SQL ON DATA STREAMS

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STREAMS & DYNAMIC TABLES

SQL WAS NOT DESIGNED FOR STREAMS

• 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.

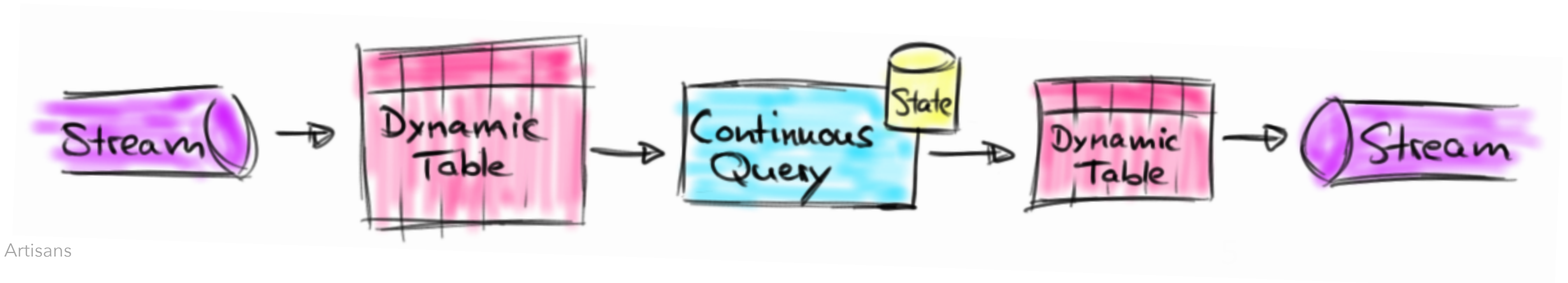
DATABASE SYSTEMS RUN QUERIES ON STREAMS

- 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

