SQL on Data Streams

Flink SQL Training

https://github.com/ververica/sql-training

ververica

Streams & Dynamic Tables

SQL Was Not (Originally) Designed for Streaming Data

Table are bounded multisets.	↔	Streams are infinite sequences.
DBMS queries can access all data.	↔	Streaming queries receive data over time.
DBMS queries return a finite result.	↔	Streaming queries continuously emit results and never complete.

Database Systems Run Queries on Streams

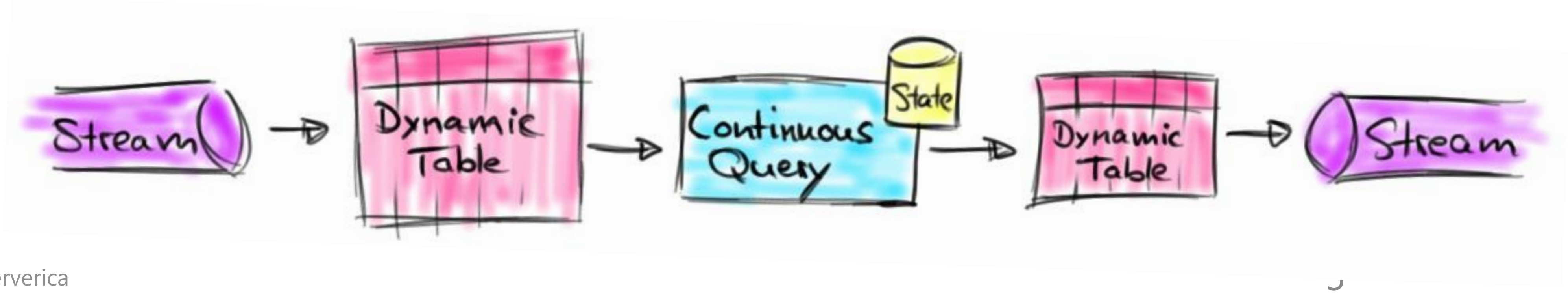
- Materialized views (MV) are similar to regular views, but persisted to disk or memory
  - Used to speed-up analytical queries
  - MVs need to be updated when the base tables change
- MV maintenance is very similar to SQL on streams
  - Base table updates are a stream of DML statements
  - MV definition query is evaluated on that stream
  - MV is query result and continuously updated

Continuous Queries in Flink

- Core concept is a *"Dynamic Table"*
  – Dynamic tables are changing over time

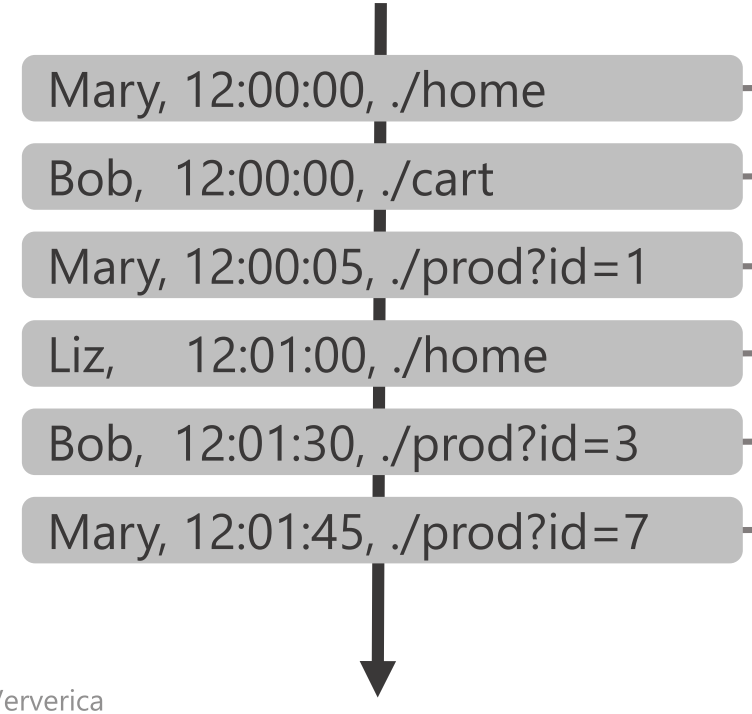
- Queries on dynamic tables
  – produce new dynamic tables (which are updated based on input)
  – do not terminate

