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APACHE Spark™

What is Stream Processing?

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Stream processing is a type of computing method where inputs are processed as continuous flows of data instead of in batch jobs. In other words, it allows for real-time processing of "streams" of data that are generated continuously from different sources.

Here's a detailed explanation:

1. **Real-Time Processing:** Stream processing is designed to act on real-time and streaming data with "event time" processing. This means the system can make decisions and take actions based on the current data coming in, not on data that's been stored and processed.

2. **Continuous and Infinite Data Sets:** Unlike batch processing, where data is collected over a period of time and then processed all at once, stream processing works on live, constantly updating data. It treats data as an unending stream and makes computations on the fly.

3. **Fault-Tolerance:** In stream processing, data is processed as it arrives, so if there's a failure, you don't lose all your progress. Most stream processing systems have in-built recovery mechanisms.

4. **Statefulness**: Stream processing is often stateful, which means it maintains some information about its past in order to process the present. For example, a stream processing system might keep a running total of the number of events it has seen so far.

5. **Scalability**: Stream processing systems can often handle large volumes of incoming data, and can be designed to scale with the size of the input.

6. **Windowing**: Stream processing systems often use a concept called "windowing," where they treat the data in the stream as if it were broken up into chunks (or "windows") of time. This allows them to perform calculations over those windows.

What is Stream Processing?

Assume you are running a popular news website, and you want to track the number of views on your articles in real time. Here, every click on an article is data that can be processed. Instead of waiting to gather all the data and then processing it, stream processing would allow you to track these views as they happen.

The stream processing system might work like this:

- An event is generated every time someone views an article.
- This event is immediately sent to the stream processor.
- The stream processor maintains a count of views for each article.
- When an event comes in, the stream processor updates the count for the relevant article.
- The updated count is then immediately available for use elsewhere in the system, for example, in a real-time dashboard showing the most popular articles.

In this way, you can keep a real-time track of your article views, which would not be possible with a batch processing system.

What is Stream Processing?

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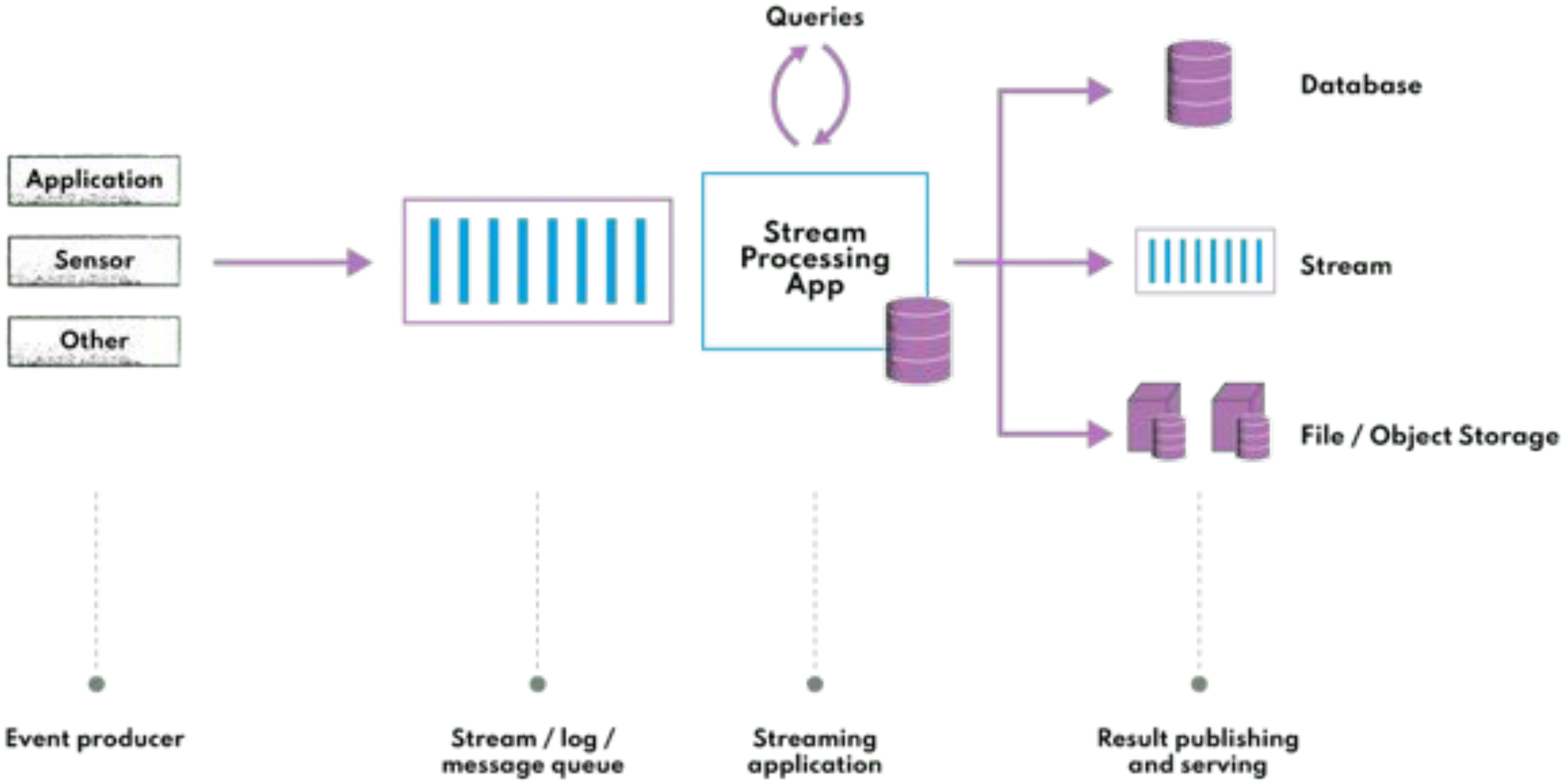