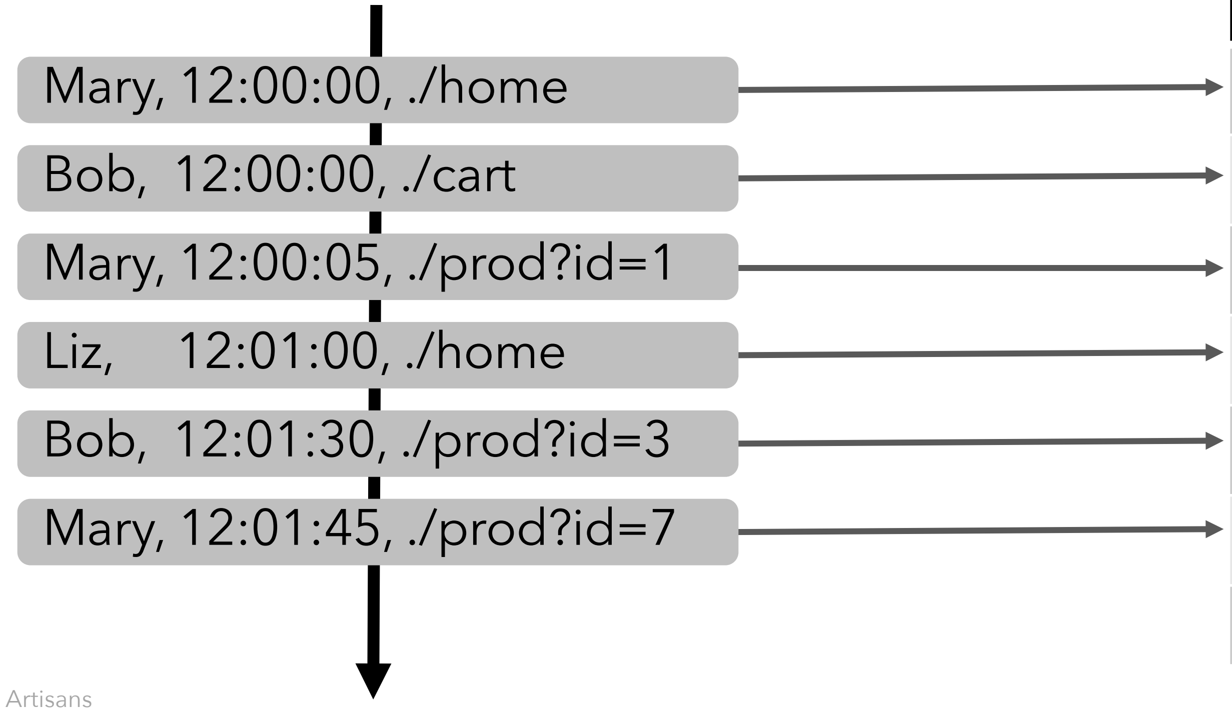
CONTINUOUS QUERIES IN FLINK

- 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



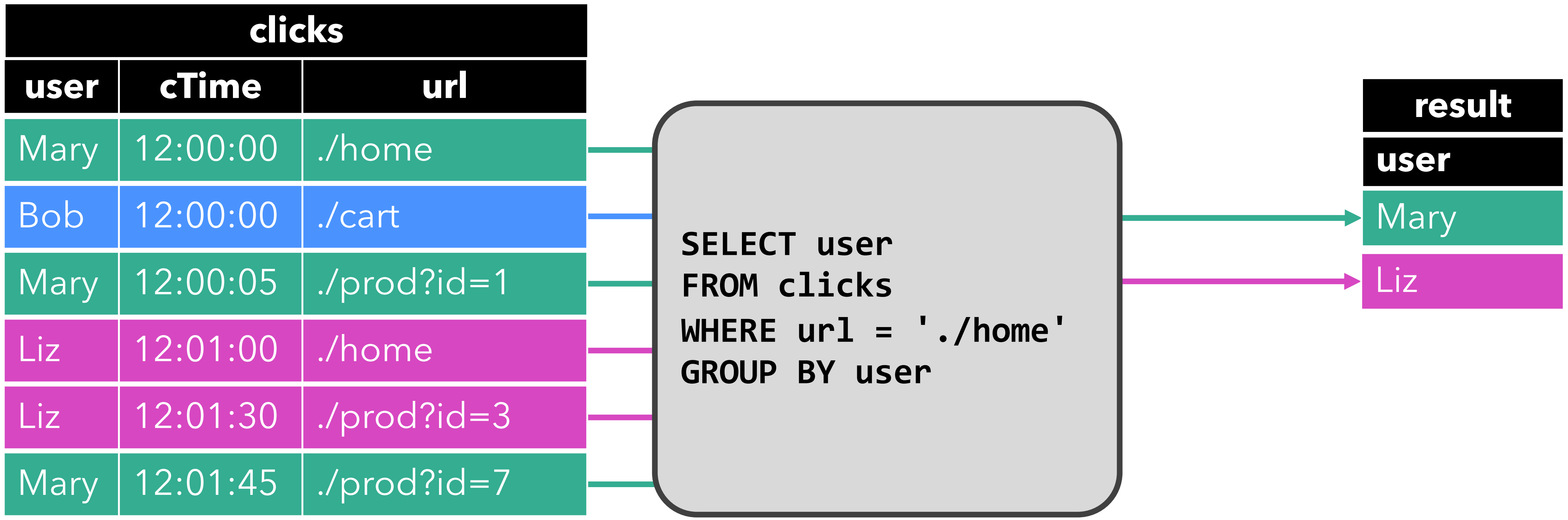
STREAM → DYNAMIC TABLE: APPEND

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


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

