CS4225/CS5425 Big Data Systems for Data Science

Steaming Processing

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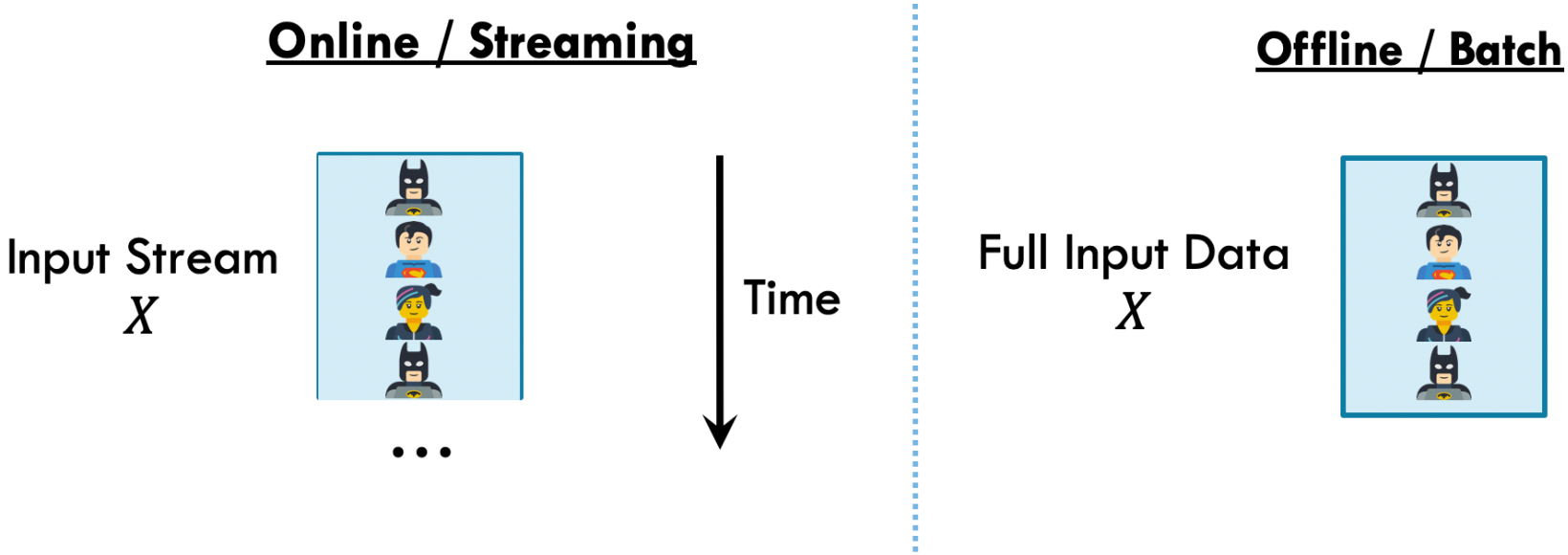
Today's Plan

- Introduction
- Spark
- Flink

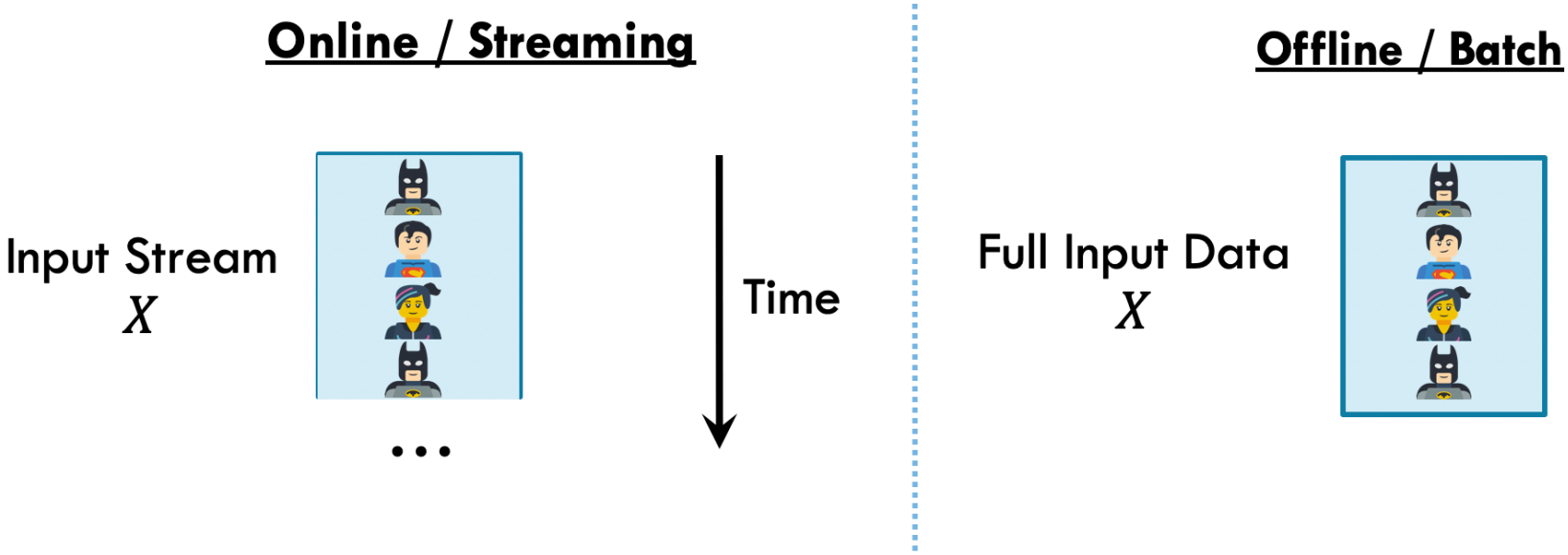
Streams: Motivation

- In many settings, the data is **arriving over time**; it is not received all at once
  - Streaming (or "online") approaches are designed to process their input **as it is received**
  - This is in contrast to offline or batch approaches that operate on the full dataset, all at once



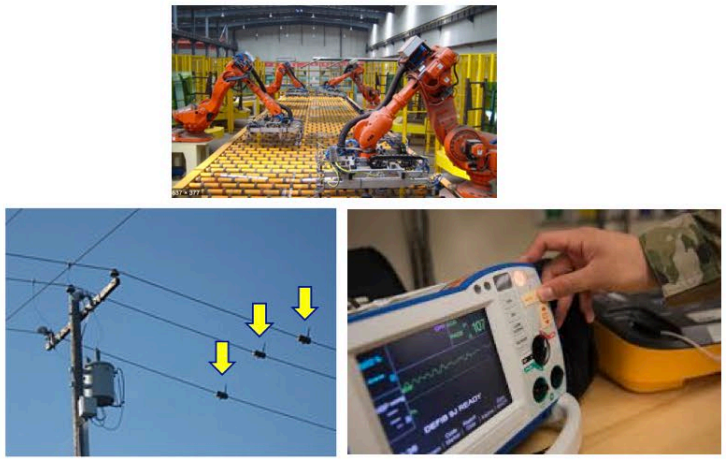
Streaming Data

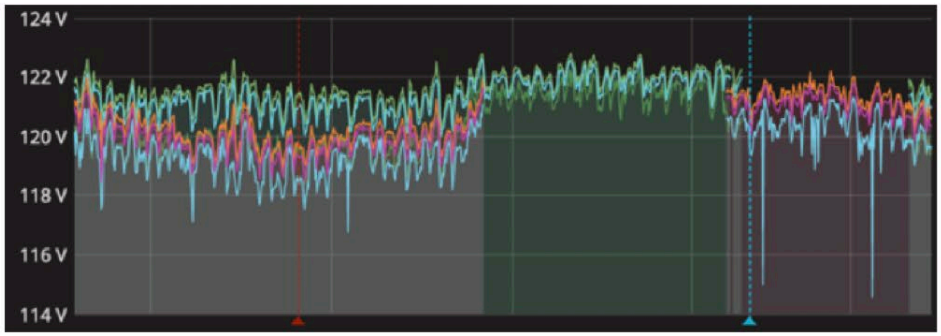
- Input elements enter at a rapid rate from **input ports** (e.g. receiving data from a sensor, from a TCP connection, from a file stream, or from a message queue)
  - Elements of the stream are sometimes referred to as ‘tuples’
  - The stream is potentially infinite; **the system cannot store the entire stream accessibly** (due to limited memory)



Example Applications

- In many real settings, data is **high volume** and **constantly arriving over time**





Sensor data (industrial, environmental, medical, etc)

Example Applications

- In many real settings, data is **high volume** and **constantly arriving over time**

Online user activity data

Example Applications

- In many real settings, data is **high volume** and **constantly arriving over time**

Financial Transactions
(e.g. credit card fraud detection)

Stock Trades Data
(e.g. trades, orders, prices)

https://www.kaggle.com/borismarjanovic/price-volume-data-for-all-us-stocks-etfs

02 Sep 2020	OMO STORE	S$3.30
02 Sep 2020	FACEBK [redacted] V2 650-5434800 CA USD2.00	S$2.81
02 Sep 2020	FACEBK [redacted] 650-5434800 CA USD3.00	S$4.22
02 Sep 2020	FACEBK [redacted] 650-5434800 CA USD2.00	S$2.81
02 Sep 2020	FACEBK [redacted] 650-5434800 CA USD3.00	S$4.22
02 Sep 2020	FACEBK [redacted] 650-5434800 CA USD5.00	S$7.03
02 Sep 2020	FACEBK [redacted] 650-5434800 CA USD50.00	S$70.45
02 Sep 2020	FACEBK [redacted] 2 650-5434800 CA USD10.00	S$14.10
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03 Sep 2020	FACEBK [redacted] 650-5434800 CA USD1.33	
03 Sep 2020	OMO STORE	S$3.00
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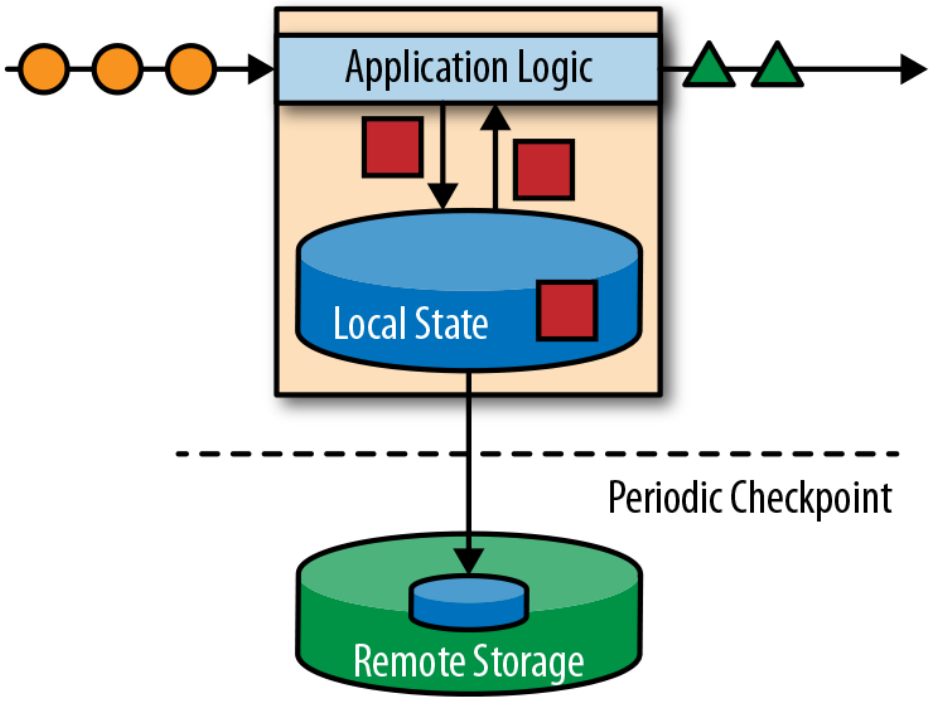
Stateful Stream Processing

- not just perform trivial record-at-a-time transformations
- the ability to store and access intermediate data
- state can be stored and accessed in many different places including program variables, local files, or embedded or external databases



Today's Plan

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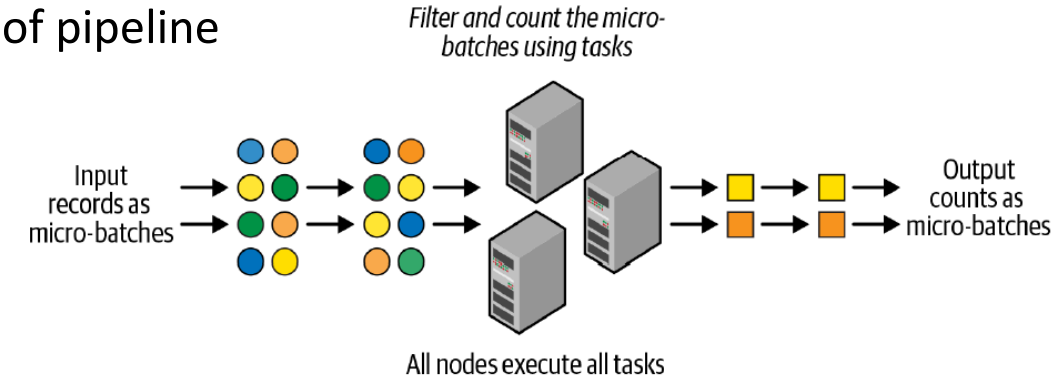
- Spark
- Flink

