An Optimization Framework for Map-Reduce Queries

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Data Processing with Map-Reduce (MR)

- MR 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

  hides the details of parallelization, data distribution, fault-tolerance, and load balancing

- Used extensively by companies on a very large scale
- Several implementations:

  Apache Hadoop, Google Sawzall, Microsoft Dryad, . . .

- Some higher-level languages that make MR programming easier:

  HiveQL, PigLatin, Scope, Dryad/Linq, . . .

- Compared to an RDB, the MR framework:
  - is better suited to large-scale data analysis on write-once in-situ data

    often used to process data as is

  - offers better fault tolerance and the ability to operate in heterogeneous environments

The MR Programming Framework

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

Background: MR *vs* SQL

- MR programs are computationally complete
- Regular SQL (join, selection, projection, group-by, having, order-by) can be directly coded using workflows of MR jobs

Example:

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

can be coded in MR as:

```
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);
```

Background: Reduce-Side Join

Example:

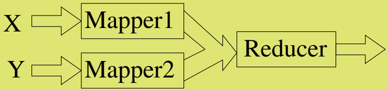
```
select x.C, y.D
  from X as x, Y as y
 where x.A=y.B
```

can be coded in MR as:

```
class Mapper1
    method map ( key, x )
        emit(x.A,(1,x));

class Mapper2
    method map ( key, y )
        emit(y.B,(2,y));

class Reducer
    method reduce ( key, values )
        for each (1,x) ∈ values
            for each (2,y) ∈ values
                emit(key,(x.C,y.D));
```



Motivation

Although the MR model is simple, it is hard to develop, optimize, and maintain non-trivial MR applications coded in a general-purpose programming language.

To achieve good performance one needs to

- tune many configuration parameters
- use custom serializers, comparators, and partitioners
- use special optimization techniques, such as in-mapper combining and in-reducer streaming

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.

There are many SQL-like MR query languages.
The most popular is HiveQL.

Goal

Build a query processing system that translates SQL-like data analysis queries to efficient MR jobs

- HDFS as the physical storage layer
    - no indexing, no data partitioning/clustering
    - no normalization
    - no data statistics
- Hadoop as the run-time engine
    - no extensions

In the future, we may relax some of these restrictions

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But, if we use SQL and completely hide the MR layer, why don't we just use a parallel RDB?

- MR is already used extensively; we can't change this
- a good query processor may simplify and improve the way programmers develop data analysis applications and will make MR computing friendlier to non-expert programmers
- MR is actually good!

What is Wrong with Existing MR Query Languages?

Two major problems (to be justified next):

1. Current MR query languages have limited expressive power, forcing users to plug-in custom MR scripts into their queries

   may result to suboptimal, error-prone, and hard-to-maintain code

2. Current MR query processors apply traditional relational query optimization techniques that may be suboptimal in a MR environment

MR-Completeness

A MR job over a relation R groups the tuples of R using the map function m and then applies the reduce function r to each group:

```
select k, r(group-values)
from R as v
group by k: m(v)
```

Current MR SQL-like query languages do not allow m and r to be nested queries and do not support access to the entire group, group-values, other than performing simple aggregations over the group elements.

Example: calculate one step of the k-means clustering algorithm by deriving k new centroids from the old

```
select avg(s.X) as X, avg(s.Y) as Y, avg(s.Z) as Z
 from Points as s
group by (select * from Centroids as c order by distance(c,s))[0]
```

How can we Reach MR-Completeness?

A MR query language must

- allow nested queries and UDFs at any level and at any place
  provided that UDFs are pure (no side effects)
- allow to operate on all the grouped data using queries
  as is done for ODMG OQL and XQuery
- support custom aggregations/reductions using UDFs
  provided that they are pure, associative, and commutative
- support recursion or transitive closure declaratively
  to capture graph algorithms, such as PageRank
- support hierarchical data and nested collections uniformly
  allowing us to query JSON and XML data
- support custom parsing and custom data fragmentation
  given that MR does not support nested data parallelism

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Can we Optimize MR Queries Using RDB Technology?

Example from TPCH:

```
select c.CUSTKEY, c.NAME, avg(o.TOTALPRICE)
  from Orders as o, Customer as c
 where o.CUSTKEY=c.CUSTKEY
 group by c.CUSTKEY, c.NAME
```

Hive evaluates this query using a join followed by a MR job (for the group-by), a total of 2 MR jobs

This query can also be evaluated using just one reduce-side join

- the set of orders fed to the reducer contains complete groups, which are ready for aggregation

This is true for all queries whose join attributes are also group-by attributes

Can we patch a relational system to generate this join/group-by plan?

Can we Patch an RDB to Generate Combined Join/Group-By Operations?

By definition, a relational operation must return flat tuples

⇒ A group-by must always be combined with aggregation within the same operator

Consider nested queries (which are important for MR-completeness).
For simple correlated queries, such as

```
select f(select h(x,y)                    (where f and h denote some code)
         from Y as y where x.A=y.B)
 from X as x
```

it is not inconceivable that an RDB optimizer could be patched to generate a reduce-side join that incorporates the group-by at the reduce stage

... but

Can we Patch an RDB ...?

