Data Intensive Computing Frameworks

Amir H. Payberah
amir@sics.se

Amirkabir University of Technology
1394/2/25

Big Data

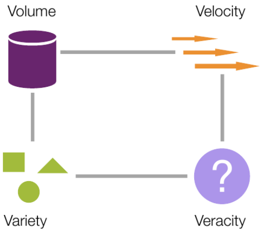
small data

big data

- Big Data refers to datasets and flows large enough that has outpaced our capability to store, process, analyze, and understand.

The Four Dimensions of Big Data

- Volume: data size
- Velocity: data generation rate
- Variety: data heterogeneity
- This 4th V is for Vacillation: Veracity/Variability/Value



Where Does
Big Data Come From?

Big Data Market Driving Factors

The number of web pages indexed by Google, which were around one million in 1998, have exceeded one trillion in 2008, and its expansion is accelerated by appearance of the social networks.∗

∗"Mining big data: current status, and forecast to the future" [Wei Fan et al., 2013]

Big Data Market Driving Factors

The amount of mobile data traffic is expected to grow to 10.8 Exabyte per month by 2016.∗

∗ "Worldwide Big Data Technology and Services 2012-2015 Forecast" [Dan Vesset et al., 2013]

Big Data Market Driving Factors

More than 65 billion devices were connected to the Internet by 2010, and this number will go up to 230 billion by 2020.∗

∗ "The Internet of Things Is Coming" [John Mahoney et al., 2013]

Big Data Market Driving Factors

Many companies are moving towards using Cloud services to access Big Data analytical tools.

Big Data Market Driving Factors

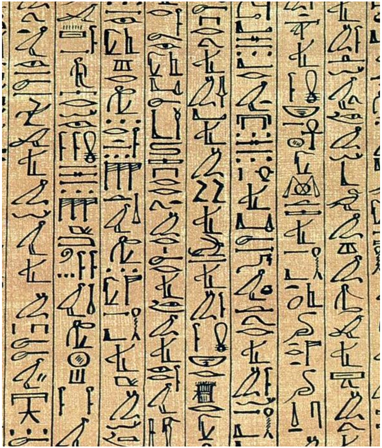
Open source communities

How To Store and Process Big Data?

But First, The History

4000 B.C

- Manual recording
- From tablets to papyrus, to parchment, and then to paper

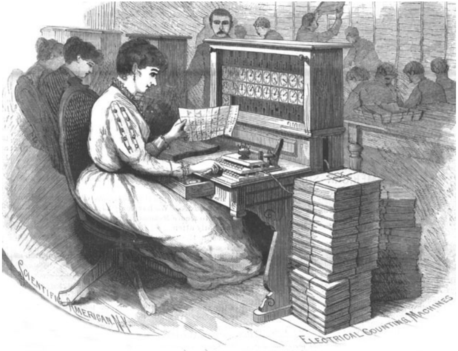


1450

- Gutenberg's printing press

1800's - 1940's

- Punched cards (no fault-tolerance)
- Binary data
- 1890: US census
- 1911: IBM appeared



1940's - 1950's

- Magnetic tapes

1950's - 1960's

- Large-scale mainframe computers
- Batch transaction processing
- File-oriented record processing model (e.g., COBOL)

1960's - 1970's

- Hierarchical DBMS (one-to-many)
- Network DBMS (many-to-many)
- VM OS by IBM $\rightarrow$ multiple VMs on a single physical node.

1970's - 1980's

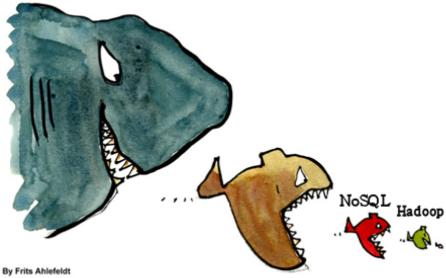
- Relational DBMS (tables) and SQL
- ACID
- Client-server computing
- Parallel processing

1990's - 2000's

- Virtualized Private Network connections (VPN)
- The Internet...

2000's - Now

- Cloud computing
- NoSQL: BASE instead of ACID
- Big Data



How To Store and Process Big Data?

