Big Data Engineering With MapReduce and Hive

Data Science Dojo

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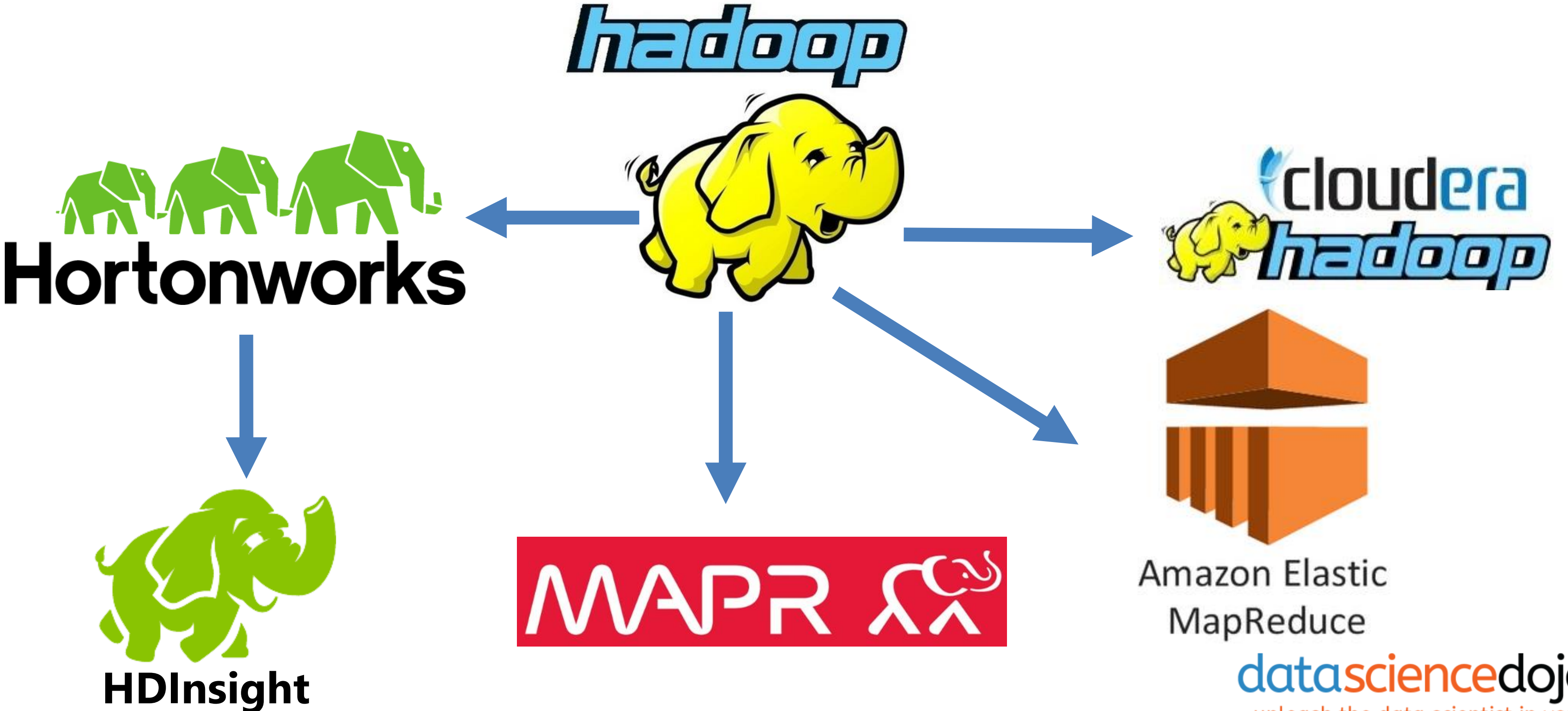
Agenda

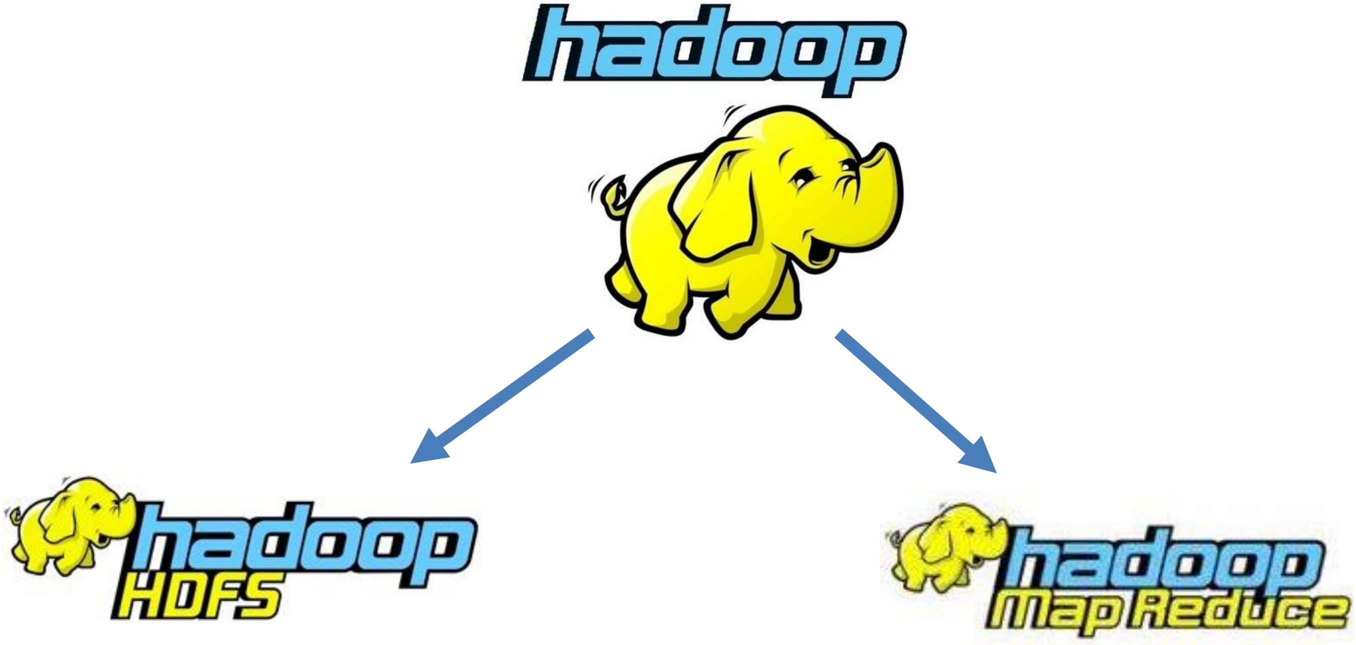
hadoop

HIVE

Hadoop Implementations

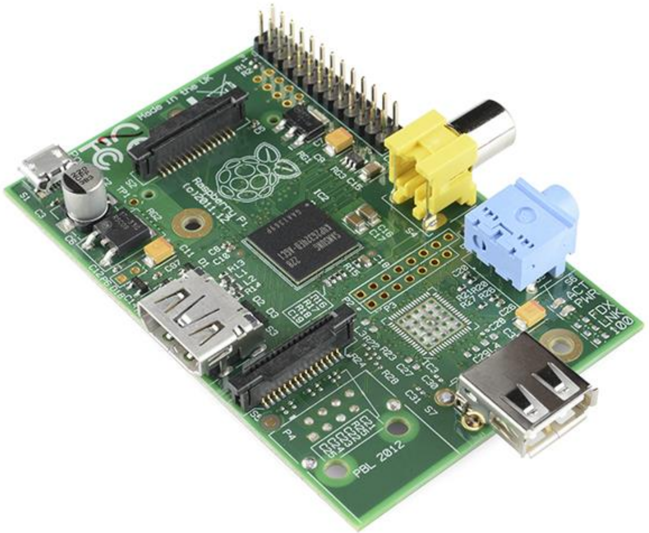


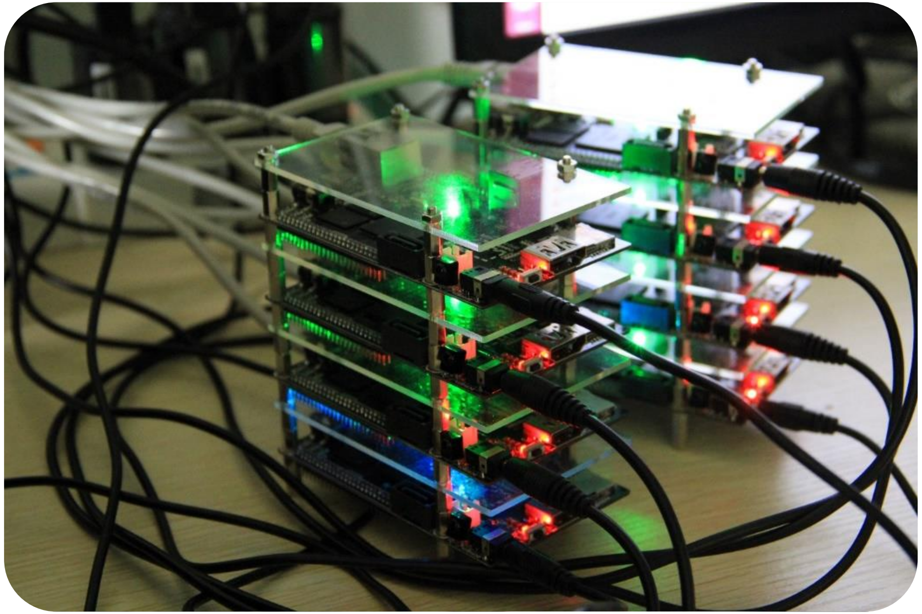
Hadoop



Turn Back The Clock, The Mainframe

Distributed Computing





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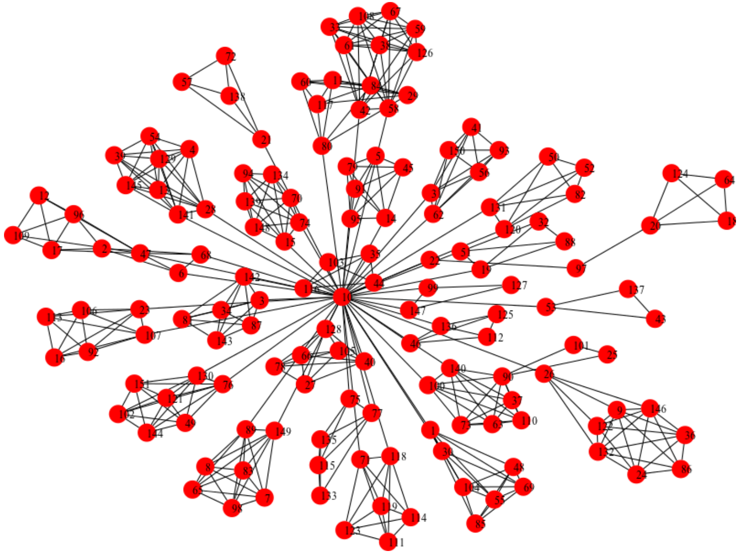
Cloud Computing



