Scalable Stream Processing - Storm, MillWheel, and Google Dataflow

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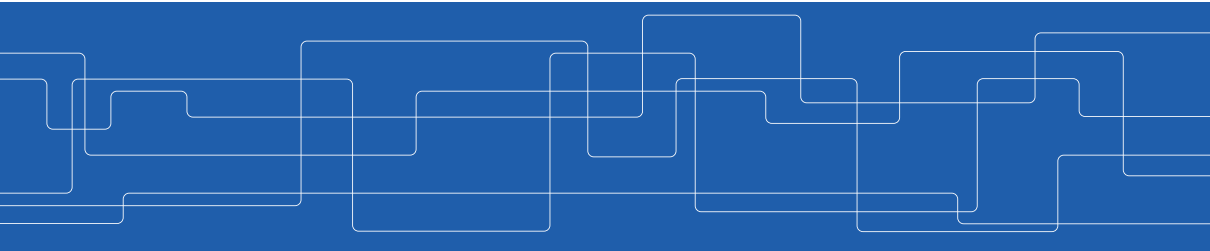
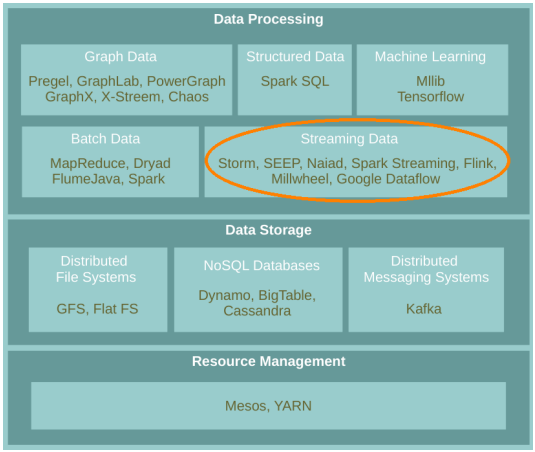


The Course Web Page

https://id2221kth.github.io

Where Are We?


Data Processing
Graph Data
Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
Spark SQL
Machine Learning
Mllib
Tensorflow
Batch Data
MapReduce, Dryad
FlumeJava, Spark
Streaming Data
Storm, SEEP, Naiad, Spark Streaming, Flink,
Millwheel, Google Dataflow
Data Storage
Distributed
File Systems
GFS, Flat FS
NoSQL Databases
Dynamo, BigTable,
Cassandra
Distributed
Messaging Systems
Kafka
Resource Management
Mesos, YARN

Stream Processing Systems Design Issues

- Continuous vs. micro-batch processing
- Record-at-a-Time vs. declarative APIs

Outline

- Storm
- MillWheel
- Google Dataflow

Storm

Contribution

- Storm is a real-time distributed stream data processing engine.
- Design issues
  - Continuous vs. micro-batch processing
  - Record-at-a-Time vs. declarative APIs

Data Model

- Stream
  - Unbounded sequence of tuples.

- Tuple
  - Core unit of data.
  - Immutable set of key/value pairs.

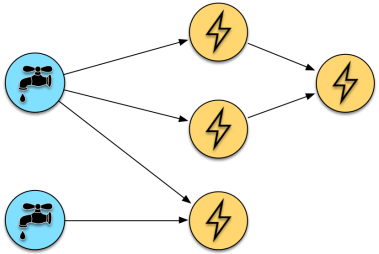
Storm Spouts and Bolts

- Spouts
  - Source of streams.
  - Wraps a streaming data source and emits tuples.

- Bolts
  - Core functions of a streaming computation.
  - Receive tuples and do stuff.
  - Optionally emit additional tuples.

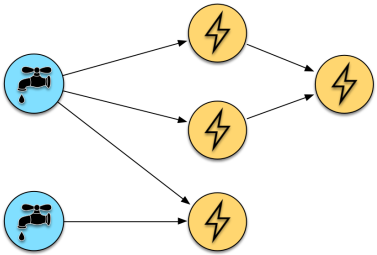
Storm Topology

- Topology
  - DAG of spouts and bolts.
  - Analogous to a job in Spark/MapReduce job.
  - One key difference is that a Spark/MapReduce job eventually finishes, whereas a topology runs forever.



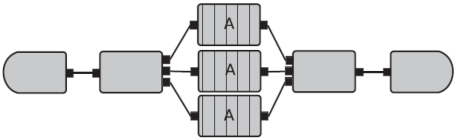
Tasks

- Task
  - Each spout or bolt executes as many tasks across the cluster.
  - A task performs the actual data processing.



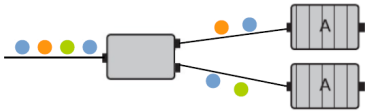
Stream Groupings (1/3)

- Stream groupings define how to send tuples from one set of tasks to another set of tasks.
- Data parallelism



Stream Groupings (2/3)

- Shuffle grouping: randomly partitions the tuples.



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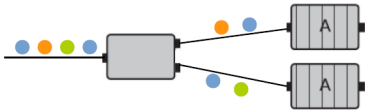
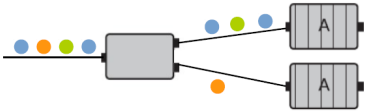
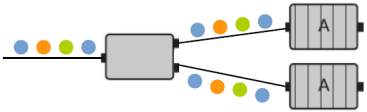


- Field grouping: hashes on a subset of the tuple attributes.



Stream Groupings (3/3)

- All grouping: replicates the entire stream to all the consumer tasks.



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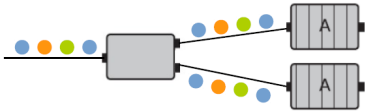
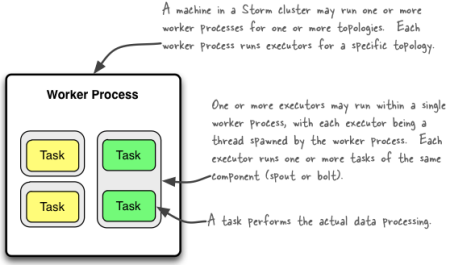


- Global grouping: sends the entire stream to one of the bolt's tasks.

