Big Data Processing

COS 418: Distributed Systems
Lecture 21
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Ex: Word count using partial aggregation

1. Compute word counts from individual files
2. Then merge intermediate output
3. Compute word count on merged outputs

Putting it together…
Synchronization Barrier

Fault Tolerance in MapReduce

- Map worker writes intermediate output to local disk, separated by partitioning. Once completed, tells master node.
- Reduce worker told of location of map task outputs, pulls their partition’s data from each mapper, execute function across data
- Note:
  - “All-to-all” shuffle b/w mappers and reducers
  - Written to disk (“materialized”) b/w each stage

Graphs are Everywhere

Users

Social Network

Collaborative Filtering

Probabilistic Analysis

Text Analysis

Graph-Parallel Computation
Properties of Graph Parallel Algorithms

- Dependency Graph
- Factored Computation
- Iterative Computation

What I Like

What My Friends Like

Iterative Algorithms

- MR doesn’t efficiently express iterative algorithms:

MapAbuse: Iterative MapReduce

- System is not optimized for iteration:

The GraphLab Framework

Graph Based Data Representation

Update Functions User Computation

Consistency Model
**Data Graph**

Data is associated with both vertices and edges

- **Graph:**
  - Social Network

- **Vertex Data:**
  - User profile
  - Current interests estimates

- **Edge Data:**
  - Relationship (friend, classmate, relative)

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**Distributed Data Graph**

Partition the graph across multiple machines:

- **Ghost vertices** maintain adjacency structure and replicate remote data.

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**Update Function**

A user-defined program, applied to a vertex; transforms data in scope of vertex

- Dollar pagerank (scope) { // Update the current vertex data
  vertex.PageRank = ε
  ForEach inPage:
    vertex.PageRank += (1 − α) × inPage.PageRank
  // Reschedule Neighbors if needed
  if vertex.PageRank changes then
    reschedule_all_neighbors;
} Selectively triggers computation at neighbors
Update Function

A user-defined program, applied to a vertex; transforms data in scope of vertex

```c
Pagerank { // Update the current vertex data
    // Reschedule Neighbors if needed
    if vertex.PageRank changes then
        reschedule_all_neighbors;
}
```

Update function applied (asynchronously) in parallel until convergence
Many schedulers available to prioritize computation

Chandy-Lamport checkpointing

**Step 1.** Atomically, one initiator:
1. Turns red
2. Records its own state
3. Sends marker to neighbors

**Step 2.** On receiving marker. non-red node atomically:
1. Turns red,
2. Records its own state,
3. Sends markers along all outgoing channels

How to handle machine failure?

- What when machines fail? How do we provide fault tolerance?
- Strawman scheme: Synchronous snapshot checkpointing
  1. Stop the world
  2. Write each machines' state to disk

Stream Processing
Simple stream processing

- Single node
  - Read data from socket
  - Process
  - Write output

Examples: Stateless conversion

- Convert Celsius temperature to Fahrenheit
  - Stateless operation: \( \text{emit} (\text{input} \times 9 / 5) + 32 \)

Examples: Stateless filtering

- Function can filter inputs
  - if (input > threshold) \{ \text{emit} \text{input} \}

Examples: Stateful conversion

- Compute EWMA of Fahrenheit temperature
  - new_temp = \( \alpha \times (\text{CtoF(input)}) + (1-\alpha) \times \text{last_temp} \)
  - last_temp = new_temp
  - \text{emit} new_temp
Examples: Aggregation (stateful)

- E.g., Average value per window
  - Window can be # elements (10) or time (1s)
  - Windows can be disjoint (every 5s)
  - Windows can be “tumbling” (5s window every 1s)

Stream processing as chain

Stream processing as directed graph

Enter “BIG DATA”
The challenge of stream processing

- Large amounts of data to process in real time
- Examples
  - Social network trends (#trending)
  - Intrusion detection systems (networks, datacenters)
  - Sensors: Detect earthquakes by correlating vibrations of millions of smartphones
  - Fraud detection
    - Visa: 2000txn/sec on average, peak ~47,000/sec

Scale “up”

<table>
<thead>
<tr>
<th>Tuple-by-Tuple</th>
<th>Micro-batch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower Latency</td>
<td>Higher Latency</td>
</tr>
<tr>
<td>Lower Throughput</td>
<td>Higher Throughput</td>
</tr>
</tbody>
</table>

Why? Each read/write is a system call into the kernel. More cycles performing kernel/application transitions (context switches), less actually spent processing data.