- Stream ↔ Dynamic table conversions



Stream → Dynamic Table: Append

- Append mode
  - Stream records are appended to table
  - Table grows as more data arrives



user	cTime	url
Mary	12:00:00	./home
Bob	12:00:00	./cart
Mary	12:00:05	./prod?id=1
Liz	12:01:00	./home
Bob	12:01:30	./prod?id=3
Mary	12:01:45	./prod?id=7
…	…	

Querying a Dynamic Table

clicks		
user	**cTime**	**url**
Mary	12:00:00	./home
Bob	12:00:00	./cart
Mary	12:00:05	./prod?id=1
Liz	12:01:00	./home
Liz	12:01:30	./prod?id=3
Mary	12:01:45	./prod?id=7

```
SELECT user
FROM clicks
WHERE url = './home'
GROUP BY user
```

result
user
Mary
Liz

Rows of result table are appended.

Querying a Dynamic Table

clicks

user	cTime	url
Mary	12:00:00	./home
Bob	12:00:00	./cart
Mary	12:00:05	./prod?id=1
Liz	12:01:00	./home
Liz	12:01:30	./prod?id=3
Mary	12:01:45	./prod?id=7

```
SELECT
  user,
  COUNT(url) as cnt
FROM clicks
GROUP BY user
```

result

user	cnt
Mary	3
Bob	1
Liz	2

Rows of result table are updated.

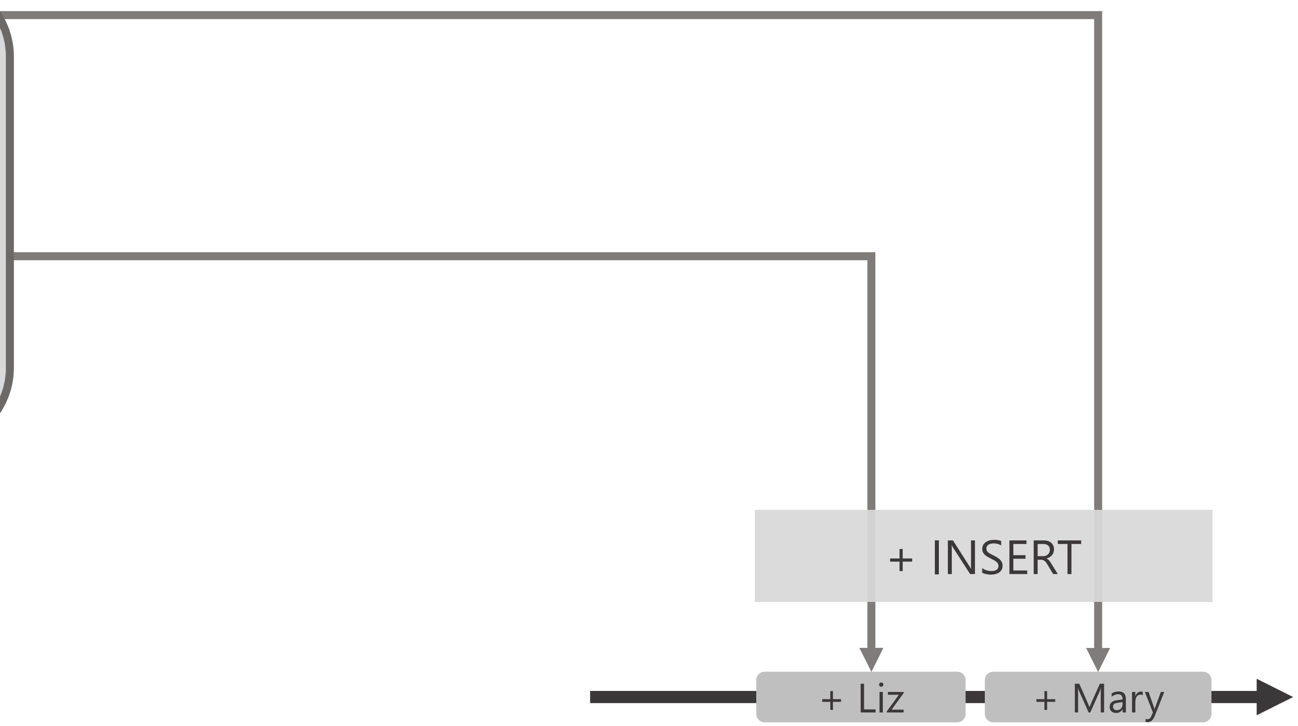
Dynamic Table → Stream

- Converting a dynamic table into a stream
- Dynamic tables might update or delete existing rows
- Updates must be encoded in outgoing stream