What Makes a Running Topology

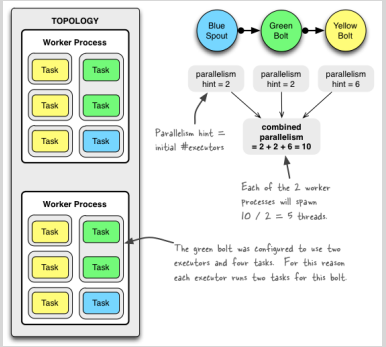
- Main entities that are used to run a topology in a Storm cluster:
  - Worker processes: each worker executes a subset of a topology.
  - Executors (threads): a thread that is spawned by a worker process, and run one or more tasks for the same component (spout or bolt).
  - Tasks: performs the actual data processing.



[http://storm.apache.org/releases/1.0.6/Understanding-the-parallelism-of-a-Storm-topology.html]

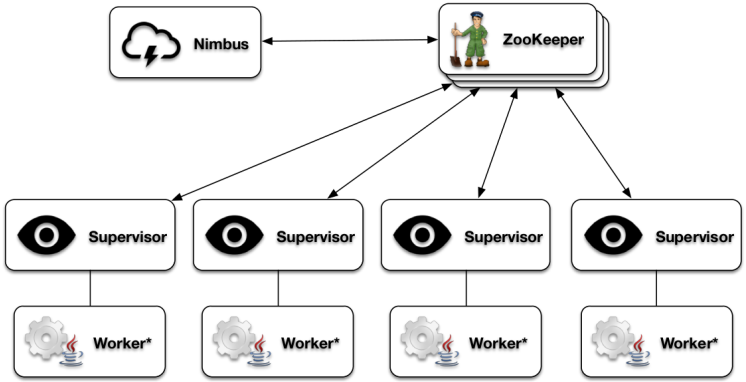
Example of A Running Topology

```
Config conf = new Config();
// use 2 worker processes
conf.setNumWorkers(2);

// set parallelism hint to 2
topologyBuilder.setSpout("blue-spout", new BlueSpout(), 2);
topologyBuilder.setBolt("green-bolt", new GreenBolt(), 2)
  .setNumTasks(4)
  .shuffleGrouping("blue-spout");

topologyBuilder.setBolt("yellow-bolt", new YellowBolt(), 6)
  .shuffleGrouping("green-bolt");

StormSubmitter.submitTopology("mytopology", conf,
  topologyBuilder.createTopology());
```



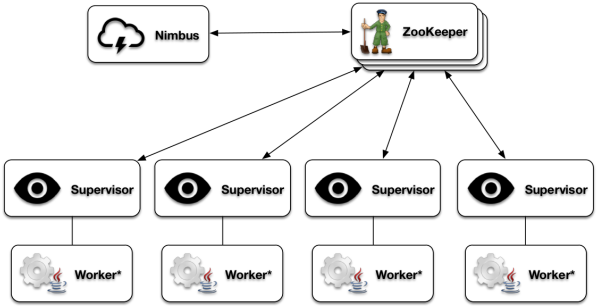
Storm Architecture

Storm Architecture (1/5)



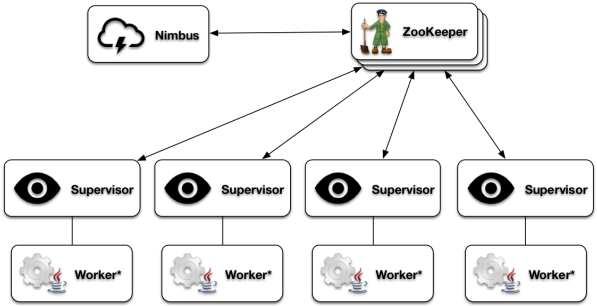
Storm Architecture (2/5)

- Nimbus
  - The master node.
  - Clients submit topologies to it.
  - Responsible for distributing and coordinating the execution of the topology.



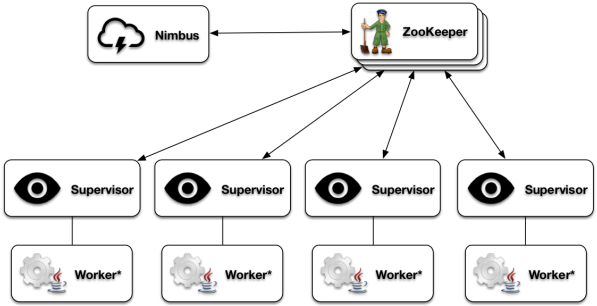
Storm Architecture (3/5)

- Worker nodes
  - Each worker node runs one or more worker processes.
  - Each worker process runs a JVM, in which it runs one or more executors.
  - Executors are made of one or more tasks, where the actual work for a bolt or a spout is done in the task.



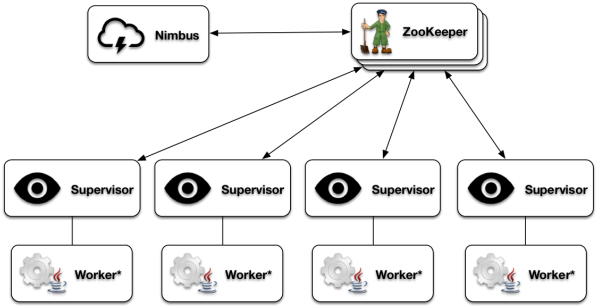
Storm Architecture (4/5)

- Supervisor
  - Each worker node runs a supervisor.
  - It receives assignments from Nimbus and spawns workers based on the assignment.
  - Contact Nimbus with a periodic heartbeat protocol, advertising the topologies that they are currently running, and any vacancies that are available to run more topologies.



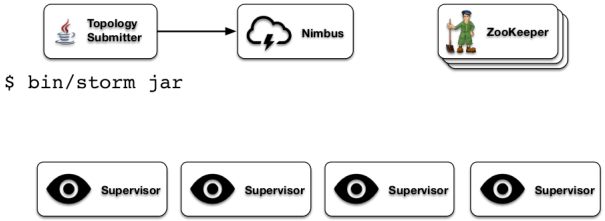
Storm Architecture (5/5)

- Zookeeper
  - Nimbus uses a combination of the local disk(s) and Zookeeper to store state about the topology.



