Distributed Aggregation for Data-Parallel Computing Interfaces and Implementations

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Dryad and DryadLINQ

Automatic query plan generation by DryadLINQ
Automatic distributed execution by Dryad
Distributed GroupBy-Aggregate

A core primitive in data-parallel computing

```
source = [upstream computation];
groups = source.GroupBy(keySelector);
reduce = groups.SelectMany(reducer);
result = [downstream computation];
```

Where the programmer defines:
```
keySelector: T → K
reducer: [K, Seq(T)] → Seq(S)
```
A Simple Example

- Group a sequence of numbers into groups and compute the average for each group

```csharp
source = <sequence of numbers>
groups = source.GroupBy(keySelector);
reduce = groups.Select(g => g.Sum()/g.Count());
```
Naïve Execution Plan

upstream computation

Map
Distribute

downstream computation

Map
GroupBy
Reduce
Consumer

g.Sum()/g.Count()
Execution Plan Using Partial Aggregation

Map
GroupBy
InitialReduce
Distribute
Merge
GroupBy
Combine
Merge
GroupBy
FinalReduce
Consumer

<\text{g.Sum()}, \text{g.Count()}>$

<\text{g.Sum(x=>x[0])},\text{g.Sum(x=>x[1])}>

g.\text{Sum}(x=>x[0])/g.\text{Sum}(x=>x[1])$
Distributed Aggregation in DryadLINQ

• The programmer simply writes:

```csharp
source = <sequence of integers>
groups = source.GroupBy(keySelector);
reduce = groups.Select(g => g.Sum()/g.Count());
```

• The system takes care of the rest
  – Generate an efficient execution plan
  – Provide efficient, reliable execution
Outline

• Programming interfaces
• Implementations
• Evaluations
• Discussion and conclusions
Decomposable Functions

• Roughly, a function H is decomposable if it can be expressed as composition of two functions IR and C such that
  – IR is commutative
  – C is commutative and associative

• Some decomposable functions
  – Sum: IR = Sum, C = Sum
  – Count: IR = Count, C = Sum
  – OrderBy.Take: IR = OrderBy.Take,
    C = SelectMany.OrderBy.Take
Two Key Questions

• How do we decompose a function?
  – Two interfaces: iterator and accumulator
  – Choice of interfaces can have significant impact on performance

• How do we deal with user-defined functions?
  – Try to infer automatically
  – Provide a good annotation mechanism
[Decomposable("InitialReduce", "Combine")]
public static IntPair SumAndCount(IEnumerable<int> g) {
    return new IntPair(g.Sum(), g.Count());
}

public static IntPair InitialReduce(IEnumerable<int> g) {
    return new IntPair(g.Sum(), g.Count());
}

public static IntPair Combine(IEnumerable<IntPair> g) {
    return new IntPair(g.Select(x => x.first).Sum(),
                       g.Select(x => x.second).Sum());
}
static public class Initial extends EvalFunc<Tuple> {
    @Override public void exec(Tuple input, Tuple output)
        throws IOException {
        try {
            output.appendField(new DataAtom(sum(input)));
            output.appendField(new DataAtom(count(input)));
        } catch (RuntimeException t) {
            throw new RuntimeException(...);
        }
    }
}

static public class Intermed extends EvalFunc<Tuple> {
    @Override public void exec(Tuple input, Tuple output)
        throws IOException {
        combine(input.getBagField(0), output);
    }
}

static protected void combine(DataBag values, Tuple output)
    throws IOException {
    double sum = 0;
    double count = 0;
    for (Iterator it = values.iterator(); it.hasNext();) {
        Tuple t = (Tuple) it.next();
        sum += t.getAtomField(0).numval();
        count += t.getAtomField(1).numval();
    }
    output.appendField(new DataAtom(sum));
    output.appendField(new DataAtom(count));
}

static protected long count(Tuple input)
    throws IOException {
    return values.size();
}