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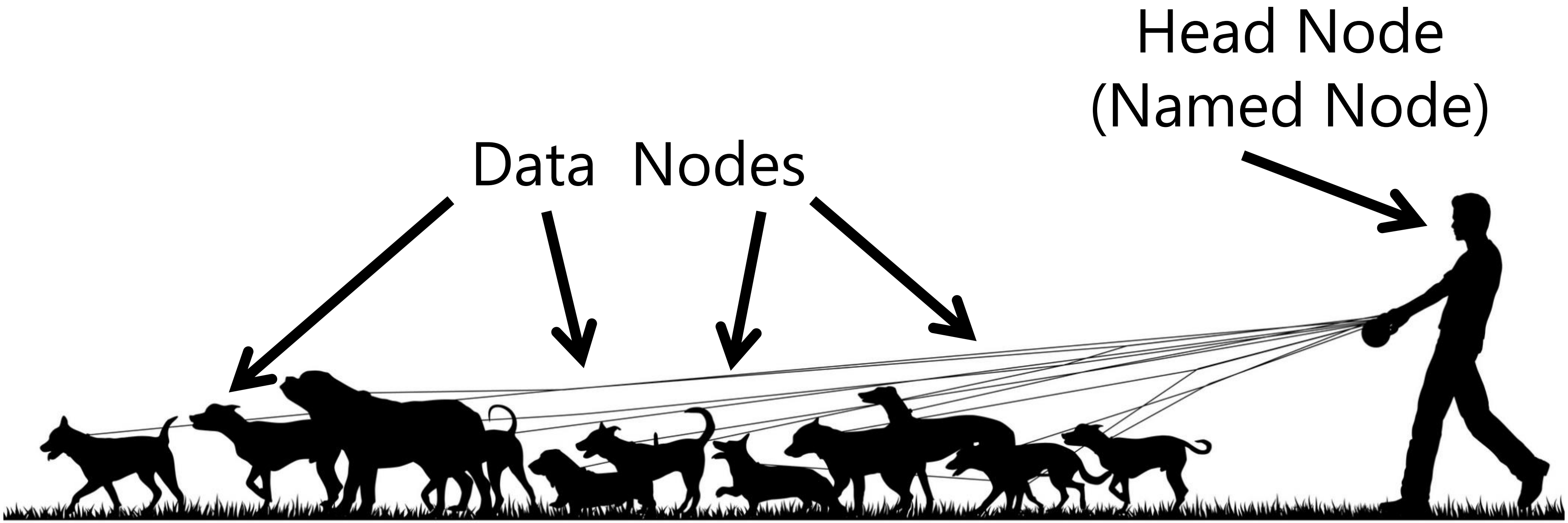
If dogs were servers...



