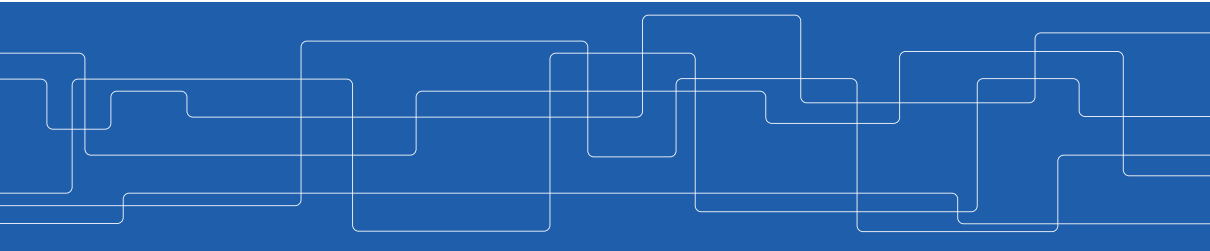
Scalable Stream Processing - Spark Streaming and Beam

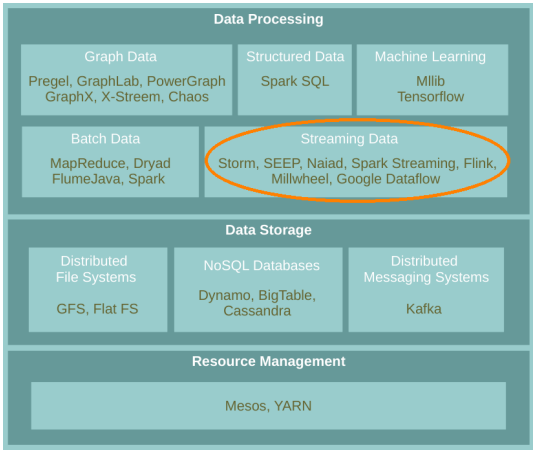
Amir H. Payberah
payberah@kth.se
26/09/2019



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

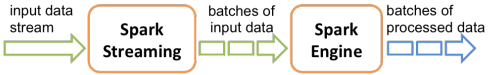
Spark Streaming

Contribution

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

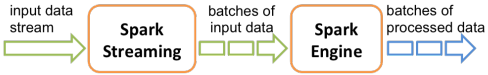
Spark Streaming

- Run a streaming computation as a series of very small, deterministic batch jobs.



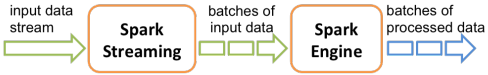
Spark Streaming

- Run a streaming computation as a series of very small, deterministic batch jobs.
  - Chops up the live stream into batches of X seconds.
  - Treats each batch as RDDs and processes them using RDD operations.



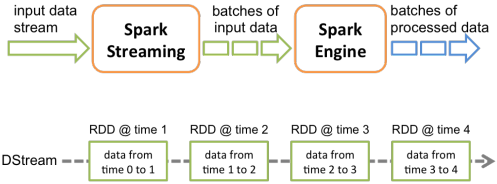
Spark Streaming

- Run a streaming computation as a series of very small, deterministic batch jobs.
  - Chops up the live stream into batches of X seconds.
  - Treats each batch as RDDs and processes them using RDD operations.
  - Discretized Stream Processing (DStream)



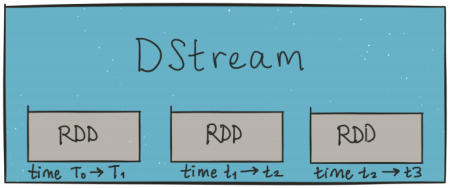
DStream (1/2)

- DStream: sequence of RDDs representing a stream of data.



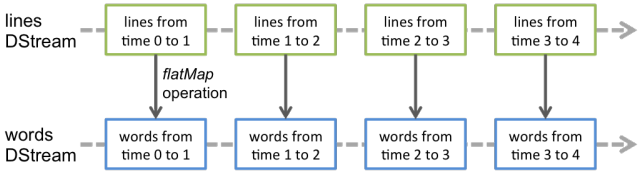
DStream (1/2)

- DStream: sequence of RDDs representing a stream of data.