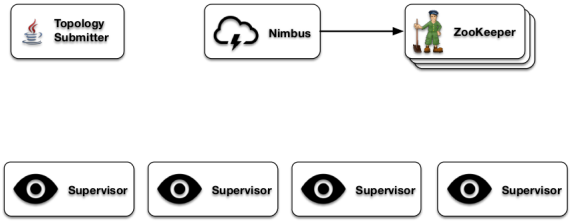
Storm Deployment (1/5)

- Topology submitter uploads topology to Nimbus.



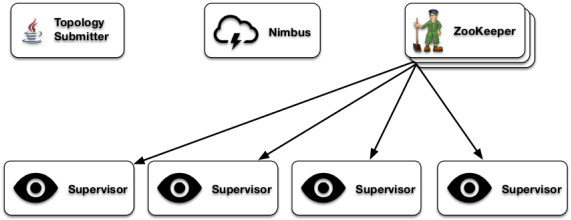
Storm Deployment (2/5)

- Nimbus calculates assignments and sends to Zookeeper.



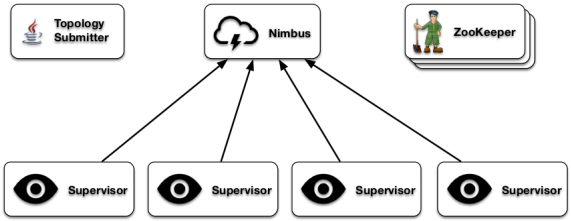
Storm Deployment (3/5)

- Supervisor nodes receive assignment information via Zookeeper watches.



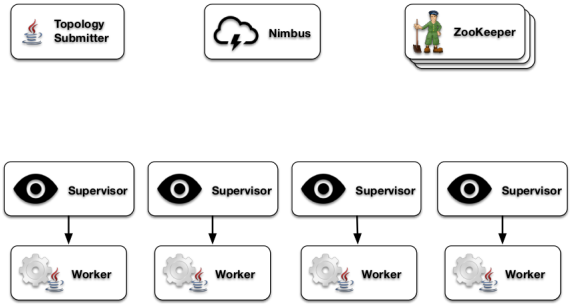
Storm Deployment (4/5)

- Supervisor nodes download topology from Nimbus.



Storm Deployment (5/5)

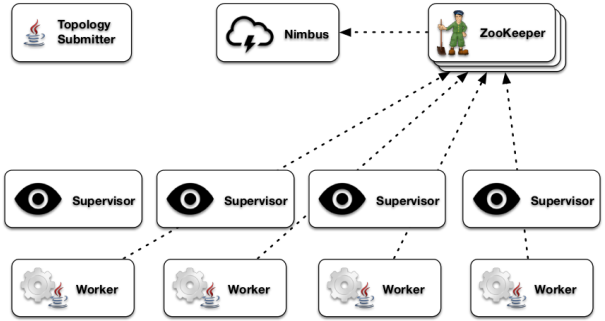
- Supervisors spawn workers (JVM processes) to start the topology.



Reliable Processing

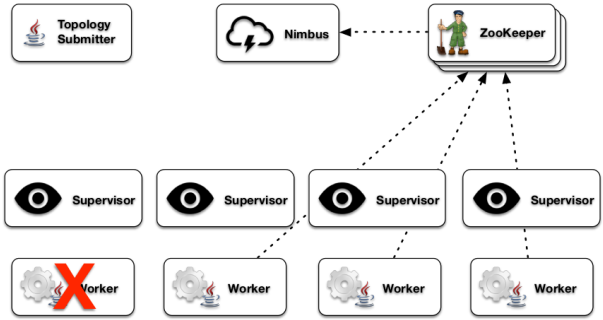
Fault Tolerance (1/4)

- Workers heartbeat back to Supervisors and Nimbus via ZooKeeper, as well as locally.



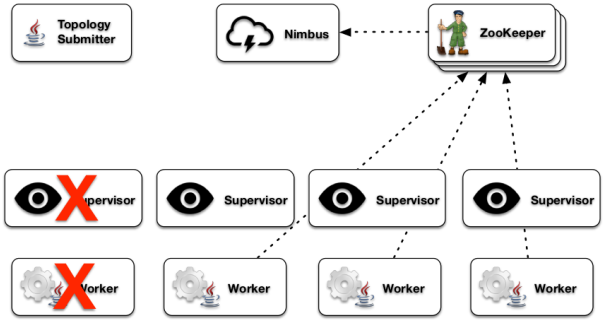
Fault Tolerance (2/4)

- If a worker dies (fails to heartbeat), the Supervisor will restart it.
- If a worker dies repeatedly, Nimbus will reassign the work to other nodes in the cluster.



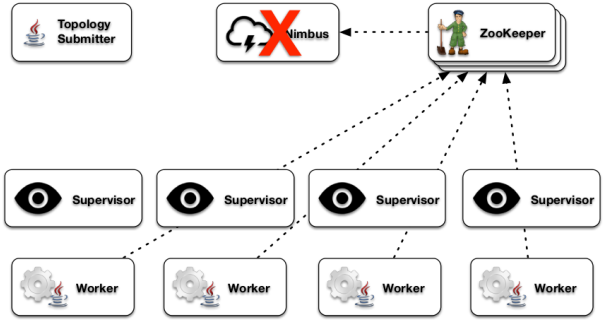
Fault Tolerance (3/4)

- If a supervisor node dies, Nimbus will reassign the work to other nodes.



Fault Tolerance (4/4)

- If Nimbus dies, topologies will continue to function normally, but won't be able to perform reassignments.

