Stateful Load Balancing for Parallel Stream Processing

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Stream Processing in 20 Years

• Data Stream Management Systems (DSMS)
  • TelegraphCQ, STREAM, Gigscope, Aurora/Borealis, System S, etc.
  • Continuous query (CQ)
  • Low-latency processing: batching → streaming
  • Query results: deterministic → non-deterministic
  • etc.

• When stream meets big data
  • S4, Storm, Spark Streaming, StreamScope, Flink, Kafka/Samza, Millwheel/Dataflow, etc.
  • 3Vs of big data: volume, velocity, variety
  • Scalability, elasticity, task scheduler, fault tolerance etc.
  • Uniformed: batching + streaming
Achieve Real-time Processing

Leverage memory
The inputs of over 90% of jobs in Facebook, Yahoo!, and Bing clusters are fitted into memory.

Increase parallelism
Reduce work per node improves latency
- Low latency scheduler
- Globe state management
- Efficient failure recovery
- Optimization of communication patterns: e.g., shuffle, broadcast
Stateful Stream Processing

State is introduced for reasons such as window-based computation, buffering, fault tolerance, etc.

• Traditional model
  ▪ Processing pipeline of nodes
  ▪ Each node maintains mutable state
  ▪ Each input record updates the state and new records are sent out

• Reconfiguration of computation
  ▪ Mutable state get lost if node fails
  ▪ State should be redistributed across nodes if the placement plan changes
  ▪ Runtime adaptation for load variations, scale-out/scale-in
  ▪ All these cases involve state migration
State Migration

Pause-migration-resume procedure

• Pause the execution (O2)
• Install new operator on target node (O2 on node 2)
• Serialize state of O2 & send to new node (node 2)
• Redirect tuples to new node (node 1 → node 2)

State migration is time-consuming and dominate
Challenge from Load Variations

Problems of load variations
1. Unmatched provision: low resource efficiency
2. Load imbalance: low processing latency and bad system throughput

Handling load variations
Operator placement & Adaptations
1. Dynamic scaling
2. Load balancing

CPU Utilization of Google cluster

- Streaming
- Batch
Two Optimization Problems

Dynamic reconfiguration

Load variations, e.g., changes of data rate and data distribution
Commensurate provision: adaptive data partitioning to achieve load balancing and to scale the number of parallel instances of each operator to avoid over-provisioning or under-provisioning.

Communication minimization

Reduce data shuffle
Optimizing the operator placement to minimize cross-node communication can significantly reduce the resource consumption in a DSPE.
Project Enorm

Enorm was launched in 2013 at SDU, 1 faculty and 3 PhD students. A distributed stream processing engine (DSPE) extends Apache Storm with some essential properties such as:

- flexible window computation,
- elastic resource management, operator placement strategies,
- automatic scaling,
- load balancing,
- globe state management,
- optimized fault-tolerance,
- etc.

Enorm borrows the basic concept from Storm:

- Spout, Bolt, Topology (operator graph)
- Task & its execution model
- Stream grouping schemes
Basic Concepts of Storm

**Spout**
Ingest source streams from Kestrel and Kafka queues or read data from Twitter streaming API, HDFS, Hive, etc.

**Bolts**
Processes input streams and produces new streams. It could be user-defined functions or standard SQL operators, such as Filters, Aggregation, Joins, etc.

**Topology (operator graph)**
A directed acyclic graph (DAG) of spouts and bolts
Parallel Stream Processing with Storm

**Task & execution**
Spouts and bolts execute as many tasks
Tasks are scheduled and spread across the storm cluster

![Diagram of Storm cluster and task execution](image)

**Stream grouping**
It defines how to dispatch output tuples.
- **Shuffle grouping**: pick a random task
- **Fields grouping**: mod hashing on a subset of tuple fields
- **All grouping**: send to all tasks
Operator Model

Operator model

**Input, output**: relational stream
**Function, sliding window**
**Processing state**, e.g., stateful or stateless
**Partition key** for stream grouping
- 1. **Shuffle grouping** for stateless operator
- 2. **Key grouping** for stateful operator

Parallel processing

Operator instances $\mathcal{I} = \{o^1, \cdots, o^m\}$
Substreams $\mathcal{S} = \{s^1, \cdots, s^p\}$
Assignment $\mathcal{F}_C: \mathcal{S} \rightarrow \mathcal{I}$

Plan 1: $s^1, s^4 \rightarrow o^1, s^2 \rightarrow o^2, s^3 \rightarrow o^3$
Plan 2: $s^1 \rightarrow o^1, s^2 \rightarrow o^2, s^3, s^4 \rightarrow o^3$
Component-based Parallelization (CBP)

Component

An induced subgraph C of the operator graph is said to be a component if and only if C is connected and its operators are compatible.

Compatibility: A set of operators are compatible iff the intersection of their partitioning keys is not empty. It is non-transitive.

Connectivity: Communication in a node is replaced by local memory access and thus intra-component communications are eliminated.

Example

A simplified version of Linear Road Benchmark that calculates tolls with a position-speed stream

5 operators: traffic statistics, accident detection, toll calculation, ...

