Big Data Engineering with Distributed Systems

Data Science Dojo

Agenda

- Introduction:
  - Data engineering for data scientists
  - The “5 Vs” of Big Data
- A key problem – machine learning at scale
- Distributed computing with Apache Hadoop & Hive
- Hadoop in the Azure cloud
- Machine learning at scale with Apache Mahout
- Distributed computing v2.0 – Apache Spark

Data Engineering for Data Scientists

Driving a car

vs

Servicing a car

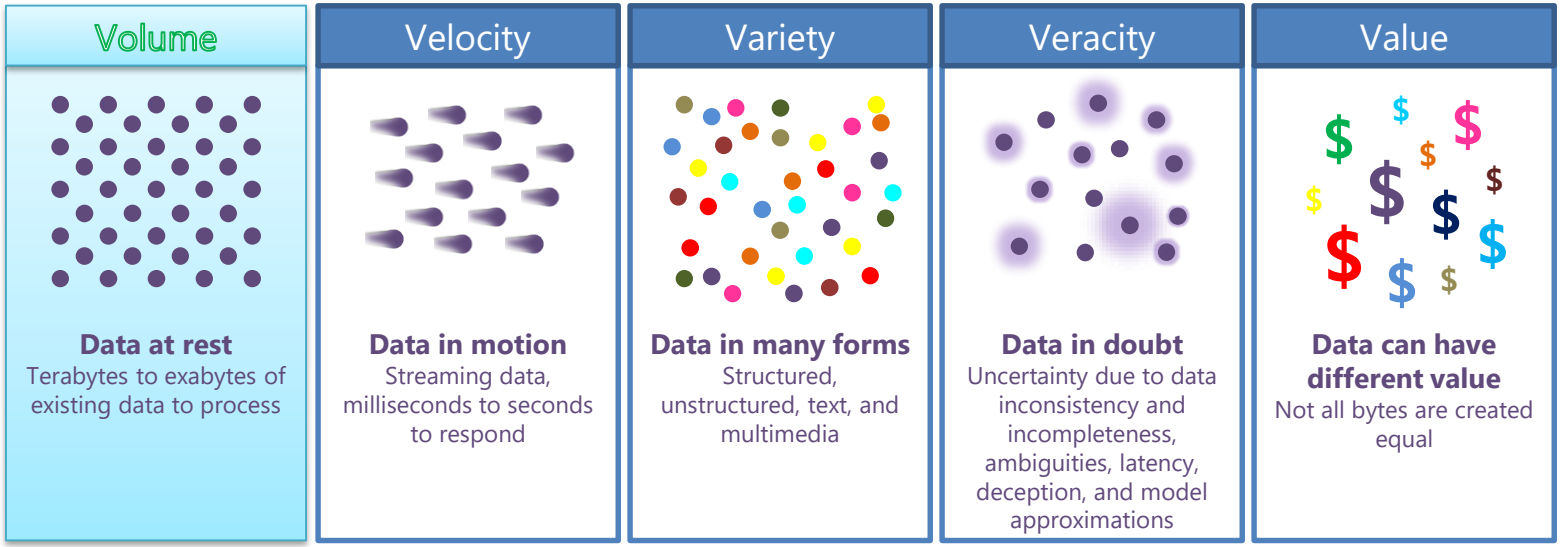
Goals:

- Teach you about data engineering topics/concepts

Non goals:

- Managing or administering a Hadoop cluster

5 Vs of Big Data

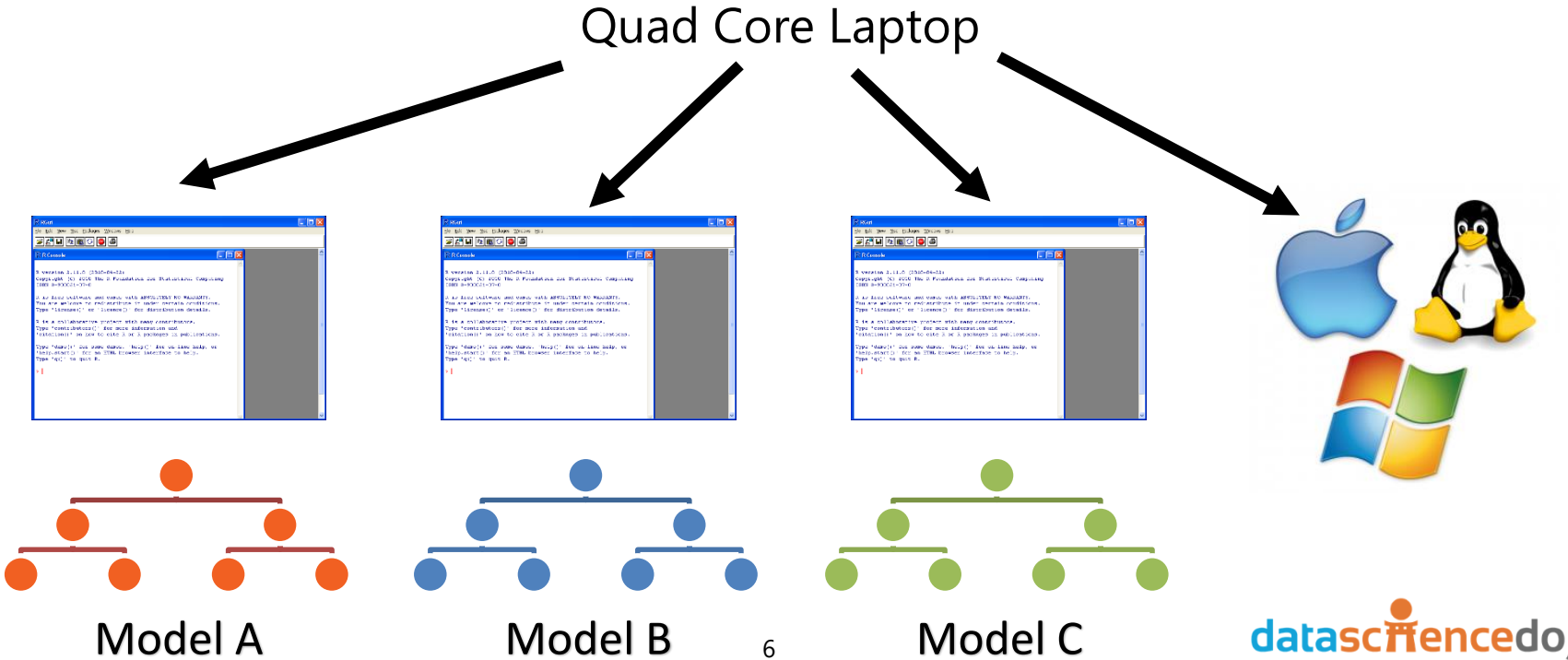


- **Goal:** As data scientists we want cost-effective access to the raw materials for our data products!

MACHINE LEARNING AT SCALE

OSS R Limits

- Single core
- Single threaded



OSS R Limits

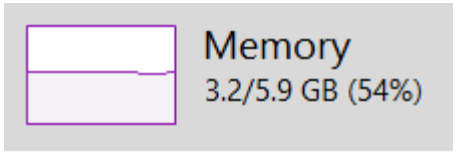
- Single core
- Single threaded
- All in memory (RAM)
- Vectors & Matrices capped at 4,294,967,295 elements (rows) if 32-bit version; 2^32 - 1

OSS R Limits: RAM

- All in memory (RAM)

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

Laptop Example:



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

*R data frames actually bloats data files by 3x

$$R\ Data\ Limit = \sim 1.52gb\ \div 3 = \sim 506.7mb$$

OSS R Limits: RAM

INSTANCE	CORES	RAM	DISK SIZES [1]	PRICE
M64MS	64	1,750.00 GiB	**2,000** GB	$10.34/hr
M128S	128	2,000.00 GiB	**4,000** GB	$13.34/hr

Azure's VM with largest RAM*:

$$Max\ Data\ Limit = (\ 2000gb\ x\ 80\%\ ) - 1gb$$

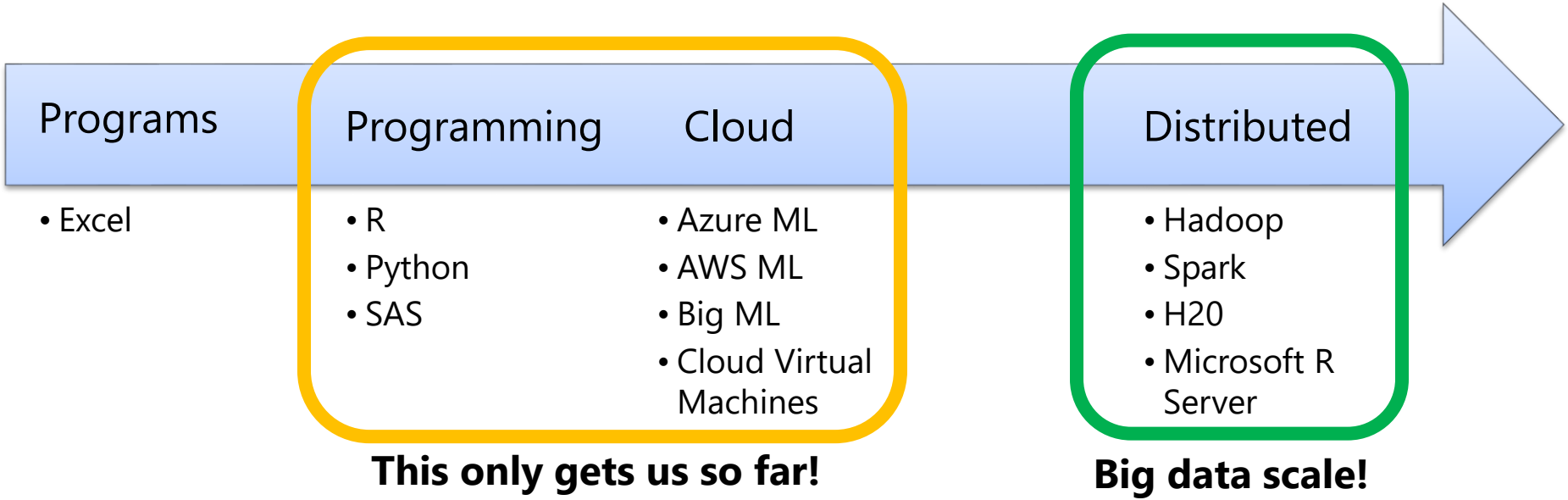
$$Max\ Data\ Limit = {\sim}1600gb$$

$$R\ Data\ Limit = {\sim}1600gb\ \div 3 = {\sim}533.33\ gb$$

24x7x52 Annual Cost: $116,938.44!

