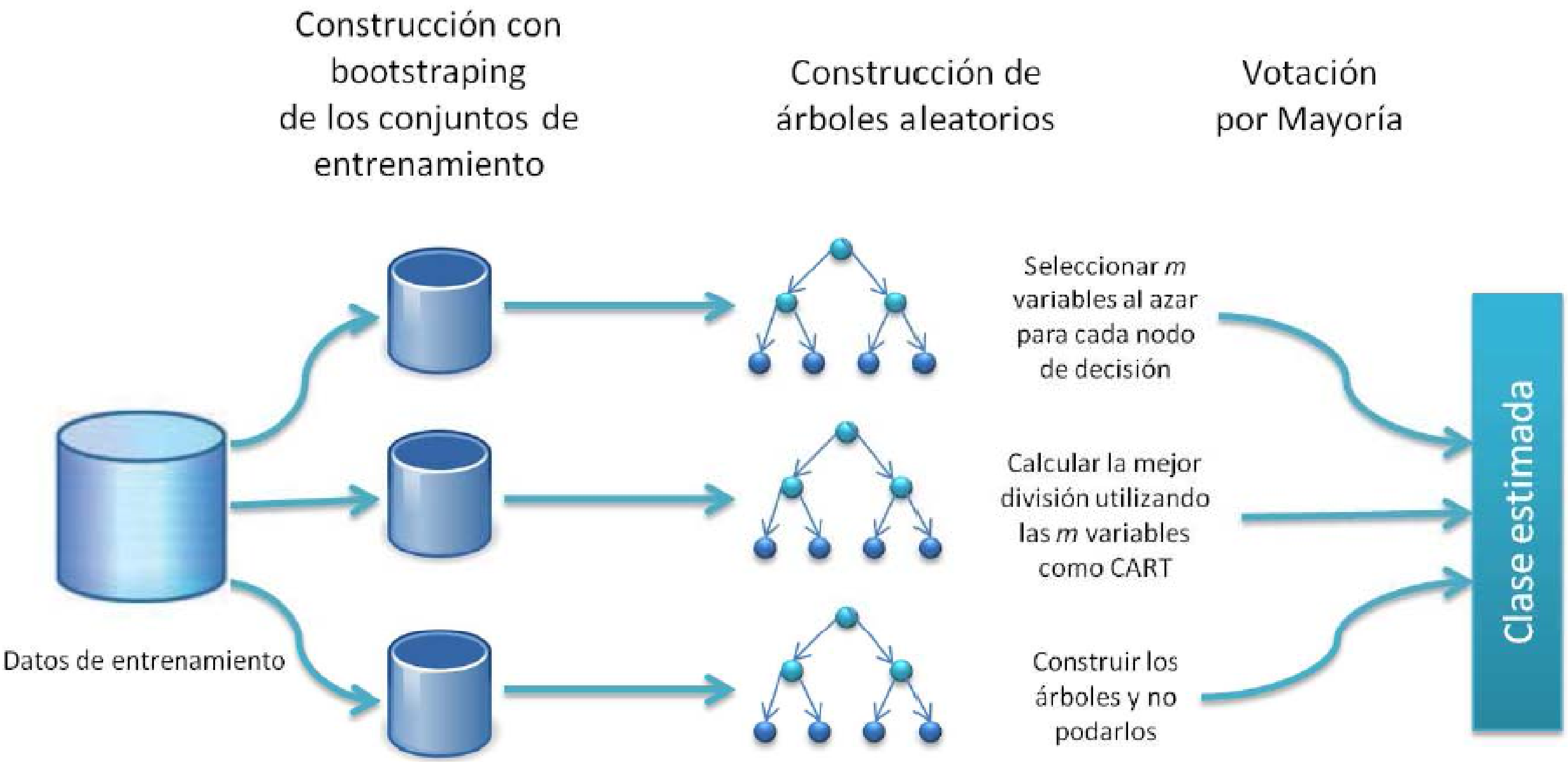
Algunos datos:
von Neumann introduced the minimax algorithm in 1928
363 features
The evaluator network converges in about 72 hours on a machine with 2x10-core Intel Xeon E5-2660v2 CPU.
Giraffe is able to play at the level of an FIDE International Master

Ref: arxiv.org/abs/1509.01549 **: Giraffe: Using Deep Reinforcement Learning to Play Chess**

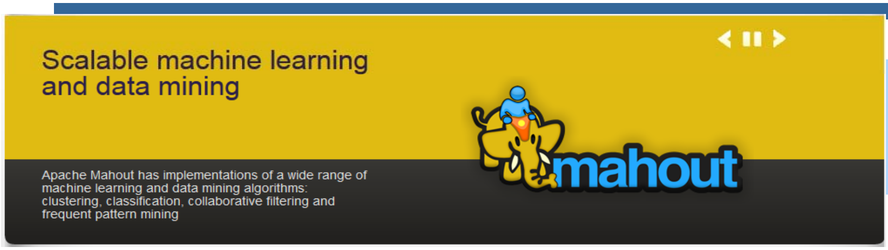
Mahout. Caso de estudio



Caso de estudio:
Random Forest para KddCup99



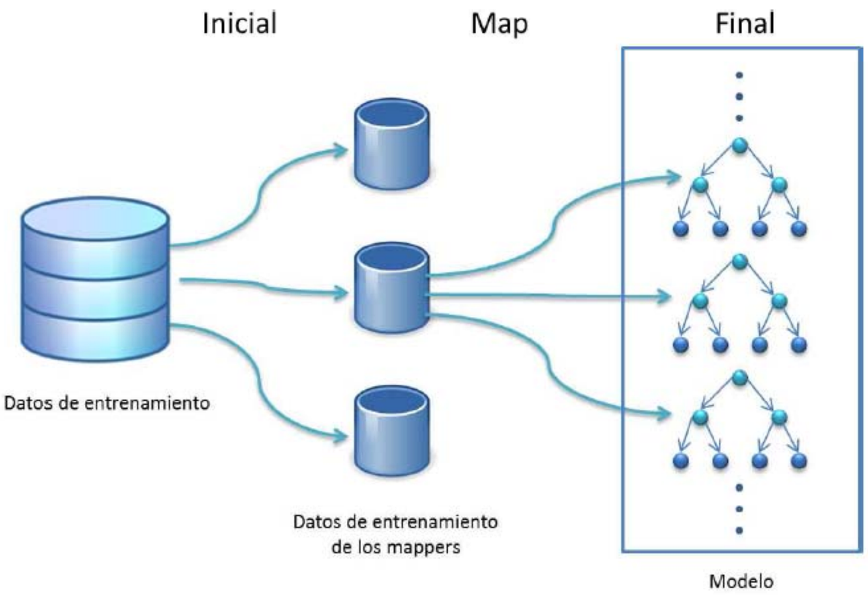
Mahout. Caso de estudio

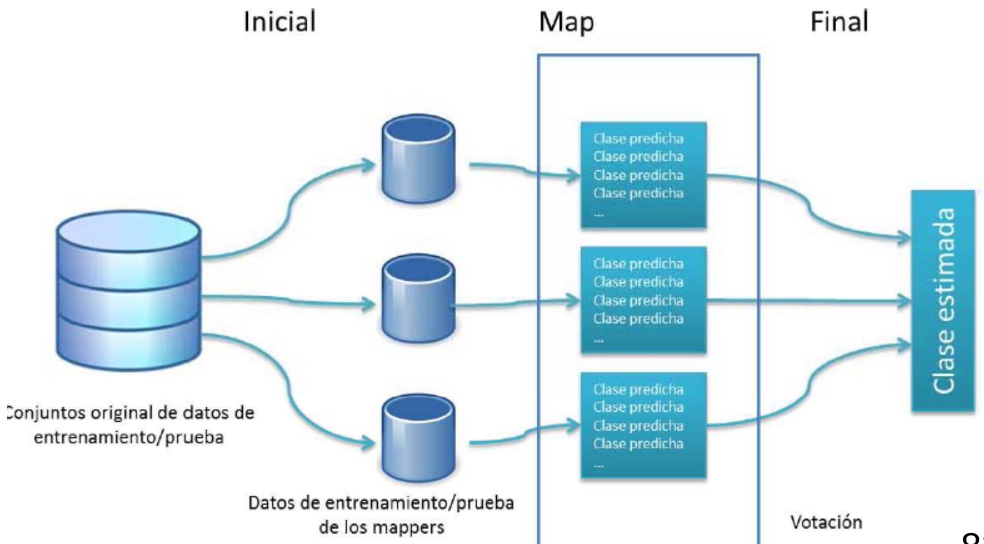


Caso de estudio:
Random Forest para KddCup99

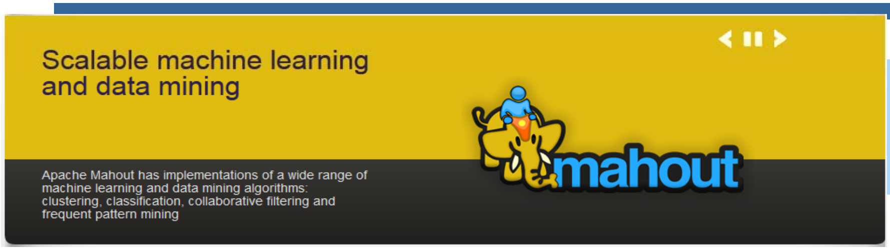
Implementación RF Mahout Partial: Es un algoritmo que genera varios árboles de diferentes partes de los datos (maps). Dos fases:

Fase de Construcción **Fase de Clasificación**





Mahout. Caso de estudio



Caso de estudio:
Random Forest para KddCup99

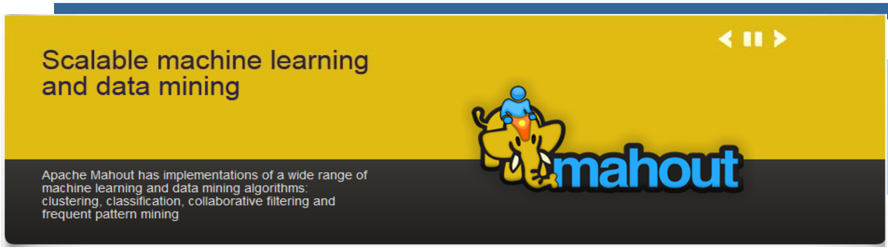
Class	Instance Number
normal	972.781
DOS	3.883.370
PRB	41.102
R2L	1.126
U2R	52

Tiempo en segundos para ejecución secuencial

Datasets	RF		
	10%	50%	full
DOS_versus_normal	6344.42	49134.78	NC
DOS_versus_PRB	4825.48	28819.03	NC
DOS_versus_R2L	4454.58	28073.79	NC
DOS_versus_U2R	3848.97	24774.03	NC
normal_versus_PRB	468.75	6011.70	NC
normal_versus_R2L	364.66	4773.09	14703.55
normal_versus_U2R	295.64	4785.66	14635.36

Cluster ATLAS: 16 nodos
-Microprocessors: 2 x Intel E5-2620 (6 cores/12 threads, 2 GHz)
- RAM 64 GB DDR3 ECC 1600MHz
- Mahout version 0.8

Mahout. Caso de estudio



Caso de estudio:
Random Forest para KddCup99

Class	Instance Number
normal	972.781
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PRB	41.102
R2L	1.126
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	10%	50%	full
DOS_versus_normal	6344.42	49134.78	NC
DOS_versus_PRB	4825.48	28819.03	NC

Tiempo en segundos para Big Data con 20 particiones

Datasets	RF-BigData		
	10%	50%	full
DOS_versus_normal	98	221	236
DOS_versus_PRB	100	186	190
DOS_versus_R2L	97	157	136
DOS_versus_U2R	93	134	122
normal_versus_PRB	94	58	72
normal_versus_R2L	92	39	69
normal_versus_U2R	93	52	64

Cluster ATLAS: 16 nodos
-Spark Random Forest: 43.50 seconds (20 partitions)

Aprendizaje no supervisado

Mahout

Clustering	Single Machine	MapReduce
Canopy Clustering	*deprecated*	*deprecated*
k-Means Clustering	x	x
Fuzzy k-Means	x	x
Streaming k-Means	x	x
Spectral Clustering		x

MLlib

- Frequent pattern mining
  - FP-growth

- Clustering
  - k-means
  - Gaussian mixture
  - power iteration clustering (PIC)
  - latent Dirichlet allocation (LDA)
  - streaming k-means

K-means

- **Mahout: The K-Means algorithm**
- **Input**
  - Dataset (set of points in 2D) –Large
  - Initial centroids (K points) –Small
- **Map Side**
  - Each map reads the K-centroids + one block from dataset
  - Assign each point to the closest centroid
  - Output <centroid, point>

R. M. Esteves, C. Rong, R. Pais, **K-means Clustering in the Cloud – A Mahout Test**. IEEE Workshops of International Conference on Advanced Information Networking and Applications, pp.514,519, 22-25 March 2011.

K-means

Mahout: K-means clustering

- **Reduce Side**
  - Gets all points for a given centroid
  - Re-compute a new centroid for this cluster
  - Output: <new centroid>
- **Iteration Control**
  - Compare the old and new set of K-centroids If similar or max iterations reached then Stop Else Start another Map-Reduce Iteration

- **THIS IS AN ITERATIVE MAP-REDUCE ALGORITHM**

K-means

- **Map phase: assign cluster IDs**

(x1, y1) , centroid1, centroid2, … → <cluster_n, (x1, y1)>

(x2, y2) , centroid1, centroid2, … → <cluster_m, (x2, y2)>

(x3, y3) , centroid1, centroid2, … → <cluster_i, (x3, y3)>

(x4, y4) , centroid1, centroid2, … → <cluster_k, (x4, y4)>

- **Reduce phase: reset centroids**

<cluster_n, (x1, y1)> → <cluster_n, centroid_n>

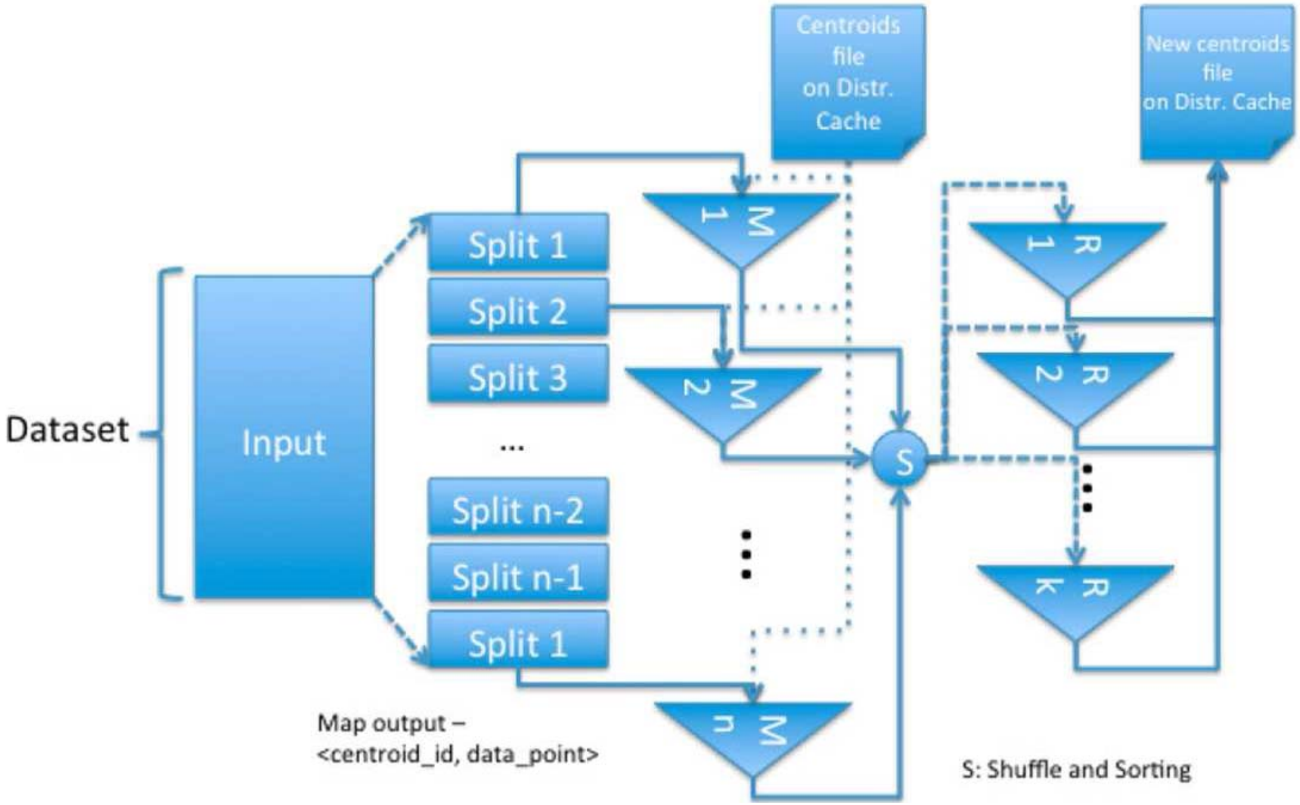
<cluster_m, (x2, y2)> → <cluster_m, centroid_m>

<cluster_i, (x3, y3)> → <cluster_i, centroid_i>

<cluster_k, (x4, y4)> → <cluster_k, centroid_k>

K-means

Mahout: K-means clustering



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K-means

K-Means: An example of limitation of MapReduce

- **What's wrong with these iterative approaches?**
  - Iterative algorithms in MapReduce chain multiple jobs together.
  - The standard MapReduce is not ready to do this.
  - Hadoop offers some snippets (Counters) to determine the stopping criteria.

