Achieving Performance and Programmability for Data-Intensive Applications with Reduction-based APIs

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The success of MapReduce in the past 2 decades

- Supports a wide range of applications
- Optimized for large input size and distributed environment

Following the pattern-based API design many works have been done:

- HaLoop, MapReduce-MPI for Graph, Disco, Mariane
- Smart
- Spark
Spark:

- Interfaces: Transformations & Actions
- Data Structure: Resilient Distributed Datasets
- Implementations: Scala
- Advantages: Fast, In-memory, Expressive, Better Resilience Control

Transformations and Actions in Spark [2]
The goal in this work has been on programmability.

Parallel programming can be done by many.

What about performance?

MPI ecosystem focused almost entirely on performance.

Common wisdom is Choose One!

Can we achieve both performance and programmability?
• Design of Reduction Based MapReduce Variants
  • Achieving Performance and Programmability

• Implementation of Systems:
  • Smart: An Efficient In-Situ Analysis Framework
  • Smart Streaming: A High-Throughput Fault-tolerant Online Processing System
  • A Pattern-Based API for Mapping Applications to a Hierarchy of Multi-Core Devices
Reduction Object API:

Generate_key: \(<\text{Input Type}>\) \rightarrow k
Accumulate: k, \(<\text{Input Type}>\times k, \text{list}(<v>)\) \rightarrow k, \text{list}(<v>)
Merge: k, \text{list}(<v>) \times k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)
Post_combine: k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)

I: API Design
Programmability:

- **Strict Constraints**

  Merge: strict binary, associative, commutative ↔ Reduce: N-ary

  Fewer lines of code, less functionality overlap, and directly reuse Map-Reduce code
Efficiency: better memory efficiency & locality:

Redundant intermediate results

Input values are instantly accumulated to local accumulators
MR-like API:

Map: \(<\text{Input Type}> \rightarrow \text{list}(<k, v>)\)

Merge: \(k, \text{list}(<v>) \times k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)\)

Post_combine: \(k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)\)

Some temp results are still generated

Same function is reused at different stage
### Effective lines of code:

<table>
<thead>
<tr>
<th></th>
<th>MR API</th>
<th>RO API</th>
<th>MR-like API</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-means</td>
<td>36</td>
<td>19</td>
<td>19</td>
</tr>
<tr>
<td>SVM</td>
<td>44</td>
<td>28</td>
<td>21</td>
</tr>
<tr>
<td>Linear Regression</td>
<td>43</td>
<td>26</td>
<td>19</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>36</td>
<td>17</td>
<td>17</td>
</tr>
</tbody>
</table>
• Design of Reduction Based MapReduce Variants
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In-Situ Analytics on Simulations

• Driver: Cannot Write all Data to Disk
  • Computation/ I/O Ratio has been changing

• In-Situ Algorithms
  • Implemented with low-level APIs like OpenMP/MPI
  • Manually handle all the parallelization details

• Motivation
  • Can the applications be mapped more easily to the platforms for in-situ analytics?
  • Can the offline and in-situ analytics code be (almost) identical?
Opportunity

• Explore the **Programming Model Level** in In-Situ Environment
  • Between application level and system level
  • Hides all the parallelization complexities by simplified API
  • A prominent example: **MapReduce**
Challenges

• Hard to Adapt MR to In-Situ Environment
  • MR is not designed for in-situ analytics
• Mismatches
  • Programming View Mismatch
  • Memory Constraint
Programming View Mismatch

- Scientific Simulation
  - Parallel programming view
  - Explicit parallelism: partitioning, message passing, and synchronization
- MapReduce
  - Sequential programming view
  - Partitions are transparent
- Need a Hybrid Programming View
  - Exposes partitions during data loading
  - Hides parallelism after data loading
Memory Constraint Mismatch

• MR is Often Memory/Disk Intensive
  • Map phase creates intermediate data
  • Sorting, shuffling, and grouping do not reduce intermediate data at all
  • Local combiner cannot reduce the peak memory consumption (in map phase)

• Need Alternate MR API
  • Avoids key-value pair emission in the map phase
  • Eliminates intermediate data in the shuffling phase
Bridging the Gap

- Addresses All the Mismatches
  - Loads data from (distributed) memory, even without extra memcpy in time sharing mode
  - Presents a hybrid programming view
  - High memory efficiency with alternate API
  - Implemented in C++11, with OpenMP + MPI
Original Map-Reduce API:

Map: <Input Type> → list<k, v>
Combine: k, list<v> → list<k, v> (Local)
Reduce: k, list<v> → list<k, v>
Reduction Object API:

Generate_key: $<\text{Input Type}> \rightarrow \text{list}(<k>)$
Accumulate: $k, <\text{Input Type}> \times k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)$
Merge: $k, \text{list}(<v>) \times k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)$
Post_combine: $k, \text{list}(<v>) \rightarrow k, \text{list}(<v>)$
Two In-Situ Modes

**Time Sharing Mode:**
Minimizes memory consumption

**Space Sharing Mode:**
Enhances resource utilization when simulation reaches its scalability bottleneck
System Overview
Ease of Use

• Launching Smart
  • No extra libraries or configuration
  • Minimal changes to the simulation code
  • Analytics code remains the same in different modes

• Application Development
  • Define a reduction object
  • Derive a Smart scheduler class
    • $\text{gen\_key(s)}$: generates key(s) for a data chunk
    • $\text{accumulate}$: accumulates data on a reduction object
    • $\text{merge}$: merges two reduction objects
Launching Smart in Space Sharing Mode

Listing 2: Launching Smart in Space Sharing Mode

```c
void simulate(Out* out, size_t out_len, const Param& p) {
    /* Initialize both simulation and Smart. */
    #pragma omp parallel num_threads(2)
    #pragma omp single
    {
        #pragma omp task // Simulation task.
        {
            omp_set_num_threads(num_sim_threads);
            for (int i = 0; i < num_steps; ++i) {
                /* Each process simulates an output
                   partition of length in_len. */
                smart->feed(partition, in_len);
            }
        }
        #pragma omp task // Analytics task.
        for (int i = 0; i < num_steps; ++i)
            smart->run(out, out_len);
    }
}
```
Launching Smart in Time Sharing Mode

Listing 1: Launching Smart in Time Sharing Mode

```c
void simulate(Out* out, size_t out_len, const Param& p) {
    /* Each process simulates an output partition of data type In and length in_len. */
    // Launch Smart after simulation in the parallel code region.
    SchedArgs args(num_threads, chunk_size, extra_data, num_iters);
    unique_ptr<Scheduler<In, Out>> smart(new DerivedScheduler<In, Out>(args));
    smart->run(partition, in_len, out, out_len);
}
```
**Node Scalability**

- **Setup**
  - 1 TB data output by Heat3D; time sharing; 8 cores per node
  - 4-32 nodes
Thread Scalability

Setup
- 1 TB data output by Lulesh; time sharing; 64 nodes
- 1-8 threads per node
Smart vs. Spark

- To Make a Fair Comparison
  - Bypass programming view mismatch
    - Run on an 8-core node: multi-threaded but not distributed
  - Bypass memory constraint mismatch
    - Use a simulation emulator that consumes little memory
  - Bypass programming language mismatch
    - Rewrite the simulation in Java and only compare computation time

40 GB input and 0.5 GB per time-step

### K-Means Histogram

<table>
<thead>
<tr>
<th># of Threads</th>
<th>Smart</th>
<th>Spark</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15550</td>
<td>344</td>
</tr>
<tr>
<td>2</td>
<td>10403</td>
<td>424</td>
</tr>
<tr>
<td>4</td>
<td>7750</td>
<td>210</td>
</tr>
<tr>
<td>8</td>
<td>6559</td>
<td>105</td>
</tr>
</tbody>
</table>

**62X**

### Histogram

<table>
<thead>
<tr>
<th># of Threads</th>
<th>Smart</th>
<th>Spark</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>10361</td>
<td>344</td>
</tr>
<tr>
<td>2</td>
<td>6697</td>
<td>173</td>
</tr>
<tr>
<td>4</td>
<td>4766</td>
<td>96</td>
</tr>
<tr>
<td>8</td>
<td>3992</td>
<td>27</td>
</tr>
</tbody>
</table>

**92X**
Smart vs. Spark (Cont’d)

- **Faster Execution**
  - Spark 1) emits intermediate data, 2) makes immutable RDDs, and 3) serializes RDDs and sends them through network even in the local mode
  - Smart 1) avoids intermediate data, 2) performs data reduction in place, and 3) takes advantage of shared-memory environment (of each node)

