A Distributed Architecture, FileSystem, & MapReduce

Stony Brook University
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Classical Data Mining
Classical Data Mining

- CPU
- Memory (64 GB)
- Disk
Classical Data Mining

Diagram shows a box with layers labeled CPU, Memory (64 GB), and Disk. The layers are interconnected with arrows indicating the flow of data or processing.
Classical Data Mining

- CPU
- Memory (64 GB)
- Disk
IO Bounded

Reading a word from disk versus main memory: $10^5$ slower!

Reading many contiguously stored words is faster per word, but fast modern disks still only reach 150MB/s for sequential reads.

IO Bound: biggest performance bottleneck is reading / writing to disk.

(starts around 100 GBs; ~10 minutes just to read).
Classical Big Data Analysis

Often focused on efficiently utilizing the disk.
e.g. Apache Lucene / Solr

Still bounded when needing to process all of a large file.
IO Bound

How to solve?
Distributed Architecture (Cluster)
Distributed Architecture (Cluster)

In reality, modern setups often have multiple cpus and disks per server, but we will model as if one machine per cpu-disk pair.
Distributed Architecture (Cluster)

Switch ~1Gbps

Rack 1

Switch ~1Gbps

Rack 2

Switch ~10Gbps

...
Challenges for IO Cluster Computing

1. Nodes fail
   1 in 1000 nodes fail a day

2. Network is a bottleneck
   Typically 1-10 Gb/s throughput

3. Traditional distributed programming is often ad-hoc and complicated
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   **Duplicate Data**

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   **Bring computation to nodes, rather than data to nodes.**

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   **Stipulate a programming system that can easily be distributed**
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**MapReduce** Accomplishes
Distributed File System

Before we understand MapReduce, we need to understand the type of file system it is meant to run on.

The filesystem itself is largely responsible for much of the speed up MapReduce provides!
Characteristics for Big Data Tasks

Large files (i.e. >100 GB to TBs)

Reads are most common

No need to update in place (append preferred)
Distributed File System

(e.g. Apache Hadoop DFS, GoogleFS, EMRFS)

C, D: Two different files

(chunk server 1) (chunk server 2) (chunk server 3) (... chunk server n)

(Leskovec at al., 2014; http://www.mmds.org/)
Distributed File System

(e.g. Apache HadoopDFS, GoogleFS, EMRFS)

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Components of a Distributed File System

Chunk servers (on Data Nodes)

- File is split into contiguous chunks
- Typically each chunk is 16-64MB
- Each chunk replicated (usually 2x or 3x)
- Try to keep replicas in different racks

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**Name node (aka master node)**
- Stores metadata about where files are stored
- Might be replicated or distributed across data nodes.

**Client library for file access**
- Talks to master to find chunk servers
- Connects directly to chunk servers to access data

(Leskovec at al., 2014; http://www.mmds.org/)
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What is MapReduce?

1. A style of programming

input chunks => **map tasks** | **group_by keys** | **reduce tasks** => output

“|” is the linux “pipe” symbol: passes stdout from first process to stdin of next.

E.g. counting words:

```
tokenize(document) | sort | uniq -C
```
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2. A system that distributes MapReduce style programs across a distributed file-system.

(e.g. Google’s internal “MapReduce” or apache.hadoop.mapreduce with hdfs)
What is MapReduce?
What is MapReduce?

- **Map**: Extract what you care about.
  - **line => (k, v)**

- **Reduce**: Process the extracted data.
What is MapReduce?

Map

extract what you care about.

sort and shuffle

many (k, v) => (k, [v1, v2]), ...

Input chunks

Key-value pairs (k, v)

Keys with all their values (k, [v, w,...])

Combined output

Reduce tasks

Group by keys
What is MapReduce?

Map

- Extract what you care about.

Reduce

- Aggregate, summarize

Diagram:
- Input chunks
- Key-value pairs (k, v)
- Group by keys
- Sort and shuffle
- Keys with all their values (k, [v, w, ...])
- Combined output
What is MapReduce?

