Big data frameworks

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Who am I?

- Postdoctoral researcher at Università degli Studi di Bergamo
- Member of the Unibg Security laboratory (Unibg Seclab)
- Research interests:
  - Mobile & cloud security
  - Enforcement of privacy requirements
- Open source project: Anonymization of large data collection using Apache Spark [GitHub]

Tutoring schedule

We have 18 hours of tutoring

- Wednesday 27/11 (16:00 - 19:00)
- ~~Friday 29/11 (10:30 - 13:30)~~
- Tuesday 03/12 (8:30 - 10:30)
- Wednesday 04/12 (16:00 - 19:00)
- Friday 06/12 (10:30 - 13:30)
- Tuesday 10/12 (8:30 - 10:30)
- Wednesday 11/12 (16:00 - 18:00)
- Friday 13/12 (10:30 - 13:30)

Time management

On Tuesday

- Lecture: 8.50 - 9.35
- Pause: 9.35 - 9.45
- Lecture: 9.45 - 10.30

On Wednesdays

- Lecture: 16.00 - 16.45
- Pause: 16.45 - 16.55
- Lecture: 16.55 - 17.40
- Pause: 17.40 - 17.50
- Lecture: 17.50 - 18.35

On Fridays

- Lecture: 10.30 - 11.15
- Pause: 11.15 - 11.25
- Lecture: 11.25 - 12.10
- Pause: 12.10 - 12.20
- Lecture: 12.20 - 13.05

Outline

- Big data
- Hadoop Distributed File System
- MapReduce
- Pig & Hive
- Apache Spark
- To Be Continued…

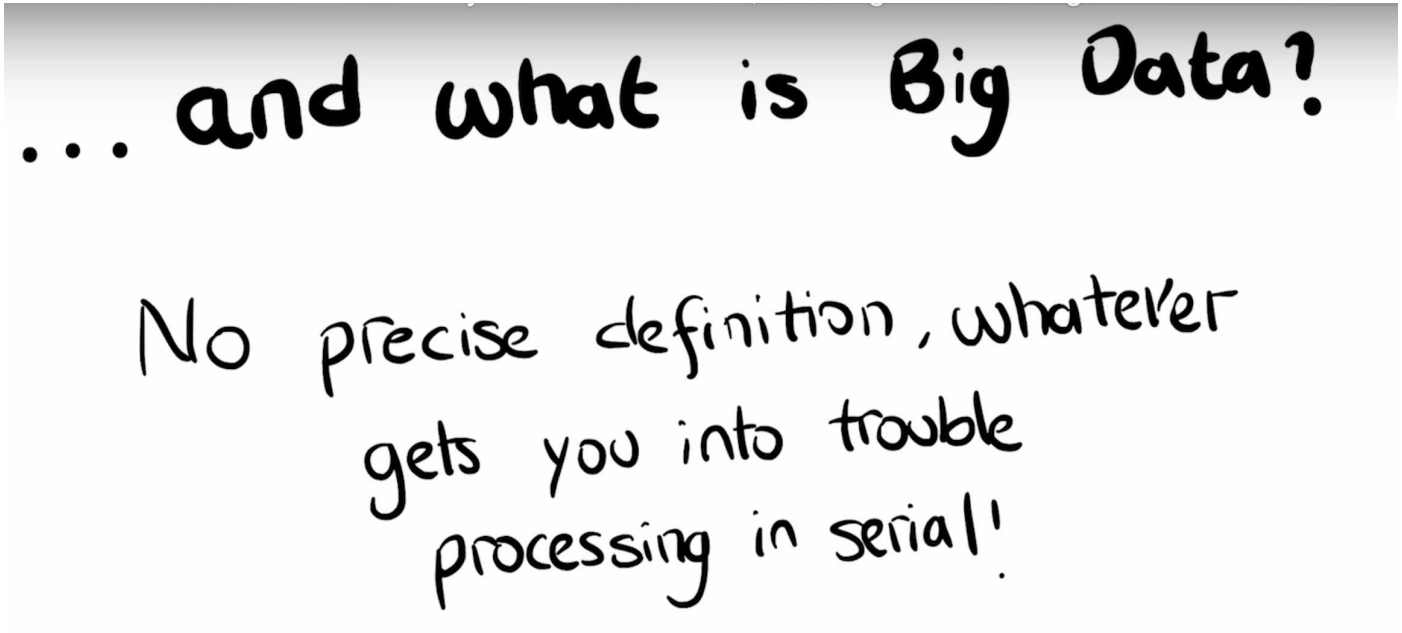
What is Big Data?

What is Big Data?

"**Big Data**" is the catch-all term for massive amounts of data as well as for frameworks and R&D initiatives aimed at working with them efficiently.

Image source: erpinnews.com

A short definition of Big Data



A nice definition from this year's PRACE Summer of HPC presentation "Convergence of HPC and Big Data".

The three V's of Big Data

It is customary to define Big Data in terms of three V's:

- Volume (the sheer volume of data)
- Velocity (rate of flow of the data and processing speed needs)
- Variety (different sources and formats)

The three V's of Big Data

Data arise from disparate sources and come in many sizes and formats. Velocity refers to the speed of data generation as well as to processing speed requirements.

Volume	Velocity	Variety
MB	batch	table
GB	periodic	database
TB	near-real time	multimedia
PB	real time	unstructured
...	...	...

Reference: metric prefixes

1000000000000000000000000	10^{24}	yotta	Y	septillion
1000000000000000000000	10^{21}	zetta	Z	sextillion
1000000000000000000	10^{18}	exa	E	quintillion
1000000000000000	10^{15}	peta	P	quadrillion
1000000000000	10^{12}	tera	T	trillion
1000000000	10^{9}	giga	G	billion
1000000	10^{6}	mega	M	million
1000	10^{3}	kilo	k	thousand

Note: 1 Gigabyte (GB) is 10^9 bytes. Sometimes GB is also used to denote 1024^3 or 2^30 bytes, which is actually one *gibibyte* (GiB).

Structured vs. unstructured data

By *structured* data one refers to highly organized data that are usually stored in relational databases or data warehouses. Structured data are easy to search but unflexible in terms of the three "V"s.

Unstructured data come in mixed formats, usually require pre-processing, and are difficult to search. Structured data are usually stored in noSQL databases or in *data lakes* (these are scalable storage spaces for raw data of mixed formats).

Examples of structured/unstructured data

Industry	Structured data	Unstructured data
e-commerce	• products & prices • customer data • transactions	• reviews • phone transcripts • social media mentions
banking	• financial transactions • customer data	• customer communication • regulations & compliance • financial news
healthcare	• patient data • medical billing data	• clinical reports • radiology imagery

Big Data in 2025

Data Phase	Astronomy	Twitter	YouTube	Genomics
Acquisition	25 zetta-bytes/year	0.5–15 billion tweets/year	500–900 million hours/year	1 zetta-bases/year
Storage	1 EB/year	1–17 PB/year	1–2 EB/year	2–40 EB/year
Analysis	In situ data reduction	Topic and sentiment mining	Limited requirements	Heterogeneous data and analysis
	Real-time processing	Metadata analysis		Variant calling, ~2 trillion central processing unit (CPU) hours
	Massive volumes			All-pairs genome alignments, ~10,000 trillion CPU hours
Distribution	Dedicated lines from antennae to server (600 TB/s)	Small units of distribution	Major component of modern user's bandwidth (10 MB/s)	Many small (10 MB/s) and fewer massive (10 TB/s) data movement

doi:10.1371/journal.pbio.1002195.t001

This table[1] shows the projected annual storage and computing needs in four domains (astronomy, social media, genomics)

[1] Stephens ZD et al. "Big Data: Astronomical or Genomical?" In: *PLoS Biol* (2015).

The three V's of Big Data: additional dimensions

Three more "V"s to be pondered:

- Veracity (quality or trustworthiness of data)
- Value (economic value of the data)
- Variability (general variability in any of the aforementioned characteristics)

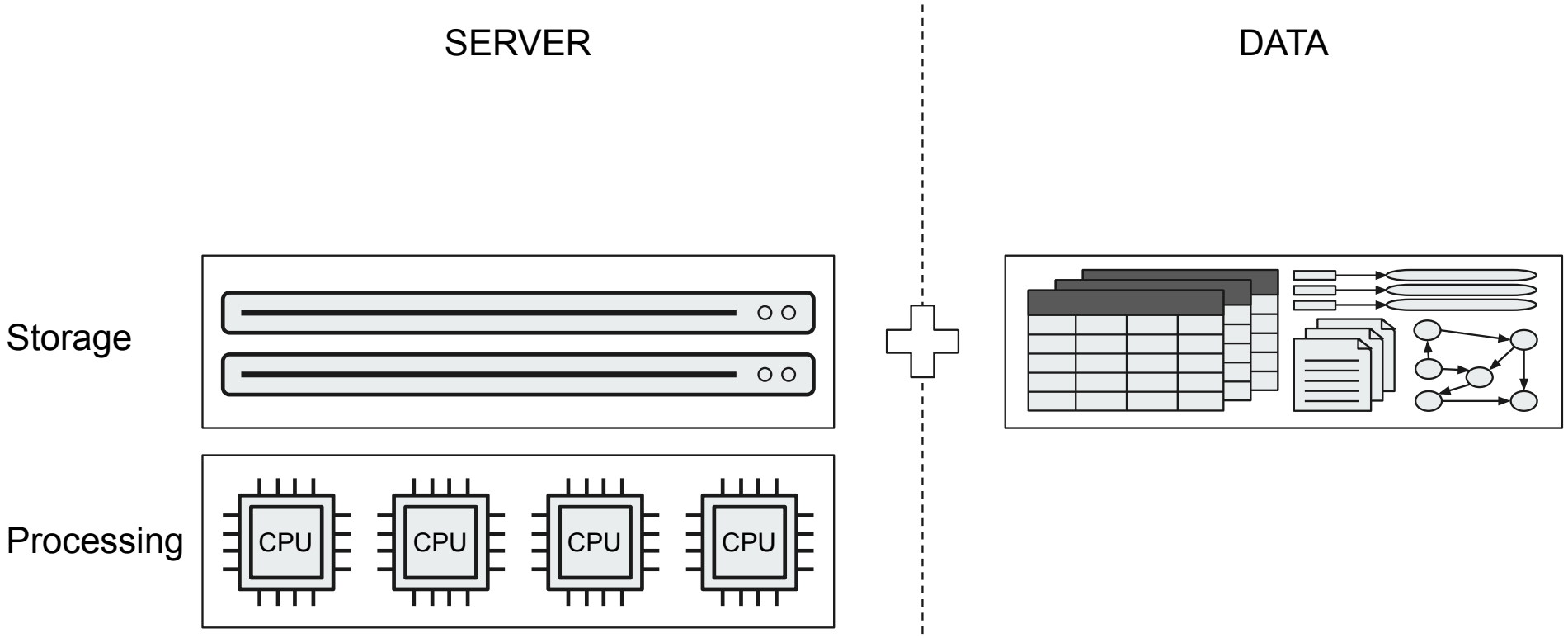
The challenges of Big Data

Anyone working with large amounts of data will sooner or later be confronted with one or more of these challenges:

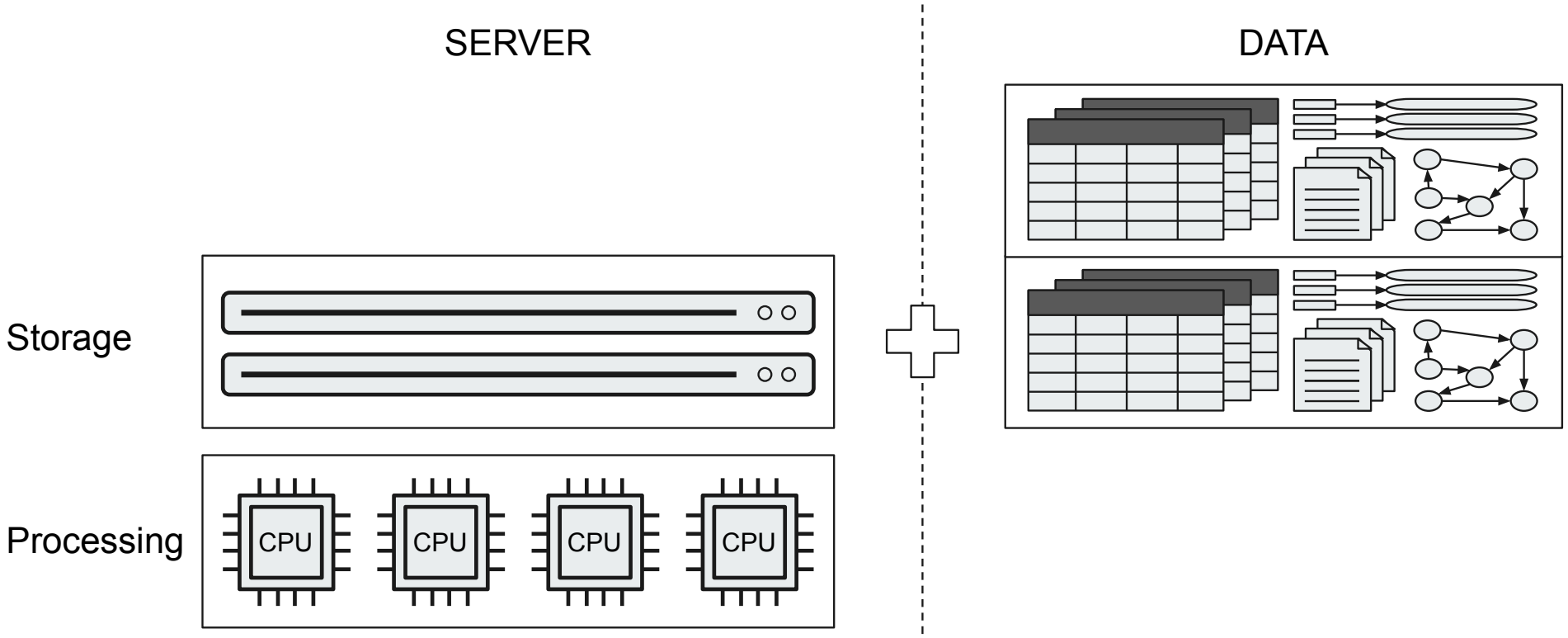
- disk and memory space
- processing speed
- hardware faults
- network capacity and speed
- need to optimize resources use

But how should we scale our systems?

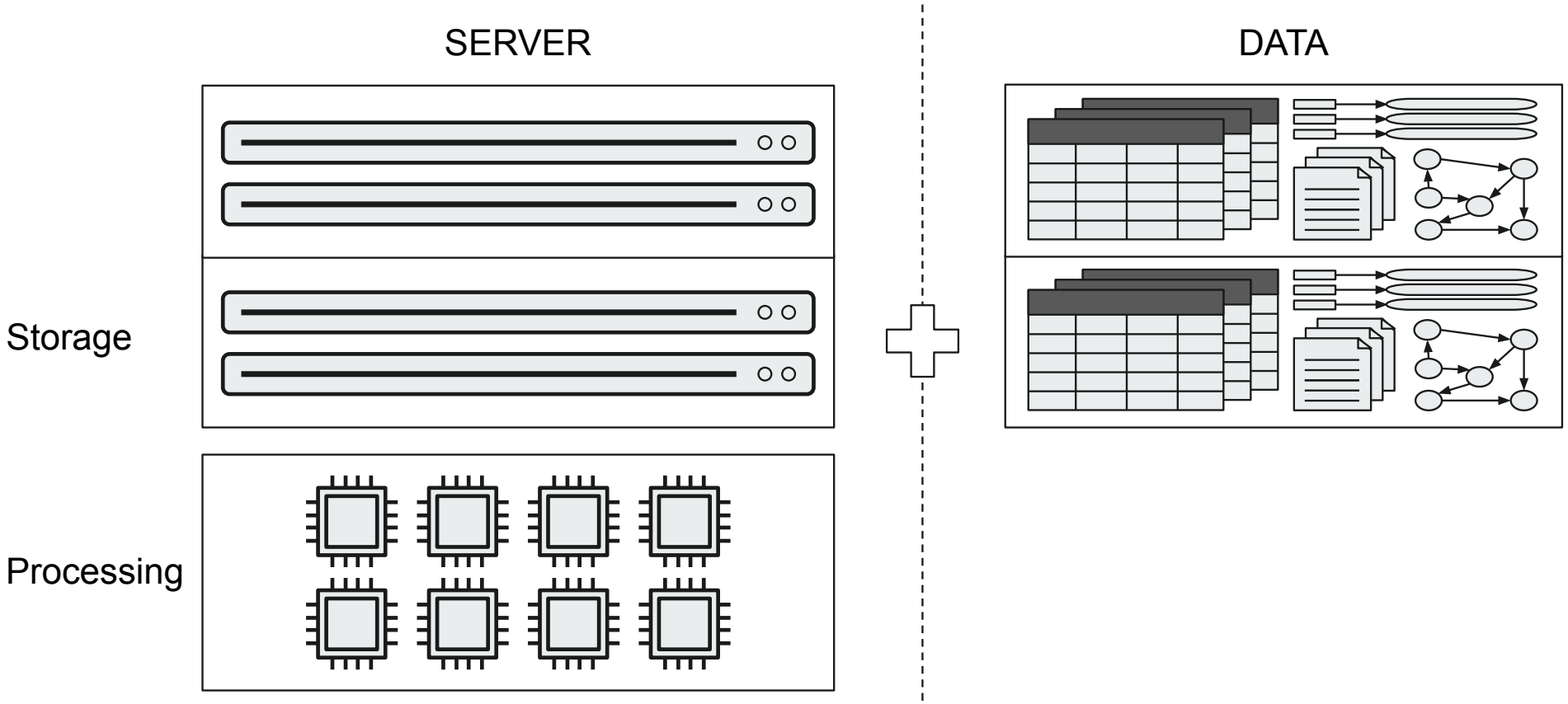
Initial setup



What if the data volume doubles?



Vertical scaling



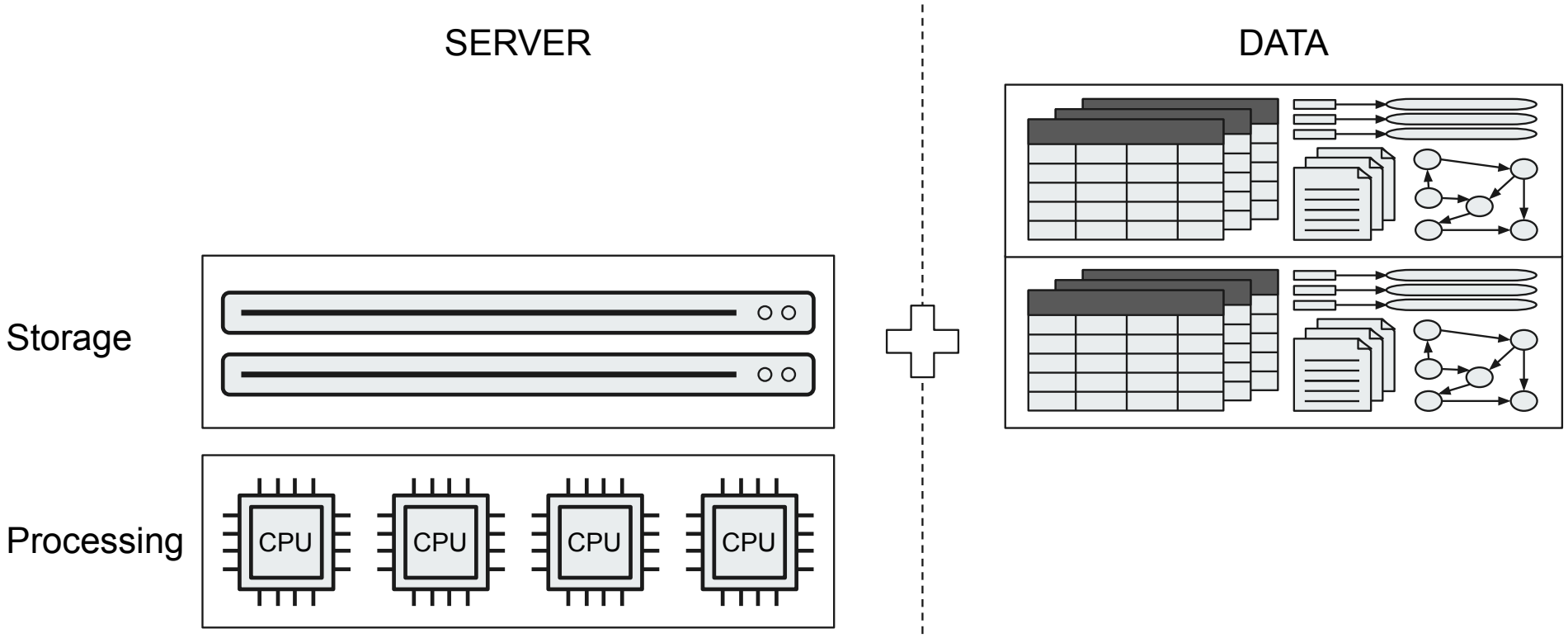
Limitations

- **Maintenance window with downtime**
  Unless you have a backup server that can handle operations and requests, you will need some considerable downtime to upgrade your machine

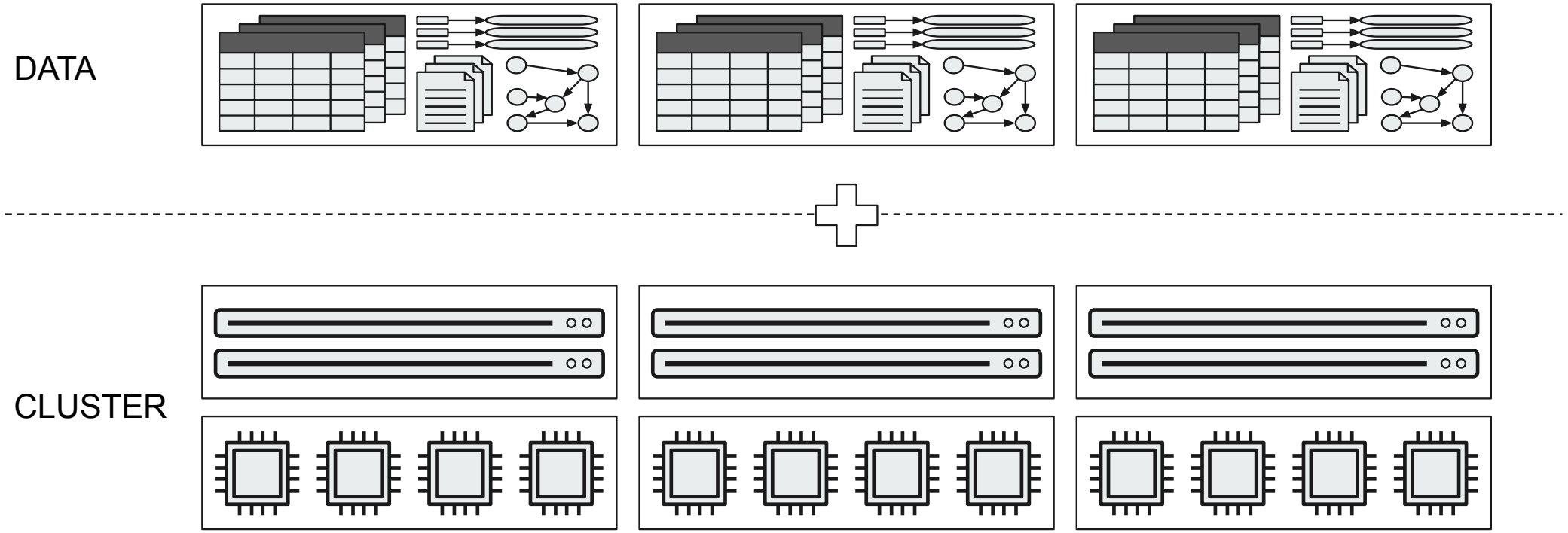
- **Single point of failure**
  Having all your operations on a single server increases the risk of losing all your data if a hardware or software failure were to occur

- **Upgrade limitations**
  There is a limitation to how much you can upgrade a machine

What is the alternative?



Horizontal scaling



~~Limitations~~ → Advantages

- ~~**Maintenance window with downtime**~~ → **Upgradability and flexibility**
  If you run your application layer on separate machines (horizontally scaled), they are easier to decouple and upgrade without downtime

- ~~**Single point of failure**~~ → **Reliability and availability**
  Horizontal scaling can provide you with a more reliable system. It increases redundancy and ensures that you are not dependent on one machine

- ~~**Upgrade limitations**~~ → **The only limit is $$$**
  There is no practical limit to how many machine you may put together, the only limit is the financial ability to buy more servers

Limitations

- **Complexity of maintaining and operating the architecture**
  Distributed systems are complex to design, program and debug. You have to take into account the network limits (latency and bandwidth) and make the system reliable to partial failures

- **Limited software support**
  This problem is less and less existing as most of the development these days is oriented towards the development of microservices and cloud native solutions

The Hadoop distributed computing architecture

Hadoop for distributed data processing

Hadoop is a framework for running jobs on clusters of computers that provides a good abstraction of the underlying hardware and software.

"*Stripped to its core, the tools that Hadoop provides for building distributed systems—for data storage, data analysis, and coordination—are simple. If there's a common theme, it is about raising the level of abstraction—to create building blocks for programmers who just happen to have lots of data to store, or lots of data to analyze, or lots of machines to coordinate, and who don't have the time, the skill, or the inclination to become distributed systems experts to build the infrastructure to handle it.* [2]"

[2] White T. *Hadoop: The Definitive Guide*. O'Reilly, 1988.

Hadoop: some facts

Hadoop[3] is an open-source project of the Apache Software Foundation. The project was created to facilitate computations involving massive amounts of data.

- its core components are implemented in Java
- initially released in 2006. Last stable version is 3.3.1 from June 2021
- originally inspired by Google's MapReduce[4] and the proprietary GFS (Google File System)

[3] Apache Software Foundation. *Hadoop*. url: https://hadoop.apache.org.

[4] J. Dean and S. Ghemawat. "MapReduce: Simplified data processing on large clusters." In: *Proceedings of Operating Systems Design and Implementation (OSDI)*. 2004. url: https://www.usenix.org/legacy/publications/library/proceedings/osdi04/tech/full_papers/dean/dean.pdf .

Hadoop's features

Hadoop's features addressing the challenges of Big Data:

- scalability
- fault tolerance
- high availability
- distributed cache/data locality
- cost-effectiveness as it does not need high-end hardware
- provides a good abstraction of the underlying hardware
- easy to learn
- data can be queried trough SQL-like endpoints (Hive, Cassandra)

Mini-glossary of Hadoop's distinguishing features

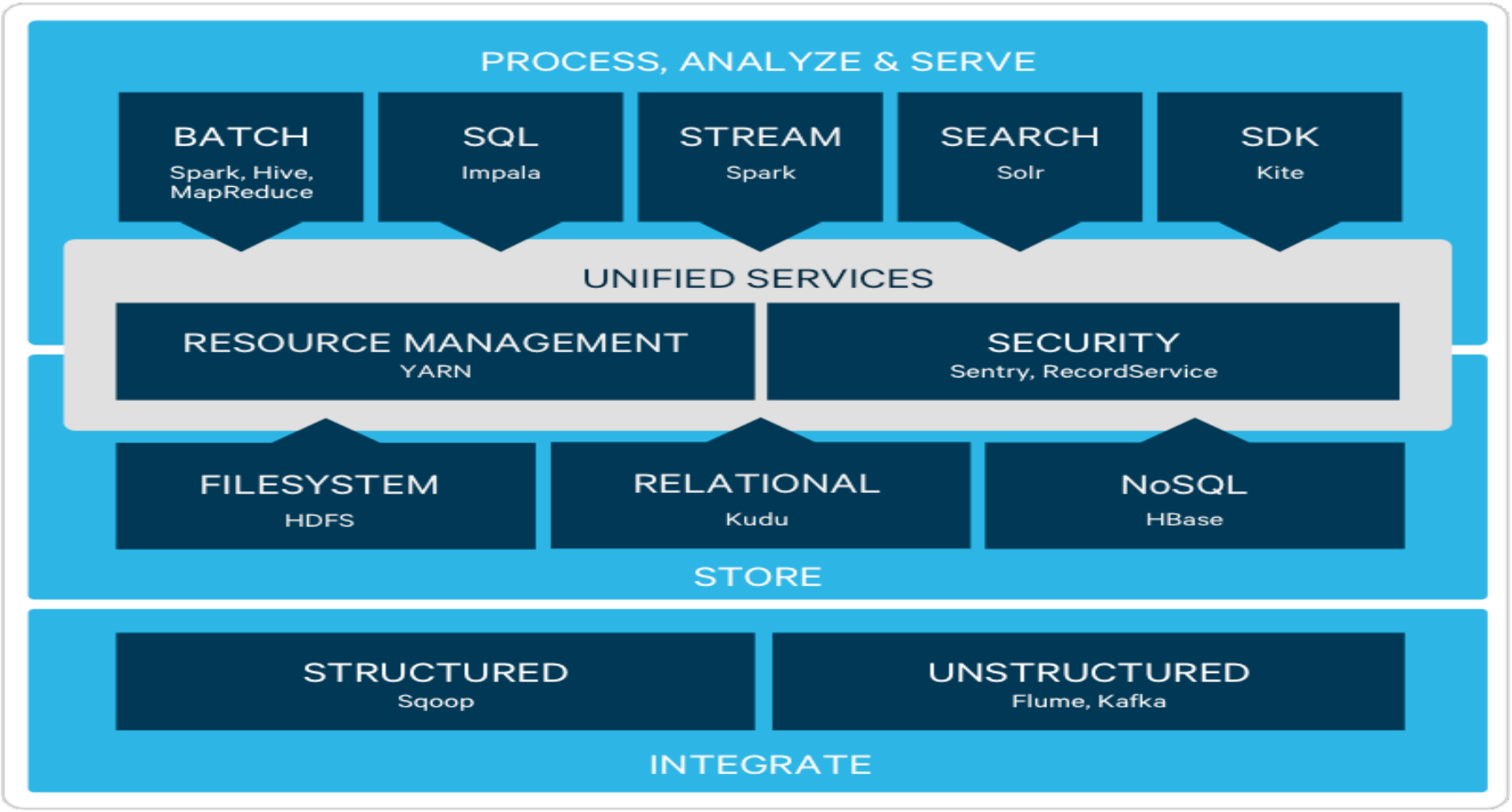
- ***fault tolerance***: the ability to withstand hardware or network failures (also: *resilience*)
- ***high availability***: this refers to the system minimizing downtimes by eliminating single points of failure
- ***data locality***: task are run on the node where data are located, in order to reduce the cost of moving data around

The Hadoop core

The core of Hadoop consists of:

- Hadoop common, the core libraries
- HDFS, the Hadoop Distributed File System
- MapReduce
- the YARN (Yet Another Resource Negotiator) resource manager

The Hadoop ecosystem



There's a whole constellation of open source components for collecting, storing, and processing big data that integrate with Hadoop.

Image source: Cloudera

The Hadoop Distributed File System (HDFS)

HDFS stands for Hadoop Distributed File System and it takes care of partitioning data across a cluster.

In order to prevent data loss and/or task termination due to hardware failures HDFS uses either

- replication (creating multiple copies —usually 3— of the data)
- erasure coding

Data redundancy (obtained through replication or erasure coding) is the basis of Hadoop's fault tolerance.

Replication vs. Erasure Coding

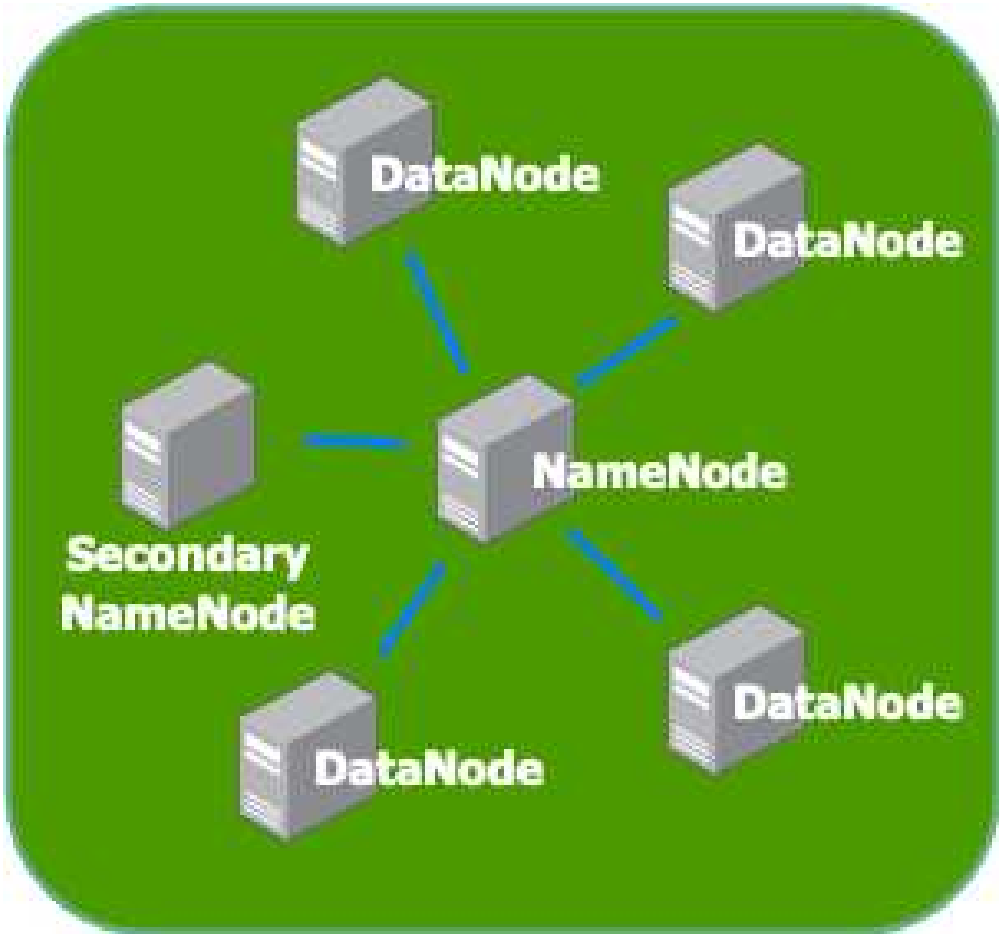
In order to provide protection against failures one introduces:

- data redundancy
- a method to recover the lost data using the redundant data

Replication is the simplest method for coding data by making n copies of the data. n-fold replication guarantees the availability of data for at most $n-1$ *failures and it has a storage overhead of 200% (this is equivalent to a storage efficiency of 33%).*

Erasure coding provides a better storage efficiency (up to to 71%) but it can be more costly than replication in terms of performance.

