Big Data Engineering with Distributed Systems

Data Science Dojo

datasciencedojo
unleash the data scientist in you

Machine Learning Scaling

Programs	Programming	Cloud	Distributed
• Excel	• Python • R • SAS	• Azure ML • AWS ML • Watson Analytics • Big ML • Cloud Virtual Machines	• Hadoop • Spark • H20 • Revolution R

Excel: Cell Meta Data

	A	B	C	D	E
1	Sepal.Leng	Sepal.Widt	Petal.Leng	Petal.Widt	Species
2	5.1	3.5	1.4	0.2	setosa
3	4.9	3	1.4	0.2	setosa

E2 Cell = Application, Address, AllowEdit, Areas, Borders, BottomPadding, Comment, Column, ColumnIndex, Creator, **Font,** FitText, Height, HeightRule, ID, Interior, LeftPadding, NestingLevel, RightPadding, Row, RowIndex, Shading, Tables, TopPadding, VerticalAlignment, **Value,** Width, WordWrap

“Value”: “Setosa”


```
"Font":{
    "Application": "Microsoft Excel",
    "Background": None,
    "Bold": True,
    "Color": 0,
    "ColorIndex": 5,
    "Creator": "XCEL",
    "FontStyle": "Bold Italic",
    "Italic": True,
    "Name": "Comic Sans MS",
    "OutlineFont": True,
    "Parent": None,
    "Shadow": False,
    "Size": 12,
    "Strikethrough": False,
    "Subscript": False,
    "ThemeColor": 12,
    "ThemeFont:": 2,
    "TintAndShade": 1,
    "Superscript": False,
    "Underline": False,
}
```

R Limits

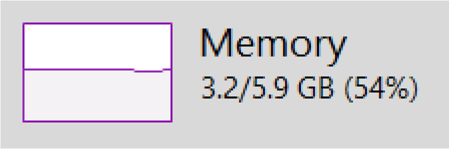
- Single core
- Single threaded
- All in memory (RAM)
- Vectors & Matrices capped at 4,294,967,295 elements; 2^32 - 1

R Limits: RAM

- All in memory (RAM)

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

Phuc’s Laptop Example:



$$Max\ Data\ Limit = (\,5.9gb - \ 3.2gb)\ x\ 80\%$$
$$Max\ Data\ Limit = {\sim}2.16gb$$

datasciencedojo
unleash the data scientist in you

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

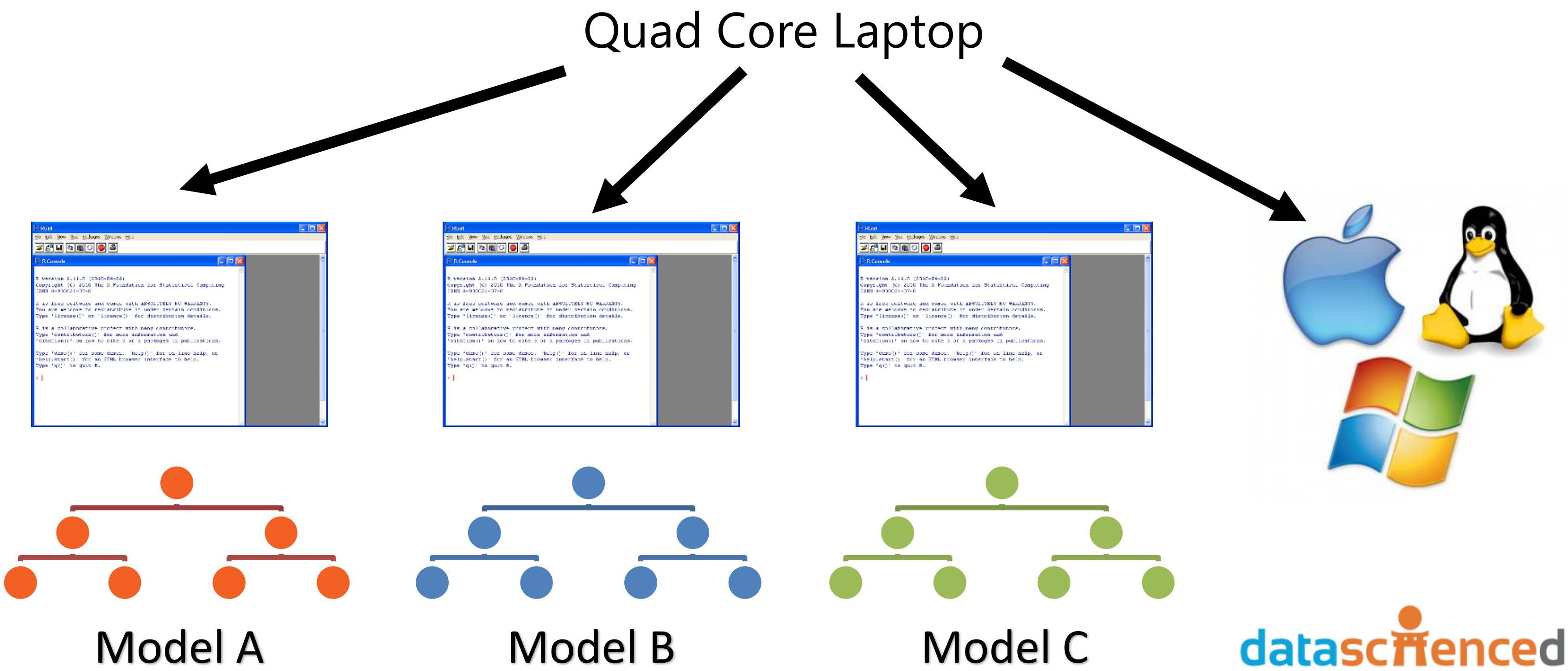
$$Max\ Data\ Limit = (\ 448gb - 1gb\ )\ x\ 80\%$$

$$Max\ Data\ Limit = \sim\mathbf{357.6gb}$$

unleash the data scientist in you

R Limits: Single Core

- Single core
- Single threaded



Machine Learning Scaling

Programs	Programming	Cloud	Distributed
• Excel	• Python • R • SAS	• Azure ML • AWS ML • Watson Analytics • Big ML • Cloud Virtual Machines	• Hadoop • Spark • H20 • Revolution R

Distributed R Solutions:

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

Agenda

hadoop

HIVE

From a Data Scientist's Perspective

Goals:

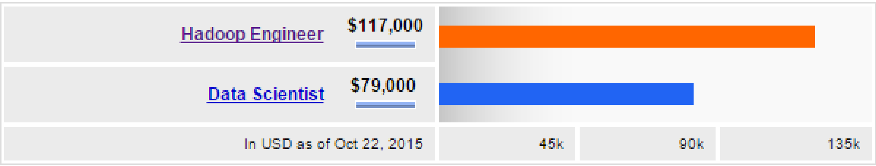
- Teach you how to leverage an existing Hadoop cluster, self-service data query

Not goals:

- Managing or administering a Hadoop cluster

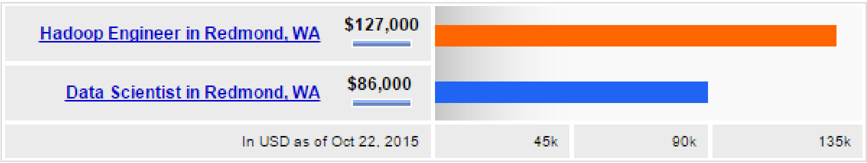
Hadoop Engineers

Average Salary of Jobs Matching Your Search

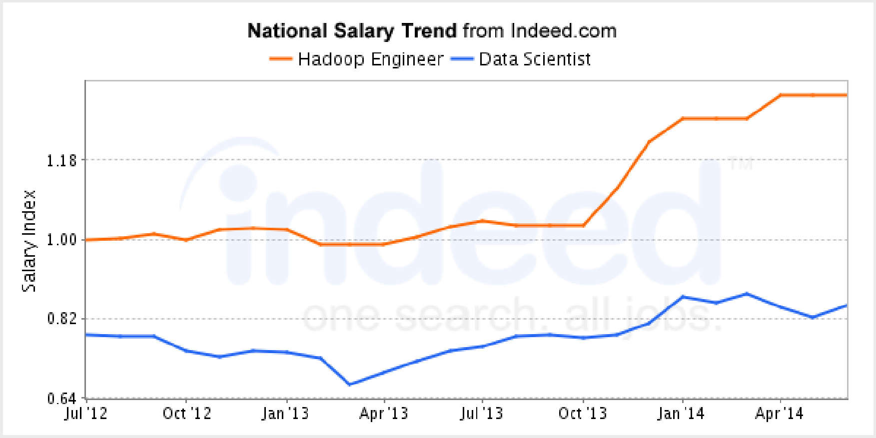


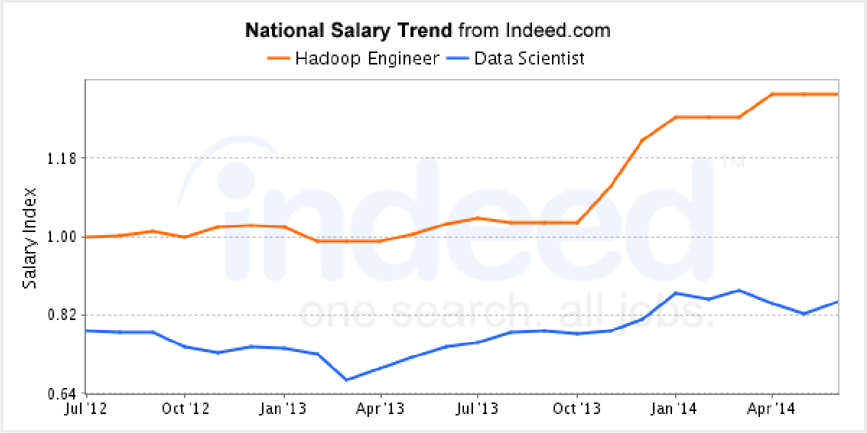
Average Hadoop Engineer salaries for job postings nationwide are 47% higher than average Data Scientist salaries for job postings nationwide.

Average Salary of Jobs Matching Your Search



Average Hadoop Engineer salaries for job postings in Redmond, WA are 47% higher than average Data Scientist salaries for job postings in Redmond, WA.