*Data collected 06/07/2017

Machine Learning Scaling

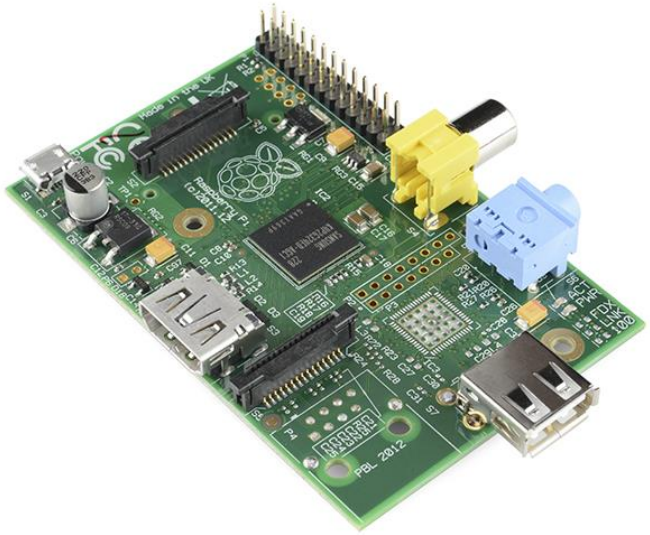


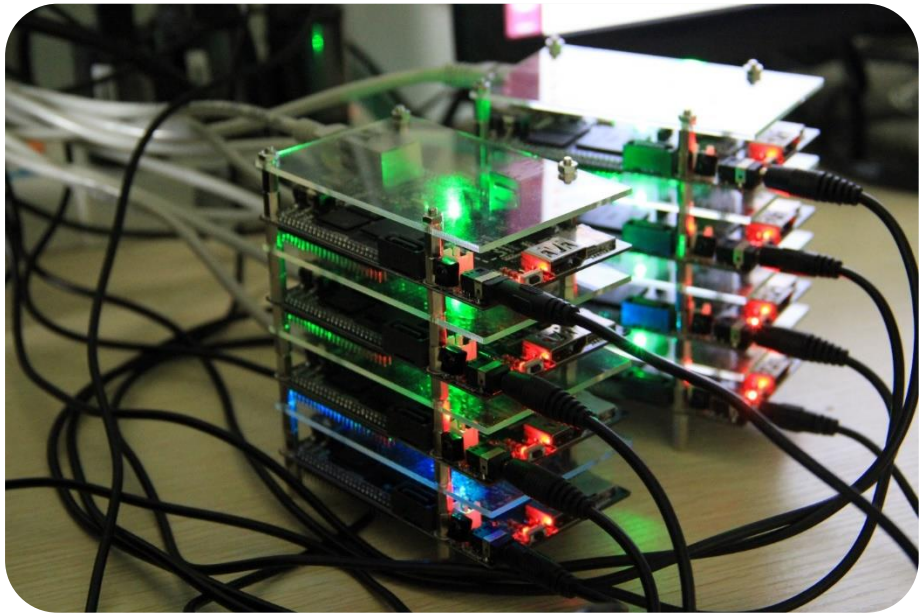
DISTRIBUTED COMPUTING WITH APACHE HADOOP

Turn Back The Clock, The Mainframe

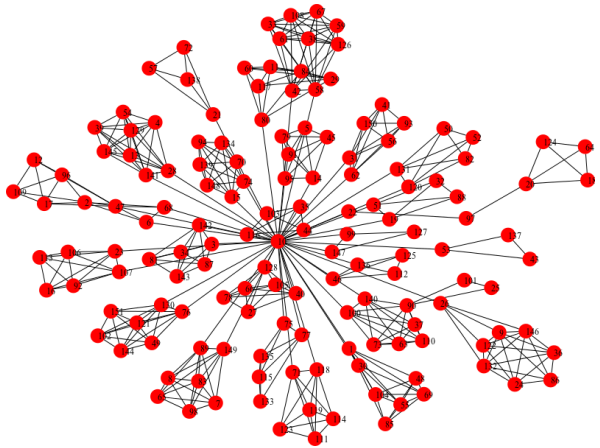
- “Big Iron”
- Backbone of computing for decades.
- Still widely used.
- “Scale-up” model of shared computing.
- Core platform is cost effective, ecosystem is not (e.g., software licensing).
- The original VM host!

Distributed Computing



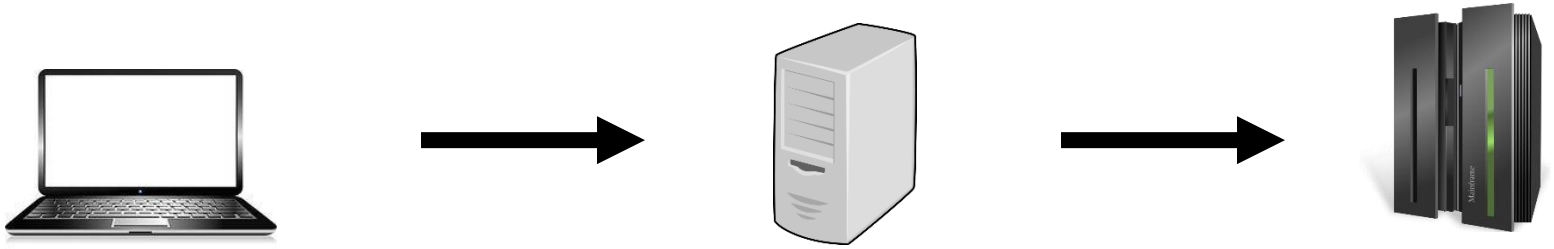


Cloud Computing



- Conceptually – a combination of mainframe and distributed computing.
- VM hosts are now the “Big Iron”.
- Many VMs work together to distribute workloads.
- Some workloads on dedicated HW (e.g., SAP HANA).

Scaling Computational Power



Old Scaling:

- Vertical Scaling, Scaling UP
- High performance computers

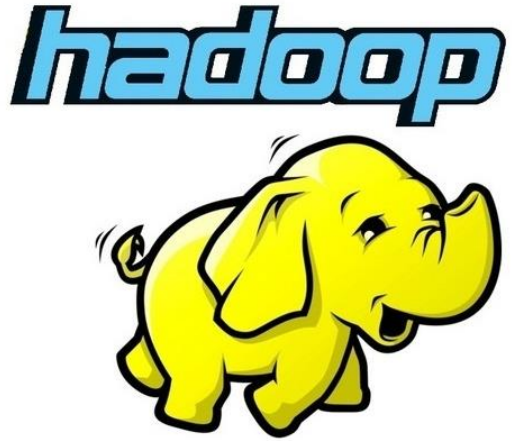
New Scaling:

- Horizontal Scaling, Scaling OUT
- Commodity hardware, distributed

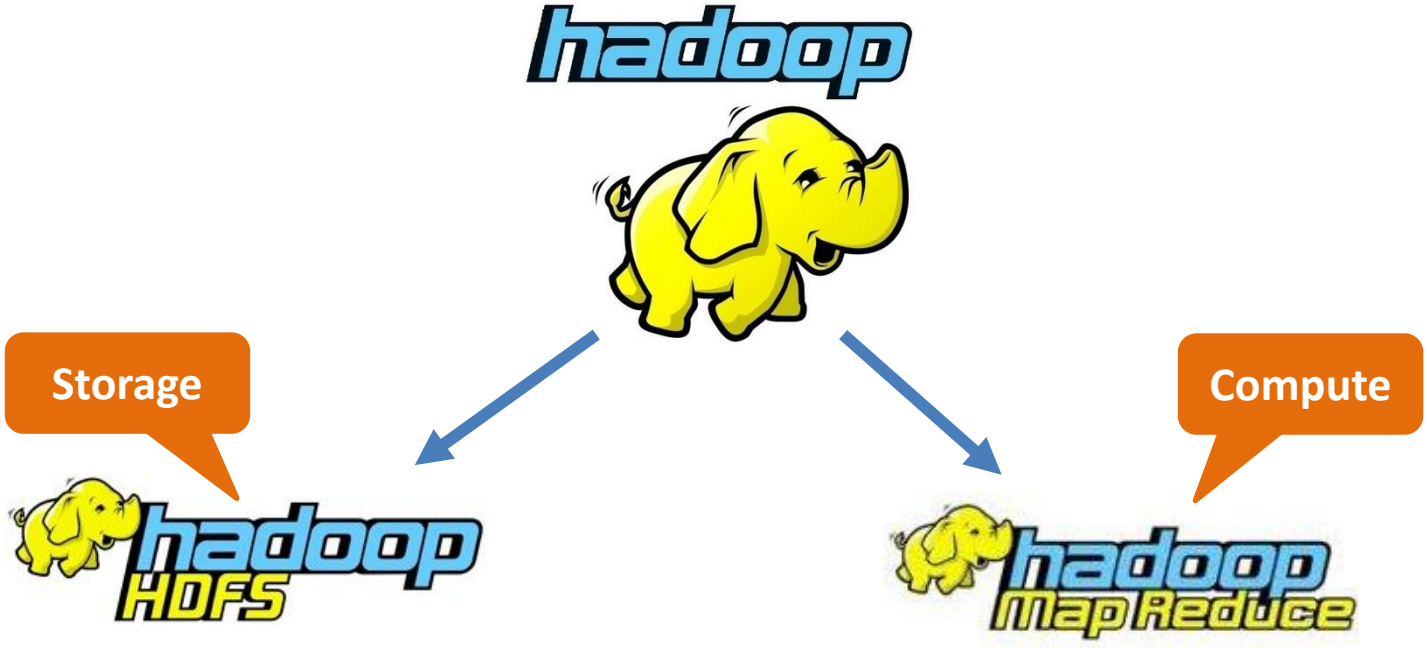
datasciencedojo
data science for everyone

What is Hadoop?

- OSS Platform for distributed computing over Internet-scale data.
- Originally built at Yahoo!
- Implementation of ideas (e.g., MapReduce) published by Google.
- The de facto standard big data platform.
- Named after a stuffed animal belonging to Doug Cutting's son.



Hadoop at Base



Distributed batch processing engine for big data.