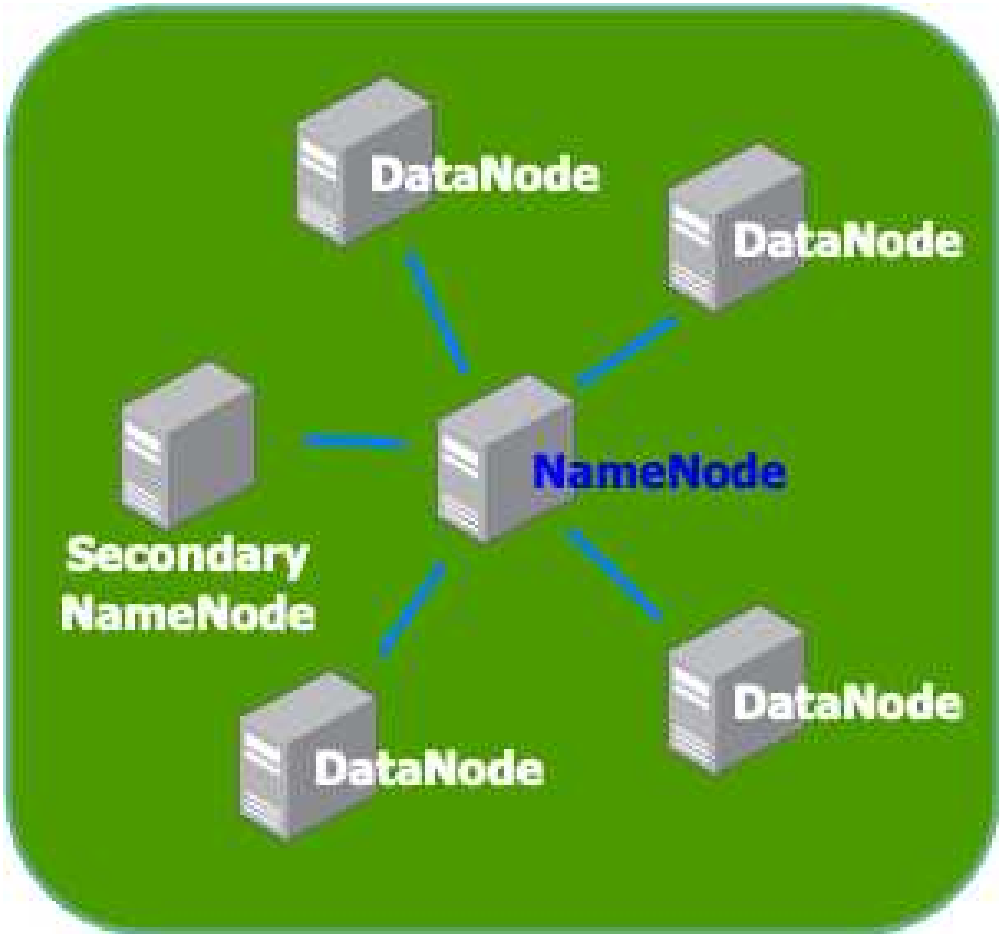
HDFS architecture



A typical Hadoop cluster installation consists of:

- a NameNode
- a secondary NameNode
- multiple DataNodes

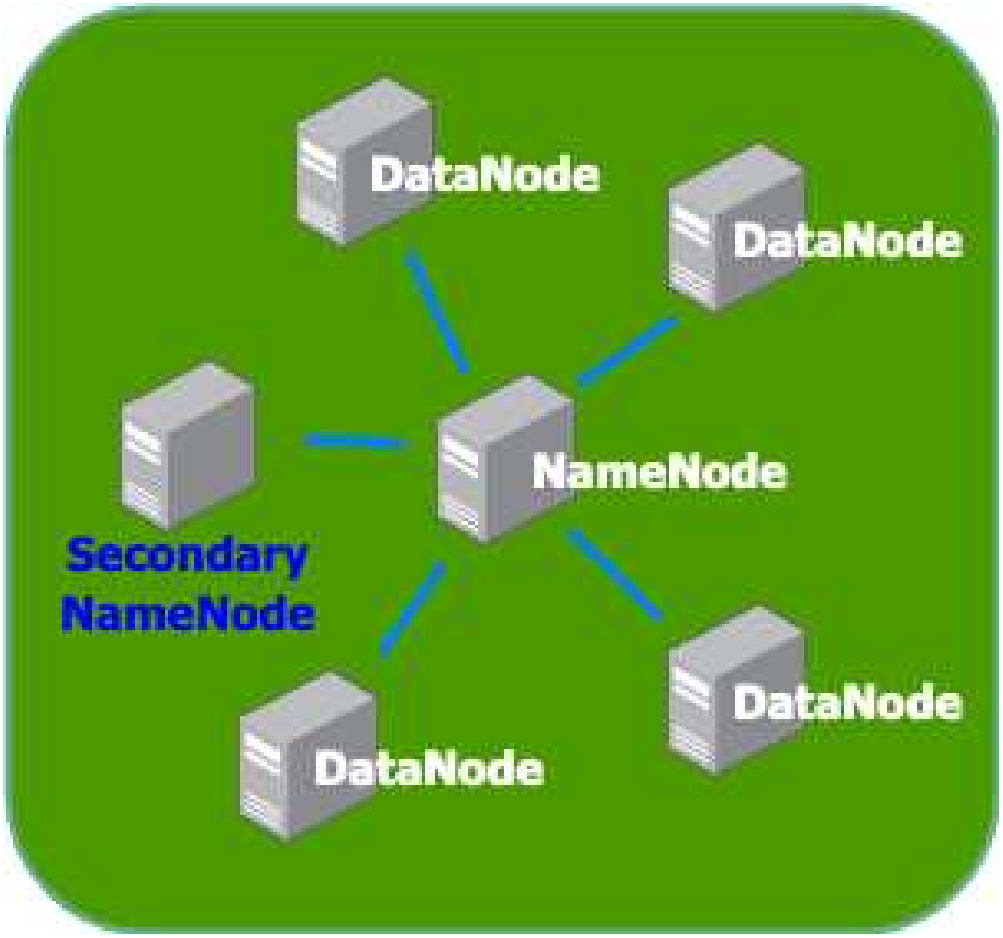
HDFS architecture: NameNode



NameNode

The NameNode is the main point of access of a Hadoop cluster. It is responsible for the bookkeeping of the data partitioned across the DataNodes, manages the whole filesystem metadata, and performs load balancing

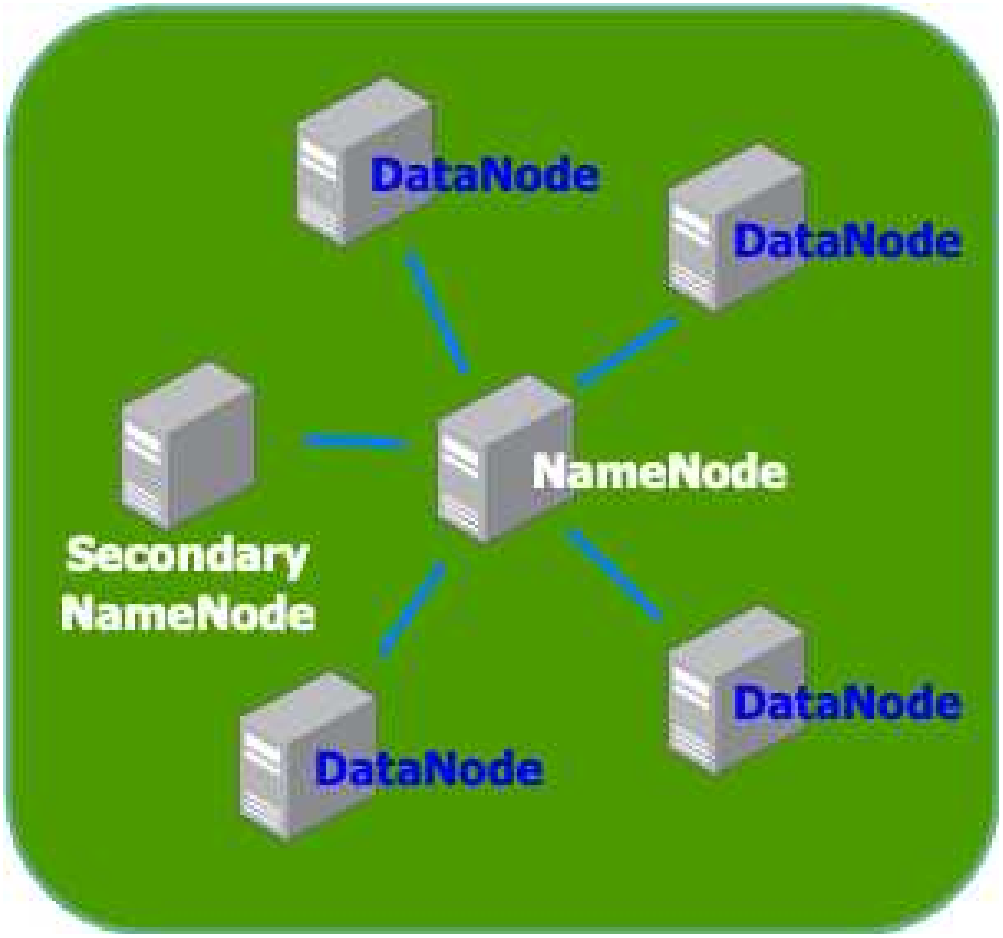
HDFS architecture: Secondary NameNode



Secondary NameNode

Keeps track of changes in the NameNode performing regular snapshots, thus allowing quick startup.
An additional *standby node* is needed to guarantee high availability (since the NameNode is a single point of failure).

HDFS architecture: DataNode



DataNode

Here is where the data is saved and the computations take place (data nodes should actually be called "data and worker nodes")

HDFS architecture: internal data representation

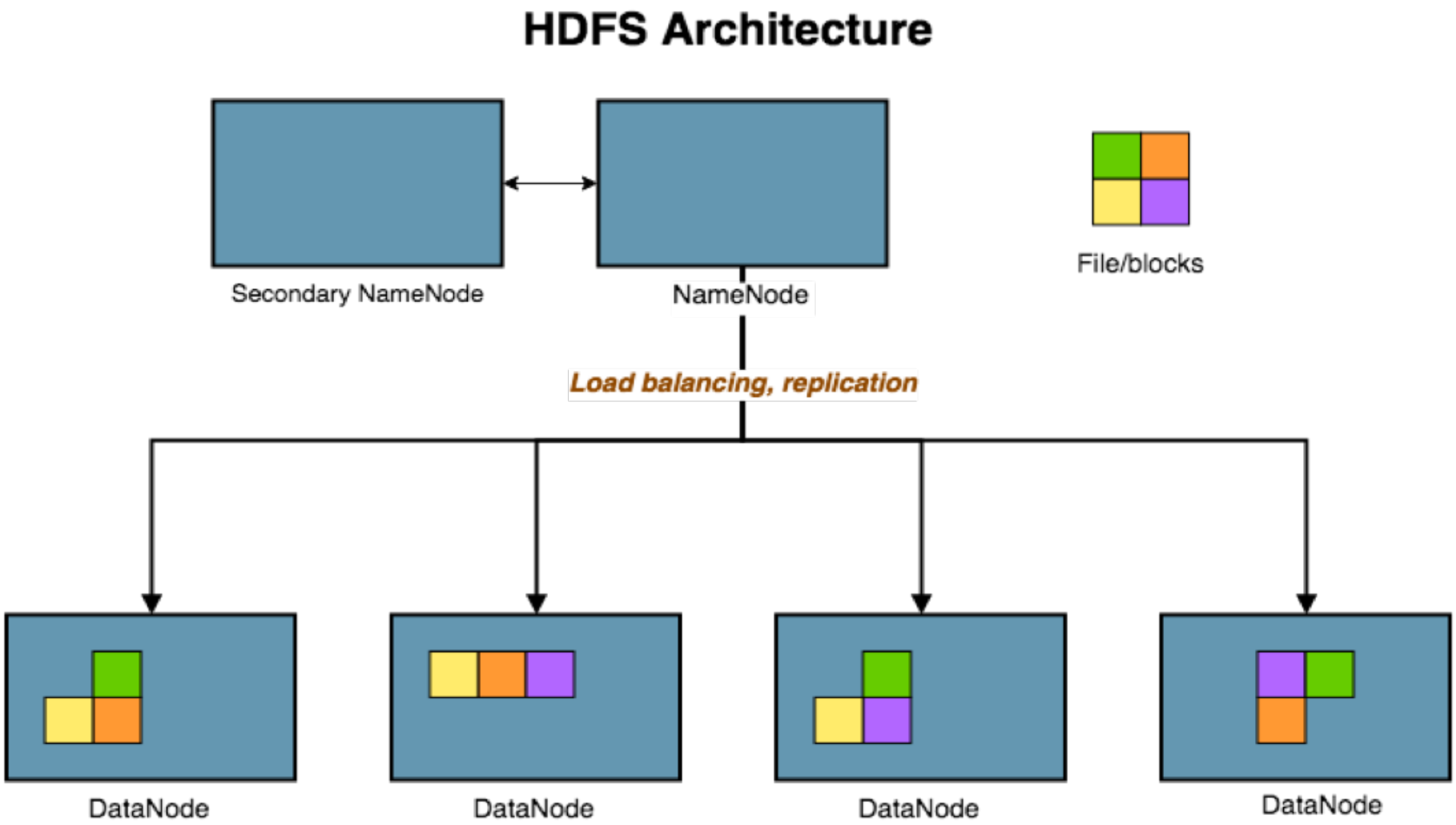
HDFS supports working with very large files.

Internally, data are split into *blocks*. One of the reason for splitting data into blocks is that in this way block objects all have the same size.

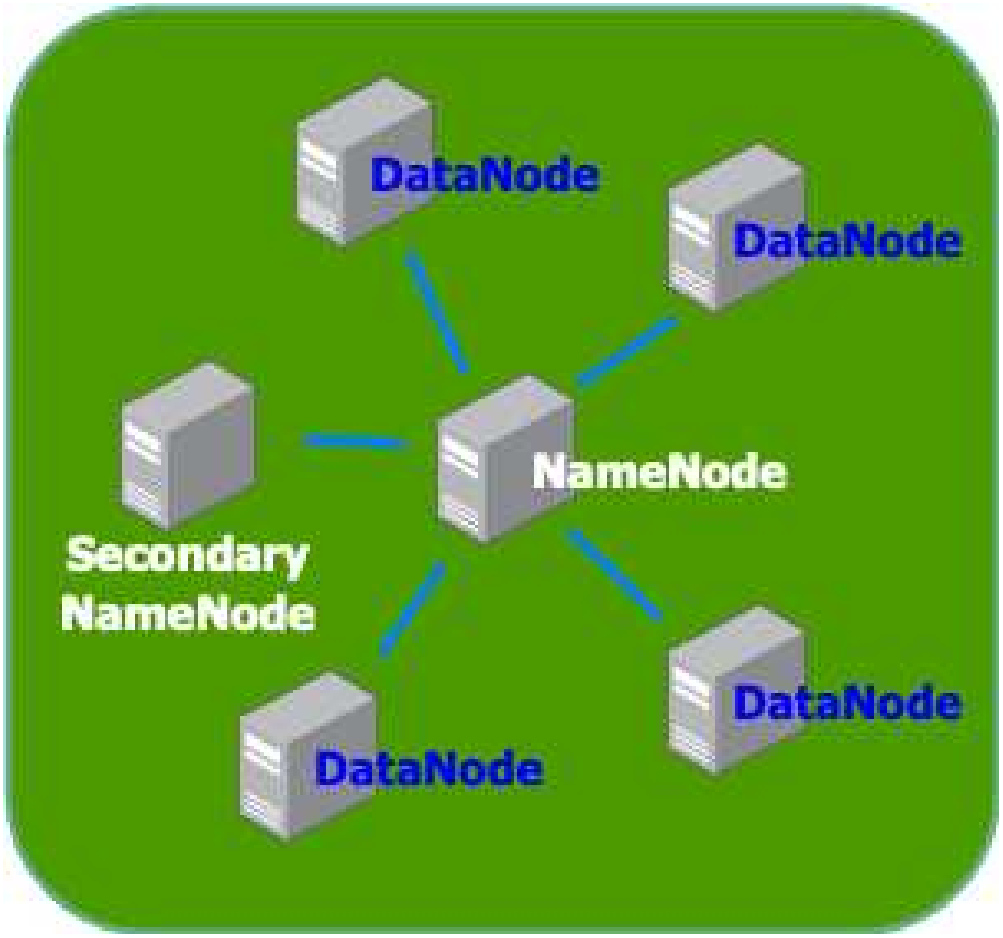
The block size in HDFS can be configured at installation time and it is by default 128MiB (approximately 134MB).

Note: Hadoop sees data as a bunch of records and it processes multiple files the same way it does with a single file. So, if the input is a directory instead of a single file, it will process all files in that directory.

HDFS architecture



DataNode failures



Each DataNode sends a Heartbeat message to the NameNode periodically. Whenever a DataNode becomes unavailable (due to network or hardware failure), the NameNode stops sending requests to that node and creates new replicas of the blocks stored on that node.

The WORM principle of HDFS

The Hadoop Distributed File System relies on a simple design principle for data known as Write Once Read Many (WORM).

"*A file once created, written, and closed need not be changed except for appends and truncates. Appending the content to the end of the files is supported but cannot be updated at arbitrary point. This assumption simplifies data coherency issues and enables high throughput data access.* [5]"

The data immutability paradigm is also discussed in Chapter 2 of "Big Data".[6]

[5] Apache Software Foundation. *Hadoop*. url: https://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html.

[6] Warren J. and Marz N. *Big Data*. Manning publications, 1988.

HDFS hands-on exercises

Basic HDFS filesystem commands

One can regard HDFS as a regular file system, in fact many HDFS shell commands are inherited from the corresponding bash commands.

To run a command on an Hadoop filesystem use the prefix `hdfs dfs`, for instance use:

```
hdfs dfs -mkdir myDir
```

to create a new directory `myDir` on HDFS.

Note: One can use interchangeably `hadoop` or `hdfs dfs` when working on a HDFS file system. The command `hadoop` is more generic because it can be used not only on HDFS but also on other file systems that Hadoop supports (such as Local FS, WebHDFS, S3 FS, and others).

Basic HDFS filesystem commands

Basic HDFS filesystem commands that also exist in bash

`hdfs dfs -mkdir`	create a directory
`hdfs dfs -ls`	list files
`hdfs dfs -cp`	copy files
`hdfs dfs -cat`	print files
`hdfs dfs -tail`	output last part of a file
`hdfs dfs -rm`	remove files

Basic HDFS filesystem commands

Here's three basic commands that are specific to HDFS.

`hdfs dfs -put`	Copy single src, or multiple srcs from local file system to the destination file system
`hdfs dfs -get`	Copy files to the local file system
`hdfs dfs -usage`	get help on hadoop fs

Basic HDFS filesystem commands

To get more help on a specific `hdfs` command use: `hdfs -help <command>`

```
$ hdfs dfs -help tail
# -tail [-f] <file> :
#   Show the last 1KB of the file.

#   -f  Shows appended data as the file grows.
```

Some things to try

```
# create a new directory called "input" on HDFS
hdfs dfs -mkdir input
# copy local file wiki_1k_lines to input on HDFS
hdfs dfs -put wiki_1k_lines input/
# list contents of directory ("-h" = human)
hdfs dfs -ls -h input
# disk usage
hdfs dfs -du -h input
# get help on "du" command
hdfs dfs -help du
# remove directory
hdfs dfs -rm -r input
```

Some things to try

What is the size of the file `wiki_1k_lines`? What is its disk usage?

```
# show the size of wiki_1k_lines on the regular filesystem
ls -lh wiki_1k_lines
# show the size of wiki_1k_lines on HDFS
hdfs dfs -put wiki_1k_lines
hdfs dfs -ls -h wiki_1k_lines

# disk usage of wiki_1k_lines on the regular filesystem
du -h wiki_1k_lines
# disk usage of wiki_1k_lines on HDFS
hdfs dfs -du -h wiki_1k_lines
```

Disk usage on HDFS

The command `hdfs dfs -help du` will tell you that the output is of the form:

`size disk space consumed filename.`

You'll notice that the space on disk is larger than the file size (38.6MB versus 19.3MB):

```
hdfs dfs -du -h wiki_1k_lines
# 19.3 M  38.6 M  wiki_1k_lines
```

This is due to replication. You can check the replication factor using:

```
hdfs dfs -stat 'Block size: %o Blocks: %b Replication: %r'
    input/wiki_1k_lines
# Block size: 134217728 Blocks: 20250760 Replication: 2
```

Disk usage on HDFS

From the previous output:

```
Block size: 134217728 Blocks: 20250760 Replication: 2
```

we can see that the HDFS filesystem currently supports a replication factor of 2.

Note that the Hadoop block size is defined in terms of *mebibytes*, in fact 134217728 bytes corresponds to 128MiB and 134MB. One MiB is larger than a MB since one MiB is $1024^2 = 2^{20}$ bytes, while one MB is 10^6 bytes.

From Map Reduce & Apache Hadoop to Apache Spark

A Brief History

2004
MapReduce paper

2010
Spark paper

2016
Spark 2.0

2002		2004		2006		2008		2010		2012		2014		2016	2020

2002
MapReduce @Google

2006
Hadoop @Yahoo!

2008
Hadoop summit

2014
Apache Spark top-level

2020
Spark 3.0

Why interest on Map-reduce?

- MapReduce offers a **scalable distributed** computing platform for handling **large volumes** of data and mining petabytes of **unstructured information**

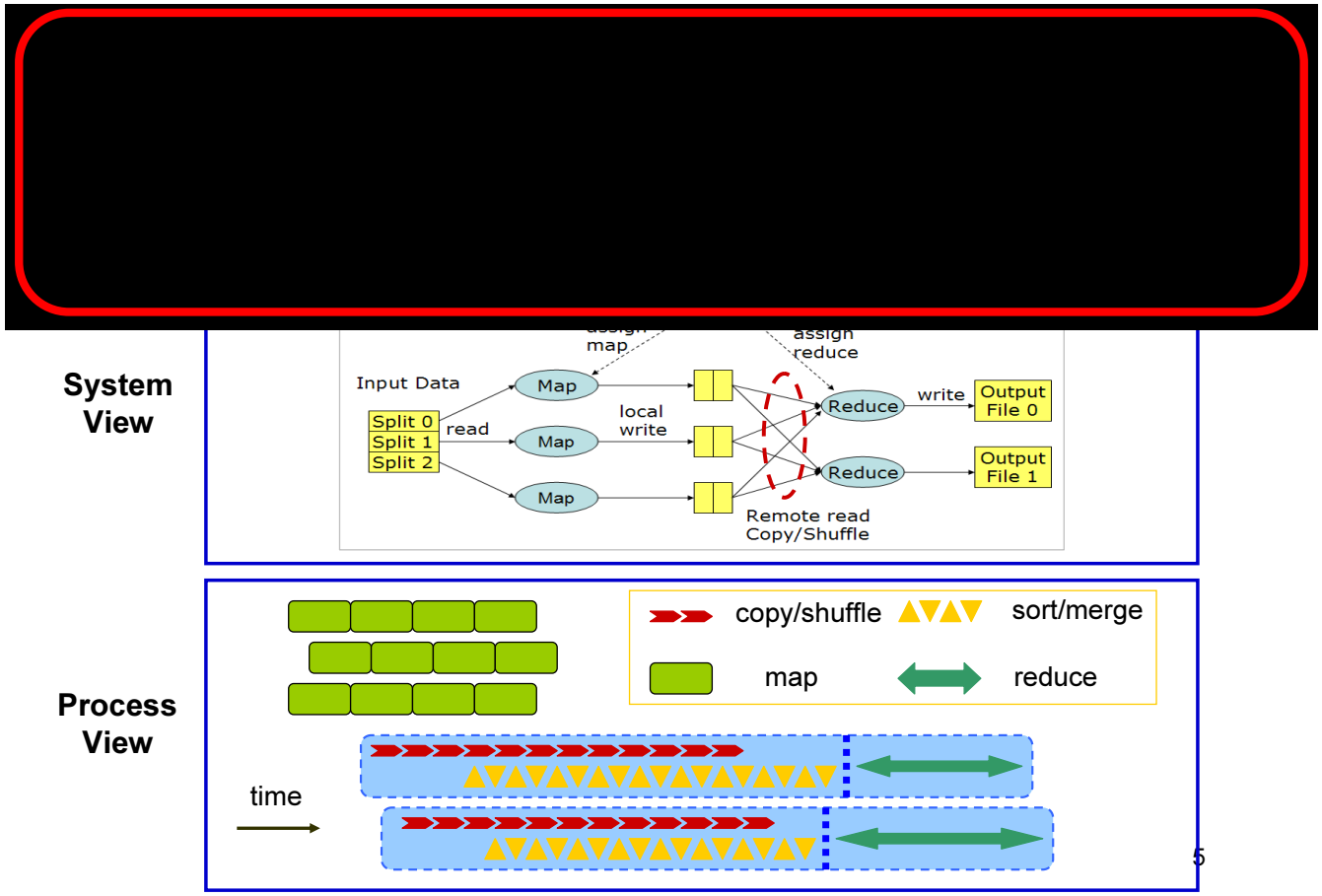
- It has been used to support **data analytics** applications, e.g., **sentiment**, **clickstream**, **sensors**, **geo-location**, **server logs** analyses

- We take a historical perspective, the core ideas are seminal also for modern frameworks

Early days motivations for MapReduce

- Google need for large-Scale Data Processing:
  - Want to use 1000s of CPUs
  - But don't want hassle of ***managing*** things
- Map-reduce Architecture provides:
  - **Automatic** parallelization & distribution
  - **Fault tolerance**
  - I/O **scheduling**
  - **Monitoring** & status updates

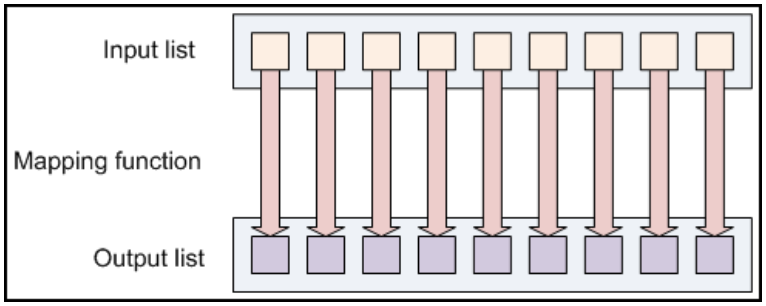
Map-reduce overview

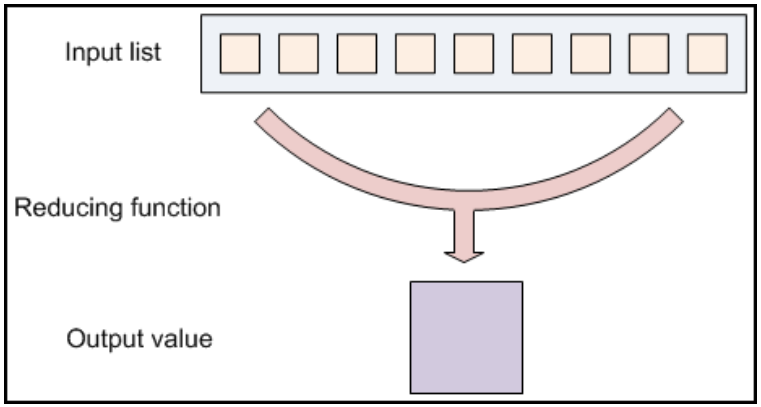


Courtesy of IBM

Function view

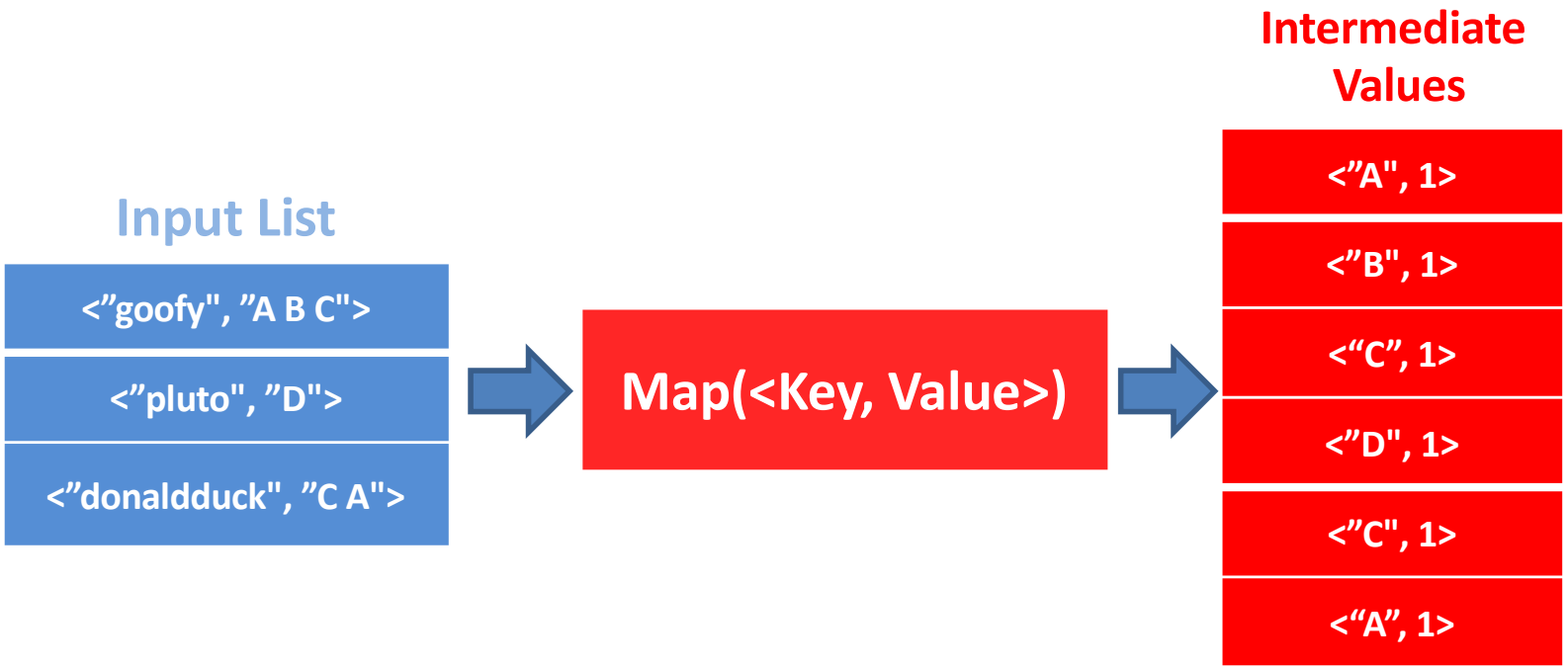
- Input: a **set** of **key/value pairs**
- User supplies two functions:
  - **map(k,v) → list(k1,v1)**
  - **reduce(k1, list(v1)) → v2**
- **(k1,v1)** is an **intermediate** key/value pair
- **Output** is the **set** of **(k1,v2)** pairs



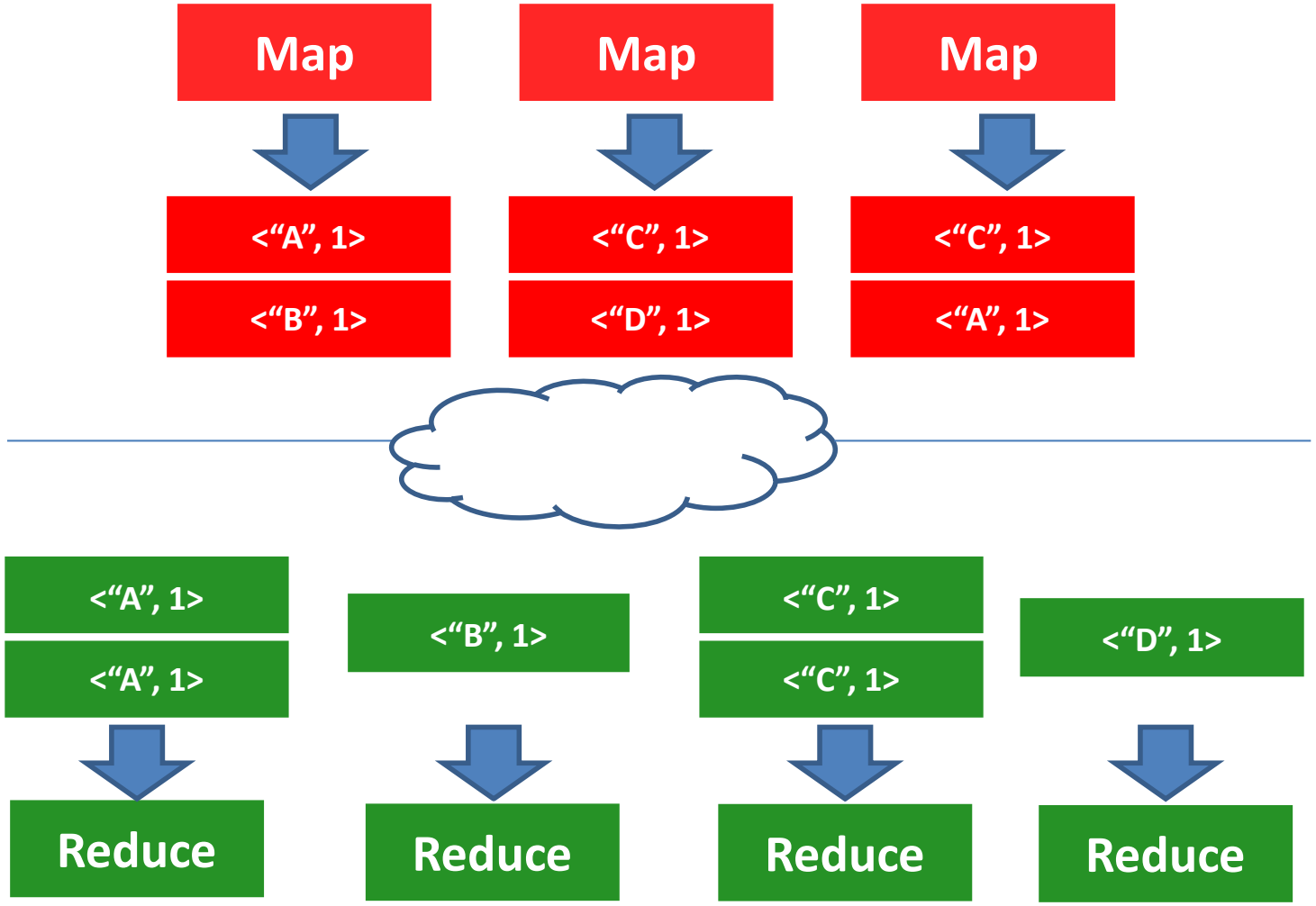


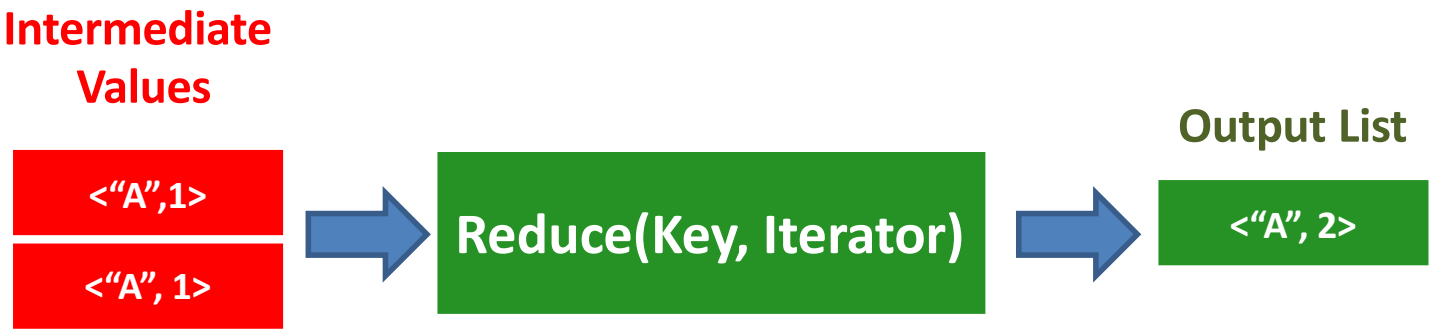
An example: Word Count

- We have many large files of words
- **Count** the number of times each **distinct word** appears in the files
- *Sample application*: analyze web server logs to find **popular URLs**



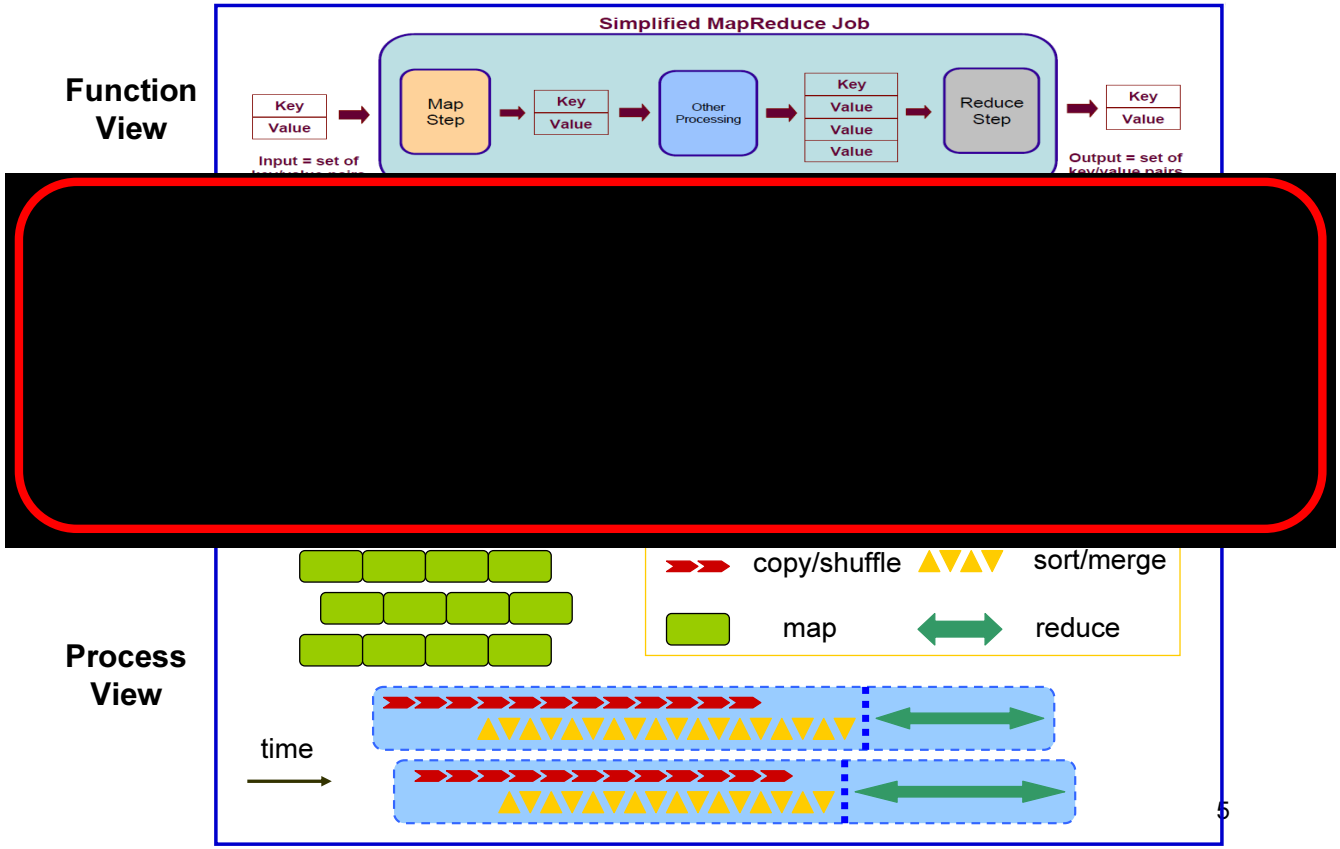

```
let map(String document_content)=
foreach Word word in document_content :
        emit(word, 1)
```


Map
Map
Map
<“A”, 1>
<“B”, 1>
<“C”, 1>
<“D”, 1>
<“C”, 1>
<“A”, 1>
<“A”, 1>
<“A”, 1>
<“B”, 1>
<“C”, 1>
<“C”, 1>
<“D”, 1>
Reduce
Reduce
Reduce
Reduce




```
let reduce(Word word, Iterator<int> occurences) =
int total_occurences = 0;
foreach int o in occurences :
        total_occurences += o;
emit(word, total_occurences);
```

