Data Stream Management

Big Data Management

UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

DTIM
www.essi.upc.edu/dtim

Knowledge objectives

1. Define a data stream
2. Distinguish the two kinds of stream management systems
3. Recognize the relevance of stream management
4. Enumerate the most relevant characteristics of streams
5. Explain to which extent a DBMS can manage streams
6. Name 10 differences between DBMS and SPE
7. Characterize the kinds of queries in an SPE
8. Explain the two parameters of a sliding window
9. Explain the three architectural patterns
10. Explain the goals of Spark streaming architecture
11. Draw the architecture of Spark streaming

Understanding Objectives

1. Identify the need of a stream ingestion pattern
2. Identify the need of a near-real time processing pattern
3. Identify the kind of message exchange pattern
4. Simulate the mesh-join algorithm
5. Estimate the cost of the mesh-join algorithm
6. Use windowing transformations in Spark streaming

Basics

Tens of thousands of elements/events per second

- Internet traffic analysis
- Trading on Wall Street
- Fraud detection (i.e., credit cards)
- Highway traffic monitoring
- Surveillance cameras
- Command and control in military environments
- Log monitoring
  - Google receives several hundred million search queries per day
- Click analysis
  - Yahoo! Accepts billions of clicks per day
- RFID monitoring
  - Venture Development Corporation predicted in 2006 that RFID can generate in Walmart up to 7TB/day (≈ 292GB/hour ≈ 5GB/minute ≈ 80MB/second)
- Scientific data processing (i.e., sensor data)
  - One million sensors reporting at a rate of ten per second would generate 3.5TB/day (only 4 bytes per message)
  - Large Hadron Collider (LHC) at CERN
    - Collisions are produced at 40MHz, which generates approximately 40TB/second
      - Cluster of 39 nodes with a total memory of 18TB and 1658 cores, containing 32 HBase region servers

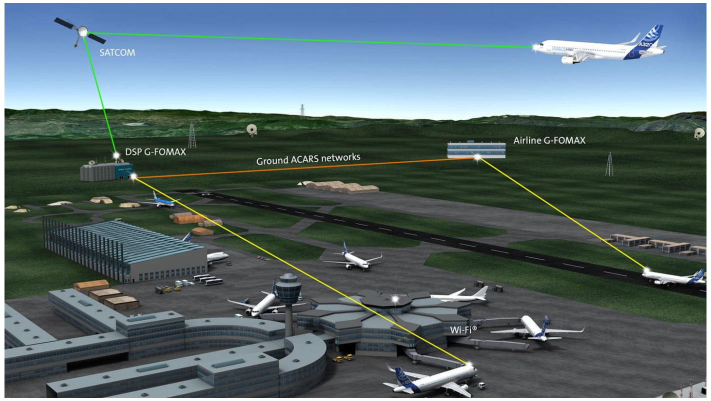
Danish wind turbines

- One park:
  - 100+ turbines
- One turbine:
  - 500 sensors
  - More than 2500 derived data streams
- One sensor:
  - 8 bytes sampled at 100+Hz

100 turbines*2500 streams*100 samples/sec = $25 \cdot 10^6$ samples/second
8bytes*$25 \cdot 10^6$ samples/second*3600seconds/hour*24hours/day = 17.5TB/day
17.5TB/day*365 days/year = 6+ PB/year/park

Having thousands of parks and storing 20+ years of history …

Aerospace corporation



Collins Corp.

- One (not big) airline
  - 125 planes
- One plane:
  - 24.000 sensors (Flight Operations & Maintenance Exchanger, FOMAX)
  - 10 hours/day 1 plane is flying 10 hours/day
- One sensor
  - 8 bytes sampled at 20+Hz

125 planes*24.000 sensors*20 samples/sec = $60 \cdot 10^6$ samples/second
8 bytes*$60 \cdot 10^6$ samples/second*3600seconds/hour = 1.73TB/hour
1.73TB/hour*10 hours/day*365 days/year = 6+ PB/year

Having tens of airlines and storing 10+ years of history …

Streaming use cases

- Triggers
  - Rise alerts
- Data enrichment
  - Join static data
- Continuous learning
  - Create ML models online
- Streaming ETL
  - Pre-processing (filter, aggregate, etc.) before storage

https://www.datanami.com/2015/11/30/spark-streaming-what-is-it-and-whos-using-it

Stream characterization

1. Arrival rate not under the control of the system
   - Faster than processing time -- algorithms must work with only one pass of the data
2. Unbounded memory requirements -- Some drastic reduction is needed
3. Keep the data moving -- Only volatile storage
4. Support for near-real time application -- Latency of 1 second is unacceptable
   - Need to scale and parallelize
5. Arrival order not guaranteed -- Some data will be delayed
6. Imperfections must be assumed -- Some data will be missing
7. There is temporal locality -- Data (characteristics) evolve over time
8. **Approximate** (not accurate) **answers** are acceptable
   - Deterministic outputs

Data Stream Management System (DSMS)

"Class of software systems that deals with processing streams of high volume messages with very low latency"

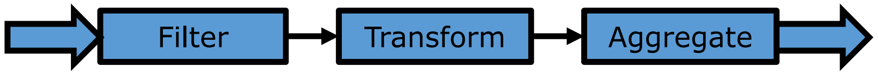
M. Stonebraker

- Concept introduced in 1992
- Messages constantly arrive at a high pace
- Sub-second latency

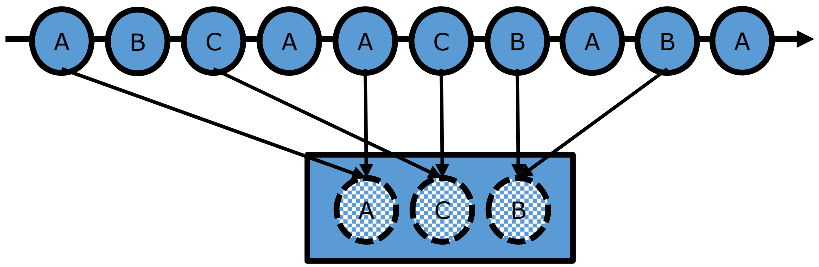
D. B. Terry et al. *Continuous Queries over Append-Only Databases*. SIGMOD Conference 1992

