XML Query Optimization in Map-Reduce

Leonidas Fegaras, Chengkai Li, Upa Gupta,
and Jijo J. Philip

University of Texas at Arlington

Data Processing using Map-Reduce

- Introduced by Google in 2004
- It facilitates the parallel execution of ad-hoc, long-running large-scale data analysis tasks on a shared-nothing cluster of commodity computers connected through a high-speed network
- Several implementations:
  - Apache Hadoop, Google Sawzall, Microsoft Dryad, …
- Used extensively by companies (on a very large scale):
  - Yahoo!, Facebook, Google, ...
- There are some higher-level languages that make map-reduce programming easier:
  - HiveQL, PigLatin, Scope, Dryad/Linq, ...

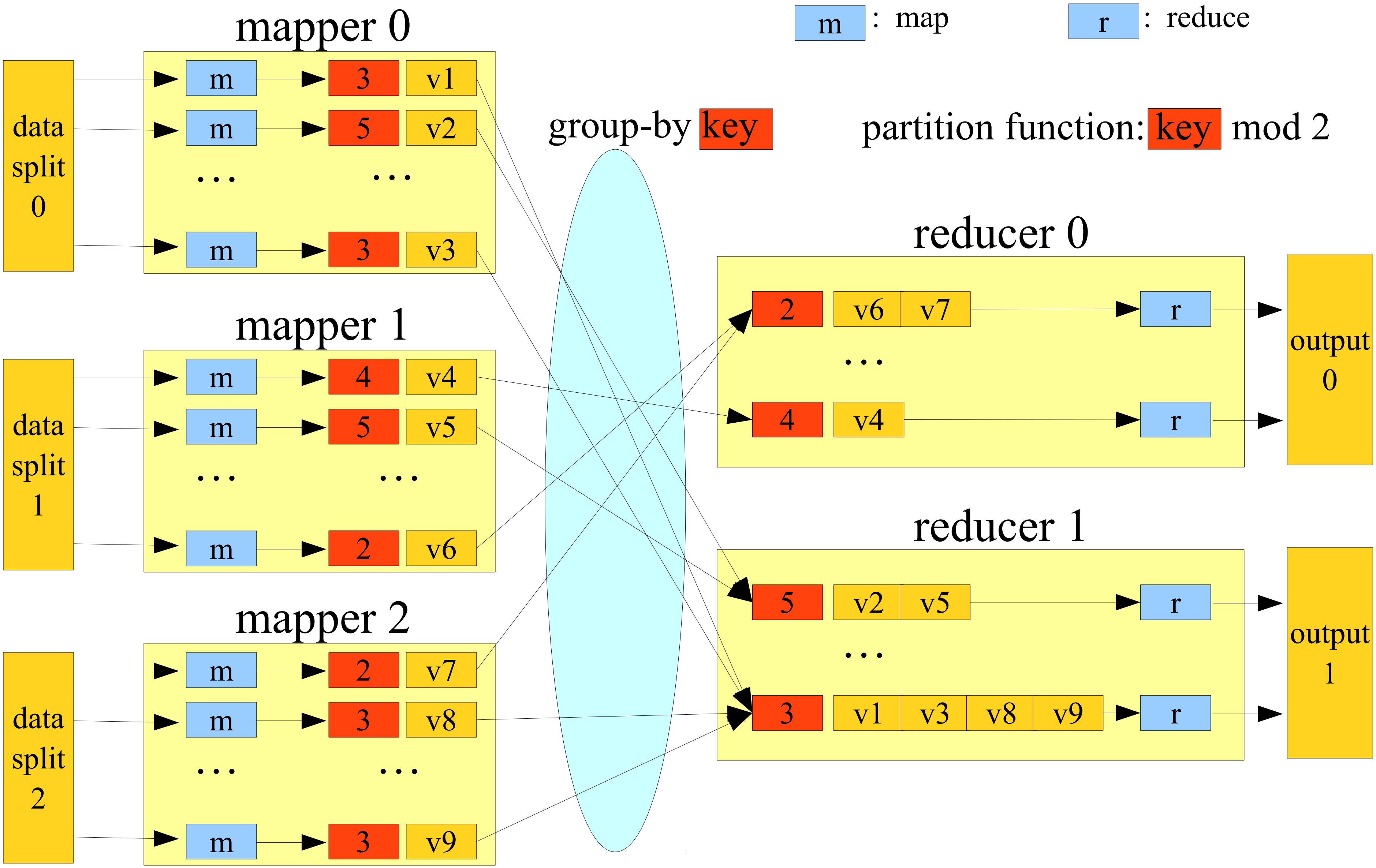
Data Processing using Map-Reduce

- Still a controversial topic in the DB community
  - *parallel databases*: need to model and load the data before processing
  - *map-reduce*: better suited to a small number of ad-hoc queries over **write-once raw data**
    - better fault tolerance and ability to operate in heterogeneous environments
    - indexes may not be applicable:
      - they are not very useful when processing most of the data
      - the amortized cost of index creation/population may exceed the cost benefit of using the index
- There are some recent systems that try to bridge the gap between map-reduce and RDB:
  - Hive
  - Pig
  - HadoopDB
  - Manimal
  - Hadoop++

The Map-Reduce Model

- Very simple model: need to specify a map and a reduce task
  - the map task specifies how to process a single key/value pair to generate a set of intermediate key/value pairs
  - the reduce task specifies how to merge all intermediate values associated with the same intermediate key
- … but, many configuration parameters to adjust for better performance

Example with 3 Mappers and 2 Reducers



Map-Reduce *vs* SQL

- Map-reduce programs are computationally complete
- Standard SQL (join, selection, projection, group-by, having, order-by) can be directly coded into map-reduce workflows
- Example:

```
select v.A, sum(v.B) from R v group by v.A
```

- Map-reduce pseudo-code in Hadoop:

```
class Mapper
    method map ( key, v ):
        emit(v.A, v);

class Reducer
    method reduce ( key, values ):
        int c = 0;
        for each v ∈ values do c += v.B;
        emit(key,c);
```

Motivation

- Although the map-reduce model is simple, it is