HDFS & MapReduce

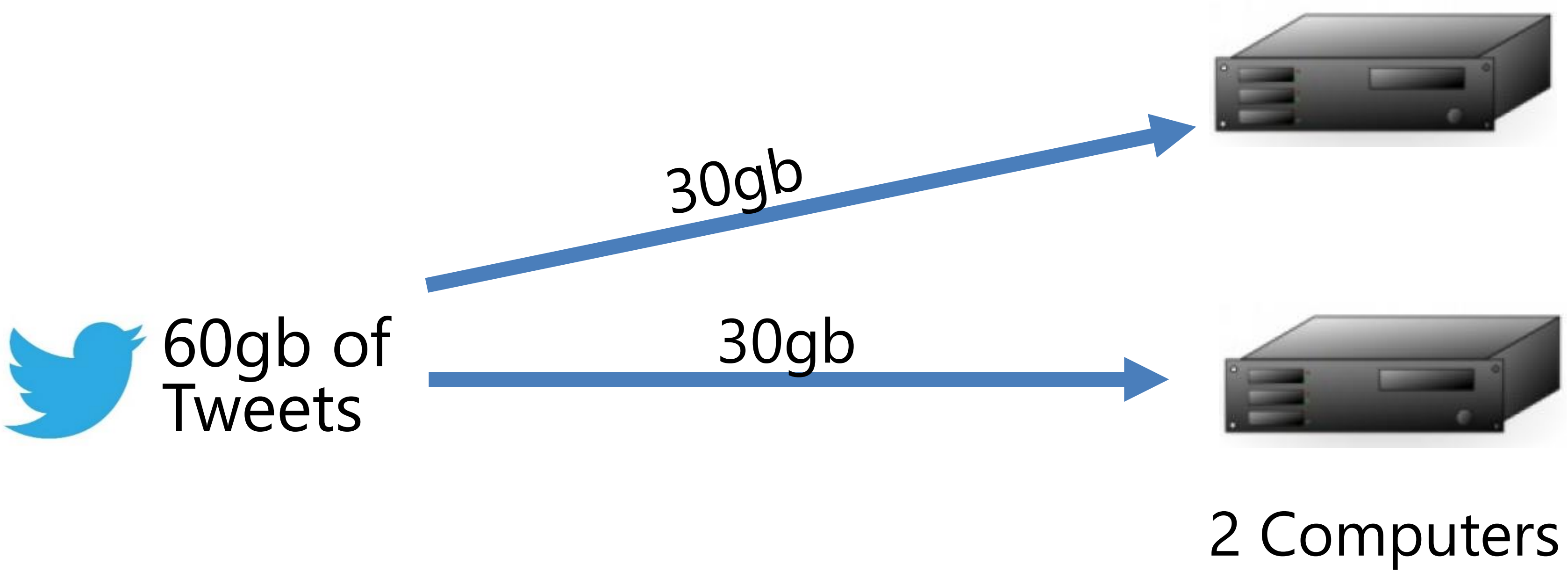
60gb of Tweets

60gb

1 Computer

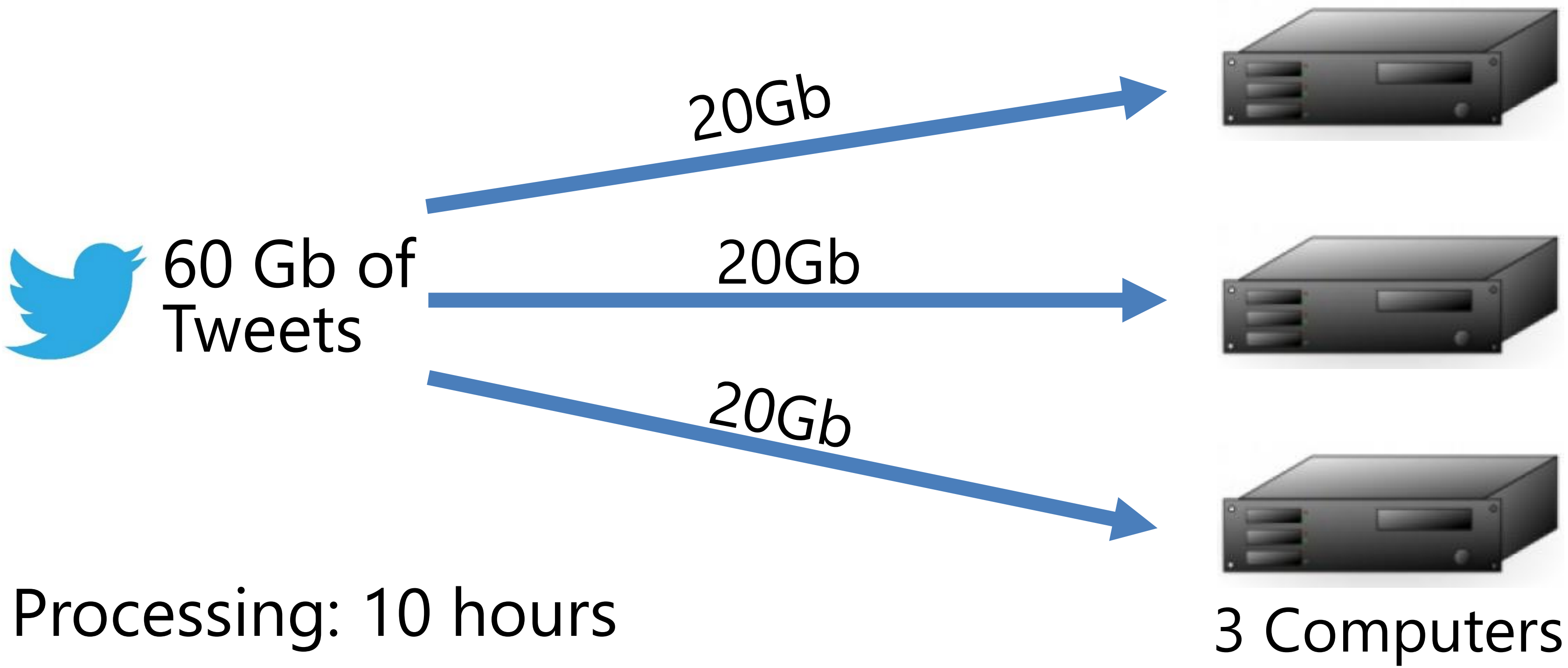
Processing: 30 hours

HDFS & MapReduce



Processing: 15 hours

HDFS & MapReduce



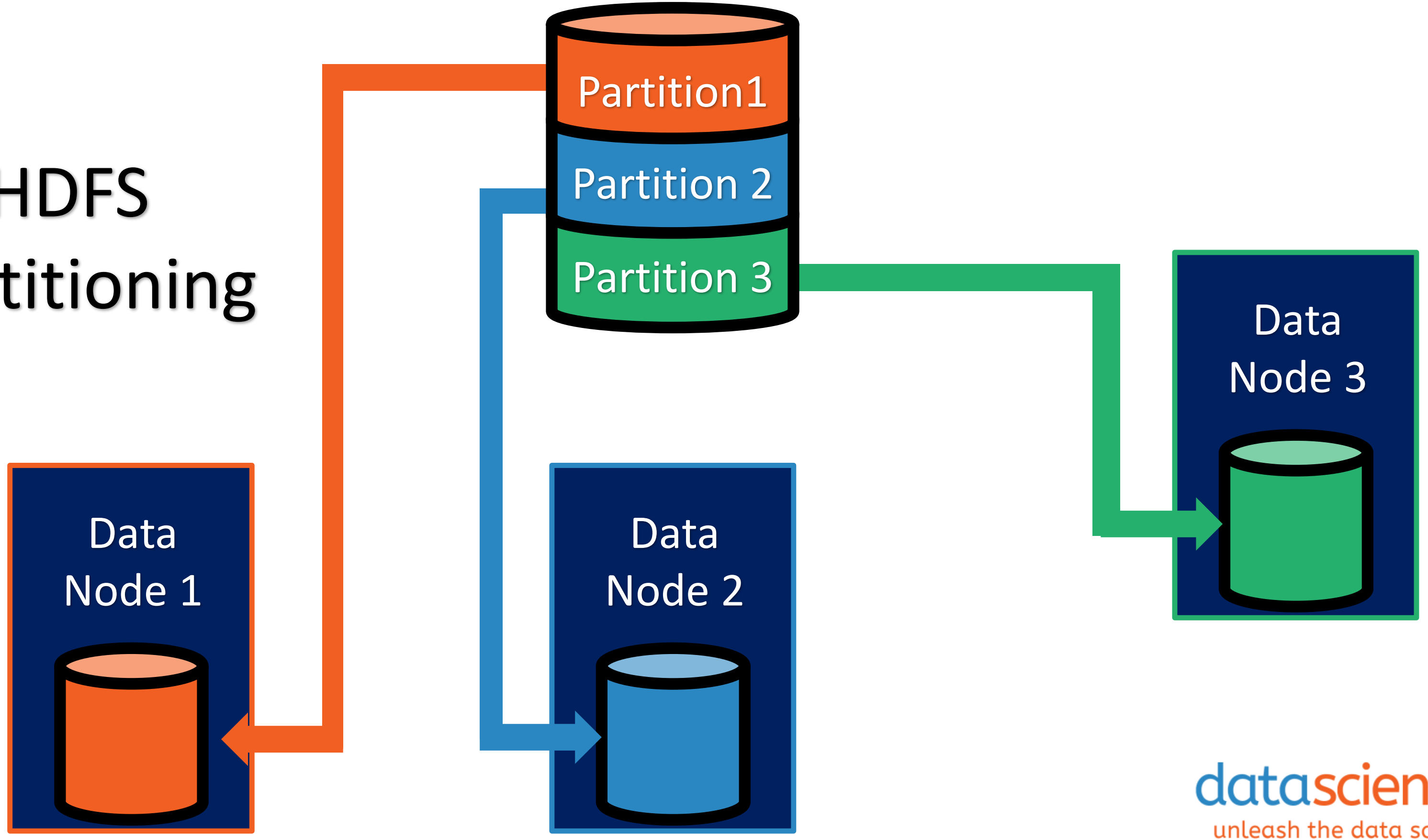
Processing: 10 hours

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



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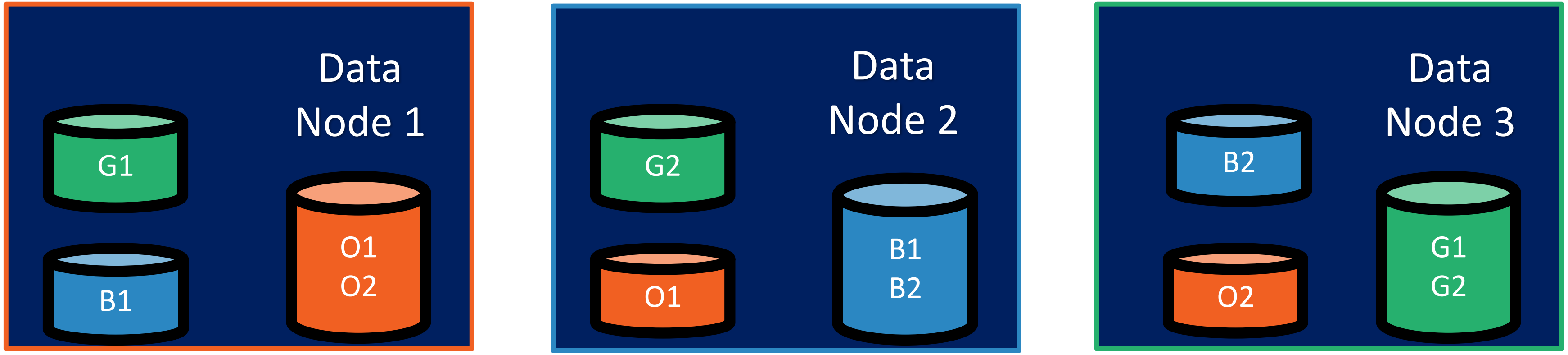
HDFS Redundancy



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);
      }
    }
  }
```

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

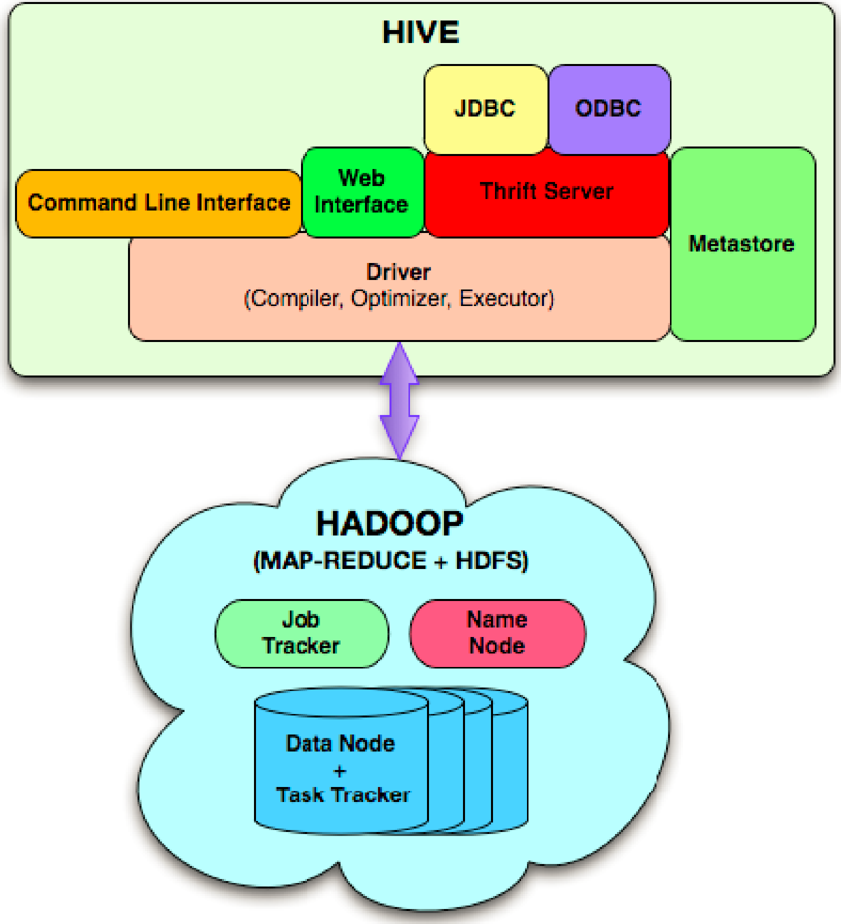
Oozie: Workflow management

Pig: Simpler scripting for MapReduce transformations

Sqoop: Data import and export

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

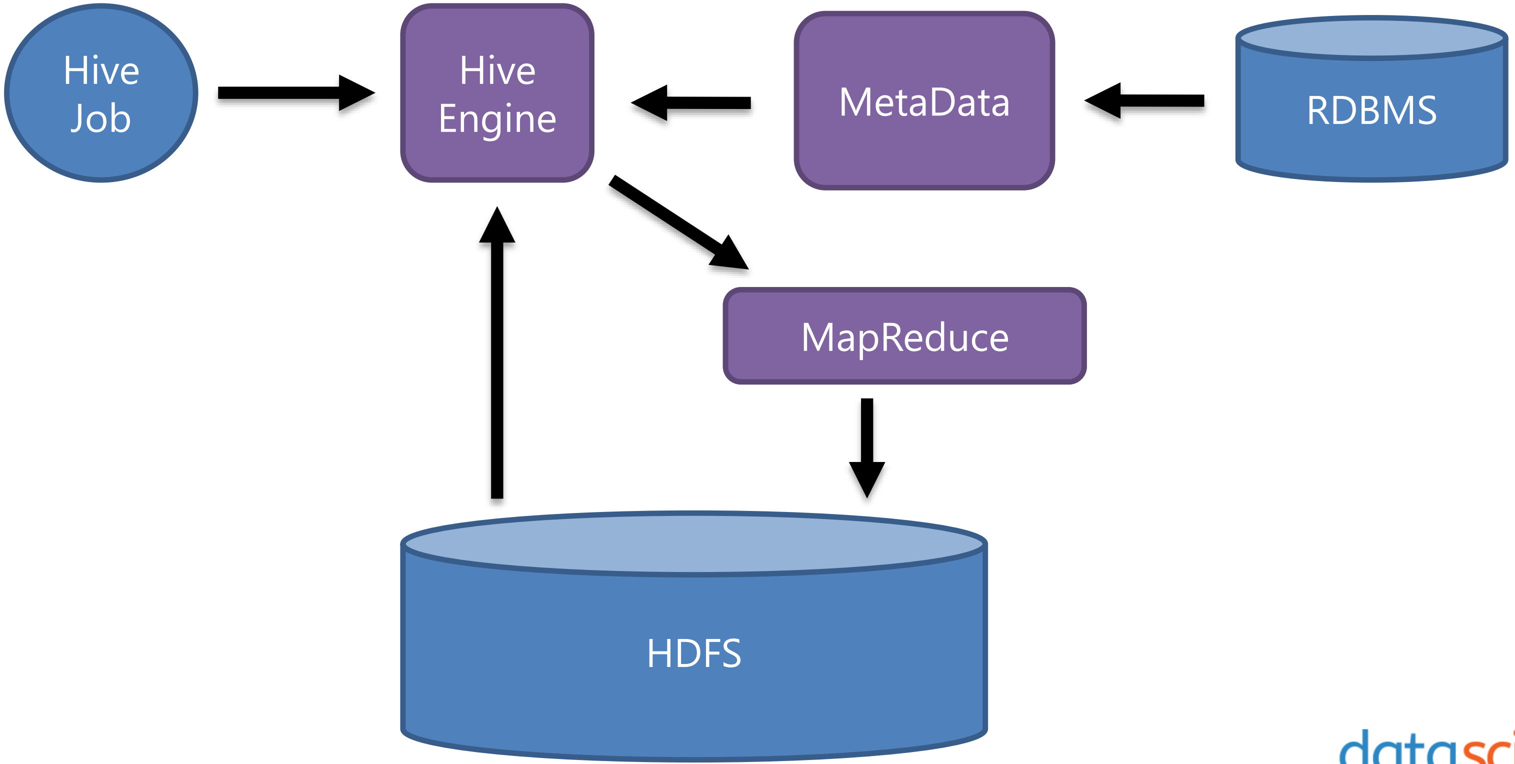
Zookeeper: Coordinates processes in distributed systems

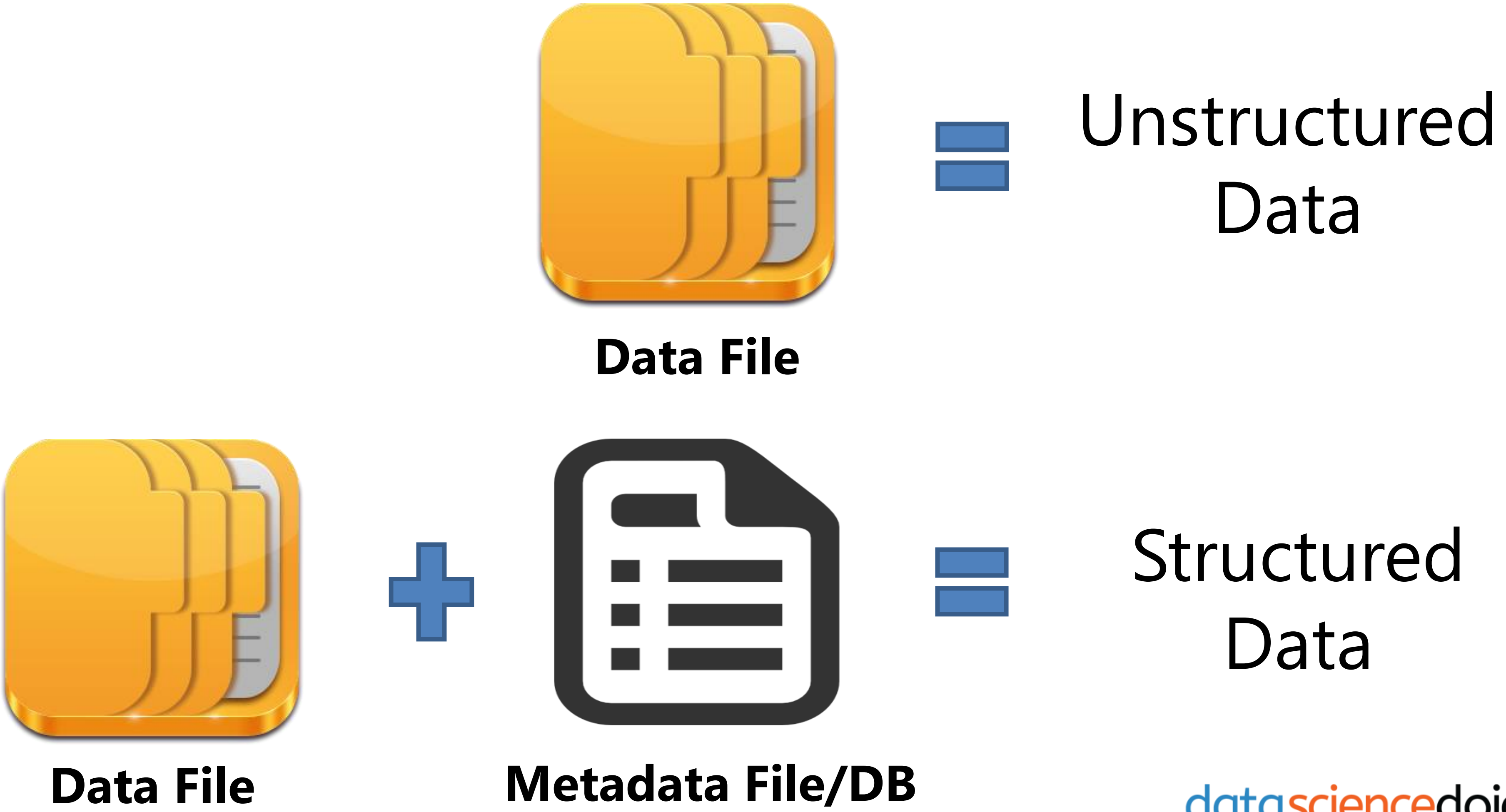

HIVE
JDBC
ODBC
Command Line Interface
Web Interface
Thrift Server
Metastore
Driver
(Compiler, Optimizer, Executor)
HADOOP
(MAP-REDUCE + HDFS)
Job Tracker
Name Node
Data Node
+
Task Tracker

Hive Jobs

HiveQL Statement → Translation & Conversion → MapReduce Job

Hive Architecture




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 pres
    "source":"<a href=\"http://twitterfeed.com\" re
    "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,
```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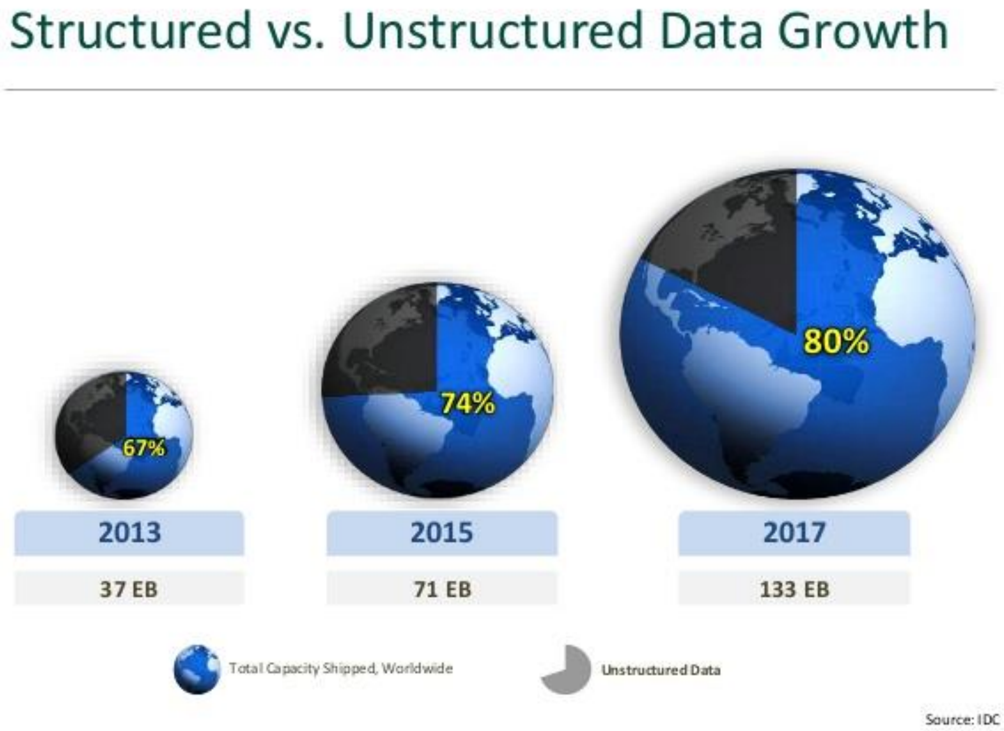
Why Hive?