Map-reduce overview



Courtesy of IBM

System view: Hadoop 1.0 implementation

- Metadata management
- Access control
- Single node

- Job scheduling
- Single node

Master Nodes

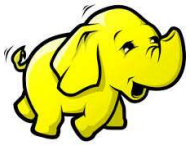
Name Node

Job Tracker

Slave Nodes

Data Node

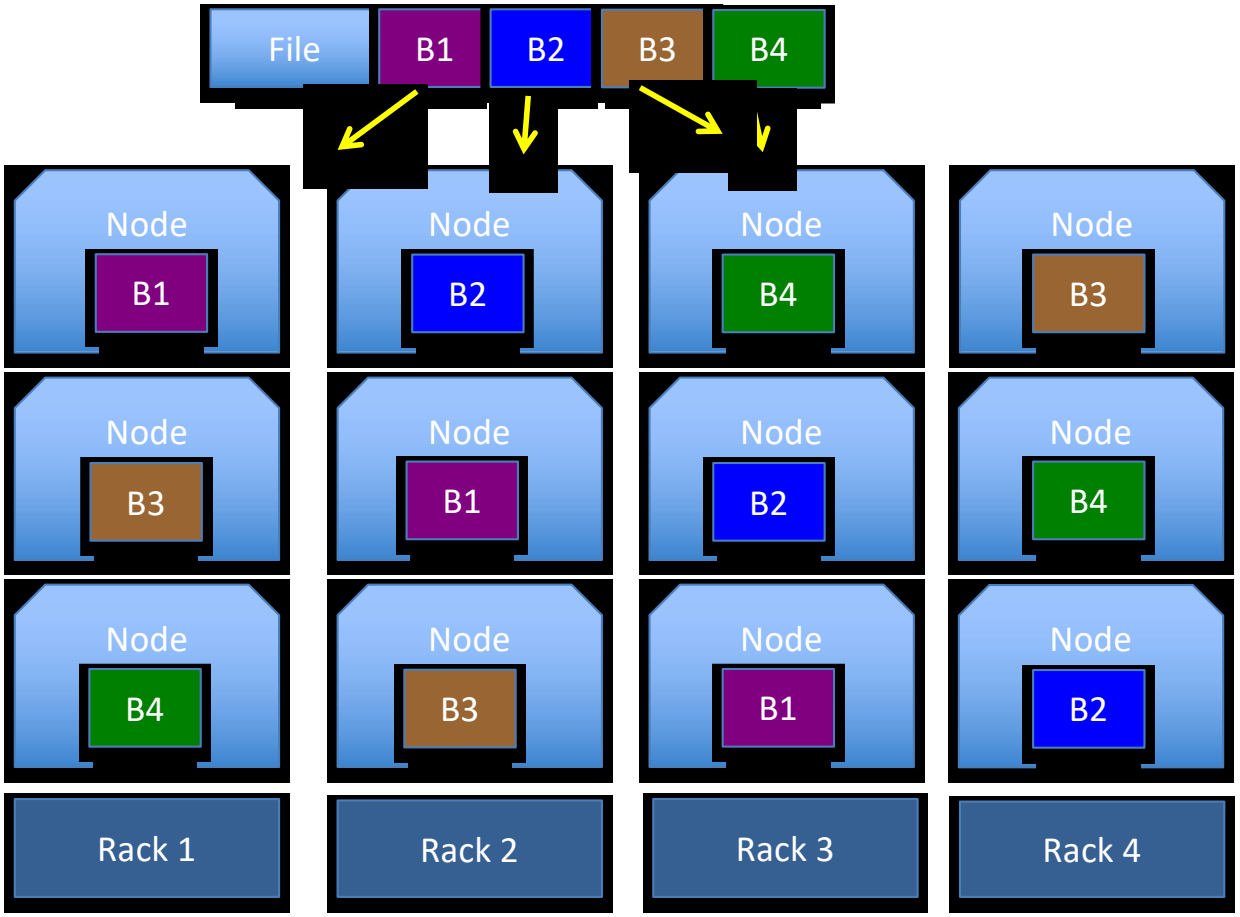
Task Tracker



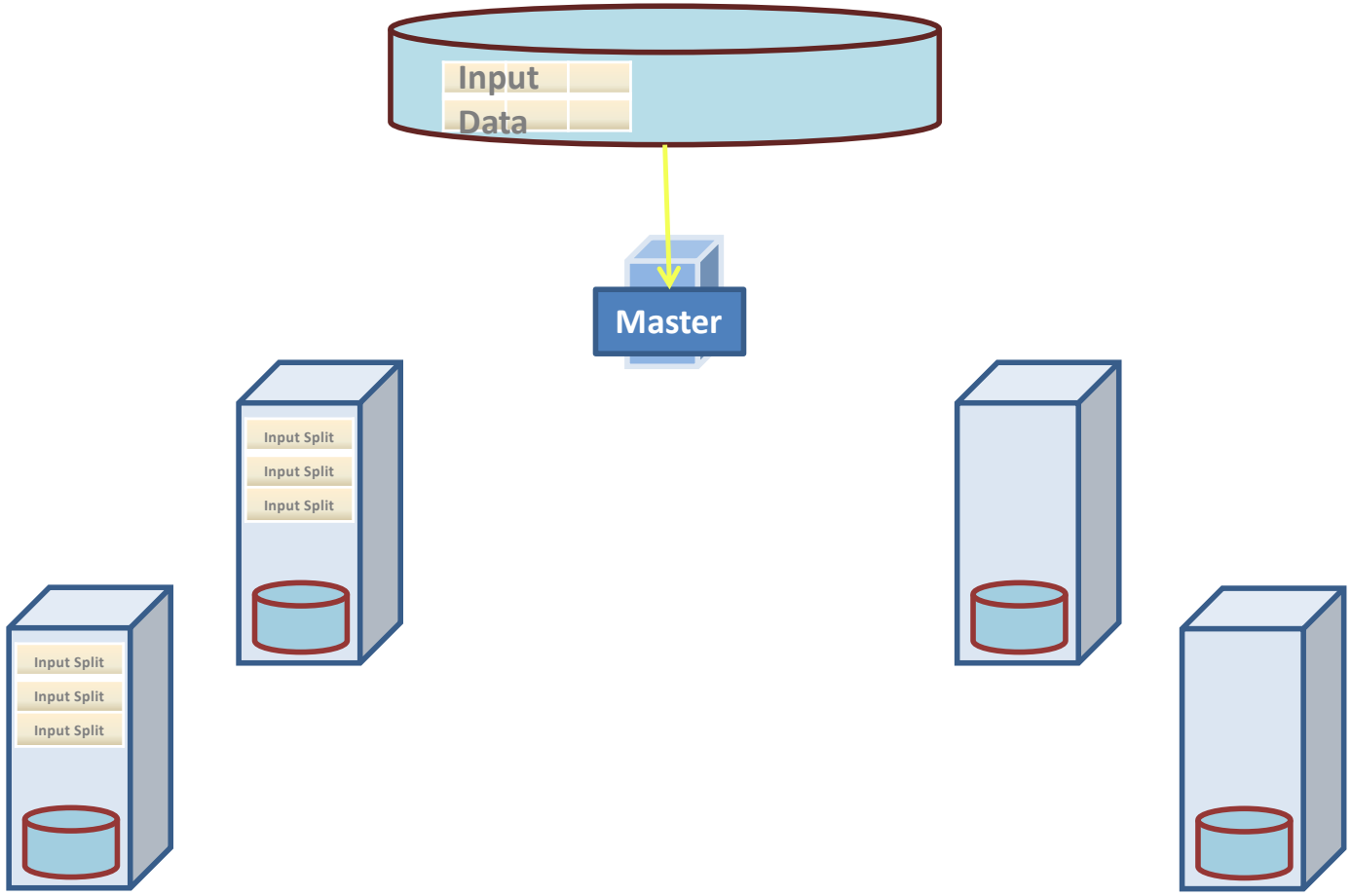
- Block management
- Multiple nodes

- Job management
- Multiple nodes

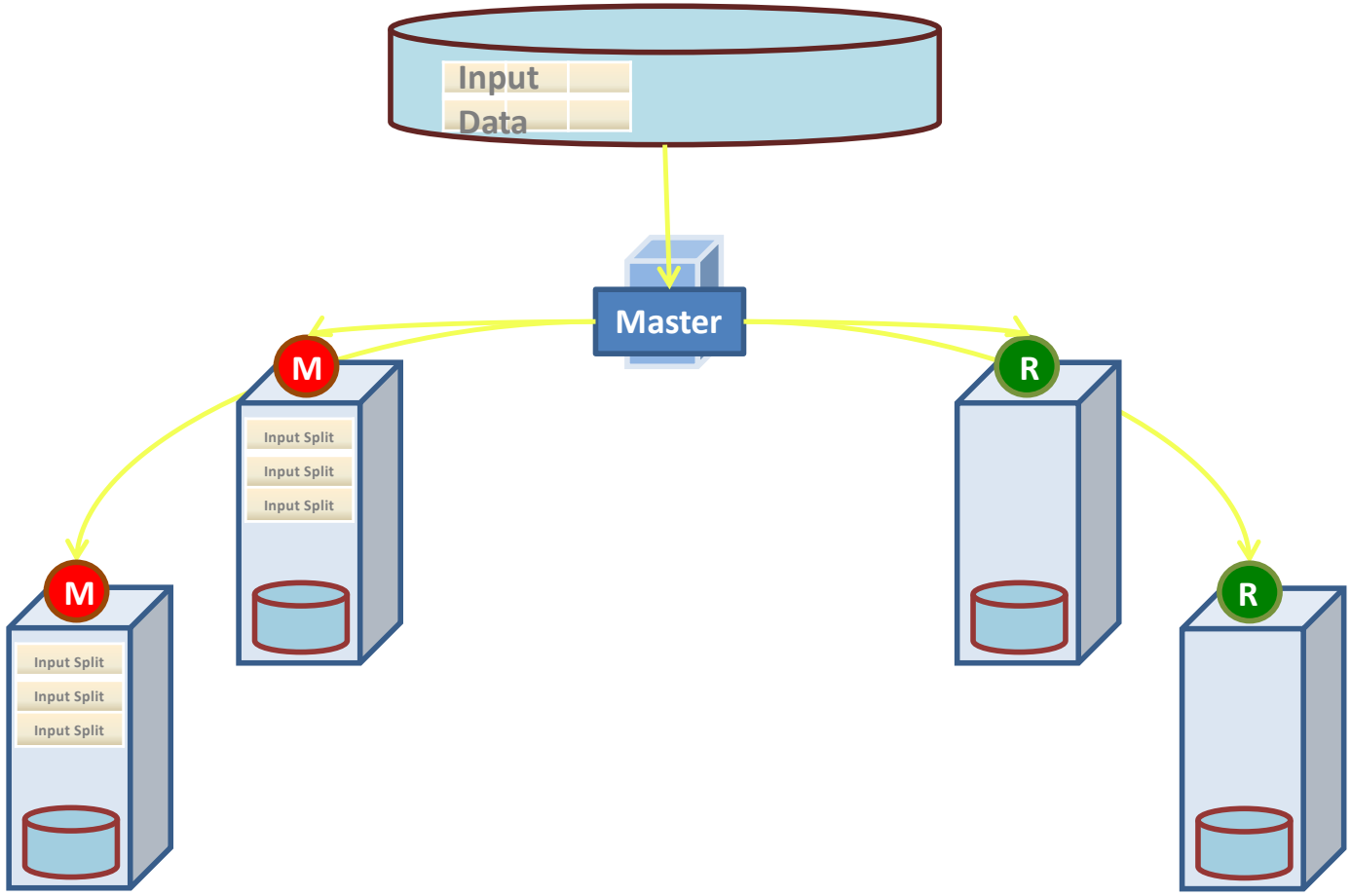
Storing data: HDFS



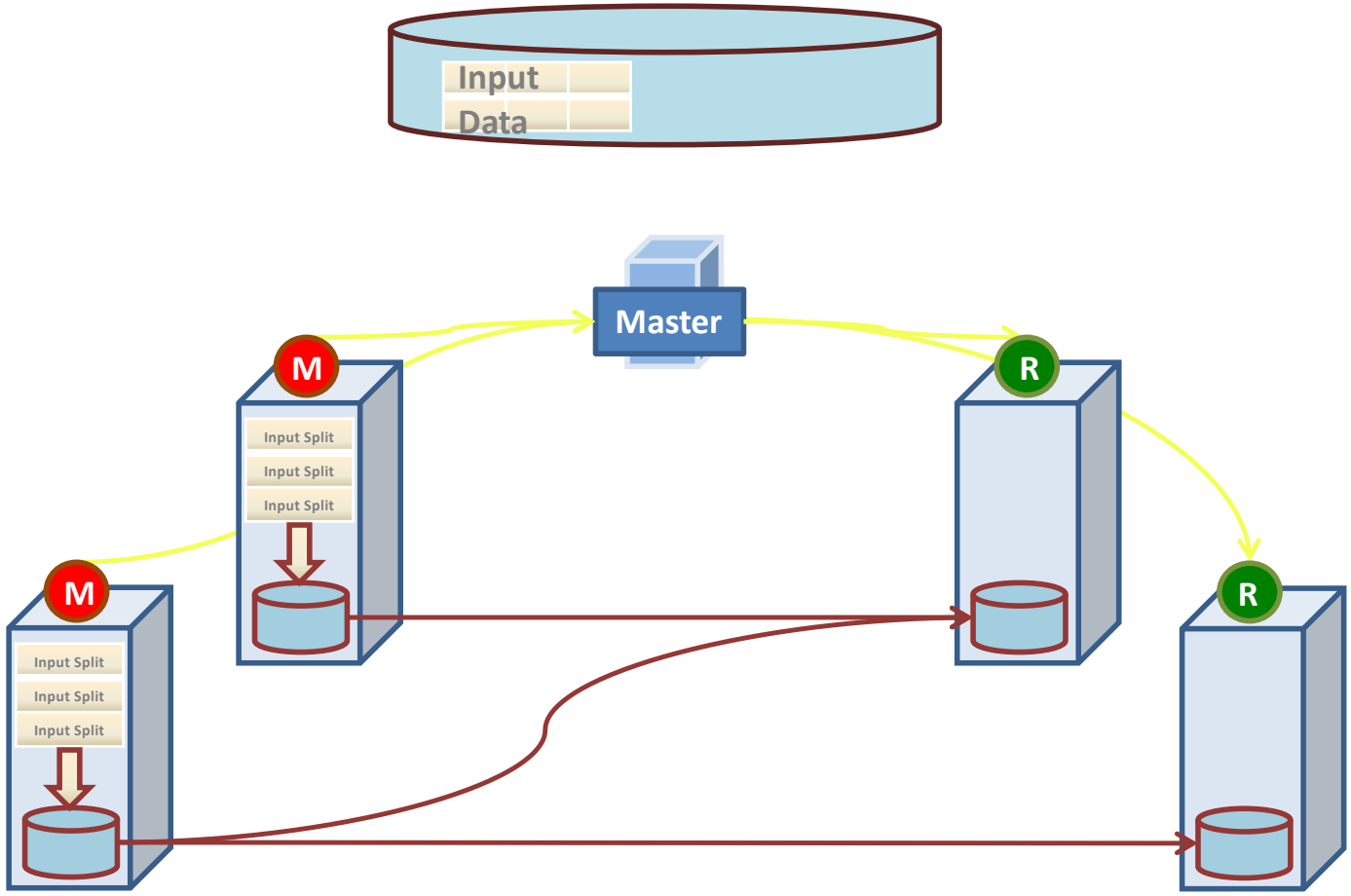
System view – Execution (Hadoop 1.0)



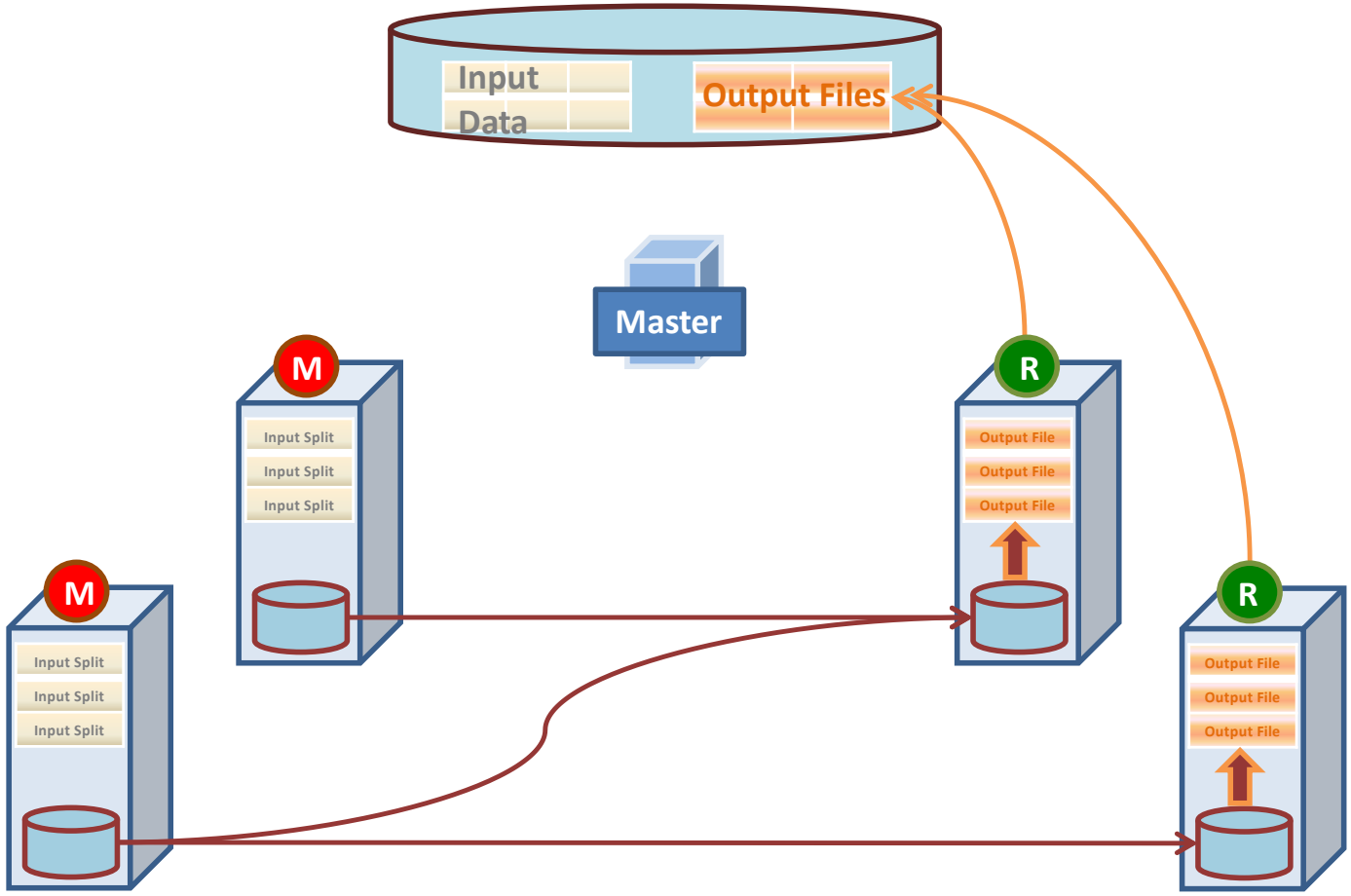
System view – Execution (Hadoop 1.0)



System view – Execution (Hadoop 1.0)



System view – Execution (Hadoop 1.0)

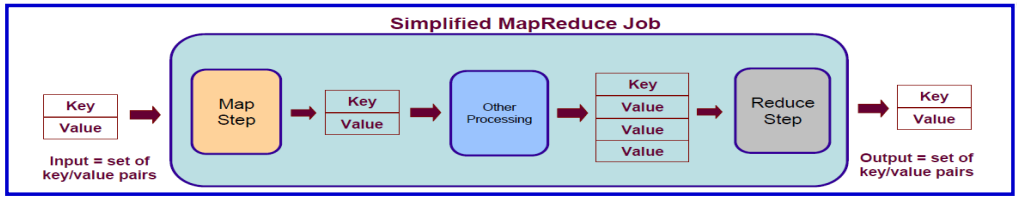


Failures

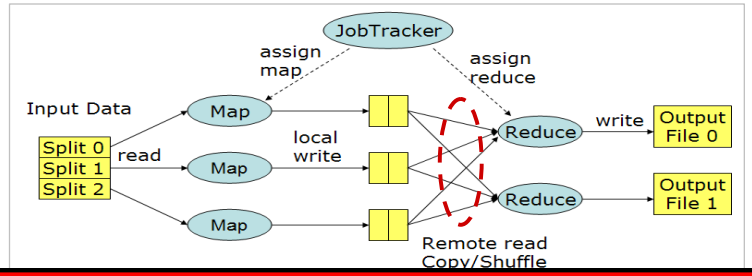
- Master **pings workers** periodically to detect failures
- Map worker failure:
  - Possible intermediate data loss
  - Map tasks restarted on another node with the same input splits
- Reduce worker failure:
  - Reducer tasks are restarted on another node
- **Highly fault-tolerant framework**

Map-reduce overview

Function View



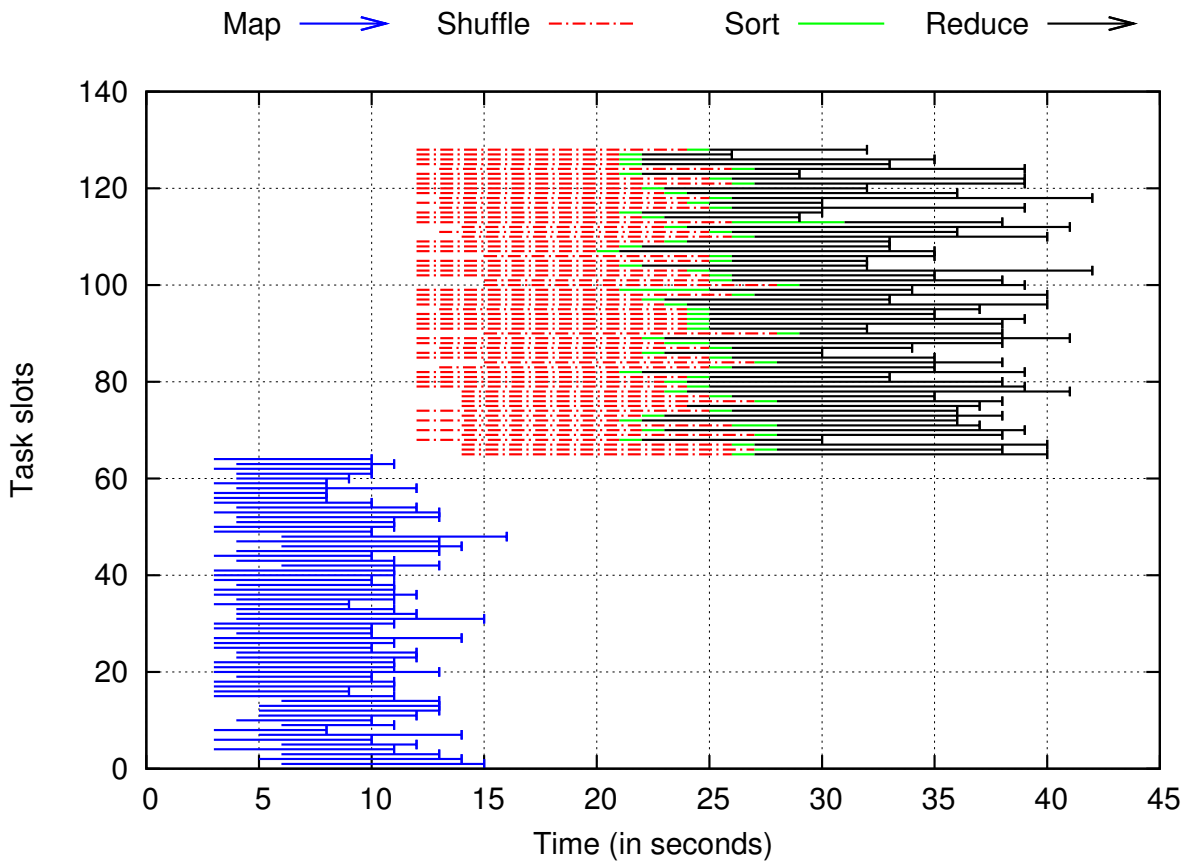
System View



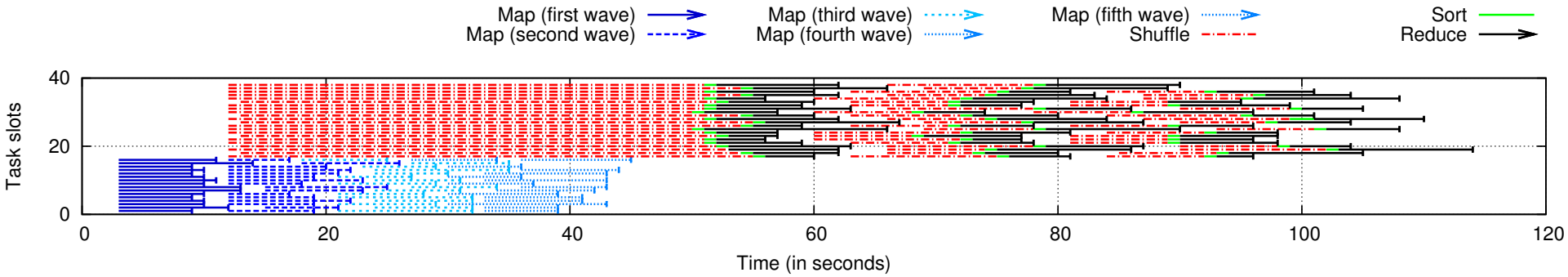
[redacted]

Courtesy of IBM

Process view



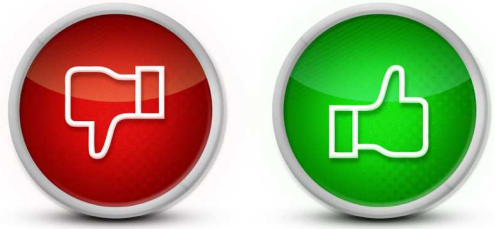
Process view



Source: A. Verma, L. Cherkasova, R.H. Campbell.
ARIA: Automatic Resource Inference and Allocation for mapreduce environments, ICAC 2011.

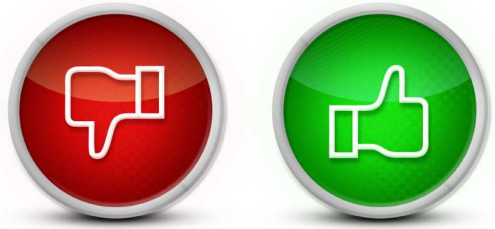
Hadoop Pros & Cons

Hadoop 1.0 pros



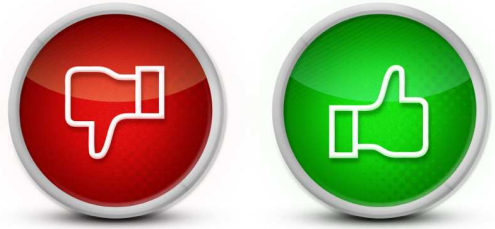
- "Simple" and easy to use
  - A programmer defines his job with only map and reduce functions, **without** having to **specify physical distribution** of his **job** across nodes
- Fault tolerance
  - MapReduce is **highly fault-tolerant** (continue to work in spite of an average of 1.2 failures per analysis job at Google)
- Flexible
  - **No dependency on data model** and schema (good for irregular or unstructured data)

Hadoop 1.0 cons



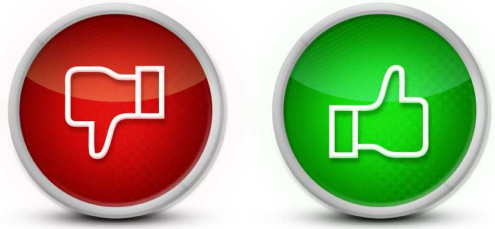
- A **single fixed dataflow**
  - The dataflow is fixed, many **complex algorithms** are **hard** to **implement** in a single job
  - Some algorithms that **require multiple inputs are not well supported** since the dataflow of MapReduce is originally designed to read a single input and generate a single output
- No high-level language
  - **No declarative language** like SQL in DBMS and any query optimization technique
- No schema and **no index**
  - Each item is parsed at reading input and transform it into data objects for data processing, causing performance degradation

Hadoop 1.0 cons



- Low efficiency
  - With fault-tolerance and scalability as its primary goals, MapReduce operations are **not** always **optimized for I/O efficiency**. In addition, Map and Reduce are **blocking** operations
  - **No** specific **execution** plans and **does not optimize** plans like DBMS does to minimize **data transfer** across nodes

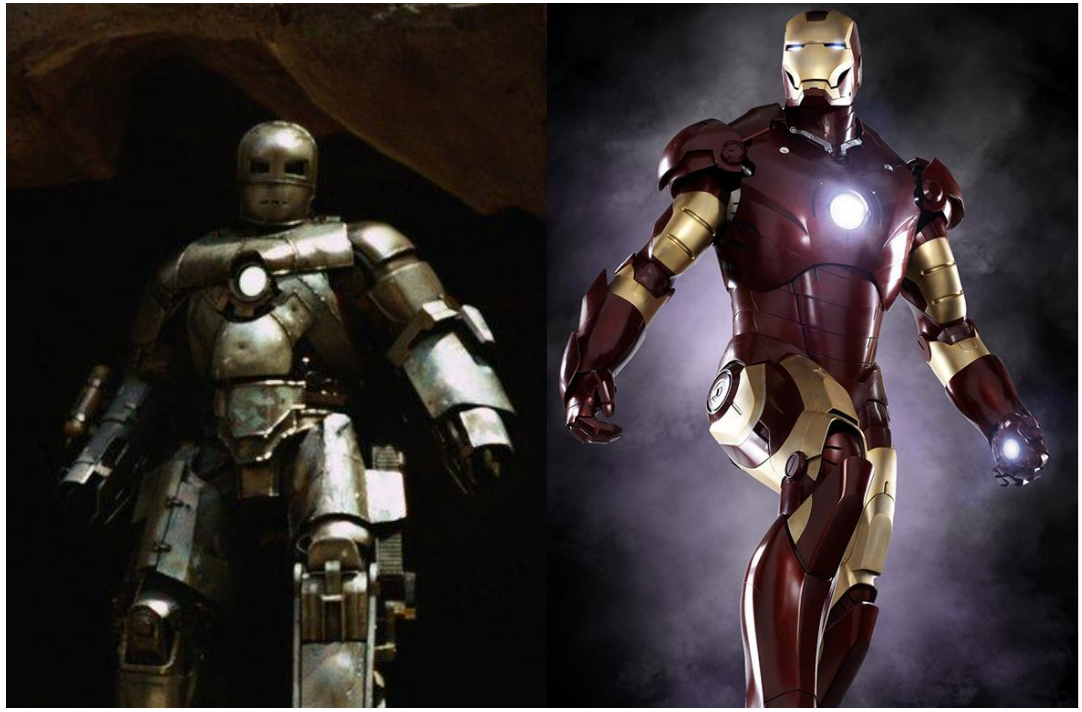
Comparing Hadoop with commercial data warehouses



- Hadoop **2~50 times slower**, except in data loading
- Hadoop 1.0 was scalable but achieved **very low efficiency per node**, around 5MB/s processing rate, repeating a mistake that previous studies on HPC did *focusing on scalability but missing efficiency*

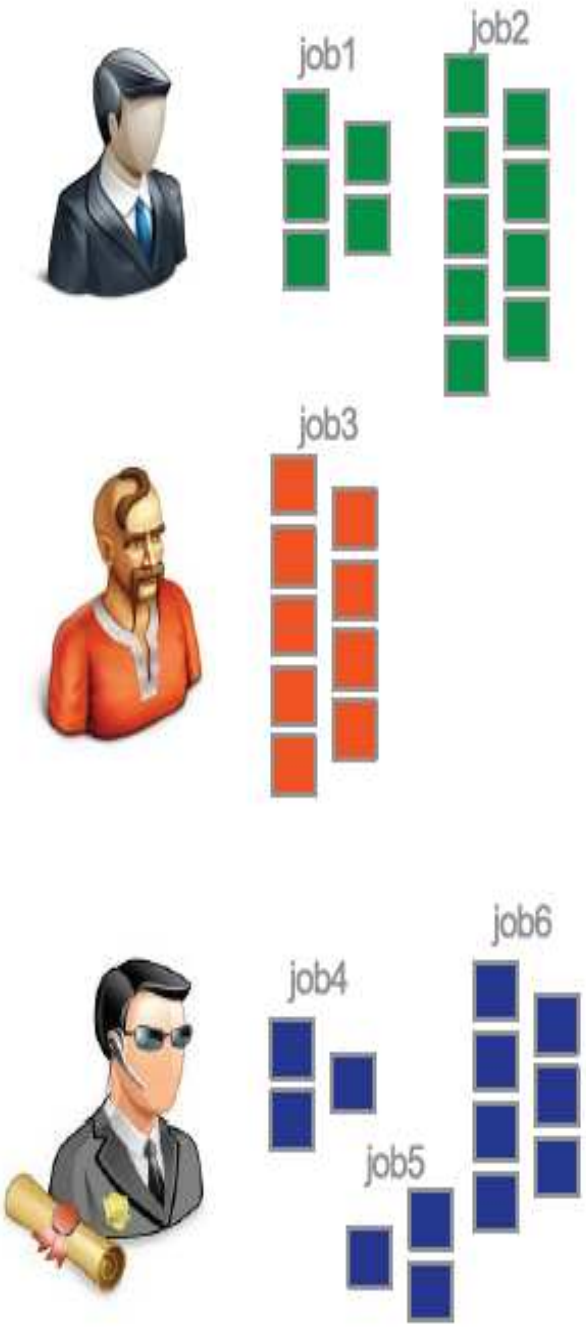
Source: K. H. Lee, Y. J. Lee, H. Choi, Y. D. Chung, and B. Moon. Parallel data processing with MapReduce: a survey. *SIGMOD Rec.* 40(4), 2011.

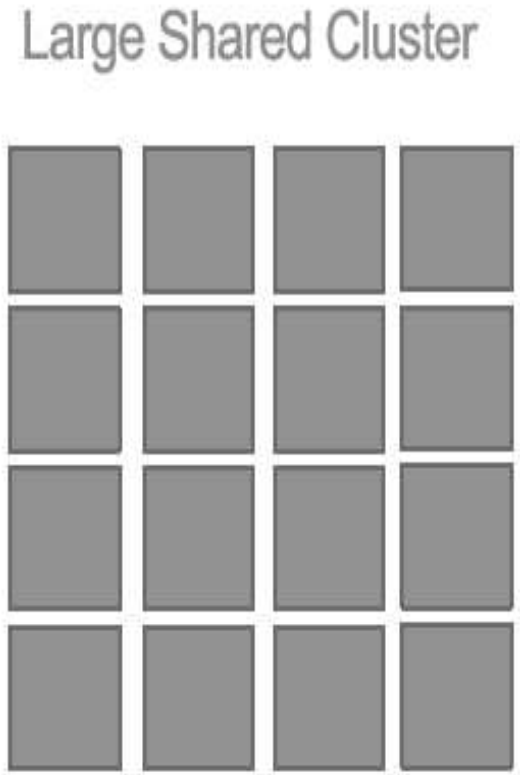
Hadoop evolution



Hadoop 1.0 → Hadoop 3.2.1

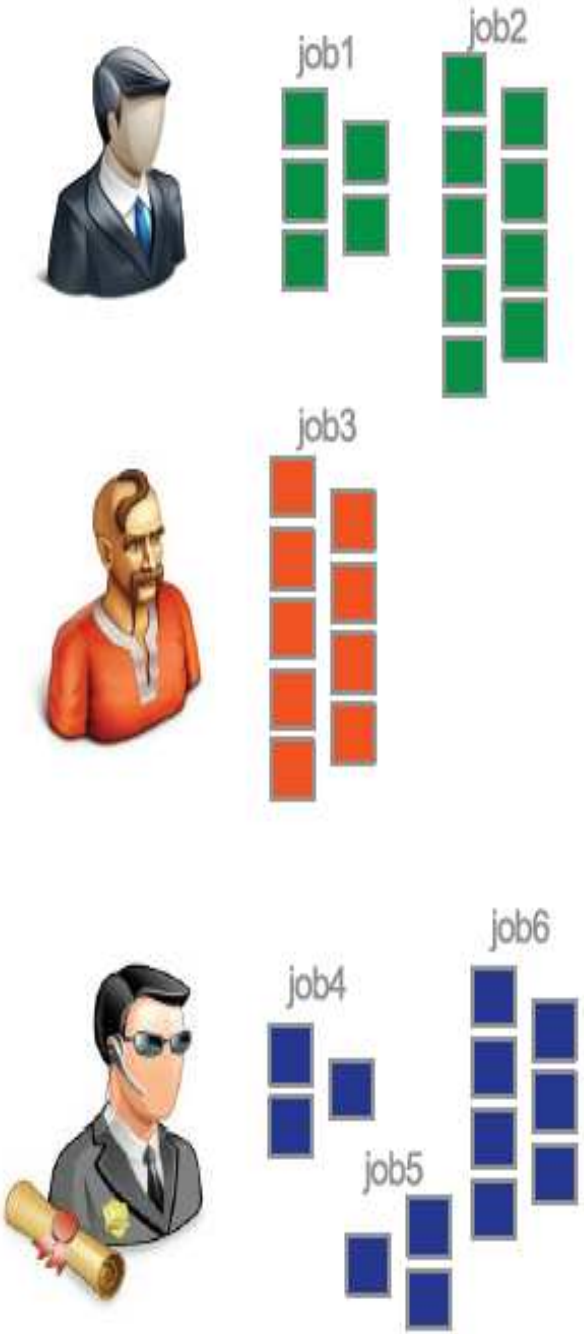
Hadoop 1.0





Courtesy of Microsoft

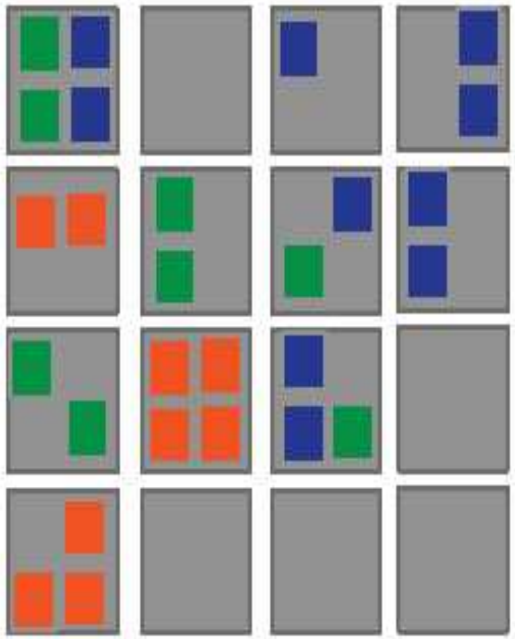
Hadoop 1.0



Problems to solve

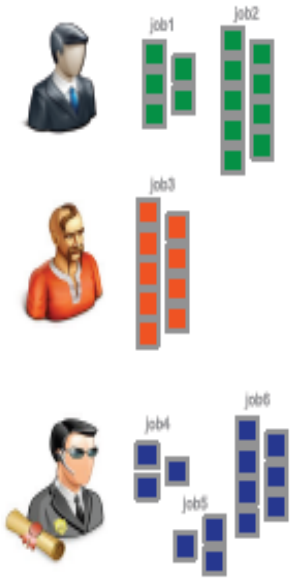
- Who runs?
- Where?
- How much resources?
- Order of execution
- Monitor progress
- Handle failures

Large Shared Cluster



Courtesy of Microsoft

Hadoop 2.x



Resource Management

- Who runs?
- Where?
- How much resources?