Kinds of systems

- Stream Processing Engine
  - Focus on
    - Near-real time processing and scalability
    - Offering windowing operations to define aggregates
  - Tools
    - Spark streaming
    - Flink
    - Storm
    - S4



- Complex Event Processing/Pattern Matching Engine
  - Focus on
    - Offering windowing operations to define indicators (based on thresholds)
    - Express complex temporal correlations
  - Tools
    - Esper
    - Aleri
    - StreamBase
    - T-Rex
    - Huawey PME
    - Orange CRS network monitoring



Pattern

SPE vs CEP

Stream Processing Engine	**Complex Event Processing**
Keep data moving	**Pattern** identification
Window aggregates definition	**Pattern** expressions
Handle stream imperfections	
Integrate stored and streamed data	**State** management
High availability of **processing**	High availability of **patterns**
Process distribution	**States** distribution

Challenges of SPE

They try to handle data in same way when processed in batch and also when processed in stream

1) Unify batch and live parallel processing model
2) Out-of-order processing
   - *Low watermark* Buffer defined by low watermark
3) State management
   - Custom user-defined state with stateful operators
     - Provide consistency guarantees in front of failures
4) Fault tolerance and high availability
   - Provide *at-least-once* and *exactly-once* semantics
     - Maintaining snapshots of states, migrating states and scaling out
5) Load management and elasticity
   - *Load shedding* and *back-pressure* When one operator cannot process further data, tell higher level not to send that which is then propagated upwards

P. Carbone et al. *Beyond Analytics: The Evolution of Stream Processing Systems*. SIGMOD Conference, 2020

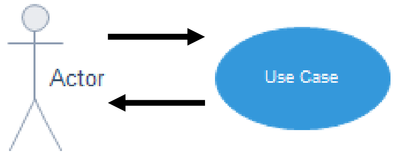
Load shedding - sampling stream, Don't process everything. Process only something that we want not everything

Characterization of operations in SPE

Kinds of system interaction

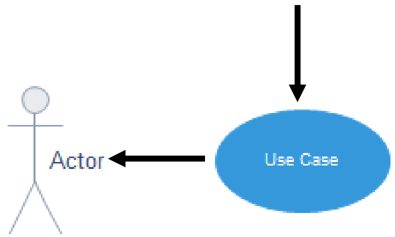
Traditional
Non streaming

CRUD



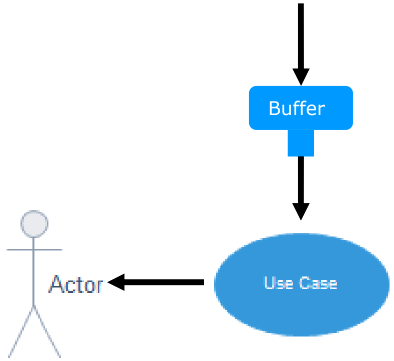
Data arrives at its own pace

Stream



Data arrives at its own pace
There is buffer present which accumulates the data
at some other frequency, it is sent to user

Micro-batch



Kinds of queries

- Depending on the trigger
  - Standing query is there, waiting for data to arrive
  - Ad-hoc when user requires sth, sends signal to system
- Depending on the output
  - Alerts can be alert, signal, boolean, flag
  - Result set returns some result set
- Depending on the inputs what is system using to answer the query
  - Based on a summary of history stream is infinite cannot store everything
    - Synopsis/Sketches
  - Based on the *X* last elements
    - Based on the last element (*X*=1) generate output based on last element
    - Sliding window (*X*>1) generate output based on last n elements

Tumbling&Sliding window examples

WINDOW DURATION = 5
SLIDING DURATION = 5

window duration and sliding duration coincide
each stream is only present in one window

20.6	20.5	20.6	20.5	20.5	20.5	20.4	20.4	20.3	20.2	20.1	20.0	20.1	20.1	20.2	20.1	20.0	19.9	20.0	20.1

WINDOW DURATION = 5
SLIDING DURATION = 3

window and sliding duration is not same

Two queries will be considering some element twice

19.5	19.6	19.7	19.8	19.9	20.0	20.1	20.0	20.1	20.1	20.1	20.2	20.2	20.3	20.4	20.5	20.5	20.4	20.5	20.5

When window_size > slide_size, some elements processed twice
When slide_size > window_size, some elements are skipped processing

