Scalable Stream Processing - Spark Streaming and Beam

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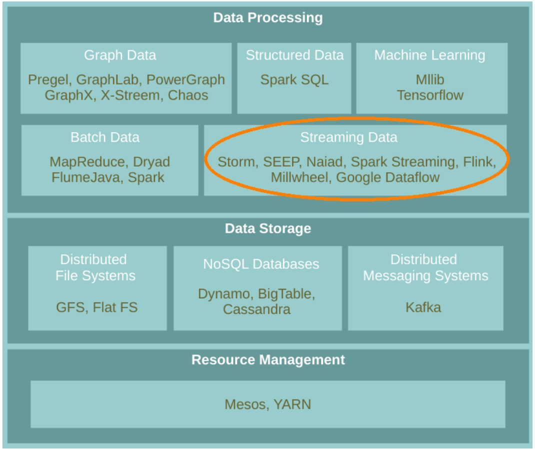
The Course Web Page

https://id2221kth.github.io

The Questions-Answers Page

https://tinyurl.com/bdenpwc5

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
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GFS, Flat FS
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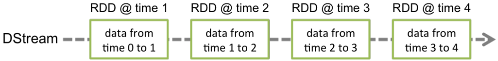
Spark Streaming

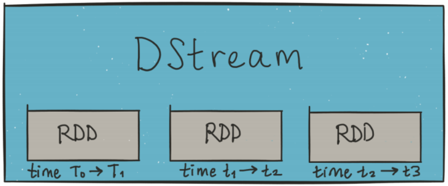
Spark Streaming

- 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)

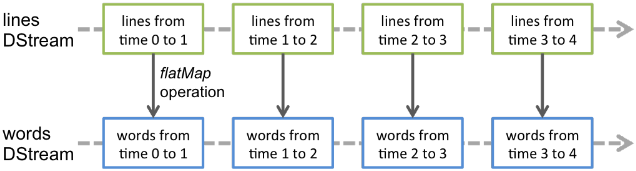
- DStream: sequence of RDDs representing a stream of data.





DStream (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

- 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)
```

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

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.
- `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)

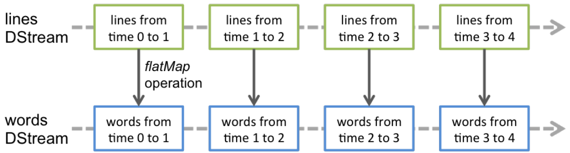
- Create a DStream that represents streaming data from a TCP source.
- Specified as hostname (e.g., localhost) and port (e.g., 9999).

```
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()
```

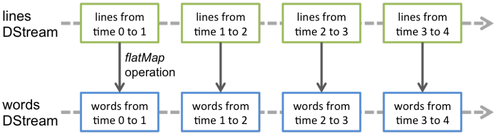
Example - Word Count (5/6)

- Start the computation and wait for it to terminate.

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

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

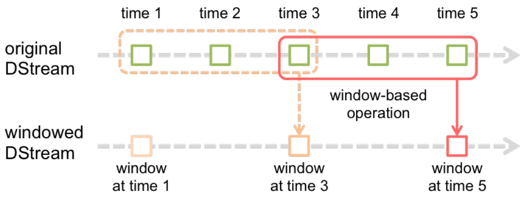
Example - Word Count (6/6)

```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.
- 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

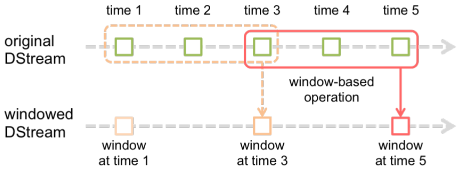


Window Operations (2/2)