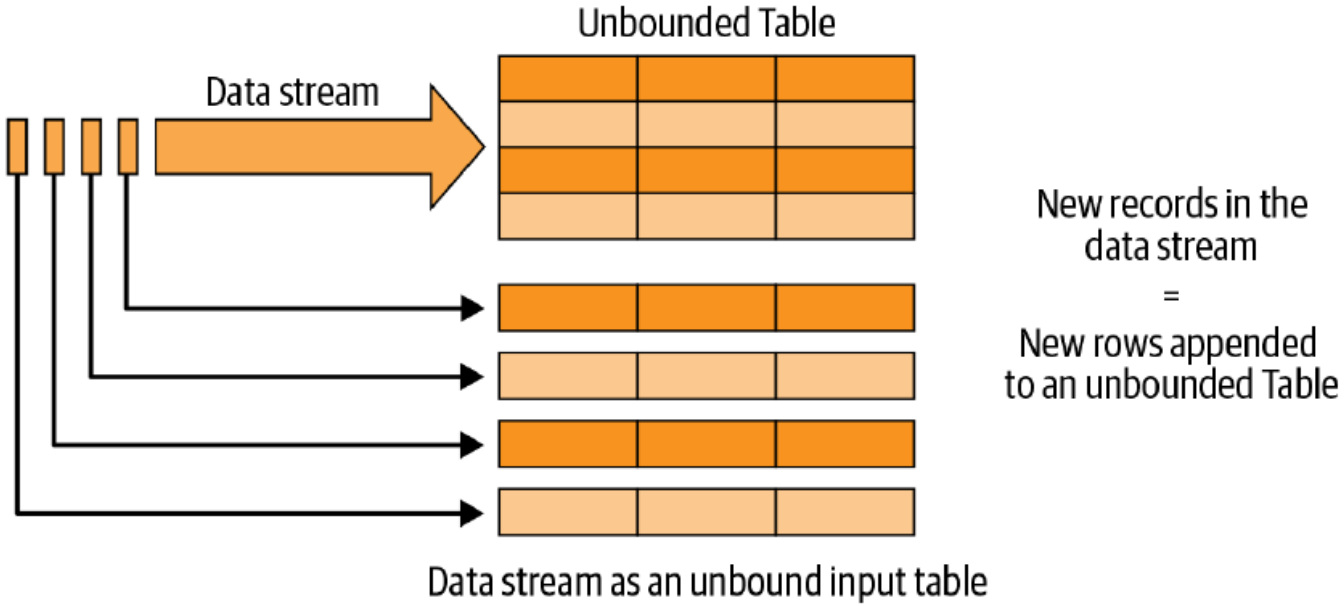
Micro-Batch Stream Processing

- Structured Streaming uses a micro-batch processing model
  - divides the data from the input stream into micro batches
  - each batch is processed in the Spark cluster in a distributed manner
  - small deterministic tasks generate the output in micro-batches
- Advantages
  - quickly and efficiently recover from failures
  - deterministic nature ensures end-to-end exactly-once processing guarantees
- Disadvantages: latencies of a few seconds
  - This is actually OK for many applications
  - Application may incur more than a few seconds delay in other parts of pipeline

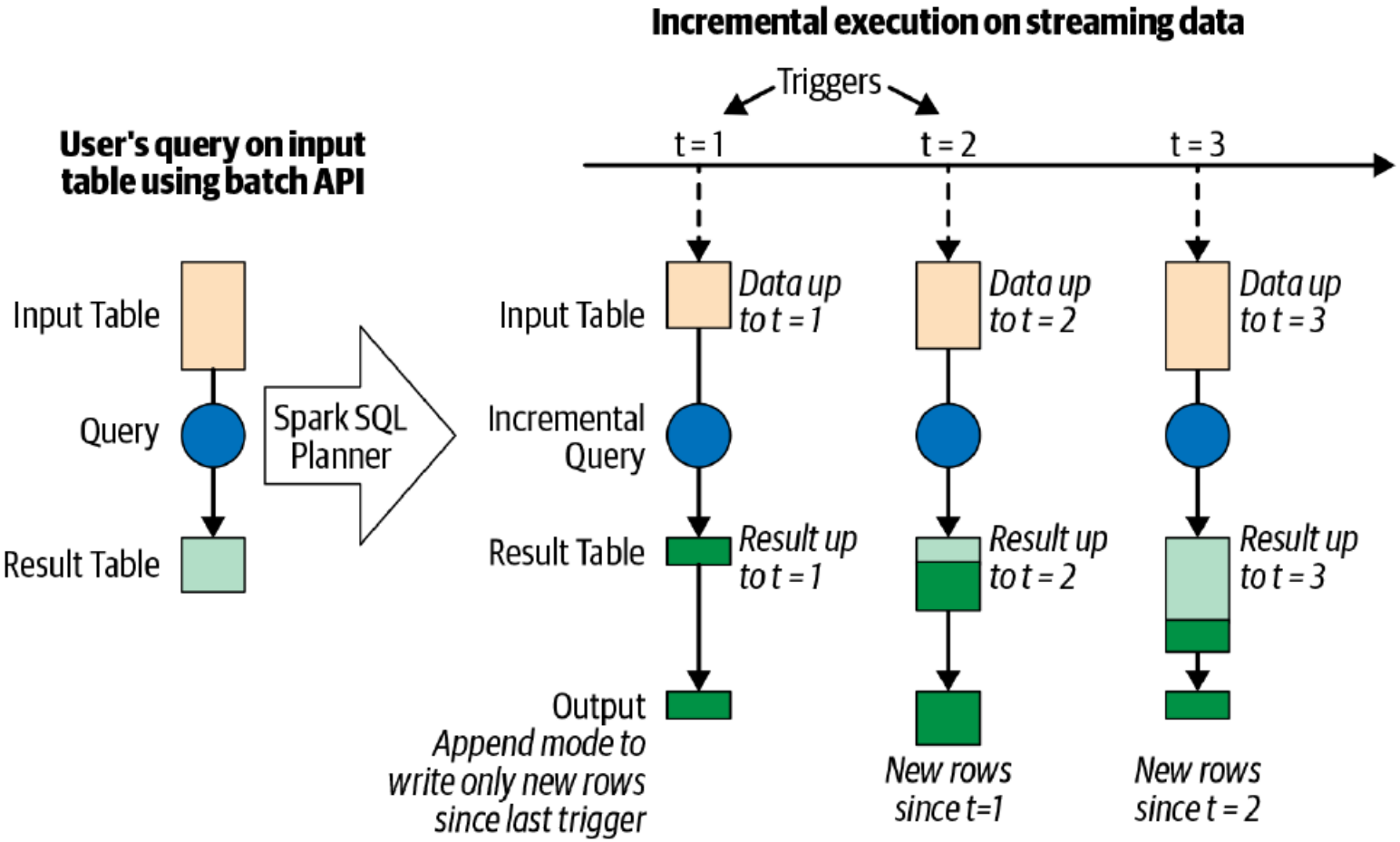


The Philosophy of Structured Streaming

- For developers, writing stream processing pipelines should be as easy as writing batch pipelines.
  - A single, unified programming model and interface for batch and stream processing
  - A broader definition of stream processing
- The Structured Streaming programming model: data stream as an unbounded table



The Structured Streaming processing model



Users express query on streaming data using a batch-like API and Structured Streaming incrementalizes them to run on streams.

Five Steps to Define a Streaming Query

- Step 1: Define input sources
- Step 2: Transform data
- Step 3: Define output sink and output mode
  - Output writing details (where and how to write the output)
  - Processing details (how to process data and how to recover from failures)
- Step 4: Specify processing details
  - Triggering details: when to trigger the discovery and processing of newly available streaming data.
  - Checkpoint Location: store the streaming query process info for failure recovery
- Step 5: Start the query

Practical 3: Spark Streaming

Practical 3: Spark Streaming

This notebook provides a structure streaming example using Spark.

Source: https://github.com/databricks/Spark-The-Definitive-Guide

Cmd 2

```
1  spark.conf.set("spark.sql.shuffle.partitions", 5)
```

Command took 0.11 seconds -- by aixin@comp.nus.edu.sg at 2/13/2023, 4:24:58 PM on Test

Cmd 3

```
1  static = spark.read.json("/databricks-datasets/definitive-guide/data/activity-data/")
2  dataSchema = static.schema
3
```

▸ (3) Spark Jobs

▸ static: pyspark.sql.dataframe.DataFrame = [Arrival_Time: long, Creation_Time: long ... 8 more fields]

Command took 38.53 seconds -- by aixin@comp.nus.edu.sg at 2/13/2023, 4:25:06 PM on Test

Cmd 4

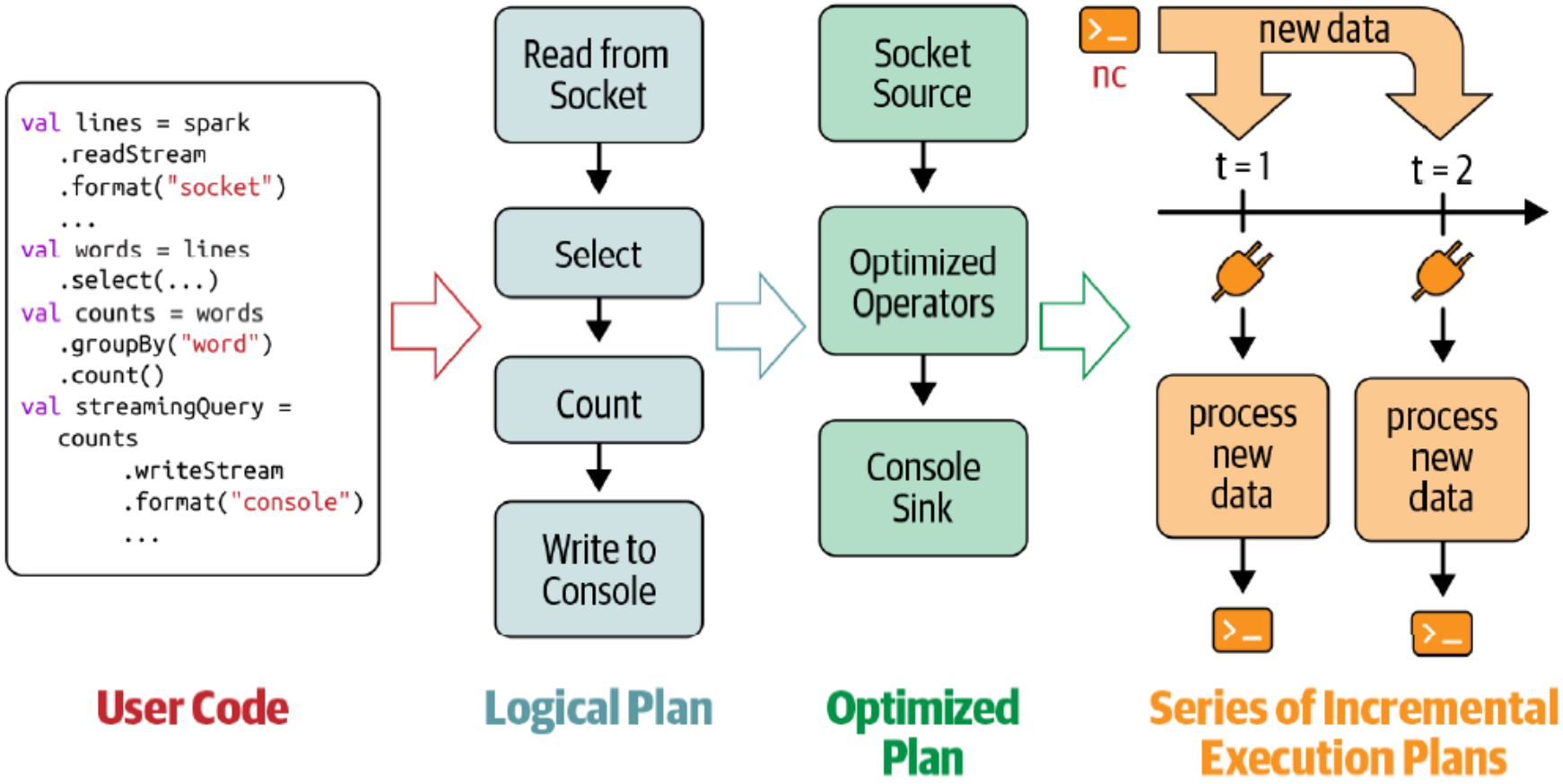
```
1  streaming = spark.readStream.schema(dataSchema).option("maxFilesPerTrigger", 1)\
2    .json("/databricks-datasets/definitive-guide/data/activity-data")
3
```

▸ streaming: pyspark.sql.dataframe.DataFrame = [Arrival_Time: long, Creation_Time: long ... 8 more fields]

Command took 0.52 seconds -- by aixin@comp.nus.edu.sg at 2/13/2023, 4:03:19 PM on Test

Cmd 5

Incremental execution of streaming queries

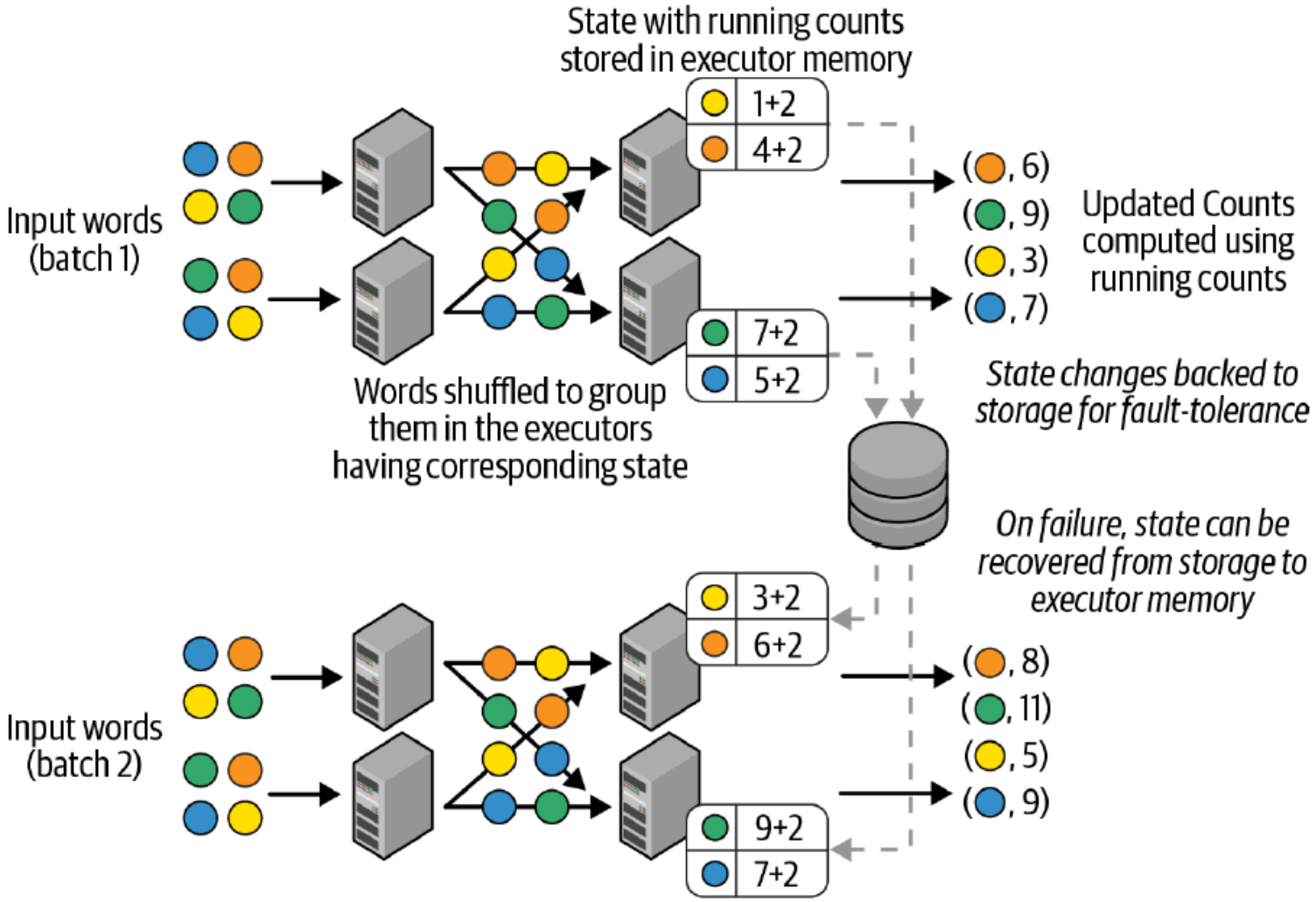


Data Transformation

- Stateless Transformation
  - Process each row individually without needing any information from previous rows
  - Projection operations: select(), explode(), map(), flatMap()
  - Selection operations: filter(), where()

- Stateful Transformation
  - A simple example: DataFrame.groupBy().count()
  - In every micro-batch, the incremental plan adds the count of new records to the previous count generated by the previous micro-batch
  - The partial count communicated between plans is the state
  - The state is maintained in the memory of the Spark executors and is checkpointed to the configured location to tolerate failures.

