COMP 322: Fundamentals of Parallel Programming

Lecture 8: Map Reduce

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COMP 322 Lecture 8 27 January 2017

Worksheet #7 solution: Associativity and Commutativity

Recap:
A binary function f is *associative* if f(f(x,y),z) = f(x,f(y,z)).
A binary function f is *commutative* if f(x,y) = f(y,x).

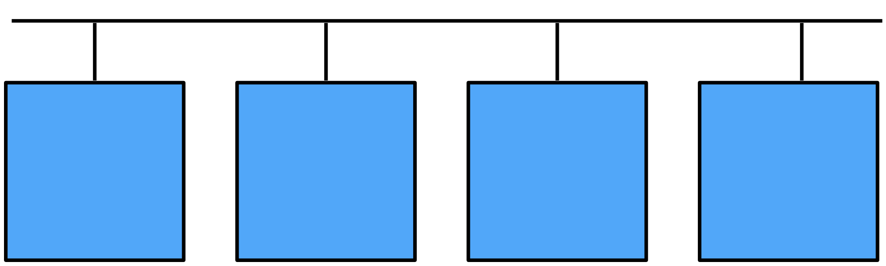
Worksheet problems:
1) Claim: a Finish Accumulator (FA) can only be used with operators that are *associative and commutative.* Why? What can go wrong with accumulators if the operator is non-associative or non-commutative?
You may get different answers in different executions if the operator is non-associative or non-commutative e.g., an accumulator can be implemented using one "partial accumulator" per processor core.
2) For each of the following functions, indicate if it is associative and/or commutative.
a) f(x,y) = x+y, for integers x, y, is associative and commutative
b) g(x,y) = (x+y)/2, for integers x, y, is commutative but not associative
⇒ *Incorrect answers found in some worksheets: Associative / Both / Neither*
c) h(s1,s2) = concat(s1, s2) for strings s1, s2, e.g., h("ab","cd") = "abcd", is associative but not commutative
⇒ *Incorrect answers found in some worksheets: Commutative / Neither*

Streaming data requirements have skyrocketed

- AT&T processes roughly 30 petabytes per day through its telecommunications network
- Google processed roughly 24 petabytes per day in 2009
- Facebook, Amazon, Twitter, etc, have comparable throughputs
- Two Sigma maintains over 100 teraflops of private computing power, continuously computing over 11 petabytes of quantitative data
- In comparison, the IBM Watson knowledge base stored roughly 4 terabytes of data when winning at Jeopardy

Parallelism enables processing of big data

- Continuously streaming data needs to be processed at least as fast as it is accumulated, or we will never catch up
- The bottleneck in processing very large data sets is dominated by the speed of disk access
- More processors accessing more disks enables faster processing



Parallelism enables "Cloud Computing" as a Utility

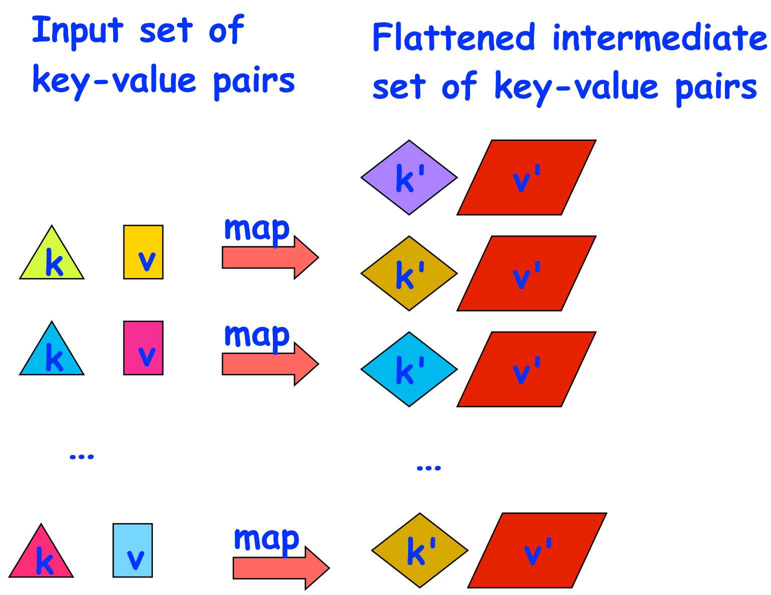
- Offers computing, storage, communication at pennies per hour
  - *Leverage Parallelism to Achieve Energy-Efficient High Performance*
- No premium to scale:

