Discretized Streams: Fault-Tolerant Streaming Computation at Scale

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Motivation

- Faults and stragglers inevitable in large clusters running "big data" applications.
- Streaming applications must recover from these quickly.
- Current distributed streaming systems, including Storm, TimeStream, MapReduce Online provide fault recovery in an expensive manner.
  - Involves hot replication which requires 2x hardware or upstream backup which has long recovery time.

Previous Methods

- Hot replication
  - two copies of each node, 2x hardware.
  - straggler will slow down both replicas.
- Upstream backup
  - nodes buffer sent messages and replay them to new node.
  - stragglers are treated as failures resulting in long recovery step.

- Conclusion : need for a system which overcomes these challenges

- Voila ! D-Streams

Computation Model

- Streaming computations treated as a series of deterministic batch computations on small time intervals.
- Data received in each interval is stored reliably across the cluster to form input datatsets
- At the end of each interval dataset is subjected to deterministic parallel operations and two things can happen
  - new dataset representing program output which is pushed out to stable storage
  - intermediate state stored as resilient distributed datasets (RDDs)

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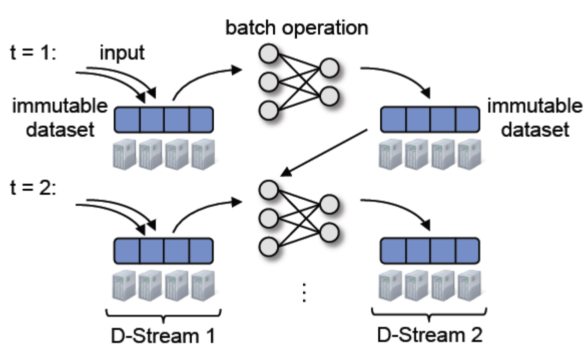
D-Stream processing model



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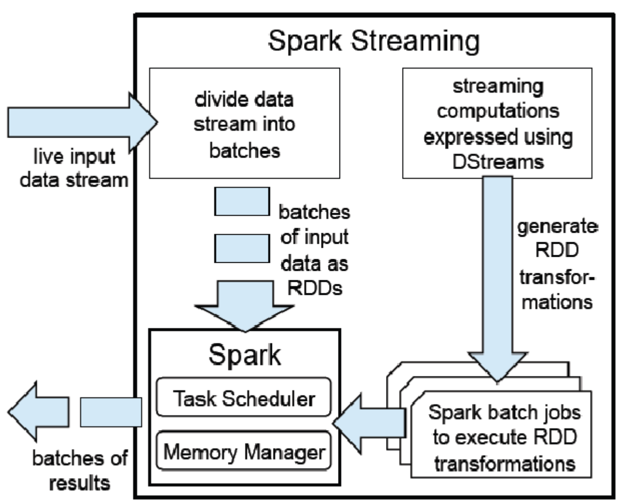
What are D-Streams ?

- sequence of immutable, partitioned datasets (RDDs) that can be acted on by deterministic transformations
- transformations yield new D-Streams, and may create intermediate state in the form of RDDs
- Example :-
  - pageViews = readStream("http://...", "1s")
  - ones = pageViews.map(event => (event.url, 1))
  - counts = ones.runningReduce((a, b) => a + b)

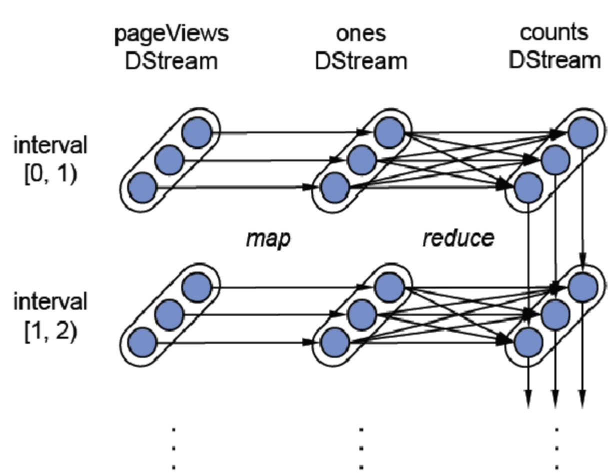
High-level overview of Spark Streaming system



Recovery

- D-Streams & RDDs track their lineage, that is, the graph of deterministic operations used to build them.
- When a node fails, it recomputes the RDD partitions that were on it by re-running the tasks that built them from the original input data stored reliably in the cluster.
- Checkpointing of state RDDs is done periodically

