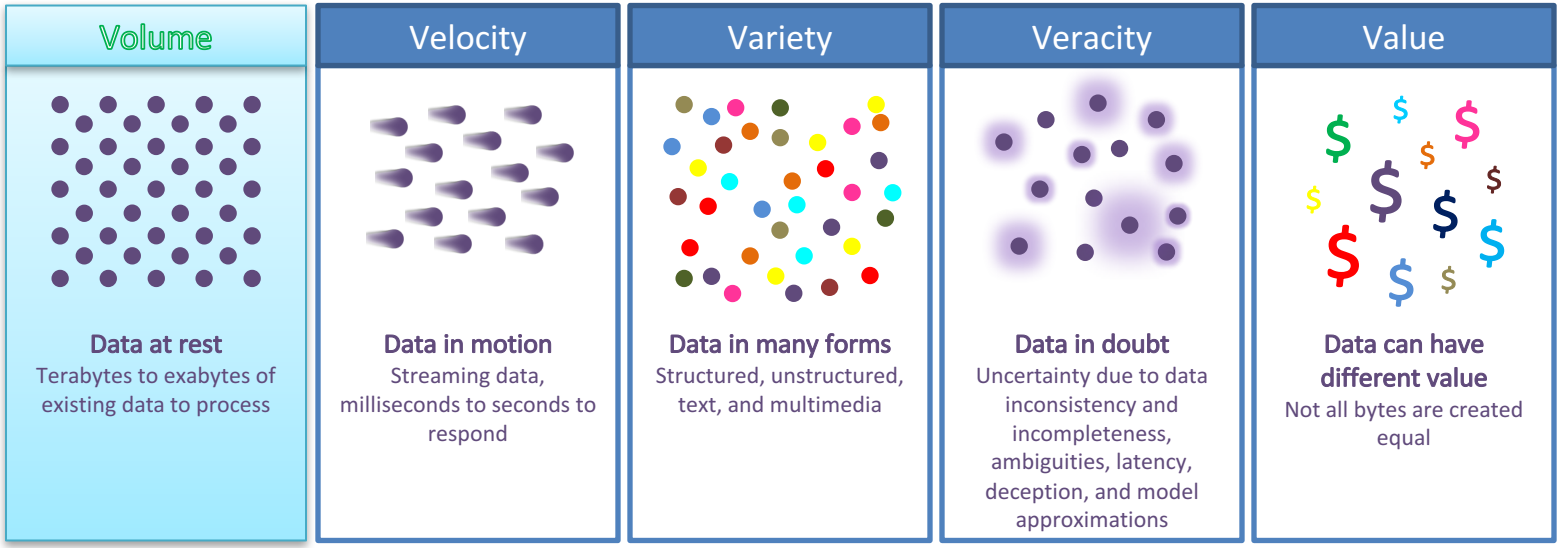
Big Data Engineering

Data Science Dojo

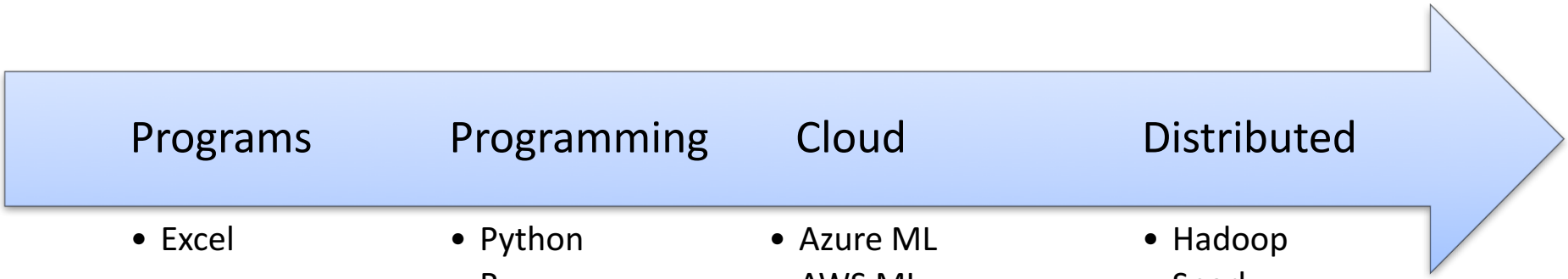
5 Vs of Big Data



- **Batch Processing:** Save all your raw data and process at once

MACHINE LEARNING AT SCALE

Machine Learning Scaling



- Excel
- Python
- R
- SAS
- Azure ML
- AWS ML
- Big ML
- Cloud Virtual Machines
- Hadoop
- Spark
- H20
- Revolution R

R Limits

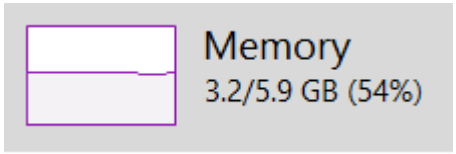
- Single core
- Single threaded
- All in memory (RAM)
- Vectors & Matrices capped at 4,294,967,295 elements (rows) if 32-bit version; 2^32 - 1

R Limits: RAM

- All in memory (RAM)

$$Max\ Data\ Limit = (\ Total\ RAM\ Access\ x\ 80\%) - Normal\ RAM\ Usage$$

Laptop Example:



$$Max\ Data\ Limit = (\ 5.9\ GB\ x\ 80\%)\ - 3.2\ \text{GB}$$
$$Max\ Data\ Limit = \sim 1.52 GB$$

*R data frames actually bloats data files by 3x

R's Data Limit = $1.52 GB\ \div 3 = 518.8\ MB$

R Limits: RAM

INSTANCE	CORES	RAM	DISK SIZES	PRICE
G1	2	28 GB	384 GB	$0.67/hr (~$498/mo)
G2	4	56 GB	768 GB	$1.34/hr (~$997/mo)
G3	8	112 GB	1,536 GB	$2.68/hr (~$1,994/mo)
G4	16	224 GB	3,072 GB	$5.36/hr (~$3,988/mo)
G5	32	448 GB	6,144 GB	$9.65/hr (~$7,180/mo)

Azure's Biggest Virtual Machine

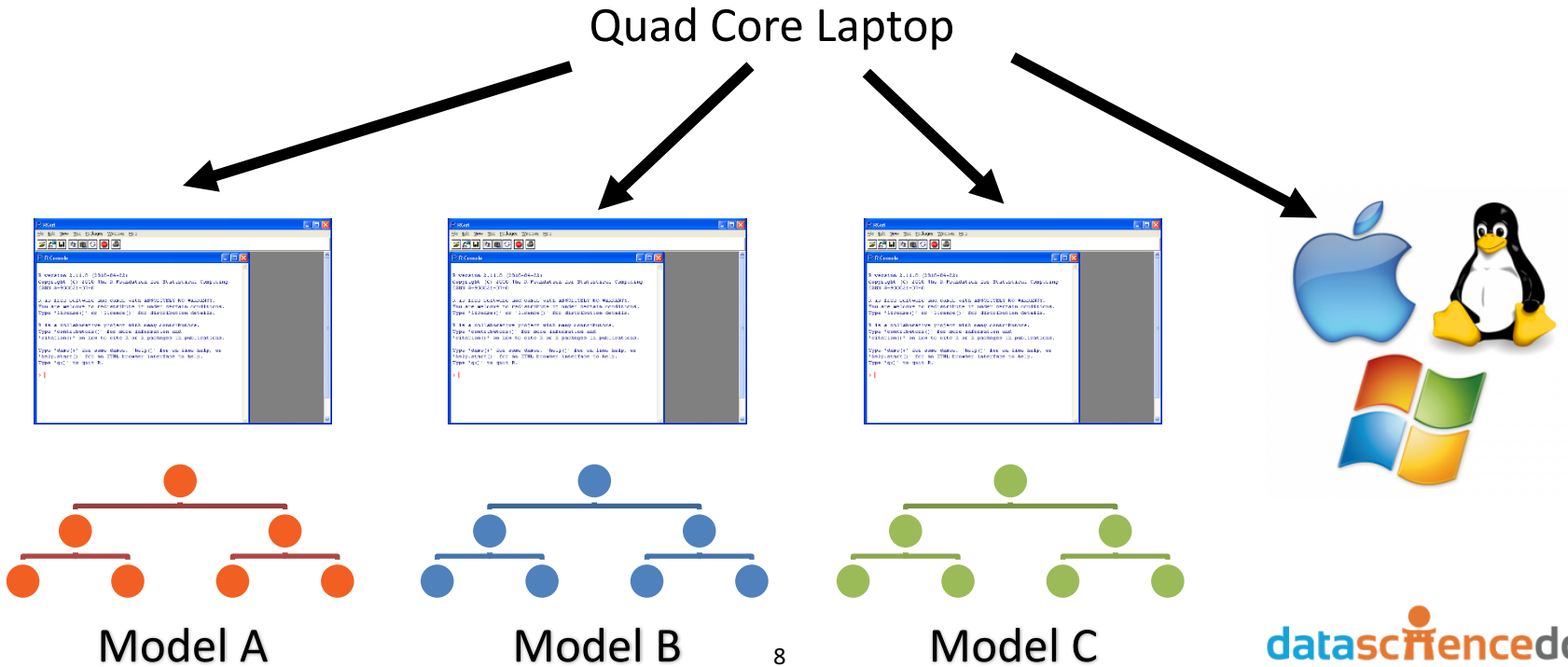
$$Max\ Data\ Limit = (\ 448gb\ x\ 80\%\ ) - 1GB$$

$$Max\ Data\ Limit = \sim \mathbf{357.4gb}$$

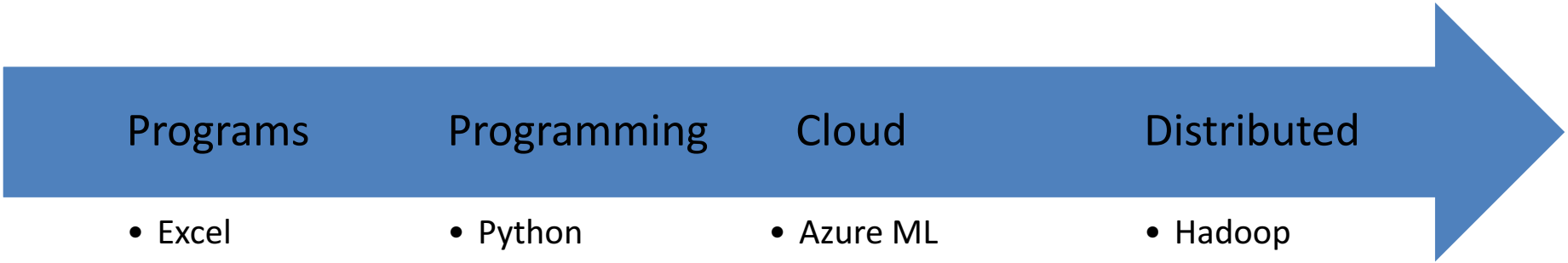
datasciencedojo
data science for everyone

