Agenda

- Introduction on Stream Processing Models [done]
- Declarative Language: Opportunities, and Design Principles [done]
- Comparison of Prominent Streaming SQL Dialects for Big Stream Processing Systems
- Conclusion

Our Focus

- Prominent Big Stream Processing Engines that offer a declarative SQL-like interface.
 - Flink,
 - Spark Structured Streaming, and
 - Kafka SQL (KSQL)

Flink SQL

- Available since version 1.3, it builds on Flink Table API (LINQ-style API)
- Uses Apache Calcite of parsing, interpreting and planning, while execution relies on FLINK Runtime.
- Relevant concepts: windows as group-by function, temporal tables, match-recognize (not today)

Spark Structured Streaming

- Available since Spark 2.0, it extends Dataframe and Datasets to Streaming Datasets
- SQL-like programming interface that relies on Catalyst for optimization
- Relevant Concepts: Complete, Append, and Update modes/

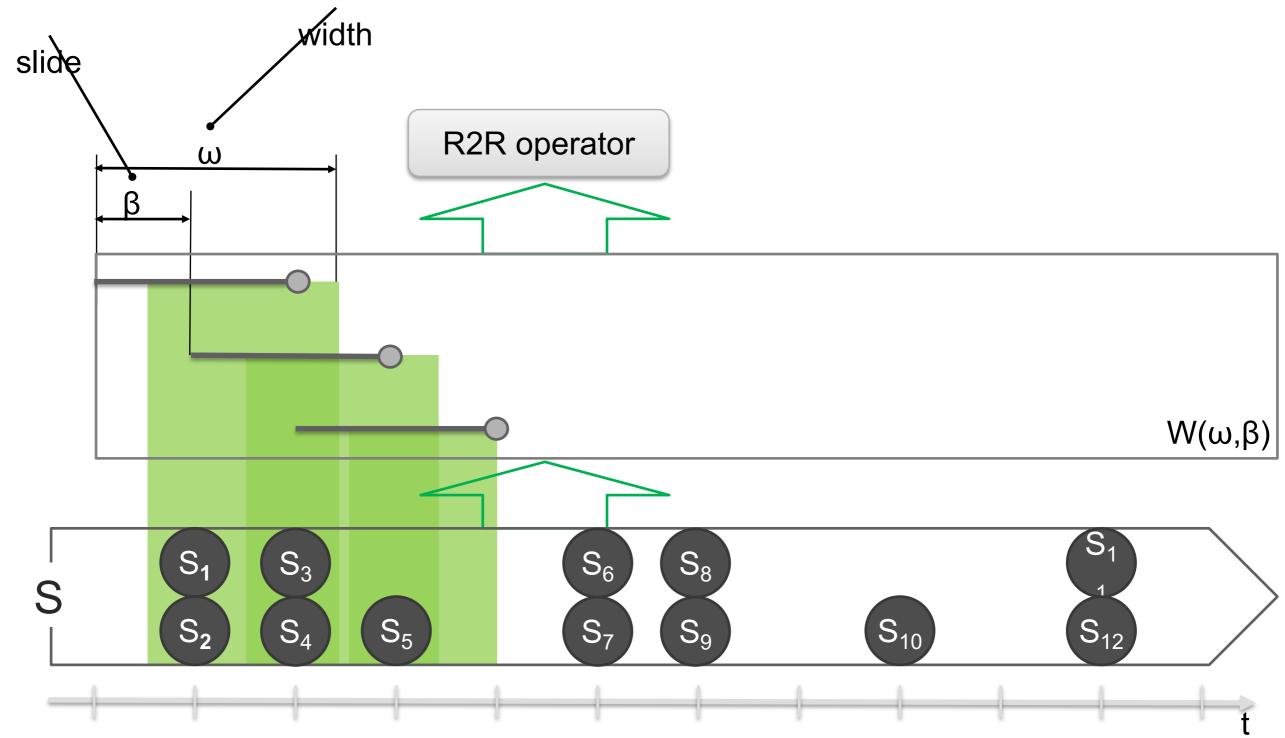
Kafka SQL (KSQL)

- Available since Kafka 1.9/2 (or confluent platform 5)
- builds directly on top of KStreams Library
- Relevant Concepts: simplicity is the key, relation (compacted) topic vs table/stream