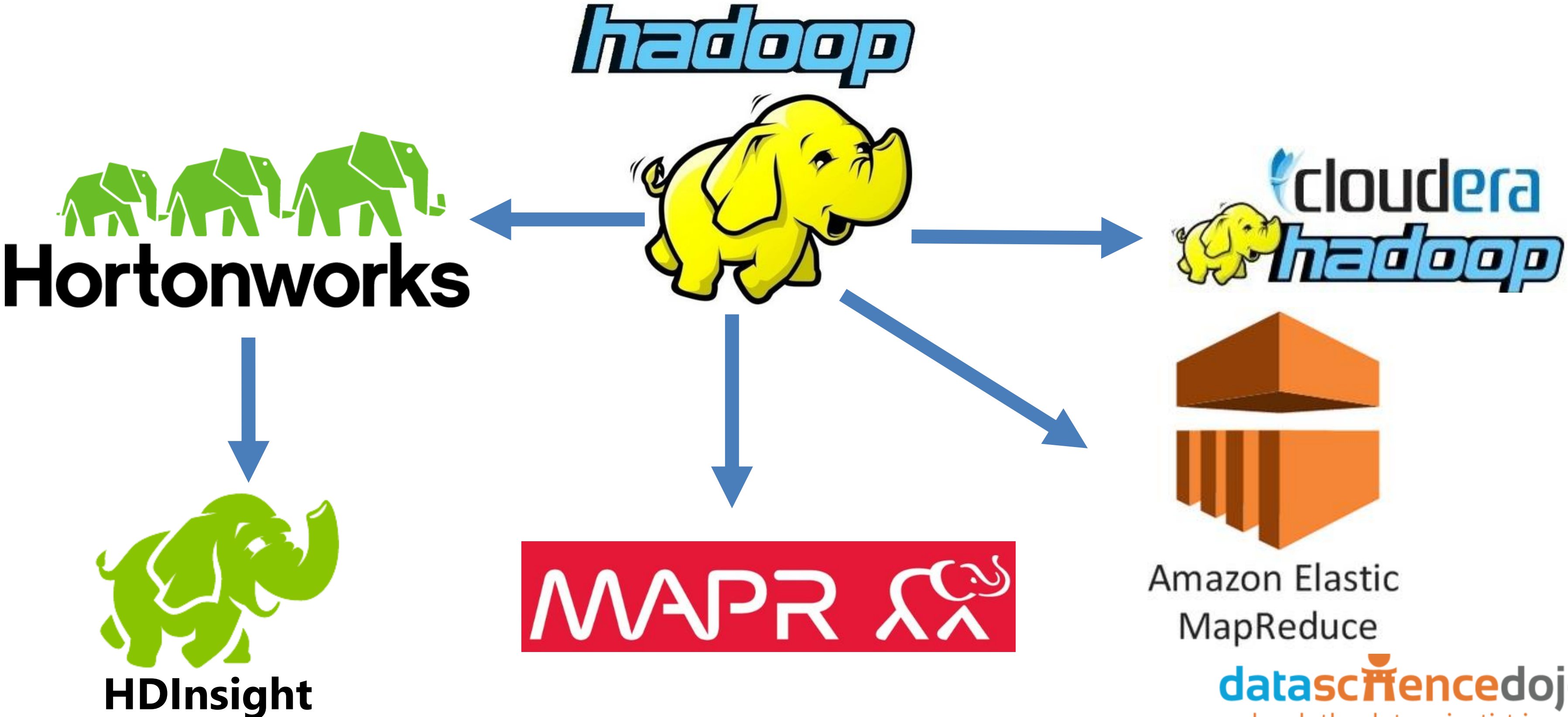




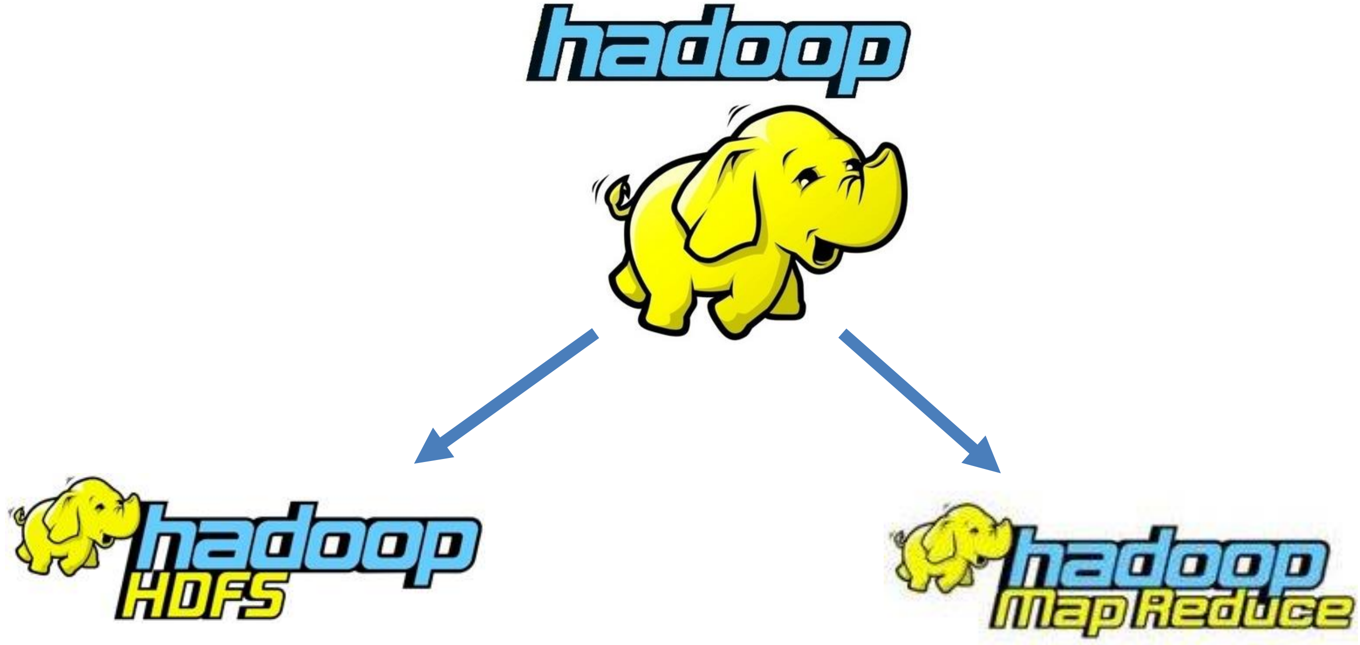
Source: Ineed.com

datasciencedojo
unleash the data scientist in you

Hadoop Implementations



(Vanilla/Base) Hadoop

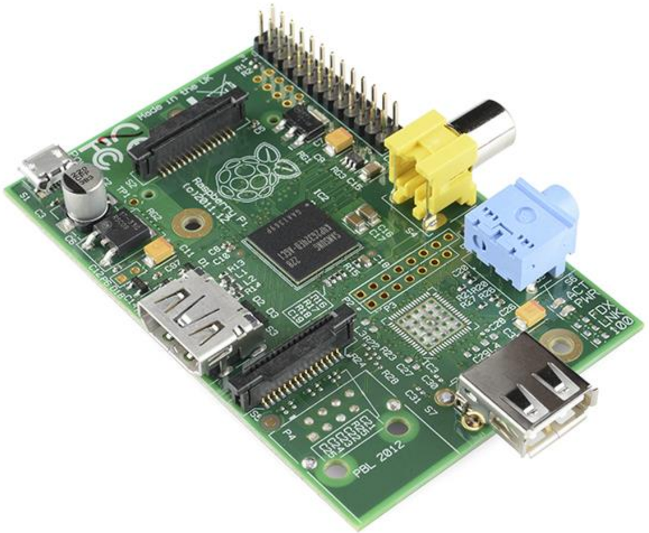


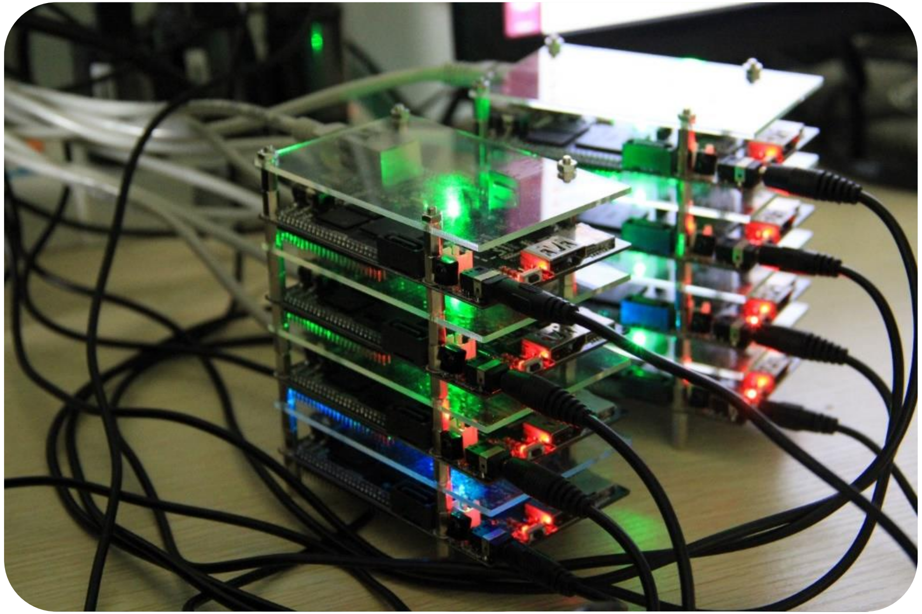
Processing engine for distributed batch processing.

Turn Back The Clock, The Mainframe

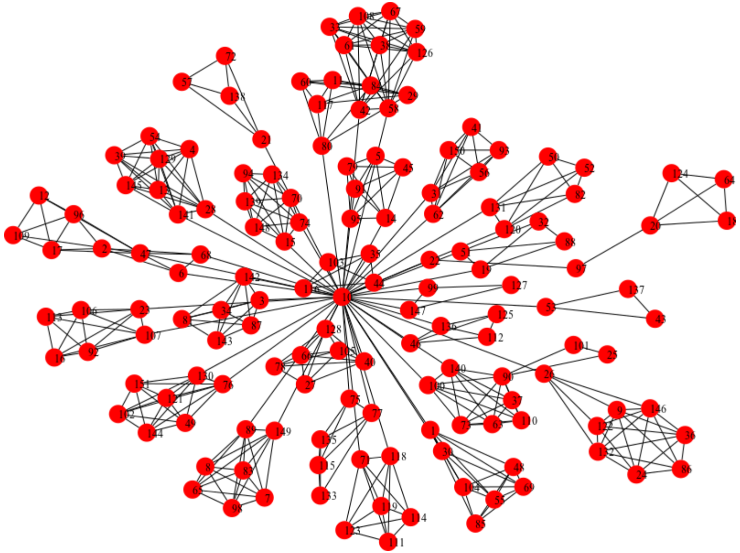
datasciencedojo
unleash the data scientist in you

Distributed Computing



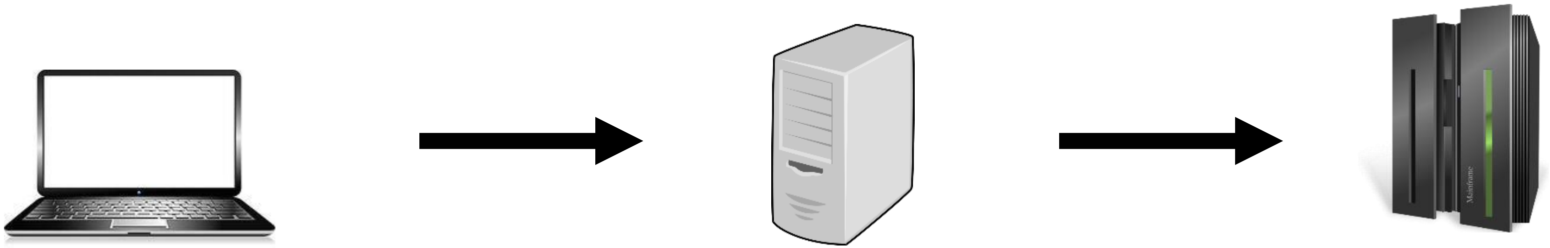


Cloud Computing



datasciencedojo
unleash the data scientist in you

Scaling Computational Power



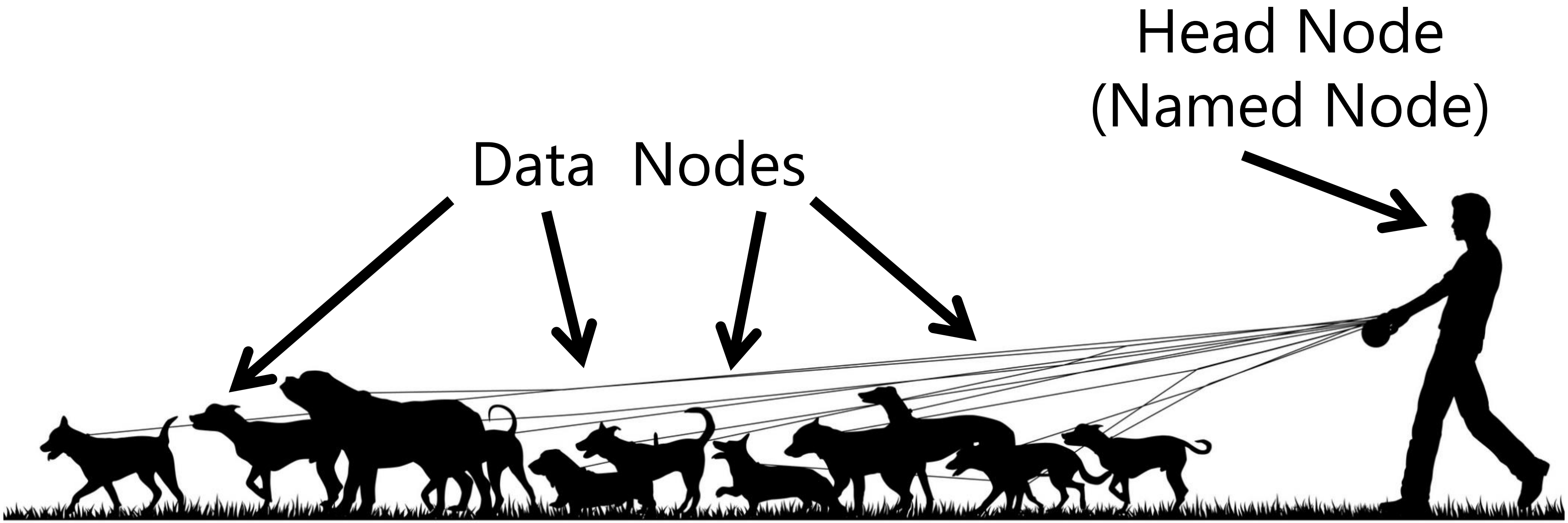
Old Scaling:

- Vertical Scaling, Scaling UP
- High performance computers

New Scaling:

- Horizontal Scaling, Scaling OUT
- Commodity hardware, distributed

If dogs were servers...