R Limits: Single Core

- Single core
- Single threaded



Machine Learning Scaling



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- Revolution R

Distributed R Solutions:

https://cran.r-project.org/web/views/HighPerformanceComputing.html

Date Engineering for Data Scientists

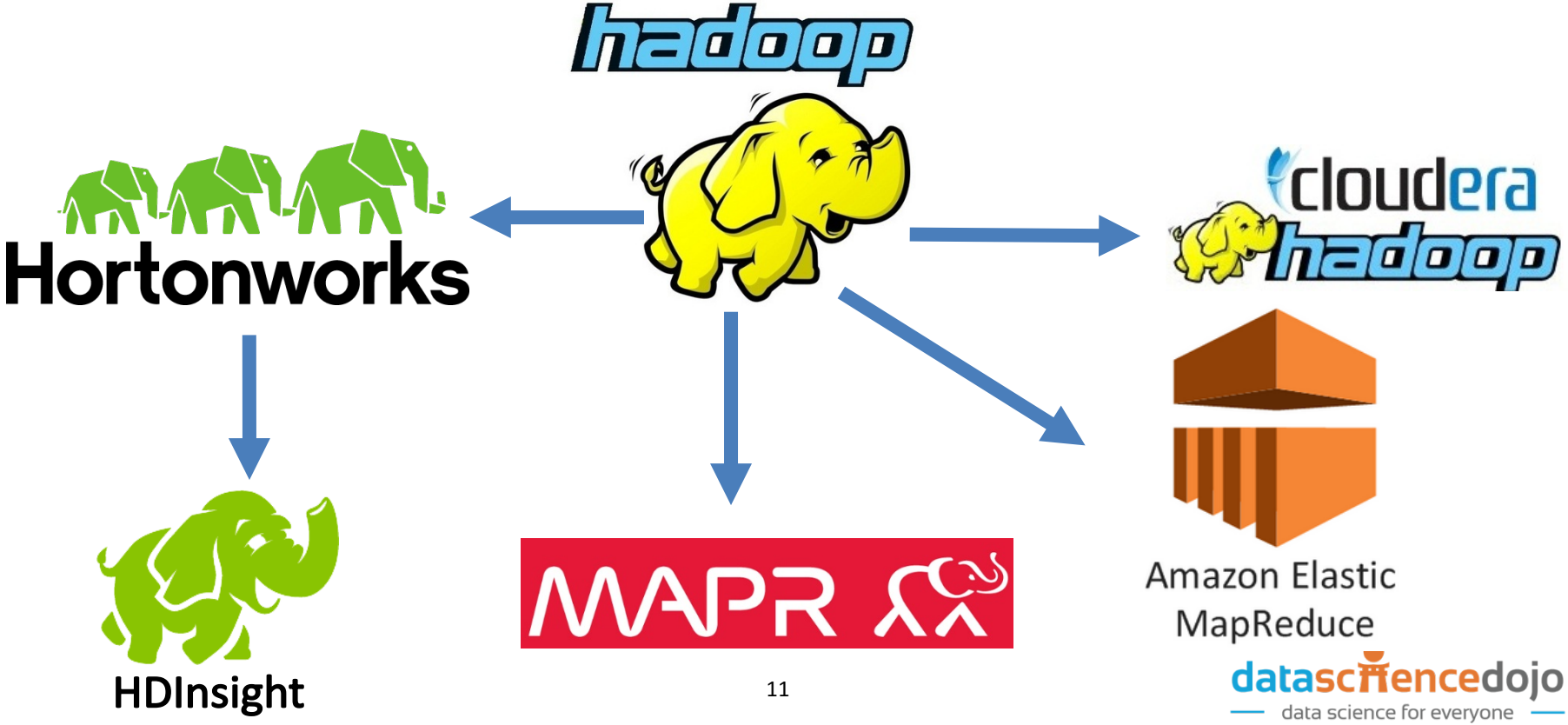
Goals:

- Teach you how to leverage an existing Hadoop cluster, self-service data query

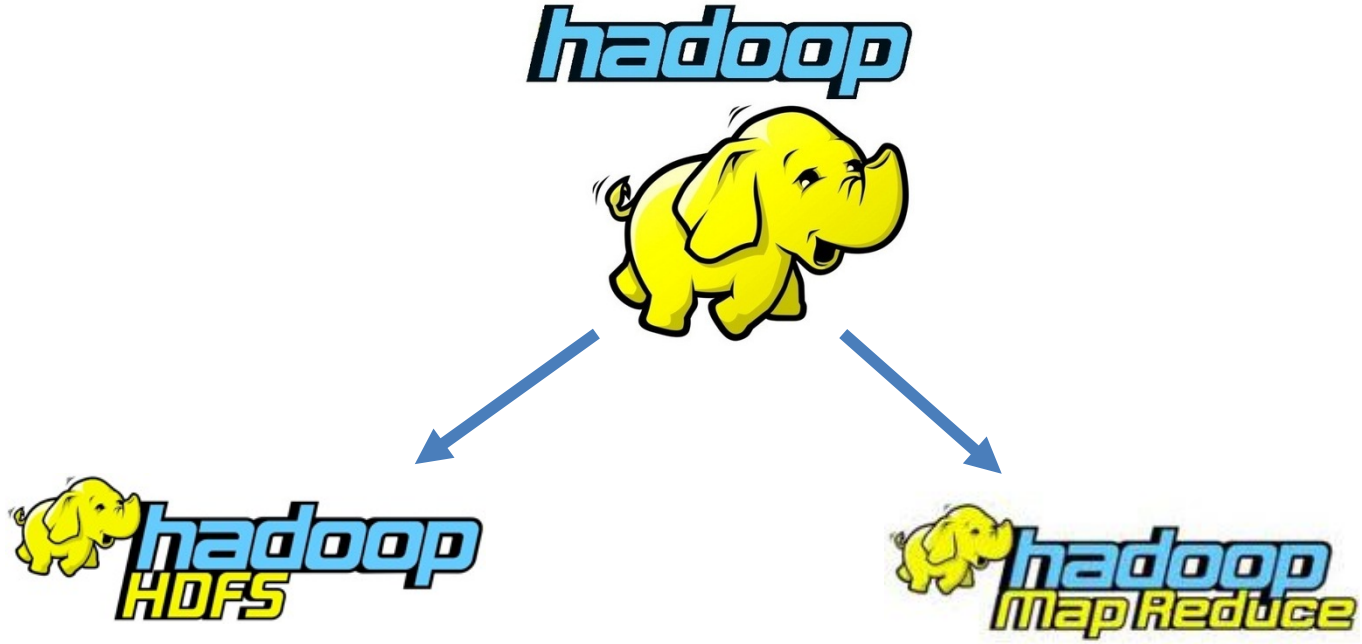
Non goals:

- Managing or administering a Hadoop cluster

Hadoop Implementations



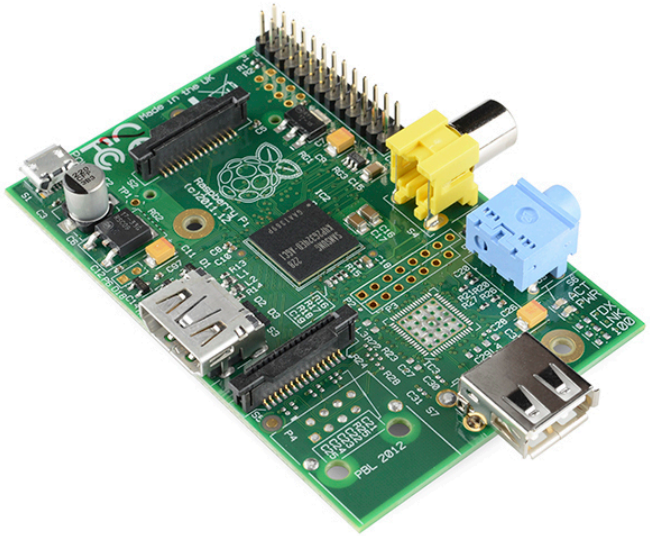
(Vanilla/Base) Hadoop

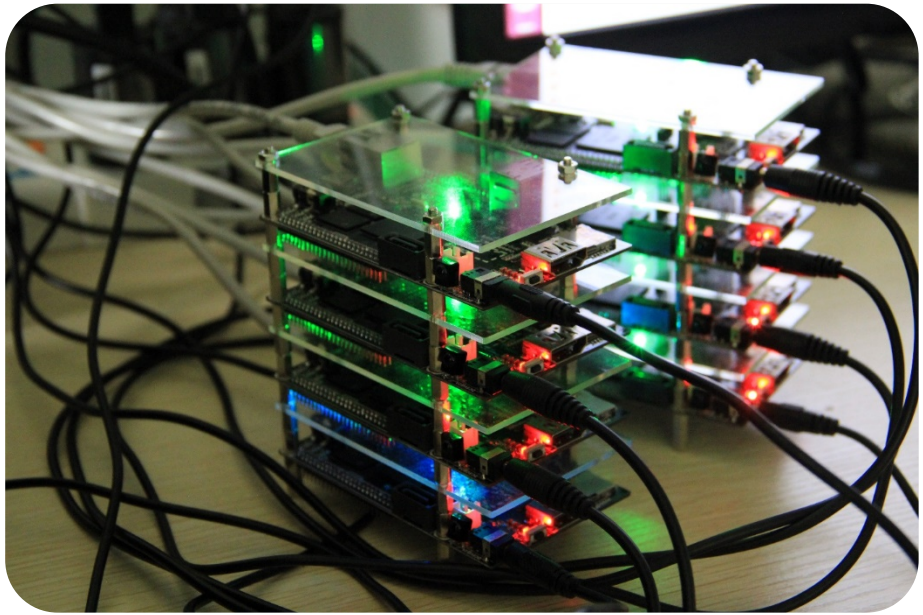


Processing engine for distributed batch processing.