- **Main issues:**
  - MapReduce jobs have high startup costs.
  - Repetitive Shuffle.
  - Results are serialized to HDFS.

K-means

K-Means Clustering using Spark

Focus: Implementation and Performance

K-means

MLlib: K-means clustering

k-means pseudo-code:

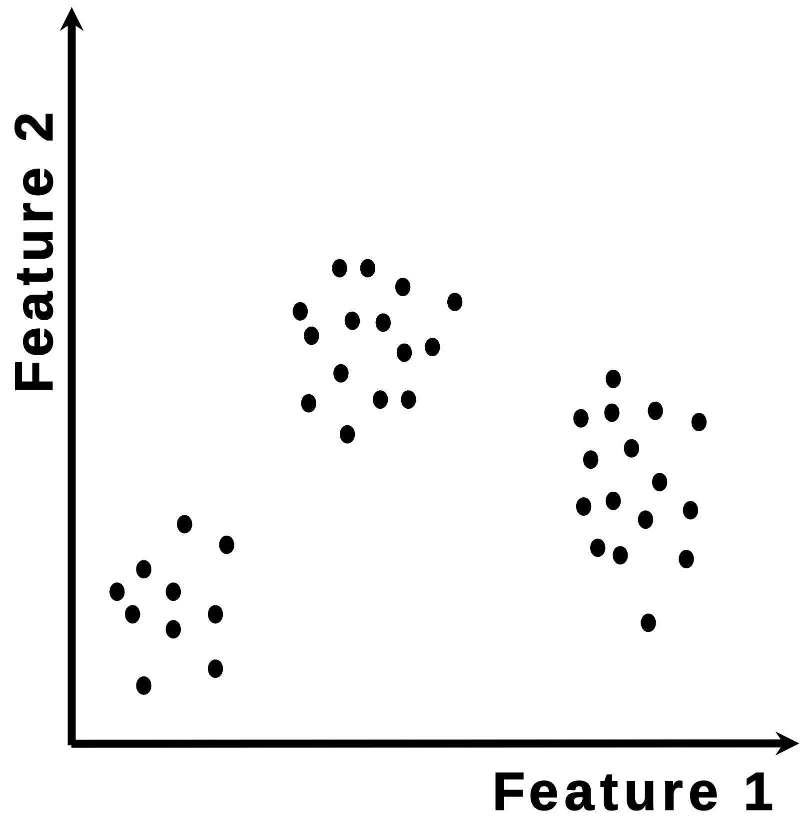
- Initialize K cluster centers
- Repeat until convergence:
  Assign each data point to the cluster with the closest center.
  Assign each cluster center to be the mean of its cluster's data points.

k-means MLlib source

```
centers = data.takeSample(
    false, K, seed)
while (d > ε)
{
 closest = data.map(p =>
     (closestPoint(p,centers),p))
 pointsGroup =
     closest.groupByKey()
 newCenters =pointsGroup.mapValues(
     ps => average(ps))
 d = distance(centers, newCenters)
 centers = newCenters.map(_)
}
```

K-Means Algorithm

- Initialize K cluster centers
- Repeat until convergence:
  - Assign each data point to the cluster with the closest center.
  - Assign each cluster center to be the mean of its cluster’s data points.



K-Means Algorithm

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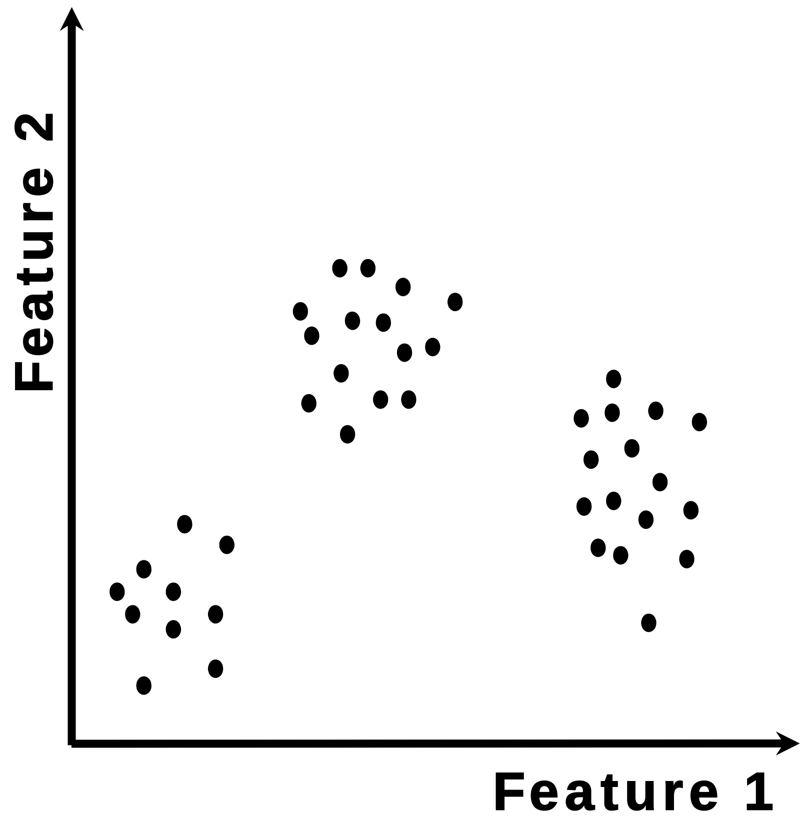

K-Means Algorithm

- **Initialize K cluster centers**

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centers = data.takeSample(
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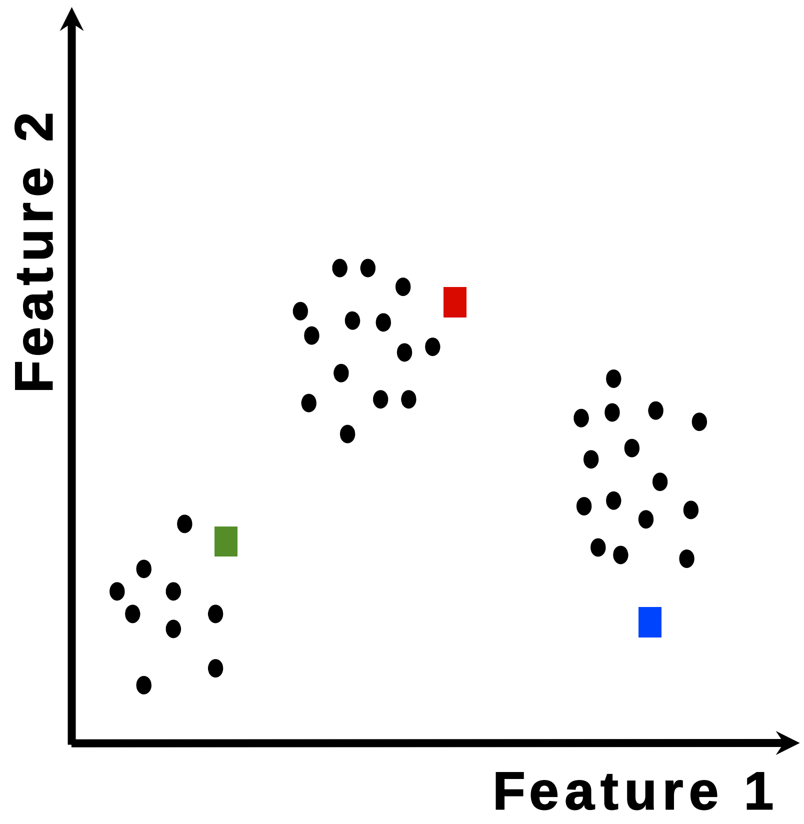

K-Means Algorithm

- Initialize K cluster centers

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centers = data.takeSample(
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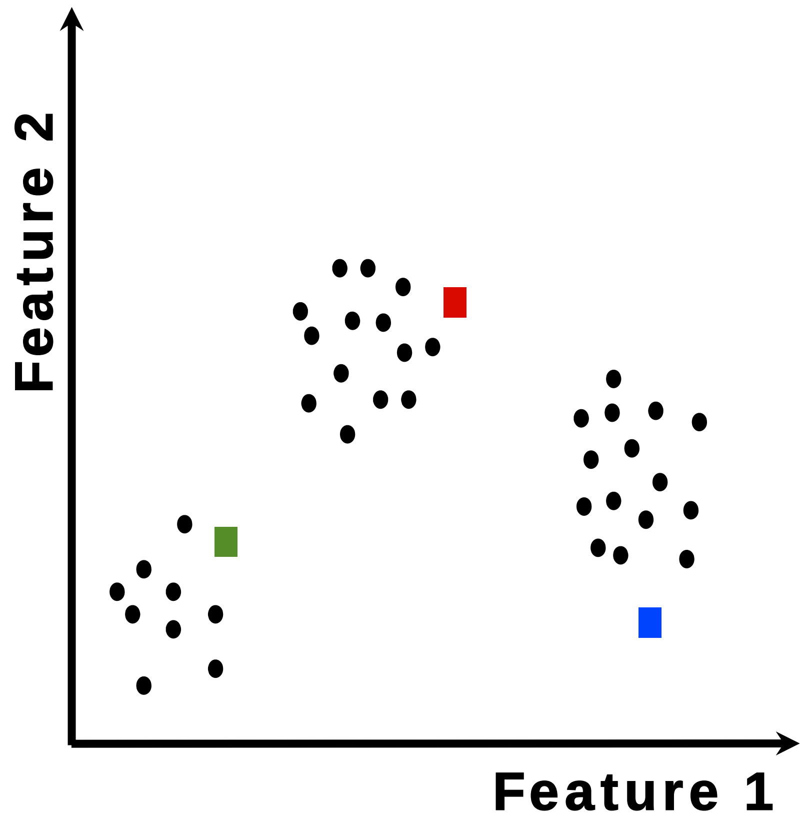

K-Means Algorithm

- Initialize K cluster centers

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    false, K, seed)
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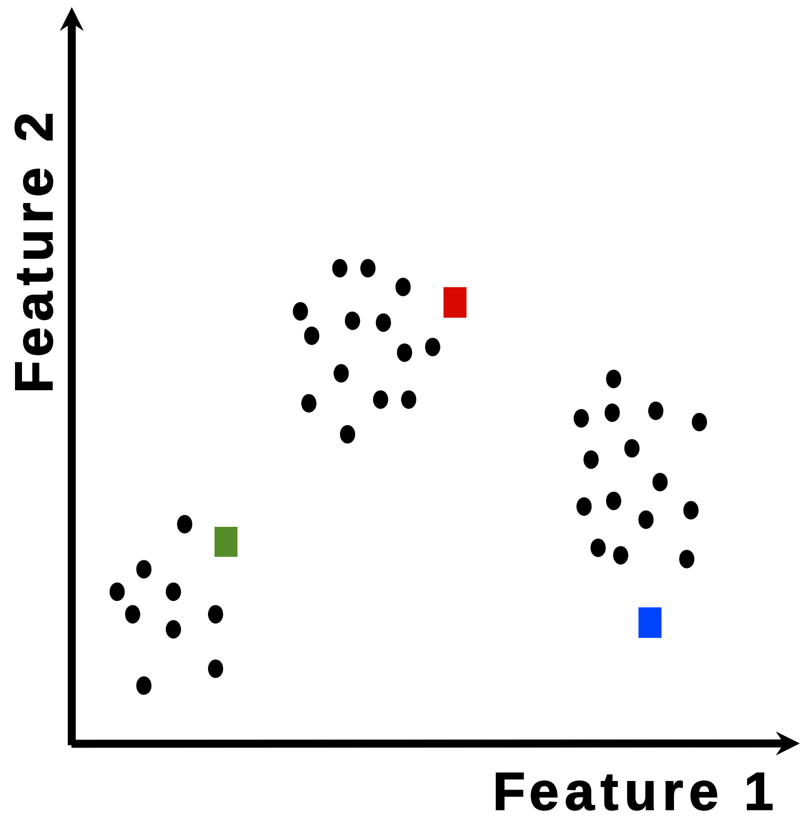


K-Means Algorithm

- Initialize K cluster centers

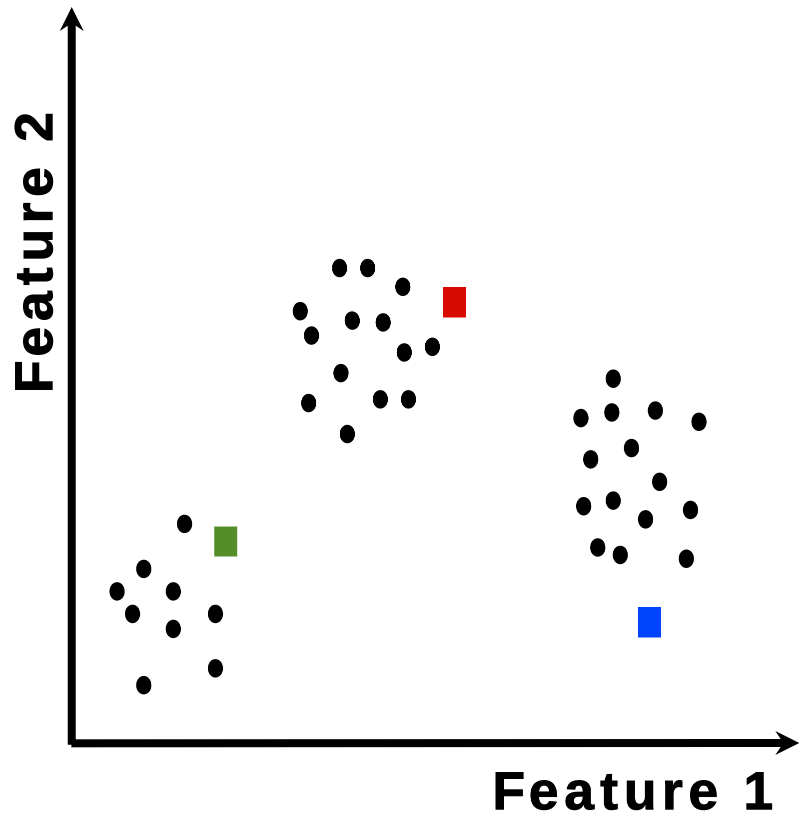
```
centers = data.takeSample(
    false, K, seed)
```

- Repeat until convergence:

```
closest = data.map(p =>

(closestPoint(p,centers),p))
```

Assign each cluster center to be the mean of its cluster's data points.



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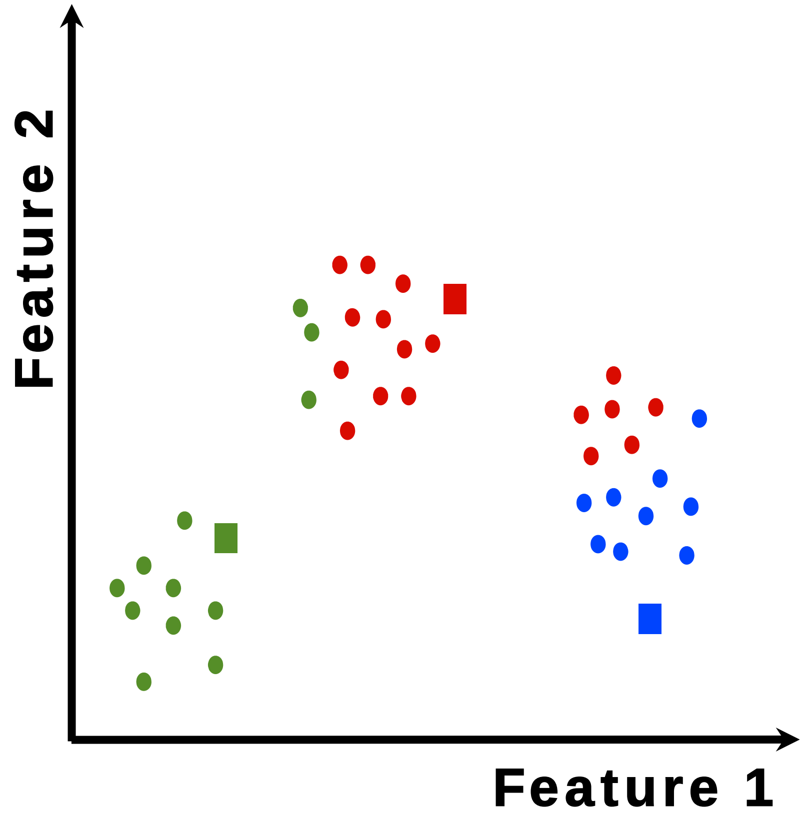

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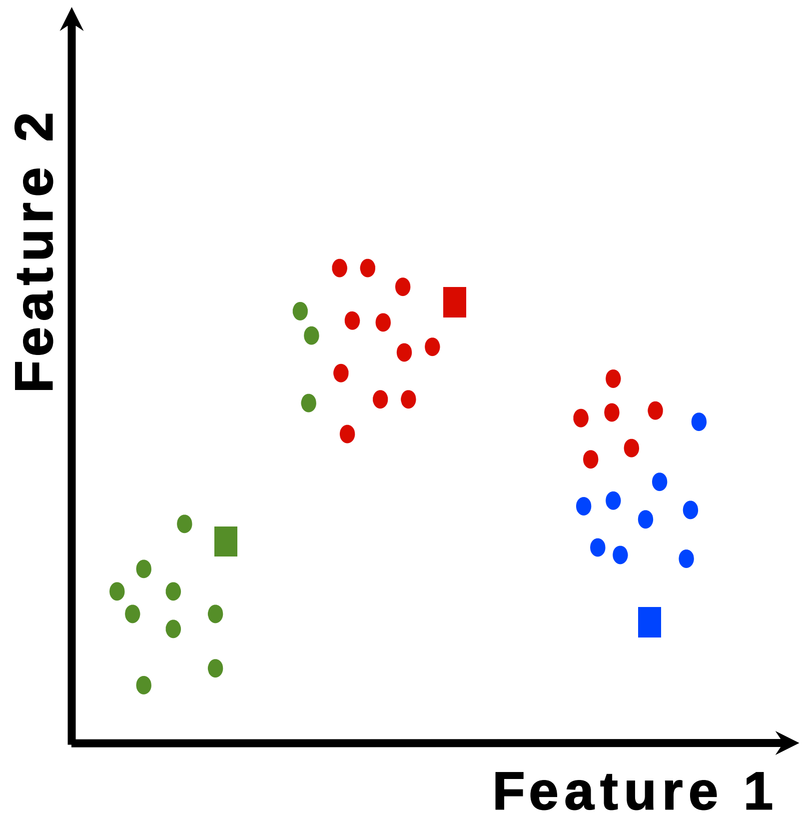