Dynamic Table → Stream: Append-only

clicks	
user	**url**
Mary	./home
Bob	./cart
Mary	./prod?id=1
Liz	./home
Bob	./prod?id=3

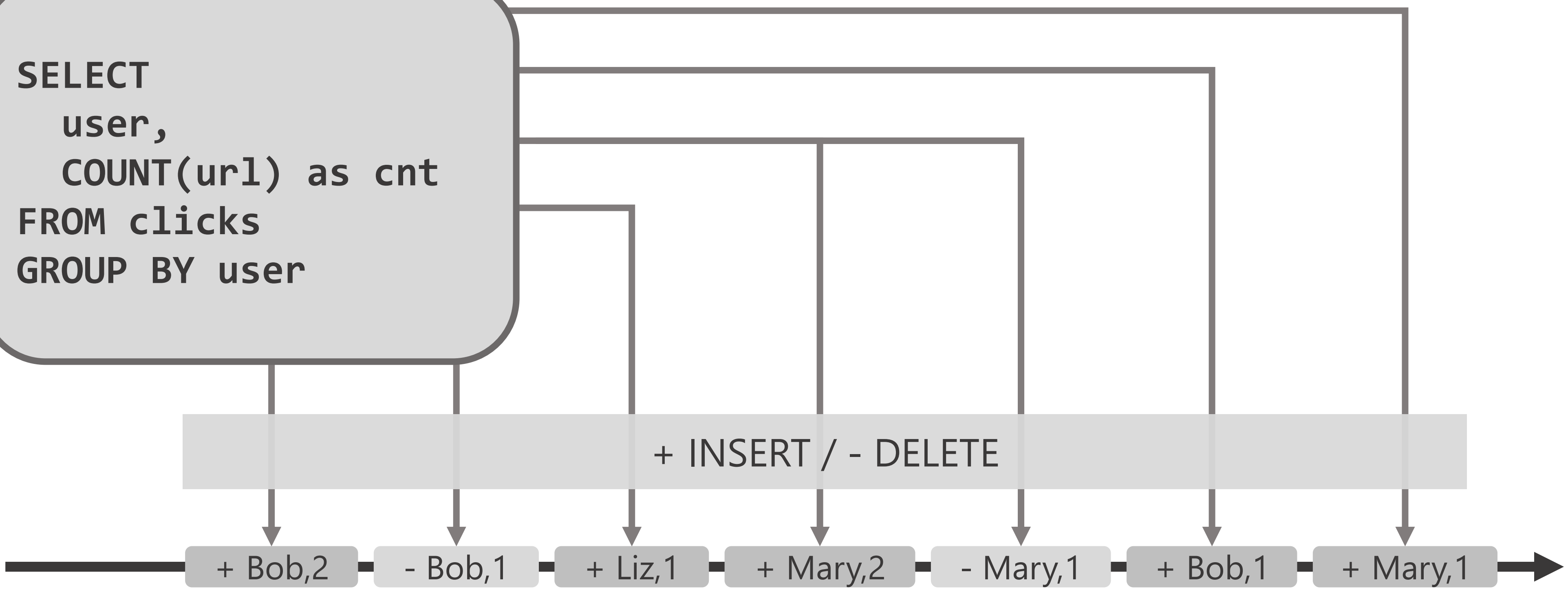
```
SELECT user
FROM clicks
WHERE url = './home'
GROUP BY user
```



Dynamic Table → Stream: Retraction

clicks	
user	**url**
Mary	./home
Bob	./cart
Mary	./prod?id=1
Liz	./home
Bob	./prod?id=3