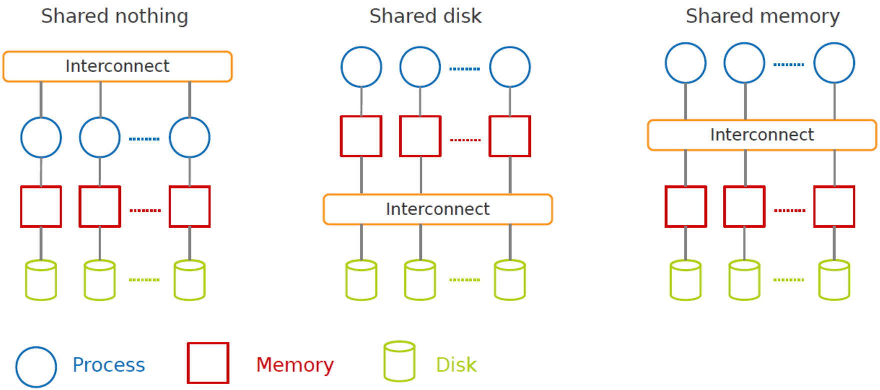
Scale Up vs. Scale Out (1/2)

- Scale up or scale vertically: adding resources to a single node in a system.
- Scale out or scale horizontally: adding more nodes to a system.

Scale Up vs. Scale Out (2/2)

- Scale up: more expensive than scaling out.
- Scale out: more challenging for fault tolerance and software development.

Taxonomy of Parallel Architectures



DeWitt, D. and Gray, J. "Parallel database systems: the future of high performance database systems". ACM Communications, 35(6), 85-98, 1992.

APACHE HBASE

mahout

GraphX

hadoop

StratoSphere
Above the Clouds

Storm

GraphLab

S4 distributed stream computing platform

HIVE

Spark

cassandra

Two Main Types of Tools

- Data store
- Data processing

Data Store

Data Store

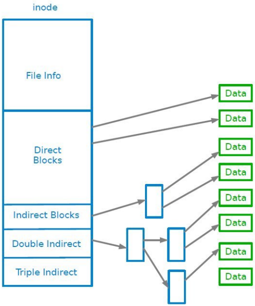
- How to store and access files? File System

What is Filesystem?

- Controls how data is stored in and retrieved from disk.

What is Filesystem?

- Controls how data is stored in and retrieved from disk.



Distributed Filesystems

- When data outgrows the storage capacity of a single machine.

Distributed Filesystems

- When data outgrows the storage capacity of a single machine.
- Partition data across a number of separate machines.

Distributed Filesystems

- When data outgrows the storage capacity of a single machine.
- Partition data across a number of separate machines.
- Distributed filesystems: manage the storage across a network of machines.

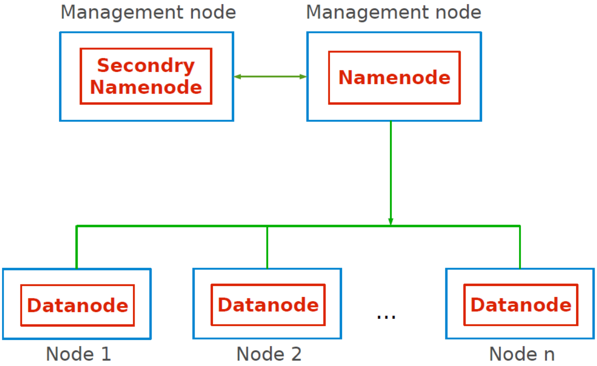
Distributed Filesystems

- When data outgrows the storage capacity of a single machine.
- Partition data across a number of separate machines.
- Distributed filesystems: manage the storage across a network of machines.

HDFS (1/2)

- Hadoop Distributed FileSystem
- Appears as a single disk
- Runs on top of a native filesystem, e.g., ext3

HDFS (2/2)



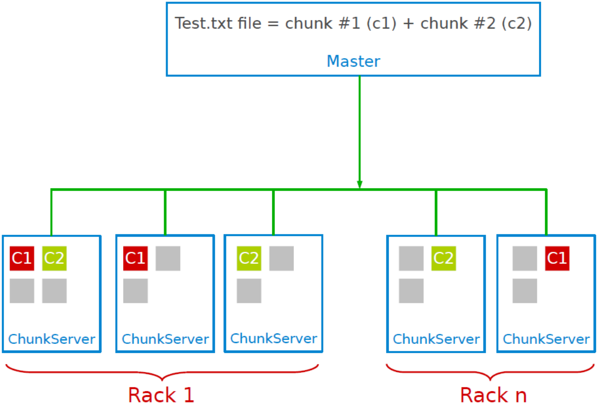
Management node
Management node
Secondry Namenode
Namenode
Datanode
Datanode
...
Datanode
Node 1
Node 2
Node n

Files and Blocks (1/2)

- Files are split into blocks.
- Blocks, the single unit of storage.
    - Transparent to user.
    - 64MB or 128MB.