- `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.
- 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])
```

- 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`.
- `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`.
- `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`

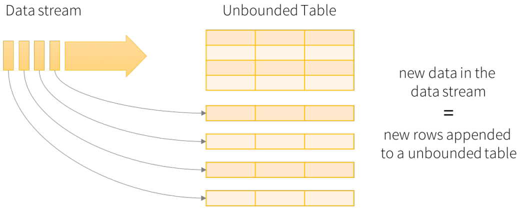
Example - Stateful Word Count (4/4)

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



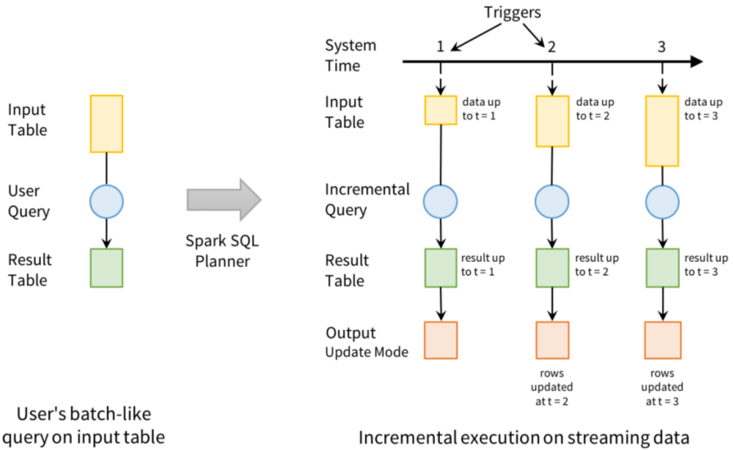
Data stream as an unbounded table

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.

- 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

- 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.builder.master("local[2]").appName("appname").getOrCreate()

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()
```