DStream (2/2)

- Any operation applied on a DStream translates to operations on the underlying RDDs.



StreamingContext

- `StreamingContext` is the main entry point of all Spark Streaming functionality.

```
val conf = new SparkConf().setAppName(appName).setMaster(master)
val ssc = new StreamingContext(conf, Seconds(1))
```

- The second parameter, `Seconds(1)`, represents the time interval at which streaming data will be divided into batches.

Input Operations

- Every input DStream is associated with a `Receiver` object.
  - It receives the data from a source and stores it in Spark's memory for processing.

Input Operations

- Every input DStream is associated with a `Receiver` object.
  - It receives the data from a source and stores it in Spark's memory for processing.
- Basic sources directly available in the `StreamingContext` API, e.g., file systems, socket connections.

Input Operations

- Every input DStream is associated with a `Receiver` object.
  - It receives the data from a source and stores it in Spark's memory for processing.
- Basic sources directly available in the `StreamingContext` API, e.g., file systems, socket connections.
- Advanced sources, e.g., Kafka, Flume, Kinesis, Twitter.

Input Operations - Basic Sources

- Socket connection
  - Creates a DStream from text data received over a TCP socket connection.

```
ssc.socketTextStream("localhost", 9999)
```

Input Operations - Basic Sources

- Socket connection
  - Creates a DStream from text data received over a TCP socket connection.

```
ssc.socketTextStream("localhost", 9999)
```

- File stream
  - Reads data from files.

```
streamingContext.fileStream[KeyClass, ValueClass, InputFormatClass](dataDirectory)

streamingContext.textFileStream(dataDirectory)
```

Input Operations - Advanced Sources

- Connectors with external sources
- Twitter, Kafka, Flume, Kinesis, ...

```
TwitterUtils.createStream(ssc, None)

KafkaUtils.createStream(ssc, [ZK quorum], [consumer group id], [number of partitions])
```

Transformations (1/2)

- Transformations on DStreams are still lazy!
- DStreams support many of the transformations available on normal Spark RDDs.

Transformations (1/2)

- Transformations on DStreams are still lazy!
- DStreams support many of the transformations available on normal Spark RDDs.
- Computation is kicked off explicitly by a call to the `start()` method.

Transformations (2/2)

- `map`: a new DStream by passing each element of the source DStream through a given function.

Transformations (2/2)

- `map`: a new DStream by passing each element of the source DStream through a given function.
- `reduce`: a new DStream of single-element RDDs by aggregating the elements in each RDD using a given function.

Transformations (2/2)

- `map`: a new DStream by passing each element of the source DStream through a given function.
- `reduce`: a new DStream of single-element RDDs by aggregating the elements in each RDD using a given function.
- `reduceByKey`: a new DStream of (K, V) pairs where the values for each key are aggregated using the given reduce function.

Example - Word Count (1/6)

- First we create a `StreamingContex`

```
import org.apache.spark._
import org.apache.spark.streaming._

// Create a local StreamingContext with two working threads and batch interval of 1 second.
val conf = new SparkConf().setMaster("local[2]").setAppName("NetworkWordCount")
val ssc = new StreamingContext(conf, Seconds(1))
```

Example - Word Count (2/6)

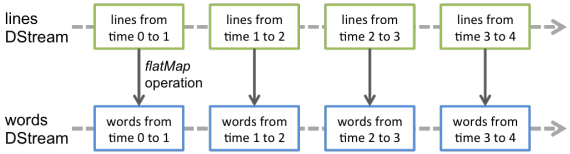
- Create a DStream that represents streaming data from a TCP source.
- Specified as hostname (e.g., localhost) and port (e.g., 9999).

```
val lines = ssc.socketTextStream("localhost", 9999)
```

Example - Word Count (3/6)

- Use `flatMap` on the stream to split the records text to words.
- It creates a new DStream.

```
val words = lines.flatMap(_.split(" "))
```



Example - Word Count (4/6)

- Map the `words` DStream to a DStream of `(word, 1)`.
- Get the frequency of words in each batch of data.
- Finally, print the result.

```
val pairs = words.map(word => (word, 1))

val wordCounts = pairs.reduceByKey(_ + _)

wordCounts.print()
```

