Data Management in Large-Scale Distributed Systems

Stream processing

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References

- The lecture notes of V. Leroy
- Designing Data-Intensive Applications by Martin Kleppmann
  - Chapter 11

In this lecture

- Introduction to Stream Processing
- Transmitting data streams
- An overview of Stream Processing engines

Agenda

Introduction

Transmitting event streams: Message brokers

Stream processing

The lambda architecture

An unbounded dataset

Batch processing

- Data are stored in files
- Process the whole data at once
- Examples: Hadoop MapReduce, Spark, etc.

In many use-cases, new data are generated continuously

- Data from sensors
- Data from social networks
- Web traffic
- Etc.

Near real-time processing

In many cases, data should be processed as *early* as possible:

- Detecting fraudulent behavior
- Identifying malfunctioning systems
- Monitoring trends (social networks, system load)

Adapting batch processing systems?

Near real-time processing

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Adapting batch processing systems?

- Processing all the data of the day at the end of each day

Near real-time processing

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Adapting batch processing systems?

- Processing all the data of the day at the end of each day
  - High latency ☹
- We need to process data more *frequently*
  - **This is what stream processing engines do**

Stream vs Batch processing

Batch processing

- Good for analyzing a static dataset
- Focuses on throughput
- Allows running complex analysis requiring multiple iterations on the data

Stream processing

- Good to analyze *live* data
- Continuously updates results based on new data
- Focuses on latency (between data production and update of the results)
- Processes data once

Stream processing computation

Stream analytics

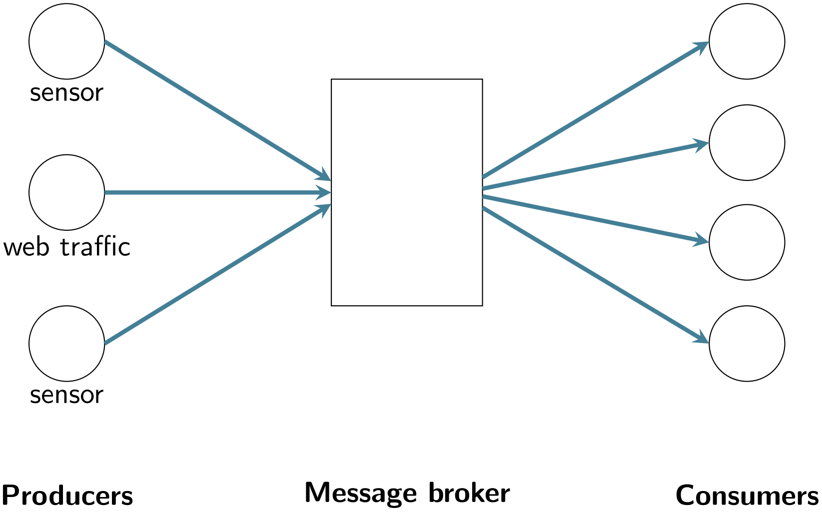
- Measuring event rates
- Computing rolling statistics (average, histograms, etc)
- Comparing statistics to previous values (detecting trends)
- Sampling data
- Filtering data
- Applying basic machine learning algorithms

Questions related to stream processing

- How to transmit data from the producers to the consumers?
  - With multiple producers and/or consumers?
- How to process events in a distributed way?
- How to deal with failures?
- How to reason about time?
- How to maintain a state over time?

Agenda

Motivation


sensor
web traffic
sensor
Producers
Message broker
Consumers

Challenges

Routing messages

- Some consumers are only interested in some messages
- Some messages are useful for multiple consumers

Performance

- Amount of produced data might be huge
- Data might me produced faster than they are processed

Fault tolerance

- Clients might connect/disconnect at any time

Log-based message broker

Main principles

- Maintain a log of all the messages received
  - Append-only sequence of records on disk
- Each record is identified with a sequence number
- The offset of each client in the log can be stored