K-Means Algorithm

- Initialize K cluster centers

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centers =data.takeSample(
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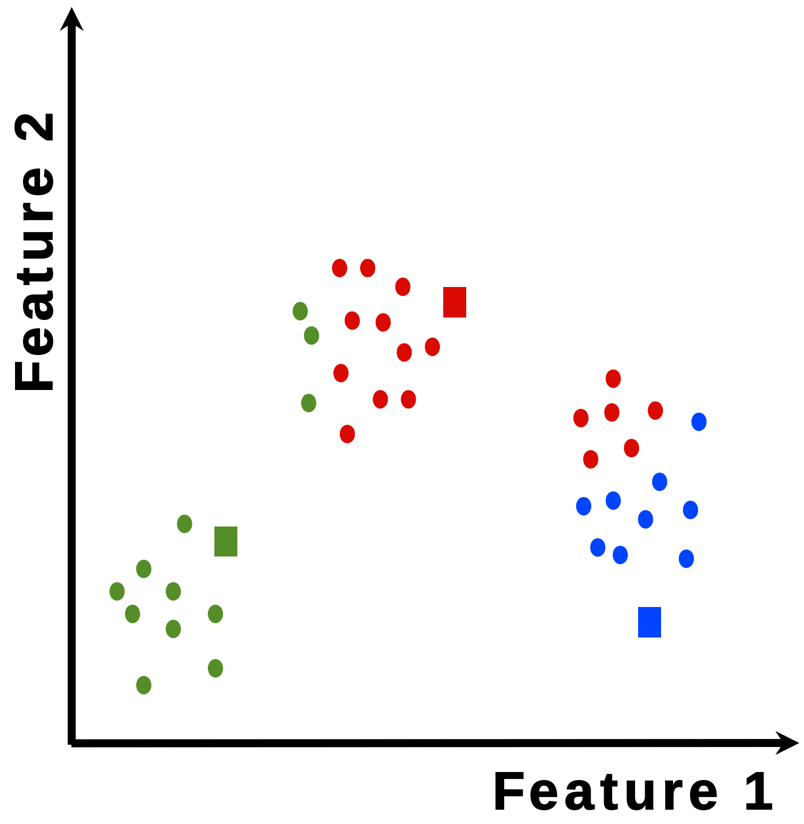
```

- Repeat until convergence:

```
closest = data.map(p =>

(closestPoint(p,centers),p))

pointsGroup =
    closest.groupByKey()
```



K-Means Algorithm

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```

- Repeat until convergence:

```
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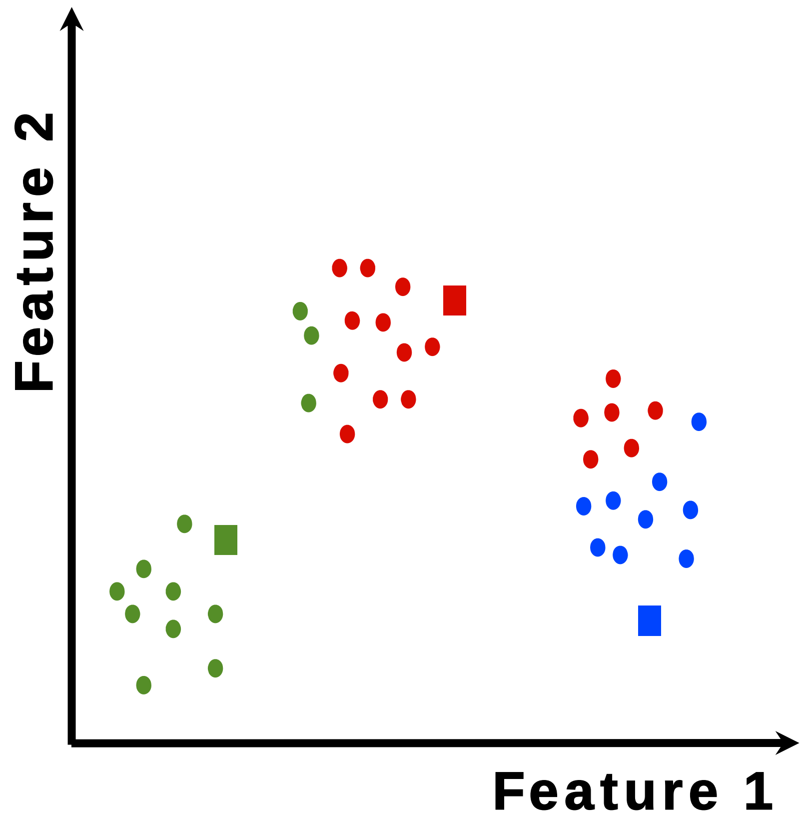
pointsGroup =
    closest.groupByKey()

newCenters =
pointsGroup.mapValues(
    ps => average(ps))
```



K-Means Algorithm

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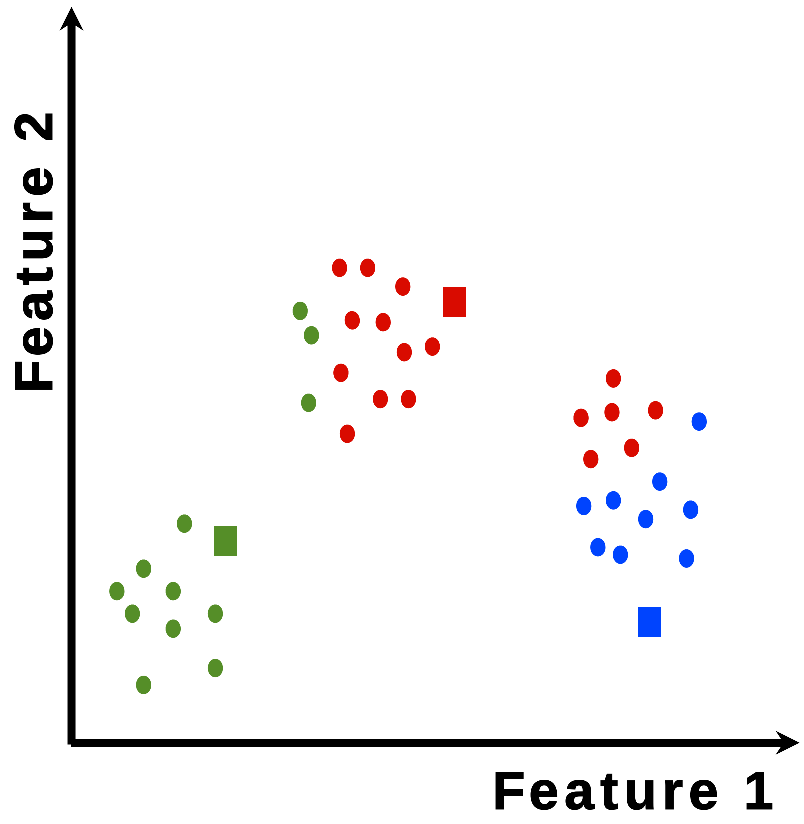

K-Means Algorithm (proceso interativo utilizando los bloques en memoria)

- Initialize K cluster centers

```
centers = data.takeSample(
    false, K, seed)
```

- **Repeat until convergence:**

```
closest = data.map(p =>

  (closestPoint(p,centers),p))
pointsGroup =
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newCenters =
pointsGroup.mapValues(
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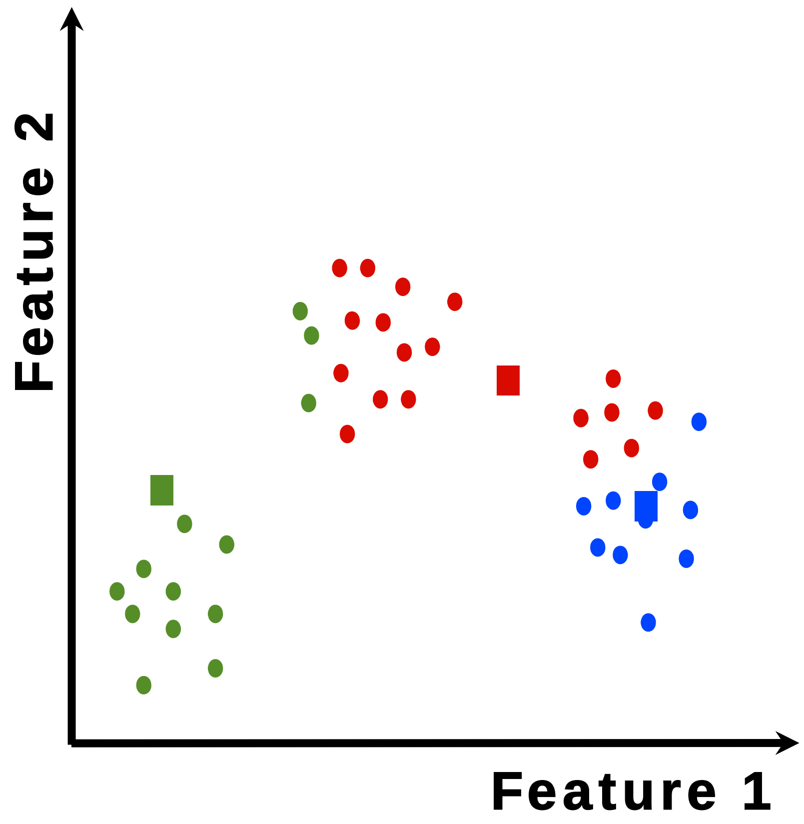


K-Means Algorithm

- Initialize K cluster centers

```
centers = data.takeSample(
    false, K, seed)
```

- **Repeat until convergence:**

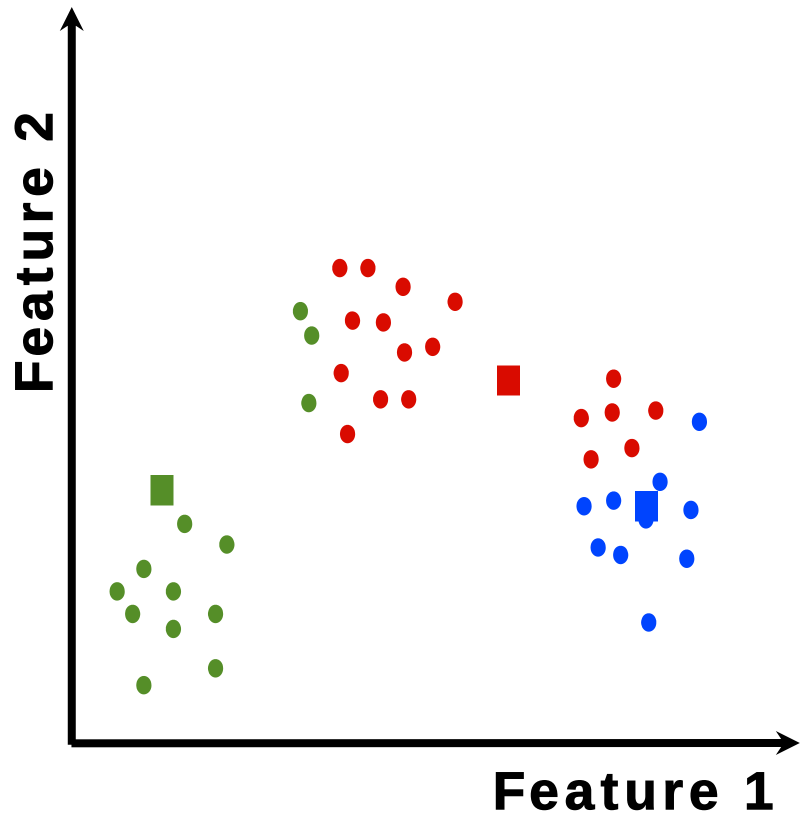
```
while (dist(centers, newCenters) > ε)

closest = data.map(p =>

(closestPoint(p,centers),p))

pointsGroup =
    closest.groupByKey()

newCenters =pointsGroup.mapValues(
    ps => average(ps))
```



K-Means Algorithm

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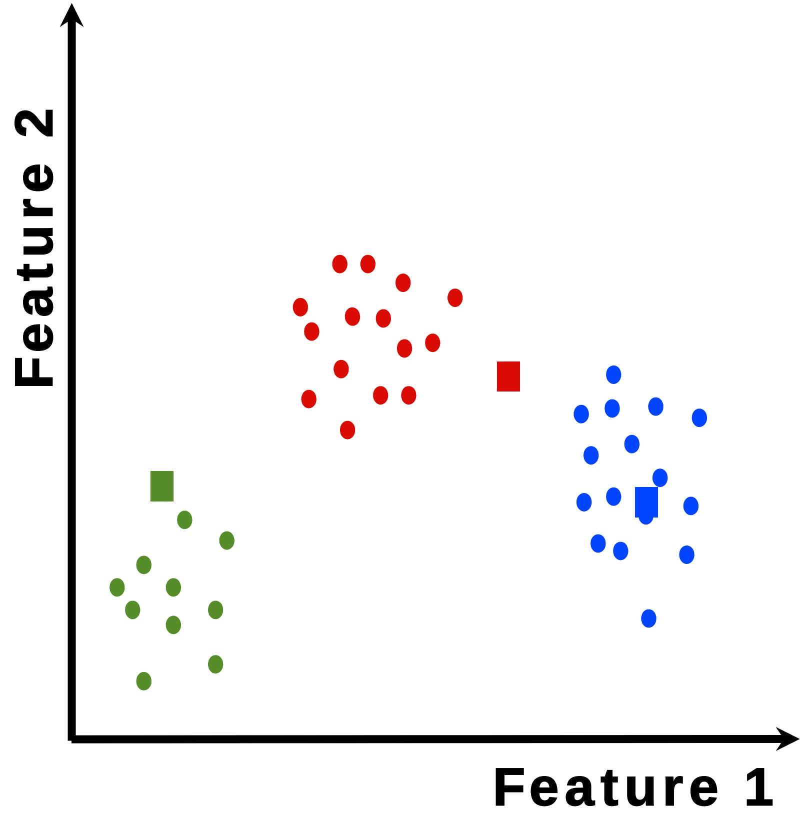

K-Means Source

```
centers = data.takeSample(
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while (d > ε)
{
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  pointsGroup =
      closest.groupByKey()

  d = distance(centers, newCenters)

  newCenters
  =pointsGroup.mapValues(
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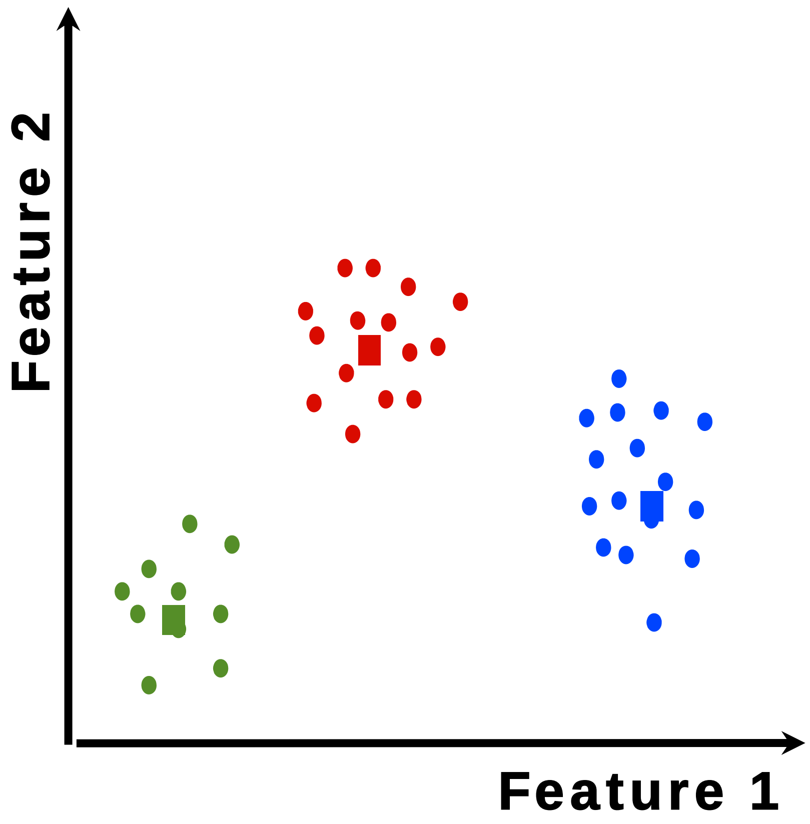
  centers = newCenters.map(_)

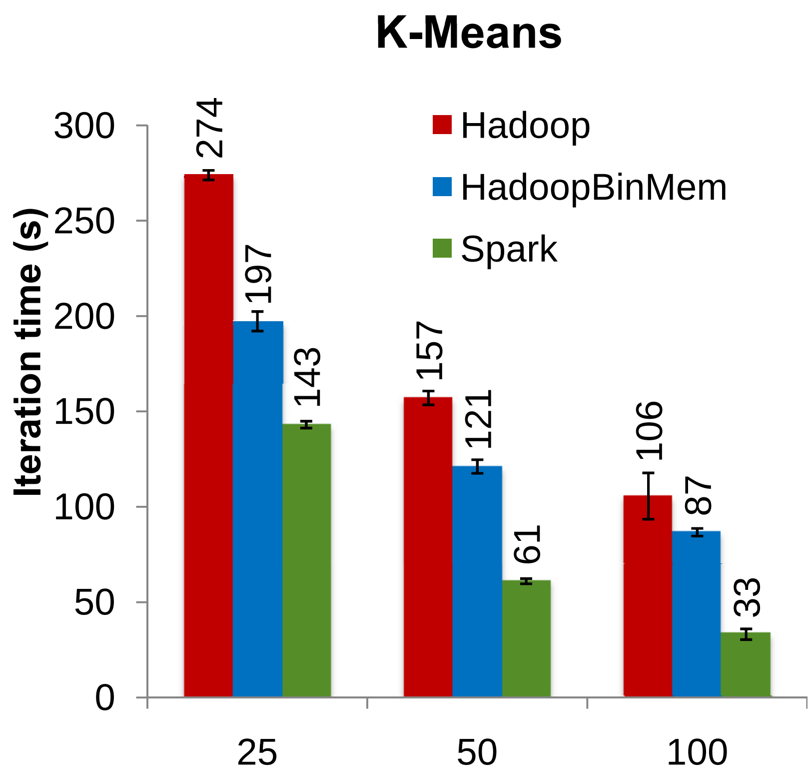
}
```



K-Means Performance

Lines of code for K-Means
Spark ~ 90 lines –

Hadoop ~ 4 files, > 300 lines



[Zaharia et. al, NSDI'12]

Aprendizaje no supervisado

MLlib: FP-growth

Mllib implements a parallel version of FP-growth called PFP, as described in

Li et al., PFP: Parallel FP-growth for query recommendation. RecSys'08 Proceedings of the 2008 ACM conference on Recommender systems Pages 107-114

PFP distributes the work of growing FP-trees based on the suffices of transactions, and hence more scalable than a single-machine implementation.