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

Limitations



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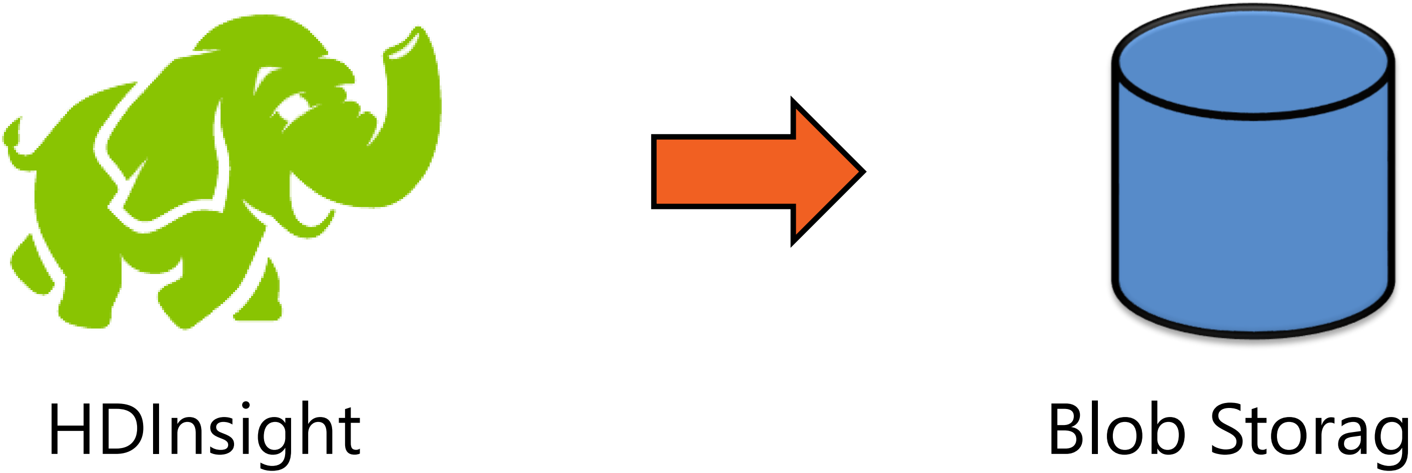
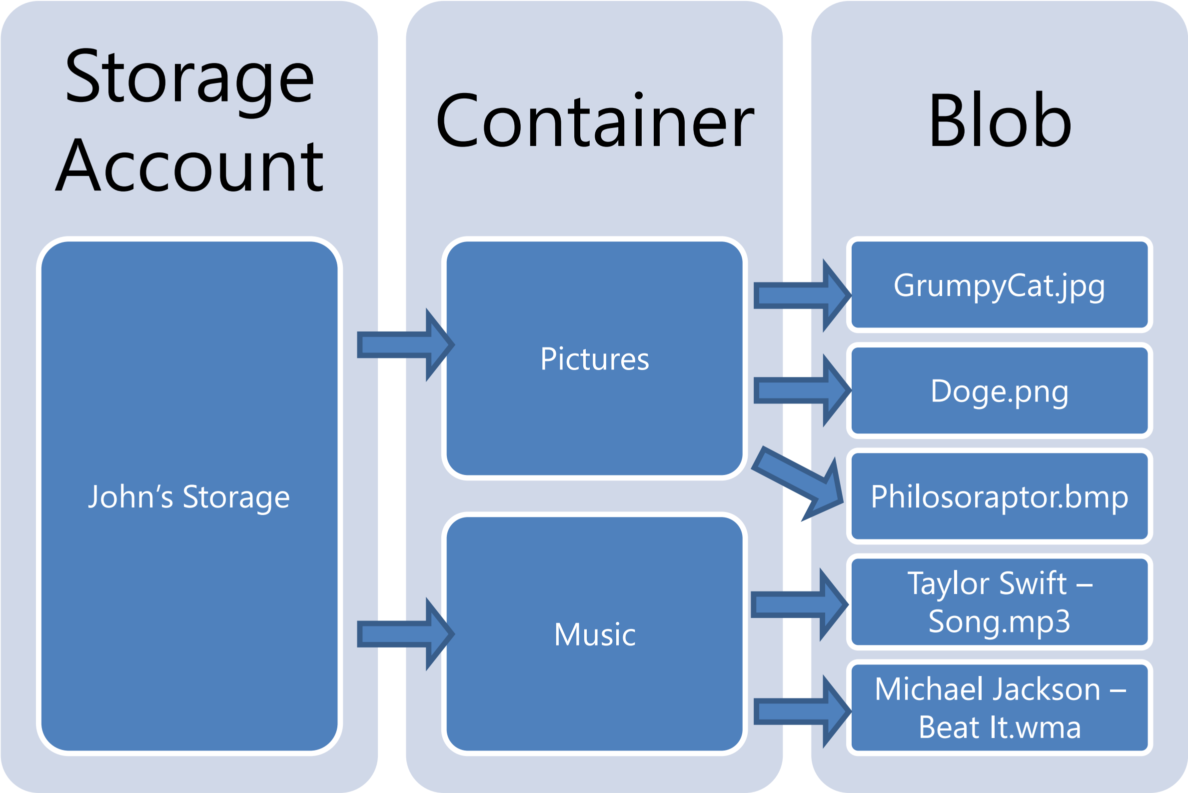
Azure Blob Storage



