Aalto University
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Stream Processing and Big Data Platforms

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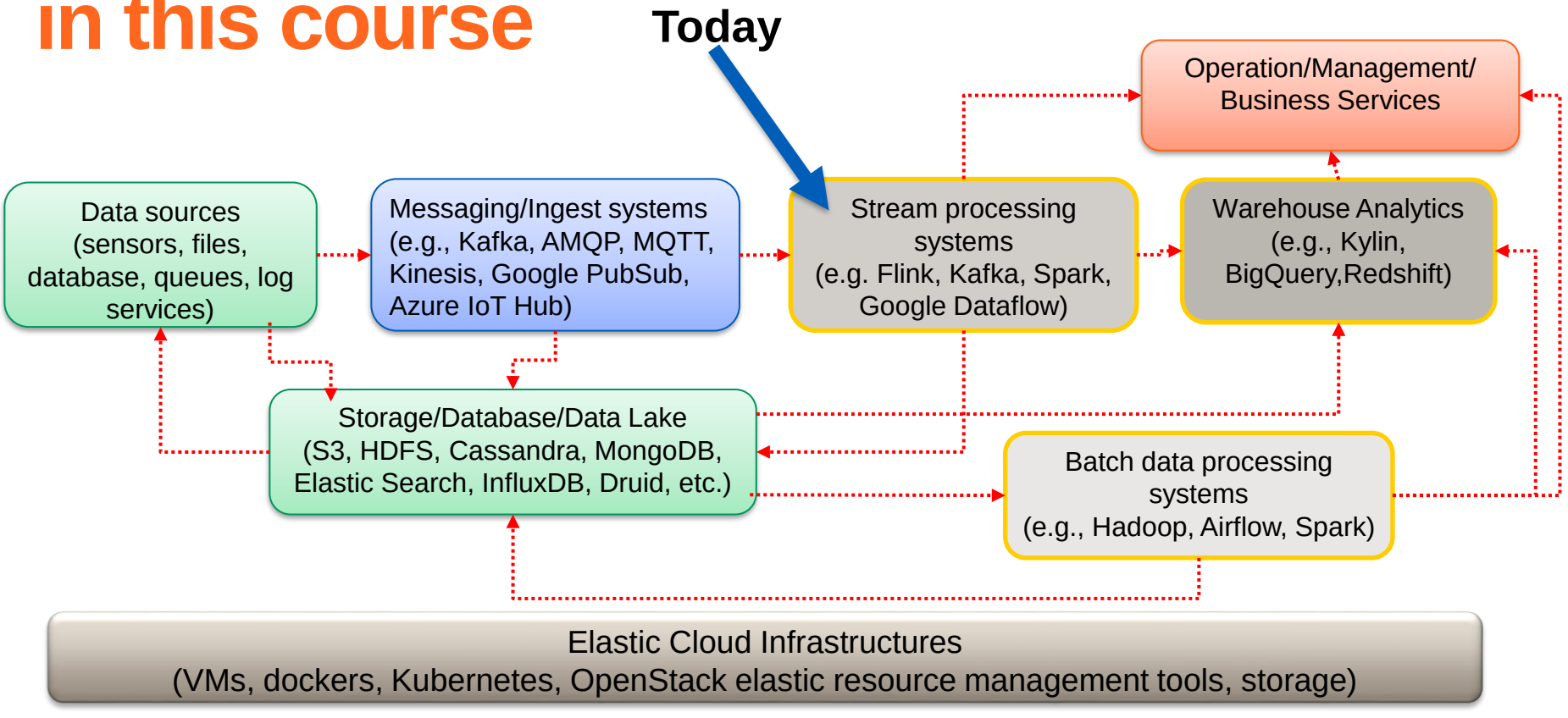
Learning objectives

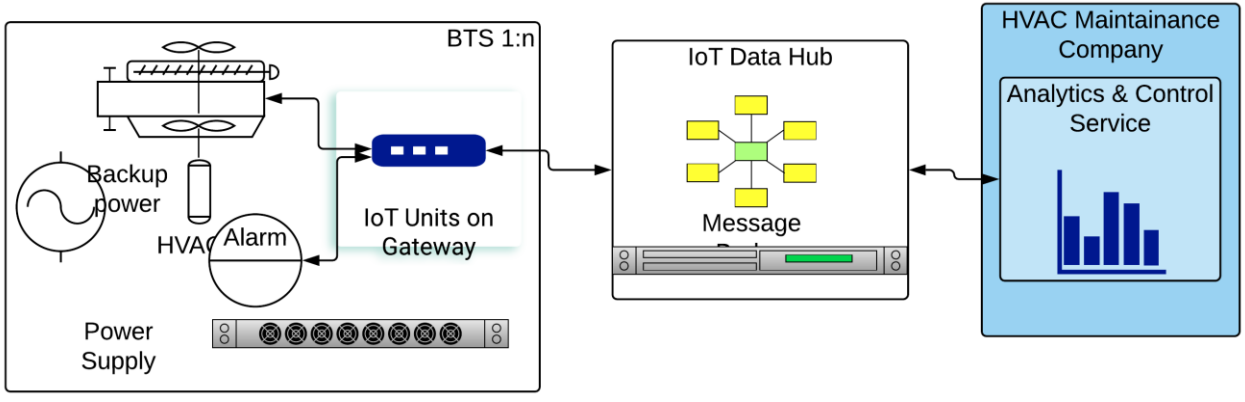
- **Understand fundamental concepts and techniques in stream processing in big data**
- **Able to design stream processing analytics in big data platforms and applications**
- **Able to select and use common stream processing frameworks**

Big data at large-scale: the big picture in this course



Motivating examples

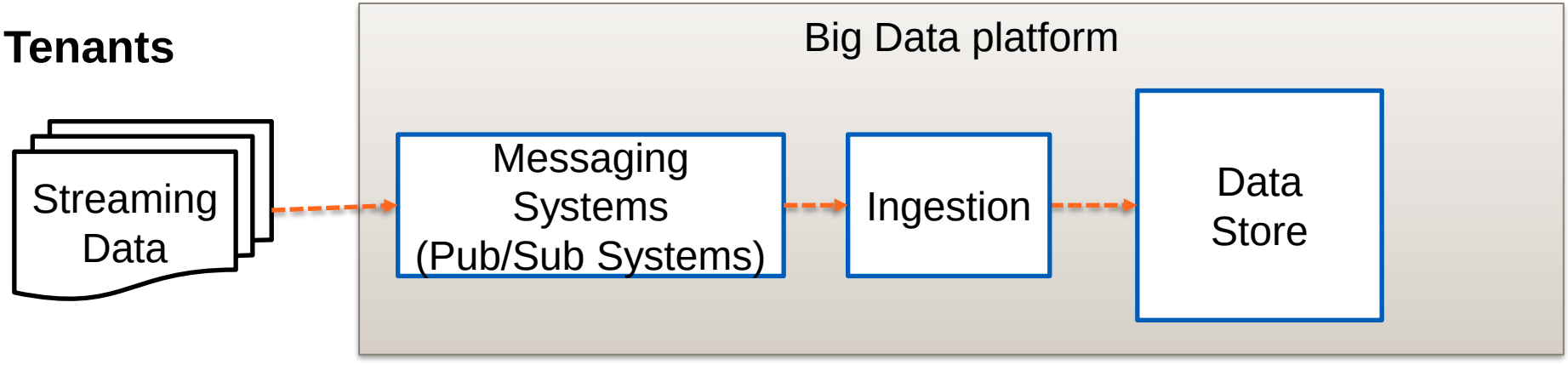
Near real-time monitoring and anomaly detection for equipment and sites: what if you have 200K of BTS



We need to analyze streaming data in a near-real time manner

Many other scenarios: fraud detection in online payment, stock market monitoring, traffic detection, etc.

Recall: near-real time streaming data ingestion

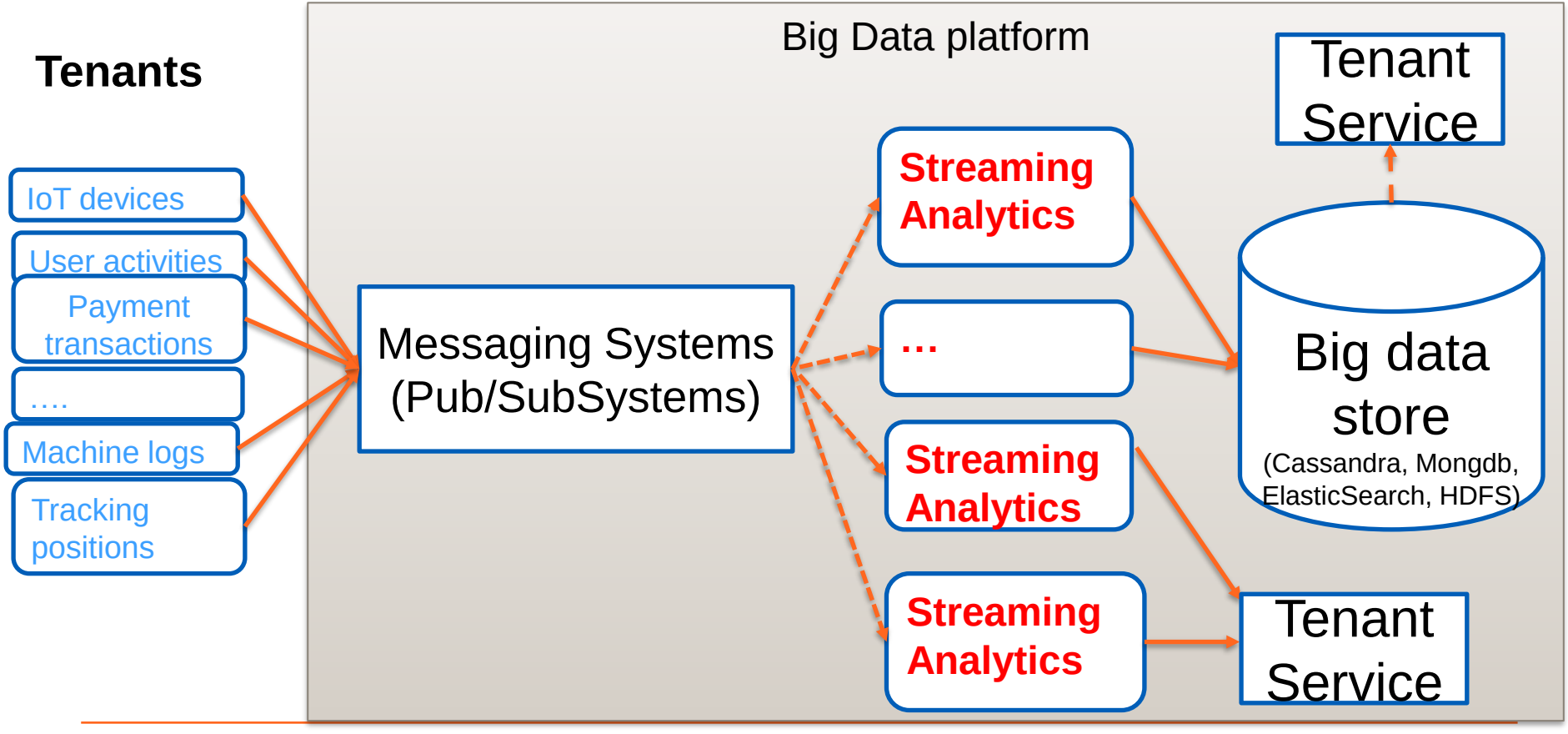


- **Ingestion**
  - Mostly we ingest raw data without/little processing, e.g., IoT data
- **Data is unbounded from different places in different orders!**

