Scalable Stream Processing - Spark Streaming and Beam

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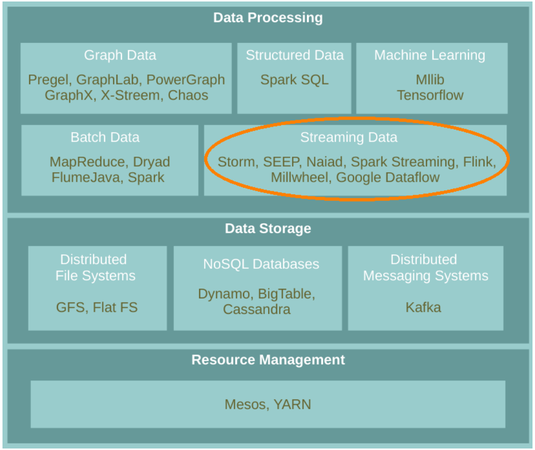
The Course Web Page

`https://id2221kth.github.io`

`https://tinyurl.com/f6x544h`

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

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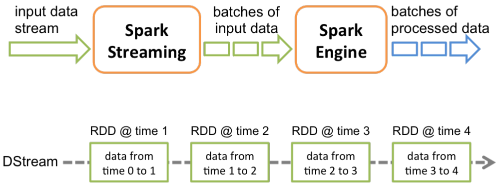
  - Discretized Stream Processing (DStream)

DStream (1/2)

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



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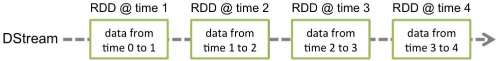
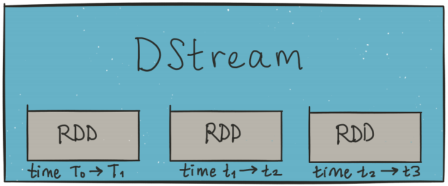
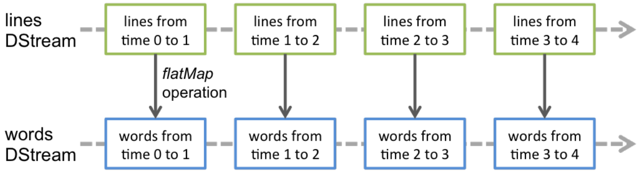




DStream (2/2)

- 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

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  - It receives the data from a source and stores it in Spark's memory for processing.

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Input Operations

- Every input DStream is associated with a `Receiver` object.
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- 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.

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

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

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```

- 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.

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- 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)

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- `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)

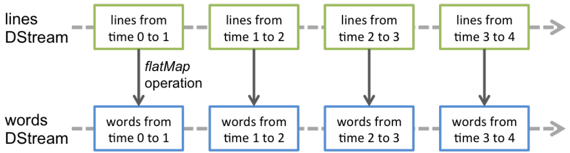
- Create a DStream that represents streaming data from a TCP source.
- Specified as hostname (e.g., localhost) and port (e.g., 9999).

```
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()
```

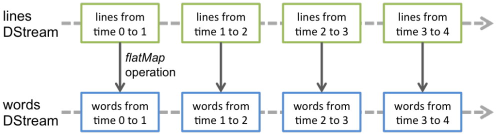
Example - Word Count (5/6)

- Start the computation and wait for it to terminate.