HDFS & MapReduce

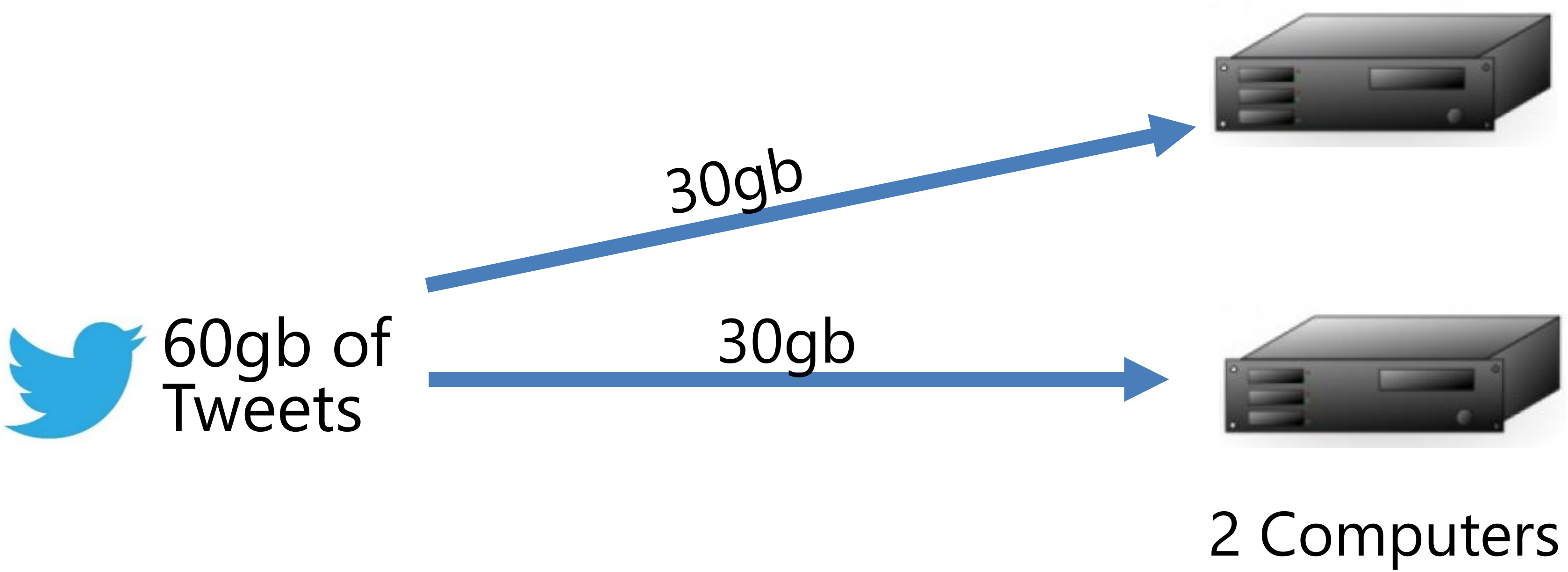
60gb of Tweets

60gb

1 Computer

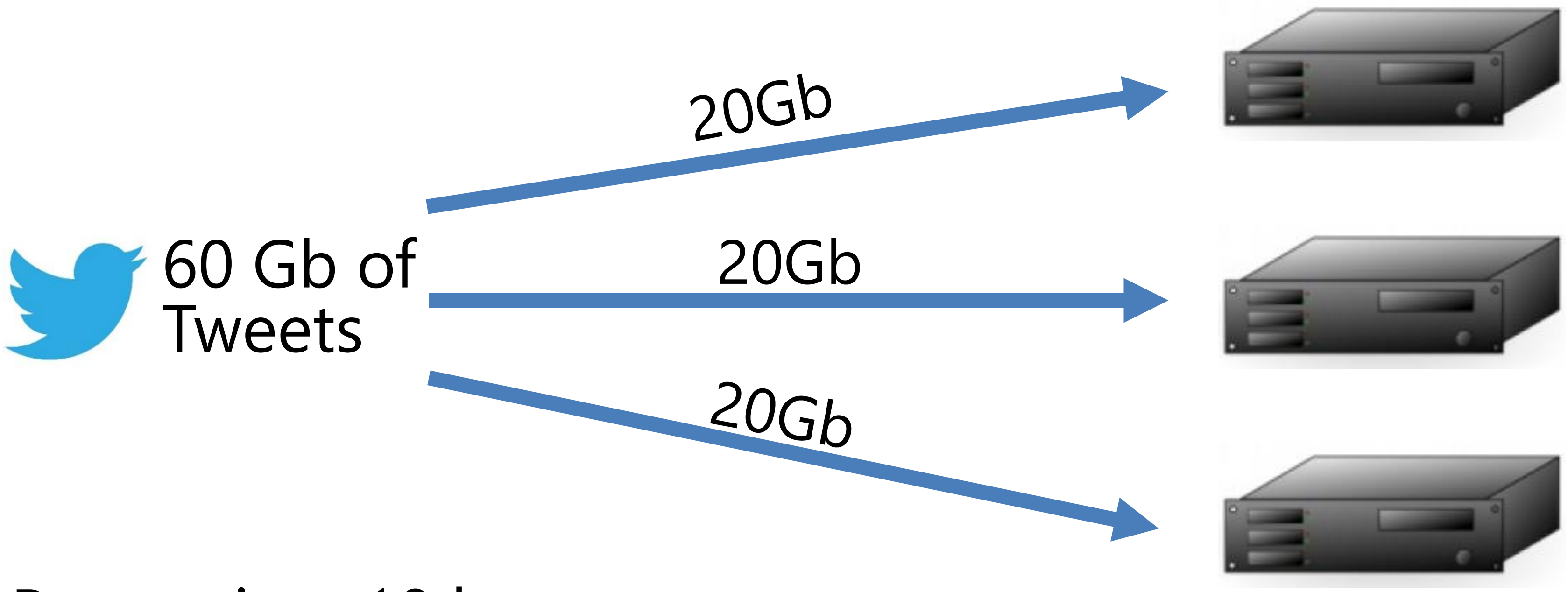
Processing: 30 hours

HDFS & MapReduce



Processing: 15 hours

HDFS & MapReduce



Processing: 10 hours

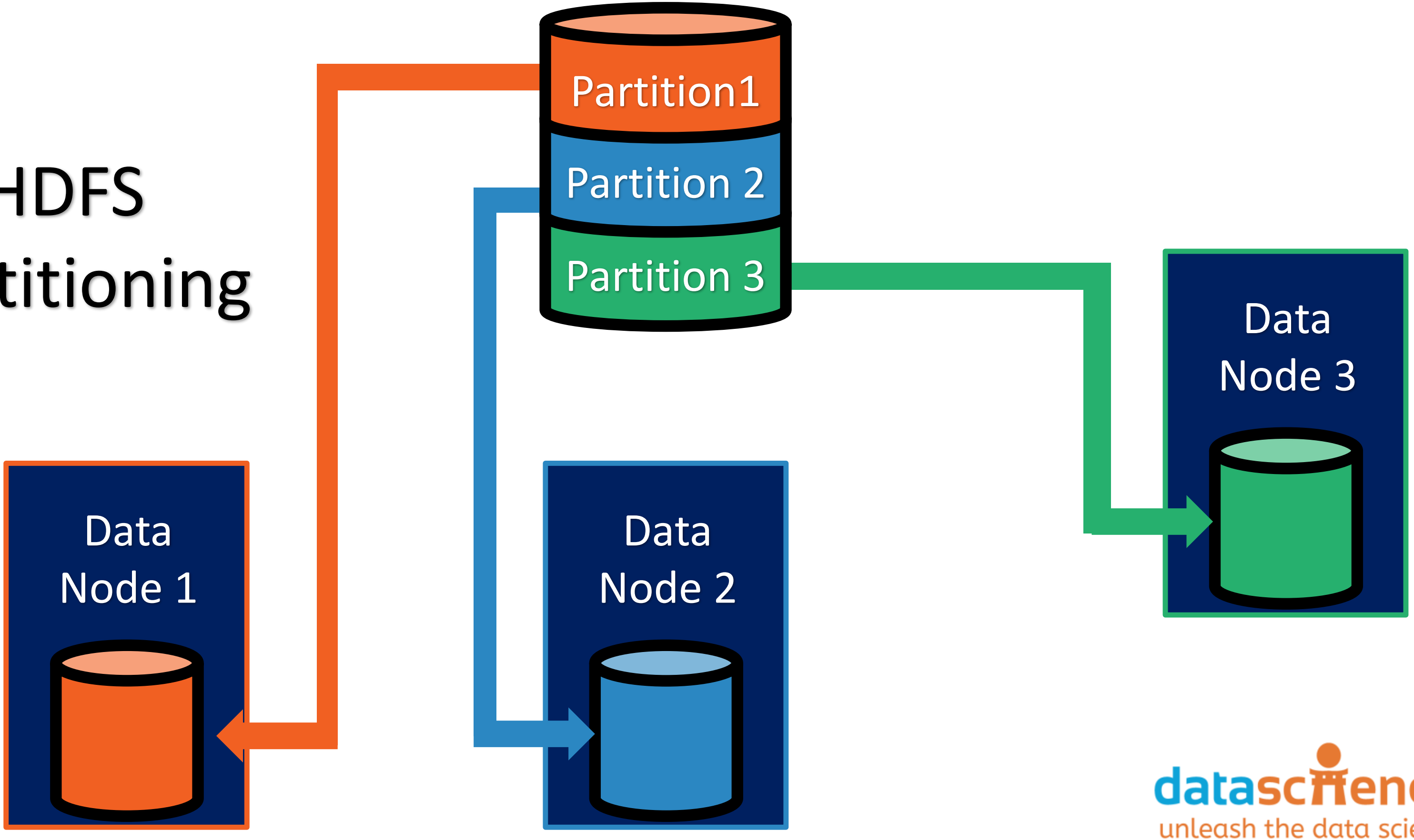
3 Computers

Most Cases, Linear Scaling Of Processing Power

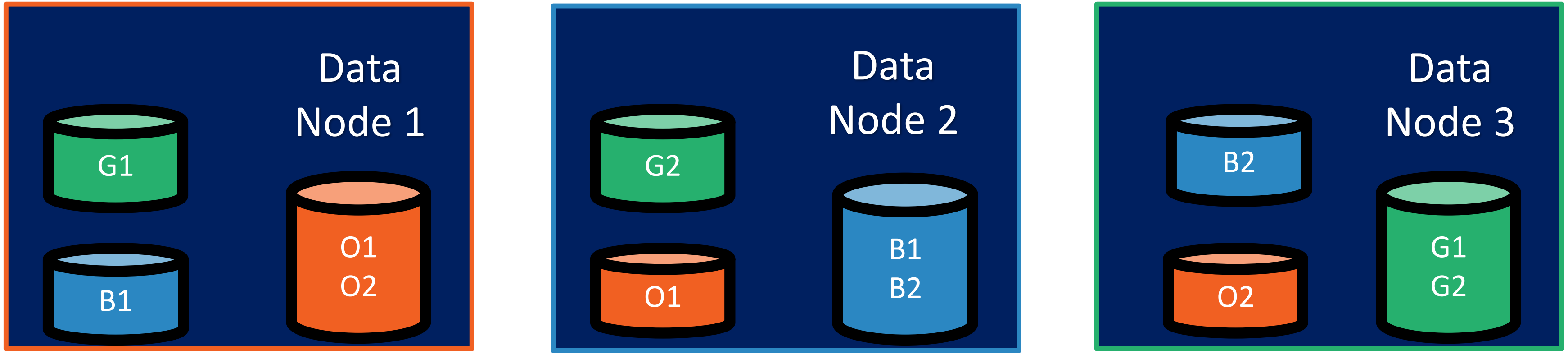
Number of Computers	Processing Time (hours)
1	30
2	15
3	10
4	7.5
5	6
6	5
7	4.26
8	3.75
9	3.33