Distributed state management in Structured Streaming



Stateful Streaming Aggregations

- Aggregations Not Based on Time
  - Global aggregations

```
runningCount = sensorReadings.groupBy().count()
```

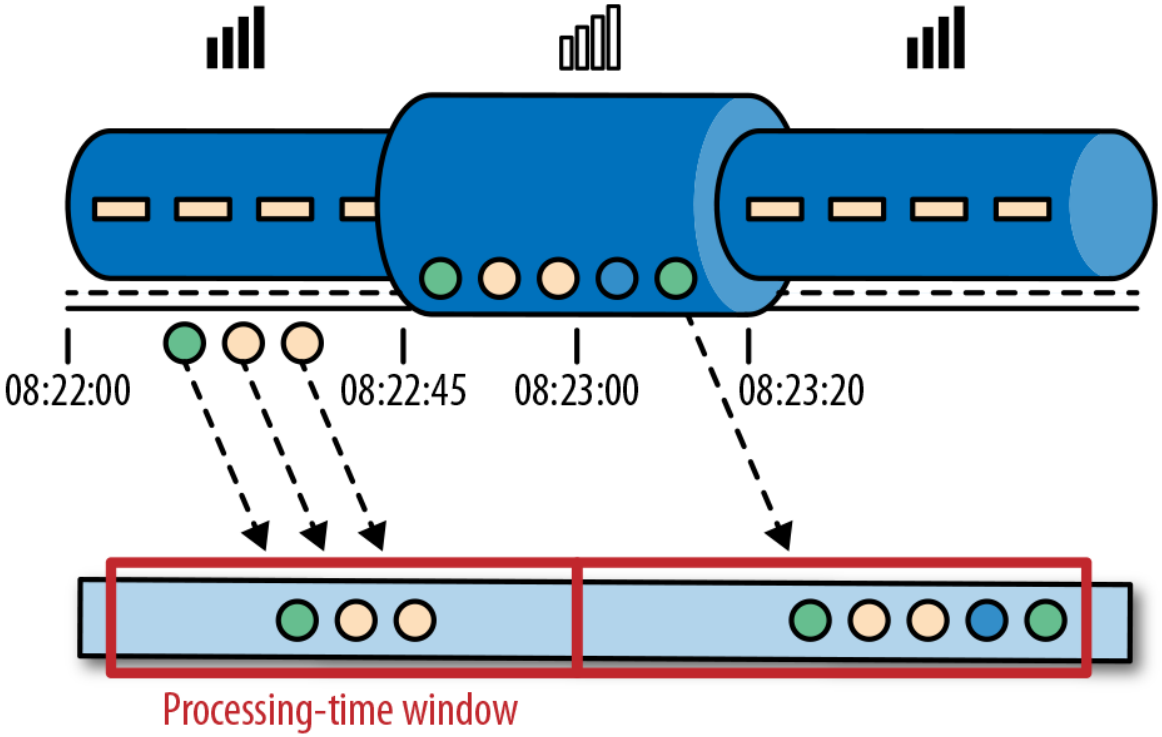
  - Grouped aggregations

```
baselineValues = sensorReadings.groupBy("sensorId").mean("value")
```

  - All built-in aggregation functions in DataFrames are supported
    - sum(), mean(), stddev(), countDistinct(), collect_set(), approx_count_distinct(), and etc.

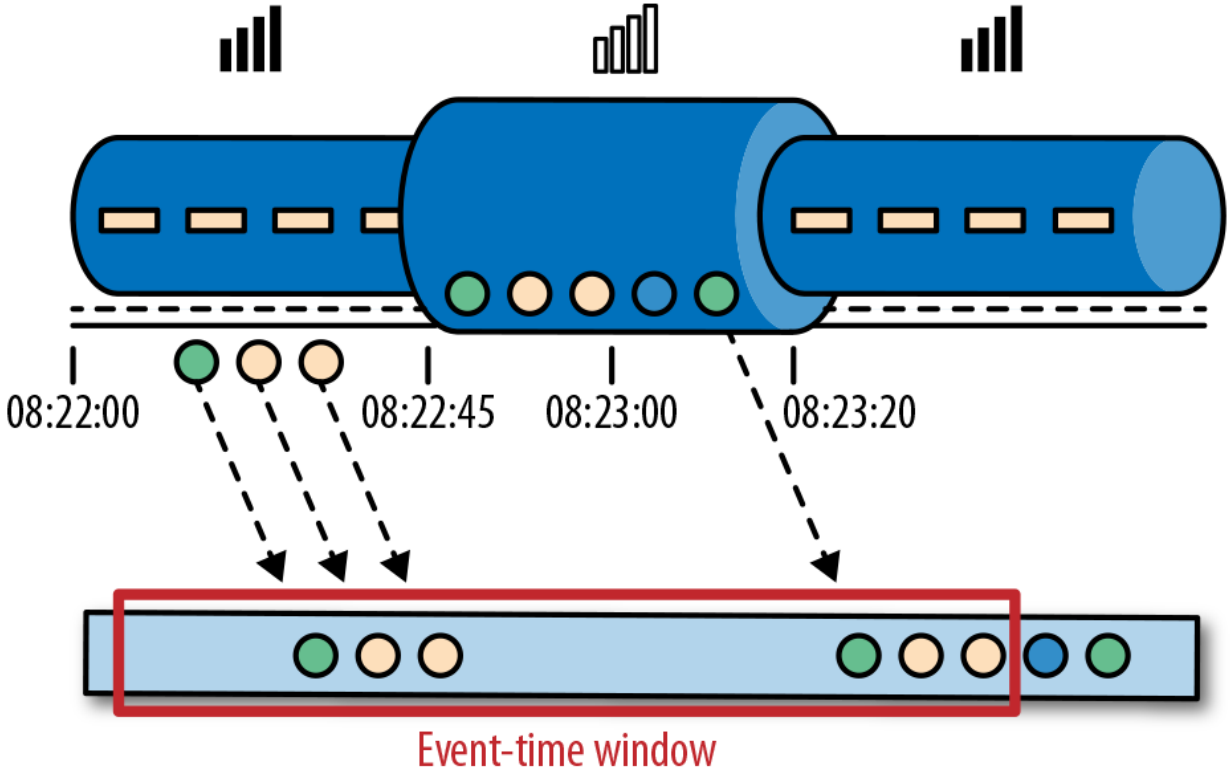
Time Semantics

- Processing Time: the time of stream processing machine



Time Semantics

- Event Time: the time an event actually happened



Time Semantics

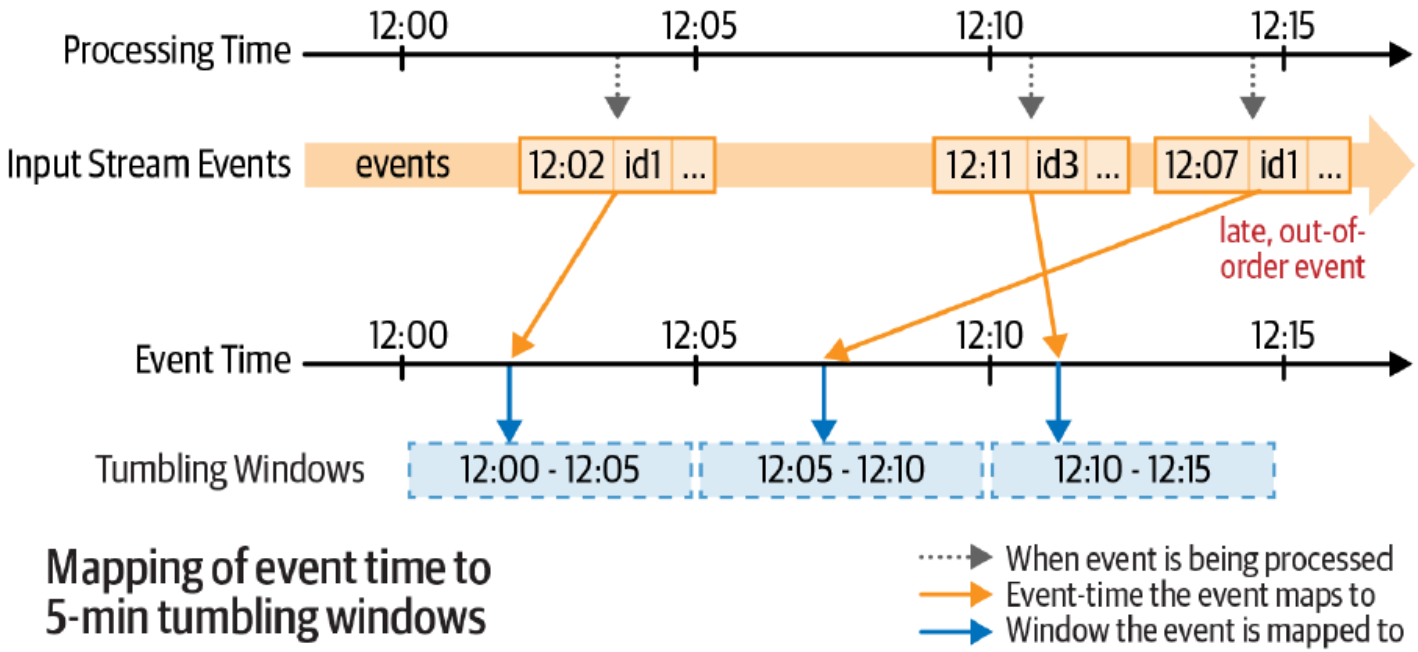
- Event time completely decouples the processing speed from the results.
- Operations based on event time are predictable and their results are deterministic.
- An event time window computation will yield the same result no matter how fast the stream is processed or when the events arrive at the operator.
- how long do we have to wait before we can be certain that we have received all events that happened before a certain point of time?

