MapReduce

A programming model for processing large datasets

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Outline

- **MapReduce**, the programming model
- Hadoop, an open-source implementation

- Pig, a high-level abstraction layer

What is MapReduce?

- A data-parallel programming model designed for high scalability and resiliency
- Pioneered by Google. Also designed Percolator – *incrementally processing updates*
  - *Implementation in C++*
- Popularised by the open-source Hadoop project
  - Used at Yahoo!, Facebook, Amazon, …

MapReduce Applications

- At Google
  - Index construction for Google Search, Article clustering for Google News, Statistical machine translation
- At Yahoo!
  - "Web map" powering Yahoo! Search, Spam detection for Yahoo! Mail
- At Facebook
  - Ad optimisation, Spam detection
- In research
  - Astronomical image analysis, Bioinformatics, Analysing Wikipedia conflicts, Natural language processing, Particle physics, Ocean climate simulation
- Among others…

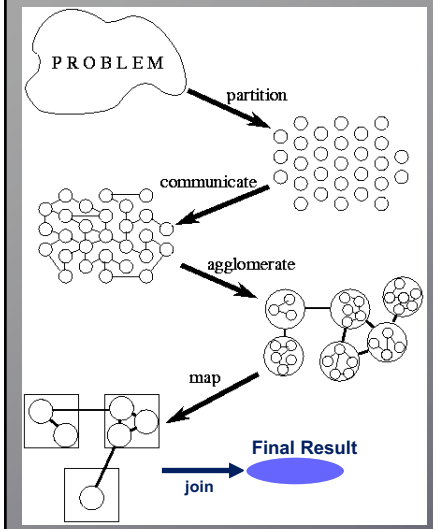
Parallel Programming

- Process of developing programs that express what computations should be executed in parallel.
- Parallel computing
  - use of two or more processors (computers), ***usually within a single system***, working simultaneously to solve a single problem
- Distributed computing
  - any computing that involves ***multiple computers remote from each other*** that each have a role in a computation problem or information processing

Parallel vs. Distributed Computing

Characteristic	*Parallel*	*Distributed*
Overall Goal	Speed	Convenience
Interactions	Frequent	Infrequent
Granularity	Fine	Coarse
Reliable	Assumed	Not Assumed

Parallel Programming Approach



- Partitioning
  - Computation, data are decomposed into small tasks.
- Communication
  - Coordinate task execution
- Agglomeration
  - Tasks are combined to larger tasks
- Map
  - Assigned to a processor
- Join

Parallel Programming Paradigms

- Data parallelism
  - All tasks apply the same set of operations to different data
  - Example:

```
for i ← 0 to 99 do
  a[i] ← b[i] + c[i]
endfor
```

  - Operations may be performed either synchronously or asynchronously
  - Fine grained parallelism
  - *Grain Size* is the average number of computations performed between communication or synchronization steps

Parallel Programming Paradigms

- Task parallelism
  - Independent tasks apply different operations to different data elements
  - Example

$$a \leftarrow 2$$
$$b \leftarrow 3$$
$$m \leftarrow (a + b) / 2$$
$$s \leftarrow (a^2 + b^2) / 2$$
$$v \leftarrow s - m^2$$

  - Concurrent execution of tasks, not statements
  - Problem is divided into different tasks
  - Tasks are divided between the processors
  - Coarse grained parallelism

Parallel Programming Examples

- Adding a sequence of n numbers
  - Sum = A[0] + A[1] + A[2] + … + A[n-1]
  - Code:

```
sum ← 0
for i = 0 to  n-1 do
    sum ← sum + A[i]
end for
```

  - Sequential or parallel?

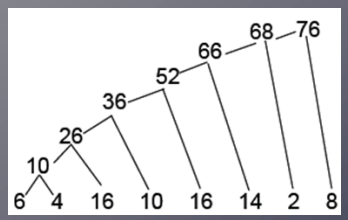
Parallel Programming Example I

- Adding a sequence of n numbers
  - Sum = A[0] + A[1] + A[2] + … + A[n-1]
  - Code:

```
sum ← 0
for i = 0 to  n-1 do
    sum ← sum + A[i]
end for
```

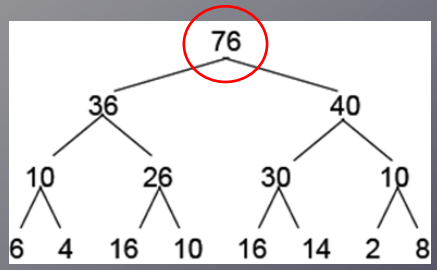
  - Example: : 6 4 16 10 16 14 2 8

    sum ← 0 + 6
    sum ← 6 + 4
    sum ← 10 + 4
    …



Parallel Programming Example I

- Adding a sequence of n numbers
  - Sum = A[0] + A[1] + A[2] + … + A[n-1]
  - In parallel:
    - Add pairs of values producing 1st level results,
    - Add pairs of 1st level results producing 2nd level results
    - Sum pairs of 2nd level results
    - …