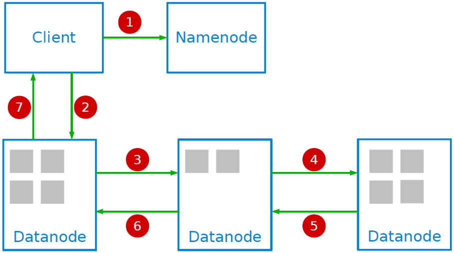
Files and Blocks (2/2)

- Same block is replicated on multiple machines: default is 3



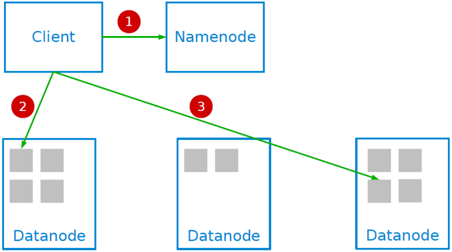
HDFS Write

- 1. Create a new file in the Namenode's Namespace; calculate block topology.
- 2, 3, 4. Stream data to the first, second and third node.
- 5, 6, 7. Success/failure acknowledgment.



HDFS Read

- 1. Retrieve block locations.
- 2, 3. Read blocks to re-assemble the file.



What About Databases?

Database and Database Management System

- Database: an organized collection of data.

Database and Database Management System

- Database: an organized collection of data.

- Database Management System (DBMS): a software that interacts with users, other applications, and the database itself to capture and analyze data.

Relational Databases Management Systems (RDMBSs)

- RDMBSs: the dominant technology for storing structured data in web and business applications.

- SQL is good
  - Rich language and toolset
  - Easy to use and integrate
  - Many vendors

Relational Databases Management Systems (RDMBSs)

- RDMBSs: the dominant technology for storing structured data in web and business applications.

- SQL is good
  - Rich language and toolset
  - Easy to use and integrate
  - Many vendors

- They promise: ACID

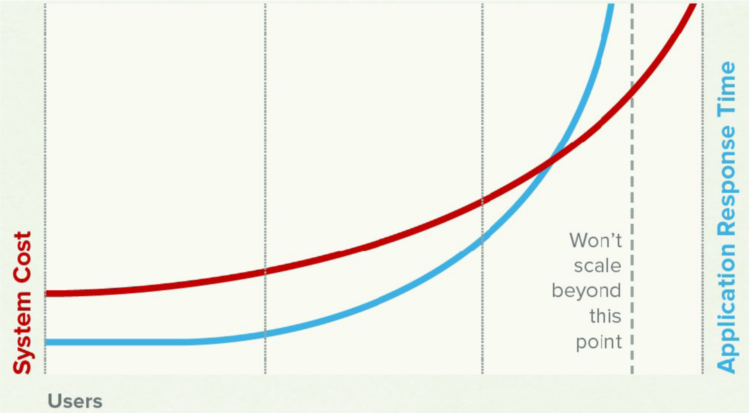
ACID Properties

- Atomicity
- Consistency
- Isolation
- Durability

RDBMS Challenges

- Web-based applications caused spikes.
  - Internet-scale data size
  - High read-write rates
  - Frequent schema changes

Scaling RDBMSs is Expensive and Inefficient



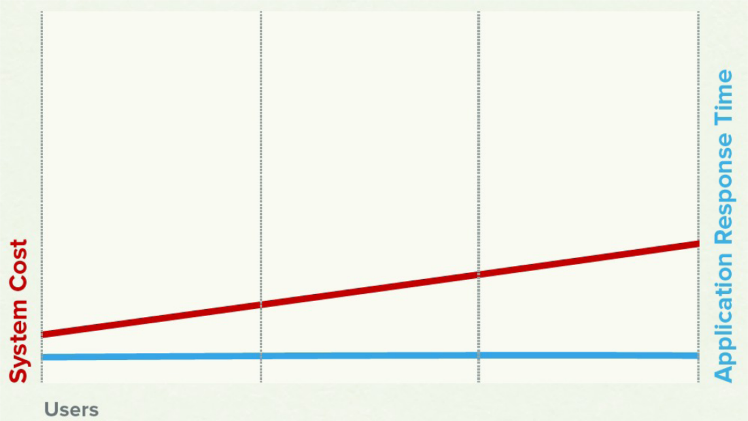
[http://www.couchbase.com/sites/default/files/uploads/all/whitepapers/NoSQLWhitepaper.pdf]