HDFS

HDFS Partitioning



HDFS Redundancy



unleash the data scientist in you

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);
      }
    }
```

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

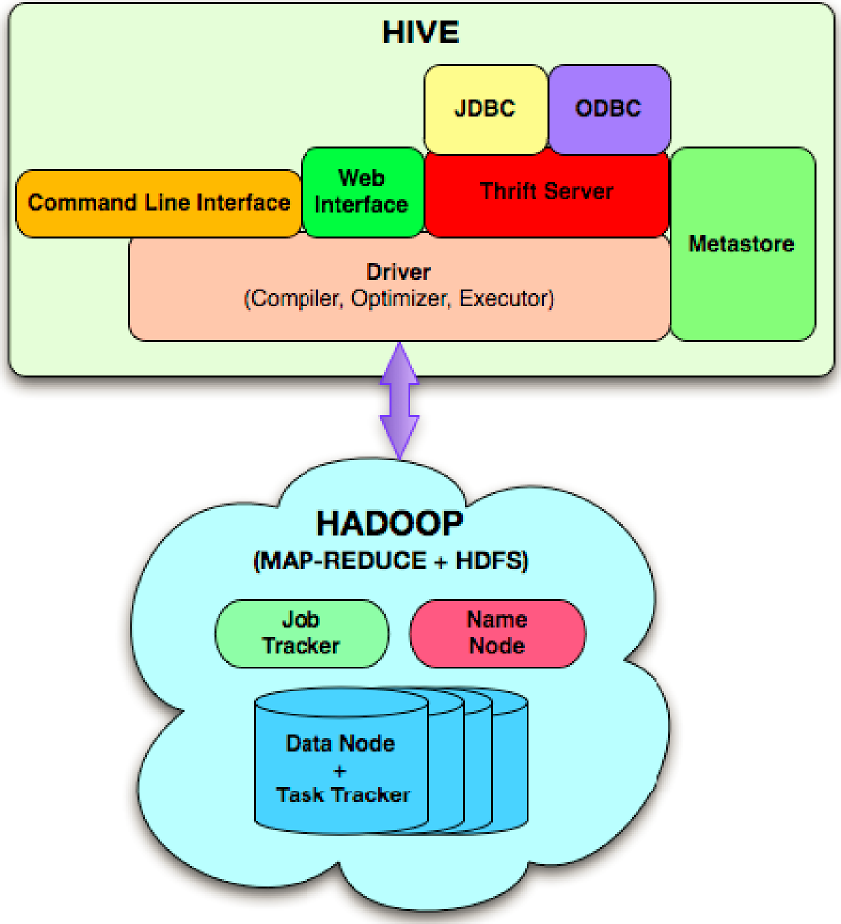
Pig: Simpler scripting for MapReduce transformations

Sqoop: Data import and export

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

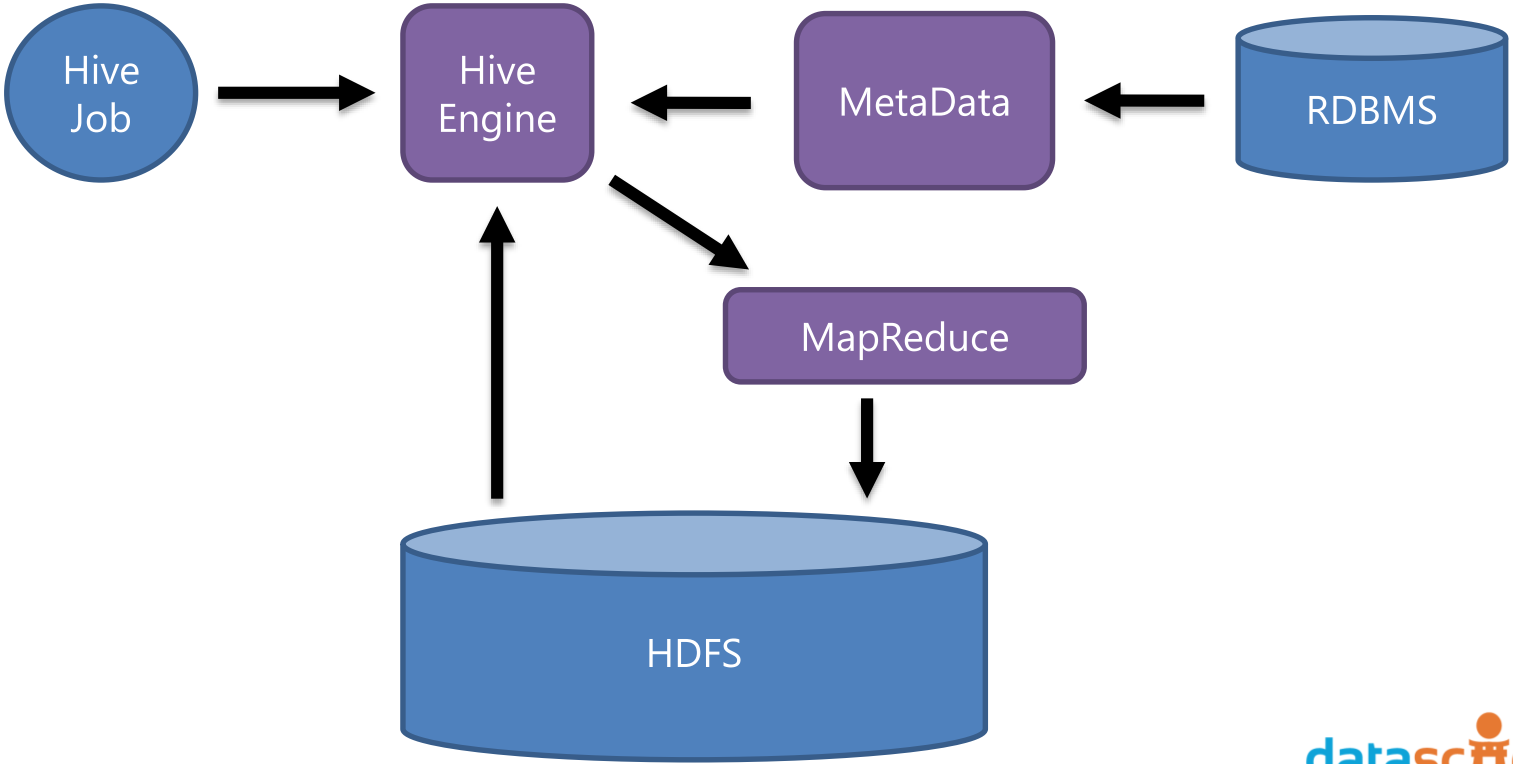
Zookeeper: Coordinates processes in distributed systems


HIVE

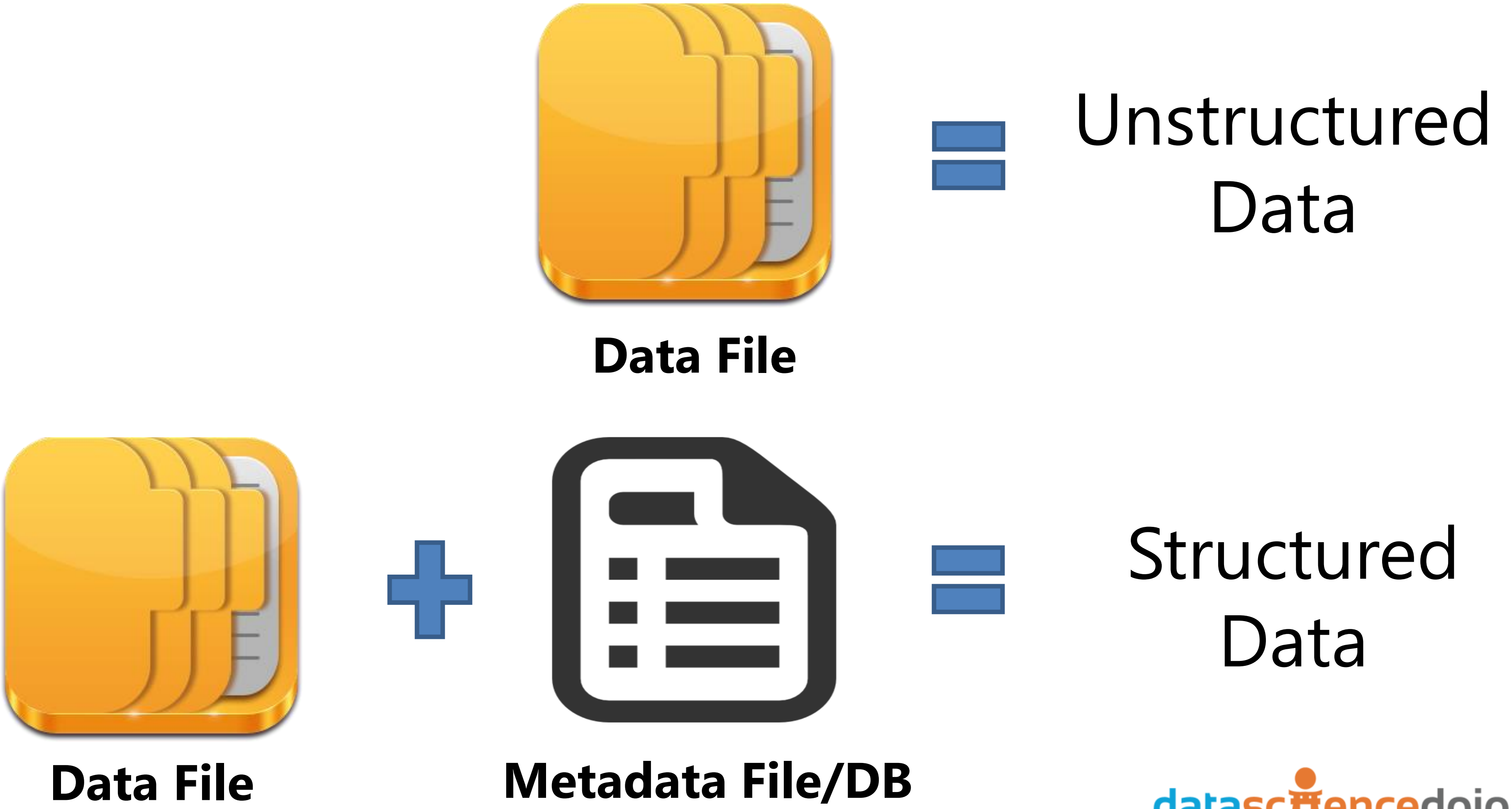

HIVE
JDBC
ODBC
Command Line Interface
Web Interface
Thrift Server
Metastore
Driver
(Compiler, Optimizer, Executor)
HADOOP
(MAP-REDUCE + HDFS)
Job Tracker
Name Node
Data Node
+
Task Tracker

Hive Jobs

Hive Architecture



datasciencedojo
unleash the data scientist in you


Data File
Unstructured Data
Data File
Metadata File/DB
Structured Data

Semi Structured Data

Self Describing

Flat Files

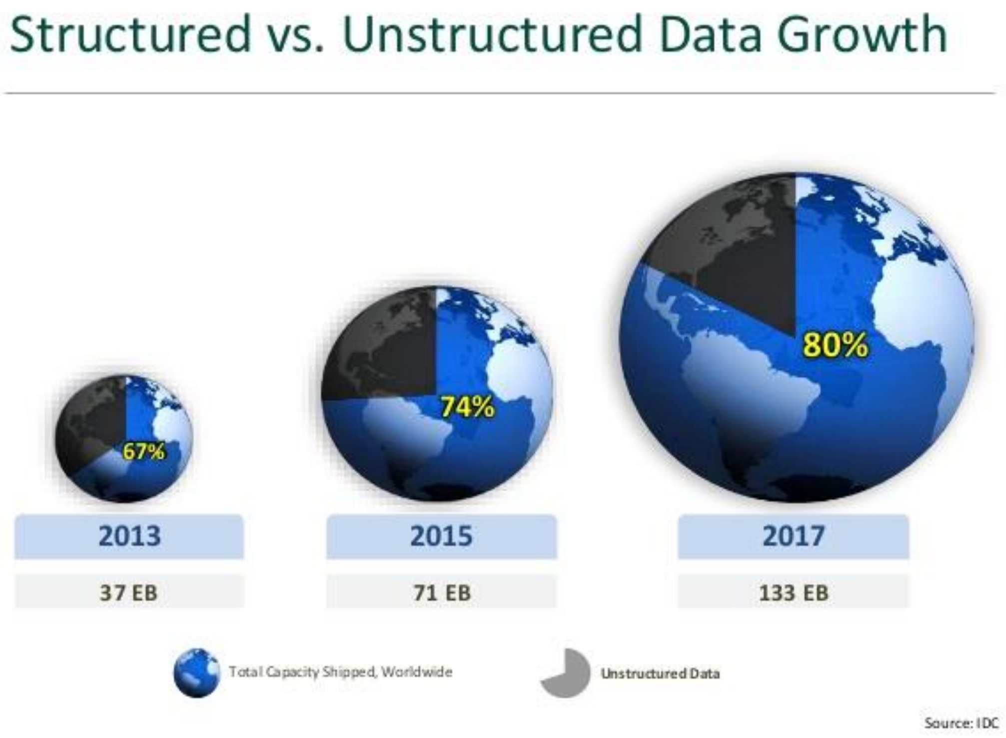
- XML
- JSON
- CSV
- TSV