Parallel Programming Example II

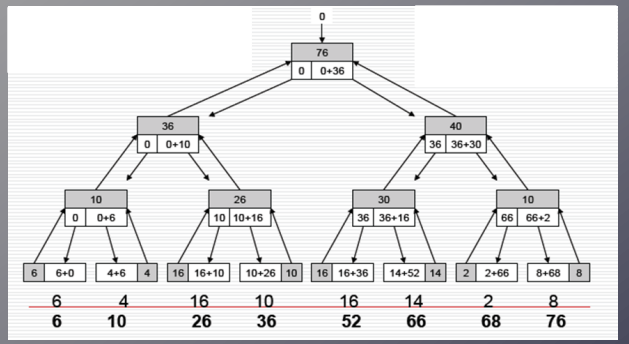
- Computing the prefix sums
  - A[i] is the sum of the first i+1 elements
  - Code:

```
for i = 1 to  n-1 do
    A[i] ← A[i] + A[i-1]
end for
```

  - So:
    - A[0] is unchanged
    - A[1] = A[1] + A[0]
    - A[2] = A[2] + (A[1] + A[0])
    - …
    - A[n-1]= A[n-1] + (A[n-2] + (…(A[1] + A[0]) …)
  - Example:
    - Input: 6 4 16 10 16 14 2 8
    - Output: 6 10 26 36 52 66 68 76

Parallel Programming Example II

- Computing the prefix sums
  - A[i] is the sum of the first i elements
  - Example:
    - Input: 6 4 16 10 16 14 2 8
    - Output: 6 10 26 36 52 66 68 76



Traditional HPC systems

- CPU-intensive computations
  - Relatively small amount of data
  - Tightly-coupled applications
  - Highly concurrent I/O requirements
  - Complex message passing paradigms such as MPI, PVM, …
  - Developers might need to spend some time designing for failure

Challenges

- Data and storage
  - Locality, computation close to the data
- In large-scale systems, nodes fail
  - MTBF (Mean time between failures) for 1 node = 3 years
  - MTBF for 1000 nodes = 1 day
  - Solution: Built in fault-tolerance
- Commodity network = low bandwidth
- Distributed programming is hard
  - Solution: simple data-parallel programming model: users structure the application in “map” & “reduce” functions, system distributes data/work and handles faults
  - Not all applications can be parallelised: tightly-coupled computations

What requirements?

- A simple data-parallel programming model, designed for high scalability and resiliency
  - Scalability to large-scale data volumes
  - Automated fault-tolerance at application level rather than relying on high-availability hardware
  - Simplified I/O and tasks monitoring
  - All based on cost-efficient commodity machines (cheap, but unreliable), and commodity network

Core concepts

- Data distributed in advance, persistent (in terms of locality), and replicated
- No inter-dependencies / shared nothing architecture
- Applications written in two pieces of code
  - And developers do not have to worry about the underlying issues in networking, jobs interdependencies, scheduling, etc…

The model

- A map function processes a key/value pair to generate a set of intermediate key/value pairs
  - Divides the problem into smaller 'intermediate key/value' pairs
- The reduce function merges all intermediate values associated with the same intermediate keys
- Run-time system takes care of:
  - Partitioning the input data across nodes (blocks/chunks typically of 64Mb to 128Mb)
  - Scheduling the data and execution
  - Node failures, replication, re-submissions
  - Coordination among nodes

Map function

- A map function processes a key/value pair to generate a set of intermediate key/value pairs
  - Divides the problem into smaller 'intermediate key/value' pairs
- Map: (key1, val1) → (key2, val2)
- Ex:
  - (line-id, text) → (word, 1)
  - (2, the apple is an apple) → (the,1), (apple,1), (is,1), (an,1), (apple,1)

Reduce function

- The reduce function merges all intermediate values associated with the same intermediate key
- Reduce: (key2, [val2]) → [results]
- Ex:
  - (word, [val_1,val_2,…]) → (word, Σval_i)
  - (the,1), (apple,1), (is,1), (an,1), (apple,1) → (an,1), (apple,2), (is,1), (the,1)

Map/Reduce

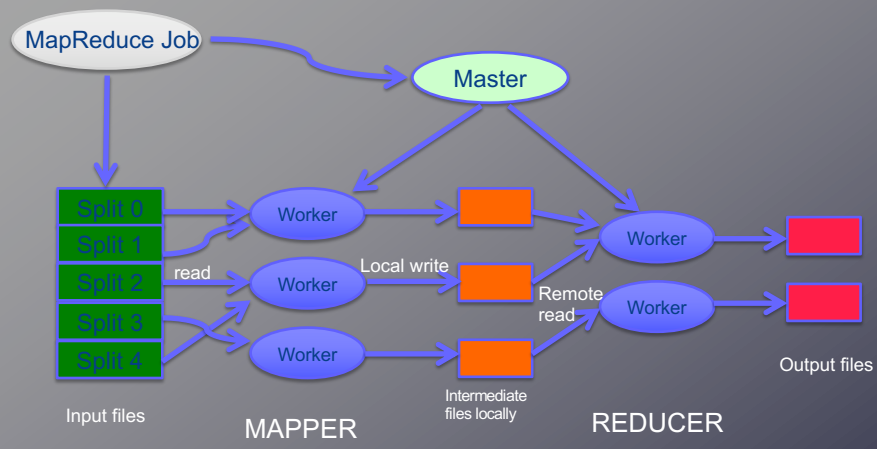
Map

- Iterate over a large number of records
- Extract something of interest from each