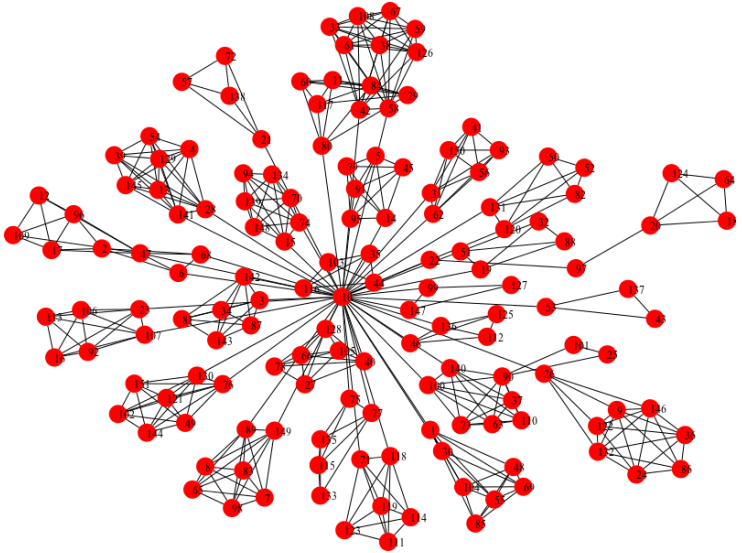
Turn Back The Clock, The Mainframe

Distributed Computing

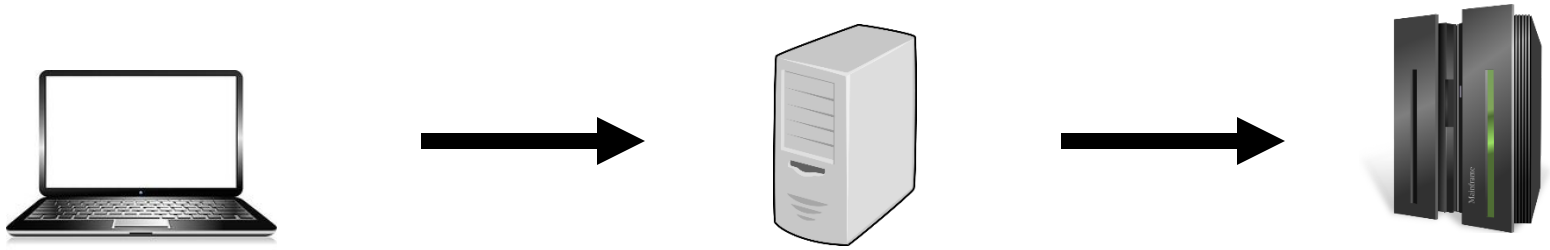




Cloud Computing



Scaling Computational Power



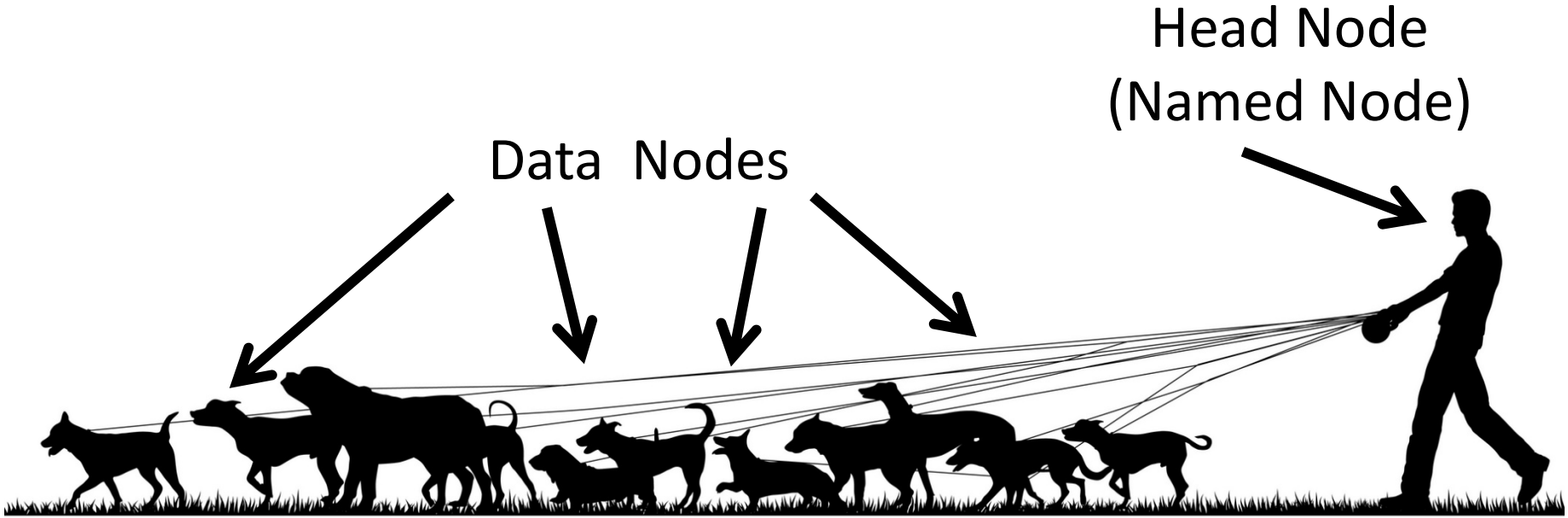
Old Scaling:

- Vertical Scaling, Scaling UP
- High performance computers

New Scaling:

- Horizontal Scaling, Scaling OUT
- Commodity hardware, distributed

If dogs were servers…



HDFS & MapReduce

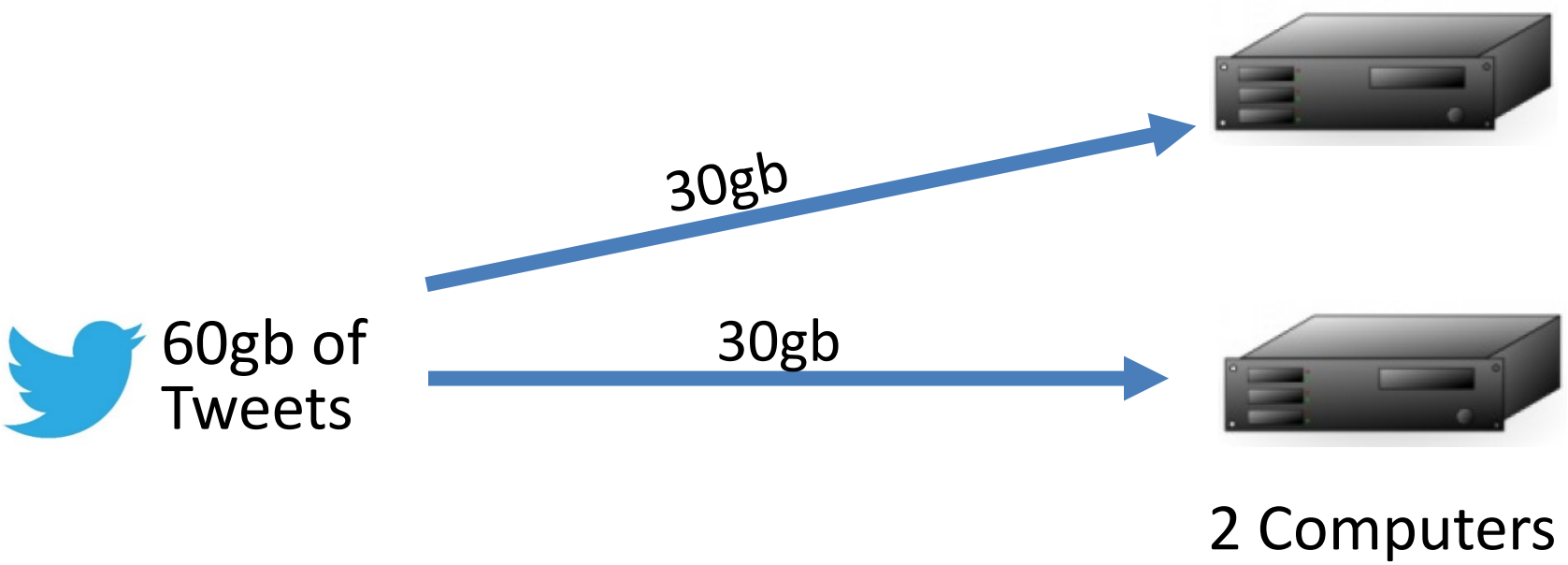
60gb of Tweets

60gb

1 Computer

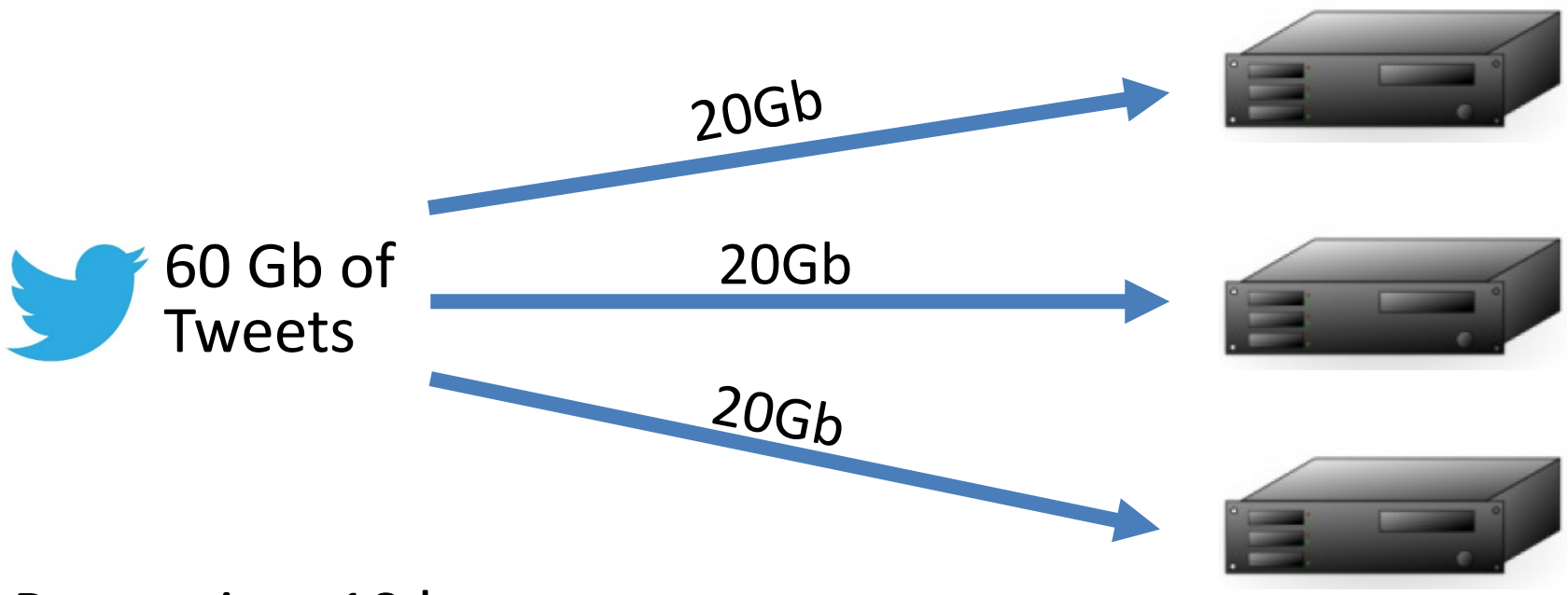
Processing: 30 hours

HDFS & MapReduce



Processing: 15 hours

HDFS & MapReduce



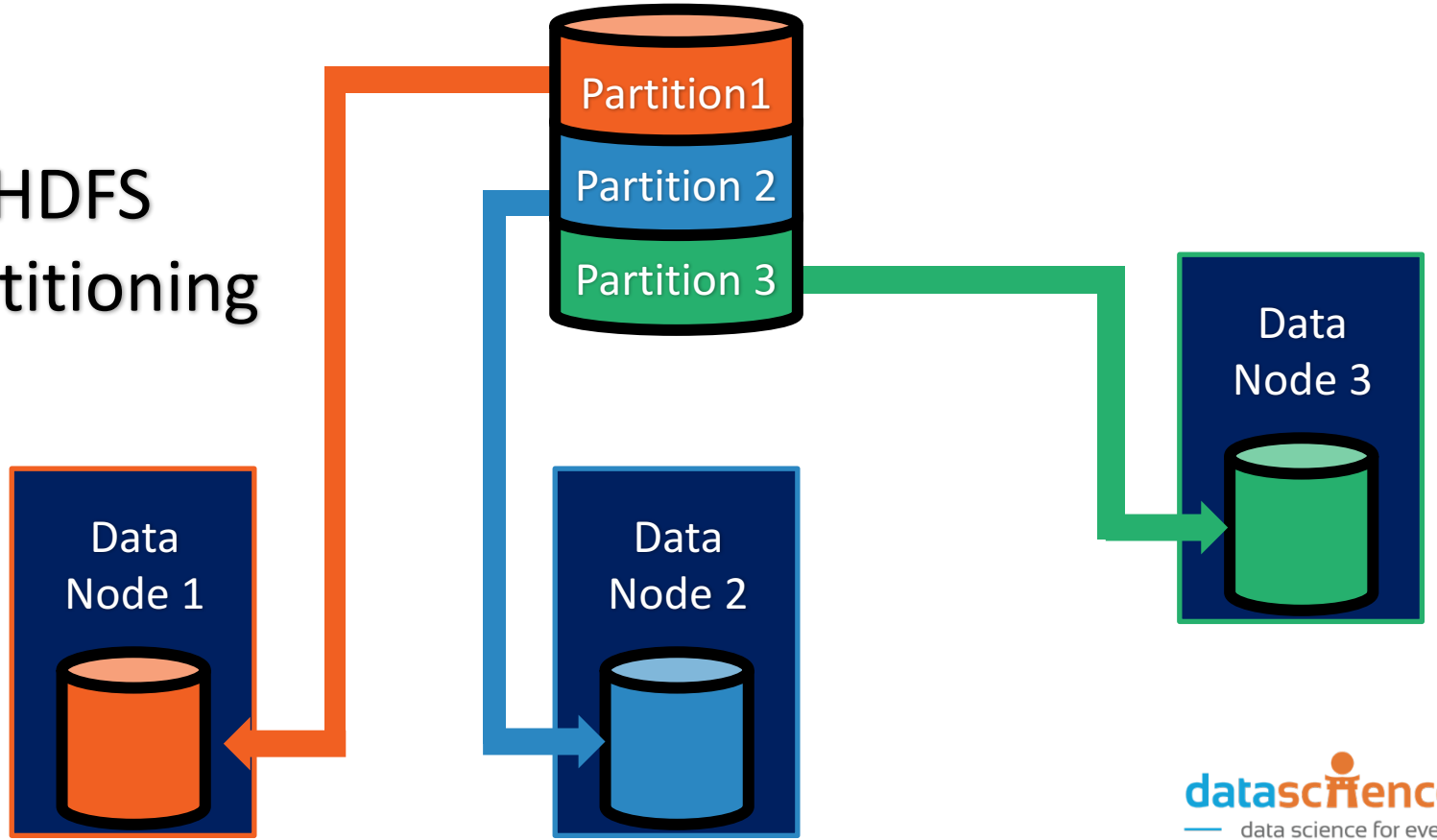
Processing: 10 hours

Most Cases, Linear Scaling Of Processing Power

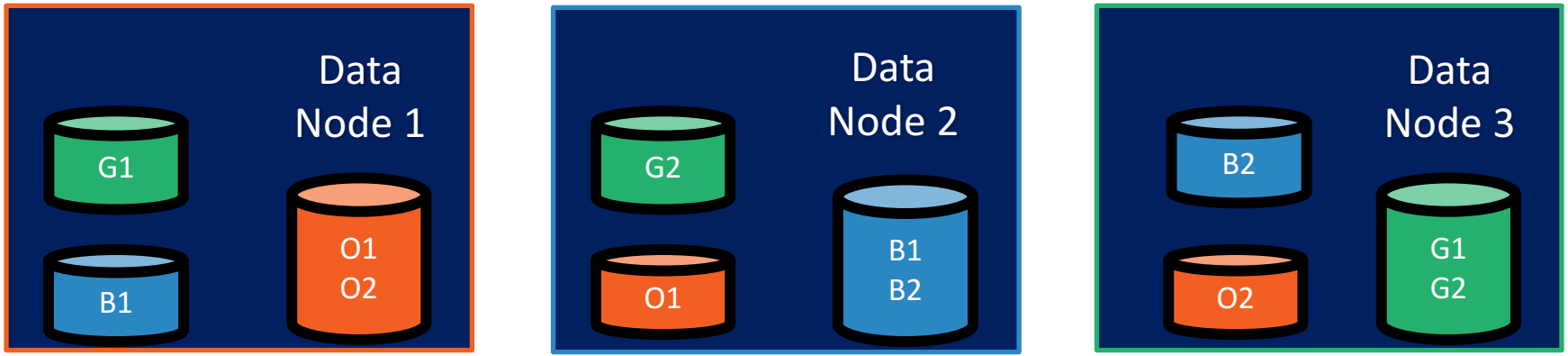
Number of Computers	Processing Time (hours)
1	30
2	15
3	10
4	7.5
5	6
6	5
7	4.26
8	3.75
9	3.33

HDFS

HDFS Partitioning



HDFS Redundancy



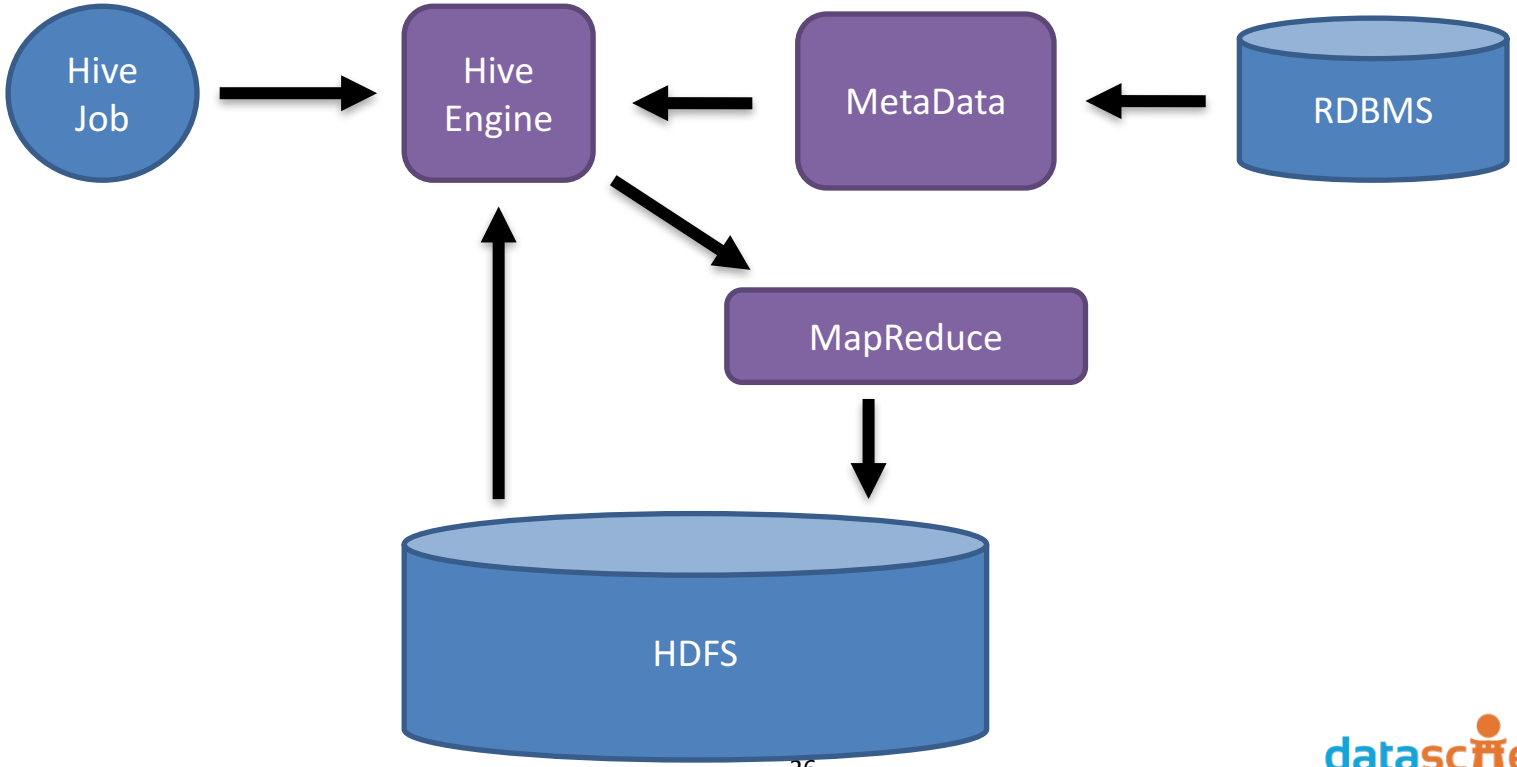
Limitations with MapReduce

- ~70 lines of code to do anything
- Slow
- Troubleshooting multiple computers
- Good devs are scarce
- Expensive certifications

```java
package org.apache.hadoop.examples;

import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import org.apache.hadoop.util.GenericOptionsParser;

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);
      }
    }
  }
```

Hive Jobs

Hive Architecture



Data File

=

Unstructured Data

Data File

+

Metadata File/DB

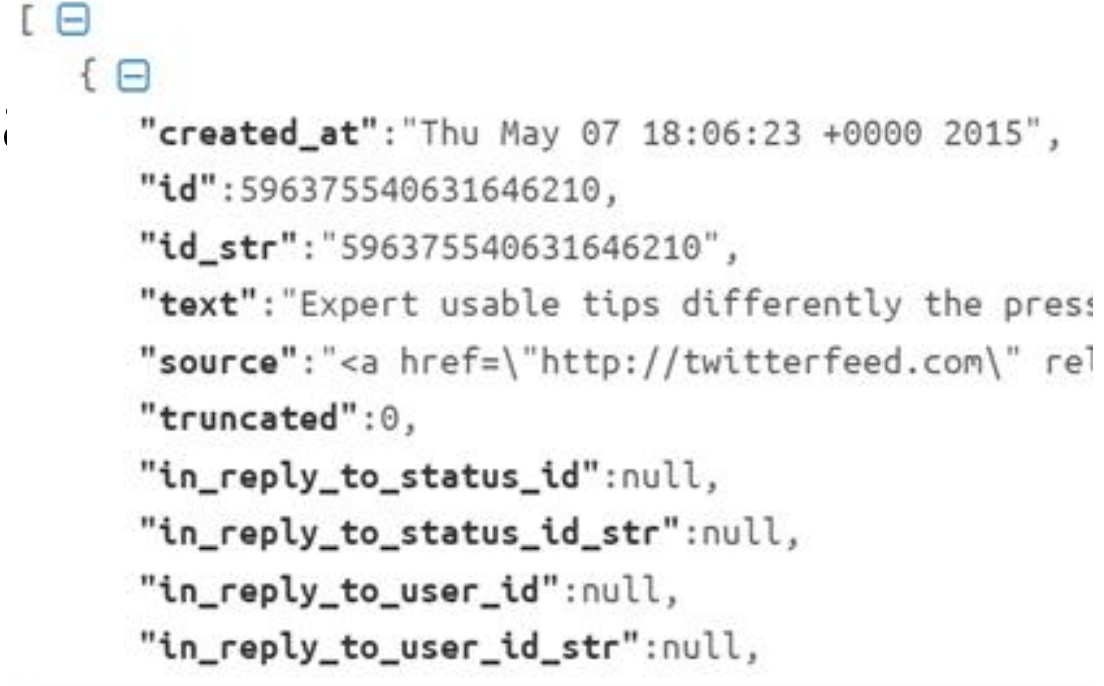
=

Structured Data

Semi Structured Data

Self Describing Fi
Files

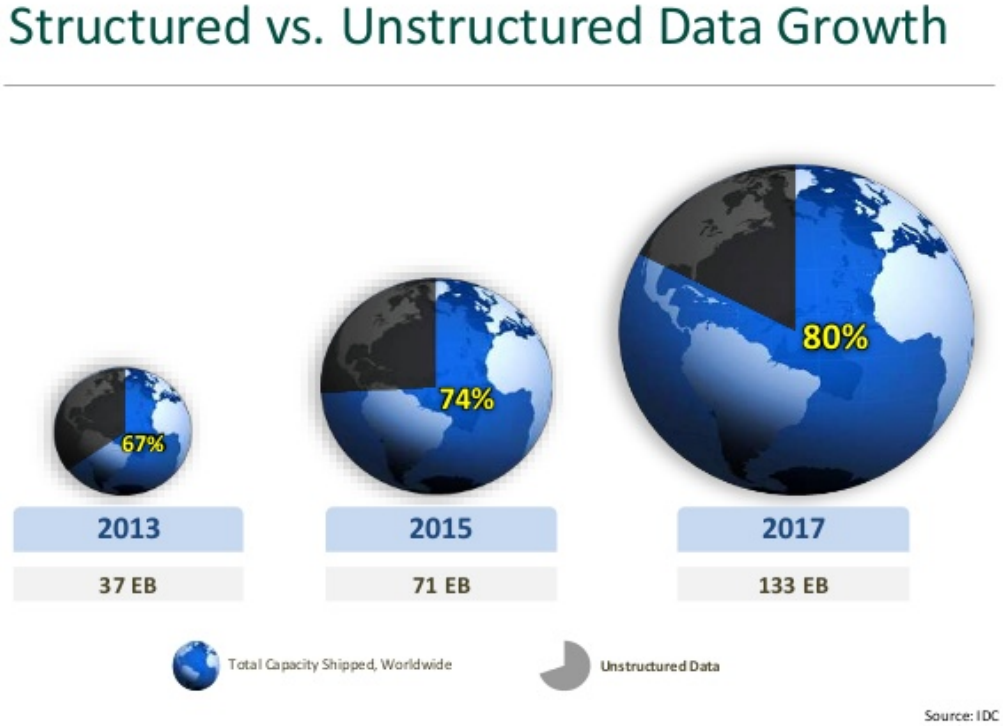
- XML
- JSON
- CSV
- TSV



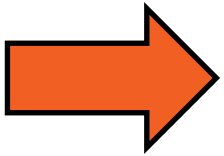
Why Hive?