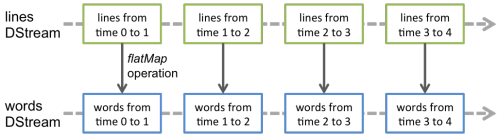
Example - Word Count (5/6)

- Start the computation and wait for it to terminate.

```
// Start the computation
ssc.start()

// Wait for the computation to terminate
ssc.awaitTermination()
```

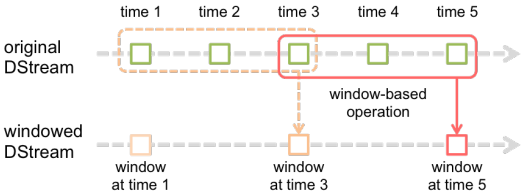
Example - Word Count (6/6)

```scala
val conf = new SparkConf().setMaster("local[2]").setAppName("NetworkWordCount")
val ssc = new StreamingContext(conf, Seconds(1))

val lines = ssc.socketTextStream("localhost", 9999)
val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))
val wordCounts = pairs.reduceByKey(_ + _)
wordCounts.print()

ssc.start()
ssc.awaitTermination()
```



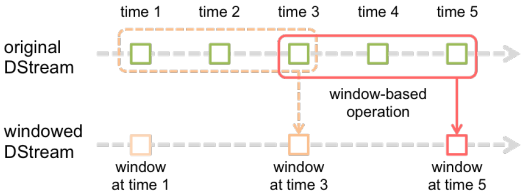
Window Operations (1/2)

- Spark provides a set of transformations that apply to a over a sliding window of data.



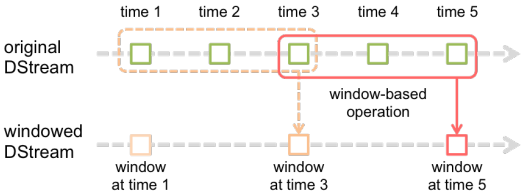
Window Operations (1/2)

- Spark provides a set of transformations that apply to a over a sliding window of data.
- A window is defined by two parameters: window length and slide interval.



Window Operations (1/2)

- Spark provides a set of transformations that apply to a over a sliding window of data.
- A window is defined by two parameters: window length and slide interval.
- A tumbling window effect can be achieved by making slide interval = window length



Window Operations (2/2)

- `window(windowLength, slideInterval)`
  - Returns a new DStream which is computed based on windowed batches.

Window Operations (2/2)

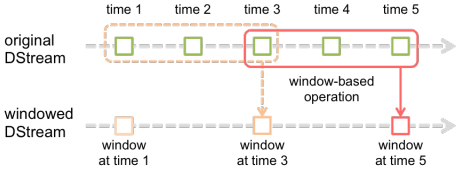
- `window(windowLength, slideInterval)`
  - Returns a new DStream which is computed based on windowed batches.
- `reduceByWindow(func, windowLength, slideInterval)`
  - Returns a new single-element DStream, created by aggregating elements in the stream over a sliding interval using func.

Window Operations (2/2)

- `window(windowLength, slideInterval)`
  - Returns a new DStream which is computed based on windowed batches.
- `reduceByWindow(func, windowLength, slideInterval)`
  - Returns a new single-element DStream, created by aggregating elements in the stream over a sliding interval using func.
- `reduceByKeyAndWindow(func, windowLength, slideInterval)`
  - Called on a DStream of (K, V) pairs.
  - Returns a new DStream of (K, V) pairs where the values for each key are aggregated using function func over batches in a sliding window.

Example - Word Count with Window

```
val conf = new SparkConf().setMaster("local[2]").setAppName("NetworkWordCount")
val ssc = new StreamingContext(conf, Seconds(1))

val lines = ssc.socketTextStream("localhost", 9999)
val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))
val windowedWordCounts = pairs.reduceByKeyAndWindow(_ + _, Seconds(30), Seconds(10))
windowedWordCounts.print()

ssc.start()
ssc.awaitTermination()
```



What about States?

- Accumulate and aggregate the results from the start of the streaming job.
- Need to check the previous state of the RDD in order to do something with the current RDD.