  - hard to develop programs for complex data analysis tasks
  - hard to optimize general map-reduce programs expressed in a general-purpose programming language
- As is evident from the success of the RDB technology
  - program optimization would be more effective if the programs were written in a higher-level query language that hides the implementation details and is amenable to optimization

MRQL: a Map-Reduce Query Language

- An SQL-like query language for expressing map-reduce computations
- MRQL is powerful enough to express most common data analysis tasks over many forms of raw data:
  - XML text documents
  - line-oriented text documents with comma-separated values
- The MRQL syntax has been influenced by some functional query languages, such as ODMG OQL and XQuery
- The MRQL semantics is based on the work by the functional programming community on list comprehensions with group-by and order-by
- Our goal:

To develop a novel framework for optimizing and evaluating map-reduce computations expressed in MRQL

Why not SQL?

Need to capture most map-reduce computations declaratively, within the query language, without using explicit calls to map-reduce jobs

- otherwise, we may get suboptimal/error-prone/hard-to-maintain code

1. Must allow arbitrary queries/UDFs for the group-by and aggregation expressions *(to make it m-r complete)*

```
select k, r(x)
  from x in X
 group by k: m(x)
```

after group-by, x is lifted to a bag (a group); r can be a query/UDF over bags

2. Must support hierarchical data and nested collections uniformly
   - need to optimize XML/JSON queries
3. Must allow arbitrary query nesting
   - otherwise, must explicitly use outer-joins/group-bys
     - ugly
     - lost optimization opportunities
4. Must support recursion (for PageRank, etc)

Optimization

- We can leverage on the relational query optimization technology, but ...
  - the MRQL physical operators are different
  - cost factors are different
  - must deal with nested collections and nested queries
- Example:

```
select x
 from x in X
where x.D > sum( select y.C
                   from y in Y
                  where x.A=y.B )
```

- A RDBMS may do a left-outer join between X and Y on x.A=y.B and group the result by the x key
  - requires 2 map-reduce jobs
- Often better: one reduce-side join, which requires 1 map-reduce job