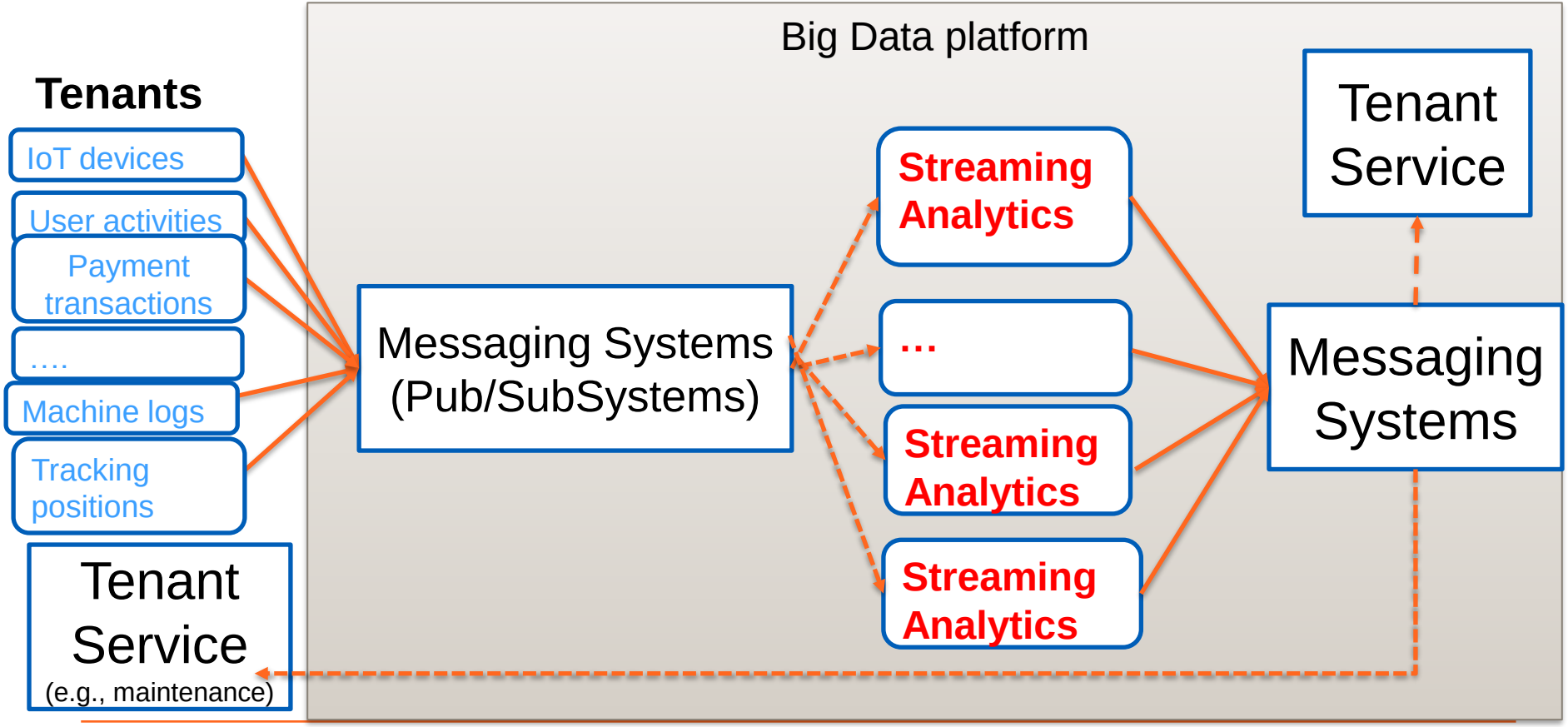
Stream processing in big data

- **Processing big data coming from streams at near real time**
  - The data element is “small” but voluminous and delivered in a near-real time manner
  - High and volatile throughput, low service latency
- **Require large-scale computing infrastructures and many other platform services**
  - Task parallelism: multiple tasks processing data
  - Data parallelism: data is partitioned into concurrent/parallel data streams → not like in data at rest

Near realtime streaming data processing



Near realtime streaming data processing



Stream processing and big data platforms

- **Stream processing is a component of big data platforms**
  - A big data technology for pre-processing, ingestion and high-level analytics
- **Stream processing services as big data platforms**
  - a big data platform offers mainly stream processing services
  - Analytics on the fly as the first class
    - *Historical analytics results as the second class*
  - E.g., IoT analytics, e-commerce user activities, fraud detection

Example in the cloud – stream processing and big data platforms

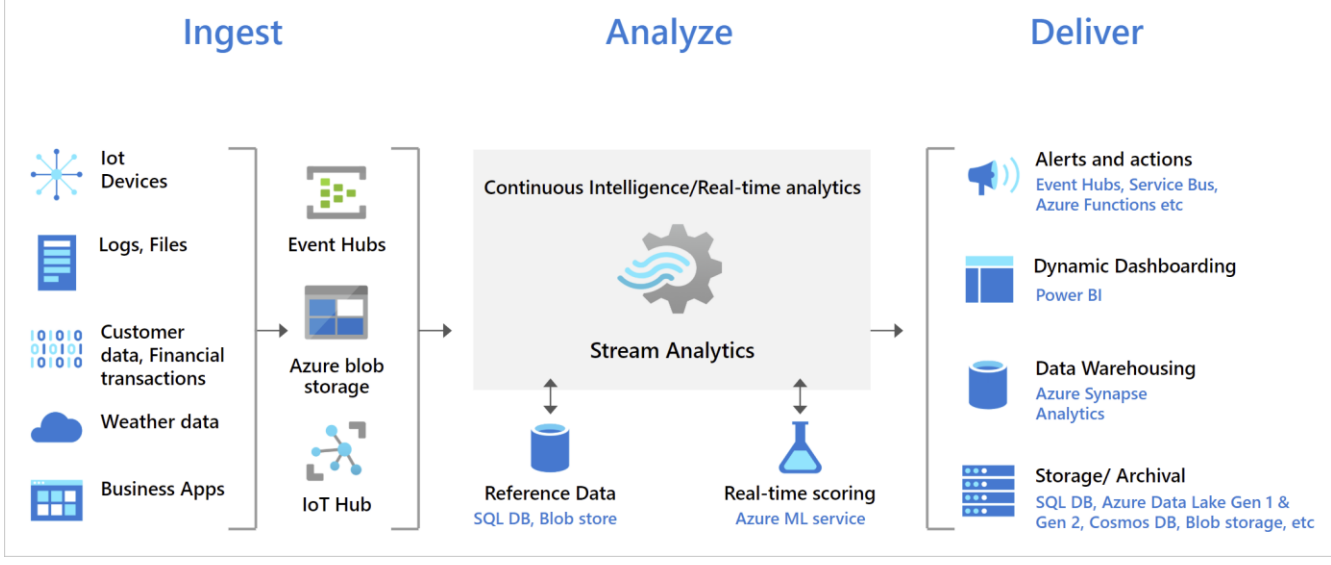
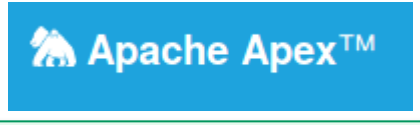


Figure source:
https://docs.microsoft.com/en-us/azure/stream-analytics/stream-analytics-introduction

Long history, e.g., complex event processing (CPE) from enterprise computing

Esper CEP



Our practices focus on Apache Flink, Apache Kafka and Apache Spark which are used intensively in business systems and big cloud platforms

Stream Processing – Key concepts

Data stream programming

Data stream: a sequence/flow of data units

Data units are defined by applications: a data unit can be data described by a primitive data type or by a complex data type, a serializable object, etc.

Streaming data: produced by (near)realtime data sources as well as (big) static data sources → unbounded and bounded

- Examples of data streams
  - Continuous media (e.g., video for video analytics)
  - Discrete media (e.g., stock market events, twitter events, system monitoring events, comments, notifications)

Events/Records

In many applications: data is generated continuously and needs to be processed in near real-time

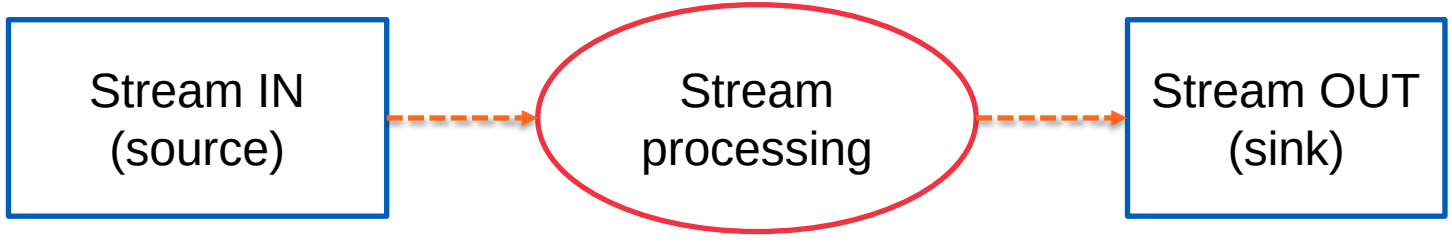
We focus on unbounded discrete events/records/messages

Event/record representation and streams

- **Data Sources:**
  - via message brokers, database, websocket, different IO adapters/connectors, etc.
- **Data Sink**
  - Message systems, databases, files, etc.
- **Data Representation & views**
  - POJO (Plain Old Java Object), CSV, Arvo format, etc.
  - SQL-alike tables