Big Data Analytics: 3 Comentarios finales

Image Credit: [Shutterstock]()

Without Analytics, Big Data is Just Noise

Guest post by Eric Schwartzman, founder and CEO of [Comply Socially]()

http://www.briansolis.com/2013/04/without-analytics-big-data-is-just-noise/

Big Data Analytics: 3 Comentarios finales

Mahout

Classification	Single Machine	MapReduce
Logistic Regression - trained via SGD	x	
Naive Bayes / Complementary Naive Bayes		x
Random Forest		x
Hidden Markov Models	x	
Multilayer Perceptron	x	

Casi ausencia de algoritmos para big data preprocessing

MLlib

MLlib types, algorithms and utilities

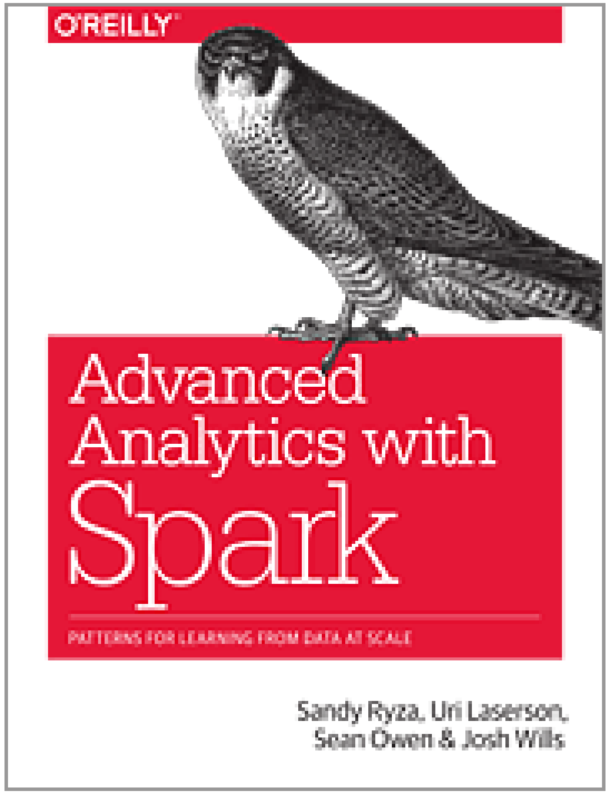
This lists functionality included in spark.mllib, the main MLlib API.

- Data types
- Basic statistics
  - summary statistics
  - correlations
  - stratified sampling
  - hypothesis testing
  - random data generation
- Classification and regression
  - linear models (SVMs, logistic regression, linear regression)
  - naive Bayes
  - decision trees
  - ensembles of trees (Random Forests and Gradient-Boosted Trees)
  - isotonic regression
- Collaborative filtering
  - alternating least squares (ALS)
- Clustering
  - k-means
  - Gaussian mixture
  - power iteration clustering (PIC)
  - latent Dirichlet allocation (LDA)
  - streaming k-means
- Dimensionality reduction
  - singular value decomposition (SVD)
  - principal component analysis (PCA)
- Feature extraction and transformation
- Frequent pattern mining
  - FP-growth
- Optimization (developer)
  - stochastic gradient descent
  - limited-memory BFGS (L-BFGS)
- PMML model export

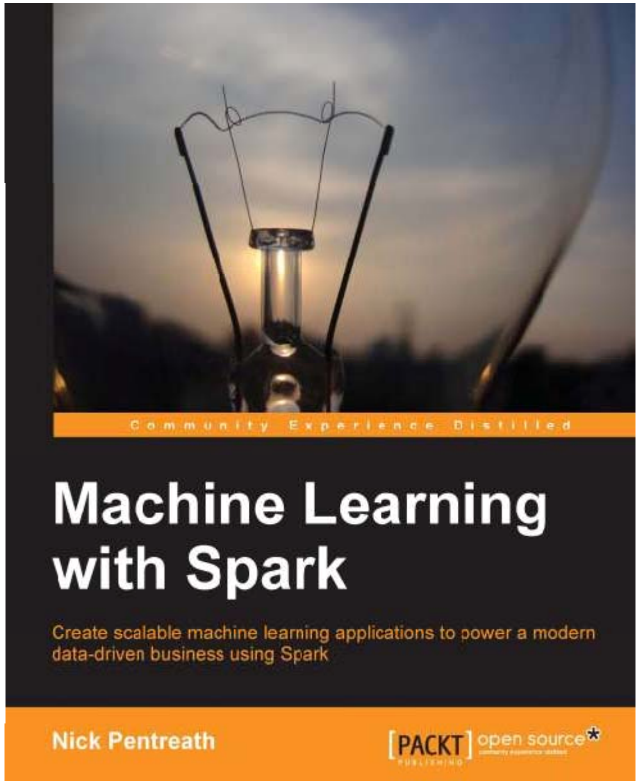
https://spark.apache.org/mllib/

Version 1.4.1

Big Data Analytics: 2 libros

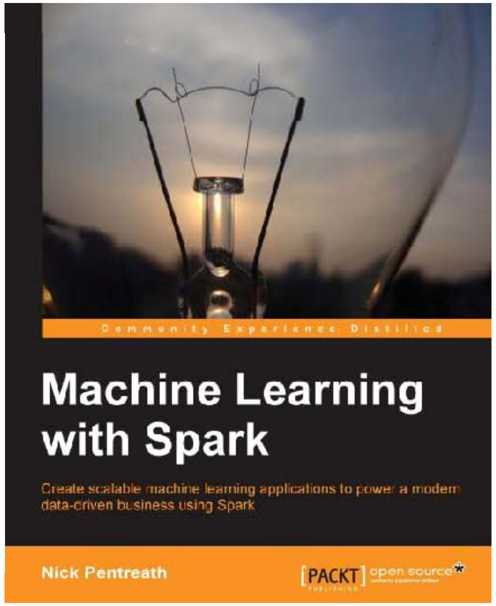


9 cases of study



10 chapters giving a quick glance on Machine Learning with Spark

Big Data Preprocessing



A short introduction to data preparation with Spark – Chapter 3

Chapter 3: Obtaining, Processing, and Preparing Data with Spark

Big Data Preprocessing

https://spark.apache.org/docs/latest/mllib-guide.html

MLlib - Feature Extraction and Transformation

- TF-IDF
- Word2Vec
  - Model
  - Example
- StandardScaler
  - Model Fitting
  - Example
- Normalizer
  - Example
- Feature selection
  - ChiSqSelector
    - Model Fitting
    - Example

Spark MLlib

MLlib - Dimensionality Reduction

- Singular value decomposition (SVD)
  - Performance
  - SVD Example
- Principal component analysis (PCA)

ChiSqSelector

ChiSqSelector stands for Chi-Squared feature selection. It operates on labeled data with categorical features. ChiSqSelector orders features based on a Chi-Squared test of independence from the class, and then filters (selects) the top features which are most closely related to the label.

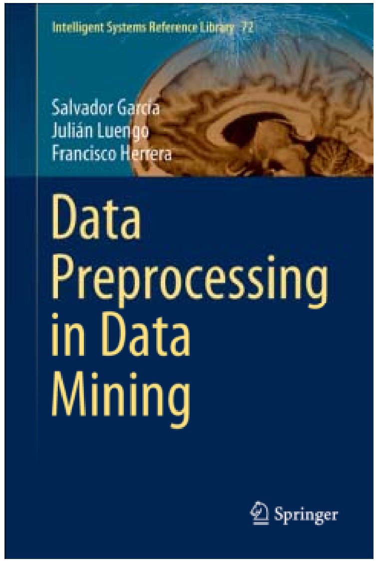
Model Fitting

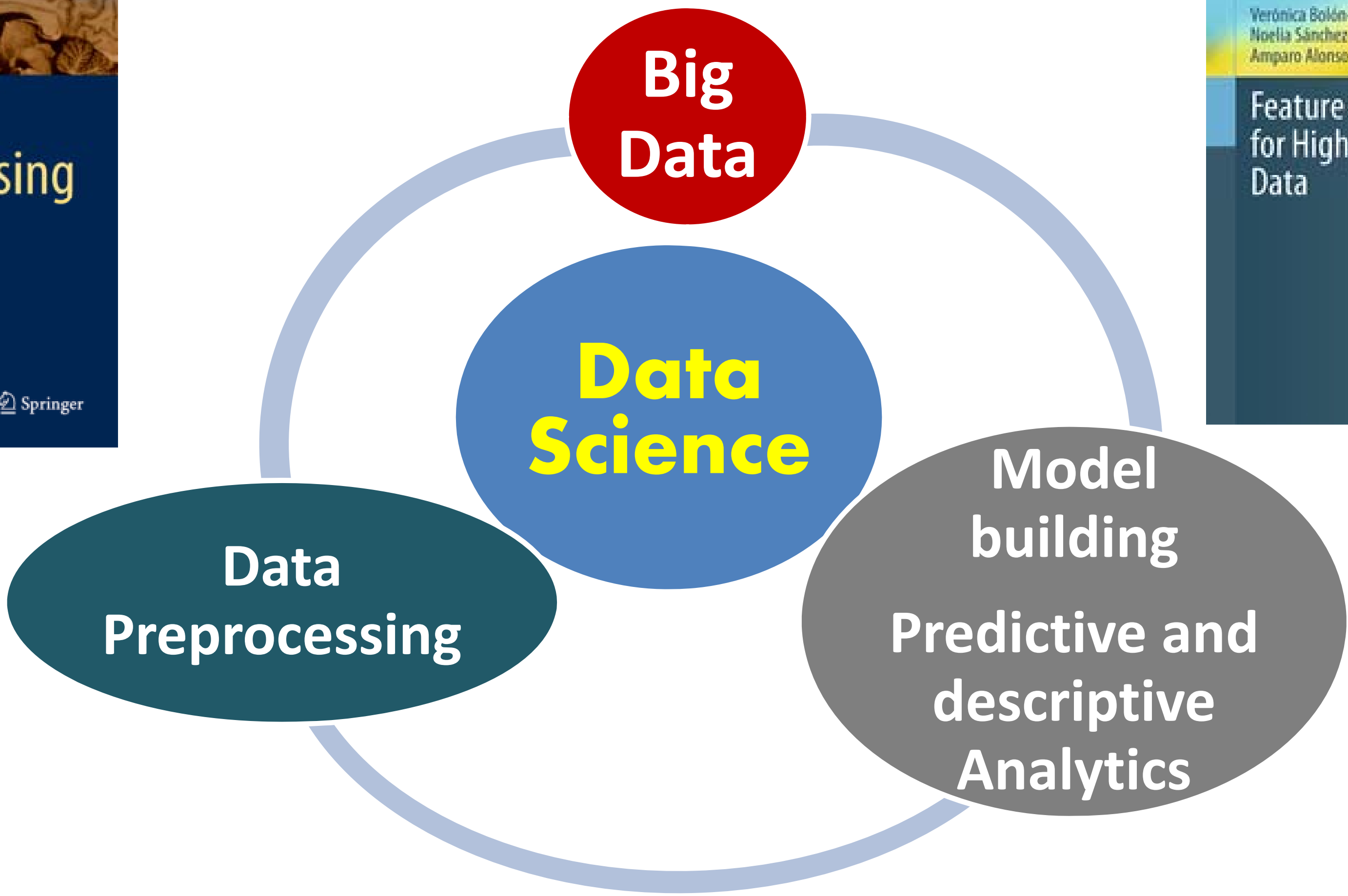
ChiSqSelector has the following parameter in the constructor:

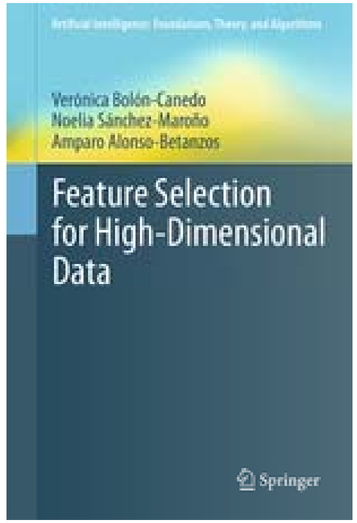
- numTopFeatures number of top features that the selector will select (filter).

Big Data Analytics:
Big Data Preprocessing

¡Se requieren datos de calidad para diseñar modelos de calidad!.







Preprocesamiento de datos en Big Bata

2 propuestas recientes (UGR-UdC): (Journal submission)

An Information Theoretic Feature Selection Framework for Big Data under Apache Spark

Sergio Ramírez-Gallego, Héctor Mouriño-Talín, David Martínez-Rego, Verónica Bolón-Canedo, Amparo Alonso-Betanzos, José Manuel Benítez, and Francisco Herrera

Algorithm 1 Main FS Algorithm

```
Input: D                                                        Data set
Input: |S_θ|                                                    Number of features to select
Output: S_θ                                                     Index list of selected features
  calcs ← calculateRelevances(D)
  criterions ← initCriterions(calcs)
  p_best ← extractTopRelevant(criterions, 1)
  S ← Set(p_best)
  while |S| < |S_θ| do
    calcs ← calculateMIAndCMI(criterions, p_best)
    criterions ← updateCriterions(criterions, calcs)
    p_best ← extractTopCriterions(criterions, 1)
    S ← addTo(p_best, S)
  end while
  return S
```

Preprocesamiento de datos en Big Bata

2 propuestas recientes (UGR-UdC): (WIRES DMKD)

Distributed Entropy Minimization Discretizer for Big Data Analysis under Apache Spark

Sergio Ramírez-Gallego*, Salvador García* Héctor Mouriño-Talín†, David Martínez-Rego†‡, Verónica Bolón-Canedo†, Amparo Alonso-Betanzos†, José Manuel Benítez* and Francisco Herrera*

IEEE BigDataSE, 2015

Journal contribution:

S. Ramírez-Gallego, S. García, H. Mouriño-Talin, D. Martínez-Rego, V. Bolón, A. Alonso-Betanzos, J.M. Benitez, F. Herrera. ***"Data Discretization: Taxonomy and Big Data Challenge",*** **WIRES Data Mining and Knowledge Discovery, 2016, In press.**

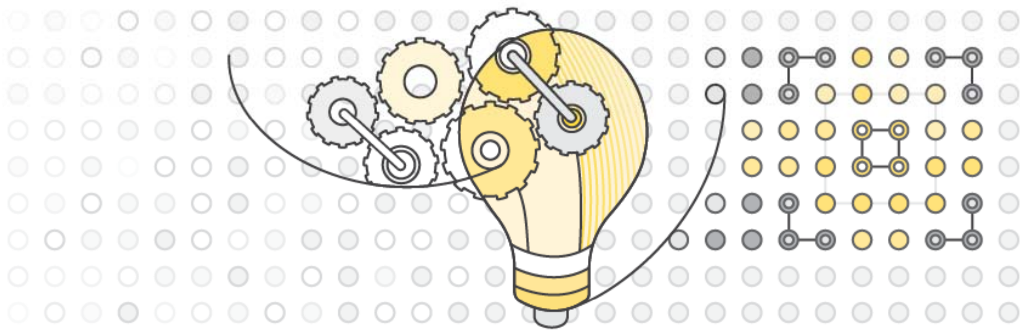
Algorithm 1 Main discretization procedure

```
Input: S Data set
Input: M Feature indexes to discretize
Input: maxbins Maximum number of cut points to select
Input: maxcand Maximum number of candidates per partition
Output: Thresholds Cut points by feature
comb ←
map s ∈ S
    v ← zeros(k)
    v(c) ← 1
    for all A ∈ M do
        EMIT < (A, A(s)), v >
    end for
end map
distinct ← reduce(comb, sum_vectors)
sorted ← sort_by_key(distinct)
first ← first_by_part(sorted)
boundaries ← get_boundary_points(sorted, first)
boundaries ←
map b ∈ boundaries
    < (att, point, )q >← b
    EMIT < (att, (point, q)) >
end map
(small, big) ← divide_attributes(boundaries, maxcand)
sthresholds ← select_thresholds(small, maxbins, maxcand
for all att ∈ keys(big) do
    bthresholds ← bthresholds +
select_thresholds(big(att), maxbins, maxcand)
end for
return(union(bthresholds, sthresholds))
```

Big Data Analytics: 3 Comentarios finales

Amazon Machine Learning

Amazon Machine Learning es un servicio que facilita a desarrolladores de todos los niveles de habilidad el uso de la tecnología de aprendizaje automático. Amazon Machine Learning proporciona asistentes y herramientas de visualización que le guían a lo largo del proceso de creación de modelos de aprendizaje automático (ML) sin tener que aprender complicados algoritmos y tecnología de ML. Una vez que los modelos están listos, Amazon Machine Learning le permite obtener predicciones de su aplicación con facilidad utilizando API sencillas, sin tener que implementar código de generación de predicciones personalizado ni gestionar infraestructuras.