  1000 computers @ 1 hour
  = 1 computer @ 1000 hours
- Illusion of infinite scalability to cloud user
  - As many computers as you can afford
- Leading examples: Amazon Web Services (AWS), Google App Engine, Microsoft Azure
  - Economies of scale pushed down datacenter costs by factors of 3-8X
  - Traditional data centers utilized 10% - 20%
  - Make profit offering pay-as-you-go use service at less than your costs for as many computers as you need
  - Strategic capability for company's needs
- Challenge: portable and scalable parallelism at cloud scale
  - One solution: leverage functional programming with MapReduce pattern

MapReduce Pattern

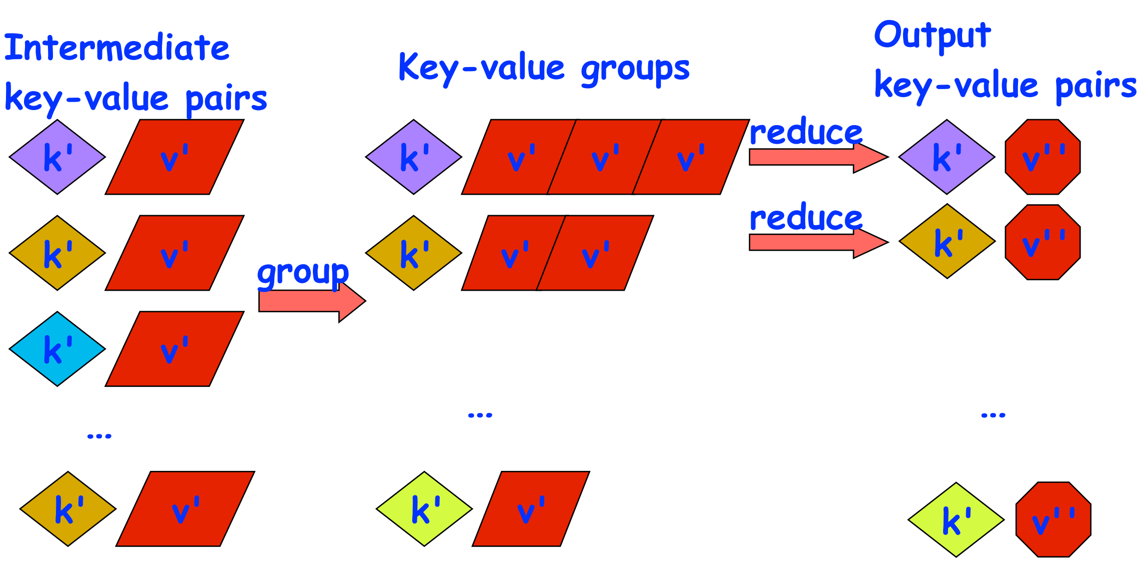
- Apply Map function f to user supplied record of key-value pairs
- Compute set of intermediate key/value pairs
- Apply Reduce operation g to all values that share same key to combine derived data properly
  - Often produces smaller set of values
- User supplies Map and Reduce operations in functional model so that the system can parallelize them, and also re-execute them for fault tolerance

MapReduce: The Map Step



Source: http://infolab.stanford.edu/~ullman/mining/2009/mapreduce.ppt

MapReduce: The Reduce Step



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Map Reduce: Summary

- Input set is of the form {(k1, v1), . . . (kn, vn)}, where (ki, vi) consists of a key, ki, and a value, vi.
  - Assume that the key and value objects are immutable, and that equality comparison is well defined on all key objects.
- Map function f generates sets of intermediate key-value pairs, f(ki,vi) = {(k1' ,v1'),...(km',vm')}. The kj' keys can be different from ki key in the in of the map function.
  - Assume that a flatten operation is performed as a post-pass after the map operations, so as to avoid dealing with a set of sets.
- Reduce operation groups together intermediate key-value pairs, {(k', vj')} with the same k', and generates a reduced key-value pair, (k',v''), for each such k', using reduce function g

Google Uses MapReduce For …

- Web crawl: Find outgoing links from HTML documents, aggregate by target document
- Google Search: Generating inverted index files using a compression scheme
- Google Earth: Stitching overlapping satellite images to remove seams and to select high-quality imagery
- Google Maps: Processing all road segments on Earth and render map tile images that display segments
- More than 10,000 MR programs at Google in 4 years, run 100,000 MR jobs per day (2008)