Kinds of operations

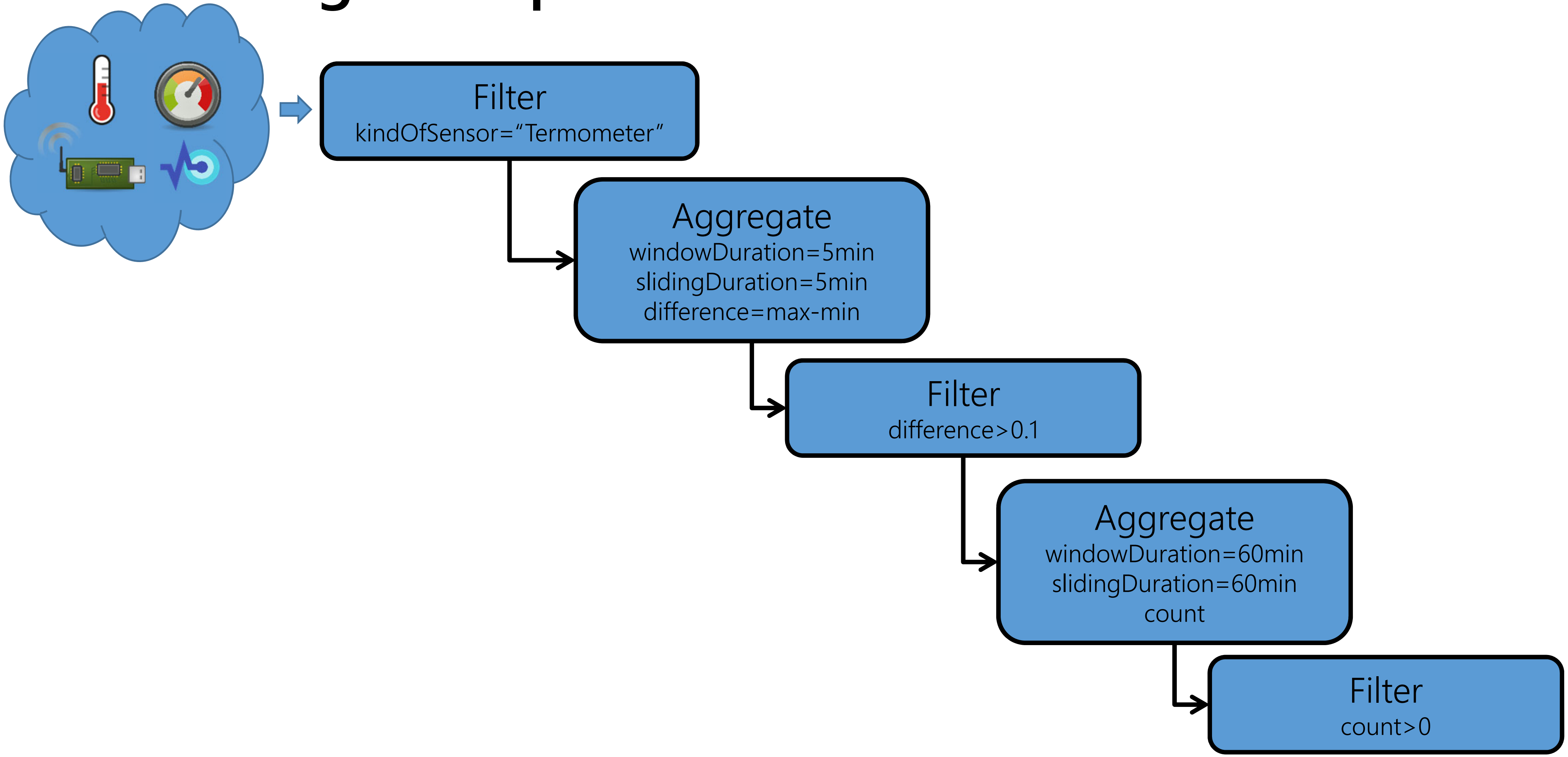
Filter — Get some message, some are filtered some are not