Not Only SQL

NoSQL

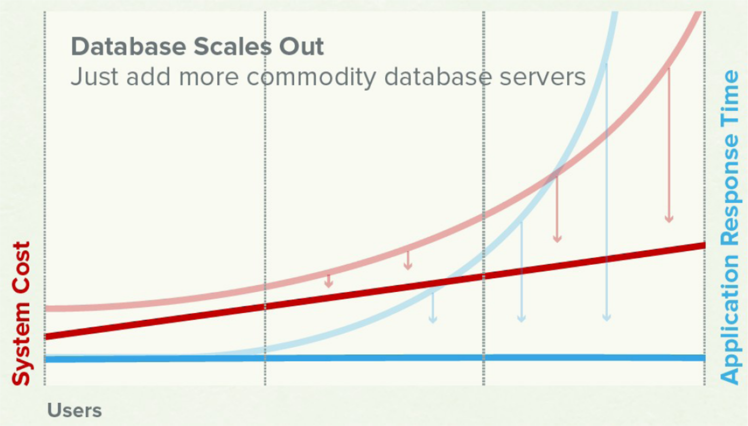
- Avoidance of unneeded complexity
- High throughput
- Horizontal scalability and running on commodity hardware

NoSQL Cost and Performance



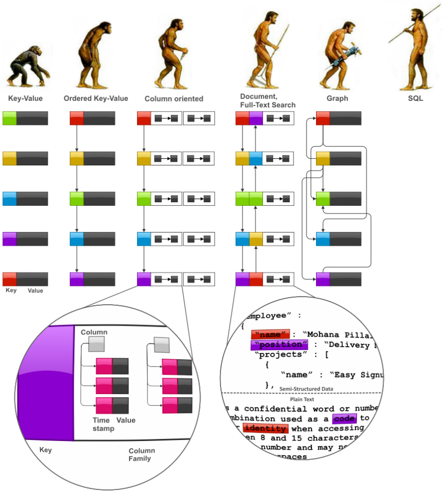
[http://www.couchbase.com/sites/default/files/uploads/all/whitepapers/NoSQLWhitepaper.pdf]

RDBMS vs. NoSQL



[http://www.couchbase.com/sites/default/files/uploads/all/whitepapers/NoSQLWhitepaper.pdf]

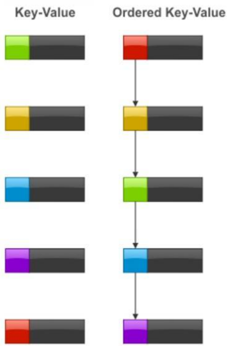
NoSQL Data Models



[http://highlyscalable.wordpress.com/2012/03/01/nosql-data-modeling-techniques]

NoSQL Data Models: Key-Value

- Collection of key/value pairs.
- Ordered Key-Value: processing over key ranges.
- Dynamo, Scalaris, Voldemort, Riak, ...

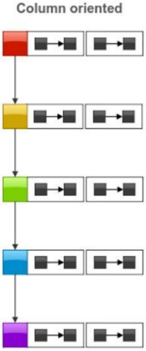


NoSQL Data Models: Column-Oriented

- Similar to a key/value store, but the value can have multiple attributes (Columns).

- Column: a set of data values of a particular type.

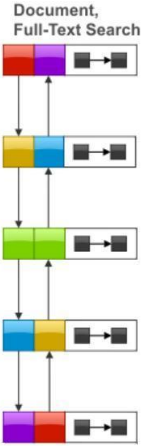
- BigTable, Hbase, Cassandra, ...



NoSQL Data Models: Document-Based

- Similar to a column-oriented store, but values can have complex documents, e.g., XML, YAML, JSON, and BSON.
- CouchDB, MongoDB, ...

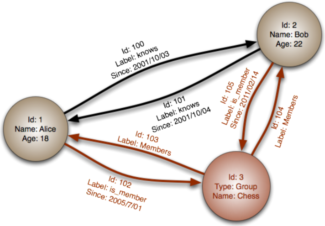
```
{
    FirstName: "Bob",
    Address: "5 Oak St.",
    Hobby: "sailing"
}

{
   FirstName: "Jonathan",
   Address: "15 Wanamassa Point Road",
   Children: [
        {Name: "Michael", Age: 10},
        {Name: "Jennifer", Age: 8},
   ]
}
```

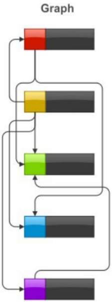


NoSQL Data Models: Graph-Based

- Uses graph structures with nodes, edges, and properties to represent and store data.

- Neo4J, InfoGrid, ...





Data Processing

Challenges

- How to distribute computation?
- How can we make it easy to write distributed programs?
- Machines failure.

Idea

- Issue:
  - Copying data over a network takes time.