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



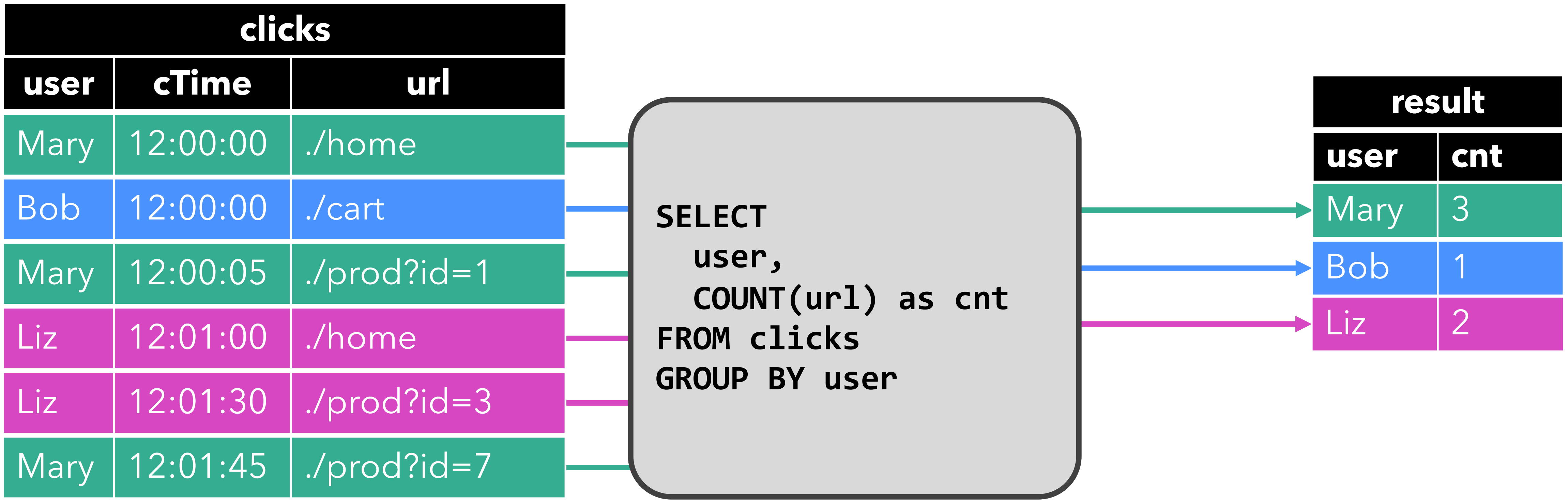
clicks		
user	**cTime**	**url**
Mary	12:00:00	./home
Bob	12:00:00	./cart
Mary	12:00:05	./prod?id=1
Liz	12:01:00	./home
Liz	12:01:30	./prod?id=3
Mary	12:01:45	./prod?id=7

```