Project — Get some message, output only part of it

Lookup — Enrich with data present in database

Aggregation — Get n messages
Result is composition of messages

Processing example

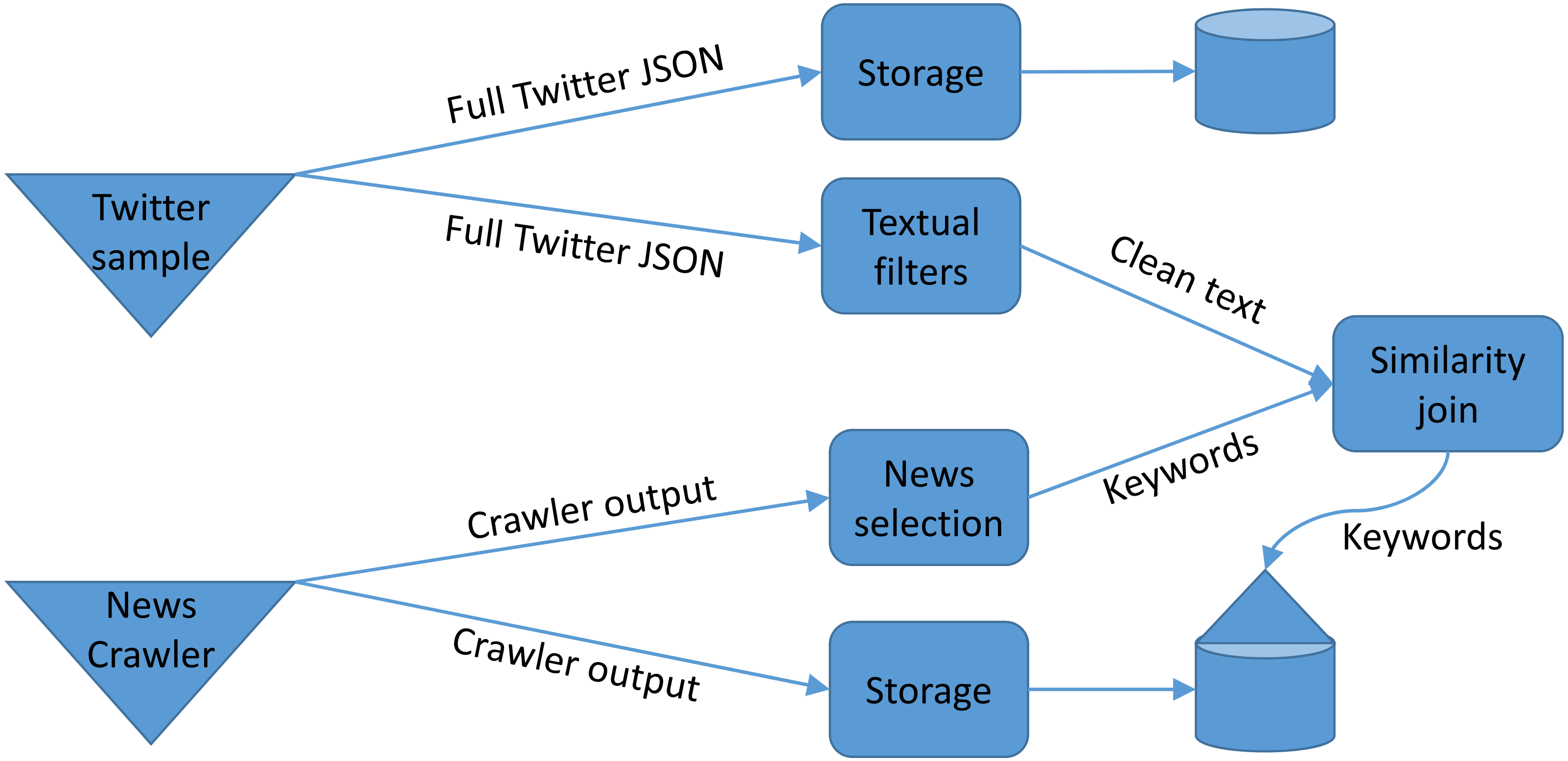


Binary operations

Two streaming data
Join should happen
For join to happen data coming from two streams should coincide at same time which is unlikely

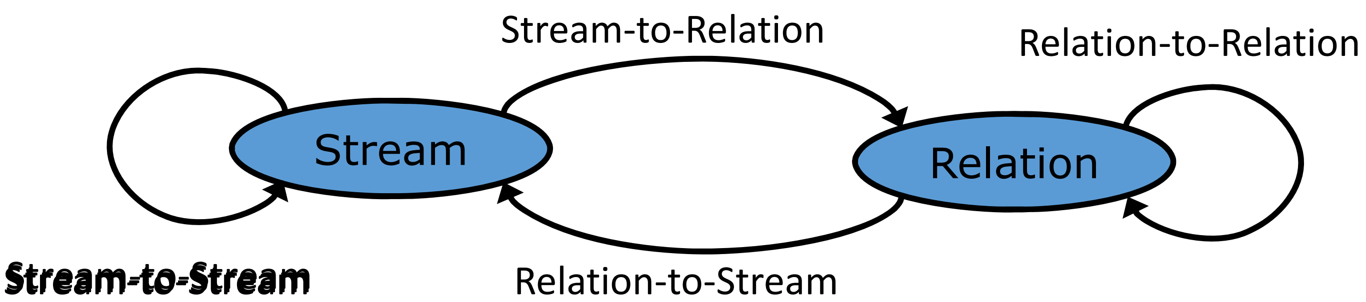
Solution - materialize both (or just one, both actually not needed) and do indexing

Stream-to-Stream

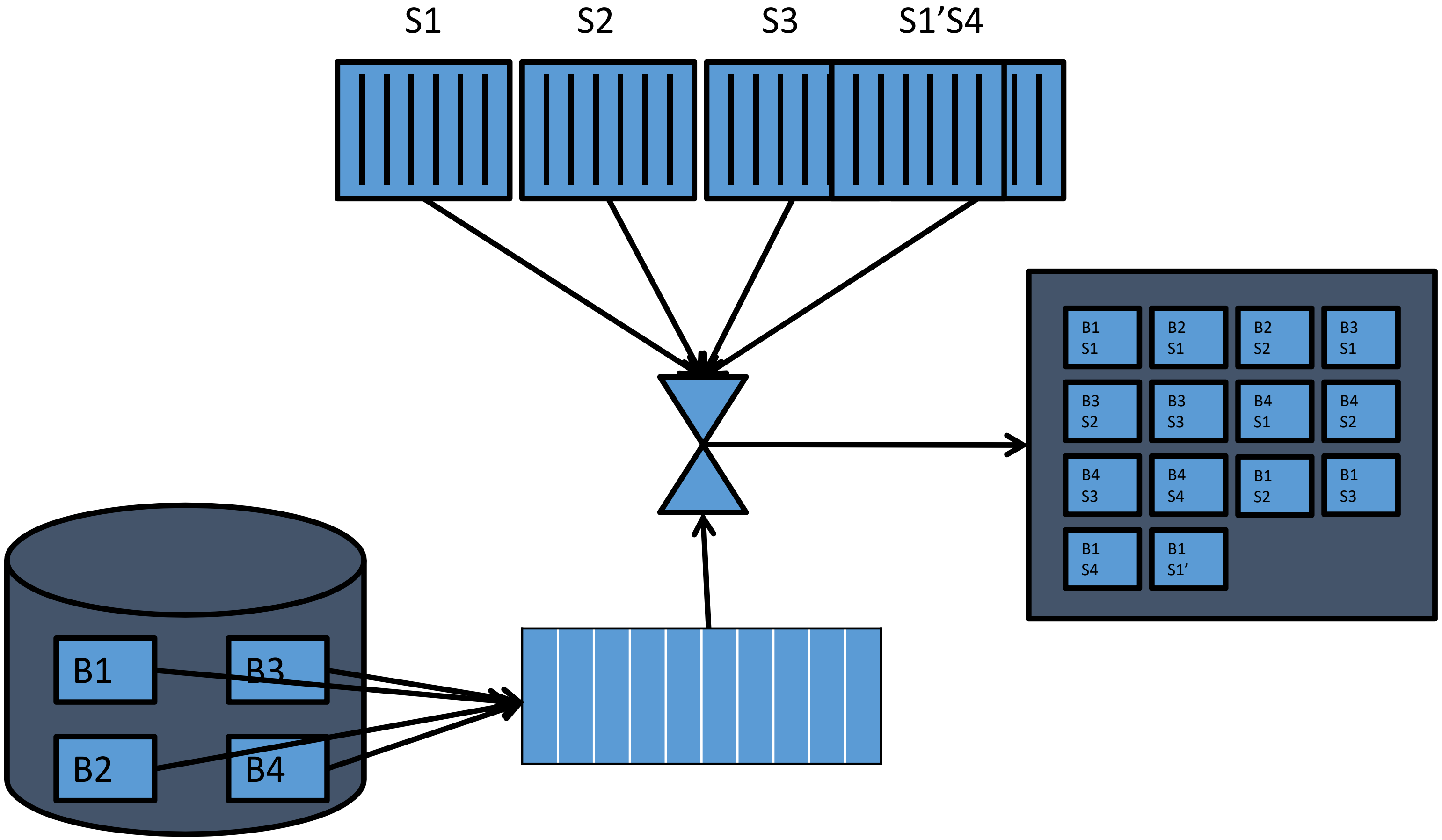


Kinds of binary operations

3 possibilities
1. Stream to relation
2.
3. Relation to relation - not interested for now