What about States?

- Accumulate and aggregate the results from the start of the streaming job.
- Need to check the previous state of the RDD in order to do something with the current RDD.
- Spark supports stateful streams.

Checkpointing

- It is mandatory that you provide a checkpointing directory for stateful streams.

```
val ssc = new StreamingContext(conf, Seconds(1))
ssc.checkpoint("path/to/persistent/storage")
```

Stateful Stream Operations

- `mapWithState`
  - It is executed only on set of keys that are available in the last micro batch.

```
def mapWithState[StateType, MappedType](spec: StateSpec[K, V, StateType, MappedType]):
    DStream[MappedType]

StateSpec.function(updateFunc)
val updateFunc = (batch: Time, key: String, value: Option[Int], state: State[Int])
```

Stateful Stream Operations

- `mapWithState`
  - It is executed only on set of keys that are available in the last micro batch.

```
def mapWithState[StateType, MappedType](spec: StateSpec[K, V, StateType, MappedType]):
    DStream[MappedType]

StateSpec.function(updateFunc)
val updateFunc = (batch: Time, key: String, value: Option[Int], state: State[Int])
```

- Define the update function (partial updates) in `StateSpec`.

Example - Stateful Word Count (1/4)

```
val ssc = new StreamingContext(conf, Seconds(1))
ssc.checkpoint(".")

val lines = ssc.socketTextStream(IP, Port)
val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))

val stateWordCount = pairs.mapWithState(StateSpec.function(updateFunc))

val updateFunc = (key: String, value: Option[Int], state: State[Int]) => {
  val newCount = value.getOrElse(0)
  val oldCount = state.getOption.getOrElse(0)
  val sum = newCount + oldCount
  state.update(sum)
  (key, sum)
}
```

Example - Stateful Word Count (2/4)

- The first micro batch contains a message a.

Example - Stateful Word Count (2/4)

- The first micro batch contains a message a.
- `updateFunc = (key: String, value: Option[Int], state: State[Int]) => (key, sum)`
- Input: `key = a`, `value = Some(1)`, `state = 0`

Example - Stateful Word Count (2/4)

- The first micro batch contains a message a.
- `updateFunc = (key: String, value: Option[Int], state: State[Int]) => (key, sum)`
- Input: `key = a`, `value = Some(1)`, `state = 0`
- Output: `key = a`, `sum = 1`

Example - Stateful Word Count (3/4)

- The second micro batch contains messages `a` and `b`.

Example - Stateful Word Count (3/4)

- The second micro batch contains messages `a` and `b`.
- `updateFunc = (key: String, value: Option[Int], state: State[Int]) => (key, sum)`
- Input: `key = a`, `value = Some(1)`, `state = 1`
- Input: `key = b`, `value = Some(1)`, `state = 0`

Example - Stateful Word Count (3/4)

- The second micro batch contains messages `a` and `b`.
- `updateFunc = (key: String, value: Option[Int], state: State[Int]) => (key, sum)`
- Input: `key = a`, `value = Some(1)`, `state = 1`
- Input: `key = b`, `value = Some(1)`, `state = 0`
- Output: `key = a`, `sum = 2`
- Output: `key = b`, `sum = 1`

Example - Stateful Word Count (4/4)

- The third micro batch contains a message `b`.

Example - Stateful Word Count (4/4)

- The third micro batch contains a message `b`.
- `updateFunc = (key: String, value: Option[Int], state: State[Int]) => (key, sum)`
- Input: `key = b`, `value = Some(1)`, `state = 1`

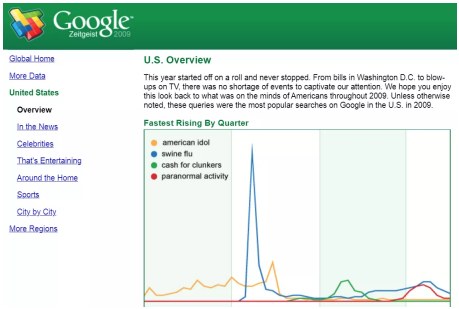
Example - Stateful Word Count (4/4)

