

Data Analysis with



3. Spark Structured Streaming

What is Streaming Data

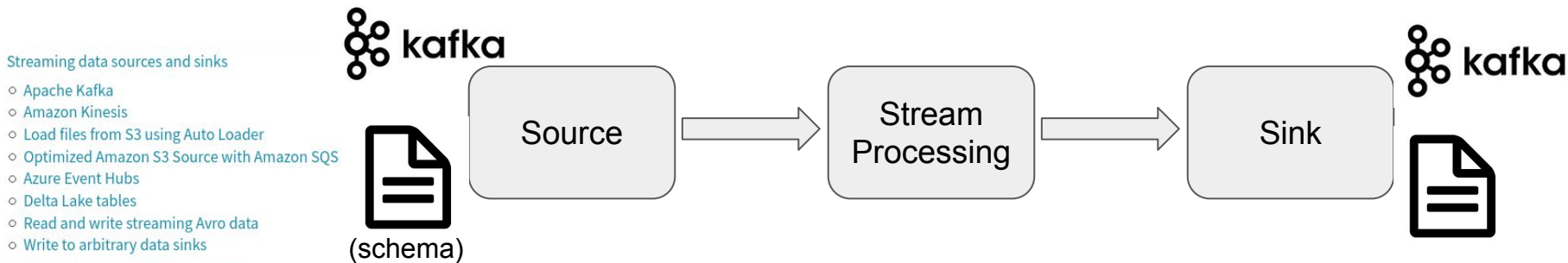
- Continuously generated data
- Coming from many data sources simultaneously
- Small in size (kB range)
- Examples: IoT, stock market, recommendation based on geo-location, electricity consumption...

Difference between Batch and Stream Processing

	Batch processing	Stream processing
Data scope	Queries or processing over all or most of the data in the dataset.	Queries or processing over data within a rolling time window, or on just the most recent data record.
Data size	Large batches of data.	Individual records or micro batches consisting of a few records.
Performance	Latencies in minutes to hours.	Requires latency in the order of seconds or milliseconds.
Analyses	Complex analytics.	Simple response functions, aggregates, and rolling metrics.

Streaming

- Unbounded data sets (in opposition to finite data sets);
- Unbounded data processing (in time);
- Spark Structured Streaming: fault-tolerant exactly-once processing



Stream processing models

● Traditional vs micro-batch model

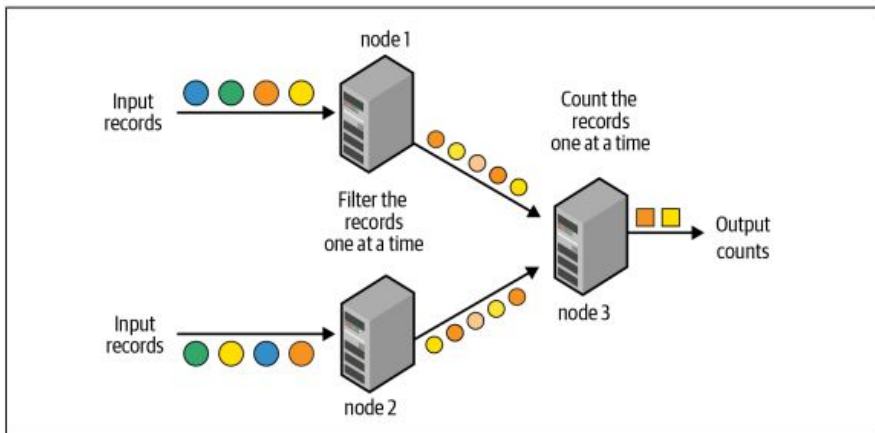


Figure 8-1. Traditional record-at-a-time processing model

- redundancy
- + latency (ms)