Lineage graph for RDDs



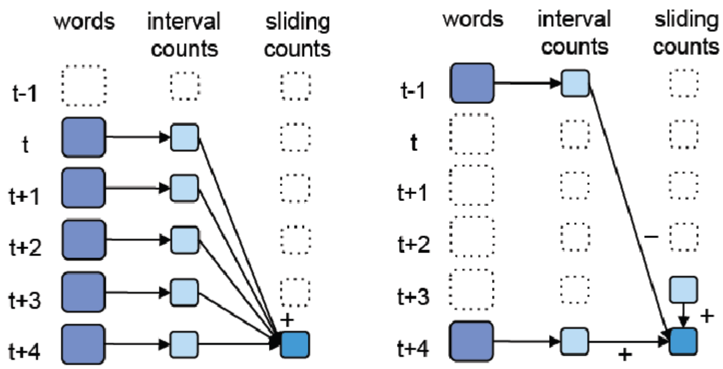
D-Stream API

- Users register one or more streams using a functional API
- Input streams can either be read by listening on a port or periodically loading from secondary storage
- Two types of operations can be performed on these streams :
  - Transformations – which create a new D-Stream from one or more parent streams
  - Output operations – which let the program write data to external systems.

D-Stream API

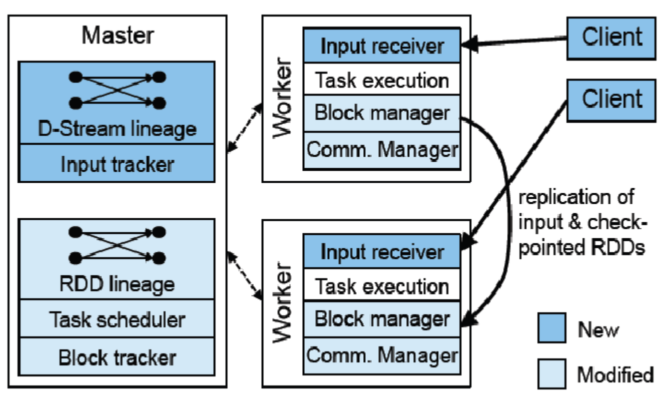
- D-Streams also provides several stateful transformations for computations spanning multiple intervals.
- Windowing : groups all the records from a sliding window of past time intervals into one RDD.
  - e.g. words.window("5s")
- Incremental aggregation : several variants of an incremental reduceByWindow operation
  - pairs.reduceByWindow("5s", (a, b) => a + b)

reduceByWindow execution



(a) Associative only (b) Associative & invertible

Components of Spark Streaming



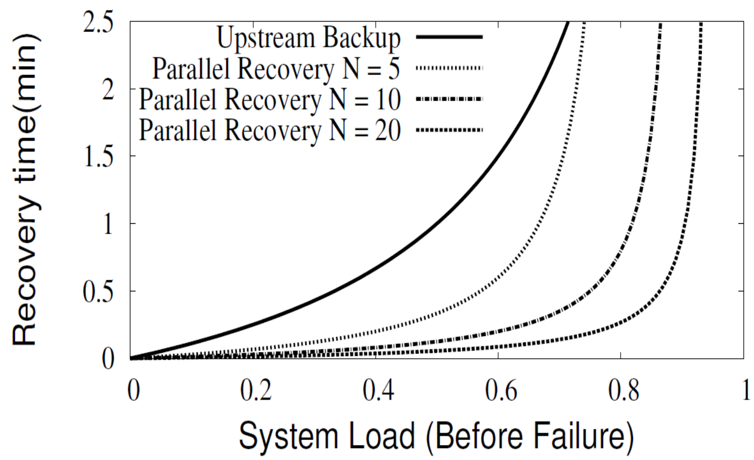
System Architecture

- D-Streams is implemented in a system called Spark Streaming
- This is based on a modified version of Spark processing engine from the same group (NSDI '12)
- Spark Streaming consists of three components
  - A **master** that tracks the D-Stream lineage graph and schedules tasks to compute new RDD partitions.
  - **Worker nodes** that receive data, store the partitions of input and computed RDDs, and execute tasks.
  - A **client library** used to send data into the system.

Fault and Straggler Recovery

- Parallel Recovery
  - All tasks which were running on a failed node are recomputed in parallel on other nodes
  - Motivation behind this : upstream backup takes long time to recover when the load is high
  - Parallel recovery catches up with the arriving stream much faster than upstream backup

Parallel recovery vs upstream backup



Fault and Straggler Recovery

- Straggler Mitigation
  - a task runs more than 1.4x longer than the median task in its job stage is marked as slow
  - They show that this method works well enough to recover from stragglers within a second.
- Master Recovery
  - At the start of each interval the current state of computation is written into stable storage.
  - Workers connect to the new master when it comes up and inform it of their RDD partitions

Evaluation

- Spark streaming was evaluated using three applications :
  - Grep, which finds the number of input strings matching a pattern
  - Word- Count, which performs a sliding window count over 30s
  - TopKCount, which finds the k most frequent words over the past 30s
- These applications were run on “m1.xlarge” nodes on Amazon EC2, each with 4 cores and 15 GB RAM