watermarks

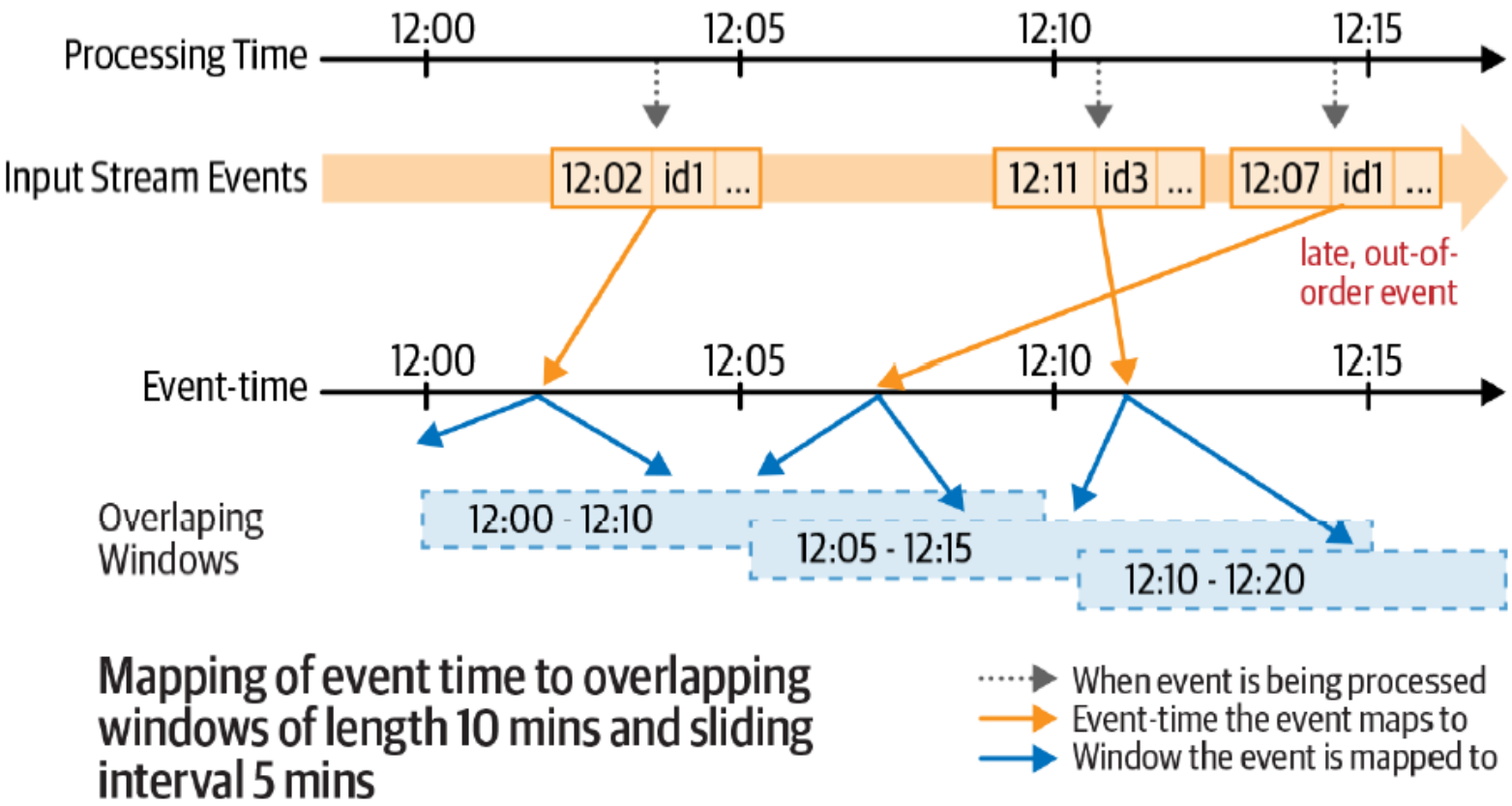
Stateful Streaming Aggregations

- Aggregations with Event-Time Windows

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

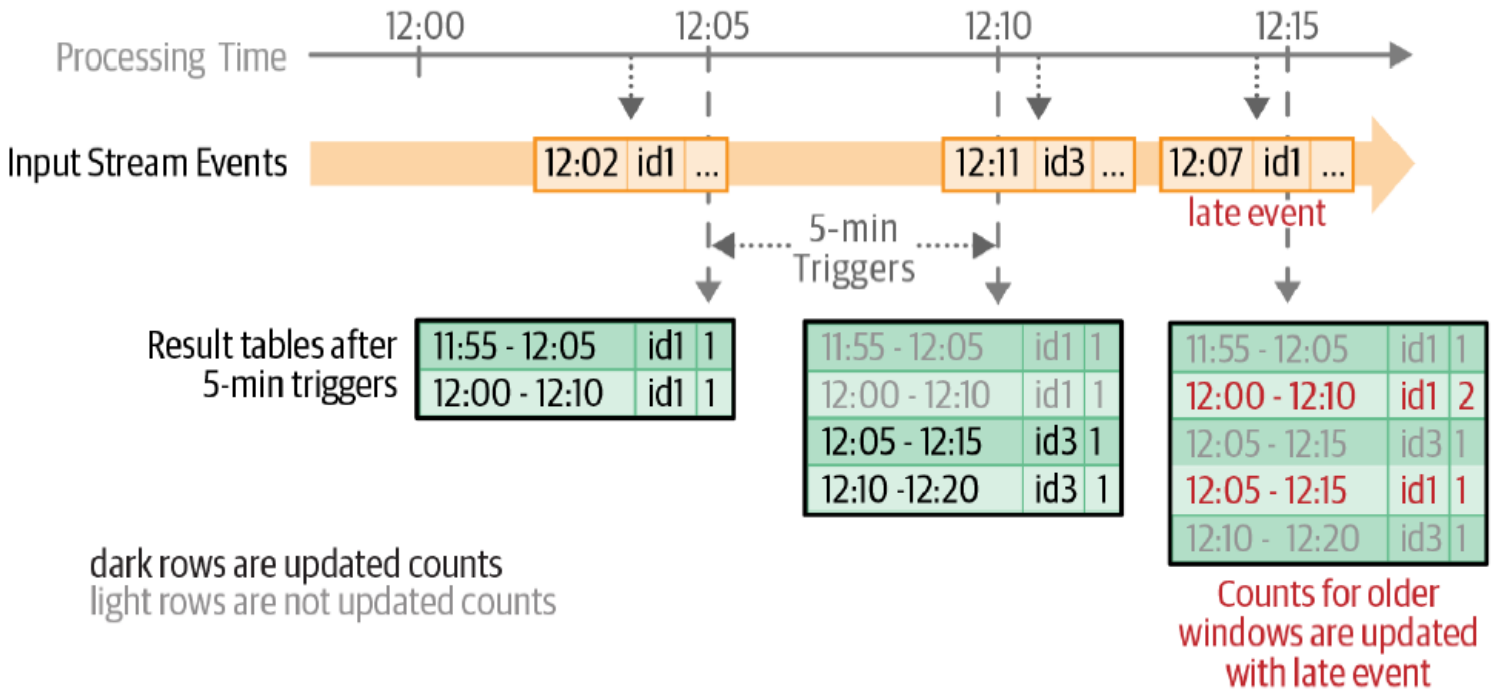


```
(sensorReadings
  .groupBy("sensorId", window("eventTime", "10 minute", "5 minute"))
  .count())
```



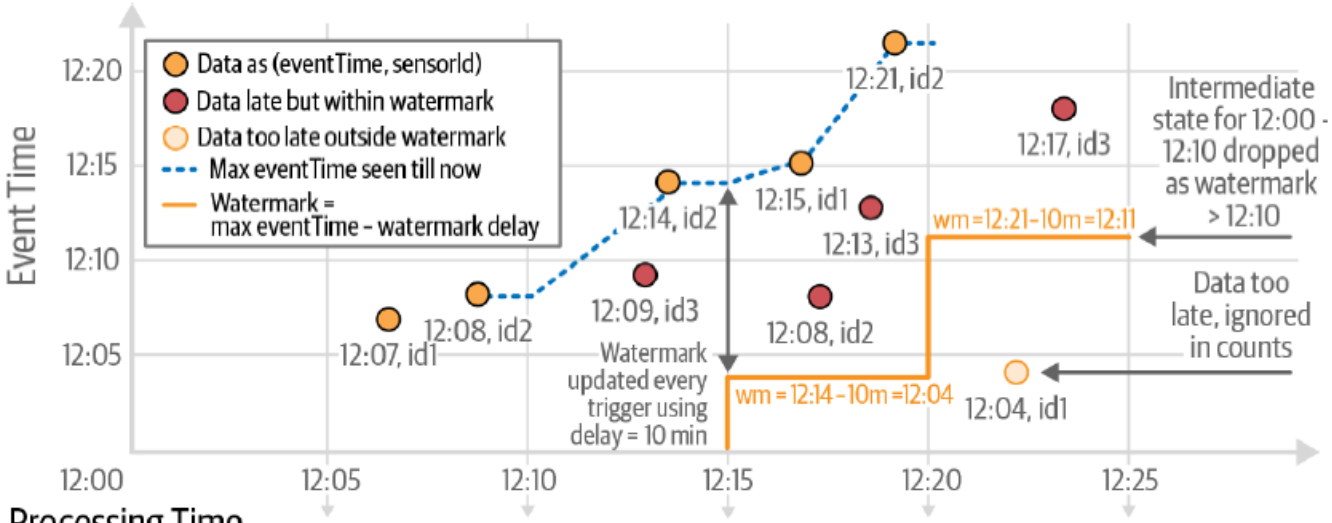
Mapping of event time to overlapping windows of length 10 mins and sliding interval 5 mins

- Updated counts in the result table after each five-minute trigger



Handling Late Data with Watermarks

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



12:00 - 12:10	id1	1
12:00 - 12:10	id2	1
12:05 - 12:15	id1	1
12:05 - 12:15	id2	1

12:00 - 12:10	id1	1
12:00 - 12:10	id2	1
12:00 - 12:10	id3	1
12:05 - 12:15	id1	1
12:05 - 12:15	id2	2
12:05 -12:15	id3	1
12:10 -12:20	id2	1

12:00 - 12:10	id1	1
12:00 - 12:10	id2	2
12:00 - 12:10	id3	1
12:05 - 12:15	id1	2
12:05 - 12:15	id2	3
12:05 - 12:15	id3	2
12:10 - 12:20	id2	1
12:10 - 12:20	id1	1
12:10 - 12:20	id3	1
...		

12:00 - 12:10	id1	1
12:00 - 12:10	id2	2
12:00 - 12:10	id3	1
12:05 - 12:15	id1	2
12:05 - 12:15	id2	3
12:05 - 12:15	id3	2
12:10 - 12:20	id2	1
12:10 - 12:20	id1	1
12:10 - 12:20	id3	2
...		

Result Tables after each trigger

dark rows are updated counts

Table *not* updated with too late data (12:04, id1)

Table updated with late data (12:17, id3)

Watermarking in Windowed Grouped Counts

Performance Tuning

- Besides tuning Spark SQL engine, a few other considerations
  - Cluster resource provisioning appropriately to run 24/7
  - Number of partitions for shuffles to be set much lower than batch queries
  - Setting source rate limits for stability
  - Multiple streaming queries in the same Spark application

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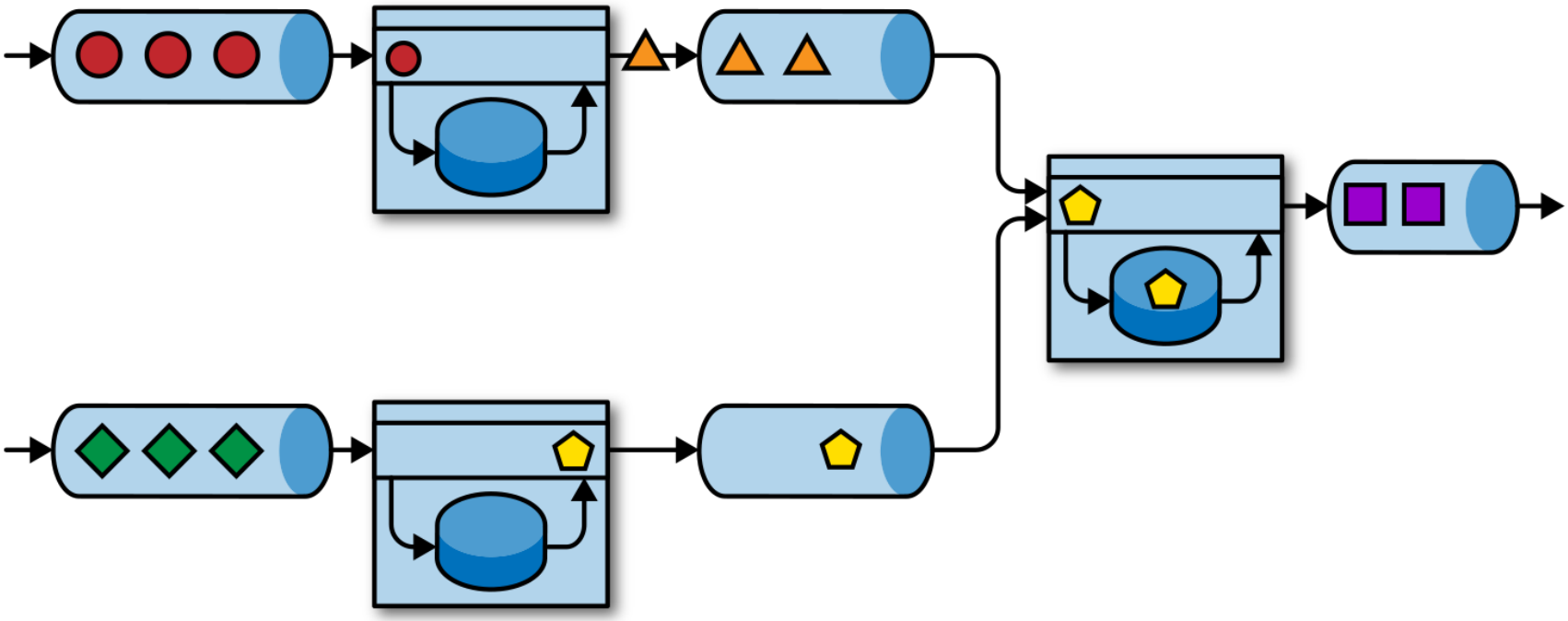
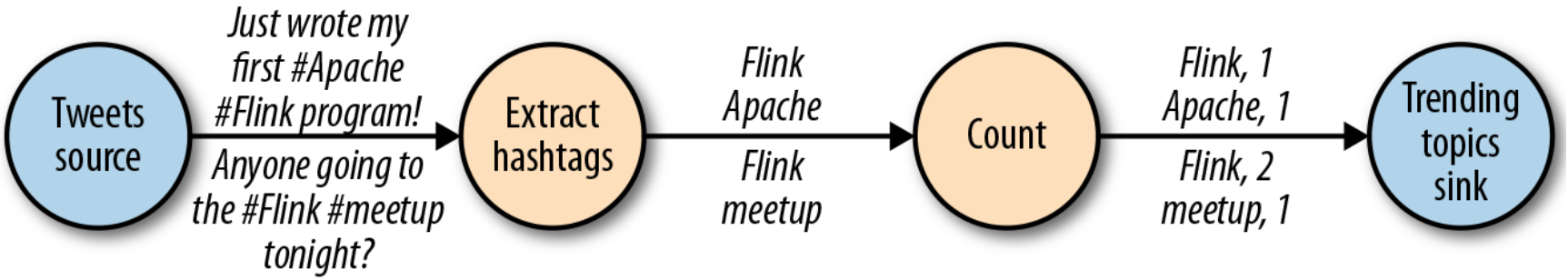
Event-driven streaming application



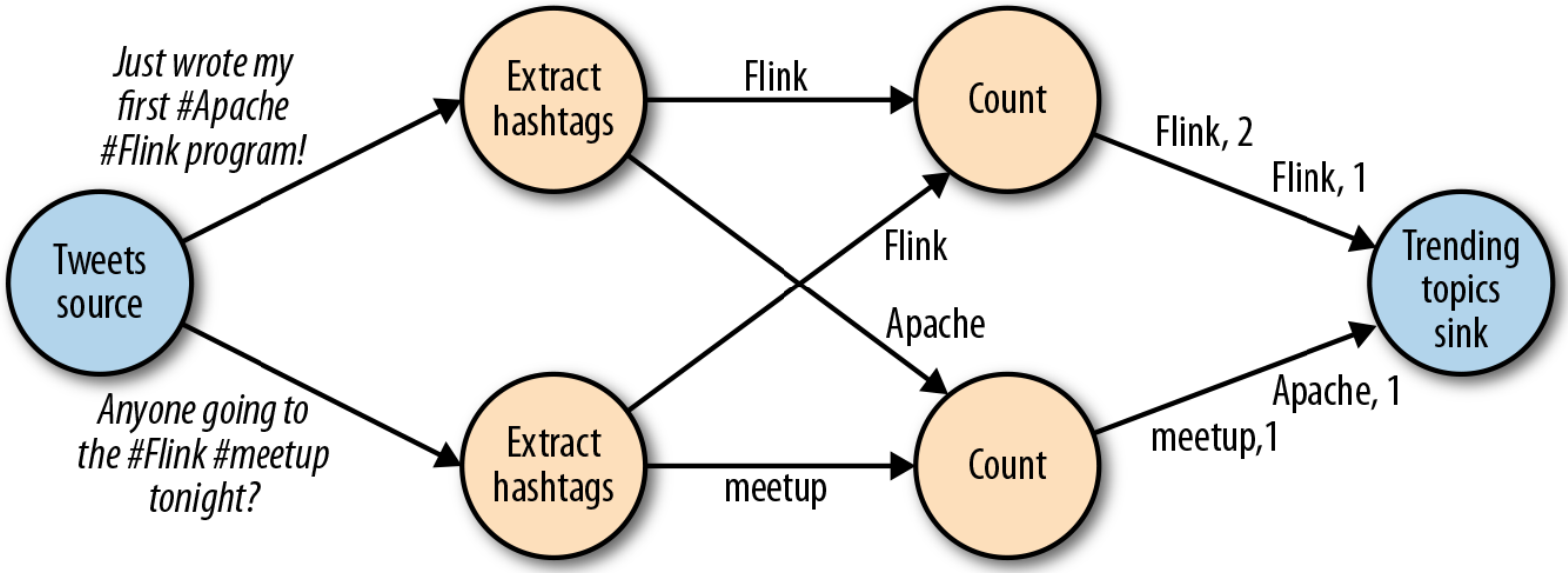
Dataflow Model

- Dataflow Graph
  - A logical dataflow graph to continuously count hashtags (nodes represent operators and edges denote data dependencies)