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

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

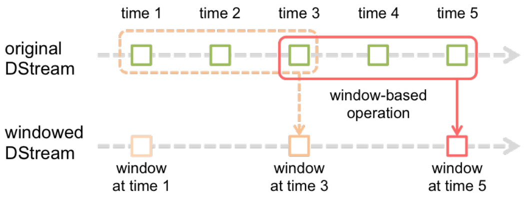
Example - Word Count (6/6)

```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.



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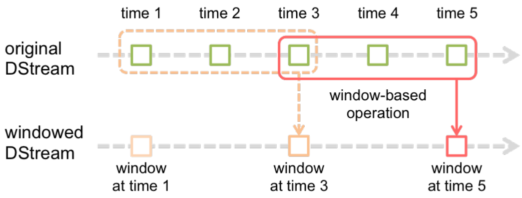
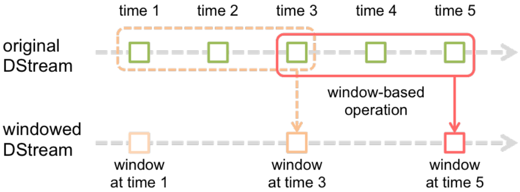
- A window is defined by two parameters: window length and slide interval.



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



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- `window(windowLength, slideInterval)`
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  - Returns a new single-element DStream, created by aggregating elements in the stream over a sliding interval using func.

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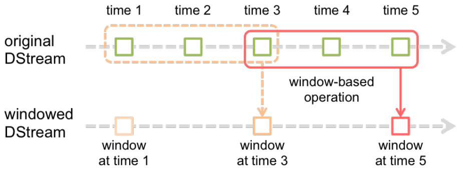
  - Returns a new DStream which is computed based on windowed batches.
- `reduceByWindow(func, windowLength, slideInterval)`
  - Returns a new single-element DStream, created by aggregating elements in the stream over a sliding interval using func.
- `reduceByKeyAndWindow(func, windowLength, slideInterval)`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

```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 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.

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- 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)

```scala
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`.

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

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- The third micro batch contains a message `b`.
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- Input: `key = b`, `value = Some(1)`, `state = 1`

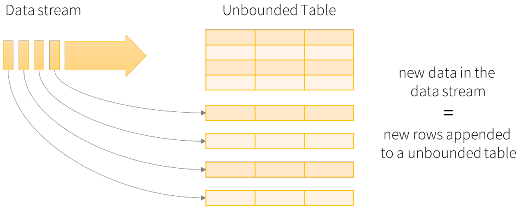
Example - Stateful Word Count (4/4)

- 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`

Structured Streaming

Structured Streaming

- Treating a live data stream as a table that is being continuously appended.



Data stream as an unbounded table

Programming Model (1/2)

- Defines a query on the input table, as a static table.
  - Spark automatically converts this batch-like query to a streaming execution plan.

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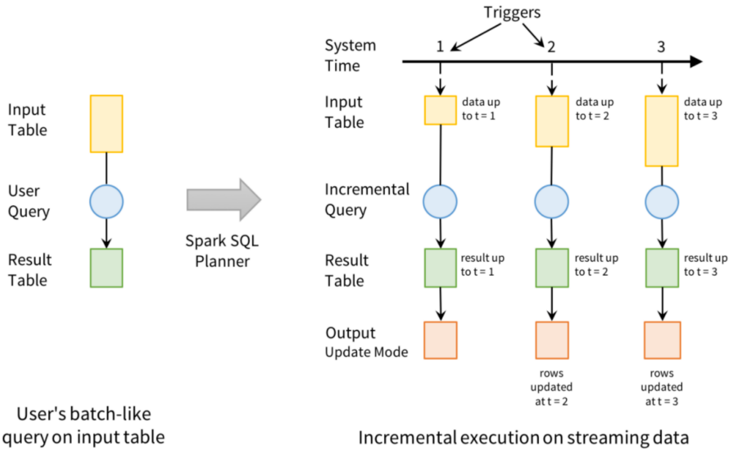
- Specify triggers to control when to update the results.
  - Each time a trigger fires, Spark checks for new data (new row in the input table), and incrementally updates the result.

Programming Model (2/2)



Output Modes

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- Three output modes:

1. Append: only the new rows appended to the result table since the last trigger will be written to the external storage.
2. Complete: the entire updated result table will be written to external storage.
3. Update: only the rows that were updated in the result table since the last trigger will be changed in the external storage.

Five Steps to Define a Streaming Query (1/5)

- Define input sources.
- Use spark.readStream to create a DataStreamReader.

```
val spark = SparkSession...

val lines = spark.readStream.format("socket")
    .option("host", "localhost")
    .option("port", 9999)
    .load()
```

Five Steps to Define a Streaming Query (2/5)

- Transform data.
- E.g., below counts is a streaming DataFrame that represents the running word counts.