Spark Structured Streaming

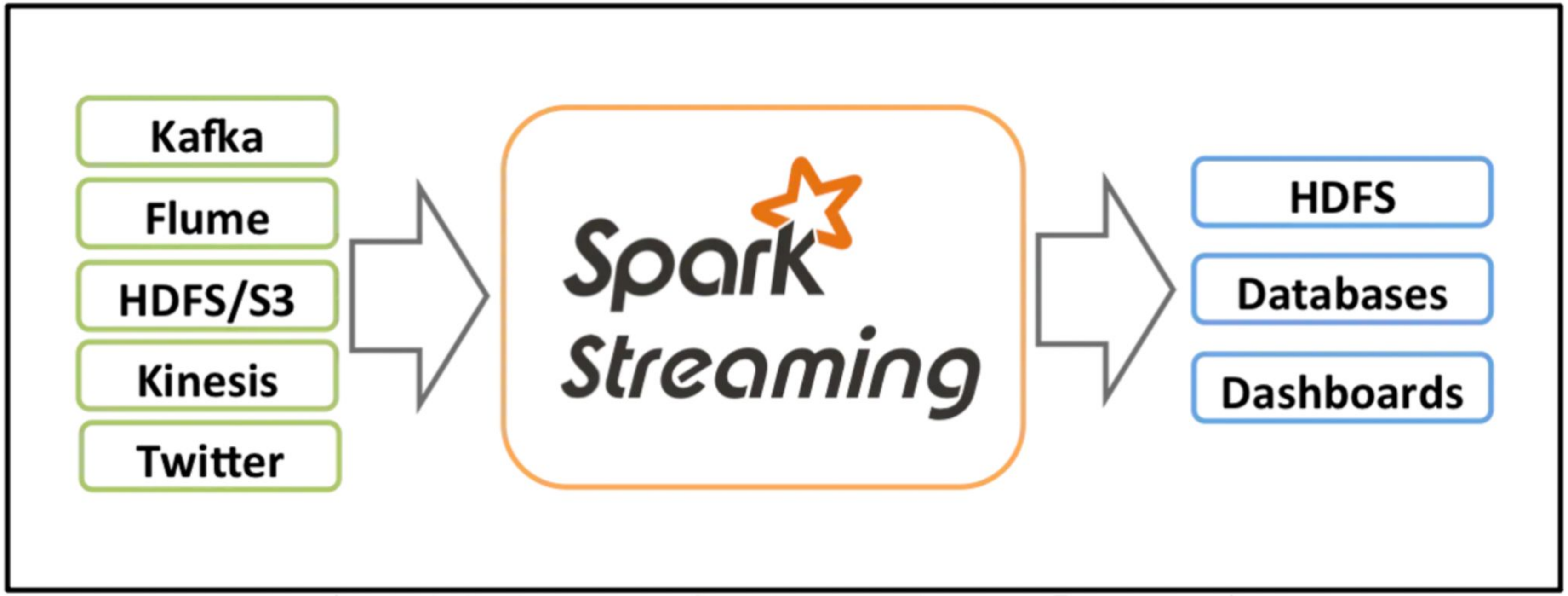
Apache Spark Structured Streaming is a scalable and fault-tolerant stream processing engine built on the Spark SQL engine. It allows you to express computations on streaming data in the same way you would express them on static data. The Spark SQL engine will take care of running it incrementally and continuously, and updating the final result as streaming data keeps arriving.

Here are some key features of Spark Structured Streaming:

- **Ease of Use:** The high-level APIs in the Scala, Java, Python, and R programming languages, and built-in support for structured data using Datasets and DataFrames, make it easy to build complex streaming analytics tasks.
- **Event Time Processing:** It supports event-time based processing, which means you can handle out-of-order or late data, and perform window-based operations based on the event-time.
- **Fault Tolerance**: It guarantees end-to-end exactly-once fault-tolerance through checkpointing and Write-Ahead Logs, which means any operation you perform on your streaming data will provide the same result even after a failure.
- **Integration**: It's fully integrated with Spark ecosystem components, like MLlib and Spark SQL, enabling powerful interactive analytics, machine learning model application, and more.
- **Multiple Data Sources and Sinks**: It can consume from and produce to multiple data sources like Kafka, Flume, Kinesis, or TCP sockets, and write outputs to file systems, databases, and live dashboards.
- **Backpressure Handling**: It can handle backpressure automatically, meaning it can slow down the data ingestion rate as needed.
- **Stateful Stream Processing**: It allows stateful stream processing with operations like ***mapGroupsWithState*** and ***flatMapGroupsWithState***, where you can maintain arbitrary state while continuously updating it with new information.

Spark Structured Streaming

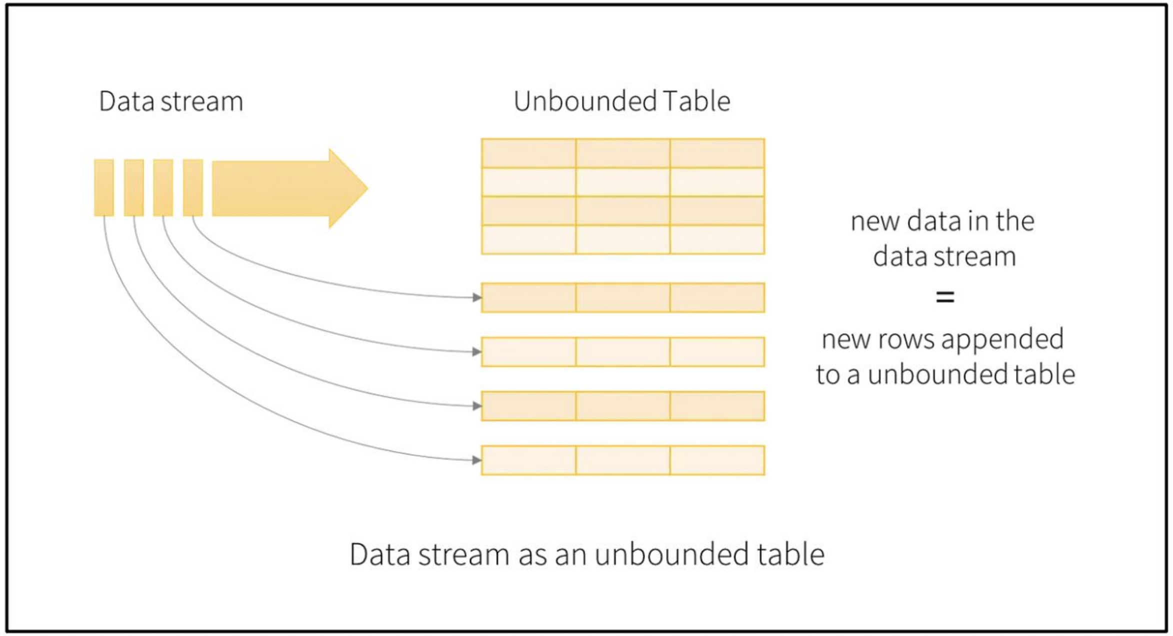
Spark Streaming has 3 major components: input sources, streaming engine, and sink. Input sources generate data like Kafka, Flume, HDFS/S3, etc. Spark Streaming engine processes incoming data from various input sources. Sinks store processed data from Spark Streaming engine like HDFS, relational databases, or NoSQL datastores.