Se ofertan tecnologías para clasificación, predicción y recomendaciones, con un enfoque de servicio que puede parecer que prescinde del profesional de la analítica. **¿?**

¿Oportunidad o amenaza para los expertos en Ciencia de Datos?

Los expertos son necesarios en el uso de herramientas de Analytics y Big Data.

https://aws.amazon.com/es/machine-learning/

Índice

- **Big Data. Big Data Science**
- **¿Por qué Big Data? Google crea el Modelo de Programación MapReduce**
- **Tecnologías para Big Data: Ecosistema Hadoop (Hadoop, Spark, …)**
- **Big Data Analytics: Librerías para Analítica de Datos en Big Data. Casos de estudio**
- **Algunas aplicaciones: Salud, Social Media, Identificación**
- Big Data en el grupo de investigación SCI^{2}S
- Comentarios Finales

Algunas aplicaciones: Salud

HEALTHCARE ORGANIZATIONS HAVE COLLECTED EXABYTES OF DATA LAST YEARS

BIG DATA AND DISEASE PREVENTION:

From Quantified Self to Quantified Communities

Meredith A. Barrett,[1,2] Olivier Humblet,[1,2*] Robert A. Hiatt,[3] and Nancy E. Adler[1]*

Big data can facilitate action on the modifiable risk factors that contribute to a large fraction of the chronic disease burden, such as physical activity, diet, tobacco use, and exposure to pollution.

Big Data, Vol.1, 3, 2013

Wikipedia y la detección de la gripe

Wikipedia is better than Google at tracking flu trends?

Detect pandemic risk in real time

Wikipedia traffic could be used to provide real time tracking of flu cases, according to the study published by John Brownstein.

Wikipedia Usage Estimates Prevalence of Influenza-Like Illness in the United States in Near Real-Time
David J. McIver , John S. Brownstein**,** Harvard Medical School, Boston Children's Hospital, Plos Computational Biology, 2014.

Redes sociales, big data y medidas de salud pública

Studies: Health, Social Media and Big Data

You Are What You Tweet: Analyzing Twitter for Public Health

Discovering Health Topics in Social Media Using Topic Models
Michael J. Paul, Mark Dredze, Johns Hopkins University, Plos One, 2014

Analyzing user messages in social media can measure different population characteristics, including public health measures.

A system filtering Twitter data can automatically infer health topics in 144 million Twitter messages from 2011 to 2013. ATAM discovered 13 coherent clusters of Twitter messages, some of which correlate with seasonal influenza (r = 0.689) and allergies (r = 0.810) temporal surveillance data, as well as exercise (r = .534) and obesity (r =2.631) related geographic survey data in the United States.

Algunas aplicaciones

TV AUDIENCE MEASUREMENT WITH BIG DATA

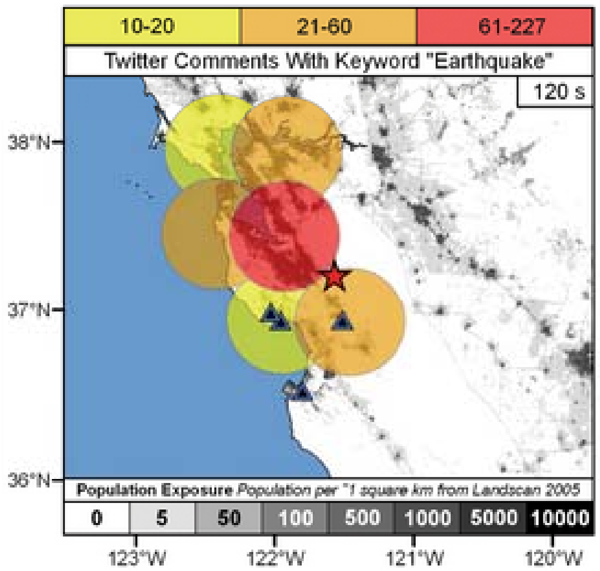
Shawndra Hill
Operations and Information Management,
University of Pennsylvania, Philadelphia, Pennsylvania

"COMBINING MARKETING AND INFORMATION SYSTEMS METHODS, SOCIAL MEDIA TEXT MINING, AND TRADITIONAL CLV METHODS, WE ARE ABLE TO PREDICT FUTURE VIEWERSHIP ON AN INDIVIDUAL LEVEL."

Algunas aplicaciones

Earthquakes and Social Media

U.S. Geological Survey: Twitter Earthquake Detector (TED)



The United States Geological Survey Twitter searches increases in the volume of messages on earthquake and has been able to locate earthquakes with 90% accuracy.

Algunas aplicaciones: La banca es un ámbito de aplicación importante

Expansión.com

Domingo, 08.12.13. Actualizado a las 11:02

BBVA da un paso al frente en 'big data'

El banco ha actualizado todo su sistema de almacenamiento de datos corporativo para tener acceso desde un único punto a todas las 'islas de información' de la entidad en el mundo y consolidarse como un referente mundial en innovación tecnológica.

BBVA

Innova Challenge API

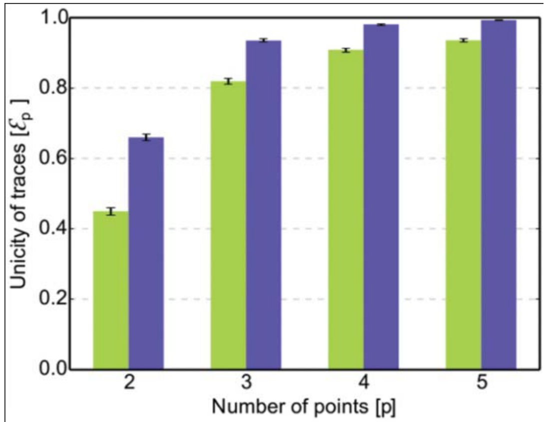
Available statistics services

Algunas aplicaciones

PRIVACIDAD EN INTERNET »

Cuatro compras con la tarjeta bastan para identificar a cualquier persona

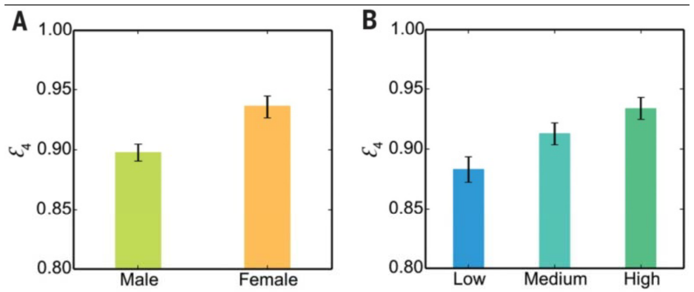
- Los patrones de uso de las tarjetas permiten descubrir la identidad del 90% de una muestra de 1,1 millones de personas anónimas, según demuestra un estudio del MIT



IDENTITY AND PRIVACY

Unique in the shopping mall: On the reidentifiability of credit card metadata

Yves-Alexandre de Montjoye,[1]* Laura Radaelli,[2] Vivek Kumar Singh,[1,3] Alex "Sandy" Pentland[1]



Large-scale data sets of human behavior have the potential to fundamentally transform the way we fight diseases, design cities, or perform research. Metadata, however, contain sensitive information. Understanding the privacy of these data sets is key to their broad use and, ultimately, their impact. We study 3 months of credit card records for 1.1 million people and show that four spatiotemporal points are enough to uniquely reidentify 90% of individuals. We show that knowing the price of a transaction increases the risk of reidentification by 22%, on average. Finally, we show that even data sets that provide coarse information at any or all of the dimensions provide little anonymity and that women are more reidentifiable than men in credit card metadata.

http://www.sciencemag.org/content/347/6221/536

http://elpais.com/elpais/2015/01/29/ciencia/1422520042_066660.html

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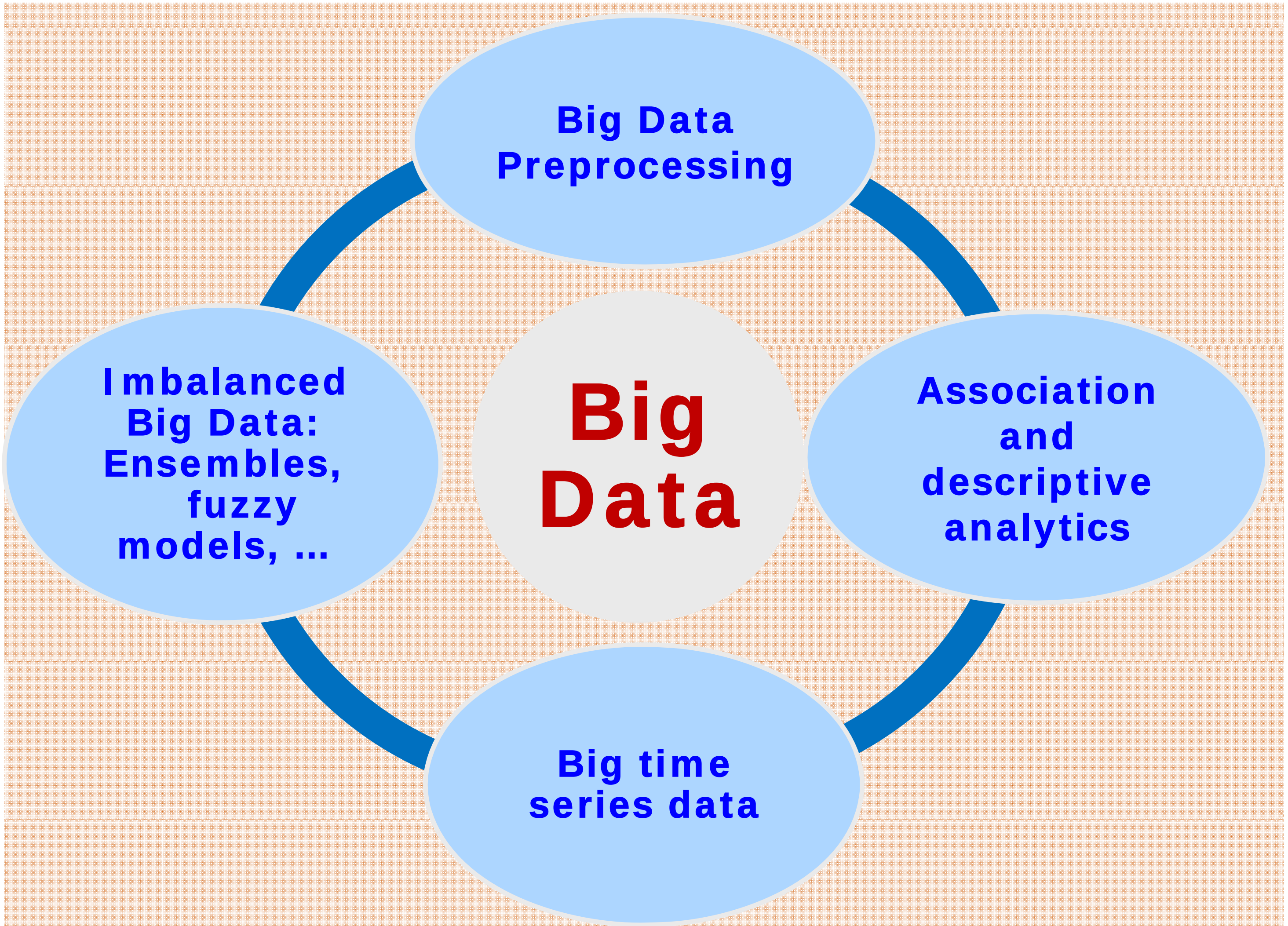
Big Data at SCI²S - UGR

http://sci2s.ugr.es/BigData



Big Data at SCI^{2}S - UGR

http://sci2s.ugr.es/BigData

SCI^{2}S website

Home » Thematic Sites » Big Data: Algorithms for Data Preprocessing, Computational Intelligence, and Imbalanced Classes

Big Data: Algorithms for Data Preprocessing, Computational Intelligence, and Imbalanced Classes

The web is organized according to the following summary:

1. Introduction to Big Data
2. Big Data Technologies: Hadoop ecosystem and Spark
3. Big Data preprocessing
4. Imbalanced Big Data classification
5. Big Data classification with fuzzy models
6. Big Data Applications
7. Dataset Repository
8. Literature review: surveys and overviews
9. Keynote slides
10. Links of interest

This **Website** contains SCI^{2}S research material on algorithms for data preprocessing, computational intelligence and classification with imbalanced datasets in the scenario of Big Data. All information shown here is related to the following SCI^{2}S review and papers:

Big Data at SCI^{2}S - UGR

http://sci2s.ugr.es/BigData

Nuestros modelos: Big Data with Fuzzy Models

Fuzzy Rule Based System for classification

Fuzzy Rule Based System with cost sensitive for imbalanced data sets

Sara Del Río

https://github.com/saradelrio

Chi-FRBCS-BigData-Ave
Chi-FRBCS-BigData-Ave: MapReduce implementation of the Chi et al.'s approach.

Chi-FRBCS-BigData-Max
Chi-FRBCS-BigData-Max: MapReduce implementation of the Chi et al.'s approach.

Chi-FRBCS-BigDataCS
Chi-FRBCS-BigDataCS: MapReduce implementation of the basic Chi et al.'s algorithm

Big Data at SCI²S - UGR

http://sci2s.ugr.es/BigData

Nuestros modelos: Imbalanced Big Data

Preprocessing: Random undersampling, oversampling
Cost sensitive

Sara Del Río

https://github.com/saradelrio

[hadoop-imbalanced-preprocessing](#)
MapReduce implementations of random oversampling, random undersampling and "Sy Echnique" (SMOTE) algorithms using Hadoop

[RF-BigDataCS](#)
RF-BigDataCS: A cost-sensitive approach for Random Forest MapReduce algorithm to

Bioinformatic Applications

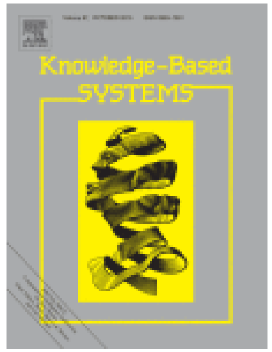
Research Article

Provisional PDF

An Effective Big Data Supervised Imbalanced Classification Approach for Ortholog Detection in Related Yeast Species

Deborah Galpert Cañizares, Sara del Río, Francisco Herrera, Evys Ancede Gallardo, Agostinho Antunes, and Guillermin Agüero-Chapin

ROSEFW-RF: The winner algorithm for the ECBDL'14 big data competition: An extremely imbalanced big data bioinformatics problem Original Research Article
Pages 69-79
Isaac Triguero, Sara del Río, Victoria López, Jaume Bacardit, José M. Benítez, Francisco Herrera



Big Data at SCI^{2}S - UGR

http://sci2s.ugr.es/BigData

Nuestros modelos: Big Data Preprocessing

Isaac Triguero

Evolutionary data reduction

https://github.com/triguero

Popular repositories

MR-EFS
This project includes the implementation of evolutionary feature s

MRPR
This repository includes the MapReduce implementation propose

ROSEFW-RF
This project contains the code used in the ROSEFW-RF paper.

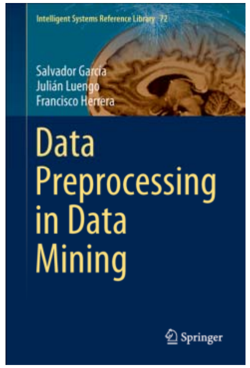
Spark Packages — Feedback — Register a package — Login

spark-MDLP-discretization (homepage)
Spark implementation of Fayyad's discretizer based on Minimum Description Length Principle (MDLP)
@sramirez / ★★★★★ (4)

Spark Packages — Feedback — Register a package — Login

spark-infotheoretic-feature-selection (homepage)
Feature Selection framework based on Information Theory that includes: mRMR, InfoGain, JMI and other commonly used FS filters.
@sramirez / ★★★★★ (4)

BIG DATA Preprocessing



Sergio Ramírez

Feature selection and discretization

https://github.com/sramirez

fast-mRMR
An improved implementation of the classical f...