→ Goals

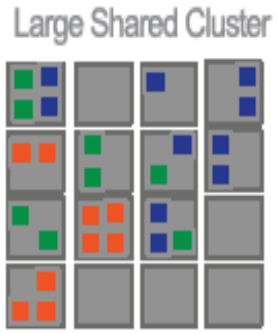
- Cluster throughput
- Scheduling Invariants
- Efficiency (locality)

Application Workflow

- Order of execution
- Monitor progress
- Handle failures

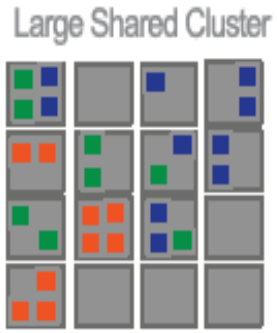
→ Goals

- Fault tolerance
- App Semantics



Courtesy of Microsoft

Hadoop 2.x

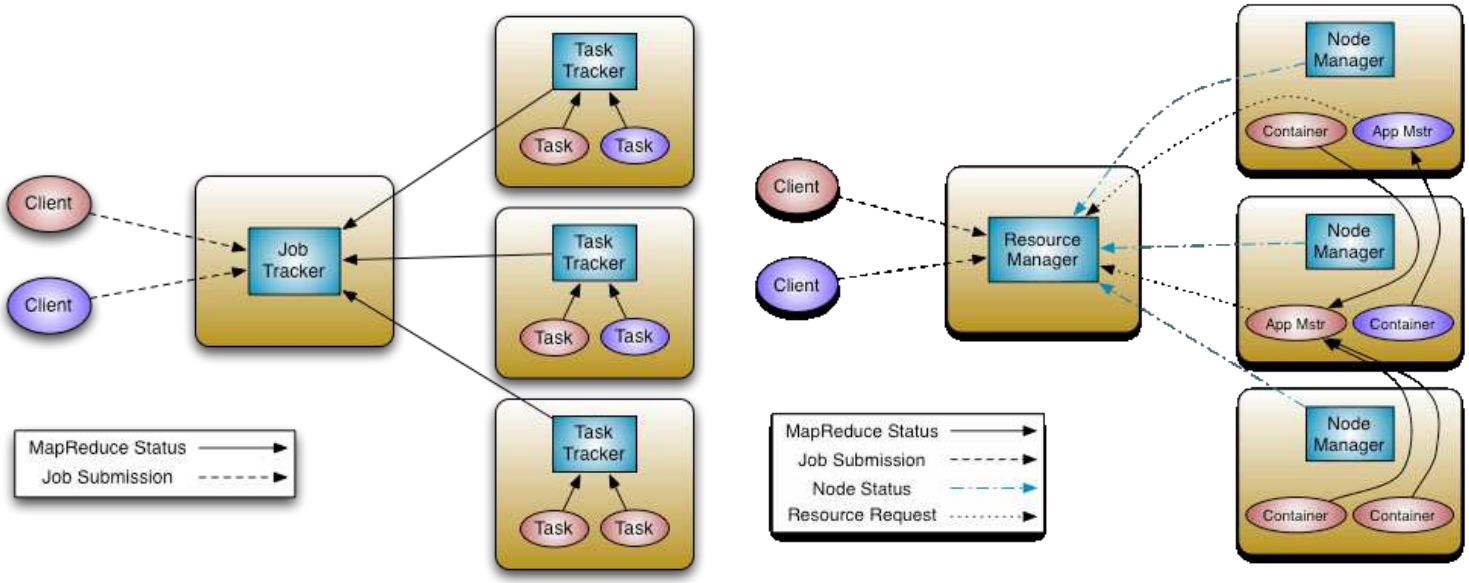


- **R**esource **M**anager and **A**pplication **M**asters implemented within **YARN**: **Yet Another Resource Negotiator**

Courtesy of Microsoft

Computational nodes architecture

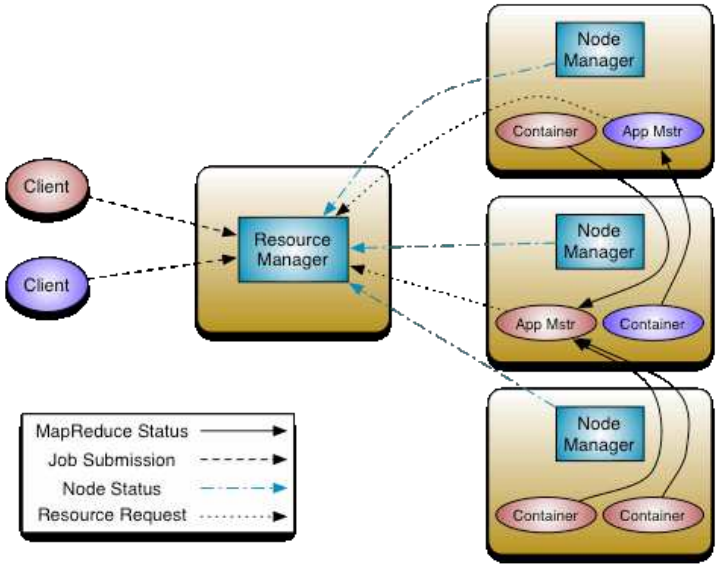
- Job and task trackers have been replaced



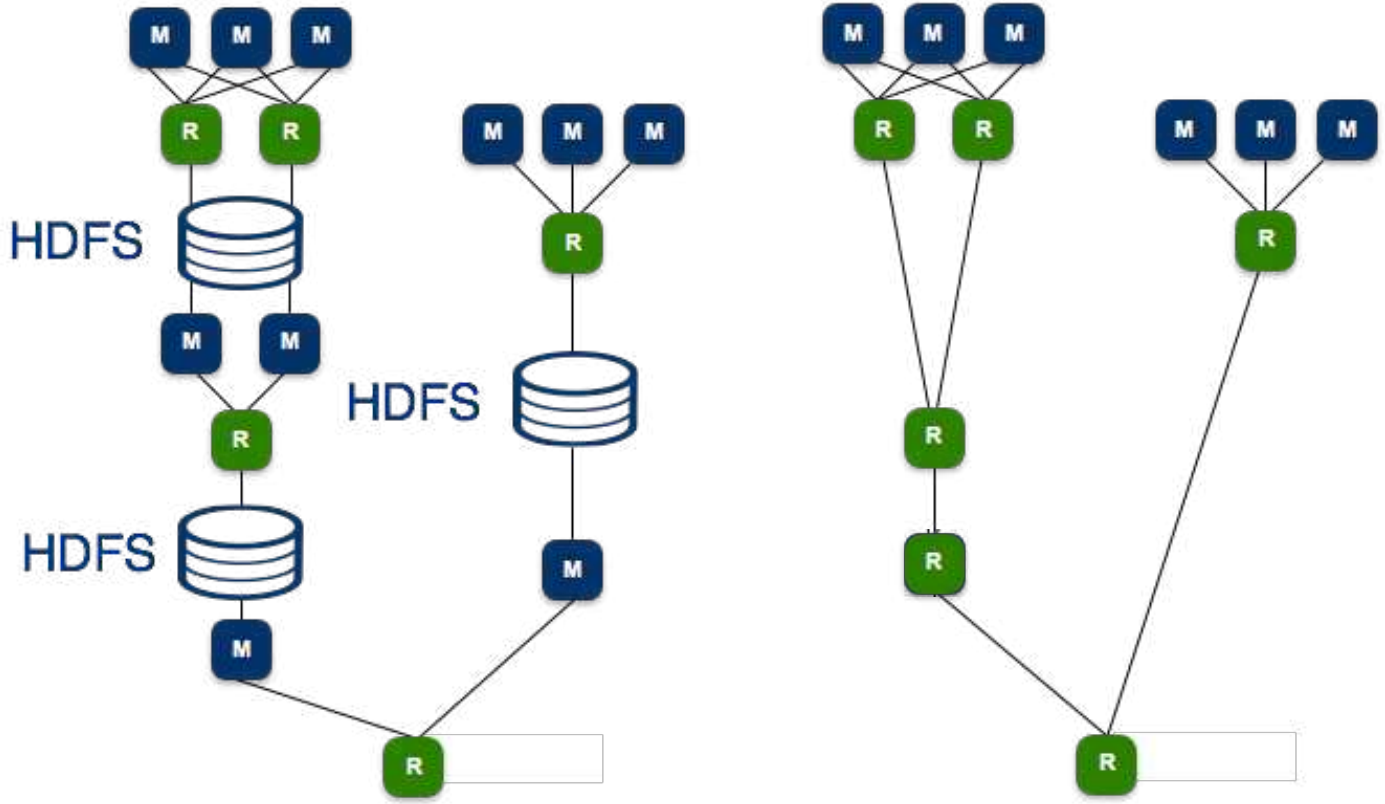
Computational nodes architecture

- Job and task trackers have been replaced

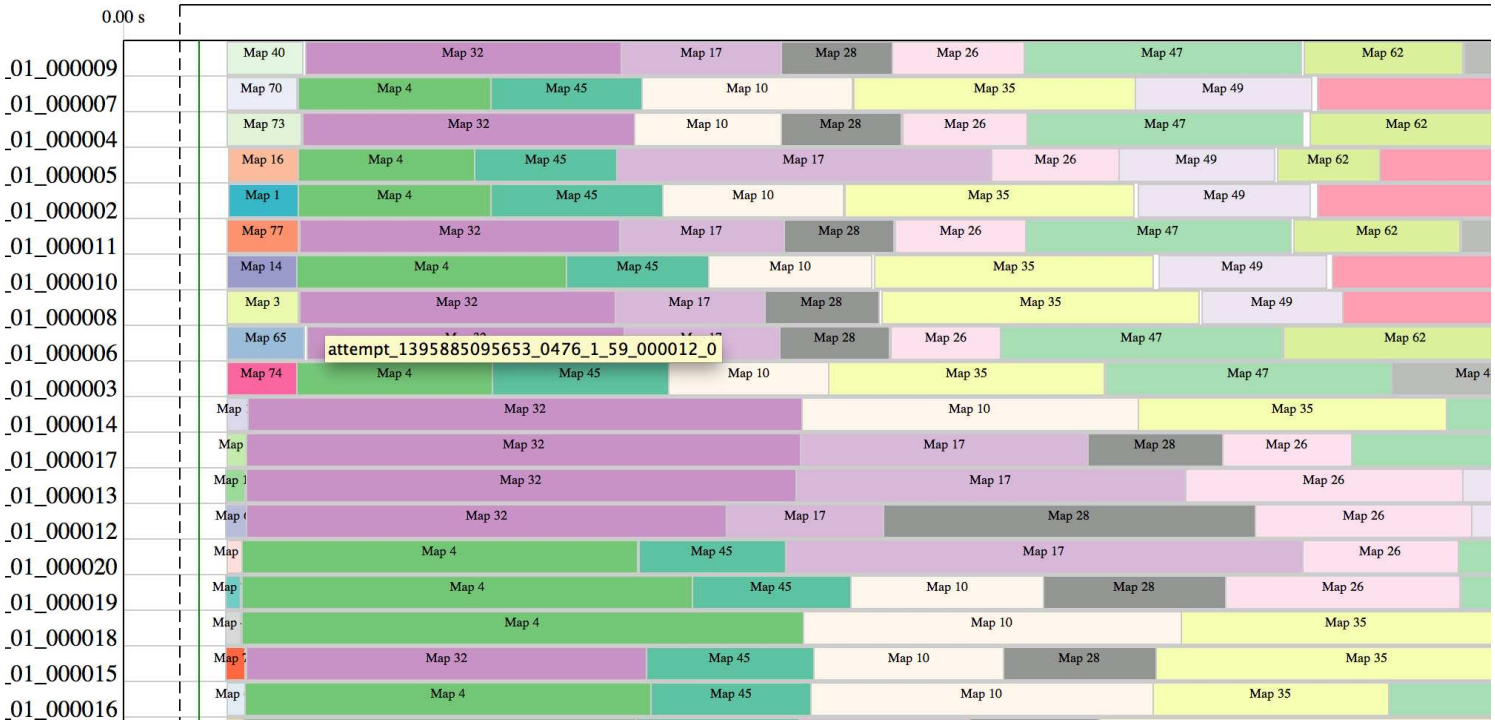
- Resource Manager:
  - Global resource scheduler
  - Hierarchical queues
- Application Master:
  - Per-application
  - Manages application scheduling and task execution
- Node Manager:
  - Per-machine agent
  - Manages the life-cycle of containers
  - Container resource monitoring



Generic DAGs (Apache Tez)



YARN Dynamic resource allocation



Bikas Saha Apache Tez: Accelerating Hadoop Data Processing
http://www.slideshare.net/hortonworks/apache-tez-accelerating-hadoop-query-processing

Hadoop 2.x vs. 3.x

- HDFS Fault Tolerance:
  - Hadoop 2.x: handled by replication (which is wastage of space)
  - Hadoop 3.x: handled by erasure coding, **50% instead of 200%** overhead
- Containers:
  - Hadoop 3.x provides Docker support in Linux containers executors
- GPUs:
  - Hadoop 3.x enables scheduling of additional resources, such as disks and GPUs for better support of deep learning & machine learning applications
  - Deep learning models (in TensorFlow) can run on Hadoop YARN cluster where data resides

Performance degradation

- The network is a bottleneck:
  - Copy shuffle phase limit jobs execution performance
  - Network optimizations
    - load balancing across multiple paths
    - traffic prioritization and isolation
    - data aggregation and compression
- The disk is a bottleneck:
  - Caching data in memory
- Stragglers:
  - Tasks that take much longer to complete than other tasks in the job
  - Outliers caused by poorly performing machines that cause tasks scheduled on them to take longer
  - Work may have been unevenly divided across tasks, skews

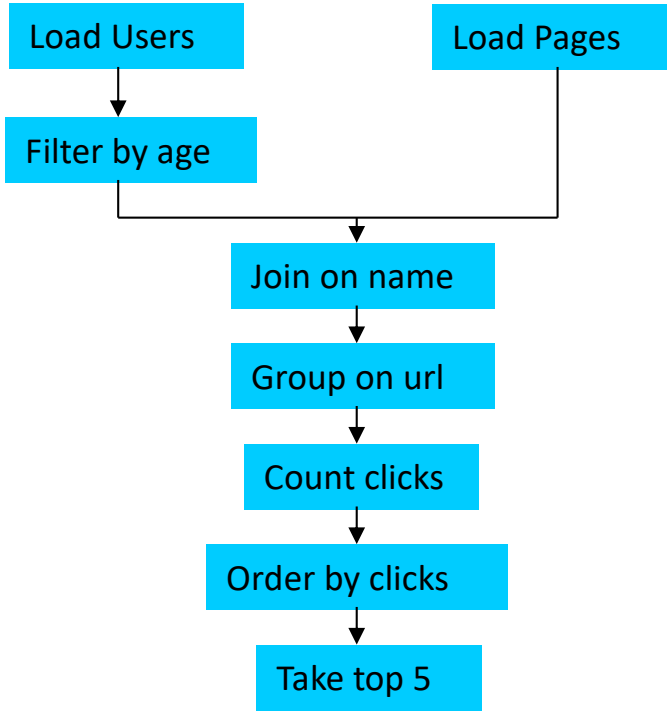
Pig & Hive

Need for High-Level Languages

- Hadoop is great for large-data processing!
  - But writing Java programs for everything is verbose and slow
  - Not everyone wants to (or can) write Java code
- Solution: develop higher-level data processing languages
  - Pig: Pig Latin is a bit like Perl
  - Hive: HQL is like SQL
- Common idea:
  - Higher-level language “compiles down” to Hadoop jobs

Motivation by example

Suppose you have user data in one file, website data in another, and you need to find the top 5 most visited pages by users aged 18 - 25.



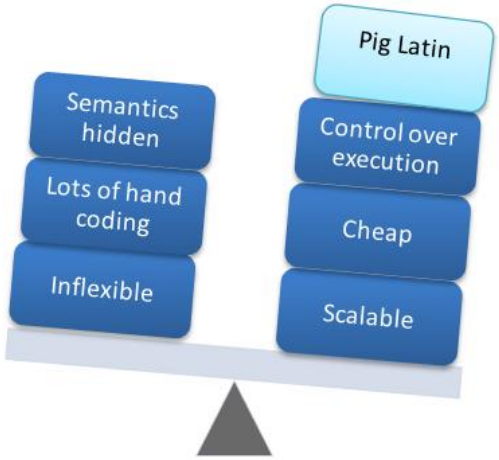
In Map Reduce

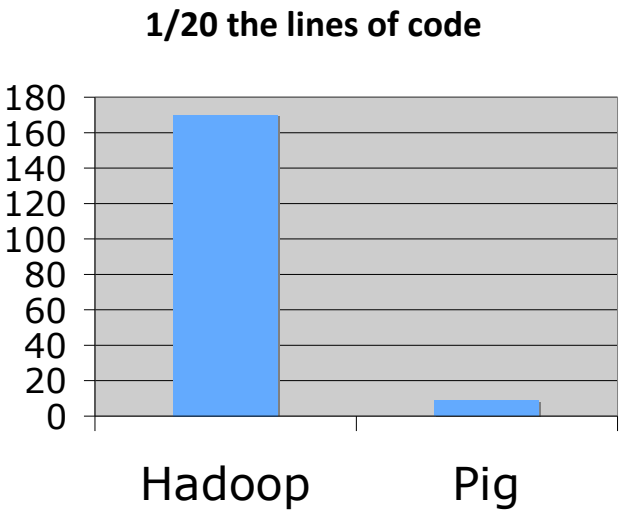
```
import java.io.IOException;
import java.util.ArrayList;
import java.util.Iterator;
import java.util.List;

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.io.Writable;
import org.apache.hadoop.io.WritableComparable;
import org.apache.hadoop.mapred.FileInputFormat;
import org.apache.hadoop.mapred.FileOutputFormat;
import org.apache.hadoop.mapred.JobConf;
import org.apache.hadoop.mapred.KeyValueTextInputFormat;
import org.apache.hadoop.mapred.Mapper;
import org.apache.hadoop.mapred.MapReduceBase;
import org.apache.hadoop.mapred.OutputCollector;
import org.apache.hadoop.mapred.RecordReader;
import org.apache.hadoop.mapred.Reducer;
import org.apache.hadoop.mapred.Reporter;
import org.apache.hadoop.mapred.SequenceFileInputFormat;
import org.apache.hadoop.mapred.SequenceFileOutputFormat;
import org.apache.hadoop.mapred.TextInputFormat;
import org.apache.hadoop.mapred.jobcontrol.Job;
import org.apache.hadoop.mapred.jobcontrol.JobControl;
import org.apache.hadoop.mapred.lib.IdentityMapper;

public class MRExample {
    public static class LoadPages extends MapReduceBase
        implements Mapper<LongWritable, Text, Text, Text> {

        public void map(LongWritable k, Text val,
                OutputCollector<Text, Text> oc,
                Reporter reporter) throws IOException {
            // Pull the key out
            String line = val.toString();
            int firstComma = line.indexOf(',');
            String key = line.substring(0, firstComma);
            String value = line.substring(firstComma + 1);
            Text outKey = new Text(key);
            // Prepend an index to the value so we know which file
            // it came from.
            Text outVal = new Text("1" + value);
            oc.collect(outKey, outVal);
        }
    }
    public static class LoadAndFilterUsers extends MapReduceBase
        implements Mapper<LongWritable, Text, Text, Text> {

        public void map(LongWritable k, Text val,
                OutputCollector<Text, Text> oc,
                Reporter reporter) throws IOException {
            // Pull the key out
            String line = val.toString();
            int firstComma = line.indexOf(',');
            String value = line.substring(firstComma + 1);
            int age = Integer.parseInt(value);
            if (age < 18 || age > 25) return;
            String key = line.substring(0, firstComma);
            Text outKey = new Text(key);
            // Prepend an index to the value so we know which file
            // it came from.
            Text outVal = new Text("2" + value);
            oc.collect(outKey, outVal);
        }
    }
    public static class Join extends MapReduceBase
        implements Reducer<Text, Text, Text, Text> {

        public void reduce(Text key,
                Iterator<Text> iter,
                OutputCollector<Text, Text> oc,
                Reporter reporter) throws IOException {
            // For each value, figure out which file it's from and
store it
            // accordingly.
            List<String> first = new ArrayList<String>();
            List<String> second = new ArrayList<String>();

            while (iter.hasNext()) {
                Text t = iter.next();
                String value = t.toString();
                if (value.charAt(0) == '1')
first.add(value.substring(1));
                else second.add(value.substring(1));
                reporter.setStatus("OK");
            }

            // Do the cross product and collect the values
            for (String s1 : first) {
                for (String s2 : second) {
                    String outval = key + "," + s1 + "," + s2;
                    oc.collect(null, new Text(outval));
                    reporter.setStatus("OK");
                }
            }
        }
    }
    public static class LoadJoined extends MapReduceBase
        implements Mapper<Text, Text, Text, LongWritable> {

        public void map(
                Text k,
                Text val,
                OutputCollector<Text, LongWritable> oc,
                Reporter reporter) throws IOException {
            // Find the url
            String line = val.toString();
            int firstComma = line.indexOf(',');
            int secondComma = line.indexOf(',', firstComma);
            String key = line.substring(firstComma, secondComma);
            // drop the rest of the record, I don't need it anymore,
            // just pass a 1 for the combiner/reducer to sum instead.
            Text outKey = new Text(key);
            oc.collect(outKey, new LongWritable(1L));
        }
    }
    public static class ReduceUrls extends MapReduceBase
        implements Reducer<Text, LongWritable, WritableComparable,
Writable> {

        public void reduce(
                Text key,
                Iterator<LongWritable> iter,
                OutputCollector<WritableComparable, Writable> oc,
                Reporter reporter) throws IOException {
            // Add up all the values we see

            long sum = 0;
            while (iter.hasNext()) {
                sum += iter.next().get();
                reporter.setStatus("OK");
            }

            oc.collect(key, new LongWritable(sum));
        }
    }
    public static class LoadClicks extends MapReduceBase
        implements Mapper<WritableComparable, Writable, LongWritable,
Text> {

        public void map(
                WritableComparable key,
                Writable val,
                OutputCollector<LongWritable, Text> oc,
                Reporter reporter) throws IOException {
            oc.collect((LongWritable)val, (Text)key);
        }
    }
    public static class LimitClicks extends MapReduceBase
        implements Reducer<LongWritable, Text, LongWritable, Text> {

        int count = 0;
        public void reduce(
            LongWritable key,
            Iterator<Text> iter,
            OutputCollector<LongWritable, Text> oc,
            Reporter reporter) throws IOException {

            // Only output the first 100 records
            while (count < 100 && iter.hasNext()) {
                oc.collect(key, iter.next());
                count++;
            }
        }
    }
    public static void main(String[] args) throws IOException {
        JobConf lp = new JobConf(MRExample.class);
        lp.setJobName("Load Pages");
        lp.setInputFormat(TextInputFormat.class);
        lp.setOutputKeyClass(Text.class);
        lp.setOutputValueClass(Text.class);
        lp.setMapperClass(LoadPages.class);
        FileInputFormat.addInputPath(lp, new
Path("/user/gates/pages"));
        FileOutputFormat.setOutputPath(lp,
            new Path("/user/gates/tmp/indexed_pages"));
        lp.setNumReduceTasks(0);
        Job loadPages = new Job(lp);

        JobConf lfu = new JobConf(MRExample.class);
        lfu.setJobName("Load and Filter Users");
        lfu.setInputFormat(TextInputFormat.class);
        lfu.setOutputKeyClass(Text.class);
        lfu.setOutputValueClass(Text.class);
        lfu.setMapperClass(LoadAndFilterUsers.class);
        FileInputFormat.addInputPath(lfu, new
Path("/user/gates/users"));
        FileOutputFormat.setOutputPath(lfu,
            new Path("/user/gates/tmp/filtered_users"));
        lfu.setNumReduceTasks(0);
        Job loadUsers = new Job(lfu);

        JobConf join = new JobConf(MRExample.class);
        join.setJobName("Join Users and Pages");
        join.setInputFormat(KeyValueTextInputFormat.class);
        join.setOutputKeyClass(Text.class);
        join.setOutputValueClass(Text.class);
        join.setMapperClass(IdentityMapper.class);
        join.setReducerClass(Join.class);
        FileInputFormat.addInputPath(join, new
Path("/user/gates/tmp/indexed_pages"));
        FileInputFormat.addInputPath(join, new
Path("/user/gates/tmp/filtered_users"));
        FileOutputFormat.setOutputPath(join, new
Path("/user/gates/tmp/joined"));
        join.setNumReduceTasks(50);
        Job joinJob = new Job(join);
        joinJob.addDependingJob(loadPages);
        joinJob.addDependingJob(loadUsers);

        JobConf group = new JobConf(MRExample.class);
        group.setJobName("Group URLs");
        group.setInputFormat(KeyValueTextInputFormat.class);
        group.setOutputKeyClass(Text.class);
        group.setOutputValueClass(LongWritable.class);
        group.setOutputFormat(SequenceFileOutputFormat.class);
        group.setMapperClass(LoadJoined.class);
        group.setCombinerClass(ReduceUrls.class);
        group.setReducerClass(ReduceUrls.class);
        FileInputFormat.addInputPath(group, new
Path("/user/gates/tmp/joined"));
        FileOutputFormat.setOutputPath(group, new
Path("/user/gates/tmp/grouped"));
        group.setNumReduceTasks(50);
        Job groupJob = new Job(group);
        groupJob.addDependingJob(joinJob);

        JobConf top100 = new JobConf(MRExample.class);
        top100.setJobName("Top 100 sites");
        top100.setInputFormat(SequenceFileInputFormat.class);
        top100.setOutputKeyClass(LongWritable.class);
        top100.setOutputValueClass(Text.class);
        top100.setOutputFormat(SequenceFileOutputFormat.class);
        top100.setMapperClass(LoadClicks.class);
        top100.setCombinerClass(LimitClicks.class);
        top100.setReducerClass(LimitClicks.class);
        FileInputFormat.addInputPath(top100, new
Path("/user/gates/tmp/grouped"));
        FileOutputFormat.setOutputPath(top100, new
Path("/user/gates/top100sitesforusers18to25"));
        top100.setNumReduceTasks(1);
        Job limit = new Job(top100);
        limit.addDependingJob(groupJob);

        JobControl jc = new JobControl("Find top  100 sites for users
18 to 25");
        jc.addJob(loadPages);
        jc.addJob(loadUsers);
        jc.addJob(joinJob);
        jc.addJob(groupJob);
        jc.addJob(limit);
        jc.run();
    }
}
```

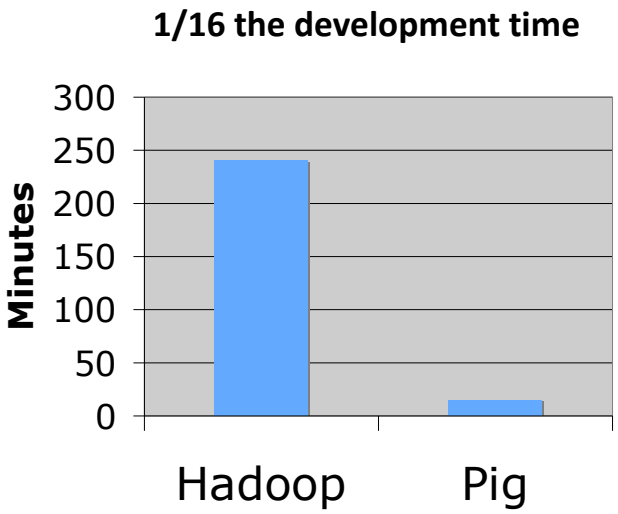
In Pig Latin

```
Users = load 'users' as (name, age);
Fltrd = filter Users by
        age >= 18 and age <= 25;
Pages = load 'pages' as (user, url);
Jnd = join Fltrd by name, Pages by user;
Grpd = group Jnd by url;
Smmd = foreach Grpd generate group,
       COUNT(Jnd) as clicks;
Srtd = order Smmd by clicks desc;
Top5 = limit Srtd 5;
store Top5 into 'top5sites';
```

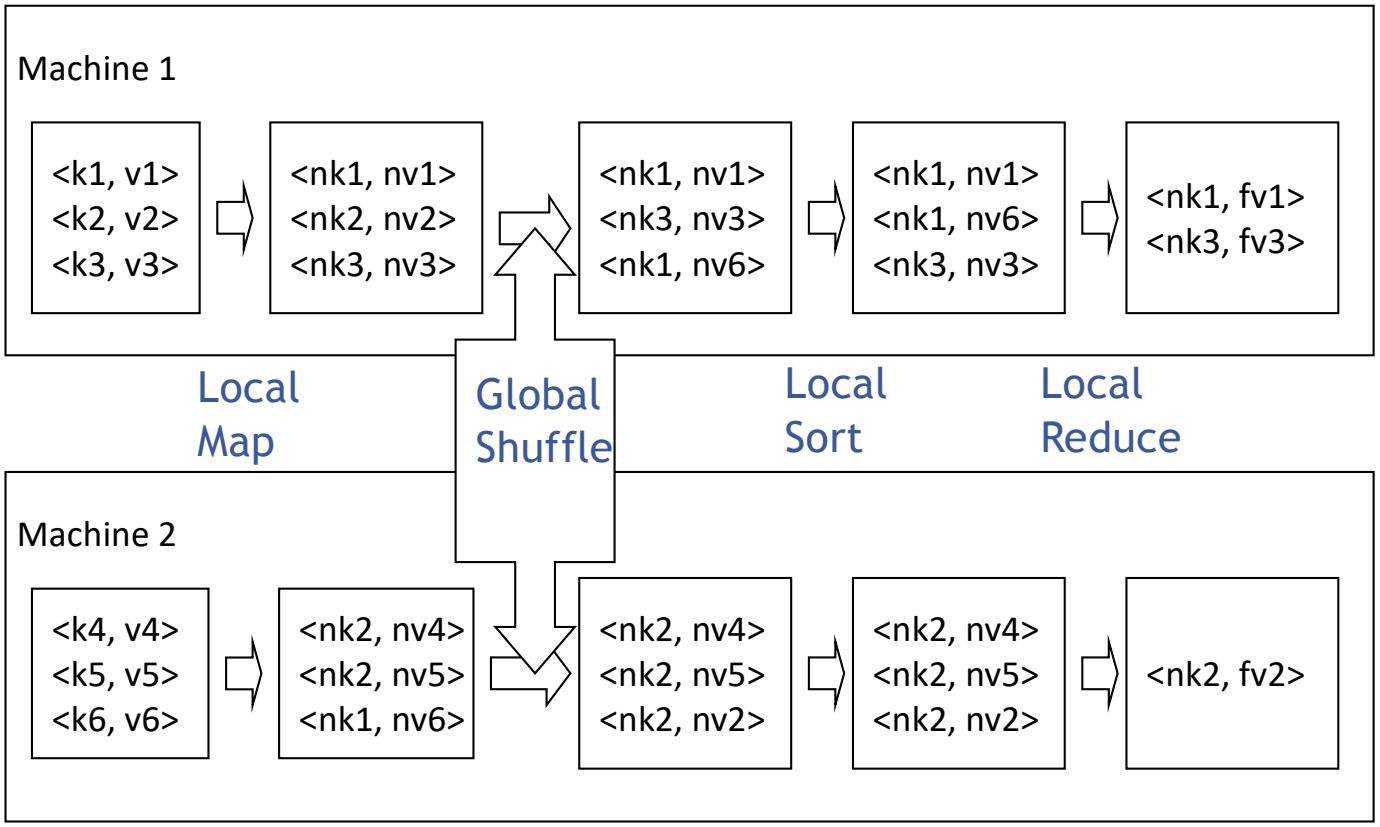
Java vs. Pig Latin







(Simplified) Map Reduce



Hive QL – Join

page_view

pageid	**userid**	time
1	**111**	9:08:01
2	**111**	9:08:13
1	**222**	9:08:14

X

user

userid	age	gender
111	25	female
222	32	male

=

pv_users

pageid	age
1	25
2	25
1	32

```
INSERT INTO TABLE pv_users
SELECT pv.pageid, u.age
FROM page_view pv JOIN user u
        ON (pv.userid = u.userid);
```

Hive QL – Join in Map Reduce

page_view

pageid	**userid**	time
1	**111**	9:08:01
2	**111**	9:08:13
1	**222**	9:08:14

user

userid	age	gender
111	25	female
222	32	male

Map

key	value
111	<**1**,1>
111	<**1**,2>
222	<**1**,1>

key	value
111	<**2**,25>
222	<**2**,32>

Shuffle
Sort

key	value
111	<**1**,1>
111	<**1**,2>
111	<**2**,25>

key	value
222	<**1**,1>
222	<**2**,32>

Reduce

pageid	age
1	25
2	25

pageid	age
1	32

Hive QL – Group By

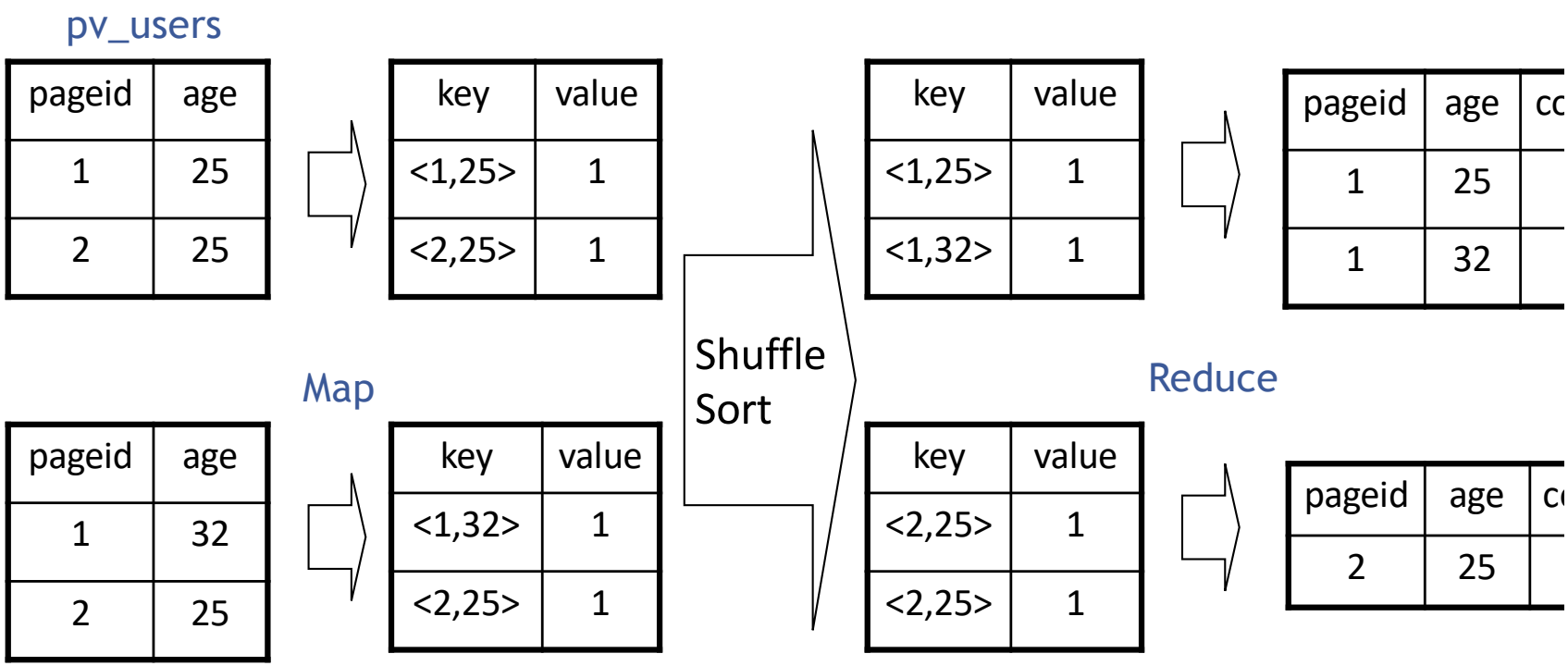
pv_users

pageid	age
1	25
2	25
1	32
2	25

pageid	age	count
1	25	1
2	25	2
1	32	1

```
SELECT pageid, age, count(1)
FROM pv_users
GROUP BY pageid, age;
```

Hive QL - Group By in Map Reduce



Hive QL – Group By with Distinct

page_view

pageid	userid	time
1	111	9:08:01
2	111	9:08:13
1	222	9:08:14
2	111	9:08:20

pageid	count_distinct_userid
1	2
2	1

```
SELECT pageid, COUNT(DISTINCT userid)
FROM page_view GROUP BY pageid
```

Hive QL – Group By with Distinct in Map Reduce

page_view

pageid	userid	time
1	111	9:08:01
2	111	9:08:13

pageid	userid	time
1	222	9:08:14
2	111	9:08:20

Shuffle and Sort

key	v
<1,111>	1
<2,111>	1
<2,111>	1

key	v
<1,222>	1

Reduce

pageid	count
1	1
2	1

pageid	count
1	1

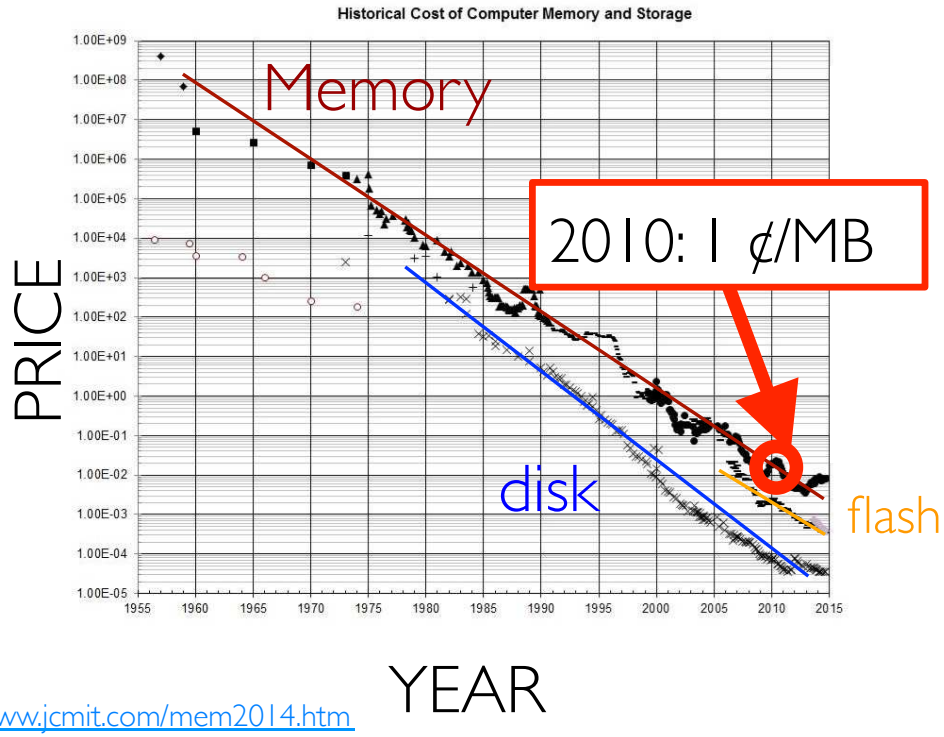
2019

Urs Hölzle
@uhoelzle

@JeffDean @GCPcloud R.I.P. MapReduce. After having served us well since 2003, today we removed the remaining internal codebase for good.