(Leskovec at al., 2014; http://www.mmds.org/)
The Map Step

Input key-value pairs

Intermediate key-value pairs

(map)

(map)

(Leskovec at al., 2014; http://www.mmds.org/)
The Sort / Group By Step

Intermediate key-value pairs

Key-value groups

Group by key

(Leskovec et al., 2014; http://www.mmds.org/)
The Reduce Step

(Leskovec et al., 2014; http://www.mmds.org/)
What is MapReduce?

(Leskovec at al., 2014; http://www.mmds.org/)
What is MapReduce?

Map: \((k,v) \rightarrow (k', v')^*\)

(Written by programmer)

Group by key: \((k_1', v_1'), (k_2', v_2'), \ldots \rightarrow (k_1', (v_1', v', \ldots)),
\quad (k_2', (v_1', v', \ldots)), \ldots\)

(system handles)

Reduce: \((k', (v_1', v', \ldots)) \rightarrow (k', v'')^*\)

(Written by programmer)
Example: Word Count

tokenize(document) | sort | uniq -C
Example: Word Count

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Map: extract what you care about.

Reduce: aggregate, summarize

sort and shuffle
Example: Word Count

The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/machine partnership. "The work we're doing now -- the robotics we're doing -- is what we're going to need ....................

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(The, 1)
(crew, 1)
(of, 1)
(the, 1)
(space, 1)
(shuttle, 1)
(Endeavor, 1)
(recently, 1)

Big document (key, value)
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Example: Word Count

@abstractmethod
def map(k, v):
    pass

@abstractmethod
def reduce(k, vs):
    pass
Example: Word Count (version 1)

```python
def map(k, v):
    for w in tokenize(v):
        yield (w,1)

def reduce(k, vs):
    return len(vs)
```
def map(k, v):
    counts = dict()
    for w in tokenize(v):
        try:
            counts[w] += 1
        except KeyError:
            counts[w] = 1
    for item in counts.iteritems():
        yield item

def reduce(k, vs):
    return sum(vs)

Example: Word Count (version 2)

- Counts each word within the chunk (try/except is faster than "if w in counts")
- Sum of counts from different chunks
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   Typically 1-10 Gb/s throughput  **(Sort & Shuffle)**
   Bring computation to nodes, rather than data to nodes.

3. Traditional distributed programming is often ad-hoc and complicated  **(Simply requires Mapper and Reducer)**
   Stipulate a programming system that can easily be distributed
Example: Relational Algebra

Select

Project

Union, Intersection, Difference

Natural Join

Grouping
Example: Relational Algebra

Select
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Example: Relational Algebra

Select

$R(A_1, A_2, A_3, ...)$, Relation $R$, Attributes $A_*$

return only those attribute tuples where condition $C$ is true
Example: Relational Algebra

**Select**

\[ R(A_1, A_2, A_3, \ldots) \], Relation \[ R \], Attributes \[ A_\ast \]

return only those attribute tuples where condition \( C \) is true

```
def map(k, v):  # v is list of attribute tuples
    for t in v:
        if t satisfies C:
            yield (t, t)

def reduce(k, vs):
    For each v in vs:
        yield (k, v)
```
Example: Relational Algebra

**Natural Join**

Given $R_1$ and $R_2$ return $R_{\text{join}}$ -- union of all pairs of tuples that match given attributes.
Example: Relational Algebra

Natural Join

Given $R_1$ and $R_2$ return $R_{\text{join}}$ -- union of all pairs of tuples that match given attributes.

```python
def map(k, v):
    # v is ($R_1$=(A, B), $R_2$=(B, C)); B are matched attributes
    for (a, b) in $R_1$:
        yield (b, ($R_1$, a))
    for (b, c) in $R_2$:
        yield (b, ($R_2$, c))
```
Example: Relational Algebra