static protected double sum(Tuple input)
    throws IOException {
    double sum = 0;
    for (Iterator it = values.iterator(); it.hasNext();)
        sum += t.getAtomField(0).numval();
    return sum;
}
Accumulator Interface in DryadLINQ

```
[Decomposable("Initialize", "Iterate", "Merge")]
public static IntPair SumAndCount(IEnumerable<int> g) {
    return new IntPair(g.Sum(), g.Count());
}

public static IntPair Initialize() {
    return new IntPair(0, 0);
}

public static IntPair Iterate(IntPair x, int r) {
    x.first += r;
    x.second += 1;
    return x;
}

public static IntPair Merge(IntPair x, IntPair o) {
    x.first += o.first;
    x.second += o.second;
    return x;
}
```
Accumulator Interface in Oracle

STATIC FUNCTION ODCIAggregateInitialize
( actx IN OUT AvgInterval ) RETURN NUMBER IS
BEGIN
  IF actx IS NULL THEN
    actx := AvgInterval (INTERVAL '0 0:0:0.0' DAY TO
                        SECOND, 0);
  ELSE
    actx.runningSum := INTERVAL '0 0:0:0.0' DAY TO SECOND;
    actx.runningCount := 0;
  END IF;
  RETURN ODCIConst.Success;
END;

MEMBER FUNCTION ODCIAggregateIterate
( self IN OUT AvgInterval, val IN DSINTERVAL_UNCONSTRAINED ) RETURN NUMBER IS
BEGIN
  self.runningSum := self.runningSum + val;
  self.runningCount := self.runningCount + 1;
  RETURN ODCIConst.Success;
END;

MEMBER FUNCTION ODCIAggregateMerge
(self IN OUT AvgInterval, ctx2 IN AvgInterval ) RETURN NUMBER IS
BEGIN
  self.runningSum := self.runningSum + ctx2.runningSum;
  self.runningCount := self.runningCount +
                        ctx2.runningCount;
  RETURN ODCIConst.Success;
END;
Decomposable Reducers

• Recall our GroupBy-Aggregate:

```csharp
groups = source.GroupBy(keySelector);
reduce = groups.SelectMany(reducer);
```

• Intuitively, `reducer` is decomposable if every leaf function call is of form $H(g)$ for some decomposable function $H$

• Some decomposable reducers
  – Average: $g$.Sum()/$g$.Count()
  – SDV: $\sqrt{g$.Sum($x=>x^2$)-$g$.Sum()*$g$.Sum()}
  – $F(H_1(g), H_2(g))$, if $H_1$ and $H_2$ are decomposable
Implementation

Aggregation steps:
- G1+IR
- G2+C
- G3+F
Implementations

• Key considerations
  – Data reduction of the partial aggregation stages
  – Pipelining with upstream/downstream computations
  – Memory consumption
  – Multithreading to take advantage of multicore machines

• Six aggregation strategies
  – Iterator-based: FullSort, PartialSort, FullHash, PartialHash
  – Accumulator-based: FullHash, PartialHash
Iterator PartialSort

- G1+IR and G2+C
  - Keep only a fixed number of chunks in memory
  - Chunks are processed in parallel: sorted, grouped, reduced by IR or C, and emitted

- G3+F
  - Read the entire input into memory, perform a parallel sort, and apply F to each group

- Observations
  - G1+IR can always be pipelined with upstream
  - G3+F can often be pipelined with downstream
  - G1+IR may have poor data reduction
  - PartialSort is the closest to MapReduce
Accumulator FullHash

• G1+IR, G2+C, and G3+F
  – Build an in-memory parallel hash table: one accumulator object/key
  – Each input record is “accumulated” into its accumulator object, and then discarded
  – Output the hash table when all records are processed

• Observations
  – Optimal data reduction for G1+IR
  – Memory usage proportional to the number of unique keys, not records
    • So, we by default enable upstream and downstream pipelining
  – Used by DB2 and Oracle
Evaluation