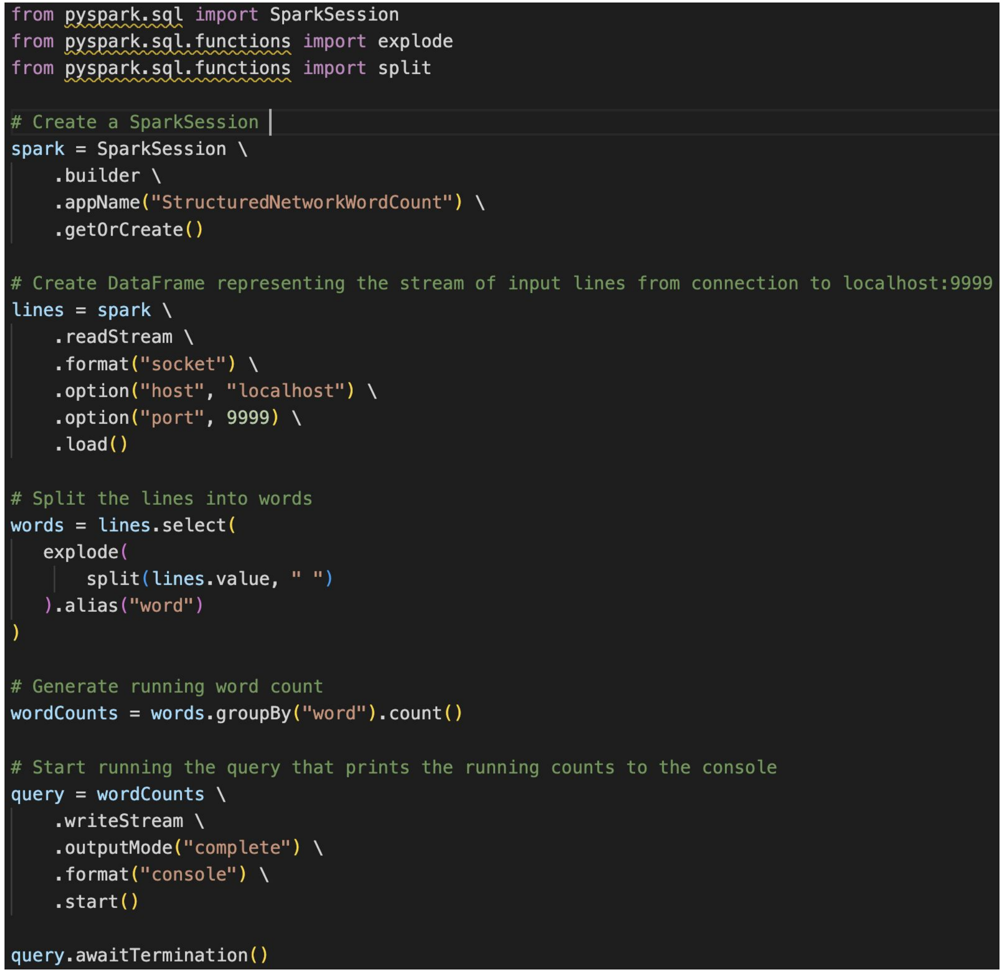
Spark Structured Streaming

Let’s conceptualise Spark Streaming data as an **unbounded table** where new data will always be appended at the end of the table.

Spark will process data in **micro-batches** which can be defined by **triggers**. For example, let's say we define a trigger as 1 second, this means Spark will create micro-batches every second and process them accordingly.


Data stream
Unbounded Table
new data in the data stream
=
new rows appended to a unbounded table
Data stream as an unbounded table

Word Count - Spark Structured Streaming



```python
from pyspark.sql import SparkSession
from pyspark.sql.functions import explode
from pyspark.sql.functions import split

# Create a SparkSession
spark = SparkSession \
    .builder \
    .appName("StructuredNetworkWordCount") \
    .getOrCreate()

# Create DataFrame representing the stream of input lines from connection to localhost:9999
lines = spark \
    .readStream \
    .format("socket") \
    .option("host", "localhost") \
    .option("port", 9999) \
    .load()

# Split the lines into words
words = lines.select(
   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()
```

Word Count - Spark Structured Streaming

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- A SparkSession is first created using SparkSession.builder.getOrCreate()
- Then a streaming DataFrame is created on the input data (in this case, a socket source is used which listens to localhost:9999).
- This DataFrame (lines) represents the unbounded table containing the streaming data. This table contains one column of strings (value), and each line in the streaming text data becomes a row in the table.
- Next, the split function splits each line into words, and the explode function is used to turn the array of words into a dataset of words.
- Finally, groupBy is called on this dataset to count the occurrences of each word.

When you start a streaming query, Spark will continually fetch data from the source into memory and append it to an "input table". Every trigger interval, a new batch of data is appended to the input table, as if you're adding more rows to a table in a database.

For a word count, Spark will recompute the counts each time new data arrives based on the aggregation query you've defined (i.e., groupBy("word").count() in the previous example). This computation generates a Result Table, and the current result is written out to the console (or any other sink you've defined).

Output Modes - Spark Structured Streaming

There are three output modes which define what will be written to the sink:

- **Complete Mode**: The entire updated Result Table will be written to the sink after every trigger. This is what we're doing in our word count example. This mode is applicable to aggregations where the result is expected to be small, such as counts.

- **Append Mode**: Only the new rows appended to the Result Table since the last trigger will be written to the sink. This is applicable when you have a Result Table that's growing incrementally, like a running total.

- **Update Mode**: Only the rows in the Result Table that were updated since the last trigger will be written to the sink.

let's consider a simple Structured Streaming job that reads data from a stream, performs some computation on it, and writes the result to some sink. The input data is a stream of numbers, and the computation is a running count of how many times each number has been seen.