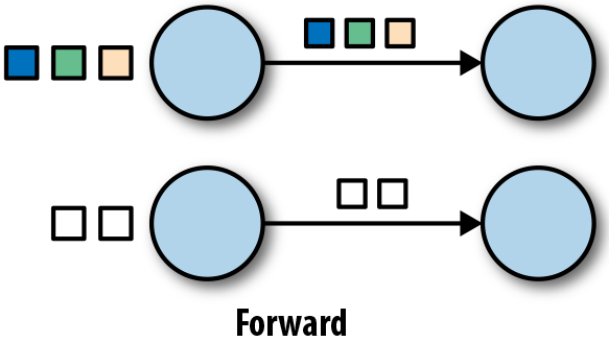
Dataflow Model

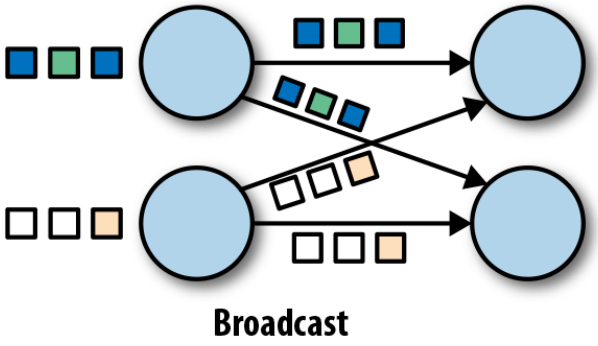
- A physical dataflow plan for counting hashtags (nodes represent tasks)

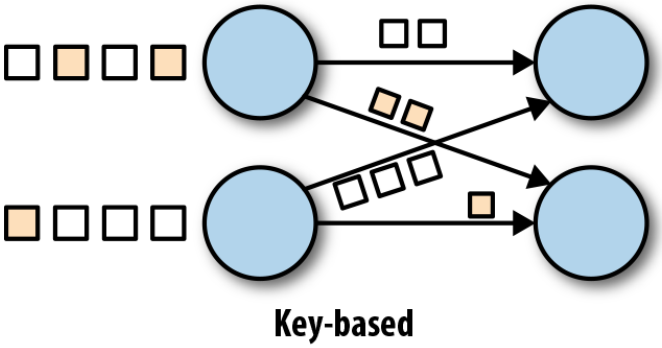


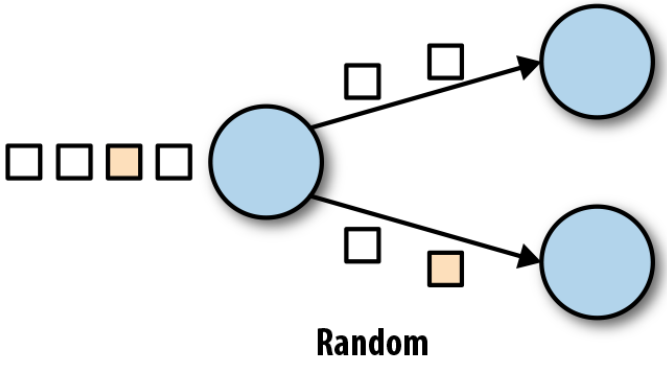
Dataflow Model

- Data Exchange Strategies



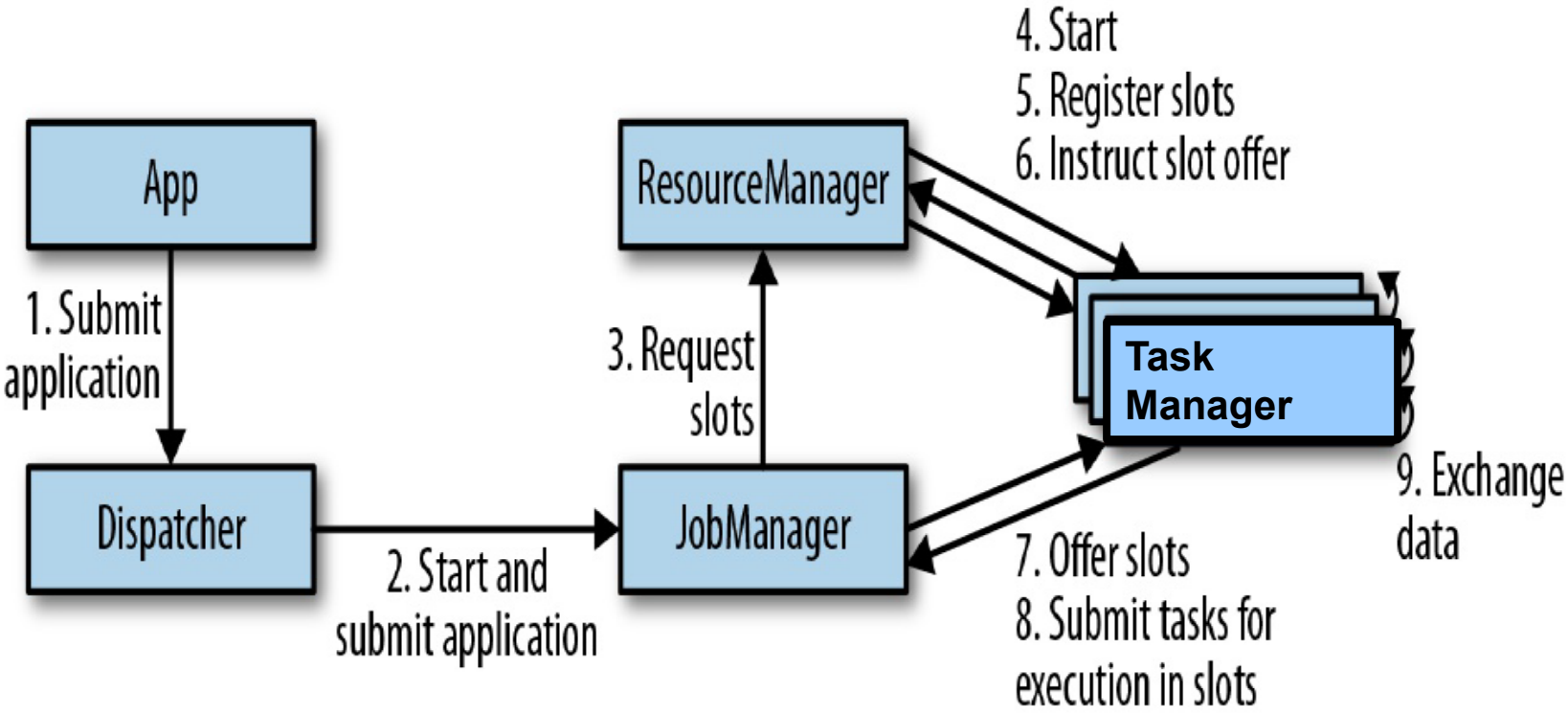






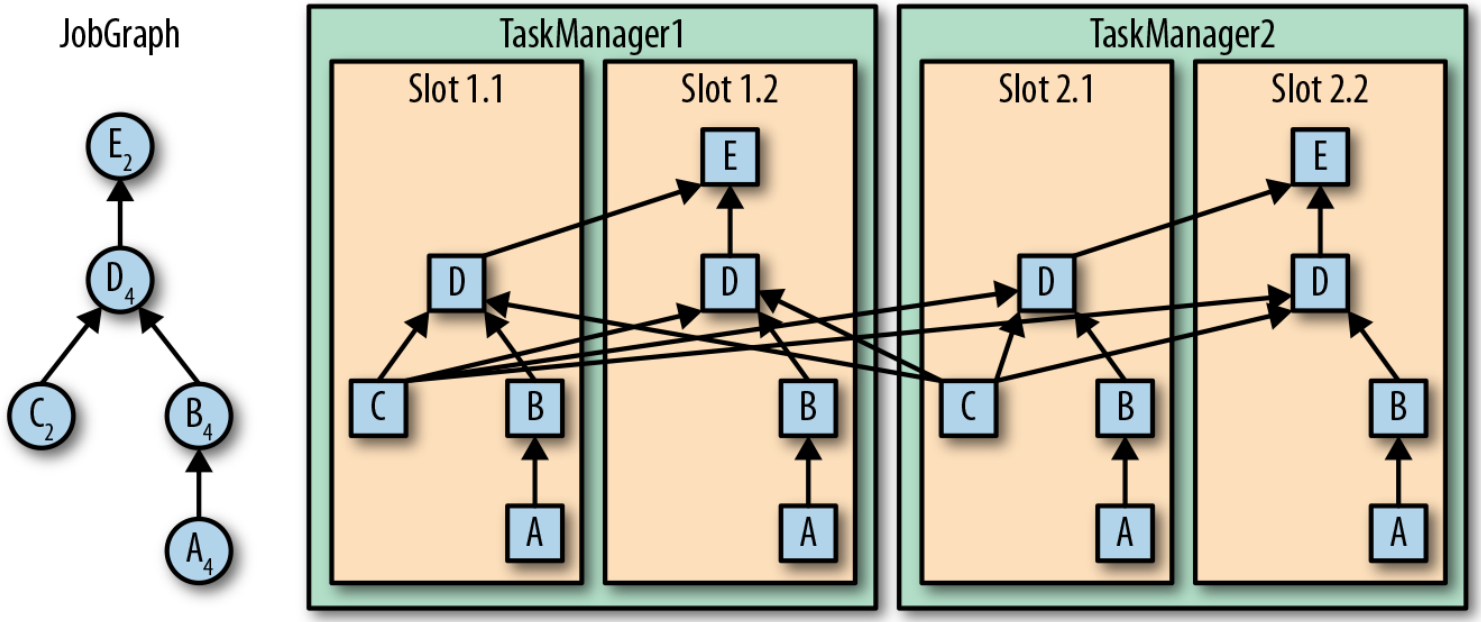
System Architecture

- Flink is a distributed system for stateful parallel data stream processing.



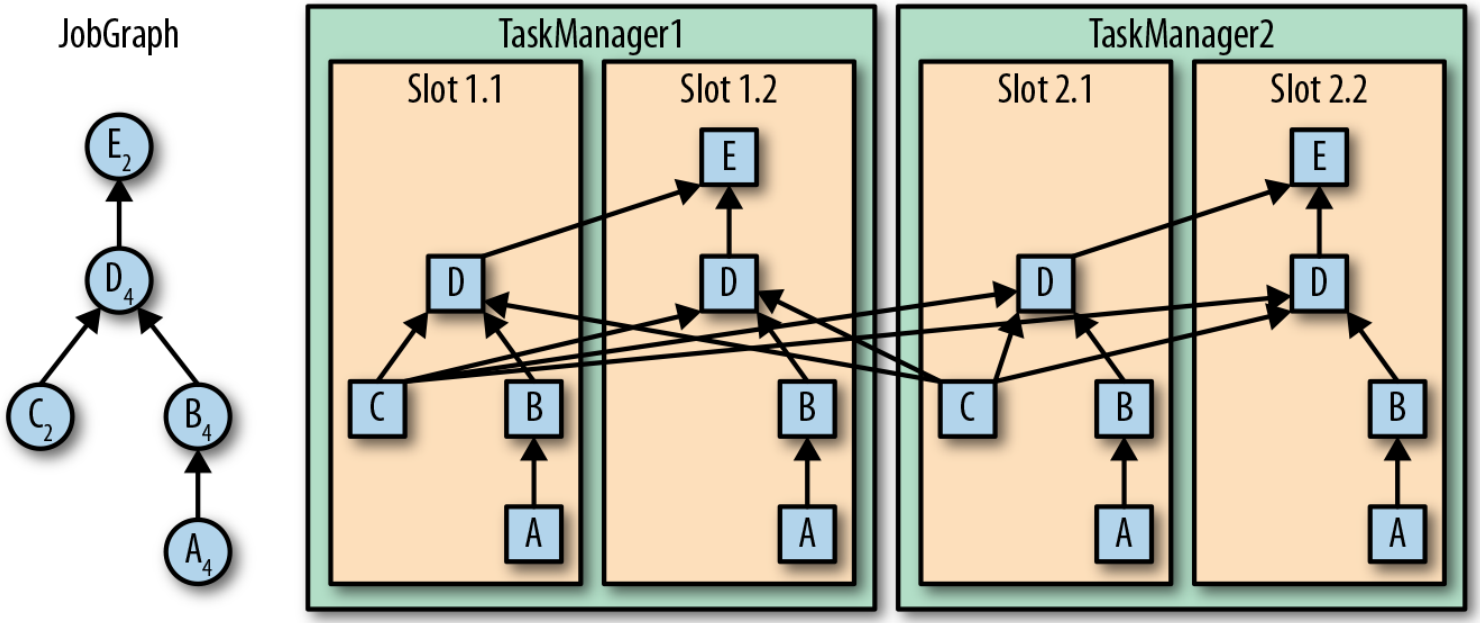
Task Execution

- A TaskManager can execute several tasks at the same time:
  - tasks of the same operator (data parallelism)
  - tasks of different operators (task parallelism)
  - tasks from a different application (job parallelism)



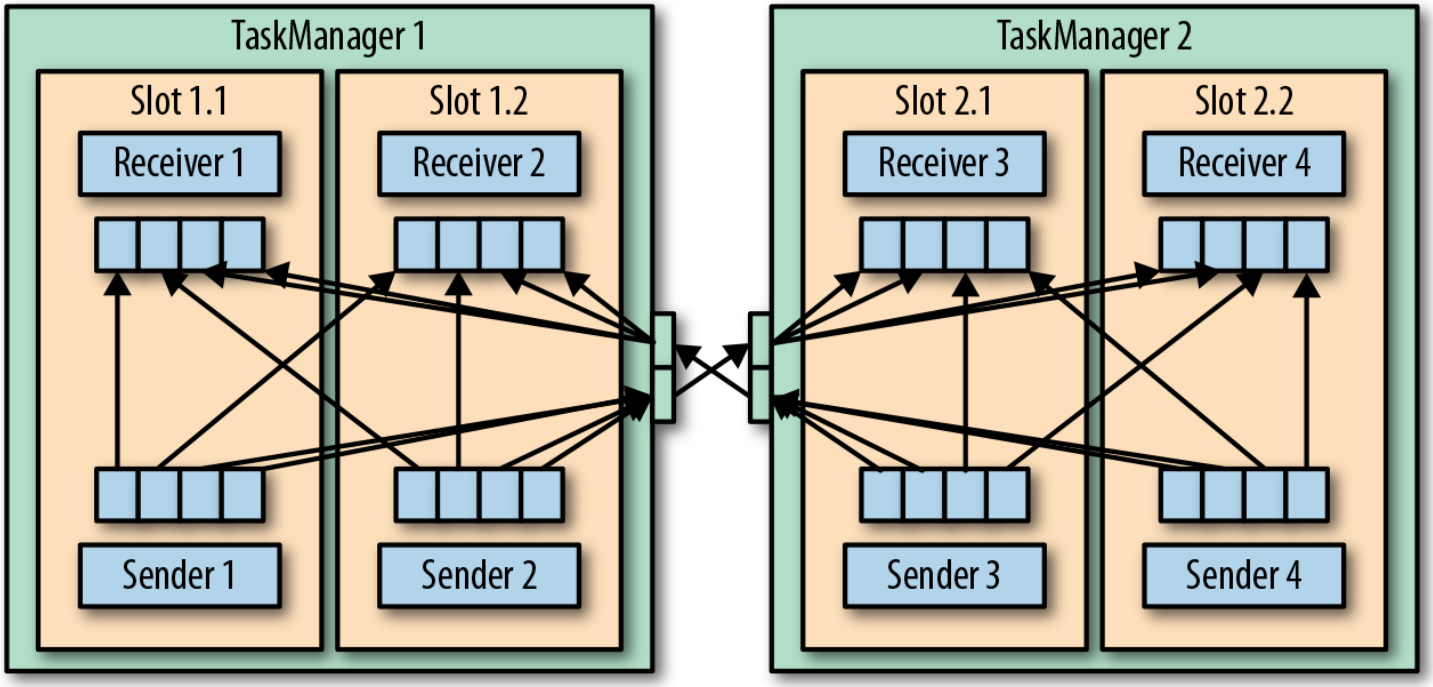
Task Execution

- A TaskManager
  - offers a certain number of processing slots to control the number of tasks it is able to concurrently execute.
- A processing slot
  - can execute one slice of an application—one parallel task of each operator of the application.