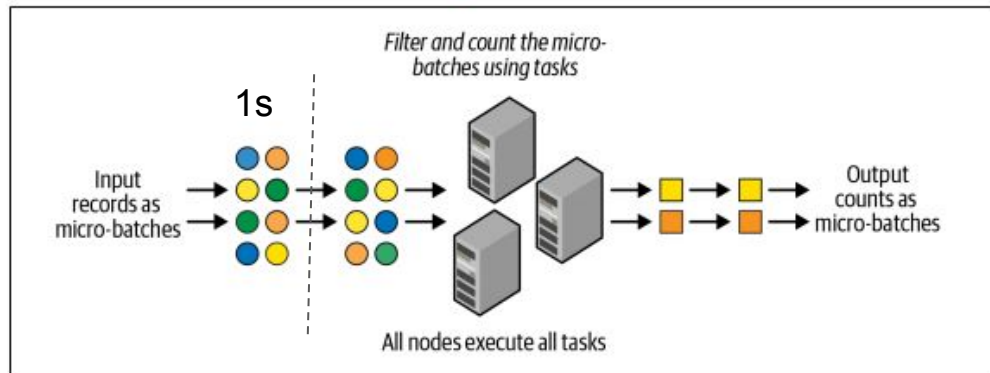
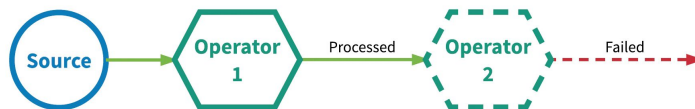


Figure 8-2. Structured Streaming uses a micro-batch processing model

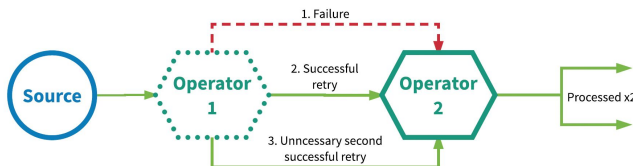
- + redundancy
- latency (100 ms: exactly-once)

Different processing semantics

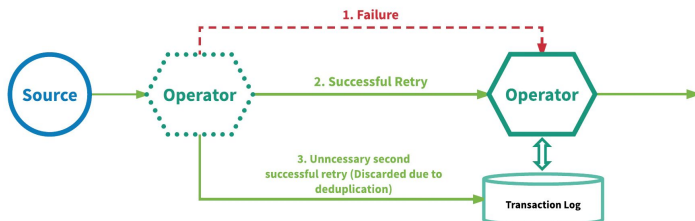
- At-most-once



- At-least-once

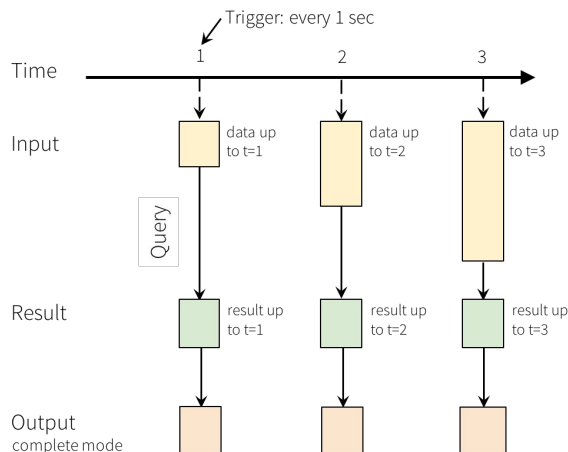
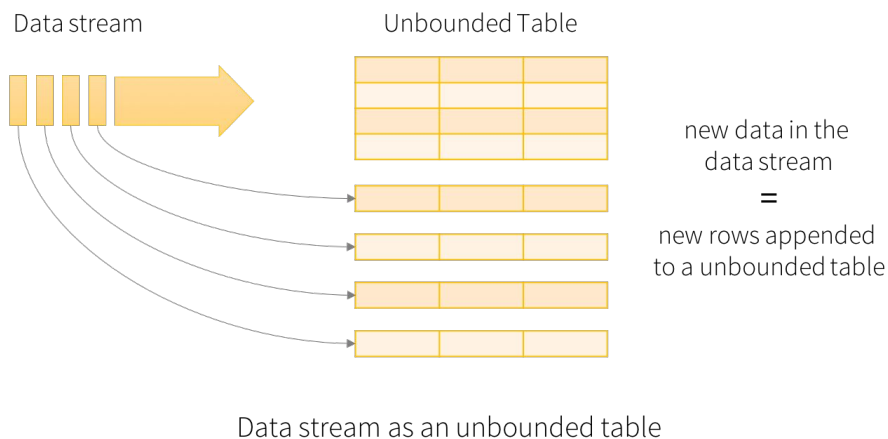