Idea

- Issue:
  - Copying data over a network takes time.
- Idea:
  - Bring computation close to the data.
  - Store files multiple times for reliability.

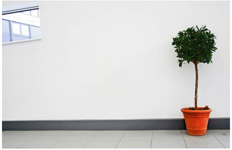
MapReduce

- A shared nothing architecture for processing large data sets with a parallel/distributed algorithm on clusters.

Simplicity

- Don't worry about parallelization, fault tolerance, data distribution, and load balancing (MapReduce takes care of these).
- Hide system-level details from programmers.

Simplicity!



Warm-up Task (1/2)

- We have a huge text document.
- Count the number of times each distinct word appears in the file

Warm-up Task (2/2)

- File too large for memory, but all $\langle \texttt{word}, \texttt{count} \rangle$ pairs fit in memory.

Warm-up Task (2/2)

- File too large for memory, but all $\langle \texttt{word}, \texttt{count} \rangle$ pairs fit in memory.

- `words(doc.txt) | sort | uniq -c`
  - where `words` takes a file and outputs the words in it, one per a line

Warm-up Task (2/2)

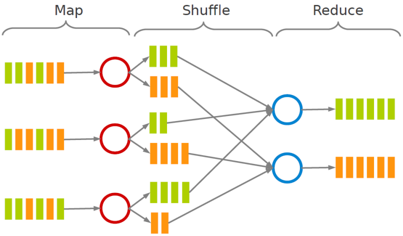
- File too large for memory, but all $\langle \texttt{word}, \texttt{count} \rangle$ pairs fit in memory.
- `words(doc.txt) | sort | uniq -c`
  - where `words` takes a file and outputs the words in it, one per a line
- It captures the essence of MapReduce: great thing is that it is naturally parallelizable.

MapReduce Overview

- `words(doc.txt) | sort | uniq -c`

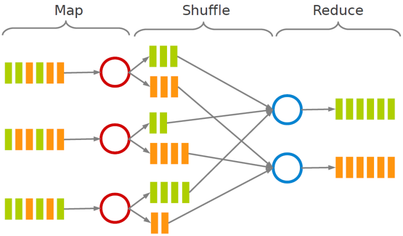
MapReduce Overview

- `words(doc.txt) | sort | uniq -c`
- Sequentially read a lot of data.



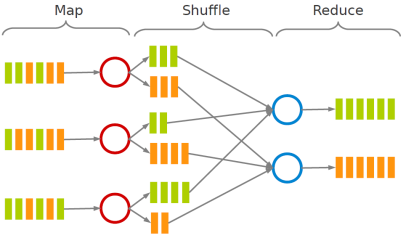
MapReduce Overview

- `words(doc.txt) | sort | uniq -c`
- Sequentially read a lot of data.
- Map: extract something you care about.



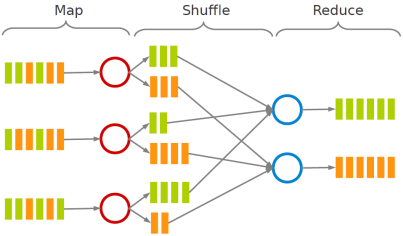
MapReduce Overview

- `words(doc.txt) | sort | uniq -c`
- Sequentially read a lot of data.
- Map: extract something you care about.
- Group by key: sort and shuffle.



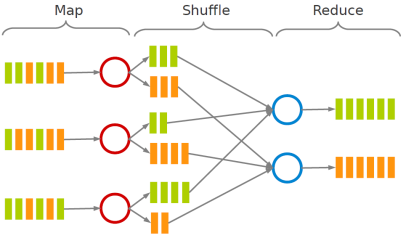
MapReduce Overview

- `words(doc.txt) | sort | uniq -c`
- Sequentially read a lot of data.
- Map: extract something you care about.
- Group by key: sort and shuffle.
- Reduce: aggregate, summarize, filter or transform.



MapReduce Overview

- `words(doc.txt) | sort | uniq -c`
- Sequentially read a lot of data.
- Map: extract something you care about.
- Group by key: sort and shuffle.
- Reduce: aggregate, summarize, filter or transform.
- Write the result.



Example: Word Count

- Consider doing a word count of the following file using MapReduce:

```
Hello World Bye World
Hello Hadoop Goodbye Hadoop
```

Example: Word Count - map

- The map function reads in words one a time and outputs (word, 1) for each parsed input word.