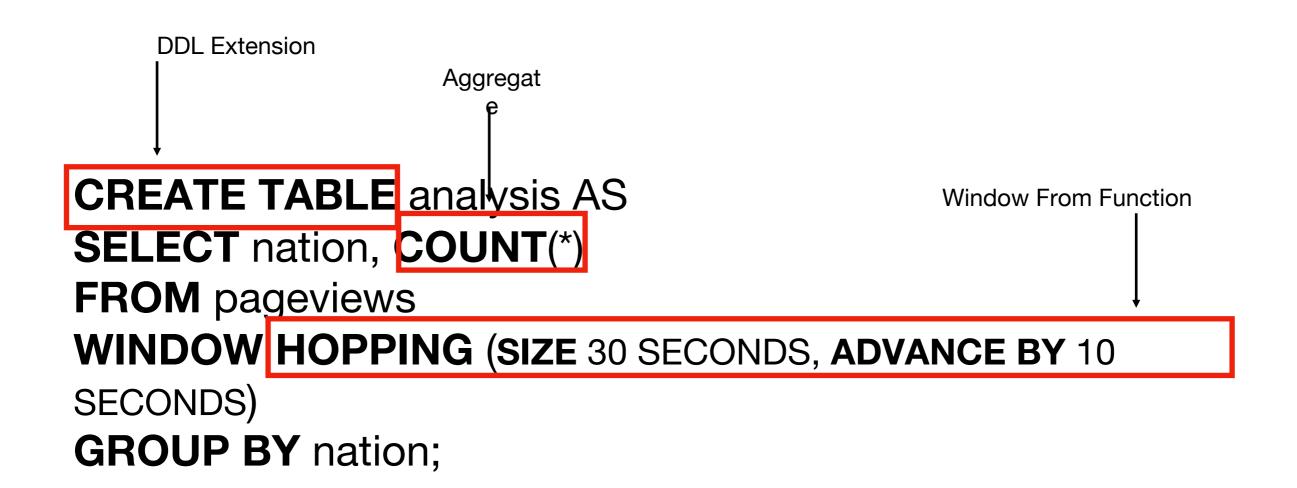
Time-Window Operators & Aggregates

- Sliding Window
- Tumbling Window
- Session Window
- Aggregations: COUNT, SUM, AVG, MEAN, MAX, MIX