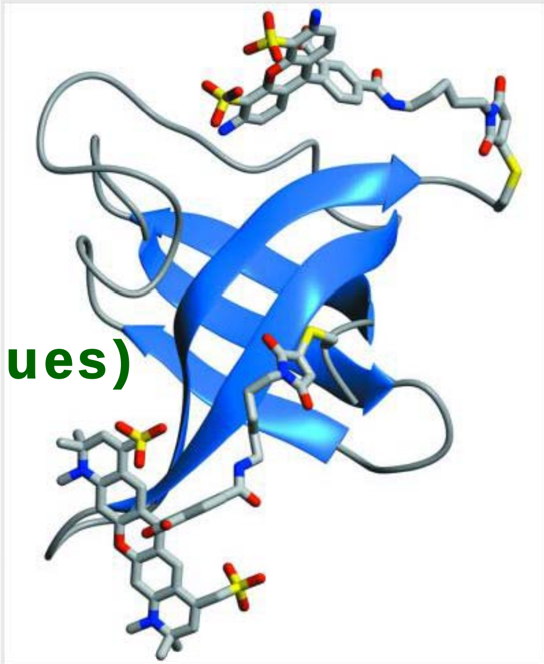
spark-infotheoretic-feature-sel...
This package contains a generic implementati...

spark-MDLP-discretization
Spark implementation of Fayyad's discretizer...

ECBDL'14 Big Data Competition
Vancouver, 2014

ECBDL'14 Big Data Competition 2014: Self-deployment track

Objective: Contact map prediction



Details:

- 32 million instances
- 631 attributes (539 real & 92 nominal values)
- 2 classes
- 98% of negative examples
- About 56.7GB of disk space

Evaluation:

True positive rate · True negative rate
TPR · TNR

http://cruncher.ncl.ac.uk/bdcomp/index.pl?action=data

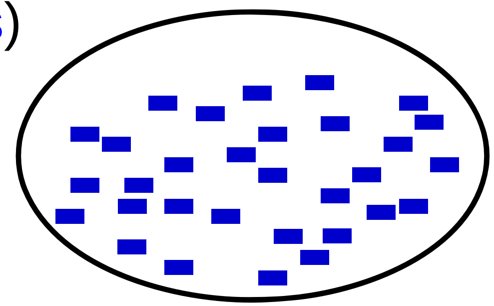
J. Bacardit et al, Contact map prediction using a large-scale ensemble of rule sets and the fusion of multiple predicted structural features, Bioinformatics 28 (19) (2012) 2441-2448

Evolutionary Computation for Big Data and Big Learning Workshop

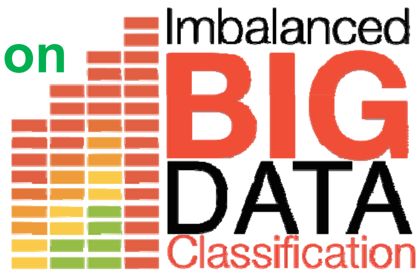
ECBDL'14 Big Data Competition 2014: Self-deployment track

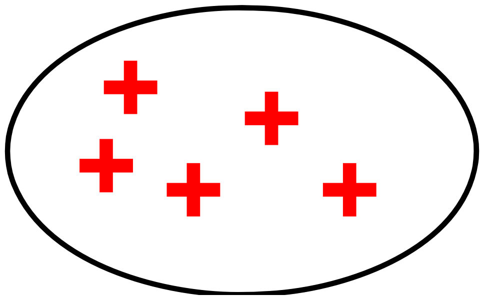
The challenge:

- Very **large** size of the training set
  - Does not fit all together in memory.
- Even large for the test set (5.1GB, 2.9 million instances)



- Relatively **high dimensional** data.
- Low ratio (<2%) of true contacts. Imbalance rate: > 49
  - **Imbalanced problem!**
  - **Imbalanced Big Data Classification**





Imbalanced Big Data Classification

A MapReduce Approach

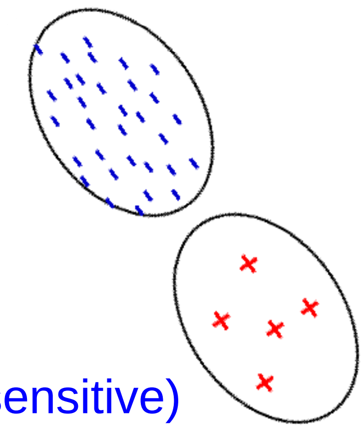
32 million instances, 98% of negative examples

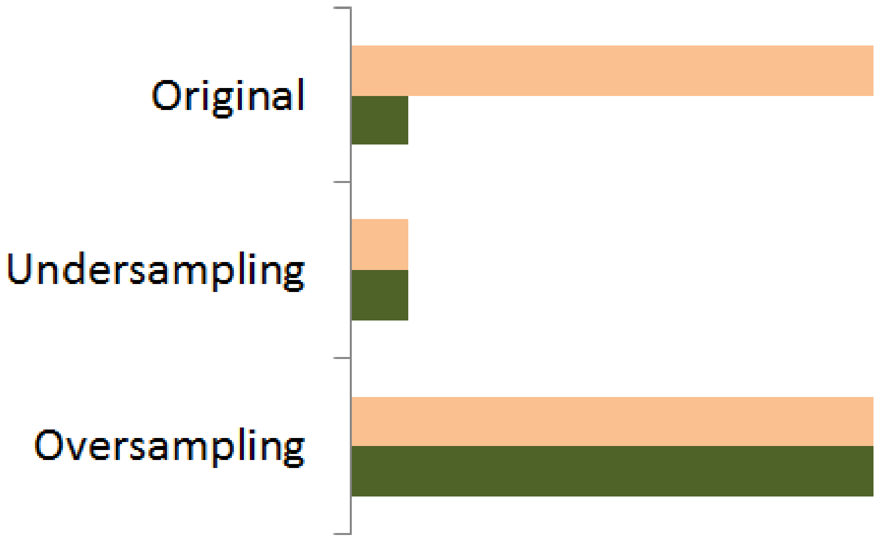
Low ratio of true contacts (<2%). Imbalance rate: > 49.

Imbalanced problem!

Previous study on extremely imbalanced big data:
S. Río, V. López, J.M. Benítez, F. Herrera, On the use of MapReduce for Imbalanced Big Data using Random Forest. *Information Sciences 285 (2014) 112-137.*

- Over-Sampling
  - Random
  - **Focused**
- Under-Sampling
  - Random
  - Focused
- Cost Modifying (cost-sensitive)
- Boosting/Bagging approaches (with preprocessing)

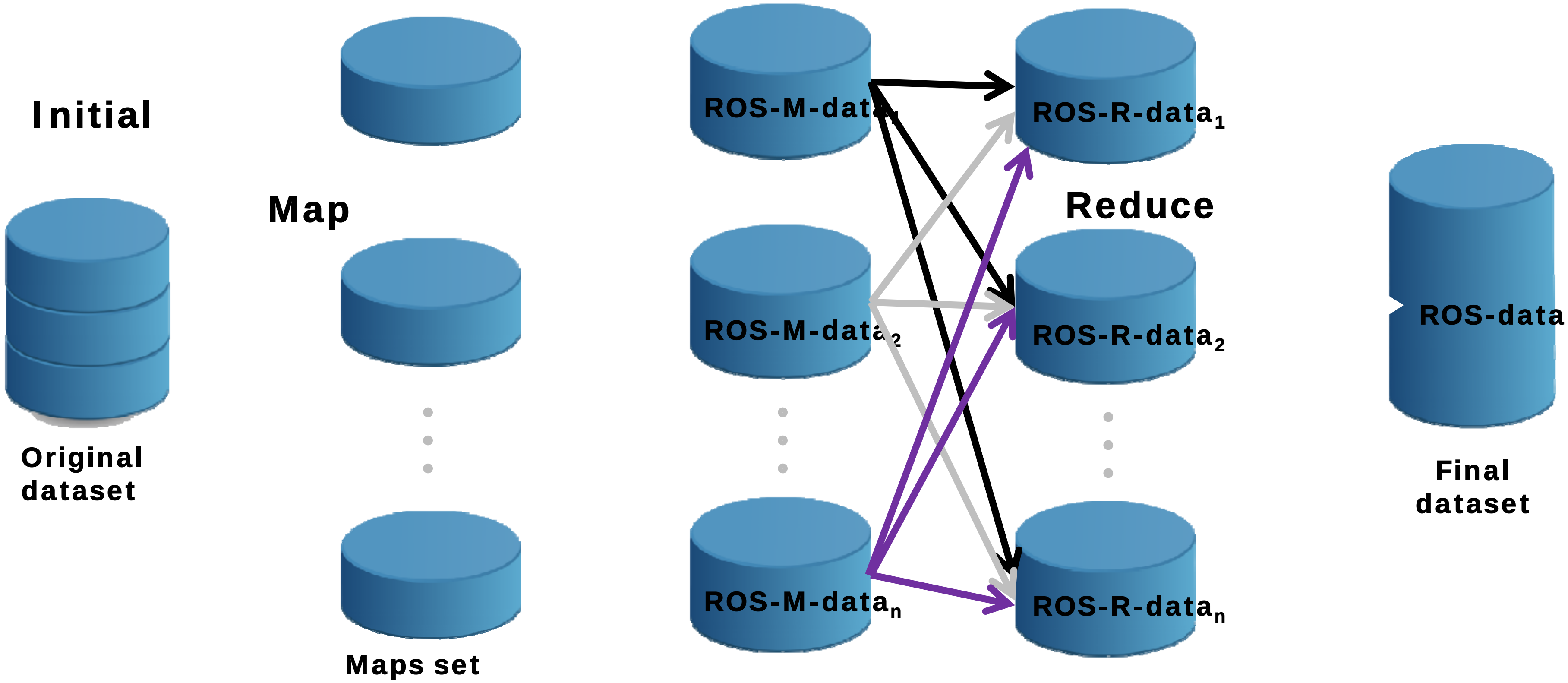




ECBDL'14 Big Data Competition

A MapReduce Approach for Random Oversampling

Low ratio of true contacts (<2%).
Imbalance rate: > 49. Imbalanced problem!



S. Río, V. López, J.M. Benítez, F. Herrera, On the use of MapReduce for Imbalanced Big Data using Random Forest. Information Sciences, 2014.

ECBDL'14 Big Data Competition

We initially focused on

- ❑ **Oversampling rate: 100%**

RandomForest:

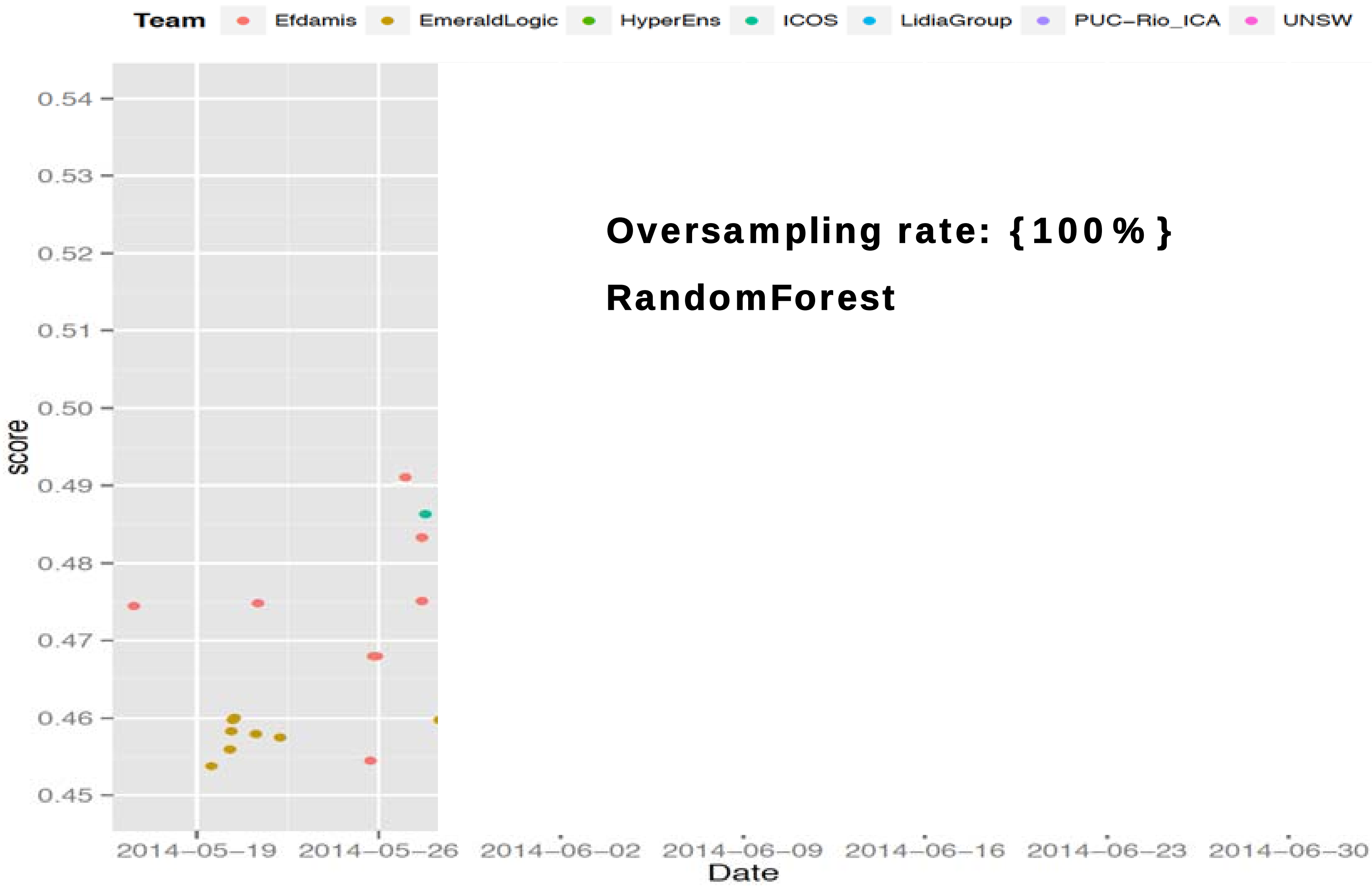
- ❑ Number of used features: 10 (log n +1); Number of trees: 100
- ❑ Number of maps: {64, 190, 1024, 2048}

Nº mappers	TPR_tst	TNR_tst	TNR*TPR Test
64	0,601723	0,806269	0,485151

Very low TPR (relevant!)

How to increase the TPR rate?

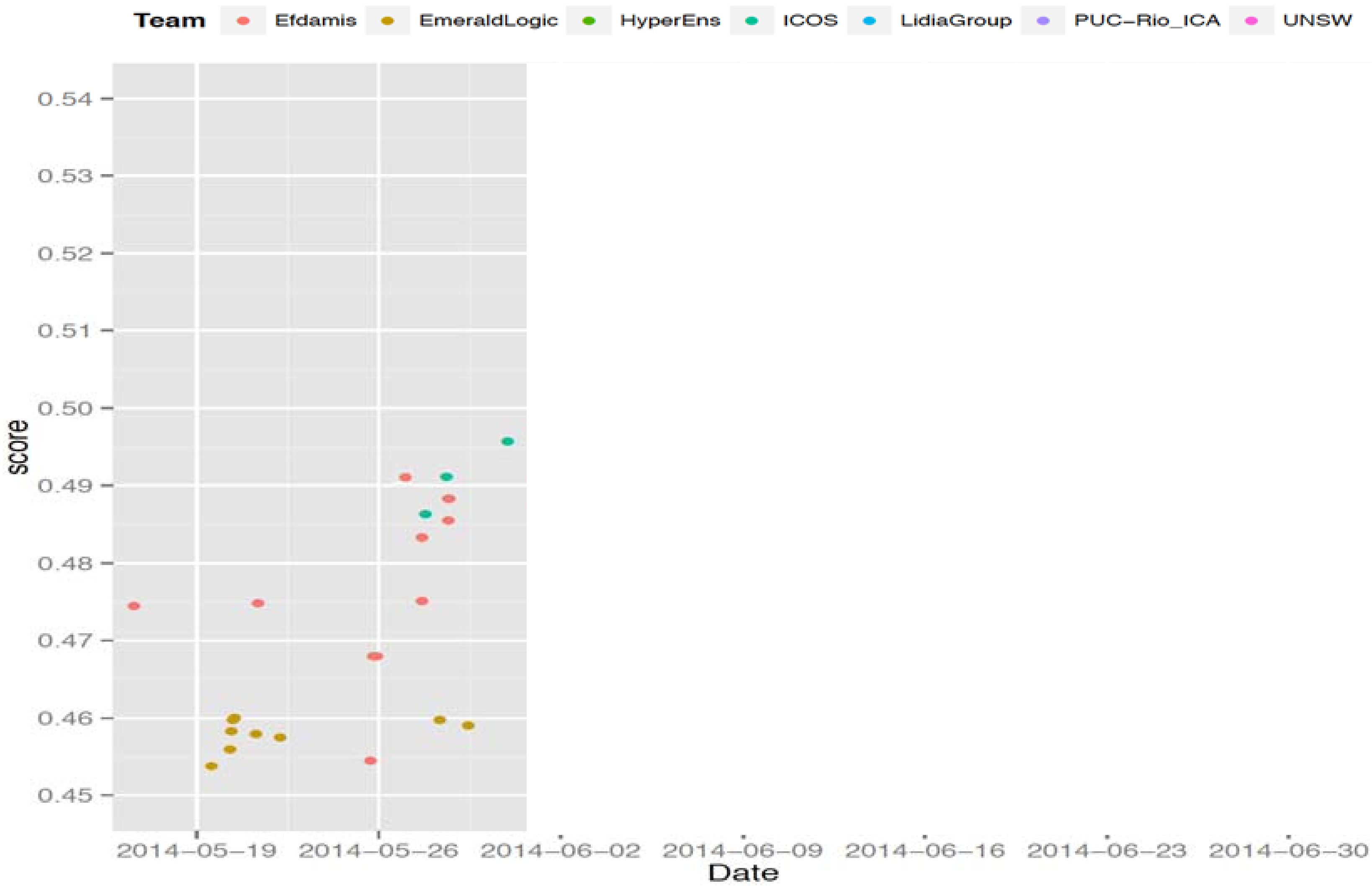
ECBDL'14 Big Data Competition



Oversampling rate: {100%}

RandomForest

ECBDL'14 Big Data Competition



ECBDL'14 Big Data Competition

How to increase the TPR rate?