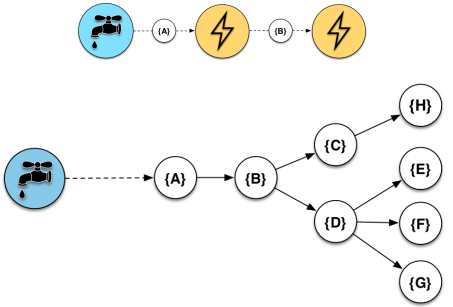


Reliable Processing (1/6)

- Storm provides two types of semantic guarantees:
  - At most once: each tuple is either processed once, or dropped in the case of a failure.
  - At least once (reliable processing): it guarantees that each tuple that is input to the topology will be processed at least once.

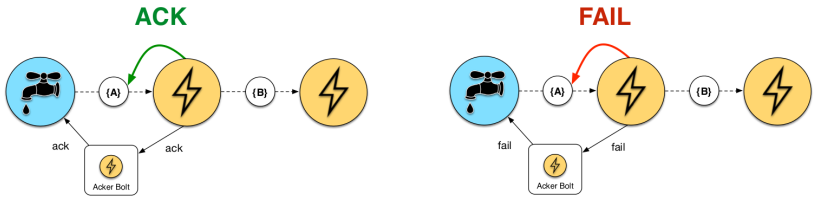
Reliable Processing (2/6)

- Bolts may emit tuples anchored to the ones they received.
  - Tuple B is a descendant of Tuple A.
- Multiple anchorings form a Tuple tree.



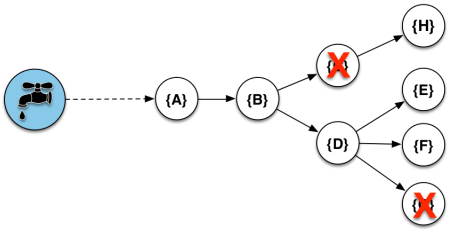
Reliable Processing (3/6)

- Bolts can acknowledge that a tuple has been processed successfully.
- Acks are delivered via a system-level bolt.
- Bolts can also fail a tuple to trigger a spout to replay the original.



Reliable Processing (4/6)

- Any failure in the tuple tree will trigger a replay of the original tuple.
- How to track a large-scale tuple tree efficiently?



Reliable Processing (5/6)

- Tuples are assigned a 64-bit message id at spout.
- Emitted tuples are assigned new message ids.
- These message ids are XORed and sent to the acker bolt along with the original tuple message id.
- When the XOR checksum goes to zero, the acker bolt sends the final ack to the spout that admitted the tuple, and the spout knows that this tuple has been fully processed.
  - $a \oplus (a \oplus b) \oplus c \oplus (b \oplus c) == 0$

Reliable Processing (6/6)

- It is possible that due to failure, some of the XOR checksum will never go to zero.
- The spout initially assigns a timeout parameter to each tuple.
- The acker bolt keeps track of this timeout parameter, and if the XOR checksum does not become zero before the timeout, the tuple is considered to have failed.
  - The data source will replay it back in the subsequent iteration.

Word Count in Storm

Word Count - Random Sentence Spout

```
public static class RandomSentenceSpout extends BaseRichSpout {
  SpoutOutputCollector _collector;
  Random _rand;

  public void open(Map conf, TopologyContext context, SpoutOutputCollector collector) {
    _collector = collector;
    _rand = new Random();
  }

  public void nextTuple() {
    Utils.sleep(100);
    String[] sentences = new String[]{ ... };
    String sentence = sentences[_rand.nextInt(sentences.length)];
    _collector.emit(new Values(sentence));
  }

  public void declareOutputFields(OutputFieldsDeclarer declarer) {
    declarer.declare(new Fields("sentence"));
  }
}
```

Word Count - Split Sentence Bolt

```
public static class SplitSentence extends BaseBasicBolt {
  public void execute(Tuple tuple, BasicOutputCollector basicOutputCollector) {
    String sentence = tuple.getStringByField("sentence");
    String words[] = sentence.split(" ");
    for (String w : words) {
      basicOutputCollector.emit(new Values(w));
    }
  }

  public void declareOutputFields(OutputFieldsDeclarer declarer) {
    declarer.declare(new Fields("word"));
  }
}
```

Word Count - Word Count Bolt

```
public static class WordCount extends BaseBasicBolt {
  Map<String, Integer> counts = new HashMap<String, Integer>();

  public void execute(Tuple tuple, BasicOutputCollector collector) {
    String word = tuple.getString(0);
    Integer count = counts.get(word);
    if (count == null) count = 0;
    count++;
    counts.put(word, count);
    LOG.info("Count of word: " + word + " = " + count);
    collector.emit(new Values(word, count));
  }

  public void declareOutputFields(OutputFieldsDeclarer declarer) {
    declarer.declare(new Fields("word", "count"));
  }
}
```

Word Count - Topology

```
 public static void main(String[] args) throws Exception {
  TopologyBuilder builder = new TopologyBuilder();

  builder.setSpout("spout", new RandomSentenceSpout(), 5);

  builder.setBolt("split", new SplitSentence(), 8).shuffleGrouping("spout");
  builder.setBolt("count", new WordCount(), 12).fieldsGrouping("split", new Fields("word"));

  Config conf = new Config();
  conf.setMaxTaskParallelism(3);
  LocalCluster cluster = new LocalCluster();
  cluster.submitTopology("word-count", conf, builder.createTopology());

  Thread.sleep(10000);
  cluster.shutdown();
}
```

Run the Word Count Topology

```
# Start ZooKeeper
cd zookeeper
cp conf/zoo_sample.cfg conf/zoo.cfg
./bin/zkServer.sh start

# Start Storm Cluster on Local machine
cd apache-storm
./bin/storm nimbus
./bin/storm supervisor
./bin/storm ui # http://localhost:8080/index.html

# Run the example WordCount
cd storm-wordcount
mvn clean install
cd ../apache-storm
./bin/storm jar ../storm-wordcount/target/storm-example-1.0-jar-with-dependencies.jar
  wordcount.WordCountTopology WordCount

# To kill the topology
./bin/storm kill WordCount
```

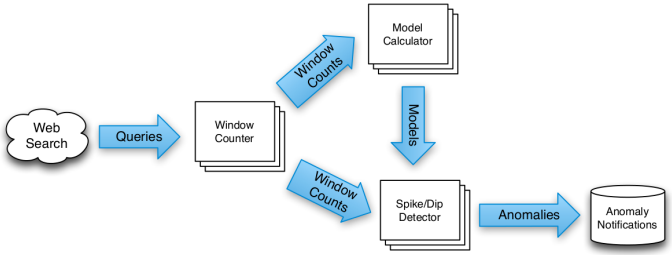
MillWheel

Motivation

- Google's Zeitgeist pipeline: tracking trends in web queries
- Builds a historical model of each query.
- Performs anomaly detection.