Here's what the first few batches of input and output might look like:

Batch 1: Input: [1, 2, 2, 3, 3, 3]
Output (running count): [(1, 1), (2, 2), (3, 3)]

Batch 2: Input: [1, 2, 2, 4]
Output (running count): [(1, 2), (2, 4), (3, 3), (4, 1)]

Output Modes - Spark Structured Streaming

And here's how each output mode would handle these batches:

- **Complete Mode:** In complete mode, the entire updated Result Table is written to the sink after every trigger. This means that after batch 1, the output would be **[(1, 1), (2, 2), (3, 3)]**, and after batch 2, the output would be **[(1, 2), (2, 4), (3, 3), (4, 1)]**.

- **Append Mode**: In append mode, only the new rows appended in the Result Table since the last trigger will be written to the sink. After batch 1, the output would be **[(1, 1), (2, 2), (3, 3)]** (same as complete mode, since all these rows are new). However, after batch 2, the output would just be **[(4, 1)]**, because that's the only completely new row. Append mode wouldn't output the updated counts for 1 and 2 because those aren't new rows, they're existing rows that have been updated.

- **Update Mode**: In update mode, only the rows in the Result Table that were updated since the last trigger will be written to the sink. So after batch 1, the output would be **[(1, 1), (2, 2), (3, 3)]**. After batch 2, the output would be **[(1, 2), (2, 4), (4, 1)]** - it includes the updated counts for 1 and 2, as well as the new row for 4, but not the unchanged count for 3.

So in summary:

- **Complete** mode gives you the entire Result Table every time. It's like taking a complete snapshot of your computation's current state after every batch.

- **Append** mode only gives you completely new rows. It's suitable for when your Result Table is effectively growing over time with new data, such as when you're just adding new rows and not updating existing ones.

- **Update** mode gives you any rows that are new or have been updated. It's a middle ground between complete and append mode, giving you a view of what's changed in your Result Table since the last batch.

If we are calling it as a unbounded table then at which stage it will cause memory issue?

And here's how each output mode would handle these batches:

While Spark Structured Streaming conceptualizes the stream as an "unbounded table", it doesn't literally store all the data of the stream in memory indefinitely. This is because doing so would indeed lead to memory issues over time, especially for long-running streams with a lot of data.

The way Spark Structured Streaming handles this issue depends on the type of operations being performed on the stream:

- **Stateless operations**: For stateless operations (like mapping and filtering), where the processing of each record is independent of the processing of other records, Spark doesn't need to keep any old data around. Once it has processed a piece of data, it can free up the memory that data was occupying.

- **Stateful operations**: For stateful operations (like aggregations and windowed computations), where the processing of some records depends on the processing of other records, Spark uses a combination of techniques to manage memory:

    - **Incremental updates**: For many stateful operations, Spark can update the state incrementally as new data arrives, without needing to keep all past raw data. For example, for a word count, it can just maintain a running count for each word, updating the counts as new data comes in.

    - **Watermarking**: For windowed computations and handling late data, Spark uses a technique called watermarking to limit how much old data it needs to remember. The watermark is a threshold in event-time, and any data older than this threshold is considered "too late" and is dropped.

    - **State expiration**: For arbitrary stateful operations, Spark allows you to specify a time-to-live for the state data. Any state data that has not been updated for this length of time will be cleared.

What if memory is full due to state maintenance after Aggregation function ?

- **Scaling horizontally**: You can add more worker nodes to your Spark cluster, increasing the total memory available for state maintenance.

- **State Expiration**: If your use case allows it, you can define a timeout after which the state for old keys will be removed. This can be done using the mapGroupsWithState operation in Structured Streaming, which allows you to define a timeout for the state.

- **Aggregations**: For certain types of queries, you can make use of built-in aggregations that maintain a small state, like counts, sums, or averages. You can also use approximate data structures (like HyperLogLog for unique count, or t-digest for median) that give you an approximate result but use fixed memory.

- **State Store Compression:** Spark also supports compressing the stored data, which can help to reduce memory footprint. You can enable this by setting the configuration spark.sql.streaming.stateStore.compression.codec to a valid compression codec, such as lz4, lzf, snappy, zstd, or none.

- **Increase memory overcommit**: Overcommit is a scenario where the operating system allows more memory to be allocated to processes than the physical memory actually available. By increasing memory overcommit, you can use more memory for Spark tasks, but be careful as it may cause out-of-memory errors.

- **Checkpointing**: You can enable checkpointing in order to periodically save the state of a stream. However, this does not directly solve the memory issue, but it does provide fault tolerance so that if your job fails due to memory problems or any other reason, it can be restarted from the checkpoint.

- **Optimize for Network Traffic**: If your task generates a large amount of network traffic (which can also consume significant memory), you might consider decreasing the batch interval, or repartitioning your data.