- **Greater (Thread) Scalability**
  - Spark launches extra threads for other tasks, e.g., communication and driver’s UI
  - Smart launches no extra thread

- **Higher Memory Efficiency**
  - Spark: over 90% of 12 GB memory
  - Smart: around 16 MB besides 0.5 GB time-step
Smart vs. Low-Level Implementations

- **Setup**
  - Smart: time sharing mode; Low-Level: OpenMP + MPI
  - Apps: K-means and logistic regression
  - 1 TB input on 8–64 nodes

- **Programmability**
  - 55% and 69% parallel codes are either eliminated or converted into sequential code

- **Performance**
  - Up to 9% extra overheads for k-means
  - Nearly unnoticeable overheads for logistic regression
• Design of Reduction Based MapReduce Variants
  • Achieving Performance and Programmability

• Implementation of Systems:
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II: Stream Processing

Continuous Stream Processing:
- One record at a time
- Low latency

  e.g. Storm, Flink, Samza ...

Discrete Stream Processing:
- A micro-batch of records
- Coherent with batch jobs
- Locality

  e.g. Spark Streaming
A part of data pipeline, commonly used to ingest events and act as source for downstream processing or ETL

- Topic Based
- Scalability:
  - Partitioned Topics
  - Parallel Consuming
- Fault-tolerance:
  - Duplication
  - Checkpointing
- Interface: cppkafka
Workflow:
- Master Node:
  - Get checkpoint
  - Schedule workload
- Worker Node:
  - Fetch messages
  - Accumulate messages
- Master Node:
  - Final Reduction
  - Commit Checkpoint
System Design

Fault-tolerance:

- A heart-beat mechanism implemented using OpenMP/MPI
- On-disk checkpointing of progress and state
- Dynamic load re-balancing upon failure/suspension of worker

API:

- Reduction-Object based abstraction
- Micro-batch size control
- Sliding window width control

Sliding window processing
MPI and OpenMP Collaboration:

- Using Mvapich2: For HPC environment and error handling
- MPI Run-through-stabilization: \texttt{--disable-auto-cleanup}
- Process Communication: Non-blocking, point to point send and receive
- Multi-Threading: 1-2 I/O threads (control, data) and a pool of reduction threads
- Thread-safety: MPI \texttt{send} and \texttt{receive} commands protected by critical zone
II: Experiments

Environment:
- 32 nodes, each with two quad-core Intel E5640
- 12GB RAM
- 40GB/s Infiniband interconnect
- Kafka on 5 nodes

Throughput:
- Ours v.s. Spark v.s. Flink
- Sustainable throughput

Fault-tolerance:
- Ours v.s. Spark
- One worker down

<table>
<thead>
<tr>
<th></th>
<th>Batch Size: 1s on Spark or equivalent size.</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-means</td>
<td>Number of Means: 8</td>
</tr>
<tr>
<td></td>
<td>Number of Dimensions: 16 (128 bytes)</td>
</tr>
<tr>
<td>Linear Regression</td>
<td>Number of Features: 15</td>
</tr>
<tr>
<td></td>
<td>Labels: 1</td>
</tr>
<tr>
<td></td>
<td>Number of Dimensions: 16 (128 bytes)</td>
</tr>
<tr>
<td></td>
<td>Regularization Parameter: 0.1</td>
</tr>
<tr>
<td></td>
<td>Step Size: 1.0</td>
</tr>
<tr>
<td></td>
<td>Include Interception: Yes</td>
</tr>
<tr>
<td>Histogram</td>
<td>Number of Dimensions: 1 (8 bytes)</td>
</tr>
<tr>
<td></td>
<td>Number of Buckets: 10</td>
</tr>
<tr>
<td>Moving Average</td>
<td>Number of Dimensions: 1 (8 bytes)</td>
</tr>
<tr>
<td></td>
<td>Window size: 3s or equivalent size.</td>
</tr>
<tr>
<td></td>
<td>Sliding interval: 1s</td>
</tr>
</tbody>
</table>
II: Experiments

Throughput:

(a) K-Means Throughput

(b) Linear Regression Throughput

(c) Histogram Throughput

(d) Moving Average Throughput
II: Experiments

Fault-tolerance: single worker down

(a) K-Means Throughput Loss

(b) Linear Regression Throughput Loss

(c) Histogram Throughput Loss

(d) Moving Average Throughput Loss
Discussions

Throughput:
- The throughput of our framework significantly outperforms existing frameworks.
- Our framework shows scalability as good as Spark.
- In window based applications, throughput is capped by parallelism of Kafka partition.