Existing systems

- Apache Kafka
- Amazon Kinesis Data Streams

Kafka

https://kafka.apache.org/

- Originally developed at LinkedIn
- Open-source
- Used by many companies

Kafka main principles

A partitioned log

The log is divided into multiple partitions

- Each partition has its own monotonically increasing sequence number
- Partitions can be hosted on different machines

Advantages of logs

- Old records can be replayed
  - Clients can arrive late or disconnect
  - Question: How to do garbage collection?
    - Note that filling a 6TB disk takes half a day
- Data are buffered in the log
  - Deal with the case where the consumers are slower than the producers

Kafka communication abstractions

Topics

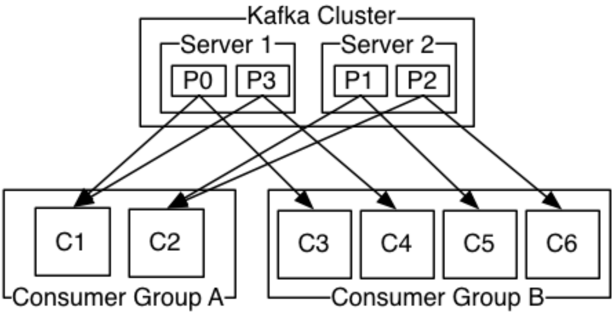
- Partitions are grouped into logical topics
- A producer can send to multiple topics

Consumer groups

- Consumers gather themselves into consumer groups
- A consumer group can register to one or several topics
- Multiple groups can register to the same topic
- Each record is delivered to one consumer in each registered group
  - Records from one partition are send to exactly one consumer in a group
  - Total-order delivery is only ensured inside partitions

Kafka consumer groups

source https://kafka.apache.org/documentation/#gettingStarted



2 types of communication patterns

- Load balancing
- Broadcasting

Kafka fault tolerance

Data availability

- A Kafka cluster spans multiple nodes
- Partitions are replicated on multiple nodes

Dealing with consumer disconnections/failures

- Offset of the consumer in the log partition is recorded permanently
- The same/another consumer can start processing records from this point
- Provided delivery semantics:
  - *At-least-once*
  - *At-most-once*
  - In some cases *exactly-once* semantic can be ensured (relies on transaction mechanisms)

Agenda

Stream processing engines

Description

- A set of transformations is applied to a stream of records
  - A program is a graph of transformations (Directed acyclic graph)
  - Transformations are the same operations as in batch processing systems

Examples

- Storm
- Flink
- Samza
- Spark streaming

Graph of transformations (Flink)

source https://ci.apache.org/projects/flink/flink-docs-release-1.6/concepts/programming-model.html

```
DataStream<String> lines = env.addSource(
                                new FlinkKafkaConsumer<>(…));
```

Source

```
DataStream<Event> events = lines.map((line) -> parse(line));
```

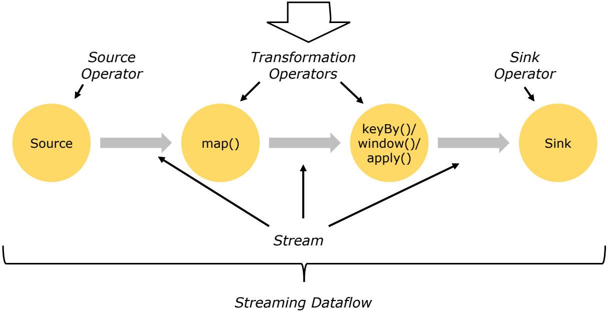
Transformation

```
DataStream<Statistics> stats = events
        .keyBy("id")
        .timeWindow(Time.seconds(10))
        .apply(new MyWindowAggregationFunction());
```