MapReduce: State of Practice

- Apache Hadoop now dominates use of the MapReduce framework
- Often, Hadoop map and reduce functions are *no longer written directly*
  - *Instead, a user writes a query in a very high level language and uses another tool to compile the query into map/reduce functions!*
    - Hive *(another Apache project) compiles SQL queries into map/reduce*
    - Pig *(yet another Apache project) compiles direct relational algebra into map/reduce*

MapReduce: State of Practice

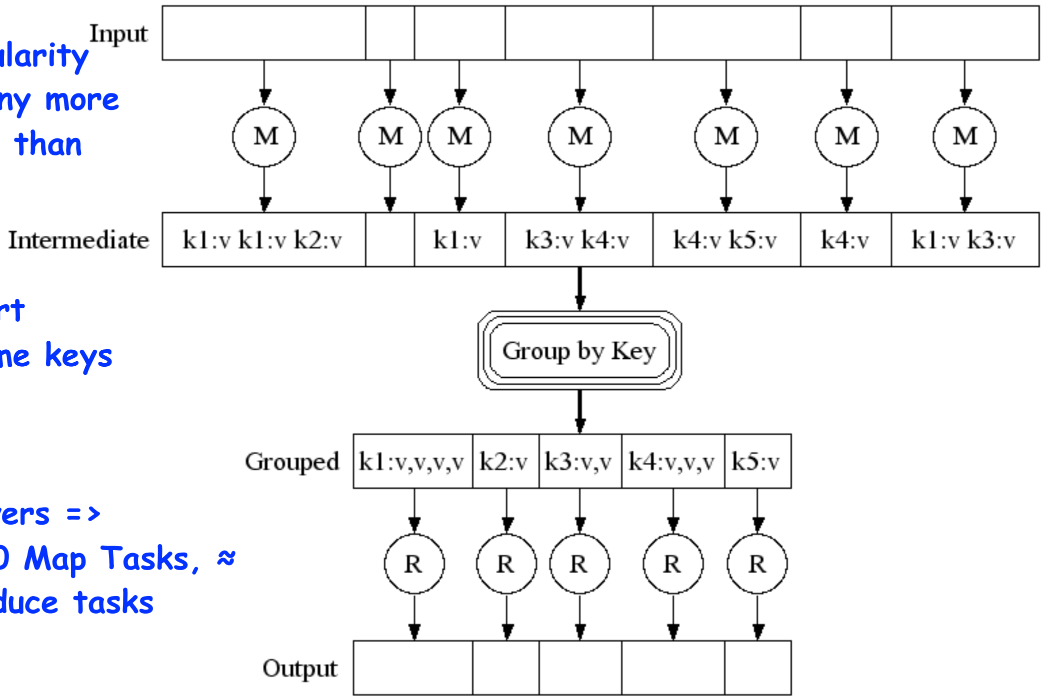
- Eventually, users started realizing that a much larger class of algorithms could be expressed as an iterative sequence of map/reduce operations
  - Many machine learning algorithms fall into this category
- Tools started to emerge to enable easy expression of multiple map/reduce operations, along with smart scheduling
- Apache Spark: General purpose functional programming over a cluster
  - Caches results of map/reduce operations in memory so they can be used on subsequent iterations without accessing disk each time
  - Tends to be 10-100 times faster than Hadoop for many applications

MapReduce Execution

Fine granularity tasks: many more map tasks than machines

Bucket sort to get same keys together

2000 servers => ≈ 200,000 Map Tasks, ≈ 5,000 Reduce tasks



WordCount example

In: set of words

Out: set of (word,count) pairs

Algorithm:

1. For each in word W, emit (W, 1) as a key-value pair (map step).
2. Group together all key-value pairs with the same key (reduce step).
3. Perform a sum reduction on all values with the same key(reduce step).

- All map operations in step 1 can execute in parallel with only local data accesses
- Step 2 may involve a major reshuffle of data as all key-value pairs with the same key are grouped together.
- Step 3 performs a standard reduction algorithm for all values with the same key, and in parallel for different keys.

PseudoCode for WordCount

```
<String, Integer> map(String inKey, String inValue):
  // inKey: document name
  // inValue: document contents
  for each word w in inValue:
    emitIntermediate(w, 1) // Produce count of words

<Integer> reduce(String outKey, Iterator<Integer> values):
  // outKey: a word
  // values: a list of counts
   Integer result = 0
   for each v in values:
     result += v // the value from map was an integer
   emit(result)
```


Example Execution of WordCount Program