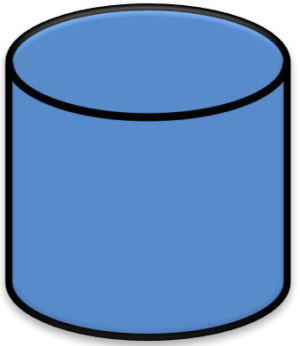
- SQL spoken here (HiveQL)
- ODBC driver
- BI Integration
- Supports only Structured Data

Limitations



Azure Blob Storage

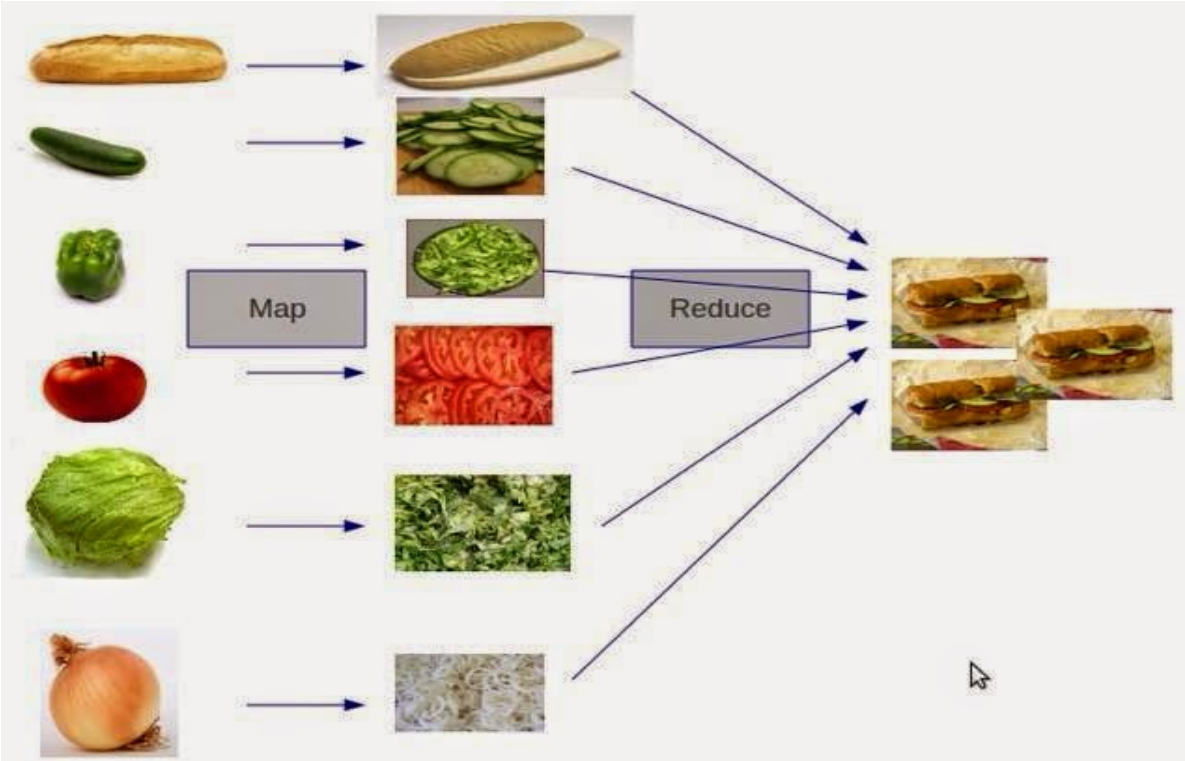




HDInsight

Blob Storage

MapReduce – Sandwich Analogy

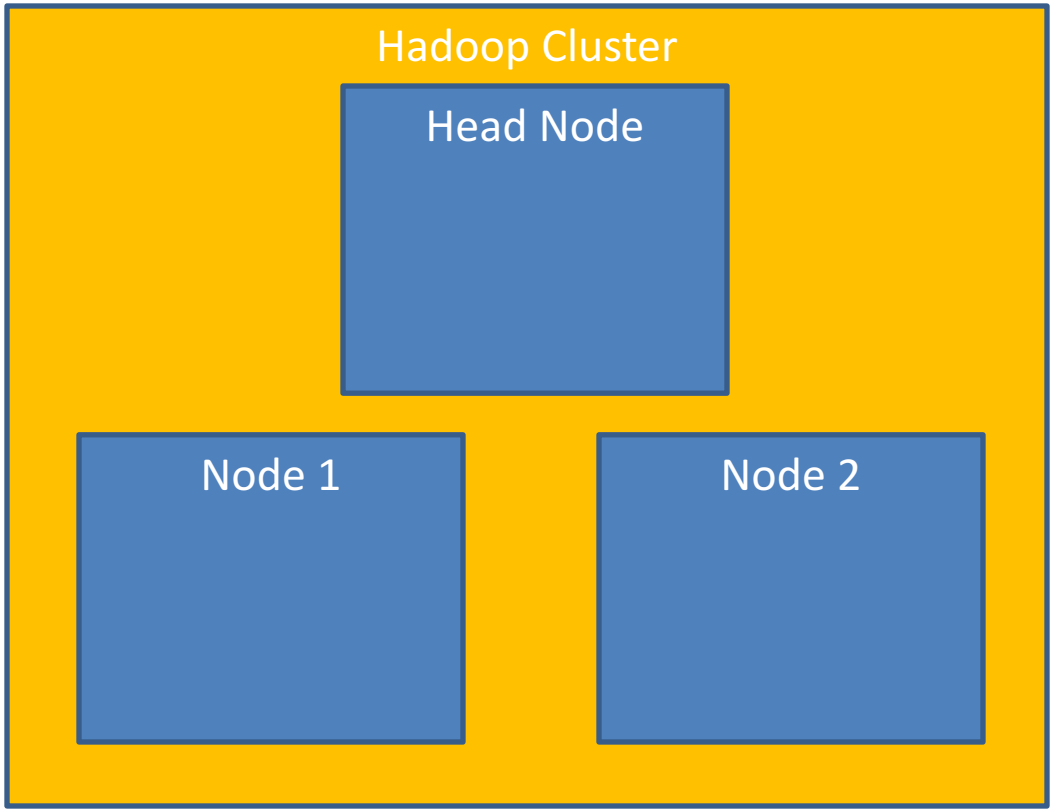


MapReduce, via Playing Cards

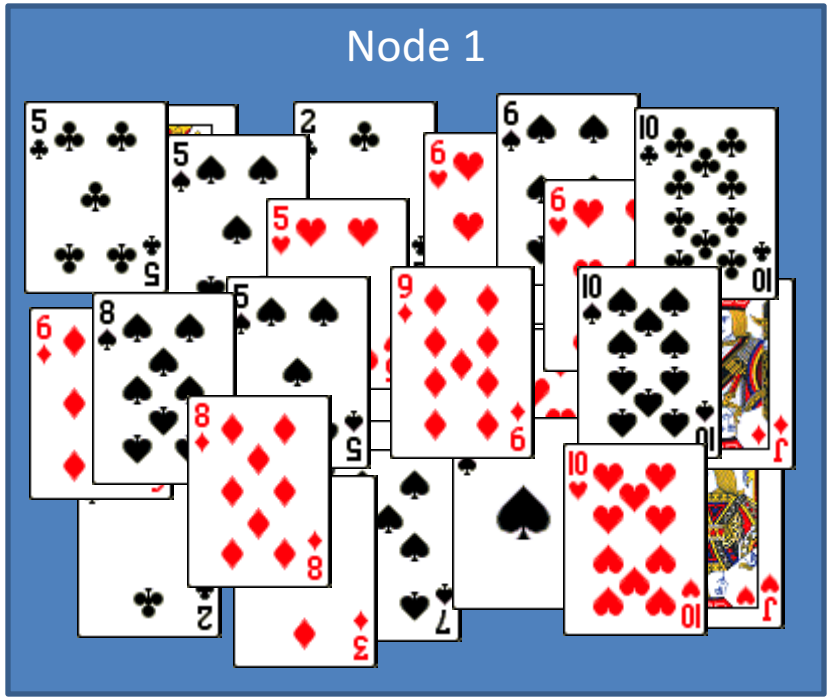
Let’s count the number of spades, clubs, hearts, and diamonds in a stack of cards, the way map reduce would.

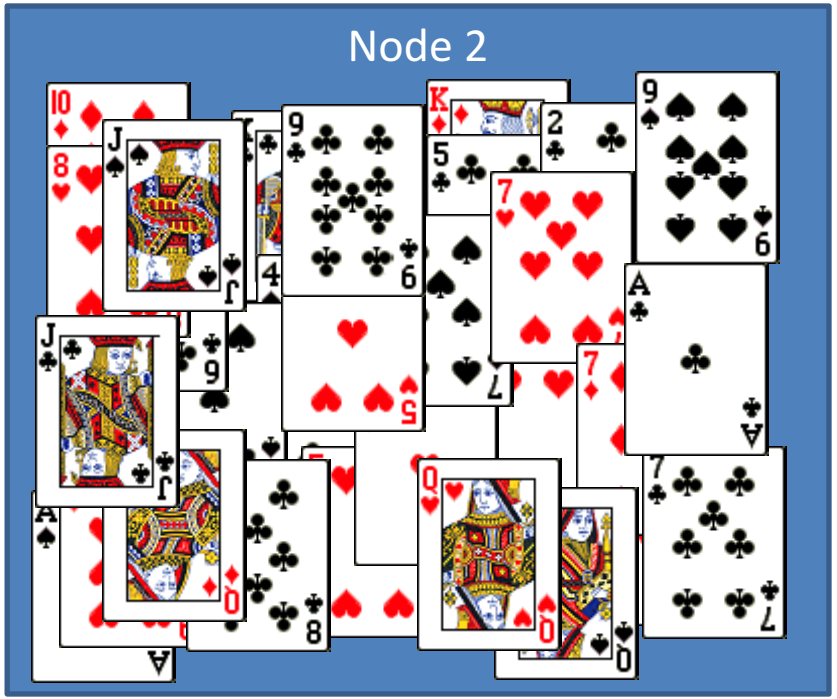
- Each card represents a row of data
- Each suit & number represents an attribute of the data