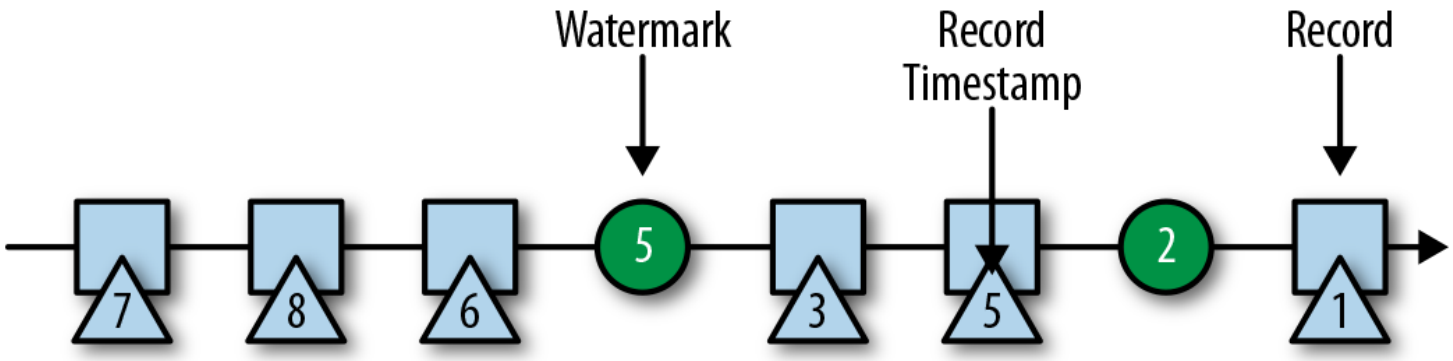
Data Transfer in Flink

- The tasks of a running application are continuously exchanging data.
- The TaskManagers take care of shipping data from sending tasks to receiving tasks.
- The network component of a TaskManager collects records in buffers before they are shipped.



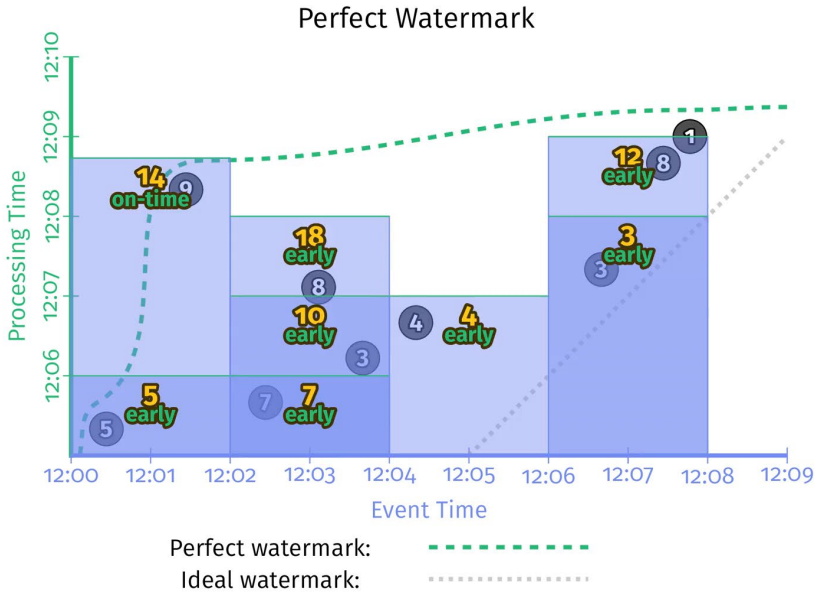
Even-Time Processing

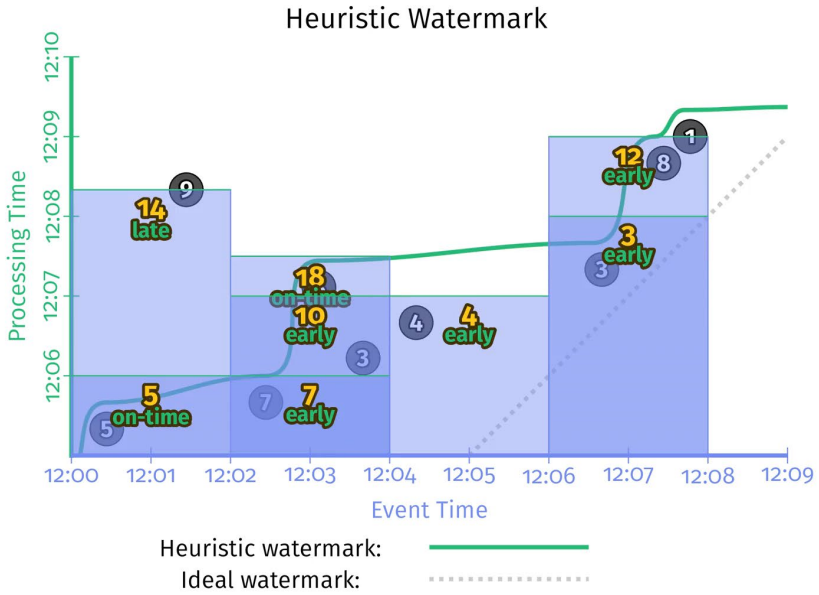
- Timestamps
  - Every record must be accompanied by an event timestamp
- Watermarks
  - a Flink event-time application must also provide watermarks
  - Watermarks are used to derive the current event time at each task in an event-time application
  - In Flink, watermarks are implemented as special records holding a timestamp as a Long value. Watermarks flow in a stream of regular records with annotated timestamps.



A Simple Counting Example

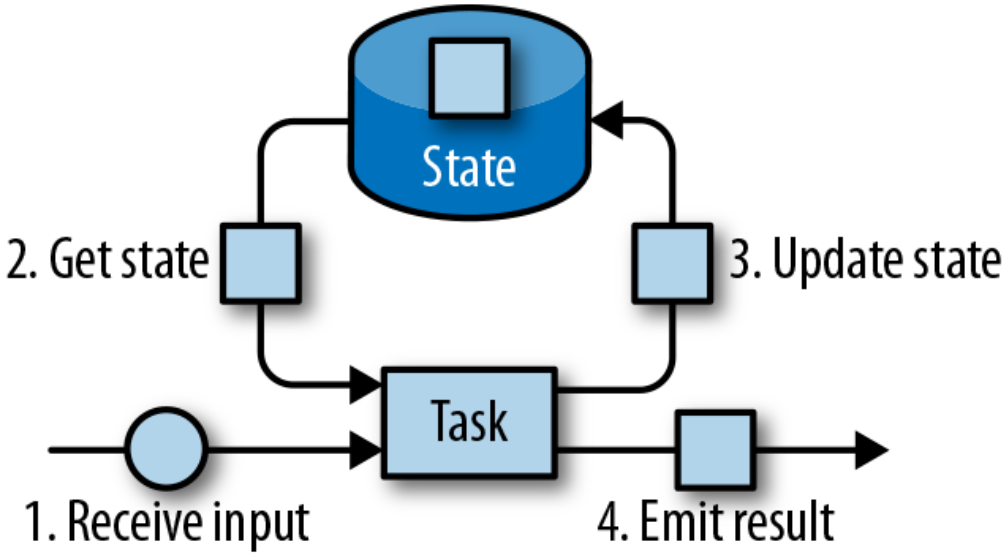
```
PCollection<KV<Team, Integer>> totals = input
  .apply(Window.into(FixedWindows.of(TWO_MINUTES))
                .triggering(AfterWatermark()
                                .withEarlyFirings(AlignedDelay(ONE_MINUTE))
                                .withLateFirings(AfterCount(1))))
  .apply(Sum.integersPerKey());
```





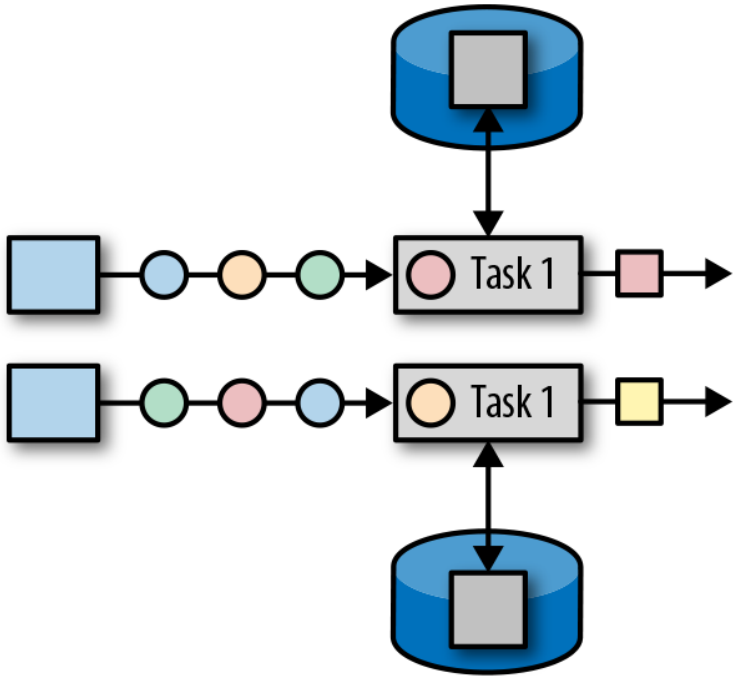
State Management

- A stateful stream processing task
  - all data maintained by a task and used to compute the results of a function belong to the state of the task



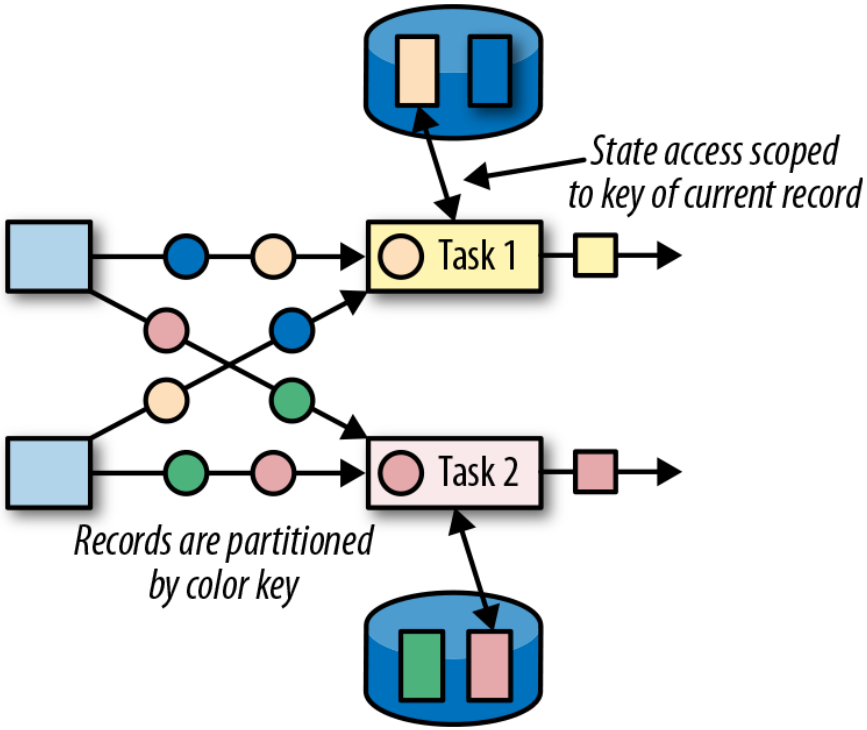
State Management

- Operator State
  - Scoped to an operator task
  - All records processed by the same parallel task have access to the same state
  - Operator state cannot be accessed by another task of the same or a different operator



State Management

- Keyed State
  - maintains one state instance per key value
  - partitions all records with the same key to the operator task that maintains the state for this key



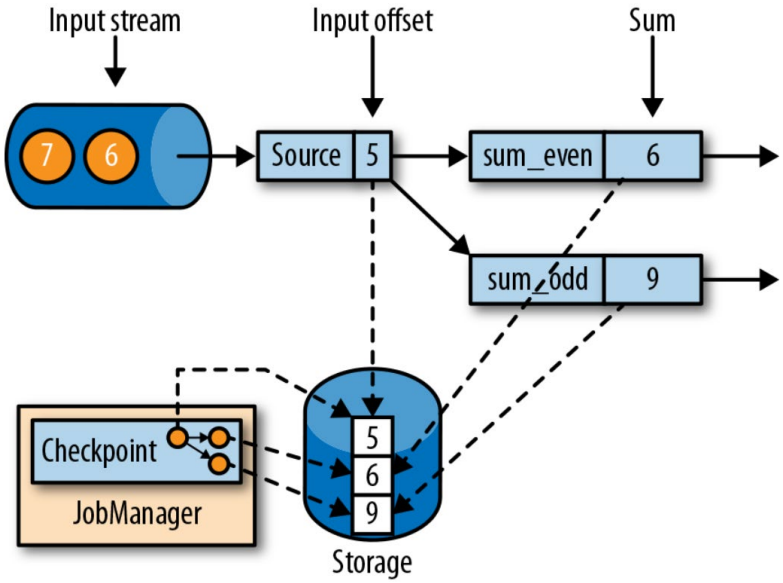
State Management

- State Backend
  - Local State Management
    - a task of a stateful operator typically reads and updates its state for each incoming record.
    - each parallel task locally maintains its state in memory to ensure fast state accesses
  - Checkpointing
    - A TaskManager process may fail at any point, hence its storage must be considered volatile
    - Checkpointing the state of a task to a remote and persistent storage
    - The remote storage for checkpointing could be a distributed filesystem or a database system

Checkpoints

- Consistent checkpoints: similar to Spark micro-batch checkpoints
  1. Pause the ingestion of all input streams
  2. Wait for all in-flight data to be completely processed, meaning all tasks have processed all their input data.
  3. Take a checkpoint by copying the state of each task to a remote, persistent storage. The checkpoint is complete when all tasks have finished their copies.
  4. Resume the ingestion of all streams.