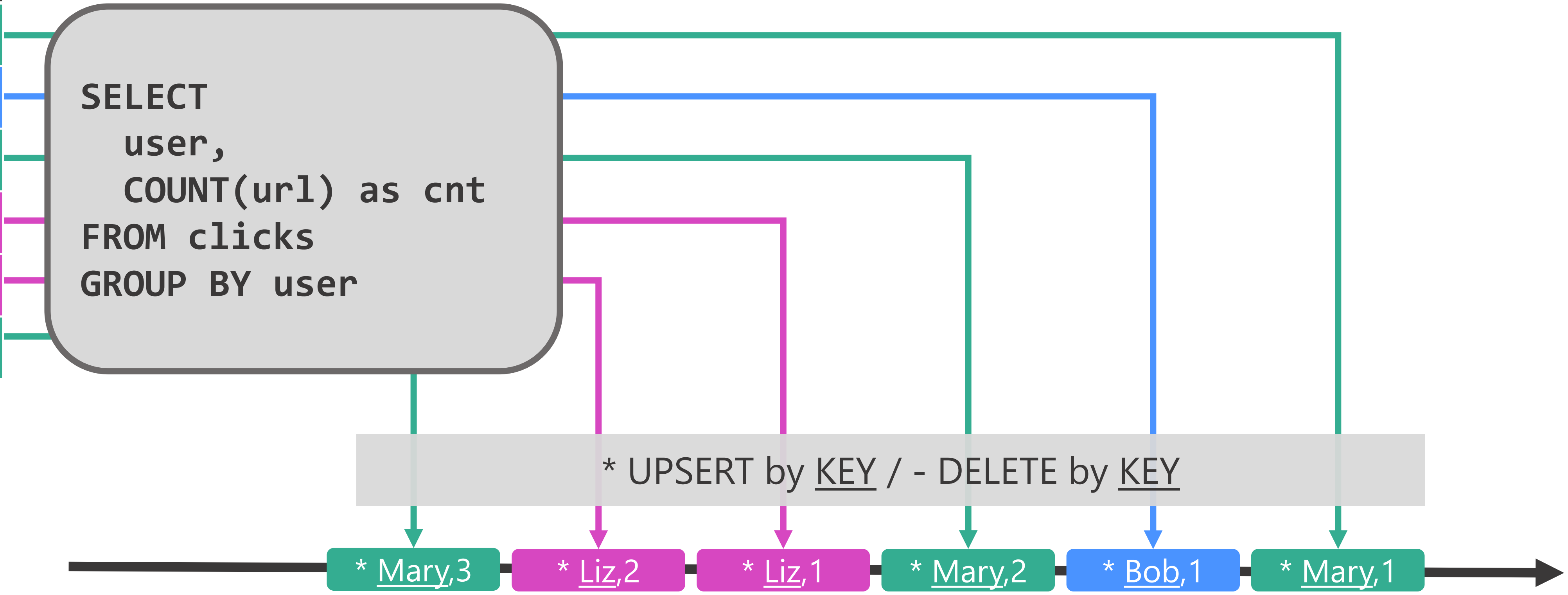
```sql
SELECT
  user,
  COUNT(url) as cnt
FROM clicks
GROUP BY user
```



Dynamic Table → Stream: Upsert

clicks	
user	**url**
Mary	./home
Bob	./cart
Mary	./prod?id=1
Liz	./home
Liz	./prod?id=3
Mary	./prod?id=7

```
SELECT
  user,
  COUNT(url) as cnt
FROM clicks
GROUP BY user
```



Summary

- Streams are interpreted as changelog for a Table
  - Flink 1.7 supports append-only stream to table conversion
  - Upsert and Insert/Update/Delete conversions are on the roadmap
- SQL queries on dynamic tables yield another dynamic table
  - Input and query determines whether resulting dynamic table is append-only or updating
- Dynamic tables can be converted back into streams
  - Append-only, Upsert, or Retraction

Event & Processing Time

How Is Time Handled in Flink SQL?