MR was a seminal idea in 2003 but we've learned a lot since then. [There are new systems that] express pipelines more naturally with less code, and you get both batch and streaming from the same code.

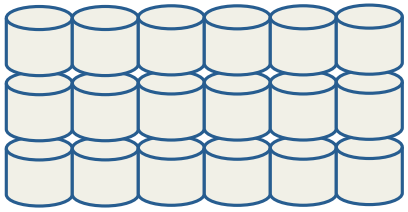
Tech Trend: Cost of memory



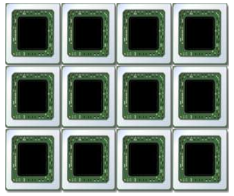
Lower cost means can put more memory in each server

http://www.jcmit.com/mem2014.htm

Hardware for Big Data

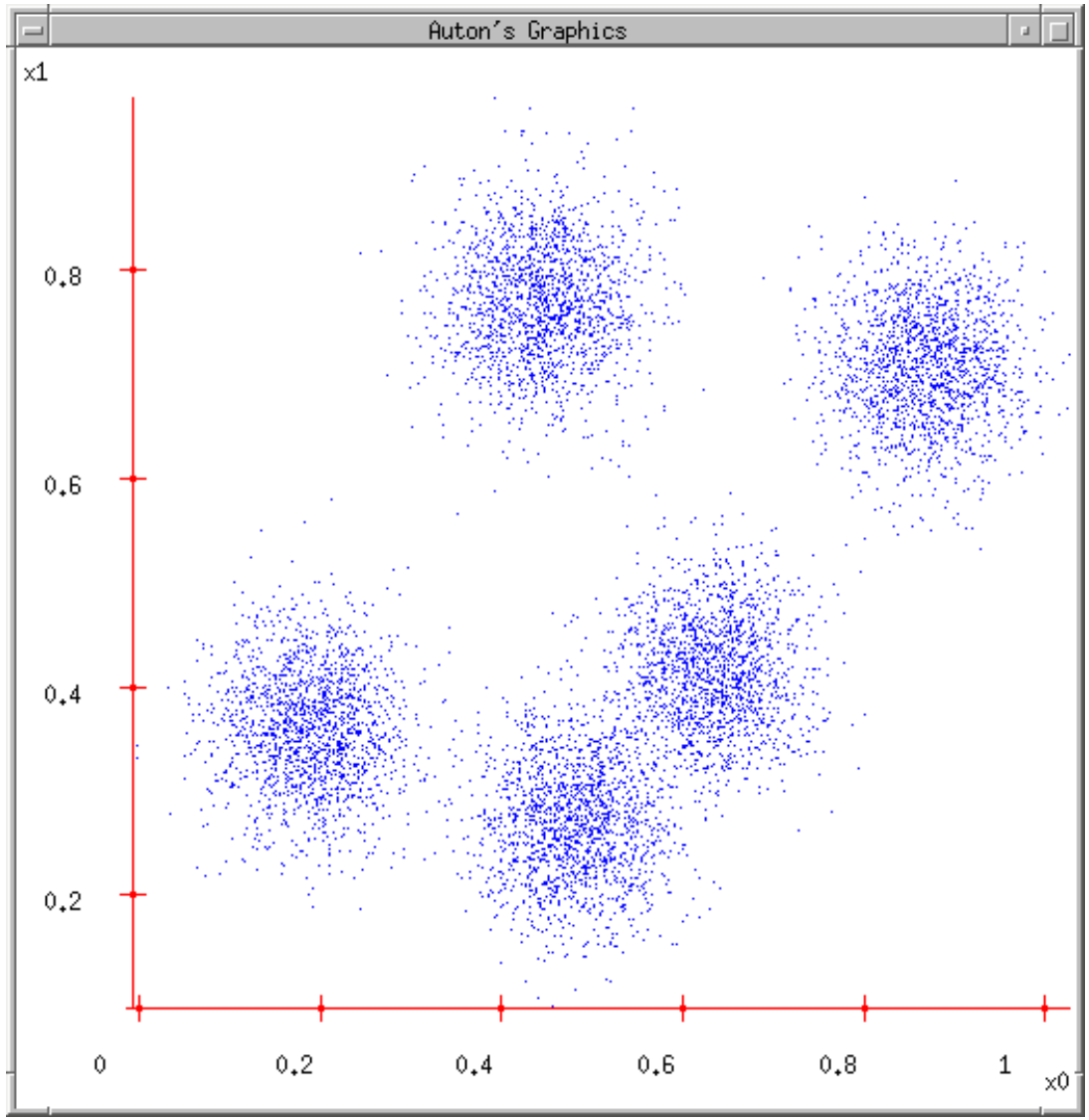


Lots of hard drives



… and CPUs

Machine learning algorithms are iterative in nature. An example: K-Means



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Andrew W. Moore

K-means clustering

- Input: K, set of points
- Place centroids c_1, c_2, …, c_k at random locations (alternatively add random lables to points)
- Repeat until convergences:
  - for each cluster j=1…K:
    - new centroid c_j = mean of all points P_i assigned to cluster j
  - for each point P_i:
    - find nearest centrod c_j
    - assing point P_i to cluster j
- Stop when none of the cluster assignments change

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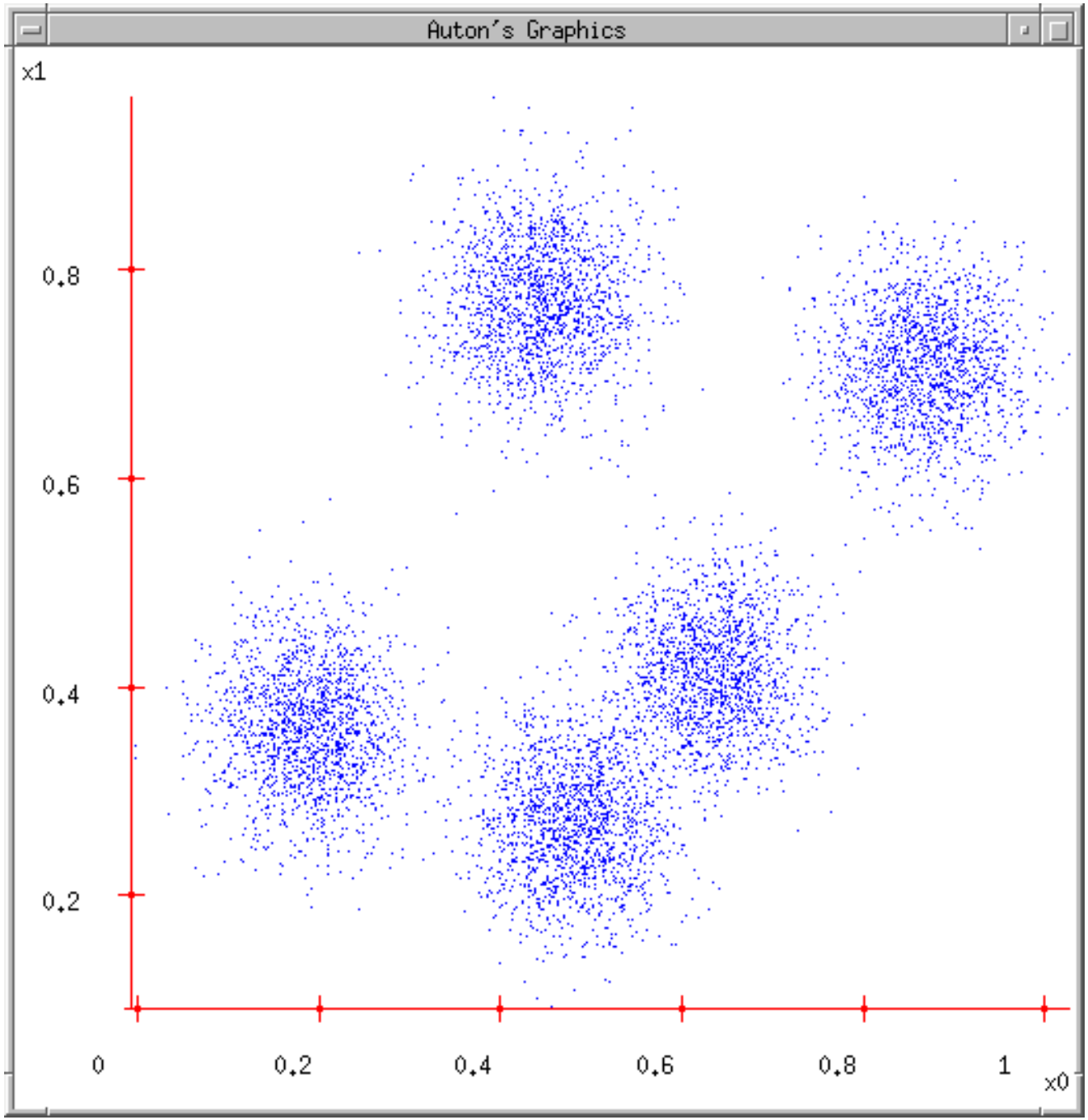
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*



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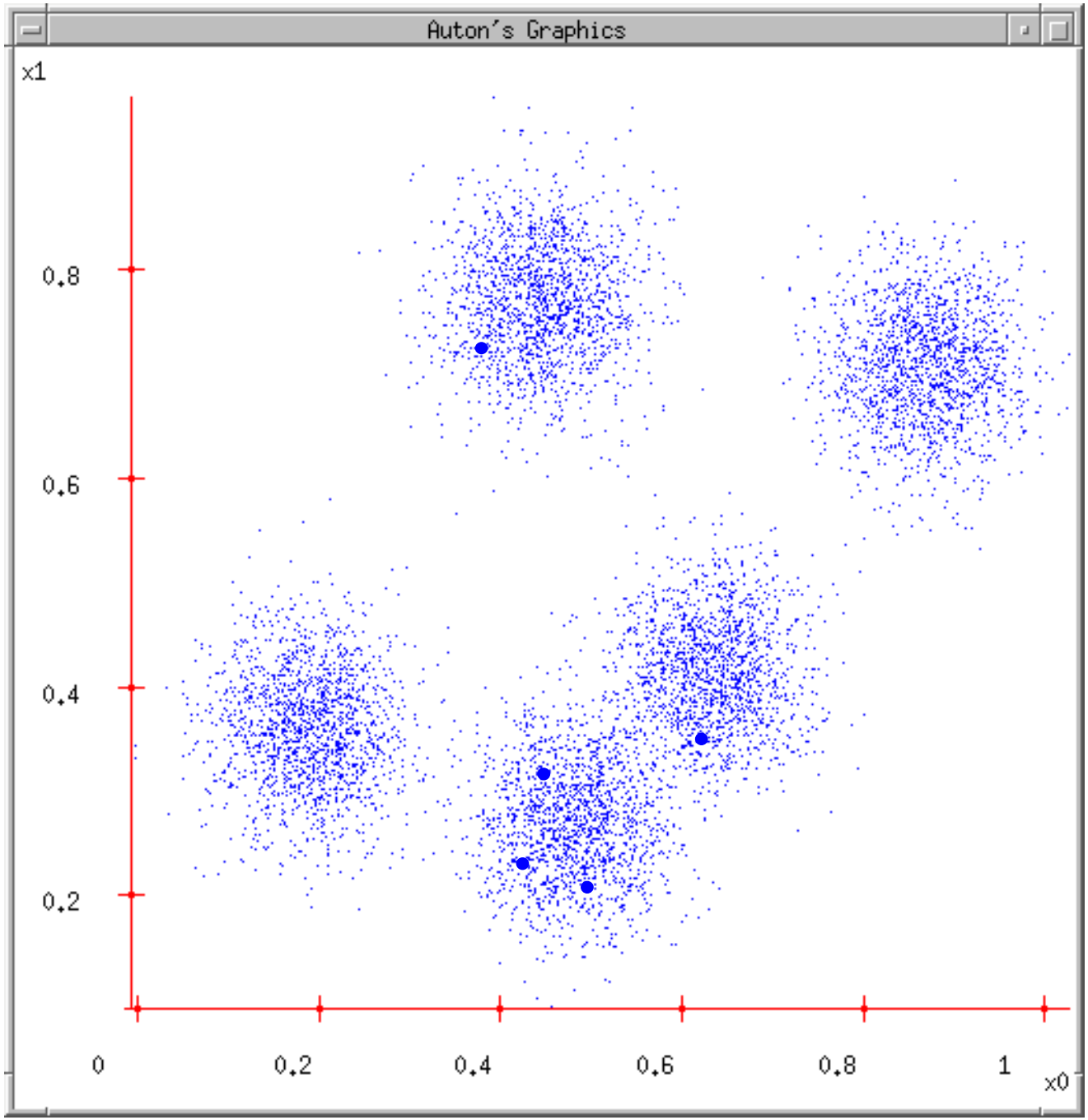
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations



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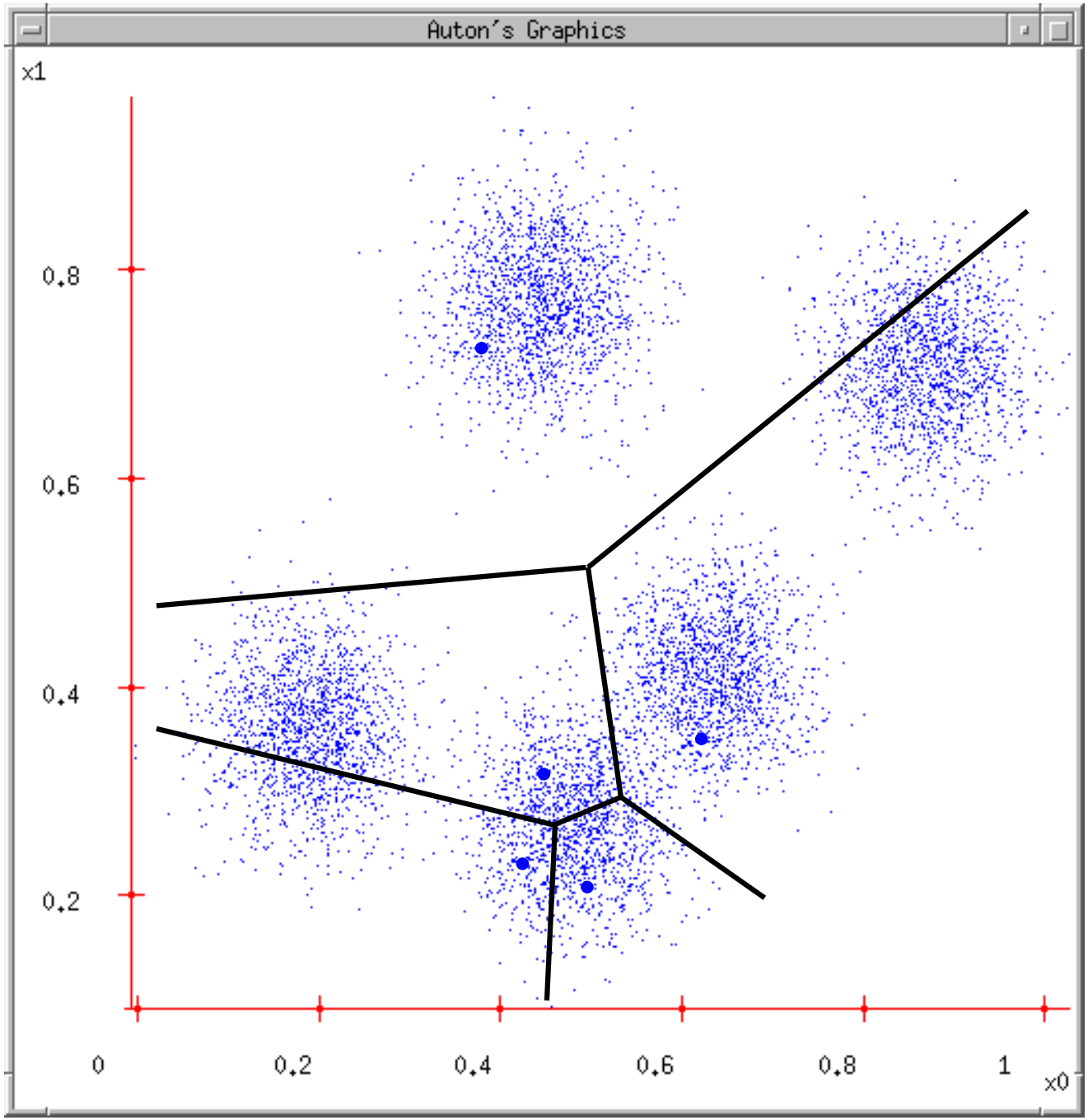
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to. (Thus each Center "owns" a set of datapoints)



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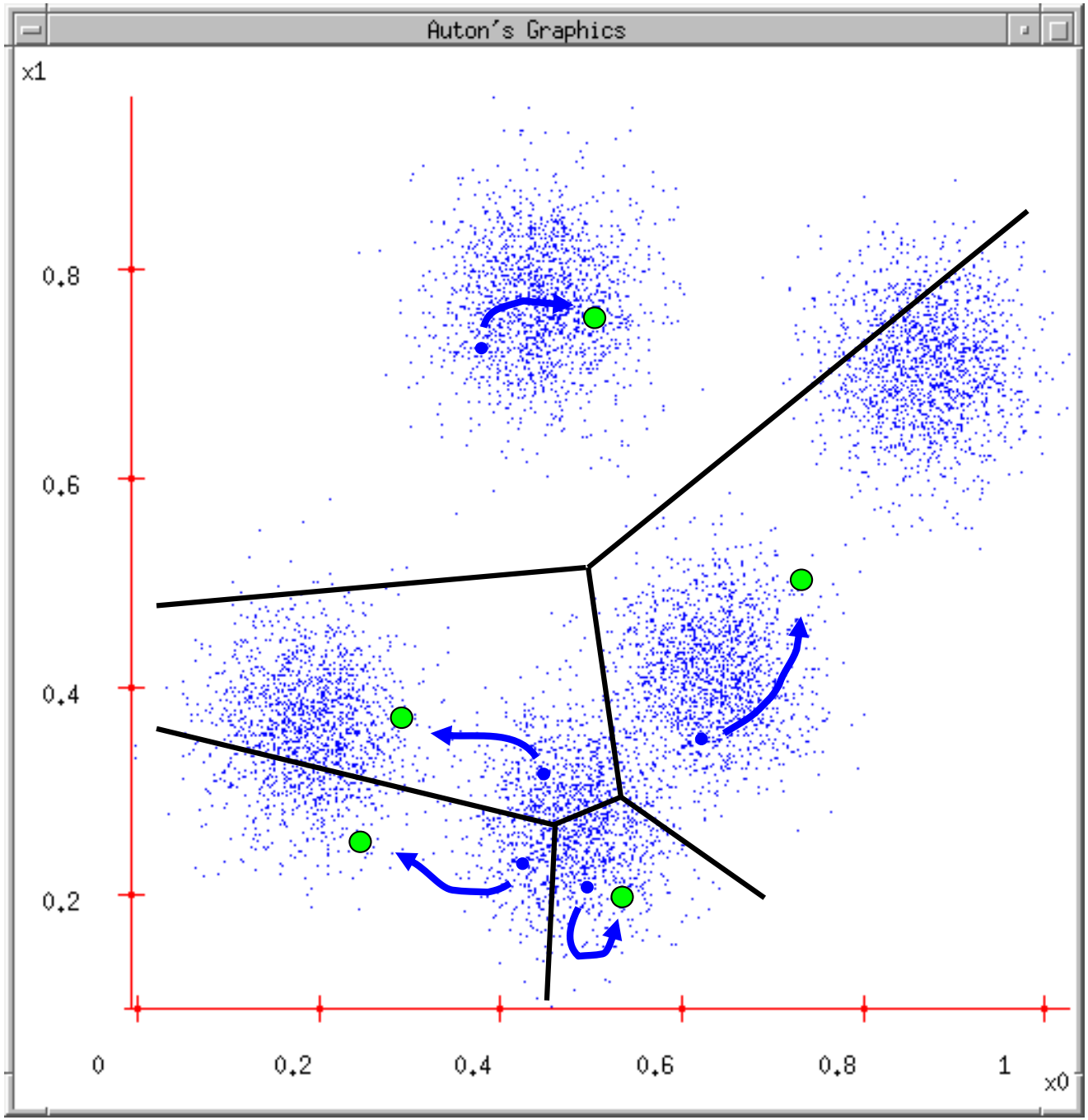
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns



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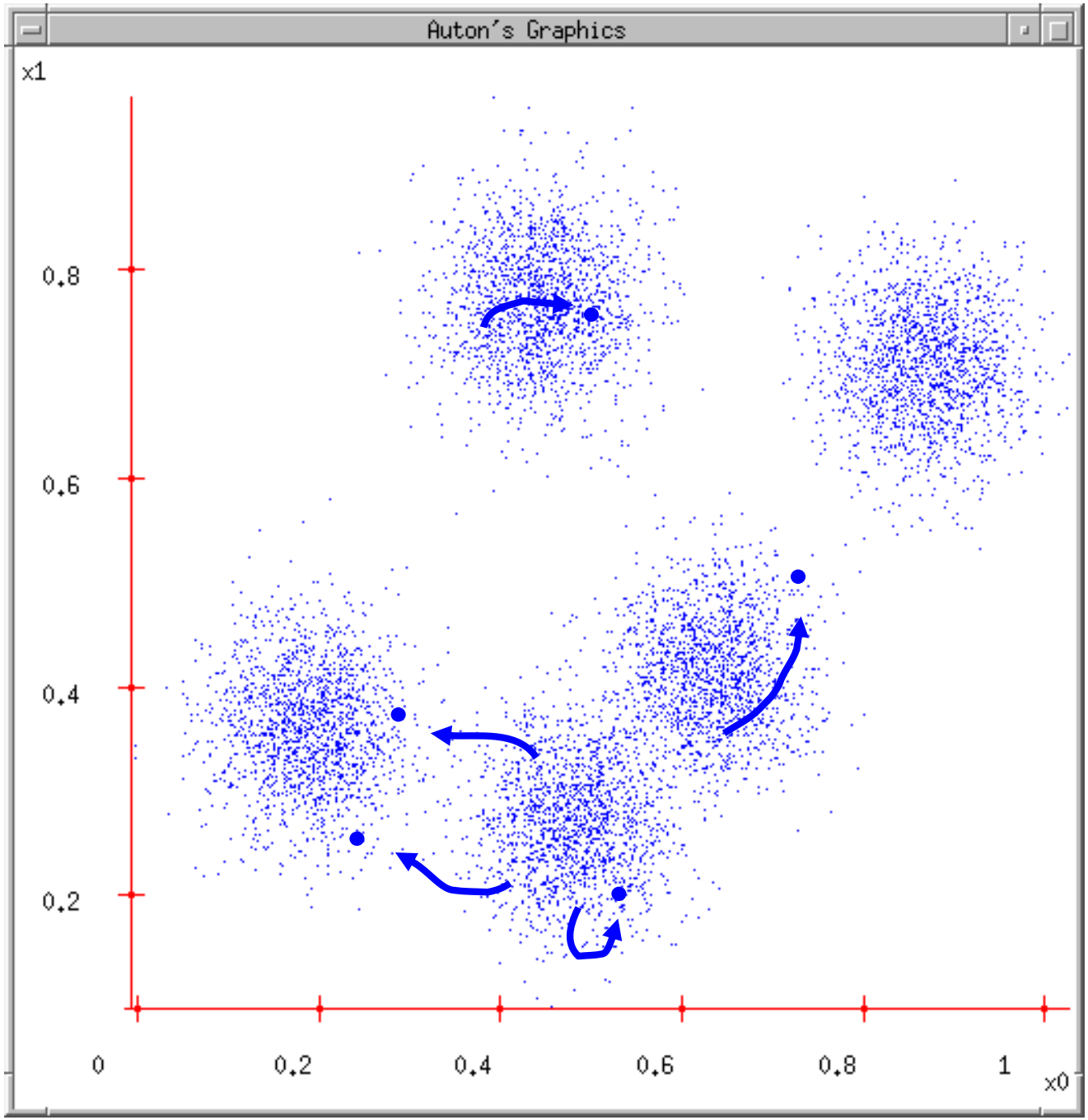
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns…
5. …and jumps there
6. …Repeat until terminated!



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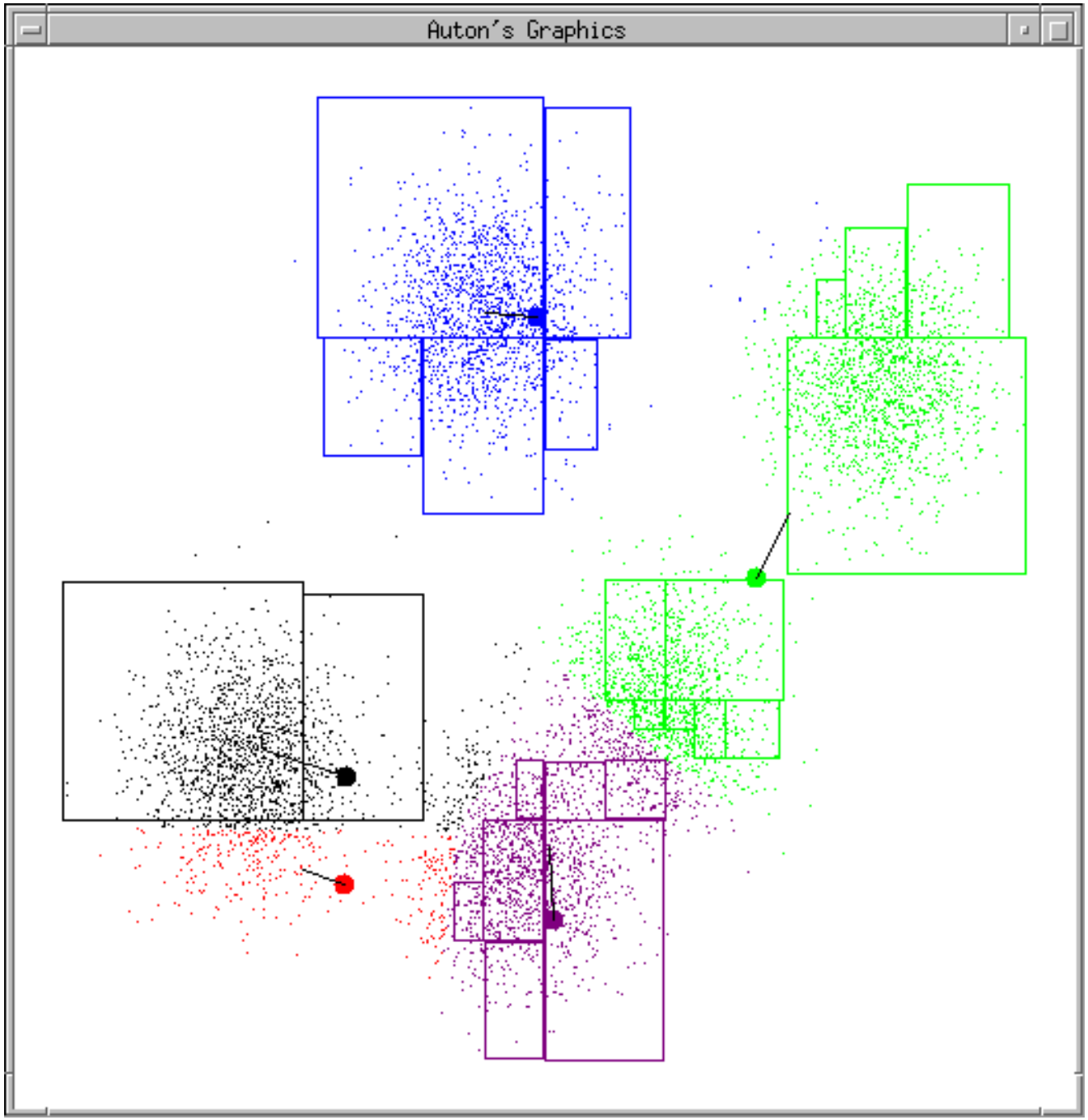
K-means continues…



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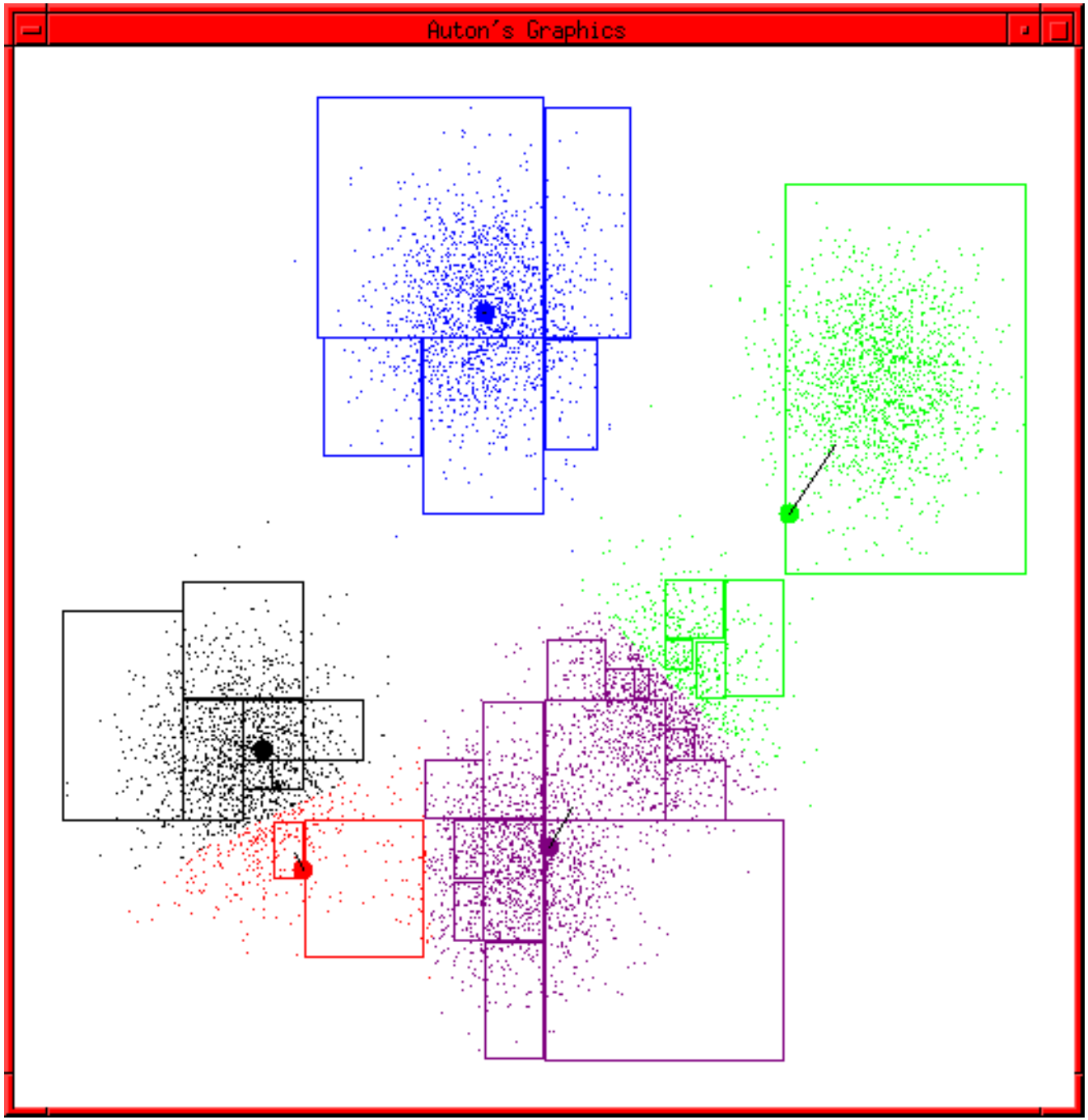
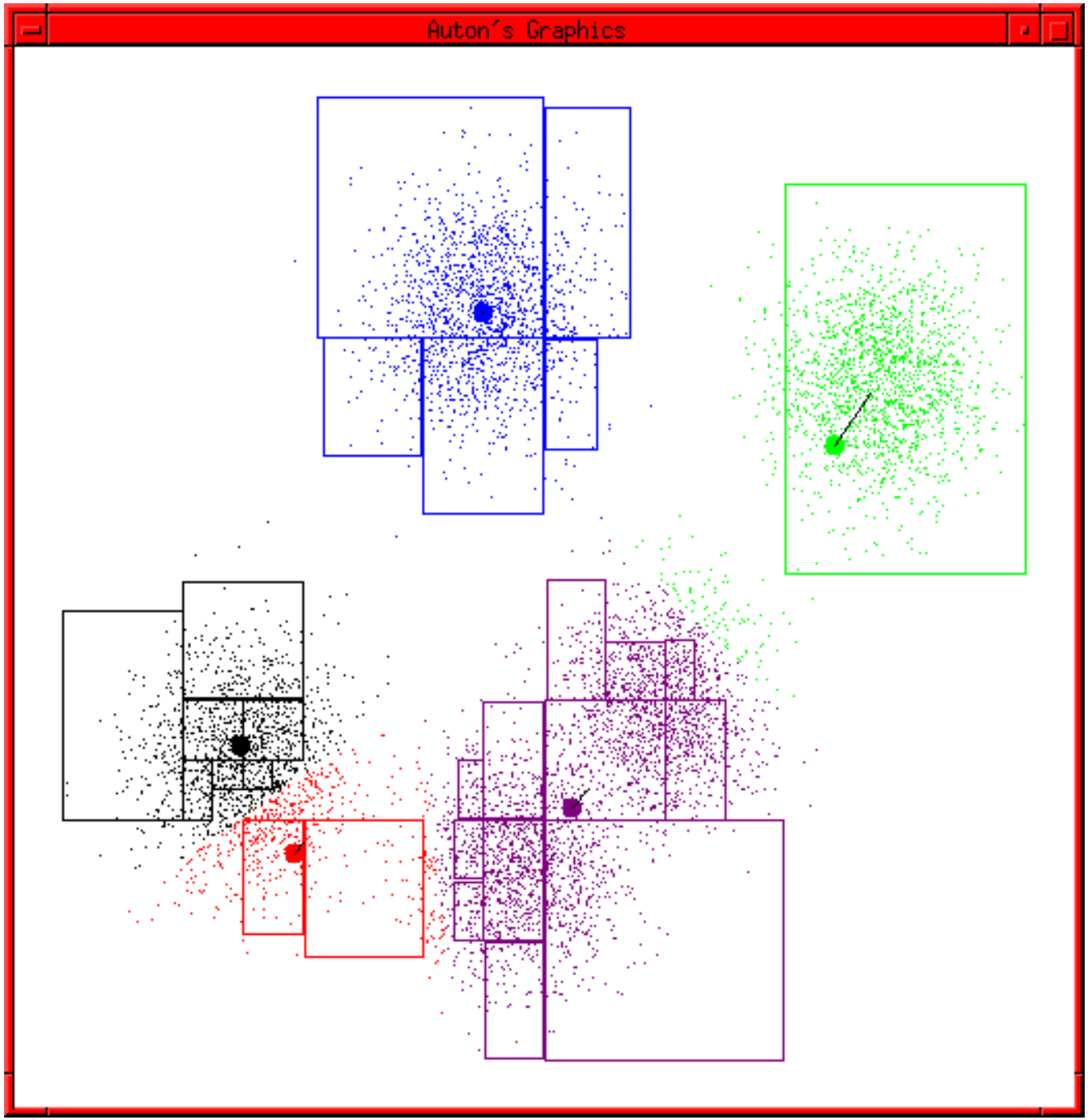
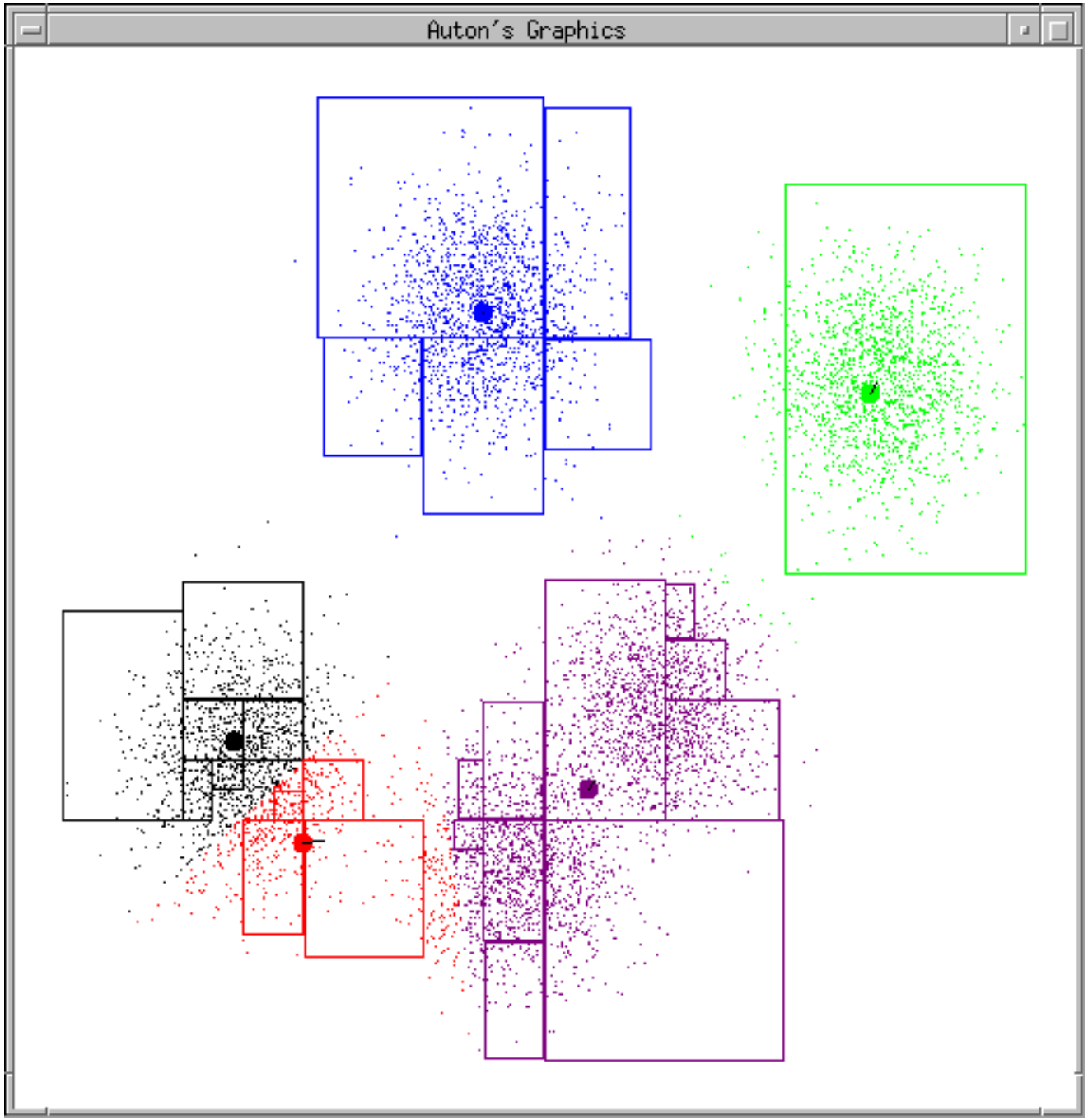
K-means continues…