```
[
  {
    "created_at":"Thu May 07 18:06:23 +0000 2015",
    "id":596375540631646210,
    "id_str":"596375540631646210",
    "text":"Expert usable tips differently the press
    "source":"<a href=\"http://twitterfeed.com\" rel
    "truncated":0,
    "in_reply_to_status_id":null,
    "in_reply_to_status_id_str":null,
    "in_reply_to_user_id":null,
    "in_reply_to_user_id_str":null,
```

Why Hive?

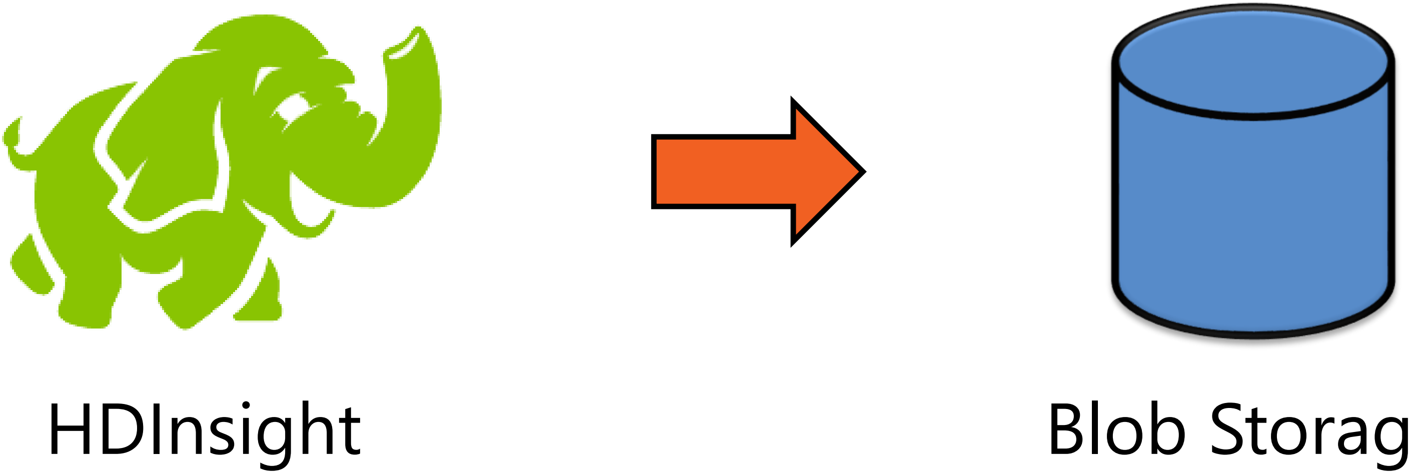
- SQL spoken here (HiveQL)
- ODBC driver
- BI Integration
- Supports only Structured Data

Limitations

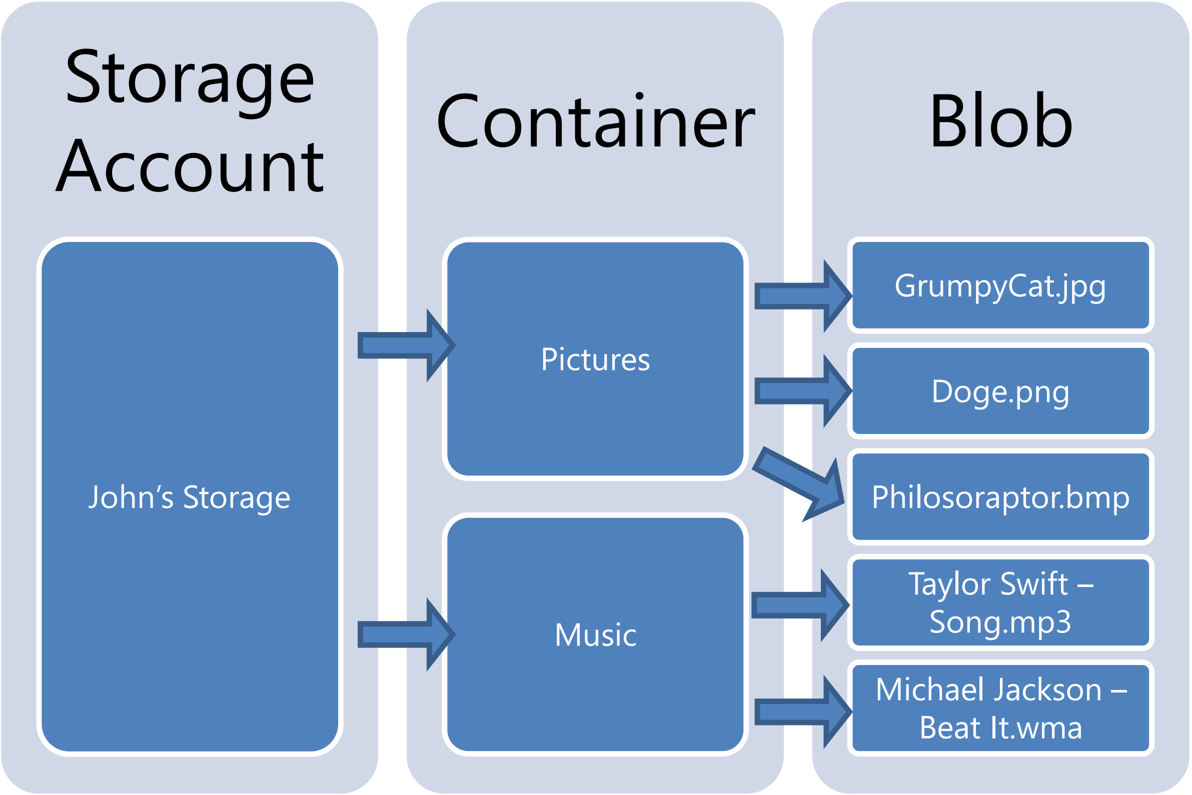


datasciencedojo
unleash the data scientist in you

Azure Blob Storage



Azure Blob Storage



datasciencedojo
unleash the data scientist in you

When to Use Each

vs

vs

C#
Java
MapReduce

Hive

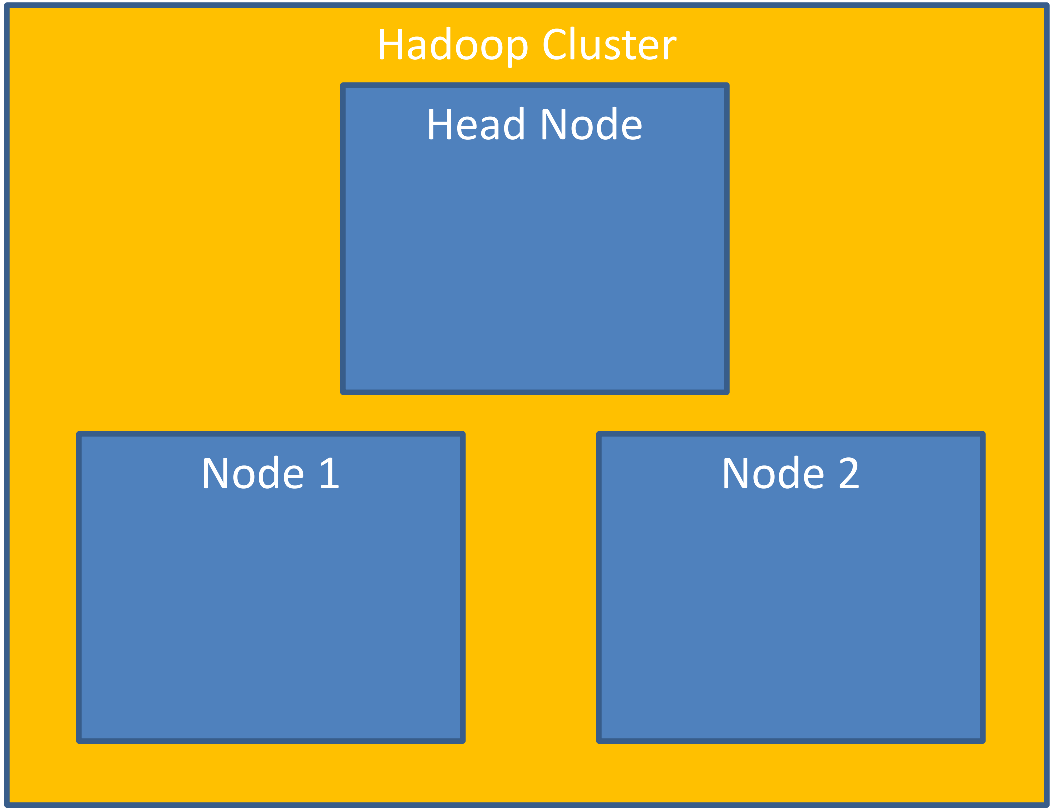
Pig

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

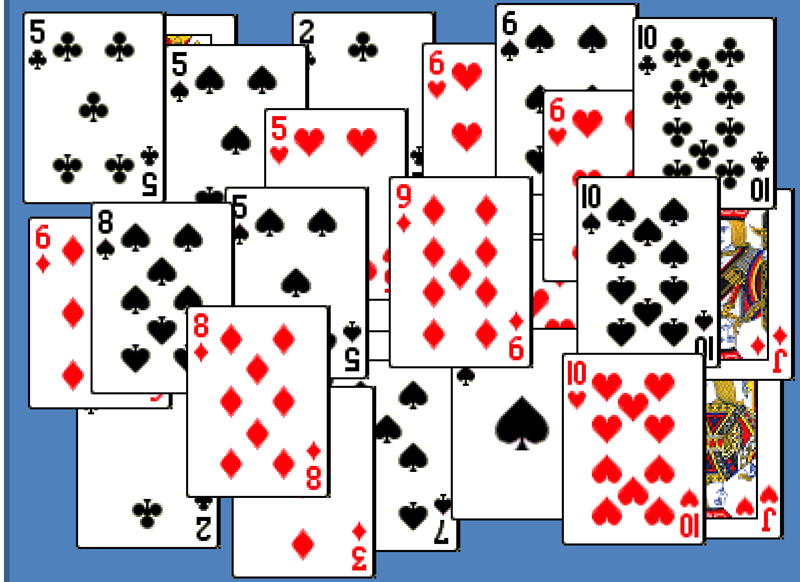
Using a 2 Data Node Cluster



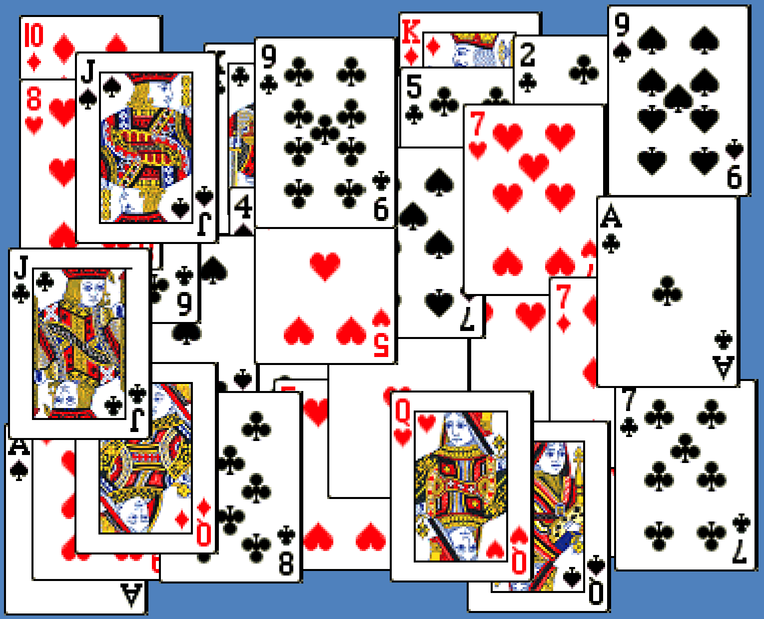
datasciencedojo