- The third micro batch contains a message `b`.
- `updateFunc = (key: String, value: Option[Int], state: State[Int]) => (key, sum)`
- Input: `key = b`, `value = Some(1)`, `state = 1`
- Output: `key = b`, `sum = 2`

Google Dataflow and Beam

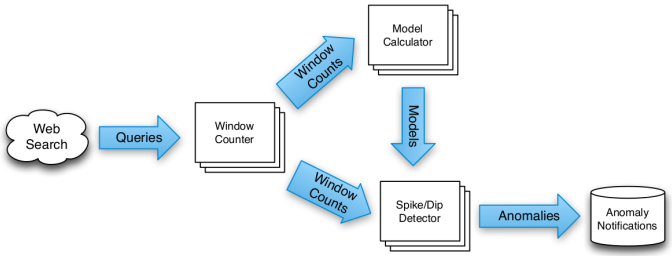
History

- Google's Zeitgeist: tracking trends in web queries.
- Builds a historical model of each query.
- Google discontinued Zeitgeist, but most of its features can be found in Google Trends.



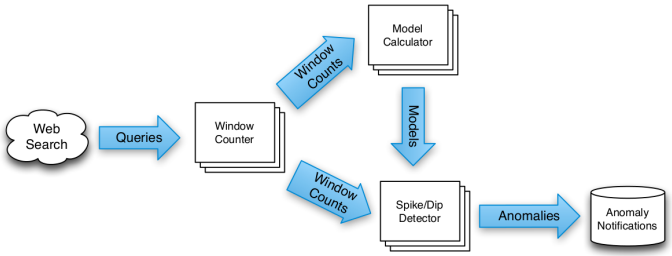
MillWheel Dataflow

- MillWheel is a framework for building low-latency data-processing applications.



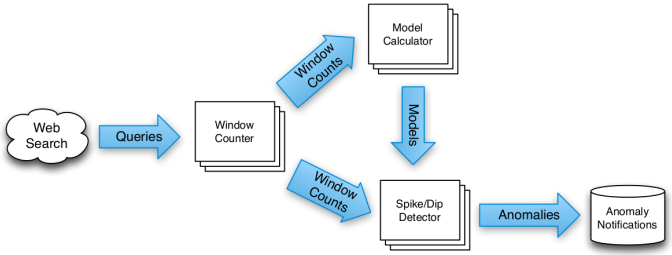
MillWheel Dataflow

- MillWheel is a framework for building low-latency data-processing applications.
- A dataflow graph of transformations (computations).



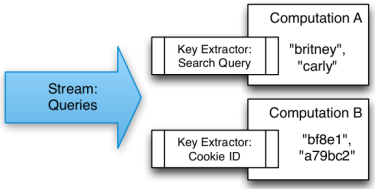
MillWheel Dataflow

- MillWheel is a framework for building low-latency data-processing applications.
- A dataflow graph of transformations (computations).
- Stream: unbounded data of (key, value, timestamp) records.
  - Timestamp: event-time



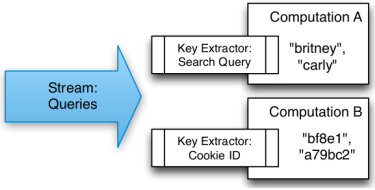
Key Extraction Function and Computations

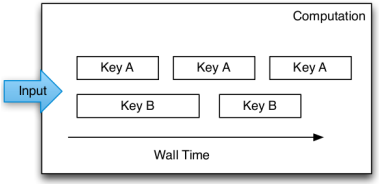
- Stream of (key, value, timestamp) records.
- Key extraction function: specified by the stream consumer to assign keys to records.



Key Extraction Function and Computations

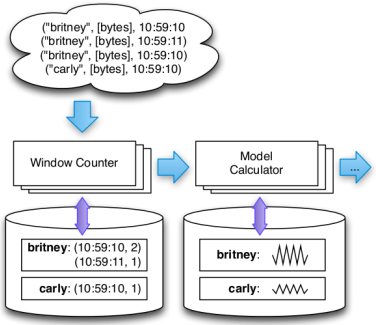
- Stream of (key, value, timestamp) records.
- Key extraction function: specified by the stream consumer to assign keys to records.
- Computation can only access state for the specific key.
- Multiple computations can extract different keys from the same stream.