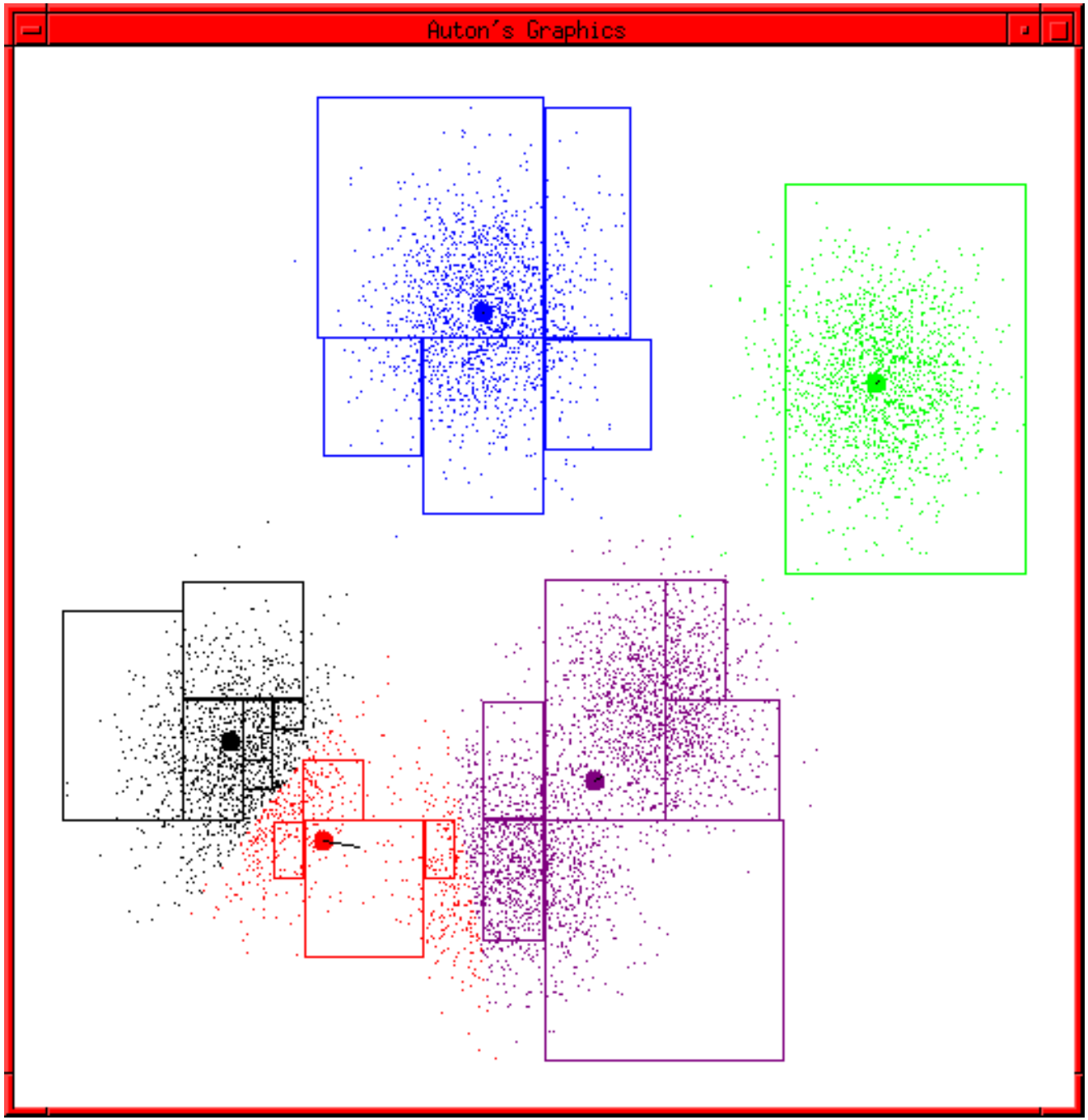
K-means continues…



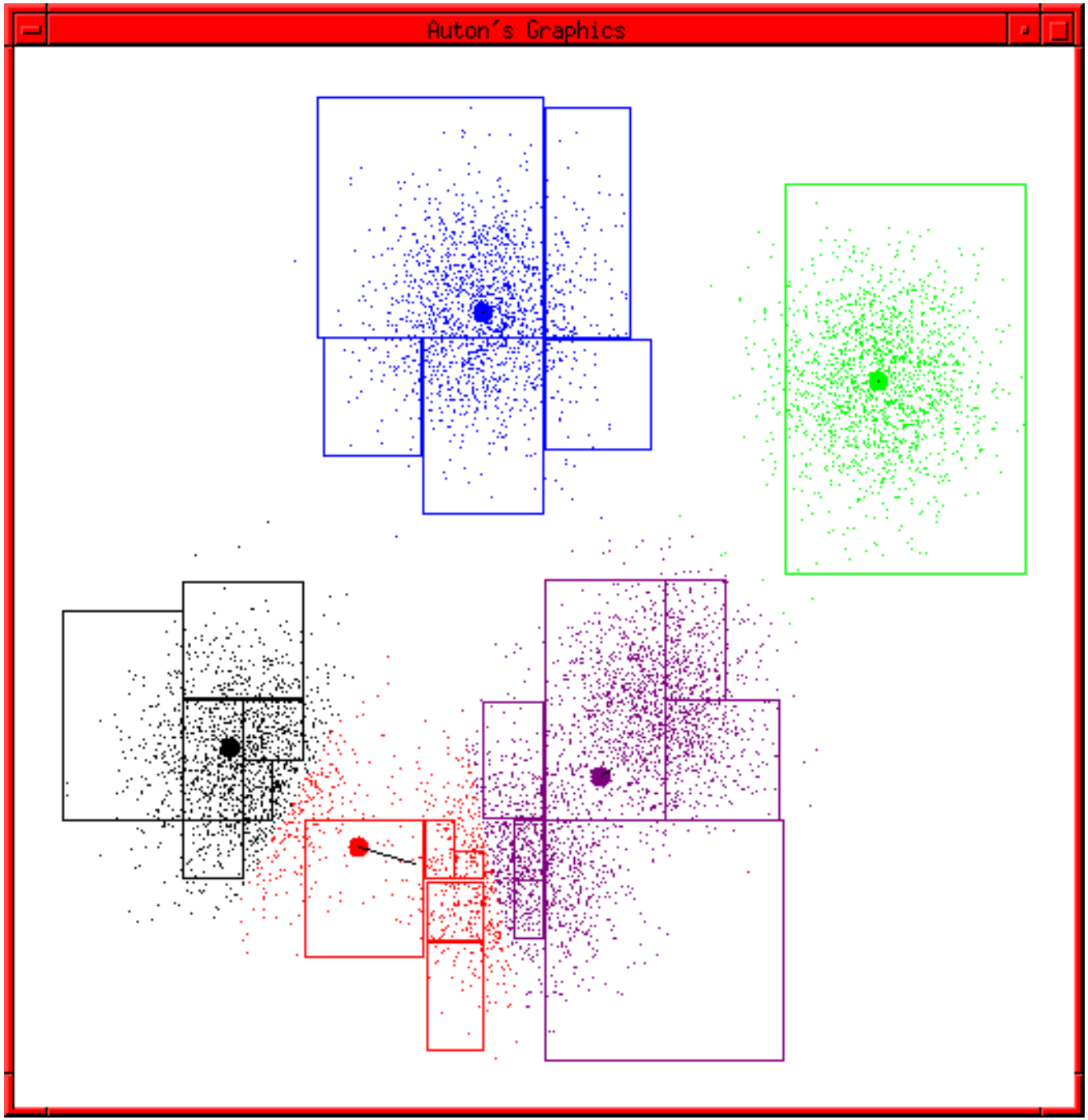
K-means continues…



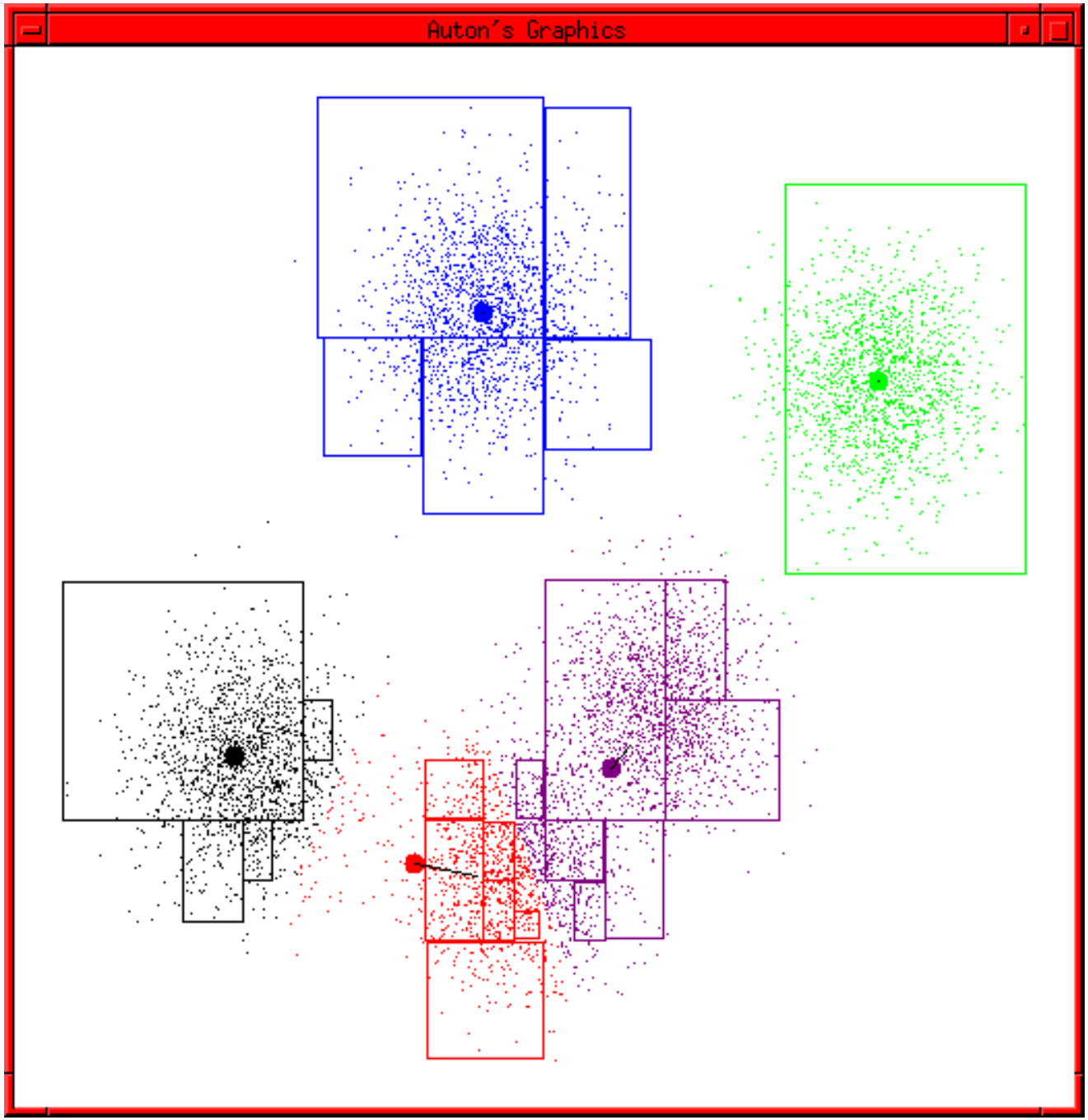
K-means continues…



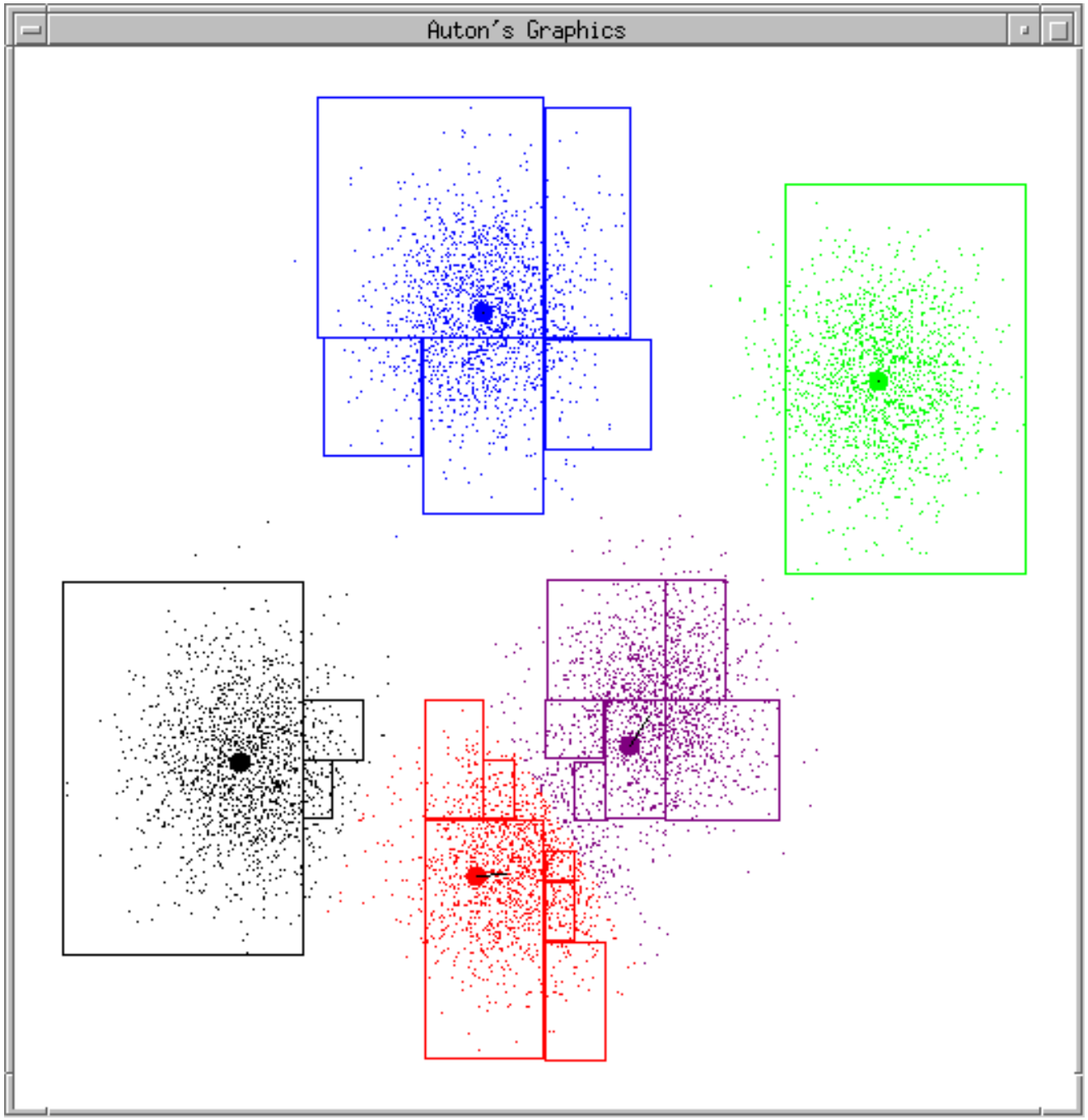
K-means continues…



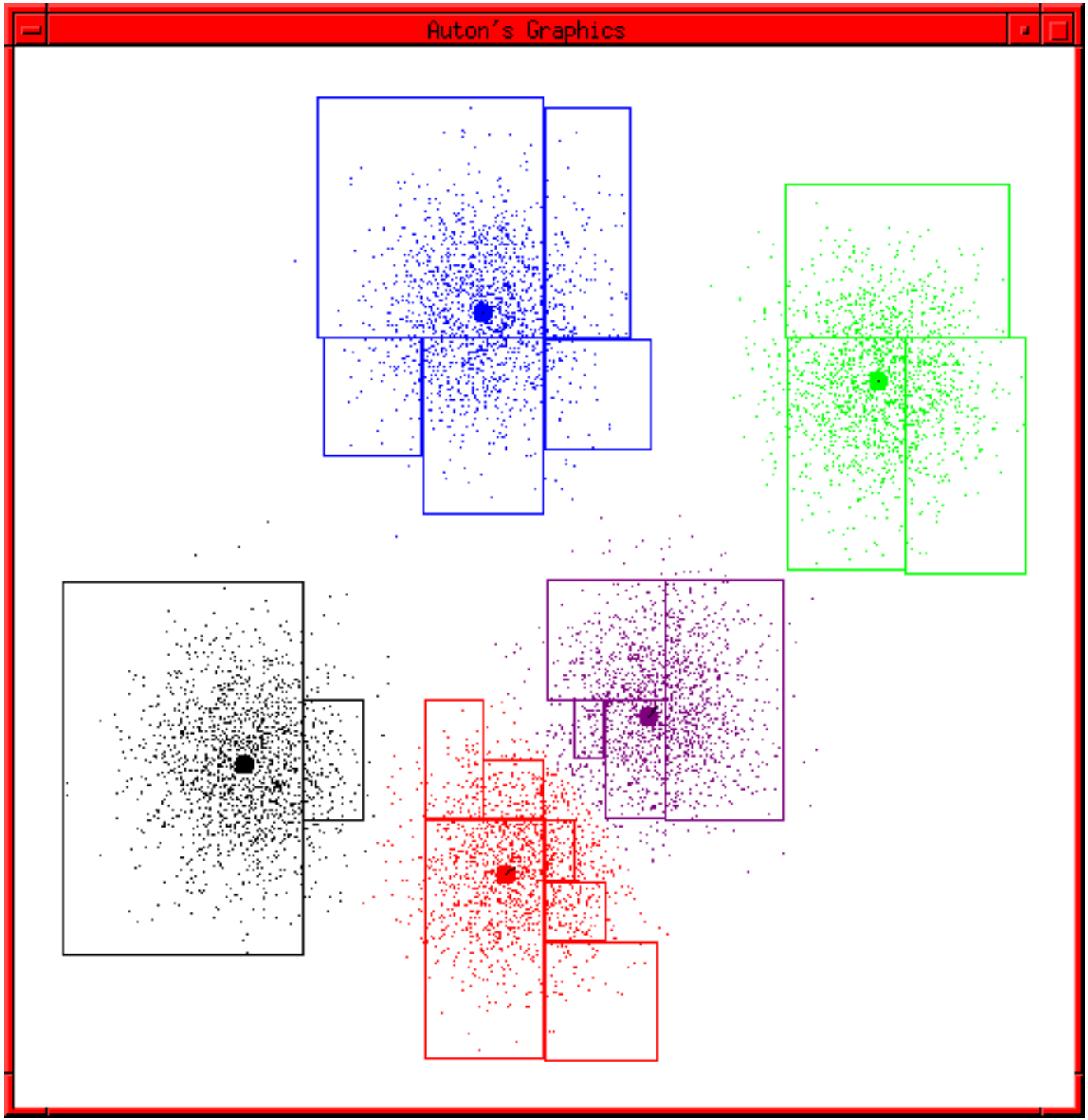
K-means continues…



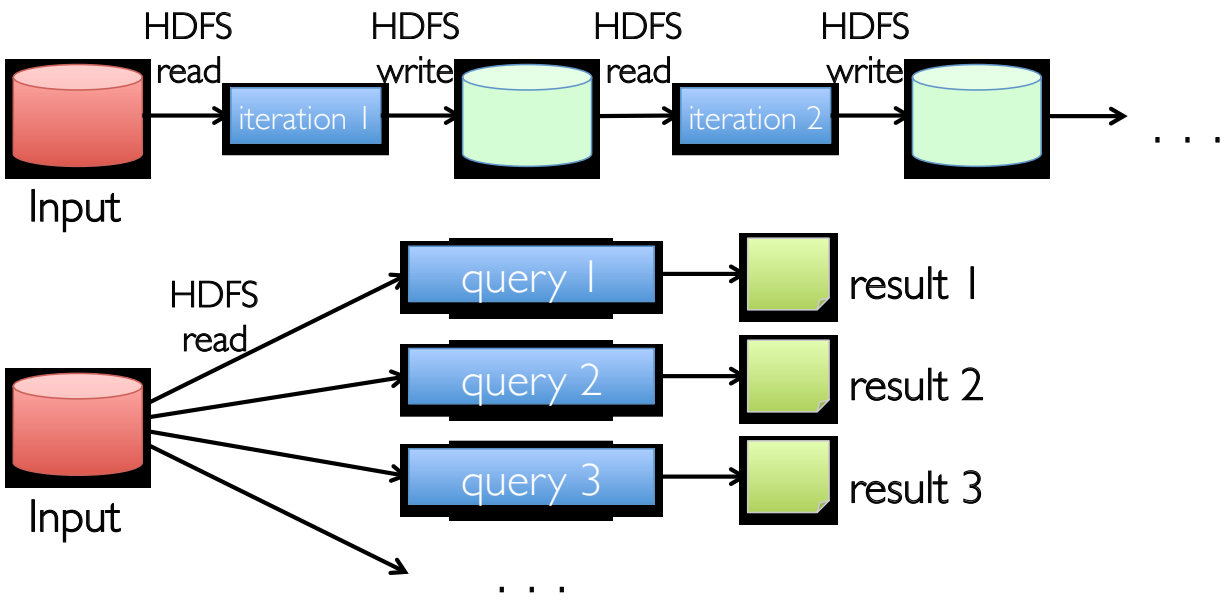
K-means continues…



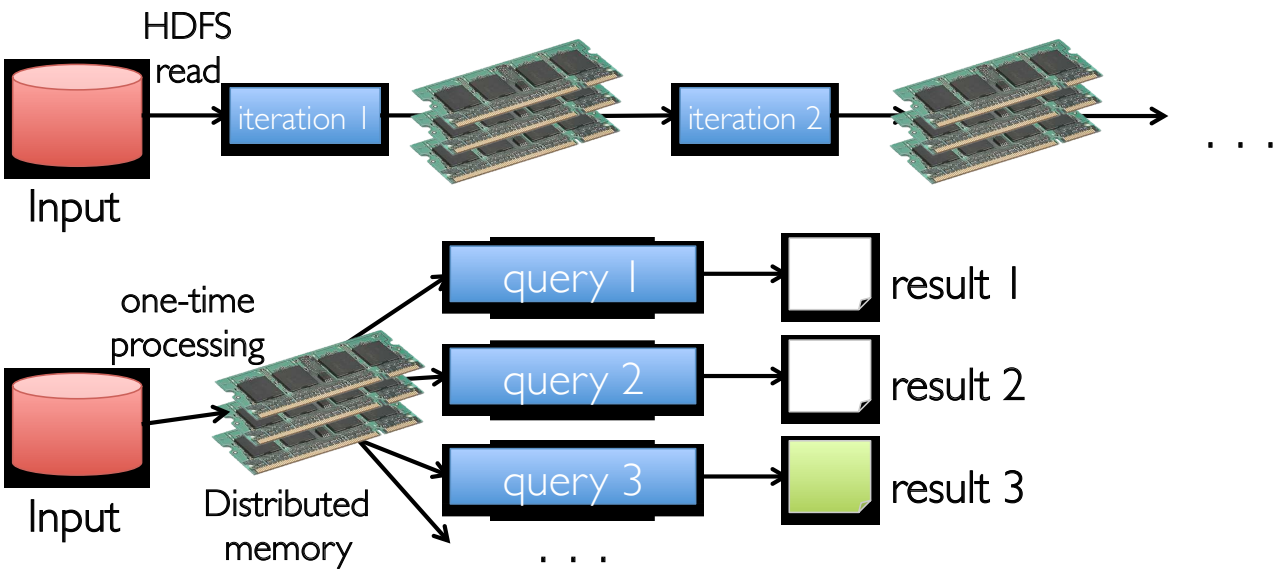
K-means terminates



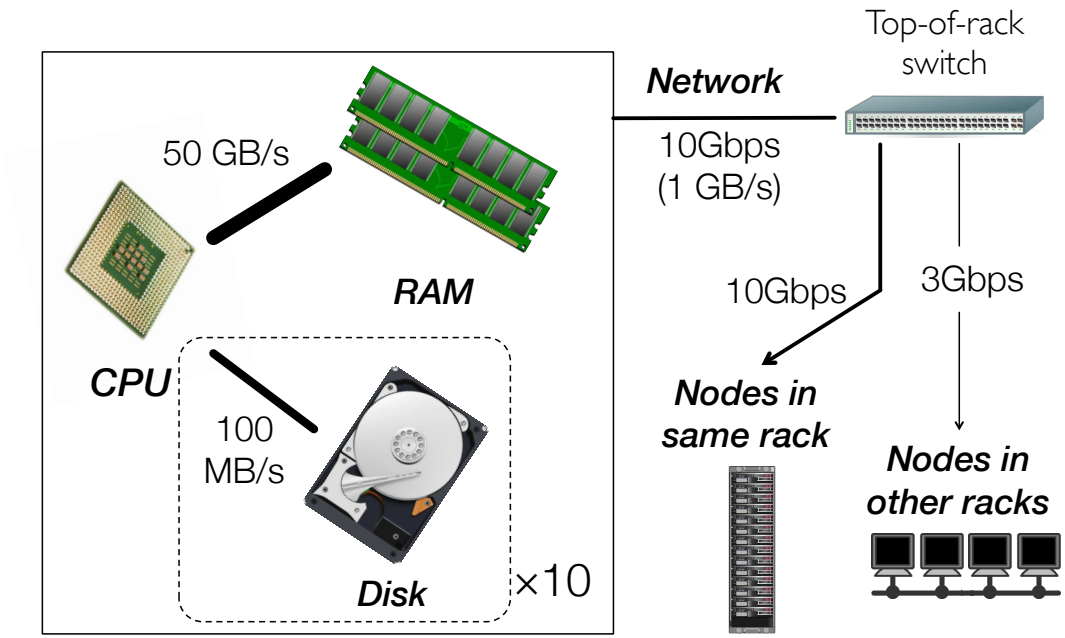
Use memory instead of disks



Use memory instead of disks



Use memory instead of disks



What is Spark?

- Fast, expressive cluster computing system compatible with Apache Hadoop
  - Works with any Hadoop-supported storage system (HDFS, S3, Avro, …)
- Improves **efficiency** through:
  - In-memory computing primitives → Up to 100× faster
  - General computation graphs
- Improves **usability** through:
  - Rich APIs in Java, Scala, **Python**, R → Often 2-10× less code
  - Interactive shell

On-Disk Sort Record:

Time to sort 100TB

2013 Record: Hadoop

2100 machines

72 minutes

2014 Record: Spark

207 machines

23 minutes

Also sorted 1PB in 4 hours

databricks

Source: Daytona GraySort benchmark, sortbenchmark.org

Word count

```java
public class WordCount {
  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }

  public static class IntSumReducer
       extends Reducer<Text,IntWritable,Text,IntWritable> {
    private IntWritable result = new IntWritable();

    public void reduce(Text key, Iterable<IntWritable> values,
                       Context context
                       ) throws IOException, InterruptedException {
      int sum = 0;
      for (IntWritable val : values) {
        sum += val.get();
      }
      result.set(sum);
      context.write(key, result);
    }
  }

  public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    String[] otherArgs = new GenericOptionsParser(conf, args).getRemainingArgs();
    if (otherArgs.length < 2) {
      System.err.println("Usage: wordcount <in> [<in>...] <out>");
      System.exit(2);
    }
    Job job = new Job(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setCombinerClass(IntSumReducer.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    for (int i = 0; i < otherArgs.length - 1; ++i) {
      FileInputFormat.addInputPath(job, new Path(otherArgs[i]));
    }
    FileOutputFormat.setOutputPath(job,
      new Path(otherArgs[otherArgs.length - 1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
}
```

WordCount in 50+ lines of Java MR

Word count

```java
public class WordCount {
  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
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        context.write(word, one);
      }
    }
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       extends Reducer<Text,IntWritable,Text,IntWritable> {
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                       Context context
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      int sum = 0;
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        sum += val.get();
      }
      result.set(sum);
      context.write(key, result);
    }
  }

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    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    for (int i = 0; i < otherArgs.length - 1; ++i) {
      FileInputFormat.addInputPath(job, new Path(otherArgs[i]));
    }
    FileOutputFormat.setOutputPath(job,
      new Path(otherArgs[otherArgs.length - 1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
}
```
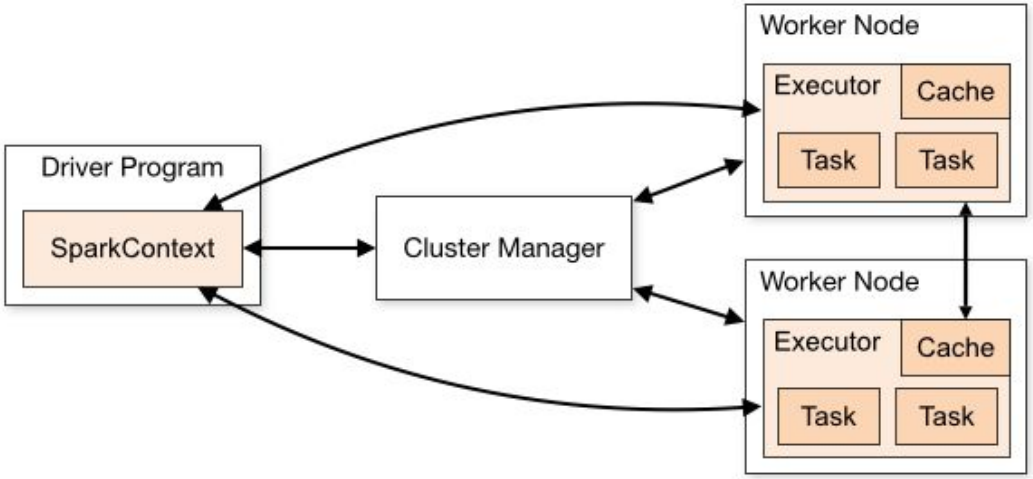

WordCount in 50+ lines of Java MR

```python
text_file = sc.textFile("hdfs://...")
counts = text_file.flatMap(lambda line: line.split(" ")) \
             .map(lambda word: (word, 1)) \
             .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs://...")
```

WordCount in 3 lines of Spark

Cluster Mode (1/2)

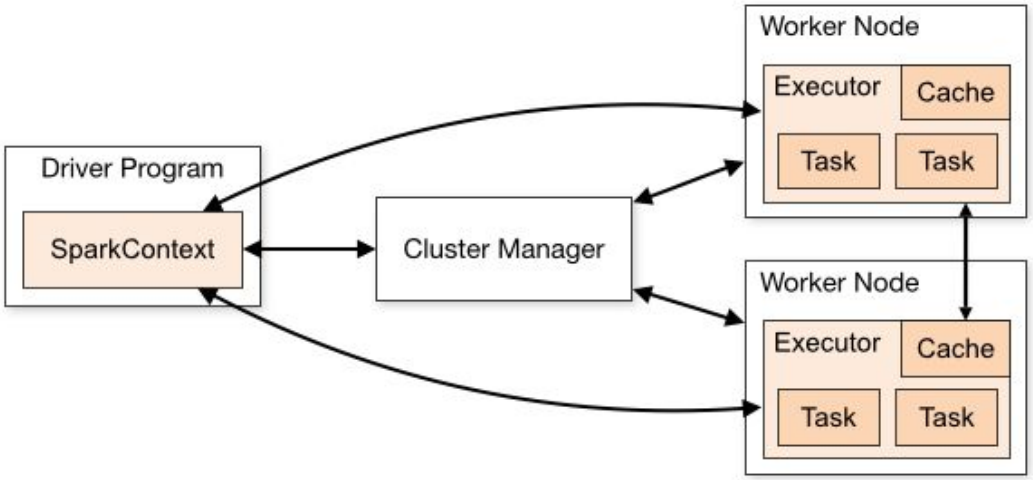


A Spark application runs coordinated by the **SparkContext** in the main program (called the *driver program*)

The SparkContext:

1. Acquires **executors** on nodes in the cluster, which are processes that run computations and store data for your application
2. Sends your application code (defined by JAR or Python files) to the executors
3. Sends **tasks** to the executors to run

Cluster Mode (2/2)



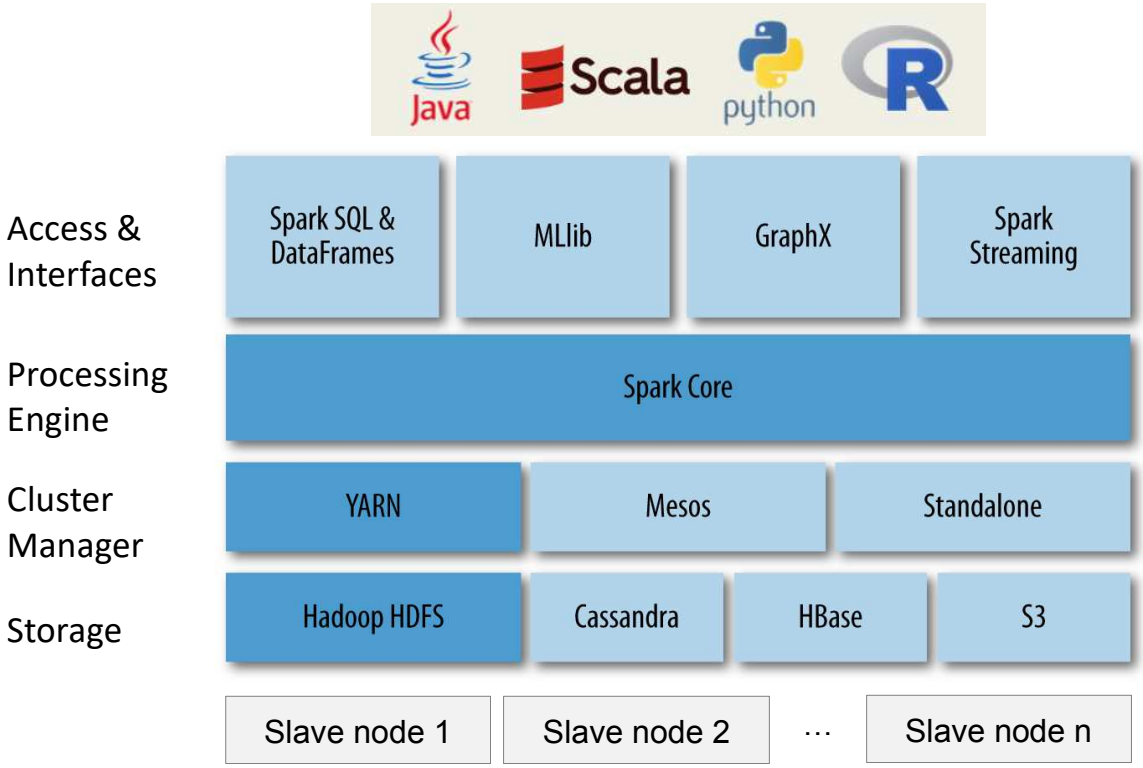
Each application gets its own executor processes

Benefit: Isolation of applications from each other (both scheduling and executor side)
Disadvantage: Data cannot be shared across different Spark applications without writing it to external storage

Spark is agnostic to the underlying cluster manager

Because the driver schedules tasks on the cluster, it should be run close to the worker nodes

Spark Stack



https://www.safaribooksonline.com/library/view/data-analytics-with/9781491913734/ch04.html

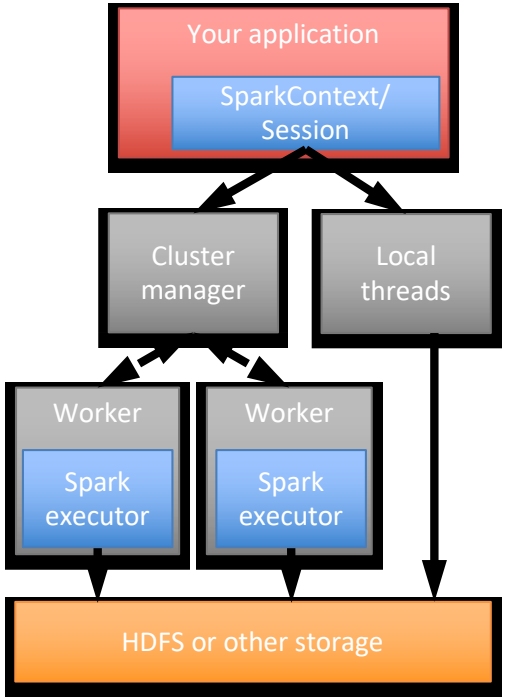
Spark core
Resilient Distributed Datasets (RDDs)

Key Idea

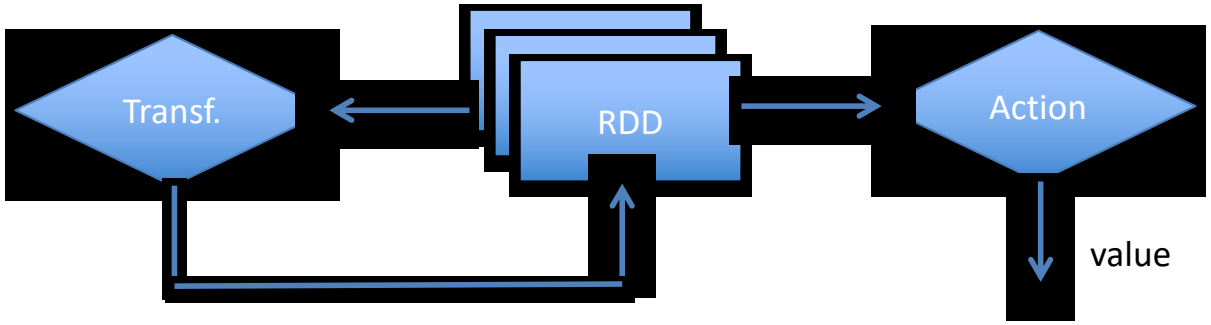
- Resilient distributed datasets (RDDs)
  - Immutable collections of objects spread across a cluster (partitions)
  - Built through parallel transformations (map, filter, etc)
  - Automatically rebuilt on failure
  - Controllable persistence (e.g., caching in RAM)

Software Components

- Spark runs as a library in your program (one instance per app)
- The starting point of any Spark program is the SparkContext/Session
  - Contains various methods to manipulate RDD/DataFrames
- Runs tasks locally or on a cluster
  - Standalone, Mesos or YARN cluster
- Accesses storage via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, …



Operations



- Transformations (e.g., map, filter, groupBy, join)
  - Lazy operations to build RDDs/DataFrames from other RDD/DataFrames
- Actions (e.g., count, collect, save)
  - Return a result or write it to storage

Why lazy operations are good?