- The map function output is:

```
(Hello, 1)
(World, 1)
(Bye, 1)
(World, 1)
(Hello, 1)
(Hadoop, 1)
(Goodbye, 1)
(Hadoop, 1)
```

Example: Word Count - shuffle

- The shuffle phase between map and reduce phase creates a list of values associated with each key.
- The reduce function input is:

```
(Bye, (1))
(Goodbye, (1))
(Hadoop, (1, 1))
(Hello, (1, 1))
(World, (1, 1))
```

Example: Word Count - reduce

- The reduce function sums the numbers in the list for each key and outputs (word, count) pairs.

- The output of the reduce function is the output of the MapReduce job:

```
(Bye, 1)
(Goodbye, 1)
(Hadoop, 2)
(Hello, 2)
(World, 2)
```

Example: Word Count - map

```
public static class MyMap extends Mapper<...> {
  private final static IntWritable one = new IntWritable(1);
  private Text word = new Text();

  public void map(LongWritable key, Text value, Context context)
    throws IOException, InterruptedException {
    String line = value.toString();
    StringTokenizer tokenizer = new StringTokenizer(line);

    while (tokenizer.hasMoreTokens()) {
      word.set(tokenizer.nextToken());
      context.write(word, one);
    }
  }
}
```

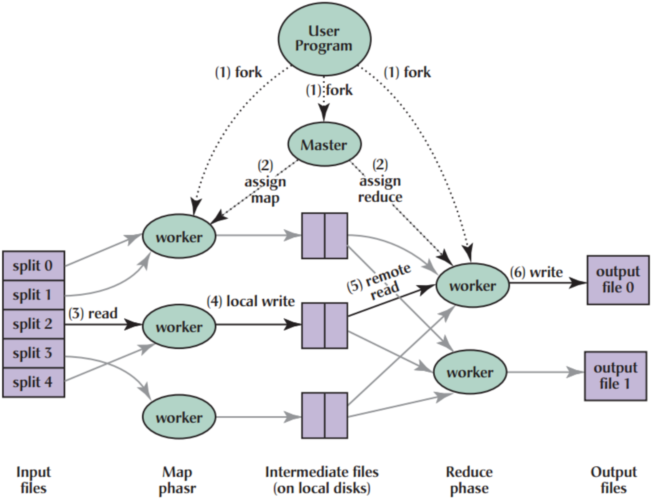
Example: Word Count - reduce

```
public static class MyReduce extends Reducer<...> {
  public void reduce(Text key, Iterator<...> values, Context context)
    throws IOException, InterruptedException {
    int sum = 0;

    while (values.hasNext())
      sum += values.next().get();

    context.write(key, new IntWritable(sum));
  }
}
```

Example: Word Count - driver

```
public static void main(String[] args) throws Exception {
  Configuration conf = new Configuration();
  Job job = new Job(conf, "wordcount");

  job.setOutputKeyClass(Text.class);
  job.setOutputValueClass(IntWritable.class);

  job.setMapperClass(MyMap.class);
  job.setReducerClass(MyReduce.class);

  job.setInputFormatClass(TextInputFormat.class);
  job.setOutputFormatClass(TextOutputFormat.class);

  FileInputFormat.addInputPath(job, new Path(args[0]));
  FileOutputFormat.setOutputPath(job, new Path(args[1]));

  job.waitForCompletion(true);
}
```

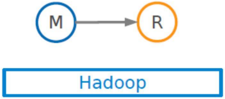
MapReduce Execution



J. Dean and S. Ghemawat, "MapReduce: simplified data processing on large clusters", ACM Communications 51(1), 2008.

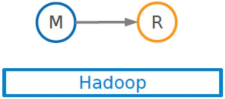
MapReduce Weaknesses

- MapReduce programming model has not been designed for complex operations, e.g., data mining.

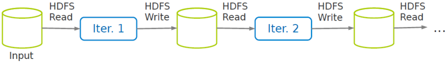


MapReduce Weaknesses

- MapReduce programming model has not been designed for complex operations, e.g., data mining.



- Very expensive, i.e., always goes to disk and HDFS.



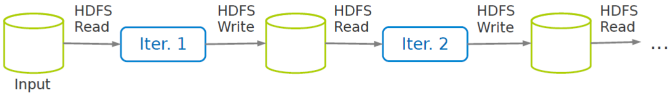
Solution?

Spark

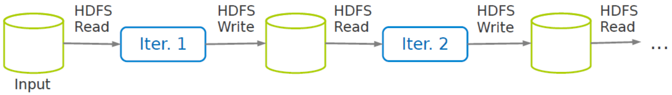
Spark

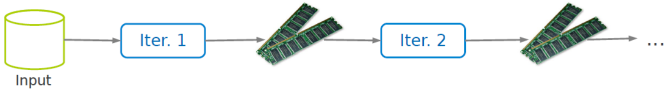
- Extends MapReduce with more operators.
- Support for advanced data flow graphs.
- In-memory and out-of-core processing.