HDFS & MapReduce

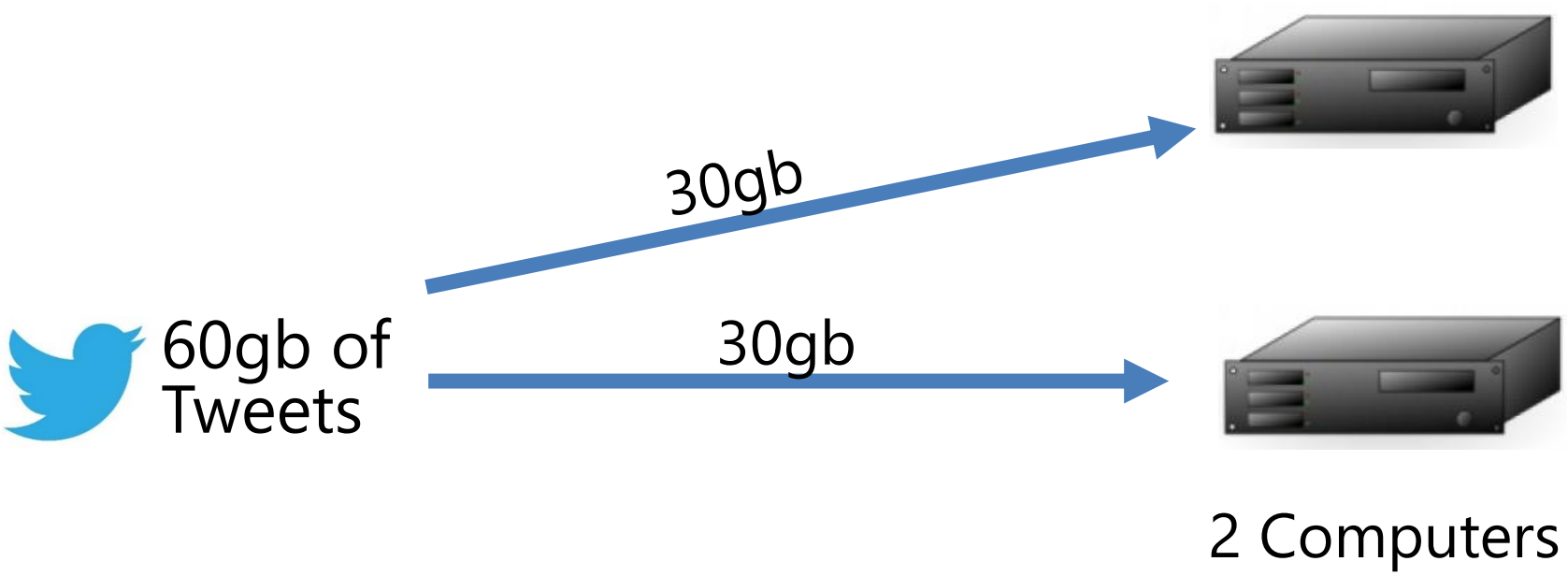
60gb of Tweets

60gb

1 Computer

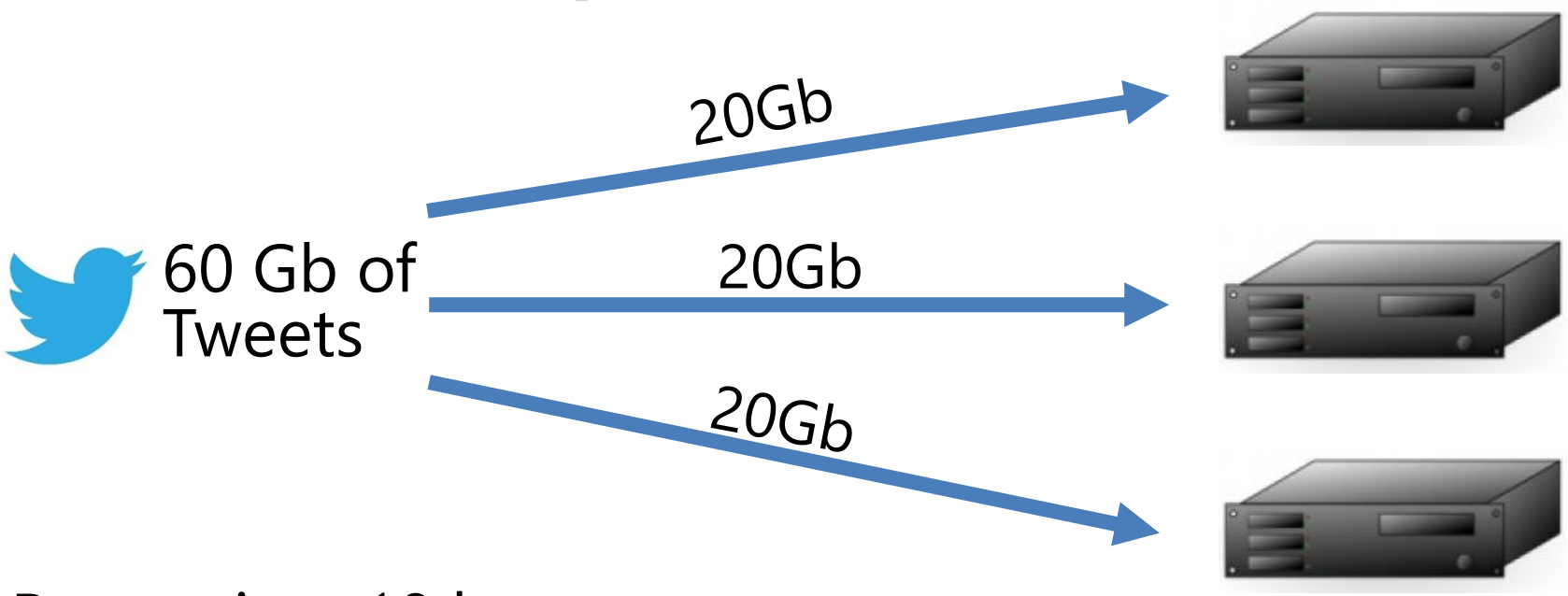
Processing: 30 hours

HDFS & MapReduce



Processing: 15 hours

HDFS & MapReduce

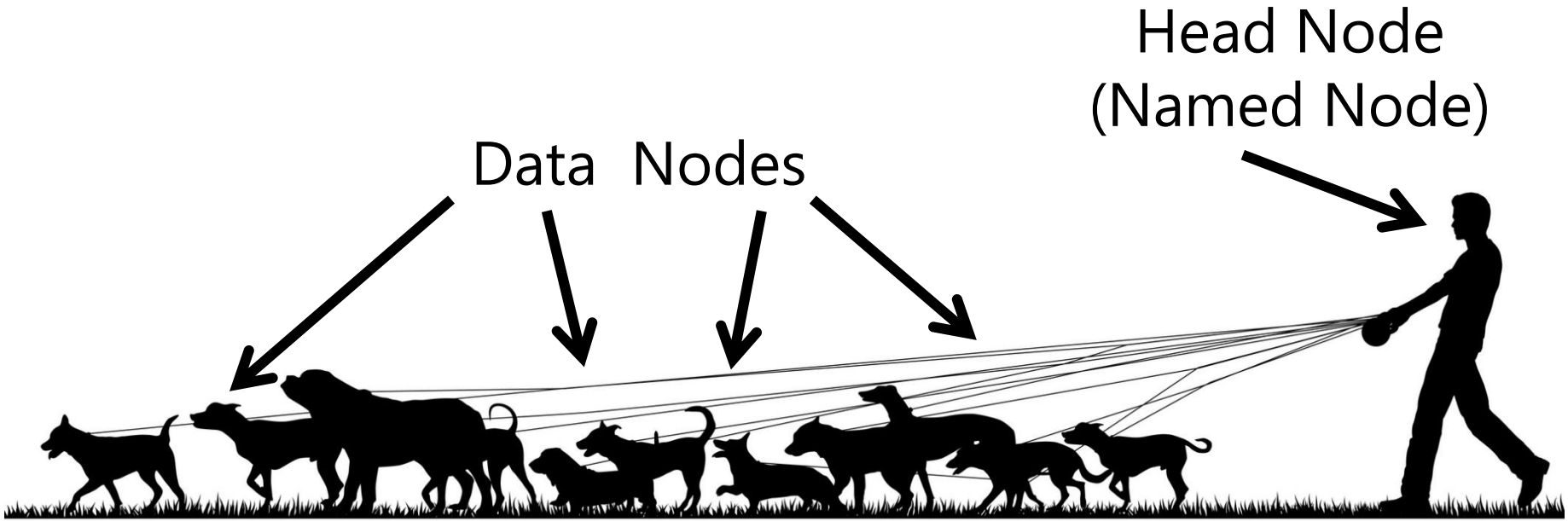


Processing: 10 hours

Most Cases, Linear Scaling Of Processing Power

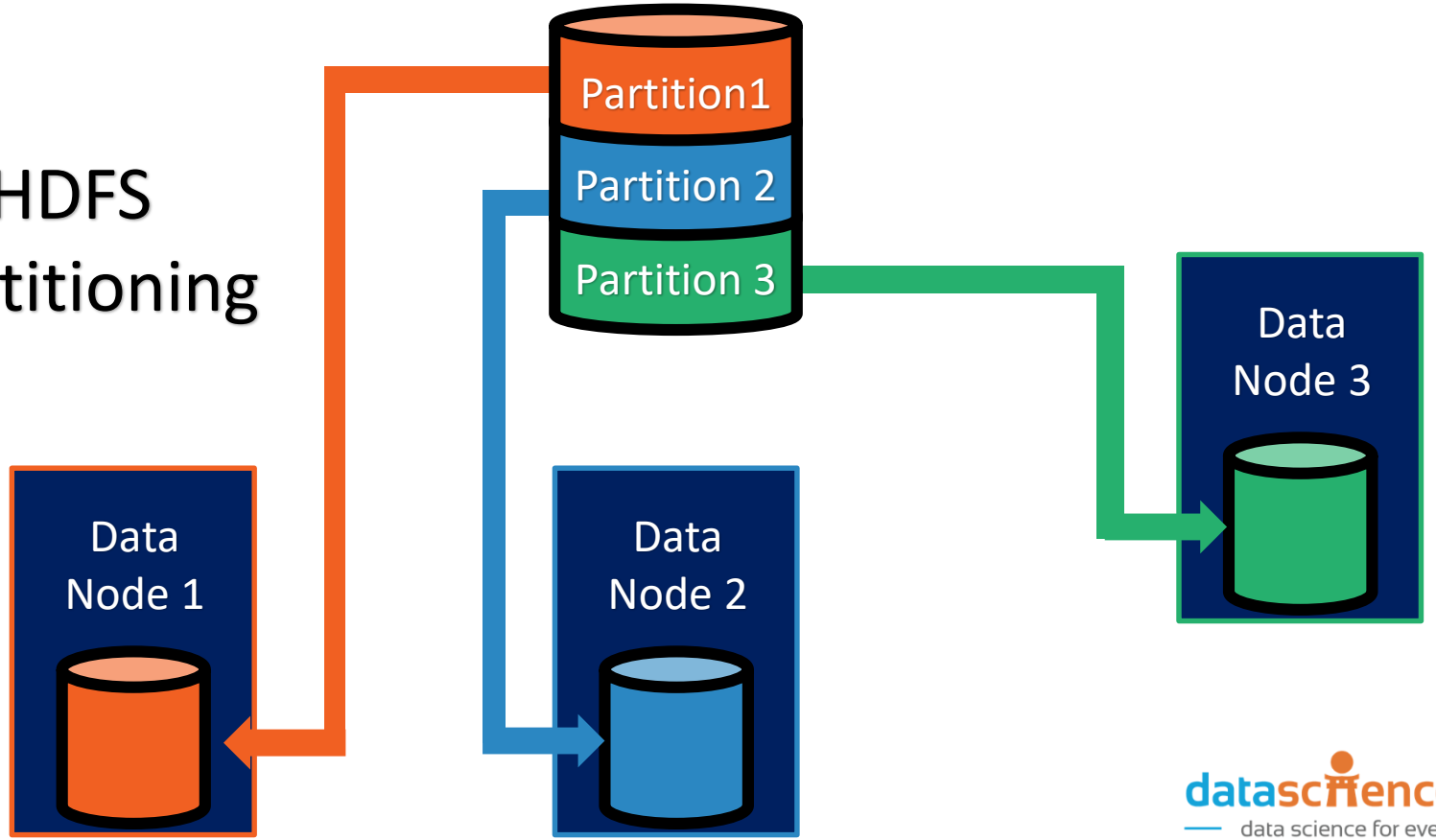
Number of Computers	Processing Time (hours)
1	30
2	15
3	10
4	7.5
5	6
6	5
7	4.26
8	3.75
9	3.33