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
```

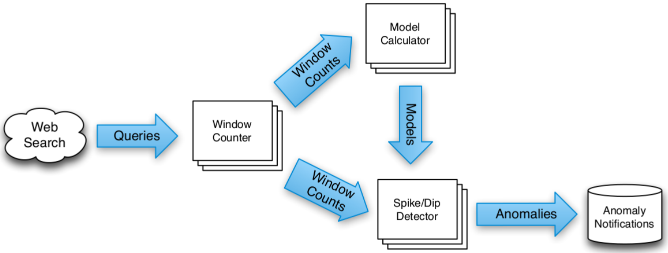
- SQL commands

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

Google Dataflow and Beam

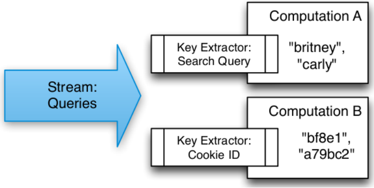
MillWheel Dataflow

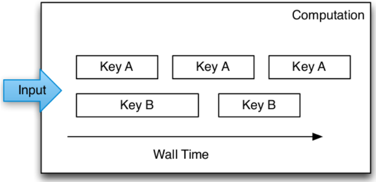
- MillWheel is a framework for building low-latency data-processing applications.
- A dataflow graph of transformations (computations).
- Stream: unbounded data of (key, value, timestamp) records.
  - Timestamp: event-time



Key Extraction Function and Computations

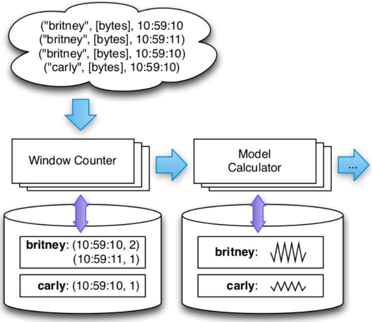
- Stream of (key, value, timestamp) records.
- Key extraction function: specified by the stream consumer to assign keys to records.
- Computation can only access state for the specific key.
- Multiple computations can extract different keys from the same stream.





Persistent State

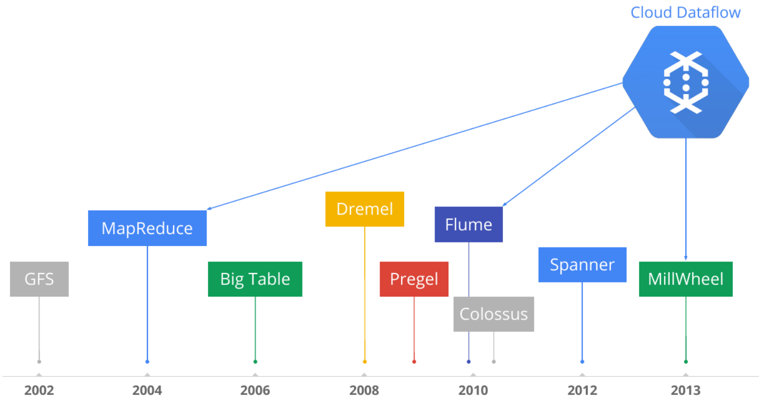
- Keep the states of the computations
- Managed on per-key basis
- Stored in Bigtable or Spanner
- Common use: aggregation, joins, ...



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)

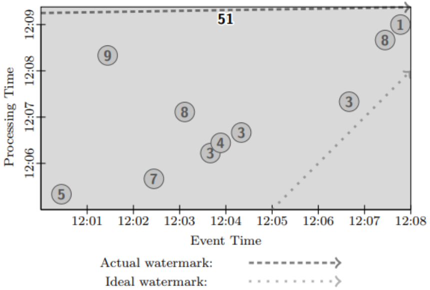
- Open source Cloud Dataflow SDK
- Express your data processing pipeline using FlumeJava.
- If you run it in batch mode, it executed on the MapReduce framework.
- If you run it in streaming mode, it is executed on the MillWheel framework.

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.

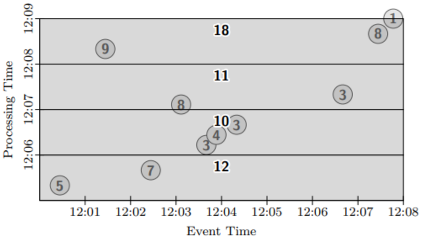
Example (1/3)

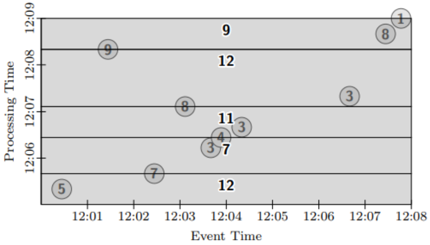
- Batch processing



Example (2/3)

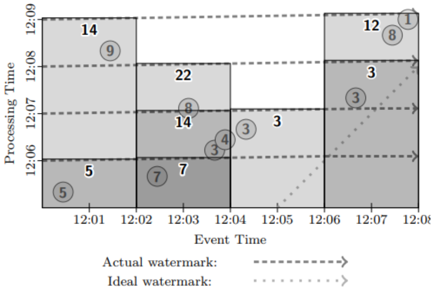
- Trigger at period (time-based triggers)
- Trigger at count (data-driven triggers)

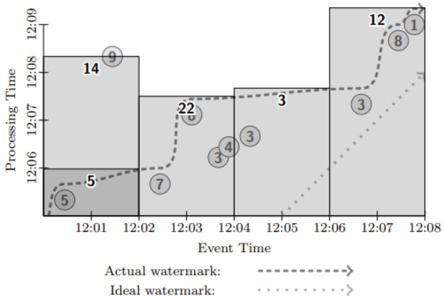




Example (3/3)

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





Where is Apache Beam?

From Google Cloud Dataflow to Apache Beam

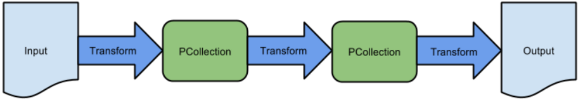
- In 2016, Google Cloud Dataflow team announced its intention to donate the programming model and SDKs to the Apache Software Foundation.
- That resulted in the incubating project Apache Beam.

Programming Components

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

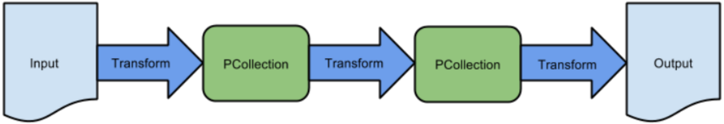
Pipelines

- 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



PCollections (1/2)

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



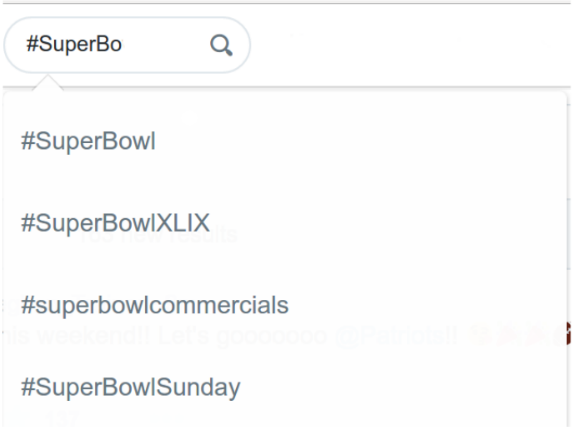
PCollections (2/2)

```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

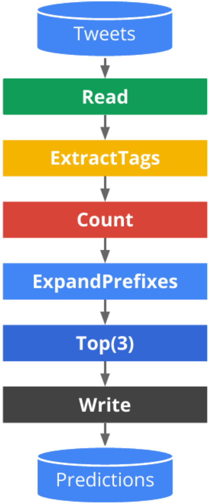
- A processing operation that transforms data
- Each transform accepts one (or multiple) `PCollections` as input, performs an operation, and produces one (or multiple) new `PCollections` as output.
- Core transforms: `ParDo`, `GroupByKey`, `Combine`, `Flatten`

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
  - 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?