- If you tell Spark to operate on a set of data:
  - it listens to what you ask it to do
  - it writes down some shorthand for it so it doesn't forget, and then does absolutely nothing
  - it will continue to do nothing, until you ask it for the final answer

- Often work magically goes away, postpone operations for optimization:
  - You first ask Spark to filter a petabyte of data to find all the point of sale records for the Milan store
  - Then you ask to give you just the first result that comes back
  - Postponing operations, Spark will just find the first Milan POS record
    - much easier than first filtering everything, then picking out only the first line

Example: Mining Console Logs

- Load error messages from a log into memory, then interactively search for patterns

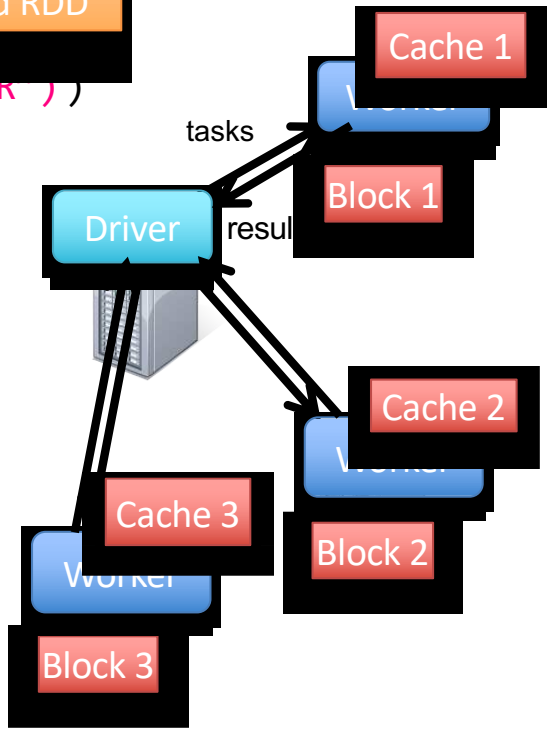
Base RDD

Transformed RDD

```
logLines = spark.textFile("hdfs://...")
errorsRDD = logLines.filter(lambda s: s.startswith("ERROR"))
messagesRDD = errorsRDD.map(lambda s: s.split('\t')[2])
messagesRDD.cache()
```

Action

```
messagesRDD.filter(lambda s: "foo" in s).count()
messagesRDD.filter(lambda s: "bar" in s).count()
. . .
```



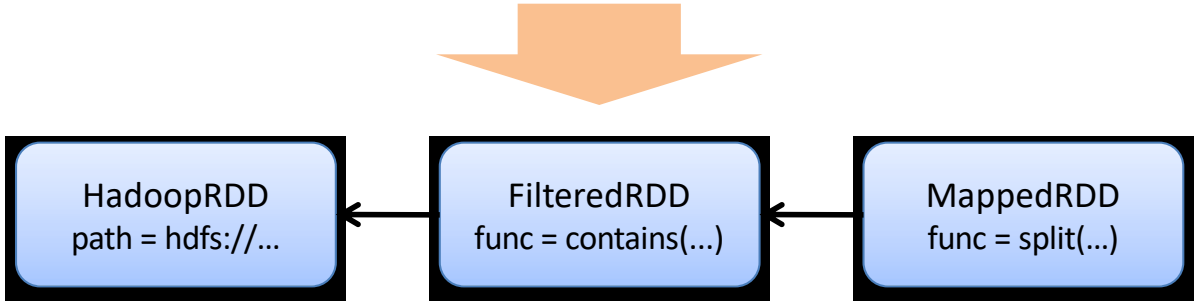
Result: full-text search of Wikipedia in <1 sec
(vs 20 sec for on-disk data)

Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

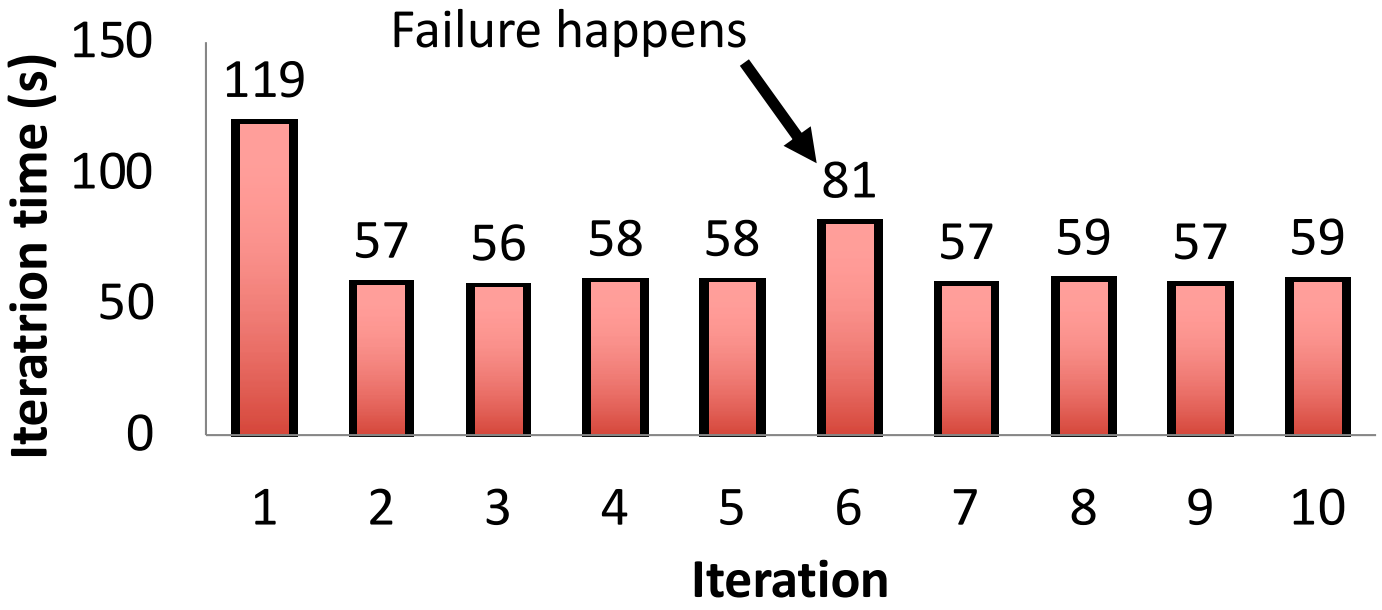
RDD Fault Tolerance

RDDs track the transformations used to build them (their *lineage*) to recompute lost data

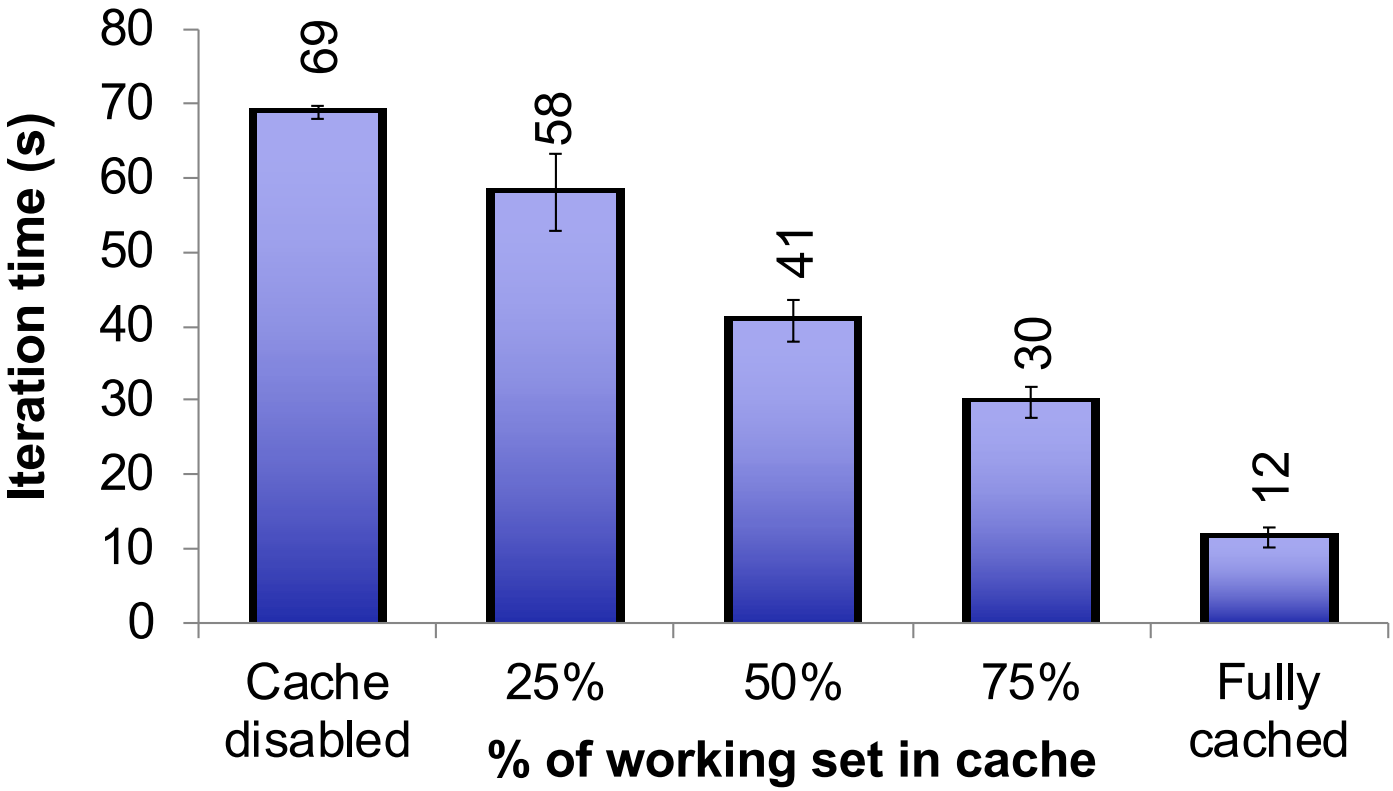
E.g:
```
messages = textFile(...).filter(lambda s: s.contains("ERROR"))
                         .map(lambda s: s.split('\t')[2])
```



Fault Recovery Test



Behavior with Less RAM



Pig and HIVE?

- The latest release of Pig and Hive compile into Spark jobs and not only MapReduce

- High level languages and integration with Machine Learning libraries, etc.

```
pig -x spark
```

```
hive> set hive.execution.engine=spark;
```

Performance degradation?

- Network optimizations:
  - Can only reduce job completion time by a median of at most 2%
  - Not a bottleneck because much less data is sent over the network than is transferred to and from disk
  - Network I/O is mostly even on 1Gbps networks

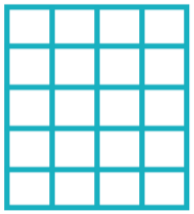
- Disk access optimization or elimination
  - Can only reduce job completion time by a median of at most 19%
  - CPU utilization is typically much higher than disk utilization
  - Use more sophisticated serialization and compression techniques

- Optimizing stragglers:
  - Can only reduce job completion time by a median of at most 10%
  - Java garbage collection and disk data transfer time

K. Ousterhout, R. Rasti, S. Ratnasamy, S. Shenker, B. G. Chun.
Making Sense of Performance in Data Analytics Frameworks. USENIX 2015

DataFrames

From RDDs to DataFrames



- Most data is structured (e.g., CSV, ...)
  - Programming RDDs inevitably ends up with a lot of tuples (x[0],x[1], ...)
- Functional transformations (e.g., map/reduce) are not as intuitive

From RDDs to DataFrames

```
pdata.map(lambda x: (x.dept, [x.age, 1])) \
  .reduceByKey(lambda x, y: [x[0] + y[0], x[1] + y[1]]) \
  .map(lambda x: [x[0], x[1][0] / x[1][1]]) \
  .collect()
```

databricks

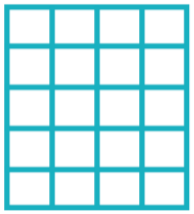
From RDDs to DataFrames

```
pdata.map(lambda x: (x.dept, [x.age, 1])) \
  .reduceByKey(lambda x, y: [x[0] + y[0], x[1] + y[1]]) \
  .map(lambda x: [x[0], x[1][0] / x[1][1]]) \
  .collect()
```

```
data.groupBy("dept").avg("age")
```

databricks

DataFrames in Spark



- Distributed collection of data grouped into named columns (i.e., RDD with schema)
- Provides abstraction for selecting, filtering, aggregating and plotting structured data
  - Selecting required columns
  - Joining different data sources
  - Aggregation (count, sum, average, etc)
- Domain-specific functions designed for common tasks
  - Metadata
  - Sampling
  - User Defined Functions (UDFs)
- Available in Python, Scala, Java, and R (via SparkR)

DataFrames in Spark

- Immutable once constructed
- Track lineage
- Enable distributed computations

- How to construct DataFrames
  - Reading from file(s)
  - Transforming an existing DFs (Spark or Pandas) or RDDs
  - Parallelizing a python collection list
  - Applying transformations and actions

Create a DataFrame from a csv file

```
In [1]: df_data_1 = spark.read.format('org.apache.spark.sql.execution.datasources.csv.CSVFileFormat')\
            .option('header', 'true').load('2015-summary.csv')
        df_data_1.take(5)
```

```
Out[1]: [Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='Romania', count='15'),
         Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='Croatia', count='1'),
         Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='Ireland', count='344'),
         Row(DEST_COUNTRY_NAME='Egypt', ORIGIN_COUNTRY_NAME='United States', count='15'),
         Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='India', count='62')]
```

https://www.rita.dot.gov/bts/help_with_data/aviation/index.html

Create a DataFrame from a csv file

- Getting the schema

```
df_data_1.printSchema()
```

```
root
 |-- DEST_COUNTRY_NAME: string (nullable = true)
 |-- ORIGIN_COUNTRY_NAME: string (nullable = true)
 |-- count: string (nullable = true)
```

Filter – US outgoing flights

```
us_from_flights=df_data_1.filter("ORIGIN_COUNTRY_NAME =='United States'")

# Alternatively, using Pandas-like syntax
us_from_flights=df_data_1[df_data_1.ORIGIN_COUNTRY_NAME =='United States']
us_from_flights.show()
```

```
+--------------------+-------------------+-----+
|   DEST_COUNTRY_NAME|ORIGIN_COUNTRY_NAME|count|
+--------------------+-------------------+-----+
|               Egypt|      United States|   15|
|          Costa Rica|      United States|  588|
|             Senegal|      United States|   40|
|             Moldova|      United States|    1|
|              Guyana|      United States|   64|
|               Malta|      United States|    1|
|            Anguilla|      United States|   41|
|             Bolivia|      United States|   30|
```

Filter – US outgoing flights

- Select only destination and number of flights

```
us_from_flights=df_data_1.filter(“ORIGIN_COUNTRY_NAME
=='United States’”).select("DEST_COUNTRY_NAME", "COUNT")

us_from_flights.show()
```

```
+--------------------+-----+
|   DEST_COUNTRY_NAME|COUNT|
+--------------------+-----+
|               Egypt|   15|
|          Costa Rica|  588|
|             Senegal|   40|
|             Moldova|    1|
|              Guyana|   64|
|               Malta|    1|
|            Anguilla|   41|
```

Filter – US outgoing flights

- Select only destination and number of flights

```
us_from_flights=df_data_1.where("ORIGIN_COUNTRY_NAME
=='United States'").select("DEST_COUNTRY_NAME", "COUNT")

us_from_flights.show()
```

```
+--------------------+-----+
|   DEST_COUNTRY_NAME|COUNT|
+--------------------+-----+
|               Egypt|   15|
|          Costa Rica|  588|
|             Senegal|   40|
|             Moldova|    1|
|              Guyana|   64|
|               Malta|    1|
|            Anguilla|   41|
```

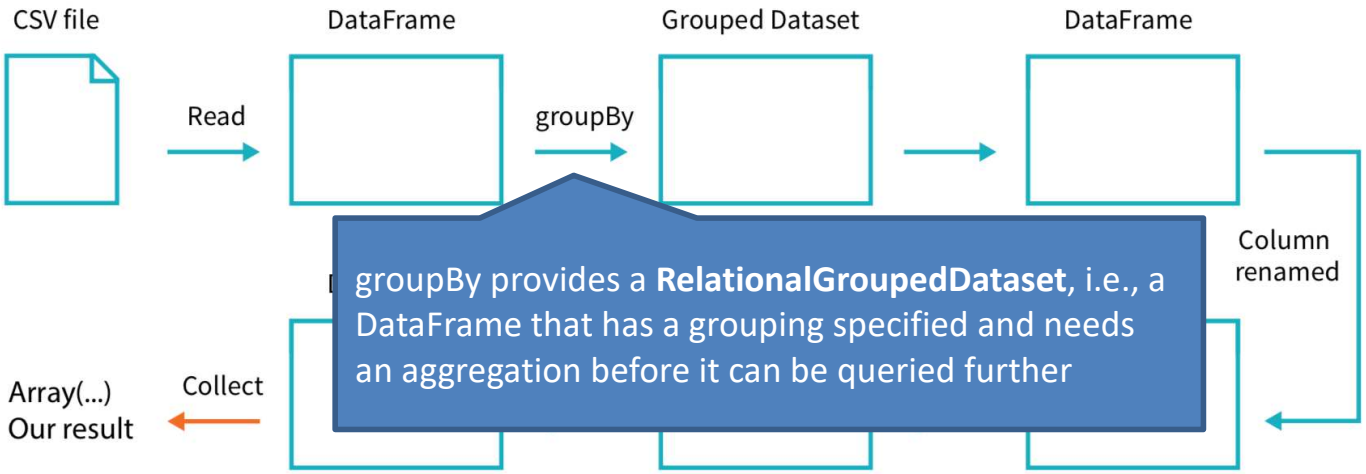
Filter – Applying types

- Find out the top five destination countries

```
from pyspark.sql.types import DoubleType
from pyspark.sql.functions import desc
df_flights2015=df_data_1.withColumn(“count”,df_data_1[“count”].cast(“double”))

df_flights2015.groupBy(“dest_country_name”).\
sum(“count”).\
withColumnRenamed(“sum(count)”,”destination_total”).\
sort(desc(“destination_total”)).limit(5).collect()
```

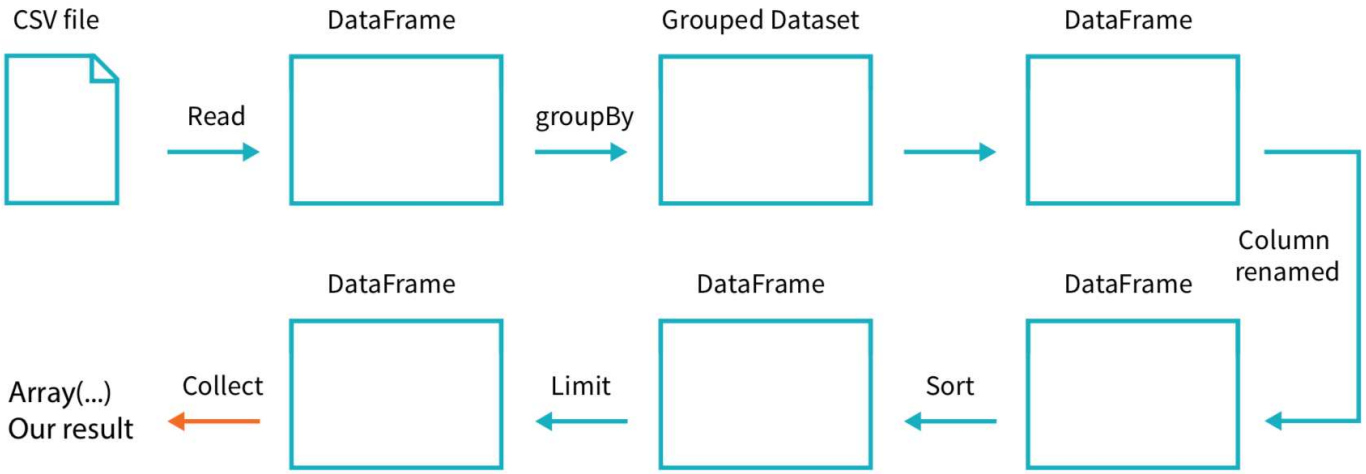
```
[Row(DEST_COUNTRY_NAME='United States', destination_total=411352.0),
 Row(DEST_COUNTRY_NAME='Canada', destination_total=8399.0),
 Row(DEST_COUNTRY_NAME='Mexico', destination_total=7140.0),
 Row(DEST_COUNTRY_NAME='United Kingdom', destination_total=2025.0),
 Row(DEST_COUNTRY_NAME='Japan', destination_total=1548.0)]
```

Filter – Lineage



groupBy provides a **RelationalGroupedDataset**, i.e., a DataFrame that has a grouping specified and needs an aggregation before it can be queried further

Filter – Lineage



Joining two DataFrames

- Let's evaluate the flights delta between 2015 and 2014

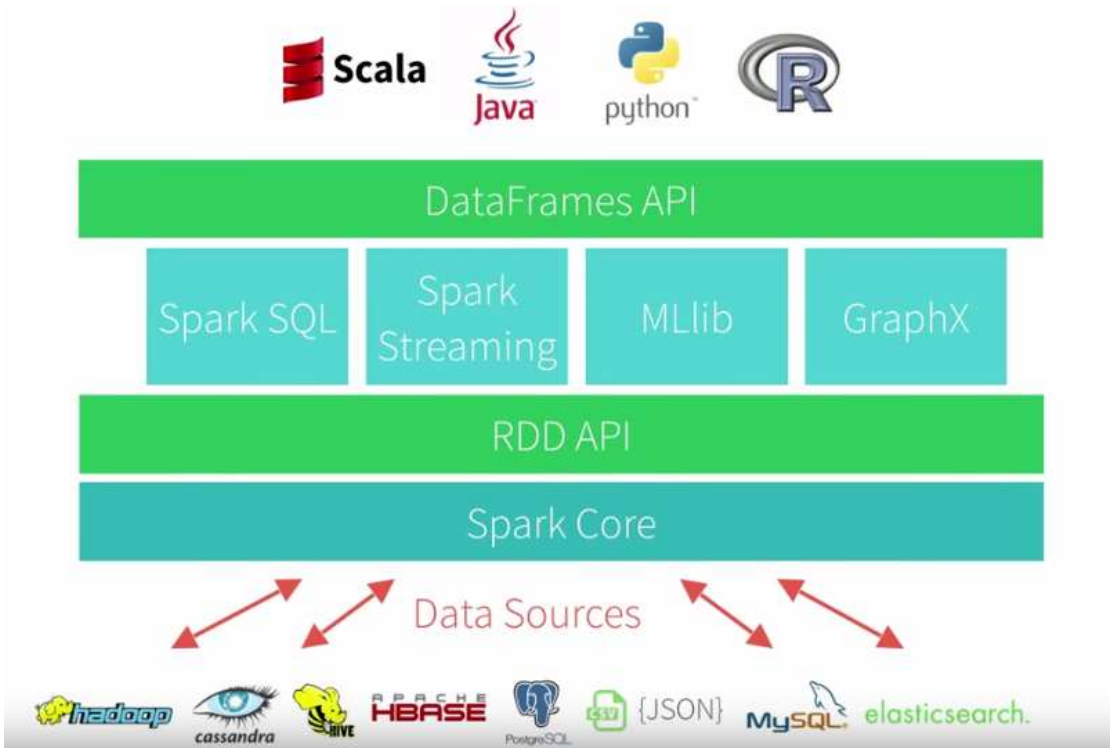
```
df_data_2 = spark.read\
.format('org.apache.spark.sql.execution.datasources.csv.CSVFileFormat')\
.option('header', 'true')\
.load(cos.url('2014-summary.csv',
'apccourse2017180c7db5912f304fcd8f4cf0d147b8b65c'))
df_data_2.take(5)
df_flights2014=df_data_2.withColumn("COUNT",
df_data_2["COUNT"].cast("double")).withColumnRenamed("COUNT","COUNT2014")
```

Joining two DataFrames

```
df_join=df_flights2014\
.join(df_flights2015,(df_flights2014.DEST_COUNTRY_NAME==\
                      df_flights2015.DEST_COUNTRY_NAME)&\
                      (df_flights2014.ORIGIN_COUNTRY_NAME==\
                      df_flights2015.ORIGIN_COUNTRY_NAME))\
.select(df_flights2014.DEST_COUNTRY_NAME,\
        df_flights2014.ORIGIN_COUNTRY_NAME,"COUNT2014","COUNT")

df_join.take(5)
```

```
[Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='Romania', COUNT2014=12.0, COUNT=15.0),
 Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='Croatia', COUNT2014=2.0, COUNT=1.0),
 Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='Ireland', COUNT2014=291.0, COUNT=344.0),
 Row(DEST_COUNTRY_NAME='United States', ORIGIN_COUNTRY_NAME='India', COUNT2014=62.0, COUNT=62.0),
 Row(DEST_COUNTRY_NAME='Egypt', ORIGIN_COUNTRY_NAME='United States', COUNT2014=11.0, COUNT=15.0)]
```

Where is Spark today?

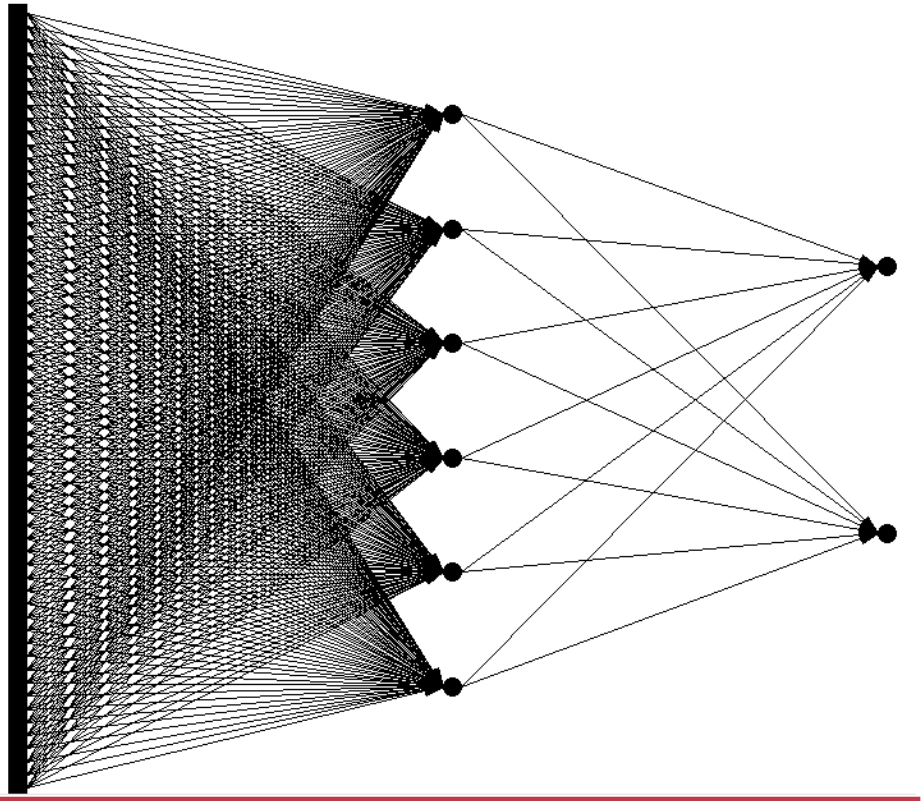


- Strengthening streaming
- Extend MLlib to deep learning

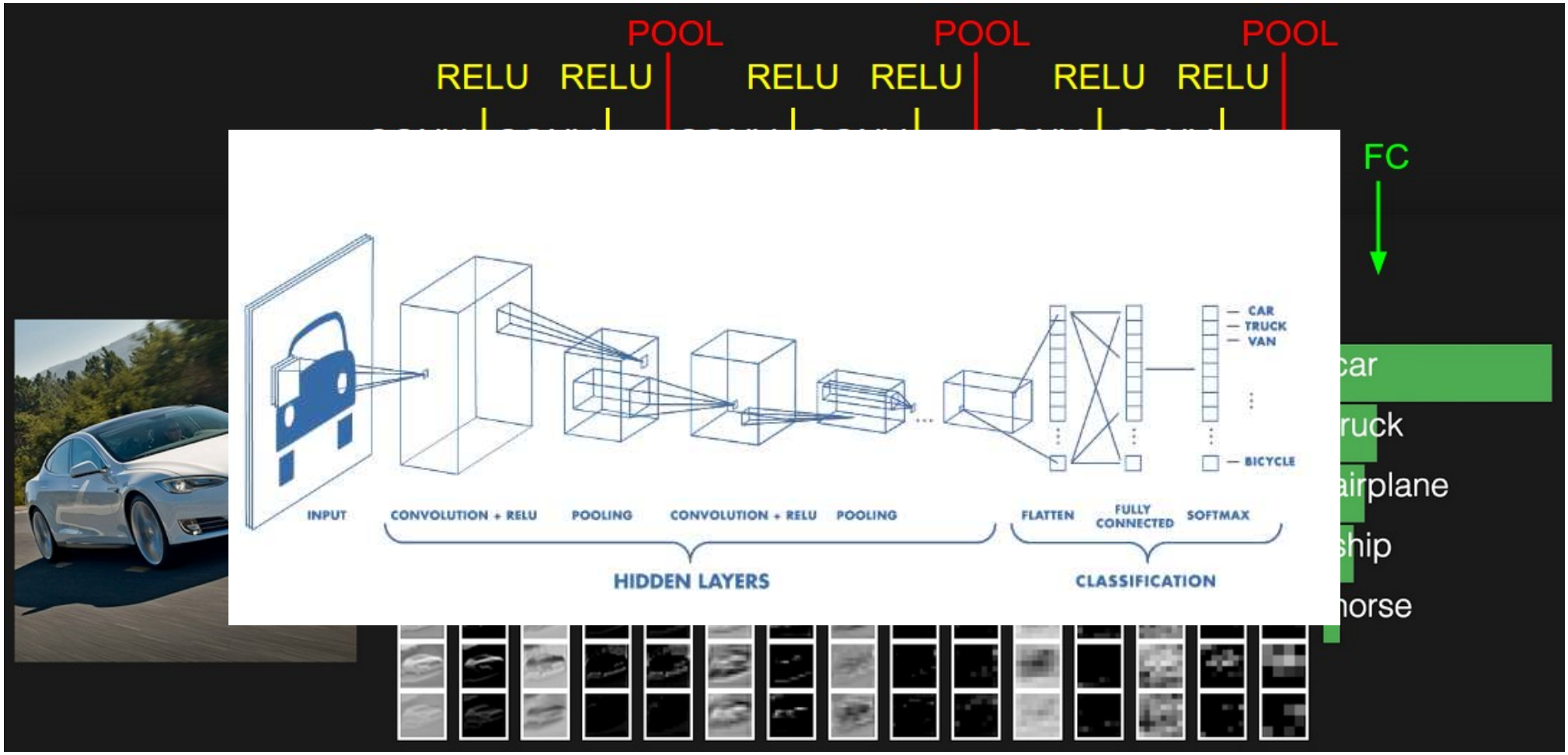
ANNs – Feedforward Networks

- Network architecture
  - 60 input (one for each frequency bin)
  - 6 hidden
  - 2 output (0-1 for “Steve”, 1-0 for “David”)

“Hello”



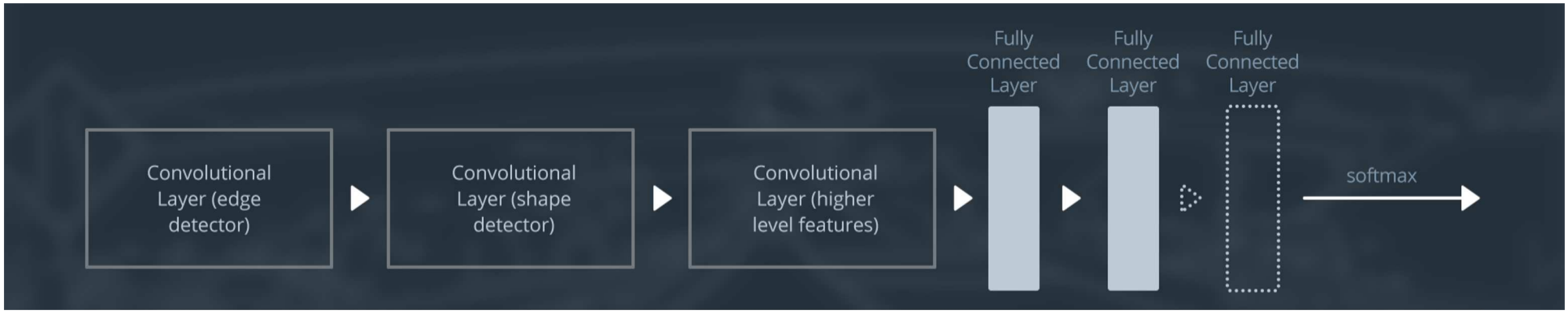
Convolutional Neural Networks and Deep Learning