If dogs were servers…



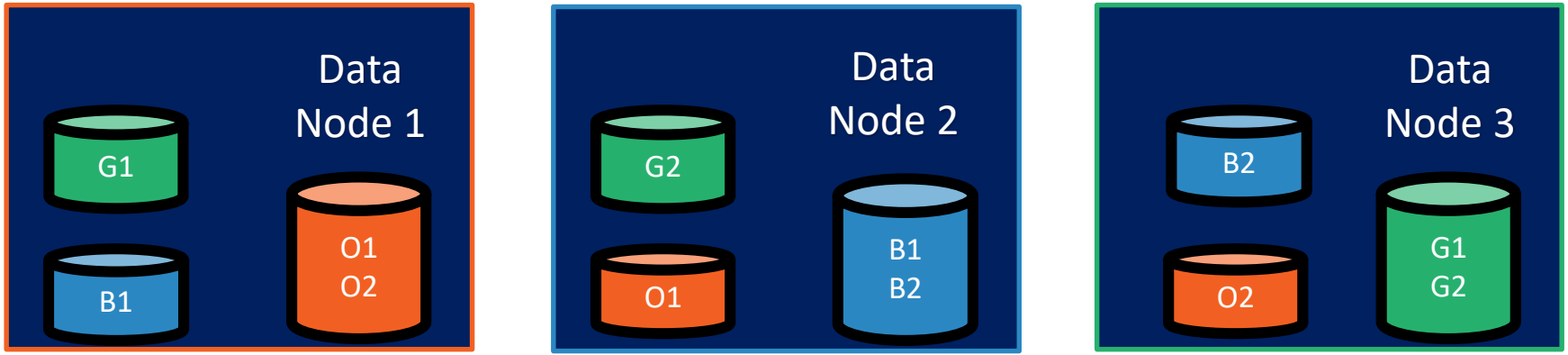
HDFS

HDFS Partitioning

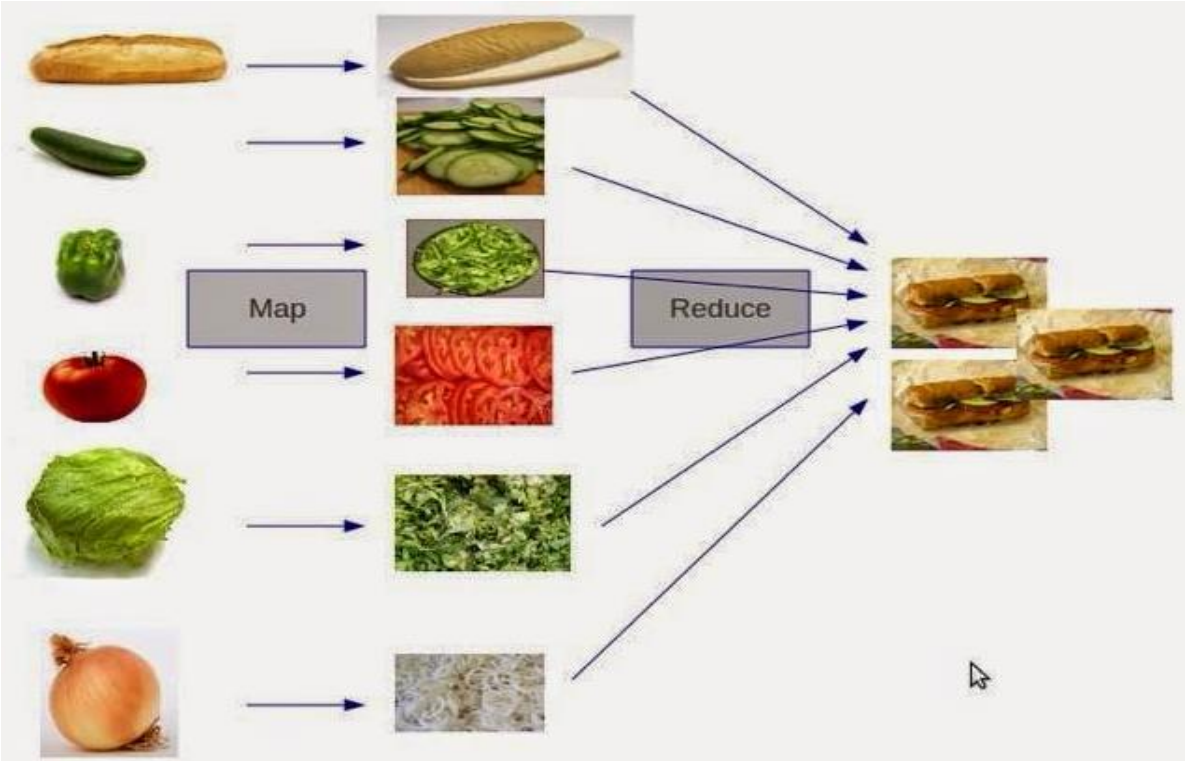


datasciencedojo
data science for everyone

HDFS Redundancy



MapReduce – Sandwich Analogy



Limitations with MapReduce

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

```
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);
      }
    }
```

DISTRIBUTED COMPUTING WITH APACHE HIVE

What is Hive?

- Abstraction built on top of MapReduce & HDFS.
- Makes Hadoop look like an RDBMS (e.g., coding in SQL).
- Developed by Facebook to democratize Hadoop
- Applies structure to data at runtime ("schema on read").

Schema on Read

Data File

=

Unstructured Data

Data File

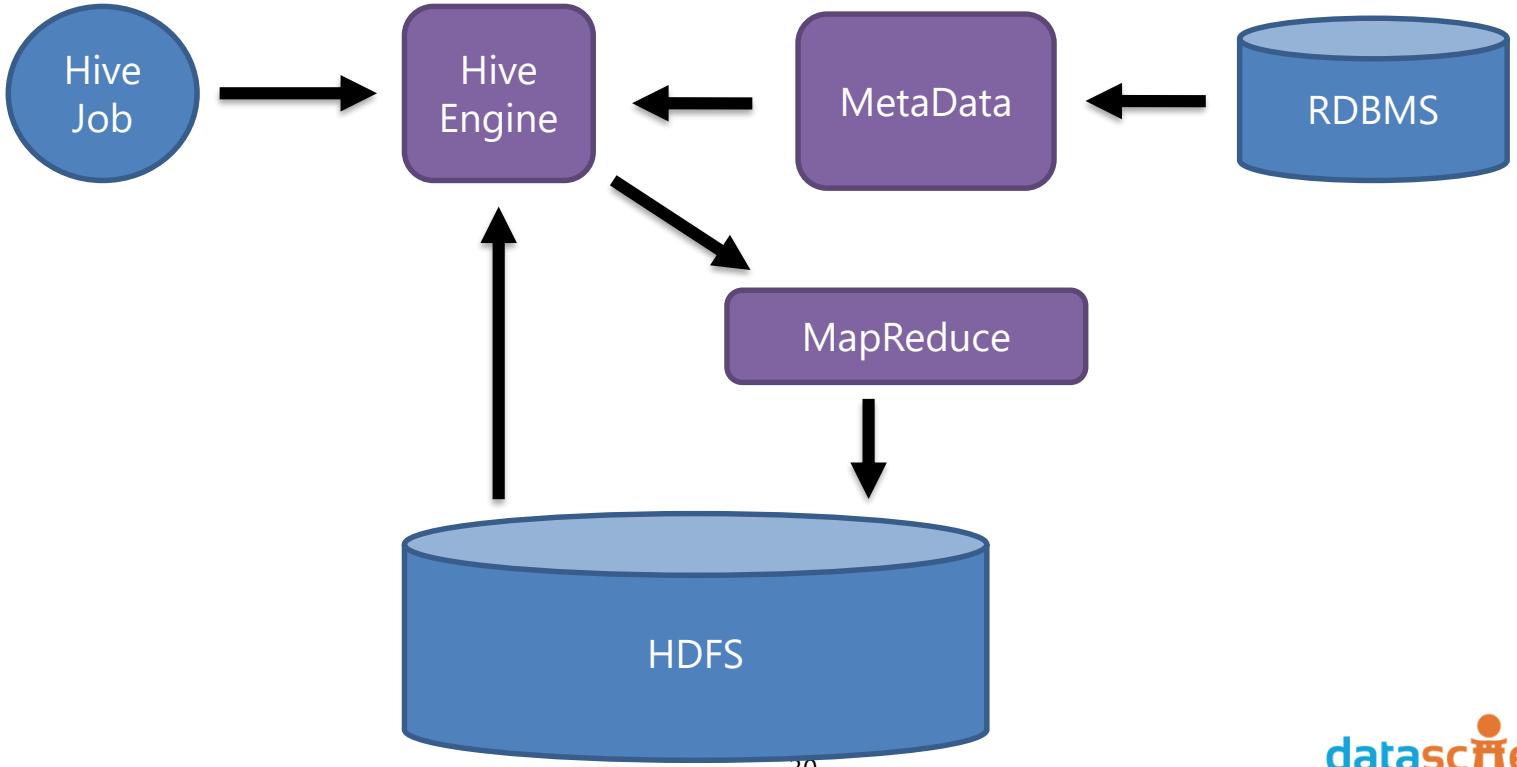
+

Metadata File/DB

=

Structured Data

Hive Architecture



Hive Jobs

Word Count Revisited

```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);
      }
    }
  }
```

vs.

```
SELECT word,
        COUNT(*) AS word_count
FROM words
GROUP BY word
```

SQL Don’ts in HIVE

SELECT * FROM ANYTHING: This brings back everything. Everything doesn’t fit on a single computer.

JOIN: Join will take hours or days to perform and eat up all cluster bandwidth for everyone else trying to use it in the queue.

ORDER BY: Sorting is very computationally expensive.

Sub Queries: A sub query essentially creates a secondary table, which will be huge in HIVE.

Interactivity: SQL in DBMS is interactive because its almost instantaneous.