Sliding/Hopping Window



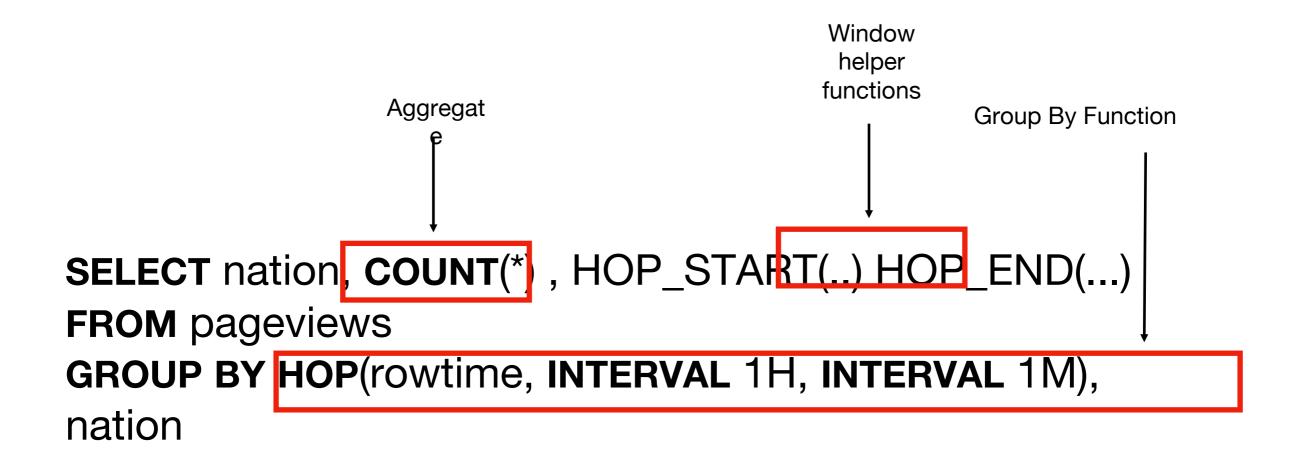
KSQL Hopping Window



Results

SELECT * **FROM** analysis

Flink SQL Hopping Window



Results

```
1> (Egypt,2019-06-24 11:38:00.0,2019-06-24 11:38:01.0,1)
1> (Egypt,2019-06-24 11:39:00.0,2019-06-24 11:39:01.0,1)
1> (Egypt,2019-06-24 11:40:00.0,2019-06-24 11:40:01.0,1)
1> (Egypt,2019-06-24 11:41:00.0,2019-06-24 11:41:01.0,1)
2> (Italy,2019-06-24 11:42:00.0,2019-06-24 11:42:01.0,1)
2> (Italy,2019-06-24 11:43:00.0,2019-06-24 11:43:01.0,1)
2> (Italy,2019-06-24 11:44:00.0,2019-06-24 11:45:01.0,1)
2> (Italy,2019-06-24 11:45:00.0,2019-06-24 11:45:01.0,1)
2> (Italy,2019-06-24 11:46:00.0,2019-06-24 11:46:01.0,1)
2> (Italy,2019-06-24 11:47:00.0,2019-06-24 11:47:01.0,1)
2> (Italy,2019-06-24 11:48:00.0,2019-06-24 11:48:01.0,1)
3> (Estonia,2019-06-24 11:49:00.0,2019-06-24 11:49:01.0,1)
```

. . .