Using a 2 Data Node Cluster

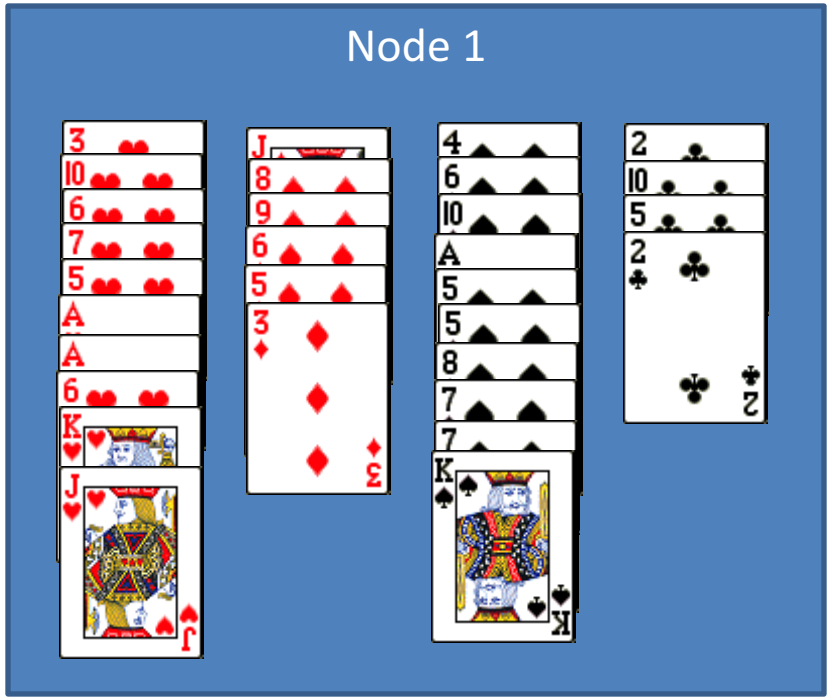


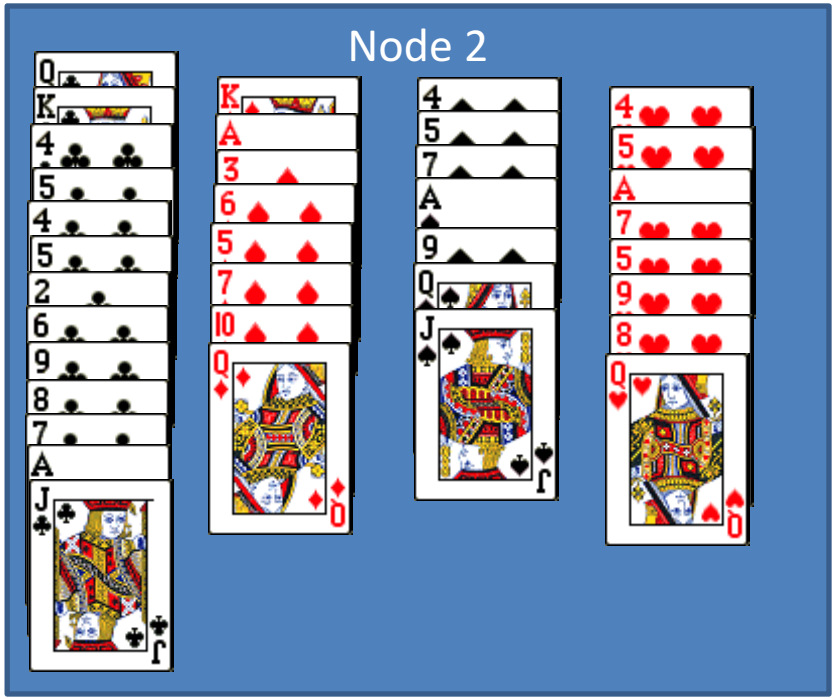
Mapping: Each Node's HDFS



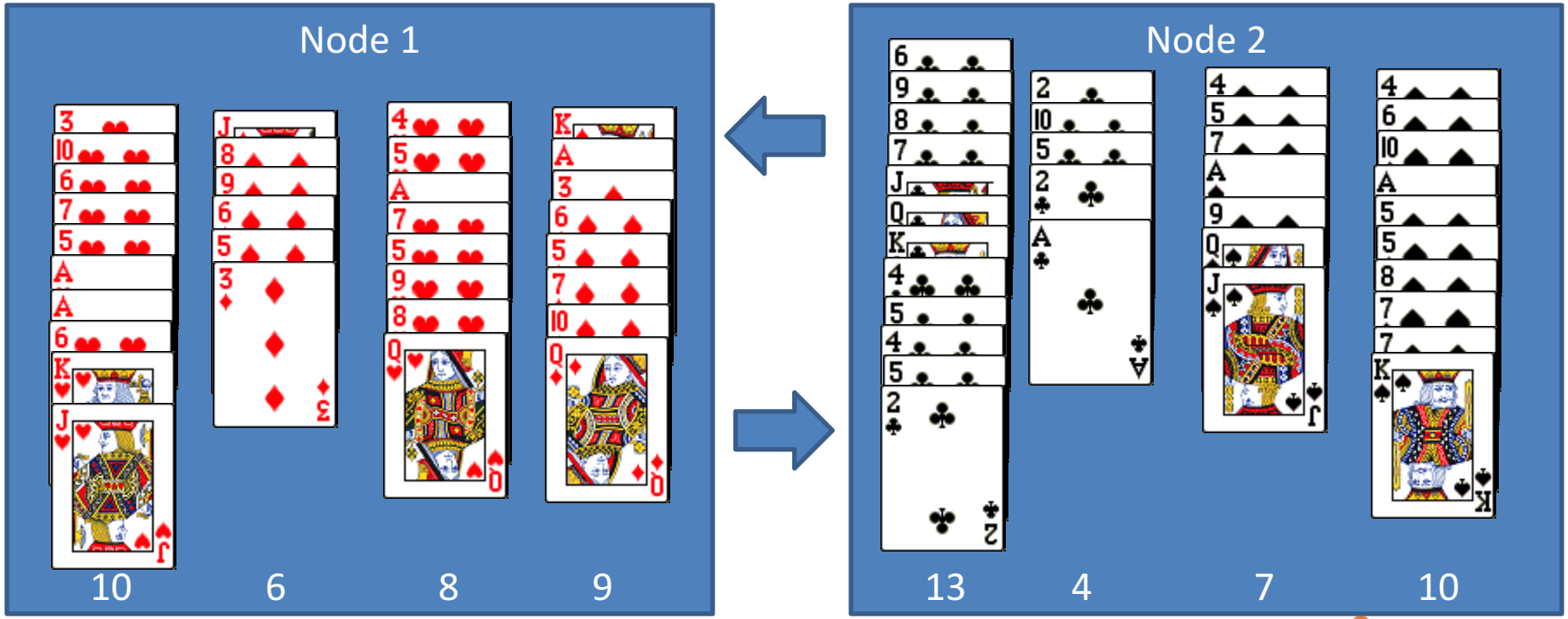


Mapping: Node Sorting





Mapping: Node Shuffle, Data Transfer



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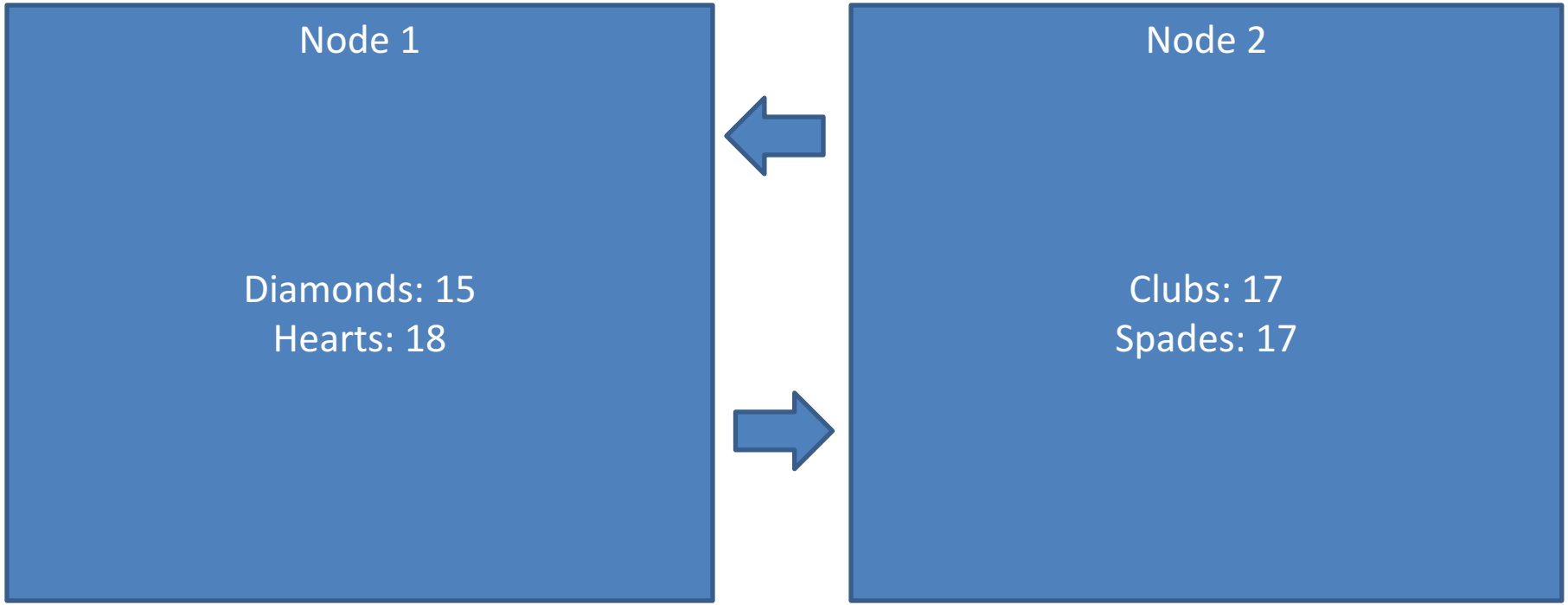


Execution Engine: Tez

The Stinger Initiative

2011, the world got together and declared MapReduce to be terrible.

- 44 companies
- 145 developers
- 392k lines of Java code

Hadoop 2.0 with Yarn & Tez

- Tez dropped hive query times by **90%, 100x performance**
- Utilizes Apache Yarn
  - Yarn: resource manager for multi-cluster computing
- Introduced partial in-memory, local head nodes
- Rewrote HiveQL as an actual language, instead of translation

Ambari: Cluster provisioning, management, and monitoring

Avro (Microsoft .NET Library for Avro): Data serialization for the Microsoft .NET environment