- Exactly-once



Programming model

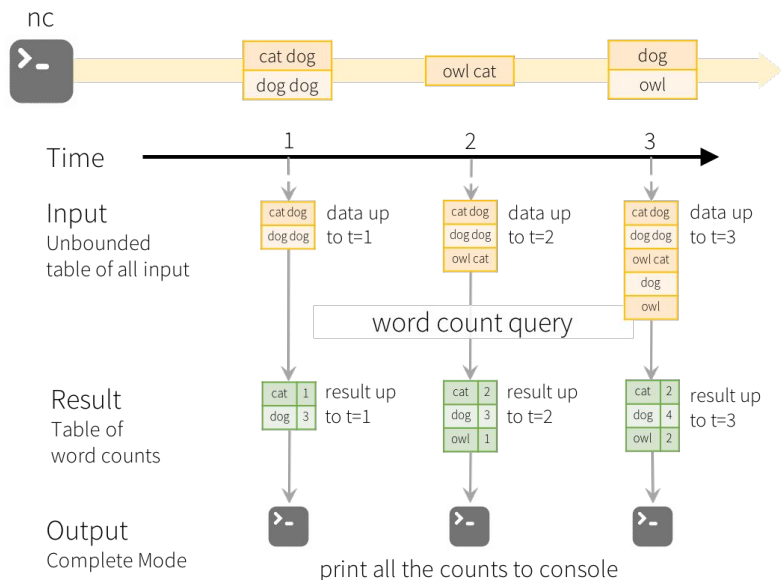
- Streaming computation as standard batch-like query



Programming Model for Structured Streaming

Programming model: example

• Word count

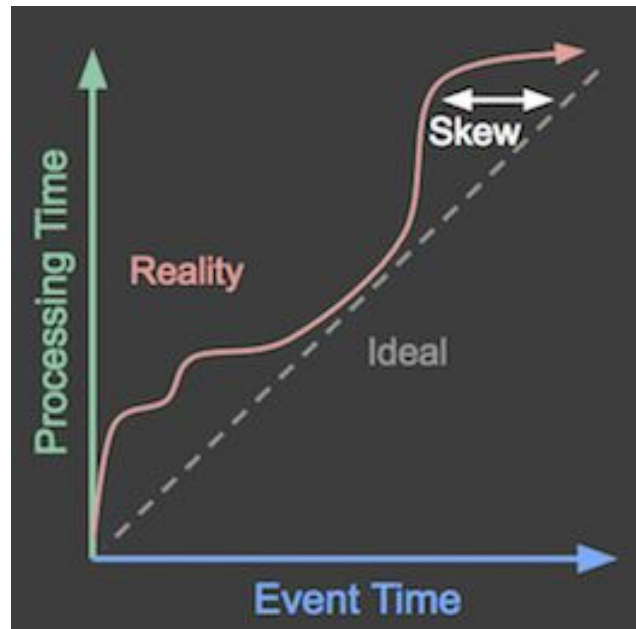


Output modes:

- complete - writes all the rows of a Result Table
- append - writes "new" rows only
- update - writes only the rows that were updated

Event-time vs Processing time

- event time - when the data was generated
- processing time - when Spark received the data