Azure Blob Storage



When to Use Each

VS

VS

C#
Java
MapReduce

Hive

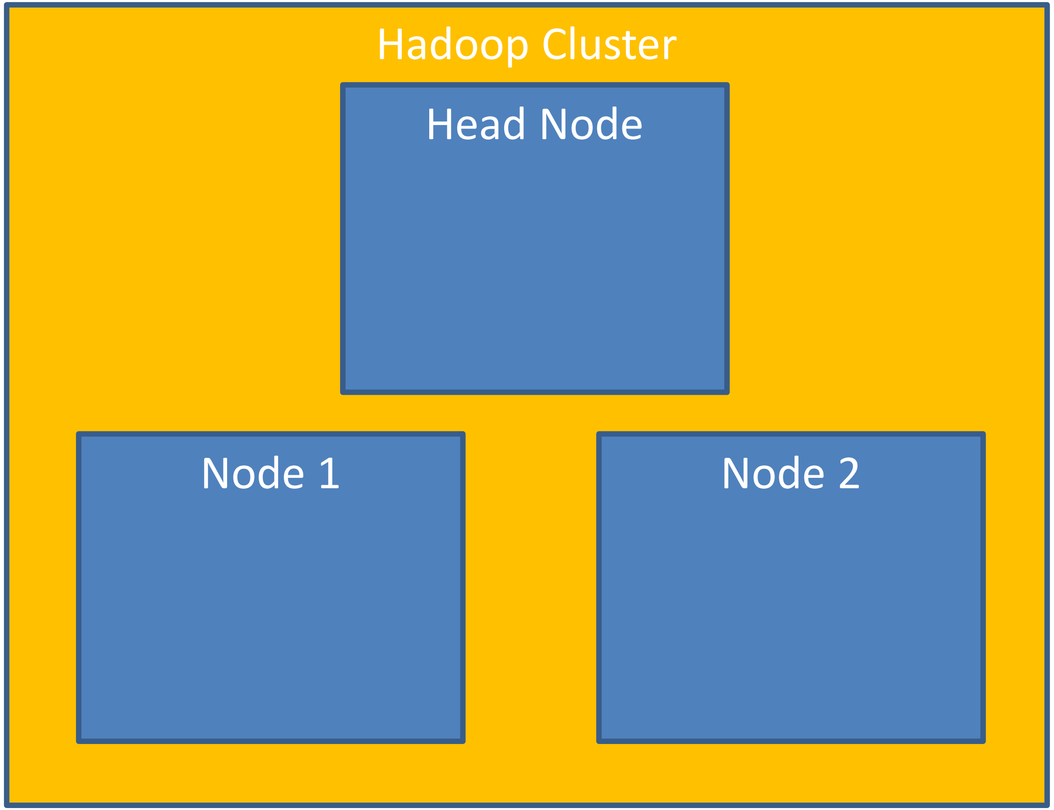
Pig

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 suite represents an attribute of the data

Using a 2 Data Node Cluster



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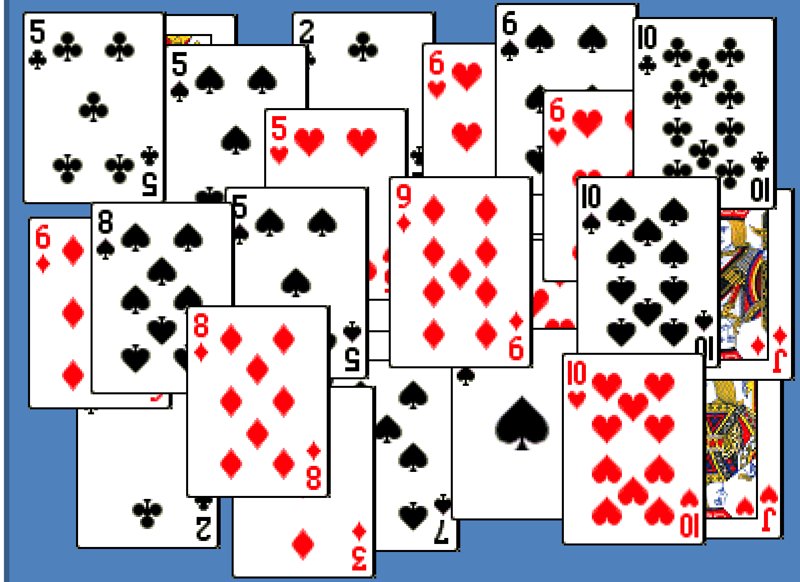
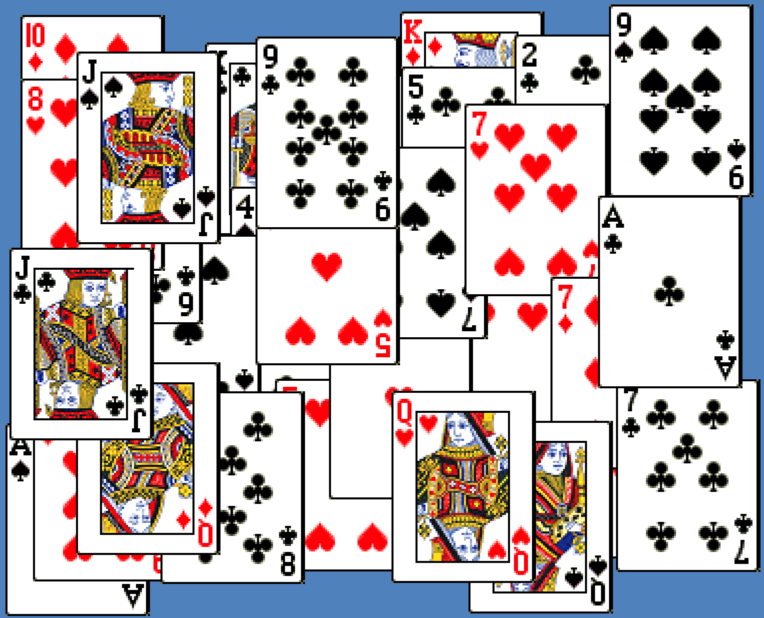
Mapping: Each Node's HDFS