Scale “out”

```python
Tuple-by-Tuple
input ← read
if (input > threshold) {
    emit input
}

Micro-batch
inputs ← read
out = []
for input in inputs {
    if (input > threshold) {
        out.append(input)
    }
}
emit out
```
**Stateless operations: trivially parallelized**

- Aggregations:
  - Need to join results across parallel computations

**State complicates parallelization**

- Aggregations:
  - Need to join results across parallel computations

**Parallelization complicates fault-tolerance**

- Aggregations:
  - Need to join results across parallel computations
Can parallelize joins

- Compute trending keywords
  - E.g.,

  portion tweets
  Sum / key
  - blocks -
  Sum / key
  Sort
  top-k

Can parallelize joins

- Hash partitioned tweets

  portion tweets
  Sum / key
  Sort
  top-k
  portion tweets
  Sum / key
  Sort
  top-k
  portion tweets
  Sum / key
  Sort
  top-k

Parallelization complicates fault-tolerance

- Hash partitioned tweets

  portion tweets
  Sum / key
  Sort
  top-k
  portion tweets
  Sum / key
  Sort
  top-k
  portion tweets
  Sum / key
  Sort
  top-k

A Tale of Four Frameworks

1. Record acknowledgement (Storm)
2. Micro-batches (Spark Streaming, Storm Trident)
3. Transactional updates (Google Cloud dataflow)
4. Distributed snapshots (Flink)
Apache Storm

- Architectural components
  - Data: streams of tuples, e.g., Tweet = <Author, Msg, Time>
  - Sources of data: “spouts”
  - Operators to process data: “bolts”
  - Topology: Directed graph of spouts & bolts

Fault tolerance via record acknowledgement (Apache Storm -- at least once semantics)

- Goal: Ensure each input “fully processed”
- Approach: DAG / tree edge tracking
  - Record edges that get created as tuple is processed.
  - Wait for all edges to be marked done
  - Inform source (spouts) of data when complete; otherwise, they resend tuple.
- Challenge: “at least once” means:
  - Operators (bolts) can receive tuple > once
  - Replay can be out-of-order
  - ... application needs to handle.

Apache Spark Streaming: Discretized Stream Processing

- Split stream into series of small, atomic batch jobs (each of X seconds)
- Process each individual batch using Spark “batch” framework
  - Akin to in-memory MapReduce
- Emit each micro-batch result
  - RDD = “Resilient Distributed Data”
Fault tolerance via micro batches (Apache Spark Streaming, Storm Trident)

- Can build on batch frameworks (Spark) and tuple-by-tuple (Storm)
  - Tradeoff between throughput (higher) and latency (higher)
- Each micro-batch may succeed or fail
  - Original inputs are replicated (memory, disk)
  - At failure, latest micro-batch can be simply recomputed (trickier if stateful)
- DAG is a pipeline of transformations from micro-batch to micro-batch
  - Lineage info in each RDD specifies how generated from other RDDs
- To support failure recovery:
  - Occasionally checkpoints RDDs (state) by replicating to other nodes
  - To recover: another worker (1) gets last checkpoint, (2) determines upstream dependencies starting at checkpoint (downstream might filter)

Fault Tolerance via transactional updates (Google Cloud Dataflow)

- Computation is long-running DAG of continuous operators
- For each intermediate record at operator
  - Create commit record including input record, state update, and derived downstream records generated
  - Write commit record to transactional log / DB
- On failure, replay log to
  - Restore a consistent state of the computation
  - Replay lost records (further downstream might filter)
- Requires: High-throughput writes to distributed store

Fault Tolerance via distributed snapshots (Apache Flink)

- Rather than log each record for each operator, take system-wide snapshots
- Snapshotting:
  - Determine consistent snapshot of system-wide state (includes in-flight records and operator state)
  - Store state in durable storage
- Recover:
  - Restoring latest snapshot from durable storage
  - Rewinding the stream source to snapshot point, and replay inputs
- Algorithm is based on Chandy-Lamport distributed snapshots, but also captures stream topology

Fault Tolerance via distributed snapshots (Apache Flink)

- Use markers (barriers) in the input data stream to tell downstream operators when to consistently snapshot
Optimizing stream processing

• Keeping system performant:
  – Careful optimizations of DAG
  – Scheduling: Choice of parallelization, use of resources
  – Where to place computation
  – …

• Often, many queries and systems using same cluster concurrently: “Multi-tenancy”