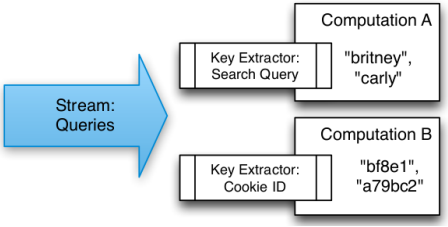
MillWheel Dataflow

- A graph of user-defined transformations (computations).
- Stream: unbounded data of (key, value, timestamp) records.
- Timestamp: wall clock time when the event occurred (event-time).



Key Extraction Function

- Key extraction function: specified by the stream consumer to assign keys to records.



Key Extraction Function

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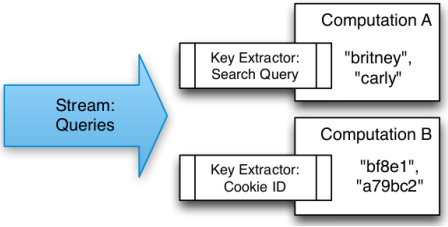
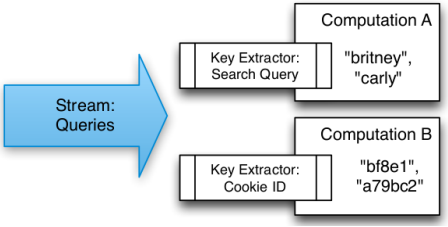
- Computation can only access state for the specific key.
- Multiple computations can extract different keys from the same stream.



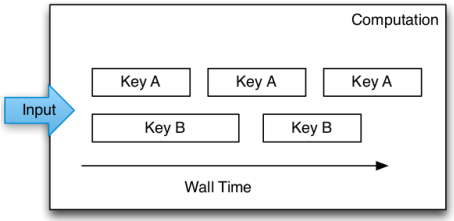
Key Extraction Function

- Key extraction function: specified by the stream consumer to assign keys to records.
- Computation can only access state for the specific key.
- Multiple computations can extract different keys from the same stream.
- A computation subscribes to zero or more input streams and publishes one or more output streams.



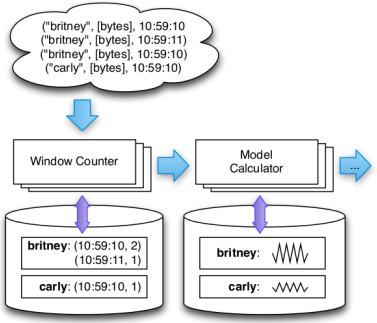
Computation

- Application logic lives in computations.
- Users can add and remove computations from a topology dynamically.
- Runs in the context of a single key.
- Parallel per-key processing.



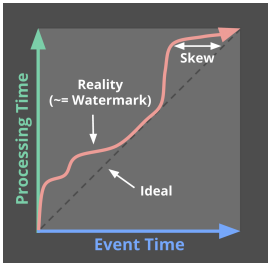
Persistent State

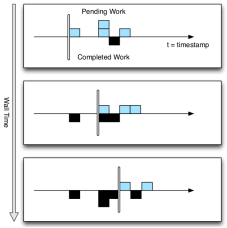
- Managed on per-key basis
- Stored in Bigtable or Spanner
- Common use: aggregation, joins, ...



Low Watermarks (1/3)

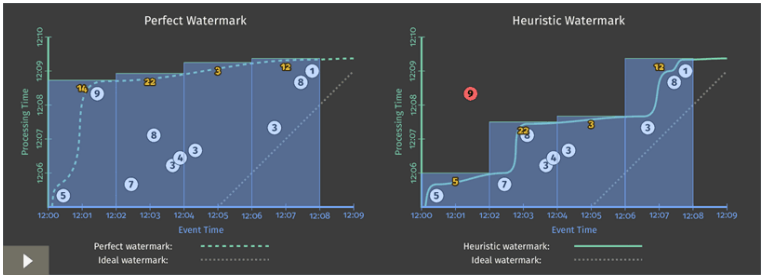
- Low watermark: captures the progress of event time completeness as processing time progresses.
- Think of low watermark as a function $F(P) \rightarrow E$.
  - P and E are points in processing time and event time.
  - E is the point up to which the system believes all inputs with event times less than E have been observed.





Low Watermarks (2/3)

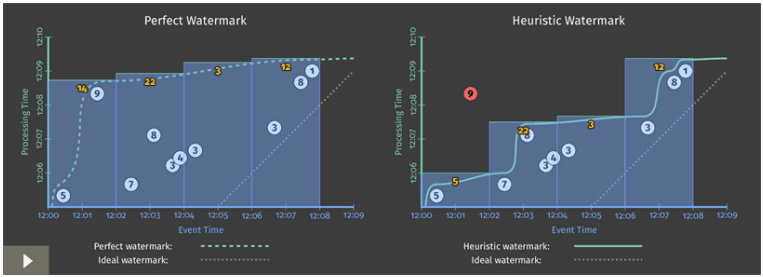
- Low watermark values are seeded by injectors that send data into MillWheel.
- Perfect vs. heuristic warermarks.



[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-102]

Low Watermarks (2/3)

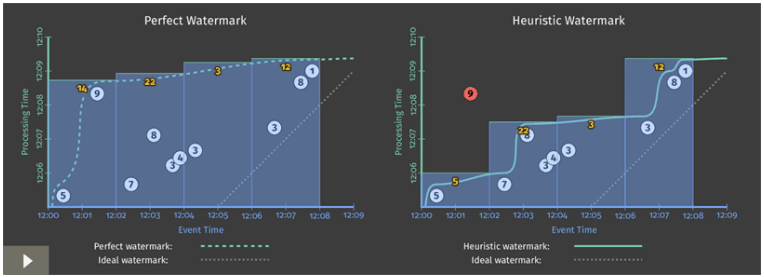
- Low watermark values are seeded by injectors that send data into MillWheel.
- Perfect vs. heuristic warermarks.
- Slow vs. fast warermarks.