Spark vs. Hadoop

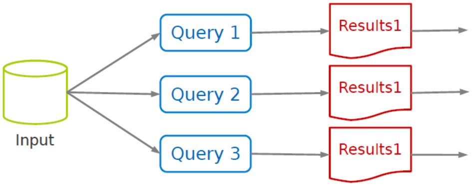


Spark vs. Hadoop

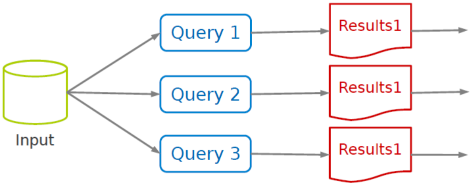


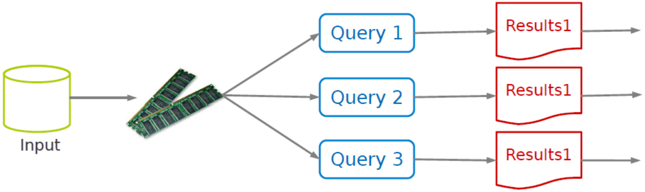


Spark vs. Hadoop



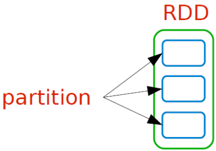
Spark vs. Hadoop



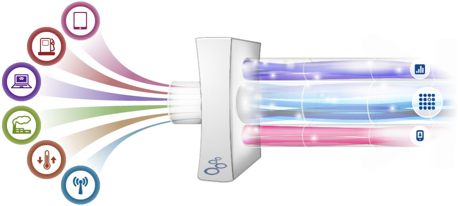


Resilient Distributed Datasets (RDD)

- Immutable collections of objects spread across a cluster.
- An RDD is divided into a number of partitions.
- Partitions of an RDD can be stored on different nodes of a cluster.



What About Streaming Data?



Motivation

- Many applications must process large streams of live data and provide results in real-time.

Motivation

- Many applications must process large streams of live data and provide results in real-time.

- Processing information as it flows, without storing them persistently.

Motivation

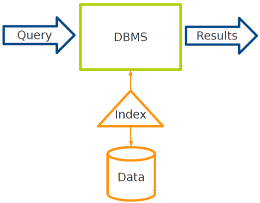
- Many applications must process large streams of live data and provide results in real-time.

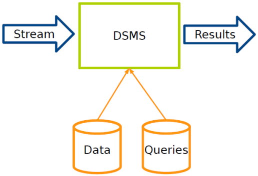
- Processing information as it flows, without storing them persistently.

- Traditional DBMSs:
  - Store and index data before processing it.
  - Process data only when explicitly asked by the users.

DBMS vs. DSMS (1/3)

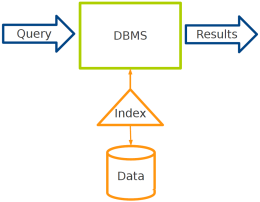
- DBMS: persistent data where updates are relatively infrequent.
- DSMS: transient data that is continuously updated.

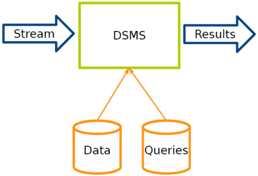




DBMS vs. DSMS (2/3)

- DBMS: runs queries just once to return a complete answer.
- DSMS: executes standing queries, which run continuously and provide updated answers as new data arrives.



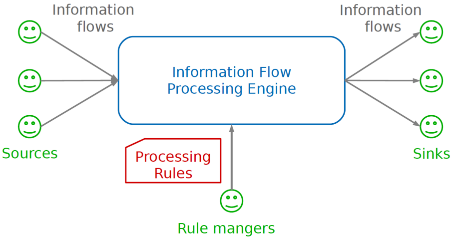


DBMS vs. DSMS (3/3)

- Despite these differences, DSMSs resemble DBMSs: both process incoming data through a sequence of transformations based on SQL operators, e.g., selections, aggregates, joins.