unleash the data scientist in you

Mapping: Each Node's HDFS

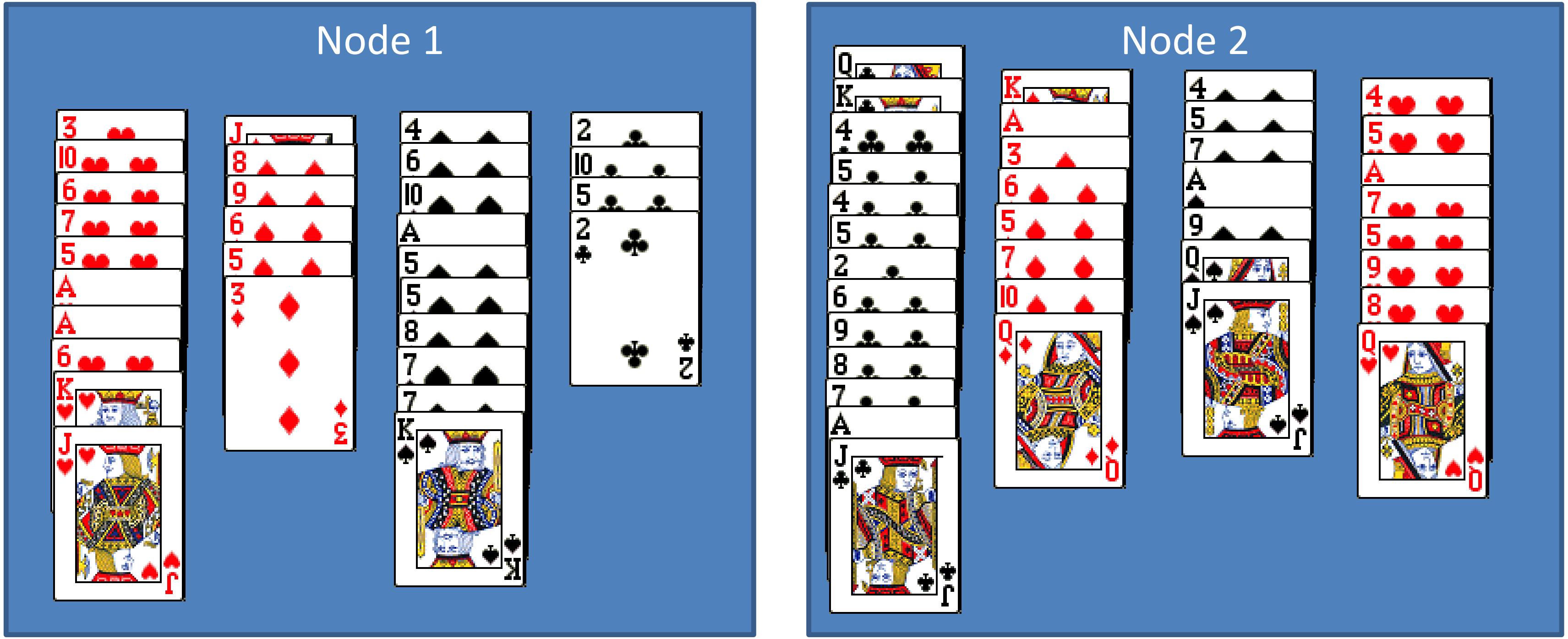
Node 1



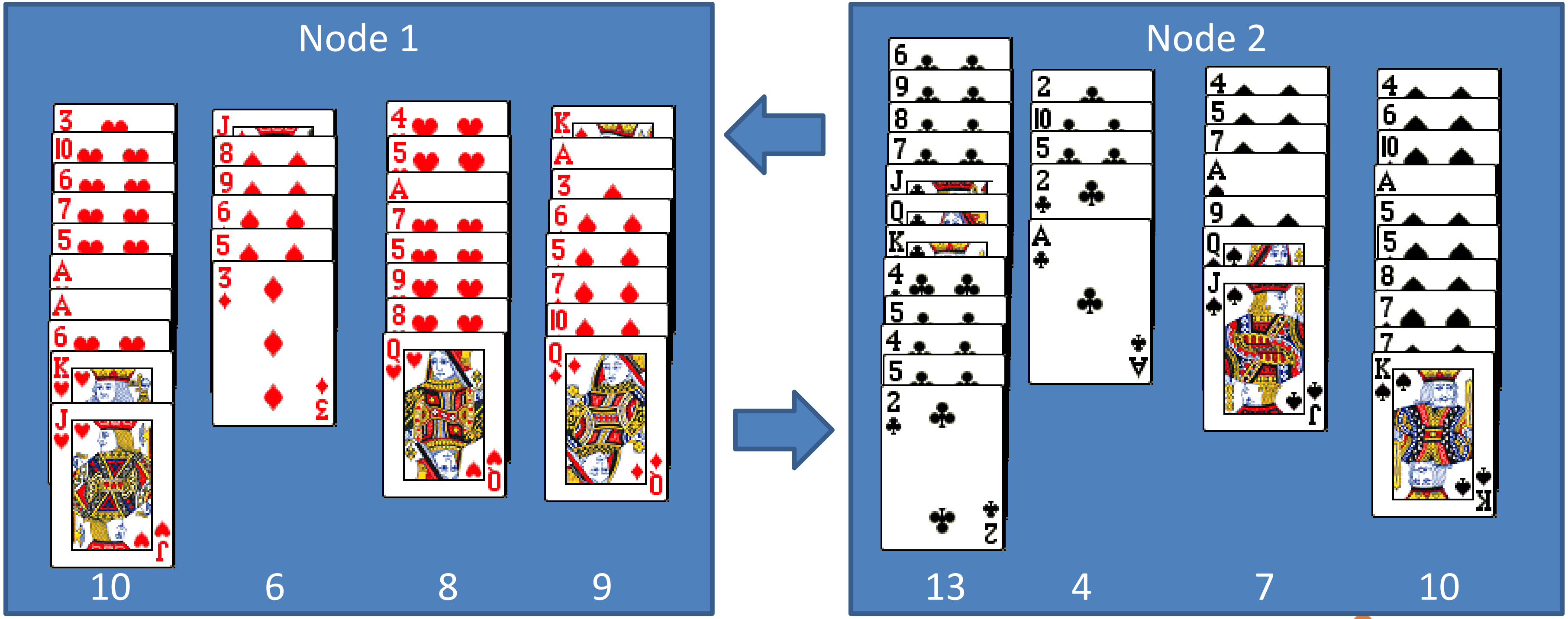
Node 2



Mapping: Node Sorting



Mapping: Node Shuffle, Data Transfer



Mapping: Node Shuffle, Data Transfer

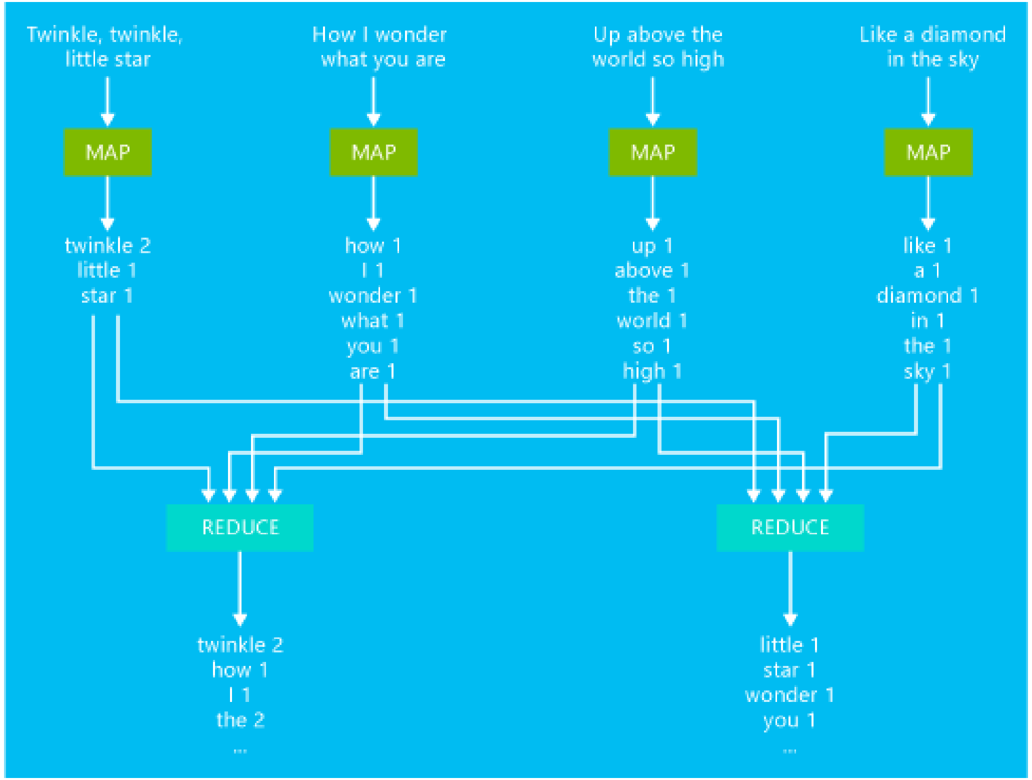
Node 1

Diamonds: 15
Hearts: 18

Node 2

Clubs: 17
Spades: 17

Word Count, via MapReduce()



Source: https://azure.microsoft.com/en-us/documentation/articles/hdinsight-use-mapreduce/

Databases

Rank & Title	IMDb Rating
1. The Shawshank Redemption (1994)	9.2
2. The Godfather (1972)	9.2
3. The Godfather: Part II (1974)	9.0
4. The Dark Knight (2008)	8.9
5. 12 Angry Men (1957)	8.9

movie	year	rating	director
Aliens	1986	8.2	James (I) Cameron
Animal House	1978	7.5	John (I) Landis
Apollo 13	1995	7.5	Ron Howard
Batman Begins	2005	NULL	Christopher Nolan
Braveheart	1995	8.3	Mel (I) Gibson
Fargo	1996	8.2	Ethan Coen
Fargo	1996	8.2	Joel Coen
Few Good Men, A	1992	7.5	Rob Reiner
Fight Club	1999	8.5	David Fincher

Normalization, joining