[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-102]

Low Watermarks (3/3)

- Late records: records sbehind the low watermark.
- Process them according to the application, e.g., discard or correct the result.



[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-102]

Delivery Guarantees - Strong Productions

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  - If an ACK is not received, the record can be re-sent.
  - Exactly-one delivery: duplicates are discarded by MillWheel at the recipient.

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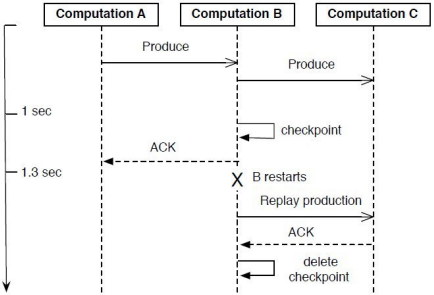
- The checkpoints allow fault-tolerance.
  - If a processor crashes and is restarted somewhere else any intermediate computations can be recovered.
- When a delivery is ACKed the checkpoints can be garbage collected.
- The Checkpoint→Delivery→ACK→GC sequence is called a strong production.

Delivery Guarantees - Weak Productions (1/2)

- Disable the exactly-once and/or strong production guarantee for applications that do not need it.
- Weak production is when Millwheel users can allow events to be sent before the checkpoint is committed to persistent storage.

Delivery Guarantees - Weak Productions (2/2)

- Weak production checkpointing prevents straggler productions from occupying undue resources in the sender (Computation A) by saving a checkpoint for receiver (Computation B).

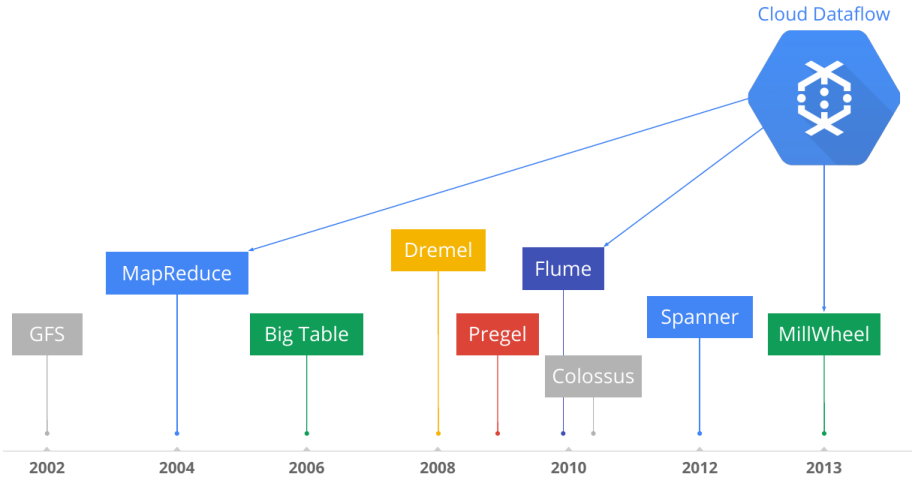


Google Cloud Dataflow

Google Cloud Dataflow (1/4)

- Google managed service for batch and stream data processing.
- Design issues
  - Continuous vs. micro-batch processing
  - Record-at-a-Time vs. declarative APIs

Google Cloud Dataflow (2/4)



Google Cloud Dataflow (3/4)

- FlumeJava: dataflow programming model
- MapReduce: batch processing
- MillWheel: stream processing

Google Cloud Dataflow (4/4)

- Open source Cloud Dataflow SDK
- Express your data processing pipeline using FlumeJava.

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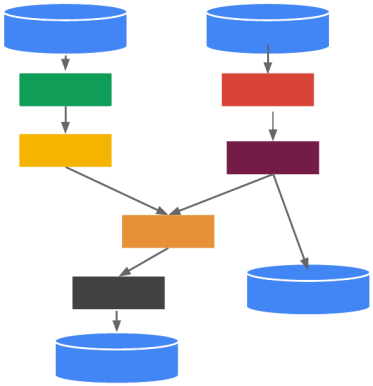
Google Cloud Dataflow (4/4)

- Open source Cloud Dataflow SDK
- Express your data processing pipeline using FlumeJava.
- If you run it in batch mode, it executed on the MapReduce framework.
- If you run it in streaming mode, it is executed on the MillWheel framework.

Programming Model

- Pipeline, a directed graph of data processing transformations
- Optimized and executed as a unit
- May include multiple inputs and multiple outputs
- May encompass many logical MapReduce or Millwheel operations
- PCollections conceptually flow through the pipeline

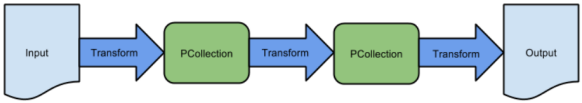


Dataflow Main Components

- Pipelines
- PCollections
- Transforms
- I/O sources and sinks

Pipelines (1/2)

- A pipeline represents a data processing job.
- Directed graph of operating on data.
- A pipeline consists of two parts:
  - Data (`PCollection`)
  - Transforms applied to that data

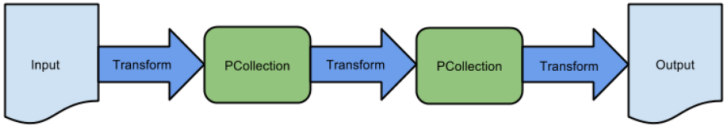


Pipelines (2/2)

```
public static void main(String[] args) {

  // Create a pipeline
  PipelineOptions options = PipelineOptionsFactory.create();
  Pipeline p = Pipeline.create(options);

  p.apply(TextIO.Read.from("gs://..."))   // Read input.
   .apply(new CountWords())               // Do some processing.
   .apply(TextIO.Write.to("gs://..."));   // Write output.

  // Run the pipeline.
  p.run();
}
```