Fault-tolerance:
- The failure detection and load balancing are dynamic and non-blocking.
- The throughput loss is roughly proportional to the resource loss.
- The failure of master node requires the whole system restart from checkpoint.
- When using 64 nodes, the F-T performance can be limited by the parallelism of Kafka partition.

Latency:
- With the same microbatch size and smaller batch processing time, our in batch latency < Spark’s.

Average in-batch latency

\[
\begin{array}{c|c}
\text{Spark} & 1\text{batch} = n \text{ records} \\
\hline
\text{Ours} & 1 \text{ batch} \\
\end{array}
\]

\[
t_{\text{start}} \quad t_1, \text{ours finish} \quad t_2, \text{spark finish} \quad t
\]

\[
t_2/2 \quad t_1/2
\]
• Operating over stream data, Kafka support not perfect
• Micro-batch processing with desirable throughput and scalability.
• Efficient failure detection for node failures/suspension.
• Design of Reduction Based MapReduce Variants
  • Achieving Performance and Programmability

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  • **Smart**: An Efficient In-Situ Analysis Framework
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  • **A Pattern-Based API for Mapping Applications to a Hierarchy of Multi-Core Devices**
IoT Devices:
- Limited in clock frequency, memory size, and cache size
- Multi-core CPU structure: RPi 3B+ with a quad core

Hierarchical Structure:
- Devices are of very different processing capabilities
- A vertical hierarchy from sensors to cloud
- Limited bandwidth
- Latency sensitive applications
• Extend the Reduction Object APIs to broader types of applications.

• IoT and Fog computing requires high CPU/memory efficiency.

• Heterogenous IoT devices and requires special optimizations.

• We want to offload the computation to the whole network.
Basic Concepts:

2-D Sliding Window

2-D Integral Image

III: Application
III: Application

Feature Selection:

(a) Edge Features
(b) Line Features
(c) Four-rectangle features

Cascaded Detection:

Features:
- Input Image
- Test 1
- Test 2
- ... Test n
- Accept ROI
- Reject ROI, return
API Design:
- Reduction-Object
- Image Processing: pyramid, sliding window, convolution
- User defined transformation

<table>
<thead>
<tr>
<th>genKey</th>
<th>Generate one (or multiple) key(s) for each input element</th>
</tr>
</thead>
<tbody>
<tr>
<td>accumulate</td>
<td>Accumulate an input pair to the accumulator</td>
</tr>
<tr>
<td>merge</td>
<td>Merge two accumulators with the same Key</td>
</tr>
<tr>
<td>window</td>
<td>Perform operation on a sequence of windows</td>
</tr>
<tr>
<td>pyramid</td>
<td>Generate a pyramid representation</td>
</tr>
<tr>
<td>convolution</td>
<td>Perform a convolution on the given coordinate</td>
</tr>
</tbody>
</table>
Load Balancing For Multi-scale Detection
- The detection is often on multiple scales of one image
- The load for each level of scale can be calculated
- The work can be off-loaded to different scales of network after a load test.

Pyramid representation of an image
III: Optimizations

Re-use of Partial Results:
• For Haar-like feature selection
• Result reuse between adjacent windows
III: Experiment

Comparing Scalability of Our Framework with OpenCV on AWS Time(s)/Cores

(a) Haar-Cascade  
(b) LBP-Cascade  
(c) HOG-SVM

Comparing Scalability of Our Framework with OpenCV on Raspberry-PiTime(s)/Cores

(a) Haar-Cascade  
(b) LBP-Cascade  
(c) HOG-SVM
Running Time for Distributed Application with Different Layers of Images Processed on Desktop

Desktop = 15 x Rpi
Observations:

- Overall speedups on 16 cores of 9.46x and 7.57x for Haar and LBP-Cascade.
- For HOG-SVM ours show better scalability.
- On Rpi using one core, ours is faster by 17% - 35% over OpenCV.
- The sweet spot in load balancing experiment matches with our prediction.
Our results have shown that we can effectively parallelize and scale across cores on both edge and central device.

Our framework overall out performs OpenCV in all three applications.

We are also able to reduce latency by dividing the work between edge and central devices.
Conclusions

- Can achieve performance and programmability
- Pattern-based APIs enable new optimizations
- Many more applications/scenarios can be considered