```
import org.apache.spark.sql.functions._

val words = lines.select(split(col("value"), "\\s").as("word"))

val counts = words.groupBy("word").count()
```

Five Steps to Define a Streaming Query (3/5)

- Define output sink and output mode.
- Use DataFrame.writeStream to define how to write the processed output data.

```
val writer = counts.writeStream.format("console").outputMode("complete")
```

Five Steps to Define a Streaming Query (4/5)

- Specify processing details.

```
\\ word count details
import org.apache.spark.sql.streaming._

val checkpointDir = "..."

val writer2 = writer
    .trigger(Trigger.ProcessingTime("1 second"))
    .option("checkpointLocation", checkpointDir)
```

Five Steps to Define a Streaming Query (5/5)

- Start the query.
- streamingQuery represents an active query and can be used to manage the query.

```
val streamingQuery = writer2.start()
```

Streaming Data Sources and Sinks - Files (1/2)

- Reading from files.

```
import org.apache.spark.sql.types._

val inputDirectoryOfJsonFiles = ...

val fileSchema = new StructType()
    .add("key", IntegerType)
    .add("value", IntegerType)

val inputDF = spark.readStream
    .format("json")
    .schema(fileSchema)
    .load(inputDirectoryOfJsonFiles)
```

Streaming Data Sources and Sinks - Files (2/2)

- Writing to files.

```
val outputDir = ...
val checkpointDir = ...
val resultDF = ...

val streamingQuery = resultDF
    .writeStream
    .format("parquet")
    .option("path", outputDir)
    .option("checkpointLocation", checkpointDir)
    .start()
```

Streaming Data Sources and Sinks - Kafka (1/2)

- Reading from Kafka.

```
val inputDF = spark
    .readStream
    .format("kafka")
    .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
    .option("subscribe", "events")
    .load()
```

Streaming Data Sources and Sinks - Kafka (2/2)

- Writing to Kafka.

```
val counts = ... // DataFrame[word: string, count: long]
val streamingQuery = counts
    .selectExpr("cast(word as string) as key", "cast(count as string) as value")
    .writeStream
    .format("kafka")
    .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
    .option("topic", "wordCounts")
    .outputMode("update")
    .option("checkpointLocation", checkpointDir)
    .start()
```

Basic Operations (1/2)

- Most of operations on DataFrame/Dataset are supported for streaming.

```
case class Call(action: String, time: Timestamp, id: Int)

val df: DataFrame = spark.readStream.json("s3://logs")
val ds: Dataset[Call] = df.as[Call]
```

- Selection and projection

```
df.select("action").where("id > 10") // using untyped APIs
ds.filter(_.id > 10).map(_.action) // using typed APIs
```

Basic Operations (2/2)

- Aggregation

```
df.groupBy("action") // using untyped API
ds.groupByKey(_.action) // using typed API
```

- SQL commands

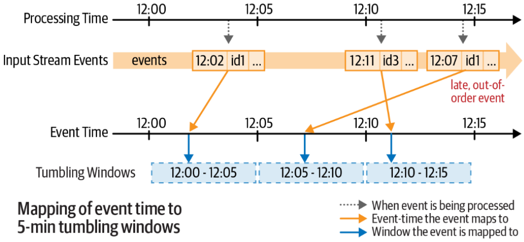
```
df.createOrReplaceTempView("dfView")
spark.sql("select count(*) from dfView") // returns another streaming DF
```

Window Operation (1/3)

- Aggregations over a sliding event-time window.
- E.g., below is expressing a five-minute count.