Idea: To increase the ROS percentaje

- Oversampling rate: {100, 105, 110, 115, 130}

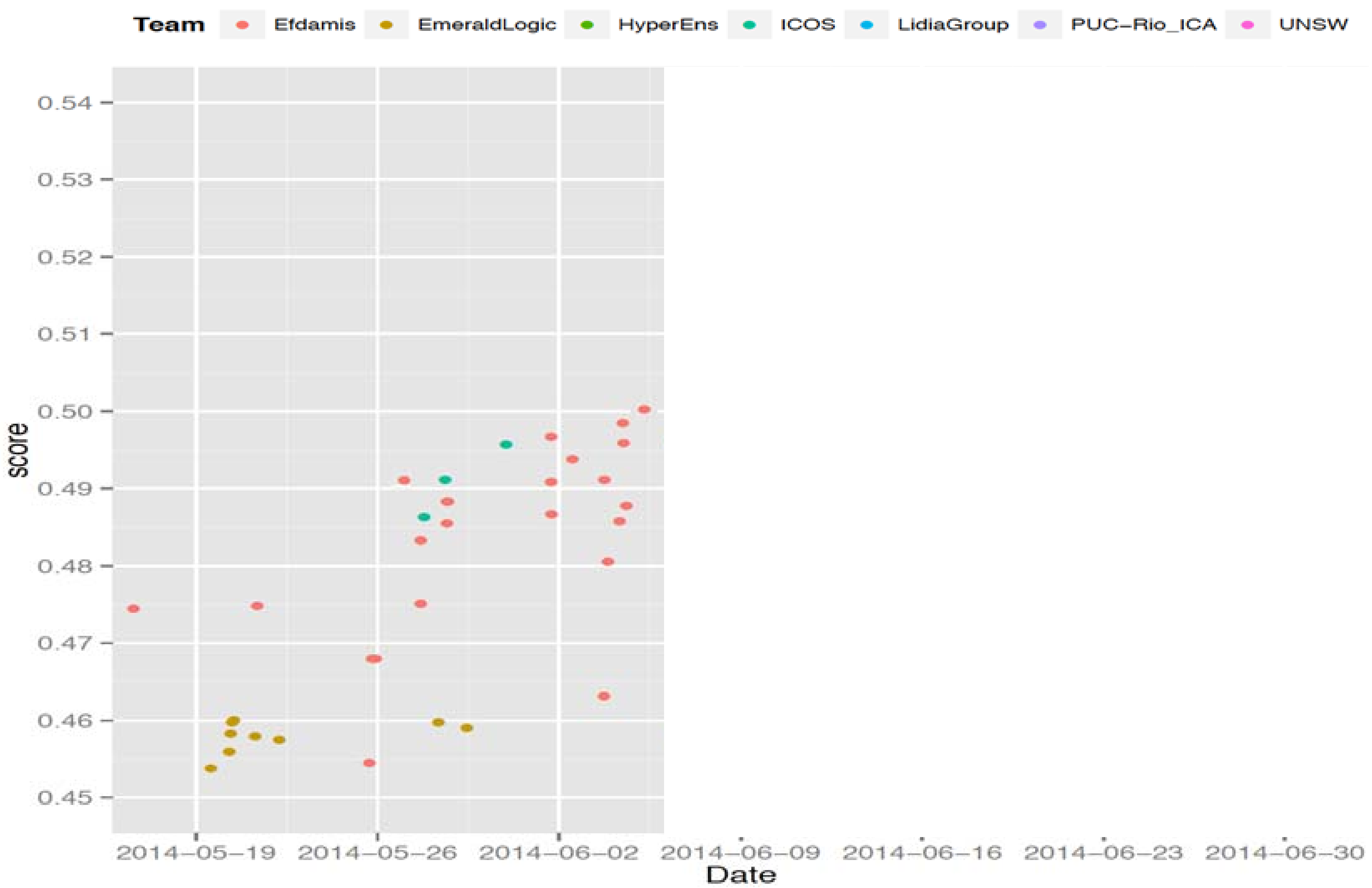
RandomForest:

- Number of used features:10; Number of trees: 100

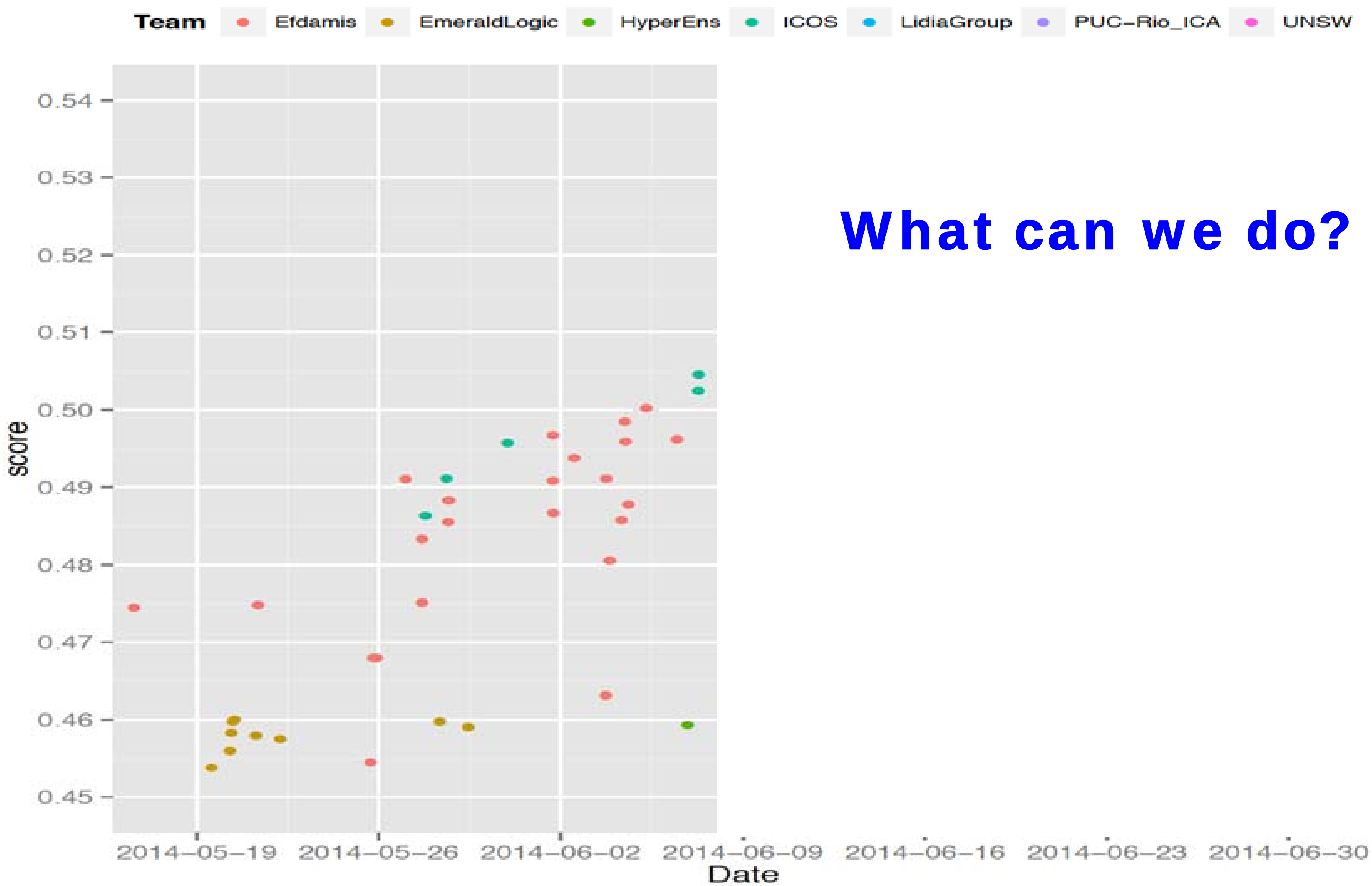
Algorithms	TPR	TNR	TNR*TPR Test
ROS+RF (RS: 100%)	**0.6351**	**0.7733**	**0.491186**
ROS+RF (RS: 105%)	0.6568	0.7555	0.496286
ROS+RF (RS: 110%)	0.6759	0.7337	0.495941
ROS+RF (RS: 115%)	**0.7041**	**0.7103**	**0.500175**
ROS+RF (RS: 130%)	0.7472	0.6609	0.493913

The higher ROS percentage, the higher TPR and the lower TNR

ECBDL'14 Big Data Competition



ECBDL'14 Big Data Competition



What can we do?

ECBDL’14 Big Data Competition

ECBDL’14 Big Data Competition 2014

Our approach:

1. **Balance the original training data**
   - ❑ **Random Oversampling**
   - ❑ **(As first idea, it was extended)**
2. **Learning a model.**
   - ❑ **Random Forest**
3. **Detect relevant features.**
   1. **Evolutionary Feature Weighting**

Classifying test set.

ECBDL'14 Big Data Competition

How to increase the performance?

Third component: MapReduce Approach for Feature Weighting for getting a major performance over classes

Map Side

- ❑ Each map read one block from dataset.
- ❑ Perform an **Evolutionary Feature Weighting** step.
- ❑ **Output:** a real vector that represents the degree of importance of each feature.
- ❑Number of maps: 32768 **(less than 1000 original data per map)**

Reduce Side

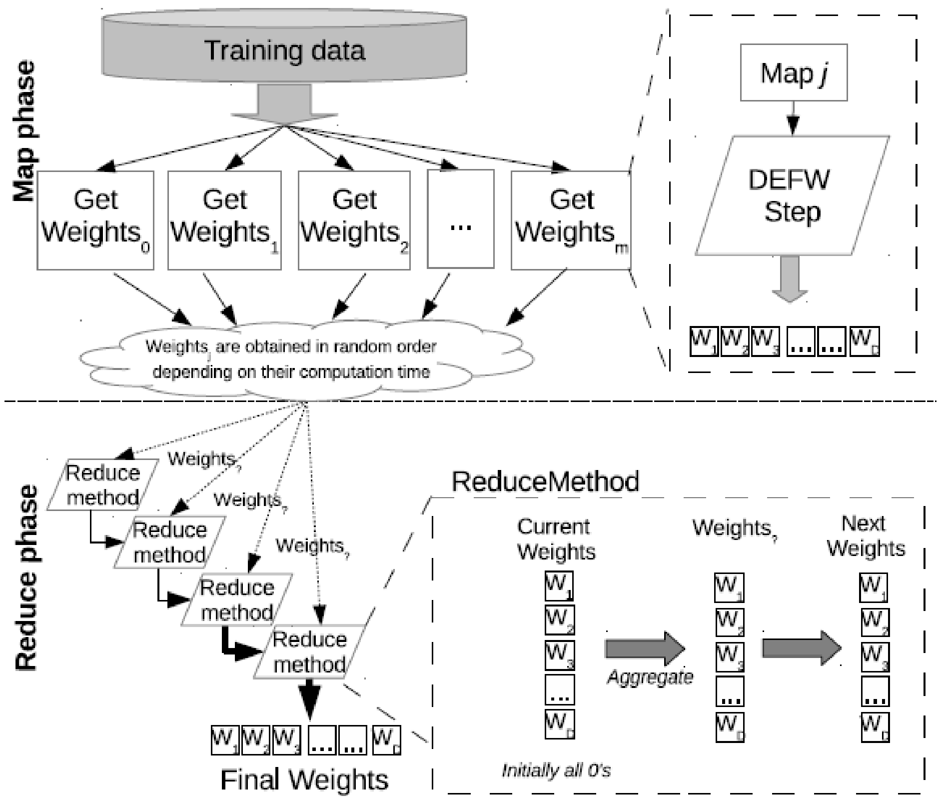
- ❑ Aggregate the feature's weights
- ❑ A feature is finally selected if it overcomes a given threshold.
- ❑ **Output:** a binary vector that represents the final selection

I. Triguero, J. Derrac, S. García, F. Herrera, Integrating a Differential Evolution Feature Weighting scheme into Prototype Generation. Neurocomputing 97 (2012) 332-343

ECBDL'14 Big Data Competition

How to increase the performance?

Third component: MapReduce Approach for Feature Weighting for getting a major performance over classes



ECBDL'14 Big Data Competition

Evolutionary Feature Weighting.

It allows us to construct several subset of features (changing the threshold).

	64 mappers			
Algorithms	TNR*TPR Training	TPR	TNR	TNR*TPR Test
ROS+RF (130% - Feature Weighting 63)	0.726350	0.66949	0.775652	0.519292
ROS+RF (115% - Feature Weighting 63)	0.736596	0.652692	0.790822	0.516163
ROS+RF (100% - Feature Weighting 63)	0.752824	0.626190	0.811176	0.507950

ECBDL'14 Big Data Competition

Last decision: We investigated to increase ROS until 180% with 64 mappers

	64 mappers			
Algorithms	TNR*TPR Training	TPR	TNR	TNR*TPR Test
ROS+ RF (130%+ FW 90+25f+200t)	0.736987	0.671279	0.783911	0.526223
ROS+ RF (140%+ FW 90+25f+200t)	0.717048	0.695109	0.763951	0.531029
ROS+ RF (150%+ FW 90+25f+200t)	0.706934	0.705882	0.753625	0.531971
ROS+ RF (160%+ FW 90+25f+200t)	0,698769	0.718692	0.741976	0.533252
ROS+ RF (170%+ FW 90+25f+200t)	0.682910	0.730432	0.730183	0.533349
ROS+ RF (180%+ FW 90+25f+200t)	0,678986	0.737381	0.722583	0.532819

To increase ROS and reduce the mappers number lead us to get a trade-off with good results