DSMS

- Source: produces the incoming information flows
- Sink: consumes the results of processing
- IFP engine: processes incoming flows
- Processing rules: how to process the incoming flows
- Rule manager: adds/removes processing rules



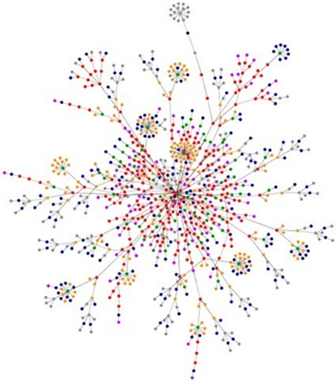
Spark Streaming

Flink

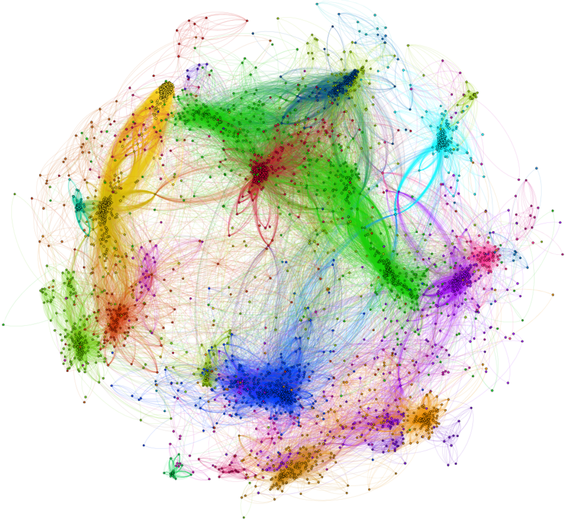
Storm

S4 distributed stream computing platform

What About Graph Data?



Large Graph



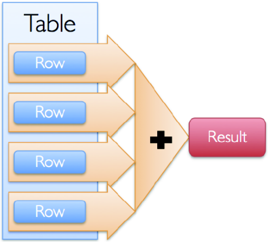
Large-Scale Graph Processing

- Large graphs need large-scale processing.
- A large graph either cannot fit into memory of single computer or it fits with huge cost.

Data-Parallel Model for Large-Scale Graph Processing

- The platforms that have worked well for developing parallel applications are not necessarily effective for large-scale graph problems.

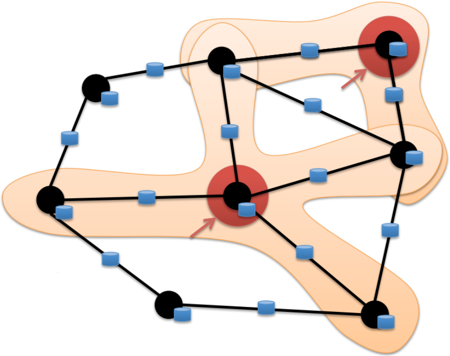
- Why?



Graph Algorithms Characteristics

- Unstructured problems: difficult to partition the data
- Data-driven computations: difficult to partition computation
- Poor data locality
- High data access to computation ratio

Graph-Parallel Processing

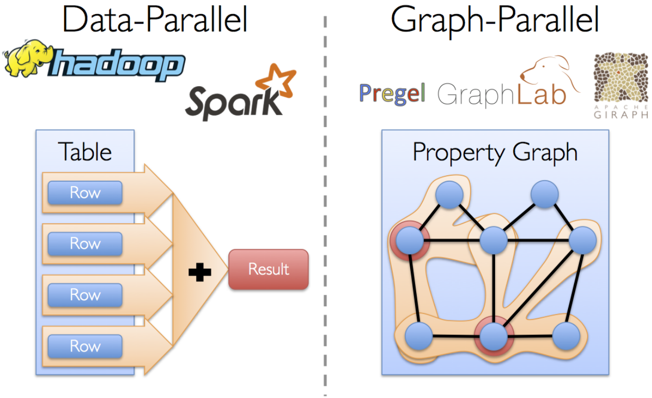


- Computation typically depends on the neighbors.

Graph-Parallel Processing

- Restricts the types of computation.
- New techniques to partition and distribute graphs.
- Exploit graph structure.
- Executes graph algorithms orders-of-magnitude faster than more general data-parallel systems.

Data-Parallel vs. Graph-Parallel Computation



Vertex-Centric Programing

- Think as a vertex.
- Each vertex computes individually its value: in parallel
- Each vertex can see its local context, and updates its value accordingly.

APACHE GIRAPH

GraphLab

GraphX

Flink

Summary

Summary

- Scale-out vs. Scale-up

Summary

- Scale-out vs. Scale-up

- How to store data?
  - Distributed file systems: HDFS
  - NoSQL databases: HBase, Cassandra, ...

Summary

- Scale-out vs. Scale-up

- How to store data?
  - Distributed file systems: HDFS
  - NoSQL databases: HBase, Cassandra, ...

- How to process data?
  - Batch data: MapReduce, Spark
  - Streaming data: Spark stream, Flink, Storm, S4
  - Graph data: Giraph, GraphLab, GraphX, Flink

Questions?