DStreams vs Spark Structured Streaming

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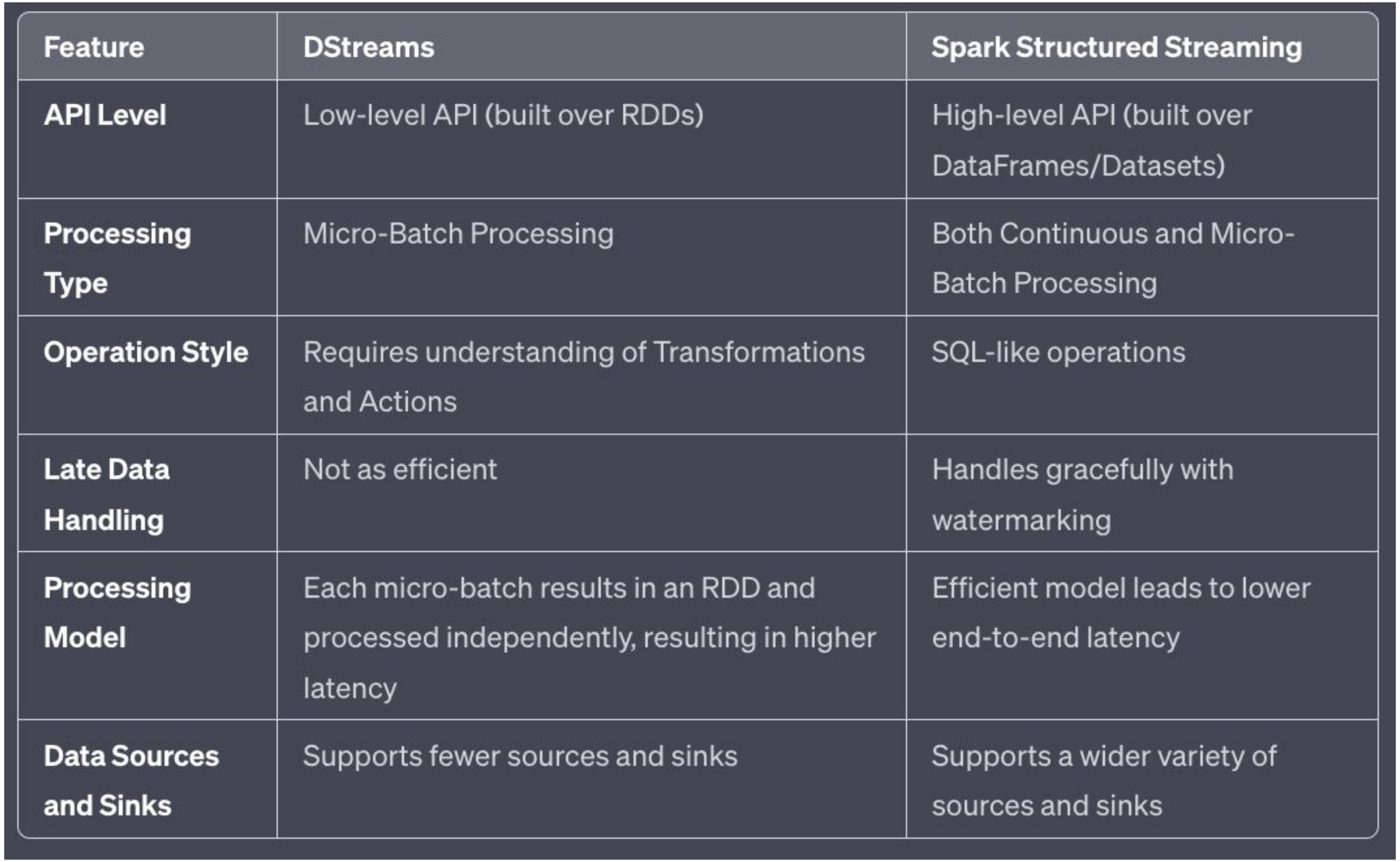

Feature	DStreams	Spark Structured Streaming
API Level	Low-level API (built over RDDs)	High-level API (built over DataFrames/Datasets)
Processing Type	Micro-Batch Processing	Both Continuous and Micro-Batch Processing
Operation Style	Requires understanding of Transformations and Actions	SQL-like operations
Late Data Handling	Not as efficient	Handles gracefully with watermarking
Processing Model	Each micro-batch results in an RDD and processed independently, resulting in higher latency	Efficient model leads to lower end-to-end latency
Data Sources and Sinks	Supports fewer sources and sinks	Supports a wider variety of sources and sinks

File Source - Spark Structured Streaming

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File1.json

```
{"userId": "user1", "timestamp": "2023-07-23T00:00:00Z"}
{"userId": "user2", "timestamp": "2023-07-23T00:01:00Z"}
```

File2.json

```
{"userId": "user1", "timestamp": "2023-07-23T00:02:00Z"}
{"userId": "user3", "timestamp": "2023-07-23T00:03:00Z"}
```

We can use Structured Streaming in Spark to process files as they arrive in a directory. We'll use the **readStream** method to **monitor** a directory for new files. It does not process the files that were present in the directory before the streaming computation started.

This is different from batch processing, where you might use the **read** method to process all files present in a directory at once.

Keep in mind that **"new files"** means files that are newly added to the directory. Files that are already present when the streaming computation starts, or files that are simply modified after the streaming computation has started, will not be processed. It is recommended to move or copy atomic files into the directory to avoid Spark picking up incomplete files.

We can configure **spark.sql.streaming.schemaInference** property to get the source schema during run time itself.

File Source - Spark Structured Streaming

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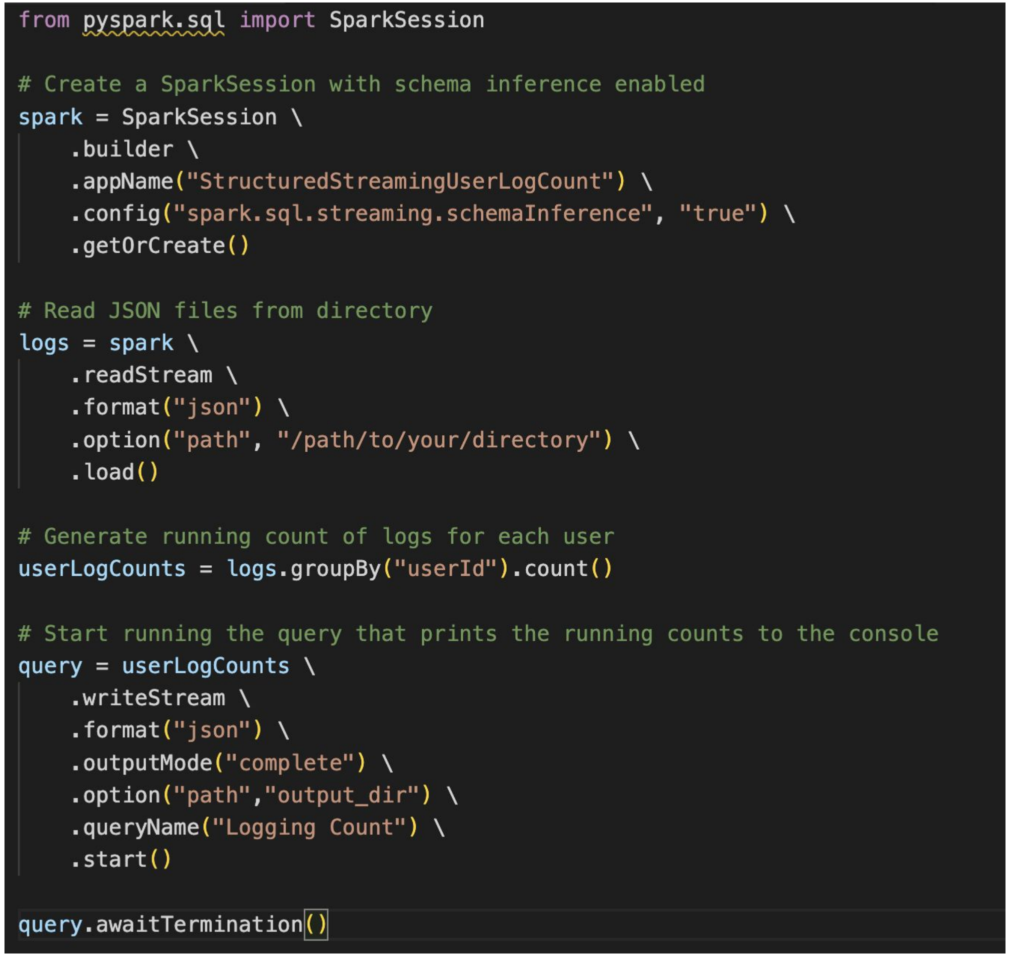

```
from pyspark.sql import SparkSession

# Create a SparkSession with schema inference enabled
spark = SparkSession \
    .builder \
    .appName("StructuredStreamingUserLogCount") \
    .config("spark.sql.streaming.schemaInference", "true") \
    .getOrCreate()

# Read JSON files from directory
logs = spark \
    .readStream \
    .format("json") \
    .option("path", "/path/to/your/directory") \
    .load()

# Generate running count of logs for each user
userLogCounts = logs.groupBy("userId").count()

# Start running the query that prints the running counts to the console
query = userLogCounts \
    .writeStream \
    .format("json") \
    .outputMode("complete") \
    .option("path","output_dir") \
    .queryName("Logging Count") \
    .start()

query.awaitTermination()
```