```
SELECT
   m.name AS movie,
   m.year AS year,
   m.rank AS rating,
   CONCAT(d.first_name, " ", d.last_name)
      AS director
FROM movies AS m
JOIN movies_directors AS md
   ON m.id = md.movie_id
JOIN directors AS d
   ON md.director_id = d.id
;
```

Movie Information

movie	year	rating	director
Aliens	1986	8.2	James (I) Cameron
Animal House	1978	7.5	John (I) Landis
Apollo 13	1995	7.5	Ron Howard
Batman Begins	2005	NULL	Christopher Nolan
Braveheart	1995	8.3	Mel (I) Gibson
Fargo	1996	8.2	Ethan Coen
Fargo	1996	8.2	Joel Coen
Few Good Men, A	1992	7.5	Rob Reiner
Fight Club	1999	8.5	David Fincher

Database = Normalization

director

id	first_name	last_name
24758	David	Fincher
66965	Jay	Roach
72723	William	Shatner

movie_directors

director_id	movie_id
24758	112290
66965	209658
72723	313398

movies

id	name	year	rank
112290	Fight Club	1999	8.5
209658	Meet the Parents	2000	7
210511	Memento	2000	8.7

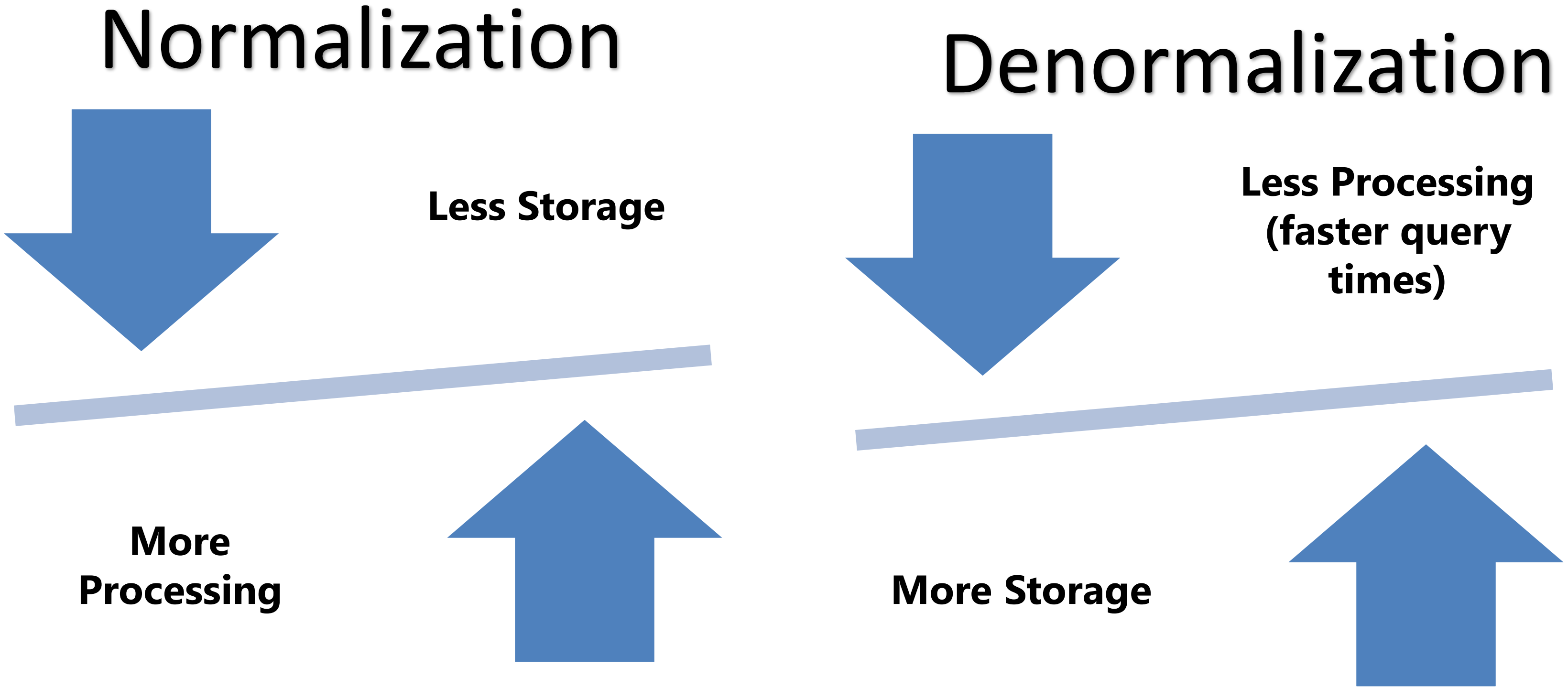
Data Warehouse = Denormalization

student	course	grade
Bart	Computer Science 142	B-
Milhouse	Computer Science 142	B+
Bart	Computer Science 143	C
Lisa	Computer Science 143	A+
Milhouse	Computer Science 143	D-
Ralph	Computer Science 143	B
Lisa	Computer Science 154	A+
Nelson	Computer Science 154	D+
Ralph	Informatics 100	D+

Tables:

- Students Table
- Courses Table
- Roster Table

Trade-Offs


Normalization
Less Storage
More
Processing
Denormalization
Less Processing
(faster query
times)
More Storage

Costs, Storage vs Processing

Processing

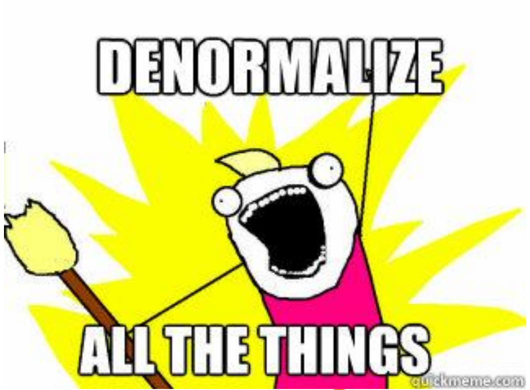
US – N. Virginia	US – N. California	EU – Ireland

Standard On-Demand Instances	Linux/UNIX Usage	Windows Usage
Small (Default)	$0.085 per hour	$0.12 per hour
Large	$0.34 per hour	$0.48 per hour