Working with XML Data

- Each map worker is assigned a data split that consists of *data fragments*
  - for a text file: a single line in the file $\Rightarrow$ a relational record
  - for an XML document: the choice for a suitable fragment size and structure may depend on the actual application
- XML fragmentation
  - cannot use existing XML parsers
    - a data split may start at an arbitrary point in the XML document
    - XML elements may cross data split boundaries
  - built on top of the existing Hadoop XML input format
  - uses a set of synchronization tags to start parsing a data split
  - uses a stream-based XPath processor to extract elements from a data split

```
source( {"article","incollection","book","inproceedings"},
        Xpath( .[year=2009]/title ),
        "dblp.xml" )
```

Physical Operators

- The map-reduce operation: MapReduce (m, r) S

```
select w
 from z in (select r(key,y)
             from x in S,
                  (k,y) in m(x)
            group by key: k),
       w in z
```

Functional parameters:

m: map

r: reduce

- Types:

S: $bag(\alpha)$

m: $\alpha \rightarrow bag(\kappa \times \gamma)$

r: $\kappa \times bag(\gamma) \rightarrow bag(\beta)$

MapReduce (m, r) S: $bag(\beta)$

- Semantics:

MapReduce (m, r) = concatMap(r) ∘ groupBy ∘ concatMap(m)

where groupBy: $bag(\alpha \times \beta) \rightarrow bag(\alpha \times bag(\beta))$

Implementation of MapReduce

- MapReduce (m, r) S is implemented in Hadoop as a single map-reduce job:

```
class Mapper
    method map ( key, value ):
        for each (k, v) ∈ m(value) do emit(k, v);

class Reducer
    method reduce ( key, values ):
        B ← ∅;
        for each w ∈ values do B ← B ∪ {w};
        for each v ∈ r(key,B) do emit(key,v);
```

- For most cases, B is not materialized (using streaming)

Reduce-Side Join

- Reduce-side join: MapReduce2 (m_x, m_y, r) (X, Y)

```
select w
 from z in (select  r(x',y')
               from x in X,
                    y in Y,
                    (kx,x') in m_x(x),
                    (ky,y') in m_y(y)
             where kx = ky
            group by k: kx),
      w in z
```

Functional parameters:

m_x: left map

m_y: right map

r: reduce

- Implemented in Hadoop as a single map-reduce job that uses two map classes
  - After map: X values are tagged with 0, Y values are tagged with 1
  - The reducer separates the X from the Y values and calls r

Example

- Query:

```
select ( cat, os, count(p) )
 from p in XMark,
        i in p.profile.interest
 group by ( cat, os ):  ( i.@category,  count(p.watches.@open_auctions) )
```

- Physical plan:

in-memory processing

```
MapReduce(λp. select ( ( i.@category,count(p.watches.@open_auctions) ), p )
                  from i in p.profile.interest,
            λ((cat,os),ps). { ( cat, os, count(ps) ) } )
  ( XMark )
```

The MRQL Optimizer

- Based on an algebra that uses a generalized join operator that does data nesting *during* the join
  - avoids the need for an explicit group-by to nest data for a nested query
- It uses a novel cost-based optimization framework to map the algebraic forms to efficient workflows of physical plan operators
  - uses a polynomial heuristic algorithm for query graph reduction
  - handles deeply nested queries, of any form and at any nesting level, and converts them to near-optimal join plans
  - optimizes dependent joins (used when traversing nested collections and XML data)
- There is no cost model yet
  - We plan to develop an adaptive optimization method to
    - incrementally reduce the query graph at run-time
    - enhance the reduce stage of a map-reduce operation to generate enough statistics to decide about the next graph reduction step

Current Status

- MRQL is implemented in Java on top of Hadoop 0.21.0

  http://lambda.uta.edu/mrql/

- Can process the full MRQL syntax
- Can process two kinds of text documents:
  - XML documents
  - record-oriented text documents that contain basic values separated by user-defined delimiters
- Supports two kinds of joins:
  - reduce-side join
  - fragment-replicate join (using Hadoop's distributed cache)
- Supports four processing modes:
  - in-memory evaluation using Java vectors
  - Hadoop single node deployment
  - Hadoop cluster deployment
  - compilation to Java code for Hadoop cluster deployment