Triggers - Spark Structured Streaming

In Spark Structured Streaming, a trigger determines when the system should check for new data and process it. By default, it's set to process the data as soon as the system has completed processing the last batch of data, but you can set it to a fixed time interval or to only process one batch of data and then stop.

Here are three types of triggers:

- **Default Trigger (Processing Time):** If no trigger setting is explicitly specified, the system will check for new data as soon as it finishes processing the last batch. This is called "micro-batch" processing. If the system is idle (i.e., there is no new data to process), it will just wait until new data arrives.

- **Fixed Interval Micro-Batches**: The system will check for new data at a fixed interval, regardless of whether the system has finished processing the last batch of data.

- **One-Time Micro-Batch:** The system will process one batch of data and then stop. This is useful for testing and debugging.

Triggers - Spark Structured Streaming

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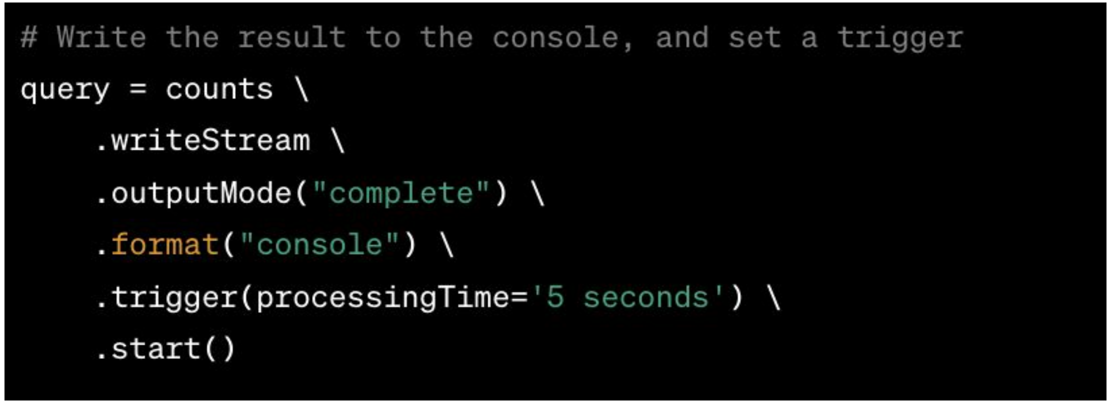
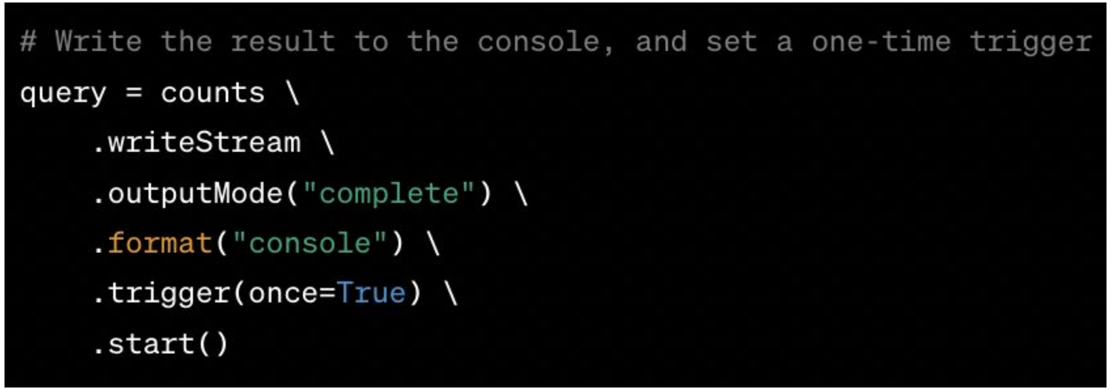


```
# Write the result to the console, and set a trigger
query = counts \
    .writeStream \
    .outputMode("complete") \
    .format("console") \
    .trigger(processingTime='5 seconds') \
    .start()
```



```
# Write the result to the console, and set a one-time trigger
query = counts \
    .writeStream \
    .outputMode("complete") \
    .format("console") \
    .trigger(once=True) \
    .start()
```

In a Spark cluster, an operation like aggregation is distributed across multiple nodes, with each node processing a part of the data. But how does Spark ensure that the previous state is considered in an operation like aggregation, given that the data is scattered across different nodes?