Spark Structured Streaming Hopping Window

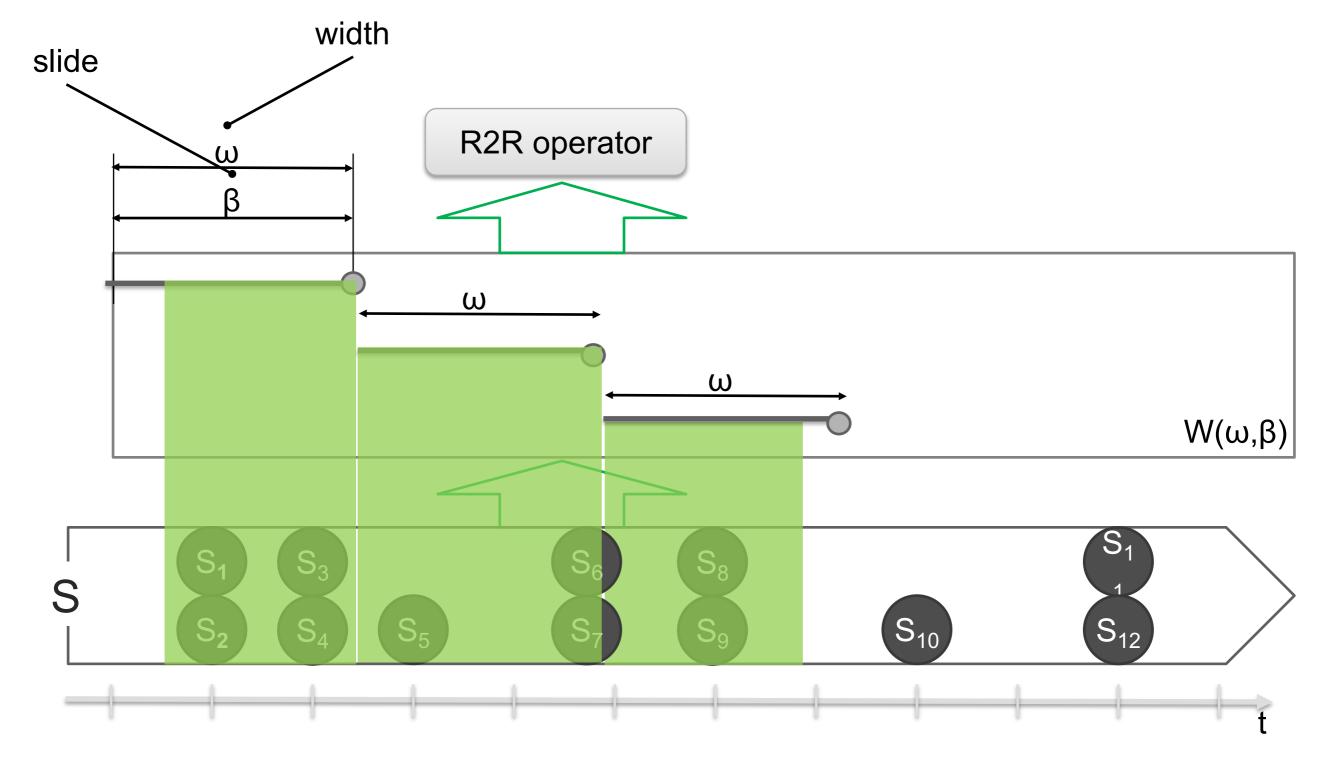
```
val df = pageviews
.groupBy(
```

window(\$"timestamp", "1 hour", "1 minute"), \$"nation") count()