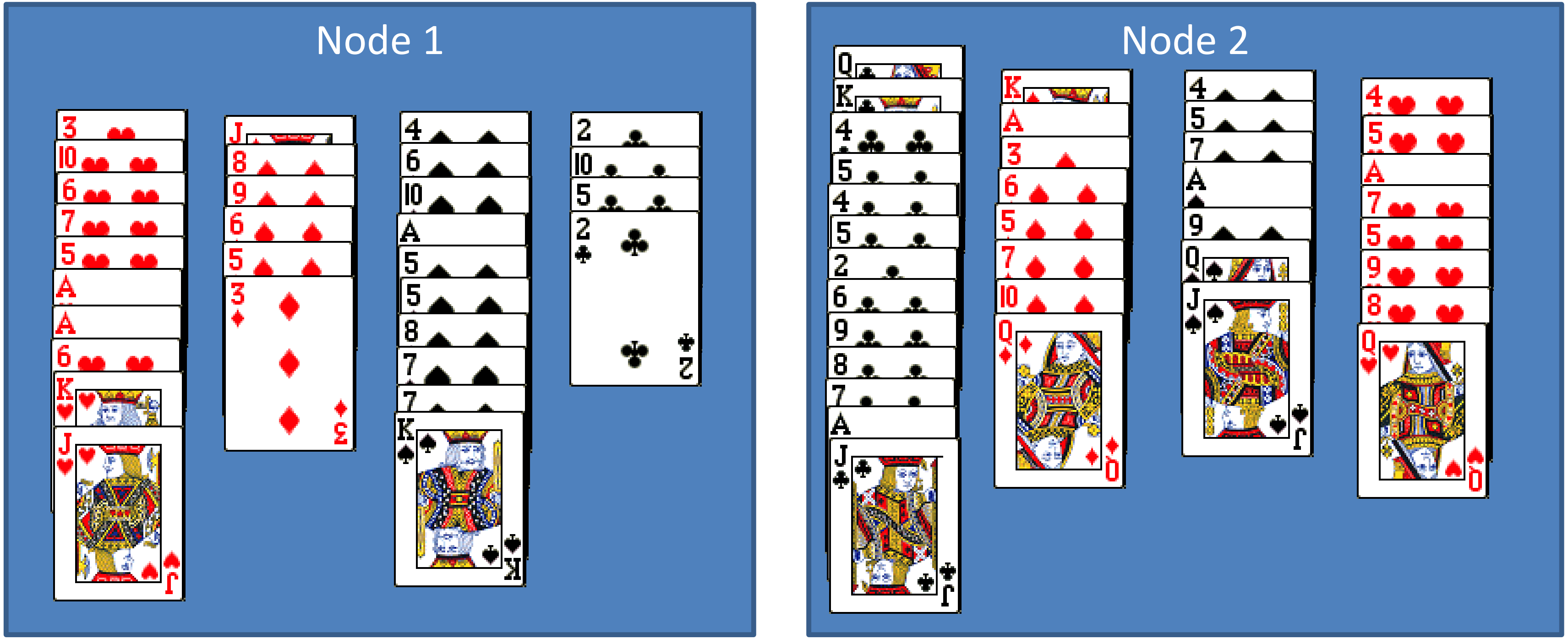
Node 1



Node 2



Mapping: Node Sorting



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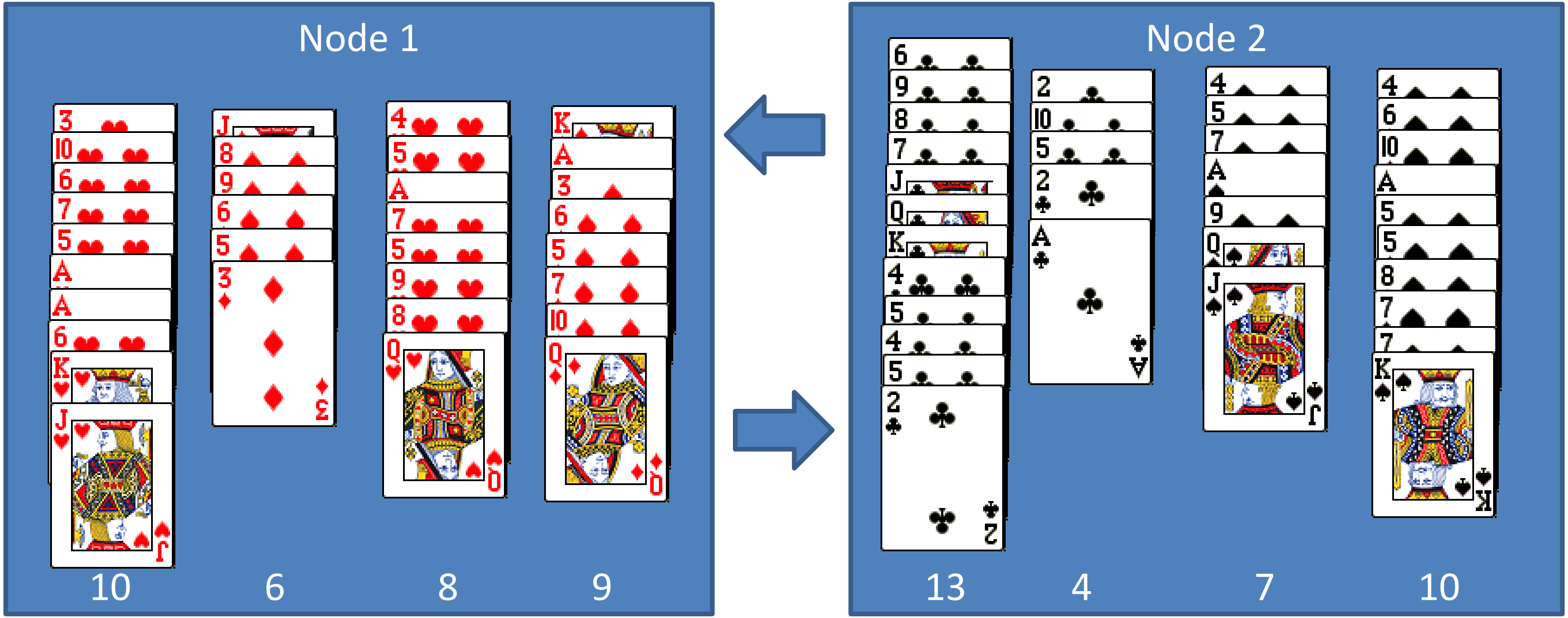
Mapping: Node Shuffle, Data Transfer



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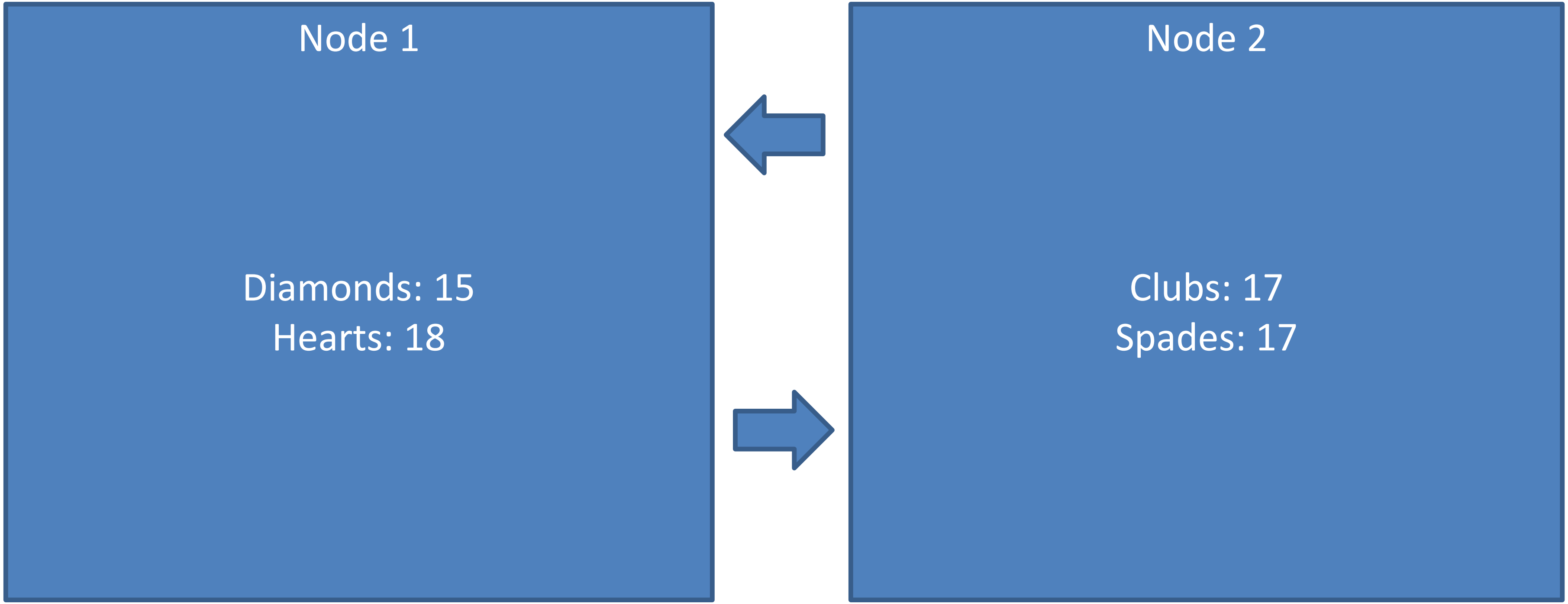
Mapping: Node Shuffle, Data Transfer



Database = Normalization

select * from **courses**;

id	name	teacher_id
10001	Computer Science 142	1234
10002	Computer Science 143	5678
10003	Computer Science 154	9012
10004	Informatics 100	1234

select * from **students**;

id	name	email	password
123	Bart	bart@fox.com	bartman
404	Ralph	ralph@fox.com	catfood
456	Milhouse	milhouse@fox.com	fallout
789	Nelson	muntz@fox.com	haha!
888	Lisa	lisa@gmail.com	vegan

select * from **grades**;

student_ids	course_id	grade
123	10001	B-
123	10002	C
456	10001	B+
888	10002	A+
888	10003	A+
404	10004	D+
456	10002	D-
404	10002	B
789	10003	D+

Normalization, joining

```
select
    g.student_id,
    c.name as course,
    g.grade as grade
from grades as g
join courses c
    on g.course_id = c.id
join students s
    on g.student_id = s.id
;
```

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+

Data Warehouse = Denormalization

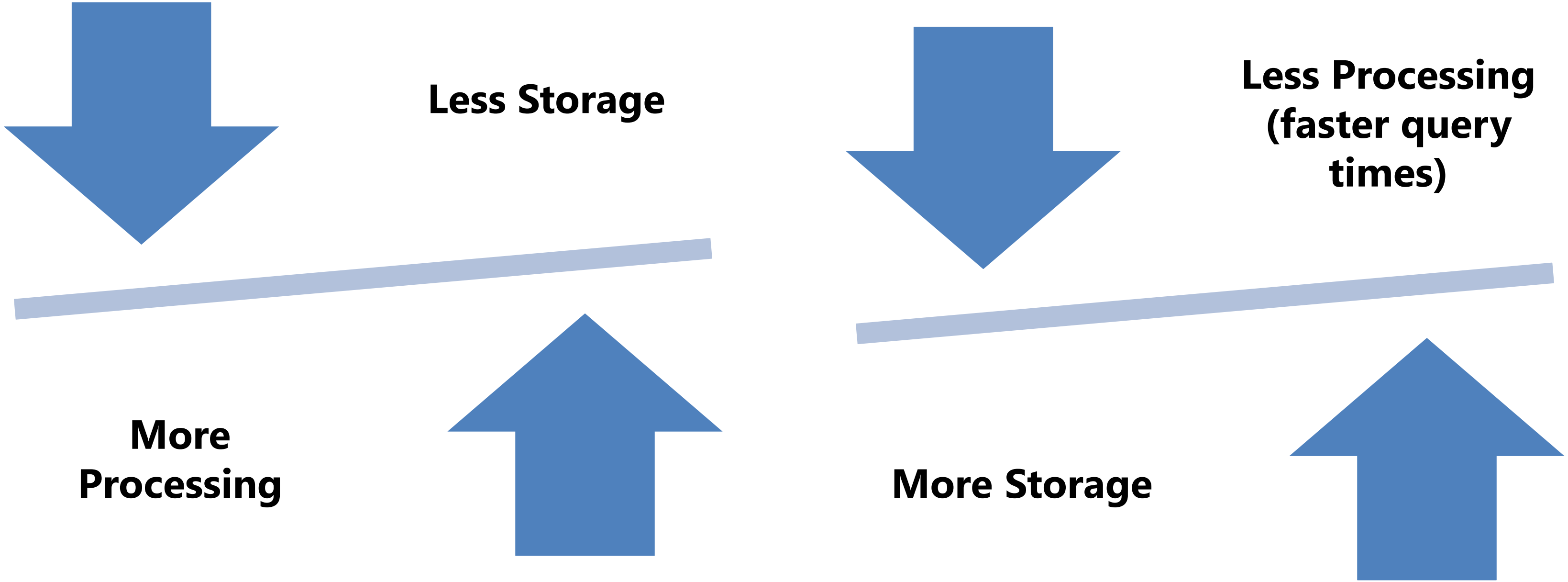
student	course	grade
Bart	Computer Science 142	B-
Milhouse	Computer Science 142	B+
Bart	Computer Science 143	C
Lisa	Computer Science 143	A+
Milhouse	Computer Science 143	D-
Ralph	Computer Science 143	B
Lisa	Computer Science 154	A+
Nelson	Computer Science 154	D+
Ralph	Informatics 100	D+

Tables:
- Students Table
- Courses Table
- Roster Table

Trade-Offs

Normalization

Denormalization



Costs, Storage vs Processing

Storage

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

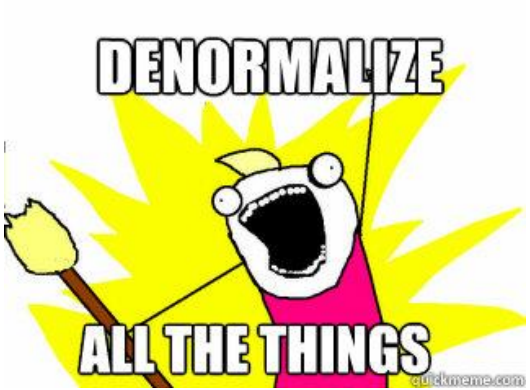
Standard On-Demand Instances	Linux/UNIX Usage	Windows Usage
Small (Default)	$0.085 per hour	$0.12 per hour
Large	$0.34 per hour	$0.48 per hour
Extra Large	$0.68 per hour	$0.96 per hour