Natural Join

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        yield (b, ($R_2$, c))

def reduce(k, vs):
    r1, r2 = [], []
    for (S, x) in vs:  # separate rs
        if S == r1: r1.append(x)
        else: r2.append(x)
    for a in r1:  # join as tuple
        for each c in r2:
            yield (R_{\text{join}}, (a, k, c))  # k is
```
Data Flow

- **Input:** Big document

- **Intermediate:**
  - $k1:v$, $k1:v$, $k2:v$
  - $k1:v$
  - $k3:v$, $k4:v$
  - $k4:v$, $k5:v$
  - $k4:v$
  - $k1:v$, $k3:v$

- **Group by Key:**
  - Grouped:
    - $k1:v$, $v$, $v$, $v$
    - $k2:v$
    - $k3:v$, $v$
    - $k4:v$, $v$, $v$
    - $k5:v$

- **Output:**

---

**MAP:**
Read input and produces a set of key-value pairs

**Group by key:**
Collect all pairs with same key (Hash merge, Shuffle, Sort, Partition)

**Reduce:**
Collect all values belonging to the key and output

---

Data Flow: In Parallel

(Leskovec at al., 2014; http://www.mmds.org/)
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Data Flow

DFS → Map → Map’s Local FS → Reduce → DFS
Data Flow

MapReduce system handles:

● Partitioning
● Scheduling map / reducer execution
● Group by key
● Restarts from node failures
● Inter-machine communication
Data Flow

- Schedule map tasks near physical storage of chunk
- Intermediate results stored locally
- Master / Name Node coordinates
Data Flow

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- Intermediate results stored locally
- Master / Name Node coordinates
  - Task status: idle, in-progress, complete
  - Receives location of intermediate results and schedules with reducer
  - Checks nodes for failures and restarts when necessary
    - All map tasks on nodes must be completely restarted
    - Reduce tasks can pickup with reduce task failed
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DFS → MapReduce → DFS → MapReduce → DFS
Data Flow

Skew: The degree to which certain tasks end up taking much longer than others.

Handled with:

- More reducers than reduce tasks
- More reduce tasks than nodes
Data Flow

**Key Question:** How many Map and Reduce jobs?
Data Flow

Key Question: How many Map and Reduce jobs?

\( M: \) map tasks, \( R: \) reducer tasks

A: If possible, one chunk per map task.

\[ M >> |\text{nodes}| \]

(better handling of node failures, better load balancing)

\[ R < M \]

(reduces number of files stored in DFS)
Communication Cost Model

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

(2) Communication: Moving key, value pairs
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(1) Computation: Map + Reduce + System Tasks

(2) Communication: Moving key, value pairs

Ultimate Goal: wall-clock Time.
Communication Cost Model

How to assess performance?

(1) **Computation: Map + Reduce + System Tasks**

- Mappers and reducers often single pass $O(n)$ within node
- System: sort the keys is usually most expensive
- In any case, can add more nodes

(2) **Communication: Moving key, value pairs**

Ultimate Goal: wall-clock Time.
Communication Cost Model

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

(2) Communication: Moving key, value pairs

Often dominates computation.
- Connection speeds: 1-10 gigabits per sec;
  HD read: 50-150 gigabytes per sec
- Even reading from disk to memory typically takes longer than operating on the data.
Communication Cost Model

How to assess performance?

Communication Cost = input size +
(sum of size of all map-to-reducer files)

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(2) Communication: Moving key, value pairs

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  HD read: 50-150 gigabytes per sec
- Even reading from disk to memory typically takes longer than operating on the data.
- Output from reducer ignored because it’s either small (finished summarizing data) or being passed to another mapreduce job.
Example: Natural Join

$R_1, R_2$: Relations (Tables)

\[
\text{Communication Cost} = \text{input size} + (\text{sum of size of all map-to-reducer files})
\]

\[
= |R| + |S| + (|R| + |S|)
\]

\[
= O(|R| + |S|)
\]
Exercise:

Calculate Communication Cost for
“Matrix Multiplication with One MapReduce Step”
(see MMDS section 2.3.10)
Last Notes: Extra

- Performance Refinements:
  - Backup tasks (aka speculative tasks)
    - Schedule multiple copies of tasks when close to the end to mitigate certain nodes running slow.
  - Combiners (like word count version 2)
    - Do some reducing from within map before passing to reduce
    - Reduces communication cost
  - Override partition hash function
    E.g. instead of hash(url) use hash(hostname(url))