- Flink SQL supports Event and Processing Time
- Tables may include *Time Attributes*
  - Time Attributes provide access to event or processing time
  - Time Attributes are (mostly) treated as regular attributes
  - Time Attributes have special type extended from SQL TIMESTAMP
- Time Attributes are declared with the table schema

Event Time Attribute

- Event time attributes carry an actual timestamp

- Timestamps are extracted during table scan
  - Typically taken from an existing field

- Watermarks are generated based on the timestamps
  - Different strategies available

- Event time attributes can be used like a regular TIMESTAMP attribute
  - Event time property (and watermark alignment) are lost when it is modified

Processing Time Attribute

- Processing time attributes are virtual and do not hold data
  - Local machine time is queried on attribute access

- A processing time attribute can be used like a regular TIMESTAMP
  - Loses its processing time property when being modified

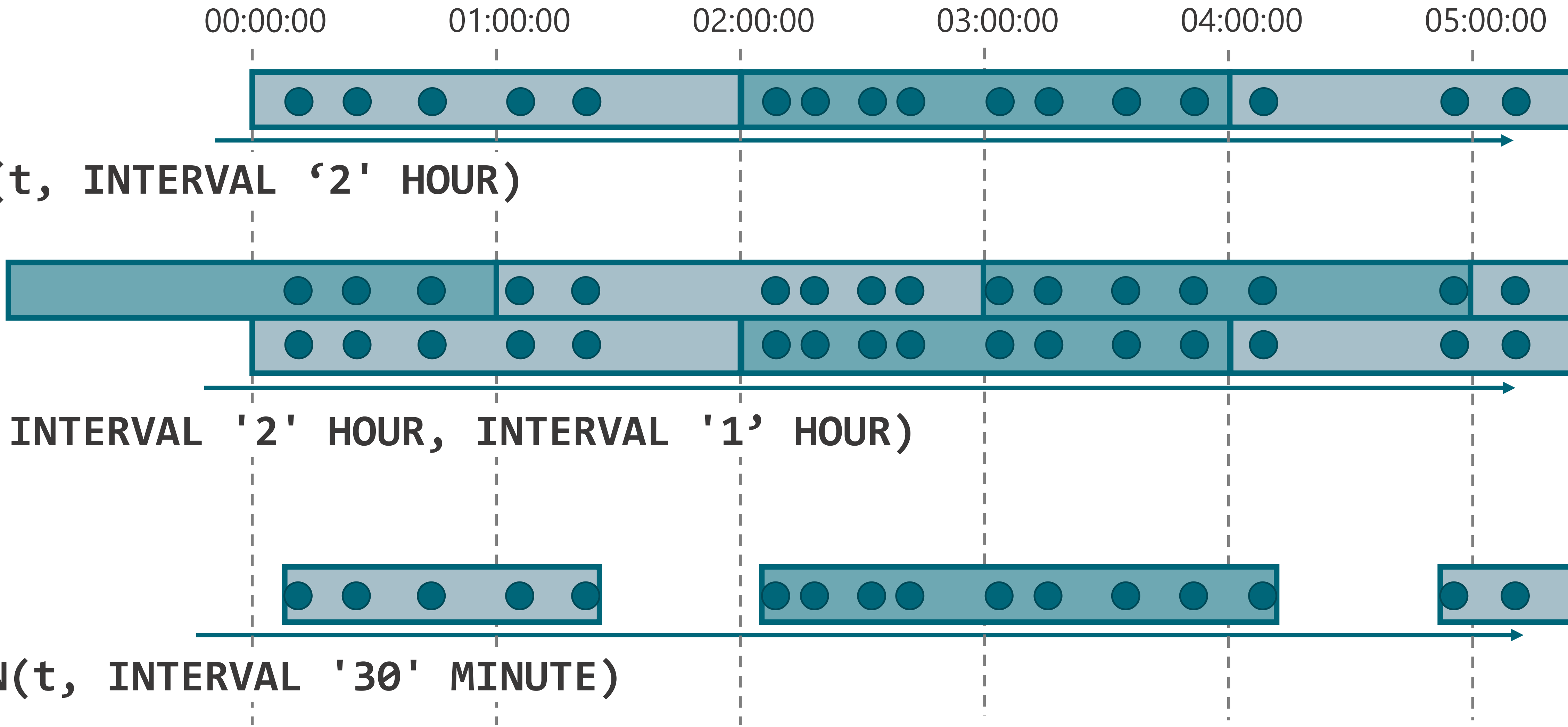
How Are Time Attributes Used?