Meshjoin algorithm example



Meshjoin algorithm

- Algorithm
  - Performs a cyclic scan of the table and keeps a sliding window of the stream in memory

```
while true do
    read next block of R into a memory page/buffer
    if memory is full then
            dequeue w messages
    endif
    foreach m in memory do
            generate m join R (for the current block)
    endforeach
endwhile
```

D = Time to retrieve one block
C = CPU time to process one message
B = Blocks of R
R_S= Stream messages per page
w = Stream messages removed per loop
λ = Arrival-stream rate (messages/sec)
μ = Service-join rate (messages/sec)

Rate at which data between stream and relation are joined

to keep stream
+1 = buffer of memory
+1 = for output

- Cost (in time) of one loop (assuming M+2 memory pages)
  - $D+M \cdot R_S \cdot C = D+(B \cdot w/R_S) \cdot R_S \cdot C = D+w \cdot B \cdot C$
- Considerations (aiming at $\lambda \leq \mu$) Our target is to maximize, service rate, processing rate should be more than arrival rate
  - We try to maximize μ given M
    - $w = M \cdot R_S/B \Rightarrow M = B \cdot w/R_S$ kati ota deque garne = memory ma kati ota msg cha/number of blocks
    - $\mu = w/(D+w \cdot B \cdot C) = 1/(D/w+B \cdot C)$ service rate = kati ota dequeue garyo/ 1 loop lai kati time lagyo
  - This would almost always be faster than Row Nested Loops If index used
    - $\mu = 1/(h \cdot D+D)$ going through table

going through index

Using mesh join algorithm for joining stream and relation is much faster than using row nested loop

Stream processing

Relational temporary tables

Possible
but not scalable
because writing to disk is not good

Solution
write in temporary table - is not stored in disk

CREATE GLOBAL TEMPORARY TABLE <tablename> (...)
[ON COMMIT {<u>DELETE ROWS</u>|PRESERVE ROWS}];

- Relational mapping
  - Each element is a tuple
  - The sliding window is a relation
- Data is not persistent
  a) Transaction specific
  b) Session specific

Snapshot can be created per transaction or per session

- Does **not** support:
  - Foreign keys
  - Cluster
  - Partitions
  - Parallelism

Databases vs Streams

data is stored in disk
except in case of temporary table

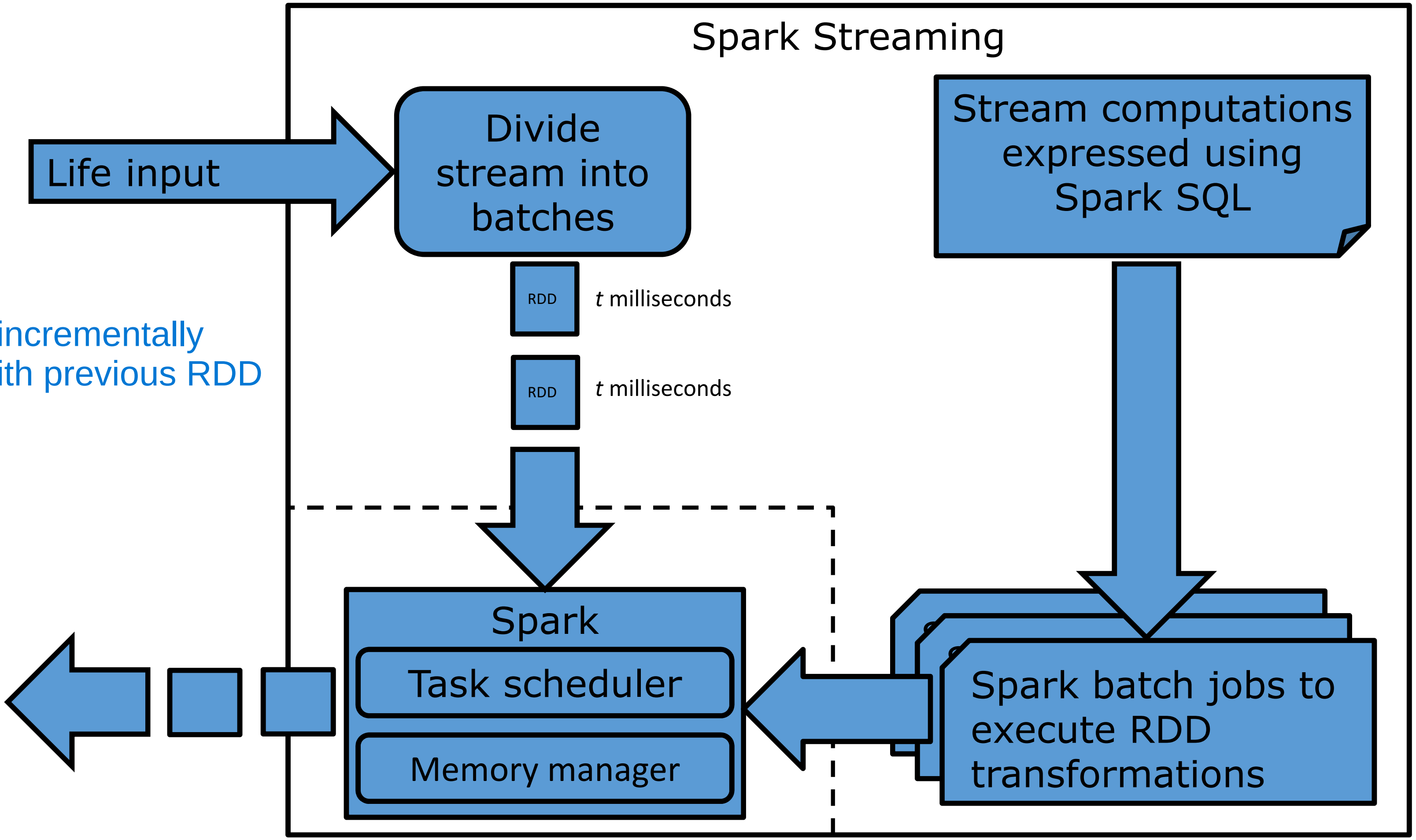
	Database management	Stream management
Data	Persistent	Volatile
Access	Random any row/column can be accessed	Sequential
Queries	One-time	Continuous
Support	Unlimited disk	Limited RAM
Order	Current state	Sorted ordered acc to arrival of messages
Ingestion rate	Relatively low	Extremely high
Temporal requirements	Little	Near-real time expect sth near real time
Accuracy	Exact data	Imprecise data
Heterogeneity	Structured data	Imperfections
Algorithms	Multiple passes	One pass if we miss once, missed