Stream processing

High level view

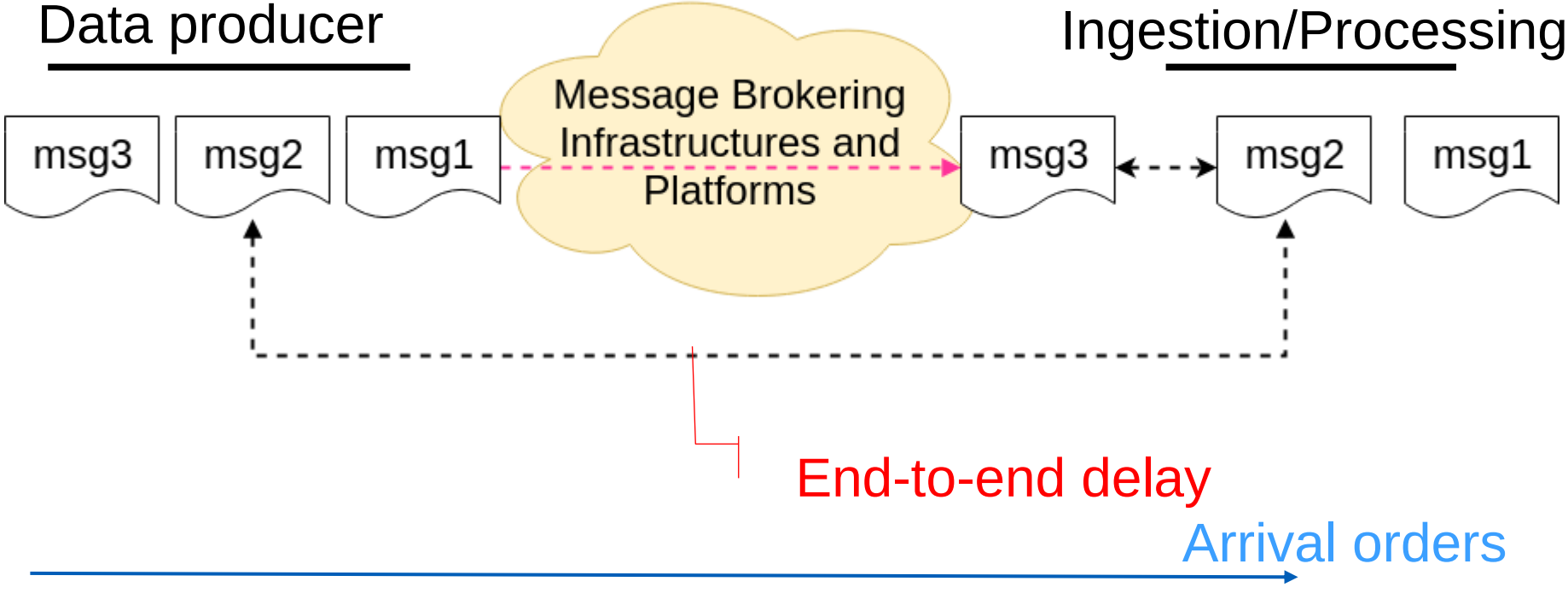


Multiple streams, a set of events

Some key issues

- **Data order & delivery**
  - Late data, out of order data
- **Times associated with events**
- **Data parallelism**
  - Key-based data processing
- **Task parallelism**
  - Stateful vs stateless processing

Key issues in streaming data: delay and out of order

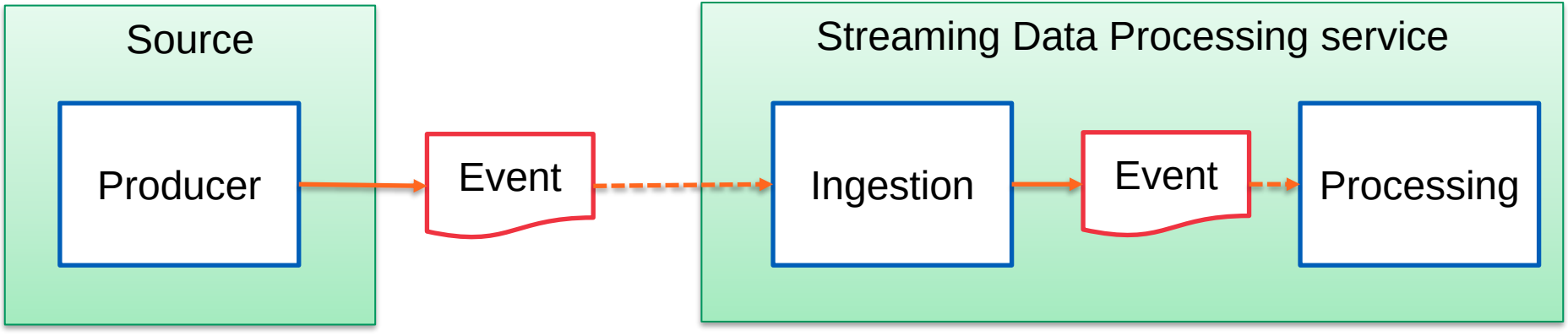


Without event time, do we know the delay or out of order?

What is the consequence of delay/out of order for processing?

Key issues in streaming data: the notion of times

Times associated with data and processing



Event time

Ingestion time

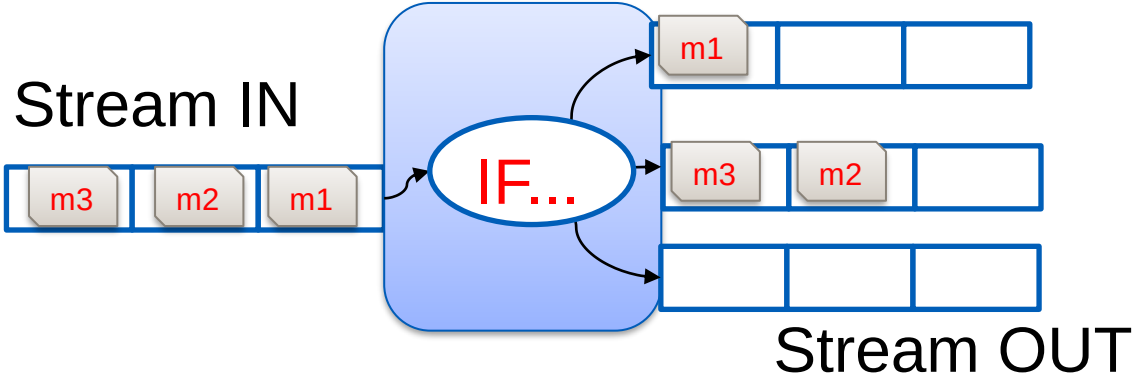
Processing time

Which time is important for analytics (from business viewpoint)?

Data parallelism: partition stream data based on some keys for analytics

Split based on keys?

One-record vs batch of records



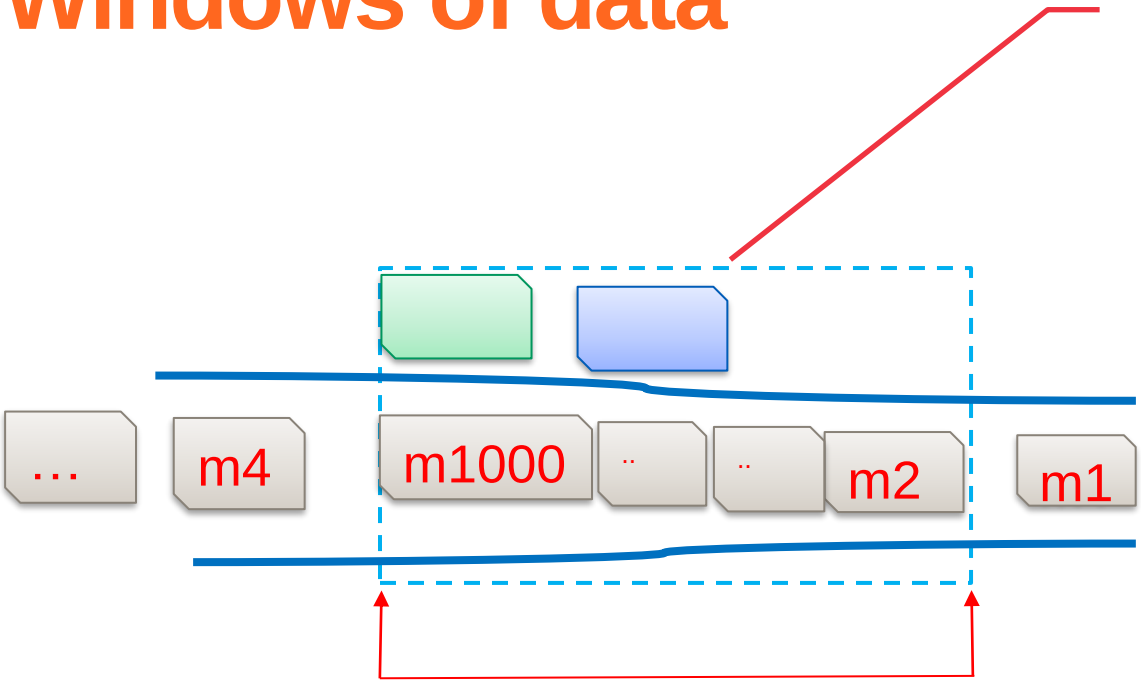
Can be processed in parallel using multiple nodes

With keyed data: enable parallel processing based on the keys

Windows of data

Window is used to group data for processing:

Which constraints are used to determine a window?



a stream of events

Sliding/Tumble window size: time or size of events

Arrival order

Windowing

- **Windows size: time or number of records (not popular)**
- **Tumbling window:**
  - identified by size, no gap between windows
- **Sliding window:**
  - identified by size and a sliding internal
- **Session Window:**
  - identified by “gap” between windows

Functions applied to Windows of data

If we

- specify a set of conditions for the window and events within the window

then we can

- Apply functions to events in the window that match these conditions

Task parallelism: we can have a lot of such functions executed in parallel in multiple compute nodes

Example

Monitoring working hours of taxi drivers (assume events about pickup/drop captured at near realtime):

- **Windows: 12 hours**
- **Partitioning data/Keyed streams: licenseID**
- **Function: determine working and break times and check with the law/regulation**

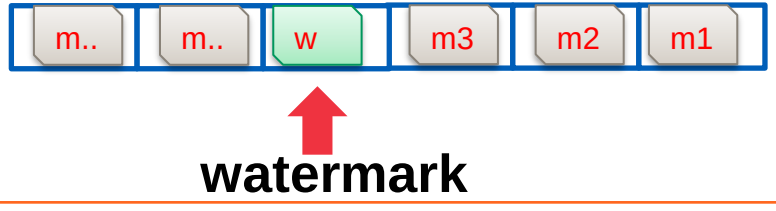
Source: https://www.infoworld.com/article/3293426/how-to-build-stateful-streaming-applications-with-apache-flink.html

What if events come late into the windows?