- Some operations require time attributes in certain clauses
  - GROUP BY windows
  - OVER windows
  - Time-windowed joins
  - Joins with temporal tables

- The clicks table is used for the following examples
  - cTime (clickTime) is an event time attribute.

user	cTime	url
Mary	12:00:00	./home
Bob	12:00:00	./cart
Mary	12:00:05	./prod?id=1
…	…	…

GROUP BY Windows



TUMBLE(t, INTERVAL ‘2' HOUR)

HOP(t, INTERVAL '2' HOUR, INTERVAL '1’ HOUR)

SESSION(t, INTERVAL '30' MINUTE)

GROUP BY Window Aggregation

Compute number of clicks per hour and user

Time attribute

```
SELECT user,
       TUMBLE_END(cTime, INTERVAL '1' HOURS) AS endT,
       COUNT(url) AS cnt
FROM clicks
GROUP BY TUMBLE(cTime, INTERVAL '1' HOURS),
         user
```

Time attribute

GROUP BY Window Aggregation

clicks		
user	**cTime**	**url**
Mary	12:00:00	./home
Bob	12:00:00	./cart
Mary	12:02:00	./prod?id=2
Mary	12:55:00	./home
Bob	13:01:00	./prod?id=4
Liz	13:30:00	./cart
Liz	13:59:00	./home
Mary	14:00:00	./prod?id=1
Liz	14:02:00	./prod?id=8
Bob	14:30:00	./prod?id=7
Bob	14:40:00	./home

```
SELECT
 user,
 TUMBLE_END(
   cTime,
   INTERVAL '1' HOURS)
  AS endT,
  COUNT(url) AS cnt
FROM clicks
GROUP BY
 user,
 TUMBLE(
  cTime,
  INTERVAL '1' HOURS)
```

result		
user	**endT**	**cnt**
Mary	13:00:00	3
Bob	13:00:00	1
Bob	14:00:00	1
Liz	14:00:00	2
Mary	15:00:00	1
Bob	15:00:00	2
Liz	15:00:00	1

Rows are appended to result table.

OVER Window Aggregation

Compute for each click
how often the URL was clicked in the previous 10 minutes

```
SELECT
  user,
  url,
  COUNT(*) OVER (
    PARTITION BY url
    ORDER BY cTime
    RANGE BETWEEN INTERVAL ’10’ MINUTE PRECEDING AND CURRENT ROW)
FROM clicks
```

Time attribute

Why Are Time Attributes Special?

- Time attribute values are (quasi) monotonously increasing

- Operators know when rows are no longer needed
  - Watermarks (event time) or wall-clock time (processing time)

- Time-based operators automatically prune their state
  - Only hold the relevant “tail” of the stream is kept in state

Time Attributes and Non-Windowed Operators

- Non-windowed aggregations and joins do not forward time attributes
  - Window operators cannot be applied on their results!

- Non-windowed join does not preserve timestamp order
  - Any row in the state could be join with any new arriving row
  - Order of time attributes is not maintained
  - Non-windowed joins must not emit time attributes.

- Non-windowed aggregation does not forward time attributes
  - Time attributes are converted to regular TIMESTAMP attributes and lose their property
  - `SELECT cTime, COUNT(*) FROM clicks GROUP BY cTime`
    - `cTime` is regular `TIMESTAMP`
  - `SELECT user, MAX(cTime) AS cTime FROM clicks GROUP BY user`
    - `cTime` is regular `TIMESTAMP`

Time Attributes and Batch Processing

- Porting SQL queries from streaming to batch or vice versa

- Queries on event time attributes
  - Batch table requires time attribute of type TIMESTAMP

- Queries on processing time attributes
  - Not supported by batch queries
  - What would be the semantics anyway?

Queries & State

Stateless and Stateful Operators

- Stateless operators
  - Filter
  - Projection
- Stateful streaming operators
  - Window Aggregation (GROUP BY, OVER)
  - Window Joins
- Stateful materializing operators
  - Aggregation
  - Joins

Stateful Materializing Operators

- Materializing operators may never remove state

- The aggregation needs to maintain a count for every user forever.
  - Every user could click at any point in time

- The aggregation state is continuously growing
  - Unless key domain is bounded

- Joins need to materialize all input rows in state

```
SELECT
  user,
  COUNT(url) as cnt
FROM clicks
GROUP BY user
```

Managing State Size

- Query state might grow indefinitely
- Slowly growing state can be addressed by scaling the query
  - `SELECT user, COUNT(*) FROM logins GROUP BY user;`
- State can be automatically pruned
  - `SELECT session, COUNT(*) FROM clicks GROUP BY session;`
  - Rows and persisted results can be removed after an idle timeout