Operations on streaming DataFrames

- The syntax is very similar than what we saw with static DFs

```
df = ... # streaming DataFrame with IOT device data with schema { device: string, deviceType: string, signal: double, time: DateType }

# Select the devices which have signal more than 10
df.select("device").where("signal > 10")

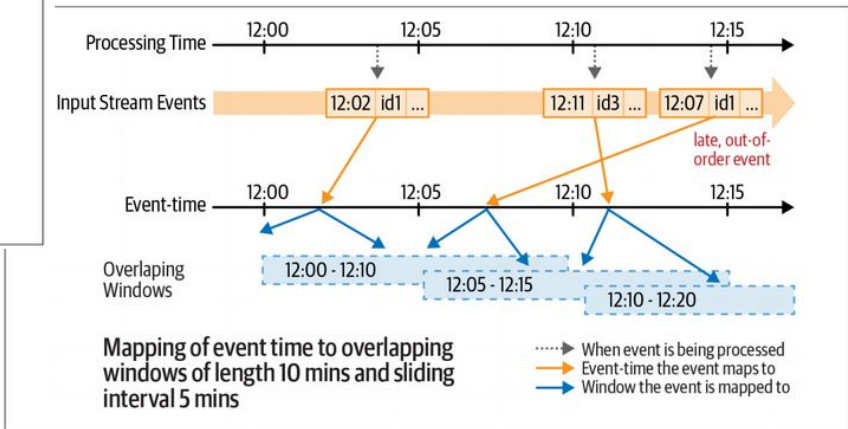
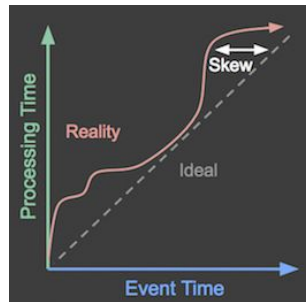
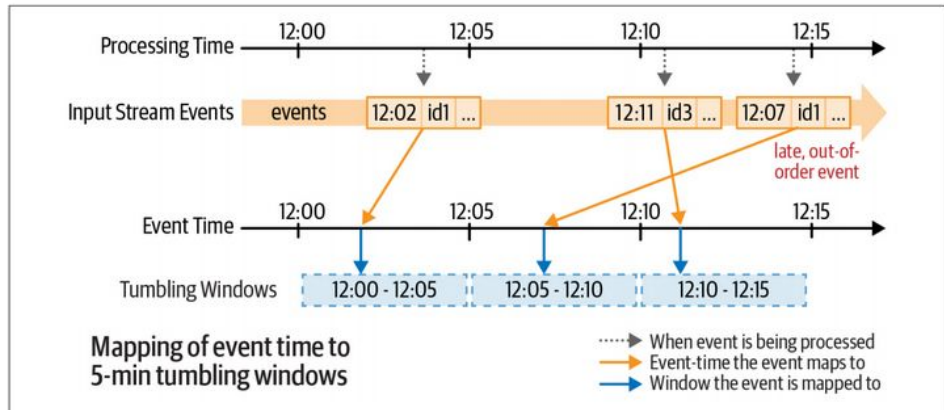
# Running count of the number of updates for each device type
df.groupBy("deviceType").count()
```