Partitioning compatibility: Operators has common attribute

<table>
<thead>
<tr>
<th>Operator</th>
<th>Partition Key</th>
</tr>
</thead>
<tbody>
<tr>
<td>O1: Forwarder</td>
<td>{Ts, Vid, XWay, Dir, Seg, Spd, Pos, Type}</td>
</tr>
<tr>
<td>O2: AcdDetector</td>
<td>{Ts, Vid}</td>
</tr>
<tr>
<td>O3: AvgSpeed</td>
<td>{Vid, XWay, Dir, Seg}</td>
</tr>
<tr>
<td>O4: SegVolume</td>
<td>{Xway, Dir, Seg}</td>
</tr>
<tr>
<td>O5: TollCalculator</td>
<td>{Xway, Dir, Seg}</td>
</tr>
</tbody>
</table>
Component-based Parallelization

Optimization goals
1. Runtime resource reconfiguration: Unmatched provision, imbalance
2. Communication cost minimization: Operator placement, task allocation

CBP essentials
Leverage the compatibility of operators
Intra-query parallelism
Intra-operator parallelism
Scalability of OBP
Grouping Schemes

Key grouping and state movement

Load balancing in adaptation
Each substream is marked with the number of tuples
The same number of state partition with its load
Change the assignment
16 state movements
Minimum Cost Load Balancing (MCLB)

Problem Statement

• Given a uneven assignment $F_1$, the execution of load balancing is to compute a new assignment $F_2$ that balances load for all instances.
• The MCLB problem asks for such an assignment $F_2$ with the minimum state movements.

• Bi-objective optimization problem
• Complexity
  • NP-hard
  • Approximate solutions
Statistics Measurement

- **Substreams** $s_1 \ldots s_p$ statistic windows of length $\Delta$
- **Histogram** $Y_t = (y_{1t}, y_{2t}, \ldots, y_{pt})^T$
  - $y_{it}$ records the load for $s_i$ at the t-th window

Average load & load variance
\[
\begin{aligned}
\bar{y}_t &= \frac{1}{p} \sum_{i=1}^{p} y_{it} \\
var(Y_t) &= E[Y_t^2] - (E[Y_t])^2
\end{aligned}
\]

- **Substream** $s_i$ can be represented as a load series $X_i = (y_{i1}, \ldots, y_{im})$

Average load & load variance
\[
\begin{aligned}
E[X_i] &= \frac{1}{m} \sum_{t=1}^{m} y_{it} \\
var(X_i) &= E[X_i^2] - (E[X_i])^2 \\
cov(X_1, X_2) &= E[X_1X_2] - E[X_1]E[X_2] \\
\rho_{12} &= \frac{cov(X_1, X_2)}{\sqrt{var(X_1)} \cdot \sqrt{var(X_2)}}
\end{aligned}
\]
Metrics

- Encoding the assignment as a matrix: \( \mathbf{A} = [a_{ij}]_{p \times n} \)
- For instances \((o^1, \ldots, o^n)\), the load vector \( L_t = (l_{1t}, l_{2t}, \ldots, l_{nt})^T \) at t-th window is given by a linear transformation \( \mathbf{A}^T \mathbf{Y}_t = \bar{l}_t \)

Load imbalance

\[
\text{var}(L_t) = \frac{1}{n} \sum_{i=1}^{n} (l_{it} - \bar{l}_t)^2
\]

Normally we use \( |\text{max} - \text{min}| \) to measure imbalance

State movements

Given an uneven assignment \( F_1 \) and a new assignment \( F_2 \), a state partition \( \psi \) will be moved to another instance if the allocations given by \( F_1 \) and \( F_2 \) are different, i.e., \( \mathcal{F}_1(s_i) \neq \mathcal{F}_2(s_i) \)

\[
\psi(\mathcal{F}_1, \mathcal{F}_2) = \mathbf{x} \cdot \mathbf{d} = \sum_{i=1}^{p} x_i d_i
\]

\( x_i \) is a binary variable, \( x_i = 1 \) if \( \mathcal{F}_1(s_i) \neq \mathcal{F}_2(s_i) \)

\( \mathbf{d} = (d_1, \ldots, d_p)^T \)
Eager Load Balancing (ELB)

**Basic idea**
- ELB performs LB eagerly for each statistic window and attempts to reduce state movements as many as possible
- Heuristics:
  - (1) Distribute hot spots as evenly as possible
  - (2) Fit the load of each instance into $[v, u]$ and make it close to $\frac{v + u}{2}$

**Phase 1: identify overloaded and underloaded instances**
- Calculate load vector $L_t = (l_{1t}, \ldots, l_{nt})$ with $Y_t$ and $F_1$
- Calculate overall load $w = \sum_{j=1}^{n} l_{jt}$, average load $\bar{l} = \frac{w}{\pi}$, and new parallelism $\pi = \lceil \frac{2w}{u + v} \rceil$
- Add/remove $|\pi - n|$ and identify overloaded instance set $OI$ and underloaded instances $UI$ by compare their load with $\bar{l} = \frac{w}{\pi}$
Eager Load Balancing (example)