Do we need to deal with late, out of order events?

Support lateness

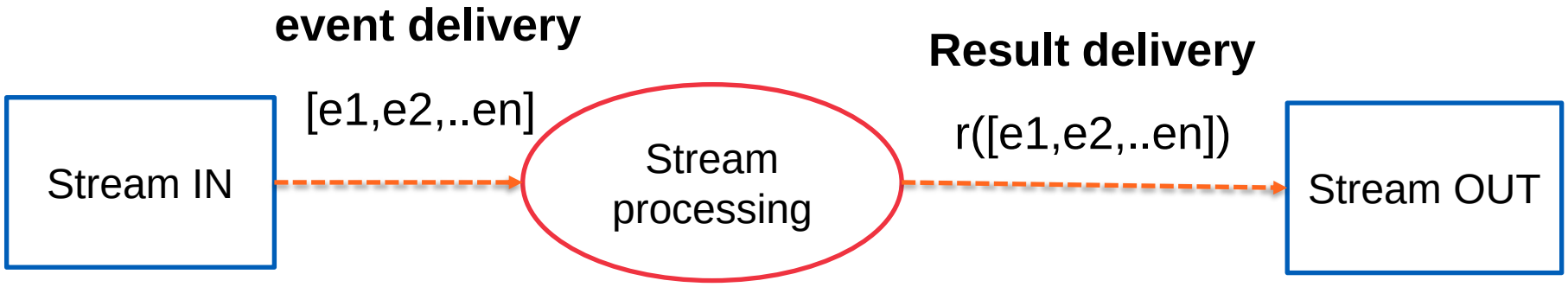
- **Identify timestamp of events**
- **Identify watermark in streams**
  - A watermark is a timestamp
  - A watermark indicates that no events which are older that the watermark should be processed
  - Enable the delay of processing functions to wait for late events
- **Using watermark to ignore late data → computing under "incompleteness assumption"**



Delivery guarantees

Exactly once? at least once? or at-most-once

End-to-end?



What if the stream processing fails and restarts

Message and processing guarantees

- **Message guarantees are the job of the broker/messaging system**
- **Processing guarantees are the job of the stream processing frameworks**
- **They are highly connected if messaging systems and processing frameworks are tightly coupled (e.g., Kafka case)**

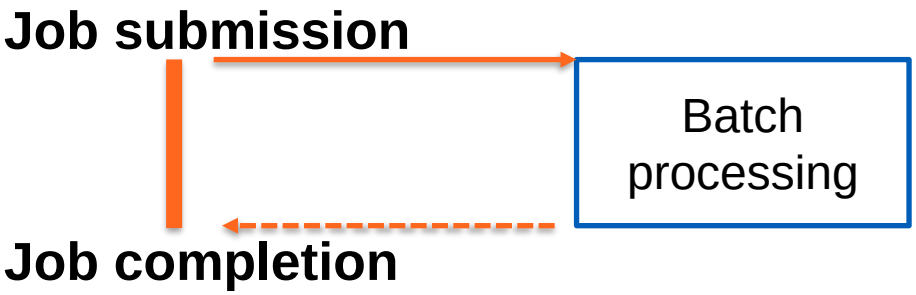
End-to-end exactly once

- **Exactly once for processing is not enough**
- **Messaging systems must support**
  - redeliver messages/data, recoverable data
- **Sink and output must support exactly one**
  - idempotent results, roll back
- **Coordination among various components**

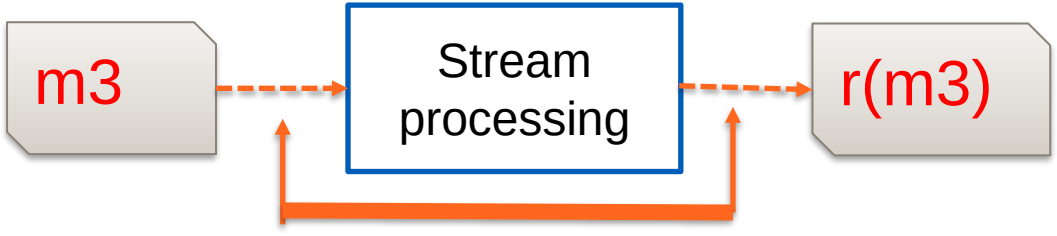
Further reading:
https://flink.apache.org/features/2018/03/01/end-to-end-exactly-once-apache-flink.html
https://www.confluent.io/blog/simplified-robust-exactly-one-semantics-in-kafka-2-5/
https://docs.microsoft.com/en-us/azure/hdinsight/spark/apache-spark-streaming-exactly-once

Performance metrics

Response time



(e.g., MapReduce/Hive, Spark SQL)



Service time/latency

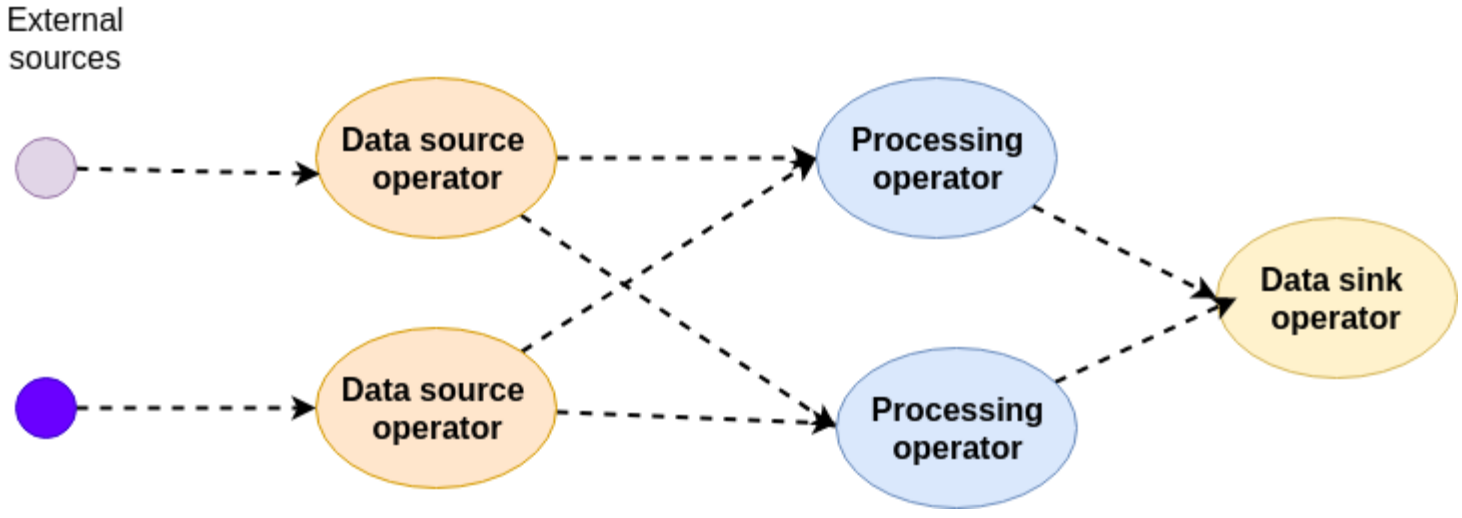
Latency and Throughput

- **Service latency**
  - Subseconds! E.g., milliseconds
  - Max, min or percentile? → up to application requirements
- **Throughput**
  - How many events can be processed per second?
- **Goal: low latency and high throughput!**

Structure of streaming data processing programs (1)

- **We have multiple streams of data, different functions for processing data, multiple computing nodes**
- **Data exchange between tasks**
  - Links in task graphs reflect data flows
- **Stream processing**
  - Centralized or distributed (in terms of computing resources)

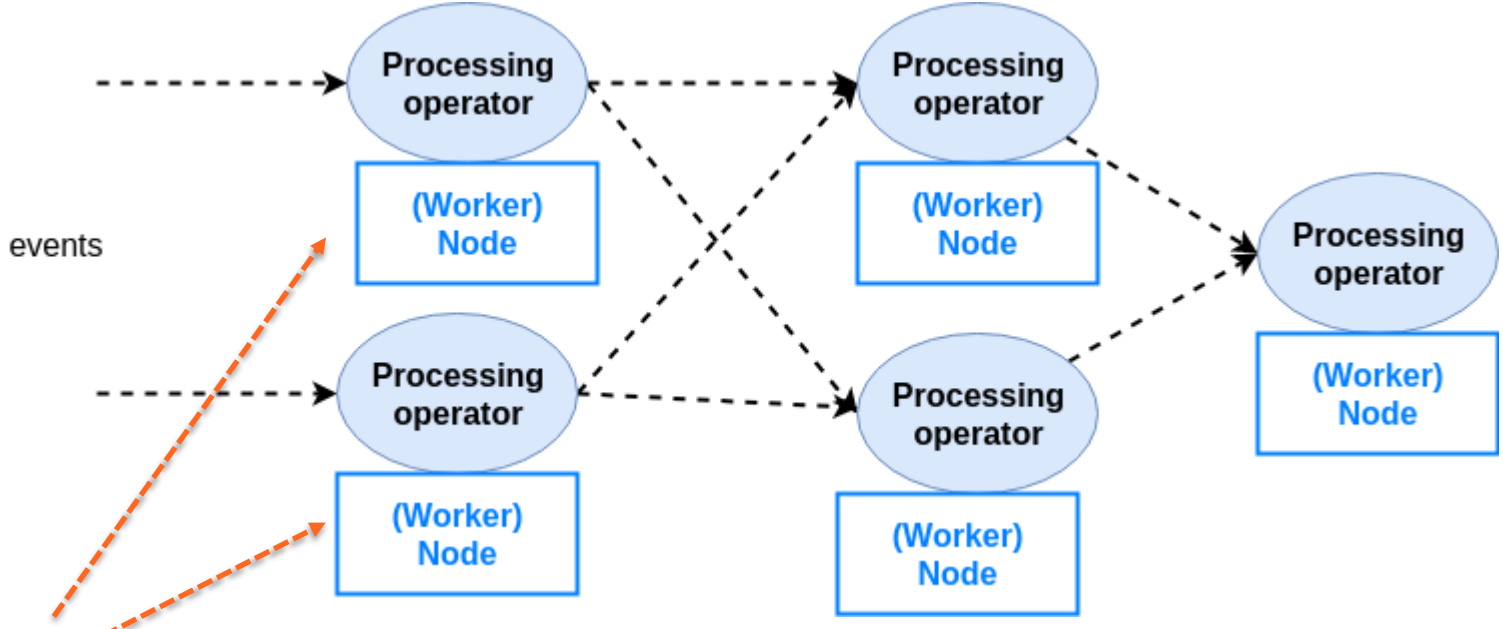
Structure of streaming data processing programs (2)