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

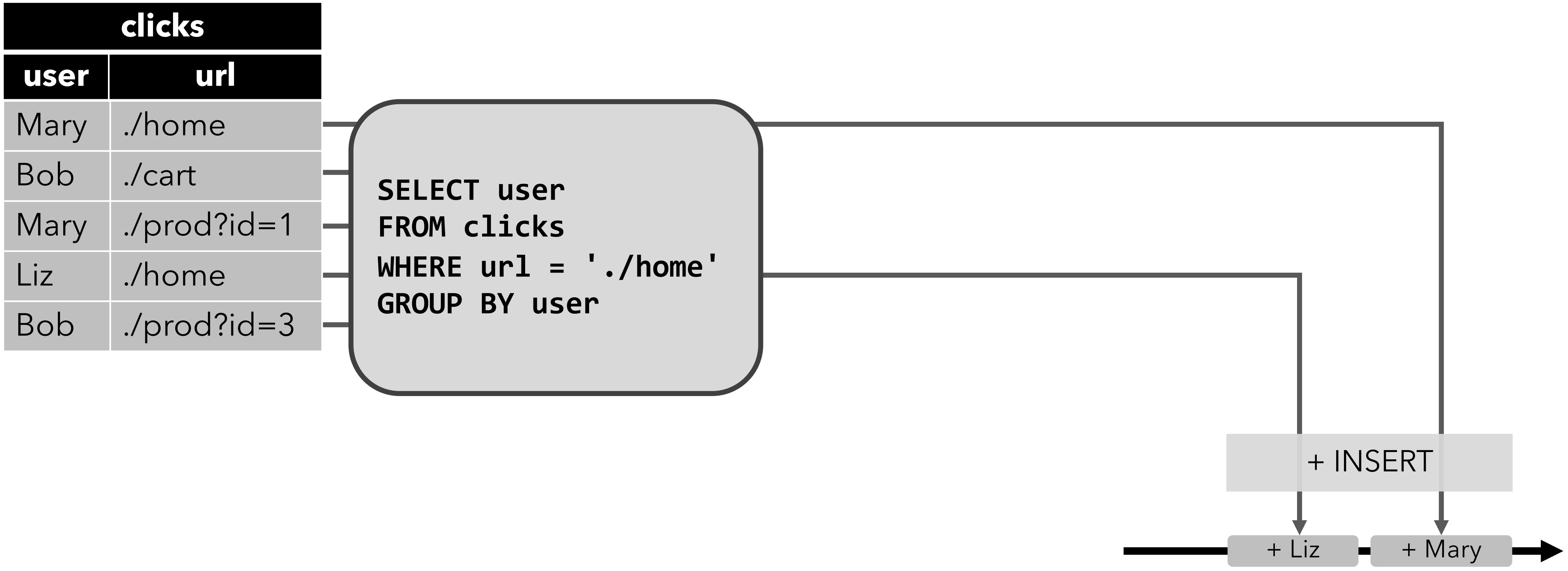
user	cnt
Mary	3
Bob	1
Liz	2

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

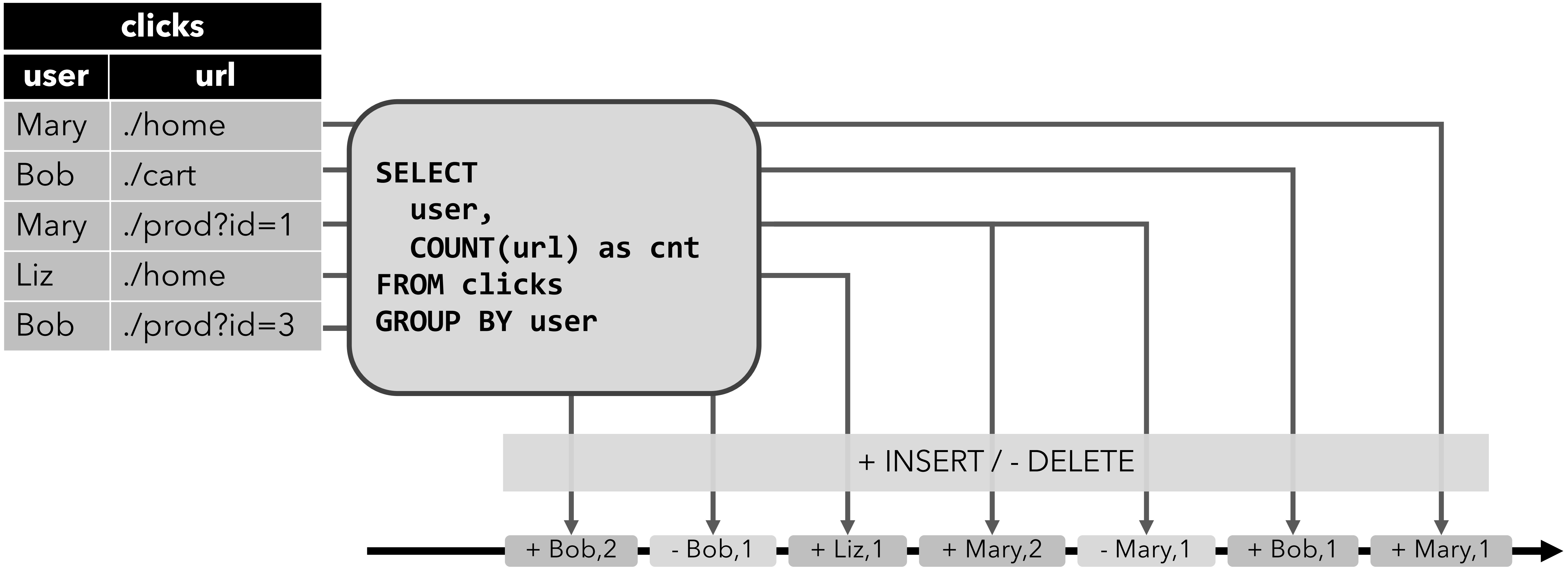
DYNAMIC TABLE → STREAM: APPEND-ONLY



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
```