Phase 2: identify substreams to be reassigned
1. Each time we choose the largest substream from an overloaded instance < \( \theta = \min\{l_j t - \bar{t}, \frac{u - v}{2}\} \)

Phase 3: reassign the identified substreams in PQ
1. Substreams in UI are listed a descending order of loads
2. The reassignment processes in a first-fit procedure
3. The instance will be removed from UI and added into OI if it is overloaded
Correlation-based Load Balancing (CLB)

**Basic idea**

1. CLB execute a LB every $m$ ($m>1$) statistic windows with an assignment that fits for the $m$ histograms $\mathbf{Y} = (Y_1, \ldots, Y_m)$
2. The cost for state movements can be ignored if $m$ is large enough.
3. Substreams are view as load series and to reduce imbalance by minimize correlation among the substreams assigned to the same instance.

**Overall load imbalance**

$$\sum_{j=1}^{m} \text{var}(L_j) = \sum_{j=1}^{m} \left( \frac{1}{n} \sum_{i=1}^{n} l_{ij}^2 - \overline{l}_j^2 \right) = \frac{1}{n} \sum_{j=1}^{m} \sum_{i=1}^{n} l_{ij}^2 - \sum_{j=1}^{m} \overline{l}_j^2$$

For the i-th instance assigned with substreams $S_i = \{s_1, \ldots, s_r\}$

$$\sum_{i=1}^{n} \text{var}(N_{i}) = \frac{1}{m} \sum_{i=1}^{n} \sum_{j=1}^{m} l_{ij}^2 - \sum_{i=1}^{n} \eta_i^2$$

$$\eta_i = E(N_i) = \sum_{s_i \in S_i} E(X_i)$$

Load series $N_i = X_1 + \cdots + X_r$

**The equivalence**

$$\min \sum_{j=1}^{m} \text{var}(L_j) \iff \min \sum_{i=1}^{n} \text{var}(N_i)$$
Correlation-based Load Balancing (cont.)

In addition

\[
\text{var}(X) - \sum_{k=1}^{n} \text{var}(N_k) = 2 \sum_{X_i \in S_k, X_j \in S_z, k \neq z} \text{cov}(X_i, X_j)
\]

The right component is \textit{cross covariance} which counts the covariance of the substreams that falls into different subsets.

Load series \(X = X_1 + \cdots + X_p\)

\[
\text{var}(X) = \text{var}(X_1 + \cdots + X_p)
\]

Minimize load imbalance \(\mathcal{h}(\mathcal{F})\), is equivalent to a partition of \(S\) into subsets \(S_1 \ldots S_n\) that maximize

\[
\min \mathcal{h}(\mathcal{F}) \Leftrightarrow \max \text{var}(X) - \sum_{k=1}^{n} \text{var}(N_k)
\]
Experimental Evaluation

Tested solutions

ELB, CLB

PKG: Implements key grouping that tuples are randomly distributed to two downstream instances, but it is designed for stateless LB

UHLB: Universal hash function rather than key grouping

Simulation

- A simple topology with 3 operators
- Load imbalance
- Percentage of state movements

Processing latency

- A simple topology for counting words every 1 minute
- Processing latency
- Speedup of throughput
Simulation Results

**Synthetic stream s1, s2**

Data rate: Poisson process $X(t)$

$$\lambda : Prob\{Z_m \leq \tau\} = 1 - e^{-\lambda \tau}, \lambda = 10000$$

Distribution: Gaussian and Zipf

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**Fig. 1 Load imbalance over time**

**Fig. 2 Percentage of state movements**
The experiments are conducted on EC2 with medium VM instances. We evaluated the processing latency by explicitly scaling out the operator WordCounter that counts the occurrence for each word every 1 minute over the Twitter stream.

<table>
<thead>
<tr>
<th>latency</th>
<th>CLB</th>
<th>ELB</th>
<th>PKG</th>
<th>UHLB</th>
</tr>
</thead>
<tbody>
<tr>
<td>max</td>
<td>1103.13</td>
<td>1109.51</td>
<td>1551.30</td>
<td>1505.13</td>
</tr>
<tr>
<td>mean</td>
<td>0.76</td>
<td>0.73</td>
<td>0.92</td>
<td>1.01</td>
</tr>
<tr>
<td>median</td>
<td>0.30</td>
<td>0.33</td>
<td>0.38</td>
<td>0.38</td>
</tr>
<tr>
<td>95%</td>
<td>1.12</td>
<td>0.68</td>
<td>1.70</td>
<td>1.89</td>
</tr>
</tbody>
</table>

Table 1. Processing latencies (ms)
Conclusions and Future Work

• Enorm Project
  • Problems in stream processing
  • Stateful stream computation
  • Challenge of load variation

• Stateful load balancing
  • Formulate the minimum cost load balancing as bi-objective optimization problem
  • Two approximate algorithms
  • Experimental results shows the effectiveness of ELB and CLB

• Future work
  ▪ More effective algorithms
  ▪ Experimental comparisons
THANKS

Questions?