Execution Engine: Tez

The Stinger Initiative

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

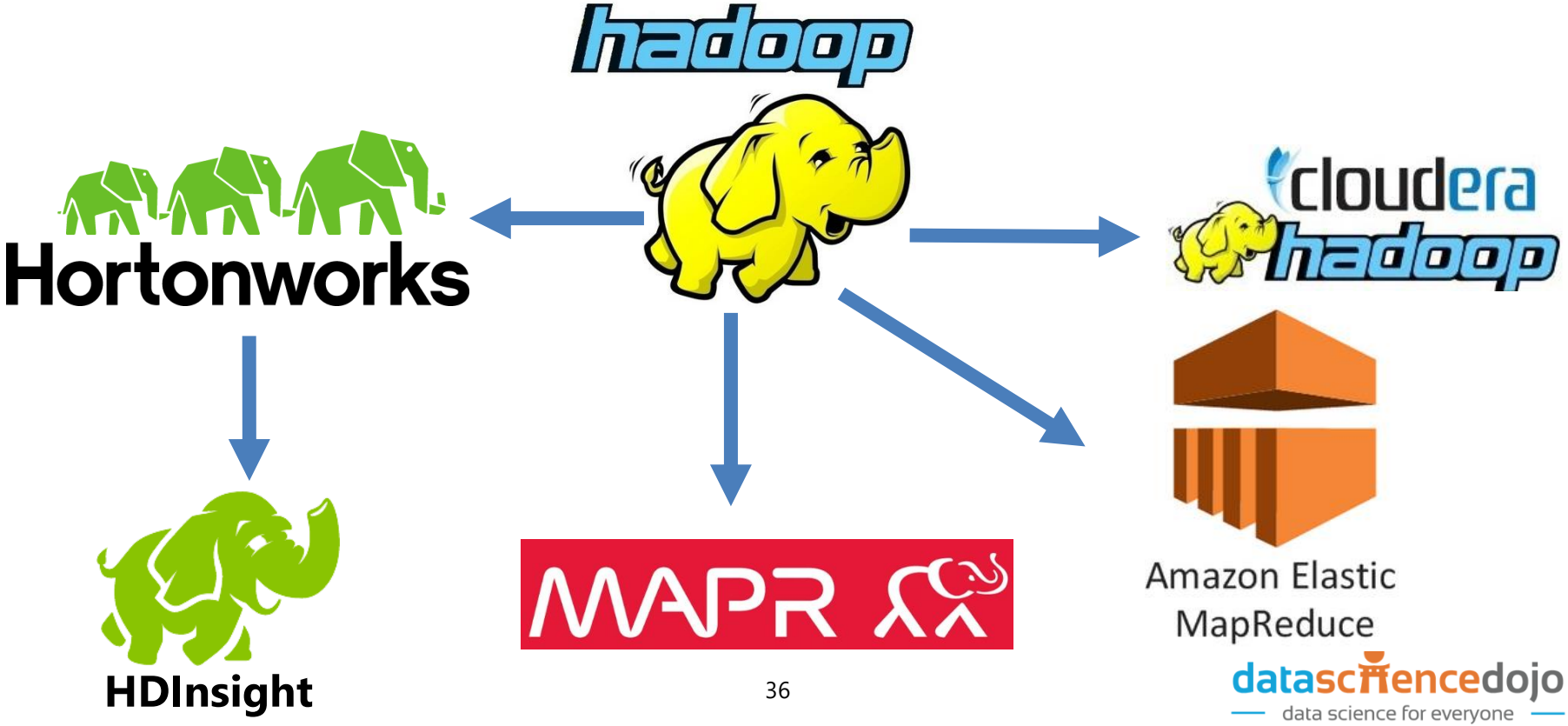
- 44 companies
- 145 developers
- 392k lines of Java code

Hadoop 2.0 with Yarn & Tez

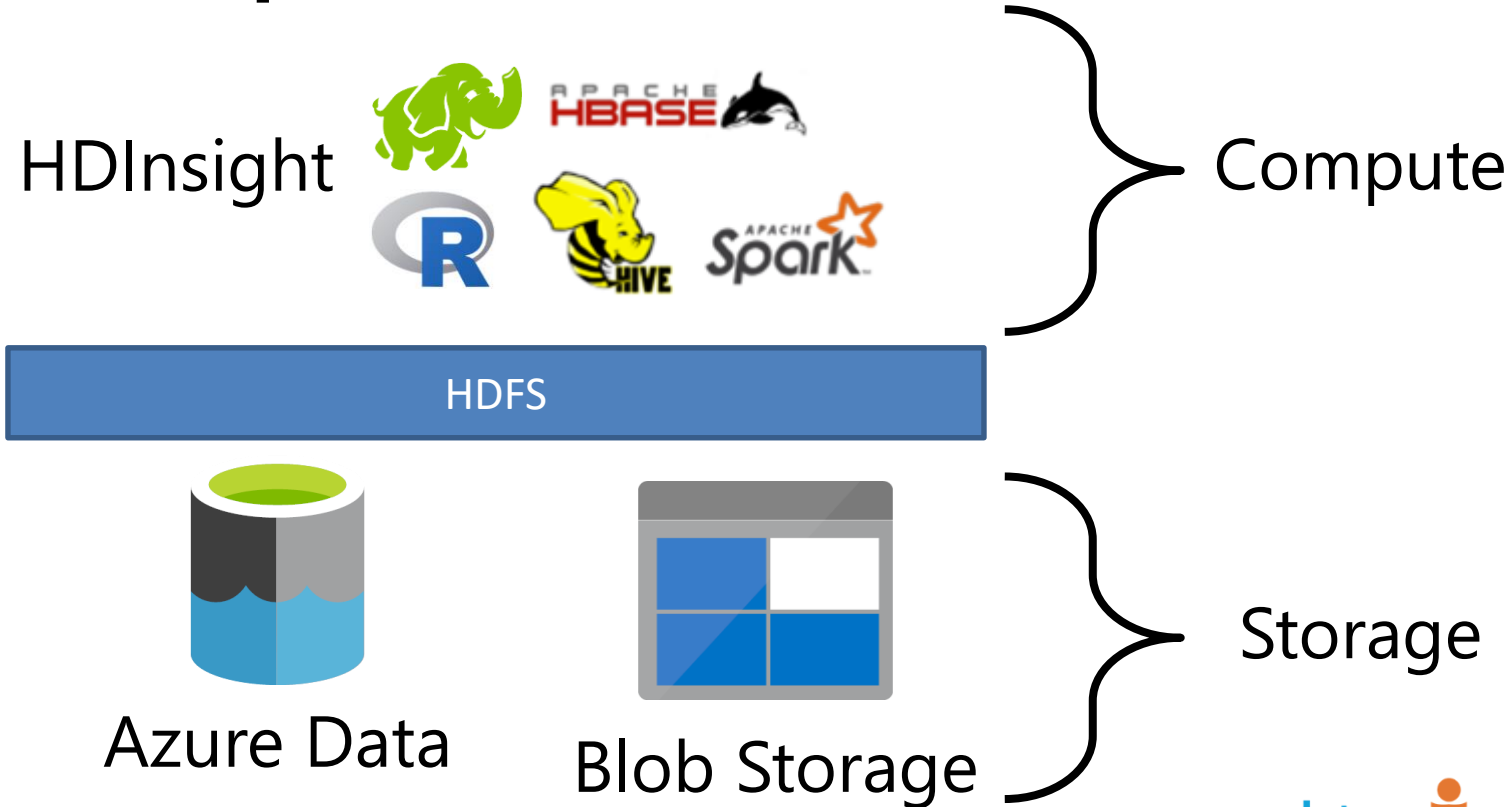
- Tez dropped Hive query times by **90%, 100x performance**
- Utilizes Apache Yarn
  - Yarn: resource manager for multi-cluster computing
- Introduced partial in-memory, local head nodes
- Rewrote HiveQL as an actual language, instead of translation

HADOOP IN THE AZURE CLOUD

Hadoop Implementations



Hadoop in Azure



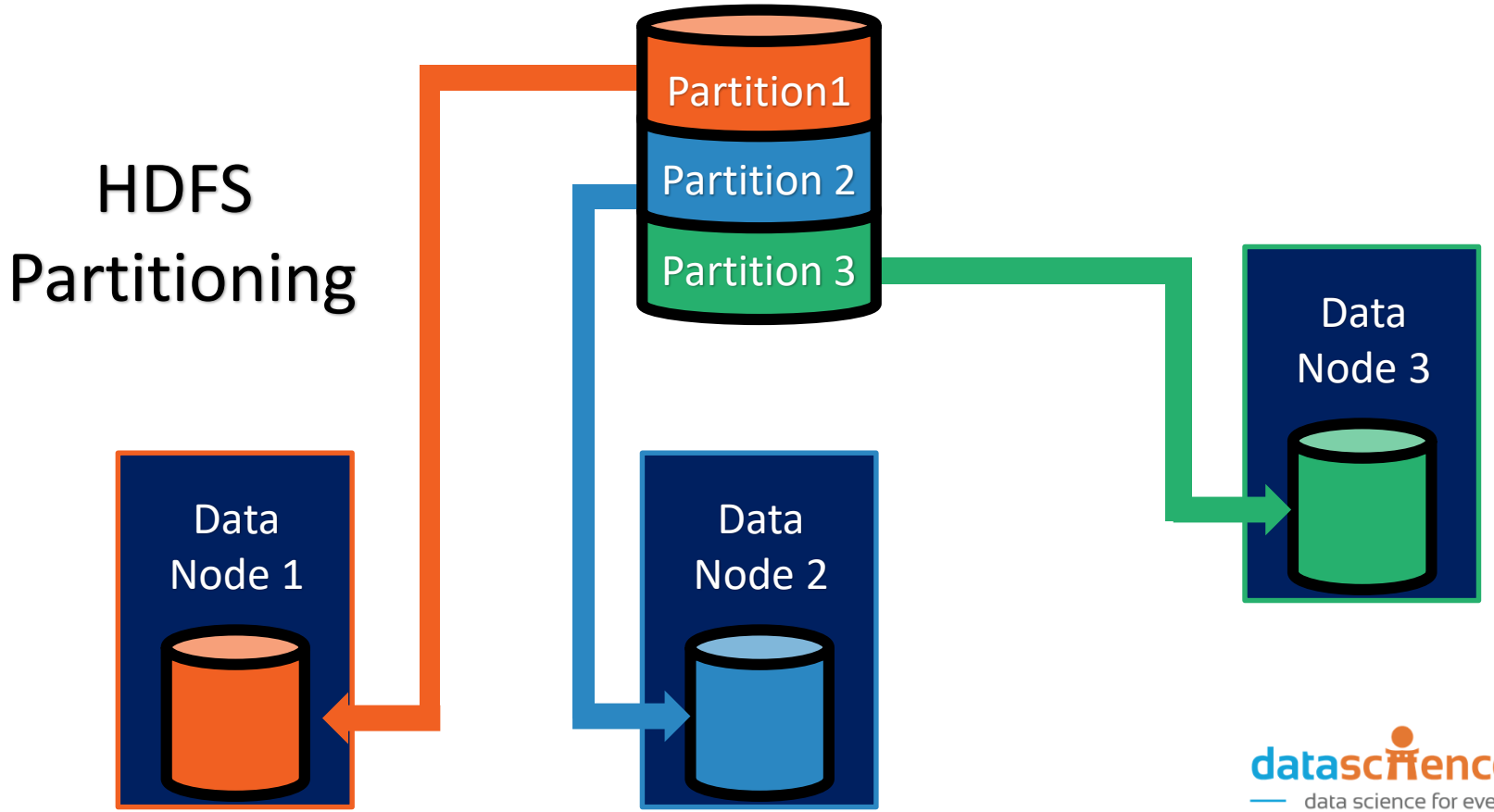
MACHINE LEARNING AT SCALE - REVISITED

What is Mahout?