Persistent State

- Keep the states of the computations
- Managed on per-key basis
- Stored in Bigtable or Spanner
- Common use: aggregation, joins, ...



Delivery Guarantees

- Emitted records are checkpointed before delivery.
  - The checkpoints allow fault-tolerance.

Delivery Guarantees

- Emitted records are checkpointed before delivery.
  - The checkpoints allow fault-tolerance.
- When a delivery is ACKed the checkpoints can be garbage collected.

Delivery Guarantees

- Emitted records are checkpointed before delivery.
  - The checkpoints allow fault-tolerance.
- When a delivery is ACKed the checkpoints can be garbage collected.
- If an ACK is not received, the record can be re-sent.

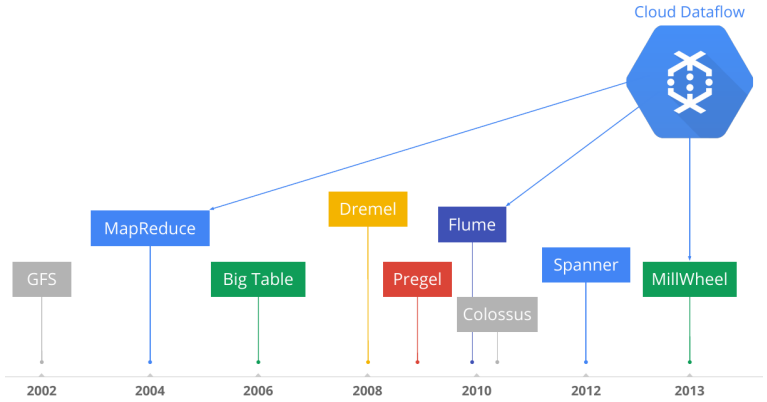
Delivery Guarantees

- Emitted records are checkpointed before delivery.
  - The checkpoints allow fault-tolerance.
- When a delivery is ACKed the checkpoints can be garbage collected.
- If an ACK is not received, the record can be re-sent.
- Exactly-one delivery: duplicates are discarded by MillWheel at the recipient.

What is Google Cloud Dataflow?

Google Cloud Dataflow (1/2)

- Google managed service for unified batch and stream data processing.



Google Cloud Dataflow (2/2)

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

Google Cloud Dataflow (2/2)

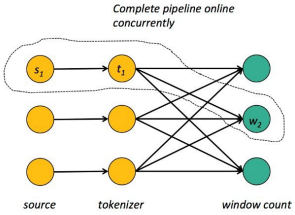
- Open source Cloud Dataflow SDK
- Express your data processing pipeline using FlumeJava.
- If you run it in batch mode, it executed on the MapReduce framework.

Google Cloud Dataflow (2/2)

- 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.

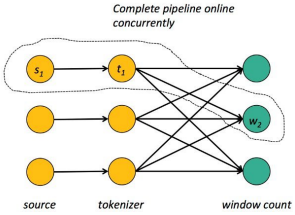
Programming Model

- Pipeline, a directed graph of data processing transformations



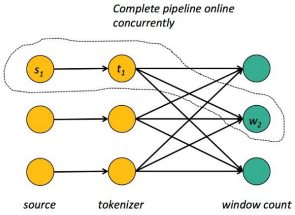
Programming Model

- Pipeline, a directed graph of data processing transformations
- Optimized and executed as a unit



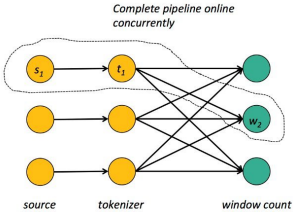
Programming Model

- Pipeline, a directed graph of data processing transformations
- Optimized and executed as a unit
- May include multiple inputs and multiple outputs



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



Windowing and Triggering

- Windowing determines where in event time data are grouped together for processing.