In the case of operations like **reduce** or **groupByKey**, Spark shuffles the data so that all values associated with a single key end up on the same node. This shuffling of data is an expensive operation in terms of network I/O, but it's necessary to perform operations that require knowledge of the entire dataset.

For example, in case of aggregating counts for a word stream, Spark would distribute the task of counting words in each batch across different nodes. The nodes would each maintain a local count for the words. Spark would then shuffle the data so that the final count for each word from all the nodes is aggregated on a single node.

To make this work, you generally need to ensure that you have partitioned your data in a way that allows it to be evenly distributed across the nodes and that there is sufficient memory to hold the shuffled data. If the state grows too large to fit in memory, you may need to increase the memory allocated to Spark or adjust your application to reduce its memory usage.

Checkpointing - Fault Tolerance

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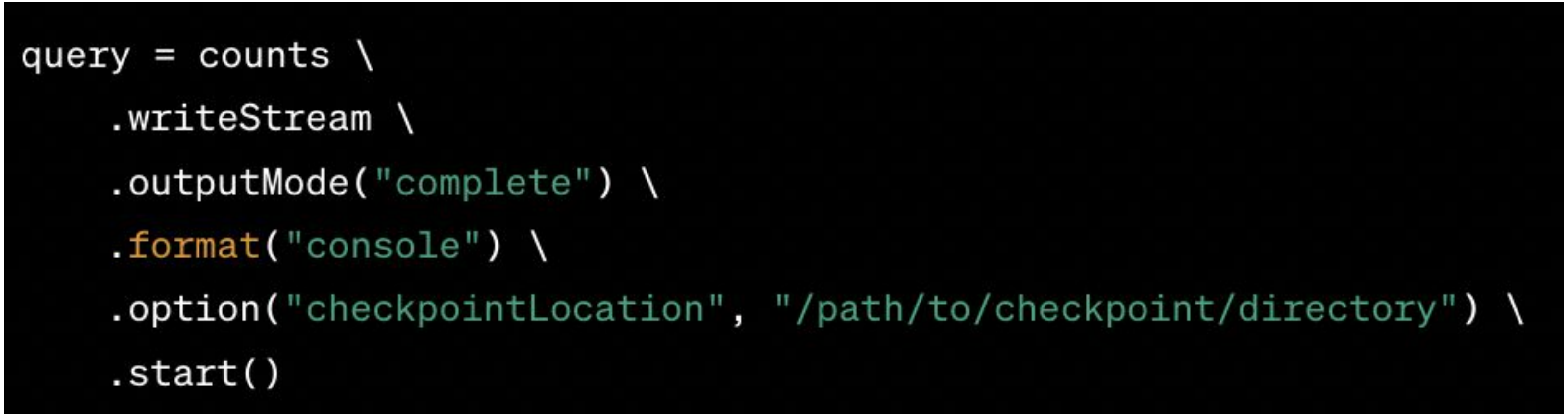
Checkpointing in Spark Structured Streaming is a mechanism that periodically persists metadata about the streaming query to a fault-tolerant storage system, like HDFS, Amazon S3, etc. This is crucial in case of failure recovery, i.e., to ensure that the streaming processing can continue where it left off, providing resilience in the face of failures.

The checkpoint data includes:

- **Metadata** - Configuration, StreamingQuery id, etc.
- **Offset** - The point till where the data has been read and processed.
- **State data** - In case of stateful operations, like window or mapGroupsWithState.

To configure checkpointing, you can specify the checkpoint directory path when you start a streaming query. Here's how you can do it:



```
query = counts \
    .writeStream \
    .outputMode("complete") \
    .format("console") \
    .option("checkpointLocation", "/path/to/checkpoint/directory") \
    .start()
```

Exactly once in Structured Streaming

The **exactly-once** processing semantics in Spark Structured Streaming means that each record will affect the final results exactly once, even in the case of failures. This is a crucial property for many applications, to ensure accurate results.

To achieve this, Spark Structured Streaming uses the following mechanisms:

- **Fault-tolerance through Checkpointing**: As mentioned above, Spark periodically saves the progress information to the checkpoint directory. If a query is restarted after a failure, it will start processing from the saved offset in the checkpoint directory, thus no data will be missed.

- **Source semantics**: The source must either be replayable or acknowledgeable. Replayable sources can replay data if needed, while acknowledgeable sources acknowledge data after it is processed, so it won't deliver the same data twice.

- **Sink Idempotency**: The sink, where the output is written, should be idempotent for exactly-once semantics, i.e., rerunning the same results will not change the output data. **For example**, overwriting a file in the file sink or upserting a row in the database. To achieve exactly-once in Kafka type of sinks is complicated.

Stateless vs Stateful Transformations

<u>Stateless Transformations</u>

Stateless transformations are those where each batch is processed independently and the processing of a batch does not depend on the data in other batches. The processing engine does not need to remember any data across batches for these transformations.

Examples of stateless transformations include:

Select: Extracting a subset of columns from the data.

```
df = streaming_df.select("name", "age")
```

Filter: Filtering data based on some condition.

```
df = streaming_df.filter(streaming_df.age > 21)
```

Stateless vs Stateful Transformations

Stateful Transformations

Stateful transformations are those where the processing of a batch might depend on the data in other batches, meaning the processing engine needs to remember data across batches.

Examples of stateful transformations include:

Aggregation: Like calculating the count, sum, average, etc. Aggregations on streaming data are a series of consecutive windowed aggregations. The result of an aggregation operation changes as new data is added over time.

```
from pyspark.sql.functions import count
df = streaming_df.groupBy("name").count()
```

Arbitrary stateful processing: **mapGroupsWithState** and **flatMapGroupsWithState** allow you to define your own stateful processing logic. This could involve maintaining a complex state, updating it based on new data, and defining a timeout condition to remove old state.

```
def update_func(key, values, state):
    # define your stateful processing logic here
    pass

df = streaming_df.groupByKey(lambda row: row.key).mapGroupsWithState(update_func)
```

How groupBy and mapGroupsWithState are different?

In the context of Spark Structured Streaming, the **groupBy** operation followed by aggregations like **count()** or **sum()** does involve maintaining some state across batches. This is necessary for providing updated results that take into account data from both the current and previous batches.

These operations **don't allow** the developer to **manually define or manage** the state that's kept between batches, like **mapGroupsWithState** or **flatMapGroupsWithState** do. These latter functions give you the ability to define an **arbitrary** state, update it based on new data, and also define a timeout condition to remove old state.