Scale drives Deep Learning progress

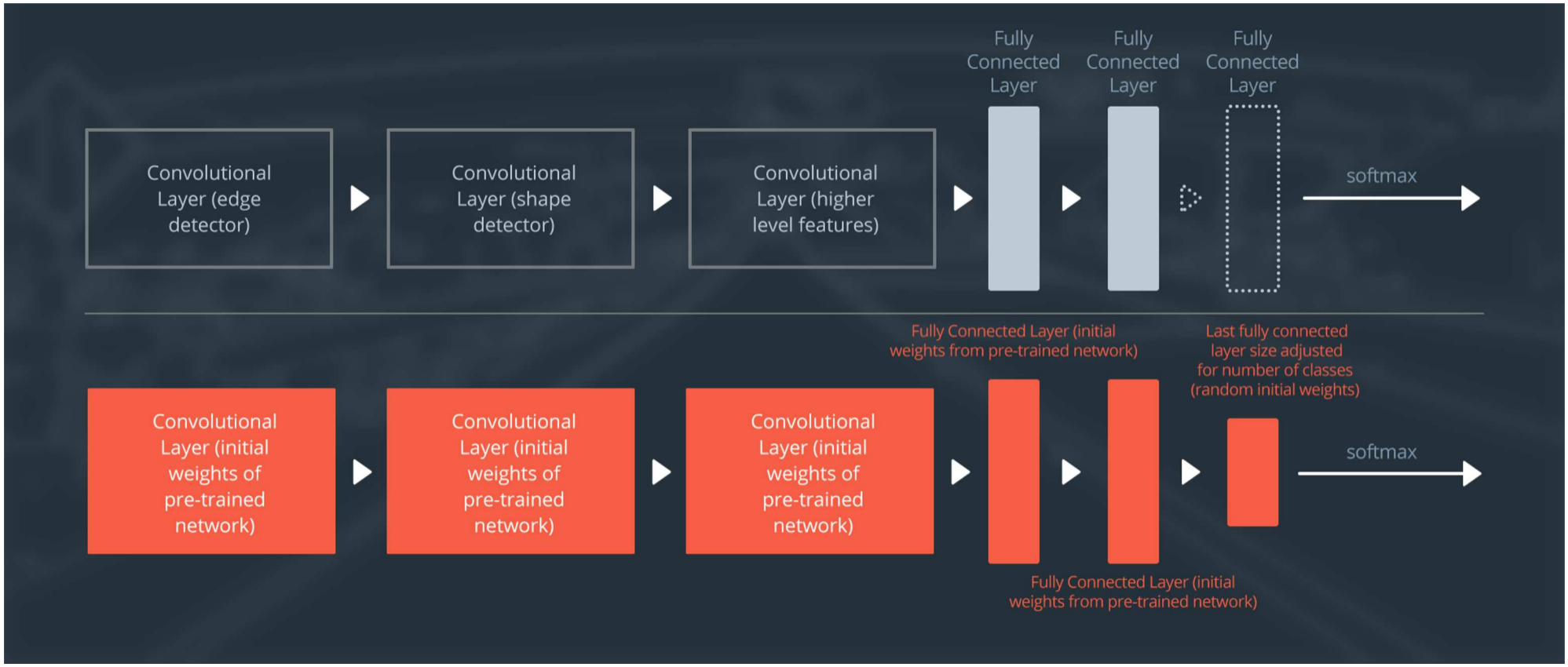
- Same ideas as in the in 1940s:
  - Labeled datasets were thousands of times too small
  - Computers were millions of times too slow

SparkDL – Transfer learning



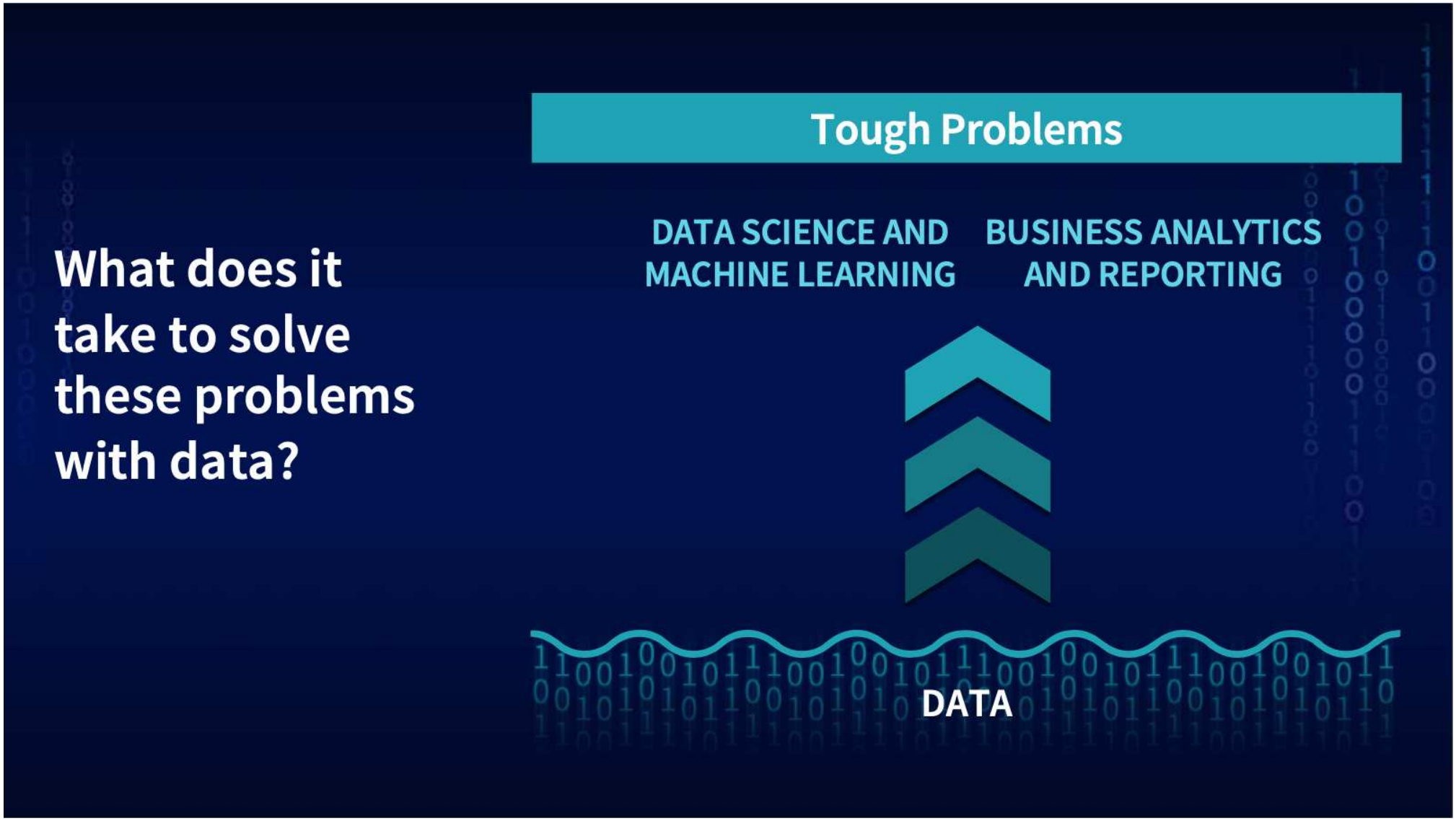
Source: https://www.yuchao.us/2017/04/self-driving-car-nd-a3.html

SparkDL – Transfer learning



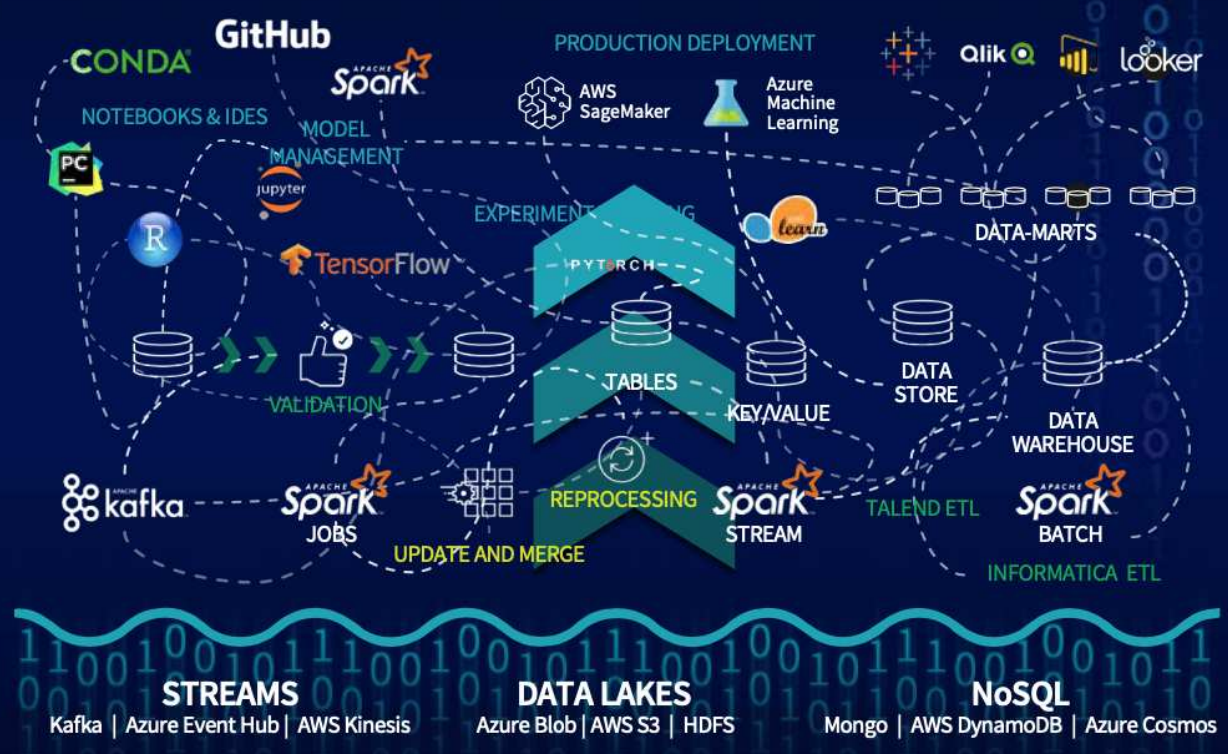
Source: https://www.yuchao.us/2017/04/self-driving-car-nd-a3.html

New projects at databricks

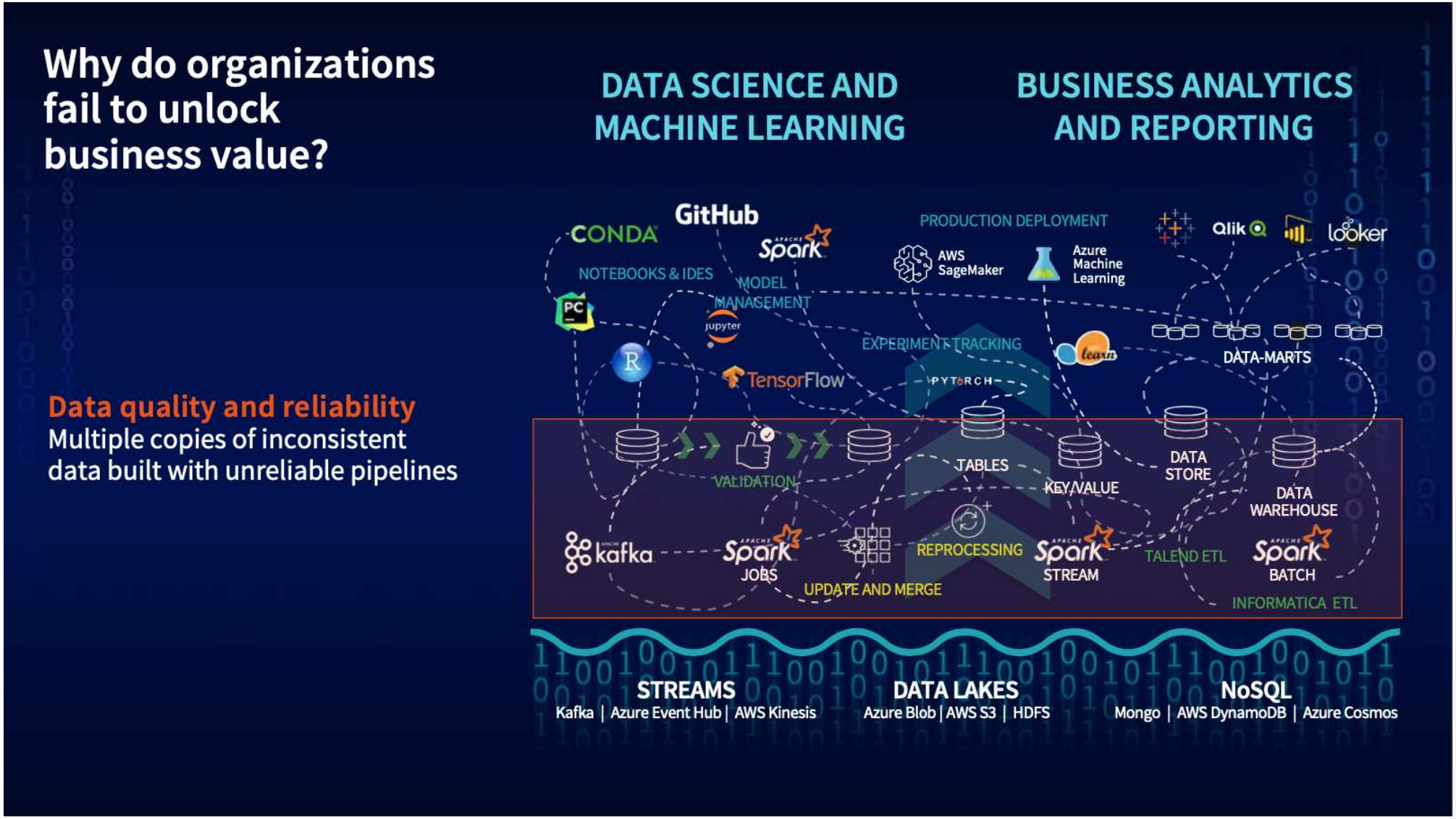


New projects at databricks

Organizations are failing to solve these problems due to data, tech and people silos



New projects at databricks

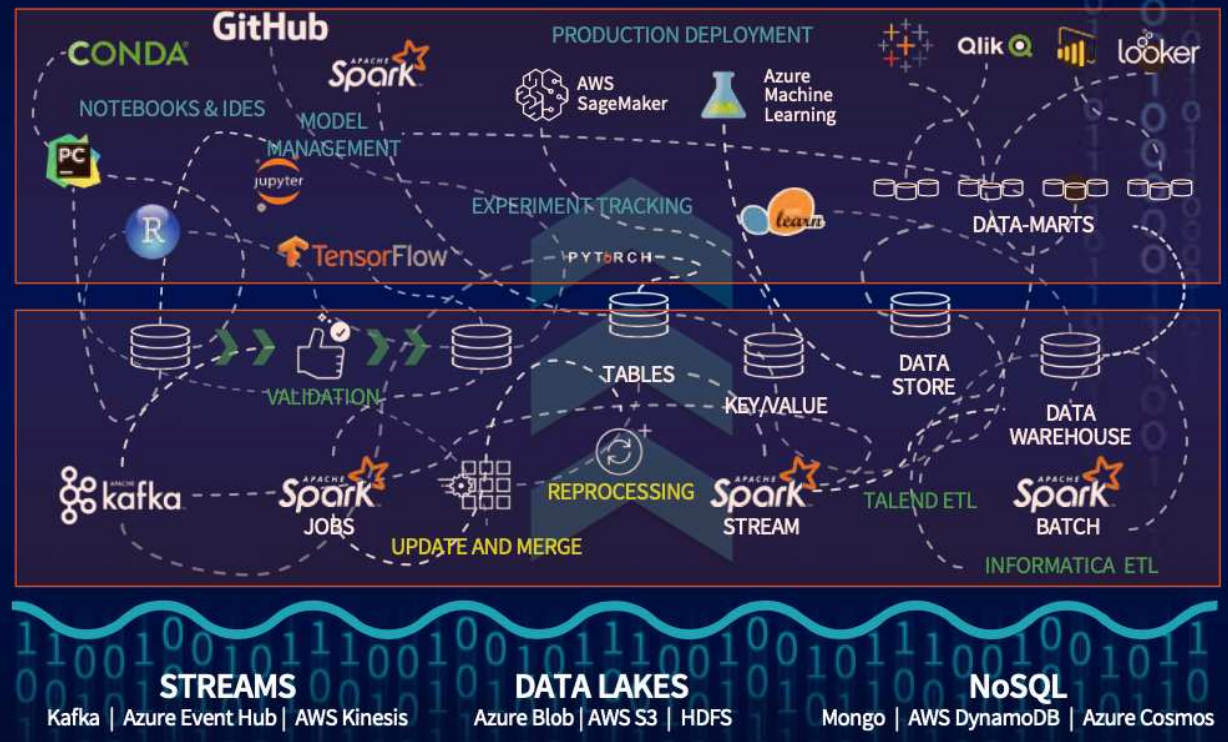


New projects at databricks

Why do organizations fail to unlock business value?

Disparate technologies
Must stitch together dozens of software frameworks

Data quality and reliability
Multiple copies of inconsistent data built with unreliable pipelines



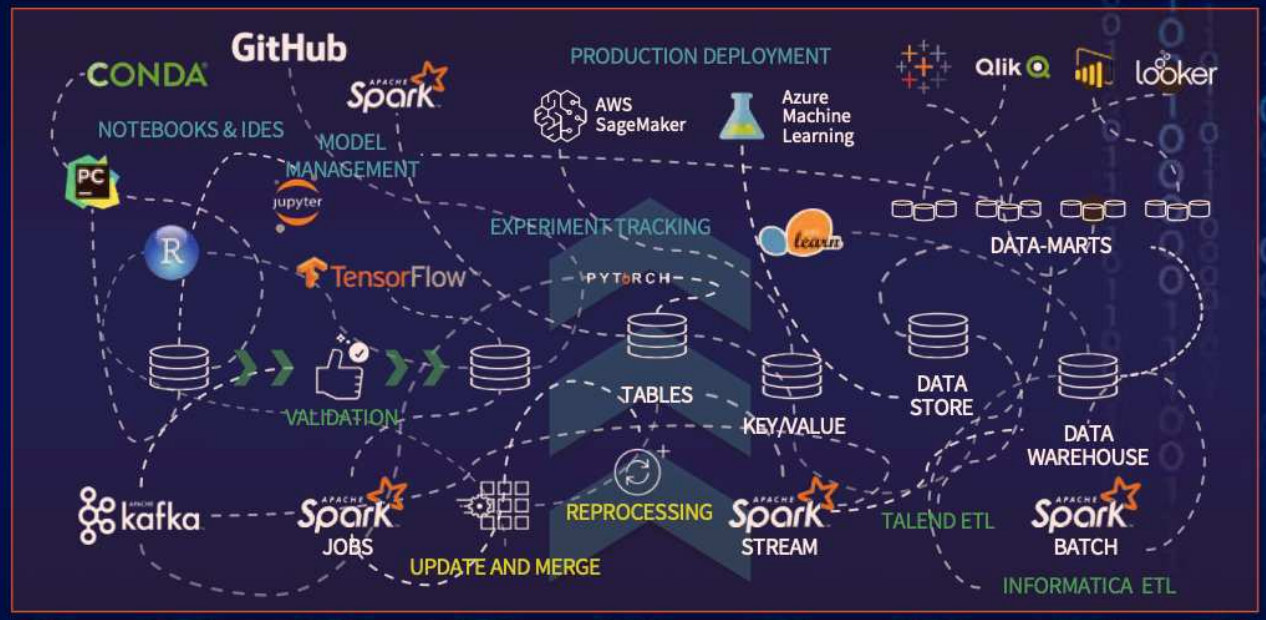
New projects at databricks

Why do organizations fail to unlock business value?

Disparate technologies
Must stitch together dozens of software frameworks

Data quality and reliability
Multiple copies of inconsistent data built with unreliable pipelines

Fragmented security
End-to-end security and enterprise SLAs are a nightmare

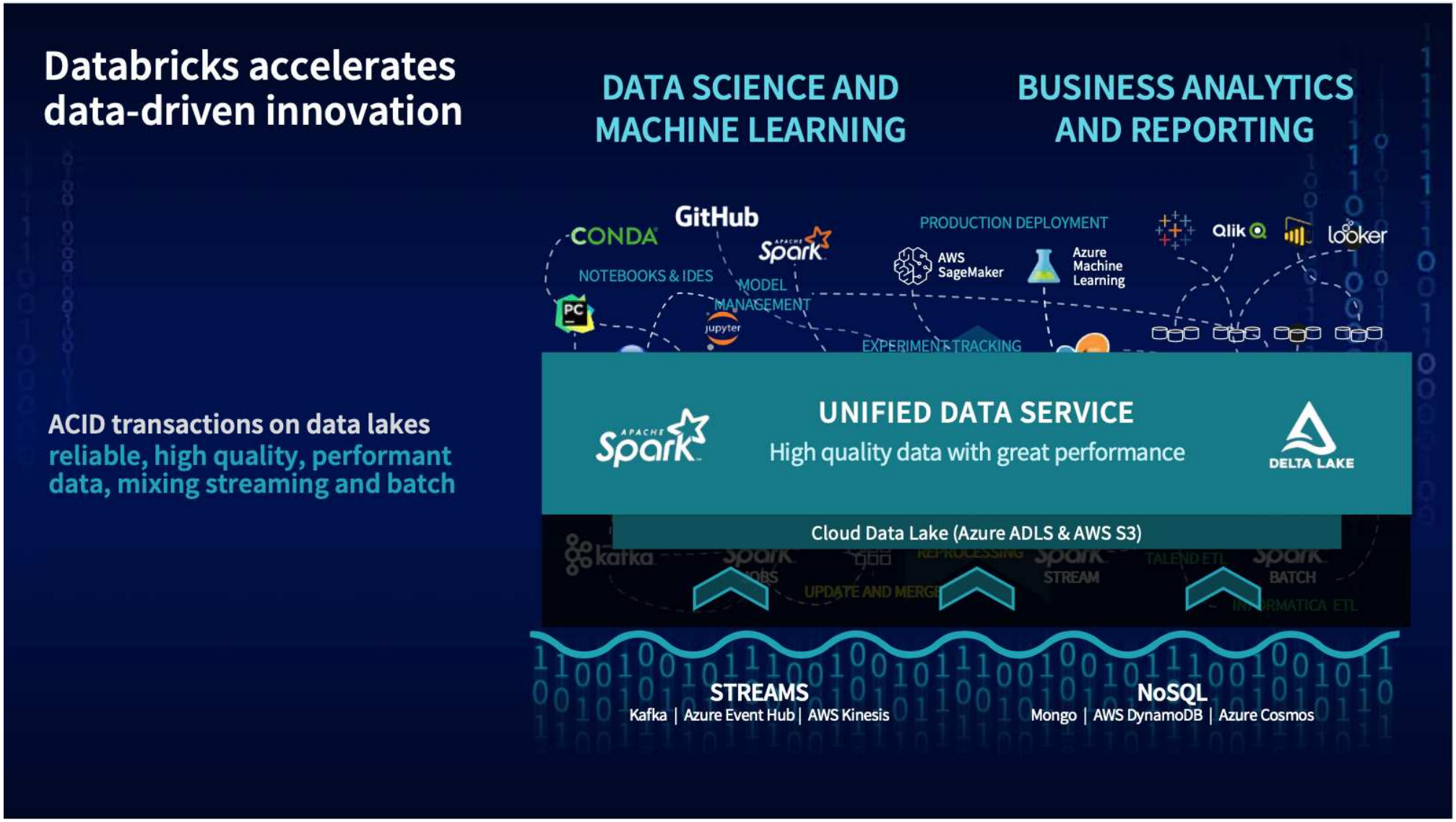


STREAMS
Kafka | Azure Event Hub | AWS Kinesis

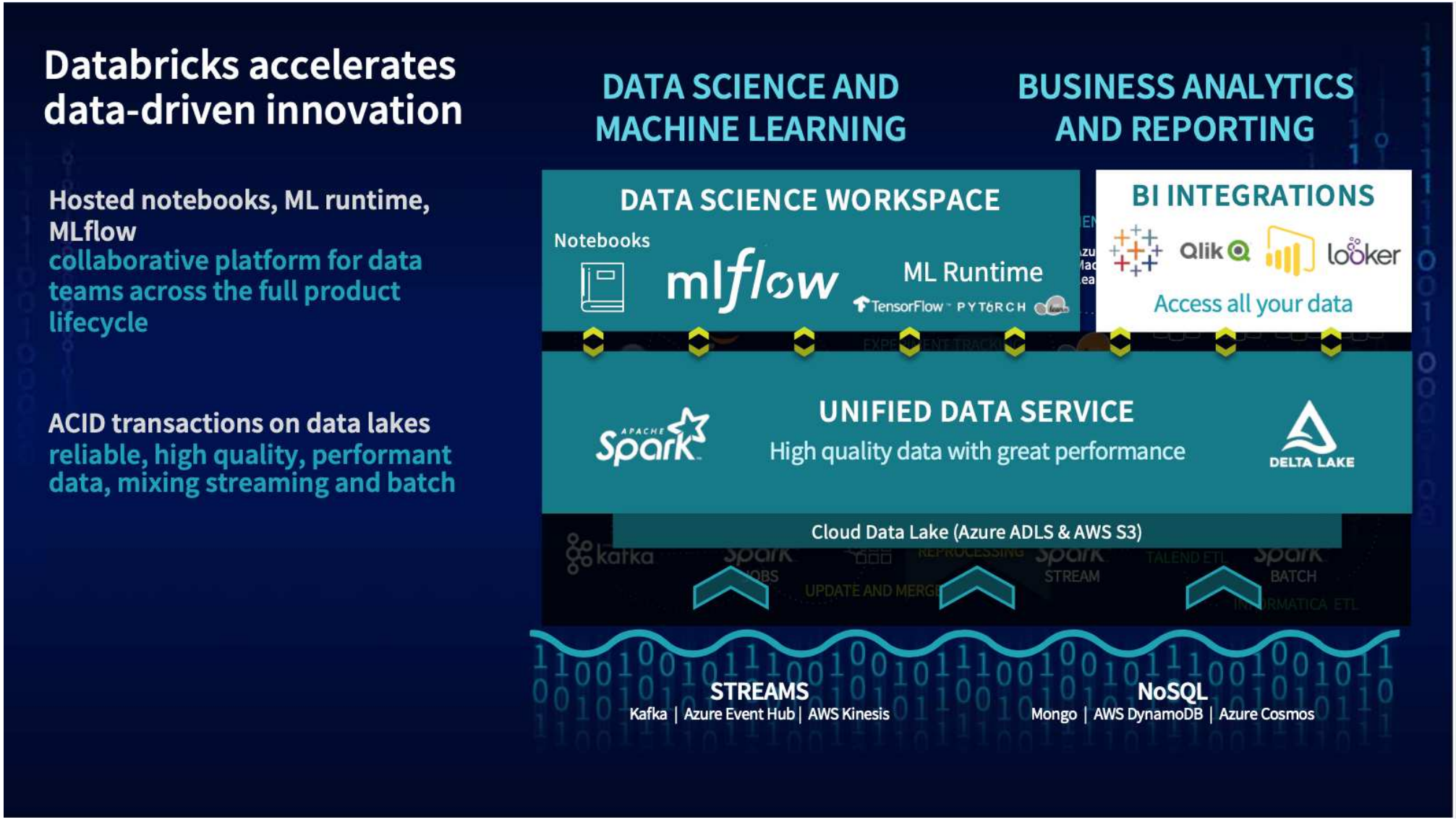
DATA LAKES
Azure Blob | AWS S3 | HDFS

NoSQL
Mongo | AWS DynamoDB | Azure Cosmos

New projects at databricks



New projects at databricks



New projects at databricks

Databricks accelerates data-driven innovation

Hosted notebooks, ML runtime, MLflow
collaborative platform for data teams across the full product lifecycle

ACID transactions on data lakes
reliable, high quality, performant data, mixing streaming and batch

Managed enterprise cloud service
End-to-end security, SLAs, and administration

DATA SCIENCE AND MACHINE LEARNING

BUSINESS ANALYTICS AND REPORTING

DATA SCIENCE WORKSPACE

Notebooks

mlflow

ML Runtime

TensorFlow · PYTORCH

BI INTEGRATIONS

Qlik · looker

Access all your data

UNIFIED DATA SERVICE

Spark

High quality data with great performance

DELTA LAKE

ENTERPRISE CLOUD SERVICE

aws

Enterprise Security

Simple Administration

Production Scale

Azure

AICPA SOC · FedRAMP · HIPAA · PCI DSS · GDPR · ISO

Spark 3.0

	Data Warehouse	Hadoop M/R	Apache Spark
Separate Compute & Storage	✗	✓	✓
More than SQL (i.e ML)	✗	✓	✓
Open Source at Scale	✗	✓	✓
SQL & Optimization	✓	✗	✓
Data Model & Catalog	✓	✗	✓
ACID Transactions	✓	✗	Delta Lake
Data Science at Scale	✗	✗	Koalas

3.0

Spark 3.0

Spark 3.0: Pluggable Data Catalog

DataSourceV2

- Pluggable catalog integration
- Improved pushdown
- Unified APIs for streaming and batch

```
df.writeTo("catalog.db.table")
  .overwrite($"year" === "2019")
```

Parquet

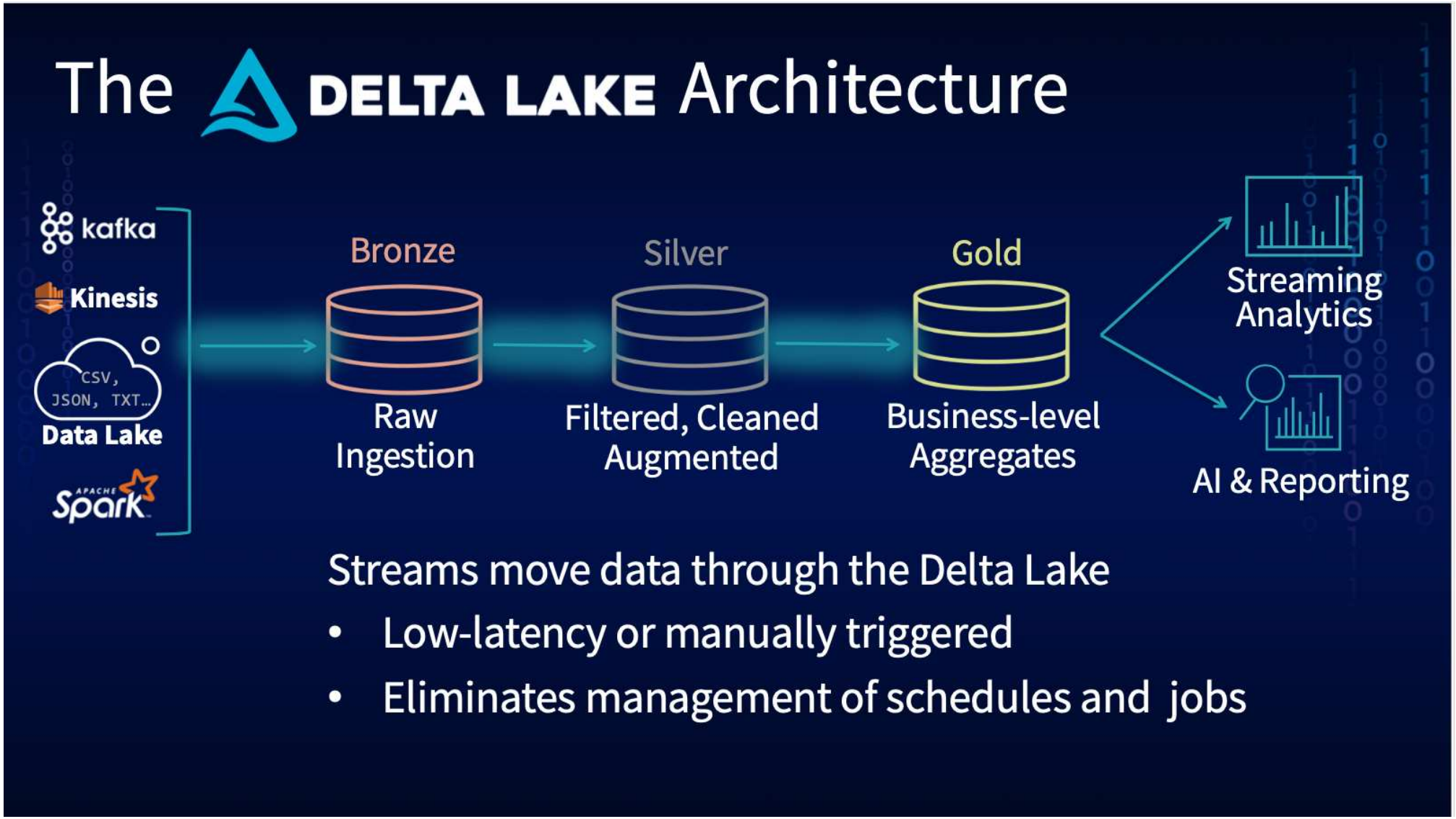
cassandra

DELTA LAKE

kafka

Apache orc

Spark 3.0


The DELTA LAKE Architecture
kafka
Kinesis
CSV, JSON, TXT…
Data Lake
Spark
Bronze
Raw Ingestion
Silver
Filtered, Cleaned Augmented
Gold
Business-level Aggregates
Streaming Analytics
AI & Reporting
Streams move data through the Delta Lake
• Low-latency or manually triggered
• Eliminates management of schedules and jobs

Spark 3.0

This works great on my laptop…

```
import pandas as pd
df = pd read_csv('my_data.csv')
df.columns = ['x', 'y', 'z1']

df['x2'] = df.x * df.x
```

… but what if I have more data?

```
import databricks.koalas as ks
df = ks.read_delta('/lake/data')
df.columns = ['x', 'y', 'z1']

df['x2'] = df.x * df.x
```

Koalas

Spark 3.0

mlflow

Open source machine learning platform

- Works with any ML library, algorithm, language, etc
- *Open interface* design (use with any code you already have)

mlflow Tracking

Record and query experiments: code, data, confs, results

mlflow Projects

Packaging format for reproducible runs and workflows

mlflow Models

General format that standardizes deployment paths

new

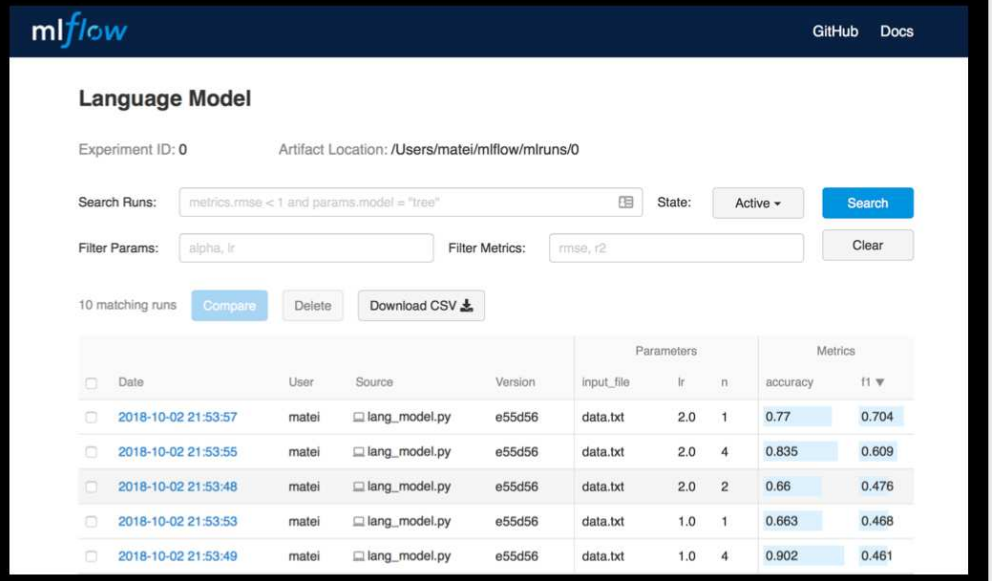
mlflow Model Registry

Centralized model management, review & sharing

databricks

MLflow Tracking

```
data   = load_text(file)
ngrams = extract_ngrams(data, N=n)
model  = train_model(ngrams,
                     learning_rate=lr)
score  = compute_accuracy(model)

mlflow.log_param("data_file", file)
mlflow.log_param("n", n)
mlflow.log_param("learning_rate", lr)
mlflow.log_metric("score", score)

mlflow.keras.log_model(model)
```



Track parameters, metrics, output files & code version

databricks

Thanks for your attention...

...any questions?

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Credits

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- Giovanna Roda. Introduction to Hadoop. PRACE Autumn School ’21, 27–28 September 2021
- Danilo Ardagna. From MapReduce & Apache Hadoop to Apache Spark. PhD course on Data Management For Large-scale Analytics