Discretized Streams: Fault-Tolerant Streaming Computation at Scale

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Streaming Computations

Processing large data sets in real time with low latency.

a) Static data computation

b) Streaming data computation
Motivation
Goals

- Scalability to hundreds of nodes.
- Second-scale latencies.
- Fast recovery from failures and stragglers.
- Minimal overhead beyond base processing.
Continous Operator Model

- Computations are divided into *long-living, stateful* operators.
- Operator processes input records.
- Changes its' state.
- Sends new records in response.
Node Replication

- Nodes are duplicated.
- Synchronization protocols ensure data ordering.
- On failure we switch to other node.
- Fast Recovery
- 2x Costs
Upstream Backup

- Each node buffers send data.
- On failure state is recovered by resending data to hot standb node.
- **No Fast Recovery**
Problem

Computations are tightly integrated with mutable state which is hard to move around.
CHALLENGE ACCEPTED
Remedy

- Make state immutable and treat it just as any other input data.
- Tasks become stateless.
- Batch processing systems - MapReduce.
Discretized Streams - DStreams

- Created by gathering streaming data from small time intervals.
- Allow small overhead to gather data.
- Sequence of immutable, small partitioned datasets.
- Can also be created:
  - by applying transformations on other DStreams.
  - from stored data.
  - by combining few DStreams.
Discretized Stream Processing

• Run a stream computation as a series of deterministic batch jobs.

• Try to make batches small to allow low latency.

• Keep intermediate state data in cluster memory to further reduce latency - resilient distributed datasets (RDD).
Discretized Stream Processing

\[ \text{time} = 0 - 1: \]
- Input: replicated dataset stored in memory

\[ \text{time} = 1 - 2: \]
- Input

\[ \text{batch operations} \]

\[ \text{Output or State: non-replicated dataset stored in memory} \]
Page view count

creating a DStream

views = readStream("http:...", "1 sec")
ones = views.map(ev => (ev.url, 1))
counts = ones.runningReduce((x,y) => x+y)

t: 0 - 1
map
reduce
t: 1 - 2
views ones counts
Lineage graph

- Lineage - a set of tasks used to build certain data.
- DStreams and RDD's track their lineage.
- When node fails or slows down lineage allows us to recompute lost data by re-running tasks used to build them.
- Data is being periodically checkpointed to prevent long recomputations and lineages.
Parallel Recovery

- Data from different timesteps to be recomputed in parallel.
- Partitions within datasets can be recomputed in parallel.
Straggler Recovery

- Detect slow tasks - e.g. those running 2x slower than other tasks.
- Speculatively run copies of those tasks on other machines in parallel.
- Masks the impacts of slow nodes in the system.
Spark Implementation

- **Master** - tracks lineage graphs and schedules tasks.

- **Worker Nodes** - receive data, store states and data, execute tasks

- **Client** - sends data into system.
Spark Implementation
Consistency

- Consider page view count system in which each node is responsible for gathering data from one country.
- If one node fails then snapshot of their states becomes inconsistent.
- In DStreams data is naturally discretized into intervals and failurea/stragglers are being recovered swiftly.
Late Records

- In DStreams record is placed in batch when it arrives at the system.
- Data can be sorted by external timestamp.
- System can wait before processing each batch for late records.
- We can recompute old interval in future as if the node has failed.
- Also we can use incremental reduce operations.
Summary

- Latency - 0.5 - 2s.
- Consistency - Records processed atomically with interval they arrive.
- Late records - Slack time or app-level correction.
- Fault recovery - Fast parallel recovery.
- Straggler recovery - speculative execution.
Thank You