```
// The sensorReadings DataFrame has the generation timestamp as a column named eventTime

sensorReadings.groupBy("sensorId", window("eventTime", "5 minute")).count()
```



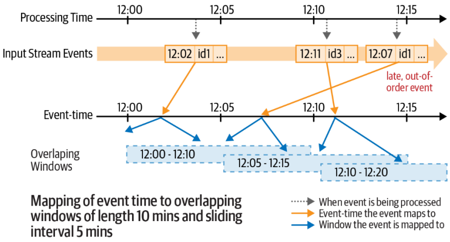
Mapping of event time to 5-min tumbling windows

Window Operation (2/3)

- Computing counts corresponding to 10-minute windows sliding every five minutes.

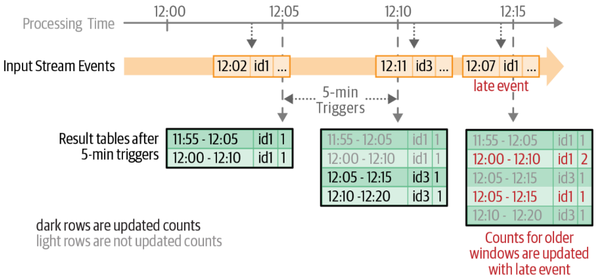
```
import org.apache.spark.sql.functions.*

sensorReadings.groupBy("sensorId", window("eventTime", "10 minute", "5 minute")).count()
```



Window Operation (3/3)

- Assume that the input records are processed with a trigger interval of five minutes.
- The state of the result table at each of the micro-batches is shown in this figure.



Handling Late Data

- A watermark is defined as a moving threshold in event time that trails behind the maximum event time seen by the query in the processed data.
- The trailing gap (watermark delay) defines how long the engine will wait for late data to arrive.

```
sensorReadings
    .withWatermark("eventTime", "10 minutes")
    .groupBy("sensorId", window("eventTime", "10 minutes", "5 minute"))
    .mean("value")
```

Stateful Operations

- Stateful processing using groupByKey() and mapGroupsWithState().

```
def arbitraryStateUpdateFunction(
    key: K,
    newDataForKey: Iterator[V],
    previousStateForKey: GroupState[S]
    ): U

val inputDataset: Dataset[V] = ...// input streaming Dataset

inputDataset.groupByKey(keyFunction) // keyFunction() generates key from input
    .mapGroupsWithState(arbitraryStateUpdateFunction)
```

Stateful Operations - Example (1/3)

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- Input data (V): case class UserAction(userId: String, action: String)
- Keys (K): String (that is the userId)
- State (S): case class UserStatus(userId: String, active: Boolean)
- Output (U): UserStatus, as we want to output the latest user status.

Stateful Operations - Example (2/3)

- Define a function that is called with new user actions.

```
def updateUserStatus(
    userId: String,
    newActions: Iterator[UserAction],
    state: GroupState[UserStatus]): UserStatus = {
        val userStatus = state.getOption.getOrElse { new UserStatus(userId, false) }
        newActions.foreach { action => userStatus.updateWith(action) }
        state.update(userStatus)
        return userStatus
    }
```

Stateful Operations - Example (2/3)

- Define a function that is called with new user actions.
- Two situations we need to handle: whether a previous state exists for that key (i.e., userId) or not.

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```

Stateful Operations - Example (2/3)

- Define a function that is called with new user actions.
- Two situations we need to handle: whether a previous state exists for that key (i.e., userId) or not.
- Accordingly, we will initialize the user's status, or update the existing status with the new actions.

```
def updateUserStatus(
    userId: String,
    newActions: Iterator[UserAction],
    state: GroupState[UserStatus]): UserStatus = {
        val userStatus = state.getOption.getOrElse { new UserStatus(userId, false) }
        newActions.foreach { action => userStatus.updateWith(action) }
        state.update(userStatus)
        return userStatus
    }
```

Stateful Operations - Example (3/3)

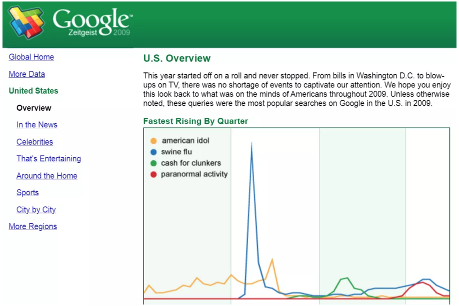
- Apply the function on the actions.
- We group the input actions Dataset using groupByKey() and then apply the updateUserStatus function using mapGroupsWithState().