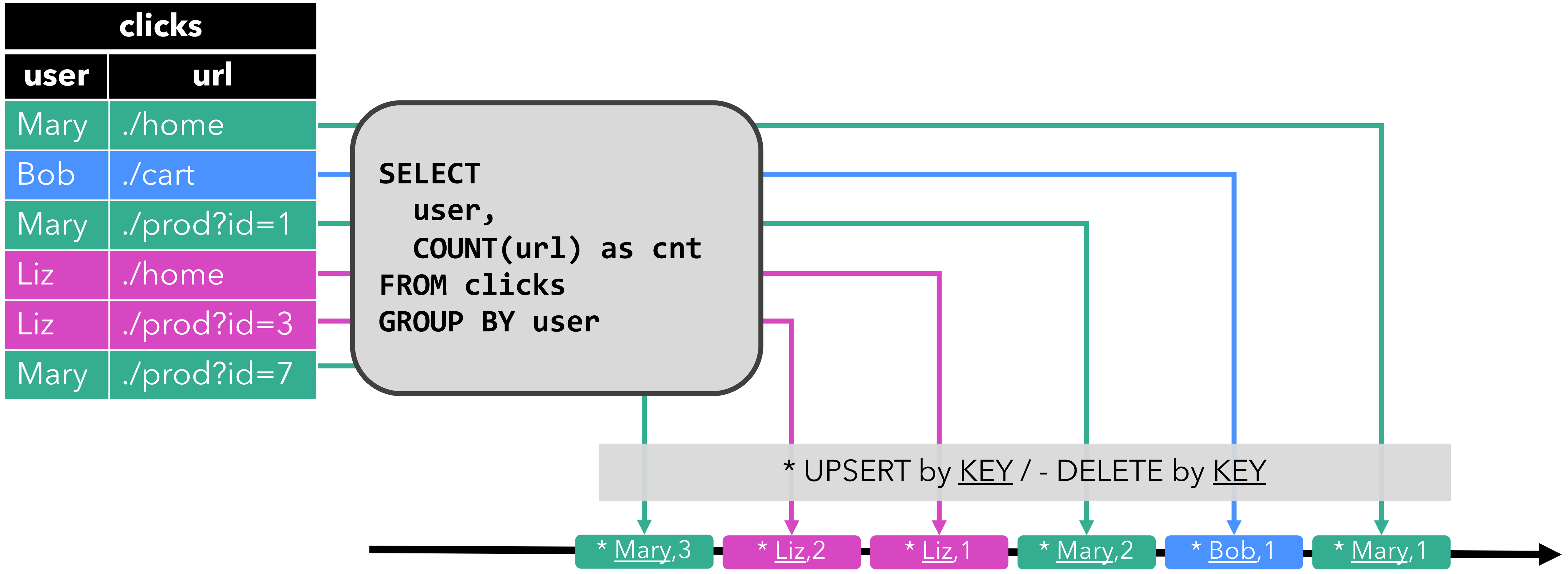
DYNAMIC TABLE → STREAM: RETRACTION



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

```
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 1.6.0 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
  - Event time property (and watermark alignment) are lost when being modified

PROCESSING TIME ATTRIBUTE

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

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

HOW ARE TIME ATTRIBUTES USED?

- Some operators require time attributes in certain clauses