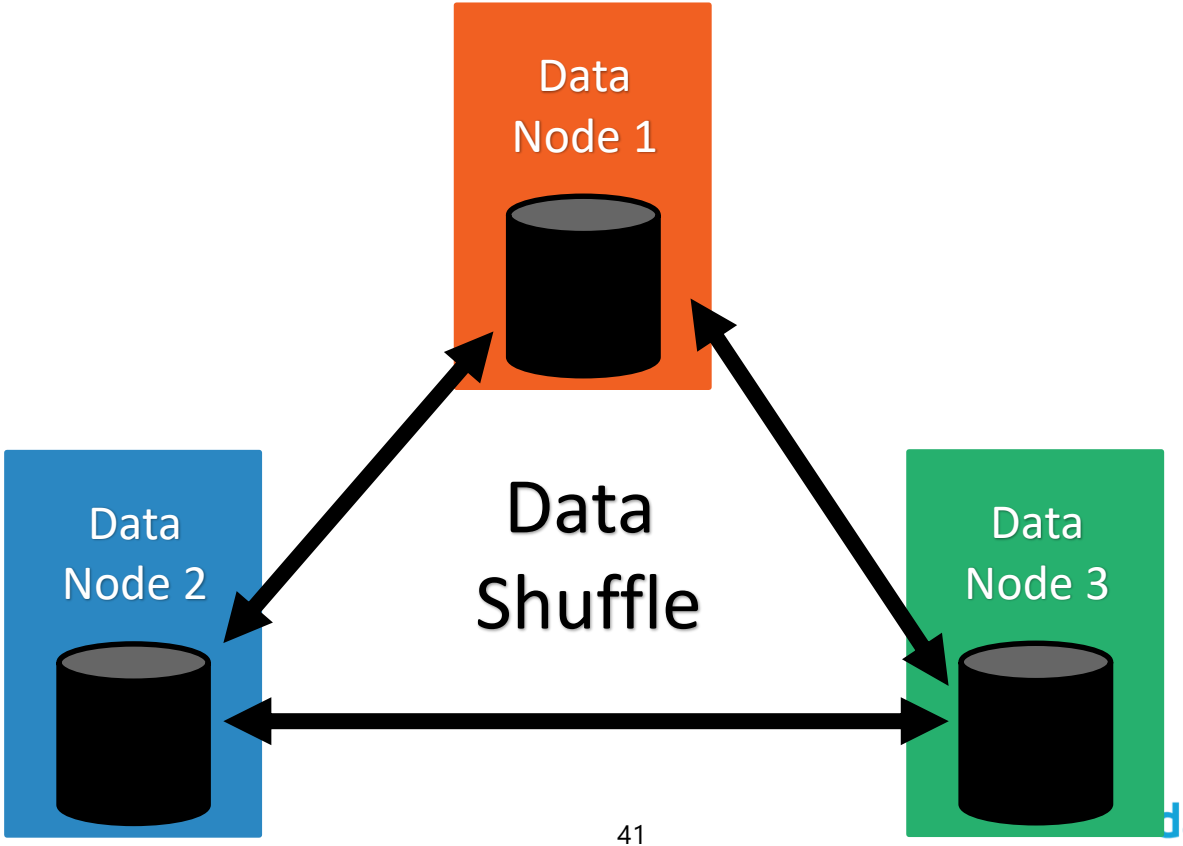
- Distributed Machine Learning platform.
- Built on top of MapReduce and HDFS.

- Script-based and command line interfaces.
- R-like language implementation.

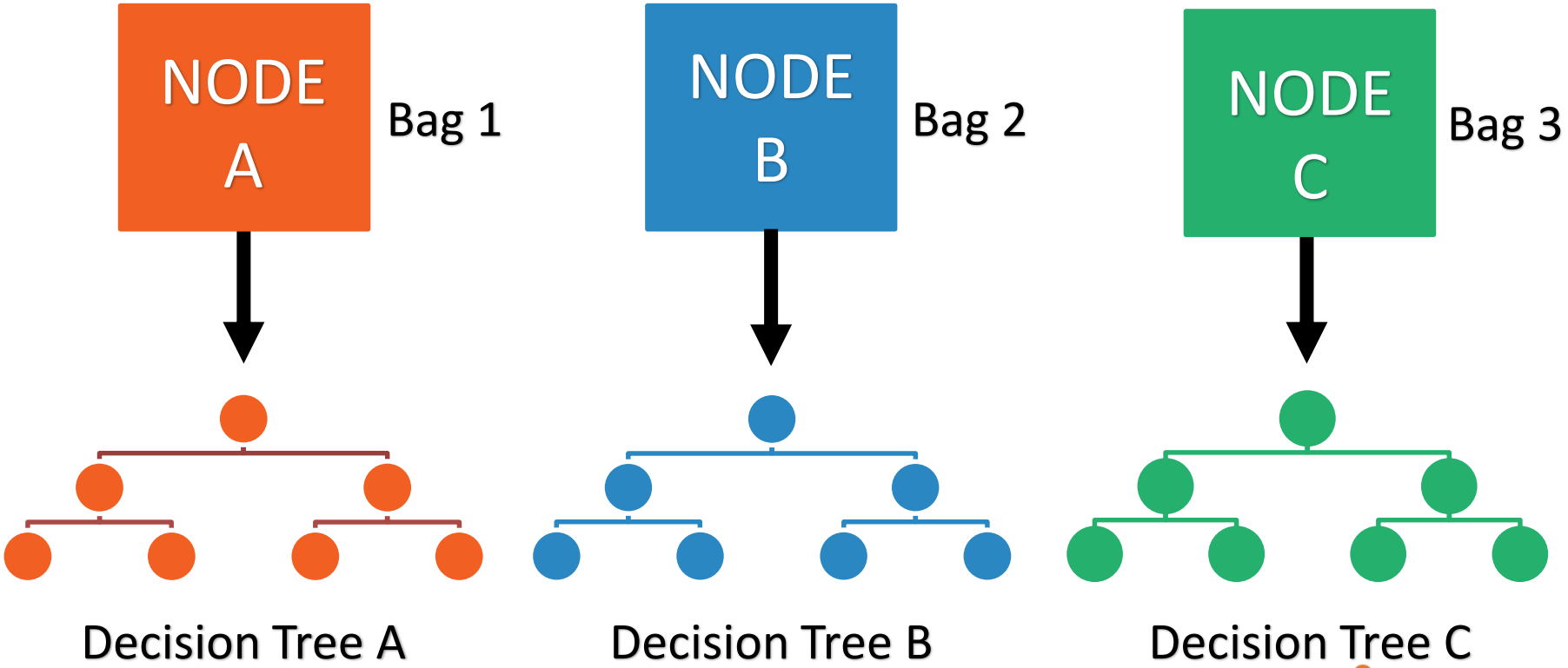
Distributed Random Forest



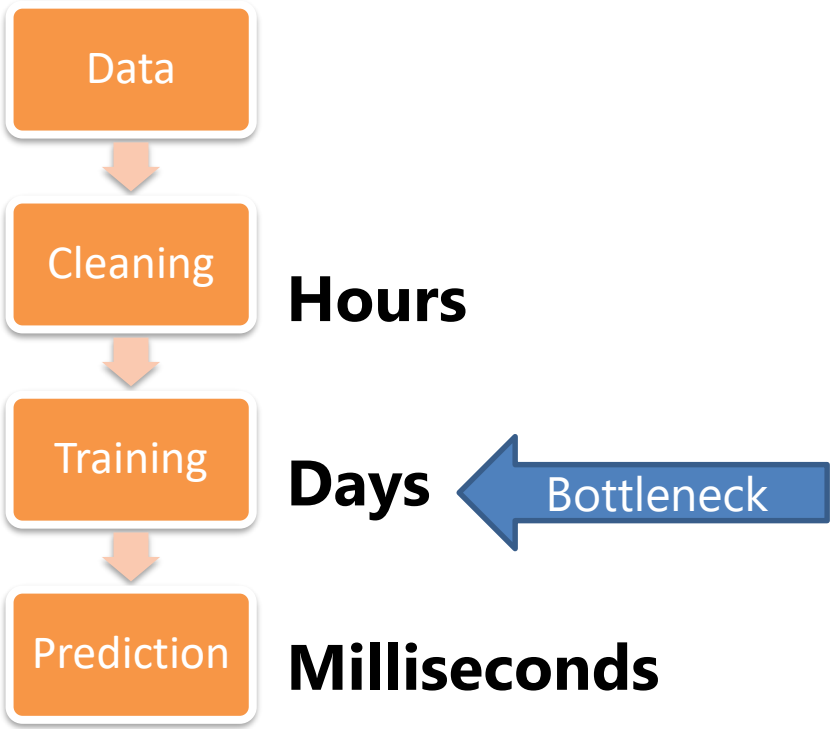
Distributed Random Forest



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

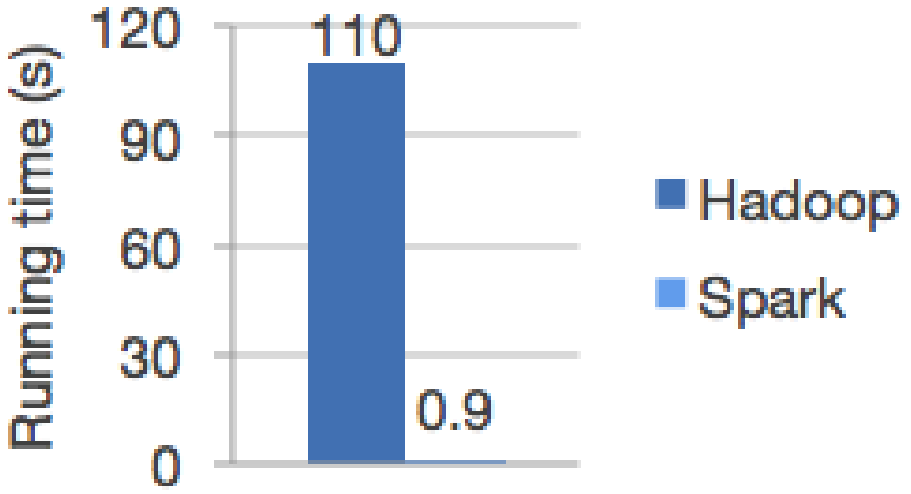
DISTRIBUTED COMPUTING V2.0 – APACHE SPARK

What is Spark?

- "A fast and general engine for large-scale data processing."
- Designed to incorporate the goodness of Hadoop and address Hadoop's shortcomings.
- Can complement Hadoop via integration with both HDFS and Hive.

Why Spark? Improved Perf!

- Up to 10x faster than Hadoop working with data from disk.
- Up to 100x faster working with data stored in memory!



Big Data, Faster!

3x faster on 10x fewer machines!

Daytona GraySort Contest: Sort 100 TB of data!