PCollections (1/2)

- A parallel collection of records
- Immutable
- Must specify bounded or unbounded



PCollections (2/2)

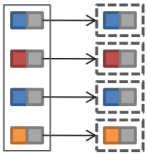
```
// Create a Java Collection, in this case a List of Strings.
static final List<String> LINES = Arrays.asList("line 1", "line 2", "line 3");

PipelineOptions options = PipelineOptionsFactory.create();
Pipeline p = Pipeline.create(options);

// Create the PCollection
p.apply(Create.of(LINES)).setCoder(StringUtf8Coder.of())
```

Transformations

- A processing operation that transforms data
- Each transform accepts one (or multiple) `PCollections` as input, performs an operation, and produces one (or multiple) new `PCollections` as output.
- Core transforms: `ParDo`, `GroupByKey`, `Combine`, `Flatten`

Transformations - ParDo

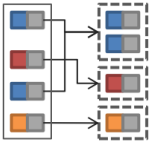
- Processes each element of a PCollection independently using a user-provided DoFn.



```
// The input PCollection of Strings.
PCollection<String> words = ...;

// The DoFn to perform on each element in the input PCollection.
static class ComputeWordLengthFn extends DoFn<String, Integer> { ... }

// Apply a ParDo to the PCollection "words" to compute lengths for each word.
PCollection<Integer> wordLengths = words.apply(ParDo.of(new ComputeWordLengthFn()));
```

Transformations - GroupByKey

- Takes a `PCollection` of key-value pairs and gathers up all values with the same key.



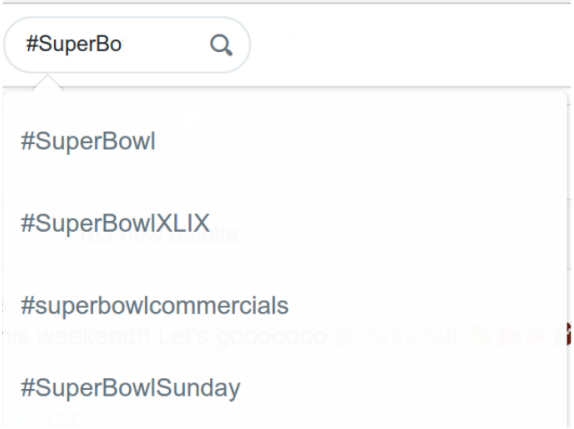
```
// A PCollection of key/value pairs: words and line numbers.
PCollection<KV<String, Integer>> wordsAndLines = ...;

// Apply a GroupByKey transform to the PCollection "wordsAndLines".
PCollection<KV<String, Iterable<Integer>>> groupedWords = wordsAndLines.apply(
  GroupByKey.<String, Integer>create());
```

Transformations - Join and CoGroubByKey

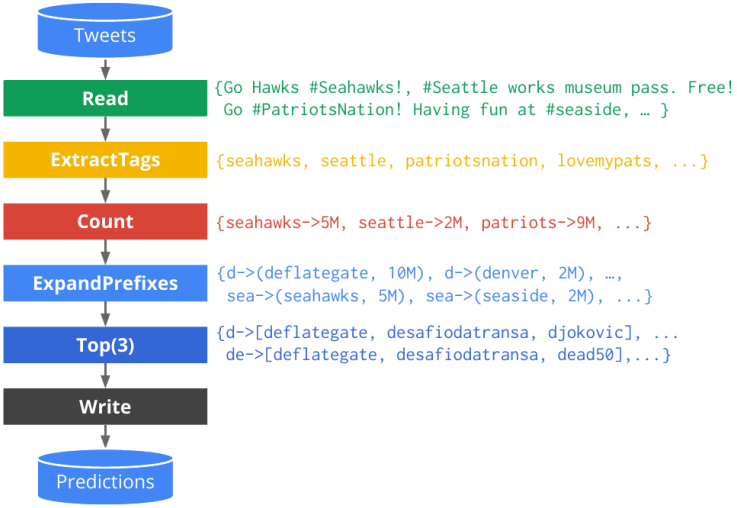
- Groups together the values from multiple PCollections of key-value pairs.

```
// Each data set is represented by key-value pairs in separate PCollections.
// Both data sets share a common key type ("K").
PCollection<KV<K, V1>> pc1 = ...;
PCollection<KV<K, V2>> pc2 = ...;

// Create tuple tags for the value types in each collection.
final TupleTag<V1> tag1 = new TupleTag<V1>();
final TupleTag<V2> tag2 = new TupleTag<V2>();

// Merge collection values into a CoGbkResult collection.
PCollection<KV<K, CoGbkResult>> coGbkResultCollection =
  KeyedPCollectionTuple.of(tag1, pc1)
                       .and(tag2, pc2)
                       .apply(CoGroupByKey.<K>create());
```

Example: HashTag Autocompletion (1/3)



Example: HashTag Autocompletion (2/3)



Example: HashTag Autocompletion (3/3)


```
Pipeline p = Pipeline.create();
p.begin()
    .apply(TextIO.Read.from("gs://…"))
    .apply(ParDo.of(new ExtractTags()))
    .apply(Count.perElement())
    .apply(ParDo.of(new ExpandPrefixes())
    .apply(Top.largestPerKey(3))
    .apply(TextIO.Write.to("gs://…"));
p.run();
```

Windowing and Triggering

Windowing and Triggering

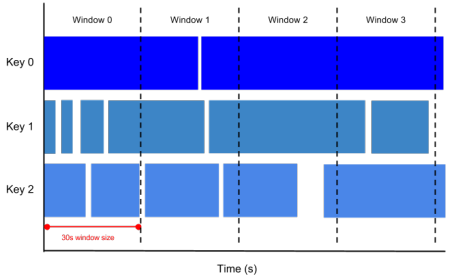
- Windowing determines where in event time, data are grouped together for processing.
- Triggering determines when in processing time the results of groupings are emitted as panes.