  - GROUP BY windows
  - OVER windows
  - Time-windowed joins

- 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 WINDOW AGGREGATION

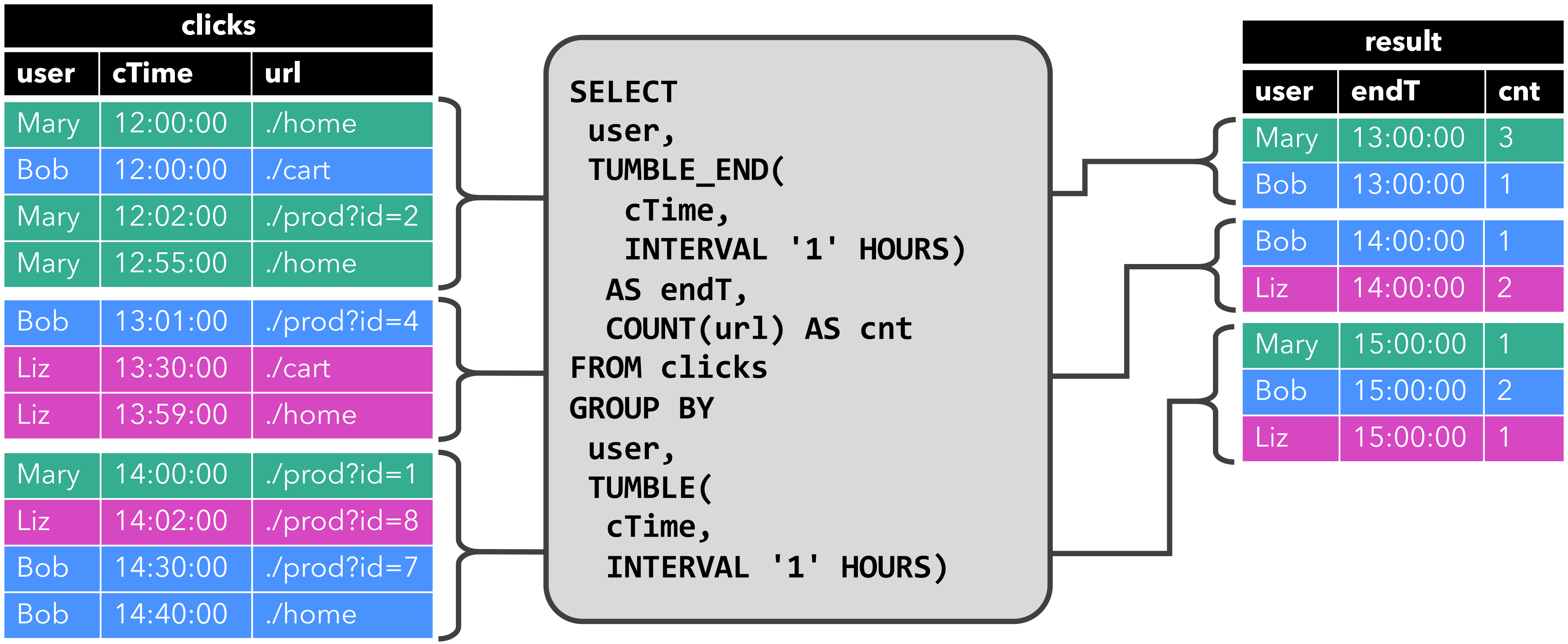
- Compute number of clicks per hour and user

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

TIME-WINDOWED JOIN

- Find all product URLs that were clicked by a user less than 5 seconds after being served.
  - Assuming a table `serves` with an event time attribute `sTime`

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