Windowing and Triggering

- Windowing determines where in event time data are grouped together for processing.
  - Fixed time windows (tumbling windows)
  - Sliding time windows
  - Session windows

Windowing and Triggering

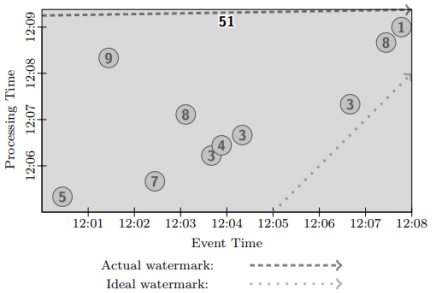
- Windowing determines where in event time data are grouped together for processing.
  - Fixed time windows (tumbling windows)
  - Sliding time windows
  - Session windows
- Triggering determines when in processing time the results of groupings are emitted as panes.

Windowing and Triggering

- Windowing determines where in event time data are grouped together for processing.
  - Fixed time windows (tumbling windows)
  - Sliding time windows
  - Session windows
- Triggering determines when in processing time the results of groupings are emitted as panes.
  - Time-based triggers
  - Data-driven triggers
  - Composit triggers

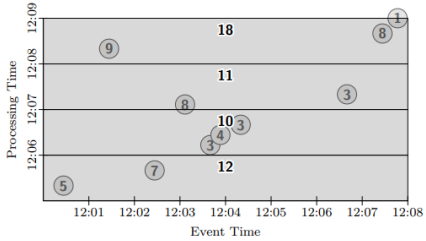
Example (1/3)

- Batch processing



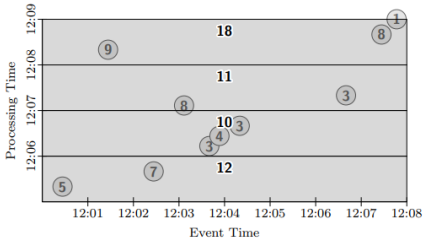
Example (2/3)

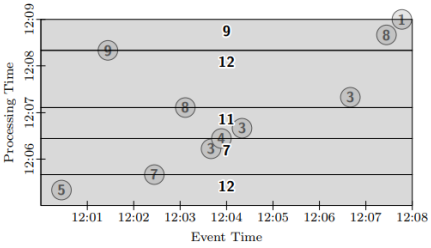
- Trigger at period (time-based triggers)



Example (2/3)

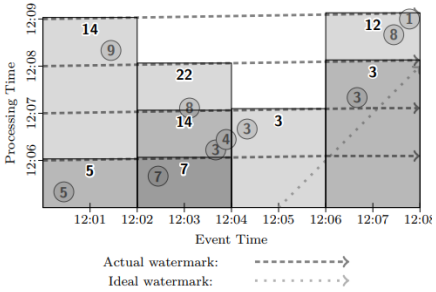
- Trigger at period (time-based triggers)
- Trigger at count (data-driven triggers)





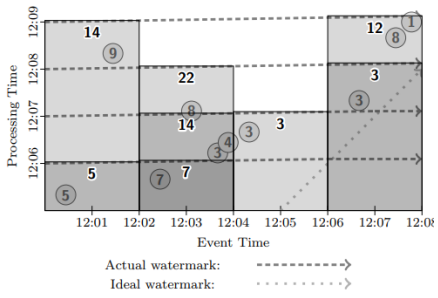
Example (3/3)

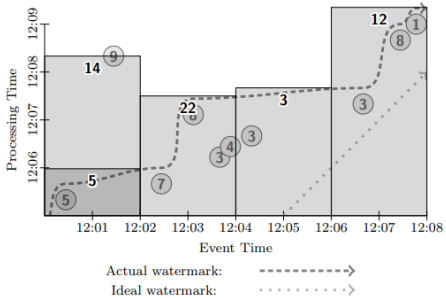
- Fixed window, trigger at period (micro-batch)



Example (3/3)

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





Where is Apache Beam?

From Google Cloud Dataflow to Apache Beam

- In 2016, Google Cloud Dataflow team announced its intention to donate the programming model and SDKs to the Apache Software Foundation.

From Google Cloud Dataflow to Apache Beam

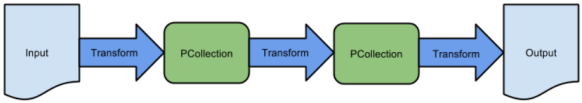
- In 2016, Google Cloud Dataflow team announced its intention to donate the programming model and SDKs to the Apache Software Foundation.
- That resulted in the incubating project Apache Beam.