HBase: Non-relational database for very large tables

HDFS: Hadoop Distributed File System

Hive: SQL-like querying

Mahout: Machine learning

MapReduce and YARN: Distributed processing and resource management

Oozie: Workflow management

Pig: Simpler scripting for MapReduce transformations

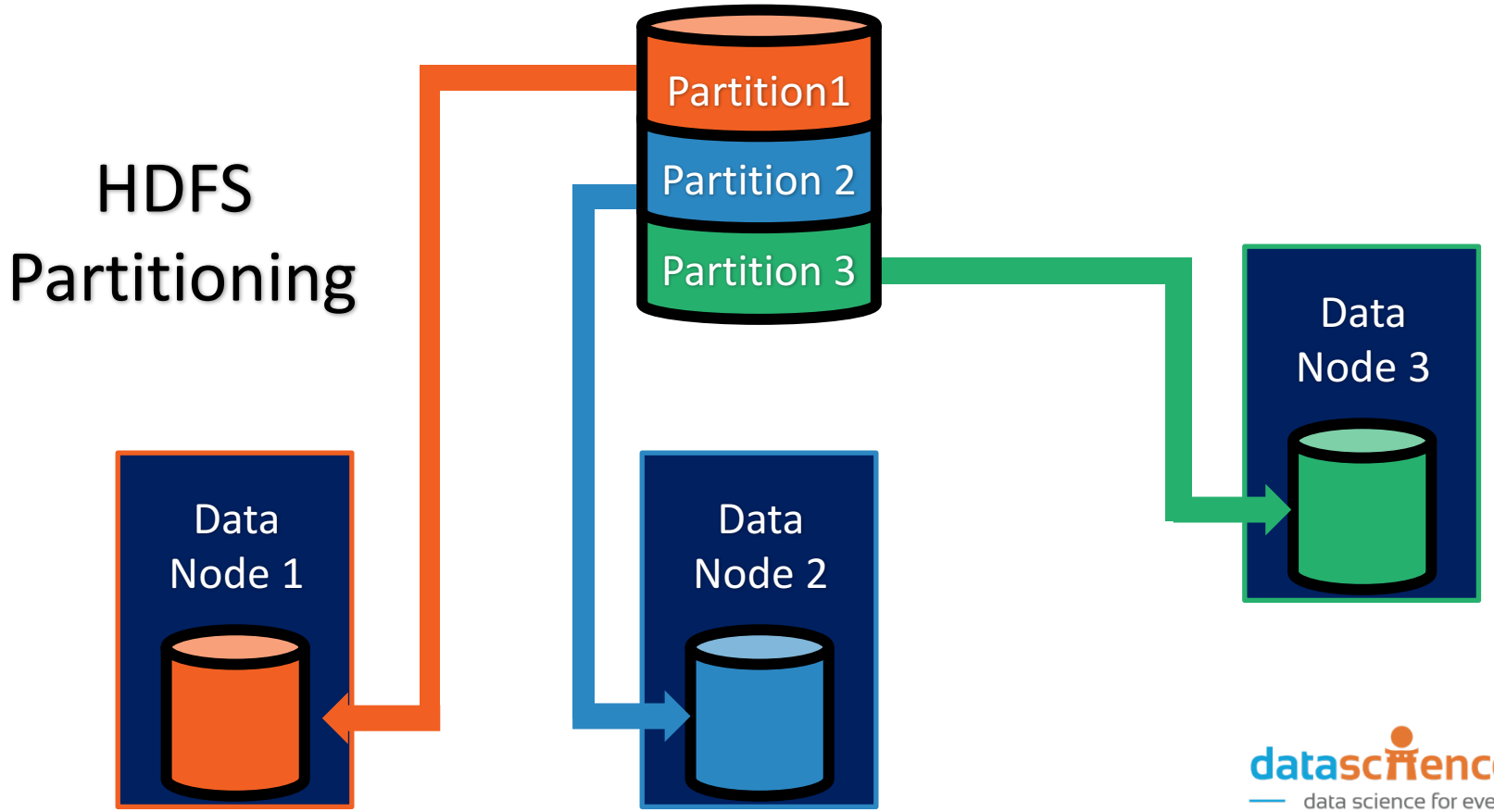
Sqoop: Data import and export

Storm: Real-time processing of fast, large data streams

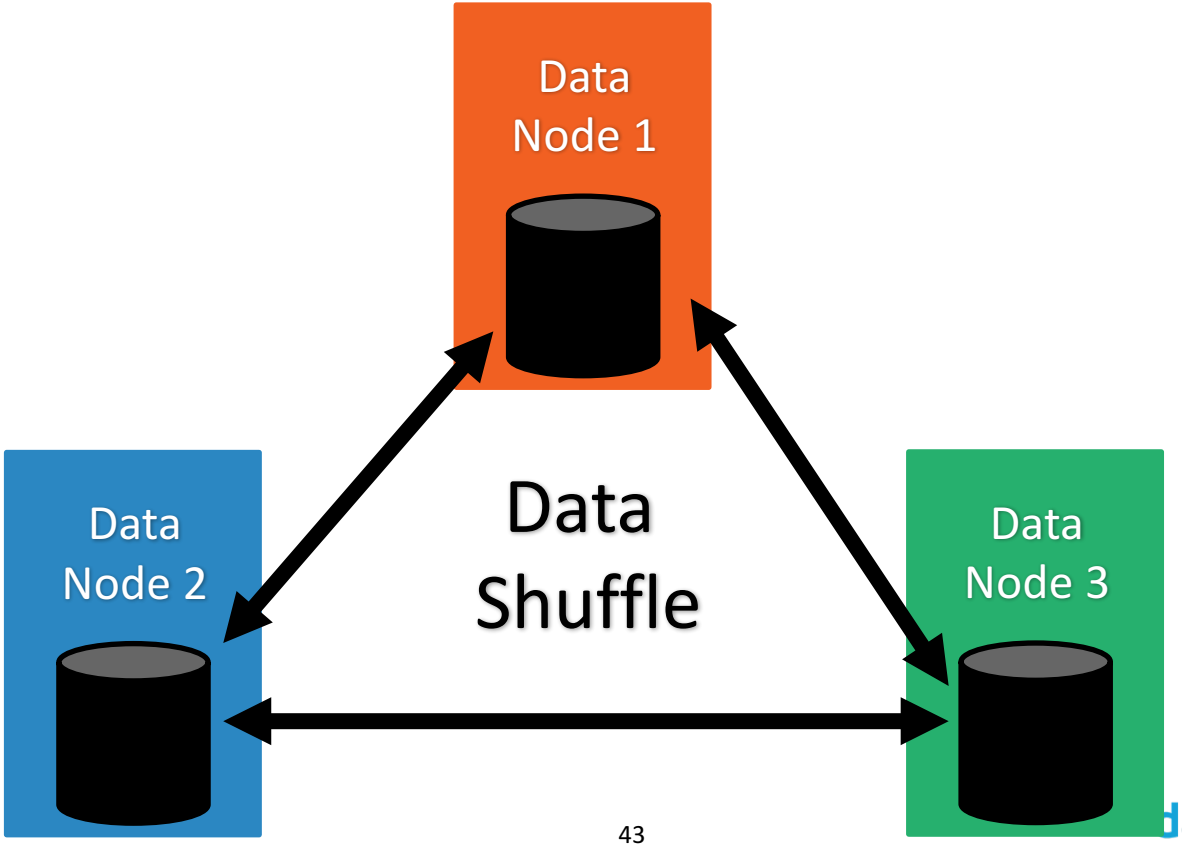
Zookeeper: Coordinates processes in distributed systems

- Distributed Machine Learning
- Installed into Hadoop & Spark
- R-like language Implementation

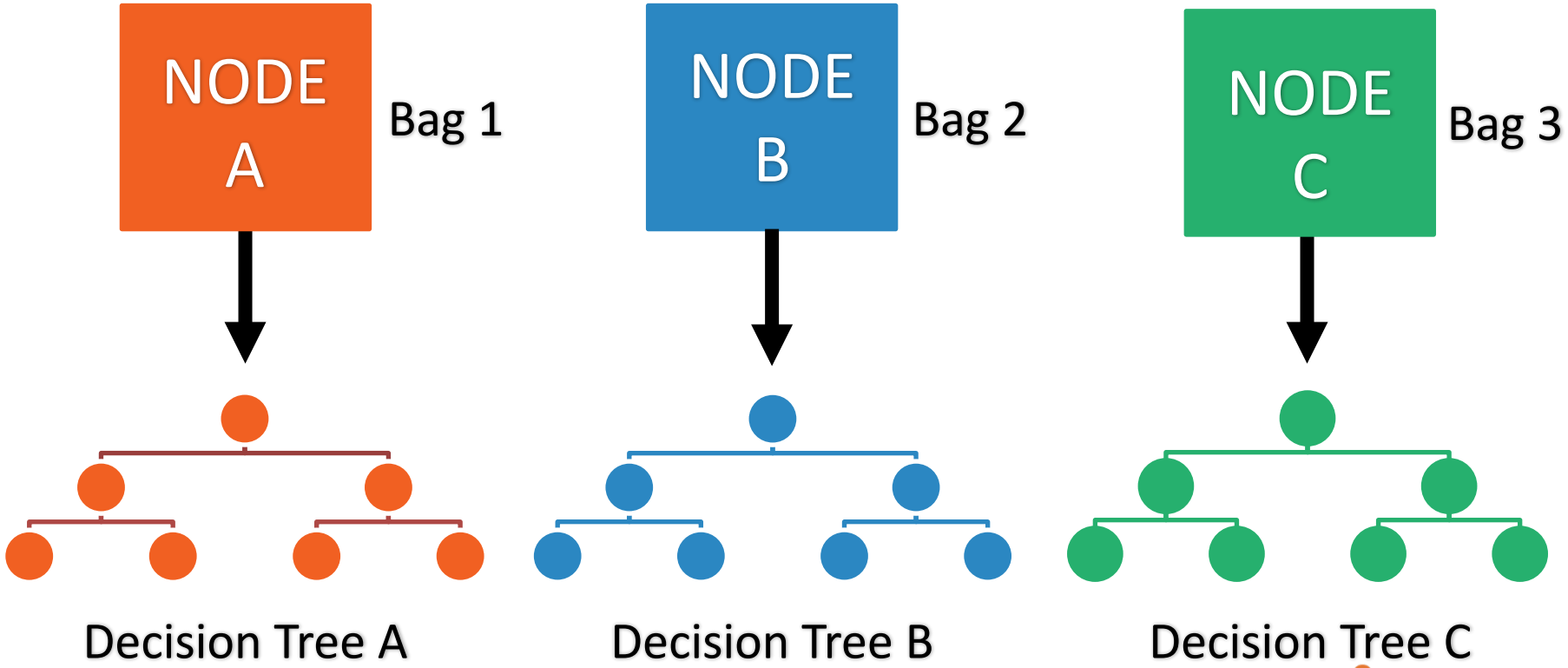
Distributed Random Forest



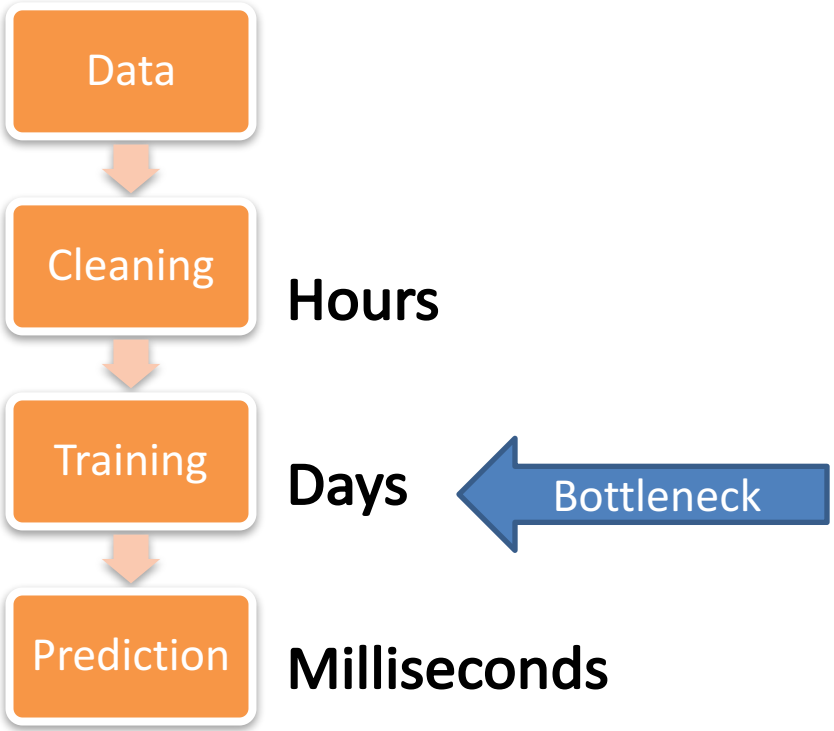
Distributed Random Forest



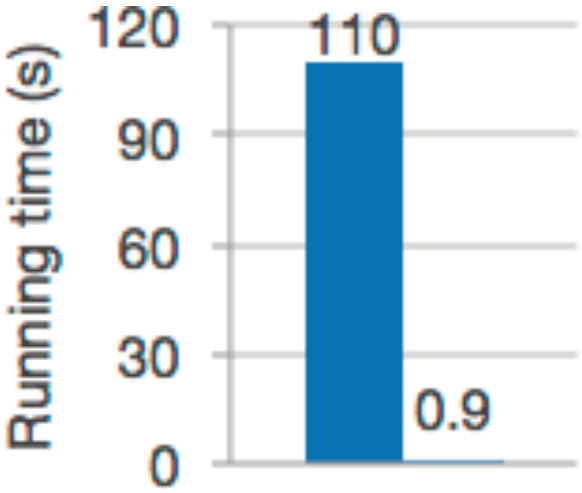
Distributed Random Forest



Processing Times - Machine Learning



- Large scale systems are only needed for training
- Phones can use models outputted by mahout to predict new data
- After a model is trained, save the model to any IO file type and reload it where you want