Previous World Record:

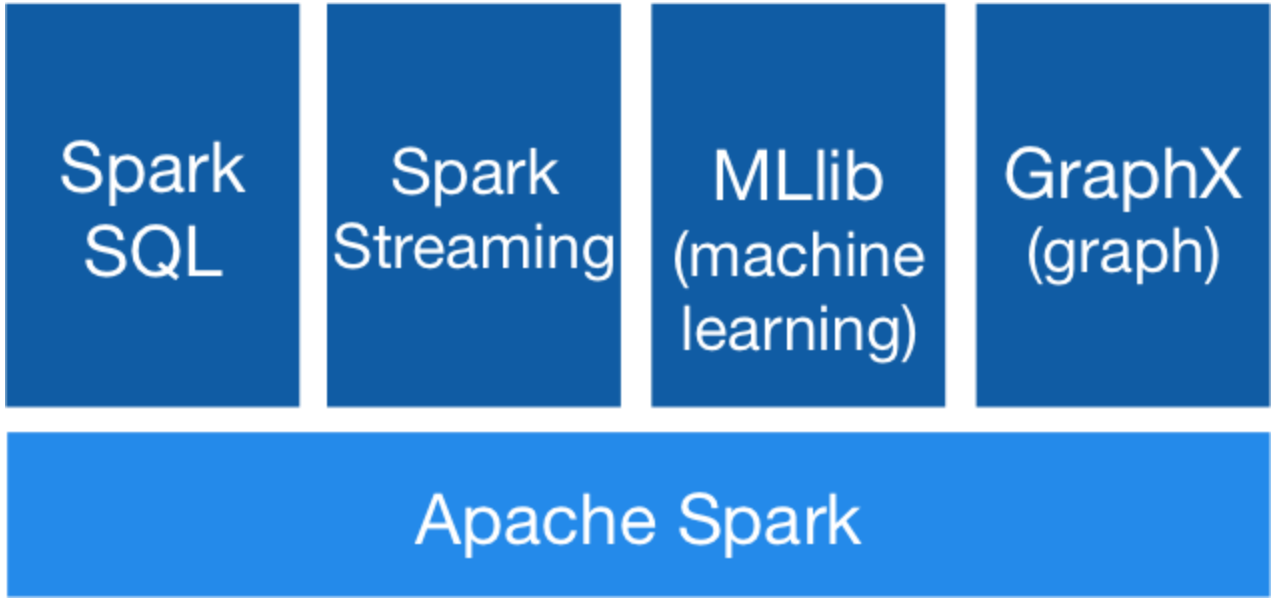
- Method: Hadoop
- Yahoo!
- 72 Minutes
- 2100 Nodes

2014:

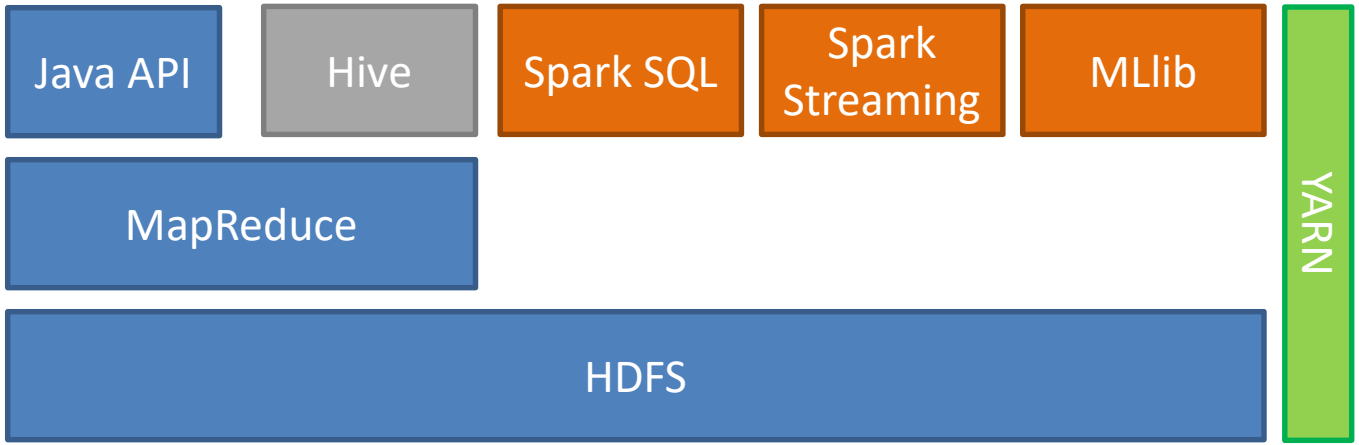
- Method: Spark
- Databricks
- 23 Minutes
- 206 Nodes

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

Conceptual Architecture



Spark and Hadoop



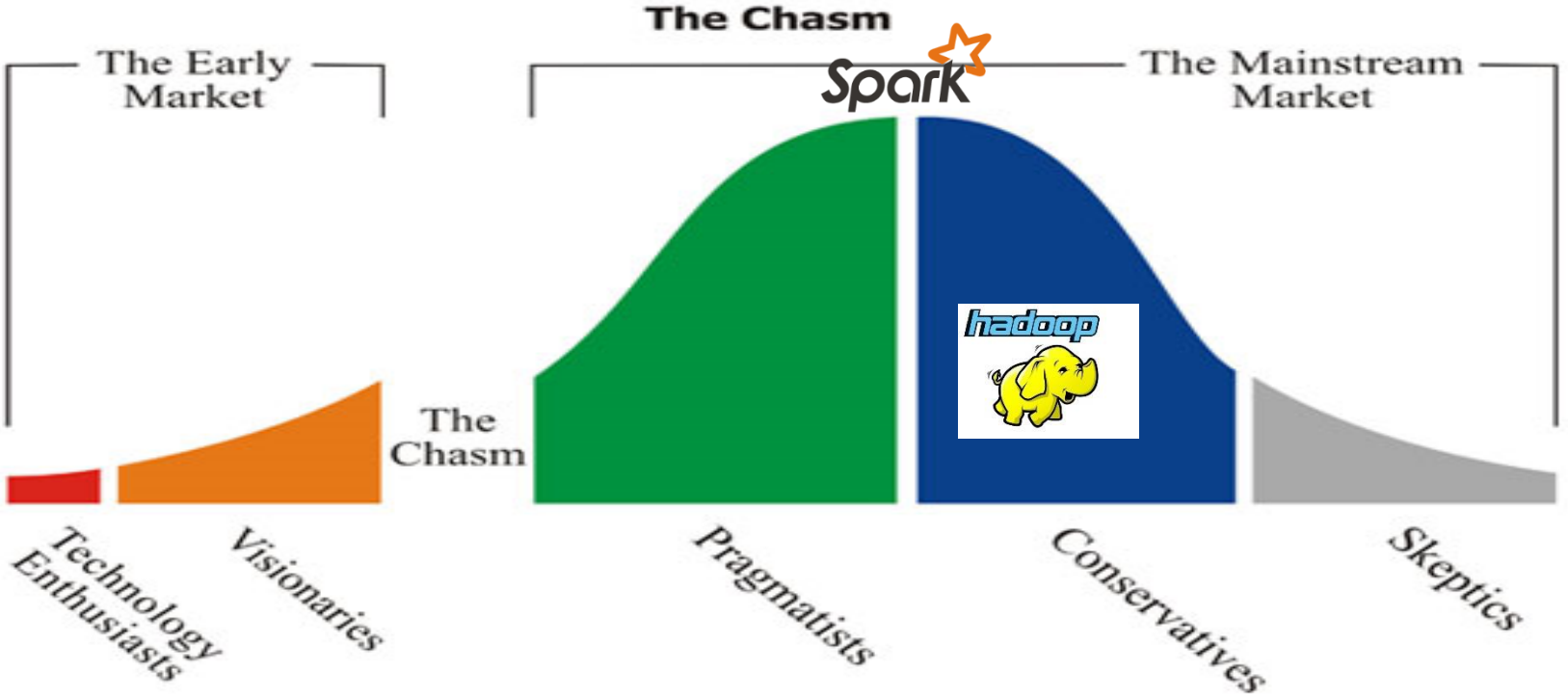
- Spark can be deployed on a Hadoop cluster and share cluster resources via YARN.
- Spark, however, does not require Hadoop!

Why is Spark Faster?

- First, Spark processing implements *lazy execution*:
  - Data operations are either *transformations* or *actions*.
  - Transformations are not executed immediately, but are stored.
  - When an action is issued, Spark evaluates all stored transformations and optimizes processing before executing.

- Second, Spark performs most processing in-memory:
  - RAM is far faster than using disk storage – even SSD drives.
  - More RAM in the cluster allows Spark to processes data faster.