Idle State Clean UP

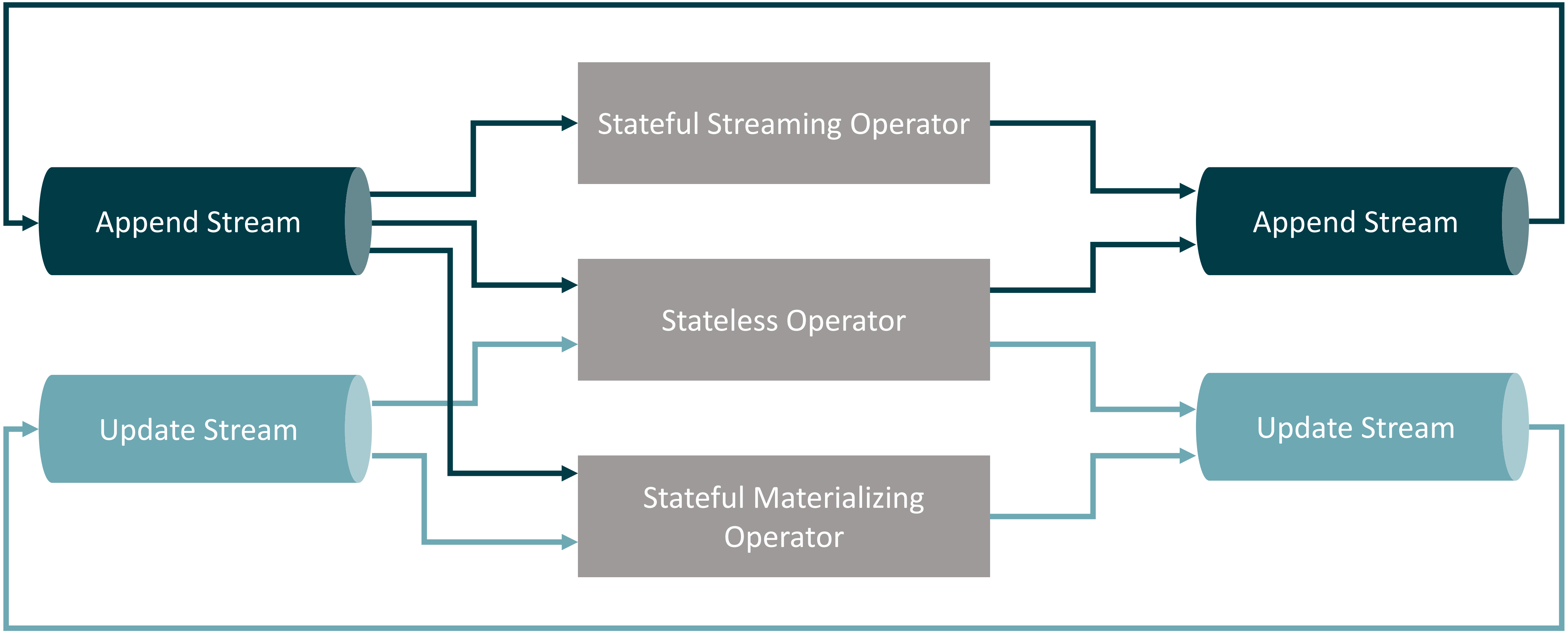
- The query result is not updated when state is removed
- Query result remains consistent if removed state is not needed again
- Query result becomes inconsistent if query needs to access state that was removed!
- Trade the accuracy of the result for size of state

Appending and Updating Input and Output

- Stateful materializing operators may produce updates
  - All required state is available
  - Previous input can be updated
  - Results can be updated

- Stateful streaming operators cannot handle updates
  - State is evicted based on time
  - Results cannot be updated because state might be gone

Append And Update Input and Output



Summary

Summary

- Query Evaluation on Dynamic Tables
  - Stream -> Dynamic Table -> Stream conversions
  - append-only, update, retraction
- Event-Time and Processing-Time in SQL
  - Time attributes & windowed operators
- Queries and State
  - State management and automatic clean up

Hands On Exercises

Running Queries on Streams

Continue with Session 4
"Running Queries on Streams"
in the SQL training wiki:

https://github.com/ververica/sql-training/wiki

We are here to help!

www.ververica.com

@VervericaData