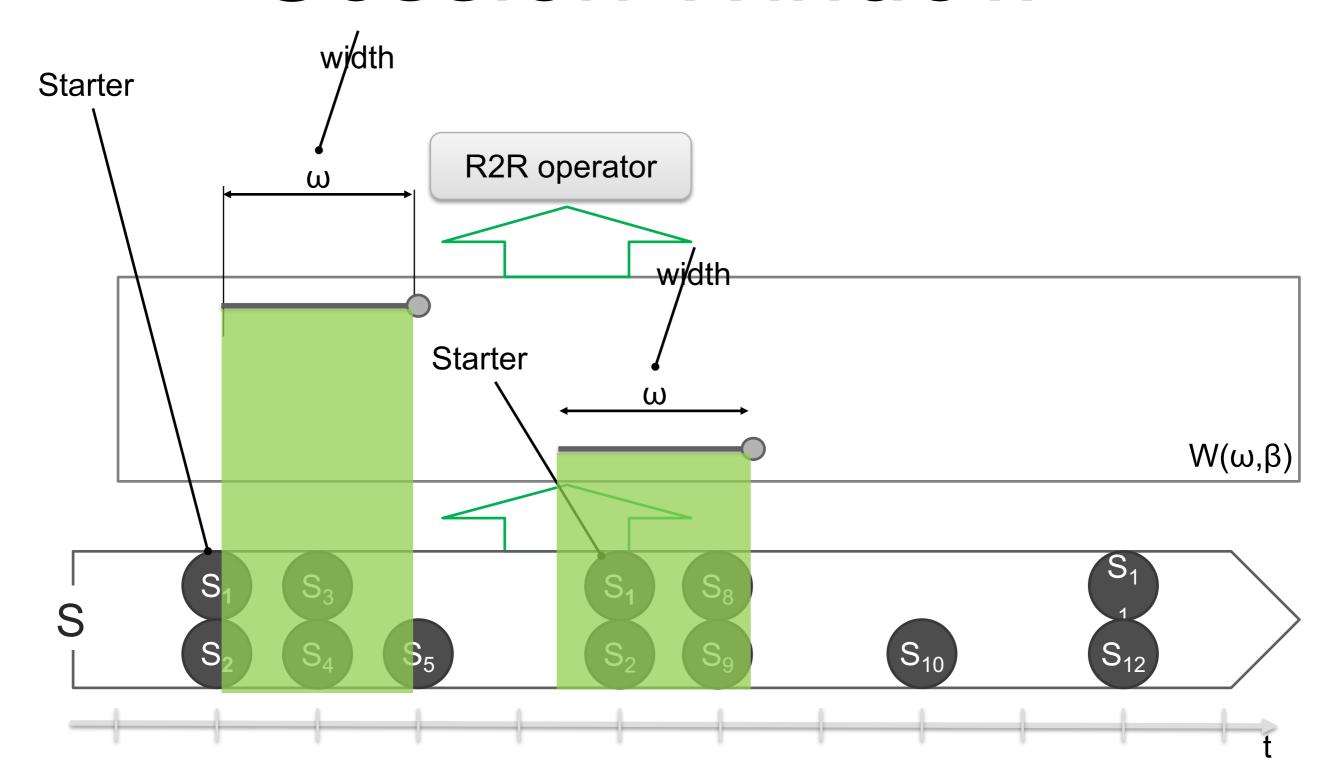
Aggregat

Window operator

Tumbling Window



Session Window



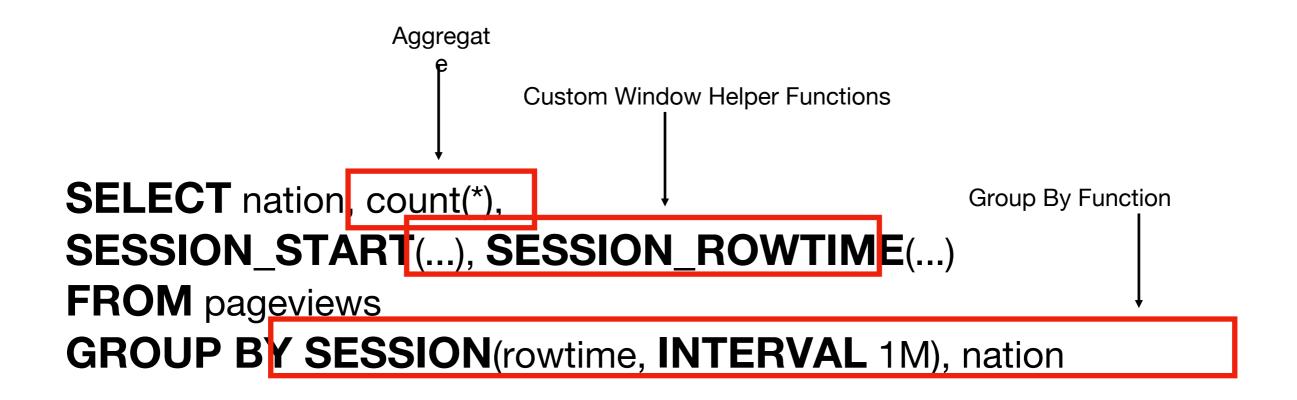
KSQL Session

```
DDL Extension
                Aggregat
CREATE TABLE analysis AS
SELECT nation, COUNT (*),
TIMESTAMPTOSTRING(windowstart(), 'yyyy-MM-dd
HH:mm:ss') AS window_start_ts,
                              Window From Function
TIMESTAMPTOSTRING(windowend(), 'yyyyy-MM-dd
HH:mm:ss') AS window_end_ts
FROM pageviews WINDOW SESSION (1 MINUTE)
GROUP BY nation;
```

Results

```
Page_82 | 2019-06-24 11:47:45 | 2019-06-24 11:47:45 | 1
Page_73 | 2019-06-24 11:47:46 | 2019-06-24 11:47:46 | 1
Page_16 | 2019-06-24 11:47:49 | 2019-06-24 11:47:49 | 1
Page_54 | 2019-06-24 11:47:25 | 2019-06-24 11:47:53 | 2
Page_68 | 2019-06-24 11:47:55 | 2019-06-24 11:47:55 | 1
Page_25 | 2019-06-24 11:47:40 | 2019-06-24 11:47:58 | 2
Page_17 | 2019-06-24 11:47:59 | 2019-06-24 11:47:59 | 1
Page_92 | 2019-06-24 11:48:02 | 2019-06-24 11:48:02 | 1
Page_83 | 2019-06-24 11:48:05 | 2019-06-24 11:48:05 | 1
Page_86 | 2019-06-24 11:48:07 | 2019-06-24 11:48:07 | 1
```

Flink SQL Session



Results

```
3> (Estonia,1,2019-06-24 11:52:55.538,2019-06-24 11:52:56.538,2019-06-24 11:52:56.537)
2> (Italy,1,2019-06-24 11:52:56.132,2019-06-24 11:52:57.132,2019-06-24 11:52:57.131)
1> (Egypt,1,2019-06-24 11:52:56.633,2019-06-24 11:52:57.633,2019-06-24 11:52:57.632)
3> (Estonia,1,2019-06-24 11:52:57.136,2019-06-24 11:52:58.136,2019-06-24 11:52:58.135)
2> (Italy,1,2019-06-24 11:52:57.64,2019-06-24 11:52:58.64,2019-06-24 11:52:58.639)
1> (Egypt,1,2019-06-24 11:52:58.643,2019-06-24 11:52:59.141,2019-06-24 11:52:59.14)
3> (Estonia,1,2019-06-24 11:52:59.147,2019-06-24 11:53:00.147,2019-06-24 11:53:00.146)
1> (Egypt,1,2019-06-24 11:52:59.648,2019-06-24 11:53:00.648,2019-06-24 11:53:00.647)
3> (Estonia,1,2019-06-24 11:53:00.152,2019-06-24 11:53:01.152,2019-06-24 11:53:01.151)
2> (Italy,1,2019-06-24 11:53:00.653,2019-06-24 11:53:01.653,2019-06-24 11:53:01.652)
```