Processing

US – Standard | US –

Storage

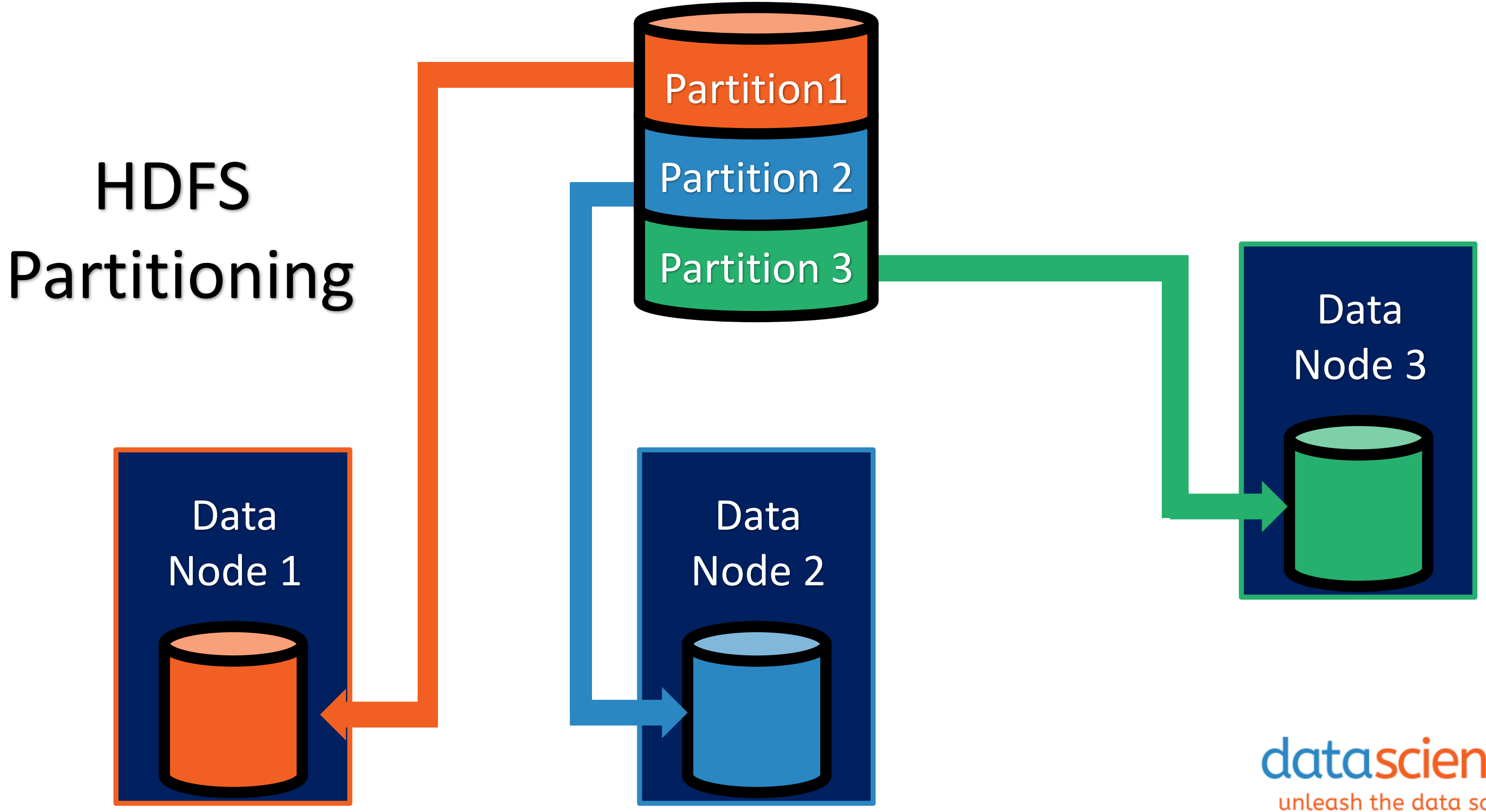
Tier	Pricing
First 50 TB / Month of Storage Used	$0.150 per GB
Next 50 TB / Month of Storage Used	$0.140 per GB
Next 400 TB /	$0.130 per GB



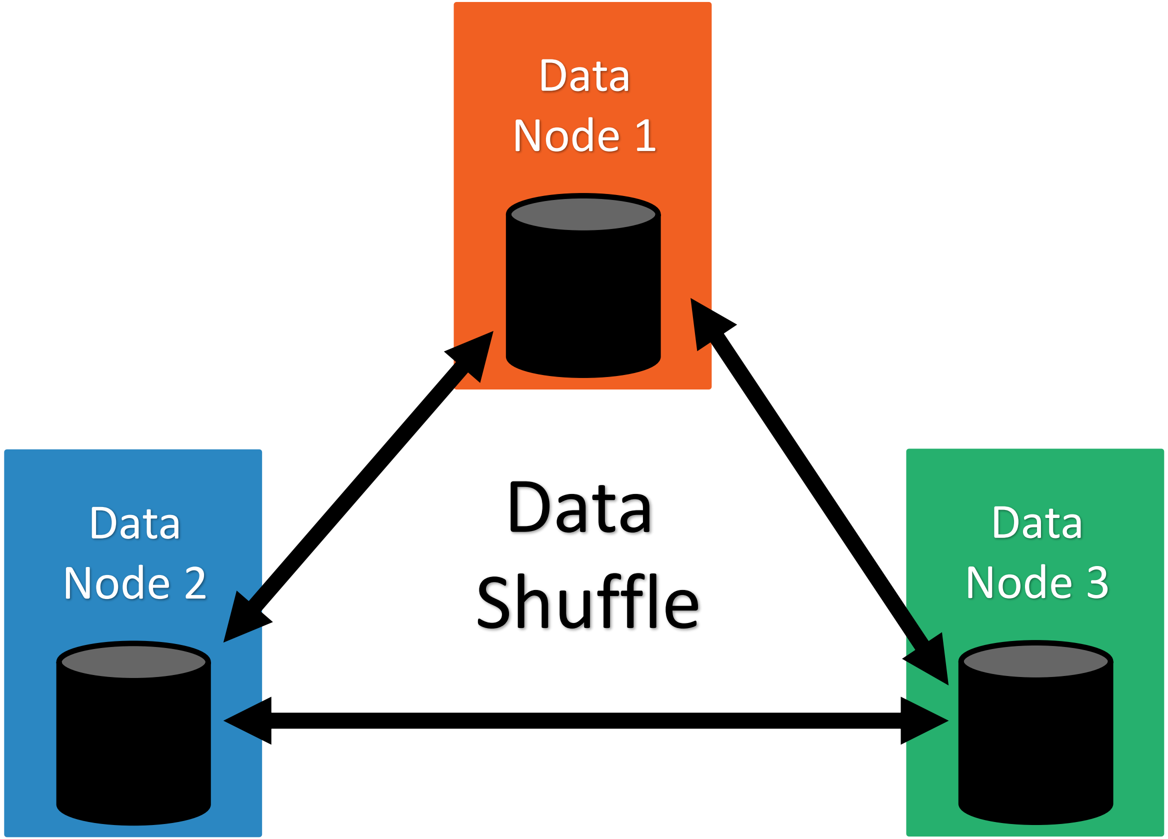
mahout

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

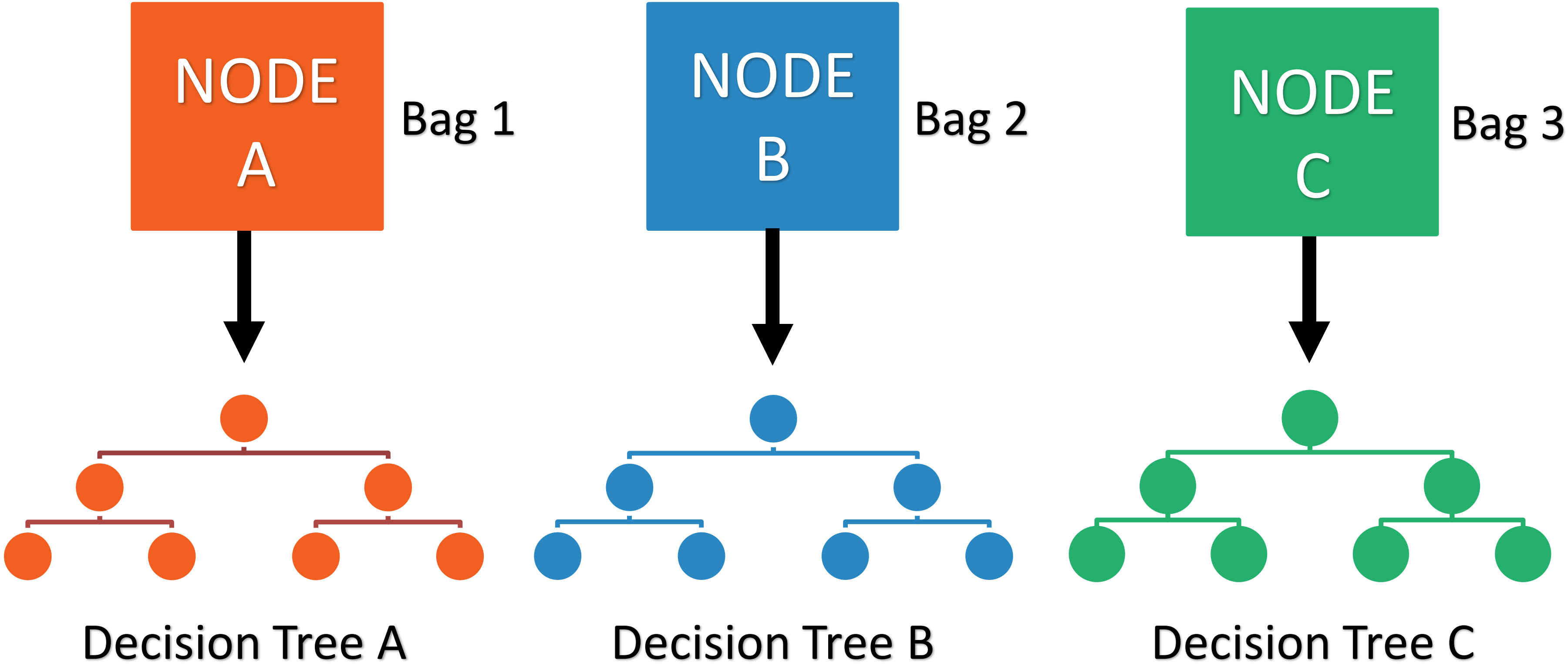
Distributed Random Forest



Distributed Random Forest



Distributed Random Forest



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Classification

	PC	Mahout	Spark
Logistic Regression - trained via SGD		<10m	
Naive Bayes			
Random Forest			
Hidden Markov Models			
Multilayer Perceptron			

Source: https://mahout.apache.org/users/basics/algorithms.html

Recommendation Engines

	PC	Mahout	Spark
User-Based Collaborative Filtering			
Item-Based Collaborative Filtering			
Matrix Factorization with ALS			
Matrix Factorization with ALS on Implicit Feedback			
Weighted Matrix Factorization, SVD++			