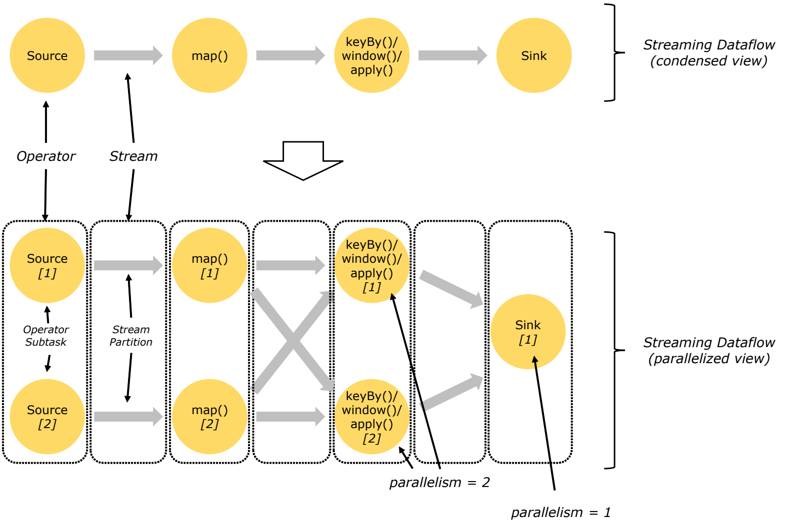
Transformation

```
stats.addSink(new RollingSink(path));
```

Sink



Parallel Dataflow (Flink)



About the notion of time

To run computations on a continuous stream, it has to be split into windows.

Size of the windows

- 1 event: Each event is processed separately (Storm)
- Windows limits is defined based on:
  - Amount of data received
  - Time
  - Activity (concept of sessions)

2 reference times co-exists in the system

- Event time: time at which the events happened
- Processing time: time at which the events are processed
  - Most systems build windows based on the processing time

About the notion of time

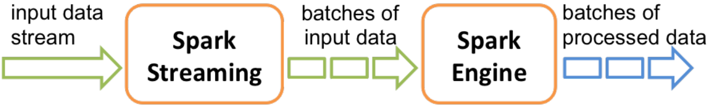
Window type

- Tumbling window: Fixed-size window, each event belongs to one window
- Hopping window: Fixed-size window, windows overlap
  - hop size $=$ time between the generation of two windows
  - hop size $<$ window size
- Sliding window: Fixed-size window
  - A new window is considered at each time step
- Session window: No fix size, group together events that happened closely together in time

Spark Streaming

Based on micro-batches

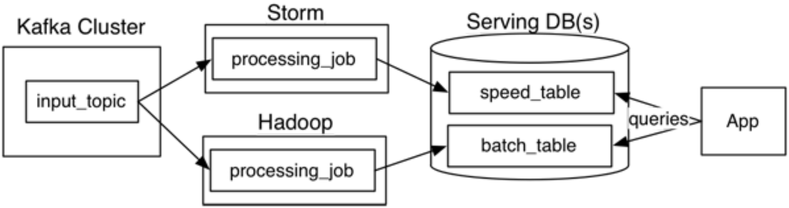
- The data stream is divided into micro-batches
  - Tumbling windows
  - Typically 1 to 4 seconds
- Each micro-batch is a RDD
- Multiple receivers can be created to manipulate multiple data streams in parallel
  - The receiver tasks are distributed over the workers



Agenda

The Lambda architecture

source https://www.oreilly.com/ideas/questioning-the-lambda-architecture



The Lambda architecture

Motivations

- Combination of batch processing and stream processing in a single architecture
  - Stream processing allows building fast (approximate) views of the data
  - Batch processing is used for more complex (and accurate) data analysis

Limits

Architecture becoming less popular (lambda-less architecture)

- Maintaining two code bases is costly
- Processing engines start allowing doing both (Spark, Flink)
  - Stream processing engines are becoming more mature, they allow running more complex computations
  - Log-based message brokers allow processing the same record multiple times

Additional references

Mandatory reading

- `https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101`, T. Akidau, 2015.

Suggested reading

- *Apache Flink: Stream and Batch Processing in a Single Engine.*, P. Carbone et al., IEEE, 2015.
- `https://www.oreilly.com/ideas/questioning-the-lambda-architecture`, J. Kreps, 2014.