- **Data source operator: represents a source of streams**
- **Processing operators: represents processing functions**
- ***Native* versus *micro-batching***

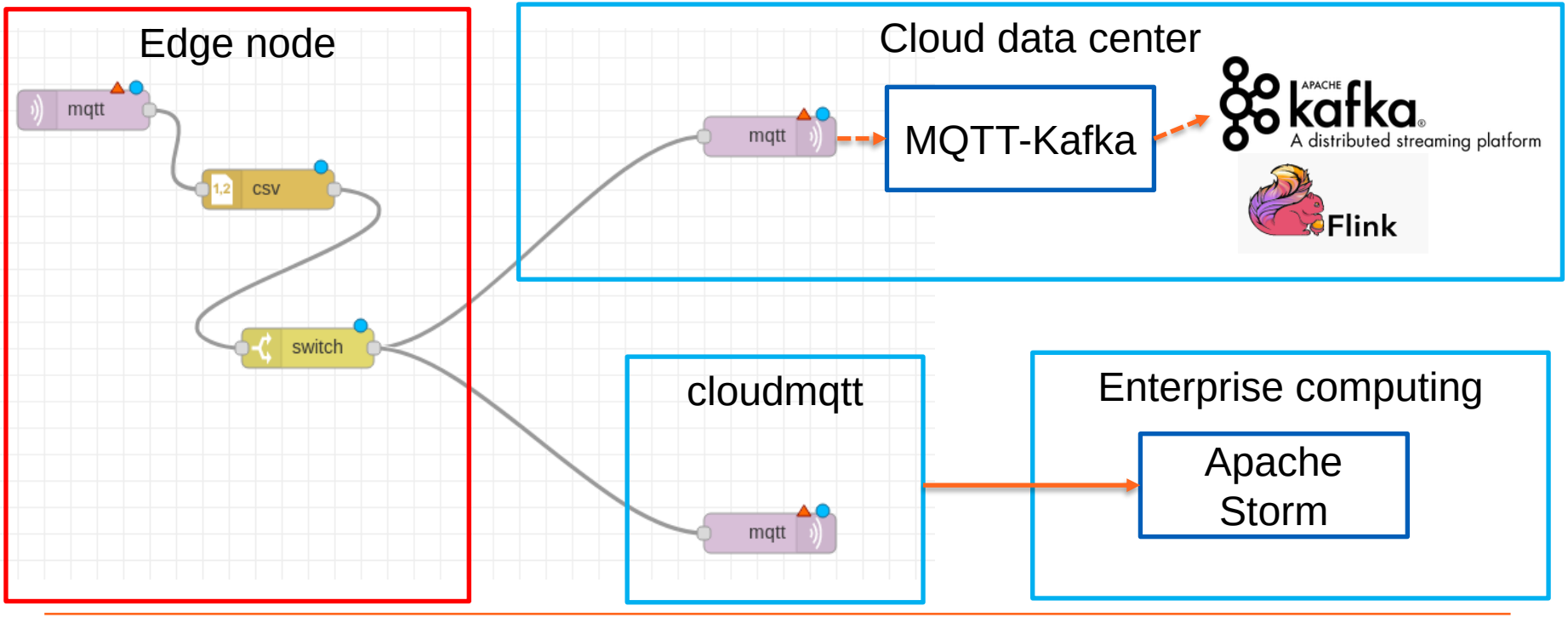
Distributed processing topology in a cluster

A graph of tasks (running operators); all tasks are running



Nodes of a cluster (VMs, containers, Kubernetes)

Distributed processing topology in cross distributed sites



Common concepts in existing frameworks

- **The way to connect data streams and obtain events**
  - Focusing very much on connector concepts and well-defined event structures
  - Assume that existing systems push the data
- **The way to specify "analytics"**
  - Statements and how they are glued together to process flows of events
  - High-level, easy to use
- **The engine to process analytics tasks/operators**
  - Centralized in the view of the user → so the user does not have to program complex distributed applications
  - Underlying it might be complex (for scalability purposes)
- **The way to push results to external components**

Common concepts in existing frameworks - programming level

- **How to write streaming program?**
- **With programming languages**
  - Low level APIs
  - DSL
  - Java, Scala, Python (Spark, Flink, Kafka)
- **High-level data models**
  - KSQL
- **Flow/pipeline description**
  - Node-RED/GUI-based flow editors

Common concepts in existing frameworks - key common concepts

- **Abstraction of streams**
- **Connector library for data sources/sinks**
  - Very important for application domains
- **Runtime elasticity**
  - Add/remove (new) operators
  - Add/remove underlying computing nodes
- **Fault tolerance**

Why are the richness and the diversity of connectors important?

Where do you find most of concepts that we have discussed

- **Apache Storm**
  - *https://storm.apache.org/*
- **Apache Spark (Structured Streaming)**
  - *https://spark.apache.org/*
- **Apache Kafka Streams and KSQL**
  - strongly bounded to Kafka messaging
- **Apache Flink**
  - native, clustered, better data sources/sinks

Practical learning paths

- **Path 1: if you don't have a preference and need challenges**
  - Apache Flink Stream API (e.g., with RabbitMQ/Kafka connectors)
- **Path 2: many of you have worked with Kafka**
  - Kafka Streams DSL (everything can be done with Kafka)
- **Path 3: for those of you who are working with Spark (and Python is the main programming language)**
  - Apache Spark Structured Streaming
- **Path 4: for those who deal with MQTT brokers**
  - Apache Storm (but also Kafka, …): Spout and Bolt API or Stream API

Examples of Apache Flink

Apache Flink

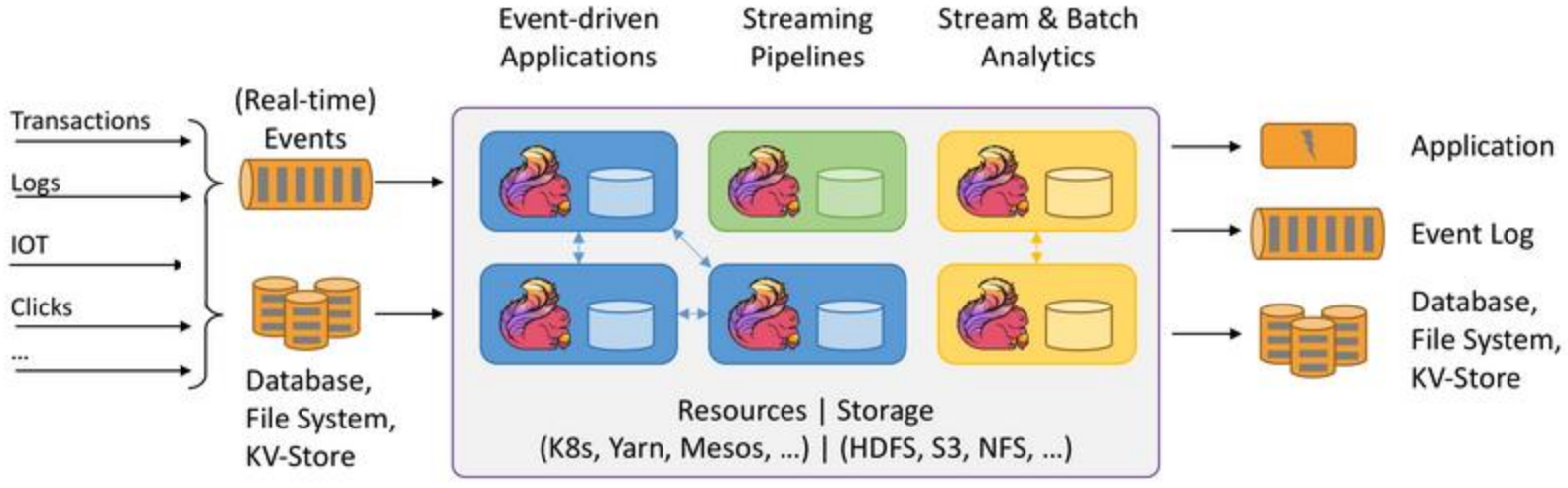
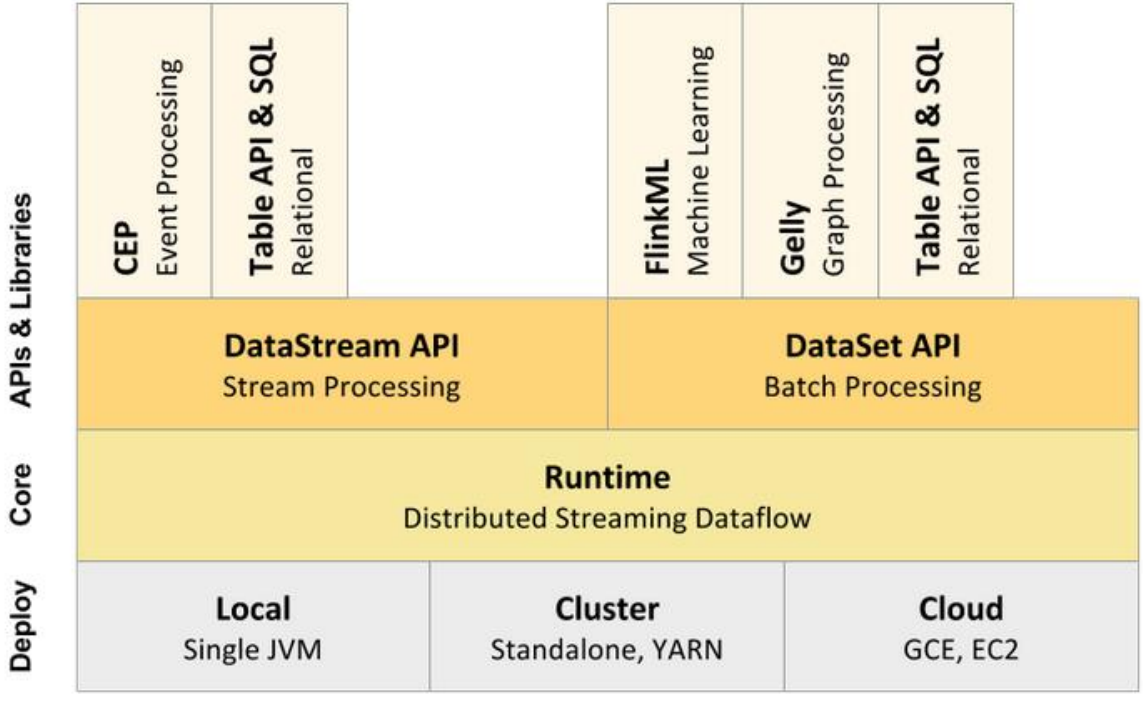