Programming 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

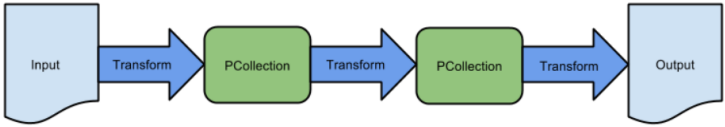


Pipelines (2/2)

```
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)

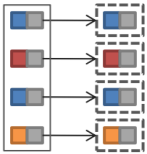
```
// Create a Java Collection, in this case a List of Strings.
static final List<String> LINES = Arrays.asList("line 1", "line 2", "line 3");

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

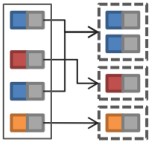
- Processes each element of a PCollection independently using a user-provided DoFn.



```
// 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.



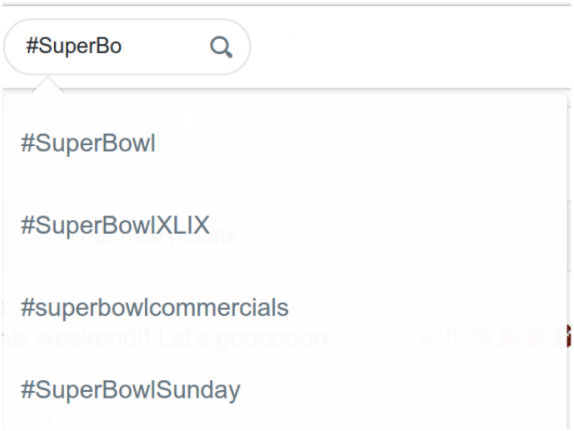
```
// A PCollection of key/value pairs: words and line numbers.
PCollection<KV<String, Integer>> wordsAndLines = ...;

// 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)



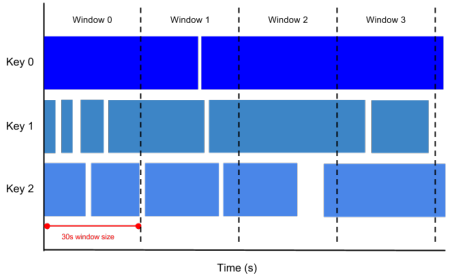
Example: HashTag Autocompletion (2/3)

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 (1/2)

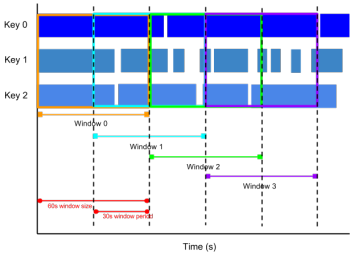
- Fixed time windows




```
PCollection<String> items = ...;

PCollection<String> fixedWindowedItems = items.apply(
  Window.<String>into(FixedWindows.of(Duration.standardSeconds(30))));
```

Windowing (2/2)

- Sliding time windows




```
PCollection<String> items = ...;

PCollection<String> slidingWindowedItems = items.apply(
  Window.<String>into(SlidingWindows.of(Duration.standardSeconds(60))
                                    .every(Duration.standardSeconds(30))));
```

Triggering

- E.g., emits results one minute after the first element in that window has been processed.

```
PCollection<String> items = ...;

items.apply(
  Window.<String>into(FixedWindows
        .of(1, TimeUnit.MINUTES))
            .triggering(AfterProcessingTime.pastFirstElementInPane()
                                           .plusDelayOf(Duration.standardMinutes(1)));
```

Summary

Summary

- Spark
  - Mini-batch processing
  - DStream: sequence of RDDs
  - RDD and window operations
  - Structured streaming
- Google cloud dataflow
  - Pipeline
  - PCollection: windows and triggers
  - Transforms

References

- M. Zaharia et al., "Spark: The Definitive Guide", O'Reilly Media, 2018 - Chapters 20-23.
- M. Zaharia et al., "Discretized Streams: An Efficient and Fault-Tolerant Model for Stream Processing on Large Clusters", HotCloud'12.
- 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
  `https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-102`

Questions?