Spark streaming goals

With Spark, we can achieve
1. Scalability
2. Minimal Overhead
3. Recovery from failure

- Scalability to hundreds of nodes
- Minimal overhead
  - Sub-second latency
    - End-to-end: ~100milliseconds
- Recovery from faults and stragglers
  - On reception, data is replicated to a second executor in another worker
  - State (i.e., summary) is periodically (e.g., every 10 RDDs) saved to a reliable file system

Micro-batch processing engine



This RDD is incrementally processed with previous RDD

Inside Spark Stream processing, there is regular spark engine.

Structured Stream

- Based on Dataframes only difference is different output modes
  - Different output modes generate ...
    - Complete: ... the whole result
    - Append: ... only new rows (which are not allowed to change) previous rows are not allowed to change
    - Update: ... only the rows that changed in output, get only rows that changed
- Any number of stream queries can be started in a single Spark session
- Incremental processing
  - Maintains intermediate state for partial aggregates (implemented as watermarking)
    - Late data can update aggregates of old windows correctly
    - Supports stream-stream joins
- Two execution modes
  1. Micro-batch processing When small latency is acceptable
     - Exactly-once and fault-tolerance guarantees
  2. Continuous processing Expensive
     - At-least-once guarantees Done when latency is not acceptable
       - Only for map-like operations

https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html

Input/Output

- Input sources
  - Parquet files (in a directory)
  - Kafka
  - Socket (in the driver) for test not scalable
  - Rate (key-value pairs self-generation for testing/benchmarking purposes) test
- Triggers
  - End of processing previous batch (default) too much overhead
  - Fixed Interval (establishes max frequency)
  - One-time/Available-now
  - Continuous
- Output sinks
  - Parquet files (in a directory)
  - Kafka
  - Foreach/ForeachBatch
  - Console (for debugging)
  - Memory (for debugging)

https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html

Structured Streaming example

```
# Create DataFrame representing the stream of input lines from connection to host:port
lines = spark.readStream.format('socket').option('host', host).option('port', port).load()

# Split the lines into words
words = lines.select(
    # explode turns each item in an array into a separate row
    explode(split(lines.value, ' ')).alias('word')
    )

# Generate running word count
wordCounts = words.groupBy('word').count()

# Start running the query that prints the running counts to the console
query = wordCounts.writeStream.outputMode('complete').format('console').start()

query.awaitTermination()
```

wait forever

https://github.com/apache/spark/blob/v3.3.1/examples/src/main/python/sql/streaming/structured_network_wordcount.py

Unsupported dataframe operations

- Multiple chained aggregations
- Limit/Take
- Sorting
- Distinct
- Outer joins
- Count (requires grouping)
- Foreach (requires writing the stream first)
- Show (use console)

6,7,8 allowed but are not same as regular dataframe

Architectural patterns for stream/event processing

Architectural patterns

A. Stream ingestion how to guarantee that we do not loose anything

B. Near-real time
  - Non-partitioned
    - Get profile information (lookup) needed for decisions
    - Requires nearly no coding beyond the application-specific logic
  - Partitioned
    - Define a key to partition data
      - Match incoming data to the subset of the context data that is relevant to it

C. Pattern matching

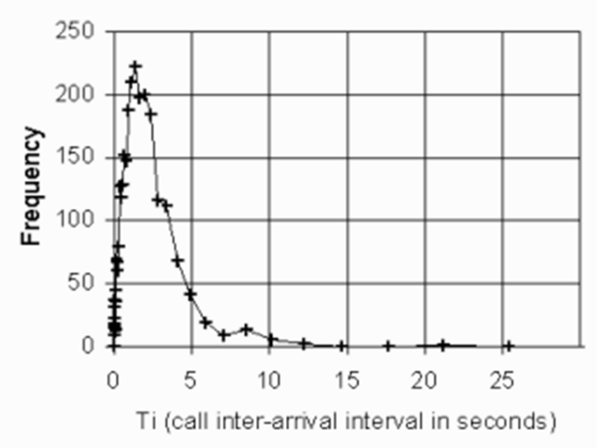
D. Complex topology
  - Aggregation
  - Machine learning

how to do aggregation, ML

https://blog.cloudera.com/architectural-patterns-for-near-real-time-data-processing-with-apache-hadoop