Figure source: https://flink.apache.org/

Apache Flink

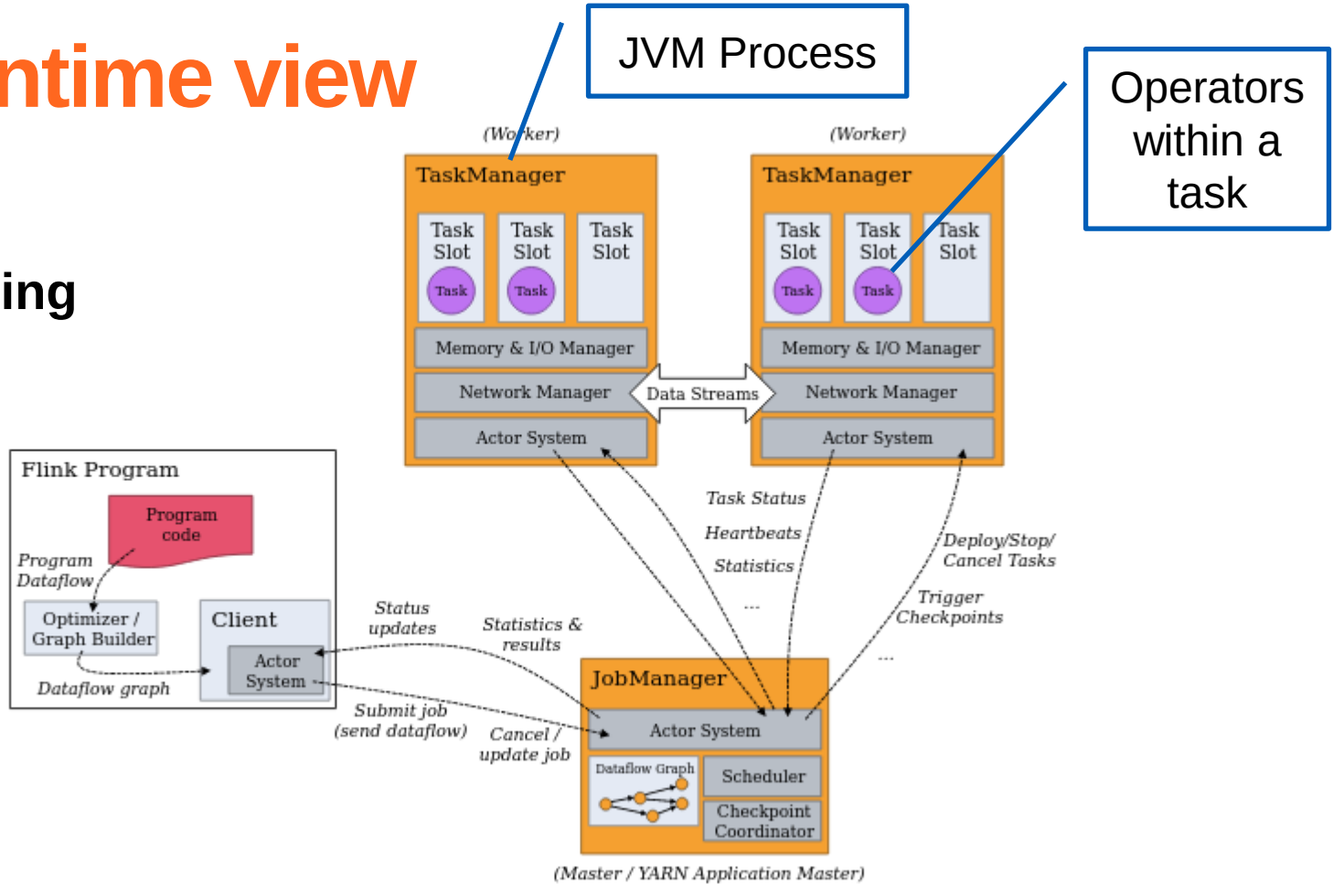


We focus only on DataStream API for understanding studied concepts

Source: https://ci.apache.org/projects/flink/flink-docs-release-1.9/internals/components.html

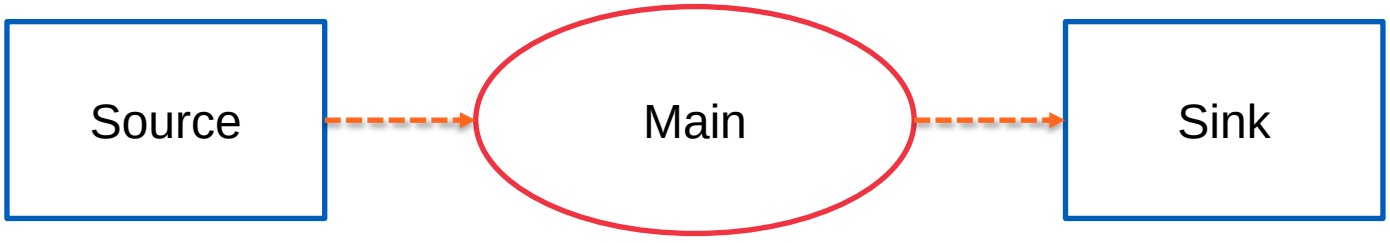
Flink runtime view

- **Parallelism**
- **Checkpointing**
- **Monitoring**



Source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/concepts/flink-architecture.html

Main elements in Flink applications



- **Rich set of sources and sinks via many connectors**

Connectors

- **Major systems in big data**
- **We have used many of them in our study**
  - Apache Kafka
  - Apache Cassandra
  - Elasticsearch (sink)
  - Hadoop FileSystem
  - RabbitMQ
  - Apache NiFi
  - Google PubSub

Main

- **Setting environments**
- **Handling inputs and outputs via data streams**
- **Key functions for processing data**
- **Stream processing flows**

Bounded and unbounded streams

Stream processing flows

Split streaming data into different windows with a key for analytics purposes

Keyed Windows

```
stream
       .keyBy(...)               <-  keyed versus non-keyed windows
       .window(...)              <-  required: "assigner"
      [.trigger(...)]            <-  optional: "trigger" (else default trigger)
      [.evictor(...)]            <-  optional: "evictor" (else no evictor)
      [.allowedLateness(...)]    <-  optional: "lateness" (else zero)
      [.sideOutputLateData(...)] <-  optional: "output tag" (else no side output for late data)
       .reduce/aggregate/fold/apply()      <-  required: "function"
      [.getSideOutput(...)]      <-  optional: "output tag"
```

Source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/dev/stream/operators/windows.html

Stream processing flows

Handling streaming data without a key for analytics purposes

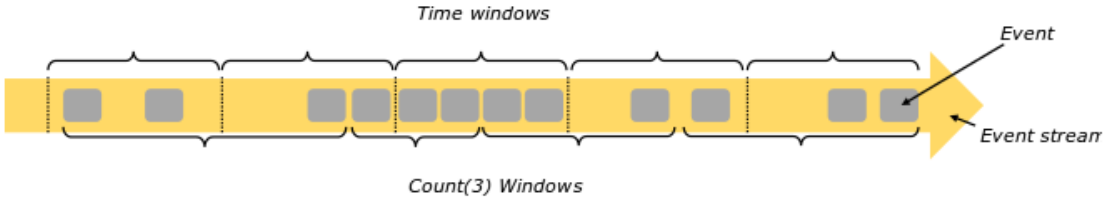
Non-Keyed Windows

```
stream
       .windowAll(...)           <-  required: "assigner"
      [.trigger(...)]            <-  optional: "trigger" (else default trigger)
      [.evictor(...)]            <-  optional: "evictor" (else no evictor)
      [.allowedLateness(...)]    <-  optional: "lateness" (else zero)
      [.sideOutputLateData(...)] <-  optional: "output tag" (else no side output for late data)
       .reduce/aggregate/fold/apply()      <-  required: "function"
      [.getSideOutput(...)]      <-  optional: "output tag"
```

Source: https://ci.apache.org/projects/flink/flink-docs-release-1.9/dev/stream/operators/windows.html