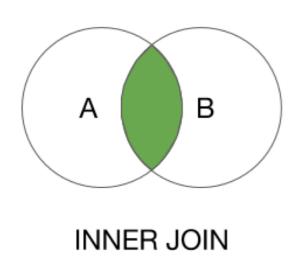
1> (Egypt, 1, 2019-06-24 11:53:01.158, 2019-06-24 11:53:02.158, 2019-06-24 11:53:02.157)

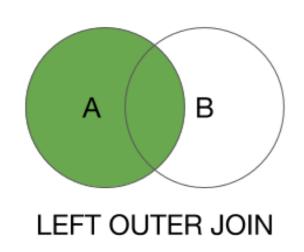
Recap

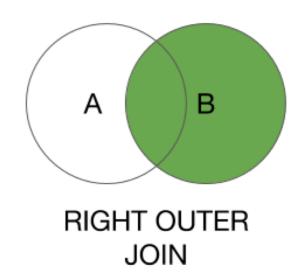
| | Landmark | Tumble | Hop | Session | Aggregates |
|-----------|----------|--------------|--------------|---------|--------------|
| KSQL | implicit | ✓ | ✓ | ✓ | Standard SQL |
| Flink SQL | implicit | \checkmark | \checkmark | ✓ | Standard SQL |
| SSS | implicit | ✓ | X | X | Standard SQL |

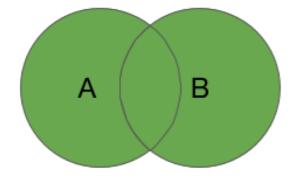
Table 1: Time-Based Window Operators and aggregates across different systems.

Recap on RA JOINS

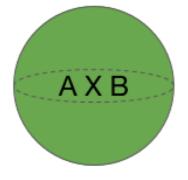










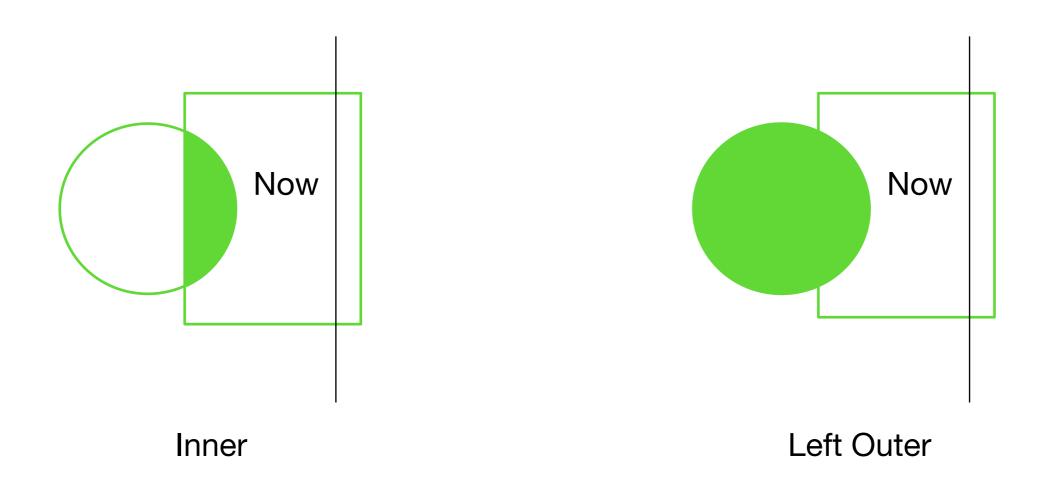


CARTESIAN (CROSS) JOIN

Stream-Table Joins

- Inner Joins
- Left-Outer Join
- Right-Outer Join
- Full-Outer Join

Stream-Table Joins



KSQL Left-Join

```
CREATE STREAM SENSOR_ENRICHED AS
SELECT S.SENSOR_ID, S.READING_VALUE, I.ITEM_ID
FROM SENSOR_READINGS S
LEFT JOIN ITEMS_IN_PRODUCTION I ON
S.LINE_ID=I.LINE_ID;
```