In contrast, with groupBy followed by count() or sum(), Spark automatically manages the state, which in this case is the count or sum of values, and you as a developer don't have the control to define the state or update it based on your own logic.

Windowing

Windowing is a mechanism to divide the data into time windows so that you can apply transformations on those windows. This allows you to perform operations on data that fell into a specific time frame.

In Spark Structured Streaming, windows are defined by two values, the **window size** and **slide duration**. Window size defines the length of the window, and slide duration determines how frequently new windowed data should be computed.

Here's an example of using window operations in Spark Structured Streaming:

```
from pyspark.sql.functions import window

          # Calculate the average sensor reading every 1 minute, based on event time
          df = df.groupBy(
              window(df.event_time, "1 minute")
          ).avg("reading")
```

In this example, window is a function that automatically groups data into windows of 1 minute, based on the event time. Then, for each window, we calculate the average sensor reading.

One thing to remember is that in order to use **event-time** based windowing, you need to have a **column** in your DataFrame that represents the event time, which can be parsed from the data itself.

Windowing

For example, if we have a 1-minute window that starts at 10:00:00 and ends at 10:01:00, then all records with an event time that falls within that time frame (i.e., >=10:00:00 and <10:01:00) will be included in that window.

To illustrate, let's assume you have the following streaming data:

time	value
10:00:05	1
10:00:15	2
10:00:45	3
10:01:05	4
10:01:25	5
10:01:55	6

If you define a 1-minute window starting at 10:00:00, it will contain the first three records (with times 10:00:05, 10:00:15, and 10:00:45), and a window starting at 10:01:00 will contain the last three records (with times 10:01:05, 10:01:25, and 10:01:55).

Sliding Windowing

In Spark Structured Streaming, the window slide duration determines how often the window operation is performed, i.e., how frequently a new set of data is processed.

If you specify a 1-minute window with a 1-minute slide (which is the default), then a new window will be generated every minute. This means that every minute, the system will look back over the previous minute of data and perform the window operation on that data.

Here's an example:

```
from pyspark.sql.functions import window

# Calculate the sum of "value" for each 1-minute window, sliding every 1 minute
df = df.groupBy(
    window(df.time, "1 minute", "1 minute")
).sum("value")
```

In this case, a new window starts every minute, so you will get separate windows for the data from 10:00 to 10:01, from 10:01 to 10:02, from 10:02 to 10:03, and so on.

Sliding Windowing

However, you can also specify a slide duration that's different from the window duration. For example:

```
from pyspark.sql.functions import window

    # Calculate the sum of "value" for each 2-minute window, sliding every 1 minute
    df = df.groupBy(
        window(df.time, "2 minutes", "1 minute")
    ).sum("value")
```

In this case, a new window starts every minute, but each window covers 2 minutes of data. So you will get overlapping windows: one for the data from 10:00 to 10:02, another for the data from 10:01 to 10:03, and so on.

Note that when you specify a slide duration, the system will perform the window operation at the frequency specified by the slide duration, not for each incoming record. If no slide duration is specified, it defaults to the window duration, which means a new window is generated for every duration of time specified by the window size.

When and Why we should use Windowing?

There are several situations where you might want to use windowing:

- **Aggregating Data over Time**: When you want to aggregate data over certain time intervals, windowing can be very useful. For example, you might want to calculate the total number of transactions per hour, or find the maximum temperature per day from a stream of weather data.

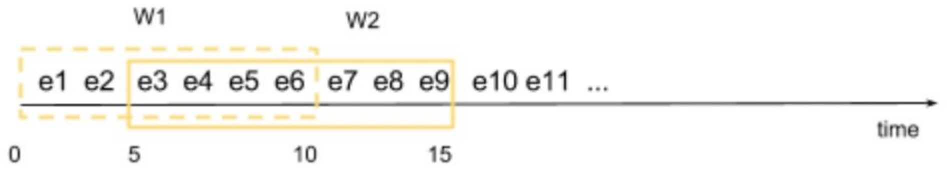
- **Detecting Trends**: If you're interested in detecting trends or patterns over time, you would use windowing. This can help you observe how your data changes over time. For instance, you might want to track how many times a particular error occurs in your application logs every 15 minutes.

- **Handling Late Data:** In real-world streaming applications, it's not uncommon for data to arrive late due to network issues or other delays. Windowing, especially when combined with watermarking (a feature that allows you to specify how late the data can be), can help handle late data and still produce accurate results.

- **Resource Efficiency**: By focusing computation on a specific window of data, you can reduce the amount of memory and computation resources needed compared to processing the entire stream.

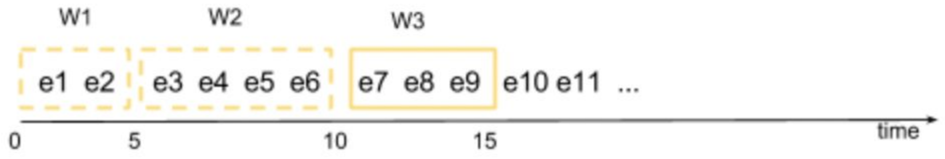
Tumbling window vs Sliding window

- **Sliding Windows:** Sliding windows, on the other hand, can overlap. The "slide interval" of a sliding window determines how frequently a new window is created. If the slide interval is less than the window duration, you end up with overlapping windows. For instance, if you have a window duration of 1 minute and a slide interval of 30 seconds, you would get windows like 10:00-10:01, 10:00:30-10:01:30, 10:01-10:02, 10:01:30-10:02:30, and so on. Each event can belong to multiple windows, depending on when it occurs.



- **Tumbling Windows**: In tumbling windows, also known as hopping or fixed windows, each record in the stream belongs to exactly one window. These windows do not overlap and are mutually exclusive. This means if you have a tumbling window of 1 minute, you would get windows like 10:00-10:01, 10:01-10:02, 10:02-10:03, and so on. Each event belongs to exactly one of these windows.

  The concept of a tumbling window is represented by setting the **window duration equal to the slide duration**. That's because tumbling windows are a series of fixed, non-overlapping time intervals.


W1
W2
W3
e1 e2 e3 e4 e5 e6 e7 e8 e9 e10 e11 ...
time
0
5
10
15