Windows and Times

Windows



Times

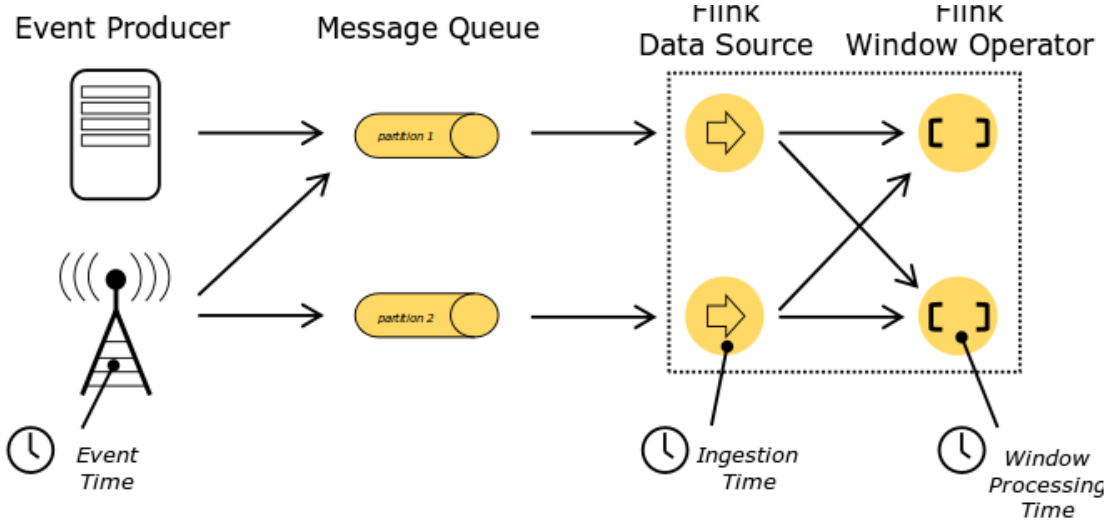
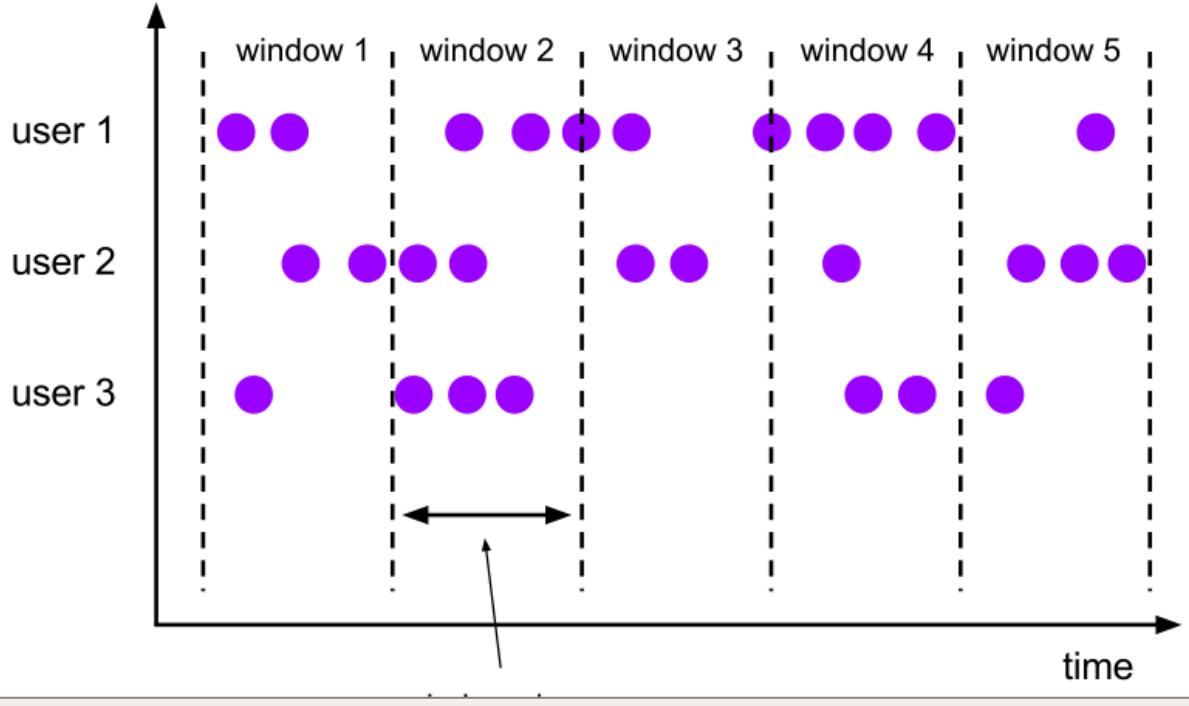


Figure source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/concepts/timely-stream-processing.html

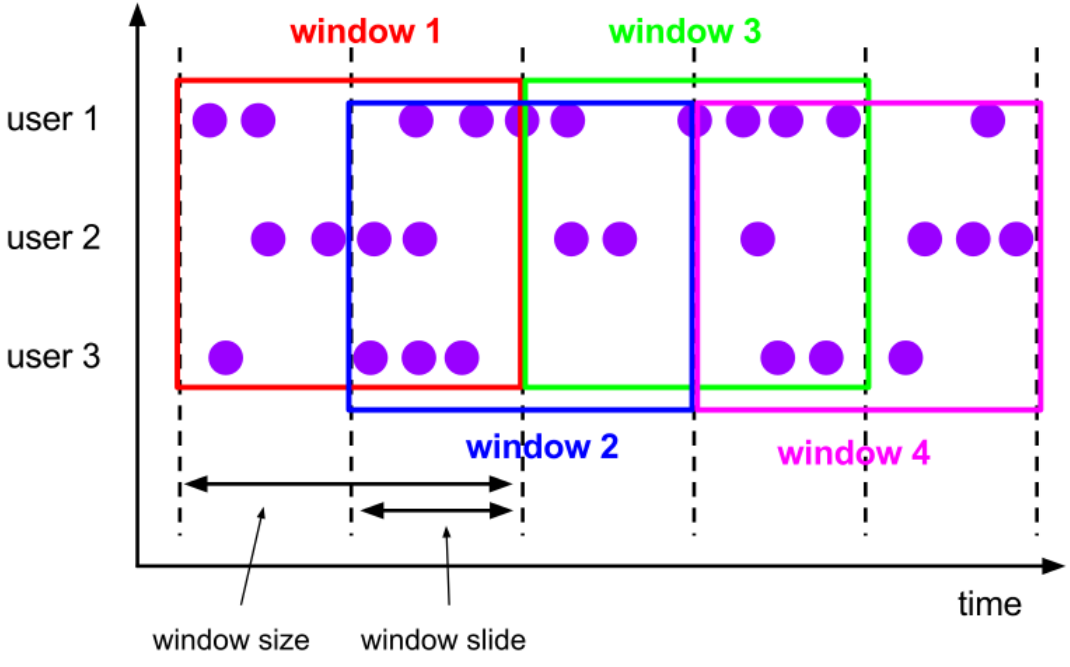
Batch/Tumbling Windows



Use cases:
Period computation (e.g. stock, temperature, IoT data)

Figure source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/dev/stream/operators/windows.html

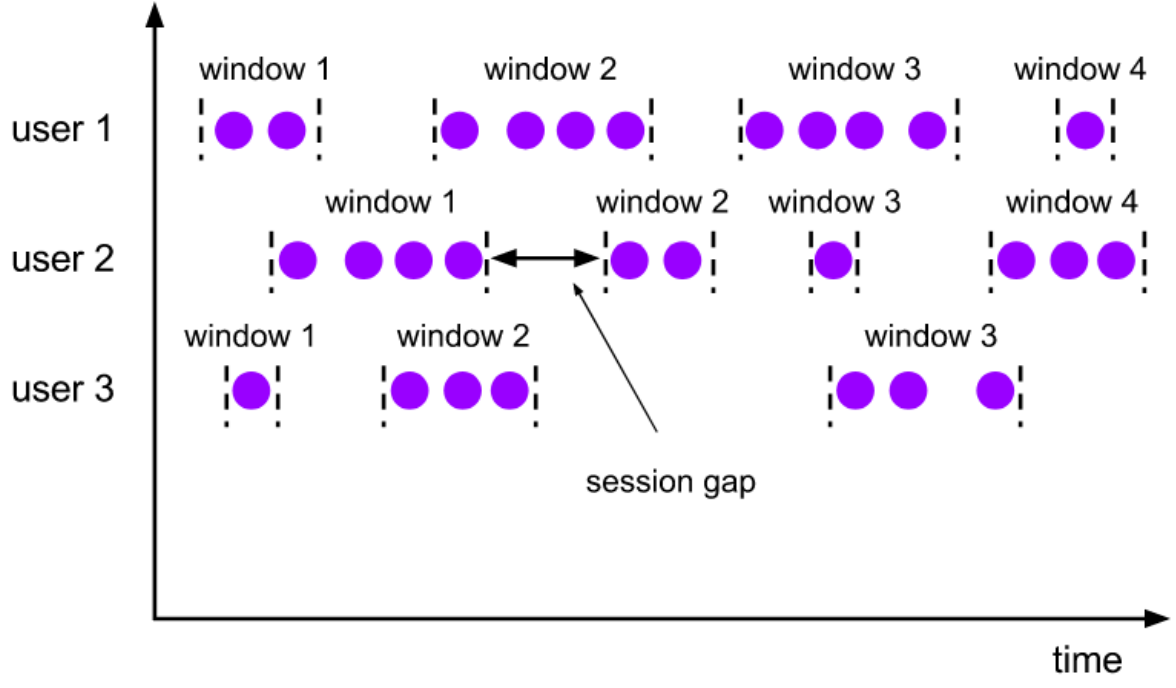
Sliding windows



Use cases:
Moving average

Figure source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/dev/stream/operators/windows.html

Session Windows



Use cases:
Web/user activities
clicks

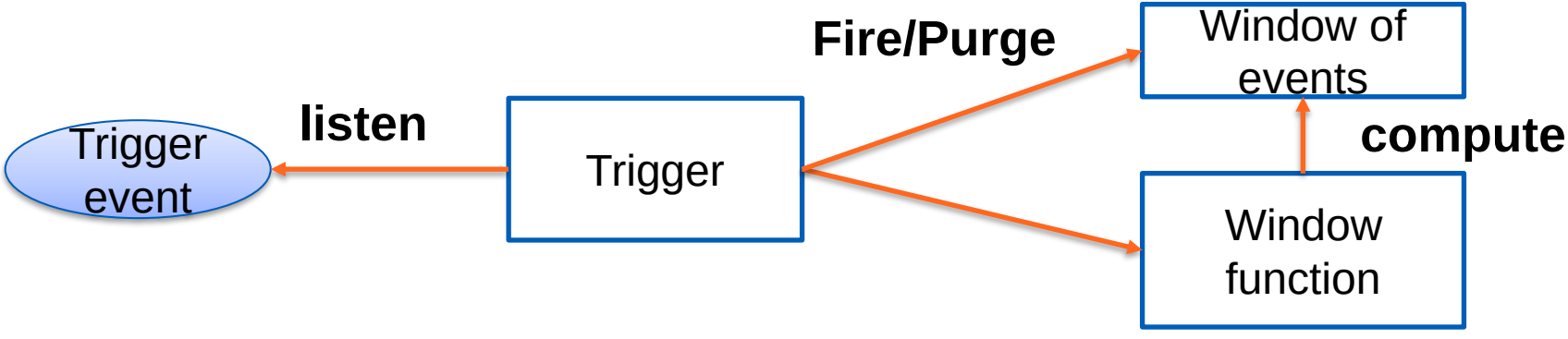
Figure source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/dev/stream/operators/windows.html

Window Functions

- **Reduce Function**
  - Reduce two inputs
- **Aggregate Function**
  - Add an input into an accumulator
- **Fold Function**
  - Combine input with an output
- **ProcessWindow Function**
  - Get all elements of the windows and many other information so that you can do many tasks

Triggers & Evictor

- **Trigger: determine if a window is ready for window functions**



Evictor: actions after the trigger fires and before and/or after the windows function is called