```
val userActions: Dataset[UserAction] = ...
val latestStatuses = userActions
    .groupByKey(userAction => userAction.userId)
    .mapGroupsWithState(updateUserStatus _)
```

Google Dataflow and Beam

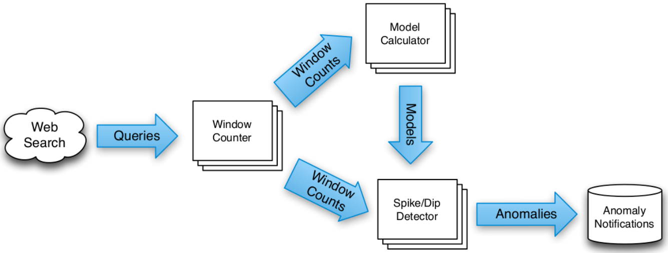
History

- 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.



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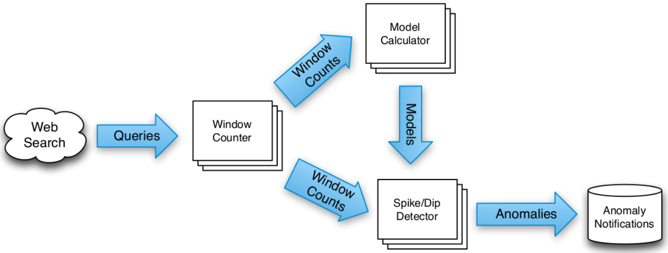
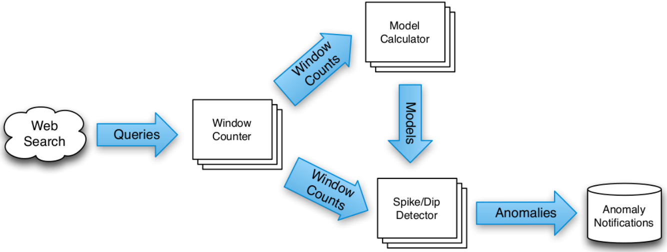


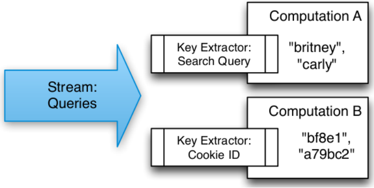
MillWheel Dataflow

- 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



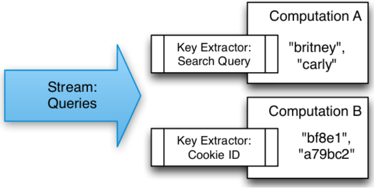
Key Extraction Function and Computations

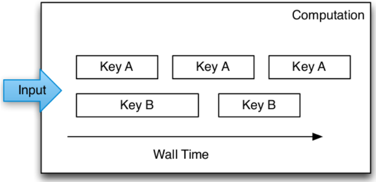
- Stream of (key, value, timestamp) records.
- Key extraction function: specified by the stream consumer to assign keys to records.



Key Extraction Function and Computations

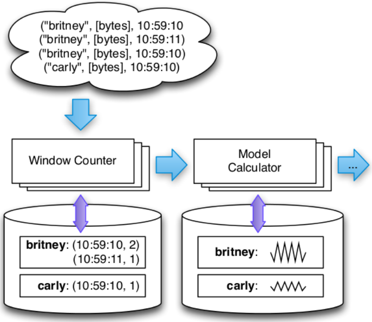
- Stream of (key, value, timestamp) records.
- Key extraction function: specified by the stream consumer to assign keys to records.
- Computation can only access state for the specific key.
- Multiple computations can extract different keys from the same stream.





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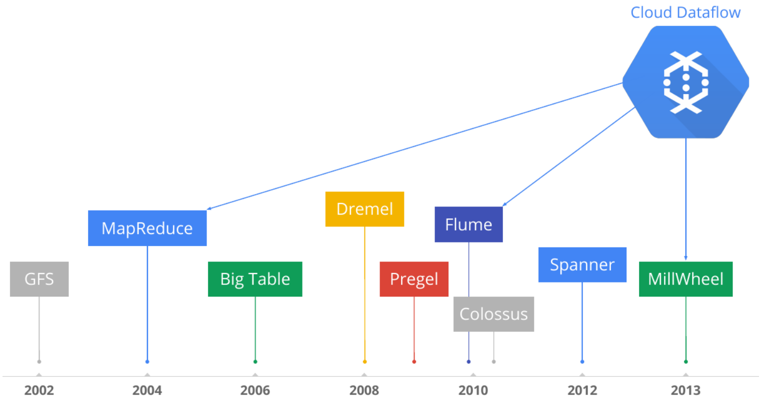
- When a delivery is ACKed the checkpoints can be garbage collected.
- If an ACK is not received, the record can be re-sent.
- Exactly-one delivery: duplicates are discarded by MillWheel at the recipient.

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)

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- Express your data processing pipeline using FlumeJava.

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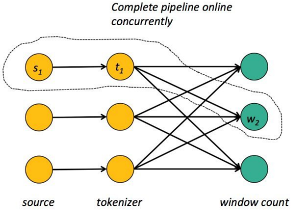
- Open source Cloud Dataflow SDK
- Express your data processing pipeline using FlumeJava.