- SQL-like and RDD-like operations

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

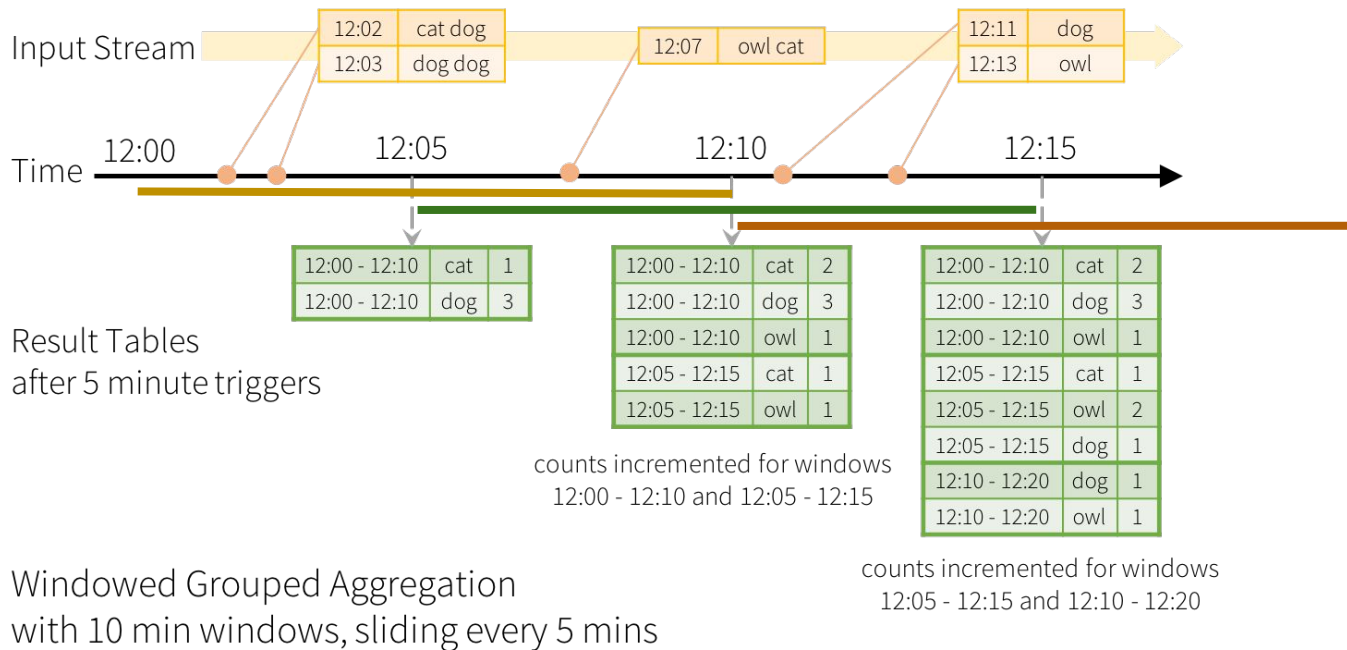
- several operations are not supported: distinct, take(n), limit, chained aggregations, some types of joins...