Flink SQL LEFT-JOIN

```
SELECT S.SENSOR_ID, S.READING_VALUE, I.ITEM_ID FROM SENSOR_READINGS S LEFT JOIN ITEMS_IN_PRODUCTION I ON S.LINE_ID=I.LINE_ID;
```

Results

```
4> (true,0,10.12666825646483,0)
4> (true,0,10.96399203326454,0)
1> (true,2,10.874856720766067,2)
4> (true,0,10.268731915130621,0)
1> (true,2,10.786008348182463,2)
4> (true,1,10.360322470661394,1)
4> (true,0,10.809087822653261,0)
4> (true,1,10.238883138171406,1)
1> (true,2,10.776781799073452,2)
4> (true,1,10.528528144000497,1)
4> (true,0,10.532966430120872,0)
4> (true,1,10.449756056124912,1)
```

4> (true,1,10.66021657541424,1)

Spark Structured Streaming LEFT-JOIN

val itemsInProduction = spark.read. ...

val sensorReadings = spark.readStream. ...

val enrichedSensorReadings = sensorReadings.join(itemsInProduction, "LINE_ID", "left-join")

Recap

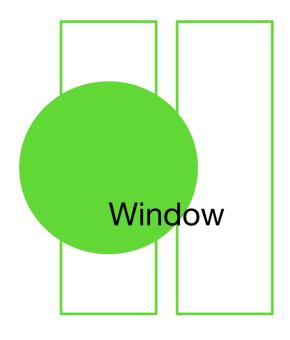
| | Inner | Left Outer | Right Outer | Full Outer |
|-----------|--------------|--------------|--------------------|------------|
| KSQL | S | S | NS | NS |
| Flink SQL | S | S* | S* | S* |
| SSS | S, Stateless | S, Stateless | NS | NS |

Table 2: Stream-Static Joins. [S]upported, [N]ot[S]upported. S*, Flink memory usage might grow indefinitely, Temporal Tables can be used to avoid it.

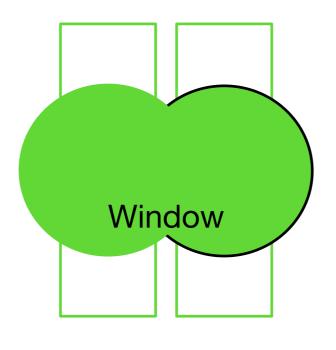
Stream-Stream Joins

- Inner Joins
- Left-Outer Join
- Right-Outer Join
- Full-Outer Join

Stream-Table Joins



Left Outer



Window

Right Outer

Full Outer

Flink SQL Inner Join

SELECT * FROM IMPRESSIONS, CLICKS
WHERE IMPRESSION_ID = CLICK_ID AND
CLICK_TIME BETWEEN IMPRESSION_TIME - INTERVAL
'1' HOUR AND IMPRESSION_TIME

Spark Structured Streaming Inner Join val impressions a spark read Structured

val clicks = spark.readStream. ...

// Apply watermarks on event-time columns

val imprWithWtmrk = impressions.withWatermark("impressionTime", "2 hours")

val clicksWithWatermark =

clicks.withWatermark("clickTime", "3 hours")

Val imprWithWtmrk.join(clicksWithWatermark, expr(""" clickAdId = impressionAdId AND clickTime >= impressionTime AND clickTime <= impressionTime + interval 1 hour"""))

Recap

| | Inner | Left Outer | Right Outer | Full Outer |
|-----------|--------|---------------|----------------|------------|
| KSQL | S, win | S, win | S, win | S, win |
| Flink SQL | S | S* | S* | S* |
| SSS | S | S + w on left | S + w on right | NS |

Table 3: Stream-Stream Joins. [S]upported, [N]ot[S]upported, [W]atermark, [Win]dow. S*, Flink memory usage might grow indefinitely.

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- Introduction on Stream Processing Models [done]
- Declarative Language: Opportunities, and Design Principles [done]
- Comparison of Prominent Streaming SQL Dialects for Big Stream Processing Systems [done]
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DEMO

KSQL and Flink

survey of spark structured streaming notebook