- If you run it in batch mode, it executed on the MapReduce framework.
- If you run it in streaming mode, it is executed on the MillWheel framework.

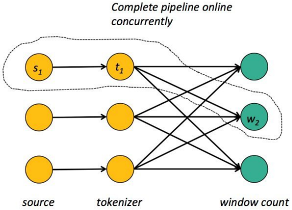
Programming Model

- Pipeline, a directed graph of data processing transformations



Programming Model

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



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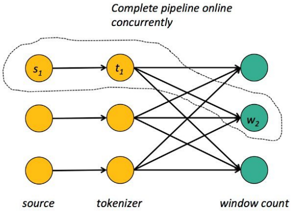
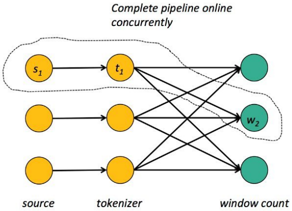


Programming Model

- 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

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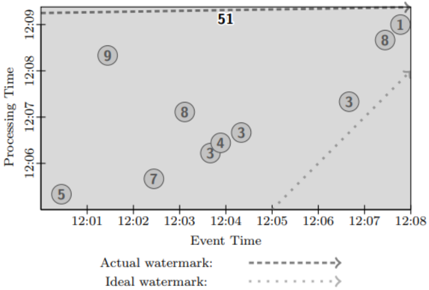
  - Sliding time windows
  - Session windows
- Triggering determines when in processing time the results of groupings are emitted as panes.
  - Time-based triggers
  - Data-driven triggers
  - Composit triggers

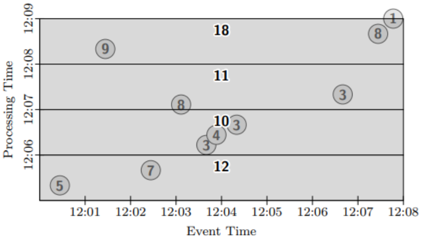
Example (1/3)

- Batch processing



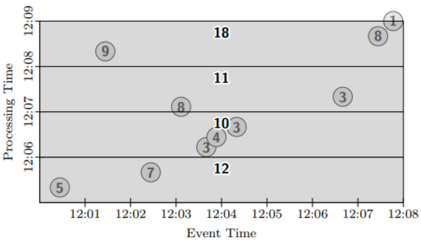
Example (2/3)

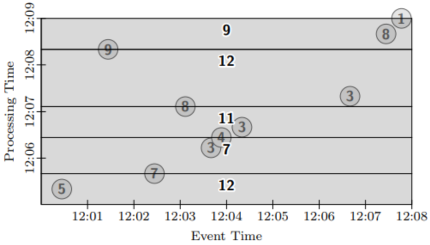
- Trigger at period (time-based triggers)



Example (2/3)

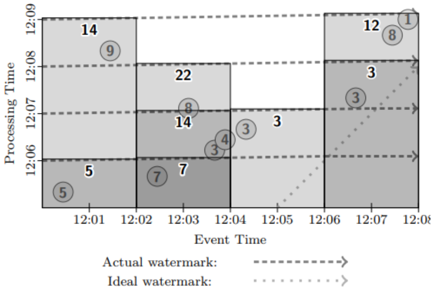
- Trigger at period (time-based triggers)
- Trigger at count (data-driven triggers)





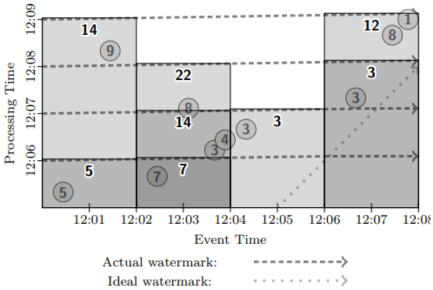
Example (3/3)

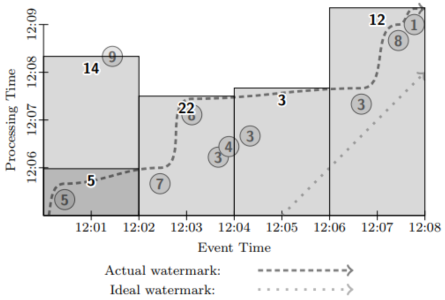
- Fixed window, trigger at period (micro-batch)



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

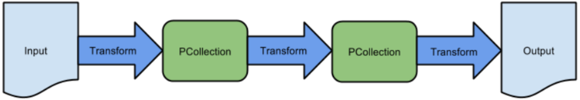
- In 2016, Google Cloud Dataflow team announced its intention to donate the programming model and SDKs to the Apache Software Foundation.
- That resulted in the incubating project Apache Beam.

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

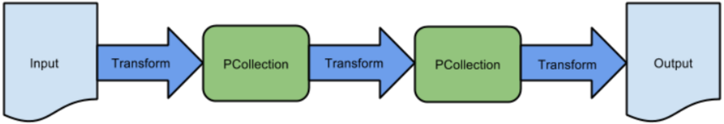


Pipelines (2/2)

