Discretized Streams: Fault-Tolerant Streaming Computation at Scale

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Motivation and Goal

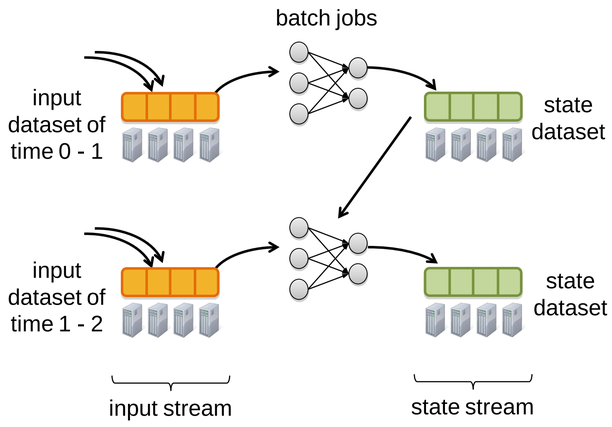
- Many important applications must process large data streams at second-scale latencies
- Need a system for building large-scale apps that
  - Scales to 10s - 100s of nodes with second-scale latencies
  - Efficiently recovers from node failures and slow nodes

Existing Systems

- Traditional streaming systems use *continuous operator* model with mutable state
- Do not have fast AND efficient fault-tolerance
  - *Node replication*: not cost-efficient
  - *Upstream backup*: slow recovery
- Do not handle slow nodes well

Discretized Stream Processing

- **Observation:** Batch processing like MapReduce have efficient techniques for fault-tolerance and straggler mitigation
- **Key Idea:** Treat streaming computations as series of batch jobs with small batches of data
  - Apply known recovery techniques at smaller timer intervals
  - Try to make batch sizes as small as possible
- **Processing Model:**
  - Input data and intermediate state data stored in cluster memory as immutable, partitioned datasets
  - Previous state dataset + next input dataset = new state dataset



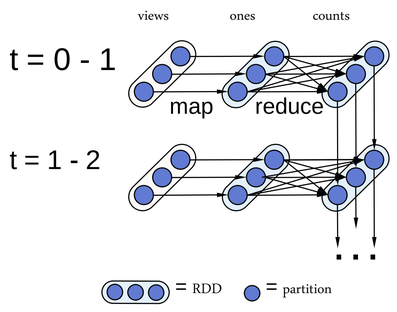
- **Programming Abstraction**: **Discretized Stream (DStream)** is a series of partitioned datasets representing a stream of data
- **Example:** Running count of page views using DStreams

```
views = readStream("http:...", "1s")

ones = views.map(ev => (ev.url, 1))

counts = ones.runningReduce(_ + _)
```

runningReduce(_ + _) combines the page view counts of previous interval with that of the current interval to generate the running count

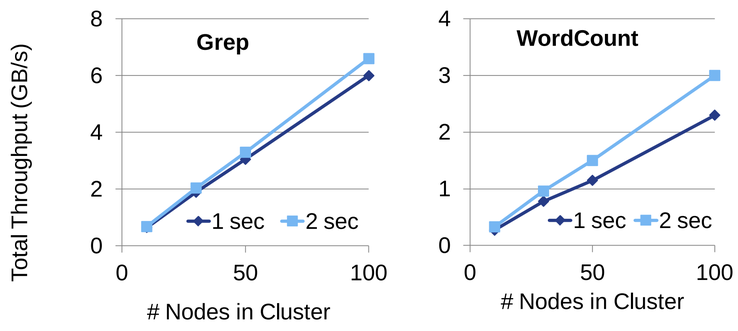


Benefits

- **Parallel Recovery on Failure**: Rebuild lost partitions of datasets in parallel on multiple existing nodes; faster than upsteam backup and more cost-efficient than node replication
- **Straggler Mitigation:** Detect slower tasks and speculatively run them on other nodes
- **Integration with batch+interactive processing:** Combine live data with historic data, make ad-hoc queries on live streams

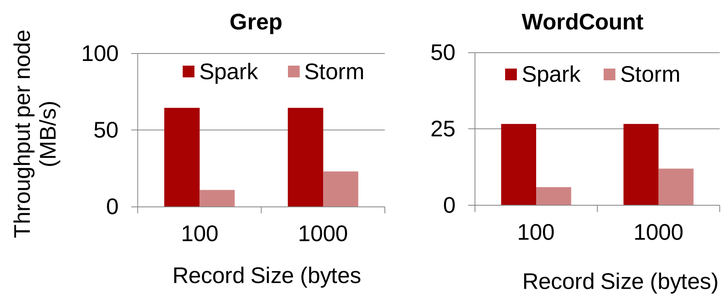
Evaluation

- Can process **6 GB/sec (60M records/sec)** from 100 data streams on **100 nodes** at **1 second** latency



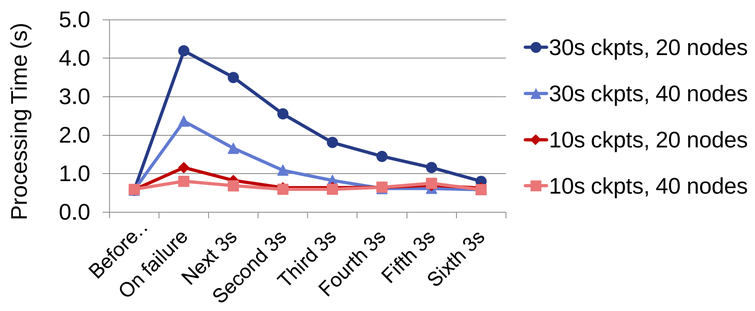
Maximum throughput different cluster sizes

- Higher throughput than Storm
  - Spark Streaming: **670k** records/sec/node
  - Storm: **115k** records/sec/node

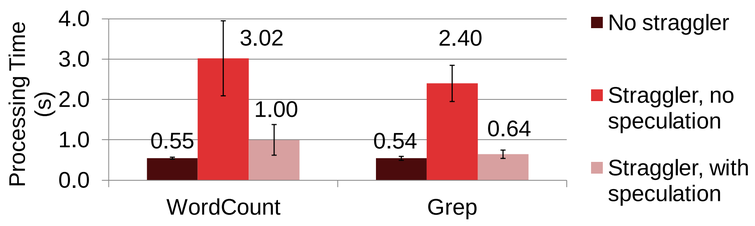


Maximum throughput with different record sizes

- Fast recovery from node failures and stragglers



Effect of checkpoint interval and cluster size on failure recovery times



Effect of speculative execution on stragglers

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