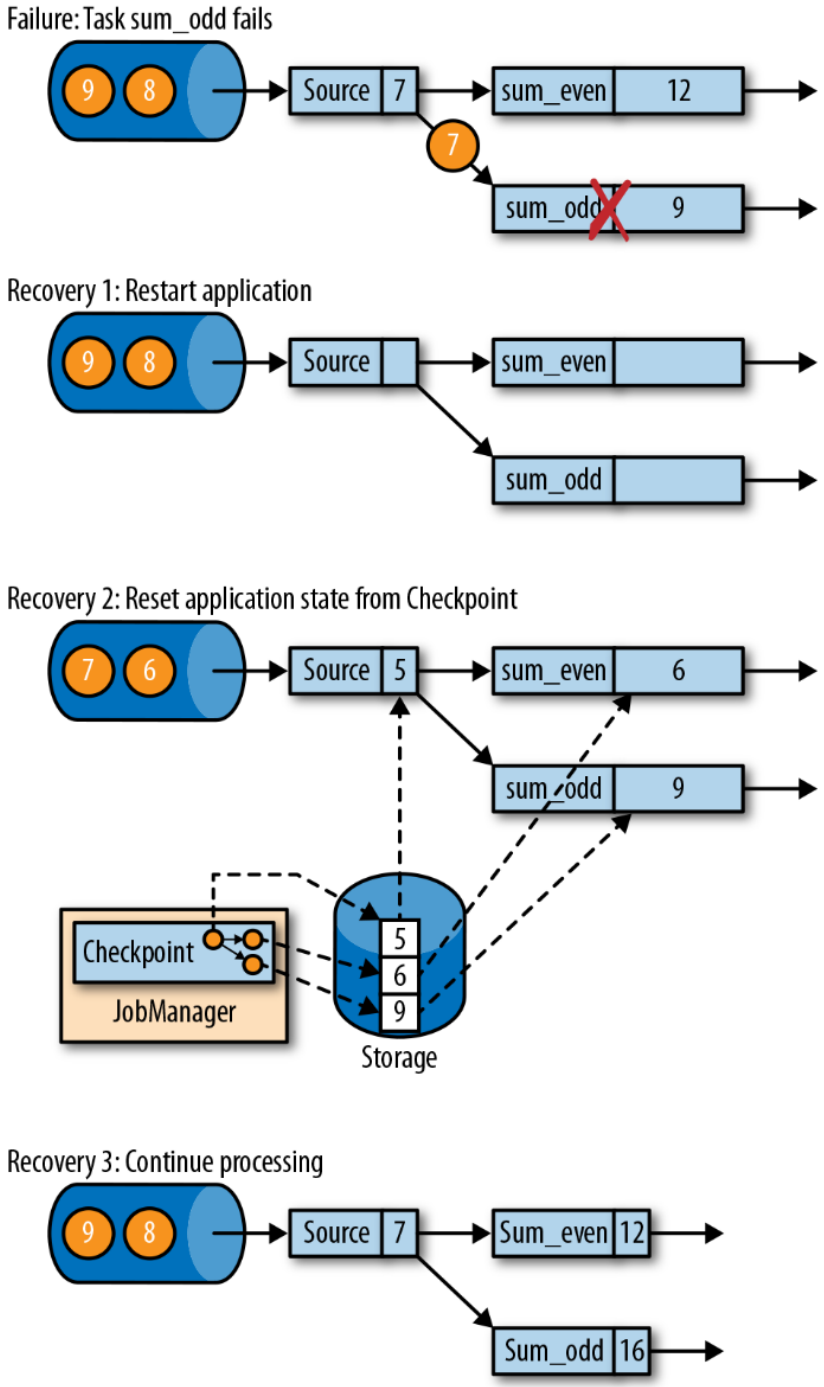
Stop-the-world



A consistent checkpoint

Failure Recovery from a consistent checkpoint

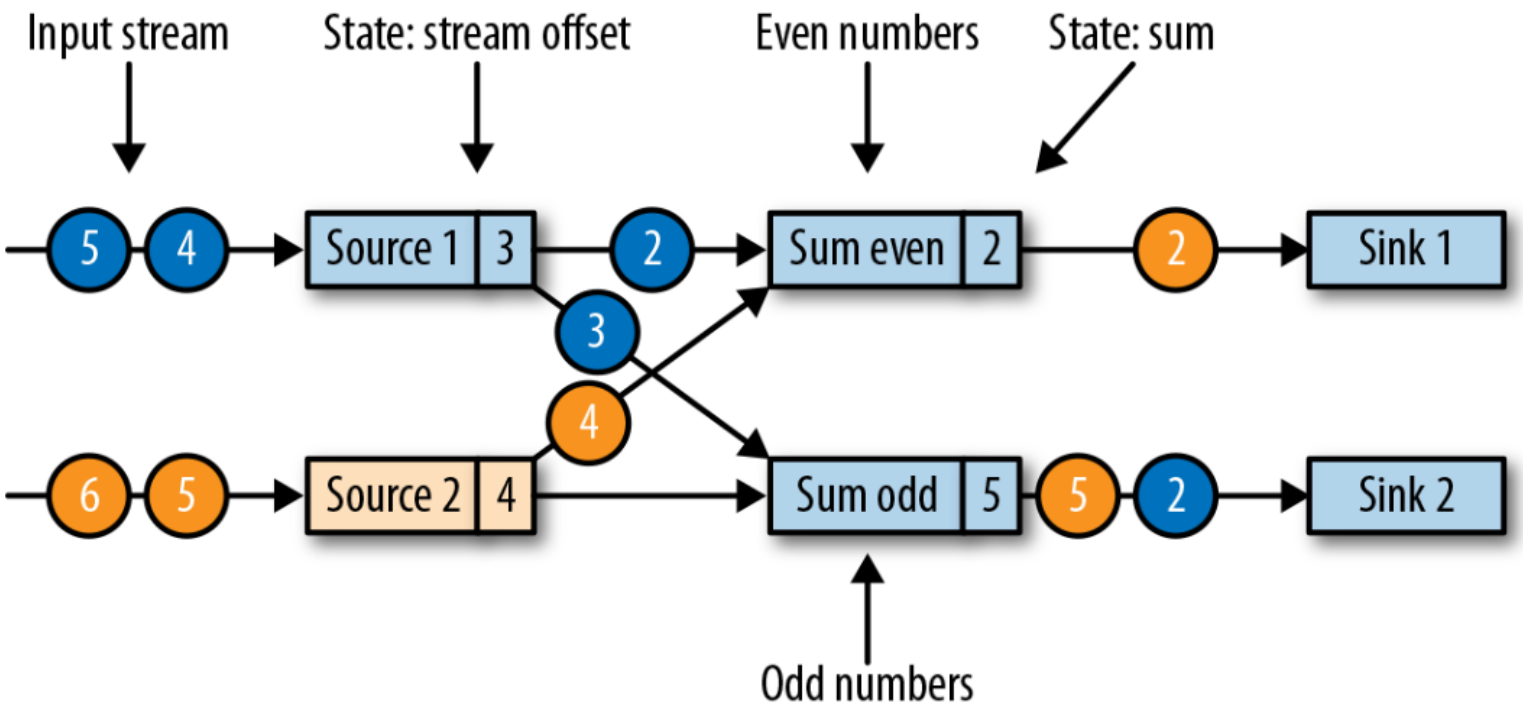
1.Restart the whole application.
2.Reset the states of all stateful tasks to the latest checkpoint.
3.Resume the processing of all tasks.



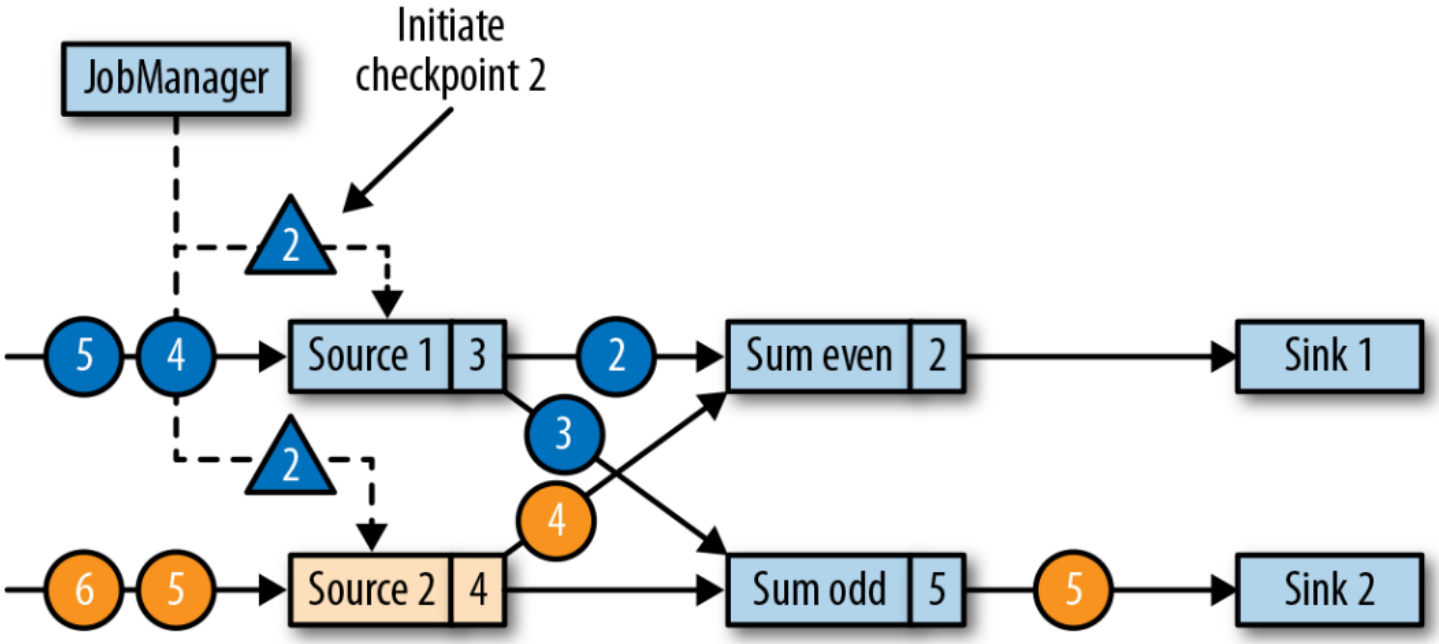
Checkpoints

- Flink's Checkpointing Algorithm
  - based on the Chandy–Lamport algorithm for distributed snapshots
  - does not pause the complete application but decouples checkpointing from processing
  - some tasks continue processing while others persist their state
- More details
  - uses a special type of record called a *checkpoint barrier*
  - checkpoint barriers are injected by source operators into the regular stream of records and cannot overtake or be passed by other records
  - A checkpoint barrier carries a checkpoint ID to identify the checkpoint it belongs to and logically splits a stream into two parts
  - All state modifications due to records that precede a barrier are included in the barrier's checkpoint and all modifications due to records that follow the barrier are included in a later checkpoint.

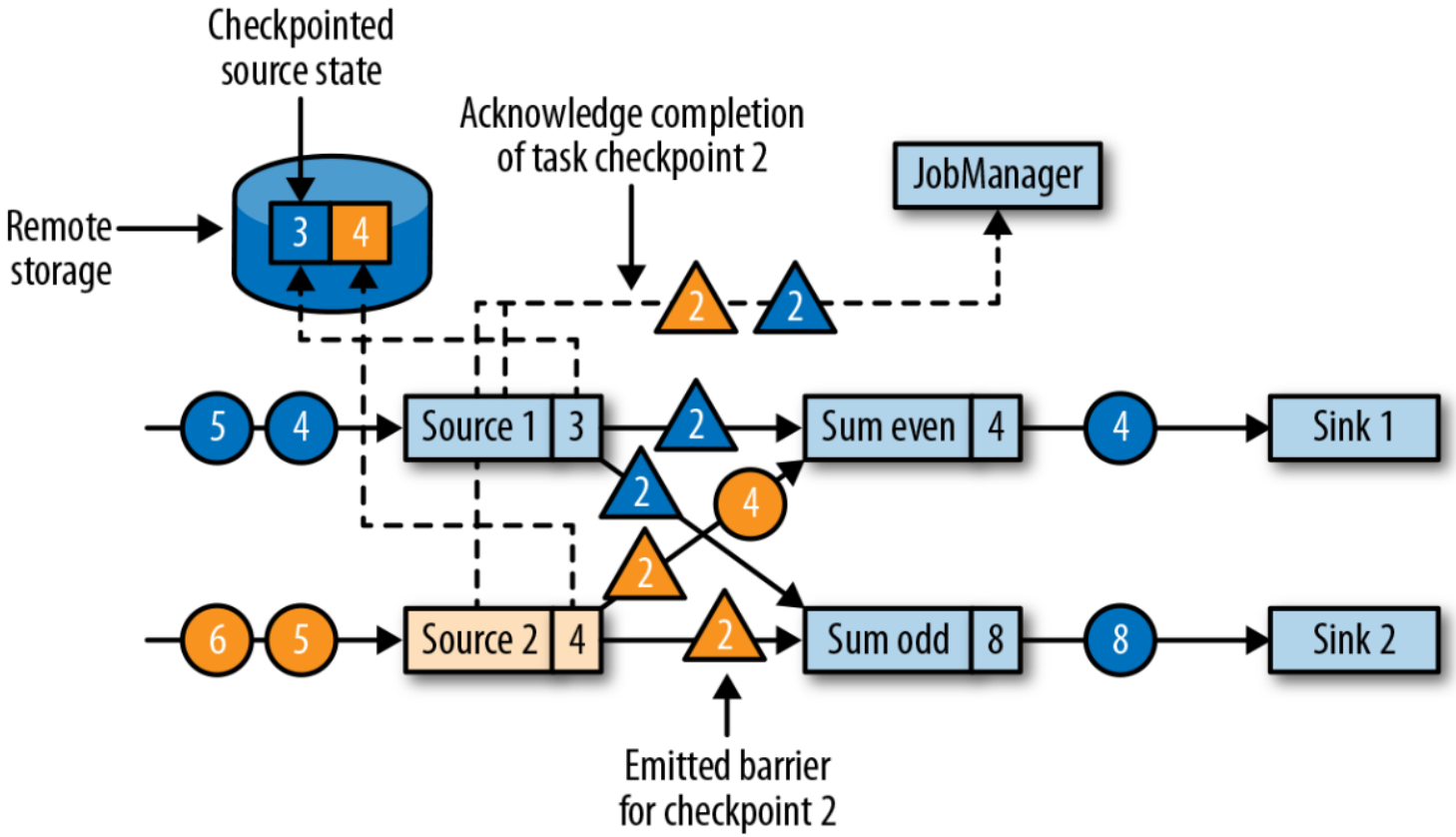
- Streaming application with two stateful sources, two stateful tasks, and two stateless sinks