Technology adoption life cycle



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

QUESTIONS

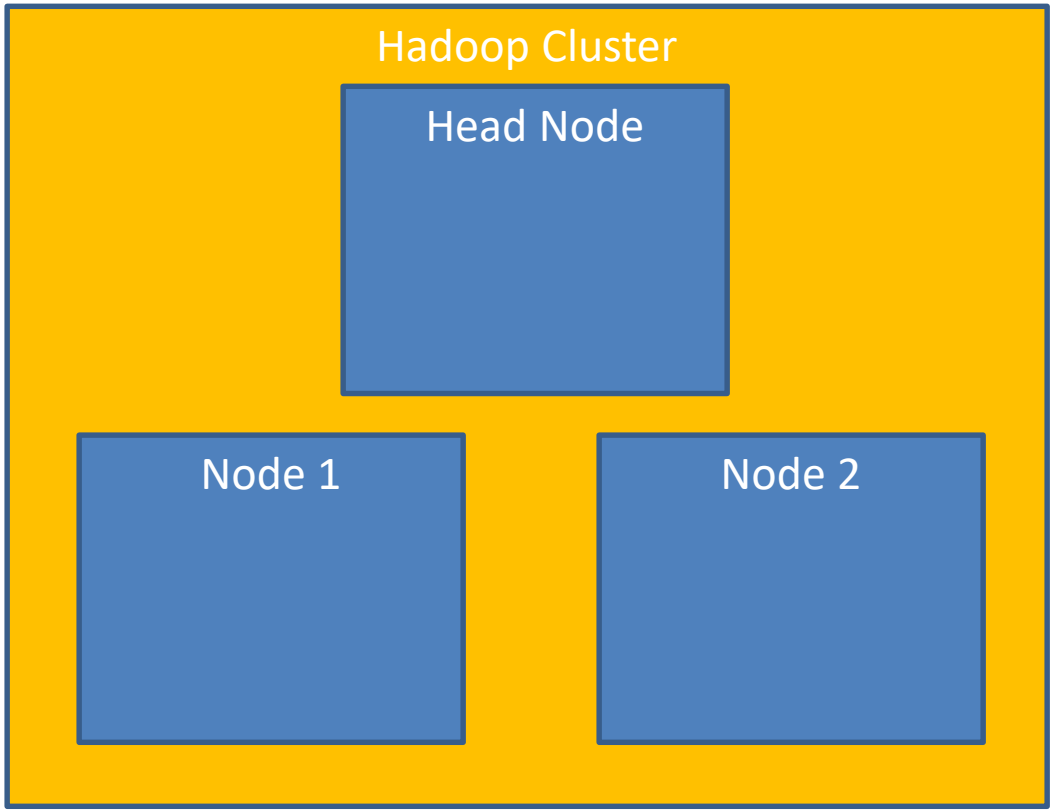
APPENDIX

MapReduce, via Playing Cards

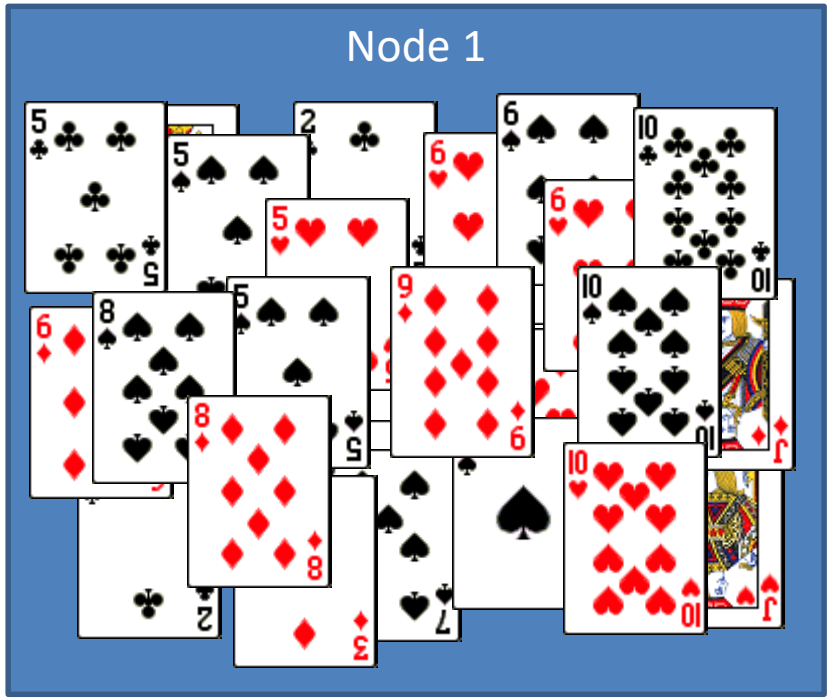
Let's count the number of spades, clubs, hearts, and diamonds in a stack of cards, the way map reduce would.

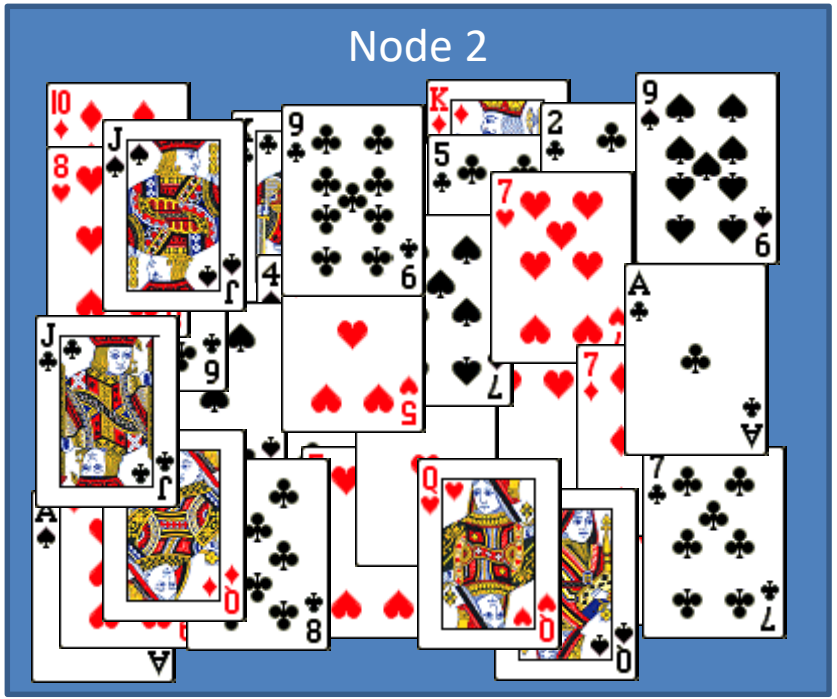
- Each card represents a row of data
- Each suit & number represents an attribute of the data

Using a 2 Data Node Cluster

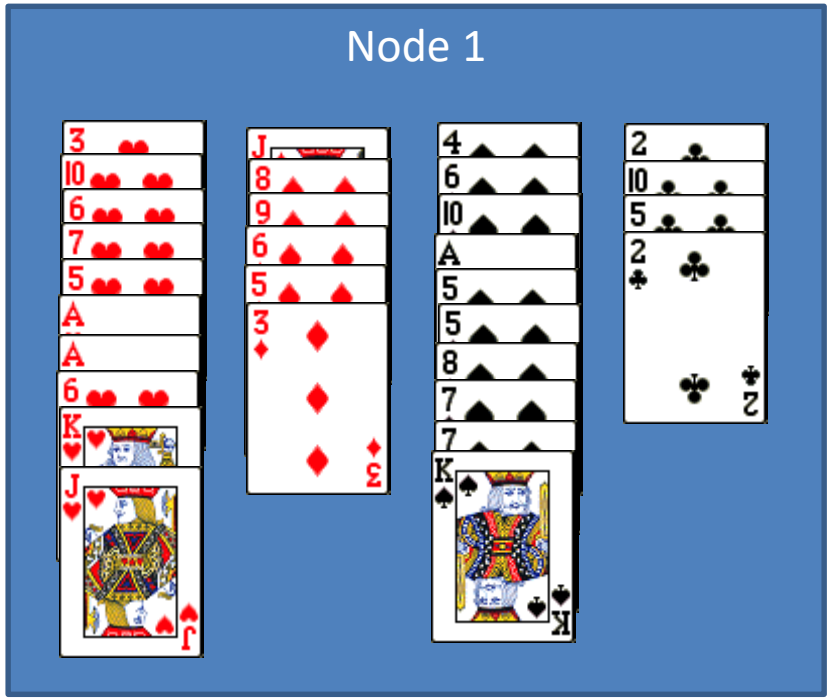


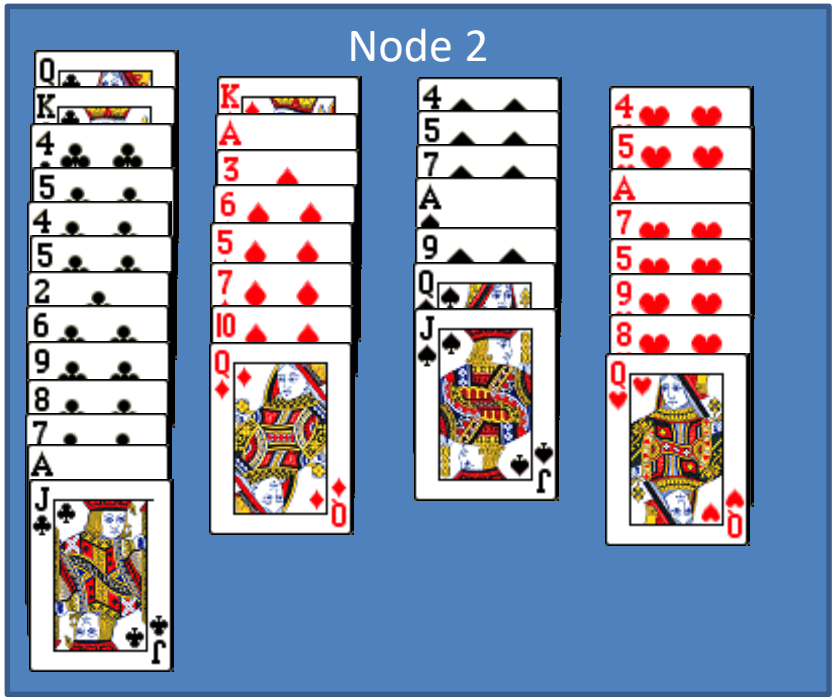
Mapping: Each Node's HDFS



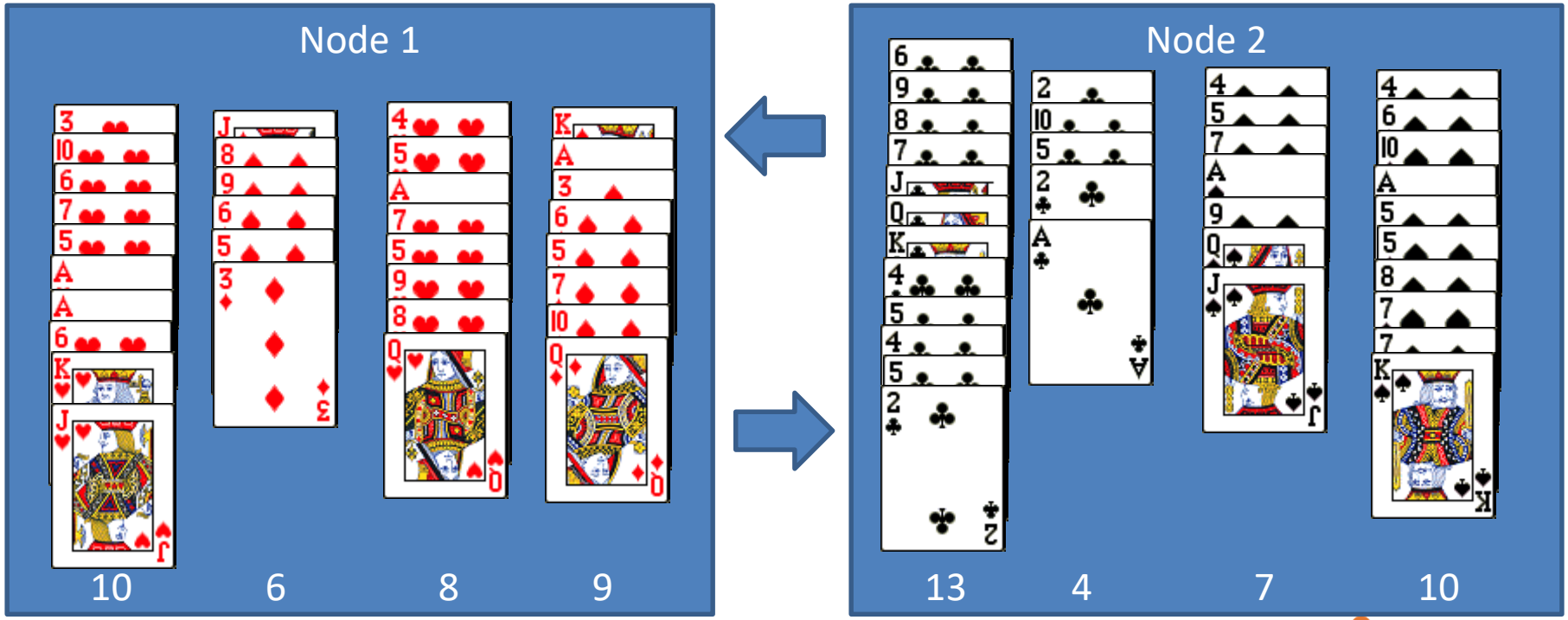


Mapping: Node Sorting





Mapping: Node Shuffle, Data Transfer



Mapping: Node Shuffle, Data Transfer