But what about this double-nested query:

```
select f(select g(select h(x,y,z) from Z as z where z.C=y.D)
          from Y as y where x.A=y.B)
 from X as x
```

One good plan is to use two reduce-side joins (2 MR jobs only):

1. a join between X and Y that emits a nested set of pairs (x,ys): for each x, the set ys contains all the matching values y
2. a join between the result and Z, which computes the final query result at the reduce stage

The reducer of the 2^{nd} join receives two sets (mixed) from the two inputs: the set XY from the first join, which is the nested set (x, ys), and the set Zs of z tuples, and evaluates in memory:

select f(**select** g(**select** h(x, y, z) **from** $z \in$ Zs)
from $y \in ys$)
from $(x, ys) \in$ XY

(pseudo-SQL)

Can we Patch an RDB ...?

The reduce-side join plan again:

1. a join between X and Y that emits a nested set of pairs (x,ys): for each x, ys contains all the matching values y
2. a join between the result and Z, which computes the final query result at the reduce stage

It is impossible to capture the first join as a purely relational operator

$\Rightarrow$ need nested relations!

Side note:

- Some MR query languages use outer-joins with group-bys to simulate nested queries
- Bad idea!

  may miss opportunities of using a combined join/group-by

MRQL: the Map-Reduce Query Language

Oh great, yet another query language!

- The MRQL syntax has been influenced by some functional query languages, such as ODMG OQL and XQuery
- The MRQL semantics is based on list comprehensions with group-by and order-by
- It is implemented in Java on top of Hadoop
- Allows arbitrary query nesting, UDFs, custom aggregations, and custom parsers
- Can operate on complex data, such as nested collections and trees
- Can process:
  - record-oriented text documents that contain basic values separated by user-defined delimiters
  - XML and JSON documents
  - binary encoded documents

Note: This work is about optimizing MR queries. It can apply to other suitable languages, such as OQL and XQuery

The MRQL Physical Operations: The MR Operation

A MR job:

$$\text{MapReduce}(m, r)\, S$$

transforms a data set S of type $\{\alpha\}$ into a data set of type $\{\beta\}$ using a map function m and a reduce function r with types:

$$\begin{array}{ll} m\text{:} & \alpha \rightarrow \{\, (\kappa, \gamma)\, \} \\ r\text{:} & (\kappa, \{\gamma\}) \rightarrow \{\beta\} \end{array}$$

Semantics:

$$\text{MapReduce}(m, r)\, S = \text{concatMap}(r)\, (\text{groupBy}(\text{concatMap}(m)\, S))$$

where:

$$\begin{array}{ll} \text{concatMap}(f) : \ \{\alpha\} \rightarrow \{\beta\}, & \quad \text{given that } f : \ \alpha \rightarrow \{\beta\} \\ \text{groupBy} : \ \ \{(\kappa, \alpha)\} \rightarrow \{(\kappa, \{\alpha\})\} & \end{array}$$

concatMap generalizes π, σ, and μ

MRQL is MR-Complete

Any

$\text{MapReduce}(m, r)\, S$

can be expressed in MRQL as:

```
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
```

The MRQL Physical Operations: The Reduce-Side Join

The reduce-side join

$$\text{ReduceSideJoin}(m_x, m_y, r)\,(X, Y)$$

joins the data set X of type $\{\alpha\}$ with the data set Y of type $\{\beta\}$ to form a data set of type $\{\gamma\}$, where

m_x: $\alpha \to \{\,(\kappa, \alpha')\,\}$
m_y: $\beta \to \{\,(\kappa, \beta')\,\}$
r : $(\,\{\alpha'\}, \{\beta'\}\,) \to \{\gamma\}$

The mappers m_x and m_y calculate the join keys κ and the reducer r combines the tuples from X and Y that correspond to the same join key

Its semantics is given in terms of concatMap, groupBy, and union

Other join implementations: MapJoin (1 map job), MapJoinReduce (1 MR job), and BlockNestedLoop (1 map job)

The MRQL Query Algebra

Most important algebraic operators: concatMap, groupBy, union, and join

The MRQL join is a restricted version of ReduceSideJoin. It joins the bag X of type $\{\alpha\}$ with the bag Y of type $\{\beta\}$ to form a bag of type $\{\gamma\}$:

$$\text{join}(k_x, k_y, r)\,(X, Y)$$

where

k_x: $\alpha \to \kappa$
k_y: $\beta \to \kappa$
r : $(\,\{\alpha\}, \{\beta\}\,) \to \{\gamma\}$

Algebraic Optimization

Some optimizations:

- Fusing a join with a group-by if the group-by key is the same as the join key:

$$\begin{aligned}&\text{join}(\,\pi_1,\ k_y,\ r\,)\,(\,\text{groupBy}(X),\ Y\,)\\ =\ &\text{join}(\,\pi_1,\ k_y,\ \lambda(xs,ys).r(\,\text{groupBy}(xs),\ ys)\,)\,(\,X,\ Y\,)\end{aligned}$$

  where $\pi_1(x,y) = x$

- Converting a self-join into a simple MapReduce operation that operates over the input data set once:

$$\begin{aligned}&\text{join}(\,k_x,\ k_y,\ r\,)\,(\,X,\ X\,)\\ =\ &\text{MapReduce}(\,\lambda x.\,\{(k_x(x),(1,x)),(k_y(x),(2,x))\},\\ &\qquad\lambda(k,s).\,r(\,\textbf{select}\ x\ \textbf{from}\ (1,x)\in s,\\ &\qquad\qquad\textbf{select}\ x\ \textbf{from}\ (2,x)\in s\,)\,)\ X\end{aligned}$$

Example: The PageRank Algorithm

A web graph is represented as a set of links, where each link has a source, a destination, the total number of its outgoing links, and its current PageRank

One step of the PageRank algorithm derives a new set of edges from the old set, changing only their rank:

```
select m.source, m.dest, m.count, c.rank
  from (select n.dest, sum(n.rank/n.count) as rank
          from Graph as n
         group by n.dest) as c,
       Graph as m
where m.source = c.dest
```

(SQL query)

Needs just 1 MR job:

- fuse the join with the group-by ⇒ a self-join over Graph
- convert the self-join to a single MR job

The Complete PageRank in MRQL

```
graph = select ( key, n.to )
          from n in source(line,"graph.csv",...)
        group by key: n.id;                              preprocessing: 1 MR job

size = count(graph);

select ( x.id, x.rank )
from x in
    (repeat nodes = select < id: key, rank: 1.0/size, adjacent: al >
                     from (key,al) in graph                init step: 1 MR job
     step select (< id: m.id, rank: n.rank, adjacent: m.adjacent >,
                  abs((n.rank-m.rank)/m.rank) > 0.1)
           from n in (select < id: key, rank: 0.25/size+0.85*sum(c.rank) >
                        from c in ( select < id: a, rank: n.rank/count(n.adjacent) >
                                      from n in nodes, a in n.adjacent )
                       group by key: c.id),
                m in nodes
          where n.id = m.id)                               repeat step: 1 MR job
order by x.rank desc;                                      postprocessing: 1 MR job
```

The MRQL Query Optimizer

- uses a novel cost-based optimization framework to map 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
- handles dependent joins (used for nested collections and XML data)

Our cost model is currently incomplete
We plan to develop an adaptive optimization system to

- incrementally reduce the query graph at run-time
- extend the reduce stage of a map-reduce operation to generate enough statistics to decide about the next graph reduction step

Future Work

- Self-tuning
- Want to query both raw data and structured data, such as RDBs and key/value indexes, in the same query language
- Want to capture scientific data & computations
  - need to introduce the concept of data neighborhood
    - need to be able to access 'adjacent' data (eg, for data smoothing)
- Want to define complex custom parsers declaratively
  - need to go beyond Regular Expressions to capture LALR grammars

Related Work

- Many higher-level languages:

  HiveQL, PigLatin, PACT/Nephele, SCOPE, Dryad/Linq,...
- *HadoopDB*: a hybrid scheme between MR and parallel databases
- *Manimal*: analyzes the MR code to find opportunities for using B^+-tree indexes, projections, and data compression
- *Asterix*: a scalable platform to store, manage, and analyze large volumes of semistructured data

  uses its own distributed data store, Hyracks
- *YSmart*: intra-query optimization by factoring out correlated operations

How does MRQL Compare with Hive?

- For simple join/group-by queries:

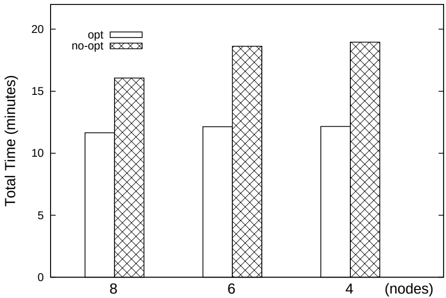
  they are about the same
- For queries that need optimization, such as fusing joins with group-bys, self-joins etc:

  MRQL is a clear winner
- For complex/nested queries, nested data, complex aggregations:

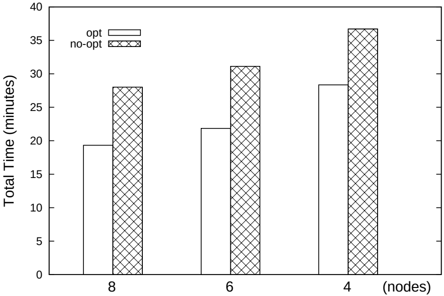
  no competition

Performance Evaluation

PageRank evaluation over DBLP (865MB XML) and the Hungarian Web (734MBs, 500K nodes 14M links)
Setup: 8 nodes/32 cores



(B) PageRank over DBLP data with/without optimization



(C) PageRank over the Hungarian Web with/without optimization