Extra Large	$0.68 per hour	$0.96 per hour

Storage

US – Standard | US –

Storage	
Tier	**Pricing**
First 50 TB / Month of Storage Used	$0.150 per GB
Next 50 TB / Month of Storage Used	$0.140 per GB
Next 400 TB /	$0.130 per GB



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

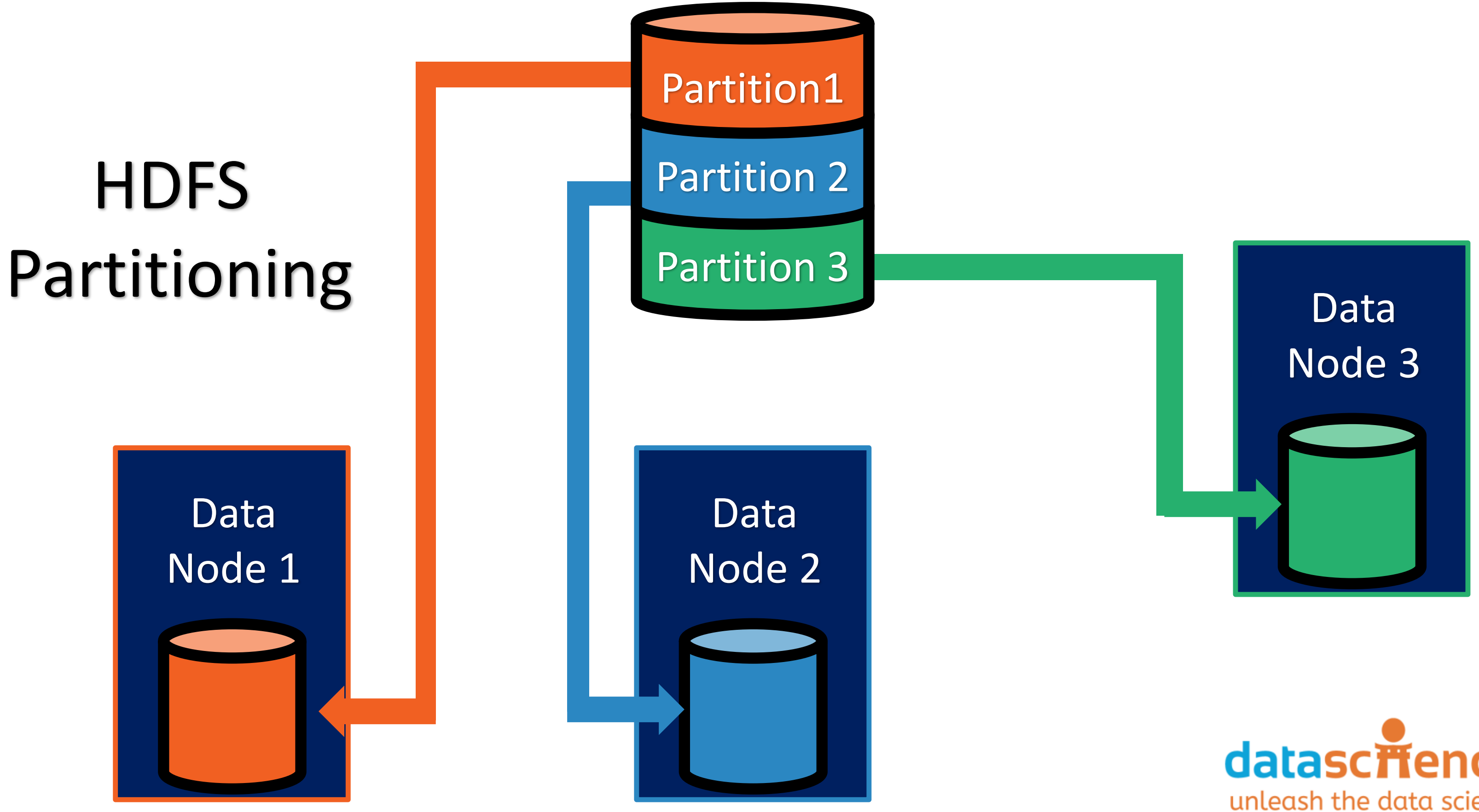
Hadoop 2.0 with Yarn & Tez

- 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

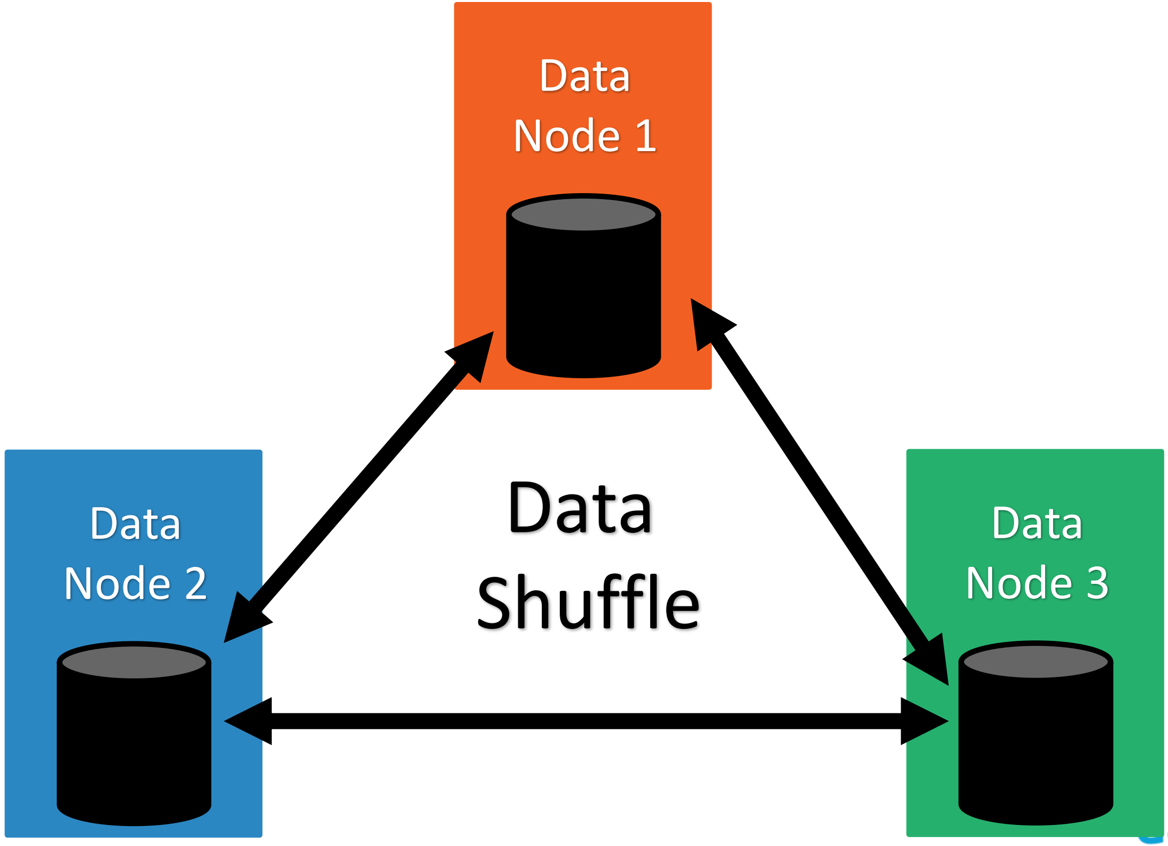
mahout

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

Distributed Random Forest

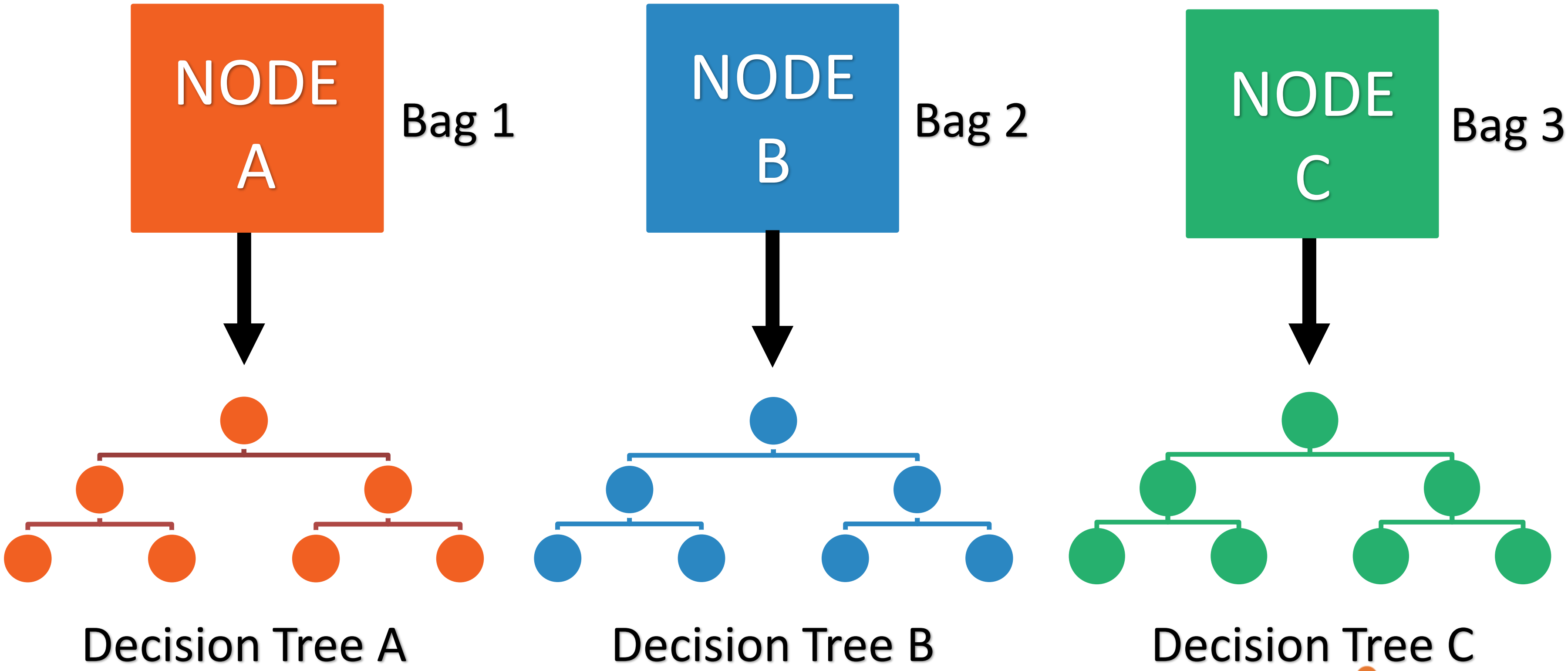


Distributed Random Forest

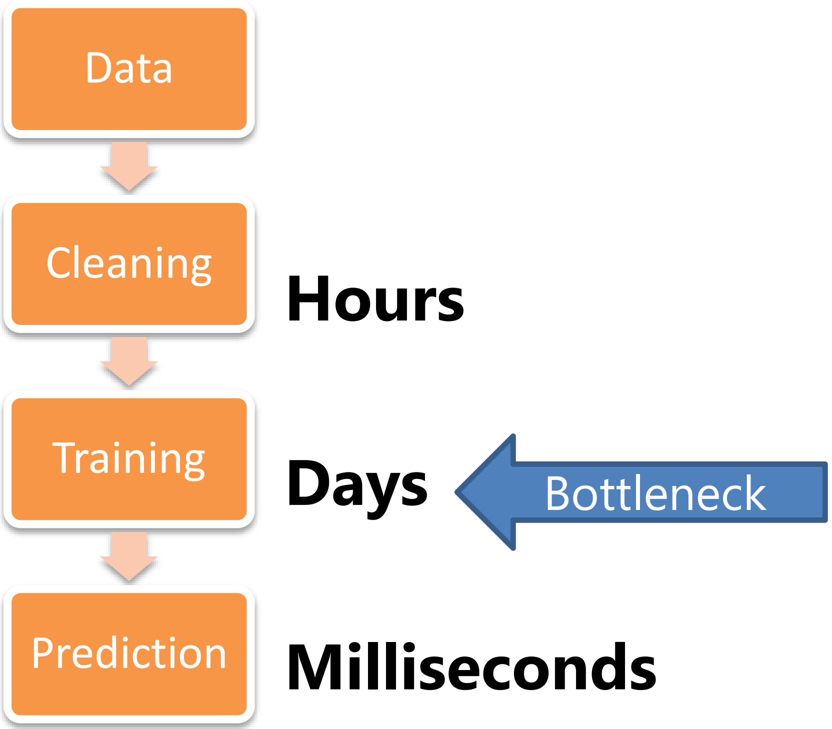


datasciencedojo
unleash the data scientist in you

Distributed Random Forest



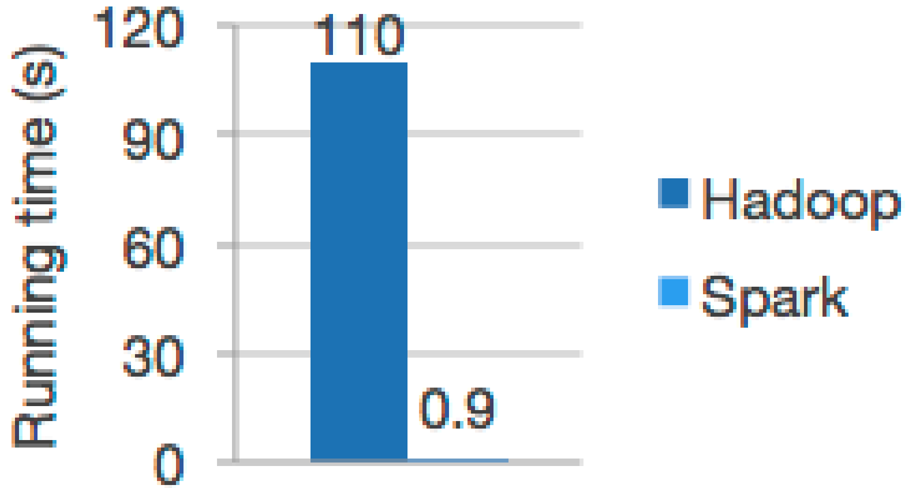
Processing Times - Machine Learning



- 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

datasciencedojo
unleash the data scientist in you

Spark



In-Memory: 100x times faster than Hadoop

Spark

3x faster on 10x few machines

Datona GraySort Benchmark: Sort 100 TB of data

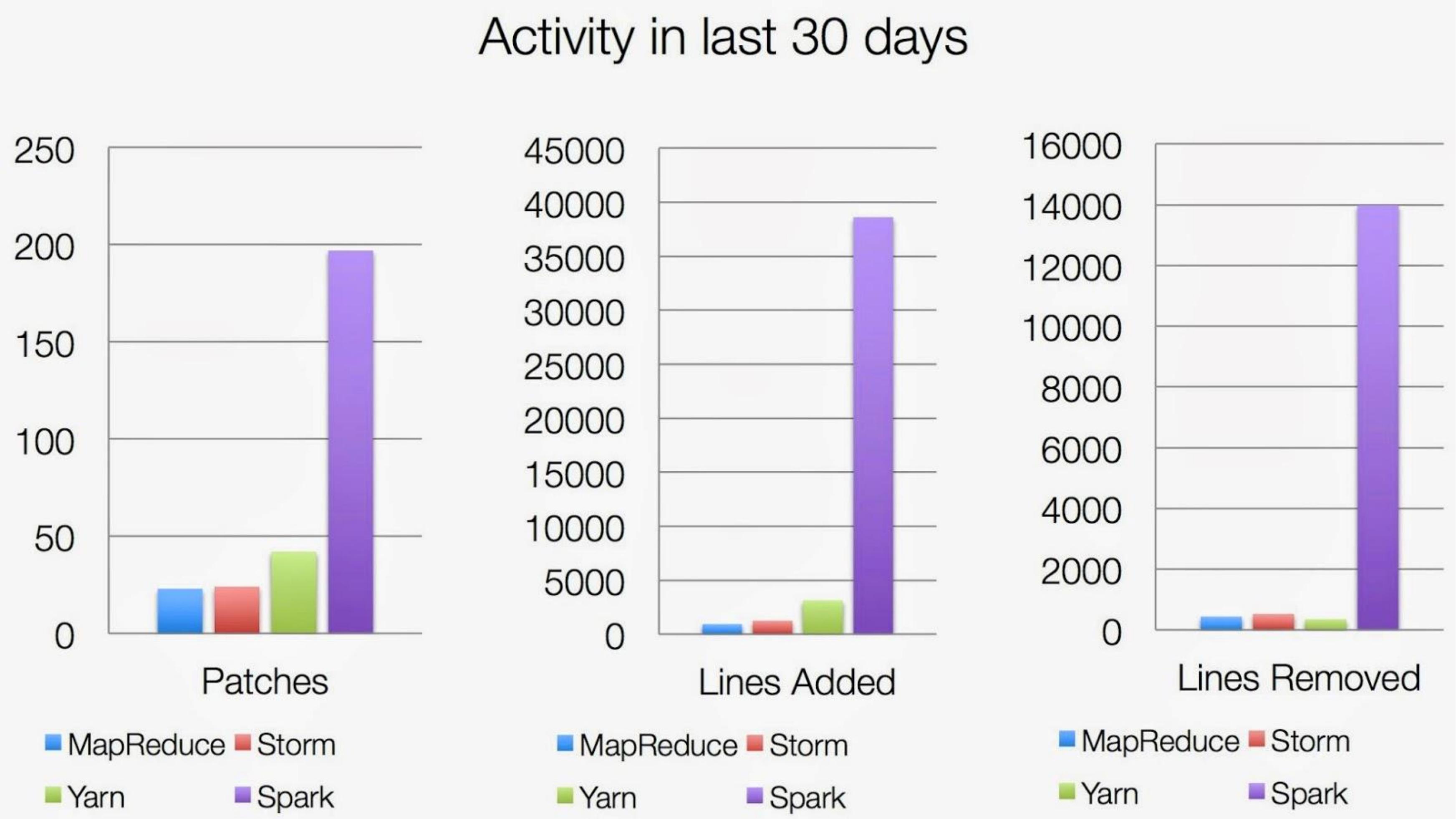
Previous World Record:

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

2014:

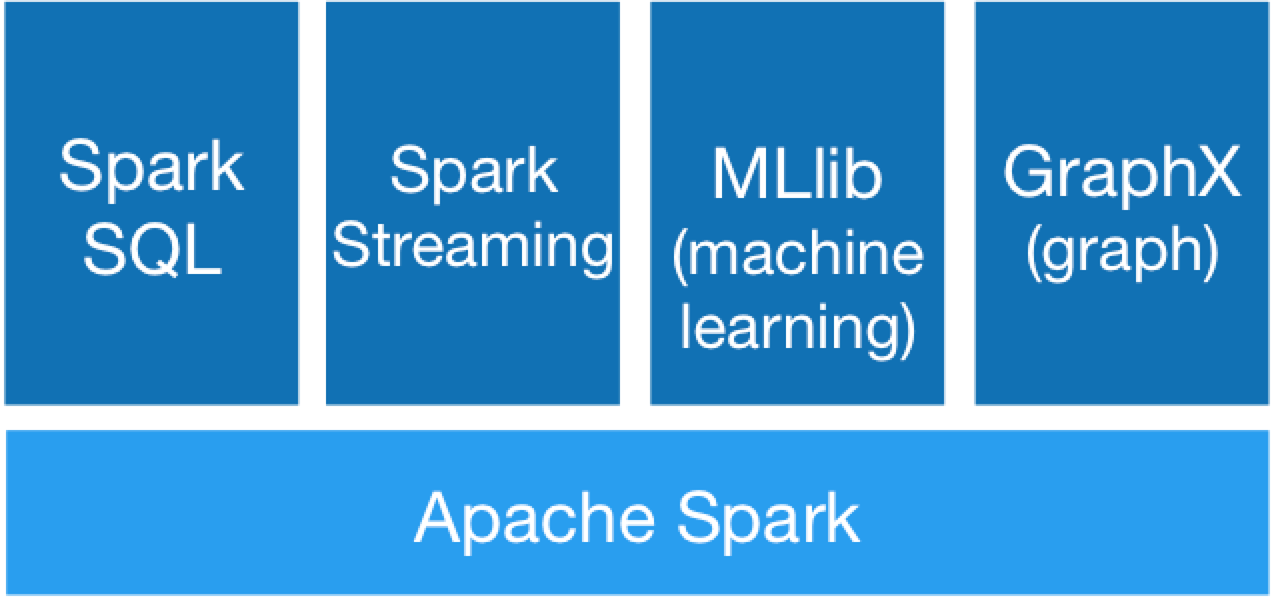
- Method: Spark
- Databricks
- 23 Minutes
- 206 Nodes

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

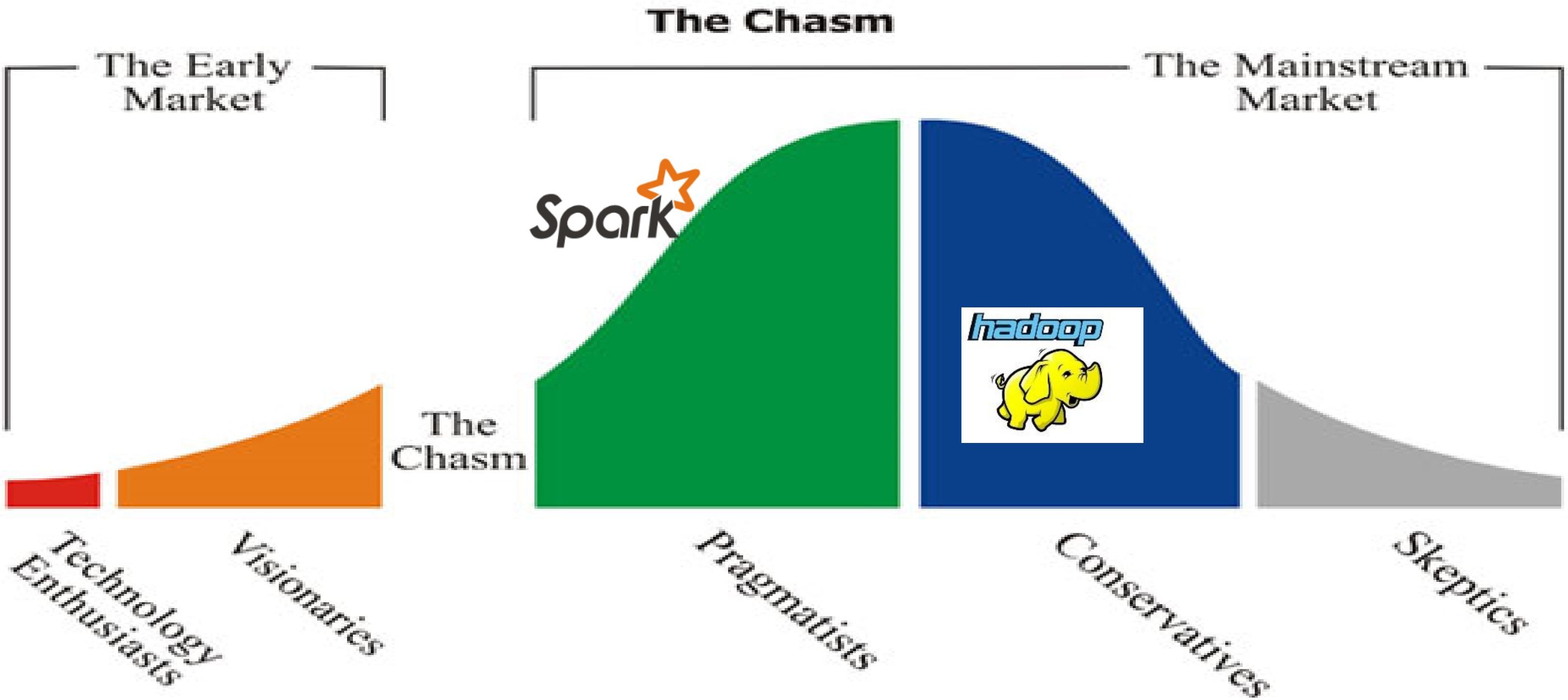


Source: Xiangrui Meng, Data Bricks

Spark


Spark SQL
Spark Streaming
MLlib (machine learning)
GraphX (graph)
Apache Spark

Technology adoption life cycle



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

datasciencedojo
unleash the data scientist in you

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
unleash the data scientist in you