```
SELECT url
FROM clicks c, serves s
WHERE s.url LIKE ‘./prod%’ AND
      s.url = c.url AND
      s.user = c.user AND
      c.cTime BETWEEN s.sTime AND s.sTime + INTERVAL ‘5’ SECOND
```

Time attributes

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 AND 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

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

- The aggregation state is continuously growing
  - Unless key domain is bounded
- Joins need to materialize all input rows in state

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

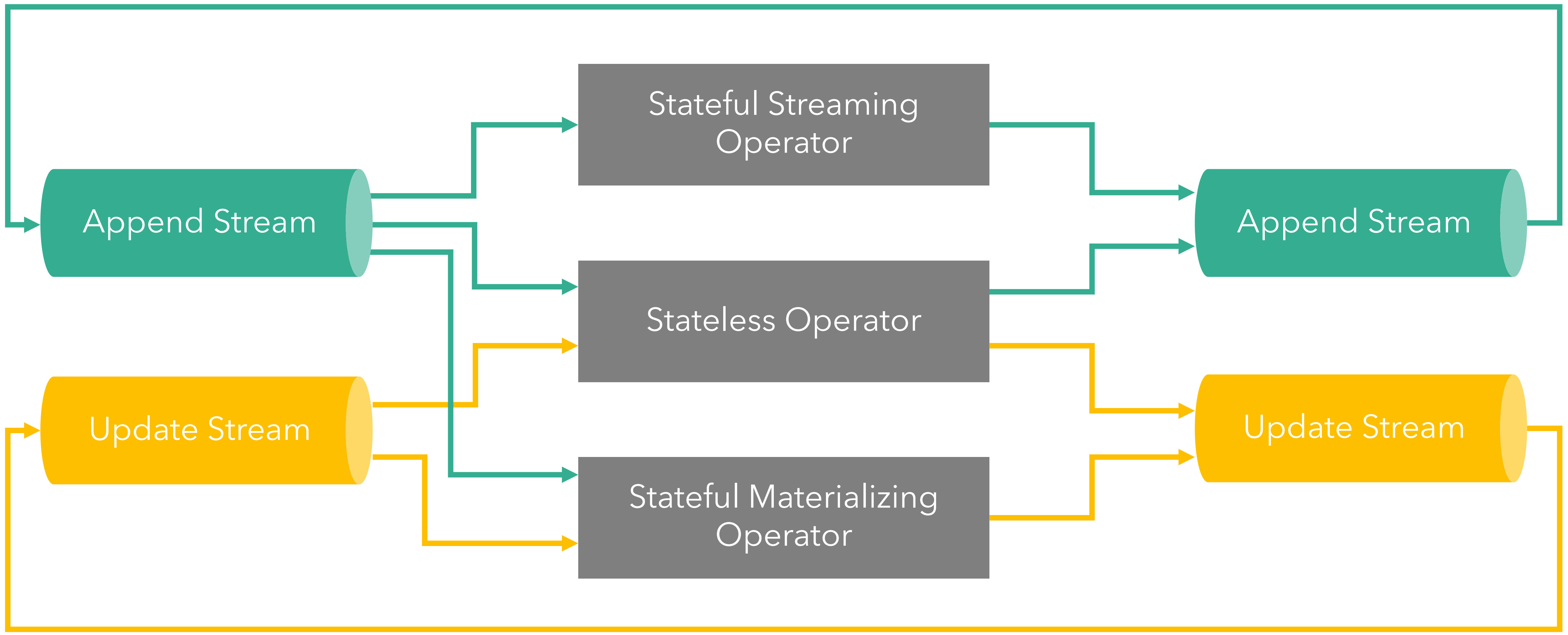
- The query result is not updated when state is removed
- Query result remains consistent if removed state is not needed again
- Query result becomes inconsistent if query needs to access state that was removed!
- Trade the accuracy of the result for size of state

APPEND AND UPDATE 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



OTHER CONSTRAINTS?

- A change of an input table may only trigger a partial re-computation of the result table

```
SELECT user, RANK() OVER (ORDER BY lastLogin) FROM users;
```

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

RUNNING QUERIES ON STREAMS

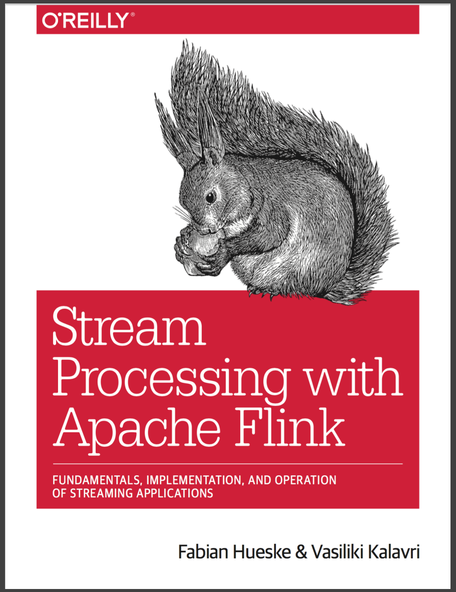
Continue with Session 4 "Running Queries on Streams"
in the SQL training wiki:

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

We are here to help!

THANK YOU!

@fhueske
@dataArtisans
@ApacheFlink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