Fault tolerance

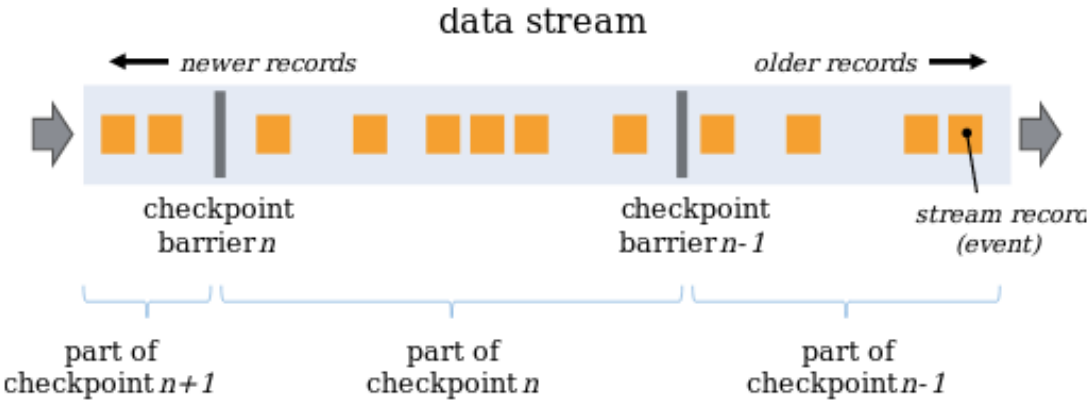


Figure source: https://ci.apache.org/projects/flink/flink-docs-release-1.12/concepts/stateful-stream-processing.html

- **Principles: checkpointing, restarts operators from the latest successful checkpoints**
- **Need support from data stream sources/sinks w.r.t. (end-to-end) exactly once message receiving and result delivery**

Example with Base Transceiver Station

Data in our git

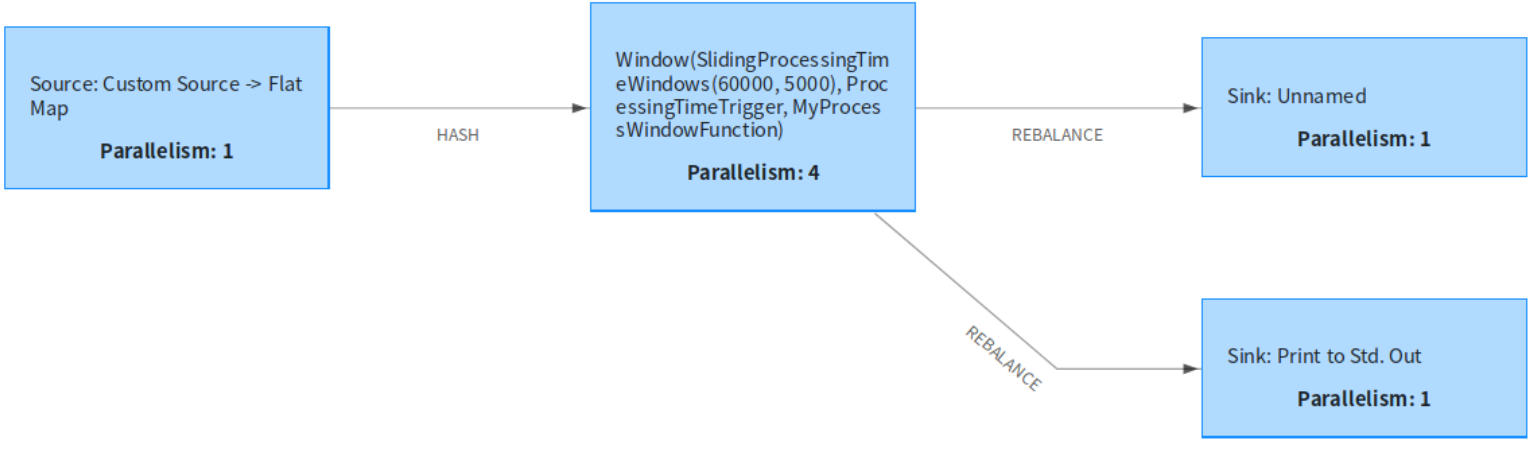
station_id,datapoint_id,alarm_id,event_time,value,valueThreshold,isActive,storedtime
1161115016,121,308,2017-02-18 18:28:05 UTC,240,240,false,
1161114050,143,312,2017-02-18 18:56:20 UTC,28.5,28,true,
1161115040,141,312,2017-02-18 18:22:03 UTC,56.5,56,true,
1161114008,121,308,2017-02-18 18:34:09 UTC,240,240,false,
1161115040,141,312,2017-02-18 18:20:49 UTC,56,56,false,

Simple example

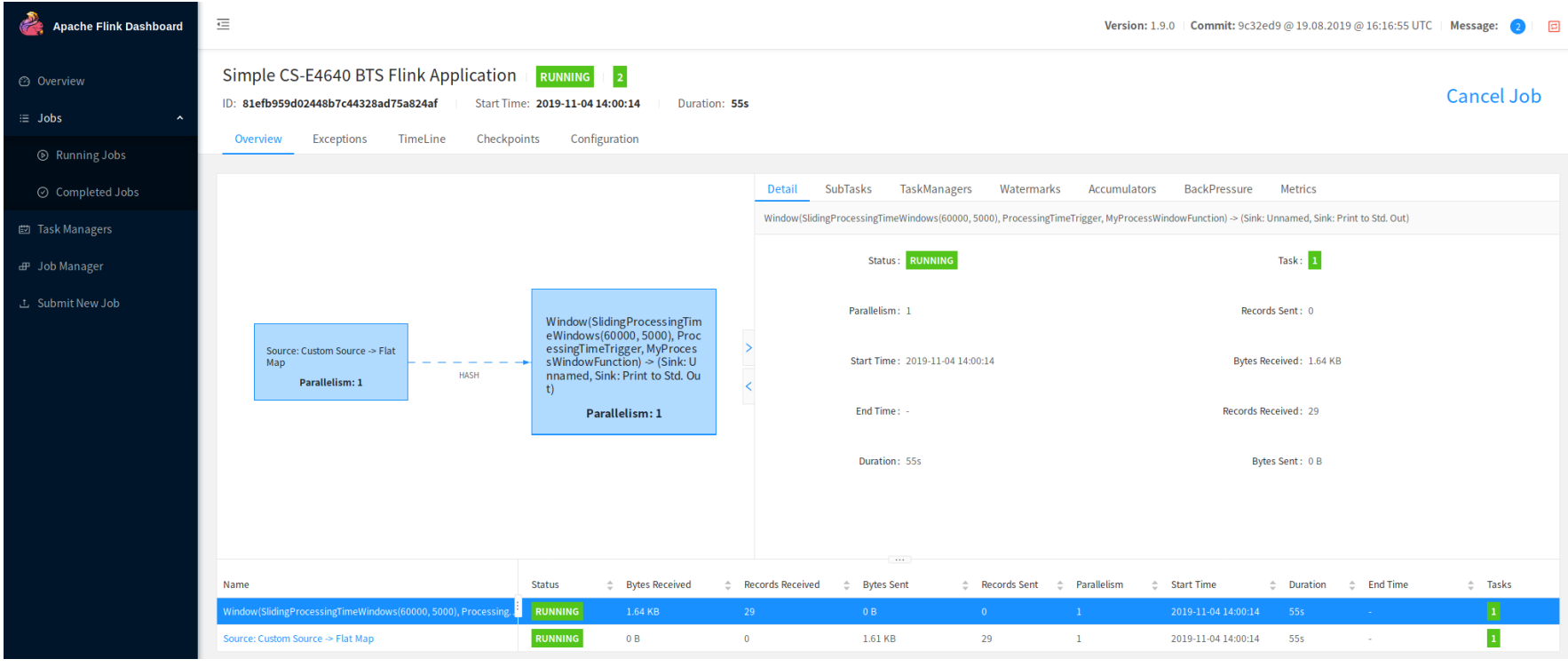
See the code in our git:

https://version.aalto.fi/gitlab/bigdataplatforms/cs-e4640/-/blob/master/tutorials/streamingwithflink/code/simplebts

Simple example



Monitoring


Apache Flink Dashboard
Overview
Jobs
Running Jobs
Completed Jobs
Task Managers
Job Manager
Submit New Job
Version: 1.9.0 | Commit: 9c32ed9 @ 19.08.2019 @ 16:16:55 UTC | Message: 2
Simple CS-E4640 BTS Flink Application RUNNING 2
ID: 81efb959d02448b7c44328ad75a824af | Start Time: 2019-11-04 14:00:14 | Duration: 55s
Cancel Job
Overview Exceptions TimeLine Checkpoints Configuration
Source: Custom Source -> Flat Map
Parallelism: 1
HASH
Window(SlidingProcessingTimeWindows(60000, 5000), ProcessingTimeTrigger, MyProcessWindowFunction) -> (Sink: Unnamed, Sink: Print to Std. Out)
Parallelism: 1
Detail SubTasks TaskManagers Watermarks Accumulators BackPressure Metrics
Window(SlidingProcessingTimeWindows(60000, 5000), ProcessingTimeTrigger, MyProcessWindowFunction) -> (Sink: Unnamed, Sink: Print to Std. Out)
Status: RUNNING
Task: 1
Parallelism: 1
Records Sent: 0
Start Time: 2019-11-04 14:00:14
Bytes Received: 1.64 KB
End Time: -
Records Received: 29
Duration: 55s
Bytes Sent: 0 B
Name Status Bytes Received Records Received Bytes Sent Records Sent Parallelism Start Time Duration End Time Tasks
Window(SlidingProcessingTimeWindows(60000, 5000), Processing... RUNNING 1.64 KB 29 0 B 0 1 2019-11-04 14:00:14 55s - 1
Source: Custom Source -> Flat Map RUNNING 0 B 0 1.61 KB 29 1 2019-11-04 14:00:14 55s - 1

One of the successful project from Europe: originally from TU Berlin

Alibaba cloud:

“Flink can process over 472 million transactions per second during business peaks, which is truly astronomical”

Source: https://www.alibabacloud.com/blog/why-did-alibaba-choose-apache-flink-anyway_595190

“Amazon Kinesis Data Analytics is the easiest way to transform and analyze streaming data in real time with Apache Flink” (From https://aws.amazon.com/kinesis/data-analytics/)

Summary

- **Focus:**
  - Practical programming with one of the stacks:
    - *Apache Flink Stream API (with different connectors)*
    - *Apache Spark*
    - *Kafka Streams*
  - Check the common concepts in other tools/systems
- **Action:**
  - Work on use cases where you can use stream analytics (as a user/developer) → there are many interesting analytics
  - Provision services for stream processing (as a platform)

Thanks!

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rdsea.github.io