• Example applications
  – **WordStats** computes word statistics in a corpus of documents (140M docs, 1TB total size)
  – **TopDocs** computes word popularity for each unique word (140M docs, 1TB total size)
  – **PageRank** performs PageRank on a web graph (940M web pages, 700GB total size)

• Experiments were performed on a 240-node Windows cluster
  – 8 racks, 30 machines per rack
Example: WordStats

```csharp
var docs = PartitionedTable.Get<Doc>("dfs://docs.pt");

var wordStats =
    from doc in docs
    from wc in from word in doc.words
        group word by word into g
        select new WordCount(g.Key, g.Count())
    group wc.count by wc.word into g
    select ComputeStats(g.Key, g.Count(), g.Max(), g.Sum());

wordStats.ToPartitionedTable("dfs://result.pt");
```
WordStats Performance

• Comparison with baseline (no partial aggregation)
  – Baseline: 900 seconds
  – FullSort: 560 seconds
  – Mainly due to additional disk and network IO

• Comparison with MapReduce
  – Simulated MapReduce in DryadLINQ
    • 16000 mappers and 236 reducers
    • Machine-level aggregation
  – MapReduce: 700 seconds
    • 3x slower than Accumulator PartialHash
WordStats Data Reduction

• The total data reduction is about 50x

<table>
<thead>
<tr>
<th>Strategy</th>
<th>G1+IR</th>
<th>G2+C</th>
<th>G3+F</th>
</tr>
</thead>
<tbody>
<tr>
<td>FullSort</td>
<td>11.7x</td>
<td>2.5x</td>
<td>1.8x</td>
</tr>
<tr>
<td>PartialSort</td>
<td>3.7x</td>
<td>7.3x</td>
<td>1.8x</td>
</tr>
<tr>
<td>AccFullHash</td>
<td>11.7x</td>
<td>2.5x</td>
<td>1.8x</td>
</tr>
<tr>
<td>AccPartialHash</td>
<td>4.6x</td>
<td>6.15x</td>
<td>1.85x</td>
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<tr>
<td>IterFullHash</td>
<td>11.7x</td>
<td>2.5x</td>
<td>1.8x</td>
</tr>
<tr>
<td>IterPartialHash</td>
<td>4.1x</td>
<td>6.6x</td>
<td>1.9x</td>
</tr>
</tbody>
</table>

• The partial strategies are less effective in G1+IR
  – Always use G2+C in this case
Discussion and Conclusions

• Programming Interfaces
  – Have big impact on the actual performance
    • Accumulator interface was the winner
  – DryadLINQ offers better interfaces than Hadoop and databases
    • Better integration with the existing programming languages and their type systems
    • Enable compositions of decomposable functions
  – Iterator is somewhat easier to program with
    • Adopted by .NET and LINQ
    • Adopted by MapReduce/Hadoop
Discussion and Conclusions

• Implementations
  – Accumulator-FullHash was the winner
    • Database folks got it right here 😊
    • PartialSort (closest to MapReduce) was the second worst strategy
  – Need to choose between various optimizations
    • Rack-level aggregation?
    • FullHash or PartialHash?
    • Pipelining or not?
    • ...
Discussion and Conclusions

• GroupBy-Aggregate is an extremely important primitive for data-parallel computing

• We need to get its programming model right!
Dryad/DryadLINQ Availability

• Freely available for academic use
  – http://connect.microsoft.com
  – Dryad in binary, DryadLINQ in source
  – Will release Dryad source in the future

• Will release to Microsoft commercial partners
  – Free, but no product support
Software Stack

Applications

Other Applications

DryadLINQ

Other Languages

Dryad

CIFS/NTFS

SQL Servers

Azure Platform

TidyFS

Cluster Services

Windows Server

Windows Server

Windows Server

Windows Server