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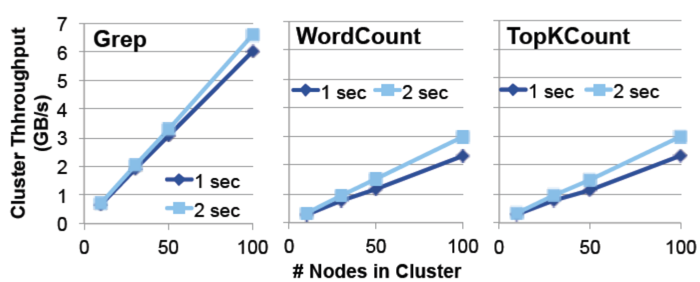
Results



Maximum throughput attainable under a given latency bound (1 s or 2 s) by Spark Streaming

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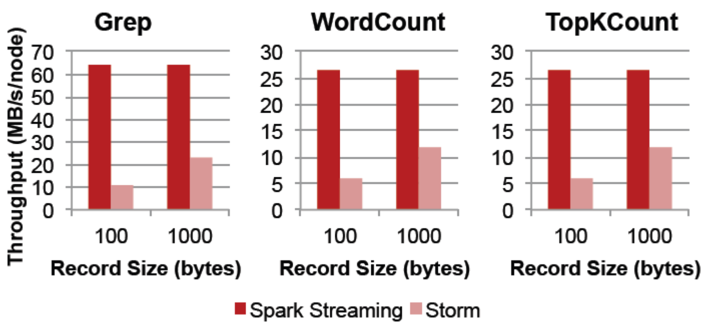
Results



Throughput vs Storm on 30 nodes

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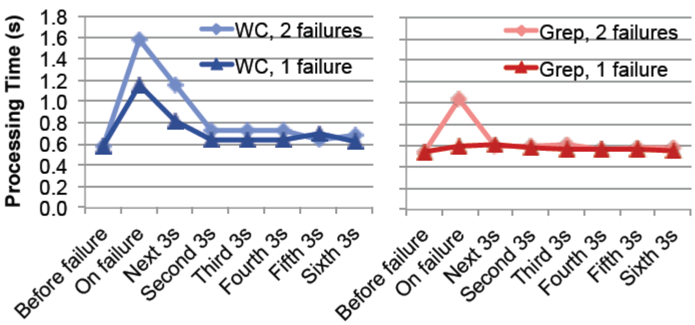
Results



Interval processing times for WordCount(WC) and Grep under failures

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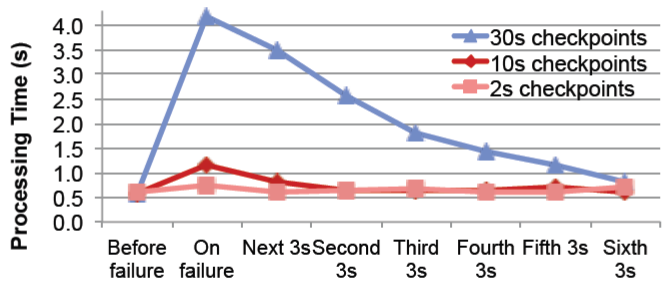
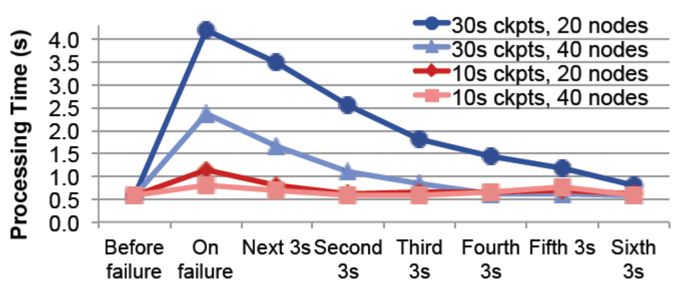
Results



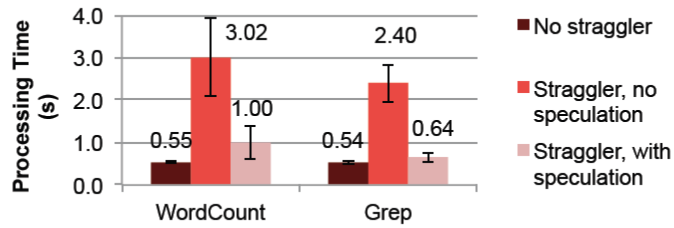
Effect of checkpoint in WordCount

Results



Recovery of WordCount on 20 & 40 nodes

Results



Processing time of intervals in Grep & WordCount in normal operation as well as in the presence of a straggler, with and without speculation

Conclusion

- By breaking computations into short, deterministic tasks and storing state in lineage-based data structures (RDDs), Dstreams can use powerful recovery mechanisms.
- D-Streams has a fixed minimum latency due to batching data. However the show that the total delay of 1-2 seconds is still tolerable for many real world uses

Thanks

Questions?