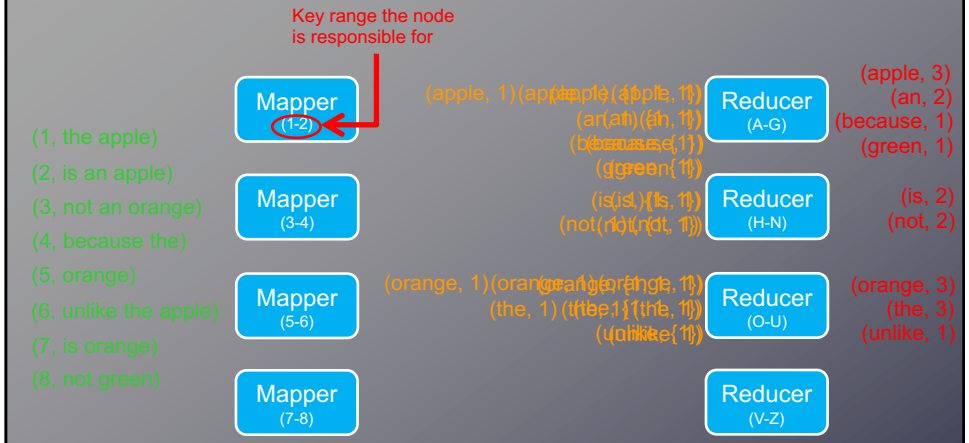
Reduce

- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

MapReduce execution



Simple example: Word count



Simple Word Count

```
#key: offset, value: line
def mapper():
      for line in open("doc"):
          for word in line.split():
        output(word, 1)

#key: a word, value: iterator over counts
def reducer():
    output(key, sum(value))
```

K-Means

- Given a set of objects, group these objects into k "clusters"
- *K-means* algorithm is implemented in 4 steps:
  - Step 1
    - Given k, partition objects into *k* nonempty subsets
  - Step 2
    - Compute seed points as the centroids of the clusters of the current partition
    - The centroid is the centre (mean point) of the cluster
  - Step 3
    - Assign each object to the cluster with the nearest seed point
  - Step 4
    - Go back to Step 2 until no more new assignment

K-Means in MapReduce

- Mapper:
  - Input: <nodeID, [centroidIDs]>
  - Emit: <centroidID, nodeID>
- Reducer:
  - Input: <centroidID, nodeID>
  - Reduce → <centroidID, [nodeIDs]>
    - Recompute centroid position from positions of nodes in it
  - Emit:
    - <centroidID, [nodeIDs]>
    - <centroidID, [nodeIDs]> → <nodeID, [centroidIDs]>
- Repeat until no change

Optimisation: The Combiner

- A combiner is a local aggregation function for repeated keys produced by the map
- Works for associative functions like sum, count, max
- Decreases the size of intermediate data / communications
- map-side aggregation for Word Count:

```
def combiner(key, values):
    output(key, sum(values))
```

Some examples…

- **Distributed Grep**:
  - Map function emits a line if it matches a supplied pattern
  - Reduce function is an identity function that copies the supplied intermediate data to the output
- **Count of URL accesses**:
  - Map function processes logs of web page requests and outputs <URL, 1>
  - Reduce function adds together all values for the same URL, emitting <URL, total count> pairs
- **Reverse Web-Link graph**:
  - Map function outputs <tgt, src> for each link to a tgt in a page named src
  - Reduce concatenates the list of all src URLS associated with a given tgt URL and emits the pair: <tgt, list(src)>
- **Inverted Index**:
  - Map function parses each document, emitting a sequence of <word, doc_ID>
  - Reduce accepts all pairs for a given word, sorts the corresponding doc_IDs and emits a <word, list(doc_ID)> pair
  - Set of all output pairs forms a simple inverted index

Exercise: host size

- Suppose we have a large web corpus
- The metadata file has lines of the form (URL, size, date, …)
- For each host, find the total number of bytes, i.e. the sum of the page sizes for all URLs from that host

Execution

- A distributed file system providing a global namespace (GFS, HDFS, ...)
- Map invocations distributed across multiple machines by automatically partitioning the input data into a set of splits / chunks
- Reduce invocations are distributed by partitioning the intermediate key space into R pieces using a hash function

Execution

- Single *master* controls job execution on multiple *slaves*
- Mappers preferentially placed on same node or same rack as their input block
  - Locality, to minimise network usage
- Mappers save outputs to local disk before serving them to reducers
  - Allows recovery if a reducer crashes
- Redundant execution & storage (usually 3+ copies of the data)

Distributed file systems

- A distributed implementation of the classical time sharing model of a file system, where multiple users / locations share files and storage resources.
- Key aspects: dispersion & multiplicity
- Primary issues: Naming, Transparency, & Fault tolerance
- Examples: NFS, AFS, GFS, HDFS