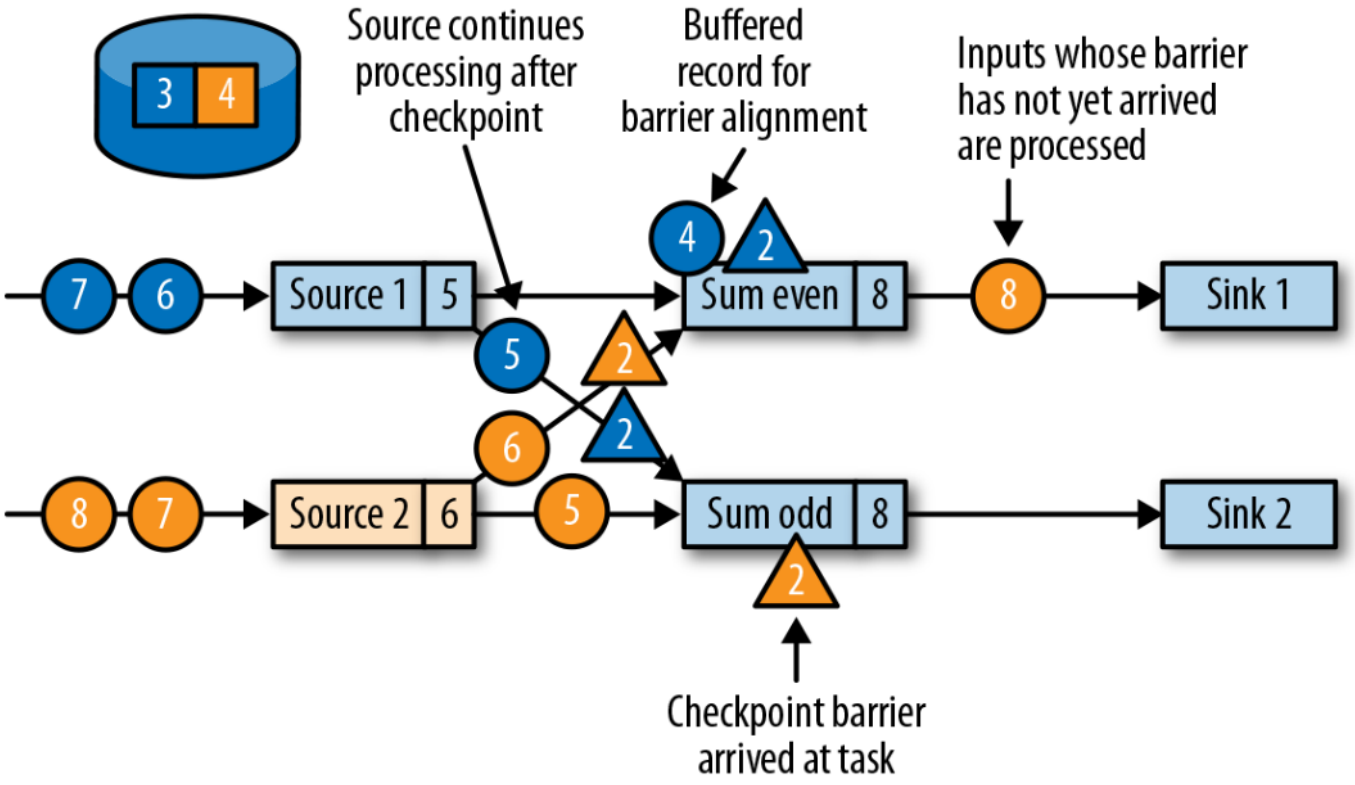
- JobManager initiates a checkpoint by sending a message to all sources



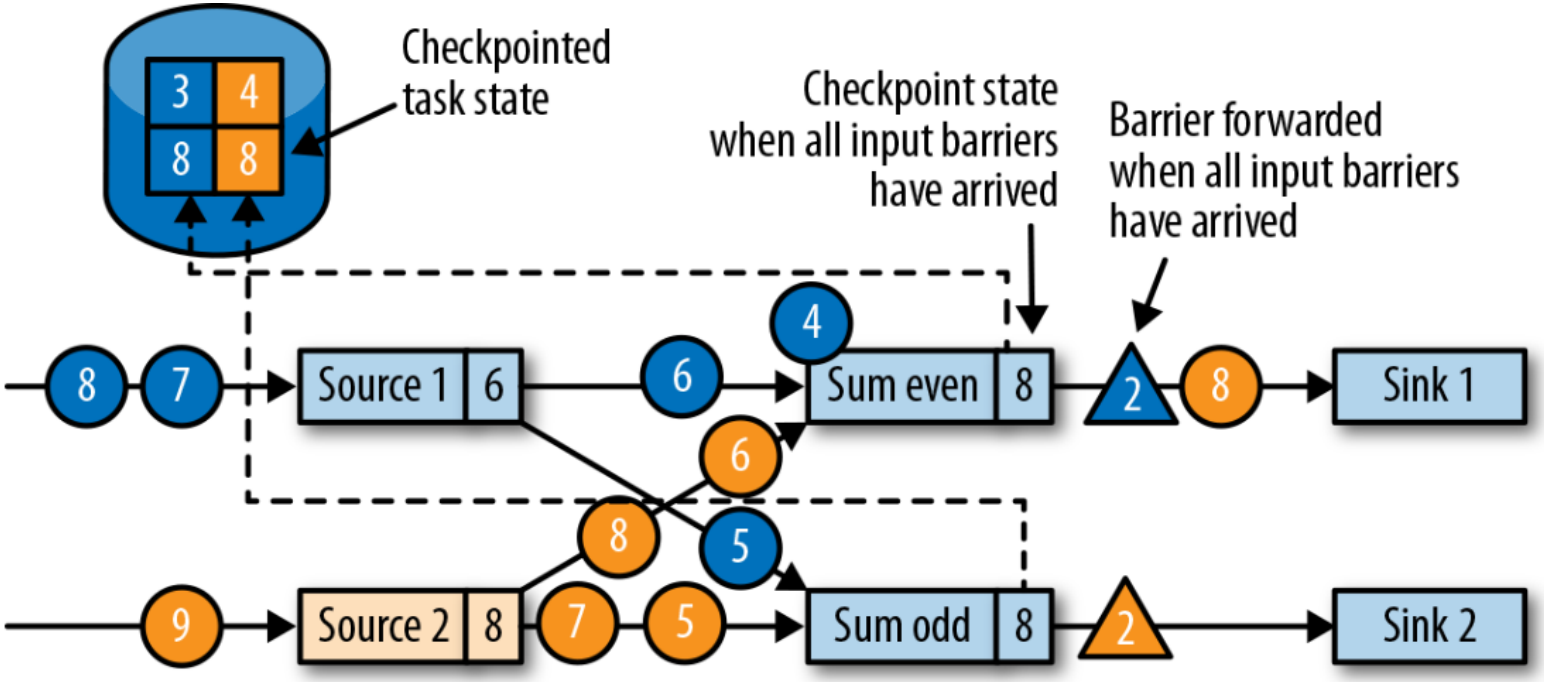
- Sources checkpoint their state and emit a checkpoint barrier



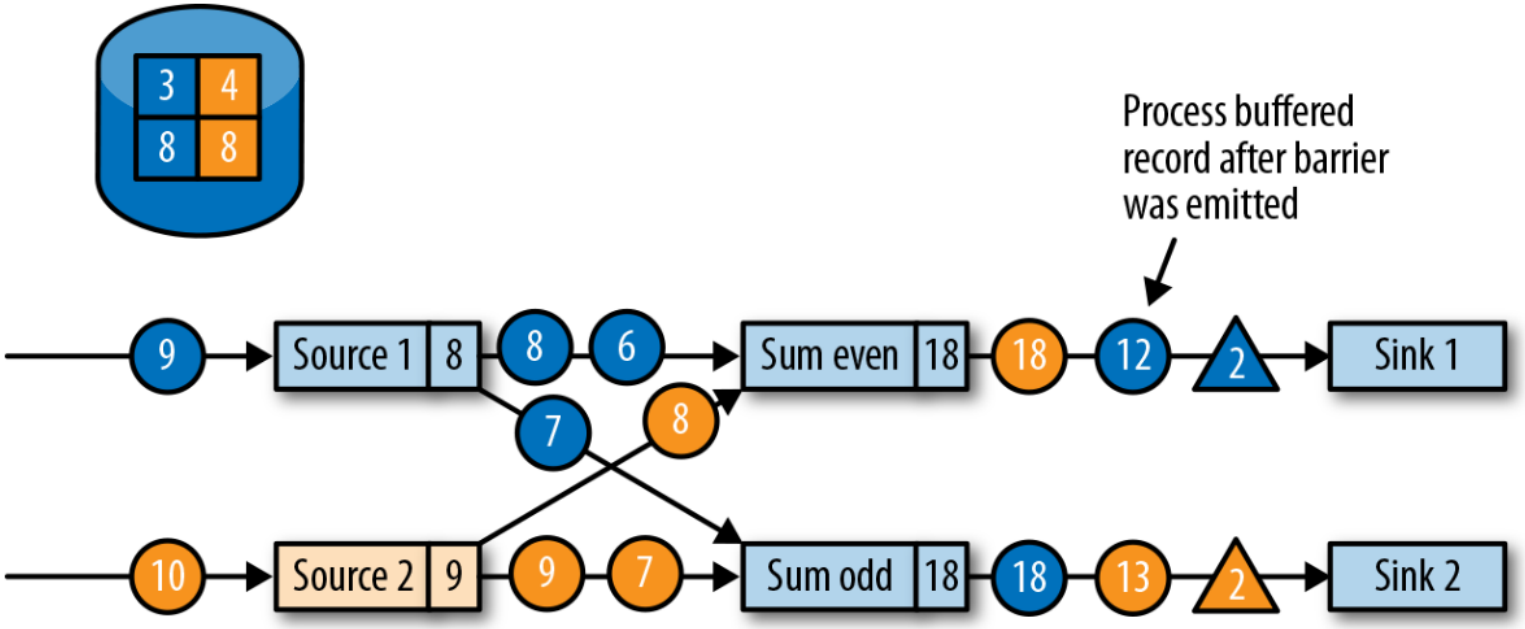
- Tasks wait to receive a barrier on each input partition
- Records from input streams for which a barrier already arrived are buffered
- All other records are regularly processed



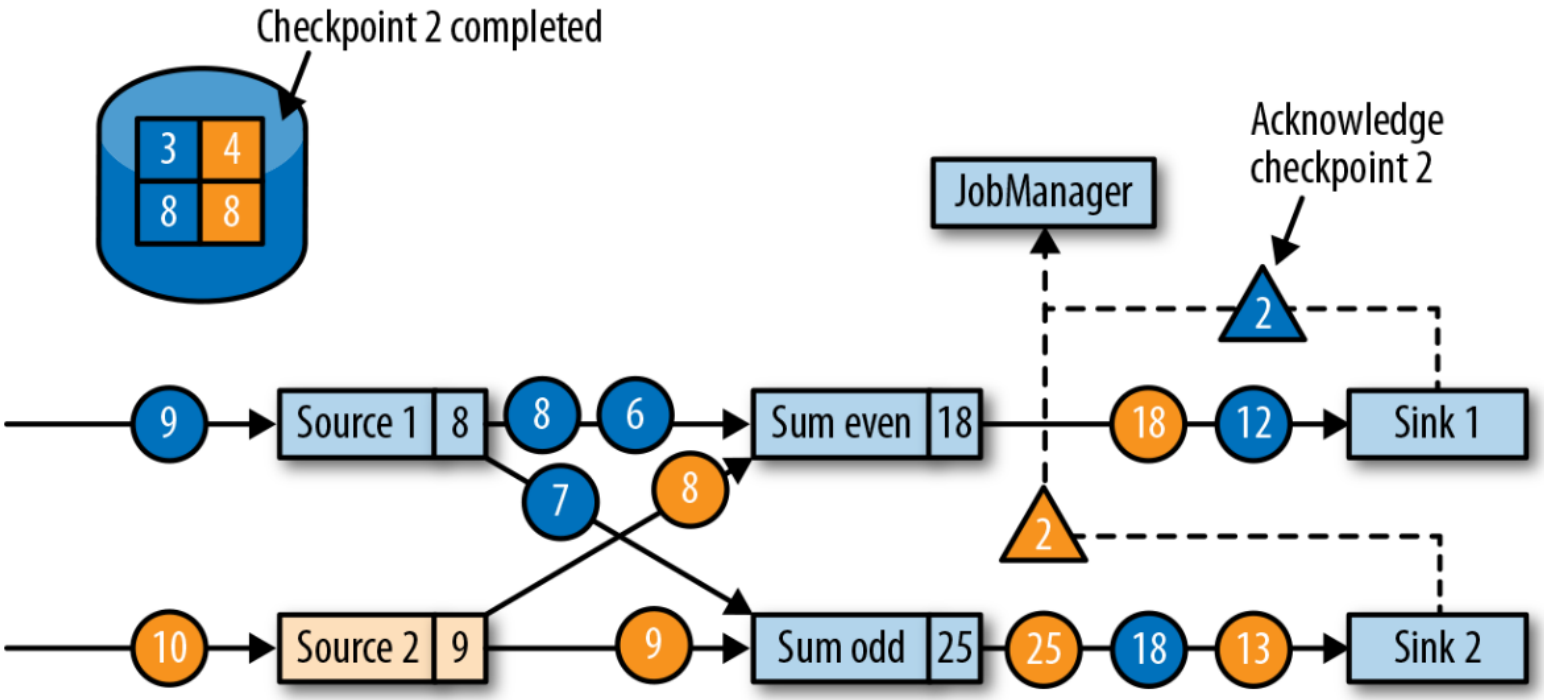
- Tasks checkpoint their state once all barriers have been received, then they forward the checkpoint barrier



- Tasks continue regular processing after the checkpoint barrier is forwarded



- Sinks acknowledge the reception of a checkpoint barrier to the JobManager
- a checkpoint is complete when all tasks have acknowledged the successful checkpointing of their state



Conclusion: a comparison between Spark vs. Flink

- Spark
  - Microbatch streaming processing (latency of a few seconds)
  - Checkpoints are done for each microbatch in a synchronous manner ("stop the world")
  - Watermark: a configuration to determine when to drop the late events
- Flink
  - Real-time streaming processing (latency of milliseconds)
  - Checkpoints are done distributedly in an asynchronous manner (more efficient ➔ lower latency)
  - Watermark: a special record to determine when to trigger the even-time related results
    - Flink uses late handling functions (related to watermark) to determine when to drop the late events

Acknowledgements

- CS4225 slides by He Bingsheng and Bryan Hooi
- Jules S. Damji, Brooke Wenig, Tathagata Das & Denny Lee, “Learning Spark: Lightning-Fast Data Analytics”
- Bill Chambers, Matei Zaharia, “Spark: The Definitive Guide”
- Fabian Hueske and Vasiliki Kalavri, “Stream Processing with Apache Flink”, 2019
- Tyler Akidau, Slava Chernyak and Reuven Lax, “Streaming Systems”, 2018