In-Memory: 100x times faster than Hadoop

3x faster on 10x few machines

Datona GraySort Benchmark: Sort 100 TB of data

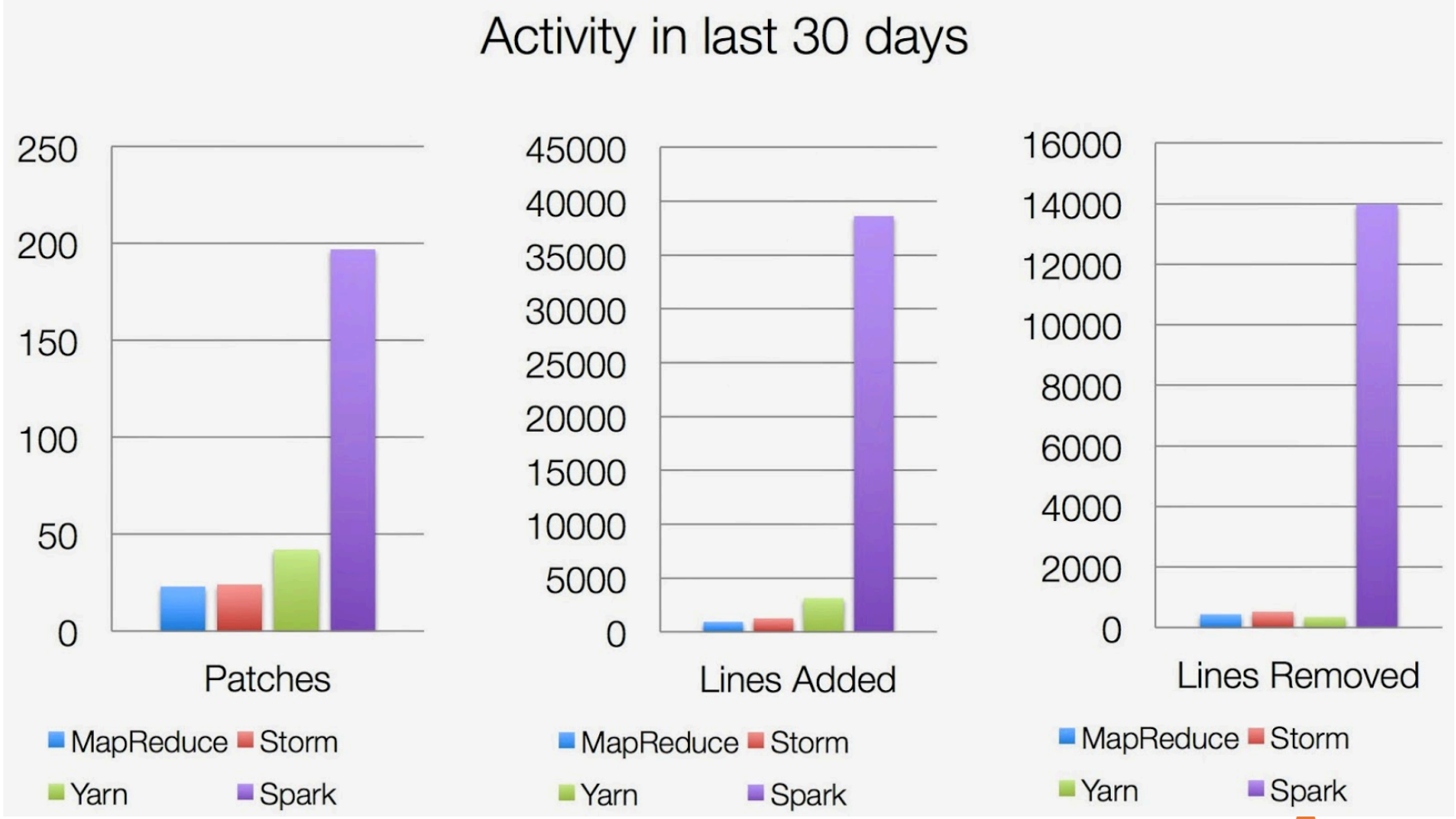
Previous World Record:

- Method: Hadoop
- Yahoo!
- 72 Minutes
- 2100 Nodes

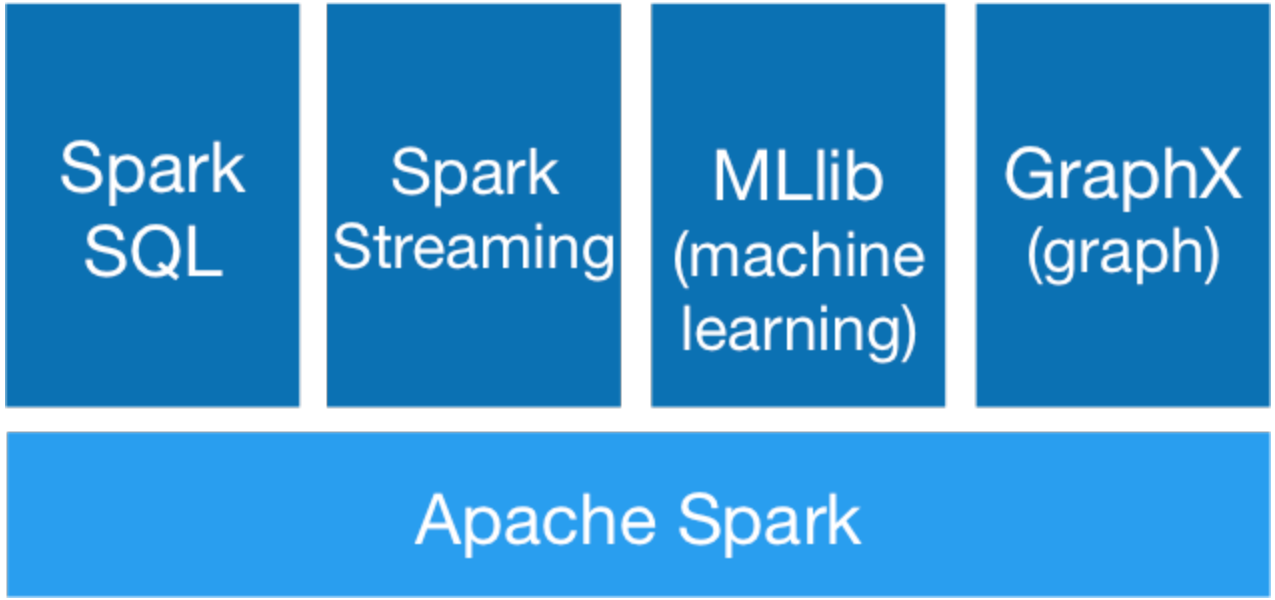
2014:

- Method: Spark
- Databricks
- 23 Minutes
- 206 Nodes

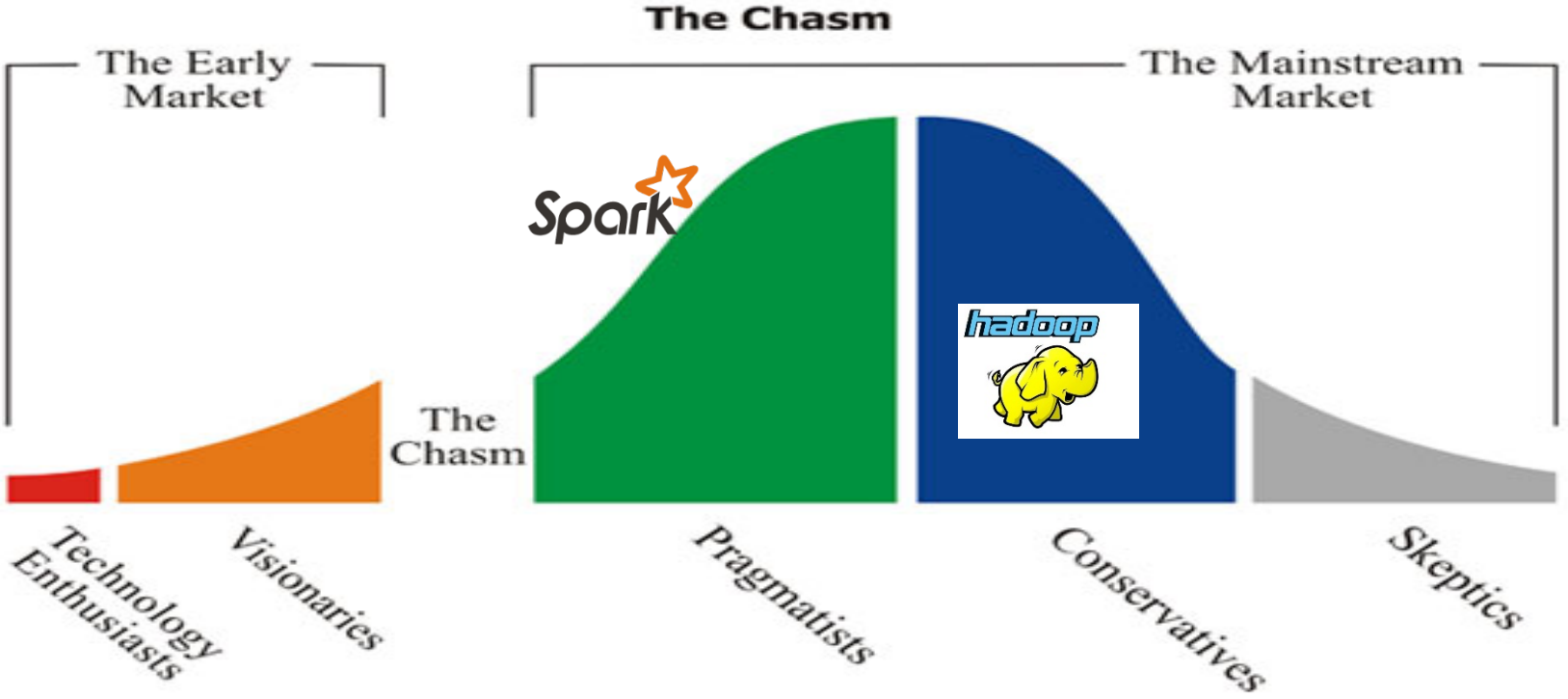
Source: https://databricks.com/blog/2014/10/10/spark-petabyte-sort.html



Source: Xiangrui Meng, Data Bricks



Technology adoption life cycle



Source: http://carlosmartinezt.com/2010/06/technology-adoption-life-cycle/

QUESTIONS

Enjoying the bootcamp?

We'd love it if you could write a short review of Data Science Dojo!

Switch Up (https://www.switchup.org/bootcamps/data-science-dojo) Course Report (https://www.coursereport.com/schools/data-science-dojo)

Your reviews help other people find and attend our bootcamp.

datasciencedojo
data science for everyone