ROS 170 – 85 replications of the minority instances

ECBDL'14 Big Data Competition

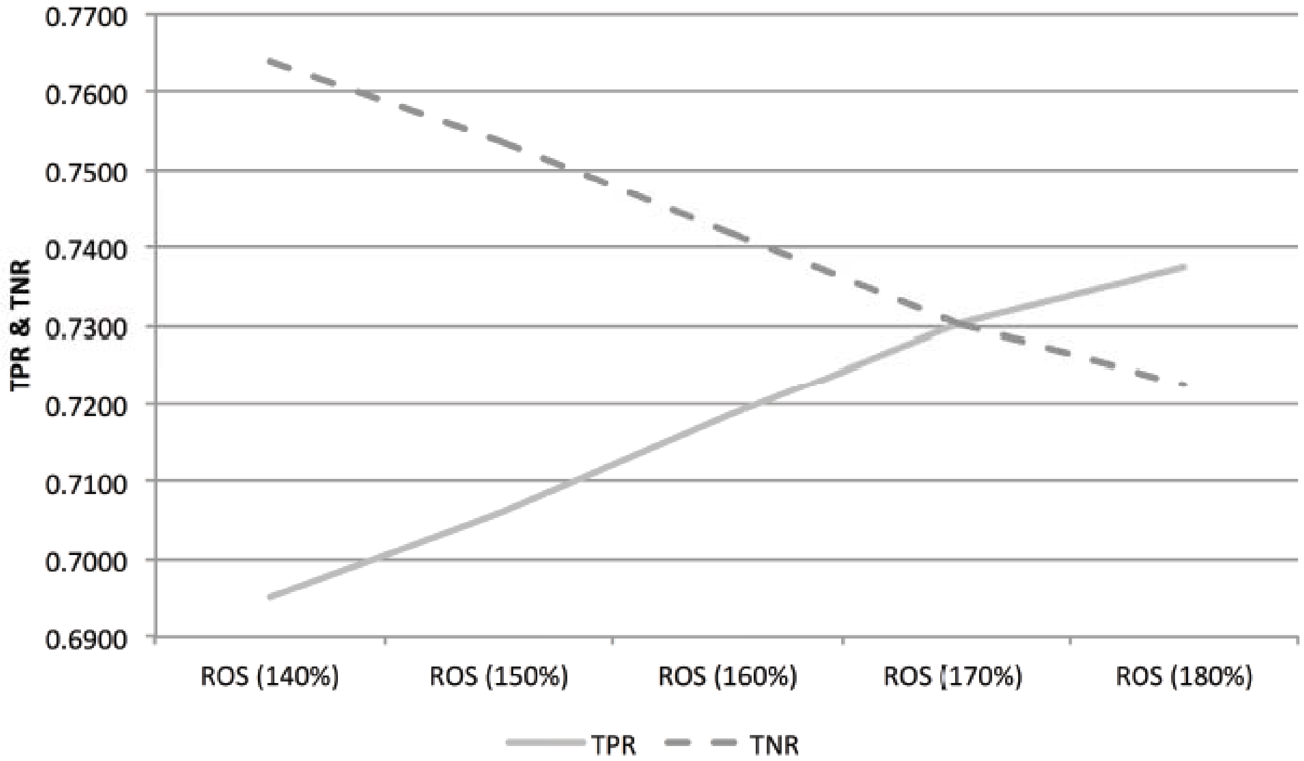


Figure 8: TPR vs. TNR varying the ROS percentage

ROS 170 – 85 replications of the minority instances
Experiments with 64 maps

ECBDL'14 Big Data Competition

Evolutionary Computation for Big Data and Big Learning Workshop

Results of the competition: Contact map prediction

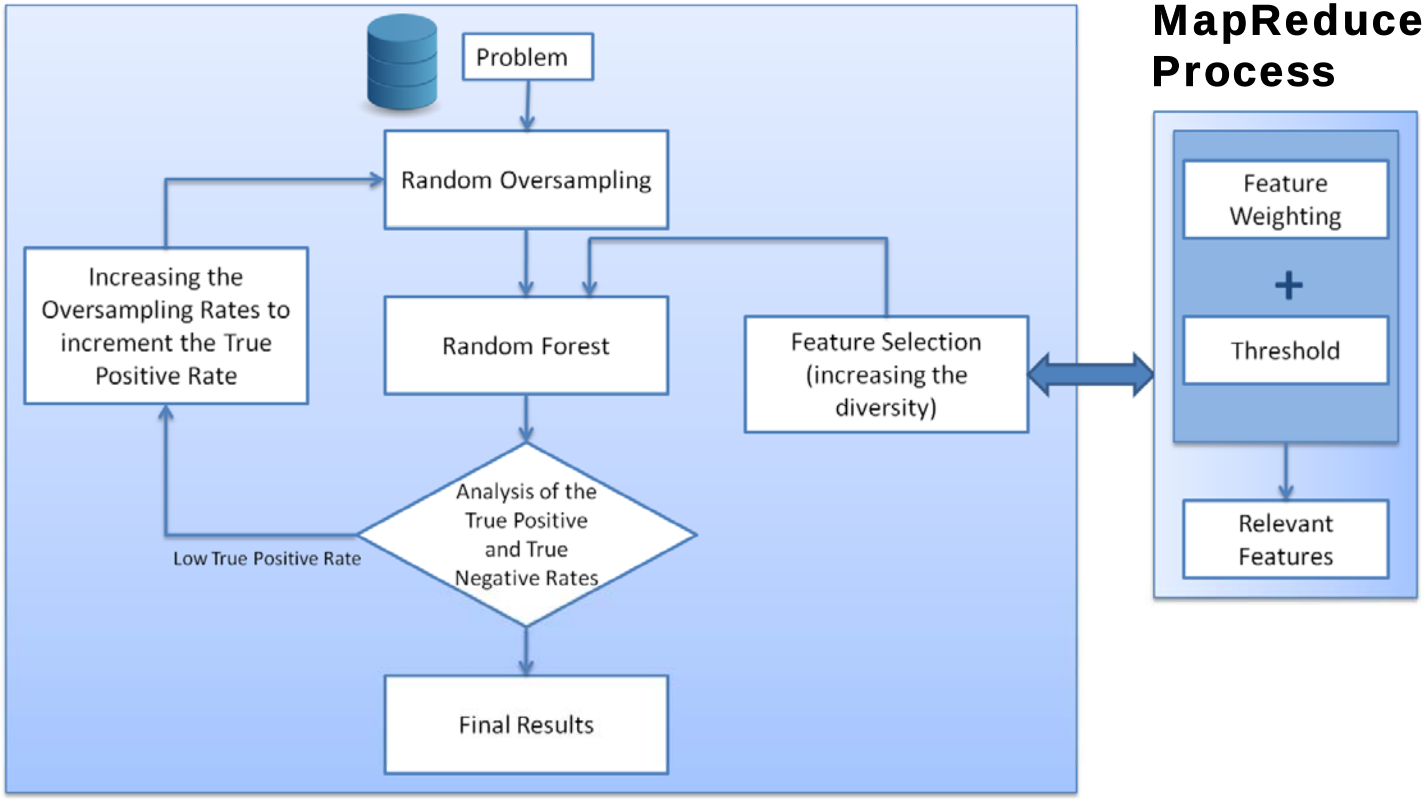
Team Name	TPR	TNR	Acc	TPR · TNR
Efdamis	**0.730432**	**0.730183**	**0.730188**	**0.533349**
ICOS	**0.703210**	**0.730155**	**0.729703**	**0.513452**
UNSW	**0.699159**	**0.727631**	**0.727153**	**0.508730**
HyperEns	0.640027	0.763378	0.761308	0.488583
PUC-Rio_ICA	0.657092	0.714599	0.713634	0.469558
Test2	0.632009	0.735545	0.733808	0.464871

EFDAMIS team ranked first in the ECBDL'14 big data competition

http://cruncher.ncl.ac.uk/bdcomp/index.pl?action=ranking

ECBDL'14 Big Data Competition
Our algorithm: **ROSEFW-RF**

Iterative MapReduce Process



MapReduce Process

I. Triguero, S. del Río, V. López, J. Bacardit, J.M. Benítez, F. Herrera.
ROSEFW-RF: The winner algorithm for the ECBDL'14 Big Data Competition: An extremely imbalanced big data bioinformatics problem.
Knowledge-Based Systems, Volume 87, October 2015, Pages 69–79

https://github.com/triguero/ROSEFW-RF

ECBDL'14 Big Data Competition

At the beginning ROS+RF (RS: 100%)

Nº mappers	TPR_tst	TNR_tst	TNR*TPR Test
64	0,601723	0,806269	0,485151

At the end

	64 mappers			
Algorithms	TNR*TPR Training	TPR	TNR	TNR*TPR Test
ROS+ RF (160%+ FW 90+25f+200t)	0,698769	0.718692	0.741976	0.533252
ROS+ RF (170%+ FW 90+25f+200t)	0.682910	0.730432	0.730183	0.533349
ROS+ RF (180%+ FW 90+25f+200t)	0,678986	0.737381	0.722583	0.532819

BIG DATA Preprocessing

Modelos de calidad están basados en datos de calidad.

ECBDL’14 Big Data Competition

ECBDL’14: Evolutionary Computation for Big Data and Big Learning Workshop
July 13th, 2014
GECCO-2014, Vancouver, Canada

This is to certify that team EFDAMIS, formed by Isaac Triguero, Sara del Río, Victoria López, José Manuel Benítez and Francisco Herrera, ranked **first** in the ECBDL’14 big data competition

Jaume Bacardit, organizer
ECBDL’14 big data competition

Índice

- Big Data. Big Data Science
- ¿Por qué Big Data? Google crea el Modelo de Programación MapReduce
- Tecnologías para Big Data: Ecosistema Hadoop (Hadoop, Spark, …)
- Big Data Analytics: Librerías para Analítica de Datos en Big Data. Casos de estudio
- Algunas aplicaciones: Salud, Social Media, Identificación
- Big Data en el grupo de investigación SCI^{2}S
- Comentarios Finales

Comentarios Finales

Unas palabras sobre BigDADE I

Big 2015 DADE I

1er Workshop en Big Data y Análisis de Datos Escalable.

17:30-18:40

Miércoles 11. Salón de Actos
ESII

BIGDADE 1 – Conferencia:
"Open Data". Asunción Gómez (UPM).

Moderador/a: Amparo Alonso

18:40-20:00

Miércoles 11. Salón de Actos
ESII

4 trabajos

BIGDADE 2 – Preprocesamiento:
Selección de instancias y características en BigData.

Moderador/a: Francisco Herrera

9:00-11:00

Jueves 12. Aula Bernardino del Campo (1.11)

BIGDADE 3 – Clasificación escalable en BigData.

6 trabajos

Moderador/a: César García Osorio

11:30-12:30

Jueves 12. Aula Bernardino del Campo (1.11)

BIGDADE 4 – Aprendizaje no supervisado en BigData

3 trabajos

Moderador/a: María José del Jesus

Comentarios Finales

Oportunidades en Big Data

Big Data es un área emergente y en expansión.
Las posibilidades de desarrollo de algoritmos para nuevos datos, aplicaciones reales … es un nicho de investigación y desarrollo en los próximos años.

Comentarios Finales

http://elpais.com/elpais/2015/03/26/buenavida/1427382655_646798.html

¿Qué es eso del 'big data'?

- Lo mencionan en conferencias, charlas y facultades. Aclaramos el concepto de moda. O lo que es lo mismo: lo que todas las empresas quieren saber de usted

EVA VAN DEN BERG | 31 MAR 2015 - 12:28 CEST

Tiene continua repercusión en la prensa

Comentarios Finales

- La paralelización de los algoritmos de aprendizaje automático junto al particionamiento de datos pueden proporcionar algoritmos de calidad con MapReduce.
  - Paticionando datos y aplicando el algoritmo a cada parte.
  - Centrando la atención en la fase de combinacion (**reduce**). La combinación de modelos es un reto en el diseño de cada algoritmo.
- Data Mining, Machine learning and data preprocessing: Inmensa colección de algoritmos frente a los pocos algoritmos en big data analytics.

Comentarios Finales

Machine learning: Huge collection of algorithms
Big data: A small subset of algorithms

Para el diseño y/o adaptación de cualquier algoritmo es necesario diseñar de forma adecuada una fase de fusión de información por cuanto siempre será necesario utilizar funciones Map y Reduce cuando la base de datos sea muy grande.

Igualmente los procedimientos iterativos requieren de un diseño adecuado para optimizar la eficiencia.

Todavía se está en una fase muy temprana de diseño de algoritmos de aprendizaje automático para big data.

El preprocesamiento de datos es esencial para mejorar el comportamiento de los algoritmos de aprendizaje. El diseño de estos algoritmos para big data está en una fase muy incipiente.

Comentarios Finales

Data Mining, Machine learning and data preprocessing:
Inmensa colección de algoritmos

Big Data Analytics

Big Data: Un pequeño conjunto de algoritmos

Big Data Preprocessing:
Unos pocos métodos de preprocesamiento.

Deep learning:
Redes neuronales para procesamiento
de señales/imágenes en grandes volúmenes.

Comentarios Finales

Big data and analytics:
Un gran reto que ofrece múltiples oportunidades

- **Pequeño conjunto de algoritmos**
  Es necesario rediseñar nuevos algoritmos.
- **Modelo de Computación**
  - Precisión y aproximación
  - Requiere “eficiencia” en los algoritmos.

- **Datos de calidad para modelos de calidad en big data**
  Modelos/Decisiones de calidad están basados en datos de calidad.
- **Preprocesamiento en Big Data**
  - Análisis del ruido en datos
    Métodos automáticos de limpieza
  - Procesamiento de valores perdidos
  - Big Data Reduction

Comentarios Finales

Hacia donde vamos?: 3 etapas de Big Data

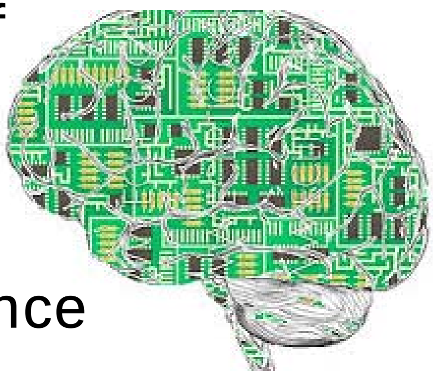
http://www.kdnuggets.com/2013/12/3-stages-big-data.html

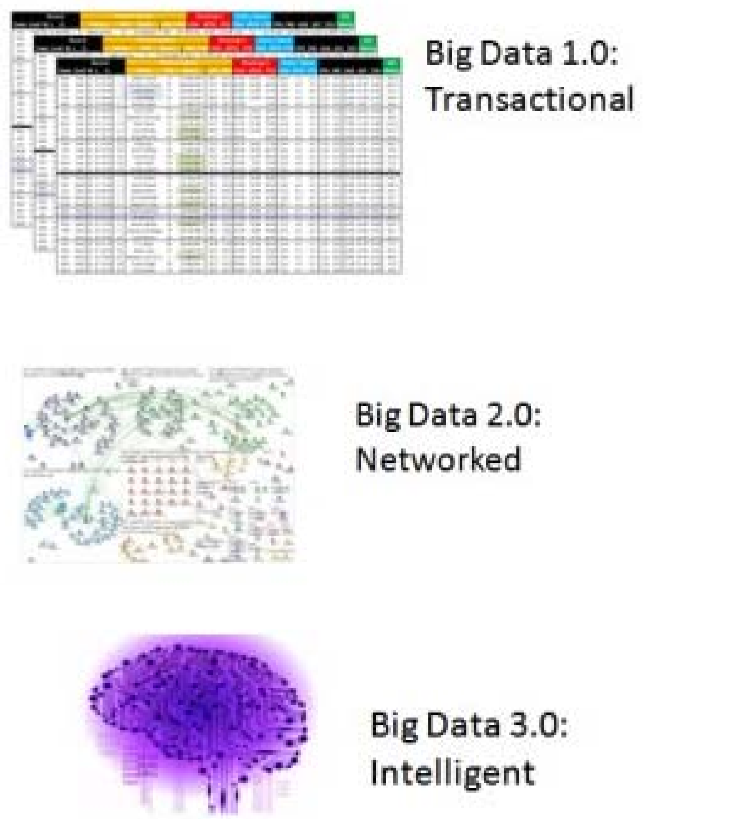
By Gregory Piatetsky, Dec 8, 2013.

Big Data 3.0: Intelligent

Google Now, Watson (IBM) ...

Big Data 3.0 would be a combination of data, with huge knowledge bases and a very large collection of algorithms, perhaps reaching the level of true Artificial Intelligence (Singularity?).





Comentarios Finales

Una demanda creciente de profesionales en “Big Data” y “Ciencia de Datos”

Oportunidades en Big Data (en España)

http://www.revistacloudcomputing.com/2013/10/espana-necesitara-60-000-profesionales-de-big-data-hasta-2015/?goback=.gde_4377072_member_5811011886832984067#!

España necesitará 60.000 profesionales de Big Data hasta 2015

22 octubre, 2013 Eventos 18

España necesitará 60.000 profesionales de Big Data hasta 2015

“España va a necesitar alrededor de sesenta mil profesionales del Big Data de aquí a 2015”, así lo ha asegurado Francisco Javier Antón, Subdirector General de Tecnologías del Ministerio de Educación, Cultura y Deportes en una mesa redonda sobre beneficio y aplicación de Big Data en pymes, moderada por Daniel Tapias de Sigma Technologies, celebrada durante el 4º Congreso Nacional de CENTAC de Toledo.

“Existe una demanda mundial para formar a 4,4 millones de profesionales de la gestión Big Data desde ingenieros, gestores y científicos de datos”, comenta Antón. Sin embargo, “las empresas todavía no ven en el Big Data un modelo de negocio”, lamenta. “Solo se extrae un 1% de los datos disponibles en la red”, añade. “Hace falta formación y concienciación.

Comentarios Finales

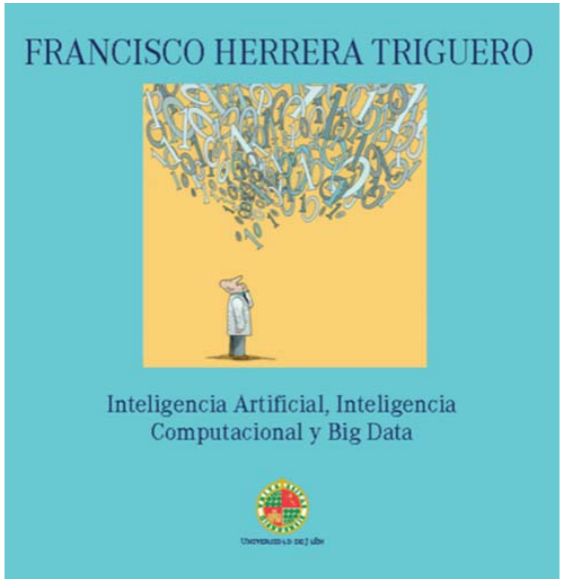
Nubes de datos
Sergio García y Lola Moral
Noviembe 2014

Las grandes colecciones de datos nos van a conducir a nuevas innovaciones (en la industria, ciencia, sociedad)

Ben Chams - Fotolia

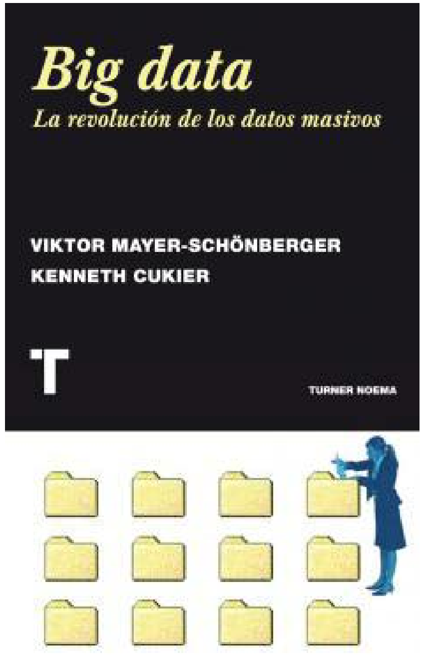
Comentarios Finales

2 Lecturas rápidas:



Capítulo 3.

http://issuu.com/secacult_uja/docs/libro_francisco_herrera.indd



A. Fernandez, S. Río, V. López, A. Bawakid, M.J. del Jesus, J.M. Benítez, F. Herrera, **Big Data with Cloud Computing: An Insight on the Computing Environment, MapReduce and Programming Frameworks.** *WIREs Data Mining and Knowledge Discovery 4:5 (2014) 380-409*

BIG DATA

Big Data