Windows: tumbling, overlapping

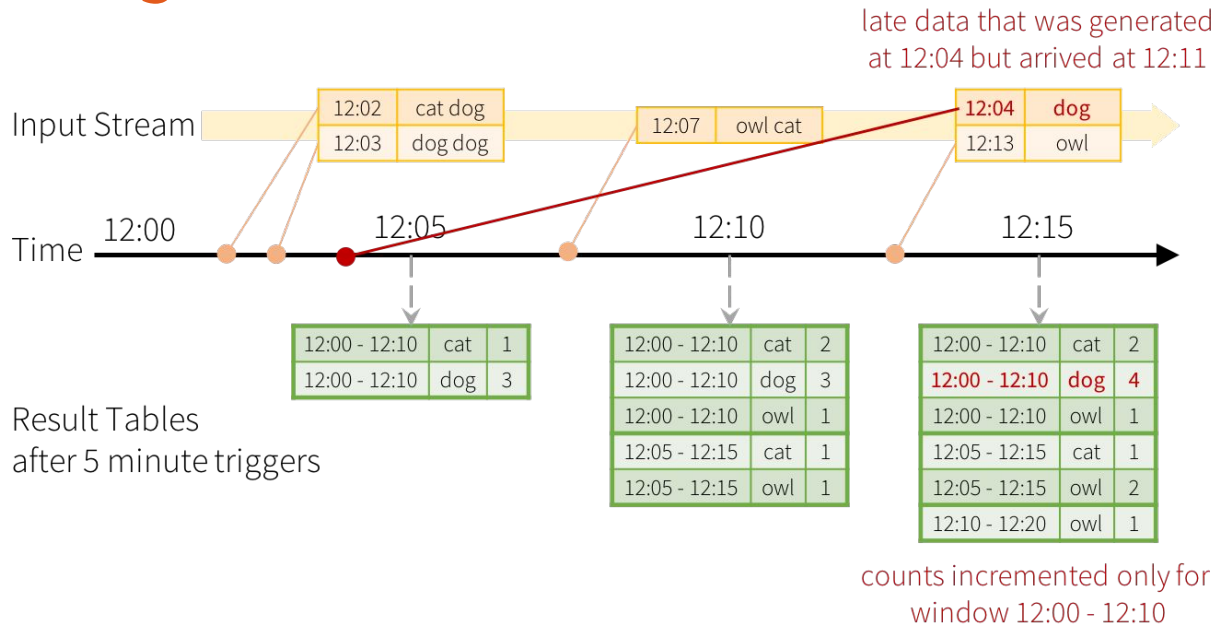


- Each event belongs to one or more windows

Aggregations over a sliding event-time window



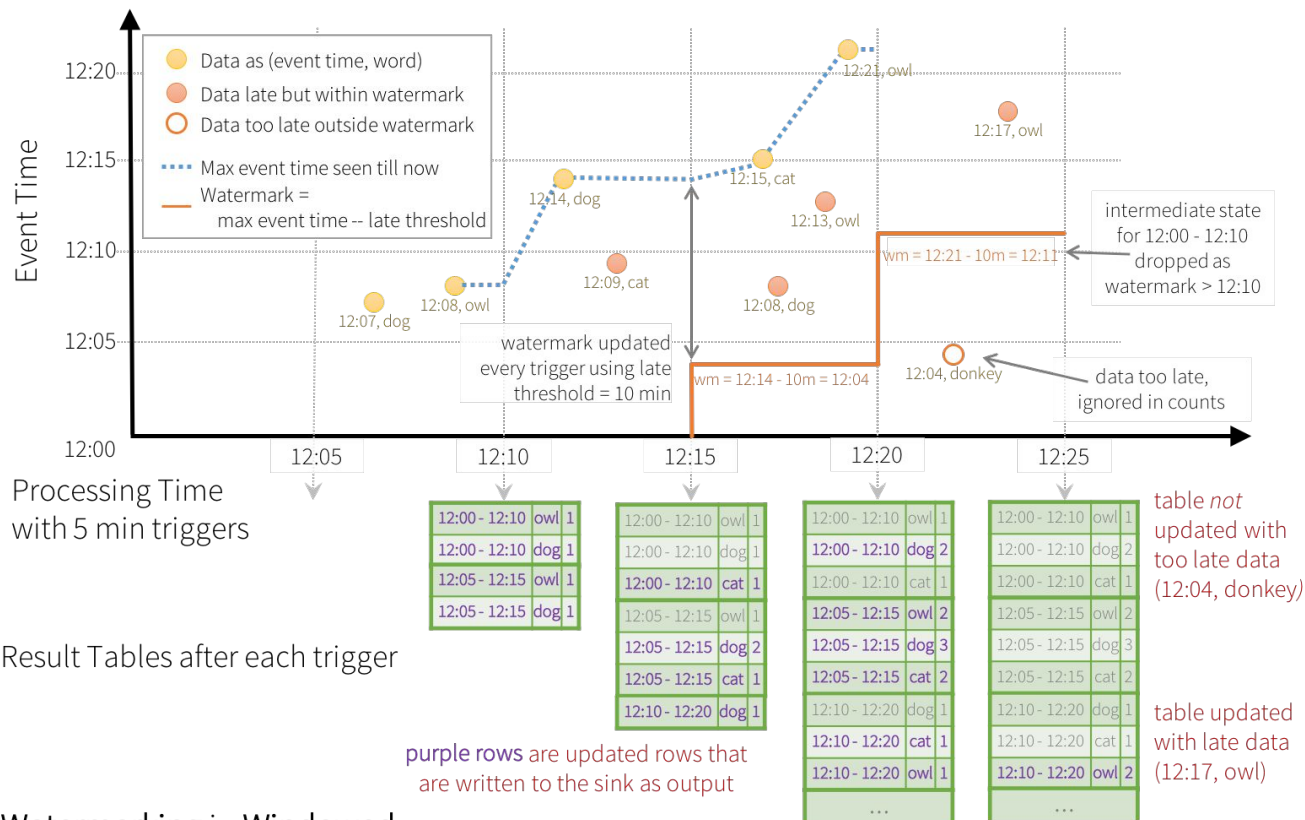
Handling late data



Late data handling in
Windowed Grouped Aggregation

How long will we wait?

Watermarking



Watermarking in Windowed
Grouped Aggregation with Update Mode

Vocabulary

- **Event-time** - a time when the event happens
- **Processing time** - a time when we receive the data of the event
- **Trigger** - how often we will collect the data
- **Window** - for how long will we collect the data
- **Watermark** - when the late data is discarded (how late is too late)