Windowing (1/4)

- Logically divide up or groups the elements of a `PCollection` into finite windows.
- Each element in a `PCollection` is assigned to one or more windows.
- Windowing functions:
  - Fixed time windows
  - Sliding time windows
  - Session windows

Windowing (2/4)

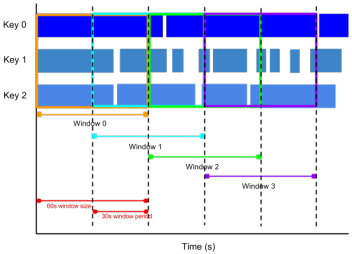
- Fixed time windows
- Represents the time interval in the data stream to define bundles of data, e.g., hourly




```
PCollection<String> items = ...;
PCollection<String> fixed_windowed_items = items.apply(
  Window.<String>into(FixedWindows.of(1, TimeUnit.MINUTES)));
```

Windowing (3/4)

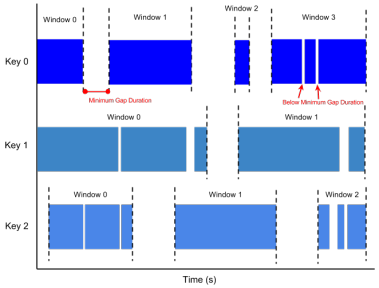
- Sliding time windows
- Uses time intervals in the data stream to define bundles of data, however the windows overlap.




```
PCollection<String> items = ...;
PCollection<String> sliding_windowed_items = items.apply(
    Window.<String>into(SlidingWindows
      .of(Duration.standardMinutes(30))
      .every(Duration.standardSeconds(5))));
```

Windowing (4/4)

- Session windows
- Defines windows around areas of concentration in the data.
- Useful for data that is irregularly distributed with respect to time, e.g., user mouse activity
- Applies on a per-key basis




```
PCollection<String> items = ...;
PCollection<String> session_windowed_items = items.apply(
  Window.<String>into(Sessions.withGapDuration(Duration.standardMinutes(10))));
```

Triggers

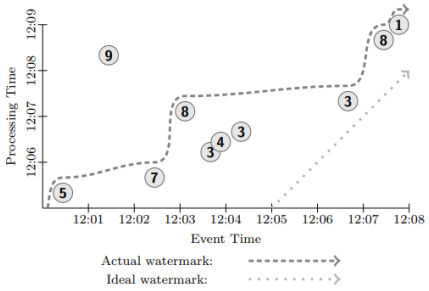
- Determine when to emit elements into an aggregated window.
- Provide flexibility for dealing with time skew and data lag.
  - Example: deal with late-arriving data.
  - Example: get early results, before all the data in a given window has arrived.

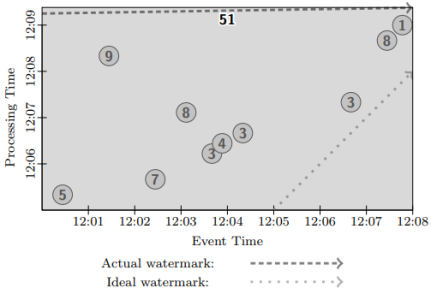
Triggers

- Determine when to emit elements into an aggregated window.
- Provide flexibility for dealing with time skew and data lag.
  - Example: deal with late-arriving data.
  - Example: get early results, before all the data in a given window has arrived.
- Three main types of triggers:
  - Time-based triggers
  - Data-driven triggers
  - Composit triggers

Example (1/3)

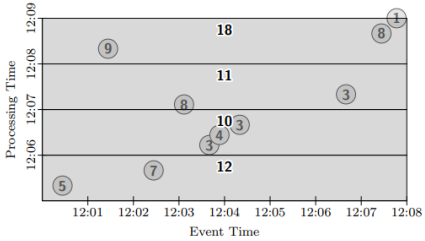
- Batch processing

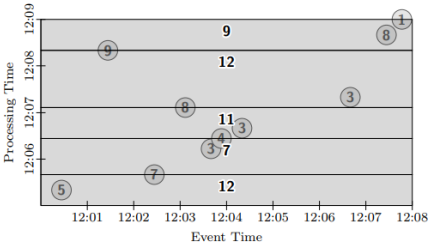




Example (2/3)

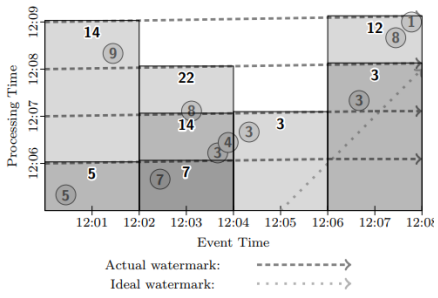
- Trigger at period
- Trigger at count

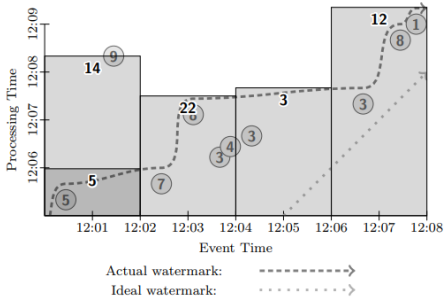




Example (3/3)

- Fixed window, trigger at period (micro-batch)
- Fixed window, trigger at watermark (streaming)





Summary

Summary

- Storm
  - Tuple and stream
  - Spout, bolt, and topology
  - Nimbus, worker, supervisor, and zookeeper
  - Reliable processing: xored ids

Summary

- MillWheel
  - DAG of computations
  - Persistent state: per-key
  - Low watermark
  - Exactly-one delivery

Summary

- Google cloud dataflow
  - Pipeline
  - PCollection: windows and triggers
  - Transforms

References

- A. Toshniwal et al., “Storm @ twitter”, ACM SIGMOD 2014.
- T. Akidau et al., “MillWheel: fault-tolerant stream processing at internet scale”, VLDB 2013.
- T. Akidau et al., “The dataflow model: a practical approach to balancing correctness, latency, and cost in massive-scale, unbounded, out-of-order data processing”, VLDB 2015.
- The world beyond batch: Streaming 102
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Questions?

Some slides and pictures were derived from Derek G. Murray (Google) slides.