```java
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)

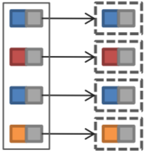
```java
// Create a Java Collection, in this case a List of Strings.
static final List<String> LINES = Arrays.asList("line 1", "line 2", "line 3");

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

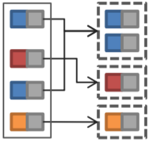
- Processes each element of a `PCollection` independently using a user-provided `DoFn`.



```java
// 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.



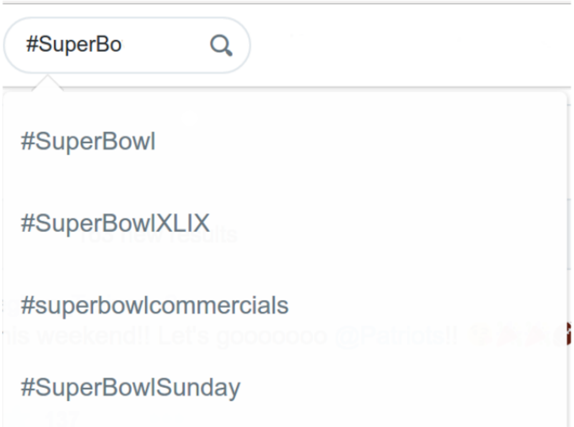
```
// A PCollection of key/value pairs: words and line numbers.
PCollection<KV<String, Integer>> wordsAndLines = ...;

// 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.

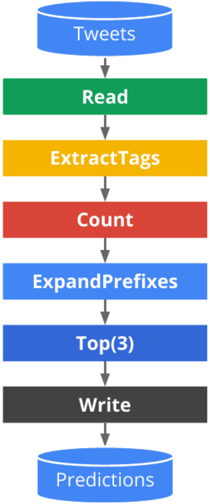
```java
// Each data set is represented by key-value pairs in separate PCollections.
// Both data sets share a common key type ("K").
PCollection<KV<K, V1>> pc1 = ...;
PCollection<KV<K, V2>> pc2 = ...;

// 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();
```

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

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Questions?