Source: https://mahout.apache.org/users/basics/algorithms.html

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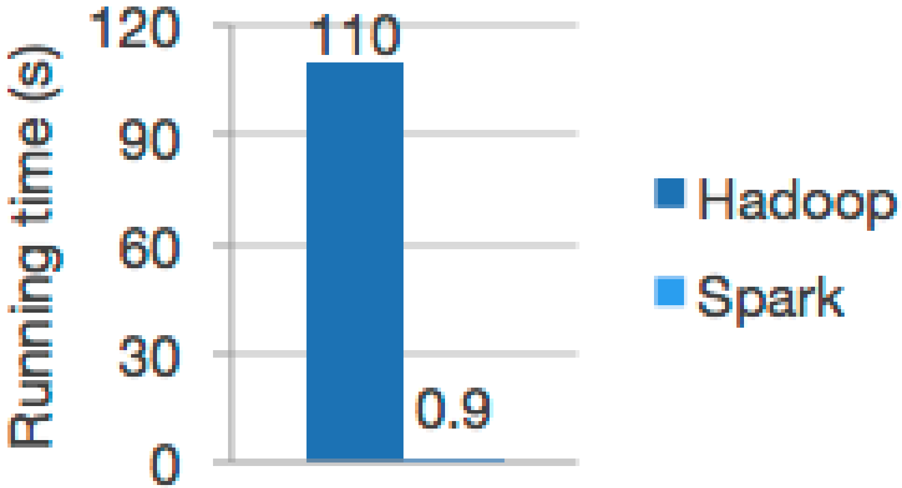
Clustering

	PC	Mahout	Spark
k-Means Clustering			
Fuzzy k-Means			
Streaming k-Means			
Spectral Clustering			

Source: https://mahout.apache.org/users/basics/algorithms.html

Spark



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

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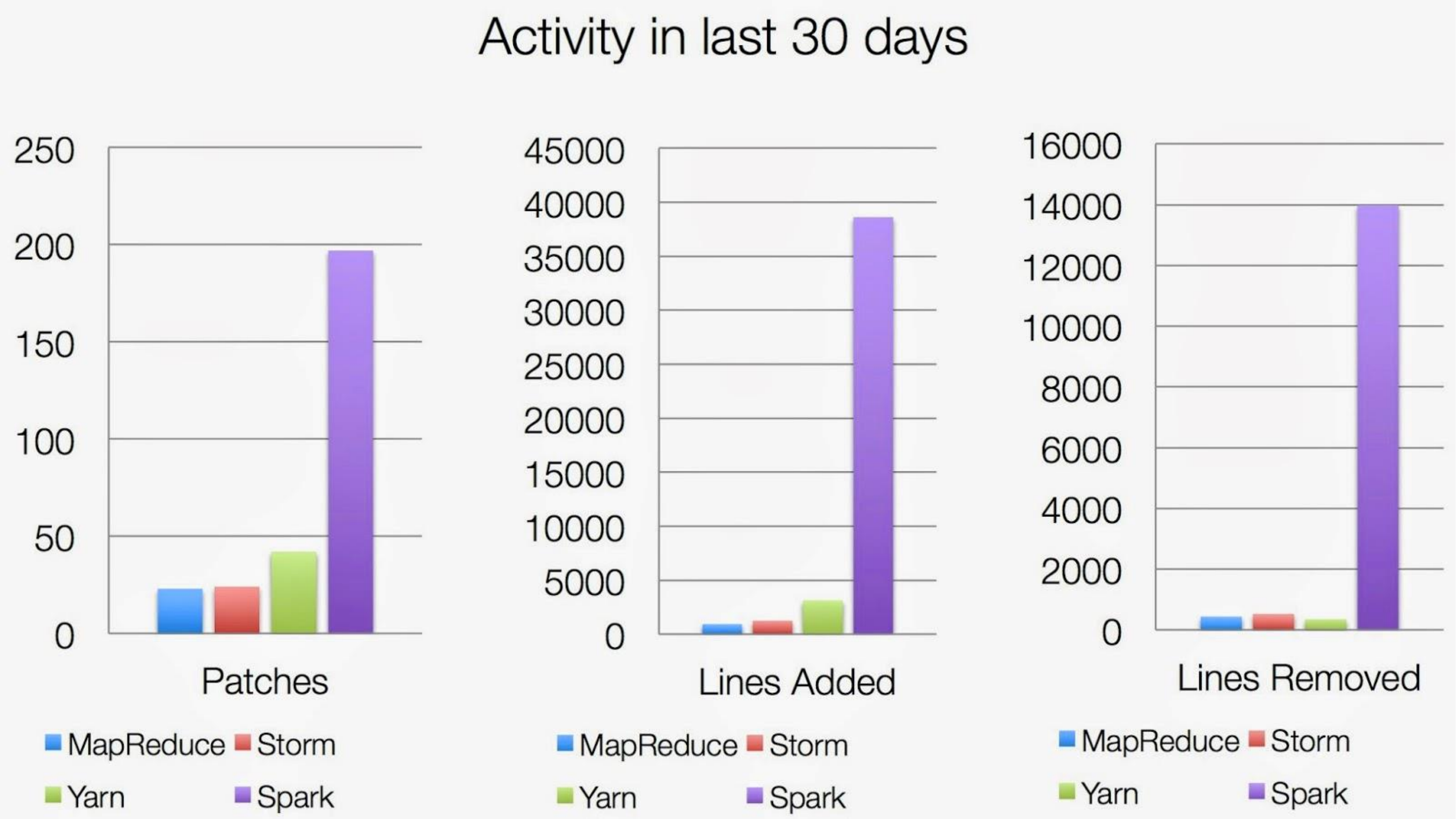
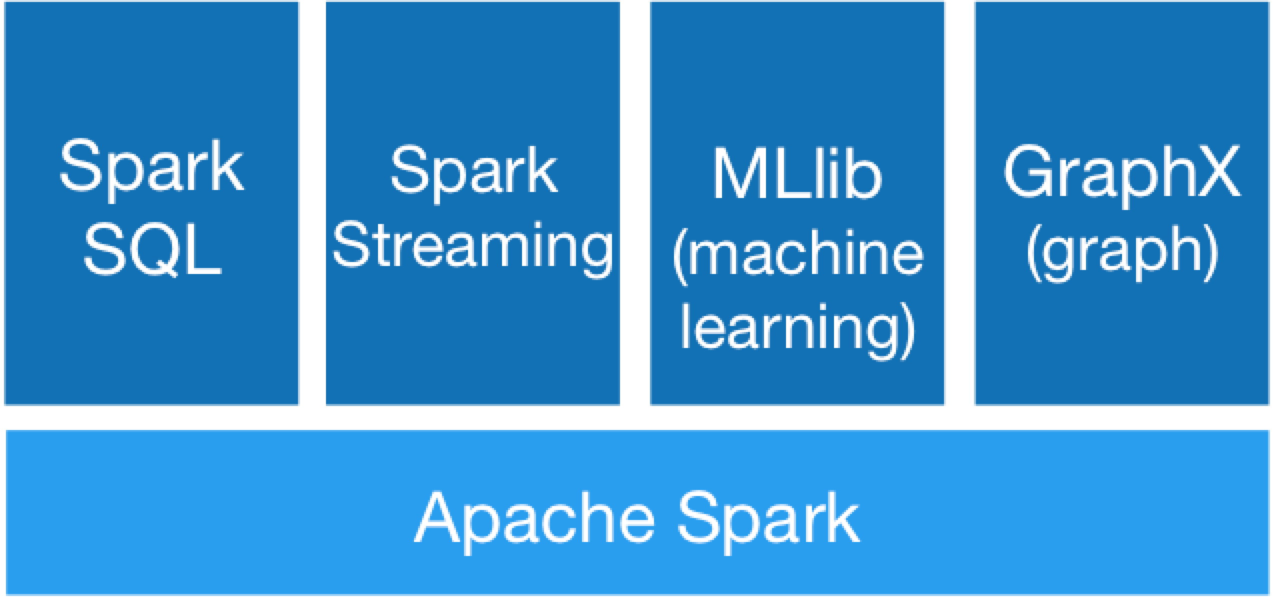
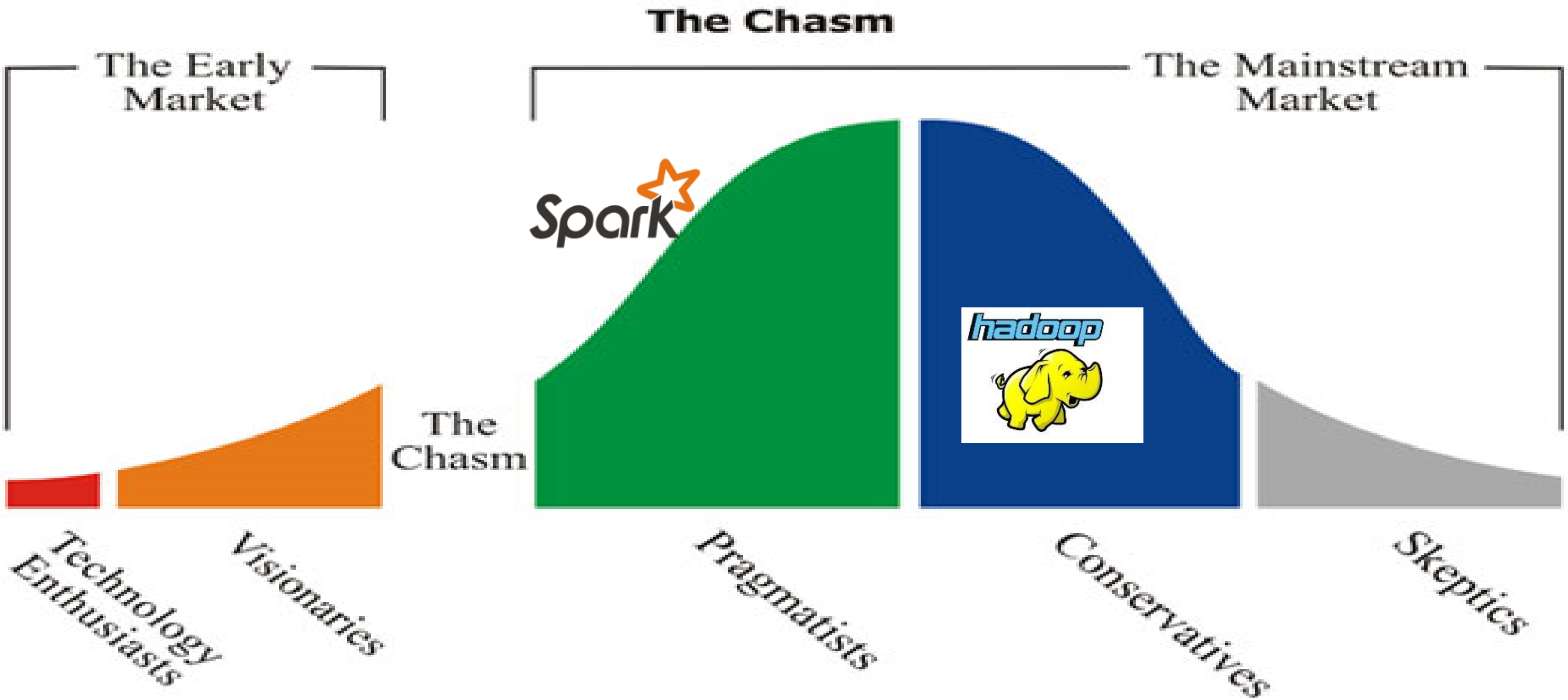


Source: Xiangrui Meng, Data Bricks

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/

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QUESTIONS