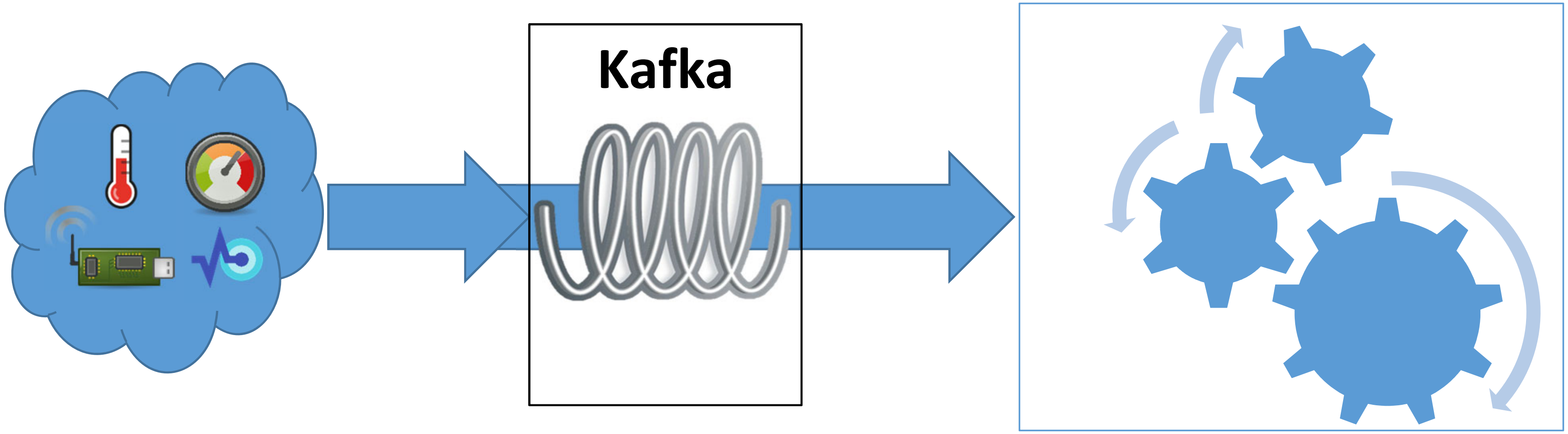
A. Stream ingestion

- The objective is to not lose any event



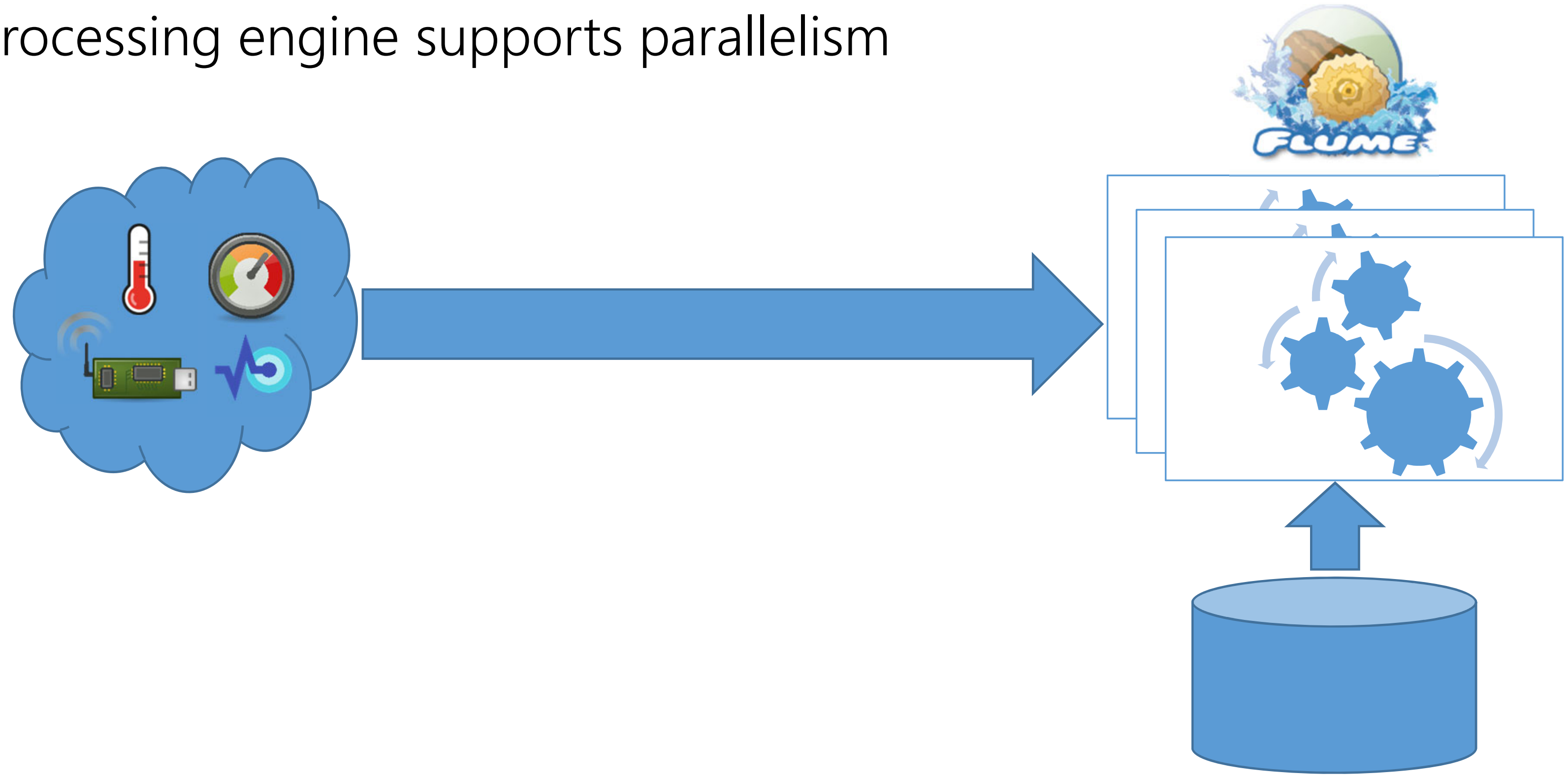
By D. Sharp

Kafka - buffering role



B. Near-real time event processing (I)

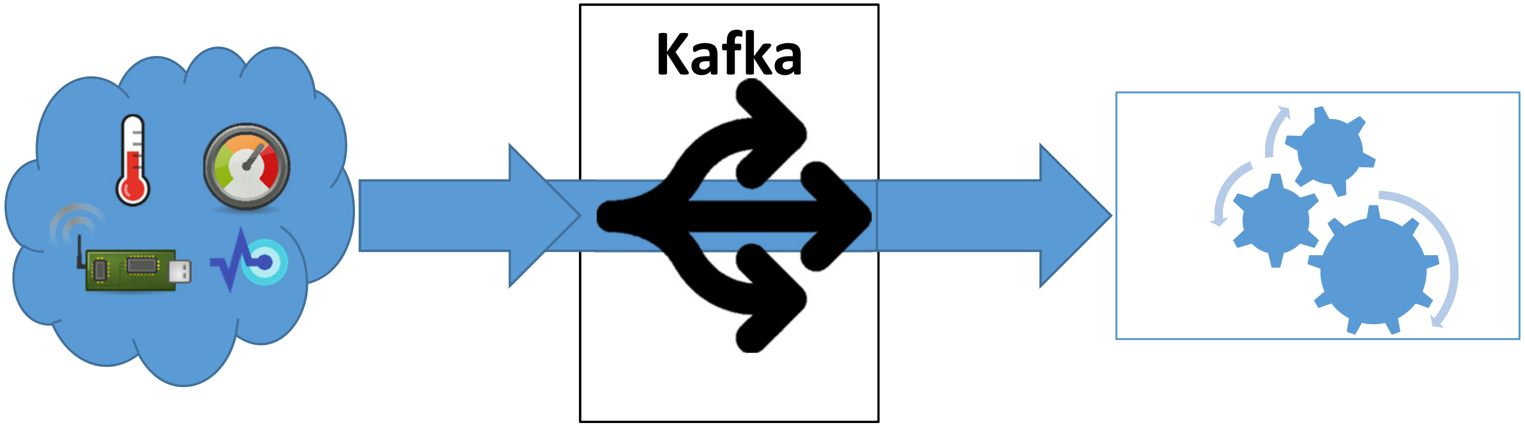
- The objective is to react as soon as possible
  - Processing engine supports parallelism



B. Near-real time event processing (II)

- The objective is to react as soon as possible
  - Processing engine does not support parallelism

Kafka as broker

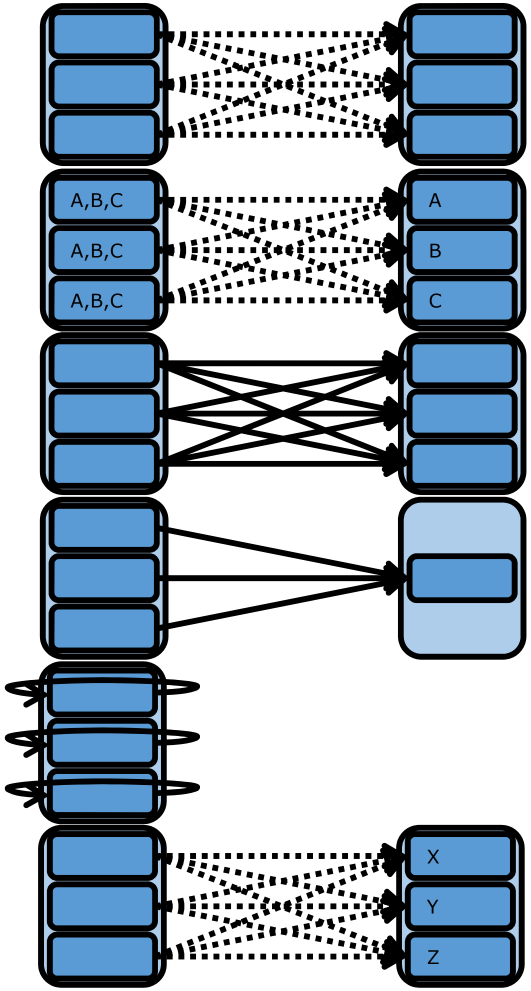


To catch up with less inter arrival rate, we use buffer
Ex: Kafka

C. Complex Event Processing

- Pattern matching
  - State keeps all potential matches
    - Tree
    - NFA (Non-deterministic Finite Automata)
- Hard to distribute
- Consider
  - Time constraints
  - Absence of events
  - Re-emitting complex events

D. Complex topology



- Shuffle grouping
  - Random

load balancing

- Fields grouping
  - Same value, same task
- All grouping
  - Broadcast to all task
- Global grouping
  - All data converges to one task
- None grouping
  - Execution stays in the same thread (if possible)
- Direct grouping
  - Producers direct the output to a concrete task

It can use information that is not in the message (e.g., the current workload of each machine) to decide where to send it

Closing

Summary

- Stream definition and characterization
  - Complex event processing
- Streaming architectural patterns
- Streaming operations
  - Sliding windows
  - Binary operations
- Spark streaming
  - Architecture

References

- M. Stonebraker et al. *The 8 Requirements of Real-Time Stream Processing*. SIGMOD Record 34(4), 2005
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- T. Akidau et al. *The Dataflow Model: A Practical Approach to Balancing Correctness, Latency, and Cost in MassiveScale, Unbounded, OutofOrder Data Processing*. VLDB, 2015
- I. Flouris. *Issues in complex event processing: Status and prospects in the Big Data era*. J. of Systems and Software 127, 2017
- P. Carbone et al. *Beyond Analytics: The Evolution of Stream Processing Systems*. SIGMOD Conference, 2020

Transformations vs Output operations on RDDs

- Transformations
  - Stateless (depend on current RDD)
    - Same as in plain Spark
  - Stateful (depend on past RDD)
    - window(windowDur, slidingDur)
    - reduceByWindow(windowDur, slidingDur, aggregation)
    - updateStateByKey(function)
    - mapWithState(function)
- Actions
  - save
  - foreachRDD(sparkCode)

Note: Both windowDuration and slidingDuration must be multiples of batchDuration